Scope
Volume 13 Number 01 March 2023

Building Shadow detection using Aerial Imagery: Review

Mohamed Naajim, Dr. Ashima Gambhir, Dr. Aarti Chugh,

Department of Computer Science, Amity University Gurugram, Haryana - 122412,

Email: mohamednaajim98@gmail.com

Abstract:

Aerial images are widely used in various remote sensing tasks and research to improve remote sensing in unmanned aerial vehicles (uav). Building and shadow detection is an important task for urban planning, disaster response, and environmental monitoring. Aerial imagery is a valuable source of data for building and shadow detection due to its high spatial resolution and ability to capture large areas. In recent years, machine learning-based methods have shown promising results in detecting buildings. In this review, we provide an overview of the state-of-the-art techniques for building and shadow detection using aerial imagery, with a focus on machine learning-based methods. We discussed the datasets for aerial imagery used for building shadow detection for different machine learning based methods and its applications. We also highlight the challenges and future directions in this field.

Keywords: Shadow detection ,remote sensing, aerial images ,cnn ,building detection

Introduction:

Building and shadow detection is critical for a various remote sensing application. Accurate detection of shadows can aid in comprehending the orientation, size, and shape of a building, as well as determine its height. Because of its high spatial resolution and capacity to cover wide areas, aerial imagery has emerged as a key source of data for building shadow detection .

Deep learning methods have begun to use aerial imagery as a source of data since they have proven successful in analyzing and extracting information from it. One of the primary advantages of aerial imagery is its ability to provide a bird's eye view of the area and enable a more detailed understanding of the surroundings. As a result, deep learning models that are more precise and efficient can be built. Large and diverse datasets, which can be difficult to obtain and label, are often needed for training deep learning systems for aerial imagery. However, recent developments in machine learning have made it possible to create data collecting and labelling techniques that are more effective, like transfer learning and automatic annotation.

Furthermore, the detection of buildings and shadows in aerial images has shown great potential for deep learning. Cnn architecture has been widely used in aerial images for object detection and segmentation. By automatically learning complex feature representations from images, these networks can recognize the location, kind, and shape of buildings, as well as their shadows. Deep learning for building and shadow detection in aerial images encounters multiple challenges, including the complexity and diversity of the environment, the necessity for accurate registration and georeferencing of the image, and the need for robust models that can generalize to unseen data. For addressing these difficulties, improved algorithms and methodologies that can efficiently exploit the vast amounts of data included in aerial images must be developed .

Traditional computer vision methods for detecting shadows rely on handcrafted features and threshold-based methods. However, these systems usually struggle with complex scenarios and require a high degree of manual involvement. Machine learning-based techniques in building and shadow detection have demonstrated promising results with recent developments in deep learning. These methods make use of the capabilities of cnns to automatically learn key properties from data, resulting in improved performance.

In this review paper, we have provided an overview of the different techniques used in previous research for building and shadow detection using aerial imagery, with a focus on both traditional and deep learning-based method. We also discuss about application of aerial imagery for remote sensing. We also highlight the challenges and future directions in this field, including data availability, shadow detection in complex environments, multi-modal data fusion, and integration with other technologies. By providing a comprehensive review of the current and future directions in building shadow detection, this review aims to facilitate further research and development in this field.

Literature review:

In this literature review, we will look at several studies on remote sensing, building and shadow detection using aerial images for both classical and deep learning-based methods. Some of the researchers based on building and object detection using aerial images like aghayari et al. (2023) proposed a building detection method based on inception resnet unet and unet architectures using aerial imagery. They compared the performance of these architectures and concluded that the inception resnet unet model performed better in terms of accuracy and speed. Atik et al. (2022) compared the performance of various yolo versions for object detection from aerial images and found that yolov5s outperformed other yolo models in terms of accuracy and speed. Jawaharlalnehru et al. (2022) proposed an improved yolo algorithm for target object detection from unmanned aerial vehicle (uav) images. They introduced a novel feature extraction module that effectively captures the target object's features, resulting in higher detection accuracy. Shi et al. (2023) proposed an automatic shadow detection method in high-resolution multispectral remote sensing images using a convolutional neural network (cnn) model. They used a cnn-based segmentation approach to separate shadow regions from other regions.

Remote sensing is an essential tool for monitoring and analyzing large areas from the aerial images. With the advances in deep learning, the detection of objects in remote sensing images has become increasingly accurate and efficient. We will now explore recent studies that have employed deep learning techniques for object detection in remote sensing imagery. Lu et al. (2021) proposed an attention and feature fusion ssd (single shot detector) for remote sensing object detection. The authors used a resnet-50 network with an attention mechanism to generate features maps, which were then fused with the features maps generated by the ssd. The proposed method achieved state-of-the-art performance on the nwpu vhr-10 and dota datasets. Li et al. (2020) compared three popular object detection models, faster r-cnn, yolo v3, and ssd, for the detection of agricultural greenhouses in high-resolution satellite images. The authors found that faster r-cnn and yolo v3 outperformed ssd in terms of detection accuracy, but yolo v3 had a faster inference speed. Song et al. (2018) proposed an approach for estimating solar photovoltaic potential based on rooftop retrieval from remote sensing images. The authors used a deep learning model to detect and locate rooftops in remote sensing images, and then estimated the solar potential based on the rooftop areas and orientation. The proposed approach achieved promising results in both accuracy and efficiency. Bouguettaya et al. (2022) presented a comprehensive review of deep learning techniques for crop classification in uav imagery. The authors discussed various deep learning architectures, data pre-processing techniques, and transfer learning strategies for crop classification. They also provided an analysis of the strengths and limitations of existing approaches and suggested potential research directions. Waqas zamir et al. (2019) introduced the isaid dataset, a large-scale dataset for instance segmentation in aerial images. The isaid dataset includes 2,806 high-resolution aerial images with 57,521 labeled instances of 23 object categories. The dataset has been widely used for the evaluation of instance segmentation algorithms in aerial images. Unmanned aerial vehicles (uavs) and their integration with deep learning techniques have shown promising results in disaster management applications such as flood detection. Munawar et al. (2021) demonstrated the effectiveness of an integrated aerial imagery and convolutional neural network approach for flood detection using uavs. The study found that the deep learning model achieved high accuracy in detecting flooded areas, and the use of uavs allowed for timely and cost-effective acquisition of data in disaster-stricken areas.

Recent research studies investigate shadow detection in aerial images using machine learning, multi-thresholding segmentation, and other techniques. Zhou et al. (2021) proposed a shadow detection and compensation method for remote sensing images in complex urban areas. The authors used a shadow detection network (sdn) to detect the shadow regions, and then they applied a shadow compensation network (scn) to compensate for the shadow regions. The proposed method achieved high accuracy in detecting shadows and compensating for them, even in complex urban environments. Ghandour and jezzini (2019) proposed a building shadow detection method based on multi-thresholding segmentation. The authors segmented the image into multiple regions based on their texture, color, and intensity, and then they applied a thresholding method to detect the shadow regions. The results showed that the proposed method achieved high accuracy in detecting building shadows.ufuktepe et al. (2021) proposed a learning-based shadow detection method in aerial imagery using automatic training supervision from 3d point clouds. They used a combination of cnn and point cloud-based algorithms to extract relevant features from the images and improve the detection accuracy. Alvarado-robles et al. (2021) proposed an approach for shadow detection in aerial images based on multi-channel statistics. They used three different channels to extract information from the images and obtain better detection results. Quispe and sulla-torres (2020) proposed an automatic building change detection method on aerial images using convolutional neural networks and handcrafted features. They used a cnn model to extract features from the images and a handcrafted feature-based change detection algorithm to identify changes in buildings. Mei et al. (2023) proposed a difference-aware attention network (d2anet) for multi-level change detection from satellite imagery. They used a novel difference-aware attention mechanism to effectively capture the differences between images at different levels.pulakurthi (2019) proposed a shadow detection method in aerial images using machine learning techniques. They used a combination of supervised and unsupervised learning algorithms to extract relevant features and detect shadows in the images. Zhou and sha (2020) proposed a building shadow detection method on ghost images. They used an image restoration technique to remove the shadow from the original image and obtain a ghost image, which was then used to detect the building shadow. Valanarasu and patel (2023) proposed a fine-context shadow detection method using shadow removal. They used a deep learning-based approach to remove the shadows from the images and extract relevant features for shadow detection.

In summary, the literature research indicates that numerous machine learning and computer vision algorithms have been developed to address remote sensing and remote sensing in building and shadow detection from aerial images. These methods include models such as unet architecture, yolo architecture, and ssd architecture, as well as other classic methods. These approaches have shown promising outcomes and have the potential to be applied in a variety of real-world situations.

Methodology

Aerial images have been a key to remote sensing applications, and research has been conducted for numerous real-time remote sensing scenarios [16][14]. In this section, we'll look at building and shadow detection algorithms for remote sensing in aerial imagery. Traditional approaches as well as deep learning-based methods have been applied for construction and shadow detection [5][13].

Traditional methods for building and shadow detection in aerial images include the use of image processing techniques that rely on handmade features and rules to detect shadows. These methods often require a sequence of stages such as image pre-processing, feature extraction, segmentation, and classification [11][9]. Threshold-based segmentation is a popular technique that divides the image into shadowed and non-shadowed regions by applying a threshold value to the image [4]. Another method is edge-based segmentation, which uses edges seen in the image to distinguish between shadow and no-shadowed regions [9]. Other common techniques include morphological operations, which use a series of mathematical operations to change the size and form of image features, and region-growing segmentation, which groups regions with similar pixel values together.[23] while traditional methods have been successful in some applications, they are frequently constrained by their reliance on handcrafted features and rules, which can take time to design and may not generalize well to new cases. Deep learning-based algorithms have emerged as a strong alternative for building and shadow detection in aerial data in recent years [6][13]. These approaches can generate feature representations directly from data and have produced cutting-edge results in a variety of remote sensing applications [12][15].

Deep learning-based methods for building and shadow detection in aerial imagery have gained popularity in recent years due to their superior performance compared to traditional methods. These methods typically utilize cnn architecture, which are powerful tools for feature extraction and classification [13]. In these methods a deep learning model is trained using large amounts of labeled data. The labeled data typically consist of images of various scenes containing buildings and shadows, with annotations indicating the locations of the buildings and shadows. The model learns to recognize patterns and features in the images that are associated with buildings and shadows and can then be used to detect these objects in new, unlabeled images [14].

One approach for building and shadow detection using deep learning is object detection. Object detection algorithms identify the location and extent of objects within an image, including buildings and shadows. One of the most well-known object detection techniques is yolo (you only look once) [2][3]. It is a real-time object detection system that uses a single neural network to predict bounding boxes and class probabilities from entire images in a single evaluation. Faster r-cnn is an additional technique. (region-based convolutional neural network) [16]. This technique employs a two-stage object detection methodology, first generating region recommendations and then categorizing them as either building or shadow. Another notable deep learning-based method is the ssd (single shot detector), which predicts the positions and classes of objects in an image using a single feed-forward cnn [15].

Here's a comparison of yolo, faster rcnn, and ssd based on different attributes for detection in aerial imagery:

Table 1: Comparison between yolo, faster rcnn and ssd using different attributes [2][15][16].

Attribute	Yolo	Faster rcnn	Ssd
Architecture	One-stage object detection	Two-stage object detection	One-stage object detection
Speed	Fast	Slower than yolo	Fast
Accuracy	Moderate	High	Moderate
Object detection quality	Good	Good	Good
Robustness	Suffers in complex environments	Robust in complex environments	Robust in complex environments
Training time	Fast	Slow	Fast
Network size	Smaller	Larger	Smaller
Gpu memory usage	Low	High	Low

Overall, yolo is faster and smaller, but with moderate accuracy and object detection quality. Faster rcnn has higher accuracy and good object detection quality but is slower and requires more gpu memory [16]. Ssd is fast, smaller, and has good object detection quality, but has moderate accuracy. The choice of model depends on the specific application requirements, such as speed, accuracy, and robustness in complex environments [15][16].

Another approach for building and shadow detection is semantic segmentation, it involves labeling each pixel of an image with a specific class. This implies that the precise boundaries of the objects are not only detected but also determined at the pixel level [23]. Fully convolutional networks (fcn), is a neural network architecture that replaces traditional neural network's fully connected layers with convolutional layers, allowing it to receive input of any size and produce output of corresponding size, which is useful for image segmentation applications [25]. Unet is intended to capture both low-level and high-level imagine features as well as perform pixel-level categorization. It is made up of an encoder and a decoder. The encoder oversees extracting features from the input image, while the decoder oversees reconstructing the output image using the extracted features [1][26]. Segnet is built on an encoder-decoder architecture that takes an input image and predicts a pixel-by-pixel output mask, with each pixel in the output mask corresponding to a certain class label in the input image [25][26]. Deeplab employs atrous convolution, a modified version of convolutional neural networks, to increase the field of view of filters without increasing the number of parameters. This enables dense image pixel tagging, which is useful for tasks like building and shadow recognition in aerial images. It has been demonstrated to achieve cutting-edge performance in a variety of remote sensing applications. These are some deep learning models that have been used for semantic segmentation. These models are trained on labelled datasets to learn how to assign each pixel of an image to the correct object or shadow label [25][27].

For a better understanding of image segmentation in aerial images. Let's compare the semantic segmentation model using various attributes.

Table 2: Comparison between fcnn, unet, segnet and deeplab using different attributes [25][26][27]

Attribute	**Fcnn**	**Unet**	**Segnet**	**Deeplab**
Input resolution	Medium	High	Low	High
Model capacity	Low	High	Medium	High
Training speed	Fast	Medium	Fast	Slow
Inference time	Fast	Slow	Fast	Slow
Boundary clarity	Low	High	Medium	High
Detail preservation	Low	High	Low	High
Object detection	No	No	No	Yes
Semantic segmentation	Yes	Yes	Yes	Yes
Instance segmentation	No	Yes	No	Yes
Performance	Moderate	High	Moderate	High
Applications	General purpose	Building and road extraction, land-use classification	Object detection, urban land-use classification	Building extraction, object detection, urban land-use classification

Based on the comparison table, deeplab gives the highest accuracy and best performance among the compared models for building and shadow detection in aerial imagery. In comparison to previous models, it has a greater intersection over union score, smaller loss, and faster processing time [27]. However, it necessitates more memory and computational power. Unet and segnet also provide good performance with moderate memory requirements, however fcnn has the lowest accuracy and the largest memory requirements of the examined models. Overall, the ideal model relies on the application's specific requirements and constraints [26].

Let's look at different remote sensing as well as building and shadow detection models in aerial images which has been researched in recent years and look at the technology's and dataset used in those models as well as limitation of the model.

Table 3: Comparison of previous research

Citation	Technique used	Dataset	Findings	Gap identified
[1]	Inception resnet unet, unet architectures	Inria aerial image	Outperformed traditional methods for building detection	Lack of analysis of shadow detection
[3]	Improved yolo algorithm	Pascal voc2012	Improved accuracy for target object detection	Lack of evaluation on large-scale datasets
[13]	Deeply supervised convolutional neural network	Aerial images shadow detection dataset	Outperformed traditional methods for shadow detection	Lack of research on other types of shadow imagery
[14]	Faster r-cnn, yolov3	Stanford uav dataset	Yolov3 outperformed faster r-cnn for car detection	Lack of analysis of other object detection methods
[16]	Faster r-cnn, yolov3, ssd	Gf-1, gf-2 satellite image.	Faster r-cnn outperformed yolov3 and ssd for greenhouse detection	Lack of comparison with other object detection methods
[21]	Deep learning techniques	Uav imagery	Improved accuracy for crop classification	Lack of comparison with traditional crop classification methods

From the above table, it can be inferred that multiple algorithms, including cnns, fcnns, yolo, unet, segnet, and deeplab, have been applied in research publications for a variety of tasks, including building detection, object detection, crop classification, and shadow detection in aerial images [1][16]. For evaluation, many studies have used open-source datasets including coco, inria aerial images,aisd shadow detection dataset and various satellite and uav based dataset. Additionally, it has been noted that certain studies have pointed out weaknesses in current methodologies and offered suggestions for advancements in upcoming investigations. The growth of deep learning methods in the field of aerial image processing has largely been supported by the results of this research.

In conclusion, building and shadow detection in aerial imagery is an important application of remote sensing that has been addressed by traditional as well as deep learning-based methods. Traditional methods rely on handcrafted features and rules, while deep learning-based methods generate feature representations directly from data. Object detection and semantic segmentation are two popular approaches for building and shadow detection. Yolo, faster rcnn, and ssd are commonly used object detection methods, while fcn, unet, segnet, and deeplab are frequently employed for semantic segmentation. Each approach has its own strengths and weaknesses, and the choice of method depends on the specific application requirements such as speed, accuracy, and robustness in complex environments. Overall, deep learning-based methods have demonstrated superior performance compared to traditional methods and will likely continue to be a focus of research in this field.

Remote sensing application of building and shadow detection in aerial imagery:

Urban planning and development: Shadow detection can be used to assess the impact of new constructions on the surrounding environment. By detecting and analyzing the shadows cast by buildings, urban planners can determine the potential impact of new constructions on the surrounding buildings, vegetation, and public spaces [17].

Disaster response and management: In the aftermath of natural disasters such as earthquakes or floods, building shadow detection can help emergency responders identify areas with potentially hazardous conditions such as collapsed structures or unstable buildings. This information can then be used to prioritize search and rescue efforts [20].

Environmental monitoring: Shadow detection can also be used to monitor the impact of climate change on ecosystems. For example, by analyzing changes in shadow patterns over time, researchers can determine the effects of deforestation or the spread of invasive species on the surrounding environment [17][20].

Energy efficiency: Shadow detection can be used to optimize the placement and orientation of solar panels. By analyzing the shadows cast by nearby buildings and vegetation, researchers can determine the most effective placement and angle for solar panels to maximize energy output [18].

Military and surveillance: Shadow detection can be used for military applications such as target recognition and tracking. In surveillance, it can be used to detect suspicious activities or intrusions in sensitive areas such as military installations or high-security facilities [19].

Challenges and future directions:

Building and shadow detection in aerial images can be used in remote sensing, but they come with limitations. The availability of high-quality and diverse datasets is one of the main challenges to developing shadow detection models that use aerial images. The quantity and quality of data available for training and testing these models affects their accuracy and performance. Therefore, efforts should be made to develop and maintain freely accessible datasets that cover various geographic locations, hours of the day, and weather conditions [22].

In complex conditions another difficulty is developing shadow detection algorithms that can precisely identify shadows in challenging locations including cities, forests, and mountainous terrain. Shadows in these surroundings can be affected by a variety of elements such as overlapping shadows, topographical features, and vegetation. More study is required to construct models that can manage these complexities and aspects to overcome this difficulty [16][18].

Aerial imagery is often complemented by other data sources such as lidar, hyperspectral imaging, and thermal imaging. The integration of these different data sources can provide a more comprehensive understanding of the environment and improve the accuracy of shadow detection models. However, combining and analyzing different data types can be challenging and requires the development of new techniques and models for multi-modal data fusion [28].

Integration with other technologies shadow detection can be combined with other technologies such as object detection, semantic segmentation, and change detection to create more comprehensive solutions for various applications. However, the integration of these technologies also poses challenges such as the need for more computing resources and the development of more complex models. Future research should focus on developing models that can efficiently integrate with other technologies to create more powerful and effective solutions.

Conclusion

In conclusion, remote sensing and building shadow detection models have grown in popularity in recent years. Deep learning approaches such as object detection and semantic segmentation have shown considerable gains in accuracy and performance when compared to previous methods.

This article gives an overview of the many approaches and models used in aerial imaging. It also addresses the different applications and challenges related with building and shadow detection models using aerial imagery.

Future research in this subject should focus on addressing the issues of data availability, shadow detection in challenging circumstances, multi-modal data fusion, and integration with other technologies. Furthermore, efforts should be made to construct models that can manage various sorts of shadows and lighting circumstances, as well as models that can be applied in real-time.

Reference

1. Aghayari, s., et al. "Building detection from aerial imagery using inception resnet unet and unet architectures." Isprs annals of the photogrammetry, remote sensing and spatial information sciences 10 (2023): 9-17.
2. Atik, muhammed enes, zaide duran, and roni özgünlük. "Comparison of yolo versions for object detection from aerial images." International journal of environment and geoinformatics 9.2 (2022): 87-93.
3. Jawaharlalnehru, arunnehru, et al. "Target object detection from unmanned aerial vehicle (uav) images based on improved yolo algorithm." Electronics 11.15 (2022): 2343.
4. Shi, lu, jing fang, and yue-feng zhao. "Automatic shadow detection in high-resolution multispectral remote sensing images." Computers and electrical engineering 105 (2023): 108557.
5. Ufuktepe, deniz kavzak, et al. "Learning-based shadow detection in aerial imagery using automatic training supervision from 3d point clouds." Proceedings of the ieee/cvf international conference on computer vision. 2021.
6. Alvarado-robles, gilberto, et al. "An approach for shadow detection in aerial images based on multi-channel statistics." Ieee access 9 (2021): 34240-34250.
7. Quispe, diego alonso javier, and jose sulla-torres. "Automatic building change detection on aerial images using convolutional neural networks and handcrafted features." International journal of advanced computer science and applications 11.6 (2020).
8. Mei, jie, yi-bo zheng, and ming-ming cheng. "D2anet: Difference-aware attention network for multi-level change detection from satellite imagery." Computational visual media (2023): 1-17.
9. Pulakurthi, prasanna reddy. Shadow detection in aerial images using machine learning. Rochester institute of technology, 2019.
10. Zhou, guoqing, and hongjun sha. "Building shadow detection on ghost images." Remote sensing 12.4 (2020): 679.
11. Valanarasu, jeya maria jose, and vishal m. Patel. "Fine-context shadow detection using shadow removal." Proceedings of the ieee/cvf winter conference on applications of computer vision. 2023.
12. Li, meilin, et al. "Method of building detection in optical remote sensing images based on segformer." *Sensors* 23.3 (2023): 1258.
13. Luo, shuang, huifang li, and huanfeng shen. "Deeply supervised convolutional neural network for shadow detection based on a novel aerial shadow imagery dataset." *Isprs journal of photogrammetry and remote sensing* 167 (2020): 443-457.
14. Ammar, adel, et al. "Aerial images processing for car detection using convolutional neural networks: Comparison between faster r-cnn and yolov3." *Arxiv preprint arxiv:1910.07234* (2019).
15. Lu, xiaocong, et al. "Attention and feature fusion ssd for remote sensing object detection." *Ieee transactions on instrumentation and measurement* 70 (2021): 1-9.
16. Li, min, et al. "Agricultural greenhouses detection in high-resolution satellite images based on convolutional neural networks: Comparison of faster r-cnn, yolo v3 and ssd." *Sensors* 20.17 (2020): 4938.
17. Zhou, tingting, et al. "Shadow detection and compensation from remote sensing images under complex urban conditions." *Remote sensing* 13.4 (2021): 699.
18. Song, xiaoyang, et al. "An approach for estimating solar photovoltaic potential based on rooftop retrieval from remote sensing images." *Energies* 11.11 (2018): 3172.
19. Zhang, ying, and daiyin zhu. "Height retrieval in postprocessing-based videosar image sequence using shadow information." *Ieee sensors journal* 18.19 (2018): 8108-8116.
20. Munawar, hafiz suliman, et al. "Uavs in disaster management: Application of integrated aerial imagery and convolutional neural network for flood detection." *Sustainability* 13.14 (2021): 7547.
21. Bouguettaya, abdelmalek, et al. "Deep learning techniques to classify agricultural crops through uav imagery: A review." *Neural computing and applications* 34.12 (2022): 9511-9536.
22. Waqas zamir, syed, et al. "Isaid: A large-scale dataset for instance segmentation in aerial images." *Proceedings of the ieee/cvf conference on computer vision and pattern recognition workshops*. 2019.

23. Ghandour, ali j., and abedelkarim a. Jezzini. "Building shadow detection based on multi-thresholding segmentation." *Signal, image and video processing* 13.2 (2019): 349-357.
24. Faltermeier, florian l., et al. "Improving semantic segmentation of roof segments using large-scale datasets derived from 3d city models and high-resolution aerial imagery." *Remote sensing* 15.7 (2023): 1931.
25. Chai, dengfeng, et al. "Cloud and cloud shadow detection in landsat imagery based on deep convolutional neural networks." *Remote sensing of environment* 225 (2019): 307-316.
26. Abdollahi, abolfazl, biswajeet pradhan, and abdullah m. Alamri. "An ensemble architecture of deep convolutional segnet and unet networks for building semantic segmentation from high-resolution aerial images." *Geocarto international* 37.12 (2022): 3355-3370.
27. Mahmud, mat nizam, et al. "Altitude analysis of road segmentation from uav images with deeplab v3+." *2022 ieee 12th international conference on control system, computing and engineering (iccsce)*. Ieee, 2022.
28. He, guangjun, et al. "Sar and multi-spectral data fusion for local climate zone classification with multi-branch convolutional neural network." *Remote sensing* 15.2 (2023): 434.