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Spatial Dependence and Neighbourhood Effect: Explaining Economics, Politics, and Society across the World

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Abstract. In this paper the authors present the results of a large-scale study that proposes a holistic approach to assess spatial distribution of various social phenomena across the world. 70 statistical indicators describing the political, economic, military, sociodemographic and ideological and value factors that determine the structure of modern international relations were selected and underwent a set of spatial econometrics procedures. For this purpose, such methodological instruments were chosen as dasymetric mapping, geographical anamorphosis, Moran's I, local indicators of spatial association clustering (LISA) and multidimensional scaling. The authors illustrate each step with an overview of the obtained results for all or certain indicators, for instance, those which demonstrated statistically significant LISA clustering results for the Balkan countries. Furthermore, the authors proposed Spatial Dependence Index (SDI) to identify where the spatial influence is identified separately from other factors on the examples of such statistical indicators as GDP PPP per capita, religiosity level, suicide rates, etc. The conducted research was aimed to test the methods of spatial econometrics to the political map of the world, it shows a set of tools capable of explaining the changing structure of world politics and revealing the transformations of local clusters in different regions of the world. The authors conclude that the proposed spatial econometrics approach is holistic and helps to identify and interpret state behaviour patterns and, in broad sense, social phenomena through the geographical lens. The findings from this study support the use of GeoDA software and make a significant contribution to understanding the degree of space influence on phenomena distribution and international relations in general.

Keywords: spatial dependence, spatial association, Moran's I, spatial dependence index, neighbourhood effect.

Research area: social sciences.

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Пространственная зависимость и эффект соседства: объясняя экономические, политические и социальные отношения в мире

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Аннотация. В данной статье авторы представляют результаты масштабного исследования, предлагающего целостный подход к оценке пространственного распределения различных социальных явлений в мире. 70 статистических показателей, описывающих политические, экономические, военные, социально-демографические и идейно-ценностные факторы, определяющие структуру современных международных отношений, были отобраны и прошли комплекс процедур пространственной эконометрики. Для этого были выбраны такие методологические инструменты, как дазиметрическое картирование, географическая анаморфоза, индекс Морана, локальные индикаторы кластеризации пространственной автокорреляции (LISA) и многомерное шкалирование. Авторы иллюстрируют каждый шаг обзором полученных результатов для всех или определенных показателей, например, тех, которые продемонстрировали статистически значимые результаты кластеризации LISA для стран Балканского полуострова. Кроме того, авторы предложили индекс пространственной зависимости (ИПЗ или SDI), чтобы определить, где пространственное влияние проявляется отдельно от других факторов на примере таких статистических показателей, как ВВП по ППС на душу населения, уровень религиозности, уровень самоубийств и др. Проведенное исследование было направлено на апробацию методов пространственной эконометрики к политической карте мира, оно показывает набор инструментов, способных объяснить меняющуюся структуру мировой политики и определить трансформации локальных кластеров в различных регионах мира. Авторы приходят к выводу, что предложенный подход пространственной эконометрики является целостным и помогает устанавливать и интерпретировать модели поведения государств и в широком смысле – социальные феномены через географическую призму. Результаты данного исследования поддерживают использование программного обеспечения GeoDA и вносят значительный вклад в понимание степени воздействия пространства на распределение явлений и международные отношения в целом.

Ключевые слова: пространственная зависимость, пространственная автокорреляция, индекс Морана, индекс пространственной зависимости, эффект соседства.

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Introduction

Space rarely represents homogeneous entity: states differ from each other in terms of GDP, political regimes, level of religiosity, etc. However, states are not scattered like stars in space, they are situated near and far from other states, interact with each other and influence their neighbours directly, for example, in wars, and indirectly, for instance, through implementing internal policies. But how are social, political and economic phenomena distributed across the world? Spatial econometrics can be helpful to answer that question. The increase in the use of spatial econometrics instruments has been witnessed recently on local and regional where they have proved to be effective when we speak about spatial effects on real estate prices in Italy (Copiello, 2020), crime rates in Indonesia (Hardiawan et al., 2019) and suicide rates in Brazilia (Lobo et al., 2020).

Nevertheless, the current academic literature on spatial econometrics demonstrates the lack of studies on a worldwide scale. The authors of this study have proposed a comprehensive approach to explain the global distribution of various phenomena with the methods of spatial econometrics. We collected data on 70 indicators divided into seven groups – politics, economics, demography, international influence, quality of life and values and conducted a set of spatial econometrics procedures using GeoDA software. Our aim was to reflect the spatial structure of contemporary international relations, their characteristics and key influencing factors. Therefore, the principal research questions were the following: what global patters of national spatial distribution can be identified with the help of Moran's and LISA (local indicators of special association) statistics? Can we separate the geographic influence on the distribution of social, economic, political, etc. phenomena around the globe from any other statistical pattern?

The creation of spatial distribution maps of the selected indicators can make it possible to identify the presence of spatial relation among them. We analysed not only the impact of a single parameter on a set of countries but also mutual influence of the indicators by multi-dimensional scaling to determine the optimal geostatistical neighbourhood for each country. Still, it is impossible to present the results of such a big and thorough research in one article, so this paper will focus on presenting the methodological kit, including the proposed Spatial Dependence Index (SDI), and the key findings for each of its component.

Theoretical background

The idea to use spatial analysis for identifying the influence of geographical factors is not new for social sciences (Enos, 2017): one of the principal contributors to the spatial econometrics, Luc Anselin together with John

O'Loughlin focused on the geographical context of international relations in Africa. They concluded that spatial effects (dependence, heterogeneity and proximity) can be identified, modelled and interpreted within the interstate relations in Africa in 1966–1978, thus proving that geographical context cannot be omitted provided that proper spatial modelling procedures are applied (O'Loughlin and Anselin, 1991).

Another attempt to reconcile geographical and political perspectives was made by Harvey Starr who claimed that the context behaviour mode of thinking best joins political and geographic perspectives. He shares the view of L. Anselin and J. O'Loughlin that sheer standard regression techniques are not adequate in distinguishing between different forms of spatial effects, but international relations will surely benefit from the methods being developed to provide spatial analysis (Starr, 1991).

This research belongs to the row of empirical literature: while some scholars focused on spatial patterns of technology diffusion (Coe et al., 1997; Keller, 2002; López-Bazo et al., 2004), other studies were devoted to those political, social and economic factors in neighboring countries that can have an impact on growth (Ades and Chua, 1997; Easterly and Levine, 1998; Lall and Yilmaz, 2001; Murdoch and Sandler, 2002, Lim, 2016). Another cluster of spatial dependence studies focuses on states and regions converging within groups, for instance, Ramajo, J. et al. (2003), Carrington, A. (2003), Baumont, C. et al. (2003). Last but not least, there is a vast field of standard spatial econometric analysis covered by such authors as Le Gallo, J. et al. (2003), Moreno, R. and Trehan, B. (1997), Rey, S.J. and Montouri, B.D. (1999) and Weidmann, N.B. et al. (2010).

Nevertheless, this study is different in the sense that this is the first attempt to provide a holistic outlook on global geographic interconnectedness of economic, social, political and cultural relations.

Methods and data

The authors of this study have proposed a comprehensive approach to explain the distribution of various phenomena with the methods of spatial econometrics. In the beginning we collected 12 expert opinions from the scholars with different academic background (geographers, political scientists, economists and sociologists), which indicators most accurately reflect the positions of countries in the world. Based on the expert views we selected 70 indicators (Table 1) describing politics, economics, demography, human capital, values and the international influence of the state, and we collected a database of all countries of the world. We used a wide range of reliable statistic resources, including United Nations, World Bank, International Monetary Fund, Transparency International databases.

The next step was to conduct a set of spatial econometrics procedures using QGIS and GeoDA software (Table 2). Our aim was to re-

Table 1. Indicators collected within the study

#	Indicator	Source	Time Period
Politics			
1	Polity IV Index	Polity Project	2018
2	Age and marital status, which entitle to vote	Inter-parliamentary Union	2019
3	Share of women in parliament (lower chamber)	Inter-parliamentary Union	2019
4	Share of women in parliament (upper chamber)	Inter-parliamentary Union	2019
5	Freedom of press	Freedom House	2017
6	Political rights	Freedom House	2017
7	Corruption perception index	Transparency International	2017
8	Bertelsmann Sustainable Governance Index	Transparency International	2017
9	Bertelsmann Transformation Index	Transparency International	2017

Continuation of Table 1

#	Indicator	Source	Time Period
	Economics		
10	Nominal Gross Domestic Product	International Monetary Fund	2017
11	Gross Domestic Product based on Purchasing Power Parity	International Monetary Fund	2017
12	Gross Domestic Product based on Purchasing Power Parity per capita	International Monetary Fund	2017
13	Contribution of agriculture to total GDP	Central Intelligence Agency, the World Factbook	2017
14	Output per worker	International Labour Organization	2017
15	Unemployment rate	Central Intelligence Agency, the World Factbook	2017 or the most recent year
16	Poverty headcount ratio at $ 3.20 a day	World Bank	2017 or the most recent year
17	Gini Index	World Bank	2017 or the most recent year
18	Population living in slums	World Bank	2014
19	Budget deficit or surplus	Central Intelligence Agency, the World Factbook	2017 or the most recent year
20	Public debt	Central Intelligence Agency, the World Factbook	2017 or the most recent year
21	CO^2 emissions (metric tons per capita)	World Bank	2014
22	Employment in industry, female (% of female employment) (modeled ILO estimate)	International Labour Organization	2018
23	Electric power consumption (kWh per capita)	World Bank	2014
24	Made or received digital payments (% age 15+)	Global Findex database	2017
25	Individuals using the Internet (% of population)	World Bank	2017
	Demographics		
26	Total population	World Bank	2018 or the most recent year
27	Population growth (annual%)	World Bank	2018
28	Life expectancy at birth, total (years)	World Bank	2017
29	Population, female (% of total population)	World Bank	2018
30	Population ages 0–14 (% of total population)	World Bank	2018
31	Rural population (% of total population)	World Bank	2018
32	International migrant stock (% of population)	World Bank	2015
33	Refugee population by country or territory of asylum	UNHCR's Refugee Data Finder	2018 or the most recent year
34	Ethnic and Cultural Diversity Index (Fearon's Index)	Stanford	2003
	Life Quality		
35	Adolescent fertility rate (births per 1,000 women ages 15–19)	World Bank	2017
36	Expected years of school	World Bank	2017
37	Learning-adjusted years of school	World Bank	2017
38	School enrollment, primary (gross), gender parity index (GPI)	World Bank	2015

Continuation of Table 1

#	Indicator	Source	Time Period
39	School enrollment, tertiary (gross), gender parity index (GPI)	World Bank	2015
40	Suicide rates per 100 000 people	World Health Organization	2016
41	Incidence of HIV, ages 15–49 (per 1,000 uninfected population ages 15–49)	World Bank	2017
42	Prevalence of HIV, total (% of population ages 15–49)	World Bank	2017
43	Antiretroviral therapy coverage (% of people living with HIV)	World Bank	2017
44	Immunization, DPT (% of children ages 12–23 months)	World Bank	2017
45	Incidence of tuberculosis (per 100,000 people)	World Health Organization	2017
46	Rates of overweight and obesity	World Health Organization	2016
47	Probability of survival to age 5	World Bank	2016
48	Adult mortality rate (probability of dying between 15 and 60 years per 1000 population)	World Bank	2016
	International influence		
50	Globalization Index	KOF Swiss Economic Institute	2017
51	GDP based on PPP, share of world	International Monetary Fund	2017
52	IMF Members' Quotas and Voting Power	International Monetary Fund	2019
53	State Power Index	European Political Strategy Centre	2017
54	Military Strength Ranking	Global Firepower	2019
55	Military expenditure (% of GDP)	World Bank	2018
56	Fragile States Index	The Fund for Peace	2017
57	Global Competitiveness Index	World Economic Forum	2017
58	Total natural resources rents (% of GDP)	World Bank	2017
59	Global Innovation Index	Cornell University, INSEAD and WIPO	2017
60	Number of patents	World Intellectual Property Organisation (WIPO)	2017
61	Research and development expenditure (% of GDP)	World Bank	2016
	Values		
62	Generalized trust (“Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?”)	World Values Survey	2014
63	Willingness to fight for country in the case of war	World Values Survey	2014
64	General national pride	World Values Survey	2014
65	Subjective Well-Being	World Values Survey	2014
66	Autonomy Index	World Values Survey	2014
67	Political interest	World Values Survey	2014
68	Post-Materialist index	World Values Survey	2014
69	Religiosity level	World Values Survey	2014
70	Hofstede's Power distance Index	Hofstede Insights	2015
71	Uncertainty Avoidance Index	Hofstede Insights	2015

Source: Own research, 2021

Table 2. Methodological steps and their purpose

Methodological steps	Purpose
Indicator selection	Choosing by the criteria: – recent data – global coverage
Box plot to count: – mean – median – max/min values	Making a brief statistical overview of the indicator
Spatial autocorrelation calculation (Moran's I)	Evaluating spatial distribution pattern across the world
LISA-clustering analysis	Identifying clusters of neighbouring states with high/low values
Spatial Dependence Index	Separating the influence of spatial factors from the others

Source: Own research, 2021

flect the spatial structure of contemporary international relations, their characteristics and key influencing factors. The creation of spatial distribution maps of the selected indicators can make it possible to identify the presence of spatial relation among them. We analysed not only the impact of a single parameter on a set of countries but also mutual influence of the indicators by multi-dimensional scaling to determine the optimal geostatistical neighbourhood for each country.

After collecting 70 indicators we mapped the structure of its spatial distribution, calculated Moran's I (Moran, 1948) for all UN states and compared the obtained Moran's I finding where the spatial association was the highest and the lowest. The purpose was to identify, which of the social phenomena in the world have spatial dependence and which do not, or figuratively speaking, which phenomena in the world spread like an epidemic from one neighbouring country to another or not. We used two neighbourhood matrices – geometric centroids and political capitals and opted for calculating a spatial weighting matrix using the k-nearest neighbour method due to its advantages described in academic literature (Fix and Hodges, 1951), (Holmes and Adames, 2001). With this method, the radius from the centroid (median centre) of the state is extended until it reaches a given number of centroids of neighbours. In an experimental way, it has been determined that the most relevant for the purposes of the project is to calculate the matrix for k = 8. A connectivity graph for this parameter has been constructed for all countries in the world to check.

The Moran's I evaluates spatial association for the entire data set, it was important to weigh spatial association between neighbouring units for the objectives of the study. Local Indicators of Spatial Association (LISA) were calculated for this purpose using the following formula:

$$L = \frac{N}{\sum_j \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(z_i - \acute{z})(z_j - \acute{z})}{\sum_i (z_i - \acute{z})^2}$$

where N is number of cells, z_i – is the calculated indicator for the cell i, w_{ij} – is an estimate of spatial weights, reflecting whether i and j are neighbours, such that if they are not, it is equal to zero, and if they are $\frac{1}{|\delta_i|}$, where $|\delta_i|$ – is the number of neighbours of the cell (Anselin, 1995). LISA values were mapped for countries with p-value below 0.05.

The authors attempted to separate the spatial effects of social phenomena from other statistical patterns. For this purpose, we suggested Spatial Dependence Index (SDI) for each pair of indicators calculated in the following way:

$$SDI = M^2_{(x,y)} - R^2_{(x,y)}$$

where *x* and *y* are a dependent and independent variable, $M_{(x,\ y)}$ is the bivariate Moran's I between them and $R^2_{(x, y)}$ is the determination coefficient between them.

The determination coefficient shows the correlation between indicators x and y, while the bivariate Moran's I shows the correlation between indicator x and the average indicator y in neighbouring x, i.e. the spatial association between x and y. This index can be considered a pure indicator of the influence of spatial factor on the phenomenon distribution, as it subtracts the basic degree of non-spatial correlation between phenomena from the spatial association (Moran, 1948; Cliff, and Ord, 1973). The SDI statistic thus assesses the effect of space and enhances or weakens the relationship between indicators x and y and allows to draw conclusions about the areas in which space has the most significant impact on international processes.

Finally, at the fourth stage, a multidimensional scaling (MDS) for all 70 indicators was carried out, where the authors' goal was to create a map, in which the proximity between countries would reflect their similarities, i.e., to imagine what the world would look like if the neighbourhood effect was dominant and similar countries would draw each other like molecules (Torgerson, 1952), (Shepard, 1962), (Mead, 1992).

In a Euclidean (geographic) metric for p variables, the distance between observations x_i and x_j in p-dimensional space is defined as

$$d_{ij} = \|x_i - x_j\| = \sum_{k=1}^{p} (x_{ik} - x_{jk})^2$$

The task of multivariate scaling in this case is to find such points $z_1, z_2, \ldots, z_n$ in two-dimensional space, which will maximally correspond to the distance between them in multidimensional space. This is achieved by using the following function:

$$S(z) = \sum_i \sum_j (d_{ij} - \|z_i - z_j\|^2$$

The final step for MDS was cluster analysis of the world countries using the 70 collected indicators and the k-means method. Clustering divides the whole set of objects into a number of statistical clusters specified by the researcher, so that the mean values for the clusters for each of the variables differed as much as possible. Clustering was done by median values for k = 2, 3, 4, 5, 6, 8, 10, 14 and 20. The resulting clusters were visualized in cluster maps.

The above-described set of research instruments made it possible to reach the results outlined in the following section.

Research findings

Moran's I values

If we observe the results of Moran's I for the 70 indicators, the greatest spatial association among neighbouring countries is observed in the indicators related to demography and human capital. For example, Moran's I values exceed 0,7 concerning the number of young people in the neighbouring countries and the child mortality rate. Political and economic indicators such as the level of corruption or budget deficits are demonstrating the least spatial association. The biggest and least values of Moran's I are present in Table 3.

LISA-clustering analysis

As for the results of LISA analysis, it is worth noting, that in many cases LISA-clustering produces results are consistent with the concept of the North–South global divide, for instance, GDP based on PPP per capita.

To demonstrate the explanatory capacity of LISA clustering, this LISA map clearly shows Western European and Arabian clusters with high levels of GDP based on PPP per capita, and African and South Asian clusters with low levels of GDP per capita at PPP. Countries with missing data have been removed from the sample to reduce inaccuracy in the calculations. However, it is in the Western European and African clusters that the significance of neighbourhood factors reaches its highest values in contrast with the North Africa or East Asia.

Spatial Dependence Index

The next step was to find the extreme values of the proposed Spatial Dependence Index. As we suggested, SDI makes it possible to assess which aspects of a state's position depend more on its internal characteristics and which on external ones. As it turned out, the majority of indicators are connected with internal fea-

Table 3. Top-10 Moran's I values among selected global development indicators

Indicators	Moran's I
Population ages 0–14 (% of total population)	0,725
Probability of survival to age 5	0,721
Life expectancy at birth, total (years)	0,707
Poverty headcount ratio at $ 3.20 a day	0,706
Gini Index	0,626
Global Innovation Index	0,623
Expected years of school	0,615
Global Competitiveness Index	0,603
Incidence of tuberculosis (per 100,000 people)	0,575
Religiosity level	0,567
Least values	
Public debt	0,044
Nominal Gross Domestic Product	0,041
GDP based on PPP, share of world	0,037
Total population	0,037
Gross Domestic Product based on Purchasing Power Parity	0,037
State Power Index	0,036
School enrollment, tertiary (gross), gender parity index (GPI)	0,036
Bertelsmann Transformation Index	0,015
Budget deficit or surplus	0,009
School enrollment, primary (gross), gender parity index (GPI)	-0,026

Source: Own research, 2021

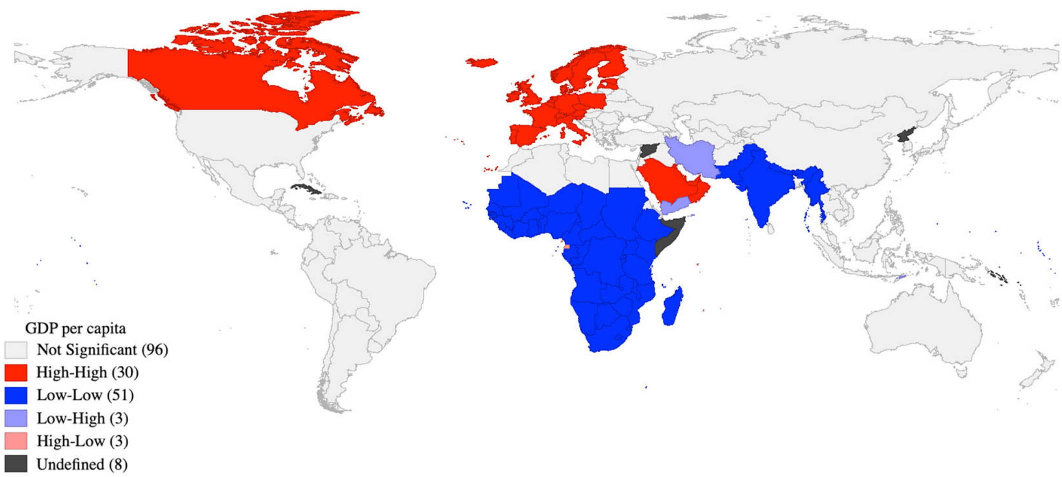

Fig. 1. Local Indicators of Spatial Association of GDP PPP per capita

Source: Own results based on IMF (2017)

Table 4. Calculated SDI values for 24 randomly selected pairs of indicators

#	Indicators	Squared bivariate Moran's I	Determination coefficient $R^2_{(x, y)}$	Spatial Dependence Index
1	Religiousity level – Autonomy index	0,185	-0,78	0,965
2	Autonomy index – Religiousity level	0,16	-0,78	0,94
3	General national pride – Autonomy index	0,116	-0,5	0,616
4	Autonomy index – General national pride	0,073	-0,5	0,573
5	Gini Index – Contribution of agriculture to total GDP	0,048	0,021	0,027
6	Gini Index– GDP PPP per capita	0,162	0,14	0,022
7	Military expenditure (% of GDP) – Globalisation Index	0,003	0,001	0,002
8	Globalisation Index – Military expenditure (% of GDP)	0,002	0,001	0,001
9	Contribution of agriculture to total GDP – Gini Index	0,02	0,021	-0,001
10	Military expenditure (% of GDP) – Global Innovation Index	0,004	0,008	-0,004
11	Religiousity level – International migrant stock (% of population)	0,002	0,041	-0,039
12	International migrant stock (% of population) – Religiousity level	0,001	0,041	-0,04
13	Global Innovation Index – Military expenditure (% of GDP)	0,007	0,08	-0,073
14	GDP PPP per capita – Gini Index	0,048	0,14	-0,092
15	Corruption perception index –International migrant stock (% of population)	0,019	0,173	-0,154
16	International migrant stock (% of population) – Corruption perception index	0,01	0,173	-0,163
17	GDP PPP per capita – Contribution of agriculture to total GDP	0,147	0,317	-0,17
18	Religiousity level – Corruption perception index	0,175	0,386	-0,211
19	Contribution of agriculture to total GDP – GDP PPP per capita	0,106	0,317	-0,211
20	Global Innovation Index – Globalisation Index	0,406	0,75	-0,344
21	Corruption perception index – Religiousity level	0,041	0,386	-0,345
22	General national pride – Religiousity level	0,123	0,5	-0,378
23	Religiousity level – General national pride	0,09	0,5	-0,41
24	Globalisation Index – Global Innovation Index	0,104	0,75	-0,646

tures of the state; thus, it was the more interesting to find examples when the role of the external factors is more significant. For instance, an unexpected SDI value was identified: the share of agriculture is not related to population growth in the state itself but is more connected with the latter indicator in neighbouring countries. However, there are still thousands of calculations to test such hypotheses and identify, where correlation implies causation. In the Table 4 there are calculated values of SDI for 24 randomly selected pairs of indicators. It is observable, that there are more negative values of SDI which implies that in many cases for this selection the geographical factor is playing an important and yet negative role on spatial distribution of the social phenomenon in neighboring countries.

Table 5. Calculation of the anomalous SDI values with suicides per 100,000 population as an independent variable

#	Indicators	Squared bivariate Moran's I	Determination coefficient $R^2_{(x, y)}$	Spatial Dependence Index
1	Suicide rates per 100 000 population – Religiosity level	0,250	0,374	-0,124
2	Suicide rates per 100 000 population – Learning-adjusted years of school	0,138	0,243	-0,105

To illustrate the logic of this index, let us look at the following example of SDI concerning suicide rates per 100 000 population: it was used as the independent variable, with all the rest of 69 indicators as the dependent variables. As in the case of Moran's I, we were interested in extreme values of the SDI, subject to high values of the determination coefficient and bivariate Moran's I. For the suicide rate, four such indicators were identified:

- Religiosity level (average value according to the respondents' answers to the question "How important is God in your life?")
- Learning-adjusted years of school (calculated by multiplying the estimates of expected years of school by the ratio of most recent harmonized test scores to 625).

The results of the SDI calculation are presented in Table 5 and both negative. This can be interpreted as follows: spatial factors significantly determine that states with higher suicide rates have such neighbours whose population is characterised by a lower degree of religiosity and lower duration of schooling.

In both cases the determination coefficient is higher in absolute values than the squared bivariate Moran's I, which indicates the bigger role of other factors cumulatively presented in the determination coefficient than spatial factors. Still, it can be stated that space explains 12,4 % of the relationship between suicide rates and religiosity level and 10.5 % of the relationship between suicide rates and learning-adjusted years of school.

As with any research, limitations exist that need to be discussed. In this section we provide an overview of positive outcomes and limitations of the conducted research. On the one hand, we have obtained a static picture of the states' political, social and economic indicators related to 2014–2019: it does not tell us much about dynamics and transformation in the spatial dependence processes across the world; partly because it was beyond the scope of this study. Thus, the results we obtained are more snapshots, although very comprehensive ones, referring to a contemporary timeframe rather than a dynamic overview of the transition the states have overgone in the last 10–20 years.

Conclusion

This paper has presented and discussed opportunities that spatial econometrics provides for analysis of social, political and economic phenomena distributed not within the concrete region or country but for the whole globe. The study has focused on several spatial analysis tools – Moran's I (univariate and bivariate), local indicators of spatial association and multidimensional scaling – for 70 indicators on state development and its position in international relations. Furthermore, the authors proposed Spatial Dependence Index to indicate where the space influence is identified, and demonstrated that it has significant explanatory capacity on the examples of suicide rates, religiousity levels and GDP per capita.

The paper has the following theoretical contribution: firstly, it expands the body of knowledge on spatial distribution of social phenomena, such as poverty, state power, democracy, religiosity, etc., across the world. Secondly, the applied approach helps to discover, where space distribution does not correlate with the conventional perception of interstate positions and relations, for instance, according to the concept of the North–South global divide.

The current economic and political landscape of the world map is characterised on the one hand by the persistence of considerable heterogeneity, and on the other by the high speed of regional integration processes. In other words, we can state that at the beginning of the 21st century economic expediency has overcome the barriers of local heterogeneity: differences between countries localised in one region have become less important compared to their shared similarities against the background of global threats and the need to form common markets to accelerate economic growth. In this situation, we can state that regional economic blocs of countries, united by common features in the face of external and internal challenges, are emerging in the world. In the terms of spatial econometrics, it means the emergence of stable clusters of spatial autocorrelation in the world, where there is a significant correlation in the basic parameters of state development among neighbouring countries.

Neighbouring states often experience similar economic problems, such as environmental disasters, crop failures, or something that is very relevant today, pandemics, that invariably affect several countries at the same time. Countries develop similar instruments as a response to similar problems, which ultimately leads to the creation of regional integration complexes (Kholina and Massarova, 2013). Geoinformation modelling can help us determine, for example, where national response measures may be more appropriate for dealing with external risks, and which problems are best left for international institutions.

Spatial econometrics methods introduced for the world political map help to resolve the perennial dispute between geographic determinism in geopolitics (which claims that the structure of physical space is a key factor in political processes) and geographic nihilism (which states that the importance of space in political processes can be neglected) using mathematical statistics. It turns out that we can measure the degree of influence of space – that space is a probabilistic quantity. It turned out that the spatial factor was weak in certain areas (for example, when it comes to the spread of political regimes, values or corruption) and incredibly strong in others (such as electoral behaviour, demographic policy or conflict).

Despite the above-mentioned limitations of the work, it is still a very detailed picture with 70 dimensions and large opportunities to explore spatial patterns all over the globe. As each indicator has a profile with dasymetric mapping, geographical anamorphosis, Moran's I, and local indicators of spatial association, this holistic approach helps to identify and interpret state behaviour patterns and, more generally, social phenomena through the geographical lens.

The findings from this study support the use of GeoDA software and make a significant contribution to understanding the degree of space influence on phenomena distribution and international relations in general. What remains uncovered is methods and instruments to distinguish and disprove correlations that seem logically plausible but in reality, are just random statistical patterns.

References

Ades A., Chua H. B. Thy Neighbor's curse: regional instability and economic growth. In: *Journal of Economic Growth*, 1997, 2(3), 279–304. DOI: 10.1023/A:1009782809329.

Anselin L. Local indicators of spatial association – LISA. In: *Geographical analysis*, 1995, 27(2), 93–115. DOI: 10.1111/j.1538–4632.1995.tb00338.x.

Baumont C., Ertur C., Le Gallo J. Spatial convergence clubs and the European regional growth process, 1980–1995. In: *European regional growth*, 2003, 131–158. DOI: 10.1007/978–3–662–07136–6.

Carrington A. A divided Europe? Regional convergence and neighbourhood spillover effects. In: *Kyklos*, 2003, 56(3), 381–393. DOI: 10.1046/j.0023–5962.2003.00226.x.

Cliff A. D., Ord J. K. *Spatial Autocorrelation.* London, Pion Ltd., 1973.

Coe D. T., Helpman E., Hoffmaister A. W. North-south R&D spillovers. In: *The Economic Journal,* 1997, 107(440), 134–149. DOI: 10.1111/1468–0297.00146.

Copiello S. Spatial dependence of housing values in Northeastern Italy. In: *Cities*, 2020, 96, 102444. DOI: 10.1016/j.cities.2019.102444.

Easterly W., Levine R. Troubles with the neighbours: Africa's problem, Africa's opportunity. In: *Journal of African Economies,* 1998, 7(1), 120–142. DOI: 10.1093/oxfordjournals.jae.a020941.

Enos R.D. *The space between us: Social geography and politics.* Cambridge University Press, 2017.

Fix E. Hodges J.L. Discriminatory analysis – nonparametric discrimination: consistency properties. In: *US Air Force School of Aviation Medicine*, 1951. Report 4, Project 21–49–004, 261–279.

Hardiawan D., Yusuf A.A., Muljarijadi B. The impact of expenditure inequality and socioeconomic on crime rates in Indonesia. Cross sectional study using spatial econometrics and geographically weighted regression, *Achieving and Sustaining SDGs 2018 Conference: Harnessing the Power of Frontier Technology to Achieve the Sustainable Development Goals (ASSDG 2018)*, Bandung, West Java, Indonesia, 2018, Atlantis Press.

Holmes C.C., Adams N.M. A probabilistic nearest neighbour method for statistical pattern recognition. In: *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 2002, 64(2), 295–306. DOI: 10.1111/1467–9868.00338.

Keller W. Geographic localization of international technology diffusion. In: *American Economic Review*, 2002, 92(1), 120–142.

Kholina V., Massarova A. Latin America from crisis to sustainable growth: image change and new development paradigms. In: *Miscellanea Geographica: Regional Studies on Development*, 2013, 17(2), 12–19.

Lall S.V., Yilmaz S. Regional economic convergence: Do policy instruments make a difference? In: *The annals of regional science*, 2001, 35(1), 153–166. DOI: 10.1007/s001680000035.

Le Gallo J., Ertur C., Baumont C. A spatial econometric analysis of convergence across European regions, 1980–1995. In: *European regional growth*, 2003, 99–129. Springer, Berlin, Heidelberg. DOI: 10.1007/978–3–662–07136–6.

Lim U. Regional income club convergence in US BEA economic areas: a spatial switching regression approach. In: *The Annals of Regional Science,* 2016, 56(1), 273–294. DOI: 10.1007/s00168–015–0739–0.

Lloyd C. *Spatial data analysis: an introduction for GIS users.* Oxford university press, 2010. 56–60.

Lobo G.D., De Souza Almeida F.M., Danelon A.F., Rocha A.B., Almeida A.N. Could the agrochemical poisoning increase suicide attempts in the Brazilian rural areas? An econometric approach using spatial analysis methods. *2020 Annual Meeting, July 26–28, Kansas City, Missouri* (No. 304593). Agricultural and Applied Economics Association, 2020.

López-Bazo E., Vayá E., Artís M. Regional Externalities and Growth: Evidence from European Regions. In: *Journal of Regional Science*, 2004, 44, 43–73. DOI: 10.1111/j.1085–9489.2004.00327.x.

Mead A. Review of the development of multidimensional scaling methods. In: *Journal of the Royal Statistical Society: Series D (The Statistician)*, 1992, 41(1), 27–39. DOI: 10.2307/2348634.

Moran P.A. The interpretation of statistical maps. *In Journal of the Royal Statistical Society. Series B (Methodological)*, 1948, 10(2), 243–251.

Moreno R. Trehan B. Location and the Growth of Nations. In: *Journal of Economic Growth*, 1997, 2, 399–418.

Murdoch J.C., Sandler T. Civil wars and economic growth: Spatial dispersion. In: *American Journal of Political Science*, 2004, 48(1), 138–151. DOI: 10.1111/j.0092–5853.2004.00061.x.

O'Loughlin J., Anselin L. Bringing geography back to the study of international relations: Spatial dependence and regional context in Africa, 1966–1978. In: *International Interactions*, 1991, 17(1), 29–61. DOI: 10.1080/03050629108434769.

Ramajo J., Márquez M., Salinas M. *Spatial patterns in EU regional growth: New evidence about the role of location on convergence*. University of Extremadura, Spain-EU, 2003.

Rey S.J. and Montouri B.D. U.S. Regional Income Convergence: A Spatial Econometric Perspective. In: *Regional Studies*, 1999, 33. 143–156.

Shepard R.N. The analysis of proximities: multidimensional scaling with an unknown distance function. In: *Psychometrika*, 1962, 27(2), 125–140. DOI: 10.1007/BF02289630.

Starr H. Joining political and geographic perspectives: Geopolitics and international relations. In: *International Interactions*, 1991, 17(1), 1–9.

Torgerson W. S. Multidimensional scaling: I. Theory and method. In: *Psychometrika*, 1952, 17(4), 401–419. DOI: 10.1080/03050629108434767.

Weidmann N. B., Kuse D., Gleditsch K. S. The Geography of the International System: The CShapes Dataset. In: *International Interactions*, 2010, 36(1). 86–106. DOI: 10.1080/03050620903554614.