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Evaluating Spatial-Plan Consistency Through Probabilistic Machine-Learning Land-Use/Land-Cover Suitability: Insights from Bogor Regency, Indonesia

Abstract: Sustainable development is contingent upon the efficient management of land resources for resolving spatial challenges such as land-use conflicts and fragmentation. A land-suitability model offers a potential instrument for assessing land-use/land-cover (LULC) consistency with spatial plans. This study employed a data-driven probabilistic approach using a support vector machine (SVM) algorithm and error-correcting output codes (ECOCs) for incorporating 11 physical parameters to generate spatial grids that reflected land-suitability levels. The probabilistic outputs were derived by calibrating SVM decision values using Platt scaling within the ECOC framework, enabling a reliable estimation of class-wise land-suitability probabilities. The model achieved the highest probability value of 0.9952, with an average of 0.8251; this demonstrated its potential for assessing the consistency of land use/land cover with spatial plans. The model exhibited robust performance and substantial agreement between the predictions and actual data, with an overall accuracy of 88.56% and a kappa index of 0.873. Additionally, the study utilized a land-suitability model and non-weighted overlay relevance matrix to identify discrepancies in Bogor Regency's spatial plan, quantifying the compliant and non-compliant land areas for each LULC class within specified spatial-plan zones. The evaluation revealed a significant misalignment, with 25–45% of agricultural land uses that included wetland and dryland agriculture, plantations, and inland fish farms being allocated within settlement zones; this indicated a mismatch between spatial plans and land suitability. These findings underscored the importance of evaluating and revising the spatial plan to enhance its alignment with land suitability.

Keywords: land suitability, probabilistic method, spatial plan, sustainable land-use planning

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1. Introduction

Evaluating spatial plans according to land-use/land-cover (LULC) distribution is a strategic method for obtaining an optimal LULC in regional planning. Spatial-planning evaluation is a multifaceted process that requires an approach that is capable of addressing key concerns and providing relevant information to policymakers about the impacts of spatial-planning instruments [1]. By aligning spatial plans with LULC suitability, optimal land use can be achieved in sustainable planning. Land suitability facilitates the identification of the most-suitable LULC for each location according to its distinctive features [2, 3]. This approach enables the identification of feasible spatial plans that effectively address land-use allocation and planning issues [4, 5]. Such evaluations can assist in mitigating issues that include the agricultural land fragmentation and urban sprawl that is caused by uncontrolled expansion [6, 7]. Land-fragmentation and land-use conflicts underscore the importance of land-use planning as an essential component of sustainable development [8, 9]. In this context, land-suitability analysis is crucial for identifying suitable locations for different land-use classes, ensuring that land-allocation decisions align with an area's specific characteristics (thereby promoting sustainable land-use planning) [10].

Spatial-planning evaluation encompasses beyond the design and implementation stages and incorporates governance-related factors [11]. Evaluation methods are essential for analyzing land-suitability and spatial-extent availability as potential and constraints of land for specific uses [12]. A spatial-planning evaluation distinguishes two main perspectives: conformance, and performance. The conformance perspective assesses how well planning objectives align with actual outcomes. This approach utilizes quantitative methods, such as field surveys and spatial analysis; however, it has drawbacks, including a lack of ability for explaining gaps between objectives and results (since spatial plans are treated mainly as benchmarks). Conversely, the performance perspective emphasizes the significance of spatial plans in decision-making processes, acknowledging that plans are not rigid blueprints but rather subject to interpretation and adjustment. In Indonesian spatial-planning practice, for instance, local governments may reallocate designated agricultural zones into settlements due to population-growth pressures (as can be seen in peri-urban areas such as IKN Nusantara, the north coast of West Java, and Jakarta) [13–15]. Similarly, previous studies have also demonstrated that protected zones in Sulawesi were modified based on field negotiations despite existing zoning regulations [16]. These two perspectives reinforce one another [17].

Several studies have evaluated spatial planning through land suitability using various approaches, including the developments of suitability indices and scoring for spatial planning [18]. However, the suitability indices that have been presented in previous studies have often been limited in applicability and were specific to the study areas despite utilizing comprehensive evaluation frameworks that were not always practical for broader applications [19]. Land-suitability assessments that utilized remote sensing and spatial analysis with physical parameters have been employed to evaluate existing settlements for their potential use in development planning [16]. While this study successfully identified and assessed land suitability, its scope was restricted to settlement areas; the evaluation process remained predominantly qualitative. However, many rely on index-based or scoring techniques that are often subjective and limited to qualitative interpretation [10, 19].

To overcome such limitations, this study adopts a probabilistic machine-learning approach using a support vector machine (SVM) algorithm and error-correcting output codes (ECOCs) to classify land suitability based on 11 physical parameters. This data-driven method allows for the derivation of suitability as probability values, thus providing quantitative confidence levels for each LULC class. Unlike prior studies that have relied on heuristic weights or local scoring, our approach improves the objectivity, enhances the model generalizability, and enables a fine-resolution spatial analysis using grid-based modeling. Furthermore, this study integrates the suitability output with a relevance matrix to identify spatial mismatches, offering a novel and data-driven framework for evaluating spatial-plan alignment more systematically.

Recent developments have highlighted the strengths of probabilistic and data-driven approaches in spatial-planning and land-use evaluation. Techniques such as ensemble classifiers, Bayesian inference, and probabilistic optimization have proven to be effective in quantifying uncertainty and generating confidence-weighted suitability maps – particularly in dynamic and complex landscapes [20]. Probabilistic frameworks have been used to detect land-cover changes [21], optimize land use under planning constraints [20], and enhance land-cover classifications using Sentinel-2 imagery [22]. Additionally, the robustness of probabilistic SVMs in handling complex terrains have been highlighted for improving LULC-mapping accuracy [23].

Support vector machines (SVMs) have particularly demonstrated strong performance due to their capacities to manage multi-dimensional inputs and nonlinear class boundaries. Their applications have included crop mapping in Iran using fused Sentinel-1 and -2 data (92% accuracy, kappa – 0.86) [24] and spatial allocation in Java using ECOC-SVM with ecological footprint analysis (86.46% accuracy, kappa – 0.812) [25]. Optimization techniques such as firefly algorithm optimization have boosted accuracy in soybean-suitability classification [26]. Comparative studies have confirmed SVMs' robustness across various agricultural contexts, where they have performed competitively against ensemble methods like gradient boosting [27, 28]. These findings have supported the use of SVM-ECOC frameworks for producing accurate data-driven assessments for spatial planning.

Land-suitability assessment is essential for ensuring that land use aligns with physical characteristics and land potential [17, 18]. Numerous studies have emphasized the importance of using measurable parameters such as slope, soil, and climate to produce accurate and systematic evaluations [29–31]. Methods like MCDA and AHP have been applied to prioritize criteria based on expert judgments, with data being normalized to standardized scales for consistent analysis [25, 31, 32]. These approaches have helped to address spatial complexity and support effective land allocation in planning. Building on these foundations, [25] employed FAO-based land characteristics, applying min-max normalization within a 0–1 range and distributing values spatially using the maximum combined area (MCA) method. Similarly, Nyeko [32] emphasized the role of physical indicators in defining land capacity through a GIS-integrated MCDA framework that combined empirical data with expert assessments. Collectively, these studies have demonstrated that integrating standardized physical parameters with spatial and decision-support tools is fundamental for robust and context-sensitive land-suitability evaluations.

Numerous studies have employed deterministic and probabilistic approaches in land-suitability analyses. While deterministic approaches often overlook uncertainties in decision-making, the probabilistic approach provides more-comprehensive information about the accuracy and confidence level of analysis results [33]. This approach has demonstrated effectiveness in enhancing the accuracy and reliability of the assessments by determining suitable agricultural land [23] and peatland [24] as well as identifying spatial allocations and potential land uses at sub-national levels [20, 25]. Furthermore, data-driven and probabilistic approaches such as machine learning and supervised learning could enable the use of empirical data to train land-suitability-prediction models [26].

The data-driven probabilistic land-suitability approach mitigates the subjectivity that is associated with deterministic methods that involve subjective weighting and scoring by utilizing data patterns and probabilities that are obtained from machine learning. Furthermore, the use of the non-weighted overlay relevance matrix method reduces uncertainties in evaluation outcomes by providing a more objective framework for decision-making in spatial planning. The use of non-weighted overlay methods for evaluating spatial-plan and land-use alignment has been explored in previous studies. For instance, a similar approach was applied to assess land suitability within spatial-planning regulations in Sulawesi, Indonesia, by intersecting zoning layers with suitability assessments [16]. A subsequent study integrated suitability analysis and spatial constraints using non-weighted overlays to evaluate land-allocation effectiveness on Java Island [25]. These studies have highlighted the utility of rule-based overlays in identifying spatial mismatches even though they often lack probabilistic confidence measures; these are addressed in the present study through their integration with machine-learning outputs. This approach is valuable for evaluating spatial planning from a conformance perspective, as it facilitates the identification of discrepancies between existing spatial plans and land suitability. The objective of this research is to evaluate the alignment of spatial plans with land-suitability models, thus ensuring that any spatial planning aligns with the land's potential and characteristics; this promotes more-informed and sustainable decision-making.

2. Material and Methods

2.1. Study Area

The study area that was selected in this research was Bogor Regency in West Java Province, Indonesia (Fig. 1).

Fig. 1. Map of study area

The selection of this location was based on several essential variables that were related to sustainable spatial planning, including the regional potential, economic development rate, and population growth. The region's potential incorporates agriculture, industry, and smart-city development – all of which contribute to sustainable development and growth. Bogor Regency is endowed with significant natural resources, providing a strong foundation for the advancement of its agricultural sector. According to recent statistical data, agriculture ranks among the top-five economic contributors – accounting for 5.19% of the region's gross regional domestic product (GRDP) [34]. On the other hand, the industrial sector demonstrates a dominant role, contributing 52.41% to the GRDP in 2023; this indicated its substantial potential to enhance regional revenue.

Additionally, the region has demonstrated a proactive commitment to developing a smart city; this was reflected in the enactment of Regent Regulation No. 77 of 2020, which established the Smart City Masterplan of Bogor Regency. This initiative is strategically aligned with the regional spatial-planning framework, thereby ensuring that the integration of digital innovation and spatial governance becomes a cornerstone in promoting sustainable and technologically adaptive regional development [35].

This potential must be optimized through effective and balanced land use in sustainable spatial planning to serve diverse sectors [8, 36]. Implementing sustainable spatial planning in Bogor Regency may enhance land-use management for diverse requirements (including agricultural, housing, and industry) while ensuring a balance between development and environmental conservation.

2.2. Data and Methodology

The spatial unit that was used to represent the LULC location was a 5-arcsecond (≈154.15 m × 154.15 m at the equator) resolution grid that contained values for 11 parameters alongside the LULC class label. The LULC data was the main parameter and label of this research. This LULC data was reclassified into ten classes: forest, wetland agriculture, dryland agriculture, plantation, settlement, public facilities, pasture, inland fish farm, transportation, and protected area (Fig. 2).

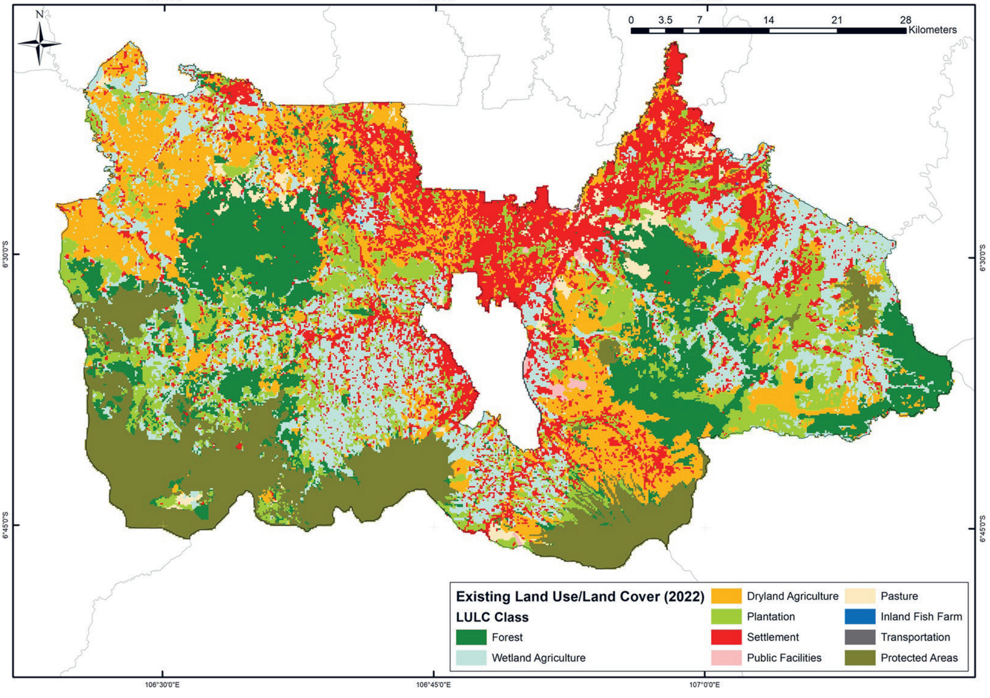

Fig. 2. LULC of Bogor Regency (2022)

The physical characteristics of the land were employed as parameters to determine the land-suitability-probability values through machine learning. This study identified and selected 11 physical parameters following a rigorous evaluation using Spearman correlation and multicollinearity tests; this was refined from an original set of 12 parameters. The values of the 11 parameters were normalized and then incorporated into the grid using the maximum combined area (MCA) method.

For spatial consistency, the analysis used a standardized 5-arcsecond (5″ × 5″) grid (≈154.15 m at the equator) as the common spatial unit. All of the data sets – ranging from climate, topography, soil, vegetation, hydrology, and land cover – were first reprojected to a common coordinate reference system (WGS 1984 UTM Zone 48S). Following this, each data set was resampled as needed to match the grid resolution. The maximum combined area (MCA) method was applied to ensure that each grid cell contained a single representative value [25]. For both the categorical and continuous data, the value that was assigned to a grid cell corresponded to the value that occupied the largest proportion of the area within that cell. In other words, the most spatially dominant value was selected based on the pixel-level distribution inside the 5″ × 5″ grid, as illustrated in Figure 3, which depicts the gridded representation of the spatial plan in Bogor Regency.

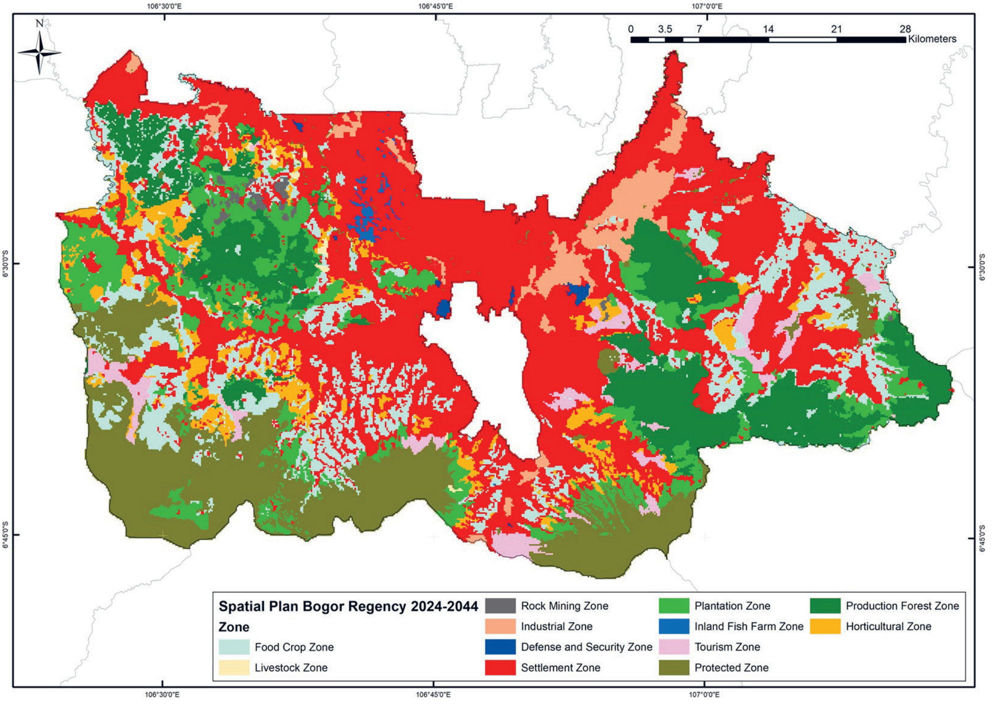

Fig. 3. Spatial plan of Bogor Regency (2024–2044)

For example, if a grid cell intersected three different soil types, the one that covered the largest area was assigned. For continuous parameters such as slope or NDVI, the pixel values were similarly grouped into predefined classes (e.g., slope ranges), and the class with the most significant coverage area was selected. This approach was implemented using the zonal analysis tools in GIS to produce a harmonized and reproducible data set, thus ensuring consistent input for machine-learning classification and evaluation of the spatial-plan alignment. This ensured that each grid cell consistently contained a complete and comparable set of 11 physical parameters along with the corresponding LULC label. Employing this gridded spatial-data structure and MCA standardization ensured that a fair, systematic, and reproducible framework for spatial analysis, machine-learning classification, and subsequent overlay with the spatial-plan data was established.

This study categorized the physical parameters into four groups: topography, climate, soil and vegetation, and hydrology. Land-suitability modeling incorporated various physical parameters such as the elevation, slope, topographic position index (TPI), topographic wetness index (TWI), drainage/river density, precipitation, temperature, soil type, normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and water supply (Table 1).

Table 1. Data information

No.	Data	Product – Source	Year	Scale/Resolution
1	Spatial-plan map of Bogor Regency (2024–2044)	Bogor Regency government	2024	1:50,000 (or 25 m)
2	LULC data (Bogor Regency)	Indonesia's base map – Geospatial Information Agency (Indonesia)	2022	1:25,000 (or 12.5 m)
3	Elevation, slope, topographic-position index, topographic-wetness index, drainage/river density	DEMNAS data-processing results – Geospatial Information Agency (Indonesia)	2018	5–11.75 m
4	Precipitation	CHIRPS – Climate Hazards Center, UC Santa Barbara	2022	5 km
5	Temperature	MODIS (Moderate-Resolution Imaging Spectroradiometer) – NASA and USGS	2022	1 km
6	Soil type	Ministry of Agriculture (Indonesia)	2016	1:50,000
7	NDVI, NDWI	Sentinel-2 – European Space Agency	2022	10 m
8	Water supply	Grid, ecosystem service index and water-availability data-processing results – Ministry of Public Works and Public Housing (Indonesia)	2016	5′ ≈ 154.15 m

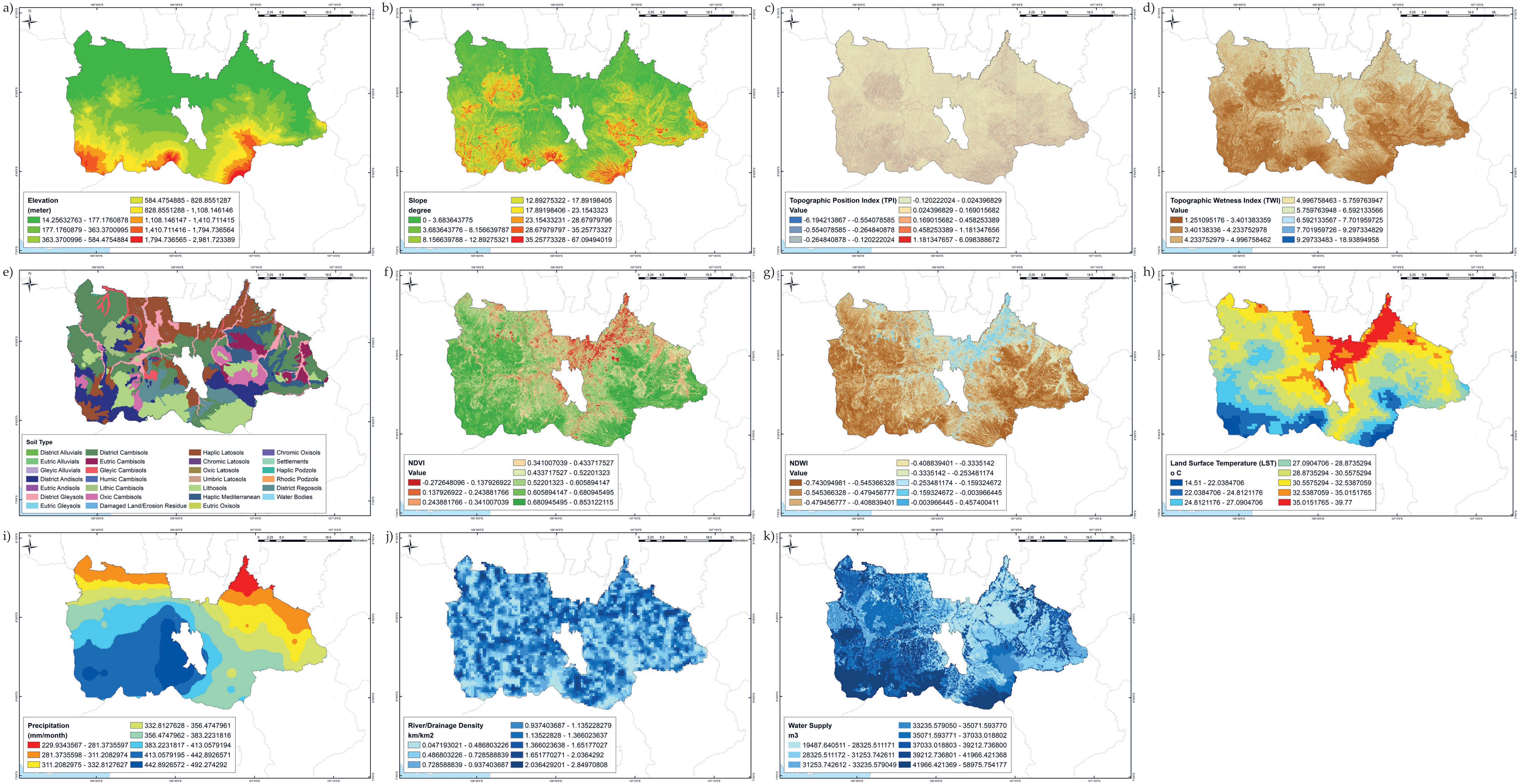

Fig. 4. Land's physical parameters: a) elevation; b) slope; c) TPI; d) TWI; e) soil type; f) NDVI; g) NDWI; h) temperature; i) precipitation; j) river/drainage density; k) water supply

This study employed a data-driven probabilistic approach that utilized machine learning for land-suitability assessment. The LULC data served as the training label (Fig. 2), whereas the physical land parameters determined the probabilistic suitability value for each LULC class. The physical parameters served as features that separated the classes using SVM. The 11 parameters that were utilized in this study are illustrated in Figure 4 (on the interleaf); these physical parameters (excluding protected areas) were used to classify the suitability scores for 9 classes of LULC. The SVM algorithm combined with ECOC served as a classifier, and the probability values of the land suitability for the nine classes of LULC were determined. The land-suitability model results and LULC area allocation were utilized to assess the alignment between the spatial plan and LULC.

Figure 5 presents the methodology that was employed in this research.

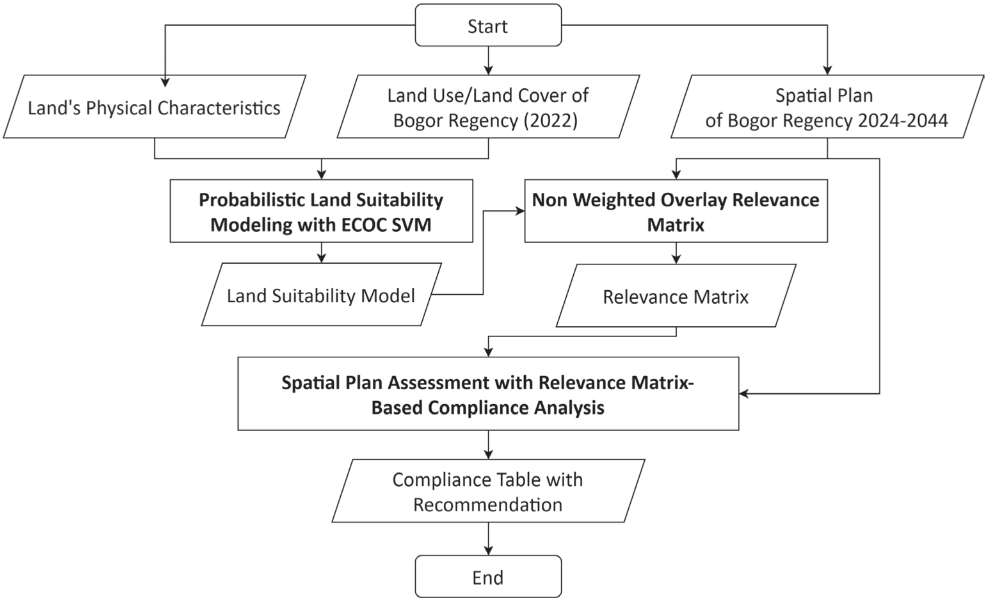

Fig. 5. Research methodology

This research addressed land-suitability assessment as a multiclass classification problem and implemented a combination of ECOC and SVM to resolve the multiclass classification problem. SVM is a supervised machine-learning technique that was designed to solve binary classification tasks; it transforms input data into a high-dimensional feature space to identify the optimal separating hyperplane. This minimizes the training set errors and maximizes the margins between the distinct classes [37–39]. ECOC transforms a multiclass classification issue into several binary-classification tasks, enhancing the fault tolerance and mitigating the bias and variance that was produced by the learning algorithm [40, 41]. Classification using ECOC has the ability to correct errors in order to address any inaccuracies that were caused by the decoding process and to determine the probability of the prediction outcomes [12, 42]. This study used ECOC combined with SVM to obtain the land-suitability-prediction classes and probability values for each class of LULC (which was also applied to prior research) [32].

Although the SVM outputs deterministic-class labels, this study employed a probabilistic adaptation by calibrating the decision values of each binary SVM classifier using Platt scaling. This post-processing technique fit a logistic function to the SVM decision values to estimate posterior probabilities. These calibrated probabilities were then aggregated using the ECOC decoding scheme and normalized so that the probabilities for all of the LULC classes for each grid cell summed to one. This approach was conceptually similar to the implementation in the fitcecoc function in MATLAB [43] and has been validated in previous studies [25, 44, 45].

To enhance the model performance and ensure methodological transparency, this study evaluated multiple kernel functions for the SVM base learner, including linear, polynomial, and the radial basis function (RBF). Among these, the RBF kernel consistently outperformed the others in terms of classification accuracy and generalization – particularly when modeling the non-linear relationships that were present in the 11 physical parameters. This finding aligned with prior research in land-use-suitability modeling such as Safitri et al. [25] and Nurkholis et al. [26], which similarly demonstrated the superior performance of the RBF kernel in spatial-classification tasks.

To identify the optimal model configuration, we performed grid-search-based hyperparameter tuning over logarithmically spaced values for penalty parameter C (ranging from 0.1 to 100) and kernel coefficient γ (ranging from 0.001 to 1). The combination that yielded the highest average classification accuracy was selected based on five-fold cross-validation; this cross-validation strategy was chosen to balance robust performance estimation with computational efficiency – particularly considering the iterative nature of hyperparameter optimization.

This study offered several scientific contributions to the field of spatial-planning evaluation. First, it introduced a data-driven probabilistic approach to land-suitability modeling by employing a combination of a support vector machine (SVM) and error-correcting output codes (ECOCs), thus allowing for the generation of suitability probabilities across multiple LULC classes. Unlike conventional deterministic methods that rely on subjective weightings or scoring systems, the probabilistic framework provided more objective, reproducible, and uncertainty-aware results. Second, this research integrated 11 rigorously selected physical parameters (which were validated through multicollinearity and correlation tests) into a multiclass classification model that produced high-resolution predictions on a standardized 5″ × 5″ grid system based on the Indonesian Multiscale Grid System (IMGS). This spatial framework enhanced data interoperability and precision, thus making it highly relevant for national-scale land planning efforts. Third, the study introduced the application of a non-weighted overlay relevance matrix, which operationalized spatial-plan evaluation by quantifying the degree of alignment between the modeled land suitability and formal spatial-zoning designations. This matrix-based evaluation enabled the systematic identification of non-compliant zones and provided spatially explicit insights for policymakers. By combining machine learning with spatial-planning standards and regulations, the approach bridged the gap between data science and urban planning, offering a scalable and transferable evaluation framework that was applicable to other regions beyond the case study of Bogor Regency.

The decision to adopt ECOC-SVM over other classification models was based on its strong theoretical foundation and empirical performance in land-suitability-classification tasks. While alternative machine-learning methods such as random forest, XGBoost, and multilayer perceptron (MLP) neural networks were considered, ECOC-SVM consistently demonstrated superior performance during the preliminary trials. Additionally, the ECOC-SVM framework supported probability calibration through Platt scaling, thus enabling the generation of interpretable probabilistic outputs – an essential requirement for spatial-decision support. In contrast, other models either lacked direct probability calibration (e.g., XGBoost) or required more-complex tuning procedures with limited added benefit given the data sets' characteristics. The choice of ECOC-SVM thus reflected a balance among predictive accuracy, interpretability, and computational efficiency.

Evaluating the alignment of spatial plans and land-suitability models requires understanding the relationship between LULC and the spatial-plan zone. The non-weighted overlay relevance matrix generates a relevance matrix that indicates the degree of alignment between the model and the spatial plan (including the distribution of their respective areas). The level of relevance is determined from an analysis of the correlation between the LULC class and the zoning within the spatial plan, utilizing technical documents on spatial planning, the Regulation of the Minister of Agrarian Affairs and Spatial Planning/Head of the National Land Agency of Indonesia No. 14/2021, Standar Nasional Indonesia (Indonesian National Standard, SNI) 7645-1:2014 Klasifikasi Penutup Lahan (Land-Cover Classification), Katalog Unsur Geografi Indonesia (Indonesian Geographic Element Catalogue), and previous research [46]. Mulya et al. [46] proposed a logical matrix to assess the alignment between LULC and spatial patterns; however, the classification was limited to five LULC classes and six spatial-pattern categories; this may have not adequately captured the complexity of real-world spatial dynamics.

To enhance the transparency and consistency in the assessment, the relevance levels (high, moderate, and low) were determined through a structured mapping that systematically associated each LULC class with the most aligned spatial zone. This mapping was based on the definitions and functional roles that were outlined in the Regulation of the Minister of Agrarian Affairs and Spatial Planning/Head of the National Land Agency No. 14/2021, Standar Nasional Indonesia 7645-1:2014 as well as the technical spatial-planning document of Bogor Regency. "High relevance" was assigned when the LULC class directly conformed to the intended function of a spatial-planning zone, while “low relevance” indicated no functional or regulatory connection between the two. “Moderate relevance” captured instances of partial or conditional alignments – often reflecting planning regulations for mixed-use or multifunctional land use. For example, dry agriculture was classified as being moderately relevant within production forest zones due to regulatory allowances for limited agricultural activity in Bogor Regency. This structured mapping framework provided a normative basis for interpreting the relevance matrix that is presented in Table 3 in Chapter 3.

The relevance matrix facilitated the analysis and assessment of the spatial plans, thus enabling evaluations based on the produced matrix. The results of the relevance matrix between the LULC from the land-suitability model and the spatial plan are provided in Table 3 (serving as a basis for generating compliance and recommendations for each LULC class).

3. Results

The land-suitability model that was produced in this study was comprised of an array of grids that contained 11 physical parameters as well as LULC information. Each grid of the suitability modeling results contained nine probability values of land suitability for each LULC class. This study showed that the probability value represented the suitability level of the LULC class. The ECOC algorithm was combined with SVM to generate land-suitability-probability values. The suitability value for each LULC class was within a grid range from 0 to 1, with the totals of the probability values consistently equaling 1. A higher probability value in a grid indicated greater suitability for the corresponding LULC class within that grid. An example of the probability values that were associated with each land cover for Grids X, Y, and Z is shown in Table 2. Grids X, Y, and Z are examples of three adjacent grids; each grid had a probability value (0.00 to 1.00) for nine LULC classes.

Table 2 shows that Grid X had the highest probability value for dryland agricultural land; this indicated that Grid X had the highest suitability for dryland agricultural. For Grid Y, the highest suitability was forest, followed by plantation as the second-ranked suitability. Meanwhile, Grid Z was the most suitable to be used for settlements. With the probability value indicating the level of land suitability, the spatial plan could be evaluated based on the alignment between the spatial plan and the model with the highest level of land suitability.

To gain an overview of the overall model’s predictive confidence, Figure 6 illustrates the distribution of the highest probability values across all of the grid cells. This graph captured the range and frequency of the model’s strongest suitability assignments, thus serving as an indicator of classification certainty throughout the study area. The land-suitability model indicated that the highest probability value for the overall model was 0.9952, with an average of 0.8251 (as illustrated in Figure 6). It also revealed that the highest frequency of the values occurred within the probability range of 0.9–0.95. Additionally, a significant proportion of the grids exhibited probability values that exceeded the average (as indicated by the red line in Figure 6), with 73,828 out of the 128,678 grids (57.37%).

Table 2. Probability value of each LULC class for each grid (example)

LULC class	GRID X	GRID Y	GRID Z
1. Forest	0.065778	0.490896	0.005168
2. Wetland Agriculture	0.027885	0.041991	0.003565
3. Dryland Agriculture	0.786831	0.024668	0.054821
4. Plantation	0.094152	0.434313	0.092583
5. Settlement	0.018224	0.006534	0.426143
6. Public Facilities	0.000332	0.000122	0.000070
7. Pasture	0.006749	0.001457	0.417638
8. Inland Fish Farm	0.000008	0.000003	0.000002
9. Transportation	0.000039	0.000016	0.000009
Sum	1	1	1

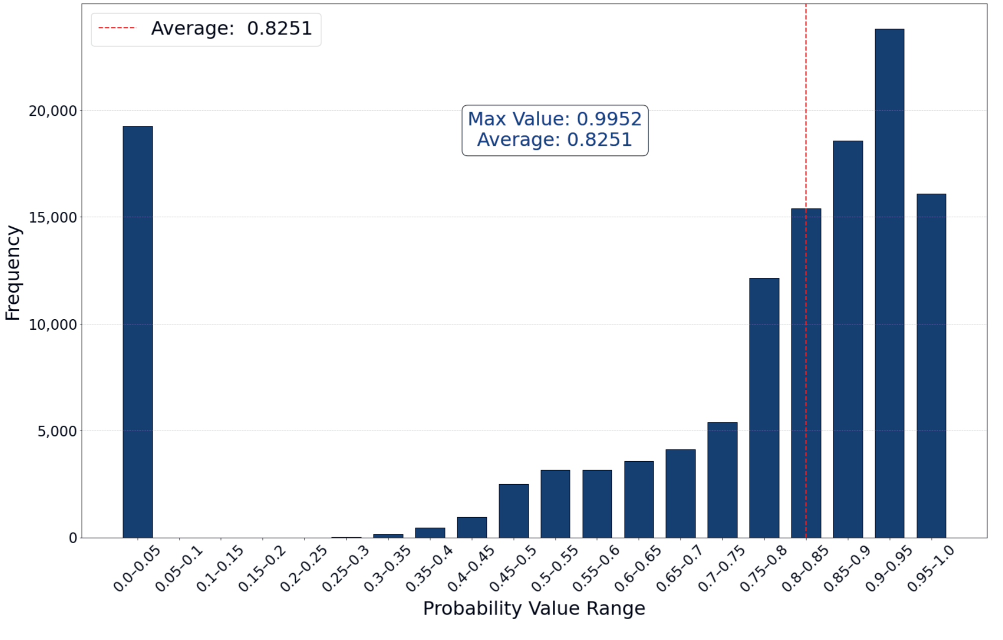

Fig. 6. Distribution of highest probability values

The land-suitability model with the highest probability value for each grid is illustrated in Figure 7. To enable a spatial comparison, the official spatial plan was classified into 12 functional zones and subsequently converted into a 5″ × 5″ grid spatial unit using the maximum combined area (MCA) method (Fig. 3). This method assigned the dominant land class to each cell based on the maximum overlap with the source pixels. This spatial framework was derived from the Indonesian Multi-scale Grid System (IMGS), which provides standardized grid hierarchies that range from 1°30′ to 5″ cells and is fully aligned with the national topographic map-indexing system [47, 48]. The 5″ grid resolution has been widely used in environmental applications such as population distribution [49] and greenhouse-gas emission modeling, thus enabling spatial aggregation while preserving the fine-scale heterogeneity [48]. In comparison, global grid systems such as GPWv4 adopt coarser resolutions (e.g., 30″, ca. 1 km), which may not capture land-use detail at the local governance level; thus, the 5″ grid is deemed to be more suitable for evaluating spatial-plan consistency and LULC suitability within regency-scale-planning contexts.

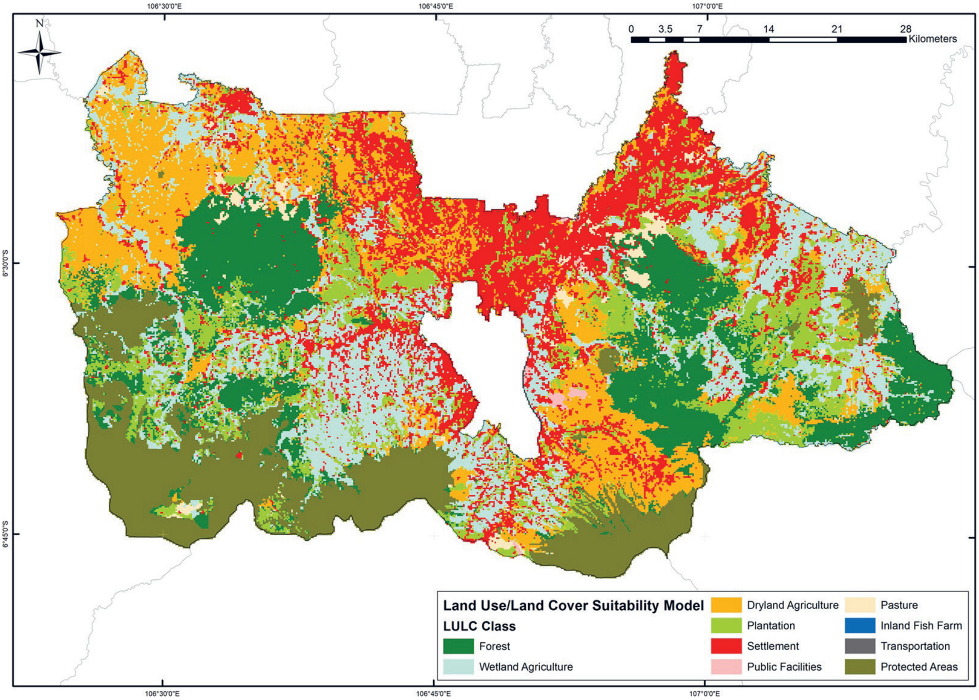

Fig. 7. LULC-suitability model (highest probability value)

The alignment between the modeled suitability outcomes and the existing spatial plan was systematically assessed through the relevance matrix (as presented in Table 3). This matrix represents a relevance matrix that show the area distribution of each LULC class across the various spatial-plan zones in hectares; the columns represent the LULC classes, and the rows represent the spatial-planning-zone types. For instance, the total forest cover area of 3128.4 ha (1) is within the horticultural zone (A). Table 3 provides an overview of the dominant LULC classes in each spatial-plan zone as well as those LULC classes that did not align with the existing spatial-plan zone. The matrix categorizes the relevance into three levels:

– High Relevance (indicated by green cells): this indicates complete alignments between the LULC and the spatial zone regarding the function and purpose. These areas are deemed to be suitable as they are and require no modifications.
– Moderate Relevance (shown in yellow): this reflects a partial alignment between the LULC and the intended function of the spatial zone. Adjustments in this context may involve either maintaining or altering the existing LULC and are guided by specific conditions and evaluative criteria. Rather than prescribing a standardized response, this category allows for flexibility in decision-making, enabling land-use adjustments to be made based on the specific characteristics and contextual conditions of each case.
– Low Relevance (represented by red cells): this reflects a function, purpose, or impact mismatch. Changes are recommended for the areas in this category, but any modifications must consider any constraints that are related to altering the land-use or spatial-zone functions.

Table 3. Relevance matrix showing area distributions [ha] of modeled LULC classes within official spatial-plan zone

LULC	1	2	3	4	5	6	7	8	9	10	Total Area
A	3128.4	2272.0	6550.0	3239.4	488.5	–	40.1	–	–	23.6	15,742.0
B	26,344.2	1118.6	7308.5	3226.2	203.0	–	696.3	–	–	4.7	38,901.5
C	–	–	–	–	–	–	–	–	–	44,992.6	44,992.6
D	1524.2	698.5	1937.2	2942.5	391.7	365.7	299.6	–	–	21.2	8180.6
E	–	533.3	231.3	28.3	66.1	–	–	21.2	–	–	880.3
F	11,781.4	2326.4	8449.1	6509.6	318.6	–	665.4	–	–	47.2	30,097.7
G	4032.7	20,940.1	24,298.0	16,812.1	46,367.6	342.2	1387.8	7.1	129.8	158.1	114,475.5
H	–	40.1	271.4	92.0	193.5	–	56.6	–	9.4	–	663.1
I	188.8	684.4	925.2	927.7	5912.7	127.5	684.5	–	–	9.4	9460.3
J	193.5	23.6	94.4	59.0	26.0	–	932.1	–	–	9.4	1338.0
K	47.2	42.5	287.9	103.8	160.5	–	21.2	–	–	–	663.1
L	3092.8	25,509.1	4155.7	4764.0	523.9	–	44.8	–	–	153.4	38,243.7
Total Area	50,333.2	54,188.8	54,508.7	38,704.7	54,652	835.4	4828.5	28.3	139.2	45,419.7	303,638.4

Relevance: High | Moderate | Low

Explanations: 1 – forest; 2 – wetland agriculture; 3 – dryland agriculture; 4 – plantations; 5 – settlements; 6 – public facilities; 7 – pasture; 8 – inland fish farm; 9 – transportation; 10 – protected area; A – horticultural zone; B – production-forest zone; C – protected zone; D – tourism zone; E – inland-fish-farm zone; F – plantation zone; G – settlement zone; H – defense and security zone; I – industrial zone; J – mining zone; K – livestock zone; L – food-crop zone.

4. Discussion

An initial assessment of the land-suitability model's performance is essential before evaluating its alignment with the existing spatial plan. Subsequently, the alignment analysis between the spatial plan and the most suitable LULC class (or the LULC class with the highest level of suitability) involves identifying the distribution of the LULC area that is contained within the spatial-plan zone. This approach enables a focused evaluation of how well the spatial plan incorporates ideal areas that align with the land-suitability criteria.

4.1. Land-Suitability-Model's Performance

The land-suitability-model's performance was assessed by utilizing performance metrics; these were derived from the confusion matrix that is presented in Table 4. This research used the accuracy, precision, recall, specificity, and F1 score to assess the effectiveness of the land-suitability model. The model showed varying performances among the different LULC classes (Table 5). The evaluation results showed high performances for the wetland agriculture and settlements classes, with accuracy, precision, recall, and F1-score values all above 90%; this indicated the model's effectiveness in classifying these two classes. However, the inland-fish-farm class had the lowest performance, with a very low accuracy and recall of 46.16% (despite having a precision of 100%). This indicated that the model could predict the inland-fish-farm class correctly but failed to identify many existing inland fish farms. The plantation class exhibited a relatively low accuracy (75.69%) and F1 score (79.94%), suggesting that the model struggled with consistently identifying suitable plantation areas; this resulted in a significant number of false negatives. The model also faced challenges in distinguishing plantation areas from other classes such as dryland agriculture and forest; this was likely due to the similarities in their physical characteristics. These limitations indicated the model's difficulty in balancing accurate identifications and minimizing misclassifications.

The overall accuracy, kappa statistic, and micro-metric (precision, recall, and F1 score) metrics were used to evaluate the overall performance of the model (Table 6). The overall accuracy of the model reached 88.56%, thus indicating that the model had a high ability to accurately classify land suitability for the majority of the data. The kappa index of 0.873 showed a high agreement between the model predictions and the actual data; this showed that the model was very reliable in predicting the correct classes. Micro precision and recall indicated that 88.56% of the model's predictions were correct with low error rates. The high precision and recall values led to a high F1 score, indicating that the model was effective and balanced in predicting without compromising either metric. This balance reflected the model's consistency in identifying the correct class while minimizing errors.

Table 4. Confusion matrix between LULC-suitability model and existing LULC data

		LULC-Suitability Model										Total [ha]
		1	2	3	4	5	6	7	8	9	10	
Existing LULC	1	44,330.2	533.3	1868.9	1958.4	398.8	0	28.3	0	0	0	49,117.9
	2	271.3	50,408.7	1055.0	646.6	245.4	0	4.7	0	0	0	52,631.7
	3	2477.8	1276.6	46,310.5	2475.5	1364.0	2.4	35.4	0	0	0	53,942.2
	4	3065.2	1665.8	4066.0	32,784.1	1713.2	0	21.2	0	0	0	43,315.6
	5	184.0	283.1	1078.5	809.4	49,332.6	33.0	167.6	0	2.4	0	51,890.7
	6	0	0	16.5	2.4	221.9	792.9	14.2	0	2.4	0	1050.2
	7	4.7	11.8	103.8	23.6	1343.0	7.1	4557.0	0	2	0	6053.4
	8	0	9.4	9.4	4.7	9.4	0	0	28.3	0.0	0	61.4
	9	0	0	0	0	23.6	0	0	0	132.1	0	155.7
	10	0	0	0	0	0	0	0	0	0	45,419.7	45,419.7
Total [ha]		50,333.2	54,188.8	54,508.7	38,704.7	54,652	835.4	4828.5	28.3	139.2	45,419.7	303,638.4

Table 5. Performance metrics for each LULC class [%]

LULC Class	Class Accuracy	Precision	Recall	Specificity	F1 Score
1. Forest	90.25	88.07	90.25	97.13	89.15
2. Wetland Agriculture	95.78	93.02	95.78	98.16	94.38
3. Dryland Agriculture	85.85	84.96	85.85	95.99	85.40
4. Plantation	75.69	84.70	75.69	97.25	79.94
5. Settlement	95.07	90.27	95.07	97.42	92.61
6. Public Facilities	75.50	94.92	75.50	99.98	84.10
7. Pasture	75.28	94.38	75.28	99.89	83.75
8. Inland Fish Farm	46.16	100.00	46.16	100.00	63.16
9. Transportation	84.85	94.92	84.85	100.00	89.60
Macro-Average	80.49	91.69	80.49	98.42	84.68

Table 6. Performance metrics for model [%]

Overall Accuracy	Kappa Statistic	Micro Precision	Micro Recall	Micro F1 Score
88.56	0.873	88.56	88.56	88.56

The model that was developed in this study achieved a high overall accuracy of 88.56%, utilizing 11 carefully selected physical parameters and a hybrid error-correcting output code (ECOC) and support vector machine (SVM) classification approach. In comparison, a previous study achieved 86.46% using ECOC-SVM with nine parameters [25], while it reported significantly lower performance (51.39% accuracy) with the *k*-nearest neighbor (kNN) algorithm and only four parameters [50]. Another study implemented eight parameters with random forest and SVM, yielding accuracies of 76.0% and 64.5%, respectively [38]. These findings suggested that both the classification of architecture and the number of input features substantially influenced the model's performance. This supports the hypothesis that increasing the diversity and number of relevant physical parameters enhances model generalizability and predictive performance when combined with a probabilistic classification framework such as ECOC-SVM. Such an integration enables finer discrimination among LULC classes – particularly in complex or heterogeneous environments.

A more nuanced analysis indicates a strong positive association between the number of well-selected input parameters and the classification accuracy. As the number of physical variables increases from 4 to 11, accuracy improves by more than 37%. This enhancement stems from the increased representational capacity of the model, capturing diverse land characteristics such as topography, climate, hydrology, soil type, and vegetation indices. However, the accuracy gains tend to plateau beyond a certain point – especially when additional variables introduce redundancy or noise. Hence, 9-to-11 parameters appears to represent an optimal range that balances predictive power with model simplicity.

It is also important to highlight the role of ECOC in improving classification robustness by decomposing the multiclass land-suitability problem into multiple binary classification tasks. This modular structure mitigates common issues in imbalanced high-dimensional data sets such as class overlap or underrepresentation by improving decision-boundary clarity and error-correction capacity. When coupled with SVM's strength in handling nonlinear separability, the ECOC-SVM framework demonstrates superior generalization across LULC classes.

Therefore, the term "leads to better accuracy" reflected not only a numerical improvement in performance metrics (such as the overall accuracy and the kappa statistic of 0.873) but also enhanced the model's reliability and class-specific consistency (e.g., high F1 scores) and reduced its misclassification errors. These attributes confirmed that integrating a well-structured feature set with an appropriate multiclass learning framework yields a robust and transferable land-suitability model that is suitable for spatial-planning evaluation.

The findings aligned with recent advances in land-suitability and spatial-planning research – especially that which applied integrated data-driven methods to support sustainable decision-making. For instance, one study examined maize suitability in Poland under climate and water-stress scenarios using the analytic hierarchy process (AHP) and climate projections and emphasizing the need to adapt land-use plans to emerging environmental challenges [51]. Similarly, a spatial-suitability framework was developed for renewable energy siting that incorporated both physical and legal constraints – an approach that was highly relevant to the present study's evaluation of the consistency between the LULC and the spatial zoning [52].

Expanding upon this, the application of multilayer perceptron models has been shown to enhance spatial prioritization in energy-infrastructure planning [52]. This supported the hypothesis that artificial-intelligence-based approaches offer superior complexity management as compared to traditional multi-criteria decision-making (MCDM) methods. Furthermore, the integration of policy layers into land-use evaluations for Central Europe has reinforced the importance of combining biophysical information with policy-making tools – a strategy that was adopted in the present study by applying administrative zoning as a consistency constraint [53].

In non-European contexts, methodological advancements have been introduced through the use of ensemble machine learning and decision-tree optimization for land-suitability mapping with Sentinel imagery [38]. Previous studies [38, 52, 53] have validated the use of hybrid data sources; accordingly, this study fuses multiple environmental predictors. Additionally, an artificial neural network-cellular automata (ANN-CA) model combined with Internet of Things (IoT) technologies has been proposed for territorial spatial planning, emphasizing the role of high-resolution real-time data as a critical component in predicting spatial suitability, thereby complementing our use of probabilistic SVM for modeling spatial consistency [18]. These studies [18, 38, 52, 53] have collectively supported the need for flexible, interpretable, and policy-sensitive ML models in land-allocation planning under multi-dimensional constraints.

4.2. Spatial-Plan Evaluation

The land-suitability model serves as a preliminary tool for identifying spatial-plan zones that require further evaluation for revision. This study used the model to detect deviations in the existing spatial plan of Bogor Regency. This approach involved calculating the area of each modeled LULC class within the specific spatial zones. These distributions determined the total land area that was appropriately allocated for its designated purpose and the area of the non-compliant zones.

The spatial plan was categorized into 12 zones to assess the compliance and deviations based on the LULC-suitability model. As shown in Table 3, the distribution of the land area between the LULC and the spatial-plan zones was analyzed in order to identify discrepancies within the existing spatial plan. The results of the consistency analysis between the spatial plan and the land suitability are detailed in Table 7 (highlighting the distribution of the compliant and non-compliant areas).

Table 7 outlines a set of recommendations that were derived from the evaluation of land suitability in relation to the existing spatial-zoning regulations. These recommendations aim to enhance the alignment between spatial planning and the biophysical capacity of the land. While based on a technical land-suitability analysis, the implementations of these recommendations must also be grounded in relevant policy and regulatory frameworks at both the local and national levels.

In the context of Bogor Regency, several planning and environmental-policy documents provide a basis for supporting the optimization of sustainable LULCs. These documents include the Regional Spatial Plan of Bogor Regency 2024–2044 [54] as well as the strategic environmental assessment (SEA) for the Revision of the Spatial Plan of Bogor Regency 2022–2043 [55]. Notably, the recommendation to preserve agricultural land as a means to support food security was grounded in Law No. 41 of 2009 on the Protection of Sustainable Agricultural Land [56], which also serves as a legal foundation for the formulation of the Regional Spatial Plan of Bogor Regency. This law underscores the government's commitment to conserving the existence and continuity of agricultural land use through the designations of sustainable food agricultural land areas in Bogor Regency.

Furthermore, the SEA document for Bogor Regency emphasizes the importance of restricting land conversion from non-built-up to built-up areas in order to preserve ecological functions and land-carrying capacity [55]. Accordingly, the recommendations that were outlined in Table 7 (such as retaining the agricultural land that is currently located within settlement zones and reclassifying them as food-crop zones) are not only ecologically relevant but also consistent with the regional-development priorities. These recommendations contribute to sustainable land-use planning and the promotion of long-term food security within the local-development framework.

Table 7. Evaluation results for alignment between spatial-plan zone and land-suitability model

LULC Class	Compliant	Non-Compliant	Recommendation
1. Forest	52% within production forest zone	23% within plantation zone, and 8% within settlement zone	evaluation is required for areas that are classified as forest but are planned for conversions into plantation and settlement zones in spatial plan; recommendation is to maintain these areas as forest
2. Wetland agriculture	47% within food-crop zone	39% within settlement zone	agricultural land within settlement zones should be repurposed for agricultural use and changed into food-crop zones to support food security

Table 7. cont.

3. Dryland agriculture	12% within horticultural zone, 0.5% within livestock zone, and 8% within food-crop zone	45% within settlement zone	dominance of settlement zone within dryland agriculture land indicates mismatch with spatial plan; agricultural land within settlement zone should be repurposed for agricultural use to support food security
4. Plantation	17% within plantation zone	43% within settlement zone	non-compliant allocation suggests need for zoning adjustments; recommendation is to repurpose plantations within settlement zone according to their land suitabilities as plantations
5. Settlement	85% within settlement zone	11% within industrial zone	alignment with spatial plan is high; however, addressing proximity between industrial zones and residential areas is crucial for mitigating potential conflicts and ensuring sustainable urban development
6. Public facilities	44% within tourism zone, and 15% within industrial zone	–	tourism and industrial zones are categorized as public infrastructure, which is relevant
	41% within settlement zone		public facilities are relevant for supporting public infrastructure needs within settlement zone
7. Pasture	0.4% within livestock zone, 0.8% within horticultural zone, and 0.9% within food-crop zone	29% within settlement zone	recommendation is to reallocate pastures within settlement zones according to their land suitabilities (such as for livestock or horticultural zones)
	14% within production-forest zone, and 14% within plantation zone		pastures within production forest and plantation zones remain relevant, as they can serve as forms of crop diversification in these zones
8. Inland fish farm	75% within inland-fish-farm zone	25% within settlement zone	inland fish farms within settlement areas should be separated from settlement zone
9. Transportation	93% within settlement zones and 7% within defense and security zone	–	relevant to need for access, connectivity, and defense/security facilities

The spatial plan of Bogor Regency allocates 114,475.5 ha (about 37.7% of the total area) for settlement zones. Conversely, the food-crop zones contain wetland agriculture only have 38,243.7 ha (12.6%), while the horticultural zones that include dryland agriculture are only allocated 15,742 ha (5%). The allocation of the settlement zone in the spatial plan of Bogor Regency correctly designates 40.5% of the land for residential use (thus, aligning with its suitability for such use). However, other land classes with high suitabilities for LULCs that are outside settlements are still significantly distributed within the settlement zones (Fig. 8). For instance, 20,940 ha (18.3%) of the settlement zones should be allocated for wetland agriculture, while 24,928 ha (21.2%) is more suitable for dryland agriculture. Moreover, 16,812 ha (14.7%) should be designated as plantations, and 4,032 ha (3.5%) should be designated as forest areas.

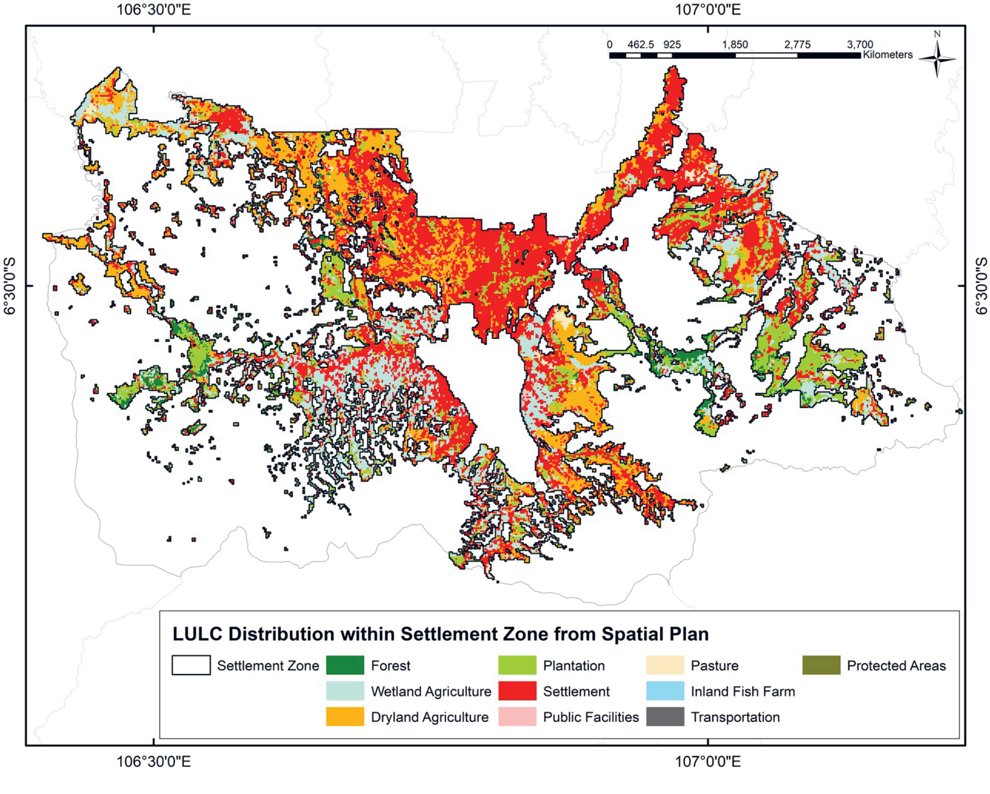

Fig. 8. LULC distribution within settlement zone from Bogor Regency spatial plan

Figure 9a illustrates the allocation discrepancies, revealing that regions allocated as settlement zones have a high probability of being classified as suitable for dryland agriculture according to the land-suitability model. Similar findings are shown in Figure 8b for wetland agriculture; this indicates a discrepancy when land that is physically most suitable for agriculture is allocated for settlements and is, consequently, not being utilized for its optimal use. Inefficient LULC use can lead to profit losses, slower economic growth, and environmental harm [57]. Land should be used based on its capacity, with settlements on unproductive lands and agriculture on productive/fertile areas. Misallocations such as converting farmlands for urban use risk flooding, pollution, and resource depletion, thus fueling climate change and environmental instability [54, 55].

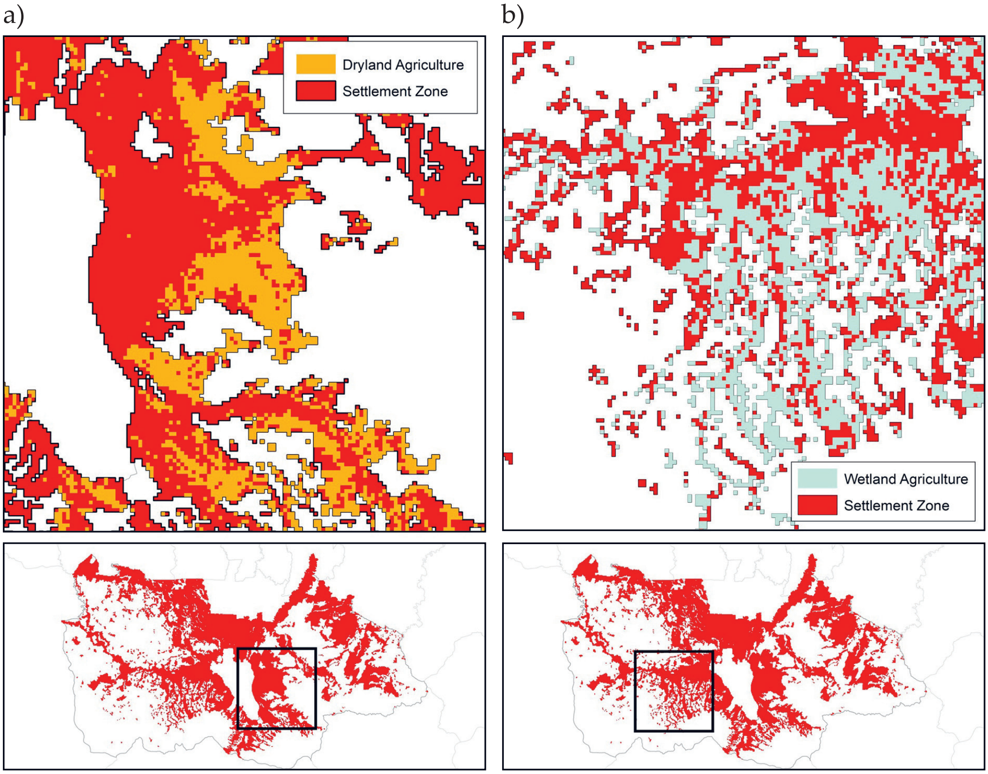

Fig. 9. Discrepancies within settlement zone: a) dryland agriculture; b) wetland agriculture

The modeling results also showed that wetland agriculture covers 54,188.7 ha, of which 38.6% (20,940.1 ha) has been allocated for settlement zones. Similarly, dryland agriculture covers 54,508.17 ha, with 43.4% (24,298 ha) being designated for settlement zones. This discrepancy suggests a need for land-use planning to more effectively assess the physical suitability for agricultural productivity, thus ensuring that agricultural land is preserved as productive land. Law No. 41 of 2009 on Sustainable Food Agricultural Land Protection underscores the Indonesian Government's commitment to maintaining and enhancing sustainable agricultural land, allocating 38,195.4 ha in Bogor Regency as a sustainable food agricultural area. The spatial plan allocates 38,243.7 ha for food-crop zones and 15,742 ha for horticultural zones; this reflects a focus on food-crop preservation, while horticultural zones remain vulnerable to conversions. Hence, specific measures are necessary to safeguard the remaining horticultural zones against misuse. Regulatory frameworks are critical in strengthening land-use monitoring and control [59]. While Indonesia's government already has spatial-planning monitoring and control regulations, local governments face considerable challenges in their practical implementations. In this regard, participatory urban-planning monitoring offers a practical alternative to improve monitoring effectiveness [60].

The significant allocation of settlement zones (38% of the total land) indicates that Bogor Regency is focused on fulfilling housing demands to support the growing population. The distributions of agricultural zones (which cover only 18% of the total area) might lead to food-security challenges when food demand increases due to population expansion. The transformation of agricultural lands into settlement zones can result in several implications; this includes reduced food-crop yields, which may threaten long-term food security [60, 61]. Moreover, these changes are permanent, signifying that converted agricultural lands cannot revert to their original uses. The conversion of this productive land also entails several implications, including increased land prices and socio-economic effects such as increasing food costs, reliance on external food supplies, and a reduced standard of life [62].

The land distribution in the Bogor Regency spatial plan is advised to focus on those areas that are more functionally relevant and align with the land suitability. The prevalence of LULC-class distributions for settlements indicate that current spatial planning mainly focuses on fulfilling settlement needs; this is potentially due to governmental policies or higher housing demands due to urbanization. To produce an improved spatial plan, balancing basic human needs with the assurance of environmental sustainability in spatial planning is crucial. Consequently, assessing the carrying capacity and land suitability will be essential in achieving optimal and sustainable land-use planning.

If unaddressed, these spatial inconsistencies may constrain the sustainability of Bogor Regency's urban system by exacerbating land-use conflicts and undermining environmental resilience. Aligning spatial plans with ecological suitability can strengthen the environmental-carrying capacity, reduce the development fragmentation, and improve the spatial coherence, thus directly contributing to sustainable urban-development goals. Achieving SDG11 requires integrative approaches that address spatial, ecological, and social dimensions through evidence-based planning – particularly in Global South contexts [63]. Moreover, enhancing land-use suitability can foster urban livability and public health – especially in peri-urban areas with high population pressures or limited infrastructures (in the context of Hong Kong) [64]. These implications also align with the studies that have demonstrated the importance of coupling ecological resilience with adaptive urban land-use models in order to support long-term sustainability transitions [65]. Taken together, our findings indicated that land-suitability modeling can serve not only as a technical tool for spatial-plan evaluation but also as a strategic instrument for advancing inclusive, resilient, and health-sensitive urban development.

In addition to the current evaluation of spatial-plan alignment, this model presents several opportunities for further development. Incorporating a temporal dimension such as projecting future land-use changes under demographic or climate scenarios would allow for more-anticipatory spatial planning. Furthermore, integrating socio-economic variables such as population density, infrastructure accessibility, and land value could provide a more nuanced picture of spatial suitability that is aligned with on-the-ground conditions. Incorporating disaster-risk indicators like flood and landslide susceptibility would also enhance the model's relevance for climate-resilience planning. Beyond analytical refinement, spatial-optimization techniques (e.g., genetic algorithms, NSGA-II) could be employed to propose optimal land allocations that minimize fragmentation and better align with policy goals. The model could also benefit from ecological-footprint-based estimations to assess land demand in a more environmentally grounded manner. Finally, participatory validation that involves local stakeholders and extends the model to regional or provincial scales would increase its practical utility, promote broader applicability across jurisdictions, and support integrated spatial-governance frameworks.

5. Conclusion

The results of land-suitability modeling using 11 physical parameters to classify the probability value of suitability for 9 LULC classes using the ECOC-SVM method demonstrated excellent prediction performance, achieving an overall accuracy of 88.56%. This reliable land-suitability model showed its potential as a robust tool for evaluating the alignment between the LULC and the existing spatial plan. However, the evaluation in this study was limited to identifying those areas with discrepancies. The evaluation findings indicated notable discrepancies between settlement zones and agricultural land. Specifically, 45% of dryland agriculture, 43% of plantations, 39% of wetland agriculture, 29% of pastures, and 25% of inland fish farms are located within areas that are designated for settlement zones in the existing spatial plan. These findings highlighted the government's prioritization of housing development at the expense of addressing other critical needs such as food security. Moreover, the results suggested that the Bogor Regency's government still needs to adopt a sustainable approach to spatial planning. Several aspects could enhance the assessment to yield more practical recommendations for revising the spatial plan, such as identifying alternative locations to address these discrepancies. While the findings provided a basis for spatial-plan revisions, more-detailed recommendations could be achieved by analyzing the specific needs of each LULC class. Furthermore, employing this land-suitability model as an evaluative instrument could be extended to any kind of land-use planning. This approach would strengthen the model's applicability to broaden land-use policy and planning.

Comparable efforts in Europe have also demonstrated the utility of integrating machine learning and spatial regulations in land-suitability and spatial-planning evaluations. For example, climate-adaptive planning has been emphasized in maize-suitability modeling in Poland [66], while spatial-decision support has been applied to renewable-energy siting under legal constraints [51]. The effectiveness of neural networks and AHP–GIS methods in addressing spatial complexity and aligning with policy frameworks has also been highlighted [49, 50]. In the Middle East and Asia, recent studies have similarly shown that combining environmental data, remote sensing, and intelligent models such as artificial neural networks with cellular automata (ANN-CA) and SVM offers robust frameworks for evaluating land suitability across multiple spatial scales [18, 24, 38]. The consistency of our findings with these international efforts reinforces the global relevance of probabilistic ML-based approaches in modern spatial planning.

For future research, several directions can be proposed to enhance the analytical robustness and policy relevance of the model. First, incorporating disaster-risk variables (e.g., flood and landslide susceptibilities) and socioeconomic indicators (e.g., population pressure, infrastructure accessibility, or land value) may improve the contextual validity of the land-suitability predictions. Second, integrating ecological-footprint-based land-demand estimations could support a more-environmentally-grounded approach to spatial allocation. Third, applying spatial-optimization techniques could help generate recommended land-use configurations that minimize fragmentation and better align with planning goals. Fourth, participatory validation that involve local stakeholders and government agencies is recommended to ensure that the model's outcomes are acceptable, feasible, and sensitive to on-the-ground realities. Furthermore, incorporating temporal projections such as simulating land-use changes under demographic or policy scenarios would support forward-looking spatial assessments. Coupled with optimization-based scenario generation, this would enable adaptive land-use alternatives that balance development, conservation, and equity. These improvements could enhance the model's utility for dynamic and policy-relevant planning. Finally, extending the model to a regional or provincial scale would allow for cross-boundary spatial-plan-consistency assessments, thus enabling broader applications in integrated and sustainable spatial governance.

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CRediT Authors' Contributions

D. S. H.: conceptualization, methodology, data curation, investigation, writing – original draft, writing – review & editing, visualization.

S. S.: conceptualization, methodology, data curation, investigation, writing – review & editing, supervision.

A. R.: conceptualization, methodology, supervision.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work that was reported in this paper.

Data Availability

The public data in this article include:
- land-use/land-cover data and DEMNAS available at https://tanahair.indonesia.go.id/;
- rainfall data available at https://data.chc.ucsb.edu/products/CHIRPS-2.0/;
- MODIS data available at https://earthexplorer.usgs.gov;
- Sentinel-2 imagery available at https://browser.dataspace.copernicus.eu.

Use of Generative AI and AI-Assisted Technologies

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