Assessment of crop-land suitability by the multi-criteria evaluation approach and geographic information system: A scoping review

Dang Tuyet Minh

(Thuyloi University, 175 Tay Son Street, Dong Da District, Hanoi City, Vietnam)

Abstract: The crop-land suitability assessment (LSA) is important for managing land and water resources and developing sustainable agricultural systems. In the field of determining the suitability of cropland, the multi-criteria evaluation approach (MCEA) or multi-criteria decision-making (MCDM) is becoming more popular as a tool for analyzing difficult situations and obtaining logical conclusions. The 75 relevant publications from 2010 to 2023 were reviewed and summarized in this paper to precisely explain and identify MCEA application areas and decision-making problems resolved within the crop-land suitability assessment. The findings indicated that the MCDM or MCEA techniques have been applied with or without remote sensing, Agricultural Land Use Evaluation System, parametric methods, etc. for land suitability evaluation. This study also contributes to the classification of criteria used for this purpose. A total of 117 parameters from six groups: soil properties, climate, topography, hydro-geomorphology, land use compatibility, and hazard are necessary for LSA.

Keywords: Crop-land suitability assessment; Land suitability assessment; MCDM; MCEA

Citation: Dang Tuyet Minh. 2024. Assessment of crop-land suitability by the multi-criteria evaluation approach and geographic information system: A scoping review. Agricultural Engineering International: CIGR Journal, 26(2): 57-78.

1 Introduction

Land suitability analysis (LSA) for crops is essential for agriculture development and planning. According to FAO (1976), LSA is the procedure of determining the suitability of a specific type of land for cultivating a given crop based on its ideal growth needs. Crop-land suitability is identified by comparing the land characteristics and the crop requirements (Khan et al., 2022). The results of the evaluation process answer questions such as where to grow and how to grow? (Bisht et al., 2022). Nowadays, there are many approaches to assess crop-land suitability. Each of them has its particularities, relying on specific research purposes. According to Akpoti et al. (2019), the LSA methods can be classified as traditional and modern approaches. The former has used biophysical characteristics to assess crop alternatives using quantitative, qualitative, and parametric techniques. The latter, modern land suitability assessment (LSA) methods are those that integrate geographic information system (GIS) and machine learning algorithms, or multi-criteria decision-making or multi-criteria evaluation approaches, and remote sensing techniques (Mugiyo et al., 2021). Some techniques have been labeled "traditional" but are still in use, such as Boolean logic (Elaalem et al., 2010), multiple linear regression models (Leroux et al., 2019), weighted linear combination (WLC) (Subandi et al., 2019), multivariate statistics (Akpoti et al., 2019), weighted overlay (WO) (Hassan et al., 2020), and parametric method (the stories and the square root) (Ghanbarie et al., 2016). In most traditional approaches, socio-

---

Received date: 2023-07-05 **Accepted date:** 2024-01-10

***Corresponding author: Dang Tuyet Minh.** Lecturer, Thuyloi University, Vietnam. Email: dtminh@tlu.edu.vn. Tel: +84983180297.

economic information, and infrastructure is scarcely used, although this data is necessary for performing crop-land suitability assessments (Mugiyo et al., 2021). Moreover, categorical data are infrequent in traditional techniques, except for the qualitative and WLC methods.

The fundamental distinction between modern and traditional approaches is that the former is successful in mapping regions with uniform characteristics taking into account a variety of factors, thus they can offer solutions to more complex problems. As a result, modern methods may utilize more time-consuming or complicated algorithms and processes than traditional techniques (Mugiyo et al., 2021). The primary modern LSA methods are categorized as follows: (1) computer-aided overlay mapping; (2) artificial intelligence methods; and (3) multi-criteria decision making (MCDM) and multi-criteria evaluation (MCEA) (Bera et al., 2017). This review focuses on the third method of modern LSA approaches in LSA for crops. Because of the numerous variables related to decision-making, LSA has been determined as a multi-criteria assessment problem. In order to solve these difficulties, MCDA was established in the 1960s to aid decision-makers in combining several possibilities into a possible or retrospective framework (Adem Esmail and Geneletti, 2018). The MCDM approach can be divided generally into two categories: (1) A method for determining criteria weights; (2) A technique for ranking/ selection of alternatives (Nadkarni and Puthuvayi, 2020). For several crops, MCDM and MCEA seem to be applicable in GIS-based land suitability evaluations (Khan et al., 2022). According to Mugiyo et al. (2021), GIS-based MCDA techniques are effective because numerous production criteria may be analyzed and weighted based on their relative impact on crop growth conditions. GIS is a helpful tool to analyze multiple geospatial data with higher accuracy in LSA. GIS enables the creation of models that aid in the generation of crop-land suitability maps from a collection of thematic data such as topography, climate, soil, socio-economic, etc. (Zolekar and Bhagat, 2015). Therefore, in order to handle complicated problems of land suitability evaluation with the best alternatives, the MCDM process has been combined with geospatial technique in numerous research (Mendas and Delali, 2012). This procedure applied a weight overlay algorithm for multi-criteria assessment with GIS to analyze the suitability of cropland. In addition, some studies investigated the applicability of MCDM and GIS in combination with traditional algorithms such as or modern models such as TOPSIS (Bagherzadeh and Gholizadeh, 2016), FNN (Jiao and Liu, 2007), etc. to determine the most suitable areas for crops. Among the various MCDM techniques, the analytic hierarchy process (AHP) proposed by Saaty (2005) is one of the most popular used algorithms (Subramanian and Ramanathan, 2012) and has been applied in a wide range of application fields. Several recent publications have concentrated on the use of AHP in particular areas such as flood hazard zone (Ba et al., 2021; Dung et al., 2021), construction (Darko et al., 2019), etc. According to Jafari and Zaredar (2010), the combination of the AHP approach is one of the widely used techniques for spatial multi-criteria analysis with GIS in determining the crop suitability index.

Recently, there have been a number of papers reviewed for land suitability evaluation. While Aburas et al. (2015) analyzed land suitability by using AHP and GIS for urban growth, Mugiyo et al. (2021) offered decision-makers and researchers the most reliable techniques and necessary criteria in developing LSA for neglected and underutilized crop species. Just like Mugiyo et al. (2021), Singha and Swain (2016) emphasized the applications of several methods for assessing the appropriateness of crop-land for sustainable agriculture in developing nations. Unlike the above authors, Bisht et al. (2022) has only focused on one method, MCEA technique combined with geospatial technology, to determine the crop suitability index. However, this publication has not explored all the studies using this method nor mentioned the combination of this method with other technologies which are gaining popularity in recent years. In order to fill the gaps, this review provides an overview of the hybrid methods using more than one technique to evaluate land suitability for crops including MCDM and major parameters used to identify that appropriateness. This review can assist academics, experts, and decision-makers in generating standards and guidelines for an effective crop suitability mapping process for increased agriculture productivity.

2 Methodology

An effective literature review, according to Levy and Ellis (2006), establishes a solid foundation for advancing science. This paper uses a systematic literature review approach that utilizes precise and explicit criteria to identify, evaluate, and synthesize particular topics of literature. The following is the description of systematic literature review criteria utilizing hybrid methods (including MCEA and MCDM methods) applied in this study.

2.1 Formulate the research questions

In the present paper, the authors established questions related to the use of MCEA and MCDM techniques in assessing crop-land suitability. The problems formulated in the paper include: What crops have been used MCEA or MCDM techniques to assess land suitability? What kind of MCDM or MCEA techniques have been applied? What parameters have been used to evaluate land suitability for crop production?

2.2 Select and access the literature

In order to collect a comprehensive set of data, an objective search strategy was required to find publications related to LSA for crops. Prior to beginning the literature search work, three databases including Scopus, Google Scholar, and Web of Science were assessed. The results showed that Scopus covers many publishers, including the most popular publishers for research relevant to this paper's topic (e.g., ACM, IEEE, Springer, Elsevier), is less inclusive than Google Scholar but is more inclusive than Web of Science. However, unlike Google Scholar, Scopus allows filtering of non-peer-reviewed publications, such as technical reports (Daun et al., 2023). For these reasons, this review used Scopus to implement the data search.

To achieve the main objective of this study, we examined numerous publications discussing hybrid methods (including MCEA and MCDM techniques) for crop-land suitability evaluation. Based on this strategy, which consisted of two main steps we conducted our study. The first step involved selecting journals relevant to the research topic based on scientific journal rankings (SJR-Scimago Journal and Country Rank), or conferences related to and the second is the choice of key phrases within those selected articles. Because the ranking of journals has been largely constant over time, the default year of 2010 was chosen for this study. The journals of all possible nations in these categories were taken into account. The search syntax used for searching including “MCEA” or “MCDM” or “AHP” or “Fuzzy AHP” or “ANP” or “TOPSIS” or “ELECTRE”, and “crop-land/ land suitability” or “land suitability evaluation/ assessment/ analysis” or “agriculture-land suitability”.

2.3 Evaluate the quality of the literature included in the review

The search was restricted to keywords, titles, and abstracts and resulted in the identification of 223 research publications. However, there were some duplicate articles and not all of the identified articles related to the main topic of the present paper. Therefore, an evaluation of each article's contents was then conducted to remove unrelated papers or duplicates. Following the screening, 74 publications were eventually considered valid with the research topic. The full-length publications were downloaded and utilized for further analysis. The details of the studies were retrieved such as the nations where the research was performed, methods or models applied, crops studied, and the thematic parameters utilized in analyzing land suitability and these findings are presented in Tables 1 to 4.

Table 1 Analytic hierarchy process (AHP) method used in crop-land suitability assessment

Crop	Thematic factors							Reference	Nation
	Climate	Topography	Soil properties	Hydro-Geomorphology	Scio-economic	Land Use Compatibility	Hazard		
Apple	E	Sl	SD; ST; S	PRi; PID;	PA; Dis_R			(Madrigal-Martínez and Puga-Calderón, 2018)	Peru
	T	Sl	SM; ST; SDr; SD					(Kim and Shim, 2018)	Korea
Cereal	RF; T	Ele; Sl	SD; ST; SDr; pH		AM; PRo	LULC		(Debesa et al., 2020)	Ethiopia
Coffee	T; RF	Sl; Ele	Sty; SG	WR; Ge	Dis_R			(Mighty, 2015)	Jamaica
Cotton	RF, T, M	Sl	pH; OC; ST; SD; SDr; EC; ESP					(Sathiyamurthi et al., 2022)	India
Citrus	T; A; RF		pH; SA; STy	GWQ; R				(Rasheed and Naz, 2016)	Pakistan
	T; M; RF; ST	Sl; Ele; As		PRi	Pro; PS; PIPD			(Tercan and Dereli, 2020)	Turkey
Jute and Lentil			OC; N; P; K; Zn; pH; ST; EC					(Singha and Swain, 2018)	India
Maize	T	El; Sl	pH; CCE; ESP; EC; ST					(Tashayo et al., 2020)	Iran
			pH; OM; EC; ST;	GWQ				(Sheikh et al., 2017)	Pakistan
	RF; T	Sl	STy					(Chivasaa et al., 2019)	Zimbabwe
Maize, groundnut	RF	Sl, SE,	OM; STy			LULC		(Salifu et al., 2022)	Ghana
Mango	RF; T	Sl	OC; ST; BD					(Salunkhe et al., 2022)	India
Orange and Tea		Sl	pH; OM; CEC; P; K; SD; ST	DS			Fl	(Nguyen et al., 2019)	Vietnam
Organic farming		Sl	SD; SG	Ge	Dis_R	LULC		(Mishra et al., 2015)	India
Potato			pH; EC; N; P; Z; OC; ST;					(Singha et al., 2019)	Bengal
Rapeseed	RF; T	As; Sl	pH; EC; CCE; ST			LU; NDVI		(Ostovari et al., 2019)	Iran
Rice		Re	OM; CEC; pH; SEC; BS; OC; ST; SD; SDr	IC				(Nguyen and Khuong, 2019)	Vietnam
	RF	El; Sl,	SM; STy	WC; IS; DS	Dis_R		SE; DR	(Adrian et al., 2022)	Indonesia
	RF; T	Sl	pH; ST; pH			LULC		(Lamidi and Ijaware, 2022)	Nigeria
	T	Sl; As	pH; P; OM'; ST; SS; SD; EC; K; SCC; SLC	Dis_SW; Dis_WW	Dis_R; Dis_RMP; Dis_PC; PASC; PRC	LU		(Maddahi et al., 2014)	Iran
	RF; T	Sl	ST; pH; SD					(Ayehu and Besufekad, 2015)	Ethiopia
	RF; T	Sl; Re	ST; SD; pH; TN; AP; K; MN	WRA; Ge				(Roy and Saha, 2018)	India
	T; M	Sl	ST; pH; SD					(Kihoro et al., 2013)	Kenya
Saffron	RF; T; SH; NFD;M	El; Sl; As	EC; ST; pH;					(Maleki et al., 2017)	Iran
Sorghum		Sl	Ca; CEC; pH; P; OM; OC' Na; N; EC; Mg; K; ST;			LU		(Ahmed and Jeb, 2014)	Nigeria

Crop	Thematic factors							Reference	Nation
	Climate	Topography	Soil properties	Hydro-Geomorphology	Scio-economic	Land Use Compatibility	Hazard		
			SDr; SD						
	RF; T	Sl	SD; OM; pH; EC; CEC; Ca; P; N; Na; Mg; K					(Tadesse and Negese, 2020)	Ethiopia
Sugarcane		Sl; Ele; SO	SD; WHC; ST					(Alburo et al., 2019)	Philippines
Wheat		Sl	OM; CaCO3; CEC; pH; EC; ST; SD					(Khallouf et al., 2019)	Syria
Wheat, Vegetables	RF; T; Eva	Ele; Sl	EC, pH, ESP, OM, ST, SDr CaCO3, CEC, AWC, FC, BD	ICI	LS			(AbdelRahman et al., 2022)	Egypt
Wheat and barley	RF; T	Sl; Ele;	pH; OC; P; CEC; PBS; TN; SD; BD; AWC; ST					(Fekadu and Negese, 2020)	Ethiopia
Wheat		Sl	ST; pH; SoSa; SD; SDr; N; P; K	GWQ		LULC		(Dadhich et al., 2017)	India
Pistachio, Strawberry, Almond, Walnut tree	RF; CH; CHU; M;	Ele;	OM; pH	Bi				(Quinta-Nova and Ferreira, 2020)	Portugal
Onion, Cabbage, Potatoes, rice, sweet potatoes, cassava	RF; T	Sl; Ele	Sty; BS; ST; SD			LU		(Maulana and Kanai, 2022)	Indonesia

Accessibility to Market (AM); Aridity (A); Aspect (As); Available Water Capacity (AWC); Base Saturation (BS); Biogeography (Bi); Bulk density (BD); Calcium (Ca); Calcium Carbonate (CaCO3); Canal: (C); Cation Exchange Capacity (CXC); Cation Exchangeable Capacity (CEC); Chilling Hours (CH); Coarse Fragments (CF); Crop heat units (CHU); Density of Rural labor Force (DRF); Disaster Risk (DR); Distance from Main Road (Dis_R); Distance from Population Centers/ Working Populations (Dis_PC); Distance from residential areas with work opportunities (Dis_RA); Distance from the Villages (Dis_V); Distance from Rice Milling Plant (Dis_RMP); Distance to city (Dis_C); Distance from surface water/ river/ stream (Dis_SW); Distance from Water Well/ Pump and Spring (Dis_WW); Drainage System (DS); Ecoregions (E); Electrical Conductivity: (EC); Elevation (Ele); Equivalent (CCE); Evapotranspiration (Eva); Exchangeable Bases (EB); Exchangeable Sodium Percentage (ESP); Fertilization (F); Flooding (Fl); Geology (Ge); Gravel (Gr); Groundwater Depth (GD); Groundwater Potentiality (GP); Ground Water Quality (GWQ); Gypsum (G); Inundation Land Type (ILT); Iron (Fe); Irrigation Capability Index (ICI); Irrigation Condition (IC); Irrigation System (IS); Labor Availability (LA); Land Accessibility (LA); Land Capability (LC); Land Form (LF); Land Use Land Cover (LULC); Landscape (LS); Length of growing period (LGP); Lime (L); Lithology (Li); Magnesium (Mg); Mean Weight Diameter (MWD); Micro Nutrients (MN); Moisture (M); Molybdenum (Mb); Natural Fertility (NF); Nitrogen (N); Normalized Difference Vegetation Index (NDVI); Number of frost days (NFD); Organic Carbon (OC); Organic Matter (OM); Percent Base Saturation (PBS); Permeability (Pe); pH; Phosphorous (P); Pigment Depth (PD); Population Areas (PA); Potassium (K); Productivity (Pro); Proximity to Agricultural Service Centers (PASC); Proximity to irrigation ponds and dam lakes (PIPD); Proximity to Irrigation Ditch (PID); Proximity to River (PRi); Proximity to the Rural Cooperative (PRC); Proximity to Road (PRo); Proximity to Town (PT); Proximity to settlements (PS); Proximity to

Water Surface (PWS); Road (Ro); Rainfall (RF); Relief (Re); River: (R); Salinity and Alkalinity (SA); Salinity (S); Slope (Sl); Sodicity & salinity (SoSa); Soil-Cadmium Concentrations (SCC); Soil consistency (SC); Soil Depth (SD); Soil erosion: (SE); Soil Drainage/Drainage Capacity (SDr); Soil Group (SG); Soil Hydrology (SH); Soil Infiltration Capacity (SIC); Soil Morphology (SM); Soil-Lead Concentrations (SLC); Soil Reaction (SR); Soil Texture (ST); Soil type (STy); Soil Structure (SSt); Soil Water Content (SWC); Soil soluble Chlorine (SSC); Sum of Exchangeable Cation (SEC); Sunshine time (ST); Surface Stoniness (SS); Temperature (T); Total Nitrogen (TN)\; Vertical Properties (VP); Water Holding Capacity (WHC); Water resources Availability (WRA); Water Coverage (WC); Water Reserve (WR); Water Resources Properties (WRP).

Table 2 Fuzzy analytic hierarchy process (FAHP) method used in crop-land suitability assessment

Crop	Thematic factors							Reference	Nation
	Climate	Topography	Soil properties	Hydro-Geomorphology	Socio-Economic	Land Use Compatibility	Hazard		
Alfalfa	RF; T; M	Sl; Ele	pH; OM; SD; SCS	Dis_SW	Dis_R; Dis_C; DRF			(Deng et al., 2014)	China
Banana		Sl	ST; SD; SDr; pH; S; VP					(Koca et al., 2022)	Turkey
Durum wheat		Sl	Pe; pH; EC; CaCO3; CEC; ST; SD	WR; SDr;	Dis_R; LA			(Mendas and Delali, 2012)	Algeria
Orange			Natural, Economic and Social Factors					(Tung et al., 2022)	Vietnam
Paddy	RF; T: M	Sl; El;	pH; ST					(Sarkar et al., 2021)	Bengal
Rice	T; M;	Sl; As;	pH; P; K; OM; ST; SS; SD; EC;	Dis_SW; Dis_WW	Dis_R; Dis_RMP;Dis_RA			(Maddahi et al., 2017)	Iran
Rubber		Sl	pH, OM; ST; STh; STy					(Tran et al., 2020)	Ethiopia
Sorghum			SD; ST; SC;					(Kahsay et al., 2018)	Ethiopia
Tobacco	RF; T; ST	Re; Ele; Sl	SSC; pH, ST; SOC, AN, AP, AK; Ca; Mg; Mb					(Zhang et al., 2015)	China
wheat		Re	ST; CEC; ESP; G; CaCO3; SD; pH	GD; H				(Mokarram et al., 2010)	Iran
Wheat		Ele; Sl; As	ST; pH; EC; OM; L; SD					(Kılıc et al., 2022)	Turkey
Barley		Sl; Re;	pH: G; SA; CaCo3; ST; SD;	GD; PD				(Hamzeh et al., 2014)	Iran

Table 3 Analytic Network Process (ANP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and ELimination and Choice Expressing REality (ELECTRE) methods used in crop-land suitability assessment

Crop	Thematic factors							Reference	Nation
	Climate	Topography	Soil properties	Hydro-Geomorphology	Availability	Land Use Compatibility	Hazard		
ANP method									
Maize		Sl; Ele	SR; SD; ST; CF; SDr; CEC					(Kenzong et al., 2022)	Cameroon
Wheat and barley	T	As; Sl; Ele	SD; ST; SDr; pH; OM; EC; CEC; P; N; Ca;	Dis_SW	Dis_R			(Yohannes and Soromessa, 2018)	Ethiopia
Maize	T, RF	Sl;	ST; CF; SD; G; CaCO3; AWC; pH; OC; P; K; CEC; EC; ESP	DS			Fl	(Seyedmohammadi et al., 2019)	
TOPSIS method									
Wheat	RF; T	Sl;	ST; SDr; SD; pH; EC; OC; ESP; CaCO3; G				Fl	(Bagherzadeh and Gholizadeh, 2016)	Iran

Maize; Rapeseed; Soybean	Climate	Sl	SD; pH; EC; ESP; CaCO3; G					(Seyedmohammadi et al., 2018)	
Wheat	RF; T	Sl	ST; EC; EPS; CaCO3; Gr; SD; OC; pH; G; SDr				Fl	(Bagherzadeh and Gholizadeh, 2016)	Iran
				ELECTRE method					
Rice	RF	Sl;	SDr; SD; pH; OM	SE				(Ali et al., 2020)	

Table 4 Hybrid method used in crop-land suitability assessment

Crop	Thematic factors							Reference	Nation
	Climate	Topography	Soil properties	Hydro-Geomorphology	Socio-economic	Land Use Compatibility	Hazard		
				AHP and others					
Agriculture		Ele; Sl	SD; SS; Sty; SWC	PWS	PR; PT	LULC		(Yalew et al., 2016)	Ethiopia
Cassava	RF; T;	Ele; Sl	SG	WRA		LULC; NDVI		(Purnamasari et al., 2019)	Indonesia
Cereal	RF; T	Ele; Sl	ST; SD; SDr; Sty; pH; OC			LULC		(Abebe, 2020)	Ethiopia
Cereal	RF; T; LGP; M;	Sl	pH; N; P; K; SDr; SoSa; SD; ST; Pro			LULC	SE	(Singh et al., 2018)	India
Cocoa	RF	Sl	STy			LULC		(Tenkap and Balogun, 2020)	Nigeria
Gram	RF	Re; Sl	STy	GP; IS		LULC		(Mustak et al., 2015)	India
maize			EC; OC;pH;CEC; BS; N; P; K; CaCO3; ST; SD; AWC					(Mustafa et al., 2011)	India
Maize, Wheat	RF; T	Sl	SDr; ST; SD; Sty; SS			LU		(Mulugeta, 2010)	Ethiopia
Maize	RF	Sl; Ele	STy	Dis_SW	Dis_R	LC		(Habibie et al., 2021)	Indonesia
Paddy	RF; T; TWI	Sl; Ele	ST;	Gr; Li		LULC		(Ramu et al., 2022)	India
Potatoes	RF; T	Re	pH; ST; SD SDr					(Kamau et al., 2015)	Kenya
Potato	RF; T;	Ele; Sl;; As	pH; CEC; OM; N; P; K; ST; EC					(Iliqu ń Trigoso et al., 2020)	Peru
Pulse	RF; T	Sl; Ele;	ST; SD; S; pH; SDr; ILT			LULC		(Hossen et al., 2021)	Bangladesh
Rice	T		EC; pH; SDr; STy;					(Raza et al., 2018)	Pakistan
Rice	RF; T	Sl	pH; ST; SD; SDr					(Robertson and Oinam, 2023)	India
Tea	RF; T	Ele; Sl	ST, pH; SD; STy	Dis_SW	Dis_R	LULC; NDVI		(Das et al., 2020)	Bangladesh
RIce	M	Sl	ST; AWC; pH; EC; Nutrients (N, P, K) and MN			LULC		(Kumar and Patel, 2020)	India
Rice		Sl	STy		LA	LULC		(Yangouliba et al., 2020)	Burkina Faso
Cereal	RF; T; M	Sl	pH; ECE; OC; SDr; ST					(Shaloo et al., 2022)	India
Maize	RF; T	Sl	CEC; OC pH; ST; CF;	WRP				(Bilas et al., 2022)	China
Rice	RF; T; SH	Ele; Sl; T	STy; SD; F;	IC			Fl	(Tong et al., 2021)	Vietnam
				Fuzzy AHP and others					

Crop	Thematic factors							Reference	Nation
	Climate	Topography	Soil properties	Hydro-Geomorphology	Socio-economic	Land Use Compatibility	Hazard		
Wheat		Sl	ST; SD; SDr; SS; Ph; s; CaCO3; OM	IS;		NDVI		(Tuğaç, 2021)	Turkey
Cacao; Coffee; Clove; Pepper	RF; T	Sl	pH; BS; CEC; OC; ST; SD; SEC					(Sappe et al., 2022)	Indonesia

3 Results and discussion

3.1 Distribution of publications based on study regions, crops, and decision techniques

This section discusses 75 publications related to the major topic of the paper. The findings revealed that the majority of crops mentioned in the studies were rice, maize, wheat, cereal, potato, and sorghum. Another review study also drew a similar conclusion about the main crops when researching methods to assess crop-land suitability (Mugiyo et al., 2021). In addition to information on major crops, the countries where the studies were performed were also extracted from full-length papers. Most of the studies are conducted in India, Ethiopia, Iran and some Asian countries such as Indonesia, China, Vietnam, Turkey, etc. On the contrary, it seems that MCDM is rarely used for some nations in Africa such as Burkina Faso, Cameroon, Egypt, Ghana, Kenya, Nigeria, Tanzania, etc. (Only one research has been reported in each country). This might be due to lack of technology, funds, and/or expertise, experts (Gebre et al., 2021). From the selected literature, it can be seen that the MCDM and MCEA techniques including AHP, FAHP, ANP, ELECTRE, and TOPSIS have been applied with or without remote sensing or Agricultural Land Use Evaluation System, FAO, parametric methods, etc. for land suitability evaluation. Table 5 lists the methods and the number of studies used them.

Table 5 Approaches for analyzing crop-land suitability

Method	Reference	Total
AHP	(AbdelRahman et al., 2022; Ahmed and Jeb, 2014; Alburo et al., 2019; Ayehu and Besufekad, 2015; Chivasaa et al., 2019; Dadhich et al., 2017; Debesa et al., 2020; Fekadu and Negese, 2020; Khallouf et al., 2019; Kihoro et al., 2013; Kim and Shim, 2018; Lamidi and Ijaware, 2022; Maddahi et al., 2014; Madrigal-Martínez and Puga-Calderón, 2018; Maleki et al., 2017; Maulana and Kanai, 2022; Mighty, 2015; Mishra et al., 2015; Adrian et al., 2022; Nguyen and Khuong, 2019; Nguyen et al., 2019; Ostovari et al., 2019; Quinta-Nova and Ferreira, 2020; Rasheed and Naz, 2016; Roy and Saha, 2018; Salifu et al., 2022; Salunkhe et al., 2022; Sathiyamurthi et al., 2022; Sheikh et al., 2017; Singha and Swain, 2018; Singha et al., 2019; Tadesse and Negese, 2020; Tashayo et al., 2020; Tercan and Dereli, 2020)	34
ANP	(Kenzong et al., 2022; Seyedmohammadi et al., 2019; Yohannes and Soromessa, 2018)	3
FAHP	(Deng et al., 2014; Hamzeh et al., 2014; Kahsay et al., 2018; Kılıc et al., 2022; Koca et al., 2022; Maddahi et al., 2017; Mendas and Delali, 2012; Mokarram et al., 2010; Sarkar et al., 2021; Tran et al., 2020; Tung et al., 2022; Zhang et al., 2015)	12
TOPSIS	(Bagherzadeh and Gholizadeh, 2016; Seyedmohammadi et al., 2018)	2
ELECTRE	(Ali et al., 2020)	1
Hybrid method		23
AHP, RS, GIS	(Abebe, 2020; Das et al., 2020; Habibie et al., 2021; Hossen et al., 2021; Iliquín Trigoso et al., 2020; Kamau et al., 2015; Kumar and Patel, 2020; Mulugeta, 2010; Mustafa et al., 2011; Mustak et al., 2015; Purnamasari et al., 2019; Ramu et al., 2022; Raza et al., 2018; Robertson and Oinam, 2023; Singh et al., 2018; Shaloo et al., 2022; Tenkap and Balogun, 2020; Yalew et al., 2016; Yangouliba et al., 2020)	
FAHP, RS, GIS	(Tuğaç, 2021)	
FAHP and PCA model	(Sappe et al., 2022)	
AHP and Agricultural Land Use Evaluation System (ALUES software)	(Bilas et al., 2022)	
AHP and Techniques for Order of Preference with Similarity to Ideal Solution	(Tong et al., 2021)	

The distribution of MCDM and MCEA approaches discussed is shown in Figure 1. Among 75 reviewed studies, AHP technique could be observed from 34 research (46%). The predominance usage of AHP over the other approaches is due to the fact that it is simpler, more adaptable, and requires fewer cognitive abilities than any other form of MCDM (Ananda and Herath, 2009). In addition, the hybrid approach using more than one technique (including MCDM and MCEA) was also a prevalent method for analyzing crop-land suitability with 23 papers (31%). The use of ELECTRE, ANP, and TOPSIS techniques were identified to be insignificant for assessing land suitability (only 1 to 3 studies). It was noted that the FAHP method can classify and generate crop-land suitability maps with high accuracy, but there are not many studies using this method (12 studies).

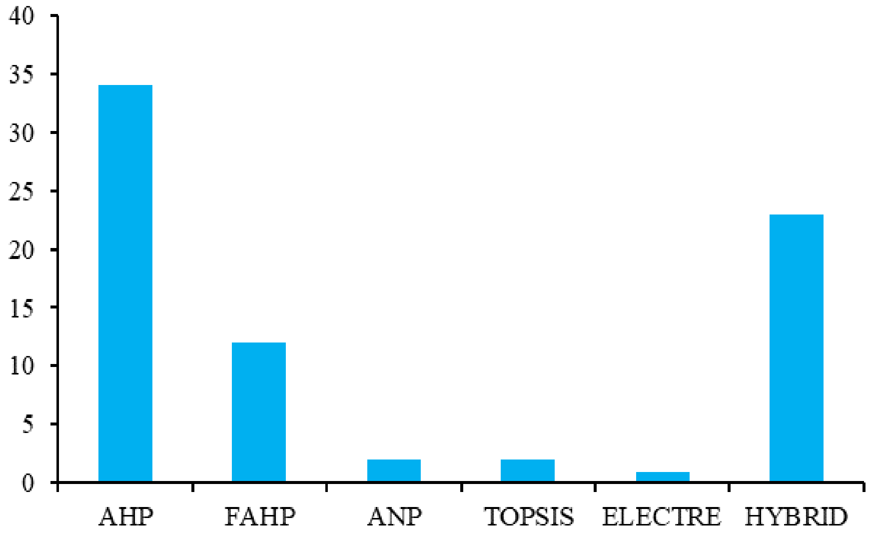

Figure 1 Distribution of MCDM/ MCEA techniques for crop-land suitability

3.2 MCDA/MCEA techniques and tools used to assess crop-land suitability

The thematic layers of different input factors with various MCDA techniques such as AHP, ANP, FAHP, etc. can be incorporated into a GIS environment for crop-land suitability identification. Below is an in-depth analysis of the methods and their advantages and disadvantages

3.2.1 AHP

The AHP is widely used and recognized as one of the most useful approaches in determining the weights of parameters, and addressing various problems based on complicated variables at different stages (Shaloo et al., 2022). According to Maddahi et al. (2014), the AHP method is regarded as one of the most useful MCDM approaches to analyze and evaluate land appropriateness for various crops. The integration of AHP and GIS in evaluating crop-land suitability has great potential to increase the effectiveness and accuracy of obtained results (Chivasaa et al., 2019). The AHP takes into account a set of criteria that involved land suitability evaluation as well as alternative options before making the optimal decision. In this method, the pairwise comparison matrix was generated based on the relative importance of one variable over another to determine the factor weights according to the AHP preference scale (Rodcha et al., 2019). There are four steps to calculate the weights of the evaluated criteria based on the pairwise comparison matrix, that is (1) Creating the judgments; (2) Determining the assigned ranks; (3) Developing the normalized pairwise comparison matrix; (4) Calculating the weights (Bisht et al., 2022). AHP can handle complicated spatial scenarios, but they are subjective and have some restrictions in consistency (Alkimim et al., 2015). Therefore, although AHP is widely employed in MCDM, it is insufficient to remove any ambiguity in the data, since the characteristics of the data utilized influence whether the data is certain or uncertain. On the other hand, the AHP is one of the MCDM techniques that is most frequently used, however when there are more than nine criteria or indications to take into account, consistency is difficult to determine (Saaty, 2002).

Previous studies have shown that AHP has many advantages in determining the suitability of cropland, such as integrating the tangible and intangible aspects of issues, putting more emphasis on group goals than individual ones, and constantly brainstorming for better answers (Dyer et al., 1992). According to Han et al. (2021), compared with the traditional crop-land appropriateness assessment approach, the AHP assessment findings are more precise and objective. Additionally, a regional scale study of each land unit may be conducted to determine the impact of each evaluation element on the suitability of various crops. Furthermore, this method is considerably simpler to understand and can be calculated using MATLAB or Python, which are basic software programs. Additionally, AHP has been identified to be better to other approaches because it can handle many criteria and compensate for both qualitative and quantitative data (Bisht et al., 2022). The technique does, however, have significant drawbacks, such as the way it expresses the issue of environmental unpredictability (Belton and Gear, 1983), hierarchy-induced deuce deficiency (Millet and Harker, 1990), the potential for linguistic mistakes when answering the AHP questionnaire (Kocaoglu and Niwa, 1991). Besides, traditional AHP may not consistently yield reliable results, thus resulting in low result reliability. Based on expert assessments, the relative relevance of two factors is represented by the weights of each index. However, the opinions of different experts differ, which could lead to a bias in the conclusion when it is assessed using a single weight index (Peng et al., 2021). Although there are many advantages and some disadvantages, the combined method of GIS and AHP might provide a higher-quality database and guide map for decision-makers evaluating crop-land displacement to achieve appropriate agricultural production (Shaloo et al., 2022).

3.2.2 FAHP

Although AHP is more commonly employed for MCDM to handle the problem of human uncertainty, it is still insufficient to deal with the inherent ambiguity and inaccuracy involved in mapping decision-makers' perceptions to actual numbers (Rodcha et al., 2019). In order to solve uncertainty and vagueness caused by AHP shortcomings, Zadeh (1965) developed a fuzzy set theory (Lermontov et al., 2011). FAHP is an integration of a fuzzy logic approach and the AHP method. According to Kahsay et al. (2018), FAHP is an AHP method developed with a fuzzy logic theory that converts the AHP scale into a fuzzy triangle scale to determine the priority of the criterion. The FAHP was considered the base approach in LSA in various research. This approach tackles ambiguous data and valuable knowledge that decision-makers can use in uncertain circumstances. According to the findings of Hosini (2020), in determining land suitability, FAHP evaluation is more accurate than the ordinary parametric method. Moreover, the comparison of the results of FAHP and FAO methods based on the observed yields in validation fields indicated that the former has higher precision than the latter method (Hamzeh et al., 2014)

The literatures indicated that uncertainty of weighting by expert judgments of the FAHP method can be improved. The uncertainty concerning the bias of expert opinions is resolved by the FAHP (Rodcha et al., 2019). Furthermore, compared to the parametric approach, the fuzzy-based method was more sensitive and adaptable, better reflecting the actual conditions of the area. In comparison to AHP, the primary benefit of FAHP is that it is more appropriate to the fuzzy law of human thinking (Zhang et al., 2013). Additionally, using the FAHP method provides the advantage of simultaneously considering both quantitative and qualitative data, in contrast to traditional methods like the square root method, which heavily rely on expert opinions to rank the most critical criteria (De la Rosa and van Diepen, 2009).

3.2.3 ANP

Although there are other ways to calculate weightings, ANP is one of the best procedures to apply to various and heterogeneous variables (Seyedmohammadi et al., 2019). The ANP is a generalized form of the AHP and was proposed by Satty in 1980. It is a nonlinear structure that has having bilateral interactions (Azizi et al., 2014) and structures a decision-making problem into a network (Mokarram et al., 2019). In the ANP analysis, a concept model was initially created to establish relationships between the criteria and alternatives. It also employs a pair-wise comparison technique to calculate the weights of the structural components before ranking the decision’s options (Bisht et al., 2022). The ANP was chosen by Seyedmohammadi et al. (2019) as the method to calculate the weights of the criteria influencing crop-LSA since it can offer solutions in a challenging multi-criteria decision environment. Like the AHP technique, a pair-wise comparison of the relative significance of factors within groups and for the relationship of parameters within and among groups is the first step of the ANP technique. The degree of consistency of the pair-wise comparison matrices is considered acceptable if the consistency ratio is lower than 0.1.

According to Yang and Tzeng (2011), the ANP technique was created to address the hierarchical flaws in the AHP method. Furthermore, a "supermatrix" is created using the ANP approach to figure out the composite weights of the parameters (Schulze-González et al., 2021). But when applied alone, the ANP technique has certain shortcomings that might result in inconsistent judgment and low-quality results (Kheybari et al., 2020).

3.2.4 TOPSIS method

TOPSIS is the most well-known MCDM model proposed first by Hwang and Yoon (1981) in 1981 (Tzeng and Huang, 2011). Like the AHP, TOPSIS can be used to analyze a set of factors and supply decision-makers an idea of the weights or prioritized ranking of those criteria (Bagherzadeh and Gholizadeh, 2016). The fundamental logic of TOSIS is to identify the ideal solution and negative ideal solution. The method for ranking preferences by similarity to the ideal solution is that alternatives selected must have the furthest distance from negative ideal solution and the closest distance from the positive ideal solution (Hwang and Yoon, 1981). This model has been successfully used in the land evaluation method (Prakash, 2003). TOPSIS model consists of seven steps: (1) Establishing data matrix; (2) Standardizing data and preparing normalized matrix; (3) Determining weights for indicators; (4) Generating dimensionless weight matrix; (5) Calculating positive ideal and negative ideal; (6) Determining relative closeness; (7) Ranking alternatives. In order to assess the accuracy of this method, the findings obtained from TOPSIS models can be compared with those of the parametric method in (Bagherzadeh and Gholizadeh, 2016). As a result, the coefficient of identification between the parametric land index values and the corresponding TOPSIS preferred values showed a strong correlation between the two methods (Bagherzadeh and Gholizadeh, 2016).

As assistant decision-making tools, TOPSIS has clear benefits including practicality, conciseness, and systematization. There are two issues to pay attention when applying TOSSIS to multi-objective decision problems. Firstly, according to (Wang, 2018), the basic factors that should be carefully considered when breaking down and simplifying multiobjective decision-making situations, without taking into account the possibility of adding or missing variables. Furthermore, factors that exhibit significant differences cannot be effectively compared within the same layer.

3.2.5 ELECTRE method

ELECTRE is an MCDM approach that utilizes the idea of outranking through pairwise comparison of different choices based on each relevant criterion (Govindan and Jepsen, 2016). In order to select the dominant alternative, ELECTRE is utilized in the ranking process based on the concordance and discordance index (Ali et al., 2020). Evaluations carried out using ELECTRE will result in the best alternative ranking relationship under the supposition that alternative one can be preferred to the others. When the options are equally valuable, it is necessary to prioritize all factors that are mutually convincing and not conflicting. The ELECTRE method has six stages, which are as follows: (1) Make a paired comparison for matrix normalization; (2) Calculate the preference matrix; (3) Come to decision a set index of concordance and discordance; (4) Determine the matrix of concordance and discordance; (5) Compute the threshold to create the dominant concordance and discordance matrix; (6) Establish the matrix of dominant aggregation (Ali et al., 2020). This method is suitable for choice and elimination processes. However, its drawback is in calculating the weights of the criteria. Therefore, ELECTRE has been integrated with other approaches for analyzing land suitability. In particular, A combination of fuzzy-AHP for criterion weighting and the ELECTRE method for ranking have proven effective in creating web-based information systems with perfect results (Ali et al., 2020)

3.2.6 Integration of MCDM and others

In addition to the methods described above, the hybrid approach is also used extensively for crop-LSA. Most are a combination of AHP and FAHP and remote sensing technology in a GIS environment. Many researchers have assessed land suitability using RS and MCDM to raise crop yield and decrease environmental footprints and input material costs (Dhami et al., 2012, Shaloo et al., 2022). According to Mugiyo et al. (2021), this integration might offer a superior database and guide map for decision makers taking into account farmland substitution to improve agriculture productivity. Remote sensing methods will provide data frequently and at an inexpensive value to allow interference for crop recovery at the proper time (Ennouri and Kallel, 2019). Several types of selected information on available resources such as land use, land cover, soil humidity, soil type, crop nature and state, slope, elevation, etc. can be extracted from satellite images (Blaschke et al., 2008). In addition, remote sensing data was utilized to determine the Normalized difference vegetation index time series of crops and to derive geomorphologic units (Baroudy et al., 2020), soil-adjusted and atmospherically resistant vegetation index, atmospherically resistant vegetation index, modified soil-adjusted vegetation index, etc. (Binte Mostafiz et al., 2021). However, RS data alone cannot recommend crop-land appropriateness for a region unless it is integrating this information with site-specific soil and climatic data (Martin and Saha, 2009).

In identifying land suitability using MCDM, the challenge often met is the considerable subjectivity of researchers in judging the importance of land attributes. In order to address this problem, numerous researchers employed principle component analysis (PCA) in evaluating crop-land suitability to investigate the interests of several conflicting land characteristics (Sappe et al., 2022). Although some scientists utilized PCA to decrease dimensional data into a few criteria (Nguyen et al., 2020; Said et al., 2020), Ranjbar et al. (2016) stated that not lessening data is the most precise approach to assess land quality and provide reliable results. Therefore, in evaluating crop-land suitability, PCA is used to analyze the significance of soil properties without decreasing it to a few data (Sappe et al., 2022).

In addition to combining the MCDM and RS, the combination of the FAHP method and principal component analysis is appropriate for transforming numerical data of different magnitudes into membership function values and indicating land suitability. The principal component analysis is an efficient approach for calculating the weights of several variables in a systematic and objective manner (Sappe et al., 2022). In this method, Fuzzy is applied for normalizing features, and PCA is used to analyze conflicts of interests between attributes.

In order to determine the level of suitability for cultivating a certain crop in the region, the combined method of AHP and Agriculture Land Use Evaluation System (ALUES) can be used. ALUES is a program that assesses land suitability for producing various crops. ALUES is a highly optimized library with main algorithms written in C++. In evaluating land suitability, this software uses fuzzy logic methods to analyze the land suitability of a specific region based on input criteria such as topography, rainfall, temperature, topography, and soil properties, and the AHP was utilized to calculate the weight of those input factors (Bilas et al., 2022). Also, according to Bilas et al. (2022), based on ALUES, assessment of land suitability can be performed by mapping the input features of a land unit into the suitability class of the target parameter.

The integration of AHP, GIS, and technology for order of preference by similarity to the ideal solution is also used in modeling the crop-land suitability. In this approach, according to Tong et al. (2021), using the structured AHP, expert opinions are utilized to calculate the weights of specified criteria, and technology for order of preference by similarity to the ideal solution evaluates the potential for crop cultivation on the land to create a ranking. In addition, GIS is employed to operate the spatial analyst module, and is also used to detect suitable variables. This approach can be performed following nine steps: (1) Generate a set of criteria; (2) Identify the relative importance of each criterion; (3) Determine the average proportion of alternatives; (4) Calculate the weighted average of the results; (5) Normalize the way in which alternatives; (6) Compute the value of the normalized standard in a given case; (7) Calculate the optimal fuzzy positive ideal solution and the optimal fuzzy negative ideal solution; (8) Determine the distance between each solution and the coefficients in close proximity; (9) Establish the ranking order for the alternatives (Tong et al., 2021).

The use of each algorithm of the multi-criteria assessment method can be applied to the analysis of crop-land suitability. However, each approach has different advantages and disadvantages. Therefore, to get the best results, algorithms should be integrated together. In addition, in order to improve crop compatibility mapping for climate-smart agriculture, future research should concentrate on utilizing artificial intelligence (AI) and machine learning techniques (MLMs), which have gained popularity recently and can be coupled with MCE and GIS (Bisht et al., 2022). In addition, since expert opinions can vary at any time, the study can analyze a time series to enhance the model precision. As a result, the procedure should be repeated and assessed on a regular basis until the model is stable, and then it should be confirmed using a sampling plot in the field (Rodcha et al., 2019).

3.3 Identification of the necessary criteria for crop-land suitability evaluation

The identification of criteria in crop-land suitability assessment differs among scientists. There are numerous physical factors used for evaluating land suitability such as climate, topography, land use, soil (Dula, 2010; Mulugeta, 2010). However, Debesa et al. (2020) emphasized that these are not the only parameters that identify the suitability of a given crop-land. It is necessary to consider other criteria such as socio-economic, infrastructure, etc. The degree of contribution of different factors’ can be solved effectively when arranged into multiple groups and at different levels. Some authors divided these criteria into high and lower parameters based on the judgments of experts (Jahanshiri et al., 2020). The former factors are natural or biophysical criteria that directly influence crop cultivation such as precipitation, temperature, soil fertility, etc. The latter ones are socio-economic factors that do not directly affect crop growth but have an impact on how appropriate a land use is for a certain purpose. Others grouped variables into five categories: hydrology, soil, and landscape characteristics, socio-economic and technical indicators, land use, and land cover (Mugiyo et al., 2021). Byeon et al. (2018) organized into various groups including soil, climate, topography, land use, land cover, socio-economic/ infrastructure, and irrigation. In this paper, using previous studies as references, the main factors were selected for analyzing the crop-land suitability can be classified into the following classes: climate, topography, soil properties, hydro-geomorphology, socio-economic, land use compatibility, and hazard. The criteria and sub-criteria used in analyzing crop-land suitability are summarized in Table 6.

Table 6 The criteria and sub-criteria used in crop-land suitability evaluation

Criteria	Sub-criteria	Number
Soil properties	Available Water Capacity (AWC); Mean Weight Diameter (MWD); Soil consistency (SC); Soil Drainage/Drainage Capacity (SDr); Soil Depth (SD); Soil Hydrology (SH); Soil Group (SG); Soil Infiltration Capacity (SIC); Soil Morphology (SM); Soil Reaction (SA); Surface Stoniness (SS); Soil Texture (ST); Soil type (STy); Soil Structure (SSt); Soil Water Content (SWC); Base Saturation (BS); Bulk density; BD; Cation Exchange Capacity (CXC); Cation Exchangeable Capacity (CEC), Calcium Carbonate Equivalent (CCE); Calcium (Ca); CaCO3; Iron (Fe); Coarse Fragments (CF); Electrical Conductivity: (EC); Exchangeable Bases (EB); exchangeable sodium percentage (ESP); Fertilization (F); Gravel (Gr); Inundation Land Type (ILT); Gypsum (G); Land Capability (LC); Lime (L); Magnesium (Mg); Micro Nutrients (MN); Molybdenum (Mb); Natural Fertility (NF);Nitrogen (N); Organic Carbon (OC); Organic Matter (OM); Phosphorous (P); Percent Base Saturation (PBS); pH; potassium (K); Permeability (Pe); Salinity and Alkalinity (SA); Salinity (S); Soil Soluble Chlorine (SSC); Sodicity & salinity (SoSa); Sum of Exchangeable Cation (SEC); Soil-Cadmium Concentrations (SCC); Soil-Lead Concentrations (SLC); Productivity (Pro); Total Nitrogen (TN)\; Vertical Properties (VP); Water Holding Capacity (WHC);	56
Topography	Aspect (As); Elevation (Ele); Relief (Re); Slope (Sl)	4
Climate	Aridity (A); Chilling Hours (CH); Crop heat units (CHU); Ecoregions (E); Evapotranspiration (Eva); Length of growing period (LGP); Moisture (M); Number of frost days (NFD); Rainfall (RF); Temperature (T); Sunshine time (ST)	11
Hydro-Geomorphology	Biogeography (Bi); Canal: C; Distance from surface water/ river/ stream (Dis_SW); Distance from Water Well/ Pump and Spring (Dis_WW); Drainage System (DS); Irrigation Condition (IC); Irrigation Capability Index (ICI); Irrigation System (IS); Geology (Ge); Proximity to irrigation ponds and dam lakes (PIPD); Proximity to River (PRi); Proximity to Irrigation Ditch (PID); Proximity to Water Surface (PWS); River: (R); Water resources Availability (WRA); Water Coverage (WC); Water Reserve (WR); Water Resources Properties (WRP); Groundwater Depth (GD); Ground Water Quality (GWQ); Groundwater Potentiality (GP); Pigment Depth (PD); Lithology (Li);	23
Scio-economic	Distance from Main Road (Dis_R); Distance from Rice Milling Plant (Dis_RMP); Distance from Population Centers/ Working Populations (Dis_PC); Distance from residential areas with work opportunities (Dis_RA); Distance from the Villages (Dis_V); Distance to city (Dis_C); Density of Rurallabor Force (DRF); Labor Availability (LA); Landscape (LS); Land Accessibility (LA); Population Areas (PA); Road (Ro); Accessibility to Market (AM); Proximity to Agricultural Service Centers (PASC); Proximity to the Rural Cooperative (PRC); Proximity to Road (PRo); Proximity to Town (PT); Proximity to settlements (PS)	18
Land Use Compatibility	Lan Use Land Cover (LULC); NDVI	2
Hazard	Disaster Risk (DR); Flooding (Fl); Soil erosion: SE;	3
	Sum	117

Table 7 summarized the techniques, criteria group and the number of studies used them for LSA. From this review, most studies confirm that soil is the most dominant and indispensable criterion when assessing crop suitability. Only 1 study (Tercan and Dereli, 2020) suggested that meteorological and topographical conditions play a major role in citrus cultivation planning. In the criteria related to soil properties, some soil chemical characteristics such as pH, CEC, EC, OM, P, N, Ca, etc. and some soil physical features such as soil depth, soil texture, soil drainage, etc. were mentioned in many studies. Field soil sampling methods were utilized to assess the quantity and spatial distribution of soil components and nutrient availability (Yohannes and Soromessa, 2018). After soil characteristics, topography parameters are also assessed as necessary and indispensable with 66 studies. Topography is strongly associated with the normal growth of soil. Topographical factors used in the studies include slope, elevation, relief, and aspect. In which, slope and elevation were the prevalent criteria in this group because they were evaluated as one of the most important topographical conditions (Tercan and Dereli, 2020). While elevations have an impact on crop-land suitability due to their influence on variations in temperature and changes in plant cover (Memarbashi et al., 2017), slopes have a direct effect on soil nutrients, soil thickness, and agricultural productivity (Han et al., 2021). Although the aspect has a significant impact on farming operations and crop output by affecting soil temperature and water content (Ostovari et al., 2019), but only 9 out of 66 studies included this factor in the analysis model.

Table 7 Techniques, criteria groups and a number of studies used them for LSA

Method	Total	Climate	Topography	Soil properties	Hydro-Geomorphology	Socio-Economic	Land Use Compatibility	Hazard
AHP	34	24	30	33	13	8	10	2
FAHP	12	4	9	12	5	3	0	0
ANP	3	2	3	3	2	1	0	1
TOPSIS	2	2	2	2				1
ELECTRE	1	1	1	1	1	0	0	0
HYBRID	23	20	21	23	9	3	15	2
Total	75	53	66	74	30	15	25	6

Another group of factors that are also preferred when assessing crop-land suitability is climate. The scientists insisted that, these criteria provided a highly efficient procedure for deciding on suitable regional planning for crop cultivation (Tercan and Dereli, 2020). Among 75 reviewed studies, climate criteria could be found from 53 studies including aridity, chilling hours, crop heat units, ecoregions, evapotranspiration, length of growing period, moisture, number of frost days, rainfall, temperature, sunshine time. However, most of the factors used in this group are rainfall and temperature. With respect to heat, the growing season and ripening of crops are determined by the average temperature during the crop development period. The development of crops and yields are impacted by the amount of rainfall (Han et al., 2021). Although evaluated with high weight when analyzing land suitability, others such as aridity, chilling hours, crop heat units, ecoregions, evapotranspiration, length of growth period, number of frost days, and sunshine time were utilized limited in the studies. For parameters related to hydro-geomorphology and land use compatibility, the number of studies using these factors to analyze land suitability accounts for just over a third of the total number of studies. A thorough understanding of land use and land cover (LULC) is essential for crop suitability assessment and effective environmental management (Mugiyo et al., 2021). However, of all possible approaches, that may identify land suitability, only 33.3% used LULC. The socio-economic and hazard criteria group appeared to be of the least interest to scientists. The socio-economic factors such as rural labor force, landscape, population area, road, distance from main road, rice milling plant, population center, village, city, etc. Most factors in this group have a weight rank at moderate level. For hazard factor groups, not only are they used the least among the groups, but the criteria of this group are also assessed to have the least impact on crop-land suitability. Although there are many criteria influenced LAS and it is impossible to consider all of them, according to Madrigal-Martínez and Puga-Calderón (2018), each group of parameters has some degree of significance in evaluating the crop-land suitability and it is not suggested to exclude any of them. In order to choose the appropriate criteria, it is necessary to pay attention to the crop growth conditions and the actual situation in the study area.

4 Conclusion

The application of MCEA-based GIS for identifying the best land suitability for farming is a critical approach due to flexibility of the models such as ease of understanding, different types of criteria both quantitative and qualitative can be used, etc. By combining GIS and Multi Criteria, it is possible to manage the criterion data, generate criterion layers, determine attributes using spatial analysis, combine decision criteria using modelling, conduct sensitivity analyses, and create the maps required for evaluating crop-land suitability. The review found techniques of multi-criteria assessment were used to analyze the appropriateness of crop-land including AHP, FAHP, ANP, TOPSIS, and ELECTRE. In which, the AHP technique and the combination of AHP and other methods such as remote sensing, FAO framework, ALUES software, etc. are used the most. Otherwise, although ANP, TOPSIS, and ELECTRE are considered the most well-known MCDM models, they do not seem to be in common use in studies. Furthermore, as a result of the study, it has been revealed that 117 criteria of seven groups (climate, topography, soil properties, hydro-geomorphology, socio-economic, land use compatibility, and hazard) play an important role in assessing land suitability. Notably, the factors related to the properties of the soil are always assigned high weight and are necessary to be included in the model calculation. This review can help and will be valuable as a prepared resource for individuals who are interested in integrating GIS and MCDA as a useful tool for crop-land suitability evaluation.

Declaration of competing interest

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

Acknowledgments

Thanks to two anonymous reviewers and editorial comments for their valuable comments in the earlier version which helped us to improve the quality of the manuscript.

References

AbdelRahman, M. A. E., A. M. Saleh, and S. M. Arafat. 2022. Assessment of land suitability using a soil-indicator-based approach in a geomatics environment. *Scientific Reports*, 12(1): 18113.

Abebe, S. 2020. GIS and remote sensing based physical land suitability analysis for culitivation oF selected cool weather cereal crops, Misha District, Hadiya Zone, South Central Ethiopia. *Preprints*, 2020080671. https://doi.org/10.20944/preprints202008.0671.v1.

Aburas, M. M., S. H. Abullah, M. F. Ramli, and Z. H. Ash'aari. 2015. A review of land suitability analysis for urban growth by using the GIS-based analytic hierarchy process. *Asian Journal of Applied Sciences*, 3(6): 869-876.

Adem Esmail, B., and D. Geneletti. 2018. Multi-criteria decision analysis for nature conservation: a review of 20 years of applications. *Methods in Ecology and Evolution*, 9(1): 42–53.

Adrian, Widiatmaka, K. Munibah, and I. Firmansyah. 2022. Evaluate land suitability analysis for rice cultivation using a GIS-based AHP multi-criteria decision-making approach: Majalengka Regency, West Java Province. *IOP Conference Series: Earth and Environmental Science: IOP Publishing*, 1109: 012062.

Ahmed, M., and D. N. Jeb. 2014. Land suitability for sorghum using multicriteria evaluation (MCE) and analytical hierarchy process (AHP) in Bunkure Kano State, Nigeria. *IOSR Journal of Agriculture and Veterinary Science*, 7(9): 25-37.

Akpoti, K., A. T. Kabo-bah, and S. J. Zwart. 2019. Agricultural land suitability analysis: State-of-the-art and outlooks for integration of climate change analysis. *Agricultural Systems*, 173: 172-208.

Alburo, J. L. P., J. N. M. Garcia, P. B. Sanchez, and P. C. S. Cruz. 2019. Application of analytical hierarchy process (AHP) in generating land suitability index (LSI) for sugarcane in central Mindanao, Philippines. *Journal of the International Society for Southeast Asian Agricultural Sciences*, 25: 148-158.

Ali, I., V. Gunawan, and K. Adi. 2020. Decision Support Systems for Land Suitability Evaluation on Rice Cultivation using ELECTRE Method. *E3S Web of Conferences: EDP Sciences*, 202: 14004.

Alkimim, A., G. Sparovek, and K. C. Clarke. 2015. Converting Brazil's pastures to cropland: An alternative way to meet sugarcane demand and to spare forestlands. *Applied Geography*, 62:75-84.

Ananda, J., and G. Herath. 2009. A critical review of multi-criteria decision making methods with special reference to forest management and planning. *Ecological Economics*, 68(10): 2535-2548.

Ayehu, G. T., and S. A. Besufekad. 2015. Land suitability analysis for rice production: A GIS based multi-criteria decision approach. *American Journal of Geographic Information System*, 4(3): 95-104.

Azizi, A., B. Malekmohammadi, H. R. Jafari, H. Nasiri, and V. Amini Parsa. 2014. Land suitability assessment for wind power plant site selection using ANP-DEMATEL in a GIS environment: case study of Ardabil province, Iran. *Environmental Monitoring and Assessment*, 186: 6695-6709.

Ba, D. N., N. N. Quynh, L. P. Thi, and M. D. Tuyet. 2021. Evaluation and validation of flood hazard zoning using Analytical Hierarchy Process and GIS: A case study of Lam River basin (Vietnam). *Вестник Санкт-Петербургского университета Науки о Земле*, 66(4):

831-851.

Bagherzadeh, A., and A. Gholizadeh. 2016. Modeling land suitability evaluation for wheat production by parametric and TOPSIS approaches using GIS, northeast of Iran. *Modeling Earth Systems and Environment*, 2: 126.

Baroudy, A. A. E., A. M. Ali, E. S. Mohamed, F. S. Moghanm, M. S. Shokr, I. Savin, A. Poddubsky, Z. Ding, A. M. S. Kheir, A. A. Aldosari, A. Elfadaly, P. Dokukin, and R. Lasaponara. 2020. Modeling land suitability for rice crop using remote sensing and soil quality indicators: the case study of the nile delta. *Sustainability*, 12(22): 9653.

Belton, V., and T. Gear. 1983. On a short-coming of Saaty's method of analytic hierarchies. *Omega*, 11(3): 228-230.

Bera, S., M. Ahmad, and S. Suman. 2017. Land suitability analysis for agricultural crop using remote sensing and GIS-A case study of Purulia District. *International Journal for Scientific Research & Development*, 5(6): 999-1004.

Bilas, G., N. Karapetsas, A. Gobin, K. Mesdanitis, G. Toth, T. Hermann, Y. Wang, L. Luo, T. M. Koutsos, D. Moshou, and T. K. Alexandridis. 2022. Land suitability analysis as a tool for evaluating soil-improving cropping systems. *Land*, 11(12): 2200.

Binte Mostafiz, R., R. Noguchi, and T. Ahamed. 2021. Agricultural land suitability assessment using satellite remote sensing-derived soil-vegetation indices. *Land*, 10(2): 223.

Bisht, H., R. Jain, and R. P. Singh. 2022. Cropland suitability assessment using multi criteria evaluation techniques and geo-spatial technology: A review. *The Indian Journal of Agricultural Sciences*, 92(5): 554-562.

Blaschke, T., S. Lang, and G. Hay. 2008. *Object-based Image Analysis: Spatial Concepts for Knowledge-driven Remote Sensing Applications*. Berlin, Springer Verlag.

Byeon, D. H., S. Jung, and W. H. Lee. 2018. Review of CLIMEX and MaxEnt for studying species distribution in South Korea. *Journal of Asia-Pacific Biodiversity*, 11(3): 325-333.

Chivasaa, W., O. Mutanga, and C. Biradarc. 2019. Mapping land suitability for maize (Zea mays L.) production using GIS and AHP technique in Zimbabwe. *South African Journal of Geomatics*, 8(2): 265-281.

Dadhich, G., P. R. Patel, and M. H. Kalubarme. 2017. Agriculture land suitability evaluation for wheat cultivation using geomatics for Patan District, India. *International Journal of Agricultural Resources, Governance and Ecology*, 13(1): 91-108.

Darko, A., A. P. C. Chan, E. E. Ameyaw, E. K. Owusu, E. Pärn, and D. J. Edwards. 2019. Review of application of analytic hierarchy process (AHP) in construction. *International Journal of Construction Management*, 19(5): 436-452.

Das, A. C., R. Noguchi, and T. Ahamed. 2020. Integrating an expert system, gis, and satellite remote sensing to evaluate land suitability for sustainable tea production in bangladesh. *Remote Sensing*, 12(24): 4136.

Daun, M., A. M. Grubb, V. Stenkova, and B. Tenbergen. 2023. A systematic literature review of requirements engineering education. *Requirements Engineering*, 28(2): 145-175.

De la Rosa, D., and C. A. van Diepen. 2009. *Qualitative and Quantitative Land Evaluations*. Oxford, UK: Eolss Publishers.

Debesa, G., S. L. Gebre, A. Melese, A. Regassa, and S. Teka. 2020. GIS and remote sensing-based physical land suitability analysis for major cereal crops in Dabo Hana district, South-West Ethiopia. *Cogent Food & Agriculture*, 6(1): 1780100.

Deng, F., X. Li, H. Wang, M. Zhang, R. Li, and X. Li. 2014. GIS-based assessment of land suitability for alfalfa cultivation: A case study in the dry continental steppes of northern China. *Spanish Journal of Agricultural Research*, 12(2): 364-375.

Dhami, J., S. Roy, A. S. Nain, and R. Panwar. 2012. Suitability analysis of apple and pear using remote sensing and GIS in Uttarakhand. *Journal of Agrometeorology*, 14(4): 464-474.

Dula, W. D. 2010. GIS and Remote Sensing Based Land Suitability Analysis for Agricultural Crops in Mojo Watershed, Upper Awash Sub Basin, Ethiopia. M.S. thesis, Addis Ababa University.

Dung, N. B., N. Q. Long, D. T. An, and D. T. Minh. 2021. Multi-geospatial flood hazard modelling for a large and complex river basin with data sparsity: a case study of the Lam River Basin, Vietnam. *Earth Systems and Environment*, 6: 715-731.

Dyer, R. F., E. H. Forman, and M. A. Mustafa. 1992. Decision support for media selection using the analytic hierarchy process. *Journal of Advertising*, 21(1): 59-72.

Elaalem, M., A. Comber, and P. Fisher. 2010. Land Suitability analysis comparing Boolean logic with fuzzy analytic hierarchy process. In *Accuracy 2010 Symposium*, 245-247. Leicester, UK, 20-23 July.

Ennouri, K., and A. Kallel. 2019. Remote sensing: an advanced technique for crop condition assessment. *Mathematical Problems in Engineering*, 2019: 9404565.

FAO. 1976. A framework for land evaluation. Rome: FAO.

Fekadu, E., and A. Negese. 2020. GIS assisted suitability analysis for wheat and barley crops through AHP approach at Yikalo sub-watershed, Ethiopia. *Cogent*

Food & Agriculture, 6(1): 1743623.

Gebre, S. L., D. Cattrysse, E. Alemayehu, and J. Van Orshoven. 2021. Multi-criteria decision making methods to address rural land allocation problems: A systematic review. *International Soil and Water Conservation Research*, 9(4): 490-501.

Ghanbarie, E., A. A. Jafarzadeh, F. Shahbazi, and M. Servati. 2016. Comparing parametric methods (the square root and the storie) with the fuzzy set theory for land evaluation of khaje region for wheat. *International Journal of Advanced Biotechnology and Research*, 7(s4): 343-351.

Govindan, K., and M. B. Jepsen. 2016. ELECTRE: A comprehensive literature review on methodologies and applications. *European Journal of Operational Research*, 250(1): 1-29.

Habibie, M. I., R. Noguchi, M. Shusuke, and T. Ahamed. 2021. Land suitability analysis for maize production in Indonesia using satellite remote sensing and GIS-based multicriteria decision support system. *GeoJournal*, 86: 777-807.

Hamzeh, S., M. Mokarram, and S. K. Alavipanah. 2014. Combination of Fuzzy and AHP methods to assess land suitability for barley: Case Study of semi arid lands in the southwest of Iran. *Desert*, 19(2): 173-181.

Han, C., S. Chen, Y. Yu, Z. Xu, B. Zhu, X. Xu, and Z. Wang. 2021. Evaluation of agricultural land suitability based on RS, AHP, and MEA: A case study in Jilin Province, China. *Agriculture*, 11(4): 370.

Hassan, I., M. A. Javed, M. Asif, M. Luqman, S. R. Ahmad, A. Ahmad, S. Akhtar, and B. Hussain. 2020. Weighted overlay based land suitability analysis of agriculture land in Azad Jammu and Kashmir using GIS and AHP. *Pakistan Journal of Agricultural Sciences*, 57(6): 1509-1519.

Hosini, Y. 2020. Evaluation of land suitability for irrigation using fuzzy analytic hierarchy process. *Iran Agricultural Research*, 39(1): 77-86.

Hossen, B., H. Yabar, and T. Mizunoya. 2021. Land suitability assessment for pulse (green gram) production through remote sensing, GIS and multicriteria analysis in the coastal region of Bangladesh. Sustainability, 13(22): 12360.

Hwang, C. L., and K. Yoon. 1981. *Multiple Attribute Decision Making- Methods and Applications A State-of-the-Art Survey*. Heidelberg: Springer Berlin.

Iliquín Trigoso, D., R. Salas López, N. B. Rojas Briceño, J. O. Silva López, D. Gómez Fernández, M. Oliva, L. Q. Huatangari, R. E. T. Murga, E. B. Castillo, and M. Á. B. Gurbillón. 2020. Land suitability analysis for potato crop in the Jucusbamba and Tincas Microwatersheds (Amazonas, NW Peru): AHP and RS–GIS approach. *Agronomy*, 10(12): 1898.

Jafari, S., and N. Zaredar. 2010. Land suitability analysis using multi attributedecision making approach. *International Journal of Environmental Science and Development*, 1(5): 441-445.

Jahanshiri, E., N. M. Mohd Nizar, T. A. S. Tengku Mohd Suhairi, P. J. Gregory, A. S. Mohamed, E. M. Wimalasiri, and S. N. Azam-Ali. 2020. A land evaluation framework for agricultural diversification. *Sustainability*, 12(8): 3110.

Jiao, L., and Y. Liu. 2007. Model of land suitability evaluation based on computational intelligence. *Geo-spatial Information Science*, 10(2): 151-156.

Kahsay, A., M. Haile, G. Gebresamuel, and M. Mohammed. 2018. Land suitability analysis for sorghum crop production in northern semi-arid Ethiopia: Application of GIS-based fuzzy AHP approach. *Cogent Food & Agriculture*, 4(1): 1507184.

Kamau, S. W., D. N. Kuria, and M. K. Gachari. 2015. Crop-land suitability analysis using GIS and remote sensing in Nyandarua. *Journal of Environment and Earth Science*, 5(6): 121-131.

Kenzong, B., D. Bitondo, P. A. Tamfuh, G. S. K. Kameni, J. G. Vounang, R. K. Enang, E. Temgoua, and D. Bitom. 2022. Assessing and Mapping Land Suitability Units for Maize (Zea mays L) Production Using Integrated DEMATEL-ANP Model and GIS in the Foumbot Agricultural Basin (Cameroon Western Highlands). *Journal of Geoscience and Environment Protection*, 10(6): 57-85.

Khallouf, A., S. A. Mohammed, and W. Almesber. 2019. AHP and GIS based land suitability analysis for wheat cultivation in central Syria. *Jordan Journal of Agricultural Sciences*, 15(2): 51-64.

Khan, M. A., R. Ahmad, and H. H. Khan. 2022. Multi-criteria land suitability analysis for agriculture using AHP and remote sensing data of northern region India. In *Geographic Information Systems and Applications in Coastal Studies*, eds. Y. Zhang, and Q. Cheng, ch. 6, 102432. London, UK: IntechOpen Limited.

Kheybari, S., F. M. Rezaie, and H. Farazmand. 2020. Analytic network process: An overview of applications. *Applied Mathematics and Computation*, 367:124780.

Kihoro, J., N. J. Bosco, and H. Murage. 2013. Suitability analysis for rice growing sites using a multicriteria evaluation and GIS approach in great Mwea region, Kenya. *SpringerPlus*, 2: 265.

Kılıc, O. M., K. Ersayın, H. Gunal, A. Khalofah, and M. S. Alsubeie. 2022. Combination of fuzzy-AHP and GIS techniques in land suitability assessment for wheat

(*Triticum aestivum*) cultivation. *Saudi Journal of Biological Sciences*, 29(4): 2634-2644.

Kim, H., and K. Shim. 2018. Land suitability assessment for apple (Malus domestica) in the Republic of Korea using integrated soil and climate information, MLCM, and AHP. *International Journal of Agricultural and Biological Engineering*, 11(2): 139-144.

Koca, Y. K., M. Acar, and Y. Ş. Turgut. 2022. Combination of FAHP and GIS Techniques in Land Suitability Assessment for Banana Cultivation. *Research Square*, https://doi.org/10.21203/rs.3.rs-2284644/v1.

Kocaoglu, D. F., and K. Niwa. 1991. *Technology Management: The New International Language*. Piscataway: IEEE.

Kumar, R., and G. Patel. 2020. Assessment of Agro-Land Suitability for Rice (Oryza sativa L.) in Bhal Area of Gujarat Using GIS and Remote Sensing. *International Journal of Current Microbiology and Applied Sciences*, 9(4): 1207-1214.

Lamidi, A. J., and V. A. Ijaware. 2022. Land Suitability for None-Rice Cultivation Areas in Ekiti State Using a GIS-Based Analytic Hierarchy Process Approach. *European Journal of Environment and Earth Sciences*, 3(5): 51-59.

Lermontov, A., L. Yokoyama, M. Lermontov, and M. A. S. Machado. 2011. A fuzzy water quality index for watershed quality analysis and management. In *Environmental Management In Practice*, ed. E. Broniewicz, ch. 20, 387-410. London, UK: IntechOpen Limited.

Leroux, L., M. Castets, C. Baron, M. J. Escorihuela, A. Bégué, and D. L. Seen. 2019. Maize yield estimation in West Africa from crop process-induced combinations of multi-domain remote sensing indices. *European Journal of Agronomy*, 108: 11-26.

Levy, Y., and T. Ellis. 2006. A Systems Approach to Conduct an Effective Literature Review in Support of Information Systems Research. *Informing Science*, 9: 181-212.

Maddahi, Z., A. Jalalian, M. K. Zarkesh, and N. Honarjo. 2014. Land suitability analysis for rice cultivation using multi criteria evaluation approach and GIS. *European Journal of Experimental Biology*, 4(3): 639-648.

Maddahi, Z., A. Jalalian, M. K. Zarkesh, and N. Honarjo. 2017. Land suitability analysis for rice cultivation using a GIS-based fuzzy multi-criteria decision making approach: central part of Amol district, Iran. *Soil and Water Research*, 12(1): 29-38.

Madrigal-Martínez, S., and R. J. Puga-Calderón. 2018. Land suitability and sensitivity analysis for planning apple growing in mala's valley, Peru. *Bioagro*, 30(2): 95-106.

Maleki, F., H. Kazemi, A. Siahmarguee, and B. Kamkar. 2017. Development of a land use suitability model for saffron (*Crocus sativus* L.) cultivation by multi-criteria evaluation and spatial analysis. *Ecological Engineering*, 106: 140-153.

Martin, D., and S. Saha. 2009. Land evaluation by integrating remote sensing and GIS for cropping system analysis in a watershed. *Current Science*, 96(4): 569-575.

Maulana, H., and H. Kanai. 2022. Potential agricultural land suitability visualization using augmented reality geographic information system (AR-GIS). *Journal of Engineering Science and Technology*, 17(2): 1422-1435.

Memarbashi, E., H. Azadi, A. A. Barati, F. Mohajeri, S. V. Passel, and F. Witlox. 2017. Land-use suitability in Northeast Iran: Application of AHP-GIS hybrid model. *ISPRS International Journal of Geo-Information*, 6(12): 396.

Mendas, A., and A. Delali. 2012. Integration of MultiCriteria Decision Analysis in GIS to develop land suitability for agriculture: Application to durum wheat cultivation in the region of Mleta in Algeria. *Computers and Electronics in Agriculture*, 83: 117-126.

Mighty, M. A. 2015. Site suitability and the analytic hierarchy process: How GIS analysis can improve the competitive advantage of the Jamaican coffee industry. *Applied Geography*, 58: 84-93.

Millet, I., and P. T. Harker. 1990. Globally effective questioning in the analytic hierarchy process. *European Journal of Operational Research*, 48(1): 88-97.

Mishra, A. K., S. Deep, and A. Choudhary. 2015. Identification of suitable sites for organic farming using AHP & GIS. *The Egyptian Journal of Remote Sensing and Space Science*, 18(2): 181-193.

Mokarram, M., H. R. Pourghasemi, and J. P. Tiefenbacher. 2019. Comparison analytic network and analytical hierarchical process approaches with feature selection algorithm to predict groundwater quality. *Environmental Earth Sciences*, 78: 625.

Mokarram, M., K. Rangzan, A. Moezzi, and J. Baninemeh. 2010. Land suitability evaluation for wheat cultivation by fuzzy theory approach as compared with parametric method. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 38(Part II): 140-145.

Mugiyo, H., V. G. Chimonyo, M. Sibanda, R. Kunz, C. R. Masemola, A. T. Modi, and T. Mabhaudhi. 2021. Evaluation of land suitability methods with reference to neglected and underutilised crop species: A scoping review. *Land*, 10(2): 125.

Mulugeta, H. 2010. Land suitability and crop suitability analysis using remote sensing and GIS application; a case study in Legambo woreda, Ethiopia. M.S. thesis, Addis Ababa University, Ethiopia.

Mustafa, A. A., M. Singh, R. N. Sahoo, N. Ahmed, M. Khanna, A. Sarangi, and A. K. Mishra. 2011. Land suitability analysis for different crops: a multi criteria decision making approach using remote sensing and GIS. *Researcher*, 3(12): 61-84.

Mustak, S., N. K. Baghmar, and S. K. Singh. 2015. Land Suitability Modeling for gram crop using remote sensing and GIS: A case study of Seonath basin, India. *Bulletin of Environmental and Scientific Research*, 4: 6-17.

Nadkarni, R. R., and B. Puthuvayi. 2020. A comprehensive literature review of multi-criteria decision making methods in heritage buildings. *Journal of Building Engineering*, 32: 101814.

Nguyen, H., T. Nguyen, N. Hoang, D. Bui, H. Vu, and T. Van. 2020. The application of LSE software: A new approach for land suitability evaluation in agriculture. *Computers and Electronics in Agriculture*, 173: 105440.

Nguyen, H. H., and M. H. Khuong. 2019. Applying AHP method and GIS to evaluate land suitability for paddy rice crop in Quang Xuong district, Thanh Hoa province. *Can Tho University Journal of Innovation and Sustainable Development*, 11(3): 1-10.

Nguyen, M. H., T. T. Nguyen, T. H. N. Hoang, Q. D. Bui, and T. T. H. Vu. 2019. Comparison of Land Suitability Evaluation Methods for Development Plan of Orange and Tea Trees in Western Nghe An, Vietnam. In Proceeding of the 1st International Conference on Economics, Development and Sustainability (EDESUS Proceeding 2019) “Global Changes and Sustainable Development in Asian Emerging Market Economies”.

Ostovari, Y., A. Honarbakhsh, H. Sangoony, F. Zolfaghari, K. Maleki, and B. Ingram. 2019. GIS and multi-criteria decision-making analysis assessment of land suitability for rapeseed farming in calcareous soils of semi-arid regions. *Ecological Indicators*, 103: 479-487.

Peng, G., L. Han, Z. Liu, Y. Guo, J. Yan, and X. Jia. 2021. An application of fuzzy analytic hierarchy process in risk evaluation model. *Frontiers in Psychology*, 12: 715003.

Prakash, T. N. 2003. Land suitability analysis for agricultural crops: a fuzzy multicriteria decision making approach. Enchede, The Netherlands: ITC.

Purnamasari, R. A., T. Ahamed, and R. Noguchi. 2019. Land suitability assessment for cassava production in Indonesia using GIS, remote sensing and multi-criteria analysis. *Asia-Pacific Journal of Regional Science*, 3: 1-32.

Quinta-Nova, L. C., and D. Ferreira. 2020. Land suitability analysis for emerging fruit crops in central Portugal using GIS. *Agriculture and Forestry/Poljoprivreda i Sumarstvo*, 66(1): 41-48.

Ramu, P., B. Sai Santosh, and K. Chalapathi. 2022. Crop-land suitability analysis using geographic information system and remote sensing. *Progress in Agricultural Engineering Sciences*, 18(1): 77-94.

Ranjbar, A., H. Emami, R. Khorasani, and A. R. Karimi Karoyeh. 2016. Soil quality assessments in some Iranian saffron fields. *Journal of Agricultural Science and Technology*, 18: 865-878.

Rasheed, H., and N. Naz. 2016. Modeling the land suitability using GIS and AHP for cotton cultivation in Punjab, Pakistan: Modeling the land for cotton cultivation. *Pakistan Journal of Scientific & Industrial Research Series A: Physical Sciences*, 59(2): 96-108.

Raza, S. M. H., S. A. Mahmood, A. A. Khan, and V. Liesenberg. 2018. Delineation of potential sites for rice cultivation through multi-criteria evaluation (MCE) using remote sensing and GIS. *International Journal of Plant Production*, 12: 1-11.

Robertson, N., and B. Oinam. 2023. Rice suitability mapping using the analytic hierarchy process approach in a river catchment. *Global Journal of Environmental Science and Management*, 9(1): 141-156.

Rodcha, R., N. K. Tripathi, R. Prasad Shrestha. 2019. Comparison of cash crop suitability assessment using parametric, AHP, and FAHP methods. *Land*, 8(5): 79.

Roy, J., and S. Saha. 2018. Assessment of land suitability for the paddy cultivation using analytical hierarchical process (AHP): A study on Hinglo river basin, Eastern India. *Modeling Earth Systems and Environment*, 4: 601-618.

Saaty, T. L. 2005. The Analytic Hierarchy and Analytic Network Processes for the Measurement of Intangible Criteria and for Decision-Making. In: *Multiple Criteria Decision Analysis: State of the Art Surveys. International Series in Operations Research & Management Science*, 78: 345-405. Springer, New York

Said, M. E. S., A. M. Ali, M. Borin, S. K. Abd-Elmabod, A. A. Aldosari, M. M. Khalil, and M. K. Abdel-Fattah. 2020. On the use of multivariate analysis and land evaluation for potential agricultural development of the northwestern coast of Egypt. *Agronomy*, 10(9): 1318.

Salifu, E., W. A. Agyare, and S. Abdul-ganiyu. 2022. Evaluation of land suitability for crop production in Northern Ghana using GIS and AHP based techniques. *International Journal of Environment and Geoinformatics*, 9(4): 46-56.

Salunkhe, S., S. Nandgude, and H. Bhange. 2022. Land suitability analysis for Mango using AHP method.

Research Square, https://doi.org/10.21203/rs.3.rs-1781790/v1.

Sappe, N. J., S. Baja, R. Neswati, and D. Rukmana. 2022. Land suitability assessment for agricultural crops in Enrekang, Indonesia: combination of principal component analysis and fuzzy methods. *SAINS TANAH-Journal of Soil Science and Agroclimatology*, 19(2): 165-179.

Sarkar, B., P. Das, N. Islam, A. Basak, M. Debnath, and R. Roy. 2021. Land suitability analysis for paddy crop using GIS-based Fuzzy-AHP (F-AHP) method in Koch Bihar district, West Bengal. *Geocarto International*, 37(25): 8952-8978.

Sathiyamurthi, S., S. Saravanan, R. Sankriti, M. Aluru, S. Sivaranjani, and R. Srivel. 2022. Integrated GIS and AHP techniques for land suitability assessment of cotton crop in Perambalur District, South India. *International Journal of System Assurance Engineering and Management*, 15(1): 267-278.

Schulze-González, E., J. P. Pastor-Ferrando, and P. Aragonés-Beltrán. 2021. Testing a recent DEMATEL-based proposal to simplify the use of ANP. *Mathematics*, 9(14): 1605.

Seyedmohammadi, J., F. Sarmadian, A. A. Jafarzadeh, M. A. Ghorbani, and F. Shahbazi. 2018. Application of SAW, TOPSIS and fuzzy TOPSIS models in cultivation priority planning for maize, rapeseed and soybean crops. *Geoderma*, 310: 178-190.

Seyedmohammadi, J., F. Sarmadian, A. A. Jafarzadeh, and R. W. McDowell. 2019. Integration of ANP and Fuzzy set techniques for land suitability assessment based on remote sensing and GIS for irrigated maize cultivation. *Archives of Agronomy and Soil Science*, 65(8): 1063-1079.

Shaloo, R. P. Singh, H. Bisht, R. Jain, T. Suna, R. S. Bana, S. Godara, Y. S. Shivay, N. Singh, J. Bedi, S. Begam, M. Tamta, and S. Gautam. 2022. Crop-suitability analysis using the analytic hierarchy process and geospatial techniques for cereal production in North India. *Sustainability*, 14(9): 5246.

Sheikh, A. B., S. Parvez, M. Ikram, and H. Baber. 2017. Land Suitability assessment for maize crop in Okara District using GIS techniques. *International Journal of Life Sciences Research*, 5(2): 37-44.

Singh, P., R. K. Upadhyay, H. P. Bhatt, M. P. Oza, and S. Vyas. 2018. Crop suitability analysis for cereal crops of Uttar Pradesh, India. In *ISPRS TC V Mid-term Symposium "Geospatial Technology – Pixel to People"*, 353-360. Dehradun, India, 20-23 November.

Singha, C., and K. C. Swain. 2016. Land suitability evaluation criteria for agricultural crop selection: A review. *Agricultural Reviews*, 37(2): 125-132.

Singha, C., and K. C. Swain. 2018. Soil profile based land suitability study for jute and lentil using AHP ranking. *International Journal of Bio-resource and Stress Management*, 9(3): 323-329.

Singha, C., K. C. Swain, and B. K. Saren. 2019. Land suitability assessment for potato crop using analytic hierarchy process technique and geographic information system. *Journal of Agricultural Engineering*, 56(3): 223-233.

Subandi, E. L., Widiatmaka, and M. Ardiansyah. 2019. Use of WLC (weighted linear combination) to determine land priorities for development of paddy fields in gorontalo regency, Indonesia. *International Journal of Engineering and Management Research*, 9(3): 58-63.

Subramanian, N., and R. Ramanathan. 2012. A review of applications of Analytic Hierarchy Process in operations management. *International Journal of Production Economics*, 138(2): 215-241.

Tadesse, M., and A. Negese. 2020. Land suitability evaluation for sorghum crop by using GIS and AHP techniques in Agamsa sub-watershed, Ethiopia. *Cogent Food & Agriculture*, 6(1): 1743624.

Tashayo, B., A. Honarbakhsh, M. Akbari, and M. Eftekhari. 2020. Land suitability assessment for maize farming using a GIS-AHP method for a semi-arid region, Iran. *Journal of the Saudi Society of Agricultural Sciences*, 19(5): 332-338.

Tenkap, P. E., and B. O. Balogun. 2020. Land suitability for cocoa production in Idanre, Ondo State, Nigeria. *Journal of Agricultural Biotechnology and Sustainable Development*, 12(2): 19-33.

Tercan, E., and M. A. Dereli. 2020. Development of a land suitability model for citrus cultivation using GIS and multi-criteria assessment techniques in Antalya province of Turkey. *Ecological Indicators*, 117: 106549.

Tong, T. H., M. P. Pham, T. Q. Bui, T. M. H. Nguyen, T. T. N. Nguyen, A. E. Balakirev, and A. H. Lahori. 2021. Land suitability modeling for ricecrop based on an integrated multi-criteria decision making in Quang Tri province of Vietnam. *Geography, Environment, Sustainability*, 14(3): 63-72.

Tran, T. M. C., D. H. Le, N. P. Q. Le, T. H. Nguyen, T. T. Tran, and N. H. Trinh. 2020. Assessment of physical land suitability by GIS-based fuzzy AHP for rubber plantation at the Nam Dong district, Thua Thien Hue province. *Journal of Vietnamese Environment*, 12(2):

108-113.

Tuğaç, M. G. 2021. GIS-Based Land Suitability Classification for Wheat Cultivation Using Fuzzy Set Model. *International Journal of Agriculture Environment and Food Sciences*, 5(4): 524-536.

Tung, P. G., T. T. M. Chau, N. T. Hai, T. T. Tan, and T. N. Ha. 2022. Assessment of land suitability for land use type of orange planting in Nam Dong district, Thua Thien Hue province. *Hue University Journal of Science: Agriculture and Rural Development*, 131(3D): 97-111.

Tzeng, G. H., and J. J. Huang. 2011. *Multiple Attribute Decision Making: Methods and Applications*. Boca Raton, FL, USA: CRC Press.

Wang Y. 2018. Application of TOPSIS and AHP in the multi-objective decision-making problems. *MATEC Web of Conferences: EDP Sciences*, 228: 05002.

Yalew, S. G., A. Van Griensven, M. L. Mul, and P. van der Zaag. 2016. Land suitability analysis for agriculture in the Abbay basin using remote sensing, GIS and AHP techniques. *Modeling Earth Systems and Environment*, 2: 101.

Yang, J. L., and G. H. Tzeng. 2011. An integrated MCDM technique combined with DEMATEL for a novel cluster-weighted with ANP method. *Expert Systems with Applications*, 38(3): 1417-1424.

Yangouliba, G. I., D. Kwawuvi, and A. Almoradie. 2020. Suitable land assessment for rice crop in Burkina Faso using GIS, remote sensing and multi criteria analysis. *Journal of Geographic Information System*, 12(6): 683-696.

Yohannes, H., and T. Soromessa. 2018. Land suitability assessment for major crops by using GIS-based multi-criteria approach in Andit Tid watershed, Ethiopia. *Cogent Food & Agriculture*, 4(1): 1470481.

Zadeh, L. A. 1965. Fuzzy sets. *Information and Control*, 8(3): 338-353.

Zhang, J., Y. Su, J. Wu, and H. Liang. 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.

Zhang, X., C. Fang, Z. Wang, and H. Ma. 2013. Urban construction land suitability evaluation based on improved multi-criteria evaluation based on GIS (MCE-GIS): Case of New Hefei City, China. *Chinese Geographical Science*, 23: 740-753.

Zolekar, R. B., and V. S. Bhagat. 2015. Multi-criteria land suitability analysis for agriculture in hilly zone: Remote sensing and GIS approach. *Computers and Electronics in Agriculture*, 118: 300-321.