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THE ANALYSIS OF THE PHENOMENON OF SPATIAL AUTOCORRELATION OF INDICES OF AGRICULTURAL OUTPUT

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Abstract: The agricultural production depends on natural and economic conditions. Weak environmental conditions could be compensated by using the high technology, which requires capital. The agricultural production should evolve in a similar way in countries with similar natural conditions, i.e. spatial autocorrelation should take place. The aim of this article is to present the spatial autocorrelation of indices of agricultural output. The local and global I Moran's statistics were used and the changes in the dynamics of agricultural production in the EU in 2010-2011 were presented.

Keywords: spatial autocorrelation, indices of agricultural output, the European Union

INTRODUCTION

The agriculture in EU is diversified in terms of the agrarian structure. This is due to mostly to natural conditions and the level of advancement of structural transformation. There are general trends of structural change to reduce the number of farms and to stimulate the growth area of farms. The ability to effectively compete on the community market is a slow processes and require the mobilization mechanisms stimulating at EU level and at national level[1].

On the basis the agricultural census in the European Union we can conclude that the number of farms fell by almost 20% in the years 2003-2010, the area

[1] Babiak J., Zmiany w strukturze rolnictwa krajów Unii Europejskiej, Rocznik Integracji Europejskiej, 2010, nr 4, https://repozytorium.amu.edu.pl/jspui/bitstream/10593/1512/1/babiak.pdf

of land used for agricultural purposes decreased by almost 2% in this same period. The average area of farms has increased from 12 ha in 2003 to 14 ha in 2010. More than 80% of total number of farms is located in Romania, Italy, Poland, Spain, Greece, Hungary and France[2].

Meat and other animal products in the EU-27 represented 156.5 billion € in 2011, i.e. 41% of the total value of farm production and 11% more than in 2010. However, this increase must not be seen as a sign of recovery from the 2009 crisis, since feed costs increased dramatically in 2011, thus further hampering farmers' income. Animal feed is indeed the most important livestock production cost factor and represented in 2011 up to 83% of the farm gate value of poultry. The EU-27 farm animals are fed with 470 billion t of feedstuffs, thereof app. half are roughages produced on farm, 10% are grains produced on farm, 10% are purchased feed materials and 30% are industrial compound feed[3].

The production of meat in the EU-27 increased by 1.4% between 2010 and 2011, thus offsetting the dramatic contraction of production in 2009, due in particular to the drop in EU consumption for all categories of animal products except poultry. Pig production increased despite the high feed costs which continue to rise in 2012. The meat consumption in the EU-27 is stable around 90 kg/capita/year. Poultry meat is the second most consumed meat in the EU-27 with 23.3 kg/capita/year in 2011, far behind pig meat (41.2 kg/capita/year). The EU livestock sector contributes positively to the commercial balance, in particular pork and cheese, with self sufficiency ratio of resp. 109 and 106[4].

In 2011, the EU cereal harvest reached a usable production of 285.7 million tonnes, due to favourable yields, mainly in maize (+8.9%). Animal feed use slightly decreased to 167 million tonnes, resulting in an almost unchanged domestic use of 271.3 million tonnes. In 2011, the real value of EU crop production is estimated to have increased by 7.5% due to higher prices (5.7%) and volumes (1.7%). Prices rose for most crops markedly for cereals (18.3%), oilseeds (15.1%), forage plants (12.8%) and protein crops (11.6%) with the exception of fresh vegetables (-9.7%), olive oil (-1.4%) and flowers (-1.2%). Most products recorded higher volumes, in particular sugar beet (11%), wine, potatoes and fruits while lower volumes were recorded for protein crops (-16.3%)[5].

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2 Struktura rolnictwa w Unii Europejskiej, Bieżąca informacja o rolnictwie na świecie Nr 49/2011, http://www.minrol.gov.pl/pol/Informacje-branzowe/Opracowania-publikacje/Informacje-o-rolnictwie-na-swiecie/biezaca-informacja-o-rolnictwie-na-swiecie-nr-49-2011

3 http://www.fefac.eu/file.pdf?FileID= 39499

4 ibidem; Global livestock production system, Rome, 2011www.fao.org/docrep014/i2414e/ I 2414e.pdf

5 Agriculture in the European Union Statistical and economic Information 2011, http://ec.europa.eu/agriculture/statistics/agricultural/2011/pdf/full-report_en.pdf; Global

METHODOLOGY

Since the 1950s, several spatial methods of analysis have been developed and modified to improve our ability to detect and characterize spatial patterns. These stem from several fields of study, having more or less different goals, mathematical approaches and underlying assumptions[6.]

In its most general sense, spatial autocorrelation is concerned with the degree to which objects or activities at some place are similar to other objects or activities located nearby. Its existence is reflected in the proposition which Tobler (1970) has referred to as the "*first law of geography: everything is related to everything else, but near things are more related than distant things*". Spatial autocorrelation can be interpreted as a descriptive index, measuring aspects of the way things are distributed in space, but at the same time it can be seen as a causal process, measuring the degree of influence exerted by something over its neighbors'.

The aim of the analysis is to determine the spatial interrelationships and interactions between neighboring objects, in this case the EU countries. Observations made at different locations may not be independent. For example, measurements made at nearby locations may be closer in value than measurements made at locations farther apart. Spatial autocorrelation measures the correlation of a variable with itself through space, it can be positive or negative. Positive spatial autocorrelation occurs when similar values occur near one another and negative - occurs when dissimilar values occur near one another[7].

The Moran's index and Geary's coefficient summarize the strength of associations between responses as a function of distance, and possibly direction. These indices are usually applied in ecology and geographical sciences. Fortin et al., for example, used these spatial autocorrelation coefficients to compare the capacity of different sampling designs and sample sizes to detect the spatial structure of a sugar-maple tree density data set gathered from a secondary growth forest. Moran's index is one of the oldest indicators of spatial autocorrelation. It is applied to zones or points which have continuous variables associated with their

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crop production review, 2011 http://www.usda.gov/oce/weather/pubs/Annual/GlobalCropProduction Review2011.pdf

6 Anselin, L. (1995). Local indicators of spatial autocorrelation – LISA, Geographical Analysis 27, 93 – 115; Cressie, N.A.C. (1993). Statistics for Spatial Data ,Wiley, New York Perry, J.N. (1995). Spatial analysis by distance indices, Journal of Animal Ecology 64, 303 – 314

7 Gunaratna N., Liu Y., Park J., Spatial Autocorrelation, http://www.stat.purdue.edu/~bacraig/ SCS/Spatial%20Correlation%20new.doc; Wang J., Zhang Z., Su B., Zhang L., A case research on economic spatial distribution and differential of agriculture in China, An application to Hunan province based on the data of 1999, 2006 and 2010, Agricultural Sciences, Vol.3, No.8, 996-1006 (2012)

intensities. For any continuous variable, x_i, a mean can be calculated and the deviation of any observation from that mean can also be calculated. The statistic then compares the value of the variable at any one location with the value at all other locations. It is formally defined by

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (1)$$

where: $\bar{x}$ is the mean of the x variable, w_{ij} are the elements of the weight matrix[8], and S_0 is the sum of the elements of the weight matrix: $S_0 = \sum_i \sum_j w_{ij}$.

Moran's index varies between –1.0 and +1.0. When nearby points have similar values, the cross-product is high; and when nearby points have dissimilar values, the cross-product is low. In other words, an I value which is high indicates more spatial autocorrelation than an I which is low[9]. In the absence of autocorrelation and regardless of the specified weight matrix, the expectation of Moran's I statistic is $-1/(n-1)$, which tends to zero as the sample size increases. For a row-standardized spatial weight matrix, the normalizing factor S_0 equals n (since each row sums to 1), and the statistic simplifies to a ratio of a spatial cross product to a variance. A Moran's I coefficient larger than $-1/(n-1)$ indicates positive spatial autocorrelation, and a Moran's I less than $-1/(n-1)$ indicates negative spatial autocorrelation[10].

Geary's C statistic[11] is based on the deviations in responses of each observation with one another:

$$C = \frac{n-1}{2S_0} \frac{\sum_i \sum_j w_{ij} (x_i - x_j)^2}{\sum_i (x_i - \bar{x})^2} \quad (2)$$

8 The weight matrix can be specified in many ways: (1) the weight for any two different locations is a constant, (2) all observations within a specified distance have a fixed weight, (3) K nearest neighbors have a fixed weight, and all others are zero, (4) weight is proportional to inverse distance, inverse distance squared, or inverse distance up to a specified distance.

9 Silva E. Da, Silva A., De Paiva A., Nunes R, Diagnosis of lung nodule using Moran's index and Geary's coefficient in computerized tomography images, Pattern Analysis and Applications January 2008, Vol. 11, Issue 1, pp 89-99

10 Gunaratna N., Liu. Y., Park J., op.cit.; Plant R. E., Spatial Data Analysis in Ecology and Agriculture Using R, CRC Press, 2012

11 Geary R.C., The Contiguity Ratio and Statistical Mapping, The Incorporated Statistician, 1954, 5 (3), pp 115–114

The values of C typically vary between 0 and 2. The theoretical value of C is 1, that indicates that values of one zone are spatially unrelated to the values of any other zone. Values less than 1 (between 0 and 1) indicate positive spatial autocorrelation while values greater than 1 indicate negative spatial autocorrelation.

This coefficient does not provide the same information of spatial autocorrelation given by Moran's index, because it emphasizes the differences in values between pairs of observations comparisons rather than the covariation between the pairs. So the Moran's index gives a more global indicator whereas the Gearys coefficient is more sensitive to differences in small neighborhoods[12].

Moran's I is a more global measurement and sensitive to extreme values of, whereas Geary's C is more sensitive to differences in small neighborhoods. In general, Moran's I and Geary's C result in similar conclusions. However, Moran's I is preferred in most cases since Cliff and Ord (1975, 1981) have shown that Moran's I is consistently more powerful than Geary's C[13].

In addition to the global statistics the local statistics of spatial autocorrelation were calculated. It can be assumed that the interpretation of the local statistics are similar to the global statistics. If we get a negative value for the local Moran's statistics, we can conclude that the i-th country is surrounded by countries (neighbors) which are different from each other due to the test feature. In the case of the positive talk about similar countries (neighbors) in the i-th country setting. Local statistics are called LISA statistics. Local Moran statistic is given by formula:

$$I(w) = \frac{\left(x_i - \bar{x}\right)\sum_{i=j}^{n} w_{ij}\left(x_i - \bar{x}\right)}{\sum_{i=j}^{n}\left(x_i - \bar{x}\right)^2} \quad (3)$$

RESULTS AND CONCLUSIONS

The study included 27 member states of the European Union, statistical data were taken from Eurostat databases and the World Bank. The following variables were taken under consideration:

x_1 – indices of agricultural crop output at producer prices – 2010;
x_2 - indices of agricultural crop output at producer prices – 2011;
x_3 - indices of agricultural animal output at producer prices – 2010;
x_4 – indices of agricultural animal output at producer prices – 2011.

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[12] Silva E. Da, Silva A., De Paiva A., Nunes R, op.cit.
[13] Gunaratna N., Liu Y., Park J., Spatial Autocorrelation, http://www.stat.purdue.edu/~bacraig/ SCS/Spatial%20Correlation%20new.doc

Table 1 shows the statistical characteristics of the variables.

Table 1 Statistical characteristics of the variables

variables	x_1	x_2	x_3	x_4
mean	6731	7334	5076	5574
standard deviation	9652,6	10169,3	6406,6	7070,5
coefficient of variation	143,4%	138,7%	126,2%	126,9%
min	45	50	68	69
max	37668	38839	22452	24720

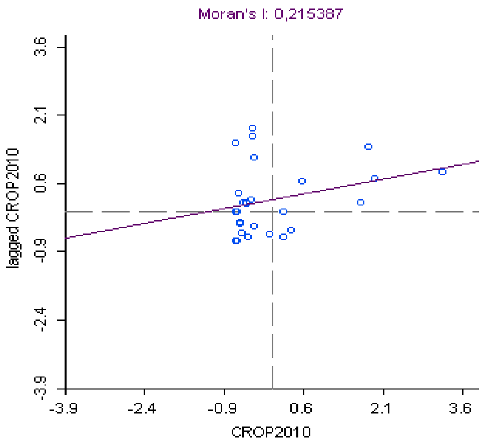
Source: own calculation based on EUROSTAT data

Analyzing the results contained in Table 1, it is clear that variables taken under consideration diversify the area in terms of growth of agricultural production (value of the coefficients of variation exceeds the value of 100%). The data shows an increasing trend of average growth of indices of agriculture animal and crop output at producer prices in the EU member states.

The study of spatial autocorrelation of indices of agricultural animal and crop output at producer prices have been carried out under the assumption of contact matrix W. The calculated value of the global I Moran's statistics indicates that in the adopted study period a moderate spatial autocorrelation can be observed.

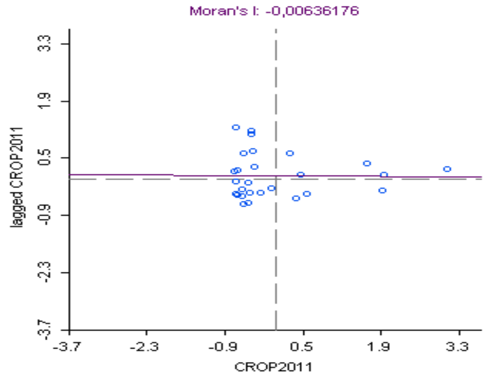
It is either positive, that is, there is a tendency to focus on individuals with similar levels of indices of agriculture animal and crop output at producer prices. All obtained values of I Moran's statistics are statistically significant (p-value <0.05) (Fig. 1-4).

Figure 1. Moran's I scatterplot for the variable x_1



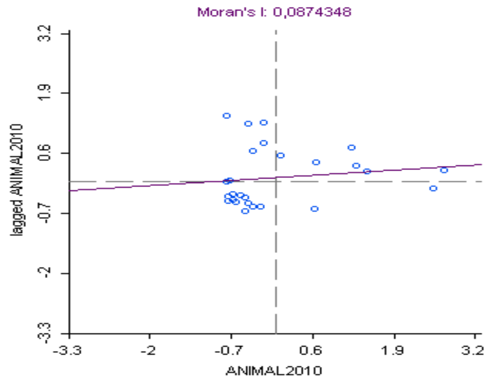
Source: calculations in the GeoDa based on EUROSTAT data

Figure 2. Moran's I scatterplot for the variable x_2



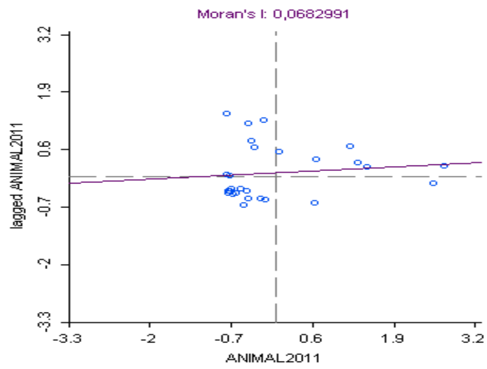
Source: calculations in the GeoDa based on EUROSTAT data

Figure 3. Moran's I scatterplot for the variable x_3



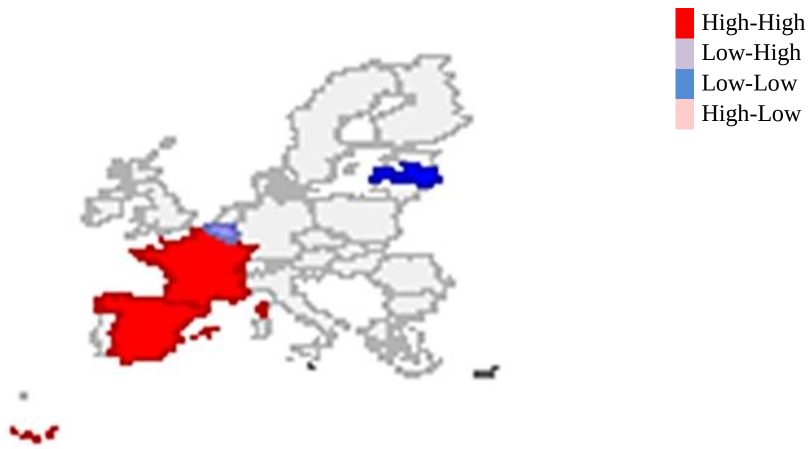
Source: calculations in the GeoDa based on EUROSTAT data

Figure 4. Moran's I scatterplot for the variable x_4



Source: calculations in the GeoDa based on EUROSTAT data

Figure 5. Map of affiliations of objects to quarters of Moran scatterplot (variable x_1)

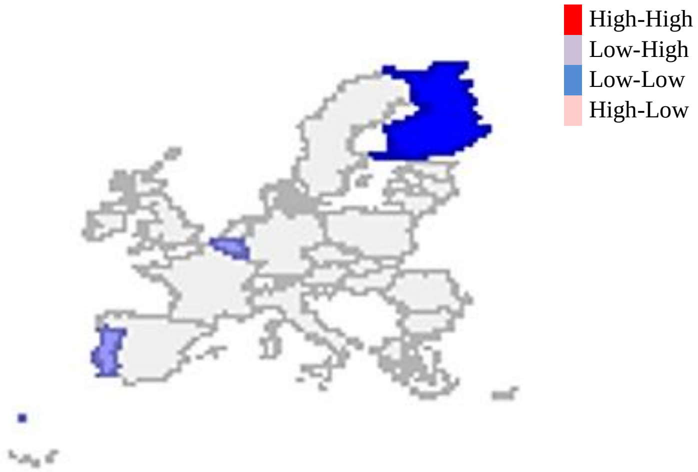


Source: calculations in the GeoDa based on EUROSTAT data

Figure 6. Map of affiliations of objects to quarters of Moran scatterplot (variable x_2)

Source: calculations in the GeoDa based on EUROSTAT data

Figure 7. Map of affiliations of objects to quarters of Moran scatterplot (variable x_3)



Source: calculations in the GeoDa based on EUROSTAT data

Figure 8. Map of affiliations of objects to quarters of Moran scatterplot (variable x_4)

Source: calculations in the GeoDa based on EUROSTAT data

The four quadrants in the Moran scatter plot provide a classification of four types of spatial autocorrelation. Areas that are significant are labelled with these categories in the "High-High/Low-Low" dataset produced in the Moran analysis, and are colored in the Moran scatter plot and Local Moran maps as well.

The map contains information on only those locations that have a significant Local Moran statistic. While every region in the dataset will be represented in the Moran scatterplot, only those with Local Moran statistic p-values <0.05 are significant. Any island locations are considered missing values because they have no adjacent neighbors.

Figures 5-8 shows that the space can be divided into clusters with similar values of local I Moran's statistics. Clustering of countries with similar I Moran's statistics indicates the existence of spatial autocorrelation. The direction of the relationship was changing in the analyzed period, which leads to the conclusion about the need for in-depth research and an explanation of the reasons for this phenomenon.

SUMMARY

The I Moran's and Gettis statistics indicate the type and strength of spatial dependency, which allows to identify the structures and changes. On the basis of the positive I Moran's statistics (statistically significant) it can be concluded the positive spatial autocorrelation of indices of agricultural crop and animal output at producer prices in 2010 and 2011.

The neighboring countries in the European Union were similar in terms of crop and animal agricultural output at producer prices. At the same time it should be noted that there the need for further studies decomposition crop and animal agricultural output at producer prices in the European Union.

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