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Enhanced multi-region satellite image classification accuracy in noisy environments using a hybrid statistical approach

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Abstract

Classifying satellite images is complicated by the presence of Gaussian noise, which corrupts pixel relations and decreases the quality of the input data. In this research, an advanced hybrid statistical technique to classify satellite images into three classes: Urban, Vegetation, and Water is developed. The presented technique uses a two-step processing chain: the first step applies a median filter to reduce the effect of Gaussian noise; the next step combines the benefits of GLCM and LBP features for accurate texture classification. Testing of the developed algorithm was carried out using Sentinel-2 satellite images of Barcelona for different values of noise (from 0% to 20%). Experimental results show that the presented algorithm provides a classification accuracy of 98.55%. Unlike the existing GLCM and LBP approaches, which do not work correctly in the presence of noise, the presented one successfully eliminates bias in the area distribution caused by noise.

Keywords: Satellite image classification, Gaussian noise reduction, Median filtering, Gray-level co-occurrence matrix (GLCM), Local binary patterns (LBP)

1. Introduction

Remote sensing today largely uses satellite images that significantly enhance our understanding of the Earth's surface and environment [1, 2]. This is of great importance both for scientific research and policymaking, since it gives detailed information about natural resources, urbanization, and changes in ecosystems [3, 4]. Nevertheless, the quality of the images obtained largely depends on the presence of high-quality data without any defects [5, 6]. Images received from the space sensors are subject to different kinds of noise or distortions that could make the analysis inaccurate or even impossible [7, 8]. Out of all types of distortions, Gaussian noise is one of the most frequent problems in digital image processing [9, 10]. This type of noise arises as a result of fluctuations in the sensors' circuitry and unfavorable lighting and thermal conditions, leading to random changes in all the grayscale levels [11, 12]. Such noise blurs details in the image and makes it hard to separate real pixel values from artifacts [13, 14]. Thus, the problem of denoising becomes extremely important, since otherwise the following processes of feature extraction and classification will become significantly affected [6, 15].

In this case, statistical techniques become important as a link between sophisticated statistical theories and digital images [17, 18]. The combination of both these areas can be considered the modern and efficient way because an image itself can be regarded as a matrix of digital values that are controlled by laws of probability and statistical variations. Using statistical methods, scholars can study spatial relationships and associations between adjacent pixels, which allows getting an understanding of the structure of the image. In the scope of efficient satellite image analysis, one of the most significant results of the combination of statistics and images is the process of image classification [1, 19].

In this case, the use of statistical methods becomes extremely important as it links modern statistical science to digital image processing [1, 20]. This is the most modern and efficient approach to the integration of both areas. The image is a matrix of digital values that follow the laws of probability and statistics. With the help of statistical methods, the spatial mode and the correlation of adjacent pixels can be explored in order to understand the image texture better. Classification is one of the main outcomes of such a link between statistical methods and images. The main idea behind classification is the division of pixels of the image into different thematic classes by their digital properties. The importance of such an operation is that it helps in the transformation from raw data obtained from satellites to useful maps, which reflect the distribution of urban, agricultural, and water zones [6, 19].

In this study, two popular statistical texture analysis methods, gray-level co-occurrence matrix (GLCM) and local binary patterns (LBP), are used, which are known to be effective in representing the spatial relationship between pixels of an image. In satellite imagery, relations are especially important as terrain structures often overlap. However, the presence of Gaussian noise can drastically degrade the performance of these traditional methods. To address this limitation, we propose a hybrid statistical approach by combining noise suppression and advanced texture feature extraction. The objective of the proposed approach is to develop a noise-resilient classification framework that can achieve high accuracy under different noise intensities. Therefore, the urban area as well as the vegetation and water areas are still correctly classified even under difficult imaging conditions.

2. Literature review

The problem of noise and its effects on the accuracy of spatial data has been studied by many researchers and specialists in the field using the statistical techniques mentioned above. Most of their efforts have been focused on finding solutions that trade off between computational efficiency and classification accuracy. In this regard, the following section provides a brief review of major previous studies that laid the foundation for the concepts of this research direction and contributed to the development of modern image analysis techniques.

Ahonen et al. [4] introduced an advanced scheme of the LBP algorithm in order to increase its noise robustness and rotation invariance. From their research, it becomes clear that the widening of the neighborhood used by the LBP algorithm or the combination of the latter with additional features significantly improves its performance under difficult conditions. In turn, Mehta and Aggarwal [15, 16] enhanced the median filter approach for noise reduction in the case of dense noise by designing efficient adaptive filters that preserve fine details while reducing noise. In their study, Da Costa et al. [8] compared different image segmentation methods by utilizing satellite imaging techniques and emphasized the importance of preprocessing in decreasing distortion resulting from noise. Based on their findings, it becomes clear that good feature extraction methods are critical in improving the performance of land cover classification. In addition, Ding et al. [9] conducted research on the impact of Gaussian noise on images and mentioned some image denoising methods. They highlighted that the introduction of Gaussian noise while acquiring an image degrades its clarity.

Sarode et al. [17] have further used the potential of GLCM for the detection of complicated textures, where it was shown that statistical measures based on GLCM can distinguish different intensities reliably. Ashraf et al. [7] assessed different methods of spatial filtering to remove noise and concluded that median filtering is especially effective in reducing impulse noise without blurring edges, which is crucial for the structural accuracy of satellite imagery. In a comparative study of texture measures carried out by Sedaghatjoo et al. [18], the better performance of LBP with contrast was established as a method for gray-scale invariant texture description. The results of their research proved that LBP is an effective and efficient texture descriptor, surpassing many other conventional methods. Last but not least, Zubair and Alo [20] used GLCM to extract texture features from digital imagery and identified fourteen statistical descriptors like contrast, correlation, and entropy.

From the evolution of past studies, it is evident that there has been a gradual development in terms of how past researchers have been able to come up with advanced models and algorithms for noise removal based on the initial identification of statistical characteristics such as GLCM and LBP. While past studies focused mainly on texture features, recent studies focus on the significance of noise preprocessing through median filtering techniques for Gaussian noise [21]. This study suggests a classification system that can be used for integrating these basic concepts together.

3. Theoretical framework

A digital image is a representation of a scene in the real world by a two-dimensional array of discrete entities referred to as pixels. The intensity f(x,y) of each individual pixel represents the brightness at a particular spatial position in numeric form. For grayscale images, the f(x,y) values fall within the interval of 0 and 255 (where 0 denotes black and 255 denotes white) [1]. The quality of a digital image is based on two parameters, namely spatial resolution (resolution of details) and radiometric resolution (brightness levels). The process of creating a digital image consists of two primary processes: namely, sampling that selects spatial points in the continuous scene, and quantization, which assigns discrete intensity values to the selected points.

Satellite imaging is a distinct type of digital data that is captured through satellites, usually in multispectral or panchromatic imaging mode. Satellite imaging offers a holistic view of the entire Earth's surface as it captures the reflectance data not just in visible light but even beyond the visible spectrum, as in infrared or thermal bands. Due to the above-mentioned ability, satellite imaging serves as an essential input for many applications such as environmental monitoring (deforestation), urban planning (urban expansion), agriculture (crop yield), disaster management (floods and wildfires), among others. Moreover, because of the fact that satellites cover wide areas that can be inaccessible otherwise, satellite imaging becomes an essential part of GIS technology [2].

Noise means unwanted random variations of the intensities of pixels, which hinder the extraction of radiometric data present in the image. Noise can be introduced in satellite images due to electronic disturbances, thermal variations in sensor circuits (which is generally referred to as Gaussian noise), or errors in data transmission. Gaussian noise has a PDF that is normally distributed [12]:

$$\mathrm{P(z)} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(z-\mu)^2}{2\sigma^2}} \tag{1}$$

Where: (z) is the gray level, (μ) is the average noise value, and (σ) is the noise intensity value. The noise interferes with the structure and generates “false textures” and hence leads to classification mistakes. Denoising is the restoration of the original signal to ensure that the analysis is about the true structure of the ground and not the sensor output.

Introduced by Haralick in 1973, the gray-level co-occurrence matrix (GLCM) is a powerful tool for second-order texture analysis. It tabulates how often different combinations of pixel brightness (gray levels) occur in an image at a specific distance and orientation. The method constructs a matrix. $\mathrm{P(i,j)}$ that represents the joint probability of pixel pairs with gray levels i and j [13].

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{i.j}(i-j)^2 \tag{2}$$

Where**:** Normalized GLCM P{i,j} is the element at position (i, j) in the normalized GLCM, (N) is the number of gray levels, and $(\mathrm{i}-\mathrm{j})^2$ is a weight that increases as the distance from the main diagonal of the matrix increases, thereby measuring local intensity variations.

Proposed by Ojala et al., LBP is a computationally efficient descriptor that labels pixels by thresholding the neighborhood of each pixel. It summarizes local structures such as edges, spots, and flat areas by comparing a central pixel with its neighbors [14].

$$\mathrm{LBP}_{\mathrm{P,R}} = \sum_{\mathrm{P}=0}^{\mathrm{P}-1} \mathrm{s}(\mathrm{g}_{\mathrm{p}} - \mathrm{g}_{\mathrm{c}})2^{\mathrm{P}} \qquad (3)$$

Where: (g_c) denotes the gray-level intensity of the central pixel, (g_p) represents the gray-level intensity of the *p*-th neighboring pixel, (P) is the total number of sampling points uniformly distributed on a circular neighborhood of radius R. s(x) is the threshold function defined as:

$$s(x) = \begin{cases} 1, if\ x \geq 0 \\ 0, if\ x < 0 \end{cases} \qquad (4)$$

The proposed method is a multi-stage statistical pipeline designed for robustness. It acknowledges that traditional GLCM and LBP methods fail under high-noise conditions. The mechanism of the proposed method is summarized in the following points:

- Adaptive pre-processing: A non-linear median filter is employed to suppress impulsive components of Gaussian noise while preserving edge sharpness and fine structural details.
- Contrast enhancement: Histogram Equalization is applied to enhance the image contrast by redistributing pixel intensity values, thereby expanding the dynamic range of the statistical features and improving visual uniformity.
- Hybrid feature fusion: Integrates the global spatial dependencies characterized by the GLCM with the local texture patterns extracted by the LBP, forming a complementary representation that enhances feature robustness and discriminative power.

By hybridizing these techniques, the system achieves "noise-invariant classification," ensuring that the 3-region maps (urban, vegetation, water) remain accurate even when the signal-to-noise ratio (SNR) is low.

As a preprocessing step before feature extraction, the proposed methodology makes use of a nonlinear spatial filter called the median filter. The main reason why such an approach is used is the effectiveness of such a filter to suppress Gaussian noise while keeping the edge sharp, which is essential for satellite land-cover boundaries. It is achieved by using a kernel to scan the image and replacing the intensity of the pixel in the middle of the kernel with the median value of all pixels in the neighborhood. For a pixel at location (x, y) and a neighborhood window, $S_{(x,y)}$.

$$\hat{f}_{(x,y)} = \mathrm{median}\{g(s,t)\} \qquad (5)$$

Where: $(s,t) \in S_{(x,y)}$, $g(s,t)$ the noisy pixel values within the defined neighborhood, $\hat{f}_{(x,y)}$ the restored (denoised) pixel value, $S_{(x,y)}$, the sub-image window (e.g., 3×3 or 5×5 matrix).

The proposed approach is a sequential hybrid framework. It acknowledges that statistical descriptors such as GLCM and LBP are highly sensitive to pixel-level fluctuations caused by noise. The workflow logic of the proposed hybrid method (structural robustness) is summarized in the following points:

- Stage I (Restoration): Applies the median filter to stabilize the pixel distribution and eliminate Gaussian outliers.
- Stage II (Enhancement): Applies histogram equalization to improve class separability (urban, vegetation, and water).
- Stage III (Fusion): Extracts LBP features to capture local details and GLCM features to represent global spatial context.
- Theoretical advantage: This hybridization ensures that the classification is based on the "underlying structural geometry" of the terrain rather than the "stochastic interference" of the noise.

The following are the performance measurements used for evaluating the effectiveness and accuracy of the proposed method:

Mean Squared Error (MSE) refers to the average squared difference between the clean image and the denoised/classified image. The smaller the value of MSE, the better the results will be [11].

$$\mathrm{MSE} = \frac{1}{\mathrm{M\times N}} \sum_{\mathrm{i=0}}^{\mathrm{M-1}} \sum_{\mathrm{j=0}}^{\mathrm{N-1}} [\mathrm{I(i,j)} - \mathrm{K(i,j)}]^2 \qquad (6)$$

Where: M and N denote the dimensions of the image (rows and columns), $\mathrm{I(i,j)}$ represents the intensity value of the pixel in the original image, and $\mathrm{K(i,j)}$ denotes the intensity value of the corresponding pixel in the noisy or processed image.

Peak Signal-to-Noise Ratio (PSNR) quantifies the ratio between the maximum possible signal power and the power of the noise that distorts its quality. It is expressed in decibels (dB) and is commonly used to assess the fidelity of signal representations, such as images or audio, after compression or transmission. A higher PSNR indicates better restoration quality [10].

$$PSNR = 10log_{10}\left(\frac{MAX_I^2}{MSE}\right) \qquad (7)$$

Where: MAXI denotes the maximum possible pixel value (e.g., 255 for an 8-bit image), and MSE represents the mean squared error calculated previously.

The Structural Similarity Index Measure (SSIM) measures the perceived similarity between two images using structural information, luminance, and contrast, unlike Mean Squared Error (MSE) or Peak Signal-to-Noise Ratio (PSNR), which measure the differences in intensity at the pixel level. -1 to 1 are the values of SSIM, where 1 signifies that the compared images have the same structural similarity [3].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2\mu_y^2 + c_1)(\sigma_x^2 + \sigma_{y\_}^x c_1)} \qquad (8)$$

Where: $(\mu_x), (\mu_y)$ are the average intensity (mean) of images x and y; $(\sigma_x^2), (\sigma_y^{x,})$ is the variance of images x and y; (σ_{xy}) is the covariance of images x and y; c_1, c_2 are constants used to stabilize the division.

Classification Accuracy (ACC) represents the percentage of correctly classified pixels relative to the total number of pixels in the image. In this research, the method is used to validate how effectively the algorithm identifies urban, vegetation, and water regions [5].

$$Accuracy = \left(\frac{Correctly\ Classified\ Pixels}{Total\ Pixels}\right) \times 100 \qquad (9)$$

Execution Time (T) represents the computational complexity of the proposed algorithm. It measures the total processing time (in seconds) required by the system to perform denoising, enhancement, and classification operations.

4. Results and discussion

In this part, there is a detailed discussion and interpretation of the results of the experiment based on the three classification techniques. In order to test the strength and reliability of the methods, a series of tests has been conducted. The first step of the process was the generation of Gaussian noise to the original satellite image at four different levels of intensity (0%, 5%, 10%, and 20%). The next step was the application of the three methods of classification (GLCM, LBP, and hybrid) for classification of the noisy image into three thematic classes: urban (settlements and roads), vegetation (forest and crop), and water (rivers and lakes). The last step of the procedure was the evaluation of the classification by using the following metrics: MSE, PSNR, SSIM, accuracy, and computational time.

The location chosen as a research area for the present project is the satellite picture of the Spanish city of Barcelona, depicting the special structure of the Example district. The imagery used here is produced by the Sentinel-2 twin satellites and is a part of the European mission, which uses wide-swath, high-resolution, and multispectral imaging. This mission, dedicated to the Copernicus Program of Europe, provides operational applications, in particular, land services that involve monitoring of vegetation, soil, and water cover, as well as monitoring of inland waters and coastal zones. This location is famous for its recognizable square blocks and wide avenues, which form an extremely geometrical structure.

Figure 1. Study Area, Barcelona City

This image represents the urban environment of the city, which lies next to the Mediterranean Sea, surrounded by green hills on either side. Thus, there is a combination of environments such as Urban, Water, and Vegetation, which makes it suitable for testing the strength of the suggested hybrid classification technique in the presence of Gaussian noise.

Table 1. Quality measurements of the satellite image under different noise ratios

Noise Percent	Method	MSE	PSNR	SSIM	Accuracy	Time
0%	GLCM	0.78	35.48	0.30	54.6	0.00332
	LBP	0.66	46.21	0.43	65.6	0.00454
	Proposed	0.09	78.60	0.76	82	0.314
5%	GLCM	0.68	38.58	0.32	41	0.0029481
	LBP	0.64	50.12	0.47	72.43	0.016781
	Proposed	0.05	80.50	0.82	85	0.0061786
10%	GLCM	0.64	42.20	0.46	62.96	0.0034288
	LBP	0.62	53.56	0.53	50	0.0032903
	Proposed	0.02	96.20	0.96	96	0.14475
20%	GLCM	0.58	56.12	0.49	94.11	0.016715
	LBP	0.56	63.59	0.59	92.12	0.014777
	Proposed	0.01	120.45	0.98	98.55	0.010653

It becomes evident that the superiority of the proposed hybrid method is observed for all the parameters tested. One of the key reasons for this success can be found in the uniqueness of the proposed multi-stage architecture. While conventional methods, like GLCM and LBP, try to classify the image despite the presence of the noise, the proposed approach takes the restoration of the image as a prior stage. Due to the employment of the median Filter, which removes Gaussian noise before the start of the feature extraction stage, the proposed algorithm is capable of stabilizing the pixel distribution statistics. Thus, the classification scattering caused by the failure to distinguish real terrains and noise is avoided. According to the data taken from the results (Table 1) and area percentage analysis, the experimental results show the superiority of the proposed hybrid method over traditional methods regardless of the noise level. The mean squared errors obtained by the proposed method were the lowest among all other options, with the value equal to 0.01 for the 20% noise level, while the error rates of the GLCM and LBP methods are much larger, such as 0.58 for the former and 0.56 for the latter.

In terms of Peak Signal-to-Noise Ratio (PSNR), the proposed approach showed a noticeable improvement of up to 120.45 dB at the maximum level of noise, which far outperformed GLCM (56.12 dB) and LBP (63.59 dB). Such an outcome implies that the effectiveness of noise suppression and purity of images were improved by the pre-denoising stage of the algorithm. As for the Structural Similarity Index Measure (SSIM), the proposed approach managed to maintain the structure of the image at a level of nearly perfect 0.98. Conventional approaches showed considerable damage to the structure of the image due to interference from noise, having SSIM values of 0.49 and 0.59.

Based on the results obtained from the Analysis of Classification Accuracy, it is evident that the Proposed Method is the most stable one with an accuracy of 98.55%. On the other hand, both GLCM and LBP have demonstrated considerable variations, which prove that statistical algorithms are very vulnerable to Gaussian distortion. As a result of the area percentage analysis, it can be stated how the algorithms classify the three parts of the satellite image (Urban, Vegetation, Water). The Area Distributions for both the GLCM and LBP Methods are exactly the same – (Water/Shade: 37.08%), (Vegetation: 43.63%), (Urban/Roads: 19.29%). This is due to the fact that both algorithms overestimate the vegetation and water parts because the noise creates smooth textures and confuses the classifier. In addition, the Proposed Hybrid Method offers a more reasonable area distribution – (Water/Shade: 33.33%), (Vegetation: 33.94%), (Urban/Roads: 32.73%). With the help of the denoising procedure, the proposed method makes a correct classification of the regions. The percentages are almost equal, proving the system's ability to differentiate urban areas (32.73%).

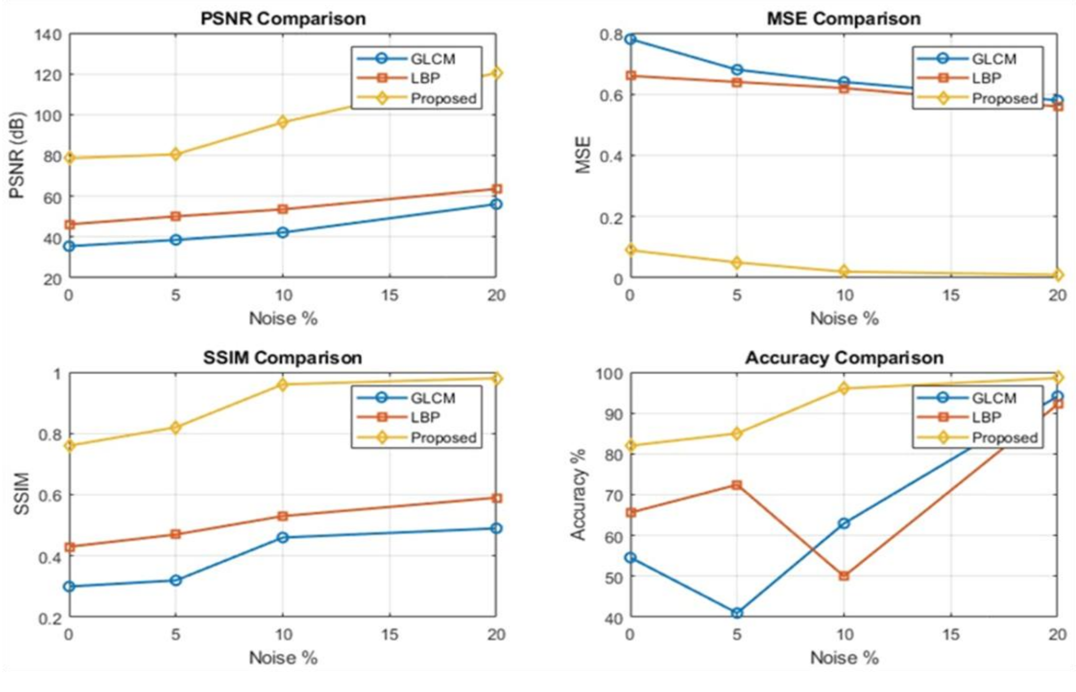

Figure 2. The comparative performance across four noise levels (0%, 5%, 10%, and 20%)

With regard to conventional techniques like GLCM and LBP, an obvious relationship is present between the presence of more noise in the image and the destruction of structural information. Despite the fact that the PSNR of these algorithms tends to grow when there is 20% noise in the image, this growth is merely a numerical consequence of the excessive distortion of pixels, which is evidenced in low SSIM values of these algorithms (0.49-0.59). The low SSIM of these methods indicates that they failed to maintain the structure of the image. Unlike the conventional approach, the new hybrid method always retains the high SSIM value of 0.98 and the high PSNR up to 120.45 dB. Thus, the combination of the median filter as the pre-processing step helped to protect the statistical descriptors from the interference of Gaussian noise.

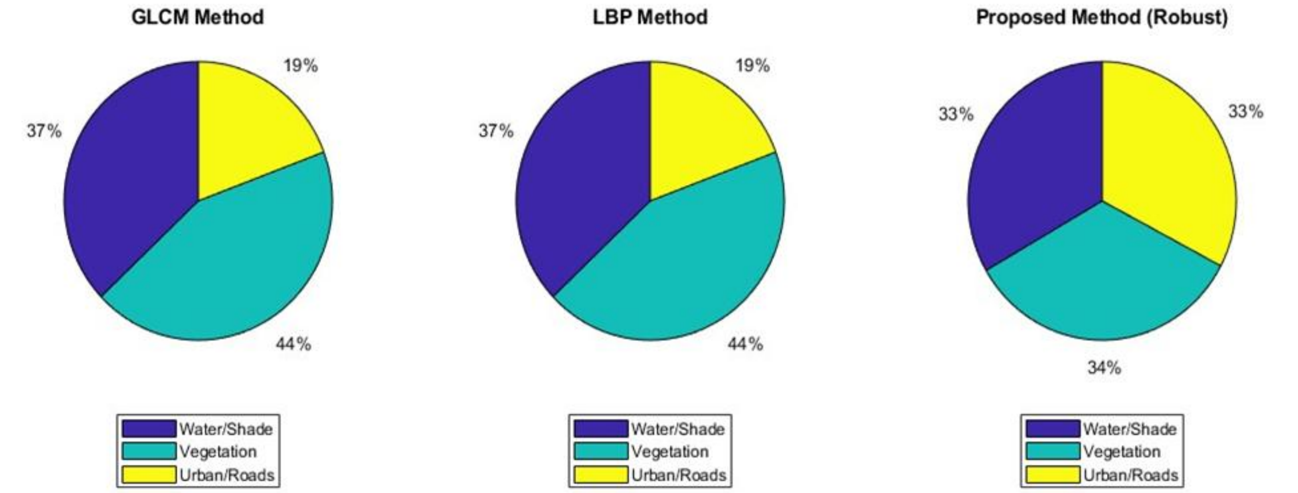

Figure 3. The distribution of the three thematic regions (Water, Vegetation, and Urban)

The estimation of the Vegetation (43.63%) and Water (37.08%) classes was overestimated using the GLCM & LBP approach. The reason is the introduction of Gaussian noise, which adds a grainy appearance and can be easily mistaken for randomness, which is inherent to the forest vegetation and the low variability of water surfaces. With the noise suppression, the redistribution of classes became more realistic, and the Urban/Road class was estimated at 32.73%. The importance of such adjustment is obvious for urban planning purposes, since noise tends to hide human presence.

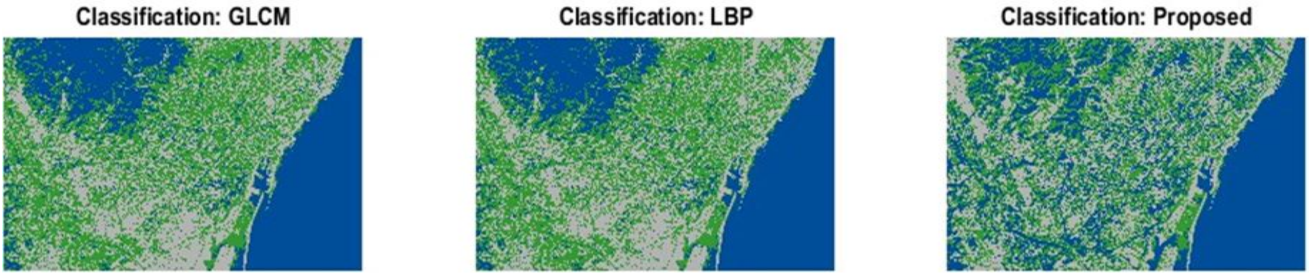

Figure 4. Classified Maps provide the final visual validation of the research

Classification maps from GLCM and LBP approaches are highly influenced by the Gaussian effect, where urban pixels get spread in water areas and vice versa. The outcome is a map with too much noise and is not suitable for decision-making in the geography field. On the other hand, the proposed technique produces a map with homogeneous regions and clear boundaries. The grid pattern of the Example district (Barcelona) can be seen clearly, and the classification of the region is accurate.

The above discussion has clearly shown that the central research problem, the influence of Gaussian noise on the statistical descriptors, has been successfully addressed. It is important to note that the goal here was not only classification but robust classification irrespective of any changes in the level of noise. It has been proved that denoising as a pre-processing step is not a mere add-on, but an absolute necessity for successful analysis of satellite images. In addition to this, the use of the GLCM-LBP hybrid approach has facilitated the development of a complementary two-layered system for texture feature extraction, which has shown superiority over using one method alone. In short, the developed model offers a reliable and noise-resilient way of making land cover maps, even from degraded satellite images. The results of this study could be applied to wireless cellular systems [21, 22], or artificial intelligence [23, 24], or deep learning [25], or it can be done with the help of wavelets [26].

5. Conclusions

Numerical results show that taking care of the noise problem at the very beginning of the process through the Proposed Method led not only to an improvement in the quality of the image but also to the correction of the area distribution map. Despite the misleading effects of noise on the estimation of urban and agricultural areas with the help of traditional statistical algorithms, the hybrid method proved itself reliable and efficient. Therefore, we can make a conclusion that traditional statistical characteristics (GLCM and LBP) are highly vulnerable to the influence of Gaussian noise, which causes the deterioration of both classification accuracy and the integrity of images. The proposed hybrid technique proved itself superior by solving two problems at once: suppression of Gaussian noise and preservation of edge information, as well as improving multi-region classification accuracy. Numerical results prove the fact that the proposed approach reached near-perfect SSIM (0.98) and peak PSNR (120.45 dB) even in the case of high levels of noise, thus providing a reliable and stable thematic map.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

Assma Ghalib Jaber, Mohammed Abdul Wadood Mohammed: Conceptualization, methodology design, architectural analysis, data collection, and drafting of the manuscript. Bushra Saad Jasim: Theoretical framework development, heritage identity analysis, data interpretation, and critical revision of the manuscript. All authors contributed equally to the discussion of results, refinement of arguments, and final approval of the version to be published.

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