UDK 332.334.2:004.422.3:711.143
Original scientific paper / Izvorni znanstveni članak

Distance Based Synthetic Measure of Agricultural Parcel Locations

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ABSTRACT. The paper aims to define the location factor (LF) as a synthetic, quantitative measure of agricultural parcel locations. Multivariate comparative analysis and the original formula based on the weighted distance to selected places, were used to determine the location factor. The factor allows the objective description of parcel locations and replaces several locational characteristics by one variable which simplifies the computational process and could be used in many applications. The LF also works as a similarity measure in parcel clustering and could be applied in a variety of spatial analyses at the municipality level, in public investment planning, land consolidation or land value map making.

Keywords: location factor, location characteristics, agricultural lands.

1. Introduction

Each property is spatially unique and location is always an intrinsic attribute that directly determines the value of any parcel. "Location, location, location" the well-known Pearson's statement, (Peterson and Flanagan 2009) is a credo for appraisers because it emphasises the importance of location adjustment within any appraisal model. Considerable research indicates that the location of a parcel, especially agricultural, depends on many factors, one of which is access to urban centres and road infrastructure, suggesting that proximity to markets gives a greater price than land equally fertile in a distant part of the country (Cavailhès and Wavresky 2003, Plantinga et al. 2002). Delbecq et al. (2014) and O'Donoghue et al. (2015) argued that accessibility to customers, services, employment opportunities and rural amenities are of the utmost importance when determining the price of agricultural land. Scientists and appraisals also highlight the significant role of neighbourhood specific characteristics which are crucial to the conversion

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of farmland to non-farming uses (Ward et al. 1999, 2002, Drescher et al. 2001, Sklenicka et al. 2013).

Geographical location is an important prerequisite for mass appraisal and automated valuation modelling (Nilsson and Johansson 2013, Maleta and Bielecka 2014), land fragmentation and consolidation (Hudecová et al. 2017, Demetriou et al. 2013), spatial planning, especially the potential of diversification and non-agricultural use of land (Walford 2001) as well as land sustainability (Drobne and Lisec 2009, Ma and Swinton 2011). Location expressed as parcel accessibility also plays an important role in surveying (Pokonieczny et al. 2016), logistics (Moscicka et al. 2016) risk assessment (Calka et al. 2017) and also cultural heritage protection. Moscicka (2015) proved that linking movable monuments with a location simplifies access to resources and gives new opportunities for heritage management. A reliable evaluation of the value of land parcels is essential for a number of applications, investment decisions, and policy. As a spatially fixed asset, land is one of the primary sources of property tax revenues (Nilsson and Johansson 2013). This makes both commercial and governmental parties interested in the value of the land. Moreover, agricultural programmes such as land consolidation or subsidiary policy are definitely based on the geographical location of parcels as well as their spatial pattern (Janus et al. 2017).

Literature provides different methods of including geographic location in property valuation which could be classified under the four following groups:

(1) Simple distance based methods that rely in general on van Thunen's reverse theory of agricultural location (Sinclair 1967). This theory says that the results of crop production and productivity from one land unit are greater if there is an increased distance of the parcel from the municipality centre and other influences of urbanisation (Wigier 2012).

(2) Extended distance based methods including not only distance to the city centre or planning zone, but also proximity to the homestead, roads, water bodies, forests or other geographical features that could affect land prices.

(3) Spatial autocorrelation methods based on Tobler's first law of geography which says that "everything is related to everything else, but near things are more related than distant things" (Tobler 1970). This law is the foundation of the definitive theories of spatial dependence and spatial autocorrelation and is employed specifically for the inverse distance weighting method for spatial interpolation and to support the regionalised variable theory for kriging.

(4) Synthetic location measure including proximity or travel time from a parcel to selected objects or locations. This measure could be express as an equation or a surface.

Distance based methods are generally used in hedonic models, where proximity, considered generally as a Euclidean distance to selected geographical objects, are rated or weighted depending on their correlation with sales prices. The influence of location-based factors varies in regions and countries. Sklenicka et al. (2013) found that in the Czech Republic significantly higher prices of land parcels were found close to existing built-up areas and the next most powerful factors were: municipality population, travel time to the capital city. Similar observations have been made by Bitner et al. (2017) for the south part of Poland where the price of land property decreases with growing distance to the city centre by about 10 PLN

(2.35 EUR) with each kilometre. Location also reflects the proximity of farmland to roads (Choumert and Phélinas 2015), the homestead (Kuethe et al. 2011), forest and water bodies (Demetriou 2015). Greater distances to the homestead determine smaller revenues due to greater transport-related costs (Demetriou 2016). The proximity of forests, water bodies, and protected areas also reduces agriculture production income due to legal and environmental restrictions (Ma and Swinton 2011, Maleta and Calka 2015). But on the other hand, the proximity of natural amenities gives the possibility of other, non-agricultural uses of the land parcels (Aguiar et al. 2007).

The development of information technology and geographical information systems means that statistical analysis is increasingly supplemented with geostatistical analyses which results in the consideration of the spatial autocorrelation between a property's transaction price and its geographical location. This type of research has been carried out by e.g. Tu et al. (2007), Chica-Olmo et al. (2013), Cellmer et al. (2014), Maleta and Calka (2015). They all found that such an approach is promising, however the results are not yet fully satisfying. In addition, scientists worked on an indicator that provides a more complex picture of parcel geographical location and its impact on the sale price. In the year 1982 O'Connor introduced Location Value Response Surface (LVRS) that requires spatial interpolation of property prices or error term (O'Connor 1982). This factor was further modified by D'Amato (2010), who found that a location adjustment factor derived from a mathematical iteration gives better results than one based on geostatistics. The results obtained by D'Amato (2010) have motived Nilsson and Johansson (2013) who elaborated the synthetic measure, which captures the distance to all locations where economic activities (employment, services and other urban amenities) are concentrated.

All mentioned applications of parcel location require a huge number of detailed data as well as GIS based multi-criteria (MCDA) or multi-attribute decision analysis (MADA) software. Agricultural land is always considered in $R^{n,m}$ dimension where n is the number of properties and m the number of attributes used for an analysis. Every attribute that is analysed is called a criterion and should have an assigned weight based on its importance. Malczewski, a pioneer in GIS-based multi-attribute and multi-criteria analyses, underlined that spatial planning, land sustainability and land management are the most obvious multi-attribute applications (Malczewski 2004, 2006). MCDA has also been successfully implemented in real property market analysis. Drobne et al. (2008) and Maliene (2011) noticed that as location is the basic characteristic of land, the use of spatial multi-attributes analysis methods has become a necessity in land market analysis.

An analysis of the literature clearly shows that one of the main problems when developing models for estimating the value of property is taking geographical location into account. The existing solutions based on distance or autocorrelation models are dissatisfying, due to the considerable variation within the property market. The purpose of this paper is to determine the location factor (*LF*) as a measure designating the location of the agricultural parcels based on weight distances to community centres, roads, and the homestead as well as water bodies and forest. Moreover, the *LF* could work as a grouping variable, enabling the use of spatial statistics methods to allot the clusters of similar farmlands. The location factor is universal and could be applied in a variety of spatial analyses at the municipality level, in public investment planning, land consolidation or land value map making.

The paper is structured as follows: the next section (section 2) presents the research methods, section 3 describes the study area and data used. It is followed by a description of the results and discussion (section 4). Finally, brief concluding remarks and the advantages and limitations of the research findings are presented (section 5).

2. Research methodology

The multivariate statistics introduced by Czekanowski (1913) and Hellwig (1968), based on simplifying the multi-attribute reality by reducing the dimension of space, was used to process location attributes and finally compute the location factor (*LF*). The *LF* was calculated according to the author's own method as a weighted average of the value of the diagnostic variables divided by a constant 5, in accordance with the formula (1):

$$LF_i = \frac{\sum_{j=1}^{m} x_{ij} \times w_j}{5}, \tag{1}$$

where:

LF_i – the synthetic factor of the i-agricultural parcel

x_{ij} – the empirical data of the i-agricultural parcel and j-characteristic, where $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$, by what $n, m > 1$

w_j – the weight of the j-attribute, designated in accordance with the formula (3).

The transformation of the weighted average value of diagnostic variables, by dividing them by a constant 5, resulted in a normalization of the *LF* range [0, 1]. To designate the weighting coefficients of diagnostic characteristics the author's own formula (2) was applied, based on the correlation ratio (η – eta):

$$w_j = \frac{\left|\eta_{yx}\right|}{\sum_{j=1}^{m}\left|\eta_{yx}\right|}, \tag{2}$$

where:

η_{yx} – is the correlation ratio of variable y (parcel price) and x (j-location characteristic) and

$$w_j \in [0,1], \quad \sum_{j=1}^{m} w_j = 1\,. \tag{3}$$

The correlation ratio (η) called the Pearson's nonlinear correlation coefficient was calculated by the use of equations (4). The advantage of the correlation ratio (η) is the fact that it does not depend on the shape of the curve expressing the relationships between the variables. It could be used to study the linear and nonlinear correlations of variables as well as for the analysis of a large number of observations:

$$\eta_{yx}^2 = \frac{\sigma_{\bar{y}}^2}{\sigma_y^2}, \quad \text{where} \quad \sigma_{\bar{y}}^2 = \frac{\sum_x n_x \left(\bar{y}_x - \bar{y}\right)^2}{\sum_x n_x} \quad \text{and} \quad \sigma_y^2 = \frac{\sum_{x,i} \left(\bar{y}_{xi} - \bar{y}\right)^2}{n}, \tag{4}$$

where:

η_{yx} – correlation ratio of variable y and x

$\bar{y}_x$ – mean of the variable y of the category x

$\bar{y}$ – mean of the variable y (the whole population)

σ_y^2 – variance of variable y and x

n_x – the number of observations in category x

n – the number of the population.

The diagnostic (dependent) location-based variables were selected after an in-depth study of the literature presented in the Introduction section. The distances to the city centre and roads are perceived to be of utmost importance by researchers and appraisals. They are used in agricultural land valuation in many countries e.g. Poland (Bitner et al. 2017), Sweden (Nilsson and Johansson 2013), Russia (Prishchepov et al. 2011), USA (Nivens et al. 2002, Bastain et al. 2002). Moreover, the proximity of environmental amenities like water, forests and protected areas also plays a significant role in shaping the selling prices of parcels due to the possibility of land use change, which was stressed among others by Aguiar et al. (2007).

Finally, due to the environmental diversity of the analysed area, five location attributes were considered. They were distances to (1) the municipality (community) centre, perceived as the Office of Local Authorities', (2) paved roads, (3) homestead buildings, as well as the vicinity of (4) forests and (5) water bodies. All distances were computed as a Euclidean distance from the parcel centroid (the geometric centre). The reason for this decision was the infrastructure characteristics of the analysed area, in particular the relatively dense road network ensuring access to the road for each parcel and the location of the built-up area along the main roads. Simplification related to the use of Euclidean distance as an alternative to network analysis, has been successfully used in many studies, e.g. Bastian et al. (2002), Nilsson and Johansson (2013) as well as by Prishchepov et al. (2011) for land taxation in Russia.

Water vicinity was determined on the basis of the watercourse density index, computed as a relation of all watercourse lengths to the municipality area (km/km^2). While the forest was determined on the basis of woodland density expressed as the area covered by forest and woodlands divided by the total municipality area.

Moreover, the *LF* was used as a similarity measure to identify the clusters of land parcels described by similar locational characteristics (i.e. those that are spatially autocorrelated), based on the global and local Moran's *I* statistic. The global Moran's *I* statistic was determined by the following equation (5):

$$I_g = \frac{N}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(k_i - \bar{k}\right)\left(k_j - \bar{k}\right)}{\sum_{i=1}^{n}\left(k_i - \bar{k}\right)^2}, \tag{5}$$

where:

N – number of objects that are included in the study

w_{ij} – elements of spatial weight matrix (neighbourhood)

k_i, k_j – are the values of the variable for the spatial objects i and j

$\bar{k}$ – this is the mean value of the variable for all objects.

The value of I_g depends somewhat on the assumptions built into the spatial weights (w_{ij}) matrix $\mathbf{W}$, elaborated according to equation (6) (Getis and Aldstadt 2004):

$$\mathbf{W} = \begin{bmatrix} w_{11} & \cdots & w_{1N} \\ \vdots & \ddots & \vdots \\ w_{N1} & \cdots & w_{NN} \end{bmatrix}, \tag{6}$$

where:

w_{ij} – the elements of spatial weight matrix, size $N \times N$, based on inverse of the Euclidean distance.

Weights matrices are row-standardized with the values of each of its rows summing to one. The global Moran's I autocorrelation coefficients were verified through a test for checking the significance of Moran's coefficient. This test served the purpose of verifying the hypothesis about a lack of correlation between the standardized value and the spatial lag of the studied variable. Formulation of hypotheses:

$H_0: \quad I = 0$

$H_1: \quad I \neq 0$

On the basis of the test statistics, p value was estimated and then compared with the chosen significance level α:

if $p \leq \alpha \Rightarrow$ reject H_0 and accept H_1

if $p > \alpha \Rightarrow$ there is no reason to reject H_0.

The acceptance of the null hypothesis means no spatial autocorrelation, which means that the values of *LF* are randomly distributed in the study area. The rejection of the null hypothesis, and the acceptance of the alternative hypothesis, means the existence of the spatial autocorrelation. Therefore the value of location factors is clustered or dispersed. The calculations have been performed for the corrected significance level α with Bonferroni correction: $\alpha 1 = \alpha / k$ where k is the mean number of the adjoining parcels. The results of the global spatial autocorrelation are presented in the Moran's scatter plot.

The local Moran's I statistic was used to identify the spatial clusters of parcels that are autocorrelated. The statistic was calculated on the basis of the formula (7):

$$I_{li} = \frac{\left(k_i - \bar{k}\right)\sum_{i=1}^{n} w_{ij}\left(k_j - \bar{k}\right)}{\sum_{i=1}^{n}\left(k_j - \bar{k}\right)^2}, \tag{7}$$

where:

n – the number of objects (parcels) that are included in the study

w_{ij} – the elements of spatial weight matrix (neighbourhood)

k_i, k_j – the values of the variable for the spatial objects i and j

$\bar{k}$ – the mean value of the variable for all objects.

The analysis of *LF* spatial auto-correlation has been conducted for each of the three parcel clusters, defined in the pre-processing stage of this study. Parcels have been grouped using a k-means approach (Gašparović et al. 2017), based on the similarity of their structural characteristics, such as: area, shape, soil fertility and cropland type. These attributes were selected after an in-depth literature study, described in detail in the work by Maleta (2017). The purpose of parcel grouping into structural groups was to divide the local market into relatively homogeneous structural areas, which facilitated the estimation of parcels values and the impact of the location on this value.

3. Study area and data used

The study was carried out for Krotoszyce municipality, located in south west Poland, in Lower Silesian province, Legnicki county (Fig. 1).

Fig. 1. *Krotoszyce municipality location (source: https://www.google.pl/maps).*

This is a small municipality, the area of which is 68 sq. km (Central Statistical Office 2014). Krotoszyce's economy is strictly related to agriculture, this is due to the fertile soil (including alluvial soil and black earth). The land structure is dominated by 84% of cropland (87% of which is arable land). 8.1% of the municipality area is taken by building sites, whereas 7.9% by forests. The building sites are mainly located along the main roads.

The study covered parcels intended for agricultural purposes in the Local Spatial Development Plan of the Municipality. The information on agricultural lands and location attributes were taken from the three public, national wide, registers: Lands and Buildings Register (EGiB) and Database of the Topographical Objects (BDOT10k), and the Register of Real Estate Prices and Values (RCiWN). The lands and buildings register (EGiB), also called cadastre, is maintained by the District Governor's Office in Legnica under the responsibility of the Surveyor General of Poland. It continuously covers the whole country's territory and comprises 33 million cadastral parcels (Izdebski 2017). Data, available in vector format and a local coordinate reference system (Kadaj 2016), consists of 2979 land parcels. The Database of Topographical Objects (BDOT10k) is a seamless vector database, storing topographical data for the whole country. Data are organised in several thematic layers out of each the following were used in this study: administrative units, forests, watercourses, roads network, and land use. RCiWN deliver data on purchase-sale transaction prices of agricultural lands, buildings and apartments. The study used the data of 370 parcels from 2003 to 2013.

4. Results and discussion

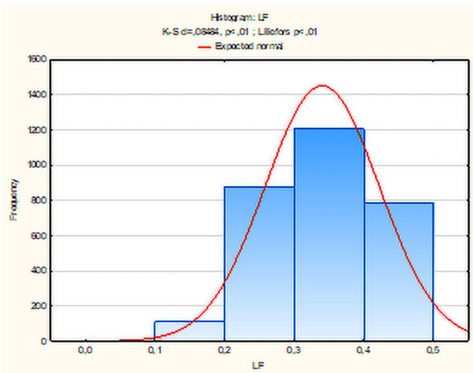
The location factor (*LF*) is based on the three distance-based parcel characteristics, i.e. distances to: paved roads, the municipality centre and the homestead buildings. The remaining two locational characteristics, namely distance to water bodies and water courses as well as distance to forests, were rejected at the early (pre-processing) stage of the research. The reason for such a decision came from the analysis of spatial distribution and the area covered by forest and water bodies. Forests mainly occupy areas at the fringe of the municipality and along the only watercourse. In general, forest takes up 7.9% of the municipality area. In comparison, the woodland density of the Lower Silesian province equals 29.7% (Central Statistical Office 2015), and of Poland 30.7%. River network density, calculated as watercourse length per one square km, is also very low, and equals 0.59. In addition, there are no drainage and irrigation facilities in the analysed area.

The analysed factors have proven to be extremely important, which is confirmed by the high values of nonlinear correlation coefficient. Moreover, they impact on location characteristics in very similar, and varies from 31% for distance to the paved road, to 35% for distance to the municipality centre (Table 1). As found be Maleta (2017) these factors are not mutually correlated.

Table 1. *Pearson's nonlinear correlation coefficients and weights of the location characteristics.*

Location characteristic	**Pearson's nonlinear correlation coefficient (correlation ratio η_{yx})**	**Weight (%)**
Distance to the paved road	0.89	31
Distance to the municipality centre	0.98	35
Distance from the homestead buildings	0.94	34

The values of synthetic *LF* are normally distributed with standard deviation equals to 0.08, and mean 0.340 and median 0.337 (Fig. 2).



Statistics	**Location factor (*LF*)**
Minimum	0.130
Maximum	0.500
Arithmetic mean	0.340
Median	0.337
Standard deviation	0.080

Fig. 2. *LF histogram and descriptive statistics.*

The spatial distribution of *LF* (Fig. 3), presented in the form of a choropleth map, shows that 60% of the land parcels take the *LF* values from 0.27 to 0.41. These parcels are found in the central and eastern parts of the research area, as well in the north-south strip of the main road and built-up area concentrations. The highest values of the *LF* indicator (more than 0.41) characterised 612 (20.7%) parcels located in the vicinity of built-up areas and directly on the main road. The lowest values *LF* takes for 18.9% of parcels, generally located in the western part of the municipality. Here the access to sales markets is hindered by the river as well as green areas like parks, bushes, and forests. On the other hand, environmental amenities create better conditions for organic farming and non-agricultural activities, e.g. tourism.

A detailed analysis of the *LF* spatial autocorrelation was conducted in a previously selected parcel cluster (see section Research methodology). A brief description of those clusters, based on Maleta (2017) is given below. Cluster I groups parcels with a strongly elongated shape, similar to a rectangle, with an area which varied in size from 0.5 ha to 5 ha. The production capacity measured by soil fertility is good. The second cluster (Cluster II) includes parcels of a regular shape and area exceeding 1 ha. The agricultural conditions are better than in cluster I due to fertile soil, as well as the favourable size and shape of parcels. Cluster III comprises

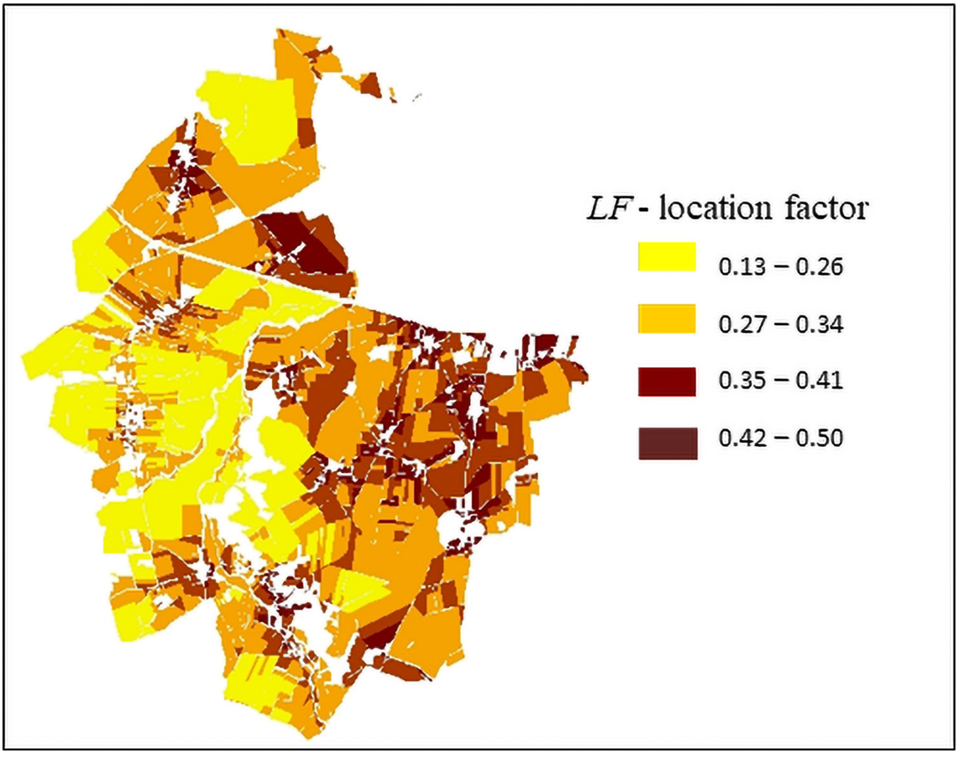


Fig. 3. *Geographic distribution of the location factor (LF).*

small, square parcels (area of 0.1 ha to 0.5 ha) well suited for organic agriculture production, orchards or home gardens (Maleta 2017).

The global Moran's *I* coefficient (Table 2) in described clusters takes values ranged from 0.279 to 0.491.

Table 2. *The global Moran's I statistic of the location factor (LF).*

Statistic	Cluster I	Cluster II	Cluster III
Analysed variables	*LF*	*LF*	*LF*
Significance level	0.05	0.05	0.05
Moran's *I*	0.346	0.279	0.491
Expected *I*	–0.001054	–0.001381	–0.000767
Variance *I*	0.000012	0.000008	0.000012
Z statistic	81.4901	75.1656	113.5383
p-value	<0.000001	<0.000001	<0.000001

The value p calculated with the assumption of randomness, as in the case of the assumption of normality, was less than the standard assumed significance level $\alpha = 0.05$. Because $I > E(I)$ and $Z(I) > 0$ it could be concluded that there is a clear positive spatial autocorrelation in all analysed clusters. The high value of Z test statistic in I, II and III clusters, confirms that the global autocorrelation is significant at a significance level less than 0.000001. The significance test of the global Moran's statistic enabled the rejection of the null hypothesis, as well as the acceptance of the alternative hypothesis. This confirms the existence of spatial autocorrelation.

This means that agricultural parcels with high values of *LF* are surrounded by parcels with high values and parcels with low values of *LF* are surrounded by parcels with low values. The difference in variance determined for both cases of significance level testing is negligible, which proves the high spatial stability of *LF*. The graphic presentation of the global spatial autocorrelation is presented by the Moran's scatter plots (Fig. 4).

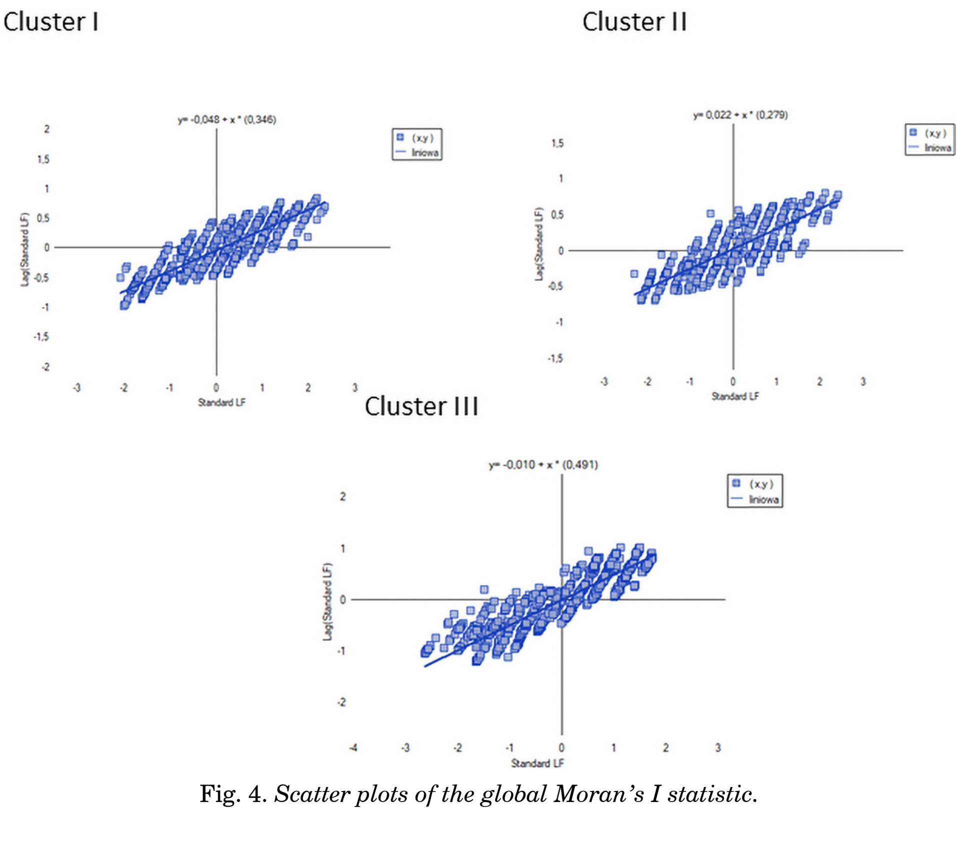


Fig. 4. *Scatter plots of the global Moran's I statistic.*

The diagrams show the positive spatial autocorrelation. Points that represent parcels lie in the first and the third quarters of the coordinate system and near the line (straight line). The increase of *LF* is reflected in the increase of *Lag* (standard *LF*). Global Moran's coefficient takes values greater than 0 ($I > 0$) and indicates the presence of clusters of similar values i.e. positive autocorrelation. On this basis, it was concluded that in separate groups, the positive spatial autocorrelation occurs in the municipality of Krotoszyce. This means that the values of *LF* are not randomly distributed in the clusters. Their distribution is related to the location of parcels in geographic space. Thus, parcels of similar location, which are geographically close, are more similar to one another in terms of the analysed variable than those which are remote, and they have the ability to create the spatial clusters with similar values of variable.

Two types of parcel groups of similar location were found in each of the clusters (Fig. 5). Statistically significant parcels characterised by high *LF* value (High-High) are marked in red. In contrary, parcels described by low *LF* (Low-Low) are emphasised in blue.

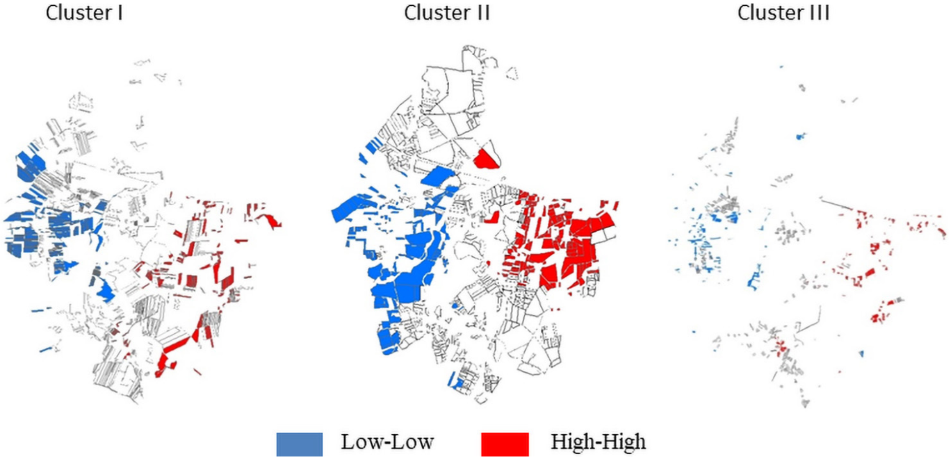


Fig. 5. *Autocorrelated group of parcels in previously defined clusters.*

Hence, the area of the Krotoszyce rural community was divided into nine locational classes (Fig. 6). These classes vary in distance to paved roads, the distance to the community, and the distance to homestead buildings.

Parcels in each of the locational classes (Fig. 6) are located in a meridian, referring to the dominant structure of the built-up centre of the community, the course of the main road, and thus the value of *LF*. The average *LF* values range from 0.21 to 0.45 (Fig. 7). The location factor assumes the highest value of 0.45 in class 7 (cluster III), and the lowest 0.21 in class 3 being part of cluster I. Most parcels comprise classes 8 (568 parcels) and 2 (518 parcels), the average value of *LF* in these classes takes the values of 0.38 and 0.31, respectively. Parcels with high *LF* values (High-High type) are concentrated in classes 1, 4 and 7, while the lowest in classes 3, 6 and 9 (Low-Low type of autocorrelation).

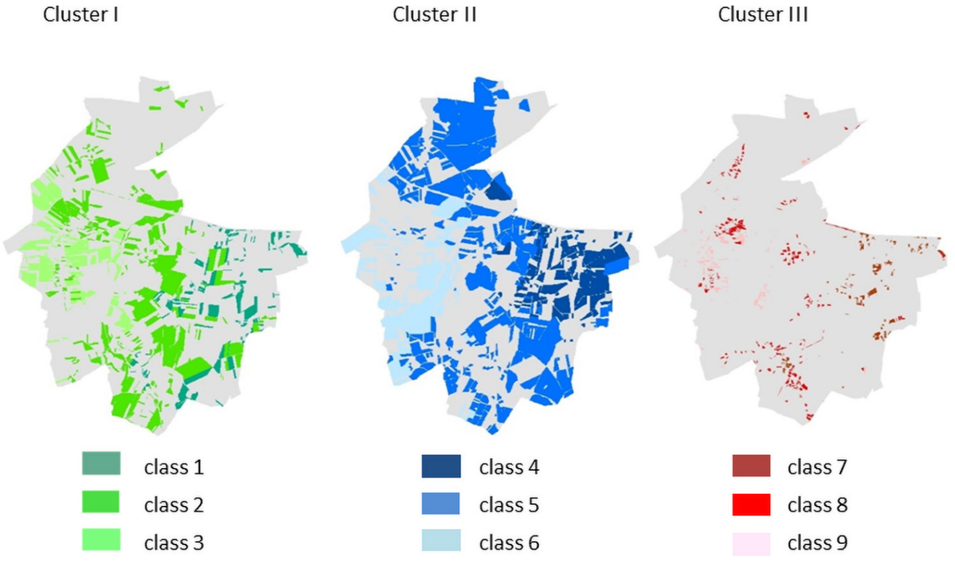


Fig. 6. *The locational classes of agricultural parcels.*

Fig. 7. *The average values of LF in the location classes.*

5. Conclusion

The elaborated location factor is a synthetic measure that refers to the location of the parcel. The *LF* factor gives the possibility of designating the location of parcels objectively and replacing the location characteristics with one variable. There is also an option of the application of GIS tools, which plays an important role in the designation of the location factor. Operations on thematic layers enable a fully automated and quick acquisition of data describing parcel accessibility to selected locations. The *LF* synthetic indicator was designated on the author's own formula using the author's own method of the weighting of the location characteristics. The *LF* works also as a similarity measure on the basis of which the grouping of agricultural parcels was carried out. The strength of the relationship between parcels was determined on the basis of spatial autocorrelation, which enabled the identification of clusters of parcels, similar in terms of location, called location classes.

The *LF* could be used for agricultural land values maps elaboration. The elaborated methodology allotting the location classes helps in defining land values prices. The location factor is universal and could be used for various spatial analyses, where the distance to the selected place plays an important role. It could be also applied to various tasks implemented in the municipality, relating to spatial planning. On the basis of the *LF* indicator, it is possible to assess whether the planned public investment may be located in a given area when the distance to specific places in the municipality is taken into account.

The developed *LF* factor also has some drawbacks that cause a generalisation of the obtained results. They are related to the applied statistical and spatial methods and relatively uniform environmental and economic conditions of the analysed area. Adoption of the Euclidean distance instead of network analysis is definitely one of the main constraints. The limited number of places essential from the point of view of the market for agricultural production as well as environmental amenities are further limitations. In our future research we would try to overcome these limitations. In particular, we will test the *LF* in some municipalities that are environmentally and infrastructurally diverse.

References

Aguiar, A. P. D., Camara, G., Escada, M. I. S. (2007): Spatial statistical analysis of land-use determinants in the Brasilian Amazonia: Exploring intra-regional heterogeneity, Ecological Modelling, 209(2–4), 169–188.

Bastian, Ch. T., McLeod, D. M., Germino, M. J., Reiners, W. A., Blasko, B. J. (2002): Environmental amenities and agricultural land values: a hedonic model using geographical information system data, Ecological Economics, 40, 337–349.

Bitner, A., Litwin, U., Michalczewska, A. (2017): Cartographic and statistical methods in the analysis of local real estate market as exemplified by Rabka-Zdrój, Geomatics, Land management and Landscape, 1, 7–15.

Calka, B., Nowak Da Costa, J., Bielecka, E. (2017): Fine Scale Population Density Data and its Application in Risk Assessment, Geomatics, Natural Hazards and Risk, 8(2), 1440–1455.

Cavailhès, J., Wavresky, P. (2003): Urban influences on periurban farmland prices, European Review of Agricultural Economics, 30(3), 333–357.

Cellmer, R., Beĺej, M., Ǵrobek, S., Šubic Kovač, M. (2014): Urban land value maps – a methodological approach, Geodetski Vestnik, 58(3), 535–551.

Central Statistical Office (2014): GUS 2014, Gmina wiejska Krotoszyce, powiat legnicki, Statystyczne Vademecum Samorzřdowca, Urzřd Statystyczny, Wrocĺaw.

Central Statistical Office (2015): GUS 2015, LeŹnictwo, Gĺówny Urzřd Statystyczny, Warszawa.

Chica-Olmo, J., Cano-Guervos, R., Chica-Olmo, M. (2013): A coregionalized model to predict housing prices, Urban Geography, 34(3), 395–412.

Choumert, J., Phélinas, P. (2015): Determinants of agricultural land values in Argentina, Ecological Economics, 110, 134–140.

Czekanowski, J. (1913): Zarys metod etatystycznych w zastosowaniu do antropologii, "Prace Towarzystwa Naukowego Warszawskiego" 1913, nr 5.

D'Amato, M. (2010): A location value response surface model for mass appraising: An "iterative" location adjustment factor in Bari, Italy, International Journal of Strategic Property Management, 14(3), 231–244.

Delbecq, B. A., Kuethe, T. H., Borchers, A. M. (2014): Identifying the Extent of the Urban Fringe and Its Impact on Agricultural Land Values, Land Economics, 90(4), 587–600.

Demetriou, D. (2015): A GIS-based hedonic price model for agricultural land, Proceedings Vol. 9535, Third International Conference on Remote Sensing and Geoinformation of the Environment, Paphos, Cyprus.

Demetriou, D. (2016): The assessment of land valuation in land consolidation schemes: The need for a new land valuation framework, Land Use Policy, 54, 487–498.

Demetriou, D., Stillwell, J., See, L. (2013): A new methodology for measuring land fragmentation, Computers, Environment and Urban Systems, 39, 71–80.

Drescher, K., Henderson, J., McNamara, K. (2001): Farmland Prices Determinants, Paper presented at American Agricultural Economics Association Annual Meeting, August 5–8, 2001, Chicago, Illinois.

Drobne, S., Lisec, A. (2009): Multi-attribute Decision Analysis in GIS: Weighted Linear Combination and Ordered Weighted Averaging, Informatica, 33, 459–474.

Drobne, S., Lisec, A., Bogataj, M. (2008): GIS Analysis of Rural Land Market in Slovenia, Proceedings of 11th AGILE International Conference on Geographic Information Science 2008, University of Girona, Spain, 1–11.

Gašparović, M., Zrinjski, M., Gudelj, M. (2017): Analysis of Urbanization of Split, Geodetski list, 71(3), 189–202.

Getis, A., Aldstadt, J. (2004): Constructing the Spatial Weights Matrix Using a Local Statistic, Geographical Analysis, 36(2), 90–104.

Hellwig, Z. (1968): Zastosowanie metody taksonomicznej do typologicznego podziaĺu krajów ze wzglêdu na poziom rozwoju oraz zasoby i strukturê wykwalifikowanych kadr, Przeglr̀d Statystyczny,15(4), 307–327.

Hudecová, L'., Geisse, R., Gašincová, S., Bajtala, M. (2017): Quantification of Land Fragmentation in Slovakia, Geodetski list, (71)4, 327–338.

Izdebski, W. (2017): Analysis of the cadastral data published in the Polish Spatial Data Infrastructure, Geodesy and Cartography, 66(2).

Janus, J., ěopacka, M., John, E. (2017): Land consolidation in mountain areas, Case study from southern Poland, Geodesy and Cartography, 66(2), 241–252.

Kadaj, R. (2016): Empirical methods of reducing the observations in geodetic networks, Geodesy and Cartography, 65(1), 13–40.

Kuethe, T. H., Ifft, J., Morehart, M. (2011): The influence of urban areas on farmland values, Choices, 2nd Quarter, 26(2).

Ma, S., Swinton, S. M. (2011): Valuation of ecosystem services from rural landscapes using agricultural land prices, Ecological Economics, 70, 1649–1659.

Malczewski, J. (2004): GIS-based land-use suitability analysis: a critical overview, Progress in Planning, 62(1), 3–65.

Malczewski, J. (2006): Ordered weighted averaging with fuzzy quantifiers: GIS-based multicriteria evaluation for land-use suitability analysis, International Journal of Applied Earth Observation and Geoinformation, 8, 270–277.

Maleta, M. (2017): Methods of elaborating agricultural land values map, PhD thesis, Military University of Technology, Warsaw.

Maleta, M., Bielecka, E. (2014): Cluster analysis of land properties for the purpose of mass appraisal, SGEM 2014, Vol. II, 129–136.

Maleta, M., Calka, B. (2015): Examining spatial autocorrelation of real estate features using Moran statistics, 15th International Multidisciplinary Scientific GeoConference SGEM 2015, SGEM 2015 Conference Proceedings, June 18–24, 2015, Vol. 2, 841–848.

Maliene, V. (2011): Specialised property valuation: Multiple criteria decision analysis, Journal of Retail & Leisure Property, 9(5), 443–450.

Moscicka, A. (2015): European Data Model in GIS for movable heritage, Geografie, 120(4), 527–541.

Moscicka, A., Pokonieczny, K., Tomala, J. (2016): Selection of Optimal Measurement Point Density in Travel Time Mapping: Warsaw Airport Case Study, 2016 Baltic Geodetic Congress (BGC Geomatics), Gdansk, 211–216.

Nilsson, P., Johansson, S. (2013): Location determinants of agricultural land prices, Jahrb Reg wiss, 33, 1–21.

Nivens, H. D., Kastens, T. L., Dhuyvetter, K. C., Featherstone, A. M. (2002): Using satellite imagery in predicting Kansas farmland values, Journal of Agricultural and Resource Economics, 27, 464–480.

O'Connor, P. (1982): Locational valuation derived directly from the real estate market with the assistance of response surface techniques, Lincoln Institute of Land Policy.

O'Donoghue, C., Lopez, J., O'Neill, S., Ryan, M. (2015): A Hedonic Price Model of Self-Assessed Agricultural Land Values, Paper prepared for presentation at the 150th EAAE Seminar "The spatial dimension in analysing the linkages between agriculture, rural development and the environment" Jointly Organised between Scotland's Rural College (SRUC) and Teagasc Scotland's Rural College, Edinburgh, Scotland, October 22–23, 2015.

Peterson, S., Flanagan, A. (2009): Neural Network Hedonic Pricing Models in Mass Real Estate Appraisal, Journal of Real Estate Research, 31(2), 147–164.

Plantinga, A. J., Lubowski, R. N., Stavins, R. N. (2002): The effects of potential land development on agricultural land prices, J Urban Econ, 52(3), 561–581.

Pokonieczny, K., Calka, B., Bielecka, E., Kaminski, P. (2016): Modeling Spatial Relationships between Geodetic Control Points and Land Use with Regards to Polish Regulation, 2016 Baltic Geodetic Congress (BGC Geomatics), Gdansk, 2016, 176–180.

Prishchepov, A., Radeloff, V., Müller, D., Dubinin, M., Baumann, M. (2011): Determinants of agricultural land abandonment in post-soviet European Russia, "Will the "BRICs Decade" continue? – Prospects for trade and growth" 23–24 June 2011, Halle (Saale), Germany.

Sinclair, R. (1967): Von Thünen and urban sprawl, Annals of the Association of American Geographers, 57(1), 72–87.

Sklenicka, P., Molnarova, K., Pixovaa, K. C, Salek, M. E. (2013): Factors affecting farmland prices in the Czech Republic, Land Use Policy, 30(1), 130–136.

Tobler, W. (1970): A computer movie simulating urban growth in the Detroit region, Economic Geography, 46(Supplement), 234–240.

Tu, Y., Sun, H., Yu, S. (2007): Spatial autocorrelations and urban housing market segmentation, Journal of Real Estate Finance and Economics, 34, 385–406.

Walford, N. (2001): Book Review of: Agricultural policy in the European Union, European Urban and Regional Studies, 8(2), 179–180.

Ward, R. D., Weaver, J. R., German, J. C. (1999): Improving CAMA Models using geographic information systems/response surface analysis location factors, Assessment Journal, 6(1), 30–38.

Ward, R. D., Guilford, J., Jones, B., Pratt, D., German, J. C. (2002): Piecing together location: three studies by the Lucas County research and development staff, Assessment Journal, 9(5), 15–48.

Wigier, M. (2012): Time and space in long-term development of agriculture and rural areas – a retrospective approach, Journal of Agribusiness and Rural Development, 2(24), 263–272.

Sintetska mjera lokacije poljoprivredne parcele na temelju udaljenosti

SAŽETAK. Cilj je ovog rada odrediti faktor lokacije (LF) kao sintetsku, kvantitativnu mjeru lokacije poljoprivredne parcele. Viševarijantna komparativna analiza i originalna formula, koja se temelji na težinskoj udaljenosti do odabranih mjesta, korišteni su za određivanje faktora lokacije. Faktor omogućuje objektivni opis lokacija parcele te zamjenjuje nekoliko lokacijskih karakteristika jednom varijablom što pojednostavljuje računski postupak i može se koristiti za mnoge primjene. LF je također primjeren kao mjera sličnosti u raspoređivanju parcela u skupine te se može primijeniti u raznim prostornim analizama na razini općina, u planiranju javnih ulaganja, komasaciji ili izradi karata vrijednosti zemljišta.

Ključne riječi: faktor lokacije, karakteristike lokacije, poljoprivredna zemljišta.

Received / Primljeno: 2018-04-23

Accepted / Prihvaćeno: 2018-10-04