Investigations into relationships between climate, crop production and migration in Malawi

A thesis submitted for the degree of Doctor of Philosophy

by

Rebecca Clare Parrish

Department of Life Sciences
College of Health, Medicine and Life Sciences
Brunel University London

June 2024

Author Note: This research was funded by the London NERC DTP under grant code NE/L002485/1

Abstract

Across the world, climate change is affecting migration patterns through changes to natural resources and people's livelihoods. In Malawi, the developing agrarian economy is particularly vulnerable to climate change through changing crop production and food security, which may ultimately drive people to migrate in search of alternative income sources.

Critical examination of literature yielded a conceptual model for 'climate migration'. This model was then applied to the case study of Malawi and used to inform a set of regression models for a number of system compartments. Models utilised data from Malawi's periodic Integrated Household Surveys (IHS) to examine associations between various predictor variables and crop production, food security and migration outcomes. By isolating the climate change signal, a negative relationship was also found between crop production and maximum temperature anomaly. Significant relationships were identified between maximum temperature and a small decrease in odds of prolonged hunger. However, studying the years preceding a household survey did not identify any relationship with crop production during survey years, nor did a multi-level crop production model identify any association with a range of climate variables. Sociodemographic predictors were found to be highly significant, including, gender, household wealth and farm size. Modest relationships were identified between migration status and food security metrics. In general, non-migrants were found to experiencing higher food insecurity than migrants though high district variation was uncovered. Prolonged hunger was associated with increased migration odds.

These modest findings also challenge popular narratives which may over-assert the current known role of climate change as a driver of migration. Further research is recommended particularly focusing on a range of rainfall data, extreme events and a wider range of agro-climatic variables. More detailed migration data is also called for to better understand these relationships. Variables should be explored as both drivers of migration as well as impeding migration through a 'trapping effect'.

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List of Abbreviations

ABM	Agent Based Modelling
BIASS	Bipartisan Ideological Awareness in Social Sciences
BIC	Bayesian Information Criterion
CMIP6	Sixth phase of the Coupled Model Inter-comparison Project
EBPM	Evidence Based Policy Making
EICC	Ecological Impacts of Climate Change
EKC	Environmental Kuznets curve
FAO	Food and Agricultural Organization of the United Nations
FCS	Food Consumption Score
FEWSNET	Famine Early Warning System Network
FISP	Farm Input Subsidy Program
GCM	General Circulation Model
GCM	Global Compact for Migration
GCR	Global Compact for Refugees
HDDS	Household Dietary Diversity Score
IHS	Integrated Household Survey
IHPS	Integrated Household Panel Survey
IPCC	Intergovernmental Panel on Climate Change
KHDSS	Karonga Health and Demographic Surveillance System
LCBCCAP	Lake Chilwa Basin Climate Change Adaptation Project
LGP	Length of Growing Period
LSMS	Living Standards Measurement Survey
MHM	Migration and Health in Malawi study
MLSFH	Malawi Longitudinal Study of Families and Health
NDVI	Normalised Difference Vegetation Index
NSO	National Statistics Office (of Malawi)
PC	Principal Component
PCA	Principal Component Analysis
PDSI	Palmer Drought Severity Index
SADC	Southern African Development Community
SE	Standard error
SSP	Shared Socioeconomic Pathway
VIF	Variance Inflation Factor

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Author's Declaration

I declare that all the material contained in this thesis is my work.

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I declare that while registered as a candidate for the University's research degree, I have not been a registered candidate or an enrolled student for another award of the University or other academic or professional institution.

The funding of this research has been done through the London NERC Doctoral Training Programme (DTP) under grant code NE/L002485/1.

I confirm that I have undertaken the programme of related studies in connection with the
programme of research following the requirements of my research degree registration.

Acknowledgements

Preparing this thesis has not been an easy task and has been a long time in the making. It is no overstatement to say that it would not have been possible without the love and support of many people. Whilst some have contributed to this thesis directly through their tutelage, patience and wisdom, many others have also contributed through their support and friendship. I thank you all so much for believing in me, for helping me and for showing me kindness.

Heartfelt thanks go to my supervisors, Ariana Zeka and Tim Colbourn. Thank you for your endless patience and excellent guidance. I also give thanks to my fantastic, wider supervisory team: Shakoor Hajat, Paolo Lauriola, and Giovanni Leonardi and to Carina King, Grassman 'Sweet Papaya' and Congo for your help in making my Malawian travels so successful. Other academics who have kindly donated time and mentoring to whom I am very grateful include Ilan Kelman, Calum Nicholson, Zaid Chalabi, Eileen Cox, Mark Maslin, Derek Groen. I thank my MSc and BSc tutors who first set me on this path: Mike Tennant, Jan Zika and Arnaud Czaja. I also am so thankful to everyone in the Brunel PGR and Finance teams, especially Maria Webb, Edwin Routledge and Alice Baynes, and to the DTP administrative staff for all their support. To everyone at NERC, IOM, and CSaP, thank you for giving me such excellent work opportunities and support along the way.

To my incredible family, thank you for believing in me, supporting my dreams (however daft), and for giving me so much in my life. It is unquestionable that without you I never would be where I am today. I can never say thank you enough for everything you have given me in life. And to Mrs. Harlow, thank you for teaching me how to be kind, and to believe in myself.

And to the countless friends who have helped me along the way, despite self-doubt I've found I've always been good enough for you, and your support means a lot. Special shout outs to Jas for his excellent proof-reading. Thank you also to Zuoyi, James, Becki, Chandra, Fuen, Alwyn, Alex, Peter, Sam, Abbi, Phil, Duncan, Seonaid, Chaz and the entire JCL gang, Manuel, Alvaro, and to Virginia, Elder and everyone at Salsateca! To my fellow PhD students at Brunel, IGH and from the London NERC DTP, I am so thankful for your comradery, support and the very many laughs. I wish you all the best in your post-PhD lives!

I'd also like to thank my friends and current colleagues at Mott MacDonald for your understanding and support in creating a healthy work-life balance. And finally, to all those I may not be in contact with anymore but who helped me on my way and taught me so much: Julie, Sharon, Mark and all my friends from EY. Thank you. Zikomo abwenzi!

1 INTRODUCTION

1.1 CHAPTER OBJECTIVES

The aim of this thesis is to explore the impacts of climate change on the migration patterns of people, referred to hereafter as 'climate migration', within Malawi. The overarching hypothesis that will transect this thesis is that climate change impacts migration through a variety of pathways as demonstrated in Figure 1.4 and as described further in section 1.2 below.

The thesis will investigate this hypothesis via a critical analysis of climate migration literature and through a range of exploratory analyses and epidemiological models. More specifically, this thesis will address the hypothesised links between climate change and migration through the following research objectives:

1) To conduct a critical literature review of the drivers of migration in the context of climate change.
2) To investigate how climate change can impact crop production and food security in Malawi using three cross-sectional studies from Malawi's Integrated Household Surveys (IHS).
3) To investigate the determinants of internal migration within Malawi, considering climate as both a direct and indirect driver.
4) To discuss the implications of these research findings for the field of climate migration and to provide critical insights into popular climate migration narratives and for policy-making.

The objectives of this chapter are to introduce the field of climate migration and the context of Malawi, and to provide a high-level critique of existing literature across a range of epistemologies. This critique will identify both research gaps and key advantages and shortcomings of different methodological approaches. Finally, this critique will inform the hypotheses and approaches that shall be explored in subsequent chapters with consideration for how this these approaches will help address the gaps identified.

1.2 AN INTRODUCTION TO THE FIELD OF CLIMATE MIGRATION

The academic field of climate migration has a relatively short yet fascinating history, peppered with scientific, public and political milestones and challenges. Throughout history, migration has been presented as both a normative behaviour and as a response to environmental change (Warner et al., 2010). Indeed, climate-driven ecological change has been a driving force for the dispersion of humans ever since their emergence over 150,000 years ago (Finlayson, 2005). Fast forward to modern times, migration continues to be a normative process for many, interjected with numerous periods of mass internal and international migrations due to a combination of socio-economic, political, and environmental drivers. Recent examples include the many millions of people displaced following World War II - many of whom became recognised as refugees under the newly formed UN Convention Relation to the Status of Refugees (the Geneva Convention) of 1951; mass refugee crises in the aftermath of decolonisation efforts across the African continent (Anthony, 1991); and more recently, the Syrian war (Kelley et al., 2015); the 2014 'crisis' of Central American immigrants seeking asylum in the US (Abdou, 2020); and the ongoing (2022) war in Ukraine (UNHCR, 2022).

Internal migration often does not gain the popular or scientific spotlight that international migration does, however it is well recognised that internal migration is an important response to environmental, economic and social stimuli. Internal migration numbers are increasing due to national urbanisation and development trends – the mobility transition curve (Zelinksy 1971), as well as increased displacement due to conflict or environmentally-related disasters such as hurricanes and floods. (In)famous examples of internal migration include during the 1930s North American dust bowl (Alexeev, Good and Reuveny, 2005), the 1984-85 Ethiopian famine, which led to 2.5million people to be internally displaced, as well as 400,000 people to cross borders, and the death of as many as 1.2 million (Schewel and Asmamaw 2021). Further complicating migration dynamics in this case study was one of the Federal government's response which forced the resettlement of 600,000 Ethiopians from the Northern regions as a famine relief measure, though it may also have had counter-insurgency motives (DeWaal 1991). Recently, the 2022 floods of

Pakistan, affected a third of the country (Amin et al., 2023) and internally displaced over 8 million people (IDMC, 2023).

Adding to the complexities of internal migration research is the challenge of identifying and tracking the numbers of affected persons. For example, following the 2005 hurricane Katrina, it is estimated that even two years after the event, roughly a third of pre-Katrina residents of New Orleans had not returned, though this number is highly contested, little studied and their current whereabouts remains unknown (Fussell, Sastry and Vanlandingham, 2010). Environmental-related disasters account for a large proportion of internal migration and displacement. The Internal Displacement Monitoring Centre (IDMC) reported that weather-related events were responsible for 98% of all disaster displacement in 2020 (IDMC, 2021) and so it remains surprising that internal displacement receives less attention than international movements. 'Voluntary' migration as an adaptive (or maladaptive) strategy is also popularly considered as a primarily cross-border migration response, either across regions or continents (such as the European Migration 'crisis' of 2015 (Baldwin-Edwards et al., 2019)). However, internal migration is likely a more common approach (Kumari Rigaud et al., 2018). Such adaptive internal migration may include an evolution of pre-existing circular migration in line with seasonal work, semi-permanent or permanent intranational migration in search of work or to live with family, or rural-urban migration in line with the socio-economic pull of urban hubs.

It is important to note in each of these examples environmental change is never the sole driver of migration. It is widely accepted today that migration is almost unfailingly due to a myriad of interconnected, dynamic drivers. It is also widely accepted that climate change acts as a 'threat multiplier' (Cauchi et al., 2019; Dodson et al., 2020) or could even be described as an existential risk to many aspects of human health and livelihoods. For example, the 2019 Tropical Cyclone Idai which hit Mozambique and southern Malawi. Reports are unclear but various sources suggest Idai displaced between 86,976 (IDMC, 2019) and 125,000 (Humanitarian Coalition, 2019) in Malawi alone. Mester et al. (2023) estimated that climate change increased displacement risk by 2.7-3.2%, equivalent to 12 600–14 900 individuals. As such it follows that a climate change signal exists, undetectably perhaps, in all migration decisions. As the climate continues to change throughout the 21st century, it will likely serve as a threat magnifier of other migration drivers (Watts et al., 2017).

Whilst terms such as ‘climate refugee’ are not recognised legally, migration and conflict are considered key mechanisms by which climate change has become a priority on the global agenda, for example, as a global health concern (McMichael, Woodruff and Hales, 2006; McMichael, Barnett and McMichael, 2012; Burrows and Kinney, 2016; Watts et al., 2016), a security risk (Bettini, 2013), a humanitarian crisis (Gloninger, 2019) or a climate adaptation strategy (often accused of being pushed onto vulnerable communities by neoliberal agents (Felli & Castree, 2012; Lyster, 2019)).

Migration as a determinant of health, and as an intermediary step by which climate change impacts health, is a relatively new framing born out of global health literature. Emerging from ideas such as ecological public health (Bowles et al., 2013; Butler & Harley, 2010; Lang & Rayner, 2012; A. J. McMichael et al., 2006), and planetary health (Whitmee et al., 2015), it is now widely acknowledged that climate change is a major threat to global health through a number of pathways (Watts et al., 2015). More optimistically, the Lancet Countdown on Climate Change and Health reframed climate change as a global health opportunity in 2017 (Watts et al., 2017), possibly in attempt to mitigate increasingly defeatist and alarmist rhetoric. As summarised by the Lancet Countdown, a yearly tracker of key health indicators that are being affected by climate change, literature currently focuses largely on heat related impacts, infectious disease and food and water security, but migration and health has been receiving increasing consideration in recent years, (predicated on the assumption that climate change is a driver of mass migration). Recently, the Lancet Migration collaboration was launched following the Commission on Migration and Health which called for universal and equitable access to health services, acknowledging the impacts of migration on the health needs of migrant communities, as well as their ability to access healthcare (Abubakar et al., 2018; Orcutt et al., 2020).

The impacts of climate change as a threat magnifier of agricultural outputs and food security are a key pathway through which climate change is thought to affect migration patterns. However, the interlinkages between climate change, migration and food systems are complex. For some, migration can result in improved food security for both the migrant(s) and at origin, offered through remittance provided by out-migrants and resultant poverty alleviation (Adams and Page, 2005). However, there is also evidence that in certain circumstances, large scale out-migration can increase the vulnerability of the local agricultural sector and hence local food security due to reduces unsustainability of the labour force (Craven and Gartaula, 2015). Internal migration or many global south rural-rural journeys, in search of alternative livelihoods or farmland then the results have mixed success, often resulting in so-called 'sustainable migration' for alternative, improved agricultural productivity and food security (Carte, Radel and Schmook, 2019), or else resulting in reduced food security due to the challenges associated with starting a new life (Suckall, 2015). In extreme instances, It therefore follows that, depending on the existing context, the existing profile of migrant stocks and flows, the impact of climate change being experienced in situ, that the impact of climate change upon the efficacy and perceptions of migration should also vary. For example, in situations where at origin subsistence farming is becoming untenable due to climate change, then it may be the case that climate change is an added push factor for out-migration, mediated by farming techniques and household in situ adaptive capacity (Hermans-Neumann, Priess and Herold, 2017). In other situations, where climate change is exacerbating poverty traps, it may be that climate change is an added glue factor, further locking individuals or communities into immobility (Bowles, Butler and Friel, 2013).

Despite advances in conceptual thinking as well as popular narratives about so-called 'climate refugees', the evidence basis for climate migration through empirical research remains thin, with high spatial unevenness. Many geographies and communities suffer from a paucity of studies whilst others have proven to be popular 'hot spots' of interest by researchers (Piguet et al., 2018). Without a consistent and robust scientific basis for understanding the relationships between climate change and migration, and without conceptual models which are applicable to any global context (including fast-paced changes in economically developing contexts and the contexts of vulnerable peoples), policymakers, global health practitioners, and migrant and non-migrant communities may struggle to address current and emerging challenges that climate change presents.

Climate change impacts are idiosyncratic to different geographical regions. So too are the unique combination of cultural, socioeconomic, political, demographic and environment factors experienced by each community across the globe. The dynamics and interplay of each of these factors together means that the impacts on existing and emerging migration and on population health will be unique at the local level (Mcmichael et al., 2015). For this reason, climate migration has been studied in this thesis using a localised case study of Malawi. This thesis explores how climate change may be affecting migration internally within Malawi, taking a household level viewpoint, and considering how households in different districts and levels of urbanisation respond to climate stimuli.

1.3 INTRODUCING MALAWI

The southern African country of Malawi has been selected as a case study for this thesis due to its unique combination of factors; a subsistence agrarian economy, population boom, rapid urbanisation and climate change. In combination these factors present significant threats to Malawi's food security, economy and population health (Suckall et al., 2015). Malawi is also an example of a data-poor nation, for which empirical studies are sparse and hampered by a lack of high-quality or granular data with which to conduct studies.

Malawi is a landlocked, low-income nation located at the very base of the Great Rift Valley. The country is 118,480 km^2 of which roughly 40% is arable and roughly one third is covered by Lake Malawi, the ninth largest lake in the world (and home to one of the largest varieties in fish species globally!) (Turner et al., 2001). As such, Malawi's topography and climate is highly varied. The main industry of the country is subsistence level farming, relying on rain-fed crops (Chidanti-Malunga, 2011), with 85% of the population employed in subsidence, household agriculture (National Statistics Office Government of Malawi, 2020) and agricultural exports constituting 23% of the economy (World Bank, 2021). Malawi is ranked amongst the lowest income countries in the world, with 20.5% of Malawians living in relative extreme poverty (as defined by local poverty metrics, whereby extreme poverty (or 'ultra-poor') is attributed to persons whose consumption per capita is lower than Malawi's minimum food consumption metrics (National Statistics office Government of Malawi, 2021). As of 2020, 73.5% of the country were in absolutely poverty (living on less than $1.90 per day) (World Bank, 2021). Malawi is experiencing ongoing, rapid population growth, at a rate of 2.8% with estimates of a population of 48 million in the next 50 years (Kohler et al., 2015). Urbanisation is a growing trend, with the population in cities currently expanding at a rate of 4.6% per annum (National Statistics Office Government of Malawi, 2020).

Malawi's climate is sub-tropical with two distinct seasons; the wet (running November to April) when roughly 95% of the rains fall, and the dry season (May to October) (FEWS NET, 2016). Due to the highly varied topography, the northern highlands experience a more temperate climate, whilst the lowlands around Lake Malawi and the Shire Valley in the southern are distinctly hotter. Due to the varied topography, both air temperature and rainfall is largely varied across the country. Malawi is split into 19 ecological livelihood zones (Figure 1.1) defined by commonalities of geography, food production systems and markets, and 32 districts, all of which practice rainfed, smallholder farming as the primary source of household food (FEWS NET, 2016c). The small volume of excess household farm produce is usually sold at market to supplement household wealth.

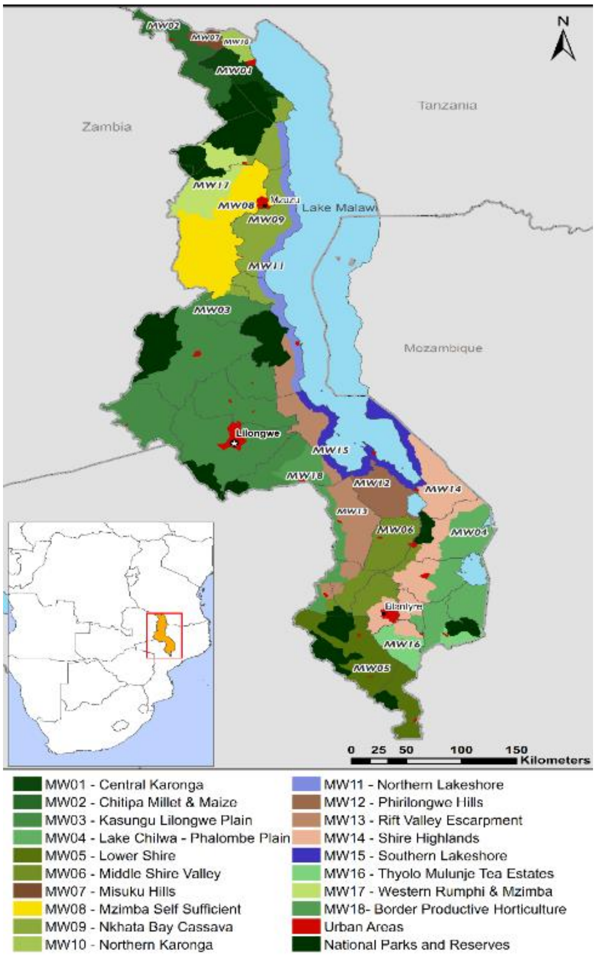

Figure 1.1 An overview of Malawi. Figure from: (FEWS NET, 2016c)

1.3.1 Historic climate Change in Malawi

Climate change in Malawi is manifesting as increasing average temperatures as well as an increase in the number of warm days (i.e., the frequency and duration of heatwaves) (WHO & UNFCCC, 2015). Changes in rainfall includes a shortening and delayed onset of the rainy season as well as a reduction in the number of extremely wet days (days with >20mm rainfall) (Haghtalab et al., 2019).

Rising temperatures and changing profiles of the rainy season increases the health risk of Malawians through food insecurity and malnutrition, as well as related diseases such as childhood pneumonia. Vector borne diseases such as malaria and dengue as well as heat-related deaths in the elderly are also projected to increase (WHO & UNFCCC, 2015).

1.3.2 Background on crop harvesting, food security and migration in Malawi

As highlighted in Figure 1.2, crops are planted and grow during the rainy season (November – April inclusive) and harvested during the dry season. The first harvest of 'green maize' occurs as early as February – March in some districts, whilst most of the Maize harvesting occurs in April. The period from April - July and September - December are when household harvests are utilised to feed households. The lean season signals when harvest stocks tend to run low between roughly November to April. Climatic conditions of the rainy season immediately preceding harvest are thought to have a strong influence on the crop production of that year. For example, the climate of the 2015-2016 rainy season (November 2015 – April 2016) are hypothesised to have a strong influence upon crop production collected during 2016 (Feb for green maize and April for most of the main Maize harvest).

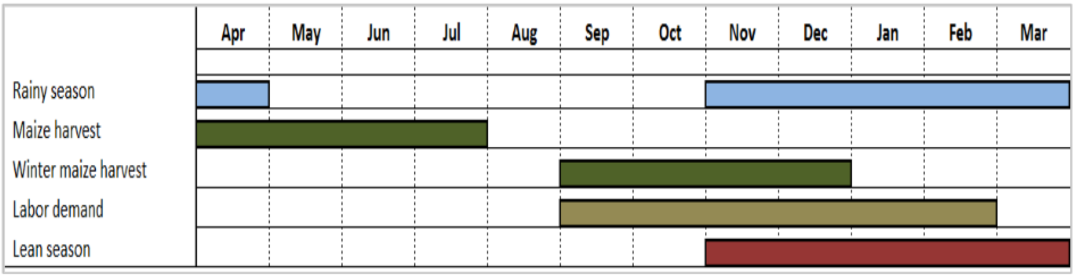

Figure 1.2 Seasonal calendar for Malawi. (FEWS NET, 2016c)

Year round food security is a concern for many Malawians, particularly during the lean season. Food security is often conceptualised along four, hierarchical dimensions (Figure 1.3). Availability refers to presence of food source(s), access refers to the ability to procure food from a sufficient range of food sources, considering for example through physical access, safety nets, affordability and purchasing power. Utility refers to the bodies ability to process the food consumed as well as the nutritional value provided, stability refers to how stable through time the food source(s) are (Schmidhuber & Tubiello, 2007).

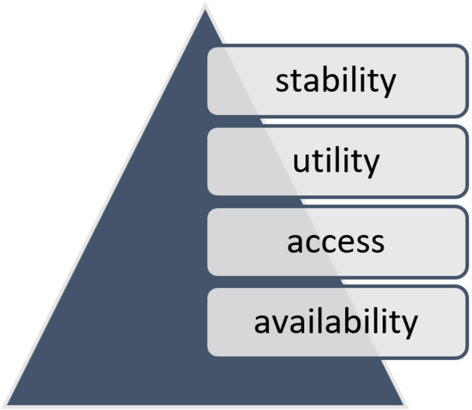

Figure 1.3 Hierarchical representation of the key dimensions of food security

Although well theoretically defined, measuring food security is a perennial challenge due to its complex and multifaceted construction (Barrett, 2010), its composition of social, economic, political as well as environmental components, as well as data paucity. In previous decades, food availability was popularly the focus of many studies and is largely based on food production, often at the national or global scale (Barrett, 2010). However, this fails to capture subnational variations in food distribution. Food access has more recently taken over as a dominant dimension of food security studies. Access to food incorporates economic as well as social and cultural values and may vary at the household level due to inequality and wealth variations between within and households within a community. Food utilisation considers nutrition value and uptake of consumed food and such, is often the focus of nutritional health studies rather than food security.

Different dimensions can be measured through different metrics, each with various strengths and weaknesses, or proxies can be used to describe food security more generally, which may be affected by multiple dimensions. Hunger, a subjective measure of lack of food and hence, of food insecurity can be collected at the individual or household level for example by surveying respondents with questions related to feelings of hunger over a certain periods (e.g. a day and night) (Deitchler et al., 2011). Undernutrition (insufficient daily calorific intake) is popularly used, particularly in children where it is easier to quantify undernutrition through anthropometric measurements such as stunting (height-for-age) and wasting (weight-for-height) (Lloyd et al., 2018; World Health Organization (WHO), 2010).

Poverty and food expenditure have also been used as proxies for food access, each with underlying assumptions and bias in their measurements (Webb et al., 2006). Overreliance on any one single measure jeopardises policy interventions designed at alleviating food insecurity (Barrett, 2010; Webb et al., 2006). All metrics face data paucity challenges within many nations, with Malawi proving no exception.

As a low-income country, Malawi's population of smallholder farmers often struggle to achieve high crop yields (production quantity per unit area). Food security across Malawi may worsen over time due to population growth and the need for ancestral land to serve more people of the extended family over time (Kambewa, et. al., 2023) as well as continued sensitive to poor weather (Findlay, 2011) and climate change. In response, the Government of Malawi deployed a range of political instruments and economic incentives to stimulate crop production rises. These initiatives achieved varying degrees of efficacy, with multiple impacts on rural livelihoods and the strategies used by households to improve their wealth and food security (Peters, 2006, Harrigan, 2003). Throughout the 1970s and 1980s, subsidy programmes were used in attempt to support crop production and food self-sufficiency (Frankenberger et al., 2003). These were largely rescinded during the 1990s however following periodic droughts and food crises, most notably in 1991-1993, 2001-2003 and 2005, food subsidy programmes once again gained popularity. In 1998 the controversial 'Starter Pack' programme was introduced, providing free packs of Maize and legume seeds for all households (Harrigan, 2008). Later, in 2005, following poor rains and the food crisis of 2004/05 season, the Government of Malawi introduced the Farming Input Subsidy Programme (FISP) with the aim of improving crop production and food security by providing vouchers which subsidise the purchase of household fertiliser, seed and pesticides (Kawaye & Hutchinson, 2018). The FISP has been both praised and criticised, with some arguing that it greatly contributed to improved crop yields across the nation (Kawaye & Hutchinson, 2018; CDM and FUM, 2017; Michigan State University (2015); Chibwana et al., 2010) and other studies suggesting that reported crop yields were inflated for political purposes (Messina, Peter & Snapp, 2017) and that furthermore, reliance of subsidy programmes are not a sustainable approach for Malawi's agricultural development (Messina, Peter & Snapp, 2017).

Another avenue to support the Government are currently pursuing to support livelihoods and development is the National Social Support Policy (NSSP). Under the NSSP a set of [Malawi] National Social Support Programmes (MNSSP and MNSSP-II) were launched, including notably, the Social Cash Transfer Policy which funds monthly cash payments to the ultra-poor of Malawi (approximately 10% of the population) to support common purchases including food, livestock, agricultural inputs as well as educational supplies and school fees (GoM, 2022; GoM 2016).

There is evidence that such approaches protect food security and support resilient livelihoods for the many Malawians (Otchere & Handa, 2022). Other studies suggest that such subsidy programmes create a dependency on government subsidies, NGO and international aid, however the consensus seems to be that such schemes are broadly positive (Chibwana et al., 2010; Harrigan, 2008). Despite such schemes, food insecurity, chronic poverty and climate sensitivity means that many Malawians continue to live within a precarious context. Compounding these challenges, Malawi was also an epicentre of the HIV/AIDS epidemic which, by 2001 affected 22% of households (Frankenberger et al., 2003; Zulu et al., 2004; Loevinsohn, 2015).

Urbanisation, food insecurity, poverty and HIV as well as pre-existing, normative migration habits have all contributed to the migration patterns observed in Malawi throughout the 20th century and first decades of the 21st century. Under normal conditions (in the absence of climate change), normative migration patterns typically include young adults partaking in economically-drive circular migration (Beegle & Poulin, 2013). There is also some evidence that climatic events (drought) increase (mainly male) economic migration (Becerra-Valbuena & Millock, 2021). Marriage has also always been a key migration driver. Historically, marriage migration followed matrilocal patterns (i.e. men would move to their brides location), but it is now more common that women move for marital reasons (Beagle & Poulin, 2013). Children typically move to follow their parents or for schooling, but the HIV/AIDS epidemic also increased childhood migration (independent of the parents movement) as a household scoping strategy (Ansell & Blerk, 2004). HIV/AIDS status also appears to have a feedback impact upon marital security and hence upon migration, as well as migrants more likely to be HIV positive, most often due to engagement in HIV risk behaviours (Anglewicz 2012).

1.4 HYPOTHESES TO BE EXPLORED THROUGH THIS THESIS

Figure 1.4 outlines the hypothesised pathways through which climate change may impact upon migration around Malawi. It is hypothesised that climate change may directly impact migration (pathway 1→5) for example, by farmers identifying that climate change presents a threat to future livelihoods and migration to cities in efforts to diversify incomes. More likely, this impact would be mediated through the ease of migration (“mobility” factors), education, and other economic and sociodemographic aspects of an individual, which affects their aspirations and capability to migration (pathway 1→6→7→5) (Suckall et al., 2017). Mobility and other sociodemographic factors are highly likely to moderate any migration pattern regardless of other, upstream drivers (such as pathway 1→2→3→6→7→5).

Perhaps the most likely situation for many Malawians, is the hypothesis that climate change is driving changes in crop production (pathway 1→2) (Stevens & Madani, 2016), with direct implications on household food security (pathway 1→2→3) for Malawi’s smallholder farming population. Food security in turn may drive migration either directly (pathway 3→5), for example during extreme food insecurity / famine situations (Loevinsohn, 2015), or as mediated through the changing economic status and poverty levels of Malawian’s who may become poorer and less able to support their household farm and may therefore look to migrate in search of alternative employment, for example, in Malawi’s growing cities (pathway 3→4→5). This pathway is the key hypothesis that forms the focus for this thesis.

An alternative hypothesis is that climate change may reduce migration by reducing the ability of Malawians to migrate, due to increased poverty and food insecurity (pathway 1→2→3→4→5). For example, reduced crop production may affect a family’s income, as less sellable surplus is produced and more money is spent on farming activities (e.g., labour, fertiliser, grain). In increasingly extreme situations, households may sell their assets to supplement income. The subsequent reduction in household wealth may reduce their capability to relocate, especially permanently or over longer distances. This effect is referred to as ‘trapping’ and is an emergent hypothesis in climate migration literature (Black et al., 2011), though it remains largely under-explored. Like pathway 1→2→3→5) identified in the previous paragraph, this trapping effect will also be a key hypothesis explored throughout the thesis.

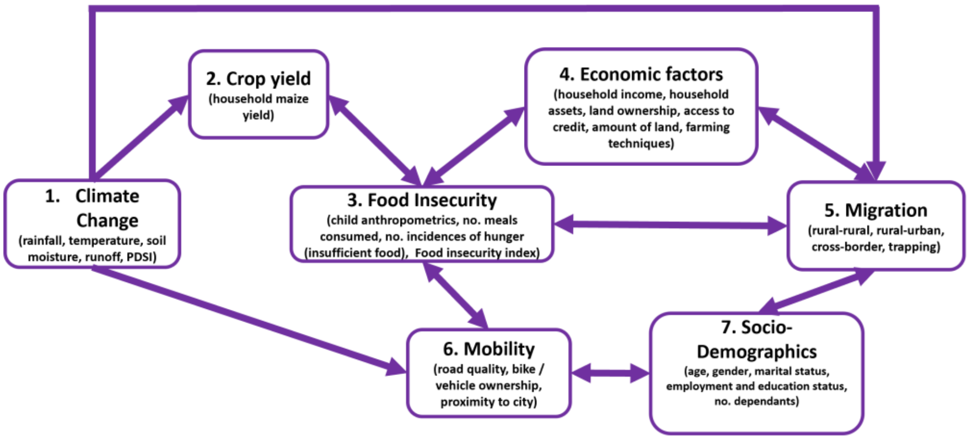

Figure 1.4 High level hypothesis of how climate change impacts migration which is further explored within this thesis. Arrows between factors describes that the preceding factor has an effect upon the succeeding factor. This affect could be net positive or negative. It is acknowledged that there are other relevant factors, and these are also explored and commented upon within the relevant thesis chapter(s).

1.5 METHODOLOGICAL APPROACHES

Climate migration has been explored by a wide range of academic disciplines across the sciences, arts and humanities. Unsurprisingly, each discipline is largely self-contained and abides by a unique, well-established dogma, underlying assumptions, data limitations, as well as methodological approaches and suffers from limited cross-pollination with other disciplines. Such tribalism is of course not unique to the field of climate migration, but rather is a basal trait of humanity which has naturally manifested within science (Clark & Winegard, 2020). However, climate migration represents the apex of the two vogue and highly politicised fields of migration – drawing largely from social sciences, and climate change – drawing originally from natural scientific fields but with applications across all disciplines. Furthermore, as a vogue and contentious issue, political drivers of climate migration research are significant. Resultantly, a siloed approach to understanding climate migration fails to recognise underlying biases within each field and can further fail to result in meaningful results, with unobstructed benefits for policy and, ultimately, for affected persons that political interventions are designed to support. A poignant example of this is the regular framing of the results of climate change research as evidence of a national security threat (particularly to nations of the Global North), with interventions including enhanced border control (Baldwin-Edwards et al., 2019; Kita & Raleigh,

2018) and attempts to 'manage' climate migration at the source (typically nations within the Global South) (Boas et al., 2019; Piguet et al., 2018).

With a view to avoiding the shortfalls of tribalism, I conducted a literature review and brief critique of available methodologies from across the field of climate migration. This allowed me to try and reduce researcher bias within subsequent chapters, having learnt lessons from existing works (Kelman et al., 2016), and equipped with the appropriate methodologies for answering the research questions outlined in section 1.1. This literature review is not systematic in design and not intended to provide a comprehensive insight into climate migration literature. Rather its intent is to cover a range of key schools of thought across several disciplines. This was achieved via informal peer group discussions to identify key authors, journals and schools of thought. Using these references as a starting point, forward citation searching was carried out on the Web of Science and Google Scholar databases from which a range of papers and authors were consulted.

1.5.1 A review of climate migration research approaches

The links between climate change and migration have been interrogated through the lenses of social sciences such as anthropology and sociology, epidemiology, economics as well as computer sciences, to name but a few, and the impact of different epistemologies on conclusions is complex and often overlooked (Eklund et al., 2016). Piguet et al., (2010, 2018) and McLeman (2013) present a comprehensive overview of the main approaches to exploring climate migration, considering both approach as well as geography and funding sources that underpin empirical studies to date (McLeman, 2013; Piguet, 2010; Piguet et al., 2018). Table 1.1 elucidates this point by demonstrating a selection of fields which contribute to the study of climate migration.

Table 1.1 An overview of the range of scientific disciplines which contribute to the study of climate migration, its drivers, and impacts.

Discipline	Description
Human geography	Offers a range of frameworks and tools for studying human migration and its drivers.
Anthropology	Through the study of human behavior, anthropological methods offer a deeper insight into the decision-making process behind migration, as well as the impacts of migration upon individual and societal wellbeing.

Ethnography	Ethnography offers a unique and rich insight into people's opinions and decision-making.
Political sciences	Political sciences may be used to explore the effects of policy on immigration, as well as the geographic, economic and social drivers of migration policy and sentiment.
Economics	Both macro and micro economics can be used to quantify migration as well as study the economic drivers and impacts of migration. For example. In the case study of Malawi, econometric modelling could be applied in the study of the impact of failed crops on household wealth and as such on migration.
Mathematics	A range of mathematical models are used in the study of migration such as system dynamic models, agent-based models, gravity models, diffusion models
Epidemiology	Environmental epidemiology can be used in the study of migration and its drivers. For example, the field of ecological public health supports the exploration of the relationships between the biological and material realms (Reis et al., 2015).
Disaster Risk Reduction	Disaster Risk Reduction relates mainly to sudden-onset events and short-term, forced displacement and as such provides cross-over to the field of migration science.
Environmental sciences / Agricultural sciences / hydrology / climate modelling	These are examples of fields which are relevant to the drivers of migration. For example, in the case study of Malawi, agricultural sciences may help model the impacts of climate change on crop production.
Computer sciences	Computer science is used in migration studies to model and simulate migration and its quantifiable drivers and impact.
Sociologists	Sociology can be used to study migration and its impacts at the societal level, with special interest in demographic makeup and social structure of migrant (and non-migrant) communities.
Demography	The study of population dynamics and structure places migration as a core component.

1.5.1.1 Qualitative approaches

Popular methodologies include the use of qualitative studies including focus groups and semi-structured interviews to understand migrants' individual decisions and reasoning. For example, In 2015, Suckall et al., (2015) used migration systems theory to interrogate circular migration and its implications in Malawi. Following this work, in 2017 Suckall et al used a capabilities-aspiration conceptual model, deployed a mixed-methods approach including both interviews and focus groups, triangulated using quantitative survey data results. (Jørstad & Webersik, 2016) used semi-structured interview and focus groups with women participating in the Lake Chilwa Basin Climate Change Adaptation Project (LCBCCAP) aimed at improving local conditions and understanding the effectiveness of adaptation strategies for fishing communities around Lake Chilwa in Malawi. Such models are highly localised and generally non-reproducible but provide value by introducing new hypothesis and possible drivers which could apply across much of the rest of society for future research to explore. However, the ability of future researchers to do so is highly dependent on data availability which remains a challenge, particularly in data poor countries, such as Malawi. Narrative analysis methods have been used to garner a range of insights into the evolution and genealogy behind the climate migration discourse, for example, those critiquing the impacts of neoliberalism within research institutes, governments and intergovernmental bodies upon climate migration discourse (Baldwin, 2013; Boswell et al., 2011; Hartmann, 2010; Lyster, 2019; Methmann & Oels, 2015; Nash, 2018; Telford, 2018). Other methods, such as grounded theory and thematic analysis, appear little used in climate migration literature, though are regularly employed within wider migration studies in order to generate theories without a priori knowledge.

Having conducted a literature review of climate migration social science literature, including both studies of the climate-migration events itself, as well as political sciences literature considering into high-level discourse, I have identified risks that traditional quantitative research methods (such as those discussed in the following paragraphs) often overlook. High-level narratives seem to have impact on the conceptual models and hypothesise used to drive empirical research questions and methods (as well as researcher funding for such work). Furthermore, there appears to be geographical discrepancy within existing body of literature, with many nations (usually within the Global South) proving to be popular research specimens for researchers (usually from the Global North), whilst other nations lack much, if any, research. This uneven geography is perhaps also culpable for a regularly reported criticism of climate migration, that it carries deeply neoliberal undertones (Felli & Castree, 2012; Lyster, 2019; Nash, 2019; Piguet et al., 2018), As such, the discussions of my research will not only consider the direct results of my work but the wider implications for the field of climate migration and future migration, climate and climate-migration policy, including a critique of the drivers of much climate migration literature itself.

1.5.1.2 **Quantitative approaches**

Statistical models (as commonly seen within epidemiological and econometric research) are popularly deployed. Examples include regression models such as multi-level models (Fisher & Lewin, 2013), econometric models (Isik & Devadoss, 2007; Lewin et al., 2012), temporal regression models (Ezra & Kiros, 2001; Gasparrini et al., 2015; Gray & Bilsborrow, 2013; Henry et al., 2004; Thiede et al.,

2016) and spatial models such as cluster analyses (Lohela et al., 2012; Nesbitt et al., 2016; Neumann et al., 2015) and gravity models (Kumari Rigaud et al., 2018; Mastrorillo et al., 2016). Such models provide an essential toolkit for identifying and examining the relationship between climate change and migration and are popularly used. However, a key limitation of such approaches can occur in the face of data paucity. Data paucity can be addressed through a range of means including data collection initiatives, data imputation or through combining other methods such as mixed-methods or systems-based approaches. A second, less acknowledged limitation is the potential shortcomings of a reductionist approach that such models epitomise. In the field of climate migration – where drivers of migration are known to be complex and interconnected, the idea that such complexity can be methodologically reduced to a simple set of variables that inter-relate, requires careful conceptualisation and justification.

Economic approaches such as economic bargaining theory can also be used to explain some micro-level migration decisions such as the ‘healthy-migrant’ effect, whereby young and fit-for-work individuals may be more likely to move in search of work and remittance opportunities (Hunter & Simon, 2017). However, since climate change exists only as a macro-factor, such micro-level considerations within current models of climate migration are often lacking. A major benefit of statistical approaches is that they can be used to explore and empirically quantify relationships including the use of interaction terms to account for hypothesised interactions between determinants as a means to address complexity of the climate-migration nexus. Lags in time and space can also be accounted for either through modelling techniques or through the design of variables included within models.

Traditional epidemiological methods such as regression modelling also has additional short-comings: Cross-sectional analyses do not allow for the temporal nature of drivers. Time-series analyses are often impeded due to lack of sufficient data and the ability to control interactions between drivers across a range of temporal and spatial resolutions. Gravity-models can capture linear push and pull factors at the macro level, though may struggle with ecological fallacy and in modelling of more nuanced relationship between driver and migration outcome. Recent developments in mathematical models offer useful insight.

Complex systems approaches describe a range of modelling methods which attempt to capture the complexity and multiple interactions of real-world systems. In climate migration, the most popular complex systems approach is that of Agent-Based Modelling (ABM) (An, 2012; Smith et al., 2010). Agent-based models are bottom-up models which explore the responses of agents (where an agent is an individual or community) to stimuli, including agent-to-agent interactions. ABMs have become popular within the climate migration field with multiple examples exploring different interactions (Barbieri et al., 2010; Entwisle et al., 2016; Kniveton et al., 2011). The advantage of such models includes the ability to fully acknowledge the individualistic nature of a decision to migrate, as well as to attempt to capture dynamicity of different determinants, as well as the ability to introduce non-rationality and different behavioural distributions within the agent population. However, such models require numerous assumptions to be made about how agents behave under baseline circumstances (Klabunde & Willekens, 2016). They must also deal with high levels of complexity and resultant uncertainty which can jeopardise the usefulness of the model for future interventions, particularly in a global health context, unless the model's results can be validated with strong empirical evidence. Achieving this would require substantial data gathering including through participatory approaches and standardised modelling protocols (Schulze et al., 2017).

Multi-Agent Systems (MAS), somewhat similar to ABMs, consists of multiple decision-making agents. These agents operate and cooperate within a shared environment to pursue common or non-common goals. Another emerging complex systems approach is dynamic simulation modelling (DSM). Reuveny (2021) created a pilot DSM to explore the integrated outcomes on migration and health outputs at host and source sites under the ecological impacts of climate change (EICC) as well as other non-EICC factors (such as socio-political and economic). With further development, DSMs may support a deeper understanding and ability to model real-life, complex situations applicable to specific contexts.

Complex system approaches to climate migration such as those by (Entwisle et al., 2016; Kniveton et al., 2011; Mastrorillo et al., 2016; McLeman, 2013) must be chosen appropriately based on the assumed relevant determinants and their interactions, as choice of methods may have significant impact on the study results. The advantage of such systems approaches is that driver dynamics and interactions may be inbuilt and allowed to alter in time steps. The individual nature of human decisions may also be captured through ABMs. However, ABMs require high resolution data and are generally only applicable for small geographical scales.

A key challenge for any climate migration modelling approach, statistical or complex modelling regards data availability and quality. Migration datasets are largely based on cross-sectional survey and census data whilst information about health and wellbeing, disaggregated by migration status, is largely lacking. Furthermore, collecting and disseminating such data presents significant ethical and privacy concerns. For many migration drivers, proxies may be used. For instance, the Normalised Difference Vegetation Index (NDVI) may act as a proxy for natural resource availability (van der Geest et al., 2010). Henderson et al. (2017) use a simple count of manufacturing industries as a proxy for urban industrial capacity when analysing the relationship between climate change and urbanisation in an African context (Henderson et al., 2017). Lu et al. (2016) suggest the possibility of using out-migration rates as a proxy for changes in habitability (Lu et al., 2016). Neumann and Hilderink (2015) present a range of possible datasets such as GLASOD for soil degradation and LADA for biomass production of earth observation land degradation data (Neumann & Hilderink, 2015). However, each of these datasets has its own challenges concerning spatial and temporal resolution, uncertainty and effectiveness as a proxy. Furthermore, misalignment of datasets at the spatial, temporal and social level creates further challenges in appropriately modelling migration determinants. Other, more squidgy drivers such as perceived political stability and social networks remain elusive to measurement and under-represented in quantitative studies.

Other approaches have been proposed to deal with complexity and dynamicity. Barbieri et al., (2010) use a combined economic-demographic-climate model to understand the interactions between different classes of drivers over time (using appropriate proxies) in the Northeast region of Brazil (Barbieri et al., 2010). Another emerging method is the use of Shared Socioeconomic Pathways (SSPs) to provide a combined set of scenarios for future population, urbanisation and wealth factors

(Riahi et al., 2017). The SSPs are designed to be used in conjunction with climate change representative concentration pathways (RCPs) for future radiative forcing emission scenarios. Application of this approach can be seen within the Groundswell report (2018) who combine the RCPs and SSPs into three scenarios and use gravity-modelling to provide a view of internal migration for three global regions (Kumari Rigaud et al., 2018).

1.5.1.3 Mixed methods

The final, and arguably underutilise approach is that of mixed-methods research. Whilst the need for cross-disciplinary approaches is often acknowledged, they are rarely applied and difficult to achieve in practice.

Climate migration is almost exclusively studied under a positivistic framing, meaning that knowledge is assumed to be objective and measurable. This limits capacity for subjectivity, especially concerning factors such as an individual's level of agency or perceived security. Mixed-methods research which combines different types of data and / or analytical strategies can help address such issues by combining traditional (such as statistical) research methods with analysis of qualitative or subjective datasets (Small, 2011) such as the confirmatory approach used by Suckall et al., (2017).

1.5.2 My approach

The research questions presented in section 1.1 are answerable through a range of methods including through analysis of both qualitative and quantitative data. However, data availability creates a major constraint. The most in-depth and nationally representative surveys which can support and intranational study within Malawi includes the decadal census (last conducted in 2018), and the Integrated Household Survey's, a World Bank Living Standards Measurement Study (LSMS) conducted through the National Statistics Office of Malawi. Five surveys have been conducted in total: IHS1 in 1998, IHS2 in 2004-05, IHS3 in 2010-11, IHS4 in 2015-16 and IHS5 in 2019-20. Considering these data, statistical analysis via regression modelling was identified as the most appropriate methodological toolkit for this research. However, in attempt to address some of the shortfalls identified in the previous section some nuances shall be introduced. Prior to setting up the regression model, a critical literature review and conceptual model will be created to help drive the construction of an empirical model. The conceptual model (see chapter 2) will also attempt to capture lessons learnt from different disciplines, and avoid the aforementioned pitfalls of scientific tribalism. The empirical modelling will employ a stepwise build approach to ensure consideration of key variables to produce robust, well-fitting, and theoretically coherent models. Furthermore, the models developed within this thesis - both conceptual in chapter 2, and empirical in chapters 3 and 4, are critiqued as part of the discussion contained within chapter 5 where implications of this thesis for the field of climate migration are considered. Building upon some of the shortfalls identified above, as well as those identified throughout my research, this critique is then further expanded to consider the pitfalls and opportunities of the field of climate migration itself. The critique shall consider how mine (and others) research is shaped by wider societal values, and how in turn the field helps to shape future policy and discourse. A further breakdown of this thesis by chapter is contained in the next section.

1.6 SCOPE FOR THESIS

The research aims laid out in section 1.1 will be addressed throughout the chapters of this thesis as follows:

1.6.1 Chapter 2 – A critical analysis of the drivers of human migration in the presence of climate change: a new conceptual model

This chapter captures an in-depth, critical literature review of current climate migration studies and conceptual thinking and empirical studies. The resulting discussion and conclusions culminate in a new migration typology and conceptual model for the drivers of migration. This model is then applied to the context of Malawi from which a Malawi-specific hypothesis regarding the possible nature of the relationships between climate change and migration is deduced. This Malawi model and hypothesis is then tested empirically in subsequent chapters.

1.6.2 Chapter 3 - The impacts of climate on crop production and food security in Malawi; an epidemiological approach

The conceptual model developed in chapter 2 is applied empirically, to explore the relationships present between climate factors and the hypothesized intermediate migration drivers of household crop production, food security and wealth. Specifically, the pathway 1→2→3 as outlined in Figure 1.4 is explored. Findings are then discussed and (theoretically) extrapolated to consider how future climate change may continue to affect the livelihoods and migration drivers for Malawians.

1.6.3 Chapter 4 – Exploring internal migration and its drivers within Malawi

A migration profile of Malawi's population is described and the observable drivers of internal migration within Malawi are analysed. The chapter considers both the direct relationship between climate change and migration, as well as the indirect impacts of migration on Malawi through the intermediate factors of crop production, food security and wealth, building on insights from previous chapters. The primary pathways under consideration are pathway 1→2→3→4→5 and pathway 1→5 (Figure 1.4).

1.6.4 Chapter 5 – Discussion, future work and concluding thoughts

This chapter discusses the findings from all previous chapters, including a discussion of limitations and their impacts upon this research and implications for future research and policy. I will then take a step-back and consider the 'bigger picture', taking a critical view not just of this thesis, but of the field of 'climate-migration' itself. This critique, inspired by my research, will be created via a critical literature review that shall consider the evolution of the field, from its inception and founding principles, to current day popular narratives, their limitations, and possible future directions for the field. Finally, this chapter will offer some concluding remarks upon the research and overall thesis.

1.7 List of Author's Publications

The work presented in this thesis has led to the following publications.

- **Lauriola P, Parrish, R, Leonardi G, Colbourn T, Hajat S, Zeka A. I determinanti dei movimenti migratori in conseguenza di cambiamenti climatici: brevi spunti introduttivi: Some hints on drivers of human migrations due to climate change. Sistema Salute, 63, 2 2019: pp. 196-210** (Lauriola et al., 2019)
- **Parrish R, Colbourn T, Lauriola P, Leonardi G, Hajat S, Zeka A. A Critical Analysis of the Drivers of Human Migration Patterns in the Presence of Climate Change: A New Conceptual Model. Int. J. Environ. Res. Public Health 2020,17, 6036; doi:10.3390/ijerph17176036** (Parrish et al., 2020)

- Extracts from this paper are included within this chapter under section 1.2. Furthermore, this paper forms the basis and a majority of the content of chapter 2. This is permissible under both the MDPI journals[1] copyright statement which allows for reuse providing appropriate citation, and under Brunel University code of practice for research degrees[2].

- **Franklinos L, Parrish R, Burns R, Caflisch A, Mallick B, Rahman T, Routsis V, López A, Tatem A, Trigwell R. Key opportunities and challenges for the use of big data in migration research and policy. UCL Open: Environment. 2021;(3):06. doi:10.14324/111.444/ucloe.000027** (Franklinos et al., 2021)

1.8 CHAPTER SUMMARY

The main aim of this chapter was to introduce the field of climate-induced migration as a field of research which combines thinking from climate science, demographics and social sciences, as well as global health studies. This chapter has also introduced the context of Malawi, emphasising both vulnerability of Malawi to climate change, as well as the lack of studies and data as a hinderance to Malawi's global health and climate change adaptation planning. Having identified the need for improved understanding of the climate migration paradox and the call for more empirical data, particularly in the Malawian context, we will now consider this in more detail in the following chapters, starting with a thorough literature review of existing data and conceptual models and how these are applied to the Malawian context.

[1] https://www.mdpi.com/authors/rights
[2] https://students.brunel.ac.uk/documents/Policies/code-of-practice-for-research-degrees.pdf

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2 A Critical Analysis of the Drivers of Human Migration Patterns in the Presence of Climate Change: A New Conceptual Model

2.1 Chapter objectives

In the previous chapter I introduced the field of climate migration and briefly explained its emergence and popular framings including as a global health agenda item, a security risk (as conceptualised by mainly developed countries), a humanitarian crisis, or a climate adaptation opportunity. The introduction also identified and critiqued various methodologies and epistemologies applied to the study of climate migration. A key gap identified was the need for statistical approaches to be very well grounded and conceptualised in order that reductionist shortfalls may be avoided. As such, the objectives of this chapter are:

1) To conduct a thorough and critical literature review of the drivers of climate migration
2) To develop an environmental migration typology and conceptual model which is transferable across any case study.
3) To apply this conceptual model to the case study of Malawi and deduce a Malawi-specific model from which the relationships between climate change and migration can be hypothesised.

The results of this Malawi-specific model and the hypothesised relationships will then be further explored via empirical research in subsequent chapters.

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2.2 Introduction

Both migration and climate change have been receiving increased scientific, political, and popular attention over the last couple of decades. In the UK and Europe this is particularly true since 2015 and the onset of the so-called ‘migration crisis’ when in a single year, over 1 million people entered Europe and an estimated 3771 people lost their lives in the Mediterranean (Baldwin-edwards et al., 2019; Goodman et al., 2017). The response by the European public and politicians was varied and often deeply polarised, with both calls for humanitarian compassion, better border controls and anti-migrant rhetoric (Goodman et al., 2017) emerging.

Meanwhile, climate science as well as advocacy for climate action has been experiencing a gradual increase in awareness and support since the 1970s and international political action since the creation of the United Nations Framework Convention on Climate Change (UNFCCC) in New York in 1992 (McLeman & Gemenne, 2018).

Interest in these two high profile fields meets in the study of climate migration. The topic of climate migration is perhaps so popular because it captures the zeitgeist of climate change, with discourse frequently lamenting unequal and unjust impacts that are being felt around the world (Bettini, 2013). Climate migration can be analysed under a range of guises including notably that of a mechanism through which climate change is affecting global health. Indeed, migration and conflict are considered key mechanisms by which climate change has become a priority global health concern (Burrows & Kinney, 2016; C. McMichael et al., 2012; Watts et al., 2018). These and other indirect health impacts of climate change are often under-recognised and under-researched. The Covid-19 pandemic is a poignant example of how the special circumstances of migrant communities creates unique and extreme health vulnerabilities: whilst some migrants living in displacement camps are unable to practise good hygiene and social distancing, other migrants are finding themselves denied their right to asylum, neglected or turned away at borders due to travel restrictions and fear of new waves of infection.

Furthermore, many studies fail to demonstrate adequate application of a conceptual framework through which to frame and identify the linkages between climate change and migration. Failure to do so can result in researcher bias, results that are not locally contextualised and which can result in spurious findings and unsuitable next steps such as ineffective healthcare interventions and even maladaptive climate action (Magnan et al., 2016; Sutcliffe & Court, 2005).

The aims of this paper are to provide a critical review of existing climate-migration literature; from this I also suggest modifications to existing conceptualisation of climate migration by providing a new conceptual model of the system of migration determinants. The model is designed to be pan-disciplinary and transferable to any geographic or social context. I advocate the systematic application of theory in climate migration studies which may help better geographic representation (Piguet et al., 2018) and improve our understanding of how climate change is impacting migration with contextual relevance to policy makers and public health interventions. Finally, I apply this model to a case study of Malawi to demonstrate how doing so can improve understanding of the local context and result in well-grounded and policy-relevant insights into the true impacts of climate change on migration.

2.3 A CRITICAL REVIEW OF CLIMATE MIGRATION LITERATURE

In order to improve conceptual modelling, several critical issues related to climate change and migration have been identified and discussed here. A key characteristic of migration is the multi-causal nature of its drivers. Climate change may act as a direct driver of displacement but in many cases is also inextricably linked to other, dynamic and interacting social, political, demographic and economic drivers (Black et al., 2011; Foresight, 2011; Tacoli, 2011). A popular constructed narrative is that climate change acts as a threat magnifier of existing migration drivers. This can result in many empirical studies identifying economic factors rather than climate factors dominate the decision to migrate (Ezra & Kiros, 2001; C. Gray & Bilsborrow, 2013; Henry et al., 2003). However, it is possible that such studies overlook the mediated effect of climate change through other factors such as agriculture (Falco et al., 2019). It is now largely acknowledged that the relationship between climate change and migration is complex, dynamic, and non-directional.

Another critical issue relates to the multifaceted nature of climate change itself. Scholars typically outline several classes of climate change: a change in climate variability; changes in frequency and magnitude of fast-onset climatic events (including extreme weather events, droughts, floods, and heatwaves); and slow-onset climate change, including long term changes in average temperature, rainfall and chronic drought or flooding (Neumann & Hilderink, 2015). This wide temporality as well as severity of climate change must be accounted for when discussing the implications of climate change on future population movements.

Migration itself may occur over a range of spatial scales – from movements between rural and urban areas, to international migration - as well as a range of temporal scales such as short-term migration, circular migration, to permanent moves. The decision of each individual to migrate may also carry different levels of human agency. The decision to migrate is due to an aggregation of micro-level (typically household or individual) and macro (societal) level drivers. As such, each potential migrant has their own unique profile of factors and drivers. Such individualistic situations are often described in terms of the individual or community's vulnerability (C. L. Gray & Mueller, 2012; Neumann et al., 2015; Raleigh et al., 2008). This presents a key challenge in many existing studies, which struggle to reconcile drivers at the macro and micro demographic scales.

A key challenge remains the paucity and compatibility of datasets regarding both migration and potential drivers thereof, and the scarcity of such data at appropriate spatial and temporal levels, particularly in low income and in indigenous communities. The necessity for localised quantitative studies can result in fragmented analyses of specific time scales, geographies, types of migration and drivers thereof. Furthermore, this can make it difficult to summarise and build a global narrative of the risks of climate change to human security (McLeman, 2013). The resultant synthesis is that the impacts of climate change on migration is complex, multi-faceted and dynamic. As such, increased attention on the upstream drivers of migration is called for.

Some authors argue that there is also some limitation in theoretical development and so in recent years there has been a push to promote a more sophisticated theoretical understanding of how climate change may interact with other drivers of migration (Black et al., 2011; Falco et al., 2019; Hunter et al., 2015). This has allowed the narrative to evolve through time: the traditional narrative suggests a more simplistic view of climate change as a blanket push driver resulting in large-scale waves of migration (C. L. Gray & Mueller, 2012). However, newer frameworks appreciate the multi-driver nature of migration as well as the resilience and adaptive strategies of affected individuals and communities. Nevertheless, such frameworks still struggle to capture the dynamic nature of such drivers including feedback and lag times, as well as the interactions between drivers themselves through time. The rising concept of ecological public health goes some way to attempt to address this, yet many policy-facing groups remain slow on the uptake (Lang & Rayner, 2012). Understanding of climate-induced migration is further skewed by the discipline of researchers: each scientific discipline - be it epidemiology, economics, political sciences or anthropology, carries with it its own intrinsic assumptions and methodologies (Eklund et al., 2016; Hunter et al., 2015; Morris et al., 2017) which can perpetuate the fractured nature of the literature. Therefore, to advance the understanding of the impacts of climate change on migration requires a truly inter-disciplinary response.

The collective result of these challenges is that current understanding of climate-induced migration is geographically uneven, and studies are often non-transferable to other settings which presents an obstacle for policy makers and health intervention design. To aid design of interventions, scientists, and decision-makers (such as governments and humanitarian agencies) should engage with each other at all points of the intervention design and implementation. This can help ensure that interventions are contextually relevant, evidence-based and that their impacts can be measured and evaluated.

2.3.1 A new conceptual framework

2.3.1.1 Migration typology

From the challenges identified in the above critical analysis, a new conceptual framework of climate migration is provided. Migration, as a subjective concept, cannot carry one single definition and is highly contextualised. This however is often neglected within most quantitative studies. In particular, the terms ‘environmental migration’ and ‘climate migration’ lack unanimous definitions across academic, NGO and political actors. Migration exists as a normative behaviour in most communities globally but may also manifest as forced displacement, other involuntary, or voluntary movements. Furthermore, often overlooked in climate migration literature is the possible inhibiting effect of climate change on migration, resulting in reduced mobility rather than driving migration events (Nawrotzki & Bakhtsiyarava, 2017; Schewel, 2019).

Many scholars advocate the need for appropriate migration typologies and several have been presented. For instance, Stojanov et al. (2014) argue the need for contextualisation of climate drivers on a community in order to appropriately discern climate driven migration from normative or otherwise induced movement. Renaud et al. (2011) also comment on the difficulty of identifying the environmental signal within migration drivers and present a decision-making framework and accompanying typology of environmentally induced migration (Renaud et al., 2011). Carling (2002) created the first iteration of the aspiration-capability framework which describes voluntary or involuntary, mobility or immobility, based on both desire and ability to migrate (Carling, 2002).

Based on a review of a large variety of both qualitative and quantitative literature, we identify four dimensions which quantify migration: societal, temporal, spatial, and agency levels. “Societal level” refers to the level of society affected, from micro scale (individual and household level) to macro (community, regional or population level). “Temporal level” refers to the time duration of the migration, short-term may consist of a matter of months, long-term is typically considered to be a year or more though there is much range within empirical studies, and permanent migration represents the longest form of migration. “Spatial level” refers to the physical distance covered by the migration. Short distance may consider anywhere from intra-community and intra-regional movements, to movements within the country and includes movements to between rural and urban hubs. Long-distance constitutes international movements across large geographical areas. Whilst some cross-border movements may only require a few miles of travel and as such may be considered short-distance, a large amount of international movements covers multiple countries and sometimes continents. Such movements are of international political interest, though do not represent a large quantity of migrants or types of mobility (IOM, 2019; Khattab & Mahmud, 2019). The spatial scale, like the societal scale may also be summarised in terms of macro (generally medium or large distance) and micro (small, community level distances) and may align to climate and economic macro or micro level determinants. “Agency level” refers to the level of choice afforded to each migrant, existing as a continuous scale between the extremes of totally involuntary (in other words, forced), to totally voluntary. Agency in particular is difficult to measure and can be highly subjective based on the researcher (and person undertaking the migration). It should be noted that all four dimensions are continuous variables and hence demarcations used should be contextually modulated. By applying generalised demarcations however, we classify five key categories of environmentally induced migration. The first category is forced displacement, also referred to as distress migrants (Raleigh et al., 2008) or temporary displaced migrants (Stojanov et al., 2014). The second category is adaptive migration at the decision of the migrant(s) (Black et al., 2011) . Whilst this is a voluntary movement, a crucial caveat is applied here to note that such migration may not be truly voluntary; whilst many scholars and decision-makers consider it as such, there is an emergent narrative arguing that migration due to longer-term environmental or economic degradation, or erosion of human security constitutes a type of forced migration, rather than a voluntary or adaptive movement (Internal Displacement Monitoring Centre [IDMC], 2018b). The third category is proactive migration at the decision of wider authority such as local or national government referred to as 'planned resettlement' (C. McMichael et al., 2012). Agency of such migrants is difficult to detemrine based on how forced the resettlement is and the genealogy (power imbalances) between the government and local communities. The fourth category is for trapped populations, which refers to a lack of mobility due to at risk populations becoming trapped by environmental and socioeconomic barriers such as poverty (Internal Displacement Monitoring Centre [IDMC], 2018b). The final category is immobility which represents a lack of mobility at the presumed decision of the person(s) at environmental risk. Examples of such immobility could be the decision not to move away from ancestral lands (Black et al., 2013; Internal Displacement Monitoring Centre [IDMC], 2018b) or a limited capacity to exercise agency and make a migration decision due to specific vulnerabilities.

Table 2.1 summarises these classifications according to the four dimensions outlined. Throughout the remainder of this paper, we shall use the term 'climate migration' for simplicity.

Table 2.1 Summary of the five categories of migration and their general qualities defined in terms of societal, temporal, spatial and agency levels.

	Type of migration	Societal Level	Temporal level	Spatial level	Agency level
1	Forced Displacement	Macro	Short-term	Short-distance	Low
2	Migration as an adaptive response	Micro	Varied	Varied	Varied
3	Planned resettlement	Macro	Permanent	Short-distance	Low/Medium
4	Trapped	Micro	Varied	n/a	Low
5	Immobile	Micro	Varied	n/a	Varied

2.3.2 Drivers of migration

A newly proposed conceptual framework for identifying the determinants of any given migration is presented in Figure 2.1 below. This framework is an updated iteration of prior models which, over time, have converged to agree that migration is generally the result of a combination of upstream drivers, split into five categories: social, economic, political, demographic and environmental. However, consideration of interactions and evolution of these drivers through time, societal and spatial scale remains low. Climate change is presented as an external driver which is expected in many contexts to act as a threat magnifier by exaggerating negative, push factors for vulnerable populations (Adger et al., 2015; A. J. McMichael et al., 2006; Neumann & Hermans, 2015). Attributes of climate change are split into three categories: physical, biological / ecological, and anthropogenic impacts (Bowles et al., 2013; Mcmichael et al., 2015): The physical effects of climate change may be fast-onset or slow-onset. Fast-onset includes sudden events such as extreme weather or disaster events. Slow onset consists of more gradual changes of mean values such as annual rainfall, rainfall variability and chronic droughting and flooding. Secondary, or ecological climate aspects may include changes in land cover, flora and fauna habitats, including disease vectors and pollinators. Tertiary or anthropogenic aspects include subsequent changes to anthropogenic systems such as crop production and fish or game catch.

The model aims to build upon this a priori understanding by providing deeper discussion of the complexity of driver interactions, driver dynamicity and the evolution of both drivers, and their linkages over time and spatial scale. Importantly, the range of possible migration outcomes receives greater attention in this conceptual model, with recognition that different combinations of causal determinants and their contextual circumstances may result in different migratory responses, including differences in the level of agency of a migrant. The model is designed with the purpose of being pan-disciplinary and as such, relevant in any academic or non-academic context. The model presents not only a theoretical exercise, but a frame of thinking to support quantitative studies, with a view to informing future research, data collection or intervention design.

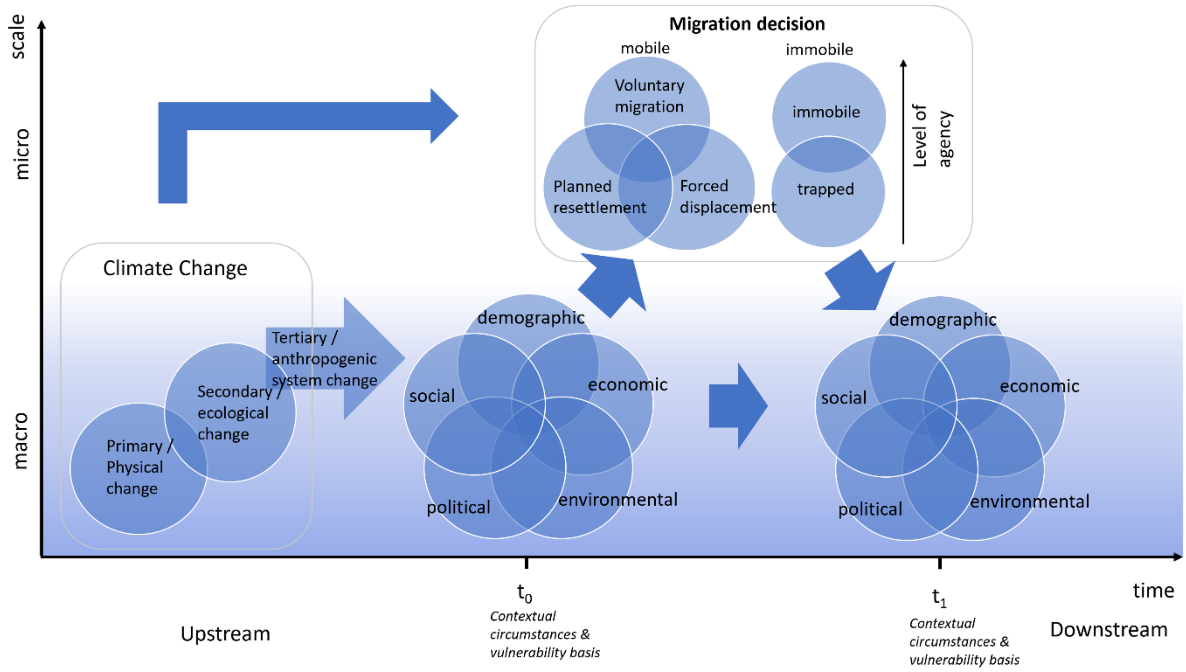

Figure 2.1 A conceptualisation of the pathways through which climate change may impact upon a system of vulnerability determinants that influence an individual's migration decision

Drivers within each of the five classes may act as push agents - encouraging movement away from the origin or pull agents – attracting movement to a host area. Bowles et al. (2013) also identify glue and fend factors. Glue factors act to cement a potential migrant in his/her home location such as cultural and family ties, whilst fend factors deter migration into an area such as hostile immigration policies. Recent studies highlight that climate change may act as a glue factor in many situations, rather than as a push factor as is often popularised (Nawrotzki & Bakhtsiyarava, 2017). Climate change is a sub-category of environmental drivers which may be further categorised into three classes (Brooks et al., 2005; Foresight, 2011; Mcmichael et al., 2015). These are perhaps best described as primary physical effects, secondary biological and ecological effects, and tertiary anthropogenic effects (Bowles et al., 2013; Mcmichael et al., 2015). Climate change is segregated here from other environmental factors and framed as an externality to the determinant system. This facilitates investigation of the impacts of climate change as an upstream pressure to all five classes of drivers. Each of the five categories are described in further detail below.

To demonstrate the temporal nature of the system, the model is presented on a set of axes with time on the horizontal dimension with arbitrary time points t_0 and t_1. This encourages consideration of the dynamicity of all determinants, as well as the changing nature of their interactions through time. As such, feedback implication on both host and source environments and communities of a migration decision may be decoded. Externalities, such as future climate shocks or political interventions such as climate mitigation, which may alter the system and resultant migration can also be presented and their impacts conjectured. The y-axis depicting scale of impact refers simultaneously to the societal and spatial level of impact thereby encouraging the disparate nature of drivers on these scales to be considered. Micro refers to small scale, individual or household level factors whilst macro may be factors affecting large distances and large numbers of people.

Within the next section we take a more granular view of each of the key families of drivers and consider how each may directly or indirectly impact migration. This analysis is not exhaustive but attempts to provide a detailed summary of drivers over time and space, thereby encouraging a more nuanced and detailed exploration of the complexity of climate change over time and space.

2.3.2.1 Climate Change

All climate factors are considered to occur at the macro spatial scale (Figure 2.1), which correlates to the macro societal impact level as described in Table 2.1 above. Temporality of climate factors varies as the true speed of climate change varies geographically. As such there can be no definitive definition for fast- or slow- onset but are arbitrarily set and should be contextually derived by scholars for their study area. Furthermore, some aspects may manifest across multiple timeframes. Table 2.2 outlines the key climate factors by the three classes described.

Table 2.2 Key climate change characteristics that increase population vulnerability to environmentally induced migration

Determinant	Temporal scale
Physical aspects	
Changes in extreme or annual mean rainfall, resulting in a range of effects including droughts and floods	multi-level
Increased extreme weather events	fast
Land (including coastal) erosion	slow
Sea level rise	slow
Changes in average temperatures and temperature extremes	slow
Biological / ecological aspects	
Desertification	slow
Deforestation	slow
Soil degradation	multi-level
Changes to freshwater ecosystems including fish and other aquatic populations	slow
Changes to marine ecosystems including fish and other aquatic populations	slow
Changes to terrestrial ecosystems including changes to flora and fauna and vector-borne disease spread	multi-level
Anthropogenic aspects	
Changes in crop production and agricultural productivity	multi-level
Changes in fishing catch	slow
Changes in water availability and security	multi-level

2.3.2.1.1 Physical effects

It is well established that climate change is increasing the frequency and magnitude of extreme weather events and climate shocks, which can be a direct cause of forced displacement. Nevertheless, in such natural hazard events, socially constructed vulnerabilities often govern the extent and type of migration responses which occur. Myers et al. (2008) in a study of displacement due to Hurricane Katrina in 2005, identified a range of social vulnerability factors which had a significant impact upon outmigration from affected places. (Myers et al., 2008). IDMC estimated that Tropical Cyclone Idai in 2019 displaced roughly 616,550 people, including 86,976 within Malawi (IDMC, 2019) whilst the Humanitarian Coalition (2019) estimated more than 125,000 displaced. Those in poor housing and socioeconomic situation being particularly vulnerable (Mester et al., 2023). Similarly, Gray and Bilsborrow (2013) identified within an Ecuadorian household migration survey, that household vulnerability factors such as home ownership, connectedness of household (to roads and schools), and poverty level, all confounded the environmental signal in the causes of observed migrations.

Less clear is the extent to which long-term or chronic climate change affects migration. Chronic changes may include changes in average temperature, average rainfall, rainfall variability or extent of periodic drought and flooding. Such changes often impact migration via mediating biological and anthropogenic factors such as impeded agricultural outputs (Gasparrini et al., 2015; Henry et al., 2003), adverse health outcomes (Gasparrini et al., 2017; Kjellstrom et al., 2009), or labour productivity (Butler & Harley, 2010). In such examples, the extent of climate factor as a driver of migration compared to other socio-demographic and economic factors is seen to vary greatly across studies. To better understand such relationships, we classify these indirect impacts as biological or anthropogenic (secondary or tertiary).

2.3.2.1.2 Biological / ecological and anthropogenic effects

Biological or secondary impacts are as a result of physical climate change, which may lead to changes in regional geochemistry, and flora and fauna. Such biological changes may alter vulnerability of human populations. For instance, climate change may drive changes in the distribution of disease vectors (Mcmichael et al., 2015; Watts et al., 2015).

Anthropogenic or tertiary aspects of climate change comprise the resultant alterations to human systems. Within the model, the tertiary, anthropogenic impacts of climate change are presented as an arrow that interlink to the system of dynamic, ever changing social, economic, political, demographic (and other environmental) factors. Whilst these contextual factors change of themselves, climate change may be an upstream driver of changes and are therefore intrinsically linked. Examples of tertiary climate impacts may include changes in anthropogenic land use and land availability due to sea level rise. Alterations, for example in crop production and fish catch, may have direct implications to socioeconomic factors for example due to reduced agricultural output (Gasparrini et al., 2015), food security (Warner et al., 2019), and therefore upon urbanisation rates due to rural to urban migration (Bowles et al., 2013). Such anthropogenic pathways generally act over a longer temporal scale and can lead to the climate signal being masked by more proximal factors. As such, understanding of their impact on migration remains inconclusive (Parham et al., 2015) and less studied than direct physical impacts (Brooks et al., 2005). Furthermore, additional consideration is needed to assist the recognition of dynamic interactions between the physical, ecological and anthropogenic aspects of climate change.

2.3.2.2 Other migration drivers

There are of course a range of other drivers of migration which are important to understand as well as how they may be affected by climate change. It is usually a combination of drivers that culminates in an individual's decision to migrate and in what manner. Within the context of climate change, we refer to this aggregation of drivers (climatic and other) as the 'vulnerability profile' which will be unique to each individual. We now present a more detailed view of some key drivers within each of the five main classes identified. These are outlined in Table 2.3 below.

Table 2.3 Non-climatic drivers of migration. Drivers are split into five classes: social, economic, political, demographic and environmental. Societal level refers to the societal scale at which drivers typically impact. Some drivers may exist both as micro and macro factors. Temporal scale refers to the typical time-scale of change in each driver. Whilst there is no set demarcations, slow change refers to a change typically over years or decades whilst fast refers to changes which may occur immediately or over a short time-frame of months. Static implies that factor is not usually time-varying.

Determinants of migration	Societal scale	Temporal scale
Social		
Family and societal relations and expectations	micro	slow
Migration and social networks (including remittance networks)	micro	slow
Changes in marital status	micro	slow
Education level	micro	slow or static
Ethnicity	multi-level	static
Economic		
Average household income	micro	multi-level
Key economic activity of household	micro	multi-level
Cost of living (e.g. consumer prices relative to income)	multi-level	multi-level
Employment rates and opportunities	multi-level	multi-level
Land availability and rights	macro	slow
Political		
Level of institutionalisation and infrastructure (governmental and other)	multi-level	slow
Conflict / security	multi-level	multi-level
Governance: policy incentives and state support initiatives and effectiveness of implementation and decision-making by government	macro	slow
Specific migration policy and cultural sentiment towards migrants	macro	multi-level

Demographic		
Gender	micro	static
Marital status	micro	slow
Age	micro	slow
Ethnicity	multi-level	static
Sex ratio	macro	static
Population density	macro	slow
Population growth rate	macro	slow
Age ratio	macro	slow
Population morbidity and mortality	macro	multi-level
Environmental		
Soil quality	macro	slow
Land use / quality and degradation	macro	slow
Air quality	macro	Slow
Food security	macro	multi-level
Water security	macro	multi-level

As well as existing as intermediary drivers, each of these drivers may have direct impacts on migration decisions. For example, Henry et al. (2003) using regression modelling and Gray and Bilsborrow (2013) using discrete time-event history modelling both found that high literacy rates and economic status can act as significant push factors for migration. Ezra and Kiros (2001) also found marital status and poverty level acted as push factors. Warner et al. (2009) clearly identified the role of government relocation policy on driving planned resettlement of communities away from flood plains in Mozambique. Such epidemiological methods are well utilised for analysing such direct causes, however each analysis is limited to a specific type of migration and set of pre-assumed key drivers. It is not possible within this paper to examine in depth, the nature and relationships of each driver, rather the author's focus on presenting a broad overview, elucidating the multi-level and multi-temporal nature of migration drivers, as well the dynamicity of the drivers and their linkages. Some key examples are used to demonstrate such complexities.

2.3.2.2.1 Social drivers

Many studies examine the importance of social factors such as migration networks (Chikhungu & Madise, 2014; Romankiewicz & Doevenspeck, 2015; Schmeidl, 1997; Suckall et al., 2015). Education and literacy rates have also commonly been identified as determinants of vulnerability (Adger et al., 2015; Bilsborrow & Henry, 2012; Entwisle et al., 2016; Findlay, 2011; Krieger et al., 2014).

Social drivers such as education and poverty may also alter other drivers. For example, other studies have identified that in poor areas of Malawi where rain-fed agricultural practices reigned, the predominant climate change adaptation approach was not seasonal migration but the introduction of irrigation techniques to increase crop yield (Findlay, 2011; Joshua et al., 2016). However, Joshua et al. (2016) concluded that increased irrigation triggered increased water insecurity and hence water conflict. This interaction between poverty and adaptation approach has significant implications for future vulnerability levels and on future social and political factors. Of course, such impacts are not isolated to only impoverished communities. Developed countries with lower poverty levels can also suffer compound impacts of climate change on other social determinants. However, developed countries generally have a higher capacity to mitigate or adapt to such changes resulting in different outcomes (migration and other), with different distributions across the community ([Core Writing Team, 2014).

2.3.2.2.2 Economic drivers

Closely linked to social factors are economic considerations such as employment opportunity and household wages (Chidanti-Malunga, 2011) at the micro societal level. Poverty is also a key determinant of an individual’s vulnerability and hence ability to migrate (Ezra & Kiros, 2001; C. Gray & Bilsborrow, 2013; Warner et al., 2009). Macro level factors such as average employment rates and average income of a community may also act as push or pull factors which have often been identified as the dominant drivers of migration (Black et al., 2011; Gasparrini et al., 2015). There also exists a debate on the role of failed politicised economic models such as ‘trickle down’ and ‘rent seeking ‘as being largely responsible for the increase in wealth gaps and rising relative poverty (Hunter et al., 2015). These economic models may contribute to future migration behaviour due to relations between poverty and mobility (Warner et al., 2010) and the effect of inequality gradients acting as sinks for migration (IOM & UNDESA, 2012). For instance in the Malawian example given above, Findlay (2011) also comments on the additional causes of food insecurity beyond water scarcity, including soil erosion, socioeconomic factors including vulnerability to poverty, ability to financially withstand crop failures, low food utilisation and infrastructural factors such as high transport costs.

2.3.2.2.3 Political drivers

Political drivers are largely absent from environmental migration quantitative studies and yet present a significant category of migration drivers. Possibly the most influential and most studied of this category is the role of political insecurity on migration. Whilst the role of political insecurity and conflict is a well acknowledged driver of migration, the role of climate change in driving political instability remains contested (Raleigh et al., 2008). Burrows and Kinney (2016) present an overview of multiple pathways through which climate change may lead to or exacerbate conflict such as through increasing rural to urban migration, resource competition or dispute between migrant and host communities. Sokolowski et al. (2014) also discuss the role of political interventions such as efforts for conflict resolution, international relief, and immigration policy such as the closing of borders, and their impact upon migration outcomes (Sokolowski and Banks, 2014; Sokolowski, Banks and Hayes, 2014).

Though largely overlooked in general climate migration literature, some models do focus on political drivers of migration with relatively accurate predictions (IOM & UNDESA, 2012; UNHCR, 1996). Sokolowski and Banks (2014) modelled population displacements that occurred in Syria in 2013 using UNHCR guidelines for factors prompting departure. Indeed, the Syrian conflict can be argued to contain both political and climate determinants in the mass displacement that has resulted (Kelley et al., 2015).

Other political drivers include level of governance and trust in government and the level of institutionalisation and infrastructure within a community. Indeed, infrastructure and governmental and non-governmental organisations are critical intervention nodes and as such their connection to environmental migration form an important area of potential study. Other policies such as water, food and agricultural policy also co-interact and may result in a range of normative and adaptive migration approaches. For example, Loevinsohn (2015) studied the 2002 Malawian food crisis and identified primary causal factors to be both environmental drought and the underinvestment by the national government in agricultural stock. Loevinsohn further identified that 39% of households interviewed during 2002 had migrant family members working seeking alternative income (Loevinsohn, 2015).

Crack-down on immigration policies in western communities such as Britain, the EU and the USA, will also have significant impact upon future migration trends (Baldwin-edwards et al., 2019). With climate change expected to impact the numbers of both internal and international migrants in the future, existing dichotomies between the evidence on migration drivers and the political response to it, will undoubtedly renew pressure on migration issues.

2.3.2.2.4 Demographic drivers

Demographic factors at the micro level (such as age, gender, ethnicity) as well as at the macro level (such as average living conditions, affluency, diaspora presence) can act as push or pull factors as well as interact with other factors. Indeed, the combined effect of climatic drivers and demographic drivers have resulted in many developing countries being the most vulnerable nations to climate change and has helped to drive research and narratives around climate justice (Schlosberg, 2012) and climate refugees (van der Geest et al., 2010). Rapid urbanisation is often a trend in such locations, leading to slum development, poor infrastructure and high vulnerability to future climate change, not to mention other shocks such as the COVID-19 pandemic.

In developed countries, different demographic challenges such as population ageing may also impact upon population mobility and health. For example, an older population may result in a reduced willingness to move and increased mental health burden of doing so (Munro et al., 2013). Conversely, countries with aging populations can benefit from the ‘healthy-migrant’ effect (Marois et al., 2019). As such, appreciating the demographic factors, their dynamics and interactions is essential to understanding climate risk on future sustainable development and population changes. When modelling future environmental migration it therefore is essential to take into account the demographic situation of the study area.

2.3.2.2.5 Environmental drivers

As noted in section 2.3.3.1 above, climate change is a key driver of environmental change, with secondary (ecological) and tertiary (anthopogenic) impacts of climate change being related to environmental quality and habitability of certain environments. Beyond these factors, there are many other environmental factors, unrelated to climate change, which may be influenced by, or influence other socio-political factors, often overlooked in environmental-migration studies. For example, changes in land use, urbanisation, over-exploitation of natural resources, environmental pollution and geophysical natural hazards may each be key determinants of migration. Such environmental changes often have strong feedback loops, for example rural to urban migration having significant repercussions on environmental degradation, air and water pollution, energy consumption and greenhouse gas emissions (Rafiq et al., 2017).

Environmental drivers have found to be critical in many development studies. The Environmental Kuznets curve ("EKC") hypothesis purports that the early stages of economic development are coupled to environmental degradation and has been found to be true in many contexts (Dinda, 2004). In the context of urbanisation led by adaptive migration, this hypothesis suggests that urbanisation will result in further environmental degradation, with significant implications for future development (Black et al., 2013; Weiss & Mcmichael, 2004), health (Leach et al., 2017), political security (Mulwafu, 2000), and internal migration (Kumari Rigaud et al., 2018).

2.3.2.2.6 Multi-dimensional drivers

Some factors, such as food and water security do not fit neatly into a single category as they may have dimensions in each of the five categories. For instance, food security, as discussed in chapter 1, consists of a hierarchy of considerations, availability may be most relevant as an environmental factors whilst access is primarily economic, social and political, food utility and stability similarly are a combination of each of the factors. Depending on the purpose of study, scholars may classify food security as for instance, an economic factor, or may choose to acknowledge the multi-dimensionality and array of metrics available when attempting to measure a complex phenomenon such as food security. Whatever the classification and definition of food security, as introduced in chapter 1, there are a variety of pathways through which it may influence a individual or households migration decision.

2.3.3 Applying the model to the case study of Malawi

We now provide a brief example of applying the conceptual model to a case study. As described within Chapter 1, Malawi is a climate vulnerable society due to high reliance small-scale, rainfed agriculture, employing the majority of Malawians. Economic support for the agricultural industry exists primarily in the form of subsidies. Despite this, food insecurity and poverty are very high across Malawi. Normative migration is predominantly economic (largely circular) as well as for marriage. Already Malawi has witnessed an annual mean temperature increase of 0.9˚C since the 1960s, and whilst local rainfall patterns are difficult to accurately model, there has been an observed increase in frequency and magnitude of drought and flood events (Verhage et al., 2018).

By conducting an in-depth literature review of Malawi's political, demographic, environmental, social and economic makeup and then applying the conceptual approach described above by considering the impacts of climate change (primary, secondary and tertiary) to each key factor, we arrive at the case-specific model shown in Figure 2.2 below.

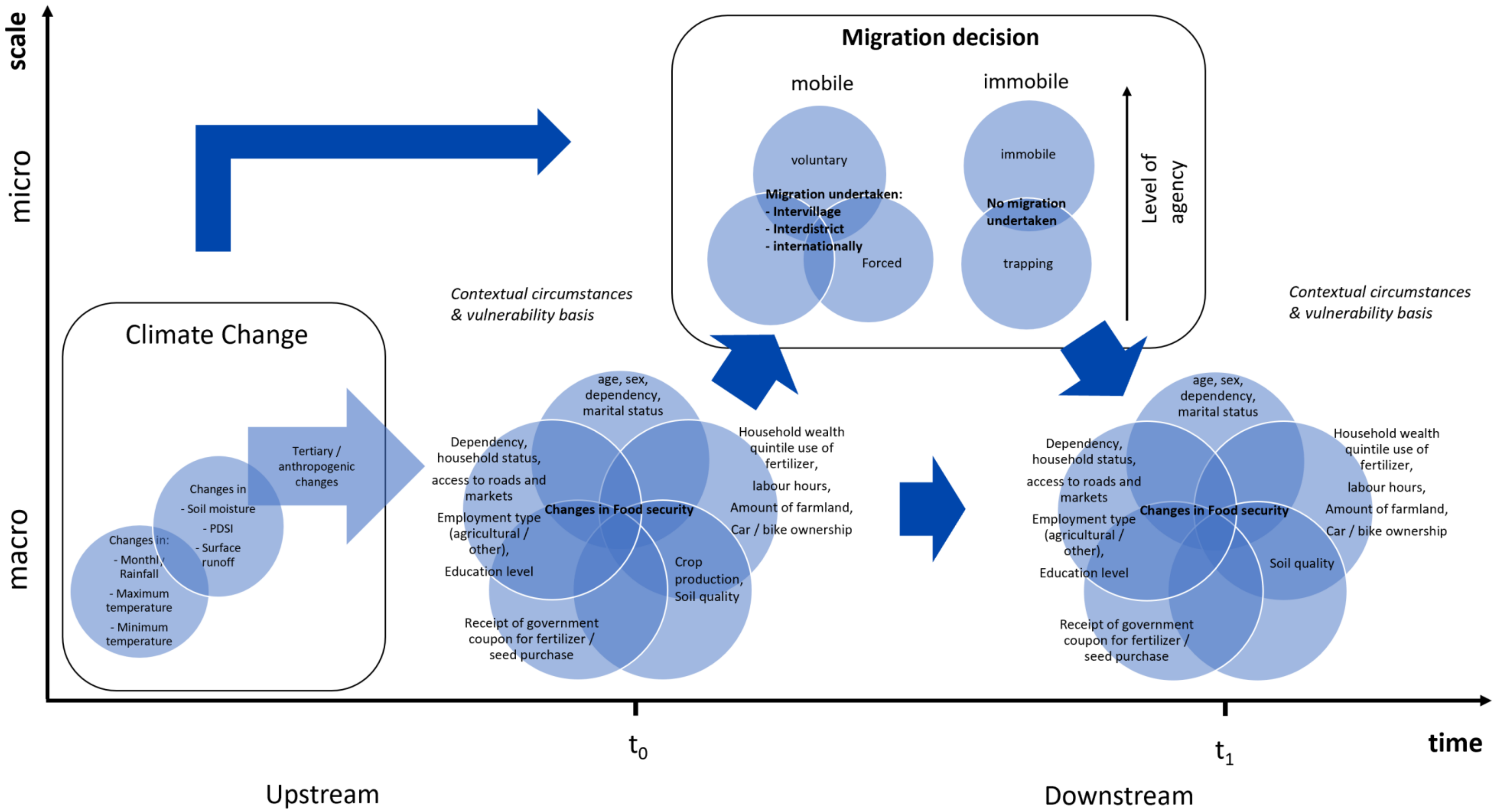

Figure 2.2 A conceptual model exploring the relationships between climate change and migration in the context of Malawi.

A key advancement of this Malawi specific-model is that each variable is quantifiable using observational datasets. As such, it demonstrates how the application of the generalized conceptual model (Figure 2.1) to a local context (Figure 2.2), allows the creation of an astute, practical and measurable model, from which well grounded, policy-relevant research questions may be formulated and tested. By applying this methodological process, the Malawi-specific model generated, is based on well-grounded assumptions and it holistically identifies key variables that may be of relevance for future empirical investigation. The Malawi specific model highlights the key variables identified through datasets (refer to chapter 3 for more information on the data), and, as with the general model, the pathways through which these variables are hypothesized to affect / be affected by each other. This shall form the basis of the empirical models explored in the subsequent chapters of this thesis. Specific variables that should be considered for each factor outlined in Figure 2.2 can be found in Appendix A. These variables were identified through an iterative process based on the Malawi context as well as initial explorations into data availability. Subsequent chapters shall utilise this table as a starting point, from which specific data for each variable will be explored and determined whether they are suitable for inclusion in statistical models.

2.4 COMPLEXITIES WITHIN THE MODEL

Complexities naturally arise when taking an upstream, systems-thinking approach to migration determinants. There are two key complexities identified. Firstly, the acknowledgement of multi-level interactions and feedbacks between drivers. Secondly the dynamicity of drivers and their connections over time and space. Despite these complexities, models must be transparent and provide results from which simplicity may be derived in order to be useful for decision-makers and intervention planning.

To aid reflection upon such interactions, Figure 2.3 depicts a simple representation of the interactions between individual and classes of drivers. Each class of driver is represented by a funnel, from which a combination of both macro and micro drivers is filtered from an interconnected reservoir where drivers from different classes interact on a range of temporal, spatial and social scales. The combination of drivers at the individual migrant level results in a unique vulnerability profile and context which determines the migration decision made by each potential migrant. This is particularly useful when considering composite or multi-dimensional determinants such as food security, water security, wellbeing– which are difficult to attribute to a single class and often only measurable using indexes, proxies or other indicators such as principal components, but which may be highly relevant in an individual's particular vulnerability profile and decisioning.

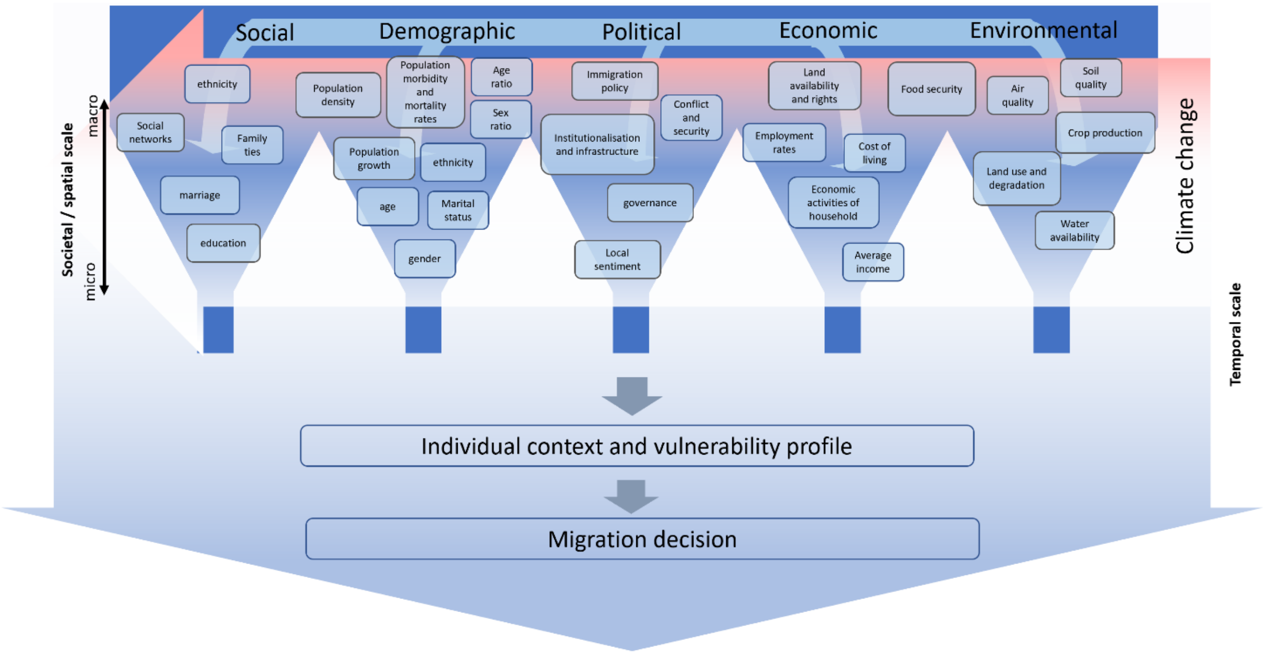

Figure 2.3 A simple representation of interactions between drivers and classes of drivers, and the role of climate change as a source of external pressure on all drivers simultaneously.

Climate change is again presented as an externality, cross-cutting all other driver classes and acting across the temporal and societal levels. As in Figure 2.1, each driver may vary over both time and spatial dimensions. However, modelling such dynamicity requires simultaneous understanding of drivers, their interactions, and their evolution through time and space. The insight that such dynamic modelling would allow may enable the effective identification of suitable intervention nodes for public health, land use and immigration policy to name but a few.

The concept of vulnerability profile's allows for the acknowledgement that each migrant has a unique set of drivers due to the multi-level and multi-temporal combination of factors he or she is subjected to. In this way the aggregate vulnerability may be conceived as a meta-driver of migration. The concept of vulnerability describes the ability of an individual or community to withstand and recover from a risk such as a disaster event (Raleigh et al., 2008). Other ways to consider meta-drivers includes resilience, and adaptive capacity (Gallopin, 2006; McLeman & Smit, 2006; Tanner et al., 2015). Whilst vulnerability is a commonly used meta-driver in much climate migration literature, resilience is often the currency of choice in the fields of disaster management and climate change adaptation

(Weichselgartner & Kelman, 2014). However, these terms are broad and often overlap and are even used interchangeably, rendering their distinction and usefulness within scientific analysis questionable. Despite this, such meta-drivers are the dialogue of choice for policymakers and must be utilised for research to have political relevance. However, care should be taken when referring to such meta-drivers and the contributing drivers as explored above must be contextually relevant and carefully selected.

2.5 CONCLUSIONS

Previous conceptual models explore the linkages between climate change and migration with different assumptions and perspectives. The 2011 Foresight report identified five key families of drivers and concluded that migration may be an adaptive strategy in the face of climate change and represents possibly the best to-date, globally accepted conceptual model for climate migration. The report disputes the long-time argument that migration represents a failure to adapt in situ. This conclusion however fails to consider several key aspects of migration: firstly, the agency and social wellbeing of migrants involved at each stage of the migration process (prior to movement, in transit, and at host destination). Secondly, the level of agency afforded to would-be migrants during the migration decision - even as a supposedly proactive adaptation measure. Finally, the delicate line between forced and voluntary movement, based upon a composition of drivers and the bias of the person(s) awarding the classification.

The ongoing Lancet Commission on Climate change and health also presented an interesting framework where migration as a result of climate change is framed as a significant health challenge and opportunity (Watts et al., 2018) but does not give a large amount of consideration to intermediate drivers and various pathways by which climate change may drive migration or produce trapped, left-behind communities. Helping to close this gap, and drawing on a range of political and economic, as well as health literature, the model presented by Sellers, Ebi and Hess (2019) considers a puzzle of immediate and longer-term drivers of social instability, with both climate shocks and migration as contributing factors and possible outcomes (Sellers et al., 2019). McMichael et al. (2012) also present a foundational model whereby the basic links between climate change and migration are presented though driver interactions and dynamics are not discussed in depth.

Whilst this and other conceptual models encourage an upstream approach to environmentally-induced migration, putting such thinking into practise presents further challenges. The paucity of empirical studies limits our understanding of how global climate change may threaten development and public health, particularly regarding the indirect impacts of climate change. Lack of suitable data and quantitative metrics needed to conduct such studies remains a perennial challenge. It is essential that these challenges be overcome through future data collection and empirical modelling.

Ultimately, climate change presents a critical challenge for future migration across the globe and has significant implications for public health, human security and sustainable development. Climate change is already and will continue over the coming decades to contribute to large numbers of displaced persons (Internal Displacement Monitoring Centre [IDMC], 2018a), refugees (UNHCR, 2015), internal migrants (Kumari Rigaud et al., 2018), international migrants (Nawrotzki & Bakhtsiyarava, 2017) and immobile and trapped persons (Schewel, 2019). As such, better understanding of the relationship between climate change and migration is essential for effective future policy planning in all sectors. This can be achieved through the systematic and homogenous application of robust conceptual frameworks to local contexts. A lack of data, particularly for low-income and indigenous settings is a key set back which obstructs furthering our understanding. It also hinders the ongoing desire from academia, national and international policymakers to count how many, and identify who are the climate migrants of today and of the future.

This research has attempted to demonstrate the need for a flexible and pan-disciplinary approach to environmentally induced migration. Research which crosscuts traditional discipline boundaries, in accordance with the global health viewpoint, is encouraged when using such a conceptual framework in the study of climate migration. In this way, traditional pitfalls may be avoided, better reconciliation of macro and micro determinants may be achieved and more visibility of the dynamics of drivers and hence a more accurate understanding of their role in driving migration may be elucidated. However, the review within this research is non-exhaustive and draws lightly on a wide range of literature and academic standpoints. As such, it is designed to demonstrate a nuanced approach to climate migration theory and application, rather than present a comprehensive “how-to” guide. In particular, the paper draws overly from literature produced by researchers from the Global North and is influenced by a eurocentric standpoint for example by the prevalent framing of climate migration as an adaptive opportunity for ‘victims’ of climate change.

2.6 CHAPTER SUMMARY

This chapter has created a new conceptual model and applied this to the Malawian context. Within this context, the economic importance, as well as climate vulnerability of Malawi’s agrarian society have been identified. It is therefore hypothesised that a key mechanism through which climate change may impact Malawians, which may even ultimately lead to a change in a decision regarding migration, is through the impacts upon subsistence crop production and food security, as well as a range of other sociodemographic variables as outlined in Figure 2.2. As such, the impacts of climate change upon household crop production and food security shall be explored empirically within the next chapter.

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APPENDIX A

A descriptive table providing an overview of each variable included within the Malawi specific model.

Variable	Brief description and justification for inclusion
Climate variables	
Precipitation	Total precipitation, measured in mm per month, is a central aspect of weather and important indicator in long-term climatic changes.
air temperature	Air temperature (degrees Celsius) is a key climate factors and as such forms a core part of any terrestrial climate change investigation.
Soil moisture	Soil moisture (mm) represents the amount of plant extractable water (measured in mm each month) contained within the a grid of soil, measured in mm per volume (Abatzoglou et al., 2018; Wang-Erlandsson et al., 2016). As such, soil moisture presents an interesting metric to examine the impacts of climate change on crop production and hence, upon people's livelihoods.
Water surface runoff	It is hypothesized that high surface runoff events may be a primary cause of localized flooding which may lead either directly to displacement of persons, or to the damage of crop, property and life that may directly or indirectly impact upon a migration decision. Whilst this is not an indicator of climate change, it is highly related to precipitation measures and can be derived from general circulation models (GCMs) and as such is included within this category.
Palmer Drought Severity Index (PDSI)	The Palmer Drought Severity Index is an index of relative dryness, initially created by Palmer in 1965 (Palmer, 1965) and as such provides an insightful measure in areas that are drought-vulnerable or are undergoing long-term drying, such as Malawi.

	Droughts are hypothesized to be both a direct driver of movement (in extreme cases) as well as a key determinant of food security, due to the relationship between crop production and drought (Government of Malawi, 2016).
Crop production	
Amount (mass) of crops produced	As a subsistence farming society, it is hypothesized that in Malawi, climate change may impact food insecurity and people's livelihoods via impacting household crop production.
Food security	
Food security proxies such as hunger (lack of sufficient food), average number of meals consumed, child anthropometric measurements	In any society, food security is a key component to a sustainable livelihood. Within the context of subsistence agrarian societies, such as much of rural Malawi, it is therefore hypothesized that food insecurity is a key determinant in the decision of whether to move and when. It is further hypothesized that, without food system interventions, climate change may increase food insecurity in the long term due to a gradual drying and warming of the climate which may have negative consequences for maize production from traditional farming techniques that rely on rainfed irrigation (Niang et al., 2014). Alternatively, food security may be symptomatic of poverty and indeed may act to increase poverty if a household is forced to divert earnings for food purchases, rather than investment in farms / schooling / other opportunities. Through this mechanism, food insecurity may decrease the likelihood of moving due to the rising poverty barrier, the so-called 'trapping effect' (Black et al., 2011). There are various ways to measure food security each with different strengths and weaknesses. Possible measures including tried and tested metrics such as child anthropometric measurements, and number of meals consumed (taking a

	contextual approach to what the 'normal' number of meals for a food secure household would be. Another, qualitative measure is survey responses around hunger and whether a household had sufficient food to feed themselves through time.
Political (/ economic)	
Access to subsidy programmes / coupons	Malawi has a long history of utilising agricultural subsidies and social cash transfer programmes to support agricultural livelihoods. These have the intended affect of improving farmers crop yields and hence improve food security and alleviate poverty. Therefore, access to and participation in government subsidy schemes via receipt and use of coupons, predominantly for fertiiser and seed purchasing may be a valuable contributing factor to crop production and food security.
Economic factors	
Household assets: fixed assets including land ownership as well as livestock and household goods	Income is an important determinant of household level food security because of the relationship between income and purchasing power. Richer households with more disposable cash are better able to purchase grain, farming equipment (such as fertiliser, seed and irrigation tools) or processed food (ready-to-eat) than poorer households. As such they are less vulnerable to food security during periods of poor environmental or economic conditions and therefore less vulnerable to forced migration. Asset ownership such as mobile phones, tvs, fridges, furniture are a common way in which the relative wealth of a household can be determined. In subsistence contexts such as Malawi, household assets as well as land ownership (size and quality) can be more accurate measures of wealth than income. Household assets are an important determinant of household level food security because of the relationship between assets

	(as a proxy for wealth) and purchasing power (Hjelm et al., 2016). Furthermore, in climate migration literature, some studies find that household assets act as a confounder of migration, as saleable assets (such as livestock or furniture) presents an alternative adaptive approach to migration during lean times (Suckall et al., 2017). Furthermore, some studies suggest that the more capital a household has in land, the less food insecure they are likely to be due to increased ability to grow food for both subsistence and as an income source (Peters, 2006; Skjeflo, 2013). Fixed assets (such as land, building materials, some livestock) may affect a household's willingness to move that requires partial or total abandonment of such investments and emotional attachment (Assa et al., 2013). As such it is hypothesized within this thesis that household assets are relevant within the migration decision.
Amount of land farmed	It is assumed that the more land available to an agent for subsistence farming, the higher the household crop production and as such, the higher the household income, food security and resilience to future climate change.
Farming practices	Farming practices may include variables such as use of irrigation schemes, the hours spent on household labour, whether labourers are employed to help on the farm, whether additional support is utilised (e.g., tractors, oxen). Farming practices can also refer to climate change adaptation schemes that may already be in place in certain parts of Malawi. For example, though much of Malawian agriculture is rain-fed, there are many localised irrigation schemes, both government and community planned to combat increases in local rainfall variability and increased periods of extreme rainfall conditions (Joshua et al., 2016). In *dambo* (wetland) areas, adaptation strategies include increased management of water resources and uptake of government funded water

	pumps (Chidanti-Malunga, 2011; Joshua et al., 2016). Other adaptive strategies include crop diversification, livelihood diversification (for example increased instances of fishing) (Chidanti-Malunga, 2011), circular migration (Suckall et al., 2015), and perhaps even marital migration (Entwisle et al., 2016; Myroniuk, 2017). Participation in subsidy schemes such as the FISP or SCTP may also impact a households economics and food security (Government of Malawi, 2016; Pauw & Thurlow, 2014).
Social (Socioeconomic)	
Car / bike ownership	Car and bicycle ownership are a household asset that can be used as a proxy for identifying the wealth index of a household (Hjelm et al., 2016; National Statistics Office (NSO) [Malawi], 2016). Furthermore, such assets can be valuable in increasing an agent's mobility and hence access to food from geographically further afield than less mobile households. Furthermore, such mobility increases the resilience of a household and as such may have downstream impacts upon a migration decision (Adger et al., 2002). There are no studies that examine the relationship between vehicle or bicycle ownership with food security or propensity to migrate. However, it is intuitively hypothesized that better transportation methods make transportation easier and as such increase migration when other factors make the migration decision desirable.
Proximity to main road	There are no current studies identified that study the relationship between road quality and quantity, with migration in Malawi. However there are studies that suggest that proximity to main roads impact upon other demographic aspects such as geospatial trends in HIV hot-spots in Malawi (Zulu et al., 2014), due to the effect of proximity to roads on facilitating travel. Furthermore, climate change, through

	physical extreme weather events, may contribute to road erosion and as such climate change may have an indirect impact upon migration based on the physical difficulty of moving due to poor roads (Arndt et al., 2014).
Proximity to city	Cities are often considered as pull factors attracting migration. There is evidence from gravity-model that suggest that proximity to city influences migration decisions (Henry et al., 2003; Mastrorillo et al., 2016).
Employment type	Employment type is commonly associated with migration decisions and the type of migration undertaken based on human and financial capital that different types of employments provides. Employment status i.e. employed or unemployed (Mastrorillo et al., 2016), industry for example arable, pastoral, ganyu or construction (Henry et al., 2004) and employment productivity markers that equates to income bracket such as size of farmland (C. Gray & Bilsborrow, 2013; Henry et al., 2004; Skjeflo, 2013) or level of ganyu income (Lewin et al., 2012) are all found to be relevant variables in the migration decision.
Education level	Education is a well-documented confounder that is found to be relevant in migration decisions. Generally it is thought that the higher the level of education, the higher the likelihood of undertaking migration (Lewin et al., 2012; Suckall et al., 2017).
Number of dependents	Individual migration decisions often consider aspects such as age, gender, education and number of dependents as this affects mobility (ability to move) and alternative adaption options such as encouraging migration for work or marriage of some family members to provide remittances and reduce incumbency upon remaining members (Lewin et al., 2012; Raleigh, 2011).
Social network	It is well established that social networks are an important dimension in a migration decision, with potential migrants more likely to move to areas where they have established

	connections (Myroniuk, 2017). In Malawi, social networks are intrinsic to migration decision for example through kinship, marriage, divorce, escape and widowhood (Myroniuk, 2017). Social networks are also an important impact of migration, as migration can either strengthen or diminish social networks which can in turn have serious implications for wellbeing, access to healthcare and mental and physical health of migrants (Carr, 2005; C. McMichael et al., 2012).
demography	
Age **Gender** **Marital status**	Individual demographic characteristics of gender, age and marital status are well established demographic determinants of an individuals' vulnerability, and as such, to their propensity to migrate, and decisions regarding when and where, as well as the duration of migration.
Dependency	Whether or not an individual is dependent or not, based on age (for example, in Malawi being under 15 years old is classified as a child, or being 65 or older. This is a rough measures because it does not account that some children are the head of a household (e.g., if their parents have died or moved away) and does not account for disability.
Migration	
Individual and household level movements. **District, regional and national (cross-border) movements**	Measuring migration is highly challenging. It is important for studies to define the migration flow under scrutiny and select relevant spatial and temporal resolution that is most relevant to addressing the research question. These movements could be analysed at the individual, household (micro) levels, or district, regional and national level (macro). In the Malawian context where movement is closely linked to food security, both district level and household level movements are of interest. Since food security typically varies seasonally with harvest and crop availability (Food and Agriculture Organization, 2015), seasonal movements are

	considered key, as are longer term movements in response to chronic or longer-term changes in food security. Short-term and circular movements are also thought to be relevant in climate change adaptation literature (Findley, 1994; Suckall et al., 2015) though such small-scale movements are difficult to monitor due to data sparsity.

3 THE IMPACTS OF CLIMATE CHANGE ON CROP PRODUCTION AND FOOD SECURITY IN MALAWI; AN EPIDEMIOLOGICAL APPROACH

3.1 CHAPTER OBJECTIVES

In the previous chapter, a conceptual model was developed as a tool for understanding and exploring the relationships between climate change, crop production, food security and migration. This conceptual model was applied to the case study of Malawi from which a Malawi specific model was derived (Figure 3.1). The aims of this chapter are to now use this understanding to quantitatively explore the relationship between the factors identified as outlined in red of the model. In particular, this chapter shall investigate whether and to what extent, climate change is associated with changes in crop production and food security. This is to explore the hypothesis outlined in section 1.4 that climate may impact upon crop production which in turn (combined with other contextual circumstances) may affect household food security.

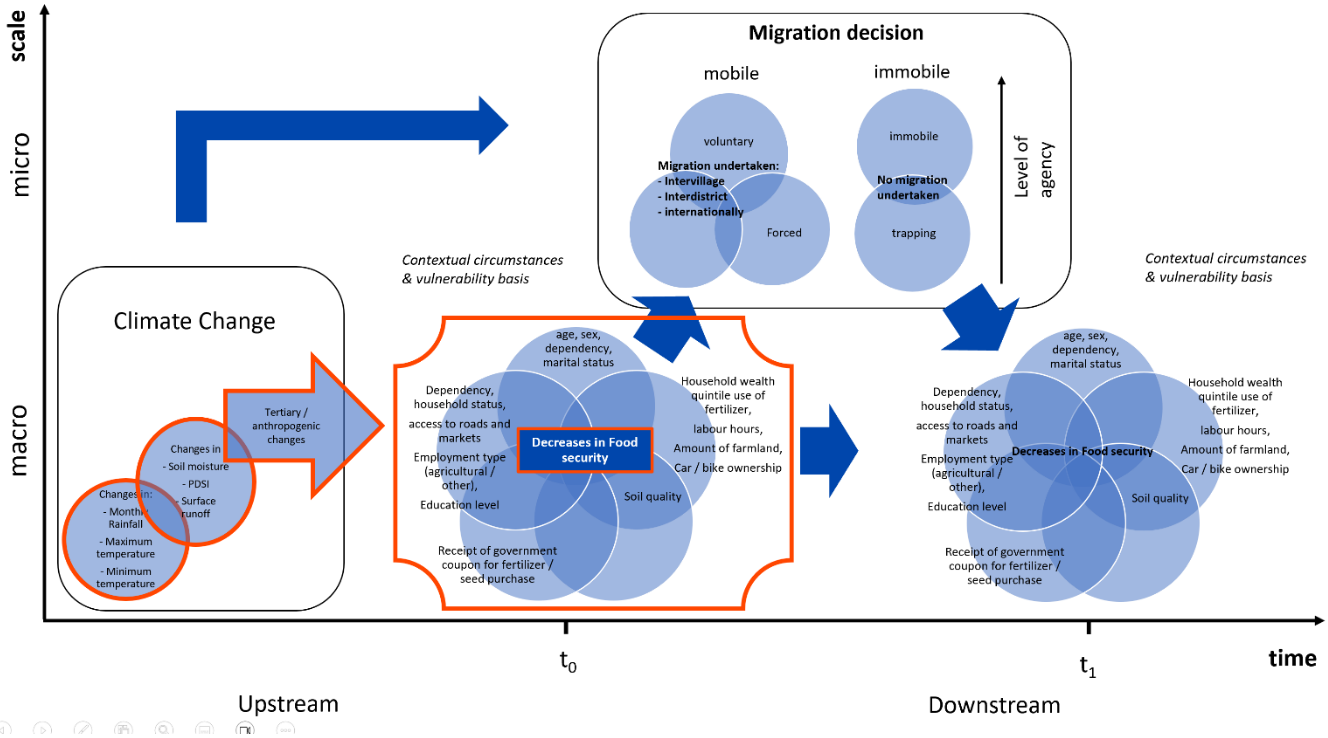

Figure 3.1 Conceptual model of the key relationships and determinants of crop production and food security in the context of Malawi.

3.2 INTRODUCTION

Crop growing in Malawi abides by a predominantly rainfed, smallholder farming model and is therefore highly climate sensitive and vulnerable to climate change. As maize is the staple crop, accounting for approximately 54% of calorific consumption (Msowoya et al., 2016) and 80-90% of farmland (Msowoya, 2013; Stevens & Madani, 2016), the response of maize crop to climate change is a priority research and policy area. Most studies to date focus on how future temperature and rainfall are projected to affect maize production (Jones & Thornton, 2003; Knox et al., 2012; Stevens & Madani, 2016). Few studies take a wider view of other secondary climate variables (such as hydrological variables) and few consider other crops, despite ongoing crop diversification as both a national plan (FAO, 2019) and climate adaptation responses of farmers (Chikabvumbwa et al., 2022; Mango et al., 2018; Snapp & Fisher, 2015). Studies to date tend to conduct analyses either at regional levels (such as Africa, or sub-Saharan Africa (Jones & Thornton, 2003; Knox et al., 2012; Wheeler et al., 2000), at the national level (Ngwira et al., 2014; Stevens & Madani, 2016) or at a subnational level, focusing on a specific locale (Chidanti-Malunga, 2011; Joshua et al., 2016; Msowoya et al., 2016; Warnatzsch & Reay, 2020). Despite being a small country, situated at the bottom of the Great Rift Valley, Malawi is home to a variety of ecologies, topographies and livelihoods and yet retains relative homogeneity across a range of factors such as wealth, child mortality and staple crop choice. As such, there is value in conducting research that takes an intra-country view and which offers insight into common responses to climate change as well as idiosyncrasies of different places within the country.

The focus of this chapter will be to build a series of regression models to explore how climate variables alongside other socioeconomic and demographic factors, impact upon household crop production, seeking to identify whether districts that experience more adverse climatic circumstances in the years immediately preceding a national household survey are more inclined to exhibit lower levels of food production. The chapter will then consider how climate, along with crop production, is related to food security as measured through a range of metrics. Three cross-sectional Integrated Household Surveys (IHS) will be used to assess relationships at three different points in time, focusing on the wet seasons for 2010/11, 2015/16 and 2019/20. Any results that are replicated across all three models adds robustness to the findings. Furthermore, through this comparison it may be possible to postulate potential trends through time e.g., due to climate change. Finally, the chapter shall also attempt to address the scarcity of studies which consider multiple crops, beyond the staple crop maize, and provide a high level of spatial granularity, considering the household level and district level results across the country, facilitating an exploration of inter-district variation.

3.3 DATA AND METHODOLOGY

3.3.1 Climate variables

Historic climate data has been constructed from the TerraClimate climatology dataset (Abatzoglou et al., 2018). TerraClimate is a combined climate and climatic water balance dataset, built from a combination of several climate gridded datasets. As such it provides a high spatial and temporal granularity of both climatic and hydrological parameters of interest (Table 3.1). TerraClimate variables provide monthly temporal granularity, which may hide any extreme events during any month (e.g., a cold or hot snap that can affect crop growth, but which only lasts a period of days), however, it provides a longer term outlook of climate variables and climate change through the decades. Furthermore, it provides good spatial granularity across the country which could not be achieved with sparse meteorological observed datasets available for Malawi. Climate variables for the wet season November – April (aligning with the main crop growing season), the 12 months prior to the main harvest as well as the two-year, three-year, four-year, five-year, 10-year and 20-year wet season average values prior to the main harvest were gathered and explored. Climate variables were provided with a ~4km spatial granularity and as a monthly time series.

Table 3.1 Climate and hydrological variables

Shortname	Units	Spatial resolution	Temporal resolution	Level	Data source
Accumulated monthly precipitation	mm	~4km	monthly	District	TerraClimate

'Palmer Drought Severity Index'	unitless	~4km	Monthly	District	TerraClimate
'Minimum 2-m air Temperature'	Degrees celsius	~4km	Monthly	District	TerraClimate
'Maximum 2-m air Temperature'	Degrees celsius	~4km	Monthly	District	TerraClimate
Monthly total 'runoff_amount'	mm	~4km	Monthly	District	TerraClimate
'Soil Moisture at End of Month'	mm	~4km	monthly	District	TerraClimate
Average district Agroecological zone Tropical - warm/semiarid Tropical- warm/subhumid Tropic - cool/semiarid Tropic – cool/subhumid	n/a	District	Cross-sections for 2011,2016,2020	District	IHS

District average values were constructed firstly by reverse geocoding the climatology using the Stephen Morse online batch geocoder (Morse, 2006), to assign a district code to each latitude and longitude value within the dataset see (Appendix B for list of district /region codes). Secondly, district climate values were constructed by taking the average of all coordinates within each district. Since the Morse geocoder (which relies on (© OpenStreetMap Contributors, n.d.) (openstreetmap.org)) does not segregate Malawi's city administration boundaries (for the four cities of Mzuzu, Lilongwe, Blantyre, Zomba) from the districts in which they reside, these boundaries had to be coded as separate districts manually by constructing polygons around each city central boma coordinates (boma refers to the local town centre, and coordinates were obtained from © OpenStreetMap contributors). Polygons were drawn from visual evaluation of city boundaries and then assigning all latitude and longitude coordinates within each polygon to the relevant city district. Climate average values for each of the four cities were sensitivity tested via T-test and it was confirmed that removal of city coordinates from the wider district within which they reside, did not alter the wider district average climate values. It was also noted that there was no significant difference in city and rural district climate values (suggesting that heat island effect and land cover do not currently affect Malawi's localised climate). This appears appropriate given the small geographical size and relatively high greenness of Malawi's cities. It should be noted that the small island district of Likoma (106) was not included within the IHS3 survey.

Temporally, the monthly values were manipulated to produce a range of climate variables for testing. The mean, variance, maximum, and minimum values were calculated for each period, by district. These periods included: wet season immediately preceding the survey, the 12-month period preceding the survey, the 2-,3-,4-,5-,10- and 20-year wet season averages preceding a survey. Additionally, 1-year and 2-year offset wet season values were constructed.

To construct household level climate variables, households inherit the district average values. Whilst this removes some spatial granularity that would otherwise be achieved using household survey data, this was thought to be appropriate due to the approximate nature of the climate data available and because the effects of climate change are likely to be localised at the district, rather than at the household level.

In addition to climate variables, the agroecological zone was collected for each latitude, longitude coordinates of the household (offset by up to 5km by the IHS for anonymity). This data was obtained by the IHS zones using the WorldClim climate data as well as length of growing period (LGP) data from IIASA (National Statistics Office, 2020). A district agroecological value was then created using the mode agroecological value of the grid points within that district.

3.3.2 Crop production, food security and other sociodemographic variables

Variables which were hypothesised to have an impact upon crop production were identified through the conceptual model (Figure 3.1). Data for these variables, concerning crop production, food security metrics and other sociodemographic variables were then obtained from Malawi's Integrated Household Surveys (IHS). The IHS series are World Bank Living Standards Measurement Studies conducted periodically (approximately every 3-4 years) and most recently in 2019-2020 (IHS5), 2015-2016 (IHS4), and 2010-11 (IHS3). The surveys are representative at the district, regional and national level as well as at the rural and urban demarcations. Representative sampling was achieved using a two-stage stratified sampling of approximately 10,000-13,000 households for each survey year. The surveys contain a range of variables on household wealth, assets, demographics, food security, farming practices and crop production amongst other things (Table 3.2). Based on the timing of this research, the fourth Integrated Household Survey, IHS4 (the latest survey at the point of research commencement) was used as a reference cross-section in order to explore the data and build a point-in-time view of the data quality and descriptive statistics. Following this insight, a final short-list of viable variables was gathered for each of the third (IHS3), fourth (IHS4) and fifth (IHS5) surveys. A range of other variables from the surveys was considered (based on theoretical justification for inclusion within Figure 3.1, but ultimately excluded due to a high quantity of missing data (>20%) or poor data quality (e.g., nonsensical entries, large number of outliers, uninterpretable responses). Table 3.2 contains only the final list of variables that were included within the study. Excluded variables include farming practices, hours spent engaged in household agriculture, amount of fertiliser utilised, and use of government coupons.

For the purposes of this study, only those households that engaged in household agriculture during the main harvest wet seasons were included within the analysis. This represents the vast majority (~75%) of observations and, after applying survey household weightings (provided within survey and calculated via an adjusted inverse probability of household selection), represents a similar proportion of Malawi's population.

Three crop production variables were initially created: maize production (kg), "other subsistence crop production (kg)" and "all food crop production (kg)" with the latter variable equalling the sum of the former two. "All food crop production" consists of the crops outlined in Table 3.2, which represents over 90% of all reported food grown in 2016 (the reference year for which this study was initialised) and a similar proportion for the 2011 and the 2020 cross-sections.

It should be noted that a very small proportion (~3-5%) of households were reporting their crop production for the prior year (e.g., in the IHS4, a small number of respondents interviewed in early 2015 were therefore reporting their crops for the 2015, main harvest rather than the 2016 harvest). However, it has been approximated that all households are reporting for the latter harvest (i.e., either the 2011, 2016 or 2020 harvests, rather than the 2010, 2015 or 2019). Since crop production reported within the survey were done so using a variety of non-standard units, all household production values were converted into kilograms (kg), using information on local units and conversions provided during the third Integrated Household Survey (National Statistics Office (NSO), 2011). Where conversion information was not available, assumptions were used as detailed in (Appendix C). These values were validated against the nationally reported values within the Malawi's National Statistics Office (NSO) or the FAO depending on data availability (FAO, 2024a).

For the reference harvest of 2016, 24% of households reported that they did not grow crops other than maize, or else there was missing data against entries for the quantity produced, leading to severe discrepancies when attempting to validate the total "other subsistence crops" grown at the national level. To reduce the uncertainty due to this, the analysis across the three surveys focuses only on maize production to ensure that all households reported a quantity, although the "all food production" variable is also analysed for IHS4. The benefit of focusing on just maize production is that it is the staple crop of Malawi, and therefore an important consideration in crop production and food security studies and that there is excellent coverage and good data completeness. The drawback of focusing only on maize for the cross-survey comparison is that it is a missed opportunity to explore the relationships with other crop production, which could be an important contribution to climate – agriculture research. Lack of representation in the 'all food production' variable due to many households not growing more than one crop, is a source of uncertainty within the variable.

A range of socioeconomic variables were investigated. Household wealth was included because an essential component of crop production is the ability to buy seed and fertiliser (and any other farming equipment or labour input - excluded from this study due to lack of viable data). Wealth also has a presumed association between richer households and better quality land. Measuring wealth of a household was done by construction of wealth quintiles via a Principle Component Analysis using recoded, binary variables from the following list: ownership of a gas stove, ownership of fridge, ownership of a tv, whether household has access to improved sanitation (VIP latrine, latrine with roof, flush toilet), access to improved roofing material (concrete, iron, clay), access to improved water supply (piped, sandpipe, protected well, borehole, bottled bowser), access to improved lighting fuel (gas or electric), and ownership of one or more cell phones (Filmer & Pritchett, 2001; National Statistics Office (NSO) [Malawi] and ICF, 2017).

Three variables were created to explore ruralness of households. Household proximity to the nearest concrete road, and proximity to a large *boma* (town with more than 10,000 inhabitants), and whether the household is located in an urban or rural locale (taking data directly from the IHS). A district variable for average distance was calculated as the mean of the household values in each district. The justification was to test whether these variables of spatial 'connectivity' could provide a proxy for the level of development (connectivity and urbanisation) of the district, with the hypothesis that the more urban the district, the better the market access and opportunities and hence the higher the crop production.

Household size and the plot size per household member, and per dependant for each household was included to control for the fact that household size affects the intended production (i.e., larger households have more mouths to feed) and because land size affects the maximum total quantity that could be produced, regardless of other variables. By producing a variable of plot size per dependent it was also possible to account for the fact that younger children (<15 years) consume less than adults on average. Plot size per person (household member) was calculated as the total plot size of the household (sum of garden sizes for each plot) divided by the household size. For plot size per dependent the total household plot size was divided by number of dependents reported (people aged under 15, or over 65) residing in the household (for households with no dependents the plot size is divided by 1 to preserve the value).

Other household demographic variables included were sex of the head of the household, with *a priori* suggesting that women carry a higher burden of household chores and may have less access to credit and farming opportunities than men (Assa, Gebremariam & Mapemba, 2013; Ragasa, 2019) as well as different cultural approaches (Chidanti-Malunga, 2011).

Agro-economic variables also included whether or not the household used an inorganic fertiliser and the average (modal) soil quality of the household plots in that district. Data regarding farming practices were explored including quantity of fertiliser used, hours spent engaged in household agriculture, engagement in farm labour (*ganyu*), irrigation practice and farming equipment availability, however issues with data quality (>30% missing or erroneous data) were identified meaning that these variables were excluded from the study. The list of final variables included within the study are provided in Table 3.2.

Migration status was also examined, with the hypothesis that, since household land holdings are inherited either matrilineally (for the main national tribe, Chewa) or patrilineally (e.g., in Tumbuka in the north), an in-migrant to an area who has not moved into the area for marriage (and hence takes on the land of the spouse's family), may struggle to obtain land. Lands that are obtained are potentially more likely to have lower-quality soil and hence farm outputs than the land farmed by non-migrants or migrants who moved for marriage. It is also an important variable for inclusion based on the conceptual model Figure 3.1 which postulates relationships between crop production and migration status and so was included for thoroughness of the thesis. Migration status was created as both a categorical variable and a binary variable. The categorical variable was constructed by assigning each household head into one of the following, mutually exclusive categories: non-migrant, international migrant (born outside Malawi), inter-district migrant (born in a district other than that of current residence), or intervillage migrant (born in another village / town within the same district of current residence). The binary variable was constructed by aggregating the migrant types from the categorical variable such that household members were either non-migrants, or migrants (born anywhere other than their current place village / town of residence).

Table 3.2 Variables included within analysis

Category	**Variable**	**Variable type**	**level (district or household)**	**Units**
Crop Production (economic / environmental)	Maize production	Numeric	Household	Kg
	Total crop production for other subsistence crops including:	Numeric	Household	Kg
	Groundnut (Chalimba) [11]			
	Rice [17]			
	Sweet potato [28]			
	Sorghum [32]			

	Beans [34]			
	Soyabean [35]			
	Pigeonpea (Nandola) [36]			
	Nkhwani [42]			
	Peas [46]			
	Total food production (Maize and other subsistence crops)	Numeric	Household	Kg
demographic	Number of people in the household (household size)	Numeric	Household	Na
	Number of dependents (<14years old) in the household	Numeric	Household	na
	Sex of household head	Categorical	Household	Male / Female
	Household head is an international migrant	Categorical	Household	Yes / No
	Household head is an inter-district migrant	Categorical	Household	Yes / No
	Household head is an intervillage migrant	Categorical	Household	Yes / No
	Average number of dependents (<15 years old or >65 years old) per household	Numeric	Household	na
economic	Wealth quintile of household	Categorical	Household	Na
	Whether the household use any (inorganic) fertiliser on one or more household plots	Categorical	Household	Yes / No
	Average plot size per household dependant	Numeric	Household	acres
social	Proximity to a main road	Numeric	Household and district (two variables)	Km
	Proximity to a town of 10,000+ inhabitants	Numeric	Household and district (two variables)	Km
	Does household reside in an urban or rural area ("reside")	Categorical	Household	
	Does household engage in subsistence (household) farming	Categorical	Household	Yes / No
environmental	Average plot soil quality for each household (a numeric variable is assigned of 1 (good), 2 (fair), or 3 (poor)	Numeric	Household	na
Food security metrics	Whether household has experienced prolonged hunger (3+ consecutive months of hunger) in the last 12 months	Categorical	Household	Yes / No
	Presence of severe or moderate wasting in any child in the household	Categorical	Household	Yes / No
	Presence of severe stunting in any child in the household	Categorical	Household	Yes / No
	Average number of daily meals consumed by children (5-17years)	Numeric	Household	na

3.3.3 Food security metrics

It was assumed that crop production of households is a strong determinant of food security of a household (which may in turn be a determinant of a migration decision as per the conceptual model). As such, following the analysis of crop production, an analysis of food security was conducted.

Due to the challenges in accurately capturing food security and the data paucity in the Malawian context, a range of different metrics were considered. Firstly, a variable called prolonged hunger was created based on a survey question which asked respondents to report whether, in the last 12 months, they had been faced with a situation when they did not have enough food to feed the household and in which months of the past year this occurred (National Statistics Office (NSO) [Malawi], 2017). This is a common occurrence across Malawi and as such, prolonged hunger was then defined as a period of three consecutive months or more when a household responded positively to this survey question. Secondly, child anthropometric measurements were used to calculate the height-for-age (stunting) and weight-for-height (wasting) z-scores of children (5-59months in age and minimum of 45cm height) with scores of <=-2 constituting moderate malnourishment, and scores of <=-3 indicating severe malnourishment (Bloem, 2007). This was then converted into a household level, binary variable (from an individual level, ordinal variable) by assigning a value of 1 for all households where moderate or severe malnutrition was present (in 1 or more children), and a 0 where it was not.

3.3.4 Methodology

Firstly, descriptive statistics and an overview of the distribution of each variable was created. This was done at both national and district levels. Differences in climate, crop and sociodemographic variables at the district level were explored to identify any clustering at the district level.

Secondly, one-to-one relationships between crop production variables and each hypothesised explanatory variable (as outlined in Table 3.2) were explored using a range of statistical tests. The appropriate test was selected based on the type (categorical / numeric), and parametric nature of each variable. These included Wilcoxon, ANOVA, Chi-squared, t-tests and single variable linear regression (used in place of a correlation test due to use of complex survey data for which a test for correlation would be non-representative).

One-to-one relationships were also explored between crop production and other exploratory climate variables (as described in section 3.3.1) including the one-year, two-year, three-year, four-year, five-year, 10-year and 20-year average wet season climate for the years preceding and inclusive of a survey. Climate variables including a one-year and two-year offsets were also explored. For example, the 2015-2016 crop production was compared to the 2014/2015 wet season average climate variables.

Thirdly, a step-wise approach was used to construct single level, multi-variable regression models, one to explore the relationship between crop production and various climatic and other (sociodemographic) variables and a second to explore how food security relates to these variables. Inclusion of variables was based on a combination of theoretical justification for inclusion (as determined through the application of the conceptual model produced in Chapter 2), size and statistical significance of the coefficient for each explanatory variable, lowest deviance, highest R^2 value and negligible collinearity between explanatory variables (as identified using a Variance Inflation Factor (VIF) of roughly less than 5). Both linear and logistic regression techniques were used, depending upon the nature of the dependent variable.

Fourthly, mixed-effects (multi-level) regression models were produced to both identify those variables which are clustered at the district level, and to replicate the step-wise regression approach using two levels; household level, and district level. The benefits of using a mixed-effects model is that inclusion of a random effect for inter-district variation, as well as residual random effects describing intra-district variation, allows for a more accurate determination of whether the relationships observed are significant even in presence of district variability. Regression modelling was performed to assess the relationship between crop production as the response variable, to climate and various socioeconomic and demographic predictors. Regression modelling was then performed to assess food security as a response variable to crop production and other socioeconomic and demographic predictors.

Fifthly, the final multi-level models produced in step four were replicated for three cross-sectional surveys. The IHS4 survey (covering the 2015-16 crop season) was used as the reference cross-section, then the same steps were repeated for the IHS3 (survey covering the 2010-11 crop season), and the IHS5 survey (covering the 2019-2020 season). The three cross-sections were then qualitatively compared to each other, creating a pseudo-longitudinal analysis and to assess the robustness of findings on the relationships between maize production and each explanatory variable included despite data and model uncertainties. This light-touch visual comparative analysis allows exploration of any perceptible changes in relationships over time and to therefore help to postulate if there are any temporal trends across the 10-year period.

Finally, in order to explore the impacts of climate change, a descriptive analysis of climate change within Malawi was performed and then a final linear regression model was constructed using the climate anomalies for the survey years from a 1980-2010 climate baseline period and modelled as predictors of crop production.

3.3.4.1 Linear regression

Linear regression was used to model the response of crop production to explanatory variables (Equation 1) where Y represents the crop production in tonnes, X_n is the explanatory variable, β_0 is the intercept, representing the value in Y - the mass of crops produced, when all other explanatory variables are zero or set to their reference category (for categorical explanatory variables). β_n is the average change in crop production due to a unit change in each of the explanatory variables, and ε represents the residual error term.

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \varepsilon \tag{1}$$

3.3.4.2 Logistic regression

Logistic regression was used to build two models, one to model the response of prolonged hunger experienced by households, and one to model the presence of moderate or severe wasting. Equation 2 represents the logistic model where *Y* represents the response variable, expressed as the logit, the natural log odds of the response variable of (where the log odds are described by Equation 3). β_0 is the intercept, representing the baseline log odds for Y, when the log odds of all other explanatory variables is zero or set to their reference category (for categorical explanatory variables). It follows therefore that $\exp(\beta_0)$ provide the baseline odds of the response occurring. β_n are the log odds (the log of the odds ratio) describing the relative change in log odds for a unit change in each X_n on top of the reference value β_0. ε represents the residual error term.

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \varepsilon \tag{2}$$

The equation to describe the odds of a household experiencing hunger, or the odds of a household experiencing wasting within the logistic regression models (Equation 2) is expressed in Equation 3.

$$Y = \ln \frac{probability}{(1 - probability)} \tag{3}$$

3.3.4.3 Multi-level regression

After exploring the variables using simple linear or logistic regression models, multi-level models were produced to distinguish between those variables that are clustered at the district level and those that are household level. Only variables that demonstrated strong relationships with crop production in previous models, as well as strong theoretical justification based on the conceptual model and observed empirical relationships were included for consideration within the multi-level model, and only maize production was considered due to good data completeness for this dependant variable in order to reduce data uncertainty.

The multi-level model was built using the following conceptual steps. Firstly, district level variables were identified through *a priori* assumptions and through review of district level summary statistics, from which it was determined which variables should be defined at the district level. Other variables were examined for clustering but none were identified. Secondly, the following two-level model was constructed. Maize production can be described by the following equation.

$$household.maize_{ij} = \beta_{0j} + e_{ij} \tag{4}$$

Where β_{0j} is the national household maize production for household i, for each district j, and e_{ij} describes the residual variance of household maize production. Average maize production by district is predicted by the characteristics of each district (district level variables) and can therefore be described by the following equation.

$$\beta_{0j} = \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + \cdots + \mu_{0j} \tag{5}$$

Where γ_n represent the fixed effect parameters at the district level (j), describing how the district characteristics (X_n) for district j affects the relationship between household maize and the predictor value in that district. μ_{0j} represents the deviation for the average household maize production for households in district j from the national average household maize production and is referred to as the random effect of the multi-level model.

Another way of expressing the above two-level model, is as a mixed-effects model, by substituting the second equation into the first:

$$household.maize_{ij} = \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + \cdots + \mu_{0j} + e_{ij} \tag{6}$$

As identified in previous models, household maize production is described by a suite of explanatory variables not only at the district level (β_{0j}) but also at the household level, as described by the equation (7). Within equation (7), the slopes described by β_1, β_2 and so on, are not district dependant (in other words, cannot be describes as β_{nj} because no theoretical justification has been identified which suggests that the relationships between household level explanatory variables may have a different relationship (slope) with crop production based on district.

$$household.maize_{ij} = \beta_{0j} + \beta_1 X_1 + \beta_2 X_2 + \cdots + e_{ij} \tag{7}$$

Finally, substituting equation 5 into equation 7 achieves the final mixed-effects model (equation 8). A stepwise approach was used to identify the optimal combination of district and household level variables, with the final model presented chosen based on a combination of theoretical need for inclusion, observed statistical significance of the coefficients found during the stepwise approach, and with consideration for parsimony and interpretability of results.

$$household.maize_{ij} = \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + \cdots + \beta_1 X_1 + \beta_2 X_2 + \cdots + \mu_{0j} + e_{ij} \quad (8)$$

In summary, equation (8) demonstrates that household maize production can be modelled based on relationship with district variable fixed effects (γ_k), household level fixed effects (β_k) and the random effects μ_{0j} and e_{ij}, where μ_{0j} describes the variance between districts (interdistrict), and e_{ij} which describes within district (intra-district) variance.

3.4 RESULTS AND DISCUSSION

3.4.1 Crop production

Appendix F (Table F.1) provides estimates of the national yield for each of the three survey years main harvests (2011, 2016, 2020) as well as a breakdown of production by crop type (including maize and other subsistence crops) for the 2016 main harvest (Table F.2).

The distribution of average crop production per household varies by district as summarised in Appendix F (Table F.3). The data demonstrated a strong right skew because some households operate industrial farms, whilst the majority of households are smallholder farms. In line with most years, the southern districts have a lower average household production than the northern and central regions (Chikabvumbwa et al., 2022; FEWS NET, 2016c). The greatest production appear to occur in central districts of Ntchisi, Lilongwe (city and wider district), Mchinji, Dedzu and Ntcheu. Important to crop production is amount of farmland available to the household, as well as household wealth, which is in turn driven partially by land ownership. There is a higher proportion of wealthier households within the northern and central regions, than in the south, as well as a higher average land holding size (FEWS NET, 2016c).

Focusing on maize production as the most accurate and complete variable (almost all household report growing maize), the average household maize production and total district production for each of the three cross-sections are summarised in Table 3.3. Whilst both total district production and average household production appear reasonably similar across the three surveys, (being of approximately similar magnitudes), there are some discrepancies, particularly in IHS3 which appear unusually high compared to the other two surveys. It was also noted that for some districts, the total district production does not appear consistent with the average household production. For this reason, the estimated number of households within the district was constructed using the survey weightings. The estimated number of households appear to reconcile well with the population projections provided within the 2008 census data (National Statistics Office (NSO) [Malawi], 2009). The number of estimated households is somewhat smaller for IHS3 than for IHS4,5 which may explain why the per household production appears somewhat higher, (however, this does not take into account that not all households engage in agriculture). Nevertheless, it is thought that the survey findings are broadly in line with expectations. It was noted that 2010/11 was a bounteous harvest and produced more than in 2015/16 (as noted in Appendix F) accounting for higher per household production even despite population growth affecting later surveys.

Table 3.3 Total district Maize production (tonnes) and average household Maize production per district for each of the three survey cross-sections: IHS3 (2010/11), IHS4 (2015/16) and IHS5 (2019/20)

District	Total district Maize production (tonnes)			Estimated number of households in district which engage in agriculture[3]			Average(median) household Maize production (kg)		
	IHS3	**IHS4**	**IHS5**	**IHS3**	**IHS4**	**IHS5**	**IHS3**	**IHS4**	**IHS5**
National	***2,990,114***	***2,054,080***	***2,111,660***	***2,518,444***	***2,979,440***	***3,217,880***	***500 (IQR 949)***	***300 (IQR 500)***	***250 (IQR 449.5)***
101	39,176	25,558	36,868	39,251	54,622	53,453	491.7	278.63	491.7
102	27,149	19,944	6,335	58,613	82,019	80,023	327.8	135	50
103	23,404	8,582	11,130	46,150	52,543	58,342	327.8	300	200
104	25,914	32,077	32,116	37,441	49,603	52,551	500	409.75	500
105	163,676	42,614	325,138	171,269	51,902	222,440	600	550	600
106	NA	73	131	NA	2,201	2,859	NA	50	50
107	6,232	10,664	13,816	34,921	54,646	57,907	500	500	400

[3] Based on the household weightings (modified inverse probability of sample selection) and corroborated against 2008 census data.

201	383,603	146,287	110,205	138,108	186,213	188,344	1750	450	400
202	34,430	34,557	31,705	67,972	79,357	79,502	400	350	200
203	110,199	110,948	76,962	49,527	68,072	70,974	1000	850	450
204	401,891	264,823	150,505	127,431	187,599	182,874	2298	650	400
205	115,547	51,321	63,216	76,081	105,762	104,244	750	300	300
206	242,574	422,383	257,400	271,593	350,858	389,705	600	550	300
207	232,276	137,358	124,166	103,322	139,948	123,757	1700	600	350
208	225,264	168,272	132,455	139,140	177,415	195,575	1149	350	350
209	212,099	117,031	120,860	111,200	142,260	159,657	1000	375	400
210	132,396	80,813	81,056	164,017	245,450	235,197	950	475	350
301	113,739	65,942	141,678	180,904	262,039	265,146	400	200	200
302	62,463	38,496	45,282	116,744	139,401	177,031	300	150	175
303	67,029	26,484	49,264	140,731	93,680	171,125	350	175	200
304	59,634	58,653	30,445	71,564	175,693	87,833	416	250	300
305	56,055	22,996	31,312	86,650	84,004	118,776	400	200	250
306	11,220	11,351	17,049	21,453	24,544	31,135	250	300	350
307	45,014	43,920	60,488	149,337	170,563	178,567	300	200	250
308	38,099	23,131	42,651	125,464	131,482	165,224	200	150	175
309	38,196	19,775	25,482	76,154	87,170	99,380	250	150	150
310	20,546	9,892	11,882	106,308	128,416	132,466	50	25	0
311	7,396	4,251	5,154	60,697	67,560	72,387	50	16.39	0
312	58,846	22,990	27,275	77,760	99,550	105,923	360	200	200
313	20,301	15,640	16,730	25,661	36,556	33,581	350	300	400
314	11,418	7,457	7,520	23,297	34,974	24,777	500	295	350
315	4,515	9,797	15,993	172,873	231,218	201,946	300	250	250

3.4.2 Food security

There is a relatively high prevalence of extreme malnutrition within children in Malawi, with approximately 1.64% of children suffering extreme acute malnutrition (“wasting”) and 3.91% suffering moderate wasting. Considering chronic malnutrition (“stunting”), 1.49% of children are estimated to be extremely stunted and 24.3% being moderately stunted. The distribution of the z-scores of Malawi’s child population in 2016, comparing nutrition levels to the WHO standard population, are provided within Appendix G.

Other measures of food security were considered and compared to child anthropometric measures (Table 3.4).

Table 3.4 Metrics for measuring food security nationally within Malawi

Food Security metric	2010/11	2015/16	2019/20
Prevalence of extreme stunting (in the population of children 6-60months)	2.12%	1.57%	1.66%
Prevalence of extreme wasting (in population of children 6-60 months)	1.59%	1.56%	1.82%
Prevalence of moderate stunting (in population of children 6-60months)	21.72%	25.32%	25.38%
Prevalence of moderate wasting (in population of children 6-60 months)	0.34%	4.35%	0.30%
Prevalence of household prolonged hunger	21.71&	53.74%	33.92%
Median number of meals consumed daily by 5-17year olds.	2 (SE 0.26)	2 (SE 0.26)	2 (SE 0.26)

These food security metrics are not designed to be directly comparable however it is clear that prolonged hunger is significantly more prevalent than extreme child malnutrition (wasting and stunting).

Considering prolonged hunger as the most prevalent and robust metric for food security based on available data within the IHS, a district breakdown of prolonged hunger for each cross-section was calculated (Appendix G, Table G.1). Across most districts, 2015/16 appears to be the most food insecure year, in line with national statistics as well as the anecdotal knowledge that the 2015/16 main harvest was poor. Visual inspections suggests however that this trend is more pronounced in certain districts and that hunger is not homogenous across the country nor through time. For example. Chitipa (101) and Karonga (102), the southern districts of Machinga (302), rural Zomba (303) and Zomba City (314) and Chiradzulu (304) all exhibit a very large increase in prolonged hunger between the IHS3 and IHS4 cross-sections.

The household survey also collected data on the self-reported reason for hunger, summarised in Table 3.5, with prolonged hunger being selected as the most consistent and prevalent metric across the three surveys. Across each of the three surveys drought appears to be the single largest factor, accounting for between 25%

and 50% of reported hunger. Although drought is a hydrological event and not necessarily related to climate anomalies (a reduction in seasonal rainfall), other common causes of drought such as over utilisation of groundwater or river water, or poor irrigation practices, are rare in the Malawian context and as such, it is likely that rainfall is directly related to the localised drought. However, the impact of drought upon hunger appears highest during 2015/16, even though the average monthly rainfall was higher that year than in 2010/11 (and did not diverge largely from the 30-year average wet season rainfall (see section 3.4.6). It may be that drought is a localised event which modelled district average climate values were unable to capture, or that average monthly rainfall is not the best proxy for identifying drought events. PDSI (another indicator of dryness built using a water-balance model and including both temperature and rainfall) was significantly below the 30-year average for both 2010/11 and 2015/16 and somewhat lower for the 2019/20 wet season. Further studies into this relationship including data with higher temporal and spatial granularity may be beneficial.

Table 3.5 Reasons reported for lack of food which contributed to household hunger.

Reason given for food insecurity (of those who experienced prolonged hunger)	2010/11	2015/16	2019/20
No reason given	0.10%	0.02%	0.00%
Drought	36.87%	51.93%	25.39%
Pest	0.96%	0.22%	2.19%
Small land	9.28%	6.99%	9.58%
Lack of farm input	41.96%	20.65%	34.70%
Market price	4.42%	14.77%	16.35%
Transport cost	0.19%	0.04%	0.06%
Market empty	0.17%	0.38%	1.16%
Flood	1.19%	1.24%	5.91%
Other	4.85%	3.76%	4.66%

3.4.3 Construction of wealth quintiles

The first component of the PCA accounts for 39% of the variation (standard deviation of 1.77) within the variables and was adopted as the index of wealth which was then apportioned into quintiles across the population. Considering the loadings for the first component (PC1), we see positive associations with all variables. We may interpret this component as an index for overall wealth since the loadings are all in the same direction and it is common sense to interpret a higher number of household assets or improved infrastructure with a higher wealth status. Table 3.6 highlights the loadings for the first component, demonstrating the contribution that each of the original variables makes to the first component.

Table 3.6 loadings for first component of each explanatory variable

Asset ownership	Loadings of each variable for first component		
	IHS3	IHS4	IHS5
Gas stove	0. 39	0.40	0.36
fridge	0. 42	0.45	0.43
tv	0. 43	0.46	0.43
Improved water supply	0. 17	0.03	0.30
Improved roofing material	0. 30	0.22	0.26
Improved sanitation	0. 14	0.14	0.12
Improved lighting fuel	0. 43	0.48	0.44
Ownership of one or more cell phones	0. 398	0.36	0.37

3.4.4 Relationships between climate and crop production

One of the main aims of this chapter was to explore which variables demonstrate the strongest relationship with crop production in the Malawian context, using household survey data. After having identified and constructed key variables of interest – crop (maize) production, food security and wealth quintile by household, I conducted an exploratory analysis of the relationships between these and with other variables identified within the conceptual model.

The hypothesis laid out at the beginning of this chapter (Figure 3.1) identified a range of climatic factors that may affect crop production. However it is well established that various other environmental factors will contribute to crop production such as soil quality, and other agroclimatic variables (Mumo, Yu & Fang, 2018, Fisher and Lewin 2013), as well as socioeconomic variables such as household income and wealth, farming practices, access to government fertiliser and credit schemes, household connectivity (distance to roads and markets which enable trade and purchasing of fertiliser, seed and ease of undertaking and securing ganyu (casual labour) (Kankwamba, Kadzamira & Pauw , 2018, Fisher and Lewin 2013, FEWS NET 2016, Snapp and Fisher 2015). As stated in section 3.3, only variables with sufficient data quality and which demonstrated individually statistically significant relationships with the dependant variable(s) (i.e. crop production) were explored within the regression models.

Firstly, descriptive statistics were explored for key variables identified within the conceptual model, for which sufficiently robust data was available. Table 3.7 provides the descriptive statistics for each of the household level socioeconomic and demographic variables that were identified as having a statistically significant relationship with crop production. Their descriptive statistics disaggregated at the district can be found in Appendix D.

Table 3.7 Descriptive statistics of potential explanatory variables

Variable		**Summary statistics**		
		IHS3	**IHS4**	**IHS5**
Wealth quintiles		n/a – by definition, the population is split equally into wealth quintiles based on the PCA analyses described above.		
Proximity to a main road (km)		Mean = 9.22	Mean = 9.24	Mean = 9.14
Proximity to a town of 10,000+ inhabitants (km)		Mean = 33.00	Mean = 32.64	Mean = 21.00
Proportion of inhabitants who reside in an urban area		0.15	0.19	0.16
Average (median) plot size per household dependant (acres)		0.4	0.5	0.6
Average (median) plot size per household member (acres)		0.17	0.25	0.25
Proportion of households with a female head of household		0.20	0.25	0.28
Proportion of Malawians who engage in subsistence (household) farming		0.84	0.80	0.82
Proportion of household heads who are migrants.	**Non-migrant**	0.52	0.50	0.51
	International migrant	0.03	0.02	0.02
	Inter-district migrant	0.24	0.22	0.22
	Intervillage migrant	0.21	0.25	0.25
Proportion of population who are migrants (including children)	**Non-migrant**	0.71	0.68	0.68
	International migrant	0.01	0.01	0.01
	Inter-district migrant	0.14	0.13	0.13
	Intervillage migrant	0.14	0.18	0.18
Average household size		Mean = 5.64 s.d. = 2.27 Median, mode = 5	Mean = 5.19 S.d. = 1.99 Median, mode = 5	Mean = 5.35 s.d. = 2.17 Median, mode = 5
average proportion of households that used inorganic fertiliser on one or more plots		0.73	0.56	0.51

Proportion of households with good soil quality (3)	0.12	0.13	0.12
Proportion of households with fair soil quality (2)	0.45	0.38	0.37
Proportion of households with poor soil quality (1)	0.43	0.48	0.51

The descriptive statistics suggest that most of the shortlist variables are similar across the three cross-sections. Proximity to town shows a small negative trend which may suggest improved road networks over the decade 2010 – 2020. This is to be expected as Malawi develops and urbanisation trends. It is therefore unusual that a similar trend was not observed for the proportion of residents in urban areas, which would be expected to increase. It is thought therefore that road (and boma) distance is not an accurate proxy for household connectivity nor as a descriptor of the level of development / urbanisation of the district. Proximity to town statistics look reasonable at the national level, with a decreasing trend in line with urbanisation, however there are unusual discrepancies at the district level (Appendix D). It is plausible that urbanisation trends in Malawi manifests in an increase in size of existing trading centres (already above 10,000 inhabitants) which means that average distance from such hubs doesn't vary for most rural households.

Interestingly, the plot size per dependant appears to be increasing. This is surprising since the population of Malawi is increasing which would drive a decrease in plot size per dependant. Upon consultation of the age profiles of the population at each cross-section, there is virtually no change in the quartile values or interquartile range (across the three surveys: Q1 = 8, Q2 = 16 - 17, Q3 = 32 - 33, IQR = ~24). However, the number of dependents registered in each household has slightly decreased (IHS3 the median number is 3 and the IQR is 2, but by 2019/20 the median is 2 with an IQR of 2). The fertility rate in Malawi is also reducing and so this trend may be explained if the stock of dependants (under 15s) is reducing faster than fertility. For example, as under 15s come of age or leave home and are therefore excluded from this calculation. Plot size per household also does not show any obvious trend. Alternatively it may be the case that the suggested apparent trend in plot size per dependant is not a true trend but natural variation across the surveys.

The proportion of female headed households may be rising slightly. Migrant stock (proportion of the population who reported being migrants) appears to be stable. There is a significant reduction in the proportion of households that use fertiliser between IHS3 and IHS4. The Fertiliser Input Subsidy Programme (FISP) that was first introduced in 2005/06 was reformed in 2016/17 after a programme review in 2016 identified that the cost of fertiliser had increased from MK2100 in 2005/06, to MK16,000 by 2015/16 (Michigan State University, 2015). It is likely therefore that, even with the FISP, many farmers will have reduced their fertiliser usage due to costs by 2015/16. The FISP was reformed in 2016/17, fertiliser subsidy was once again increased (CDM & FUM, 2017, Messina, Peter & Snapp, 2017).

Next, statistical tests identifying the relationship between each variable and household Maize produced, were analysed, (Appendix E) at the national level (E.1) and district level (E.2). Results of the statistical testing were used to determine the shortlist of variables for inclusion within the regression analyses.
Those variables were introduced step-wise into a multivariable regression model. The results of the final regression model are summarised in Table 3.8.

Table 3.8 household level regression model results for the relationship between household crop production, sociodemographic and climate variables,

		2010/11 wet season main harvest			2015/16 wet season main harvest			2019/20 wet season main harvest		
		Coeff	Standard error	p-value	Coeff	Standard error	p-value	Coeff	Standard error	p-value
Explanatory variables										
Reference	Kg Maize at intercept	-1309.19	384.048	0.000655	982.3135	274.6254	0.00035	-1293.89	540.477	0.016688
2nd wealth quintile	Kg Maize when moving into the 2nd quintile	100.719	58.431	8.48E-02	94.2771	38.2712	0.013782	78.8525	51.1348	0.123097
3rd wealth quintile	Kg Maize when moving into the 3rd quintile	59.579	59.648	3.18E-01	171.3215	47.9264	3.53E-04	77.8465	43.1308	0.071126
4th wealth quintile	Kg Maize when moving into the 4th quintile	207.279	70.884	3.46E-03	359.9787	52.953	1.13E-11	244.0688	62.0636	8.47E-05
5th wealth quintile	Kg Maize when moving into the 5th quintile	534.685	106.103	4.76E-07	661.3447	106.5424	5.63E-10	755.215	157.7339	1.71E-06
Sex of household head	Kg Maize for females (compared to males)	-321.352	44.711	7.09E-13	-133.68	33.8204	7.79E-05	-152.78	56.7943	7.16E-03
Household size	Kg Maize per additional household member	163.434	16.435	2.00E-16	124.1342	15.1776	3.26E-16	126.5312	49.7446	1.10E-02
Plot size per household member	Kg Maize per additional acre land per dependant	1145.09	153.934	1.10E-13	890.3128	132.4317	1.89E-11	1374.546	666.8188	3.93E-02
Use of fertiliser	Kg Maize when introducing fertiliser (any quantity)	634.971	44.553	2.00E-16	263.3661	40.4562	7.93E-11	204.3553	60.3674	7.14E-04
Maximum wet season monthly temperature	Kg Maize per 0.1*degrees C temperature rise	900.527	122.39	1.51E-13	-124.918	74.177	9.22E-02	495.131	111.663	9.36E-06
Mean wet season monthly rainfall	Kg Maize per 10mm additional rainfall	-105.76	8.21	2.00E-16	-56.904	3.915	2.00E-16	-41.335	9.275	8.43E-06
	N (number of observations)	9814			8915			8698		
	R^2	0.10			0.13			0.10		

Whilst building the model it was noted that migration status of household head (treated as a binary variable for whether or not the household head was born in the place of current residence) did not have any impact upon the model and the coefficient was both very small (positive) and statistically not significant, as such it has been omitted from the model. This suggests that being a migrant does not impact the ability of the household to achieve crop production levels comparable to non-migrant households. This counters the alternative hypothesis proposed within the conceptual model, that being a migrant into an area would impact upon the quantity and quality of land from which a household is able to cultivate crops. It may alternatively be that the signal is masked by other, more impactful variables such as sex and wealth. This could be due to low granularity of the variable used (binary variable for lifetime in-migration without more specific consideration of migration source or destination, or reason for migration (e.g., if moving in with family, land availability may be less limited). Alternatively, it could be the case that the relationship between migration and maize production is nonlinear. For instance, low income migrants may have a negative relationship with crop production, whilst higher income migrants (who have the capital to be able to move) are more likely to also be able to afford land and other farming inputs, producing a positive relationship with crop production. As an important crux of this thesis, this relationship will be explored further In Chapter 4.

As expected, higher (richer) wealth quintiles have a positive relationship with crop production. In particular, being within the fourth or fifth (richest two) wealth quintiles has a much larger, significant effect upon crop production. This is likely because wealthier households have a larger land holding and are better able to afford labour, farming equipment and fertiliser, the biggest determinants of crop production (FEWS NET, 2016c) and to take advantages of economies of scale. However, it is also hypothesized that very rich families may not engage in subsistence farming at all, though it is likely that such a trend is not detected through use of wealth quintiles as a relatively course measure of wealth. Use of wealth percentiles would be recommended to explore this further, or else a comparison between wealth of those households who report that they do not partake in subsistence farming. It was also noted that use of fertiliser had a large impact upon production, as expected. Similarly household size and plot size have a significant impact on production.

As hypothesized within the conceptual model, climate drivers have a statistically significant impact upon crop production. It was interesting to note that it was rainfall and not hydrological parameters (surface runoff, soil moisture and PDSI) that demonstrated the strongest relationship. Other climate-hydrological variables such as PET, rainy season onset and duration (or dry season duration), 10-day rainfall data, may warrant investigation in future studies. There is an unusual, negative coefficient value shown in the IHS4 model though this is much smaller than for the other years so could be erroneous - approximately zero for small temperature fluctuations. Mean rainfall consistently shows a small negative relationship with Maize production, suggesting that for each additional 10mm of rain that falls during the wet season (growing season), the crop production reduces by between 41kg (IHS5) to 105kg (IHS3). This is in line with the one-to-one relationships explored (Appendix E), but does not align with the hypothesis that higher rainfalls facilitate better crop growth. It is possible that there is a nonlinear relationship between rainfall and crop production, with too much rainfall (e.g., resulting in soil water logging and root rot) having a detrimental impact on growing crops. However, the levels of rainfall exhibited during survey years were not considered extremely wet (see section 3.4.6 for further discussion on this) and so it is not thought likely that such widespread crop destruction / ruin due to heavy rainfall or flood is a likely explanation. A similar relationship was found with the soil moisture variable which was excluded from the final model due to high collinearity with rainfall. There also appears to be a potential decreasing trend across the three surveys, with the strength of the relationship between rainfall and maize production reducing between each of the three surveys. This may not be a true trend but natural variation or else due to data quality. If it is a true trend then it may signify that rainfall is reducing its impact on crop production over time, perhaps because the strength of other variables is masking the impact of rainfall, or as they become increasingly important over time, such as fertiliser usage, agricultural practices and land availability. Overall, it is likely that the average wet season rainfall data is insufficient for modelling against crop production. Alternative indicators or with better granular such as average daily rainfall data, 10-day rainfall, onset of rainy season or duration / extent of wet season, or alternatively the dry season may be better at identifying any relationship with crop production.

Female household heads have a lower average crop production. A likely explanation is the known gender inequality, resulting in reduced access of women to employment and to agricultural improvement initiatives (Bezner Kerr et al., 2019; Fisher & Lewin, 2013; Ragasa et al., 2019) or to assets necessary to support farming, particularly of cash crops (Me-Nsope & Larkins, 2016). This is an important consideration for policy-makers and health planners who should consider gender within future subsidy programmes or other agricultural schemes.

Whilst the R-squared values for the models are small, this is unsurprising for such a dataset. The Q-Q plot of the Residuals of the maize models do not appear to be normally distributed, with a large difference between the predicted and observed values particularly in the 3rd and 4th quantiles of the data (Appendix K). This could indicate that linear regression is a limited exploratory tool for such a relationship. A nonlinear relationship between climate variables and crop production is a reasonable hypothesis. For example, higher temperatures and wetter conditions may be more favourable for maize and many other crops, up until a certain threshold, when conditions may become too hot and wet, or due to interactions with other edaphic (soil-related) factors (He et a., 2021). Further exploration of this may require more advanced functions of the predictor variables to be used, or for splines to be introduced. In particular, it is noted that Malawi's climate does not vary at the household level but at a wider spatial level (as noted within the conceptual model presented in Chapter 2).

3.4.4.1 Multi-level model

The climate and agro-ecological variables were constructed at the district level and therefore, to improve the above model, these variables were explored (in a step-wise fashion) using multi-level regression., Climate-based variables were set at the district level (group level) with random effects accounting for interdistrict variability, and other sociodemographic variables were retained at the household level. The final multi-level regression model results including both random and mixed effects are shown in Table 3.9.

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Table 3.9 Multi-level regression results for crop production

		IHS3			IHS4			IHS5		
Variables	**Unit**	**Coefficient Estimate**	**Standard Error**	**P value**	**Coefficient Estimate**	**Standard Error**	**P value**	**Coefficient Estimate**	**Standard Error**	**P value**
(Intercept)	*Kg Maize at intercept*	-1809.49	1988.38	0.3702	28.09	1073.91	0.9793	-1227.36	840.09	0.1509
Mean wet season monthly rainfall	*Kg Maize per 10mm additional rainfall*	-69.21	42.49	0.1144	-36.78	15.41	0.0238	-28.91	16.02	0.0796
Maximum wet season monthly temperature	*Kg Maize per 0.1*degrees C temperature rise*	9.80	5.92	0.1086	0.98	3.12	0.7556	4.1142	2.46	0.1009
2nd wealth quintile	*Kg Maize when moving into the 2nd quintile*	155.82	68.31	0.0226	40.73	49.30	0.4087	56.33	76.24	0.4600
3rd wealth quintile	*Kg Maize when moving into the 3rd quintile*	299.97	71.84	0.0000	111.69	51.48	0.0301	59.37	78.15	0.4470
4th wealth quintile	*Kg Maize when moving into the 4th quintile*	490.32	74.30	0.0000	350.69	54.12	0.0000	226.97	81.68	0.0055
5th wealth quintile	*Kg Maize when moving into the 5th quintile*	881.61	83.46	0.0000	713.68	64.74	0.0000	742.13	93.20	0.0000
Sex of household head	*Kg Maize for females (compared to males)*	-314.86	51.06	0.0000	-121.50	36.18	0.0000	-149.28	55.76	0.0074
Household size	*Kg Maize per additional household member*	148.66	11.19	0.0000	125.74	9.41	0.0000	127.67	13.75	0.0000
Plot size per household member	*Kg Maize per additional acre land per person*	1025.53	77.18	0.0000	851.75	38.90	0.0000	1341.981	53.626	0.0000
random effects		**Variance**			**Variance**			**Variance**		
Inter-district variability (μ)		5.167E+05			1.13E+05			3.61E+04		
Residual (ε)		1.21E+09			7.16E+08			2.02E+09		
Number of observations (n)		**level 1 (household)**	**Level 2 (district)**		**level 1 (household)**	**Level 2 (district)**		**level 1 (household)**	**Level 2 (district)**	
		9814	31		8915	32		8698	32	

There appears to be agreement across the three models for the relationships between Maize production and the explanatory variables that were found to contribute to the best fitting and most parsimonious model. This adds robustness to the findings which are replicable across three cross-sections, though no obvious temporal trends were seen, based on a simple comparison of each model coefficients across the three discrete time-points. The magnitude and significance of the final suite of variables also appears broadly similar to the single level model. However, the notable departure between the multi-level model and the single-level model is that, upon inclusion of a random effect to account for inter-district variance in variables, that the temperature variables (for the most part) are much smaller and no longer statistically significant. It is possible that this is because the climate signal is far smaller than other relationships which may explain why a significant relationship was identified as a one-to-one relationship (Appendix E) but not within the multi-level, multivariable model. Other explanations may include low data granularity, or that the suite of available climatic variables were not sufficient to capture the relationship between climate and farming output. The association between maize production and rainfall reduced in coefficient size but continued to show a negative relationship with potentially significant results for IHS4 and IHS5. Perhaps alternative variables regarding rainfall may be more appropriate (such as rainy season onset and duration or PET [potential evapotranspiration]). It is also possible that microclimates or localised agricultural conditions such as soil quality or other geographical variables such as soil slope and type may be relevant and considered for future, in-depth studies. It should be noted that soil quality as reported within the IHS as well as soil moisture, PDSI, runoff and agro-ecological zone (as described within section 3.3) were all explored but not found to contribute to the fit of the model and were therefore ultimately excluded.

3.4.4.2 Temporal exploration of crop production and climate

Having explored the relationship between climate variables and crop variables at each survey, I proceeded to explore whether districts that experience more adverse climatic circumstances in the years immediately preceding a national household survey were more inclined to exhibit lower crop production during the year of the survey.

The first step was to conduct a simple Pearson correlation test to identify if there was an observable relationship between district total maize production and a range of climate variables: time-averaged and offset. Climate variables constructed included rainfall and maximum temperature for the wet season of that year, as well as the two-year average, three-year, four-year, five-year, 10-year and 20-year averages for the years leading up to the survey year (inclusive of the survey year). Offsets were constructed which consisted of the prior year rainfall and temperature (in other words, a one-year offset) and the rainfall and temperature from two-years prior (two-year offset). By exploring offsetting and average climate data over a multi-year period it was possible to examine any potential relationship with migration that may exist accounting for a time lag. It is hypothesised that, although a poor wet season could lead to low crops and food insecurity in the same year, the effect may not occur instantaneously, but it may be more likely that a period of two to five years of poor rains may impact upon the ability of a household to produce crop or to experience food insecurity (and ultimately, to make a migration decision).

Results yielded no significant associations (see Appendix I for results). As such, no further analysis was conducted. The next steps therefore were to take an alternative approach to the effects of climate over time, by exploring climate anomalies. Refer to section 3.4.6.3 for more details.

3.4.5 Relationships between climate, crop production and food security

As identified within the conceptual model, it is hypothesized that household crop production has a direct impact upon food security, and subsequently on a migration decision. For example, according to the Famine Early Warning System Malawi, as of November 2016, the central and southern regions of Malawi were in a food security crisis (FEWS NET, 2016b). This was attributable to below average rainfall during the 2015/16 planting season (FEWS NET, 2016a).

As such, following completion of the multi-level regression model for exploring maize production, the impacts of maize production upon food security were explored. Appendix H outlines the one-to-one relationship between crops and food security metrics via simple logistic regression. The results confirm a negative relationship between maize production and prolonged hunger, with each additional tonne of maize produced resulting in decreased odds of prolonged hunger by a factor of 0.74-0.8. Interestingly when using presence of moderate or severe wasting in children in the household, the results are not consistent across the three surveys. This may be because the sample size is much smaller for childhood wasting and may not be representative nationally, because households without eligible children (6-59 months and for which anthropometric measurements were taken) were excluded.

Choosing therefore prolonged hunger as the most reliable metric for food security, a multi-level regression model was produced with prolonged hunger as the dependant variable and maize production, amongst other variables were explored using a step-wise approach. The final multi-level regression results are outlined in Table 3.10.

Table 3.10 multi-level regression model results for the relationship between prolonged hunger and other variables including, maize production and climate

		IHS3				IHS4				IHS5			
Variables	**Unit**	**Coefficient [ln(odds)]**	**Standard Error**	**Odds ratio**	**P value**	**Coefficient [ln(odds)]**	**Standard Error**	**Odds ratio**	**P value**	**Coefficient [ln(odds)]**	**Standard Error**	**Odds ratio**	**P value**
(Intercept)	*link function at intercept*	4.8400	2.4100	126.4694	0.0400	3.3400	0.8890	28.2191	0.0001	2.9400	0.6750	18.9158	0.0000
Maize production (kg)	*Factor change in link per kg Maize produced*	-0.0002	0.0000	0.9998	0.0000	-0.0002	0.0000	0.9998	0.0000	-0.0001	0.0000	0.9999	0.0000
2nd wealth quintile	*Factor change in link when moving into the 2nd quintile*	-0.3290	0.0050	0.7196	0.0000	-0.2830	0.0041	0.7535	0.0000	-0.1220	0.0037	0.8851	0.0000
3rd wealth quintile	*Factor change in link when moving into the 3rd quintile*	-0.3950	0.0053	0.6737	0.0000	-0.4440	0.0042	0.6415	0.0000	-0.2030	0.0038	0.8163	0.0000
4th wealth quintile	*Factor change in link when moving into the 4th quintile*	-0.7120	0.0057	0.4907	0.0000	-0.7600	0.0044	0.4677	0.0000	-0.4570	0.0041	0.6332	0.0000
5th wealth quintile	*Factor change in link when moving into the 5th quintile*	-1.6600	0.0085	0.1901	0.0000	-1.6700	0.0057	0.1882	0.0000	-1.0200	0.0053	0.3606	0.0000
Sex of household head	*Factor change in link for females (compared to males)*	0.3750	0.0038	1.4550	0.0000	0.1830	0.0029	1.2008	0.0000	0.2310	0.0027	1.2599	0.0000
Household size	*Factor change in link per additional household member*	0.1020	0.0009	1.1074	0.0000	0.0715	0.0008	1.0741	0.0000	0.0764	0.0007	1.0794	0.0000
Plot size per person	*Factor change in link per additional acre land per person*	-0.2480	0.0070	0.7804	0.0000	-0.1220	0.0035	0.8851	0.0000	-0.1970	0.0037	0.8212	0.0000
Mean wet season monthly rainfall	*Factor change in link per additional 10mm rainfall*	-0.0618	0.0519	0.9401	0.2300	0.0109	0.0276	1.0110	0.6928	-0.0051	0.0324	0.9950	0.8800
Maximum wet season monthly temperature	*Factor change in link per 0.1 °C temperature risk*	-0.0170	0.0072	0.9831	0.0175	-0.0113	0.0031	0.9888	0.0002	-0.0122	0.0030	0.9879	0.0000
random effects		**Variance**				**Variance**				**Variance**			
Inter-district variability (μ_0)		0.8069				0.5915				0.3709			
Number of observations (n)		**level 1 (household)**	**Level 2 (district)**			**level 1 (household)**	**Level 2 (district)**			**level 1 (household)**	**Level 2 (district)**		
		9814	31			8915	32			8698	32		

Within this model, for each additional tonne of maize produced, the odds of prolonged hunger decreases as expected. However, the reduction is very small, with for every 1kg of maize, the odds of having experienced prolonged hunger are reduced by roughly 0.02% (1 – exp[coeff]) for each of the three surveys. Other variables have a much larger impact. Belonging to the highest two wealth quintiles has a larger impact and, unsurprisingly results in reduced odds of prolonged hunger. Female-headed households demonstrates an interesting and significant (0.05 level) positive impact, increasing odds of prolonged hunger by between 20-45% compared to male-headed households. It is hypothesized that the sex of the household head affects food security not only through crop production but through other determinants of household wealth, with women heads less likely to be in higher wealth quintiles. However, nuance should be included within such discussion of the role and solutions to gender inequality, with some studies suggesting that women household heads are not exclusively victims of gender and are not always undercut by their male counterparts (Nkhoma & Kayira, 2016) and that many unique opportunities exist to improve both gender equality and, as such, food security for female-headed households.

Rainfall does not show a significant relation with prolonged hunger . Maximum temperature however appears also to have a small impact, with each 0.1°Cwarming decreasing the odds by 1.12 to 1.69%. Whilst this observation may be explicable because of the observed relationship between higher temperatures and increased crop production, it is unclear why there would be any other direct impact upon prolonged hunger. I hypothesize that the impact is moderated by crop production but that the survey data regarding prolonged hunger is a more reliable metric than the crop quantities that have been estimated through a range of conversion factors (Appendix C) that may have introduced a large amount of uncertainty into the quantities. Furthermore, food security is determined through production of other food crops, cash crops and the purchasable food availability and accessibility (i.e., affordability). These factors, particularly other subsistence crops may be more impacted by climate than Maize, though they probably contribute less to macro-nutrient food security since Maize is the staple crop across Malawi.

3.4.6 The impacts of climate change

So far the relationships between climate variables and sociodemographic factors have been explored upon crop production and, subsequently the impacts of crop production and these factors upon food security. The conceptual model (Chapter 2) also considers that within the context of climate change, the climatic factors are not stationary through time and therefore perhaps neither are the relationships. The three cross-sections explored have broadly reconciled with each other, adding robustness to the relationships observed. However, no discernible trend was observed from which statements about the impacts of climate change over the 10-year study period could be made. Equally, comparison of the average climate values of the pre-survey climate (one year, two-year, five-year and thirty-year), with the crop production achieved during each survey wet-season similarly identified no significant relationship between variables. As such there is currently no evidence that climate change in Malawi has yet had a measurable effect upon crop production.

This section examines in more detail any observed trends in climate change in Malawi using the TerraClimate dataset, and then postulates what the future impacts of climate change upon crop production and prolonged hunger could be.

3.4.6.1 Historic climate change in Malawi

Understanding both the current climatic context of Malawi as well as any observed trends regarding climate change is important in order to synthesise hypotheses about which climate variables are most important for exploring the relationship between climate change and crop production. Using historic modelled data to gain insight of climate change in Malawi, there has been a slight observed warming and wetting trend across the country. Figure 3.2 shows the temporal trend in rainfall, soil moisture, surface runoff, PDSI, maximum temperature, and minimum temperature, during the last sixty-years (January 1958 – December 2020). There is a clear bi-seasonal trend and only negligible trend of warming and wetting over time.

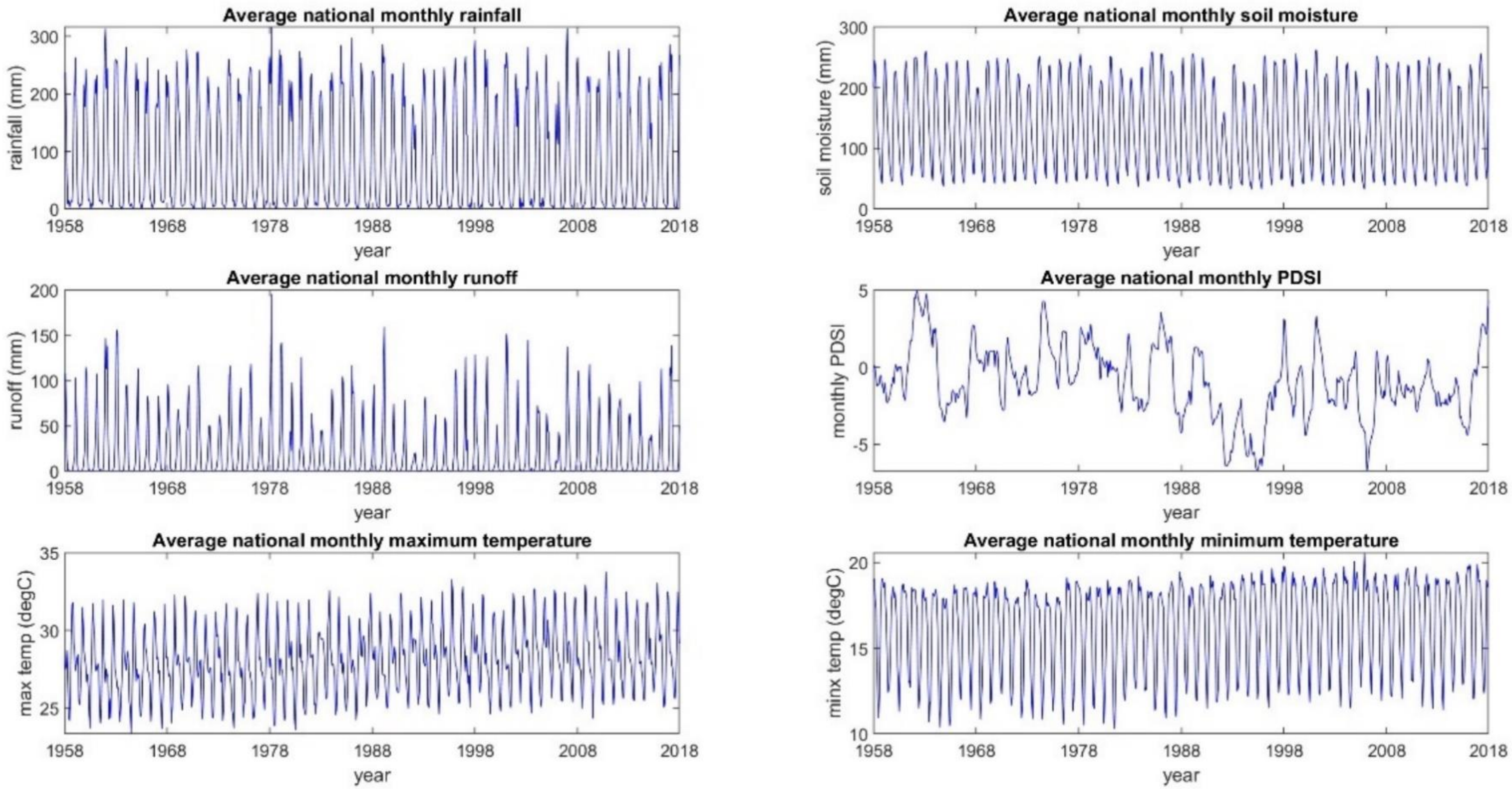


Figure 3.2 time series data for nationally averaged, monthly climate variables: TOP LEFT: rainfall (mm); TOP RIGHT: soil moisture (mm); MIDDLE LEFT: surface water runoff (mm); MIDDLE RIGHT: average monthly PDSI; BOTTOM LEFT: maximum temperature (°C); and BOTTOM RIGHT: minimum temperature (°C)

Considering just the wet season there still appears to only be a slightly visible trend (Figure 3.3). The line of best fit (using a least squares regression fit) for change in monthly rainfall shows negligible trend over this time frame. Monthly rainfall shows a trend of increase of 0.08mm per month with runoff and soil moisture similarly increasing by a very small degree. Temperature also shows a small rising trend of 0.01°C per month for maximum temperature and 0.02°C for minimum temperature. However, caution should be applied when analysing trends, particularly in rainfall, due to known uncertainties within General Circulation Models (GCMs) when downscaled (Haghtalab et al., 2019; Ngongondo et al., 2011), particularly due to the varied topography of Malawi. There is also much data paucity within local weather station data. In fact, Ngongondo et al., (2011) identified a small drying trend between 1960-2006 and as such, the trends shown within the TerraClimate dataset warrant further investigation for Malawi.

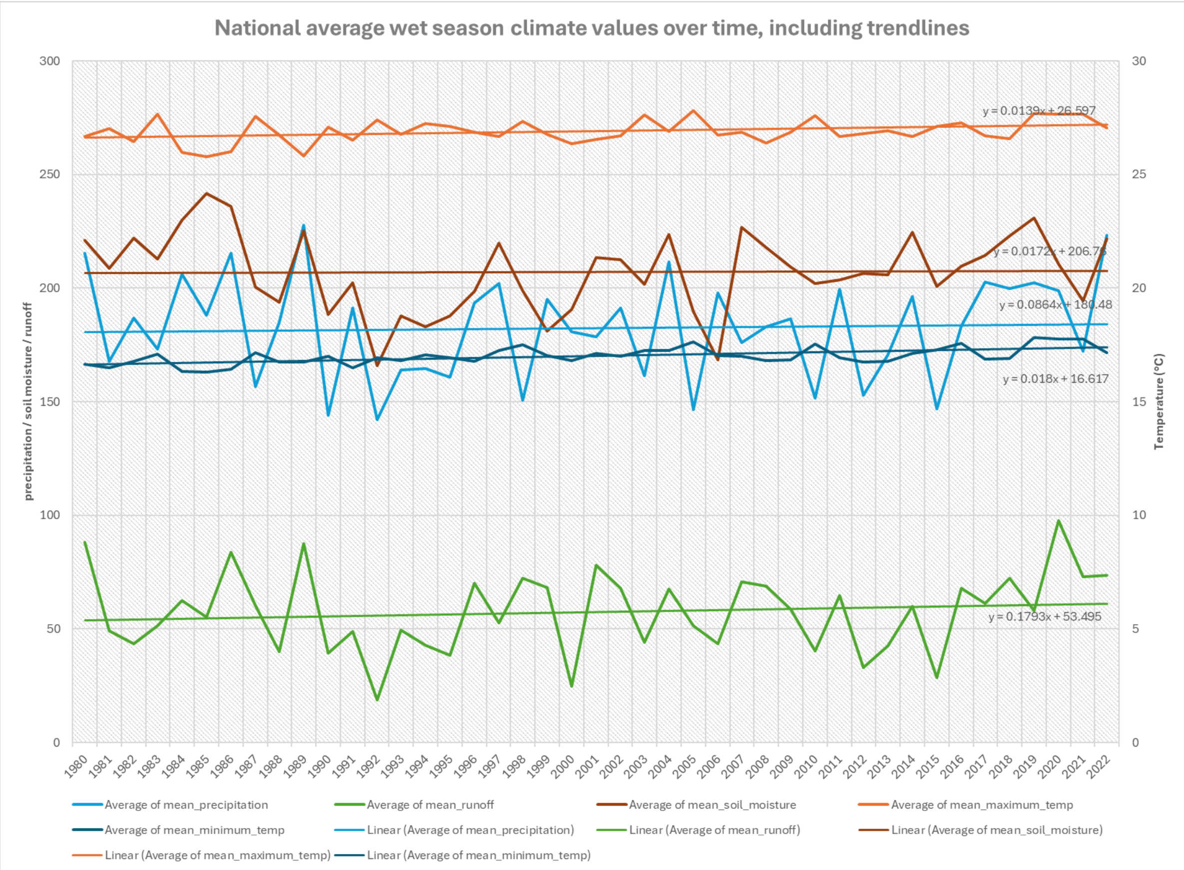


Figure 3.3 National trend line for wet season climate variables over time.

3.4.6.2 Climate of the wet seasons of study

Table 3.11 summarises the national wet season climate descriptive statistics for each wet season within the study period as well as for a baseline period of 1980-2010 which is a commonly chosen baseline period in line with WMO recommendations[4].

Table 3.11 Descriptive statistics for the survey wet seasons in Malawi

Climate variable	Mean value	Standard deviation	Maximum value	Minimum value
2010/11 wet season				
Average Monthly rainfall (mm)	180.70	105.52	473.60	4.00
Average monthly minimum temperature (°C)	16.86	2.44	23.57	11.09
Average monthly maximum temperature (°C)	26.96	2.50	35.14	20.82
Average soil moisture (at month's end) (mm)	190.98	115.02	454.57	15.24
Average monthly Palmer Drought Severity Index (PDSI)	-3.20	1.55	3.05	-5.93
Average monthly surface runoff (mm)	61.87	79.20	309.07	0.00
2015/15 wet season				
Average Monthly rainfall (mm)	194.07	98.06	522.16	23.49
Average monthly minimum temperature (°C)	17.75	2.43	22.87	11.76
Average monthly maximum temperature (°C)	27.21	2.46	34.58	20.00
Average soil moisture (at month's end) (mm)	216.60	117.15	454.57	15.14
Average monthly Palmer Drought Severity Index (PDSI)	-3.97	1.49	2.26	-7.01
Average monthly surface runoff (mm)	68.84	79.49	435.71	1.00
2019/20 wet season				
Average Monthly rainfall (mm)	228.51	110.34	485.61	7.50
Average monthly minimum temperature (°C)	17.71	2.31	23.83	12.44
Average monthly maximum temperature (°C)	27.61	2.22	34.57	21.60
Average soil moisture (at month's end) (mm)	232.18	110.51	454.57	16.54
Average monthly Palmer Drought Severity Index (PDSI)	2.82	2.65	9.32	-2.6
Average monthly surface runoff (mm)	100.87	101.65	392.45	0.00
1980-2010 baseline period				
Average Monthly rainfall (mm)	160.85	320.97	282.77	93.23
Average monthly minimum temperature (°C)	16.52	2.5	20.56	10.53
Average monthly maximum temperature (°C)	28.03	2.06	32.83	23.95
Average soil moisture (at month's end) (mm)	132.86	72.62	264.53	33.1
Average monthly Palmer Drought Severity Index (PDSI)	-1.94	2.4	4.17	-7.72
Average monthly surface runoff (mm)	20.00	33.66	180.78	0.00

[4] Whilst this study was in progress the WMO updated their baseline to be 1991-2020. However, as work was already in progress, I have retained the previously recommended baseline of 1981-2010. Furthermore, in order to determine the anomaly of climate variables during the survey years, it was sensible to utilise a recent but historic baseline rather than near-present day climate. Refer to https://wmo.int/media/news/updated-30-year-reference-period-reflects-changing-climate (Last Accessed May 2024) for further details.

1990-2020 baseline period				
Average Monthly rainfall (mm)	161.7677	289.72	285.01	95.74
Average monthly minimum temperature (°C)	18.64	8.78	23.32	8.44
Average monthly maximum temperature (°C)	28.95	5.63	35.15	17.56
Average soil moisture (at month's end) (mm)	169.58	1740	412.45	32.97
Average monthly Palmer Drought Severity Index (PDSI)	-2.05	0.14	-0.23	-3.33
Average monthly surface runoff (mm)	40.40	201.27	157.59	5.05

To gain insight into whether each wet season was anomalous I used a Wilcoxon test to compare the wet season monthly average values for the survey years, to a 1980-2010 baseline (to ascertain any climate change signal) as well as to the current 30-year monthly average wet season (1992-2020) which can determine if the survey years were abnormal for the current time period (Table 3.12).

Results suggest that the majority of climate factors for IHS4 (2015/16) and IHS5 (2019/20) were distinctly different (wetter and warmer) than the 1980-2010 baseline (only 2016 soil moisture was not significantly wetter). This confirms the presence of a climate change trend within the dataset. The 2010/11 wet season was largely not different to the 1980-2010 climate. Considering the present-day climate baseline period (1990-2020) once again the 2010/11 climate does not appear to have deviated from the baseline, however the 2015/16 and 2019/20 were once again found to be significantly wetter and warmer, with the exception of 2015/16 (IHS4) maximum temperature and soil moisture.

Table 3.12 Wilcoxon results for differences in the average of survey year wet season climate values, and the 30-year average values for the historic baseline (1980-2010) and the present-day baseline (1990-2020)

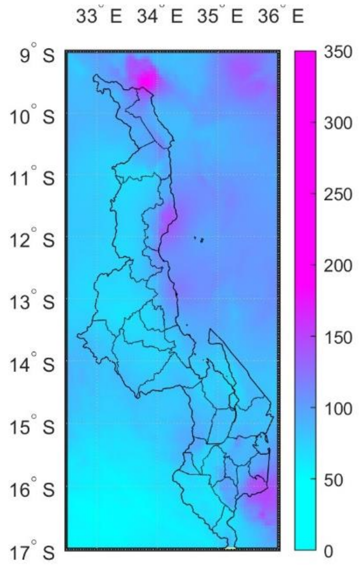
Variable	Wet season	Survey year wet season mean value	1980-2010 wet season mean	Test statistic	p-value	1990-2020 wet season mean	Test statistic	p-value
Precipitation (mm)	2010/11	180.70	160.85	5.8165e+05	0.9791	179.38	15784832	0.9020
	2015/16	194.07		642297	0.0103		606165	0.0072
	2019/20	229.52		7.3202e+05	0.0000		691097	0.0000
Minimum temperature (°C)	2010/11	16.86	16.52	5.6899e+05	0.6143	16.68	1.5823e+07	0.1142
	2015/16	17.75		6.9369e+05	0.0000		6.2792e+05	0.0002
	2019/20	17.30		6.8638e+05	0.0000		6.2001e+05	0.0009
Maximum temperature (°C)	2010/11	26.96	28.03	589457	0.7240	28.22	15800543	0.5635
	2015/16	27.21		637883	0.0173		578206	0.1493
	2019/20	27.19		690991	0.0000		6.2666e+05	0.0003

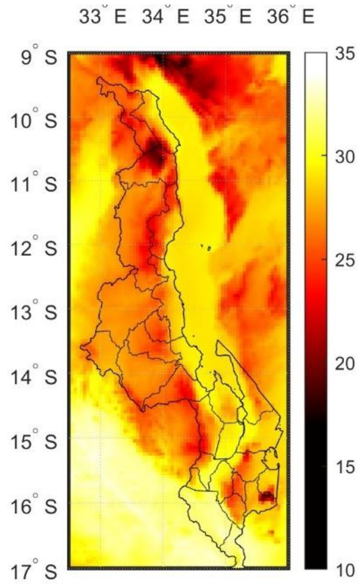
Mean soil moisture (mm)	2010/11	190.98	132.86	541855	0.1011	130.79	15820478	0.1424
	2015/16	216.60		6.1558e+05	0.1479		582310	0.1041
	2019/20	230.36		6.6187e+05	0.0007		625784	0.0003
Mean PDSI	2010/11	-3.20	-1.94	4.3473e+05	0.0000	-2.25	1.5877e+07	0.0001
	2015/16	-3.97		3.3744e+05	0.0000		355371	0.0000
	2019/20	-0.58		1.0100e+06	0.0000		970369	0.0000
Mean surface runoff (mm)	2010/11	61.87	20.00	569222	0.6213	19.86	1.5796e+07	0.7233
	2015/16	68.94		647064	0.0057		612341	0.0030
		77.99		7.1831e+05	0.0000		678729	0.0000

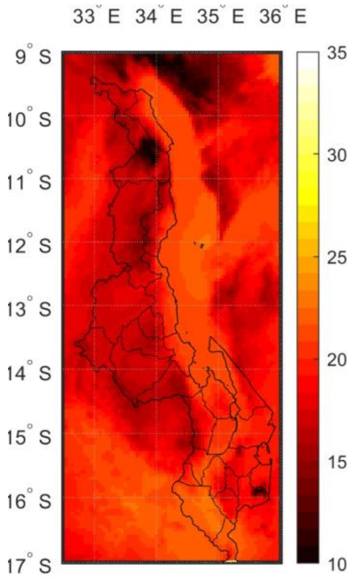
The spatial distribution of these variables is demonstrated in Figure 3.4.

Average monthly rainfall | **Average monthly maximum temperature** | **Average monthly minimum temperature**

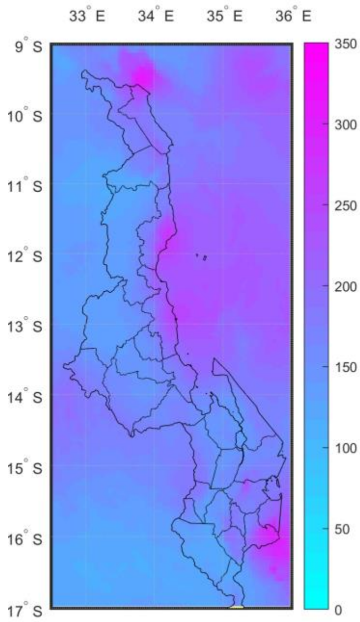
1980-2010 average wet season

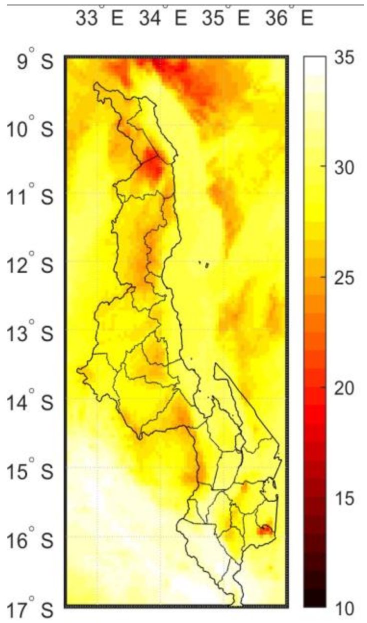


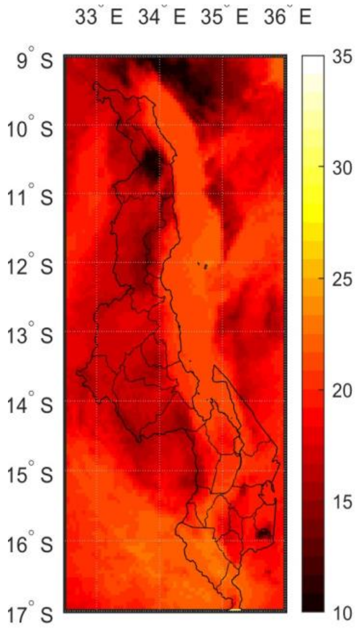




2010/11 average wet season







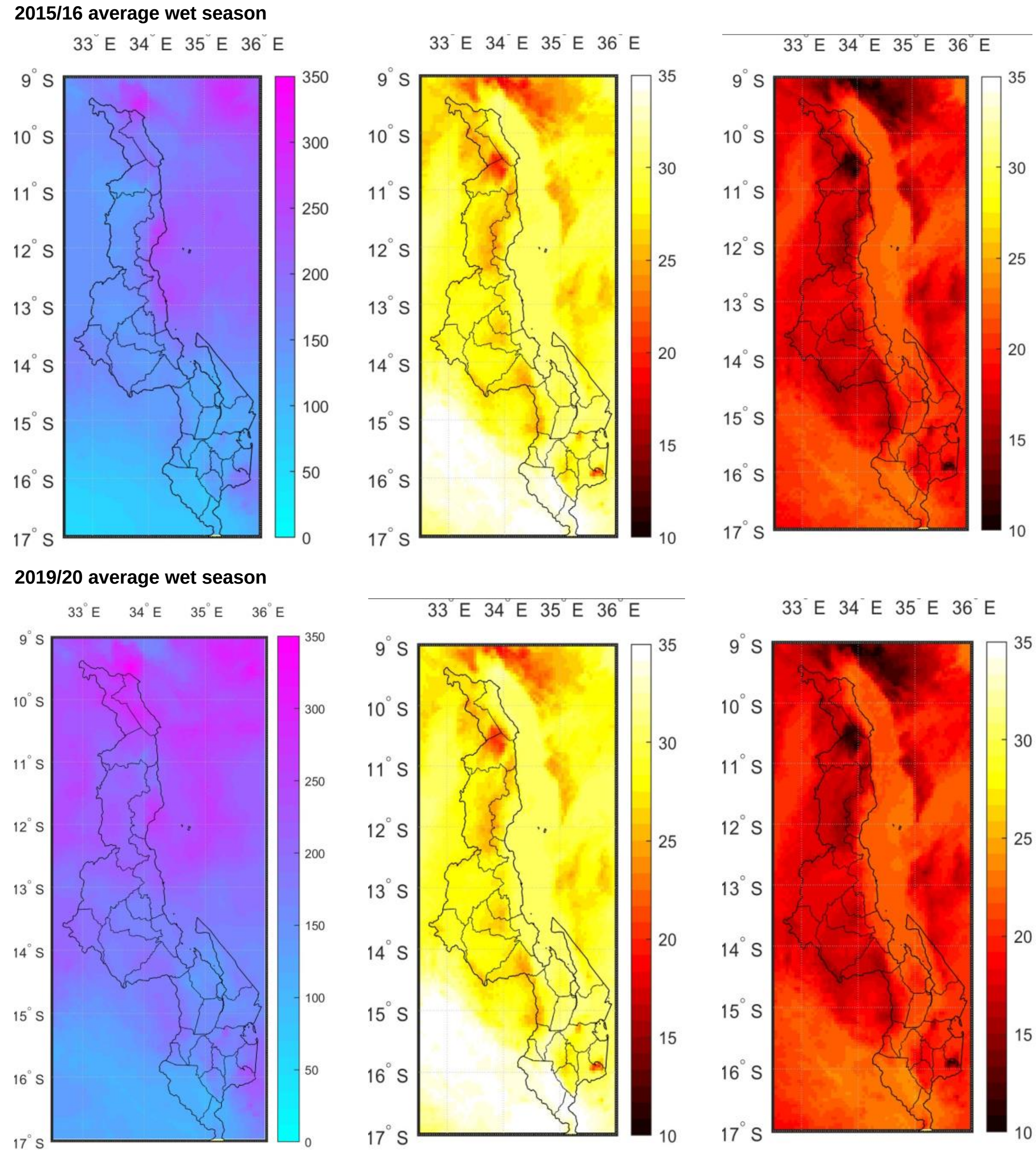


Figure 3.4 modelled average monthly precipitation (left), average monthly maximum temperature (centre) and average monthly minimum temperature (right) for wet seasons. SOURCE: TerraClimate

The spatial pattern appears similar across each of the three survey wet seasons and is also similar to the 30 year wet season baseline (1980-2010). However, as expected, the baseline period appears slightly drier than any of the survey years and slightly cooler . The spatial profile appears to closely follow the topography of Malawi, with districts near the lake showing much higher temperatures and more rainfall due to the lower altitudes. There appear to be rainfall 'hot spots' in the far north near Chitipa and Karonga districts, as well as central lakeside districts of

Nkhatabay and Nkhotakota and the southern districts of Mulanje and Phalombe. Temperatures follow the topography of the country quite closely, with the lake and lowlands being far hotter than the higher altitudes, and a high-altitude cold spot located in the northern districts of Chitipa and Rumphi.

The 2019/20 wet season appears to be somewhat wetter than the others, particularly in the northern and central districts, corroborated by IFRC (2021) reports of widespread flooding. It is also worth mentioning that tropical cyclone Idai affected Malawi causing extremely heavy rainfall, predominantly the southern districts, in the previous wet season (2018/19). It is estimated that 975,588 people were affected overall (IFRC, 2021), and it is highly likely that Idai had consequences not only for the 2018/19 growing season and resultant crop production, but with impacts on the following year (2019/20) crop production also due to displacement of peoples, destruction of property and damage to agricultural lands. The 2019/20 wet season also received above average rainfall (though not related to any reported extreme events).

According to famine early warning system network Malawi, the, 2015-16 wet season received below average rainfall (FEWS NET, 2016a), and would support the higher levels of drought-driven food insecurity (Table 3.5) for that year. This appears to be reflected in the TerraClimate PDSI metric which is lower than for other survey years, but not within the rainfall metric (Table 3.12). This may suggest that rainfall is not being well represented within the TerraClimate dataset, which struggles to represent the 2015/16 reduced rainfall, or that average monthly rainfall is not a sufficient metric to measure drought and which therefore may impede the regression modelling of how rainfall impacts upon crop production and food security.

The TerraClimate findings do broadly reconcile to the empirical data from a selection of weather stations (National Statistical Office (NSO) [Malawi], 2018). Reconciliation was performed based on a spatial Pearson correlation analysis. Whilst the TerraClimate dataset does appear to roughly reconcile with sparse meteorological overview data, more research is recommended to support improved climate data at a high spatial granularity, especially in light of the potentially erroneous 2015/16 modelled rainfall results. This point, whilst already acknowledged within literature and addressed through a variety of studies (Haghtalab et al., 2019; Msowoya et al., 2016; Ngongondo et al., 2011; Warnatzsch & Reay, 2019) is particularly pertinent for Malawi due to the recognition of Malawi's economy as being both climate vulnerable, and undergoing rapid urbanisation (National Statistics Office (NSO) [Malawi], 2019) and crop diversification incentives (FAO, 2019) (both as part of economic development goals and as climate adaptation initiatives ((Environmental Affairs Department [Government of Malawi], 2006).

Future projections of climate change can be further improved with the recent publication of the ensemble model results from the sixth phase of the Coupled Model Inter-comparison Project (CMIP6), which utilises the shared socioeconomic pathways for future economic development and emission scenarios (IPCC, 2021; O'Neill et al., 2017; Riahi et al., 2016) replacing the stand-in representative concentration pathways used to date for most climate projection models.

3.4.6.3 Analysis of climate anomaly against crop production

The next step was to explore if crop production may have been affected by a deviation from the average temperature and rainfall due to climate change. The climate anomaly for rainfall and maximum temperature was constructed and then compared to the district total maize produced. The anomaly is defined as the delta (difference) between the survey year values for average monthly rainfall (mm) and maximum temperature (°C), and the average values for all wet season months between 1980 and 2010, taken as the climate baseline period.

The anomalies were plotted on maps and visually examined (Appendix J) and appeared to be potentially sizeable. The spatial pattern appears slightly different for each of the three survey years and may be due to natural climatic variability or due to factors such as topology, land cover, proximity to Lake Malawi. Next, the anomalies were averaged by district and then correlated against crop production. The national results for the correlation across districts are shown in Table 3.13.

Table 3.13 Pearson's correlation results for district level total maize production and climate variables. Climate variables include either a delta or a time-averaged variable. Delta's are described as the climate anomaly for *survey year compared to a 1980-2010 baseline. Time-averaged climate variables are the average wet season climate averaged over either 2,3,4,5,10 or 20 years preceding the survey year.*

time period	**climate variable**	**Correlation with district total maize production**
2010.11 wet season	average monthly rainfall anomaly (mm)	-0.3913
2010.11 wet season	average monthly maximum temperature anomaly (°C)	-0.7636
2015.16 wet season	average monthly rainfall anomaly (mm)	-0.3548
2015.16 wet season	average monthly maximum temperature anomaly (°C)	-0.4619
2019.20 wet season	average monthly rainfall anomaly (mm)	0.0671
2019.20 wet season	average monthly maximum temperature anomaly (°C)	-0.5068

Whilst these results do not show a clear association, the correlation between crop production and maximum temperature anomaly is compelling. As such, the anomaly was substituted in place of the absolute climate values into the regression model produced in previous sections to test if the climate change signal showed a measurable association with crop outputs. Results are shown in Table 3.14.

Table 3.14 multi-level linear regression model for crop production. Climate change is captured as measured using the anomaly in rainfall and maximum temperature values from a 1980-2010 baseline)

		IHS3			IHS4			IHS5		
Variables	**Unit**	**Coefficient Estimate**	**Standard Error**	**P value**	**Coefficient Estimate**	**Standard Error**	**P value**	**Coefficient Estimate**	**Standard Error**	**P value**
(Intercept)	*Kg Maize at intercept*	632.09	158.76	0.00	-397.27	177.33	0.03	-110.56	184.09	0.55
Maximum wet season monthly temperature delta	*Kg Maize per 0.1*degrees C temperature rise above the 1980-2010 baseline*	-610.73	891.25	0.00	-0.085	420.15	1.00	-67.702	198.74	0.00
2nd wealth quintile	*Kg Maize when moving into the 2nd quintile*	142.88	67.99	0.04	38.58	49.37	0.43	49.01	76.04	0.52
3rd wealth quintile	*Kg Maize when moving into the 3rd quintile*	282.35	71.41	0.00	109.30	51.58	0.03	53.6	77.87	0.49
4th wealth quintile	*Kg Maize when moving into the 4th quintile*	472.5	73.85	0.00	348.44	54.26	0.00	223.79	81.3	0.01
5th wealth quintile	*Kg Maize when moving into the 5th quintile*	860.27	82.9	0.00	713.53	64.89	0.00	737.24	92.74	0.00
Sex of household head	*Kg Maize for females (compared to males)*	-315.42	51.04	0.00	-122.85	36.18	0.00	-144.26	55.78	0.01
Household size	*Kg Maize per additional household member*	149.03	11.18	0.00	126.11	9.41	0.00	126.29	13.74	0.00
Plot size per household member	*Kg Maize per additional acre land per household member*	1027.42	77.09	0.00	853.60	38.90	0.00	1335.26	53.69	0.00
random effects		**Variance**			**Variance**			**Variance**		
Inter-district variability (μ_0)		2.21E+05			1.42E+05			2.78E+04		
Residual (ε)		1.12E+09			7.16E+08			2.02E+09		
Number of observations		9814			8915			8698		
Number of groups		31			32			32		

The results appear inconclusive. Although the temperature anomaly shows statistically significant results, the coefficient shows huge variation across the three surveys, and is near zero for the 2015/16 wet season (IHS4). Interpretation of the negative results shown in 2010/11 and 2019/20 is that the larger the anomaly, for each 0.1°C rise, crop production is reduced by between roughly 0kg (IHS4) and as much as 610kg (IHS3). These results are not in line with findings of previous models which suggested a positive association between rising maximum temperatures and crop production, as well as with a reduced odds of prolonged hunger. Given this and the lack of consistency across the models it may be that the associations observed, despite a significant p-value are not evidence of a true relationship.

3.4.6.4 Future crop production under climate change scenarios

In the future, climate projections from most Global Climate Models (GCMs) suggest that Malawi will continue to warm. Using the multi-model ensemble results from CMIP6 (Arias et al., 2021, World Bank Group, 2021) in the near future, the 2030s (2020-2039) Malawi is projected to warm by between 0.6°C (southern region) under the first shared socioeconomic pathway (SSP1) and by 0.75°C (northern region) under SSP5. In the far future, by the 2080s (2080-2099) the climate is projected to warm by between 0.6°C (southern region) under SSP1 and by 4.37°C (southern region) under SSP5. Rainfall projections contain far more uncertainty, with central estimates for both SSP1 and SSP5 suggesting that by the 2030s there will be very little change in annual rainfall, though the uncertainty, particularly during the wet season remains high. This ambiguity continues to the 2080s with the central estimate remaining near a net zero annual change. Spatial resolution and certainty for GCM data is relatively poor for Malawi, particularly concerning rainfall projections (Warnatzsch & Reay, 2019). This may indicate that models are not yet projecting future changes in rainfall very well, or that climate change is manifesting not as a change in total rainfall but in changes in the intensity of heavy rainfall events and dry spells (in other words, intra-annual variation in rainfall) or timing and duration of the rainy season (Haghtalab et al., 2019).

The above analyses have provided some limited and inconclusive evidence of a relationship between the climate variables explored and crop production, or with prolonged hunger. It is therefore not possible to hypothesise with confidence what the impact of further climate change as described above may do to Malawi's future crop and food security outlook. Under the original hypothesis, adverse climate change was predicted to have a negative impact upon crop production and hence upon food security. Therefore, as the climate continues to warm it was thought that it would drive a continued negative impact. The results of this study are insufficient to either nullify or support this hypothesis. This calls into question the appropriateness of the initial hypothesis, or else suggests that further testing may benefit from alternative or more granular datasets and more advanced statistic methods. This emphasises the urgent need for more research into spatially downscaled future projections. This will be particularly prudent to support future crop-climate studies and crop diversification initiatives as a climate change adaptation response, which will further necessitate understanding of how each of these crops may be affected by climate variables in the future.

Based on the above inconclusive findings, it is hypothesized that climate does not have a linear relationship with crop production or food security. For example, extreme rainfalls and temperatures beyond a threshold would have a strongly negative effect on crop production and food security due to heat stress, whilst extreme heavy rainfall, or drought could destroy agricultural land and yield (Bradshaw et al., 2022). Extreme events in Malawi are not well captured in modelled data and are often localised and as such were outside the scope of this nationwide study.

3.5 Conclusions

This chapter has explored the point-in-time relationships between a range of climate variables, crop production and food security metrics across three cross-sections - for the 2010/11, 2015/16 and 2019/20 main harvests. The three points in time have been visually compared to identify any potential trends in time. Despite some evidence of a small warming and wetting trend since 1980, there is inconclusive evidence that such climate change over this period, or the point-in-time climate during the three survey years, have a significant association with crop production or prolonged hunger prevalence of those years. Monthly rainfall during the wet season of crop growth, and the average maximum monthly temperature showed the best one-to-one relationships with crop production and prolonged hunger (compared to other climatic variables) however, when included within multi-level regressions they showed inconclusive associations. Significant relationships were identified between maximum temperature and a small decrease in odds of prolonged hunger (Table 3.10) and by isolating the climate change signal, a negative relationship was also found between crop production and maximum temperature anomaly (Table 3.14). However, studying the years preceding a survey did not identify any relationship with crop production during survey years (section 3.4.4.2), nor did the multi-level crop production model identify much of a relationship with climate variables (Table 3.9). Rainfall showed a very small and potentially significant negative relationship with crop production (for IHS4 and IHS5) and no clear relationship with prolonged hunger. There are also issues with the rainfall data in that it appears not to have adequately modelled the 2015/16 drought, even though drought was a more significant driver of hunger that year than other survey years (Table 3.5). This suggests that the monthly rainfall variable may not successfully modelling the relationship between climate and crop production or prolonged hunger and that alternative measures may be important for future studies (see section 3.5.1 below).

The effects of sociodemographic variables explored, particularly sex of the head of household, the plot size per person, and the wealth quintile the household belongs to had much stronger associations than climatic factors. These socioeconomic and demographic variables appear to be very important for crop production and should be considered in future research. In particular, inclusive, wealth-sensitivity and gender-sensitivity should be given to future research and interventions for agricultural and development, such as involvement in credit schemes, quantity of fertiliser used, and eligibility criteria for government programmes.

Further research is also recommended into the potential nonlinear relationship between climate change and crop production, as well as the exploration of alternative (potentially more fruitful) climate variables, and enhanced data granularity. Further research should also focus not only on maize production but on a more diverse range of crops. This is particularly important as Malawi continues to pursue crop diversification.

3.5.1 Future work

Future work may include expansion of the analysis along five key lines of enquiry. Firstly, alternative and more granular climate indicators may be explored. In particular, future studies may benefit from exploring alternative variables regarding rainfall such as rainy season onset, rainy season duration, and PET [potential evapotranspiration]) (FAO, 2024b). More granular (e.g., daily or 10-daily) rainfall data may also be helpful in order to account for the variation in water sensitivity of maize during the growing season (wet season). For instance, maize reaches peak water requirements during the flowering and early grain fill stage, approximately 60-90 days after planting (Wikifarmer, n.d.) and so a variable that captures rainfall during that window (the timing of which will vary across the country due to different planting dates) may yield interesting results. The analysis has also identified discrepancies and large data paucity in the availability of meteorological datasets, as well as the accuracy of some modelled climate data. Future studies should focus on achieving improved accuracy of rainfall projections at a high spatial granularity, to support crop studies and intervention design, particularly in climate sensitive regions, such as Malawi and south and east Africa.

Secondly, to better understand how climate change affects crop production, a more granular temporal analysis should be conducted. For example, rather than using three cross-sections through time, a timeseries analysis could be conducted using more granular climate data (which would capture climate change with more certainty) and the yearly nationally reported production across Malawi. However, such datasets would lose the household level factors such as wealth, number of dependants and sex. Time series models may show a more accurate and possible stronger relationship between crop production and climate variables (in line with the hypotheses laid out in this thesis) however this should not be done at the sacrifice of socioeconomic and demographic granularity, as this study has demonstrated their importance. Due to data paucity and lack of time series datasets concerning high spatial granularity datasets for household crop production, and food security, additional data such as retrospective surveys may be required.

Thirdly, further research is recommended into crop diversification, concerning how different crops are affected differently by climate as well as climate variability and climate change. Crop diversification in this context refers to a variety of axes including ongoing aims by the Malawian government to diversity maize species, encourage sustainable and climate smart agricultural practices (Kaczan et al., 2013) as well as aims to encourage staple crops other than maize, such as sweet potato (Chidanti-Malunga, 2011) and pigeonpea (Me-Nsope & Larkins, 2016). Household crop diversity can be measured through a variety of existing approaches such as a crop diversification index (e.g., Simpson's index) or by considering dietary diversity of consumed subsistence crops such as the Household Dietary Diversity Score (HDDS) or Food Consumption Score (FCS) (Snapp & Fisher, 2015). Future studies of crop production should also aim to consider other key determinants of production including labour availability and land holdings. Both these determinants are collected as part of the integrated household survey questionnaires however the data quality was not sufficient for inclusion within this analysis. Future studies may wish to apply data interpolation techniques to address missing data and then consider inclusion of these variables within future crop production models.

Fourthly, a more in-depth analysis of food security may be possible through a variety of avenues. For instance, a detailed review of childhood malnutrition could be conducted through use of ordinal child anthropometric data (such as wasting and stunting z-scores) within a Poisson regression. Given the multi-dimensionality of food security and since this study has elucidated that different food security metrics deliver different results, additional consideration for the most appropriate food security metric when designing future studies or policy interventions is essential. For example, global health studies and policy are interested perhaps not in food availability itself, but the consequences of food availability on undernutrition and the host of other health issues that are well associated with undernutrition (Black et al., 2008; Lloyd et al., 2011). Historically however, studies investigating the impacts of climate change upon food security have focused on food availability and crop production, with more research still needed to improve understanding and projections for how climate change will affect food access (through market prices), utility and stability in the future (Schmidhuber & Tubiello, 2007). Future studies to understand the impact of climate change or other aspects (such as future nutrition interventions like Malawi's Farm Input Subsidy Programme (FISP) (Ajefu et al., 2021; Kawaye & Hutchinson, 2018; Pauw & Thurlow, 2014) should carefully choose the most appropriate food security metric to capture the effect of interest most accurately.

Finally, a key hypothesis laid out in the conceptual model but which was found not to exhibit an empirical relationship, was the impacts of migration status upon crop production and food security. It was hypothesized that being a migrant into an area may reduce crop production and food security due to poorer or smaller landholdings available to in-migrants. However, no such relationship was identified. A possible reason for this is that the majority of Malawians migrate along familial lines, such as moving to marry, divorce or to live with relatives. As such, land may continue to be available through extended family connections and as such, not impact upon the ability of migrants to grow crops. Lack of relationship may also be due to the high level migration variable created, which only considered lifetime migration without consideration for source location, host location, time of migration or reason. This hypothesis may benefit from a more detailed investigation and will be further explored in the following chapter.

3.6 CHAPTER SUMMARY

This chapter has used statistical modelling to explore the relationship between climate variables, crop production and food security. Significant relationships were identified between maximum temperature and a small decrease in odds of prolonged hunger. By isolating the climate change signal, a negative relationship was also found between crop production and maximum temperature. Rainfall showed a very small and potentially significant negative relationship with crop production and no clear relationship with prolonged hunger. The chapter also identified that other factors such as land holdings, wealth and sex of the household head had the largest impacts. Migration status of the head of household was not found to have relationship with either household maize production. I will use this insight to next interrogate in different ways, the hypothesis that climate factors, through food security metrics and internal migration in Malawi are related.

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APPENDIX B

District and region codes

District / region	code
Region	
Northern region	1
Central region	2
Southern region	3
District	
Chitipa	101
Karonga	102
Nkhatabay	103
Rumphi	104
Mzimba	105
Likoma	106
Mzuzu City	107
Kasungu	201
Nkhotakota	202
Ntchisi	203
Dowa	204
Salima	205
Lilongwe	206
Mchinji	207
Dedza	208
Ntcheu	209
Lilongwe City	210
Mangochi	301
Machinga	302
Zomba Non-City	303
Chiradzulu	304
Blantyre	305
Mwanza	306
Thyolo	307
Mulanje	308
Phalombe	309
Chikwawa	310
Nsanje	311
Balaka	312
Neno	313
Zomba City	314
Blantyre City	315

APPENDIX C

Conversion factors used to calculate crop production for each crop code. Unless otherwise stated, conversion factors are taken from the conversion note prepared during the third Integrated Household Survey (IHS3), prepared by the National Statistics Office of the Government of Malawi (National Statistics Office (NSO), 2011). Where insufficient information about a local quantity unit was available, assumptions have been made as listed in the following table.

Original unit code	original unit	kg equivalent	Additional details
MAIZE [1]			
1	KILOGRAM	1	
2	50 KG BAG	50	
3	90 KG BAG	90	
6	NO. 10 PLATE	0.3	Without additional details for a No.10 plate it is assumed that the No.10 and No.12 plates carry roughly the same volume.
7	NO. 12 PLATE	0.3	
5	PAIL (LARGE)	16.39166667	Average pail size taken as the mean of the three pails described by Malawi NSO.
10	BALE	780	Bale size calculated using information from (Edwards, 2020). Assumed dimensions of a bale of 72 inches in diameter and 60 inches wide. 72 x 72 x 60 x .005 = 1,555 lb. per bale 1,555 pounds per bale ÷ 2,000 lb. per ton = .78 tons = 780kg per bale
11	BASKET (DENGU)	15.19	Assumes a basket is the same as a large pail (see unit 5 above)
n/a	n/a	n/a	used when 0 maize is reported (due to missing data)
4	PAIL (SMALL)	4.07	Average pail size taken as the mean of the three pails described by Malawi NSO.
12	OX-CART	1149	Assumed dimensions of a typical Malawian ox-cart, multiplied by the density of raw maize are: of 0.5m*2m*1.5m *766 kg/m^3 = 1149kg (Crossley et al., 2009)
8	BUNCH	0.03	assume a medium sized piece of Maize with mass of approximately 30g per piece / bunch
9	PIECE	0.03	assume a medium sized piece of Maize with mass of approximately 30g per piece / bunch
13	Basin	4.95	average of all sizes provided by NSO
13	basin (small)	2.47	assumed half a standard sized basin
13	BASIN LA MULINGO	4.945555556	Mulingo is the Chichewan word for 'standard' and as such a mulingo basin is assumed to carry same amount as Basin (see entry above)
13	Bucket (5 litre) (Ndowa)	3.83	Mass contained within a 5 litre bucket is calculated assuming average density of maize of 766kg/m^3 (density of Maize as per density of Maize = 766kg/m^3 (Rodrigues et al., 2014)

13	Dengu	15.19	Dengu is a type of basket assumed to have same dimensions as a large pail
13	Granary	24065	Typical Malawian granaries are relatively small structures (roughly house sized) as per this report. Approximate dimensions are 2.5m x pi*(2m^2) = 14.14m^3 *766 kg/m^3 density of Maize = 24065kg
13	NKHOKWE	24065	Nkhokwe is the Chichewan word for granary so have used same assumption as for granary
13	GRANARY (SMALL)	6016	Assumed dimensions of a small granary are 2.5m * (pi*1m^2)*766 kg/m^3 density of maize = 6016kg
13	HEAP	1.8	Heaps are assumed to contain roughly 6 pieces (cobs) of Maize based on anecdotal observations of maize heaps sold in local markets. Assumes a mass of a single hob of 30g
13	winnower	0.3	A winnower is a large, shallow bowl used for winnowing (cleaning and separating) raw (wheat) grain. Assumed to have same volume as a plate (No. 10 plate).
13	lichelo	0.3	A lichelo and a winnower are the same thing.
13	MEDIUM WEAVING BASKET	15.19	assumed same as basket (dengu) which in turn is assumed to be the same as a large pail. Large pail taken from http://siteresources.worldbank.org/INTLSMS/Resources/3358986-1233781970982/5800988-1271185595871/Malawi_IHS3_Food_Item_Conversion_Factors.pdf
13	THREE TONE	3000	assumes metric ton
13	Tin	0.6	for Maize flour (not unprocessed maize presumably). Assume Tin dimensions 0.1m * pi*0.05m^2. Maize density is 766
13	TWO TURN	2000	assume this is an error by field officer, should spell two ton
13	blank	n/a	omitted due to not enough data to be able to make an assumption
13	100 KG BAG	100	
13	TONE	1000	assumes metric ton
13	3 TUN CAR	3000	assumes metric ton
13	70 KG BAG	70	
13	75 KG BAG	75	
	wheelbarrow	127.68	Assumes a 28liter volume of a standard wheelbarrow
GROUNDNUT: CHALIMBANA [11] and CG7 [12]			
1	KILOGRAM	1	
2	50 KG BAG	50	
4	PAIL (SMALL)	4.08	Average pail size taken as the mean of the three pails described by Malawi NSO.

5	PAIL (LARGE)	12.24	Assumes a large pail of three times the capacity of a small pale based on pictures provided by Malawi NSO
13	90 KG BAG	90	
13	100 KG BAG	100	
13	PAIL (40 LITRE)	22.0664	We assume that the groundnut are weighed prior to being shelled. The bulk density of groundnut is approximately hey reported that the bulk density varied between 538.02 and 565.30 kg m^{-3}. (Akcali et al., 2007). For purpose of this study, we take an average of these limits, equivalent of 551.66kg/m^3. 40litres is equivalent to 0.04m^3. Therefore the mass of groundnuts contained within a 40l pail is approximately 0.04*551.66 = 22.0664 kg.
13	HAIF	0	Not enough information regarding this, it is assumed to be a typo. Only one entry was made with units provided as HAIF and as such it has been omitted from the analysis by setting the conversion value to 0.
13	70 KG BAG	70	
13	PAIL	4.08	Assume this is the same as a small pail
13	PAIL (20 LITRE)	11.0332	Half that of a 40 litre pail
13	BASIN (SMALL)	0.93	Average basin size taken from Malawi NSO conversion information
13	LICHELO	0.213	A lichelo (also referred to as a winnower) is a large wicker plate used for separating shells and kernels. It is approximately the same size as a large plate. Information is not provided about whether such plates are heaped or flat so we assume they are flat and about the same dimensions as a No.12 plate (Malawi NSO). (0.25+0.17+0.22)/3=0.213kg
13	BASIN LA MULINGO	0.93	Standard basin.
13	PHAZI PLATE	0.213	A phazi is a large plate and is therefore estimated to carry the same mass of peanuts as a number 12 plate. (0.25+0.17+0.22)/3=0.213kg
13	PAIL (MEDIUM)	8.08	Based on the visuals provided (Malawi NSO). We estimate a medium pale to have twice the volume of a small pale. Therefore the mass of groundnuts it can hold is also doubled and is therefore estimated at 2 x 4.08kg = 8.08kg
Blank	Blank	0	
13	Blank	0	Not enough information and therefore omitted from analyse by setting kg conversion factor to 0.
Rice [17]			
1	KILOGRAM	1	
2	50 KG BAG	50	
5	PAIL (LARGE)	8.82	A medium pail of rice carries 5.88kg according to Malawi conversion information. As per the visuals a large pail is estimated to be 1.5 times the size of a medium pail and is therefore estimated to carry 5.88*3/2=8.82kg

Blank	Blank	0	
13	100 KG BAG	100	
13	50 KG BAG	50	
13	70 KG BAG	70	
13	90 KG BAG	90	
13	PAIL (LARGE)	8.82	A medium pail of rice carries 5.88kg according to Malawi NSO. As per the visuals a large pail is estimated to be 1.5 times the size of a medium pail and is therefore estimated to carry 5.88*3/2=8.82kg
13	TIN	1.1388	Assume Tin dimensions 0.1m * pi*0.05m^2. Density of milled rice varieties is constant at about 1.45 g/ml =1450kg/m^3 (Bhattacharya, 2013) therefore, mass of rice contained within a tin is estimated at 0.1*pi*0.05^2*1450 = 1.1388kg
Sweet Potato [28]			
1	KILOGRAM	1	
2	50 KG BAG	50	
4	PAIL (SMALL)	4.79	
5	PAIL (LARGE)	18.33	Information for the quantity of sweet potato in a large pail is not provided by Malawi NSO however there is information regarding Irish potato which is assumed to have approximately the same density. Whilst weight and density of potatoes varies by starch content, dryness and variety of potato, we use an irish potato weight as a proxy for sweet potato. Large pail of Irish potatoes = (18.02+19.62+17.36)/3 = 18.33kg
12	OX-CART	879.75	Assumed dimensions for a Malawian ox-cart are storage area are 0.5m*2m*1.5m. Density of sweet potato is estimated to be between 595 and 578 kg/m^3 acording to Ghanan varieties (Teye & Abano, 2012)and therefore assume a sweet potato density of (595+578)/2 = 586.5kg/m^3. Sweet potato mass contained within an ox-cart (assuming no air gaps between potatoes when packing) is therefore; 0.5*2*1.5*586.5 = 879.75kg
13	90 KG BAG	90	
13	DENGU	18.33	A Dengu is a basket which is estimated to have the same carrying capacity be the same size as a large pail which can carry 18.33kg of irish potatos (used as a proxy for sweet potato).
13	TONE	1000	
13	70 KG BAG	70	
13	BAGS	0	Insufficient information to make an estimation. Only one entry is made using this unit and it has therefore been omitted by setting the kg conversion factor to zero.

13	Blank	0	
Sorghum [32]			
1	KILOGRAM	1	
2	50 KG BAG	50	
4	PAIL (SMALL)	10.2	We assume that only the sorghum grain is gathered and transported. Average mass of grain is 0.044g and density of 1.02g/cm^3. (Simonyan et al., 2007). Assuming the volume of a small pail is approximately 10litres (=10000cm^3) then the mass of Sorghum grain in a small pail is = 1.02/1000*10000 = 10.2kg 10l = 10000cm3 1g = 0.001kg 10l contains 56850 kg
5	PAIL (LARGE)	30.6	Based on visual comparison it is estimated that a large pail is 3 times the size of a small pail. Therefore estimated mass of a large pail of Sorghum = 10.2*3 = 30.6
Blank	Blank	0	
13	70 KG BAG	70	
13	BASIN (SMALL)	2.17	
13	BAGS	0	Insufficient information is available about bags and these values have therefore been set to nill.
13	BASIN LA MULINGO	4.34	A mulingo basin is a standard size basin that is assumed to be the twice the size of a small basin for which values are available.
13	WINNOWER	0.19	Assumed to have the same carrying capacity as a large (No.12) plate for which an average of the three regional values was taken. = (0.21+0.11+0.25)/3 = 0.19
13	LICHELO	0.19	A lichelo is another name for a winnower
13	BASIN	2.17	Assumed to be the same as a small basin
Beans [34]			
1	KILOGRAM	1	
2	50 KG BAG	50	
4	PAIL (SMALL)	7.21	Assumed volume of a small pail is 10l and that the average density of bean is 0.721 g/cm3 (*Density of Beans, Soy in 285 Units of Density*, n.d.). Mass = 10l * 10000(cm^3/l) * 0.000721kg/cm^3 = 7.21kg
5	PAIL (LARGE)	21.63	Assumed volume of a large pail is 30l and contains 3 times the content of a small pail = 7.21*3 = 21.63kg
13	TIN	0.38	Estimated to have a similar volume and hence carries the same mass of beans as a cup. Cups contain an average of 0.48kg (white beans) or (0.31 0.32 0.41)/3 = for brown beans.

			Since no information is provided regarding variety of bean collected, we take an average of both white bean and black beans. = 0.48+(0.31+0.32+0.41)/4) = 0.38kg
13	90 KG BAG	90	
13	BASIN (SMALL)	4.09	
13	10 KG BAG	10	
13	PAIL (MEDIUM)	14.42	Assumed volume of a medium pail is 20l. = 7.21*2 = 14.42kg
13	BASIN	4.09	
13	TINA	0.38	This is assumed to be a typing error due to the manual input nature of this field. Assumed value is 'TIN'.
13	BUCKET	14.42	Bucket is assumed to be the same size as a medium pail (20litres).
13	PAIL	14.42	This is assumed to refer to a medium size pail, which is estimated to have a volume of 20litres.
13	BASIN (LARGE)	8.18	A large basin is assumed to have the twice the volume of a standard basin therefore can contain 4.09*2 = 8.18kg
13	BASIN LA MULINGO	4.09	Same as a medium sized basin.
13	PAIL (40 LITRE)	28.84	We assumed that a small pail has a volume of 10litres and therefore holds a mass of 7.21kg. Therefore a 40litre pail holds 4 times this amount = 4*7.21 =
13	NO 12 PLATE	0.25	Take average from the all the regional values provided for both white and brown beans. = (0.27 0.23 0.30 + 0.24 0.23 0.23) / 6 = 0.25kg
13	LICHELO	0.25	Assumed to have the same volume as a large (No.12) plate.
	Blank	0	Eight entries had to be ignored because no units were provided.
Soyabean [35]			
1	KILOGRAM	1	
2	50 KG BAG	50	
4	PAIL (SMALL)	7.21	Assumed volume of a small pail is 10litres and assumed density of 0.721 g/cm3 (*Density of Beans, Soy in 285 Units of Density*, n.d.). Mass = 10l * 10000(cm^3/l) * 0.000721kg/cm^3 = 7.21kg
5	PAIL (LARGE)	21.63	Assumed volume of a large pail is 30l and contains 3 times the content of a small pail = 7.21*3 = 21.63kg
13	90 KG BAG	90	
13	75 KG BAG	75	

13	30 KG BAG	30	
13	BASIN (SMALL)	4.09	
13	PAIL (LARGE)	21.63	Assumed volume of a large pail is 30l and contains 3 times the content of a small pail = 7.21*3 = 21.63kg
13	Blank	0	Insufficient information
13	EGGS	0	Assumed to be an error. Only one entry made providing these units.
13	50 KG BAG	50	
13	PAIL	14.42	This is assumed to refer to a medium size pail, which is estimated to have a volume of 20litres.
PIGEONPEA(NANDOLO) [36]			
1	KILOGRAM	1	
2	50 KG BAG	50	
4	PAIL (SMALL)	8.66	Assume volume of a small pail is 10litres and that the average density of pigeon pea legumes is 7.23116oz/US cup = 0.866kg / litre cup (*Density of Pigeon Peas (Red Gram), Mature Seeds, Raw in 285 Units*, n.d.) So in a small pail there is 0.866*10 = 8.66kg
5	PAIL (LARGE)	25.98	Assume the volume of a large pail is three times that of a small pail.
13	TIN	0.42	Assume that a tin has roughly the same volume as a cup. Cups can contain 0.42kg according to Malawi NSO.
13	CHIGOBA	4.33	A Chigoba is a Malawian term for a bucket which is estimated to be 5 litres. Using an assumed density of pigeon pea is 7.23116 oz/cup or 0.866kg/litre Mass = 5 * 0.866 = 4.33kg
13	WINNOWER	0.32	A winnower is a large shallow bowl used for separating grain and is estimated to have approximately the same volume as a large (no.12) plate.
13	70 KG BAG	70	
13	BASIN (SMALL)	3.56	Assume that a small basin is half the size of a medium (standard) sized basin which contains 7.11kg (Malawi NSO).
13	MABESENI AWIRI AMULINGO	14.22	This Chichewan phrase translates to ‘2 basins of the same size’ so we assume a standard size basin (Basin la Mulingo) and multiply by two. = 2 * 7.11 = 14.22kg
13	BUCKET	17.32	Assume a bucket is the same size as a medium pail and has a volume of 20litres. Assume density of pigeon pea legumes is 7.23116oz/US cup = 0.866kg / litre cup 0.866*20 =17.32kg
13	BASIN LA MULINGO	7.11	
13	BASIN	7.11	

13	LICHELO	0.32	Assume that this is the same size as a No.12 plate
13	BAGS	0	Insufficient information regarding this value and so entries have been set to nill
13	50 KG BAG	50	
13	75 KG BAG	75	
13	PHAZI PLATE	0.32	Assume that this is the same size as a No.12 plate
13	PAIL (MEDIUM)	17.32	Assume volume of a medium pail is 20litres which is twice that of a small pail.
13	GRAMS	0.001	
NKHWANI [42]			
1	KILOGRAM	1	
2	50 KG BAG	50	
4	PAIL (SMALL)	6.2	Assume that a small pail (approximate volume is 10litres) can carry 50 large heaps of Nkhwani and that a large heap has a mass of (0.69+0.52+0.66)/3 = 0.62kg. Therefore mass in a small pail = 10 * 0.62 = 6.2kg
5	PAIL (LARGE)	18.6	Assume the volume of a large pail is three times that of a small pail and as such can carry three times as much Nkhwani. = 3*6.2 = 93.6kg
7	NO 12 PLATE	1.86	Assume that a No 12 plate (heaped) can carry 3 heaps of Nkhwani = 3 * 0.62 = 1.86kg
8	BUNCH	0.23	Average from across three regions as provide in the Malawi NSO conversion note (0.16+0.25+0.27) / 3 = 0.23kg
9	PIECE	0.03	
12	OX-CART	465	Assume the dimensions of an ox-cart to be 0.5m*2m*1.5m = 1.5m^3 And that the dimension of a nkhwani heap (large) to be 0.20*0.20*0.05 = 0.002m^3. Therefore an ox-cart can contain 750 large heaps. Each (large) heap has a mass of (0.69 0.52 0.66)/3 = 0.62kg. Therefore the mass of an ox-cart carrying nkhwani is 0.62*750 = 465kg
13	BASKET (LARGE)	18.6	Assume same as a large pail. Assume the volume of a large pail is three times that of a small pail. = 3*6.2 = 93.6kg
13	BASKET	18.6	Assume same as a large pail. Assume the volume of a large pail is three times that of a small pail. = 3*6.2 = 93.6kg
13	50 KG BAG	50	
13	DENGU	18.6	A dengu is a basket which is estimated to carry the same mass as a large pail. = 3*6.2 = 93.6kg
Peas [46]			
1	KILOGRAM	1	

2	50 KG BAG	50	
5	PAIL (LARGE)	7.99	Assume a volume of 30 litres and a density of pears of 66.57 g per metric cup (*Density of Peas, Edible-Podded, Raw (Chopped) in 285 Units*, n.d.) equivalent to 0.26628kg per litre. Therefore a large pail contains 0.266*30=7.99
13	PAIL	5.33	Assume a volume of 20litres and a density of peas of 66.57 g per metric cup equivalent to 0.26628kg per litre (*Density of Peas, Edible-Podded, Raw (Chopped) in 285 Units*, n.d.).
13	PAIL (SMALL)	2.66kg	Assume a volume of 10litres and a pea density of 0.26628kg per litre.
13	BASIN	2.18	The dimensions of a basin are unknown. However, the density of peas is approximately 0.3* the density of pigeonpea (=0.866kg/litre). According to (National Statistics Office (NSO), 2011), a basin of pigeonpea contains 7.11kg. It is therefore estimated that a basin of pigeonpea contains 0.3*7.11 = 2.18kg

APPENDIX D

District level descriptive statistics

Wealth quintiles

District	Wealth quintile 1			Wealth quintile 2			Wealth quintile 3			Wealth quintile 4			Wealth quintile 5		
	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5
101	0.71	0.69	0.58	0.16	0.15	0.17	0.03	0.09	0.05	0.05	0.02	0.06	0.04	0.05	0.15
102	0.43	0.32	0.36	0.21	0.17	0.18	0.16	0.20	0.19	0.13	0.16	0.10	0.07	0.15	0.17
103	0.52	0.51	0.46	0.20	0.16	0.13	0.10	0.16	0.10	0.07	0.07	0.11	0.11	0.10	0.21
104	0.59	0.57	0.56	0.18	0.17	0.10	0.10	0.08	0.10	0.05	0.07	0.03	0.08	0.11	0.21
105	0.01	0.48	0.02	0.16	0.16	0.11	0.33	0.09	0.18	0.30	0.08	0.29	0.19	0.19	0.38
106	NA	0.96	0.49	NA	0.02	0.07	NA	0.02	0.01	NA	0.00	0.07	NA	0.00	0.36
107	0.21	0.09	0.16	0.10	0.09	0.10	0.10	0.07	0.10	0.10	0.15	0.05	0.49	0.60	0.60
201	0.11	0.12	0.20	0.27	0.22	0.33	0.22	0.25	0.20	0.24	0.33	0.19	0.16	0.09	0.09
202	0.46	0.34	0.40	0.17	0.23	0.18	0.13	0.18	0.13	0.10	0.09	0.10	0.14	0.16	0.18
203	0.73	0.48	0.54	0.12	0.24	0.22	0.05	0.16	0.10	0.04	0.06	0.07	0.05	0.06	0.07
204	0.16	0.12	0.19	0.30	0.24	0.26	0.22	0.27	0.25	0.17	0.25	0.23	0.15	0.12	0.07
205	0.46	0.32	0.37	0.14	0.31	0.27	0.14	0.24	0.14	0.18	0.07	0.09	0.07	0.07	0.13
206	0.02	0.06	0.07	0.19	0.21	0.26	0.33	0.30	0.32	0.26	0.23	0.24	0.20	0.20	0.11
207	0.22	0.17	0.38	0.24	0.30	0.23	0.18	0.23	0.18	0.19	0.20	0.15	0.16	0.10	0.06
208	0.16	0.14	0.14	0.30	0.26	0.25	0.32	0.30	0.33	0.14	0.21	0.18	0.07	0.10	0.10
209	0.16	0.20	0.18	0.28	0.24	0.27	0.18	0.20	0.21	0.22	0.26	0.20	0.16	0.10	0.14
210	0.02	0.01	0.01	0.06	0.05	0.02	0.06	0.08	0.08	0.26	0.26	0.33	0.60	0.60	0.56
301	0.03	0.04	0.03	0.22	0.22	0.33	0.37	0.32	0.25	0.26	0.28	0.29	0.12	0.14	0.10
302	0.19	0.25	0.16	0.32	0.28	0.29	0.21	0.24	0.24	0.20	0.13	0.18	0.07	0.10	0.12
303	0.07	0.37	0.12	0.22	0.30	0.28	0.25	0.15	0.20	0.24	0.13	0.21	0.22	0.05	0.19
304	0.37	0.08	0.31	0.23	0.21	0.25	0.15	0.24	0.22	0.12	0.37	0.11	0.12	0.09	0.11
305	0.34	0.35	0.23	0.23	0.21	0.17	0.12	0.18	0.18	0.14	0.15	0.21	0.17	0.11	0.20
306	0.83	0.86	0.77	0.04	0.02	0.05	0.01	0.01	0.06	0.03	0.04	0.03	0.09	0.07	0.10
307	0.04	0.13	0.16	0.14	0.17	0.16	0.24	0.24	0.22	0.34	0.32	0.32	0.24	0.13	0.14
308	0.09	0.18	0.17	0.21	0.18	0.11	0.32	0.27	0.29	0.26	0.19	0.31	0.13	0.18	0.12
309	0.44	0.41	0.42	0.25	0.32	0.23	0.12	0.16	0.20	0.11	0.08	0.09	0.07	0.03	0.06
310	0.29	0.19	0.25	0.31	0.34	0.18	0.16	0.18	0.20	0.20	0.21	0.16	0.04	0.08	0.21
311	0.69	0.59	0.41	0.14	0.21	0.23	0.08	0.09	0.14	0.04	0.04	0.05	0.06	0.08	0.17
312	0.38	0.32	0.37	0.25	0.25	0.13	0.13	0.17	0.17	0.18	0.13	0.19	0.07	0.13	0.14
313	0.86	0.77	0.64	0.08	0.08	0.14	0.01	0.04	0.08	0.01	0.06	0.07	0.05	0.05	0.07
314	0.32	0.32	0.35	0.08	0.08	0.06	0.07	0.05	0.05	0.06	0.08	0.07	0.47	0.46	0.48
315	0.00	0.00	0.00	0.01	0.00	0.01	0.02	0.05	0.07	0.20	0.15	0.18	0.76	0.80	0.73

Sociodemographic variables identified within the conceptual model (Figure 3.1)

District	Proportion of inhabitants who reside in urban areas			Proximity to a main road (km)			Proximity to a town of 10,000+ inhabitants (km)			Proportion of households with a female head of household			Average household size		
	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5
101	0.08	0.09	0.07	4.46	5.03	10.90	70.14	67.99	25.64	0.15	0.26	0.19	6.04	5.08	5.51
102	0.20	0.19	0.20	3.32	2.55	3.07	26.96	26.27	28.54	0.20	0.22	0.18	6.28	5.13	5.85
103	0.05	0.09	0.04	4.15	4.32	5.33	32.84	32.71	20.25	0.21	0.26	0.29	6.49	6.64	6.33
104	0.10	0.11	0.07	3.81	4.32	5.47	68.34	68.72	28.12	0.17	0.25	0.19	6.15	5.42	5.83
105	0.00	0.04	0.00	8.54	9.20	6.10	39.41	37.09	32.99	0.15	0.27	0.25	5.66	5.27	5.40
106	NA	0.12	0.00	NA	60.79	57.43	NA	99.48	63.89	NA	0.29	0.31	NA	5.56	6.20
107	1.00	1.00	1.00	1.28	1.51	1.72	3.56	4.53	4.48	0.15	0.27	0.19	5.75	5.58	5.36
201	0.04	0.11	0.07	13.34	14.19	8.72	31.27	32.93	29.94	0.12	0.23	0.18	6.02	5.58	5.60
202	0.09	0.10	0.03	2.81	3.39	4.00	31.09	31.23	30.14	0.21	0.27	0.21	5.95	5.89	6.20
203	0.04	0.04	0.04	6.60	7.46	6.35	52.97	50.55	12.39	0.15	0.24	0.15	5.90	5.32	5.42
204	0.03	0.03	0.03	6.47	7.26	4.88	42.00	39.31	15.04	0.12	0.19	0.27	4.87	4.31	4.37
205	0.06	0.08	0.07	4.16	5.73	5.46	16.81	19.88	15.48	0.21	0.29	0.27	5.70	5.01	5.68
206	0.00	0.00	0.00	10.36	11.21	11.82	28.03	30.09	28.69	0.16	0.27	0.27	5.80	5.07	5.17
207	0.03	0.03	0.05	12.98	14.40	9.38	76.03	74.62	28.41	0.19	0.28	0.16	6.08	5.14	5.80
208	0.02	0.07	0.03	12.38	10.06	11.32	28.51	27.95	24.26	0.22	0.29	0.26	5.67	5.15	5.14
209	0.03	0.00	0.03	5.03	5.53	6.46	34.14	33.00	19.72	0.27	0.34	0.33	5.40	5.10	5.12
210	1.00	1.00	1.00	2.44	2.84	2.75	7.31	10.16	7.53	0.15	0.14	0.14	5.92	5.45	5.31
301	0.02	0.03	0.08	14.18	12.63	13.23	33.51	31.79	25.86	0.23	0.47	0.43	5.90	4.86	5.60
302	0.04	0.10	0.04	29.42	30.27	31.04	37.55	37.35	41.06	0.22	0.35	0.42	5.44	5.33	5.20
303	0.00	0.00	0.00	11.28	12.84	9.84	19.83	19.44	18.17	0.26	0.32	0.32	5.38	5.38	5.48
304	0.04	0.05	0.00	5.34	4.76	4.41	25.24	25.19	20.35	0.27	0.41	0.40	5.13	4.63	5.11
305	0.00	0.00	0.00	5.08	5.06	5.05	20.95	20.18	18.84	0.21	0.38	0.33	5.16	4.66	4.93
306	0.15	0.09	0.06	7.55	8.82	6.23	57.74	59.12	11.21	0.22	0.32	0.30	5.41	5.16	5.31
307	0.00	0.00	0.08	9.54	11.26	8.81	37.07	40.50	13.06	0.25	0.39	0.40	5.01	4.82	4.82
308	0.00	0.02	0.00	7.77	7.11	6.97	57.65	60.20	13.85	0.30	0.38	0.33	5.38	5.31	5.22

309	0.05	0.00	0.00	34.29	35.73	34.44	55.51	53.83	17.16	0.25	0.36	0.28	5.19	5.34	5.20
310	0.00	0.03	0.05	10.01	9.82	10.13	52.87	53.92	16.27	0.15	0.27	0.25	5.53	5.44	5.14
311	0.09	0.06	0.09	6.47	8.46	7.49	31.08	33.96	19.64	0.17	0.31	0.25	5.18	5.37	5.27
312	0.06	0.11	0.09	5.39	6.73	6.41	14.90	16.02	15.22	0.32	0.41	0.34	5.40	5.00	5.37
313	0.00	0.00	0.00	12.23	11.46	11.00	49.27	48.51	26.57	0.20	0.29	0.28	5.70	5.37	5.12
314	1.00	1.00	1.00	0.95	1.44	1.46	3.50	3.49	3.78	0.19	0.23	0.30	5.62	5.15	5.27
315	1.00	1.00	1.00	1.63	1.28	1.68	7.30	7.97	7.20	0.14	0.18	0.21	5.35	4.83	5.07

Migration status summary

District	Proportion of household heads who are non-migrants			Proportion of household heads who are International migrant			Proportion of household heads who are Inter-district migrant			Proportion of household heads who are Intervillage migrant		
	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5	IHS3	IHS4	IHS5
101	0.59	0.62	0.71	0.05	0.06	0.03	0.06	0.03	0.04	0.30	0.30	0.22
102	0.58	0.60	0.65	0.05	0.03	0.02	0.09	0.15	0.13	0.28	0.22	0.20
103	0.44	0.63	0.48	0.08	0.04	0.06	0.24	0.24	0.29	0.24	0.08	0.17
104	0.42	0.57	0.57	0.02	0.03	0.02	0.29	0.22	0.22	0.27	0.18	0.19
105	0.68	0.57	0.66	0.02	0.04	0.03	0.10	0.16	0.15	0.20	0.22	0.16
106	NA	0.75	0.62	NA	0.06	0.03	NA	0.17	0.18	NA	0.02	0.17
107	0.11	0.08	0.12	0.05	0.09	0.03	0.71	0.69	0.69	0.13	0.14	0.15
201	0.42	0.48	0.52	0.04	0.02	0.02	0.41	0.34	0.27	0.14	0.16	0.20
202	0.44	0.55	0.50	0.06	0.02	0.01	0.30	0.26	0.32	0.20	0.17	0.16
203	0.64	0.71	0.67	0.00	0.00	0.00	0.12	0.13	0.13	0.24	0.16	0.19
204	0.58	0.62	0.73	0.01	0.01	0.00	0.17	0.13	0.11	0.23	0.24	0.16
205	0.48	0.56	0.44	0.02	0.02	0.01	0.22	0.20	0.28	0.29	0.22	0.27
206	0.73	0.61	0.51	0.00	0.01	0.00	0.10	0.12	0.11	0.16	0.26	0.38
207	0.55	0.58	0.54	0.04	0.01	0.02	0.26	0.16	0.20	0.16	0.24	0.24
208	0.65	0.51	0.60	0.02	0.02	0.02	0.10	0.10	0.08	0.23	0.36	0.30
209	0.65	0.59	0.57	0.03	0.01	0.01	0.18	0.19	0.16	0.15	0.21	0.25
210	0.17	0.17	0.10	0.04	0.01	0.02	0.63	0.63	0.67	0.16	0.19	0.21
301	0.64	0.53	0.61	0.03	0.06	0.04	0.14	0.13	0.14	0.19	0.28	0.21
302	0.57	0.52	0.56	0.03	0.04	0.02	0.17	0.16	0.12	0.23	0.29	0.30
303	0.41	0.48	0.39	0.01	0.02	0.01	0.21	0.16	0.21	0.37	0.34	0.39
304	0.42	0.55	0.45	0.02	0.02	0.00	0.20	0.11	0.20	0.37	0.33	0.36
305	0.49	0.57	0.55	0.02	0.01	0.00	0.27	0.17	0.22	0.22	0.26	0.22
306	0.44	0.38	0.50	0.09	0.07	0.06	0.26	0.20	0.18	0.21	0.35	0.26
307	0.60	0.58	0.62	0.01	0.02	0.00	0.13	0.08	0.06	0.26	0.32	0.31

308	0.53	0.50	0.63	0.01	0.03	0.00	0.11	0.11	0.05	0.34	0.36	0.32
309	0.59	0.54	0.57	0.01	0.00	0.00	0.12	0.07	0.09	0.29	0.38	0.33
310	0.65	0.59	0.54	0.04	0.03	0.02	0.15	0.15	0.15	0.15	0.23	0.29
311	0.72	0.58	0.65	0.05	0.05	0.04	0.11	0.08	0.10	0.11	0.29	0.20
312	0.51	0.44	0.44	0.02	0.01	0.02	0.35	0.29	0.32	0.12	0.26	0.23
313	0.42	0.33	0.42	0.05	0.04	0.03	0.34	0.39	0.35	0.19	0.23	0.19
314	0.18	0.15	0.17	0.05	0.02	0.02	0.45	0.47	0.47	0.32	0.36	0.35
315	0.17	0.22	0.23	0.02	0.05	0.02	0.75	0.57	0.61	0.06	0.16	0.15

Agricultural information

District	Proportion of Malawians who engage in subsistence (household) farming			Average (median) plot size per household dependant (acres)			proportion of households with good soil quality (1			proportion of households with fair soil quality (2)			proportion of households with poor soil quality (3)			Proportion of households that used inorganic fertiliser (on one or more plots)		
	IHS3	**IHS4**	**IHS5**	**IHS3**	**IHS4**	**IHS5**	**IHS3**	**IHS4**	**IHS5**	**IHS3**	**IHS4**	**IHS5**	**IHS3**	**IHS4**	**IHS5**	**IHS3**	**IHS4**	**IHS5**
101	0.98	0.93	0.92	0.46	0.84	0.85	0.39	0.46	0.60	0.48	0.51	0.38	0.02	0.03	0.02	0.87	0.62	0.55
102	0.94	0.83	0.65	0.31	0.66	0.53	0.54	0.49	0.52	0.36	0.47	0.45	0.03	0.04	0.03	0.51	0.38	0.35
103	0.58	0.50	0.63	0.24	0.48	0.51	0.50	0.61	0.56	0.42	0.26	0.37	0.06	0.13	0.07	0.39	0.49	0.41
104	0.87	0.86	0.83	0.37	0.88	0.90	0.50	0.46	0.55	0.45	0.42	0.38	0.06	0.12	0.07	0.78	0.75	0.64
105	0.95	0.84	0.93	0.56	1.05	0.92	0.43	0.27	0.38	0.49	0.56	0.47	0.14	0.18	0.15	0.85	0.64	0.58
106	NA	0.19	0.68	NA	0.23	0.28	NA	0.18	0.54	NA	0.18	0.19	0.27	0.65	0.27	NA	0.89	0.87
107	0.23	0.26	0.35	0.40	0.93	0.72	0.35	0.41	0.43	0.53	0.47	0.42	0.14	0.12	0.16	0.85	0.82	0.78
201	0.98	0.92	0.90	0.59	1.17	1.26	0.44	0.54	0.52	0.44	0.34	0.33	0.14	0.12	0.15	0.85	0.51	0.48
202	0.88	0.73	0.82	0.32	0.70	0.68	0.55	0.52	0.51	0.36	0.40	0.45	0.03	0.09	0.04	0.66	0.54	0.50
203	0.97	0.91	0.97	0.56	1.24	1.30	0.54	0.56	0.47	0.37	0.35	0.43	0.08	0.09	0.10	0.79	0.51	0.43
204	0.94	0.94	0.86	0.54	1.00	1.19	0.39	0.44	0.40	0.48	0.33	0.36	0.14	0.17	0.10	0.81	0.50	0.50
205	0.94	0.77	0.87	0.40	0.58	0.78	0.55	0.59	0.47	0.36	0.26	0.38	0.12	0.15	0.15	0.60	0.45	0.44
206	0.90	0.88	0.84	1.37	0.81	0.86	0.26	0.57	0.50	0.60	0.31	0.32	0.16	0.12	0.18	0.78	0.57	0.42
207	0.91	0.88	0.93	0.56	0.99	1.07	0.53	0.65	0.56	0.38	0.24	0.21	0.20	0.10	0.23	0.85	0.58	0.40
208	0.97	0.92	0.95	0.43	0.70	0.79	0.50	0.56	0.44	0.32	0.38	0.41	0.12	0.06	0.15	0.73	0.52	0.57
209	0.97	0.90	0.97	0.62	0.73	0.91	0.20	0.60	0.44	0.50	0.36	0.45	0.08	0.05	0.11	0.85	0.72	0.64
210	0.41	0.30	0.31	0.25	0.80	0.76	0.70	0.65	0.57	0.25	0.27	0.34	0.07	0.07	0.08	0.73	0.67	0.66
301	0.96	0.90	0.92	0.44	0.59	0.56	0.31	0.48	0.59	0.63	0.40	0.31	0.07	0.13	0.09	0.61	0.47	0.45
302	0.98	0.97	0.93	0.41	0.57	0.59	0.25	0.34	0.67	0.63	0.49	0.26	0.05	0.17	0.07	0.79	0.63	0.61
303	0.97	0.96	0.92	0.35	0.78	0.93	0.59	0.49	0.48	0.29	0.37	0.40	0.10	0.15	0.12	0.84	0.73	0.48
304	0.97	0.95	0.94	0.32	0.54	0.60	0.35	0.26	0.40	0.50	0.53	0.40	0.15	0.21	0.20	0.89	0.74	0.72
305	0.93	0.85	0.79	0.44	0.65	0.58	0.38	0.42	0.42	0.50	0.41	0.45	0.11	0.17	0.13	0.84	0.81	0.72
306	0.94	0.89	0.93	0.59	0.74	0.94	0.42	0.33	0.45	0.54	0.48	0.47	0.05	0.20	0.08	0.78	0.78	0.70
307	0.84	0.91	0.95	0.31	0.53	0.53	0.32	0.23	0.54	0.58	0.49	0.33	0.11	0.28	0.13	0.84	0.61	0.72

308	0.98	0.82	0.97	0.27	0.57	0.46	0.50	0.35	0.51	0.37	0.49	0.41	0.07	0.16	0.09	0.76	0.46	0.50
309	0.96	0.95	0.98	0.35	0.60	0.55	0.53	0.34	0.55	0.41	0.51	0.38	0.06	0.15	0.07	0.82	0.52	0.50
310	0.87	0.78	0.77	0.50	0.76	0.66	0.73	0.63	0.50	0.22	0.29	0.46	0.04	0.08	0.04	0.10	0.14	0.07
311	0.88	0.81	0.67	0.55	0.57	0.45	0.82	0.68	0.57	0.15	0.27	0.35	0.07	0.05	0.07	0.09	0.14	0.06
312	0.96	0.88	0.89	0.58	0.75	0.66	0.21	0.50	0.58	0.53	0.41	0.31	0.10	0.08	0.11	0.68	0.48	0.51
313	0.99	0.10	0.92	0.67	0.81	0.83	0.39	0.31	0.52	0.56	0.52	0.38	0.06	0.17	0.10	0.59	0.62	0.59
314	0.52	0.76	0.53	0.30	0.85	0.57	0.60	0.54	0.61	0.33	0.34	0.24	0.15	0.12	0.15	0.88	0.84	0.75
315	0.02	0.77	0.23	0.17	0.55	0.51	0.36	0.58	0.61	0.55	0.31	0.31	0.07	0.11	0.07	0.84	0.68	0.70

APPENDIX E

Statistical test results for key explanatory variables and Maize production (nationally)

Table E.1 contains national level results and Table E.2 contains district results.
As expected, wealth appears to have a strong relationship with Maize production. Female headed households appear to have a consistently, strong negative relationship with Maize production. Being a migrant appears to have a very small, positive impact. This relationship is the opposite direction to that hypothesised in the conceptual model but is a very small and largely insignificant relationship. Given that much migration occurs for familial reasons (particularly marriage or to live with parents), this may mean that many migrants are able to inherit familial land through their spouse / in-laws, and therefore the hypothesis that migrants access less or lower quality land may not hold.

Household size appears important with larger households producing more crop, as expected in order to meet the higher demand. Plot size also shows a positive relationship with a larger impact than households size. This is also anticipated because more land facilitates a larger production volume. Soil quality appears to have a positive relationship, though use of fertiliser appears to have a much larger effect.

All climate variables reported demonstrated statistically significant relationships. It is interesting that there is a small negative relationship between average monthly rainfall and production. Extreme rainfall resulting in flooding and land loss or crop rotting due to saturated soils (as noted within the soil moisture coefficients similarly) could cause this relationship however this is negated by the observation that maximum rainfall has a smaller negative relationship than mean rainfall. Such a scenario could also emerge if the rainfall were to occur at the wrong time (for example too early or too late in the growing season. Alternatively, it could be the case that there is a non-linear relationship between rainfall and crop production whereby there is a positive relationship up until a certain point at which point the rainfall is too high and crop production plateau and then fall away beyond this wetness level. However, exploring this more complex hypothesis is beyond the scope of this study. It has also been noted in Table 3.5 that flooding only accounts for a very small proportion of hunger within households suggesting that high rainfall is not responsible for catastrophic crop loss in flooded areas (assuming that rainfall is the predominant driver of most flooding). The positive trend between maximum rainfall and PDSI conditions appears in line with expectations. Drought was repeatedly reported as the reason for lack of food (Table 3.5). It is assumed that years when households report a lack of food, those households are also experiencing lower crop production in those years. However, similar to average and maximum monthly rainfall, minimum rainfall was found to have a negative relationship with crop production (though the coefficient for minimum rainfall appears spurious) suggesting that years of lower rainfall (such as drought years) were not a major, direct driver of food insecurity and low crop production. The climate variables constructed at district level may not be adequate if there is a nonlinear relationship between drought and amount of rainfall, and that alternative drought indicators may be appropriate such as Drought and Overwhelmed Water Key Indicator (DOWKI) (Kapsambelis et al., 2022) or Standard Precipitation Index (SPI) (Collados et al., 2022) or including rainfall variability (CVR) (Ngongondo, Gottschalk & Alemaw, 2011). Alternative agroclimatic variables would be better for modelling relationships between climate and crop production, such as onset and extent of the rainy or dry seasons (Tadross, 2005, Haghtalab et al., 2019).

It was interesting to note that the inter-seasonal variance in minimum temperature also appeared to positively affect crop production, suggesting that crop (maize in particular) are receptive to wider temperature fluctuations (Wheeler et al., 2000). However, due to weak theoretical justification and available evidence for why this relationship was observed, it was considered that this might be a chance relationship, and so was excluded from the final model. Less surprising is that the higher the temperature, the higher the production, presumbaly due to better growing conditions. It is likely that this is also a non-linear relationship however maximum temperatures did not vary significantly and likely did not exceed the maximum growing temperatures for Maize. Finally, as expected, the prevailing ecological conditions have a strong impact upon production.

Table E.1 Statistical test results for key explanatory variables and Maize production (nationally)

Explanatory variable	Test used	IHS3 Maize			IHS4 Maize Production			IHS5 Maize		
		Test score	t value	P-score	Test score	t value	P-score	Test score	t value	P-score
Sociodemographic variables (household level)										
Wealth quintile of the household	Kruksall Wallis ANOVA	340.27		<2e-16	398.84		<2e-16	461.87		<2e-16
Is household in an urban or rural area	Wilcoxon	-1.3338		0.18	-3.06		0.0022	0.14		0.89
Proximity of household to a main road (km)	Simple linear regression	-7.2	-3.47	0.00052	-1.2	-0.57	0.57	-10.07	-6.98	3.10E-12
Proximity of household to a town of 10,000+ inhabitants (km)	Simple linear regression	3.42	2.57	0.01	2.94	3.47	0.00052	-0.54	-0.17	0.87
Average plot size per household dependant (acres)	Simple linear regression	819.88	19.38	<2e-16	545.14	9.82	<2e-16	575.9	2.28	0.023
Average plot size per household member (acres)	Simple linear regression	1556.79	15.73	<2e-16	1378.28	13.88	<2e-16	1056.11	4.03	5.59e-05
Sex of the head of household	Wilcoxon	-13.28		<2e-16	-15.51	9.82	<2e-16	-13.41		<2e-16
Migration status (YES / NO) of the head of the household	Wilcoxon	2.24		0.03	2.74	9.82	0.0062	2.48		0.013
Average household size	Simple linear regression	141.7	10.19	<2e-16	87.48	7.01	2.62E-12	46.27	3.01	0.0026
Average soil quality of the households plots	Kruksall Wallis ANOVA	32.102		1.10E-07	2475.7		<2e-16	21.18		2.56E-05
Use of inorganic fertiliser on one or more plots	Wilcoxon	653.02		<2e-16	326.53		<2e-16	555.11		<2e-16
Climate variables (district level)										
Interseason variance of minimum temperature	Simple linear regression	729.51	12.65	<2e-16	603.52	16.3	<2e-16	330.15	5.98	2.33E-09
Maximum precipitation	Simple linear regression	-6.89	-14.99	<2e-16	-3.64	-18.16	<2e-16	-1.31	-3.03	0.0024
Mean precipitation	Simple linear regression	-14.05	-16.06	<2e-16	-7.23	-17.66	<2e-16	-5.5	-8.19	3.10E-16
Minimum precipitation	Simple linear regression	-62.06	-20.22	<2e-16	-25	-15.38	<2e-16	-6.32	-5.47	4.58E-08

Maximum PDSI	Simple linear regression	96.61	7.93	2.49E-15	-228.26	-19.1	<2e-16	87.27	4.62	3.82E-06
Mean monthly soil moisture	Simple linear regression	-4.9	-16.31	<2e-16	-3.44	-16.05	<2e-16	-2.11	-10.29	<2e-16
Maximum temperature	Simple linear regression	146.68	11.33	<2e-16	66.35	10.08	<2e-16	71.52	6.45	1.16E-10
Predominant district agroecological zone	Wilcoxon	890.97		<2e-16	521.45		<2e-16	406.76		<2e-16

Table E.2 Statistical test results for exploring relationship between household crop maize production and other household variables, for each district

IHS3

District	**Wealth quintile of the household**	**Is household in an urban or rural area**	**Average plot size per household dependant (acres)**	**Average plot size per household member (acres)**	**Sex of the head of household**	**Migration status (YES / NO) of the head of the household**	**Average household size**	**Average soil quality of the households plots**	**Use of inorganic fertiliser on one or more plots**
test used	*Kruksall Wallis ANOVA*	*Wilcoxon*	*Simple linear regression*	*Simple linear regression*	*Wilcoxon*	*Wilcoxon*	*Simple linear regression*	*Kruksall Wallis ANOVA*	*Wilcoxon*
101	df = 4, Chisq = 48.11, p-value = 3.385e-09	t = -2.8845, df = 371, p-value = 0.004149	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 894.2 139.9 6.392 4.92e-10 *** as.numeric(plot.size.per.dep) 223.6 228.4 0.979 0.328	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 812.8 125.6 6.470 3.09e-10 *** as.numeric(plot.size.pp) 726.9 551.8 1.317 0.189	t = -2.7038, df = 371, p-value = 0.00717	t = -0.22197, df = 371, p-value = 0.8245	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1076.97 451.48 2.385 0.0176 * as.numeric(hhsize) -10.79 67.13 -0.161 0.8724	df = 2, Chisq = 6.2245, p-value = 0.04567	df = 2, Chisq = 42.15, p-value = 2.148e-09

102	df = 4, Chisq = 10.957, p-value = 0.0288	t = 2.5335, df = 327, p-value = 0.01176	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 440.89 47.95 9.195 < 2e-16 *** as.numeric(plot.size.per.dep) 219.09 71.67 3.057 0.00242 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 476.82 44.19 10.789 < 2e-16 *** as.numeric(plot.size.pp) 266.04 100.74 2.641 0.00867 **	t = -0.99515, df = 327, p-value = 0.3204	t = -1.4233, df = 327, p-value = 0.1556	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 352.46 81.77 4.310 2.16e-05 *** as.numeric(hhsize) 36.04 17.34 2.078 0.0385 *	df = 2, Chisq = 2.0407, p-value = 0.3616	t = 4.4878, df = 327, p-value = 9.981e-06
103	df = 4, Chisq = 18.295, p-value = 0.001493	t = 15.855, df = 198, p-value < 2.2e-16	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 952.9 351.5 2.711 0.0073 ** as.numeric(plot.size.per.dep) 109.1 290.9 0.375 0.7079	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 820.5 293.6 2.795 0.00571 ** as.numeric(plot.size.pp) 943.4 976.2 0.966 0.33503	t = 0.29488, df = 198, p-value = 0.7684	t = -1.2827, df = 198, p-value = 0.2011	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 70.08 729.29 0.096 0.924 as.numeric(hhsize) 168.62 168.75 0.999 0.319	df = 2, Chisq = 0.82026, p-value = 0.6641	t = 5.1767, df = 198, p-value = 5.526e-07
104	df = 4, Chisq = 27.479, p-value = 2.637e-05	t = -0.22234, df = 307, p-value = 0.8242	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 721.60 84.35 8.555 5.72e-16 *** as.numeric(plot.size.per.dep) 267.13 237.32 1.126 0.261	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 730.7 105.6 6.918 2.67e-11 *** as.numeric(plot.size.pp) 550.1 676.3 0.814 0.417	t = 1.7153, df = 307, p-value = 0.08729	t = -0.23047, df = 307, p-value = 0.8179	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 623.95 361.52 1.726 0.0854 . as.numeric(hhsize) 44.51 57.17 0.779 0.4368	df = 2, Chisq = 4.212, p-value = 0.1235	t = 3.15, df = 307, p-value = 0.001794

105	df = 4, Chisq = 25.018, p-value = 7.263e-05	NA - all households are urban	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 730.6 171.0 4.273 2.5e-05 *** as.numeric(plot.size.per.dep) 412.0 228.0 1.808 0.0716 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 859.8 157.1 5.471 8.66e-08 *** as.numeric(plot.size.pp) 453.0 359.2 1.261 0.208	t = -1.1117, df = 341, p-value = 0.267	t = -0.66501, df = 341, p-value = 0.5065	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 445.99 185.91 2.399 0.01698 * as.numeric(hhsize) 124.99 45.94 2.720 0.00685 **	df = 2, Chisq = 3.7062, p-value = 0.1583	t = 6.2498, df = 341, p-value = 1.227e-09
106	NA	NA	NA	NA	NA	NA	NA	NA	NA
107	df = 4, Chisq = 9.6765, p-value = 0.05697	NA - all households are urban	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 544.2 147.6 3.688 0.000443 *** as.numeric(plot.size.per.dep) 476.1 192.9 2.468 0.016046 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 637.1 136.9 4.653 1.5e-05 *** as.numeric(plot.size.pp) 658.4 437.0 1.507 0.136	t = -0.50307, df = 70, p-value = 0.6165	t = -2.485, df = 70, p-value = 0.01535	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 381.16 207.72 1.835 0.0708 . as.numeric(hhsize) 68.11 41.92 1.625 0.1087	df = 2, Chisq = 1.0516, p-value = 0.5934	t = 3.6578, df = 70, p-value = 0.0004889
201	df = 4, Chisq = 13.547, p-value = 0.009741	t = 4.6467, df = 367, p-value = 4.71e-06	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 2583.3 310.4 8.323 1.71e-15 *** as.numeric(plot.size.per.dep) 445.3 346.6 1.285 0.2	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 2866.5 232.7 12.316 <2e-16 *** as.numeric(plot.size.pp) 100.4 331.2 0.303 0.762	t = -3.603, df = 367, p-value = 0.0003579	t = -0.50751, df = 367, p-value = 0.6121	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1145.74 434.15 2.639 0.008668 ** as.numeric(hhsize) 346.89 90.82 3.820 0.000157 ***	df = 2, Chisq = 13.083, p-value = 0.001617	df = 2, Chisq = 1059.9, p-value < 2.2e-16

202	df = 4, Chisq = 6.8298, p-value = 0.1482	t = 2.7447, df = 304, p-value = 0.006418	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 478.64 84.25 5.681 3.13e-08 *** as.numeric(plot.size.per.dep) 387.63 199.34 1.945 0.0528 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 477.78 71.83 6.652 1.35e-10 *** as.numeric(plot.size.pp) 839.49 385.97 2.175 0.0304 *	t = -2.3808, df = 304, p-value = 0.01789	t = 2.3661, df = 304, p-value = 0.01861	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 735.67 143.54 5.125 5.29e-07 *** as.numeric(hhsize) -15.30 22.13 -0.692 0.49	df = 2, Chisq = 3.5705, p-value = 0.1695	t = 4.937, df = 304, p-value = 1.311e-06
203	df = 4, Chisq = 21.974, p-value = 0.0002648	t = 0.39282, df = 365, p-value = 0.6947	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1005.9 662.6 1.518 0.1298 as.numeric(plot.size.per.dep) 1961.4 1059.4 1.851 0.0649 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1041.9 790.9 1.317 0.189 as.numeric(plot.size.pp) 4126.9 2749.7 1.501 0.134	t = -2.5809, df = 365, p-value = 0.01024	t = 0.98243, df = 365, p-value = 0.3265	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 296.95 475.35 0.625 0.533 as.numeric(hhsize) 407.53 97.94 4.161 3.96e-05 ***	df = 2, Chisq = 30.802, p-value = 3.797e-07	t = 5.4481, df = 365, p-value = 9.382e-08
204	df = 4, Chisq = 38.184, p-value = 2.448e-07	t = -2.9488, df = 366, p-value = 0.003395	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 2511.4 328.8 7.638 2.07e-13 *** as.numeric(plot.size.per.dep) 1038.4 426.4 2.435 0.0154 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 3005.7 253.5 11.855 <2e-16 *** as.numeric(plot.size.pp) 1073.7 453.5 2.367 0.0184 *	t = -5.2581, df = 355, p-value = 2.52e-07	t = -2.2319, df = 355, p-value = 0.02624	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 2119.98 509.49 4.161 3.98e-05 *** as.numeric(hhsize) 240.62 99.76 2.412 0.0164 *	df = 2, Chisq = 1.8657, p-value = 0.3944	t = 7.1881, df = 355, p-value = 3.907e-12

205	df = 4, Chisq = 16.537, p-value = 0.002757	t = 0.75135, df = 353, p-value = 0.4529	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1212.1 181.3 6.685 9.01e-11 *** as.numeric(plot.size.per.dep) 933.8 347.3 2.689 0.00751 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1456.6 164.4 8.859 <2e-16 *** as.numeric(plot.size.pp) 844.3 545.1 1.549 0.122	t = -0.75295, df = 353, p-value = 0.452	t = -0.10231, df = 353, p-value = 0.9186	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1003.12 271.83 3.690 0.000259 *** as.numeric(hhsize) 130.73 57.16 2.287 0.022791 *	df = 2, Chisq = 5.2864, p-value = 0.07254	t = 1.6301, df = 353, p-value = 0.104
206	df = 4, Chisq = 76.629, p-value = 1.172e-14	NA - all households are rural	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 855.14 94.67 9.032 <2e-16 *** as.numeric(plot.size.per.dep) 267.51 120.45 2.221 0.0268 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 923.06 83.83 11.012 <2e-16 *** as.numeric(plot.size.pp) 321.76 203.02 1.585 0.114	t = -5.1016, df = 495, p-value = 4.807e-07	t = 0.88074, df = 495, p-value = 0.3789	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 400.36 142.39 2.812 0.00512 ** as.numeric(hhsize) 124.58 31.06 4.011 6.99e-05 ***	df = 2, Chisq = 15.438, p-value = 0.0005002	t = 7.2528, df = 495, p-value = 1.584e-12
207	df = 4, Chisq = 3.5619, p-value = 0.4698	t = 1.4007, df = 328, p-value = 0.1622	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 2358.6 352.6 6.690 9.64e-11 *** as.numeric(plot.size.per.dep) 408.2 385.6 1.059 0.291	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 2508.6 334.0 7.510 5.65e-13 *** as.numeric(plot.size.pp) 368.7 712.0 0.518 0.605	t = -4.8273, df = 328, p-value = 2.126e-06	t = 1.6407, df = 328, p-value = 0.1018	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 652.7 490.9 1.330 0.1846 as.numeric(hhsize) 388.7 118.1 3.292 0.0011 **	df = 2, Chisq = 5.5375, p-value = 0.06421	t = 3.9675, df = 328, p-value = 8.925e-05

208	df = 4, Chisq = 24.931, p-value = 7.42e-05	t = 0.22827, df = 357, p-value = 0.8196	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1175.4 183.9 6.393 5.11e-10 *** as.numeric(plot.size.per.dep) 1069.2 351.2 3.044 0.0025 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1463.4 192.7 7.593 2.77e-13 *** as.numeric(plot.size.pp) 1079.9 795.0 1.358 0.175	t = -2.9902, df = 357, p-value = 0.002981	t = 0.59106, df = 357, p-value = 0.5549	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1297.44 412.82 3.143 0.00181 ** as.numeric(hhsize) 87.75 76.71 1.144 0.25340	df = 2, Chisq = 7.1631, p-value = 0.02884	t = 6.9693, df = 357, p-value = 1.545e-11
209	df = 4, Chisq = 24.102, p-value = 0.0001045	t = 0.96571, df = 376, p-value = 0.3348	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 950.7 297.3 3.198 0.00150 ** as.numeric(plot.size.per.dep) 1328.3 435.0 3.054 0.00242 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1447 242 5.978 5.24e-09 *** as.numeric(plot.size.pp) 1317 696 1.892 0.0593 .	t = -2.2758, df = 376, p-value = 0.02342	t = 1.2566, df = 376, p-value = 0.2097	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1104.25 249.94 4.418 1.3e-05 *** as.numeric(hhsize) 181.05 55.26 3.276 0.00115 **	df = 2, Chisq = 13.86, p-value = 0.001108	t = 1.5882, df = 376, p-value = 0.1131
210	df = 4, Chisq = 18.16, p-value = 0.001552	NA - all households are urban	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1345.5 274.3 4.904 1.88e-06 *** as.numeric(plot.size.per.dep) 1072.4 427.6 2.508 0.0129 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1397.5 241.7 5.783 2.64e-08 *** as.numeric(plot.size.pp) 1761.0 625.3 2.816 0.00532 **	t = -0.64273, df = 210, p-value = 0.5211	t = -1.9016, df = 210, p-value = 0.0586	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 2269.59 382.51 5.933 1.21e-08 *** as.numeric(hhsize) -99.35 60.59 -1.640 0.103	df = 2, Chisq = 35.142, p-value = 8.843e-08	t = 0.79288, df = 210, p-value = 0.4287

301	df = 4, Chisq = 38.412, p-value = 2.204e-07	t = -0.090794, df = 358, p-value = 0.9277	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 375.46 83.66 4.488 9.71e-06 *** as.numeric(plot.size.per.dep) 525.67 158.94 3.307 0.00104 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 342.4 107.6 3.182 0.00159 ** as.numeric(plot.size.pp) 1163.7 421.7 2.760 0.00608 **	t = -0.85627, df = 358, p-value = 0.3924	t = 1.1876, df = 358, p-value = 0.2358	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 391.24 104.43 3.746 0.000209 *** as.numeric(hhsize) 55.72 18.87 2.953 0.003353 **	df = 2, Chisq = 16.059, p-value = 0.0003881	t = 5.1765, df = 358, p-value = 3.777e-07
302	df = 4, Chisq = 24.396, p-value = 9.205e-05	t = 5.0607, df = 375, p-value = 6.558e-07	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 478.88 65.08 7.358 1.19e-12 *** as.numeric(plot.size.per.dep) 135.86 80.63 1.685 0.0928 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 523.32 59.01 8.868 <2e-16 *** as.numeric(plot.size.pp) 87.84 125.01 0.703 0.483	t = -4.9002, df = 375, p-value = 1.427e-06	t = 2.9122, df = 375, p-value = 0.003803	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 240.09 73.26 3.277 0.001145 ** as.numeric(hhsize) 67.95 19.59 3.468 0.000585 ***	df = 2, Chisq = 6.5318, p-value = 0.03925	df = 2, Chisq = 36.037, p-value = 3.381e-08
303	df = 4, Chisq = 55.663, p-value = 1.448e-10	NA - all households are rural	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 483.90 41.63 11.624 <2e-16 *** as.numeric(plot.size.per.dep) 37.29 54.34 0.686 0.493	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 509.35 42.40 12.013 <2e-16 *** as.numeric(plot.size.pp) -37.18 93.87 -0.396 0.692	t = -4.2189, df = 363, p-value = 3.105e-05	t = 0.83218, df = 363, p-value = 0.4059	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 384.54 61.62 6.241 1.22e-09 *** as.numeric(hhsize) 26.21 10.99 2.385 0.0176 *	df = 2, Chisq = 18.558, p-value = 0.0001176	df = 2, Chisq = 100.94, p-value < 2.2e-16

304	df = 4, Chisq = 73.856, p-value = 7.989e-14	t = -2.9488, df = 366, p-value = 0.003395	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 959.5 333.4 2.878 0.00424 ** as.numeric(plot.size.per.dep) -224.7 377.3 -0.596 0.55178	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1020.3 305.5 3.340 0.000925 *** as.numeric(plot.size.pp) -767.3 619.4 -1.239 0.216247	t = -2.8772, df = 366, p-value = 0.004247	t = 2.0129, df = 366, p-value = 0.04486	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -177.1 373.8 -0.474 0.6359 as.numeric(hhsize) 246.8 126.8 1.945 0.0525 .	df = 2, Chisq = 11.107, p-value = 0.004208	t = 3.2048, df = 366, p-value = 0.00147
305	df = 4, Chisq = 18.233, p-value = 0.001333	NA - all households are rural	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 706.3744 175.5247 4.024 6.98e-05 *** as.numeric(plot.size.per.dep) 0.8725 130.9975 0.007 0.995	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 738.3 162.6 4.540 7.71e-06 *** as.numeric(plot.size.pp) -106.5 187.2 -0.569 0.57	t = -1.5467, df = 356, p-value = 0.1228	t = 1.4218, df = 356, p-value = 0.156	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 192.13 291.96 0.658 0.511 as.numeric(hhsize) 122.36 91.67 1.335 0.183	df = 2, Chisq = 12.565, p-value = 0.002083	t = 5.1275, df = 357, p-value = 4.824e-07
306	df = 4, Chisq = 8.8679, p-value = 0.0668	t = 0.48966, df = 349, p-value = 0.6247	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 570.086 96.832 5.887 9.22e-09 *** as.numeric(plot.size.per.dep) -4.982 41.552 -0.120 0.905	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 593.05 97.17 6.103 2.76e-09 *** as.numeric(plot.size.pp) -77.01 100.37 -0.767 0.443	t = -2.0558, df = 349, p-value = 0.04054	t = -0.34958, df = 349, p-value = 0.7269	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 530.793 298.130 1.780 0.0759 . as.numeric(hhsize) 7.703 51.646 0.149 0.8815	df = 2, Chisq = 12.885, p-value = 0.001789	df = 2, Chisq = 20.962, p-value = 3.801e-05

307	df = 4, Chisq = 68.186, p-value = 1.469e-12	NA - all households are rural	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 341.43 30.32 11.261 <2e-16 *** as.numeric(plot.size.per.dep) 113.19 54.90 2.062 0.0401 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 375.45 27.55 13.627 <2e-16 *** as.numeric(plot.size.pp) 60.80 68.27 0.891 0.374	t = -0.86221, df = 291, p-value = 0.3893	t = -0.092873, df = 291, p-value = 0.9261	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 246.29 55.31 4.453 1.21e-05 *** as.numeric(hhsize) 32.19 11.56 2.784 0.00573 **	df = 2, Chisq = 5.0763, p-value = 0.08076	df = 2, Chisq = 185.87, p-value < 2.2e-16
308	df = 4, Chisq = 21.843, p-value = 0.0002805	NA - all households are rural	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 278.90 22.65 12.314 <2e-16 *** as.numeric(plot.size.per.dep) 101.01 83.83 1.205 0.229	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 305.15 27.64 11.038 <2e-16 *** as.numeric(plot.size.pp) 52.86 67.18 0.787 0.432	t = -5.2135, df = 363, p-value = 3.117e-07	t = 2.3926, df = 363, p-value = 0.01724	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 213.43 38.40 5.558 5.28e-08 *** as.numeric(hhsize) 23.60 8.86 2.664 0.00808 **	df = 2, Chisq = 11.13, p-value = 0.004163	df = 2, Chisq = 28.508, p-value = 1.098e-06
309	df = 4, Chisq = 21.115, p-value = 0.0003842	t = -1.9529, df = 363, p-value = 0.0516	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 389.8 121.0 3.221 0.00139 ** as.numeric(plot.size.per.dep) 325.3 236.8 1.374 0.17041	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 456.5 117.5 3.884 0.000122 *** as.numeric(plot.size.pp) 324.9 272.6 1.192 0.234025	t = -2.6405, df = 363, p-value = 0.008637	t = 0.84366, df = 363, p-value = 0.3994	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 379.64 183.09 2.074 0.0388 * as.numeric(hhsize) 33.71 47.59 0.708 0.4793	df = 2, Chisq = 5.657, p-value = 0.06041	df = 2, Chisq = 18.197, p-value = 0.0001395

310	df = 4, Chisq = 2.7637, p-value = 0.5989	NA - all households are rural	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 219.78 71.48 3.075 0.00234 ** as.numeric(plot.size.per.dep) 105.64 118.68 0.890 0.37422	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 223.96 70.94 3.157 0.00179 ** as.numeric(plot.size.pp) 202.53 225.57 0.898 0.37012	t = -1.9058, df = 253, p-value = 0.05781	t = 3.3083, df = 253, p-value = 0.001075	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -95.47 164.63 -0.580 0.5625 as.numeric(hhsize) 84.07 41.89 2.007 0.0458 *	df = 2, Chisq = 0.17206, p-value = 0.9176	t = 1.5833, df = 253, p-value = 0.1146
311	df = 4, Chisq = 6.0489, p-value = 0.1995	t = 3.6463, df = 229, p-value = 0.0003293	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 217.71 61.64 3.532 0.000498 *** as.numeric(plot.size.per.dep) -19.71 26.00 -0.758 0.449077	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 221.05 59.75 3.699 0.000271 *** as.numeric(plot.size.pp) -47.65 41.80 -1.140 0.255445	t = 0.13361, df = 229, p-value = 0.8938	t = -0.75275, df = 229, p-value = 0.4524	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 163.151 89.510 1.823 0.0697 . as.numeric(hhsize) 8.998 13.368 0.673 0.5016	df = 2, Chisq = 1.6434, p-value = 0.441	df = 2, Chisq = 24.198, p-value = 1.014e-05
312	df = 4, Chisq = 41.909, p-value = 4.857e-08	t = -1.9198, df = 364, p-value = 0.05566	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 706.14 76.02 9.289 <2e-16 *** as.numeric(plot.size.per.dep) 111.41 76.07 1.465 0.144	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 783.925 76.650 10.227 <2e-16 *** as.numeric(plot.size.pp) 9.271 104.634 0.089 0.929	t = -2.5503, df = 364, p-value = 0.01117	t = 0.73635, df = 364, p-value = 0.462	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 284.30 139.83 2.033 0.04276 * as.numeric(hhsize) 113.20 33.75 3.354 0.00088 ***	df = 2, Chisq = 3.0638, p-value = 0.2175	df = 2, Chisq = 520.2, p-value < 2.2e-16

313	df = 4, Chisq = 1.2745, p-value = 0.8655	NA - all households are rural	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 648.8 152.7 4.249 2.71e-05 *** as.numeric(plot.size.per.dep) 194.7 122.1 1.595 0.112	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 563.6 128.3 4.392 1.46e-05 *** as.numeric(plot.size.pp) 651.1 240.1 2.712 0.007 **	t = -1.0661, df = 378, p-value = 0.287	t = -0.80958, df = 378, p-value = 0.4187	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 320.6 183.6 1.746 0.0816 . as.numeric(hhsize) 102.1 52.1 1.960 0.0507 .	df = 2, Chisq = 4.8715, p-value = 0.08891	df = 2, Chisq = 50.649, p-value = 4.789e-11
314	df = 4, Chisq = 14.737, p-value = 0.006426	NA - all households are urban	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 457.8 202.8 2.257 0.0251 * as.numeric(plot.size.per.dep) 1022.9 695.8 1.470 0.1431	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 431.8 243.1 1.776 0.0772 . as.numeric(plot.size.pp) 2374.9 1775.5 1.338 0.1825	t = 1.0395, df = 203, p-value = 0.2998	t = -0.56656, df = 203, p-value = 0.5716	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1209.48 467.64 2.586 0.0104 * as.numeric(hhsize) -69.64 66.42 -1.049 0.2956	df = 2, Chisq = 1.9087, p-value = 0.3868	t = 5.4245, df = 203, p-value = 1.644e-07
315	df = 2, Chisq = 5.8522, p-value = 0.07938	NA - all households are urban	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 191.59 95.11 2.014 0.0583 . as.numeric(plot.size.per.dep) 771.91 519.05 1.487 0.1534	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 175.21 80.89 2.166 0.0432 * as.numeric(plot.size.pp) 2199.36 1006.50 2.185 0.0416 *	t = 3.6373, df = 19, p-value = 0.001753	t = 0.34753, df = 19, p-value = 0.732	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 500.64 275.12 1.820 0.0846 . as.numeric(hhsize) -29.89 48.48 -0.616 0.5449	df = 2, Chisq = 72.57, p-value = 4.837e-07	t = -0.78259, df = 19, p-value = 0.4435

IHS4

District	Wealth quintile of the household	Average plot size per household dependant (acres)	Average plot size per household member (acres)	Sex of the head of household	Migration status (YES / NO) of the head of the household	Average household size	Average soil quality of the households plots	Use of inorganic fertiliser on one or more plots
Test used	*Kruksall Wallis ANOVA*	*Simple linear regression*	*Simple linear regression*	*Wilcoxon*	*Wilcoxon*	*Simple linear regression*	*Kruksall Wallis ANOVA*	*Wilcoxon*
101	df = 4, Chisq = 20.623, p-value = 0.0004785	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 535.05 230.51 2.321 0.0208 * as.numeric(plot.size.per.dep) -27.57 163.03 -0.169 0.8658	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 558.4 183.9 3.037 0.00257 ** as.numeric(plot.size.pp) -106.4 226.7 -0.469 0.63904	t = -3.5984, df = 352, p-value = 0.0003661	t = 1.3585, df = 352, p-value = 0.1752	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 94.56 323.47 0.292 0.770 as.numeric(hhsize) 98.77 94.17 1.049 0.295	df = 2, Chisq = 40.518, p-value = 4.715e-09	df = 2, Chisq = 47.322, p-value = 2.293e-10
102	df = 4, Chisq = 3.9944, p-value = 0.409	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 294.31 129.33 2.276 0.0237 * as.numeric(plot.size.per.dep) 110.31 87.52 1.260 0.2088	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 335.0 112.5 2.977 0.0032 ** as.numeric(plot.size.pp) 124.9 105.6 1.182 0.2383	t = 0.19503, df = 244, p-value = 0.8455	t = -0.062734, df = 244, p-value = 0.95	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -74.96 280.27 -0.267 0.789 as.numeric(hhsize) 101.56 81.50 1.246 0.214	df = 2, Chisq = 4.3868, p-value = 0.1137	df = 2, Chisq = 23.782, p-value = 1.183e-05

103	df = 4, Chisq = 32.101, p-value = 6.561e-06	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 376.99 46.36 8.131 1.14e-13 *** as.numeric(plot.size.per.dep) 40.29 44.29 0.910 0.364	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 397.53 41.78 9.515 <2e-16 *** as.numeric(plot.size.pp) 15.63 65.09 0.240 0.811	t = -1.6045, df = 159, p-value = 0.1106	t = 2.5171, df = 159, p-value = 0.01282	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 221.17 73.39 3.013 0.00301 ** as.numeric(hhsize) 32.25 15.13 2.132 0.03456 *	df = 3, Chisq = 453.55, p-value < 2.2e-16	df = 2, Chisq = 43.564, p-value = 4.418e-09
104	df = 4, Chisq = 12.048, p-value = 0.01843	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 584.13 90.40 6.462 3.91e-10 *** as.numeric(plot.size.per.dep) 202.43 72.89 2.777 0.00581 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 541.9 101.6 5.333 1.85e-07 *** as.numeric(plot.size.pp) 575.6 227.0 2.535 0.0117 *	t = -1.8281, df = 316, p-value = 0.06848	t = -0.41206, df = 316, p-value = 0.6806	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 358.73 148.54 2.415 0.01630 * as.numeric(hhsize) 87.33 32.38 2.697 0.00737 **	df = 2, Chisq = 3.4927, p-value = 0.1761	df = 2, Chisq = 9.8793, p-value = 0.007721
105	df = 4, Chisq = 47.393, p-value = 5.897e-09	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 572.11 90.62 6.313 9.68e-10 *** as.numeric(plot.size.per.dep) 375.69 71.50 5.255 2.80e-07 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 695.30 91.09 7.633 2.98e-13 *** as.numeric(plot.size.pp) 568.92 124.41 4.573 7.00e-06 ***	t = -0.71796, df = 306, p-value = 0.4733	t = 0.91664, df = 306, p-value = 0.3601	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 513.98 178.89 2.873 0.00435 ** as.numeric(hhsize) 111.54 41.25 2.704 0.00723 **	df = 2, Chisq = 9.156, p-value = 0.01099	df = 2, Chisq = 15.562, p-value = 0.000506

106	t = 2.2154, df = 30, p-value = 0.03447	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -21.06 24.38 -0.864 0.395 as.numeric(plot.size.per.dep) 583.54 36.29 16.081 2.72e-16 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 37.700 16.437 2.294 0.029 * as.numeric(plot.size.pp) 602.038 3.411 176.488 <2e-16 ***	t = 2.1422, df = 30, p-value = 0.04041	t = 0.86711, df = 30, p-value = 0.3928	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 563.51 442.83 1.273 0.213 as.numeric(hhsize) -78.69 74.68 -1.054 0.300	df = 2, Chisq = 16.916, p-value = 0.001277	t = -0.36559, df = 30, p-value = 0.7172
107	df = 4, Chisq = 10.753, p-value = 0.03629	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 734.46 123.10 5.966 4.59e-08 *** as.numeric(plot.size.per.dep) 47.95 27.93 1.717 0.0895 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 747.24 125.15 5.971 4.5e-08 *** as.numeric(plot.size.pp) 94.64 62.65 1.511 0.134	t = -2.2995, df = 91, p-value = 0.02376	t = 0.15139, df = 91, p-value = 0.88	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 519.18 232.90 2.229 0.0283 * as.numeric(hhsize) 53.39 42.95 1.243 0.2170	df = 2, Chisq = 16.1, p-value = 0.0006077	df = 2, Chisq = 2.5638, p-value = 0.2825
201	df = 4, Chisq = 37.847, p-value = 2.915e-07	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 217.7 204.8 1.063 0.2887 as.numeric(plot.size.per.dep) 502.2 198.1 2.536 0.0117 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 356.3 180.0 1.979 0.0486 * as.numeric(plot.size.pp) 895.1 412.7 2.169 0.0308 *	t = -1.5715, df = 342, p-value = 0.117	t = 1.3815, df = 342, p-value = 0.168	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 796.86 264.37 3.014 0.00277 ** as.numeric(hhsize) 17.40 40.14 0.433 0.66496	df = 2, Chisq = 13.322, p-value = 0.001453	df = 2, Chisq = 28.286, p-value = 1.257e-06

202	df = 4, Chisq = 50.884, p-value = 2.421e-09	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 445.3 112.0 3.974 9.59e-05 *** as.numeric(plot.size.per.dep) 328.5 124.5 2.637 0.00896 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 481.0 109.7 4.383 1.82e-05 *** as.numeric(plot.size.pp) 679.5 328.6 2.068 0.0398 *	t = -4.4683, df = 226, p-value = 1.247e-05	t = 0.097493, df = 226, p-value = 0.9224	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 125.85 169.33 0.743 0.45812 as.numeric(hhsize) 109.19 34.03 3.208 0.00153 **	df = 2, Chisq = 6.5583, p-value = 0.03947	df = 2, Chisq = 99.602, p-value < 2.2e-16
203	df = 4, Chisq = 33.875, p-value = 1.634e-06	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1300.3 165.4 7.860 5.45e-14 *** as.numeric(plot.size.per.dep) 394.3 102.7 3.838 0.000148 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1424.5 164.0 8.686 < 2e-16 *** as.numeric(plot.size.pp) 698.6 188.8 3.699 0.000253 ***	t = -3.2468, df = 331, p-value = 0.001287	t = 0.48645, df = 331, p-value = 0.627	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 965.26 328.20 2.941 0.00350 ** as.numeric(hhsize) 195.26 72.73 2.685 0.00762 **	df = 2, Chisq = 0.2838, p-value = 0.8678	df = 2, Chisq = 29.198, p-value = 8.407e-07
204	df = 4, Chisq = 18.99, p-value = 0.0009673	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 615.5 206.6 2.980 0.003087 ** as.numeric(plot.size.per.dep) 660.6 183.8 3.594 0.000372 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1117.9 170.0 6.578 1.75e-10 *** as.numeric(plot.size.pp) 634.5 256.3 2.476 0.0138 *	t = -3.977, df = 349, p-value = 8.489e-05	t = 0.76871, df = 349, p-value = 0.4426	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 398.38 331.73 1.201 0.23060 as.numeric(hhsize) 257.30 82.98 3.101 0.00209 **	df = 2, Chisq = 27.636, p-value = 1.68e-06	df = 2, Chisq = 44.534, p-value = 7.947e-10

205	df = 4, Chisq = 18.614, p-value = 0.00121	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 565.79 83.18 6.802 6.96e-11 *** as.numeric(plot.size.per.dep) 207.11 110.37 1.877 0.0617 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 596.70 78.92 7.561 6.76e-13 *** as.numeric(plot.size.pp) 298.01 188.71 1.579 0.115	t = -1.3466, df = 262, p-value = 0.1793	t = -0.35186, df = 262, p-value = 0.7252	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 499.72 150.54 3.32 0.00103 ** as.numeric(hhsize) 46.18 34.45 1.34 0.18127	df = 2, Chisq = 9.0622, p-value = 0.01163	df = 2, Chisq = 17.135, p-value = 0.000249
206	df = 4, Chisq = 67.272, p-value = 6.881e-13	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 437.5 226.7 1.929 0.0543 . as.numeric(plot.size.per.dep) 1108.3 259.9 4.265 2.42e-05 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 660.5 254.0 2.601 0.00959 ** as.numeric(plot.size.pp) 1842.9 640.5 2.877 0.00419 **	t = -4.708, df = 469, p-value = 3.299e-06	t = 1.8967, df = 469, p-value = 0.05848	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 446.06 302.35 1.475 0.14080 as.numeric(hhsize) 228.67 77.86 2.937 0.00348 **	df = 2, Chisq = 1.255, p-value = 0.5344	df = 2, Chisq = 18.199, p-value = 0.0001327
207	df = 4, Chisq = 41.44, p-value = 6.616e-08	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 523.5 125.4 4.174 3.84e-05 *** as.numeric(plot.size.per.dep) 571.4 108.4 5.273 2.45e-07 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 620.7 289.7 2.143 0.0329 * as.numeric(plot.size.pp) 1137.6 689.9 1.649 0.1001	t = -2.6098, df = 326, p-value = 0.009478	t = 1.6476, df = 326, p-value = 0.1004	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 596.6 274.2 2.175 0.0303 * as.numeric(hhsize) 119.1 59.8 1.991 0.0473 *	df = 2, Chisq = 16.824, p-value = 0.0002743	df = 2, Chisq = 4.0465, p-value = 0.1339

208	df = 4, Chisq = 31.755, p-value = 3.982e-06	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 518.9 207.1 2.505 0.01271 * as.numeric(plot.size.per.dep) 728.0 264.8 2.750 0.00629 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 709.9 148.9 4.769 2.76e-06 *** as.numeric(plot.size.pp) 1022.3 331.2 3.086 0.00219 **	t = -4.9344, df = 341, p-value = 1.26e-06	t = 1.2754, df = 341, p-value = 0.203	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 187.99 301.97 0.623 0.5340 as.numeric(hhsize) 195.83 87.44 2.240 0.0258 *	df = 2, Chisq = 10.799, p-value = 0.004915	df = 2, Chisq = 33.882, p-value = 9.695e-08
209	df = 4, Chisq = 27.239, p-value = 2.793e-05	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 585.5 176.8 3.312 0.00103 ** as.numeric(plot.size.per.dep) 425.1 195.4 2.176 0.03025 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 757.2 140.4 5.394 1.3e-07 *** as.numeric(plot.size.pp) 433.3 235.6 1.840 0.0667 .	t = -1.4519, df = 339, p-value = 0.1475	t = -0.50172, df = 339, p-value = 0.6162	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 513.81 295.37 1.740 0.0828 . as.numeric(hhsize) 96.31 65.16 1.478 0.1403	df = 2, Chisq = 6.7635, p-value = 0.03514	df = 2, Chisq = 83.019, p-value < 2.2e-16
210	df = 4, Chisq = 280.82, p-value < 2.2e-16	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 330.0 172.9 1.909 0.0583 . as.numeric(plot.size.per.dep) 979.4 239.6 4.088 7.32e-05 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 548.9 191.4 2.867 0.00479 ** as.numeric(plot.size.pp) 1733.5 637.8 2.718 0.00740 **	t = -2.1486, df = 139, p-value = 0.0334	t = 0.83027, df = 139, p-value = 0.4078	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1612.78 711.81 2.266 0.025 * as.numeric(hhsize) -81.02 123.34 -0.657 0.512	df = 2, Chisq = 3.757, p-value = 0.1567	df = 2, Chisq = 27.682, p-value = 3.325e-06

301	df = 4, Chisq = 19.147, p-value = 0.0009153	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 179.02 36.91 4.851 1.9e-06 *** as.numeric(plot.size.per.dep) 151.60 72.45 2.092 0.0372 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 253.88 26.66 9.522 <2e-16 *** as.numeric(plot.size.pp) 82.59 71.83 1.150 0.251	t = -4.0097, df = 329, p-value = 7.527e-05	t = 0.34386, df = 329, p-value = 0.7312	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 193.576 34.031 5.688 2.84e-08 *** as.numeric(hhsize) 21.408 7.485 2.860 0.0045 **	df = 2, Chisq = 5.6308, p-value = 0.06133	t = 1.9196, df = 329, p-value = 0.05578
302	df = 4, Chisq = 10.079, p-value = 0.04108	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 170.54 37.86 4.505 9.13e-06 *** as.numeric(plot.size.per.dep) 223.04 109.91 2.029 0.0432 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 30.85 151.74 0.203 0.839 as.numeric(plot.size.pp) 874.98 668.47 1.309 0.191	t = -1.5928, df = 343, p-value = 0.1121	t = -1.32, df = 343, p-value = 0.1877	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 406.99 327.20 1.244 0.214 as.numeric(hhsize) -20.10 56.96 -0.353 0.724	df = 2, Chisq = 2.6843, p-value = 0.2627	df = 2, Chisq = 7.5205, p-value = 0.02425
303	df = 4, Chisq = 9.9886, p-value = 0.04253	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 214.09 37.59 5.695 2.58e-08 *** as.numeric(plot.size.per.dep) 94.51 37.87 2.496 0.013 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 264.55 25.88 10.222 <2e-16 *** as.numeric(plot.size.pp) 77.97 25.50 3.057 0.0024 **	t = -1.7165, df = 357, p-value = 0.08694	t = 0.70468, df = 357, p-value = 0.4815	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 256.64 56.18 4.568 6.78e-06 *** as.numeric(hhsize) 10.54 11.95 0.882 0.378	df = 2, Chisq = 6.1626, p-value = 0.04712	df = 2, Chisq = 28.461, p-value = 1.134e-06

304	df = 4, Chisq = 31.44, p-value = 4.438e-06	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 254.43 29.46 8.636 < 2e-16 *** as.numeric(plot.size.per.dep) 171.94 48.62 3.537 0.000459 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 329.85 21.89 15.071 <2e-16 *** as.numeric(plot.size.pp) 89.37 45.58 1.961 0.0507 .	t = -1.8518, df = 358, p-value = 0.06488	t = 0.14804, df = 358, p-value = 0.8824	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 199.92 52.12 3.836 0.000148 *** as.numeric(hhsize) 39.38 13.63 2.890 0.004084 **	df = 2, Chisq = 10.06, p-value = 0.00701	df = 2, Chisq = 22.385, p-value = 1.929e-05
305	df = 4, Chisq = 17.513, p-value = 0.001848	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 186.31 34.44 5.41 1.24e-07 *** as.numeric(plot.size.per.dep) 188.61 57.68 3.27 0.00119 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 259.21 24.14 10.736 <2e-16 *** as.numeric(plot.size.pp) 186.90 74.96 2.493 0.0132 *	t = -0.23605, df = 320, p-value = 0.8135	t = 0.94527, df = 320, p-value = 0.3452	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 238.585 41.730 5.717 2.48e-08 *** as.numeric(hhsize) 20.791 9.847 2.111 0.0355 *	df = 2, Chisq = 7.2808, p-value = 0.02734	df = 2, Chisq = 11.58, p-value = 0.003389
306	df = 4, Chisq = 16.304, p-value = 0.003083	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 344.91 52.41 6.581 1.89e-10 *** as.numeric(plot.size.per.dep) 140.33 73.56 1.908 0.0573 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 379.81 35.74 10.627 <2e-16 *** as.numeric(plot.size.pp) 211.61 90.91 2.328 0.0205 *	t = -3.9779, df = 324, p-value = 8.58e-05	t = 2.8766, df = 324, p-value = 0.004286	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 124.36 215.51 0.577 0.564 as.numeric(hhsize) 90.70 60.81 1.491 0.137	df = 2, Chisq = 7.4303, p-value = 0.0254	df = 2, Chisq = 5.7063, p-value = 0.05912

307	df = 4, Chisq = 31.731, p-value = 4.088e-06	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 166.68 23.18 7.192 4.31e-12 *** as.numeric(plot.size.per.dep) 203.06 42.38 4.792 2.50e-06 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 227.98 23.90 9.540 <2e-16 *** as.numeric(plot.size.pp) 193.71 75.25 2.574 0.0105 *	t = -3.6567, df = 332, p-value = 0.0002969	t = 2.157, df = 332, p-value = 0.03173	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 210.83 40.44 5.214 3.26e-07 *** as.numeric(hhsize) 20.33 10.39 1.958 0.0511 .	df = 2, Chisq = 1.0041, p-value = 0.6058	df = 2, Chisq = 41.159, p-value = 3.767e-09
308	df = 4, Chisq = 13.226, p-value = 0.01135	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 154.66 18.27 8.465 1.15e-15 *** as.numeric(plot.size.per.dep) 109.13 32.21 3.388 0.000798 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 157.70 19.66 8.02 2.39e-14 *** as.numeric(plot.size.pp) 225.21 69.08 3.26 0.00124 **	t = -1.2706, df = 301, p-value = 0.2049	t = 1.414, df = 301, p-value = 0.1584	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 170.400 35.802 4.760 3.02e-06 *** as.numeric(hhsize) 11.877 7.893 1.505 0.133	df = 2, Chisq = 2.5167, p-value = 0.2856	df = 2, Chisq = 25.628, p-value = 4.569e-06
309	df = 4, Chisq = 6.2343, p-value = 0.185	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 199.81 25.78 7.752 1.05e-13 *** as.numeric(plot.size.per.dep) 74.79 27.96 2.675 0.00784 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 226.40 32.77 6.908 2.42e-11 *** as.numeric(plot.size.pp) 77.68 47.42 1.638 0.102	t = -1.631, df = 342, p-value = 0.1038	t = -0.48032, df = 342, p-value = 0.6313	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 146.72 35.30 4.157 4.08e-05 *** as.numeric(hhsize) 23.11 11.45 2.017 0.0444 *	df = 2, Chisq = 16.188, p-value = 0.0003678	df = 2, Chisq = 8.2592, p-value = 0.0169

310	df = 4, Chisq = 4.9075, p-value = 0.3011	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 119.04 38.24 3.113 0.00215 ** as.numeric(plot.size.per.dep) 59.14 48.16 1.228 0.22108	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 157.17 39.82 3.947 0.000113 *** as.numeric(plot.size.pp) 18.29 36.21 0.505 0.614143	t = -1.4278, df = 183, p-value = 0.1551	t = -0.29894, df = 183, p-value = 0.7653	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 70.68 56.90 1.242 0.216 as.numeric(hhsize) 20.84 13.24 1.574 0.117	df = 2, Chisq = 0.51849, p-value = 0.7719	df = 2, Chisq = 185.47, p-value < 2.2e-16
311	df = 4, Chisq = 38.454, p-value = 4.949e-07	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 82.88 46.80 1.771 0.0783 . as.numeric(plot.size.per.dep) 69.49 81.78 0.850 0.3967	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 145.31 27.93 5.203 5.5e-07 *** as.numeric(plot.size.pp) -50.82 47.55 -1.069 0.287	t = 1.0916, df = 173, p-value = 0.2765	t = -0.13102, df = 173, p-value = 0.8959	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 17.536 29.820 0.588 0.55727 as.numeric(hhsize) 24.955 7.972 3.130 0.00205 **	df = 2, Chisq = 4.4953, p-value = 0.1087	df = 2, Chisq = 166.06, p-value < 2.2e-16
312	df = 4, Chisq = 34.862, p-value = 1.06e-06	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 178.95 20.11 8.90 < 2e-16 *** as.numeric(plot.size.per.dep) 110.06 29.99 3.67 0.000282 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 218.61 22.70 9.631 <2e-16 *** as.numeric(plot.size.pp) 128.37 62.19 2.064 0.0398 *	t = -3.7408, df = 336, p-value = 0.0002156	t = 4.004, df = 336, p-value = 7.668e-05	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 164.225 42.292 3.883 0.000124 *** as.numeric(hhsize) 23.996 9.222 2.602 0.009675 **	df = 2, Chisq = 3.5393, p-value = 0.172	df = 2, Chisq = 7.7078, p-value = 0.02214

313	df = 4, Chisq = 36.199, p-value = 5.955e-07	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 438.28 43.11 10.165 <2e-16 *** as.numeric(plot.size.per.dep) 36.26 38.29 0.947 0.344	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 451.43 39.57 11.410 <2e-16 *** as.numeric(plot.size.pp) 44.28 51.82 0.854 0.393	t = -2.4385, df = 338, p-value = 0.01526	t = 2.4542, df = 338, p-value = 0.01462	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 230.00 79.79 2.882 0.00420 ** as.numeric(hhsize) 53.14 17.16 3.097 0.00212 **	df = 3, Chisq = 807.72, p-value < 2.2e-16	df = 2, Chisq = 22.923, p-value = 1.529e-05
314	df = 4, Chisq = 22.744, p-value = 0.0002516	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 223.05 56.92 3.918 0.000127 *** as.numeric(plot.size.per.dep) 221.28 77.11 2.870 0.004608 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 321.56 51.54 6.239 3.12e-09 *** as.numeric(plot.size.pp) 263.07 159.29 1.652 0.1	t = 0.67562, df = 178, p-value = 0.5002	t = 1.2593, df = 178, p-value = 0.2096	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 320.25 122.59 2.612 0.00976 ** as.numeric(hhsize) 22.43 22.71 0.988 0.32457	df = 2, Chisq = 3.3248, p-value = 0.1926	t = 5.0167, df = 178, p-value = 1.266e-06
315	df = 2, Chisq = 60.528, p-value = 8.454e-09	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 266.14 82.72 3.217 0.00249 ** as.numeric(plot.size.per.dep) 223.88 115.05 1.946 0.05838 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 223.05 89.31 2.497 0.0165 * as.numeric(plot.size.pp) 871.17 430.55 2.023 0.0494 *	t = -1.9341, df = 42, p-value = 0.05986	t = 1.2859, df = 42, p-value = 0.2055	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 110.03 132.48 0.831 0.4109 as.numeric(hhsize) 60.51 27.15 2.229 0.0312 *	df = 2, Chisq = 0.77335, p-value = 0.6818	df = 2, Chisq = 70.151, p-value = 1.321e-09

IHS5

Explanatory variable	Wealth quintile of the household	Average plot size per household dependant (acres)	Average plot size per household member (acres)	Sex of the head of household	Migration status (YES / NO) of the head of the household	Average household size	Average soil quality of the households plots	Use of inorganic fertiliser on one or more plots
Test used	*Kruksall Wallis ANOVA*	*Simple linear regression*	*Simple linear regression*	*Wilcoxon*	*Wilcoxon*	*Simple linear regression*	*Kruksall Wallis ANOVA*	*Wilcoxon*
101	df = 4, Chisq = 37.623, p-value = 3.358e-07	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 361.03 66.36 5.440 1.05e-07 *** as.numeric(plot.size.per.dep) 467.04 74.51 6.268 1.17e-09 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 468.91 98.25 4.772 2.76e-06 *** as.numeric(plot.size.pp) 815.24 259.28 3.144 0.00182 **	t = -1.7608, df = 324, p-value = 0.07922	t = 0.92632, df = 324, p-value = 0.355	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 501.00 129.40 3.872 0.000131 *** as.numeric(hhsize) 63.89 26.22 2.437 0.015366 *	df = 2, Chisq = 22.656, p-value = 1.758e-05	df = 2, Chisq = 30.645, p-value = 4.39e-07
102	df = 4, Chisq = 20.912, p-value = 0.0004783	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 64.57 24.40 2.646 0.00871 ** as.numeric(plot.size.per.dep) 113.80 46.58 2.443 0.01532 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 95.73 23.81 4.02 7.87e-05 *** as.numeric(plot.size.pp) 153.08 102.77 1.49 0.138	t = 0.76656, df = 231, p-value = 0.4441	t = 1.7922, df = 231, p-value = 0.0744	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 85.202 31.324 2.720 0.00702 ** as.numeric(hhsize) 9.544 5.700 1.674 0.09540 .	df = 2, Chisq = 2.0544, p-value = 0.3596	df = 2, Chisq = 290.72, p-value < 2.2e-16

103	df = 4, Chisq = 1.3383, p-value = 0.8544	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 164.00 42.11 3.894 0.000136 *** as.numeric(plot.size.per.dep) 242.41 65.98 3.674 0.000309 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 193.20 39.53 4.888 2.14e-06 *** as.numeric(plot.size.pp) 440.54 129.20 3.410 0.000791 ***	t = 0.98963, df = 193, p-value = 0.3236	t = 1.1158, df = 193, p-value = 0.2659	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 400.377 64.713 6.187 3.6e-09 *** as.numeric(hhsize) -14.106 9.332 -1.512 0.132	df = 2, Chisq = 1.5108, p-value = 0.4712	df = 2, Chisq = 38.8, p-value = 2.12e-08
104	df = 4, Chisq = 18.505, p-value = 0.001276	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 694.54 91.36 7.602 5.63e-13 *** as.numeric(plot.size.per.dep) 87.42 51.54 1.696 0.0911 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 742.34 82.08 9.044 <2e-16 *** as.numeric(plot.size.pp) 94.10 109.54 0.859 0.391	t = -3.1221, df = 254, p-value = 0.002004	t = -0.085775, df = 254, p-value = 0.9317	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 567.46 151.91 3.736 0.000231 *** as.numeric(hhsize) 45.80 27.08 1.691 0.092029 .	df = 2, Chisq = 7.3463, p-value = 0.02676	df = 2, Chisq = 14.724, p-value = 0.0007803
105	df = 4, Chisq = 37.817, p-value = 3.42e-07	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1082.6 362.3 2.988 0.00305 ** as.numeric(plot.size.per.dep) 444.5 175.6 2.532 0.01188 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 723.9 200.5 3.611 0.00036 *** as.numeric(plot.size.pp) 1608.7 675.8 2.380 0.01794 *	t = -0.96305, df = 290, p-value = 0.3363	t = 1.0219, df = 290, p-value = 0.3077	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1232.80 458.83 2.687 0.00763 ** as.numeric(hhsize) 83.69 71.00 1.179 0.23944	df = 2, Chisq = 5.6382, p-value = 0.0613	df = 2, Chisq = 27.933, p-value = 1.622e-06

106	df = 3, Chisq = 7.0292, p-value = 0.1094	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -5.422 17.181 -0.316 0.755745 as.numeric(plot.size.per.dep) 303.231 76.245 3.977 0.000807 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 14.52 30.20 0.481 0.636 as.numeric(plot.size.pp) 635.04 421.38 1.507 0.148	t = -1.0951, df = 19, p-value = 0.2871	t = -0.38145, df = 19, p-value = 0.7071	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -19.099 46.927 -0.407 0.689 as.numeric(hhsize) 16.254 9.983 1.628 0.120	df = 2, Chisq = 5.6463, p-value = 0.08582	t = -5.5776, df = 19, p-value = 2.225e-05
107	df = 4, Chisq = 19.423, p-value = 0.001255	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 602.3 194.8 3.092 0.00254 ** as.numeric(plot.size.per.dep) 283.4 191.5 1.480 0.14182	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 810.8 160.3 5.057 1.79e-06 *** as.numeric(plot.size.pp) 119.6 187.0 0.639 0.524	t = -0.9118, df = 106, p-value = 0.3639	t = 1.5198, df = 106, p-value = 0.1315	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 301.62 317.31 0.951 0.344 as.numeric(hhsize) 111.22 75.02 1.483 0.141	df = 2, Chisq = 7.1396, p-value = 0.03163	t = 3.9339, df = 106, p-value = 0.0001496
201	df = 4, Chisq = 14.197, p-value = 0.007475	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 338.72 93.60 3.619 0.000342 *** as.numeric(plot.size.per.dep) 237.96 73.25 3.248 0.001278 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 295.3 125.8 2.347 0.01952 * as.numeric(plot.size.pp) 660.0 248.4 2.656 0.00828 **	t = -3.5553, df = 336, p-value = 0.0004316	t = -0.23155, df = 336, p-value = 0.817	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 466.29 163.47 2.852 0.00461 ** as.numeric(hhsize) 43.71 31.48 1.389 0.16590	df = 2, Chisq = 1.2544, p-value = 0.5347	df = 2, Chisq = 18.097, p-value = 0.0001488

202	df = 4, Chisq = 40.582, p-value = 1.117e-07	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 353.24 71.14 4.965 1.19e-06 *** as.numeric(plot.size.per.dep) 190.80 50.39 3.786 0.000187 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 330.71 66.29 4.989 1.07e-06 *** as.numeric(plot.size.pp) 517.42 170.38 3.037 0.00262 **	t = 0.069134, df = 280, p-value = 0.9449	t = 1.4184, df = 280, p-value = 0.1572	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 424.89 106.62 3.985 8.61e-05 *** as.numeric(hhsize) 16.70 19.05 0.876 0.382	df = 2, Chisq = 5.7612, p-value = 0.05777	df = 2, Chisq = 501.02, p-value < 2.2e-16
203	df = 4, Chisq = 76.912, p-value = 3.675e-14	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 575.44 114.80 5.013 8.95e-07 *** as.numeric(plot.size.per.dep) 393.31 48.89 8.044 1.75e-14 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 397.4 169.7 2.342 0.019775 * as.numeric(plot.size.pp) 1250.3 363.3 3.442 0.000655 ***	t = -3.1398, df = 317, p-value = 0.00185	t = -1.889, df = 317, p-value = 0.0598	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 563.0 308.1 1.828 0.0686 . as.numeric(hhsize) 121.1 60.6 1.998 0.0466 *	df = 2, Chisq = 6.6702, p-value = 0.03687	df = 2, Chisq = 21.69, p-value = 2.784e-05
204	df = 4, Chisq = 107.77, p-value < 2.2e-16	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 209.1 303.7 0.689 0.4917 as.numeric(plot.size.per.dep) 630.9 290.0 2.176 0.0304 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 228.6 411.5 0.555 0.579 as.numeric(plot.size.pp) 1383.6 847.1 1.633 0.104	t = -5.7645, df = 282, p-value = 2.146e-08	t = -0.080136, df = 282, p-value = 0.9362	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 182.03 335.98 0.542 0.588 as.numeric(hhsize) 177.87 78.94 2.253 0.025 *	df = 2, Chisq = 2.0176, p-value = 0.366	df = 2, Chisq = 18.006, p-value = 0.0001623

205	df = 4, Chisq = 10.911, p-value = 0.02953	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 665.12 105.70 6.293 1.12e-09 *** as.numeric(plot.size.per.dep) 80.60 89.72 0.898 0.37	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 587.7 140.8 4.174 3.94e-05 *** as.numeric(plot.size.pp) 369.0 343.2 1.075 0.283	t = -1.8939, df = 296, p-value = 0.05921	t = -0.87623, df = 296, p-value = 0.3816	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 657.86 145.57 4.519 8.98e-06 *** as.numeric(hhsize) 17.20 24.56 0.700 0.484	df = 2, Chisq = 1.4762, p-value = 0.4789	df = 2, Chisq = 29.258, p-value = 8.757e-07
206	df = 4, Chisq = 68.585, p-value = 4.307e-13	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 118.7 161.7 0.734 0.463333 as.numeric(plot.size.per.dep) 719.5 210.9 3.412 0.000704 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 332.6 156.8 2.121 0.0345 * as.numeric(plot.size.pp) 1098.2 450.3 2.439 0.0151 *	t = -4.7059, df = 449, p-value = 3.371e-06	t = 1.4571, df = 449, p-value = 0.1458	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 284.80 228.52 1.246 0.2133 as.numeric(hhsize) 121.29 52.47 2.312 0.0213 *	df = 2, Chisq = 4.2269, p-value = 0.122	df = 2, Chisq = 29.749, p-value = 5.565e-07
207	df = 4, Chisq = 42.002, p-value = 5.358e-08	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -32.15 259.96 -0.124 0.902 as.numeric(plot.size.per.dep) 969.59 227.38 4.264 2.65e-05 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 439.5 203.5 2.160 0.03155 * as.numeric(plot.size.pp) 1312.1 500.3 2.623 0.00914 **	t = -3.7514, df = 318, p-value = 0.0002089	t = -0.67678, df = 318, p-value = 0.499	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -72.5 436.5 -0.166 0.868 as.numeric(hhsize) 230.3 110.0 2.094 0.037 *	df = 2, Chisq = 1.2999, p-value = 0.5228	df = 2, Chisq = 10.697, p-value = 0.005193

208	df = 4, Chisq = 41.699, p-value = 6.027e-08	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 306.2 69.4 4.412 1.40e-05 *** as.numeric(plot.size.per.dep) 477.9 88.4 5.406 1.26e-07 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 401.68 93.41 4.300 2.27e-05 *** as.numeric(plot.size.pp) 822.62 284.20 2.895 0.00406 **	t = -3.7306, df = 321, p-value = 0.0002258	t = 1.4123, df = 321, p-value = 0.1588	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 653.47 176.92 3.694 0.00026 *** as.numeric(hhsize) 18.45 34.56 0.534 0.59378	df = 2, Chisq = 10.9, p-value = 0.004706	df = 2, Chisq = 17.925, p-value = 0.0001632
209	df = 4, Chisq = 61.166, p-value = 1.896e-11	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 687.9 288.0 2.389 0.0175 * as.numeric(plot.size.per.dep) 126.0 113.3 1.113 0.2666	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 683.1 276.9 2.466 0.0142 * as.numeric(plot.size.pp) 278.7 240.0 1.161 0.2465	t = -5.6428, df = 321, p-value = 3.677e-08	t = 0.73048, df = 321, p-value = 0.4656	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 187.6 222.2 0.844 0.399 as.numeric(hhsize) 144.5 87.6 1.649 0.100	df = 2, Chisq = 5.9037, p-value = 0.05367	df = 2, Chisq = 22.679, p-value = 1.746e-05
210	df = 4, Chisq = 241.97, p-value < 2.2e-16	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 675.9 403.1 1.677 0.09586 . as.numeric(plot.size.per.dep) 618.8 184.2 3.359 0.00101 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 889.9 393.1 2.264 0.0252 * as.numeric(plot.size.pp) 931.1 109.6 8.496 3.05e-14 ***	t = -0.3301, df = 136, p-value = 0.7418	t = -0.40156, df = 136, p-value = 0.6886	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 884.46 706.23 1.252 0.213 as.numeric(hhsize) 80.76 118.63 0.681 0.497	df = 2, Chisq = 10.72, p-value = 0.005755	df = 2, Chisq = 370.66, p-value < 2.2e-16

301	df = 4, Chisq = 39.638, p-value = 1.407e-07	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -2111.9 851.6 -2.480 0.01364 * as.numeric(plot.size.per.dep) 3574.9 1216.9 2.938 0.00354 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -2139.4 923.2 -2.317 0.02110 * as.numeric(plot.size.pp) 6882.0 2531.9 2.718 0.00691 **	t = -2.0836, df = 329, p-value = 0.03797	t = 1.4408, df = 329, p-value = 0.1506	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1371.0 899.5 1.524 0.128 as.numeric(hhsize) -159.7 138.7 -1.151 0.250	df = 2, Chisq = 3.7104, p-value = 0.1581	df = 2, Chisq = 114.48, p-value < 2.2e-16
302	df = 4, Chisq = 16.897, p-value = 0.002418	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 209.86 32.35 6.488 3.46e-10 *** as.numeric(plot.size.per.dep) 115.41 50.26 2.296 0.0223 *	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 169.46 37.02 4.578 6.83e-06 *** as.numeric(plot.size.pp) 347.52 124.80 2.785 0.00569 **	t = -2.5619, df = 308, p-value = 0.01089	t = 2.3071, df = 308, p-value = 0.02171	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 197.108 38.671 5.097 6.03e-07 *** as.numeric(hhsize) 20.121 7.771 2.589 0.0101 *	df = 2, Chisq = 14.847, p-value = 0.0007105	df = 2, Chisq = 25.575, p-value = 4.631e-06
303	df = 4, Chisq = 21.771, p-value = 0.0002993	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 271.463 21.219 12.793 < 2e-16 *** as.numeric(plot.size.per.dep) 48.696 9.908 4.915 1.42e-06 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 274.86 20.90 13.151 < 2e-16 *** as.numeric(plot.size.pp) 92.25 12.31 7.495 6.51e-13 ***	t = -1.106, df = 321, p-value = 0.2696	t = 0.88902, df = 321, p-value = 0.3747	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 282.215 60.852 4.638 5.13e-06 *** as.numeric(hhsize) 7.675 12.634 0.608 0.544	df = 2, Chisq = 7.5814, p-value = 0.0236	df = 2, Chisq = 37.615, p-value = 1.895e-08

304	df = 4, Chisq = 56.302, p-value = 1.484e-10	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 324.58 33.51 9.685 <2e-16 *** as.numeric(plot.size.per.dep) 87.09 46.53 1.872 0.0622 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 326.34 28.91 11.287 <2e-16 *** as.numeric(plot.size.pp) 182.62 86.32 2.116 0.0352 *	t = -1.9641, df = 309, p-value = 0.05042	t = 1.5945, df = 309, p-value = 0.1118	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 255.95 49.02 5.221 3.27e-07 *** as.numeric(hhsize) 31.27 12.76 2.451 0.0148 *	df = 2, Chisq = 4.3303, p-value = 0.1165	df = 2, Chisq = 7.7473, p-value = 0.0218
305	df = 4, Chisq = 20.58, p-value = 0.0005163	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 259.87 28.96 8.974 < 2e-16 *** as.numeric(plot.size.per.dep) 104.90 37.43 2.802 0.00542 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 313.80 25.47 12.320 <2e-16 *** as.numeric(plot.size.pp) 67.44 54.51 1.237 0.217	t = -0.98105, df = 282, p-value = 0.3274	t = -0.83776, df = 282, p-value = 0.4029	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 250.607 40.911 6.126 3.03e-09 *** as.numeric(hhsize) 22.837 9.676 2.360 0.0189 *	df = 2, Chisq = 8.0511, p-value = 0.01889	df = 2, Chisq = 12.424, p-value = 0.002292
306	df = 4, Chisq = 122.76, p-value < 2.2e-16	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 298.29 85.55 3.487 0.000569 *** as.numeric(plot.size.per.dep) 300.36 83.66 3.590 0.000391 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 368.76 80.07 4.606 6.29e-06 *** as.numeric(plot.size.pp) 521.75 186.02 2.805 0.00539 **	t = -1.7477, df = 275, p-value = 0.08164	t = 1.9699, df = 275, p-value = 0.04985	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 185.04 119.16 1.553 0.12162 as.numeric(hhsize) 94.46 33.82 2.793 0.00559 **	df = 2, Chisq = 14.287, p-value = 0.0009457	df = 2, Chisq = 4.6002, p-value = 0.1022

307	df = 4, Chisq = 45.317, p-value = 1.19e-08	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 274.61 31.94 8.597 2.8e-16 *** as.numeric(plot.size.per.dep) 158.98 49.02 3.243 0.0013 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 309.06 31.68 9.756 <2e-16 *** as.numeric(plot.size.pp) 220.20 95.11 2.315 0.0212 *	t = -1.7605, df = 349, p-value = 0.0792	t = 1.4453, df = 349, p-value = 0.1493	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 220.58 50.06 4.407 1.4e-05 *** as.numeric(hhsize) 35.68 12.76 2.797 0.00545 **	df = 2, Chisq = 17.682, p-value = 0.0001798	df = 2, Chisq = 53.633, p-value = 1.474e-11
308	df = 4, Chisq = 30.49, p-value = 6.8e-06	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 180.32 31.35 5.751 1.94e-08 *** as.numeric(plot.size.per.dep) 166.05 45.25 3.670 0.000281 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 233.02 30.51 7.637 2.18e-13 *** as.numeric(plot.size.pp) 138.55 78.45 1.766 0.0783 .	t = -3.025, df = 347, p-value = 0.002672	t = 0.71658, df = 347, p-value = 0.4741	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 126.25 29.34 4.303 2.19e-05 *** as.numeric(hhsize) 33.79 8.27 4.086 5.45e-05 ***	df = 2, Chisq = 4.9649, p-value = 0.08503	df = 2, Chisq = 40.676, p-value = 4.457e-09
309	df = 4, Chisq = 46.531, p-value = 7.492e-09	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 207.5 30.4 6.826 4.12e-11 *** as.numeric(plot.size.per.dep) 92.4 33.0 2.800 0.0054 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 206.19 27.84 7.406 1.07e-12 *** as.numeric(plot.size.pp) 191.42 97.56 1.962 0.0506 .	t = -3.4445, df = 335, p-value = 0.0006448	t = 0.44625, df = 335, p-value = 0.6557	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 216.19 87.24 2.478 0.0137 * as.numeric(hhsize) 11.18 17.08 0.654 0.5133	df = 2, Chisq = 4.739, p-value = 0.0951	df = 2, Chisq = 27.721, p-value = 1.649e-06

310	df = 4, Chisq = 8.4624, p-value = 0.07921	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 73.07 22.47 3.252 0.00129 ** as.numeric(plot.size.per.dep) 59.96 35.99 1.666 0.09686 .	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 63.69 26.77 2.379 0.0181 * as.numeric(plot.size.pp) 154.58 96.08 1.609 0.1088	t = -0.11283, df = 267, p-value = 0.9102	t = -0.13753, df = 267, p-value = 0.8907	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 131.116 51.855 2.528 0.012 * as.numeric(hhsize) -2.598 9.003 -0.289 0.773	df = 2, Chisq = 0.62669, p-value = 0.7313	t = 4.0474, df = 267, p-value = 6.789e-05
311	df = 4, Chisq = 4.8429, p-value = 0.3071	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 92.58 19.98 4.635 6.05e-06 *** as.numeric(plot.size.per.dep) 36.88 31.88 1.157 0.249	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 113.313 15.204 7.453 1.92e-12 *** as.numeric(plot.size.pp) -2.514 31.851 -0.079 0.937	t = -1.8592, df = 226, p-value = 0.0643	t = -0.53323, df = 226, p-value = 0.5944	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 46.32 23.95 1.934 0.0543 . as.numeric(hhsize) 14.97 6.28 2.384 0.0180 *	df = 2, Chisq = 5.0933, p-value = 0.0806	t = 5.5609, df = 226, p-value = 7.543e-08
312	df = 4, Chisq = 11.155, p-value = 0.02663	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 192.64 28.73 6.706 9.39e-11 *** as.numeric(plot.size.per.dep) 148.61 48.50 3.064 0.00238 **	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 236.11 27.72 8.518 7.02e-16 *** as.numeric(plot.size.pp) 181.26 82.22 2.205 0.0282 *	t = -3.3642, df = 312, p-value = 0.0008634	t = 2.052, df = 312, p-value = 0.041	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 200.027 44.862 4.459 1.15e-05 *** as.numeric(hhsize) 23.238 9.855 2.358 0.019 *	df = 2, Chisq = 1.3695, p-value = 0.505	df = 2, Chisq = 7.0759, p-value = 0.03025

313	df = 4, Chisq = 46.476, p-value = 9.887e-09	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 489.87 60.75 8.064 2.22e-14 *** as.numeric(plot.size.per.dep) 87.24 53.40 1.634 0.103	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 487.90 61.99 7.871 7.91e-14 *** as.numeric(plot.size.pp) 184.66 118.52 1.558 0.12	t = -1.7083, df = 278, p-value = 0.08869	t = -0.26743, df = 278, p-value = 0.7893	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 243.70 114.22 2.134 0.03375 * as.numeric(hhsize) 73.84 27.85 2.651 0.00848 **	df = 2, Chisq = 6.2881, p-value = 0.04465	df = 2, Chisq = 29.932, p-value = 6.732e-07
314	df = 4, Chisq = 21.605, p-value = 0.0004323	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 22.74 133.96 0.170 0.865429 as.numeric(plot.size.per.dep) 792.22 206.61 3.834 0.000183 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 266.78 43.91 6.076 9.4e-09 *** as.numeric(plot.size.pp) 1044.03 35.56 29.359 < 2e-16 ***	t = -0.23178, df = 153, p-value = 0.817	t = -0.52213, df = 153, p-value = 0.6023	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 1291.8 665.0 1.942 0.0539 . as.numeric(hhsize) -135.1 118.1 -1.144 0.2544	df = 2, Chisq = 2.6142, p-value = 0.2736	df = 2, Chisq = 3.8476, p-value = 0.1496
315	df = 3, Chisq = 135.75, p-value = 3.417e-16	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 82.63 59.42 1.391 0.169 as.numeric(plot.size.per.dep) 499.50 97.35 5.131 2.47e-06 ***	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 172.44 56.07 3.076 0.00299 ** as.numeric(plot.size.pp) 876.03 314.54 2.785 0.00688 **	t = -0.11142, df = 70, p-value = 0.9116	t = 0.73696, df = 70, p-value = 0.4636	Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 43.07 110.62 0.389 0.69822 as.numeric(hhsize) 75.34 25.20 2.989 0.00386 **	df = 2, Chisq = 3.9102, p-value = 0.1493	t = 0.23558, df = 70, p-value = 0.8144

Appendix F

Crop production statistics

The total Maize production was estimated for each of the three households surveys under study and compared to the FAO nationally reported values for validation.

F.1 Estimated national Maize production for the main harvest during 2011, 2016 and 2020. Data source: IHS3,4,5 respectively

MAIZE PRODUCTION	Total production (tonnes)	Total production according to FAO **(tonnes)**
2011 (IHS3)	2,990,114	**3,699,147 (error = 19%)**
2016 (IHS4)	2,054,080	**2,369,493 (error = 13%)**
2020 (IHS5)	2,111,660	**4,581,000 (error = 54%)**

Crop production for the 2016 survey by crop type.

F.2 Estimated national crop production for Malawi, 2016. Data source: IHS4

Crop[5]	**Total production (tonnes)**	**Total production (million kcal)**
Maize [1]	2,054,080 (49% of all food)	7,189,281 (84% of all food)
Groundnut (Chalimba) [11]	142,867	810,055
Rice [17]	25,505	93,603
Sweet potato [28]	42,274	36,355
Sorghum [32]	18,644	61,340
Beans [34]	17,251	57,447
Soyabean [35]	60,473	90,710
Pigeonpea (Nandola) [36]	44,573	152,884
Nkhwani [42]	134,921	28,333
Peas [46]	1,668,073	701
Subsistence crops (excluding Maize)	**2,154,581 (51% of all food)**	**1,331,429 (16% of all food)**
TOTAL CROPS	**4,208,661**	**8,520,710**

F.3 Summary statistics for average household production of Maize and of all other food crops for each district, during 2016 harvest. Data source: IHS4

District	**Maize**			**Other subsistence crops**		
	Average (median) production per household (kg)	**IQR (kg)**	**Total district crop production (tonnes)**	**Average production per household (kg)**	**IQR (kg)**	**Total district crop production (kg)**
Chitipa (101)	279	320	25,558	87.2	131.14	30,760,775

[5] Number in square bracket refers to the collapsed crop code used to identify each crop within the IHS4 survey. Further details can be found within the IHS4 data dictionary available at: Malawi - Fourth Integrated Household Survey 2016-2017 (worldbank.org) [Last accessed 02 January 2022]

Karonga (102)	135	168.05	19,944	203.92	304.32	29,010,740
Nkhatabay (103)	300	350	8,582	150	350	10,821,304
Rumphi (104)	410	504.15	32,077	100	167.74	4,891,356
Mzimba (105)	550	964.56	42,614	180.46	296.16	8,249,922
Likoma (106)	50	117.22	73	18.33	93	9,758
Mzuzu City (107)	500	836.1	10,664	64.89	111.18	567,278
Kasungu (201)	450	800	146,287	175	350	54,121,798
Nkhotakota (202)	350	450	34,557	300	650	28,447,291
Ntchisi (203)	850	1898	110,948	281.19	633.09	42,603,125
Dowa (204)	650	1423.5	264,823	168.6	420	44,762,905
Salima (205)	300	550	51,321	100	200	7,120,095
Lilongwe (206)	550	1300	422,383	150	310	62,338,783
Mchinji (207)	600	950	137,358	200	350	36,568,687
Dedza (208)	350	825	168,272	75	200	18,182,434
Ntcheu (209)	375	600	117,031	50	80	7,619,443
Lilongwe City (210)	475	900	80,813	81	317.8	12,365,490
Mangochi (301)	200	200	65,942	50	139.8	13,031,575
Machinga (302)	150	230	38,496	50	150	17,144,295
Zomba Non-City (303)	175	275	26,484	75	175	12,601,755
Chiradzulu (304)	250	300	58,653	72.6	150	20,352,713
Blantyre (305)	200	300	22,996	75	150.98	9,566,635
Mwanza (306)	300	350	11,351	100	200	4,144,231
Thyolo (307)	200	300	43,920	75	137.2	20,130,518
Mulanje (308)	150	152.5	23,131	85	130.2	11,746,136
Phalombe (309)	150	150	19,775	50	108	7,934,734
Chikwawa (310)	25	150	9,892	62.4	175	9,132,777
Nsanje (311)	16	200	4,251	20	100	3,775,230
Balaka (312)	200	200	22,990	50	91.2	4,717,036
Neno (313)	300	350	15,640	50	115	2,906,883
Zomba City (314)	295	375	7,457	35	110.98	1,419,856
Blantyre City (315)	250	350	9,797	50	140	3,353,610

APPENDIX G

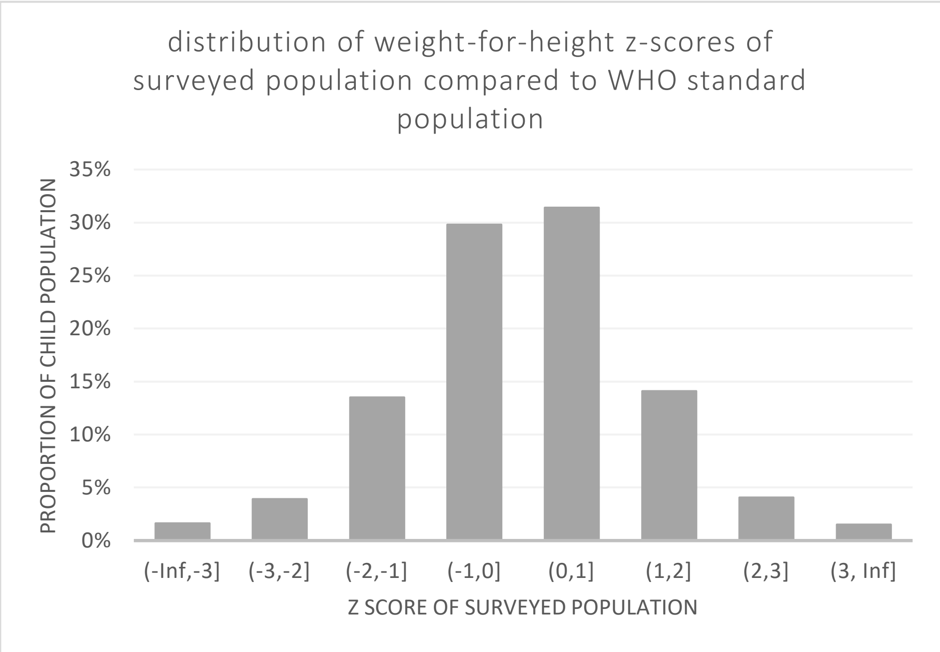


Figure G.1 top graph: weight-for-height (wasting) z-scores, and bottom graph: height-for-age (stunting) z-scores of Malawi population against WHO standard population. Data source: IHS4

Table G.1 Proportion of households that experience prolonged hunger

District	Proportion of households that have experienced prolonged hunger in the 12-months prior to the survey		
	IHS3	IHS4	IHS5

101	9.86%	48.21%	20.70%
102	9.48%	50.34%	32.35%
103	8.73%	21.46%	9.28%
104	4.91%	32.97%	16.68%
105	22.47%	33.20%	16.15%
106	NA	21.96%	6.97%
107	7.24%	14.08%	10.23%
201	14.96%	55.26%	39.21%
202	15.05%	39.31%	17.23%
203	17.30%	37.04%	22.15%
204	17.50%	49.12%	38.18%
205	26.41%	55.40%	41.30%
206	12.35%	54.51%	42.67%
207	17.68%	58.61%	26.11%
208	28.52%	46.36%	29.74%
209	34.19%	41.40%	30.50%
210	6.40%	19.32%	9.30%
301	21.66%	60.56%	42.29%
302	27.38%	75.40%	50.34%
303	12.91%	65.62%	48.45%
304	8.76%	57.75%	37.67%
305	6.54%	46.42%	31.26%
306	37.56%	50.44%	46.82%
307	25.72%	55.45%	31.30%
308	28.26%	59.22%	36.25%
309	27.85%	74.37%	42.93%
310	60.55%	78.62%	39.08%
311	65.41%	85.21%	33.76%
312	44.50%	60.34%	42.08%
313	43.75%	58.28%	41.92%
314	3.05%	31.03%	16.40%
315	7.22%	17.86%	18.37%

APPENDIX H

Table H.1 Results of logistic regression exploring impacts upon food security due to household maize production

Dependant variable	Explanatory variable	Test used		IHS3 Maize			IHS4 Maize				IHS5 Maize			
			Coeff (Log odds)	**Odds ratio**	**t value**	**P-score**	**Coeff (Log odds)**	**Odds ratio**	**t value**	**P-score**	**Coeff (Log odds)**	**Odds ratio**	**t value**	**P-score**
Prolonged Hunger	Household maize production (tonnes)	simple logistic regression	-0.2237 (SE 0.017)	0.8000	-12.92	0.0000<2e-16	-0.2951 (SE 0.017)	0.7445	-17.65	<2e-16	-0.279 (SE 0.040)	0.7564	-7.01	0.0000 <2e-16
		n =		46729				39955				40346		
Presence of moderate or severe childhood household wasting	Household maize production (tonnes)	simple logistic regression	0.2696 (SE 0.05383)	1.3094	-5.008	0.00005.66E-07	-0.3845 (SE 0.055)	0.6808	11.34	<2e-16	-0.2058 (SE 0.13)	0.8140	-1.602	0.109
		n =		6504				4748				5039		

APPENDIX I

Table I.1 Pearson's correlation results for district level total maize production and climate variables. Climate variables include either a delta or a time-averaged variable. Delta's are described as the climate anomaly for survey year compared to a 1980-2010 baseline. Time-averaged climate variables are the average wet season climate averaged over either 2,3,4,5,10 or 20 years preceding the survey year.

time period	climate variable	Correlation with district total maize production
2010.11 wet season	Delta average monthly rainfall (mm)	-0.3913
2010.11 wet season	Delta average monthly maximum temperature (°C)	-0.7636
2015.16 wet season	Delta average monthly rainfall (mm)	-0.3548
2015.16 wet season	Delta average monthly maximum temperature (°C)	-0.4619
2019.20 wet season	Delta average monthly rainfall (mm)	0.0671
2019.20 wet season	Delta average monthly maximum temperature (°C)	-0.5068
2010.11 wet season	Average monthly rainfall (mm)	-0.3956
2010.11 wet season	Average monthly maximum temperature (°C)	0.0812
2010.11. 2 year wet season	Average monthly rainfall (mm)	-0.3723
2010.11. 2 year wet season	Average monthly maximum temperature (°C)	0.0911
2010.11 3 year wet season	Average monthly rainfall (mm)	-0.3650
2010.11 3 year wet season	Average monthly maximum temperature (°C)	0.0963
2010.11 4 year wet season	Average monthly rainfall (mm)	-0.3477
2010.11 4 year wet season	Average monthly maximum temperature (°C)	0.0923
2010.11 5 year wet season	Average monthly rainfall (mm)	-0.3328
2010.11 5 year wet season	Average monthly maximum temperature (°C)	0.0990
2010.11 10 year wet season	Average monthly rainfall (mm)	-0.3095
2010.11 10 year wet season	Average monthly maximum temperature (°C)	0.1082
2010.11 20 year wet season	Average monthly rainfall (mm)	-0.371
2010.11 20 year wet season	Average monthly maximum temperature (°C)	0.1201
2015.16 wet season	Average monthly rainfall (mm)	-0.3293
2015.16 wet season	Average monthly maximum temperature (°C)	0.0260
2015.16. 2 year wet season	Average monthly rainfall (mm)	-0.2886
2015.16. 2 year wet season	Average monthly maximum temperature (°C)	0.0333
2015.16 3 year wet season	Average monthly rainfall (mm)	-0.2555
2015.16 3 year wet season	Average monthly maximum temperature (°C)	0.0329
2015.16 4 year wet season	Average monthly rainfall (mm)	-0.2792
2015.16 4 year wet season	Average monthly maximum temperature (°C)	0.0392
2015.16 5 year wet season	Average monthly rainfall (mm)	-0.2963
2015.16 5 year wet season	Average monthly maximum temperature (°C)	0.0367
2015.16 10 year wet season	Average monthly rainfall (mm)	-0.2839
2015.16 10 year wet season	Average monthly maximum temperature (°C)	0.0325
2015.16 20 year wet season	Average monthly rainfall (mm)	-0.2937
2015.16 20 year wet season	Average monthly maximum temperature (°C)	0.0381
2019.20 wet season	Average monthly rainfall (mm)	-0.104
2019.20 wet season	Average monthly maximum temperature (°C)	0.0722
2019.20 2 year wet season	Average monthly rainfall (mm)	-0.2697
2019.20 2 year wet season	Average monthly maximum temperature (°C)	0.0805
2019.20 3 year wet season	Average monthly rainfall (mm)	-0.2776

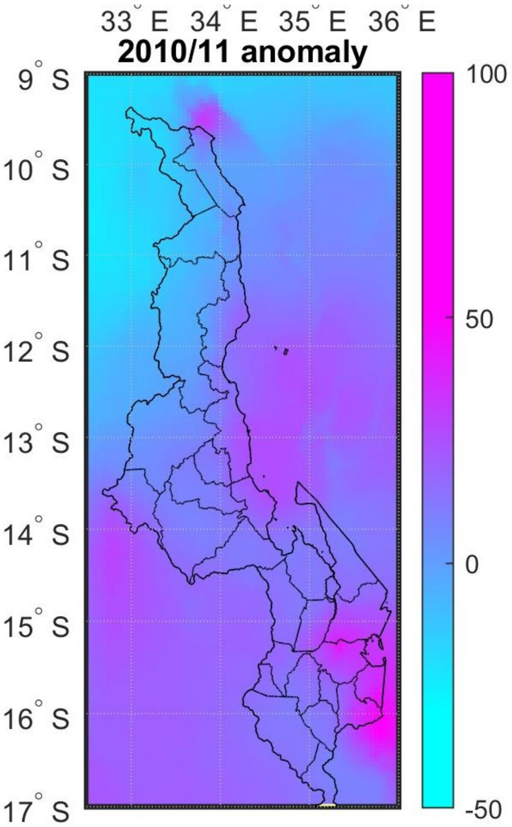
2019.20 3 year wet season	Average monthly maximum temperature (°C)	0.0973
2019.20 4 year wet season	Average monthly rainfall (mm)	-0.3128
2019.20 4 year wet season	Average monthly maximum temperature (°C)	0.0972
2019.20 5 year wet season	Average monthly rainfall (mm)	-0.3252
2019.20 5 year wet season	Average monthly maximum temperature (°C)	0.0999
2019.20 10 year wet season	Average monthly rainfall (mm)	-0.3371
2019.20 10 year wet season	Average monthly maximum temperature (°C)	0.1040
2019.20 20 year wet season	Average monthly rainfall (mm)	-0.3263
2019.20 20 year wet season	Average monthly maximum temperature (°C)	0.1077
2010.11 1-year offset	Average monthly rainfall (mm)	-0.3194
2010.11 1-year offset	Average monthly maximum temperature (°C)	0.1067
2010.11 2-year offset	Average monthly rainfall (mm)	-0.2864
2010.11 2-year offset	Average monthly maximum temperature (°C)	0.1114
2015.16 1- year offset	Average monthly rainfall (mm)	-0.2800
2015.16 1-year offset	Average monthly maximum temperature (°C)	0.1055
2015.16 2-year offset	Average monthly rainfall (mm)	-0.2315
2015.16 2-year offset	Average monthly maximum temperature (°C)	0.1065
2019.20 1-year offset	Average monthly rainfall (mm)	-0.2484
2019.20 1-year offset	Average monthly maximum temperature (°C)	0.0887
2019.20 2-year offset	Average monthly rainfall (mm)	-0.2666
2019.20 2-year offset	Average monthly maximum temperature (°C)	0.1277

APPENDIX J

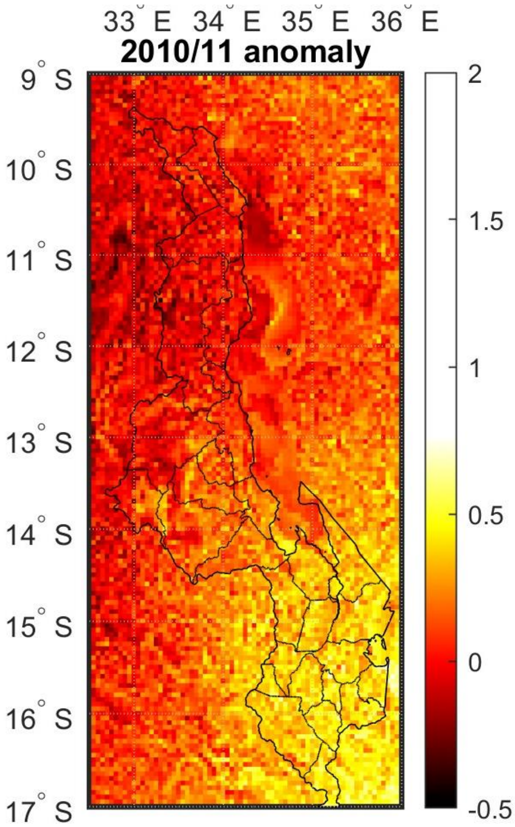
Figure J.1 Maps of the climate anomalies (delta between survey year wet season climate and 1980-2010 baseline) for precipitation and maximum temperature

2010/11 wet season

Precipitation (mm)



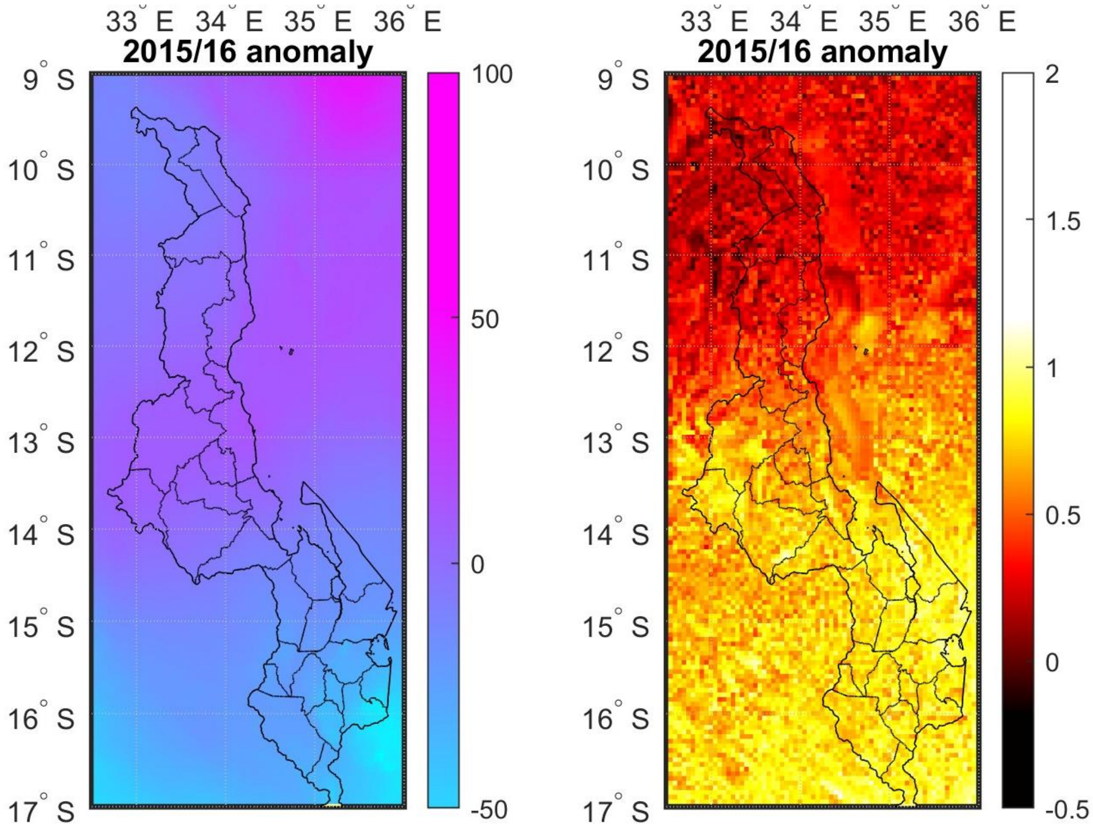
Maximum temperature (°C)



2015/16 wet season

Precipitation (mm)

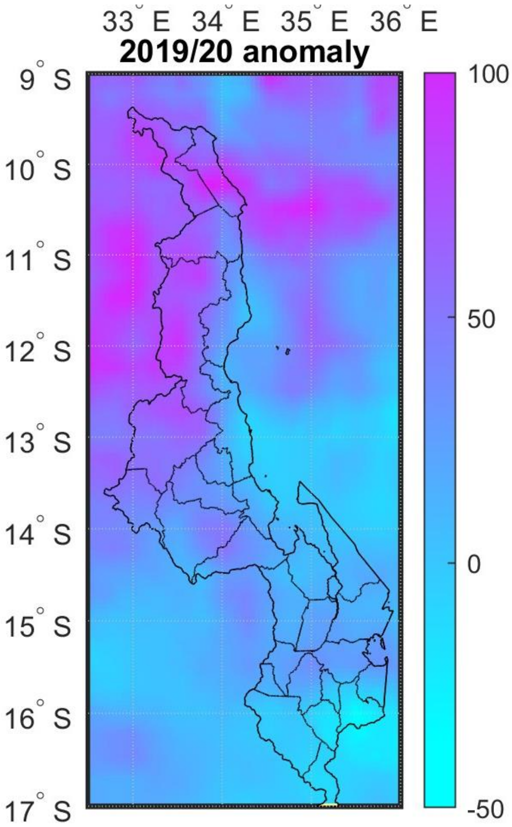
Maximum temperature (°C)

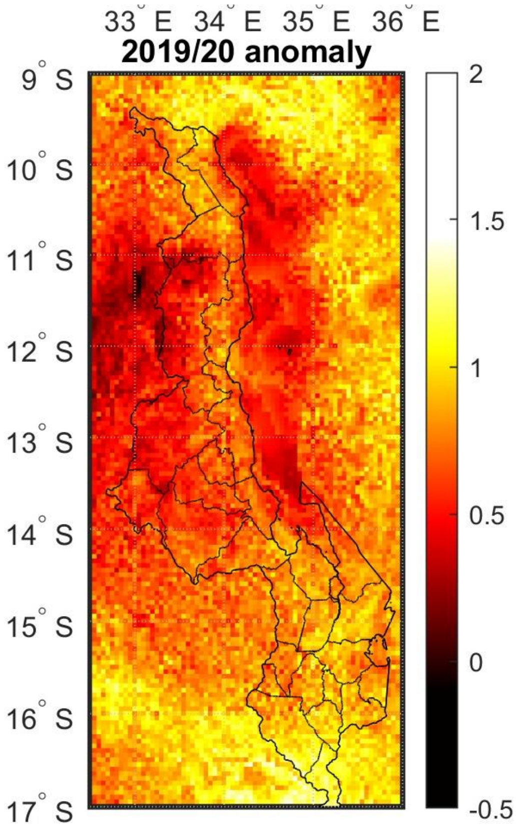


2019/20 wet season

Precipitation (mm)

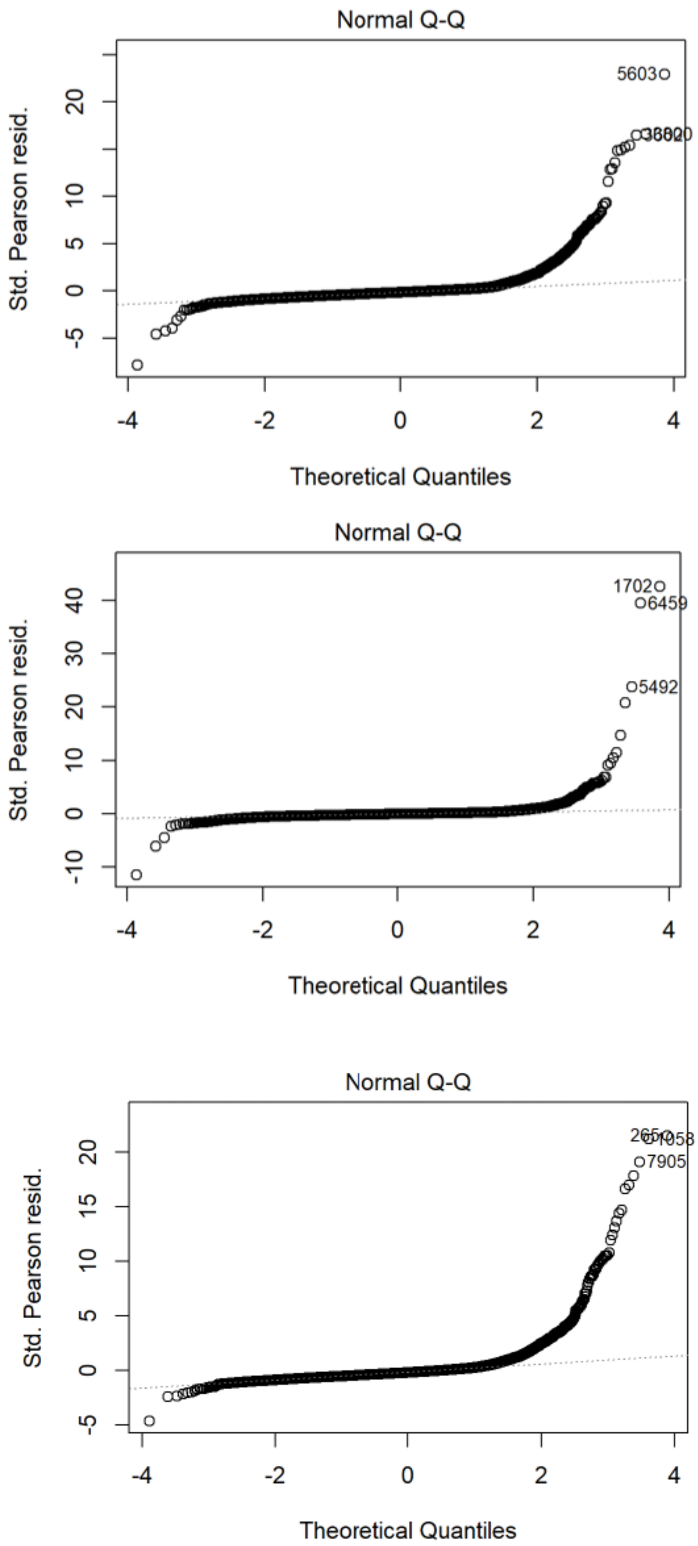
Maximum temperature (°C)


33° E 34° E 35° E 36° E
2019/20 anomaly
9° S
10° S
11° S
12° S
13° S
14° S
15° S
16° S
17° S
100
50
0
-50


33° E 34° E 35° E 36° E
2019/20 anomaly
9° S
10° S
11° S
12° S
13° S
14° S
15° S
16° S
17° S
2
1.5
1
0.5
0
-0.5

APPENDIX K

Figure K.1 Q-Q plots of residual errors within the multi-variable linear regression for maize production for TOP: IHS3, MIDDLE: IHS4 and BOTTOM: IHS5



4 AN EXPLORATION INTO THE DRIVERS OF INTRANATIONAL MIGRATION WITHIN MALAWI

4.1 CHAPTER OBJECTIVES

The previous chapter explored the relationship between climate variables, crop production and food security within Malawi. Results of the models included consideration of migration status of the household head, but identified no statistically significant relationship between migration status and crop production. The hypothesis derived from the conceptual model developed in Chapter 2, was that, for the Malawian context, climate change may impact upon migration through the pathway of affected crop production and food security, with migration in turn, affecting an individual's vulnerability profile including factors such as wealth, security and future livelihood practices and successes. The purpose of this chapter is to further interrogate the relationships between food security and migration, presenting an exploratory analysis of how food security may be a driver of migration, as well as how migration may impact upon food security. The analysis shall also consider the direct links between migration and climate factors (Figure 4.1).

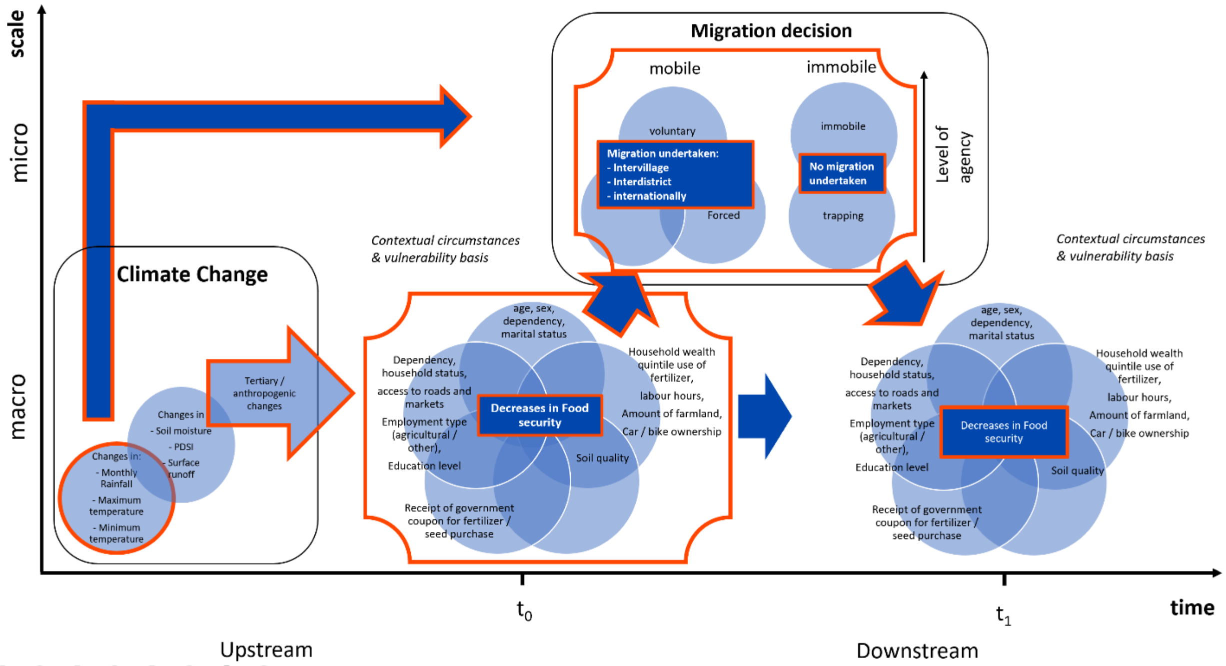


Figure 4.1 Conceptual model of the key relationships and determinants of crop production and food security in the context of Malawi. Indicators and pathways for study within this chapter are outlined in red.

4.2 INTRODUCTION

Climate migration has been rising up the political and research agenda for several decades, most notably since references to ‘environmental migration’ and ‘environmental refugees’ first emerged in the 1980s (Hinnawi & UNEP, 1985; Jacobson, 1988; Myers, 1993). Perhaps one of the most famous papers that spurred the discussion of environmental refugees was published by Norman Myers (2001) who, following a growing obsession with counting migrants, estimated an (oft quoted) number of some 200 million individuals who migrate due to climate change by 2050 (Myers, 2001). Since then, many scholars have struggled to better understand and attempt to quantify how and to what extent climate change impacts migration. Some studies take a global view such as Norman Myers and until recently, the Lancet Countdown (Watts et al., 2017). Other studies have taken a regional view, such as the World Bank’s Groundswell report, which estimated 143 million internal migrants by 2050 (Kumari Rigaud et al., 2018). Other studies take a national or sub-national view, with much of the African continent presenting a plethora of climate change vulnerable case studies, such as Ethiopia (Ezra & Kiros, 2001; Hermans-Neumann et al., 2017), Burkina Faso (Henry et al., 2003, 2004) and Malawi (Lewin et al., 2012; Nicholson, 2020; Suckall et al., 2017).

Malawi's economy is climate sensitive due to reliance upon rainfed agriculture for as much as 85% of Malawians (National Statistics Office Government of Malawi, 2020). Climate change has already been found to be impacting the rainy season including through increased rainfall variability, time of onset of the rains, and number of extremely wet or dry days (Haghtalab et al., 2019). As such, it is commonly hypothesized that climate change induced delays or changes in the rainy season may be an upstream driver of migration. In particular in Malawi it is hypothesized that poor rains and drought may lead to migration decisions (Suckall et al., 2015). However, empirical studies remain sparse and somewhat inconclusive. Becerra-Valubuena and Millock (2021) found that both temporary migration as well as small-scale migration for marriage is a common adaptive response to local climate shocks such as floods and droughts (Becerra-Valbuena & Millock, 2021). Lewin, Fisher and Weber (2012) found a small negative association between rainfall variability and rural out-migration (Lewin et al., 2012) whilst Suckall, Fraser and Forster (2017) found little impact of climate on the aspirations of would-be migrants, but a potential erosion of the capability of households to engage in migration (the so-called 'trapping' effect). Suckall et al., (2015) also found a potential relationship between climate change and reverse-urbanisation (urban to rural migration) due to the effects of climate change on migrant workers engaging in casual labour in Malawi's cities. Since the livelihoods of many urban migrants remains dependent upon rural produce and transport routes (e.g., accessibility of food or fuel which urban migrants purchase, damage to roads and supply routes), then poor rains and reduced agricultural outputs adversely affect city-dwelling economic migrants, who subsequently return to rural locations of origin.

A large reason why these hypotheses remain little tested is data paucity on migration. The Malawi Integrated Household Survey (IHS) series is World Bank Living Standards Measurement Study series consisting of five cross-sectional studies conducted between 1997 and 2020 which include survey questions regarding place of birth, time and reason for latest migration. A subset of the IHS is the Integrated Household Panel Survey (IHPS), a panel study which follows up with the same households at each survey cross-section, creating a longitudinal study. The IHPS was baselined in 2010 and then followed up with participants in three subsequent surveys in 2013, 2016 and 2019 (National Statistics Office [NSO] Malawi, 2014).

More granular household studies exist such as the Karonga Health and Demographic Surveillance System (HDSS) (Crampin et al., 2012) however, such studies lack a country-wide perspective. The Migration and Health in Malawi (MHM) dataset is a population-based longitudinal migration study of 1809 individuals, conducted between 2007 and 2013 (Anglewicz et al., 2017) integrated with the Malawi Longitudinal Study of Families and Health (MLSFH), but which has a smaller sample size and time range than the periodic Integrated Household surveys and panel survey.

In Chapter 2, I hypothesized the multifaceted and dynamic way in which climate change may be impacting migration patterns in Malawi (Chapter 2, figure 2.2). This is pulled out in more detail within Figure 4.1 above. The relationship between food security and migration is thought to be bi-directional, with the potential for climate-induced crop failures and deterioration of livelihoods to act as either a push-factor for out-migration from an area, or a glue-factor to trap a household in situ, due to the rising poverty and reduced means of migration. Furthermore, migration may impact upon the livelihoods of migrants and their families, for example by allowing migrants to achieve economic diversification, improving their conditions as well as to engage in remittance networks. Alternatively, migration may be a maladaptive strategy, creating challenges and increased food and health risks for the migrants. As identified within the conceptual model, all migration decisions are driven by an aggregation of factors, with food security not being the only consideration. Limited data as well as the complex system of (often highly localised) determinants impedes empirical explorations of these relationship.

Further complicating the relationship is the many forms that migration can take for example as identified within Chapter 2, Table 2.1. Internal migration within Malawi is common place and includes temporary, permanent and circular migration for seasonal employment and economic diversification (Suckall et al., 2015, Parrish et al., 2020); permanent rural to urban migration resulting from urbanisation trends (Barrios et al., 2006; Brown, 2011); displacement due to flood or drought events; permanent (or semi-permanent) relocation for reasons such as marriage, widowhood or divorce (Myroniuk, 2017). International migration into Malawi is also common and Malawi acts as both a transition and as a host country for migrant workers (International Organization of Migration, 2014). Malawi is also a host for a small number of refugees, mostly from Mozambique, with an estimated 53,575 refugees residing in Malawi as of 2017 (UNHCR, 2023). Emigration from Malawi is also common, predominantly in search of work to South Africa or to other nations within the Southern Africa Development Community region (SADC). More recently there is also an increasing interest in the potential of government-initiated and community participatory resettlement schemes, as a proactive adaptation measure to mitigate the risks of climate change (Nicholson, 2020).

In chapter 3 I found limited evidence that a change in climate variables are associated with changes in crop production and food security. Sociodemographic variables, particularly the gender of the household head, along with plot size and wealth had a much larger impact upon crop production and especially upon food security metrics. The methods also considered whether the migration household head was a migrant but did not disaggregate by type of migrant or time since migration. This approach yielded no discernible relationship and as such, migration status was excluded from the results. Time of migration and reason for migration (e.g., for familial or work-related reasons) is thought to be particularly important but was not examined within chapter 3, nor was the bi-directional nature of the relationship (thought to be multi-directional, with food insecurity being hypothesized as a driver of migration, but with migration also having an impact upon food security of the person(s) in transit and in their host location).

As such, the aims of this chapter are to conduct a more in-depth epidemiological exploration of the relationship between migration status, food security and climate factors. This is in an attempt to test the hypotheses that climate change may either be driving migration through the pathway of affected crop production and rising food insecurity, or else that climate change may be leading to the trapping effect, reducing migration due to rising poverty (with rising food insecurity being symptomatic of this).

Any discernible, direct impacts between climate change and migration will also be explored, as will an insight into the possible impacts of migration status upon food security.

4.3 DATA AND METHODOLOGY

4.3.1 Data

In continuation of the exploration conducted in the previous chapter, this analysis utilised the climate variables provided by the TerraClimate climatology (Abatzoglou et al., 2018), and the sociodemographic data from Malawi's Integrated Household Surveys suite, focusing on the surveys conducted in 2016 (IHS4) and 2019 (IHS5). The IHS is a World Bank Living Standards Measurement Study conducted using a two-stage stratified sampling of approximately 10,000-13,000 households at each survey, representative at the national, district, urban and rural levels.

In addition, the study utilised the Integrated Household Panel Survey (IHPS), a subset of the IHS that is representative at the national, rural and urban levels (not district or regional levels). The IHPS, although a subset of the IHS has been treated as a separate dataset because there is no publicly available key that can link the panel household ID's to the full survey IDs. The IHPS baseline was constructed using a subset of the third IHS (IHS3) in 2010/11. 102 out of 204 Enumeration Areas were included, with 3247 households (7682 individuals) baselined to create the panel in 2010. These households were tracked and interviewed again in 2013 (including migration, births and deaths), resulting in a panel of 4,000 households comprising 10,035 individuals. In 2016, due to budget constraints, only 2508 of those households were then followed up (8,995 individuals from the original baseline) as a subset of the IHS4. Finally, in 2019 all households from 2016 were followed up resulting in a final panel survey of 2178 households and 14,649 individuals as a subset of the IHS5 (National Statistics Office [NSO] Government of Malawi, 2020). The panel survey collected the same data as the full household survey, but is not representative at the district or regional levels. Despite this, the advantage of the IHPS is that it provides a longitudinal overview, with a migration history, as well as sociodemographic (including food security) history for each participant.

The full household survey (IHS) datasets were utilised to create cross-sections of migration stock and food security in Malawi (in 2015/16 and in 2019/20) that could provide a highly powerful (large N) view of living standards in Malawi at the district level. The data also contained information on time of migration allowing for an analysis of migration over time.

The panel survey (IHPS) was used for its longitudinal power to explore the relationship between food security and migration, hypothesizing migration as an outcome of food security during the previous survey cross-section. However, since the data is not representative at the district level, it could only provide insight into net migration in and around Malawi, and not out-migration from districts.

4.3.1.1 Climate variables

District level climate and water data for the variables shown in Table 4.1 were constructed firstly by reverse geocoding the climatology using the Stephen Morse online batch geocoder (Morse, 2006), to assign a district code to each latitude and longitude value within the dataset see (Appendix B for list of district / region codes). Secondly, district climate values were constructed by taking the average of all coordinates within each district. The four urban districts (Mzuzu, Lilongwe, Zomba and Blantyre) were constructed manually using average values of the data points contained manually drawn city boundaries as viewed on OpenStreetMap (© OpenStreetMap Contributors, n.d.) (openstreetmap.org)).

To explore any association between climate and migration, the wet season monthly rainfall was utilised as was the two-year, three-year, four-year and five-year average wet season rainfall, defined as the average monthly rainfall during rainy season months (November to April inclusive) for the previous years (e.g., for the 2016 three-yearly rainfall the values for 2015-16, 2014-15 and 2013-14 were averaged). This was to address the hypothesis that, if climate were a driver of migration, that its influence upon the decision to migrate may not be instantaneous but based on a series of poor seasons.

Table 4.1 Climate and hydrological variables from the TerraClimate dataset

Shortname	Units	Temporal resolution	Spatial resolution

Accumulated monthly precipitation	mm	~4km	monthly
'Palmer Drought Severity Index'	unitless	~4km	Monthly
'Minimum 2-m air Temperature'	Degrees Celsius	~4km	Monthly
'Maximum 2-m air Temperature'	Degrees Celsius	~4km	Monthly
Monthly total 'runoff amount'	mm	~4km	Monthly
'Soil Moisture at End of Month'	mm	~4km	Monthly
Three-year average wet-season rainfall.	Mm	~4km	Monthly

4.3.1.2 Food security, crop, migration, and sociodemographic variables

Variables which were hypothesised to have an impact upon food security and migration were identified through the conceptual model (Figure 4.1). Data for these variables were then obtained from Malawi's Integrated Household Surveys. Food security metrics that were explored included average number of meals consumed, child anthropometrics and presence of prolonged hunger. Due to timing of this study IHS4 (2016) was used for the analysis of daily meals consumed and child anthropometric measurements and IHS5 data (2020), which was published and became available mid-way through research, was used to analyse prolonged hunger. IHS5 was utilised for this final analysis as it presented the latest and most up-to-date view of migration and food security within Malawi. Findings from Chapter 3 also suggested that prolonged hunger appeared to be the most reliable food security metric. Alongside the publication of the IHS5 in 2020, was the latest stage of the IHPS, which therefore covered 4 points in time (2010, 2013, 2016, 2019).

Sociodemographic variables were investigated at both the household and individual level, depending upon the analysis being conducted. Household variables included household wealth, migration status of the head of the household, and food security of the household. Individual level variables included sex, age and migration status of the individual. Individuals within a household inherit the food security of the household. The district, region and urbanness (whether a household is located in an urban or rural area) of the household was also considered.

In addition to these and individual variables, a timeseries of national level crop production data over time was obtained from the FAO (FAOSTAT, 2023). Average household crop yield was estimated by dividing the national crop yield by the estimated number of households within the country each year, using Population and Housing census data from 1998, 2008 and 2018.

4.3.1.2.1 Defining wealth

Measuring wealth of a household was done by construction wealth quintiles via a Principle Component Analysis using recoded, binary variables from the following list: ownership of a gas stove, ownership of fridge, ownership of a tv, whether household has access to an improved sanitation (VIP latrine, latrine with roof, flush toilet), access to improved roofing material (concrete, iron, clay), access to improved water supply (piped, sandpipe, protected well, borehole, bottled bowser), access to improved lighting fuel (gas or electric), and ownership of one or more cell phones (Filmer & Pritchett, 2001; National Statistics Office (NSO) [Malawi] and ICF, 2017).

4.3.1.2.2 Food security metrics

Following on from Chapter 3, three household level food security metrics were considered. Child anthropometric measures of severe or moderate stunting and severe or moderate wasting. All households (households with an eligible child) inherit the average malnutrition status of all eligible children within the household. Households without eligible children were excluded.

The average number of daily meals consumed by 5-17 year olds was also considered and provided a variable at the household level.

Finally, prolonged hunger was defined from a survey question regarding whether in the last 12 months, a household had been faced with a situation when they did not have enough food to feed the household (National Statistics Office (NSO) [Malawi], 2017). A metric for ‘presence of prolonged hunger’ was then created for any households who reported insufficient food for a period of three or more consecutive months. Based on the findings of the previous chapter, prolonged hunger was treated preferentially as the most reliable for testing the hypotheses in this thesis.

4.3.1.2.3 Migration variables

For the purposes of this study, two different migration variables were explored using the IHS data: lifetime migration, and final (i.e., most recent) migration. Life-time migration is defined as the final (as at the time of measurement) migration from place of birth to current place of enumeration, and each person was assigned to one of four categories: non-migrant, international migrant, interdistrict migrant and intervillage migrant. International migrants are defined as those persons who were born outside of Malawi. Interdistrict migrants are defined as those who were born in another district to the one of current residence. Intervillage household migrants were defined as people who were born in another place within the same district as current residence. A household level metric was also created whereby only the head of the household migration status was relevant. This life-time migration status variable was built using the IHS full survey data and used for statistical testing of the relationships with child anthropometrics and number of meals.

The second migration variable explored was the most-recent migration, considering not where the person was born, but when they moved into the current village or urban centre of enumeration (or if they had always resided there). This was constructed using the IHPS data and was utilised for the longitudinal study. This metric provided a fuller picture of the migration history of participants during the panel survey period, creating a binary variable describing if a person had moved since the last survey point. This question was asked at four points in time (2010, 2013, 2016, 2019) and therefore a longitudinal dataset was created which could determine whether a migration had occurred during each period of study: prior to 2007, between 2007 and 2009 (inclusive), between 2010 and 2012 (inclusive), between 2013 and 2015 (inclusive), between 2016 and 2019 (inclusive). Because the IHPS was not representative at the district level, in- and out-migration were not explored, only net migration within the country was calculated. This limitation also meant that the migration status was not disaggregated by migrant type (intervillage, interdistrict or international).

IHS5 data was used to summarise the number of migrants (lifetime) nationally which provided a timeseries of the number of migrants within the country. Taking a temporal view for the number of people who reported undertaking a migration each year provided a national view of net migration (i.e. the number of migration journeys that took place) and a district level out-migration per year. To do this, the district population each year were obtained from the 1987, 1998, 2008 and 2018 population and housing census data (National Statistics Office (NSO) [Malawi], 1988, National Statistics Office (NSO) [Malawi], 1999, National Statistics Office (NSO) [Malawi], 2009, National Statistics Office (NSO) [Malawi], 2019). Linear interpolation was used to estimate the populations (nationally and per district) in between these years.

For the analysis of net migration over time, to reduce recall bias, only migrations since 1987 were explored and time of migration was aggregated into periods. 1987 was initially selected such that the period 1 January 1987 – 31 December 2016 as a thirty-year period. Mid-way through this research, the IHS5 study was published, providing an additional four years of data to 2020 such that the final migration study period is 34 years.

Disaggregating the migration status of the population by district of departure (source district) provided insights into out-migration. It was also possible to analyse in-migration via disaggregation by district of enumeration. Non-migrant households were defined as those households whose household head was born in the same place (town or village) of current residence. Self-proclaimed reason for migration was also obtained (available within the IHS survey as well as the IHPS).

Limitations of the lifetime migration binary variable (from the IHS), and the longitudinal final migration variable (using IHPS) include residual recall bias within the period of consideration. Furthermore, although the IHPS attempts to build a relatively complete migration history of participants, it would not capture multiple migrations in between study periods. For example if, when asked in 2016, someone had moved multiple times between 2013 and 2016, only the latest migration in that period would be captured. This is not thought to be a likely situation for many people and any such rapid migrations are not hypothesised to be due to food security of crop production considerations. As such, the migration history provided by the IHPS is considered to be adequate for the purposes of this study.

4.3.2 Methodology

To conduct a comprehensive exploration of the relationships between climate, food security and migration, a range of analyses were conducted. Descriptive statistics were created for the state of migration and of food security across Malawi and through time. The relationship between migration and food security were then explored bi-directionally, as identified within the conceptual model: poor food security (predictor) could be a driver of migration (response variable), but migration status could also be a determinant (predictor) of food security, as discussed in chapters 2 and 3. A range of analyses were conducted separately to explore each hypothesized direction of the relationship. Climate change as a potential direct driver of migration is also explored.

Due to the timing of this research, both the IHS4 and IHS5 surveys, as well as the IHPS were utilised for the study to utilise the most up-to-date analysis possible. Where analyses use the IHS4 data, this is because the analysis was conducted prior to the publication of IHS5. As such, the analyses of meal consumption and child anthropometrics utilises the IHS4 data. Prolonged hunger, as well as the overview of migration in Malawi utilises the more recent IHS5 data. Benefits of switching to the IHS5 data also meant that there was a greater temporal range for which migration could be analysed, as the survey included an additional 4 years of data.

4.3.2.1 Overview of internal migration

Firstly, descriptive analyses were undertaken to understand internal migration (net migration, district out-migration and district in-migration) within Malawi, temporally and spatially.

Contingency tables were created to understand demographic profiles of migrants and their reasons for migration. Descriptive analysis was conducted for the reasons for migration compared to food security status and reasons for any self-reported hunger. This analysis considered climate-related factors of drought and flood and any possible relationship between the reasons for hunger and the reasons for migration within the context of climate change. Descriptive analyse included both visual inspection and Spearman correlation tests.

4.3.2.2 The relationship between food security and migration – statistical testing

Next, relationships between migration and possible predictor variables, including crop production, food security and climate variables were statistically interrogated.

4.3.2.2.1 Chi-squared tests

Chi-squared test and simple logistic regression models were constructed to statistically explore migration as a response variable, and the hypothesized predictor variables of food security, climate variables, crop production and sociodemographic data as described in Table 3.2 (Chapter 3). For these statistical analyses, only the number of lifetime migrants was used (as a binary variable for whether someone was a lifetime migrant or not), without consideration for source or host location. Each of the three food security metrics were examined in turn.

4.3.2.2.2 Regression modelling of familial (head of household) migration and food security variables

Following statistical testing, both linear and logistic regression was used to further understand the relationship between food security and migration. Given the bi-directional hypothesized relationship, regression was conducted in two forms: firstly, using food security as the response variable and in-migration as a predictor. Secondly, with out-migration as the response variable and food security as a predictor.

To begin with, average daily number of meals was modelled as the response variable, and in-migration as a binary the explanatory variable in accordance with linear regression model described by Equation (9).

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \varepsilon \tag{9}$$

where Y represents the average number of daily meals of children as a discrete, numeric variable. X_n is the explanatory variable, β_0 is the intercept, representing the number of meals when all explanatory variables are zero or set to their reference category. β_n is the average change in the number of meals consumed due to a unit change in each of the explanatory variables, and ε represents the residual error term. This step was conducted only for the average number of daily meals as this was the most complete dataset with almost no missing data for households included (those with children aged 5-17years – approximately 82% of households).

This regression analysis was also disaggregated by region (considering whether a household was situated in either the northern, central or southern region of Malawi) and by the urbanness - whether the household is situated in a city (Mzuzu, Lilongwe, Zomba, Blantyre) or a rural district (all other districts). Under this hypothesis, region and urbanness of the household is based on the place of enumeration, in other words, measuring the effect of in-migration upon subsequent food security. In this way, the model attempts to assess the 'successfulness' of the migration by considering the outcome / situation resulting from the migration, rather than the migration of origin.

At the national level one final model was then produced which modelled the number of meals consumed as predicted by migration status of the household head, introducing region of in-migration as a predictor variable within the model. A range of other variables (as identified within the conceptual model) were introduced in a step-wise fashion. Each model was compared using deviance value, considerations for collinearity of predictors, and changes in the coefficients achieved by introduction of new explanatory variables. The best model is presented and is defined by having negligible collinearity between explanatory variables, the best fit and lowest Bayesian Information Criterion (BIC) score.

4.3.2.2.3 Longitudinal study of migration (individual level) and prolonged hunger

To explore whether food insecurity could be a determinant of out-migration (the response variable), prolonged hunger was explored in further detail using the IHPS longitudinal study of all reported migrations that took place within the study period. The analysis involved a mixed effects logistic regression analysis to explore the migration period during which a migration took place (or if one did not take place) and using prolonged hunger through time as a predictor variable. This enabled an exploration of whether experiencing prolonged hunger (during the survey year) affected the odds of undertaking a migration in the subsequent three-year period, up to the next survey point. Since the longitudinal study involved repeated measurements of participants, a mixed-effects model was built to explore the relationships for each participant, and to allow for correlated random effects due to those repeated measurements (four measurements, conducted in 2010, 2013, 2016, 2019 at each survey point), of each participant (14,649 individuals). The model was constructed by conceptualising migration between survey years (*i*) where *i* = 1,2,3,4 to correspond with the four survey years 2010, 2013, 2016, 2019, and using person (*j*) being surveyed as the grouping variable to account for repeat measurements. Therefore migration can be described by the equation:

$$migration_{ij} = \beta_{0j} + \epsilon_{ij} \tag{10}$$

Where β_{0j} represents the log odds of migrating (for any person at survey year) and is the residual variation. Since likelihood of a migration event will vary by person (j) in line with the vulnerability profiles described in chapter 1) we can therefore express β_{0j} as:

$$\beta_{0j} = \gamma_0 + \gamma_1 X_1 + \cdots + \gamma_n X_n + \mu_{0j} \tag{11}$$

Where X_n are the predictors of migration such as prolonged hunger of a person in the survey year prior to the migration measurement, and γ_{nj} are the fixed effect coefficients and μ_{0j} is the random effect describing variability between people (inter-person).

Through substitution, the mixed effect logistical regression model for takes the form of

$$migration_{ij} = \gamma_0 + \gamma_1 X_1 + \cdots + \gamma_n X_n + \mu_{0j} + \epsilon_{ij} \tag{12}$$

Where $migration_{ij}$is the logit (log odds) of a migration occurring in either <2007, 2007-2009, 2010-2012, 2013-2015, or 2016-2019 periods. $\gamma_0$is the intercept, representing the odds of a migration in the reference category. γ_n are the log odds describing the relative change in log odds for a unit change in each X_n on top of the reference value. μ_j and ϵ_{ij} are the random effects for inter-person and intra-person (for repeat measurements at different survey years) variability respectively.

4.3.2.3 Migration due directly to climate change

Using the temporal data for year of final (latest) migration variable, net-migration trends were overlaid with climate data and crop production data to see if there were any graphically observable correlations. This overview was performed at the national level to compare climate data with national net migration quantities and at the district level to explore out-migration from source districts (using IHS4 data).

Plotted climate data included rainfall and temperature for the wet season of that year. By presenting as a timeseries it was possible to explore relationships between variables in the same year, as well as to identify any time lags. This was to test the hypothesis that a poor wet season could lead to low crops and food insecurity in the same year, a migration would be unlikely to occur instantaneously, but it may be more likely that a period of two to five years of poor rains may impact upon migration - either by encouraging migration in search of alternative work (under better climate conditions) or as a trapping effect whereby consecutive poor harvests and resultant poverty increase may hamper migration ability. These plots were disaggregated by district due to the highly localised nature of rainfall and to explore out-migration at the district level.

4.4 RESULTS AND DISCUSSION

4.4.1 An overview of internal migration in Malawi (IHS5)

As of 2019, 68% of Malawians were non-migrants, with the remaining 32% comprising mainly of intervillage migrants (18%), and interdistrict migrants (13%). Only 0.8% of the population were immigrants from other countries.

Figure 4.2 shows net internal migration as a proportion of the national population each year between 1987 and 2019 (the final survey point used, IHS5 was completed part way through 2020 and so the net migration in 2020 is not fully reflected).

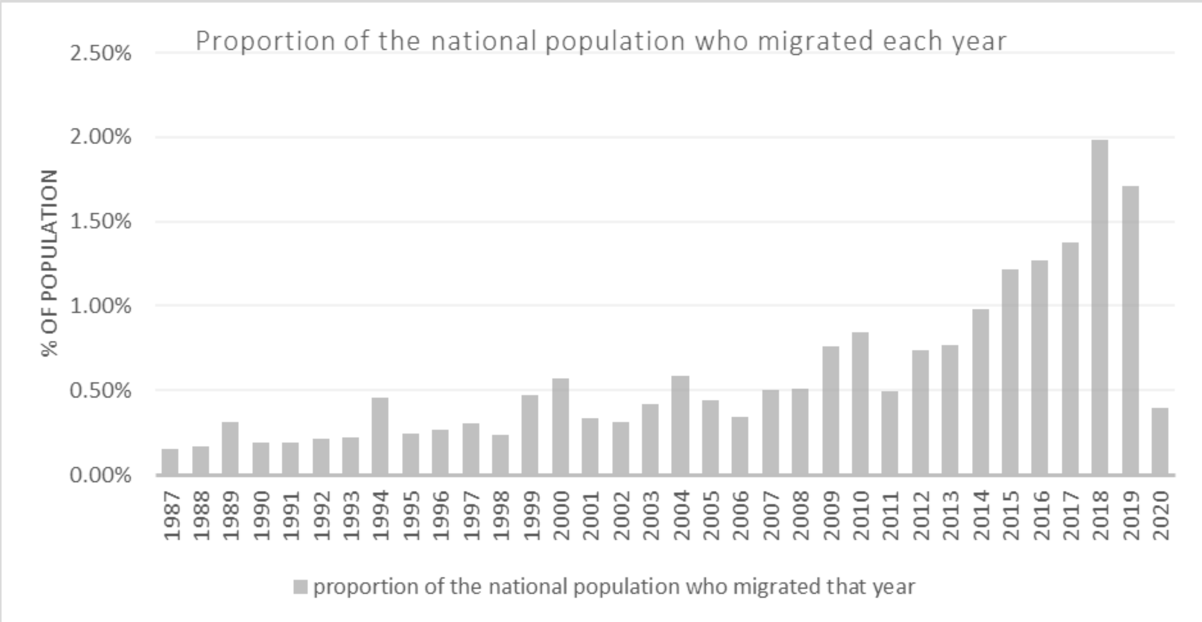


Figure 4.2 Net migration per year as a proportion of the population who undertook a journey each year. IHS5

Using 2020 as a baseline year of study, disaggregating by wealth (Table 4.2) identifies a statistically significant association between household wealth and an individual's migration status (as tested using a chi-squared, $X^2 = 2956.7$, $p < 2.2e\text{-}16$) with higher wealth (fifth quintile) associated with a larger proportion of all migration types, particularly for interdistrict migrants. This is in line with literature which suggest that richer households have more resources to finance a migration, including a move across a greater distance where the support available by local networks of family and friends may be lower, acting as a deterrent for migration for many households (Nawrotzki et al., 2015).

Table 4.2 descriptive statistics – contingency tables for frequency (number of people) in each demographic category. Bracketed numbers are the proportion of the total population (migrant and non-migrant). Chi-squared results for whether the difference in frequencies is statistically significant. (IHS5)

		Migrant type				
		non migrant	**international migrant**	**interdistrict migrant**	**intervillage migrant**	**chi-squared results**
wealth quintile	**1**	2,674,538 (0.74)	30,470 (0.01)	326,925 (0.09)	589,950 (0.16)	X-squared = 2956.7, df = 12, p-value < 2.2e-16
	2	2,744,414 (0.76)	25,347 (0.01)	259,018 (0.07)	583,431 (0.16)	

	3	2,705,307 (0.74)	19,889 (0.01)	302,006 (0.08)	614,961 (0.17)	
	4	2,395,805 (0.66)	28,711 (0.01)	526,160 (0.14)	678,787 (0.19)	
	5	1,817,883 (0.5)	53,016 (0.01)	989,354 (0.27)	768,132 (0.21)	
sex	**male**	5,966,039 (0.68)	69,198 (0.01)	1,202,647 (0.14)	1,478,965 (0.17)	X-squared = 34.5, df = 3, p-value = 1.005e-05
	female	6,371,908 (0.68)	88,235 (0.01)	1,200,814 (0.13)	1,756,296 (0.19)	
presence of child wasting in the house	**no**	1,931,426 (0.87)	12,071 (0.01)	96,326 (0.04)	180,779 (0.08)	X-squared = 1236.5, df = 6, p-value < 2.2e-16
	yes	76,794 (0.89)	1,073 (0.01)	3,032 (0.03)	5,838 (0.07)	
	not eligible	10,329,727 (0.65)	144,289 (0.01)	2,304,104 (0.15)	3,048,644 (0.19)	
presence of severe childhood stunting	**no**	1,751,051 (0.87)	12,308 (0.01)	83,737 (0.04)	162,440 (0.08)	X-squared = 1239.5, df = 6, p-value < 2.2e-16
	yes	2,60,718 (0.86)	835 (0)	15,621 (0.05)	24,573 (0.08)	
	no eligible children	10,326,178 (0.65)	144,289 (0.01)	2,304,104 (0.15)	3,048,248 (0.19)	
presence of prolonged hunger	**no**	7,802,496 (0.65)	117,165 (0.01)	1,858,767 (0.16)	2,205,075 (0.18)	X-squared = 532.79, df = 3, p-value < 2.2e-16
	yes	4,535,451 (0.74)	40,268 (0.01)	544,695 (0.09)	1,030,186 (0.17)	
average daily number of meals (5-17yrs)	**0**	1,442,584 (0.58)	30,563 (0.01)	461,194 (0.19)	5,46,367 (0.22)	X-squared = 1867.1, df = 15, p-value < 2.2e-16
	1	365,820 (0.76)	4,159 (0.01)	23,409 (0.05)	85,692 (0.18)	
	2	5,737,751 (0.76)	40,169 (0.01)	575,215 (0.08)	1,176,962 (0.16)	
	3	4,682,525 (0.64)	77,900 (0.01)	1,250,192 (0.17)	1,363,264 (0.18)	
	4	109,268 (0.41)	4,129 (0.02)	91,407 (0.34)	60,931 (0.23)	
	5	0 (0)	511 (0.11)	2,045 (0.44)	2,045 (0.44)	

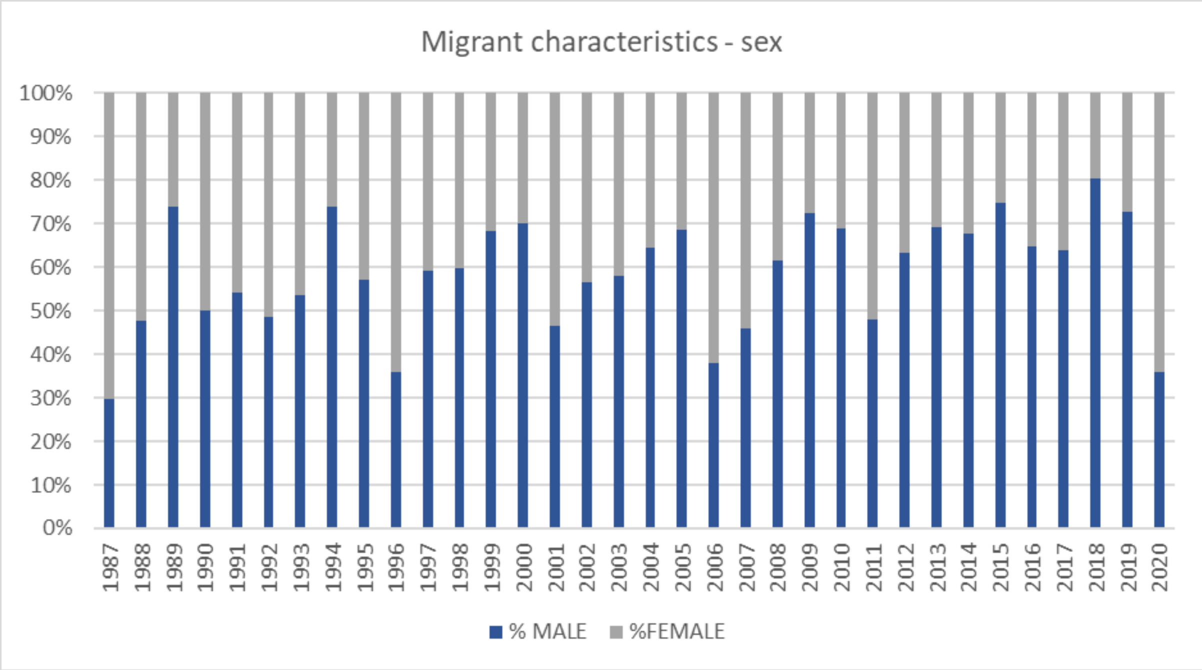
Analysing by sex also showed a small but statistically significant relationship as determined through a chi=squared test, X^2 = 34.5, p = 1.005e-05 (Table 4.2). The differences-by-sex appear to be weighted mainly by the larger number of female international and intervillage migrants. However, due to the high number of observations, these significances may be due to the size of the numbers being considered, considering the proportion of the population (the bracketed numbers), the differences appear only to be comparatively small.

Examining the reason for migration showed a clear trend, with females far more inclined to move for familial reasons and males more likely to be economic migrants, moving for work. The reason for higher female intervillage migration is most likely for marriage (Table 4.3 Number (and proportion) of migrants who move, by r), whilst the difference between male and female international in-migration is less than 1%. It is clear that the majority of migrants (both male and female) move for familial reasons, including marriage, divorce or quarrel, and because parents / relatives moved (predominantly for dependants).

Table 4.3 Number (and proportion) of migrants who move, by reason for migration, disaggregated by sex (IHS5)

Reason for migration	Number of Males (proportion of all migrants)	Number of Females (proportion of all migrants)	TOTAL Proportion of population
PARENTS MOVED	431,037 (0.3)	428,281 (0.14)	0.28
TO LIVE WITH RELATIVES	229,171 (0.16)	253,734 (0.08)	0.15
SCHOOLING	16,413 (0.01)	18,673 (0.01)	0.01
MARRIAGE	292,407 (0.2)	788,045 (0.25)	0.35
FAMILY QUARREL	5,690 (0)	11,826 (0)	0.01
DIVORCE	6,690 (0)	22,062 (0.01)	0.01
RETURN FROM WORK ELSEWHERE	31,394 (0.02)	19,400 (0.01)	0.02
JOB TRANSFER	70,009 (0.05)	19,178 (0.01)	0.03
LOOK FOR WORK	188,941 (0.13)	41,428 (0.01)	0.07
START NEW JOB OR BUSINESS	104,114 (0.07)	29,310 (0.01)	0.04
LOOKING FOR LAND TO FARM	33,709 (0.02)	29,666 (0.01)	0.02
TO RECOVER FROM ILLNESS	728 (0)	2,285 (0)	0.00
OTHER (SPEC)	20,611 (0.01)	21,042 (0.01)	0.01

Interrogating these trends further by year of migration showed that consistently through time, females are more likely to move for familial reasons and males for work (Figure 4.3). Male migration appears to show an interesting, pseudo-cyclic trend – a year-on-year rise in migration, reaching a peak and followed by a sharp dip. This may be evidence of work-related, circular migration. It is hypothesized that this is related to work availability and harvest success, with poor harvests acting as a push-factor and causing increased work-related migration (usually rural to urban) in search of casual labour. On good harvest years, such circular migration is unnecessary and so the number of work-related migrants is lower.



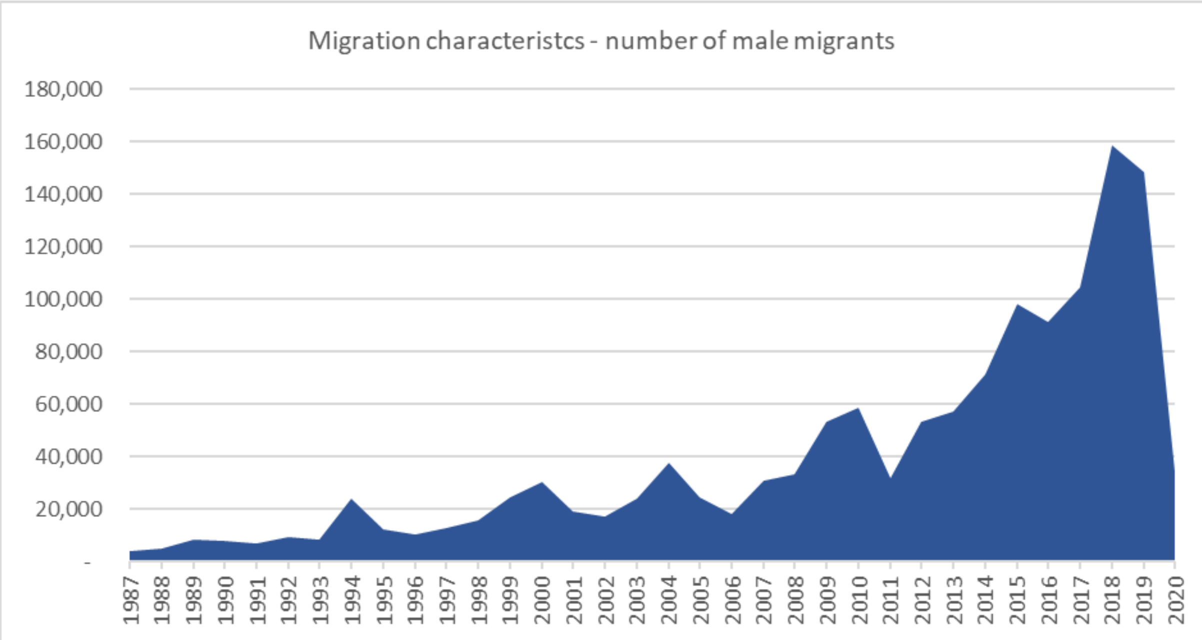


Figure 4.3 TOP – proportion of male and female (internal) migrations each year; BOTTOM – the absolute number of internal migrations undertaken by males each year. (IHS5)

Reviewing migration over time by age showed that the age profiles of migrants appears relatively stable, though with perhaps a small increase in the proportion of migrants consisting of young people (under 5s, and under 15 years) (Figure 4.4).

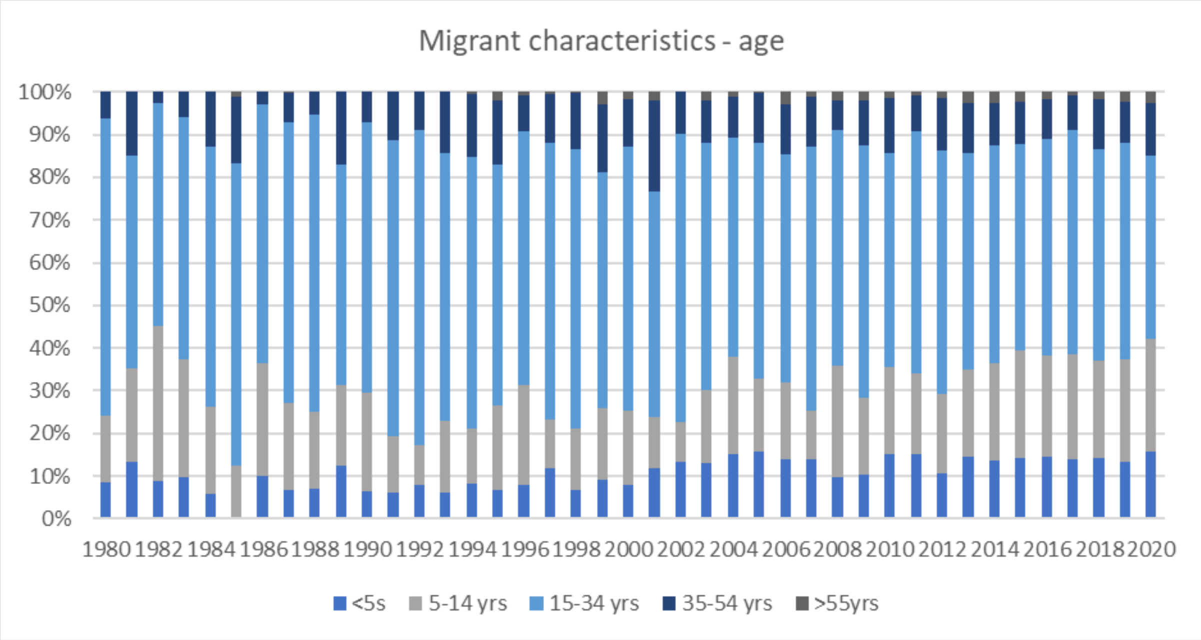


Figure 4.4 Proportion of migrants each year, by age group (IHS5)

Next, considering the hypothesis laid out in the conceptual model, that prolonged and migration are related, I reviewed the proportion of those experiencing hunger at each survey point in time, against how many are also migrants (Figure 4.5). In line with the possible increase in hunger over time (Table 3.4, chapter 3), it also appears that the proportion of those who are migrants also increases in a similar manner (noting that 15/2016 harvest was poor and resulted in increased hunger).

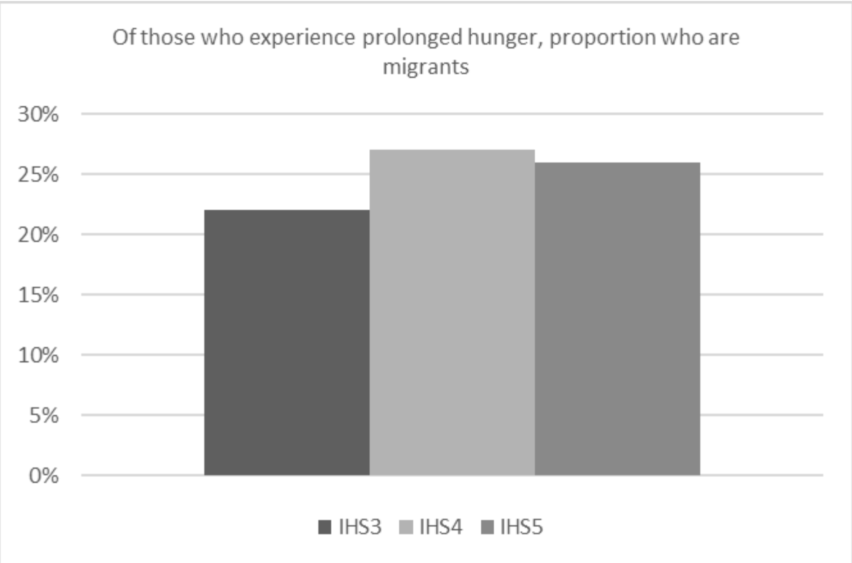
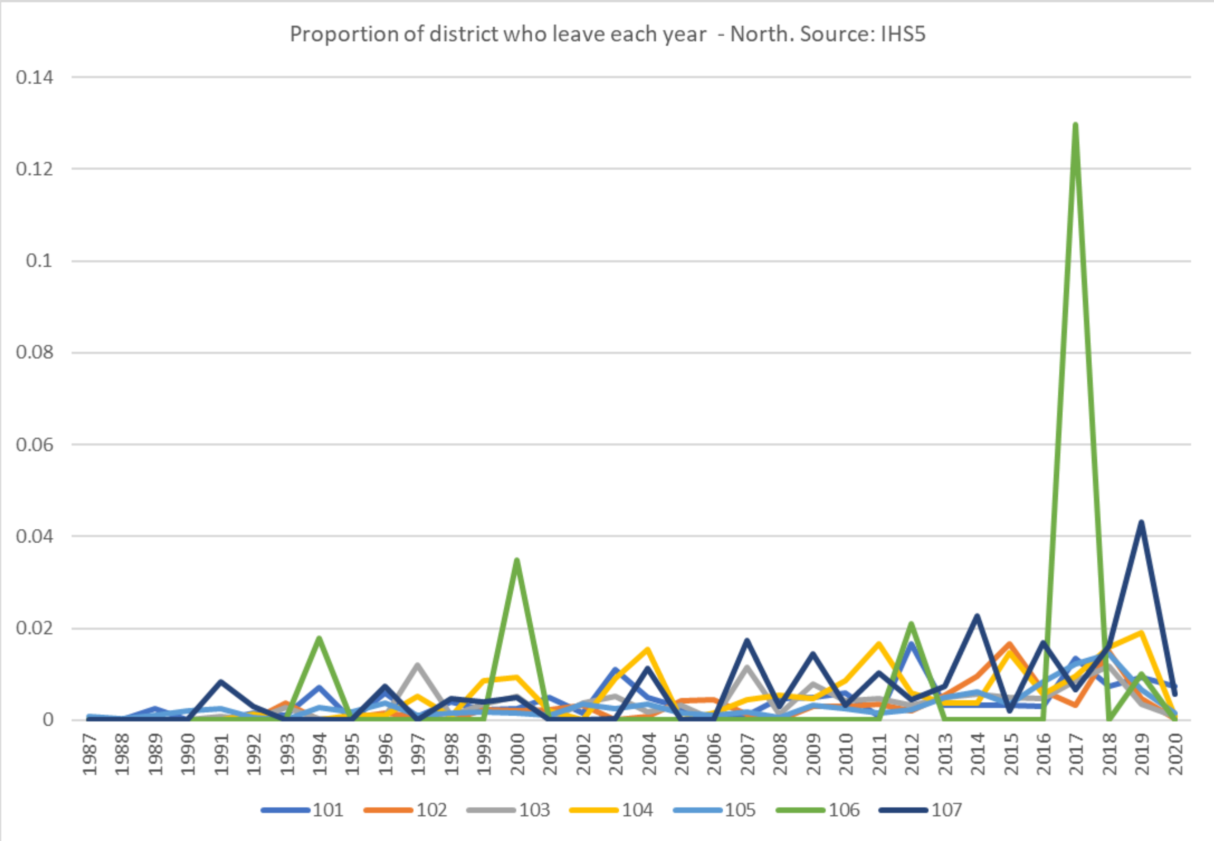
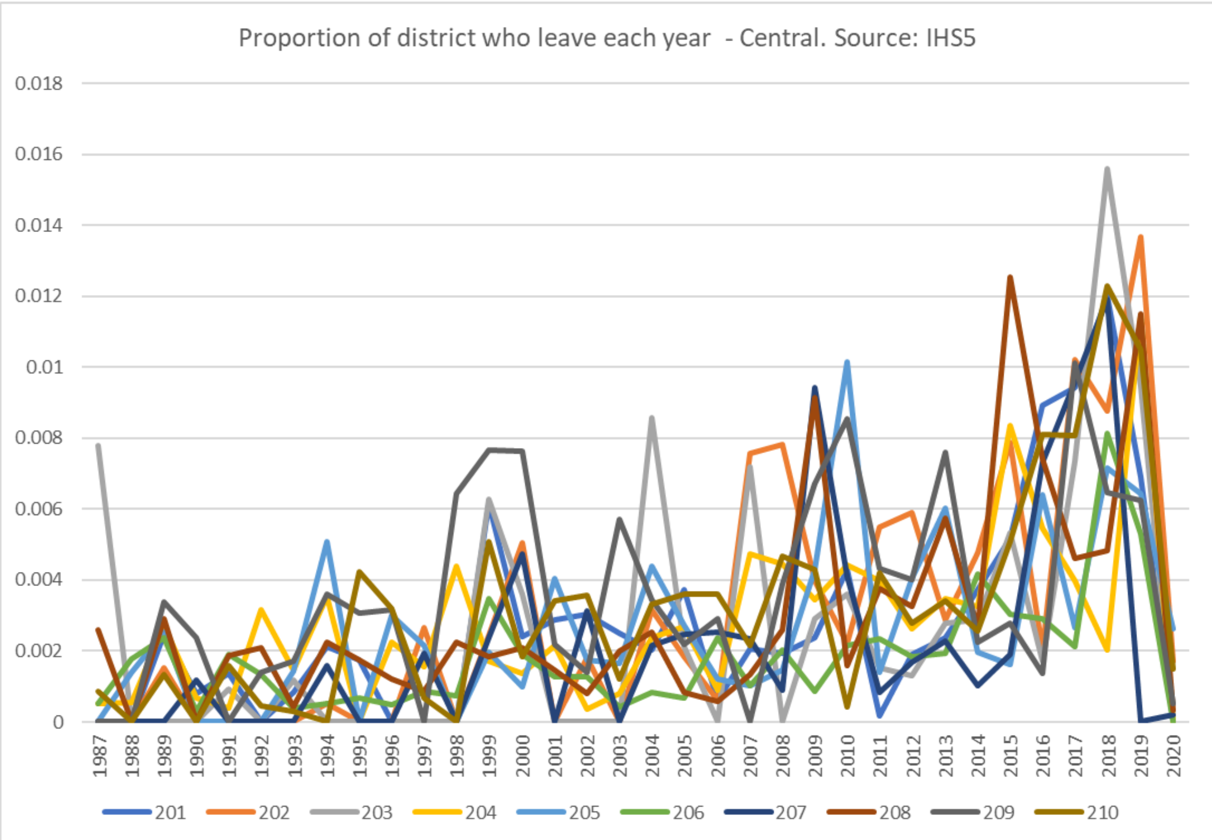


Figure 4.5 Of those in the national population who expressed they had experienced prolonged hunger at the time of interview, the proportion of those who were also migrants (had ever undertaken a migration) for IHS3 (2010/11), IHS4 (2015/16) and IHS5 (2019/20).

Finally, to support comparison of climate, crop production and resultant food security as a push-factors for out-migration, I reviewed out-migration by district of origin.


Proportion of district who leave each year - North. Source: IHS5
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
101 102 103 104 105 106 107


Proportion of district who leave each year - Central. Source: IHS5
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
201 202 203 204 205 206 207 208 209 210

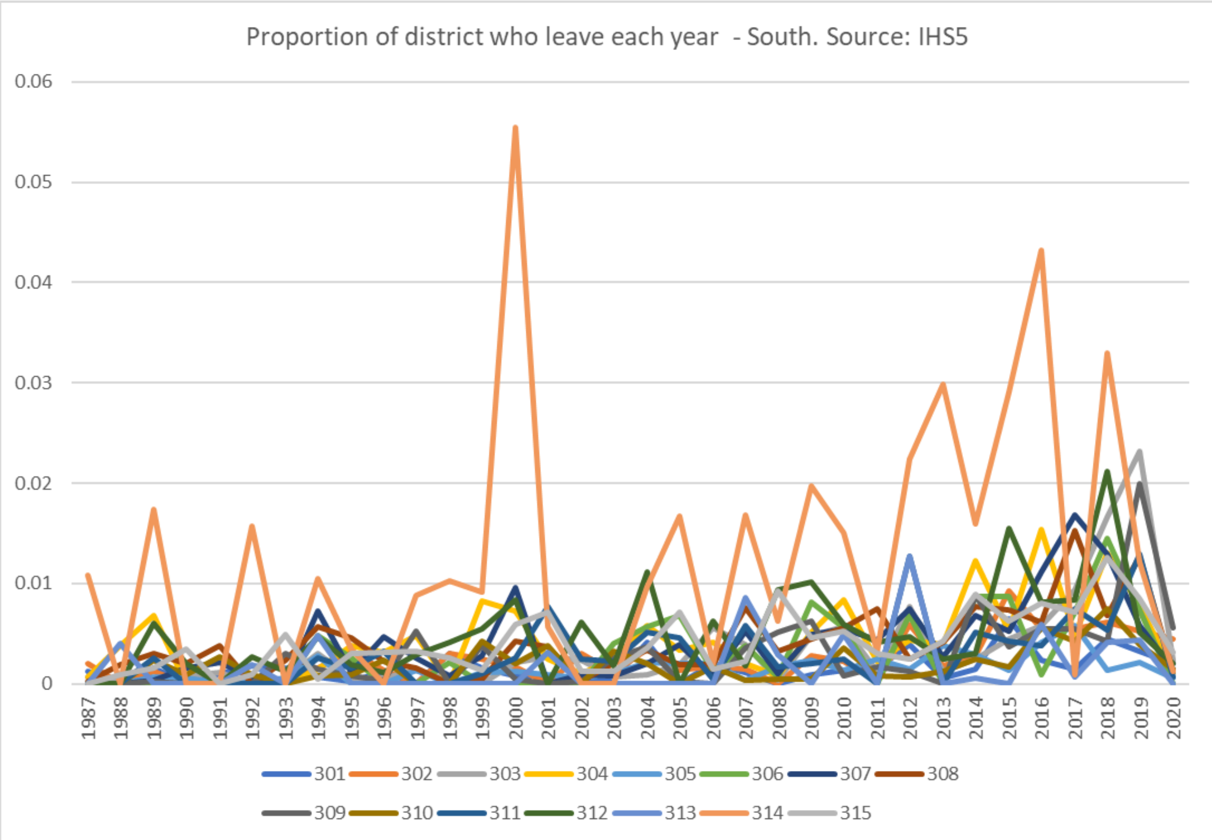


Figure 4.6 District breakdown of the proportion of the population each year, who undertake a migration journey. (IHS5)

The graphs demonstrate that, for most districts, a general trend of increasing migration, with small fluctuations can be observed. The districts that show exceptions to the general trend are the island of Likoma (district 106) and the city of Zomba (district 314). As a small island, it is unsurprising that Likoma experiences much higher and more variable migration trends than other districts. Although the trends appear extreme, since Likoma's population is only approximately 15,000 people (as of 2020), even the large spike of 13% in 2017 represents only ~1,500 individuals. Zomba City also shows a lot more variation in migration than other southern districts, possibly due to it being a much smaller (and newer) city than Blantyre. The out-migration appears to be greater in southern districts – averaging 3.7%, compared to 2.8% for central districts and 0.4% for northern districts. A time series of out-migration for each district, overlaid with climate data can be viewed in Appendix L. Visual inspections of these graphs does not identify any correlation between district out-migration and climate trends over time. However, it is known that the south is typically of lower wealth (Appendix D), and experiences lower crop production values (Table 3.3) (Chikabvumbwa et al., 2022; FEWS NET, 2016), and is also more climate sensitive, particularly to floods and other acute climate events such as cyclones (Chidanti-Malunga, 2011). Higher migration flows out of southern district may therefore be anticipated as more people move in search of work or to be with family as a coping mechanism for poverty or failed household livelihoods (including subsistence farming). Whilst climate change has not yet been observed to have impacted migration based on visual inspection, it remains hypothesized therefore that in the future, increasing frequency of extreme events such as droughts and floods, may mean that climate change exacerbates out-migration from the south of Malawi in particular.

4.4.2 The relationship between food security and migration – statistical testing

This section summarises the findings of various investigations into the relationships between food security metrics and migration metrics, disaggregated by district.

4.4.2.1 Child anthropometrics and migration status in 2016 (IHS4)

Table 4.4 presents a contingency table of household wasting presence by migration status. Visual inspections suggest a very slight relationship of lower wasting within migrant population than within the non-migrant population. This may indicate that those households who have migrated may be less impoverished (and therefore less prone to child wasting). This could support the hypothesis that only the richer households are able to engage in migration and, conversely, that poorer populations are more prone to the trapping effect which climate migration literatures suggests may be an increasing effect of climate change. There is no discernible difference in presence of severe stunting between migrant and non-migrant populations.

Sub-setting the population to consider only households with children eligible for child anthropometric measurements of food security (n = 5242 out of 12447 households), a chi-squared test was conducted for those households within each district, to determine if the proportions of observed childhood malnutrition were significantly different (α ~0.05). The results (Table 4.4) suggest no relationship between migration status and prevalence of child malnutrition across most districts. The exceptions are Dowa (204), Mchinji (207) and Chiradzulu (304) where it appears there was more severe stunting within migrant populations, and Likoma island (106), Mzuzu city (107) and rural Lilongwe (206) where there appears to be significantly more wasting within migrant populations. However, with 32 districts, setting α ~0.05 would yield 1-2 chance significant results. It might be therefore that only Mzuzu city (p=8.94e-7) that shows a strongly significant results with child wasting (setting α ~0.001).

The findings appear somewhat inconclusive, which may be attributable to the lower power of this analysis, resultant from dividing the population up into district and excluding households without eligible children. The findings regarding higher migrant child malnutrition, is also somewhat surprising, with descriptive data (Table 4.2) showing that, at the national level, a larger proportion of migrants are in the highest two wealth quintiles than non-migrants. This may support the suggestion that either only richer households can afford to migrate, or that migration is a successful adaptation measure for many, with migrants better able to economically diversify and build wealth than non-migrants. Literature suggests the first of these two scenarios - that only relatively rich households are able to afford to relocate to cities (Suckall et al., 2015). Under this framing, I would expect city migrants to exhibit lower levels of child malnutrition however, the results to do not support this. Alternatively, the relationship between migration, wealth and food security may be more complex, with nonlinear, multi-direction relationships. For example, richer households may be more able to undertake migration and may experience better food security, but low income households with low food security may also be more likely to migrate in search of economic opportunities. Households in mid-wealth brackets may be less inclined to migrate as well as be less inclined to high food security than richer households.

Table 4.4 Contingency tables (as proportions of the district population) cross-tabulating migration status and whether or not there is child wasting / stunting present in the household in 2016. Chi-squared test results for statistical difference in observed proportions.

District	**Proportion of households with migration status:**	**Proportion of households where wasting not present**	**Proportion of households where wasting present**	**X^2 value**	**p-value**	**Proportion of households where stunting not present in household**	**Proportion of household where severe stunting present**	**X^2 value**	**p-value**

101	non-migrant	21087 (0.9254)	1700 (0.0746)	0.0230	0.8836	22521 (0.9883)	266 (0.0117)	0.1984	0.6468
	migrant	2229 (0.9356)	153 (0.0644)			2382 (1)	0 (0)		
102	non-migrant	34507 (0.9654)	1238 (0.0346)	0.7047	0.4196	35331 (0.9884)	415 (0.0116)	0.2309	0.6304
	migrant	4186 (1)	0 (0)			4186 (1)	0 (0)		
103	non-migrant	26120 (0.9784)	578 (0.0216)	0.3641	0.5321	26412 (0.9893)	286 (0.0107)	0.9629	0.2575
	migrant	2335 (1)	0 (0)			2243 (0.9607)	92 (0.0393)		
104	non-migrant	19630 (0.9774)	454 (0.0226)	0.3036	0.5576	19989 (0.9953)	95 (0.0047)	0.0624	0.7699
	migrant	1750 (1)	0 (0)			1750 (1)	0 (0)		
105	non-migrant	20700 (0.9476)	1144 (0.0524)	0.2198	0.6587	21375 (0.9786)	468 (0.0214)	0.6704	0.4054
	migrant	3834 (0.9265)	304 (0.0735)			4138 (1)	0 (0)		
106	non-migrant	689 (0.9871)	9 (0.0129)	6.4361	0.0092	688 (0.9863)	10 (0.0137)	0.0753	0.7721
	migrant	47 (0.8027)	12 (0.1973)			59 (1)	0 (0)		
107	non-migrant	20273 (0.9972)	58 (0.0028)	11.22	8.938e-07	20219 (0.9945)	112 (0.0055)	0.1534	0.6535
	migrant	3772 (0.9016)	412 (0.0984)			4184 (1)	0 (0)		
201	non-migrant	79839 (0.936)	5458 (0.064)	0.9817	0.2319	84948 (0.9959)	349 (0.0041)	0.1314	0.6687
	migrant	15572 (0.9802)	314 (0.0198)			15886 (1)	0 (0)		
202	non-migrant	33359 (0.9051)	3499 (0.0949)	0.3118	0.5896	36248 (0.9835)	609 (0.0165)	0.4258	0.5236
	migrant	9483 (0.8785)	1311 (0.1215)			10461 (0.9691)	333 (0.0309)		
203	non-migrant	29610 (0.9288)	2270 (0.0712)	0.2619	0.5426	31583 (0.9907)	298 (0.0093)	0.2598	0.5884
	migrant	4765 (0.9551)	224 (0.0449)			4989 (1)	0 (0)		
204	non-migrant	68581 (0.9438)	4084 (0.0562)	0.7935	0.2971	72424 (0.9967)	241 (0.0033)	2.9066	0.0425
	migrant	16594 (0.9802)	335 (0.0198)			16355 (0.9661)	573 (0.0339)		
205	non-migrant	48268 (0.9609)	1966 (0.0391)	0.8392	0.37	49405 (0.9835)	828 (0.0165)	0.3461	0.5817
	migrant	5639 (1)	0 (0)			5639 (1)	0 (0)		
206	non-migrant	131188 (0.9276)	10245 (0.0724)	6.4892	0.0122	138544 (0.9796)	2888 (0.0204)	0.0021	0.9497
	migrant	11334 (0.775)	3291 (0.225)			14346 (0.981)	278 (0.019)		
207	non-migrant	57893 (0.9491)	3102 (0.0509)	0.5926	0.4429	60084 (0.9851)	912 (0.0149)	4.844	0.0485

	migrant	4007 (1)	0 (0)			3556 (0.8873)	452 (0.1127)		
208	non-migrant	68500 (0.9194)	6009 (0.0806)	1.3393	0.2767	581182 (1)	0 (0)	NA	NA
	migrant	6878 (1)	0 (0)			176740 (1)	0 (0)		
209	non-migrant	64117 (0.9314)	4721 (0.0686)	2.2457	0.1584	67394 (0.979)	1444 (0.021)	0.6583	0.4752
	migrant	11274 (1)	0 (0)			11274 (1)	0 (0)		
210	non-migrant	84045 (0.9612)	3389 (0.0388)	1.1354	0.3483	85375 (0.9764)	2059 (0.0236)	0.5368	0.4118
	migrant	30541 (0.9304)	2283 (0.0696)			32507 (0.9904)	317 (0.0096)		
301	non-migrant	132763 (0.9205)	11469 (0.0795)	0.0116	0.917	142336 (0.9869)	1896 (0.0131)	0.4697	0.4235
	migrant	22027 (0.9151)	2042 (0.0849)			24069 (1)	0 (0)		
302	non-migrant	85767 (0.9416)	5317 (0.0584)	0.6589	0.437	88341 (0.9699)	2744 (0.0301)	1.2744	0.2694
	migrant	3728 (1)	0 (0)			3382 (0.9072)	346 (0.0928)		
303	non-migrant	39171 (0.9347)	2737 (0.0653)	1.798	0.199	39829 (0.9504)	2078 (0.0496)	0.3435	0.4719
	migrant	6441 (1)	0 (0)			6288 (0.9763)	153 (0.0237)		
304	non-migrant	71758 (0.9328)	5172 (0.0672)	0.1638	0.7201	75946 (0.9872)	984 (0.0128)	13.131	0.0006
	migrant	5615 (0.9037)	598 (0.0963)			5147 (0.8283)	1067 (0.1717)		
305	non-migrant	27216 (0.9623)	1067 (0.0377)	0.2807	0.5841	225558 (1)	0 (0)	NA	NA
	migrant	6497 (0.9411)	407 (0.0589)			98441 (1)	0 (0)		
306	non-migrant	10691 (0.9896)	112 (0.0104)	0.2673	0.5957	68208 (1)	0 (0)	NA	NA
	migrant	3251 (0.9803)	65 (0.0197)			38028 (1)	0 (0)		
307	non-migrant	61618 (0.9192)	5417 (0.0808)	0.9006	0.3543	66078 (0.9857)	957 (0.0143)	0.1490	0.7093
	migrant	4583 (1)	0 (0)			4583 (1)	0 (0)		
308	non-migrant	52496 (0.9706)	1588 (0.0294)	0.2351	0.6099	51627 (0.9546)	2457 (0.0454)	0.0054	0.9356
	migrant	5625 (0.9493)	300 (0.0507)			5679 (0.9584)	246 (0.0416)		
309	non-migrant	44968 (0.954)	2167 (0.046)	0.6428	0.4336	46942 (0.9959)	192 (0.0041)	0.0547	0.7986
	migrant	3113 (1)	0 (0)			3113 (1)	0 (0)		
310	non-migrant	58731 (0.9126)	5621 (0.0874)	0.1378	0.7581	64077 (0.9957)	276 (0.0043)	0.0559	0.7983
	migrant	3766 (0.8823)	502 (0.1177)			4268 (1)	0 (0)		

311	non-migrant	30885 (0.8586)	5086 (0.1414)	0.3335	0.5642	35349 (0.9827)	621 (0.0173)	0.2110	0.6654
	migrant	1994 (0.9178)	179 (0.0822)			2173 (1)	0 (0)		
312	non-migrant	49352 (0.9363)	3357 (0.0637)	1.3541	0.2699	52047 (0.9874)	662 (0.0126)	0.2546	0.6594
	migrant	5361 (1)	0 (0)			5361 (1)	0 (0)		
313	non-migrant	16506 (0.9734)	452 (0.0266)	0.1536	0.6662	16853 (0.9938)	105 (0.0062)	0.3795	0.5491
	migrant	5972 (0.9824)	107 (0.0176)			6079 (1)	0 (0)		
314	non-migrant	10029 (0.9426)	611 (0.0574)	0.3125	0.5823	9806 (0.9216)	834 (0.0784)	2.5922	0.0753
	migrant	4692 (0.9633)	179 (0.0367)			4799 (0.9853)	71 (0.0147)		
315	non-migrant	69667 (0.981)	1348 (0.019)	0.5432	0.4756	70371 (0.9909)	644 (0.0091)	0.2573	0.6164
	migrant								

In summary, this child anthropometric review does not provide any evidence to support the hypothesis that food insecurity may be driving migration (particularly rural to urban migration). In the next section I analyse the relationships using other metrics of food security including the average number of meals consumed, and presence of prolonged hunger within a household, and then explore the relationships using regression modelling.

4.4.2.2 Daily meals consumed by children (5-17years) and migration status in 2016 (IHS4)

Migration status and the average number of daily meals consumed by children (aged 5–17 years) is now considered (Figure 4.7). Since the number of meals is a numeric variable with relatively low variance, the differences appear minor and it appears that the distribution of the number of meals is similar for both migrant and non-migrant households for most districts. However, chi-squared tests found statistically significant differences (α~.001) for almost all districts (Table 4.5). Further investigation is therefore conducted via regression modelling in the following section.

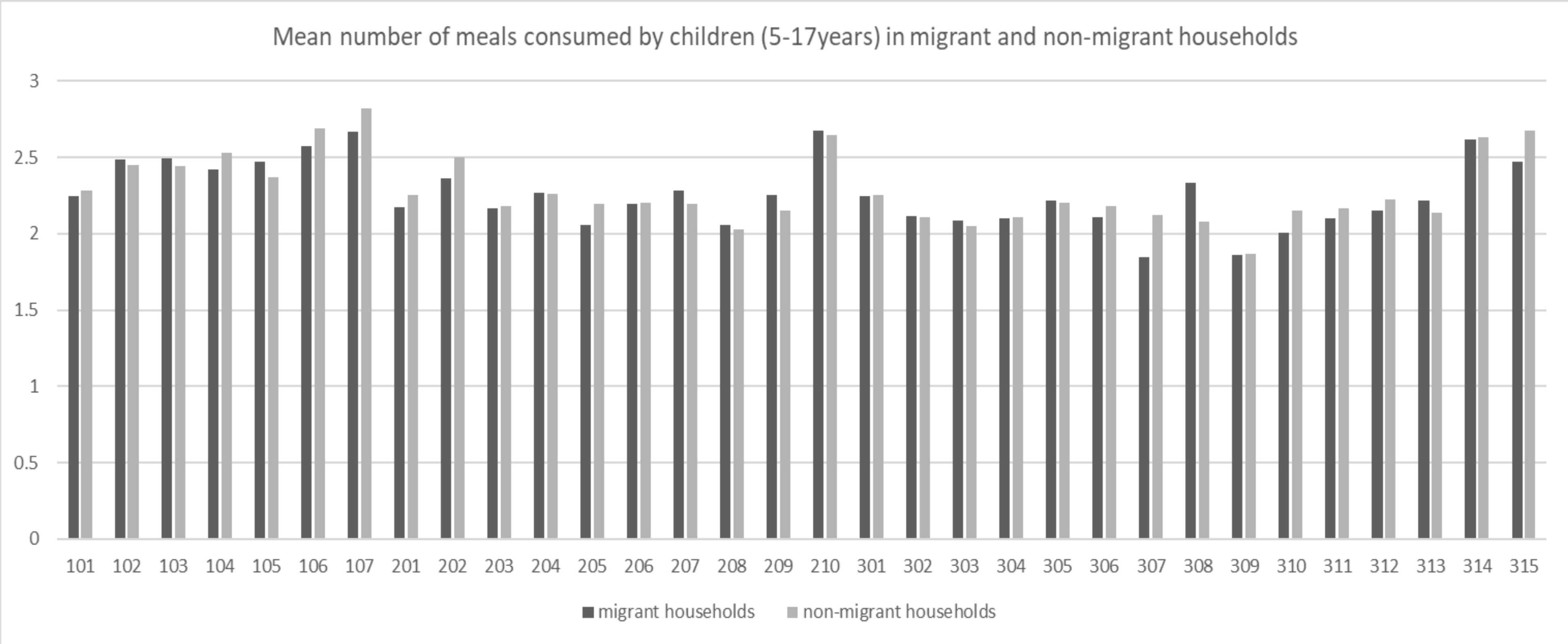


Figure 4.7 For each district, the mean number meals consumed by children (5-17years) for both migrant households, and non-migrant households. Dark grey bars represent mean number of meals consumed by migrant households. Light grey bars represent mean number of meals consumed by non-migrant households.

Based on these preliminary findings, there is some limited evidence to suggest that migration and average number of meals consumed may be related. The results do show marginal inter-district differences between food security metrics, providing useful insight for future studies when designing studies to measure food security and migration. However, it may also be possible that there are errors in the data. For example, a considerable number of 5-17 year olds reported eating zero meals per day on average (the questionnaire did not specify a time period) which may be a limitation of the data which may be further explored in future research.

Table 4.5 Chi-squared results for the differences in the average number of daily meals consumed (5-17year olds) between migrant and non-migrant populations in 2016

District	***Migrant status (0 = non-migrant, 1 = migrant)***	***Proportion of the population by average number of daily meals (5-17yrs)***					***chi-squared test***	***p-value***
		0	**1**	**2**	**3**	**4**		
101	0	0.11109	0.009208	0.372628	0.501971	0.005102	3.8694	0.3834
	1	0.124138	0.002897	0.386903	0.476844	0.009218		
102	0	0.083907	0	0.324746	0.561167	0.03018	15.8	0.003938
	1	0.104159	0	0.257409	0.578768	0.059664		
103	0	0.056791	0.005108	0.385875	0.542935	0.009291	46.102	3.818e-08
	1	0.09099	0.009202	0.234378	0.646169	0.019262		
104	0	0.070173	0.007454	0.265377	0.635342	0.021653	24.358	5.811e-05
	1	0.127757	0.001751	0.236551	0.591398	0.042542		
105	0	0.082601	0.010803	0.381207	0.504225	0.021164	35.58	1.112e-06
	1	0.099313	0.015042	0.251757	0.584775	0.049113		
106	0	0.056802	0.01487	0.122391	0.79665	0.009287	5.1858	0.3324
	1	0.100426	0.012506	0.106561	0.770211	0.010296		
107	0	0.058317	0.004133	0.076227	0.778752	0.082571	17.171	0.003319
	1	0.113933	0.000814	0.078943	0.716135	0.090175		
201	0	0.094219	0.016141	0.436777	0.44483	0.008032	19.404	0.0007977
	1	0.143823	0.01613	0.389325	0.426498	0.024224		
202	0	0.067318	0.005653	0.304439	0.607443	0.015148	15.541	0.006048
	1	0.116836	0.005426	0.297236	0.558001	0.022501		
203	0	0.13195	0.01379	0.400238	0.452856	0.001166	46.612	1.018e-08
	1	0.150079	0.038735	0.340687	0.438651	0.031848		
204	0	0.120352	0.009209	0.387682	0.45443	0.028326	43.507	8.595e-07
	1	0.176828	0.003841	0.245447	0.518592	0.055291		
205	0	0.09377	0.02797	0.468634	0.409625	0	43.496	2.867e-09
	1	0.194611	0.010926	0.335863	0.4586	0		
206	0	0.089802	0.021432	0.500776	0.37473	0.01326	33.213	4.768e-05
	1	0.136893	0.015862	0.380614	0.449611	0.01702		
207	0	0.051556	0.051987	0.557732	0.325817	0.012908	29.083	8.097e-06
	1	0.082404	0.025399	0.446735	0.419089	0.026372		

208	0	0.123731	0.020637	0.562043	0.293589	0	36.369	2.969e-07
	1	0.121887	0.069697	0.437119	0.371298	0		
209	0	0.116907	0.002887	0.489114	0.391092	0	66.168	3.196e-12
	1	0.140678	0.018875	0.300672	0.526591	0.013184		
210	0	0.0789	0.00425	0.164746	0.692501	0.059603	53.45	9.02e-09
	1	0.104284	0.000908	0.076983	0.747739	0.070086		
301	0	0.156777	0.015294	0.2526	0.567345	0.007983	16.518	0.007121
	1	0.15399	0.003346	0.306867	0.511121	0.024675		
302	0	0.061613	0.014006	0.678992	0.244142	0.001247	24.214	7.291e-05
	1	0.104542	0.003808	0.564866	0.324588	0.002196		
303	0	0.066992	0.052851	0.641893	0.237257	0.001008	26.347	1.869e-05
	1	0.089543	0.073433	0.503337	0.330871	0.002816		
304	0	0.122161	0.007499	0.51568	0.347801	0.006858	19.945	0.0006189
	1	0.153061	0.005752	0.465609	0.33799	0.037587		
305	0	0.11143	0.029661	0.413818	0.432971	0.01212	30.801	3.339e-06
	1	0.130141	0.043625	0.361205	0.406558	0.058471		
306	0	0.099032	0.035253	0.457827	0.399807	0.008081	40.815	1.089e-07
	1	0.171789	0.014141	0.377416	0.404729	0.031925		
307	0	0.075015	0.047953	0.552844	0.324188	0	48.041	1.854e-09
	1	0.199366	0.075439	0.406845	0.318351	0		
308	0	0.062668	0.058108	0.615957	0.261849	0.001419	86.862	3.829e-16
	1	0.068832	0.033209	0.404888	0.484075	0.008997		
309	0	0.050205	0.155714	0.668587	0.125494	0	14.463	0.002968
	1	0.089101	0.133287	0.602501	0.175112	0		
310	0	0.055808	0.055571	0.570923	0.314388	0.003311	62.932	2.787e-12
	1	0.162002	0.048013	0.415104	0.369578	0.005302		
311	0	0.068408	0.036476	0.56161	0.328848	0.004658	29.76	6.742e-06
	1	0.133038	0.035596	0.437547	0.387895	0.005924		
312	0	0.084093	0.002454	0.521337	0.389255	0.00286	22.676	0.0003952
	1	0.134111	0.002933	0.456644	0.387295	0.019017		
313	0	0.129365	0.021731	0.434652	0.40801	0.006242	20.85	0.001597
	1	0.138927	0.02389	0.34275	0.47238	0.022054		
314	0	0.097625	0	0.174856	0.629094	0.098425	17.62	0.001249
	1	0.130891	0.001404	0.142605	0.570985	0.154115		
315	0	0.086995	0.006361	0.123476	0.711332	0.071835	25.706	8.506e-05
	1	0.164021	0.013573	0.09339	0.647937	0.081079		

To address limited power of the district-by-district models the next step was to create regression models at the regional level, using an urban / rural division (with the four cities of Mzuzu, Lilongwe, Blantyre and Zomba categorised as ‘urban’ and all other locations categorised as ‘rural’ (Table 4.6). These models identified that in the north and south of the country, international migration has a significant, positive relationship with the number of meals consumed. It also appears that being an interdistrict migrant is positively associated with an increase in the number of meals consumed in all regions except for the four cities ('urban districts'). Intervillage migration appears also to have a positive relationship with the number of meals in the central and rural districts only.

Table 4.6 Regional linear regression models for number of daily meals consumed by children (5-17years) as predicted by migration status of the household head in 2016 (IHS4).

Spatial unit of analysis	***Reference (non-migrant)***		***Head of household is international migrant***		***Head of household is interdistrict migrant***		***Head of household is intervillage migrant***	
	Coeff (SE)	**p-value**	**Coeff (SE)**	**p-value**	**Coeff (SE)**	**p-value**	**Coeff (SE)**	**p-value**
Northern	2.14 (0.034)	$<2x10^{-16}$	0.35 (0.1)	0.00086	0.19 (0.065)	0.003	0.11 (0.069)	0.11
Central	1.92 (0.027)	$<2x10^{-16}$	0.17 (0.16)	0.3	0.36 (0.05)	1.37xe-12	0.11 (0.05)	0.021
Southern	1.93 (0.02)	$<2x10^{-16}$	0.26 (0.11)	0.022	0.19 (0.05)	0.00026	0.050 (0.042)	0.23
Urban districts	2.30 (0.08)	$<2x10^{-16}$	0.14 (0.21)	0.53	0.12 (0.09)	0.21	-0.07 (0.12)	0.59
Rural districts	1.92 (0.02)	$<2x10^{-16}$	0.22 (0.08)	0.0078	0.15 (0.04)	$5.7x10^{-5}$	0.07 (0.03)	0.022

These positive relationships support the hypothesis that wealthier families are more able to migrate and support more meals for household dependants, rather than being a migrant reduces your food security due to lack of farmland. Alternatively, this could be evidence that migration is a successful form of adaptation and that migrant families (assuming that they migrate for economic reasons) are able to improve their wealth and hence food security.

Under the hypothesis that household wealth is the causal factor impacting both migration outcome and household food security, a linear regression model (conducted nationally rather than by district or region) was constructed. The model considers the average number of daily meals consumed by children (5-17 years) as predicted by both wealth and migration type as explanatory variables (Table 4.7). These results confirm a much stronger signal and positive relationship for wealthier households (particularly in the fifth (richest) wealth quintile), than for migration status upon households upon number of meals.

Table 4.7 multi-variable linear regression analysis of the number of daily meals consumed by children predicted by household wealth and the migration status of the household head.

	Coeff (SE)	p-value
Explanatory variables		
Reference (non-migrant, wealth quintile [1])	1.74 (0.02)	$<2x10^{-16}$
Wealth quintile [2]	0.068 (0.03)	0.027
Wealth quintile [3]	0.26 (0.03)	$2.41x10^{-16}$
Wealth quintile [4]	0.34 (0.04)	$<2x10^{-16}$
Wealth quintile [5]	0.67 (0.04)	$<2x10^{-16}$
Household head international migrant	0.16 (0.08)	0.046
Household head interdistrict migrant	0.08 (0.04)	0.012
Household head intervillage migrant	0.02 (0.03)	0.398
R2	**0.05**	

Finally, to complement the above analysis was repeated using a single multivariable regression model but, instead of having a different model for each region, I create a single model and include a categorical variable for the region (northern, central (reference), southern) as well as a binary variable to identify whether the household is urban (located within one of the four cities: Mzuzu, Lilongwe, Zomba or Blantyre) or rural (Table 4.8). Under this approach, the effect of migration status is slightly reduced and becomes statistically insignificant (α~.05). The results show that households located in the north had a statistically significant positive relationship with number of meals consumed. These minor findings suggest that the general relationship between number of meals consumed by children is generally homogenous across the country and that wealth is an important factor, more so than migrations status, with little regional or urban / rural effects noted.

Table 4.8 multi-variable linear regression analysis of the number of daily meals consumed by children predicted by household wealth, migration status of the household head and accounting for the region and urban / rural determination of the district.

	Coeff (SE)	p-value
Explanatory variables		
Reference (non-migrant, wealth quintile [1], rural, central district)	1.71 (0.03)	$<2x10^{-16}$
Wealth quintile [2]	0.10 (0.03)	0.0007
Wealth quintile [3]	0.30 (0.03)	$<2x10^{-16}$
Wealth quintile [4]	0.38 (0.04)	$<2x10^{-16}$
Wealth quintile [5]	0.68 (0.04)	$<2x10^{-16}$
Household head international migrant	0.14 (0.08)	0.08

Household head interdistrict migrant	0.06 (0.03)	0.07
Household head intervillage migrant	0.03 (0.03)	0.31
Household is located in urban district	0.07 (0.05)	0.15
Household is located in northern region	0.27 (0.03)	$<2x10^{-16}$
Household is located in southern region	-0.04 (0.03)	0.14
R2	**0.05**	

4.4.2.3 Prolonged hunger and migration status in 2016 (IHS4)

4.4.2.3.1 District level overview of prolonged hunger and migration (IHS4)

Table 4.9 below shows a district overview of prolonged hunger prevalence, by migration status in 2016. There appears to be strong regional differences. In northern and central districts there appears to be a higher prevalence of prolonged hunger within non-migrant populations than within migrant populations. Overall nationally, it appears that non-migrants may suffer prolonged hunger more than migrants. However, unlike the child anthropometrics analysis, many of the differences do appear to be statistically significant. There also appears to be regional differences – with many of the southern districts, 301, 302, 303, 304, 309, 310, 311, 312, 313 exhibiting the opposite trend - more prolonged hunger within the migrant communities (though some of these results are not statistically significant). The central district of Mchinji 207 on the border with Zambia also show this relationship.

Table 4.9 Contingency table of prevalence of prolonged hunger in 2016 within migrants and non-migrants (IHS4)

District	Prolonged hunger status	proportion of non-migrants	proportion of migrants	Chi squared results
National	0	62.06%	37.94%	X-squared = 704.14, df = 1, p-value < 2.2e-16
	1	72.78%	27.22%	
101	0	49.80%	50.20%	X-squared = 19.293, df = 1, p-value = 1.632e-05
	1	61.72%	38.28%	
102	0	43.40%	56.60%	X-squared = 44.24, df = 1, p-value = 5.528e-10
	1	60.43%	39.57%	
103	0	77.26%	22.74%	X-squared = 5.7985, df = 1, p-value = 0.02347

	1	82.17%	17.83%	
104	0	64.33%	35.67%	X-squared = 7.7481, df = 1, p-value = 0.0081
	1	71.10%	28.90%	
105	0	63.23%	36.77%	X-squared = 11.688, df = 1, p-value = 0.0008212
	1	71.43%	28.57%	
106	0	75.31%	24.69%	X-squared = 3.7993, df = 1, p-value = 0.05543
	1	81.77%	18.23%	
107	0	85.37%	14.63%	X-squared = 1.7877, df = 1, p-value = 0.2641
	1	82.86%	17.14%	
201	0	41.07%	58.93%	X-squared = 0.90853, df = 1, p-value = 0.3755
	1	43.38%	56.62%	
202	0	57.26%	42.74%	X-squared = 1.3538, df = 1, p-value = 0.2566
	1	60.04%	39.96%	
203	0	60.96%	39.04%	X-squared = 3.6148, df = 1, p-value = 0.07845
	1	65.90%	34.10%	
204	0	47.14%	52.86%	X-squared = 5.0972, df = 1, p-value = 0.04056
	1	52.93%	47.07%	
205	0	40.04%	59.96%	X-squared = 36.577, df = 1, p-value = 3.164e-09
	1	57.30%	42.70%	
206	0	44.08%	55.92%	X-squared = 17.148, df = 1, p-value = 0.0001114
	1	53.51%	46.49%	
207	0	36.92%	63.08%	X-squared = 6.644, df = 1, p-value = 0.0111
	1	43.94%	56.06%	
208	0	52.09%	47.91%	X-squared = 5.8901, df = 1, p-value = 0.01981
	1	59.15%	40.85%	
209	0	56.62%	43.38%	X-squared = 12.304, df = 1, p-value = 0.0008867
	1	66.51%	33.49%	
210	0	75.68%	24.32%	X-squared = 15.229, df = 1, p-value = 0.0005753
	1	82.03%	17.97%	
301	0	39.98%	60.02%	X-squared = 0.61551, df = 1, p-value = 0.4511

	1	37.86%	62.14%	
302	0	21.60%	78.40%	X-squared = 17.153, df = 1, p-value = 0.0001151
	1	31.75%	68.25%	
303	0	32.20%	67.80%	X-squared = 4.4848, df = 1, p-value = 0.03989
	1	37.77%	62.23%	
304	0	41.98%	58.02%	X-squared = 0.033159, df = 1, p-value = 0.8609
	1	42.57%	57.43%	
305	0	49.54%	50.46%	X-squared = 11.534, df = 1, p-value = 0.0008215
	1	59.17%	40.83%	
306	0	46.69%	53.31%	X-squared = 5.6588, df = 1, p-value = 0.02068
	1	52.80%	47.20%	
307	0	39.33%	60.67%	X-squared = 21.194, df = 1, p-value = 7.972e-06
	1	54.41%	45.59%	
308	0	36.59%	63.41%	X-squared = 32.779, df = 1, p-value = 3.3e-06
	1	52.05%	47.95%	
309	0	24.58%	75.42%	X-squared = 3.0935, df = 1, p-value = 0.08297
	1	29.28%	70.72%	
310	0	17.85%	82.15%	X-squared = 15.306, df = 1, p-value = 0.000278
	1	26.49%	73.51%	
311	0	14.31%	85.69%	X-squared = 0.11677, df = 1, p-value = 0.738
	1	14.97%	85.03%	
312	0	36.22%	63.78%	X-squared = 1.0097, df = 1, p-value = 0.3469
	1	38.87%	61.13%	
313	0	42.77%	57.23%	X-squared = 0.35057, df = 1, p-value = 0.5868
	1	41.33%	58.67%	
314	0	64.68%	35.32%	X-squared = 4.8859, df = 1, p-value = 0.04987
	1	70.01%	29.99%	
315	0	84.39%	15.61%	X-squared = 8.9072, df = 1, p-value = 0.005017
	1	78.44%	21.56%	

These findings suggest that there may be a relationship between food insecurity and migration after all. However, as noted in section 4.4.2.2 above, wealth is the likely causal factor affecting both hunger and migration status.

4.4.2.3.2 District level insights investigation into reasons for hunger and reason for migration (IHS4)

This section explores if and how climate is related to food security and migration throughout Malawi. The self-reported reason for prolonged hunger is presented for migrant and non-migrant households in Table 4.10. The results show slightly higher prevalence of prolonged hunger in non-migrant populations, including for both climate-related reasons of droughts and floods though the large amount of missing data for the reasons provided are important to note.

Table 4.10 Contingency table for reason for prolonged hunger in 2016 for migrant and non-migrant households (IHS4)

Reason for hunger	Migrant households	Non-migrant households
No information provided	34.06%	23.07%
Inadequate household stocks due to drought/ poor rains	27.49%	39.27%
Inadequate household food stocks due to crop pest damage	0.15%	0.24%
Inadequate household food stocks due to small land size	3.82%	5.04%
Inadequate household food stocks due to lack of farm inputs	11.89%	15.87%
Food in the market was very expensive	16.63%	11.92%
Unable to reach the market due to high transportation costs	0.05%	0.03%
No food in the market	0.85%	0.61%
Floods/water logging	0.67%	0.87%
Other	4.40%	3.08%
Total	*100%*	*100%*

By focusing upon "Inadequate household stocks due to drought / poor rains" as the primary climate-related (and hence climate change-related) reason for hunger (flooding was excluded due to the low number of households that reported this reason), I conducted an inter-district comparison for migrant and non-migrant households within each district. It should be noted that there is very poor data for this survey, with 2398 out of 6364 migrant respondents (38%) not reporting their reason for migration (Table 4.11). As such these results were not used as the basis for any conclusions about the migration reason and climate factors. They were instead used to develop the hypotheses and ideas for future research questions.

Table 4.11 Migration status of people who reported hunger due to drought / poor rains in 2016.

District	Number of non-migrants who experienced drought-based hunger	Number of migrants who experienced drought-based hunger	non-migrant population	migrant population	proportion of the non-migrant population who experienced drought-based hunger	Proportion of the migrant population who experienced drought-based hunger
101	31,249	9,227	154,222	70,377	20.26%	13.11%
102	59,760	18,698	225,222	126,248	26.53%	14.81%
103	40,421	15,540	205,669	76,182	19.65%	20.40%
104	44,689	14,950	150,516	73,706	29.69%	20.28%
105	29,704	14,067	138,922	86,237	21.38%	16.31%
106	631	119	8,070	2,399	7.82%	4.97%
107	4,307	4,777	90,553	153,264	4.76%	3.12%
201	144,842	78,412	550,761	318,328	26.30%	24.63%
202	63,441	22,672	259,525	135,886	24.44%	16.68%
203	50,986	17,553	210,874	87,777	24.18%	20.00%
204	128,691	64,835	522,934	284,848	24.61%	22.76%
205	98,879	32,131	322,638	112,804	30.65%	28.48%
206	274,072	78,109	1,104,794	402,319	24.81%	19.41%
207	66,762	22,585	460,153	157,340	14.51%	14.35%
208	202,412	60,078	581,182	176,740	34.83%	33.99%
209	195,969	50,501	443,692	149,203	44.17%	33.85%
210	33,062	23,927	436,411	680,957	7.58%	3.51%
301	563,072	232,825	738,437	326,794	76.25%	71.25%
302	374,372	95,339	493,426	140,098	75.87%	68.05%
303	187,052	59,286	302,592	108,324	61.82%	54.73%
304	223,991	55,253	544,930	134,010	41.10%	41.23%
305	92,543	33,001	225,559	98,441	41.03%	33.52%
306	39,719	14,824	68,208	38,028	58.23%	38.98%
307	226,172	36,120	532,457	126,285	42.48%	28.60%
308	175,309	44,840	425,599	156,603	41.19%	28.63%
309	172,213	42,378	309,870	76,505	55.58%	55.39%
310	313,949	93,086	403,916	150,869	77.73%	61.70%
311	179,206	64,793	206,650	84,177	86.72%	76.97%
312	222,184	84,971	289,689	123,865	76.70%	68.60%
313	57,987	31,944	92,528	67,892	62.67%	47.05%
314	12,673	18,257	53,416	96,411	23.73%	18.94%
315	11,631	22,219	452,264	479,163	2.57%	4.64%
			Total population	*16,307,759*		

The results of Table 4.10 and Table 4.11 demonstrate that across most districts, non-migrants experienced more drought-related hunger than migrants, with the differences appearing to be slightly larger in southern districts. Only Blantyre city (315) showed an exception, with a slightly higher proportion of migrants experiencing drought-based hunger, than non-migrants, though the difference is only ~2% of the population.

The most common reason for migration is for familial reasons (Table 4.3), and this was found to also be true for those migrants who experience drought-related hunger. 37% of those migrants moving for familial reasons (whilst 3% moved for work, 2% for land, 1% for ‘other reasons’ and 57% not providing a reason for their move. Migration for food security or poverty reasons were not survey response options. So far, there is therefore no suggestion of an association between migration occurring for reasons related to poor climate and resultant poor food security.

A key limitation of this study is that the available food security metrics (prolonged hunger, child malnutrition and average number of meals) are only capable of capturing food security during the 2015-2016 rainy season and the subsequent harvest season (i.e., the 2016 calendar year), whilst migration may have occurred in previous seasons (and therefore clearly not being driven by 2016 food insecurity). The above inconclusive findings do not suggest that the decision to migrate is directly due to food security concerns, or else is heavily confounded by other, economic determinants. These may be such determinants as the ability to adapt to food insecurity in situ, for example through reliance on family for support, income or saleable household assets, as suggested within the conceptual model Figure 4.1. For example, a prevailing hypothesis is that, before taking the decision to migrate, many households find other ways to support themselves such as by selling household assets to generate income or undertake seasonal migration (undetected empirically) in search of *ganyu* (casual labour). Such precautions can prove successful but may also render a household more vulnerable to future shocks (Lewin et al., 2012). Households may also encourage younger members (non-household heads) to migrate to support household income or alleviate the number of dependents. For example, some studies have found relationships between marriage (usually of a household’s female children) increased following drought (Findley, 1994). Other studies find that young men are more likely to move to the cities in search of work (Becerra-Valbuena & Millock, 2021; Henry et al., 2004).

It is also possible that food security is a driver of migration but that it was not detected in the above explorations due to poor data, as well as a lack of inclusion of other, economic pathways.

4.4.2.3.3 District level investigation of prolonged hunger and migration over time (IHS5)

Based on the above results, it appears that prolonged hunger is the most promising food security metric when not considering reason for hunger. Therefore, I next considered that food security (as measured by prolonged hunger) and migration could be linked but that a time lag may be present. Under this hypothesis, food insecurity may drive migration in search of alternative income, and it may be expected that as prevalence of prolonged hunger increases, migration in the following year(s) may increase. I tentatively conceptualised prolonged hunger as a proxy measure of general ‘liveability’ of a situation, or, in other words, a high-level metric to describe the overall vulnerability profile (Figure 2.3). Under this framing it is hypothesised that when the vulnerability is high (as evidenced by a significant prevalence of prolonged hunger), then people may be compelled to undertake a migration. Alternatively, under the trapping hypothesis, increased prevalence of prolonged hunger, associated with increasing poverty, may be reflected in reduced migration in the subsequent years since hunger was experienced.

Consulting the IHPS longitudinal dataset, in line with previous findings from 2016, Table 4.12 demonstrates that there is significantly more prolonged hunger within non-migrant populations at each point in time, than in migrant populations. In both populations (migrant and non-migrant) we also continue to see a trend of increasing hunger, with 2016 being a year of particularly high prolonged hunger prevalence. However, it is noted that the proportion of migrants and non-migrants who experienced prolonged hunger in 2016 was far lower than the findings of the full survey (Table 4.9). It is not clear why this difference is observed since both the panel and full survey are nationally representative and were expected to closely align. It is presumed therefore to be due to data limitations and warrants further investigation.

Nevertheless, since the general trends appear consistent between panel and full survey, there appears a reasonable trend across the different years included within the panel survey, and because of value of a temporal analysis which the panel survey enables, I proceeded to analyse the panel data.

Table 4.12 Total proportion of the population where prolonged hunger is present, regardless of time of migration (IHPS) or reason for hunger

	Migrants	Non-migrants
2010	2.86%	19.53%
2013	4.69%	29.50%
2016	10.74%	54.71%
2019	10.29%	49.65%

Figure 4.8 presents a district level insight into the prevalence of prolonged hunger (in 2020) within migrant households (residing in that district) and non-migrant households within that district. In general, prevalence of prolonged hunger appears broadly similar across migrant and non-migrant populations across the districts. In general, non-migrants appear to have a slightly higher prevalence of prolonged hunger than migrant populations. Southern districts (districts 301-315), except for the two cities, Zomba (314) and Blantyre (315), show higher levels of hunger for both migrant and non-migrant households than the richer northern districts. In the north, districts Nkhatabay (103) and Likoma (106) appear to have slightly lower hunger levels compared to other districts across both populations. Within the central region, Lilongwe City (210), as well as Dedza (208) and Ntcheu (209) demonstrates the opposite trend to other districts, with what appears to be quite significantly lower levels of hunger in the non-migrant communities than in migrants. In general, there appears to be less prolonged hunger in the four cities (Mzuzu – 107, Lilongwe – 210, Zomba – 314, Blantyre – 315). Unlike most other districts, city migrant having higher prevalence of hunger than non-migrant populations.

Unsurprisingly, urban areas are connected to a transformation of food systems and of food security of urbanites (de Bruin et al., 2021) and these findings of lower levels of hunger in the four cities is consistent with literature. Mkusa and Hendriks (2021) identified lower levels of food insecurity in each of the four cities than in rural districts. This may not be surprising, with a larger proportion of the labour force in cities engaging in employment other than agriculture and associated higher income levels and increased food security (Mkusa & Hendriks, 2021). However, cities (particularly Lilongwe and Blantyre) also have a high proportion of inhabitants living in informal settlements, associated with lower quality of housing and WaSH (Water, Sanitation and Hygiene) which could also be signals of lower food security, particularly of food stability and utility metrics (which are outside the scope of this study). Since urban migrants appear to have consistently higher prolonged hunger than their rural counterparts, it may be the case that urban migrants make up a higher proportion of these informal settlements and urban poor. The stark difference in the hunger of rural versus urban migrants may suggest that the destination has a significant impact on the economic experience of the migrants, with urban migrants finding themselves in increased food insecurity. Given the observed prolonged hunger of urban migrants, the ongoing trend of urbanisation, and the hypothesized impact of climate change on increasing adaptive (urban) migration, this hypothesis warrants further investigation into the reasons for the divergence of food security in urban and rural migrants such as job opportunities, remittance and social networks, housing and WaSH and governmental support programmes, local attitudes towards urban migrants and urban migrant attitudes and aspirations. It should be further investigated whether it is the urban migration that leads to reduced food security, or whether it is the already food insecure households who are more likely to undertake a migration to a city, and whether and why such migrations fail to achieve the desired outcome of improved livelihood and improved food security (at least in the short term).

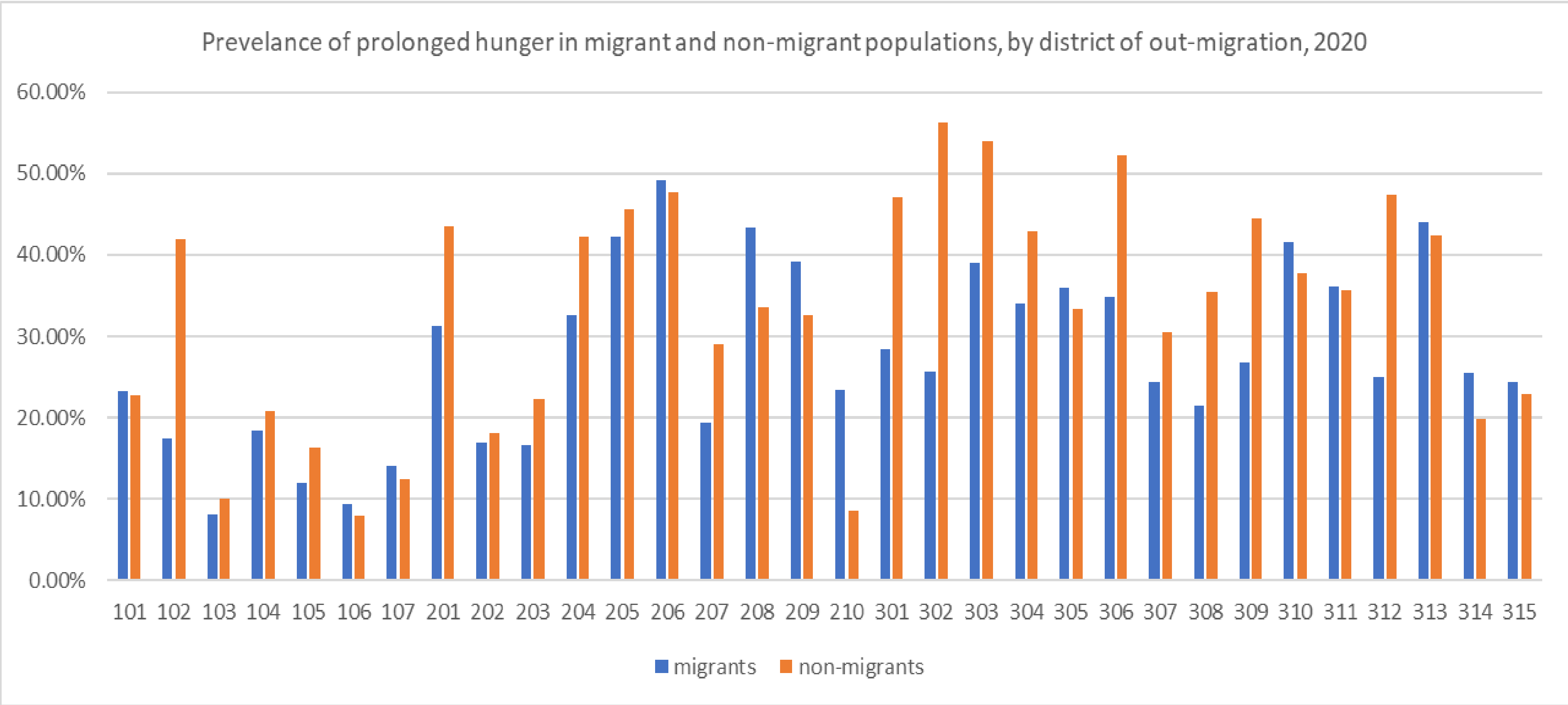


Figure 4.8 proportion of migrants that experience prolonged hunger in 2020, by district of origin (district of out-migration) (IHS5)

4.4.2.3.4 Using the IHPS to explore migration and prolonged hunger

To investigate prolonged hunger as a driver of a subsequent migration event in more detail, I consulted the IHPS longitudinal study to build a picture of prolonged hunger in the same household, at four different time points (2010, 2013, 2016 and 2019), in conjuncture with each participants migration history between survey cross-sections[6].

Firstly, the frequency of migration journeys and prolonged hunger prevalence were summarised and a chi-squared tests conducted, identifying strongly significant relationships (Table 4.13).

Table 4.13 Chi-squared results for prevalence of prolonged hunger by period of migration

Survey year	Prolonged hunger status 0 = not present 1 = present	Period of migration						X^2 value	p value
		[<2010]	[2007-2009]	[2010-2013]	[2013-2016]	[2016-2019]	did not migrate		
2010	**0**	945,978 (0.0676)	310,729 (0.0222)	357,500 (0.0256)	437,373 (0.0313)	1,090,235 (0.078)	10,841,904 (0.7753)	165.26	< 2.2e-16
	1	173,086 (0.0429)	68,795 (0.0171)	47,021 (0.0117)	99,848 (0.0247)	127,054 (0.0315)	3,518,925 (0.8722)		
2013	**0**	848,582 (0.0716)	298,999 (0.0252)	292,375 (0.0247)	431,807 (0.0364)	940,893 (0.0793)	9,045,353 (0.7628)	210.36	< 2.2e-16
	1	270,482 (0.0439)	80,525 (0.0131)	112,146 (0.0182)	105,413 (0.0171)	276,396 (0.0449)	5,315,477 (0.8628)		
2016	**0**	483,350 (0.0777)	179,660 (0.0289)	205,493 (0.033)	272,733 (0.0438)	581,039 (0.0933)	4,502,274 (0.7233)	270.47	< 2.2e-16
	1	635,713 (0.0539)	199,864 (0.0169)	199,028 (0.0169)	264,488 (0.0224)	636,250 (0.0539)	9,858,556 (0.8359)		
2019	**0**	508,821 (0.0705)	198,539 (0.0275)	240,648 (0.0333)	270,321 (0.0374)	584,699 (0.081)	5,415,434 (0.7502)	154.28	4.76E-11
	1	610,243 (0.0565)	180,985 (0.0168)	163,873 (0.0152)	266,900 (0.0247)	632,590 (0.0586)	8,945,396 (0.8283)		

Secondly, a temporal view of the reason for moving is considered. As identified within previous sections, the largest reason for moving, consistently across all years, was for family – including marriage, divorce, family quarrels, to live with relatives or because parents moved. Indeed, the trend in moving for familial reasons (particularly marriage and to be with relatives) appears to be increasing (Figure 4.9). The conceptual model did not highlight familial reasons as a major pathway through

[6] It is possible that the migration history is not complete if multiple migrations occur in between survey points, which are three-yearly. However, it is thought (as indicated by the cyclic nature of migration in Figure 4.3) that cyclic migration does not occur with higher frequency (i.e. multiple times in a three year period) and, as such, that the three-year cross-sections are likely to capture the vast majority of migrations that occur between 2010 and 2020.

which climate change would impact migration. However, there is some evidence that in certain contexts within Malawi, droughts may increase the odds of marriage in young women, with marriage used as a household coping strategy to the economic shock of low crop production during severe droughts (Andriano and Behrman, 2020; Molotsky, 2019; Caruso et al., 2022).

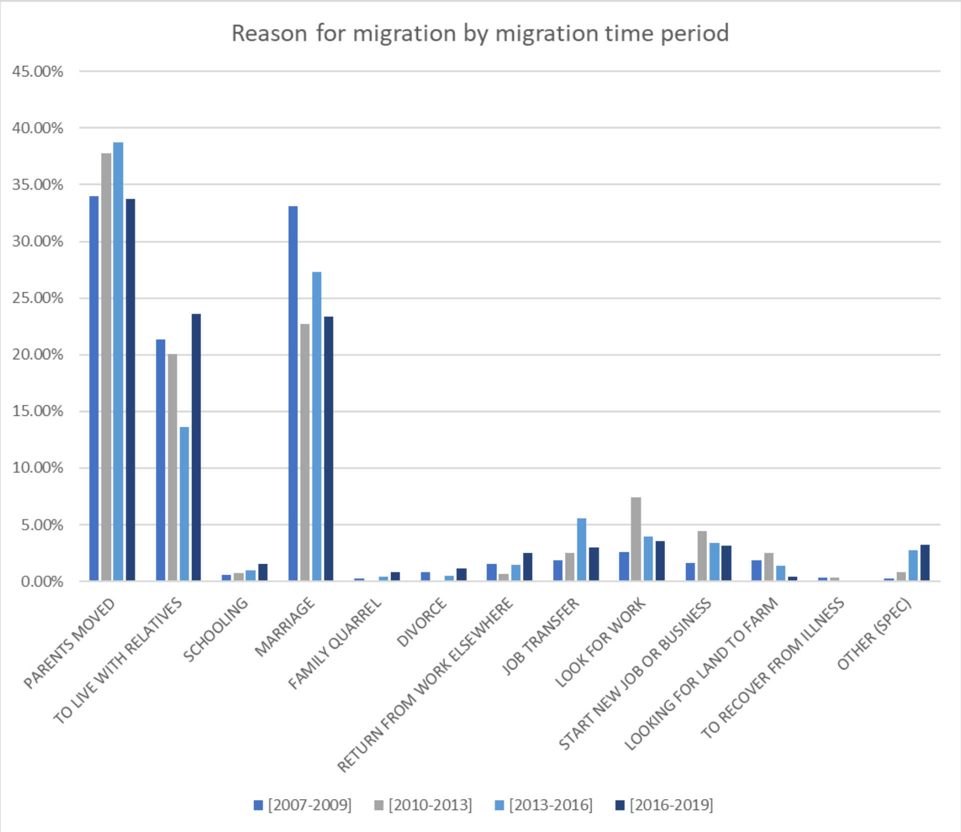


Figure 4.9 Proportion of migrants by reason for migration. TOP reason for moving across all reasons, BOTTOM a focus on proportion of migrations for reasons related to work (return from work, job transfer, looking for work or to start a new job or business) or to land (looking for land to farm).

Next, the IHPS data was used to construct a mixed effects regression analysis (allowing correlation between random effects for repeat measurements per participant) to explore how age, sex and prolonged hunger at each of the first three survey point (2010, 2013, 2016) might affect the odds of migrating during the subsequent period (2010-2013, 2013-2016, 2016-2019 respectively). Wealth quintile of the household was also included however this was assumed to be static in time and only the wealth quintile of the household as measured in 2010 is included and assumed to remain constant at all other survey points. The results are shown in Table 4.14.

Table 4.14 multi-level logistic regression model for whether a range of predictor values including age, sex and prolonged hunger status act as drivers of migration in the subsequent period, as a response. IHPS

Fixed effect variable	Logit [log odds] coeff	Odds ratio (exp[coeff])	standard error	z-value	p-value
Reference Group (2010, prolonger hungry absent, male, young person (<15 yrs), poorest wealth quintile)	-20.6800	0.0000	2.29E-05	-902864	<2e-16
Prolonged hunger present that year	1.1250	3.0802	2.29E-05	49125.2	<2e-16
Sex (female)	-3.2140	0.0402	2.29E-05	-140296	<2e-16
Age	0.0120	1.0121	2.29E-05	525.4	<2e-16
Random variable	**Variance**	**Correlation**			
Intercept (Person)	1720.1				
Year	365.5	-0.94			
Number of observations	37440				
Groups (number of people)	14057				

Prolonged hunger appears to have a significant association with subsequent migration, with an OR of 3.08 signifying that for those who experience prolonged hunger, the odds of migrating in the subsequent period is three times greater than those who did not experience prolonged hunger. Being female carries a much lower migration odds than for men whilst for each additional year of age, migration odds a very slightly increased (roughly 1%).

Wealth quintile was omitted from the final model. Whilst it is well acknowledged that wealth is an important variable for consideration, when included in the model, the wealth quintile variable resulted in spurious outcomes. The wealth quintile variable used was based on a Principle Component Analysis (PCA) for information regarding goods ownership as reported in IHS3. (Refer to Chapter 3 for further details on construction of wealth quintiles). It was assumed that wealth quintile, as a relative coarse measure of wealth, was static through time and therefore wealth quintile of panel participants during 2013, 2016 and 2019 follow-ups, was inherited. However, based on the nonsensical results when wealth quintile was added into the model, this assumption may not be valid. Future studies should look to include time-dependent wealth quintile, or alternative measures of wealth (such as wealth deciles) within future studies. This would support the hypothesis that migration can support diversification, remittance streams and positive adaptation, or alternatively may support the hypothesis that a lack of migration (for example due to the trapping effect) may indeed worsen poverty traps and result in wealth stagnation or decline. Under either scenario, wealth should be more closely considered in future studies.

4.4.3 The impacts of climate change on internal migration

The final aspect of this analysis was to explore any direct links that may exist between climate change and out-migration, bypassing the hypothesized intermediate step of affected food security. The observed trends in migration (in search of land or work) does not appear to follow a similar trend in climate variables. Indeed, the majority of migrants appear to move for familial reasons (Table 4.3) which is not hypothesised to be affected by climate change according to the conceptual model. To explore further if there could be any relationship between migration and climate, I explored out-migration at the district level, considering district climate factors. Within Figure 4.3, a cyclic trend in male migration was observed, which was presumed to reflect circular, economic migration. If so, it would be expect that economic migration is related to crop production (and to favourability of climate conditions). This was examined visually within Figure 4.10 which plots proportion of population who migrated in search of work or land (dominated by males but not exclusively) against national crop production (FAOSTAT, 2023) and national rainfall data.

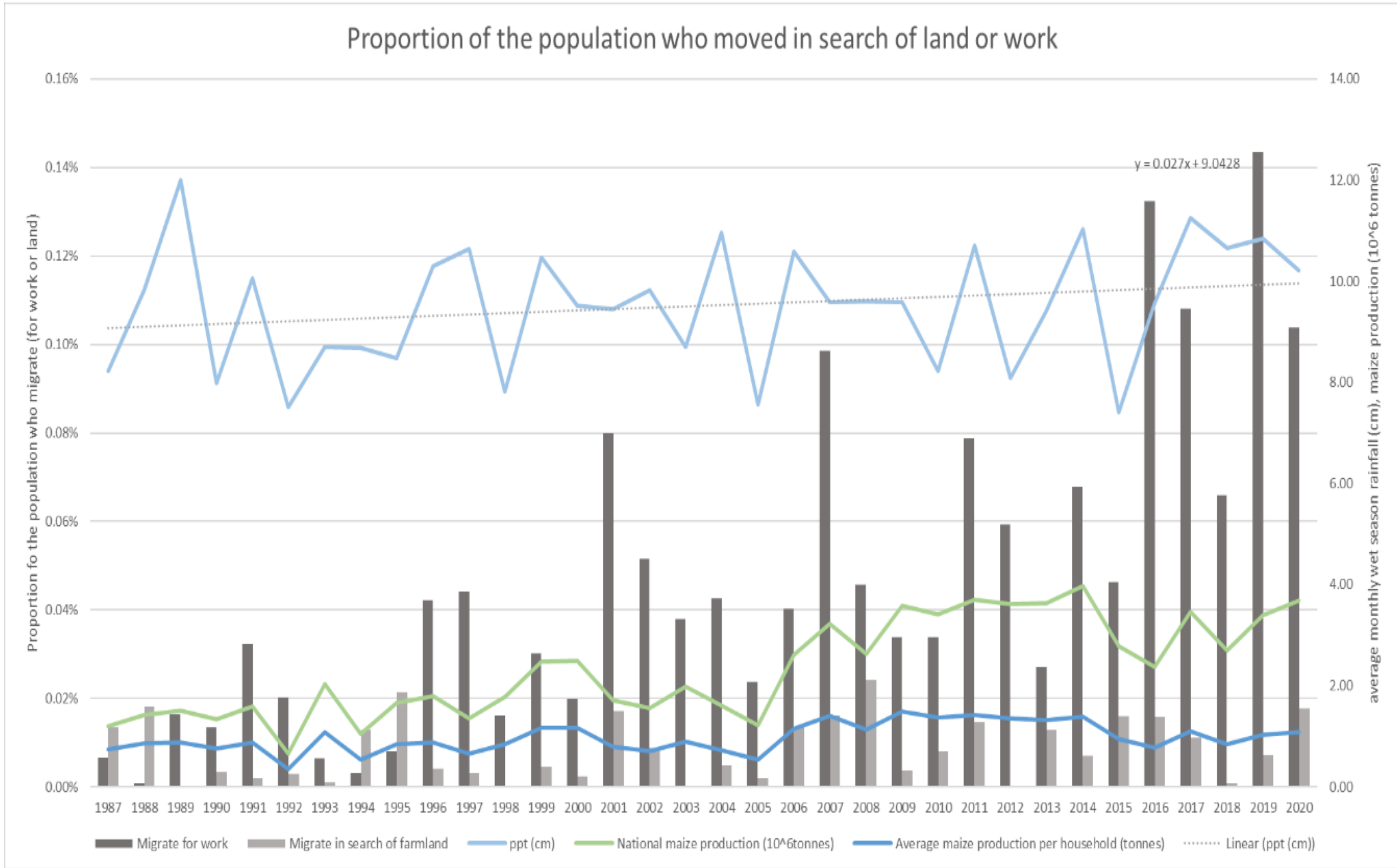


Figure 4.10 Annual timeseries of crop, migration and climate 1987-2020. Green line represents national crop production (10^6 tonnes) and the deep blue line represents average household crop production (tonnes). Pale blue line represents the average monthly rainfall of the wet season for each year and, to demonstrate climate change, the trend line (ordinary least squares regression) is also added. The bars represent the proportion of the population who undertook a migration each year, with deep grey bars representing migration for work, and pale grey representing migration in search of farmland. (IHS5)

Figure 4.10 shows a general increasing trend in migration for work-related reasons over the last three decades, with a somewhat cyclic trend every few years. Notable troughs (reductions in the growth trend) occur in migration 1993, 1998, 2005, 2009-10, and 2013 whilst notable spikes are in 1991, 2001, 2007 and 2016. Migration in search of land shows a less clear trend with the proportion of the population moving staying relatively constant at between 0% and 0.02%. Although these are only national trends which, through a high level of spatial averaging may hide true relationships, Figure 4.10 does appear to show a potential small relationship between years of very poor rainfall and national crop production (such as in the years 1992, 2005, 2016). However, crop production and rainfall do not have high correlation (Spearman's rank coefficient of 0.2975) and the complex nature of this relationship has been further examined in the previous chapter. It appears that the poor crop years of 1992, 1994, 1997, (2002), 2005, (2008), 2016, and 2018 matches up only slightly with the peak economic migration, which occurred in years of 1991, 1997, 2001, 2007, 2011, 2014, 2016, 2019. This appears to show some correlation, with peak net migration occurring in the same year as poor harvests. Crop production and the number of economic migrants shows a Spearman's rank coefficient value of 0.701. Whilst growing crop production is likely driven by a growing population, this does not also explain why the proportion of population who are migrants is increasing. However, if the observed relationship were to be causal, this may be evidence that crop production is a driving factor of circular, (economic) migration. Interestingly, the positive direction of this relationship is counter to the original hypothesis (that it is poor harvests that drive migration). Therefore an alternative may be that strong crop production drives migration through increased means, or due to necessity to sell surplus or engage in further business.

Next, at the district level I plotted out-migration by district and overlay this with climate data (see figures in Appendix L). The graphs show no discernible relationship: out-migration that occurs each year by district of origin does not appear to coincide with particular troughs in the rainfall (as expected if poor rainfall were to drive out-migration). This is in line with the above findings and as discussed in depth in Chapter 3, that climate variables (using rainfall as a single, primary variable) and crop production do not appear to have a strong relationship and as such are not expected to drive out-migration. It may be that, as observed in Chapter 3, climate change in Malawi is currently manifesting as very small changes in average monthly rainfall during wet seasons and as such any relationship between small, slow-onset changes is undetectable.

It is still theoretically plausible that gradual changes in climate are and will continue to have impacts upon crop production and hence on livelihood diversification and rural to urban migration, this has so far been undetected. Future studies may benefit from consulting different, acute climate variables such as onset of rainy season, duration of rainy season or the occurrence and severity of extreme events such as droughts, floods and typhoons.

4.4.3.1 The impacts of future climate change (beyond 2020)

Due to the low quality of data and limited findings, the model results of this study have not been extrapolated to explore the impacts of future climate change upon migration through either direct or indirect pathways (as mediated by food security and household economic circumstances). However, the findings can be used to induce new hypotheses about the future of migration in Malawi, considering both climate change projections as well as other development pathways that Malawi is pursuing.

As outlined in Chapter 3, the bi-seasonal nature of Malawi's climate, with around 95% of the annual rainfall occurring during the rainy season (November to April) (FEWS NET, 2016), makes projections of rainfall highly uncertain with the latest results from the Coupled Model Intercomparison Project sixth run (CMIP6) suggest little overall change in annual rainfall (Arias et al., 2021). Given that longer term rainfall patterns have been suggested to have a negative relationship with migration for urban areas and the south of the country, this supports a hypothesis that any future changes in rainfall patterns may have an impact upon migration patterns. In particular, if in the longer-term, the rainy season becomes drier it is thought that this could be a contributing factor to increased rural to urban migration. Future research may benefit from improved and localised (district or regional level) rainfall projections trends in order to support further investigation into these relationships and to improve an understanding of if and how climate change is affecting migration.

4.4.4 Summary of findings

The cumulative result of these findings is that the relationship between food security and migration status is very difficult to discern and there is inconsistency across the different metrics. Prolonged hunger showed a statistically significant relationship with migration outcomes with high district differences. In general, non-migrants appear to have a higher prevalence of prolonged hunger than migrant populations. A breakdown by district showed a large degree of district variation, with many districts in the north and central region showing statistically higher prolonged hunger in non-migrant households, whilst many southern districts showed higher rates of hunger in migrant households. Results of the longitudinal study suggest that experiencing prolonged hunger makes odds of migrating roughly three times higher in the subsequent three-year period. Child anthropometric analysis did not show any conclusive results, possibly due to the low power of the study as compared to other metrics of food security. Considering the number of meals consumed as explained by migration status, there was some evidence that migrant children (or the children of migrants) in general consume more meals. Rural households demonstrated a positive association with the number of meals consumed with the effect being larger for international and interdistrict migrants than intervillage migrants.

Reasons for these discrepancies could include poor data quality, with large amounts of missing data for key variables. It is also likely that the complexity and multi-directional nature of the relationship between migration and food security obfuscates any overall trends.

Finally, considering the direct impacts of climate change upon migration, at both the national and district level, no discernible trend was uncovered.

4.5 CONCLUSION

Overall, the findings of this chapter are ambiguous. There is some, limited evidence to suggest that migrants may be general richer, and more food secure than non-migrants. Explanation for this may be that only those with means are more likely to undertake a migration. Conversely, those without means and who suffer poverty and food insecurity, may be less likely to migrate. This could preliminarily suggest that the trapping effect is a possible emerging trend within Malawi. It may also suggest that migration can work as a positive adaptive measure to achieve better food security, presumably through improved livelihoods and wealth generation. For example, the longitudinal study tentatively found that that experiencing prolonged hunger increases the odds of undertaking a migration. If such migrations then successfully resulted in increased food security, then this would help explain why migrant populations are more food secure overall. However, this conclusion should not be overstated due to various other factors not considered within this study and due to data limitations. Even if a strong relationship between migration and improved future food security were evidenced, as migration continues to increase (in the accelerating rates observed), in the future this positive relationship could flatten and even reverse, as competition for jobs (particularly casual labour in urban areas) may increase and therefore act to reduce the positive effect of migrating upon food security. Trapping remains under researched within climate migration literature and the findings of this chapter advocate for more consideration of such a relationship between climate change and mobility. This is particularly the case for the low-income context of Malawi.

A key limitation of this study is the perennial challenge of data quality. Additional studies will benefit from data imputation through predictive modelling or else through additional data collection for example through retrospective migration surveys. When undertaking additional data collection, survey data designers and collection officers may benefit by focusing on reason for migration, paying particular attention to climate-related considerations, as well as a more detailed migration history (so that more complex trends including various modes of circular migration and district net-migration (including both in-migration and out-migration) can be better analysed. Alternative data collection and variables could be explored to explore different measures of food security, particularly the number of meals consumed and the hunger experienced by households, and with improved knowledge of migration history. Surveillance sites, such as the ongoing Karonga Health and Demographic Surveillance System (Crampin et al., 2012) could support such research questions but limits the geographical range of insight that can be achieved. As climate change continues to affect country wide conditions and crop production (Kachulu, 2018; Stevens & Madani, 2016), additional geographic range will become necessary, particularly in light of the interdistrict differences in food security. Future work may also benefit from addressing a wider array of household and community level determinants identified within the conceptual model (Figure 4.1) through additional data sources such as inclusion in training and awareness of climate change to farmers and local communities as well as other educational, community interventions, credit clubs or agricultural cooperatives (Fisher & Lewin, 2013). Future research may look to build upon the models created with more detailed measures of factors such as wealth and acute climate shocks. Alternative, more detailed measures of wealth will be important for inclusion within models, as it has been identified that wealth may be different prior and post migration and is an important determinant of both migration and food security. Furthermore, migration may be an important determinant of wealth, if the migration is successful in creating new economic opportunities and subsequent wealth generation. This bidirectional and nonlinear relationship should be explored in more detail. Whilst overall climate trends in rainfall and temperature appear to show little relationship, acute shocks, particularly drought and flood events should be considered as these are likely to impact migration more directly based on literature and the reported reason for migration available within the IHS. Country wide, spatially detailed flood and drought databases are sparse and so developing such datasets may provide value for future migration studies. Using any insights from such modelling, future drought and flood prone areas may be identified and specific intervention measures could be prepared accordingly.

Findings from this study are far from conclusive proof of a causal link between migration and food security. However, there is some evidence to suggest inter-district variation, as well as the existence of links between food security, migration, wealth, and urbanisation (Parrish et al., 2020). As urbanisation is also highly localised, future food security and future migration studies should continue to pursue a cross-country view, adopting a higher spatial granularity (such as inter-regional, inter-district or inter-village). Specific to Malawi, future studies should also consider exploring rural to rural and rural to urban patterns, particularly for Malawi’s four cities and emerging large urban centres, which may look different and evolve differently as Malawi continues to urbanise.

Future research questions may also consider how familial relationships may be impacted by climate change, and as such impact upon migration. This study found that moving for family (marriage, divorce and to be with relatives) is the predominant driver of migration and as such, I now put forth the hypothesis that, if climate change has indirect impacts upon how family members interact with each other, for example through farm labour demand and supply, remittance networks or marriage and divorce rates, then these links may be particularly impactful in Malawi. For example, poor crop production could increase the reliance of urban migrants upon reverse remittances (Suckall et al., 2015), affect marriage rates (Andriano and Behrman, 2020; Molotsky, 2019; Caruso et al., 2022), or even alter family planning, based on concerns for crop yield (Kidanu, Rovin & Hardee, 2009) and therefore affect adaptive migration rates and destinations in the future. The future application of conceptual models such as the one presented in chapter 2, as well as modelling should continue to explore these pathways. I tentatively suggest system models such as ABMS and MAS may be appropriate approaches for such studies.

Future research may also benefit from considering the apex of migration, urbanisation and food security. This is particularly prominent for Malawi which is experiencing rapid change in all three aspects: with continued urbanisation and growth of both the four major cities and rural *boma's* (main town centres in rural districts), increasing migration trends (both circular and as normally expected in line with urbanisation) and finally, of ongoing challenges of population food security, particularly moderated by urbanism. The process of urbanisation also has potential benefits for the co-evolution of connected rural areas (de Bruin et al., 2021).

Policymakers, media outlets (particularly those from the global north building anti-migrant rhetoric (Boas et al., 2019) are recommended to exercise due caution when making ascertains about the impacts of climate change upon migration as the evidence base appears convulated and in many cases (such as this study) inconclusive at points. The call for further data and insight into climate migration is repeated regularly from local, national and international bodies such as the UN GCM (Global Compact for Safe, Orderly and Regular Migration, 2018), Lancet Migration (Abubakar et al., 2018) and would be beneficial to better understand if and how climate change is impacting migration patterns. Findings from this study support such calls for more investigation and improved data however this should be done with sensitivity for both the needs and impacts of such surveillance upon migrants, as well as with consideration for the context within such data is being collected and the narratives that they contribute to. There are concerns that additional information on migration status may have adverse impacts upon climate-migrants (Franklinos, Parrish et al., 2021, Abubakar et al., 2018). Whilst no studies currently explore the effects of such grand narratives upon the lived experiences of climate migrants (Boas et al., 2019) in Malawi, it is conceivable that in the future, internal migrants within Malawi as well as members of the Malawian diaspora may be impacted by these concerns and such sentiments may even be a factor that contributes to an individual's profile that drives a migration decision, as discussed in chapter 2.

Malawi also faces an array of interfacing development challenges including covid-19 pandemic recovery, climate change and ongoing development for example in areas of irrigation (Schuenemann et al., 2018; Stedman et al., 2018), agricultural subsidy programmes (Ajefu et al., 2021; Kawaye & Hutchinson, 2018; Pauw & Thurlow, 2014), disaster risk management and spatial planning schemes (Brown, 2011), other economic diversification schemes (Government of Malawi, 2020) and continued support and recovery from the HIV / AIDS epidemic. Improved understanding of existing or likely future migration 'hotspots' or areas prone to 'trapping', may support targeting interventions that prevent vulnerable households from being forced to migrate in lieu of other alternatives. As tentatively suggested within this study, it may be the case that migration in the present or near-future is not significantly driven by food security (or indirectly by climate change) which remains useful for decision-makers and demographers for urban or development planning in pursuit of equitable resource delivery and livelihood diversification (Kakota et al., 2015).

4.6 Chapter Summary

This chapter has explored how food security, migration, and climate change are related, with limited findings to connect food security (climate driven or otherwise) with migration status. Modest findings indicate that climate change may be a driver of migration in the south and in urban districts and that migration may be associated with better food security.

This limited evidence basis certainly warrants further investigation and is in stark contrast to many alarmist narratives about so called ‘climate-migrants’ that have become prevalent in western politics and media and have become popular lines of scientific enquiry over the last couple of decades. So much so has the idea of ‘climate migration’ captured the imagination of policymakers, citizens, and scientists that the field of ‘climate migration’ has flourished often without due assessment of its basic drivers, underpinning philosophies and sufficient evidence-base. Left unchecked, such quagmire could lead to poor policy-decisions with significant consequences for the lives of migrants, host communities and those left behind. The next chapter of this thesis shall include a discussion of the findings of this thesis as well as use some of these questions to critique the field of ‘climate migration’ itself, challenging some basic principles and assertions, (including those that have led to the creation of previous chapter within this very thesis!). In so doing, the chapter will present both a pan-disciplinary and reflexive discussion of climate migration and the model that has been the topic of study throughout this thesis.

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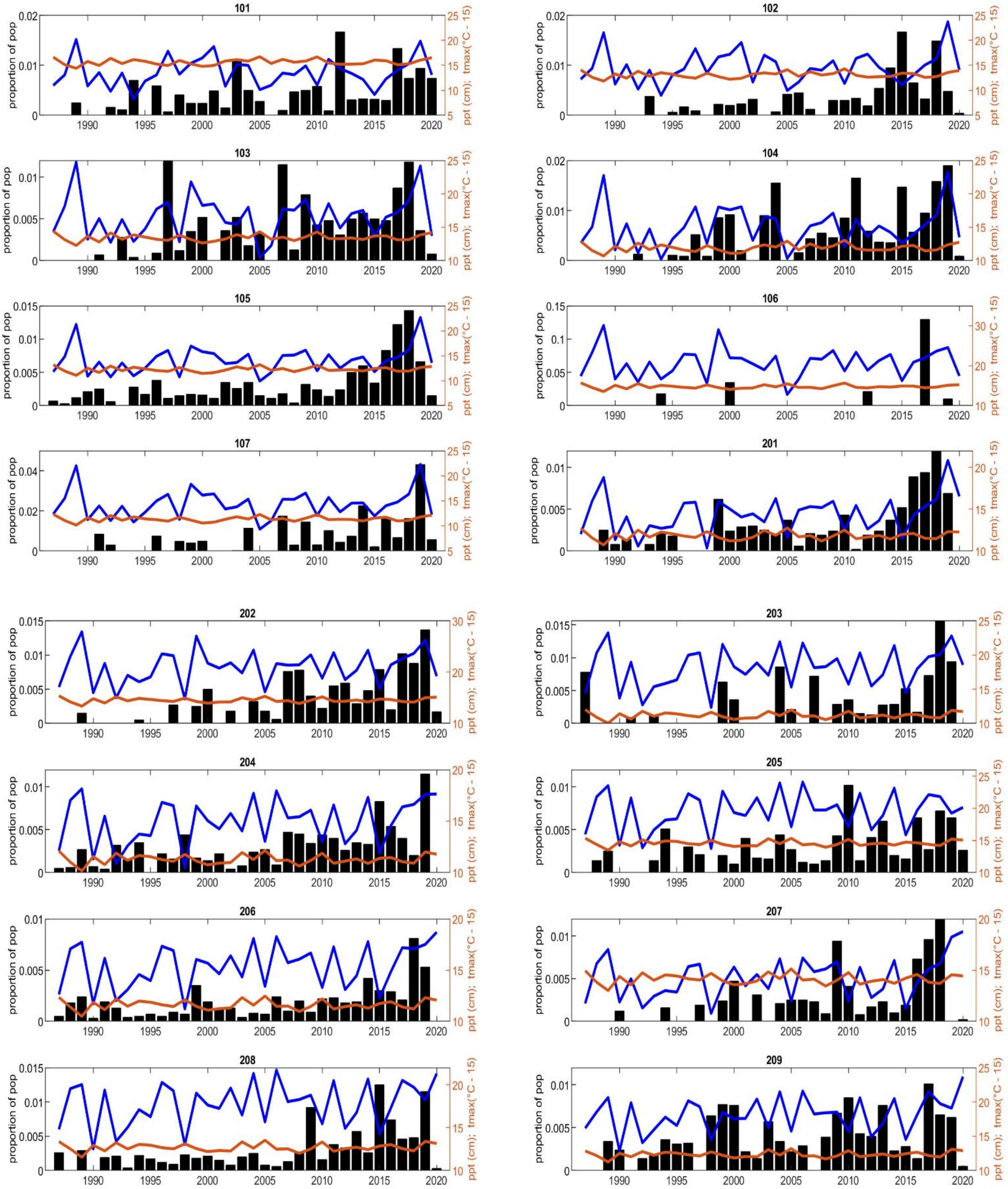
APPENDIX L
District level out-migration and climate trends



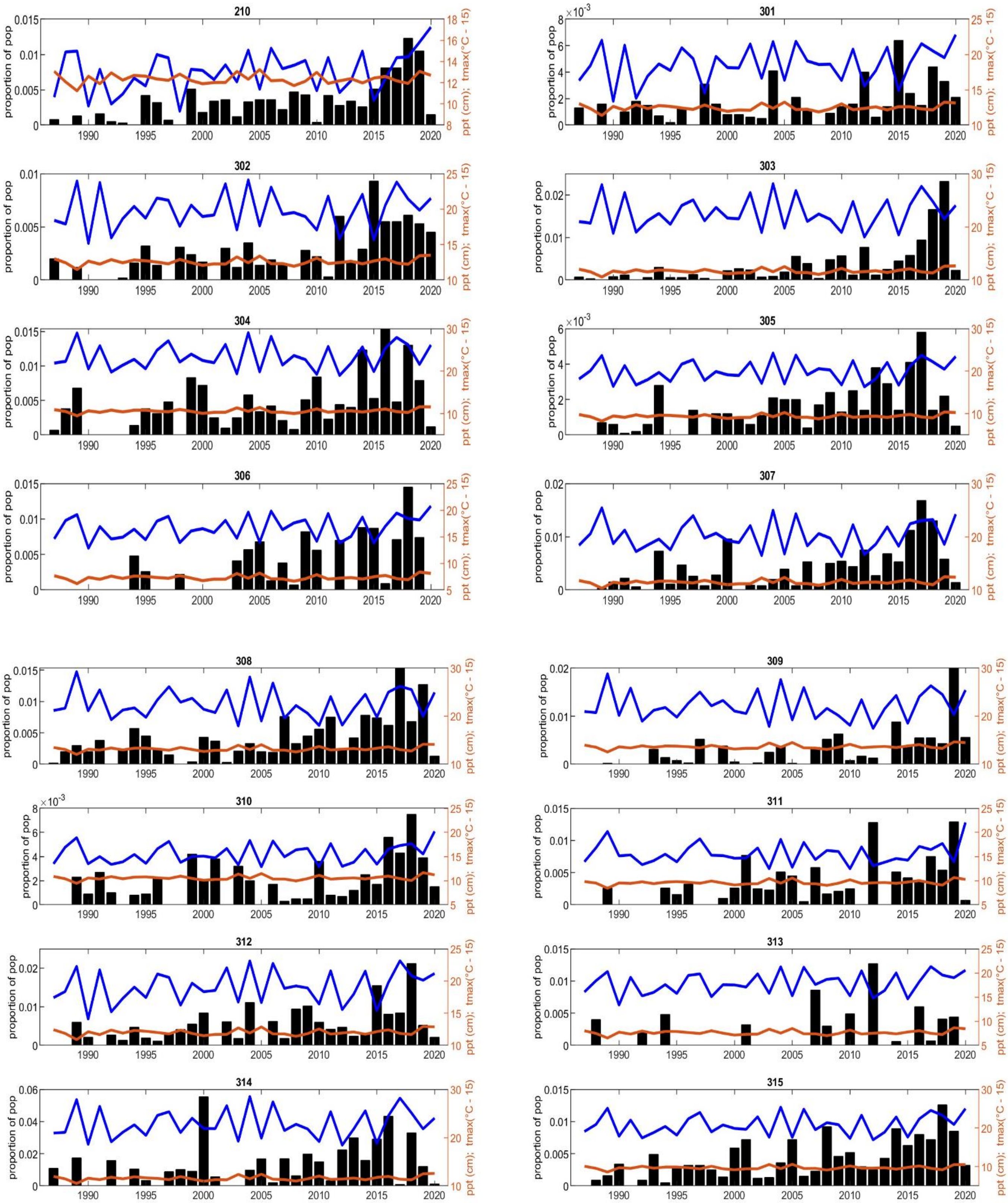


Figure K.1 District level graphs for proportion of population who undertook out-migration each year (black bars), maximum monthly temperature (°C-15) (orange line) and monthly average rainfall (mm) (blue line).

5 A DISCUSSION OF THE IMPACTS OF THIS THESIS, FUTURE WORK AND CONCLUDING THOUGHTS

5.1 CHAPTER OBJECTIVES

The purpose of this thesis has been to provide an answer to the research question presented at the beginning of this thesis, which asked whether and, if so, how climate change impacts upon migration. The previous chapters have each explored the relationship between climate change and migration, within the context of global health, through a variety of pathways as hypothesised and presented in Figure 5.1. Chapter 2 developed a conceptual model as outlined in the below figure and applied it to the context of Malawi. Chapters 3 and 4 then conducted empirical analyses of the relationships for Malawi using data from Malawi's Integrated Household Survey (IHS) data. The aims of this final chapter are:

1) to summarise the key findings from the preceding chapters
2) to discuss the implication of the findings, the limitations of the work and any cross-cutting themes or gaps identified on future research.
3) to consider the wider implications of this thesis for the field of climate migration and including a critique of the field itself based on the insights gained from this research.
4) To provide concluding thoughts about this thesis.

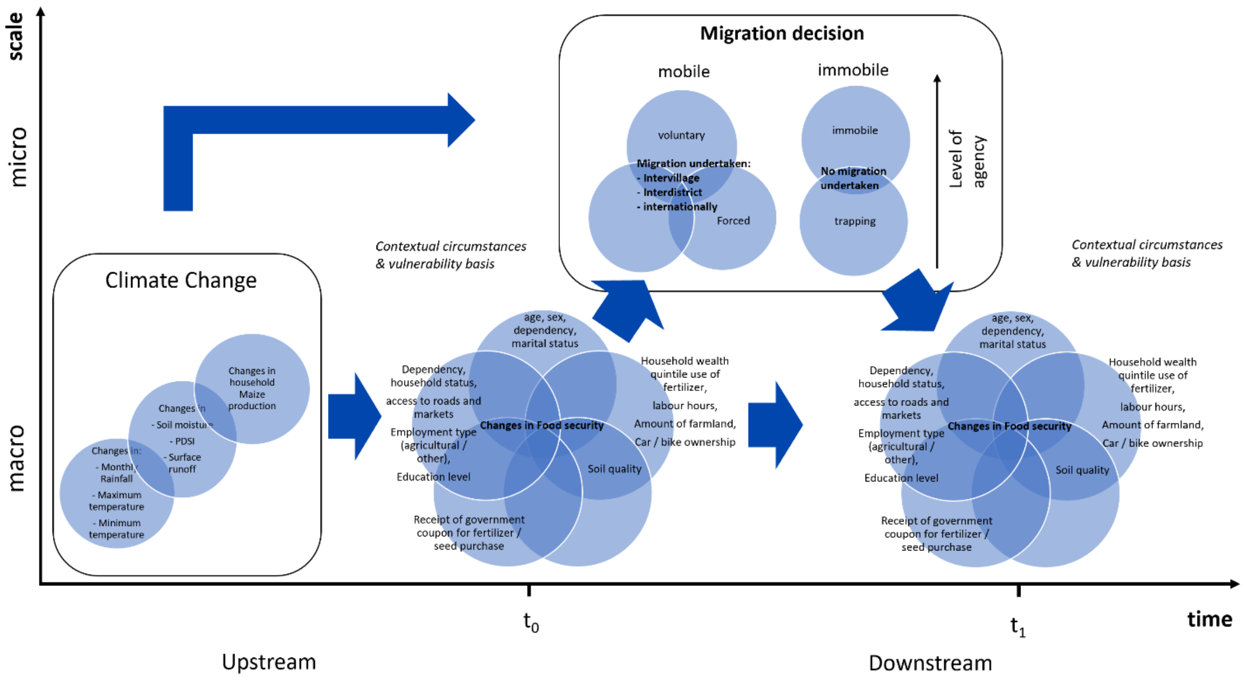


Figure 5.1 High level hypothesis of how climate change impacts migration which is further explored within this thesis. Arrows between factors describes that the preceding factor has an effect upon the succeeding factor. This affect could be net positive or negative. It is acknowledged that there are other relevant factors, and these are also explored and commented upon within the relevant thesis chapter(s).

5.2 SUMMARY OF MAIN FINDINGS

5.2.1 Chapter 1 – Introduction

The introductory chapter provided a brief introductory literature review to the field of climate migration as well as of existing studies of climate migration and the approaches taken. The key outcomes of this chapter were to identify several underlying assumptions within the field of climate migration, including framing of climate migrants, particularly international migrants, as either a global health risk, security threat, or a humanitarian crisis. Over the last couple of decades, the field of climate change and health have crystallised around the concept of mass migration as a mediating socioeconomic factor through which climate change impacts upon population health (Boas et al., 2019; Watts et al., 2021). Internal migration, which constitutes the majority of migration due to conflict or natural hazards, and therefore may include much climate migration (though not all), remains underexplored. Despite advances in conceptual thinking, research and data remains sparse and spatially patchy. Furthermore, much research that is available is thought to carry neoliberal undertones. This is something that will be explored further within the wider discussion at the end of this chapter (section 0). Science tribalism was also identified as a potential barrier which can hinder researchers from objectively critiquing the limitations or underlying dogma of their field, or from gaining insights from other fields. Finally, the introduction outlined the approach that the remaining chapters would take.

5.2.2 Chapter 2 – A critical analysis of the drivers of human migration in the context of climate change: A new conceptual model

This chapter identified several shortcomings of the existing conceptual models for climate migration, including the challenges of encapsulating the dynamic, inter-relatedness of intermediate drivers of migration, the multifaceted nature of climate change itself, the multiple dimensions required to define climate migration typology and data paucity as a hinderance to testing hypotheses of climate migration. It was also found that conceptual models are not routinely applied and underlying assumptions supporting empirical models are not always supported. Due to the highly contextualised nature of climate migration, findings from empirical models are largely non-transferable to other settings which means that insights for policy may be unclear, and that appropriation of findings can lead to maladaptive solutions. The insights from the literature were used to produce a new migration typology specific for environmental migration and capturing all identified dimensions of migration which are relevant not only to the measurable variables of migration (distance travelled, time away from home, extent of community affected (from an individual moving to a mass migration) but also to subjective lived experience of affected persons through the level of agency they had in the decision to migrate. The typology highlights immobility, including trapping (involuntary) and voluntary non-migration which are often overlooked outcomes in many climate migration studies. A new conceptual model was then produced with benefits that it captures both time, spatial and societal scale within the model, with climate change presented as an exogenous variable acting upon a dynamic system of social, demographic, environmental, social and political factors. Finally, the model was applied to the case study of Malawi from which the hypothesized pathways through which climate change impacts migration in Malawi were created.

5.2.3 Chapter 3 – The impacts of climate on crop production and food security in Malawi; an epidemiological approach

Regression models were developed to explore the relationship between climate variables and crop production and with food security indicators in Malawi. Using a multi-level linear regression, significant relationship was found between maize production with wealth (in particular, being in the richest wealth quintile having a very large positive impact upon crop production), sex (with females producing between less than their male counterparts) and plot size (with larger plots sizes per person increasing crop production). Although using a single level linear regression identified significant impacts of maximum temperature and monthly precipitation and crop production (with higher temperatures increasing crop production and higher rainfall having a negative effect), within the multi-level model these associations were smaller and temperature was no longer significant. However, by then isolating the climate change signal by regressing crop production against the climate anomaly compared to a 1980-2010 baseline, a negative (statistically significant) relationship was found between crop production and maximum temperature. These results may suggest that chronic climate change is not related to maize production, or else is so far having a only negligible impact. Alternatively, the granularity of these models or choice of monthly average rainfall as the climate indicator may be insufficient to identify any small climate signal that does exist (but of a lower magnitude than other determinants).

Using multi-level logistic regression modelling for prolonged hunger, significant relationships were identified between maximum temperature and a small decrease in odds of prolonged hunger which is counter to the original hypothesis rising maximum temperatures (a proxy for climate change) would be worsening crop production and hence odds of prolonged hunger.

These findings can inform future research questions and model development for example by suggesting alternative climate parameters for exploration. It is hoped such research may eventually help to inform targeted global health and development interventions. For example, in support of development initiatives at the intersections of gender, climate change and development. Lifetime migration status does not appear to impact crop production based on this empirical evidence.

5.2.4 Chapter 4 – Exploring internal migration and its drivers within Malawi

Results of statistical tests and regression analyses found limited and inconclusive relationships between food security indicators and migration. It was found that the average number of meals consumed by children were found to be higher if the head of the household is a migrant in rural districts (urban districts do not show this trend: Mzuzu, Lilongwe, Blantyre and Zomba). This could be due to wealthier families being more able to migrate as well as to feed the family. As such, wealth is probably a determinant of both migration and number of meals consumed. The flip side of this hypothesis is that poorer families are both less able to feed their families and to migrate, which suggests that the 'trapping' hypothesis – that poverty traps reduce migration, and that climate change may actually reduce migration due to increasing poverty, rather than increase it, may be more appropriate for exploring internal migration within Malawi. In contrast to the number of meals consumed, a district by district comparison of child malnutrition (using child anthropometrics) found that in Mzuzu city, migrant children had significantly more wasting than non-migrant children, however this analysis had reduced power and may not be reliable.
Finally, using the IHPS longitudinal study, a multi-level regression model using panel survey data found that experiencing prolonged hunger increased the odds of migrating in the next survey period by three.

Exploring the direct impacts of longer term climate average upon migration, no discernible trends were identified. It was discussed that possibly, longer term climate change is not yet substantial enough to have a perceptible impact upon crop production or migration as yet or else that the variables utilised are not optimal to identify small associations that may be present. It was also considered that climate change is probably not resulting in a linear trend. There could be a tipping point at some point in the future when climate change is sufficiently severe that it results in ecological breakdown and massive crop production losses and reducing in habitability of areas (for example due to desertification), and that such catastrophic changes may drive migration. Acute events such as droughts and floods are more likely to have impacts upon crop production, food insecurity and sudden-onset migration (e.g., involuntary displacement or same year economic migration) and future studies should explore these climate factors.

5.3 Research Limitations

5.3.1.1 Causality

This thesis has provided an exploration into if and how climate variables impact upon crop production, food security and ultimately, migration. However, the descriptive epidemiological analyses conducted are limited in several ways. Most crucially, none of the findings made are capable of proving a causal relationship between variables, but rather are used to identify statistically significant relationships. The relationships identified could be due to one factor directly driving another but could also be casual relationships with (an)other factor(s) being responsible for observed trends (most likely wealth determinants).

Causal inference is no simple task and the field of epidemiology amongst other have a long history of discussing and disagreeing on the best way to define and measure a causal relationship between a cause or exposure (such as a drought or decrease in yearly rainfall) and the effect of interest (such as a migration event). Recent approaches to causal inference suggest that a range of methods may be appropriate and that pluralistic causal explanations are acceptable through a variety of methods, each with their own set of assumptions and limitations (Krieger & Smith, 2016). In their paper Krieger and Smith (2016) point out that causality is not something empirically black and white but is a narrative tool and that “epidemiology, like any science, needs a flexible, multi-faceted and historically-informed approach to causal inference” (Krieger & Smith, 2016).

This is indeed a welcome news for the field of climate migration which by necessity require a flexible and pluralistic approach to causal inference. In their recent nature commentary, Boas et al (2019) comment that the research agenda for the field of ‘climate mobilities’ moving forwards needs to better interrogate the assumption that climate change and migration are linearly related, with most scholars in the field readily noting (as I do in my introductory chapter) that migration is almost unfailingly due to a myriad of interconnected drivers (Boas et al., 2019). Both the ability and indeed the need for causal inference are called into question in this case. And yet, without strong justification for a causal inference, how can climate migration research hope to helpfully inform interventions, whether for public health, development, or migration policies? This discussion has advanced beyond the limitations of just this thesis but into a potential crack in the very foundations of climate migration literature and shall be further analysed in section 5.5 below.

5.3.1.2 Data and methodological limitations

Limited variables have been explored and there is a mix of both time-dependant and time-independent variables. For instance, using three cross-sectional surveys means that variables such as migration status and prolonged hunger, were captured at only three points in time, when in reality they can vary with higher frequency, particular for those who undertake seasonal work or circular migration, or experience high (sub-yearly) fluctuations in food security and stability. Other variables, such as many of the climate variables used within chapter 3 and 4 are specific only monthly average values, which were also combined to obtain wet season values as well as multi-year values and offsets. Other potentially important variables (as outlined by the conceptual model, such as soil type, farming practices, labour availability or more accurate descriptors of household wealth and hunger (for IHPS only), have a high level of missing, or unreliable data which means they have either been omitted or, included but with the caveat that the resultant model is not representative of Malawian society. Any subsequent findings therefore are not indicative but rather suggestive of possible relationships for which future research to corroborate is required. The exclusion of such variables may have led to erroneous coefficient values of those variables which were included, particularly if key interactions between explanatory variables were excluded.

To explore how the change in climate over time has (and will continue) to impact upon the relationships observed will require additional analyses using for example using more detailed data. For example. crop production may require more granular variables such as 10-day rainfall data at a specific window post planting. Additional variables should also be considered such rainy season onset and duration metrics, and extreme events such as drought, flood and typhoons, for example using binary variables for whether or not an event occurred (i.e., the exposure to an event) and some amalgam measure which captures magnitude, duration and extent. An important follow-on study would involve the use of climate projections to suggest possible future crop production and food security scenarios for Malawi, based on the understanding of the relationships identified within this study. Any such studies would require significant assumptions about not only which climate scenarios should be utilised, but about population growth and dynamics (including migration, fertility and mortality) and economic development (including both agricultural, technological and industrial advancements) all of which may introduce high levels of uncertainty in the conclusions drawn.

5.3.1.3 Epistemological challenges

Within the introductory chapter of this thesis, epistemological shortfalls, the risks of science tribalism and the influence of neoliberal politics on research agendas, both in general and pertaining to climate migration in particular, were identified. Attempts to overcome this were made via a thorough review of a wide range of literature and construction of a conceptual model that was then used as the basis for the subsequent statistical modelling. Furthermore, a part of this research included a short trip to Malawi where informal conversations were held with a variety of agents across the Government, Malawi University for Science and Technology and civil society. This helped to shape my thinking as well as to help inform my conceptual model but were not captured as forms of evidence (interviews) and could not be considered a participatory approach (whereby individuals and local communities are involved in the research itself not just as study subjects) (Prokopy et al., 2013). It is folly to think that I have been able to entirely overcome these obstacles and future work could include a wider range of methods for example including mixed methods research or participatory approaches in attempt to address this.

5.4 EMERGING, CROSS-CUTTING THEMES AND OPPORTUNITIES FOR FUTURE WORK

The findings of this study are relatively inconclusive. There is some tentative evidence to support that study identified the hypothesis that within Malawi, climate change may be increasing the ‘trapping’ effect, whereby climate change may work against the rising migration trend due to increasing poverty and rising food insecurity of agricultural households. It has also been suggested that the relationships between climate, crop production, food security and migration are nonlinear, requiring more sophisticated modelling approaches as well as more nuanced narratives around climate migration, in line with the conceptual model presented in Chapter 2. Alongside these findings, and the consideration of the various limitations (as outlined in the previous section), I consider that there is need for further research in two ways. Firstly, further research building upon this study can improve understanding of climate migration in Malawi and inform Malawian policy-makers on issues such as projecting population dynamics (in particular, population movements), urban planning, economic diversification and climate action planning. Secondly, further research which can feed into the wider, intergovernmental and international discourse around climate migration and challenge many of the underlying assumptions and help to highlight and challenge neoliberal, even at times neocolonial distortions where present within social and political narratives. This will be further explored within section 5.5.

Further research based upon this thesis could be improved in several ways grouped under the themes of causality, data and future methods, and epistemological challenges.

5.4.1 The issue of causality

Future research should seek to appropriately conceptualise and contextualise the hypothesized relationship(s) between climate change and other variables, such as the model presented in chapter 2. Through so doing, empirical studies may have a strong contextual and theoretical grounding and may more reasonably suggest a causal model. Under the framing of global health studies and epidemiological approaches, such causality could then be further interrogated using an appropriate method(s) such as those described by Krieger and Smith to achieve the 'loveliest' explanation (Krieger & Smith, 2016).

Outside of epidemiology, other methods for deducing causality between climate change, crop production, food security levels and ultimately, the decision to migrate may be possible but each will experience its own limitations. In complex situations where there are multiple determinants in a decision to migrate (as has been interrogated extensively through this thesis), a reasonable assertion of causality may never be achievable. What is achievable however is greater understanding of the relationships between factors, both through time and space and within different contexts, for different persons. Equipped with this understanding, scientific advisers, global health interventionists and policymakers are better able to understand the possible outcomes of an intervention and respond accordingly.

A serious caveat needs to be provided in a discussion about causality within climate migration. The pursuit of causal determination has plagued the field of climate migration since its inception, proving an elusive object for researchers and policymakers - who often assume a causal relationship without sufficient evidence. Indeed, most scientists admit that providing a causal link between climate change and migration may be impossible and, in any case, would only partially explain the cause of migration in virtually all instances of a migration taking place. Yet despite this, other researchers and policymakers alike continue to struggle conceptually with the issue of causality in climate migration research and policymaking. This is likely because many forms of migration, particularly forced migration resulting in a request for asylum, require a definitive cause, so that refugee status can be legally granted (or denied). Only certain criteria or ‘causes’ of migration may result in refugee status being granted so there are political and legal incentives to ensure the reason can be established. Claims on limited humanitarian funding or the good will of host communities also can increase tension and raise questions about the complex causes of migration and appropriate responses. This was seen during the migration ‘crisis’ in the late 2010s (2015 onwards) in Europe (Abdou, 2020; Baldwin-Edwards et al., 2019; Gloninger, 2019; S. Goodman et al., 2017). As such, pursuit of causality within future research should tread carefully, considering both the integrity of such pursuits for causality, and the most appropriate methods, as well retain an awareness for the ongoing politicisation of the causality discussion in climate migration research and policy making, and impacts upon research grants and research itself.

5.4.2 Tackling data paucity and quality issues

Poor data is a common challenge not only in the field of climate migration but across all research areas, and can be particularly the case in many developing setting. Future research that builds upon the findings within this thesis and similar works will doubtless benefit from an increase in datasets and the quality of data within. This can be addressed both through additional data collection or use of complementary datasets to supplement the primary dataset, but can also be improved upon through techniques such as data imputation.

This section considers ways in which this research could be expanded in the future through better data via 1) consideration for other variables and use of complementary datasets which would help improve the models developed within this thesis, 2) consider the use of techniques such as imputation or improved data collection to achieve higher data quality for this research, 3) consider the use of mixed methods research or future data collection to build upon the findings made in this thesis, and 4) the implications of more data across the field of climate migration.

5.4.2.1 Incorporation of additional data variables and datasets

Future research as follow-up to this research should take a more detailed approach based on the hypothesis and ideas synthesized from this research. Since maize production and total food crop production were affected by climate variables differently, this warrants further investigation and studies should not over-rely on how climate change is affecting maize production, as a proxy for future food availability in Malawi. This will become increasingly important as agricultural interventions continue to pursue crop diversity and drought resistant variants (Mango et al., 2018; Pauw & Thurlow, 2014). Follows-up studies could also consider how to incorporate other variables which were identified within the conceptual model as being important, but for which indicators are difficult to identify or find datasets for. Examples include factors such as access to credit, and strength of informal support networks (such as familial relationship living in other parts of the country).

The thesis also identified differences in the presence and distribution of food security, and how it relates to climate and migration variables depending on the indicator chosen. Each of the three indicators explored: prolonged hunger, average number of meals consumed, and child anthropometrics, are generalised measures of food security however contain slightly different assumptions. For example, the use of prolonged hunger as a measure of food security is predicated on food being consumed if it is available and affordable. Where hunger is present it therefore cannot comment on if the root cause of the hunger is high market prices, or lack of availability for instance due to failed harvests.

Finally, different climate variables may also support the analysis. For example. Interesting relationships were found between the interannual variance in minimum monthly temperature and crop production as well as between drought and migration. Further analysis of these effects through carefully defined climate variables may deepen understanding of this relationship. In particular, rainfall variables beyond total amount of rainfall may be beneficial. For example. Haghtalan et al (2019) used a series of variables to explore the impacts of climate change on the rainy season including onset and end of the rainy season (in days since an arbitrary date each year), the length of the rainy season (in days) and the number of extreme events (defined as days when >20mm of rain fell) (Haghtalab et al., 2019). Based on the findings of my research I put forward the hypothesis that a delayed onset of the rainy season may be negatively correlated with crop production (as such a delay would result in a shorter growing season). I further postulate that delay in the rainy season (possibly with a lag of some number of years) may also be negatively correlated with migration, due to the trapping mechanism that has been discussed within this thesis.

5.4.2.2 Imputation and opportunities to improve data quality

Missing data was a prevalent issue for many variables for which data was collected within Malawi's Integrated Household Survey's. For the most part, these variables were therefore excluded from the research or else it is acknowledged where the datasets used carry high uncertainty due to the lack of data and the findings may therefore be non-representative of Malawi's population thereby further obfuscating an already complex mix of explanatory variables for the outcome of interest (whether that be crop production, food security or a migration event).

A common method for addressing low data quality, in particular missing addressing improved data through imputation techniques. Although this was beyond the scope of this research, imputation for variables which are hypothesised as being highly important could be performed and then these variables can be explored statistically and, if appropriate, included within the models constructed.

Other measures that may help to improve data quality could be to provide enhanced training and opportunities for field data collection officers, explore different modes of data collection where appropriate, for example considering the different data quality outputs for surveys conducted in person, via the phone, online or by post. Such relatively novel data collection techniques would need to be designed with the target participants in mind, considering issues such as internet and postal access as well as participant literacy, survey engagement, enjoyment and perceived value (Rogelberg et al., 2001). Existing feedback and monitoring of data completeness and quality between survey's could also perhaps be further investigated so that each successive survey can be improved, such that there is less missing data and data entries are more reliable. Participatory approaches in survey design and data collection with survey participants may also support well understood and reported data collection as well as provide community buy-in to research matters and resultant findings or intervention designs (Bezner Kerr et al., 2019; Jørstad & Webersik, 2016; Prokopy et al., 2013).

5.4.2.3 Mixed methods research and use of complementary datasets

As identified within the methodological literature review in chapter 1 (see section 1.3), mixed methods research and the corresponding use of multiple datasets may be highly beneficial in approving data quality as well as the contextualisation of data and findings. To further the work of this thesis, other datasets such as alternative climatologies which incorporate different climate variables of interest or other hydrological variables (such as alternative measures of drought or flood as well as alternative rainfall parameters such onset and duration of the rainy season, and intra-seasonal variability in rainfall) may be of great interest in exploring the links between climate change and migration as well as climate change and hunger.

Weather station data which is not publicly available as a secondary dataset but which is collected by Malawi's Meteorological Services Department may also provide valuable insight to both test the accuracy of gridded datasets (such as the TerraClimate dataset) or of GCM and RCM datasets (Haghtalab et al., 2019; Ngongondo et al., 2011). (Haghtalab et al., 2019; Ngongondo et al., 2011; Warnatzsch & Reay, 2019).

Finally, it is increasingly acknowledged across the sciences that other forms of knowledge such as indigenous knowledge should not be overlooked and provide valuable insight to traditional datasets and methods. It would be of benefit to future studies of climate change, migration, and health in Malawi to consider indigenous knowledge which may provide not only to be a valuable data source, but which will provide a framework for contextualising research (Kalanda-Joshua et al., 2011).

5.4.2.4 Wider implications of calls for more data in climate migration research and policy

Considering the implications of data paucity across the field of climate migration, this is a perennial issue, particularly in data sparse settings (such as Malawi) and the call for more data is regularly cited within climate migration research by various actors across both research and policy-making mandates (Abubakar et al., 2018; Franklinos et al., 2021; Global Compact for Safe, Orderly and Regular Migration, 2018). Perhaps no more evident is this than the 2018 Global Compact for Migration (GCM) and its sister compact, the Global Compact for Refugees (GCR). The GCM was a landmark intergovernmental political instrument which laid out a framework agreed upon by the UN General Assembly for addressing the topics of migrants around the world which laid in its very first objective the need for more data collection (Global Compact for Safe, Orderly and Regular Migration, 2018). Whilst such calls for more data may be both beneficial there are many ethical considerations and challenges that are appropriate to consider before undertaking such additional data collection. As discussed at a 2018 workshop organised by myself and my colleague Lydia Franklinos to discuss the role of Big Data in migration research and policy, the call for more data carries many challenges including both potential harm and loss of agency to those whose data is being collected, potential misappropriation of such data for example to facilitate deportation of undocumented migrants, ethical concerns about appropriate data collection and storage, the exchange and use of data to perpetuate and deepening power imbalances between different agents (Franklinos et al., 2021).

In summary, data for data’s sake may at best be inefficient use of research grant money and at worst, lead to the exploitation of migrants particularly those who are in vulnerable positions. Nevertheless, appropriately targeted data collection exercises can also improve the availability and quality of data which can inform well-designed interventions. For example. The UCL-Lancet Commission on Migration and Health (2018) called for a Global Migration and Health Observatory to collect and collate a strong evidence base for health indicators.

5.4.3 Epistemological open-mindedness, cross-disciplinary research and fighting the tribal instinct!

Epistemological risks that have been identified and described within this thesis are difficult to overcome but it is something that I recommend should be considered by researchers. There are a range of ways to reduce siloed thinking. Mixed methods research as well as transdisciplinary research and communications can support this aim. Transdisciplinary research and research that is well communicated outside of the silo in which it is produced is regularly called for but difficult to achieve (Hunter, 2018). It is often the case that, even when a research projects or departments include researchers across multiple disciplines, that the research objectives are distinctly separate and assigned to different, homogenous groups of researchers (grouped by discipline) and so the tribal instinct prevails!

Tribalism presents an obstacle not only to transdisciplinarity research (Choi & Pak, 2007) but also preserves the risks of ignorance, lack of reflexivity and enforced homogeneity of thinking that emerges from overly tribal mentality (Beck, 2012). Such enforced homogeneity and criticism of scepticism of an ideology (whether one's own or another) seems to be in somewhat direct conflict with the scientific method. Furthermore, Clark and Winegard (2020) commented on the risk that ideological homogeneity can distort one's cognitive reasoning, thereby silently reinforcing research biases. The authors also described the 'BIASS' (Bipartisan Ideological Awareness in Social Sciences) moment as the ensuant renaissance within the social sciences whereby many researchers readdressed politically relevant assumptions of the field (Clark & Winegard, 2020). Could it be time for the climate migration field to have its own BIASS moment.

Having critiqued the field (and other scientific) fields for epistemological shortfalls, it seems prudent that I should also reflect on these shortcomings within my own research. As stated in Chapter 1, I firstly identified and then attempted to reduce my tribal research instincts by consulting literature from across a range of disciplines. This was easier said than done for one needs to navigate the labyrinth of scientific journals and have awareness of a wide range of authors and schools of thought. I also found that each discipline carries its own vernacular meaning that many papers were difficult to comprehend without significant effort and background research into the field. Plain language is no easy feat, especially when talking as an expert speaking to a niche within an already specialised field! As a native English speaker, I cannot help but feel lucky that I do not have the added challenge that second-language speakers face (Elnathan, 2021), like so many researchers around the globe, particularly in many developing countries where much climate migration research is focused, but not conducted out of (Piguet et al., 2018). Despite my native speaking advantage, I struggled to digest certain literature from outside the field of environmental epidemiology and as such, my literature retained a bias to this field. Without having conducted a systematic review, I cannot claim to have achieved good coverage across the literature or a comprehensive overview of the literature. Nevertheless, my attempts culminate in a bashful head nod to multidisciplinary research. The critical analysis and conceptual model constructed in Chapter 2 presented an opportunity to consolidate my thoughts. Whilst it was only a meagre attempt to transcend some of the more often touted shortfalls of this field (such as neoliberalism, geographical unevenness, an eagerness of popular media to jump to conclusions, and an apparent lack of cross-pollination of ideas between scientific tribes), it allowed me to raise awareness of these issues within myself and, hopefully, any person who reads or utilises this research. If all early career researchers undertake their own version of this due diligence, we can help to ensure that not only is our research robust, but that we are serving a robust wider, research purpose with robust communication channels to the wider community (e.g., policy makers, media and general public). Through so doing I hope that science continues to contribute, positively, to societal understanding and evolution.

A month-long trip to Malawi as well as two policy internships (courtesy of NERC funding) presented a fantastic opportunity to ground-truth some of my ideas and assumptions, provide invaluable insight into the survey preparation and administering process (not related to Malawi's Integrated Household Survey) as well as insight into how scientific evidence is digested and utilised within international policy discussions. I found these insights invaluable. Observing the implementation of health research in Malawi and survey administration not only helped determine the variables I wished to explore but allowed me to better understand the survey data and how to cleanse, manipulate and explore it. It also allowed me to understand the challenges and opportunities faced by survey designers and implementers which inspired the above suggestions. My policy internships provided a stark contrast to academic research and inspired much of the following discussion. Such internships and fieldwork are of course not feasible for every study but perhaps the following denouement could be considered by early career researchers – to understand as full as possible, the context of one's research prior to commencement: This would include not only literature review of scientific literature and methods, but a reflective review of grey literature, history and culture of both the study subject, and of the research field within which we each sit.

5.5 Taking a step back: A critique of the field of climate migration research

Having critiqued and reflected upon both the approach and findings of this thesis, finding multiple shortcomings not only in data and methods, but in conceptualisation, transferability, and even epistemology and tenets, I became inspired to take a step-back and further understand and critically explore the wider field of climate migration, its origins and inclinations. Undertaking such due diligence is important for any researcher but perhaps is arguably more so for the field of climate migration due to its relative infancy, fast evolution, the complexity of migration drivers and, most keenly, because of the highly political implications of the research for policy makers, researchers and society. Although the findings of this thesis are a humble contribution to the wider literature, the insights and reflections i have gathered have identified the importance of a deeper investigation which I venture to do within this section.

The following section is the culmination of a literature review of social science readings on the origins and impacts of the field of climate migration itself. This critique shall consider the evolution of the field, from its inception and founding principles, to current day popular narratives, their limitations, and possible future directions for the field. The hope is that, by better understanding the wider field of climate migration, I may better understand how my research contributes to any wider discussions, the intended and the actual impact that research such as mine might have, and how to produce the most efficacious research possible in the future.

5.5.1 A critique of climate migration discourse

The climate migration field of inquiry has evolved significantly over the last 40 years or so. Through its various incarnations it has held as its central tenet, the assumption that climate change has a causal relationship with migration. It is therefore assumed that those who migrate due (partially or entirely) to climate change can be identified and counted, with a view to providing appropriate political response to protect, govern, manage or otherwise ‘deal’ with ‘them’.

And yet, what is so exceptional about those migrants incited to move in part or in whole due to events linkable to climate change, that sets them apart from those who migrate for any other amalgam of reasons? It is widely accepted today that migration is almost unfailingly due to a myriad of interconnected, dynamic drivers. Furthermore, it is widely accepted that climate change acts as a ‘threat multiplier’ (Cauchi et al., 2019; Dodson et al., 2020) or could even be described as an existential risk to many aspects of human health and livelihoods. As such it follows that a climate change signal exists, undetectably perhaps, in all migration decisions. Nevertheless, it is the case that this woolly faction of migrants has received specialist attention by both scientific and policy-making communities. This disparate group of persons have inherited many guises over time including ‘environmental refugees’ (Hinnawi & UNEP, 1985) ‘ecological migrants’ (Wood, 2001), ‘environmentally induced migrants’, ‘environmental migrants’ (International Organization for Migration (IOM), 2011), ‘climate refugees’ (Gemenne, 2015) and doubtless many more. Even wider ranging is the array of estimates for the numbers of such persons that have existed through time. Scholars and policy-makers alike appear fascinated by the question of ‘how many such migrants are there / will there be by a given time?” Answers to this question have ranged impressively from between 10 million (Jacobson, 1988) in 1988 to as many as 1 billion by 2100 (Watts et al., 2017). It is well acknowledged that each of these estimates is flawed and highly uncertain, though arguably still informative in some manner. However, from these questions and their various, iterative answers, a new question emerges: “Why are we so obsessed with counting, especially when we can’t even agree on what it is we are trying to count?” Surely if we are not able to agree on who or what we are trying to count, then achieving reasonable estimates is not only methodically challenging but conceptually untenable.

These questions can all be traced back to the ‘causality problem’ at the heart of the field of climate migration. The ‘causality problem’ refers to the assumed causal relationship between climate change and a migration event even though it remains an elusive subject to measure, especially when many studies adopt positivistic approaches and most climate change data is probabilistic, meaning that direct attribution of climate change to an event such as migration is challenging. Scholars acknowledge that causality cannot be ‘proven’ (Boas et al., 2019) and yet continue to assume it to be true and call for further research with the tenuous implication that such a relationship will be proven in the future in what I refer to here as the ‘causality paradox’. By assuming a causal relation, it follows that a climate migrant can be defined and identified based on presence of this relationship and that therefore, with more data and more research, a value with increasing certainty, can be attribute to the number of people to which this formula applies. And yet, since first inception roughly forty years ago, research has not reduced uncertainty around so called ‘climate migrants’ but rather has increased it (Nicholson, 2021) We put forth that despite the significant evolution of the field and its lexicon, scholars have yet to be address this fundamental paradox of causality.

We arrive at this conclusion following a critical analysis of the various stages of the field from emergence to modern day. We interrogate key literature from the frame of both scientific curiosity as well as within the frame of an issue of significant public and political interest. We do this in acknowledgement that both migration and climate change are the height of public and political contention and as such, the framing of any piece of research and the way it harmonises or discords with the dominant narrative is highly relevant. We also consider some of the key milestones, science-policy nodes and challenges faced by the field that may help to explain the current state of research and suite of inconclusive and often ambiguous conclusions made.

5.5.2 A critical timeline of the field of climate migration research and evolving framings

Whilst other scholars such as McLeman and Gemmene (2018) and Nash (2018) have provided excellent, succinct overviews of the evolution of climate migration research, we summarise some key themes and obstacles here, focusing on the interplay of political and scientific discourse.

A key framing of climate migration is one of securitisation. The end of the Cold War in 1991 is often credited with a renewed search for emerging threats to borders and national security and protection of oversea interests by colonial powers, of which environmental change was one (Adelman, 2001; McLeman & Gemenne, 2018). The events of 9/11 in 2001 further increased national security concerns relating to migration and border control (Humphrey, 2013). More recently, the Arab Spring and the European migration 'crisis' threw renewed awareness and political and public interest in refugee and migration policy, with a focus on irregular migration and border control (Baldwin-Edwards et al., 2019). These events fed into an increasingly popular narrative that climate change is increasing the numbers of international migrants around the world, with particular emphasis on global south to global north migration routes (Ransan-Cooper et al., 2015), possibly due to a racialisation of migrants by the West whereby migration rhetoric and policy is affected by underlying ideas of the racial Otherness (Telford, 2018). Alongside and perhaps driven by these events was an increasing interest in migration research by academics as well as availability of public funding (Baldwin-Edwards et al., 2019).

The climate change narrative has been steadily evolving in parallel with this migration security narrative. Since the adoption of the Kyoto protocol in 1997, effectively operationalising the UNFCCC, climate science has been growing in volume, scope and prominence (McLeman & Gemenne, 2018). Alongside this rise in political interest, academic interest bloomed and so too has the utilisation of climate science within public discourse (Berglez & Al-Saqaf, 2020). There have been increases in both support for, and denial of the climate science, as well as of science writ large (Berglez & Al-Saqaf, 2020; Iyengar & Massey, 2019). Climate denialism has been found to depend upon a range of factors including education, gender, political persuasion and use of system-justifying ideologies (Hornsey et al., 2016;

Milfont et al., 2021). Furthermore, polarised views on the role of climate science has also gone hand in hand with the increasingly partisan nature of politics in western democracies and the rise of populism (Huber et al., 2020; Swyngedouw, 2010), not to mention the epoch of fake news and social media fuelled ‘cancel culture’ (Haidt, 2020).

The fields of climate change and migration therefore meet at an extraordinary triumvirate of contemporary challenges: 1) the need for natural science (the traditional home of climate change science) and social science (the home of migration studies) to interface 2) the need for the sciences to inform policy and 3) the need for science and policy to both have visible and positive public impact - an increasingly challenging feat in a populist, technological world. From the 1920s, migration research became increasingly interested in the environmental hazards which could affect migration. In the latter half of the twentieth century, environmental scientists became increasingly interested in the socioeconomic impacts of natural hazards (McLeman & Gemenne, 2018). At each node of these different scientific lenses, increased insight and nuance was introduced to the climate migration discourse as well as a drive for more interdisciplinary research. The narrative moved from an overly simplistic linear relation between climate shocks and mass migration, to more nuanced ideas appreciating the multicausality of migration and the plethora of migration outcomes (Parrish et al., 2020). Whilst fast-onset events and international movements were an early focus, recent years have seen increased interest in slow onset climate change as a driver of mobility as well as focus on internal movements (Kumari Rigaud et al., 2018), as well as focus on trapped persons (The Government Office for Science; London, 2011). The overarching narrative of climate migration has in turn also evolved from being expressed as a humanitarian issue and a failure to adapt, to one of resilience and empowerment (Methmann & Oels, 2015). Meanwhile many countries notably in the global north continue to pursue a securitisation framing (Boas et al., 2019; Nash, 2018a). The impact of such framings on future policy and research direction should not be underestimated. The humanitarian frame would have a significant impact upon the climate migration discourse and support the erroneous use of such terms as ‘climate refugees’ on altruistic yet scientifically questionable grounds. Meanwhile, the securitisation approach has continued to have significant impact upon policy direction, especially in light of the 2015 European migration ‘crisis’ and rise of populist governments (Boswell et al., 2011). The ‘resilience’ framing is also fraught with neoliberal ideology and risks diverting attention from mitigation mandates in developed countries responsible for the majority of greenhouse gas emissions, to adaptation mandates in countries of migrant origin (Felli & Castree, 2012). This creates a form of unconscious victim blaming whereby developing locations and migrant source populations inherit the responsibility to ‘fix’ the ‘problem’ and that resultant outcomes including migrants undertaking irregular migrations, migrant smuggler (note the difference to human traffickers (de Massol de Rebetz, 2021, İçduygu, 2021), and inhabitants of migrant camps, are dehumanised (Campana & Gelsthorpe, 2021, İçduygu, 2021) within popular discourse. This is perhaps unsurprising given that almost the entire climate migration discourse is dominated by the global north and has been throughout its evolution (Scoville-Simonds et al., 2020). Power imbalances between actors (for example, between the global north and global south) are likely also to be responsible for both producing discourse through both research and as powerful actors on the international political stage (Nash, 2018b; Telford, 2018). A possible positive outcome of a resilience building framing may be that developing countries will take the opportunity to develop climate resilient economies, utilising climate finance that will become more widely available in line with a resilience framing. Developed nations are yet to prove this hypothesis however. At the 16th Conference of the Parties of the UNFCCC (COP16) in 2009 in Copenhagen, developed member states pledged to donate 100 billion USD per year in climate finance by 2020 but at COP26 in 2021 in Glasgow, they were still far short (Timperley, 2021).

Even disregarding frame, the scope of climate migration literature has been increasing to include drivers other than just climate change as well as impacts other than migration (Boas et al., 2019). The aim here is a logical step towards understanding the complexity of interaction between a multitude of migration drivers. However, it also further dilutes and obfuscates an already nebulous research field thereby rendering its research findings indeterminate (Nicholson, 2021).
The aforementioned pursuit of interdisciplinary research is also marred by science tribalism and the hierarchy of science as perceived by policy makers. By working in silos scientists fail to co-create and to learn valuable lessons provided by other,

related disciplines. Furthermore, tribalism outlaws unorthodox ideas, discourages challenging of status quo and thereby encourages a homogenous discussion (Clark & Winegard, 2020; Haidt, 2020). It is also the case that much social science and humanities research is regularly under-funded and utilised by governments compared to natural sciences (Overland & Sovacool, 2020). It seems therefore that the climate migration discourse, despite naturally existing across a range of sciences may well be suffering from a lack of transdisciplinarity and essential self-reflexion. Meanwhile, intranational and international political tribalism serves to further polarise opinion and undermines attempts at international migration and climate change policy (IOM, 2019). Time and time again it is pointed out that research within the climate migration field should be interdisciplinary (Boas et al., 2019; Hunter, 2018; Parrish et al., 2020) but this remains an elusive feat, with an array of logistical as well as ideological, methodological and psychological challenges (Albert et al., 2015; J. Goodman & Marshall, 2018).

Beyond academic interdisciplinarity, the international policy fora also gained diversity throughout the climate migration narrative. Throughout the last forty years interest and involvement has steadily increased from UN Agencies such as IOM, UNHCR as well as the UNFCCC, alongside States following the Nansen Initiative (2013) (Nash, 2018a). Meanwhile, border control is an increasingly alarmist and contentious issue in the current age of sovereignism (Abdou, 2020). This increase in UN cross-dialogues is systematically fraught with bureaucratic challenges and turf wars, as well as challenges of international relations, geo-politics and different framings used by different governance actors (Abdou, 2020). It is no wonder then that the political impetus and funding for further climate migration research is highly politicised, fragmented and pre-destined to fit within a particular framing determined by the interested parties. The resultant lack of reflexivity on the part of climate migration research is perhaps understandable in this context (Ransan-Cooper et al., 2015). Alongside this rise in high-level political interest was the rise of evidence-based policy making (EBPM) since 1997 (Baldwin-Edwards et al., 2019; Wells, 2007). EBPM as a mode of policy-making served to further intwine science and policy narratives and increasingly politicise research agendas (Baldwin-Edwards et al., 2019). It is possible that EBPM is also partially responsible for the call for more data on migration that is regularly bespeeched by both academic and policy facing actors.

Pertinent examples include the 2018 Global Compact for Migration's first stated objective, to gather and utilize disaggregated data (Global Compact for Safe, Orderly and Regular Migration, 2018), and the UCL-Lancet Commission on Migration and Health 2018 call for a Global Health Observatory (Abubakar et al., 2018). Implicit within such calls is the assumption that with more data comes more understanding and reduced uncertainty around how climate change impacts migration. It is assumed that more data will improve visibility of who, when and where the climate migrants are or will be. As such, we suggest such calls fail once again to address the causality paradox despite this being their intent. We further add a word of caution and ask those who would call for more data "who will this help?". Whilst high level monitoring may be beneficial for top-down policy and research interests, it can also be exploited for discriminatory purposes by state actors and may be met with scepticism and fear by those whose data is being collected (Franklinos et al., 2021; Lamber et al., 2019). Although EBPM and the associated politicisation of climate migration research, it is conceivable that this situation is preferable to reliance on non-evidence-based policy. Under such a scenario, climate migration research landscape may look drastically different, but the policy landscape would inevitably be rhetoric driven, with limited opportunities for ground-truthing or platforms for researchers to identify and provide impartial advice or evidence brokerage to decision-makers.

5.5.3 The science policy interface in the context of climate migration: a reverse-technocratic model?

Policy making needs have always driven climate migration research (McLeman & Gemenne, 2018). The above account is interjected with examples of how policy has had significant and direct influence upon the migration and environmental research agendas. Whilst typically policy may be driven at least in part, by the findings of research, either especially commissioned for policy purposes, or from general consensus that literature provides. This is classically referred to as a technocratic model (Rapley et al., 2014). A traditional technocratic or linear model assumes that once the nature of a problem has been described by science, responsibility moves then to policy makers to determine what could and should be done (Rapley et al., 2014). Whilst evidently true in the case of climate migration research that findings are being used to inform policy, it is perhaps more largely the case that political discourse is driving not only research funding but the research agenda and underlying biases. We describe the science-policy interface described above as a reverse-technocratic model. In this reverse-technocratic model we suggest that an unprecedented amount of information exchange and influence in fact moves in reverse, with policy narratives determining not only what research must be conducted but also setting the framing of the question, be it neoliberal (Felli & Castree, 2012; Lyster, 2019), security (Boas et al., 2019) or humanitarian (ref). In this way, the policy imperative may also pre-empt the conclusions that science shall feedback to policy-makers. Under such conditions the usefulness of new research is jeopardised if it exhibits cognitive dissonance with the overarching policy narrative it has been designed to serve (Boswell et al., 2011). Whilst successful science for policy necessitates a close relationship, much research identifies models of co-production as being more appropriate than linear models (Nowotny et al., 2001; Rapley et al., 2014; Sarewitz & Pielke, 2007).

5.6 CONCLUDING THOUGHTS

Within this thesis I have explored the dynamic and multi-directional relationships between climate change and migration, focusing on the pathway of climate impacts upon crop production and food security, which in turn are hypothesised drivers of migration. I have focused on statistical approaches, having first consulted a broad range of literature across the applied sciences including ethnography and migration studies, demography, geography, agricultural sciences, economics and global health science as well as climate science. Through review of this wide range of literature I have attempted to identify both epistemological and methodological shortfalls and overcome them through development of a conceptual model and migration typology. This conceptual model was then contextualised for the case study of Malawi thereby allowing statistical analysis to be well grounded with reasonable hypotheses and variables for modelling real life.

Initial findings from my literature review raised several questions both specific to the climate migration mechanism within Malawi, but also within the wider field of climate migration studies itself. The field is a challenging one for a number of reasons both political, epistemological and methodological. Recent efflorescence of studies into climate migration have produced important insights into how climate change is and may continue to affect migration, both directly and as mediated through aspects such as work opportunities, habitability, disaster recovery and health. The methodological toolkit used to explore climate migration has likewise grown to cover a range of approaches from social science-based interviews and survey analysis to highly complex systems modelling. In the future, if the different findings made across different scientific disciplines and approaches can be brought together, there will be benefits for future researchers, but more importantly, for those who are and will be affected by climate migration, and for decision-makers at all societal levels (from local community stakeholders to funders and world leaders). However, trans-disciplinary research and communication are currently under-utilised and very difficult to achieve. Perhaps the field of climate migration – a politically vogue topic and located at convergence of the social and natural sciences, can serve as a lightning rod to encourage further integration between scientific fields as well as between scientists, decision-makers and affected communities.

Considering the case study of Malawi, data paucity is a key challenge to studies, particularly complex systems approaches where it is hard to validate models against real-world knowable relationships and as such, high uncertainties remain. Statistical approaches were used (and I continue to recommend) based on data availability, but there are many opportunities to improve the data used for example through data imputation or through mixed-methods approaches which combine different data sources. As a climate vulnerable, agrarian economy undergoing rapid population growth, Malawi's economy needs to diversify in order to avoid future food security disasters which may be exacerbated by climate change. Further research into the impacts of climate change in Malawi will be of benefit for Malawi's policy-makers, community leaders and NGO network to support these goals and help Malawi become a climate resilient economy, supporting diversity within Malawi such as the different experiences of men and women, children and adults, rich and poor, and urban and rural households.

Ultimately, climate change presents a critical challenge for future migration across the globe and has significant implications for public health, human security and sustainable development. Despite underlying issues in the field, such as the causality paradox, it is largely agreed that climate change is already and will continue to contribute to large numbers of migrants. Affected migration types may include involuntary displacement (for example due to climate, hydrological or meteorologically related disasters), or as supposedly voluntary or adaptive measures, for example in search of new homes and livelihoods in the face of increasingly difficult climate adaptation challenges in situ. As suggested within this thesis, climate change may also increase cases of immobility of trapping which warrants further study both by researchers, and should be a consideration by policy-makers for example when preparing climate adaptation plans and other measures that make assumptions about how communities at scale respond to climate change. As such, better understanding of the relationship between climate change and migration is essential for effective future policy planning in all sectors. This can be achieved through the systematic and homogenous application of robust conceptual frameworks to local contexts, such as the framework which has been created and applied within this thesis.

The quantitative analyses undertaken within this thesis have identified some modest relationships between climate factors, crop production, food security and internal migration within Malawi. These relationships warrant further research to deepen the understanding of how climate change and in particular, aspects surrounding variability of weather (both temperature and precipitation) and the onset and variability of rainfall during the rainy season which is so heavily relied upon to irrigate Malawi's crops. Further research could focus not only on Maize production but on a more diverse range of crops. This is particularly important as Malawi continues to pursue crop diversification. In the future, improved data and analyses of crop production successes (under climate change) should include higher spatial granularity and should consider a range of crop types, and a range of climate-related drivers (such as minimum temperatures, rainfall variability, onset and end of the rainy season, and extreme rainfall events, soil moisture, PDSI and flood data). This in turn can also facilitate understanding of how climate change is impacting Malawi's food security though other considerations are important to include. As has been seen, food security can be defined on several hierarchical levels (availability, access, utility and stability) with different metrics used to measure different levels. This thesis has focused on the metrics of hunger, child anthropometric measurements and number of meals consumed. The selection of these food security metrics was primarily driven by data availability as well as literature which suggests that these are tried and tested metrics for describing food security. Considering the theory of food security however, these metrics could describe more than one aspect of the food security hierarchy. For example, prolonged hunger captures both food availability but also stability (for a period of at least three months). Child stunting is regularly used as a measure of chronic malnutrition which may arise due to lack of food availability, accessibility and is likely also an indicator that food supply is unstable. Wasting is a measure of acute malnutrition which may similarly be driven by sudden lack of food availability or access, or due to food utility issues or sudden onset stability issues. Finally, average number of meals consumed by children (aged 5-17 years) likewise could be used to describe both food access or food availability. Whilst these generic measures are helpful to explore the relationship between climate, crop, food and migration, targeted interventions may better benefit from more specific understanding of where the food security issues lie – for example considering not only crop production as means of ensuring that there is food available to Malawians, but a reliable road network and distribution channels may also be affected by severe climate events in the future and thereby jeopardise access routes and stability. Further research should consider a range of food security metrics should continue to be interrogated for their relationships with crop production and, if appropriate, directly with climate change.

As suggested by the findings of this thesis, the links between climate change and migration are complex and difficult to discern, with climate change being only one (perhaps small) part of a complex myriad of migration drivers. There remains currently only limited empirical evidence to support the hypothesis that climate change is driving mass migration. It is therefore perhaps unfounded that within much scientific and popular grand narratives, there is much rhetoric of the risks (and often alarmist or xenophobic implications) about ‘climate migrants’ or ‘climate refugees’, which western politicians and media oftentimes claim will arrive on mass and present a national security risk. Whilst there is also little evidence to disprove these claims, pursuit of evidence-based policy and the dogma of the scientific method would suggest that such claims should not be over touted without further investigation and more nuanced discussions. Nevertheless, climate change is no doubt an enormous risk to societies across the globe and should not be put off. Perhaps awareness of this is part of what is driving a more emotive rhetoric.

The disconnect between the empirical findings of these thesis challenge and the voracity of such rhetoric lead me to consider critically the field of climate migration itself – the political drivers for such research, possible underpinning biases / assumptions, and lack of due diligence in the continued pursuit of counting and treating climate migrants as a distinct category of migrant, despite the acknowledged impossibility of such a task. If migration is unfailing multi-causal, and if climate change is an existential threat to modern society, then surely all migrants are climate migrants? There are likely some cases where climate change can be attributed as a main driver of forced migration, for example in the case of migration away from small atolls due to inhabitability caused by sea level rise (Watts et al., 2021). However, much narrative around climate migration does not focus on these specific cases but takes a western-centric and oft alarmist view about impending mass migration from the global south to the global north.

Based on these considerations, the final aspect of these thesis was to discuss implications of my research on the field of climate migration considering ideas around causality, data paucity and tribalism as well as the need to critical reflect upon underlying narratives and motivations for the field itself. In turn this then inspired a literature review with the aim of analysing and critiquing the field of climate migration itself. The resultant critique elucidates the importance of a wider appreciation for the motivations behind an individual research project in order that underlying drivers and influences may be identified and considered accordingly.

In the future, participatory approaches, mixed-methods and improved transdisciplinary research and communications may be of benefit not only to researchers and decision-makers but may also counter some of the underpinning biases and rhetoric that has built up around this topic in recent years. Such approaches can also increase the data pool from which secondary studies such as conducted within this thesis can be performed. This could help to improve the quality and availability of data and further improve understanding of the relationships between climate change and other social, economic and demographic factors. A caveat to this statement is that future researchers should continue to exert diligence when considering for the appropriateness of secondary datasets to address their specific research question (which the dataset was not originally collected for). Continued acknowledgment and respect for the complexity of the climate change – migration nexus is needed. With such acknolwedgement researchers and decision-makers can avoid reductionist approaches and siloed thinking, for example when making assumptions about over-simplified, monodirectional, linear relationship between climate change and migration. This thesis has demonstrated such linear relationships may not be the case found this may not be the case and that quantitatively describing such relationships is exceedingly challenging and nuanced.

Finally, on the topic of communicating research - to other researchers, to policy makers and to civil society, this is being increasingly recognised as an essential step for early career researchers. Climate migration narratives may benefit from strong and honestly brokered communication of both the current evidence base for climate migration, as well as clear messaging on the need to consider the frames used to talk about climate migrants.

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