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Identification of the potential for roof greening using remote sensing and deep learning

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ABSTRACT

Under the mounting pressure from global warming, green roofs emerge as a valuable source for climate adaptation, particularly in compact metropolises where green space is limited. Consequently, there is a need to quantitatively evaluate the potential for roof greening where it is most needed and suitable. Despite the increasing importance of this issue, there have been limited studies on the effectiveness of remote sensing and deep learning in identifying the potential for roof greening in many cities. To address this, we have created a GreenRoof dataset, comprising approximately 6400 pairs of remote sensing images and corresponding masks of roofs with high greening potential in four European cities. Afterward, we exploit the capabilities of deep learning methods to identify roofs that are suitable for greening from remote sensing images. Using 15 German cities as a case study for future urban rooftop planning, we estimate the spatial potential for retrofitting green roofs. Structural parameters for prioritizing green roof implementation include vegetation coverage, thermal environment, and building density. Results indicate that the total area suitable for green roof retrofitting exceeds 20 % of the roof area in the 15 German cities examined. The spatial analysis effectively reflects variation in demand and suitability for green roof retrofitting across different cities. In conclusion, this study provides a versatile screening approach utilizing remote sensing, deep learning, and spatial analysis, which can be readily adapted to inform municipal policies in other cities aiming to promote green roofs and enhance sustainable urban development.

1. Introduction

The report from the Intergovernmental Panel on Climate Change (IPCC) (Lee et al., 2023) indicates that global warming has elevated the global mean surface temperature by 1.1 °C, comparing the periods from 1850 -1900 to 2011–2020. This trend is associated with an uptick in the intensity and frequency of extreme weather events, which inflict severe impacts on ecosystems, infrastructure, and human communities (Diffenbaugh et al., 2017; Rossati, 2017; Wang et al., 2017). Mitigating global warming requires a range of climate actions focused on fostering sustainable practices and curbing greenhouse gas emissions. One recent research (Massaro et al., 2023) indicates that urban vegetation significantly contributes to reducing the urban population's exposure to heat extremes. As vegetation offers cooling effects through the processes of evapotranspiration and shading, numerous cities worldwide have undertaken greening initiatives. These efforts include expanding parks, planting street trees, and installing green roofs (Karteris et al., 2016; Li et al., 2015). Regrettably, often the limited available space in combination with the high costs of urban land renders establishing or maintaining tree-planted areas prohibitively expensive, if not entirely unfeasible. Roof greening, however, without the need for additional space, offers a comparatively resource-efficient solution for enhancing green infrastructure in densely built environments (Liu et al., 2022).

Green roofs incorporate vegetation, soil, and a waterproofing membrane on top of buildings. The vegetation on green roofs cools the air, thanks to the evapotranspiration process, which contributes to the decrease in indoor and outdoor temperatures. In this case, green roofs offer the benefit of mitigating the urban heat island (UHI) effect (Alcazar et al., 2016; Langemeyer et al., 2020), ensuring thermal comfort during the summer (He et al., 2020; Herath et al., 2021; Leichtle et al., 2023;

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Sharma et al., 2018), and addressing urban green inequality issues (Guo et al., 2024). Additionally, green roofs offer numerous environmental advantages, including the alleviation of noise pollution, reduction of stormwater runoff, and improvement of air quality (Manso et al., 2021; Shafique et al., 2018; Tomson et al., 2021; Vijayaraghavan, 2016).

Given the prevalence of existing buildings in cities, it is valuable to undertake a thorough examination of the feasibility of implementing green roofs as retrofits for these structures. Delving into potential assessment methods for roof greening holds practical significance in formulating effective planning policies to construct eco-friendly and more climate-resilient cities. Various types of data have been employed to identify the potential of roof greening at city-scale. Some studies rely on existing geodata that include different characteristics of buildings. Municipal census data are employed to assess the suitability of implementing green roofs in Seoul (Gwak et al., 2017) and Shenzhen (Hong et al., 2019), respectively. Based on both national and municipal census data, (Silva et al., 2017) and (Slootweg et al., 2023) ensure the viability of retrofitting green roofs in Lisbon and Amsterdam, respectively. Some research additionally adopts Light Detection and Ranging (LiDAR) data to acquire precise three-dimensional (3D) building models. These studies aim to delineate the roofs as well as the slope of roofs to identify the suitability of roof greening in cities such as Lisbon, Braunschweig, Liege, Nador, and Donosti-San Sebastián (Gandini et al., 2023; Grunwald et al., 2017; Joshi et al., 2020; Lambarki et al., 2022; Santos et al., 2016). This is because roofs with slopes of 10° or more demand increased consideration compared to flat roofs (Joshi et al., 2020; Silva et al., 2017; Slootweg et al., 2023). Non-flat roofs experience faster drying, posing a risk to planted vegetation. Furthermore, such roofs have an elevated risk of erosion, necessitating more intricate and costly structural measures. Compared to airborne LiDAR data, spaceborne or airborne optical remote sensing data are generally more cost-effective and readily available for covering large geographic areas. Moreover, aerial imagery has become freely available in many cities, making it easier for researchers, planners, and policymakers to use remote sensing data in their work. Through visual interpretation, (Shao et al., 2021) manually delineates flat roofs on aerial imagery in Luohe. By analyzing remote sensing images, (Xu et al., 2021) utilize a deep learning method to discern whether buildings feature flat or sloped roofs in Xiamen. However, existing studies predominantly focus only on one city or a specific area in the city, with limited attention to conducting potential assessments for large scale analysis across multiple cities. In this research, we close this gap using remote sensing imagery and deep learning methods.

As mentioned above, green roofs offer a range of environmental and socioeconomic advantages. For instance, they can significantly lower the expense of cooling through the evapotranspiration and shading of vegetation, especially in exposed urban areas with high building density, where the temperature is often measured high in summer (Leichtle et al., 2023). Green roofs also serve a vital function in offering areas for relaxation and educational purposes by incorporating greenery in areas with a general lack of available green spaces (Gwak et al., 2017). However, the potential advantages of green roofs can be different based on structural parameters, e.g., vegetation coverage, thermal environment, and building density in a particular neighborhood. When retrofitting green roofs for sustainable urban development, it is an advantage to select locations that maximize these benefits while operating within budgetary constraints. The objective of this study is to undertake a thorough analysis of the feasibility of roof greening in neighborhoods taking into account different structural settings.

Against this background, the contribution of our paper is threefold: (1) We address the task of mapping roofs with high greening potential from aerial imagery. We develop and provide a GreenRoof dataset to the science community, consisting of around 6.4 K pairs of aerial images covering four cities across Europe and their annotated masks of roofs with high greening potential. (2) We evaluate the capabilities of our deep learning network to identify roofs appropriate for greening and validate this by comparing with results obtained from official geodata. (3) We apply the approach to 15 German cities to investigate the potential for roof greening. In particular, we highlight some key parameters that allow a spatial prioritization of green roofs: vegetation cover in the surrounding area, thermal environment, and building density.

By integrating aerial remote sensing data with deep learning models, this study enhances the precision and scalability of roof greening potential assessments, moving beyond traditional survey or statistical methods. This advancement provides a replicable framework that can be applied to other urban areas worldwide. Therefore, one key innovation of this study lies in its methodological generalization capabilities and, thus, in its broad applicability. Unlike previous studies, which typically focus on isolated or specific cities, our study spans multiple cities with diverse urban environments. On the one hand, our GreenRoof dataset is multi-city, enabling broader generalizability and cross-city comparisons, which are crucial for identifying green roof potential in various urban contexts. On the other hand, this study investigates both large and small cities and areas of various densities in Germany, filling a gap in cross-regional roof greening potential assessment.

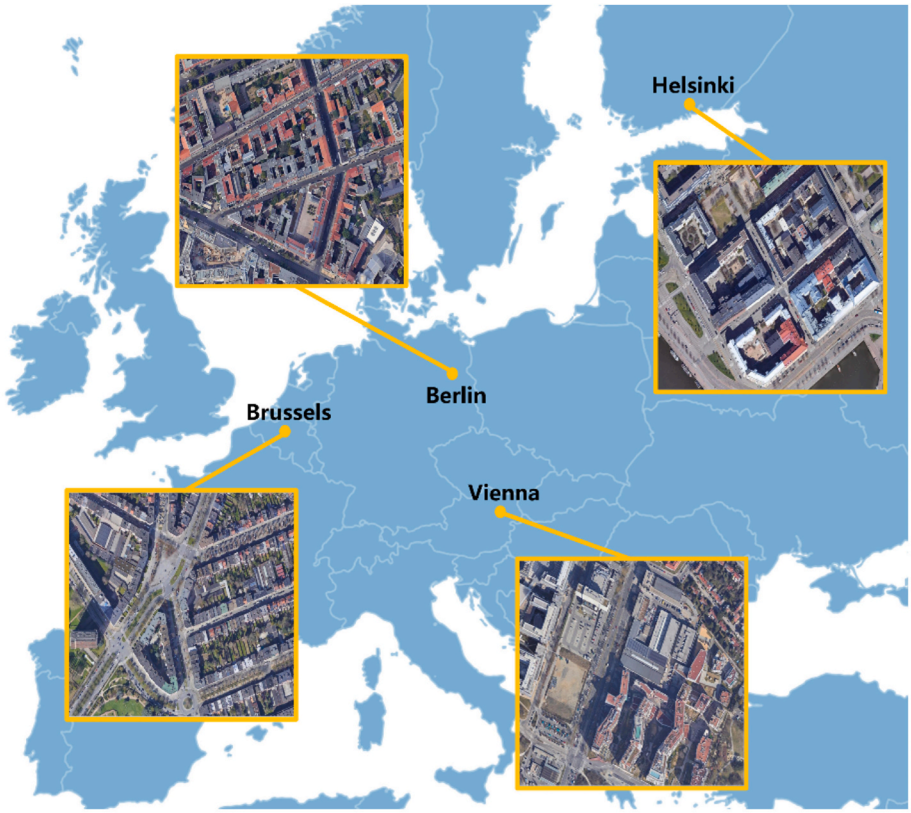
2. Data sets and study areas

In this study, we establish a geographically diverse dataset, which we call “the GreenRoof dataset”, encompassing four European cities. Recent IPCC climate change scenarios (IPCC, 2022) project that European cities are among the most exposed globally to rising temperatures, with urban areas expected to experience disproportionately high-temperature increases (Taubenböck et al., 2024). This emphasizes the critical need for adaptive strategies, such as roof greening, to enhance urban resilience in Europe.

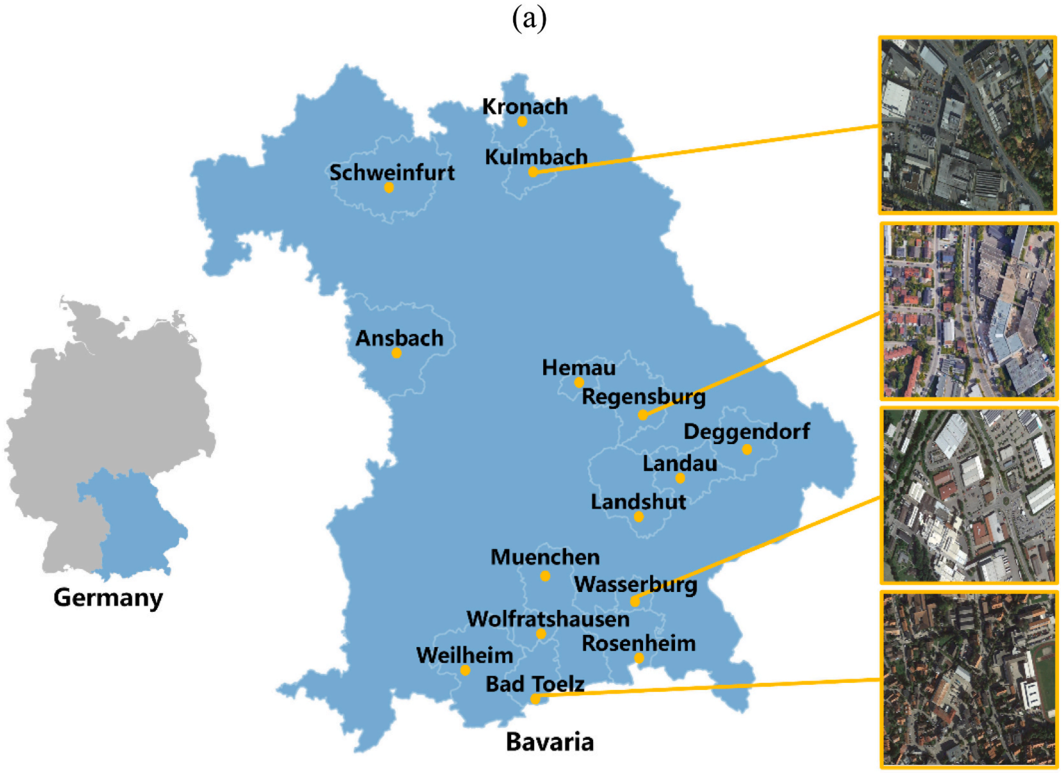
Fig. 1 (a) illustrates the cities included: Berlin, Germany; Brussels, Belgium; Helsinki, Finland; and Vienna, Austria. On the one hand, remote sensing images and 3D building models of these cities are publicly accessible for research. On the other hand, they feature a variety of structural characteristics of building patterns and urban climates being large capital cities with cultural significance, economic importance, and political relevance within Europe. Berlin and Vienna experience a moderate continental climate with warm summers, cold winters, and notable UHI effects in densely built-up areas. Brussels has a temperate maritime climate, with mild winters and moderate summers but frequent rain and humidity. Located in Northern Europe, Helsinki has a cold climate with long, snowy winters and mild summers.

The GreenRoof dataset comprises 6400 pairs of remote sensing images and their corresponding greening potential maps with ground reference annotations. Each image is sized at 512×512 pixels and has three spectral bands (Red, Green, and Blue). Employing a 7:1:2 ratio, we randomly partitioned the 6400 image-map pairs into training, validation, and test data for each city (Table 1). Fig. 2 illustrates the example data in the GreenRoof dataset.

The remote sensing imagery of the GreenRoof dataset is collected from different sources, and its spatial resolution ranges from 0.1 m/pixel to 0.2 m/pixel (Table 2). We implemented a time- and cost-efficient pipeline to generate pixel-wise annotations for roofs with high greening potential as follows: Initially, 3D building models corresponding to remote sensing imagery were collected from various sources (Table 2). Subsequently, we calculated the slope of individual roofs based on existing 3D building models. More specifically, the 3D models of cities utilized in this study are level of detail (LOD) 2 models. These include basic roof shapes and heights, which allow for slope calculation by analyzing the orientation and angles of roof planes. In LOD2 data, roofs are often segmented into individual planes with defined coordinates. For each roof plane, we calculate the surface normal vector that represents the perpendicular direction to the roof plane. The slope is computed relative to the horizontal plane using the normal vector. We further annotated the roofs whose slopes fulfilled the structural roof criterion. Due to maintenance challenges, erosion, etc., we considered



(a)



(b)

Fig. 1. (a) Geospatial distributions of four European cities in our GreenRoof dataset. The illustrated building patterns and types reveal variable types across locations and cities with different potentials for roof greening. (b) Geospatial distributions of 15 cities in the state of Bavaria, Germany.

Table 1
Data Split in the GreenRoof dataset.

City	Train	Val	Test
Berlin	1120	160	320
Brussels	1120	160	320
Helsinki	1120	160	320
Vienna	1120	160	320

roofs with high greening potential to have a slope between 0 and 10° (assessments in Silva et al., 2017; Joshi et al., 2020; and Slootweg et al., 2023). All data were then cropped into patches with dimensions of 512 × 512 pixels without overlap among neighboring patches. Finally, to address potential inaccuracies, a manual verification process was employed, discarding any noisy data where annotations were incorrect or missing for roofs with high greening potential.

Furthermore, we chose 15 cities to investigate the effectiveness of remote sensing and deep learning for identifying the potential of roof greening. These 15 cities are situated in the state of Bavaria, located in Southeast Germany (Fig. 1 (b)), a region characterized by a continental and Alpine-influenced climate. Bavarian cities experience significant seasonal temperature variations, with warm summers and cold winters, as well as periodic heatwaves that intensify UHI effects in densely populated areas. We have selected these cities because the mapping agency in the state of Bavaria, Germany, has recently released remote sensing images at 0.4 m/pixel and 3D building models for the whole state under an open data license (Vermessungsverwaltung, 2023). The chosen cities, Wolfratshausen, Weilheim, Wasserburg, Schweinfurt, Rosenheim, Regensburg, Muenchen, Landshut, Landau, Kulmbach, Kronach, Hemau, Deggendorf, Bad Toelz, and Ansbach, collectively accommodate approximately 3 million residents. Their spatial boundaries are established by administrative delineations. These 15 cities display variations in size, gross domestic product (GDP), and population. Consequently, investigating these cities can be considered a reliable representation of various urban patterns.

Considering the positive effects of green roofs, we also aim to identify in this study suitable locations for green roof retrofitting by incorporating three structural parameters, including vegetation coverage, thermal environment, and building density. We do this against the background that green retrofitting should be prioritized where there is less green space per se, where it is already better, or where the building density is very high. Specifically, Landsat 8 OLI/TIRS satellite imagery (Table 3) corresponding to 15 German cities in the summertime (June, July, and August) of 2023 (Roy et al., 2014) have been used. Based on mean values of the normalized difference vegetation index (NDVI) (Rouse et al., 1974) and the land surface temperature (LST) (Li et al., 2013), derived from the three-month composites, the diverse structural parameters of vegetation coverage and thermal environment are represented. Building density maps of 15 German cities are derived from open 3D building models (Vermessungsverwaltung, 2023).

3. Methodology

3.1. Overview

This paper outlines a two-step process for identifying the potential of roof greening, comprising 1) extraction of roofs possibly suitable for greening from remote sensing imagery and 2) geographic-spatial evaluation of roof greening potential for climate adaptation.

Initially, the GreenRoof dataset covering four European cities is employed to pre-train a deep learning model. Subsequently, we adopt two strategies to identify roofs possibly suitable for greening from

Table 2
Data source used for GreenRoof dataset.

City	Country	Remote sensing imagery		3D building model
		Spatial resolution	Source	Source
Berlin	Germany	0.2 m/pixel	https://www.berlin.de/sen/sbw/stadtdaten/geoportal/landesvermessung/geotopographie-atkis/dop-digitale-orthophotos	https://www.adv-online.de/AdV-Produkte/Weitere-Produkte/3D-Gebaeudemodelle-LoD
Brussels	Belgium	0.1 m/pixel	https://datastore.brussels/web/urbis-download	https://datastore.brussels/web/urbis-download
Helsinki	Finland	0.2 m/pixel	https://hri.fi/data/en/dataset/helsingin-ortoilmakuvat	https://hri.fi/data/en_GB/dataset/helsingin-3d-kaupunkimalli
Vienna	Austria	0.15 m/pixel	https://www.wien.gv.at/stadtentwicklung/stadtvermessung/geodaten/orthofoto	https://www.data.gv.at/katalog/dataset/generalisiertes-dachmodell

Table 3
Characteristics of Landsat 8.

Band	Spectral region	Spatial resolution
Band 1	Coastal Aerosol	30 m/pixel
Band 2	Blue	30 m/pixel
Band 3	Green	30 m/pixel
Band 4	Red	30 m/pixel
Band 5	Near infrared (NIR)	30 m/pixel
Band 6	Short wavelength infrared 1 (SWIR1)	30 m/pixel
Band 7	Short wavelength infrared 2 (SWIR2)	30 m/pixel
Band 8	Panchromatic	15 m/pixel
Band 9	Cirrus	30 m/pixel
Band 10	Thermal infrared 1 (TIR1)	100 m/pixel
Band 11	Thermal infrared 2 (TIR2)	100 m/pixel

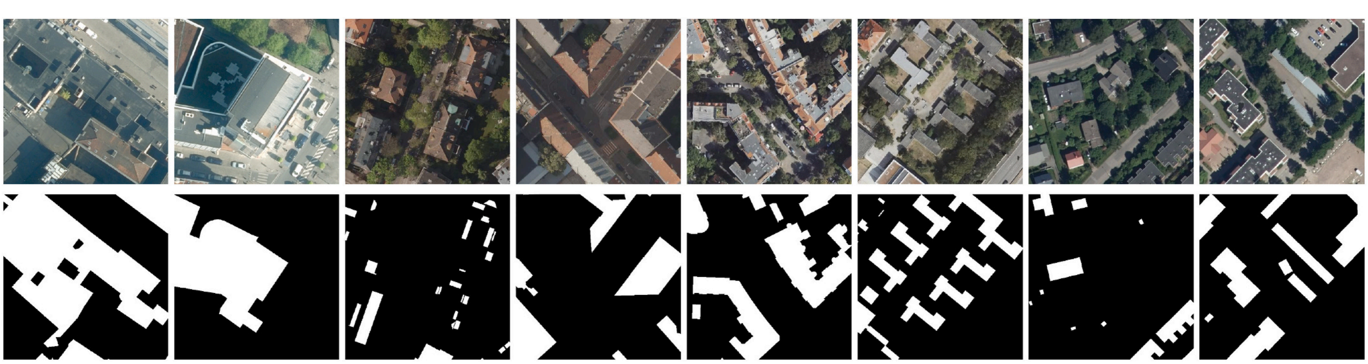


Fig. 2. Example data in the GreenRoof dataset. The first row refers to remote sensing imagery, while the second row denotes masks for roofs with high greening potential.

remote sensing imagery collected from 15 Bavarian cities: (a) a direct application of the pre-trained model and (b) a fine-tuning of the pre-trained model with local samples.

Based on the prediction as well as the official data, a geographic-spatial evaluation of roof greening potential is subsequently established using three structural parameters (vegetation coverage, thermal environment, and building density) to represent the demand for roof greening in specific neighborhoods. The analysis of both data sets in parallel is the basis for determining the accuracy of the remote sensing approach. A detailed illustration of the process is illustrated in Fig. 3.

3.2. Extraction of roofs possibly suitable for greening

In this study, we localize the feasibility of green roofs based on the

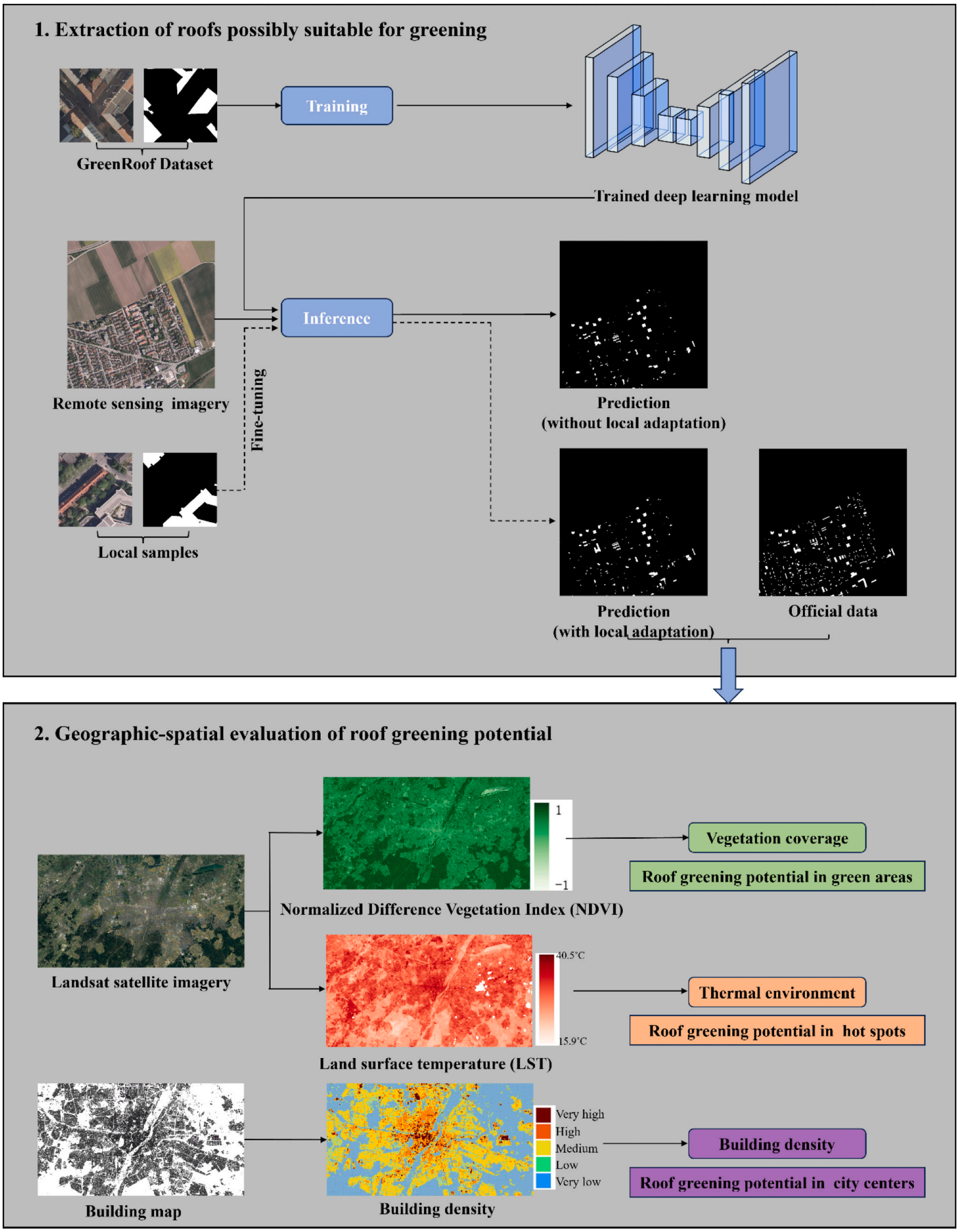


Fig. 3. Study design and major research steps.

physical properties of the roof. According to the concept used here, green roofs are potentially possible on flat roofs and pitched roofs with a maximum slope of 10°. While some open-source products (e.g., OpenStreetMap (OSM) (OpenStreetMap contributors, 2023), Microsoft (Microsoft), and Google (Sirko et al., 2021)) provide building maps, the information on roof slopes is, however, not incorporated into these data. However, visual features in remote sensing images enable the identification of specific roof types possibly suitable for greening. Leveraging advances in deep learning techniques, certain convolutional neural networks (CNNs) proficiently learn these visual features, facilitating target identification.

In our study, a vital module of the implemented framework is the deep learning model, which significantly impacts the final extraction results of potential green roofs. Hence, we have evaluated the performance of different CNNs. To validate the effectiveness of the local adaptation strategy, we carry out an analysis of results that are obtained by CNNs in relation to official data, respectively.

3.2.1. Convolutional neural networks

CNNs are powerful deep learning architectures extensively applied in image segmentation tasks, where the goal is to assign a category label to each pixel in an image. For roof greening suitability, CNNs are trained to recognize features linked to flat or gently sloping surfaces—key criteria for greening potential—by processing labeled image data from previously identified green roofs. As CNNs learn to map these features, they assign each pixel a probability of being part of a suitable or non-suitable roof, enabling accurate and efficient segmentation. Specifically, this study uses CNNs to segment images into 'potential green roof' and 'non-potential green roof' classes. Six CNNs including U-Net (Ronneberger et al., 2015), Efficient-UNet (Baheti et al., 2020), DeepLab v3+ (Chen et al., 2018), HRNet (Yuan et al., 2020), SegFormer (Xie et al., 2021), FC-DenseNet (Jégou et al., 2017) are applied, tested and compared for segmenting roofs suitable for roof greening. These six CNNs have been tested as they are popular networks in building segmentation tasks (Wang et al., 2023).

Initially, we utilize the training and validation sets of the GreenRoof dataset to train different CNNs. To evaluate the accuracy of potential green roofs extracted by the CNNs, two widely used metrics, Intersection over Union (IoU) and F1 score (Li et al., 2024), are employed. The respective formulas are as follows:

$$IoU = \frac{TP}{TP + FP + FN} \tag{1}$$

$$F1\ score = \frac{2 \times precision \times recall}{precsion + recall} \tag{2}$$

$$precision = \frac{TP}{TP + FP} \tag{3}$$

$$recall = \frac{TP}{TP + FN} \tag{4}$$

where FN, FP, and TP indicate the numbers of false negatives, false positives, and true positives, respectively. These metrics are computed at the pixel level. The F1 score represents the harmonic mean between precision and recall. The CNN model that exhibits the most favorable outcomes in the test set of the GreenRoof dataset is chosen for the application.

3.2.2. Local adaptation strategy

Subsequently, we implement two strategies to identify potential green roofs in 15 Bavarian cities. The first approach is without local adaptation, which involves directly applying the pre-trained model based on the four cities to infer information from the unseen remote sensing imagery. The second strategy is local adaptation. Here, we additionally collect a small amount of training (140 pairs of patches) and validation (60 pairs of patches) samples in each German city. All samples are randomly distributed in each city to ensure a good representation of different building types in the city center and in rural areas. For each city, the pre-trained model undergoes fine-tuning with local samples before being used for inference. The effectiveness of local adaptation is assessed by comparing the results from the two strategies. In addition, we also compare and evaluate these strategies in reference to official data. Here, we apply the approach that acquires more similar metrics (e.g., the total area of potential green roofs) to the official data for further study.

3.3. Geographic-spatial evaluation of roof greening potential

Green roofs offer environmental and socioeconomic benefits, encompassing reduced energy expenditures for cooling and the establishment of recreational areas (Gwak et al., 2017; Langemeyer et al., 2020). Based on these benefits, the prioritization of implementing green roofs may differ depending on diverse spatial conditions. For instance, the demand for green roof retrofitting is higher in regions characterized by low vegetation coverage and high temperatures. Geographic-spatial analysis of roof greening potential is capable of finding areas with expected stronger effects and thus with higher priority for green roof retrofitting, providing essential support for decision-making processes.

For the implementation of greening transformations on existing buildings, this study conducts a spatial analysis considering three structural parameters to describe different urban settings: vegetation coverage, thermal environment, and building density. Specifically, we calculate the ratio of potential green roofs to all roofs based on structural parameters and this ratio serves to measure the greening potential. Then, we compare the ratios derived from our prediction with those from official data. The motivation is to investigate if the deep learning method and remote sensing data provide sufficient accuracy to identify the roof greening potential when official geodata are unavailable.

3.3.1. Vegetation coverage

Since existing green infrastructure contributes to reducing the demand for new green spaces like green roofs, surrounding vegetation coverage is chosen as one indicator to evaluate the demand for roof greening.

Specifically, the NDVI is calculated to quantify surrounding vegetation coverage.

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{5}$$

where NIR and RED are near-infrared and red bands of Landsat 8 satellite imagery, and high values of NDVI suggest areas with more vegetation cover. In consequence, we consider areas with NDVI values above a certain threshold as "green" and rate this area less relevant for green roof retrofitting. However, variations among different thresholds result in divergent outcomes. A larger threshold of NDVI indicates a smaller amount of green areas within the city. Due to discrepancies between the thresholds of NDVI and the specific characteristics of 15 cities, one certain threshold may not be suitable for deriving comprehensive results. Hence, this study systematically adopts different thresholds (i.e., 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, and 0.8) in NDVI to define green urban areas. This offers flexibility for urban planners to determine roof greening priority in particular cities and adjust the thresholds accordingly. The roof greening potential in areas of various surrounding green fractions can then be derived.

3.3.2. Thermal environment

Green roofs can regulate urban temperatures by cooling rooftop areas through the evapotranspiration of vegetation. Thus, green roofs play a crucial role in actively mitigating the UHI effect (Langemeyer et al., 2020) that refers to the phenomenon of urban areas experiencing higher temperatures than their rural surroundings due to human activities (Leichtle et al., 2023). To investigate UHI patterns, we identify urban hot spots that have temperatures higher than the overall average.

LST derived from remote sensing data is commonly used to examine variations of UHI patterns (Guha et al., 2019). Landsat 8 satellite imagery in summer (June, July, and August) of the year 2023 were acquired and processed to retrieve LSTs following the method in (Ermida et al., 2020). The mean summertime LST (averaged over June, July, and August) in 2023 is used to define urban hot spots, as outlined below (Ananyeva & Emmanuel, 2023; Guha et al., 2019):

$$LST > a + 0.5 \times b \tag{6}$$

where a and b represent the mean and standard deviation of the LST in the urban areas, respectively. In this study, the urban areas within the city correspond to artificial impervious areas that are defined in (Gong et al., 2020). Afterward, the roof greening potential in urban hot spots can be derived by overlaying the potential green roofs with urban "hot" spot maps.

3.3.3. Building density

Each city's variability in urban morphology and pattern exhibits diverse requirements and varying suitability levels for roof greening. To determine the number of potential green roofs in suburban or peripheral urban structures compared to inner-city areas and other centers, we categorize building patterns in terms of building density to spatially identify the target classes mentioned. This helps to define spatial priorities for green roof retrofitting.

Using building maps from official data (Vermessungsverwaltung, 2023), building density is calculated within each 100 m × 100 m grid cell. K-means clustering (Hartigan & Wong, 1979) is employed to categorize these grid cells into five types: very high, high, medium, low, and very low dense regions. This overcomes the binary conceptualization of 'high' and 'low'. The goal of the five categories is to incorporate transition areas between high and low-density regions, allowing a more nuanced spatial analysis (Li et al., 2022; Zhou et al., 2004) in suburban or peripheral urban structures, inner-city areas, and city centers. This allows us to evaluate the roof greening potential in dependence on the particular structural density of urban areas.

4. Results

4.1. Results of extracted potential green roofs

4.1.1. Comparison among different convolutional neural networks

This section compares the performance of various CNNs through quantitative measures (Table 4) and qualitative outcomes (Fig. 4) on the test set of the GreenRoof dataset. The findings indicate that U-Net outperforms other networks, showcasing superior results with an F1 score of 61.41 % and an IoU of 44.31 %. U-Net is structured with a contracting pathway to grasp contextual information and a mirrored expanding pathway, attaining precise segmentation masks. The above comparison underscores the effectiveness and robustness of U-Net in mapping potential green roofs, which can serve as the foundational framework for subsequent experiments.

Table 4
Numerical results of different CNNs for mapping potential green roofs (%).

Method	F1 score	IoU
U-Net (Ronneberger et al., 2015)	61.41	44.31
Efficient-UNet (Baheti et al., 2020)	58.00	40.84
DeepLab v3+ (Chen et al., 2018)	56.73	39.60
HRNet (Yuan et al., 2020)	54.02	37.00
SegFormer (Xie et al., 2021)	48.33	31.87
FC-DenseNet (Jégou et al., 2017)	60.62	43.50

4.1.2. Comparison between local adaptation and non-local adaptation

The effectiveness of remote sensing and deep learning in identifying the roof greening potential is investigated by comparing the performance of the two strategies - local adaptation and non-local adaptation - in 15 German cities. We first compare the ratios of potential green roofs to all roofs at an aggregated level of all 15 cities. When compared to the ratio obtained by the strategy without local adaptation (15.59 %), the ratio obtained by the strategy with local adaptation (20.30 %) is more similar to that from official data (29.75 %). Thus, the strategy with local adaptation enhances the model performance (i.e., an average improvement of 5.58 % in the ratio of potential green roofs vs. all roofs for 15 cities is measured) by utilizing the annotated samples from the local city. Fig. 4 also illustrates that the general roof patterns for green retrofitting can be derived from CNNs, though the deviations in accuracy mainly stem from inaccuracies in defining the precise boundaries of individual roofs.

We further conduct a comparison of ratios on individual cities (Fig. 5). Despite leveraging local training samples, the deep learning model still exhibits underestimations of potential green roofs compared to official data in all cities. Specifically, an average underestimation of 7.65 % in the ratio of potential green roofs vs. all roofs) is observed across all 15 cities. The underestimation varies significantly among different cities. The underestimation is severe in Schweinfurt (i.e., 18.83 %), while our prediction is very similar to official data in Weilheim (i.e., 0.06 %). This performance discrepancy arises from substantial differences (e.g., building materials and urban morphology) between the Bavarian cities and the four European cities involved in the GreenRoof dataset.

Fig. 6 showcases potential green roofs that are identified from remote sensing imagery, suggesting that the deep learning approach can effectively identify roofs possibly suitable for greening. However, human intervention may be further necessary to address some exceptional circumstances. In addition, we did not incorporate buildings that are already greened in this analysis but classified them as potential green roofs if the physical parameters fit.

4.2. Spatial variation of roof greening potential

4.2.1. Differences of roof greening potential in non-green vs. green urban areas

To understand cities' differences and similarities, we divide the 15 cities into three categories based on their building areas, i.e., large, medium, and small cities. For each category, we derive the ratio of all roofs in green urban areas that are defined by different NDVI thresholds. The building areas of 15 cities are shown in Fig. 7 (a) and these cities are then ranked as large, medium, and small cities. Fig. 7 (b) shows the curves for each city and those for the average of each category. The NVDI threshold was observed to be associated with the division of green areas and non-green areas. A higher NDVI threshold value corresponds to a smaller share of green areas within the cities, leading to a reduced ratio of roofs located in green areas. Given an NDVI threshold, large cities usually have a lower ratio of roofs located in green areas when compared to medium and small ones.

Fig. 8 illustrates the roof greening potential in green urban areas and non-green urban areas, which are obtained by our prediction as well as from official data as a reference. The greening potential in green areas and non-green areas varies according to the thresholds of NDVI. However, our prediction shows a similar trend as the official data. Specifically, the greening potential in non-green areas is higher than that in green areas when the NDVI threshold is smaller than 0.6, suggesting that the promotion of green roofs in German cities holds significant potential. We also find the roof greening potential in non-green areas differs in each city. The largest city among our sample Muenchen shows a relatively high proportion of potential green roofs in non-green areas, indicating great opportunities for roof greening within this city. Nevertheless, small cities such as Bad Toelz and Hemau have relatively

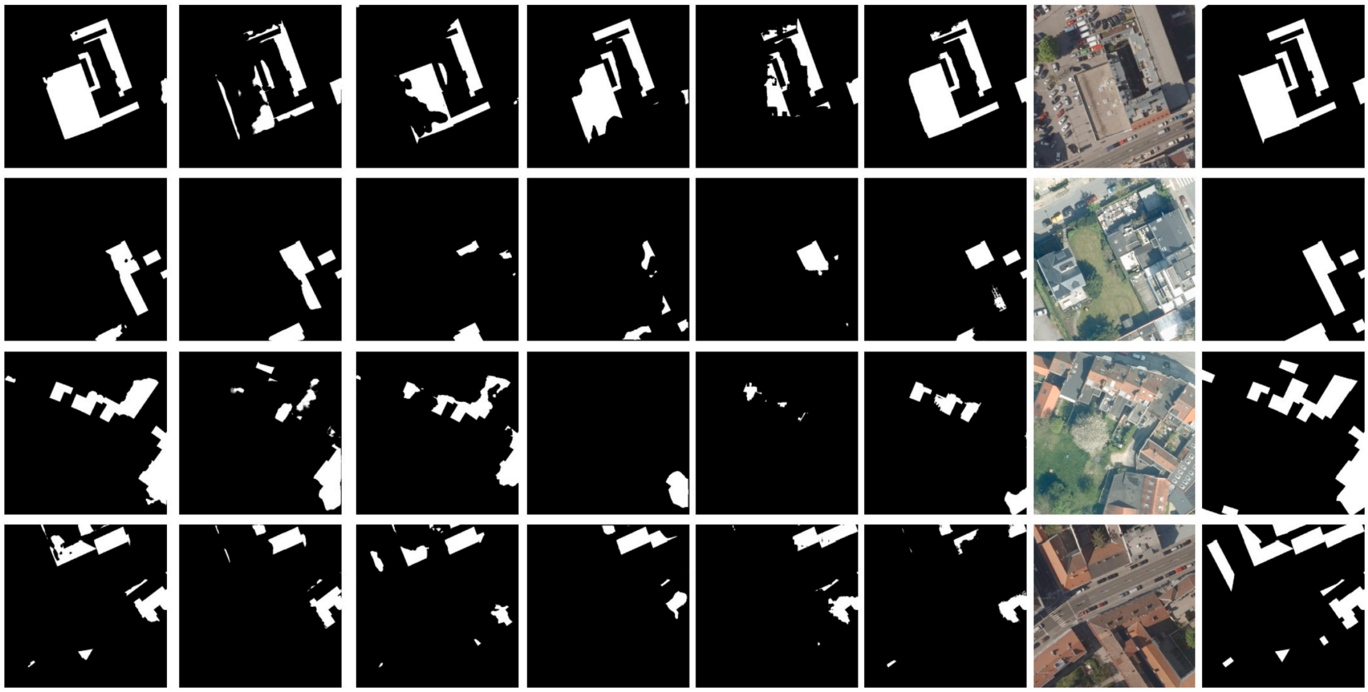


Fig. 4. Prediction results on the Greenroof dataset. Columns from left to right are: U-Net (Ronneberger et al., 2015), Efficient-UNet (Baheti et al., 2020), DeepLab v3+ (Chen et al., 2018), HRNet (Yuan et al., 2020), SegFormer (Xie et al., 2021), FC-DenseNet (Jégou et al., 2017), remote sensing image, and ground truth mask.

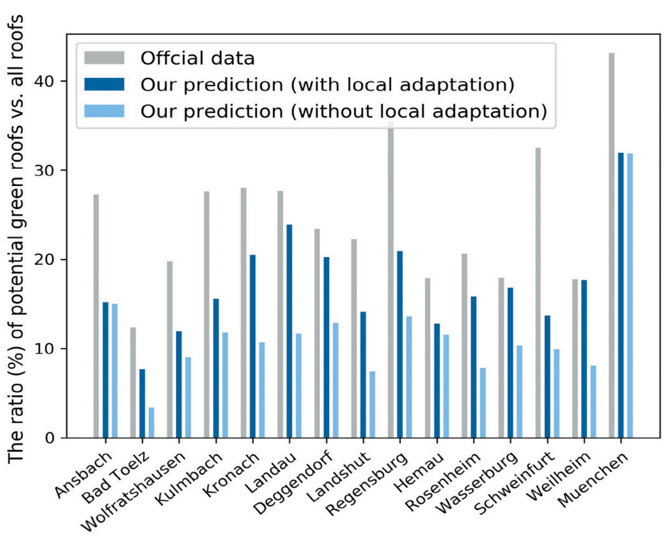


Fig. 5. The ratios of potential green roofs to all roofs obtained from different sources in 15 Bavarian cities.

low potential for roof greening in non-green urban areas.

4.2.2. Roof greening potential in urban hot spots

According to the evaluation of official data, we calculate the ratio of roofs in 15 cities located in urban hot spots (Fig. 9). The ratios of 15 cities show a wide variety, where 37 % of roofs are in hot spots of Muenchen and only 2 % of roofs are in hot spots of Hemau. This variation between a large and a small city clearly reveals the different challenges of cities.

Fig. 10 presents the ratio of potential green roofs to all roofs in hot spots per city from our prediction as well as from official data as a reference. Despite being derived from various sources, the same pattern is observed, a larger share of roofs for green roof retrofitting is found in hot spots than in non-hot spots. Kulmbach and Landau have comparatively large proportions of roof greening potential in urban hot spots. This suggests that these cities have significant potential to regulate urban climate by retrofitting green roofs.

4.2.3. Roof greening potential across areas of varying building density

Fig. 11 comprises pie charts illustrating the share of roofs across various building density regions for each city based on official data. Hemau has the largest share (50.00 %) of roofs located in city centers (i.e., regions with very high and high building densities), while this ratio is smallest in Kulmbach (24.08 %). Fig. 12 depicts the quantity of potential green roofs in 15 city centers obtained from official data and our prediction, respectively. Official data and our prediction exhibit a consistent trend where more potential green roofs are situated in city centers than in non-city centers. In the comprehensive evaluation of all cities, the city centers of Landau, Regensburg, and Muenchen, contribute to the relatively high potential for roof greening. This observation suggests that densely populated urbanized neighborhoods in these cities have significant potential for retrofitting green roofs, aligning with potential benefits for local communities.

5. Discussion

5.1. Methodological implications

This study demonstrates a method that allows deriving the potential for roof greening from remote sensing data using deep learning. To thoroughly evaluate roof greening potential, we have considered different structural parameters that incorporate vegetation coverage, thermal environment, and building density. Our approach is designed to be scalable and adaptable to different cities, as demonstrated by our application across various urban settings in Europe. The methodology can be applied to cities with similar data availability, enabling broader applications for green roof planning beyond European contexts.

Since not all cities, especially outside Europe and North America, have detailed 3D building models available, a deep learning model trained on high-resolution remote sensing images offers flexibility by allowing roof greening potential identification without the need for 3D

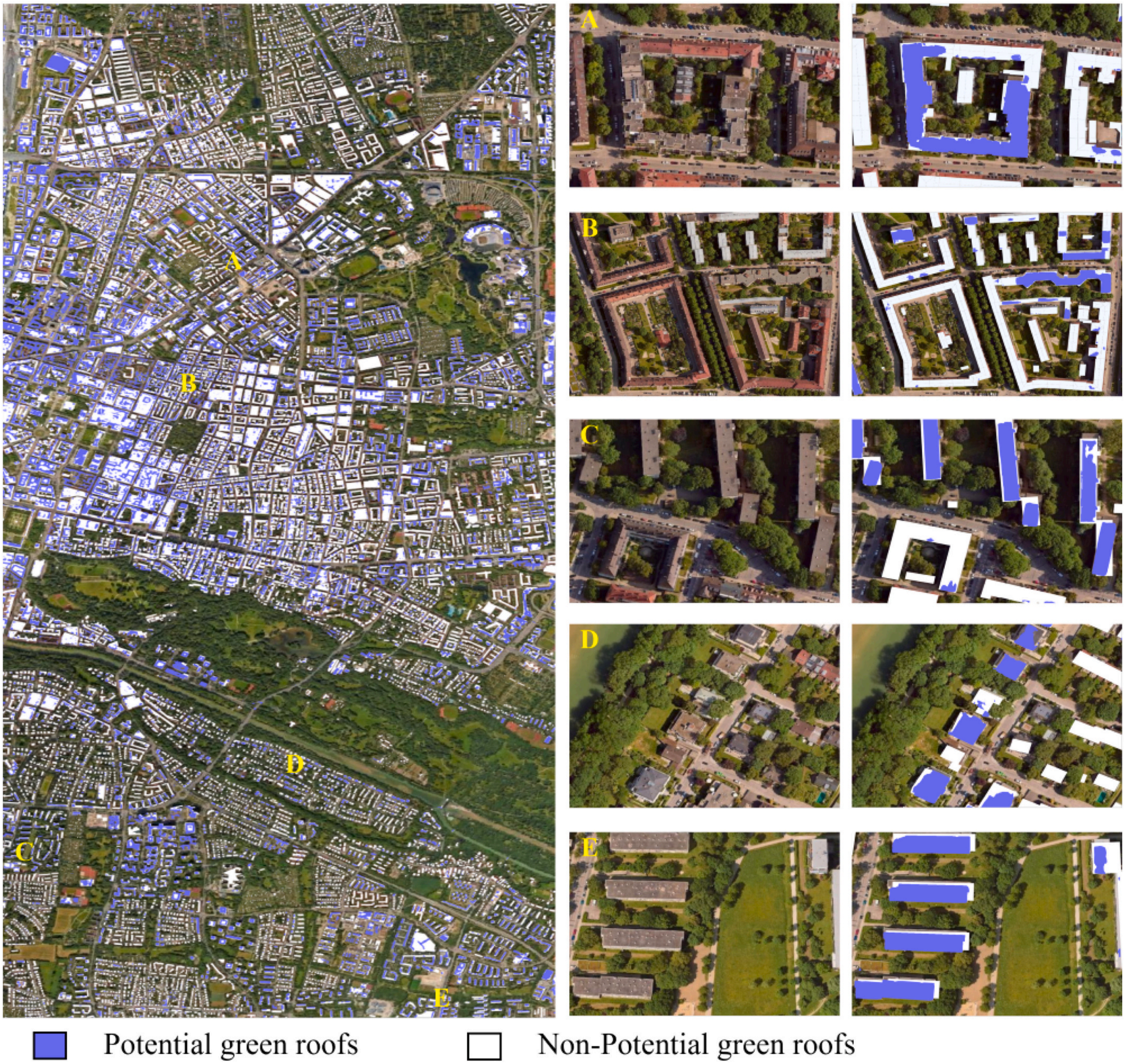


Fig. 6. Zoomed-in results of predicted potential green roofs for a sample urban area.

models. This makes our approach more widely applicable and practical for global urban settings, where remote sensing data may be more accessible than 3D building models or very high resolution (VHR) digital surface models.

A critical aspect of our method is the quality and availability of remote sensing imagery, which significantly impacts the accuracy of results. When high-quality VHR remote sensing imagery is accessible, the approach has proven to achieve high accuracy in delineating roof features and estimating greening potential. However, in regions with limited or lower-quality data, uncertainties in the predictions may increase, particularly in identifying roof boundaries or classifying roof types. Despite these challenges, the methodology is flexible and can accommodate varying levels of data quality by further incorporating additional training data. For instance, we have shown that fine-tuning the model with localized datasets allows adapting to the specific urban morphologies of different regions. This adaptability highlights the model's potential to serve as a versatile tool for urban greening initiatives worldwide, even in cities where only basic geospatial data are available.

5.2. Research innovations

This study advances roof greening potential assessment by addressing critical limitations in existing research. The main innovation is that our research has a broader geographic scope. Unlike former studies limited to single cities (Gandini et al., 2023; Hong et al., 2019; Silva et al., 2017; Slootweg et al., 2023), our study investigates cities across different building patterns and urban climates, offering greater generalizability and insight into roof greening potential across diverse urban contexts. Moreover, the application of U-Net for the segmentation of potential green roofs in this study, offering higher precision and scalability, represents a methodological advancement over manual visual

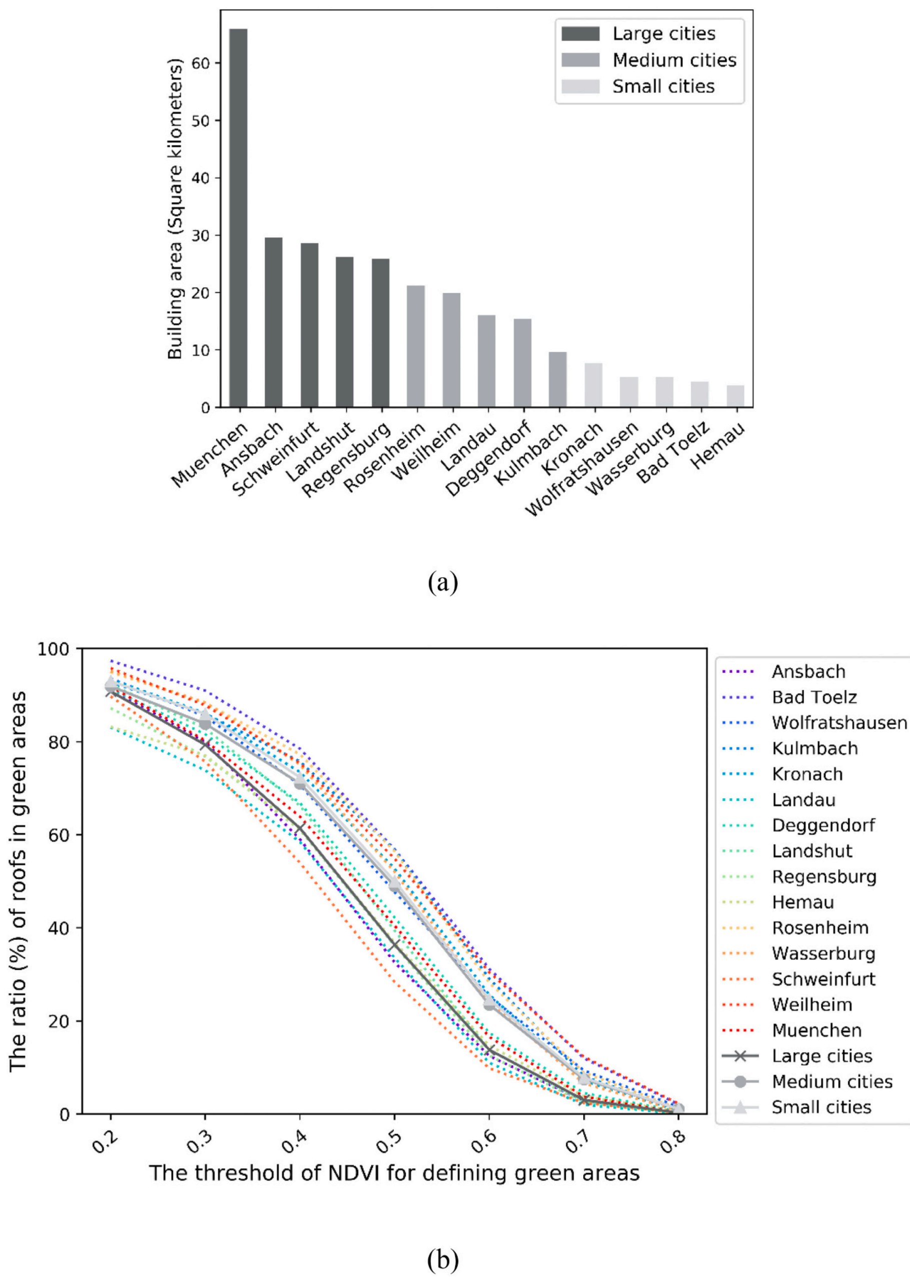


Fig. 7. (a) Based on building areas, 15 cities are categorized into three types: large, medium, and small. (b) The ratio of roofs in green areas that are defined by different NDVI thresholds. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

interpretation (Lambarki et al., 2022; Shao et al., 2021) or traditional mapping methods (Karteris et al., 2016) in prior studies. While past studies have sometimes included certain parameters (Joshi et al., 2020; Santos et al., 2016; Zhou et al., 2019), our approach goes further by integrating a comprehensive set of factors—vegetation coverage, thermal environment, and building density—as part of the green roof prioritization framework. This multi-criteria prioritization offers a more nuanced analysis that supports cities in developing targeted strategies to implement green roofs where they will have the greatest environmental impact, such as in areas with high heat retention or limited green space. The inclusion of these additional parameters sets our work apart by making it directly applicable to cities aiming for sustainability and resilience.

Our method holds considerable implications for sustainable urban development. This is because the results derived from our method can support city-level efforts to create more livable urban spaces through promoting green roofs. On the one hand, our approach identifies specific rooftops suitable for greening, offering data-driven insights for policymakers and urban planners looking to implement green roofs effectively. On the other hand, this research also incorporates urban climate and environmental factors. This helps to identify rooftops that could provide the greatest environmental benefits, thus contributing to climate resilience in urban areas vulnerable to extreme heat.

5.3. Limitations and future research directions

In what follows, we discuss the limitations of this study from three aspects- data, methodology, and application.

In this research, remote sensing imagery collected from airborne sensors is utilized. Deep learning models facilitate mapping roofs that are possibly suitable for greening from remote sensing imagery. However, a significant challenge for similar large-scale applications lies in

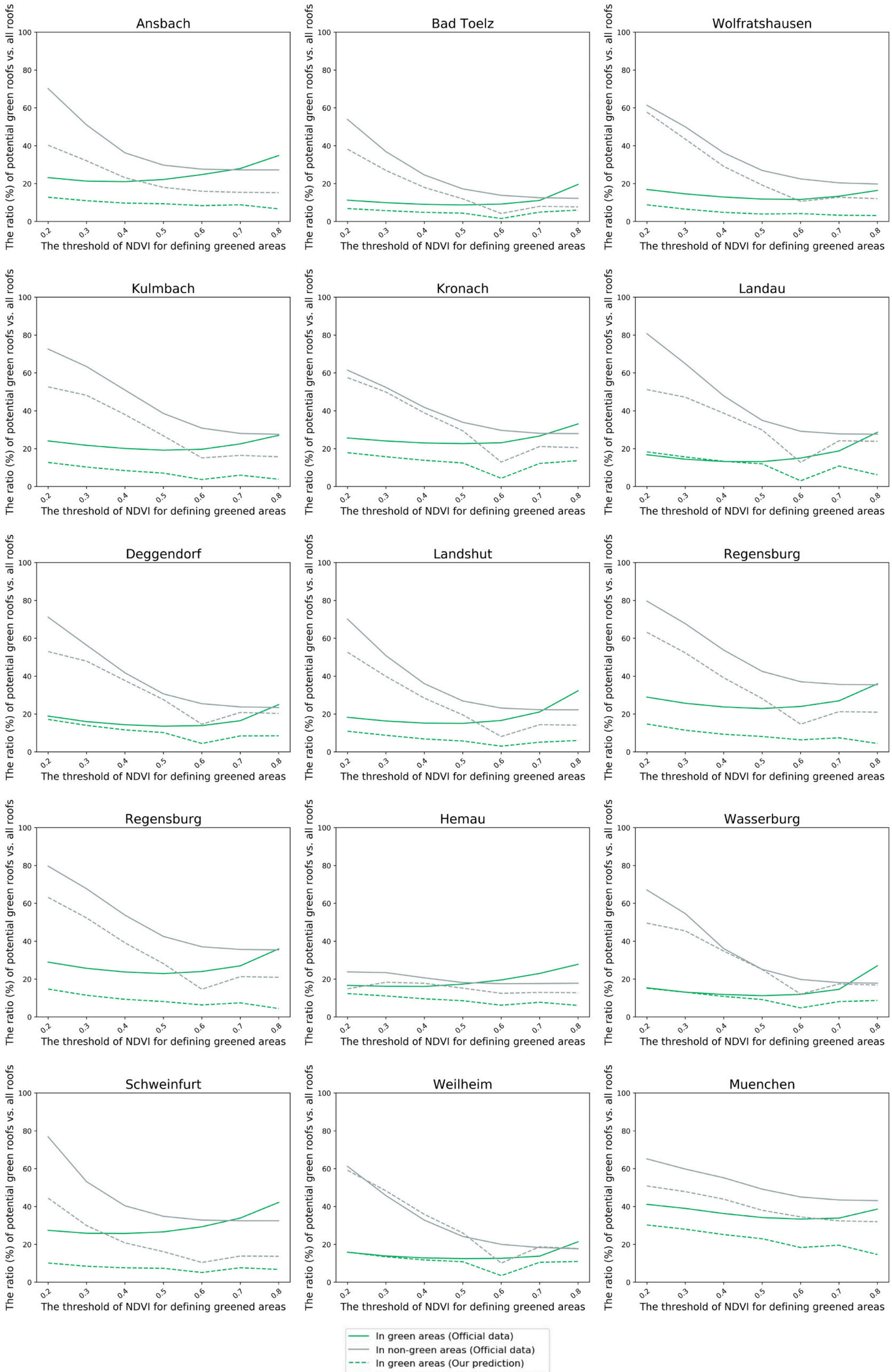


Fig. 8. Spatial variation of roof greening potential in green and non-green areas. Green areas are defined by different NDVI thresholds. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

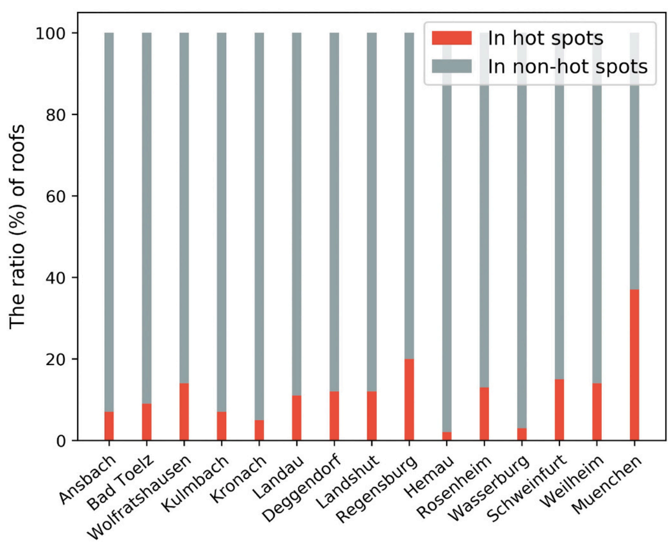


Fig. 9. The ratio of roofs in hot spots.

obtaining such high-quality VHR remote sensing imagery. If such datasets are not available, this can be overcome by harnessing alternative remote sensing data sources. For example, commercial satellites like Pleiades or WorldView offer remote sensing imagery with the necessary very high spatial resolution (~0.3 m/pixel). Theoretically, these satellite datasets cover the entire globe and are more cost-effective than aerial imagery. Nonetheless, the costs associated with such VHR data remain prohibitive for national, continental, or global applications. Lower resolution remote sensing data have shown to not allow for accuracies that are good enough for the assessment of green roof potential (Shao et al., 2021). We considered different structural parameters for geographic-spatial evaluation by exploiting data encompassing open-source Landsat satellite imagery and official building maps. For cities where official building maps are not publicly accessible, data from Microsoft (Microsoft) or OpenStreetMap (OpenStreetMap contributors, 2023), which has released open building footprints worldwide, is an option. However, the accuracy is also not always satisfactory (Herfort et al., 2023). Beyond this, the classification of building outlines and densities from remote sensing data also has proven high potential (Li et al., 2022; Standfuß et al., 2023).

Methodologically, the geographic-spatial evaluation of potential green roofs heavily depends on the accuracy of potential green roofs extracted from deep learning approaches. Hence, it is crucial to address the methodological challenges associated with the deep learning model. Based on the quantitative evaluation in the test set of the GreenRoof dataset, U-Net demonstrates the highest accuracy among the six CNNs considered. U-Net achieves an F1 score of 61.41 % and an IoU of 44.31 %, respectively. Despite the strategy with local adaptation achieving high accuracies, uncertainties persist. Specifically, an average underestimation of 7.65 % in the ratio of potential green roofs vs. all roofs is observed in the 15 cities in our sample. This underestimation could affect the model's precision when applied to new cities, particularly where roof structures or materials differ significantly from those in our European sample cities. In this case, users should be aware of the model's tendency to underestimate and may consider applying local adjustments or thresholds to improve accuracy in new urban contexts. We recommend that future studies use this model as a preliminary screening tool, followed by more localized analysis where possible to refine the assessment. For example, exploring domain adaptation or domain generalization methods (Li et al., 2024) has been shown to improve the mapping results of potential green roofs, alleviating the underestimation. However, the constant underestimation allows for general conclusions from our prediction. Our findings generally suggest plausible geographic-spatial evaluation results, as confirmed by the similar trends derived from our prediction when comparing them to the official data. Therefore, for cities lacking 3D building models, our model provides an accessible, albeit approximate, tool for assessing green roof potential.

From an application standpoint, we only consider the slope of building roofs as the indicator for roof greening. Some semantic attributes and geometric structures of buildings, such as age, structure stability, roof material, functional type, and roof superstructures, are not considered due to the absence of adequate training data. Thus, automatic detection and identification of these building characteristics at the city scale are currently unattainable. Old buildings are deemed unsuitable for roof greening due to their historical significance or potential load capacity limitations that may compromise safety (Hong et al., 2019). The greening of roofs naturally presupposes a certain structural stability of the building (Taubenböck et al., 2009; Aravena Pelizari et al., 2021). Moreover, implementing green roofs using materials such as brick or steel has shown to be challenging (Hong et al., 2019). Compared to residential buildings, public and commercial buildings exhibit favorable suitability levels for green roof retrofitting (Liu et al., 2022). Furthermore, mapping the net available roof area is essential, considering obstructions like elevator shafts and chimneys (Joshi et al., 2020).

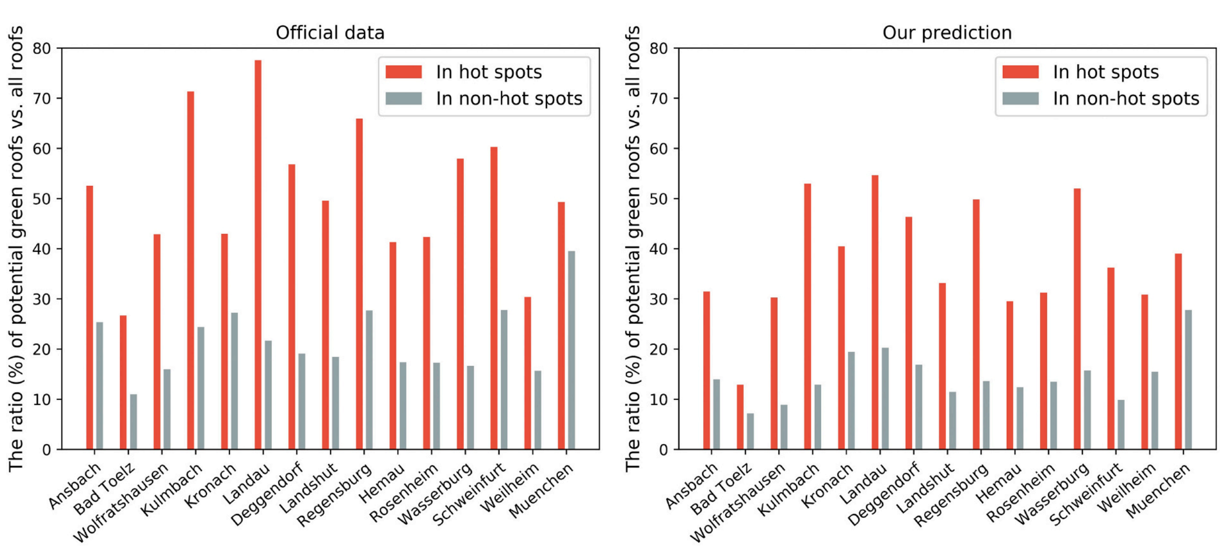


Fig. 10. Spatial variation of roof greening potential in hot spots and non-hot spots.

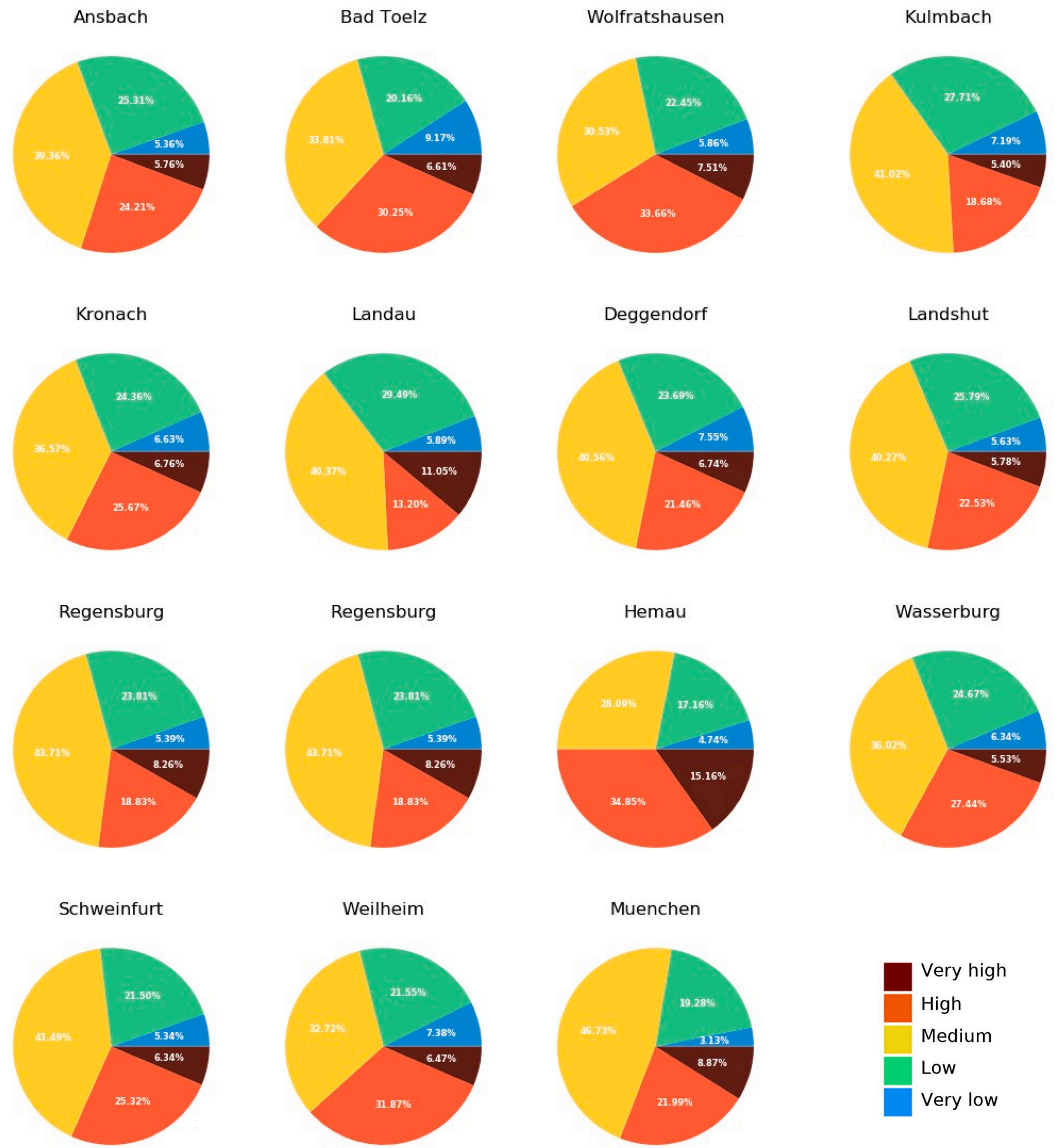


Fig. 11. The share of roofs in different building density regions.

Therefore, future studies are suggested to incorporate more building characteristics to identify the potential of roof greening. In this study, spatial prioritization in green roof planning is tailored to structural parameters, including vegetation coverage, thermal environment, and building density. However, other parameters (e.g., natural hazards and air quality) are also crucial to quantitatively identifying the priority of green roof retrofitting in cities and are not considered in our research. The significant capacity of green roofs to substantially reduce rainwater runoff and delay runoff peaks suggests a greater potential benefit in mitigating urban flooding during heavy rainstorms (Liu et al., 2022). Green roofs also help to enhance air quality by utilizing vegetation as sinks for pollutants. Therefore, the evaluation of green roof implementation at a city scale should consider areas with high vulnerability to floods and with dense road infrastructure.

6. Conclusion

The challenges posed by global warming on the environment,

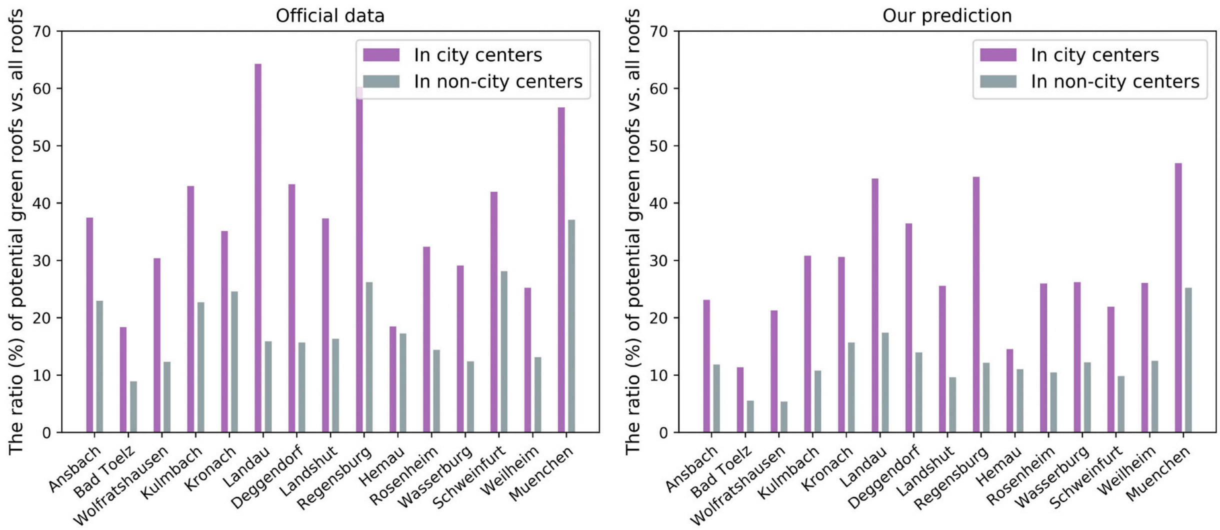


Fig. 12. Spatial variation of roof greening potential in city centers.

ecosystems, and human societies raise public concerns. To address this, vegetation is recognized as a crucial element to mitigate increased temperature by offering ecosystem services. However, in metropolitan areas, a lack of green space and land resources has led to an intensified focus on roof greening as they can leverage underexplored space to improve vegetation coverage. While some cities are actively promoting green roofs, the overall coverage remains limited. Therefore, there is a need to identify the potential for roof greening on existing buildings.

This paper creates GreenRoof, a public dataset of four European cities, including remote sensing images and ground reference masks of potential green roofs with slopes lower than 10°. This study incorporates deep learning methods, specifically semantic segmentation networks, to extract potential green roofs (candidate rooftops for green roof retrofitting) from remote sensing images. Additionally, structural parameters involving vegetation coverage, thermal environment, and building density are utilized to conduct spatial analysis for potential green roofs. The results derived from remote sensing and deep learning are closely aligned with those obtained by official geodata, offering both theoretical insights and practical significance. Therefore, combining remote sensing with deep learning offers an operational method for evaluating green roof potential on a city-wide scale and is especially valuable in cities lacking 3D building data. Furthermore, the results of quantitative and qualitative analyses for 15 cities indicate excellent roof greening potential in Germany, with potentially suitable buildings accounting for more than 20 % of the total building area. Our study advances methodological precision and offers a scalable, multi-city framework that integrates multiple key factors for green roof prioritization, presenting a rational foundation for decision-makers and urban planners to allocate resources toward sustainable urban development more effectively than many past research works.

CRediT authorship contribution statement

Qingyu Li: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Hannes Taubenböck:** Writing – review & editing, Formal analysis, Conceptualization. **Xiao Xiang Zhu:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition.

Declaration of competing interest

Qingyu Li reports financial support was provided by the Excellence Strategy of the Federal Government and the Länder. Hannes Taubenböck reports financial support was provided by the Bavarian Ministry of Economic Affairs, Regional Development and Energy. Xiaoxiang Zhu reports financial support was provided by the German Federal Ministry for Economic Affairs and Climate Action. Xiaoxiang Zhu reports financial support was provided by the Munich Center for Machine Learning. Xiaoxiang Zhu reports financial support was provided by the Munich Center for Machine Learning. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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