Towards a coupled migration and weather simulation: South Sudan conflict

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Abstract. Multiscale simulations present a new approach to increase the level of accuracy in terms of forced displacement forecasting, which can help humanitarian aid organizations to better plan resource allocations for refugee camps. People's decisions to move may depend on perceived levels of safety, accessibility or weather conditions; simulating this combination realistically requires a coupled approach. In this paper, we implement a multiscale simulation for the South Sudan conflict in 2016-2017 by defining a macroscale model covering most of South Sudan and a microscale model covering the region around the White Nile, which is in turn coupled to weather data from the Copernicus project. We couple these models cyclically in two different ways: using file I/O and using the MUSCLE3 coupling environment. For the microscale model, we incorporated weather factors including precipitation and river discharge datasets. To investigate the effects of the multiscale simulation and its coupling with weather data on refugees' decisions to move and their speed, we compare the results with single-scale approaches in terms of the total validation error, total execution time and coupling overhead.

Keywords: Agent-Based Modelling · Multiscale Simulation · Refugee Movements · Data Coupling.

1 Introduction

Internal conflicts, environmental disasters, or severe economic circumstances force people to displace from their homes [1]. For instance, people still struggling with the continuation of violence and instability which led to escalating food insecurity and drastic economic decline in South Sudan after the civil crisis in 2013. All these had resulted in the displacement of people who became forced migrants to find safety in camps located in neighbouring countries [2]. By mid-December 2016, more than 3 million South Sudanese had been forced to flee their homes. Hence, one in four people in South Sudan had been uprooted, their lives disrupted, their homes destroyed, and their livelihoods decimated [3]. United Nations Office for the Coordination of Humanitarian Affairs (OCHA)

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identified 7.5 million people out of a population of 12 million in need of humanitarian assistance [4]. Computational models can forecast refugees' arrival time and counts to the camps. It helps humanitarian aid organizations to allocate enough resources for refugees [4]. Among the computational models, agent-based modelling (ABM) can provide such insights and information [1].

ABM hybrid techniques are the best way to understand the complex decision-making processes of social systems like agent behaviours and their relationships [5,6,7]. A lot of efforts have been made in ABM to simulate forced displacement [8,9,10,11]. More recent research in ABM's hybrid techniques is integration and data coupling in simulation, particularly their varied number of approaches. Groen et al. [12] identified four popular approaches to couple and integrate simulation models including, multi-scale integration, multi-paradigm integration, multi-platform/multi-architecture integration and multi-processing integration. Among these approaches, multiscale simulations are more inherent for scientific problems like forced displacement forecasting to create more accurate models. However, multiscale simulations face several challenges. In general, formulating generic frameworks for multiscale modelling and simulation is a big challenge [13]. To study the effects of policy decisions on ABM, Gilbert et al. [14] and Suleimenova et al. [15] examined ABM in complex systems, such as human movement, to provide insights for governments, stakeholders and policymakers. Searle et al. [16] proposed a generic framework by designing an ABM to simulate conflict instances and decisions behind the movement of refugees fleeing conflict-affected areas.

In more detail, Alowayyed et al. [17] investigated computational challenges regarding coupling between a range of scales. Incorporating external factors affecting conflict events is another challenge that needs to be tackled [12]. Furthermore, due to incomplete or small size datasets, forecasting forced displacement does still suffer major challenges like outdated statistical methods and poor refugees arrival estimations [18,19]. Besides, despite the necessity of investigating the effects of climate, weather conditions and seasonal factors on refugees movement, there is very limited research in the literature to identify how they influence movements, particularly adverse conditions that might restrict possible migration paths. A study showed the correlation coefficient between arrivals in different countries and different weather-related variables [20]. Abel et. al [21] stated that climate change will increase the number of refugees fleeing from conflicts and also low precipitation level will increase conflicts which in turn cause rising the number of refugees. Black et al. [22] studied the drivers of refugees movements through different climatic related problems, such as sea level, fluctuations and intensity of storms and rainfall patterns, temperature rise and changes in weather conditions.

In [23], we presented the FLEE agent-based simulation approach where a complex system is modelled as a set of autonomous decision-making agents that behave accordingly with their environment based on a set of rules. Each agent in FLEE acts as a forcibly displaced person and tries to move between locations, attempting to reach the safety zone (i.e., camps). In this paper, we focus on imple-

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menting coupling ability which allows us to connect simulations of multiple scales of movement in different regions regarding their different circumstances like new rules, policy decisions or weather conditions. To test the proposed coupling model and investigate the effects of the aforementioned decisions and changes to our FLEE ABM assumptions, we select the South Sudan conflict as our test scenario and construct a multiscale (macro-scale and micro-scale) model to explore the establishment of data coupling between such models.

The rest of the paper is set out as follows. In Section 2, we explain a multiscale Flee model. Section 3 discusses the effort on the coupling approaches for multiscale simulations. We explain the South Sudan multiscale simulation and coupling with weather datasets in Section 4. Section 5 presents the experimental preliminary results with discussion. Finally, Section 6 concludes and briefly outlines future work.

2 Flee : A Multiscale Approach

The developed multiscale simulation prototype in this work is based on the Flee code[3][23]. The Flee code is an ABM kernel, written in Python 3, which predicts the distribution of fleeing refugees across target camps. Flee is optimised for simplicity and flexibility, and support simulations with 100,000s of agents on a single desktop.

Our proposed prototype divides the whole model into two sub-models, namely, macroscale and microscale models. Each sub-model is executed independently and agents pass between them during the simulation. In this model, each location in the location graph, where agents pass through the coupling interface, should be registered as coupled locations. In addition to coupled locations, all microscale model's conflict locations should be added to the macroscale model as ghost locations. It means that although they are added to the macroscale model, they don't have any link to other macroscale locations and this is why they are named ghosts locations. They are a special type of coupling locations where (a) the macroscale model inserts agents into these locations according to the normal FLEE agent insertion algorithm and (b) at each time step, the coupling interface transfers all agents from each ghost location to the microscale model. Figure 1 illustrates the schematic scale Separation Map for data coupling between macroscale and microscale models.

3 Coupling Approaches

In this section, we highlight the use of two different cyclic (two-way) coupling approaches to interconnect macroscale and microscale models: coupling through file I/O and coupling using MUSCLE3. We also describe the acyclic (one-way) coupling with the ECMWF Climate Data Store, which we have used to incorporate weather data into the microscale model.

[3] http://www.github.com/djgroen/flee

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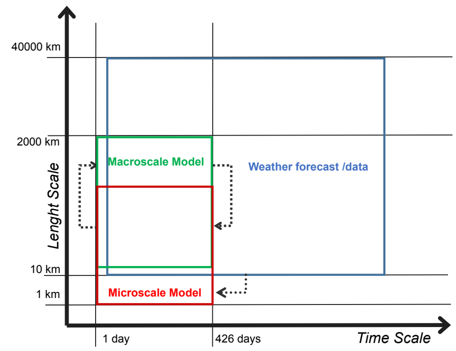

Fig. 1: Scale Separation Map of our model. The macro- and micro-scale model have identical time scales and overlapping spatial scales, and are coupled cyclically. In addition, the micro-scale model receives data from the weather forecast data source (or from ECMWF Climate Data Store in the case of historical data).

3.1 File Coupling

File I/O is a coupling approach to exchange data between two sub-models. By establishing this approach, exchanged data, such as the number of new agents added to each location, can be passed between sub-models models using a local shared file system. In this work, the number of all agents passing between sub-models through coupled and ghost locations are stored in the format of CSV files. Both sub-models fill their coupled CSV files, in a parallel fashion, to make sure that both sub-models are synchronized in terms of simulation time steps when all necessary coupled inputs files are checked at the start of each iteration. Compared to other approaches, this method is straightforward to implement and debug and easy to maintain, but lacks flexibility and can lead to high I/O overhead for large problems.

3.2 MUSCLE3 Coupling

MUSCLE3 [24], the Multiscale Coupling Library and Environment, aims to simplify the scale-separated coupled simulation. It contains two main components: the MUSCLE library, i.e., `libmuscle`, and the MUSCLE Manager. The `libmuscle` handles the data exchange over the network between each sub-model in a peer-to-peer fashion. The MUSCLE Manager sets up sub-model instances configuration and coordinates the connections between them. A model can be described to the Manager using yMMSL, a YAML-based serialisation of the Multiscale Modelling and Simulation Language (MMSL). Figure 2(a) shows the architecture of MUSCLE3 and figure 2(b) represents the used yMMSL in our design.

To implement our coupling strategy with MUSCLE3, we defined two main compute elements, `macro` and `micro`, which represent the macro and micro mod-

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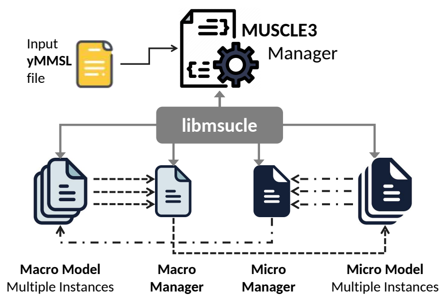
els, and two manager elements, `micro_manager` and `macro_manager`, which handle the inputs from multiple instances of each sub-models. By starting the simulation, each lunched sub-model will be registered into the coupling system by MUSCLE3 manager. In this example, 10 concurrent macro and micro sub-model will be executed. Each sub-model instance will simulate the agent's movement between locations on each day. To Exchange the data, since we have multiple instances, we designed a manager sub-model to (a) gather data from each instance of the sub-models, (b) combine the founded `newAgents` per location by each instance into one, and (c) pass to the other model, e.g., `macro_manager` will collect and combine data from all `macro` instances, and pass to all `micro` instances.



(a) architecture

```
ymmsl_version: v0.1
model:
  name: mscalecity_test
  compute_elements:
    micro_manager: micro_manager
    macro_manager: macro_manager
    macro:
      implementation: macro
      multiplicity: 10
    micro:
      implementation: micro
      multiplicity: 10
  conduits:
    micro.out : micro_manager.in
    micro_manager.out : macro.in
    macro.out : macro_manager.in
    macro_manager.out : micro.in
```

(b) yMMSL file

Fig. 2: Implemented Macro-Micro coupling approach by MUSCLE3

In particular, MUSCLE 3 provides valuable features: coupling different sub-model instances, spatial and temporal scale separation and overlap, settings management, and combining features. At the time of writing, we have established these features and we are scrutinizing the simulation to ensure coupling rules are scientifically robust. We plan to perform a performance test of the different coupling approaches once this scrutiny exercise has concluded.

4 South Sudan Multiscale Simulation

For the South Sudan multiscale simulation, we use a cyclic (two-way) coupling between a more approximate model that captures most of South Sudan as a macroscale model (see Fig.3(a)) comprising 8 regions of South Sudan and 14 camps in 4 neighbouring countries, including Uganda, Kenya, Sudan and Democratic Republic of Congo (DRC), and a more detailed model that captures the region around the White Nile as a micro model (see Fig.3(b)). In the microscale model, we aim to capture key walking routes, roads, and river crossings in the

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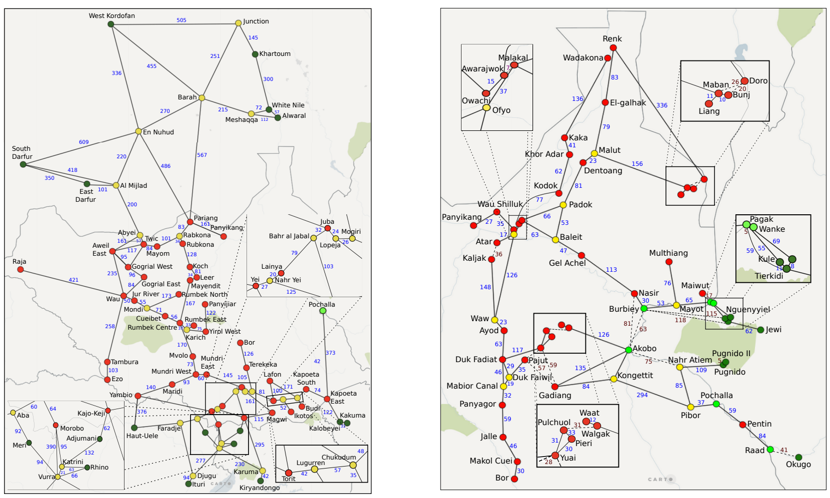
mountainous areas in eastern South Sudan. We also increase the level of detail in terms of locations and incorporate a broader range of relevant phenomena, such as weather conditions. The microscale model focuses on forced migrant movements from Upper Nile and Jonglei regions towards Ethiopian camps in Gambela. We create both models for the same conflict period between 1 June 2016 and 31 July 2017. More detailed maps of macroscale and microscale models' locations are depicted in Figures 3(a) and 3(b) wherein each, red points represent conflict locations, yellow points are towns and green points show camps. Besides, to couple macroscale and microscale models, four coupled locations co-exist in both models for passing agents between both models. Moreover, as described before, the microscale model has additional algorithm assumptions which include three types of routes: drive, walk and river that affect the agents' movement speed.



(a) Macroscale Model (b) Microscale Model

Fig. 3: South Sudan Location Graphs

4.1 Weather Coupling in South Sudan Microscale Model

South Sudan experiences a tropical climate, characterized by a rainy season which differs by location but generally falls between April and November, followed by a drier season. Annual rainfall ranges from 700 - 1,300 mm in the north of the country, to 1,200 - 2,200 mm in the southern upland areas. Most of this rainfall occurs in the wet season, therefore monthly rainfall averages less than 10 mm in the dry season and above 200 mm in the rainy season in the Bahr el Ghazal and Eastern Equatoria. The temperature averages are normally high, above 25°C, and exceeding 35°C in March which is the hottest month which is

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depicted in Figure 4. Since freezing temperature is non-existent in a tropical climate, and storms and strong winds are rare, floods and droughts represent South Sudan most frequent natural disasters in the past decades. They are also the most damaging natural disasters in South Sudan in terms of the number of affected people, as seen in Figure 5. Flooding mainly occurs between July and September, when heavy rains fall in most parts of the country, leading to the flooding of the Nile River tributaries [25]. Therefore, we consider using precipitation and river discharge most influential on refugee movement in our simulation.

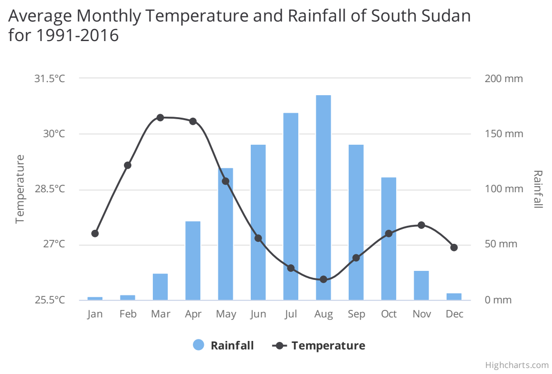

Fig. 4: Average Monthly Temperature and Rainfall of South Sudan for 1991-2016

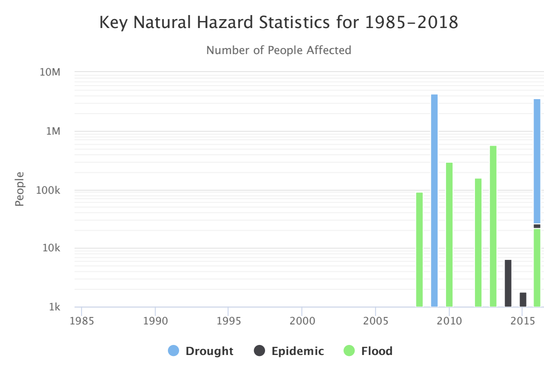

Fig. 5: Key Natural Hazard Statistics of South Sudan for 1985-2018

The purpose of coupling with ECMWF's weather forecasts is to improve the simulation model forecasts through the inclusion of such data. Therefore, to couple the microscale model with weather datasets like river discharge and precipitation levels and study their effects on agents' movement, we have to answer how they can affect refugees' decision to move from a location and their speed?. More importantly, all these assumptions need to be reflected in a rule set for coupling microscale model with weather datasets. For this aim, we examine our prototype in the real case of South Sudan's conflict with real data provided by UNHCR, ACLED, and of course weather data provided by ECMWF.

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To couple the microscale model with the weather datasets, the overall strategy is the static file coupling. We have analysed 40 years of precipitation data for South Sudan and surrounding areas, to identify the precipitation range for each location. This range is used to set the thresholds which trigger the agents' movement speed changes accordingly. The data is retrieved from the Climate Data Store (CDS) by using CDSAPI for the years 2016 and 2017. Daily aggregations and conversion from m/day to mm/day were calculated for the period of simulation 01/06/2016 to 31/07/2017 using xarray Python library. The data is prepared for three smaller regions of interest: Upper Nile, Jonglei and Gambelais which is saved as CSV files - one file for each day to be compatible with other input files for the microscale model (see Fig 6).

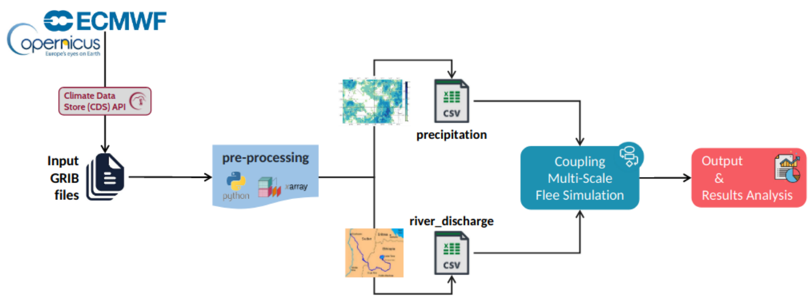

Fig. 6: Coupled Weather and Migration Simulation

The datasets used for these calculations include:

– Daily average precipitation data per month, calculated from 40 years ERA5 climate reanalysis, for the South Sudan simulation locations. It consists of two parameters:
  - N - number of rainy days within that month
  - tp - Total precipitation
– Daily precipitation data (ERA5 climate reanalysis [26]) for the microscale model for the South Sudan area:
  - Latitude range = 11.75 - 6.0, Longitude range = 31.0 - 35.25
  - Time range: 01-06-2016 till 31-07-2017

Day	Bor_Akobo	Juba_Bor	Renk_Alwaral	...
0	0.1	0.465	3.6	...
1	...	...	...	...
...	...	...	...	...

Table 1: Sample structure for precipitation input file

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The steps of the implemented weather coupling are as follows:

1. Using Precipitation data for 40 years to identify total precipitation range the given date and location's latitude and longitude.
2. Calculating midpoint location for all routes in input data.
3. Creating precipitation.csv in the format as shown in table 1, including the total precipitation for each microscale model routes midpoints.
4. Going through the precipitation.csv to find total precipitation for each link at the given time step.
5. Calculating the movement speed by using two thresholds. The first threshold is 5mm which means if total precipitation is below this amount, the speed will not change. For the second threshold, if the total precipitation is bigger than 75% of the average level of that location and bigger than 15 mm, the link will be considered closed. Any other precipitation levels which will be in the middle of these thresholds means the route distance will be doubled. Table 2 summarizes these assumptions.

Move_speed	No change in speed	Double the distance	Close the link
	$tp < X1$	$X1 < tp < X2$	$X2 < tp$
	`Low Level`	`High Level`	`Vey High Level`

Table 2: Level of Precipitation vs Move_speed

Furthermore, we use daily river discharge data from Global flood forecasting system (GloFAS [27]) to explore the threshold for closing the route considering values of river discharge for return periods of 2, 5 and 20 years. Currently, because of having only one crossing route, we only use a simple rule with one threshold to define the river distance. If the river discharge at the midpoint of the given route is more than the average of that point in history, 8000 m3/s, the link will be closed (see Fig. 7). The datasets used in this part are:

- River discharge data (GloFAS historical reanalysis dataset) for the same temporal and horizontal range as total precipitation
- River discharge data for 2, 5 and 20 years return period filtered to White Nile area, also calculated from GloFAS historical reanalysis dataset

In summary, to couple the South Sudan multiscale model with weather datasets, we take the following steps. We construct macroscale and microscale models individually for the South Sudan conflict. We incorporate more location types in the microscale model to increase the level of detail (e.g. forwarding hubs and marker locations). We also add new route types, such as key walking routes, driving roads, and crossing rivers. Then, we interlink the two models, using two coupling approaches, File Coupling and Model coupling with MUSCLE3. Then, we integrate the weather datasets into the microscale model, including precipitation level and river discharge provided by Copernicus Climate Change Service (C3S) and ECMWF.

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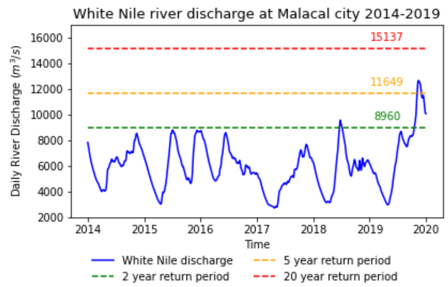

Fig. 7: River discharge values at Malacal city crossing for the period between 2014 and 2019

5 Results and Discussion

To demonstrate a highly detailed model of the South Sudan conflict and forecast forced displacement, we take five approaches to investigate the coupling within multiscale simulations and also coupling with external datasets like weather datasets and their effects on refugees' speed and their decisions to move or stay. These approaches are:

1. Singlescale Simulation (Uncoupled Serial Mode)
2. Multiscale Agent-based Simulation (File Coupling)
3. Multiscale Agent-based Simulation (MUSCLE3 Coupling)
4. Multiscale Agent-based Simulation + Weather Coupling (File Coupling)
5. Multiscale Agent-based Simulation + Weather Coupling (MUSCLE3 Coupling)

In the first approach, we only simulate the whole South Sudan location graph using FLEE rule set 2.0 in serial mode or singlescale only for comparison with multiscale approaches. It means that the serial mode doesn't follow the multiscale ruleset which needs dividing the whole model into sub-models. In approaches 2 and 3, we investigate multiscale simulations without weather coupling by using File I/O and MUSCLE3 coupling between sub-models. In approaches 4 and 5, we incorporate weather data into our multiscale simulations and again we use File I/O and MUSCLE3 coupling to pass agents between sub-models. The simulation is performed on a node with 32 cores, and a total of 12GB of memory. For the comparison, table 3 illustrates the results of these simulations on the Eagle supercomputer, including the total execution time, total validation error and coupling overhead for the aforementioned approaches.

Also, we deliberately avoid minimizing the validation error by calibrating existing model parameters against data. Because, it might lead to over-fitting which not only reduces the reusability of our simulations in new contexts, but also makes it highly sensitive to the (often incomplete) validation data sources we use. Therefore, we mostly incorporate data sources as model input, and combine them with our general knowledge and qualitative data about human behaviour.

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Approaches		Total Validation Error	Total Execution Time (hh:mm)	Coupling Overhead
Whole South Sudan (Serial Mode)		0.431	02:21	1
Multiscale Simulation	File Coupling	0.507	01:25	0.60
	MUSCLE3 Coupling	0.507	01:25	0.56
Multiscale Simulation + Weather Coupling	File Coupling	0.510	09:01	3.83
	MUSCLE3 Coupling	0.509	09:17	3.95

Table 3: Comparison of the Simulation Approaches

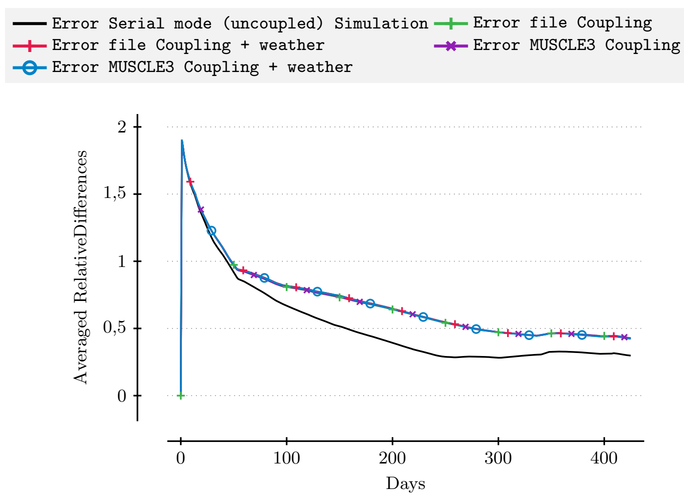

Fig. 8: Overview of the averaged relative differences for the taken approaches

As results show, the total validation error of the serial mode approach, which is 0.431, is lower than multiscale approaches (0.507). However, the total execution time of multiscale approaches, which is 01:25 for both second and third approaches, is lower than serial mode (02:21) and they are pretty much lower than the approaches coupled with weather datasets (09:01 and 09:17). Hence, we can claim that despite having slightly higher validation error, multiscale approaches are much faster than the serial mode approach. Furthermore, to explain the reasons for high execution time for the weather coupled approaches, we have to point out that they ran longer in the early versions, and after a lot of optimizations we got to this time. To justify this, it can be said that perhaps due to the coupling and integration with static datasets and repeated reading of such data at each time step, the execution time of these approaches increases. The third column in table 3 demonstrates these as the Coupling Overhead which assumes the serial mode as a benchmark to calculate the deviations of other

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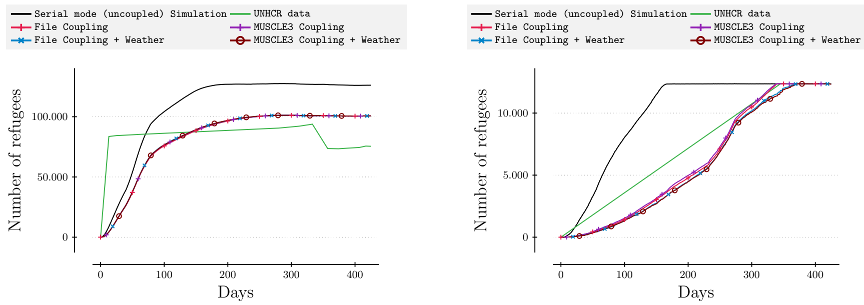

(a) Macroscale Model (b) Microscale Model

Fig. 9: Sample camps simulation results for 426 days from 1 Jun 2016 till 31 July 2017

approaches. Therefore, the coupling overhead for serial mode is 1. The values 0.60 and 0.56 complying faster pace of multiscale approaches without weather coupling, and values 3.83 and 3.95 are for weather coupled approaches which comply with their lower pace comparing to the serial mode.

Nevertheless, the overall validation error for the South Sudan simulation is relatively high, because many people do not use the main routes and their choice of destination is strongly affected by the weather conditions. We are in the process of incorporating these phenomena in these simulations, and the validation errors presented for the multiscale simulations represent preliminary, not final, results.

The overview plots for the averaged relative differences for Serial mode (uncoupled) simulation (black line), file coupling (red line), file coupling (green line) file coupling + weather (red line), MUSCLE3 coupling (violet line) and MUSCLE3 coupling + weather (blue line) for the aggregated macroscale and microscale models are illustrated in figure 8. However, because both file and MUSCLE3 coupling approaches do the same data exchange and the weather coupled models are very limited in this case, all the coupled results are are overlapping in this figure. Besides, the simulation results for sample camps at both macro (Kakuma) and micro level (Okugo) regions are depicted to show the difference between taken approaches at the camp arrival forecasting level (see Fig. 9(a) and 9(b)).

6 Conclusion

In this paper, we presented a multiscale simulation approach for modelling forced migration in South Sudan, and described how different coupling approaches have an effect on the total execution time, validation error and coupling overhead. We investigated file I/O based and MUSCLE3 based coupling approaches. Also, we integrated a weather data source with our microscale model, to determine realistic agent movements e.g. the changes in road accessibility due to flooding.

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Our multiscale models result in a higher validation error than our single-scale models, which points towards the need to add further details in our coupling implementation and do a larger-scale validation exercise. Besides, the location graph needs to be revised and the coupled locations should be reconsidered to properly simulate refugees' movement in multiscale models. In terms of runtime, we find out that the macro-micro model coupling outperforms the weather coupling, that needs to be improved considerably.

In general, modelling the South Sudan conflict while taking all these aspects into account is a highly demanding endeavour, mainly because the collection of input and validation data is often very challenging. We, therefore, see this work as a first major step in a sequence of iterations towards a highly detailed population displacement model of this conflict.

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