EEET ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology, 2025, 26(3), 1–16
https://doi.org/10.12912/27197050/199323
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Received: 2024.12.05
Accepted: 2025.01.20
Published: 2025.02.01

Mapping agrotourism potential using geospatial data and random forest: A case study from Bali

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ABSTRACT

Bali, Indonesia, renowned for its cultural heritage and natural beauty, has untapped potential in agrotourism, offering a sustainable avenue for economic diversification and cultural preservation. This study aims to identify and map agrotourism potential in Gianyar Regency using advanced geospatial analysis and the Random Forest algorithm, integrating antrophogenic and environmental variables. Ten key factors were analyzed, including proximity to tourist attractions, tourism facilities, and road networks, as well as environmental variables such as NDVI, LSWI, elevation, slope, temperature, and rainfall. A total of 410 data points, including 111 existing agrotourism locations, were utilized to develop and validate the model. The Random Forest algorithm demonstrated strong performance, achieving an accuracy of 86%, a recall of 72%, and an F1 score of 78%. The model's high specificity (92%) and low false positive rate (8%) underscored its reliability in excluding unsuitable areas while accurately classifying high-potential zones. Variable importance analysis revealed NDVI (13.13%) and LSWI (13.11%) as the most critical factors, highlighting the significance of soil fertility and moisture in agrotourism suitability. The zoning map categorized land into five potential levels, with 10.11% identified as having very high potential, concentrated in subdistricts like Tegallalang and Payangan. Tegallalang, with its iconic Subak rice terraces, exemplifies the integration of agricultural sustainability and cultural heritage, while Payangan offers interactive horticulture and plantation experiences. Priority villages for development, including Tampaksiring, Kedewatan, and Keliki, demonstrated >50% agrotourism potential, underscoring their suitability for targeted investment and strategic planning. This study provides a robust framework for data-driven agrotourism development, combining geospatial technology with sustainable tourism strategies. It highlights the importance of optimizing natural and cultural assets to enhance Bali's global appeal while ensuring economic and environmental sustainability. Future research should refine zoning models with additional parameters and collaborative approaches to maximize the potential of agrotourism in rural areas.

Keywords: sustainability tourism, GIS, zoning, land suitability, anthropogenic, environment, subak, tourism planning.

INTRODUCTION

Bali, Indonesia, is internationally renowned as a tourism destination, offering a diverse array of attractions centered on its cultural heritage, natural beauty, and vibrant traditions (Adhika and Putra, 2021; Mudana et al., 2021; Putri and Saputra, 2022). While mainstream tourism sectors such as beach tourism and cultural tourism are well-developed, agrotourism, which integrates agricultural practices with tourism activities, remains underexplored. Agrotourism represents a sustainable alternative for diversifying Bali's tourism economy while promoting rural development and environmental conservation (Budiasa and Ambarawati, 2014). It provides visitors with opportunities to engage in agricultural activities, fostering a deeper appreciation for traditional farming methods and rural lifestyles. Additionally, agrotourism benefits local communities by generating alternative income streams, preserving traditional practices, and encouraging sustainable land-use management (Satriawan et al., 2015). However, the strategic development of agrotourism has been hindered by the absence of precise planning frameworks and insufficient integration of innovative technologies.

The determination of agrotourism potential has been a significant area of research, especially in regions like Bali where agriculture and tourism converge (Amir, 2023; Lanya et al., 2018). Several studies have assessed agrotourism suitability using various methods and variables, such as tourist attractions, agricultural land use potential, accessibility, and socioeconomic factors (Rosardi et al., 2022; Wicaksono et al., 2024). While these studies provide valuable insights, their methodologies often rely on conventional approaches, such as manual delineation, field surveys, and participatory techniques, which present several limitations in terms of scalability, precision, and efficiency.

For instance, Lanya et al. (2018) conducted a manual delineation survey of agrotourism potential in Bali, focusing on coconut and banana ecosystems. Their research identified specific sites, such as Subak Erjeruk and Sangen, where these crops could be developed for agrotourism. However, this approach required extensive fieldwork and manual mapping, limiting its applicability to small-scale areas. The time-intensive nature of manual delineation makes it impractical for regional-scale zoning and highlights the need for more efficient and scalable methodologies. Similarly, Wiranatha et al. (2024) utilized the analytic hierarchy process (AHP) method, involving 20 key informants to prioritize criteria for agrotourism development in Bali. Their findings emphasized the importance of attractions, local community involvement, and accessibility. While AHP provides a structured decision-making framework, it relies heavily on expert judgments and is constrained by the subjective biases of the respondents (Munier and Hontoria, 2021; Tavana et al., 2023). Additionally, this method is not data-driven and lacks the capacity to incorporate large-scale spatial variability or temporal changes in environmental conditions. Sardiana (2018) applied a participatory rural appraisal (PRA) approach to assess agrotourism potential in the Sanur Tourism area. The study involved extensive community engagement through interviews, focus group discussions, and field observations. While this approach effectively captured local perspectives and promoted community involvement, it was limited to a small area covering three villages. The reliance on qualitative methods and descriptive analysis restricted the scalability and generalizability of the findings to other regions or larger spatial extents.

These previous studies demonstrate the importance of agrotourism research but also reveal significant methodological weaknesses. Most notably, conventional approaches are time-intensive, limited in spatial scale, and often rely on subjective data collection methods. The lack of integration between spatial data and advanced analytical techniques limits the potential for precise and efficient agrotourism zoning. Furthermore, these methods are unsuitable for regional-scale implementations, as they require substantial time and resources to replicate across larger areas. Despite the progress made by these studies, there remains a critical gap in the integration of geospatial technologies and advanced machine learning techniques for agrotourism zoning. The existing methodologies lack the scalability, precision, and data-driven capabilities necessary for regional-scale implementation. To address these challenges, integrating remote sensing, geospatial data, and machine learning offers a promising alternative. Remote sensing provides large-scale, up-to-date environmental data, while geospatial analysis allows for the spatial integration of diverse variables. When combined with machine learning, these tools enable the identification of complex patterns and relationships that traditional methods cannot capture.

Among machine learning algorithms, the random forest (RF) algorithm has gained recognition for its robustness in handling complex, nonlinear datasets (Wang et al., 2021; Zhang et al., 2020). RF is particularly effective in applications requiring variable importance analysis, such as identifying key drivers of land-use suitability (Pimenta et al., 2021; Singh et al., 2022; Tikuye et al., 2023). Its ability to process diverse environmental and anthropogenic variables makes it suitable for agrotourism zoning, which requires a nuanced understanding of natural resources and human influence. RF's additional advantages include its resilience to overfitting, capacity to handle missing data, and interpretability compared to other algorithms such as neural networks or gradient boosting methods (Islam et al., 2023; Jun, 2021). Globally, RF has been widely used in environmental modeling and land-use planning, producing high levels of validity and reliability, making it the preferred choice for this research (Amini et al., 2022; Brokamp et al., 2017; Fox et al., 2017).

This study builds on the limitations of previous research by leveraging the integration of remote sensing, geospatial data, and machine learning to develop a scalable, data-driven zoning framework for agrotourism. By incorporating diverse variables such as vegetation indices (NDVI, LSWI), elevation, slope, temperature, rainfall, proximity to tourist attractions, road networks, and tourism facilities, the study overcomes the limitations of traditional methodologies. The use of RF ensures high accuracy and interpretability while enabling regional-scale analysis that is both efficient and precise.

This research seeks to address the gaps identified in previous studies by developing a geospatial and data-driven zoning framework for agrotourism in Gianyar Regency, Bali. Unlike prior studies that employed GIS-based methods in isolation, this research contributes to the field by integrating geospatial and machine learning techniques to generate a reproducible zoning framework. The study also evaluates the relative importance of influencing factors, providing actionable insights for policymakers and stakeholders in land-use planning. By focusing on the interaction of environmental and anthropogenic variables, this research provides a comprehensive approach to agrotourism zoning. It fills critical gaps in the literature by demonstrating the applicability of RF in the context of agrotourism, a domain that has historically lacked methodological innovation. The study's findings offer a replicable model for optimizing land use while fostering sustainable tourism development in similar regions.

METHODE

Research case study

Gianyar Regency, geographically located between 8°19'12" – 8°38'24" South Latitude and 115°12'00" – 115°21'35" East Longitude (Figure 1), is one of nine regencies/cities in Bali Province. It spans an area of 36.800 hectares, accounting for 6.53% of Bali's total land area. The regency consists of seven districts, with Payangan District being the largest, covering 75.88 km² or 20.62% of the total area. This is followed by Tegallalang District (61.80 km², 16.79%), Sukawati District (55.02 km², 14.95%), Gianyar District (50.59 km², 13.75%), Tampaksiring District (42.63 km², 11.58%), and Ubud District (42.38 km², 11.52%), while Blahbatuh District is the smallest, with an area of 39.70 km² (10.79%).

The regency extends from the northern highlands to the southern coastal plains along the

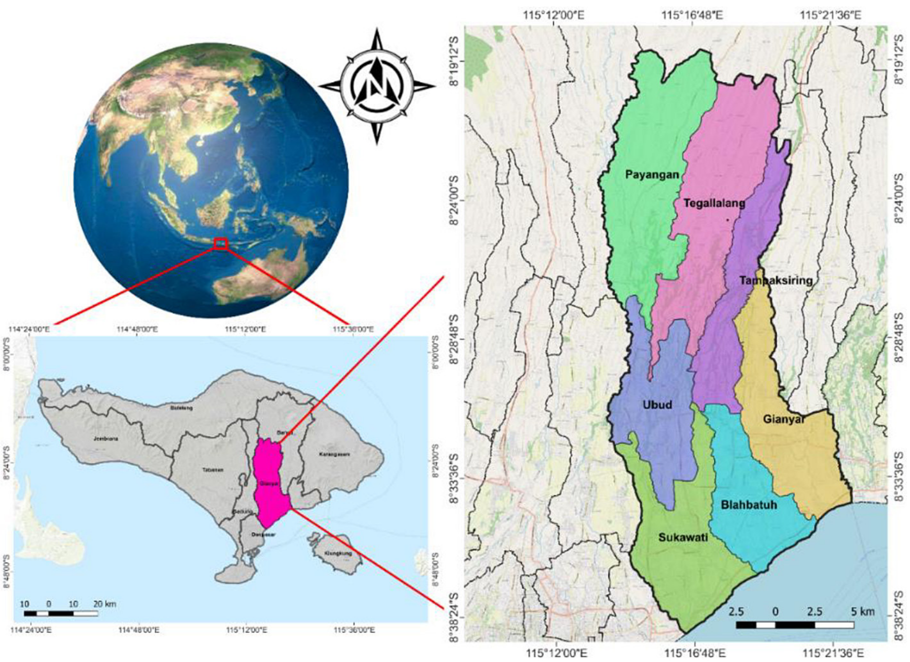

Figure 1. Research site

Indonesian Ocean. The northern part features undulating terrain, with elevations reaching up to 750 meters above sea level, covering 2,463.5 hectares. The southern region comprises flat lowlands, including approximately 20 kilometers of black sand beaches. Despite its geographic diversity, Gianyar lacks significant natural lakes or mountains, distinguishing it from other regions in Bali.

Based on the Systematic Geological Map of Indonesia, Bali Sheet (Purbo-Hadiwidjojo, 1971), Gianyar Regency shares a uniform geological structure across its territory. The region is dominated by young volcanic rocks from the Buyan-Beratan and Batur volcanic groups, formed during the Quaternary period. These formations primarily consist of volcanic breccia, sandy tuff, and laharic deposits. This geological composition is not exclusive to Gianyar but extends to other parts of Bali, including Tabanan, Badung, Klungkung, and Denpasar City.

The regency's soils are predominantly regosol, formed from marine deposits and intermediate volcanic ash. This soil type is widespread across eastern Bali, covering Gianyar, Klungkung, Bangli, eastern Buleleng, and Karangasem. Although regosol soils are relatively low in fertility, they support diverse agricultural practices when managed effectively. This unique combination of volcanic geology and regosol soils creates a foundation for agricultural activities, making Gianyar an ideal candidate for agrotourism development.

Data collection and processing

This study utilizes geospatial data encompassing various variables relevant to the zonation of potential agrotourism areas in Bali. These variables are grouped into two main categories to ensure a comprehensive analysis:

The first category, anthropogenic variables, includes distance from tourist attractions, proximity to tourism facilities (such as hotels and restaurants), and distance from major roads. These variables are essential for evaluating the influence of human activities on agrotourism potential in specific locations. The second category, environmental variables, comprises distance from rivers, elevation, slope, land surface temperature, rainfall, and land use. Vegetation density, measured using NDVI (normalized difference vegetation index) and LSWI (land surface water index), is derived from remote sensing data, allowing for an accurate assessment of environmental conditions relevant to agrotourism.

The data processing phase involved compiling and analyzing these variables on the Google Earth Engine platform, resulting in a well-structured dataset ready for modeling. The final dataset consists of 410 data points, of which 111 represent existing agrotourism locations, while 299 are non-agrotourism sites.

Dataset partitioning for model training and validation

To ensure the model is adequately trained and evaluated, the dataset is divided into training and validation sets with a 70:30 ratio. Specifically, 288 data points were assigned to the training set to construct the Random Forest model, while 122 data points were set aside for validation purposes. This randomized split is crucial to reduce potential bias and provide an accurate assessment of the model's performance on unseen data.

Implementation of the random forest algorithm

Random forest, a powerful ensemble learning algorithm, comprises numerous decision trees, each trained on a unique subset of data and features. This ensemble approach enhances predictive accuracy and reduces the risk of overfitting (Biau and Scornet, 2016; Breiman, 2001; Genuer et al., 2010). The process of implementing the random forest algorithm is outlined as follows:

The first step involves determining the optimal hyperparameters, particularly the number of trees ($n_{estimators}$) and the maximum tree depth (max_depth). These parameters are fine-tuned through cross-validation to ensure that the model's performance is optimized. The choice of hyperparameters is crucial, as they directly impact the model's accuracy and ability to generalize to new data (Biau and Scornet, 2016; Cutler et al., 2007).

Each decision tree T_i in the forest is trained on a bootstrap sample, a randomly selected subset of the original data, with randomly chosen features at each split. The trees are constructed by minimizing a specified impurity criterion, such as Gini impurity or entropy. These criteria are essential for determining the best split at each node of the tree (Mustafa et al., 2024). The formula for Gini impurity, which quantifies the node's inconsistency, is as follows:

$$Gini = 1 - \sum_{i=1}^{c} p_i^2 \quad (1)$$

where: p_i represents the proportion of class iii in the node, and ccc is the number of classes. Alternatively, entropy, a measure of uncertainty in the data at a node, is calculated as:

$$Entropy = 1 - \sum_{i=1}^{c} p \log 2\, pi \quad (2)$$

In the final classification and prediction stage, each tree in the forest provides a classification outcome based on the majority vote mechanism, whereby the class predicted by the majority of trees becomes the final prediction for each data point. This ensemble-based voting mechanism reduces the variance observed in individual trees, leading to a more robust and accurate overall model. The model outputs predictions for agrotourism suitability across different locations, enabling the identification of potential agrotourism zones based on the environmental and anthropogenic variables defined earlier.

Model validation

To evaluate the random forest model's classification performance, this study employs the confusion matrix (Figure 2), a widely used tool that enables detailed analysis of prediction accuracy across different classification categories (Heydarian et al., 2022; Valero-Carreras et al., 2023). The matrix evaluates model outcomes in four main categories:

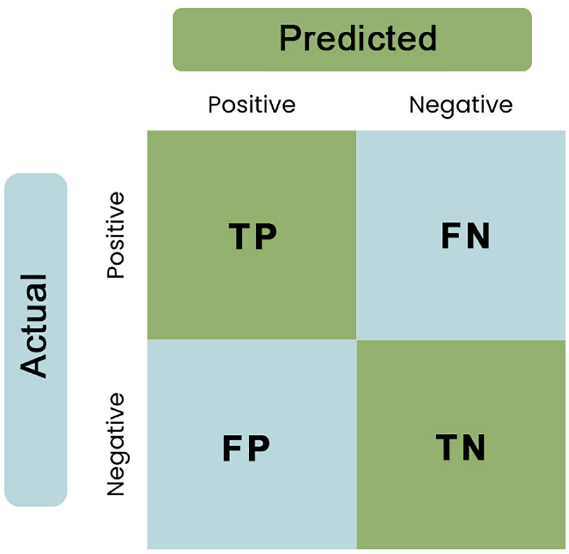

Figure 2. Validation concept using a confusion matrix

1. True positive (TP): The model correctly identifies agrotourism locations.
2. False positive (FP): The model incorrectly classifies non-agrotourism locations as agrotourism.
3. True negative (TN): The model correctly identifies non-agrotourism locations.
4. False negative (FN): The model incorrectly classifies agrotourism locations as non-agrotourism.

Using these four categories, several performance metrics are calculated to provide a comprehensive assessment of the model:

- Accuracy, defined as the proportion of correctly classified instances (both true positives and true negatives) out of the total predictions, is calculated as follows:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

- Precision measures the proportion of predicted agrotourism locations that are correctly classified and is formulated as:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

- Recall, or sensitivity, quantifies the model's ability to correctly identify agrotourism locations and is represented by:

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

- F1 Score combines precision and recall into a single metric by calculating their harmonic mean, capturing a balance between these two important metrics:

$$\text{F1}\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

These metrics collectively offer insights into the model's ability to accurately predict agrotourism zones, while the confusion matrix provides a detailed breakdown of the model's classification efficacy. Such validation is essential to ensure the model's reliability before applying it to real-world zoning decisions, particularly in areas with substantial potential for sustainable agrotourism.

Through the combination of random forest's ensemble approach and the detailed evaluation afforded by the confusion matrix, this methodology provides a rigorous and data-driven basis for identifying suitable agrotourism zones. The model leverages advanced geospatial analysis and machine learning techniques to fill existing research gaps, offering significant insights into sustainable land use planning in the context of tourism development in Bali.

RESULTS AND DISCUSSION

This study aims to develop new agrotourism zoning in Gianyar Regency, Bali Province, using a geospatial data-driven approach that integrates anthropogenic and environmental variables. By employing the random forest algorithm, this research identifies areas with high potential for agrotourism based on spatial and environmental characteristics. The analysis includes ten primary variables: three antropoghenic variables (proximity to tourist attractions, tourism facilities, and accessibility) and seven environmental variables (proximity to rivers, NDVI, LSWI, elevation, slope gradient, land surface temperature, and rainfall). The findings not only provide guidance for data-based decision-making but also support the formulation of strategic policies for sustainable and inclusive agrotourism development.

Anthropogenic variables

Socioeconomic variables play a crucial role in agrotourism zoning as they directly influence tourist appeal, the availability of supporting facilities, and accessibility. These three variables act as key indicators to understand how socioeconomic dynamics in Gianyar Regency impact agrotourism development.

Proximity to tourist attractions

Proximity to major tourist attractions is an essential indicator for determining agrotourism potential. Tourist attractions near agrotourism zones can increase their appeal and visitor flow, making agrotourism a complementary and diversified tourism product. Data indicate that Gianyar and Blahbatuh subdistricts have relatively short average distances to key tourist attractions, at 1,217.11 meters and 1,153.46 meters, respectively (Figure 3a). This proximity allows tourists to conveniently integrate agrotourism into their itineraries.

This aligns with findings by Susila et al. (2024), which emphasize that agrotourism sites located near major attractions enhance the competitiveness of the area while adding value to the destination. Moreover, this closeness

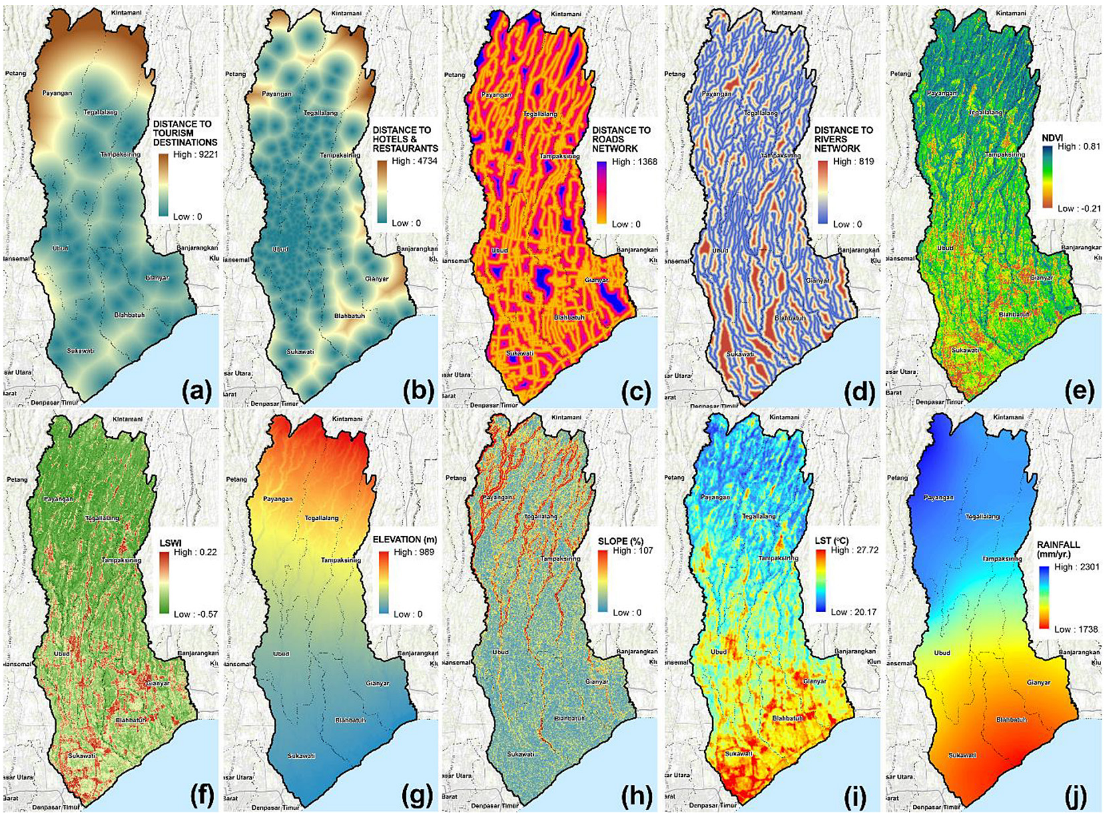

Figure 3. Research variables include distance from tourist destinations (a), distance to hotel and restaurant facilities (b), distance to road accessibility (c), land cover represented by NDVI (e) and LSWI (f), elevation (g), slope gradient (h), LST (i), and rainfall (j).

promotes local economic activities, such as traditional markets, local restaurants, and artisanal products, which can serve as additional attractions for visitors. Integrated tourism experiences in these areas present significant opportunities to diversify income sources for the local community.

Proximity to tourism facilities (hotels and restaurants)

The presence of tourism-supporting facilities such as hotels and restaurants significantly determines the feasibility of an area for agrotourism development. Ubud, with an average distance of just 258.31 meters from such facilities (Figure 3b), stands out as one of the most accessible areas in terms of tourism infrastructure. This proximity facilitates convenient access for tourists seeking unique agrotourism experiences, such as fruit picking, farming, or learning about sustainable agricultural practices. Research by Zhang et al. (2020) highlights that adequate supporting facilities can prolong tourist stays, subsequently increasing their spending in the area. This means that areas like Ubud not only attract tourists but also contribute significantly to the local economy through extended visits and increased spending.

Proximity to road networks

Road accessibility is a critical variable in agrotourism development as it impacts tourist mobility and the efficient distribution of agricultural products. Areas such as Ubud and Blahbatuh demonstrate exceptional proximity to major road networks, with average distances of 152.40 meters and 152.56 meters, respectively (Figure 3c). This ease of access enhances the attractiveness of these areas for tourists and facilitates logistical efficiency in agricultural product distribution.

Previous researchers noted that good accessibility contributes to increased tourist visits, particularly in rural tourism contexts. Furthermore, well-connected roads support the transportation of agricultural products from agrotourism zones to local and international markets, which is vital for the economic sustainability of these areas (Chi et al., 2020; Tomej and Liburd, 2020).

Environmental variables

Environmental factors are equally important in determining land suitability for agrotourism. These variables reflect the environmental characteristics that support agricultural activities while adding aesthetic value to the tourism experience.

Proximity to rivers

Proximity to rivers is an essential indicator for sustainable agriculture, as rivers serve as water sources for irrigation and natural attractions. Tegallalang and Payangan subdistricts have average distances of 117.50 meters and 129.42 meters from major river networks (Figure 3d). Rivers not only enhance land productivity but also provide opportunities for eco-tourism activities, such as scenic river views or water-based activities like rafting. Ferreira and Sánchez-Martín (2022) observed that agrotourism zones integrating natural elements such as rivers tend to have higher tourist appeal due to their authentic and nature-based experiences.

Vegetation density (NDVI)

The NDVI is a key indicator for assessing vegetation health and land fertility (Serrano-Grijalva et al., 2024). Tegallalang and Payangan subdistricts recorded NDVI values of 0.66 and 0.67, respectively (Figure 3e), indicating healthy and fertile vegetation. These areas are well-suited for developing organic agriculture or cultivating high-value crops such as coffee, tea, or exotic fruits. Dense vegetation not only enhances land productivity but also provides aesthetic value critical for agriculture-based tourism. Saroinsong (2020) emphasized that fertile vegetation significantly enhances the tourism experience while supporting environmental sustainability.

Land surface water index (LSWI)

Soil moisture, measured by the LSWI, is a critical factor in determining crop suitability (Xiang et al., 2020). Areas like Sukawati recorded a low average LSWI of -0.22 (Figure 3f), indicating low soil moisture levels. However, such areas still hold potential if modern irrigation systems, such as drip irrigation, are implemented to enhance water efficiency without compromising land productivity.

Elevation

Elevation is a major environmental factor influencing the microclimate of an area, which in turn determines the types of crops that can be cultivated (Getachew et al., 2022) and the appeal of the agrotourism zone. Payangan, with an average elevation of 596.42 meters above sea level (Figure 3g), offers a cool climate suitable for cultivating high-value horticultural crops such as tea, coffee, and upland vegetables. These conditions are ideal for market-oriented agriculture integrated with agrotourism. Elevation also provides aesthetic advantages, allowing tourists to enjoy expansive views of green rice terraces and plantations, creating unique and memorable visual experiences. Additionally, elevated areas like Payangan hold potential for educational tourism, where visitors can learn sustainable agricultural practices tailored to highland environments. Yudhari et al. (2020) confirmed that elevations 900–1000 meters offer significant microclimatic benefits for horticultural and coffee plantations, further enhancing the area's attractiveness for agrotourism.

Slope gradient

The slope gradient in Payangan, averaging 18.56% (Figure 3h), presents both challenges and opportunities for agrotourism development. While steep slopes may pose accessibility challenges, they also create unique visual appeal through iconic terraced landscapes. These terraces, traditionally used for soil conservation, not only prevent erosion but also add aesthetic value reflective of local wisdom in land management.

Moderate to steep slopes are also ideal for adventure tourism activities such as trekking, hiking, or landscape photography. In agriculture, such slopes are optimal for cultivating coffee, cocoa, or horticultural crops like strawberries, which thrive in well-drained soils commonly found on slopes. The slopes between 15–25% in highland areas are particularly suitable for eco-friendly coffee plantation development, especially when combined with agroforestry systems. Thus, the integration of modern agricultural practices and the visual appeal of terraced landscapes holds significant potential to attract tourists.

Land surface temperature

Land surface temperature is a critical factor that directly affects crop types and visitor comfort in agrotourism zones. Payangan, with an average temperature of 22.21 °C (Figure 3i), offers a cooler climate compared to other areas in Gianyar Regency. This provides an advantage for cultivating horticultural crops such as broccoli, cabbage, and carrots, as well as economically valuable plantation crops like tea and Arabica coffee.

Cool temperatures also create a comfortable environment for tourists engaging in agricultural activities or eco-tourism experiences. Visitors can enjoy farming activities while experiencing the refreshing coolness of highland areas, making it an attractive alternative to hotter tropical regions.

Rainfall

Rainfall is one of the most critical environmental factors supporting agricultural sustainability, particularly in regions integrating agriculture with tourism. Payangan, with an annual average rainfall of 2,219.30 mm (Figure 3j), benefits from abundant natural water resources. This rainfall supports wetland-based agriculture, such as irrigated rice fields requiring consistent water supplies throughout the year. Traditional irrigation systems like Bali's Subak are fully utilized to maintain land productivity and agricultural sustainability. Iconic terraced rice fields serve not only as food production systems but also as major tourist attractions where visitors can learn traditional irrigation methods and participate in farming activities.

High rainfall levels also sustain natural vegetation (Abel et al., 2021), adding ecological value to agrotourism zones. The availability of ample water enables the cultivation of water-demanding crops such as rice and horticultural plants in optimal conditions. (Erythrina et al. (2021) noted that regions receiving over 2.000 mm of annual rainfall exhibit better agricultural sustainability, particularly for paddy and horticultural crops. Additionally, abundant rainfall supports the preservation of water-based attractions such as waterfalls and small streams, enhancing their appeal as complementary tourist experiences. Thus, with its favorable rainfall and agricultural productivity, Payangan holds significant potential as an integrated agrotourism zone combining ecological sustainability and land productivity.

Model validation

The random forest model was validated to assess its accuracy in mapping potential agrotourism areas in Gianyar Regency using five key performance metrics: precision, recall, F1 score, specificity, and false positive rate (FPR) (Table 1). The model demonstrated strong performance, achieving an accuracy of 84% and a precision of 86%, ensuring accurate zoning with minimal false positives (Table 2). High precision is crucial in agrotourism planning to prevent resource misallocation. The model's overall performance, with metrics exceeding 80%, aligns with previous studies, confirming its reliability for decision-making (Bao Pham et al., 2024; Sahani and Ghosh, 2021). However, the recall rate of 72% indicates that 28% of potential areas were not detected. Enhancing recall through parameter optimization and diversified training data could reduce false negatives and improve comprehensiveness.

The F1 score of 78% indicates a well-balanced model in terms of precision and recall, supporting its effectiveness in zoning applications. The model achieved a specificity of 92%, effectively excluding unsuitable areas and improving resource allocation efficiency. Furthermore, a low FPR of 8% underscores the model's reliability in avoiding misclassification, which is critical for sustainable land management. Despite the model's high precision and specificity, further enhancements in recall are recommended to ensure broader coverage of potential agrotourism areas.

Table 1. Confusion matrix for model validation

Matrix	Predicted positive	Predicted negative
Actual positive	36	14
Actual negative	6	66

Table 2. Model validation results

Validation	Value
Accurasy	0.84
Precision	0.86
Recall	0.72
F1 score	0.78
Spesificity	0.92
FPR	0.08

Variable importance

The analysis identified key variables influencing agrotourism zoning, with NDVI (13.13%) and LSWI (13.11%) emerging as the most influential factors (Figure 4). NDVI serves as an indicator of vegetation health and soil fertility, essential for agricultural productivity and enhancing visual appeal in agrotourism destinations. LSWI, reflecting soil moisture conditions, plays a pivotal role in agricultural sustainability, with lower values indicating areas requiring irrigation enhancements.

Additionally, land surface temperature (11.64%) and proximity to tourist attractions (11.52%) were significant contributors, highlighting the importance of microclimatic conditions and accessibility in attracting tourists and supporting agrotourism development. Conversely, tourism facilities (7.50%) and proximity to rivers (7.20%) were the least influential variables, indicating their relatively minor impact compared

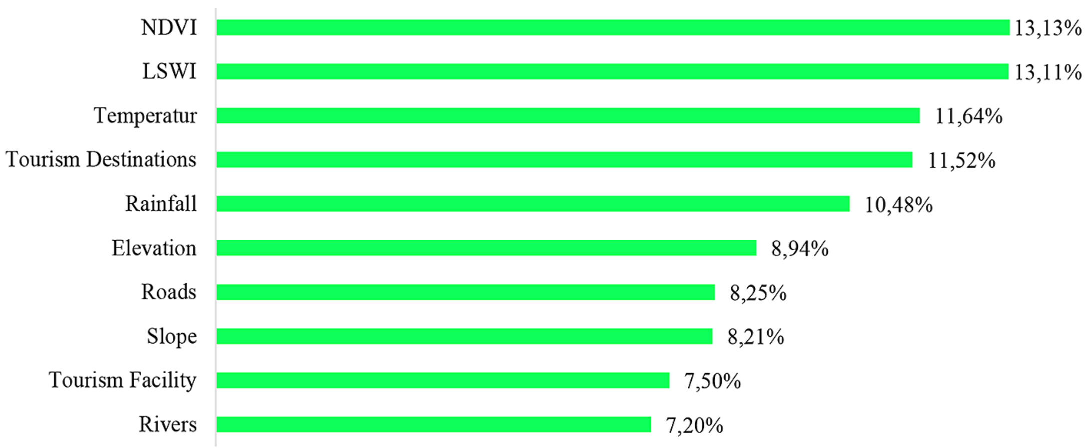

Figure 4. Important variables based on the random forest algorithm

to environmental and accessibility factors. These findings provide valuable insights for optimizing agrotourism zoning by prioritizing key determinants and ensuring a balanced approach to sustainable land use and tourism planning.

Agrotourism zoning potential in Gianyar Regency

The agrotourism zoning map of Gianyar Regency classifies land into five potential levels: very low, low, moderate, high, and very high. The study indicates that 36.25% of the area is classified as very low potential, whereas 45.46% falls under moderate to very high potential, presenting significant development opportunities (Figure 5). The distribution of agrotourism potential across subdistricts is illustrated in Figure 6, while the spatial distribution map, optimized using the random forest algorithm, is presented in Figure 7. Tegallalang and Payangan subdistricts demonstrate the highest potential for agrotourism development. Tegallalang is renowned for its rice terraces and the Subak irrigation system, a UNESCO World Heritage Site that integrates agricultural productivity with cultural heritage (Pujianiki et al., 2023). In contrast, Suamba et al. (2020; 2023) emphasized the need for improved infrastructure and diversified tourism activities to maximize Tegallalang's agrotourism potential and ensure sustainable development. Payangan's highland climate is conducive to coffee and horticultural farming, offering opportunities for educational and experiential agrotourism activities. Blahbatuh, predominantly categorized under very low potential (7.89%), faces significant challenges; however, targeted interventions such as modern agricultural techniques and infrastructure upgrades could enhance its attractiveness for agrotourism development.

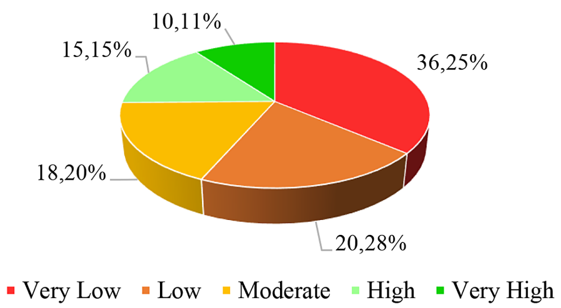

Figure 5. Percentage diagram of agrotourism zone areas

Village-level agrotourism potential

At the village level, areas with more than 40% of their land classified as high or very high potential are considered prime candidates for agrotourism development (Figure 8). Villages such as Tegallalang and Tampaksiring leverage their fertile land and proximity to tourist attractions to enhance their appeal. Conversely, villages with lower potential require strategic improvements in infrastructure and tourism amenities to unlock their potential. Key recommendations for sustainable agrotourism development include optimizing productive agricultural land, enhancing infrastructure, diversifying tourism experiences, and fostering community engagement. By adopting a data-driven approach, Gianyar Regency can

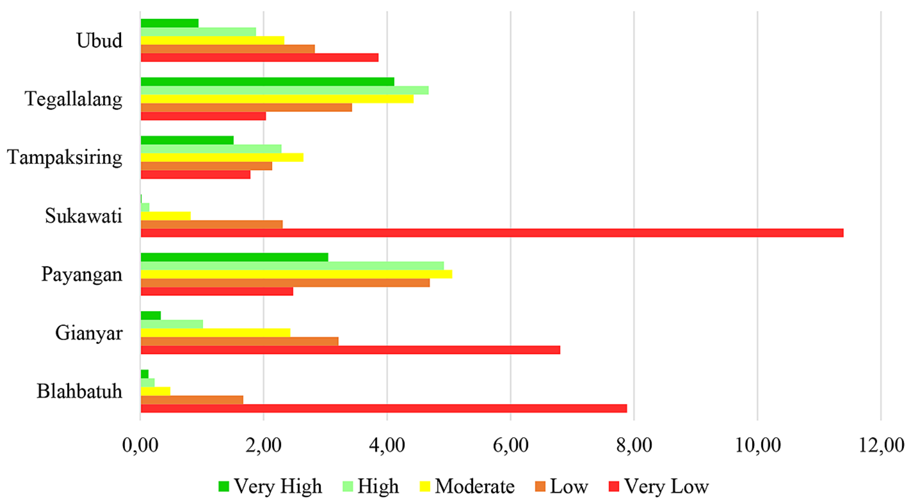

Figure 6. Graph of percentage of potential agrotourism development area by district

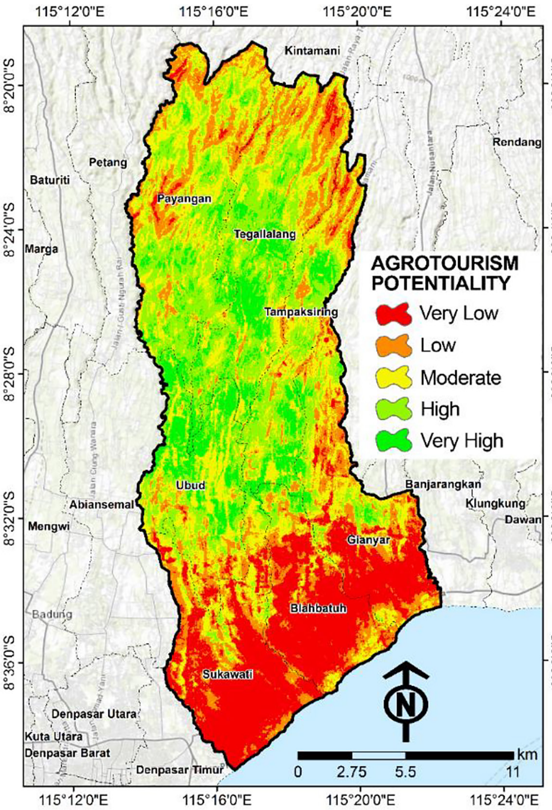

Figure 7. Zoning map of agrotourism potential in Gianyar Regency, Bali

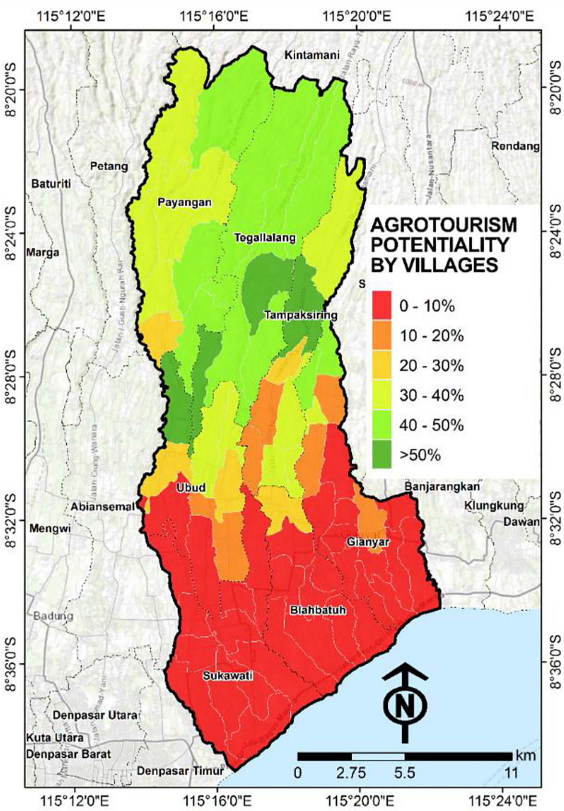

Figure 8. Village-based agrotourism development opportunity map

effectively balance economic growth with environmental conservation, positioning itself as a leading agrotourism destination.

This study presents a novel approach to mapping agrotourism potential in Bali Province by utilizing geospatial data and remote sensing through the machine learning algorithm, Random Forest. This innovative methodology offers significant novelty, particularly as research on agrotourism in this region remains limited. Previous studies in Bali have primarily relied on conventional methods, such as field surveys and interviews, making this study a significant advancement in terms of accuracy and analytical depth. Although geospatial data has been extensively used in Bali for examining agriculture, environmental conditions, and disaster management (Soniari et al., 2024; Trigunasih and Saifulloh, 2022; Trigunasih et al., 2023; Susila, et al., 2024) its application in the context of agrotourism is still underexplored. Bali, renowned as a world-class tourist destination, offers unique opportunities to integrate agrotourism into its cultural and environmental framework. Agrotourism development in this region not only provides alternative attractions for tourists but also serves as a vital effort to conserve and sustain Subak, a UNESCO-recognized cultural heritage (Bhayunagiri and Saifulloh, 2022; Susila et al., 2024). By emphasizing environmentally sustainable and conservation-oriented principles, agrotourism holds the potential to mitigate large-scale land conversion, especially in coastal areas (Bhayunagiri and Saifulloh, 2023; Diara et al., 2024).

Bali's coastal tourist destinations have experienced significant expansion in built-up land (Sunarta and Saifulloh, 2022a), resulting in several environmental issues, such as reduced urban carbon reserves (Sudarma et al., 2024), increased greenhouse gas emissions (Sunarta and Saifulloh, 2022b), and challenges related to flooding and declining urban water infiltration (Trigunasih and Saifulloh, 2022). Consequently, the development of agrotourism in upstream areas, such as Tegallalang and Payangan subdistricts, represents a critical solution for both economic opportunities and environmental preservation. These regions are prone to soil erosion (Adnyana et al., 2024; Trigunasih and Saifulloh, 2023) and landslide hazards (Diara et al., 2022, 2023; Suyarto, Diara, et al., 2023)which receives a lot of heat from the sun and rainfall. Therefore, Indonesia is prone to hydro meteorological natural disasters such as droughts, large sea waves, erosion, floods and landslides. The National Disaster Management Agency (BNPB, highlighting the importance of conservation-based land management to prevent downstream flooding in river basins (Suyarto, et al., 2023).

The sustainable management of agricultural lands designated as agrotourism zones can be enhanced through Subak-based land zoning. This approach leverages the wisdom of Bali's local farmers to achieve efficient and long-term land use (Bhayunagiri and Saifulloh, 2022). Additional measures, such as implementing optimized cropping patterns and reducing the excessive use of chemical fertilizers, are critical to preventing soil degradation (Kartini et al., 2023, 2024). Soil fertility management through site-specific fertilization and precise dosing can further improve soil fertility status and overall agricultural land quality (Susila et al., 2024; Trigunasih et al., 2023b).The innovative geospatial and machine learning approach adopted in this study provides a significant contribution to the field of agrotourism, offering practical and scientifically sound solutions for sustainable land management in Bali. By integrating geospatial, ecological, and socio-economic aspects, the findings of this research support environmental conservation, enhance agricultural productivity, and create meaningful economic benefits for local communities.

CONCLUSSIONS

This study highlights the effectiveness of integrating spatial analysis and machine learning for agrotourism zoning in Gianyar Regency, Bali. The analysis of ten key environmental and anthropogenic variables identified NDVI and LSWI as the most critical factors influencing land suitability. Proximity to tourist attractions, road accessibility, and tourism facilities further contribute to agrotourism potential. The random forest model demonstrated strong validation results, with high precision and specificity, confirming its reliability in zoning applications.

Tegallalang and Payangan emerged as the most promising sub-districts for agrotourism, with Tegallalang's cultural heritage and agricultural productivity and Payangan's horticultural potential offering diverse tourism opportunities. Strategic development in priority villages such as Tampaksiring, Kedewatan, and Kedisan, with over 50% potential, can maximize economic benefits and sustainability.

The study underscores the importance of leveraging geospatial technology and machine learning to guide resource allocation and planning. However, it is essential to acknowledge that remote sensing data are inherently dynamic, particularly in tropical regions, where vegetation indices are closely related to climate fluctuations and rainfall variability. Future research should consider incorporating dynamic parameters to enhance model accuracy and further explore economic feasibility and tourist behavior trends to optimize agrotourism development strategies. Collaborative efforts among policymakers, private stakeholders, and local communities will be crucial in translating zoning insights into actionable, sustainable development strategies.

Acknowledgements

We extend our sincere gratitude to the reviewers for their valuable suggestions and constructive input, which have significantly contributed to the improvement of this article. We also wish to acknowledge the Research and Community Service Institute of Udayana University for their generous funding support, provided under contract number B/255.620/UN14.4.A/PT.01.03/2024, dated April 17, 2024.

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