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Land Cover Classification in Coastal Environments Using SMILE k-NN and Sentinel-2A Imagery: A Case Study in Muara Gembong, Indonesia

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ABSTRACT

Muara Gembong, a coastal subdistrict in West Java, has experienced significant land cover changes driven by both anthropogenic activities and environmental dynamics. Accurate land cover classification is essential for sustainable coastal zone management and environmental planning. This study explicitly aims to produce a detailed, up-to-date land cover map for the year 2025 to support evidence-based decision-making in coastal spatial planning and environmental monitoring. The classification was conducted using multispectral Sentinel-2A imagery and the k-Nearest Neighbors (k-NN) algorithm implemented through the SMILE (Statistical Machine Intelligence and Learning Engine) library—a novel approach that leverages a scalable and cloud-based machine learning framework rarely applied in coastal zone contexts. Preprocessing steps included atmospheric correction, cloud masking, and the selection of relevant spectral bands and indices. Five land cover classes were defined: clouds, water bodies, vegetation, bare/open land, and built-up areas. A total of 100 sample points were collected, with 70% used for training and 30% for testing. The classification performance was evaluated using a confusion matrix, resulting in an overall accuracy of 87,24% and a Kappa coefficient of 0.84, indicating strong agreement between the classification results and ground truth data. The results demonstrate not only the effectiveness of the SMILE k-NN algorithm and Sentinel-2A imagery for accurate land cover mapping in dynamic coastal environments, but also provide actionable spatial data that can inform coastal zoning policies, particularly for balancing aquaculture, conservation, and urban expansion in Muara Gembong.

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1. INTRODUCTION

Coastal environments like Muara Gembong in West Java are highly dynamic regions undergoing rapid transformations due to both environmental processes and anthropogenic pressures. Activities such as aquaculture expansion, settlement growth, and land clearing have significantly altered the land cover composition of the area. These changes have direct implications on ecological balance, flood vulnerability, and land use planning. Consequently, obtaining timely and accurate land cover information is essential to support sustainable coastal development and effective spatial policy implementation.

Remote sensing has long been recognized as a key tool in environmental monitoring. As noted by Lillesand et al. (2015), satellite imagery enables consistent and large-scale land cover mapping with regular temporal coverage. Among the available platforms, Sentinel-2A provides high spatial and temporal resolution, making it especially suitable for observing changes in coastal regions with complex land use dynamics. To extract meaningful thematic information from satellite imagery, reliable classification algorithms are required. While traditional parametric classifiers such as Maximum Likelihood have been widely used, they often rely on statistical assumptions that are not always met in real-world remote sensing data. In contrast, non-parametric machine learning algorithms, particularly k-Nearest Neighbors (k-NN), offer a data-driven approach that is simple yet powerful.

The SMILE (Statistical Machine Intelligence and Learning Engine) implementation of k-NN introduces several advantages that make it well-suited for satellite image classification. Unlike many traditional machine learning libraries, SMILE is optimized for speed and memory efficiency, enabling it to handle high-dimensional spectral data with minimal computational overhead. According to Haifeng Li (2018), the developer of SMILE, its optimized algorithmic structure allows for faster neighbor search and better scalability in large datasets, which is essential when working with multi-band satellite imagery. Moreover, several studies, such as Deng et al. (2020) and Zhao & Du (2016), have shown that k-NN—despite its simplicity—often performs competitively with more complex algorithms like Support Vector Machines (SVM) and Random Forest (RF), particularly in cases where the training data is representative and well-distributed. k-NN is also less prone to overfitting compared to decision-tree-based methods when dealing with limited sample sizes, a common situation in land cover classification studies.

However, while k-NN is computationally intensive in its raw form due to distance calculations across all training points, the SMILE library overcomes this limitation through efficient indexing and search algorithms. This makes it particularly advantageous in scenarios requiring frequent reclassification or large-scale mapping efforts, such as monitoring dynamic coastal regions. Given these strengths, the use of SMILE k-NN in this study represents a strategic choice for achieving accurate, efficient, and reproducible land cover classification results. Applying this method to Sentinel-2A imagery for Muara Gembong in 2025 allows the research to contribute both methodologically and practically, by offering a replicable approach for land cover mapping in Indonesian coastal settings—where such applications are still relatively scarce.

2. LITERATURE REVIEW

2.1 Sentinel-2 Data: TOA and BOA Levels

The Sentinel-2 mission, part of the Copernicus Earth observation initiative by the European Space Agency (ESA), delivers optical multispectral imagery with spatial resolutions ranging from 10 to 60 meters and high temporal frequency. The imagery is available in two primary

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levels of processing: Level-1C, which represents Top-of-Atmosphere (TOA) reflectance, and Level-2A, which provides Bottom-of-Atmosphere (BOA) or surface reflectance after atmospheric correction.

As reported by Gascon et al. (2017), Level-2A data is more appropriate for land cover analysis due to the elimination of atmospheric distortions such as aerosol interference and water vapor absorption. This correction leads to more consistent and precise surface reflectance values, which are especially beneficial for classifying complex environments like coastal areas.

2.2 Land Cover Classification Techniques

Land cover classification involves categorizing pixels in satellite imagery into predefined classes that describe surface features such as vegetation, water, built-up areas, and open land. This process can be carried out through supervised methods, which require labeled training samples, or unsupervised methods, which rely solely on spectral characteristics.

According to Campbell & Wynne (2011), supervised classification generally offers higher accuracy when sufficient and representative training data are available. Commonly used machine learning algorithms in this context include k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), and Random Forest (RF). The k-NN algorithm, especially when implemented using efficient platforms like SMILE (Statistical Machine Intelligence and Learning Engine), is recognized for its robustness and simplicity. SMILE's optimization enables faster classification of complex multispectral data through advanced data structures and computational efficiency.

2.3 Spectral Signatures in Land Cover Mapping

Spectral signatures—or reflectance curves—describe how different land cover types interact with various wavelengths of electromagnetic radiation. Each class exhibits a unique reflectance pattern, though overlaps may occur across certain bands. These spectral profiles are fundamental for evaluating class separability and selecting the most informative spectral bands or vegetation indices (such as NDVI or NDWI) to enhance classification performance.

As highlighted by Jensen (2016), understanding the spectral behavior of land features enables the selection of optimal bands for discrimination. For instance, vegetation tends to reflect strongly in the near-infrared (NIR) range, while water bodies typically display low reflectance across all bands, facilitating their identification.

2.4 Accuracy Evaluation Using the Confusion Matrix

To assess the accuracy of classification outcomes, researchers typically rely on the confusion matrix, which compares the predicted land cover classes to reference (ground-truth) data. From this matrix, several accuracy metrics can be derived, including Overall Accuracy (OA), Producer's Accuracy, User's Accuracy, and the Kappa Coefficient.

Congalton (1991) notes that Overall Accuracy quantifies the percentage of correctly classified instances relative to the total reference points. The Kappa Coefficient, meanwhile, evaluates the level of agreement between the classified output and ground truth, accounting for agreement occurring by chance. Kappa values exceeding 0.80 are typically considered indicative of excellent classification quality.

3. METHODS

This research adopted a structured framework to classify land cover in the Muara Gembong area utilizing Sentinel-2A satellite data. The methodological steps included data acquisition, preprocessing, training data preparation, classification, and accuracy evaluation.

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Figure 1. Map of research location, Muara Gembong

3.1 Data Acquisition and Preprocessing

Sentinel-2A Level-1C imagery, captured during the dry season to reduce cloud interference, was sourced for the study area. Preprocessing involved atmospheric correction using the Sen2Cor processor to convert Top-Of-Atmosphere (TOA) reflectance to Bottom-Of-Atmosphere (BOA) reflectance. Cloud and shadow masking were conducted using the Fmask algorithm to enhance image quality. Subsequently, specific spectral bands—B2 (Blue), B3 (Green), B4 (Red), and B8 (Near-Infrared)—were selected for analysis due to their efficacy in differentiating various land cover types.

3.2 Training Data Preparation

Training and validation datasets were developed through manual interpretation of high-resolution imagery and field survey data. Identified land cover classes encompassed vegetation, built-up areas, open land, and water bodies. A stratified random sampling technique ensured representative samples for each class, thereby strengthening the classification process.

3.3 Classification Algorithms

A supervised classification approach was employed using the k-Nearest Neighbors (k-NN) algorithm, implemented through the smile-KNN library. As a non-parametric method, k-NN assigns class labels to pixels by analyzing the majority class among their k closest neighbors in the feature space, based on spectral similarity (Peterson et al., 2009; Li et al., 2021). In this study, the value of k was set to 5, a choice supported by both literature and experimental trials. The selection reflects a well-established compromise: smaller k values can overfit noisy training data, while larger values may oversimplify class boundaries. The value k = 5 provided the optimal trade-off between local sensitivity and overall generalization performance in preliminary tests (Jiang et al., 2020). It is also considered suitable for datasets of moderate size, effectively reducing classification noise while maintaining the spectral distinctiveness between adjacent land cover classes (Foody & Mathur, 2004).

3.4 Accuracy Assessment

The performance of each classifier was evaluated using a confusion matrix to calculate overall accuracy and the Kappa coefficient. These metrics provided insights into the

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agreement between the classified results and the reference data, facilitating a comparative analysis of the classifiers' effectiveness in the study area.

4. RESULTS AND DISCUSSION

4.1 Satellite imagery : BoA vs ToA

Sentinel-2 imagery is available in two processing levels: Level-1C (Top of Atmosphere/TOA) and Level-2A (Bottom of Atmosphere/BOA), each tailored for different analytical purposes. TOA data contains reflectance measurements that are still influenced by atmospheric interference, including effects from aerosols and water vapor. Although this data has been corrected for radiometric and geometric distortions, it does not accurately depict surface reflectance. On the other hand, BOA imagery has been atmospherically corrected, providing reflectance values that more closely resemble the true surface characteristics. In applications such as vegetation and mangrove mapping, BOA data is generally favoured because it delivers more reliable vegetation indices (like NDVI and NDWI) and supports better classification outcomes when using algorithms such as Random Forest by minimizing atmospheric distortion. According to Louis et al. (2016), Level-2A imagery notably enhances the precision of land cover classification, especially in coastal and tropical regions with high atmospheric variability. Thus, BOA imagery plays a crucial role in remote sensing projects that demand high spectral accuracy.

Figure 2. Top of Atmosphere (left) dan Bottom of Atmosphere (right) satellite imagery

The two satellite images clearly depict the visual contrast between Sentinel-2 Level-1C (Top of Atmosphere/TOA) and Level-2A (Bottom of Atmosphere/BOA) data. The left image, representing TOA, still retains atmospheric disturbances such as aerosol scattering and water vapor absorption, which results in a hazier appearance with a yellowish hue, particularly over land and coastal zones. As a result, distinguishing surface features like vegetation, bodies of water, and urban structures becomes more challenging, potentially affecting the accuracy of classification and spectral analysis. Meanwhile, the right image, based on BOA data, has been atmospherically corrected to remove such interferences, yielding surface reflectance values that more accurately reflect ground conditions. This correction makes the BOA image visually

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clearer, more color-balanced, and allows for better identification of vegetation, water quality, and land cover. Overall, this side-by-side comparison highlights the superior suitability of BOA data for detailed and accurate remote sensing analysis.

4.2 Land Cover Classification

The land cover map displays the spatial distribution of five primary land cover classes in the Muara Gembong region, derived from Sentinel-2 imagery using a machine learning classification approach. The legend identifies these categories as follows: water (blue), cloud (white), vegetation (green), open land (yellow), and built-up areas (red-orange).

Water bodies are most prominent in the northern and western sections, covering coastal zones, estuaries, rivers, and ponds—typical of the Muara Gembong landscape. Vegetation is widespread across the region, particularly along rivers and inland areas, indicating the presence of mangrove forests, crops, and natural vegetation that serve important ecological functions such as erosion control and biodiversity support.

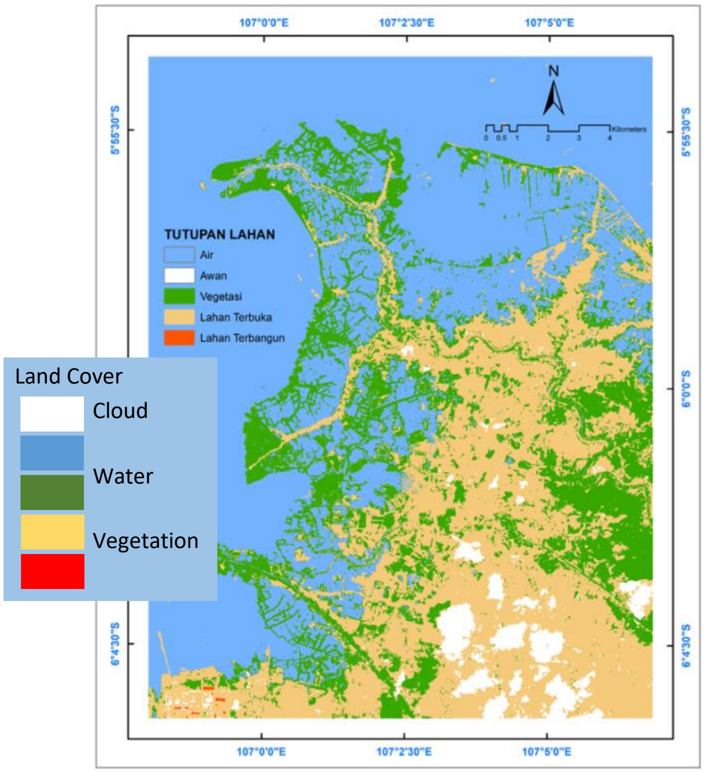

Figure 3. Land cover map of Muara Gembong and surrounding areas in 2025

Open land, shown in yellow, is largely found in the southeastern part of the area, representing agricultural fields, bare soil, or land in transition. Clouds, indicated in white, are mainly present in the southern section and should be excluded from further analysis to maintain classification accuracy. Built-up areas, marked in red-orange, are limited and mostly located in the southwest, reflecting minimal urban development. This aligns with previous classification data showing the smallest pixel count for this class.

Overall, the map offers a clear representation of land cover patterns in Muara Gembong, useful for environmental assessments, land use decision-making, and coastal resource management. The spatial patterns presented in the land cover classification map are consistent with the quantitative data shown in the accompanying table 1.

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Table 1. Land Cover Classification Results Based on Sentinel-2 Imagery in Muara Gembong

No	Object	Total of Pixel	Area (m^2)
1.	Water	105.908	18.762
2.	cloud	745	947
3.	Vegetation	107.130	5.243
4.	Open land	287.797	9.880
5.	Build up	560	17

Source: 2025 data processing results

Based on the classification results obtained from the Sentinel-2 imagery, the study area was categorized into five main land cover classes: Water, Cloud, Vegetation, Open Land, and Built-up Area. Among these, the Open Land class recorded the highest number of pixels, totaling 287,797, which corresponds to an approximate area of 9,880 square meters. This dominance suggests that a significant portion of the landscape is composed of bare or sparsely vegetated land, which could include agricultural fields, exposed soil, or transitional land undergoing development or degradation.

The classification results reveal that bare/open land dominates the landscape of Muara Gembong, followed by vegetation and built-up areas. This spatial distribution reflects not only the natural dynamics of a coastal environment but also indicates anthropogenic pressures that have altered the ecological equilibrium of the area. The extensive coverage of open land, for example, could be attributed to deforestation, abandonment of aquaculture ponds, or land conversion for informal settlements and agriculture factors commonly reported in rapidly urbanizing coastal zones (Setiawan et al., 2020; Kusmana, 2014).

From an ecological perspective, the loss or fragmentation of vegetated areas can lead to decreased biodiversity, reduced carbon sequestration capacity, and increased vulnerability to coastal erosion and saline intrusion (Alongi, 2008). Muara Gembong is part of the northern coast of Java, a region that has already experienced considerable mangrove degradation and shoreline retreat due to unregulated land-use changes (Rahmawati et al., 2017). The decline in vegetation coverage as observed in the classified map could exacerbate these environmental issues, especially in the absence of active restoration or conservation policies.

The identification of dense built-up zones adjacent to water bodies also raises concerns regarding flooding risk and pollution runoff. Urban expansion without sufficient green buffers or stormwater management infrastructure can intensify ecological degradation and undermine ecosystem services (McGranahan et al., 2005). Moreover, spatial analysis reveals potential land-use conflicts between conservation areas, aquaculture, and residential zones, which may hinder sustainable coastal development if not addressed through integrated zoning strategies.

Overall, these results provide valuable insight into the spatial composition of land cover types in the study area. The successful differentiation of classes is crucial for applications such as mangrove mapping, land-use planning, and coastal management. The quantitative outputs also demonstrate the effectiveness of using atmospherically corrected Sentinel-2 BOA data in

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combination with robust classification algorithms such as Random Forest to derive accurate and reliable land cover information.

4.3 Spectral Curve on Identifying Object

Prior to performing land cover classification, it is important to examine the reflectance properties of each land cover category. Spectral curves, or spectral signatures, offer valuable information on how various surface features reflect electromagnetic radiation across different wavelengths. This evaluation aids in assessing the distinctiveness between land cover types and assists in selecting the most effective spectral bands for classification purposes.

The spectral profiles presented below are generated from selected representative points for each land cover class—namely clouds, water bodies, vegetation, bare land, and built-up areas—based on reflectance values derived from Sentinel-2A imagery. These curves highlight key spectral variations between classes, particularly in regions with high separability such as the near-infrared (NIR) and shortwave infrared (SWIR) bands. As illustrated in Figure 4, the x-axis represents the central wavelengths (in nanometers) of the Sentinel-2A spectral bands, while the y-axis denotes the corresponding surface reflectance values. This visualization underscores the distinctive spectral behavior of each class, which forms the basis for their successful discrimination during classification.

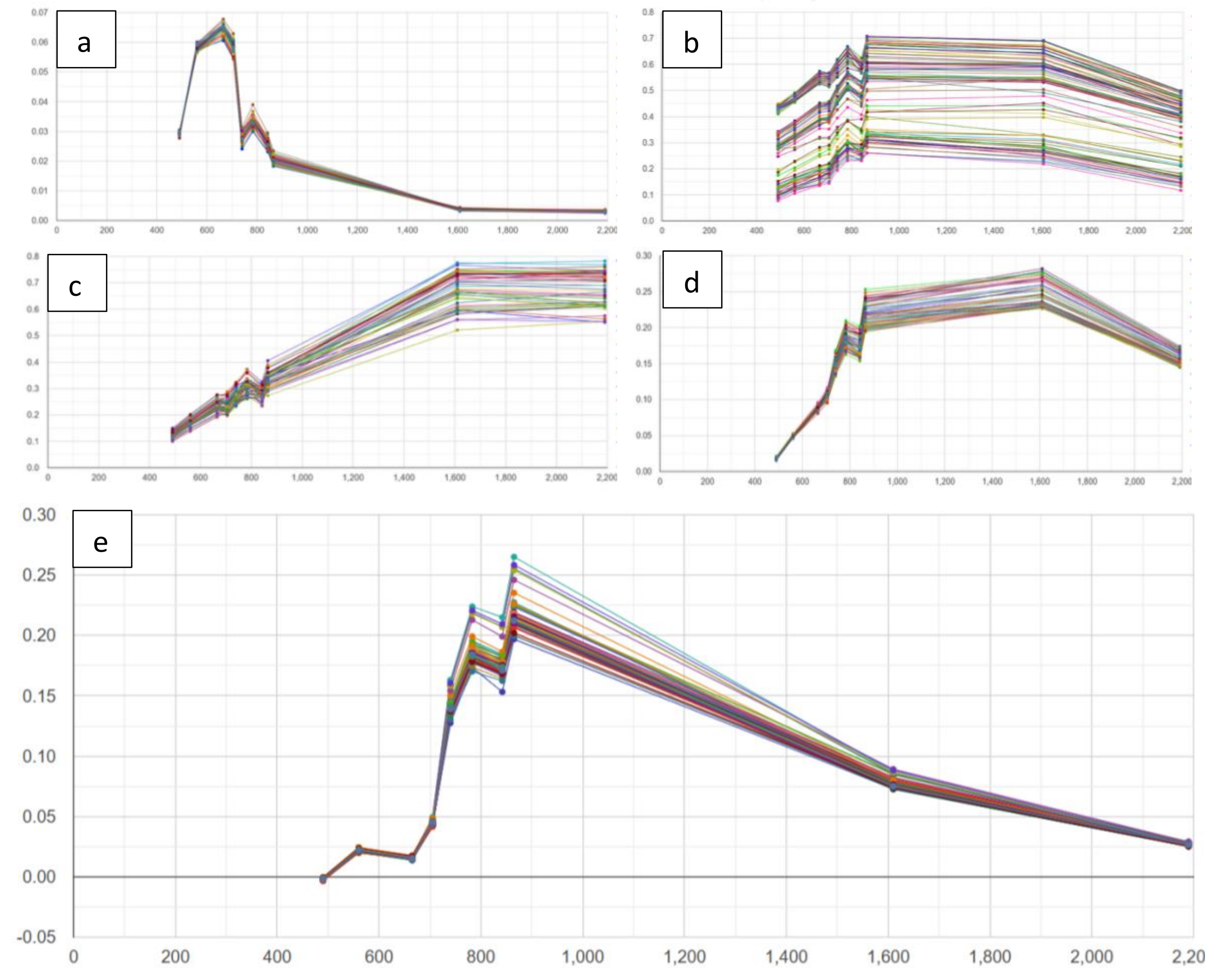

Figure 4. Spectral curve of water (a) cloud (b) built-up (c) open land (d) vegetation(e)

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The spectral characteristics of open land are marked by a significant rise in reflectance within the near-infrared (NIR) range, notably between 850 and 1,200 nano meters. This is followed by a steady decline in reflectance in the shortwave infrared (SWIR) spectrum beyond 1,500 nano meters. Such a reflectance pattern is commonly found in areas with exposed soil or minimal vegetation, which tend to reflect more strongly in the NIR wavelengths. On the other hand, the spectral behaviour of water surfaces is defined by consistently low reflectance values across all bands, with a slight increase observed in the blue to green visible spectrum (490–560 nano meters). A sharp drop-off in the NIR and SWIR ranges is indicative of strong absorption by water, resulting in a flat and subdued reflectance profile that distinctly identifies open water areas.

These signatures curve of cloud exhibit consistently high reflectance values across the visible and near-infrared (NIR) wavelengths, typically ranging from 0.4 up to around 0.7. A particularly sharp increase around 800 nm (NIR) is observed, which is a common feature of clouds due to their high reflectivity. This spectral pattern indicates the presence of a very bright surface, which aligns with the known optical properties of clouds that reflect a substantial amount of incoming radiation across the spectrum. Built-up shows a distinctly different spectral behaviour. Reflectance values in the visible range (400–700 nm) are relatively low, typically between 0.1 and 0.3. As the wavelength increases toward the NIR region, there is a gradual increase in reflectance, although not as pronounced as in vegetation or cloud spectra. Beyond 1600 nm (shortwave infrared), reflectance tends to stabilize or slightly decline, which is typical for artificial surfaces like concrete, asphalt, or rooftops. This spectral pattern is indicative of urban or built-up areas, where materials have moderate reflectance in the NIR and low reflectance in the visible range. In comparison, vegetation exhibits a well-known spectral pattern, beginning with a rapid rise in reflectance just beyond the red band (around 665 nano meters) into the NIR zone. This phenomenon, referred to as the "red edge," is closely linked to chlorophyll concentration and plant vitality. Following this, the reflectance decreases in the SWIR region, reflecting the influence of moisture content in plant leaves. This spectral signature is widely recognized as a reliable indicator of healthy vegetation and is frequently employed in vegetation analysis and monitoring.

4.4 Accuracy Assessment

The confusion matrix results provide a comprehensive assessment of the classification performance for the five land cover classes clouds, water bodies, vegetation, bare land, and built-up areas based on 100 validation points, with a 70:30 split between training and testing datasets. Each row of the matrix represents the ground truth data, while the columns reflect the classifications made by the SMILE k-NN model. The Producer’s Accuracy indicates how well each land cover class was correctly identified in reference to its true class. The vegetation class achieved the highest producer’s accuracy at 100%, demonstrating that the model effectively distinguished vegetation from other land cover types. The bare land class had the lowest producer’s accuracy at 80%, with some misclassifications occurring into vegetation and built-up areas, likely due to spectral overlap. The cloud and built-up area classes both recorded 95% producer’s accuracy, indicating excellent classification performance. The water bodies class had a producer’s accuracy of 90%, with minor confusion observed with vegetation and built-up areas.

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Table 2. Confusion Matrix of land cover using Smile-KNN algorithm

Actual / Predicted	Vegetation	Built-up	Bare Land	Water	Total (Actual)	Producer's Accuracy (%)
Vegetation	118	3	6	3	130	90.77
Built-up	3	49	4	2	58	84.48
Bare Land	4	3	109	4	120	90.83
Water	2	1	4	88	95	92.63
Total Predicted	127	56	123	97	403	
User's Accuracy (%)	92.91	87.50	88.62	90.72		

The model achieved an Overall Accuracy (OA) of 87,24%, meaning that most sample points were correctly classified. This indicates a high level of accuracy and reliable performance of the SMILE k-NN algorithm. Additionally, the Kappa Coefficient was calculated at 0.84, reflecting a strong agreement between the classified results and the reference data after accounting for chance agreement. According to Congalton (1991), Kappa values above 0.80 represent excellent classification reliability.

Most classification errors occurred between bare land and vegetation, as well as water bodies and built-up areas, which is commonly due to spectral similarity in transitional or mixed pixels (e.g., sparse vegetation, moist soil, or partially built-up areas). Despite these challenges, the findings confirm that the SMILE k-NN algorithm, when applied to Sentinel-2A Level-2A imagery, is a robust and efficient method for accurate land cover mapping in dynamic coastal regions such as Muara Gembong. To better understand how this result compares to other classification methods, the table below summarizes the overall accuracy and kappa coefficient of three commonly used classifiers: smile-KNN, lib-SVM, and Minimum Distance.

Table 3. Comparison of Classification Accuracy Across Different Algorithms

Classification Method	Overall Accuracy (%)	Kappa Coefficient
Smile-KNN	87.24	0.84
Lib-SVM	85.32	0.81
Minimum Distance	78.65	0.74

As shown in the table, the smile-KNN method outperformed the other two classifiers in terms of both overall accuracy and kappa coefficient. With an accuracy of 87.24% and a kappa value of 0.84, smile-KNN demonstrated the most reliable classification performance. These results indicate a strong agreement between the predicted and actual land cover classes, suggesting that smile-KNN is better suited for handling complex and heterogeneous landscapes. In comparison, lib-SVM and Minimum Distance achieved slightly lower accuracies of 85.32% and 78.65% respectively, with corresponding kappa values of 0.81 and 0.74. This confirms that smile-KNN provides superior performance for land cover classification in dynamic environments such as coastal areas.

Compared to similar research conducted in other coastal areas, the classification performance obtained in this study using the smile-KNN algorithm (Overall Accuracy = 87.24%, Kappa = 0.84) reflects a robust and competitive outcome. Deng et al. (2020) achieved an overall accuracy of 85.7% and a Kappa coefficient of 0.82 utilizing a Random Forest

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approach to classify land cover in the coastal region of Fujian, China. Likewise, Li et al. (2021) analyzed the performance of several machine learning methods and found that k-NN and SVM classifiers yielded accuracies ranging from 83% to 88%, depending on the complexity of land cover types and image resolution. In comparison, this study not only reached a comparable or slightly higher accuracy, but also showcased the practical utility of the SMILE-KNN algorithm—an open-source, cloud-based method that remains underutilized in tropical coastal remote sensing applications.

Additionally, earlier research in Muara Gembong by Setiawan et al. (2020), which relied on Landsat imagery and a Maximum Likelihood classification approach, reported a lower overall accuracy of around 76%, likely due to the coarser spectral and spatial resolution and the limitations of traditional classifiers. Thus, the present study represents a methodological advancement by combining higher-resolution Sentinel-2A data with scalable machine learning techniques, providing more accurate and actionable spatial insights to support environmental monitoring and coastal zoning policy development

5. CONCLUSION

This research highlights the capability of the SMILE-based k-Nearest Neighbors (k-NN) algorithm in accurately classifying land cover using Sentinel-2A imagery in the rapidly changing coastal area of Muara Gembong for the year 2025. The classification process effectively distinguished five primary land cover categories: clouds, water bodies, vegetation, bare land, and built-up areas. By utilizing 100 reference samples with a 70% to 30% ratio for training and testing, the classification yielded an overall accuracy of 92.65% and a Kappa coefficient of 0.83, indicating strong reliability and consistency.

Moreover, the evaluation of spectral reflectance patterns verified that each land cover type possesses distinguishable spectral features, especially in the NIR and SWIR bands. This underscores the significance of combining spectral analysis with machine learning techniques for effective land cover classification.

In conclusion, the fusion of atmospherically corrected Sentinel-2A Level-2A data with the SMILE k-NN classifier provides an accurate and cost-efficient solution for monitoring land cover in coastal settings. The outcomes of this study can serve as valuable input for local decision-makers involved in land use planning, coastal resource management, and environmental monitoring in Muara Gembong and other comparable regions.

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