Food Crop Land Allocation: Integrating Land Suitability Analysis and Spatial Forestry, Study Case Katingan, Indonesia

Ramdhani¹, Widiatmaka², Bambang Hendro Trisasongko^{2,3*}

¹Directorate General of Forestry Planning and Environmental Management, Ministry of Environmental and Forestry, Jl. Gatot Subroto, Jakarta, Indonesia 10270

²Department of Soil Science and Land Resources, Faculty of Agriculture IPB University, Jl. Meranti Campus IPB Dramaga, Bogor, Indonesia 16680

³Geospatial Information and Technologies for the Integrative and Intelligent Agriculture (GITIIA), P4W/CRESTPENT, IPB University, Jl. Pajajaran Campus IPB Baranangsiang, Bogor, Indonesia 16154

Received March 20, 2023/Accepted September 5, 2023

Abstract

The Indonesian government strives to expand agricultural lands, primarily beyond Java, through food estate programs. However, there has been a strong likelihood that this endeavor might intersect with forests and forest designation areas. This study aims to determine land suitability and its potential allocation for food crops at the interface of forestry and agriculture in Katingan District. Paddy (Oryza sativa L) and sorghum (Sorghum bicolor L) were selected as the crop species being analyzed, employing a coupling of the analytical hierarchy process and GIS. Forest area designation and land cover maps were incorporated into land allocation scenarios. The results showed that there were 74.254 ha in the "highly suitable" (S1) class and 130.634 ha in the "moderately suitable" (S2) class for paddy. However, after applying the scenario, they decreased by 4% and 12%, respectively. Sorghum has S1 and S2 areas of 108.956 ha and 377.493 ha, which declined by 15% and 14%, respectively, after scenario. Based on the allocation scenario, we found potential deforestation of 67 thousand ha for paddy and 205 thousand ha for sorghum, respectively. We highlighted convertible production forests (HPK) and production forests (HP) as having considerable potential for the allocation of land for food production.

Keywords: AHP, deforestation, food estate, land suitability analysis, remote sensing

*Correspondence author, email: ipbramdhani@apps.ipb.ac.id

Introduction

The Indonesian government is striving to expand agricultural lands for food crops beyond Java Island through food estate programs in several regions. This program is claimed to be a response to the FAO's warning about potential threats of global food crisis as a result of prolonged covid-19 pandemic (FAO, 2020). This is also driven by national rice production, which has significantly declined in the past five years, while the national population census reported a rise of 32,56 million people between 2010 and 2020 (BPS, 2021a). This significant population growth has a direct impact on the future rise of national food consumption. A proportion of Indonesia's vital food supply, on the other hand, continues to depend on Java Island (Widiatmaka et al., 2016). For instance, in 2020, the proportion of Java's rice production compared to the national total reached 56.05 % (BPS, 2021b). In contrast, Java's paddy field declined by 89 thousand ha between 2003 and 2015 (BPS, 2018).

As one of the countries with the largest tropical forest cover in the world after Brazil and Congo (FAO, 2020), the extensification of agricultural lands beyond Java Island has been sought, and this may intersect with forests and forest area designations (FAD). The remaining Indonesian tropical forest covers around 51% of the total land mass, or 92.13 million ha, whereas FAD occupies approximately 66% of the territory, or 125 million ha (KLHK, 2021). Prior research has revealed that the expansion of agricultural land is the primary driver of deforestation (Gibbs et al., 2010; Gaveau, 2017). Consequently, the remaining forest cover and FAD must be taken into account before expanding agricultural lands to avoid a multitude of detrimental ecological effects.

Identifying suitable lands for food crop farming is essential to reduce the risk of failure, improve productivity, and reduce environmental negative impacts (Abdelrahman et al., 2016; Araújo Costa et al., 2019). Land suitability analysis (LSA) has widely been utilized to determine the suitability of lands in a particular location for a particular type of use, including agricultural commodities, as well as the degree of suitability (FAO, 1976; Akinci et al., 2013). Recently, it has been combined with other multi-criteria decision-making (MCDM) methods, including the analytical hierarchy process (AHP) (Akinci et al., 2013), fuzzy methods (Zhang et al., 2015), crop simulation models (Ohadi et al., 2018), and GIS-based logic scoring of preference (LSP) (Montgomery et al., 2016). AHP is the most widely accepted method in agriculture and is considered the most dependable MCDM method (Kihoro et al., 2013), while its integration with GIS is popular due to its capabilities to accommodate a huge quantity of complex data and its ease in deriving the weights of a large number of criteria (Chen et al., 2010).

Although GIS-based AHP integration into LSA for agricultural purposes has widely been used, its integration with forested land cover and forestry spatial policies in Indonesia remains understudied. This article addresses these situations by constructing scenarios based on LSA results, then integrating them with forest cover and FAD to develop a scenario for allocating agricultural lands to support food production.

Method

Study area This research was conducted in Katingan Regency, Central Kalimantan Province. The site was selected because of its characteristics, including its unique upstream-to-downstream coverage, an administrative boundary in the form of an intact unit of the Katingan Watershed (DAS), and its proximity to the provincial capital. Katingan extends from the south latitude of S0°20' to S3°38' and the east longitude of E112°00' to E113°45'. It shares borders on the north by Malawi Regency and West Kalimantan Province; on the east by Gunung Mas Regency, Palangkaraya City, and Pulang Pisau Regency; on the south by the Java Sea; and on the west by East Kotawaringin Regency and Seruyan Regencies.

Katingan area stretches about 2.04 Mha (BPS Katingan, 2023), and consists of 13 districts, from north to south, i.e., Bukit Raya, Katingan Hulu, Marikit, Petak Malai, Sanaman Mantikei, Katingan Tengah, Malan Island, Tewang Sangalang Garing, Katingan Hilir, Tasik Payawan,

Kamipang, Mendawai, and Katingan Kuala. The average land surface temperature (LST) ranges from about 25.1°C to 29.8 °C, while the average relative humidity spans between 54.1% and 75.6%. The rainiest days were in December, with 14 days. The average monthly precipitation was 249 mm while the maximum rainfall of 786 mm occurred in March (BPS Katingan, 2023). According to the 2020 census, there were 162,222 inhabitants, which was about 8 people km⁻², a ratio lower than the provincial average of 17.39 people km⁻². The research location is presented in Figure 1.

Material Land suitability parameters include climate (annual rainfall and average LST), soil type, soil texture, soil depth, slope, pH, cation exchange capacity (CEC), distance to roads, and distance to water sources. The annual rainfall was derived from the Tropical Rainfall Measuring Mission (TRMM) (Huffman et al., 2007) 2011-2018 data, while the average LST was derived from the moderate resolution imaging spectroradiometer (MODIS) (Wan et al., 2015). The Ministry of Agriculture (MoA) provided the soil map, which was developed from a semi-detailed soil survey (scale 1:50,000) at district level. This map contains information including soil type, soil texture, slope, soil depth, pH, and cation exchange capacity (CEC). The proximity to roads and rivers was generated from the Indonesian base map, the Rupa Bumi Indonesia (RBI) maps at scale 1:50,000, published by the Geospatial Information Agency (GIA). Meanwhile, a forest area designation (FAD) map was sourced from the Ministry of Environmental and Forestry (MoEF) at a scale of 1:250,000. In addition, the 2022 land cover map utilizing Landsat 8 OLI/TIRS satellite imagery was produced through a semi-automated classification method employing Random Forest machine learning. These datasets are shown in Table 1.

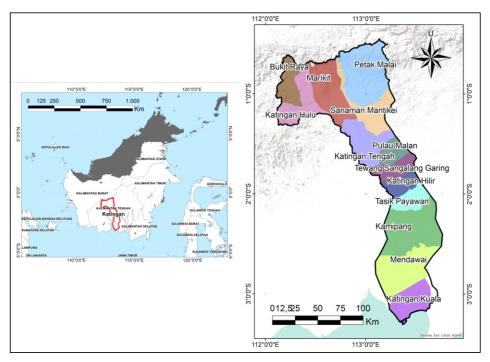


Figure 1 Area study.

Methods Land suitability analysis was conducted using the multi-criteria evaluation (MCE) method; each parameter was weighted using the AHP technique. Paddy (*Oryza sativa* L) was selected as an object study due to its role as the primary source of staple food, while sorghum (*Sorghum bicolor* L) was chosen due to its potential for food diversification.

The weight of each parameter for paddy and sorghum was decided by expert judgment. Land suitability classes refer to the FAO classification (FAO, 1976). Separate analyses of the land suitability for paddy and sorghum were performed using the respective parameter weights and sub-parameter scores. Then, land cover and FAD map were integrated to identify potential and develop land allocation scenarios. Figure 2 displays the entire process workflow.

LSA parameters *Climate* Climatic parameters used in this study included annual rainfall and the LST average. Rainfall is essential for crop cultivation because it provides water demands, facilitates nutrient absorption, and maintains soil moisture levels. However, excessive precipitation can cause waterlogging, which leads to root rot and other issues.

Table 1 Data and source

Data	Source
Annual rainfall	TRMM
Annual land surface temperature	MODIS
Soil type	MoA
Soil texture	MoA
Slope	MoA
Soil depth	MoA
Soil pH	MoA
Cation exchange capacity (CEC)	MoA
Distance to roads	GIA
Distance to water sources	GIA
Forest area designation (FAD)	MoEF
Land cover 2022	Landsat 8 classification

According to TRMM 2011-2018 data, annual rainfall ranged from 2,573–3,976 mm year⁻¹ (Figure 3a). This amount was consistent with the local government's field measurements in 2016 and 2019 of 4,054 mm year⁻¹ and 2,982 mm year⁻¹, respectively (BPS Katingan, 2020). Land surface temperature data have frequently been used in agriculture; to name a few: mapping the heat requirements of crop varieties, identifying suitable growing zones, as well as predicting crop ripening and insect infestations (Hulley et al., 2019). Averaged LST data from MODIS showed a range in value from 23 °C to 29 °C (Figure 3b). With reference to Wahyunto et al. (2016), paddy can optimally grow in an annual rainfall range of 1,500–3,000 mm year⁻¹. Hence, rainfall over 3000 mm year⁻¹ is considered unsuitable. Meanwhile, sorghum grows optimally in a range of 400–1,400 mm year⁻¹, while precipitation of more than 1,400 mm year⁻¹ falls under unsuitable category.

Soil type Based on their parent material, soils in the study area is categorized into two major groups, organic soils (peat soils) and mineral soils, respectively covering about 20.4% and 79.6% of the land mass. In the lowland areas of the southern side, extensive peat areas were protected and were predominantly forested. Referring to Figure 3c, Cambisols, Organosols, and Podzolic are dominant soil types, with respective percentages of 36.9%, 20.4%, and 21.8%. Meanwhile, mediterranean, oxisols, and regosols, are only present in a small portion of the land, which makes up a combined 0.04% of the land. In addition, there is a considerable proportion of alluvial and gleisol soils close to water sources that are suitable for the development of agricultural areas.

Soil texture Important soil properties, such as available water capacity, buffering capacity, electrical conductivity, infiltration rate, tillage conditions, pH, soil structure, nutrient retention capacity, and microbial biomass, are influenced by soil texture (Mustafa et al., 2011). For example, sand-textured soil (coarse) has a larger grain size so that each unit weight has a smaller surface area, making it difficult to hold

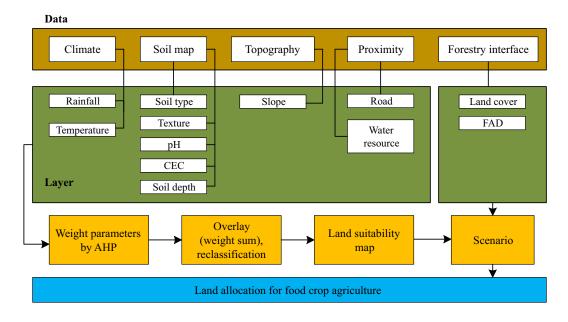


Figure 2 Workflows.

water and absorb nutrients (Sarwono, 1995). The dominant soil textures in mineral soil include fine and coarse textures (Figure 3d). Fine texture includes clay, silty clay, and sandy clay, while coarse texture is sand. According to Wahyunto et al. (2016), fine, rather fine, and medium texture classes suit both paddy and sorghum. In the meantime, organic soil dominated by a moderate level of decomposition (Hemic) could be invaluable for rice cultivation with a maximum depth of 150 cm (Wahyunto et al., 2016).

Slope This variable is considered due to its implications on erosion rates and soil fertility, as well as in land management (Akinci et al., 2013; Widiatmaka et al., 2016). The slope is divided into seven classes consisting of flat (0-1%), rather flat (1-3%), undulating (3-8%), gently sloping (8-15%), hilly (15-25%), strong hilly (25-40%), and mountainous (>40%) as shown in Figure 3e. The relatively flat class dominates an area of about 465,398 ha (22.83%) of the total area, followed by a gently sloping class of 393,902 ha (19.32%). In the central to southern parts of the study area, relatively flat slopes dominate the area. The northern region, on the other hand, has a steeper slope. Compared to relatively steep land, flat land provides greater potential for the development of agricultural expansion. It eases cultivation or mechanization while reducing the risk of soil erosion, and having more stable water conditions.

Soil depth Soil depth represents the depth at which the roots of cultivated crops may reach and utilize available water and nutrients (Akinci et al., 2013). In general, soil depth in study areas is suitable for rice and sorghum cultivation, since it exceeds 50 cm (Figure 3f). Meanwhile, regions with organic soil types (peat land) have a range of soil depth between 1 and 2 m which are classified to be marginally suitable class.

pH Generally, a neutral soil pH (6.6–7.5) is favored for the cultivation of various types of crops because nutrients can be easily absorbed, diverse in soil microbial, prevents crop stress, and promotes good soil structure, which can improve water retention, drainage, and root development (Helyar et al., 1989; Kemmitt et al., 2006). Figure 3g shows that the study area is dominated by area class: acidic (pH 4.5–5.5) with a proportion of 72.38%, followed by very acidic (pH 4.5) with a proportion of 5.42%. Referring to Wahyunto et al. (2016), the most suitable pH value for rice crop growth ranges from 5.5 to 7.0 while for sorghum it spans between 6.0 and 7.5. Meanwhile, pH >8.5 or pH <5.0 is considered unsuitable for sorghum crops.

CEC Cation exchange capacity (CEC) is a measure of the number of cations that are readily exchanged to neutralize negative charges in the soil. It is commonly utilized as a measure of soil fertility (Rhoades, 1983). By evaluating the soil's CEC, the cost of applying fertilizers and calcareous materials can be significantly decreased (Aprile & Lorandi, 2012). Higher CEC soils are better suited to absorb and provide nutrients to crops than lower CEC soils (Hardjowigeno, 1987). In the study area, the distribution of CEC values consisted of low, medium, high, and very high proportions of 35%, 38%, 5%, and 22%, respectively (Figure 3h). Even though the range of CEC values is relatively large, referring to Wahyunto et al. (2016), there are no conditions that were classified as unsuitable for either rice or sorghum.

Distance to river and road The Katingan River stretches for 650 km from upstream to downstream in Katingan Regency and consists of twelve tributaries (BPS Katingan, 2023). As an intact watershed unit, Katingan River is strategically located in the middle of the study area. Figure 3i depicts eight distance classes, where the closer the distance, the more beneficial it is for agricultural cultivation, and viceversa. Meanwhile, the length of roads in Katingan in 2021 reached 818 km, with a percentage of asphalt roads of only 25.39%, while 63.89% of roads are severely damaged. Figure 3j shows the structure of the road network, which consists of local roads and arterial roads that do not completely encircle the study area. The majority of the road network was located in the central region, which neighbors the district capital and main roads across Kalimantan. In similar conditions, the distance to the road was classified into ten classes, where the closer the distance, the more beneficial it is for agricultural cultivation.

Analytical hierarchy process Currently, the analytical hierarchy process (AHP) and other multi-criteria decisionmaking (MCDM) techniques have been combined with land suitability evaluation (Pramanik, 2016). AHP, proposed by Saaty (1980), is a method of making decisions in a complex situation and can help determine the best choice among a series of alternatives. In the AHP process, a hierarchy of criteria, sub-criteria, and alternatives is compiled and then pairwise comparisons are used to give relative weight to each parameter in the hierarchy. Meanwhile, geographic information systems (GIS) are the most appropriate analytical tool for efficiently and cost-effectively handling various criteria data on spatial and temporal scales (Greene et al., 2011). Due to its ability to easily obtain weights from a huge variety of criteria and to incorporate enormous volumes of heterogeneous data, GIS-based AHP is particularly wellliked and has been used to address a variety of decisionmaking issues (Chen et al., 2010).

In this study, only pairwise comparisons on nine predetermined parameters were performed to determine the relative weight of each parameter for rice and sorghum crop suitability. The weighted importance of each parameter was determined by consulting the opinions of a team, including experts in the fields of soil science, land resources, and plant ecology, members of agricultural faculties, the National Research and Innovation Agency (BRIN), and local agencies in charge of food crop agriculture. An illustration of a questionnaire matrix is provided in Table 2. While Table 3 provides an explanation of the scale that was given.

Overlay (weight sum) The land suitability map is produced by simple multiplication between the weighted parameters and the score of each sub-parameter based on the Equation [1].

$$S = \sum_{i=1}^{n} W_i X_i$$
^[1]

note: *S* is the total suitability score, W_i is the weight of the selected suitability criteria layer, X_i is the assigned subcriteria score of suitability criteria layer *i*, and *n* is the total number of suitability criteria layers. Furthermore, the natural break Jenk classification method was used to divide the results into four land suitability classes referring to FAO

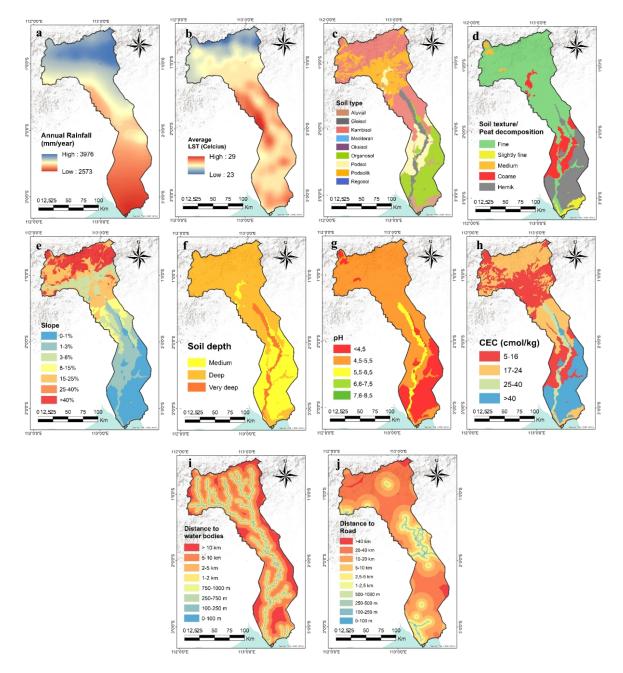


Figure 3 Land suitability parameters: annual rainfall (a), average LST (b), soil type (c), soil texture (d), slope (e), soil depth (f), pH (g), CEC (h), distance to water (i), and distance to road (j).

(1976): highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and not suitable (N). The Jenks natural breaks classification method is aimed at finding the optimum arrangement of values into separate categories. This is accomplished by minimizing each class's average deviation from the class average and maximizing each class's deviation from the averages of the other groups (Chen et al., 2013). This approach provides good adaptability and accuracy in dividing geographical environmental divisions (Chen et al., 2013).

Land allocation scenario The land suitability map was then integrated with spatial data on FAD and land cover to develop scenarios as shown in Table 4. FAD in Katingan consists of conservation forest/HK (457,514 ha or 19%), protected forest/HL (42,510 ha or 2%), permanent production forest/HP (879,433 ha or 37%), limited production forest/HPT (378,419 ha or 16%), and convertible production forest/HPK (393,410 ha or 16%), as shown in Figure 4a. Meanwhile, nonFAD areas/APL are approximately 244,191 ha or 10% of the total area. In addition, land cover in 2022 consists of forest (1,521,670 ha or 74.61%), non-forest vegetation (371,501 ha or 18.22%), built-up area (2,941 ha or 0.14%), mining (9,914 ha or 0.49%), open land (104,387 ha or 5.12%), and water bodies (28,978 ha or 1.42%), as shown in Figure 4b. The scenarios

Parameter									Neigh	nt								Parameter
ratallietei	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	rarameter
																		P_2
D																		P_3
P_1																		
																		P_{n}

XX7 · 14

Table 2 Pairwise comparison questionnaire matrix for land suitability parameters

Note: P =parameter (1n)

Table 3 The fundamental scale for pairwise comparison

Scale	Definition	Description
1	Equal importance	Two criteria enrich equally to the objective
3	Slightly important	Judgments and experience slightly favour one criteria over another
5	Essential important	Judgments and experience strongly favour one over the other
7	Really important	One is strongly favoured and its dominance established in practice
9	Absolutely important	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Adjacent	Used when intermediate importance is needed

Table 4 Land allocation scenario

Scenario		Forest an	ea desig	gnation (F	Description					
Scenario	APL	HPK	HP	HPT	HL	HK	- Description			
1. Bussines as usual										
• Forest	\checkmark						S1 and S2			
Non forest	\checkmark						S1, S2, S3			
2. Utilization FAD scena	ario									
• Forest	\checkmark	\checkmark	\checkmark	\checkmark			S1 and S2, ≤ 2 km from the forest edge			
							for HP and HPT			
Non forest	\checkmark	\checkmark	\checkmark	\checkmark			S1, S2, S3			

Note: APL = other use area; HPK = convertible production forest; HP = production forest; HPT = limited production forest; HL = protection forest; HK = conservation forest; S1 = highly suitable; S2 = moderate suitable; S3 = marginally suitable

were developed in accordance with Indonesian government regulations in the forestry sector, making their implementation possible.

Business as usual (BAU) is defined as a condition wherein land allocation takes place only outside FAD, in both unforested and forested areas. In forested areas, land suitability classes of highly suitable (S1) and moderately suitable (S2) were required. Under scenarios involving the utility of FAD, allocations were allowed in HPK, HP, and HPT zones, but marginally suitable (S3) classes might only be allocated in unforested areas. In addition, allocation in forested areas in HP and HPT was restricted to a maximum of 2 km from the forest edge. There are no restrictions on the allocation of HPK since, based on the forestry regulation, the area has been allocated for development activities outside the forestry sector. Meanwhile, HL and HK were excluded from considering the potential allocation of food crops as a form of prevention and support for preserving conservation values and the supporting life system.

Results and Discussion

Parameters weight and sub-parameter score The parameter weights were set according to the judgments of five experts. Weights were obtained through the pairwise

comparison matrices as shown in Table 5 and Table 6 for rice and sorghum crops, with a consistency ratio (CR) value of 0.043 and 0.029, respectively. Considering the suggested value threshold of 0.1, these measured values adhere to these criteria (Saaty, 1980). The calculation of the pairwise comparison matrix revealed that the distance to water sources, pH, and soil type consecutively had a greater weight than other parameters. Meanwhile, for sorghum crops, pH, soil type, and distance to road parameters exposed a greater weight than the other parameters, consecutively. The difference in parameter weights between rice and sorghum crops reflected varying the environmental conditions required for optimal crop growth by each species.

After parameters were weighted, each sub-parameter was assigned a score based on its level of suitability for rice and sorghum cultivation. The scores ranged from 1 to 10 and corresponded to the suitability criteria for each crop, as established by the technical guidelines for assessing the suitability of strategic agricultural cropland (Wahyunto et al., 2016). Scores for soil type sub-parameter were determined by expert opinion, whereas the scores for the proximity subparameter were based on prior studies (Pramanik, 2016; Widiatmaka et al., 2016; Yalew et al., 2016).

The climate parameter is an aggregate value derived from the overlaying of annual precipitation data and the LST

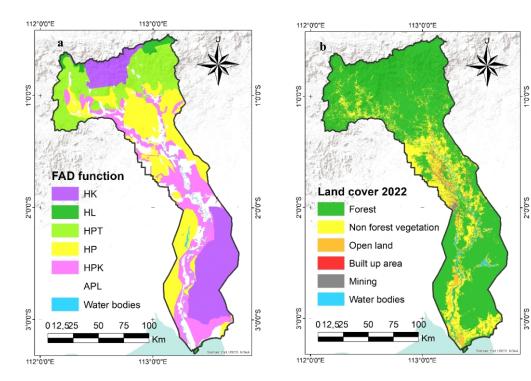


Figure 4 Forest area designation (a), land cover 2022 (b).

Table 5 Pairwise comparison matrix and weight of rice crop

-			-	-							
Parameter		1	2	3	4	5	6	7	8	9	Weight (%)
Climate	1	1	1/3	4/9	1 4/9	5/6	2/5	2/5	1 5/7	2/3	7.80
Soil type	2	3	1	1 5/7	1	1 1/2	2/3	1 1/9	1 3/8	1	13.11
Soil texture	3	2 1/4	4/7	1	1	1	2/5	1/2	5/9	3/7	7.76
Slope	4	2/3	1	1	1	1 1/6	1/2	5/9	2/5	3/7	7.27
Soil depth	5	1 1/5	2/3	1 1/9	6/7	1	1/3	1/2	5/8	1/2	7.07
pH	6	2 1/2	1 1/2	2 2/5	2	3	1	1 1/4	1 1/3	3/5	15.68
CEC	7	2 4/7	1	1 5/6	1 7/9	2	4/5	1	3/5	3/8	11.65
Distance to road	8	4/7	5/7	1 4/5	2 2/5	1 4/7	3/4	1 5/8	1	1/2	11.33
Distance to water	9	1 5/9	1	2 2/7	2 2/7	2	1 5/8	2 2/3	2 1/7	1	18.33

 $\label{eq:maximum} \begin{array}{l} \textit{Maximum eigen value} \left(\lambda_{max}\right) = 9.503, n = 9, \textit{Random index} \left(RI\right) = 1.46 \\ \textit{Concistency indeks} \left(CI\right) = (\lambda maxn)/(n1) = 0.063 \end{array}$

Consistency ratio (CR) = CI/RI = 0.043

Table 6 Pairwise comparison matrix and weight of sorgum crop

Parameter		1	2	3	4	5	6	7	8	9	Weight (%)
Climate	1	1	3/5	1	1 4/9	1	1/2	5/6	1 3/5	1 4/5	10.68
Soil type	2	1 2/3	1	1	1 2/3	1 1/9	4/5	1 3/8	2 1/2	1 2/3	14.81
Soil texture	3	1	1	1	1 5/9	1	5/8	5/6	3/4	1 2/7	10.23
Slope	4	2/3	3/5	2/3	1	3/4	5/8	5/7	4/9	1 1/6	7.52
Soil depth	5	1	1	1 1/9	1 1/3	1	3/8	3/7	5/9	1 2/7	8.89
рН	6	2 1/6	1 1/4	1 3/5	1 3/5	2 5/7	1	1 1/4	1	1 1/3	15.84
CEC	7	1 1/5	5/7	1 1/5	1 2/5	2 3/8	4/5	1	3/4	1 1/4	11.87
Distance to road	8	5/8	2/5	1 1/3	2 1/4	1 4/5	1	1 1/3	1	1 1/9	12.01
Distance to water	9	5/9	3/5	7/9	6/7	7/9	3/4	4/5	1	1	8.15

Max. eigen value $(\lambda_{max}) = 9.34$, n = 9, Random index (RI) = 1.46

Concistency indeks (CI) = $(\lambda maxn)/(n1) = 0.0425$

Consistency ratio (CR) = CI/RI = 0.029

average, where annual precipitation is identified as the main limiting factor. Consequently, the study area was classified into marginally suitable (S3) and unsuitable (N) classes for paddy crops, meanwhile for sorghum, the entire study area was considered unsuitable (N). Thus, the score given is relatively small between 3 and 5. A prior study indicated excessive precipitation and rises in precipitation proved counterproductive to food crop production (Bhardwaj et al., 2022; Massagony et al., 2022).

Furthermore, alluvial soils had the highest score, followed by gleisol, cambisol, and organosol soil for paddy cultivation. Alluvial soil is regarded as a suitable soil for paddy cultivation due to its fertility, which may provide a wide range of nutrients and minerals required for crop growth. Also, it supports better water retention and becomes an ideal texture for paddy cultivation. Meanwhile, cambisol and podzolic soils, which cover the largest area, were considered the most suitable for sorghum cultivation. The sub-parameter of soil texture is given an equal score for both types of crops; mineral soils are classified into rather fine, fine, and medium classes with scores of 10, 9, and 8, respectively. In contrast, a coarse or sandy texture causes poor water retention, low nutrient retention, and susceptibility to erosion and is considered unsuitable (N) for cultivating food crops, hence it receives a very low score. Meanwhile, the level of hemic decomposition in organic soil (peatlands) could be classified as moderately suitable (S2) and marginally suitable (S3) classes; however, a relatively low score is given as a form of safeguard in expanding agriculture areas on peatlands.

Furthermore, flat areas were judged as the most appropriate for agriculture and were therefore assigned the highest score, which declines as slope steepness increases. According to Wahyunto et al. (2016), maximum slope appropriate for rice and sorghum cultivation was 15%. Meanwhile, the soil depth in study areas exceeding 50 cm is generally suitable for rice and sorghum cultivation, thus, the score given is relatively high. In terms of soil pH, rice and sorghum have different requirements to grow optimally. Rice optimally grows in slightly acidic soil pH (5.56.5), whereas sorghum requires neutral soil pH (6.67.5) (Wahyunto et al., 2016).

In addition, the two distance parameters are given a high score for the nearest location, and viceversa. This is based on consideration of the ease of management, where the closer the location is to water sources, the less effort is required to meet the water needs of crops. Similarly, seeding, maintenance, and harvesting processes will be easier to manage the closer the area is to the road. Distribution of area and score of sub-parameters as shown in Table 7.

Land suitability map After weighing each parameter and sub-parameter, all spatial data were overlaid to generate the final value of each land analysis unit. The results showed that the total value of land analysis units for rice ranged from 3.92–9.21. Reclassification into land suitability classes (S1, S2, S3, and N) was generated using the natural breaks Jenks method in ArcGIS software. The proportion of rice land suitability generated consisted of highly suitable (S1) 4% (74,254 ha), moderately suitable (S2) 6% (130,634 ha), marginally suitable (S3) 38% (769,078 ha), and not suitable

(N) 52% (1,036,084 ha) as shown in Figure 5.

Most of the highly suitable areas (S1) were located around the Katingan riverbank. This condition was mostly driven by the distance to the river (18.33% weight). In addition, this area is characterized by gleisol soil, which is highly suitable for paddy cultivation. Meanwhile, alluvial soils located in the south of the study area (Katingan Kuala) influenced the level of land suitability in the region, marking highly suitable (S1) and moderately suitable (S2). This area has currently been a rice production center, which has propelled Katingan to emerge as the leading rice-producing regency in Central Kalimantan.

Marginally suitable area (S3), which dominates 38% of the region, is proportionally distributed from north to south. This potential can be further utilized to support rice production in conditions of limited land availability in the S1 and S2 areas. This marginal suitability is due to varying constraints on parameters. Thus, the improvement efforts required for rice farming are extremely diverse. In the southern region of the study area, for instance, the land is marginally suitable due to the existence of peatland ecosystems with hemic-decomposition levels and tidal swamp areas. In this location, rice productivity can be improved by selecting more adapted varieties or local types that are more tolerant to floods, inundation, and drought and more resistant to high soil acidity, Fe poisoning, low pH, and crops-organism issues (Susilawati et al., 2015), as well as improving cropping techniques (Cahya et al., 2022). In addition, insufficient infrastructure, such as road access and irrigation, remained to be an obstacle to agricultural development in this location, particularly in tidal swamp areas (Fahmid et al., 2022).

In the north, unsuitable classes (N) were influenced by the steep slope, while the south was characterized by peat soils, which have a very acidic pH and a very high CEC. Extremely high average annual rainfall, according to Wahyunto et al. (2016), suggested an unsuitable (N) area for growing rice and sorghum. Excessive precipitation can lead to nutrient loss, soil erosion, a lack of oxygen, crop death from root rot, fungal and bacterial threats, and a decrease in rice yields (Dulbari et al., 2018). Hence, it is important for all land categories, including S1 and S2 classes, to have proper water treatment management.

Furthermore, the distribution pattern and proportion of sorghum-suitable land are depicted in Figure 6. The figure shows that the total value of land analysis units for sorghum ranges from 3,29–8,05. Classification using the natural break jenk technique yielded a highly suitable class (S1) of 5% (108,956 ha), a moderately suitable class (S2) of 19% (377,493 ha), a marginally suitable class of 48% (976,820 ha), and an unsuitable class (N) of 28%. (574,635 ha). Similar to rice crops, a highly suitable area for sorghum crops is located around the Katingan Riverbank.

Potential land allocation The land suitability map provided the baseline for generating potential land by taking into account the current condition of the FAD functions and forest land cover. Most of the Katingan area (90%) is designated as a forest area (FAD), however, 74.61% of the area remained forested. There are almost 340 thousand ha, or 19%, of FAD currently unforested. The results showed that 43% of HPK

Table 7Distribution of area and score of sub-parameters

Parameters	Sub parameter	Description		Area	Score		
1 arameters	-	*	Area (ha)	Proportion (%)	Paddy	Sorgum	
Climate	S3	Paddy	271,716	13.32	5	-	
	Ν	Paddy	1,767,684	86.68	3	-	
	Ν	Sorghum	2,039,400	100	-	3	
Soil type	Alluvial		89,986	4.41	10	2	
• •	Gleisol		110,428	5.42	9	6	
	Cambisol		751,937	36.88	8	10	
	Mediterranean		261	0.01	6	9	
	Oxisol		312	0.02	3	7	
Organo Podsol	Organosol		415,789	20.39	7	3	
			225,772	11.07	1	1	
	Podzolic		444,039	21.78	5	8	
	Regosol		266	0.01	2	4	
Soil texture	Fine	Sandy clay, silty clay, clay	1,321,075	64.80	9	9	
	Slightly fine	Clay loam, silty clay loam, Sandy clay loam	52,347	2.57	10	10	
Medium	Medium	Loam, silt, silt loam, sandy	23,542	1.15	8	8	
	Coarse	loam Sand	226,038	11.09	1	1	
Poot	Coarse Hemic	Sallu	/	20.39	5	1 5	
	Tienne		415,789	20.39	3	3	
	Elat	0.1	465 200	20.02	10	10	
Stope (%)	Flat	0-1	465,398	22.83	10	10	
	Rather flat	1-3	349,325	17.13	9	9	
decomposition Slope (%) Soil depth (cm) pH	Undulating	3-8	351,376	17.23	8	8	
	Gently sloping	8-15	111,995	5.49	5	6	
	Hilly	15-25	393,902	19.32	3	3	
	Strong hilly	25-40	45,391	2.23	1	1	
	Mountainous	>40	321,405	15.76	1	1	
Soil depth (cm)	Mineral (very deep)	>100	111,072	5.45	10	10	
	Mineral (deep)	76–100	1,286,158	63.08	9	9	
	Mineral (medium)	51-75	225,772	11.07	8	8	
	· · · · ·		,				
	Peat soil	101-200	415,789	20.39	5	5	
pН	Very acidic	<4.5	452,145	22.18	5	1	
	Acidic	4.5-5.5	1,475,691	72.38	7	3	
	Slightly acidic	5.5-6.5	110,428	5.42	10	8	
	Neutral	6.6-7.5	261	0.01	8	10	
	Slightly alkaline	7.6-8.5	266	0.01	6	7	
$CEC cmol(+) kg^{-1}$	Low	5-16	717,801	35.21	7	7	
ele enioi(+) kg							
Soil type Soil texture Peat Recomposition Soil depth (cm) Soil depth (cm) H CEC cmol(+) kg ⁻¹	Moderate	17–24	781,698	38.34	8	8	
	High	25-40	110,689	5.43	9	9	
	Very high	>40	428,603	21.02	10	10	
Distance to road	1	0–100 m	8,314	0.41	10	10	
	2	100–250 m	12,654	0.62	9	9	
	3	250–500 m	20,037	0.98	8	8	
oil type oil texture eat ecomposition lope (%) oil depth (cm) H EC cmol(+) kg ⁻¹	4	500–1 km	39,615	1.94	7	7	
	5	1–2.5 km	105,832	5.20	6	6	
	6	2.5–5 km	153,224	7.52	5	5	
	7	5–10 km	289,165	14.19	4	4	
	8	10–20 km	589,853	28.95	3	3	
	9	20–40 km	766,217	37.61	2	2	
	10	>40 km	52,269	2.57	1	1	
Distance to water	1	0–100 m	33,638	1.65	10	10	
05001005	2	100–250 m	43,337	2.12	9	9	
	3	250–750 m	132,385	6.49	8	8	
	4	750–1 km	58,519	2.87	7	7	
	5	1–2 km	215,848	10.58	6	6	
	6	2–5 km	563,154	27.61	5	5	
	8 7		,	32.17	4	4	
		5–10 km	656,013				
	8	>10 km	336,508	16.50	3	3	

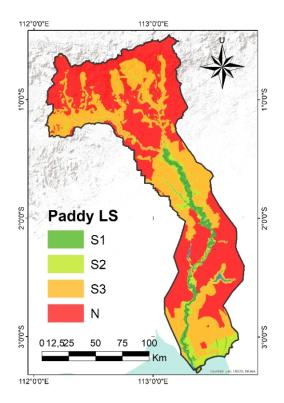


Figure 5 Land suitability map for paddy.

area, or 185 thousand ha, had no longer been forested, whereas 21% of HP area, or 107 thousand ha, exposed a similar conditions. This situation occurred in the central part of the study area, which is near the capital (Kasongan), as well as in the southern region, along the edge of the Sebangau National Park forest and the HL ecosystem restoration area. Figure 4b shows the location of HPK, which is commonly adjacent to APL. This indicates that the area is more accessible, enabling it to be prioritized in the allocation and development of agricultural lands.

A scenario for rice cropland allocation is shown in Figure 7. Based on this, the potential land allocation area for S1, S2, and S3 classes decreased by 4%, 11%, and 72%, respectively. In APL, the remaining potential allocation areas for land S1 and S2 are 37 thousand ha and 39 thousand ha, respectively. Nonetheless, around 33% of the area is still forested, which is considered deforestation potential. There is relatively significant potential for the allocation of S1 and S2 lands in HPK, with respective areas of 33 thousand ha and 59 thousand ha. However, 46% of this area remains forested. Meanwhile, there is a potential allocation of more than 82 thousand hectares of unforested S3 land on HPK. Thus, we underline the enormous allocation potential in production forests, particularly HPK

The scenario of land allocation for sorghum crops is shown in Figure 8. The potential land allocation for S1, S2, and S3 decreased by 15%, 14%, and 82%, respectively, after the implementation of the scenario. Approximately 589 thousand ha of land are potentially available for allocation, of which 35% (205 thousand ha) are currently forested. In this area, 71% is located within the FAD, which consists of HP, HPT, and HPK in the proportions of 37%, 13%, and 50%, respectively.

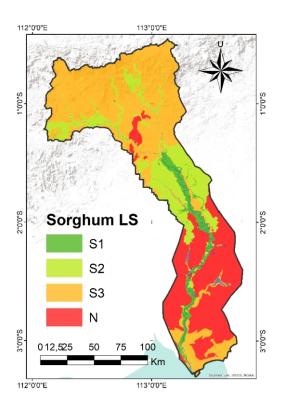


Figure 6 Land suitability map for sorghum.

The impact of land allocation As previously stated, there is potential for the allocation of paddy and sorghum, both of which exist in forested areas. Forests, however, are one of the primary sources of land for agriculture. Gibbs et al. (2010) discovered that between 1980 and 2000, more than 55% of new agricultural land in the tropics was developed from primary forest, while 28% originated from secondary forest. This condition has impacts on regional ecology, economy, and society. Prior studies have proven an increased risk of soil erosion, floods (de la Paix et al., 2013) biodiversity loss (Betts et al., 2017) warmer and drier local conditions (Lawrence & Vandecar, 2015), and other natural disasters as adverse impacts of this phenomenon. Furthermore, it is alleged that the massive expansion of agricultural lands, such as the food estate program, poses a risk of socioeconomic impact such as unequal agricultural infrastructure support triggering social conflict, no clear and clean definition of the area status, leading to tenure conflict, and insufficient infrastructure can impede food production and distribution (Yeny et al., 2022).

On the other hand, it is expected that the implementation of this potential allocation, particularly on highly suitable land, will substantially increase regional food production. For instance, assuming all potential allocations for S1 class covering an area of 71.45 thousand ha are developed as rice farming land, where the existing condition of rice fields is 22 thousand ha, there will be an additional 49.4 thousand ha of rice fields. During a single period of cultivation, using the average paddy yield of 2.65 tons per ha in Katingan, it is estimated that 131 thousand tons of grain, or the equivalent of 77.3 thousand tons of rice, would be produced. Thus, in the case of two harvesting periods annually as typical in Katingan Kuala District, the total rice production is estimated to reach 175 thousand tons year⁻¹. Referring to the average Indonesian

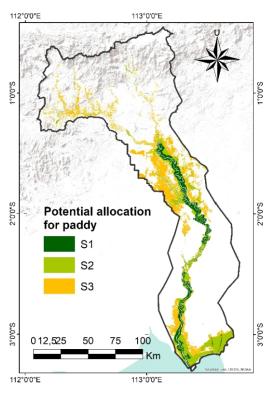


Figure 7 Potential allocation for paddy.

rice consumption of 101.65 kg capita⁻¹ year⁻¹, this production could sustain 1,7 million people, or nearly 63% of Central Kalimantan's total population. Nonetheless, we observe that 41.6% of the area is still forested, to be considered a potential deforestation risk. Given the potential for a relatively vast area, we suggest that land allocation for the development of food crops might be prioritized in non-forested areas.

Conclusion

The results showed that land in the categories of highly suitable (S1) and moderately suitable (S2) for rice was 4% (74.254 ha) and 6% (130.634 ha), respectively, while for sorghum was 5% (108.956 ha) and 19% (377.493 ha). The areas around the Katingan River were highly suitable for both types of crops. The implementation of a scenario integrating FAD and land cover resulted in a relatively slight decline in that area. The potential allocation for rice crops in classes S1 and S2 decreased by 4% and 11%, respectively, while for sorghum crops it decreased by 15% and 14%. This condition revealed that the allocation potential is dominantly located in FAD. HPK and HP, particularly, have considerable allocation potential for both rice and sorghum crops. However, it should be recalled that there is still forested land cover within the potential allocation that must be considered when deciding to exploit it. Hence, in order to conserve the remaining tropical forest, we recommend prioritizing agricultural expansion in deforested areas.

Acknowledgment

We acknowledge the support given by the Ministry of National Development Planning/National Development

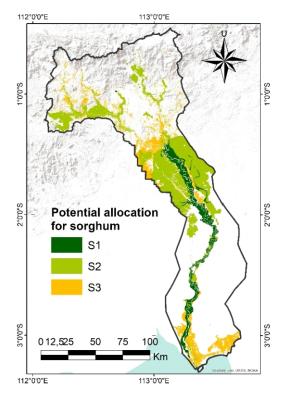


Figure 8 Potential allocation for sorghum.

Planning Agency (BAPPENAS) for providing funds and opportunities for this research. The authors would like to thank the resource person for determining the weight of the LSA parameters.

References

- Abdelrahman, M. A. E., Natarajan, A., & Hegde, R. (2016). Assessment of land suitability and capability by integrating remote sensing and GIS for agriculture in Chamarajanagar District, Karnataka, India. Egyptian Journal of Remote Sensing and Space Science, 19(1), 125–141. https://doi.org/10.1016/j.ejrs.2016.02.001
- Akinci, H., Özalp, A. Y., & Turgut, B. (2013). Agricultural land use suitability analysis using GIS and AHP technique. *Computers and Electronics in Agriculture*, 97, 71–82. https://doi.org/10.1016/j.compag.2013.07.006
- Aprile, F., & Lorandi, R. (2012). Evaluation of cation exchange capacity (CEC) in tropical soils using four different analytical methods. *Journal of Agricultural Science*, 4(6), 278–289. https://doi.org/10.5539/ jas.v4n6p278
- Araújo Costa, R. C., Pereira, G. T., Tarlé Pissarra, T. C., Silva Siqueira, D., Sanches Fernandes, L. F., Vasconcelos, V., ..., & Pacheco, F. A. L. (2019). Land capability of multiple-landform watersheds with environmental land use conflicts. *Land Use Policy*, *81*, 689–704. https://doi.org/10.1016/j.landusepol.2018.11.041

Betts, M. G., Wolf, C., Ripple, W. J., Phalan, B., Millers, K.

A., Duarte, A., ..., & Levi, T. (2017). Global forest loss disproportionately erodes biodiversity in intact landscapes. *Nature*, *547*(7664), 441–444. https://doi.org/10.1038/nature23285

- Bhardwaj, M., Kumar, P., Kumar, S., Dagar, V., & Kumar, A. (2022). A district-level analysis for measuring the effects of climate change on production of agricultural crops, i.e., wheat and paddy: evidence from India. *Environmental Science and Pollution Research*, 29(21), 31861–31885. https://doi.org/10.1007/s11356-021-179 94-2
- [BPS] Badan Pusat Statistik. (2018). *Luas lahan sawah*. Retrieved from https://www.bps.go.id/indicator/53/179/ 1/luas-lahan-sawah.html
- [BPS] Badan Pusat Statistik. (2021a). *Hasil sensus penduduk 2020*. Berita Resmi Statistik No.7/01/Th. XXIV.
- [BPS] Badan Pusat Statistik. (2021b). *Luas panen dan produksi padi di Indonesia 2020*. Jakarta: Direktorat Statistik Tanaman Pangan, Hortikultura, dan Perkebunan.
- [BPS Katingan] Badan Pusat Statistik Kabupaten Katingan. (2020). Rata-rata jumlah hujan dan curah hujan setiap bulan di Kabupaten Katingan 20152019. Retrieved from https://katingankab.bps.go.id/indicator/151/190/1/ratarata-jumlah-hujan-dan-curah-hujan-setiap-bulan-dikabupaten-katingan.html
- [BPS Katingan] Badan Pusat Statistik Kabupaten Katingan. (2023). Kabupaten Katingan dalam angka 2022. Retrieved from https://katingankab.bps.go.id/ publication/2023/02/28/7d6751ed6c2f056b68069260/ kabupaten-katingan-dalam-angka-2023.html
- Cahya, M., Suwignyo, R. A., Sodikin, E., & Baral, H. (2022).
 Increasing rice productivity in degraded peatlands using improved planting methods and rice varieties. *BIOVALENTIA: Biological Research Journal*, 8(1), 69–82. https://doi.org/10.24233/biov.8.1.2022.246
- Chen, J., Yang, S., Li, H., Zhang, B., & Lv, J. (2013). Research on geographical environment unit division based on the method of natural breaks (Jenks). *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences-ISPRS Archives*, 40(4W3), 47–50. https://doi.org/10.5194/ isprsarchives-XL-4-W3-47-2013
- Chen, Y., Yu, J., & Khan, S. (2010). Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. *Environmental Modelling and Software*, 25(12), 1582–1591. https://doi.org/10.1016/ j.envsoft.2010.06.001
- de la Paix, M. J., Lanhai, L., Xi, C., Ahmed, S., & Varenyam, A. (2013). Soil degradation and altered flood risk as a consequence of deforestation. *Land Degradation and Development*, 24(5), 478–485. https://doi.org/10.1002/

ldr.1147

- Dulbari, Santosa, E., Koesmaryono, Y., & Sulistyono, D. E. (2018). Pendugaan kehilangan hasil pada tanaman padi rebah akibat terpaan angin kencang dan curah hujan tinggi. *Jurnal Agronomi Indonesia*, *46*(1), 17–23. https://doi.org/10.24831/jai.v46i1.14376
- Fahmid, I. M., Wahyudi, Agustian, A., Aldillah, R., & Gunawan, E. (2022). The potential swamp land development to support food estates programmes in Central Kalimantan, Indonesia. *Environment and* Urbanization ASIA, 13(1), 44–55. https://doi.org/ 10.1177/09754253221078178
- [FAO] Food and Agriculture Organization. (1976). A framework for land evaluation. FAO Soils Bulletin 32. Rome: FAO.
- [FAO] Food and Agriculture Organization. (2020). *Global* forest assessment resources 2020. Main report. Rome: FAO.
- [FAO] Food and Agriculture Organization. (2020). *Early* warning early action report on food security and agriculture (AprilJune 2020). Rome. Retrieved from https://doi.org/10.4060/ca8606en
- Gaveau, D. L. A. (2017). What a difference 4 decades make: Deforestation in Borneo since 1973. CIFOR. https://www.cifor.org/knowledge/publication/6552/
- Gibbs, H. K., Ruesch, A. S., Achard, F., Clayton, M. K., Holmgren, P., Ramankutty, N., & Foley, J. A. (2010). Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. *Proceedings of* the National Academy of Sciences of the United States of America, 107(38), 16732–16737. https://doi.org/ 10.1073/PNAS.0910275107
- Greene, R., Devillers, R., Luther, J. E., & Eddy, B. G. (2011). GIS-based multiple-criteria decision analysis. *Geography Compass*, 5(6), 412–432. https://doi.org/ 10.1111/j.1749-8198.2011.00431.x
- Hardjowigeno, S. (1987). *Ilmu tanah*. Jakarta: Akademika Pressindo.
- Helyar, K. R., Porter, W. M., & Robson, A. D. (1989). Soil acidity and plant growth. Sydney: Academic Press.
- Huffman, G. J., Adler, R. F., Bolvin, D. T., Gu, G., Nelkin, E.
 J., Bowman, K. P., ..., & Wolff, D. B. (2007). The TRMM multisatellite precipitation analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *Journal of Hydrometeorology*, 8(1), 38–55. https://doi.org/10.1175/JHM560.1
- Hulley, G. C., Ghent, D., Göttsche, F. M., Guillevic, P. C., Mildrexler, D. J., & Coll, C. (2019). Land surface temperature. In G. C. Hulley, & D. Ghent (Eds.), *Taking* the temperature of the earth (pp. 57–127). Elsevier.

https://doi.org/10.1016/b978-0-12-814458-9.00003-4

- Kemmitt, S. J., Wright, D., Goulding, K. W. T., & Jones, D. L. (2006). pH regulation of carbon and nitrogen dynamics in two agricultural soils. *Soil Biology and Biochemistry*, *38*(5), 898–911. https://doi.org/10.1016/j.soilbio.2005. 08.006
- Kihoro, J., Bosco, N. J., & Murage, H. (2013). Suitability analysis for rice growing sites using a multicriteria evaluation and GIS approach in great Mwea region, Kenya. *SpringerPlus*, 2(1), 1–9. https://doi.org/ 10.1186/2193-1801-2-265
- [KLHK] Kementerian Lingkungan Hidup dan Kehutanan. (2021). Rekalkulasi penutupan lahan Indonesia tahun 2020. Jakarta: Direkorat Inventarisasi dan Pemantauan Sumber Daya Hutan. Direktorat Jenderal Planologi Kehutanan dan Tata Lingkungan. Kementerian Lingkungan Hidup dan Kehutanan RI.
- Lawrence, D., & Vandecar, K. (2015). Effects of tropical deforestation on climate and agriculture. *Nature Climate Change*, 5(1), 27–36. https://doi.org/10.1038/ nclimate2430
- Massagony, A., Tam Ho, T., & Shimada, K. (2022). Climate change impact and adaptation policy effectiveness on rice production in Indonesia. *International Journal of Environmental Studies*, 80(5), 1373–1390. https://doi.org/10.1080/00207233.2022.2099110
- Montgomery, B., Dragićević, S., Dujmović, J., & Schmidt, M. (2016). A GIS-based logic scoring of preference method for evaluation of land capability and suitability for agriculture. *Computers and Electronics in Agriculture*, 124, 340–353. https://doi.org/10.1016/ j.compag.2016.04.013
- Mustafa, A. A., Singh, M., Sahoo, R. N., Ahmed, N., Khanna, M., Sarangi, A., & Mishra, A. K. (2011). Land suitability analysis for different crops: A multi criteria decision making approach using remote sensing and GIS. *Researcher*, *3*(12), 61–84.
- Ohadi, S., Littlejohn, M., Mesgaran, M., Rooney, W., & Bagavathiannan, M. (2018). Correction: Surveying the spatial distribution of feral sorghum (*Sorghum bicolor* L.) and its sympatry with johnsongrass (*S. halepense*) in South Texas. *PLoS ONE*, *13*(7), e0200984. https://doi.org/10.1371/journal.pone.0200984
- Pramanik, M. K. (2016). Site suitability analysis for agricultural land use of Darjeeling District using AHP and GIS techniques. *Modeling Earth Systems and Environment*, 2(2), 56. https://doi.org/10.1007/s40808-016-0116-8

- Rhoades, J. D. (1983). Cation exchange capacity. Methods of Soil Analysis: Part 2 Chemical and Microbiological Properties, 9, 149–157.
- Saaty, T. L. (1980). *The analytic hierarchy process*. New York: McGraw-Hill.
- Sarwono, H. (1995). *Ilmu tanah*. Jakarta: Akademik Pressindo.
- Susilawati, Mokhtar, S., Elistya, S., Agustini, S., & Suparman. (2015). Inventarisasi sumberdaya genetik padi lokal spesifik Kalimantan Tengah. In T. P. Priyatno (Ed.), *National conference on agricultural genetic resources: Local genetic resource management as a source of regional economic growth* (274286). IAARD Press.
- Wahyunto, Hikmatullah, Suryani, E., Tafakresnanto, C., Ritung, S., Mulyani, A., ..., & Nursyamsi, D. (2016). Petunjuk teknis pedoman penilaian kesesuaian lahan untuk komoditas strategis tingkat semi detail skala 1:50.000. Bogor: Balai Besar Penelitian dan Pengembangan Sumberdaya Lahan Pertanian, Badan Penelitian dan Pengembangan Pertanian.
- Wan, Z., Hook, S., Hulley, G. (2015). MOD11A1 MODIS/Terra land surface temperature/emissivity daily L3 global 1km SIN Grid V006 (NASA EOSDIS Land Processes Distributed Active Archive Center) [Data set]. NASA EOSDIS. https://doi.org/10.5067/MODIS/ MOD11A1.006
- Widiatmaka, Ambarwulan, W., Setiawan, Y., & Walter, C. (2016). Assessing the suitability and availability of land for agriculture in tuban regency, East Java, Indonesia. *Applied and Environmental Soil Science*, 2016, 7302148. https://doi.org/10.1155/2016/7302148
- Yalew, S. G., van Griensven, A., Mul, M. L., & van der Zaag, P. (2016). Land suitability analysis for agriculture in the Abbay basin using remote sensing, GIS and AHP techniques. *Modeling Earth Systems and Environment*, 2, 101. https://doi.org/10.1007/s40808-016-0167-x
- Yeny, I., Garsetiasih, R., Suharti, S., Gunawan, H., Sawitri, R., Karlina, E., ..., & Takandjandji, M. (2022). Examining the socio-economic and natural resource risks of food estate development on peatlands: A strategy for economic recovery and natural resource. *Sustainability*, 14(7), 3961. https://doi.org/10.3390/su14073961
- Zhang, J., Su, Y., Wu, J., & Liang, H. (2015). GIS based land suitability assessment for tobacco production using AHP and fuzzy set in Shandong Province of China. *Computers* and Electronics in Agriculture, 114, 202–211. https://doi.org/10.1016/j.compag.2015.04.004