Assessment of the usability of open data in Slovakia in the context of mapping and evaluating Blue-Green Infrastructure

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Abstract: *Mapping and assessing Blue-Green Infrastructure (BGI) is crucial for identifying opportunities to enhance urban planning strategies that support ecological health and improve the quality of urban living. This study presents a novel methodology for BGI mapping and evaluation, leveraging freely available datasets in Slovakia integrated with advanced GIS tools, including deep learning methods. The proposed approach combines OpenStreetMap (OSM), LiDAR data, and orthophoto mosaics to provide a comprehensive framework for assessing urban BGI. The first section evaluates green and blue areas in the study area, highlighting differences in dataset quality. OSM data underrepresented green spaces, while water bodies were reasonably well-represented. Orthophotomosaics, analyzed using deep learning, Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI), offered more precise results, with deep learning achieving higher accuracy but requiring significant computational resources. LiDAR data accurately identified trees and shrubs but was less effective in mapping water bodies. In the second phase, we developed a BGI index by integrating the analyzed datasets and using object extraction techniques from the mentioned datasets. The final BGI index of 0.41 places the study area on the border between "Moderate" and "Good" BGI quality. This result suggests that BGI quality can be enhanced through urban interventions such as green roofs and permeable surfaces. The novelty of this study lies in the creation of a new methodology for BGI mapping in Slovakia using freely accessible datasets, providing a replicable model for similar regions. This work contributes to the field by laying the foundation for future research aimed at mapping and evaluating BGI.*

Keywords: *Blue-Green Infrastructure, open data, object extraction, deep learning, GIS*

Introduction

BGI represents a synergistic combination of natural and urban elements that support ecological stability, biodiversity, and quality of life in both urban and rural areas. It is a strategic approach to land planning and management that includes the use of elements such as green roofs, rain gardens, parks, watercourses, and wetlands (Ghofrani et al. 2017). With the growing challenges of the climate crisis, urbanization, and environmental degradation, effective mapping and evaluation of BGI has become a key tool for sustainable development. BGI is a concept that integrates natural and engineering systems to promote ecological balance, increase resilience to climate change, and improve quality of life in urban areas (Ncube and Arthur 2021). BGI is a crucial tool for enhancing biodiversity, water management, and improving the quality of life.

BGI offers numerous benefits (Fenner 2017, Hamann et al. 2020) that span ecological stability, social sustainability, and economic advantages. Ecologically, it enhances air quality (Pugh et al. 2012) and water quality through natural filtration, boosts biodiversity, and improves the land's capacity to retain stormwater (Kapetas and Fenner 2020, Kozak et al. 2020,

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O’Donnell et al. 2020). Elements such as wetlands and rain gardens are pivotal for mitigating flood risks (O’Donnell and Thorne 2020, Deely et al. 2020), reducing pressure on sewer systems, and promoting sustainable water management. Furthermore, these natural features regulate microclimates, helping to alleviate the urban heat island effect common in cities (Gunawardena et al. 2017). Social benefits are equally significant (Liao 2019). Green and blue spaces in urban settings, such as parks, water bodies, and green roofs, provide venues for recreation, relaxation, and physical activities, positively impacting the physical and mental health of residents (Venkataramanan et al. 2019). They also enhance the aesthetic appeal of urban environments, increasing residents’ satisfaction with their quality of life. Economically, BGI reduces the costs associated with technical solutions like constructing and maintaining conventional sewage systems or cooling infrastructure (Silvennoinen et al. 2017). It also increases the attractiveness of areas for residential and commercial use, potentially boosting local economies and property values in its vicinity.

While BGI offers a wide range of benefits, its implementation can present certain challenges and drawbacks (Dhakal and Chevalier 2017). One of the main obstacles is the high initial investment required. Establishing green roofs, planting vegetation, or restoring wetlands demands significant financial resources, which can be a challenge, particularly for smaller municipalities or projects with limited budgets. Maintenance also poses an issue; unlike technical solutions that may require occasional repairs, natural elements necessitate regular care, such as mowing grass, removing invasive plant species, or cleaning water bodies. Neglecting this upkeep can reduce the effectiveness of BGI systems. Space constraints in densely built-up areas can further complicate integrating BGI into existing urban structures. The lack of available land often forces compromises between different land uses, potentially limiting the scale and quality of implemented measures. Seasonal and environmental factors can also affect the efficacy of BGI. For instance, rain gardens or retention systems may be less effective during periods of extreme drought or heavy rainfall that exceed their capacity. However, these disadvantages can largely be mitigated through meticulous planning, the involvement of experts, and the active participation of local communities in the design and management of BGI systems. By addressing these challenges proactively, BGI can remain a valuable tool for sustainable urban development.

Mapping and assessing BGI are essential processes that enable effective planning (Cortinovis and Geneletti 2018), monitoring, and enhancement of its components. These processes employ modern technologies and methodologies to identify, analyze, and quantify the benefits that BGI provides to society and the environment. Mapping BGI involves identifying and spatially locating individual elements such as green spaces (e.g., parks, green roofs, forests) and water features (e.g., rivers, wetlands, retention basins). Modern technologies, such as satellite imagery and aerial photography, facilitate detailed visualization and spatial analysis. Additionally, LiDAR technology offers three-dimensional data on the structural height of vegetation and terrain topography, enhancing the accuracy of BGI mapping (Jarlath et al. 2012, Bellakaout et al. 2016, Tokarčík and Hofierka 2024b). Geharlisographic Information Systems (GIS) enable the integration and analysis of multiple data layers, contributing to precise evaluation of relationships among BGI elements (Li et al. 2022, Harlis and Seo 2024). Beyond its direct benefits, BGI mapping is also crucial for conducting advanced analyses and modeling in GIS, which can significantly aid the implementation of BGI components. For example, flood modeling in urban areas can identify regions prone to waterlogging, providing data for the placement of retention basins or rain gardens (Hofierka and Knutová 2015, Rusinko and Horáčková 2022, Ujlakiová and Tokarčík 2023, Tokarčík and Hofierka 2024a). Solar modeling, on the other hand, helps determine the most suitable locations for green roofs or photovoltaic systems by analyzing sunlight exposure (Hofierka and Kaňuk 2009, Hofierka et al. 2020, Kolečanský et al. 2021, Onačillová et al. 2022). The integration of these analyses within GIS supports decision-making processes, ensuring that BGI contributes effectively to urban sustainability.

Furthermore, open data and participatory mapping, which involve local community engagement, enhance data quality and foster a collaborative approach to BGI planning and management.

Assessment of BGI focuses on analyzing the quality and functionality of its individual components (O'Donnell et al. 2018). Environmental assessment identifies risks such as the degradation of natural elements or insufficient resilience to climate extremes. Specific indicators and metrics are used to quantify various aspects of BGI (Ncube et al. 2018). The most common method for assessing BGI is through indices, which aggregate various indicators into a single parameter, enabling easier comparisons and trend monitoring (Kremer et al. 2016, Li et al. 2022, Harlis and Seo 2024). Examples include ecological quality indices, green infrastructure indices, or urban sustainability indices. Ecosystem services, such as climate regulation, water purification, or recreational space, provide a framework for a comprehensive evaluation of benefits. Sustainability indicators, such as the ratio of green areas to the total urbanized area or the availability of public green spaces, help identify areas needing improvement. GIS analyses additionally offer spatial assessments that aid in identifying ecological corridors and the connectivity between BGI components. Combining mapping and assessment creates a comprehensive picture of the state and potential of BGI. The results of these processes serve as a basis for policy development, urban planning, and the implementation of nature-based solutions. In Slovakia, open data serves as a crucial resource for detailed mapping and evaluation. In recent years, the availability of open data across various domains such as geoinformatics, environmental protection, and urban planning has been increasing. These datasets provide potential for in-depth analysis and strategic planning; however, their application in the context of BGI remains only partially explored.

This article focuses on two main objectives. The first goal is to assess the effectiveness of using freely available datasets for mapping green and blue areas. This involves analyzing the quality, and reliability of public datasets in Slovakia, evaluating their potential for integration into the mapping and planning processes of BGI in urban areas. The second objective is to develop a new methodology for mapping and evaluating BGI based on freely accessible data. This process aims to create an innovative approach that integrates various advanced GIS tools and publicly available datasets, such as OSM, LiDAR, and orthophoto mosaic. The methodology incorporates advanced GIS techniques, including deep learning, vegetation indices, and object extraction methods, to assess the quality and potential of BGI. This approach also includes the development of a BGI index, which will serve as a model for similar regions and contribute to future research in BGI mapping and evaluation.

Methods and data

Study area

Žiar nad Hronom is a district town in the Banská Bystrica Region in central Slovakia, located in the valley of the Hron River, at the foot of the Štiavnica Mountains. It lies in a strategically advantageous position between two significant mountain ranges, the Štiavnica Mountains and the Kremnica Mountains, providing favorable conditions for industrial and agricultural activities (Žiar nad Hronom 2024a). The town is situated on the main road and rail corridor connecting central Slovakia with Bratislava and Košice. The Hron River, the second longest river in Slovakia, flows through Žiar nad Hronom. The town covers an area of 39.1 km², is located at an elevation of 272 meters above sea level, and has a population of 16,879 residents (Slovensko v kocke 2020). The area of interest is part of the urban area located in the center of Žiar nad Hronom (fig. 1). The total area of the selected location is 3.64 km². The boundary of the area of interest was delineated in such a way that it includes not only the built-up urban area but also the Hron River and a pond, as water features are crucial for the analysis of BGI. This inclusion ensures that the area contains relevant water bodies, which are important in evaluating ecological and environmental processes related to BGI.

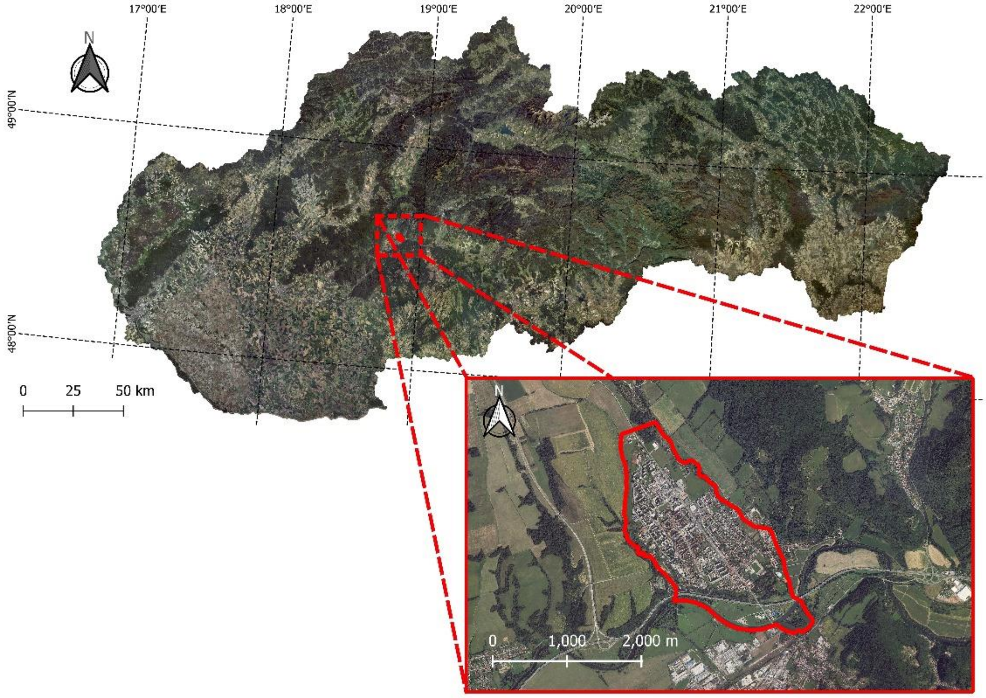

Fig. 1. *Location of the study area*
Source: ÚGKK SR (2022)

The primary reason for selecting this area is the ongoing project in the city focused on implementing water retention measures, which is closely related to the concept of BGI. This project aims to enhance flood control and improve water management, making the area particularly relevant for further research connected to BGI analysis. The inclusion of this area in the study will help evaluate the current state and potential improvements in BGI as part of the city's efforts. As reported, Žiar nad Hronom recently secured nearly 800,000 EUR in funding for water retention projects, underlining the importance of these measures in the local development plan (Žiar nad Hronom 2024b). Therefore, this area is crucial for future research that builds upon this study, as it directly correlates with the implementation of BGI initiatives in the region.

Input data and object extraction methods

For the mapping and evaluation of BGI within our study area, three main sources of freely available spatial data were used: OpenStreetMap, orthophoto mosaic, and LiDAR data. These spatial datasets were used independently to create BGI maps in order to assess their potential in the analysis and evaluation of BGI. Each of these datasets provides different types of information that are essential for comprehensive mapping and analysis of natural and urban elements. The reliability of the results is greatly influenced by the quality of the input data and the methods used to extract objects and areas. Therefore, this part of the study provides an assessment of both the data quality and the accuracy of the applied extraction methods. The separate processing using both simple and advanced GIS tools enabled the assessment of how these datasets can be used effectively for mapping blue-green infrastructure in the context of evaluating their potential. The delineation of individual areas and objects, followed by the creation of separate maps from the available spatial datasets, represents a key step in the development of a new methodological approach for the analysis and evaluation of BGI.

The OSM project, founded in 2004, has gradually evolved into the most well-known and extensive example of voluntarily managed geographic information. Thanks to the active participation of individuals from around the world, who contribute to its continuous development and updating, OSM has become a valuable and widely used source of geographic data across various fields. Several software tools are available that allow for the extraction of objects and layers, enabling quick and efficient acquisition of spatial data in vector format. In the context of our research focused on BGI, we utilized this data source to obtain polygon layers needed for BGI analysis within our study area, such as water bodies, green spaces, roads, built-up areas and buildings (Mondzech and Sester 2011). The individual areas and objects were delineated from the OSM project using the QuickOSM tool in QGIS. QuickOSM is a plugin for the QGIS software, designed specifically for extracting data from OSM. The plugin allows users to perform Overpass API queries directly within the QGIS environment, providing a powerful and efficient tool for retrieving specific features from the OSM database. Users can define the geographical area of interest and the type of features they want to extract. From a technical standpoint, QuickOSM automates and streamlines the extraction process, significantly reducing the time and effort required to retrieve data from the large and complex OSM database (3Liz 2022). However, it is important to note that QuickOSM relies entirely on the OSM database, meaning that the quality of the extracted data is contingent on the quality and completeness of the data available in OSM. As OSM is a crowd-sourced platform, the precision of the data can vary, and features may be underrepresented or inaccurately mapped. Consequently, while QuickOSM provides an efficient means of accessing and extracting data, it does not offer tools for assessing the reliability or completeness of the data extracted. Therefore, the quality of the results depends on the availability and coverage of the data within the specific geographic area, which could limit its accuracy for some applications.

Another dataset analyzed for its applicability in relation to BGI was the orthophoto mosaic, provided by the Geodesy, Cartography and Cadastre Office of the Slovak Republic. This product is made available for free online via download from the government cloud in ZIP packages, divided by regions (West, Central, and East Slovakia). For the purpose of our research, we used the orthophoto mosaic from the 2nd cycle, which took place from 2020 to 2022 (ÚGKK SR 2022). The orthophoto mosaic of Slovakia used in this study is provided in a georeferenced TIFF + TFW format, enabling correct placement and analysis of raster data in geographic space. The spatial resolution is 20 cm per pixel, ensuring a high level of detail necessary for accurate mapping and assessment of BGI (fig. 2). The orthophotomosaic contains four channels (RGBN) with 8-bit color depth, allowing for the display of the color spectrum, including infrared bands (Geoportál 2024a). For successful object classification from the orthophoto mosaic, advanced GIS tools were required to work with more complex algorithms and techniques. In our research, we applied two methods for creating the BGI map: deep learning and object extraction based on NDVI and NDWI indices. Object classification from the orthophoto mosaic using machine learning was carried out in ArcGIS Pro software. These models enable the processing of complex image data, such as orthophoto mosaics, and effectively classify objects based on learned patterns. This process is very useful for identifying and classifying different types of objects (e.g., buildings, vegetation, water bodies) on orthophoto maps, where manual classification can be time-consuming and inaccurate (Mohan and Giridhar 2022). For this purpose, we used a pre-trained model for object classification, called High Resolution Land Cover Classification, downloaded from the official ArcGIS website (Esri 2021). This model was specifically designed for land cover classification and has been tested on areas in the United States, providing reliable results for identifying various land cover types such as water, wetlands, tree canopy, shrubland, low vegetation, barren, structures, impervious surfaces, impervious roads. The pre-trained model used in this study, with an overall accuracy of 86.5% for classifying land cover into 9 categories, demonstrates a high level of reliability. This accuracy ensures that the model is robust enough to be applied in the extraction of objects for BGI mapping. Given its proven performance, this model is suitable for accurately classifying complex land cover types, including vegetation, water bodies, and urban areas, which are critical for effective BGI mapping and analysis. The following table (tab. 1) summarizes the precision, recall, and F1 score of the model on the validation dataset for classification into 9 land cover classes.

Tab. 1. *Performance metrics for High Resolution Land Cover Classification Model*

Class	Precision	Recall	F1 Score
Water	0.93614	0.93046	0.93329
Wetlands	0.81659	0.75905	0.78677
Tree Canopy	0.90477	0.93143	0.91791
Shtubland	0.51625	0.18643	0.27394
Low Vegetation	0.85977	0.86676	0.86325
Barren	0.67165	0.50922	0.57927
Structures	0.80510	0.84887	0.82641
Impervious Surfaces	0.73532	0.68556	0.70957
Impervious Roads	0.76281	0.81238	0.78682

Source: Esri (2021)

This model is based on the UNet architecture, which has been implemented within the ArcGIS API for Python. The classification itself was triggered using the 'Classify Pixels Using Deep Learning' command, designed to classify individual pixels based on the pre-trained model (ARCGIS 2024). To apply this model, we simply selected the orthophoto mosaic as the input raster and set the number of classes to 9, as required by the model. The model was then run without the need for any further adjustments to its parameters, since it is pre-trained and ready to classify the input data. This pre-trained model, downloaded from the official ArcGIS site, allowed us to classify land cover types directly, with the tool outputting a raster classified into the predefined land cover categories. It is important to note that to run this model in ArcGIS Pro, the Deep Learning Libraries must be installed and activated, as they provide the computational support needed for processing the data efficiently. The output of the modeling is a new raster file with pixels classified into the aforementioned classes. Due to the need to analyze the individual areas, we converted the output raster into a vector dataset using the “raster to polygon” tool.

In the context of BGI mapping, the orthophoto mosaic has potential due to the inclusion of four spectral bands, including the near-infrared. This allows for the calculation of the NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index), which can be used to detect specific objects and features in the landscape. The vegetation index NDVI is calculated using the formula: NDVI = (NIR + Red) / (NIR − Red), where NIR is the spectral band for near-infrared light and Red is the spectral band for red light. This index is used to detect vegetation and helps identify vegetative cover, where values close to 1 indicate dense vegetation, and values near 0 suggest areas without vegetation. The NDWI index has a similar formula but works with the green spectral band: NDWI = (Green + NIR) / (Green − NIR), where 'Green' is the green spectral band and 'NIR' is the near-infrared spectral band. NDWI is used to detect water bodies, where values close to 1 indicate water, and values close to -1 indicate dry or non-water areas (Onačillová et al. 2022). These indices were easily calculated in ArcGIS Pro using the tools available in the Raster Functions toolbox. After calculating the NDVI index, the output raster was reclassified by selecting pixels with a value of 0.4 or higher. These pixels were then converted into a vector dataset for further analysis. A similar approach was applied to the NDWI index, where pixels with values of 0.4 or higher were selected and subsequently converted into a vector dataset. This process allowed us to extract the green and blue infrastructure components, providing accurate and precise datasets for the further mapping and evaluation of BGI. The use of these thresholds helps ensure that only relevant areas contributing significantly to vegetation and water bodies are considered for inclusion in the analysis, enhancing the reliability of the results.

Fig. 2. *Orthophoto map of the study area used for extracting BGI elements*
Source: ÚGKK SR (2022)

As with the orthophotomosaic, the provider of the LiDAR data is the Geodesy, Cartography, and Cadastre Office of the Slovak Republic (ÚGKK SR 2019). These data were collected as part of the airborne laser scanning (ALS) project in Slovakia, which began in 2017 with the goal of creating a new digital elevation model (DEM) 5.0. The first cycle of the project was completed in May 2023, when the DEM 5.0 for the entire Slovak territory was released with a resolution of 1 meter. The entire data collection process and the creation of the final product were carried out by contractors, with each contractor responsible for data collection via ALS, data processing, point cloud classification into the required classes, and quality control of the ALS data and the final DEM 5.0 product. Currently, the second cycle of the project (2022–2026) is underway, with the creation of DEM 6.0. In this study, we used the classified point cloud from the first cycle of the project. Our area of interest is located in the Banská Bystrica region, where the average point density of the last return is 22 points per square meter. This density is essential for the accurate extraction of BGI elements such as vegetation and water bodies. The mandatory criteria for the collection of LiDAR data from the first cycle were set as follows: the absolute height accuracy of the point cloud in the ETRS89 system was ≤ 0.15 m, and the positional accuracy in the ETRS89-TM34 system was ≤ 0.30 m. These specifications are critical for precise mapping, ensuring that the data can be reliably used to delineate features such as trees, shrubs, and buildings in BGI mapping. For the successful extraction of objects, high-quality classification of the point cloud is essential.

The LiDAR data used in our study meet the following classification criteria: In the Ground class, a maximum of 0.5% of incorrectly classified points were allowed per 1 km² of area. For other classes, a maximum of 10% of incorrectly classified points were allowed per 1 km² (Geoportál 2024b). This ensures that the LiDAR data, from the perspective of classification, hold significant potential for BGI applications, providing a reliable foundation for accurate mapping of natural and urban elements. As in the previous cases, extraction of areas and objects is essential in the context of mapping and evaluating BGI. For this purpose, we used the "lasboundary" tool available in the LAStools package. This method allowed us to extract buildings, vegetation, and water bodies (Tokarčík and Hofierka 2024a, Tokarčík and Hofierka 2024b). When using the lasboundary tool for object extraction, we first selected the classification class from which the extraction was to be made. For our study, we utilized this tool for several classes, including Low Vegetation (03), Medium Vegetation (04), High Vegetation (05), Building (06), and Water (09). After selecting the appropriate classification, we adjusted the concavity parameter, setting its value to 0.5. This setting allowed us to capture the boundaries of objects with sufficient detail and accuracy, especially for complex features such as vegetation and buildings. The concavity parameter is crucial for determining the degree to which the boundary follows the curves of the classified objects. By setting it to 0.5, we ensured that the tool could properly follow the contours of the features, allowing for precise delineation of the object boundaries without oversimplification. We also set the disjoint parameter to ensure that during the extraction process, features with no common boundaries would be separated. This setting was crucial for maintaining the integrity of individual objects, such as trees and buildings, which may not be adjacent but still need to be classified and delineated as separate entities (Rapidlasso 2024).

BGI index calculation

As part of the assessment and mapping of BGI, we developed a simple weighted index specifically tailored to the needs of our study. It is important to emphasize that no official universal BGI index currently exists (Li et al. 2022, Harlis and Seo 2024). Consequently, our approach was to design an index that integrates analytical weights assigned to various categories of landscape elements, emphasizing their ecological and environmental contributions to BGI processes. This index was adapted from existing methodologies but customized to align with the datasets available and the specific context of our study area (Ariff et al. 2019, Li et al. 2022, Harlis and Seo 2024, Das and Kumar 2022). Given the absence of a standardized BGI index, our weighted sum approach ensures flexibility and relevance to the local environmental conditions. Each category in the index was assigned a weight proportional to its significance in supporting ecological services, such as climate regulation, biodiversity enhancement, and water retention. For example, trees and shrubs were assigned the highest weight, reflecting their critical role in regulating urban microclimates and supporting biodiversity. Similarly, green spaces, water bodies, built-up areas, and buildings were weighted based on their specific contributions to ecological processes and their potential for sustainable interventions like green roofs or permeable surfaces.

In our study, we draw on existing researches that highlights the importance of various land types and elements in the context of BGI. However, due to the absence of a universal BGI index, we assigned weight values based on our expert assessment. These weights were carefully chosen to reflect the specific environmental and urban dynamics of our study area, while considering the key roles that trees, green areas, water bodies, buildings and built-up environments play in supporting ecological functions and urban sustainability. The weights for the individual categories were set as follow:

- **Trees and Shrubs (1):** We assigned the highest weight to trees and shrubs because they play a pivotal role in various ecological processes, including stormwater management, cooling, air quality improvement, and supporting biodiversity (Ghofrani et al. 2017). Their ability to reduce the urban heat island effect and provide shade makes them essential for urban resilience, especially in the face of climate change. The weight of 1 reflects their overwhelming importance in urban BGI systems.
- **Green Areas (0.75):** Green areas such as parks, meadows, and other vegetation types also significantly contribute to BGI functions, particularly stormwater retention and the mitigation of the urban heat island effect (Pugh et al. 2012). These areas are important for maintaining the ecological balance within urban environments, reducing pollutants, and improving the quality of life. A weight of 0.75 was assigned to green areas due to their significant, yet slightly less critical, role compared to trees and shrubs.
- **Blue areas (0.5):** Water bodies, such as lakes, rivers, and ponds, were assigned a weight of 0.5, acknowledging their essential role in regulating the water cycle, managing flood risks, and maintaining aquatic biodiversity (Kapetas and Fenner 2020). Although they are crucial for environmental stability, their contribution to other ecosystem services, like cooling or air purification, is more limited compared to trees and vegetation.
- **Buildings (0.1):** Although buildings are generally seen as an obstacle to ecological processes, they are included in the index because they represent areas where BGI measures, such as green roofs or permeable surfaces, can be implemented. The weight of 0.1 reflects the fact that while buildings themselves are not inherently beneficial for BGI, they provide the opportunity for sustainable interventions within urban areas (Silvennoinen et al. 2017).
- **Built-up areas (0.05):** Built-up land, including impervious surfaces such as streets and parking lots, affects the potential for BGI measures, yet it is the least favorable category from an ecological perspective. These areas contribute minimally to ecological processes and do not offer many opportunities for integrating BGI measures, thus receiving the lowest weight of 0.05 (Gunawardena et al. 2017).

For calculating the BGI index, we use a simple weighted system, where each category of landscape element is multiplied by its assigned weight, and these values are then summed. The result is then divided by the total area of the land:

$$\text{BGI Index} = \sum(\text{area of category} \times \text{weight})/(\text{total area}).$$

To interpret the results, the BGI index values are categorized based on their ability to support ecological balance:

- **0–0.2: Low BGI quality** - the area has significantly limited ecological, climatic, and social benefits. It requires extensive interventions to improve the blue-green infrastructure.
- **0.2–0.4: Moderate BGI quality** - the area has some blue-green infrastructure, but it is not sufficiently developed to effectively support ecological and climatic functions.
- **0.4–0.6: Good BGI quality** - the area has a balanced blue-green infrastructure that provides significant benefits for both the ecosystem and its inhabitants.
- **0.6–1: High BGI quality** - the area has a well-developed blue-green infrastructure, offering extensive ecological, climatic, and social benefits, and serves as a model for sustainable development.

Results

The results of this research are divided into two main sections, reflecting the defined objectives. The first section focuses on analyzing the applicability of freely available datasets for mapping BGI. Specifically, it examines and evaluates green and water areas, which are crucial in the context of BGI. The second section introduces a methodological approach to creating a final BGI map with a weighted index, integrating various datasets for a more precise evaluation of the ecological potential of the study area.

Mapping of green and blue areas

Based on the initial results, significant differences between datasets in usability and processing demands for mapping vegetation and water surfaces were confirmed. The first dataset analyzed was OSM, utilized to identify green and blue areas within the study site. However, OSM data proved unsuitable for capturing green areas accurately, as these were underestimated in the context of the examined area (fig. 3).

The total area of green spaces identified from OSM was only 0.25 km², significantly less compared to other datasets. On the other hand, water surfaces were captured relatively accurately, with an area of 0.16 km², closely matching results from other methods. The percentage of BGI representation in OSM was merely 11.6%, with the substantial underrepresentation of green spaces making this dataset unsuitable for detailed BGI mapping in urban environments. The orthophotomosaic was one of the analyzed datasets, with its potential for mapping BGI evaluated using two different approaches: applying deep learning tools and using vegetation indices NDVI and NDWI (fig. 4). The use of vegetation indices was made possible by the potential of the orthophoto mosaic, which includes the near-infrared band. The deep learning method for analyzing the orthophotomosaic proved to be highly effective in extracting green and water areas. Results showed that green areas were identified with an area of 2.02 km² and water bodies with an area of 0.15 km², representing 59.61% of the total BGI area. This method effectively identified not only trees and shrubs but also larger green areas such as parks and gardens. However, shadows in the orthophoto mosaic sometimes caused incorrect classification of certain areas as water bodies, and smaller paved areas and paths near vegetation were often misclassified as green areas.

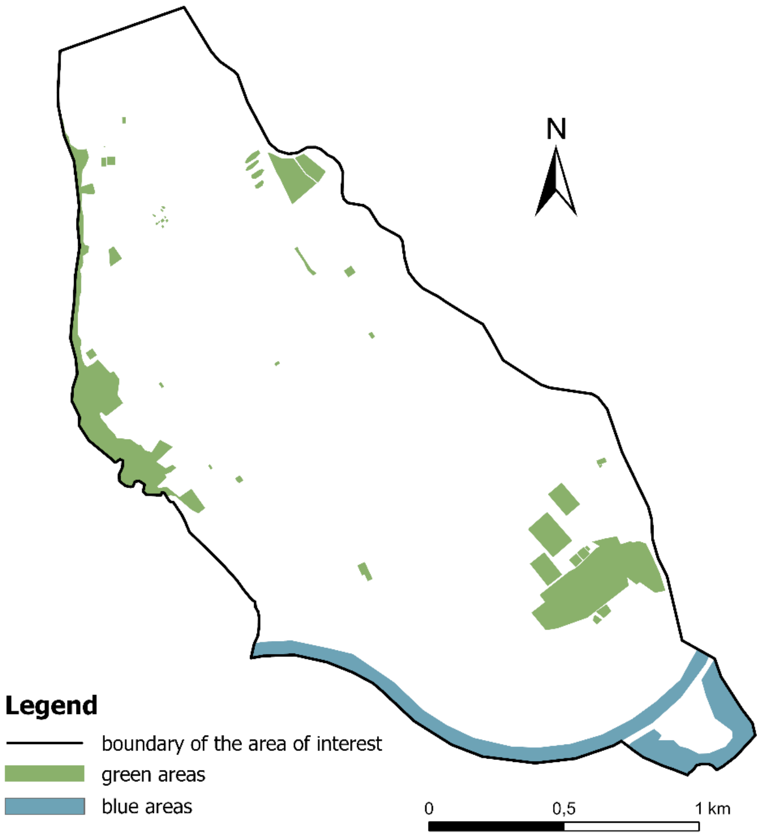

Fig. 3. Green and blue areas identified from OSM

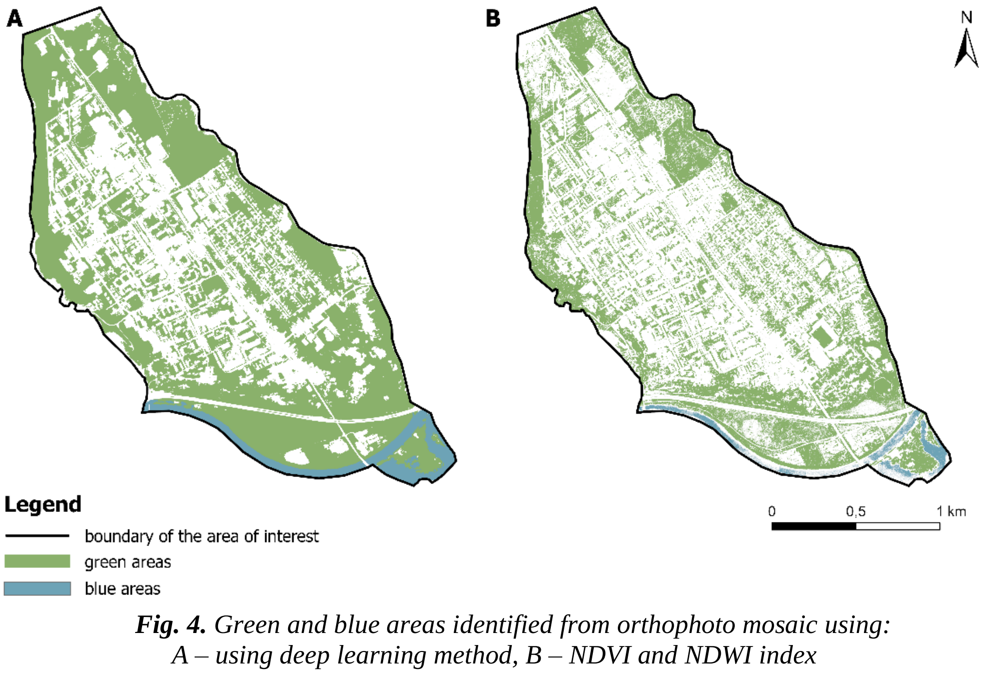

Fig. 4. *Green and blue areas identified from orthophoto mosaic using:*
A – using deep learning method, B – NDVI and NDWI index

The combination of the NDVI and NDWI indices yielded effective results in extracting green areas, such as parks and gardens. Green areas covered 1.38 km², and water bodies 0.06 km², representing 39.56% of the total BGI. The NDVI index proved to be more suitable than deep learning for identifying green areas, as deep learning often misclassified smaller built-up areas and paths near vegetation as green areas, reducing the accuracy of the results. However, problems arose when extracting water areas, as certain structures, such as buildings or asphalt surfaces, had similar index values to water. This phenomenon caused parts of non-green areas, like built-up zones, to be incorrectly classified as water bodies. Due to these challenges, we decided to select only areas with high index values (above 0.5). This approach, however, resulted in a reduced extent of identified water bodies compared to other methods. The solution to this problem could involve manual classification and filtering of the extracted polygons, which would allow for more precise separation of water bodies from other structures. However, this approach is not efficient as manual processing is time-consuming and requires a high degree of interaction. As a result, the overall effectiveness of the mapping process decreases, negatively impacting both the scope and accuracy of the analysis.

For the deep learning method, we used ArcGIS Pro and the Classify Pixel Using Deep Learning tool, leveraging a pre-trained model available from ArcGIS's official site. The model was executed in ArcGIS Pro, enabling efficient extraction of various areas, including green spaces, trees, shrubs, built-up areas, buildings, and water bodies. The processing time was around 17 hours, indicating the computational intensity of this method, but the results yielded high-quality and precise outputs. The output was a raster map, which was converted to polygon format using the Raster to Polygon tool for further processing and analysis. The NDVI and NDWI method in ArcGIS Pro was faster and more efficient as these indices are already integrated into the software. However, it required manual correction, particularly when extracting water bodies with index values similar to built-up areas. Compared to the OSM dataset, the orthophoto mosaic showed significantly greater potential for BGI mapping due to its higher accuracy and the ability to utilize advanced tools such as deep learning.

LiDAR data provided highly accurate results in identifying trees and shrubs, with approximately 0.74 km² of green areas mapped from the total area. Water bodies were delineated over a space of 0.11 km² (fig. 5). Due to the specific characteristics of LiDAR, vertical structures like trees were captured with high precision. However, areas with lower vegetation and water bodies were harder to identify and required additional processing. For water bodies, the low reflectivity of water caused challenges in detection, which affected the accuracy of their delineation. Similar to the orthophoto mosaic, the analysis of LiDAR data offers the advantage of enabling not only the identification of greenery but also the accurate delineation of other objects, particularly buildings. This approach provides detailed insights into urban structure and enhances the accuracy of mapping built-up areas.

To extract objects from LiDAR data, we used the lasboundary tool in LAStools, which effectively detects the boundaries of various objects, provided that the point cloud classification is accurate. Although processing large datasets can be time-intensive, this method is significantly faster than deep learning approaches. Tools like LAStools are particularly efficient for extracting height-differentiated features such as trees and buildings but struggle with water bodies and low vegetation. Tab. 2 provides a summary comparing the efficiency of greenery and water body extraction across datasets.

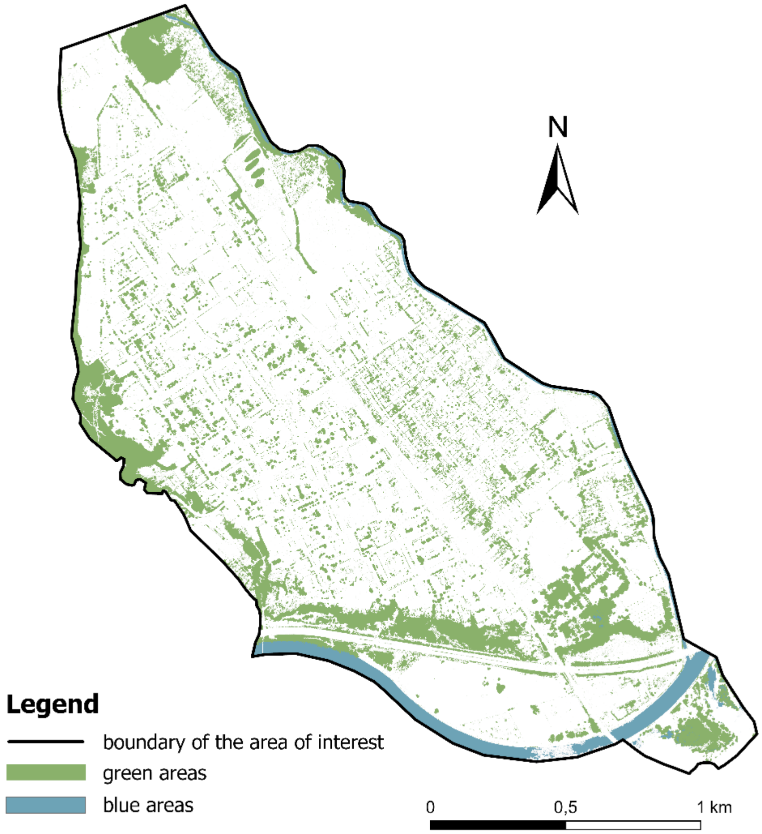

Fig. 5. *Green and blue areas identified from LiDAR data*

Tab. 2. *The sizes of green and blue areas identified based on the used data sources*

Dataset	Green areas [km^2]	Blue areas [km^2]	BGI coverage [%]
OpenStreetMap	0.25	0.16	11.60
Ortophotomosaic (deep learning)	2.02	0.15	59.61
Ortophotomosaic (NDVI and NDWI)	1.38	0.06	39.56
Lidar data	0.74	0.11	23.35

BGI map and index

The second part of the results describes the proposed methodological procedure for creating the final BGI map and calculating the BGI index based on weighted values for specific areas within the study site. This approach integrates previous extraction results and various datasets and tools to offer a comprehensive view of the area's landscape and urban components. The methodology elaborates on index calculations and weight justifications for different land types, focusing on accurate classification into categories such as trees and shrubs, green areas, blue areas, built-up areas, and buildings.

The results indicate that LiDAR data has shown the greatest potential for identifying trees and shrubs due to its accuracy and detail. This allowed for effective extraction of medium and high vegetation. As a result, the methodology was adjusted to include the extraction of trees and shrubs using the LiDAR tool, lasboundary, which facilitated precise classification of these vegetation types within the study area. The total area covered by high and medium vegetation is 0.667 km^2, accounting for 18.32 % of the total study area. Based on prior analyses, the methodology for creating the BGI map and index includes green areas identified using the NDVI index. This approach was chosen for its accuracy in differentiating vegetation, thereby minimizing the risk of misclassifying built-up areas and pathways, an issue often encountered with deep learning methods. NDVI captures the extent and characteristics of green areas, which is critical for developing a reliable BGI index and map. The total area of green spaces (excluding trees and shrubs) is 0.838 km^2, representing 23.02 % of the total research area. When examining previous results, it is evident that the size of water areas identified via OSM aligns closely with areas derived from the deep learning method. However, deep learning faced challenges, such as shadows in the orthophotomap being misclassified as water, necessitating manual filtering. Therefore, OSM data proved to be the most effective solution. This step, however, is contingent on the specific study area, requiring an individualized approach to delineate water bodies for other regions. For the final map, we used the extraction of water bodies using the QuickOSM tool, which relies on OSM data. The total area covered by blue spaces is 0.159 km^2, which accounts for 4.36 % of the area. The deep learning tool applied to orthophotomosaics has proven to be highly effective for identifying built-up areas. By analyzing the pixel values in the orthophoto, it reliably delineates features such as parking lots, roads, and industrial zones, enabling precise classification within urban landscapes. On the other hand, OSM data are too generalized and do not reflect the detailed reality, especially in smaller or more complex built-up areas. LiDAR data are not suitable for identifying areas such as parking lots or roads because these surfaces typically lack distinct height variations that LiDAR sensors capture. LiDAR technology is optimized for detecting three-dimensional structures and topographical features, such as buildings or vegetation. The NDVI index is not suitable either, as it is primarily used for vegetation analysis, not for artificial structures. Therefore, we incorporated deep learning methods, specifically the use of a pretrained model with the "Classify pixels using deep model" tool, to extract built-up areas (1.459 km^2) and integrate them into the final map. The last category included in the area assessment from the BGI perspective and methodology is buildings. For this purpose, data from airborne laser scanning were used. LiDAR data allow for more precise identification of individual buildings based on their shape and height structure, minimizing inaccuracies that may arise when using generalized OSM data. While OSM is a good source for obtaining building footprints, it often lacks current or detailed information about buildings, especially in peripheral or less urbanized areas. For this reason, buildings derived from LiDAR data were incorporated into the final BGI map. This approach is highly effective not only for identifying buildings but also for other uses, such as evaluating suitability for implementing green roofs. The area of buildings extracted from LiDAR data in our study area reaches a total of 0.516 km^2. The final BGI map, created based on the described methodology incorporating various GIS tools and spatial data sources, is shown in fig. 6.

Based on the extracted areas and their sizes, as well as the weights assigned to each area, we calculated the BGI index. The BGI index value of 0.41 places the area of interest on the boundary between "Moderate BGI Quality" and "Good BGI Quality." This indicates that while the blue-green infrastructure is relatively well-represented, there is potential for further improvement. The current vegetation and water coverage contribute effectively to functions such as cooling, air purification, and flood mitigation. However, the borderline nature of the value suggests that measures like implementing green roofs or converting impermeable surfaces into semi-permeable or permeable ones could help solidify the classification into the "Good Quality" category. These enhancements would not only improve stormwater management but also increase the area's overall ecological and climatic resilience, promoting more sustainable urban development. The methodological approach, based on integrating multi-source data, proves to be a robust and flexible tool that can be effectively applied to evaluate BGI in other cities. The values of the areas used to derive the final BGI index, based on the assigned weights, are summarized in tab. 3.

Fig. 6. *BGI map created based on the new methodological approach*

Tab. 3. *Overview of BGI classes contributing to the final index calculation*

BGI area class	Area [km^2]	Weight	Source dataset	Extraction method
Trees and shrubs	0.667	1	LiDAR data	lasboundary (LAStools)
Green areas	0.838	0.75	orthophoto mosaic	NDVI index (ArcGIS Pro)
Blue areas	0.159	0.5	OSM	QuickOSM (QGIS)
Buildings	0.516	0.1	LiDAR data	Lasboundary (LAStools)
Built-up areas	1.459	0.05	orthophoto mosaic	deep learning (ArcGIS Pro)

The calculation of the weighted BGI index within ArcGIS Pro proved to be an effective method for evaluating the quality of BGI in the study area. By utilizing the attribute table to calculate areas and weights and applying the Field Calculator and Summarize function, we were able to efficiently determine the overall BGI index. This approach, centralized within a single GIS platform, allowed for quick processing and analysis of the data. One of the key advantages of this method was its flexibility in responding to changes. Whenever adjustments to the weights or areas of specific BGI components were needed, these modifications could be made rapidly, providing an efficient means to update the index and ensure that the analysis remained relevant and current. This responsiveness to changes in the data, along with the centralized nature of the calculation, made the process not only efficient but also adaptable to the evolving urban and environmental planning needs of the study area.

The figure below (fig. 7) presents the schematic diagram of the newly developed methodological approach for BGI mapping and assessment. This framework represents a comprehensive integration of freely available datasets and advanced GIS tools, tailored to the specific requirements and conditions of the study area. Although the diagram illustrates a methodological workflow, it is an integral part of the results section, as it constitutes the primary outcome of this research.

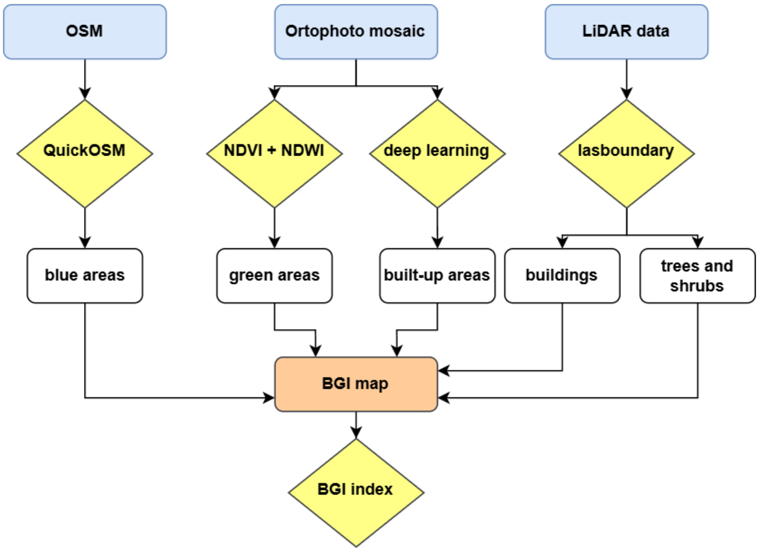

Fig. 7. *The proposed methodological framework for BGI mapping and assessment*

Discussion

The evaluation of BGI mapping in this study revealed significant differences in the quality and applicability of datasets. OSM data proved to be the least reliable for detailed BGI mapping, primarily due to its generalization and inconsistent representation of green spaces. This aligns with findings from Mondzech and Sester (2011), which highlighted the limitations of OSM in accurately capturing detailed landscape features. The substantial underrepresentation of green areas in our results underscores the challenges in relying on voluntary geographic information systems for precise urban planning. However, OSM's performance in identifying water bodies was relatively acceptable, suggesting potential for specific applications, especially when higher-resolution datasets are unavailable.

In contrast, LiDAR and orthophoto mosaic data demonstrated significantly greater reliability. LiDAR data were particularly effective in identifying vertical structures like trees, shrubs and buildings, consistent with Jarlath et al. (2012), Bellakaout et al. (2016), Tokarčík and Hofierka (2024b), who emphasized LiDAR's potential for urban objects analysis. However, as seen in our results, LiDAR's limitations in detecting water bodies due to reflectivity issues highlight the need for complementary datasets. Similarly, orthophoto mosaics provided comprehensive coverage, with deep learning tools achieving high accuracy in identifying both vegetation and water features. This reflects the findings of Mohan and Giridhar (2022), who reported the effectiveness of deep learning in extracting complex patterns in urban landscapes. The computational intensity of deep learning, while a drawback, was mitigated by its high precision and adaptability for urban analyses.

From a methodological perspective, the weighted BGI index developed in this study offers a straightforward yet practical tool for evaluating blue-green infrastructure. Unlike more complex indices, which may require extensive data processing and sophisticated modeling, this index prioritizes simplicity and efficiency, making it easily integrable within GIS platforms. Inspired by the methodologies described by Li et al. (2022) and Harlis and Seo (2024), it adapts basic principles of weighting to the specific environmental and dataset conditions of Slovakia.

This study lays the foundation for further research, for example in the context of hydrological and solar modeling, which are crucial for enhancing the ecological and functional benefits of BGI. As shown by Tokarčík and Hofierka (2024a), Onačillová et al. (2022), Rusinko and Horáčková (2022) and Hofierka et al. (2020), modeling tools can complement BGI assessments by identifying areas prone to flooding or suitable for green roofs and solar panels.

The unique contribution of this research lies in the combination of freely available datasets with advanced GIS tools to create a replicable model for BGI assessment. While the results are promising, they also highlight areas for improvement, such as increasing the resolution of the datasets or integrating community-generated data to increase accuracy. Future studies could build on this work by incorporating more comprehensive methodologies to achieve a deeper assessment and mapping of BGI. Extending the application of the proposed methodology to different urban contexts could improve its adaptability, while integrating additional datasets and advanced modeling tools could yield more detailed insights into the effective implementation of BGI in urban environments.

Conclusions

By leveraging a combination of freely available datasets such as OSM, LiDAR data, and orthophotomosaics, along with advanced GIS tools, including deep learning methods, we were able to assess and quantify green and blue spaces in urban areas. The findings indicate that while OSM data tended to underrepresent green spaces, LiDAR and orthophoto mosaics provided more accurate and precise results, with deep learning methods achieving the highest accuracy, albeit with significant computational demands. The BGI index derived from this process highlighted that the study area falls between "Moderate" and "Good" BGI quality, suggesting that urban interventions such as green roofs and permeable surfaces could significantly enhance BGI.

In addition to the overall findings, it is important to emphasize the effectiveness of the tools used for extracting BGI elements during the study. The use of deep learning methods on orthophoto mosaics facilitated the extraction of precise vegetation features, enhancing the accuracy of green space mapping. LiDAR data provided robust results for tree and shrub identification but was less effective in delineating water bodies. The ability to integrate these diverse datasets within GIS platforms such as ArcGIS Pro further amplified the analysis, allowing for seamless spatial operations and the generation of relevant indices. The efficiency of the GIS tools not only streamlined the process but also provided a flexible approach, enabling quick adjustments to dataset weights or boundary changes, essential for iterative analysis and decision-making. This demonstrated the significant potential of GIS in BGI mapping, highlighting the technology's adaptability and capacity to improve urban planning for ecological sustainability.

Given the promising results, this study lays the groundwork for further research into BGI in Slovakia, providing a replicable model that can be extended to other regions. The use of GIS tools, particularly in the context of open data, has proven invaluable in streamlining the process of BGI mapping and evaluation, providing a robust platform for future urban planning efforts aimed at improving ecological resilience and sustainability in urban areas. This study not only contributes to the body of knowledge on BGI but also emphasizes the efficiency and adaptability of GIS technologies in advancing environmental and urban planning initiatives.

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