Mapping Land Suitability for Sugarcane Crop with Fuzzy AHP and Multi-Criteria Evaluation

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Abstract

Mapping land suitability is crucial for identifying appropriate land use for site selection and land-use planning. However, climate changes exacerbate water shortages and droughts, significantly affecting land suitability and resulting in crop yield losses. Therefore, it is important to consider drought conditions in land suitability evaluations by incorporating evapotranspiration to reflect the water balance and mitigate the climate change impacts. This study aimed to map the sugarcane land suitability in Northeastern Thailand using Global Navigation Satellite System-based Precipitable Water Vapor (GNSS-PWV), fuzzy AHP and multi-criteria evaluation. Six significant criteria were selected for sugarcane land suitability mapping: the ETDI as drought index, slope, soil texture, distance from the river, distance from the road and distance from the sugar mill. Land suitability for sugarcane cultivation was evaluated by integrating the fuzzy AHP and multiple criteria evaluation. The results indicated that ETDI and distance from river were the most influential factors, with average weights of 0.66 and 0.34, respectively. Suitable areas for sugarcane were mostly found in the moderately suitable class (S2; 49.6%), followed by the marginally suitable class (S3; 36.0%) and the highly suitable class (S1; 11.2%). Actual sugarcane cultivation areas were mainly distributed in the S3 class (49.0%), followed by 43.2% in the S2 class and 6.7% in the S1 class. The S2 class areas could be enhanced to the S1 class by implementing irrigation systems and establishing small ponds to reduce the risk of drought, potentially expanding S1 class areas by 2.7 times and increasing yields by approximately 1.1 tons/ha. Potential areas within the S1 class were 6,519 km^2 with Nakhon Ratchasima province having the greatest potential areas (35%). Further research on a larger scale, covering the entire country, is necessary to improve the accuracy of the land suitability map in addressing the challenges posed by global climate change.

Keywords: Fuzzy AHP, GNSS-PWV, Land Suitability Mapping, Multi-Criteria Evaluation, Sugarcane

1. Introduction

Climate change is a significant global issue, contributing to various environmental challenges such as droughts, heat waves, storms, warming oceans, melting glaciers, and rising sea levels [1]. These changes significantly impact the agricultural sector, affecting both the quantity and quality of crop yields such as rice [2] and [3], maize [4] and [5], and sugarcane [6], especially in the countries in the tropical zone. In Thailand, sugarcane production is particularly susceptible to climate change, with severe droughts [6] and [7] causing a noticeable decrease in yields since 2015. It is projected that severe drought will continue to affect land suitability and further reduce crop yields [8][9] and [10]. Most sugarcane in Thailand is also grown in rainfed areas, especially in the Northeast and Central regions, making the crops highly vulnerable to water shortages. Consequently, sugarcane production requires specific consideration to alleviate the impacts of drought. Droughts are major natural disasters that impact the environment, society, and economy worldwide [11].

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These are often indicated in terms of drought indices, which are simple to use and consider various hydrological and meteorological parameters to characterize drought severity, duration, and spatial extent.

Agricultural drought specially refers to periods of water deficit that negatively affect crop growth and yields. Common agricultural drought indices include the Evapotranspiration Deficit Index (ETDI), the Standardized Precipitation Evapotranspiration Index (SPEI) and the Soil Moisture Deficit Index (SMDI) [12] [13] [14] and [15]. This study selects the ETDI as an agricultural drought indicator because it considers the spatial variability of hydrological variables linked to land cover, soil type and meteorological factors. In addition, this index identifies crop water stress by comparing actual evapotranspiration (AET) with potential evapotranspiration (PET), and it helps identify short-term drought impacts on agriculture [13] and [14].

Potential evapotranspiration (PET) is an important parameter reflecting the water balance, which is used to assess drought indices such as SPEI, SPI and ETDI [13] [14] [15] and [16]. Several procedures are employed to compute PET, including the eddy covariance method [17] [18] and [19], the Penman-Monteith (PM) model [20] and [21], and remote sensing technology [22] and [23]. While the eddy covariance method and PM model are suitable for small areas, remote sensing technology can estimate ET over large areas. However, the accuracy of remote sensing is limited by cloud cover, leading to overestimation and imprecision in PET calculations from MODIS and GLDAS [16] [24] and [25]. To improve the accuracy and spatial-temporal resolution of PET, GNSS-PWV is proposed as an alternative approach with continuous data and enhancing PET estimates [16]. Although GNSS-PWV has been employed in water vapor determination and climate research, its application in agricultural research remains understudied. Therefore, this study utilized PWV-derived PET to improve the accuracy and spatial-temporal resolution for PET estimation, identify drought areas, and analyze the land suitability for sugarcane cultivation.

Land suitability analysis (LSA) is a scientific technique used to determine the optimal spatial pattern for the future utilization of land based on various criteria [26] and [27]. It is widely utilized in agriculture to assess land suitability for specific crops, agroforestry, and sustainable development. Recently, the integration of Geographic Information System (GIS), Global Navigation Satellite System (GNSS) and remote sensing data has been applied in LSA, which includes Multi-criteria evaluation (MCE) methods, computer-assisted overlay mapping and Artificial Intelligence (AI) methods [28] and [29]. The MCE also known as multi-criteria decision analysis is one of the most commonly used procedures to analyze land suitability in a GIS environment, which comprises Analytical Hierarchy Analysis (AHP), Ordered Weighted Averaging (OWA), fuzzy and machine learning methods [28]. AHP and OWA use a pair-wise comparison matrix to distinguish a complex operation into couple of criteria. It is a beneficial technique for logically determining the weights of several factors. However, these methods can be biased by expert opinions. To address this issue, fuzzy AHP is employed to standardize multiple criteria [30] and reduce the uncertainty and vagueness in decision-making [28]. The fuzzy AHP technique extends the conventional AHP method and is particularly effective for analyzing land suitability for various crops [31][32] [33] and [34].

Various studies have applied LSA to determine land suitability for crops such as sugarcane [35] [36] and [37], cassava [36], tobacco [32], citrus [38], maize [4] [5] [34] and [39], wheat [34], oil palm [40], and sorghum [5]. Factors used in LSA can be categorized into four main indicators: climatic, hydrology/irrigation, soil, and socioeconomic. Climatic factors include temperature, precipitation, relative humidity, solar radiation, solar hours, wind speed, evapotranspiration, and SPI. Hydrology/irrigation indicators encompass water bodies, rivers, flooding hazards, and groundwater. Soil indicators include slope, soil texture, pH, LULC, organic carbon, soil drainage, elevation, soil type, and electrical conductivity. Socioeconomic factors consider market conditions, such as distance to roads, water sources, population density, average income, and market availability [28]. Land suitability for sugarcane cultivation has been studied in several countries such as Brazil, India and Thailand [33][35] [36] and [37]. These studies have developed land suitability maps to identify the most suitable areas for sugarcane plantations based on soil, climate, topography, land use and socioeconomic criteria. Due to potential variations under different climate change scenarios, it is important to incorporate drought conditions in land suitability evaluations. This study aims to map a precise land suitability for sugarcane cultivation in Northeastern Thailand using GNSS-PWV, along with fuzzy AHP and multi-criteria evaluation approaches. The land suitability map in this study can be as a significant tool for sustainable agriculture practices and government decision-making.

2. Data and Methods

2.1 Study Area

This study focused on Northeastern Thailand, located between latitude range 14 °N to 19 °N and longitude range 101 °E to 106°E. This region is the largest in the country, comprising 20 provinces and covering an area of 168,854 km^2. The elevation ranges from 74 to 1801 meters with a plateau in the northwest that transitions to lowlands in the east. The main soil texture is sandy, with widespread saline soils [41]. This region experiences a tropical climate influenced by the southwest and northeast monsoons. Annual precipitation varies from 1,250 to 2,500 mm with an average of about 1,384 mm during the rainy season [42]. The annual average temperature is about 26.8 °C[43]. In the production year 2020/21, the sugarcane plantation area in this region was approximately 0.74 million hectares, representing 42% of the total plantation areas [7]. Due to irregular rainfall and poor, coarse-textured sandy soils, sugarcane is the most cultivated crop, accounting for about 42% of the country's total sugarcane plantation areas [7]. Consequently, sugarcane cultivation areas in Northeastern Thailand were chosen for this case study. The study area map is illustrated in Figure 1.

2.2 Data Descriptions

Data utilized in this study were collected from different agencies. Most data are secondary data: GNSS CORS, meteorological parameters, satellite images, soil and topography data, socioeconomic data, and sugarcane cultivation areas. In addition, the primary data were obtained by interviewing the sugarcane experts for factor weighting. Table 1 shows the data used and the specifications of the data.

2.3 Methodology

The methodology for mapping sugarcane land suitability in Northeastern Thailand was developed through several processes. GNSS CORS and meteorological data were collected to analyze the Precipitable Water Vapor (PWV) using goGPS software [44], followed by the analysis of site-based PET and grid-based PET [45]. Subsequently, the grid based AET was analyzed using GRASS GIS software [46]. The Evapotranspiration Deficit Index (ETDI), serving as drought index, was then calculated by determining the difference of grid PET and AET [14]. Moreover, slope, soil texture, distance from river, distance from road, distance from sugar mill were gathered from various sources and reclassified using QGIS software. This study defined the values of factors for reclassification based on the guideline of FAO sugarcane land suitability and the literature reviews [28] [33] [39] [40] and [47] presented in Table 2. In addition, the Fuzzy AHP approach was utilized to compute the priority weighting each factor using the approach of Chang's extent analysis [48]. The suitability map was generated through weighted overlay analysis and identifying potential areas for sugarcane cultivation. The flowchart of the methodology is depicted in Figure 2.

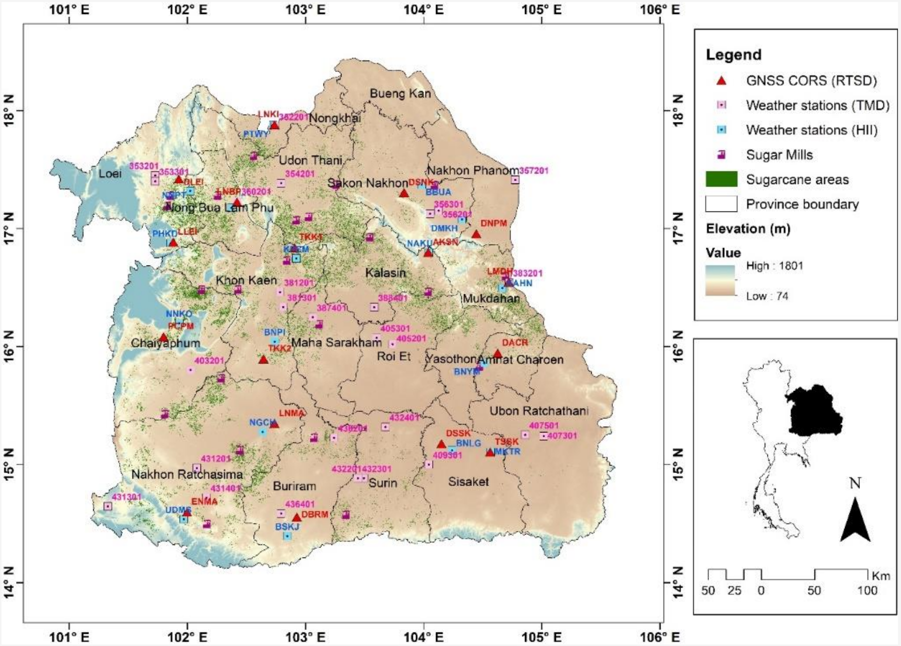

Figure 1: Map of study area in Northeastern Thailand

Table 1: Detailed information of the datasets used in this study

Parameters	Sources	Format	Spatial coverage	Temporal resolution	Temporal coverage
GNSS CORS	RTSD	Point	17 stations	30-second	2020
Meteorological data (pressure, temperature, humidity)	HII	Point	17 stations	Hourly	2020
Temperature, humidity	TMD	Point	27 stations	Daily	2020
Satellite images (MODIS LST-Day)	USGS	Raster	1 km	Daily	2020
Satellite images (Landsat8-9)	USGS	Raster	30 m	16-days	2020
Digital Elevation Model (DEM)	USGS	Raster	30 m	-	2014
Land use and land cover (LULC)	LDD	Polygon	1:25000 Level 2	-	2019
Slope	USGS	Polygon	30 m	-	2013
Soil texture	LDD	Polygon	1:25000	-	2018
Rivers	www.diva-gis.org	Line	-	-	-
Roads	www.diva-gis.org	Line	-	-	-
Sugar mills	OCSB	Point	-	-	2020
Sugarcane plantation areas	OCSB	Polygon	Plot level	Yearly	2020
Questionnaires	Interviewing 10 experts	Table	-	-	-

List of abbreviations. HII is the Hydro-Informatics Institute. LDD is the Land Development Department. LST is the Land Surface Temperature. MODIS is the Moderate Resolution Imaging Spectroradiometer. OCSB is the Office of the Cane and Sugar Board. RTSD is the Royal Thai Survey Development. TMD is the Thai Meteorological Department. USGS is the United States Geological Survey.

3. Results

3.1 Factor Reclassification

The reclassification of six criteria was assessed based on the guideline of FAO sugarcane land suitability and the literature reviews, which includes four classes as illustrated in Figure 3.

3.1.1 Evapotranspiration Deficit Index (ETDI)

The ETDI was considered as an important parameter of agricultural drought monitoring in this study. The drought-prone areas were identified by the normalized ETDI, which involved the reclassification of sub-criteria for sugarcane production (Figure 3 (a)). It could be determined that high drought risk (0.50-0.75 of Normalized ETDI) were observed in majority of the study area in south and southwest parts of the region with an area of 53.8%, followed by the very high drought risk (0.75-1.00 of Normalized ETDI, 27.6%). In addition, moderate drought risk (0.25-0.50 of Normalized ETDI, 17.3%) and low drought risk (0.00-0.25 of Normalized ETDI, 1.3%) were observed in the central part of the region (Figure 3(a)). It could be observed that the study areas predominantly consisted of high and very high drought risk, covering over 80% of the total area.

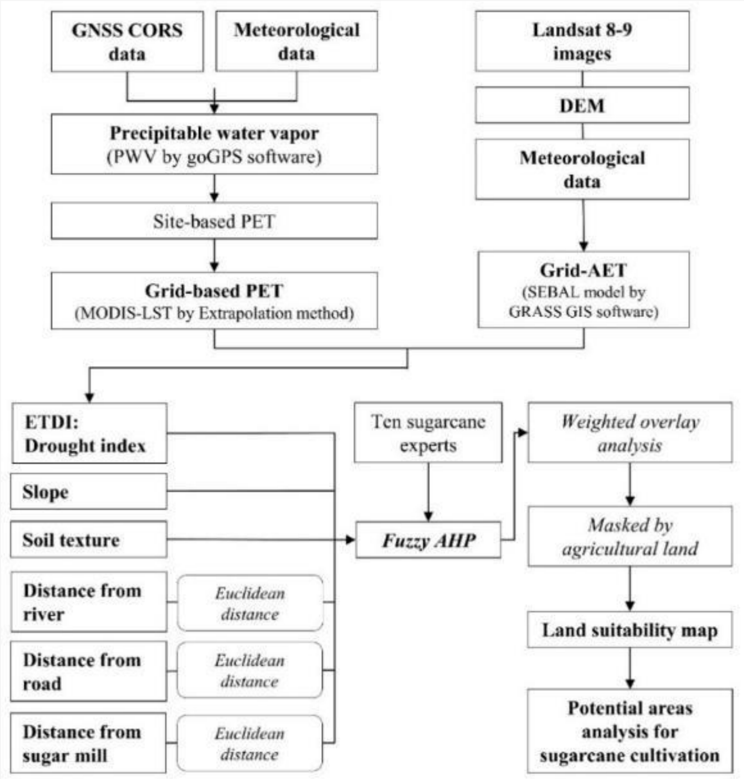

Figure 2: Flowchart of the methodology for mapping sugarcane land suitability

3.1.2 Slope

The slope is an important variable of the topographic criteria. The results displayed that the majority of areas classified by slope covered the gentle slopes (2-5%) with an area of 51.4%, followed by flat terrain (0-2%), moderate slope (5-12%), and high slope classes (>12%) with the area of 34.7%, 10.1% and 3.8%, respectively (Figure 3(b)). It was noted that the study areas predominantly consisted of gentle slopes and flat terrain, covering over 80% of the total area.

3.1.3 Soil texture

The soil texture is determined as a key component of soil physical properties that reflect the capacity of retain and drain water. The moderately suitable areas for soil texture (silty clay loam and sandy loam) covered the largest proportion at 59.9%, followed by the highly suitable (loam, sandy clay loam, silty loam, and silt, clay loam, 15.3%), unsuitable (sand, sandy clay, and clay, 14.7%), and marginally suitable (silty clay and loamy sand, 10.0%) (Figure 3(c)). It was observed that soil texture of the study areas predominantly consisted of moderately and highly suitable areas, covering over 75% of the total area.

3.1.4 Distance from the river

This parameter is related to water supply and the difficulty of irrigation for farmer fields. These results reveal that most of the areas classified by distance from the river were categorized as far from the river (5-10 km) with an area of 38.4%, while 7.2% were classified as very far from the river (>10 km) that observed in the upper part of the region. Additionally, a portion of areas were found in a moderate distance from the river (2-5 km, 33%) and proximity to the river (0-2 km, 21.4%) (Figure 3(d)), which was observed in the lower part of the region. The results indicated that a significant portion, exceeding 70% of the total area, was characterized by moderate distances (2-5 km) and far distances (5-10 km) from the river.

3.1.5 Distance from the road

This variable is the main socioeconomic factor that reflects transportation from the fields to the markets. Most of the areas classified by distance from the road were located near the road (0-4 km) with an area of 47.6%, followed by a moderate distance (4-8 km), far distance (8-16 km) and very far distance (>16 km) with percentages of 38.5, 13.2 and 0.7, respectively. Moreover, the spatial distribution of the road was relatively consistent in the whole study area (Figure 3(e)). It was noted that distance from the road of the study areas predominantly consisted of near the road (0-4 km) and moderate distance (4-8 km), covering over 80% of the total area.

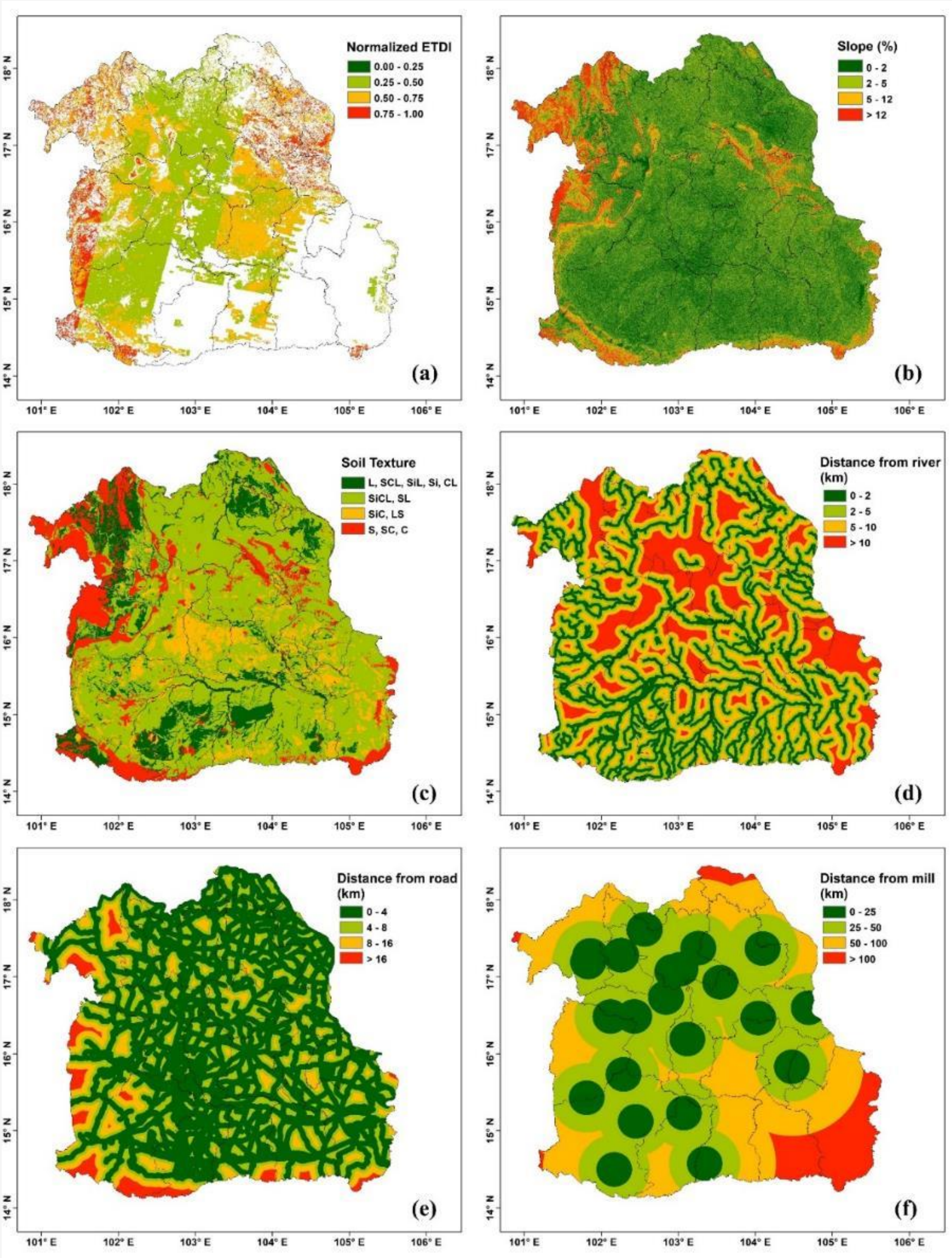

Figure 3: Criteria for the analysis (a) normalized ETDI (b) slope (c) soil texture (d) distance from river (e) distance from road and (f) distance from sugar mill

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Table 2: Criteria classification for sugarcane suitability analysis

Criteria	Factor	Class	Score
Climate	$ETDI_{norm}$	0.00 – 0.25	10
		0.25 – 0.50	7
		0.50 – 0.75	4
		0.75 – 1.00	1
Topography and Soil	Slope (%)	0-2	10
		2-5	7
		5-12	4
		> 12	1
	Soil texture	L, SCL, SiL, Si, CL	10
		SiCL, SL	7
		SiC, LS	4
		S, SC, C	1
Socio-economic	Distance from river (km)	0 – 2	10
		2 – 5	7
		5 – 10	4
		> 10	1
	Distance from road (km)	0 – 4	10
		4 – 8	7
		8 – 16	4
		> 16	1
	Distance from sugar mill (km)	0 – 25	10
		25 – 50	7
		50 – 100	4
		> 100	1

3.1.6 Distance from the sugar mill

Distance from the sugar mill is one of the socioeconomic factors that indicates in terms of transport availability and costs. Most of the areas classified by distance from sugar mill were found in the moderate distance from sugar mill (25-50 km) with an area of 53.5%, followed by a far distance (50-100 km), close distance (0-25 km) and very far distance (>100 km) with percentages of 34.0, 10.7 and 1.8, respectively. It was observed that distance from the sugar mill of the study areas predominantly consisted of moderate distance (25-50 km) and far distance (50-100 km), covering over 80% of the total area. Besides, it was noted that sugar mills were distributed throughout the entire region except for the southeast part of the region, where the sugar mill presence was notably constrained (Figure 3(f)).

3.2 Factor Weighing by Fuzzy AHP Approach

Six factors were weighed for sugarcane suitability by ten sugarcane experts using a questionnaire. The matrix of fuzzy AHP pair-wise comparison and weight calculations of ten experts were evaluated as shown in Table 3. The consistency ratio (CR) was evaluated as 0.086. This value was below the threshold of 0.10, indicating that the matrix is consistent. The results indicated that two factors affected sugarcane cultivation: normalized ETDI and distance from river. The normalized ETDI as drought index was the most significant factor for sugarcane cultivation, with an average weight of 0.66. Additionally, the distance from the river was identified as the second essential factor, with an average weight of 0.34. It is evident that other factors, comprising slope, soil texture, distance from the road, and distance from the sugar mill, were observed to have no influence on the suitability of land for sugarcane cultivation. The spatial distribution of these factors remained consistent throughout the entire study area as shown in Figure 3.

Table 3: Pair wise matrix of sugarcane land suitability by sugarcane experts using fuzzy AHP

	ETDI (F1)	Slope (F2)	Soil texture (F3)	Distance from river (F4)	Distance from road (F5)	Distance from mill (F6)	Weight
ETDI (F1)	**(1,1,1)**	(5.80,6.70,7.30)	(3.64,4.35,5.06)	(2.54,3.15,3.66)	(4.91,5.81,6.51)	(4.91,5.81,6.51)	**0.66**
Slope (F2)	(0.22,0.24,0.27)	**(1,1,1)**	(1.59,1.9,2.13)	(0.51,0.73,0.96)	(2.47,2.89,3.23)	(2.77,3.29,3.73)	**0**
Soil texture (F3)	(1.10,1.32,1.55)	(3.35,3.96,4.39)	**(1,1,1)**	(0.52,0.65,0.81)	(3.13,3.83,4.45)	(3.13,3.63,3.95)	**0**
Distance from river (F4)	(1.81,2.14,2.39)	(3.86,4.58,5.15)	(3.33,4.03,4.65)	**(1,1,1)**	(4.20,5.00,5.50)	(3.23,3.83,4.35)	**0.34**
Distance from road (F5)	(0.93,1.05,1.08)	(1.06,1.37,1.69)	(0.52,0.65,0.80)	(0.33,0.36,0.41)	**(1,1,1)**	(2.33,2.73,3.04)	**0**
Distance from mill (F6)	(0.93,1.060,1.10)	(1.08,1.40,1.73)	(0.68,0.79,0.93)	(0.60,0.73,0.90)	(1.47,1.68,1.91)	**(1,1,1)**	**0**

3.3 Land Suitability Analysis

The suitability of land for sugarcane cultivation was analyzed using the Weight Overlay Analysis method (WOA) after processing factor reclassification and weighting. The sugarcane land suitability map of this study showed four suitable classes: highly suitable class (S1), moderately suitable class (S2), marginally suitable class (S3), and not suitable class (N) as illustrated in Figure 4. The analysis included a total area of 61,566 km^2 for sugarcane land suitability. Among the entire study area, 49.6% (30,521 km^2) was covered by the S2 class, followed by 36.0% (22,209 km^2) in the S3 class and 11.2% (6,872 km^2) in the S1 class. Additionally, 3.2% (1,964 km^2) of the study area was covered a small proportion by the N class (Table 4). The S1 class areas were mostly distributed in Nakhon Ratchasima (2,370 km^2, 34.5%), followed by Khon Kaen (783 km^2, 11.4%), Chaiyaphum (645.5 km^2, 9.4%), Udon Thani (561.2 km^2, 8.2%) and Surin (452.9 km^2, 6.6%), respectively. The areas of S2 class were mostly found in Nakhon Ratchasima (6,133.1 km^2, 20.1%), followed by Roi Et (3,515.4 km^2, 11.5%), Khon Kaen (3,414.2 km^2, 11.2%), Chaiyaphum (2,650.7 km^2, 8.7%) and Udon Thani (2,338.1 km^2, 7.7%), respectively. In addition, the S3 class areas were mostly distributed in Udon Thani (3,265 km^2, 14.7%), Kalasin (2,669.2 km^2, 12.0%), Khon Kaen (2,470.8 km^2, 11.1%), Chaiyaphum (2,268.8 km^2, 10.2%) and Nakhon Ratchasima (1,832.7 km^2, 8.3%), respectively (Table 5). Furthermore, it is evident that the S1 and S2 classes were predominantly distributed in the lower part of the region due to the closer distance from Chi River and moderate drought risk zone. In contrast, the S3 and N classes were found in the upper part of the region because of the far distance from the river and high risk of drought (Figure 4).

Moreover, the existing sugarcane plantation areas in 2020, as identified by the OCSB, was utilized to overlay the land suitability map generated in the present research to assess the current situation of sugarcane land suitability (Figure 5 and Table 6). The actual sugarcane grown areas were classified into four suitable classes: S1, S2, S3, and N as demonstrated in Figure 5. It could be observed that the actual sugarcane grown areas were mostly distributed in the upper part of the region, which were predominantly found in the S3 class (49.0%, 2,593 km^2), followed by 43.2% (2,282 km^2) of the S2 class and 6.7% (353 km^2) of the S1 class. However, sugarcane crops were also grown in the areas of N class about 1.1% (59 km^2) as shown in Table 6. Furthermore, the S3 class areas were mostly concentrated in Wang Sam Mo district, Udon Thani province (129 km^2), which showed a sugarcane yield of approximately 60.6 tons/ha. However, the S1 class areas were mostly found in Phimai district, Nakhon Ratchasima province (30 km^2), with a higher sugarcane yield compared to S3 class, reaching 63.6 tons/ha. Therefore, an analysis of potential areas for sugarcane cultivation should focus on the S1 class areas to identify suitable locations for expanding sugarcane cultivation areas and increasing yield.

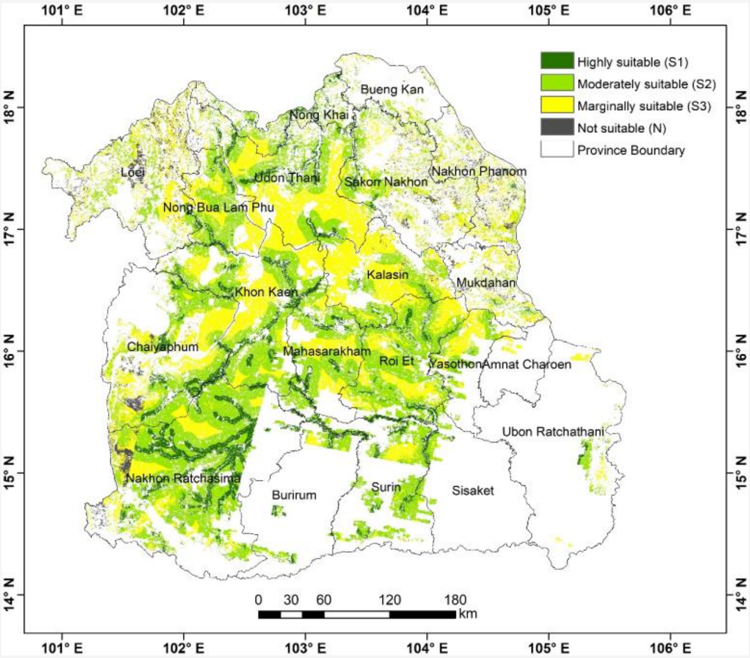

Figure 4: Land suitability for sugarcane cultivation in Northeastern Thailand

Table 4: Land suitability analysis for cultivation of sugarcane

Suitable classes	Suitable areas for sugarcane cultivation (km^2, %)
S1	6,872 (11.2)
S2	30,521 (49.6)
S3	22,208 (36.0)
N	1,964 (3.2)
Sum	**61,566**

Furthermore, the conditions of each suitable class within actual sugarcane-grown areas were analyzed, as presented in Table 7. The S1 class areas were identified by their proximity to the river (within 0-2 km) with moderate and high risks of drought. Conversely, the S2 class areas were mostly characterized by moderate to high risk of drought and were situated at distances ranging from near to moderate proximity from the river (0-5 km). On the other hand, the S3 class areas were characterized by varying degrees of drought risk: moderate, high, and very high, and were located at near, moderate, far, and very far distances from the river (ranging from 0 to over 10 km).

It was noted that the S2 class areas could potentially enhance to the highly suitable class (S1) areas for sugarcane cultivation. Notably, the distance from the river should be limited to within 2 km [49]. Consequently, the implementation of irrigation systems and the establishment of small ponds are essential in these areas to ensure a consistent water supply and mitigate the risk of drought. This approach could enhance sugarcane yields within the S2 class areas (with moderate proximity from the river (2-5 km), 968 km^2) and facilitate their transition into the areas of S1 class for sugarcane cultivation, increasing S1 class areas by 2.7 times. Moreover, the S2 class areas were mostly found in Phu Khiao district, Chaiyaphum province (178 km^2), which showed a sugarcane yield of approximately 62.5 tons/ha. This was followed by Si Bun Rueang district, Nong Bua Lam Phu province (100 km^2), Kaset Sombun district, Chaiyaphum province (78 km^2), Nam Phong district, Khon Kaen province (72 km^2), and Mueang Nong Bua Lam Phu district, Nong Bua Lam Phu province (68 km^2) respectively. Therefore, such areas could be enhanced to increase sugarcane yields, potentially raising yields by approximately 1.1 tons/ha (1.8% of the yield in the S2 class).

Table 5: Land suitability analysis for sugarcane cultivation each province

Province	Suitable areas for sugarcane cultivation (km^2, %)			
	S1	**S2**	**S3**	**N**
Amnat Charoen	0.0 (0.0)	7.5 (0.0)	92.1 (0.4)	0.4 (0.0)
Bueng Kan	36.2 (0.5)	191.8 (0.6)	128.5 (0.6)	17.8 (0.9)
Burirum	302.2 (4.4)	662.7 (2.2)	113.6 (0.5)	0.0 (0.0)
Chaiyaphum	645.5 (9.4)	2,650.7 (8.7)	2,268.8 (10.2)	235.4 (12.0)
Kalasin	111.7 (1.6)	1,454.3 (4.8)	2,669.2 (12.0)	54.8 (2.8)
Khon Kaen	783 (11.4)	3,414.2 (11.2)	2,470.8 (11.1)	0.9 (0.0)
Loei	27.8 (0.4)	996.1 (3.3)	1,601.2 (7.2)	578.1 (29.4)
Mahasarakham	352.8 (5.1)	1,908.4 (6.3)	1,048.8 (4.7)	0.1 (0.0)
Mukdahan	19.4 (0.3)	305.9 (1.0)	509.8 (2.3)	115.6 (5.9)
Nakhon Phanom	13.5 (0.2)	386.3 (1.3)	847.1 (3.8)	304.9 (15.5)
Nakhon Ratchasima	2,370.2 (34.5)	6,133.1 (20.1)	1,832.7 (8.3)	294.1 (15.0)
Nong Bua Lam Phu	195.4 (2.8)	1,438.5 (4.7)	931.3 (4.2)	18.1 (0.9)
Nong Khai	220.8 (3.2)	663.2 (2.2)	201.1 (0.9)	9.8 (0.5)
Roi Et	438.1 (6.4)	3,515.4 (11.5)	1,802.9 (8.1)	0.7 (0.0)
Sakon Nakhon	132.9 (1.9)	1,229.8 (4.0)	1,167.4 (5.3)	292.7 (14.9)
Sisaket	99.3 (1.4)	359.9 (1.2)	31.5 (0.1)	0.0 (0.0)
Surin	452.9 (6.6)	1,804.6 (5.9)	411.3 (1.9)	1.8 (0.1)
Ubon Ratchathani	47.3 (0.7)	243.4 (0.8)	163.7 (0.7)	0.3 (0.0)
Udon Thani	561.2 (8.2)	2,338.1 (7.7)	3,265 (14.7)	37.7 (1.9)
Yasothon	62.1 (0.9)	817.3 (2.7)	651.5 (2.9)	1.2 (0.1)
Total	**6,872.3**	**30,521.2**	**22,208.3**	**1,964.4**

Table 6: Land suitability on actual sugarcane grown areas

Suitable classes	Suitable areas for actual grown areas (km^2, %)
S1	353 (6.7)
S2	2,282 (43.2)
S3	2,593 (49.0)
N	59 (1.1)
Total	**5,287**

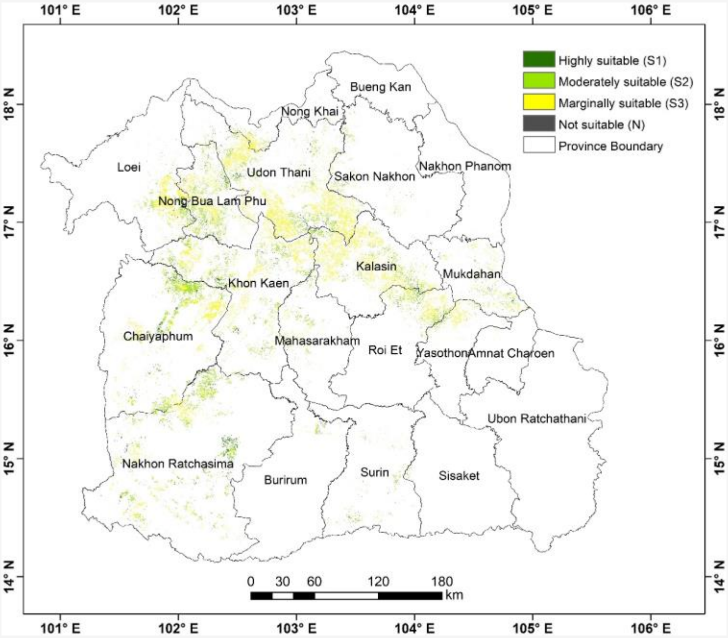

Figure 5: Land suitability areas for actual sugarcane grown areas in the Northeastern Thailand

Table 7: Conditions of each suitable class within actual sugarcane grown areas

Suitable classes	Drought risk (ETDI)	Distance from river (km)	Actual grown areas (km^2, %)
S1	Moderate	Near (0-2)	340 (96.3)
	High	Near (0-2)	13 (3.7)
Total of S1			**353**
S2	Moderate	Moderate (2-5)	580 (25.4)
	Moderate	Far (5-10)	776 (34.0)
	High	Moderate (2-5)	388 (17.0)
	High	Far (5-10)	538 (23.6)
Total of S2			**2,282**
S3	Moderate	Far (5-10)	18 (0.7)
	Moderate	Very far (> 10)	1,348 (52.0)
	High	Far (5-10)	609 (23.5)
	High	Very far (> 10)	511 (19.7)
	Very high	Near (0-2)	47 (1.8)
	Very high	Moderate (2-5)	60 (2.3)
Total of S3			**2,593**

Table 8: Potential areas for sugarcane cultivation

Suitable classes	Land suitability for sugarcane cultivation (km^2, %)	Land suitability on actual grown areas (km^2, %)	Potential areas (km^2, %)
S1	6,872 (11.2)	353 (6.7)	6,519 (11.6)
S2	30,521 (49.6)	2,282 (43.2)	28,239 (50.2)
S3	22,208 (36.0)	2,593 (49.0)	19,616 (34.8)
N	1,964 (3.2)	59 (1.1)	1,905 (3.4)
Total	**61,566**	**5,287**	**56,279**

3.4 Potential Areas Analysis

According to Table 4, the analysis of land suitability for sugarcane cultivation of the entire study area was 61,566 km^2, whereas only 5,287 km^2 was being utilized for sugarcane growing (Table 6). Interestingly, most of the land is not being utilized to its full capability, which could be expanded to cultivate sugarcane crops about 56,279 km^2 (referred to as potential areas) (Table 8 and Figure 6). These potential areas for sugarcane cultivation were predominantly distributed in the S2 class (50.2%, 28,239 km^2), followed by the S3 class (34.8%, 19,616 km^2), and the S1 class (11.6%, 6,519 km^2). Nevertheless, the S1 class displayed a relatively low utilization rate for sugarcane plantation areas due to its current use for other crops such as rice, corn, and cassava. Thus, there is an opportunity to expand sugarcane cultivation areas into the S1 class to optimize productivity (6,519 km^2, 11.6% of the potential areas).

Additionally, the analysis of potential areas on the S1 class were conducted for each province within the study area. The results indicated that the majority of potential areas in the S1 class were concentrated in Nakhon Ratchasima province with an area of 2,272 km^2 (35%). This was followed by Khon Kaen (725 km^2, 11%), Chaiyaphum (592 km^2, 9%), Udon Thani (519 km^2, 8%) and Surin (411 km^2, 7%). Despite the presence of numerous potential areas for sugarcane cultivation, these areas were primarily utilized for the cultivation of alternative crops such as rice, corn, and cassava as shown in Table 9. This observation aligns with previous findings reported by the Land Development Department in 2023. For example, recent land use statistics of Nakhon Ratchasima province in 2023 revealed that most of the areas were utilized for rice cultivation with 29.5% of the entire province area, followed by 18.6% for cassava cultivation, and only 9.9% for sugarcane cultivation [50].

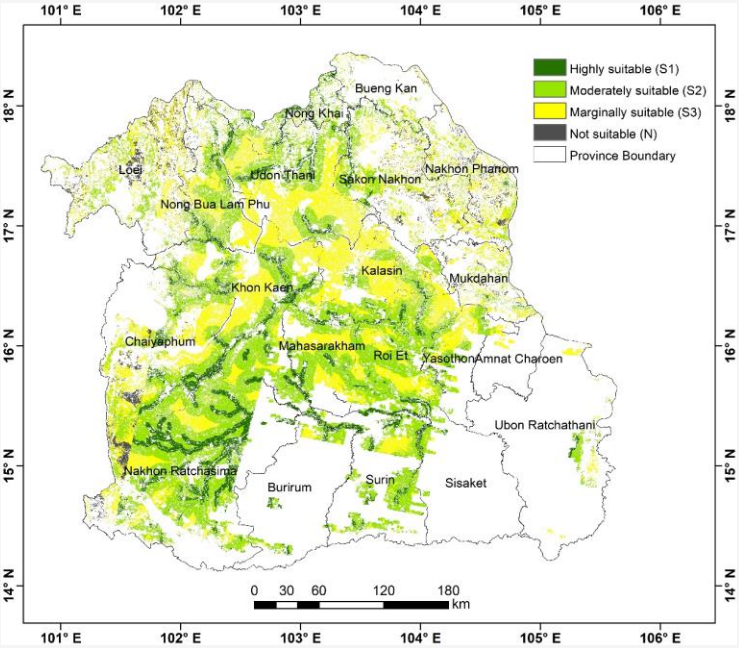

Figure 6: Potential areas for sugarcane cultivation in the Northeastern Thailand

Table 9: Land uses on potential areas for sugarcane cultivation

Land uses	Potential areas (km^2, %)				
	S1	**S2**	**S3**	**N**	**Sum**
A0: Integrated farm/Diversified farm	3 (0.0)	10 (0.1)	4 (0.1)	1 (0.0)	18 (0.0)
A1: Paddy Field	4,796 (73.6)	17,668(62.6)	9,597 (48.9)	589 (30.9)	32,650 (58.0)
A2: Field crop	1,133 (17.4)	7,297 (25.8)	6,534 (33.3)	637 (33.4)	15,601 (27.7)
A3: Perennial crop	368 (5.6)	2,371 (8.4)	2,714 (13.8)	545 (28.6)	5,998 (10.7)
A4: Orchard	42 (0.6)	260 (0.9)	300 (1.5)	85 (4.5)	687 (1.2)
A5: Horticulture	17 (0.3)	33 (0.1)	35 (0.2)	3 (0.2)	88 (0.2)
A6: Shifting cultivation	-	-	5 (0.0)	1 (0.1)	6 (0.0)
A7: Pasture and farm house	38 (0.6)	166 (0.6)	113 (0.6)	10 (0.5)	327 (0.6)
No Data	122 (1.9)	434 (1.5)	314 (1.6)	34 (1.8)	904 (1.6)
Sum	**6,519**	**28,239**	**19,616**	**1,905**	**56,279**

4. Discussions

Suitability of land was analyzed in several studies to find out the suitable land for sugarcane, which was evaluated by multiple criteria such as soil, topography, climate and socioeconomic factors [33] [35] and [37]. However, it is essential to consider drought-prone areas due to the significant influence of drought conditions on sugarcane cultivation [7]. The drought event is highly affected to reduce sugarcane crop growth, especially during the tillering stage as indicated in the study of [51], described that the drought as water deficit stress is the major threat in decreasing yield. Therefore, drought-prone areas condition was applied to enhance the accuracy of land suitability map. A previous study reported that the maize land suitability in drought-prone areas was analyzed by considering multiple criteria and drought index. The standardized precipitation index (SPI) was applied to reflect the drought severity based only on precipitation, while other meteorological parameters were not considered [39]. In this study, the evapotranspiration deficit index (ETDI) was applied to monitor drought for land suitability analysis, which considered the spatial variability based on both actual and potential evapotranspiration that link to several factors such as soil, land use and climate conditions (e.g., temperature and humidity).

In addition, potential areas within the S1 class for sugarcane cultivation were evaluated, despite currently being utilized for other crops such as rice, corn, and cassava. Many farmers persist in rice cultivation due to its status as a major crop in the country, intertwined with their traditional way of life. Additionally, rice cultivation has a shorter growth period compared to sugarcane, and promptly generates income to cover household expenses [52].

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However, the climatic and soil conditions in this region are suitable for the cultivation of a wide range of crops. Alternative crops such as corn, cassava, and sugarcane serve as viable options for both domestic consumption and exportation. In this research, these potential areas within the S1 class should be considered for sugarcane cultivation to effectively utilize their resources. In addition, our mapped result can offer valuable information for their understanding of crop conditions and plantation management. Farmers may be encouraged to transition from other crops to sugarcane. Government policies should support participatory knowledge transfer schemes on sugarcane cultivation, provide sugarcane price guarantee, and facilitate access to credit [8][52] and [53]. Furthermore, the relatively high price of sugarcane may incentivize farmers to grow this crop, which lead to a substantial expansion of sugarcane areas and increased yields to support the increasing demand for sugar, both for domestic consumption and export purposes.

This study demonstrated the effectiveness of integrating fuzzy AHP and multi-criteria evaluation approaches in mapping sugarcane land suitability; however, some limitations were also presented. The exclusive focus on drought conditions may not fully address the complexity of climate change. Further research should incorporate additional factors affecting sugarcane cultivation, such as flood risk, land use and land cover (LU/LC), soil nutrient levels, distance from groundwater, soil moisture, and climate data. Furthermore, the application of artificial intelligence (AI) and machine learning techniques can offer a more robust approach for evaluating enhanced land suitability maps to cope with future climate change scenarios [54] and [55].

5. Conclusion

The integration of fuzzy AHP and multi-criteria evaluation was employed to re-analyze the suitability of land for sugarcane cultivation, based on its capabilities. The ETDI was applied as a crucial factor in the sugarcane land suitability analysis with an average factor weighting of 0.66, determined by considering both soil and vegetation conditions. The distance from river was also considered with an average factor weighting of 0.34. The paper presented that the suitable areas for sugarcane (61,566 km^2) were mostly found in the moderately suitable class (S2; 30,521 km^2, 49.6%), followed by the marginally suitable class (S3; 22,208 km^2, 36.0%) and the highly suitable class (S1; 6,872 km^2, 11.2%). In addition, the actual sugarcane plantation areas in 2020, sourced from the Office of the Cane and Sugar Board (OCSB), on the land suitability map was studied to determine the current situation of sugarcane land suitability. These findings indicated that actual sugarcane cultivation areas on the land suitability map (5,287 km^2) were mostly cultivated in the S3 class (2,593 km^2, 49.0%), followed by 43.2% (2,282 km^2) of the S2 class and 6.7% (353 km^2) of the S1 class. In addition, potential areas for sugarcane cultivation were analyzed to expand sugarcane cultivation areas and increase yield. It was observed that potential areas in the S1 class for sugarcane cultivation were 6,519 km^2. Nakhon Ratchasima province showed the most potential areas for sugarcane cultivation (35%, 2,272 km^2), followed by Khon Kaen (11%, 725 km^2), Chaiyaphum (9%, 592 km^2), Udon Thani (8%, 519 km^2) and Surin (7%, 441 km^2). Such provinces may be encouraged to convert from currently cultivating other crops (rice, corn, or cassava) to sugarcane to optimally utilize their resources. Government policies should support the participatory knowledge transfer programs on sugarcane cultivation, sugarcane price guarantee and credit access.

Furthermore, the S2 class areas could potentially enhance by implementing irrigation systems, groundwater management, and establishing small ponds to reduce the drought risk. This approach could increase the sugarcane yield and encourage these areas into the S1 class, which expand the S1 class areas by 2.7 folds over the existing S1 class areas. The land suitability map in this study analyzed only prototype sugarcane areas in Northeastern Thailand. The different suitable sugarcane crop growth in this work can be used for crop management practices such as putting fertilizer, water management and other human controls. Therefore, future research should be studied on a larger scale covering the whole country to improve the accuracy of the map for decision-making and dealing with global climate change situations. Other factors should be incorporated to consider for mapping sugarcane land suitability, such as distance from groundwater, LU/LC, soil moisture, and climate data. Machine learning and deep learning approaches should integrate in traditional GIS-based multicriteria analysis to enhance land suitability in further studies.

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