ГЛАСНИК Српског географског друштва 106(1) 263-286
BULLETIN OF THE SERBIAN GEOGRAPHICAL SOCIETY 2026

Original scientific paper UDC 71:338.48(594)
https://doi.org/to_be_assigned

Received: December 30, 2025
Corrected: February 20, 2026
Accepted: February 27, 2026

Sawaludin[1]*, R. Marsuki Iswandi, Analuddin Kangkuso***, Laode Muhammad Golok Jaya****, Muhammad Zamrun Firihu*****, Weka Widayati*, Dewi Nurhayati Yusuf******, La Ode Restele*, Ma'ruf Kasim*******, Gusti Ayu Kade Sutariati********, Hasddin***********

* *Halu Oleo University, Department of Geography, Kendari, Indonesia*
** *Halu Oleo University, Department of Agribusiness, Kendari, Indonesia*
*** *Halu Oleo University, Department of Biology and Biotechnology, Kendari, Indonesia*
**** *Halu Oleo University, Department of Informatics Engineering, Kendari, Indonesia*
***** *Halu Oleo University, Department of Physics, Kendari, Indonesia*
****** *Halu Oleo University, Department of Soil Science, Kendari, Indonesia*
******* *Halu Oleo University, Department of Water Resources Management, Kendari, Indonesia*
******** *Halu Oleo University, Department of Agronomy, Indonesia*
********* *Lakidende University, Department of Urban and Regional Planning, Unaaha, Indonesia*

SPATIAL ASSESSMENT OF LAND SUITABILITY FOR AGRO-MARINE TOURISM ON WAWONII ISLAND, INDONESIA

Abstract: For the sustainable development of integrated coastal-based economic activities, spatially informed planning is needed to address environmental protection and livelihood improvement, particularly in small island environments that are increasingly impacted by land use pressures and environmental risks. In this study, a GIS-based machine learning method was used to evaluate and classify land suitability for maritime agrotourism development on Wawonii Island, Southeast Sulawesi, Indonesia. Twelve physical, environmental, and accessibility factors were combined within a geospatial framework and evaluated using Support Vector Machine (SVM) and Random Forest (RF) models, trained and validated on 52 existing maritime agrotourism sites. Model performance was evaluated using Receiver

[1] sawaludin_spimsc@uho.ac.id (corresponding author)
Sawaludin (https://orcid.org/0000-0001-5837-9357)
R. Marsuki Iswandi (*https://orcid.org/0000-0002-2407-101X)*
Analuddin Kangkuso (https://orcid.org/0000-0003-0258-9376)
Laode Muhammad Golok Jaya (https://orcid.org/0000-0003-0752-1207)
Muhammad Zamrun Firuhu (https://orcid.org/0000-0002-5470-9627)
Weka Widayati (https://orcid.org/0000-0002-7047-9390)
Dewi Nurhayati Yusuf (https://orcid.org/0000-0003-4595-8848)
La Ode Restele (https://orcid.org/0000-0002-0976-9778)
Ma'ruf Kasim (https://orcid.org/0000-0001-7902-8599)
Gusti Ayu Kade Sutariati (https://orcid.org/0000-0002-6135-9100)
Hasddin (https://orcid.org/0000-0002-0114-5274)

Operating Characteristic (ROC) curves, with the RF model having a higher predictive accuracy of approximately 80% (AUC ≈ 0.80) compared to the SVM model (AUC ≈ 0.60). Using the selected models, land suitability was categorized into four classes. The findings indicate that low suitability areas dominate the island, covering approximately 52.01% of the total area, while medium, high, and very high suitability classes cover 16.22%, 17.76%, and 14.01%, respectively. High and very high suitability areas are mostly found in coastal and lowland areas with gentle slopes, good accessibility, and a combination of agricultural and marine resources. Subdistrict-level analysis indicates that Central and South Wawonii are priority areas for marine agrotourism development, while other areas require more careful land use management and a conservation-oriented approach. These results clearly demonstrate the efficiency of GIS-based machine learning as a spatial decision support system for small island planning and provide quantitative and spatial evidence for the formulation of sustainable tourism policies.

Keywords: Machine learning, coastal planning, geospatial modelling, environmental constraints, small-island development, regional zoning

Introduction

Agro-marine tourism represents a form of sustainable tourism that integrates agricultural landscapes with coastal and marine environments, offering combined ecological, cultural, and economic values. This tourism concept emphasizes the utilization of both terrestrial and marine resources-such as agricultural plantations, coastal ecosystems, fisheries, and local cultural practices-to create diversified tourism experiences while supporting environmental conservation and community livelihoods. Recent studies highlight that integrated agro-tourism development relies on strong interconnectivity between local resources, stakeholders, and supporting infrastructures to achieve sustainable outcomes (Susila et al., 2024). Furthermore, contemporary research on agritourism and rural tourism underscores its growing role in promoting sustainable development through economic diversification, environmental stewardship, and community empowerment, particularly in post-pandemic contexts (Turtureanu et al., 2025). In coastal and marine settings, sustainable tourism development guided by blue economy principles further reinforces the importance of balancing economic growth with ecosystem conservation (Tegar & Gurning, 2018), while community-based management approaches have been shown to enhance both ecological protection and local economic resilience in marine tourism destinations (Kuba et al., 2024).

Indonesia, the world's largest archipelagic country with over 17,000 islands, hosts rich natural and cultural resources across diverse coastal and island environments (CountryReports.org, 2002). Its biodiversity, varied geomorphology, and strong socio-cultural traditions provide opportunities for sustainable tourism development (Suparwoko, 2012; Joeliaty, 2024). Local wisdom and traditional practices support the conservation of coastal and marine resources and can be integrated into sustainable agro-marine tourism planning (Boni et al., 2024). Tourism has become a key component of national development, especially in island and coastal areas with limited conventional economic activities (Briandana et al., 2018). In this context, agro-marine tourism offers a promising strategy to strengthen local economies by linking agriculture-based livelihoods with coastal and marine attractions while promoting environmental sustainability (Astuti et al., 2025a).

Effective development of agro-marine tourism requires a clear understanding of spatial characteristics and environmental constraints. Land suitability assessment plays a crucial role in identifying areas that are appropriate for tourism development while minimizing environmental risks and land-use conflicts (Çetin et al., 2018). Spatial assessment of land suitability evaluates how well specific land units meet environmental, physical, and accessibility requirements for designated land uses. In tourism planning, this approach supports evidence-based decision-making by aligning tourism development with ecological capacity, infrastructure availability, and socio-environmental considerations (Majewska, 2017; Rodríguez-Rangel et al., 2020).

Geographic Information Systems (GIS) have been widely applied in tourism studies to support spatial analysis, land suitability evaluation, and regional planning. GIS-based approaches enable the integration of multi-source spatial data, including land use, topography, hydrology, accessibility, and environmental constraints, to identify suitable locations for tourism activities (Magige et al., 2020; Lepetiuk et al., 2023). Recent advances in spatial modelling have further enhanced land suitability assessment by incorporating data-driven analytical techniques that improve classification accuracy and spatial representation (Kaya et al., 2019; Xing, 2024; Tan et al., 2024a; Li et al., 2024; Sperandio et al., 2025). Some recent research efforts have utilized machine learning algorithms, such as the Random Forest and Support Vector Machine models, in the context of tourism and ecotourism suitability mapping, with enhanced predictive capabilities and spatial resolution of suitable zones (Huang et al., 2024; Raha et al., 2024). Nevertheless, the majority of these efforts are mainly concerned with terrestrial tourism or general ecotourism applications, without explicitly considering the coupled land-sea interactions that are characteristic of agro-marine tourism systems, especially in small island environments.

Southeast Sulawesi Province is located within the Coral Triangle region and is characterized by diverse marine ecosystems, coastal landscapes, and agricultural resources, providing significant potential for sustainable tourism development (BPS-Statistics of Sulawesi Tenggara Province, 2022). Wawonii Island, part of the Konawe Islands Regency, exhibits a combination of coastal environments, agricultural plantations, forested landscapes, and cultural assets that are suitable for agro-marine tourism development. These characteristics are closely linked to local livelihood resilience and environmentally adaptive land-use systems in coastal settings, as highlighted in studies on urban and peri-urban farming systems in coastal cities of Southeast Sulawesi (Astuti et al., 2025b). However, tourism planning on small islands such as Wawonii faces challenges related to environmental vulnerability, land-use competition, and limited spatial information to guide sustainable development.

Despite the growing interest in tourism development in Southeast Sulawesi, spatially explicit assessments of land suitability for agro-marine tourism remain scarce. Previous studies have largely focused on general tourism potential or sector-specific analyses, with limited emphasis on integrated spatial assessment that simultaneously considers terrestrial and marine dimensions within a unified analytical framework (Lee et al., 2020; Chang et al., 2024). Moreover, few studies extend machine learning-based suitability analysis to the sub-district (administrative) level, which is essential for translating spatial modelling results into practical land-use planning and policy decisions. Consequently, there is a need for systematic spatial evaluation to support sustainable tourism planning and policy formulation at the local and regional levels.

In this context, the current study contributes to the existing body of knowledge by incorporating a GIS-based machine learning method for agro-marine tourism suitability analysis in a small island context, considering both land-related and marine-related factors in a unified spatial context. Unlike the existing body of knowledge, the current research aims to address the suitability analysis by incorporating sub-district-level analysis. Therefore, this study aims to conduct a spatial assessment of land suitability for agro-marine tourism on Wawonii Island, Indonesia. Specifically, the objectives of this study are: (1) to map the spatial distribution of land suitability classes for agro-marine tourism using a GIS-based approach, and (2) to evaluate the suitability patterns across sub-districts to support sustainable tourism planning and regional development in the Konawe Islands Regency. The findings of this study are expected to provide practical spatial information for policymakers and contribute to the sustainable management of tourism resources in small island environments.

Materials and methods

Study Area

This study was conducted on Wawonii Island, which is administratively part of the Konawe Islands Regency, Southeast Sulawesi Province, Indonesia (Figure 1). The regency consists of seven sub-districts, namely Northeast Wawonii, West Wawonii, North Wawonii, East Wawonii, Southeast Wawonii, South Wawonii, and Central Wawonii. These sub-districts exhibit varying topographic characteristics, with slope gradients ranging from 0-15% in Northeast Wawonii, 0-25% in West Wawonii, and up to 0–40% in the remaining five sub-districts. Areas with slopes between 0-15% are generally considered suitable for agro-marine tourism development due to their accessibility and lower construction constraints (Statistics of Konawe Kepulauan Regency, 2025).

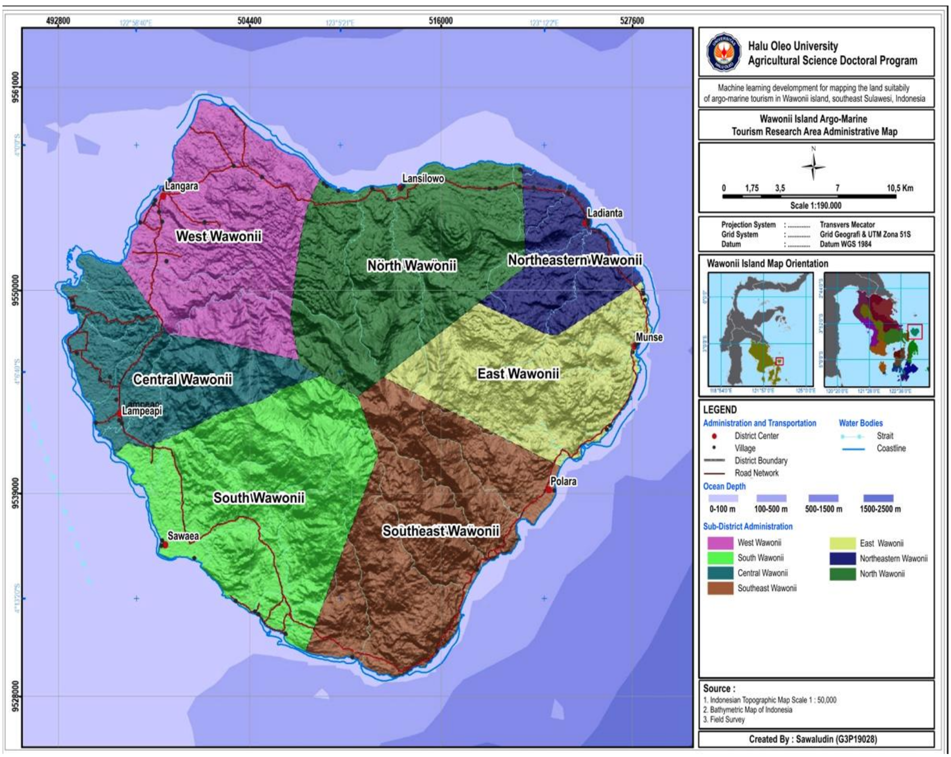


Fig. 1. Study area of Wawonii Island, Southeast Sulawesi, Indonesia

Geographically, Wawonii Island is located between 2°00′45″ South Latitude and 121°00′15″ East Longitude. The island covers a total area of approximately 1,513.98 km^2, comprising 867.58 km^2 of land and 646.40 km^2 of surrounding waters, with a coastline length of about 178 km (Statistics of Konawe Kepulauan Regency, 2025). The island's geology is dominated by cambisol and lateritic soils, with smaller areas of latosol. Forests and plantation lands cover a large portion of the island's surface, while coastal zones are characterized by mangroves and sandy beaches derived from alluvial marine and terrestrial sediments.

Topographically, Wawonii Island consists mainly of undulating to hilly lowlands, with elevations ranging from sea level to approximately 1,000 m above sea level. Areas between 50 and 1,000 m are categorized as hilly to mountainous, particularly in the southeast, north, east, and northeast parts of the island (Statistics of Konawe Kepulauan Regency, 2025). These physical characteristics strongly influence land-use patterns, infrastructure development, and tourism potential.

Hydrologically, the Konawe Islands Regency is dominated by large rivers such as the Lampeapi, Lansilowo, Ladianta, and Mosolo rivers, as well as smaller ones. The 2010 measurement showed that the Lampeapi River had the largest discharge of 13,890 m^3/s with an estimated energy capacity of 10,420 kW, followed by Mosolo River with a discharge of 5,300 m^3/s and energy capacity of 7,950 kW, and Lansilowo River with 5,100 m^3/s and 2,104 kW. There are about 23 watersheds (DAS) with a total area of ±70,514 ha, or about 81.25% of the total area, with the Lampeapi Watershed being the largest at ±9,963 ha or 14.13% (Statistics of Konawe Kepulauan Regency, 2025).

Climatically, the area has an average annual rainfall of ±1,079-2,931 mm, with an average of about 2,003 mm per year. The dry season is 3-4 months, while the rainy season is 4-6 months, with the peak in March; the dry season is in August. The average temperature is above 20°C, with a minimum temperature of 18°C. Based on Schmidt-Ferguson, the area belongs to climate types C to D, which is moderately wet and dry, suitable for rain fed agriculture, horticulture, and plantations depending on the rainfall season (Statistics of Konawe Kepulauan Regency, 2025).

Wawonii Island possesses significant agro-marine tourism potential derived from agricultural commodities such as coconut, cashew, cloves, and nutmeg, as well as marine and freshwater resources, including mangrove ecosystems, coral reefs, rivers, waterfalls, and white-sand beaches. However, the island has experienced increasing environmental pressure from nickel mining activities, which have caused land degradation, water pollution, coral reef damage, and social conflicts related to land use. These pressures pose serious challenges to the sustainability of traditional livelihoods and highlight the urgency of identifying environmentally suitable areas for alternative development pathways such as agro-marine tourism.

Data Sources

This study employed both primary and secondary spatial data to develop a land suitability model for agro-marine tourism on Wawonii Island, following established approaches in GIS-based tourism suitability and environmental modelling (Çetin et al., 2018; Xing, 2024).

Primary Data

The main data sources included Landsat 9 Operational Land Imager (OLI 2) images, which were accessed through the United States Geological Survey (USGS) Earth Explorer tool (https://earthexplorer.usgs.gov). The chosen image (Path/Row 112/63, Scene ID LC91120632022024LGN01, acquired on January 24, 2022) had a cloud cover of 5% according to its metadata. Landsat 9 OLI 2 offers multispectral imagery with a spatial resolution of 30 m in the visible, near-infrared, and shortwave infrared spectral bands and 14-bit radiometric resolution, as reported in the literature (Montanaro et al., 2022; NASA, 2021; Masek et al., 2020; Irons & Masek, 2006). For land cover classification, Bands 2 (Blue), 3 (Green), 4 (Red), 5 (Near Infrared), and 6 (Shortwave Infrared 1) were employed, which are commonly used for vegetation and land cover mapping (e.g., visible and NIR bands) (Chen et al., 2024). The images used were Level 2 (Collection 2) surface reflectance images, which have been corrected for radiometric and atmospheric conditions, geometrically corrected, and reprojected to WGS84 UTM Zone 50S for spatial registration (USGS, 2026). Additionally, visual analysis and qualitative evaluation were performed to improve classification accuracy and mitigate the influence of remaining cloud and shadow areas.

Landsat data has been extensively utilized for land use and environmental studies owing to its temporal consistency and appropriate spatial resolution for regional-scale analysis (Zhang et al., 2024; Lepetiuk et al., 2023; Magige et al., 2020). Landsat 9 data was chosen owing to its appropriate spectral, radiometric, and temporal resolution for medium-scale land cover and land use mapping on small islands. The Landsat data used in this study is described in Table 1.

Table 1. Landsat 9 imagery used in this study

Path/Row	Scence ID	Acquisition Date
112/63	LC91120632022024LGN01	Januaary 24, 2022

The Landsat imagery was processed to derive land use and forest cover maps. Visual interpretation and qualitative assessment were conducted to improve classification accuracy and minimize errors caused by cloud cover and cloud shadows, which are known to significantly affect optical satellite data in tropical regions (Ma et al., 2023).

Secondary Data

Secondary data consisted of raster and vector datasets obtained from the Regional Development Planning Agency (BAPPEDA) of the Konawe Islands Regency and other relevant institutions. These datasets were used to construct 12 spatial variables representing physical and environmental conditions relevant to agro-marine tourism suitability. Similar combinations of multi-source spatial datasets have been widely applied in tourism and environmental suitability assessments (Majewska, 2017; Rodríguez-Rangel et al., 2020).

The variables included geology, hydrology, morphology, soil type, slope, topography, watershed boundaries, disaster-prone areas, distance from rivers, and distance from roads, land use, and forest cover. The integration of these variables enables a comprehensive evaluation of environmental safety, accessibility, and landscape attractiveness for sustainable tourism development (Çetin et al., 2018; Louati et al., 2024).

Research Variables

A total of 12 physical environmental variables were selected to model agro-marine tourism land suitability (Table 2). These variables were chosen based on their relevance to tourism development, environmental sustainability, and data availability, consistent with previous GIS-based tourism suitability studies (Magige et al., 2020; Huang et al., 2024).

Physical environmental factors were emphasized because they directly influence land stability, accessibility, environmental safety, and landscape attractiveness, which are critical components of sustainable tourism planning (Majewska, 2017; Xing, 2024).

Distance-based variables, such as distance from roads and rivers, were generated using Euclidean distance analysis in ArcGIS, a commonly applied method for accessibility analysis in tourism studies (Lepetiuk et al., 2023). Land use and forest cover variables were derived from Landsat 9 image classification, while other thematic layers were obtained from secondary sources.

Table 2. Types and sources of spatial data

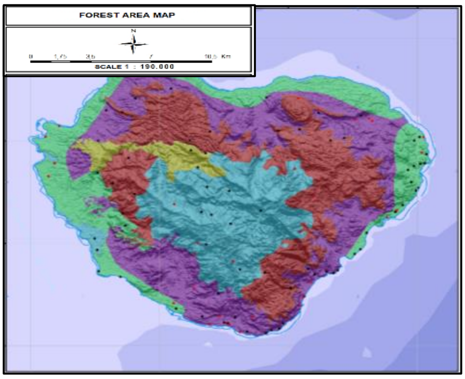
Variable	Source	Scale
Land use	Landsat 9 image processing	1:30,000
Forest	Landsat 9 image processing	1:30,000
Geology	BAPPEDA Konawe Islands Regency	1:250,000
Hydrology	BAPPEDA Konawe Islands Regency	1:250,000
Morphology	BAPPEDA Konawe Islands Regency	1:250,000
Disaster-prone areas	BAPPEDA Konawe Islands Regency	1:250,000
Distance from rivers	GIS analysis	—
Distance from roads	GIS analysis	—
Slope	BAPPEDA Konawe Islands Regency	1:250,000
Soil type	BAPPEDA Konawe Islands Regency	1:250,000
Topography	BAPPEDA Konawe Islands Regency	1:250,000
Watershed	BAPPEDA Konawe Islands Regency	1:250,000

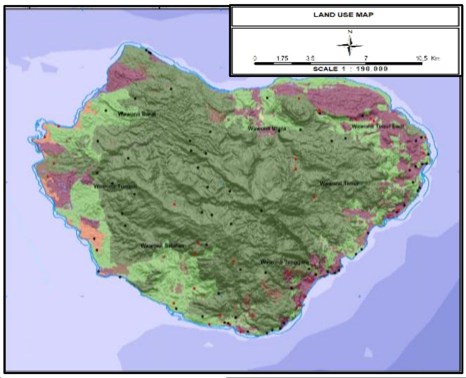
All datasets were resampled to a uniform spatial resolution of 30 m to ensure consistency during raster-based analysis and modeling, following best practices in spatial data integration (Kaya et al., 2018).

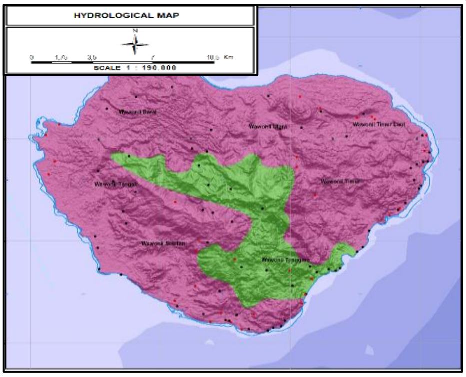
Data Preparation and Pre-processing

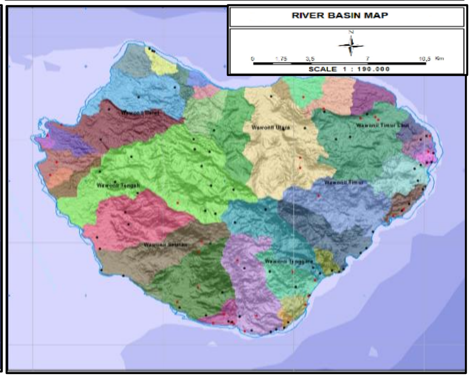
All spatial datasets were converted into raster format and standardized to the same coordinate system, spatial extent, and resolution. Data preparation was performed using ArcGIS and R Studio, which are widely used platforms for spatial analysis and environmental modeling (Kaya et al., 2018; Xing, 2024). Figure 2 illustrates the 12 spatial variables used in this study after raster preprocessing.

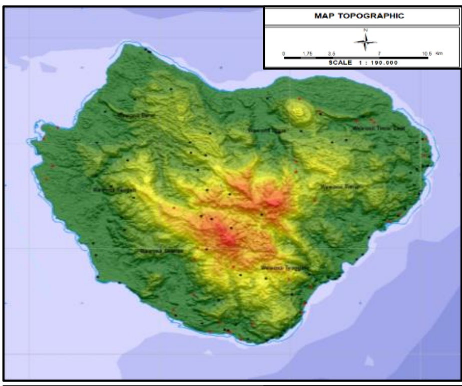
Cloud cover and cloud shadows can significantly affect the accuracy of land cover classification. Therefore, cloud masking was applied using the QA_PIXEL band of Landsat 9 imagery. Pixels identified as clouds or shadows were assigned a value of 0, while valid pixels were assigned a value of 1. This approach follows established cloud detection and masking methods for Landsat imagery (Scaramuzza et al., 2011; Ma et al., 2023).

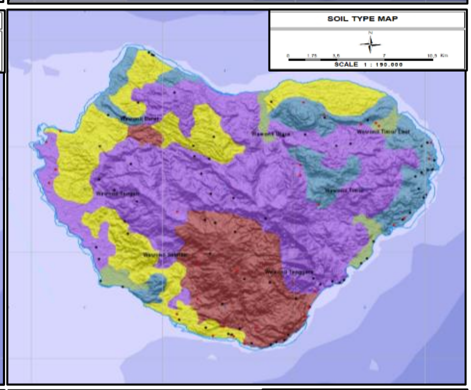

FOREST AREA MAP
SCALE 1 : 190.000

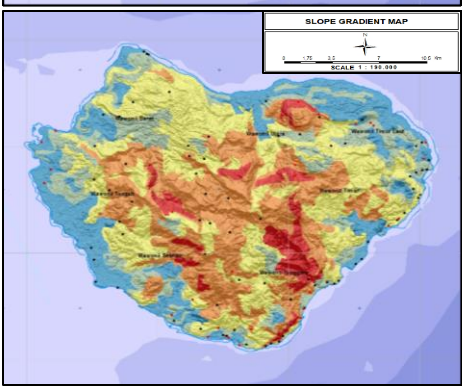

LAND USE MAP
SCALE 1 : 190.000

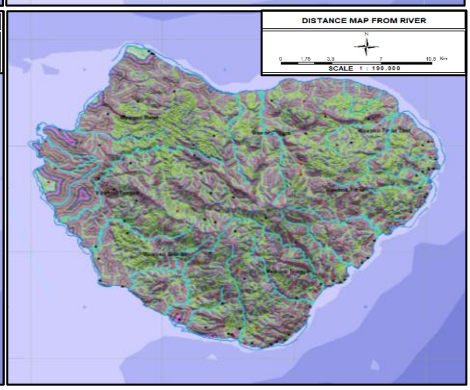

HYDROLOGICAL MAP
SCALE 1 : 190.000


RIVER BASIN MAP
SCALE 1 : 190.000


MAP TOPOGRAPHIC
SCALE 1 : 190.000


SOIL TYPE MAP
SCALE 1 : 190.000


SLOPE GRADIENT MAP
SCALE 1 : 190.000


DISTANCE MAP FROM RIVER
SCALE 1 : 190.000

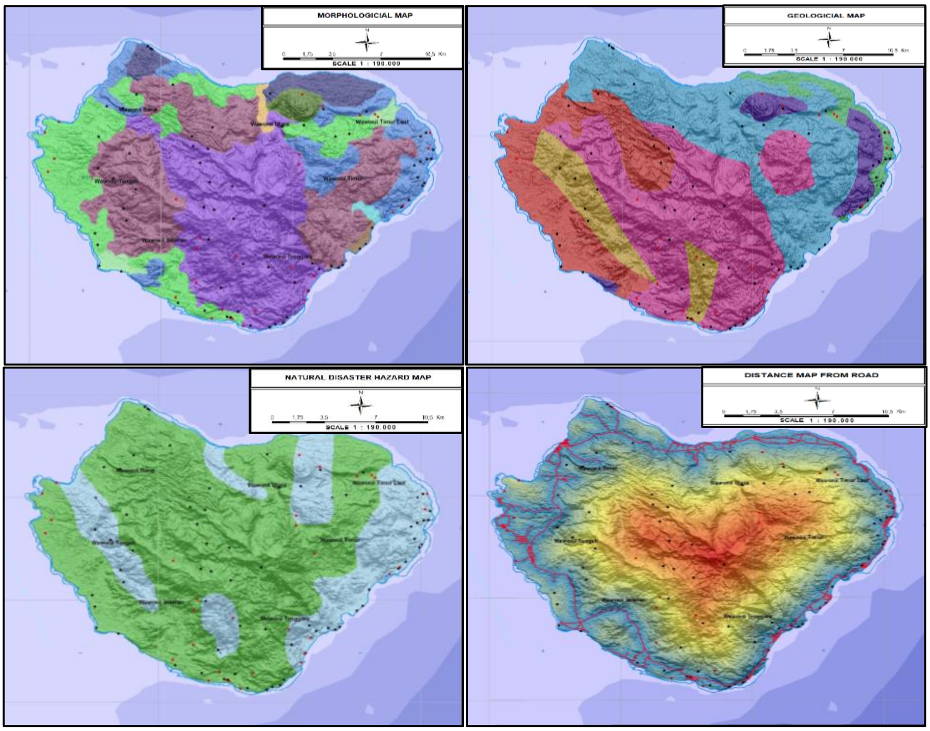


Fig. 2. Research data in raster

Agro-Marine Tourism Suitability Modeling

Spatial modeling of agro-marine tourism suitability was conducted using the R Studio environment. R Studio was selected due to its open-source nature and extensive support for spatial analysis and machine learning through specialized packages, making it suitable for reproducible geospatial research (Kaya et al., 2018; Al-Mistarehi et al., 2022).

A total of 52 existing agro-marine tourism locations were identified through field surveys using a purposive sampling approach. Similar sampling strategies have been applied in tourism suitability and spatial potential studies to ensure representative training datasets (Raha et al., 2024). The dataset was divided into 70% training data and 30% testing data to ensure robust model calibration and validation.

Two machine learning algorithms were applied: Support Vector Machine (SVM) and Random Forest (RF). These algorithms have been widely used in spatial and environmental modeling due to their ability to handle nonlinear relationships and complex interactions among predictor variables (Motevalli et al., 2018; Band et al., 2020).

Support Vector Machine (SVM)

The SVM algorithm was implemented using a radial basis function (RBF) kernel, which is suitable for handling nonlinear relationships among predictor variables (Vapnik & Chapelle, 2000; Huang et al., 2024). Model parameters, including the regularization parameter (C) and kernel width (γ), were optimized using a grid search approach with 10-fold cross-validation, a standard method to improve model generalization performance in machine learning applications (Han et al., 2012). The optimal parameter combination (C = 44;

$\gamma = 0.075$) was selected based on the highest average AUC value, indicating strong predictive performance.

Random Forest (RF)

The Random Forest algorithm was applied as an ensemble learning approach that constructs multiple decision trees and aggregates their predictions through majority voting. RF has been widely used in geoscience and environmental studies due to its robustness against overfitting and its ability to assess variable importance (Ding et al., 2018; Mizan et al., 2021).

Model optimization focused on determining the optimal number of trees (ntree) and the number of variables considered at each split (mtry). The final configuration (ntree = 500; mtry = 1) was selected because the out-of-bag error stabilized and predictive accuracy was maximized, consistent with best practices in RF modeling (Band et al., 2020; Huang et al., 2024).

Agro-Marine Tourism Suitability Modeling

To strengthen the methodology as suggested by the reviewer, we expanded the description of our machine learning approach, drawing on recent studies in environmental modeling using remote sensing and ML (Potić et al., 2017; Durlević et al., 2026) and established best practices in satellite data preprocessing (Irons & Masek, 2006; Masek et al., 2020; Montanaro et al., 2022).

A total of 52 existing agro-marine tourism locations were identified through field surveys using a purposive sampling approach. The dataset was split into 70% training and 30% testing subsets to ensure robust model calibration and validation.

The SVM and RF models were applied following best practices from geospatial ML studies. The SVM used a radial basis function kernel, with hyper parameters optimized through grid search and 10-fold cross-validation, following the approach of Potić et al., 2017. RF was implemented as an ensemble of decision trees, optimizing ntree and mtry to minimize out-of-bag error and maximize predictive accuracy (Motevalli et al., 2018), with variable importance assessed based on Durlević et al. (2026).

Following Potić et al. (2017), we emphasized integrating remote sensing-derived variables with ML models to capture spatial patterns and environmental responses. Rasterized physical, hydrological, and land cover variables-processed in accordance with Landsat best practices (Montanaro et al., 2022; NASA, 2021; Chen et al., 2024; USGS, 2026)-were used to assess agro-marine tourism suitability with high spatial fidelity. Preprocessing steps, including data standardization, spatial alignment, and cloud masking, were consistently applied to maintain model reliability, ensuring that both the input data and machine learning workflow adhere to recognized geospatial and remote sensing standards.

Results

Spatial Distribution of Agro-Marine Tourism Land Suitability

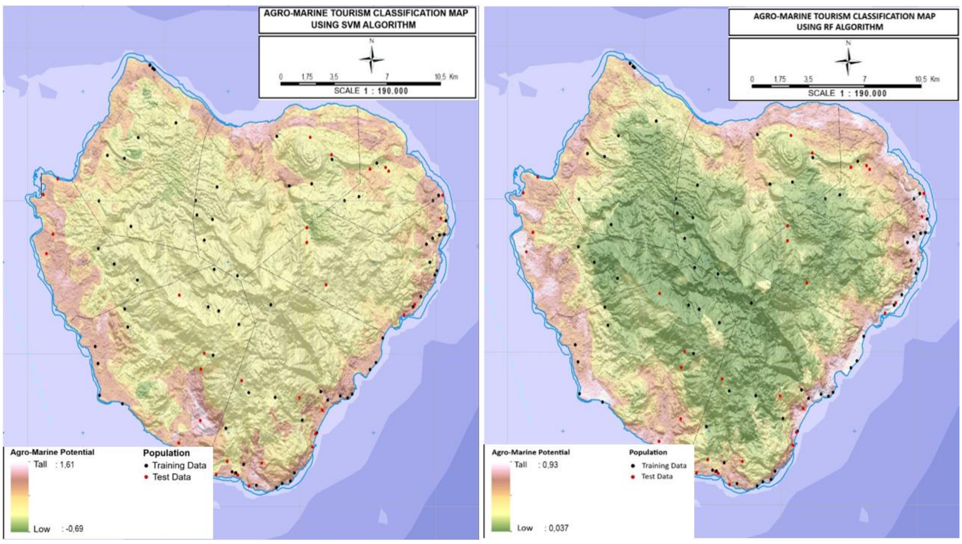
This section presents the results of GIS-based land suitability mapping for agro-marine tourism on Wawonii Island, derived from machine learning modeling and spatial analysis. The analysis encompasses model construction and performance evaluation, classification and spatial distribution of suitability classes, as well as their implications for identifying priority areas for agro-marine tourism development.

Modeling Results of Agro-Marine Tourism Land Suitability

Land suitability modeling for agro-marine tourism on Wawonii Island was conducted using two machine learning algorithms, namely SVM and RF, within a GIS-based framework. The models were trained and validated using 52 existing agro-marine tourism locations, divided into 70% training data and 30% testing data. In addition to the location data, twelve physical and environmental variables were incorporated to represent terrain conditions, accessibility, environmental safety, and landscape characteristics.

Both algorithms classified land suitability based on the relationships between the training locations and the environmental predictor variables. Model parameter selection was performed carefully to ensure optimal classification performance. For the SVM model, the regularization parameter (C) and kernel width (γ) were optimized, while for the RF model, the number of decision trees (ntree) and the number of variables randomly selected at each split (mtry) were adjusted. The resulting land suitability index maps generated by each algorithm are presented in Figure 3, where Figure 3a shows the SVM-based suitability model and Figure 3b shows the RF-based suitability model.

For the SVM algorithm, the optimal parameter combination ($C = 44$; $\gamma = 0.075$) produced suitability index values ranging from 0.50 to 1.50 (Figure 4.1a). Higher index values indicate areas with a higher probability of suitability for agro-marine tourism. In contrast, the RF model, configured with 500 decision trees and an mtry value of 1, produced suitability index values ranging from 0.37 to 0.80 (Figure 3b). In both models, spatial variations in suitability were visually represented using a color gradient from low to high suitability.



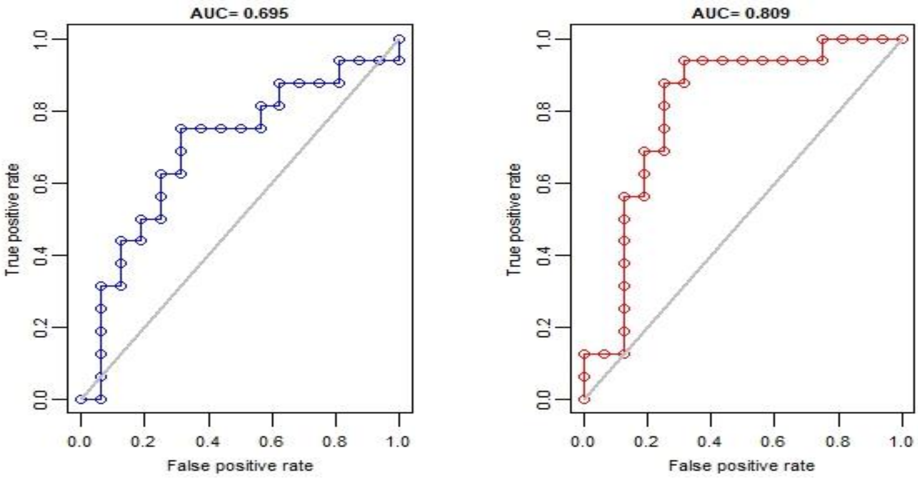
(a) *(b)*

Fig. 3. Land suitability index maps for agro-marine tourism generated using (a) SVM and (b) RF algorithms

Model Performance for Suitability Mapping

To determine which algorithm was more appropriate for mapping the spatial distribution of agro-marine tourism suitability, model performance was evaluated using the Area under the Receiver Operating Characteristic Curve (ROC-AUC). The ROC-AUC values provide an objective measure of a model's ability to distinguish between suitable and unsuitable locations.

The ROC–AUC results for both algorithms are presented in Figure 4, where Figure 4a corresponds to the SVM model and Figure 4b corresponds to the RF model.



(a) *(b)*

Fig. 4. ROC–AUC values of agro-marine tourism suitability models using (a) SVM and (b) RF algorithms.

The SVM model achieved an AUC value of approximately 0.60, which falls within the "good" classification category. Meanwhile, the RF model achieved a higher AUC value of approximately 0.80, indicating "very good" predictive performance. Although both models demonstrated acceptable accuracy for spatial suitability mapping, the RF algorithm showed stronger discrimination capability. However, the SVM model was retained for final suitability classification due to its stability in handling high-dimensional environmental variables and its effectiveness in spatial pattern representation.

Spatial Distribution of Land Suitability Classes

Based on the selected suitability model, the land suitability for agro-marine tourism on Wawonii Island was classified into four categories: low, moderate, high, and very high suitability. The classification was derived by reclassifying the continuous suitability index values into discrete classes using natural break thresholds.

The spatial distribution of these land suitability classes is illustrated in Figure 5.

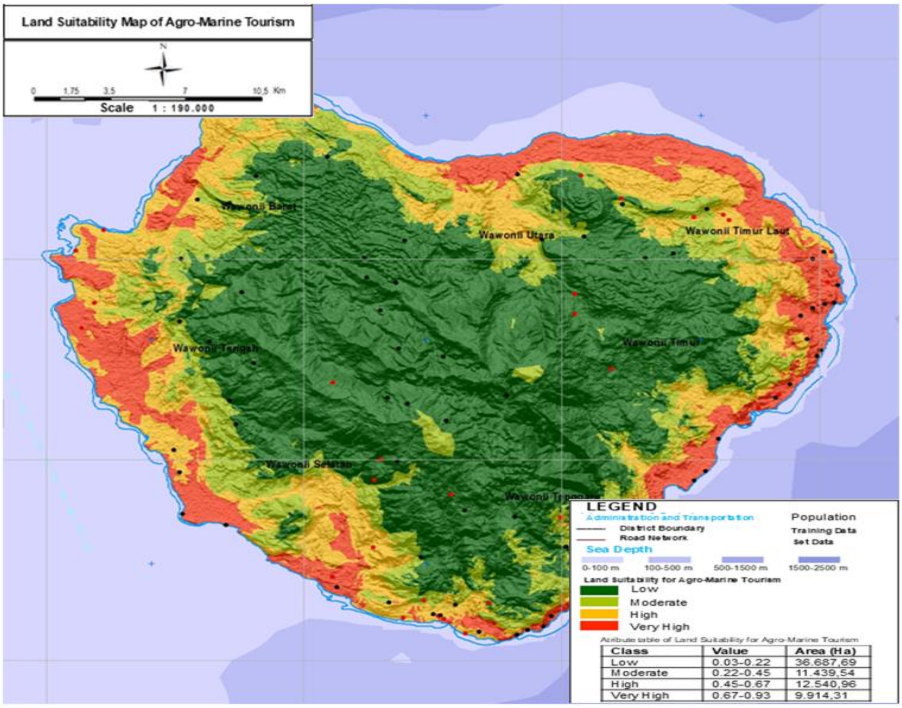


Fig. 5. Spatial distribution of land suitability classes for agro-marine tourism on Wawonii Island

The low suitability class occupied the largest proportion of the island, covering approximately 36,667.69 ha, reflecting areas with higher topographic constraints, limited accessibility, or greater environmental sensitivity. The moderate suitability class covered 11,439.54 ha, while the high suitability class covered 12,540.96 ha. The very high suitability class represented the smallest area, covering approximately 9,914.31 ha, but these areas are considered the most promising locations for agro-marine tourism development.

Overall, areas classified as high and very high suitability were predominantly distributed along coastal zones and lowland areas, where terrain conditions, accessibility, and environmental characteristics are more favorable for integrated agro-marine tourism activities. These spatial patterns demonstrate the capability of the GIS-based modeling approach to clearly differentiate levels of land suitability across the island.

Proportional Distribution of Suitability Classes

To further illustrate the dominance of each suitability class, the proportional area of each class was calculated and summarized in Figure 6.

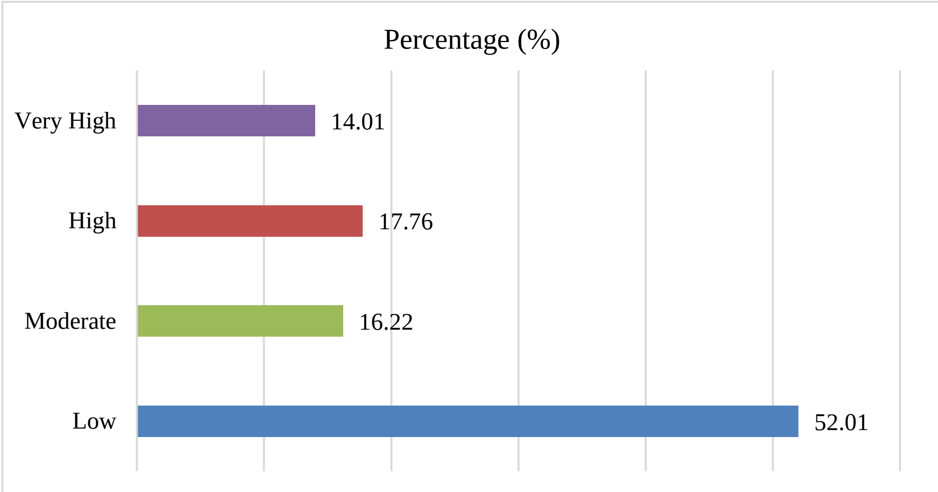


Fig. 6. Percentage of land area according to agro-marine tourism suitability classes on Wawonii Island

The results indicate that the low suitability class accounts for approximately 52.01% of the total area of Wawonii Island. The moderate and high suitability classes account for 16.22% and 17.76%, respectively, while the very high suitability class represents only 14.01% of the island. Despite its limited extent, the very high suitability class is spatially concentrated in environmentally favorable zones, highlighting priority areas for agro-marine tourism planning.

Implications of Spatial Suitability Mapping

The spatial distribution of land suitability classes generated in this study demonstrates that GIS-based machine learning approaches are effective for identifying potential agro-marine tourism areas on small islands. The classification results provide a clear spatial framework that distinguishes areas with high development potential from those requiring environmental protection or restricted use.

The resulting suitability maps serve as a scientific basis for identifying locations that are environmentally and physically appropriate for agro-marine tourism development, thereby fulfilling the first objective of this study. The detailed evaluation of suitability patterns across administrative sub-districts is addressed separately under the second research objective.

Spatial Patterns of Agro-Marine Tourism Suitability across Sub-Districts

This section evaluates the spatial variation of agro-marine tourism land suitability across sub-districts on Wawonii Island to support sustainable tourism planning and regional development in the Konawe Islands Regency. The analysis builds upon the suitability classification results presented in Figures 3–6 and focuses specifically on administrative-level differentiation using overlay analysis.

An overlay analysis between the land suitability map and sub-district administrative boundaries reveals clear spatial variation in suitability patterns across Wawonii Island (Figure 7). Each sub-district exhibits a distinct composition of suitability classes, reflecting differences in physical conditions, coastal characteristics, accessibility, and environmental constraints. This spatial heterogeneity highlights the importance of sub-district–specific planning strategies rather than uniform tourism development across the island.

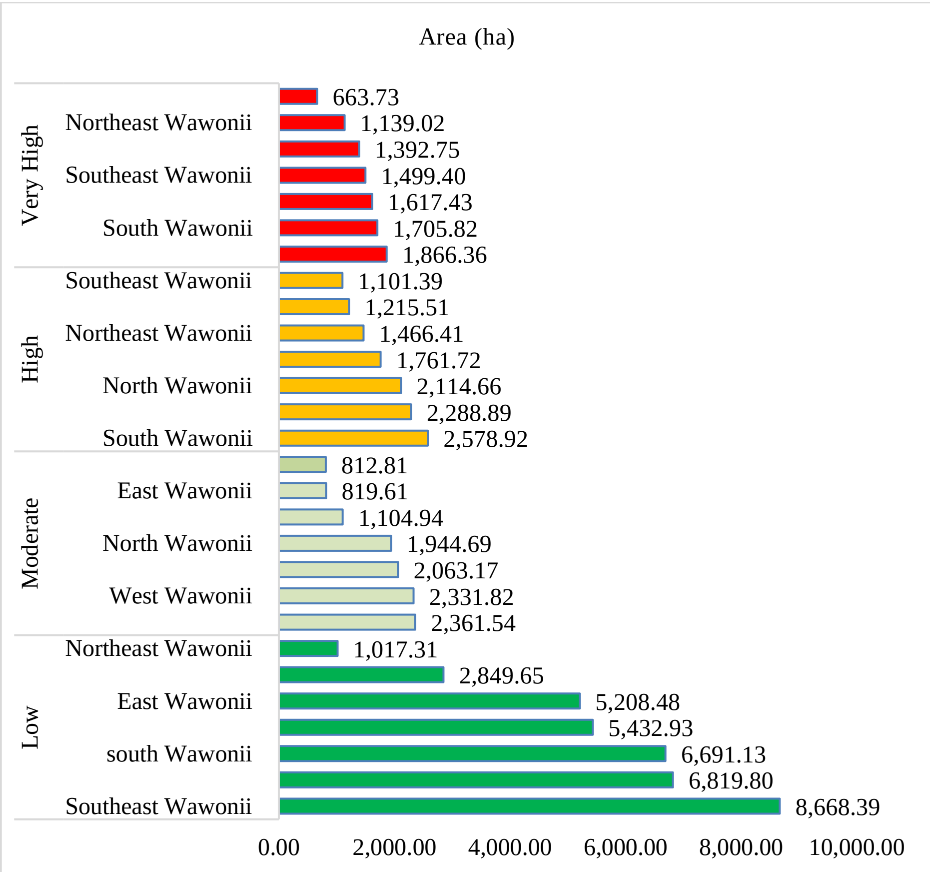


Fig. 7. Distribution of land suitability classes for agro-marine tourism across sub-districts on Wawonii Island, Konawe Islands Regency

The results show that Central Wawonii Sub-district contains the largest area classified as very high suitability, indicating its strong potential as a core zone for integrated agro-marine tourism development. In contrast, West Wawonii Sub-district exhibits the smallest extent of very high suitability land, suggesting more limited development opportunities or higher environmental constraints. Areas classified as high suitability are most extensive in South Wawonii Sub-district, whereas this category occupies a relatively smaller area in other sub-districts.

The moderate suitability class is most prominent in South Wawonii and West Wawonii Sub-districts, indicating transitional zones that may support tourism development under controlled and environmentally sensitive management approaches. Meanwhile, Northeast Wawonii and East Wawonii Sub-districts show comparatively smaller areas of moderate suitability, reflecting more restrictive physical or environmental conditions.

Across all sub-districts, the low suitability class remains dominant, although its spatial extent varies. The largest proportion of low-suitability land is observed in Southeast Wawonii Sub-district, while Northeast Wawonii Sub-district contains the smallest extent of this category. This pattern underscores the limited availability of land that is physically and environmentally appropriate for agro-marine tourism development and reinforces the need for selective, evidence-based planning.

From a regional planning perspective, the concentration of high and very high suitability classes in specific sub-districts-particularly Central and South Wawonii-provides a spatial foundation for prioritizing tourism investment and infrastructure development. These areas are characterized by favorable coastal environments, relatively gentle slopes, agricultural land use, and the presence of natural attractions such as mangroves, springs, and karst-related geomorphological features. Such conditions align with the principles of sustainable and integrated agro-marine tourism, where terrestrial and marine resources are jointly utilized.

The sub-district-level evaluation demonstrates that GIS-based land suitability mapping is an effective tool for translating spatial analysis into administrative planning units. By identifying which sub-districts possess higher development potential and which require stricter environmental protection, the results directly support sustainable tourism planning and regional development strategies in the Konawe Islands Regency. This fulfills the second objective of the study by providing spatially explicit guidance for policymakers to balance tourism development, environmental conservation, and community welfare at the sub-district scale.

Discussion

In comparison to the previous studies on the suitability of island and coastal areas for tourism, the current research has a number of unique advantages. The research combines GIS spatial analysis with machine learning models (SVM and RF), which are able to identify the complex, non-linear relationships between the variables while preserving spatial interpretability. In addition, the research is able to directly implement the results of raster suitability maps into sub-district administrative units. Finally, the research framework is able to combine ecological constraints, accessibility, and socio-environmental priorities.

This study demonstrates that integrating GIS-based spatial analysis with machine learning algorithms provides a robust framework for identifying land suitability for agro-marine tourism on small islands. The results reveal clear spatial differentiation of suitability levels across Wawonii Island, reflecting the combined influence of topography, land use, accessibility, and environmental constraints. Such spatial differentiation is a critical prerequisite for sustainable tourism planning in island environments, where land resources are limited and ecological sensitivity is high (Huang et al., 2024; Louati et al., 2024; Lieske et al., 2025).

The application of SVM and RF algorithms highlights the capacity of machine learning techniques to model complex, non-linear relationships between environmental variables and tourism suitability. Although the RF model achieved higher predictive accuracy, the SVM model demonstrated stable spatial pattern representation, supporting its use for final suitability classification. This finding reinforces recent arguments that model selection in spatial planning should balance predictive accuracy with spatial interpretability and robustness (Band et al., 2020; Xing, 2024; Tan et al., 2024b; Mutale et al., 2024).

To further prove the effectiveness of our approach, the accuracy, F1 measure, and spatial pattern stability of the RF and SVM models were evaluated. The RF model had a higher accuracy in predictive performance, while the SVM model showed stability in spatial representation. Moreover, in contrast to AHP-based methods used in other similar studies (Tebbi et al., 2025), our GIS+ML approach is highly effective in identifying complex non-linear relationships among environmental and socio-environmental variables, and it provides spatially explicit and administratively useful results. The use of high-resolution satellite imagery from Landsat 8 and 9 (Irons & Masek, 2006; Masek et al., 2020; Chen et al., 2024) further enhances the applicability and validity of the suitability maps.

The dominance of low suitability areas across Wawonii Island indicates that only a limited proportion of land is physically and environmentally appropriate for agro-marine tourism development. This pattern is largely driven by steep slopes, environmentally sensitive zones, limited accessibility, and areas affected by extractive activities such as mining. Similar spatial constraints have been widely reported in island and coastal tourism studies, emphasizing the need for selective rather than expansive tourism development strategies (Raha et al., 2024; Turtureanu et al., 2025; Pricope & Dalton, 2025). Consequently, unregulated expansion of tourism infrastructure into unsuitable areas may exacerbate land degradation and threaten coastal and marine ecosystems.

Conversely, areas classified as high and very high suitability are primarily concentrated in coastal and lowland zones, where favorable terrain, proximity to transportation networks, and the presence of agricultural and marine resources converge. These zones provide opportunities for integrated agro-marine tourism that combines plantation-based activities, coastal recreation, and ecosystem-based attractions such as mangroves and freshwater springs. This spatial configuration supports the concept of agro-marine tourism as a multifunctional land-use system that integrates agriculture, coastal ecosystems, and tourism activities (Susila et al., 2024; Aryono et al., 2024).

At the administrative scale, the sub-district-level analysis reveals significant variation in suitability patterns, underscoring the necessity of differentiated planning strategies. Central and South Wawonii sub-districts emerge as priority areas due to their relatively extensive high and very high suitability zones, supported by ecological diversity, gentle slopes, and established agricultural land use. In contrast, sub-districts dominated by low suitability areas require stricter land-use control and conservation-oriented management to prevent further environmental degradation. These findings demonstrate the value of translating spatial suitability outputs into administrative planning units to enhance policy relevance and implementation feasibility (Chang et al., 2024; Budha et al., 2025).

From a policy perspective, the land suitability framework developed in this study offers a scientific basis for aligning agro-marine tourism development with sustainable regional planning objectives in the Konawe Islands Regency. By clearly distinguishing between development-priority areas and zones requiring protection, the results can assist local governments in optimizing land-use allocation, minimizing conflicts between tourism and other sectors, and reducing environmental risks. Such evidence-based spatial planning is increasingly recognized as essential for achieving balanced tourism development in coastal and island regions (Kuba et al., 2024; Başeğmez et al., 2025).

Despite its contributions, this study has several limitations that should be addressed in future research. The analysis primarily focuses on physical and environmental variables, while socio-cultural factors, economic feasibility, and institutional capacity were not explicitly modeled. Additionally, dynamic variables such as seasonal hydrological changes and long-term climate variability were not incorporated. Future studies could enhance the framework by integrating social vulnerability indicators, cultural heritage assets, and climate-related risks, as well as by applying advanced machine learning techniques to assess scenario-based development pathways, thereby strengthening the applicability of the model for long-term sustainable tourism governance (Turtureanu et al., 2025; Appukuttan et al., 2025).

In summary, this study clearly demonstrates its novelty by combining a GIS-based machine learning approach with administrative-level outputs, explicitly balancing ecological, accessibility, and socio-environmental factors to provide a practical, evidence-based tool for guiding sustainable agro-maritime tourism development on small islands. These findings offer actionable insights for policymakers, planners, and researchers seeking to implement evidence-based and sustainable tourism strategies in ecologically sensitive island environments.

Overall, the findings confirm that GIS-based machine learning approaches are effective tools for guiding sustainable agro-marine tourism development on small islands. By providing spatially explicit and administratively relevant information, this study contributes to the development of evidence-based tourism planning strategies that balance economic development, environmental conservation, and community well-being in the Konawe Islands Regency.

Conclussion

This study demonstrates the effectiveness of integrating GIS-based spatial analysis with machine learning algorithms for mapping land suitability for agro-marine tourism on Wawonii Island, Indonesia. By combining multi-source spatial data with Support Vector Machine (SVM) and Random Forest (RF) models, the research successfully identified spatial patterns of land suitability and classified the island into four suitability levels: low, moderate, high, and very high.

The results indicate that agro-marine tourism suitability on Wawonii Island is spatially heterogeneous, with high and very high suitability classes predominantly concentrated in coastal and lowland areas. Quantitatively, the low suitability class covers approximately 36,668 ha (52% of the island), moderate 11,440 ha (16%), high 12,541 ha (18%), and very high 9,914 ha (14%). These zones are characterized by favorable topography, accessibility, and the coexistence of agricultural and marine resources, making them particularly suitable for integrated agro-marine tourism development. In contrast, the dominance of low suitability areas highlights the presence of physical constraints and environmental sensitivities that limit large-scale tourism expansion.

At the administrative level, the sub-district-based evaluation provides spatially explicit evidence to support differentiated tourism planning strategies. Central and South Wawonii Sub-districts emerge as priority areas for development, while other sub-districts require stricter land-use control and conservation-oriented management. Overall, the study fulfills its research objectives by providing a robust spatial framework that supports sustainable tourism planning and regional development in the Konawe Islands Regency.

Implications

The findings of this study have important implications for tourism planning and land-use management in small island regions. The land suitability maps provide a scientific basis for identifying priority areas for agro-marine tourism development while simultaneously highlighting zones that require environmental protection. This spatial differentiation can assist local governments in optimizing infrastructure investment, reducing land-use conflicts, and minimizing environmental risks associated with unplanned tourism growth.

From a policy perspective, the integration of suitability mapping at the sub-district level enhances the practical applicability of the results. Local decision-makers can use these findings to formulate zoning regulations, guide tourism investment, and align agro-marine tourism development with broader sustainable development objectives. Moreover, the approach supports the promotion of integrated tourism models that balance agricultural productivity, coastal ecosystem conservation, and community-based economic development.

Methodologically, this study demonstrates that GIS-based machine learning approaches are transferable and adaptable tools for tourism suitability assessment in other small islands and coastal regions facing similar environmental and developmental challenges.

Limitations and Directions for Future Research

There are a few limitations in the current study. Firstly, the study was mainly focused on physical and environmental factors, whereas socio-cultural aspects, economic viability, institutional capacity, and community attitudes were not taken into account, which are essential for the long-term sustainability and acceptance of agro-marine tourism. Secondly, the approach is based on static spatial information, which does not consider temporal aspects such as seasonal tourist demand, climate change, and environmental fluctuations, which would not be able to capture the dynamic changes in suitability maps.

Future studies should consider incorporating socioeconomic, cultural, and governance variables. The use of scenario modeling techniques through the application of advanced or hybrid machine learning techniques would also make a significant contribution.

Acknowledgements: The authors would like to express their sincere gratitude to the Regional Development Planning Agency (BAPPEDA) of the Konawe Islands Regency for providing access to spatial and secondary data used in this study. Appreciation is also extended to the United States Geological Survey (USGS) for making Landsat 9 satellite imagery freely available. The authors acknowledge the support of all field survey participants and local stakeholders on Wawonii Island who contributed valuable information during data collection. Any remaining errors are the sole responsibility of the authors.

Conflict of Interest: The authors declare no conflict of interest.

Publisher’s Note: Serbian Geographical Society stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

Al-Mistarehi, B. W., Alomari, A. H., Imam, R., & Mashaqba, M. (2022). Using machine learning models to forecast severity level of traffic crashes by R Studio and ArcGIS. *Frontiers in Built Environment, 8,* Article 860805. https://doi.org/10.3389/fbuil.2022.860805

Appukuttan, A., Deshpande, G., Jadhav, A., & Reghunath, R. (2025). Geospatial modeling of landslide susceptibility in lateritic terrain: Insights from machine learning techniques—Random forest and DBSCAN. *Discover Applied Sciences, 7*, Article 1224. https://doi.org/10.1007/s42452-025-07245-1

Aryono, G. D. P., Laksana, A., Sukmawan, I., & Huda, M. (2024). Utilization of GIS in the development of marine tourism in the provincial strategic tourism area (KSSP) of Carita. *Teknika: Jurnal Sains dan Teknologi*, *20*(2), 141–148. https://doi.org/10.62870/tjst.v20i2.28789

Astuti, T., Hasddin, Asrul, Jasman, Balaka, M. Y., Haydir, Ishak, A., Handa, M. I., Sambari, V. E. G. S., & Maladeni, E. S. (2025a). Urban farming and the nexus of economic growth and environmental sustainability in coastal cities, Indonesia. *European Journal of Sustainable Development Research,* 9(4), Article em0328. https://doi.org/10.29333/ejosdr/16773

Astuti, T., Hasddin, H., Marjani, M., Murini, M., Yusuf, M., Sondeng, S., Kasim, S., Husen, O. O., Ulyasniati, U., & Afa, M. (2025b). Urban farming and livelihood resilience in coastal cities: An economic and environmental accounting perspective from Kendari. *Bulletin of the Serbian Geographical Society,* 105(2), 189–204. https://doi.org/10.2298/GSGD2502189A

Band, S. S., Janizadeh, S., Pal, S. C., Saha, A., Chakrabortty, R., Melesse, A. M., & Mosavi, A. (2020). Flash flood susceptibility modeling using new approaches of hybrid and ensemble tree-based machine learning algorithms. *Remote Sensing, 12(21),* Article 3568. https://doi.org/10.3390/rs12213568

Başeğmez, M., Doğan, A., & Aydın, C. C. (2025). Management of sustainable urban green spaces through machine learning–supported MCDM and GIS integration. *Environmental Science and Pollution Research, 32*, 11466–11487. https://doi.org/10.1007/s11356-025-36367-7

Boni, Y., Afiat, N., Suyuti, N., Jumaidin, L. O., Melati, M., Amalia, R. R., Saranani, F., Hamid, A., Tobigo, H., & Hasddin, H. (2024). Preserving coastal and marine resources: The existence of local wisdom among the Bajau tribe. *Journal of Global Innovations in Agricultural Sciences*, *12(3),* 671-679. https://doi.org/10.22194/JGIAS/24.1336

BPS-Statistics of Sulawesi Tenggara Province. (2022). Sulawesi Tenggara Province in figures 2022. BPS-Statistics Indonesia. https://sultra.bps.go.id/en/publication/2022/02/25/b5383ab2887274d3ee7f0034/provinsi-sulawesi-tenggara-dalam-angka-2022.html

Briandana, R., Doktoralina, C. M., & Sukmajati, D. (2018). Promotion analysis of marine tourism in Indonesia: A case study. *European Research Studies Journal, 21(1),* 602–613. https://doi.org/10.35808/ersj/973

Budha, M., Thapa, M. S., Gharti, S., & Bhattarai, B. (2025). Machine learning and GIS-based simulation of urban expansion for sustainable planning in Chaurjahari of Nepal. *Discover Cities, 2,* Article 84. https://doi.org/10.1007/s44327-025-00107-w

Çetin, M., Zeren, I., Sevik, H., Cakır, C., & Akpinar, H. (2018). A study on the determination of the natural park's sustainable tourism potential. *Environmental Monitoring and Assessment, 190(3),* Article 167. https://doi.org/10.1007/s10661-018-6534-5

Chang, V., Islam, M. R., Ahad, A., Ahmed, M. J., & Xu, Q. (2024). Machine learning for predicting tourist spots' preference and analysing future tourism trends in Bangladesh. *Enterprise Information Systems, 18(12),* Article 2415568. https://doi.org/10.1080/17517575.2024.2415568

Chen, J., Wang, Y., Wang, J., Zhang, Y., Xu, Y., Yang, O., Zhang, R., Wang, J., Wang, Z., Lu, F., & Hu, Z. (2024). The performance of Landsat-8 and Landsat-9 data for water body extraction based on various water indices: A comparative analysis. *Remote Sensing, 16(11),* Article 1984. https://doi.org/10.3390/rs16111984

CountryReports.org. (2002, November 23). Indonesia. http://www.countryreports.org/content/indonesia

Ding, F., Fu, J., Jiang, D., Hao, M., & Lin, G. (2018). Mapping the spatial distribution of Aedes aegypti and Aedes albopictus. *Acta Tropica, 178,* 155–162. https://doi.org/10.1016/j.actatropica.2017.11.020

Durlević, U., Ilić, V., & Aleksova, B. (2026). Wildfire probability mapping in Southeastern Europe using deep learning and machine learning models based on open satellite data. *AI, 7(1),* Article 21. https://doi.org/10.3390/ai7010021

Han, J., Kamber, M., & Pei, J. (2012). Data mining: Concepts and techniques (3rd ed.). Morgan Kaufmann. https://doi.org/10.1016/C2009-0-61819-5

Huang, Q., Zhou, C., Li, M., Ma, Y., & Hua, S. (2024). An approach for mapping ecotourism suitability using machine learning: A case study of Zhangjiajie, *China. Land, 13(8),* 1188. https://doi.org/10.3390/land13081188

Irons, J., & Masek, J. (2006). Requirements for a Landsat data continuity mission. *Photogrammetric Engineering & Remote Sensing, 72*(10), 1102–1108. https://www.asprs.org/wp-content/uploads/pers/2006journal/october/highlight.pdf

Joeliaty, J. (2024). The impact of infrastructure development, education, tourism, and agriculture on regional economic growth in Indonesia. *The Es Economics and Entrepreneurship,* 2(3), 193–207. https://doi.org/10.58812/esee.v2i03.235

Kaya, E., Agca, M., Adiguzel, F., & Çetin, M. (2018). Spatial data analysis with R programming for environment. Human and Ecological Risk Assessment: An International *Journal, 25(1),* 1–10. https://doi.org/10.1080/10807039.2018.1470896

Kuba, D., Kuba, M. Z. D., Usman, K. S., & Wasilah. (2024). Community-based management: Marine tourism development for ecological and economic sustainability. *Journal of Economic Education and Entrepreneurship Studies,* 5(3), 467–479. https://doi.org/10.62794/je3s.v5i3.4372

Lee, Y.-J. A., Jang, S., & Kim, J. (2020). Tourism clusters and peer-to-peer accommodation. *Annals of Tourism Research, 83,* Article 102960. https://doi.org/10.1016/j.annals.2020.102960

Lepetiuk, V., Tretyak, V., & Maksymova, Y. (2023). The use of GIS technologies to determine transport accessibility in tourism. *Geodesy and Cartography, 49(3),* 166–179. https://doi.org/10.3846/gac.2023.17009

Li, A., Zhang, Z., Hong, Z., Liu, L., Liu, L., Ashraf, T., & Liu, Y. (2024). Spatial suitability evaluation based on multisource data and random forest algorithm: A case study of Yulin, China. *Frontiers in Environmental Science, 12,* Article 1338931. https://doi.org/10.3389/fenvs.2024.1338931

Li, Z., Xi, J., & Ye, S. (2025). Identifying suitable zones for tourism activities on the Qinghai–Tibet Plateau based on trajectory data and machine learning. *Land, 14(9),* Article 1885. https://doi.org/10.3390/land14091885

Louati, A., Louati, H., Alharbi, M., Kariri, E., Khawaji, T., Almubaddil, Y., & Aldwsary, S. (2024). Machine learning and artificial intelligence for sustainable tourism: A case study of Saudi Arabia. *Information, 15(9),* 516. https://doi.org/10.3390/info15090516

Ma, D., Wu, R., Xiao, D., & Sui, B. (2023). Cloud removal from satellite images using a deep learning model with the cloud-matting method. *Remote Sensing, 15(4), Article* 904. https://doi.org/10.3390/rs15040904

Magige, J. M., Jepkosgei, C., & Onywere, S. M. (2022). *Use of GIS and remote sensing in tourism.* In Z. Xiang, M. Fuchs, U. Gretzel, & W. Höpken (Eds.), Handbook of e-tourism (pp. 1335–1361). Springer. https://doi.org/10.1007/978-3-030-48652-5_118

Majewska, J. P. (2017). GPS-based measurement of geographic spillovers in tourism: Example of Polish districts. *Tourism Geographies, 19(4),* 612–643. https://doi.org/10.1080/14616688.2017.1320581

Masek, J. G., Wulder, M. A., Markham, B., McCorkel, J., Crawford, C. J., & Jenstrom, D. T. (2020). Landsat 9: Empowering open science and applications through continuity. *Remote Sensing of Environment, 248,* Article 111968. https://doi.org/10.1016/j.rse.2020.111968

Mizan, R. A., Widayani, P., & Farda, N. M. (2021). Assessment and comparison of machine learning algorithm capability in spatial modeling of dengue fever vulnerability based on Landsat 8 OLI/TIRS imagery. *Jurnal Geografi, 13(2),* 211–224. https://doi.org/10.24114/jg.v13i2.21019

Montanaro, M., McCorkel, J., Tveekrem, J., Stauder, J., Mentzell, E., Lunsford, A., Hair, J., & Reuter, D. (2022). Landsat 9 Thermal Infrared Sensor 2 (TIRS-2) stray light mitigation and assessment. *IEEE Transactions on Geoscience and Remote Sensing, 60*, 5002408, 1–8. https://doi.org/10.1109/tgrs.2022.3177312

Motevalli, A., Pourghasemi, H. R., & Zabihi, M. (2018). Assessment of GIS-based machine learning algorithms for spatial modeling of landslide susceptibility: Case study in Iran. *Comprehensive geographic information systems (*pp. 258–280). Elsevier. https://doi.org/10.1016/B978-0-12-409548-9.10461-0

Mutale, B., Withanage, N. C., Mishra, P. K., Shen, J., Abdelrahman, K., & Fnais, M. S. (2024). A performance evaluation of random forest, artificial neural network, and support vector machine learning algorithms to predict spatio-temporal land use–land cover dynamics: A case from Lusaka and Colombo. *Frontiers in Environmental Science, 12,* Article 1431645. https://doi.org/10.3389/fenvs.2024.1431645

NASA. (2021). *Landsat 9 mission overview.* NASA Goddard Space Flight Center. https://www.nasa.gov/landsat9

Potić, I. M., Ćurčić, N. B., Potić, M. M., Radovanović, M. M., & Tretiakova, T. N. (2017). Remote sensing role in environmental stress analysis: East Serbia wildfires case study (2007–2017). *Journal of the Geographical Institute "Jovan Cvijić" SASA, 67(3),* 249–264. https://doi.org/10.2298/IJGI1703249P

Pricope, N. G., & Dalton, E. G. (2025). Mapping coastal resilience: Precision insights for green infrastructure suitability. *Journal of Environmental Management, 376,* Article 124511. https://doi.org/10.1016/j.jenvman.2025.124511

Raha, S., Gayen, S. K., & Deb, S. (2024). Harnessing machine learning and ensemble models for tourism potential zone prediction for the Assam State of India. *Journal of Advanced Geospatial Science & Technology, 4(2),* 29–78. https://doi.org/10.11113/jagst.v4n2.92

Rodríguez-Rangel, M. C., Sánchez-Rivero, M., & Ramajo-Hernández, J. (2020). Spatial intensity in tourism accommodation: Modelling differences in trends for several types through Poisson models. *ISPRS International Journal of Geo-Information, 9(8),* Article 473. https://doi.org/10.3390/ijgi9080473

Sperandio, H. V., de Morais, M. S., de França, L. C. J., Mucida, D. P., Santana, R. C., da Silva, R. S., Rodrigues, C. R., de Faria, B. L., de Azevedo, M. L., & Gorgens, E. B. (2025). Land suitability modeling integrating geospatial data and artificial intelligence. *Agricultural Systems, 223,* Article 104197. https://doi.org/10.1016/j.agsy.2024.104197

Statistics of Konawe Kepulauan Regency (Badan Pusat Statistik Kabupaten Konawe Kepulauan). (2025). Konawe Kepulauan Regency in Figures 2025. Badan Pusat Statistik. https://konkepkab.bps.go.id/id/publication/2025/02/28/2bc7ffff51547123706a7098/konawe-kepulauan-regency-in-figures-2025.html

Suparwoko, W. (2012). Tourism development in Indonesia. *In Towards responsible tourism: A community-based approach to tourism development in Indonesia (Chap. IV).* LAP Lambert Academic Publishing. https://doi.org/10.13140/2.1.4103.2485

Susila, I., Dean, D., Harismah, K., Priyono, K. D., Setyawan, A. A., & Maulana, H. (2024). Does interconnectivity matter? An integration model of agro-tourism development. *Asia Pacific Management Review, 29(1),* 104–114. https://doi.org/10.1016/j.apmrv.2023.08.003

Tan, C., Huang, Q., Yang, B., Li, T., & Lei, J. (2024a). Application of random forest algorithm in regional ecotourism suitability assessment. *Journal of Geo-Information Science, 26(2),* 318–331. https://doi.org/10.12082/dqxxkx.2024.230198

Tan, Y.-C., Duarte, L., & Teodoro, A. C. (2024b). Comparative study of random forest and support vector machine for land cover classification and post-wildfire change detection. *Land, 13*(11), Article 1878. https://doi.org/10.3390/land13111878

Tebbi, H., Dridi, H., & Bouder, A. (2025). Analytic hierarchy process vs. machine learning: Mapping school suitability in Batna City, Algeria with spatial analysis. *Bulletin of the Serbian Geographical Society, 105(2),* 23–38. https://doi.org/10.2298/GSGD2502023T

Tegar, D., & Gurning, R. O. S. (2018). Development of marine and coastal tourism based on blue economy. *International Journal of Marine Engineering Innovation and Research, 2(2),* 128–132. https://doi.org/10.12962/j25481479.v2i2.365

Turtureanu, A.-G., Crețu, C.-M., Pripoaie, R., Marinescu, E. Ș., Sîrbu, C.-G., & Talaghir, L.-G. (2025). Sustainable development through agritourism and rural tourism: Research trends and future perspectives in the pandemic and post-pandemic period. *Sustainability, 17(9),* Article 3998. https://doi.org/10.3390/su17093998

USGS. (2026). *Landsat 9 Level 2, Collection 2, Tier 1 [Data set].* NASA/USGS. https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC09_C02_T1_L2

Vapnik, V., & Chapelle, O. (2000). Bounds on error expectation for support vector machines. *Neural Computation, 12(9),* 2013–2036. https://doi.org/10.1162/089976600300015042

Xing, W. (2024). Leveraging GIS for sustainable tourism development: A comprehensive spatial approach. *Applied and Computational Engineering, 106(1),* 13–18. https://doi.org/10.54254/2755-2721/106/20240911

Zhang, M., Tan, S., Liang, J., Zhang, C., & Chen, E. (2024). Predicting the impacts of urban development on urban thermal environment using machine learning algorithms in Nanjing, China. *Journal of Environmental Management, 356,* Article 120560. https://doi.org/10.1016/j.jenvman.2024.120560