

Fusion of Satellite and Drone Images for Identifying Water Bodies

Fusão de Imagens de Satélite e Drone para Identificação de Corpos D'água

Ariane Paula Barros^{1*}, Elizângela Jussara dos Santos¹, Fernanda Kristen da Silva Pedro¹, Dimas Augusto Mendes Lemes², José Picolo², Guilherme Ribeiro Sales¹, Valentino Corso¹, Cides S. Bezerra¹

Abstract: Mapping areas with water bodies is crucial for monitoring water systems and resource management, as well as for guiding urban expansion and land-use planning, thus contributing to sustainable resource management, flood prevention, and the conservation of aquatic ecosystems. While satellite images offer broad territorial coverage, drones provide high spatial resolution of the Earth's surface. In this research, the Pulse Coupled Neural Network (PCNN) [1] image fusion method and the GDAL Pansharpener method, the latter being available in QGIS, were compared to determine which is more effective in merging images to highlight water surface areas in a case study, combining the spectral coverage of satellites with the precision of drones. The implemented PCNN model was able to overcome QGIS Pansharpener method, which is based on Brovey algorithm, obtaining better metrics. This study of drone and satellite image fusion has shown to be a promising approach to overcome the limitations of these technologies when used individually.

Keywords: Image Fusion — Remote Sensing — Drone — Riverine Systems — High Resolution

Resumo: O mapeamento de áreas com corpos d'água é crucial para monitorar sistemas hídricos e gestão de recursos, bem como para orientar a expansão urbana e o planejamento do uso da terra, contribuindo assim para a gestão sustentável dos recursos, prevenção de inundações e conservação dos ecossistemas aquáticos. Enquanto as imagens de satélite oferecem uma ampla cobertura espectral, os drones fornecem alta resolução espacial da superfície da Terra. Nesta pesquisa, o método de fusão de imagens da Rede Neural Acoplada por Pulso (PCNN) [1] e o método de Pansharpener do GDAL, este último disponível no QGIS, foram comparados para determinar qual é mais eficaz na fusão de imagens para destacar áreas de superfície de água em um estudo de caso, combinando a cobertura espectral dos satélites com a precisão dos drones. O modelo PCNN implementado foi capaz de superar o método QGIS Pansharpener, que é baseado no algoritmo de Brovey, obtendo melhores métricas. Este estudo da fusão de imagens de drones e satélites mostrou-se uma abordagem promissora para superar as limitações destas tecnologias quando usadas individualmente.

Palavras-Chave: Fusão de Imagens — Sensoriamento Remoto — Drone — Sistemas Fluviais — Alta Resolução

¹ CPQD - Centro de Pesquisa e Desenvolvimento, Brazil

² Pontifícia Universidade Católica de Campinas (PUC), Brazil

*Corresponding author: arianepaulabarros2@gmail.com

DOI: <http://dx.doi.org/10.22456/2175-2745.143523> • Received: 24/10/2024 • Accepted: 02/12/2024

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1. Introduction

The study of fluvial systems, specifically rivers, lakes, and their beds, plays a crucial role in water resource management and the prevention of natural disasters [2]. Floodplain mapping represents an important tool for guiding urban expansion and land use planning, considering that mapping these areas allows for their delimitation and designation for appropriate uses [3]. Therefore, the precise monitoring of water resources is essential for sustainable resource management, flood pre-

vention, and the conservation of aquatic ecosystems.

The fusion of satellite and drone imagery emerges as a promising approach to overcome the limitations of using these technologies in isolation in watershed studies. Satellite imagery, despite their wide coverage, may not offer the necessary spatial resolution to capture finer details, while drones, despite their high resolution, are restricted by their limited range and the impact of atmospheric conditions [4].

In this paper, we focus on the fusion of satellite and drone

imagery to produce an image with better spacial and spectral resolution. Image fusion has the potential to combine the wide coverage and continuous availability of satellites with the detailed precision and flexibility of drones, offering an unique and enhanced perspective for hydrographic studies.

The practical applications resulting from this study are vast, ranging from improved watershed and water-related infrastructure management to contributing to environmental conservation efforts by facilitating more precise and detailed monitoring of changes in river courses, erosion, and sedimentation [5].

2. Theoretical reference

2.1 Remote Sensing and image fusion

Remote sensing is the technique of obtaining data and images of the Earth's surface using sensors installed on satellites and aircraft. These sensors capture information from a distance, allowing the observation and analysis of large areas without the need for direct contact [6]. Satellite images provide temporal and spectral coverage, while aerial photographs captured by drones, for instance, offer more details and spatial resolution. The fusion of information from both sources enables more efficient and detailed monitoring of specific areas, such as rivers, lakes and urban zones. By combining these images, it is possible to obtain a more comprehensive and accurate view, improving analysis and decision-making in water resource management, urban planning and environmental conservation [7].

3. Image fusion techniques

Image fusion is a technique used to combine multiple images into a single image that contains more complete and detailed information than the original images. In this context, the fusion of satellite and drone imagery [8] can improve spatial and spectral resolution, making the images more useful for various applications, such as environmental monitoring, urban planning and natural disaster detection.

Spectral fusion involves normalizing and stacking different spectral bands to highlight features not visible to the naked eye, such as the depth of lakes or the extent of flooded areas. The wavelet transform technique [9], with variations such as B-spline, Laplacian pyramid and Fourier space, are used to create images with high spatial and spectral resolution. The Gram-Schmidt spectral fusion technique [10] uses the Gram-Schmidt transformation to increase the spatial resolution of images, making water bodies more evident compared to non-fused imagery. While traditional image fusion techniques are highly effective, the evolution of technology and machine learning has brought new approaches that aim to further enhance the quality of fused images. Among these techniques are methods based on machine learning models, such as PCNN.

3.1 PCNN

Traditional methods used in geoprocessing software such as QGIS [11] rely on fixed, predetermined mathematical formulas to combine images. They are effective but limited by the rigidity of these formulas. In contrast, PCNNs are capable of learning and adapting based on image data. They adjust their parameters to achieve the best possible results, taking into account the specific characteristics of each image. This makes them more flexible and potentially more accurate in image fusion than traditional methods.

PCNN, inspired by the visual cortex of cats, was developed in 1994 by Johnson, adapting Eckhorn's model for image processing [19]. A PCNN structure adapts itself to optimize information extraction. It includes an input layer, which receives and prepares the image for processing and subsequent convolutional layers, where filters are applied to extract and enhance important features of the images. Although the application of PCNNs in the analysis of water indices such as NDWI (Normalized Difference Water Index) and MNDWI (Modified Normalized Difference Water Index) is still an emerging field of research, the approach has considerable potential to enhance the accuracy and clarity of the spectral information needed for these indices.

In this paper, this possibility was explored by applying PCNNs in image fusion followed by the implementation of NDWI and MNDWI [13].

3.2 Related works

In recent decades, significant advances have been made in the field of image fusion, mainly in remote sensing and environmental monitoring applications. Fusion techniques are essential to overcome the limitations of images obtained by different sensors, combining the high spatial resolution of images captured by drones with the vast spectral coverage provided by satellites.

Liu et al. [1] reviewed recent advances in the application of pulse-coupled neural networks (PCNN) to image processing. This technique has proven effective for image fusion due to its ability to adaptively extract and combine information from different sources. This study investigates the applicability of PCNN in various areas of image processing, including satellite and drone image fusion.

In addition, Castro and Alvim [2] discussed the impact of urbanization and hydrological risk management in the city of São Paulo, addressing how the combination of remote sensing technologies can assist in the identification and monitoring of areas subject to flooding. The use of image fusion techniques can complement this type of study by providing more precise and detailed data on the distribution and characteristics of flooded areas.

Figueiredo [3] carried out a study on the determination of flood spots using remote sensing images. The research showed how the use of multispectral image fusion techniques can be used to determine floodplains.

Huang et al. [4] reviewed the integration of remote sensing

and GIS (Geographic Information System) in monitoring river environments. They point out that the fusion of multispectral and panchromatic data from satellites and drones offers a great solution for monitoring and managing water bodies. The fusion of images makes it possible to better visualize and understand complex environmental data, allowing small changes in the water's surface to be identified.

Finally, Casagli et al. [8] explored the use of remote sensing techniques, including satellite data and drones, for environmental monitoring and urban planning. The study highlighted the effectiveness of these technologies in detecting disasters such as floods and landslides, which are common problems in densely populated urban areas.

This work provides an important basis for the use of satellite and drone image fusion techniques in environmental monitoring, especially in the identification and management of water bodies. Deep learning approaches, such as the use of PCNN, have shown good results in overcoming the limitations of traditional methods, offering better quality fusions in terms of spatial and spectral resolution.

3.3 Identification of Water Bodies

The NDWI and the MNDWI are widely used for the identification and monitoring of water bodies in remote sensing images. These indices use the near-infrared (NIR) and green (G) bands for NDWI and the G and shortwave infrared (SWIR) bands for MNDWI. Their use enhances the presence of water in multispectral images, making it easier to distinguish between water-covered areas and other surfaces such as soil and vegetation. This enhancement happens because water reflects more light in the green band (G) while absorbing more light in the NIR and SWIR bands, resulting in lower reflectance in these bands. Therefore, by subtracting the NIR/SWIR reflectance from the G reflectance and dividing the result by the sum of these reflectances, the NDWI/MNDWI amplifies the spectral signature of water, making it more evident when compared to other types of land cover [14].

$$NDWI = \frac{(G - NIR)}{(G + NIR)} \quad (1)$$

$$MNDWI = \frac{(G - SWIR)}{(G + SWIR)} \quad (2)$$

4. Methodology

The study was conducted in the city of São Paulo, one of the largest metropolises in Brazil, which presents complex challenges due to its urban density and the presence of water bodies in different contexts [15]. The specific area chosen was *Parque Ibirapuera* [Ibirapuera Park], one of the city's main green space, known for its large lakes. With its complex

hydrographic network and intense urbanization, São Paulo provides an ideal setting for the application of image fusion techniques and water body detection. The city faces several challenges related to the management of its water resources, including pollution, floods, and water scarcity, making the development of efficient monitoring methods crucial. The overall flow of steps taken in the article is illustrated in the figure below. In the following sections, we'll go through each of the steps in detail.

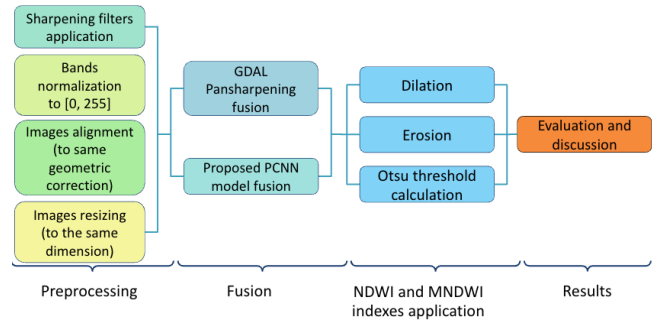


Figure 1. Methodology flowchart

4.1 Data Collection and Preprocessing

Satellite imagery from Landsat 8 [16] from June 2024 and orthophotos with high spatial resolution from 2017 were collected from the Geosampa portal [17]. Landsat 8 satellite imagery, accessible through USGS EarthExplorer platforms, was selected for the research due to its wide range of bands with high quality. With a spatial resolution of 30 meters and 11 spectral bands, bands 3 (G), 5 (NIR), 6 (SWIR1), and 7 (SWIR2) are used to calculate spectral indices such as NDWI/MNDWI, important for water body identification.

The GeoSampa orthophotos, obtained through aerial surveys conducted by the São Paulo City Hall, provide high spatial resolution images of the city. In urban areas, true orthophotos with geometric correction are available, while in suburban and rural areas, resolutions of 0.10 and 0.20 meters, respectively, are provided. These images have different spectral bands (R, G, B, and NIR). The orthophotos from GeoSampa drones underwent the weighted average composition process of the bands to obtain a single-band (panchromatic) image. The QGIS raster calculator was used for the necessary operations, where B_i represents each band (R, G, B, NIR), and n is the total number of bands, that in this case, is four:

$$Single - band = \frac{\sum_{i=1}^n B_i}{n} \quad (3)$$

This technique is effective because the averaging of spectral bands provides a balanced representation of overall light intensity, preserving important spatial details and tonal variation of different surfaces [18]. Subsequently, the resulting images were resampled to a resolution of 1 meter and used as panchromatic images in the fusion with Landsat 8 satellite data. The 1-meter resolution is sufficient to ensure good image quality

and it's a strategic choice to optimize the use of computational resources during testing. Working with a higher nominal resolution, such as the original higher resolution of the drone orthophotos, would require significantly more computational resources and increase the model training time. Resampling to 1 meter allows for more efficient testing, maintaining a balance between image quality and computational load. The bilinear method was used to resample the images from a resolution of 20cm to 1 meter in QGIS. This method calculates the weighted average of the four nearest neighboring pixels to create a new pixel. This approach resulted in a smoother and more continuous image, ideal for aerial photographs and satellite imagery.

The preprocessing of Landsat 8 images included geographic coordinate correction and clipping by extent, performed in QGIS. The projections were adjusted to the SIRGAS 2000 / UTM zone 23S system to ensure compatibility with the GeoSampa orthophotos. This correction was necessary due to the acquisition of images in different coordinate systems, avoiding incompatibilities in the joint analysis. The images were clipped to focus on the area of interest, optimizing computational resources and processing time. An algorithm was created to automate the clipping of raster images based on multiple polygons of the GeoSampa orthophoto grid, facilitating the creation of smaller images, which were named according to the areas and naming conventions of the orthophotos.

4.2 Proposed PCNN Model and Improvements

4.2.1 Applied Preprocessing

After preparing and aligning the remote sensing data, the next step was to implement the fusion of satellite and drone imagery using PCNN, a process that included several critical steps of preprocessing, training and evaluation was followed.

The implemented PCNN uses an architecture composed of three convolutional layers, which replicate the behavior of pulse coupling by iteratively combining multiband and panchromatic information. The configuration included an initial layer, that captures global characteristics using large-scale convolutions (9x9 kernel) to highlight structural and spectral details. Following that layer, the intermediate layer refines the extracted information with medium-range convolutions (5x5 kernel), simulating the local reinforcement characteristic of PCNNs. The final layer integrates the information to generate the fused output, ensuring that the most relevant spectral characteristics are preserved.

The panchromatic images from Fig. 1 (a), Fig. 2 (a), and Fig. 3 (a) and multispectral images from Fig. 1 (b), Fig. 2 (b), and Fig. 3 (b) were loaded using rasterio [20]. Sharpening filters were applied to enhance image details, the image bands were normalized to the [0, 255] range based on the actual minimum and maximum values of the bands, ensuring that negative values were eliminated. This was done to avoid excessive saturation and to ensure that the values were within the expected range. The images were then resized and aligned

to ensure that all bands had the same dimensions and geometric correction. To create the training images, bilateral filters were applied for noise reduction and the panchromatic and multispectral images were resized to have the same dimensions. Then, 128x128 pixel patches were extracted from the images to train the PCNN model, in total 3465, ensuring that the dimensions of the patches were compatible.

Cross-validation techniques and callbacks such as ModelCheckpoint, EarlyStopping, and ReduceLROnPlateau (all provided by TensorFlow Keras) were used to optimize the training and minimize the risk of overfitting.

5. Results and Discussion

The model takes as input two images: a panchromatic image (with one band, from the drone) and a multispectral image (with seven bands, from the satellite). To perform the fusion process, we selected combinations of three bands at a time from the multispectral image and fed them into the model, along with the panchromatic image, generating a fused image for each band combination. Subsequently, we calculated the metrics for each version of the trained model, evaluating the quality of the fusion.

The following metrics were calculated and evaluated: Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Correlation, Entropy (ENT), Standard Deviation (SDe), and Spectral Difference (SDi).

Table I presents the results for each training version of our proposed PCNN model. The last three columns represent the following band combinations, respectively: Red (3), Green (2), Blue (1); NIR (4), Red (3), Green (2); Red (3), SWIR 1 (5), SWIR 2 (6). Each metric was calculated by comparing the original multispectral image with the fused image generated by the proposed model.

Table 1. Metrics of proposed PCNN Fusion

Metric	[3, 2, 1]	[4, 3, 2]	[3, 5, 6]
SSIM	0.0107	0.0123	0.0188
PSNR	6.0956 dB	6.5619 dB	7.4221 dB
MSE	15977.8936	14351.2891	11772.4443
RMSE	126.4037	119.7969	108.5009
Correlation	0.2050	0.2718	0.3428
Original Mean	24.0487	32.2420	43.9376
Fused Mean	27.62541	128.3770	127.2332
Original SDe	12.6518	17.4498	22.8648
Fused SDe	73.9825	74.2212	73.9660
Original ENT	5.4989	6.0204	6.4782
Fused ENT	7.9809	7.9669	7.9552
SDi	134.8972	134.4372	130.9383

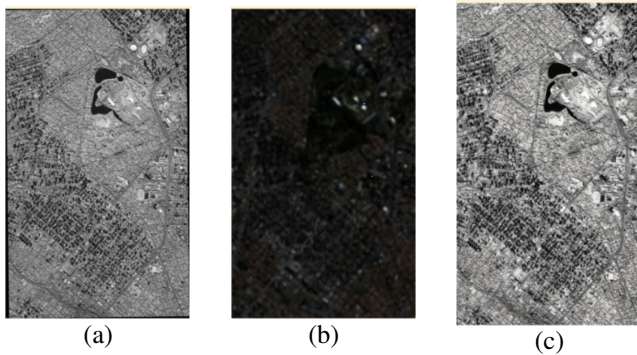


Figure 2. Panchromatic image (a); Multispectral image (R,B,G) (b), Fused image (Weight MS e PAN: 0.5) (c)

Source: Prepared by the authors (2024)

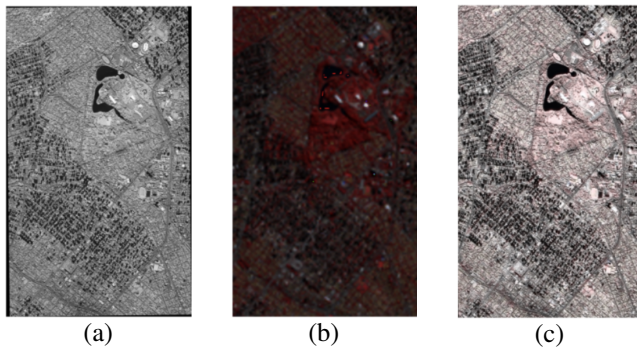


Figure 3. Panchromatic image (a); Multispectral image (NIR,R,G) (b), Fused image (Weight MS e PAN: 0.5) (c)

Source: Prepared by the authors (2024)

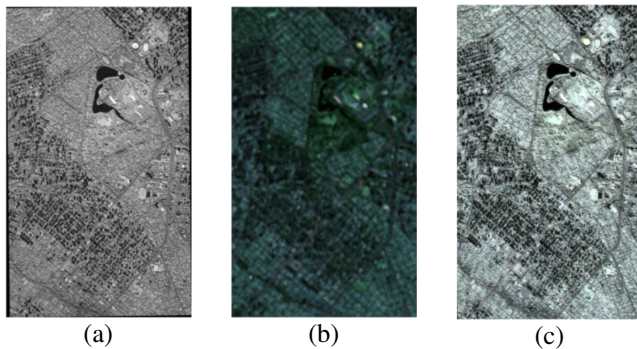


Figure 4. Panchromatic image (a); Multispectral image (R, SWIR 1, SWIR 2) (b), Fused image (Weight MS e PAN: 0.5) (c)

Source: Prepared by the authors (2024)

The combination of bands [3, 5, 6] (Red, SWIR 1, SWIR 2) showed the best evaluation metrics, with the highest SSIM and PSNR values and the lowest MSE and RMSE values. The result indicated that this combination provided the best fusion quality in terms of structural similarity, signal-to-noise ratio and average error. Therefore, the identification of water and soil using these bands was the most effective in the image fusion.

The evaluation metrics indicated some discrepancies in fusion performance, which can be attributed to the significant differences in the dimensions of the original input imagery. The imagery had the following dimensions:

- Dimensions of the panchromatic image: (2987, 5037)
- Dimensions of the multispectral image: (101, 170)
- Number of bands in the panchromatic image: 1
- Number of bands in the multispectral image: 7

For normalization, the multispectral images were resized to match the higher resolution of the panchromatic image (2987, 5037). An attempt was also made to resize the panchromatic image to the lower dimensions of the multispectral image; however, this resulted in a significant loss of detail, making the fused image unfeasible. These adjustments in the resizing and normalization processes aimed to reduce geometric distortion and maintain the integrity of the spectral information, but the significant differences in input resolutions still impacted the quality metrics of the fusion. In the future, advanced interpolation methods and super-resolution techniques could be explored to improve these results.

5.1 Evaluation of Fused Image Indices: GDAL pansharpening and PCNN

The GDAL pansharpening method was used to generate a baseline image fusion for comparison with the proposed PCNN model. In addition to supporting the integration of plugins and external code, QGIS provides standard image fusion functionality using pansharpening with the Brovey technique and a Raster Calculator for mathematical and logical operations to generate new rasters based on defined formulas that combine the bands. This functionality is widely recognized and used in the industry, facilitating the adoption by other researchers and comparison of our results with previous studies.

5.1.1 Application of NDWI/MNDWI Indices

NDWI and MNDWI indices were calculated before and after the fusion of Landsat-8 and drone imagery to evaluate water body detection. The necessary spectral bands (G and NIR for NDWI; G and SWIR for MNDWI) were extracted from Landsat-8 imagery using the rasterio library and normalized to values between 0 and 1. NDWI was calculated using bands G (band 3) and NIR (band 5) with Equation 1, while MNDWI was calculated using bands G (band 3) and SWIR (band 6) with Equation 2.

After the fusion of imagery using the PCNN model, the indices were recalculated on the fused imagery to evaluate the improvements. The same bands (G and NIR for NDWI; G and SWIR for MNDWI) were selected and the indices were recalculated with the same handling of invalid pixels. Morphological operations of erosion and dilation were applied to enhance segmentation. Fig. 4(c) displays the NDWI after image fusion using PCNN, where the definition and contrast of water bodies were significantly improved compared to Fig. 4(a) and 4(b), suggesting that PCNN provides a more precise and detailed fusion for water body detection. The MNDWI in Fig. 5(c) showed a significant improvement in the definition and contrast of water bodies compared to Fig.

5(a) and 5(b) and it also outperformed Fig. 4(c), highlighting the effectiveness of PCNN in image fusion and enhancement for water body detection in urban environments compared to NDWI. In Table II, the second and third columns pertain to the application of the NDWI index (1) on fused images by GDAL pansharpening and PCNN, respectively, while the last two columns pertain to the application of the MNDWI index (2) on fused images by GDAL pansharpening (Pans.) and PCNN, respectively.

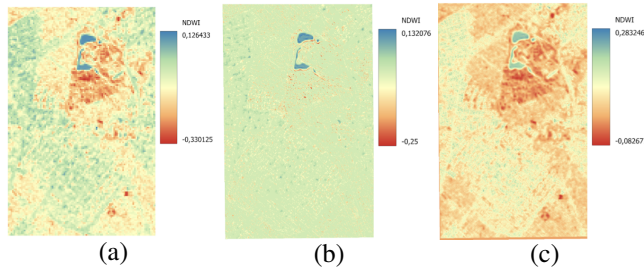


Figure 5. NDWI before fusion (a) NDWI of the fused image using pansharpening (b) and NDWI of the fused image using PCNN (c)

Source: Prepared by the authors (2024)

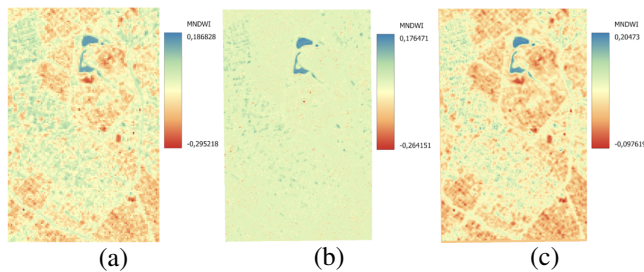


Figure 6. MNDWI before fusion (a) MNDWI of the fused image using pansharpening (b) and MNDWI of the fused image using PCNN (c)

Source: Prepared by the authors(2024)

Table 2. Metrics of Index Application

Metric	(1)Pans.	(1)PCNN	(2)Pans.	(2)PCNN
SSIM	0.7333	0.7550	0.6984	0.7176
PSNR (dB)	6.2249	6.2905	5.6463	5.6237
MSE	0.2385	0.2349	0.2725	0.2739
RMSE	0.4884	0.4847	0.5220	0.5234
Correlation	-0.0575	-0.0428	0.0165	-0.0037
Original Mean	0.5362	0.5362	0.4886	0.4886
Fused mean	0.9478	0.9739	0.9478	0.9739
Original SDe	0.1286	0.1286	0.1147	0.1147
Fused SDe	0.2219	0.1584	0.2219	0.1584
Original ENT	4.8957	4.8957	4.7949	4.7949
Fused ENT	0.2178	0.1415	0.2178	0.1415
SDi	5962755.5	5873359.0	6812622.0	6848143.0

In the color maps, values closer to 1, indicating the presence of water, are represented in shades of blue, while areas with less water presence are shown in shades of red. The indices generated with the images fused by the PCNN model (Fig. 4(c) and Fig. 5(c)), showed a greater amount of red tones, evidencing better discrimination between water and

other land covers, providing a clearer distinction between different surface types and more precise highlighting aquatic areas compared to other images. The fusion performed using pansharpening (Fig. 4(b) and Fig. 5(b)) tends to smooth out details, resulting in less sharp images that are inferior to the indices generated before fusion, although the edges of water bodies are more defined than in the non-fused image. The fusion using the PCNN model demonstrates superior performance in most evaluated metrics, especially in preserving structures and image quality. The lower entropy (0.1415 for NDWI and MNDWI) and standard deviation (0.1584 for NDWI and MNDWI) suggest that the fusion with PCNN results in images with less variation and diversity of information, which can be beneficial for certain applications. However, the slightly negative correlation (-0.0428 for NDWI and -0.0037 for MNDWI) and the higher spectral difference for PCNN (5873359.0 for NDWI and 6848143.0 for MNDWI) indicate that there may be some aspects to be adjusted to further improve the fusion.

6. Final Considerations

The fusion of satellite and drone imagery has proven to be an efficient method for overcoming the limitations of these technologies. This study compared fusion methods using QGIS and a Pulse Coupled Neural Network (PCNN) model, revealing that PCNN offers better image quality in most of the evaluated metrics. Fusion with PCNN resulted in clearer and more detailed images, more accurately highlighting water surface areas and providing better distinction between different types of land cover. Additionally, these indices help prevent and manage flood-prone areas by providing precise data on the location and extent of water bodies, enabling the mapping of vulnerable areas and facilitating the adoption of preventive measures. Despite its advancements, this research highlights the ongoing need for refinements in fusion methods. The use of new approaches based on machine learning could offer more accurate adjustments to the inherent variabilities of multispectral and panchromatic data sources. The exploration of advanced deep learning techniques could facilitate the understanding and treatment of complex aspects captured by different remote sensing modalities. Finally, as next steps, we suggest studying other neural network models and applying improvements to the presented PCNN model, particularly in the preprocessing stage.

Acknowledgements

This project was supported by the Ministry of Science, Technology and Innovation, with resources from Law No. 8,248, of October 23, 1991, within the scope of PPI-SOFTEX, coordinated by Softex and published PDI 03, DOU 01245.023862/2022-14.

Author contributions

All authors have contributed equally to the development of this work.

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