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Spatial Distribution of Eco-Innovation Performance: Evidence from European Countries

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Abstract:

Purpose: *The aim of the paper is twofold. Firstly, it attempts to assess the spatial pattern of eco-innovation performance in European countries and to identify economies which are efficient in transforming eco-innovation inputs into outputs. Secondly, it endeavours to examine eco-innovation efficiency distribution and existence of spatial externalities across European countries.*
Design/Methodology/Approach: *The sample consists of 21 European countries. We use two eco-innovations inputs and two eco-innovation outputs to measure eco-innovation performance. To calculate eco-innovation efficiency, we apply DEA method. In our research, mapping and Moran's I are employed to find the spatial pattern of eco-innovation performance.*
Findings: *The results show that high and medium-high eco-innovation inputs and eco-innovation outputs are mainly concentrated in countries in the Northern and West Central Europe, while low and medium-low eco-innovation inputs and eco-innovation outputs are performed in the East Central and Southern European countries. The findings confirm the presence of a negative spatial autocorrelation process in eco-innovation efficiency.*
Practical Implications: *Identification of the eco-innovation distribution in the spatial scope is undoubtedly of high political importance, as it should enable to adjust policy actions aimed at improving eco-innovation efficiency to spatial characteristics of a given economy.*
Originality/Value: *Since the issue of spatial characteristics of eco-innovation is still not sufficiently explored in the relevant literature, our paper attempts to fill a cognitive and methodological gap in the investigation of the spatial aspects of eco-innovation performance in the European countries.*

Keywords: *Eco-innovation, efficiency, DEA, spatial externalities.*

JEL codes: *D61, Q55, R12, R15.*

Paper Type: *Research article.*

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1. Introduction

In the face of global challenges connected with environmental changes and threats, the economic activities should focus on the search for more efficient use of resources. There is an increasing recognition that future competitiveness of economies will depend on leadership in resource-related innovation (Preston, 2012). In this perspective many countries changed their emphasis from conventional innovations to eco-innovations. This shift can be seen in European Union as the concept of eco-innovation is gradually introduced in policy documents and funding programmes. The principal strategy of the EU - Europe 2020 is focused on smart, sustainable, and inclusive growth (European Commission, 2010). As pointed out by the Flagship Initiatives for a Resource Efficient Europe and Innovation Union, its objectives can be achieved by eco-innovation. A key element of the European policy for sustainable growth within the Europe 2020 Strategy framework is the Eco-Innovation Action Plan. It is strictly focused on boosting eco-innovation that results in or aims at reducing pressures on the environment and on bridging the gap between innovation and the market (European Commission, 2011).

The eco-innovation discourse in the EU programmes has been constructed mostly around the concept of eco-efficiency (Colombo *et al.,* 2019). Extraction of natural resource is steadily increasing globally and Europe is one of the world's regions with the highest resource consumption per-capita. As the most important resource reserves are located outside of Europe, the European economy is increasingly dependent on their imports from other regions (Bleischwitz *et al.*, 2009). A key challenge for the future of EU's economy and society is to achieve the resource efficiency through implementation of eco-innovation, that should prospectively enhance its competitiveness.

Measuring eco-innovation performance helps to assess the progress made by the nations or regions in sustainable growth, and it allows to analyse the drivers of eco-innovation and its economic and environmental consequences (Kemp, 2008). The assessment of eco-innovation efficiency should be based on measurable indicators that reflect output and input dimensions of this process.

Eco-innovation, as other types of innovation, is a spatially embedded process, thus its spatial characteristics should be investigated. Spatial proximity creates the ground for knowledge exchange and technology diffusion that may induce the rate of innovation. Occurrence of positive spatial externalities is considered to be even more important for eco-innovations implementation compared to other innovations (Horbach, 2014). The observed accumulation of factors of production in a spatial proximity, at the both regional and national levels, contributes to unequal distribution of innovation performance across space (Kijek and Matras-Bolibok, 2020).

Bearing in mind the above considerations, the aim of the paper is to analyse the spatial distribution of eco-innovation performance across the European countries. As eco-innovation is a complex, multi-dimensional process, we employed variables comprising of inputs, outputs and its efficiency that should help to better understand its dynamics. To assess the eco-innovation efficiency we deployed the DEA technique which allows for the use of multiple inputs and outputs data without imposing any functional form on them. To examine eco-innovation efficiency distribution and existence of spatial externalities in the European countries we used Moran's I spatial autocorrelation. Identification of the eco-innovation distribution in the spatial scope is undoubtedly of high political importance, as it should enable to adjust policy actions aimed at improving eco-innovation efficiency to spatial characteristics of a given economy.

The reminder of the paper is organised as follows. The next section reviews the literature related to the eco-innovation efficiency: its concept, drivers, and measurement. The third section describes the data and methods adopted to calculate eco-innovation performance: inputs, outputs, and efficiency, as well as spatial correlation in eco-innovation efficiency distribution in the European countries. The fourth section presents the results of the analysis along with a brief discussion of the main findings. The final section summarises the results, discusses their policy implications, and provides some suggestions for further research.

2. Literature Review

The concept of eco-innovation is multi-dimensional and widely examined from different perspectives in the literature. A critical review of the theoretical development of the concept of eco-innovation made by Hazarika and Zhang (2019) demonstrates that the ground-work of identifying the key drivers of eco-innovation, i.e., technology push, market pull, regulatory push–pull, and firm competencies was laid by Rennings (2000) and Barney (2001). The term 'eco-innovation' was first introduced by Klemmer *et al.* (1999) and defined broadly as "all measures of relevant actors (firms, politicians, unions, associations, churches, private households) which develop new ideas, behaviour, products and processes, apply or introduce them and which contribute to a reduction of environmental burdens or to ecologically specified sustainability targets".

However, the development of definitions and analysis of eco-innovations is still continued. According to performance-based approach, eco-innovation results, throughout its life cycle, in a reduction of environmental risk, pollution, and other negative impacts of resources use (including energy use) compared to available alternatives (Kemp 2008). In order to succeed, eco-innovation should create relevant social structures, and in some cases also be able to shape them, whereas only a minority of all technological innovation is implemented purposefully to achieve this type of change (Hellström, 2007).

Eco-innovation is a particular type of innovation that aims to reduce environmental impact (Kiani Mavi *et al.*, 2019), nevertheless it shares many features with other kinds of innovations. As every other innovation process, eco-innovation is characterised with great risk and high cost (Kijek, 2013). It requires high expenditures on research and development activities, but the results of those processes are unpredictable, and could be postponed in time for many years (Matras-Bolibok, 2014). The results of the literature review of eco-innovation drivers reveal that although firms implement eco-innovations, the motivation is still similar to standard economic efficiency goals (i.e. cost saving) rather than sustainable ones (Bossle, 2016). However, eco-innovative activities seem to require more external sources of knowledge and information than innovation in general (Horbach *et al.*, 2013).

Basing on the systematic literature review of eco-innovation models, Xavier *et al.* (2017) demonstrate a predominance of generic and descriptive characteristics in their analysis. However, a cognitive gap, related to spatial aspects of eco-innovation performance, can still be found, as Mazzanti (2018) emphasizes that the lack of evidence on the spatial dimension of eco-innovations arises from constrained data availability.

Just as other types of innovation, eco-innovation should be investigated as a spatially embedded process. The tendency observed at the both regional and national levels, that the factors of production are accumulated in spatial proximity, implies that innovation activity is highly concentrated (Kijek and Matras-Bolibok, 2020). Occurrence of positive externalities leads to achievement of higher level of innovativeness only by certain locations, which in turn, contributes to unequal distribution of innovation performance across space, reinforcing the most developed economies. However, what is worth to point out, less developed economies could also benefit from implementing eco-innovations. Horbach (2014) finds that eco-innovations are more likely to be implemented in regions characterized by high poverty rates and less dependent on urbanization advantages. As eco-innovations are based on natural resources their diffusion and implementation could contribute to the economic growth of countries and regions characterised with underdevelopment and traditional structure of the economy, since path dependencies and sunk costs are less important for new eco-innovation fields (Kasztelan and Kijek, 2015).

It is also considered that spatial externalities are more important for eco-innovations compared to other innovations (Horbach, 2014). As argued by Mazzanti and Zoboli (2009) networking is an important driver of eco-innovations introduction. Moreover, eco-innovative activities seem to require more external sources of both knowledge and information, as well as intensive R&D cooperation (De Marchi, 2012). Additionally, as Scott and Storper (2007) reveal, the spatial proximity creates the ground for mutual exchanges of knowledge and successful transmission of information that ultimately may induce the rate of innovation. It should be stated that eco-innovation adoption depends not only to firms' internal features but also on 'external' factors, among which the specific geographical component should be emphasized (Antonioli *et al.,* 2016).

Eco-innovations contribute to advancing economic and social benefits jointly (Wang *et al.,* 2018). Positive environmental impact of eco-innovations makes them always socially desirable as they are a "win-win" type of strategy across the environmental and economic dimensions (Ekins, 2010). From the environmental point of view, eco-innovation appears particularly important for economy as its environmental benefits usually outweigh economic costs. Positive net effects of improved resource productivity on the economic growth occur when the benefits of higher productivity levels exceed the costs of achieving greater efficiency (Stocker *et al.,* 2015). Eco-innovation produces two types of positive externalities: usual knowledge externalities in R&D phase, and additional externalities in the adoption and diffusion phases connected with positive environmental impact (Horbach *et al.*, 2013). Whereas, from the economic point of view, implementation of eco-innovations may result in higher effectiveness of firms and their competitive advantage improvement by reducing the cost of materials and decreasing their energy dependence (Ziolkowska and Ziolkowski, 2015).

Existence of market imperfections and failures, especially in respect of environmental impacts, could lead to generation of environmental costs which exceed the market benefits. Since the private return on eco-innovation is lower than the social one, there is a need for public support to encourage private investment. The empirical eveidence strongly support the idea that environmental policy is significant in driving the adoption of eco-innovations (Cainelli *et al.*, 2020).

Assessment of the effectiveness of policy actions aiming at development of eco-innovation requires an examination of its efficiency. Considering the efficiency of eco-innovation as a concept related to productivity, its evaluation should be based on the indicators that illustrate the inputs and outputs of eco-innovation processes. As innovation is a complex process the measurement of its efficiency should comprise a set of indicators reflecting both output and input dimensions. Innovation efficiency is improved when with the same amount of innovation inputs more innovation outputs are generated, or when less innovation inputs are needed for the same amount of innovation outputs (Hollanders and Esser, 2007).

A possible method to assess the eco-innovation efficiency is DEA (Data Envelopment Analysis) which is one of the most common techniques for evaluating the performance of decision-making units (DMUs) (Kiani Mavi and Kiani Mavi, 2021). This method recommends each DMU to adjust its inputs and outputs to an optimum value (Sueyoshi and Goto, 2016).

To examine eco-innovation efficiency distribution and existence of spatial externalities spatial autocorrelation analysis can be deployed, as it enables to assess the spatial nature of geo-referenced data. Among many measures of spatial association, Moran's I statistic is the most widely used measure of and test for spatial autocorrelation (Getis, 2008).

3. Data and Methods

We used Data Envelopment Analysis (DEA) to calculate the eco-innovation efficiency. DEA is a non-parametric method aimed at calculating the relative efficiency scores of decision- making units (DMUs). DEA models can be either input-orientated or output-orientated. For the purpose of our study, we applied the output-oriented BCC model introduced by Banker, Charnes and Cooper (1984), in which variable returns to scale (VRS) are assumed. The model takes the following form:
$\psi_0 = \max\psi$,
s.t.:

$$\sum_{j=1}^{n} y_{rj}\,\lambda_j \geq \psi y_{r0}, \qquad (1)$$

$$\sum_{j=1}^{n} x_{ij}\lambda_j \leq x_{i0},$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0.$$

where: ψ is a multiplier that expands the outputs in an equi-proportional manner, DMU_o represents one of the *n* DMUs under evaluation, and x_{io} and y_{ro} are the *i*th input and *r*th output for DMU_o, respectively. If $1/\psi^* = 1$, then the DMU under evaluation is efficient. Otherwise, if $0 < 1/\psi^* < 1$ the DMU is inefficient.

In order to test the global spatial autocorrelation, we used Moran's I given by the following formula (Anselin, 1995):

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2} \qquad (2)$$

where: *n* is the number of regions, z_i is the value of region *i* of variable *z*, which is centered to the mean, and w_{ij} is *ij*th element of the row-standardized spatial weight matrix *W*. Moran's I takes value from the range [-1,1]. A positive (negative) value of Moran's I shows that there is positive (negative) spatial autocorrelation among the regions.

We included two inputs and two outputs sourced from the Global Cleantech Innovation Index (GCII) programme in our analyses (Table 1). The inputs relate to the development of eco-innovation and the outputs portray a country's ability to exploit eco-innovation. Each of these inputs and outputs are constituted by sets of indicators. General innovation drivers are a composite indicator, which shows conditions for development of entrepreneurial and innovation activity in the country. On the other hand, cleantech-specific drivers indicate how the country helps to stimulate and promote development as well as adoption of clean technologies.

Table 1. *List of eco-innovation inputs and outputs indicators*

Name of indicator	Source	Year
General innovation drivers		
General innovation inputs	INSEAD Global Innovation Index	2016
Entrepreneurial culture	Global Entrepreneurship Monitor	2016
Cleantech-specific innovation drivers		
Cleantech-friendly government policies	REN21 – Renewables 2016 Global Status Report; World Bank Group– State and trends of carbon pricing 2016; OECD & Bloomberg Philantrophies – Green bonds, Policy perspective 2015	2015-2016
Government R&D expenditure in cleantech sectors	OECD-IEA database; UN GERD database	2013-2015
Access to private finance for cleantech start-ups	Cleantech Group data	2014-2016
Country-attractiveness of Renewable Energy Infrastructure	Ernst & Young Renewable Energy Country Attractiveness Index	2015
Cleantech cluster programs & initiatives	Cleantech Group research	2016
Evidence of emerging cleantech innovation		
Patents in cleantech sectors	OECD database	2013
Early-stage private investment	Cleantech Group data	2014 - 2016
High impact cleantech start-ups	Cleantech Group data	2014 - 2016
Evidence of commericalised cleantech innovation		
Trade of cleantech commodities	UN Comtrade	2015
Renewable energy consumption	BP Statistical Review of World Energy 2016	2016
Late-stage private investment and exits	Cleantech Group data	2014 - 2016
Successful public cleantech companies	Cleantech Group, FTSE, Ardour and WilderHill indices of public cleantech companies	2016
Renewable Energy Jobs	IRENA Renewable Energy and Jobs Annual Review	2016

Source: *Own elaboration based on Sworder et al. (2017).*

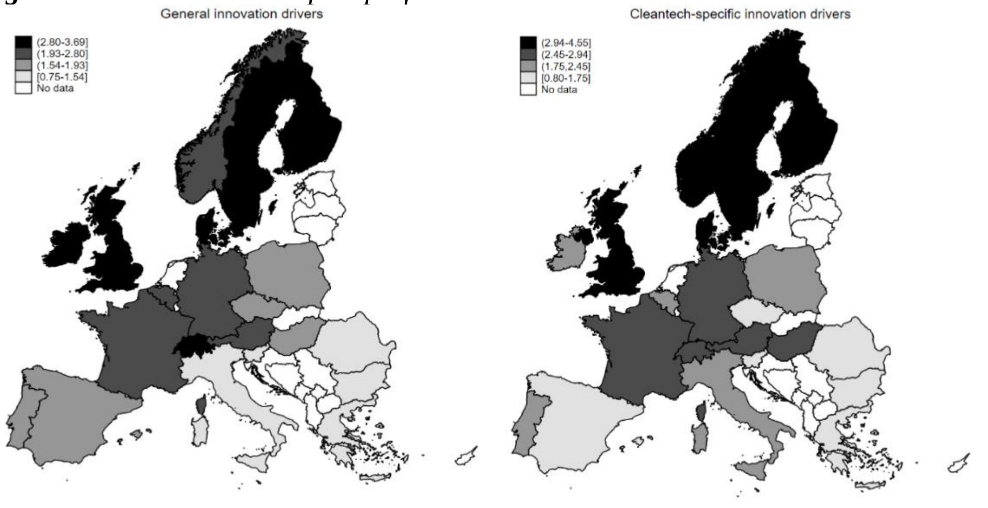
As regards the eco-innovation outputs, the former, i.e. evidence of emerging cleantech innovation, pertains to the flow green patents and the access to venture capital. The latter, i.e. evidence for commercialised cleantech innovation, measures how cleantech market functions in relation to cleantech commodity trade, renewable energy consumption, green late-stage private investments, and cleantech companies and employment dynamics.

The sample comprises 21 European countries (i.e.: Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Norway, Poland, Portugal, Romania, Slovenia, Spain Sweden, Switzerland, United Kingdom).

4. Results and Discussion

Figure 1 shows the performance of the European countries regarding general innovation drivers and cleantech-specific innovation drivers. It should be noted that the top 5 countries for general innovation drivers are Sweden, Switzerland, Denmark, UK, and Ireland. The highest scores of countries such as Sweden and Switzerland result from the features of their the innovation system, which include sophisticated government institutions and strong educational systems. Among the low performing economies, we observe such countries as Romania, Bulgaria, and Greece. In the case of cleantech-specific innovation drivers it is worth noting that the top 5 scorers include four Nordic countries (i.e. Denmark, Norway, Finland, and Sweden) and UK. The Nordic countries reveal a comparative advantage in their attempts to create cleantech-supportive incentives and support cleantech private investors and cleantech cluster organisations. In turn, low-scoring countries (i.e. Greece, Romania, and Czech Republic), suffer from the lack of the necessary public support (e.g. government R&D) for green innovations.

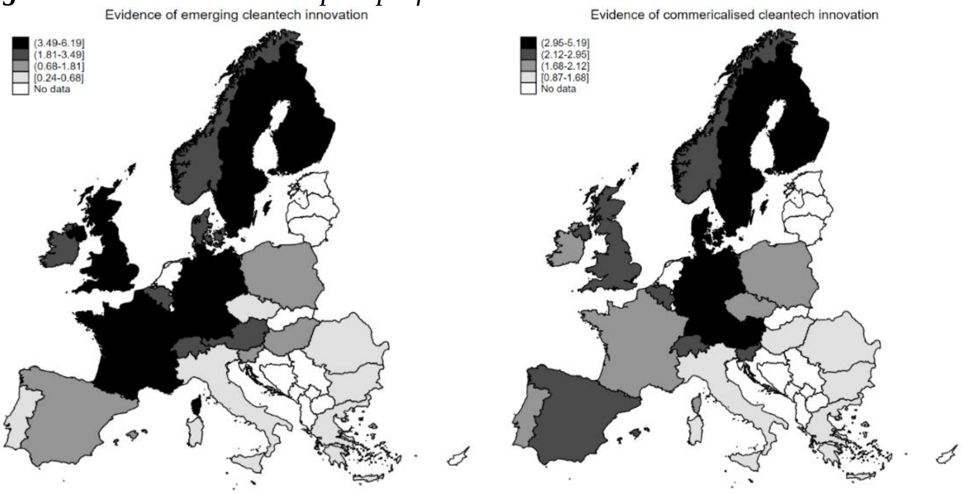
Figure 1. *Eco-innovation inputs performance*



Source: *Own elaboration.*

As seen in Figure 2, there is a large range of performance for evidence of emerging cleantech innovation among the sample countries. Noteworthy is the fact that the top 2 countries (i.e. Finland and UK) lead in early-stage investment propensity and successful cleantech start-ups. Other high-scoring countries (i.e. Germany, Sweden, and Denmark) are the front-runners in successful cleantech research. The group of low-scorers for this eco-innovation output includes Bulgaria, Portugal, Romania, and Greece. Interestingly, the Nordic countries with German and Austria are the leaders in the ranking for evidence of commercialised cleantech innovation. These countries are characterised by a high level of green energy consumption and a high number of public cleantech firms. What is interesting, Germany shows a high value of national export of cleantech-related commodities. The two Eastern-European countries (i.e. Bulgaria and Romania) are located at the end of the ranking.

Figure 2. *Eco-innovation outputs performance*

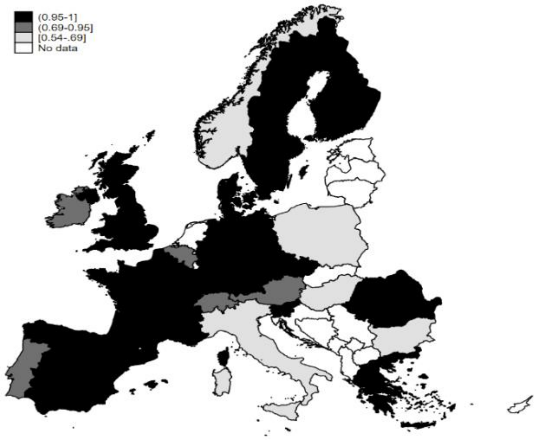


Source: *Own elaboration.*

Figure 3 shows the comparison of countries efficiency in the transformation of eco-innovation inputs into eco-innovation outputs. The group of efficient eco-innovators consists of Denmark, Sweden, Germany, Finland, France, Czech Republic, Greece, and Romania. Within this group, only Sweden and Finland appear to be able to convert high cleantech innovation inputs into high cleantech innovation outputs.

On the contrary, Czech Republic, Greece, and Romania are efficient countries, where low levels of eco-innovation inputs are combined with a moderate level of at least one of the eco-innovation outputs. The least efficient eco-innovators in our sample are Poland, Bulgaria, Hungary, and Italy. These countries tend to have a low conversion rate of a moderate level of at least one of the eco-innovation inputs into eco-innovation outputs.

Figure 3. *Eco-innovation efficiency*



Source: *Own elaboration.*

Table 2 presents the Moran's I statistics for eco-innovation inputs, eco-innovation outputs, and eco-innovation efficiency. Looking at the I Moran's statistics for eco-innovation inputs, it clearly emerges that there is a strong positive spatial autocorrelation (especially for general innovation drivers). This finding confirms the visual impression of spatial clustering provided by Figure 1. High eco-innovation inputs are concentrated in the Northern European countries, including the Nordic countries. The group of medium-high performing eco-innovators includes France and the West Central European countries. On the contrary, low eco-innovation inputs concentration is seen in the countries of the East Central Europe. The similar pattern of eco-innovation performance (spatial) distribution is seen for eco-innovation outputs (Figure 2).

Table 2. *The global Moran's I statistics*

Variable	I	p-value
General innovation drivers	0,648	0,000
Cleantech-specific innovation drivers	0.447	0,007
Evidence of emerging cleantech innovation	0.454	0,007
Eco-innovation efficiency	-0.475	0,020

Note: *The Moran's I statistics were calculated using the row-standardized contiguity weight matrix.*

Source: *Own elaboration*.

What is interesting, the Moran's I statistic is negative for eco-innovation efficiency. It means that there is a significant difference in eco-innovation efficiency between neighboring countries. Such finding suggests that high concentration of eco-innovation inputs and eco-innovation outputs does not guarantee concentration of eco-efficiency. As mentioned previously, low levels of inputs combined with moderate levels of outputs may lead to high efficiency.

5. Conclusions

The theoretical considerations and conducted empirical analysis allowed to derive following conclusions:

1. Measuring eco-innovation performance of economies enables the assessment of the progress made by the nations or regions in sustainable growth. It also allows to evaluate policy actions, as well as to determine the areas where public support is needed.
2. Given the complexity of eco-innovation process the measurement of its efficiency should comprise a set of indicators reflecting both output and input dimensions. For that reason the non-parametric DEA technique can be deployed as it allows for finding the relations between the multiple inputs and multiple outputs of eco-innovation activities.
3. As eco-innovation is a spatially embedded process, its spatial characteristics should be investigated. Identification of spatial patterns of eco-innovation process should enable to adjust policy actions aimed at improving eco-innovation efficiency to spatial characteristics of a given economy.
4. The results of the research show the level of inequality in the spatial distribution of eco-innovation performance is high. The Northern and West Central European countries hold high and medium-high scores for eco-innovation inputs and eco-innovation outputs. On the contrary, low and medium-low scoring countries in these dimensions of eco-innovation performance are mainly located in the Southern and East Central Europe. The findings reveal that there is a negative spatial autocorrelation of eco-innovation efficiency.

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