Acta Montanistica Slovaca
ISSN 1335-1788
actamont.tuke.sk

A novel index for blue-green infrastructure assessment using urban overland flow simulation and GIS analysis

Ondrej TOKARČÍK[1], Peter BLIŠŤAN[1], Ľudovít KOVANIČ[1], Patrik PEŤOVSKÝ[1], Branislav TOPITZER[1]* and *Dariusz WIĘCEK[2]*

Authors' affiliations and addresses:
[1] Institute of Geodesy, Cartography and Geographical Information Systems, Faculty BERG, Technical University of Košice, Park Komenského 19, 04001 Košice, Slovakia
e-mail: ondrej.tokarcik@tuke.sk
e-mail: peter.blistan@tuke.sk
e-mail: ludovit.kovanic@tuke.sk
e-mail: patrik.petovsky@tuke.sk
e-mail: branislav.topitzer@tuke.sk

[2] University of Bielsko-Biała, 2 Willowa st., 43-309 Bielsko-Biała, Poland
e-mail: wiecekd@ubb.edu.pl

***Correspondence:**
Ondrej Tokarčík, Institute of Geodesy, Cartography and Geographical Information Systems, Faculty BERG, Technical University of Košice, Park Komenského 19, 04001 Košice, Slovakia
e-mail: ondrej.tokarcik@tuke.sk

Acknowledgement:
This research was funded by the grant agency KEGA grant no. 055TUKE-4/2021, KEGA 003TUKE-4/2023, grant agency APVV grant no. APVV-18-0351 and Interreg grant #mountgreenfra - HUSK/2302/1.2/060.

How to cite this article:
Tokarčík, O., Blišťan, P., Kovanič, Ľ., Peťovský, P., Topitzer, B. and Więcek, D. (2025). A novel index for blue-green infrastructure assessment using urban overland flow simulation and GIS analysis. *Acta Montanistica Slovaca*, Volume 30 (3), 813-826

DOI:
https://doi.org/10.46544/AMS.v30i3.20

Abstract
This study presents a novel Blue-Green Infrastructure (BGI) index that integrates hydrological modeling, GIS-based spatial analysis, and multi-criteria evaluation through the Analytic Hierarchy Process (AHP). The index was developed to assess the suitability and prioritization of BGI measures in urban environments, with a focus on small and medium-sized cities such as Žiar nad Hronom, Slovakia. Five spatial factors—simulated water depth, proximity to hazardous areas, slope, land cover, and proximity to roads—were combined to create a comprehensive spatial assessment of BGI potential. A hydrological simulation using the open-source Itzï model provided a dynamic representation of overland flow, improving the diagnostic capacity of the index. Scenario analysis was conducted to assess the model's sensitivity and robustness under hydrological, urban, and environmental weighting schemes. The results show strong correlations between the reference and alternative scenarios (Pearson's r = 0.92–0.98), confirming the index's stability and transferability. The resulting BGI map effectively identified high-priority areas, particularly zones of natural water accumulation and green spaces with favorable slope conditions. Application of the index to school sites enabled ranking planned adaptation projects and identifying additional high-priority areas not initially included in municipal plans. The developed BGI index thus represents a practical, data-driven, and transferable tool for supporting evidence-based urban planning and the strategic implementation of nature-based solutions.

Keywords
BGI index; GIS; spatial analysis; hydrological modeling; multi-criteria evaluation; Analytic Hierarchy Process (AHP)

Introduction

The growing rate of urbanization and climate change pose significant challenges for contemporary cities, which are increasingly exposed to extreme weather events, particularly intense rainfall and heatwaves (Vojtek and Vojteková, 2016). Dense development, extensive impervious surfaces, and the reduced capacity of the landscape to naturally retain water lead to an increasing risk of surface runoff and local flooding. These phenomena not only have environmental consequences but also cause considerable economic damage and negatively affect the quality of life of urban residents. In this context, the concept of BGI, which integrates water and vegetation elements to enhance the resilience of the urban environment, is gaining increasing recognition as a promising solution (Ncube and Arthur, 2021).

BGI represents a synergistic integration 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 spatial planning and management that incorporates elements such as green roofs, rain gardens, parks, watercourses, retention basins, and wetlands (Ghofrani et al 2017; Voskamp and Van De Ven, 2015). BGI is a key tool for enhancing biodiversity, managing water resources, and improving the quality of life. It offers a wide range of benefits (Fenner, 2017; Hamann et al, 2020) related to ecological stability, social sustainability, and economic gains. Ecological benefits include improved air and water quality (Pugh, 2012) through natural filtration, increased biodiversity, and enhanced landscape capacity to retain stormwater (Kapetas and Fenner, 2020; Kozak et al, 2020; O'Donnell, et al, 2020). BGI elements such as wetlands and rain gardens play a crucial role in regulating flood risks, thereby reducing the burden on sewage systems and supporting sustainable water management (O'Donnell and Thorne, 2020; Deely et al, 2020). In recent years, BGI has become a central component of climate change adaptation strategies and has been strongly promoted at the European level through policies for sustainable urban development.

Mapping and assessment of BGI are key processes that enable effective planning (Cortinovis and Geneletti, 2018), monitoring, and improvement of its elements. The assessment of BGI focuses on analyzing the quality and functionality of individual BGI components (O'Donnell, et al, 2017). Specific indicators and metrics are applied to quantify various aspects of BGI (Ncube et al 2018). In addition, GIS analyses provide spatial evaluation that supports the identification of ecological corridors and the connectivity between BGI elements. Despite the growing importance of BGI, unified, quantitative approaches to evaluating the effectiveness of individual measures remain lacking, particularly for reducing surface runoff. Most existing methods focus on qualitative assessment or employ simplified indicators that fail to capture the complexity of the urban environment. This gap highlights the need for developing new, more precise indices that would enable comparable and objective evaluation of BGI functionality under different urban conditions.

One of the key methods that allows for a more detailed examination of the interactions between rainfall, the surface, and runoff is surface runoff simulation. Through hydrological models, it is possible to identify problematic areas of water accumulation, estimate runoff volumes, and assess the contribution of specific BGI measures to their reduction (Harlis and Seo, 2024; Kaur and Gupta, 2022). These models, combined with GIS analyses, provide a comprehensive and reliable framework for integrated assessment by enabling the use of spatial data on topography, land use, soil properties, and vegetation cover.

The main objective of this article is to develop a new index for assessing BGI, which will serve as a supportive tool for strategic, effective planning of measures in urban environments. The index is designed to reflect the specific conditions of small and medium-sized towns, which often face limited financial and technical capacities when implementing adaptation measures. An example of such a town to which this approach can be applied is Žiar nad Hronom, which was chosen as our study area. The specific combination of urban structure, existing green spaces, and technical infrastructure makes Žiar nad Hronom a representative example of a smaller Slovak town where new approaches to BGI assessment and planning can be tested. By integrating surface runoff simulation with the analytical capabilities of GIS, the new index provides a framework for identifying the most vulnerable areas while also enabling the evaluation of the potential of proposed solutions in the context of climate adaptation. The outcome is a practical tool that supports municipal authorities in decision-making on BGI investments, thereby contributing to sustainable development and enhancing the resilience of urban systems.

In developing the new index, we also drew on insights from existing approaches, among which the ITZI model holds a prominent position (Courty et al, 2017; Courty et al, 2018; Courty et al, 2019; Jamali et al, 2021). This model is designed for simulating surface runoff in urban environments and provides an important theoretical and practical framework for detailed assessment of interactions between rainfall events and surface characteristics. Its contribution lies particularly in its adaptability to different urban contexts, offering a valuable foundation for the development of our new index. In designing the index itself, the AHP statistical method was also employed, allowing for systematic weighting of criteria and their more objective integration into the final model. By combining surface runoff simulation with the ITZI model, advanced GIS analyses, and the AHP methodology, we developed an index that is both scientifically robust and practically applicable for assessing BGI.

Methods and data

The Methods and Data section is structured into three main parts. The first part provides a description of the study area, which is the city of Žiar nad Hronom. The second part focuses on the input datasets utilized in the AHP analysis, including their sources and preprocessing procedures. The final part outlines the AHP methodology, covering the scoring of datasets, the determination of criteria weights, and the computation of the BGI index.

Study area

Žiar nad Hronom is a district town located in central Slovakia, within the Banská Bystrica Region (Figure 1). It lies in the Hron River valley at the foothills of the Štiavnica Mountains, positioned between the Štiavnica and Kremnica mountain ranges. This location provides favorable conditions for both industrial and agricultural development. The town is well-connected via a major road and rail corridor linking central Slovakia with Bratislava and Košice. The Hron River, the second-longest river in Slovakia, flows through the town. Covering an area of 39.1 km² at an elevation of 272 meters above sea level, Žiar nad Hronom has a population of 16,879 (Žiar Nad Hronom, 2025).

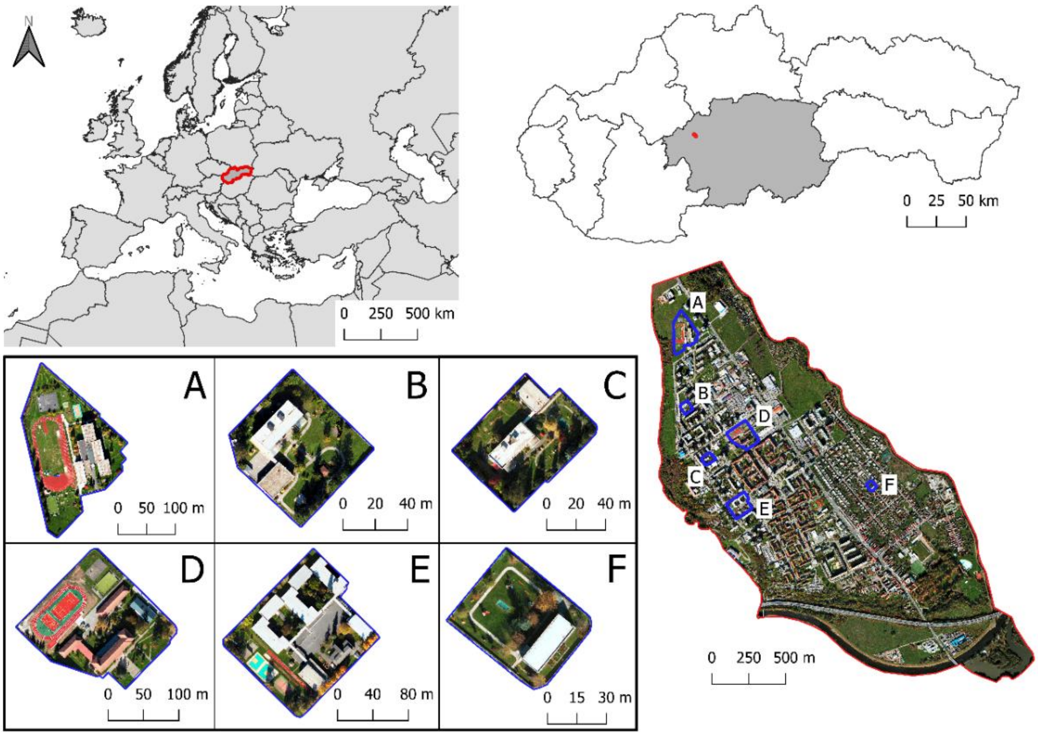

Fig. 1: Location of the study area

The study focuses on an urban area in the city center, encompassing a total of 3.64 km² (Figure 1). The city of Žiar nad Hronom represents a suitable and representative example of a Slovak town actively implementing measures to support climate change adaptation, particularly through rainwater retention and utilization. Within initiatives supported by the European Union, the city plans to implement water retention and green infrastructure measures in six selected school sites, labeled A through F, which include both primary and nursery school facilities (Table 1). These sites constitute key objects for assessing the effectiveness of BGI, and their spatial identification enables detailed analysis using GIS and the AHP methodology (Žiar Nad Hronom, 2024).

Tab. 1: Overview of school sites and planned measures.

Locality	*School*	*Number of planned measures*	*Area [m²]*
A	*Jilemnického (primary)*	*2*	*30,398*
B	*Rázusova (nursery)*	*1*	*4,636*
C	*Dr. Janského 8 (nursery)*	*1*	*4,698*
D	*Dr. Janského (primary)*	*4*	*24,005*
E	*M. R. Štefánika (primary)*	*5*	*16,968*
F	*Rudenkova (nursery)*	*1*	*2,787*

The selection of Žiar nad Hronom as the study area is justified by several factors. First, it is a medium-sized town with a typical structure of Slovak urban areas, ensuring that the study results are relevant to other cities of a similar type. Second, the combination of existing urban development, water bodies, public spaces, and school campuses enables a comprehensive analysis of the potential of BGI measures for rainwater retention and management. Third, the city's initiatives are well documented and readily available, enabling accurate identification of input data and their use in constructing the BGI index. These characteristics make Žiar nad Hronom an ideal environment for exploring methodologies for BGI assessment and overland flow simulation using GIS and AHP, with a focus on the specific locations of implemented measures.

Input datasets

The basis for constructing the new BGI index was the creation of map outputs representing the individual input datasets used in the analysis. The input datasets are presented in two separate sub-sections: the first focuses on the simulated water depth, which required a more detailed methodological description, while the second summarizes the remaining spatial datasets, including distance from risk areas, slope, land cover, and proximity to roads, which were derived using standard GIS operations. This division reflects differences in processing complexity across the datasets, while all contribute equally to the subsequent AHP-based evaluation and BGI index computation.

Simulated water depth

Simulated water depth is a key input raster for constructing the BGI index, as it integrates multiple environmental factors into a single indicator. Water accumulation in specific areas reflects the influence of terrain slope, land cover, and other physical characteristics, allowing identification of potentially suitable or high-risk areas (Harlis and Seo, 2024; Tokarčík and Hofierka, 2024). For the simulation of surface water flow, the two-dimensional Itzï model was employed, implemented within the GRASS GIS environment on a Linux operating system. The model is based on a simplified form of the Saint-Venant equations (partial inertia approach) and works with input data such as a digital elevation model, surface roughness parameters like Manning's coefficients, and rainfall data, enabling it to simulate surface water flow and flooding dynamics under varying environmental and precipitation conditions (Courty et al, 2018). Since the simulated water depth is only one of the factors in the AHP analysis, there is no scope here for a detailed mathematical or physical description of the model; more technical details, equations, and model validation are provided in the original publications (Courty et al, 2017; Courty et al, 2019). The choice of the Itzï model was motivated by its suitability for urban environments, its efficiency in handling high-resolution data, and its relatively fast computation, which makes it well-suited for simulating various rainfall and land cover scenarios (Courty et al, 2017; Jamali et al, 2021). In this study, simulated water depth was used solely as an indicator; the objective was not to calibrate or validate the model itself, but to create a map of its spatial distribution for subsequent assessment of suitability for implementing BGI measures (Beden and Keskin, 2020; Bruno et al 2022).

The primary input for the simulation was a digital surface model (DSM) derived from airborne laser scanning (ALS) data, provided as a classified point cloud by the Geodesy, Cartography, and Cadastre Office of the Slovak Republic (Tokarčík and Hofierka, 2024). Although the main product of the ALS project was a digital terrain model (DTM), for our study, a surface model including above-ground features was required, so the DSM was interpolated from the classified point cloud at a 1 m spatial resolution using the "LAS Dataset to Raster" tool in ArcGIS Pro. Vegetation points were excluded to focus on the bare surface and built structures, while the average density of last-return points was approximately 22 points per square meter, ensuring sufficient detail for high-resolution modelling (Figure 2) (Tokarčik et al, 2024).

For the distributed definition of parameters in the Itzï model, a detailed land cover map is required. To create this map, multiple freely available datasets were used. The approach combined LiDAR data, orthophoto imagery, and vector data from OpenStreetMap (OSM) to classify and delineate major land cover types (Tokarčik et al, 2024).

This integration enabled an accurate representation of natural and anthropogenic features, providing the spatial information needed to assign surface roughness and infiltration parameters in the Itzï water flow simulations. Surface hydraulic properties were represented using a map of Manning's roughness coefficients and infiltration parameters assigned to different land cover types (Figure 2).

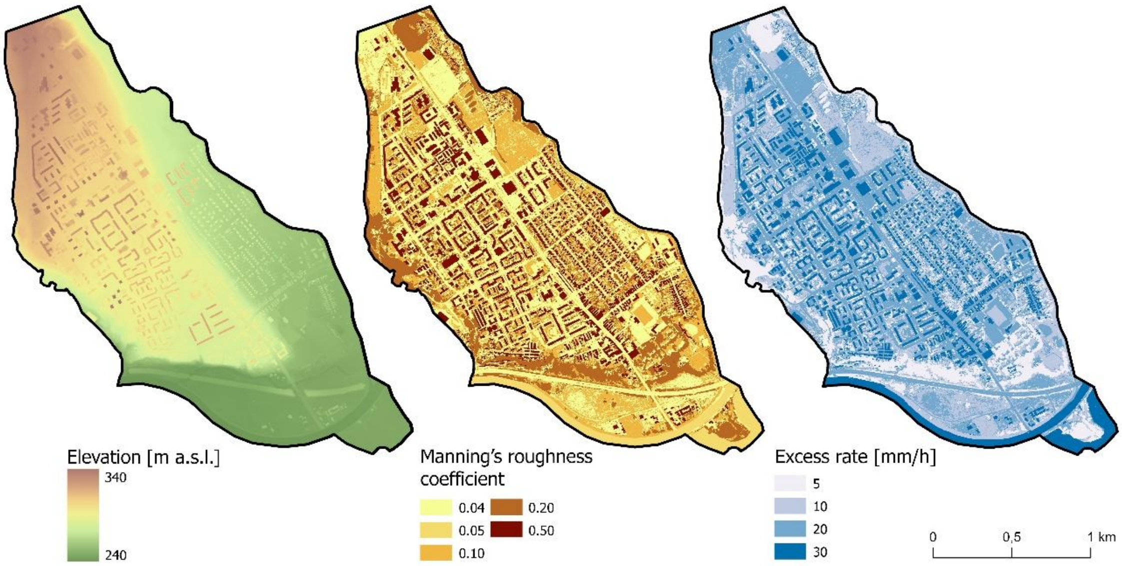

Fig. 2: Primary input maps for the Itzï model

The specific values for Manning's coefficients and infiltration rates were adopted from previous studies addressing surface water flow simulations in urban and semi-urban environments (Hofierka and Knutová, 2015; Tokarčík and Hofierka, 2024a; Tokarčík and Hofierka, 2024b; Vojtek and Vojteková, 2016). Precipitation was defined as a single event with an intensity of 30 mm and a duration of 20 minutes. For the overall analysis, it was necessary to input a single general, realistic rainfall value representative of rainfall events that commonly occur in the study area (Pecho et al, 2025). The excess rainfall rate for each land cover type was calculated as the precipitation amount minus the infiltration rate, and the values of Manning's roughness coefficient and excess rainfall rate are presented in Table 2.

Tab. 2: The values of the Manning's roughness coefficient and rainfall excess rate for land cover classes.
Other spatial datasets

Land cover	*Manning´s roughness coefficient*	*Rainfall excess rate [mm/hr.]*
buildings	*0.50*	*30*
built-up	*0.04*	*20*
grass	*0.10*	*10*
trees and shrubs	*0.20*	*5*
water	*0.05*	*30*

Another dataset used was the distance from hazardous areas. This dataset was derived from the simulated water depth raster. In the first step, areas with a simulated water depth of 5 cm or more were selected using the Reclassify tool. These areas were considered hazardous, or more precisely, locations with the highest potential for BGI implementation. The resulting raster was then converted into a vector polygon layer using the Raster to Polygon tool. To generate zones representing distances from these areas, the Multiple Ring Buffer tool was applied. This procedure resulted in a vector layer that represents the distance gradient from inundated areas. From a methodological perspective, this approach is important because implementing BGI measures is not always feasible directly in locations with the maximum inundation depth – such areas may be occupied by other land-use elements or infrastructure. Therefore, it is essential to also consider their surroundings, as measures implemented in the vicinity of such areas can contribute to reducing water depth or slowing down water accumulation.

Another dataset used was the terrain and roof slope. In several studies, slope is understood as a factor influencing water accumulation, with low-slope areas being identified as hazardous due to surface runoff concentration (Harlis and Seo, 2024; Kaur and Gupta, 2022). However, this aspect is already captured in our analysis by the simulated water depth. Therefore, in our case, slope is interpreted differently – as a factor determining the suitability of BGI implementation. Areas with steep slopes are considered unsuitable for placing measures, as conditions for water retention or stable installation of vegetative elements are limited. The input layer was a DSM without vegetation, with a 1 m spatial resolution, identical to that used in the surface water flow simulation. From this DSM, a slope raster was derived using the Slope tool in ArcGIS Pro. This raster was then used to identify areas with unsuitable slope conditions. The analysis was applied not only to terrain but also to buildings. For buildings, the average roof slope was derived from the DSM, and based on available literature, roofs were classified as suitable or unsuitable for green roof implementation depending on their slope (Grunwald et al, 2017).

The land cover layer was another key input for assessing the suitability of BGI implementation. In many studies, land cover is primarily interpreted as a factor influencing water accumulation, with built-up areas, for example, showing very limited retention potential (Harlis and Seo, 2024; Kapetas and Fenner, 2020). However, this aspect is already accounted for in our analysis through the simulated water depth raster. Therefore, in our case, land cover is considered from a different perspective – as a factor determining the feasibility of BGI measures. Different land cover types represent varying levels of suitability for implementing measures. For instance, green spaces or areas with trees and shrubs offer greater potential for establishing measures compared to built-up areas, where opportunities for new interventions are highly restricted. The land cover layer consisted of the following categories: green spaces, trees and shrubs, buildings, built-up areas, and water. These categories were then assessed in terms of their suitability for BGI implementation.

The last input layer for assessing the suitability of BGI implementation was the distance from roads layer. Accessibility and logistics are key factors for the effective implementation of BGI measures. Therefore, the suitability assessment considers distance from road infrastructure: locations closer to roads are more suitable for implementation, while roads themselves are considered the least suitable locations within the layer. The road layer was obtained from OSM, and the Multiple Ring Buffer tool was applied to create a distance-based categorization. This resulted in a layer representing the accessibility gradient for BGI implementation – from the lowest suitability directly on roads to the highest suitability in the immediate vicinity of roads.

Factor scoring and BGI index calculation

All previously described dataset layers were reclassified onto a uniform scoring scale from 1 to 5 to calculate the suitability index for BGI implementation, where 5 represents the most suitable and most needed locations for BGI measures (Table 3). This approach allows for a consistent comparison and integration of individual factors into a single comprehensive index, considering not only the physical characteristics of the area (simulated water depth, slope, land cover) but also logistical and practical implementation factors (distance from roads, distance from hazardous areas). The scoring within this scale was defined according to rules specific to each dataset.

Tab. 3: Ranking scores assigned to the BGI index factors and their classified value ranges.

Ranking score	***1***	***2***	***3***	***4***	***5***
Simulated water depth [cm]	*0.0*	*0.1 – 2.0*	*2.1 – 5.0*	*5.1 – 10.0*	*>10.0*
Proximity to hazardous areas [m]	*>100*	*100 – 51*	*50 – 21*	*20 – 11*	*<11*
Terrain slope [°]	*>15.0*	*15.0 – 10.1*	*10.0 – 5.1*	*5.0 – 2.1*	*<2.1*
Roof slope [°]	*>15.0*	*-*	*15.0 – 5.1*	*-*	*<5.1*
Land cover	*water*	*built-up areas*	*buildings*	*trees and shrubs*	*green spaces*
Proximity to roads [m]	*>300*	*300 - 201*	*200 - 101*	*100 - 31*	*<31*

Simulated water depth, ranging from 0 to 57 cm, was evaluated according to the intervals in Table 3, with the highest score of 5 assigned to locations with depths above 10 cm, while lower depths received lower scores. For the distance from hazardous areas, locations with water depth of 5 cm or more were selected, and distances were classified according to Table 3; the highest score (5) was assigned to sites less than 11 m from hazardous areas. Slope was considered as a combination of terrain and roof slopes; low terrain or roof slopes (e.g., <2.1° for terrain, <5.1° for roofs) were assigned the highest score of 5, while steep slopes received lower scores. The land cover layer assigned the highest score of 5 to green spaces, followed by trees and shrubs, then buildings with a score of 3, as they are interesting from the perspective of green roofs, built-up areas, and the lowest score of 1 to water areas. For distance from roads, locations within 30 m of a road were assigned the highest score of 5, while sites more than 300 m away received a score of 1. This scoring scheme enabled a consistent evaluation of all factors and their subsequent integration into the BGI index. An overview of all reclassified maps, including the intervals and assigned scores for each factor, is shown in Figure 3.

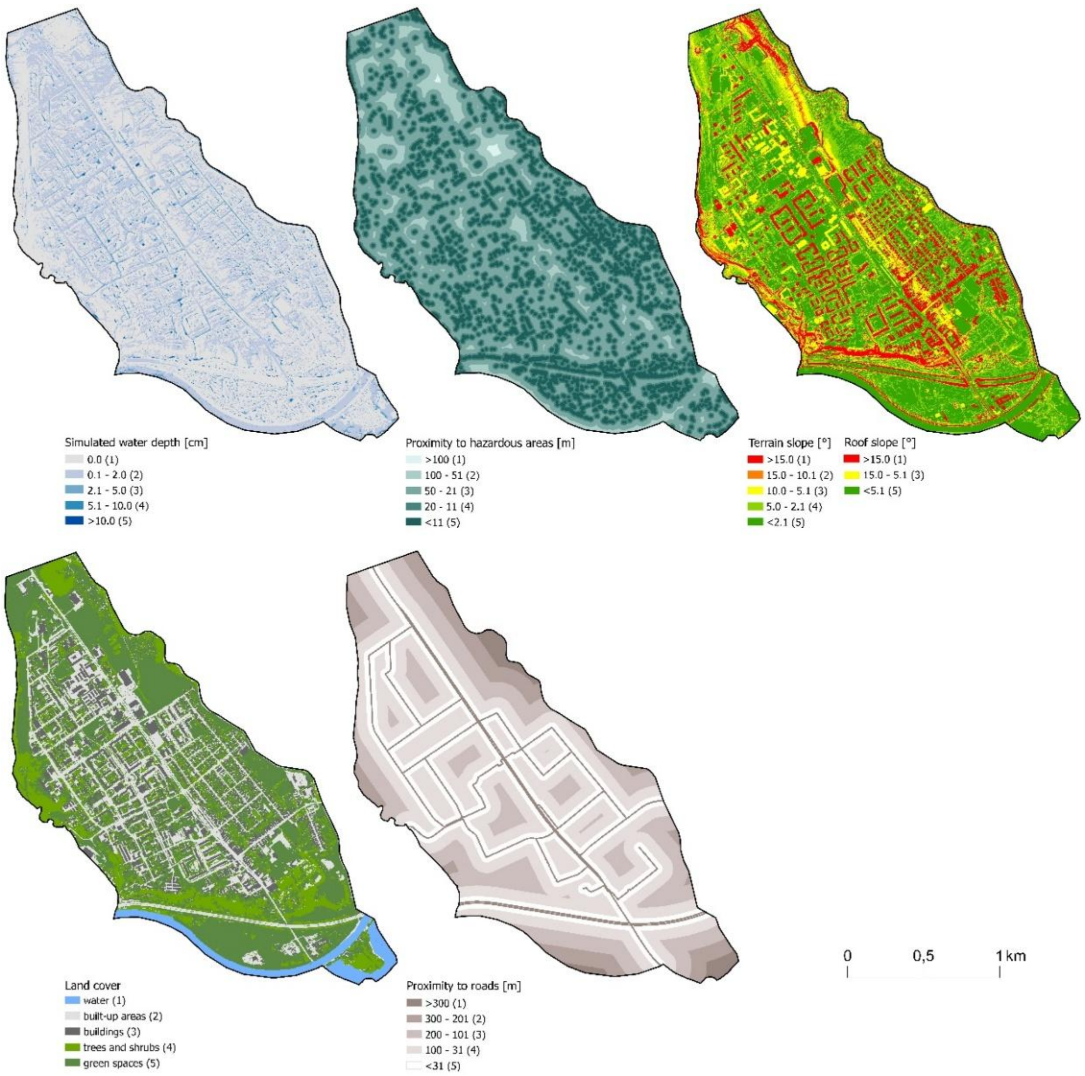

Fig. 3: Reclassified input factor maps used for the BGI index computation

For assessing the suitability of BGI implementation, it is necessary to assign a weight to each factor reflecting its relative importance. The AHP was applied for this purpose, as it provides a systematic and consistent method for determining the weights of individual criteria (Dee Fsm Russo and Camanho, 2015). A pairwise comparison matrix was constructed for each pair of factors, with their relative importance assessed using Saaty's 9-point scale (Harlis and Seo, 2024; Kapetas and Fenner, 2020). The weights were calculated in several steps. First, the sum of each column in the matrix was determined. Next, the matrix was normalized by dividing each element of a column by the sum of that column. Finally, the average of each row in the normalized matrix was computed, representing the weight of the corresponding factor. The resulting weights (Table 4) were then applied in the weighted summation of the factors to create the final BGI index. The consistency of the pairwise matrix was verified using the Consistency Index (CI) and Consistency Ratio (CR), with CI = 0.02 and CR = 0.018. A CR value below 0.1 is generally considered an indicator of good consistency, confirming that the weights were correctly assigned and the resulting index is reliable.

Tab. 4: Weights assigned to the individual factors used in the BGI index calculation

Criterion	***Weights***
Simulated water depth	*0.501*
Proximity to hazardous areas	*0.247*
Slope	*0.125*
Land cover	*0.095*
Proximity to roads	*0.032*
SUM	1.000

The weights for the individual factors in the BGI index were assigned based on their relative importance in identifying locations suitable for BGI implementation. Simulated water depth has the highest weight (0.501) because it integrates multiple key environmental and hydrological parameters, including terrain slope, surface roughness, land cover type, and other factors influencing water accumulation and potential flood risk. This factor serves as the primary indicator of potential flood impact, which is why it carries a dominant weight in the index. Proximity to hazardous areas was assigned a weight of 0.247, as placing measures near potential risk areas can significantly increase the effectiveness of interventions, even if the location itself is not directly inundated. This factor reflects both practical priority and the intervention's effectiveness. The terrain slope has a weight of 0.125, based on the feasibility of implementing measures. Steep slopes may be technically challenging or less effective to implement, while gentle slopes make it easier to realize interventions. Land cover was assigned a weight of 0.095, as different types of cover influence the practical suitability of implementing measures. This factor allows consideration of where interventions are technically and logistically easiest to implement. Proximity to roads has the lowest weight (0.032), as accessibility is a supplementary factor – closer roads facilitate logistical implementation, but roads themselves are not suitable for BGI measures. These weights reflect a combination of environmental and practical considerations, enabling reliable identification of locations with the highest potential for BGI implementation. Finally, the BGI index was calculated as a weighted sum of all factors, with each factor multiplied by its assigned weight. The calculation was performed in ArcGIS Pro using the Raster Calculator, following the formula: BGI index = (Simulated water depth × 0.501) + (Proximity to hazardous areas × 0.247) + (Slope × 0.125) + (Land cover × 0.095) + (Proximity to roads × 0.032).

In addition to the established BGI index, three alternative weighting scenarios were developed to assess the model's sensitivity to changes in the relative importance of individual criteria. These scenarios – hydrological, urban, and environmental – were designed to reflect different management perspectives and spatial conditions of the study area. The hydrological scenario increased the weight of simulated water depth by 20%, with the remaining criteria reduced proportionally. This setting represents situations where local authorities prioritize flood mitigation and surface runoff reduction. The urban scenario placed slightly greater emphasis on proximity to roads and on land cover (imperviousness), reflecting the priorities of densely built-up areas, where accessibility and urban infrastructure play a key role. Finally, the environmental scenario strengthened the influence of slope and land cover, capturing terrain stability and ecological conditions that affect vegetation growth and natural water infiltration. The adjusted weights for each scenario are summarized in Table 5 and served as the basis for recalculating the BGI index layers under varying decision-making conditions. These alternative settings enabled the subsequent evaluation of how changes in the weighting scheme influence the spatial distribution and range of BGI values, which is presented in the Results section.

Tab. 5: Weighting schemes of the BGI index used for the sensitivity analysis

Criterion	***Hydrological***	***Urban***	***Environmental***
Simulated water depth	*0.601*	*0.401*	*0.401*
Proximity to hazardous areas	*0.222*	*0.200*	*0.200*
Slope	*0.100*	*0.110*	*0.200*
Land cover	*0.060*	*0.180*	*0.170*
Proximity to roads	*0.017*	*0.109*	*0.029*

Results

Evaluation of the BGI Index and scenario analysis

The resulting BGI index map provides an overview of areas with varying suitability for implementing BGI measures (Figure 4). Index values range from 1.19 to 4.99. Areas highlighted in red indicate the highest potential, where implementing measures is most effective and necessary. These locations represent priority sites for planning and placing BGI interventions. Conversely, areas marked in green have the lowest risk, for which implementing measures would yield relatively lower benefits. This visualization enables easy identification of priorities and supports strategic decision-making to improve the environmental and climatic conditions of the studied area. The BGI index was derived using a weighted overlay of multiple spatial criteria, including hydrological, topographical, and infrastructural factors, which together capture both environmental risks and opportunities for implementing blue-green measures.

The analysis of the raster BGI index showed that the average index value across the study area is 2.58. Extreme values extracted from the raster dataset indicate that areas with the highest risk (index value > 3.5), representing the greatest potential for effective BGI implementation, cover approximately 0.13 km², or 3.6 % of the total area. Conversely, locations with the lowest risk (index value < 2), where implementing measures would be less effective, cover approximately 0.29 km², or 8% of the area. The remaining portion of the area falls within the mid-range of values, representing locations with average suitability for BGI measures.

Spatially, the highest index values are concentrated in areas where surface water naturally accumulates and where physical conditions are favorable for implementing blue-green measures. These locations are primarily green or semi-permeable surfaces with moderate slopes that enable effective water retention and infiltration. Many of them are situated near zones identified as flood-prone or adjacent to drainage pathways, confirming their functional importance in mitigating runoff impacts and improving local hydrological balance. In contrast, lower index values are typical of elevated or densely built-up areas with limited infiltration potential. This spatial distribution reflects the expected relationships among hydrological risk, terrain morphology, and land-use structure. These baseline results serve as a reference for evaluating alternative weighting scenarios and testing the model's robustness in subsequent analyses.

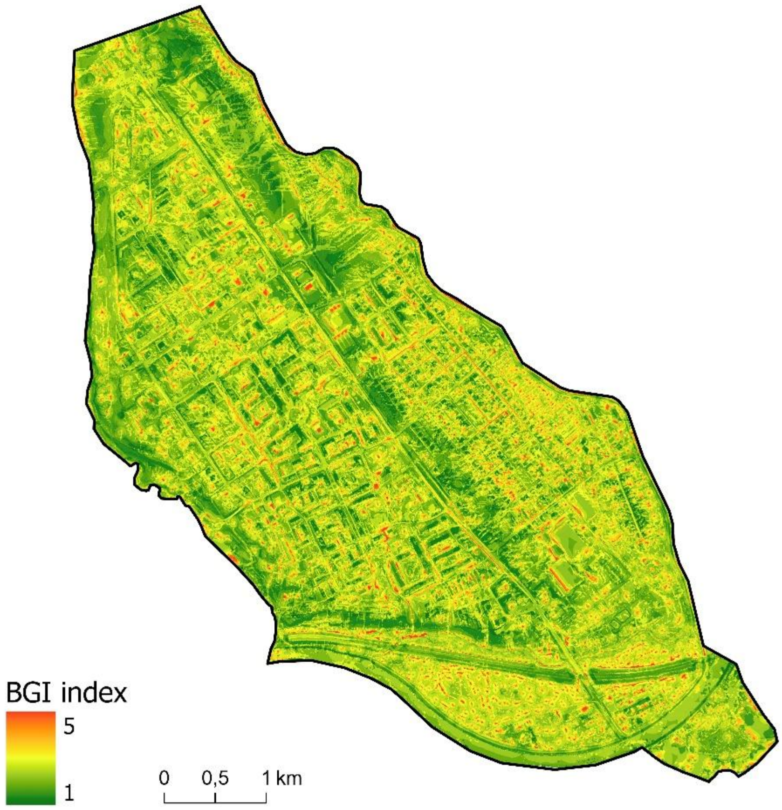

Fig. 4: BGI index map

To further evaluate the robustness of the model and the influence of individual criteria, the BGI index was recalculated under three alternative weighting scenarios – hydrological, urban, and environmental – as described in the methodology section. The recalculated BGI index maps (Figure 5) show that the overall spatial pattern of suitability remains generally consistent across all scenarios, indicating that the model is relatively stable and robust. However, local differences are evident, particularly in areas where specific factors gained higher importance.

In the hydrological scenario, areas along drainage lines, local depressions, and flood-prone zones had higher index values due to the increased weight of the simulated water-depth factor. This prioritization largely overlaps with the reference BGI index, as hydrological risk already had a dominant influence in the base model. The highest-priority areas are thus concentrated in zones where surface water naturally accumulates, confirming their importance for enhancing local retention and mitigating runoff impacts. In the urban scenario, increasing the weights of land cover and proximity to roads shifted the index distribution toward densely built-up areas and transport corridors. This reflects locations where green spaces are limited, but their establishment would provide high multifunctional benefits and be easily accessible for implementation. Consequently, priority zones are more clustered within the urban core and along main roads, highlighting the strong effect of the built environment on the model output. The environmental scenario emphasized land cover and slope, with the latter favoring areas of lower gradient that are more stable and technically suitable for BGI construction. As a result, this scenario prioritizes open, less built-up zones, where gentle terrain and vegetated surfaces support effective infiltration and ecosystem-based measures. Compared to the reference model, priority areas slightly expanded toward suburban and greenfield locations outside the densely urbanized center.

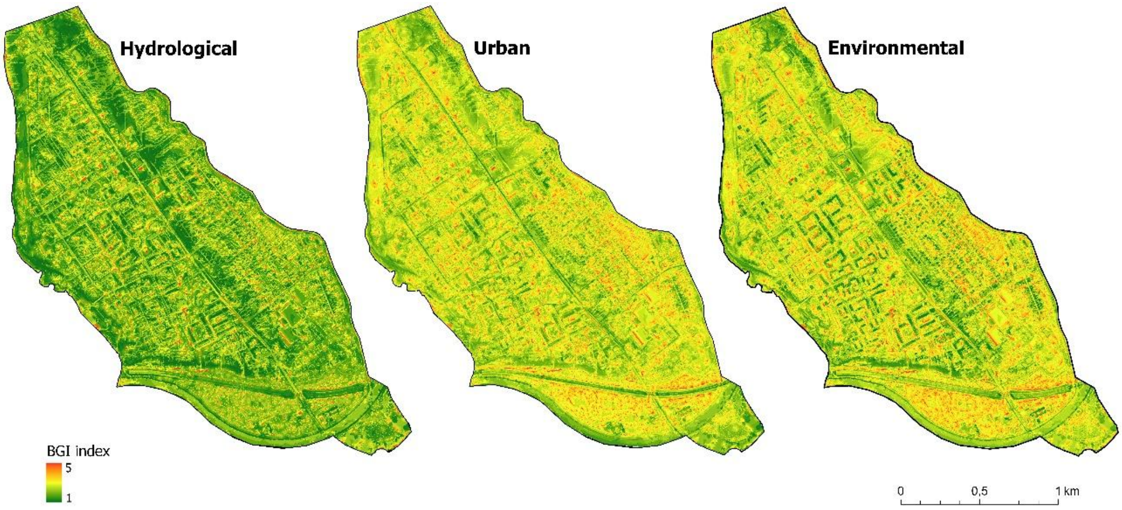

Fig. 5: BGI index maps for alternative scenarios

To complement the spatial assessment of scenario-based results, a quantitative evaluation was conducted to further examine the stability and internal consistency of the BGI index. The definition of additional weighting scenarios proved highly effective not only for identifying alternative priority settings applicable across different environments, but also for testing the model's robustness and reliability. If minor adjustments in the weighting of criteria had led to significant changes in the identification of high-priority areas, it would indicate low index stability. Therefore, this part of the analysis focuses on the statistical comparison of raster outputs derived from the individual scenarios and the reference model. Methods such as Pearson's correlation, maximum deviation, mean deviation, and the percentage of BGI index values above 3.5 were applied to quantify the degree of similarity between the results and to assess how the spatial distribution of priority areas changed under different weighting conditions. This quantitative approach allows a more objective verification of the model's sensitivity to changes in the weighting of individual criteria. An overview of the results for these indicators is presented in Table 6, which summarizes the statistical indicator values for the evaluated test rasters.

Tab. 6: Statistical evaluation of the alternative BGI index scenarios

Scenario	***Pearson correlation***	***Maximum deviation***	***Mean deviation***	***BGI index >3.5 [%]***
Reference	*1.00*	*-*	*-*	*3.6*
Hydrological	*0.98*	*0.26*	*0.22*	*3.3*
Urban	*0.92*	*0.60*	*0.22*	*5.5*
Environmental	*0.94*	*0.59*	*0.23*	*7.6*

The first step involved assessing the linear relationship between the pixel values of the reference BGI index and each scenario. The Pearson correlation coefficient (r) was calculated to quantify the strength of this relationship, where values close to 1 indicate a strong positive correlation and thus a high level of consistency between maps. As shown in Table 6, the correlation coefficients between the reference and alternative scenarios ranged from 0.92 to 0.98, confirming a very strong linear relationship. This suggests that changes in weighting have only a minor influence on the overall spatial distribution of the BGI index. The hydrological scenario (r = 0.98) shows the highest correlation with the reference, indicating that the index pattern remained almost identical, as hydrological factors already played a dominant role in the base model. The urban (r = 0.92) and environmental (r = 0.94) scenarios show slightly lower correlations, reflecting localized changes driven by the increased importance of land cover, proximity to roads, and slope.

To complement the correlation analysis, mean and maximum deviation were used to express the magnitude of differences between the reference and each scenario on a per-pixel basis. The mean deviation values around 0.22–0.23 indicate that most pixels differ by less than one-fifth of the index range, while the higher maximum deviations (up to 0.6) highlight isolated areas where the weighting adjustments caused more significant local shifts. Finally, the share of pixels with a BGI index > 3.5 represents the proportion of high-priority areas under each scenario. These values range from 3.3% to 7.6%, indicating that although the total extent of priority zones fluctuates slightly with the weighting scheme, the differences remain moderate. The relatively stable correlation and limited deviations together confirm the robustness and internal consistency of the BGI index across all tested weighting scenarios.

Application to selected school sites

The main advantage of the developed BGI index lies not only in its ability to comprehensively assess the entire study area in terms of the effectiveness of planned measures, but also in its capacity to focus on smaller localities and analyze them in greater detail. This approach enables the identification of specific sites with the highest priority for implementing BGI measures. In this study, school areas were selected as the focus locations, as the city intends to implement nature-based measures within these premises as part of an ongoing adaptation project. Another strength of the index is its universality – it can be applied to various types of urban areas and serves as a decision-support tool for evaluating the suitability and efficiency of BGI implementation. The spatial distribution of BGI index values within the selected school sites is shown in Figure 6, illustrating the variability of local conditions and highlighting zones with higher potential for effective measures.

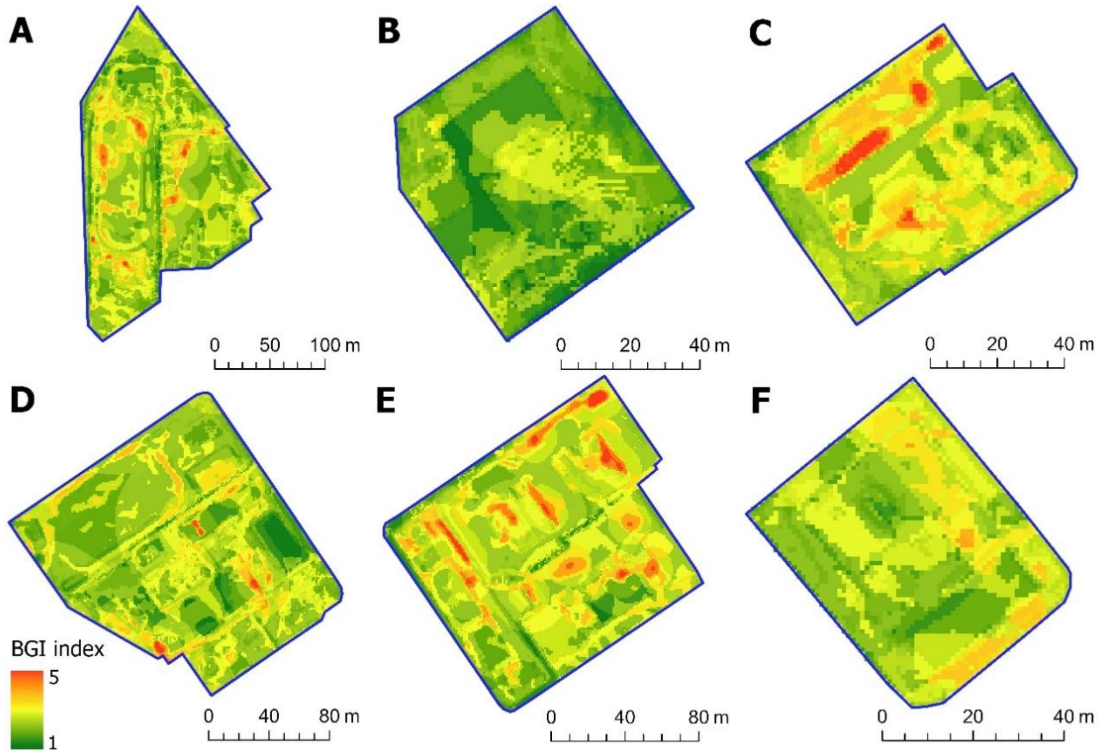

Fig. 6: Spatial distribution of BGI index values within selected school sites

To identify the most suitable locations among the selected sites, school areas were evaluated based on the mean and maximum BGI index values. The mean index value represents the overall suitability of each site, while the maximum value highlights localized hotspots with the highest potential for intervention. As shown in Table 7, the Dr. Janského 8 School achieved the highest mean BGI index (2.87) with a maximum value of 4.96 and was therefore classified as a high-priority site. Similarly, the M. R. Štefánika School (mean 2.81, maximum 4.99) also falls into the high-priority category. Sites such as Rudenkova, Jilemnického, and Dr. Janského show moderate mean values (2.66–2.67) and maximum values ranging from 3.68 to 4.47, placing them in the moderate-priority group. Finally, the Rázusova Primary School, with a mean index of 2.31 and a maximum of 3.23, represents a low-priority location for BGI implementation. These results confirm that the index enables both a general ranking of sites and a more detailed identification of internal priority zones, providing a solid foundation for spatial planning and targeted implementation of measures.

Tab. 7: Ranking of school sites based on BGI index values

Rank	*Location*	*School*	*Mean BGI index*	*Maximum BGI index*	*Priority level*
1.	*C*	*Dr. Janského 8*	*2.87*	*4.96*	*High*
2.	*E*	*M. R. Štefánika*	*2.81*	*4.99*	*High*
3.	*F*	*Rudenkova*	*2.67*	*3.68*	*Moderate*
4.	*A*	*Jilemnického*	*2.66*	*4.47*	*Moderate*
5.	*D*	*Dr. Janského*	*2.59*	*4.47*	*Moderate*
6.	*B*	*Rázusova*	*2.31*	*3.23*	*Low*

The proposed index demonstrates both diagnostic and decision-making value, as it can confirm the suitability of planned measures while also highlighting new potential risk areas that might otherwise be overlooked. For example, the area of the Andreja Kmeťa nursery school, located near zones with elevated simulated water depth, was recognized as highly suitable for implementing BGI measures. Even though this site is not part of the city's current adaptation plan, its exposure in areas with higher simulated water depth makes it a key candidate for future BGI implementation. This identification illustrates the practical applicability of the BGI index as a spatial decision-support tool, capable of pinpointing areas where BGI measures could effectively reduce flood risk and enhance local resilience. The simulated water depth and BGI index for this school site are shown in Figure 7.

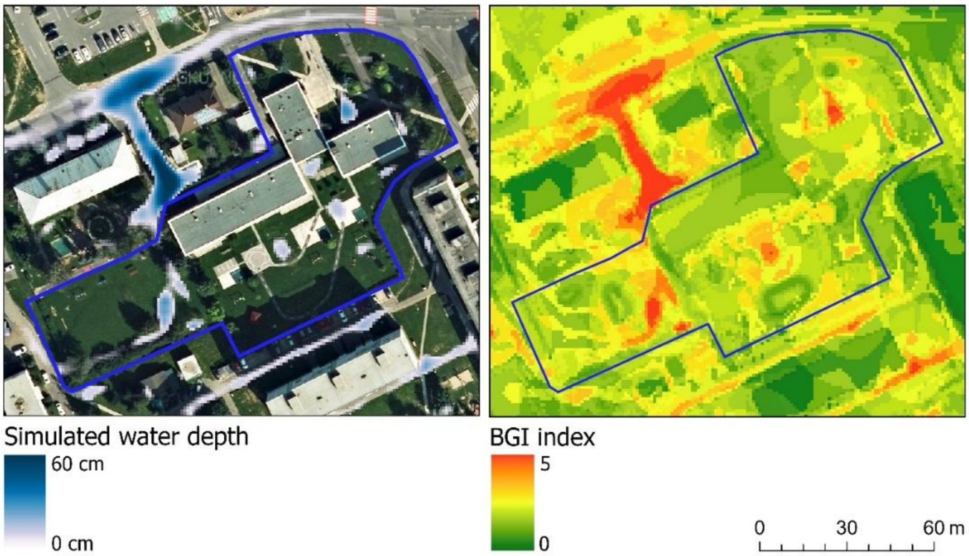

Fig. 7: BGI index and simulated water depth around the Andreja Kmeťa nursery school

Based on the calculated BGI index values, the area of the Andreja Kmeťa nursery school achieved a mean index of 2.73 and a maximum value of 4.55, ranking third among all evaluated school sites. These values clearly classify the location as a high-priority area for future BGI implementation. Compared to other assessed sites, such as the Rázusova Primary School, which exhibited a mean value of 2.31 and was classified as low-priority, this site demonstrates a significantly higher potential for the effective integration of nature-based solutions. The elevated BGI index values are primarily associated with local topographic and hydrological conditions, including the accumulation of surface runoff and reduced infiltration capacity in the surrounding area. Furthermore, simulated flood depth data confirm a heightened flood risk in the immediate vicinity of the site, reinforcing the need for targeted adaptation measures. The identification of this location thus underscores the robustness and decision-making potential of the developed BGI index, which can effectively reveal previously unconsidered yet strategically important areas for enhancing urban resilience and stormwater management.

Discussion

The results of this study confirm the analytical and practical potential of the developed BGI index as a decision-support tool for identifying priority areas for implementing BGI measures. The resulting BGI index map proved to be a highly efficient spatial output, allowing for a clear and immediate visualization of critical and high-priority zones. This map integrates multiple environmental, hydrological, and urban factors into a single composite indicator, providing a clear spatial representation of areas where BGI implementation would have the highest impact on urban resilience and environmental quality (Grunwald et al, 2017; Hamann et al, 2020; Tokarčík et al, 2024). Such spatially explicit outputs enhance the interpretability of results and support their direct application in urban planning and climate adaptation strategies (Kapetas and Fenner, 2020; Ncube and Arthur, 2021).

A major contribution of this study lies in the use of GIS-based spatial modeling and analysis, which enabled the integration of heterogeneous spatial datasets—such as topography, land cover, and hydrological simulations—into a unified analytical framework (Grunwald et al, 2017; Harlis and Seo, 2024; Kaur and Gupta, 2022). The use of raster-based continuous data ensured sufficient spatial resolution for both citywide assessment and local-scale analyses. This demonstrates the flexibility of geoinformatics methods for evaluating BGI potential and supports the growing trend of using GIS as a core analytical tool in sustainable urban planning (Grunwald et al, 2017; Voskamp and Van De Ven, 2014). The BGI index thus functions not only as an analytical model but also as a practical GIS-based tool capable of transforming complex spatial data into actionable information for decision-makers.

The robustness of the index was confirmed by recalculating the reference BGI index under three alternative weighting scenarios – hydrological, urban, and environmental. Despite moderate adjustments in the relative importance of individual criteria, the overall spatial pattern of high-priority areas remained largely consistent. The strong Pearson correlation coefficients ($r = 0.92–0.98$) between the reference and alternative scenarios indicate a high level of agreement, suggesting that the index is not overly sensitive to minor changes in parameterization [8]. This stability supports its applicability across various urban contexts and confirms that the developed approach yields reliable, transferable results.

From a methodological perspective, incorporating simulated water depth as a hydrological factor represents a key innovation compared to approaches relying solely on static terrain parameters or potential drainage density (Harlis and Seo, 2024; Kaur and Gupta, 2022). This method provides a more realistic depiction of runoff accumulation and improves the diagnostic capacity of the BGI index. Nevertheless, the lack of direct observational data for validation remains a limitation, as detailed hydrological monitoring is rarely available in medium-sized cities. Therefore, simulated water depth served as a practical proxy for flood susceptibility, emphasizing the need for cities to invest in systematic spatial data collection and monitoring systems (Tokarčík and Hofierka, 2024a; Vojtek and Vojteková, 2016).

Finally, the findings of this study open new directions for future research and model development. With the availability of more detailed spatial and hydrological data, the BGI index could be extended to include process-based hydrological modeling tools such as ITZI or other open-source runoff simulation models (Courty et al, 2017; Jamali et al, 2021; Tokarčík and Hofierka, 2024a; Vojtek and Vojteková, 2016). This would allow researchers and planners not only to identify priority areas but also to test the potential impact of proposed measures on runoff dynamics and water retention. Such integration would transform the index from a static diagnostic tool into a predictive and adaptive model, supporting iterative planning and long-term monitoring of the effects of BGI interventions (Hamann et al, 2020; Hofierka and Knutová, 2015).

Conclusion

The developed BGI index demonstrates strong analytical and practical potential as a spatial decision-support tool for identifying and prioritizing sites for blue-green infrastructure implementation. By combining GIS analyses, AHP-based weighting, and hydrological simulation of surface runoff, the index integrates multiple environmental and infrastructural parameters into a single interpretable output. The results confirm that simulated water depth is an effective hydrological indicator for identifying flood-prone areas, and the index's overall robustness was validated by high correlations across weighting scenarios. The study highlights the crucial role of spatial data and GIS modeling in supporting climate adaptation planning and emphasizes the need for municipalities to invest in systematic spatial data collection and monitoring. Furthermore, the proposed framework is easily transferable to other urban contexts, particularly where data availability is limited. Future research should focus on extending the model through process-based simulations, such as integrating ITZI or similar tools, to dynamically evaluate the effects of proposed BGI measures on runoff reduction and resilience enhancement. Overall, the index provides an efficient methodological foundation for evidence-based decision-making in sustainable urban water management.

References

Beden, N., Keskin, A. U. Flood map production and evaluation of flood risks in situations of insufficient flow data. Natural Hazards 105 (2020), 2381-2408.doi: 10.1007/s11069-020-04404-y.

Bruno, L. S., Mattos, T. S., Oliveira, P. T., Almagro, A., Rodrigues D. B. Hydrological and Hydraulic Modeling Applied to Flash Flood Events in a Small Urban Stream. Hydrology 9, 12 (2022), 223.

Cortinovis, C., Geneletti, D. Ecosystem services in urban plans: What is there, and what is still needed for better decisions. Land Use Policy 70 (2018), 298-312. doi:10.1016/j.landusepol.2020.105108.

Courty, L. G., Pedrozo-Acuña, A., Bates, P. D. Itzï (version 17.1): an open-source, distributed GIS model for dynamic flood simulation. Geoscientific Model Development 10, 4 (2017), 1835-1847. doi:10.5194/gmd-10-1835-2017.

Courty, L. G., Rico-Ramirez, M. Á., Pedrozo-Acuña, A. The Significance of the Spatial Variability of Rainfall on the Numerical Simulation of Urban Floods. Water 10, 2 (2018), 207. doi:10.3390/W10020207.

Courty, L. G., Soriano-Monzalvo, J. C., Pedrozo-Acuña, A. Evaluation of open-access global digital elevation models (AW3D30, SRTM and ASTER) for flood modelling purposes. Journal of Flood Risk Management 12, 51 (2019), e12550. doi:10.1111/jfr3.12550.

Deely, J., Hynes, S., Barquín, J., Burgess, D., Finney, G., Silió, A., Álvarez-Martínez, J. M., Bailly, D., Ballé-Béganton, J. Barrier identification framework for the implementation of blue and green infrastructures. Land Use Policy 99 (2020), 105108. doi:10.1016/j.landusepol.2020.105108.

Dee Fsm Russo, R., Camanho, R. Criteria in AHP: A Procedia computer science 55 (2015), 1123-1132.

Fenner, R. Spatial Evaluation of Multiple Benefits to Encourage Multifunctional Design of Sustainable Drainage in Blue-Green Cities. Water 9, 12 (2017), 953. doi:10.3390/w9120953.

Ghofrani, Z., Sposito, V., Faggian, R. A Comprehensive Review of Blue-Green Infrastructure Concepts. International Journal of Environment and Sustainability 6, 1 (2017), 15-36. doi:10.24102/ijes.v6i1.728.

Grunwald, L., Heusinger, J., Weber, S. A GIS-based mapping methodology of urban green roof ecosystem services applied to a Central European city. Urban Forestry & Urban Greening 22 (2017), 54-63.

Hamann, F., Blecken, G.-T., Ashley, R. M., Viklander, M. Valuing the Multiple Benefits of Blue-Green Infrastructure for a Swedish Case Study: Contrasting the Economic Assessment Tools B£ST and TEEB. Journal of Sustainable Water in the Built Environment 6, 4 (2020), 05020003. doi:10.1061/JSWBAY.0000919.

Harlis, T. A., Seo S. B. Land suitability analysis for blue-green infrastructure implementation in an urban stormwater management system in Surabaya, Indonesia. Water Science & Technology 90, 5 (2024), 1501-1519. doi:10.2166/wst.2024.265.

Hofierka, J., Knutová, M. Simulating Spatial Aspects of a Flash Flood Using the Monte Carlo Method and GRASS GIS: a Case Study of the Malá Svinka Basin (Slovakia). Open Geosciences 7 (2015), 118-125. doi:10.1515/geo-2015-0013.

Jamali, B., Haghighat, E., Ignjatovic, A., Leitão, J. P., Deletic, A. Machine learning for accelerating 2D flood models: Potential and challenges. Hydrological Processes 35, 4 (2021), e14064. doi:10.1002/HYP.14064.

Kapetas, L., Fenner, R. Integrating blue-green and grey infrastructure through an adaptation pathways approach to surface water flooding. Philosophical Transactions of the Royal Society a Mathematical, Physical and Engineering Sciences 378, 2168 (2020), 20190204. doi:10.1098/rsta.2019.0204.

Kaur, R., Gupta, K. Blue-Green Infrastructure (BGI) network in urban areas for sustainable storm water management: A geospatial approach. City and Environment Interactions 16 (2022), 100087. doi:10.1016/j.cacint.2022.100087.

Kozak, D., Henderson, H., De Castro Mazzaro, A., Rotbart, D., Aradas, R. Blue-Green Infrastructure (BGI) in Dense Urban Watersheds. The Case of the Medrano Stream Basin (MSB) in Buenos Aires. Sustainability 12, 6 (2020), 2163. doi:10.3390/su12062163.

Ncube, S., Arthur, S. Influence of Blue-Green and Grey Infrastructure Combinations on Natural and Human-Derived Capital in Urban Drainage Planning. Sustainability 13, 5 (2021), 2571. doi:10.3390/su13052571.

Ncube, S., Spray, C., Geddes, A. Assessment of changes in ecosystem service delivery – a historical perspective on catchment landscapes. International Journal of Biodiversity Science, Ecosystem Services & Management 14, 1 (2018), 145-163. doi:10.1080/21513732.2018.1489306.

O'Donnell, E., Thorne, C. Blue–Green Cities: Integrating urban flood risk management with green infrastructure. Thorne, London, 2020. doi:10.1680/bgc.64195.

O'Donnell, E., Thorne, C., Yeakley, J., Chan, F. Sustainable Flood Risk and Stormwater Management in Blue-Green Cities; an Interdisciplinary Case Study in Portland, Oregon. Journal of the American Water Resources Association 56, 5 (2020), 757-775. doi:10.1111/1752-1688.12854.

O'Donnell, E. C., Woodhouse, R., Thorne, C. R. Evaluating the multiple benefits of a sustainable drainage scheme in Newcastle, UK. Proceedings of the Institution of Civil Engineers - Water Management 171, 4 (2017), 191-202. doi:10.1680/jwama.16.00103.

Pecho, J., Markovič, L., Faško, P., Madara, M. Výdatnosť atmosférických zrážok na Slovensku sa zvyšuje. https://www.shmu.sk/en/?page=2049&id=932. Last Accessed October 16, 2025.

Pugh, T. A. M., Mackenzie, A. R., Whyatt, J. D., Hewitt, C. N. Effectiveness of Green Infrastructure for Improvement of Air Quality in Urban Street Canyons. Environmental Science & Technology 46, 14 (2012), 7692-7699. doi:10.1021/es300826w.

Tokarčík, O., Blišťan, P., Kovanič, Ľ., Peťovský, P., Topitzer, B. Assessment of the usability of open data in Slovakia in the contextof mapping and evaluating Blue-Green Infrastructure. Geographia Cassoviensis 18, 2 (2024), 119-139. doi:10.33542/GC2024-2-02.

Tokarčík, O., Hofierka, J. Designing flash flood control measures for urban areas using the Monte Carlo water flow simulation. Geomatics, Natural Hazards and Risk 15, 1 (2024), 2361806. doi:10.1080/19475705.2024.2361806.

Tokarčík, O., Hofierka, J. Využitie dát z projektu leteckého laserového skenovania v modelovaní prívalových povodní pomocou metódy Monte Carlo. Geodetický a kartografický obzor 70, 7-8(2024), 128-138.

Vojtek, M., Vojteková, J. Flood hazard and flood risk assessment at the local spatial scale: a case study. Geomatics, Natural Hazards and Risk 7, 6 (2016), 1973-1992. doi:10.1080/19475705.2016.1166874.

Voskamp, I. M., Van De Ven, F. H. M. Planning support system for climate adaptation: Composing effective sets of blue-green measures to reduce urban vulnerability to extreme weather events. Building and Environment 83 (2015), 159–167. doi:10.1016/j.buildenv.2014.07.018.

Žiar nad Hronom. Popis a poloha. https://www.ziar.sk/popis-a-poloha/. Last Accessed October 16, 2025.

Žiar nad Hronom. Zhromažďovanie dažďových vôd, jej využitie a likvidácia, Žiar nad Hronom 2024. https://www.ziar.sk/zhromazdovanie-dazdovych-vod-jej-vyuzitie-a-likvidacia-ziar-nad-hronom-2024/. Last Accessed October 16, 2025.