Exposure to human influence – a geographical field approximating intensity of human influence on landscape structure

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ABSTRACT
A new spatial variable for the land use and land cover change modelling is introduced, approximating the intensity of human influence on the landscape. The ‘exposure’ simulates the dilution of human activity from settlements (source points with information about population size or other human activity quantification) to landscape, based on the accessibility. Exposure to a settlement is directly proportional to its population size and inversely proportional to the cost distance from the settlement. Cost distance uses the sine of the slope angle as a cost raster to simulate a barrier effect of the terrain. Overall exposure to human influence summates exposure to all individual settlements in a region. The resultant raster field created for Slovakia achieves observable resemblance to the actual intensity of land use derived from Corine Land Cover map. The ArcGIS tool developed for the exposure calculation is supplemented.

1. Introduction
Land cover and land use change modelling attracts attention as the need for a rational management of the landscape is becoming increasingly important worldwide. Numerous models have been applied to explain past changes and predict those in the future, using a wide variety of statistical methods, ranging from regression (e.g. Aspinall, 2004; Rutherford & Bebi, 2008; Serra, Pons, & Saurí, 2008; Van Doorn & Bakker, 2007) or canonical correspondence analyses (Hietel, Waldhardt, & Otte, 2004) to cellular automata (Basse, Omrani, Charif, Gerber, & Bódis, 2014; Ku, 2016; Verstegen, Karssenberg, van der Hilst, & Faaij, 2014), agent-based models (Hewitt, van Delden, & Escobar, 2014; Mialhe, Becu, & Gonnell, 2012; Murray-Rust, Robinson, Guillem, Karali, & Roussevell, 2014), advanced regression trees and artificial neural networks (e.g. Smaliychuk et al., 2016; Tayyebi & Pijanowski, 2014; Wang, Ren, & Liu, 2016). The models usually do not focus only on the quality or quantity of the change, but also on its localisation. Therefore, spatial variables are necessary to be used in the models, regardless of the modelling method.

There is a wide spectrum of the variables used in the studies, representing both environmental and socioeconomic characteristics of the landscape (Bürgi, Hersperger, & Schneeberger, 2004; van Vliet, de Groot, Rietveld, & Verburg, 2015). Variables representing the intensity of human activity belong to the most important ones. There is a wide variety of their definitions, focusing on demographic, economic, agricultural and other indicators. Population size (Figure 1) may be considered as a basic indicator, used for example by Millington, Perry, and Romero-Calcerrada (2007) and Calvo-Iglesias, Fra-Paleo, and Díaz-Varela (2009), its change by Gellrich, Baur, Koch, and Zimmermann (2007). Wang et al. (2016) used GDP and other economic variables, while various agricultural variables were used by Hietel, Waldhardt, and Otte (2005), Van Doorn and Bakker (2007), Martinez (2011), or Smaliychuk et al. (2016). However, the use of these indicators is restricted by the fact that they are usually assigned to an administrative area. Population density is an efficient example. It is widely used to depict the distribution of population in landscape (e.g. Demek, Mackovčin, & Slavík, 2012; Inouye, de Sousa, de Freitas, & Simões, 2015; Ku, 2016; Martinez, 2011; Newman, McLaren, & Wilson, 2014) but the resulting picture is strongly dependent on the administrative borders, which do not always adequately approximate the actual spread of the human activity in the landscape (Figure 2).

Accessibility is a further key factor commonly used to approximate the intensity of human influence in the landscape (e.g. Eiter & Potthoff, 2016; Martinez, 2011; Shu, Zhang, Li, Qu, & Chen, 2014). Most of the studies use Euclidean distance to human settlement or road
network for its determination (Baumann et al., 2011; Łowicki, 2008; Rutherford & Bebi, 2008; Xu, McNamara, Wu, & Dong, 2013). Although this approach offers simplicity, we consider the use of cost distance much more appropriate, because barrier effects of the terrain, land cover and other factors shaping transportation routes can then be taken into account (e.g. Etter, McAlpine, Pullar, & Possingham, 2006; Martinez, 2011; Müller & Munroe, 2008; Pazúr, Lieskovský, Fernanec, & Oťaheľ, 2014; Schirpke, Leitinger, Tappeiner, & Tasser, 2012). Accessibility from human settlement may be considered as one of the most important predictors of the land use formation, reflecting ‘how far’ is human activity concentrated. However, it does not distinguish among settlements with a different intensity of human activity (quantified by population size, for example) and therefore it cannot adequately assess the intensity of human activity in the landscape.

This paper proposes the concept of variable ‘exposure to human influence’. Its main goal is to combine the intensity of human activity and accessibility in one spatial variable for the purposes of land cover and land use change modelling. While developing the concept, we tried to balance its ability to approximate the human influence in sufficient detail on the one side, and its simplicity on the other side. Under simplicity, we understand both relying on easily obtainable data and using the smallest possible number of calibration coefficients.

We are aware that there are many ways to define both source variables – human activity and accessibility. For the purpose of this initial concept, we simply use population size as the measure of human activity and terrain slope as the sole variable in accessibility calculation. However, population can be easily replaced by any other relevant point-assigned measure of human activity without any change of this concept. A small change in the equation allows to implement other determinants of accessibility.

We produced the ‘exposure to human influence map of Slovakia’ to demonstrate this concept’s ability to approximate the human influence on the landscape, especially in the hilly areas. The resultant raster field of exposure is available for detailed examination as an attachment of this article, as well as the ArcGIS tool used for the calculation.

2. Methods

Derivation of the final exposure concept consisted of three steps:

1. Defining the general exposure equation;
2. Replacing Euclidean distance by cost distance;
3. Specifying the barrier raster for cost distance calculation.

2.1. Exposure

Our exposure definition is based on the following simple principle: exposure to human influence from a settlement (‘source point’) is directly proportional to its population size (or other quantification of human activity – generally termed ‘source intensity’) and inversely proportional to the distance from this
point. It is an analogy to widespread urban gravity models, which model spatial interaction of cities, urban growth and development (Chen, 2009; Paulov, 2004). This principle is further analogous to Newton’s law of universal gravitation, Coulomb’s law of electrostatics and other inverse square laws modelling any point-source radiation in three-dimensional space:

\[
\text{Intensity} = \frac{\text{Source intensity}}{\text{Distance}^2}. \tag{1}
\]

Quadratic influence of distance can be explained by geometric dilution corresponding to point-source radiation into a three-dimensional space. However, because we are modelling the spread of the intensity into a two-dimensional space of landscape, we suggest the simple value of distance instead of its squared value. The reason is that the density of flux lines is inversely proportional to the square of the distance in 3D, but it is inversely proportional to the simple distance in 2D space.

Since exposure value in the source point (settlement) should equal source intensity, we applied the addition of the number ‘1’ in the equation denominator. Then, if the population size of the source point – centre c1 is the measure of its influence, the exposure to the centre c1 (Ex₁) is:

\[
\text{Ex}_c1 = \frac{\text{Population}_{c1}}{1 + \text{distance}_{c1}}. \tag{2}
\]

Exposure to human activity from n centres is then defined as:

\[
\text{Ex} = \sum_{i=1}^{n} \frac{\text{Population}_i}{1 + \text{distance}_i}. \tag{3}
\]

The resultant exposure values are dependent on the unit of distance; for example, exposure equals one half of the original population in the distance of one meter, one-third in two metres, etc. Therefore, we introduced distance one (d1) calibration coefficient to eliminate dependence on distance units. It is defined as the distance, in which exposure to human influence is one half of the exposure in the centre:

\[
\text{Ex} = \sum_{i=1}^{n} \frac{\text{Population}_i}{1 + (\text{distance}_i/d1)}. \tag{4}
\]

### 2.2. Cost distance

The previous concept alone would probably not yield very original results, as it would produce a raster field with circularly shaped isolines, which would probably be relatively similar to some other concepts using for example kernel density (Figure 2). Precision is obtained by replacing simple Euclidean distance with cost distance, using the barrier effect of landscape as the cost raster. We used ArcGIS tool Cost distance for this purpose. The cost distance algorithm automatically searches for the smallest cost distance path between the raster cell and the centre. The cost distance is calculated as

\[
\text{Cost distance} = \sum_{j=1}^{m} (\text{distance}_j \ast \text{barrier effect}_j), \tag{5}
\]

where \(j\) is an individual raster cell on the least-cost path and \(m\) is the set of all cells on the path. Distance \(j\) represents a distance travelled across the cell \(j\). It equals the cell size if the path crosses the cell perpendicularly to its side, or 1.414214 (square root of 2) of the cell size if it crosses the cell diagonally. The cost distance raster can be used as a representation of the accessibility. The barrier effect is the key variable affecting the shape of this raster.

### 2.3. Barrier effect

Slope gradient was used as the main measure of the barrier effect of landscape. We did not consider other factors affecting accessibility, such as land cover and road network, in order to keep simplicity of the concept. Sine of the slope was utilised because it was physically well interpretable: It was derived from the decomposition of the gravitational force on the slope, with sine representing the component of the force needed to overcome the barrier. The sine transformation of the slope was suggested for the accessibility modelling also in the work of Minár, Tremboš, and Vajlíková (1992).

Regarding Equation (5), the barrier effect should have value ‘1’ in zero-slope areas so that the cost distance on the plain surface is equal to the Euclidean distance. The value should then increase to ‘2’ in the areas where the costs needed to ensure a bi-directional transportation double the costs in the flat areas. Similarly, it should increase to ‘3’ in the areas where the costs triple. A wide range of transportation costs needs to be considered. Under ‘ensuring the transportation’, we therefore do not understand only the energy needed for physical transport of persons or goods, but also the energy for building a sufficient infrastructure and other related costs.

Two components of the barrier raster calculation were introduced to implement these requirements: the constant ‘1’ ensured the equality of cost distance to Euclidean distance in the zero-slope areas and the coefficient ‘\(k\)’ enabled calibration of the original sine-slope raster. The resulting equation is

\[
\text{Barrier effect} = 1 + k \times \sin \text{ slope}. \tag{6}
\]

Calibration of the barrier effect by the coefficient \(k\) enables change in the cost distance isolines shape. Setting the coefficient higher strengthens the barrier effect.
Figure 2. Comparison of various concepts of population dispersion representation and the actual land use intensity derived from the Corine Land Cover map.
Transport along the areas of lower slope is then preferred, even if it involves longer distance. This produces more lobed shape of the cost distance isolines. Setting the coefficient to lower values weakens the barrier effect of the slope. Transport along paths with shorter distance is preferred, even if it involves steeper slopes. This results in more compact cost distance isolines shape. Changing the ‘k’ coefficient, however, also changes the cost distance raster scale with a change in the overall value level and therefore re-consideration of ‘d1’ (4) is required.

2.4. Final definition of the exposure to human influence

Embedding cost distance calculation in the exposure equation gives

\[ Ex = \sum_{i=1}^{n} \left(1 + \left(\frac{\text{Population}_i}{\text{distance}_i(1 + k \times \text{sinslope}_i)}\right) / d1\right) \]

Calculation in ArcGIS requires two data inputs: (1) slope raster and (2) point layer of centres with numeric field providing the intensity of human influence, for example, population size. The tool works in the following steps:

(1) Calculation of the barrier raster
(2) Iterative calculation of the exposure:
   (a) Calculation of the cost distance raster of a centre i
   (b) Calculation of the exposure to the influence from the centre i,
   (c) Addition of ‘Ex_i’ to the total exposure: ‘Ex_i’ is added to a zero raster and each following ‘Ex_i’ is added to the previous total exposure raster. This approach is chosen to avoid a memory demanding process where exposure rasters of all centres required summation in one step and increased hard-disk space.

The threshold value of the exposure – the minimum ‘Ex_i’ value calculated for the centre i was introduced to enable faster calculation of the exposure for the tasks with many centres. The calculation of the cost distance ceases when exposure shrinks to the threshold value, so cost distance is calculated only for the area where resultant exposure is higher than the threshold, rather than for the complete working extent. This provides less time-consuming cost distance computation for every centre; however, the threshold should not be set too high as this would bias the final result, especially in rural areas where small impacts from many villages become important.

### Table 1. Classification of the land cover hemeroby, originally published by Walz and Stein (2014) for Germany and modified for land cover in Slovakia.

| Hemeroby                  | Corine land cover                        |
|---------------------------|------------------------------------------|
| Ahemerobic areas          | Bare rocks                               |
| Oligohemerobic areas      | Forests; natural grassland; moors and heatland; sparsely vegetated areas; inland wetlands |
| Mezohemerobic areas       | Transitional woodland-scrub; burnt areas  |
| β-Euhemerobic areas       | Pastures; land principally occupied by agriculture with significant areas of natural vegetation; water bodies; green urban areas |
| α-Euhemerobic areas       | Arable land; permanent crops; complex cultivation patterns; sport and leisure facilities |
| Polyhemerobic areas       | Discontinuous urban fabric; airports     |
| Metahemerobic areas       | Continuous urban fabric; industrial or commercial units; road and rail network; mine, dump and construction sites |

2.5. Production of the exposure to human influence map of Slovakia

The exposure concept was tested with the use of real data (Figure 1) from the 2001 Slovak population census for 2935 municipalities and town parts (Tomášiková, 2010) and slope gradient derived from EUDEM elevation model with the resolution 25 m (European Environment Agency, 2013). The exposure computation resolution was set to 100 m. Several combinations of the k and d1 coefficients were tested in order to find the combination yielding a raster image that would satisfactorily approximate the intensity of human activity.

Decisions were based on the visual comparison with the Corine Land Cover 2012 data (European Environment Agency, 2016) because statistical testing of suitability of different model design requires more complex research. Level of hemeroby was assigned to each land cover class to estimate the actual human influence intensity (Table 1). Hemeroby can be understood as an integrative measure of the impact of all human intervention on ecosystems (Walz & Stein, 2014). A slightly modified version of Walz and Stein’s (2014) Corine Land Cover to hemeroby classification was applied. Data generalisation was then performed by focal statistics with 100-m radius of five cells raster resolution to improve the hemeroby map interpretation.

The final model design of this study employs k = 25 and d1 = 100, which are also set as the default values of the attached ArcGIS tool. The resultant map was designed in ArcGIS 10.3.1. A non-linear stretch of the colour ramp was used for the resulting raster.

3. Conclusions

Although approximation of human influence intensity depicted in the Main Map’s resultant exposure raster was developed solely from two spatial sources – slope angle raster and population size point layer – it
provides great detail. Relatively higher values of the exposure can simulate the shape of the meta- and poly-hemorobic areas (settlements), a bit lower values can indicate localisation of α-euhemerobic areas (arable land), and to some extent also β-euhemerobic areas (pastures), while the lowest values point to oligo- and ahemerobic areas (forests and other natural areas). The model is also able to meaningfully approximate the exposure in the areas further from the settlements by indicating the spread of human influence along less steeply sloped areas. This portrayal often conformed to the actual land cover pattern.

The exposure to human influence is the result of a cumulative effect of the influence from all the settlements. This effect is especially observed in the flat areas with low barrier effect and large settlements (e.g. southwestern Slovakia). The average exposure value here is significantly higher than in the hilly areas, where the spread of the human influence disappears over much smaller distances. We consider this effect to be one of the most important benefits of the concept, as it allows to depict the pressure of human activity on the environment. On the other hand, this effect probably reduces the overall correlation between the exposure and the actual land use intensity, because the same values of exposure may indicate forest in flat or densely populated regions, while they may also point to urban areas in hilly or sparsely populated regions. However, we suggest that this fact should not be considered a disadvantage for land cover modelling, because we suppose that exposure can be used in combination with other variables such as accessibility, which can balance the resulting prediction. This effect can also be reduced by different calibration of the exposure calculation.

Quality of the exposure raster is directly dependent on the quality of the input slope raster and population point layer. The use of more precise DEM, or setting smaller cell size, would therefore result in a more detailed structure of the resultant exposure raster. The use of separate points for wards of large towns or municipalities with more centres would be the most significant improvement of the population point layer.

Population size is used as a proxy for human activity to demonstrate the potential of the concept. This way, the resultant raster may also be interpreted as the ‘probability of the human occurrence in the landscape’, which can be secondary considered as the measure of human activity. However, the overall quality of the information carried by the exposure raster would be largely improved by the use of more sophisticated quantification of the source intensity of human activity. The concept and the supplemented computation tool are adjusted to the use of any other measure of human activity. The exposure concept has a potential to improve the spatial resolution of many socio-economic variables (e.g. number of employees in primary sector, amount of investment and agricultural subsidies), which are traditionally measured at the administrative unit level.

There are many other options to improve this concept. While we used slope as the sole factor in landscape barrier effect (6), there is usually other information available to detail modelling of human influence spread in geographic space. The greatest issue in central Europe may be incorporation of barrier effect of water bodies and other wet areas and areas with high risk of flooding. Here, DEM-derived characteristics, such as the topological wetness index and possibly other more advanced characteristics, can provide compromise between information suitability and ease of data obtaining.

A further challenge is implementation of the land cover ‘friction’ data and corridor effects of road and rail networks introduced in research by authors such as Lieskovský et al. (2015). It is even possible that employing a network-based measure instead of cost distance would lead to results, which would be visually slightly similar to the exposure. However, it would require detailed data about the network and incorporation of network analysis, both decreasing the simplicity of the model. Besides that, these data are time-dependent and therefore the resultant exposure might be considered as time limited and unstable. Incorporation of land cover barrier effect and network-based analyses therefore seems to be promising, but it would require complex redevelopment of the model.

Alternatives also exist for the main exposure Equation (4). While we used simple distance value to preserve the principle of geometric dilution and maintain equation simplicity, other studies employed squared values (e.g. Chen, 2009; Paulov, 2004). It is difficult to determine the more appropriate approach. However, the exponent of the distance may also be made a parameter of the equation, further expanding calibration possibilities.

Questions remain in deciding the most appropriate and precise exposure calculation calibration and its further improvements. Statistical analysis comparing the predictive power of the exposure and commonly used variables is required to answer these questions and to assess the benefits of the exposure to human influence concept. This kind of assessment should be a part of a more extensive study.

**Software**

ArcGIS 10.3.1 for Desktop was used to develop the tool for the exposure computation, as well as for the graphic design of all maps. Accordingly, the tool was tested in this ArcGIS version. The tool is supplemented to this article. Please contact us in a need to run it under
other ArcGIS versions as well as in case of malfunction. ArcGIS tool used for the calculation of the exposure raster is supplemented to this article, as well as the exposure raster itself.

Acknowledgements

The authors thank Dagmar Kusendová and the Department of Human Geography and Demography, Faculty of Natural Sciences of Comenius University in Bratislava for valuable advice and data.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the Slovak Research and Development Agency under the Contracts No. APVV-0625-11 and APVV-15-0054.

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References

Aspinall, R. (2004). Modelling land use change with generalised linear models – A multi-model analysis of change between 1860 and 2000 in Gallatin Valley, Montana. Journal of Environmental Management, 72(1–2), 91–103.

Basse, R. M., Omrani, H., Charif, O., Gerber, P., & Bódis, K. (2014). Land use changes modelling using advanced methods: Cellular automata and artificial neural networks. The spatial and explicit representation of land cover dynamics at the cross-border region scale. Applied Geography, 53, 160–171.

Baumann, M., Kuenmerle, T., Elbakidze, M., Ozdogan, M., Radellof, V. C., Keuler, N. S., & Hostert, P. (2011). Patterns and drivers of post-socialist farmland abandonment in Western Ukraine. Land Use Policy, 28(3), 552–562.

Bürgi, M., Hersperger, A. M., & Schneeberger, N. (2004). Driving forces of landscape change – Current and new directions. Landscape Ecology, 19(8), 857–868.

Calvo-Iglesias, M. S., Fra-Paleo, U., & Diaz-Varela, R. A. (2009). Changes in farming system and population as drivers of land cover and landscape dynamics: The case of enclosed and semi-openfield systems in Northern Galicia (Spain). Landscape and Urban Planning, 90(3–4), 168–177.

Chen, Y. (2009). Urban gravity model based on cross-correlation function and Fourier analyses of spatio-temporal process. Chaos, Solitons and Fractals, 41, 603–614.

Demek, J., Mackovčín, P., & Slavík, P. (2012). Spatial and temporal trends in land-use changes of Central European landscapes in the last 170 years: A case study from the south-eastern part of the Czech Republic. Moravian Geographical Reports, 20(3), 2–22.

Eiter, S., & Potthoff, K. (2016). Landscape changes in Norwegian mountains: Increased and decreased accessibility, and their driving forces. Land Use Policy, 54, 235–245.

Etter, A., Mclalpine, C., Pullar, D., & Possingham, H. (2006). Modelling the conversion of Colombian lowland ecosystems since 1940: Drivers, patterns and rates. Journal of Environmental Management, 79(1), 74–87.

European Environment Agency. (2013). Digital Elevation Model over Europe (EU-DEM). Retrieved from https://www.eea.europa.eu/data-and-maps/data/eu-dem#tab-original-data

European Environment Agency. (2016). Corine Land Cover 2012 seamless vector data. Retrieved from https://www.eea.europa.eu/data-and-maps/dlc-2012-vector#tab-europ-ean-data

Gellrich, M., Baur, P., Koch, B., & Zimmermann, N. (2007). Agricultural land abandonment and natural forest regrowth in the Swiss mountains: A spatially explicit economic analysis. Agriculture, Ecosystems & Environment, 118(1–4), 93–108.

Hewitt, R., van Delden, H., & Escobar, F. (2014). Participatory land use modelling, pathways to an integrated approach. Environmental Modelling & Software, 52, 149–165.

Hietel, E., Waldhardt, R., & Otte, A. (2004). Analysing landcover changes in relation to environmental variables in Hesse, Germany. Landscape Ecology, 19(5), 473–489.

Hietel, E., Waldhardt, R., & Otte, A. (2005). Linking socioeconomic factors, environment and land cover in the German Highlands, 1945–1999. Journal of Environmental Management, 75(2), 133–143.

Inouye, C. E. N., de Sousa, W. C., de Freitas, D. M., & Simões, E. (2015). Modelling the spatial dynamics of urban growth and land use changes in the north coast of São Paulo, Brazil. Ocean & Coastal Management, 108, 147–157.

Ku, C.-A. (2016). Incorporating spatial regression model into cellular automata for simulating land use change. Applied Geography, 69, 1–9.

Lieskovský, J., Bezák, P., Spulerová, J., Lieskovský, T., Koleda, P., Dobrovodská, M., & Gimmi, U. (2015). The abandonment of traditional agricultural landscape in Slovakia – Analysis of extent and driving forces. Journal of Rural Studies, 37, 75–84.

Łowicki, D. (2008). Land use changes in Poland during transformation. Landscape and Urban Planning, 87(4), 279–288.

Martínez, J. Á. (2011). Modelling the risk of land cover change from environmental and socio-economic drivers in heterogeneous and changing landscapes: The role of uncertainty. Landscape and Urban Planning, 101(1), 108–119.

Mialhe, F., Becu, N., & Gunney, Y. (2012). An agent-based model for analyzing land use dynamics in response to farmer behaviour and environmental change in the Pampanga delta (Philippines). Agriculture, Ecosystems & Environment, 161, 55–69.

Millington, J. D. A., Perry, G. L. W., & Romero-Calcerrada, R. (2007). Regression techniques for examining land use/cover change: A case study of a Mediterranean landscape. Ecosystems, 10(4), 562–578.

Minár, J., Tremboľová, P., & Vajliková, G. (1992). The barrier effect of georelief, its forms and possibilities of evaluation. Acta Facilitatis Rerum Naturalium Universitatis Comenianae, 33, 199–212.

Müller, D., & Munroe, D. K. (2008). Changing rural landscapes in Albania: Cropland abandonment and forest clearing in the postsocialist transition. Annals of the Association of American Geographers, 98(4), 855–876.
Murray-Rust, D., Robinson, D. T., Guillem, E., Karali, E., & Rounsevell, M. (2014). An open framework for agent based modelling of agricultural land use change. Environmental Modelling & Software, 61, 19–38.

Newman, M. E., McLaren, K. P., & Wilson, B. S. (2014). Long-term socio-economic and spatial pattern drivers of land cover change in a Caribbean tropical moist forest, the Cockpit Country, Jamaica. Agriculture, Ecosystems & Environment, 186, 185–200.

Paulov, J. (2004). On an estimation of interaction flows from transportation costs. Geografičky Časopis, 56(3), 173–185.

Pazúr, R., Lieskovský, J., Feranec, J., & Oťaheľ, J. (2014). Spatial determinants of abandonment of large-scale arable lands and managed grasslands in Slovakia during the periods of post-socialist transition and European Union accession. Applied Geography, 54, 118–128.

Rutherford, G., & Bebi, P. (2008). Assessing land-use statistics to model land cover change in a mountainous landscape in the European Alps. Ecological Modelling, 212(3–4), 460–471.

Serra, P., Pons, X., & Sauri, D. (2008). Land-cover and land-use change in a Mediterranean landscape: A spatial analysis of driving forces integrating biophysical and human factors. Applied Geography, 28(3), 189–209.

Shu, B., Zhang, H., Li, Y., Qu, Y., & Chen, L. (2014). Spatiotemporal variation analysis of driving forces of urban land spatial expansion using logistic regression: A case study of port towns in Taicang City, China. Habitat International, 43, 181–190.

Smaliychuk, A., Müller, D., Prischepov, A. V., Levers, C., Kruhlov, I., & Kuemmerle, T. (2016). Recultivation of abandoned agricultural lands in Ukraine: Patterns and drivers. Global Environmental Change, 38, 70–81.

Tayyebi, A., & Pijanowski, B. C. (2014). Modeling multiple land use changes using ANN, CART and MARS: Comparing tradeoffs in goodness of fit and explanatory power of data mining tools. International Journal of Applied Earth Observation and Geoinformation, 28, 102–116.

Tomášiková, V. (2010). Demo(geo)grafický a metadataový informačný systém so zreteľom na dynamiku obyvateľstva Slovenska - source data. Bratislava: Comenius University in Bratislava.

Van Doorn, A. M., & Bakker, M. M. (2007). The destination of arable land in a marginal agricultural landscape in South Portugal: An exploration of land use change determinants. Landscape Ecology, 22(7), 1073–1087.

van Vliet, J., de Groot, H. L. F., Rietveld, P., & Verburg, P. H. (2015). Manifestations and underlying drivers of agricultural land use change in Europe. Landscape and Urban Planning, 133, 24–36.

Verstegen, J. A., Karssenberg, D., van der Hilst, F., & Faaij, A. P. C. (2014). Identifying a land use change cellular automaton by Bayesian data assimilation. Environmental Modelling & Software, 53, 121–136.

Walz, U., & Stein, C. (2014). Indicators of hemeroby for the monitoring of landscapes in Germany. Journal for Nature Conservation, 22(3), 279–289.

Wang, Q., Ren, Q., & Liu, J. (2016). Identification and apportionment of the drivers of land use change on a regional scale: Unbiased recursive partitioning-based stochastic model application. Agriculture, Ecosystems & Environment, 217, 99–110.

Xu, Y., McNamara, P., Wu, Y., & Dong, Y. (2013). An econometric analysis of changes in arable land utilization using multinomial logit model in Pinggu district, Beijing, China. Journal of Environmental Management, 128, 324–334.