ISSN 1828-5961

Marco Seccaroni
Research fellow at Milan Polytechnic with a Ph.D. in Civil and Environmental Engineering from the University of Perugia, specializing in innovative methodologies for urban space analysis using biosensors and artificial intelligence.
Affiliated with the MIT Senseable City Lab with a research focused on landscape, urban regeneration, and well-being, employing interdisciplinary approaches.

Integrating AI and GIS in urban landscape analysis and representation for enhanced community well-being

This paper examines the integration of Artificial Intelligence (AI) and Geographic Information Systems (GIS) for urban landscape analysis, focusing on the enhancement of residents' well-being through improved distribution and quality of green spaces. The study investigates two case studies: Perugia, Italy, and Oslo, Norway. Utilizing street-level imagery processed through semantic segmentation, the research quantifies the urban environment using metrics such as the Green View Index (GVI), Sky View Factor (SVF), and Building View Factor (BVF).
Perugia, with its historical architecture and compact medieval urban fabric, reveals a concentration of greenery in peripheral zones, with limited green visibility in its dense city center. In contrast, Oslo displays a more uniform integration of green spaces, ensuring high accessibility even within its central urban areas. These disparities reflect differing urban histories, geographic layouts, and planning approaches, emphasizing the challenges of achieving equitable green space distribution in varied contexts.
The findings underscore the pivotal role of green spaces in promoting psychological and physical health by mitigating urban stress and enhancing relaxation. The study also highlights the constraints of utilizing proprietary data sources such as Google Street View, advocating for the development of open-access and equitable data frameworks.
This research contributes to the field by proposing a scalable and transferable AI-driven methodology for urban landscape evaluation. The results provide actionable insights for urban planners and policymakers aimed at fostering sustainable and livable cities.

Keywords:
AI; Urban Well-Being; Landscape Analysis

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

INTRODUCTION

In recent years, the growing urbanization has led to the reduction of green spaces in cities, with significant repercussions on the psychophysical well-being of urban residents. Many studies have shown that the presence of urban green spaces offers significant benefits, such as stress reduction, air quality improvement, promotion of social cohesion, and increased outdoor physical activity (Pratiwi et al., 2022; Semeraro et al., 2021). These spaces not only contribute to improving mental health but are also associated with a reduced risk of cardiovascular diseases (Twohig-Bennett & Jones, 2018).
Urban green spaces also provide essential ecosystem services, including climate regulation, flood mitigation, and biodiversity conservation(Filazzola et al., 2019; Pulighe et al., 2016). However, planning and managing such spaces is a complex challenge, especially in densely populated cities, where access to and the quality of green spaces are often unequally distributed (Wolch et al., 2011; Xiao et al., 2019).
One of the major developments in managing urban green spaces involves the use of artificial intelligence (AI) and Geographic Information Systems (GIS). These tools allow for a deeper understanding of the urban landscape and the interactions between the natural and built environments (Coroian et al., 2021; Mazhitova et al., 2023). AI is employed to analyze urban images and automatically classify natural and artificial elements, enhancing the ability to design more sustainable and livable urban spaces (Bianconi et al., 2023; Nesbitt et al., 2019; Pratiwi et al., 2022; Seccaroni et al., 2024). GIS, on the other hand, enables the evaluation of accessibility, distribution, and quality of green spaces, facilitating more effective urban planning decisions (Heikinheimo et al., 2020) emphasizing the centrality of drawing in landscape representation and analysis to promote psycho-physical health through improved environmental design (Lin et al., 2015; Paris et al., 2023).
Recent research has highlighted the importance of considering not only the quantity of green spaces but also their quality and accessibility to maximize public health benefits. Studies conducted in cities such as Helsinki and Shanghai have shown that the accessibility and quality of green spaces are determining factors in improving the physical and psychological health of residents, especially in vulnerable communities (Heikinheimo et al., 2020; Xiao et al., 2019). This is particularly important in high-density urban contexts, where the uneven distribution of green spaces can exacerbate social inequalities (Dennis et al., 2020).
Moreover, numerous studies have highlighted the crucial role of green spaces in mitigating the effects of climate change and supporting urban adaptation. Green spaces can reduce urban temperatures, improve air quality, and contribute to stormwater management (Demuzere et al., 2014; Zhang & Chui, 2019) . However, the multifunctionality of such spaces is not always guaranteed. Effective green space design requires strategic planning that takes into account spatial location and the characteristics of the plant species used (Tran et al., 2020).
Another emerging challenge is the continuous monitoring and management of urban green spaces. The use of user-generated data, such as geographical information collected from mobile devices and social media, is opening new possibilities for better understanding the use and perception of green spaces by urban residents (Heikinheimo et al., 2020) . These data can complement traditional sources and provide a more dynamic and real-time view of the interaction between people and green spaces, thus improving urban planning decisions (Bijker & Sijtsma, 2017).

METHODOLOGY

The analysis focuses on processing street-level images, which are subsequently subjected to semantic segmentation. This process employs a convolutional neural network (CNN) model based on the ADE20K dataset, which can identify up to 150 different object classes and elements present in the images. The ADE20K dataset is one of the most comprehensive resources in the field of semantic segmentation, offering a detailed representation of numerous urban and natural elements.
The workflow begins with downloading geospatial information about the road network using OpenStreetMap (OSM), a global collaborative resource that provides accurate and up-to-date data on road structures, allowing for precise mapping of streets and urban infrastructure. This information was used as a basis to define routes and points for acquiring images through the Google Street View API. Google Street View APIs enable the retrieval of panoramic street-level photographs, covering a wide range of urban and suburban environments. The automation of the acquisition process allowed for systematic visual data collection corresponding to the predefined road network.
The collected images were then processed through semantic segmentation, which divides each image into different regions, each corresponding to a specific object class recognized by the ADE20K-based model. This allows for a detailed classification of visual elements present, such as buildings, vegetation, roads, vehicles, signage, and other urban infrastructure. The neural network architecture was optimized to accurately recognize a wide range of elements, providing a detailed visual representation of the urban space and the environmental context.
A key aspect of the analysis was the use of specific metrics to quantify the presence of natural and artificial elements in the images. Three main metrics were analyzed:
Green View Index (GVI): measures the percentage of green area in the image, calculated as the sum of areas occupied by trees, grass, ground, and plants relative to the total image area:

$$GVI = \frac{Tree + Grass + Ground + Plant}{Total\ Area}$$

An increase in GVI corresponds to a rise in positive emotions for citizens. Previous studies have shown that positive emotions (like pleasure and relaxation) significantly increase when GVI exceeds 0.5. Below this threshold, the impact of

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

ISSN 1828-5961

greenery on relaxation is minimal, while beyond this level, a pronounced positive effect is observed. Additionally, when GVI surpasses 0.6, it begins to reduce negative emotions, such as boredom and anxiety (Hao et al., 2024; Huang et al., 2022).

Sky View Factor (SVF): represents the proportion of visible sky in the image, calculated as:

$$SVF = \frac{Sky}{Total\ Area}$$

Building View Factor: expresses the percentage of the area occupied by buildings relative to the total area:

$$BVF = \frac{Building}{Total\ Area}$$

These metrics provide a quantitative measure of the visual composition of elements present in the urban space, enabling the evaluation of the distribution of vegetation, buildings, and open spaces like the sky. Integrating the semantic segmentation process with these metrics allows for an in-depth and systematic analysis of the urban landscape, supporting studies related to urban planning, environmental resource management, and understanding the interaction between built and natural spaces

CASE STUDIES

For this analysis, two case studies were selected, representing distinct yet comparable urban contexts with similar surface areas:

Perugia: A central Italian city, renowned for its rich historical heritage and evolving urban landscape;

Oslo: The capital of Norway, recognized for its focus on sustainability and the development of high-quality urban spaces.

In the case of Perugia, images were collected from all drivable roads in the city, with a step of 15 meters between each capture, ensuring comprehensive and uniform coverage of the urban fabric. For each position, two images were taken, each oriented perpendicularly to the road, one facing right and the other facing left. This methodology allowed for a thorough, lateral view of the surrounding urban environment. A total of approximately 80,000 images were processed for Perugia. This extensive dataset enables a detailed analysis of one of Italy's historic cities, characterized by a complex urban layout, significant cultural heritage, and increasing attention to urban green spaces and sustainability efforts. The large volume of data collected makes it possible to assess the distribution of natural elements, such as trees and green spaces, in relation to the city's historical architecture and evolving infrastructure.

The image acquisition process for Oslo followed the same methodology as in Perugia, with a 15-meter step between captures and two images taken at each position, perpendicularly oriented to the road. However, due to the larger size of Oslo compared to Perugia, the total number of images processed was higher, with approximately 180,000 images. Despite the larger dataset, Oslo represents an interesting case study due to its progressive approach to urban sustainability and the management of natural resources. The dataset allows for an in-depth examination of the distribution of green spaces, sky visibility, and the relationship between buildings and natural elements, which are central to Oslo's urban planning.

The systematic collection of images for both cities offers an opportunity to compare two urban contexts with distinct characteristics and approaches to urban development. Perugia, with its historical layout and evolving green areas, provides an example of a city balancing its rich heritage with modern environmental sustainability efforts. Oslo, on the other hand, is known for its harmonious integration of natural and built elements, with a strong focus on quality of life and environmental protection.

The comparison between these two case studies, based on the collected and analyzed data, highlights significant differences in the distribution of natural and artificial elements within the urban space. It offers valuable insights for future urban planning and the development of policies aimed at enhancing the quality of urban environments in diverse contexts.

Fig. 1 Example of semantic segmentation applied to an urban image: on the left, the original image captured from Google Street View; on the right, the same image segmented into various semantic categories, including buildings, vegetation, cars, road, and sidewalks, highlighted with different colors.

RESULT

The following analysis considers three main metrics: the Green View Index (GVI), Sky View Factor (SVF), and the Building View Factor (BVF) for the cities of Perugia and Oslo. The integration of spatial maps provides context to the quantitative

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

ISSN 1828-5961

results from the histograms, offering a deeper understanding of the differences between the two urban contexts, not only in terms of numbers but also in the spatial distribution of natural and built elements.

PERUGIA

The Green View Index (GVI) analysis for Perugia shows a distribution primarily concentrated between 0.25 and 0.55, with an average value of 0.36. The histogram indicates moderate green space visibility in many areas of the city, with a lower standard deviation of 0.14 and an upper deviation of 0.59, suggesting significant variability in the distribution of visible greenery.
The spatial representation of the GVI on the map clearly highlights differences between various areas of the city. The central areas of Perugia (shown in black) exhibit lower GVI values, indicating reduced visibility of green spaces. This is typical of historical, densely urbanized zones where the presence of historic buildings and higher building density limit the view of vegetation. In contrast, the peripheral areas (indicated in green) show higher GVI values, reflecting greater visibility of green spaces, likely due to the proximity to parks and less developed areas.
This GVI distribution mirrors the historical and topographical layout of Perugia, a city with a compact and hilly urban core where dense urbanization in the historic center reduces green visibility. However, the suburban and peripheral areas, benefiting from lower building density and greater integration with the surrounding natural landscape, ensure higher visibility of vegetation.
These results have important implications for urban livability. Areas with higher GVI are often associated with psychological and physical benefits,

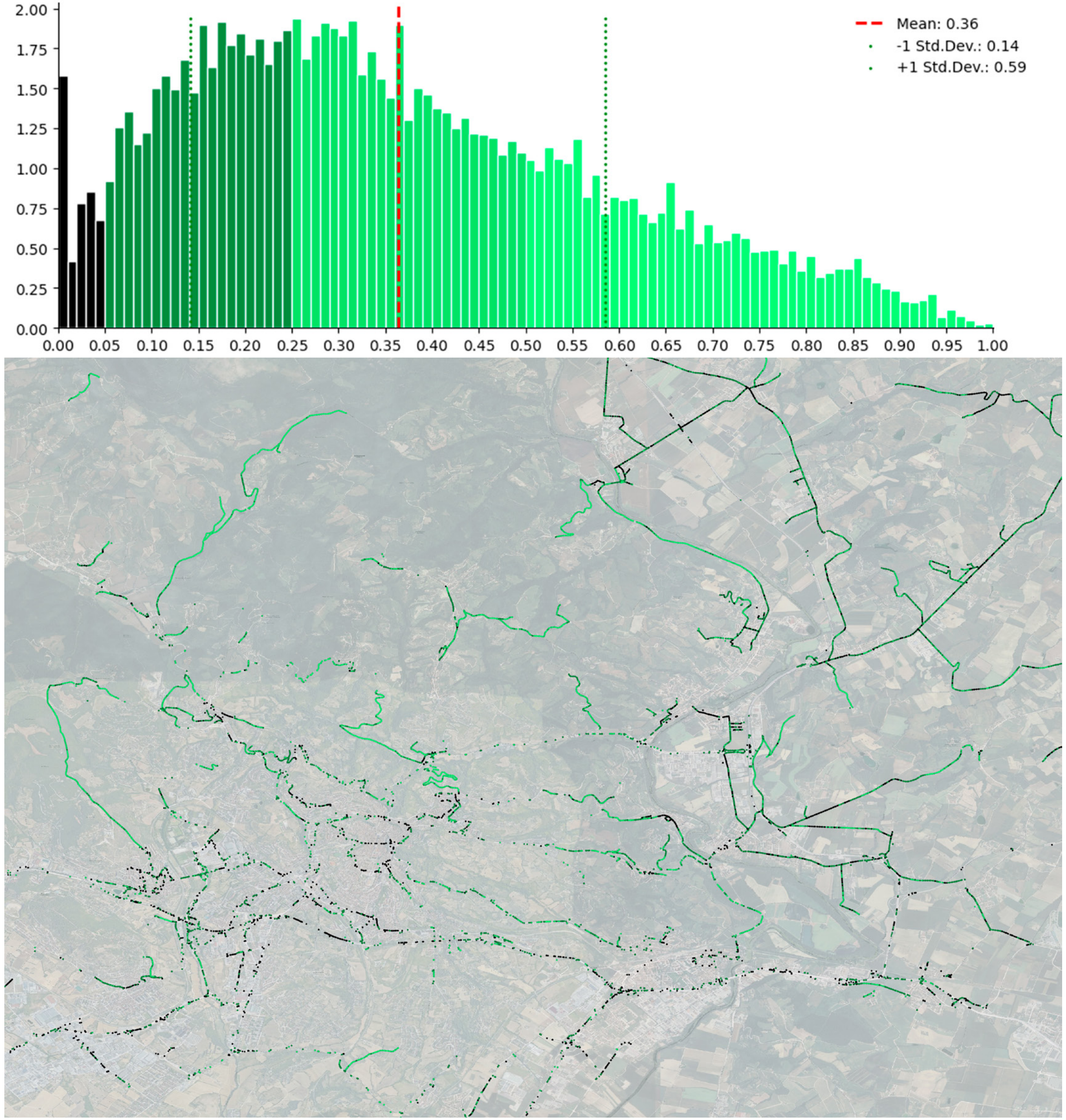


Fig. 2 Distribution of the Green View Index (GVI) in Perugia in 2023. The graph shows a concentration of GVI scores between 0.25 and 0.55, with an average of 0.36. The map highlights lower green visibility in the city center (black), while the peripheral areas show greater green space visibility (green). The analysis does not cover the entire city, as it is based solely on images from 2023.

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

ISSN 1828-5961

as the visible presence of greenery contributes to a sense of relaxation and well-being. In contrast, the more densely built-up central areas, where GVI is lower, might offer residents fewer opportunities to engage with nature, potentially negatively impacting psychological well-being and access to green spaces. This disparity underscores the importance of urban planning aimed at improving green space presence in more densely urbanized central areas to balance access to natural spaces and enhance the overall livability of the city.
The analysis of the Sky View Factor (SVF) for Perugia shows a distribution concentrated between 0.15 and 0.40, with a mean value of 0.27. The histogram demonstrates a moderate variability in sky visibility across the city, with a standard deviation of 0.15 below the mean and 0.40 above it. The majority of the surveyed locations exhibit values close to the mean, indicating that the view of the sky is neither highly obstructed nor completely open in most areas. The map provides a spatial representation of this data: the central areas of Perugia, indicated by black points, show lower SVF values, reflecting a more obstructed sky view due to the denser building fabric, typical of historic urban centers. The peripheral areas, marked in light blue, have higher SVF values, suggesting better sky visibility, which is often associated with lower building density and more open spaces. This SVF distribution aligns with the historical and topographical characteristics of Perugia. The dense central area, with its medieval architecture and compact urban form, limits sky visibility. In contrast, the more open and less developed peripheral regions allow for greater sky exposure. Sky visibility plays a critical role in the perception of urban environments, contributing to feelings of openness and enhancing the aesthetic quality of public spaces. In areas where the SVF is lower, the sense of confinement might be stronger, po-

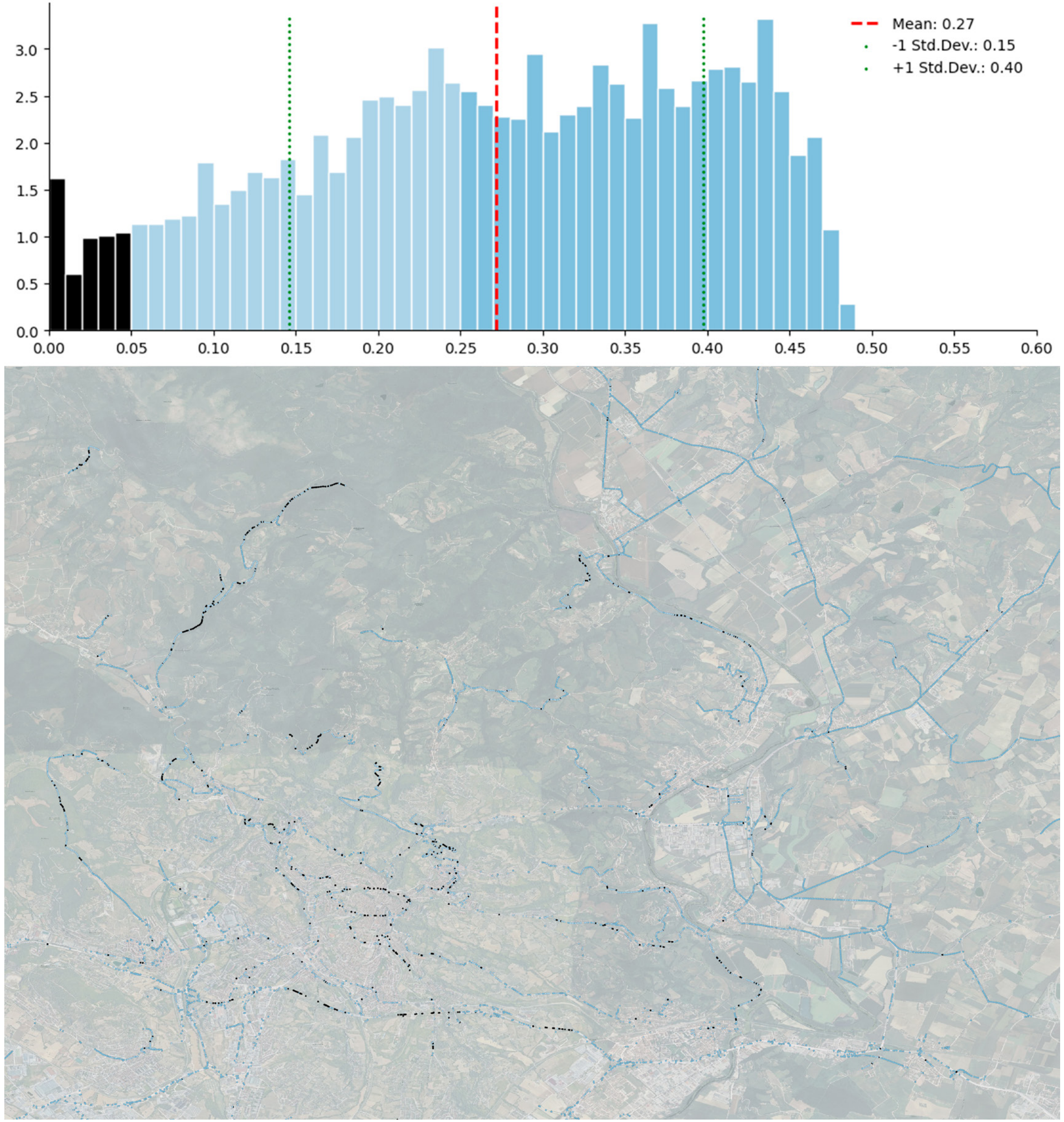


Fig. 3 Sky View Factor (SVF) distribution in Perugia for 2023. The graph shows an average SVF of 0.27, with central areas (in black) displaying limited sky visibility due to the high density of buildings, while peripheral areas (in light blue) offer better visibility. This contrast highlights the impact of urban density on the perception of openness in the urban environment.

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

tentially affecting the psychological well-being of residents. In Perugia, the varied distribution of SVF values indicates that while some areas offer a balance between built structures and sky visibility, the more central parts of the city might face challenges related to limited openness and potential feelings of visual confinement.

The analysis of the Building View Factor (BVF) for Perugia reveals a distribution heavily concentrated at low values, with an average of 0.07. The histogram shows that most of the surveyed points have very low BVF values, indicating that buildings occupy a minimal portion of the visible area across much of the city. However, the map highlights black areas, representing regions with higher building density, particularly in the historic center and some adjacent zones. This distribution confirms that while there are some densely built-up areas, most of Perugia does not have a high level of building visibility. The city's hilly terrain and historical layout, with less urban sprawl compared to modern cities, help maintain low BVF levels. The low BVF values suggest a good balance between built-up areas and open spaces, which can enhance urban livability in terms of access to natural spaces and open air. However, in areas with higher building density, where BVF values are higher, the visual dominance of buildings could reduce the perception of openness and limit access to green spaces, potentially impacting air quality and the overall well-being of residents.

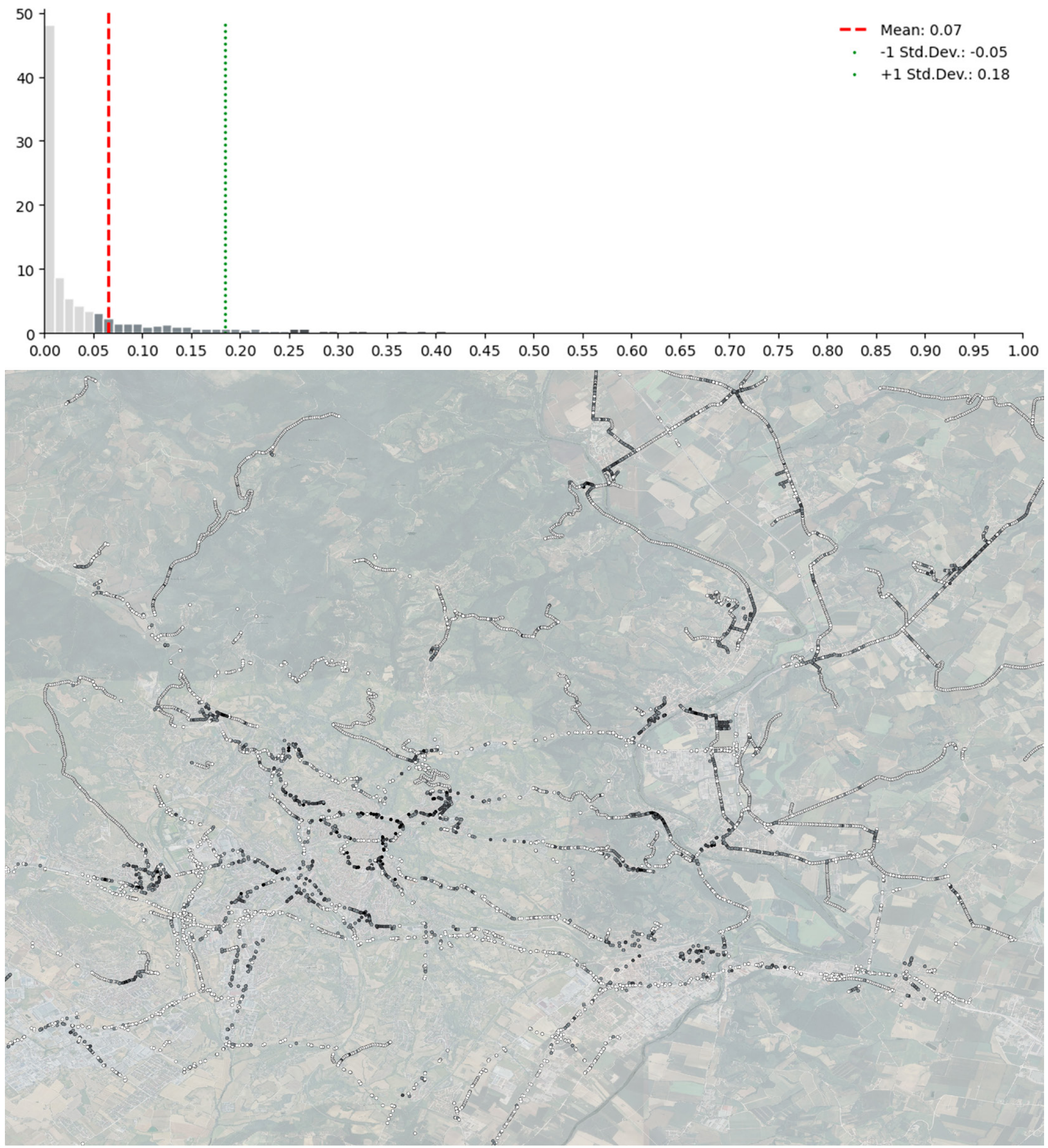


Fig. 4 Building View Factor (BVF) distribution in Perugia for 2023. The histogram shows a mean BVF of 0.07, indicating that buildings occupy a minimal portion of the visible area in most of the city. The map highlights denser built-up areas (in black), particularly in the historic center, where building visibility is higher. This reflects the city's historical layout and limited urban sprawl.

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

ISSN 1828-5961

OSLO

The Green View Index (GVI) analysis for Oslo reveals a distribution predominantly concentrated between 0.20 and 0.50, with an average value of 0.31. The GVI histogram indicates that the majority of the city exhibits moderate visibility of green spaces, with a standard deviation of 0.11 below the mean and 0.50 above it. This suggests a notable variation in the presence of visible greenery across the urban landscape.
The spatial representation of GVI in the map confirms this pattern: the central areas of Oslo (shown in black) have lower GVI values, reflecting limited visibility of green spaces. These urbanized areas, typical of city centers, are characterized by a higher density of buildings, which obstruct views of natural elements. Conversely, the peripheral areas of the city (depicted in green) show significantly higher GVI values, indicating a much greater presence of greenery. These regions likely benefit from proximity to natural features such as parks, forests, and open spaces, which are a hallmark of Oslo's urban design and its integration with surrounding natural landscapes.
This distribution of GVI suggests that while Oslo's central areas are more built-up, the city still maintains a balance, with extensive green visibility in the peripheries. The presence of these green spaces is crucial for urban livability, as numerous studies have shown the positive effects of greenery on mental and physical well-being. Higher GVI values in peripheral zones likely provide a sense of openness and relaxation, promoting a higher quality of life for residents. In contrast, the lower GVI values in the dense central areas may contribute to increased urban stress, with fewer opportunities for contact with nature, which can have psychological and environmental implications. This disparity highlights the need for careful urban planning that ensures equitable access to

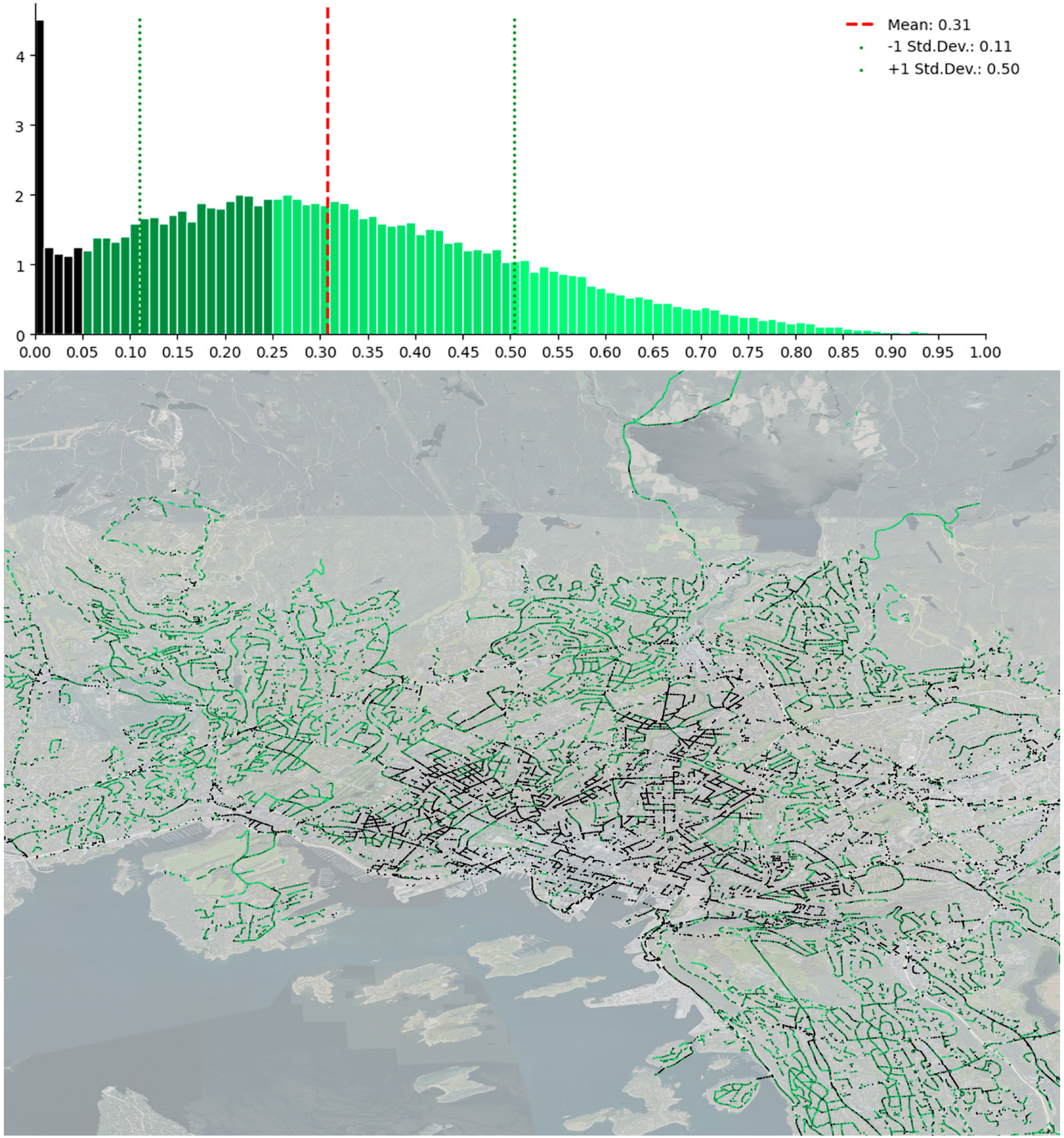


Fig. 5 The GVI analysis for Oslo in 2023 shows a distribution concentrated between 0.20 and 0.50, with an average value of 0.31. The central areas (in black) exhibit lower GVI values, indicating limited green space visibility, while the peripheral zones (in green) show greater visibility of green spaces, benefiting from proximity to parks and natural landscapes.

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

green spaces throughout the city, particularly in the more developed central areas where greenery may be lacking.

The Sky View Factor (SVF) analysis for Oslo shows a distribution concentrated between 0.10 and 0.35, with a mean value of 0.23. The histogram reveals that the majority of locations have moderate sky visibility, with a lower standard deviation of 0.12 and an upper deviation of 0.34, indicating some variation in sky visibility across the city. The map provides a clear spatial representation of this distribution. Central areas of Oslo, represented in black, exhibit lower SVF values, reflecting limited sky visibility. This is characteristic of highly urbanized areas where dense buildings and infrastructure block the view of the sky. On the other hand, the peripheral areas of the city, depicted in light blue, show higher SVF values, indicating a more open view of the sky, often associated with lower building density and more open spaces. This distribution aligns with the typical urban structure of many modern cities. Oslo's central regions, where buildings are more densely packed, naturally have lower sky visibility, while the more suburban and peripheral zones allow for a clearer view of the sky due to fewer tall buildings and the presence of larger green and open spaces.

Sky visibility is a critical aspect of urban livability, influencing how people perceive their surroundings. Greater visibility of the sky contributes to a sense of openness and freedom, while reduced visibility can lead to feelings of confinement, especially in densely built-up areas. In Oslo, the lower SVF in central areas suggests that urban planning should focus on preserving and enhancing visual access to open spaces in denser regions, where the view of the sky is obstructed. In contrast, the higher SVF in peripheral areas reflects a balance between built environments and natural surroundings, likely improving the overall quality of life for residents in these areas.

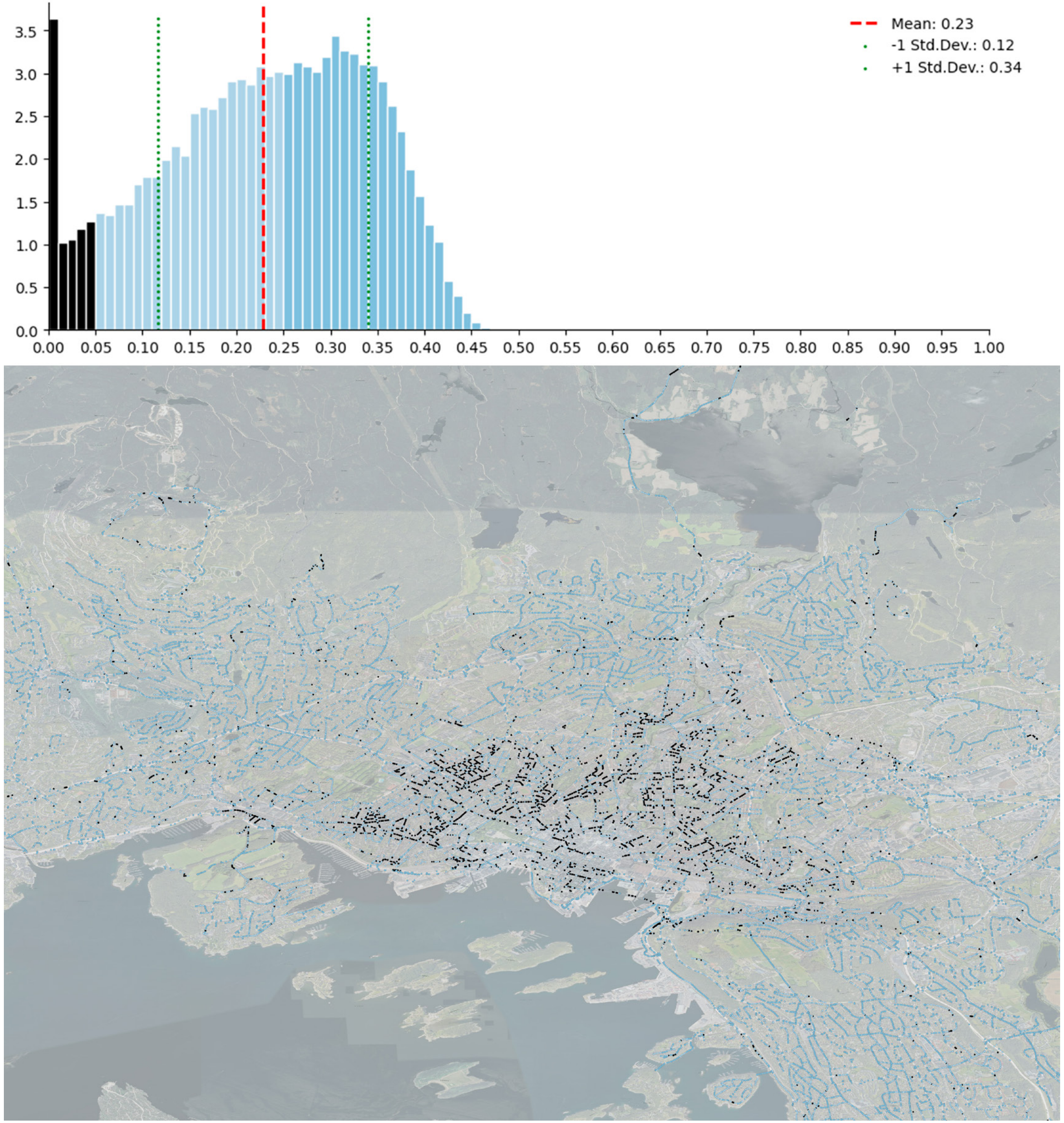


Fig. 6 The SVF analysis for Oslo in 2023 reveals a distribution concentrated between 0.10 and 0.35, with a mean value of 0.23. Central areas (in black) have lower SVF values due to dense urban development, limiting sky visibility, whereas peripheral areas (in light blue) have higher SVF, indicating clearer sky views in more open and less built-up spaces.

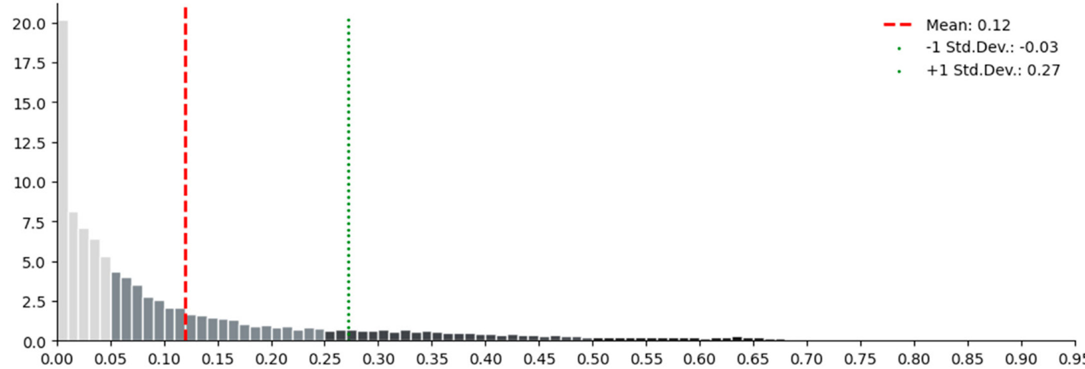
DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

The analysis of the Building View Factor (BVF) for Oslo shows a distribution heavily concentrated at very low values, with a mean of 0.12. The histogram reveals that most areas of the city have a BVF below 0.10, indicating that buildings occupy a small portion of the visible space. However, there are some zones where the BVF is significantly higher, particularly in the densely urbanized central areas, highlighted in black on the map.

The map confirms this trend, with central Oslo characterized by a high density of buildings. In these areas, buildings dominate the view, reducing the openness and limiting exposure to open and natural spaces. In contrast, peripheral areas show a lower visual impact of buildings, likely due to lower building density and greater presence of open and green spaces.

This distribution reflects the typical urban growth pattern of modern cities, where the city center is densely built, while peripheral areas maintain more open spaces. The high BVF in central zones can reduce the perception of openness and increase a sense of congestion, while areas with lower BVF, particularly in the outskirts, ensure a higher quality of life in terms of exposure to open spaces.

The comparative analysis between Perugia and Oslo, based on the Green View Index (GVI), Sky View Factor (SVF), and Building View Factor (BVF), highlights significant differences between the two cities, primarily due to their urban history, geographical layout, and development models. In Perugia, the GVI is concentrated between 0.25 and 0.55, with an average of 0.36, indicating moderate visibility of green spaces, especially in peripheral areas where building density is lower, and green spaces are more accessible. The historic city center, with its dense medieval architecture, shows lower GVI values, reflecting limited visibility of greenery. In contrast, Oslo has a GVI



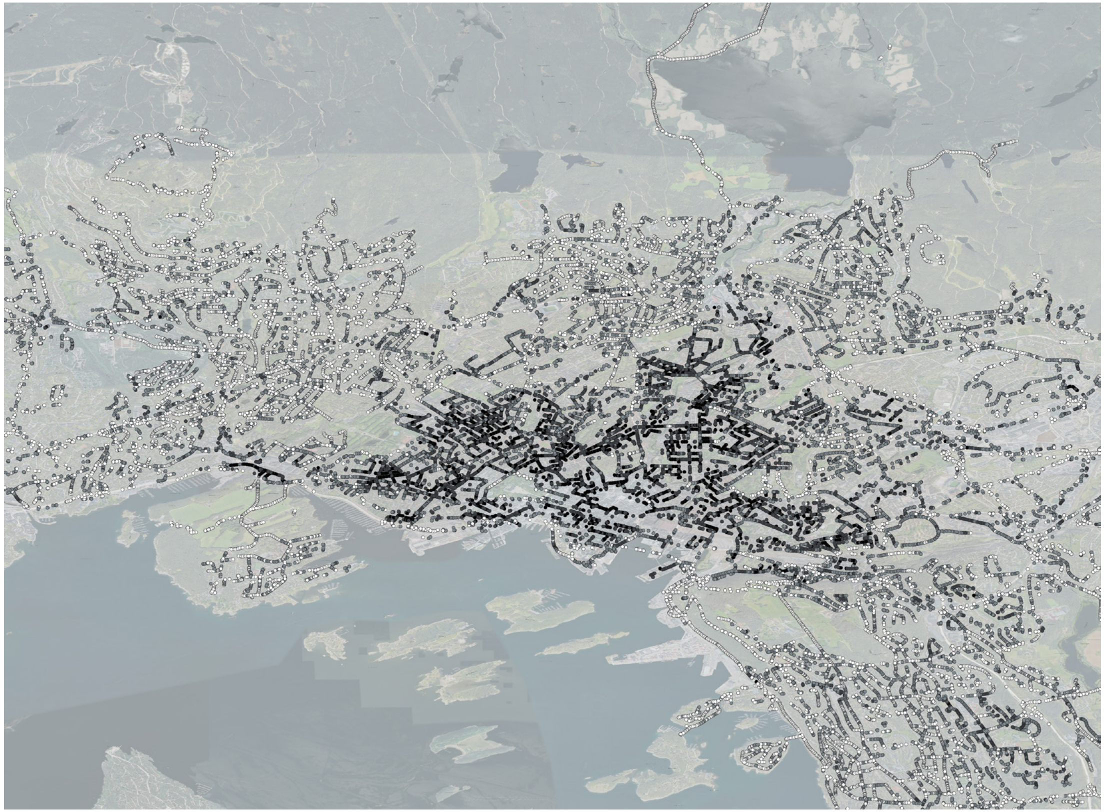


Fig. 7 Building View Factor (BVF) distribution in Oslo in 2023. The histogram shows a mean of 0.12, with the city center (in black) characterized by higher building density and elevated BVF, while peripheral areas have lower BVF, indicating less visual presence of buildings.

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

distribution concentrated between 0.20 and 0.50, with a slightly lower average of 0.31. Here, too, the central areas exhibit reduced green visibility due to the higher urban density, while the peripheral zones, characterized by proximity to large parks and natural areas, enjoy higher green visibility. Oslo's closer integration with surrounding natural landscapes is more evident than in Perugia.

The Sky View Factor (SVF) analysis reveals a similar dynamic. Perugia has an average SVF of 0.27, with values ranging from 0.15 to 0.40, reflecting moderate sky visibility. The city center suffers more from sky obstruction due to its building density and the city's hilly topography. In contrast, peripheral areas offer better sky visibility, with fewer tall buildings. Oslo shows a similar SVF distribution, though with a slightly lower average of 0.23. Central areas of Oslo have lower SVF values, primarily due to modern urban density, which obstructs sky visibility more than in Perugia. However, Oslo's peripheral areas, with fewer buildings and more open spaces, offer better sky views, creating a greater balance between natural elements and urban development.

The most striking difference between Perugia and Oslo emerges in the Building View Factor (BVF) analysis. In Perugia, the BVF is very low, with an average of only 0.07, indicating that in much of the city, particularly in the outskirts, buildings occupy a small portion of the visible space. However, in the historic center, where building density is higher, the BVF increases slightly, reflecting the medieval urban layout. Even so, it does not reach the levels typical of modern cities. In contrast, Oslo shows a BVF with a significantly higher average of 0.12. The city's center is characterized by a high density of modern buildings, dominating the visual landscape and reducing the perception of openness. However, Oslo's peripheral areas feature a lower BVF, thanks to large open spaces and lower building density.

In summary, Perugia and Oslo represent two distinct urban models. Perugia, with its historic medieval architecture and hilly terrain, maintains a balance between buildings and open spaces, with a low BVF and moderate green and sky visibility, especially in the peripheral areas. On the other hand, Oslo, while being a more modern and urbanized city, has managed to integrate large green and open spaces in its peripheral zones, mitigating the impact of dense urbanization in the central areas. Nevertheless, Oslo's higher BVF compared to Perugia indicates a more visible presence of buildings in central areas, reducing the perception of openness. In both cities, urban planning plays a crucial role in determining the quality of life. Oslo benefits from greater integration between green and urban spaces, while Perugia, with its more compact historic center, offers a different dynamic between buildings and natural spaces.

In the image of Perugia (fig. 8), areas with a GVI above 0.6 are quite sparse and mostly located in the peripheral and rural parts of the city. These areas tend to be concentrated in the hilly regions and along the city's borders, far from the historical center. This confirms that green visibility in Perugia is limited in the more urbanized and built-up areas, such as the medieval center, where dense architecture reduces the perception of natural spaces. The areas with high GVI reflect the more natural and rural traits of Perugia, where open spaces and vegetation provide greater visibility of greenery, contributing to psychological well-being. However, these areas do not seem to be directly accessible to those living or working in the city center, which may limit the positive impact of greenery on the inhabitants of more densely built-up zones.

In contrast, the image of Oslo (fig. 9) shows that areas with a GVI above 0.6 are much more evenly distributed, both in the peripheral regions and within the more central parts of the city. This highlights Oslo's better integration of green spaces within its urban fabric compared to Perugia. Green areas are visibly present even near the densest urban zones, allowing for greater accessibility to greenery for residents. The more uniform distribution of these green spaces creates a sense of openness and well-being, even in the city's central areas, where building density is higher compared to Perugia. This confirms that Oslo, despite being a more modern and densely urbanized city, has

Fig. 8 Map of Perugia filtered for Green View Index (GVI) values greater than 0.6: the green points represent areas with high GVI values, indicating locations with significant tree coverage or green spaces.

Fig. 9 Map of Oslo filtered for Green View Index (GVI) values greater than 0.6: the green points represent areas with high GVI values, indicating locations with significant tree coverage or green spaces.

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

ISSN 1828-5961

managed to balance green space well, making it accessible even to those living in the central areas.
In conclusion, while Perugia sees a concentration of high-GVI areas in the peripheries and rural zones, Oslo shows a more uniform and accessible distribution of greenery throughout the urban territory. This suggests that Oslo offers greater opportunities for daily interaction with urban greenery, even in the more central and densely populated areas, enhancing the psychological well-being of its residents. On the other hand, Perugia could benefit from urban planning initiatives that increase the presence and visibility of greenery in its central areas, to improve the quality of life in the historical heart of the city.

CONCLUSION

This study demonstrated the essential role of integrating Artificial Intelligence (AI) and Geographic Information Systems (GIS) in the analysis and management of urban landscapes, particularly for evaluating the distribution and quality of green spaces. The case studies of Perugia and Oslo revealed significant differences in the organization and accessibility of natural and built environments, with important implications for the psychological and physical well-being of residents.
AI played a crucial role in processing the vast amount of data, comprising street-level images, allowing for detailed analysis of greenery distribution through the Green View Index (GVI) and other urban landscape features. Without AI and semantic segmentation techniques, analyzing such a large volume of data across multiple urban contexts would have been impossible. Moreover, this approach is highly scalable and can be applied to other cities, enabling accurate and comparative assessments of urban characteristics.
The results showed that Perugia has a concentrated distribution of high-GVI areas, mostly located in its peripheral and rural zones, while the historic center exhibits low green visibility due to its dense medieval architecture. This limited access to greenery in central areas suggests a lower level of psychological and physical benefits for residents living in the more urbanized parts of the city. In addition, the Sky View Factor (SVF) results in Perugia also indicated reduced sky visibility in the city center, further contributing to a sense of spatial confinement.
On the other hand, Oslo exhibited a more balanced distribution of green spaces, with a higher GVI that extended from the periphery to the more central areas. This indicates better integration of greenery within the urban fabric, providing residents across the city with greater access to natural elements, which can improve psychological well-being. Oslo also displayed higher SVF values in both its central and peripheral zones, contributing to a perception of openness and higher quality of life.
However, the reliance on street-level imagery, such as Google Street View, poses certain limitations. These images are owned by private entities and are subject to changes in access policies, which could affect the future availability of such data. While alternative free platforms like Mappillary exist, they do not offer the same widespread coverage, consistency, or quality of imagery. This raises concerns about future scenarios where large corporations control vital urban analysis and planning tools, potentially limiting public access to these resources.
In conclusion, this study highlights the importance of urban planning strategies that balance green and built environments to improve residents' well-being. The integration of AI and GIS has proven crucial in supporting these decisions, enabling large-scale, detailed analyses of urban landscapes.
A significant challenge that emerged concerns the disparity in data availability between cities. Despite Perugia and Oslo having similar total areas, the number of available images differs significantly: 80,000 for Perugia and 180,000 for Oslo. This discrepancy is likely due to Oslo's more extensive road network, but it is primarily influenced by the fact that only 2023 images were considered for Perugia, and the city was not fully updated in that year. This raises concerns about the timeliness of image updates, which can directly impact the quality of urban analysis. The frequency and importance of updates often depend on the perceived significance of the city, meaning that smaller or less prominent cities may not have the same level of data availability as larger, more important ones. As a result, this can lead to a lack of homogeneity in data across cities, limiting the potential for accurate and consistent comparative analyses. Ensuring more uniform updates across cities of all sizes and significance will be essential to maintaining fair and comprehensive urban analysis in the future.
Moreover, the growing reliance on data provided by private entities raises critical questions about how to ensure these technologies remain publicly accessible and are not monopolized by private companies. Future research should explore solutions that guarantee equitable and sustainable access to urban data, promoting the use of open-source technologies and encouraging collaborations between public and private entities to protect the public interest.

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20

ISSN 1828-5961

REFERENCES

Bianconi, F., Filippucci, M., Seccaroni, M., Rolando, A., & D'Uva, D. (2023). Machine learning and landscape quality. Representing visual information using deep learning-based image segmentation from street view photos. SCIRES-IT - SCIentific RESearch and Information Technology, 13(1).

Bijker, R. A., & Sijtsma, F. J. (2017). A portfolio of natural places: Using a participatory GIS tool to compare the appreciation and use of green spaces inside and outside urban areas by urban residents. Landscape and Urban Planning, 158, 155–165.

Coroian, I., Nap, M. E., Pop, I. D., Matei, F., Salagean, T., Deak, J., Chiorean, S., Suba, E. E., Luput, I., & Ficior, D. (2021). Using GIS Analysis to Assess Urban Green Space in Terms of Real Estate Development. Bulletin of University of Agricultural Sciences and Veterinary Medicine Cluj-Napoca. Horticulture, 78(1), 36–40.

Demuzere, M., Orru, K., Heidrich, O., Olazabal, E., Geneletti, D., Orru, H., Bhave, A. G., Mittal, N., Feliu, E., & Faehnle, M. (2014). Mitigating and adapting to climate change: Multi-functional and multi-scale assessment of green urban infrastructure. Journal of Environmental Management, 146, 107–115.

Dennis, M., Cook, P. A., James, P., Wheater, C. P., & Lindley, S. J. (2020). Relationships between health outcomes in older populations and urban green infrastructure size, quality and proximity. BMC Public Health, 20(1), 626.

Filazzola, A., Shrestha, N., & MacIvor, J. S. (2019). The contribution of constructed green infrastructure to urban biodiversity: A synthesis and meta-analysis. Journal of Applied Ecology, 56(9), 2131–2143.

Hao, N., Li, X., Han, D., & Nie, W. (2024). Quantifying the Impact of Street Greening during Full-Leaf Seasons on Emotional Perception: Guidelines for Resident Well-Being. Forests, 15(1), 119.

Heikinheimo, V., Tenkanen, H., Bergroth, C., Järv, O., Hiippala, T., & Toivonen, T. (2020). Understanding the use of urban green spaces from user-generated geographic information. Landscape and Urban Planning, 201, 103845.

Huang, S., Zhu, J., Zhai, K., Wang, Y., Wei, H., Xu, Z., & Gu, X. (2022). Do Emotional Perceptions of Visible Greeneries Rely on the Largeness of Green Space? A Verification in Nanchang, China. Forests, 13(8), 1192.

Lin, C. T., Chiu, T. C., & Gramann, K. (2015). EEG correlates of spatial orientation in the human retrosplenial complex. NeuroImage, 120, 123–132.

Mazhitova, G., Sedelnikov, I., & Shugulova, D. (2023). The use of GIS technologies for planning the greening of the urban environment. InterCarto. InterGIS, 29(2), 423–436.

Nesbitt, L., Meitner, M. J., Girling, C., Sheppard, S. R. J., & Lu, Y. (2019). Who has access to urban vegetation? A spatial analysis of distributional green equity in 10 US cities. Landscape and Urban Planning, 181, 51–79.

Paris, L., Rossi, M. L., & Moschetti, A. (2023). Knowledge of urban space through saliency maps and space syntax tools. Experimentation on historic center of Rieti. DISEGNARECON, 16(31), Articolo 31.

Pratiwi, A. A. R., Risnanto, S., Chalid, A., Kusmadi, Munastha, K. A., & Witarsa, D. R. (2022). Employing AI to Develop Green Space in Urban Area. 2022 16th International Conference on Telecommunication Systems, Services, and Applications (TSSA), 1–5.

Pulighe, G., Fava, F., & Lupia, F. (2016). Insights and opportunities from mapping ecosystem services of urban green spaces and potentials in planning. Ecosystem Services, 22, 1–10.

Seccaroni, M., Vendemmia, B., & D'Uva, D. (2024). Cycling Mobility as a Means of Improving Access to Education. In B. Monardo & C. Ravagnan (A c. Di), Emerging Mobility Paradigms towards the Resilient Metropolis (pp. 166–180). Gruppo editoriale Tab S.r.l.

Semeraro, T., Scarano, A., Buccolieri, R., Santino, A., & Aarrevaara, E. (2021). Planning of Urban Green Spaces: An Ecological Perspective on Human Benefits. Land, 10(2), 105.

Tran, T. J., Helmus, M. R., & Behm, J. E. (2020). Green infrastructure space and traits (GIST) model: Integrating green infrastructure spatial placement and plant traits to maximize multifunctionality. Urban Forestry & Urban Greening, 49, 126635.

Twohig-Bennett, C., & Jones, A. (2018). The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes. Environmental Research, 166, 628–637.

Wolch, J., Jerrett, M., Reynolds, K., McConnell, R., Chang, R., Dahmann, N., Brady, K., Gilliland, F., Su, J. G., & Berhane, K. (2011). Childhood obesity and proximity to urban parks and recreational resources: A longitudinal cohort study. Health and Place, 17(1).

Xiao, Y., Wang, D., & Fang, J. (2019). Exploring the disparities in park access through mobile phone data: Evidence from Shanghai, China. Landscape and Urban Planning, 181, 80–91.

Zhang, K., & Chui, T. F. M. (2019). Linking hydrological and bioecological benefits of green infrastructures across spatial scales – A literature review. Science of The Total Environment, 646, 1219–1231.

DOI: https://doi.org/10.20365/disegnarecon.33.2024.20