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UNSUPERVISED IMAGE CLUSTERING FOR IDENTIFYING INDUSTRIAL CUSTOMER POTENTIAL IN SIDOARJO USING MULTISPECTRAL SATELLITE FEATURES

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ABSTRACT

This study investigates the use of unsupervised clustering techniques to identify potential industrial customer zones in Sidoarjo, East Java, using multispectral satellite imagery. The study employs Landsat 8 imagery, applying key spectral indices including Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Normalized Difference Water Index (NDWI) to classify land areas based on vegetation, built-up areas, and water bodies. K-means clustering was used to segment the region into distinct clusters, highlighting potential industrial areas. The industrial areas were further analyzed by calculating their spatial coverage using pixel count and spatial resolution. The estimated area of industrial zones in Sidoarjo was calculated to be 29,590 hectares, providing valuable insights for strategic energy distribution and industrial planning.

Keywords: *Satellite Imagery, Unsupervised Clustering, Industrial Customer Potential, Sidoarjo, ENVI, NDVI, NDBI, K-Means Clustering, Area Calculation*

1. INTRODUCTION

Sidoarjo, a regency in East Java, Indonesia, is known as a rapidly growing industrial hub. As a region with a growing industrial sector, Sidoarjo holds significant potential for supporting regional economic development, particularly in terms of energy provision and infrastructure. Therefore, it is crucial for utility companies, such as PLN, to identify and map potential industrial customers across various industrial zones. One effective way to achieve this is by leveraging satellite imagery technology to map areas that have the potential to become industrial customers.

Traditionally, identifying industrial areas has been done through field surveys or manual mapping, which can be time-consuming and costly. However, with advancements in remote sensing technology, satellite imagery offers a more efficient and cost-effective solution for mapping and monitoring land-use changes at a large scale. Satellite imagery provides objective and readily accessible data, enabling faster and more accurate identification and analysis of industrial areas [1]. Remote sensing with satellite imagery can provide critical information about land-use changes, which is highly relevant for infrastructure planning and energy service provision [2].

The data produced from the reflect"on o' different wave lengths recorded by sensors is known as remote sensing data. These sensors convert the wave lengths into numerical data so that it can be perceived as a graph or image [3]. Image processing software is used to handle the processing of remote sensing data; it is anticipated that this software will be able to deliver any information quickly and efficiently so that the data may be utilized for analysis and manipulation.

One of the commonly used methods in satellite image analysis is unsupervised clustering, which allows for the separation of areas based on spectral similarities without requiring prior labeling. In this context, K-means clustering is a frequently applied clustering technique to group satellite pixels into different categories, such as vegetation, built-up areas, and water bodies. Each cluster represents a distinct land-use type that can be further analyzed [4].

This study aims to apply unsupervised clustering techniques to multispectral satellite imagery to identify areas with industrial customer potential in Sidoarjo. Several spectral indices, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Normalized Difference Water Index (NDWI), were used to extract key features that distinguish between vegetation, built-up areas, and water bodies. Clustering techniques, particularly K-means, were then applied to group areas based on these features.

Through this approach, it is expected to generate a cluster map that highlights potential industrial zones, which can be used as a basis for planning infrastructure and energy resource allocation in Sidoarjo. Thus, this research not only contributes to industrial area mapping but also has the potential to support efficiency in energy management and regional development planning.

2. METHODS

The methodology for identifying industrial customer potential using image clustering began with the selection of Landsat imagery bands. To get the input of the bands images, user must first download it on earthexplorer.usgs.gov site. Figure 1 is a Flowchart of processing method using the implementation of Remote Sensing.

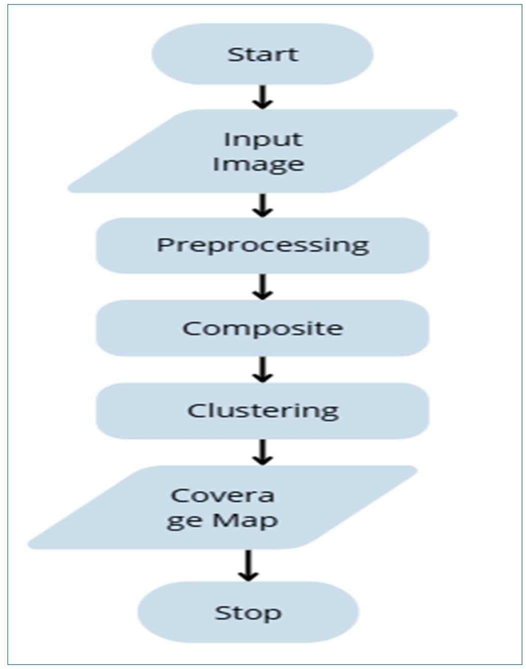

Figure 1: Flowchart of Image Processing Method

The flowchart above represents a detailed process for analyzing satellite imagery using remote sensing techniques. Here's a step-by-step explanation of each phase involved in this process

The process begins with the acquisition of satellite imagery. High-resolution multispectral satellite images are typically used in this stage. These images, often from sources like Landsat or Sentinel-2, provide valuable data that can be used for a variety of land use and environmental monitoring applications. The choice of satellite depends on the spatial, spectral, and temporal resolution required for the analysis [1].

Preprocessing: Once the satellite images are obtained, they undergo a preprocessing phase. This phase involves several key operations, such as atmospheric correction, radiometric calibration, and geometric corrections. Atmospheric correction helps to remove distortions caused by the atmosphere, while radiometric calibration ensures that the pixel values accurately represent the surface reflectance. These corrections are vital to ensure that the data is consistent and can be compared across different times or sensor types [5]. Geometric corrections ensure that the image accurately aligns with the Earth's surface.

Composite: In this phase, multiple spectral bands from the satellite image are combined to create composite images. This is done

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to enhance specific features of interest, such as vegetation, water bodies, or urban areas. For example, a combination of Red, Green, and Near-Infrared (NIR) bands is commonly used in vegetation studies because the NIR band is highly sensitive to plant health [2]. The composite image makes it easier to distinguish between different land types or environmental features.

Clustering: After preprocessing and composite creation, the next step involves unsupervised clustering, where pixels are grouped based on their spectral similarities. Clustering algorithms like K-means or ISODATA are often employed for this purpose. These algorithms automatically divide the image into several clusters, each of which represents a different land cover type (e.g., forest, water, urban). This step is essential for automating the classification of large datasets and identifying spatial patterns in the landscape [6].

Coverage Map: The final output of this process is a coverage map, which visually represents the different clusters formed during the clustering step. The map displays the different land-use classes or cover types identified from the satellite imagery. These classes can range from vegetation to urban or industrial areas, depending on the characteristics of the clusters. This coverage map provides a comprehensive view of land use and can be used for various applications, such as urban planning, environmental management, or resource allocation [7].

In conclusion, this process involves sophisticated image processing techniques that transform raw satellite data into actionable information. The combination of image preprocessing, composite creation, clustering, and visualization allows for efficient and accurate land-use classification, which is vital for informed decision-making in various fields, from environmental monitoring to urban planning.

2.1 Study Area and Data Collection

The study was conducted in Sidoarjo, East Java, Indonesia, a region characterized by a mix of industrial, agricultural, and residential land uses. Sidoarjo is known for its rapidly growing industrial sector, which makes it a focal point for energy distribution and urban planning. Satellite imagery was used to identify and map potential industrial zones, which are crucial for future infrastructure development. The primary data source for this research was Landsat 8 imagery acquired in September 2025. Landsat 8 imagery offers a spatial resolution of 30 meters per pixel, suitable for distinguishing between various land uses, including industrial zones.

2.2 Bands Input

A specific satellite, aircraft, or other vehicle provides the images used in remote sensing. These images are derived from sensor records that have unique properties within each height level, which establishes the variations in the remote sensing data [8]. Launched in 1972, Landsat is one of the distant sensing vehicles [9]. In this study, several spectral bands from satellite imagery were used to extract key features and classify land use. The Red band (0.6 - 0.7 µm) was employed primarily for vegetation analysis and land cover classification, as it is sensitive to vegetation reflectance. This band is crucial for calculating the Normalized Difference Vegetation Index (NDVI), which helps distinguish between vegetated and non-vegetated areas [1]. The Green band (0.5 - 0.6 µm) was used for vegetation health analysis, as it is sensitive to chlorophyll content in plants and is also used in NDVI calculations [2]. The Blue band (0.4 - 0.5 µm), which is sensitive to atmospheric conditions and water bodies, was utilized for detecting water and correcting atmospheric effects. This band is essential for calculating the Normalized Difference Water Index (NDWI), which helps identify water bodies and differentiate them from other land uses [10].

The Near-Infrared (NIR) band (0.7 - 1.1 µm) is particularly important in remote sensing for vegetation monitoring, as it strongly reflects from healthy vegetation. This band was used in the calculation of NDVI to assess vegetation density and also in the Normalized Difference Built-up Index (NDBI) to identify built-up areas like industrial zones [5]. The Shortwave Infrared (SWIR) band (1.2 - 1.8 µm) was employed to detect moisture content in vegetation, soil, and built-up areas, and it was used to further refine the NDBI for identifying urban areas [11]. Finally, if available, the Thermal Infrared (TIR) band (10.5 - 12.5 µm) was utilized to assess surface temperature variations, such as those caused by urban heat islands, offering insights into built-up areas and urban stress [12].

Together, these bands and indices allowed for a comprehensive analysis of land-use patterns, enabling the classification of areas into categories such as industrial zones, residential areas, vegetation, and water bodies. The integration of multiple bands and indices is vital for obtaining accurate results in land-use classification and environmental monitoring.

Table 1: Landsat Band Requirements (Source: NASA).

Spectral Band	Wavelength Range	Primary Applications	Common Indices
Red Band (B4)	0.6 - 0.7 µm	Vegetation analysis	**NDVI** (Normalized Difference Vegetation Index)
Green Band (B3)	0.5 - 0.6 µm	Vegetation health	**NDVI** (Normalized Difference Vegetation Index)
Blue Band (B2)	0.4 - 0.5 µm	Water body detection	**NDWI** (Normalized Difference Water Index)
Near-Infrared Band (B5)	0.7 - 1.1 µm	Vegetation monitoring- Land cover classification - Vegetation health	**NDVI** (Normalized Difference Vegetation Index) & **NDBI** (Normalized Difference Built-up Index)
Shortwave Infrared Band (B6&7)	1.2 - 1.8 µm	Moisture content detection	**NDBI** (Normalized Difference Built-up Index)
Thermal Infrared (TIR) Band (B10&11)	10.5 - 12.5 µm	Surface temperature analysis	**LST** (Land Surface Temperature)

2.3 Preprocessing of Satellite Images

The preprocessing of satellite images is a critical step to ensure the accuracy and reliability of the subsequent analysis. Initially, the raw satellite images undergo radiometric calibration to correct for sensor and atmospheric distortions. All spectral bands used in this study were radiometrically corrected prior to further analysis [13]. Radiometric calibration ensures that the pixel values in the images reflect the true surface reflectance, enabling consistent analysis across different images and sensors. Following this, atmospheric correction is applied using the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) module in ENVI, which removes atmospheric effects, such as water vapor and aerosols, that can distort the reflectance data. This correction is essential for obtaining accurate surface reflectance values, especially when comparing images taken at different times or from different satellites.

Figure 2: Atmospheric, Geometric and Radiometrically corrected images

Next, a Region of Interest (ROI) is defined using a shapefile boundary to isolate the specific study area, in this case, Sidoarjo. This subset operation ensures that only the relevant area is analyzed, excluding any extraneous regions from the data. This step helps improve processing efficiency and focus on the target area. Additionally, resampling may be applied if necessary, to ensure that all spectral bands align properly spatially. Resampling is particularly important when combining images from different sources or resolutions, ensuring that all data layers are spatially consistent. Together, these preprocessing steps help prepare the satellite imagery for further analysis, such as feature extraction and classification, by minimizing errors

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caused by atmospheric conditions, sensor inaccuracies, or misalignments.

Figure 3: Masking Image by Region of Interest

2.4 Feature Extraction

Feature extraction is an essential step in remote sensing image analysis, where specific characteristics of the image, such as land use or vegetation health, are isolated to aid in classification or clustering. In this study, three spectral indices Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Normalized Difference Water Index (NDWI) are extracted from the satellite imagery to differentiate between vegetation, built-up areas, and water bodies. These indices are calculated using specific formulas that combine different spectral bands of the satellite image, each index serving to highlight distinct land cover features.

2.4.1 Normalized Difference Vegetation Index (NDVI)

The NDVI is a widely used index to monitor vegetation health and density. NDVI value is acquired from mathematical formula between Near Infrared Band and Visible Red Band [14], as vegetation reflects strongly in the NIR region and absorbs strongly in the red region. NDVI is widely applied for vegetation mapping and monitoring land cover [1].

NDVI equation is the result of the subtraction of Near Infrared Band pixel value to Visible Red Band pixel value which is divided by the sum of Near Infrared Band pixel value to Visible Red Band pixel value. The NDVI was calculated from the preprocessed NIR and Red bands [3]. This process produces image with new pixel value as illustrated in Figure 6. Following is the formula of NDVI [9].

$$NDVI = \frac{NIR - Red}{NIR + \ Red}$$

NDVI process produces new image with the value of pixel ranges from -1 to +1. The positive value of pixel indicates the existence of vegetation, while the negative value of pixel indicates non-vegetation object. The classification of object constructed based on the value of NDVI is represented in Table 2 [15].

Table 2: NDVI Value.

Classifications	NDVI Value
Cloud, Water, Snow	< 0
Rocks and Bare Land	0 – 0,1
Grassland and Shrubs	0,2 – 0,3
Tropical Forests, Mangrove Forest	0,4 – 0,8

2.4.2 Normalized Difference Built-up Index (NDBI)

The NDBI is used to detect built-up areas such as urban zones, roads, and industrial areas. This index utilizes the difference between the Shortwave Infrared (SWIR) and Near-Infrared (NIR) bands, as built-up areas have a distinct spectral signature compared to natural features like vegetation or water bodies [5]. Following is the formula of NDBI.

$$NDBI = \frac{SWIR - NIR}{SWIR + \ NIR}$$

Higher values of NDBI (closer to +1) correspond to built-up areas with dense infrastructure (e.g., cities, industrial areas). Lower values (closer to 0) correspond to non-built-up areas such as vegetation or bare soil. The NDBI is useful for identifying urban and industrial areas, which are key for analyzing the potential zones for industrial customers in this study [11].

2.4.3 Normalized Difference Water Index (NDWI)

The NDWI is specifically designed to detect water bodies. It uses the reflectance in the Green band and Near-Infrared (NIR) band. Water bodies generally have a higher reflectance in the Green band and a lower reflectance in the NIR band, making them distinguishable from land-based features [10].

$$NDWI = \frac{Green - NIR}{Green + \ NIR}$$

Higher values of NDWI closer to +1 correspond to water bodies such as lakes, rivers, and reservoirs. Lower values closer to 0 or negative indicate non-water areas such as land, vegetation, or built-up areas. The NDWI is a critical index for distinguishing water bodies from surrounding land uses, and in this study, it is particularly useful for identifying areas like lakes, rivers, and other water bodies in the Sidoarjo region [10].

2.5 Composite Process

The composite process in remote sensing refers to the technique of combining multiple spectral bands into a single, more informative image. This process enhances the ability to distinguish between different land cover types or features by leveraging the unique reflectance properties of various materials in different parts of the electromagnetic spectrum. In the context of satellite imagery, composite images are often created by combining bands that emphasize specific features, such as vegetation, water bodies, or built-up areas.

In ENVI, creating a composite typically involves stacking the spectral bands together to form a multiband image. This step is essential for analyses like classification or clustering, where multiple features need to be considered simultaneously. For instance, combining the Red, Green, Blue, NIR, and SWIR bands allows for more accurate differentiation between natural and man-made features. Common composite types include true-color composites (using the Red, Green, and Blue bands) and false-color composites (using NIR, Red, and Green bands) to enhance the visibility of vegetation or water.

The composite process enables analysts to manipulate the data more effectively and highlights features that may not be visible in individual bands. Once the bands are combined, the resulting composite image can be used for further processing, such as clustering or classification.

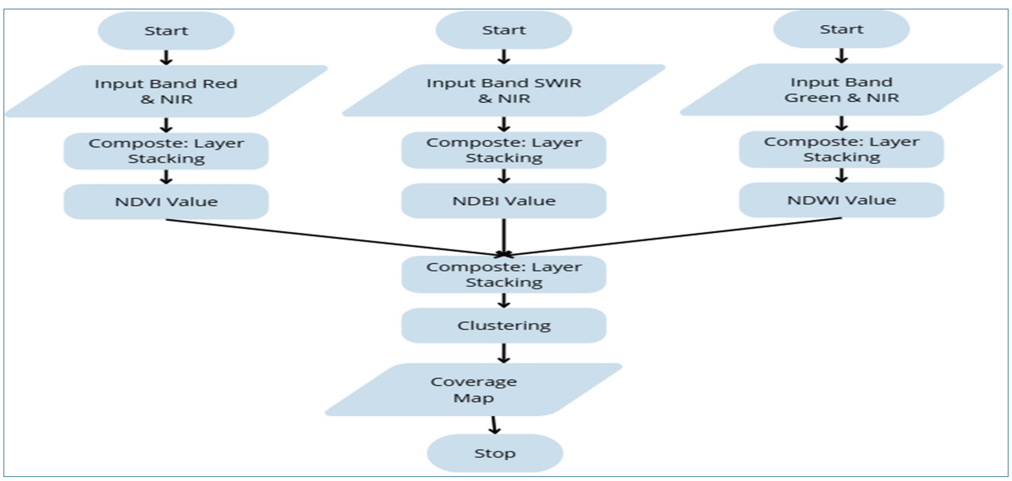

Figure 4: Layer Stacking Process

2.6 Clustering in ENVI

Clustering with ENVI using the K-means Method involves grouping pixels based on their spectral similarity, which helps in classifying different land-cover types in satellite imagery. The first step in the process is to prepare the data by calculating relevant spectral indices, such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Normalized Difference Water Index (NDWI), using the satellite bands. These indices are crucial for distinguishing between vegetation, built-up areas, and water bodies. Once the indices are calculated, the next step is to use the K-means clustering method in ENVI. This technique is an unsupervised classification algorithm that divides the image into a specified number of clusters (K) based on the spectral similarity of the selected bands or indices.

To perform K-means clustering in ENVI, the user selects the multiband image containing the calculated indices (NDVI, NDBI, and NDWI) as input. The number of clusters (K) is determined, and the K-means algorithm then iteratively assigns each pixel to one of the clusters by calculating the distance between each pixel's values and the centroid of each cluster. The number of clusters can be optimized by using methods such as the Elbow Method, which helps identify the optimal value for K based on the total within-cluster variance. Once the clustering process is complete, ENVI generates a classified image where each cluster corresponds to a different land-use type or feature, such as industrial zones, vegetation, or water bodies.

This method is especially useful for large-scale land-cover mapping and the identification of areas with potential industrial use. After clustering, further analysis can be performed, such as calculating the area of each cluster and refining the results with morphological operations to improve the accuracy and smoothness of cluster boundaries.

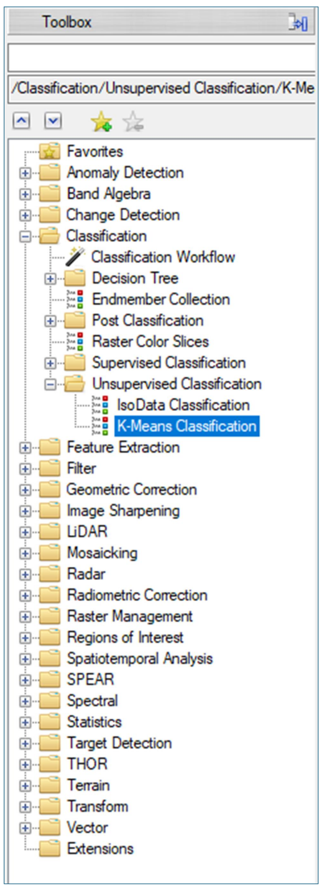

Figure 5: K-means Clustering Process in ENVI.

3. RESULTS AND DISSCUSION

3.1 Band Math

To calculate these indices, ENVI's Band Math tool was used, which enabled the creation of these indices from the satellite image bands. The NDVI was calculated using the Near-Infrared (NIR) and Red bands to assess vegetation density, with higher values indicating denser vegetation. The NDBI was derived from the Shortwave Infrared (SWIR) and NIR bands to highlight built-up areas, with higher values corresponding to urban zones. Lastly, the NDWI was calculated using the Green and NIR bands, which is effective in identifying water bodies, as water has distinct spectral characteristics in these bands.

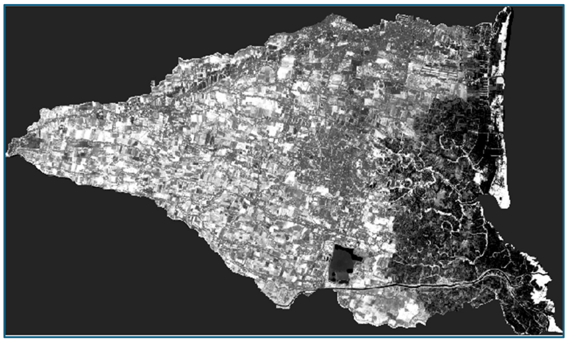

Figure 6: NDVI Image Reflecting Vegetation

The area in the image that appears bright white represents high vegetation density. This is due to the NDVI (Normalized Difference Vegetation Index), which calculates vegetation values as positive numbers. The closer the value is to 1, the brighter the area will appear in the image, indicating dense vegetation.

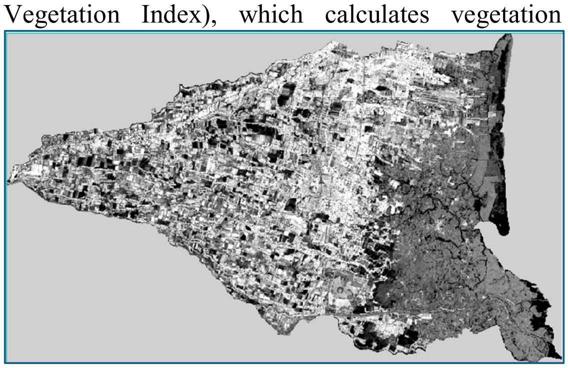

Figure 7: NDBI Image Reflecting Buildings

In the NDBI, the areas that appear brighter (closer to white) indicate a higher presence of built-up areas, such as buildings and infrastructure. This is because the NDBI calculates values that emphasize built-up surfaces as positive numbers. As the value increases towards 1, the area appears brighter, indicating urbanization and built environments. Conversely, darker areas in the image represent regions with lower built-up density, which could correspond to natural landscapes or vegetation.

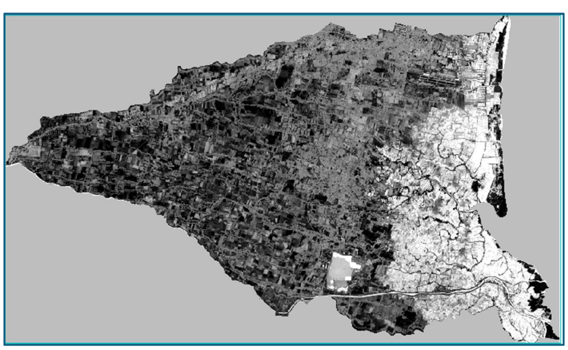

Figure 8: NDWI Image Reflecting Water Bodies

The image represents the NDWI (Normalized Difference Water Index). In this image, areas that appear brighter (closer to white) indicate the presence of water bodies such as rivers, lakes, or wetlands. NDWI highlights water features by emphasizing the reflectance differences

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between the near-infrared (NIR) and green bands. The darker regions represent land or other non-water surfaces, where the NDWI value is lower. These areas can be built-up zones, vegetation, or barren land.

3.2 Cluster Map

After the application of K-means clustering to the NDVI, NDBI, and NDWI layers, a cluster map of the Sidoarjo study area was produced. The resulting map shows three spatially distinct clusters derived from differences in spectral responses across the study area. Figure 9 illustrates the classification output, in which each cluster is represented by a different color to facilitate visual differentiation. The map provides a general overview of the spatial distribution of clustered land-cover patterns and serves as the foundation for further interpretation of land-use classes in the subsequent section.

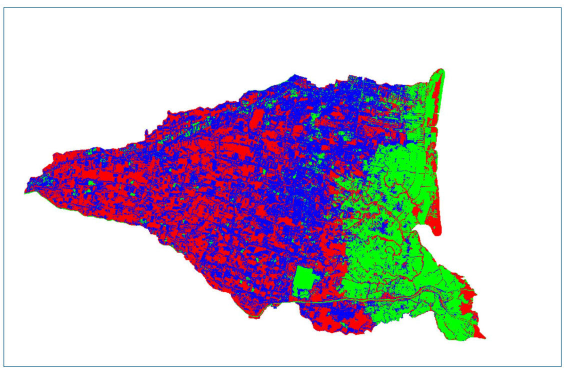

Figure 9: Cluster Map

Figure 9 presents the spatial distribution of the three clusters produced by the K-means classification in the Sidoarjo study area. Each cluster is represented by a different color to facilitate visual distinction and to highlight the variation of spectral-response patterns across the region. The map shows that the classified pixels form spatially identifiable groupings, indicating that the selected spectral indices were effective in separating land-cover patterns. This classification output provides an important basis for the subsequent interpretation of land-use classes.

3.3 Cluster Interpretation and Land Use Classification

The results of the clustering process provide useful insights into the land use distribution across Sidoarjo. Cluster 3, characterized by high NDBI and low NDVI, clearly identified the industrial zones. These zones typically have dense infrastructure and low vegetation, making them suitable for industrial customer potential. The NDBI values are high in these clusters due to the reflective nature of built-up surfaces in the shortwave infrared spectrum, which is indicative of urban areas [5]. The low NDVI values confirm the sparse vegetation or lack thereof in these areas, which is a characteristic feature of industrial zones [11].

Cluster 1, which displayed high NDVI and low NDBI, was classified as vegetated areas, including agricultural lands and forests. These areas are rich in plant life and have minimal urban development. The high NDVI values in these clusters suggest healthy vegetation and dense forests, while the low NDBI values reflect the absence of built-up structures [2].

Cluster 2 exhibited high NDWI values, identifying water bodies such as rivers, lakes, and reservoirs. These areas have distinct spectral characteristics in the Green and NIR bands, which make water bodies easy to detect using NDWI [10]. The clustering results accurately delineated water bodies in the Sidoarjo region, assisting in distinguishing them from surrounding land features.

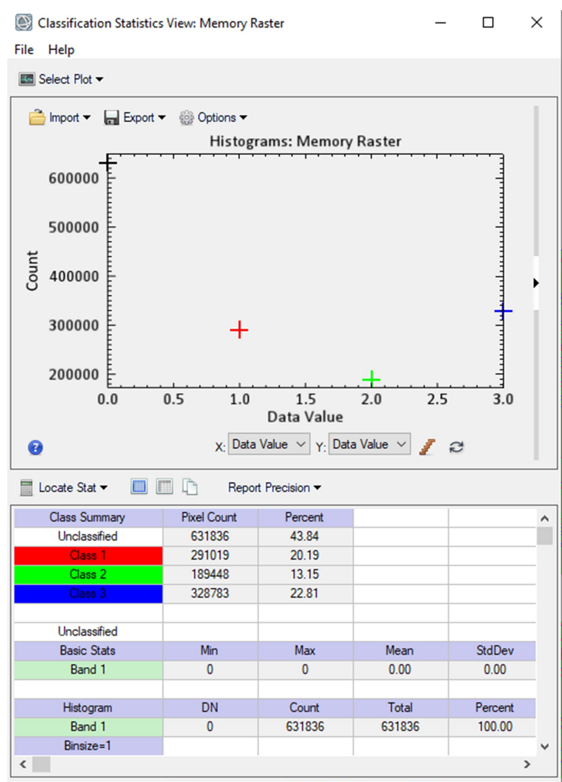

Figure 10: Classification Statistics

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The image displays the classification statistics for a raster dataset, showing the distribution of pixel values across different classes, represented by red, green, and blue. The "Class Summary" section provides the pixel count and percentage for each class. Class 1 (red) consists of 291,019 pixels, representing 20.19% of the total area. Class 2 (green) has 189,448 pixels, which account for 13.15%, while Class 3 (blue) contains 328,783 pixels, or 22.81%. Additionally, there are 631,836 unclassified pixels, making up 43.84% of the area. These **unclassified pixels correspond to areas outside the masking or ROI and are not included in the classification**. With a pixel size of 30 meters, the total area covered by each class can be calculated by multiplying the pixel count by the area each pixel represents.

3.4 Area Calculation

The area of each cluster was calculated by counting the number of pixels assigned to each cluster and multiplying by the pixel area (30m × 30m for Landsat 8). The calculation for each cluster is as follows:

Class 1 (Cluster 1 – Vegetated Areas):
The pixel count for Class 1 is 291,019 pixels. Each pixel represents 0.09 hectares. Therefore, the total area for Class 1 is calculated as:

291,019×0.09=26,190 hectares

Class 2 (Cluster 2 – Water Bodies):
The pixel count for Class 2 is 189,448 pixels. The area for Class 2 is:

189,448×0.09=17,050 hectares

Class 3 (Cluster 3 - Industrial Zones):
The pixel count for Class 3 is 328,783 pixels. The area for Class 3 is:

328,783×0.09=29,590 hectares

Therefore, the total area covered by all clusters in the study region is 72,830 hectares, representing a substantial portion of the Sidoarjo region.

4. CONCLUSIONS

This study successfully applied unsupervised clustering using K-means to classify land use in Sidoarjo based on satellite-derived indices, specifically NDVI, NDBI, and NDWI. The clustering process effectively identified key land-use categories, including industrial zones, vegetated areas, and water bodies, which are essential for urban planning and energy distribution. The areas covered by industrial zones were quantified, and the results showed that approximately 29,590 hectares are designated as industrial zones, highlighting the significant industrial development in the region.

The use of Band Math in ENVI to calculate the indices allowed for efficient extraction of relevant features from the satellite imagery, which were then used in the clustering analysis. The clustering results demonstrated a meaningful separation of land-use classes based on the spectral indices, particularly in distinguishing industrial zones, vegetated areas, and water bodies.

These results provide valuable insights for PLN and other utility companies in optimizing infrastructure and energy distribution, particularly in urban and industrial areas. The methodology demonstrated in this study is not only effective for mapping land-use types but can also be applied to other regions for similar urban planning and resource management applications.

Future work could involve refining the clustering technique with additional spectral indices, improving the temporal analysis, and exploring the use of more advanced clustering algorithms, such as Gaussian Mixture Models (GMM) or DBSCAN, to further enhance the precision and accuracy of land-use classification.

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conclusions presented in this study remain the sole responsibility of the authors. This research would not have been possible without the support and contributions of all parties involved.

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