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A protocol to model future land use scenarios using Dinamica-EGO ☆

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ABSTRACT

Land use changes are important drivers of ecosystem change. They depend on ecological, social, economic and political aspects. This work aims to develop a detailed protocol to forecast land use changes using Dinamica-Ego software. It includes the 1) time frame definition, 2) future scenarios definition, 3) identify the major driving forces of land use change, 4) collection and organize data for the modelling process, 5) calculation of landscape metrics for the base year, and 6) Dinamica-Ego modelling. Here, several sub-steps are described that involve calculating the transition matrix, preparing the raster cube, calculating the Weights of Evidence (WoE), assessing multicollinearity, revising the raster cube, validating the land use change model, adjusting the transition matrix and WoE and running the future land use simulation. The protocol explains how to simulate land use changes to 2050, showing scenarios 1) business as usual and 2) urbanization in Kaunas (Lithuania).

- The protocol details a step-by-step approach to model land use change using Dinamica-Ego;
- This protocol can be replicated in forecasting land use in any urban area;
- The results obtained using this protocol were well-validated. Therefore, the reliability is high;

Specifications table

Subject area:	Environmental Science
More specific subject area:	Land use modelling
Name of your protocol:	Modelling future land use scenarios with Dinamica-EGO
Value of the Protocol:	• A highly detailed protocol is developed to ensure consistent scenario modelling; • Applicable for the analysis of alternative future scenarios; • Adaptable to different urban extents;

Background

Land use change is an important driver of change, with positive or negative environmental impacts [1,2]. It is affected by ecological (e.g., climate), social (e.g., demography), economic (e.g., soil prices) and political (e.g., legislation) forces that normally act interdependently and in nearby geographical regions [3,4]. Forecasting land use changes has become an important tool for better

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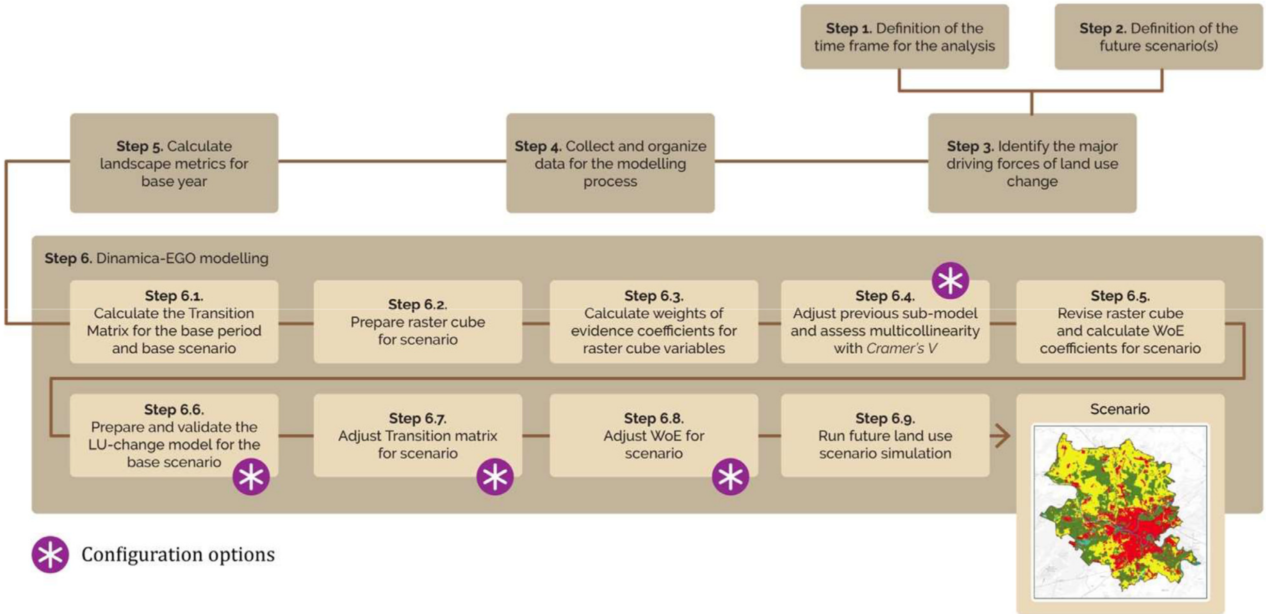


Fig. 1. Methodological steps.

planning and understanding the impacts of the drivers affecting future land use changes [5]. This exercise is normally done using different scenarios targeted to a specific year. When compared with a scenario where the future evolution is at the same pace as observed until now (usually called Business as usual, or BAU), alternative scenarios can be more (e.g., restricted urbanization, land abandonment) to less (e.g., urban development) sustainable.

Using different scenarios, we can predict the degree of human impact on the landscape, considering different choices taken in the present. This will help to plan and manage the territory and understand the potential impact on the ecosystems [6]. Forecast land use change can be conducted using methodologies such as Cellular Automata, CLUE-S model, Multi-criteria decision analysis, Land change modeller, Future Land Use Simulation Model Software and Agent-based models [6]. Several software's can be used to forecast land use changes, such as Terrset,[1] LanduseSim,[2] IDRISI SELVA,[3] QGIS Modules for Land Use Change Simulations,[4] eCognition[5] and Dinamica-Ego,[6] to mention some. Dinamica-Ego is a friendly-user model with multiple possibilities to forecast land use changes based on Cellular Automata, one of the most popular methods. Although the Dinamica-Ego has been used in previous works [e.g., 7,8] to forecast land use change, there is a lack of a compressive protocol with a precise description and practical examples that could be useful to use the software. In this work, we aim to develop a protocol that could be used to forecast land use changes, giving, for example, a case study in Lithuania, Kaunas functional urban area (FUA). Business-as-usual (BAU) scenario and urbanization scenario were shown as examples.

Description of protocol

The developed protocol involves a set of specific steps needed to achieve valid and reliable results. These steps (Fig. 1) include using the Dinamica-EGO software and previous preparatory steps. Information about the software material is described in the software website.[7] Due to the complexity of the process and the specificities of each step, we opted to include some relevant background notes in the corresponding steps.

Step 1. Define the time frame for the analysis.

First, we must set a 'reference period', defining an 'initial year' and a 'final year'. Usually, the final year corresponds to the current year, or a year not too distant, for which we can get base land use data. We also need to define the scenario year. To achieve the best possible results, the time frame for the analysis must ensure that we always consider the same difference in years from the final year

[1] https://www.clarku.edu/centers/geospatial-analytics/terrset/.
[2] http://www.landusesim.com/resources/.
[3] https://www.environmental-expert.com/software/idrisi-selva-gis-and-image-processing-software-342737.
[4] https://plugins.qgis.org/plugins/molusce/.
[5] https://geospatial.trimble.com/en/products/software/trimble-ecognition.
[6] https://csr.ufmg.br/dinamica/.
[7] https://csr.ufmg.br/dinamica/dokuwiki/doku.php.

Table 1
Data requirements for running Dinamica-EGO sub-models.

Common characteristics
Raster format
Same coordinate reference system (CRS)
Same resolution
The same number of columns
The exact number of lines
One band per image
Categorical maps in *integer32* format
Continuous maps in *real32* format

of the reference period to both the scenario year and the initial year of the reference period. If we want to simulate a LU scenario for 2050, and the year of the 'current' land use is 2020 (30 years difference), we should use 1990 LU data for the 'past' image (30 years difference). This does not need to be precise to the unit, but possible differences in the time interval should not be high (e.g., 10 years for the reference period and 50 years for the scenario year).

Step 2. Definition of the future scenario(s).

To model future land use scenarios, first, we must define each scenario according to expected, intended, or best-if-avoidable evolution. The 'simplest' scenario is the 'business-as-usual' (BAU) scenario, where we assume land use change trends that have shaped the territory's evolution during the reference period. The BAU scenario can also include current land use policies and plans (e.g., designated areas for urban expansion or nature protection). Alternative future scenarios can be defined according to different territorial development laws and plans that might be under development or according to other options regarding the balance between potentially conflicting economic, political, and environmental orientations.

The configuration of the future LU scenario tool for the BAU scenario uses the default parameters initially calculated by the Dinamica-EGO sub-models. To successfully implement alternatives, scenario options must be set and transposed to the scenario model as concrete configuration values. Such as the expected/proposed yearly change average between each land use class. The weight associated with a categorical variable, such as the mask's weight for urban and projected urban expansion areas, over their influence on transitions to and from urban land use.

Configuration options in the model involve (1) setting the weight of evidence (WoE) ranges for each variable, (2) transition rates between land use classes for the different scenarios under the form of a transition matrix, (3) patch statistics, setting specific metrics for the extension and/or creation of new patches of each land use class, and (4) WoE coefficients, setting the weight that each variable has on the change between each land use class. These configuration options are assessed in more detail in the corresponding steps.

Step 3. Identify the major driving forces of land use change.

A key aspect of modelling future land use scenarios is identifying and selecting the major driving forces of land use change for the scenario(s) under assessment. This identification should be supported by scientific literature and expert knowledge (e.g., stakeholders' consultation). These driving forces must have a spatial representation (i.e., map layers) so the model can assess their spatial relations and the land use data for the reference period. These variables can depend on the focus of the study and the scenario options. They can also be limited to geographic and temporal availability. Some variables can represent soil or other environmental factors, positively or negatively affecting land use change (e.g., slope, soil organic matter or soil biodiversity). Other data can represent administrative limitations (e.g., protected areas where urban expansion can be limited and urban expansion areas). Another important factors to consider when selecting driving forces are their original resolution, scale, and date. For example, a dataset with a resolution of 1 km will likely reduce the precision and introduce some artefacts in the results of a model working with a base resolution of 50m The Dinamica-EGO future land use scenario sub-model is fully dependent on the results of the statistical analysis of the initial input data—land use data + driving forces—done in the first steps of the modelling process. Thus, it is essential to ensure an adequate selection of the driving forces in terms of data relevance and quality.

Step 4. Collect and organize data for the modelling process.

The data needs to be collected and prepared to run the Dinamica-EGO models. Data needs to fulfil a set of specific characteristics to ensure each sub-model can run successfully, as specified in Table 1. Dinamica-EGO can work with two types of raster data: categorical data and 'continuous' data. Categorical data correspond to discrete values, representing different categories or groups, e.g., land use classes, or binary options (e.g., inside a protected area vs. outside a protected area). Continuous data can take on any value within a specified range, usually associated with a continuous scale (e.g., temperature). As base data for the scenario configuration and modelling, we will need land use datasets for the initial and final years of the reference period. Data for the driving forces will be organized into one single file per scenario, called a 'raster cube', in step 6.2.

Step 5. Calculate landscape metrics for the base year.

Before starting Dinamica-EGO modelling, it is useful to calculate a set of landscape metrics at the patch level. These metrics will be used in the calibration process in step 6.9. Dinamica-EGO allows a set of values for 3 main patch characteristics: (1) mean patch area per land use, (2) patch variance and (3) patch isometry. Dinamica-EGO set up the calculation with default values, but we suggest that we calculate and test these values during the model validation step to ensure better results. These metrics can be calculated with any GIS software (e.g., ArcGIS [9] or QGIS [10]).

Step 6. Dinamica-EGO modelling.

With all the data prepared and organized, we start the modelling process in Dinamica-EGO. The modelling process includes sub-steps to (1) calculate the transition matrix for the base period and base scenario, (2) prepare raster cube for the scenario, (3) calculate the WoE coefficients for raster cube variables, (4) adjust the previous sub-model and assess multicollinearity with Cramer's V, (5) revise raster cube for the scenario, (6) validate the LU-change model for the base scenario, (7) adjust transition matrix for the scenario, (8) calculate and adjust WoE for the scenario, and (9) run future land use scenario simulation. These steps are detailed in the following sub-sections.

Step 6.1. Calculate the Transition Matrix for the base period and base scenario.

The transition matrix is calculated with the first sub-model. This sub-model (Figure S1) analyses land use change between each land use class for the two periods (initial and current), creating a matrix with the percentages of change between each land use per year (Figure S2). This will be the basis for calibrating land use change for the different scenarios.

Step 6.2. Prepare the raster cube for the scenario.

All variables are integrated into one single raster file, each as a unique band. Each variable is loaded as a regular (continuous) or categorical map (see Figure S3 for an example of the sub-model). For each variable, we set a unique name and a unique ID. After running the sub-module, we can check the TIFF file with one band per variable.

Step 6.3. Calculate weights of evidence coefficients for raster cube variables.

Before advancing with the modelling, we need to assess the weight of each variable over the land use change in each pixel. These are called WoE and represent the coefficient or strength. The sub-model (Fig. 2) will use the land use images for the initial and final landscapes and the prepared raster cube as inputs. We also add a subset of 'dynamic' variables based on the calculation of the distances to the different land uses, automatically calculated by the model for each year. The resulting file with the WoE coefficients (Fig. 2), in the Coma Separated Values (CSV) format, can be opened in Microsoft Excel, and we can check the role of each variable in the transitions between land uses (Figure S4). These values will allow for the first calibration step in the overall model.

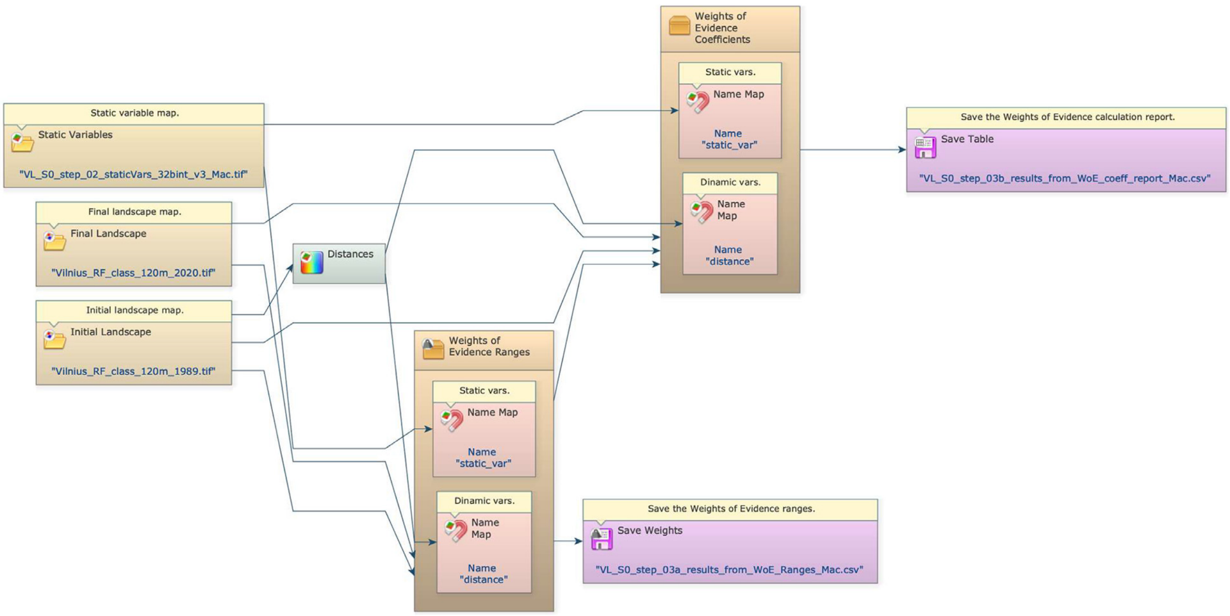


Fig. 2. Sub-model for the calculation of the weights of evidence.

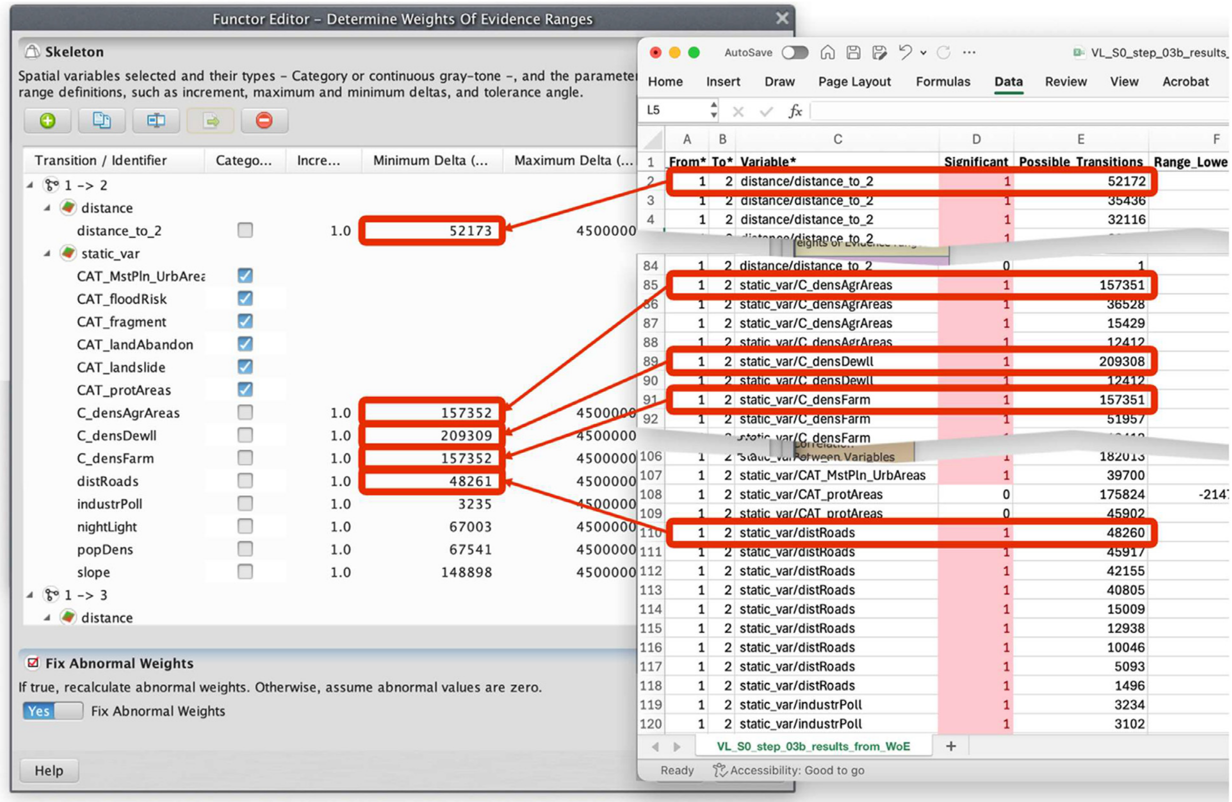


Fig. 3. Adjusting the WoE ranges according to the WoE coefficients from step 6.3.

Step 6.4. Adjust the previous sub-model and assess multicollinearity with Cramer's V.

The first calibration of the model corresponds to the configuration of the minimum delta values for the WoE. The calibrated sub-model will be the basis for assessing multicollinearity between the selected variables (Figure S5). The results from the WoE coefficient should be used to change the default values of the WoE Ranges. For each non-categorical variable, we use the value of the maximum possible transitions in the CSV file (Fig. 3, right side) and change the value of the Minimum Delta in the skeleton window in Dinamica-EGO (Fig. 3, left side). We do this only for those variables showing significant value (red column, Fig. 3, right side). The value should always be higher than the higher value registered on the CSV file (e.g., 'densAgrAreas' registered a maximum of 157,351 possible transitions, so we set the minimum delta to 157,352). This can be a lengthy process, depending on the size of the study area and the number of variables.

After configuring the WoE ranges, we run the sub-model to calculate the correlation between the pairs of maps (Figure S5), which saves the results in another CSV file. Once this is completed, we check the results for variable pairs with Cramer's V coefficient equal to or above 0.5 (Figure S6) and decide which variables to keep and discard.

Step 6.5. Revise the raster cube and calculate WoE coefficients for the scenario.

Based on the results from the previous step, if needed, we go back to the model from step 6.2 and remove one (or more) of the correlated variables from the raster cube. We then run the model to produce a revised raster cube, which will be used for the next steps. With this raster cube, we run another sub-model, similar to the model from step 6.3, to calculate the WoE coefficients, or skeleton, which will be the basis for future scenarios.

Step 6.6. Prepare and validate the LU-change model for the base scenario.

We build the simulation model after parametrizing the previous sub-models and solving potential multicollinearity issues. However, we must test the model for accuracy before simulating for the simulation year. To ensure model accuracy, the model is validated with an initial simulation for the reference period, simulating land use change from the initial to the final year. The objective is to simulate the land use of the final year of the reference period. This step will use several previously calculated parameters: (1) the transition matrix and (2) the patch parameters. The modeller contains two distinct sub-models for land use change: the expander and the patcher. The expander controls land use change by expanding any existing areas of land use. The patcher creates new land use areas inside other land use classes. They can have different configurations regarding patch medium size, variance, and patch isometry.

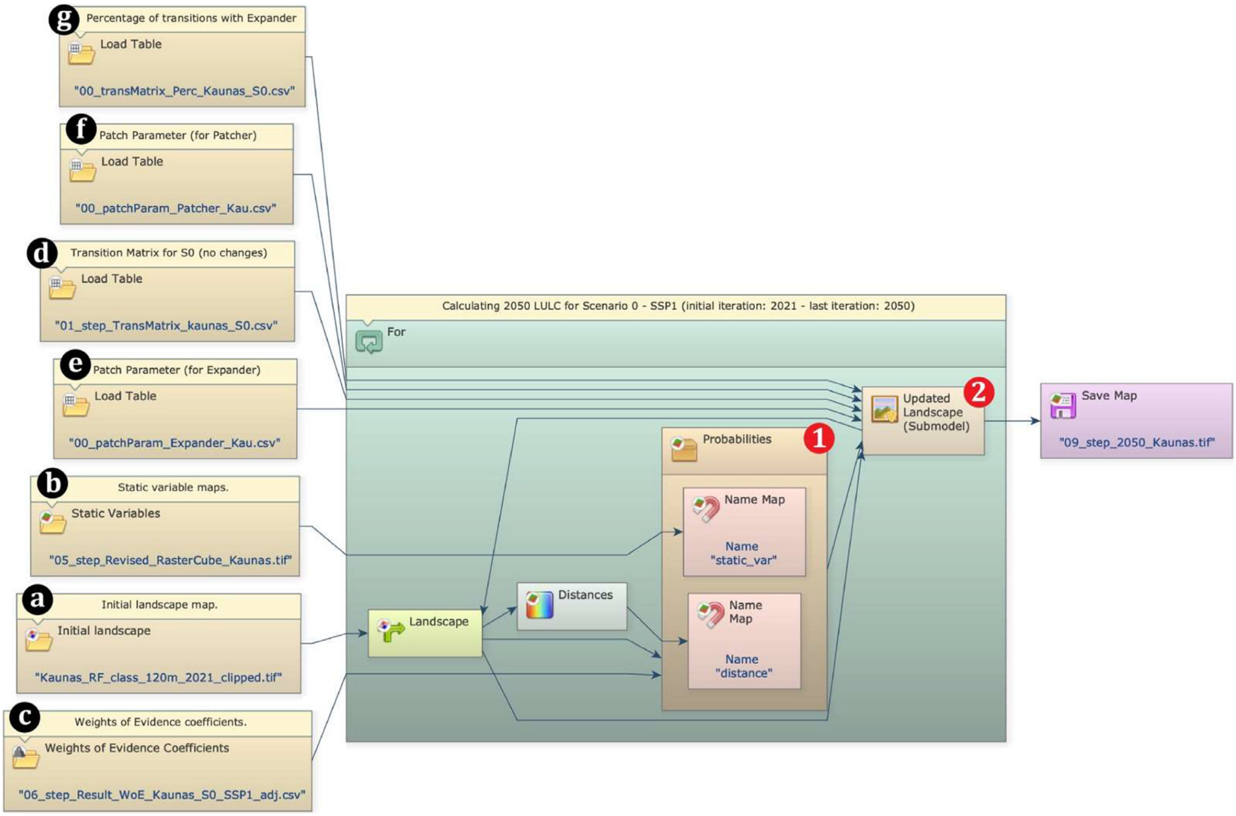


Fig. 4. Sub-model used to calculate the future land use scenario with the integration of the variables.

For the reference year model, we will need the land use layer for the first year of the reference period (Fig. 4a). We will also need the revised raster cube (Fig. 4b), the WoE coefficients from the previous step (Fig. 4c), the transition matrix from step 6.1 (Fig. 4d), two tables with patch parameters for the expander (Fig. 4e) and the patcher (Fig. 4f) modules, and one last table with the percentage of land use transitions calculated by the expander module (Fig. 4g). The base land use map (a), the raster cube (b), and the WoE coefficients (c) feed the probability module (Figure 4.1) inside the landscape calculation module. All the other parameters feed the 'Updated landscape' sub-model (Figure 4.2).

The result of this simulation is then compared to the actual data for the same year using the Reciprocal Similarity Comparison method [11]. The sub-model for validation (Figure S7) outputs the result for two different levels of validation: (a) similarities of differences, based on a pixel-to-pixel assessment, and (b) multi-window similarity of differences, based on area similarity for land use classes inside a moving window (see example of validation results in Figure S8). If the validation result is unsatisfactory, the model must be adjusted until we get a satisfactory result.

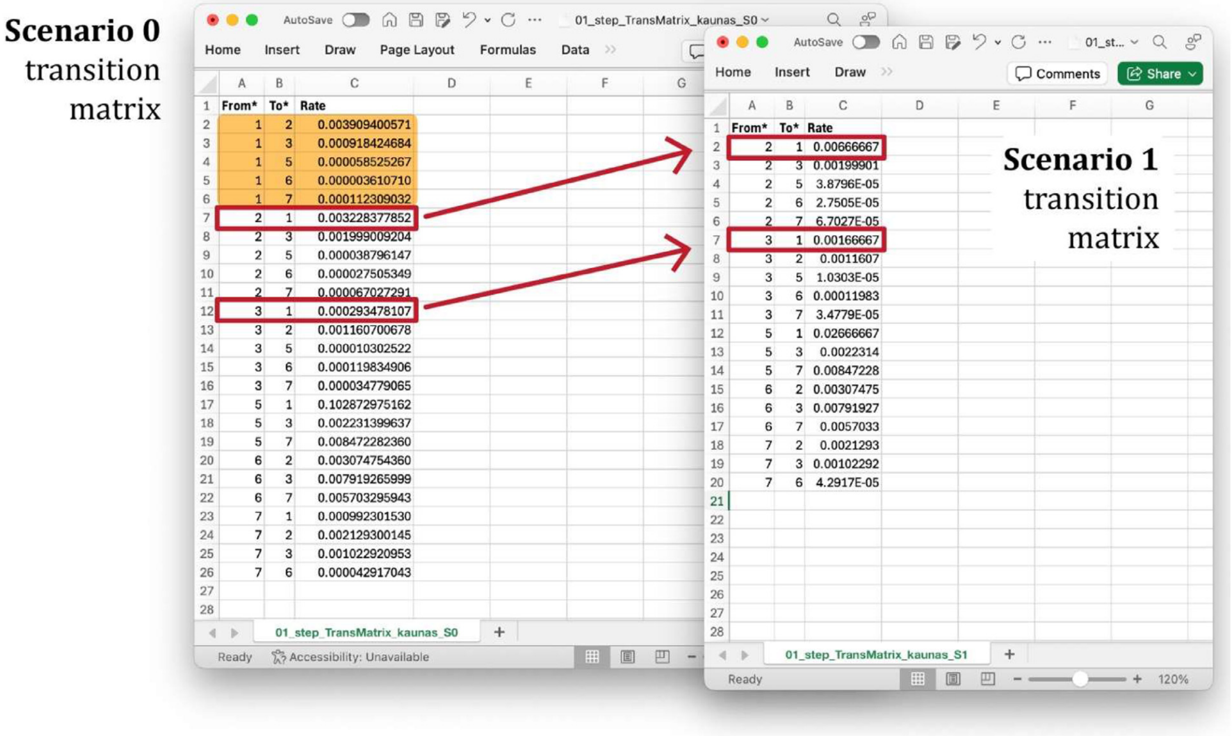
Step 6.7. Adjust the Transition matrix for the scenario.

After adjusting the model to achieve satisfactory validation, we must adjust the transition matrix for the alternative scenario to reflect scenario conditions. If the scenario considers a relevant increase in urban areas, the transition matrix should reflect this (e.g., the transition matrix for scenario 0 (BAU) identifies an average annual change from agriculture areas (class 2) to urban areas (class 1) around 4.3 % and 0.1 % from forest areas (class 3) (Fig. 5)). For instance, the alternative scenario identifies major urban growth at the expense of agricultural areas, followed by forest areas. In that case, we can prepare a new matrix with corresponding altered values, as shown for the scenario 1 transition. Notice also that while the original transition matrix identified changes from urban areas to other land uses (orange highlight in Fig. 5), we opted to consider that no urban areas would be changing to any other land use type. For this, we removed the corresponding lines in the transition matrix for scenario 1.

Important note: CSV data files outputted from Dynamic-EGO have a specific format, which, if changed, can produce unexpected results in the simulations. This is the case for both transition matrices and for WoE coefficients. When editing the different CSV files, particularly in Excel, avoid removing or adding extra columns, as this can break the data structure (see Figure S2 for an example).

Step 6.8. Adjust WoE for the scenario.

The WoE coefficients inform the model about the weight that each variable has on the land use change for each cell. The default WoE are calculated based on the statistical analysis of the land use transitions during the base period. These values are used as the



From*	To*	Rate
1	2	0.003909400571
1	3	0.000918424684
1	5	0.000058525267
1	6	0.000003610710
1	7	0.000112309032
2	1	0.003228377852
2	3	0.001999009204
2	5	0.000038796147
2	6	0.000027505349
2	7	0.000067027291
3	1	0.000293478107
3	2	0.001160700678
3	5	0.000010302522
3	6	0.000119834906
3	7	0.000034779065
5	1	0.102872975162
5	3	0.002231399637
5	7	0.008472282360
6	2	0.003074754360
6	3	0.007919265999
6	7	0.005703295943
7	1	0.000992301530
7	2	0.002129300145
7	3	0.001022920953
7	6	0.000042917043

From*	To*	Rate
2	1	0.00666667
2	3	0.00199901
2	5	3.8796E-05
2	6	2.7505E-05
2	7	6.7027E-05
3	1	0.00166667
3	2	0.0011607
3	5	1.0303E-05
3	6	0.00011983
3	7	3.4779E-05
5	1	0.02666667
5	3	0.0022314
5	7	0.00847228
6	2	0.00307475
6	3	0.00791927
6	7	0.0057033
7	2	0.0021293
7	3	0.00102292
7	6	4.2917E-05

Fig. 5. Transition matrix configuration.

default for the BAU scenarios. However, we can adjust the WoE values for specific variables we want to have a higher weight in the land use change process. For instance, categorical variables such as those corresponding to urban expansion areas set in municipal master plans can be used to ensure restrictions in attributing urban class to all pixels outside this mask. A similar example is the case of protected areas, where we can set the parameters to avoid expanding urban areas inside protected areas. We duplicate the original WoE file and change the weight value according to these rules (Fig. 6). In this case, for urban areas, we set a high positive weight for areas inside the urban mask and a high negative weight for areas outside for the changes from any land use class (From*) to the urban class (To*). For the layer of protected areas, we did not change the original weights outside these areas. However, we changed the weight inside protected areas to a negative value to ensure no pixels change from non-urban to urban.

The files should also keep the default order in the original outputs from the Dinamica-EGO sub-models. For the WoE coefficients, after adjusting the weights for the specific categorical variables, we need to reorder the data to its original structure (Fig. 7).

Step 6.9. Run future land use scenario simulation.

This step involves the integration of the results from all previous steps. The structure of the sub-model for the future scenario is the same as for the model validation in step 6.6 (Fig. 4), but with some updated inputs, which vary according to the scenario alternative. For scenario 0 (BAU), the initial landscape (a) is now the 2020 land use data, with all other inputs staying the same as for the validation scenario. For scenario 1, we also use 2020 land use data (a) and change the revised raster cube (b), the adjusted WoE coefficient file (c), the transition matrix (d), and the percentage of change for the expander (g).

After running the model for the two scenarios, we can compare the results and assess the expected impact of the configuration options on land use change for the assessed period. Here, we should have two land use maps resultant from the scenarios.

Protocol validation

We present a simplified example developed under the project to show its applicability and validity. The example is applied to the Kaunas functional urban area (FUA) in Lithuania. The time frame was set to 1989–2021 (reference period), with 2050 as the scenario year. We considered 2 different political scenarios, as defined in Table 2. These scenarios reflect case-specific trends and projected national/European goals through 2050. Scenarios of business as usual (S0-BAU) and urbanization (S1-URB) were developed based on the work of Gomes et al. [11] but adapted to the municipal scale and considering the specificities of each city (e.g., national and municipal plans).

Table 3 shows the driving forces considered under each scenario. These include variables related to environment and climate, land use regulation, social and economic characteristics, and proximity. After building the raster cube, the correlation assessment showed

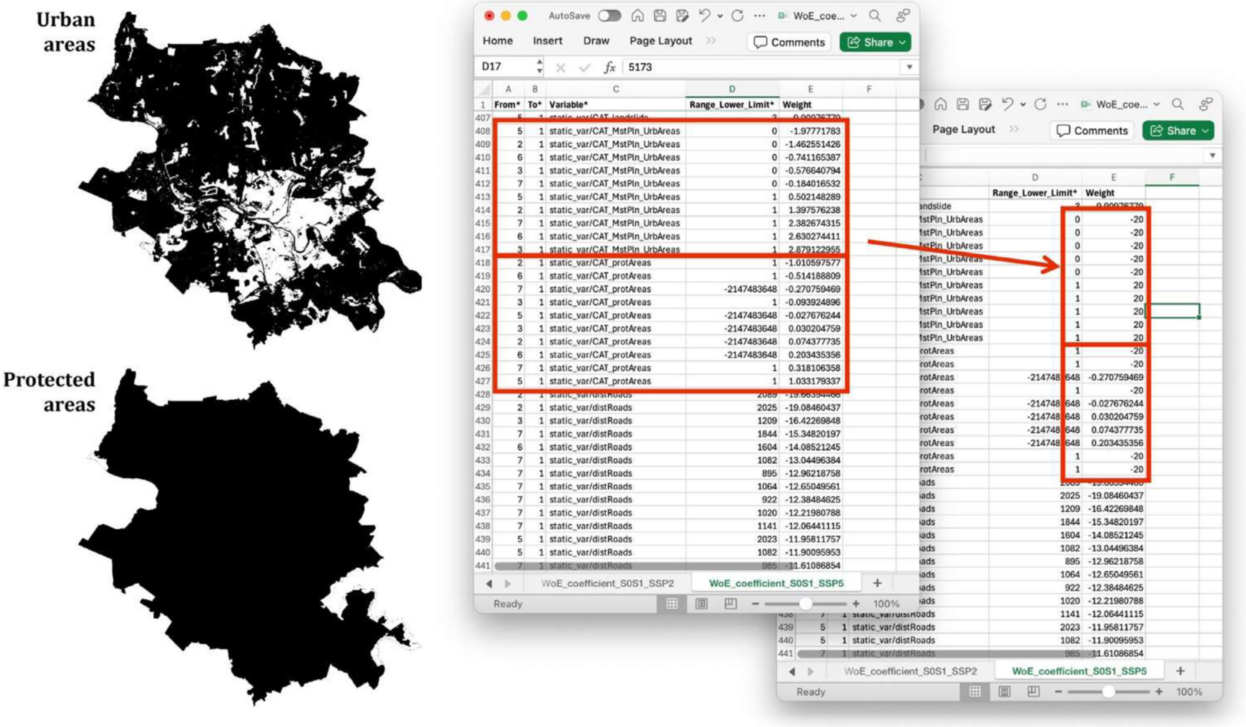


Fig. 6. Adjusting the WoE ranges according to the WoE coefficients from step 6.3.

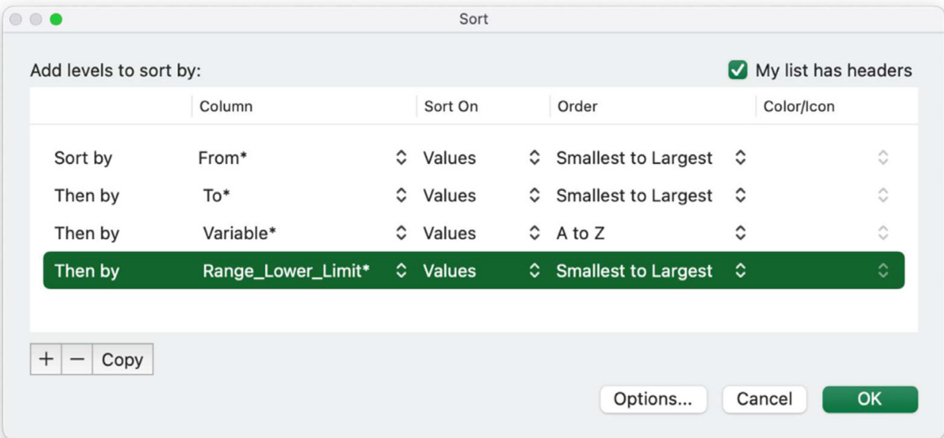


Fig. 7. Reordering the WoE coefficient data to use as input in the future scenario model in Dinamica-EGO.

Table 2
Scenario description.

Scenario	Resume
S0-BAU	This scenario assumes the observed patterns of LU change from 1989 to 2020, applied to the 2000–2050 period. Based on past LU changes, the CA approach controls the temporal changes between the selected land use classes, the observed transition probability matrix, and the calculated weights per driving force.
S1-URB	This scenario assumes that human and systemic drivers affect European and Lithuanian urbanization trends. They include economy, demography, and lifestyle changes, with increased urban sprawl due to rural exodus. The CA approach is also based on the original transition probability matrix and weights of evidence for each driving force. However, it integrates specific adjustments on the probability for change between specific land use classes (e.g., changes between cropland and urban areas) and on the attributed weights of change for specific driving forces (e.g., changes inside protected areas).

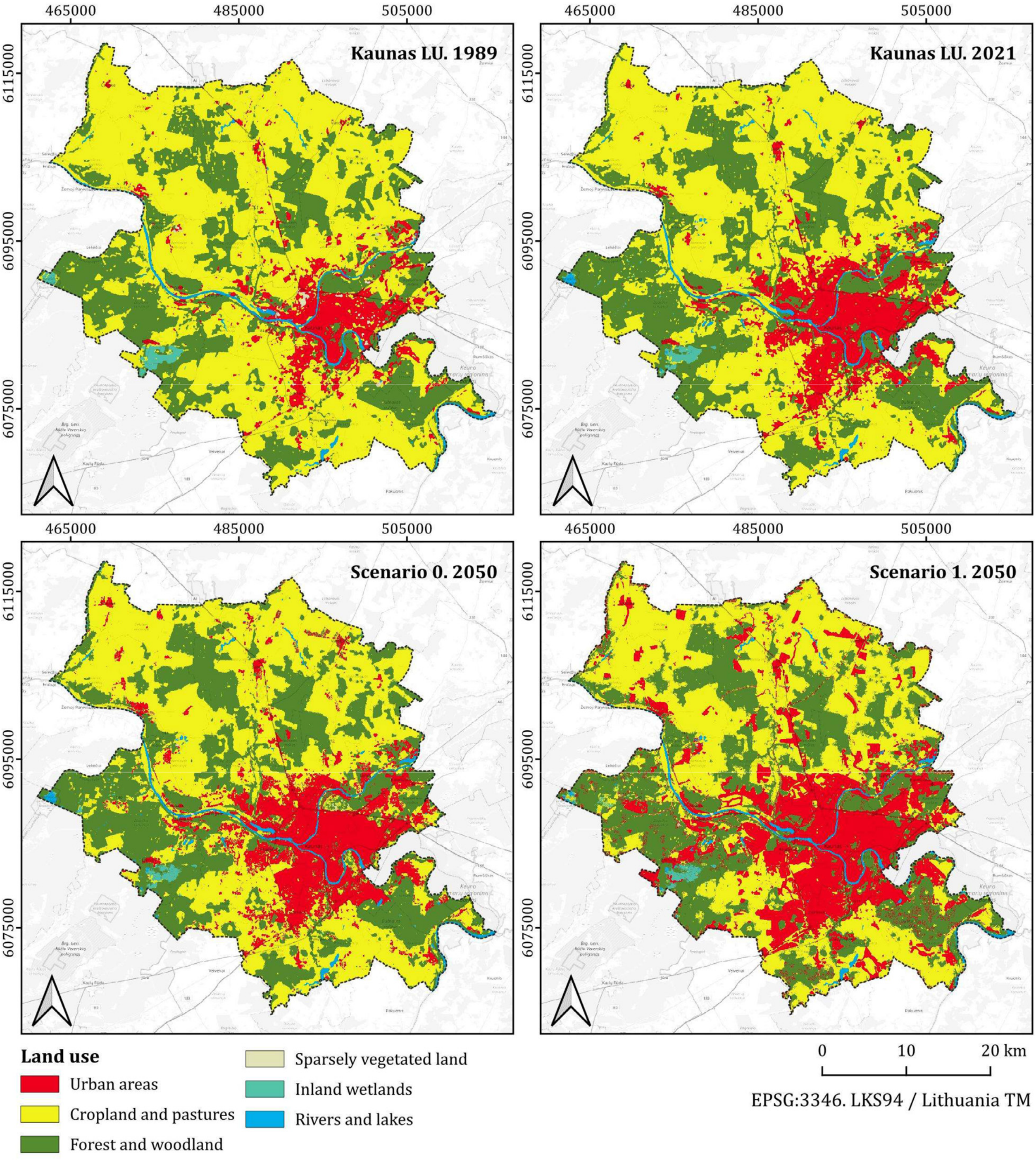


Fig. 8. Land uses in 1989, 2021 and 2050, scenario 0 (BAU) and scenario 1 (urbanization).

a high correlation (Cramer's $V \geq 0.5$) between variables 9 and 11 and 12 and 13. Therefore, we decided to remove variables 11 and 13 from the analysis. We then calculated the WoE for the revised raster cube and ran the validation sub-model to produce a scenario for 2021. The validation results showed good results, with $R = 0.578$ for the minimum similarity index and Multi-Window similarities of differences between 0.746 (min. sim.) and 0.867 (max. sim.) for window size 11. These represent good values, confirming the validity of the model. We adjusted the transition matrix for scenario 1 for both urban and urban expansion areas and protected areas, as in Fig. 5. For the configuration of the WoE coefficients, we also introduced the changes shown in Fig. 6. The protocol can be used considering other scenarios, depending on the scenario planned. This depends on the objective of the assessment. For this, it is important to identify the drivers that can affect the land use change (e.g., environmental, social, economic or political) and have these

Table 3
List driving forces for the assessed scenarios. Data type: Cont. – Continuous, Cat. – Categorical.

Thematic areas	id	Driving force /variable	Data type	Orig. scale/ resolution	Scenario	
					S0	S1
Environ. and climate	1	Slope	Cont.	25m	x	x
	2	Land fragmentation (mesh density)	Cont.	100m	x	x
	3	Soil pollution	Cont.	500m	x	x
	4	Landslide susceptibility	Cat.	200m	x	x
	5	Agriculture abandoned areas	Cat.	200m	x	x
	6	Soil Organic Carbon (topsoil)	Cont.	500m		
Land use regulation	7	Flood risk map	Cat.	100m	x	x
	8	Protected areas	Cat.	-	x	x
	9	Urban and urban expansion areas	Cat.	-	x	x
Social and economic	10	Population density	Cont.	10m	x	x
	11	Nightlight / light pollution	Cont.	500m	x	x
	12	Density of agriculture areas	Cont.	-	x	x
	13	Density of dwellings	Cont.	-	x	x
Proximity	14	Distance to main roads	Cont.	30m	x	x
	15	Distance to water areas	Cont.	30m	x	x
	16	Distance to urban areas	Cont.	30m	x	x
	17	Distance to woodland and forest	Cont.	30m	x	x
	18	Distance to grasslands	Cont.	30m	x	x

Table 4
Land use for 1989, 2021, 2050 (BAU and Urbanization).

Land use class	1989		2021		2050 (BAU)		2050 (Urbanization)	
	Km2	%	km2	%	km2	%	km2	%
Urban areas	143.7	8.9 %	219.2	13.6 %	265.7	16.4 %	390.6	24.2 %
Croplands and pastures	947.6	58.7 %	838.9	51.9 %	760.1	47.0 %	666.9	41.3 %
Forest and woodlands	482.7	29.9 %	521.4	32.3 %	552.7	34.2 %	522.1	32.3 %
Sparsely vegetated land	4.7	0.3 %	0.6	0.0 %	1.1	0.1 %	0.8	0.1 %
Inland wetlands	10.5	0.7 %	8.1	0.5 %	6.9	0.4 %	6.9	0.4 %
Rivers and lakes	26.4	1.6 %	27.5	1.7 %	29.1	1.8 %	28.3	1.8 %
Total	1615.6	100.0 %	1615.6	100.0 %	1615.6	100.0 %	1615.6	100.0 %

data at the best resolution possible. Likely, many variables can be identified, and some of them can be highly correlated. Therefore, it is key to conduct a multicollinearity analysis. It is essential to adjust the WoE, to ensure that for instance areas where urbanisation is restricted, are not considered as urbanisable areas. Finally, it is essential to validate the land use change outputs. This is key for the credibility of the results. The results obtained can be important for urban planning since managers can understand what are the impacts of the different policies on future land use changes. This will allow them to develop strategies that reduce the effects of urban sprawl on the ecosystem and their services, or the implications of rural exodus and land abandonment on afforestation.

Table 4 resumes the area results for the years 1989, 2021 and 2050 (BAU and urbanization). The results showed clear differences in the extent of the urban areas for both scenarios. The land use maps from 1989, 2021 and 2050 (BAU and urbanization) are shown in the Fig. 8.

Limitations

Limitations can derive from several factors. Land use data for the reference period derived from remote sensing can be affected by classification errors, which will affect the accuracy of the analysis at different sub-modules. Assessing large landscapes and addressing land use change between multiple land use classes adds complexity to the analysis and can increase the results' uncertainty. Understanding the effect of changing different configuration parameters is essential to ensure solid results. Testing different options in the modelling stage is particularly relevant.

Supplementary material

The supplementary material contains a set of images related to the use of Dinamica-EGO, which supports the description of the protocol.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.mex.2025.103283.

References

[1] Z. Zhang, J. Ding, W. Zhao, Y. Liu, G. Li, P. Pereira, Impacts of urbanisation on vegetation dynamics in Chinese cities, Environ. Impact. Assess. Rev. 103 (2023) 107227, doi:10.1016/j.eiar.2023.107227.
[2] J. Cusens, E.D. Barraclough, I. Elisabeth Måren, Socio-cultural values and biophysical supply: how do afforestation and land abandonment impact multiple ecosystem services? Land. use policy. 136 (2024) 106967, doi:10.1016/j.landusepol.2023.106967.
[3] D. Beillouin, R. Cardinael, D. Berre, A. Boyer, M. Corbeels, A. Fallot, F. Feder, J. Demenois, A global overview of studies about land management, land-use change, and climate change effects on soil organic carbon, Glob. Change Biol. 28 (2022) 1690–1702, doi:10.1111/gcb.15998.
[4] J. Wang, M. Bretz, M.A.A. Dewan, M.A. Delavar, Machine learning in modelling land-use and land cover-change (LULCC): current status, challenges and prospects, Sci. Tot. Environ. 822 (2022) 153559, doi:10.1016/j.scitotenv.2022.153559.
[5] M.R. Rahnama, Forecasting land-use changes in Mashhad Metropolitan area using Cellular Automata and Markov chain model for 2016-2030, Sustain. Cities. Soc. 64 (2021) 102548, doi:10.1016/j.scs.2020.102548.
[6] E. Gomes, M. Inacio, K. Bogdzevič, M. Kalinauskas, D. Karnauskaite, P. Pereira, Future land-use changes and its impacts on terrestrial ecosystem services: a review, Sci. Total. Environ. 781 (2021) 146716, doi:10.1016/j.scitotenv.2021.146716.
[7] J.S. Cruz, C.J.C. Blanco, J.F.O. Junior, Modeling of land use and land cover change dynamics for future projection of the Amazon number curve, Sci. Tot. Environ. 811 (2022) 152348, doi:10.1016/j.scitotenv.2021.152348.
[8] A. Denvir, Avocado expansion and the threat of forest loss in Michoacán, Mexico under climate change scenarios, Appl. Geogr. 151 (2023) 102856, doi:10.1016/j.apgeog.2022.102856.
[9] ESRIArcGIS Desktop: Release 10, Environmental Systems Research Institute, Redlands, CA, 2011 http://www.arcgis.com.
[10] QGIS.orgQGIS Geographic Information System, QGIS Association, 2025 http://www.qgis.org.
[11] E. Gomes, M. Inácio, K. Bogdzevič, M. Kalinauskas, D. Karnauskaitė, P. Pereira, Future scenarios impact on land use change and habitat quality in Lithuania, Environ. Res. 197 (2021), doi:10.1016/j.envres.2021.111101.