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The spatial dimension of the power system: Investigating hot spots of Smart Renewable Power Provision

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ABSTRACT

The spatial dimension of the transition to a decarbonized power system becomes increasingly apparent with more than 1.5 million renewable energy sources of electricity (RES-E) plants operating all over Germany. The information regarding the spatial distribution of RES-E generation and power demand is still divers and not yet systematically used for the strategic planning of the energy transition and energy system modelling. The objective of this study is therefore to analyse the current power demand and RES-E supply spatially highly explicit with regard to their local interplay, annual balances and the share of volatile to flexible RES-E. This is achieved through the development and implementation of a general framework to analyse spatial patterns of the power system at different scales. The area of study is the Federal State of Germany, with the assessment of different spatial resolution ranging from federal state to community level. The resulting patterns are evaluated for their statistical significance through a hot spot analysis, followed by a correlation analysis to find possible reasons for their formation. The study shows a spatial dissonance between power demand and RES-E supply. This suggests that the design of the policy framework, focused on the levelized cost of electricity, led to a spatial distribution not oriented on local power demand but rather on economic optimality for the single power plant owner. By additionally differentiating between the RES-E technologies in terms of their intermittency characteristics, conclusions on the ability of regions at different scales for Smart Renewable Power Provision are drawn, measured by a set of proposed low carbon indicators. The

spatially most detailed level reveals the diverse state of the regions with, on the one hand, already around 10% fulfilling the indicator limit of Smart Renewable Power Provision and, on the other hand, regions with no RES-E capacity installed. An algorithm for finding desirable trajectory pathways to a decentralized energy system is introduced, build on the knowledge of the current state of the local power system. Finally, the correlation analysis indicates that for the RES-E extension not only socioeconomic but also land use characteristics are important factors to consider.

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Nomenclature

C_{1-3}	density clusters
CEM	carbon emission mitigation
CEM_r	carbon emission mitigation indicator of region r
$\mathrm{CEM}_r^{\mathrm{requ.}}$	required carbon emission mitigation indicator of region r
CORINE	coordination of information on the environment
DSM	demand side management
EEG	German renewable energies act
FLH	full load hours
GDP	gross domestic product
GHG	greenhouse gas
G_i^*	general G-statistic value of feature i
Gi-Bin	confidence level
i	feature i
$\mathrm{I}_{\mathrm{LAU\ 2}}$	number of inhabitants on LAU 2 level
$\mathrm{I}_{\mathrm{NUTS\ 1}}$	number of inhabitants on NUTS 1 level
j	feature j
LAU	local administrative unit
n	total number of features
NUTS	nomenclature of territorial units for statistics
$\mathrm{P}_r^{\mathrm{RES-E}}$	produced power of RES-E in region r
$\mathrm{P}_r^{\mathrm{RES-E_{flexible}}}$	produced power of flexible RES-E in region r
$\mathrm{P}_r^{\mathrm{RES-E_{volatile}}}$	produced power of volatile RES-E in region r
p-value	probability
r	region
RES-E	renewable energy source of electricity
SIF	system integration friendliness
SIF_r	system integration friendliness indicator of region r
SP	secured production
SREPP	Smart Renewable Power Provision
SREPP_r	Smart Renewable Power Provision indicator of region r
$\mathrm{U}_{\mathrm{NUTS\ 1}}^{\mathrm{exempted\ industry}}$	demand of industry enjoying special regulations in the EEG on NUTS 1 level
$\mathrm{U}_{\mathrm{NUTS\ 1}}^{\mathrm{industry}}$	demand of industry on NUTS 1 level

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$\mathrm{U}_{\mathrm{LAU\,2}}^{\mathrm{household}}$	demand of households on LAU 2 level
$\mathrm{U}_{\mathrm{NUTS\,1}}^{\mathrm{household}}$	demand of households on NUTS 1 level
$\mathrm{U}_{r}^{\mathrm{total}}$	total demand of region r
$\mathrm{U}_{\mathrm{LAU\,2}}^{\mathrm{trade}}$	demand of trade on LAU 2 level
$\mathrm{U}_{\mathrm{NUTS\,1}}^{\mathrm{trade}}$	demand of trade on NUTS 1 level
$\mathrm{U}_{\mathrm{LAU\,2}}^{\mathrm{transport}}$	demand of transport on LAU 2 level
$\mathrm{U}_{\mathrm{NUTS\,1}}^{\mathrm{transport}}$	demand of transport on NUTS 1 level
$\mathrm{w}_{i,j}$	spatial weight between feature i and j
x_{j}	attribute value for feature j
z-score	standard deviations

1. Introduction

The decarbonisation of the energy sector is one of the most important tasks of the global society in the 21st century. An unchecked climate change will impair life conditions of a large fraction of the world's population [1]. As one option to face these challenges, the German government implemented the "energy transition". This process already started in 1991 with the enforcement of the electricity feed-in act [2], continued with the German renewable energies act (EEG) [3] and gained momentum after the Fukushima accident in 2011 with the "energy concept" [4,5]. The German government aims to mitigate greenhouse gas (GHG) emissions by 80% to 95% until 2050, compared to 1990, respectively the renewable power generation shall increase to 80% [4].

In 2014 renewable energy sources of electricity (RES-E) have already contributed 27.4% to the overall power generation in Germany, produced by roundabout 1.5 million plants. In comparison, the conventional power plant park generated 72.76% of the power consumption with 770 plants (> 10 MW nominal capacity). The current power demand on the other side is relatively constant with a slight increase of 2.9% from 2000 to 509,167 GWh in 2014.

These numbers illustrate that a power system, based on RES-E like wind, photovoltaic, biomass or water power, is of a much more decentralised nature than one based on conventional power plants. There are many advantages of the transition, GHG emission reduction, energy security improvement and economic and industrial development, to name just a few [6–9]. However, with the increasing numbers of power plants and the corresponding increase in land use change, the energy generation infrastructure becomes visible and audible to great fraction of the society, to name just the most obvious impacts. Now one of the major challenges is to coordinate the expansion and the spatial allocation of those plants for a renewable power supply in accordance with the energy policy target triangle of security of supply, cost effectiveness and

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environmental soundness [10]. Within this debate, spatial aspects play an increasing role due to the fact that RES-E are much more spread over the landscape than conventional power plants and their very different intermittency characteristics. Both factors need to be considered when aiming for local, regional and transregional supply concepts.

Studies performing an analysis of the German power system spatially highly explicit are lacking until today. The spatial resolution of the corresponding energy system models is mostly country level or even world regions [11–19] with only a few spatially more detailed models [7,20,21]. Renewable energy sources however are site dependent on at least five dimensions: (1) natural energy potential, (2) distributed power demand (3) system integration and sector interconnection, (4) ecological impacts and (5) socioeconomic effects [22–32].

The dramatic increase in the number of RES-E plants results in the rise of required land. Space however is already a limited resource in Germany due to the demand for land use from different directions, e.g. building and construction land, agriculture production, recreation [33]. These more spatial related effects have not been reflected in national energy strategies and energy planning so far [34–37].

Furthermore, the dimension of intermittency of the RES-E is not yet spatially explicitly considered [38]. The intermittent nature of the major RES-E generation however necessitates increasing amounts of balancing mechanisms and flexible power [9,39,40]. Consequently, the relevance of the integration of demand side management (DSM) into the power system modelling to foster accuracy is increasing [41]. With a distributed power system, the spatial dimension of these mechanisms becomes increasingly relevant. The potential for DSM as well as the required amount for the balancing of the power system depend on the location. The future relevance of these site-specific mechanisms highlights the need for a spatially explicit analysis of the power system.

As a starting point for a more spatial explicit strategy and planning process, information on the spatial patterns of already existing RES-E plants are necessary. To understand the role of those plants for the current and future power supply system it is obligatory to know (1) what share of the local demand could be supplied (2) how the different RES-E volatility characteristics may interact with regard to a secure supply:

In this study, regions with an efficient spatial connection of RES-E supply and power demand patterns in combination with a high share of flexible to volatile RES-E are referred to as regions of Smart Renewable Power Provision. They combine a low carbon emission based power generation with a RES-E technology mix resulting in potential complementary generation patterns, fostering security of supply [42]. Besides the achieved carbon mitigation these regions are beneficial for the power system in many ways, a few examples are: The spatial proximity of supply and demand avoids the massive extension of the transmission grid while

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the potential complementary generation patterns reduce curtailment, grid bottlenecks, extension of the transmission grid and therewith acceptance problems to name just a few [43–45].

The objective of this study is therefore to analyse the current power demand and RES-E supply spatially highly explicit with regard to their local interplay regarding annual balances and the share of volatile to flexible RES-E. This is done for the area of the Federal State of Germany, with different spatial resolution ranging from federal state to community level.

In a first step the installed capacities and the annual power output for all onshore RES-E are identified spatially explicit. Then, for both the power demand and power supply a hot spot analysis enables making statements about the currently realised RES-E supply patterns and their statistical relevance.

In the next step the regions are investigated with regard to Smart Renewable Power Provision. These regions are characterized by a good performance regarding the two indicators defined and analysed: (1) the low carbon indicator measuring the share of covered demand by RES-E production, called carbon emission mitigation indicator, and (2) the share of flexible to volatile RES-E, called system integration friendliness indicator. This enables the categorization of the current state of the regions concerning the progress towards a Smart Renewable Power Provision region and the modelling of desirable trajectory pathways. Finally reasons for the formation of progress clusters are investigated, encompassing socioeconomic, geographical and ecological aspects.

The four main questions tackled in this study are therefore, a) what is the current state of the power system at different spatial scales? b) Where are statistically significant clusters of Smart Renewable Power Provision regions, defined by the performance concerning carbon emission mitigation and system integration friendliness indicators? c) What are desirable trajectory pathways for the regions to enhance their Smart Renewable Power Provision indicator performance? d) What are possible reasons for the formation of progress clusters?

The study is structured as follows. The introduction is followed by a modelling and analysis section illustrating the data, their respective sources and explaining the analysis approaches. Section 3 contains the results of the study, followed by a discussion of the methods and results. Finally, conclusions are drawn regarding the relevance of the outcome of this study for potential stakeholders and possible future research directions.

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2. MODELLING AND ANALYSIS

2.1. Modelling

The high granularity spatial analysis aimed for in this study can only be achieved with highly detailed input data. The highest spatial resolution is the Local administrative unit (LAU) 2 level with more than 11,500 regions focusing on Germany as the area and 2014 as the year of analysis. In this section the sources and characteristics of the data are described, followed by the delineation of the steps necessary to process the data.

2.1.1. Power demand distribution

The power demand analysis follows the concept of using the most detailed data available to model the spatially explicit distribution of the power demand top-down. One of the main sources are the energy balances of the federal states of Germany. These are published yearly and encompass the emergence, transformation and use of energy resources. The most recent available energy balances for whole Germany are from the year 2011. However, the decrease of only 2.3% of the gross electricity consumption from 2011 to 2014 [46] suggests no major changes in the demand structure which allows a projection to the year of analysis of 2014.

The energy balances use a categorization of the end user into four main sectors, which is adapted for the analysis. The sectors are (1) private households, encompassing private households and customers with an annual demand lower than 10 MWh, (2) transport, meaning all rail, road, air and water transport, (3) trade, which consist of trade, commerce and services, and (4) industry, defined as mining and manufacturing industry (the definition among the federal states varies slightly).

The preliminary statistical analysis finds that the average share of demand between the categories of customers is 26% (standard deviation among the federal states 6%) for household, 3% (2%) transport, 27% (6%) trade and 45% (10%) industry [46]. Another interesting statistic is the demand per capita, 1596 kWh/capita for household, 294 kWh/capita for transport, 1423 kWh/capita for trade and 1130 kWh/capita for industry.

According to Zhou and Bialek [47] the household electricity demand highly correlates with the population, at least on the more aggregated Nomenclature of Territorial Units for Statistics (NUTS) 1 level. This facilitates a straight forward allocation of the household power demand through the very detailed population data provided by the Federal Agency for Cartography and Geodesy [48] on the LAU 2 level, see Eq. 1. LAU 2

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corresponds to communities in Germany, with around 11,500 regions in total. The extreme points of the areas of these regions vary considerably, from 17*10^3 to 1.1*10^11 m², however the majority of areas is very homogeneous. The reason for few LAU 2 regions with a high area is that cities, e.g. the two most populous cities in Germany, Berlin and Hamburg, are treated as a region.

$$U_{\mathrm{LAU\ 2}}^{\mathrm{household}} = \frac{U_{\mathrm{NUTS\ 1}}^{\mathrm{household}}}{I_{\mathrm{NUTS\ 1}}} * I_{\mathrm{LAU\ 2}} \tag{1}$$

where U is the demand and I the number of inhabitants

Although electrified individual transport is expected to grow, the still low numbers of accreditation indicate that the transport powered by electricity today mainly consist rail transport [49]. Furthermore the predominance of the passenger transport in comparison to freight transport in terms of electricity use according to [50,51] allows the allocation of the overall transport related power consumption through the population in a region. (see Eq. 2)

$$U_{\mathrm{LAU\ 2}}^{\mathrm{transport}} = \frac{U_{\mathrm{NUTS\ 1}}^{\mathrm{transport}}}{I_{\mathrm{NUTS\ 1}}} * I_{\mathrm{LAU\ 2}} \tag{2}$$

The electricity demand of the trade sector is distributed through the gross domestic product (GDP) per capita provided on NUTS 3 level [52,53]. The regional GDP data is projected from 2013 to 2014 [54]. With the GDP per capita on NUTS 1 level, it is possible to calculate a weighing factor for each NUTS 3 region. This factor multiplied with the electricity demand per capita on NUTS 1 level and the population on LAU 2 level results in the demand on LAU 2 level. (see Eq. 3)

$$U_{\mathrm{LAU\ 2}}^{\mathrm{trade}} = \frac{\frac{\mathrm{GDP}}{\mathrm{capita}}_{\mathrm{NUTS\ 3}}}{\frac{\mathrm{GDP}}{\mathrm{capita}}_{\mathrm{NUTS\ 1}}} * \frac{U_{\mathrm{NUTS\ 1}}^{\mathrm{trade}}}{\mathrm{capita}} * \ I_{\mathrm{LAU\ 2}} \tag{3}$$

The industry electricity demand is modelled similar to the trade sector. Here the same weighing factor derived from the GDP per capita is used to break the NUTS 1 level data down to LAU 2 level. The lack of correlation in some industry sectors between high electricity demand and the GDP requires a correction of this distribution. Therefore, the data is used available for companies with a high ratio of electricity demand to turnover, enjoying special regulations in the EEG. The geocoding of the location of these companies, which demand amounts to 50.6% of the total industry demand, enhances the spatial explicitness considerably. The specific demand for the companies is not available therefore, the average of 2014 is distributed uniformly, described by Eq. 4.

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$$U_{LAU\,2}^{trade} = \frac{\frac{GDP}{capita}_{NUTS\,3}}{\frac{GDP}{capita}_{NUTS\,1}} * \frac{U_{NUTS\,1}^{industry} - U_{NUTS\,1}^{exempted\ industry}}{capita} * I_{LAU\,2} + U_{LAU\,2}^{exempted\ industry} \quad (4)$$

2.1.2. Power supply distribution

The power supply is distributed spatially explicit through the geocoding of all RES-E plants. The main database used is the plant register of RES-E supported by the EEG, available from the four different transmission grid operators. The plants are geocoded according to the available address. This works for the plants with a clear address, which is not the case for wind plants for example. In this case, the data was supplemented by commercial data sources providing the exact location. Furthermore, the RES-E plants directly marketed are also geocoded and included in the database. This spatially explicit database includes around 1.5 million power plants. The different RES-E technologies are grouped by their intermittence characteristics. Wind power and photovoltaic are grouped as volatile, run of river and geothermal as non-volatile and bioenergy as flexible [55]. The resulting installed capacity fits other sources, for example [56], with only a minor difference of 5% total capacity.

The yearly power generation is calculated with the full load hours (FLH) of the plants. This data is available for the year of 2013 and around 80.2% of all plants of the year 2014, with some variations throughout the technologies. Between 2013 and 2014, only minor fluctuations in meteorological conditions relevant for the FLH of the RES-E are expected therefore the available production is used where available. When the actual FLH are not available, a theoretical one is calculated for each technology as an average of the available data, resulting in a loss of spatial explicitness. The resulting FLH are validated by the comparison with the study [57]. Finally, it is possible to calculate the site-specific production of electricity. The calculated data underestimates the production according to [57] 18% for bioenergy, 10% for photovoltaic and 3% for wind energy. The main cause is likely that the RES-E plant database only includes plants supported by feed-in tariffs, another cause is that the meteorological conditions differ slightly. The assumption that the power plants are supplying the regions they are located in can be subject to debate, especially for wind parks connected directly to the transmission grid.

2.2. Analysis

In this section, the main analysis methods (1) the hot spot analysis and (2) the Smart Renewable Power Provision analysis are introduced. The hot spot analysis is the method of choice to evaluate the spatial

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patterns for their statistical significance. The Smart Renewable Power Provision analysis introduces indicators facilitating the assessment of the power system on a local level as well as the development of desirable trajectory pathways. Finally, a correlation analysis is the method to find possible reasons for the state of the regions on their way to a decentralized power system.

2.2.1. *Hot spot analysis*

The aim of the hot spot analysis is to find statistically significant spatial clusters. It is also known as Getis-Ord Gi* statistic named after the authors introducing the general G-statistic method [58]. The general concept is to test how likely it is that the observed spatial pattern in the data set is a version of random chance, the null hypothesis. In this study, the hot spot analysis is the key for finding statistically relevant patters of power demand, RES-E supply and Smart Renewable Power Provision progress.

The hot spot analysis tests the null hypothesis by calculating to which degree the tested feature is surrounded by features with high or low attribute values within a certain threshold distance. The method used in this study additionally uses a z-transformation developed by Ord and Getis [59] referred to as standardized Getis-Ord Gi* statistic. Here the local sum of the attribute values of these features minus the expected values divided by the square root of its variance is calculated shown in the Eq. 5-7.

$$\mathrm{G}_{\mathrm{i}}^{*} = \frac{\sum_{j=1}^{n} \mathrm{w}_{i,j}\mathrm{x}_{\mathrm{j}} - \overline{\mathrm{X}}\sum_{j=1}^{n} \mathrm{w}_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} \mathrm{w}^{2}{}_{i,j} - \left(\sum_{j=1}^{n} \mathrm{w}_{i,j}\right)^{2}\right]}{n-1}}} \tag{5}$$

$$\overline{\mathrm{X}} = \frac{\sum_{j=1}^{n} \mathrm{x}_{j}}{\mathrm{n}} \tag{6}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} \mathrm{x}^{2}{}_{j}}{n} - (\overline{\mathrm{X}})^{2}} \tag{7}$$

where x_j is the value of the feature j, n the total number of features
and $\mathrm{w}_{i,j}$ the spatial weight between feature i and j

The spatial weight matrix $\mathrm{w}_{i,j}$ is of *n*n* dimension describing the spatial weight of one feature to all other features. For this study, a fixed distance band is the method for determining this weight matrix. Thus, all features in a specific distance around the currently analysed feature count with their full weight whilst the other features are neglected. This procedure ensures that the heterogeneous regions' size has no influence on the distance band of the analysis.

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The definition of the distance band depends on the purpose of analysis as well as the nature of the data. An analytical process to determine the distance band is to perform an incremental spatial autocorrelation analysis, assessing the degree of global spatial clustering at different distances. The autocorrelation is expected to peak at the distances where the processes responsible for the formation of clusters are the most distinctive [60].

The limits to determine a statistically significant clustering are shown in Table 1. Where the z-score is the standard deviations from the mean and p-value is the probability. A feature of a region with a z-score of 1.96 for example would require a p-value of < 0.05 to fall in the Gi_Bin corresponding to a 95% confidence level to be a hot spot. This means that the confidence is 95% that the observed cluster of high values is not a version of random chance.

Table 1 *Hot spot analysis confidence level z-scores and p-values*

z-score	p-value	Gi-Bin	corresponding confidence level
< -1.65 or > +1.65	< 0.10	< -1 or > +1	90%
< -1.96 or > +1.96	< 0.05	< -2 or > +2	95%
< -2.58 or > +2.58	< 0.01	< -3 or > +3	99%

2.2.2. Smart Renewable Power Provision analysis

The Smart Renewable Power Provision (SREPP) analysis builds on the power supply and power demand analysis described in the sections 2.1.1 and 2.1.2. It consists of the development of an analysis framework, followed by a characterization of the resulting regions, an algorithm to find desirable trajectory paths and finally a correlation analysis of the spatial patterns.

The SREPP analysis framework is a methodology to facilitate the categorization of the current state of the regions regarding the path to Smart Renewable Power Provision. To fit the regions into meaningful categories it is assumed that they operate in island mode, neglecting balancing effects through the power grid and storage systems. The analysis framework is segmented into two dimensions. Both dimensions are defined through the space spanned by the two indicators “carbon emission mitigation” (CEM) and “system integration friendliness” (SIF), described by Eq. 8, 9 and Figure 1.

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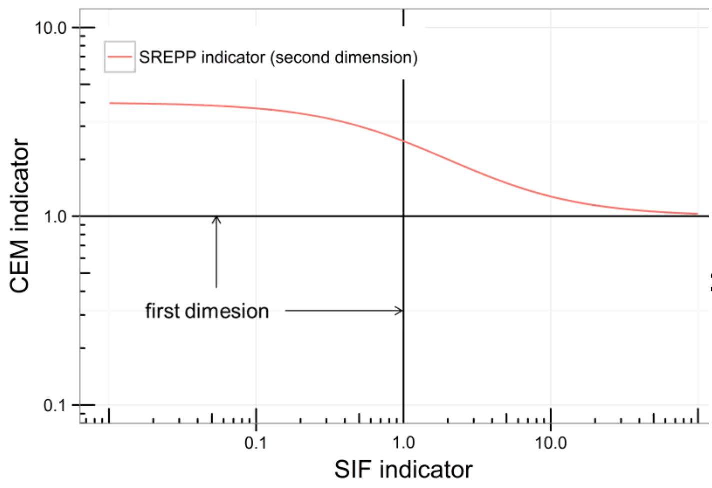

Figure 1 *Smart Renewable Power Provision analysis framework*

$$\mathrm{CEM}_r = \frac{\mathrm{P}_r^{\mathrm{RES-E}}}{\mathrm{U}_r^{\mathrm{total}}} \tag{8}$$

$$\mathrm{SIF_r} = \frac{\mathrm{P}_r^{\mathrm{RES-E_{flexible}}}}{\mathrm{P}_r^{\mathrm{RES-E_{volatile}}}} \tag{9}$$

$$\mathrm{SREPP}_r = \mathrm{CEM}_r^{\mathrm{requ.}} = \frac{\left(\mathrm{SIF}_r + \frac{(1-SP)}{SP}\right)}{\mathrm{SIF}_r + 1} \tag{10}$$

$$\lim_{\mathrm{SIF}_r \to \infty} \mathrm{SREPP}_r = \mathrm{CEM}_r^{\mathrm{requ.}} = 1 \tag{11}$$

$$\lim_{\mathrm{SIF}_r \to 0} \mathrm{SREPP}_r = \mathrm{CEM}_r^{\mathrm{requ.}} = 4 \tag{12}$$

where r is a region and P the produced power

The first dimension of the SREPP analysis framework is the subdivision of the space with two lines along the CEM and SIF indicators of one. At the intersection of these lines, the region has 100% coverage of the yearly demand through RES-E production and an equal share of flexible to volatile RES-E production. We assume that for a successful energy transition on local level (1) the renewable power provision should cover the overall power demand, mitigating GHG emissions, and (2) fluctuating and flexible renewables should have a comparable contribution to the power supply, ensuring security of supply. This first characterization helps to analyse the location of the regions in this space and draw first conclusions regarding the local state of the power system.

The second dimension of the SREPP analysis framework is introduced to evaluate the carbon emission mitigation and integration friendliness combined into one indicator called Smart Renewable Power Provision indicator (SREPP), see Eq. 10 and Figure 1. Defining condition is that with a decreasing amount of flexible to volatile RES-E production a higher coverage of the demand is necessary to guarantee security of supply. The limit for this indicator is derived by the assumption that the secured production (*SP*) of volatile RES-E generation is 20%, which results in a curve approximating the carbon emission mitigation of one for an increasing share of flexible RES-E production and four for a decreasing share, see Eq. 11 and 12. The proposed *SP* requirement can be decreased by different strategies, among them DSM and storage capacities [41,61,62].

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2.2.3. Pathways towards Smart Renewable Power Provision and correlation analysis

With the region specific performance regarding the SREPP indicator, desirable trajectory pathways are modelled for the regions not yet fulfilling the proposed target value of one. This is done by a simple shortest path algorithm, revealing how much flexible and volatile RES-E should be installed to fulfil the SREPP indicator. Finally, the SREPP indicator is used to perform a hot spot analysis, which reveals clusters of Smart Renewable Power Provision regions. The clusters are evaluated with a correlation analysis of socioeconomic factors in addition to land use characteristics to investigate reasons for the clustering. The correlation analysis uses the Pearson Product Moment correlation coefficient developed by K. Pearson [63], a measure of linear correlation.

3. RESULTS

3.1. Power demand analysis

The results of the power demand analysis on community level are shown in the Figures 2 and 3. The results are an interesting themselves and a necessary step to understand the more elaborate analysis in section 3.2. The main findings which can be extracted are: (1) how much power is consumed, (2) which category of sectors causes the demand and (3) how do the categories of sectors compare to each other in terms of energy demand, all on a spatially detailed level. The colours correspond to the yearly power demand normalized by the area on LAU 2 level for household plus transport and industry plus trade respectively. The average total power demand is 1.32 kWh/m², with a very heterogeneous distribution. In general, it can clearly be seen that there is an east to west trend of growing power demand. Exceptions are the two demand centres Berlin and Hamburg, which are characterized by a high demand and a medium to high demand in the regions in close proximity. Furthermore there are smaller cities, e.g. Dresden, Leipzig and Chemnitz, showing the same pattern of influencing the regions in close proximity. Another observation is that there seems to be a cluster of high power demand reaching from the Ruhrgebiet and Frankfurt am Main to northern Baden-Württemberg. The statistical significance of these clusters is investigated by the hot spot analysis, see section 2.2.1.

When comparing the Figures 2 and 3, it becomes clear that the trade and industry sectors are the dominating driver for the power demand. They are also more spatially spread over Germany but in general they pronounce the clustering of the inhabitant driven power demand.

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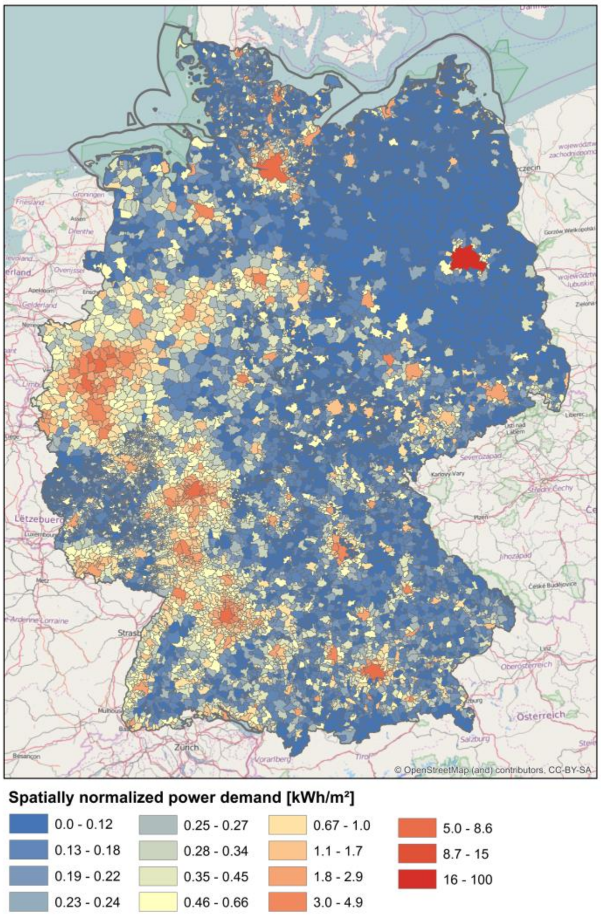

Figure 2 *Household and transport power demand on LAU 2 level*

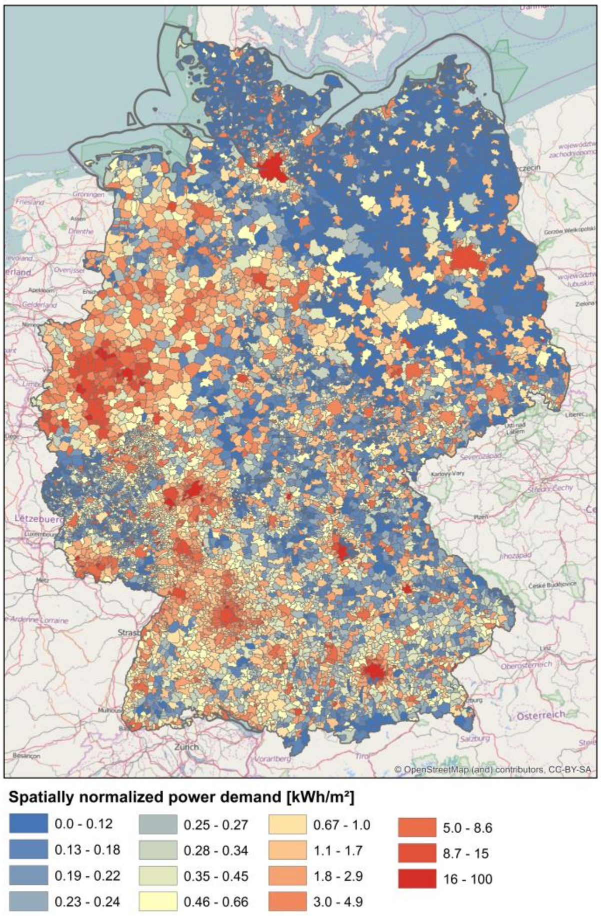

Figure 3 *Trade and industry power demand on LAU 2 level*

To investigate statistically significant clusters of power demand a hot spot analysis is performed. First the incremental spatial autocorrelation is used to analyse the clustering by distance. However multiple local maxima are possible, with smaller distances reflecting more local trends and larger distances reflecting more overall trends. The resulting correlation curve shows the peak at a distance of 70 km. For the purpose of exploring multiple scales a second distance of 40 km is chosen, meaning that every region is evaluated with all neighbouring regions in a 40 km distance radius.

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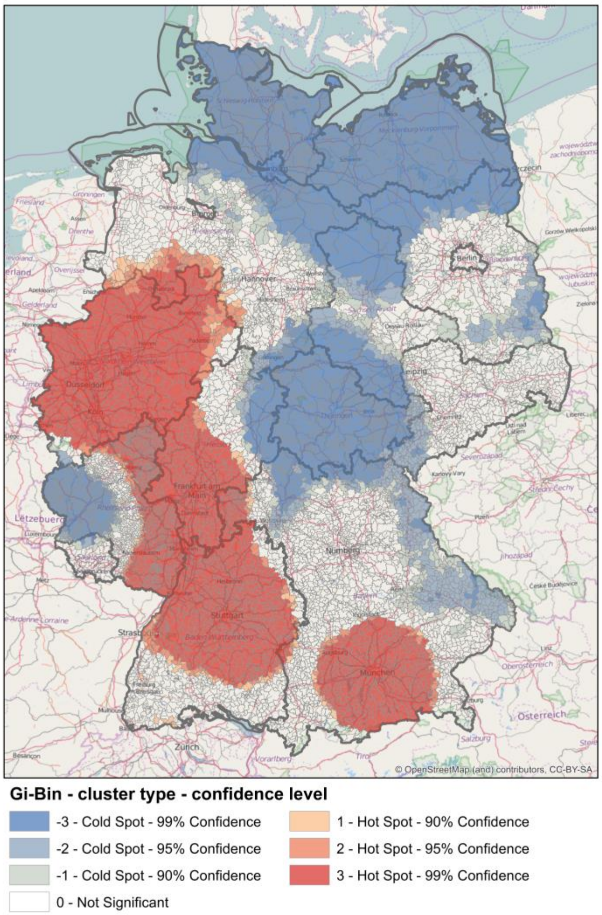

__Figure 4__ Hot spot analysis of the total power demand (70 km threshold)

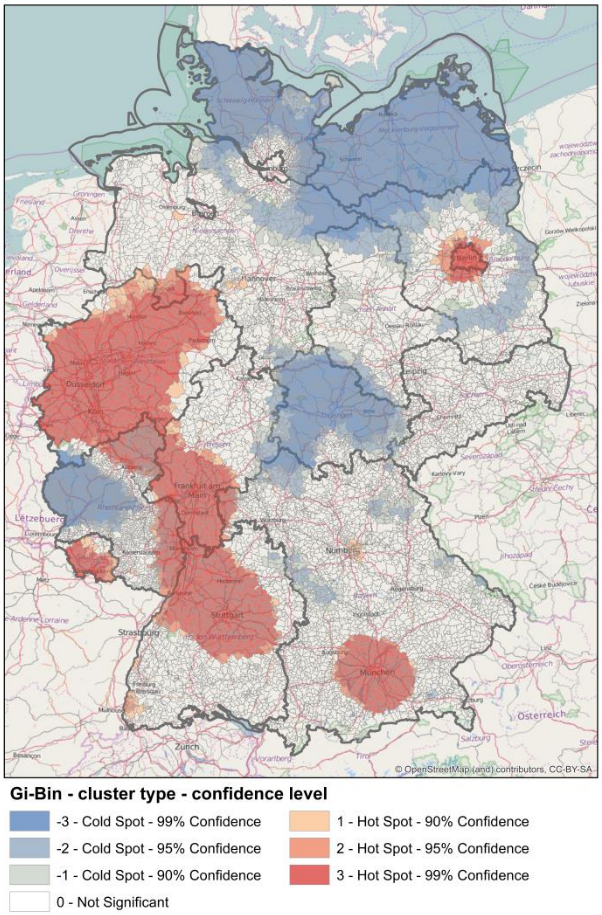

__Figure 5__ Hot spot analysis of the total power demand (40 km threshold)

The hot spot analysis of Figure 4 confirms the broad trend of clusters with a high power demand in the south and west and low demand in the north and middle of Germany. These clusters are characterized by a very high confidence level. Furthermore, Figure 5 shows that the reduction of the threshold distance to 40 km reveals more local phenomena with Berlin, Munich and most regions of the Saarland forming hot spots. Noticeable is that the inhabitant dense city of Hamburg is no hot spot in either of the distances.

3.2. *Renewable power supply analysis*

The result of the renewable power supply analysis is shown in Figure 6, the application of the same scale as the demand analysis allows a first direct comparison. The noticeable difference is that the supply of RES-E is overall much lower with an average of 0.35 kWh/m². This makes sense considering the fact that the conventional generation, still the major source of electricity, is not included. Secondly, in contrast to the demand, the supply shows a much more dispersed characteristic, the clear clustering trend of the demand is

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not reflected. For a statistical analysis again the hot spot analysis is performed. Finally, there is no identifiable single driver, for example wind speed or solar radiation, for the generation of RES-E.

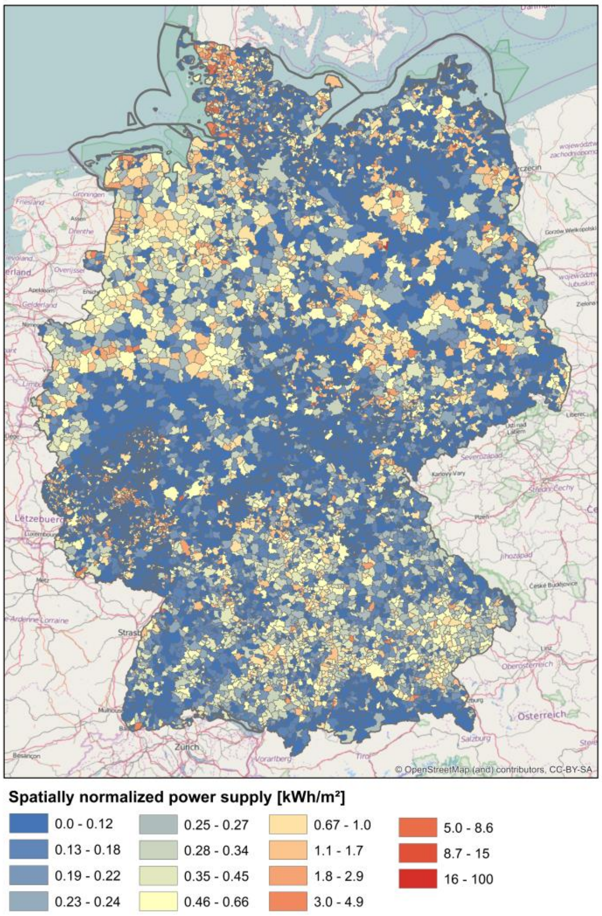

Figure 6 *Total RES-E power supply on LAU 2 level*

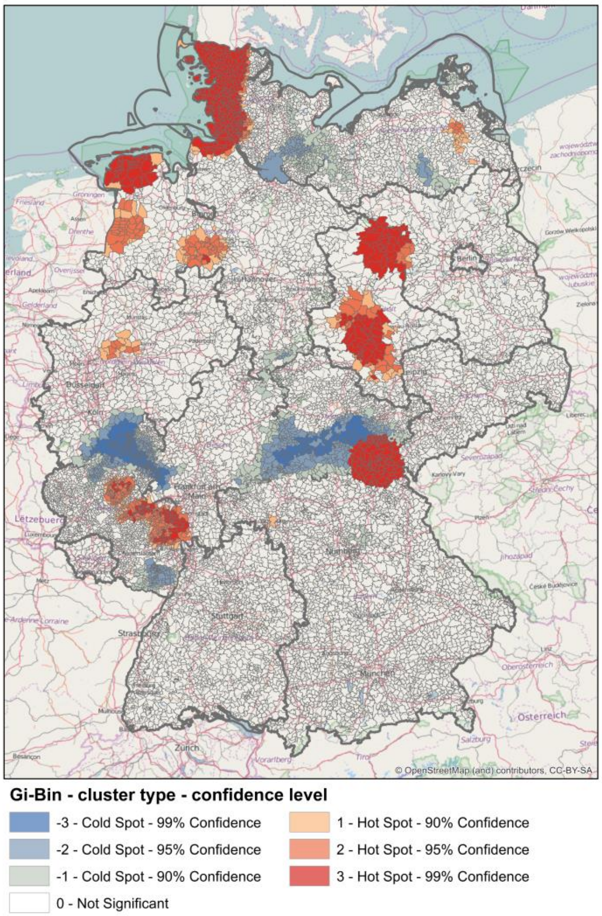

Figure 7 *Hot spot analysis of the total RES-E power supply (32km threshold)*

The explorative analysis of the autocorrelation peaked at the distance of 32 km. The corresponding hot spot analysis results in few small hot spots, shown in Figure 7. This confirms the impression of the absence of statistically significant clusters. This indicates that the extension of the renewable power plants does not follow pronounced spatial trends, such as the distribution of the demand or other aspects of the integration in the existing power system.

3.2.1. Smart Renewable Power Provision analysis

Figure 8 shows the LAU 2 regions’ distribution in the Smart Renewable Power Provision analysis framework. In the density distribution, three clusters C_{1-3} of regions form.

- C_1 is made up of regions with no RES-E production whatsoever, which include 120 of all regions.

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- C_2 forms parallel to the y-axis and is made up of regions with a certain amount of RES-E production, however only volatile RES-E, which are 6456. C_2 shows the highest density at a CEM of only 0.04. However there is a wide spread over the logarithmic axis with regions exceeding the CEM of one. Some of these regions even fulfil the SREPP indicator of one despite the lack of any flexible RES-E production.
- C_3 consists of the remaining 4645 of regions. These regions are widely spread over both axes with the densest area in the range of 0.2 to 0.7 CEM and 0.7 to 1.1 SIF.

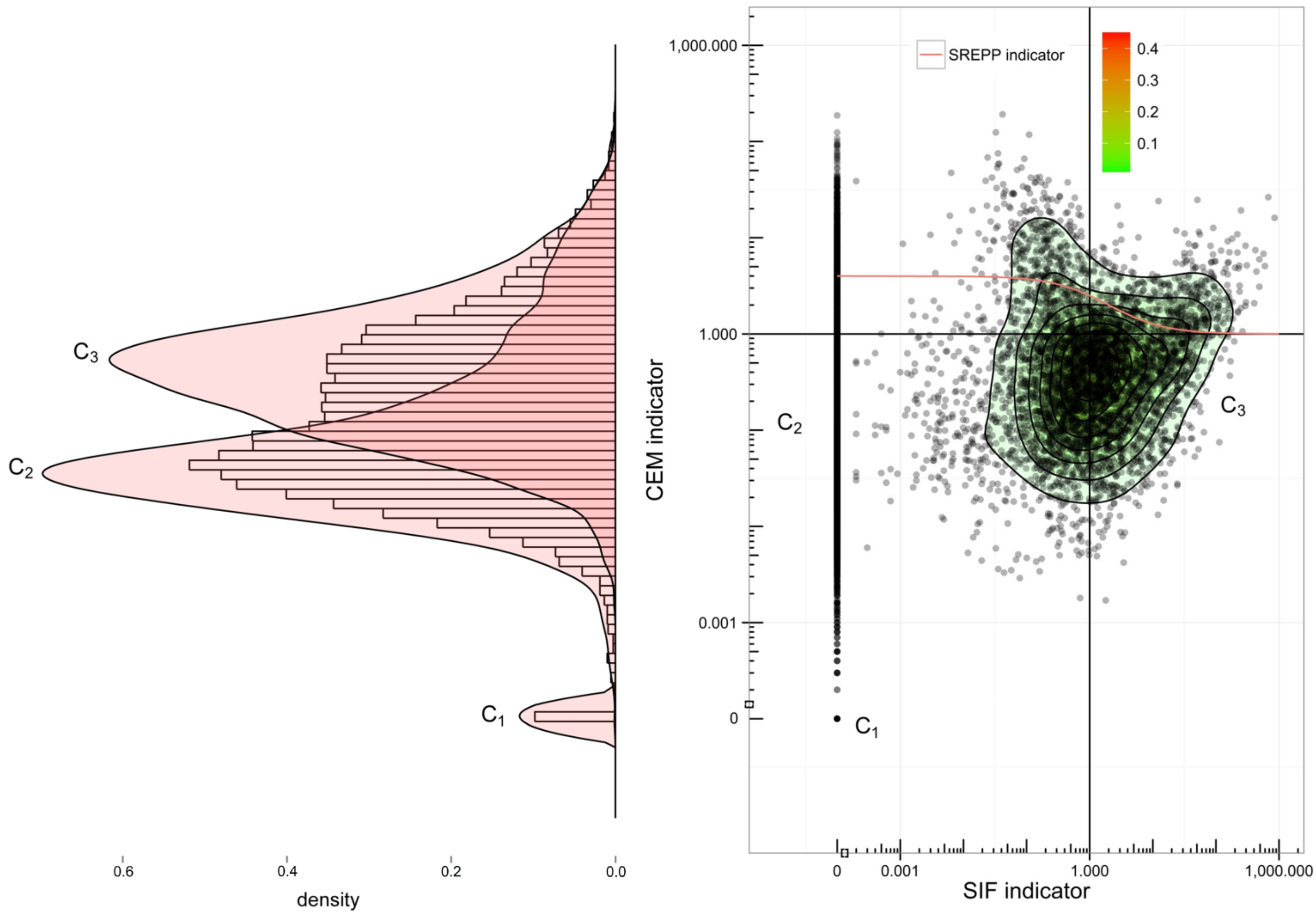

Figure 8 *Density plot of Smart Renewable Power Provision region LAU 2 level analysis*

The requirement of the SREPP indicator of one is met by 10.5% of the LAU 2 regions already. However, to put the results into perspective, Figure 9 shows the total power demand of the LAU 2 regions corresponding to the bubble size. It is clearly visible that most regions fulfilling the SREPP indicator requirement of one are characterized by a low total power demand. Additionally regions with a very high demand show mostly a low CEM indicator performance. Interesting however is that the regions with a high demand also seem to group around a SIF of one.

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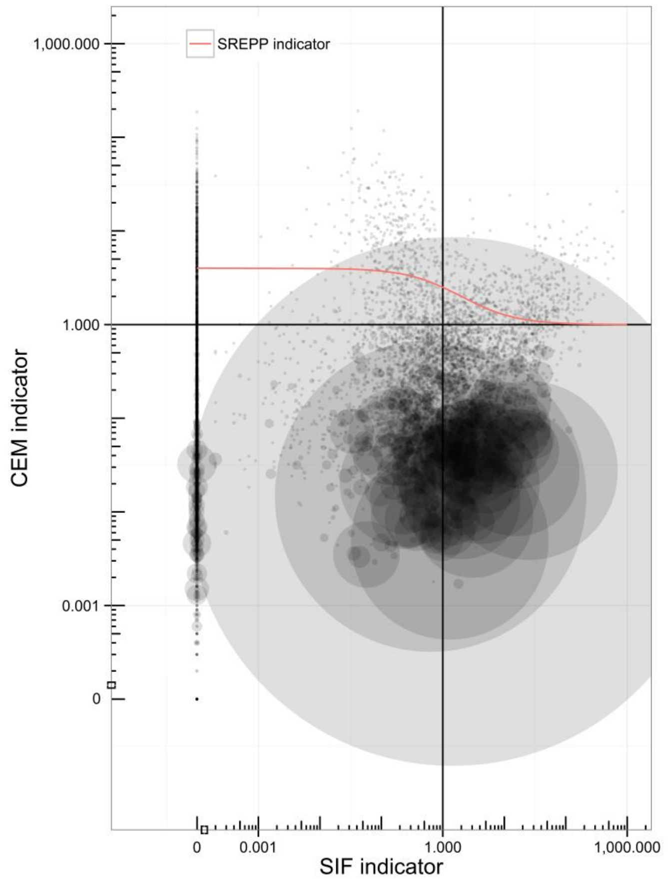

Figure 9 *Smart Renewable Power Provision region LAU 2 level analysis (bubble size corresponds to the total power demand)*

3.2.2. Pathways towards Smart Renewable Power Provision

As described above, the SREPP indicator is an approach to give individual advice on local level concerning possible directions to achieve a balance between carbon mitigation and system integration friendliness. This indicator only considers systemic aspects and neglects other factors.

Figure 10 shows the shortest distance trajectory pathways of the LAU 2 regions to fulfil the SREPP indicator of one. It consists of three main parts, the first of which is the SREPP analysis framework, introduced in section 2.2.2. However, for this figure only LAU 2 regions are shown that do not yet fulfil the SREPP indicator requirement. The second main feature is the shortest distance trajectory pathways, which show, LAU 2 specific, the distance of the current status to a status where the SREPP indicator requirement is reached. To highlight the different distances, the paths are coloured accordingly. Finally, a density plot of the proposed trajectory paths final destination, corresponding to a specific share of CEM and SIF, shows where the majority of LAU 2 regions aim for on the SREPP indicator curve under the applied analysis framework.

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It is remarkable that the paths of the regions with already high integration friendliness, above one, tend to simply increase the CEM while keeping the SIF constant. Contrary, regions with a low SIF increase both indicators with the aim of a certain range of both. This is reflected though the density clusters in the area of a SIF indicator of around 1.3 and a CEM indicator of around 2.

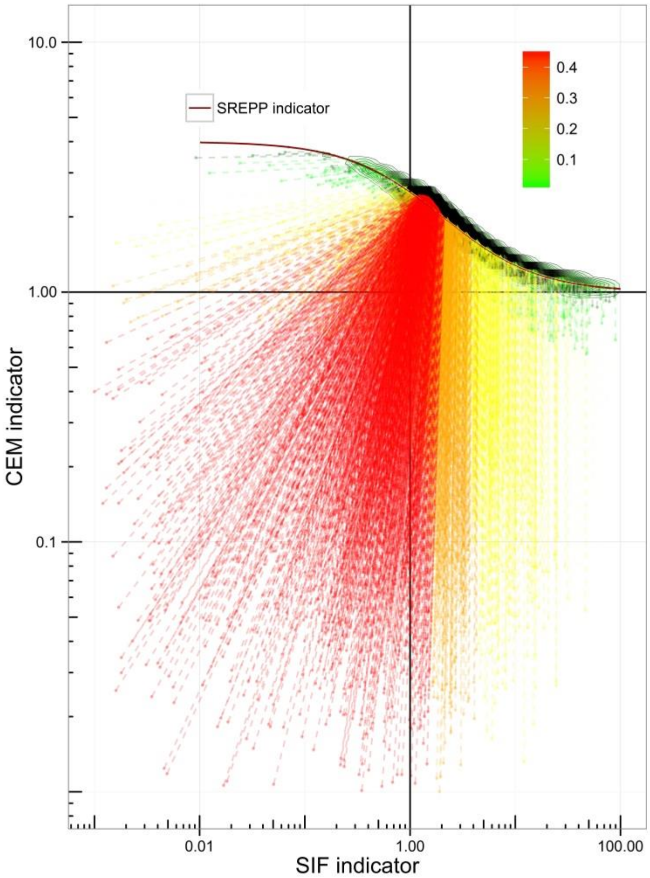

Figure 10 *Shortest distance trajectory pathways of the LAU 2 regions to fulfil the SREPP indicator of one*

Figure 11 shows the current status of LAU 2 regions on their way to regions of Smart Renewable Power Provision, defined by a SREPP indicator of one. It combines the demand and supply analysis as well as the Smart Renewable Power Provision analysis. It facilitates both, an analysis of the general patterns, examined through figure 12, as well as a spatially detailed analysis of a single LAU 2 region. This allows local as well as transregional policy makers to assess the status of their region and design policy accordingly. In contrast to the very much dispersed picture of the RES-E production, Figure 11 indicates a pattern on first glance. Noticeable is that the regions already fulfilling the SREPP indicator limit of one are mainly located in the northern part of Germany.

Figure 12 shows the associated hot spot analysis with a threshold of 40km. In contrast to the RES-E production hot spot analysis, the clusters cover a wide area of Germany, although with a more diverse

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confidence level distribution. The clustering of statistically significant cold spots in the areas of high demand in mainly south and West Germany is expected. The hot spot clusters form mainly in eastern Germany and the northern coastal areas.

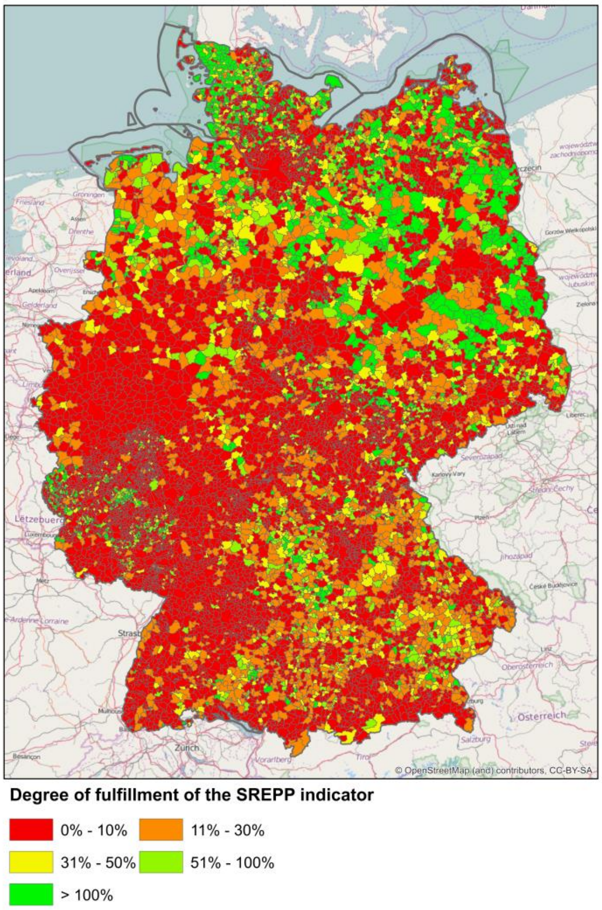

Figure 11 *Degree of fulfilment of the SREPP indicator on LAU 2 level*

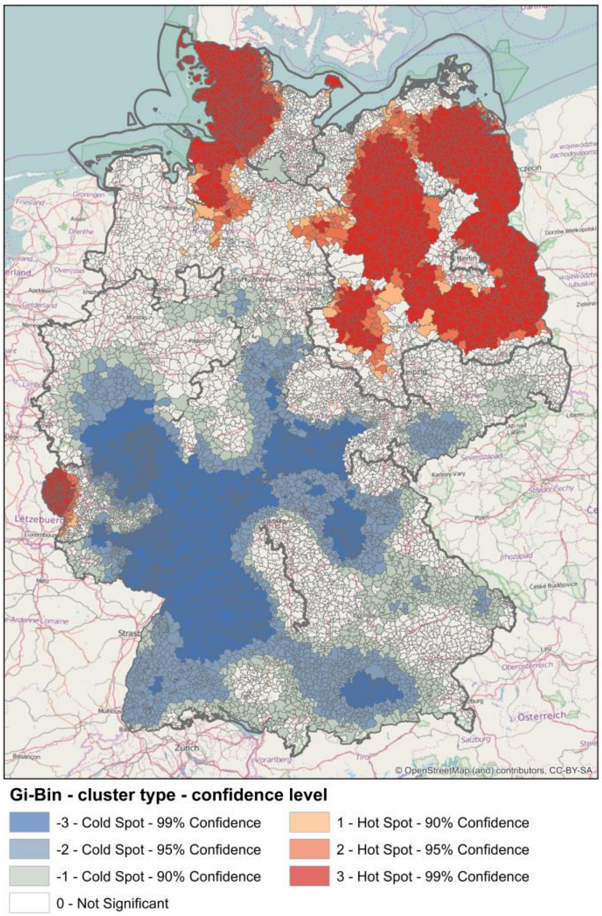

Figure 12 *Hot spot analysis of the degree of fulfilment of the SREPP indicator (40km threshold)*

3.2.3. Correlation and land use analysis

To investigate possible reasons for the current state of the local power system a correlation analysis is performed normalized to the community area. The variables considered are the input data of the power supply and demand analysis and the degree of fulfilment of the SREPP indicator. The analysis shows that the fulfilment of the SREPP indicator correlates much more with the volatile production (Pearson Product Moment correlation coefficient 0.39) compared to the flexible production (0.11). Another interesting result is that the correlation with the GDP, inhabitants and the different demand types is negative however on a very low level with -0.03 for the GDP. This contradicts the reasoning that the cold spots are predominantly caused

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by a high demand as a consequence of high GDP and inhabitant numbers. However, these factors might play an indirect role by forming the land use in these areas resulting in positive or negative conditions for the deployment of RES-E plants. To capture these characteristics of RES-E the coordination of information on the environment (CORINE) land cover data is used [64]. The analysis reveals that there is a negative correlation with the land use types associated with human settlements, e.g. with the land use type “discontinuous urban fabric” (-0.12). Additionally noticeable is that land use types not directly associated with human settlements are also negatively correlated, most pronounced the mixed forest land use type (-0.09) and broad-leaved forest (-0.09). The highest positively correlating types are the “non-irrigated arable land” (0.15) and pastures (0.05), which account for 65% and 21% of all agricultural areas. This indicates that the further expansion on a local level will depend, among other factors, on the available land use characteristics. The correlation analysis is supported by a comparison of the mean shares of selected land use types for hot and cold spots, see Figure 13. The hot and cold spots show an even more pronounced relevance of the land cover characteristics than the fulfilment of SREPP indicator. The three categories urban land, farm land and forest all show a clear trend favouring the formation of either of the two cluster types, see Table 2

Table 2 *Comparison of selected land use types dominating in hot and cold spot regions on LAU 2 level*

	Discontinuous urban fabric	Non-irrigated arable land	Pastures	Broad-leaved forest	Mixed forest
hot spot	4%	45%	16%	4%	2%
cold spot	8%	27%	11%	9%	11%

The Smart Renewable Power Provision analysis is also performed on the more aggregated levels of NUTS 3 and NUTS 1. (See Appendices) This reveals a much different picture compared to the LAU 2 level. Figure A.1 shows that already the aggregation to NUTS 3 level results in the loss of the very diverse picture of the state of the regions of Figure 11. Remarkable is that only one NUTS 3 region fulfils the SREPP indicator of one compared to 1172 LAU 2 regions. Additionally the three clusters of Figure 8 merge into just one cluster on the two more aggregated levels.

4. DISCUSSION

To the authors knowledge, this study provides the first spatially highly detailed analysis of the German power system. Through a comprehensive data collection, modelling of the spatial distribution of the power demand and supply in combination with spatial statistics it is possible to achieve an in depth analysis.

The introduction of three indicators facilitated the characterization of the LAU 2 regions with respect to the state of the local power system. Further, through considering the specific intermittency characteristics, the

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derivation of desirable trajectory paths with respect to the carbon emission mitigation as well as system integration is achieved.

The first major result is that there are spatially significant clusters of power demand whilst the RES-E supply is dispersed. Additionally there is a spatial dissonance between the RES-E production and the demand. In fact, the few hot spots of the RES-E production fall predominantly in demand cold spots. The prospected shift from the spatially very demand centre oriented conventional power plants to distributed RES-E will emphasize this effect in the future if no action is taken. There are two main strategies to cope with that. The first is a considerable increase in transmission capacity to supply the demand centres. The second strategy is to spatially organize the future deployment of RES-E capacities according to demand. This can be done by spatially explicit political support schemes or tailored market frameworks, e.g. locational pricing. With the provided approach energy strategies on local level can be formulated. This decentralization strategy would not only have the advantage of mitigating transmission expansion but could also foster acceptance though local prosumer structure.

The second major result is achieved through the categorization of the regions according to the three indicators and the derivation of desirable trajectory paths. The variety of the state of the regions on their way to a decentralized energy system on community level is interesting when consolidating the political framework for RES-E expansion. There are already communities with a "completed energy transition", e.g. the model community Jühnde (SREPP score 0.9), and communities without RES-E installation at all. This facilitates the identification of communities where an incentive for the expansion of RES-E and the optimal intermittence characteristics is preferable to achieve a decentralized energy system. The paths clearly show that a balanced intermittency characteristic should be achieved. The assumption of the *SP* of volatile RES-E is dynamic and should be subject to debate.

Linked to this assumption is the result that a SREPP indicator curve closer to one, also for regions with a high share of volatile RES-E, considerably shortens the trajectory pathways, which translates in a decrease of required RES-E capacity. This can be achieved by an array of measurements. Among them the integration of different RES-E technologies as so called virtual power plants, demand response capacities, storage capacities and system friendly RES-E. The shortened paths correspond to a saving in necessary production capacity. This induces many advantages for the energy transition, mitigation of impact on the environment and cost savings to name just a few.

The third major result is that the spatial level today used in most energy system model should be subject to scrutiny. This is especially relevant with the increasing decentralization, and is clearly visible when looking at

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the very different results for the three scales of analysis. Therefore the authors argue for the development of new approaches to capture the spatial characteristics of RES-E in energy system models.
Additionally the identification of potential relevant land cover types for the further expansion of RES-E can act as a starting point for the assessment of possible environmental effects on the landscape. Especially the most positively correlating land cover type for the fulfilment of the SREPP indicator of one can be expected to face an increasing burden through the RES-E expansion. To assess these effects, more indicators need to be implemented which cover social and environmental effects.
The limits and short comings of the approaches used are mostly caused by lack and uncertainties of data, simplifications and assumptions. The uncertainties are cause by projections to the base year and the modelling of the spatial distribution of the power demand due to lacking spatial explicit data in addition to uncertainties from the process of geocoding. Similarly the development of trajectory pathways does not include potential constraints. The simplifications and assumptions mainly concern the temporal dimension, which is simplified through the translation of the feed-in and demand profiles into a single indicator. Additionally the goal of a community specific analysis necessitates the neglect of the transmission grid and storage facilities.

5. CONCLUSION

This study is a first step in the direction of a power system analysis considering the spatial dimension with a high level of detail. With the chosen methods it is possible to show the current state of the decarbonisation of the power system on a local level. In addition the inclusion of a variety of socioeconomic and geographical data in combination with the hot spot analysis enables the identification of statistically relevant hot and cold spots of Smart Renewable Power Provision. Considering all those aspects, the developed approach can function as a guide for the further transition of the power system on a local level, with spatially highly explicit advice.
The simple modelling in this study should be complemented with elaborate energy system modelling methods to be able to gain much deeper insight. Additionally the inclusion of key aspects and the avoidance of a variety of simplifications necessary for this study would enhance this research direction considerably. Finally, to take advantage of the intermittency characteristics, it is important to translate the desirable trajectory paths in spatially explicit policy targets. This would shift the focus from a spatially unspecific incentive, purely oriented towards the single economic optimality of one power plant investor, to a spatially explicit system optimized power system. This instrument should take into account the geographic, socioeconomic and ecologic conditions of the different regions.

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APPENDICES

A.Smart Renewable Power Provision analysis on NUTS 3 level

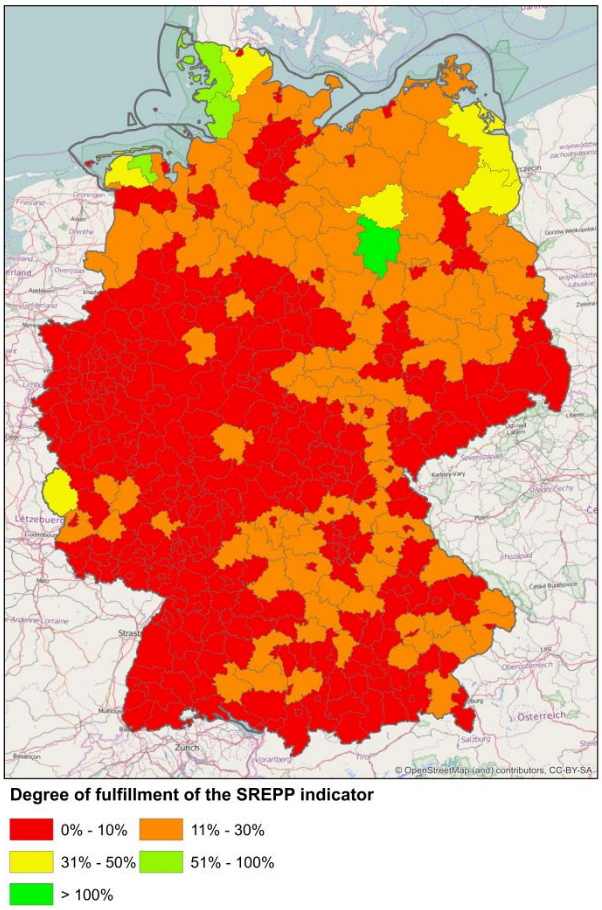

Figure A.1 *Degree of fulfilment of the SREPP indicator on NUTS 3 level*

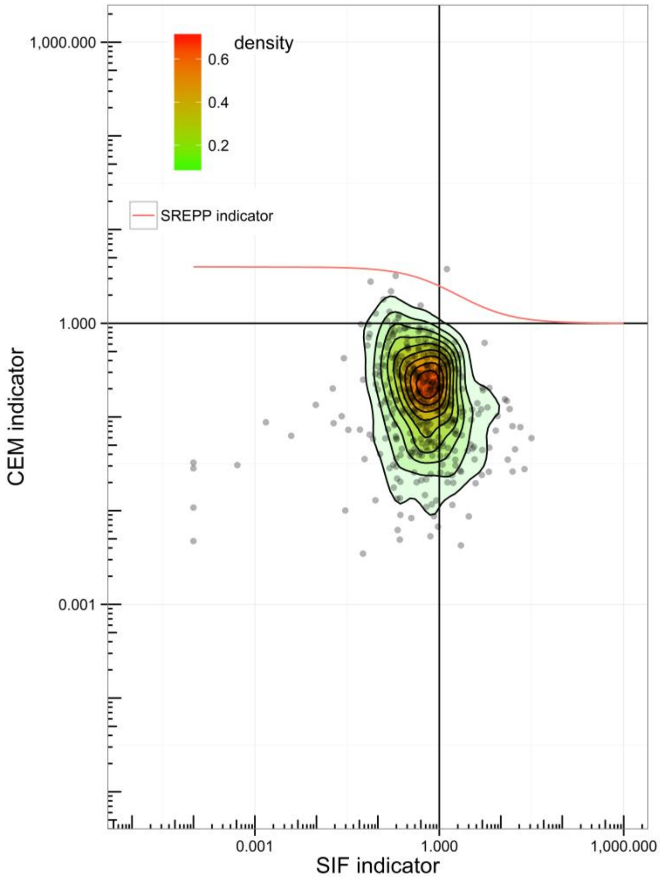

Figure A.2 *Density plot of Smart Renewable Power Provision region NUTS 3 level analysis*

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B.Smart Renewable Power Provision analysis on NUTS 1 level

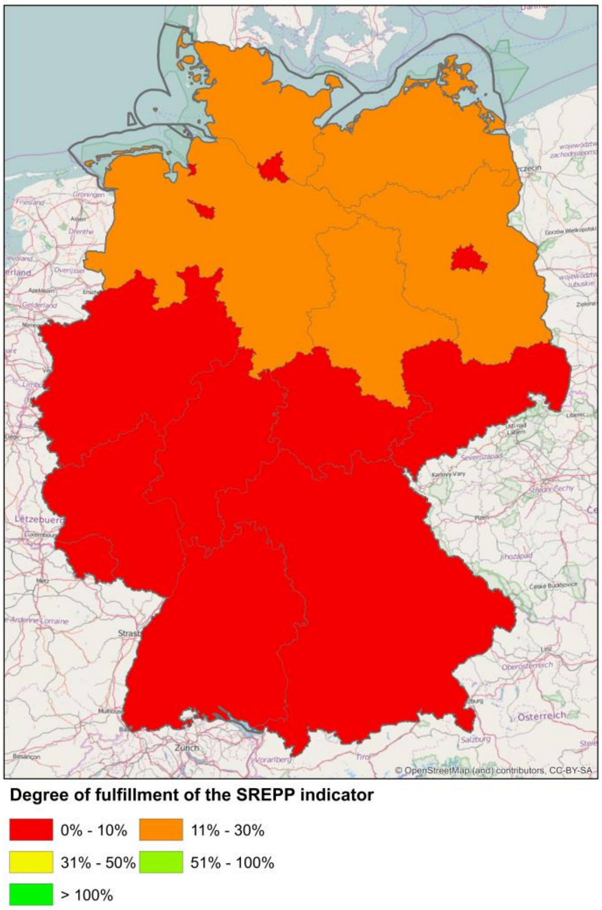

Figure B.1 *Degree of fulfilment of the SREPP indicator on NUTS 1 level*

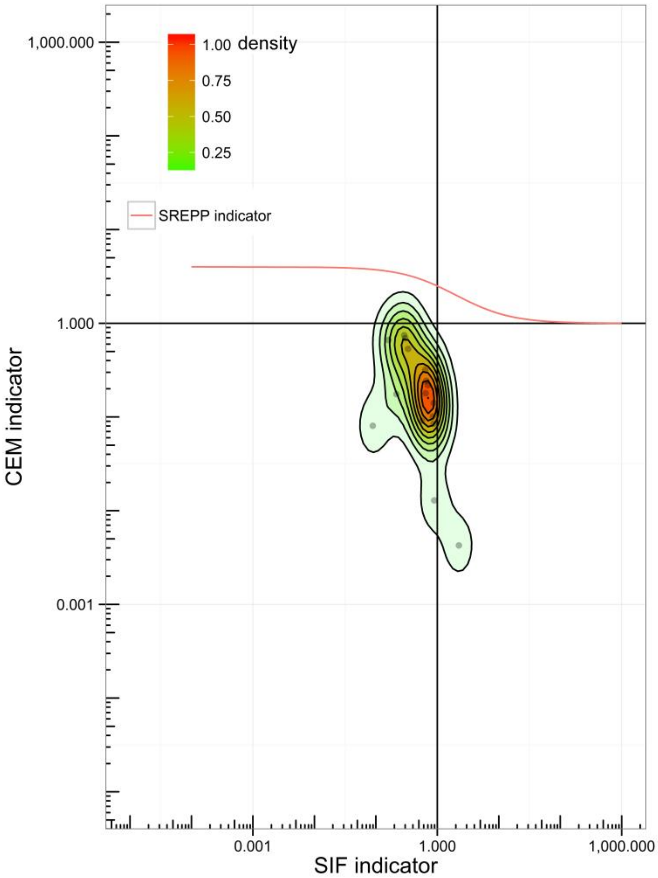

Figure B.2 *Density plot of Smart Renewable Power Provision region NUTS 1 level analysis*

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