Multi-Criteria GIS for Sponge City Planning with Open Data Sources in Vigo (Spain)

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ABSTRACT:

Sponge cities are renowned for their efficacy against extreme weather events, reducing surface runoff, managing stormwater, and mitigating flood risks. Moreover, they present multifaceted advantages by integrating blue-green infrastructure, enhancing urban sustainability, and improving water quality. The trend of their expansion beyond China marks a significant development in climate-resilient urban planning. This study pioneers the use of open data to locate suitable sites for sponge Low Impact Development (LID) solutions, showcasing Vigo (Spain) as a viable case for mid-sized cities. Input data is obtained from administrative cartography (DTM, hydrogeology, land cover, river courses, and demographic census) and satellite imagery (impervious coverage, vegetation, and surface temperature) from Landsat 8 and MODIS calculating three spectral indices (NISI, NDVI, NDIH). A robust Geographical Information System (GIS) method is proposed weighting the multi-criteria with AHP matrix. Three main potential sites are identified for deploying specific sponge LID strategies, as green roofs, green parking, or rain gardens. Nevertheless, while the method swiftly identifies intervention sites on a municipal scale, conclusive decisions necessitate terrain insights, public sentiments, urban regulations, and funding considerations.

1. Introduction

Innovative urban planning approaches have become imperative to confront the impact of climate change-induced extreme weather events. Among these approaches, the concept of "sponge cities" has gained prominence. Sponge cities represent a paradigm shift in urban design and management, emphasizing the integration of natural systems within urban landscapes to address issues of flooding, water scarcity, and environmental degradation (Gao et al., 2021).

Sponge cities are urban environments strategically designed to mimic natural sponges, capable of absorbing, storing, and purifying rainwater through the incorporation of Natural Based Solutions (NBS) (Qi et al., 2020). By leveraging techniques such as green roofs, rain gardens, permeable pavements, and constructed wetlands, sponge cities aim to reduce surface stormwater runoff, alleviate flooding, recharge groundwater, and enhance overall urban resilience against climate-related challenges (Yin et al., 2021). Moreover, sponge solutions emphasis on green spaces and natural water management systems fosters biodiversity, mitigates the urban heat island effect, and contributes to improving air quality (Guan et al., 2021).

Despite their promise, designing and implementing sponge city solutions pose various challenges. The complexities involved in integrating green infrastructure within established urban landscapes, coupled with the need for comprehensive planning and collaboration among diverse stakeholders, often present significant hurdles (Wang et al., 2021). Furthermore, the availability and accessibility of accurate data on hydrology, urban morphology, and climate patterns remain critical limitations in effectively designing and optimizing these resilient urban landscapes (Shao et al., 2016). Addressing these difficulties requires interdisciplinary approaches, innovative technologies, and leveraging open data sources to create efficient and adaptable sponge frameworks tailored to specific locations.

In this work, the use of open data is proposed for selecting potential sites for the implementation of sponge-based solutions in the city of Vigo (Spain) using a Multi-Criteria Geographic Information System (GIS). Data is collected from various free sources, including the local government, national organizations, and two satellite platforms. Additionally, specific solutions will be proposed for the sites identified by the model. This study aims to contribute to the discourse on sustainable urban development and resilient infrastructure in the face of climate change in an area exposed to the periodic passage of Atlantic storms (Pérez-Alarcón et al., 2023).

The reminder of this paper is structured as follows. In Section 2, works on sponge city solutions are compiled. The case study, input data and proposed method is explained in Section 3. Section 4 is dedicated to present and analyse the results. Section 5 is devoted to discussion and conclusion is in Section 6.

2. Related Work

Most research related to the construction and analysis of sponge cities is developed in China, as it was the first country in 2015 to propose the sponge city initiative to enhance water management in 30 urban areas from 2015 cities (Yin et al., 2021). Although the term 'sponge' mainly refers to Chinese, there have been prior initiatives with similar intentions (Nguyen et al., 2020): Best (water) Management Practices in the United States, Water Sensitive Urban Design in Australia, Sustainable Urban Drainage System in the United Kingdom. The implementation of sponge cities requires four phases of work (Nguyen et al., 2020): (1) analysing regional context including water issues; (2) developing scenarios based on climate change and population growth, (3) development the model and simulate the performance (4) planning and implementation.

The main challenge of sponge cities is to model the complex behaviour of water in urban areas, where multidisciplinary factors come into play. For this purpose, numerous models have been proposed and tested. The most employed are the Stormwater Management Model (SWMM) that is an open source software for dynamic hydrologic and hydraulic simulations of water quantity and quality (Randall et al., 2019), and the Volume Capture Ratio (VCR) that is one of the compulsory indicators launched by the Chinese Ministry of Housing and Urban–Rural Development (Liu et al., 2021). Parallel to these proposals, several researchers have proposed models based on Geographic Information Systems (GIS) (Fan and Matsumoto, 2019; Gan and Li, 2022; Zhao et al., 2018). As a result, many models conclude that by improving urban permeability, it is possible to reduce runoff by as much as 80% (Li et al., 2020).

However, all models require a large amount of multidisciplinary data. One essential piece of information is terrain topography, crucial for evaluating runoff based on elevation and slopes (Fan and Matsumoto, 2019). Another relevant data point is water quality, especially in urban areas where contamination extends beyond extreme rainfall events (Zhao et al., 2018). Several studies also consider the population distribution (Zhang et al., 2021), soil condition (Gan and Li, 2022), land use (Hou et al., 2019), the pre-existence of natural or green areas (Li et al., 2022), or watercourses (Shao et al., 2016).

Sponge-like solutions are closely linked to Low Impact Development (LID) solutions (Qiao et al., 2020), but generally, they are also associated with green infrastructure (or blue-green), although some researchers also emphasize the relevance of grey infrastructure (Fu et al., 2023). LID and ecological combinations perform better to reduce runoff than isolated solutions (Bah et al., 2023) and they are better accepted by the administration (Chi et al., 2021).

Based on the aforementioned studies, this work focuses on utilizing GIS tools for the contextual analysis phase and selection of priority areas for the implementation of sponge-like solutions. The input data will align with the study area, fulfilling the main requirements for sponge solutions and considering both the regional and climatic context. Lastly, appropriate LID-based actions will be recommended for the GIS-proposed locations.

3. Materials and Method

3.1 Case study

The municipal area of Vigo was chosen as a case study. Vigo is a coastal city with approximately 290,000 inhabitants covering an area of 100 km2, located in Iberian Peninsula. The municipality has a main urban center where most of the population resides, along with several industrial zones. The topography is diverse, characterized by numerous hills and an elevation difference of up to 150 meters between sea level and the highest point within the urban center. It also features a main river and green areas. Vigo has a warm and temperate climate, experiencing notably higher precipitation levels during the winter season compared to the summer. The city is frequently exposed to storms coming from the Atlantic Ocean.

3.2 Data selection and availability

The most relevant data for selecting areas for implementing sponge or LID solutions can be grouped into four main criteria related to runoff, environmental pollution, blue-green areas, and social aspects. The criteria, factors, and data sources are presented in an organized manner in Table 1.

Criteria	Factor	Source
Runoff	Elevation	DTM
	Slope	DTM
	Soil Permeability	Cartography Hydrogeology
	Impervious Cover	NISI - Landsat 8
Environmental air quality	Air Haze	NDHI - MODIS
	Surface Temperature	B_{10} - Landsat 8
Blue – Green infrastructure	River Buffer	Cartography rivers
	Vegetation Index	NDVI - Landsat 8
	Land Use	CORINE
Social	Population density	Demographic census

Table 1. Decision criteria and data source.

In most studies, runoff is considered one of the fundamental and essential elements. From this information, runoff models are developed, and potentially flood-prone areas are identified (Fan and Matsumoto, 2019). The morphology of the urban center in Vigo is highly relevant, as the city is composed of numerous slopes in areas with impermeable coverage.

Environmental criteria are relevant to understand water pollution and prevent its reach into protected natural or populated areas. However, pollution levels in Chinese cities, where most studies on sponge cities are developed, are not applicable to European levels (Sicard et al., 2023). Moreover, data sources on pollution are scarce. In Vigo, there is only three air quality monitors available, and information on river pollution is not accessible. Due to the insufficient spatial resolution of this data and its constraints, the air quality is calculated using satellite data.

The existence of blue-green infrastructure encompasses a wide range of information, from the presence of rivers to diverse green areas and their relation with land uses. The existence of these blue-green areas helps reduce runoff. This data is based on thematic cartography as well as satellite information.

The social criterion responds to demographic-economic aspects. The most relevant factor within this criterion is the population or its distribution, indicating the number of people affected by effects such as runoff and pollution. Although many studies use the wealth generation index of the area looking for financial support (Zhang et al., 2021), in the present case study, wealth data is only available from demographic data, Hence, it is not considered relevant for this work.

Finally, the precipitation index is relevant information for simulating flooding during extreme rainfall events. However, for locating sponge areas, there is no precipitation map available with variations at a municipal scale.

3.3 Data processing

3.3.1 Elevation and slope are fundamental factors in terrain morphology. For selecting sponge areas, priority is given to higher areas (where solutions can be applied before water flow reaches lower zones) and areas with steeper slopes, where erosion is more significant. Elevation and slope are calculated using the 5 m resolution Digital Terrain Model (DTM) available in (Centro Nacional de Información Geográfica, 2020).

The DTM is delimited to the municipal area. Furthermore, due to the substantial elevation variations within the municipal area, the

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DTM is upper-bounded to 150 m, resulting in higher resolution for altitudes where the population is concentrated. The slope is calculated from the DTM. Subsequently, a normalization function (Equation 1) is applied to normalize the elevation and slope values between 0 and 1.

$$D_{NORM0-1} = \frac{D - D_{min}}{D_{max} - D_{min}} \quad (1)$$

3.3.2 Soil permeability is relevant to understand the soil's capacity to retain water. For selecting sponge areas, priority is given to low-permeability zones that need to be increased. Hydrogeological data is available in vector format in (Xunta de Galicia, 2023). As the permeability degree of the study area is in label format, Table 2 is applied for its conversion into numerical format. Subsequently, rasterization is performed with a pixel size of 10 m.

Soil permeability degree	Priority
Very Low and anthropic	1
Low	0.8
Medium - Low	0.6
Medium - High	0.4
High	0.2
Water	0

Table 2. Priority associated with soil permeability degree.

3.3.3 The impermeability of the cover is relevant as it hinders soil absorption and promotes runoff. The cover's permeability is calculated from the Normalized Impervious Surface Index (NISI) (Su et al., 2022) (Equation 2) using the visible ($B_{blue}, B_{green}, B_{red}$) and near-infrared ($B_{NIR}$) bands of Landsat 8. The Landsat 8 resolution in the visible and infrared bands is 30 m. The selected satellite image corresponds to August 2022. Then, the normalization function (Equation 1) is applied.

$$NISI = \frac{\left(B_{blue} + B_{green} + B_{red}\right) - B_{NIR}}{\left(B_{blue} + B_{green} + B_{red}\right) + B_{NIR}} \quad (2)$$

3.3.4 Normalized Difference Haze Index (NDHI), proposed by (Zha et al., 2012), is related to air pollution. A high value indicates a high concentration of pollutants, which during rainfall can precipitate to the ground. NDHI is calculated using Equation 3 and data obtained from MODIS-Terra level 1B, with a spatial resolution of 250 meters for B_1 and 500 meters for B_4. The selected satellite image is from September 2023. Finally, the normalization function (Equation 1) is applied.

$$NDHI = \frac{B_1 - B_4}{B_1 + B_4} \quad (3)$$

3.3.5 Surface temperature is widely used for identifying urban heat islands, which are in turn associated with the presence of heat emitters, concentration of grey infrastructure and air pollution (Ulpiani, 2021). The effects of the heat island can be mitigated with the implementation of LID. Surface temperature is obtained using Landsat 8's B_{10}, with a resolution of 100 m. The selected satellite image corresponds to August 2022, where temperature contrasts of heat islands are more clearly identified. The satellite image is delimited to the study area, and the normalization function (Equation 1) is applied.

3.3.6 River distances serve as natural flood buffer zones, hence identifying and leveraging them is essential. Freshwater surfaces within the city are small and partially covered by vegetation, making satellite detection unfeasible. A shape file containing the city's rivers available in a regional database (Xunta de Galicia, 2023) is utilized. For each polyline representing a watercourse, a series of buffers are applied, and a priority value (Table 3) is assigned based on (Shen et al., 2015).

Distances to rivers (m)	Priority
0-50	1
50-100	0.8
100-200	0.6
200-500	0.4
500-1000	0.2
>1000	0

Table 3. Priority associated with distances to rivers.

3.3.7 The Normalized Difference Vegetation Index (NDVI) represents the amount and health of existing vegetation. The vegetation plays a crucial role in water absorption, slowing down runoff, and reducing pollution, therefore, improvement actions should focus on areas lacking vegetation. Vegetation surfaces are only partially mapped at the municipal level (gardens and other green areas). To achieve more comprehensive coverage, NDVI (Martinez and Labib, 2023) is utilized using Landsat 8 satellite imagery with 30 m resolution. The calculation of NDVI is shown in Equation 4. Then, the normalization function (Equation 1) is applied.

$$NDVI = \frac{B_{NIR} - B_{red}}{B_{NIR} + B_{red}} \quad (4)$$

3.3.8 The COoRdination of INformation on the Environment (CORINE) is an inventory of European land cover divided into 44 different land cover classes. Land cover types are closely related to land use (Balado et al., 2018). This information is relevant to select areas where there is a deficiency of green spaces in urban planning. CORINE information is available in vector format in the state database (Centro Nacional de Información Geográfica, 2020). The coverage is defined in 44 classes; for the study area, the classes presented in Table 4 are identified and assigned a corresponding priority. Subsequently, a rasterization is applied with a resolution of 10 m.

CORINE code	Priority
11X Urban fabric	1
12X Industrial, commercial and transport	1
13X Mine, dump, and construction	1
14X Artificial vegetated	0.6
2XX Agricultural	0.3
3XX Forest and Seminatural	0.3
4XX Wetlands	0.1
5XX Water	0

Table 4. Priority associated with CORINE codes.

3.3.9 Population density indicates how many people will be affected by extreme events, therefore actions should be prioritized where the density is higher. Population data is obtained from the electoral census (Concello de Vigo, 2019) and organized vectorially by districts. Population density is calculated using Equation 5. Subsequently, vectorial data is rasterized at a 10 m resolution and normalized using Equation 1.

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$$Density = \frac{Number\_habitants}{Distric\_area} \tag{5}$$

3.4 Multicriteria analysis

The use of the Analytic Hierarchy Process (AHP) matrix is based on the ability to address the inherent complexity in decision-making by assigning weights to multiple criteria. This method provides an analytical framework that allows for the comparison and prioritization of key factors, considering their interrelationships and subjective preferences. AHP enables a systematic and transparent approach by involving experts in evaluating both qualitative and quantitative criteria, allowing for a more informed and precise decision-making process, especially in situations where weighting factors is crucial to achieve optimal results such as the location of sponge areas (Dong et al., 2019). This method has been employed by other authors for weight assignment based on surveys or objectives (Zhang et al., 2021).

In this work, given that there are two hierarchical levels, the weight of the factors is evenly distributed within each criterion. The criterion weights are assigned using the AHP Matrix from Equation 6. These weights are based on previous studies and the quality of existing data (Table 5). As a result, greater importance is given to runoff, while criteria such as population density and blue-green infrastructure are placed in a secondary position. Environmental air quality is assigned a lower priority due to the low pollution levels in the area and the comparatively lower resolution of the data.

$$AHP_{matrix} = \begin{bmatrix} 1 & 3.00 & 2.00 & 2.00 \\ 0.33 & 1 & 0.33 & 0.50 \\ 0.50 & 3.00 & 1 & 0.50 \\ 0.50 & 2.00 & 2.00 & 1 \end{bmatrix} \tag{6}$$

Criteria	W_C	Factor	W_F
Runoff	0.41	Elevation	0.25
		Slope	0.25
		Soil Permeability	0.25
		Impervious Cover	0.25
Environmental air quality	0.11	Air Haze	0.5
		Surface Temperature	0.5
Blue – Green infrastructure	0.21	River Buffer	0.33
		Vegetation Index	0.33
		Land Use	0.33
Social	0.27	Population density	1

Table 5. Weights (W) assigned to criteria and factors.

4. Results and Analysis

The resulting map showcasing the prioritization of sponge sites is displayed in Figure 1. The interventions are focused on the urban core, where the highest population density resides, notably in areas with steeper inclines, as well as in zones lacking vegetation and with a significant population concentration. Three main areas of action can be identified, elaborated in Figure 2.

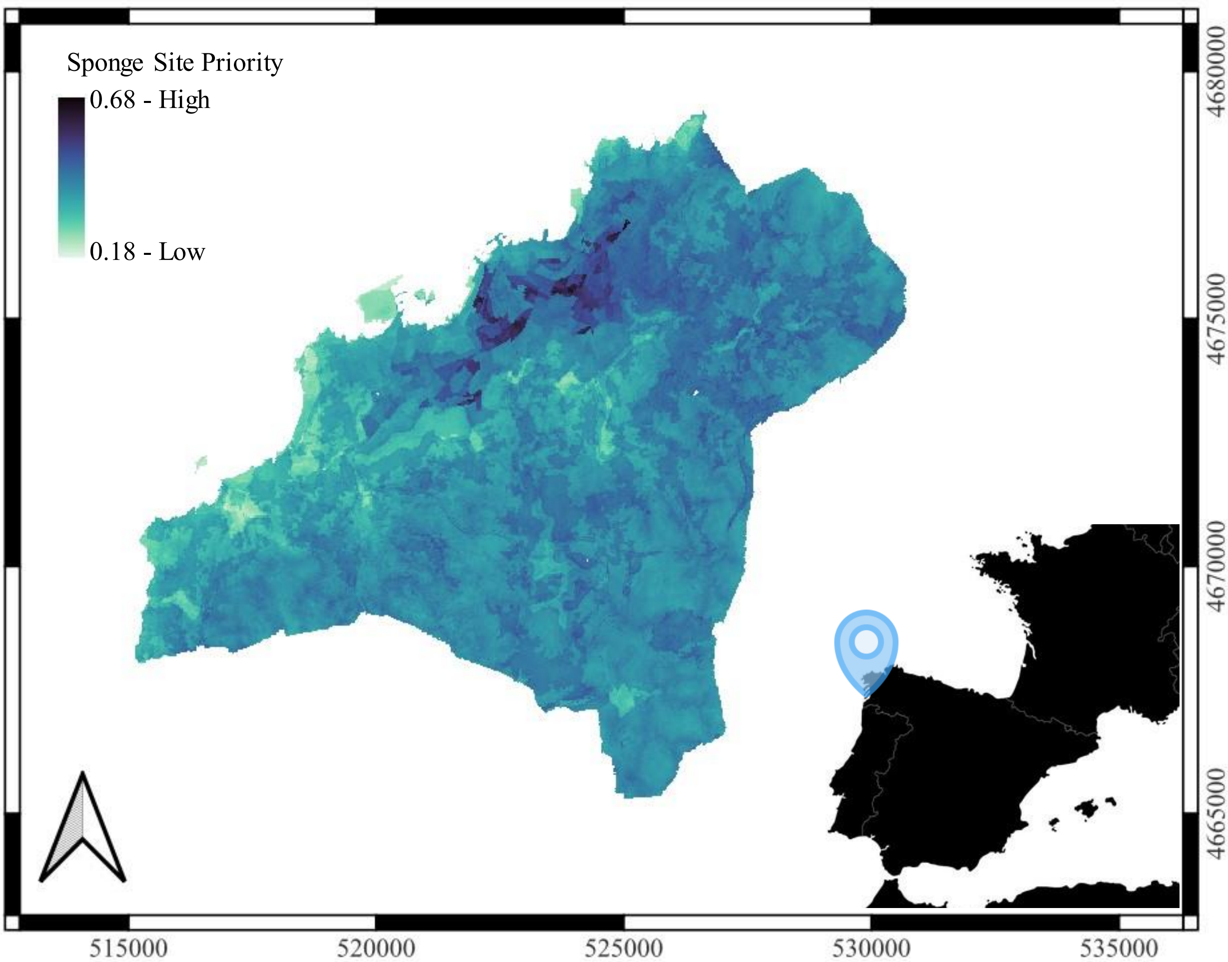

Figure 1. Sponge site location map.

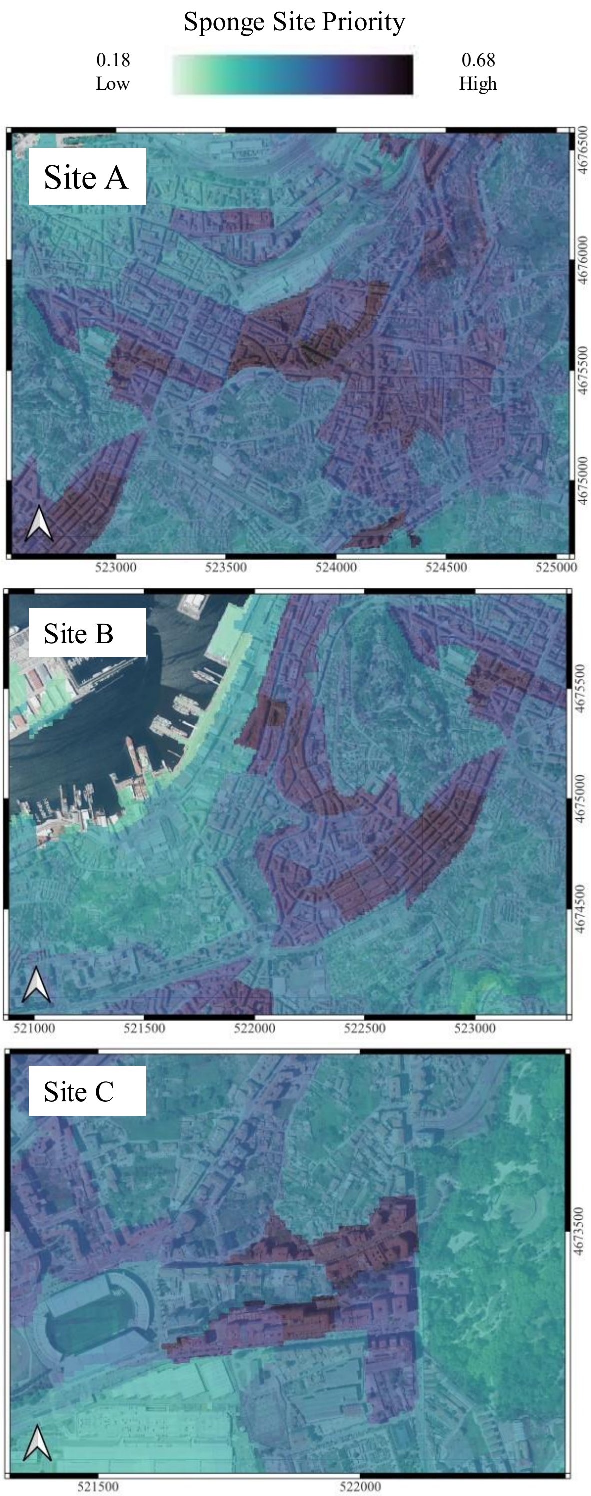

Figure 2. Relevant sponge site locations superimposed on orthoimages.

Sites A and B are the most built-up areas, located to the East (Zone A) and Southwest (Zone B) of the city's castle. In these areas, there is a notable concentration of buildings and narrow streets. Consequently, there are no extensive areas available for the construction of rainwater pools or solutions requiring pre-existing green spaces. In this scenario, the Low Impact Development (LID) solution to reduce runoff must focus on the already constructed environment. Rooftops cover the largest surface area in the study zone, so converting some rooftops into green roofs will help reduce their runoff. A green roof is a component of sponge solutions that involves covering the roof of a building with vegetation, creating a layered system that includes waterproofing, a root barrier, drainage, and a growing medium for plants. Green roofs were suitable for applying in high urbanized areas with dense buildings (Yuan et al., 2023).

Other alternatives involve interventions at the street level. In areas A and B, the existing streets have low traffic (1 or 2 lanes) with parking areas on the sides (Figure 3.a). Actions modifying the parking surface by adapting it as green parking (Bouzouidja et al., 2021) also aid in reducing runoff. Furthermore, there is the possibility of closing traffic or reducing space for vehicles and creating rain gardens (Zhang et al., 2020) to divert runoff. This solution could be particularly useful on one of the main avenues without remove car space where there is a pedestrian area between vehicle lanes but scarcely used by pedestrians (Figure 3.b); an action could be creating a rain garden in that area to channel the water there.

The site C solution is more complex because it is a small area with high construction density surrounded by green spaces and located very close to a river with frequent flooding. Additionally, the river is subsequently channeled underground, limiting its water flow capacity. In this area, even if green roofs or rain gardens are installed, the proximity of the river and runoff from other areas make it prone to flooding, requiring action upstream along the river's course. Another alternative would be to create drainage channels with green areas parallel to the river to prevent overflow.

Figure 3. City center streets (a) and Gran Vian Avenue with pedestrian space lane median (b).

5. Discussion

The proposed method has proven to be effective in identifying potential areas for the installation of sponge LID solutions. Thus, starting from open data, it is possible to analyze the entire municipality quickly. Although the final location ultimately relies on a subjective weighting that may vary considering different priorities (citizen or administrative), tests conducted by changing the weights have shown considerable consistency in the result. To understand the uncertainties, limitations and scope of a decision model, a sensitivity analysis is recommended in the future (Umair et al., 2018).

The criteria for assigning weights require further development. Although relevance was obtained based on previous studies and questions were used to obtain citizens' prioritization of factors and generate the AHP (Equation 6), the citizen questionnaires are quite subjective and vary between cities and countries.

However, the final decision regarding the sponge LID solutions requires a high level of prior knowledge, as exemplified in sites A and B compared to site C, where the same solutions cannot be applied. Additionally, the solutions are also conditioned by existing urban planning legislation, public opinion, and the investment required. In order to reduce this prior knowledge, the inclusion of 3D city models will be studied in the future work, since many of the relevant features for the implementation of LID solutions are geometric and semantic information, existing in standards such as CityGML (Kolbe et al., 2005).

The exclusive use of open data presents certain limitations. Although the four main criteria were covered and satellite images are a viable alternative to the cartography provided by the administration, aspects such as spatial resolution (Table 6) should be improved in some cases, such as air quality. MODIS B_{10} has a spatial resolution of 500 m, while the Landsat 8 bands are 30 m and the DTM is 5 m. Therefore, lower resolution data offer less detailed factors. In other cases, such as wealth generation per area, precipitation, or water pollution, data were not available at a municipal scale.

Factor	Source	Resolution
Elevation	DTM	5 m
Slope	DTM	5 m
Impervious Cover	NISI - Landsat 8	30 m
Air Haze	NDHI - MODIS	250-500 m
Surface Temperature	B_{10} - Landsat 8	100 m
Vegetation Index	NDVI - Landsat 8	30 m

Table 6. Raster resolution of input data.

6. Conclusion and future work

In this work, the use of open data has been proposed for selecting sites to implement sponge LID solutions, aiming to reduce adverse effects caused by heavy rainfall. The city of Vigo (Spain) has been chosen as a case study, demonstrating that sponge solutions can be considered in mid-sized cities outside of China.

The proposed method has combined cartographic information provided by administrations (DTM, hydrogeology, land cover, and population density) with satellite data (impervious coverage, vegetation, and surface temperature) from Landsat 8 and Air Haze from MODIS. All this information was integrated in QGIS and weighted using an AHP matrix. As a result, three potential sites for installing sponge LID solutions were identified, and measures such as green roofs and rain gardens were proposed.

However, although the method allowed for the rapid identification of intervention areas at the municipal scale, the final decision requires prior knowledge of the terrain, as well as consideration of public opinions, urban planning legislation, and public investment.

Future work will develop an improved decision-making model that incorporates additional factors like socio-economic considerations, urban development plans, and stakeholder engagement. In addition, super resolutions methods (enhance the resolution of an imaging system with Artificial Intelligence) (Wang et al., 2022) will be implemented to obtain higher resolution satellite data. Runoff with the proposed solutions will be simulated.

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