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Machine learning algorithms and geographic information system techniques to predict land suitability maps for wheat cultivation in the Central Anatolia Region

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ABSTRACT

Maintaining food security through increased agricultural production is a major concern for decision-makers, especially in areas with arid and semi-arid climatic conditions and limited natural resources. Land suitability prediction for cultivating strategic crops, including wheat, has emerged as a crucial subject for academics, decision-makers, and economists to ensure the sustainability of natural resources. This paper aims to use three soil morphological parameters, three soil physical parameters, four soil chemical parameters, and a long-term remote sensing index as input factors to produce land suitability maps for wheat cultivation based on five machine learning algorithms (MLAs): ANN, KNN, RF, SVM, and XgbTree, in the Gozlu agricultural enterprise, which is located in a semi-arid region of the Central Anatolian Plateau. To achieve this target, an inventory of 238 appropriateness points for cultivated wheat has been executed over five years, from 2019 to 2023. The outcomes revealed that the soil texture and soli available water capacity parameters were the most influential in land suitability prediction. The best performance among the MLAs was achieved by the XgbTree algorithm, which had an accuracy of 0.98 and a kappa coefficient of 0.81. Additionally, the area under the curve (AUC) was 0.90 according the receiver operating characteristics (ROC) curve approach. The results of the study demonstrated an excellent ability of the MLAs to predict land suitability for wheat cultivation in semi-arid climate conditions. This approach can play a significant role in ensuring food security and serves as an important tool for decision-makers in sustainable development. However, we propose that the approach should be examined in comparable climatic conditions with diverse crops to ensure it is a viable solution with widely cases.

Keywords: machine learning, random forest, support vector machine, land suitability, remote sensing, GIS, wheat.

INTRODUCTION

The initial step in managing and mitigating various risks often involves selecting the suitable crops for agricultural lands. Consequently, determining whether the land is appropriate for growing a certain crop can significantly influence the effectiveness or ineffectiveness of farming plans. As farmers navigate the difficulties brought on by climate change and a world economy that is changing quickly, it is essential for them to adapt to new trends [Cheshire and Woods, 2013]. Furthermore, agricultural land use demands higher performance of the soil in relation to other land uses. This necessity arises from the truth that not all lands are suitable for agriculture, and not all crops can thrive in specific soil conditions, given the varying requirements of different crops and the characteristics of soils, both physical and chemical [Velmurugan et al., 2016]. Enhancing the accessibility of land suitability data for farming crops will be extremely beneficial in helping farmers create innovative farming approaches. Concurrently, improvements in processing power and increased availability of spatial data have made land suitability research easier to do.

Traditionally, assessing of land suitability, also known as land valuation, has depended on qualitative assessments of the societal benefits associated with various land uses since it is largely used by regional administrations as a tool for land use planning [Romeijn et al., 2016]. The Food and Agriculture Organization (FAO) has created a structured method for evaluating land, providing a theoretical framework for the process [Rossiter, 1996]. In practice, land evaluation has employed a diverse range of methods. Some studies may concentrate on soil properties [El Baroudy, 2016] or climate factors [Geerts et al., 2006], while others may include socioeconomic variables [Purnamasari et al., 2019].

Numerous researchers have introduced new methodologies for mapping land suitability, such as fuzzy-logic modeling [Akumu et al., 2015], simple limitation [Oertli, 1990], linear combination [Pereira et al., 2017], and machine learning (ML) [Sarkar et al., 2021]. In addition to land suitability mapping, ML techniques have significantly advanced soil degradation and soil quality mapping [Diaz-Gonzalez et al., 2022], as well as multi-criteria evaluation (MCE) and multi-criteria decision analysis (MCDA) [Romano et al., 2015], and the analytical hierarchy process (AHP) [Dedeoğlu and Dengiz, 2019]. Despite of some limitations associated with AHP, MCDA, and MCE remain the most frequently utilized techniques for assessing land, especially in small-scale. However, these techniques can be time-consuming and expensive due to the ground surveying and sample operations, often lacking the capability to cover spatio-temporal properties effectively.

Considering this, ML and remote sensing (RS) can deal with these restrictions by providing a substitute approach to traditional land suitability mapping on large spatiotemporal scales. ML models exhibit the ability to learn from extensive datasets and can readily integrate diverse types of data [Radočaj et al., 2021]. Within the framework of digital soil mapping, also ML algorithms have been utilized to establish connections between soil parameters and auxiliary variables, thereby understanding the changes in soil types and other soil qualities throughout time and space [McBratney et al., 2003]. Various algorithms have been employed to create land suitability maps, including support vector machines (SVMs) [Sarkar et al., 2021], artificial neural networks (ANNs) [Jayaraman et al., 2021], extreme gradient boosting (XgbTree) [Ismaili et al., 2023], random forest (RF) [Radočaj et al., 2021], and K-nearest neighbor (K-NN) [Ganesan et al., 2021]. Although, ML methods remain a challenging and an emerging research field, they have shown substantial robustness and stability, enhancing their popularity and cost effectiveness in evaluating agricultural land potential [Møller et al., 2021]. The purpose of this research is to produce land suitability mapping for wheat cultivation in the Gozlu agricultural enterprise, which is located in a semi-arid region of the Central Anatolian Plateau in Turkey, using five MLAs (RF, SVM, KNN, ANN, and XgbTree). In this study, a total of ten soil parameters were selected, including three morphological indicators (depth, slope, and gravel), three physical indicators (texture, bulk density, and available water capacity), and four chemical indicators (pH, EC, $CaCO_3$, and organic matter). These parameters were combined with the LT-NDVI, which represents the biomass characteristics of the study area over five years, from 2019 to 2023, to create suitability maps based on 238 wheat suitability samples and according to FAO land suitability categories: Class S1 (highly suitable), Class S2 (moderately suitable), Class S3 (marginally suitable), and Class NS (not suitable). Consequently, this innovative approach facilitates a systematic assessment of land suitability by taking into account the aforementioned parameters. The integration of morphological indicators, physical indicators, and chemical indicators with LT-NDVI, which is associated with biomass, renders this work authentic and serves as a valuable tool for planning and management. The findings of this study will aid stakeholder groups and decision-makers in boosting regional agriculture output and achieving sustainable development goals.

MATERIAL AND METHODS

Study area

The Gozlu agricultural enterprise directorate in Konya, Turkey, which is a branch of the general directorate of agricultural enterprises, was selected as the study area. Interest area lies within the geographical coordinates of 38° 45′ 00″–38° 22′ 30″ North latitude and 32° 15′ 00″–32° 37′ 30″ East longitude (Fig. 1). This enterprise spans a vast region of 288297 decares and exemplifies the continental (semi-arid) climate characteristics unique to Anatolian Plateau. Most land is used for producing wheat, barley, and corn in the study area under a rainfed agriculture system. The province of Konya, home to the Gozlu agricultural enterprise, is subject to a climate that includes hot, dry summers and cold, rainy winters. Considering the two main climatic elements (temperature and precipitation), areas like Konya are categorized under a semi-arid climate [Abdikan et al., 2023]. The yearly average

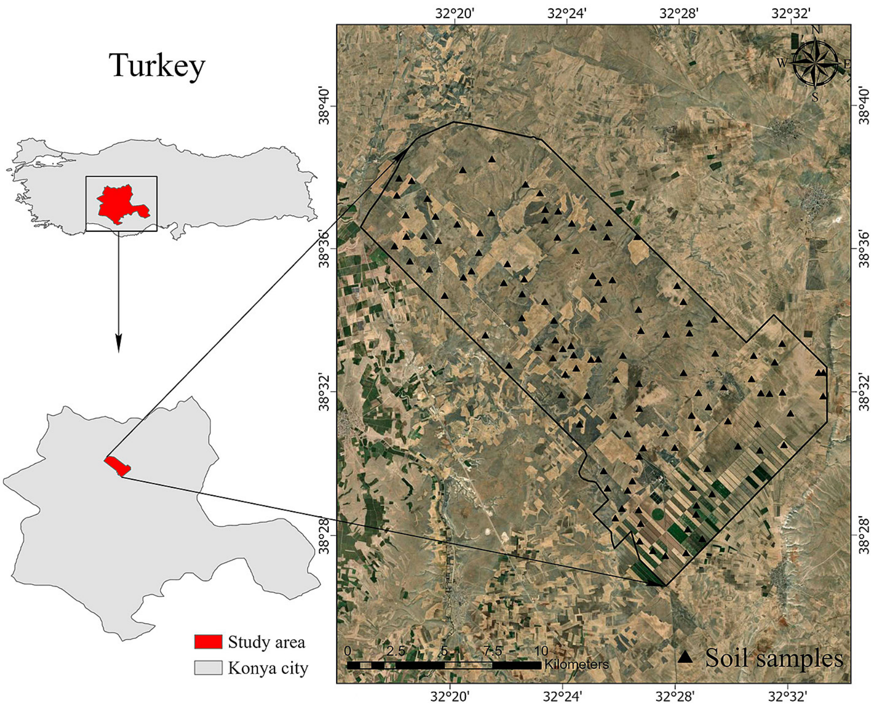

Figure 1. Gozlu agricultural enterprise map (Source: ESRI)

rainfall in Konya is approximately 326.1 mm, with May typically having the highest monthly average and August the lowest. The region's average annual temperature is around between 10.7 °C and 25.3 °C, with July is the hottest month, while January is the coldest [Özen et al., 2021].

Methodology

Upon reviewing numerous studies and literature reviews, ten soil parameters were identified as having a direct impact on wheat crop productivity. These parameters encompass both land, physical and chemical indicators (refer to Table 1). Soil sampling was carried out based on thirteen soil series: Ciftekuyu series (Ct), Akbayir series (Ab), Zengen series (Zn), Kokez series (Kz), Kap series (Kp), Kartalburnu series (Kb), Ozkent series (Oz), Gozlu series (Gz), Imranli series (Im), Kolukisa series (Kk), Arkaç series (Ak), Zebir series (Zb), Kislak series (Ks). In all, a total of 119 composite samples was obtained at a depth of 0–30 cm with a sampling density of (8–10) sample per soil series. Soil sampling was facilitated using a

Table 1. Soil parameters and their functions affecting land suitability

Land indicators	Soil parameters	Soil functions	References
Morphological indicators	Depth (cm)	Root growth, water storage capacity	[Canadell et al., 1996]
	Slope (%)	Losses by surface runoff	[Poesen et al., 2003]
	Gravel (%)	Plant growth, soil tillage, water retention	[Cousin et al., 2003]
Physical indicators	Texture	Soil infiltration rate, soil structure type, plant water relations	[Hengl et al., 2017]
	Bulk density (g/cm^3)	Soil compaction, soil aeration, soil infiltration	[Hamza and Anderson, 2005]
	Available water capacity (%)	Reserved water, plant water consumption, drought resistance	[Huang et al., 2020]
Chemical indicators	pH	Nutrient availability, microbial activity	[Kang et al., 2021]
	EC (ds/m)	Osmotic potential, ion toxicity	[Shrivastava and Kumar, 2015]
	$CaCO_3$ (%)	Nutrient fixation, soil aggregation	[Junior et al., 2020]
	Organic matter (%)	Soil quality, Plant growth, biological activity	[Luo et al., 2018]

Global Positioning System refer to (Fig. 1). Physical and chemical analyses were conducted on the soil samples after air-drying, grinding, and sieving them through a 2.0 mm mesh.

The hydrometer method was used to determine soil texture [Bedaiwy, 2012]. Bulk density was determined from undisturbed soil samples by calculating the weight (mass) of dry matter in a soil sample that fills a core of known volume [Blake and Hartge, 1986]. Field capacity was determined by placing the samples on a ceramic table of pressure unit and applying a pressure of 33 kPa to the water-saturated soil samples, wilting point was determined by applying a pressure of 1500 kPa to the water-saturated soil samples placed on the ceramic table of pressure unit [Klute, 1986]. Available water capacity was determined by calculating the difference between the field capacity and wilting point of the soil samples. pH was determined in the soil–water suspension, which was prepared at a ratio of 1:2.5 [Jones, 2018]. EC was determined in the soil–water suspension, which was prepared at a ratio of 1:2.5 [Jones, 2018]. Calcium carbonate was determined from the released carbonates using a Scheibler calcimeter [Jones, 2018]. The content of organic matter was determined by the modified Walkley-Black method [Jackson, 2005]. The analyses were carried out at the Pedology Laboratory, Selcuk University.

Figure 2 provides a summary of the approach employed in this study to generate land suitability maps according to soil parameters and the LT-NDVI index. To extract the land suitability maps, the mapping of LT-NDVI was conducted utilizing the Sentinel-2 dataset and the GEE platform [Jonsson and

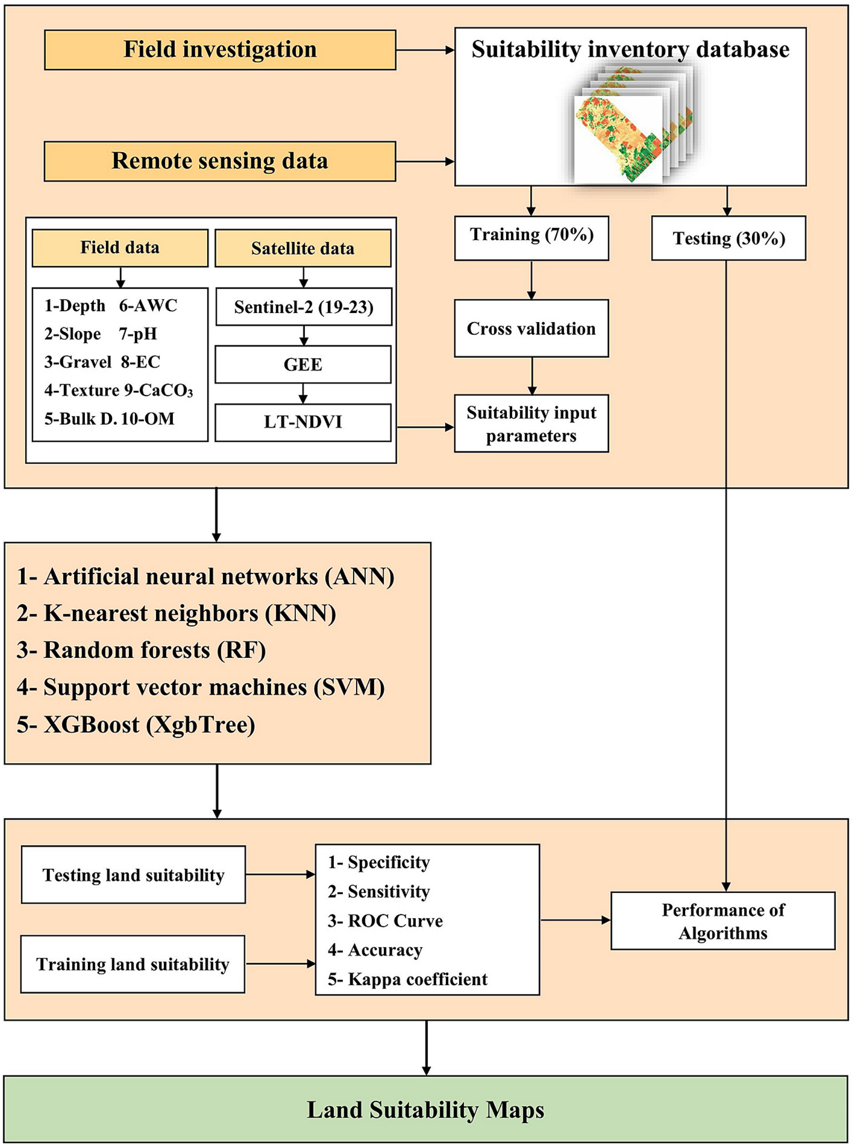

Figure 2. Flowchart of the methodology

Eklundh, 2002], along with interpolated maps derived from soil parameters using the inverse distance weighted (IDW) model. This work uses the IDW model to create a maps (Fig. 3) that illustrates soil properties using point-based soil data, the accuracy of IDW is primarily influenced by the value of the power parameter. As the distance increases, weights decrease, particularly with higher values of the power parameter. Consequently, nearby samples carry a greater weight and exert a more significant influence on the estimation [Raheem et al., 2023]. Following spatial interpolation process conducted in the ArcGIS Pro (Version: 2.5) program environment, each pixel of the rasters representing soil parameters is classified to a particular land suitability class using MLAs in the R-Studio program environment (version: 2024.04.0 + 735) [Ismaili et al., 2023].

Numerous studies utilizing NDVI data have demonstrated its effectiveness in assessing land suitability [Habibie et al., 2021; Mangan et al., 2022; Mbugua and Suksa-ngiam, 2018]. The behavior of vegetation cover reflects the soil's potential to produce biomass, whether high or low [Benabdelouahab et al., 2021]. By analyzing the NDVI values of wheat, which are closely tied to biomass production over extended periods, land suitability is determined [Ljubičić et al., 2018]. Accordingly, the wheat NDVI time series throughout its full growth cycle were derived from selected samples of wheat fields cultivated in the study area from 2019 to 2023 [Qu et al., 2021]. These profiles revealed two distinct peaks and troughs in the NDVI curve during the growth cycle of wheat [Zhong et al., 2019], which were used to spatially diagnose wheat crop across the period (2019–2023).

We utilized these data, along with various auxiliary information, to train the algorithms effectively, 238 points were identified within Gozlu agricultural enterprise which is classified into two parts: suitable and not suitable points. Subsequently, seventy percent of the suitability points (167 points) were chosen at random for training the algorithms, while the remaining thirty percent (71 points) were utilized for testing the algorithms [Ismaili et al., 2023].

Long term of NDVI

We created a five-year composite LT-NDVI utilizing Sentinel-2 dataset through the GEE platform, generating a time series from 2019 to 2023. Several studies [Benabdelouahab et al., 2021; Dedeoğlu and Dengiz, 2019] have indicated that NDVI serves as a reliable indicator of biomass production. Vegetation development reflects a variety of factors, including anthropogenic actions, plant type, pests, dryness, and deficiencies in essential nutrients, instead of just soil potential. This is why LT-NDVI were chosen as input parameter. This technique permits the removal of extraneous factors connected to meteorological conditions and crop management, therefore highlighting just the Potential for soil production (Fig. 4).

Machine learning algorithms

Random forest (RF)

The RF algorithm, an approach to ensemble machine learning, is utilized for both the regression and classification tasks. RF consists of a collection of decision trees, where each tree calculates its value based on a randomly and uniformly chosen vector from the entire forest. There is a limiting factor to overfitting as the quantity of trees within a forest expands. The average error of a forest comprising tree classifiers is contingent on the correlation and the strength of the individual trees. The process of randomly selecting features for each node split contributes to error rates. To manage this inaccuracy, estimates are made on the model's response and relevance to an increase in the number of variables included in the case [Breiman, 2001].

Support vector machine (SVM)

SVM is a widely used supervised learning algorithm applied to both classification and regression tasks, though it is mainly utilized for classification in machine learning. The primary objective of the SVM algorithm is to identify the optimal line or decision boundary that divides n-dimensional space. In this context, the best decision boundary is known as a hyperplane, and SVM selects the most critical points or vectors that help define this hyperplane. These key points are called support vectors, which give the algorithm its name, Support Vector Machine [Vapnik, 2013].

K-nearest neighbor (KNN)

The KNN algorithm, also known as k-NN, is algorithm of the most straightforward MLAs based on supervised learning. It operates under the assumption that new data is similar to

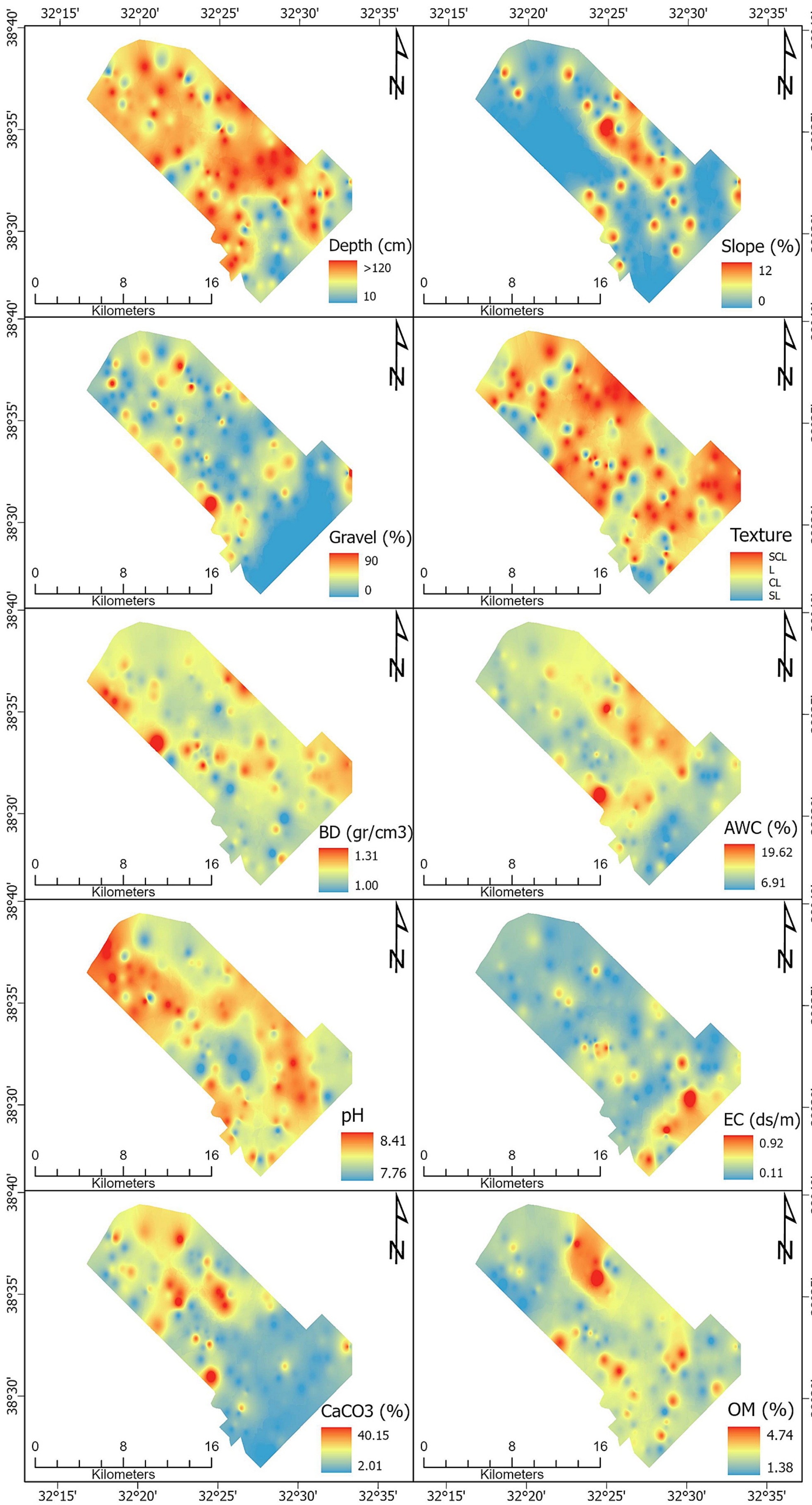

Figure 3. Spatial interpolated maps of soil parameters

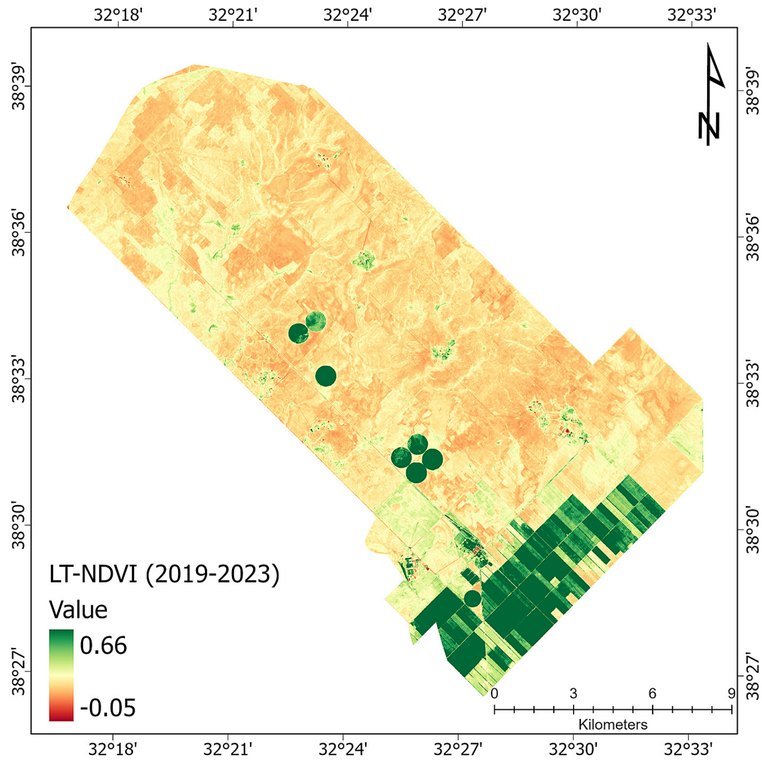

Figure 4. LT-NDVI (2019–2023)

existing data, and assigns the new instance to the category it most closely resembles. KNN can be applied to both classification and regression tasks. The algorithm works by first selecting an optimal value for K, typically an odd number, with higher values of K generally improving accuracy. The Euclidean distance between the test data point and every other data point is then determined [Jayaraman et al., 2021].

Artificial neural network (ANN)

ANN employs multi layer perceptron (MLP) structure, which is made up of three interconnected layers with many neurons: the final output layer, hidden layer, and input layer. Each neuron in the input layer is characterized by a single input and multiple output paths, each linked to various influential factors. The hidden nodes, which have multiple input and output connections per neuron, leverage weighted connections to understand and solve the problem; these weights can have either positive or negative values. Typically, ANN methodology commences the modelling phase by adjusting the weights of the various neuron links during the training phase, followed by the prediction phase, which is reliant on the models that have been developed [Sarkar et al., 2021].

Extreme gradient boosting tree (XgbTree)

XgbTree models employ a scalable MLA, featuring an end-to-end tree boosting system, to generate classifications or predictions of the desired models from a comprehensive learning database. The XgbTree is a decision tree-based algorithm that uses gradient boosting as its principal optimization method. This algorithm falls within the boosting family, where information about misclassifications from one tree is utilized to enhance the subsequent tree, forming an optimized sequence known as the 'boosting technique'. The most challenging aspect of this modeling method is parameter tuning, as decision tree algorithms are notoriously prone to overfitting. To achieve a model with minimal bias and variance, optimal hyper-tuning of the parameters is required, this enhances the model's accuracy on testing datasets while preventing it from getting unduly exact on the training dataset. Given these characteristics, XgbTree algorithm is an excellent selection for classifying land and crops, particularly when the spectral signatures are nearly identical in multispectral data [Ashoka and BV, 2022].

Adjustment of algorithms

For all algorithms, we conducted a hypertuning process to identify the optimal hyperparameters for each as follows: for the RF, we set Mtry to 10 and Mtree to 500; for KNN, we selected K as 5 for the number of neighbors; for the ANN, we used a size of 5 and a decay of 5; for SVM, the parameters were set to sigma = 3 and C index = 0.2; finally, for XgbTree, the maximum number of iterations was 200, tree depth was set to 5, the learning rate was 0.05, the minimum loss reduction was 0.05, the minimum required gamma for loss reduction was 0.01, colsample_bytree was 0.75, and the sub-sample ratio of the training instances was 0.5.

Performance assessment of machine learning algorithms

The difficulty is in choosing the right performance metric for evaluating classifiers on unbalanced datasets. While accuracy is a widely recognized gauge for evaluating classification performance, it Incompetent when it comes to classifying imbalanced datasets [Öztürk, 2017]. This study uses specificity, sensitivity, kappa coefficient, ROC through AUC curve apart from accuracy to account for class imbalance properly. Below are all the equations (Equation 1, Equation 2, Equation 3, Equation 4, and Equation 5) utilized to compute these parameters:

$$Accuracy = \frac{TN+TP}{TP+FP+TN+TP} \quad (1)$$

$$Kappa\ Coefficient = \frac{Accuracy-B}{1-B} \quad (2)$$

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

where: FN stands for false negative, FP for false positive, TN for true negative, and TP for true positive.

The ROC curve is a common metric for evaluating the results of applying MLAs. It combines sensitivity and specificity across various cutoff thresholds to generate the ROC curve. A model with an AUC close to 1 is considered perfect, conversely, an AUC value of 0.5 suggests an inaccurate model, it provides an aggregate measure of performance across all classification thresholds and can be classified as excellent from 0.9 to 1.0, very good from 0.8 to 0.9, good from 0.7 to 0.8, medium from 0.6 to 0.7, and low from 0.5 to 0.6 [Namous et al., 2021].

$$Sensitivity = \frac{TP}{TP+FN} \quad (4)$$

$$Specificity = \frac{TN}{FP+TN} \quad (5)$$

RESULTS

To evaluate the effectiveness of LT-NDVI and soil parameters in differentiating between appropriate and inappropriate regions, we utilized parameters analysis, employing ANN, K-NN, RF, XgbTree, and SVM algorithms, to identify the most critical parameters. The RF algorithm results highlight depth, pH, texture, OM, and AWC as the most significant parameters for land suitability mapping. However, the ANN, SVM, and K-NN algorithms suggest that the most influential parameters are pH, Depth, Texture, $CaCO_3$, and EC for K-NN; Texture, AWC, $CaCO_3$, slope, and Depth for ANN; Texture, AWC, Depth, Gravel, and pH for SVM. According to the XgbTree algorithm, Texture, AWC, Depth, Gravel, and pH emerge as the most pertinent parameters (Fig. 5). Overall, both soil physical, soil chemical, and soil morphological parameters seem capable of distinguishing suitable land from unsuitable land. In particular, physical metrics such as Texture and AWC, along with the land metric Depth, clearly delineate the boundaries between the land suitability classes. This is evident as these parameters rank at the top of the importance hierarchy for most algorithms.

Five ML algorithms, elaborated in the Materials and Methods section, were used to construct land suitability models. The suitable classes generated by the ANN, K-NN, RF, XgbTree, and SVM algorithms were categorized into four classes as per FAO guidelines (S1, S2, S3, and NS), using the natural break categorization technique. (Figure 6) illustrates the land suitability maps generated by the five MLAs. The RF algorithm, in particular, identified that 25.23% of the enterprise area exhibits high suitability for wheat, while the moderately suitable and marginally suitable zones encompass 19.68% and 27.66% of the enterprise area, respectively. The remaining 27.40% is classified as not suitable for wheat cultivation (Table 2). The land suitability map generated by the KNN algorithm indicated that 41.81% of the enterprise study area is not suitable. Highly suited zones comprise 50.01%, while moderately suitable zones cover 4.33% of the enterprise study area. The residual 3.82% falls within the marginally suitable class. According to the outcomes of ANN algorithm, the enterprise area has 35.16% that falls within the not suitable class, and 2.69% in the marginally suitable class, 2.91% in the moderately suitable class, and 59.23% in the highly suitable class.

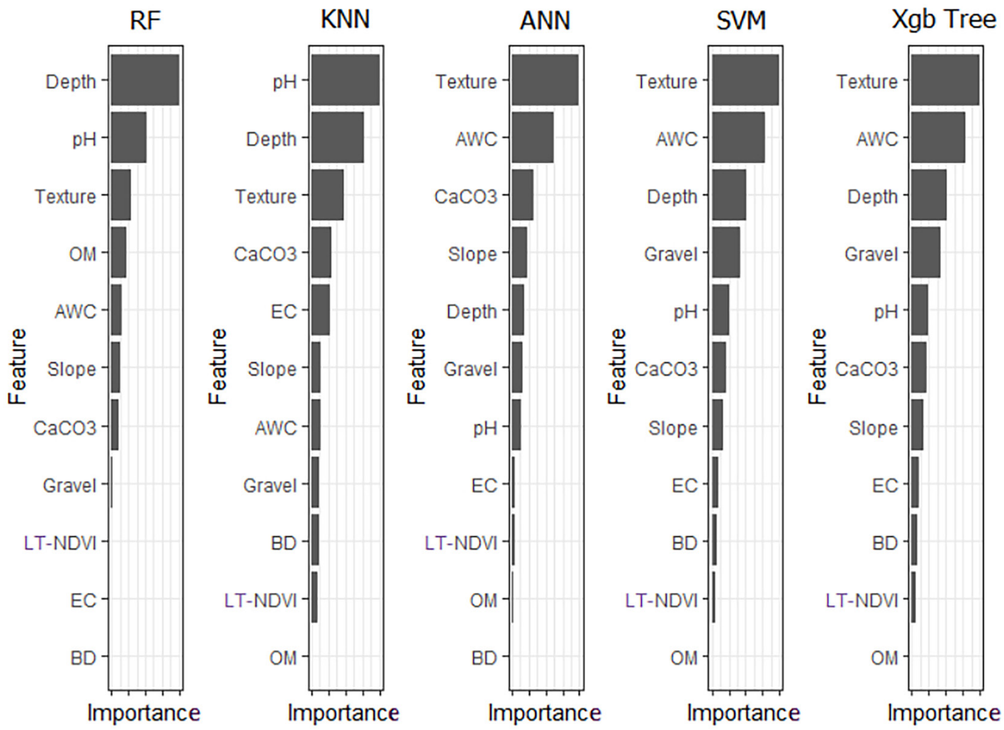

Figure 5. Importance of parameters

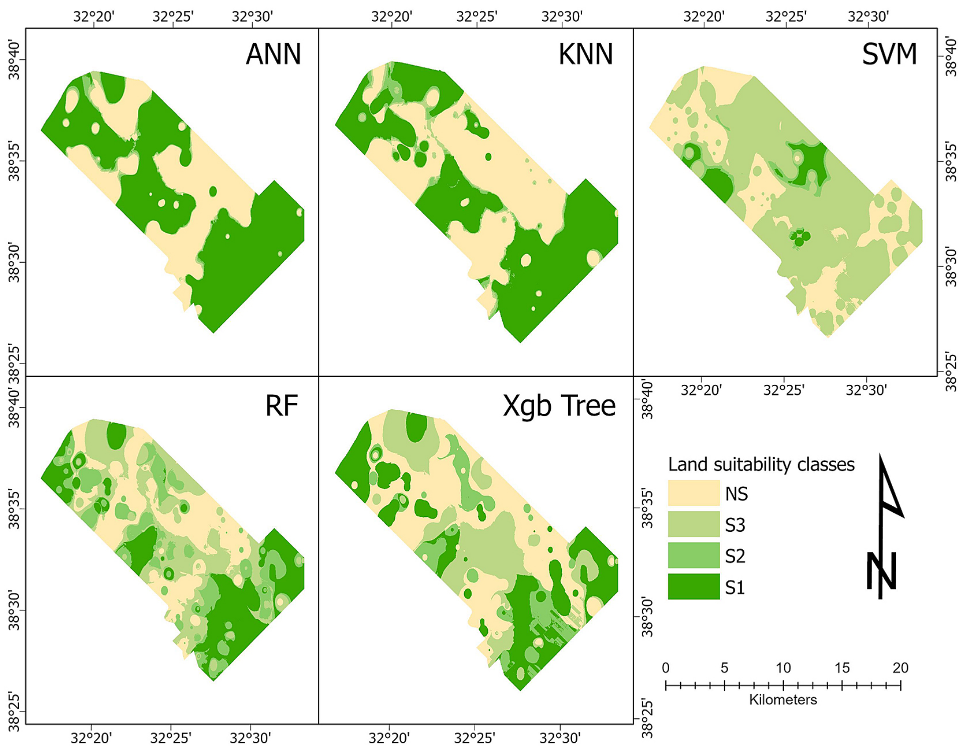

Figure 6. Land suitability maps by ML algorithms

In case of the SVM algorithm, the outcomes show that the enterprise area has a 5.90% area in the highly suitable class, the moderately suitable class and marginally suitable class at 3.29% and 64.88% respectively, 25.91% within not suitable class. Based on XgbTree algorithm, specified that 27.90% of the enterprise area exhibits highly suitable class, while the moderately suitable and marginally suitable classes encompass 11.74% and 24.34% of the area, respectively. The remaining

Table 2. The percentage of land suitability classes

Algorithm	Land suitability classes			
	S1	S2	S3	NS
RF	25.23%	19.68%	27.66%	27.40%
KNN	50.01%	4.33%	3.82%	41.81%
ANN	59.23%	2.91%	2.69%	35.16%
SVM	5.90%	3.29%	64.88%	25.91%
XgbTree	27.90%	11.74%	24.34%	36.00%

36.00% is classified as inappropriate for wheat. The results indicate that the ANN algorithm showed the largest area classified as highly suitable at 59.23%. On the contrary, the KNN algorithm classified the largest area, 41.81%, as not suitable for wheat cultivation. The RF algorithm showed the largest moderately suitable class at 19.68%. The SVM algorithm showed the largest area 64.88% classified as marginally suitable.

Figure 7 shows the ROC curves for the algorithms on both the training and validation datasets. In the training set, ANN (AUC: 0.89), RF (AUC: 0.88), and KNN (AUC: 0.80) perform comparably, while XgbTree (AUC: 0.77) and SVM (AUC: 0.79) show slightly lower performance. On the validation set, KNN, RF and XgbTree achieved excellent AUC values (AUC: 0.91, 0.90 and 0.90) respectively, followed by ANN (AUC: 0.81), and SVM (AUC: 0.75) showed lowest performance. Figure 8 compares the performance of algorithms ANN, KNN, RF, SVM, and XgbTree in terms of two metrics: accuracy and kappa. XgbTree exhibited the highest accuracy 0.98 and Kappa 0.81, followed closely by RF with an accuracy of 0.94 and a Kappa of 0.78. KNN performed moderately, with an accuracy of 0.80 and a Kappa of 0.68, while ANN has a slightly lower accuracy 0.75 and Kappa 0.56. SVM showed the least performance overall, with an accuracy of 0.71 and a Kappa of 0.49.

DISCUSSION

The benefits of the suggested approach for assessing land suitability for wheat cultivation presented in this paper, which was processed using five machine learning algorithms, ten soil parameters, and a long-term remote sensing index, include a direct and efficient application of the data, as well as accuracy in the computational aspects and an unbiased approach to the data [Møller et al., 2021]. This method overcomes two significant limitations of traditional multi-criteria approaches, as it avoids subjectivity in suitability assessment [Li et al., 2018] and allows for the inclusion of complex input data [Hengl et al., 2017]. The input dataset was prepared by utilizing many sources, including previous soil inventory reports, soil parameter analyses, and remote sensing data. The time series of the vegetation index derived from satellite data was used to define

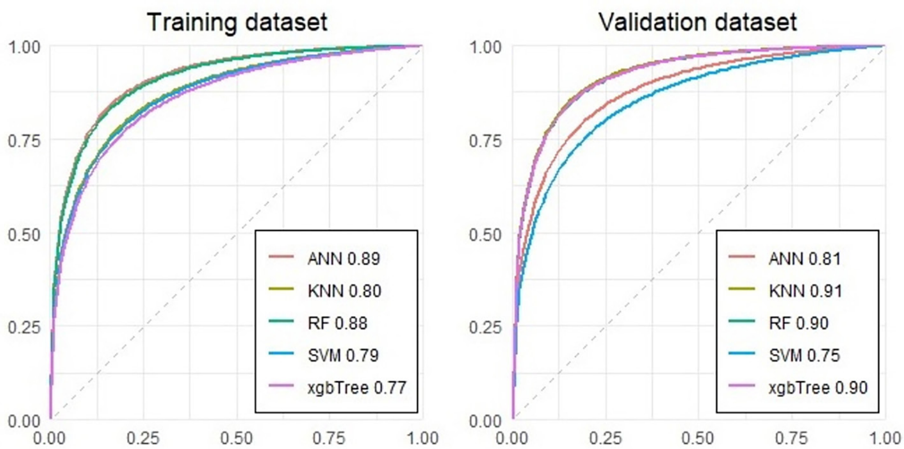

Figure 7. ROC curves displaying AUC of XgbTree, ANN, KNN, RF, and SVM algorithms

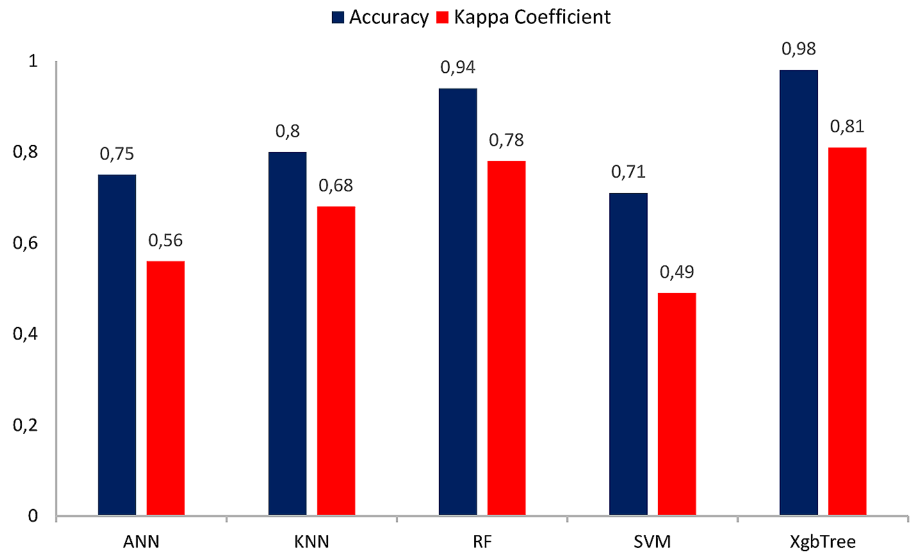

Figure 8. Chart of accuracy and kappa coefficient

wheat fields as input data and a remote sensing parameter in determining land suitability [Mangan et al., 2022].

In this case, MLAs such as ANN, KNN, SVM, RF, and XgbTree were applied to produce land suitability maps for wheat. This was based on training and validation datasets, along with ten soil parameters and a long-term remote sensing index, LT-NDVI. A significant link with the likelihood of land suitability explained by the high values of the effective parameters. According to the KNN and RF algorithms, the most efficiency parameters are texture, pH, and depth. In the case of the ANN algorithm, the most effective parameters are texture, AWC, and $CaCO_3$, while the SVM and XgbTree algorithms identify texture, AWC, and depth as the most effective parameters. Accordingly, texture and AWC are the most common effective parameters in determining land suitability across all algorithms. These results indirectly indicate that water resources are the limiting factor for land appropriateness in semi-arid conditions [Abdikan et al., 2023; Talukdar et al., 2022].

The percentage of the area classified as S1, S2, and S3 is similar according to the suitability maps produced by the RF and XgbTree algorithms, which achieved the highest accuracy in classification and prediction. The percentage of the area for these classes reached 25.23%, 19.68%, and 27.66%, respectively, for the RF algorithm, while the percentages for the XgbTree algorithm were 27.90%, 11.74%, and 24.34%. Additionally, 27.40% of the total study area was classified as not suitable according to the RF algorithm, compared to 36.00% according to the XgbTree algorithm. Both algorithms are ensemble methods based on decision trees, which are inherently capable of capturing complex non-linear relationships in data. Therefore, this common foundation significantly contributes to their performance [Abakay et al., 2024].

In the case of KNN and ANN algorithms, the areas of classes S2 and S3 are very similar and small compared to classes S1 and NS (Table 2). Therefore, visual evaluation of the maps for these two algorithms suggests that the study area is classified as either very suitable or not suitable (Figure 6). This may be because the KNN algorithm classifies data points based on the majority class among its k-neighbors. When the data is not uniformly distributed or when there is a large class imbalance, KNN algorithm can create distinct regions dominated by one class [Kim, 2021]. Similarly, ANN algorithm, especially when trained for high accuracy, can exhibit overconfidence in its predictions, leading to sharp decision boundaries. As a result, most areas are classified as either very suitable or not suitable [Eyo & Abbey, 2022]. In contrast, the RF and XgbTree algorithms often produce more accurate classifications due to their different underlying mechanisms. These algorithms use multiple decision trees, which can capture more complex relationships in the data, resulting in smoother transitions between suitability classes [Abakay et al., 2024].

Through comparing the suitability maps of all algorithms (Figure 6) and evaluating them alongside the geographical distribution of soil characteristics, we observed that the eastern region and the upper and lower western regions of the enterprise area were categorized as unsuitable for wheat cultivation according to the suitability maps produced by the ANN, KNN, RF, and XgbTree algorithms. In contrast, the SVM algorithm classified this area as marginally suitable, which is also considered weak suitability. The spatially interpolated pH map (Figure 3) can explain these results, as we noted that these areas have a high pH level according to the optimum limits for wheat cultivation [Altay et al., 2024]. Since the pH parameter is high or medium importance in determining suitability (Figure 5), these regions were classified as unsuitable for wheat cultivation.

CONCLUSIONS

The suggested approach for assessing land suitability, which utilizes MLAs, offers a promising alternative and enhancement to traditional techniques for determining the land suitability, such as GIS-based multicriteria analysis. This research intends to investigate MLAs' capabilities in addition to compare the effectiveness and robustness of the implemented algorithms: ANN, KNN, SVM, RF, and XgbTree to predict land suitability. To achieve this, three morphological indicators, three physical indicators, and four chemical indicators were utilized, along with the remote sensing index LT-NDVI. The significance of all these parameters has been established. The main advantages of this approach are its capacity to integrate different input factors, be objective in predictions, and be computationally efficient. This approach relies on soil parameter data and publicly available remote sensing data, employing GIS software and the R programming language, which enhances its accessibility on a global scale.

The results underscored that comprehending the advantages and disadvantages of every algorithm is challenging, even when conducting algorithm comparisons with specific objectives, such as robustness and prediction accuracy. According to the assessment criteria of accuracy and the kappa coefficient, the XgbTree and RF algorithms produced the optimal outcomes. The ANN and KNN algorithms exhibited a little less accurate than the XgbTree and RF algorithms regarding prediction performance, while the SVM algorithm recorded the lowest results. The results regarding the significance of the parameters indicated that soil texture and AWC have the most substantial impact on land suitability, followed by certain soil chemical parameters such as $CaCO_3$ and EC. Conversely, bulk density and organic matter were found to be the least significant. The suitability maps of all the algorithms demonstrated that the southern and central regions exhibit the highest suitability compared to other areas of the study site. This research can aid in land resource management and enhance the understanding of various parameters, including soil parameters and remote sensing indicators, that affect land suitability. Furthermore, this method can serve as a reference for later studies aimed to evaluate soil suitability in land use for cultivation different types of crops.

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