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Research Article

Evaluating spatial resolution enhancement on impervious surface detection using support vector machine

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Abstract

Impervious surface areas (ISA) have caused significant environmental and hydrological changes as a result of increasing population and urban expansion. This study investigated the effects of high spatial resolution images obtained using Gram-Schmidt pan-sharpening method and multispectral Landsat 8 Operational Land Imager (OLI) satellite imagery on classification accuracy for ISA detection. Support vector machine (SVM) was used to classify ISA and other surfaces in Uşak province. The classification results indicated that the overall accuracy of the pan-sharpened image was 92.5% and kappa value was 85%. Compared to the multispectral image, these values represent increases of 2.5% and 5%, respectively. The findings show that pan-sharpened satellite images are a valuable tool for ISA detection. This method can be particularly effective for environmental management and sustainable urban planning and design in urban areas. Additionally, the results of this study can be generalized to other regions with similar geographical and urban characteristics. This approach provides a foundation for more accurate mapping of ISA and more effective management of urban environments.

1. Introduction

Impervious surface areas (ISA), which prevent water infiltration into the soil, encompass roads, pavements, parking lots, building roofs, and concrete surfaces. Due to increasing population and related demands, impervious surfaces have expanded rapidly in areas designated for residential, commercial, and transportation purposes [1]. The detection of ISA is crucial for designing both natural environments and urban development. In this context, remote sensing technologies can analyze extensive areas rapidly and reliably. Remote sensing for ISA detection provides quicker results compared to fieldwork and other manual methods, and multispectral satellite imagery also enables detailed spectral analysis [2-4].

ISA significantly impact the hydrological cycle by preventing surface water infiltration into the soil. Factors such as urbanization and population growth contribute to the widespread increase of ISA. For instance, Omurakunova et al. (2020) highlighted that urban sprawl in Kyrgyzstan has led to a significant expansion of impervious surfaces, which correlates with economic development and urban designing strategies [5]. The increase in ISA results in heightened surface runoff, which can lead to increased flood risks, particularly in densely

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populated urban areas. Dong et al. (2021) emphasized that the rapid urbanization of cities like Beijing has resulted in a marked increase in impervious surfaces, which are defined as materials that prevent water infiltration, such as roads and rooftops [6].

The environmental impacts of ISA are multifaceted, manifesting in various issues such as elevated surface temperatures and alterations in local microclimates. Tian et al. (2018) noted that the transformation of natural landscapes into anthropogenic ones due to ISA expansion significantly exacerbates the urban heat island effect, which is a critical concern for urban environmental quality [7]. Furthermore, Liang et al. (2022) discussed how intensive economic activities and rural-to-urban migration contribute to the growth of built-up areas and ISA, leading to ecological challenges [8]. The consequences of increased impervious surfaces extend beyond immediate hydrological impacts; they also affect urban climate dynamics and water quality, as highlighted by Long et al. (2020), who noted that the expansion of ISA often comes at the decrease of vegetation cover, further intensifying urban heat effects [9].

Monitoring and accurately mapping ISA are essential for effective environmental management, water resource preservation, and urban design. The use of remote sensing technologies has become increasingly prevalent in this regard. For example, Qiao et al. (2018) examined the distribution of ISA in different functional zones of Beijing, emphasizing the importance of remote sensing in understanding urban environmental changes [10]. Similarly, Hidayati & Suharyadi (2019) conducted a comparative study of different indexes to detect ISA using Landsat 8 OLI data, underscoring the complexity of accurately mapping these surfaces [11].

Image resolution is one of the most effective factors in correctly classifying ISA. Panchromatic sharpening (pan-sharpening) integrates high spatial resolution from panchromatic images with the spectral information from lower resolution multispectral images, resulting in enhanced image quality that is crucial for accurate classification tasks. The pan-sharpened high-resolution satellite images significantly affect the accuracy of land cover classification studies using various machine learning algorithms. For instance, Liu et al. (2023) suggested a pan-sharpening model based on feature fusion and attention modules, demonstrating that their method improved classification accuracy when applied to remote sensing images [12]. This aligns with findings from Li and Cheng (2019) [13], who utilized a Convolutional Neural Network (CNN)-based pan-sharpening method for Landsat 8 images, achieving notable enhancements in classification performance due to the improved spatial resolution of the resulting images. Ghayour et al. (2021) compared various machine learning methods using Landsat 8 OLI and Sentinel-2 satellite images for land cover classification, revealing that Support Vector Machine (SVM) outperformed other methods when high-resolution images were employed. This suggests that the integration of pan-sharpening techniques can significantly enhance the effectiveness of SVM in land cover classification tasks [14]. Similarly, Khateri et al. (2020) introduced a variational approach for fusing multispectral images and panchromatic, emphasizing the importance of spatial and spectral consistency in improving classification accuracy [15]. Their findings indicate that the use of high-resolution panchromatic images can lead to better delineation of land cover types, which is critical for environmental monitoring and urban planning.

This study aims to assess the effect of multispectral satellite imagery and pan-sharpened higher spatial resolution multispectral imagery on the classification accuracy of ISA. The study has shown that using pan-sharpened satellite images to determine impervious surfaces in urban areas provides higher accuracy results than multispectral images. The results obtained with the SVM algorithm, one of the machine learning methods, emphasize that pan-sharpened images are an important tool for urban area analysis. Although the study is an evaluation conducted in Uşak province, it can provide generalizable results for other regions with similar geographical and urban characteristics. The obtained findings constitute an important step for more accurate and detailed analyses in urban planning and design, environmental management, and sustainability.

2. Materials

2.1. Study area and data

Uşak province is situated in the Inner Aegean Section, connecting Central and Western Anatolia within the Aegean region of Türkiye. The province covers an area of approximately 5341 square kilometers and has a diverse topography characterized by hills and valleys, which influence its urban development patterns [16]. Uşak has rapidly received migration and grown with the country's urbanization movement. Due to the increasing population and urbanization, it is led to significant transformations in land use and land cover. This situation has resulted in an increase in ISA. ISA detection is of great importance in the natural environment management, monitoring and designing rural-urban areas .

For this study, Landsat 8 Operational Land Imager (OLI) data from September 23, 2018, with a spatial resolution of 30 meters, was utilized to assess ISA in Uşak Province. The Landsat 8 satellite provides medium-resolution imagery that is essential for accurately mapping land use land cover detections, including the extent of impervious surfaces. The data allows for the application of various remote sensing techniques and machine learning algorithms to classify land cover types effectively. Previous studies have demonstrated the efficacy of Landsat data in monitoring land use land cover detections, particularly in rapidly urbanizing areas. The general characteristics of the Landsat 8 satellite data and satellite image used in the study are shown in Fig. 1 and Fig. 2. In this study, the classification process was performed by selecting 3000 pixels for the training area and 1000 pixels for the validation process. The same training and test data were used for both MS and pan-sharpened images.

Landsat 8	Bands	Wavelength (micrometers)	Resolution (meters)
Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	Band 1 - Ultra Blue (coastal/aerosol)	0.43 - 0.45	30
	Band 2 - Blue	0.45 - 0.51	30
	Band 3 - Green	0.53 - 0.59	30
	Band 4 - Red	0.64 - 0.67	30
	Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
	Band 6 - Shortwave Infrared (SWIR) 1	1.57 - 1.65	30
	Band 7 - Shortwave Infrared (SWIR) 2	2.11 - 2.29	30
	Band 8 - Panchromatic	0.50 - 0.68	15
	Band 9 - Cirrus	1.36 - 1.38	30
	Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100 * (30)
	Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100 * (30)

Fig. 1. Landsat 8 satellite data features [3]

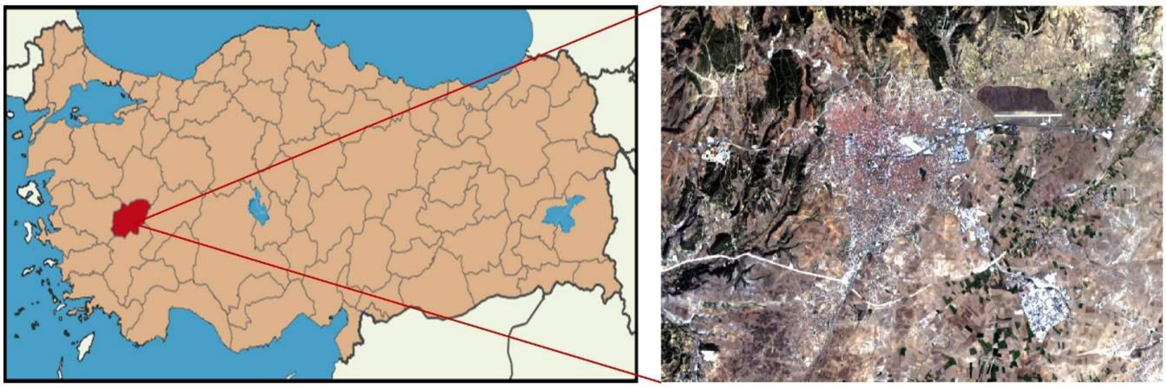

Fig. 2. Study area

3. Methodology

ISA, one of the areas that directly affect urban area design, were determined using the pixel-based SVM method. The data sets and process steps used to determine these areas are shown in Fig. 3.

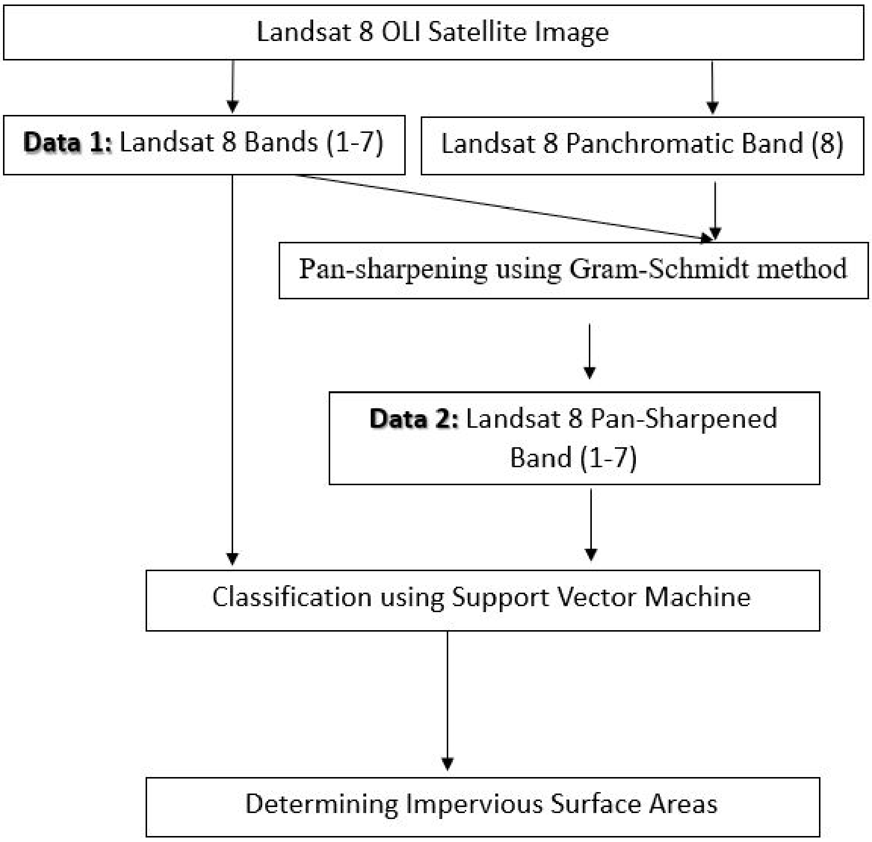

Fig. 3. General framework of the experimental study

The study created the multispectral data 1 (Band 1-7) by combining the ultra-blue, visible (Blue, Green, Red), near-infrared, and short-wave infrared bands of the Landsat 8 OLI satellite image. In the second step, pan-sharpened multispectral data 2 was obtained using the Gram-Schmidt method. Pan-sharpening integrates the high spatial resolution of the panchromatic band with the spectral resolution of the multi-spectral (MS) bands. As a result, the data 2 referred to as pan-sharpened becomes a multi-spectral image with enhanced spatial resolution. While the original data has a spatial resolution of 30 meters, the pan-sharpened data achieves a spatial resolution of 15 meters. In the third step, each data set was classified into two classes IS and other fields. The SVM, one of the machine learning methods, was used to classify the data 1 and 2 images. In the fourth step Classification results were evaluated using overall accuracy and kappa statistic metrics.

3.1. Gram-Schmidt pan-sharpening method

The Gram-Schmidt pan-sharpening method is a widely recognized technique to enhance the spatial resolution of multispectral images by integrating high-resolution panchromatic data. This method, introduced by Laben and Brower in 2000 [17], utilizes the Gram-Schmidt process to achieve a more accurate fusion of spectral and spatial information, resulting in images that maintain the spectral integrity of the original multispectral data while enhancing spatial details. The method operates by transforming the multispectral bands into a new space where the panchromatic image can be incorporated effectively, thereby minimizing color distortion and maximizing image sharpness [18].

The Gram-Schmidt pan-sharpening method offers several advantages that make it a preferred choice to enhance the spatial resolution of multispectral images. One of the primary benefits of this method is its ability to maintain the spectral integrity of the original multispectral data while improving spatial resolution. This is achieved through a mathematical transformation that minimizes color distortion, resulting in images that are both sharp and true to their original colors [18]. Additionally, the Gram-Schmidt method is known for its robustness in handling various types of remote sensing data, making it versatile across different applications. For instance, it has been successfully applied to high-resolution satellite imagery, such as WorldView-2, where it demonstrated superior performance compared to other pan-sharpening techniques like Intensity-Hue-Saturation (IHS) and Principal Component Analysis (PCA) [19, 20]. The method's effectiveness in reducing spectral distortion while enhancing spatial details has been highlighted in multiple studies, indicating its reliability in producing high-quality fused images suitable for various remote sensing studies, including vegetation and land use/land cover classification mapping [21, 22]. Moreover, the Gram-Schmidt method is computationally efficient, allowing for faster processing times without compromising the quality of the output images. This efficiency is particularly beneficial when working with large datasets, as it enables researchers to obtain high-resolution images quickly, facilitating timely analysis and decision-making [18].

3.2. Support vector machine

SVM is a powerful supervised machine learning method primarily utilized for classification studies, although it can also be applied to regression problems. SVM works by finding the optimal hyperplane that separates data points of different classes in a high-dimensional space. The key idea is to maximize the margin between the closest points of each class, known as support vectors. This approach allows SVM to create a robust decision boundary that generalizes well to unseen data, making it particularly effective in scenarios with high-dimensional feature spaces [23].

One of the significant advantages of SVM is its ability to handle linear and non-linear classification problems using kernel functions. These kernels transform the input data into a higher-dimensional space where a linear separation is possible, even if the original data is not linearly separable. Common kernel functions include sigmoid, radial basis function (RBF), and polynomial kernels, which provide flexibility in modeling complex relationships within the data [23, 24]. Additionally, SVM is known for its robustness against overfitting, especially in high-dimensional spaces, due to its structural risk minimization principle, which balances model complexity and training error [25]. Its ability to work well with small to medium-sized datasets while maintaining high accuracy makes it a popular choice among researchers and practitioners. Furthermore, SVM's performance can be enhanced through techniques such as parameter tuning and the use of ensemble methods, further solidifying its position as a leading algorithm in the machine-learning community [26]. In the study, RBF kernel was used and kernel scale was 1.

4. Results and Discussion

In this study, a high spatial resolution sharpened MS color image was created by combining the spectral resolution of multispectral (MS) bands (Band 1-7) with the high spatial resolution of the panchromatic band (Band 8) of Landsat 8 OLI satellite imagery by pan-sharpening process. The pan-sharpening process was performed using the Gram-Schmidt method. One of the advantages of this method is that multi-band data can be processed at once. MS image in RGB band combination (Fig. 4a), panchromatic band image (Fig. 4b), and pan-sharpened image (Fig. 4c) are seen in Fig. 4.

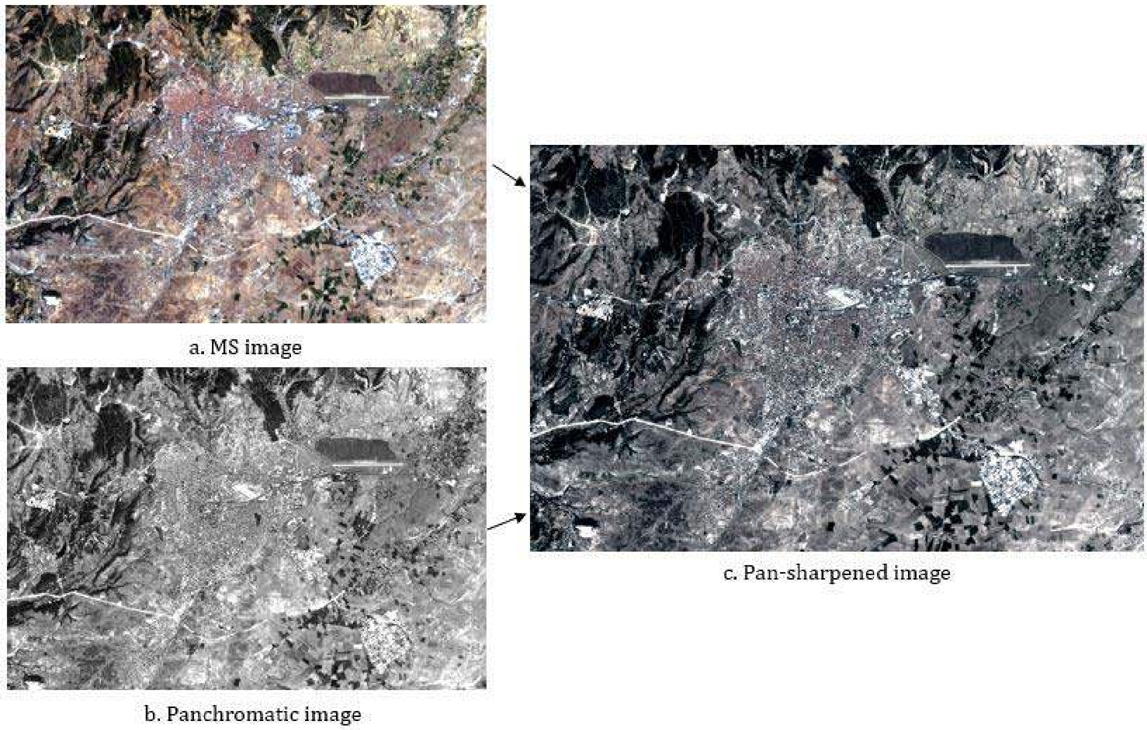

Fig. 4 a. MS image, b. Panchromatic image, c. Pan-sharpened image

The classification process was performed based on the pixel-based supervised classification approach. ISA and other areas were distinguished using the SVM method, which is one of the machine learning methods. The MS and pan-sharpened classification images are shown in Fig. 5. The classification process was analyzed using the general accuracy and kappa quantitative evaluation metrics. The obtained quantitative evaluation results are shown in Table 1.

Table 1. Classification accuracies

Dataset	Overall Accuracy	Kappa
MS image	90%	80%
Pan-sharpened image	92.5%	85%

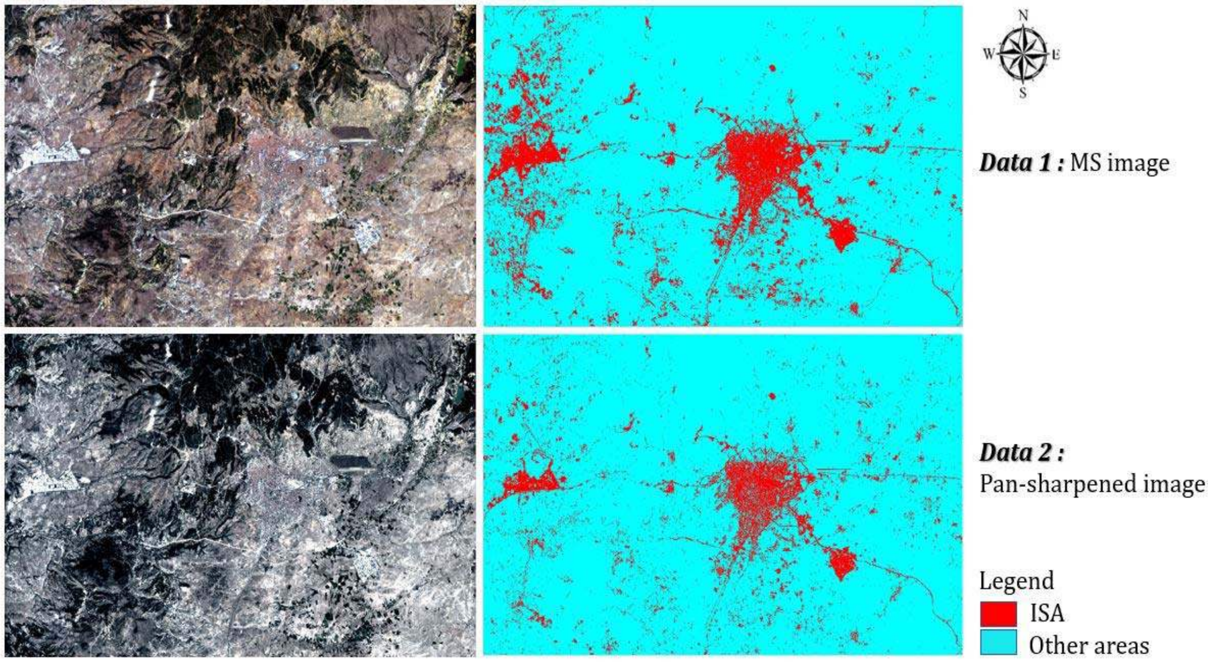

Fig. 5. Classified MS and pan-sharpened images

When the classification images (Fig. 5) are examined, it is seen that the ISA and other areas obtained with the pan-sharpened classification image (Data 2) are more accurate than those obtained with the MS classification image (Data 1) in urban areas. Hence, pan-sharpened image provided more distinct boundaries for ISA detection. The classification performance improved, particularly in areas of urban density. When the quantitative results (Table 1) are examined, it is determined that the overall accuracy of the pan-sharpened image is 2.5% higher than the classification accuracy of the MS image, and the kappa statistic value is 5% higher. In other words, the overall accuracy and kappa value were calculated as 92.5% and 85%, respectively. These results demonstrate that the pan-sharpening process positively impacts classification accuracy by enhancing spatial resolution. The increase detected in the kappa statistic value indicates a significant improvement in the reliability of the classification. According to the results obtained from the study, it is understood that the ISA located in the center and west of the image can be detected more accurately as the spatial resolution increases.

In this study, it has been shown that the detection of ISA using satellite images with increased spectral resolution by Gram-Schmidt panchromatic sharpening gives successful results. Some studies have supported that this method can significantly improve classification accuracy when applied to various land cover classifications, including wetlands, forests, and urban areas [20, 27]. Furthermore, the Gram-Schmidt method has been compared with other pan-sharpening techniques, such as the Brovey transform and Principal Component Analysis (PCA), revealing its superior performance in terms of spectral fidelity and spatial resolution [20]. Studies have shown that the Gram-Schmidt method can effectively reduce artifacts commonly associated with other pan-sharpening methods, making it a reliable choice for producing high-quality fused images [28]. However, the application of panchromatic sharpening is not without challenges. Park, Kim [29] noted that while high-spatial-resolution multispectral images produced through pan-sharpening techniques can enhance visual interpretation, they may also distort the spectral information of the original images, complicating analyses that depend on accurate spectral characteristics. This distortion can lead to misclassification in certain contexts, particularly when the spectral properties of the land cover classes are closely related. Consequently, it is crucial to carefully select and evaluate the panchromatic sharpening algorithms used, as different methods can yield varying results in classification accuracy relying on the specific characteristics of the study area [30].

5. Conclusion

Determination of ISA is an important and frequently monitored situation for the protection and management of the natural environment and monitoring of urban development. The expansion of impervious surfaces due to urbanization poses significant challenges for hydrological cycles and urban environmental quality. The integration of advanced monitoring techniques, particularly remote sensing, is crucial for addressing these challenges and informing sustainable urban planning and design practices. The integration of panchromatic sharpening techniques in satellite image classification studies has demonstrated significant potential for enhancing accuracy across various machine learning algorithms.

This study evaluated the effectiveness of remote sensing technologies for detecting ISA in urban settings. In this study, ISA in the city center of Uşak were analyzed using a pixel-based classification approach. Two different data sets were created, multispectral and pan-sharpened. The effect of the data set used on the classification result was investigated. High spatial resolution images obtained utilizing the Gram-Schmidt pan-sharpening method provided significant advantages in improving classification accuracy for ISA detection. The image classification process was performed using the SVM method, one of the most popular machine learning methods. Comparisons between multispectral and pan-sharpened images showed that pan-sharpening yielded a 2.5% higher overall accuracy and a 5% higher kappa value. This method offers a robust tool for ISA detection and environmental management, especially in areas with high urban density. The study provides foundational insights for environmental sustainability, urban planning, and natural resource conservation.

While the benefits of improved spatial resolution are evident, researchers must remain vigilant regarding the potential for spectral distortion and its implications for classification outcomes. Continued exploration of advanced panchromatic sharpening methods may further refine the balance between spatial enhancement and spectral fidelity, ultimately leading to more reliable remote sensing applications. Future research can explore the efficacy of pan-sharpening with alternative satellite datasets and classification methods on a broader scale.

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