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RESEARCH ARTICLE

# Applied One-Dimensional Convolutional Neural Network Image Fusion Sentinel-1 SAR and Sentinel-2 for Classification and Mapping Dynamics of Coastal Wetlands in Segara Anakan, Cilacap Regency, Indonesia

Muhammad Usman Zakaria [1*], Wirastuti Widyatmanti[2] , Retnadi Heru Jatmiko[2]

[1] *Master of Remote Sensing, Universitas Gadjah Mada, Yogyakarta, Indonesia.*

[2] *Department of Geography Information Science Faculty of Geography Universitas Gadjah Mada, Yogyakarta, Indonesia.*

* Corresponding author : muhammadusmanzakaria@mail.ugm.ac.id
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**Abstract**

Coastal wetlands have an important function, namely as an economic function and an ecological function, therefore the mapping and classification of wetlands is very important. However, remote sensing has limitations, namely high variability and spectral similarity between kleas. This makes the development of image fusion of SAR and optical images in classification, the combination of SAR and optical can provide better information. Over time, the CNN method of performing image fusion developed, which is a good method used to perform classification. In this study, Sentinel-2 fusion and VV polarization were used to identify the shrub classes that dominate Segara Anakan. The results of the application of CNN1D in the classification of wetlands in Segara Anakan resulted in an overall accuracy of 79.37% and a kappa of 0.76, so that CNN1D is very good at recognizing wetland classes but has limitations in recognizing Nypa which has spectral similarities with other classes. The benefit of using CNN1D that has been trained is that the model can be applied to a variety of other images. In its application, we used the image of Segara Anakan from 2019-2025 so as to gain knowledge, namely that Segara Anakan is controlled by the sedimentation process so that wetland classes increase dynamically. The massive sedimentation process in Segara Anakan was then overgrown by mangrove vegetation, besides that another trend is the change of vegetation from mangroves to nypa vegetation. This is because nypa vegetation is a vegetation that can adapt to medium to low salinity. Despite conducting a multitemporal study with a narrow gap of 6 years, the CNN1D that we have trained can classify wetlands in Segara Anakan well from 2019 to 2025. In addition, CNN1D with a light computing load can be an option if you need deep learning applications in other research.

**Keywords:** Convolutional Neural Network, Image Fusion, Wetland, Mangrove, SAR

## 1. Introduction

Wetland ecosystems are formed from the interaction between land and sea. Coastal wetland ecosystems have various forms that are very dynamic and have economic functions for the community and provide coastal protection from waves, wind and coastal abrasion (Wetlands International Indonesia, 2022). Wetlands are areas that are submerged in water, both permanently and temporarily, there are four types of wetlands based on their inundation, namely 1) permanently inundated; 2) seasonal flooding; 3) periodic flooding; and 4) seasonally waterlogged or not submerged but making the soil water-saturated (Semeniuk and Semeniuk, 1995). Wetlands are a very productive area and have a high diversity of both biological and non-biological resources, so wetlands are a very potential life support system. Wetlands play an important role in water purification and waste cleanup; climate stabilization; and mitigation from climate change (Finlayson et al., 2005). Based on the Ramsar Convention (1971), wetlands are categorized into three parts, namely terrestrial wetlands, coastal/marine wetlands and artificial wetlands (Ramsar Convention Secretariat, 2010).

Remote sensing studies for wetlands are utilized in several applications, namely hydrological monitoring, change monitoring and wetland classification (Liu et al., 2022). Remote sensing holds an important contribution in wetland mapping and monitoring, including classification, change detection and water level monitoring (Rezaee et al., 2018). Remote sensing for wetlands utilizes various sensors, starting with the use of aerial photographs, then developed with various other types of sensors, namely multispectral, hyperspectral, Synthetic Aperture Radar (SAR) and Light Detection and Ranging (LiDAR), it then developed into the integration of several remote sensing sensors, namely multispectral sensors and SAR for wetland mapping (Tiner et al., 2015). Despite the rapid development of remote sensing technology, wetland classification is still a challenge, this is because the land cover in wetlands has high variability, and wetland classes have similar spectral characteristics that make it difficult to classify (Rezaee et al., 2018). Challenges in identifying wetlands using remote sensing include 1) wetland properties, which include permanently flooded areas to periodic flooded areas; 2) environmental factors, including plant phenology, shadows caused by tall objects, hydrological fluctuations, and cloud cover; 3) technical limitations caused by however spectral values in adjacent plants can have the same value, even this also happens when using hyperspectral imagery (Tiner et al., 2015). The limitations of remote sensing for wetland studies make it necessary to develop innovative methods to improve the ability and accuracy of remote sensing, namely by using fusion techniques that integrate data from various sources that aim to obtain information with better quality so that with a combination of multiple sources it will be very useful for detecting environmental changes at the local, regional and global levels (Zoran, 2009). SAR imagery sensitive to vegetation structure and can detect the properties of wetlands with rich time series and optical imagery can capture variations in vegetation types because it is sensitive to the molecular structure of vegetation (DeLancey et al., 2020). Sentinel-1 is capable of observing the Earth's surface both during the day and at night, and its radar signals can penetrate cloud cover, making it unaffected by weather conditions (Chandra et al., 2025). So that the use of optical image fusion with SAR multitemporal has the potential to be applied to tropical areas that have high cloud cover (Reiche et al., 2015). Meanwhile, Sentinel-2 is a suitable image for the identification of coastal areas and shallow waters by having blue bands and green bands and having a fairly high spatial resolution with a wide spectral range (Aunurrahman et al., 2024).

Segara Anakan is one of the magrove ecosystems on the island of Java and has abundant biodiversity with a total mangrove forest area of 3,980 ha and has 60 types of mangrove plants (Anrozi et al., 2019). Segara Anakan experiences great dynamics due to high sedimentation in the Citanduy river resulting in the loss of the Segara Anakan lagoon area (Holtermann et al., 2009). In addition, shrubs and liana dominate most of the Segara Anakan area which characterizes damaged mangrove forests (Djohan, 2015). Mangrove damage in Segara Anakan is exacerbated by mangrove logging, land conversion, and pollution (Prayudha et al., 2024). Another study stated that Segara Anakan was degraded with indications of high NDVI values and low Mangrove Index values (Winarso et al., 2023).

In classifying shallow learning methods such as random forests, support vector machine learning (SVM), boosted regression trees and many other methods apply low-level features so that the detected spatial features are highly dependent on the user experience, which makes the shallow learning method have a weakness in extracting features on differents images (Nogueira et al., 2017). One of the methods that can be a solution in wetland mapping that tends to be complex is the Convolutional Neural Network (CNN) method which is one of the methods in deep learning that is very efficient in classifying, this is because CNN performs different extractions in various layers, namely the beginning, middle and end layers. (Rezaee et al., 2018). The architecture on CNNs can incorporate multiple stacked layers as inputs, which can come from different sources such as radar sensors (SARs) and optical sensor (DeLancey et al., 2020). In previous studies, the use of CNN for wetland studies had advantages compared to the shallow learning method shown by several studies, namely, CNN was 94% accuracy compared to Random Forest with 79% (Rezaee et al., 2018). Wetland classification using CNN had an accuracy of 81.3% compared to XGBoost with 75.5% (DeLancey et al., 2020). Wetland classification with CNN provided an accuracy of 86.93% compared to RF with an accuracy of 84.88% (Jafarzadeh et al., 2022).

In CNN there are several architectures, one of which is CNN1D. CNN1D is an architecture in CNN that performs temporal convolutions on data input through multiple kernels, the CNN1D model is based on a one-dimensional time series (Dorado-Rojas et al., 2022). CNN1D can detect sequential patterns in the temporal domain so that CNN1D can perform sequential feature extraction so that it is optimal in detecting sequences in the data sequence (Habibie et al., 2024). Based on that CNN1D extracts data at various layers so that compared to other algorithms, CNN1D requires less initial processing, 1D-CNN can fuse quickly and achieve better results (Zhou et al., 2019). CNN1D is commonly used in the analysis of one-dimensional time series data, this makes this study try to develop and modify the CNN1D model to be able to extract spectral data from Sentinel-1 and Sentinel-2 and the combination of the two in a one-dimensional sequence so as to allow the CNN1D model to treat spectral information analogously such as time series signals.

## 2. Data and Method

### 2.1. Study Area

The research location is in Laguna Segara Anakan (LSA) which is located in the southern coastal area of Cilacap Regency, Central Java Province, Segara Anakan has an area surrounded by mangrove forests and is covered by Nusa Kambangan Island with two outlets to the Indian Ocean (Holtermann et al., 2009). The location of the research is a national strategic area based on the RTRWN (National Spatial and Regional Plan through Government Regulation No.13 of 2017, namely Pangandaran – Kalipucang – Segara Anakan – Nusakambangan (Pacangsanak). The area in the study area reaches 243.7822 km2. The following in figure 1 is the research location located in Segara Anakan Lagoon, Cilacap Regency.

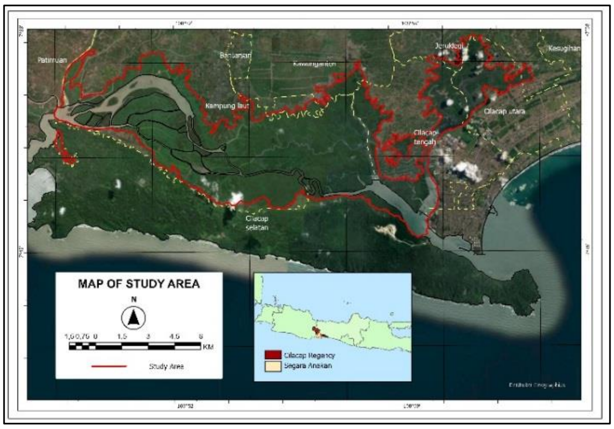


Fig 1. The Map of Segara Anakan

### 2.2. Materials

CNN requires a lot of data as a training model. In the CNN1D architecture, it does not require a spatial context but only requires a spectral value per pixel, so the data training uses sample polygons by taking the pixel value at the central point (centroid) of each polygon. In this study, good VV polarization was used for mapping of herbaceous vegetation at low altitudes (Henderson and Lewis, 2008). This is because Segara Anakan has a density of shrubland in the western part and mangroves in the east. Here is in table 1. is the image data used in this study. In order for the model's performance to be stable, in table 1 there is a five training data from different image recordings were used. We chose images with minimal cloud cover and we did not use the gap filling method to fill in the information that was covered by clouds. This is so that the pixels are not chaotic during the training and inference process, so we choose images that are clean from cloud cover in both training data and prediction data.

Table 1. Data Training and Prediction

| Years | Sentinel-2 | Sentinel-2 | Description |
|---|---|---|---|
| 2024 | 15 February | 17 February | Training data |
| 2024 | 29 February | 20 February | Training data |
| 2024 | 24 March | 21 March | Training data |
| 2024 | 23 May | 20 May | Training data |
| 2024 | 7 March | 1 March | Training data |
| 2019 | 17 April | 20 April | Temporal prediction |
| 2020 | 30 June | 25 June | Temporal prediction |
| 2021 | 16 April | 21 April | Temporal prediction |
| 2022 | 30 June | 28 April | Temporal prediction |
| 2023 | 16 May | 5 May | Temporal prediction |
| 2024 | 16 June | 16 June | Temporal prediction |
| 2025 | 30 April | 24 April | Temporal prediction |
| 2024 | 15 February | 17 February | Training data |

### 2.3. Image Prepocessing

Before processing, the data needs to be pre-processed, as this is due to the use of image fusion so it is very important to ensure that the input data has the same resolution and position to provide maximum results. The Sentinel-2 image used is Level-2A which has been corrected to BOA (Bottom of Atmosphere) so no pre-processing is required. The processing carried out on the Sentinel-2 image is resampling to 10 meters, this is done because the SWIR band has a resolution of 20 meters so resampling to 10 meters is useful for equalizing the resolution of each band. Meanwhile, the Sentinel-1 SAR image is processed through Google Earth Engine, which is an advantage of the image that is free to download and can be processed with a cloud computing system in Google Earth Engine. The Sentinel-1 image in Google Earth Engine has been applied orbit file and terrain correction. So, in this stage it is necessary to continue with the speckle filtering process with the Focal Mean method. The next stage is to resample the VV bands so that they have the same resolution as the Sentinel-2 image, which is 10 meters, so that with both images have the same resolution will make pixels can stack perfectly and produce maximum output.

### 2.4. Building Training Data

In deep learning applications, creating training data is one of the most important things to do, the diversity and amount of training data will be the basis of the model to learn about patterns and pixels in images.

Table 2. Number of Classes

| No Class | Land Cover |
|---|---|
| 0 | Water body |
| 1 | Mangrove |
| 2 | Nypa |
| 3 | Shrubland |
| 4 | Agro-Mudflat |
| 5 | Aquaculture |
| 6 | Non Wetlland (builtup, bareland, clouds) |
| 7 | Non-Wetland (inland forest) |

Data training is the result of a field survey that is reinterpreted which is then processed into polygons that are useful as data training. The creation of training data is carried out by taking polygons in each sample point area with a patch measuring 3 x 3 pixels so that the patch will extract the value of all raster bands on each polygon on both Sentinel-1 and Sentinel-2. The samples are then converted into csv to be trained data by the model. The following are the classes used in this study in table 2.

### 2.5. Feature Extraction

Fusion using CNN belongs to feature-level fusion, so the extracted features are subsequently combined for specific purposes (Singh et al., 2023). This makes it necessary to make the model able to extract the features contained in the image. In this study, several bands were used, namely red, green, blue, NIR and SWIR bands as well as VV polarization from Sentinel-1. The use of various indices will be very important to distinguish between vegetation, where mangroves with the types *of Sonneratia sp* and *Rhizophora sp* have identical reflections in the red, green, blue and NIR bands (Armanda et al., 2024). Here is in table 3. Are the features extracted by the CNN1D model.

Table 3. Feature Extractions

| Imagery | Feature | Source |
|---|---|---|
| Sentinel-2 | NDVI | (DeLancey et al., 2020) |
| | MNDWI | (Fei et al., 2025) |
| | NDMI | (Al-Maliki et al., 2022) |
| | BSI | (Jamali et al., 2022) |
| | GLCM Contrast | |
| | GLCM Correlation | |
| | GLCM Homogenity | |
| | GLCM Entropy | |
| | GLCM Dissimilarity | (Zhang et al., 2020) |
| Sentinel-1 | GLCM Angular Second Moment | |

### 2.6. Data Augmentation

Augmentation is used to expand a limited data set so that it can overcome for data-driven models (Yang et al., 2023). Augmentation this can minimize overfitting due to too little data. Augmentation aims to increase the variability of the data which makes the model better understand the various variations in the data (Marzuki et al., 2025). With data in the form of 1 dimension, the augmentation technique is carried out by adding 5% Gaussian noise to the dataset artificially doubles data 4 times to increase data variety. Augmentation is an effective step in deep learning studies, where research Nurcahya et al. (2023) using DenseNet architecture to study surface rougness found models that have not been able to learn patterns effectively. This makes it necessary to conduct training with diverse data so that performance becomes more stable.

### 2.7. Model Architecture

The model is built on CNN1D, the use of CNN as a classification method since fusion can capture prominent features of the input image (Shao and Cai, 2018), the application of this fusion is also excellent for combining images that have different characteristics such as SAR and optical imagery (Zeng et al., 2006). In this study, a convolutional layer with 128 filters containing a kernel configuration of 3 x 3 pixels was used to extract spatial features in the input image. In addition, 1 pixel of padding is applied to each convolution layer to keep the output dimensions the same as the input dimensions, aiming to optimize feature processing efficiency without losing information at the image edge. Furthermore, batch normalization, ReLU and MaxPooling1D activation were carried out to reduce dimensions. The next step is to draw to prevent overfitting of the classification results, the results of these steps are then converted into a one-dimensional vector (flattened) and followed by two fully connected layers of tang layers to produce an output layer according to the number of target classes. In figure 2 there is the architecture of model CNN1D.

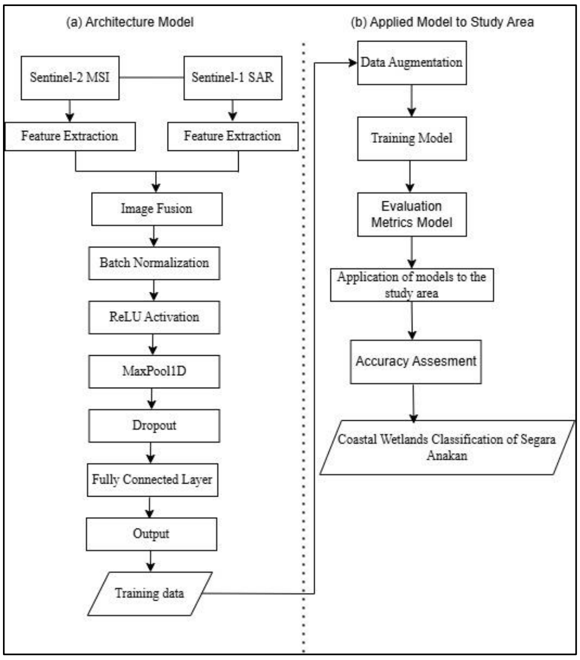


Fig 2. CNN1D Architecture

This study uses a 1-dimensional concept with input in the form of pixels in the form of numerical values that represent spectral or statistical features, in contrast to the 2-dimensional concept such as the research of Akmal et al. (2023) which uses CNN2D with the DenseNet architecture whose input is a 128x128 pixel RGB image.

## 3. Result

### 3.1. Segara Anakan Wetlands Overview

In carrying out this research, a field survey was carried out on May 8-10, 2025, in the field survey found various unique wetland habitats, namely various types of mangroves, nipah and shrubs such as Derris trifoliata and Acanthus ilicifolius. In addition, artificial wetlands such as ponds and rice fields were found. The following in table 4 are the types of wetland vegetation in Segara Anakan.

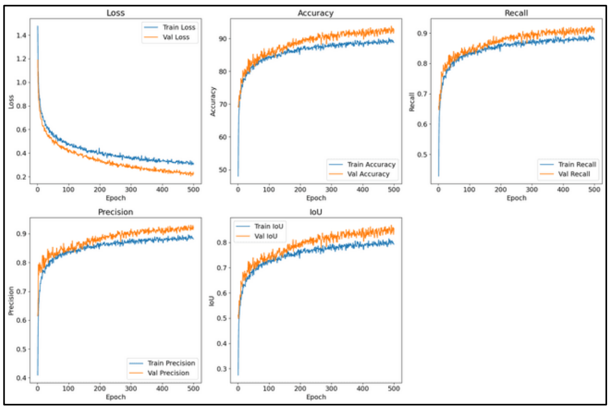


Fig 3. Model Evaluation

Table 4. Wetland Vegetation in Segara Anakan

| Documentation | Land Cover |
|---|---|
|  | Mangrove |
|  | Nypa |
|  | Shrubland *Derris trifoliata* |
|  | Shrubland *Acanthus ilicifolius* |

### 3.2. Model Evaluation

Before classification, the model needs to be trained to produce a stable and strong model. In the training process, it is divided into 80% for training and 20% for validation and 500 epochs are used to allow the model to see data repeatedly. The results of the training model showed that the train produced an accuracy of 88.78%, a loss of 0.31 precission of 0.88, a recall of 0.88 and an IoU of 0.79. Meanwhile, the validation produced an accuracy of 92.80%, loss of 0.22, precission of 0.92, recall of 0.91 and 0.85. The following in figure 3 are the results of the model evaluation.

With the results of the data training, it produces good accuracy, loss, recall, precission and IoU so that the CNN1D model has a good performance in recognizing wetland classes in Segara Anakan. The results of the model evaluation also did not show any overfitting or underfitting in certain classes.

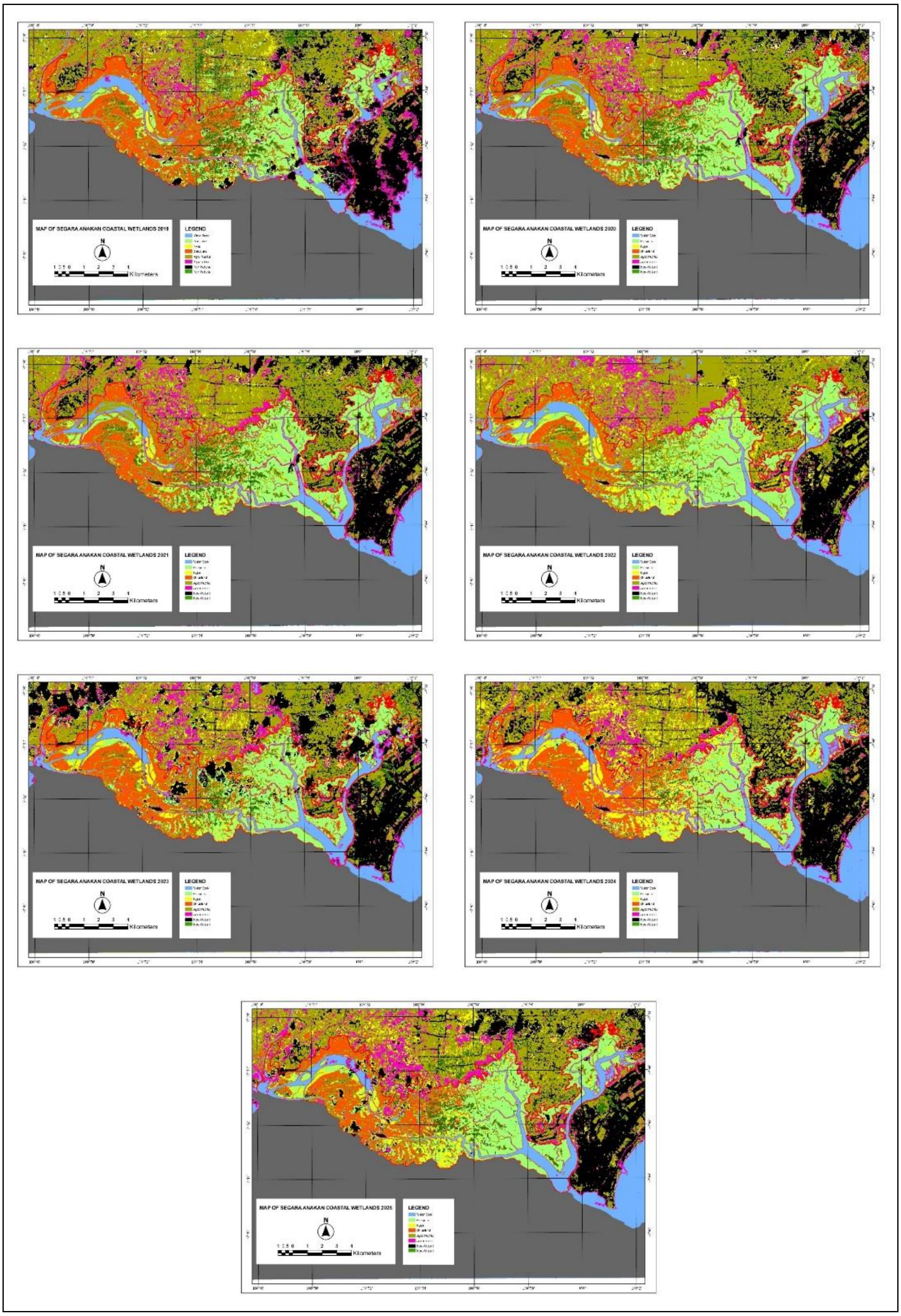

Fig 4. Dynamics of Segara Anakan 2019-2025

### 3.3. Accuracy Assessment

Accuracy assessment used the stratified random sampling method spread with the Cochran formula (1977) with a confidence level of 95% with a z-score of 1.96, a p value of 0.09 and a margin of error of 0.05 so that as many as 126 sample points. The sample is divided into samples obtained in the field and samples obtained from high resolution imagery, namely Maxar with a 50:50 ratio. The results of the accuracy test using Overall Accuracy (OA) and kappa resulted in an OA of 79.37% and a kappa of 0.76. Then in table 5 are the results of the Overall Accuracy (OA) and Producer Accuracy (PA) of each class

The PA and UA results show that the model is able to predict wetland classes very well in each wetland class. However, there is a class that is difficult to predict by the model, namely the Nypa class, this is due to the spectral similarity of the Nypa class to other classes such as mangroves and shrublands.

Table 5. Result of PA and UA

| Land Cover | PA | UA |
|---|---|---|
| Water body | 70,60 | 100 |
| Mangrove | 79,20 | 90,50 |
| Nypa | 62,50 | 71,40 |
| Shrubland | 82,40 | 87,50 |
| Agro-Mudflat | 82,40 | 58,30 |
| Aquaculture | 100 | 68,40 |
| Non Wetlland (builtup, bareland, clouds) | 73,30 | 91,70 |
| Non-Wetland (inland forest) | 100 | 87,50 |

*Source : Analysis, 2025*

### 3.4. Segara Anakan Wetland Dynamics 2019-2025

One of the advantages of using CNN is that CNN can be applied to images with different recording times by using a pre-trained model and applied to the current data set (Zhao et al., 2021). So in figure 4 is the result of the classification of coastal wetlands in Segara Anakan from 2019 to 2025 by masking the Nusakambangan island area which is not a wetland area.

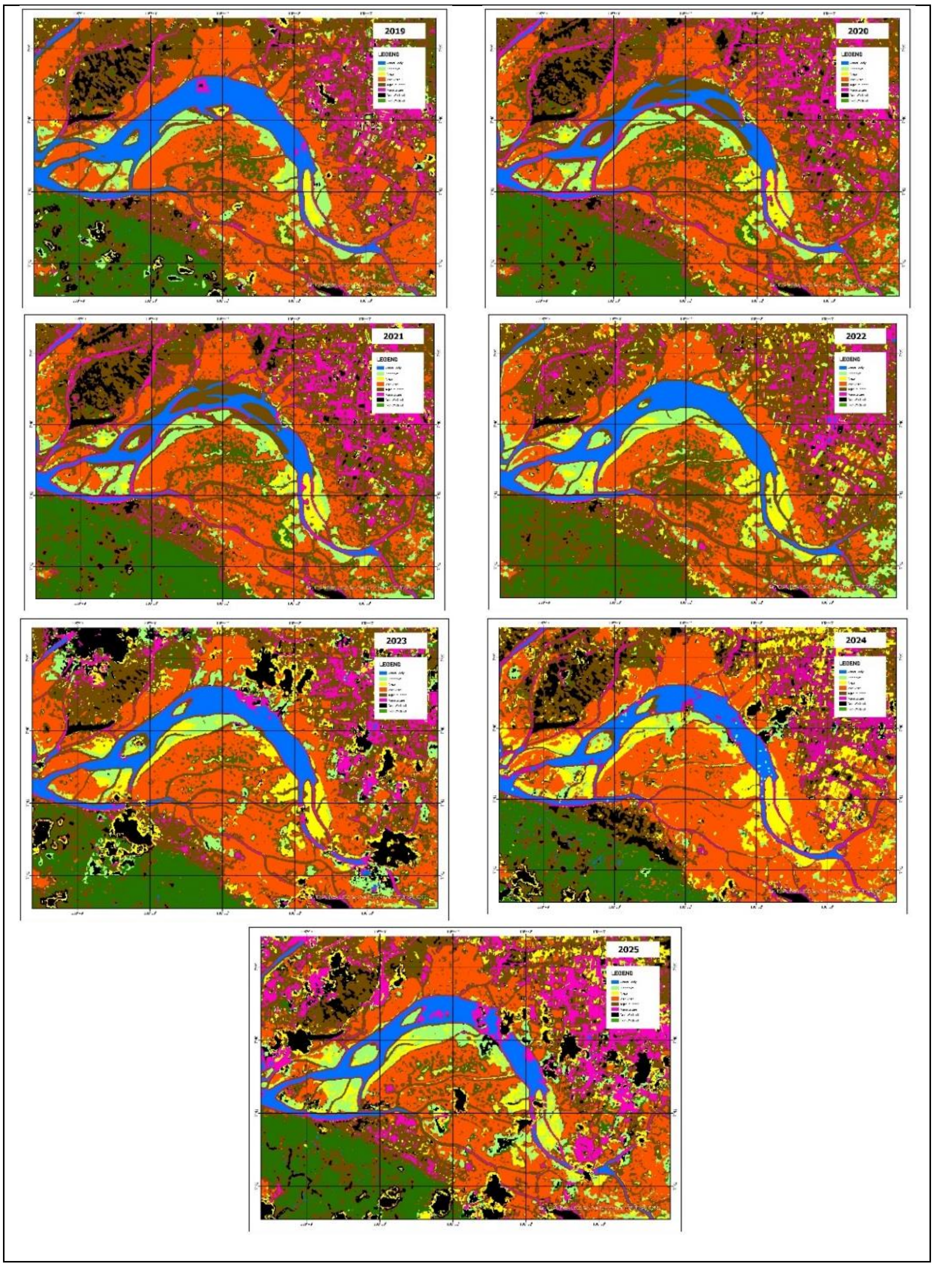


Fig 5. Dynamics of Segara Anakan Lagoon 2019-2025

The results of CNN1D in fig 4 we process on a large area covering the entire area of Segara Anakan and the surrounding area, to reduce the computational load we mask the Nusakambangan island area, besides that Nusakambangan island is not a wetland ecosystem. Then in fig 4 you can see the changes in the Segara Anakan starting in 2019 to 2025. The biggest change is in the core area of the Segara Anakan lagoon which experiences dynamics as seen in fig 5.

Table 6. Area of wetlands in Segara Anakan

| Year | Wetlands Area (ha) | | | |
|---|---|---|---|---|
| | Nypa | Mangrove | Shrubland | Aquaculture |
| 2019 | 1374,7 | 3640,78 | 3123,52 | 2690,85 |
| 2020 | 960,93 | 4068,78 | 2180,47 | 2815,51 |
| 2021 | 950,95 | 4071,55 | 2168,27 | 2817,78 |
| 2022 | 1620,26 | 4773,64 | 1789,61 | 2337,37 |
| 2023 | 2060,29 | 3697,03 | 2828,775 | 2645,05 |
| 2024 | 3062,93 | 3462,87 | 3349,32 | 2224,65 |
| 2025 | 2317,32 | 3974,79 | 2320,94 | 3148,43 |

Source : Analysis, 2025

By calculating the area of each class, the dynamics of Segara Anakan will be found multitemporally from 2019 to 2025. Multitemporal calculation will be very important to show how much the Segara Anakan changes even though it is only applied to a short temproal time, namely with a period of 6 years. So the following table 6 is the area of wetlands in Segara Anakan.

Changes in Immediately Saplings need to be identified in depth by analyzing changes from year to year. This is very important to know the location of the change and the form of change that occurs. This makes this research not only present data but also at the same time comprehensively analyze the dynamics that occur in Segara Anakan. The following in fig 6 is a map of changes analyzed from 2019 to 2025.

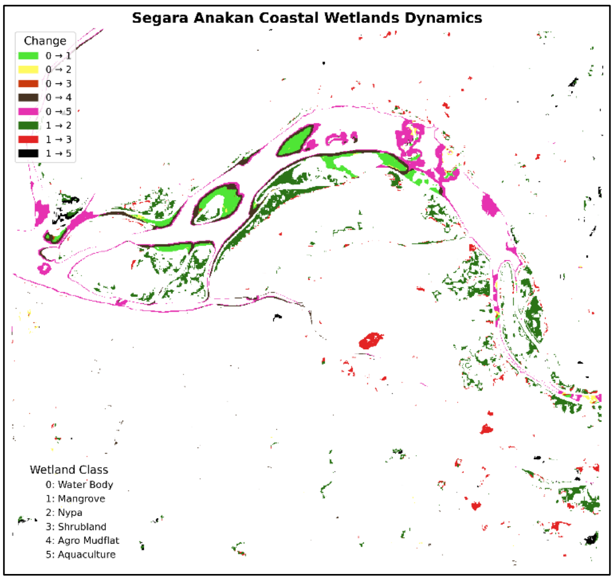


Fig 6. Map of Wetland Change in Segara Anakan 2019-2025

## 4.Discussion

The results of the model accuracy and accuracy testing can be obtained that the fusion of Sentinel-1 SAR and Sentinel-2 MSI using the CNN1D architecture obtained good results in conducting complex wetland classifications such as in Segara Anakan. This is influenced by Sentinel-1 which is a SAR image that has the ability to add 3 important factors in wetland studies, namely hydrological factors, soil moisture and vegetation type (Ramsey et al., 1999). The selection to use Sentinel-1 as the input of SAR imagery in this study is that Sentinel-1 is a SAR with an excellent C-Band for the identification of aquatic plants with a height of 1 meter, in contrast to the L-Band which is suitable for use in forested wetlands (Costa et al., 1998). This became the basis for the decision that Segara Anakan has a diverse vegetation, which is dense with mangroves in the eastern part but overgrown with shrubland and nypa in the west. The uniqueness of the study location greatly influences the classification results, where the performance of the classification often depends on the location due to the mixture of land cover (Tiner et al., 2015). So that with the location in Segara Anakan which has wetlands that tend to be not forested and dominated by shrubland and nypa, especially in the western part, the use of VV polarization in SAR inputs is used. If cross-polarization is sensitive to vegetation structure, VV polarization is useful in mapping herbaceous wetlands (Henderson and Lewis, 2008). So that the use of VV polarization was chosen in this study With an overall accuracy value of 79.37% and a kappa index of 0.76 indicates that the CNN1D model is quite good at recognizing each wetland class, but the challenge in wetlands that have complex vegetation types such as Segara Anakan is how the model can distinguish the nypa class from other vegetation, where the results of the PA and UA nypa metrics show an accuracy of 62.50% which is the lowest accuracy, This is due to the spectral similarity between Nypa and Understorey having spectral reflections similar to mangrove vegetation and terrestrial plants (Prayudha et al., 2024). The advantage of CNN1D that it only works on 1 convolutional dimension makes the model work quickly and efficiently (Yang et al., 2023). This makes CNN1D an advantage over CNN2D which works by cropping images in raster form and more complex parameters so that it has a heavy load in computation. The benefit of CNN1D in this study is that the CNN1D model that we have trained using 5 images with different recording dates is able to be applied well to predictive images, as well as produce a stable output. This makes CNN1D a suitable model for multitemporal studies, and our model can even be applied to other locations that certainly need a retraining process to adjust to the new location.

The general way of coastal wetlands in Segara Anakan is composed of various types of vegetation, namely mangrove vegetation, nypa and shrubs. Mangrove vegetation grows densely in the eastern part of Segara Anakan while nypa and shrub vegetation dominate the western part of Segara Anakan. Dynamics in Segara Anakan are controlled by sedimentation, logging, changes in land use to agricultural land and ponds, and pollution (Prayudha et al., 2024). This makes the area of wetlands in Segara Anakan increase dynamically from year to year.

Although this study conducted a temporal analysis with a narrow time span, namely 2019 to 2025, with a narrow time and image acquisition in the dry season, it can be seen in figure 6 several changes with the addition of land in the Segara Anakan lagoon area, this shows that Segara Anakan is a dynamic area. In general, the dynamics of Segara Anakan are controlled by the sedimentation process, where there is a sedimentation process that can be seen from the addition of land area in the western part of Segara Anakan or the lagoon area of Segara Anakan. The new land from this sedimentation then grows mangrove vegetation. Then another change, namely the mangrove vegetation that has grown in 2019, is seen to have changed to nipah vegetation and grows densely in areas that were formerly mangrove vegetation. Rapid vegetation growth is due to nypa being a vegetation that can grow and adapt to waters with moderate to low salinity (Prayudha et al., 2024). Where sedimentation in the Segara Anakan area can reduce the supply of seawater into the Segara Anakan stream which causes it to have lower salinity, so based on the results of the classification of the dynamics of Segara Anakan is caused by sedimentation and overgrown by mangroves and mangrove vegetation into nypa vegetation.

There is an increasing trend of every wetland vegetation among mangroves, nipah and shrubs. The biggest change can be seen in the nipah vegetation which has very significant changes, especially in 2021 to 2022 with an increase in the area of nipah from 950.95 ha to 1620.26 ha in 2021 and continues to increase slowly until 2025. The very rapid expansion of nypa is not only due to its ability to adapt to low to moderate soil salinity levels, but nypa can grow quickly because of its reproduction through its seeds carried by water (Nwobi et al., 2020). The increasing graph is not only shown by the nypa vegetation alone but also occurs in the shrubs consisting of *Acanthus ilicifolius* and *derris heterophylla*, which increase dynamically from year to year but the increase in shrubs does not occur significantly and is not even noticeable in the change map in figure 6. Nypa vegetation is the largest contributor to changes in Segara Anakan, the change of mangroves to nypa vegetation due to habitat changes both physical and chemical that occur due to nypa can block the flow of water so as to increase sedimentation and increase the amount of dirty sludge because it is mixed with waste materials, thereby reducing the physical and chemical quality of the soil (Eddy and Basyuni, 2020). Nypa in Segara Anakan is growing rapidly, where in the period from 2019 to 2025 the increase is quite significant. Although the existence of nipah changes the ecosystem both physically, chemically and biologically, of course nypa has benefits for the people in Segara Anakan who when field survey activities were carried out it was seen harvesting nypa to be used as raw materials for making various crafts.

## 5. Conclusion

The results of wetland classification using CNN1D produced an overall accuracy of 79.37% and a kappa of 0.76. This means that the CNN1D model is able to recognize most wetland classes well, but the performance that still needs to be optimized is the Nypa class, which has spectral similarities to other classes so that the model is still weak in predicting Nypa. By using 5 image data in different recordings and using augmentation techniques by doubling the data by 4 times and adding Gaussian noise by 5%, resulting in better model performance compared to without the augmentation process. The use of CNN1D has the advantage of being lighter in computational load than other models, as well as applications that produce good output, so CNN1D is the right model to be used in multitemporal studies because the trained model can be applied to other images.

The results of multitemporal mapping resulted in the conclusion that Segara Anakan is controlled by a sedimentation process that makes wetlands increase dynamically from year to year. The results of the change mapping show that the sedimentation results in Segara Anakan are then overgrown by mangroves, besides that there is also a trend of mangrove vegetation that turns into nypa caused by the rapid growth of nypa caused by its ability to adapt to low to moderate salinity levels and rapid development through seeds carried by water. Mapping using CNN1D produces knowledge that Segara Anakan is a dynamic area, so it is very important to monitor the Segara Anakan area.

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