A SPATIAL ANALYSIS OF THE RENEWABLE ENERGY POTENTIAL IN ROMANIA

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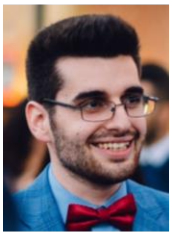

Abstract

Renewable energy is likely the way moving forward to meet global energy demands while building a sustainable future. The current study performs a spatial analysis of the renewable energy sources in Romania at an administrative level, based on aggregated installed capacity, with the aim to confirm or infirm various levels of spatial correlation for relevant renewable technologies. The current analysis takes into consideration only the technologies which are present in Romania's energy generating mix. Two geo-statistical indexes, Location Quotient and Local Moran's I, are computed, clustered and symbolized on the map. The methodology for the analysis is described along with the implementation of the geoprocessing models built in ArcGIS and published as web services.

Key words: Renewable energy sources; Local Moran's I; geoprocessing; spatial analysis; cluster and outlier analysis

1. Introduction

Fossil fuels – coal, oil and gas, which represents a finite source, play a dominant role in global energy systems, with a share of 84.3% in 2019 [1, 2]. Apart from that, the negative environmental impact generated by CO_2 emissions, though unquestionable, is difficult to fully assess.

While energy demands see constant yearly increases due to economic progress, renewable energy remains a crucial topic in mankind's target to achieve a sustainable development, given the significant climate changes the world is currently facing.

Renewable energy principles focus on infinite or renewable sources while pursuing a minimal environmental impact. To meet these objectives, a handful of technologies to generate electricity have been developed over time. Among these, hydropower, wind energy, photovoltaic technology, ocean energy systems, geothermal energy, biomass conversion and solar hydrogen have been widely validated in the real world [3].

Hydropower electricity generation is based on the simple principle of turning the mechanical energy produced by gravitational flowing water into electricity through an architecture of turbines. Implementations vary from large scale plants with vast reservoirs and dams, to smaller setups where only the river flow is redirected through a series of pipes. While large power plants usually take years to build and are very dependent on the geography, micro-hydropower is more flexible in terms of construction placement and duration at the expense of much lower energy capacity. Although, river water is considered a renewable source, the environment impact of such approaches is still debated, mainly due to stopping fish migration, river deposits or affecting water temperature.

Wind is also considered a virtually infinite power source. Wind energy generating systems are similar to hydropower to a certain extent, converting the mechanical energy of the wind by rotating aerial turbines. These turbines are usually co-located in large numbers and are called wind farms. Although they can be positioned basically on any landscape, due to higher efficiency concerns in areas with constant wind gradients, wind farms are not actually geographically-agnostic. The environmental impact includes affecting migration of various bird populations, but is still is by all means significantly lower than fossil fuel options.

Photovoltaic technologies or solar powered generating systems absorb photons from the natural light of the sun and emit electrons through photovoltaic cells grouped in panels, thus producing direct current electricity. Solar farms can be built on any area but given the fact the average daily sunlight hours affects the efficiency, the ones with known small numbers of cloudy days are preferred. Also, solar farms doesn't produce any greenhouse gases and the overall environmental impact is minimal.

Biomass usually consists of plant or animal based materials, such as wood residues or livestock waste, which are converted to fuels or directly burnt to heat water and power steam turbines which then converts the mechanical power to electricity. Biomass power plants are truly geographically-agnostic. Regarding the impact on the environment, the carbon neutrality of this approach is highly debated, although there are obvious advantages for reducing the dependency on conventional fossil fuels or reducing high impact greenhouse gasses such as methane.

2. Renewable energy potential and evolution in Romania

Romania's renewable energy sources (RES) have a distribution by technology depicted in Figure 1, with a total generation capacity of 11,190 MW [4]. It is worth mentioning these figures include large hydropower plants as well, which count for 6,100 MW of the total [5].

The share of energy from renewable sources (RES) in Romania in 2020 was 24.45% according to the National Energy and Climate Plan [7]. This puts the country on the 10th place in the European Union, which has average share of RES of 19%. Romania's target for 2030 is to reach a share of 30.75%, mainly through doubling current onshore wind capacities and tripling solar farms capacities. The main assumptions for meeting this goal include a gradually decrease of the cost of technology, reaching grid parity by 2025, but also an increase of the electricity consumption due to industrial production, living standards, heat pumps and electromobility [14].

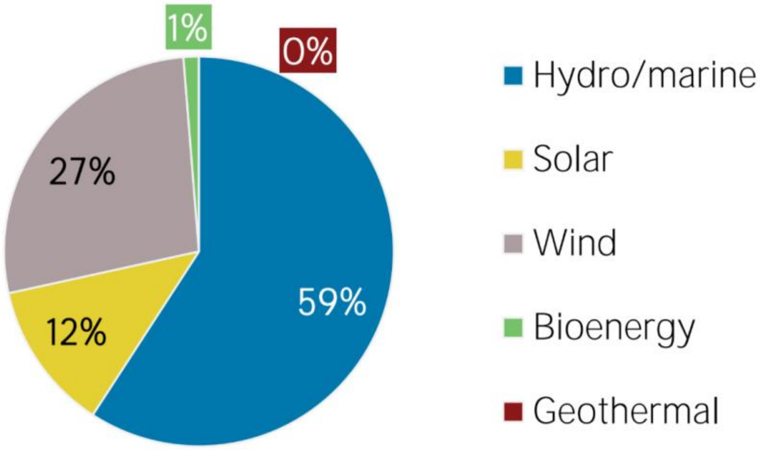

Figure 1. Structure of renewable energy mix in Romania – 2019

Regarding the potential of renewable resources, Romania has 14,435 MW of technically feasible hydropower capacity out of which 8,500 – 9,000 MW are considered economically feasible and exploitable [5].

The wind potential of Romania is the highest in Southern Europe [6, 15]. This is also enforced by the fact that the Fântânele-Cogealac Wind Farm in Dobrogea is the largest onshore wind farm in Europe.

With an average of 220 sunny days per year, Romania is also one of the most promising emerging markets for photovoltaic energy investments in the region.

Although biomass is considered as being the main type of RES in Romania, the predominant use is for household heating with firewood, estimated at 36 TWh, compared with modest capacities for generating electricity using this technology. This is subject for major improvements in the future.

Given the fact large hydropower plants highly depend on the landscape, thus making spatial analysis on power capacity redundant with river basins analysis, the current study focuses on RES excluding this type of units. Therefore, the dataset to be analyzed contains records with geographic position and installed capacity for 700 micro-hydropower plants, wind farms, solar farms and biomass plants as accredited by the National Energy Regulator [8].

Domestic implementations of renewable energy technologies that do not contribute to the national energy infrastructure haven't been taken into consideration.

3. Methodology, tools and implementation

Identifying local patterns of spatial association through visualizing a map for large datasets with geographical relevance facilitates extracting perceivable conclusions compared to other numeric analyses [16].

3.1. Location quotient

The location quotient is used to describe the spatial concentration of a phenomenon, in a multi-phenomenon context, as the ratio between the share of an indicator in its region over the global share of the same indicator as shown by the following formula [9, 16]:

$$q_{ij} = \frac{\frac{x_{ij}}{\sum_{l=1}^{m} x_{il}}}{\frac{\sum_{k=1}^{n} x_{kj}}{\sum_{k=1}^{n}\sum_{l=1}^{m} x_{kl}}} \quad (1)$$

where i is the type phenomenon for region j , and m is the number of types of phenomena.

In our case, the index has the following formula:

$$RESlocationquotient = \frac{\frac{\sum \text{RES type in an administrative unit}}{\sum \text{all RES in that administrative unit}}}{\frac{\sum \text{RES type in country}}{\sum \text{all RES in country}}} \quad (2)$$

The higher the index, the higher the concentration of that particular RES type is. A value lower than or equal to 1 indicates that the administrative unit is not specialized in that particular technology.

3.2. Local Moran's I index

The cluster and outlier analysis, identifies groupings or abnormal values based on proximity. This geostatistical method identifies five types of classes. The method indicates features that have either high or low values compared to their neighbors. Also, the technique identifies non-typical areas where a unit has a value that significantly varies from its neighbors, whether much higher or lower. There are also scenarios where no associations can be made [10].

To produce this type of analysis, a numeric index has been considered for each administrative unit in Romania, based on the aggregated installed capacity per renewable technology.

The chosen index is Local Moran's I, which is a spatial autocorrelation statistic with the following formula [11]:

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j\neq i}^{n} w_{i,j}\,(x_i - \bar{X}) \quad (3)$$

where:

$$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n} \left(x_j - \bar{X}\right)^2}{n-1} \quad (4)$$

and:

- x_i represents the base attribute for autocorrelation, in this case the sum off installed capacity per administrative unit
- $\bar{X}$ represents the arithmetic average of the aforementioned attribute
- $w_{i,j}$ represents a weighing method between feature i and feature j, in this case based on the Euclidian distance between features (administrative units)
- n is the number of records, in this case administrative units

Along with the Local Moran's I, a $z-score$ is also computed [12]. This score allows an evaluation of the correlation with the neighbor features.

$$z_{I_i} = -\frac{I_i - E[I_i]}{\sqrt{V[I_i]}} \quad (5)$$

where:

$$E[I_i] = -\frac{\sum_{j=1, j\neq i}^{n} w_{i,j}}{n-1} \quad (6)$$

and:

$$V[I_i] = E[I_i^2] - E[I_i]^2 \quad (7)$$

A high positive $z - score$ indicates that the unit is surrounded by neighbor features with similar values, while a low negative score indicates a significant variation between the feature and its neighbors, therefore a statistically significant spatial data outlier.

3.3. Geographic Information System implementation

To implement the aforementioned analyses, two geoprocessing models have been built with ArcGIS Desktop, an acknowledged GIS suite of ESRI. The authors make use of the software's builtin tools for common data and spatial operations on top of custom application logic written in Python. It is worth mentioning ArcGIS provides a ready to use instrument for the cluster and outlier analysis [13].

All of these form the geoprocessing models were published as web services, and included in an ArcGIS Online application.

Both instruments query a Microsoft Access database with the RES, excluding large hydropower plants and perform the following steps:

- they prompt the user for data input. Upon choosing the administrative unit type, county or commune, and the RES technology, they use spatial operators to intersect each database record with features and compute the sum of installed capacity per administrative unit, per technology

For the spatial concentration analysis:

- it computes the location quotient for every administrative unit, given the input RES type.
- it then symbolizes the clusters on the map using a color ramp to indicate the concentration level. The number of clusters is input for the model.

For the spatial autocorrelation analysis:

- it performs the cluster and outlier analysis (Anselin Local Moran's I) based on the aggregated capacity and generates the following output: Local I index, Z-scores and P-values for statistical significance and the cluster/outlier type.
- it then symbolizes the clusters on the map. There are 5 clusters: not significant, high-high cluster, high-low outlier, low-high outlier and low-low cluster.

4. Case Study

The Location Quotient and the Cluster and Outlier analysis instruments have been applied over the available dataset.

4.1. Spatial concentration

The output maps, for each relevant RES, are available in Figure 2. Although a number of 5 classes has been chosen, with the classification method being Natural Breaks, it can be observed that regardless of the RES, the majority of the administrative units are assigned to the cluster with the highest capacity. Given that large hydropower has been excluded from the dataset, it can be concluded that there is little variation of capacity, per RES technology in the regions where such elements exist.

Another finding is that looking at both hydro and wind farms concentration their dependency on natural and geographic factors is obvious, whereas solar and biomass have little dependency.

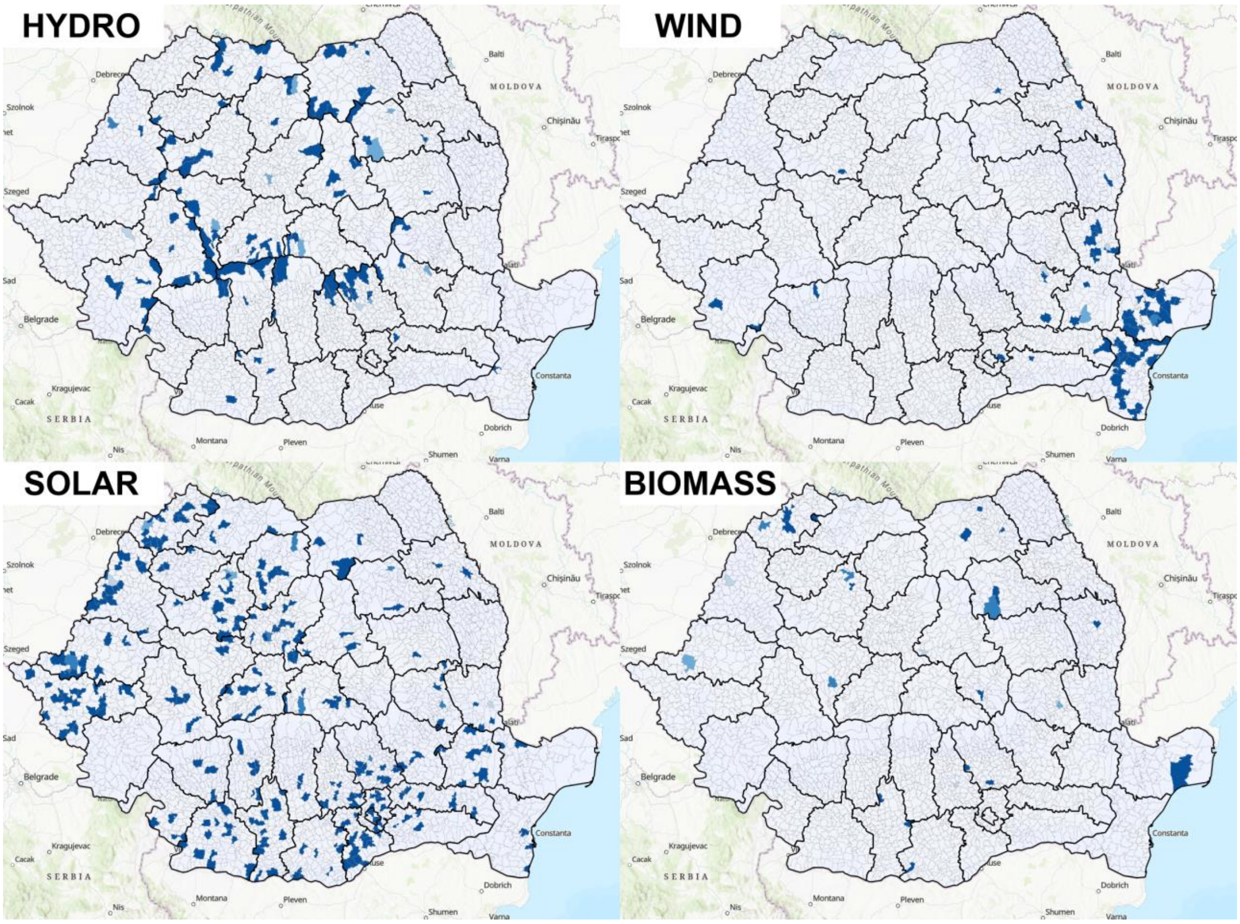

Figure 2. The location quotient for installed capacity per RES – communes

4.2. Spatial autocorrelation

The geoprocessing instrument has been run for 8 iterations, both for counties and communes, by varying the type of RES: hydro, wind, solar and biomass. The output maps are depicted in Figure 3 and Figure 4.

The purpose is to observe administrative units which might be influenced by neighbors for high or low power capacity with different RES technologies, hence identifying potential or inhibitors for new electricity plants or farms.

Analyzing the counties set of maps, Figure 3, reveals the following conclusions:

- For hydropower, only two counties seem to be influenced by proximity with others. It is known that due to a favorable geographic context, the region has one of the largest densities of hydropower plants and dams.
- The same can said about wind farms, where the concentration of such elements in Dobrogea puts the county of Constanta as being influenced by its surroundings.
- Solar farms have a wider national distribution, due to their lower dependency on the landscape than other technologies, and come in large numbers. The vast majority of clusters generated by the geostatistical tool

were considered as not significant from a spatial autocorrelation perspective. There are though 5 counties with low solar power capabilities, which are surrounded by likewise units.

- Biomass plants, given their low number, don't generate any significant findings at a county level.

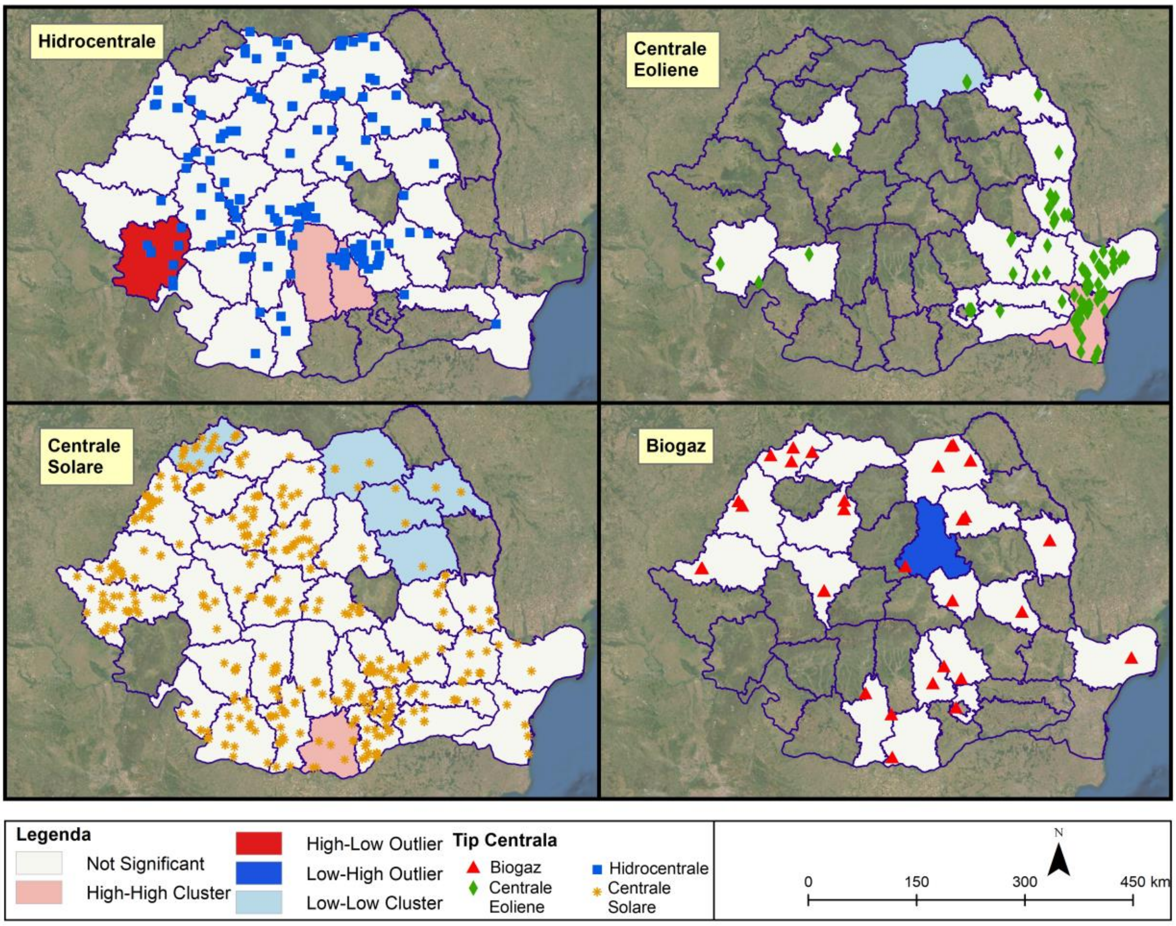

Figure 3. The cluster and outlier analysis - counties

Analyzing the communes set of maps, Figure 4, reveals the following conclusions:

- Hydropower plants are difficult to be neighbors at a commune level due to geographical constrains, therefore the clusters returned by the geoprocessing model are mainly not significant. There are some exceptions in Suceava county but an obvious explanation for this hasn't been found
- Wind farms return the same behavior as for the county perspective. That is due to the concentration in Dobrogea, but this is rather an effect of regional wind conditions than of proximity with others.
- Solar farms at commune level indicate that, at least in some areas of Transilvania, low capacity features influence low capacity neighbors.
- Biomass, due to their sporadic distribution return only non significant clusters with one exception outlier in Suceava where the largest plant of its kind in Romania resides. This one has a share of aproximately 25% of the total biomass electricity generated in Romania.

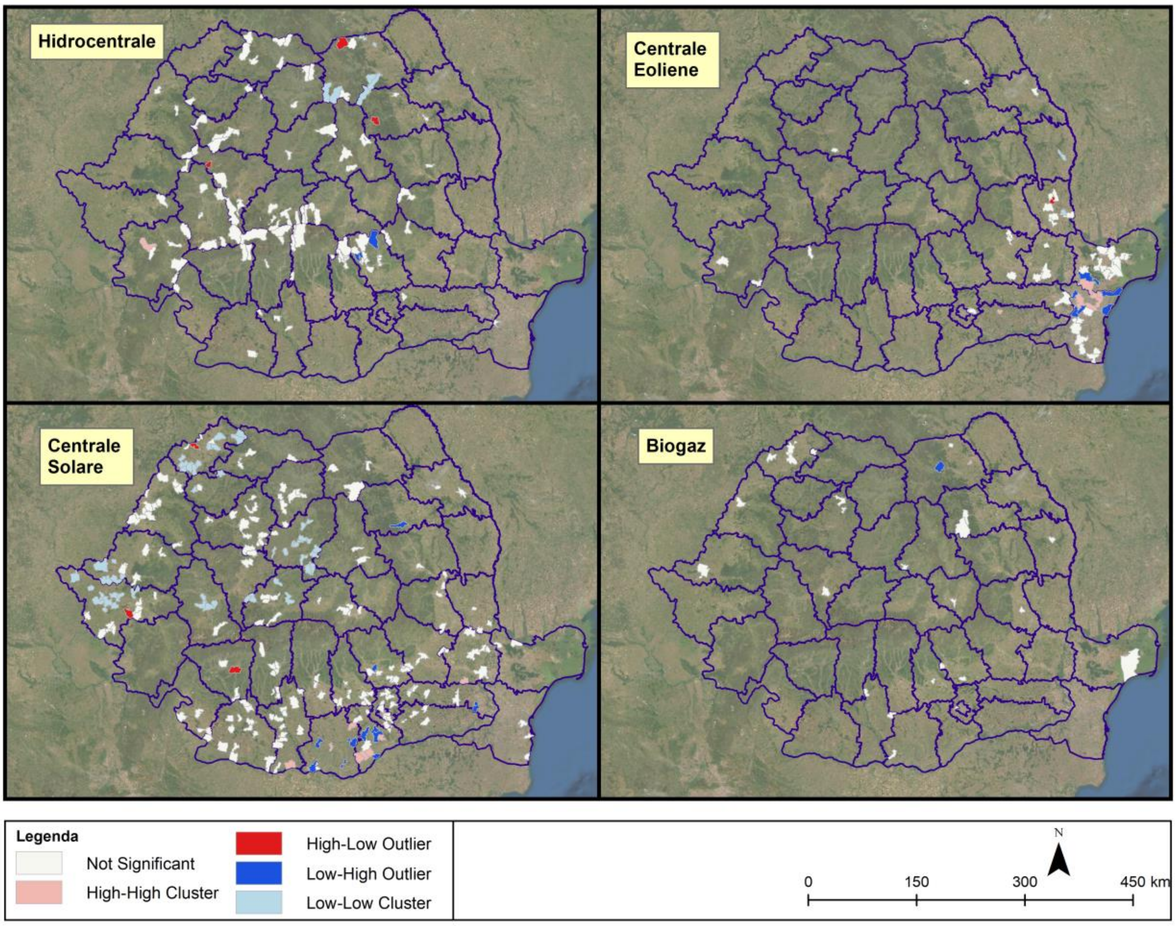

Figure 4. The cluster and outlier analysis - communes

5. Conclusions

With minor exceptions a spatial analysis at a county level vs. communes reveals very different results. Geographic conditions or other factors seem to influence the aggregated capacity per administrative unit more than proximity does. Solar farms in some areas, such as Transilvania, make exceptions describing a certain degree of saturation. In our opinion, these indicate a reasonable capacity that could be installed in the neighborhood of low capacity areas.

Therefore, the renewable energy potential in Romania, although present, is difficult to asses using the proposed spatial analysis geoprocessing model.

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