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Integrating Environmental Suitability into Urban Planning. A Grid-Based Decision Support Framework for Cluj-Napoca Metropolitan Area, Romania

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ABSTRACT

Rapid sprawl in developing cities presents significant challenges to sustainable land-use planning, often neglecting critical ecological objectives. Spatial models that can assist decision-makers with the integration of environmental factors into the planning process are useful. This study aims to develop an environmental suitability model for suburban expansion using GIS techniques, fuzzy logic, and incorporating landslide susceptibility assessment via the maximum entropy method, using the Cluj-Napoca Metropolitan Area in Romania as a case study. To demonstrate the practical application of the suitability model, we constructed a grid-based decision support framework prioritising intuitiveness, simplicity, and transparency to enhance stakeholder accessibility. The results show that a multi-criteria suitability model can inform and facilitate territorial decision-making, especially when integrated with other parameters (social, economic, and infrastructure-related) that influence development opportunities in the metropolitan area. Future directions for this research include validating the model within a multidisciplinary team, exploring diverse visualisation and communication strategies, and testing in applied planning contexts.

1. INTRODUCTION

Sprawl is the most impactful urban development pattern, posing a great threat to sustainable development goals (Wang et al., 2020; Yasin et al., 2020). The European Environment Agency (2006, p. 6) defines it as *"the physical pattern of low-density expansion of large urban areas, under market conditions, mainly into the surrounding agricultural areas"*. The negative effects of sprawl are diverse and cumulative. It causes high land uptake, which amplifies the often-ignored land crisis, although geographical space is arguably mankind's most important resource (Haber, 2007). The removal of large areas from the natural or agricultural circuit directly threatens soil resources (FAO, 2015). Energy consumption associated with typical suburban living can be an order of magnitude higher than high-density residential areas, largely as a result of increased reliance on personal automobiles (Kenworthy and Laube, 1999), therefore sprawl can be linked to difficulties in reaching climate goals. It also causes geographical segregation of communities (Thurston and Yezer, 1994), which amplifies the inequality of opportunity (Cassiers and Kesteloot, 2012). Apart from car dependency, it increases home-workplace distances (Frank, 1994), decreases social capital (Putnam, 2000), and amplifies political apathy (Hopkins and Williamson, 2012), among many other mental and physical health effects associated with the daily commute. Thus, any city or metropolitan area must prioritise fighting sprawl and its effects seriously and responsibly.

In the present study, fuzzy logic was chosen as the framework for designing a multi-criteria environmental suitability model for suburban development in the Cluj-Napoca Metropolitan Area, used as a decision support system. The model output is a single-band raster layer where a pixel's value between 0 and 1 represents its degree of environmental suitability for suburban development.

Worm et al. (2010) found that users will increasingly judge a decision support system the more complex it is, while Janssen (2001) and Hajkowicz (2008) point out that simple decision support methods are often sufficient as long as the problem is properly framed and the decision criteria are clear enough. We advance a simple decision model that can be used to extract areas suitable to incentivise development. Essentially, the suitability model functions as a spatial screening tool: although by visualising the raw results one can intuitively reach conclusions regarding the spatial distribution of the suitable areas, the model itself cannot offer an objective, transparent, and standardised method to extract such areas. Therefore, we use a grid-based reclassification to reduce the granularity of the model output and allow for comparisons between areas. We then calculate urban compactness on the same grid using the contact perimeter approach. By focusing new development towards low compactness areas, we can fight land uptake and land cover fragmentation by incentivising infill development. We consider our resulting map to serve as a simple, transparent and intuitive way to guide development decisions for a diverse array of decision-makers.

The main objective of this paper is to develop and assess a multi-criteria environmental suitability model for suburban expansion and its integration in a decision support tool. To achieve this, the research pursues three specific goals: (1) handling uncertainty by utilising a fuzzy logic framework to address the inherent ambiguity associated with environmental suitability; (2) integrating geomorphological risk by incorporating landslide susceptibility into the model using the Maximum Entropy (MaxEnt) method; and (3) operationalising decision support by constructing a simplified, grid-based framework that overlays environmental suitability with urban compactness. By prioritising transparency and intuitiveness, this model provides stakeholders with an accessible tool to bring environmental criteria to the decision-making process.

2. THEORY AND METHODOLOGY

2.1. Theoretical background

Suitability mapping using geospatial data has been well-represented in the literature since the beginning of spatial analysis. Hopkins (1977) defined suitability maps as a common approach that integrates the spatial patterns of the needs, preferences, and predictors of a certain human activity. The employment of GIS tools for such multi-criteria suitability modelling has contributed to significant methodological advancements such as applying both expert judgement and arithmetic approaches (Pereira and Duckstein, 1993) on raster data, which has become the standard data format for suitability mapping.

Within this multi-criteria framework, the geomorphological criterion is one of the key environmental factors in determining the suitability of an area for suburban development because the relationship between geomorphology and built-up space is bilateral. On the one hand, slope conditions affect suitability for development due to the differences in cost, amenity and risk. On the other hand, building on landslide-prone surfaces can amplify the risk of landslides, and, thus, the degradation of the built environment too (Adolphe et al., 2022; Miccadei et al., 2022).

The MaxEnt software (Phillips et al., 2004) was initially developed by ecologists for species distribution modelling. Later, it was adopted by the landslide susceptibility modelling community (Felicísimo et al., 2013; Kerekes et al., 2018; Vorpahl et al., 2012) as there are many similarities between the two use cases: an inventory of existing landslides can be considered equivalent to a dataset of species observations, while landslide susceptibility of a pixel can be seen as equivalent to the probability of a species being present.

While such statistical methods provide robust quantitative variables, the concept of suitability is often characterised by semantic uncertainty. This is addressed through fuzzy logic, based on the fuzzy set theory introduced by Lotfi Zadeh (1965), which uses the concept of partial truth to more closely resemble the reasoning produced by human language (Kosko and Isaka, 1993).

Fuzzy logic proves to be very useful in a multi-criteria decision-making context because the property of being "suitable" is essentially a fuzzy concept (named "linguistic variable") as any analyzed element has a certain "degree" of suitability. Such approaches work well with raster data, and fuzzy logic has been successfully used in spatial multi-criteria suitability models (Bikdeli, 2020; Gemitzi et al., 2007; Reshmidevi et al., 2009). The fuzzy approach is all the more fit for our study because we use the narrower concept of environmental suitability, therefore reducing the semantic uncertainty caused by the wider concept of suitability.

For sustainable territorial planning, geographic patterns of existing development are a key component of identifying suitable development alternatives. Urban compactness has long been regarded as a key element of sprawl (Angel et al., 2005; Ewing, 2008; Frenkel and Ashkenazi, 2008; Galster et al., 2001), as it can be a proxy for many of its undesirable geographical and ecological effects. The contact perimeter approach for calculating shape compactness was developed by Bribiesca (1997) and applied in an urban context by Steurer and Bayr (2020), as well as by Dewa et al. (2023).

This method is applicable in a bi-dimensional discrete space (in a remote sensing case, the unit being a square pixel) and uses the shape's contact perimeter to produce an index with theoretical values between 0 and 1 that characterises the shape's compactness, independent of scale. Steurer and Bayr's C_2 index is defined as follows:

$$C_2 = \frac{P_{c\max} - P_c}{P_{c\max} - P_{c\min}} \quad (1)$$

where:
- P_c is the contact perimeter (Eq. 2);
- $P_{c\min}$ is the minimum contact perimeter (Eq. 3);
- $P_{c\max}$ is the maximum contact perimeter (Eq. 4);

$$P_c = \frac{T_n - P}{2} \quad (2)$$

where:
- T_n is the cell number multiplied by the cell side number (in the case of a pixel, 4);
- P is the shape perimeter.

$$P_{c\min} = n - 1 \quad (3)$$

where:
- n is the number of cells in the shape.

$$P_{c\max} = \frac{T_n - 4\sqrt{n}}{2} \quad (4)$$

where:
- T_n is the cell number multiplied by the cell side number;
- n is the number of cells in the shape.

2.2. Study area

Cluj-Napoca Metropolitan Area (CNMA) is located in the NUTS-II Northwestern Development Region in Romania, between 44°57' - 45°29' N and 23°13' - 23°59' E (Fig. 1).

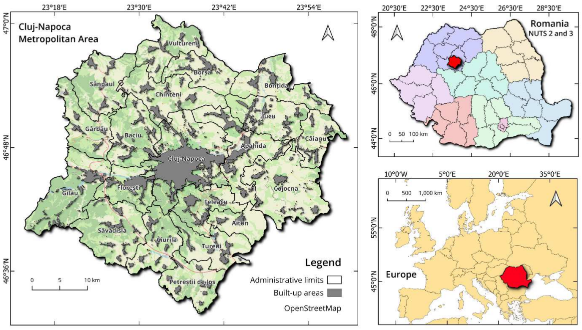

Fig. 1. Map of the study area *(source: own elaboration, using data on built-up areas and administrative boundaries from the National Agency for Cadastre and Land Registration, ANCPI, 2024).*

It has an area of 1.603 km² and a population of 411.130 of which 286.598 live in the city of Cluj-Napoca, making it the second-largest city in Romania by population. CNMA encompasses the city of Cluj-Napoca and 19 of its surrounding municipalities, which are associated with the Cluj Metropolitan Area Intercommunal Development Association (ADI ZMC, 2024).

Cluj-Napoca, often called "The capital of Transylvania", is a social and economic hotspot that has been experiencing rapid growth and development over the last decade, and its recent sprawl is a clear sign of the city's need for land uptake. However, CNMA encompasses multiple nature conservation objectives, some of them being directly affected by sprawl due to their proximity to the city (Muntean et al., 2024). Landscapes in CNMA are highly heterogeneous, with significant differences between well-developed, truly suburban municipalities and villages still conserving their rural identity (Baciu et al., 2018). Moreover, fast and under-planned suburban growth has put the metropolitan area's road infrastructure under great strain: multiple axes face congestion issues while public transportation infrastructure struggles to accommodate resident needs (Andrei, 2024; Baciu et al., 2015; Popa, 2023). This creates the need for methodical and responsible growth planning, which takes into account environmental conditions in a feasible and transparent way.

2.3. Data sources

Public data was downloaded from the GIS portal managed by the Cluj-Napoca Metropolitan Area Agency (ADI ZMC, 2024), Copernicus Land Monitoring Service portal (European Environment Agency, 2019), Protected Planet World Database on Protected Areas (UNEP-WCMC, 2024) and the geoportal of the National Agency for Cadaster and Land Registration (ANCPI, 2024). We have also used a landslide inventory created by digitising remote sensing data (Roşian et al., 2018; Roşian and Horvath, 2019). For geospatial data processing and cartography, QGIS 3.32 was used, while for modelling landslide susceptibility, MaxEnt 3.4.4 (Phillips et al., 2004) and RStudio were employed.

2.4. Study design and workflow

The main objective of the study was to develop and test the multi-criteria environmental suitability model. In order to include a geomorphological suitability criterion, it was necessary to model landslide susceptibility in the study area, which also acts as a proxy for other geomorphology-related criteria such as slope. The results of the multi-criteria suitability model are then included in a simplified decision support framework in order to provide an example of processing the raw model outputs for decision support. The complete study workflow is shown in Figure 2.

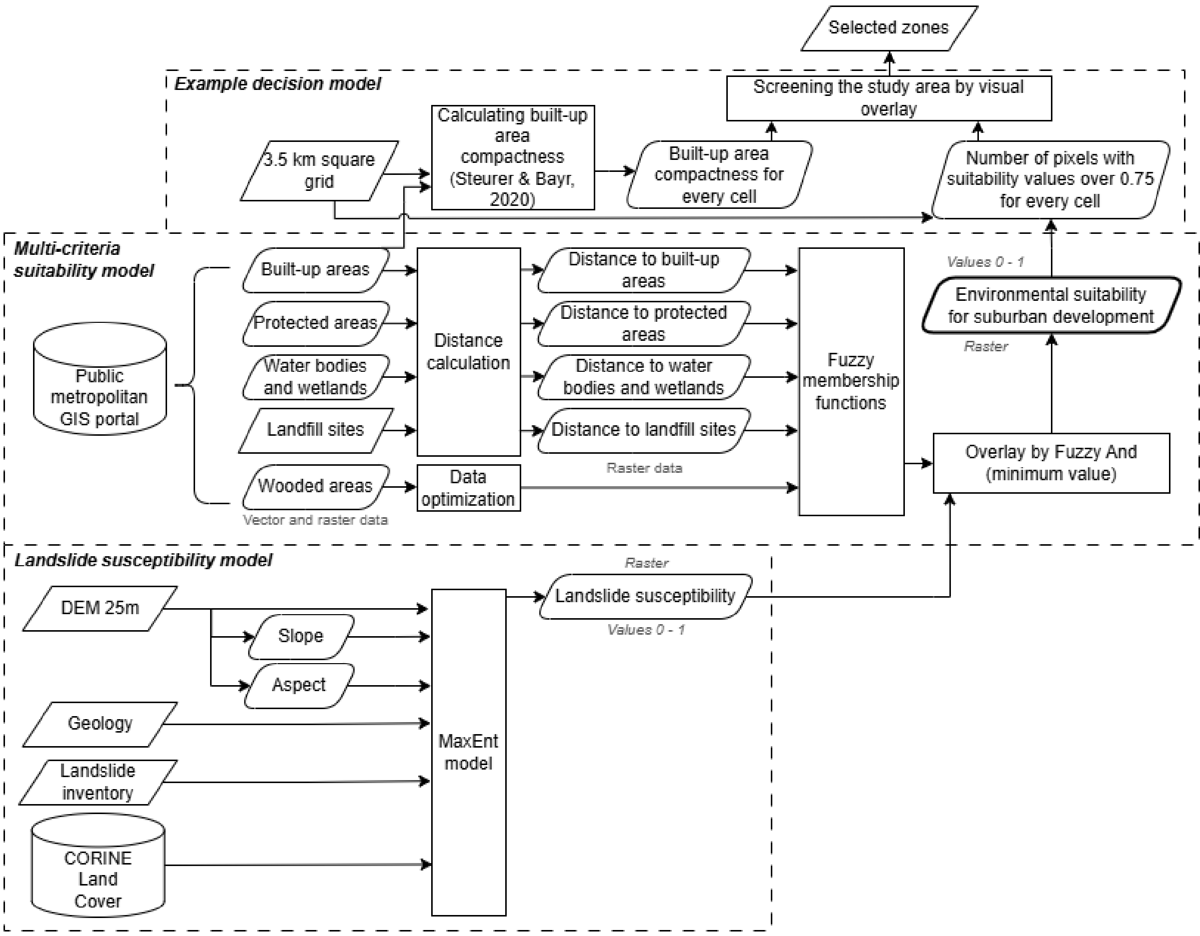

Fig. 2. Flowchart of the study design.

2.5. Modelling landslide susceptibility

The MaxEnt software was used to model landslide susceptibility. The input data consists of: 1. observations (training and test data) derived from the landslide inventory; and 2. environmental parameters as continuous variables (aspect, slope, and elevation, derived from the digital elevation model) and categorical variables (geology and land use). Observation data was obtained by generating the centroids of landslide polygons. Given the relatively high resolution of 25 metres, some large landslides have required arbitrary sectioning into multiple polygons, in order to more accurately represent ground conditions. Before training the model, a bias file was generated in RStudio using a script provided by the model developers. This step calculates a Kernel Density Estimation of the observation data to take into account the spatial autocorrelation of the observations. The model was run with the recommended settings and used the mean of a 7-fold cross-validation as the result (Fig. 3b). The mean model area under the receiver operating characteristic curve (AUC) is 0.792, which we consider a reasonable enough ability to discriminate for the scope of this study.

2.6. Suitability model design

The multi-criteria suitability model designed for this study operates by conceptualising a fuzzy set of "area units environmentally suitable for suburban development" in which the value of a pixel as an element of this set represents its degree of membership to the set. Consequently, a pixel value of 0 accounts for no membership to the set (unsuitable), whereas a pixel value of 1 accounts for maximum membership to the set (perfectly suitable).

Table 1. Fuzzy membership functions used to generate each model criterion from the input data.

Parameter (raster dataset)	Unit of measure ment	Fuzzy membership function	Function parameters	Parameter value
Distance to built-up areas	Distance (meters)	Reversed "Small" (sigmoid)	Midpoint	1000 m
			Spread	5
Distance to water bodies and wetlands		Linear	Upper membership bound	300 m
Distance to protected areas and proposed protected areas				300 m
Distance to landfill sites				3000 m
Forests	Boolean	No transformation	Forest	0
			No forest	1
Landslide susceptibility	Probability (0 – 1)	Reverse transformation (1 – x)	N/A	N/A

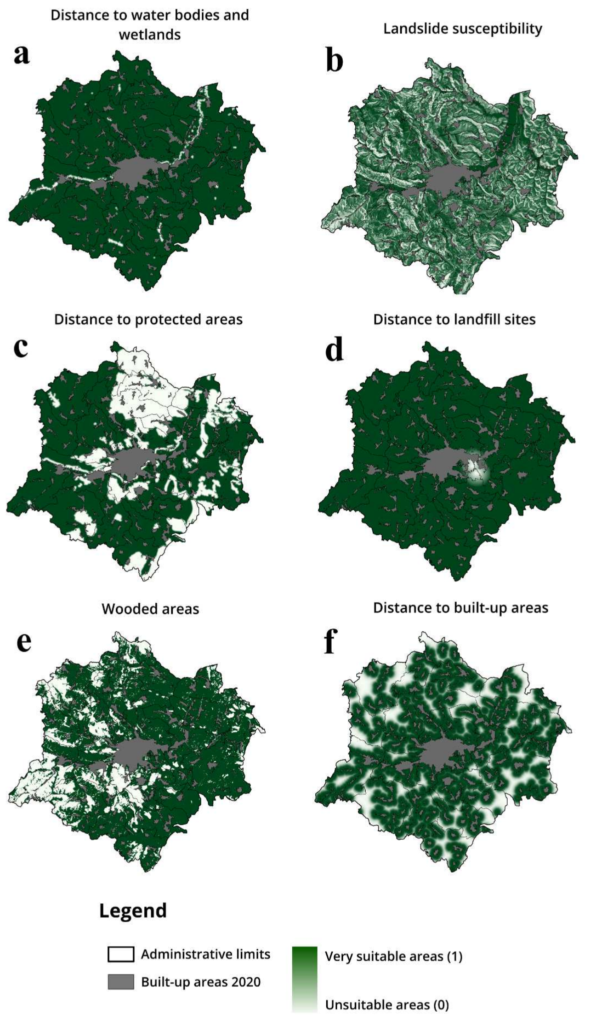

Fig. 3. Fuzzified model criteria: a) Distance to water bodies and wetlands; b Landslide susceptibility; c) Distance to protected areas; d) Distance to landfill sites; e) Wooded areas; f) Distance to built-up areas *(source: own elaboration using data on built-up areas and administrative boundaries from ANCPI, 2024).*

This fuzzy set was created by performing a standard fuzzy intersection ('Fuzzy And') on the overlay of fuzzy sets representing suitable areas for suburban development, each derived from a distinct spatial variable. Each set represents the suitability from the perspective of its respective environmental factors. The standard fuzzy intersection function simply outputs the minimum value of all the input variables – each pixel becomes as suitable as its least suitable variable. Besides the landslide susceptibility model output, input data consists of all non-overlapping remote sensing-derived layers covering environmental factors found in the Metropolitan GIS (2024). All input layers were transformed to rasters with a 25 m pixel size (the resolution of the lowest resolution input layer – the digital elevation model) by rasterising the input vector layers and resampling the input raster layers with the Nearest Neighbour method. Then, distances were calculated using QGIS to obtain the model parameters.

Fuzzy sets for each spatial variable were generated by applying fuzzy membership functions to the raw pixel values of the distance rasters. The membership functions and parameters were chosen based on expert judgements of the relationships between environmental factors and urban development (Şimşek and Alp, 2022; Zaresefat et al., 2022) (Table 1).

The linear fuzzy membership function is used to fuzzify the distance to water bodies and wetlands, the distance to protected areas and proposed protected areas, and the distance to landfill sites (Fig. 3 a, c, d). It allows for a simple and comprehensive transformation, as we can consider the intersection of the line with the upper bound (membership value of 1) as "far enough" from the geographical feature for the area to be suitable for development.

For the fuzzification of the distance to built-up areas (Fig. 3f), the reversed "Small" sigmoid membership function is used. Membership values are high for low distance values and then, starting from the function midpoint, they asymptotically approach 0 (unsuitable). This relationship encourages development closer to already built-up areas to discourage leapfrogging and promote infill development. It is better suited for this variable than a simple linear function because it does not create a hard cutoff value. The remote sensing-derived forest cover dataset was pre-processed to only include pixels that have at least 25% tree cover, in order to reduce the area and compensate for noise due to the remote sensing technique. No fuzzy membership function was applied to this dataset, as no other spatial relationships are relevant. Forest pixels have a suitability of 0, while unforested pixels have a suitability of 1 (Fig. 3e). Finally, low probabilities of landslide presence predicted by the landslide susceptibility model are assigned high suitability values (Fig. 3b).

3. RESULTS AND DISCUSSION

The example decision support framework is based on a spatial reclassification of the results using a 3.5 km grid (Fig. 4b). Empirically, we have found this grid size to balance granularity with a good representation of built-up suburban clusters in the study area (grid cells roughly cover a single peri-urban settlement).

The first step is determining each grid cell's environmental suitability for suburban development, using the suitability model results. For this, we assign each cell the number of pixels with values between 0.75 and 1 contained within it, which can be considered as the fraction of its area covered by very suitable pixels. For visualisation, grid cells are classified into 4 quantiles. We chose a relative classification method because an absolute classification requires arbitrary decisions about the category breakpoints, leading to more subjective judgements. The chosen method classifies the cell's value compared to the rest of the population (in this case, the rest of the cells in the study area), thus showing its degree of suitability among the decision alternatives.

The next step is determining the built-up space compactness for each grid cell. We have used the C2 index derived by Steurer and Bayr (2020). The calculations were performed in QGIS using the square grid and the same built-up area dataset employed in the suitability model, which is a polygon layer based on cadastre data, rasterised to a 10 m resolution for the calculations. For visualisation purposes, the cells were classified into quantiles following the same judgement used for the cell suitability classification, but using three categories labelled as "dispersed", "intermediary" and "compact". Finally, the two grids were overlaid for visual analysis (Fig. 4b).

The raw model output layer (Fig. 4a) shows a very high extent of unsuitable areas for suburban development. This is consistent with the visual analysis of the individual fuzzified criteria (Fig. 3) and the expectations from the Fuzzy And intersection. With this approach, there is no need to classify the criteria as exclusionary and non-exclusionary. The layers with high extents of unsuitable areas act as exclusionary criteria, while layers such as landslide susceptibility and distance to built-up areas account for variability and nuance within more suitable areas.

It can be observed that, while very insightful both for overviews and for small-scale analyses and case studies, the suitability model output by itself does not allow for any systematic and objective comparison method that would enable its use for true decision support. Our example of a decision support framework built on such a model (Fig. 4b) shows how a simple spatial screening of the results (in our case, using a 3.5km grid) can offer: 1. a robust and useful classification of the areas in terms of suitability for development, and 2. the opportunity to incorporate other criteria relevant for the scope of the study. This approach synthesises and transforms quantitative data into a simple hierarchical structure. We consider that this highly reduces the sensitivity of the final output to the subjective judgements made in choosing the fuzzy membership functions and their parameters. We opted for a measure of the compactness of built-up areas for every grid cell because it is an ecologically relevant criterion that cannot be integrated into the spatially continuous approach to environmental suitability. The compactness of built-up areas can be a proxy for landscape fragmentation in suburban areas, used extensively in ecology and relevant when assessing habitat loss and fragmentation (Angel et al., 2020; Fahrig, 2003; Liu et al., 2016; McInturff et al., 2020). We found no correlation between the two grid variables (a Pearson's r of 0.052; $p = 0.523$ and a Spearman's ρ of 0.135; $p = 0.098$), which shows that they are truly independent of each other, legitimising their use in overlay analysis. A visual analysis of the overlay or a more rigid arithmetic approach can be used on such a model to plan development priority or compare development project location alternatives and scenarios. The results point out important factors that constrain suburban development in Cluj-Napoca Metropolitan Area, with its inherent landscape fragmentation being one of the main aspects. The limited availability of land environmentally suitable for suburban development poses a challenge for housing demands in a growing city such as Cluj-Napoca. This may prove to be a unique challenge, as it implies the need to densify already built-up areas through infill or vertical development, while scaling the infrastructure that is already struggling to keep up with the sprawl (Baciu et al., 2018; Popa, 2023).

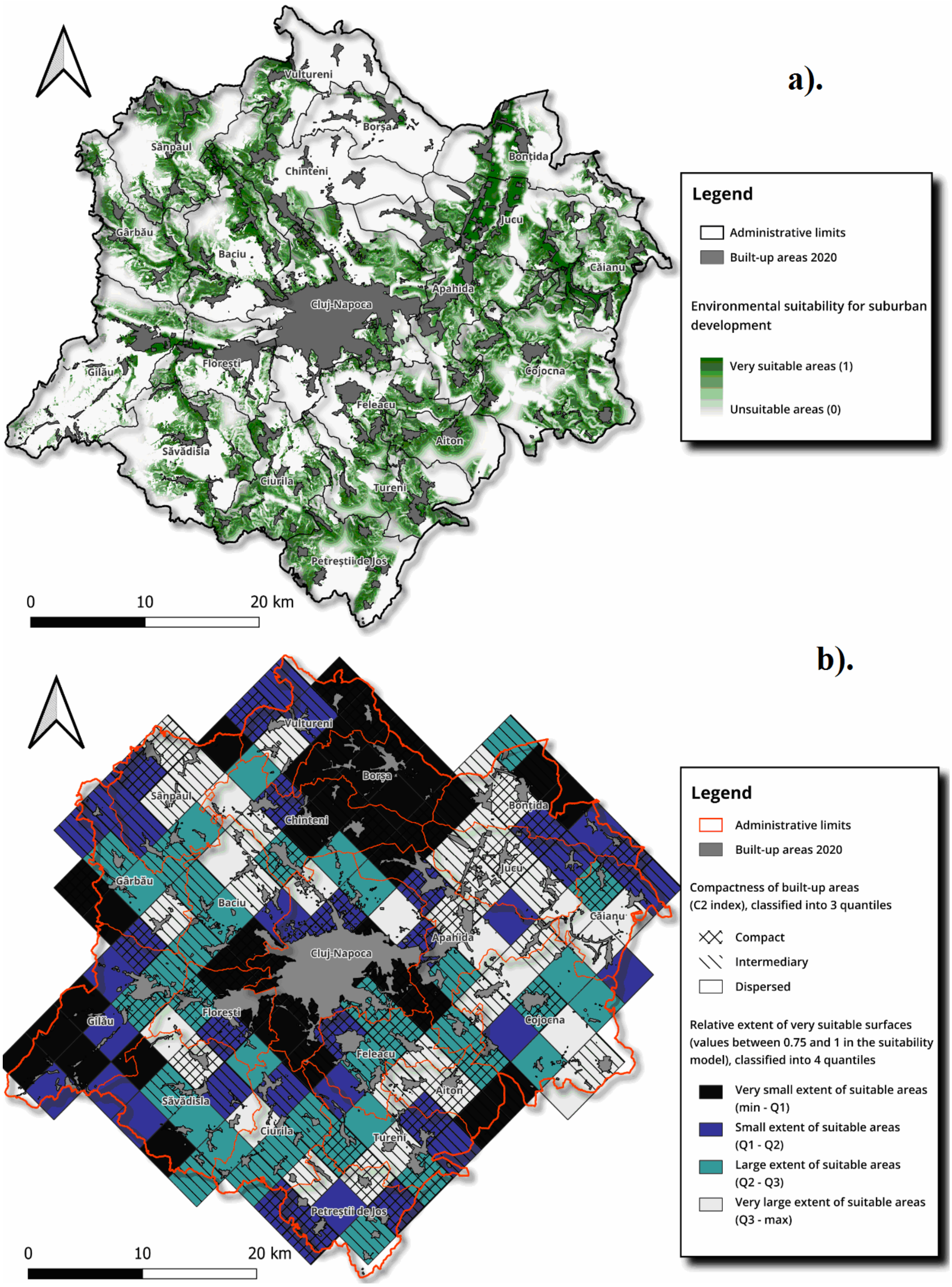

Fig. 4. a). Environmental suitability map. b). Example of grid-based decision support framework, overlaying urban compactness and the relative extent of very suitable areas on a square grid *(source: own elaboration, using data on built-up areas and administrative boundaries from ANCPI, 2024).*

Municipalities forming alliances and other forms of governing bodies is a key step in the progress of metropolitan area governance when it comes to achieving sustainable development goals (Ahrend et al., 2014; Alvarez et al., 2017; Slack, 2019). Moreover, official and publicly available spatial data infrastructure is an important tool for sustainable development (Budi and Sutanta, 2023; Rodriguez Gamez et al., 2019). In Romania, although there are various forms and degrees of association among the country's metropolitan areas, the regulatory framework still lacks substance to coordinate the efforts of local governments (Draghia, 2023). We argue that studies of urban sustainability utilising public data can serve as compelling evidence to support strategic and legal advancements in metropolitan governance everywhere, while also highlighting the potential such developments hold for improving data accessibility and transparency.

Given the nature of the concept of environmental suitability for suburban development, it is practically impossible to validate a model such as the one presented in this study. While the "suitability" of areas for natural phenomena such as habitat suitability or landslide risk can be validated by comparison with observations of the natural phenomenon (Pereira and Duckstein, 1993; Phillips et al., 2006; Reichenbach et al., 2018) and the predictive modelling of urban sprawl can be corroborated by testing the model performance in predicting sprawl using different reference years (Berling-Wolff and Wu, 2004; Guhathakurta, 2003), a model of environmental suitability for suburban development cannot be tested as there is no measurable phenomenon that can act as a proxy for model predictions. Although it is theoretically possible to monitor the wide array of environmental malfunctions arising in a neighbourhood built in an unsuitable area, they will suffer significant biases, and the costs will far outweigh the benefits of "validating" the model.

The primary utility of this suitability model lies in its interpretability, transparency, and scalability, rather than solely in quantifiable metrics. Consequently, the ultimate validation of this planning instrument is its practical efficacy in facilitating data-driven dialogue and negotiation among decision-makers. The decision support approach proposed here offers an intuitive, strategy-neutral tool that aligns with current academic and professional discourse regarding complex stakeholder systems. Its transparency, flexibility, and lightweight design are particularly well-suited for metropolitan regions characterized by unstructured planning and limited institutional capacity. The model accounts for disparities in spatial data quality and institutional power dynamics, serving as a platform to facilitate necessary negotiation and decision-making among public stakeholders.

Walling and Vaneeckhaute (2020) found that the success of an environmental decision support system is highly influenced by user and stakeholder involvement in the system model and design, which enhances both the interpretability and the perceived validity of the outputs. We recommend that future research on spatial suitability models focus on transparent and robust methods for stakeholder elicitation, tailored for each use case. In the case of a model framework similar to the one presented in this paper, we consider it essential to employ stakeholder and expert elicitation in choosing the model criteria and, most importantly, in selecting the fuzzy membership functions, fuzzy intersection methods, and linguistic variables. This can be done by using existing, tested elicitation methods (Cornelissen et al., 2003; Pedrycz, 2021; van Laarhoven and Pedrycz, 1983) or by developing novel methods, better suited to the stakeholders' needs, expectations and willingness to collaborate.

4. CONCLUSIONS

Urban sprawl is a well-documented threat to global sustainability goals. However, a significant research gap exists in providing local decision-makers with transparent, standardised tools to extract suitable development areas from complex geospatial data. In this paper, we analysed how a spatial fuzzy logic-based multi-criteria environmental suitability model can be developed and screened for use as a decision support system in suburban planning, while prioritising clarity and stakeholder accessibility.

Our results demonstrate that a nuanced modelling of suitability using a diverse array of environmental constraints provides a solid backbone for a spatial decision support system that can be further tuned to the stakeholder's needs. Our overlay of the model's results with urban compactness metrics (C_2 index) on a spatial grid proved that, in our case study, environmental suitability was independent of development geometry, highlighting a potential synergy for strategic identification of development sites.

A primary limitation of this method identified during the research is the inherent difficulty in objectively validating suitability models, as there is no measurable phenomenon that can act as a proxy for suitability. Furthermore, the selection and tuning of the fuzzy membership functions remains a fundamentally subjective process rooted in expert judgement. While our grid-based approach limits the impact of this subjectivity by reducing granularity, the model's value as an administrative decision support tool ultimately lies in its transparency and interpretability rather than quantifiable validity. Future research should focus on refining the model and decision support framework through direct stakeholder elicitation to reduce semantic uncertainty and testing the framework in real-world planning scenarios within diverse multidisciplinary teams.

Ultimately, the proposed framework serves as a scalable screening tool for metropolitan governance and highlights the potential of traditional geospatial modelling to be integrated into current deliberative decision-making processes.

5. ACKNOWLEDGEMENTS

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