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Assessing the relevance of renewable energy resources availability for the existence of Energy Cooperatives in Europe[#]

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ABSTRACT

Energy communities (ECs) are one of the key strategies of the European Union's plan to increase adoption of renewable energy sources (RES). A better understanding of factors that facilitate the existence of energy cooperatives (ECoops), the most common organizational form of ECs, might contribute improving strategies to foster larger adoption of ECs. We perform an exploratory spatial data analysis to assess if RES availability and quality, quantified using four decades of ERA5 data, co-occur with the presence of ECoops across Europe. Results show a slight predominance of ECoops where wind resources are high and opposite results for solar resources. At the continental level, the spatial relation between ECoops and the proposed indicators is rather random but local clusters develop where RES' availability is high.

Keywords: renewable energy resources, energy cooperatives, ERA5, complementarity, resources droughts, exploratory spatial data analysis.

NONMENCLATURE

Abbreviations	
ECoops	Energy Cooperatives
ECs	Energy Communities
RES	Renewable Energy sources
RESCoop	Renewable Energy Sources Cooperatives
NUTS	Nomenclature of territorial units for statistics
WGS	World Geodetic System
ECMWF	European Centre for Medium-Range Weather Forecasts
PV	Photovoltaics
LISA	Local Indicators for Spatial Association

1. INTRODUCTION

Energy communities (ECs), as proposed by the recast of the renewable energy directive (REDII) of the European Commission [1], are expected to play a key role in the energy transition. It is foreseen that ECs contribute to increase the adoption of renewable energy sources (RES) and foster the active participation of energy end-consumers in the energy transition.

ECs follow social and environmental purposes rather than economic ones. While there is evidence that for individuals there is very little economic advantage of implementing ECs compared to becoming a prosumer acting on its own (see e.g., [2]), ECs might motivate investments that otherwise would not be made, contributing to the creation of social capital, and leading to behavioral change beneficial for the energy transition [3]. This makes the creation and consolidation of ECs desirable and the understanding of how to foster them highly relevant.

The most common legal form of ECs are energy cooperatives (ECoops) [4], which are already positively contributing to the European energy transition [5]. ECoops are generally understood as democratically controlled (social) enterprises jointly owned by voluntary members who follow the same economic, social, and/or environmental goals [6]. Research on ECoops has shown that they are a source of innovation and contribute to the decentralization of the energy supply system [7]. There is also consensus that ECoops contribute positively in environmental and social terms to the energy transition and therefore the study of the drivers for their emergence has become highly relevant [8].

We argue that a better understanding of which factors facilitate the development of ECoops might help to foster a larger adoption of ECs. Studies dedicated to the drivers and conditions for the emergence of ECoops are usually based on qualitative research methods [3] and focused on single or small groups of European countries. It was only recently that a first attempt for a European wide qualitative analysis of the relationship of ECoops with potential drivers was made [9]. That study uses an exploratory spatial data analysis to evaluate the co-existence of ECoops with over a hundred indicators from the social progress index and the quality-of-life index. The authors find that from all of the indicators "life-long learning" has the largest correlation and explanatory value and that at the local level some spatial clusters appear that relate the number of ECoops at the NUTS2 and NUTS3 regions level with the indexes [9]. Moreover, that study proposes as future work e.g., to replicate the methodology for the analysis of economic indicators and RES availability to have a full picture of factors that might contribute to the existence of ECoops.

Here, we follow that lead and perform an exploratory spatial data analysis to gain a better understanding of which RES availability indicators co-occur with the existence of ECoops. The analysis is performed for Europe at the NUTS2 and NUTS3 regions levels using the database on ECoops by the European federation of Renewable Energy Cooperatives (REScoop) [10]. The RES availability indicators are calculated using 40 years of hourly ERA5 data [11] and include not only availability indicators such as yearly solar irradiation, average wind speeds, capacity factors for solar and wind power and their complementarity but also quality indicators such as resources droughts on daily and weekly scales.

2. Material and Methods

In general, we follow the methodology proposed by Lode et al. [9] to make an exploratory spatial data analysis that sheds light on the co-occurrence of selected indicators and ECoops at the NUTS2 and NUTS3 levels across Europe. In our case, the indicators are related to RES availability and quality. We consider a total of 38 indicators, which calculation is motivated by the work of Brown et al. [12] and Jurasz et al. [13]. The former evaluated wind and solar power resource droughts for western North America at the weekly scale and the latter assessed wind and solar power complementarity and resources droughts for Poland at the daily scale. Both are recent studies that rely on ERA5 data as a source for RES estimations.

2.1 Data

Three data sets are necessary to conduct our study. These include the geographic location of the ECoops, wind and solar energy related variables of ERA5 and maps with the NUTS2 and NUTS3 regions to summarize and store the calculated indicators. We obtain the data on ECoops from the REScoop database [10]. These were publicly available data from which we extracted name, address and if provided the World Geodetic System (WGS84) coordinates of each registered ECoop. While this database is a non-exhaustive source for all ECoops in the continent, it provides the most extensive available overview of European ECoops currently known. These data are not only the source for [9] but also other studies such as [14] and [5]. This data set was cleaned and completed as proposed in [9].

The ERA5 data is retrieved from the Copernicus climate data store using the API and a python script for automatic retrieval. ERA5 is the fifth generation of global reanalysis of the European Centre for Medium-Range Weather Forecasts (ECMWF). It includes hourly estimates of hundreds of atmospheric, ocean-wave and land surface variables from 1950 onwards in a spatial resolution of 0.25 degrees. We use data from the entry including data from 1979 and our data set covers the period January 1979 to December 2021 as well as the area in the bounding box 71.3, 34.66, 31.91 and -11.38 for the north, south, east, and west coordinates respectively. The variables used for the analysis are the temperature at two meters height (t2m) in grad kelvin, the horizontal speed of air moving towards the east and towards north, at a height of 100 meters above the surface of the Earth, (u100 and v100) in meters per second, and the surface solar radiation downwards (ssrd) in Joule per square meter, which is equivalent to the sum of direct and diffuse solar radiation.

The maps with the NUTS2 and NUTS3 regions are retrieved from EUROSTAT [15] in the version of 2016 to match the data in [9]. The regions kept for the analysis are the ones inside of the bounding box used for the ERA5 data i.e., overseas regions of European countries and e.g., Iceland are not included in the analysis.

2.2 Indicators

We calculate 38 indicators to quantify RES availability and quality. These are divided in three sets that are presented in tables 1.-3. We conduct a spatial clip of the ERA5 data for each one of the regions in the NUTS2 and NUTS3 data using the python libraries xarray [16], geopandas [17] and rioxarray [18]. Posteriorly, we calculate each indicator per region and store them back in the NUTS2 and NUTS3 maps respectively. The first set includes indicators related to RES considered individually (Table 1.). We calculate mean wind speed averages and average yearly cumulated global horizontal radiation as well as capacity factors for solar photovoltaic (PV) and wind power. These capacity factors are calculated as free of assumptions on technology as possible, to keep the generality of the results. This follows the line of arguments of [12,13], and we use the calculations proposed by Bett and Thornton [19].

Table 1. Indicators of RES availability (individual RES)

Indicator	Explanation
ws_avg	Mean wind speed for the entire time series in m/s averaged from all pixels in a NUTS region
ghi_avg	Mean of the yearly cumulated global horizontal irradiance in kWh/m2 averaged from all pixels in a NUTS region
pv_cf_avg	Mean capacity factor of solar PV for the entire time series averaged from all pixels in a NUTS region
wp_cf_avg	Mean capacity factor of wind power for the entire time series averaged from all pixels in a NUTS region

The second set of indicators corresponds to indicators of complementarity between the PV and wind power capacity factors (Table 2.). Complementarity is calculated using the spearman coefficient of correlation following the work of Jurasz et al. [13]. We include complementarity at the hourly, daily, weekly, and monthly temporal scales and perform the calculation for the entire time series. Moreover, on the spatial dimension we compute indicators on a pixel-by-pixel basis as well as values aggregated for each entire NUTS region (comparable to a cooper-plate assumption).

Table 2. Indicators of RES availability (complementarity of RES)

Indicator	Explanation
complement_ h_PP_avg	Average from all pixels in a NUTS region of the average hourly RES complementarity calculated per pixel
complement_ h_PP_high	Highest value from all pixels in a NUTS region of the average hourly RES complementarity for the entire time series calculated per pixel
complement_ h_PP_low	Lowest Value from all pixels in a NUTS region of the average hourly RES complementarity for the entire time series calculated per pixel
complement_ d_PP_avg	Average from all pixels in a NUTS region of the average daily RES complementarity for the entire time series calculated per pixel
complement_ d_PP_high	Highest value from all pixels in a NUTS region of the average daily RES complementarity for the entire time series calculated per pixel
complement_ d_PP_low	Lowest Value from all pixels in a NUTS region of the average daily RES complementarity for the entire time series calculated per pixel
complement_ w_PP_avg	Average from all pixels in a NUTS region of the average weekly RES complementarity for the entire time series calculated per pixel
complement_ w_PP_high	Highest value from all pixels in a NUTS region of the average weekly RES complementarity for the entire time series calculated per pixel
complement_ w_PP_low	Lowest Value from all pixels in a NUTS region of the average weekly RES complementarity for the entire time series calculated per pixel
complement_ m_PP_avg	Average from all pixels in a NUTS region of the average monthly RES complementarity for the entire time series calculated per pixel
complement_ m_PP_high	Highest value from all pixels in a NUTS region of the average monthly RES complementarity for the entire time series calculated per pixel
complement_ m_PP_low	Lowest Value from all pixels in a NUTS region of the average monthly RES complementarity for the entire time series calculated per pixel
complement_ avg_h	Average hourly RES complementarity for the entire NUTS region and the entire time series
complement_ avg_d	Average daily RES complementarity for the entire NUTS region and the entire time series
complement_ avg_w	Average weekly RES complementarity for the entire NUTS region and the entire time series
complement_ avg_m	Average monthly RES complementarity for the entire NUTS region and the entire time series

The third set of indicators comprises multiple alternatives to quantify RES droughts (Table 3). The calculation of the droughts is also motivated by Brown et al. [12] and Jurasz et al. [13] and therefore we provide indicators at the daily and weekly scale for the capacity factors of PV and wind power individually as well as assuming a combination of both in equal proportions. We assume that a day with a drought is a day when the average capacity factor from all hours of that day belongs to the lowest 1% of all days in the entire time series. Furthermore, a week with a drought is a week where the cumulated number of days with a drought belongs to the highest 1% of the entire time series. Values are calculated on a pixel-by-pixel basis and are then aggregate as mean, minimum and maximum for each NUTS region.

Table 3. Indicators of RES quality (RES droughts)

Indicator	Explanation
wp_dro_d_per_ w_mean_PP	Mean from all pixels in the NUTS region of the average number of days per week with a wind power drought
wp_dro_d_per_ w_min_PP	Minimum from all pixels in the NUTS region of the average number of days per week with a Wind Power drought
wp_dro_d_per_ w_max_PP	Maximum from all pixels in the NUTS region of the average number of days per week with a Wind Power drought
pv_dro_d_per_ w_mean_PP	Mean from all pixels in the NUTS region of the average number of days per week with a PV power drought
pv_dro_d_per_ w_min_PP	Minimum from all pixels in the NUTS region of the average number of days per week with a PV power drought
pv_dro_d_per_ w_max_PP	Maximum from all pixels in the NUTS region of the average number of days per week with a PV Power drought
wp_dro_weeks_ mean_pp	Mean from all pixels in the NUTS region of the number of weeks with the highest 1% of days with a wind power drought
wp_dro_weeks_ min_pp	Minimum from all pixels in the NUTS region of the number of weeks with the highest 1% of days with a wind power drought
wp_dro_weeks_ max_pp	Maximum from all pixels in the NUTS region of the number of weeks with the highest 1% of days with a wind power drought
pv_dro_weeks_ mean_pp	Mean from all pixels in the NUTS region of the number of weeks with the highest 1% of days with a PV power drought
pv_dro_weeks_ min_pp	Minimum from all pixels in the NUTS region of the number of weeks with the highest 1% of days with a PV power drought
pv_dro_weeks_ max_pp	Maximum from all pixels in the NUTS region of the number of weeks with the highest 1% of days with a PV power drought
comp_dro_d_per_ w_mean_PP	Mean from all pixels in the NUTS region of the average number of days per week with a drought of combined wind and PV power
comp_dro_d_per_ w_min_PP	Minimum from all pixels in the NUTS region of the average number of days per week with a drought of combined wind and PV power
comp_dro_d_per_ w_max_PP	Maximum from all pixels in the NUTS region of the average number of days per week with a drought of combined wind and PV power
comp_dro_weeks_ mean_pp	Mean from all pixels in the NUTS region of the number of weeks with the highest 1% of days with a drought of combined wind and PV power
comp_dro_weeks_ min_pp	Minimum from all pixels in the NUTS region of the number of weeks with the highest 1% of days with a drought of combined wind and PV power
comp_dro_weeks_ max_pp	Maximum from all pixels in the NUTS region of the number of weeks with the highest 1% of days with a drought of combined wind and PV power

*2.3 E*xploratory spatial data analysis

We follow three out of the four steps for the exploratory data analysis proposed in [9] and adapt them to the particularities of our data sets: (1) By conducting a spatial join between the ECoops map and the maps with RES availability and quality indicators, we assign to each ECoop the indicators of the NUTS where the ECoop is located. We calculate descriptive statistics for each indicator associated to the ECoops and compare them to the distribution of the entire set of NUTS (NUTS2 and NUTS3). We create box plots and calculate mean, standard deviation, quartiles and run a *t*-test for each indicator. With this, we aim to understand how the indicators associated to each ECoop perform in comparison to the statistics of all NUTS regions. In addition, we want to evaluate if there is a significant difference between them. (2) We cumulate the number of ECoops per NUTS2 and NUTS3 region respectively and calculate the correlation of these numbers to each one of the indicators of RES availability and quality. (3) We calculate Local Indicators for Spatial Association (LISA) using bivariate Local Moran statistics between the number of ECoops and the indicators with the highest positive and negative correlations from the previous step. We analyze if clusters of High-High (HH), High-Low (HL), Low-High (LH), Low-Low (LL) of ECoop numbers and the indicators in the neighbouring NUTS exist. The results are visualized with LISA cluster and choropleth maps. The analysis is conducted using Python libraries such as numpy [20], geopandas [17], pandas [21], scipy [22], statsmodel [23] and PySAL [24].

3. RESULTS AND DISCUSSION

3.1 Results of the descriptive statistics

The comparison between the statistics for the individual ECoops and all NUTS regions shows diverse results. Differently to the results in [9], where all indicators of individual ECoops were performing significantly better than the indicators for all NUTS regions, in our case only two thirds of the indicators have means significantly different between the individual ECoops and the NUTS regions. Moreover, this difference is not always better for the individuals ECoops. For instance, indicators related to solar energy (ghi_avg, pv_cf_avg) perform in average significantly worse for the individual ECoops. An excerpt of results for the assessment of the NUTS2 regions is presented in Table 4, but the results hold also for the NUTS3 regions.

Table 4. Summary statistics and p-value of the difference between the mean of each indicator for individual ECoops and all NUTS2 regions. *Selected results - only for indicators where the difference is significant. The first row of each indicator presents the statistics for individual ECoops and the second line for all NUTS2 regions.*

indicator	mean	Stddev	t-test	p-value
ws_avg	6.56	1.68	9.93	3.41E-22
	5.41	1.60		
ghi_avg	942.46	82.19	-11.64	2.28E-29
	1011.62	91.43		
pv_cf_avg	0.19	0.02	-11.57	4.46E-29
	0.20	0.02		
wp_cf_avg	0.26	0.09	9.78	1.37E-21
	0.19	0.10		
complement_ h_PP_avg	-0.08	0.06	2.37	0.018
	-0.09	0.06		
complement_ h_PP_high	-0.12	0.05	2.20	0.028
	-0.13	0.06		
complement_ h_PP_low	-0.01	0.06	2.87	0.004
	-0.03	0.07		
complement_ d_PP_high	-0.30	0.06	-7.79	1.71E-14
	-0.27	0.07		
complement_ d_PP_low	-0.07	0.13	4.68	3.25E-06
	-0.11	0.11		
complement_ w_PP_high	-0.45	0.08	-6.33	3.76E-10
	-0.41	0.12		
complement_ w_PP_low	-0.11	0.23	5.09	4.31E-07
	-0.19	0.19		
complement_ m_PP_high	-0.64	0.11	-6.46	1.71E-10
	-0.58	0.17		
complement_ m_PP_low	-0.15	0.37	5.39	8.93E-08
	-0.28	0.28		
complement_ avg_h	-0.11	0.06	2.20	0.0277
	-0.12	0.07		
complement_ avg_m	-0.54	0.15	-2.91	0.0037
	-0.51	0.20		
wp_dro_d_per_ w_mean_PP	0.36	0.92	-2.37	0.0182
	0.51	0.87		
wp_dro_d_per_ w_max_PP	0.64	1.40	-5.07	4.73E-07
	1.16	1.60		
wp_dro_weeks_ mean_pp	122.00	64.50	3.70	0.0002
	105.86	57.66		
pv_dro_weeks_ mean_pp	70.84	31.68	-4.08	4.80E-05
	80.54	38.73		
pv_dro_weeks_ min_pp	28.50	23.65	-2.85	0.004
	33.81	32.51		
comp_dro_ weeks_mean_pp	57.99	24.93	-2.75	0.006
	63.50	35.70		
comp_dro_ weeks_min_pp	23.71	6.19	-5.14	3.33E-07
	28.82	24.02		

3.2 Results of the correlation analysis

The correlation between individual indicators and the number of ECoops per NUTS regions is generally low. Table 5 shows the highest six positive and negative correlations for the NUTS2 regions and none of them reaches a value higher than +/- 0.254. The correlations for the NUTS3 regions are even lower in all cases and therefore not presented here. Furthermore, the results in Table 5 are in line with the results of the descriptive statistics; there is a positive correlation between ECoops and wind resources and a negative one with solar resources. These results must be interpreted with caution because of the known limitations of the ECoops dataset of REScoop (the database is non-exhaustive and therefore countries well connected with the REScoop network are more likely to be represented in the data set) but the data show indications that ECoops develop more in areas with better wind resources availability.

Table 5. Correlation between individual indicators and the number of ECoops for NUTS2 regions*. Selected results – only the indicators with the highest six positive and negative correlations.*

Indicators	Correlation coefficient
ws_avg	0.242
wp_cf_avg	0.221
complement_m_PP_low	0.153
complement_d_PP_high	-0.165
pv_cf_avg	-0.254
ghi_avg	-0.255

3.3 Results of the LISAs analysis

The LISA analysis is performed for the indicators ws_avg and ghi_avg since these are the ones with the highest positive and negative correlation coefficients respectively. Fig 1 presents the LISA analysis for ghi_avg in the NUTS2 regions. It shows that while at the continental level the number of ECoops has a negative correlation to the availability of solar resources, at the local level there are multiple HH clusters i.e., NUTS regions with high number of ECoops with neighboring NUTS regions with high solar resources availability. These results also hold for the NUTS3 regions.

In the case of wind resources availability (see Fig 2.) HH clusters are spread in the coastal areas of Ireland, UK, France, the Netherlands, Denmark, and Sweden, where wind speeds are among the highest in the continent. Fig 2 serves as an example for the results for the NUTS3 regions that also hold for the NUTS2 regions. We argue that this relation between ECoops and wind power can be explained by the need of large capitals to invest in wind power. Compared to wind turbines, investments in private PV systems can be affordable to individuals. However, private investments are not captured by the ECoops dataset and further data would be needed to strengthen this statement.

It is also important to note that a belt of NUTS regions without registered ECoops exist across the entire continent where resources availability is rather close to the average. This provides stronger signs of co-occurrence of ECoops and RES availability than in the statistical and correlation analysis for the entire continent. However, these results also must be seen as exploratory since the same analysis using a more complete ECoops dataset might lead to a different clustering.

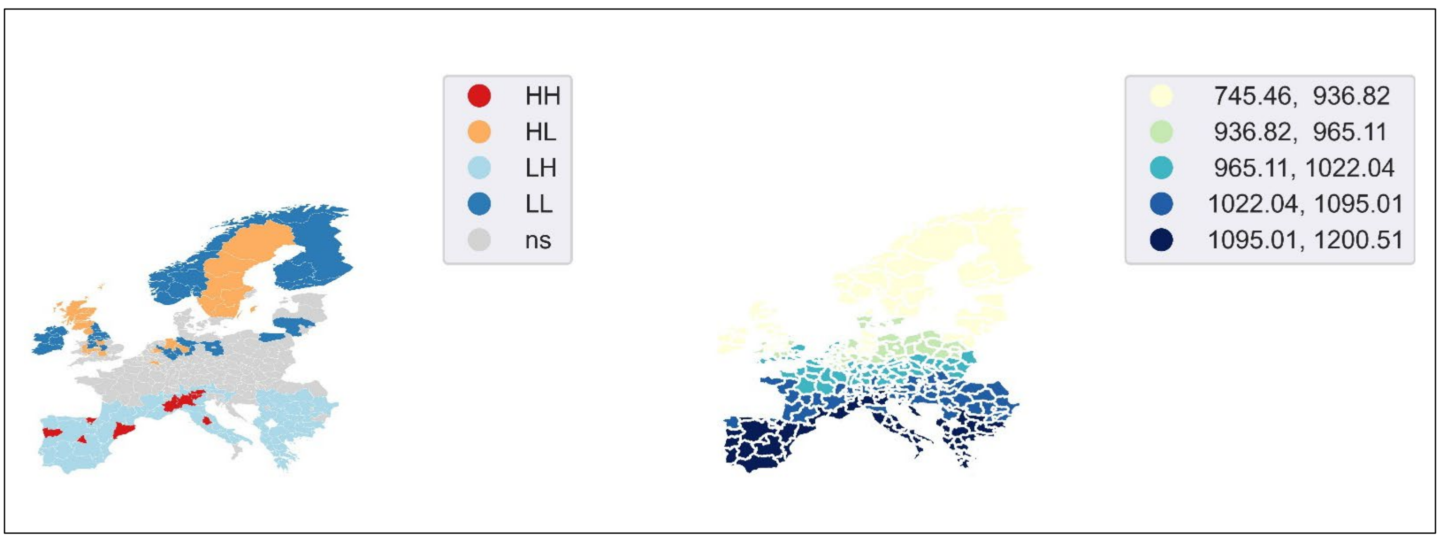

Fig. 1 Bivariate Local Moran statistics of ECoops and ghi_avg for the NUTS2 regions. Left map: clustering by HH, HL, LH and LL. Right map: choropleth map of ghi_avg in kWh/m^2/a.

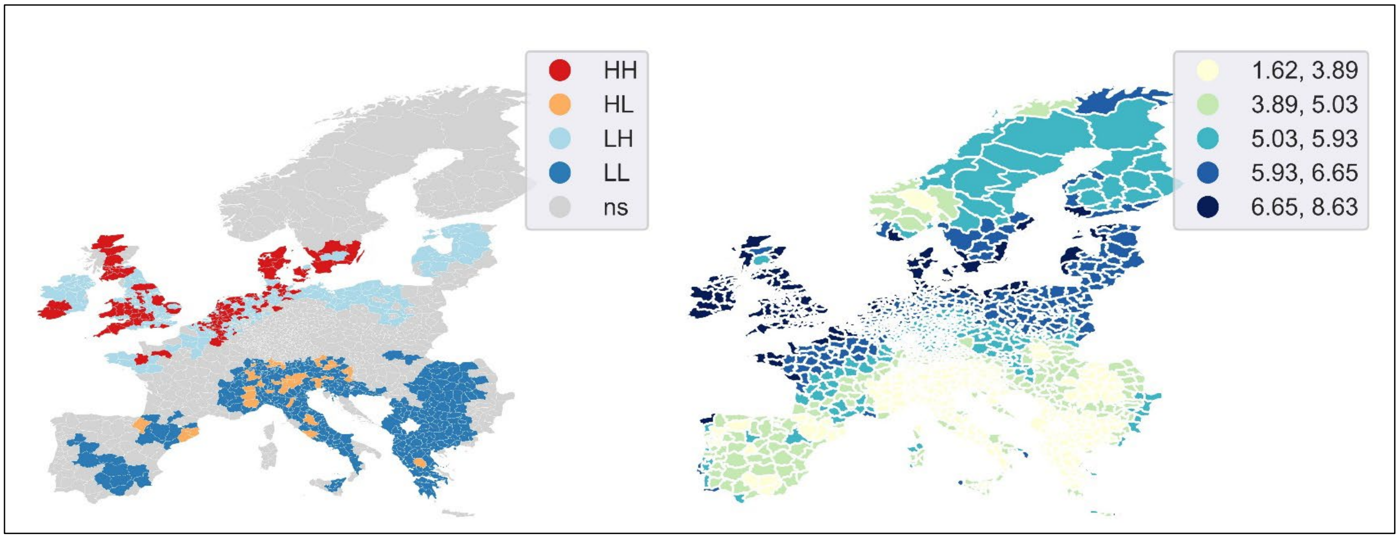

Fig. 2 Bivariate Local Moran statistics of ECoops and ws_average for the NUTS3 regions. Left map: clustering by HH, HL, LH and LL. Right map: choropleth map of ws_avg in m/s.

4. CONCLUSIONS

By performing an exploratory spatial data analysis of ECoops associated to RES availability and quality, this study provides further insights about indicators that co-occur with ECoops and can be propitious for their emergence in Europe. The statistical and correlation analysis show that, at the full continental extent, there is evidence of a moderate relation between the existence of ECoops and RES availability indicators such as average wind speed, yearly global horizontal irradiance and capacity factors for solar PV and wind power. This relation is positive for the wind power availability indicators (higher indicator values for individual ECoops than for all NUTS regions and positive correlation between number of ECoops and the indicators) and negative for the solar power availability indicators (lower indicator values for individual ECoops than for all NUTS regions and negative correlation between number of ECoops and the indicators). Moreover, Local Moran statics show that larger number of ECoops exist where RES availability is high (specially for locations with high wind speeds) and that there are large areas of the continent with average availability of resources where no ECoops at all are reported. The latter is an argument to put emphasis in fostering the creation of enabling mechanisms for the establishment of ECs in such areas to counteract increasing spatial inequalities through the uneven distribution of ECs. Moreover, to fully benefit from complementarity, ECoops should receive regional support to follow key activities that are in line with the local resource availability. To counteract negative impacts, such as regional disparities and energy poverty, distributional measures should address areas with lower resource availability. Further research should focus on the creation of an exhaustive ECoops/ECs data set that allows to increase the robustness of the analysis.

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