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# LAND COVER CHANGE DYNAMICS AND POTENTIAL ACID SULFATE SOIL FORMATION IN SEGARA ANAKAN

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## ABSTRACT

*Tropical coastal regions are highly susceptible to acid sulfate soi formation due to ecological and hydrological changes driven by land cover dynamics and sedimentation. This study analyzes land cover changes from 1990 to 2025 and their implications for ASS development in Segara Anakan, Indonesia. Landsat imagery (Landsat 5 and Landsat 8/9 OLI) was classified using Random Forest and Gradient Boosting Tree algorithms within Google Earth Engine. Classification accuracy was assessed using overall accuracy and the Kappa coefficient. Land cover classes included mangrove, nipa palm, paddy fields, aquaculture ponds, settlements, bare land, water bodies, and forest. Results reveal substantial conversion of natural vegetation into paddy fields, bare land, and settlements, particularly in low-lying tidal areas. These changes disrupted ecological conditions that previously sustained organic matter accumulation, low-energy environments, and anaerobic waterlogging—three of the five key factors for ASS formation. Field validation confirmed soil pH < 4 in high-risk areas. This research demonstrates the effectiveness of integrating multi-temporal Landsat imagery with machine learning to detect spatio-temporal land cover dynamics and to identify areas prone to ASS formation, offering valuable insights for adaptive coastal management.*

***Keywords**: Land cover change; Acid sulfate soils; Tropical coastal wetlands; Remote sensing; Machine learning classification.*

## 1. Introduction

Tropical coastal regions are highly dynamic environments that are particularly vulnerable to both natural and anthropogenic changes (Darmawan et al., 2021). One of the most critical transformations in these ecosystems is land cover change, which can trigger environmental degradation and exert long-term impacts on ecological functions (Zakia et al., 2022). For instance, Segara Anakan and the Donan River estuary in Cilacap Regency, situated in low-lying coastal zones, have undergone extensive land transformation over the past three decades (Hilmi et al., 2021). Natural ecosystems such as mangrove forests and nipa palm stands have been converted into aquaculture ponds, bare land, paddy fields, and settlements. These transformations have not only reduced biodiversity and ecosystem services but have also intensified sedimentation processes and increased the potential for acid sulfate soil formation, one of the most severe types of soil degradation in coastal environments.

The formation of acid sulfate soils is a relatively slow process, beginning with sedimentation, pyrite formation, and subsequent oxidation. Acid sulfate soils develop through the accumulation of iron (Fe)-rich sediments in coastal wetland environments. Over time, sedimentation in these wetlands leads to the formation of pyrite ($FeS_2$) (Mendonça et al., 2020; Toivonen et al., 2020). These soils remain stable under waterlogged conditions; however, when exposed to air, oxidation occurs. This process is often triggered by hydrological disturbances and land cover change (Sharapova et al., 2021; Yuniarti et al., 2022). The oxidation of pyrite minerals produces sulfuric acid ($H_2SO_4$), which can drastically lower soil pH to extremely acidic levels, often below 4 (Pupathy et al., 2020). This extreme acidity can release toxic heavy metals, damage wetland ecosystems, harm vegetation, contaminate water resources, produce foul odors, and ultimately threaten environmental quality, land productivity, and human health (Napisah et al., 2020). Therefore, identifying land cover changes in relation to the potential formation of acid sulfate soils is of critical importance.

Widyatmanti (2017) identified five key factors influencing the development of acid sulfate soils: (1) the presence of iron (Fe), (2) the presence of sulfate (S),

(3) the availability of organic matter, (4) low-energy environmental conditions, and (5) waterlogging. The third, fourth, and fifth factors are closely related to land cover conditions, such as changes in mangrove and nipa palm distribution, as well as inundation and sedimentation processes. For instance, shifts in mangrove and nipa palm vegetation indicate changes in local water salinity. Furthermore, sedimentation in Segara Anakan and alterations in inundated land directly affect flooding patterns and increase the likelihood of pyrite formation.

Nevertheless, few studies to date have explicitly examined the relationship between land cover change and acid sulfate soil formation using a long-term remote sensing approach. Yet, the availability of satellite image archives such as Landsat, which has continuously recorded Earth's surface since the 1990s, provides an opportunity for robust spatio-temporal analysis (Darmawan et al., 2021; Ihsan et al., 2023).

Given the abundance of satellite data, effective and efficient processing methods are essential. Among widely used classification algorithms, Random Forest has proven highly effective for land cover classification (Sharma et al., 2018; Talukdar et al., 2020). The integration of machine learning algorithms such as Random Forest within the Google Earth Engine (GEE) platform has demonstrated strong performance and accuracy for land cover mapping (Farda, 2017). In general, Random Forest consistently performs well for long-term monitoring. As a comparison, the Gradient Boosting Tree method is also employed, which may outperform Random Forest under optimally tuned conditions (Handoko et al., 2020). In other performance evaluations, Random Forest has often achieved high accuracy, with overall accuracy (OA) up to 98.68% and Kappa coefficients up to 0.97 (Florek & Zagdański, 2023), while Gradient Boosting Tree performance depends strongly on parameter tuning and class distribution (Hamza & Larocque, 2005).

Building on this background, the present study addresses two primary research questions: (1) What are the patterns of land cover change in the Segara Anakan and Donan River estuary between 1990 and 2025, and (2) to what extent can these changes be linked to the potential formation of acid sulfate soils? The urgency of this study lies in the need for scientific evidence to inform adaptive and sustainable coastal zone planning and management. In the face of rapid development and land conversion in coastal areas, environmental risks such as pyrite oxidation and acid sulfate soil formation must be anticipated. By leveraging the long-term Landsat archive and geospatial technologies, this research is expected to contribute not only scientifically but also practically in supporting ecosystem-based coastal resource management policies.

Understanding these processes is also essential for guiding sustainable coastal development policies in rapidly urbanizing coastal regions such as southern Central Java. Existing studies on coastal land cover change have largely focused on biodiversity loss, ecosystem services, and sedimentation processes, yet explicit connections to the formation of acid sulfate soils remain limited. Furthermore, most research emphasizes short-term observations or localized case studies, while long-term, multi-decadal analyses are scarce. This study addresses this gap by integrating multi-temporal Landsat imagery with machine learning algorithms to provide a comprehensive spatio-temporal assessment of land cover change and its implications for acid sulfate soil formation in tropical coastal wetlands. The novelty of this research lies in linking landscape transformation to soil degradation processes using a remote sensing approach spanning more than three decades, thereby offering valuable insights for sustainable coastal management.

## 2. Method

The study area in this research is located in Segara Anakan, Cilacap. Segara Anakan is a coastal lagoon located in the southern part of Java Island, Indonesia, positioned between the Java mainland and Nusakambangan Island. This region represents one of Indonesia's most significant wetland ecosystems, characterized by dynamic interactions between freshwater and seawater, forming a brackish environment that supports diverse habitats such as mangroves, nipa palms, and estuarine zones. Sediment load from rivers plays a significant role in sedimentation processes within this region. Beyond its ecological and economic functions, the Segara Anakan lagoon possesses considerable scientific value as a natural laboratory for understanding tropical coastal ecosystem dynamics. The ecological aspects of this lagoon offer opportunities for researchers to examine how land-ocean interactions shape landscapes and their influence on sustainable land use practices. Therefore, this region is not only locally important but also contributes significantly to scientific knowledge development.

The primary data utilized consisted of multi-generational Landsat satellite imagery, namely Landsat 5 Thematic Mapper (TM) and Landsat 8/9 Operational Land Imager (OLI), spanning the years 1990, 1995, 2000, 2011, 2019, and 2025. These data were acquired via the Google Earth Engine (GEE) platform with automated preprocessing. The selection of these specific years was based on decadal representation as well as the availability of cloud-free data.

Land cover classification was conducted using Random Forest and Gradient Boosting Tree algorithms. These algorithms were chosen for their ability to handle high-dimensional data and provide high accuracy in multi-class classification (Zhao et al., 2020). The identified land cover classes included mangrove, nipa palm, aquaculture ponds, rice fields, open land, water bodies, settlements, and forest.

Random Forest builds numerous decision trees in parallel using the bootstrap aggregating (bagging) technique and generates predictions based on majority voting from all trees (Gislason et al., 2005; Kulkarni & Lowe, 2016). The main strengths of Random Forest are its robustness against overfitting, computational efficiency, and its ability to handle non-linear relationships and correlations among input variables (Mellor et al., 2013). In contrast, Gradient Boosting Tree employs a boosting approach where each tree is sequentially constructed to minimize prediction errors of the preceding tree (Handoko et al., 2020). Random Forest constructs multiple decision trees in parallel using bagging (Gislason et al., 2006), while Gradient Boosting builds trees sequentially to correct errors from previous models (Handoko et al., 2020). In the context of land cover classification, Random Forest tends to excel in larger areas, while Gradient Boosting Tree demonstrates superiority in distinguishing spectrally overlapping vegetation classes, such as between mangrove and nipa palm.

Training and validation data were obtained through manual digitization based on field data, visual interpretation of high-resolution Google Earth imagery, and available thematic map references. Classification validation was performed using the confusion matrix method, calculating overall accuracy and the Kappa coefficient.

Land cover change analysis was carried out using the post-classification comparison method, which spatially compares classification results from different years to observe inter-class conversions. The interpretation of the analysis focused on changes in coastal ecosystems, particularly in identifying transitions among classes such as aquaculture ponds, rice fields, open land, and built-up areas.

The land cover change analysis was linked to the potential for acid sulfate soil formation based on Widyatmanti's (2017) framework. Of the five contributing factors (Fe, S, organic matter, low-energy environment, and waterlogging), this study highlighted three most relevant to land cover: availability of organic matter, low-energy environmental conditions, and waterlogging patterns. Field validation involved collecting soil samples at several points in areas identified as potential acid sulfate soil zones from spatial analysis results. In-situ soil pH measurements were conducted to verify acidity conditions as indicators of acid sulfate soil presence.

## 3. Result and Discussion

Land cover classification was conducted using two methods, namely Random Forest and Gradient Boosting Tree. The aim was to identify the classification method that is more effective and representative. The primary data used were Landsat 5 images for the years 1990 and 2011, and Landsat 8 images for the year 2025. The selection of analysis years was based on recorded changes during those years and the availability of images with minimal cloud cover. The following presents the classification results of Landsat 5 TM and Landsat 8

OLI/TIRS images using Random Forest and Gradient Boosting Tree classification methods.

**Table 1.** Comparison of Random Forest vs Gradient Boosting Tree

| Aspect | Random Forest | Gradient Boosting Tree |
|---|---|---|
| Model structure | Bagging | Boosting |
| Resistance to overfitting | High | Low if tuning is not optimal |
| Interpretation of Results | Simpler | Tends to be complex |
| Sensitivity to noise | More stable | More sensitive |
| Accuracy | High and stable | Uncertain |

The results of the land cover change analysis obtained from multitemporal classification will be used as an approach to identify the availability of organic matter, low-energy environments, and waterlogging patterns. This strategy also serves as an initial step in developing a geospatial-based analytical framework for the potential of acid sulfate soil that is adaptive to dynamic landscape changes. The following table presents a comparison of classification results using Random Forest and Gradient Boosting Tree. Based on the comparison, it is evident that Random Forest shows visually superior results. Additionally, Random Forest also demonstrates higher accuracy compared to the Gradient Boosting Tree.

**Table 2.** Comparison of overall accuracy and Kappa

| Tahun | Random Forest | | Gradient Boosting Tree | |
|---|---|---|---|---|
| | Accuracy | Kappa | Accuracy | Kappa |
| 1990 | 0.925 | 0.915 | 0.914 | 0.902 |
| 1995 | 0.895 | 0.881 | 0.892 | 0.878 |
| 2011 | 0.971 | 0.966 | 0.937 | 0.927 |
| 2019 | 0.964 | 0.959 | 0.947 | 0.940 |
| 2025 | 0.958 | 0.949 | 0.952 | 0.941 |

Based on the classification accuracy evaluation from 1990 to 2025, the Random Forest algorithm consistently demonstrated higher Overall Accuracy and Kappa coefficient values compared to the Gradient Boosting Tree. Although Gradient Boosting Tree in 2025 recorded accuracy values nearly equivalent to Random Forest, the consistent performance of Random Forest across the entire year range indicates better overall stability and reliability. Therefore, the multitemporal land cover analysis results used for spatial interpretation and further analysis refer to the classification outcomes produced by the Random Forest algorithm, to ensure optimal spatial representation accuracy and minimize interpretative bias in detecting land cover changes. The following table presents a comparison of land cover classification results from 1990 to 2025 using Random Forest and Gradient Boosting Tree.

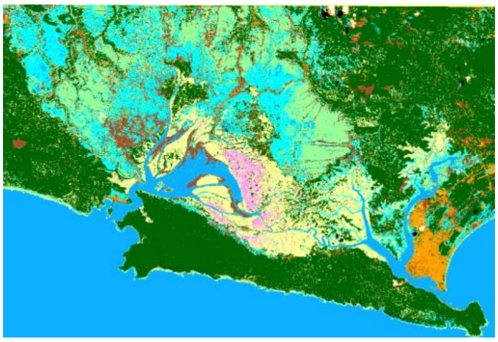


**Figure 1.** Random Forest 1990

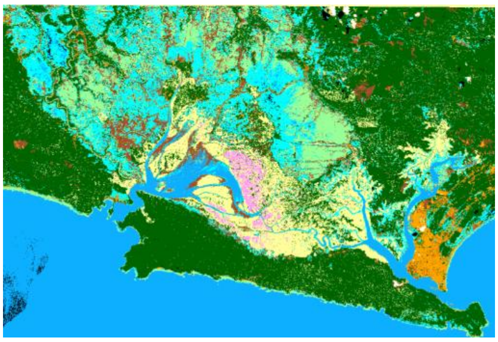


**Figure 2.** Gradient Boosting Tree 1990

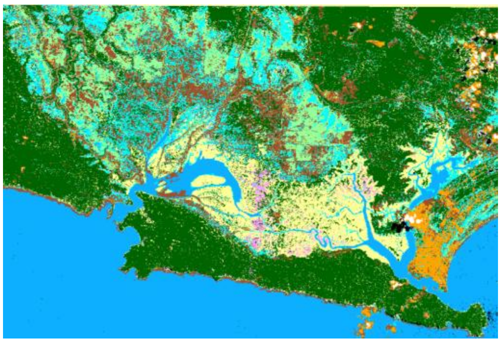


**Figure 3.** Random Forest 1995

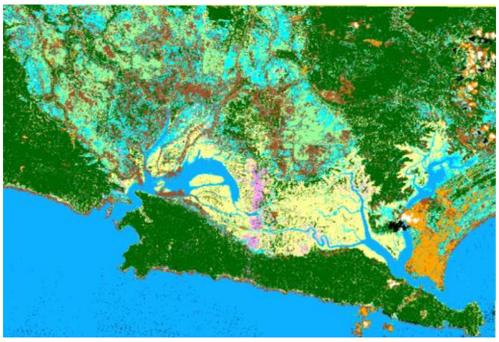


**Figure 4.** Gradient Boosting Tree 1995

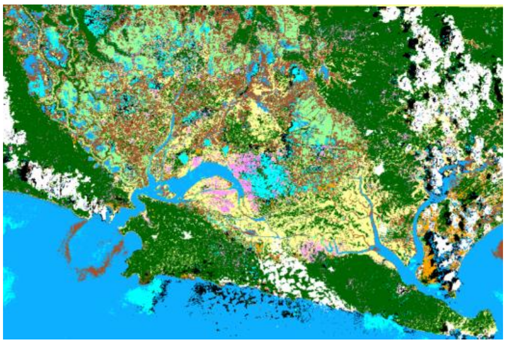


**Figure 5.** Random Forest 2000

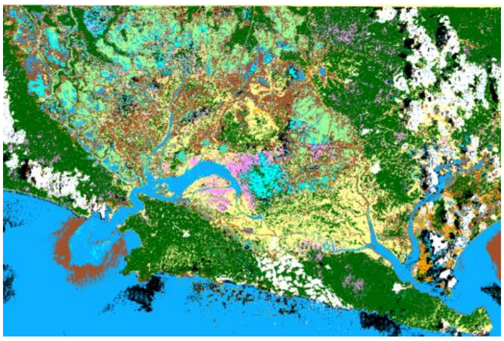
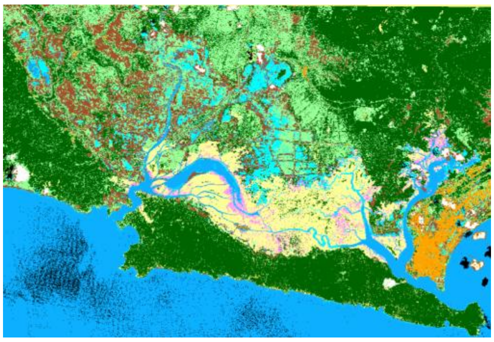


**Figure 6.** Gradient Boosting Tree 2000



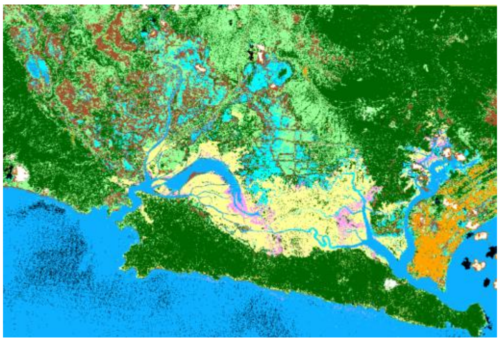
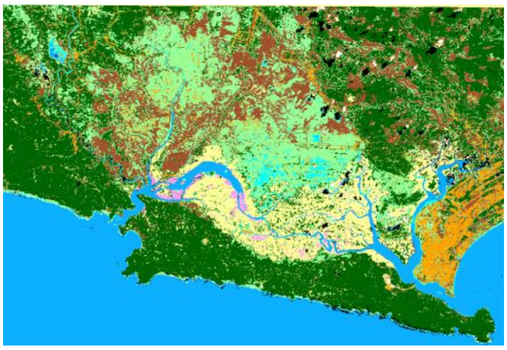


**Figure 7.** Random Forest 2011 **Figure 8.** Gradient Boosting Tree 2011



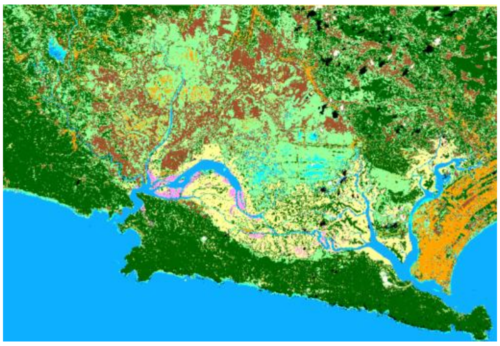
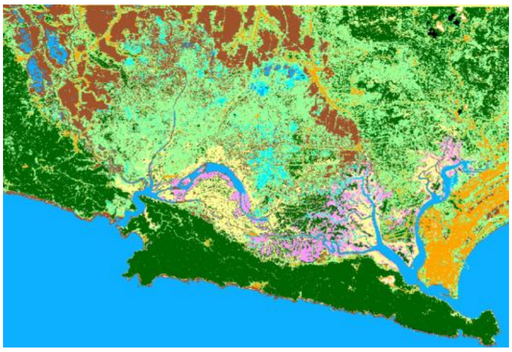


**Figure 9.** Random Forest 2019 **Figure 10.** Gradient Boosting Tree 2019



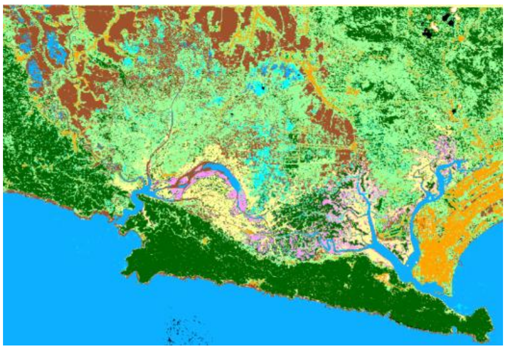


**Figure 11.** *Random Forest* 2025 **Figure 12.** Gradient Boosting Tree 2025

**Table 2.** Comparison of overall accuracy and Kappa

| Land Cover | Color (Symbol) | Changes in Land Cover Area ($km^2$) | | |
|---|---|---|---|---|
| | | **1990** | **2011** | **2025** |
| Mangrove | | 111,05 | 83,92 | 77,56 |
| Nypa palm | | 9,31 | 13,29 | 24,87 |
| Rice field | | 89,94 | 188,32 | 259,54 |
| Aquaculture pond | | 113,47 | 45,61 | 17,22 |
| Settlement | | 32,24 | 40,53 | 56,67 |
| Bare land | | 64,32 | 81,17 | 126,75 |
| Water body | | 31,99 | 28,76 | 26,61 |
| Forest | | 390,27 | 356,383 | 255,96 |
| Clouds | | 1,52 | 8,74 | 0,68 |
| Cloud shadow | | 2,92 | 0,32 | 1,13 |
| Total Area | | 847 | 847 | 847 |

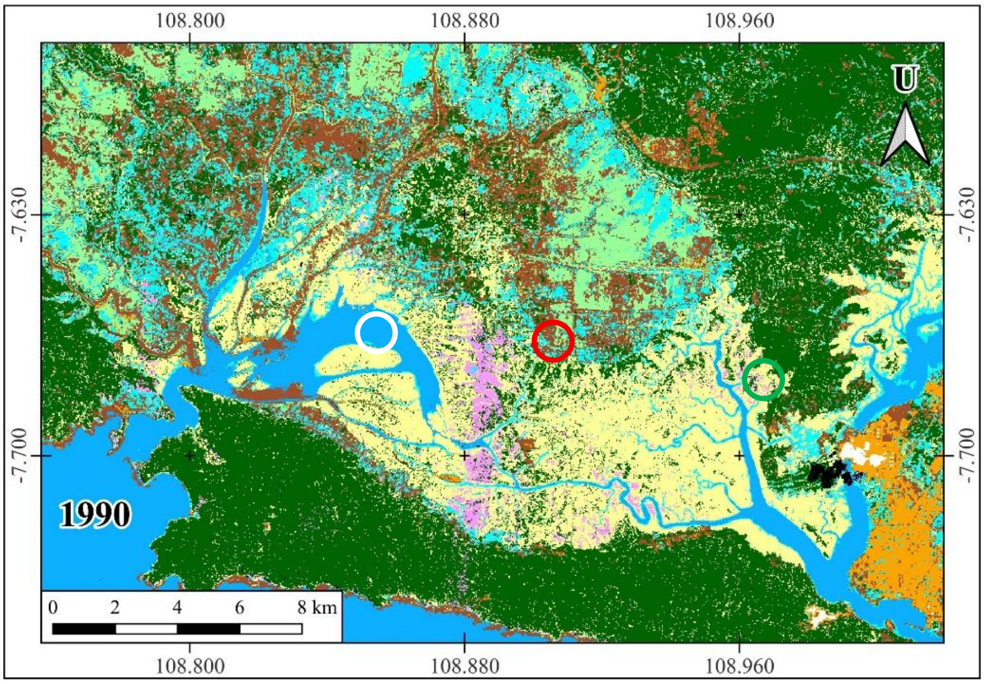



**Figure 13.** Land-cover 1990

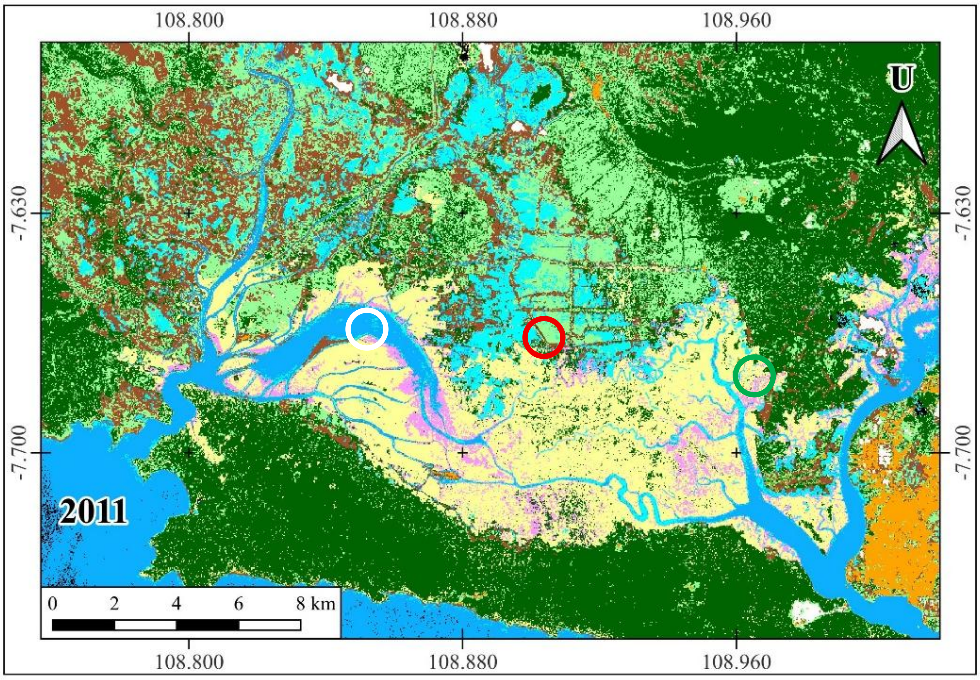



**Figure 14.** Land-cover 2011

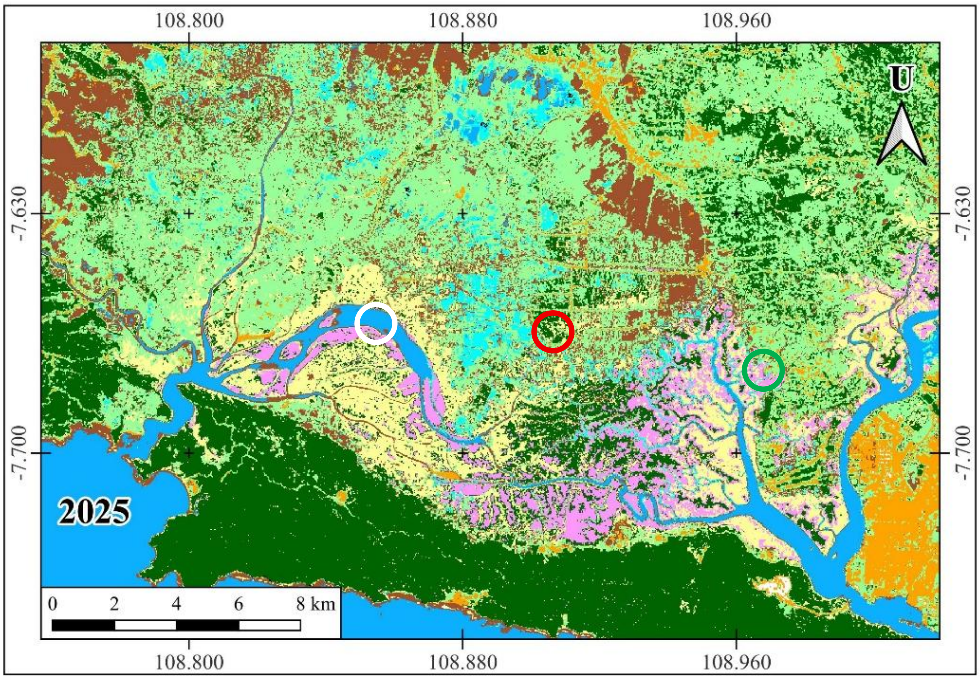



**Figure 15.** Land-cover 2025

Identification of potential acid sulfate soil formation zones was conducted by analyzing spatial land cover changes between the years 1990, 2011, and 2025, as visualized in Figures 13 – 15. These years were selected due to the significant changes observed compared to other years. Based on these maps, several areas were identified with significant conversion from natural vegetation—primarily mangrove and nipa palm—to land cover classes such as aquaculture ponds, open land, and settlements. This conversion indicates disturbances in the local ecological and hydrological systems. Furthermore, from the spatial distribution of land cover changes, potential acid sulfate soil zones are generally concentrated in lowland areas influenced by tidal fluctuations, such as the southwestern part of Segara Anakan and around the Donan River estuary. Accurate spatial identification of these risk zones is crucial for developing mitigation strategies and ecosystem-based land use planning in tropical coastal regions.

Based on multitemporal land cover classification results, a significant relationship was identified between land change dynamics and three of the five acid sulfate soil-forming factors as described by Widyatmanti (2017), namely the availability of organic matter, low-energy environmental conditions, and waterlogging patterns. The detailed linkage of each factor is as follows:Identification of potential acid sulfate soil formation zones was conducted by analyzing spatial land cover changes between the years 1990, 2011, and 2025, as visualized in Figures 13 – 15. These years were selected due to the significant changes observed compared to other years. Based on these maps, several areas were identified with significant conversion from natural vegetation—primarily mangrove and nipa palm—to land cover classes such as aquaculture ponds, open land, and settlements. This conversion indicates disturbances in the local ecological and hydrological systems. Furthermore, from the spatial distribution of land cover changes, potential acid sulfate soil zones are generally concentrated in lowland areas influenced by tidal fluctuations, such as the southwestern part of Segara Anakan and around the Donan River estuary. Accurate spatial identification of these risk zones is crucial for developing mitigation strategies and ecosystem-based land use planning in tropical coastal regions.

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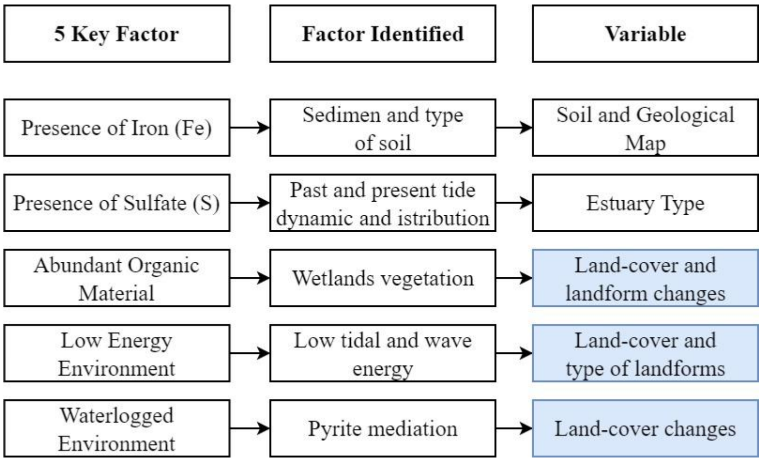


Availability of Organic Matter. The conversion of land cover from natural vegetation such as mangrove and nipa palm to aquaculture ponds or open land indicates degradation of coastal biomass, which was previously a primary source of organic matter. The roots and litter from such vegetation naturally decompose under anaerobic conditions, contributing organic content to the soil. When this vegetation disappears, besides reducing degraded organic matter input, the decomposition of root residues in an environment rich in sulfate and iron also creates conditions conducive to the formation of sulfide compounds such as pyrite ($FeS_2$). Therefore, the loss of mangrove and nipa vegetation not only signals a decrease in organic matter supply but also serves as an early indicator of the reductive sulfide phase formation in the soil. Areas marked in red exemplify changes from mangrove to rice fields and aquaculture ponds. Quantitatively, mangrove area decreased from 111.05 $km^2$ in 1990 to 77.56 $km^2$ in 2025. In addition, the conversion between mangrove and nipa can also indicate salinity changes, which are important in pyrite formation.

Low-energy environments, such as tidal swamps and lagoons that experience inundation, are primary habitats for acid sulfate soil formation due to their support of fine anaerobic sedimentation processes. Regions with low tidal and wave energy allow vegetation growth and organic matter accumulation. Such environments are characterized by tidal swamps, lagoons, and wetlands with typical vegetation (mangrove, nipa) that facilitate fine sediment accumulation.

Tidal swamps and lagoons with low wave and tidal energy—such as areas around the Donan River estuary—originally function as pockets of fine sediment accumulation. The water body area decreased from 31.99 km² in 1990 to 26.61 km² in 2025, accompanied by a drastic reduction in aquaculture ponds from 113.47 km² to only 17.22 km², indicating an infilling process and the loss of natural inundation pockets. This change implies disruption of the reductive environment that formerly supported sulfide layer formation. White circles on the map indicate river sediment accumulation. Sediments were absent in 1990, began forming small islands in 2011, and by 2025, these islands grew closer and nearly merged.

Waterlogging factors relate to groundwater dynamics and tidal influence that maintain anaerobic conditions in the sulfide layer. Conversion from rice fields or aquaculture ponds to settlements or dry land indicates interventions in local hydrology. Land drainage, dike construction, and canal development lower the groundwater table and expose previously saturated soil layers to oxygen. This process triggers pyrite oxidation into sulfuric acid ($H_2SO_4$), drastically reducing soil pH and releasing heavy metal ions toxic to aquatic organisms and vegetation. Hence, identifying land cover conversion patterns indicative of waterlogging changes is critical as a high-risk indicator of acid sulfate soil formation. Land cover changes from 1990 to 2025 in Segara Anakan and Donan estuary show significant shifts in waterlogging patterns. Rice fields increased substantially from 89.94 km² in 1990 to 259.54 km² in 2025, while aquaculture ponds sharply decreased from 113.47 km² to 17.22 km². Meanwhile, water bodies shrank from 31.99 km² to 26.61 km². White circles on the map mark locations where previously permanently inundated water bodies and aquaculture ponds have transformed into rice fields or settlements.

These changes reflect a transformation from natural, sustainable flooding patterns to human-managed artificial inundation. Aquaculture ponds and water bodies generally create stable anaerobic environments supporting organic matter accumulation and sulfide mineral formation. The loss of such cover means a reduction in natural inundation pockets and an increased potential for groundwater level fluctuations. The now-dominant rice fields maintain inundation but are seasonal and highly dependent on irrigation systems. During dry seasons or land drying periods, previously inundated soil layers may become exposed to oxygen and undergo oxidation.

Spatially, the most visible changes are in the eastern part of Segara Anakan, where many aquaculture ponds were abandoned and converted to rice fields or settlements. In the central-western part of the lagoon, rice field expansion replaced shrinking open lands and water bodies. These dynamics confirm that land cover changes directly affect waterlogging patterns, which in turn influence the stability of anaerobic conditions and the potential activation of acid sulfate soils.

The multitemporal analysis results demonstrate that land cover dynamics in Segara Anakan and Donan estuary are strongly related to three main acid sulfate soil-forming factors as described by Widyatmanti (2017). First, conversion of mangrove and nipa to aquaculture ponds, rice fields, or open land indicates organic matter supply changes. Second, changes in low-energy environments such as tidal swamps and lagoons affect sediment accumulation. Third, altered waterlogging patterns due to conversion of rice fields and aquaculture ponds to settlements or dry land lower groundwater levels and expose sulfide layers. While land cover change is not a direct indicator, its spatial interpretation can be a valuable approach for identifying high-risk zones for acid sulfate soil formation.

Field validation results show that areas identified as potential acid sulfate soil zones based on land cover changes and physiographic indicators exhibit high acidity levels. Soil pH measurements at these sites indicated values below 4, consistent with the highly acidic characteristics of acid sulfate soils. These findings reinforce the interpretation that land cover transformation, particularly the conversion of mangrove and tidal wetland areas to rice fields or settlements, plays a significant role in triggering sulfide material oxidation and acid sulfate soil formation.

These findings highlight that environmental degradation in Segara Anakan is not only an ecological concern but also a development challenge, affecting local livelihoods and regional planning. Beyond ecological impacts, land cover transformations in Segara Anakan and the Donan River estuary also pose significant socio-economic challenges. The conversion of mangrove and nipa palm ecosystems into aquaculture ponds and settlements may generate short-term economic benefits, but it simultaneously increases exposure to environmental risks such as soil acidification, reduced land productivity, and water contamination. These changes threaten local livelihoods, particularly for communities dependent on fisheries and agriculture, and complicate long-term spatial planning in the region. Incorporating acid sulfate soil risk into coastal development strategies is therefore critical to balancing economic utilization with environmental sustainability. For instance, soil acidification and declining water quality could reduce aquaculture productivity, increase farming costs, and ultimately threaten local food security and long-term spatial planning in Cilacap.

## 4. Conclusion

The comparative performance analysis of classification algorithms demonstrates that Random Forest outperforms Gradient Boosting in terms of stability, model generalization, and multi-temporal classification accuracy. Accordingly, the land cover maps employed for spatial interpretation were derived from Random Forest classification results to ensure spatial validity and reliable risk zonation.

This study reveals that land cover changes in the Segara Anakan and Donan River estuary between 1990 and 2025 contribute to the identification of potential acid sulfate soil formation, particularly in tidal and low-lying areas. The conversion of natural vegetation such as mangrove and nipa palm into aquaculture ponds, bare land, and settlements has disrupted ecological conditions that previously supported organic matter accumulation, low-energy environments, and anaerobic waterlogging—three of the five primary factors influencing acid sulfate soil development. Field validation further confirmed that areas identified as potential acid sulfate soil zones exhibited pH values below 4, thereby reinforcing the spatial interpretation derived from multi-temporal analysis.

The findings of this research provide a scientific basis for coastal spatial planning that is more adaptive to land dynamics and the potential risk of acid sulfate soils. The application of remote sensing technology integrated with machine learning has proven effective for mapping landscape transformations and supporting decision-making processes aimed at mitigating soil degradation and promoting the sustainable management of tropical coastal environments.

Future coastal management strategies should integrate remote sensing–based monitoring of land cover dynamics with field validation of soil conditions to anticipate acid sulfate soil risks. Such an approach will not only strengthen adaptive spatial planning but also safeguard ecosystem services and community livelihoods in tropical coastal regions. Incorporating ASS risk assessment into regional spatial planning is therefore essential to enhance environmental resilience and socio-economic sustainability in Indonesia's coastal zones

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**References**

Darmawan, A. A., Suhardjono, Bisri, M., & Suhartanto, E. (2021). Assessment of spatial changes of LULC dynamics, using multi temporal landsat data (case study: Lesti Sub Watershed, Malang Regency, Indonesia). IOP Conference Series: Earth and Environmental Science, 930(1), 012075. https://doi.org/10.1088/1755-1315/930/1/012075

Farda, N. M. (2017). Multi-temporal Land Use Mapping of Coastal Wetlands Area using Machine Learning in Google Earth Engine. IOP Conference Series: Earth and Environmental Science, 98, 012042. https://doi.org/10.1088/1755-1315/98/1/012042

Florek, P., & Zagdański, A. (2023). Benchmarking state-of-the-art gradient boosting algorithms for classification. ArXiv (Cornell University). https://doi.org/10.48550/arxiv.2305.17094

Gislason, P. O., Benediktsson, J. A., & Sveinsson, J. R. (2006). Random Forests for land cover classification. Pattern Recognition Letters, 27(4), 294–300. https://doi.org/10.1016/j.patrec.2005.08.011

Hamza, M., & Larocque, D. (2005). An empirical comparison of ensemble methods based on classification trees. Journal of Statistical Computation and Simulation, 75(8), 629–643. https://doi.org/10.1080/00949650410001729472

Handoko, J., Herwindiati, D. E., & Hendryli, J. (2020). Gradient Boosting Tree for Land Use Change Detection Using Landsat 7 and 8 Imageries: A Case Study of Bogor Area as Water Buffer Zone of Jakarta. IOP Conference Series Earth and Environmental Science, 581(1), 012045–012045. https://doi.org/10.1088/1755-1315/581/1/012045

Hilmi, E., Sari, L. K., Cahyo, T. N., Amron, A., & Siregar, A. S. (2021). The Sedimentation Impact for the Lagoon and Mangrove Stabilization. E3S Web of Conferences, 324, 02001–02001. https://doi.org/10.1051/e3sconf/202132402001

Ihsan, K. T. N., Harto, A. B., Sakti, A. D., & Wikantika, K. (2023). Monitoring Coastal Areas Using Ndwi From Landsat Image Data From 1985 Based

On Cloud Computation Google Earth Engine And Apps. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences/International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLVIII-M-3-2023, 109–114. https://doi.org/10.5194/isprs-archives-xlviii-m-3-2023-109-2023

Kulkarni, A., & Lowe, B. (2016). Random Forest Algorithm for Land Cover Classification. Computer Science Faculty Publications and Presentations. https://scholarworks.uttyler.edu/compsci_fac/1/

Mellor, A., Haywood, A., Stone, C., & Jones, S. (2013). The Performance of Random Forests in an Operational Setting for Large Area Sclerophyll Forest Classification. Remote Sensing, 5(6), 2838–2856. https://doi.org/10.3390/rs5062838

Mendonça, S. K. G., Moraes , E. M. V. de , Otero, X. L., Ferreira, T. O., Corrêa, M. M., de Sousa, J. E. S., Nascimento , C. W. A. do , Neves, L. V. de M. W., & Junior, V. S. de S. (2020). Occurrence and pedogenesis of acid sulfate soils in northeastern Brazil. CATENA, 196, 104937–104937. https://doi.org/10.1016/j.catena.2020.104937

Sharapova, A. V., Semenkov, I. N., Karpachevsky, A. M., Lednev, S. A., & Koroleva, T. V. (2021). Morphological and chemical properties of soils within geological complexes affected by sulfuric acid in forest-steppe of the Central Russian Upland (Russia). IOP Conference Series Earth and Environmental Science, 862(1), 012013–012013. https://doi.org/10.1088/1755-1315/862/1/012013

Sharma, A., Liu, X., & Yang, X. (2018). Land cover classification from multi-temporal, multi-spectral remotely sensed imagery using patch-based recurrent neural networks. Neural Networks, 105, 346–355. https://doi.org/10.1016/j.neunet.2018.05.019

Talukdar, S., Singha, P., Mahato, S., Shahfahad, Pal, S., Liou, Y.-A., & Rahman, A. (2020). Land-Use Land-Cover Classification by Machine Learning

Classifiers for Satellite Observations—A Review. Remote Sensing, 12(7), 1135. https://doi.org/10.3390/rs12071135

Toivonen, J., Hudd, R., Nystrand, M., & Österholm, P. (2020). Climatic effects on water quality in areas with acid sulfate soils with commensurable consequences on the reproduction of burbot (Lota lota L.). Environmental Geochemistry and Health, 42(10), 3141–3156. https://doi.org/10.1007/s10653-020-00550-1

Widyatmanti, W., & Sammut, J. (2017). Hydro-geomorphic controls on the development and distribution of acid sulfate soils in Central Java, Indonesia. Geoderma, 308, 321–332. https://doi.org/10.1016/j.geoderma.2017.08.024

Yuniarti, E., Surono, N., Susilowati, D. N., & Anggria, L. (2022). Microbial activity of potential and actual acid sulphate soil from Kalimantan Island. IOP Conference Series Earth and Environmental Science, 976(1), 012047–012047. https://doi.org/10.1088/1755-1315/976/1/012047

Zakia, R., Lestari, F., & Susiana, S. (2022). Ecological suitability of mangrove ecosystems as mangrove rehabilitation areas in the Sei Carang estuary waters of Tanjungpinang City. Akuatikisle: Jurnal Akuakultur, Pesisir Dan Pulau-Pulau Kecil, 6(2), 149–155. https://doi.org/10.29239/j.akuatikisle.6.2.149-155

Zhao, C., Wu, D., Huang, J., Yuan, Y., Zhang, H.-T., Peng, R., & Shi, Z. (2020). BoostTree and BoostForest for Ensemble Learning. ArXiv.org. https://arxiv.org/abs/2003.09737