PREPROCESSING METHODS FOR REMOTE SENSING IMAGES FOR TRAINING CLASSIFICATION MACHINE LEARNING MODELS AND ALGORITHMS

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K E Y W O R D S

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A B S T R A C T

Remote sensing images are widely used for land cover analysis, environmental monitoring, agricultural assessment, urban mapping, and object classification. However, raw images obtained from satellite, UAV, or aerial platforms often contain geometric distortions, radiometric inconsistencies, noise, shadows, and spectral variations that can reduce the accuracy of machine learning-based classification models. This paper analyzes the main preprocessing methods used to prepare remote sensing images for classification tasks, including geometric correction, radiometric correction and normalization, noise reduction and enhancement, and cloud-shadow masking. The study compares image conditions before and after preprocessing through visual analysis and demonstrates how these methods improve image clarity, feature consistency, class separability, and the reliability of training data for machine learning models.

1. Introduction

Remote sensing technologies provide valuable spatial and spectral information for observing and analyzing the Earth's surface. Images obtained from satellite, UAV, and aerial platforms are widely used in agriculture, environmental monitoring, urban mapping, land cover analysis, and disaster assessment. In machine learning-based classification, such images are used to identify vegetation, water bodies, soil areas, roads, buildings, and other surface objects. However, raw remote sensing images often contain geometric distortions, atmospheric effects, illumination differences, sensor noise, shadows, and spectral inconsistencies. These factors may reduce the quality of training data and negatively affect the performance of classification algorithms such as Support Vector Machine, Random Forest, Decision Tree, k-Nearest Neighbors, Gradient Boosting, and neural network-based models. For this reason, preprocessing is an essential stage before training machine learning models on remote sensing images. This study analyzes the main preprocessing methods used for remote sensing images, their logical sequence, and their advantages in classification model training. Special attention is given to the comparison of image conditions before and after preprocessing through visual analysis, showing how preprocessing contributes to clearer class boundaries, improved feature quality, and more accurate machine learning-based classification.

2. Materials and Methods

This study focuses on the preprocessing of remote sensing images before training machine learning-based classification models. The main purpose of the methodology is to transform raw remote sensing images into a more consistent, corrected, and informative dataset suitable for classification tasks. In this work, four main preprocessing methods are considered: geometric correction, radiometric correction and normalization, noise reduction and image enhancement, and cloud, shadow, and irrelevant region masking. These methods were selected because they directly influence the spatial accuracy, spectral consistency, visual quality, and reliability of training samples used in classification algorithms.

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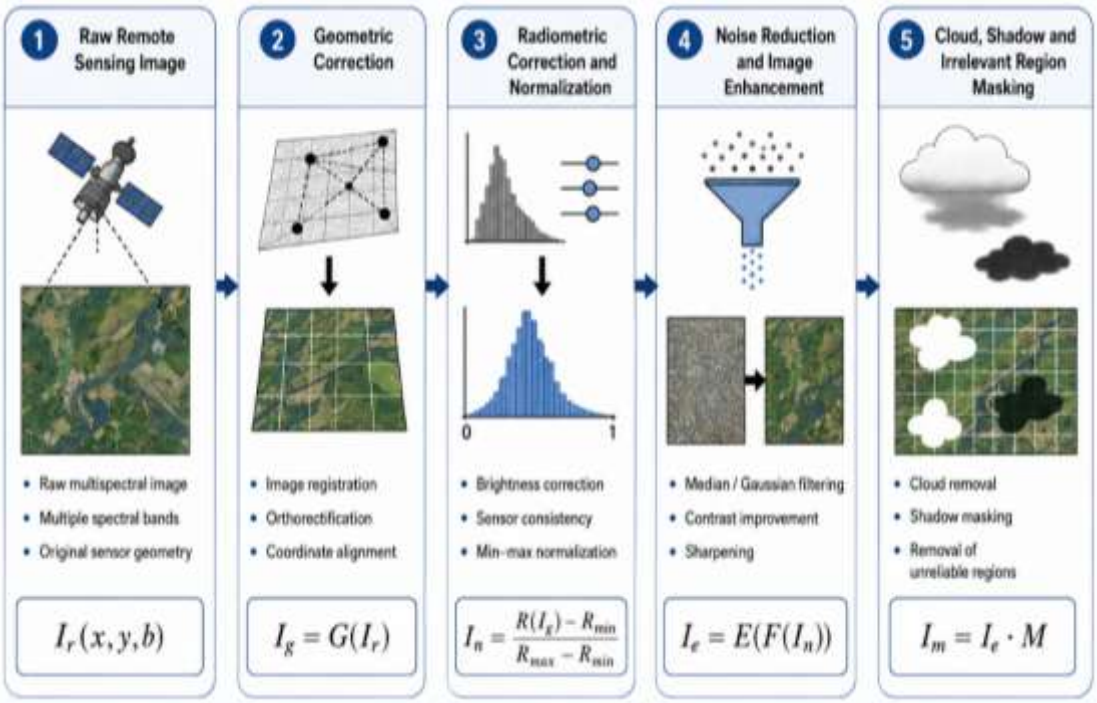


Figure 1. *The general preprocessing workflow used in this study can be represented as follows:*

This sequence was selected by us because each preprocessing stage depends on the quality of the previous one.

2.1. Geometric Correction

Geometric correction is the first preprocessing method considered in this study. Remote sensing images obtained from satellites, UAVs, or aerial platforms may contain spatial distortions caused by sensor movement, terrain relief, platform instability, viewing angle, or Earth curvature. The main task of geometric correction is to align the remote sensing image with a reference coordinate system. This process may include image registration, orthorectification, coordinate transformation, and resampling. In machine learning-based classification, geometric correction is important because each pixel or object must correspond to the correct land cover class. If the image is not geometrically corrected, the training labels may be assigned to incorrect regions, which can lead to model errors during the learning process.

In this research, geometric correction is considered as a preprocessing stage that improves the spatial reliability of image data. The corrected image can be expressed as:

$$I_g = G(I_r)$$

where I_r is the raw remote sensing image, $G(\cdot)$ represents the geometric correction function, and I_g is the geometrically corrected image. After this stage, the image becomes more suitable for extracting training samples and comparing different image layers or time periods.

2.2. Radiometric Correction and Normalization

Radiometric correction and normalization are used to improve the spectral consistency of remote sensing images. Raw images may contain differences in brightness and pixel intensity values caused by sensor characteristics, sun angle, atmospheric conditions, acquisition time, and surface reflectance variability. These differences may cause the same land cover class to appear differently in different images. For example, vegetation may appear darker or brighter depending on illumination and sensor conditions, even if its actual condition has not changed.

After radiometric correction, normalization is applied to bring pixel values or extracted features into a common numerical scale. One commonly used method is min–max normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

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where X is the original pixel or feature value, $X_{min}$is the minimum value, $X_{max}$is the maximum value, and $X_{norm}$is the normalized value. This transformation scales the values into a fixed range and makes them more suitable for machine learning algorithms. The corrected and normalized image can be represented as:

$$I_n = N(R(I_g))$$

where I_g is the geometrically corrected image, $R(\cdot)$ represents radiometric correction, $N(\cdot)$represents normalization, and I_n is the normalized image.

Radiometric correction and normalization improve model training by making spectral features more stable and comparable. This reduces the risk of incorrect classification caused by illumination differences and improves the generalization ability of the model when applied to new remote sensing images.

2.3. Noise Reduction and Image Enhancement

Noise reduction and image enhancement are applied to improve the visual and structural quality of remote sensing images. Noise may appear in images due to sensor limitations, atmospheric interference, data compression, transmission errors, or environmental conditions during image acquisition. In classification tasks, noise can create false patterns and reduce the separability between different land cover classes.

The general noise reduction process can be expressed as:

$$I_f = F(I_n)$$

where $I_n$is the normalized image, $F(\cdot)$represents the filtering operation, and $I_f$is the filtered image. Image enhancement is then used to improve the visibility of meaningful features. Enhancement methods may include contrast adjustment, histogram equalization, sharpening, and band combination. These techniques help make class boundaries clearer and improve the distinction between visually similar objects.

The enhanced image can be represented as:

$$I_e = E(I_f)$$

where $E(\cdot)$ represents the enhancement operation and I_e is the enhanced image.

The main advantage of noise reduction and image enhancement is that they improve the quality of input data before feature extraction and model training. A cleaner and visually clearer image allows classification algorithms to learn more meaningful patterns.

2.4. Cloud, Shadow, and Irrelevant Region Masking

Cloud, shadow, and irrelevant region masking is used to exclude unreliable areas from the training dataset. Remote sensing images, especially satellite images, may contain clouds, cloud shadows, water reflections, dark regions, overexposed areas, or non-target background objects. These areas may not represent the actual land cover classes and may introduce incorrect information into the classification process.

The general masking process can be written as:

$$I_m = I_e \cdot M$$

where $I_e$is the enhanced image, $M$is the binary mask, and $I_m$is the masked image. In this case, reliable pixels are usually assigned a value of 1, while unreliable or irrelevant pixels are assigned a value of 0. As a result, only valid regions are used for further dataset preparation and classification.

2.5. Dataset Preparation for Machine Learning Classification

After applying the four preprocessing methods, the corrected image is transformed into a structured dataset suitable for machine learning algorithms. At this stage, pixels, segments, or image patches are selected as samples. Each sample is described by a set of features such as spectral band values, normalized pixel values, vegetation indices, texture features, or spatial characteristics. The dataset can be represented as:

$$D = \{(x_i, y_i)\}_{i=1}^{n}$$

where $x_i$represents the feature vector of the i-th sample, $y_i$represents its class label, and $n$is the total number of samples. The prepared dataset is divided into training, validation, and testing subsets. In this research, preprocessing is considered as an essential stage before applying classification algorithms such as Random Forest,

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Support Vector Machine, Decision Tree, k-Nearest Neighbors, and Gradient Boosting.

3. Results

In this section, the effects of the selected preprocessing methods were analyzed using several remote sensing images obtained from different surface conditions. The obtained results show that preprocessing improves the spatial consistency, spectral stability, visual clarity, and reliability of remote sensing images before they are used for machine learning-based classification.

3.1. Result of Geometric Correction

At the first stage, geometric correction was applied to reduce spatial distortions in the remote sensing images. In this study, geometric correction was performed by applying a perspective transformation based on selected control points. The result showed that the corrected image became more spatially aligned and suitable for further preprocessing. After this correction, object boundaries such as roads, vegetation plots, water areas, and field borders became more consistent with the expected geometric structure.



Figure 2. Before and after images of Geometric Correction

3.2. Result of Radiometric Correction and Normalization

At the second stage, radiometric correction and normalization were applied to reduce brightness differences and improve the consistency of pixel values. These variations can negatively affect classification because the same land cover class may have different pixel values in different images. The visual result showed that vegetation, soil, water, and built-up regions became more distinguishable after normalization. Therefore, radiometric correction and normalization improved the spectral quality of the image and prepared it for more reliable feature extraction.

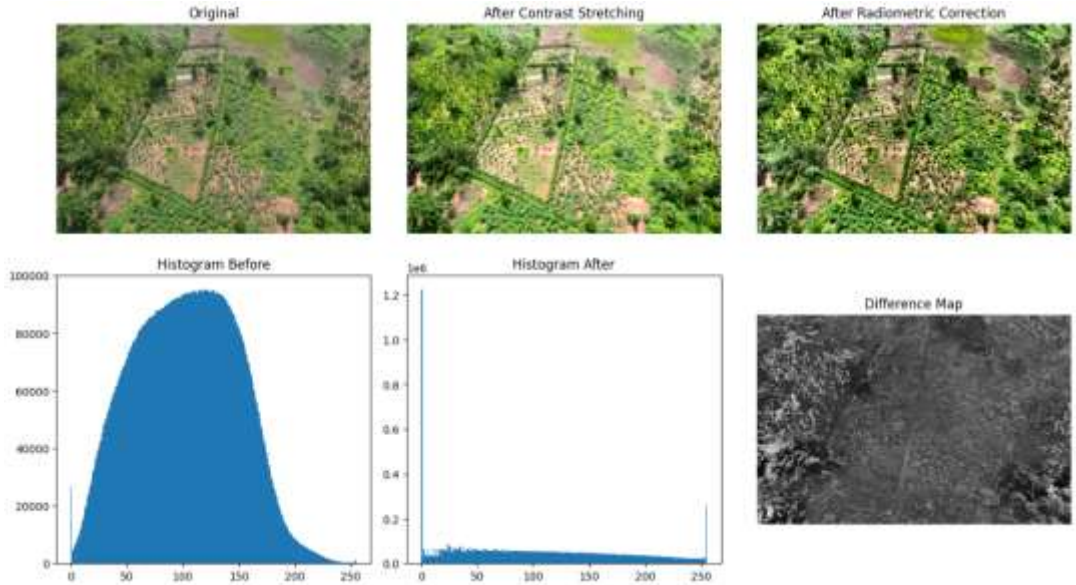


Figure 3. *The all contrasts resulting normalization*

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3.3. Result of Noise Reduction and Image Enhancement

At the third stage, noise reduction and image enhancement methods were applied to improve the visual quality of the images. In raw remote sensing images, noise may appear due to sensor limitations, atmospheric influence, compression artifacts, or acquisition conditions. If noisy images are directly used for training, the classification model may learn irrelevant variations instead of meaningful class features. In this research, Gaussian filtering was used for noise reduction, and contrast enhancement was applied to improve the visibility of object boundaries. The result showed that small random noise was reduced, while larger land cover structures remained visible. After enhancement, roads, vegetation areas, open soil, and water boundaries became more distinguishable. This improved the visual separability of classes and supported the extraction of more reliable features.



Figure 4. Noise reduction and Enhancement results

3.4. Result of Cloud, Shadow, and Irrelevant Region Masking

At the fourth stage, masking was applied to remove unreliable regions such as clouds, shadows, and irrelevant areas. These regions may create false patterns in the training dataset. For example, cloud-covered areas may be incorrectly classified as bright surfaces, while shadow regions may be confused with water bodies or dark soil. Therefore, excluding such pixels is important before model training.

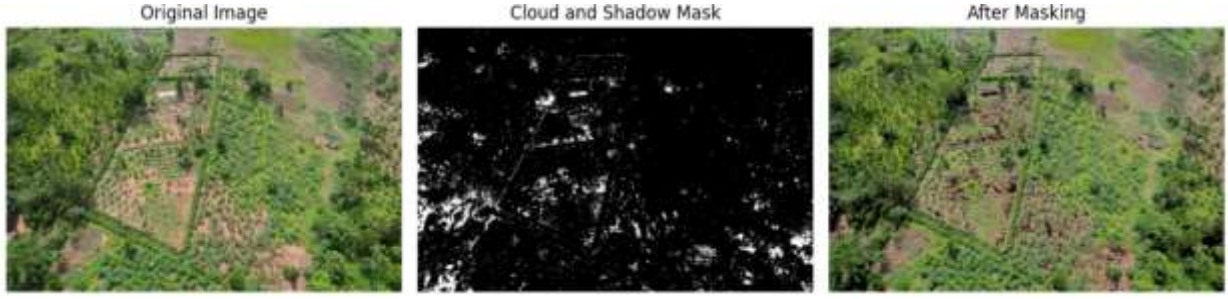


Figure 5. Resulting of Masking Process

5. Conclusion

This study examined the role of preprocessing methods in preparing remote sensing images for machine learning-based classification. The analysis focused on four main preprocessing stages: geometric correction, radiometric correction and normalization, noise reduction and image enhancement, and cloud, shadow, and irrelevant region masking. These methods were selected because they directly affect the spatial accuracy, spectral consistency, visual quality, and reliability of training data used in classification models. Based on the obtained results, preprocessing should be considered not as an optional technical step, but as a necessary methodological stage in remote sensing image classification. Future research may extend this work by evaluating the quantitative impact of each preprocessing method on classification accuracy using different machine learning algorithms such as Random Forest, Support Vector Machine, Gradient Boosting, and deep learning-based models.

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