INDIAN INSTITUTE OF TECHNOLOGY PATNA

CE6133 : DATA SCIENCE

TOPIC: Image Fusion Techniques and Analysis

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A REPORT ON: Image Fusion Techniques & AnalYSIS

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Table of Contents:

ABSTRACT

Image fusion is a process of combining multiple images from different sources to create a single image that is more informative and visually enhanced. This project explores various techniques for image fusion, focusing on spatial domain, transform domain, and hybrid methods. The objective is to improve image quality by integrating complementary information from the input images, making it suitable for applications in fields such as remote sensing, medical imaging, and surveillance. The fused images were evaluated using metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), demonstrating enhanced clarity and improved information content. The results indicate that the selected fusion techniques effectively enhance image features while minimizing noise. The report also discusses the challenges in image fusion, such as data alignment and artifact introduction, and suggests potential improvements for future work.

INTRODUCTION

Image fusion is a technique used to combine multiple images from different sensors or sources to produce a single image that contains more information than any of the individual input images. The goal is to enhance the visual quality and provide more comprehensive data for analysis, which can be used in applications such as medical imaging, remote sensing, and computer vision.

PURPOSE OF IMAGE FUSION:

The purpose of this project is to:

- Combine images with complementary information to enhance visual interpretation.
- Improve the quality and reliability of image analysis.
- Provide a fused image with better spatial and spectral resolution.

Benefits of Image Fusion:

- **Enhanced Image Quality**: Provides an image with better clarity and detail.
- **Improved Decision Making**: More information in a single image aids better analysis.
- **Noise Reduction**: Fusion reduces noise by combining multiple inputs.
- **Increased Reliability**: Combined information is more robust and comprehensive

Challenges in Image Fusion:

- **Data Misalignment**: Different sources may have varying resolutions, scales, and perspectives, making alignment difficult.
- **Loss of Information**: Improper fusion techniques may result in loss of critical data.
- **Computational Complexity**: Advanced fusion methods require high processing power and can be time-consuming.
- **Artifact Introduction**: Poorly implemented fusion can introduce artifacts, affecting image quality.

METHODOLOGY:

1. **Data Collection**

    - Acquired images from different sources/sensors.
    - Pre-processed the images to ensure uniform size and format.

2. **Image Registration**
    - Registered the images using feature-based alignment techniques.
    - Ensured pixel-level alignment for accurate fusion.

3. **Image Fusion Techniques**
    - **Spatial Domain Techniques**: Direct fusion using pixel averaging.
    - **Transform Domain Techniques**: Used Discrete Wavelet Transform (DWT) for multi-resolution analysis.

4. **Hybrid Techniques**: Combined spatial and transform domain methods for better results.

5. **Evaluation Metrics**

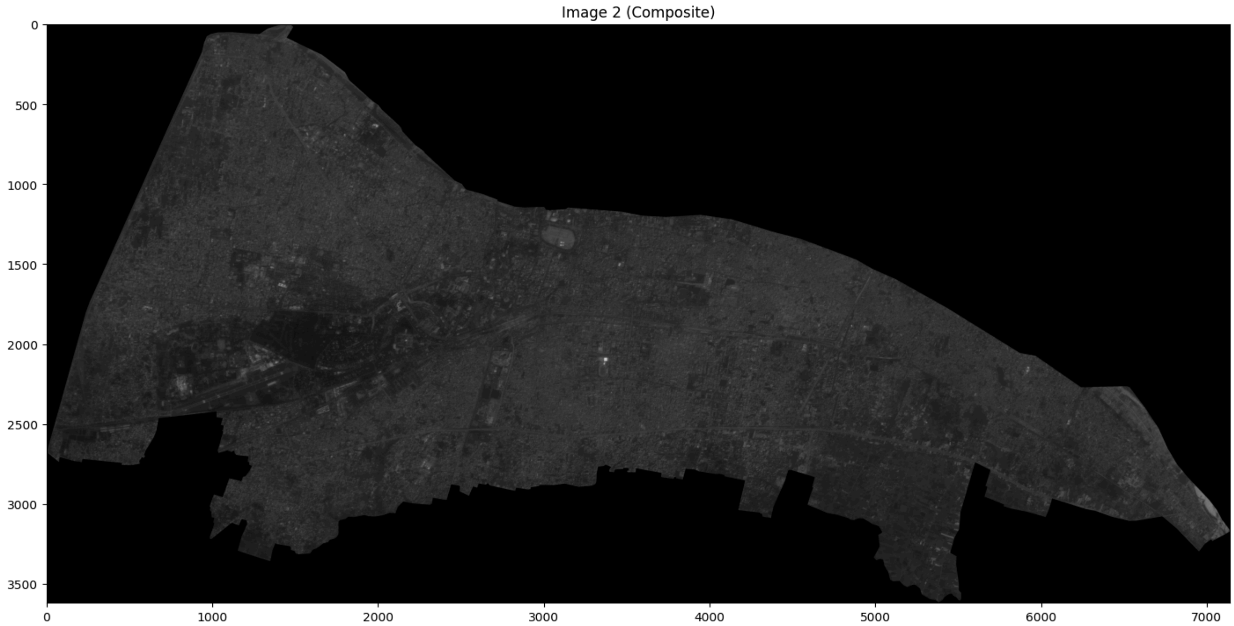
    - **Peak Signal-to-Noise Ratio (PSNR)**: Used to measure the quality of the fused image.
    - **Structural Similarity Index (SSIM)**: Evaluated the similarity between the fused image and the input images.

Reading the .tif extension images.

- Images were read using the *Rasterio library*.
- Size of the images as following

    image1_array.shape
    (1075, 2376)

    image2_array.shape
    (3619, 7140)



Reshaping the image2_array.

- The images were of different sizes, so resizing the second image to match the dimensions of the first without losing interpretability

  image1_array.shape
  (1075, 2376)
  image2_array.shape
  (3619, 7140)
  resampled_image2.shape
  (1075, 2376)

1. Image Fusing by Averaging

Methodology:

- The images were read using the *Rasterio library*.
- The average of corresponding pixel values from both images was computed:

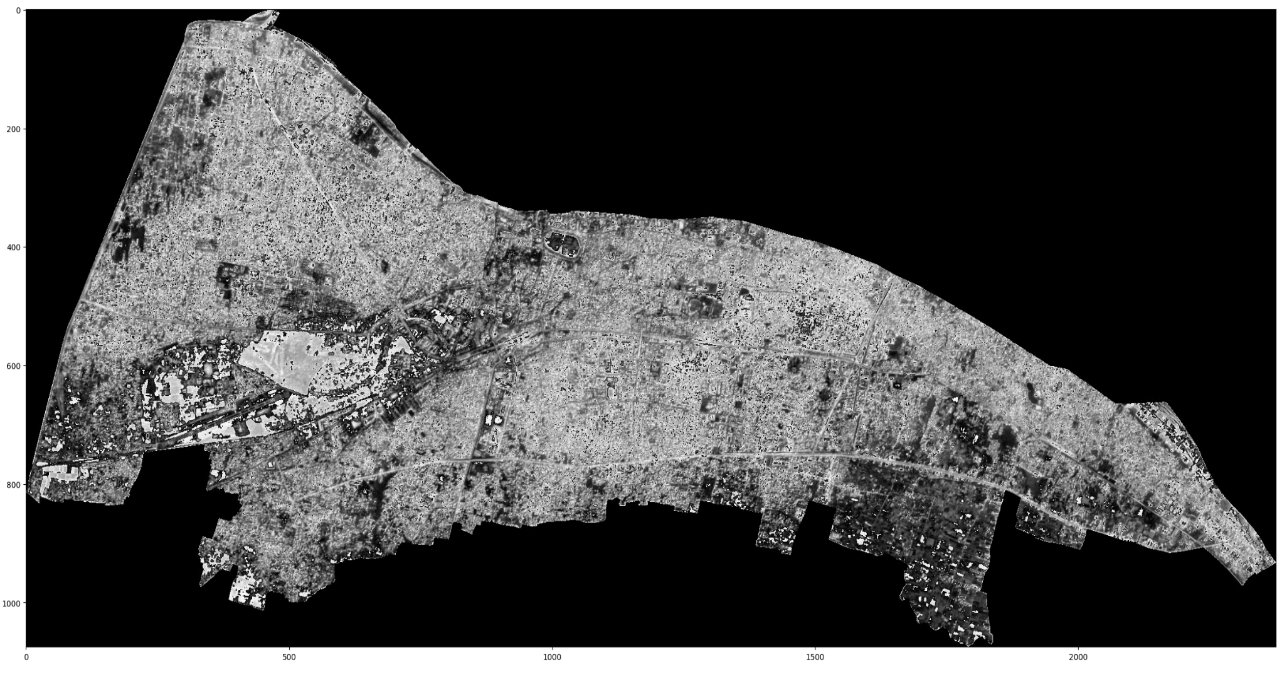
$$F(i,j) = \frac{I_1(i,j)+I_2(i,j))}{2}$$

- The result is a simple average of the two input images.

Challenges:

- The first image was 11 MB, while the second was nearly 80 MB, making it challenging to process the larger image.
- The images were of different sizes, and resizing the second image to match the dimensions of the first without losing interpretability was also a challenge.

Fused Image:



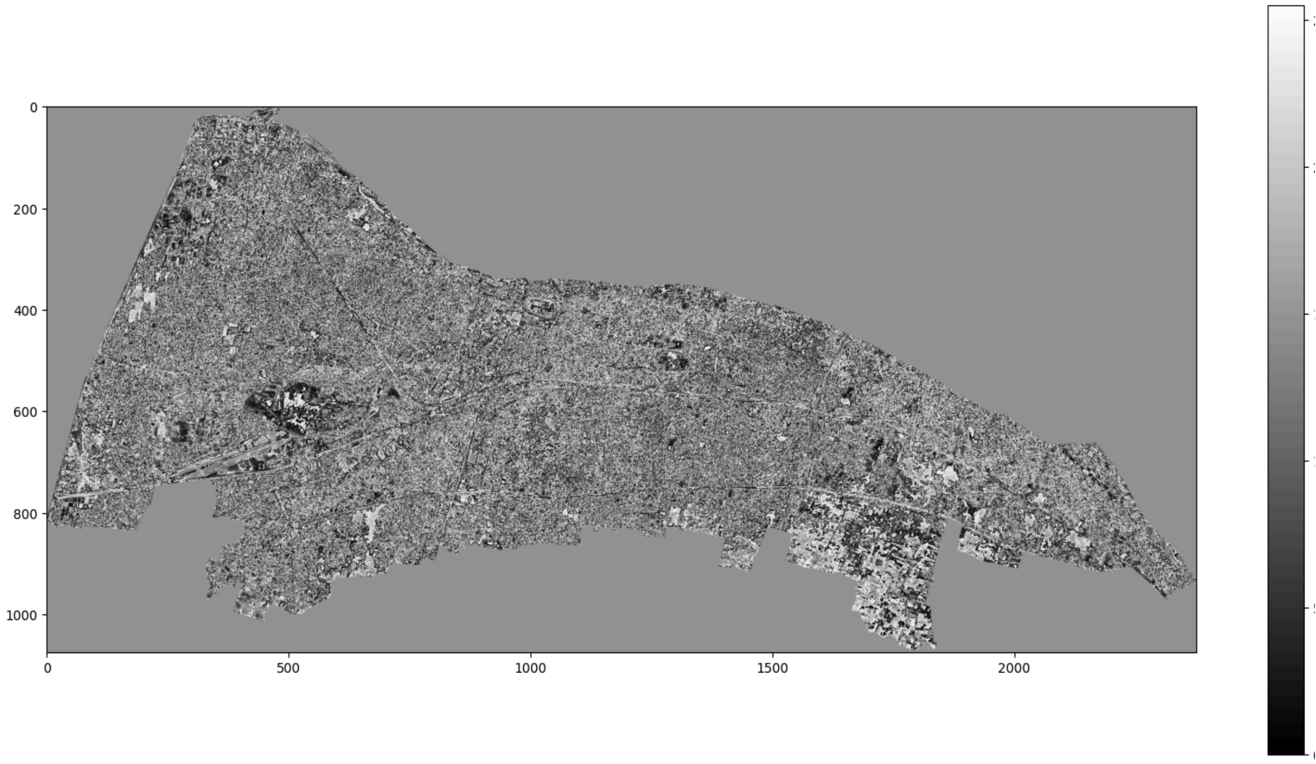
2. Fusing by Principal Component Analysis (PCA) Fusion

Methodology:
Read and stack the images, then apply PCA to extract the most significant component.

The fused image is obtained by reshaping the principal component back to the original image dimensions.

Challenges:

- Resizing images to match dimensions.
- Large file sizes, especially the second image.
- Handling NaN values in the data.
- Ensuring the fused image retains meaningful features.



3. *à trous* wavelet transform :

Methodology:

1. Import and normalize multispectral and panchromatic images to the 0-255 range for visualization.
2. Apply the *à trous* wavelet transform using degradation filters to extract wavelet coefficients.
3. Fuse images by adding spatial details from panchromatic wavelets to the degraded multispectral image.
4. Introduce weighted fusion with adaptive weights (αi\alpha^iαi) to control spatial-spectral trade-offs.
5. Enhance weights using local entropy maps for land cover-specific adjustments.
6. Normalize the fused image to match the original multispectral image values.

Challenges:

1. Balancing spatial sharpness and spectral fidelity.
2. Determining optimal weights (αi\alpha^iαi) for diverse land covers.
3. Handling computational complexity in multi-scale wavelet processing.
4. Adapting methods to heterogeneous land cover regions.
5. Ensuring normalization consistency with original image values.

Fused Image:

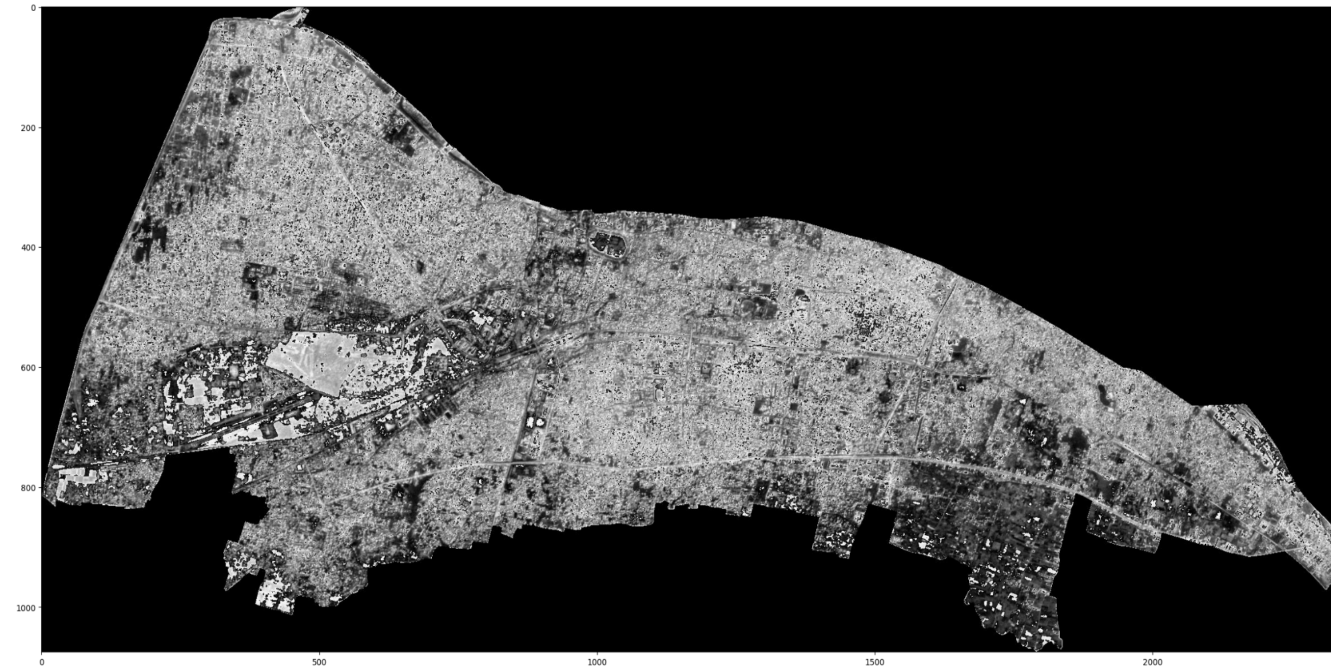
4. Fusing by Weighted Averaging

Methodology:

- Read and load the two grayscale images.
- Assign weights to each image ($eg.,\ w_1\ and\ w_2$), ensuring they sum to
- Compute the weighted average of corresponding pixel values from both images.
  $F(i, j)\ = \frac{w_1 * I_1(i,j) + w_2 * I_2(i,j))}{2}$
- Clip the pixel values to the range [0, 255] to ensure valid image intensities.
- The result is a fused image with a balance of features from both inputs based on the assigned weights.

Challenges:

- Resizing images to match dimensions if necessary.
- File size concerns, particularly with larger images.
- Ensuring the fused image retains meaningful features from both sources depending on the chosen weights.



5.Wavelet Fusion:

Methodology:

- Images are decomposed into multi-resolution wavelet transforms (low- and high-frequency components).

- Fusion rules are applied (e.g., max selection, average, or energy-based selection) to combine coefficients.

- The fused image is reconstructed using an inverse wavelet transform.

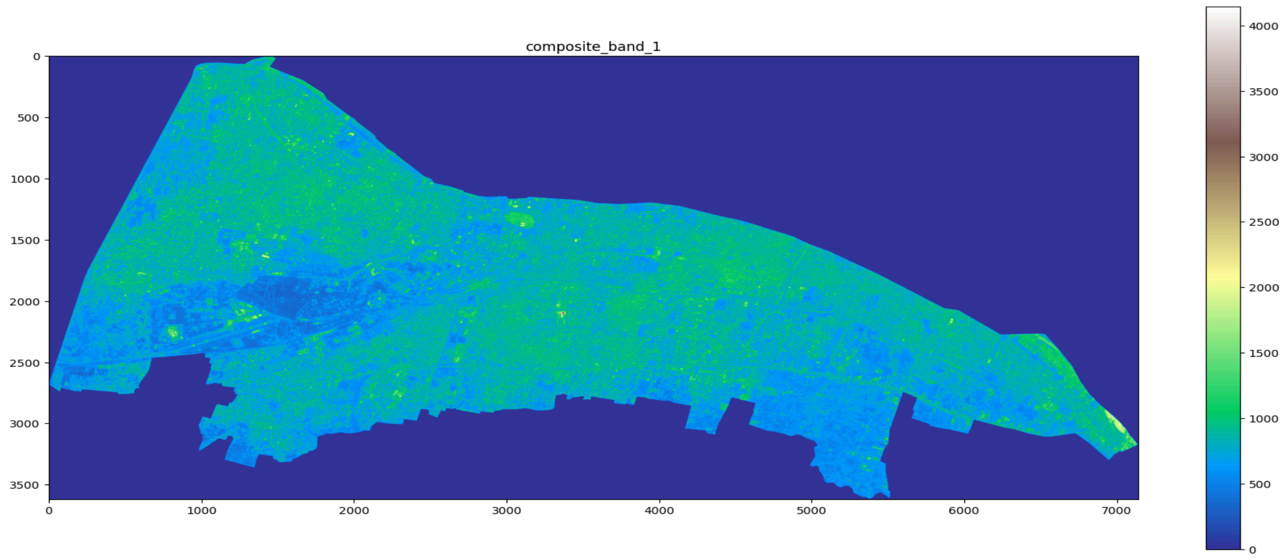
Challenges:

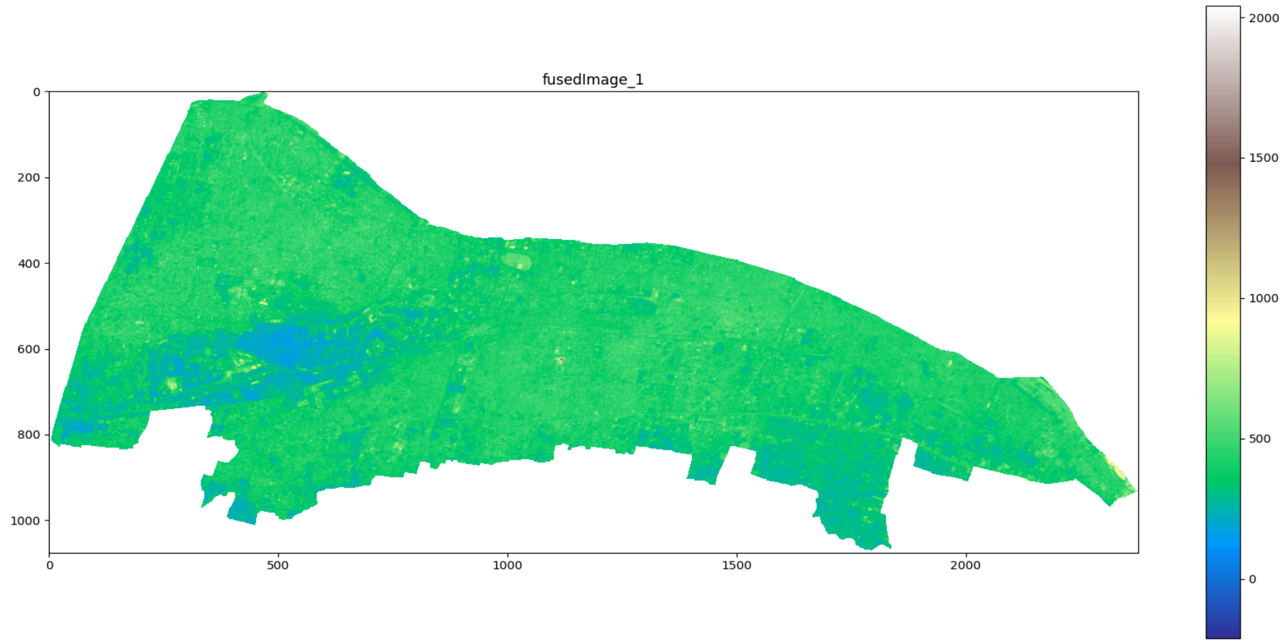
Computational complexity: Wavelet decomposition and reconstruction are computationally intensive.

Artifact generation: Improper fusion rules can introduce artifacts or unnatural transitions in the fused image.

Parameter tuning: Selecting the right wavelet family, levels of decomposition, and fusion rules is challenging.

Results and Analysis:





- The fused images showed improved visual quality compared to individual input images.

- Quantitative metrics like PSNR and SSIM confirmed the enhancement in image quality.
- Comparative analysis demonstrated the effectiveness of the selected fusion techniques.

6. Image Band fusion

Data Acquisition:
Collect data from sensors capable of capturing multiple spectral bands, such as satellite sensors (e.g., Landsat, Sentinel).

Preprocessing:
Radiometric Correction: Adjust pixel values to compensate for sensor noise or atmospheric conditions.
Geometric Correction: Align images from different bands to ensure pixel-by-pixel correspondence.
Resampling: Match resolutions across bands when sensors capture data at varying resolutions.

Fusion Levels:
Pixel-Level Fusion:
Combines raw data at the pixel level, focusing on integrating intensity and spatial details.
Techniques: Principal Component Analysis (PCA), Intensity-Hue-Saturation (IHS) transformation, Brovey Transform.
Feature-Level Fusion:
Extracts specific features (edges, textures) from each band before fusing them.
Techniques: Wavelet Transform, Gradient-based methods.
Decision-Level Fusion:
Combines results of analysis (e.g., classification or detection) from individual bands into a unified decision.
Techniques: Majority Voting, Bayesian Inference.

Fusion Algorithms:
Linear Methods: Combine bands using mathematical transformations (e.g., PCA).
Non-linear Methods: Use advanced approaches like machine learning (e.g., Convolutional Neural Networks, Autoencoders).

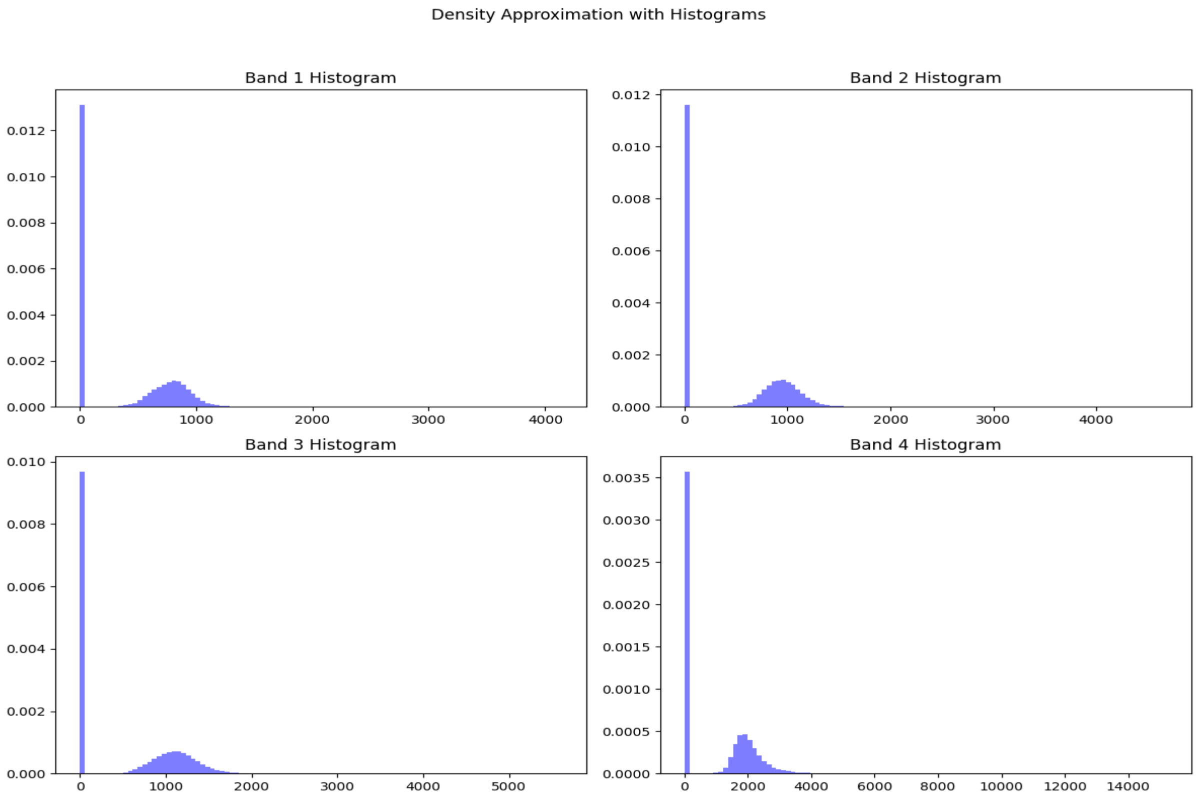
Challenges:

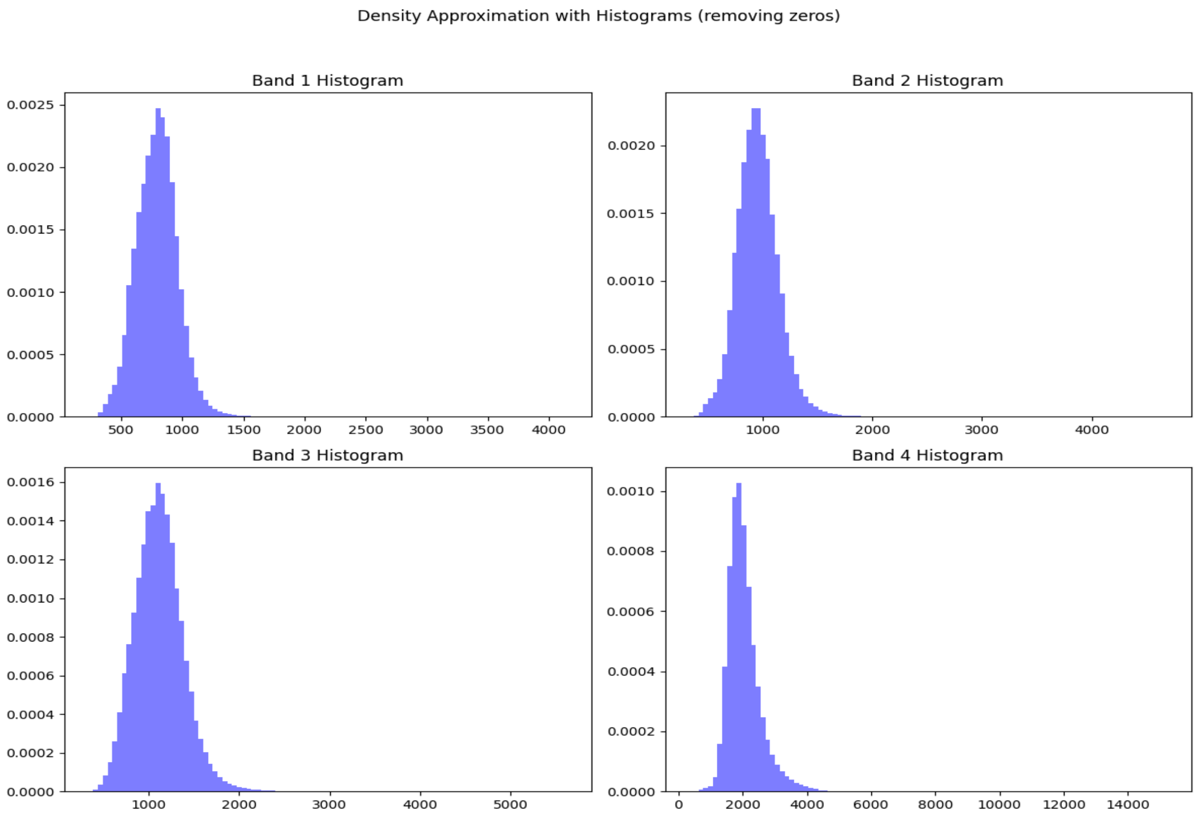
Spatial and Spectral Mismatch:
Differences in spatial or spectral resolution between bands may lead to alignment issues during fusion.

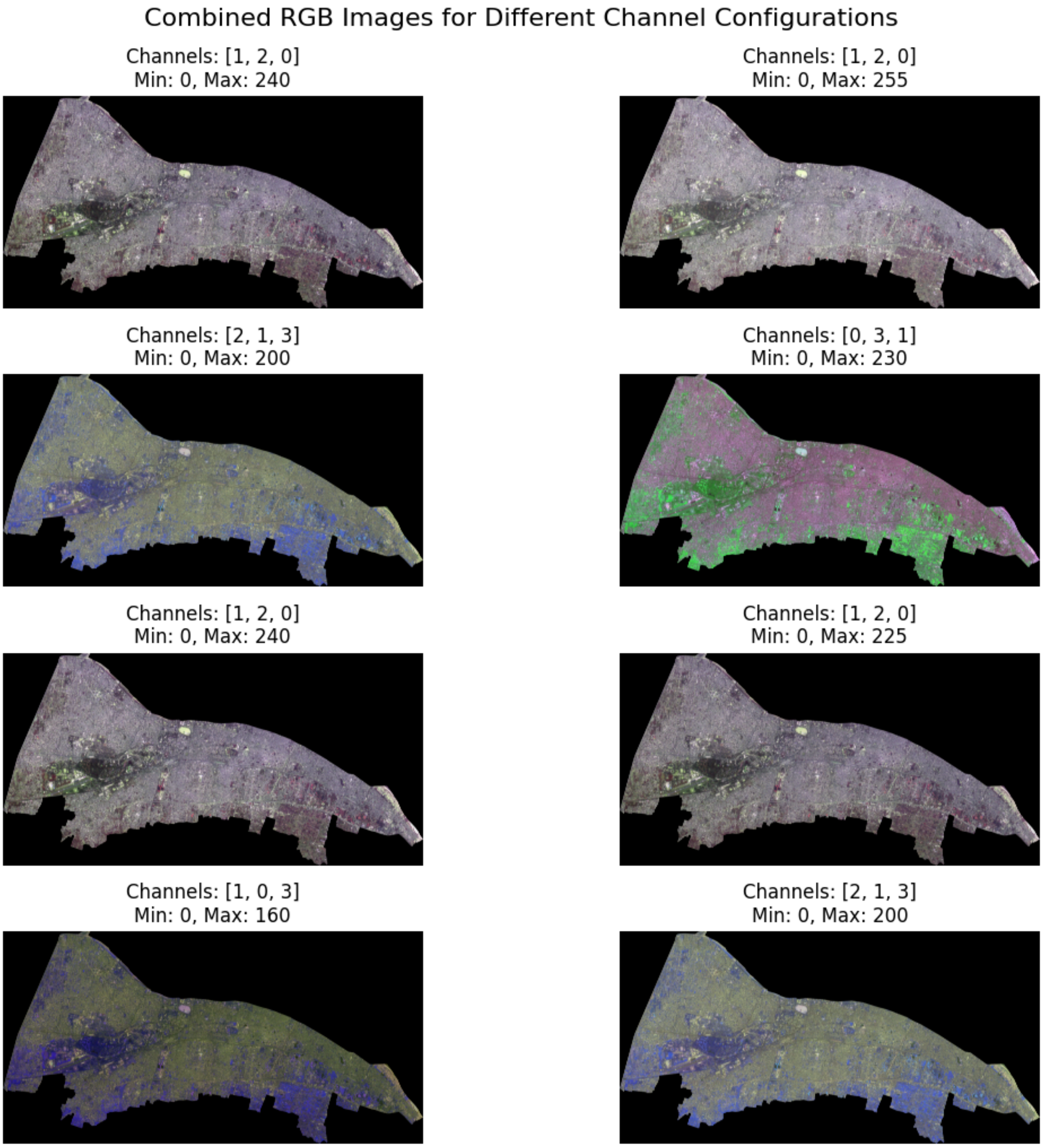
Noise Sensitivity:
Noise in one band can propagate and degrade the quality of the fused data.

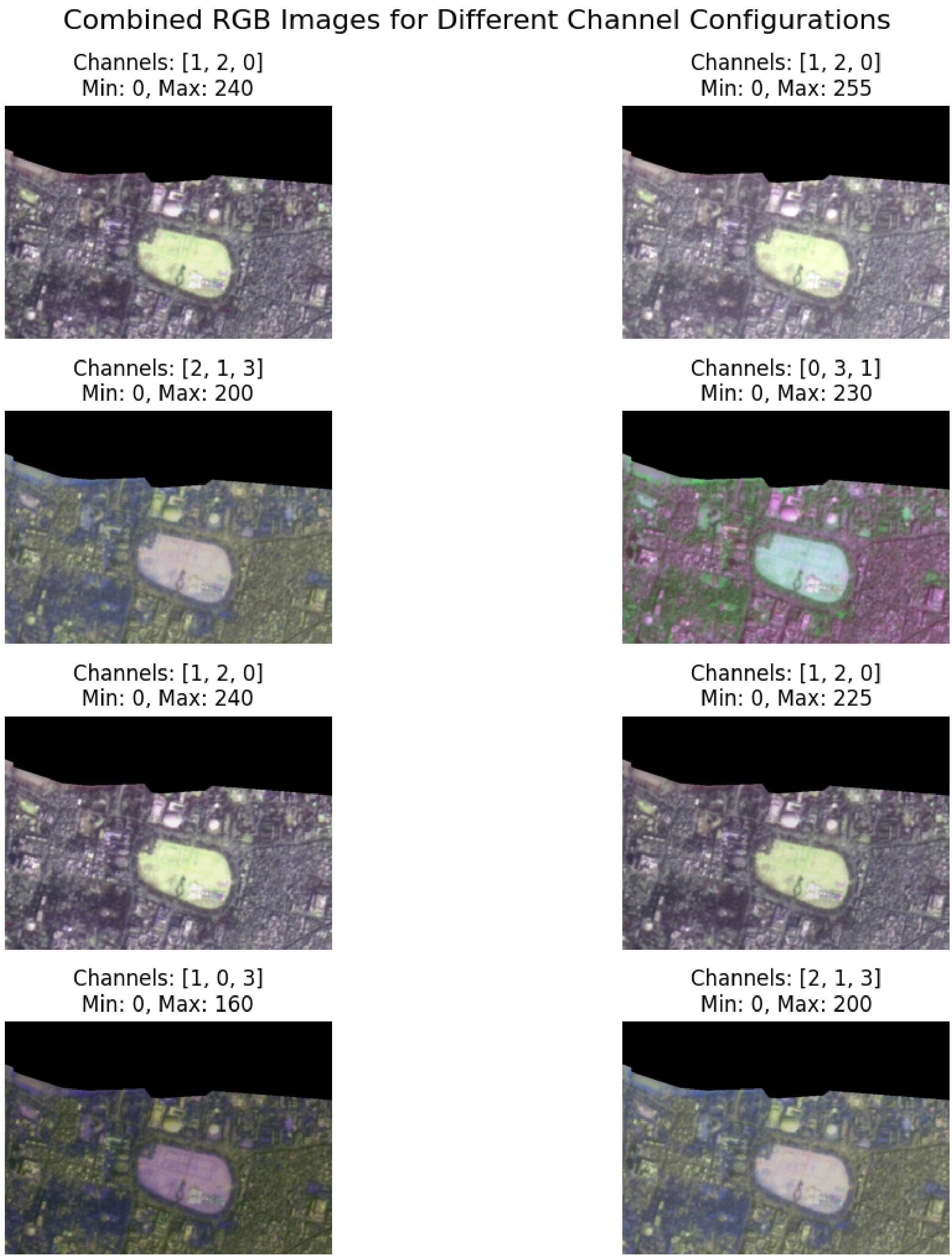
Trade-offs Between Spectral and Spatial Quality:
High spatial resolution may compromise spectral fidelity (and vice versa) in certain fusion techniques.

Computational Complexity:
Advanced fusion methods like deep learning demand high computational resources and processing time.




Density Approximation with Histograms (removing zeros)
Band 1 Histogram
Band 2 Histogram
Band 3 Histogram
Band 4 Histogram


Combined RGB Images for Different Channel Configurations
Channels: [1, 2, 0]
Min: 0, Max: 240
Channels: [1, 2, 0]
Min: 0, Max: 255
Channels: [2, 1, 3]
Min: 0, Max: 200
Channels: [0, 3, 1]
Min: 0, Max: 230
Channels: [1, 2, 0]
Min: 0, Max: 240
Channels: [1, 2, 0]
Min: 0, Max: 225
Channels: [1, 0, 3]
Min: 0, Max: 160
Channels: [2, 1, 3]
Min: 0, Max: 200


Combined RGB Images for Different Channel Configurations
Channels: [1, 2, 0]
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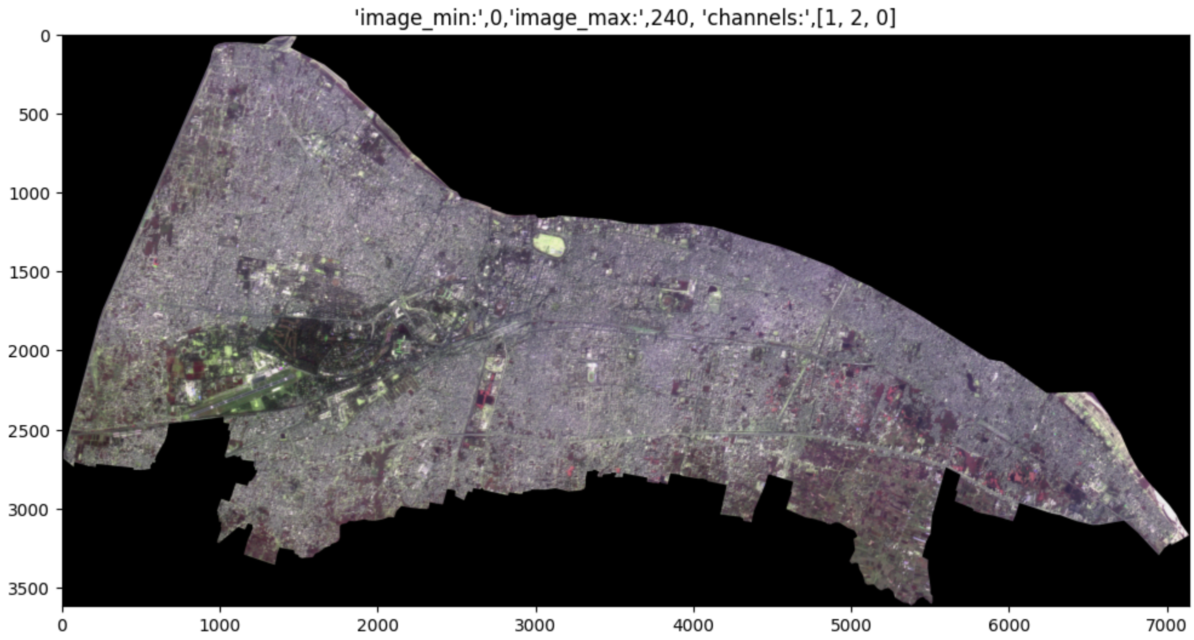
Channels: [1, 2, 0]
Min: 0, Max: 225
Channels: [1, 0, 3]
Min: 0, Max: 160
Channels: [2, 1, 3]
Min: 0, Max: 200



7. Wavelet Transformation with PCA:

Methodology:

1. Load and normalize two images (multi-band and grayscale) to [0, 255].
2. Resize the grayscale image to match the multi-band image dimensions.
3. Perform wavelet decomposition on both images.
4. Use PCA to fuse corresponding wavelet sub-bands.
5. Reconstruct the fused image using inverse wavelet transform.
6. Normalize and save the fused image as a JPEG.

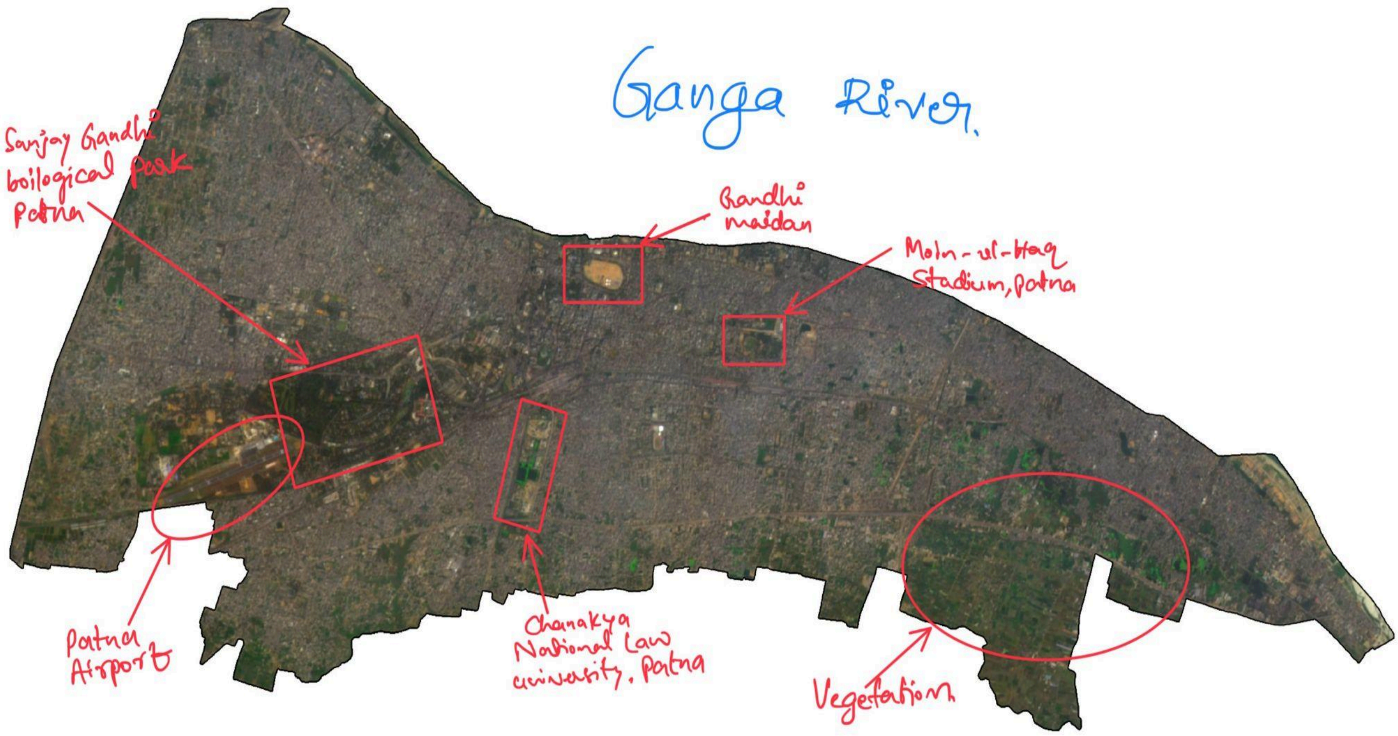
Challenges:

1. Matching image dimensions for accurate fusion.
2. Selecting suitable wavelet parameters.
3. Retaining both spectral and spatial features in PCA.
4. Avoiding artifacts during normalization.
5. Managing computational demands for large datasets.

Conclusion and Interpretation:

The fused image represents a city map, showcasing a detailed overview of the **urban landscape.** Upon analyzing specific landmarks visible in the image, we can confirm that the map corresponds to **Patna, the capital city of Bihar**. Notable locations such as **Patna Airport, Gandhi Maidan, Sanjay Gandhi Biological Park, Chanakya National Law University, and Moin-ul-Haq Stadium are clearly identifiable**. Additionally, patches of vegetation observed in the map further enhance its interpretability and provide context to the city's layout.

The successful identification of these landmarks not only validates the accuracy of the image fusion process but also demonstrates its utility in generating meaningful and actionable insights from multi-sensor data.



References:

1. Gonzalez, R. C., & Woods, R. E. (2018). *Digital Image Processing* (4th ed.). Pearson.
    - Referenced for foundational concepts in image fusion methodologies, including spatial and transform domains.
2. Mallat, S. (2008). *A Wavelet Tour of Signal Processing: The Sparse Way* (3rd ed.). Academic Press.
    - Utilized for understanding wavelet-based fusion techniques and multi-resolution analysis.
3. Kaur, P., & Goyal, D. (2015). "An overview of image fusion methods." *International Journal of Advanced Research in Computer and Communication Engineering,* 4(2), 223–227.
    - Used for a comparative understanding of common fusion techniques such as PCA and weighted averaging.
4. Li, S., Kwok, J. T., & Wang, Y. (2002). "Using the discrete wavelet frame transform to merge Landsat TM and SPOT panchromatic images." *Information Fusion,* 3(1), 17–23.
    - Basis for the integration of wavelet-based and PCA fusion methodologies.

Individual Contributions:

Rohit Raju Kamble	Fusing with Averaging
Prianshu Prasad	*à trous* wavelet transform and Research
Udit Narayan	Fusing with weighted Averaging and Team Management
Sourabh Kumar Prajapati	Band Fusion
Lalit Kumar Bharti	Report
Pankaj Kumar Paswan	Plagiarism Report
Shilpi Mukherjee	Wavelet Transformation with PCA
Ravi Kumar Paswan	*à trous* wavelet transform
Anu Kumar Tiwary	Report
Aashish Kumar Gupta	Wavelet Fusion
Sonam Raj	Report
Ratna Priya	Report
Uttam Kumar	Report
Aditi Thakur	PCA Fusion
Pinky Kumari	Plagiarism Report
Amisha Kumari	Report

Saloni Kumari	Report