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Integrating renewable energy resources in electricity distribution systems—A firm-level efficiency analysis for Sweden controlling for weather conditions[☆]

Oleg Badunenko[a,*], Astrid Cullmann[b], Maria Nieswand[c]

[a] Department of Economics and Finance, College of Business, Arts and Social Sciences, Brunel University London, Uxbridge, UB8 3PH, UK
[b] Chair of Econometrics and Business Statistics, TU Berlin and Energy, Transportation, Environment Department, German Institute for Economic Research (DIW Berlin), Mohrenstrasse 58, D-10117 Berlin, Germany
[c] IOER Research Data Centre, Leibniz Institute of Ecological Urban and Regional Development, Weberplatz 1, D-01217 Dresden, Germany

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ABSTRACT

Sweden is at the forefront of the transition of its energy sector to low-carbon technologies with profound consequences for both energy generation and its distribution. However, the impact of this transition on the performance of Electricity Distribution System Operators (DSOs) has not been thoroughly studied. The article addresses this gap by using a novel approach and detailed georeferenced firm-level, weather, and regional data in Sweden from 2014 to 2019. Our findings indicate that (i) an increase in the number of small-scale feeders and (ii) a higher degree of decentralized energy production (decentralization) both improve DSOs' cost efficiencies. Additionally, we demonstrate that DSOs have adapted well to long-term weather variability. These results have significant implications for the effective implementation of renewable energy policies.

1. Introduction

This study examines the cost efficiency effects of integrating renewable energy production units to regulated electricity distribution networks in Sweden. As a global leader in transitioning its energy sector toward climate neutrality, Sweden serves as a model for many other countries across Europe. The Renewable Energy Directive (2018/2001/EU) mandates that 40 percent of the EU's gross final energy consumption must come from renewable energy sources by 2030 to reduce greenhouse gas emissions. To achieve this target, European countries are intensifying their efforts by expanding small-scale renewable energy generation (decentralized generation). This expansion includes diverse sources of power generation such as small hydro, biomass, biogas, solar power, wind power, and geothermal power.

Electricity distribution system operators (DSOs) are required to connect small-scale renewable energy generation to their distribution grids (Johansson et al., 2020). DSOs therefore play a pivotal role in the effective integration of renewable energy resources into existing grid networks. The security and quality of electricity supply involve building, reconfiguring, and investing in current electricity distribution grids (Johansson et al., 2020; Perez et al., 2016; Ruester et al., 2014; Simpson, 2017). The managerial challenges of integrating a fundamentally new and complex component into their operations require long-term decisions. On the one hand, cost-intensive investments might lead to lower network performance. On the other hand, modernizing the distribution grid, with advanced metering, enhanced steering capabilities, and localized power generation could improve network performance. Consequently, the impact of an increasing share of decentralized power generation on DSOs' costs and cost efficiencies remains uncertain (Vesterberg et al., 2021).

The impact on firms' costs and grid efficiencies also heavily relies on geographical location (Johansson et al., 2020) and weather conditions, which are beyond managerial control. Decentralized electricity flow is characterized by the variable nature of renewable power sources (L'Abbate et al., 2008). The intermittent power output, such as that from wind energy, poses challenges in instantly balancing energy production and consumption, making larger reserve capacities essential to mitigate energy production fluctuations.[1]

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* Corresponding author.
E-mail addresses: oleg.badunenko@brunel.ac.uk (O. Badunenko), a.cullmann@tu-berlin.de (A. Cullmann), m.nieswand@ioer.de (M. Nieswand).

1 Additionally, factors like solar irradiation, orientation, and the level of self-consumption at each production unit also influence this dynamic.

2 Anaya and Pollitt (2017) deliver empirical evidence for DSOs in Brasilia. They use stochastic frontier analysis to measure the impact of weather on the efficiency of electricity distribution businesses in developing economies, without considering the impact of decentralized generation.

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Therefore, we argue that accounting for weather conditions is essential when quantifying the impact of distributed generation on the cost efficiency of DSOs as the grid layout and the decentralized power production are incrementally related to weather conditions. This is particularly true when weather conditions vary substantially within countries, whose electricity distribution companies might otherwise be comparable (Anaya and Pollitt, 2017).[2] Appendix A reveals a huge variability in weather conditions in Sweden, both in terms of extremes and averages. Weather conditions are typically not well represented by simply classifying a region as "coastal". Overlooking this variability may result in biased estimates.

This paper aims to analyze and quantify the impact of an increasing proportion of decentralized generation on the cost efficiency of DSOs. We provide empirical evidence from Sweden, a global leader in renewable energy adoption, characterized by significant weather variability across its territory. Sweden's energy market, striving for a 100 percent renewable power system by 2040, has seen a substantial rise in small-scale producers connected to the distribution grid from 2014 to 2019, with the degree of decentralization increasing on average from 0.77 in 2014 to 0.84 in 2019.

We use various metrics to measure this impact. First, we test whether an increase in the number of small and micro or medium-scale feeders is associated with cost efficiency improvements (the infrastructure hypothesis). Second, we examine whether a higher degree of decentralization in each electricity distribution area, defined as the proportion of small and micro feeders to the total number of feeders, contributes to more cost-efficient DSO operations (the decentralization hypothesis).

Our empirical analysis relies on publicly available firm-level data from the national energy market inspectorate, Energimarknadsinspektionen (EI), covering the period from 2014 to 2019. This dataset includes information on small- and micro-scale electricity production across all 178 DSOs in Sweden. By integrating this firm-level data with shapefiles that delineate the exact geographical boundaries of DSO areas, we combine high-resolution weather data and regional statistics to account for weather variability and a variety of characteristics of distribution areas. Unlike previous studies that typically analyze factors at the municipality level, we conduct precise regional mapping of external influences at the network level.

Our analysis, hence, provides new insights into the impact of renewable energy feeders on the cost efficiency of DSOs from two perspectives. First, we consider the number of small-and micro-scale feeders using renewable resources. Second, we discuss the degree of decentralization, while simultaneously accounting for weather conditions by applying geo-matched data from Swedish DSOs. The findings can be summarized as follows. First, we demonstrate that an increase in the number of small-and micro-scale feeders enhances the cost efficiency of DSOs, supporting the infrastructure hypothesis. Second, a higher degree of decentralization correlates with greater cost efficiency, providing evidence for the decentralization hypothesis. This is the first study to account for significant weather heterogeneity when analyzing the effect of decentralized generation on DSO efficiency. Third, we show that DSOs have effectively adapted to weather variations over the long term. Overall, our results indicate that DSOs have successfully integrated renewable energy in existing grid networks. These insights are relevant for European regulators and policymakers when facilitating the transition toward a greenhouse gas-neutral, decentralized energy system.

The structure of this paper is as follows: The next Section 2 provides background information summarizing the existing literature and Section 3 describes the electricity distribution sector in Sweden including the challenges associated with integrating renewable energy resources. Section 4 describes the data. Section 5 outlines the empirical strategy. Section 6 discusses our results and Section 7 concludes.

2. Related literature

In recent years, a substantial body of literature has emerged analyzing the efficiency of electricity distribution at the level of DSOs. Particularly in the context of increasingly incentive-based regulation and the calculation of X-factors, numerous studies have investigated the extent of inefficiency among DSOs worldwide, e.g. Filippini et al. (2004) in Slovenia, Cullmann (2012) and v. Hirschhausen et al. (2006) in Germany, Filippini and Wetzel (2014) in New Zealand, Giannakis et al. (2005) in the UK, Farsi and Filippini (2004) in Switzerland, Bağdadioğlu et al. (1996) in Turkey, and Campos et al. (2022) in Brazil. Due to their leading role in implementing renewable energy resources and their transparency in firm-level data provided by public regulators, the Scandinavian energy market has attracted significant research interest. Among others, Kuosmanen (2012), Kumbhakar and Lien (2017), Kumbhakar et al. (2015) Kumbhakar et al. (2020), Bjørndal et al. (2018), Kumbhakar and Hjalmarsson (1998), Musau et al. (2021), and Zeebari et al. (2023) conduct firm-level efficiency analysis of DSOs in Finland, Norway and Sweden.

A limitation of these studies is their reliance on the assumption that inefficiency is either time-variant (transient) or time-invariant (persistent). Transient inefficiency pertains to controllable non-systematic management issues that can be mitigated within a short period (Filippini and Greene, 2016). In contrast, persistent inefficiency is associated with systematic differences between DSOs in their operational environments or managerial capabilities. Consequently, short-term and long-term inefficiencies should be addressed through different management strategies.

Recently developed Stochastic Frontier models enable the estimation of firms' production (or cost) functions while decomposing the error term into noise, DSO-specific effects, and the persistent and transient inefficiency components, known as the four-component model (Colombi, 2010; Colombi et al., 2011, 2014; Tsionas and Kumbhakar, 2014; Filippini and Greene, 2016). Filippini et al. (2016) apply this model to disentangle persistent and transient efficiency for network infrastructures, specifically DSOs in New Zealand, to explore the implications of distinguishing these two types of efficiency for price cap regulation. Badunenko and Kumbhakar (2017) extend the Stochastic frontier model in the sense that factors explaining variations in persistent and transient inefficiency can be identified, and their impact (marginal effects) on output (cost) can be estimated. Badunenko et al. (2021) evaluate the efficiency of German DSO using the four-component stochastic frontier model, identifying the German reunification as a determinant of persistent inefficiency, after controlling for firm heterogeneity and random noise.

Empirical research demonstrates that various external factors–those beyond managerial control–significantly influence both cost structures and the efficiency of electricity distribution operations. Weather indicators have recently garnered considerable attention among these external factors, particularly in countries with substantial variations in weather conditions (Anaya and Pollitt, 2017). DSOs must adapt their networks to these specific conditions to mitigate the risk of system failures and enhance distribution system reliability.

Further studies highlight the importance of accounting for weather conditions to achieve robust efficiency estimates (Growitsch et al., 2010; Jamasb et al., 2012; Llorca et al., 2016). Some empirical studies, however, find that weather does not significantly affect efficiency (Korhonen and Syrjänen, 2003; Nillesen and Pollitt, 2010), while other studies suggest that specific variables may serve as proxies for weather's impact on efficiency (Yu et al., 2009). Additionally, some countries have incorporated weather variables into the regulatory evaluation of DSOs. For instance, the Norwegian Water Resources and Energy Directorate initially included snow and coastal variables in their DEA models, later expanding to factors such as snow, wind, ice, and temperature in subsequent regulatory periods.

Few empirical studies consider distributed generation when estimating the efficiency of DSOs. Vesterberg et al. (2021), using a nonparametric DEA framework in a study on Sweden, found no negative effect on efficiency, suggesting that the increasing number of decentralized energy resources does not lead to inefficiencies in distribution and supports the goal of a more sustainable energy system. Similarly, Agrell and Brea-Solís (2017) accounted for distributed generation in their cost function analysis and found no significant effect on cost differences for Swedish DSOs.

Our empirical approach differs notably from previous efficiency studies. Based on the parametric stochastic frontier analysis our analysis provides new insights into the impact of renewable energy feeders on DSOs' transient and persistent cost inefficiencies while accounting simultaneously for weather conditions using very detailed firm-level and regional information.

3. DSOs and distributed generation in Sweden

The Swedish electricity grid is structured into three distinct tiers: the national grid, and the regional and local grids. The national grid, managed by the transmission system operator Svenska kraftnät, is responsible for transmitting electricity over long distances and operates at high voltage levels of 220–400 kilovolts. This grid tier connects only large-scale power generation sources such as nuclear and hydropower plants, as well as substantial wind farms with capacities exceeding 300 megawatts (Johansson et al., 2020). Meanwhile, the regional and local grids distribute electricity to consumers, ensuring that power reaches homes and businesses.

The regional grids, operating at voltage levels of 20–130 kilovolts, transmit power from the national grid to the local grids and supply energy to high-demand industrial consumers such as smelting plants, refineries, and mines. Medium-sized generation units, including smaller wind power parks with capacities between 15 megawatts and 300 megawatts, are typically connected to the regional grids. The local grids, operating at voltage levels of 0.4–20 kilovolts, distribute electricity to households and businesses and connect to generation units with capacities of less than 15 megawatts. Distributed energy resources, such as small-scale solar plants, individual wind turbines, and very small bioenergy and hydropower plants, therefore feed into the local grids managed by DSOs (IVA, 2017).

DSOs operate as natural monopolies within their respective regions, thus they are regulated by the Swedish energy market inspectorate, Energimarknadsinspektionen (EI).

The expansion and integration of decentralized generation offer substantial opportunities, enabling DSOs to adopt a more active role as system operators (Johansson et al., 2020). However, this shift also presents significant challenges, including technological complexities and associated costs, as well as changes in both short-term and long-term distribution network management (Adefarati and Bansal, 2016; Jenkins and Perez-Arriaga, 2017; Cossent et al., 2009; Iweh et al., 2021). The integration of decentralized generation requires grid operators to manage a two-way flow of electricity. Consumers are increasingly becoming prosumers, feeding power back into the network. To support this bidirectional flow, operators must develop the necessary infrastructure while maintaining the balance between electricity supply and demand.[3]

Robust connectivity and communication systems are crucial for coordinating distributed generation. Renewable sources like solar and wind cause voltage and frequency disruptions, affecting grid stability (Iweh et al., 2021; Adefarati and Bansal, 2016). Advanced control systems are needed for real-time adjustments. High levels of distributed generation lead to voltage fluctuations and grid congestion (Mateo et al., 2017). Local solutions and complementary technologies are required to manage these issues. Smart grid technology improves grid reliability, efficiency, and sustainability through advanced digital communication and control (Johansson et al., 2020).

4. Data and descriptives

To assess the cost efficiency of DSOs in Sweden, we compile panel data by matching three data types: firm-level data, geo-referenced weather data, and regional data, all sourced from public statistics and data providers. It is worth noting that one novelty of our data is that each piece of information is geographically aligned with the specific operating area of each DSO.

4.1. Firm-level DSO data

The EI provides firm-level data including information on revenue, cost structures, and various indicators relevant to the operations and infrastructure of individual DSOs. Additionally, the dataset contains details on small- and micro-scale electricity production units connected to the grid. This information is used to evaluate the extent of local renewable energy production in the DSOs' operational areas. The data utilized in this study is publicly available through the regulatory body's website (Swedish Energy Market Inspectorate, accessible at www.ei.se), and encompasses data on all (N = 155) Swedish DSOs.

Subject to data availability, our sample includes 129 DSOs (out of a total of 155) operating across Sweden, observed over six years (2014–2019), resulting in 736 observations. The panel is unbalanced due to mergers and restructuring of some DSOs and their respective grids. We implemented data cleaning procedures, removing missing or anomalous observations, and retained only those DSOs that were observed for at least three periods. Table 1 provides the summary statistics of the variables in the final dataset. The comparison of mean values with standard deviations, along with the coefficient of variation, underscores the heterogeneity among firms and their operating environments.

Following the literature which we discuss in the data section, for our analysis, we employ three input variables: the total installed capacity of substations measured in megavolt amperes (capacity), physical labor measured in hours worked (labor),[4] and annual distribution power losses are measured in megawatt hours (losses) to control for quality.[5]

As output variables, we utilize the total number of household and industrial customer connections (customers) and the total amount of energy delivered, including both low- and high-voltage energy, measured in megawatt hours (electricity).

Additionally, the length of mains, defined as the sum of insulated and non-insulated overhead lines and cables across all operated voltage levels measured in kilometers (length), is taken into account. In our analysis, we regard length of mains as a quasi-fixed input, meaning it cannot be easily altered in the short term. Consequently, it is incorporated into our model specification as an output variable.

Fig. 1 illustrates a substantial rise in small- and micro-scale power generation facilities throughout the period under consideration. Although the trend suggests a transition from large centralized power

[3] This involves e.g., addressing new technical challenges such as voltage fluctuations, reverse power flow, network capacity and congestion, losses, short circuit currents (L'Abbate et al., 2008; Iweh et al., 2021).

[4] We derive the unit price of labor following Agrell and Brea-Solís (2017). Labor expenses are adjusted using the labor cost index for manual workers in the private sector and divided by the average hourly wage for manual workers in the energy and environmental sector (NACE code D+E). This data is sourced from the Swedish Bureau for Statistics.

[5] Grid losses, particularly in distribution networks, comprise technical and non-technical components, which may be beyond management control. However, IVA (2017) indicates that losses can vary significantly year by year based on consumption patterns and operational conditions, with voltage regulation and reactive power compensation being key factors in mitigating grid losses (Anaya and Pollitt, 2017).

Table 1
Summary statistics.

Variable	Mean	Standard deviation	Coefficient of variation	Percentiles	
				5th	95th
Capacity	180	240	1.33	16.00	647
Labor	141 612	398 700	2.82	8342	445 021
Losses	12 782	17 499	1.37	1134	54 563
Customers	18 480	23 721	1.28	1543	63 655
Electricity	358 657	449 550	1.25	20 372	1429849
Length	1737	3014	1.74	206	6198
Feeder	52.81	134	2.54	0	204
Decentralization	0.7974	0.3413	0.4280	0	1
ShrpopA	0.2315	0.2636	1.14	0.0012	0.8841
ShrpopB	0.0924	0.1649	1.79	0	0.4168
Min temp	−15.70	6.32	0.4025	−29.28	−7.03
Max temp	29.25	2.44	0.0835	24.91	32.88
Min wind	0.0410	0.0154	0.3745	0.0218	0.0703
Max wind	11.79	2.70	0.2292	8.63	16.96
Min temp, CV	−0.2064	0.0787	0.3814	−0.3408	−0.0607
Max temp, CV	0.0793	0.0170	0.2147	0.0526	0.1077
Min wind, CV	0.2151	0.1049	0.4878	0.0906	0.4414
Max wind, CV	0.1162	0.0409	0.3520	0.0521	0.1898
Temp, range	48.54	5.64	0.1161	40.87	60.38
Wind, range	12.26	2.53	0.2064	9.21	17.25
Population	32 907	42 953	1.31	1874	126 625
Population density, aggregate	0.1441	0.2088	1.45	0.0018	0.5370

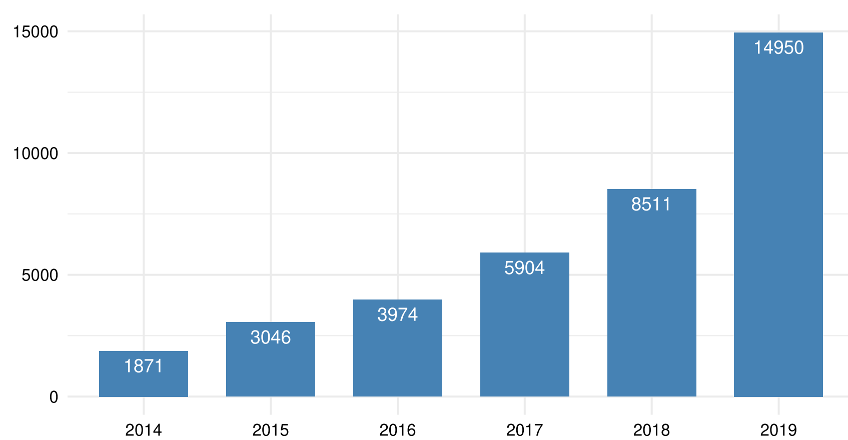

Fig. 1. Small and Micro Power-Generating Facilities connected to Swedish Distribution Grid 2014–2019.

plants to distributed renewable energy sources (Dalheim et al., 2023), there exists considerable variation among companies in terms of their grid integration. We use the number of small-scale power feeders connected to grids operated by the DSOs (feeders) to capture this development.

For testing the hypothesis that decentralization is beneficial for DSOs, we generate a measure *decentralization*, which is calculated as the proportion of feeders that are decentralized. Specifically, we divide the number of high- and low-voltage local feeders by the total number of feeders. Due to data availability, the number of observations is reduced from 736 to 681. Fig. 2 presents the distribution of this measure.

4.2. Geo-referenced weather data

The Swedish regulator supplied us with shapefiles containing precise geographical boundaries of the DSO operating areas, allowing us to integrate high-resolution GIS weather data.

Sweden extends over a considerable distance from north to south, exhibiting diverse landscapes and altitudes across its eastern and western regions. To account for this diversity, we acquire high-resolution hourly GRIB2 weather data from the Swedish Meteorological and Hydrological Institute (SMHI) using the MESAN model for the years 2015–2019 (2.5 km × 2.5 km raster), limiting the data to Sweden's boundaries to streamline computational processing.

Every point represents an hourly observation for a 2.5 by 2.5 km raster, enabling precise weather variables even for the smallest DSOs (Fig. 3). We conduct the matching in three consecutive steps:

1. Temporal analysis of high-resolution data: Computation of average, maximum and minimum values per point-data data point for a year.
2. Geographical matching with DSO areas: Matching point data with DSO areas using DSO GIS boundaries from shapefiles provided by the regulator.
3. Aggregating data per DSO area: Computing average, minimum and maximum values per DSO from analyzed point data to produce panel input data.

The result of this matching procedure is shown in Figs. 14 and 15 in Appendix A.

In our analysis, we compute various aggregated metrics, such as the annual minimum and maximum wind speeds (minwind, maxwind) and temperatures (mintemp, maxtemp), as well as their respective annual ranges (wind range, temp range). Figs. 8–13 in Appendix A show these metrics aggregating them over all years and demonstrating significant variability across the country. Our focus on wind and temperature stems from their well-documented physical correlations with infrastructure (see, e.g., L'Abbate et al., 2008; Tennet and 50 Hertz

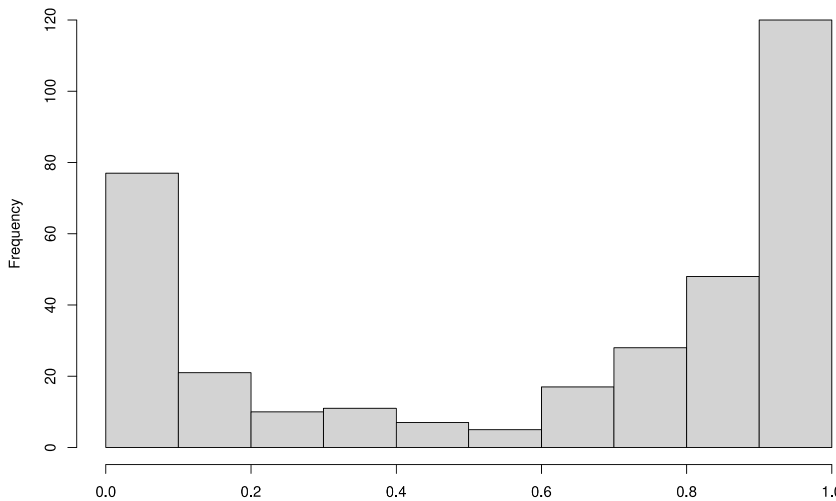

Fig. 2. Decentralization measure.

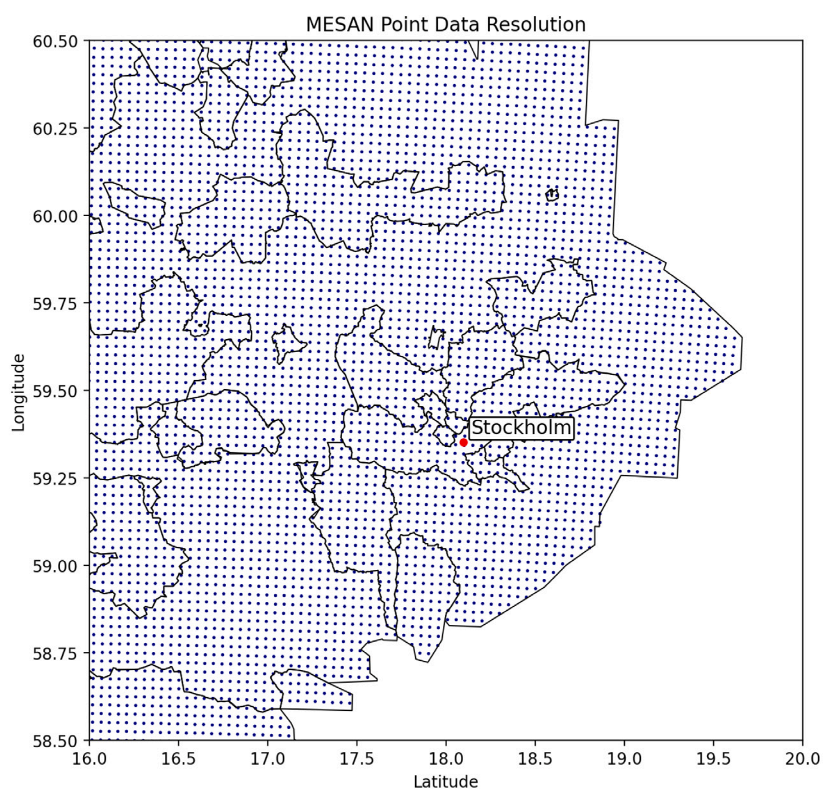

Fig. 3. MESAN point data resolution.

and Amprion and TransnetBW, 2021) and the availability of natural renewable resources.[6]

[6] Furthermore, we gathered data on variables such as snow, cloud coverage, and precipitation, among others, and incorporated them into alternative specifications. However, due to their high correlation with wind and temperature, we did not gain any additional insights. Consequently, we have opted against delving deeper into these variables within the scope of this paper.

4.3. Regional statistics

To create variables that capture the population and settlement structures within the operating network areas of DSOs, we use geo-referenced statistics provided by the Swedish Bureau for Statistics (SCB). Nationwide data are available for Demographic Statistical Areas (DeSOs), which are stable over time and can be matched to the geo-referenced shapefiles of the operating network areas. Similar to

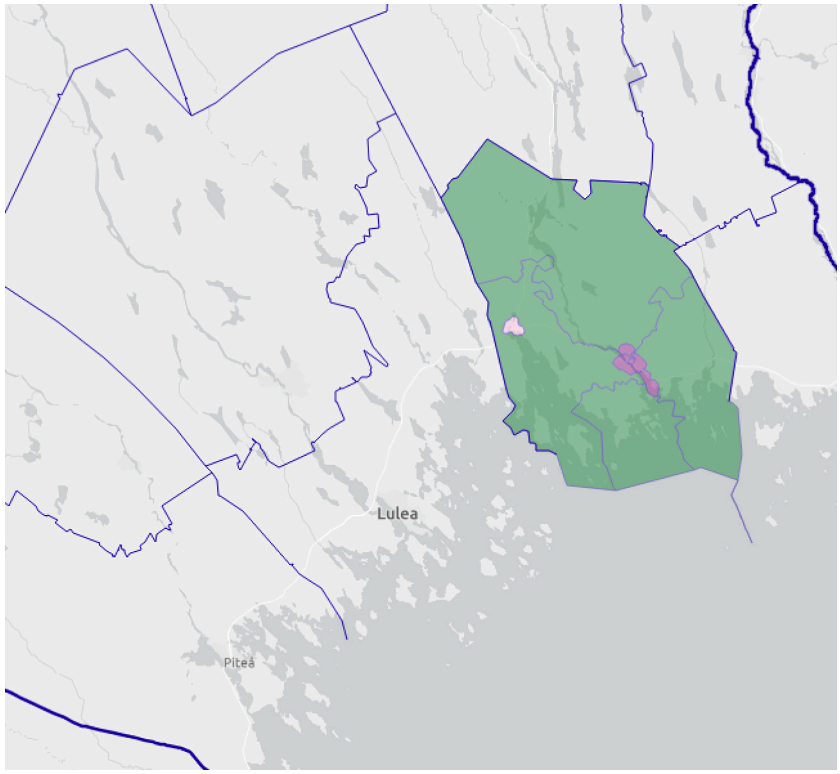

Fig. 4. DeSOs in Kalix.

weather data, this allows for well-defined measurements.[7] Moreover, this approach prevents us from using the grid connections provided in the regulatory dataset as both output and control variables.

The importance of integrating population metrics is widely recognized in regulatory endeavors and frequently included in academic analyses. Concerning sewerage, Urakami et al. (2021) emphasize that not only population densities but also settlement structures (sparsity) play crucial roles in evaluating the economics of network industries. Expanding on this perspective, we establish three metrics: Firstly, we consider the population residing in each operational network area (population). Secondly, we define population density as the ratio of inhabitants to the operational network area, measured in capita per square kilometer (population density). This metric serves as a size indicator external to the DSOs, thus lying beyond their control.

Third, through the utilization of the DeSO classification into distinct settlement types denoted as A, B, and C, we ascertain the proportions of the geographical network area covered by each category (shrpopA, shrpopB, shrpopC). According to the SCB, a DeSO categorized as type A is predominantly situated in areas outside of larger population concentrations or urban areas, indicating that type A areas are largely rural. Type B DeSOs are primarily situated within population concentrations or urban areas but not within the central town of the municipality. Category C encompasses DeSOs predominantly located within the central city of the municipality. In total, among the 5984 DeSOs, 18 percent fall into Category A, 10 percent into Category B, and 72 percent into Category C.

Kalix provides an illustrative example, comprising a total of 11 DeSOs. As depicted in Fig. 4, four DeSOs are classified as type A (highlighted in green within blue boundaries), one falls into type B (light pink), and the remaining six are categorized as type A (dark purple). This information is utilized to determine the percentage of the operating network area for each respective DSO characterized by those types.[8] It is apparent that the majority of DeSOs encompass urban areas, consequently serving the largest portion of the population. However, they occupy a relatively small geographical area. Addressing diverse settlement structures may introduce additional complexities to DSO operations, aspects not adequately captured by commonly used measures of population density.

5. Empirical strategy

5.1. Stochastic frontier input distance function

We conceptualize the production process of the DSOs as a multi-input multi-output production technology using a distance function. Generally, an input-oriented (IO) inefficiency model is preferred when inputs are treated as endogenous variables subject to choice, while outputs, primarily services, are considered exogenous and determined by demand. In input-based efficiency measurement, the input distance function is defined as

$$D^I = \max\left\{\lambda : \boldsymbol{x}/\lambda \in L(\boldsymbol{y})\right\}, \tag{1}$$

where $L(\boldsymbol{y})$ is the input requirement set, i.e., a set of inputs such that the inputs-outputs combination is technologically feasible. The input distance function is thus a function of inputs and outputs,[9] viz.,

$$D^I = f(\boldsymbol{x}, \boldsymbol{y}; \boldsymbol{\beta}). \tag{2}$$

Since the input distance function is homogeneous of degree 1 in feasible input vector $\boldsymbol{x}$, (2) can be rewritten as

$$D^I x_1^{-1} = f(\tilde{\boldsymbol{x}}_{-1}, \boldsymbol{y}; \boldsymbol{\beta}), \tag{3}$$

[7] For areas where the operating network area is partially overlapping with the DeSOs, the percentage shares of the DeSOs population are used.

[8] In instances where multiple DSOs operate within the same DeSO, weights are assigned based on the geographical share of areas.

[9] β is a vector of parameters to be estimated once f is specified.

where $\tilde{\boldsymbol{x}}_{-1} = (x_2/x_1, \dots, x_N/x_1)$ and N is the number of inputs. Taking the logs of both sides of (3) we obtain

$$-\log x_1 = \log f(\tilde{\boldsymbol{x}}_{-1}, \boldsymbol{y}; \boldsymbol{\beta}) - \log D^I. \tag{4}$$

Denoting $\log D^I = u \geq 0$ and adding a random error term to input distance function in (4) to make it stochastic, we obtain a typical composite error production stochastic frontier (SF hereafter) model

$$-\log x_1 = \log f(\tilde{\boldsymbol{x}}_{-1}, \boldsymbol{y}; \boldsymbol{\beta}) - u + v. \tag{5}$$

The last formulation is surely recognized as *stochastic input distance* (IDF) function which can be estimated using stochastic frontier models. The panel version of the IDF in (5) is given by

$$-\log x_{1,it} = \log f(\tilde{\boldsymbol{x}}_{-1,it}, \boldsymbol{y}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta}) - u_{it} + v_{it}$$

where $i = 1, \dots, n$ denotes the ith DSO and $t = 1, \dots, T_i$ denotes the time period in which DSO i is observed, v_{it} is the noise term and $u_{it} \geq 0$ is time-varying technical inefficiency. This model can be further expanded by decomposing the composite error term, $-u_{it} + v_{it}$, into four separate components (Kumbhakar et al., 2014). The first component, v_{0i}, accounts for latent heterogeneity among firms (see Greene, 2005), and the second component, u_{0i}, represents long-term or persistent inefficiency, as described by Kumbhakar and Hjalmarsson (1995); both of these components are constant over time. The third component, u_{it}, reflects inefficiency that varies with time (see Kumbhakar, 1987), while the fourth component, v_{it}, serves as the ordinary error term. Thus, the full model, incorporating all four components, can be formally represented as follows:

$$-\log x_{1,it} = \log f(\tilde{\boldsymbol{x}}_{-1,it}, \boldsymbol{y}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta}) + v_{0i} - u_{0i} - u_{it} + v_{it}, \tag{6}$$

where $u_{0i} \geq 0$ and $u_{it} \geq 0$ represent persistent and time-varying inefficiency, respectively, while v_{0i} captures latent firm heterogeneity and v_{it} is the classical random noise. In the homoscedastic four-component model, all the error components are independently and identically distributed (i.i.d.) random variables. We will use the (Badunenko and Kumbhakar, 2017) model to allow error components to be heteroskedastic by introducing their determinants.

5.2. Econometric specification

Our technology comprises three inputs (x_1, x_2, x_3), two outputs (y_1, y_2), and a quasi-fixed input represented as an output (y_3), along with R time-varying external factors organized into vectors $\boldsymbol{x}$, $\boldsymbol{y}$, and $\boldsymbol{z}$, respectively.[10] We estimate the following translog input distance function, which incorporates a linear time trend t and square t^2 to account for nonlinear technological shifts.

$$\begin{aligned}
-\log x_{1,it} = {} & \beta_0 + \sum_{k=2}^{3} \beta_{x_k} \log(x_{k,it}/x_{1,it}) \\
& + \sum_{k=2}^{3}\sum_{r=2}^{3} \beta_{x_{kr}} 0.5[\log(x_{k,it}/x_{1,it})][\log(x_{r,it}/x_{1,it})] \\
& + \sum_{m=1}^{3} \beta_{y_m} \log(y_{m,it}) + \sum_{m=1}^{3}\sum_{q=1}^{3} \beta_{y_{mq}} 0.5[\log(y_{m,it})][\log(y_{q,it})] \\
& + \beta_t t + \beta_{tt} 0.5 t^2 + v_{0i} - u_{0i} + v_{it} - u_{it},
\end{aligned} \tag{7}$$

where $\beta_{x_{kr}} = \beta_{x_{rk}}$ and $\beta_{y_{mq}} = \beta_{y_{qm}}$.

[10] Our technology modeling closely aligns with established academic and regulatory frameworks concerning DSOs, particularly in Nordic countries and Germany. For further exploration of applied methodologies in technology modeling, readers are directed to the literature referenced in Section 1. Recently, more data-driven approaches have been proposed (e.g., Duras et al., 2023). Exploring those machine-learning methods in the context of regulation in more depth could be an interesting subject of future research.

The input variables vector includes transformer capacity (x_1) measured in megawatt hours (MWh). Capacity shows the installed power of transformer stations in MVA. It also includes the total installed capacity of substations (MVA). Additionally, labor (x_2) is included, quantified by the total number of hours worked. Labor costs are specified for each DSO and adjusted using the labor cost index for manual workers in the private sector, then divided by the average hourly pay for manual workers in the energy and environmental sector (NACE code D+E). These definitions align closely with those outlined by Agrell and Brea-Solís (2017). While acknowledging criticism regarding potential distortion from outsourcing, notably the possibility of utility efficiency improvement via switching from in-house production to outsourcing, we note that there is no data available that would provide a closer approximation. The third input is annual distribution power losses (x_3) measured in MWh. Arguably, grid losses (especially in distribution networks) include technical and non-technical components, which may or may not be under the control of the management.

Outputs are the annual amount of electricity delivered (y_1) in MWh and the number of connected customers (y_2). We further include a quasi-fixed input that enters the specification as an output, i.e., the network length (y_3) in kilometers (km).

5.3. Determinants of inefficiency

Our application focuses on the role of distributed generation and weather conditions that are outside DSOs' influences on efficiency. It is informative to know what determines time-varying (and persistent) inefficiency. Hence we use Badunenko and Kumbhakar (2017) model to specify the effects of the determinants on both types of inefficiencies. More precisely, the determinants of transient inefficiency are assumed to follow a half-normal distribution with heteroskedastic variance:

$$u_{it} \sim N^+(0, \sigma^2_{u_{it}}), \text{ where } \sigma^2_{u_{it}} = \exp\left(\boldsymbol{z}_{u_{it}} \boldsymbol{\gamma}_u\right), \quad i = 1, \dots, n, \quad t = 1, \dots, T_i,$$

where $\sigma_{u_{it}}$ is time-variant and $\boldsymbol{z}_{u_{it}}$ denotes the vector of covariates that explains time-varying inefficiency. In the context of electricity distribution, other than half-normal distributional assumptions have been made in the literature (Campos et al., 2022). We model transient inefficiency as being influenced by (1) distributed generation, (2) environmental conditions (regional characteristics), and (3) weather patterns. By considering both high- and low-voltage feeders,[11] we aim to test the 'infrastructure' hypothesis (model M1) thereby assessing whether the restructuring of the electricity distribution sector is associated with increased transient efficiency. For testing the 'decentralization' hypothesis (model M2), we use the decentralization measure to explore if relying less on centralized feeders improved transient efficiency. Additionally, we account for control variables such as sparsity,[12] minimum and maximum temperatures, and the intensity of wind, factors beyond the direct control of DSOs.

Since the number of determinants is huge, one may be concerned that they are correlated and these correlations may introduce nuances to the empirical results. Fig. 5 shows the histogram of 105 correlation coefficients of inefficiency determinants.

Our analysis reveals a correlation between the lowest temperature and the coefficient of variation in both the lowest temperature and temperature range. Similarly, the strongest winds correlate with the range of wind speeds. Most of the other correlations fall within the range of

[11] We introduce them into the model in the logarithmic form to reduce the effect of extreme values. For the small number of zeros, we add a small epsilon before taking a log.

[12] Share of network area covered by type of region: Geographic regions are categorized into three types: Type A, Type B, and Type C. These variables are defined as the share of the geographical network area covered by each type of region. It allows us to consider various settlement structures that may be more relevant than population density

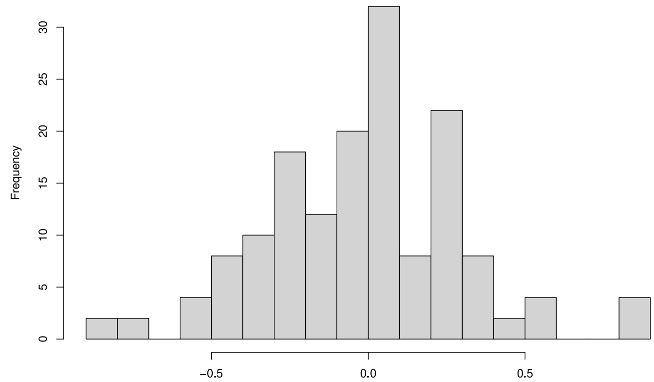

Fig. 5. Histogram of correlation coefficients of inefficiency determinants.

$(-0.5, 0.5)$. Given the importance of weather variables in controlling for environmental severity, we included them in our baseline specification. Further checks demonstrated the robustness of our main findings and conclusions to variations in the specification of weather variables.[13]

Suppose $z_{u_{1,it}}$ is one of the variables in $z_{u_{it}}$. The elasticity of inefficiency with respect to $z_{u_{1,it}}$ can be calculated as

$$\varepsilon_{u,z_{u_{1,it}}} = \frac{\partial \log u_{it}}{\partial \log z_{u_{1,it}}} \approx \frac{\partial E(u_{it})}{\partial z_{u_{1,it}}} \frac{z_{u_{1,it}}}{E(u_{it})}$$

Since u_{it} is half-normal, $E(u_{it}) = \sqrt{(2/\pi)}\sigma_{u_{it}} = \sqrt{(2/\pi)} \exp\left(\frac{1}{2} \boldsymbol{z}_{u_{it}} \boldsymbol{\gamma}_u\right)$ and granted the specification $\log \sigma^2_{u_{it}} = \boldsymbol{z}_{u_{it}} \boldsymbol{\gamma}_u$, the elasticity is given by

$$\varepsilon_{u,z_{u_{1,it}}} = \frac{\exp\left(0.5 \boldsymbol{z}_{u_{it}} \boldsymbol{\gamma}_u\right)}{\sqrt{2\pi}} \frac{\partial \left(\boldsymbol{z}_{u_{it}} \boldsymbol{\gamma}_u\right)}{\partial z_{u_{1,it}}}. \tag{8}$$

Note that elasticities in (8) are both DSO and time specific.

Similarly, the determinants of persistent inefficiency are assumed to follow a half-normal distribution with heteroskedastic variance:

$$u_{0i} \sim N^+(0, \sigma^2_{u_{0i}}), \text{ where } \sigma^2_{u_{0i}} = \exp\left(\boldsymbol{z}_{u_{0i}} \boldsymbol{\gamma}_u\right), \quad i = 1, \dots, n,$$

where $\sigma_{u_{0i}}$ is time-constant and $\boldsymbol{z}_{u_{0i}}$ denotes the vector of covariates that explains persistent inefficiency. To examine the hypothesis regarding DSOs' capacity to adapt to annual weather variations, we incorporate the coefficients of variation for minimum and maximum temperatures, as well as for the weakest and strongest winds, alongside temperature and wind strength ranges.

The model can be expanded to incorporate the heteroskedasticity related to both firm effects and the noise terms, which can be considered a production risk. While v_{0i} is regarded as random firm effects, its variance (the time-invariant component) can be seen as firm-specific production risk. Likewise, the variance of the firm-specific and time-varying shocks (v_{it}) can be understood as production risk specific to both firm and time. We define them as

$$v_{0i} \sim N(0, \sigma^2_{v_{0i}}), \text{ where } \sigma^2_{v_{0i}} = \exp\left(\boldsymbol{z}_{v_{0i}} \boldsymbol{\gamma}_{v0}\right), \quad i = 1, \dots, n,$$

$$v_{it} \sim N(0, \sigma^2_{v_{it}}), \text{ where } \sigma^2_{v_{it}} = \exp\left(\boldsymbol{z}_{v_{it}} \boldsymbol{\gamma}_v\right), \quad i = 1, \dots, n, \quad t = 1, \dots, T_i.$$

In this context, $\boldsymbol{z}_{v_{0i}}$ represents the vector of constant covariates influencing persistent production risk (the variance of random firm effects). Likewise, $\boldsymbol{z}_{v_{it}}$ represents the vector of factors affecting transient production risk (the variance of both firm-specific and time-varying random noise). In this specification, we maintain homoscedasticity for $\sigma^2_{v_{0i}}$, whereas we parameterize $\sigma^2_{v_{it}}$ to be contingent on the population in the area. This can be likened to clustering the standard errors or adjusting for scale effects. The relationship between the risk factors shows a correlation of 0.47, indicating a moderate correlation that is noteworthy but not strong enough to raise concerns for the estimation.

[13] The results are available upon request.

6. Empirical results

6.1. DSO's technology

Table 2 presents estimates of the frontier part of the input distance function specified in (7) to test the infrastructure hypothesis (model M1) and decentralization hypothesis (model M2). Drawing on the duality between the IDF and the cost function (Färe and Primont, 1995), the cost elasticity of input x_m, ε_{C,x_m} can be measured by $-\partial \log x_1/\partial \log(x_m/x_1)$. Note that variables were centered at their means. This allows interpreting the first order term of $\log(x_m/x_1)$ as the elasticity of input x_m at the mean value of x_m.[14] Conscious of space, we discuss here only the M1 estimates noting that the frontier results of M2 are very similar to those of M2. For an average DSO, the elasticity of labor input stands at 0.037, indicating statistical significance but with a relatively small impact. This small impact can be attributed to the measurement of labor input in terms of hours worked rather than the physical number of workers, such as full-time equivalents. This distinction highlights that changes in hours worked do not translate proportionally to changes in the number of employees, thereby resulting in a seemingly low elasticity value.

Conversely, power losses exert a considerable burden on DSO costs, with a 1% increase in losses leading to a 0.4% rise in costs on average. This could be caused by unpredictable consumption patterns and operational conditions. It hints at the fact, that power loss mitigating activities, such as voltage regulation and reactive power compensation, are relatively costly. Further, it could be associated with a sub-optimal location and capacity of the decentralized power generation (Iweh et al., 2021). Utilizing the homogeneity of the IDF, the transformer capacity elasticity of cost is 0.555, emerging as the most influential factor in cost determination. Not surprisingly, the number of connected customers contributes more to costs than the quantity of delivered electricity, with respective elasticities of 0.6 and 0.13 for an average DSO. Considering that electricity distribution relies heavily on networks, these estimates are reasonable and align with findings from similar empirical studies, such as those conducted on German DSOs (e.g., Cullmann, 2012). This study reveals a nonlinear technological progression, with costs initially increasing over the first three years before declining in the subsequent three years, as indicated by the quadratic specification. This nonlinear pattern can be explained by the implementation of more incentive-based regulatory regimes, which motivate companies to adopt cost-reducing measures.

6.2. Inefficiencies, their determinants, and DSOs adaptation over time

Fig. 6 shows box plots of persistent and transient efficiencies.[15] The most right box plot takes all years into account, while the middle box plots show transient efficiencies by year.

One notable point is the near absence of persistent inefficiency. Few DSOs fail to achieve near-perfect efficiency over the long term. The median transient efficiency stands at 0.96. The data indicates that transient efficiency was initially (2014) below this value, gradually increasing to a peak of 0.97 in 2017 before dropping to 0.95, which is still relatively high. Only a small number of DSOs demonstrate inefficiency in the short term.

[14] Briefly, the derivative $-\partial \log x_1/\partial \log(x_m/x_1)$ is equal to the coefficient at the first order term plus coefficients at the second order terms multiplied by log of the mean of x_m.

[15] The efficiencies for M2 show the same pattern.

Table 2
Stochastic Input Distance Function. Dependent variable: −log(capacity). p-values in parentheses.

Variable	M1		M2	
Intercept	0.087	(<1e−9)	0.081	(<1e−9)
log(labor/capacity)	0.038	(<1e−9)	0.033	(<1e−9)
log(losses/capacity)	0.413	(<1e−9)	0.421	(<1e−9)
log(customers)	−0.611	(0.001)	−0.616	(0.001)
log(electricity)	−0.127	(0.002)	−0.143	(0.001)
log(length)	−0.121	(0.057)	−0.120	(0.065)
0.5*(log(labor/capacity)^2)	0.015	(<1e−9)	0.014	(1e−4)
0.5*(log(losses/capacity)^2)	1.211	(<1e−9)	1.325	(<1e−9)
0.5*(log(customers)^2)	7.720	(0.561)	6.499	(0.627)
0.5*(log(electricity)^2)	−0.422	(0.368)	−0.520	(0.363)
0.5*(log(length)^2)	−0.003	(0.995)	0.155	(0.782)
trend	−0.026	(1e−4)	−0.025	(2e−4)
0.5*trend^2	0.007	(1e−4)	0.007	(2e−4)
log(labor/capacity)∗log(losses/capacity)	−0.013	(0.726)	−0.047	(0.195)
log(labor/capacity)∗log(customers)	0.087	(0.798)	0.210	(0.518)
log(labor/capacity)∗log(electricity)	0.147	(0.303)	0.056	(0.694)
log(labor/capacity)∗log(length)	−0.794	(9e−4)	−0.732	(0.002)
log(losses/capacity)∗log(customers)	4.809	(<1e−9)	4.050	(3e−4)
log(losses/capacity)∗log(electricity)	−0.561	(0.119)	−0.224	(0.552)
log(losses/capacity)∗log(length)	−2.059	(0.008)	−1.242	(0.238)
log(customers)∗log(electricity)	0.098	(0.967)	0.219	(0.947)
log(customers)∗log(length)	−6.734	(0.251)	−5.063	(0.404)
log(electricity)∗log(length)	1.521	(0.150)	1.117	(0.367)
Sample Characteristics				
N	129		125	
$\sum_{i=1}^{N} T_i$	736		681	
Sim. logL	1098.17		1037.80	

Note: All variables were centered at their means.

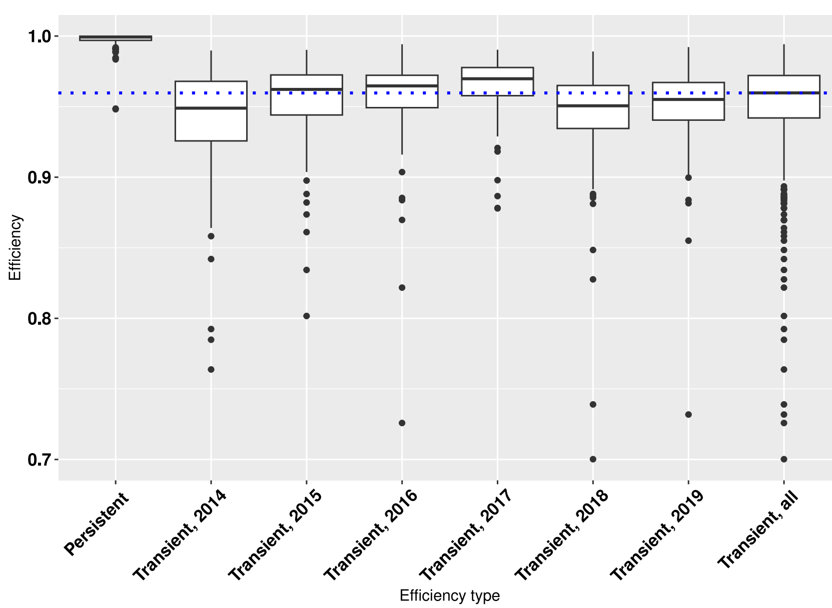

Fig. 6. Box plot of persistent and transient efficiencies. The transient efficiency is shown overall and by years. The blue dotted horizontal line shows the median value of transient efficiency in all years.

Still, even minor inefficiencies can result in significant costs for DSOs, underscoring the importance of analyzing the factors contributing to inefficiency. Table 3 displays the coefficients of the specifications outlined in Section 5.3. Both noise components exhibit statistical significance, although the aggregate population density does not significantly contribute to explaining random effects. Its magnitude indicates that higher density is associated with greater long-term risk.

The indication of minimal persistent inefficiency is evident from Fig. 6. These minor inefficiencies cannot be attributed to long-term weather conditions. The lack of significance in the aggregate weather variables suggests that the Swedish DSOs have adapted to both extreme weather conditions and weather fluctuations.

The segment labeled "4. Transient inefficiency component: $\log \sigma^2_{u_{it}}$" within Table 3 merits particular consideration. It is important to note

Table 3
Determinants of the error components. p-values in parentheses.

Variable	M1		M2	
1. Random effects component: $\log \sigma^2_{v_{0i}}$				
Intercept	−8.668	(0.002)	−7.587	(2e−4)
Population density, aggregate	2.420	(0.394)	2.955	(0.271)
2. Persistent inefficiency component: $\log \sigma^2_{u_{0i}}$				
Intercept	17.474	(0.522)	−2.647	(0.928)
Min temp, CV	−6.125	(0.704)	−21.530	(0.515)
Max temp, CV	11.075	(0.883)	5.804	(0.964)
Min wind, CV	−42.887	(0.097)	−59.988	(0.179)
Max wind, CV	−19.984	(0.491)	−11.472	(0.671)
Temp, range	−0.119	(0.751)	0.337	(0.642)
Wind, range	−1.420	(0.061)	−1.939	(0.160)
3. Random noise component: $\log \sigma^2_{v_{it}}$				
Intercept	−4.514	(<1e−9)	−4.328	(<1e−9)
log(Population)	−0.262	(1e−4)	−0.284	(<1e−9)
4. Transient inefficiency component: $\log \sigma^2_{u_{it}}$				
Intercept	−20.972	(<1e−9)	−21.516	(<1e−9)
log(Feeder)	−0.048	(0.010)		
Decentralization			−0.429	(0.081)
log(shrpopA)	−0.042	(0.286)	−0.051	(0.233)
log(shrpopB)	0.012	(0.626)	0.031	(0.277)
Min temp	−0.036	(0.030)	−0.059	(0.003)
Max temp	0.374	(<1e−9)	0.382	(<1e−9)
Min wind	22.202	(8e−4)	39.368	(<1e−9)
Max wind	0.284	(<1e−9)	0.241	(<1e−9)

that given $E(u_{it}) = \sqrt{(2/\pi)}\sigma_{u_{it}}$, a higher variance signifies either greater inefficiency or lesser inefficiency. Hence, the positive coefficient associated with the variable $z_{r,it}$ in Table 3 suggests a lower level of efficiency in this variable $z_{r,it}$. This positive coefficient at variable $z_{q,it}$ is conducive to enhancing efficiency when variable $z_{q,it}$ increases.

Weather variables appear to influence efficiency in the short term. Efficiency increases with lower minimum temperatures, likely because DSOs face fewer challenges related to extreme cold weather. Conversely, efficiency decreases with higher maximum temperatures, suggesting that milder temperatures are favorable to improved efficiency. Both excessively low and high temperatures have a detrimental effect on efficiency. These findings highlight the ongoing challenge DSOs face in managing current weather conditions. However, it is important to note that DSOs successfully undergo a process of adaptation to weather conditions over the long term. Further, the coefficients for both sparsity measures lack statistical significance, suggesting that, on average, sparsity does not affect short-term efficiency.

The magnitudes of the coefficients in Table 3 are not informative. This is because of the highly nonlinear nature of the determinants in the model. Consider again that $z_{u_{1,it}}$ to be one of the variables in $\boldsymbol{z}_{u_{it}}$. Eq. (8) has shown how to calculate elasticity $\varepsilon_{u,z_{u_{1,it}}}$ and hence provide an informative interpretation of coefficients of the determinants within lower panel of Table 3. Eq. (8) can also be used to calculate the cost elasticity of $z_{u_{1,it}}$ since $E(u_{it}) \neq 0$. With specification (7), $\varepsilon_{C,z_{u_{1,it}}} = -\partial \log f(\tilde{\boldsymbol{x}}_{-1,it}, \boldsymbol{y}_{it}, \boldsymbol{z}_{it}; \boldsymbol{\beta})/\partial \log z_{u_{1,it}} + \partial \log u_{it}/\partial \log z_{u_{1,it}}$.[16] If $z_{u_{1,it}}$ does not enter the technology,[17]

$$\varepsilon_{C,z_{u_{1,it}}} = \varepsilon_{u,z_{u_{1,it}}}. \tag{9}$$

Because feeder is specified in logarithmic form, the inefficiency elasticity remains constant at −0.02, with a corresponding elasticity of zero for DSOs where the feed is zero. The cost elasticity of feeders equals to inefficiency elasticity due to (9). An increase in the number of small-scale feeders enhances DSO cost efficiency, supporting the infrastructure hypothesis.

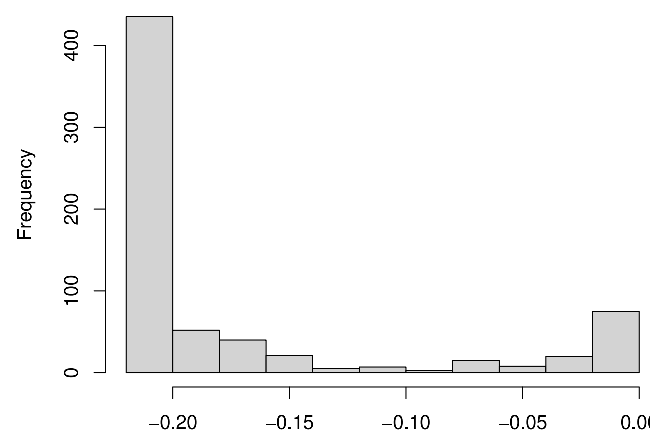

Fig. 7. Histogram of inefficiency elasticity of decentralization.

Fig. 7 shows the histogram of inefficiency elasticity of decentralization. The mean value is −0.17 implying that becoming 1% more decentralized reduces inefficiency by 0.17%.

[16] The derivation is more involved than this formula. First, the Lagrangian for the cost minimization as in Färe and Primont (1995), p.51 or Karagiannis et al. (2004), p.1047 needs to be set. Then, the envelope theorem needs to be applied to the Lagrangian with respect to the distance function determinant. Finally, the relationship of elasticity is derived analogously to Färe et al. (1986).

[17] The frontier should not include $\boldsymbol{z}_{u_{0i}}$ or $\boldsymbol{z}_{u_{it}}$ to avoid endogeneity-related issues. An additional condition for equality to hold is no allocative inefficiency.

Thus, a higher level of decentralization is linked to greater cost efficiency, offering empirical support for the decentralization hypothesis. These findings, along with the dynamics of small-scale feeders, provide compelling evidence that Sweden is succeeding in both (i) transitioning to renewable energy distribution and (ii) enhancing network performance in terms of operational costs.

7. Conclusion

In this paper, we explore the performance of electricity distribution companies in Sweden, particularly focusing on the effects of integrating decentralized generation into existing grid networks. Current European legislation and geopolitical developments put increasing pressure on European countries to transform fossil-based energy systems toward low-carbon technologies. The ongoing energy transition has important implications not only for DSOs but also for policymakers, regulators, and consumers.

Against this background, it is important to understand how the integration of decentralized power generation impacts the cost efficiency of network operators and how innovatively obtained geo-referenced, spatial information can inform the discussion. Sweden serves as an excellent case to explore this empirically due to its progressive climate targets, its advanced integration of renewable energy sources, and ultimately, due to its great variety of environmental characteristics.

In this regard, our empirical analysis provides valuable insights. Contrary to common concerns that decentralized generation might exaggerate the costs of operating distribution grid networks, our findings provide evidence for the decentralization hypothesis, that is, a positive effect of decentralization on cost efficiency. We strengthen these results by employing alternative measures of decentralized power generation and accounting for multiple factors that are beyond the control of DSOs but are closely related to grid layouts and power earnings from small and micro-scale production units, i.e., weather conditions and settlement structures of the population to be supplied. Consequently, our findings can alleviate the concerns about increases in prices due to decentralized generation. However, this issue must be separately analyzed in each specific regulatory environment.

We further show that, on average, weather conditions hardly affect the long-term (persistent) cost efficiency of DSOs. However, temperature and wind speed indeed influence short-term (transient) cost efficiencies. These findings indicate that experienced system operators have adapted their operation management well to acclimatize to extreme weather conditions but still face difficulties with unpredictable immediate circumstances. Advances in weather forecasting and additional storage capacities might help reduce those inefficiencies in the future.

More broadly speaking, our findings support policies that favor decentralized power generation. In Sweden but also other European countries, the expansion of decentralized energy production is a topic of considerable debate. Especially the fluctuations in renewable energy sources combined with the asynchronous supply and demand raise doubts about the stability of energy provision. This became particularly noticeable in Sweden during the winter of 2021 when the electricity demand was higher than usual and electricity shortages were expected. However, additional electricity demand is not limited to seasonal weather phenomena but is also associated with the ongoing electrification of the mobility and industry sector across Europe. Thorough analyses of decentralized energy systems will, therefore, remain a necessary task in the future.

Our analysis further demonstrates that relatively simple procedures can be applied to extract valuable and publicly available data to create innovative geo-referenced metrics. We argue that such metrics can significantly support and even enhance regulatory benchmarking exercises.

Firstly, the availability of shapefiles and the improved access to geo-referenced data allow for the exploitation of information that has not been commonly included in regulatory data before. An example of this would be the information about settlement structures, which might be very important in other studies, even if we could not identify a statistically significant effect in this analysis. Another example would be weather conditions, for which we illustrate the huge variability and find significant effects. Future research could further exploit existing data sources and methods, such as geoAI and simulation techniques, to enhance the set of available variables.

Secondly, matching information, e.g., about weather conditions and settlement structures with network boundaries (instead of administrative boundaries) makes the comparison of DSOs more accurate. This becomes especially relevant in areas where more than one DSO is active in a municipality and/or in cases where operating areas are widely spread.

In countries where such procedures and metrics have not yet been used for regulatory purposes, regulators should consider taking advantage of such opportunities. In addition to the informational benefits discussed above, the ability to use (publicly available) geo-information potentially reduces the burden of data provision for DSOs. For smaller companies in particular, the collection and delivery of data require considerable capacity. Focusing on the collection of truly company-specific data could even improve the quality of data delivery. A further benefit may be that regulators can independently validate the required data if its provision is not solely dependent on the regulated entities.

In summary, our study contributes to the understanding of the relationship between decentralized generation and cost efficiency, employing advanced econometric models that account for persistent and transient inefficiencies. These findings offer important insights for regulators navigating the complexities of the energy landscape, ultimately aiming to optimize cost efficiency while ensuring sustainability and affordability for consumers.

CRediT authorship contribution statement

Oleg Badunenko: Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis. **Astrid Cullmann:** Writing – original draft, Validation, Supervision, Investigation, Formal analysis, Conceptualization. **Maria Nieswand:** Writing – original draft, Visualization, Validation, Supervision, Software, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to improve language and readability, thereby making sure the originality of the text is preserved. More specifically, after using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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Appendix A

See Figs. 8–15.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108148.

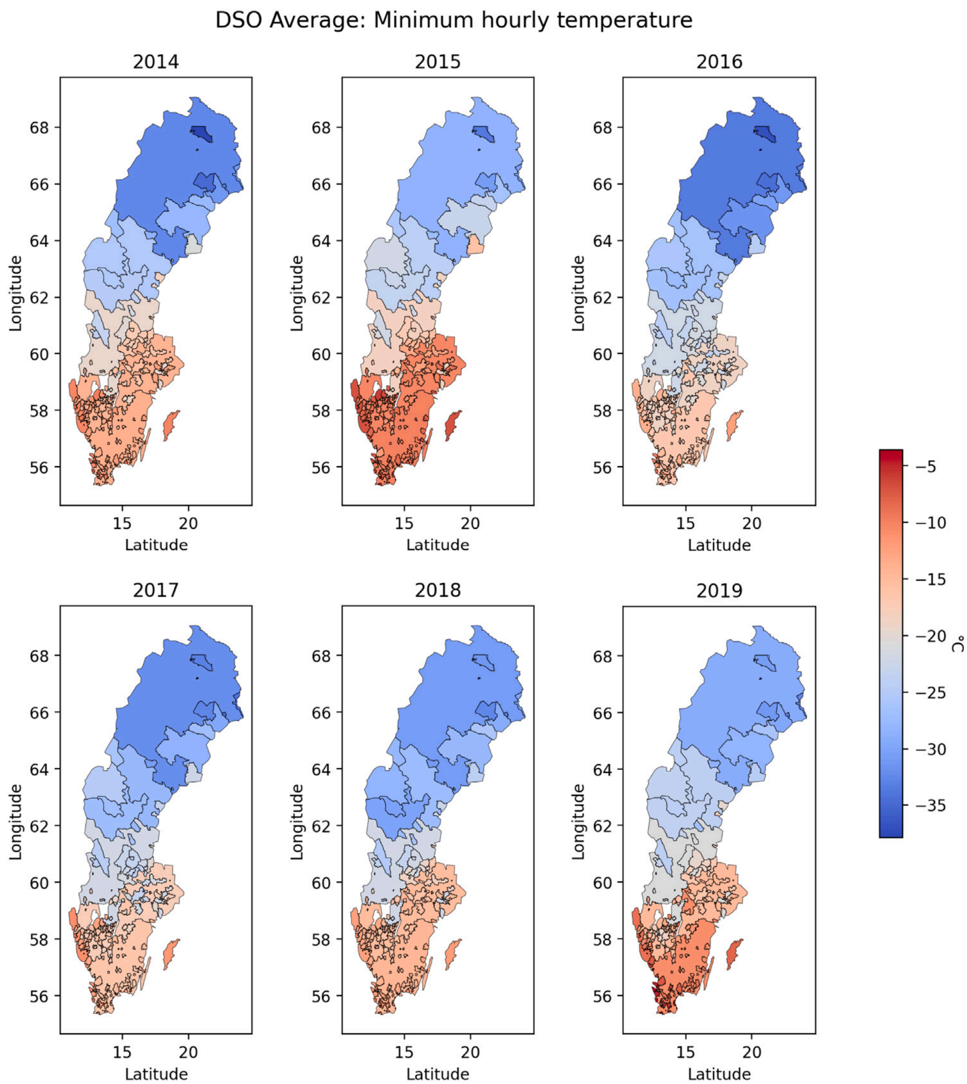

Fig. 8. Minimum temperature, averaged over all years.

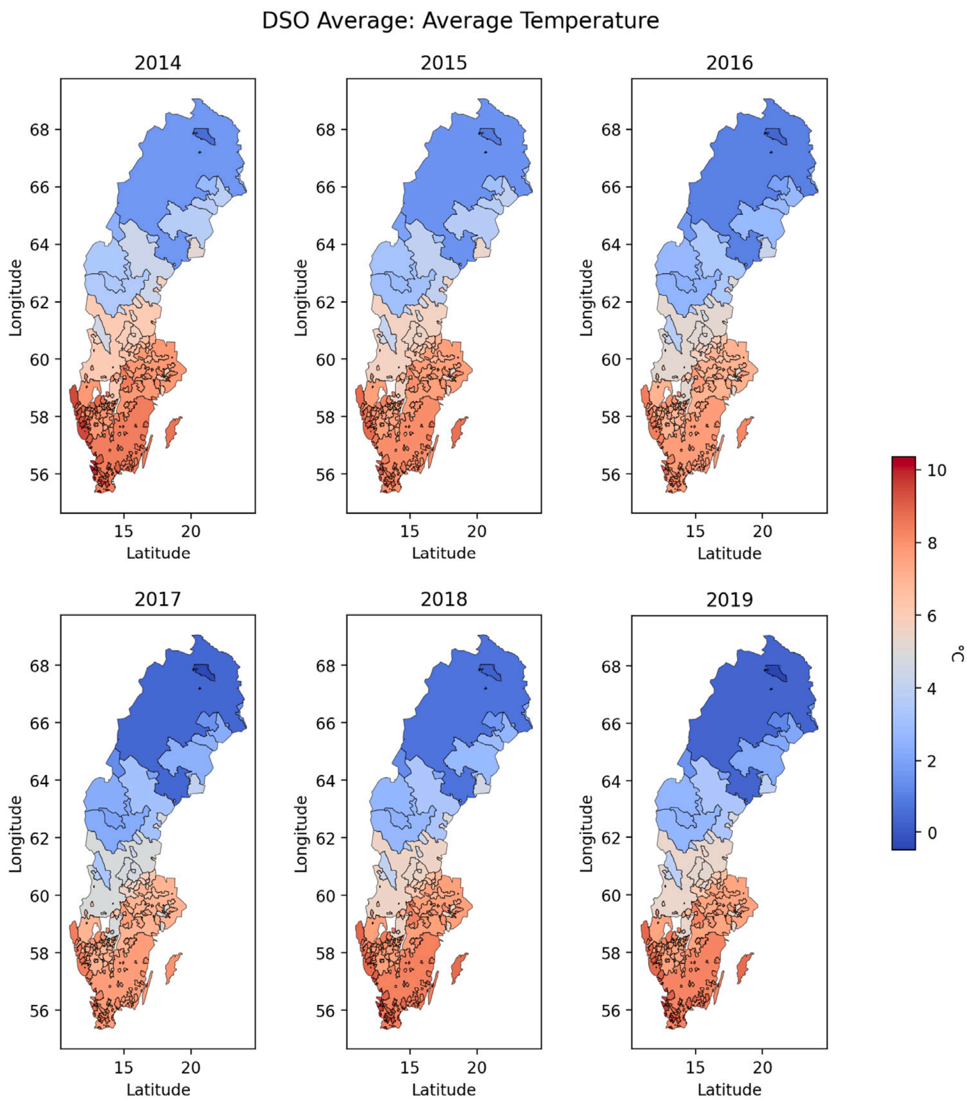

Fig. 9. Mean temperature, averaged over all years.

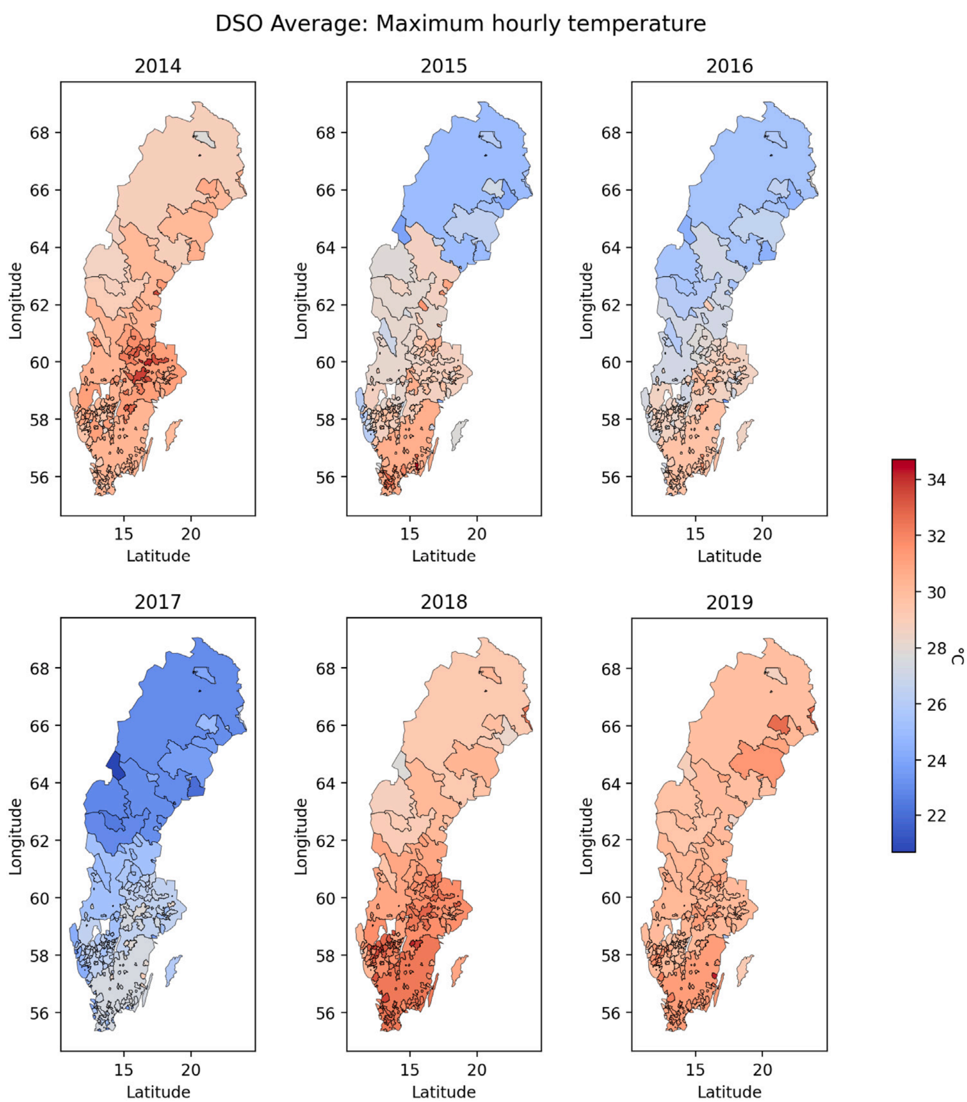

Fig. 10. Maximum temperature, averaged over all years.

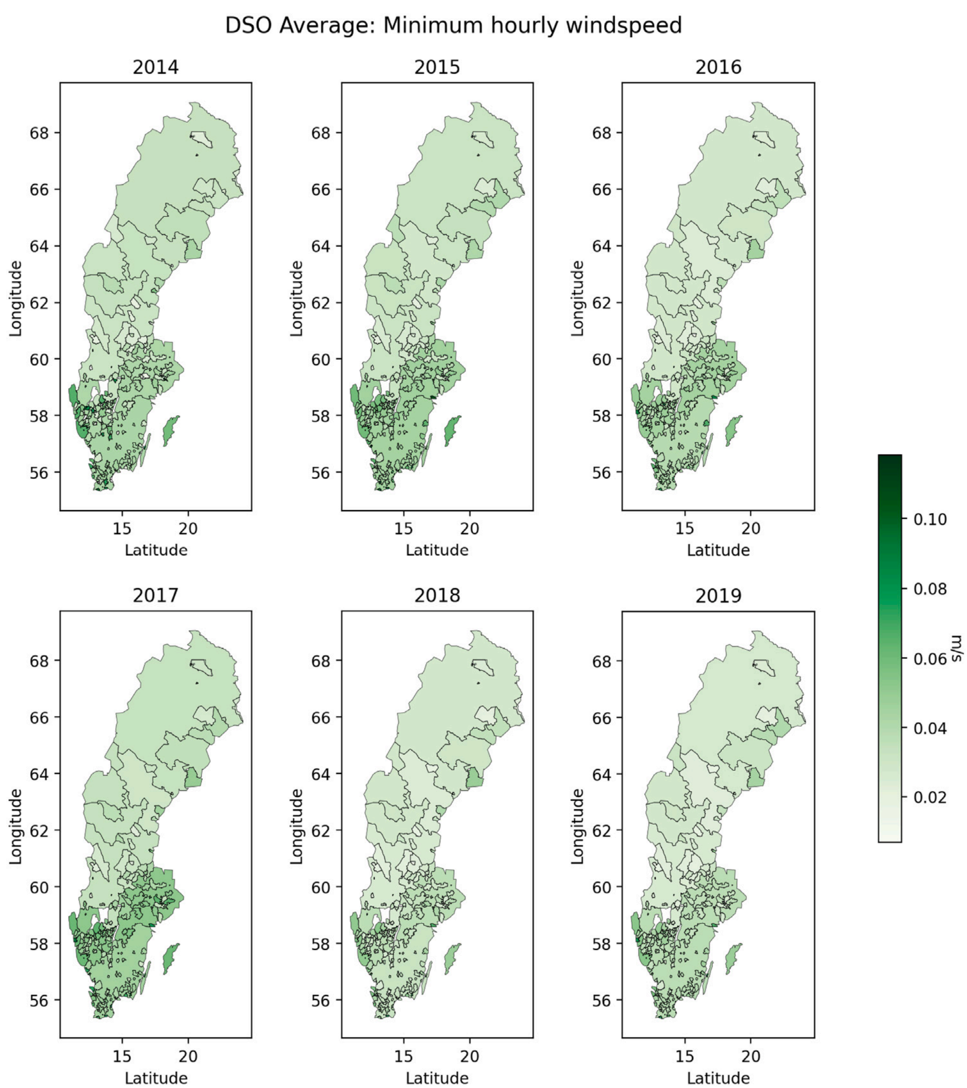

Fig. 11. Minimum wind speed, averaged over all years.

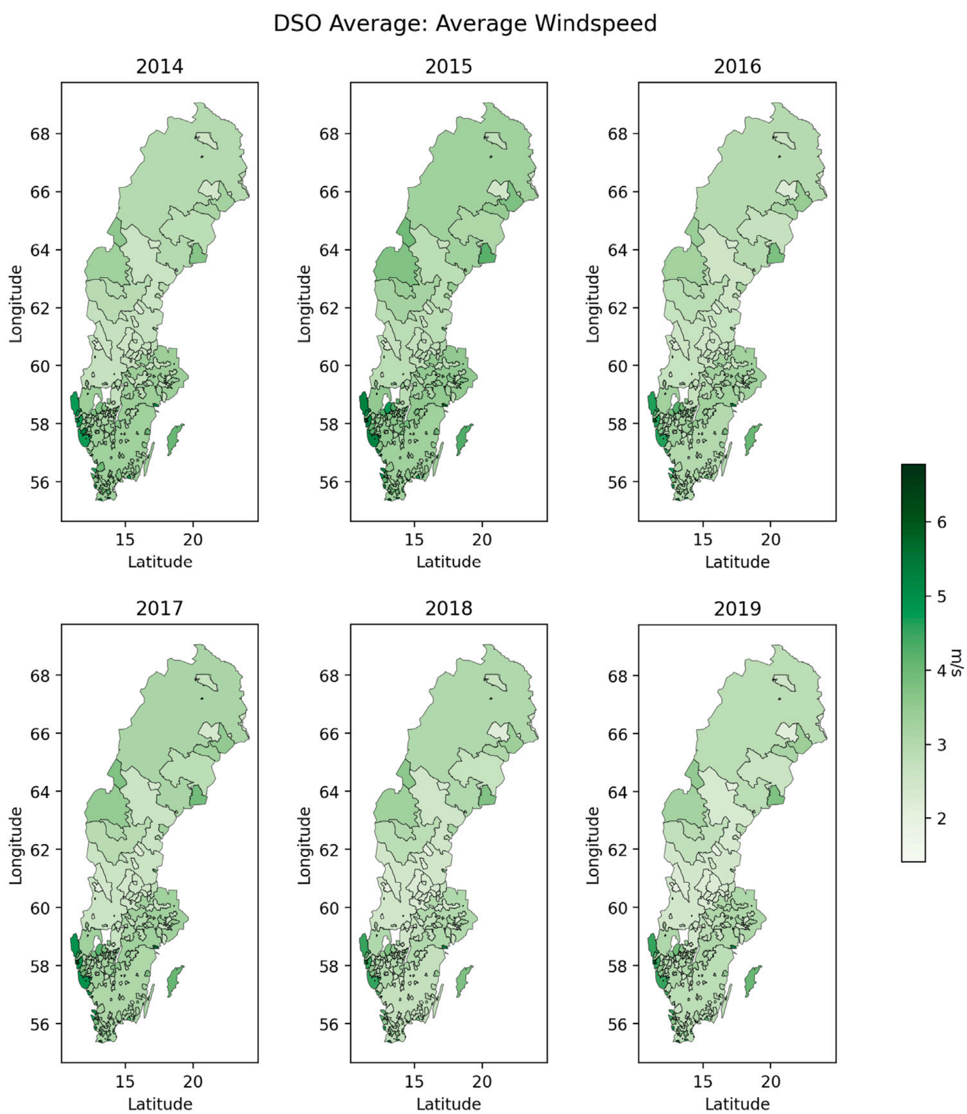

Fig. 12. Mean wind speed, averaged over all years.

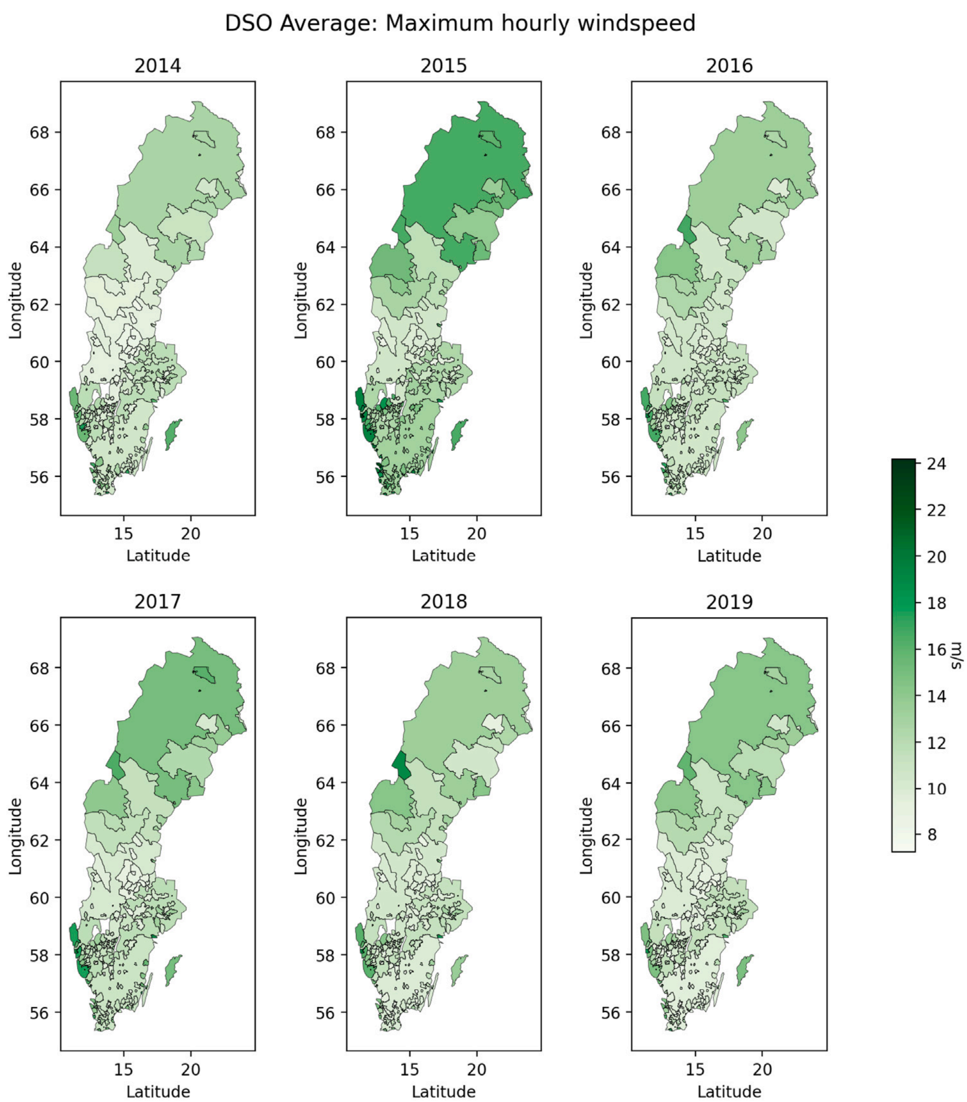

Fig. 13. Maximum wind speed, averaged over all years.

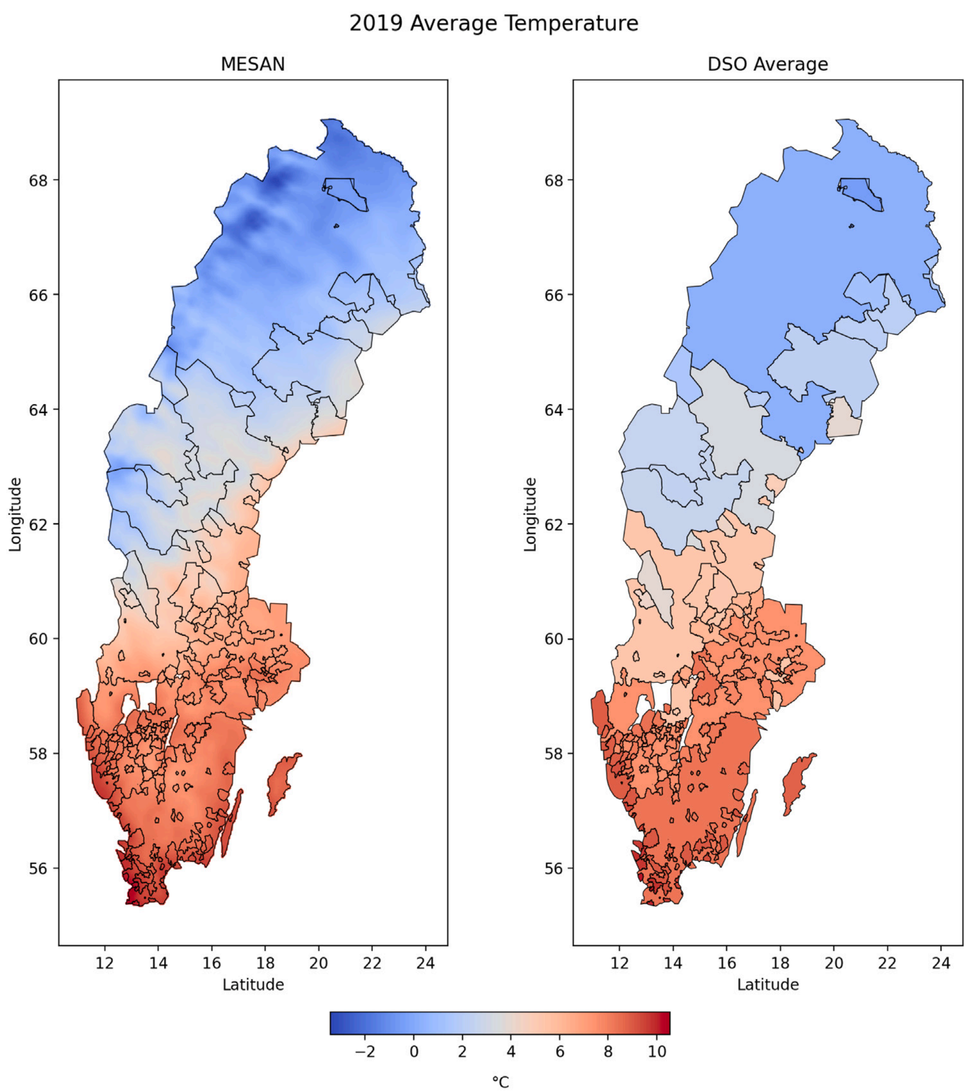

Fig. 14. Aggregation of temperature at the distribution level.

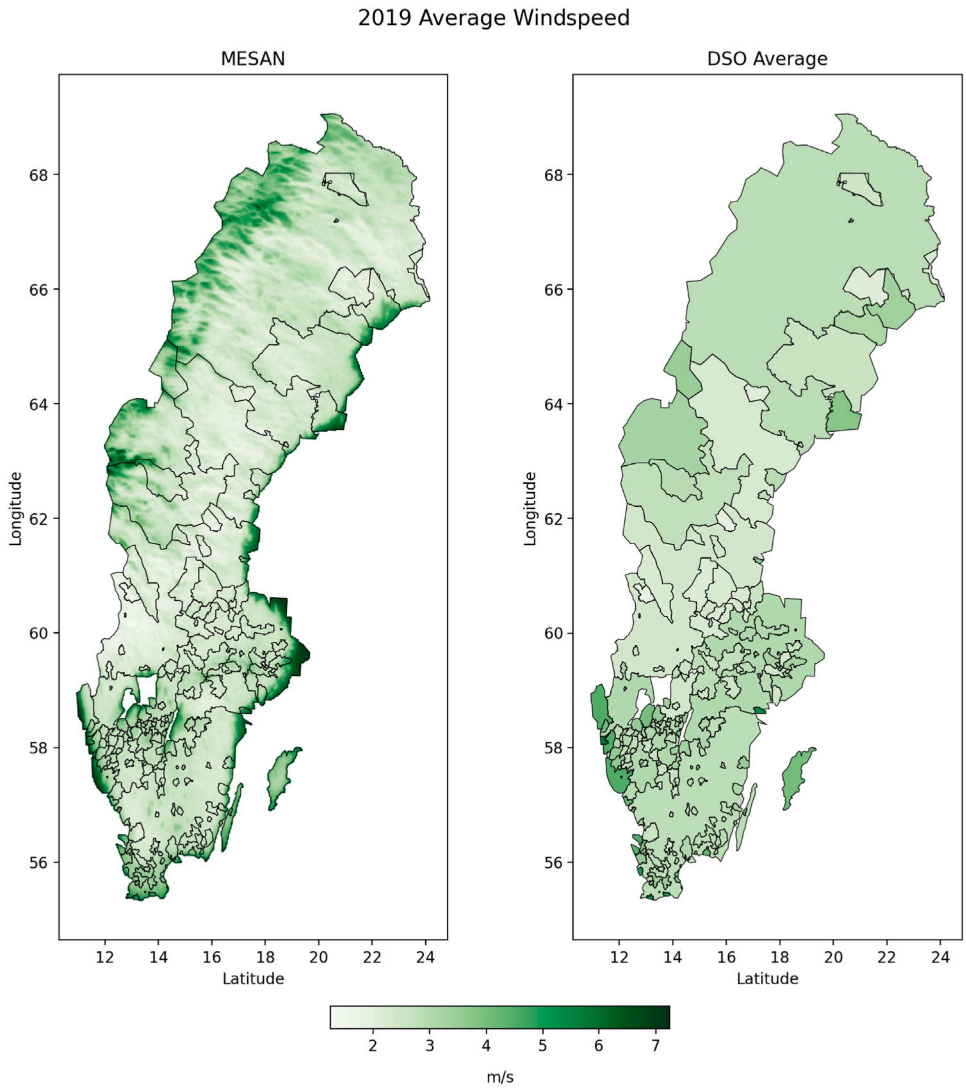

Fig. 15. Aggregation of wind speed at the distribution level.

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