Comparison of DEM-derived determinants for modelling of long-term land cover change in a large scale: case studies from Slovak Western Carpathians

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Abstract: *Studies detecting land use/cover change (LUCC) in large scales are increasing in number, and so are the studies identifying spatial determinants of these changes and creating their models. Raster datasets derived from digital elevation models (DEM) belong to a limited group of determinants that are relatively available for LUCC modelling in large scales. This study compares the performance of 12 DEM-derived determinants in models of six distinct land cover changes: urbanisation, industrialisation, agricultural intensification and extensification, afforestation, and deforestation. The changes were identified in the 1949-2010 period in a reference scale of 1:10 000 on a total area of 176 km^2 of 12 municipalities systematically selected to partially represent Western Carpathians in Slovakia. Nearly 45% of the area changed; afforestation, agricultural extensification and intensification were the most prevalent changes. Logistic regression and hierarchical partitioning were used to quantify the influence of the determinants on them. Among other commonly used determinants (elevation, slope, cost distance), vertical dissection and duration of solar radiation had an unexpectedly high influence, mostly on agricultural intensity and forest changes. However, further research is needed to verify these influences in other areas and to provide their sufficient causal interpretation.*

Keywords: *land change, LUCC model, driving forces, digital elevation model, Slovakia*

Introduction

Modelling of Land Use/Cover Change (LUCC) has been a frequent topic of scientific research during the last two decades, transcending into a multitude of research areas (Verburg et al. 2006). Fundamentally, it solves a very traditional geographical issue; a complex depiction of the relationship between geographical characteristics and land use. In former Czechoslovakia, this issue was rigorously elaborated in the landscape planning methods (e.g., Ružička and Miklós 1982), thus laying strong foundations for potential LUCC modelling in this region. However, empirical research on this relationship has been relatively scarce. Among the multitude of land cover change studies, only a fraction attempted to model these changes (e.g., Šúri 2003, Havlíček and Chrudina 2013, Pazúr et al. 2014, Lieskovský et al. 2015, Opršal et al. 2016).

Search for reasons of the LUCCs is important for their management, it is, therefore, reasonable to thoroughly study processes of human decisions about the utilisation of different parts of the landscape. Good reviews of this issue were published for example by van Vliet et al. (2015), Plieninger et al. (2016) and Bürgi et al. (2022). Naturally, LUCC determinants that are well causally interpretable are the most desirable in this search. However, they may not always be effectively utilised in practical LUCC modelling. For instance, if data about the determinants are difficult to obtain (e.g., individual motivations of landowners), or if they change together with LUCCs (e.g., road network), then the resultant model may have limited use. More generally, we are limited by the availability of the model input data (Rindfuss et al. 2004). Modelling based on well-available data with indirect causal influence may therefore often be better practically applicable than modelling based on direct causal determinants. This paper aims to evaluate the use of the well-available data in large-scale LUCC modelling.

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Scale is a principal criterion of the LUCC modelling (Verburg et al. 1999, Kok et al. 2001). It is substantial already in the phase of LUCC detection, as its change may fundamentally affect the resultant picture (e.g., Lieskovský and Lieskovská 2021). Also in the modelling phase, different determinants are important in different scales (Bürgi, Hersperger and Schneeberger 2004). Its choice depends on the goals of particular research, and it can range from global (Kuemmerle et al. 2013) to local scales (Tzanopoulos et al. 2013). We will focus on the reference scale 1:10 000 which allows a very detailed depiction of LUCCs. On the contrary, it requires a lot of effort to elaborate. Studies in this scale therefore usually cover only relatively small areas (e.g., Druga and Falťan 2014, Kanianska et al. 2014). The validity of their findings is often limited: Causes of the LUCCs are usually rather individual, determined by the phenomena specific to the given area, and thus hardly generalizable. A possible solution – a metanalysis of these studies – would probably struggle with inconsistent methodology among the studies. This paper aims to capture LUCCs in multiple study areas, systematically selected to provide a certain level of representativeness, while reasonably maintaining the expended effort.

Limitations of LUCC spatially explicit determinants at a scale of 1:10 000

The limited availability of consistent spatially explicit determinants that are well causally interpretable is a substantial issue of LUCC modelling in 1:10 000. The next paragraphs offer our attempt to review this availability in Slovakia.

The spatial resolution of the most of socioeconomic data is limited by the size of municipal areas (level LAU2), as this is the most detailed level at which they are registered. Many large-scale LUCC studies focus on just one municipal area, these data are therefore practically inapplicable because their values are spatially constant in that case. A natural step is to use data referenced to individual lots; however, the availability and homogeneity of this data is rather problematic. Another determinant is often used to depict the socioeconomic influence in space: Accessibility to the human activity source, usually expressed as Euclidean distance to the nearest source (e.g., Prishchepov et al. 2013, Pijanowski et al. 2002). But its use requires solving some issues, too. There is a need to choose suitable spatial representations of the sources, as more detailed sources (e.g., roads, houses) usually have a higher probability that they will dynamically change along with the LUCCs. The choice of accessibility conceptualisation (cf. Spiekermann et al. 2015) also matters.

Soil characteristics (whether general or directly representing soil fertility) usually pose another issue. Large-scale Slovak data do not cover its whole area, but it is available separately for agricultural and forestry areas. Moreover, neither underlying methodologies nor data itself is complementary. Further issues result from the density of the original soil survey points used to derive these maps. Climatological data are also collected in a network that is far from the reference scale 1:10 000. They are therefore dependent on spatial interpolations with the implementation of digital elevation model data.

Ultimately, characteristics derived from digital elevation models (DEM) are a rare group of determinants that are relatively easily applicable in the scale 1:10 000, thanks to ever-increasing spatial resolution of DEMs. The abundance of continental and (nearly) global models (e.g., SRTM, EU-DEM, ASTER-GDEM, WorldDEM) makes them also better comparable among different countries, as they are independent of national methodologies, unlike most soil or socioeconomic data.

Among geomorphometric characteristics, terrain elevation itself is often used (e.g., Rutherford et al. 2008, Álvarez Martínez et al. 2011). Terrain slope is a typical and important DEM-based determinant of LUCCs (e.g. Taillefumier and Piégay 2003, Müller and Munroe 2008, Pazúr and Bolliger 2017, Zhou et al. 2020). Its aspect is also used as a determinant sometimes (e.g., Rutherford et al. 2008, Schirpke et al. 2012) and morphometric characteristics of higher order (curvatures) may also potentially have some influence (used by Florinsky and Kuryakova 1996, Tasser et al. 2007, Álvarez Martínez et al. 2011), although we see higher potential in the use of wave characteristics, especially vertical dissection (i.e. elevation amplitude – the range of elevation in defined surroundings; Chen et al. 2017).

Terrain models are also used to derive several thematic characteristics. Calculation of incoming solar radiation is used to represent partial microclimatic conditions (e.g., Del Barrio et al. 1997, Álvarez Martínez et al. 2011, Pazúr et al. 2014). Some authors use positional indices (e.g., TPI; Bolliger et al. 2017, Abadie et al. 2018) or wetness indices (e.g., TWI; Del Barrio et al. 1997, Rutherford et al. 2008, Álvarez Martínez et al. 2011). As mentioned above, DEMs are used in the interpolation of climatological data, and they can also be utilised to derive cost (Rusinko and Druga, 2022) or path distances as an improvement of accessibility determinants which may allow them to serve as a spatially detailed proxy for socioeconomic data.

This paper aims to test several DEM-derived determinants in the modelling of long-term LUCCs in 12 areas in Western Carpathians with partial goals: Identification of land cover changes in 1:10 000 between 1949 and 2010; derivation of relevant spatial determinants; and quantification of their influence on land cover changes.

Study areas

In our study areas (fig. 1), we wanted to catch the whole interaction between the local population and the landscape in which it lived. We, therefore, used municipality areas, as we assumed that most of the landscape-forming influence of the local population happened inside them. To obtain a certain level of representativeness, we made a selection based on cluster analysis of all municipality areas in Western Carpathians as delimited by Minár et al. (2011).

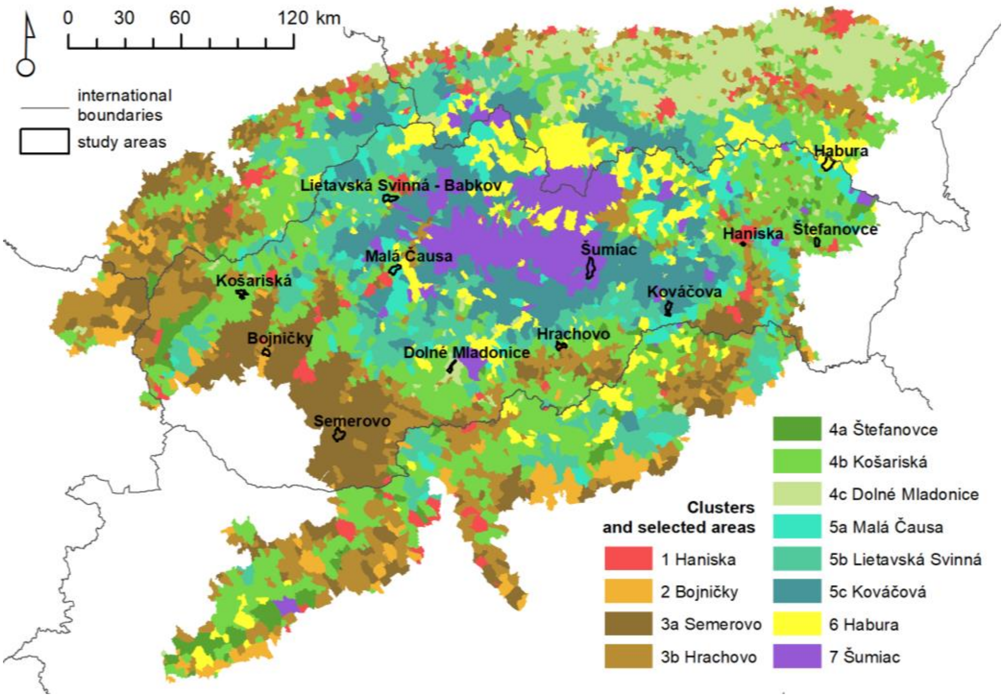

Fig. 1. *Study areas selected from clusters of similar municipal areas in Western Carpathians sensu Minár et al. (2011)*

To perform it, each area got assigned variables: average elevation and slope (based on EU-DEM), standard deviations of elevation and slope, as well as proportions of seven selected land cover classes (1, 2.1, 2.2, 2.3, 2.4, 3.1, 3.2) according to CLC 1990 (Bossard, Feranec and Otahel 2000). These variables were then replaced by their principal components to avoid multicollinearity. Weighted k-means cluster analysis was performed based on the principal components with areas used as weights. The best interpretable results were achieved with seven clusters; however, three clusters were too large, therefore we split them afterwards into two or three separate clusters using the same method. Thus, the clusters roughly represent "types of the landscape", empirically derived from the above-mentioned variables. One area was selected from each cluster. To do so, we ordered areas in each cluster according to their attribute distance from the cluster centre – smaller attribute distance means that the area is more typical for the cluster. Then we selected 10% of the areas with the smallest distance – the most typical ones. The final study areas were selected from them while considering other criteria, such as size of the area relative to the size of the cluster and a relatively even geographical dispersion. Twelve municipality areas were selected with a total area of 176.34 km^2: *Košariská, Bojničky, Semerovo, Lietavská Svinná-Babkov, Malá Čausa, Dolné Mladonice, Hrachovo, Šumiac, Kováčová, Haniska, Štefanovce* and *Habura*.

Land cover change detection

Land cover was classified by manual vectorisation of polygons of the identified land cover classes based on orthophoto-maps from 1949 and 2010 (TU Zvolen 2014, 2017). The classification methodology was derived from Druga, Falťan and Herichová (2015). We did not use whole thematic resolution, as some irrelevant classes were mapped at higher hierarchy levels, but we used the original spatial resolution: minimal mapping unit 0.1 ha, minimal polygon width 10 m and 2 m in the case of linear features (infrastructure, water courses and their accompanying classes). We then overlayed layers from both years and classified the changes into six land cover change types (fig. 2) according to tab. 1.

Tab. 1. *Derivation of land cover changes between 1949 and 2010: Urbanisation (urb), industrialisation (ind), agricultural intensification (int) and extensification (ext), afforestation (aff) and deforestation (def)*

	1949 =		2010 =		
urb	1	yes			not included
		no	1.1	yes	presence
				no	absence
ind	1.2.1	yes			not included
		no	1.2.1	yes	presence
				no	absence
int	2.3	yes	2.1/2.2/2.4	yes	presence
				no	absence
		no			not included
ext	2.1/2.2/2.4	yes	2.3	yes	presence
				no	absence
		no			not included
aff	3.1/3.2	yes			not included
		no	3.1/3.2	yes	presence
				no	absence
def	3.1/3.2	yes	2	yes	presence
				no	absence
		no			not included

According to it, *Urbanisation* indicates emergence of urban fabric (1.1) in the areas that were not artificial (1) in 1949; *industrialisation* emergence of industrial and commercial units (1.2.1) in the areas, where they were absent in 1949. *Agricultural intensification* catches transition from pastures (2.3) to arable land (2.1), permanent crops (2.2), or heterogeneous agricultural areas (2.4); *agricultural extensification* represents the opposite process. *Afforestation* catches emergence of forests (3.1) or scrub / herbaceous vegetation (3.2) in the areas, where they were absent in 1949; *deforestation* indicates transition of one of these classes specifically to agricultural area (2). These areas define presence of the change, depicted in fig. 2. Concerning absence, we distinguished between absence when the change was possible, and absence when it was not possible, which was not used in the statistical analysis (tab. 1).

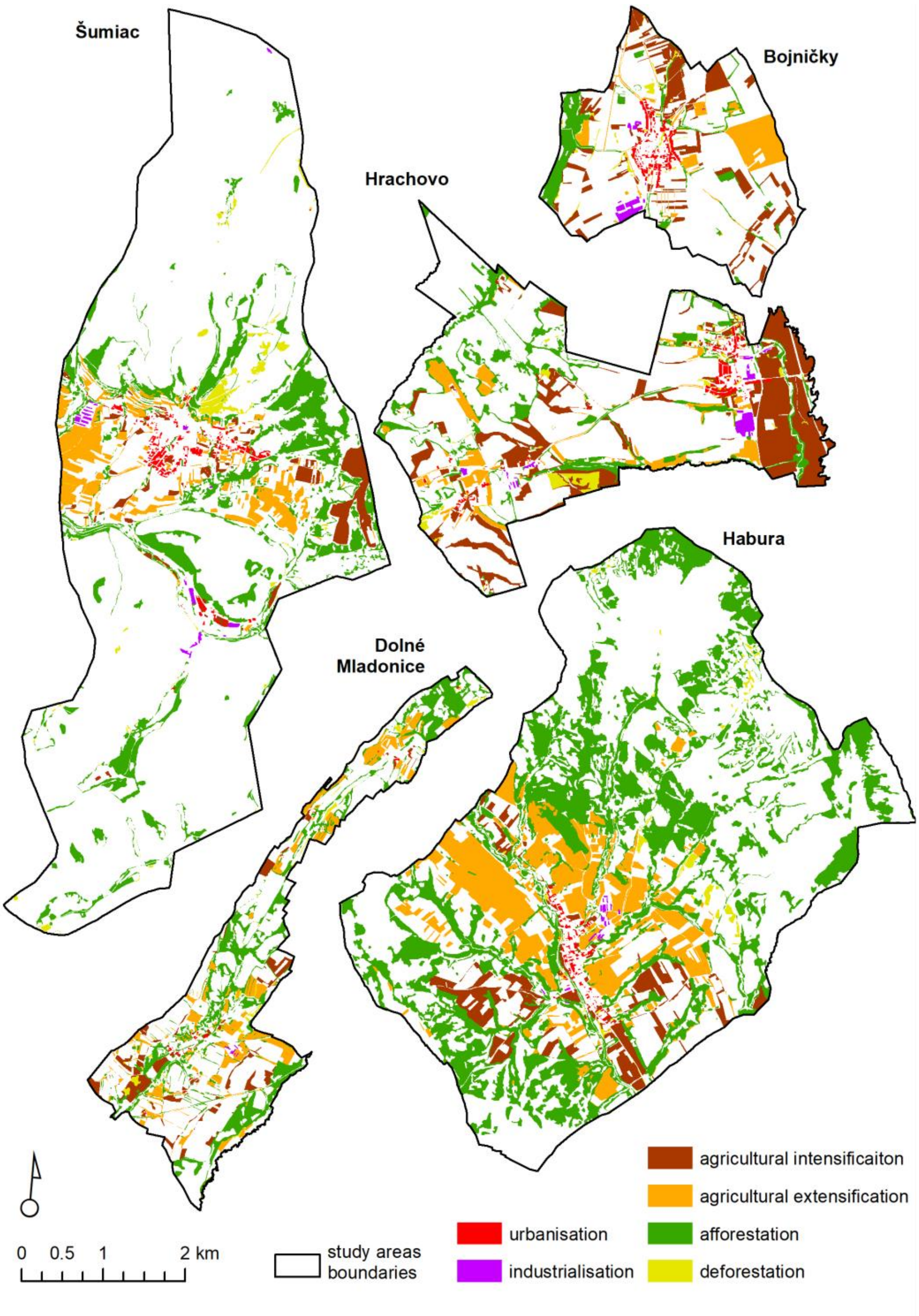

Fig. 2. *Classified land cover changes between 1949 and 2010 in the selected study areas*

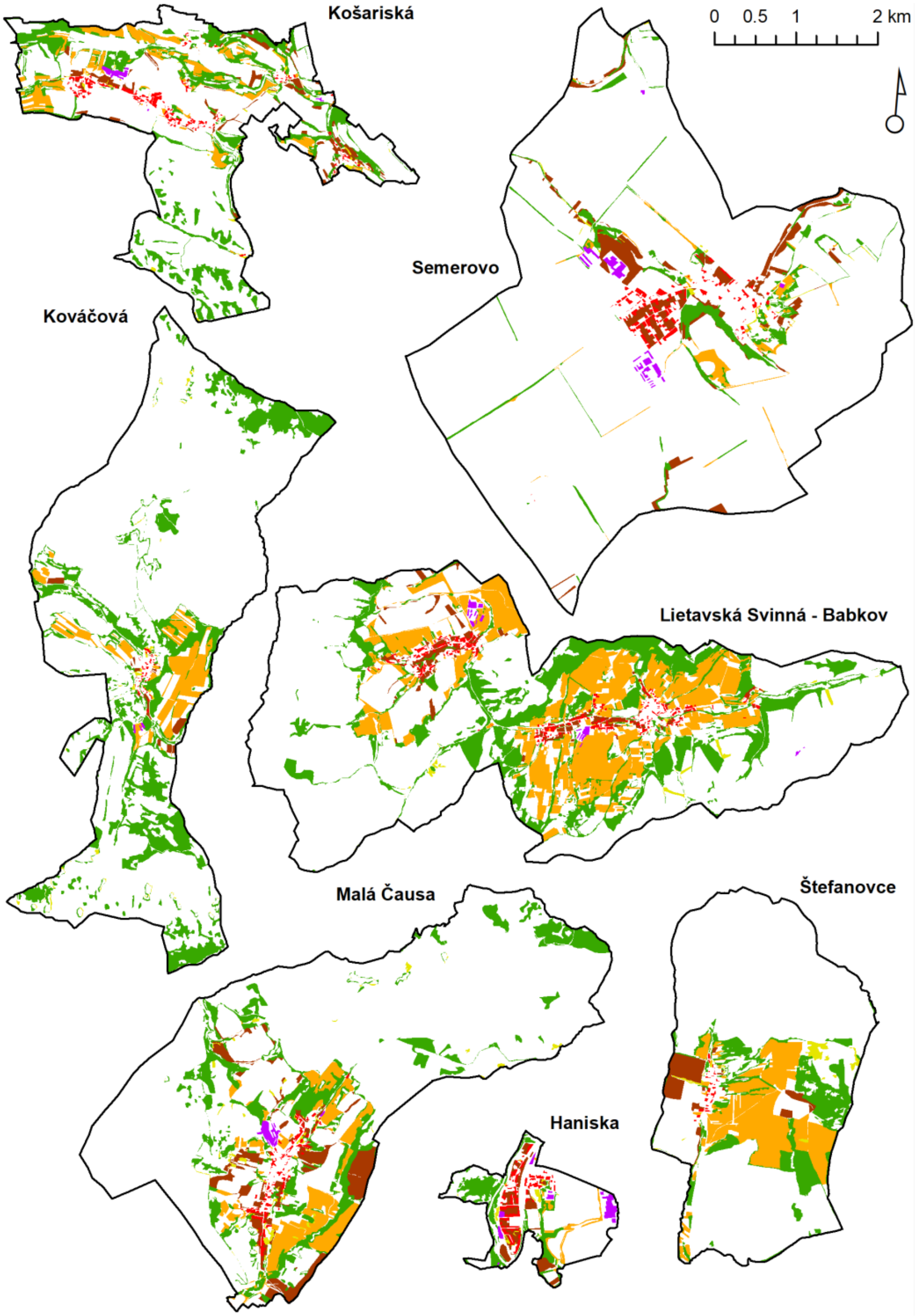

Fig. 2. (continuation) *Classified land cover changes between 1949 and 2010 in the selected study areas*

DEM-derived spatial determinants

Raster layers of the determinants (tab. 2) were derived by the tools of ArcMap 10.8 based on a national digital terrain model DMR3.5 with a resolution of 10 m (GKÚ Bratislava 2015). Its values were also used as the determinant elevation, which is often used as a proxy of vertical variability of climate characteristics (e.g., Rutherford et al. 2008, Schirpke et al. 2012). Besides it, we derived relative elevation by subtracting the minimal elevation of each municipal area. It was supposed to consider that inhabitants of higher situated villages could be forced to utilise even areas with higher altitude, as they had no better choice available.

Tab. 2. *Spatial determinants used in models of land cover change types*

abbreviation	determinant
elev	elevation
relelev	relative elevation over the lowest point of municipal area
slope	terrain slope
verti_r100	vertical dissection - range of elevation in circle, r = 100m
verti_r250	vertical dissection - range of elevation in circle r = 250m
verti_r500	vertical dissection - range of elevation in circle, r = 500m
asp_cos	cosine of the terrain aspect
solarrad	potential solar radiation during the year (direct + diffuse)
solardur	average duration of direct solar radiation during the year
twi_foc3	topographic wetness index on DEM smoothed by focal statistics (r = 3 cells)
eucdist	Euclidean distance to the closest municipality centre
costdist	slope-derived cost distance to the closest municipality centre

Slope in degrees was derived from the terrain model by the *Slope* tool as the strongest typical DEM-derived determinant, representing a wide spectrum of complications for human activity caused by the inclination of the terrain. As an alternative to this traditional determinant, we elaborated several versions of vertical dissection calculated by *Focal Statistics* as a range of elevation in a circle with radii 500 m, 250 m, and 100 m.

The aspect of the slope (tool *Aspect*) may represent insolation (as a microclimatic proxy) and possibly also exposure to prevailing wind direction. We used its cosine as a measure of the "northness" because its usual quantification in the form of directional data (0-360°) is highly unsuitable for numerical analyses. Incoming solar radiation was elaborated to represent this effect more causally: Global radiation and duration of direct radiation were calculated by the *Area Solar Radiation* tool (calculation for the whole year, each 14^{th} day, each half-hour).

GIS hydrology analyses allow to approximate water flow on the DEM surface. We used the topographic wetness index (Beven and Kirkby 1979) to approximate soil moisture:

$$TWI = \ln \frac{contributing\ catchment}{\tan slope}$$

We used a slightly smoothed DEM (*Focal statistics* – average in the radius of three cells), which was subsequently hydrologically corrected by the *Fill* tool. The contributing catchment was derived from it by *Flow accumulation*, we then added a value 1 to the resultant raster to avoid cells with value 0, and we recalculated its values to express area in m^2. We added the value 0,1° to the slope to avoid division by zero in the case of zero slopes. The resultant TWI raster is rather successful in depicting the alluvia of streams and rivers and it can therefore represent not only soil moisture but also the influence of flooding and other effects.

We elaborated on two determinants representing accessibility. Municipality centres were used as sources of human influence in both (two centres were used in *Lietavská Svinná-Babkov* which functionally consists of two villages). *Euclidean distance* was used as a standard accessibility conceptualisation, while *cost distance* allowed integrating the effect of terrain on transportation costs. The cost raster for calculation of the latter was derived from slope according to Rusinko (2020) with more detailed explanation in Druga and Minár (2018):

$$cost\ raster = 1 + 25 \cdot \sin slope.$$

The resulting determinants are visualised on fig. 3.

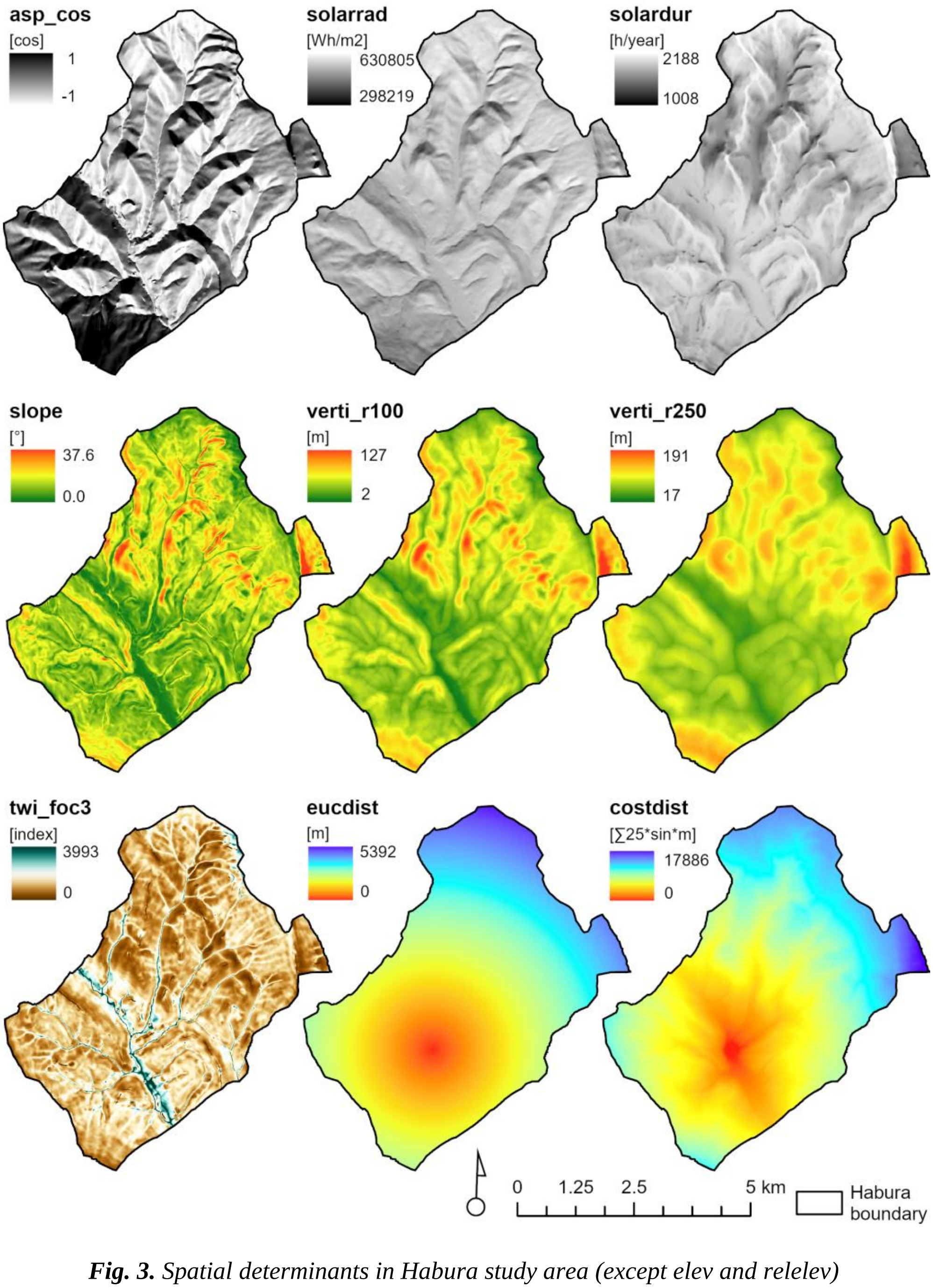

Fig. 3. *Spatial determinants in Habura study area (except elev and relelev)*

Statistical analysis

We used a standard statistical tool for quantification of the potential influence of the determinants on the spatial structure of the classified land cover changes: logistic regression (Millington, Perry and Romero-Calcerrada 2007, Molowny-Horas, Basnou and Pino 2015). We used a regular sampling in square net á 25 m; values of determinants and land cover changes were assigned to its points. A correlation matrix of the determinants was created to assess mutual correlations. Univariate logistic regression models of each determinant against each land cover change were then created. We used AUC as the indicator of the model`s explanatory power.

The explanatory power of a model based on a single determinant cannot be automatically interpreted as its causal influence. The power can be increased by multicollinearity of the determinant with other determinants which may have a more direct causal interpretation. This causality cannot be proven by statistical methods alone, but it is possible to choose the most effective from the group of mutually collinear determinants. Hierarchical partitioning is an exhaustive method for this goal. It quantifies an individual contribution of the determinant to the overall variance explained by the model involving all the assessed determinants. This contribution is calculated by comparing models consisting of all possible combinations of the determinants including the assessed determinant with their versions reduced by this determinant (Millington, Perry and Romero-Calcerrada 2007).

Results

Our analysis detected land cover change in 44.5% of the study area (fig. 4), but only 26.5% fell into land cover changes according to our classification specified in tab. 1. Urbanisation took place on 0.76%, mostly in the areas adjacent to the original settlements (fig. 2). Industrialisation (0.3%) mostly depicted the emergence of socialist cooperative farms as compact areas in the proximity of (but not necessarily adjacent to) the settlement. Agricultural extensification had a larger extent than intensification (6.8% and 4.2%) and occurred in an irregularly dispersed structure with some larger areas localised in several areas. Deforestation was similarly dispersed and relatively scarce (0.7%), while afforestation was the most prevalent change (13.7%). Other changes mostly included changes inside forest management cycle (forest cutting and regeneration).

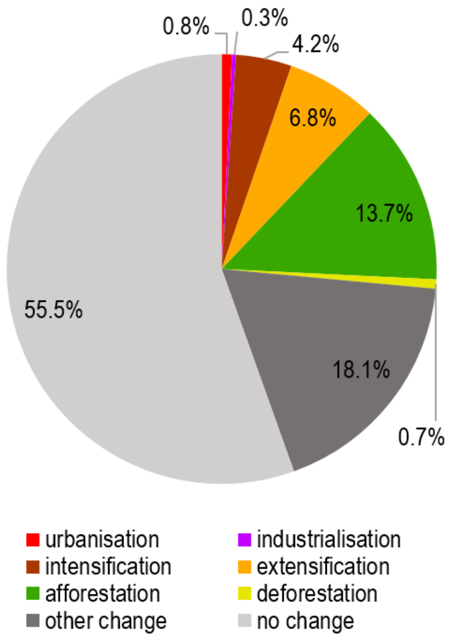

Fig. 4. *Share of land cover changes detected between 1949 and 2010 in selected study areas of Western Carpathians in reference scale 1:10 000*

The importance of the determinants (AUC, tab. 3) was different for different land cover changes. Accessibility in both forms (Euclidean and cost distance) reached the strongest results. It effectively explained urbanisation, as AUC = 0.92 reached by a univariate model using just *costdist* suggested strong influence, and its individual contribution to the explanatory power of the multivariate model (I, tab. 3) showed dominance over other predictors. Its influence was somewhat weaker in the models of industrialisation, and it had relative importance for deforestation, where *costdist* had the highest individual contribution. Cost distance produced significantly stronger models than Euclidean distance in these cases. The influence of accessibility on other changes, like extensification and afforestation, was negligible in our areas.

Tab. 3. *AUC of the univariate logistic regression models of the land cover changes and the independent contribution I of single determinants to their common explanatory power (hierarchical partitioning). Strong influence is highlighted by warm colours and weak influence by cold colours.*

	AUC · 100						independent contribution I [%]					
	urb	ind	int	ext	aff	def	urb	ind	int	ext	aff	def
elev	65.4	69.1	79.5	82.2	72.6	68.2	6.9	6.3	9.5	10.4	4.8	6.1
relelev	77.0	79.0	73.1	69.9	67.8	73.3	9.3	10.7	9.0	5.7	3.4	9.3
slope	72.6	79.7	77.3	79.2	77.3	76.2	7.6	11.6	10.4	10.9	15.5	10.1
verti_r100	73.6	80.5	81.5	82.4	79.6	77.6	7.9	11.9	13.8	13.7	14.3	11.0
verti_r250	72.2	77.2	82.8	82.8	79.1	76.0	7.6	9.4	15.1	12.3	13.2	10.2
verti_r500	67.4	73.6	82.7	82.0	77.1	74.0	6.9	7.9	15.1	11.0	10.7	9.6
asp_cos	50.8	51.8	51.1	50.9	52.0	52.6	5.9	4.5	2.1	2.4	2.5	4.5
solarrad	53.0	54.7	58.4	60.8	55.7	49.7	6.0	4.5	2.6	3.7	2.9	4.7
solardur	55.5	65.5	75.4	80.2	75.8	71.9	6.6	6.3	9.7	12.8	19.2	7.8
twi	73.4	78.2	72.0	77.7	72.0	74.2	0.4	0.7	2.7	10.7	4.5	2.2
eucdist	89.8	76.4	64.3	66.0	58.8	70.8	16.9	12.3	3.9	4.3	4.0	11.0
costdist	92.1	82.5	71.1	56.0	66.7	77.0	17.9	14.1	6.1	2.1	5.0	13.4

Tab. 4. *Correlation matrix of absolute values of Pearson R for the determinants. High values are highlighted by darker tones.*

	elev	relelev	slope	verti_r100	verti_r250	verti_r500	asp_cos	solarrad	solardur	twi_foc3	eucdist	costdist
elev	1	0.8	0.55	0.62	0.7	0.78	0.08	0.39	0.4	0.22	0.38	0.72
relelev	0.8	1	0.49	0.55	0.64	0.72	0.1	0.37	0.2	0.2	0.45	0.83
slope	0.55	0.49	1	0.94	0.84	0.75	0.1	0.09	0.75	0.33	0.18	0.46
verti_r100	0.62	0.55	0.94	1	0.93	0.83	0.09	0.04	0.74	0.31	0.2	0.51
verti_r250	0.7	0.64	0.84	0.93	1	0.94	0.06	0.05	0.7	0.29	0.23	0.57
verti_r500	0.78	0.72	0.75	0.83	0.94	1	0.02	0.16	0.63	0.27	0.25	0.62
asp_cos	0.08	0.1	0.1	0.09	0.06	0.02	1	0.75	0.32	0.06	0.04	0.06
solarrad	0.39	0.37	0.09	0.04	0.05	0.16	0.75	1	0.4	0.03	0.16	0.29
solardur	0.4	0.2	0.75	0.74	0.7	0.63	0.32	0.4	1	0.2	0.08	0.26
twi_foc3	0.22	0.2	0.33	0.31	0.29	0.27	0.06	0.03	0.2	1	0.05	0.17
eucdist	0.38	0.45	0.18	0.2	0.23	0.25	0.04	0.16	0.08	0.05	1	0.82
costdist	0.72	0.83	0.46	0.51	0.57	0.62	0.06	0.29	0.26	0.17	0.82	1

Vertical dissection reached the second strongest results, but, unlike accessibility, it appeared to be important for practically every land cover change. Its effect is largely shared with slope due to their relatively high correlation (tab. 4). It is remarkable that vertical dissection calculated in 100 m radius *verti_r100* explained all the changes slightly better than the slope. In the case of agricultural intensity changes, *verti_r250* reached even better results, thus creating the strongest among *slope* and *verti* models (AUC = 0.828). Vertical dissection has relatively higher importance to slope also according to hierarchical partitioning and this difference is substantial for agricultural intensity changes. Afforestation is the only exception when slope and vertical dissection with smaller radii are more important.

The use of relative elevation proved beneficial for urbanisation and industrialisation, according to both, AUC, and individual contribution “I”. It could be partially explained by its correlation with accessibility because it is naturally high in mountainous areas of the Western Carpathians. Absolute elevation was more important mostly for agricultural changes, interpretable as the effect of climatic conditions on agricultural decision-making during socialism, which tried to optimize production over larger regions, not just inside partial municipality areas. In the case of extensification, TWI had a relatively high influence, too.

Comparison of determinants that approximate incoming solar radiation brought also interesting results. The aspect was practically insignificant, but global radiation was barely better, as both had negligible individual contributions. However, the duration of direct solar radiation mostly had significantly higher AUC and individual contribution, and it was a relatively important determinant of agricultural and forest changes. It could be partially explained by its high correlation with slope (tab. 4), but in the case of extensification and afforestation, *solardur* has notably higher individual contribution “I” than *slope*. Therefore, it probably has an important own influence.

Discussion

DEM-derived spatial determinants are a frequent component of the LUCC models. We searched for LUCC modelling studies in the Web of Science Core Collection. In the first 100 studies that used spatial determinants (sorted by relevance), elevation was found in 61, and slope in 77 studies. None of these studies used vertical dissection. The aspect was the third most common, found in 16 studies, but most of them do not state its numerical form. If they do, then it is usually expressed in degrees or categorically, only Birhanu et al. (2021) used sine and cosine transformation. Other measures representing solar radiation effects are rarely included, we found global radiation in 3 studies, but the duration of solar radiation was not used in any. Six studies used topographic wetness index and two used morphometric curvatures.

Comparing the results of our analyses with the above-mentioned prevalence of the DEM-derived determinants in LUCC modelling studies, the performance of two determinants stands out: vertical dissection and duration of solar radiation. They both proved to have a significant influence on some land cover changes in our areas, yet they did not appear in our short meta-nalysis. Even after deeper dive into LUCC modelling studies, we were only able to find two papers utilizing vertical dissection: Verburg et al. (2000), and Chen et al. (2017). Their results showed that vertical dissection was negatively correlated with the occurrence of LUCCs.

Therefore, we consider both above-mentioned determinants to be promising, but further investigation is required. Evidence from other regions and other scales is missing. More importantly, the higher influence of these determinants on LUCCs compared to more common determinants lacks standard causal interpretation, yet. We offer some initial hypotheses.

Vertical dissection and slope derived from digital elevation models are related characteristics. The calculation of slope in a particular cell is based on elevation differences of the eight cells surrounding it. Therefore, it has the highest spatial detail possible for a given DEM resolution. The vertical dissection is usually calculated as a range of elevation in given surroundings around the cell when the surroundings are typically substantially larger than the raster resolution (fig. 3). *Slope* and *verti*, therefore, differ in two aspects. Scale is the first – while the slope is the local point-based characteristic according to the system of geomorphometric characteristics (Minár, Evans and Krcho 2013), vertical dissection is the local area-based characteristic; it represents larger surroundings and therefore its spatial detail lowers with increasing radius. The second difference originates in the different calculation – the slope is calculated from all available values while the vertical dissection reflects just the minimal and maximal value in given surroundings. Minimum and maximum are extreme values which are usually not very representative, we therefore originally anticipated that *verti* would be the less suitable determinant. The only hypothetical explanation of our empirical results that we can offer now is focused on the scale: The changes in agricultural intensity may have mostly happened in relatively compact patches, therefore the slope raster with 10 m resolution could be too detailed for their explanation. This hypothesis could be verified by comparison with alternative slope rasters derived from smoothed DEMs.

Interpretation of the surprising results of the duration of solar radiation is partially blurred by its correlation with the slope. It is caused by the fact, that the longest duration is found in areas with the low horizon in most directions (except north). In this type of terrain, this roughly applies to the top areas of ridges and to flatlands that are distant from hills, which both have typically low slope (fig. 3). Steeper slopes mean a shorter duration of solar radiation, but their values differ according to the aspect. An overall picture of the duration of solar radiation therefore fundamentally differs from the slope and vertical dissection. The individual contribution "I" (tab. 3) of this determinant is also notably higher compared to the more commonly used global solar radiation. Moreover, it is the highest among determinants of afforestation – even higher than the slope. We suggest an explanation: The duration of sunshine is a measure that is easier to observe than the amount of radiation itself, it could therefore be easier for people to decide according to it. However, we do not think that this effect could fully explain our results. Other explanations may therefore be needed.

Cost distance using the slope to derive accessibility proved to be a better (AUC) and more important (I) determinant of all land cover changes than Euclidean distance, with only agricultural extensification as an exception. Similar results were described by previous studies in Slovakia that modelled land cover change in smaller reference scales on whole its territory (Rusinko and Druga 2022). This study confirms that the advantages of cost distance apply also to modelling in larger scales.

These results could have been affected not just by the quality and character of the determinants, but also by the methods used for the land cover change detection. Some areas could have been identified incorrectly, especially using the grayscale orthophoto map of the year 1949. The most probable confusion could have occurred while distinguishing between pastures and vegetated arable land, despite the fact that the structure of herbaceous vegetation, land cover patches and many other subtle land cover features usually appeared to be sufficiently instructive for this distinction. The detection of land cover change types was also affected by their definition in tab. 1. For example, the agricultural intensification and extensification were defined narrowly – they did not include transitions among arable land, permanent crops and heterogeneous agricultural areas, as we found comparison of their agricultural intensity disputable. Afforestation and deforestation did not include changes inside the class 3.2 "transitional woodland – scrub" to avoid depicting routine changes of the forest management cycle. In general, results of this study should be interpreted relatively to the land cover change definitions in the tab 1.

Conclusions

This study identified land cover changes in the reference scale 1:10 000 in twelve municipalities in Slovak Western Carpathians. Afforestation reached the largest extent (13.7%), followed by agricultural extensification (6.8%) and intensification (4.2%). Deforestation, urbanisation, and industrialisation were each found in less than 1% of the whole area. The influence of twelve DEM-derived determinants on these changes was quantified using logistic regression analysis and hierarchical partitioning. Urbanisation and industrialisation were mostly influenced by accessibility while other determinants were more important for changes in agricultural intensity and forests. Some alternative determinants proved to have better explanatory power and higher individual contribution according to the hierarchical partitioning method than their more common counterparts: Vertical dissection reached good results compared to slope, duration of solar radiation was notably more efficient compared to global solar radiation and aspect of the terrain. Research in other regions is needed to verify these findings, as well as studies offering a better causal interpretation of their influence. If successful, these determinants may have the potential to improve LUCC models in mountainous regions.

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