



Agricultural land suitability assessment for agricultural productivity based on GIS modeling and multi-criteria decision analysis: the case of Tekirdağ province

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Abstract Grains play a significant role in meeting the nutritional needs of the increasing world population. Consequently, the need for new studies on agricultural production and land suitability assessments has increased. The present paper aims to perform agricultural land suitability assessment to evaluate agricultural productivity in Tekirdağ province to determine precise productive agricultural areas. This study combines a variety of datasets to develop a dynamic model using GIS-based multi-criteria decision analysis for land suitability assessment and agricultural productivity. The datasets used in this study are supported by terrestrial samples and processed with spatial technologies. The results of the study indicate that the agricultural potential of the provincial lands is quite high. It reveals that 65.7% of province lands are suitable for agricultural production. Of the remaining lands, 20.3% is marginally suitable while only 8% of the land is unsuitable for agricultural production. In the northwestern part, suitable land for agricultural productivity is higher compared to other parts of the study area. This part also

corresponds to the areas where industrial activities are marginal. The results also imply that agricultural activities in grain production areas must be reconsidered and replanned according to the new classification of land suitability assessment. In this respect, our study suggests that the policymakers and the government should take necessary steps to ensure the protection and sustainability of agricultural lands while planning for the industrial and settlement development in grain production areas.

Keywords Agriculture · Grains · Thrace · GIS-MCDA · ALSA

Introduction

Agriculture is one of the most basic activities, which humans embark on to meet their nutritional needs. Agriculture is among the priority concerns for human life, which cannot be replaced by political, economic, social, and technological developments (İkincikarakaya et al., 2013). In the recent couple of decades, the world has been confronted a rapid agricultural degradation process caused by major environmental problems, such as fast-expanding urbanization, climate change, drought, and erosion (Liu et al., 2017; Schmitter et al., 2018). Increasing population and threats to agricultural production led to food competition and the necessity to increase agricultural productivities (Horuz & Dengiz, 2018). Therefore,

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agricultural production gained strategic importance in the last decades. The global population is projected to increase to over 9 billion over the next four decades, with much of this growth concentrated in developing countries (Patel et al., 2015). Recent studies have reported that agricultural production should be increased by 60% to meet the consumption needs of the world population by 2030 (Korkmaz, 2007; Vurarak & Bilgili, 2015). Given that, most countries today support studies that aim at efficient agriculture (Dengiz et al., 2009) to establish sustainable agroecosystems (Dengiz & Ozcan, 2006; Dindaroglu & Canbolat, 2011).

Agricultural land suitability assessment (ALSA thereafter) is an effective way to determine the characteristics of agricultural productivity (Nouri et al., 2017). By using ALSA, the advantages and limitations of the land for agricultural production can be properly computed (Elsheikh et al., 2013; Krois & Schulte, 2014; Pan & Pan, 2012). However, to achieve better results for suitability assessment, one must consider both quantitative methods based on terrestrial data and qualitative data obtained by expert opinion (El Baroudy, 2016; Kourtit et al., 2014). Besides, it is necessary to include reliable spatial analyses and evaluations by using spatial information technologies to achieve rational results. Geographic information system (GIS) is one of the most common tools used in the management of spatial information and performing complex analyses by qualitative and quantitative methods (Dengiz & Sarioglu, 2011).

Although various methods, such as the analytical hierarchy process (AHP) (Akinci et al., 2013; Kumar & Hassan, 2013; Pramanik, 2016; Zhang et al., 2015), fuzzy logic techniques (Arsanjani et al., 2013; Boroushaki & Malczewski, 2010), artificial neural networks (Kong et al., 2016), and machine learning models (Taghizadeh-Mehrjardi et al., 2020), are common nowadays, the multi-criteria decision analysis (MCDA) is highly preferred lately for the agricultural land studies (Arabameri et al., 2019; Chen et al., 2010; Jahan et al., 2016; Joerin et al., 2001; Rodriguez-Gallego et al., 2012; Yalew et al., 2016). MCDA is an established technique, which is used when choosing variables that involve multiple criteria. Therefore, MCDA can also be used to help design a dynamic model when selecting criteria.

Recently, the dynamic models of GIS-based multi-criteria decision analysis (GIS-MCDA) are preferred

particularly in ALSA studies (Darwish et al., 2006; El Baroudy, 2011; Gbanie et al., 2013; Hamzeh et al., 2014; Malczewski, 2006; Mishelia & Zirra, 2015; Mokarram et al., 2010; Terh & Cao, 2018). Decision-makers frequently face a lack of reliable information for agricultural productivity. An inclusive GIS-MCDA analysis could offer location-based information for better decisions so that the gap between the knowledge of the decision-makers and optimum decision of the agricultural productivity can be filled (Kamali et al., 2017).

There has been an increasing interest in the agricultural practices conducted from an environmental sustainability perspective. In a similar vein, research on ALSA for agricultural productivity has drawn attention in developing countries including Turkey (Arslan, 2016). The agricultural production in Turkey is usually carried out at low-yield-high-cost conditions. While these conditions cause extreme pressure on the farmers, they sometimes cause damages to the agricultural lands due to exploitation of the lands. Using productive agricultural land beyond their capabilities may cause various problems including soil salinity, landslide, and erosion (Tugay, 2012). Further, these problems may cause food deficiency and malnutrition. To avoid such problems, policymakers must be proactively involved in protecting and improving fertile farmland. One of the most effective ways to overcome such problems is to conduct more research regarding the suitability of agricultural lands.

Tekirdağ province has one of the most important agricultural lands of the Thrace Peninsula. The province not only has larger agricultural areas compared to other provinces but also reserves one of the most fertile agricultural lands in Turkey (TUIK, 2020), which contributes to the economy of the entire country. However, increasing population and industrial activities in the region have substantially affected agricultural productivity since the beginning of the twenty-first century (Sarı & Özşahin, 2016). Specifically considering the investment plans to be implemented in the region concerning its population, settlement, and industrial pressure in the next two decades, it is extremely necessary to plan ahead for better management of the agricultural lands in the province. Yet, because of its proximity to the mega-city İstanbul, it has become a substitute center for industry and tourism in the last century (Ozsahin et al., 2019). Further, the area has attracted human population

from nearby cities (e.g., İstanbul, Edirne, and Çanakkale) leading to the rural areas becoming subject to intense human pressure. As a result, pressure from seasonal and industrial migration to the province both threaten the sustainability of fertile agricultural lands and pave the way for the destruction of natural environmental components (Ozsahin & Eroglu, 2018). Given that, the determination and effective use of the existing agricultural lands in the study area constitute a fundamental necessity for the future of the province. Preparing an inventory that would contain precise information on the agricultural characteristics of this provincial land should enable any subsequent planning to be based on solid foundations (Akgul & Basayigit, 2005).

Agricultural productivity is the key to the planning land management for both sustainable agriculture and sustainable use of natural resources (Zengin et al., 2003). Therefore, determining accurate land suitability in terms of economically viable, sustainable, and resilient production systems depends on the accurate and balanced structure between nature and the agricultural ecosystems (Jaklič et al., 2018).

GIS-based modeling has been used for various agricultural products (Montgomery et al., 2016; Pan & Pan, 2012; Zabihi et al., 2019). While these studies are informative to understand the spatial variation of agricultural products, they generally used a very limited number of factors to fully comprehend these variations. (Kamali et al., 2017). Therefore, land suitability assessment for agricultural productivity remained neglected (Balezentis et al., 2020). One of the most important features that distinguish the present study from previous studies is that many factors that have the potential to affect agricultural productivity have been analyzed and variables with an importance value of less than 1% were eliminated. Therefore, comprehensive results were aimed (Malczewski, 2004) and so the reliability of the model has been maximized.

The present study aims to use a dynamic model in which model parameters can be easily modified based on the geographical conditions of the study area (i.e., natural environment and socio-economic characteristics). Therefore, the ALSA was chosen to be applied dynamically for agricultural productivity. In this respect, a model of GIS-MCDA has been developed based on remote sensing, digital mapping, and fieldwork data of the study area. This approach was adopted to detect the spatial distribution of

agricultural productivity in the province and to determine the most suitable areas for the best agricultural production along with the other land use classes. In addition, this study aims to guide how to achieve a sustainable and productive agricultural land where similar geographic and climate conditions dominate.

In previous ALSA studies, the subject of agricultural productivity has been studied based on soil and climate characteristics (Montgomery et al., 2016; Zabihi et al., 2019). However, socio-economic factors that potentially affect agricultural productivity have been mostly ignored. In this study, natural and socio-economic factors including soil, seeds, irrigation, climate, and humans that have the potential to affect agricultural productivity were included in the model, which was selected based on the results of the variable importance. Furthermore, developing technologies, the qualitative and quantitative analyses of agricultural areas, determining the potentials of available resources, and creating databases and maps are also necessary (Dengiz & Sarioglu, 2011; Ozyazıcı et al., 2014). In this respect, the present study applies a dynamic technique regarding ALSA and agricultural productivity in the case of Tekirdağ province, which might be considered also for the other parts of the world where similar characteristics are present.

Materials and methods

Study area

The study area is the entire Tekirdağ province, which is located in the northwest of Turkey and is dominated by a wavy plateau fragmented by rivers (Fig. 1). Some plains are also formed in the coastal areas, and valleys are located down streams of the rivers. In the province, a wide variety of rocky assemblages belonging to different geological periods are observed. A humid and temperate climate is observed in the coastal areas whereas continental climate with arid and continental characteristics prevails in the inner parts of the province. Based on these climate conditions, the natural vegetation of the area is the steppe in the inner parts and temperate deciduous forest in the coastal areas. Soil taxonomy distinguished in the area includes Entisol, Alfisol, Inceptisol, Mollisol, Vertisol, and Andisol, which are spread across the study area depending on the prevailing climate

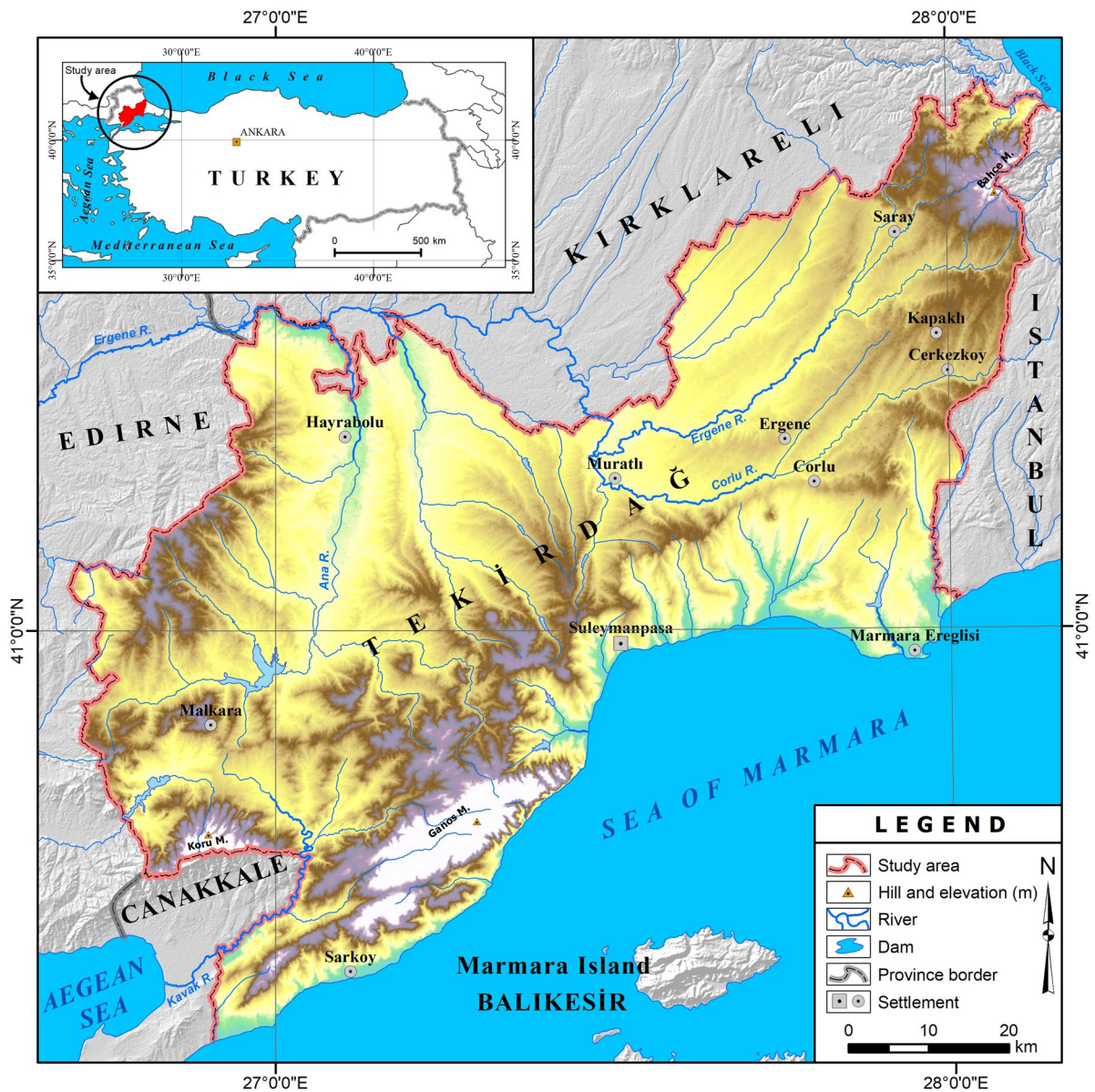


Fig. 1 The location of the study area is the Tekirdağ province

and flora characteristics (Ozsahin & Eroglu, 2018). The study area can be considered as relatively rich in surface and groundwater, which has water available for irrigation $883 \text{ hm}^3/\text{year}$, 80.75% ($713 \text{ hm}^3/\text{year}$) of surface, and 19.25% ($170 \text{ hm}^3/\text{year}$) of groundwater (Basa et al., 2017). About 90% of the drinking and potable water is obtained from groundwater and the remaining 10% is obtained from surface water in the area (Basa et al., 2017).

The study area encompasses about 400,000 ha of agricultural land. The most common agricultural products in the study area are crops. The most produced crops in the study area are wheat (*Triticum aestivum*) 192,000 ha, sunflower (*Helianthus*) 15,000 ha, barley (*Hordeum vulgare*) 13,000 ha, and canola (*Brassica napus*) 6000 ha. Besides, some fruits (10,000 ha), vegetables (4000 ha), and ornamental plants are also produced in the area (Agriculture Report, 2019).

Data

The main factors affecting the ALSA for agricultural productivity are topography, soil, seeds, irrigation, climate conditions, and human activity (Aldababseh, 2018). It is plausible to generate spatial modeling for ALSA with the correct determination of these key factors and the subfactors affecting them. In this study, we created a dynamic model based on GIS-MCDA using a diversity of variables. We used a 100-m spatial resolution to form a common resolution for the entire study area and ensure harmony between the datasets. In this context, we used a topography map (scale: 1:100,000) as a base map and DEM (resolution: 100 m) (GDM-ATLAS, 2020). Fieldwork was performed to collect soil samples and environmental data. We randomly collected 130 soil samples from the entire study area to investigate soil factors, physical and chemical measurements, and the spatial distribution of the basic characteristics (climate, topography, main material, land use, and land cover) which form the soil and affect the distribution of soil species (Ozsahin & Eroglu, 2018). We also obtained the production and yield data and human factors from published reports, data, and statistics from the study area (Agriculture Report, 2019; Farmer Registration System Report, 2019; TUIK, 2020). Besides, irrigation data was obtained from Tekirdağ State Hydraulic Works 113th Branch Directorate (DSI, 2018). Data such as grain production and yield are obtained from TUIK on a district basis. Therefore, to integrate the data into the model, we first created a vector layer then converted it to raster datasets with 100 m resolution. As for the climate data, the long-term (50 years) meteorological observations were obtained from the General Directorate of Meteorology of the Ministry of

Agriculture and Forestry (TSMS, 2020). Because soil, seed, groundwater depth, and climate data are point-featured data types, these data must be converted to raster data. Therefore, inverse distance weighted (IDW) process was applied using ArcGIS Geostatistical Analyst to these data to convert them into raster format. IDW interpolation creates continuous raster data using a linear-weighted combination of the sample points from the study area. In this way, we created a new raster dataset derived from data, which obtained from various sources. Further, new variables were integrated into the GIS-MCDA model (Table 1).

Soil samples were collected from the study area from a depth of 0–30 cm. The data obtained during the collection of the soil samples were used for training and validation purposes. Using the leave-one-out cross-validation method, 70% of the data were used for training and the remaining 30% for validation purposes.

Methods

Several models for agricultural productivity have been used in various studies; the decision support for agrotechnology transfer, agricultural production systems research (Jones et al., 2001), effects of climate changes on crop production (Jin, 1996; Sadras & Calderini, 2009), digital agriculture (Gao, 2001), functional structural plant models (Fourcaud et al., 2008; Hanan & Hearn, 2003), site suitability, and the analytic hierarchy (Mighty, 2015) are the most widely used models. Among them, MCDA combined with other methods is the most commonly used method in the last few decades (Abeysingha et al., 2015; Caglayan et al., 2020; Kourtit et al., 2014; Malczewski, 2006; Malczewski & Rinner, 2015; Vanolya et al., 2019; Yalaw et al., 2016).

Table 1 Data and the variables used in the model

Main factors	Variable no	Data source
Topography (F1)	V1–V4	GDM-ATLAS, 2020
Soil (F2)	V5–V23	Soil sample analysis (N=130) and soil map (Ozsahin & Eroglu, 2018)
Seeds (F3)	V24–V29	Agriculture Report, 2019; Farmer Registration System Report, 2019
Irrigation (F4)	V30–V32	DSI, 2018
Climate (F5)	V33–V36	TSMS, 2020
Human (F6)	V37–V42	Farmers Registration Report, 2019; TUIK, 2020

The variables (V1–V42) are defined in Appendix 1

In our study, we used a model based on GIS-MCDA in a grain production area to define a spatial distribution of the agricultural land suitability.

Agricultural productivity is affected by several factors/subfactors (FAO, 1983, 1985; Sys et al., 1991, 1993). However, the criteria to specify the number of factors are still unclear. Based on the literature, we determined 6 main factors and 42 variables for this study model (Table 1). The scoring of the determined variables has been developed according to the coefficient method. We then used the variable importance method in the R programming language to eliminate the least important variables in the model. In this step, we eliminated the variables whose value is less than 1% in the variable importance analysis. Thus, the remaining 20 factors, those with variable importance above 1%, were included in the study model (see Table 2).

To build the model, we first converted the resolution of all datasets to raster format with a resolution of 100 m. Thus, we have ruled out the problems that may arise from the resolution differences. Then, we calculated the weight values of the criteria according to the analytical hierarchy method. At this stage, we used a pairwise comparison scale. The values of the scale are between 0 and 1, where 0 indicates the least suitable and 1 indicates the most suitable area for agricultural use. Using the matrix obtained from the scaling process, we then calculated the normalized weight values of all variables. In the next stage, we merged the criteria according to the weighted linear combination method since it is a highly preferred method in agricultural studies (Dengiz & Sarioglu, 2013). Accordingly, we determined each cluster value using the equation given below:

$$C = \sum_{i=1}^n \left(\frac{K_i * K_n}{n} \right) \quad (1)$$

where C is the total value of the cluster, K_i is the weight value of the criterion, K_n is the subcriterion score, and n is the total number of parameters.

We completed the merge of the clusters using the cell statistics in the geoprocessing tools in the spatial analysis module using the ArcGIS software version 10.8. The cell statistics calculates a per-cell statistic from multiple rasters. By using this tool, we merged all the clusters based on the mean overlay analysis. Using mean overlay analysis, we combined information from one GIS layer with another to derive an

Table 2 Selected variables according to the variable importance analysis

Abbrev	Variable	Importance (%)
V27	Grain production	96.00
V25	Grain yield	55.56
V40	Fertilizer	50.19
V41	Pesticide	27.82
V36	Vegetation period	13.61
V24	Seed yield	8.32
V32	Hydrogeology	7.66
V31	Groundwater depth	7.25
V18	Calcium	4.39
V26	Fruit yield	4.11
V28	Vegetable production	4.00
V30	Distance to water source	2.62
V35	Solar radiation	2.49
V33	Temperature	2.25
V29	Fruit production	2.25
V34	Precipitation	2.24
V7	Drainage	1.96
V11	Salinity	1.89
V9	Soil reaction	1.76
V15	Nitrogen	1.63

attribute for one of the layers. In this step, we used the following equation to calculate the efficiency of the agricultural productivity (AP):

$$AP = (C1 \times C2 \times C3 \times C4 \times C5 \times C6)^{1/6} \quad (2)$$

where $C1$ is topography, $C2$ is soil, $C3$ is the seed, $C4$ is irrigation, $C5$ is climate, and $C6$ is the human factor. In the final stage, we ran the established model and created the suitability map. We classified the map into five land use classes, which had been proposed by ALSA studies: (1) *highly productive*, (2) *productive*, (3) *moderate*, (4) *marginal*, and (5) *unproductive* classes (Riquier et al., 1970; Sys et al., 1991; Dengiz & Ozcan, 2006). We then applied the ground data points that the GPS records and field observations obtained from the fieldwork for 3-year duration (2016–2018) from the Farmer Registration System (Farmer Registration System Report, 2019) for validation. Furthermore, we analyzed the correlation between the status of current agricultural activities and the productivity potentials of the study area. At this step, we used the most recent land use data by the European Union Land Use Project named CORINE (Chief Inspectorate of

Table 3 Model performance rating based on RSR, NSE, and PBIAS

Performance rating	NSE	RSR	PBIAS
Very good	$0.75 < NSE < 1.00$	$0.00 < RSR < 0.5$	$PBIAS < 10$
Good	$0.65 < NSE < 0.75$	$0.5 < RSR < 0.6$	$10 < PBIAS < 15$
Satisfactory	$0.5 < NSE < 0.65$	$0.6 < RSR < 0.7$	$15 < PBIAS < 25$
Unsatisfactory	$NSE < 0.5$	$RSR > 0.7$	$PBIAS > 25$

NSE Nash–Sutcliffe efficiency, *RSR* RMSE-observations standard derivation ratio, *PBIAS* percentage bias

Environmental Protection, 2020). Then, the land use map was overlapped with the land suitability map to reveal the suitability classes for each land use class.

Results

Calibration and validation

We performed the calibration of the model based on the yield averages of crop production between 2013 and 2015, and the validation between data between the 2016 and 2018 production years. The calibration and the validation periods have been determined by measurements from two governmental institutions (Farmer Registration System and Turkish Statistical Institute). The average yield of agricultural production is at the district level, which are the most detailed measurements obtained for the study area (Agriculture Report, 2019; Farmer Registration System Report, 2019; TUIK, 2020). We analyzed the calibration and validation results of the study using Nash–Sutcliffe efficiency (NSE), observations standard deviation ratio (RSR), and percentage bias (PBIAS). We then used the performance evaluation of the model using the model performance rating scale (Abeyasingha et al., 2015; Moriasi et al., 2007) and evaluated statistical method results (see Table 3) based on the coefficient of determination (R^2).

In the present study, a calibration was performed to optimize the structure of the model and to estimate the spatial differences in the model equations. In addition, validation was performed to check if the values assigned to the model parameters were statistically significant (see Table 3). Using statistical methods, calibration and validation values indicate optimal values for the model. The results of the mean calibration values are as follows: $NSE=0.85$, $RSR=0.36$, and $PBIAS=25.72$. Mean validation values are $NSE=0.91$, $RSR=0.28$, and $PBIAS=21.53$ (see Table 4). These mean values reflecting the overall study area are in the optimal NSE and RSR range. PBIAS values are acceptable according to the model performance rating scale (Moriasi et al., 2007, 2015).

While the statistics of the calibration period of the model represent symmetrical distributions, the values of the validation period show more negatively distorted properties (Fig. 2). In addition, the R^2 values indicate a strong positive relationship between the variables (NSE: 0.8838, RSR: 0.8314, PBIAS: 0.7797) at a 95% confidence interval.

Variable importance

Land suitability assessment for agricultural productivity is controlled by very complex factors and sub-factors. One of the most characteristic features that

Table 4 Model calibration and validation statistics for agricultural productivity

Measuring station	Calibration			Validation		
	NSE	RSR	PBIAS	NSE	RSR	PBIAS
Minimum	0.38	0.23	18.69	0.80	0.22	17.83
Maximum	0.95	0.78	43.94	0.95	0.45	31.08
Mean	0.85	0.36	25.72	0.91	0.28	21.53
Median	0.90	0.32	24.41	0.94	0.24	19.12
Std. deviation	0.17	0.16	7.45	0.06	0.09	4.98

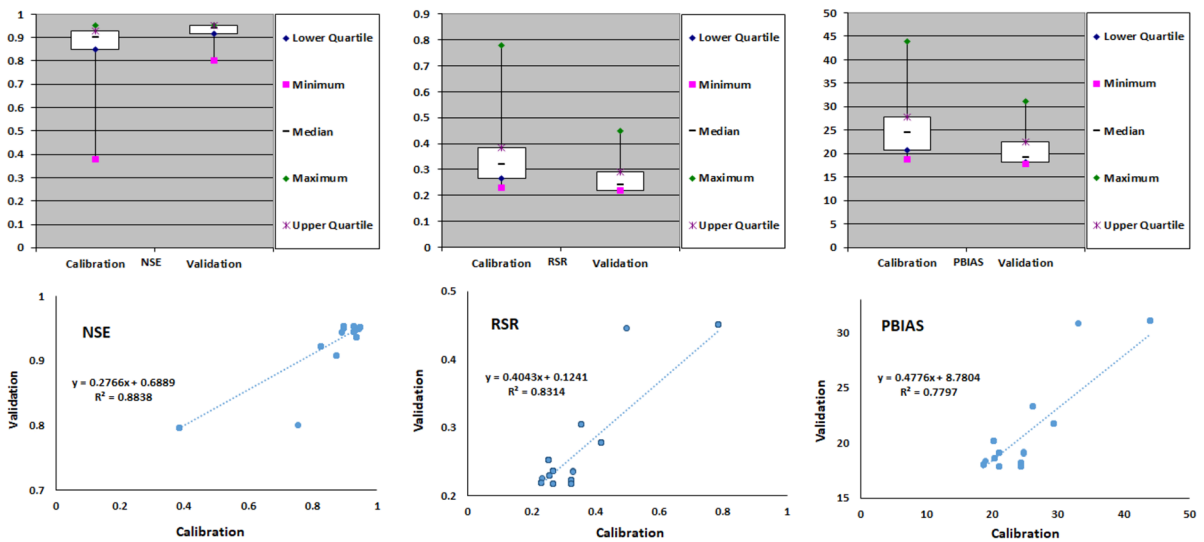


Fig. 2 Calibration and validation performance of the model

distinguish the present study from the previous studies is that it examined and incorporated many factors/subfactors in the model. However, the significance and impact degree of the factors to the model performance is one of the most important questions in the field. For this reason, an evaluation of variable importance was conducted to eliminate insignificant variables. As a result of the evaluation, variables with a factor weight value of less than 1% were excluded from the model, and so the remaining 20 variables were identified as the most effective variables in the study (see Table 2). The R^2 value of the variable importance results was determined as 82. Accordingly, although there were statistically significant changes in the *productive* and *unproductive* classes compared to the pre-elimination of the variables, no significant changes were observed in the other productivity classes. In addition, the study model determined the maximum and minimum values better using variable importance results.

Productivity

The results of the model indicate that a significant portion of the land (34%) in the study area was found to be in the *productive* class (see Table 5). The other productivity classes occupying a larger portion of the study area are *marginal* (28.8%) and *moderate* (27.9%), respectively. The *highly productive* (3.7%) and *unproductive* (5.7%) classes in the

study area are relatively insignificant compared to the total land surface area. The present study focuses on the spatial distribution, proportion, and productivity of land use classes. In this respect, not only the proportion of the land productivity but also the “location” reflects the matter of concern.

The productivity map shows that the northwestern part of the study area consists mostly of *highly productive* and *productive* classes. Most of the *marginal* and *unproductive* classes are found to be distributed in the eastern and southwestern parts of the study area (see Fig. 3). In these areas, which are mainly used as settlement and industrial activities, unsuitability is mostly related to human factors. Although the population in these areas is not very dense in winters, it is very densely populated in summers because of the tourism and summer housing.

Table 5 Distribution of ALSA classes for agricultural productivity in the study area

Productivity class	Productivity value	Area (ha)	Ratio (%)
<i>Highly productive</i>	0.65–1	197,343.0	31.3
<i>Productive</i>	0.60–0.65	226,919.1	35.9
<i>Moderate</i>	0.55–0.60	28,128.9	4.5
<i>Marginal</i>	0.50–0.55	128,287.4	20.3
<i>Unproductive</i>	0–0.50	50,643.1	8.0
Total		631,321.4	100.0

The model indicates a significant relationship between agricultural productivity and current land use classes in the study area. Furthermore, agriculture is most common (89.65%) in a *highly productive* class; however, a remarkable portion of *unproductive* lands appears to be used for agriculture as well (Table 6). However, it should be pointed that the unproductive land is only 8% of the study area as indicated in Table 5.

Further, the agricultural areas that appear to be suited in the *marginal* and *unproductive* classes are mostly located in the northeastern part of the province (see Fig. 4). One of the most *unproductive* lands is located around an industrial city, Çorlu, and its buffer area. Further, two stripes around the city are in *marginal* areas again where the industry is in play. The southwest corner of the study area appears to be the *marginal* class as this area is mostly rocky

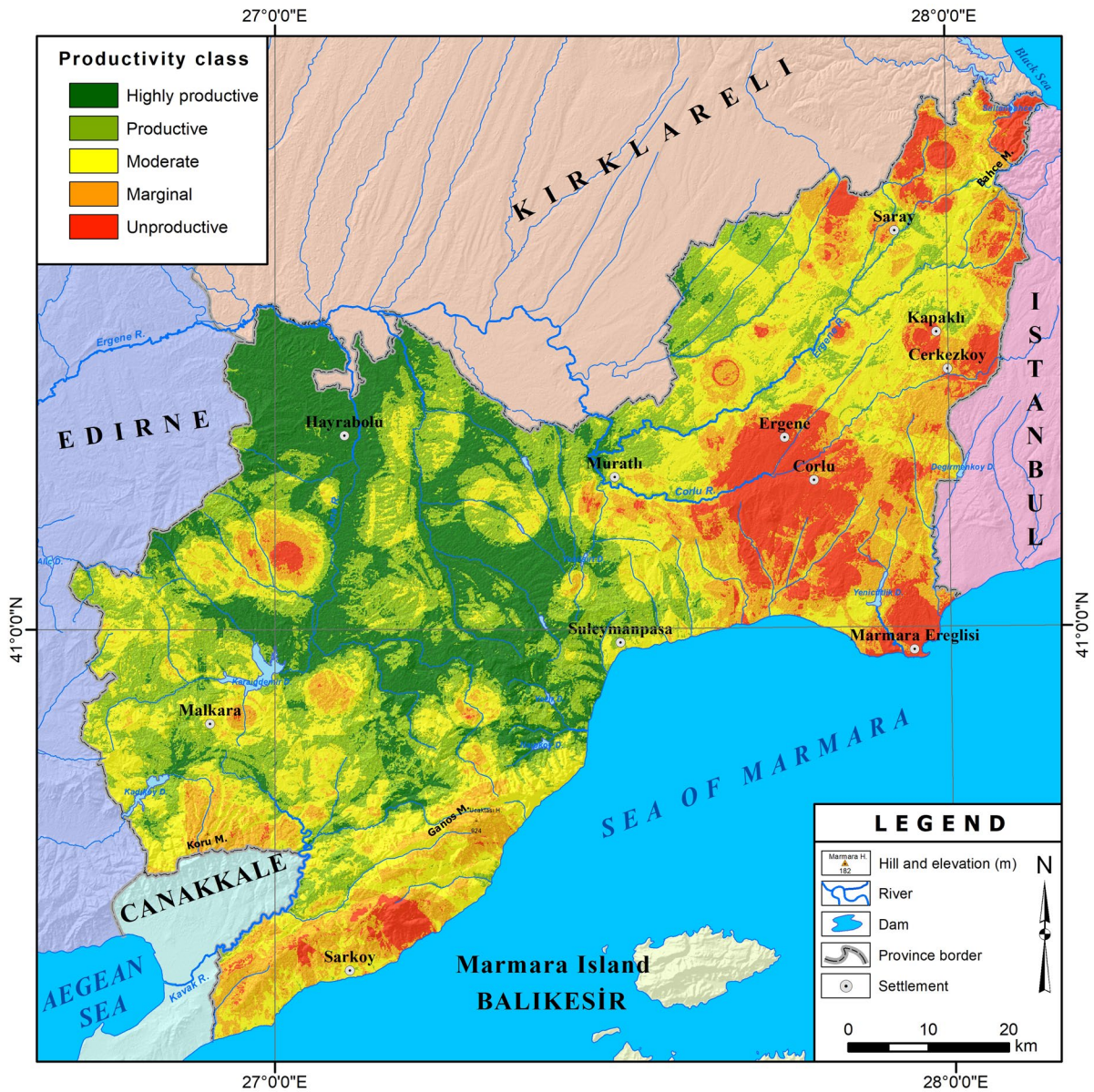


Fig. 3 Land suitability map of agricultural productivity in the study area

Table 6 Distribution of productivity classes overlapped with the current land use classes

Land use	Productivity (%)				
	<i>Highly productive</i>	<i>Productive</i>	<i>Moderate</i>	<i>Marginal</i>	<i>Unproductive</i>
Agriculture	89.65	75.75	60.26	55.38	69.10
Vineyard	0.06	0.15	0.70	1.73	0.00
Forest	2.88	13.84	30.43	30.58	9.33
Bushes	0.00	0.27	2.37	0.62	0.07
Barren	0.00	0.02	0.02	0.06	0.06
Settlements	2.09	4.92	3.00	6.78	17.99
Pasture	5.33	5.05	3.22	4.85	3.44

and mountainous, which is not suitable for agriculture (see Fig. 4). These areas are forested and covered mostly with oak trees and shrubs. Apart from these areas, the western part of the study area is covered with *highly productive* and *productive* classes.

The results indicate that the grain yield is high in the *highly productive* class (28.51%) and low in the *unproductive* class (13.79%). The fruit yield is high in the *moderate* class (25.93%) and low in the *highly productive class* (13.85%). These findings suggest that a strong relationship exists between the results of the model and the spatial distribution of grain yield (see Table 7). However, the same result does not apply to the fruit yield. Therefore, the model is appropriate for use in grain productivity.

Discussion

Agricultural land suitability depends on the following factors: topography, soil, seeds, irrigation, climate, and human activity (Liliane & Charles, 2020) (Table 8). These most basic factors, which directly affect both quality and yield, control the spatial distribution of agricultural productivity. Soil, without any doubt, plays a critical role in the spatial distribution of agricultural productivity and so it has a robust effect on ALSA (Ates & Turan, 2015; Cimrin & Boy-san, 2006; Saglam & Dengiz, 2013). The soil types in the study area exhibit deep, clay, well-drained physical properties with very low erosion risk. In terms of chemical components, the soil in the area, in general, is mildly acidic and has slightly alkaline pH values, low to medium lime, medium to rich organic matter, high in nitrogen, while indicating calcium and zinc deficiency. It also has sufficient chemical properties

for other vital elements, such as nitrogen, potassium, phosphorus, calcium, and magnesium. These findings indicate that the soil in the study area contains almost all necessary components for crop production and has more favorable conditions as compared to the rest of the agricultural lands in Turkey (Zengin et al., 2003).

Another factor that significantly affects the ALSA is the seed type (Kayacetin, 2006; Yılmaz & Kinay, 2015). The seed type is a determinant factor for crop yield grown in the study area and is characterized by the type of crops in accordance with the suitability of other conditions. The crop yield is medium to high in the study area. The average maximum yield has been determined in grains to be 1.620 kg/da. The fruit yield is 1.073 kg/da, which is quite low in the province, whereas no record of vegetable yield is obtained. In terms of production amount, crops are the most significant products of the study area (45,421.20 ton/year) followed by vegetables (2119.80 ton/year) and fruits (2632.80 ton/year) (TUIK, 2020).

Another significant factor that affects the ALSA for agricultural productivity is irrigation. The study area offers favorable conditions for both irrigated and rain-fed agriculture. Riparian areas, where continuous flow is experienced, and areas surrounding dams for irrigation are the most suitable lands for irrigated agriculture. In the study area, most of the water (about 90%) for agricultural use is obtained from groundwater. The groundwater level is high around Hayrabolu, while it is low around industrial cities (Çorlu-Ergene-Çerkezköy) where most of the population of the province is located. Like many other highly populated areas, excessive use of groundwater in the province causes a depletion of groundwater levels in recent years (Basa et al., 2017). The presence and amount of groundwater level in the study area varies according

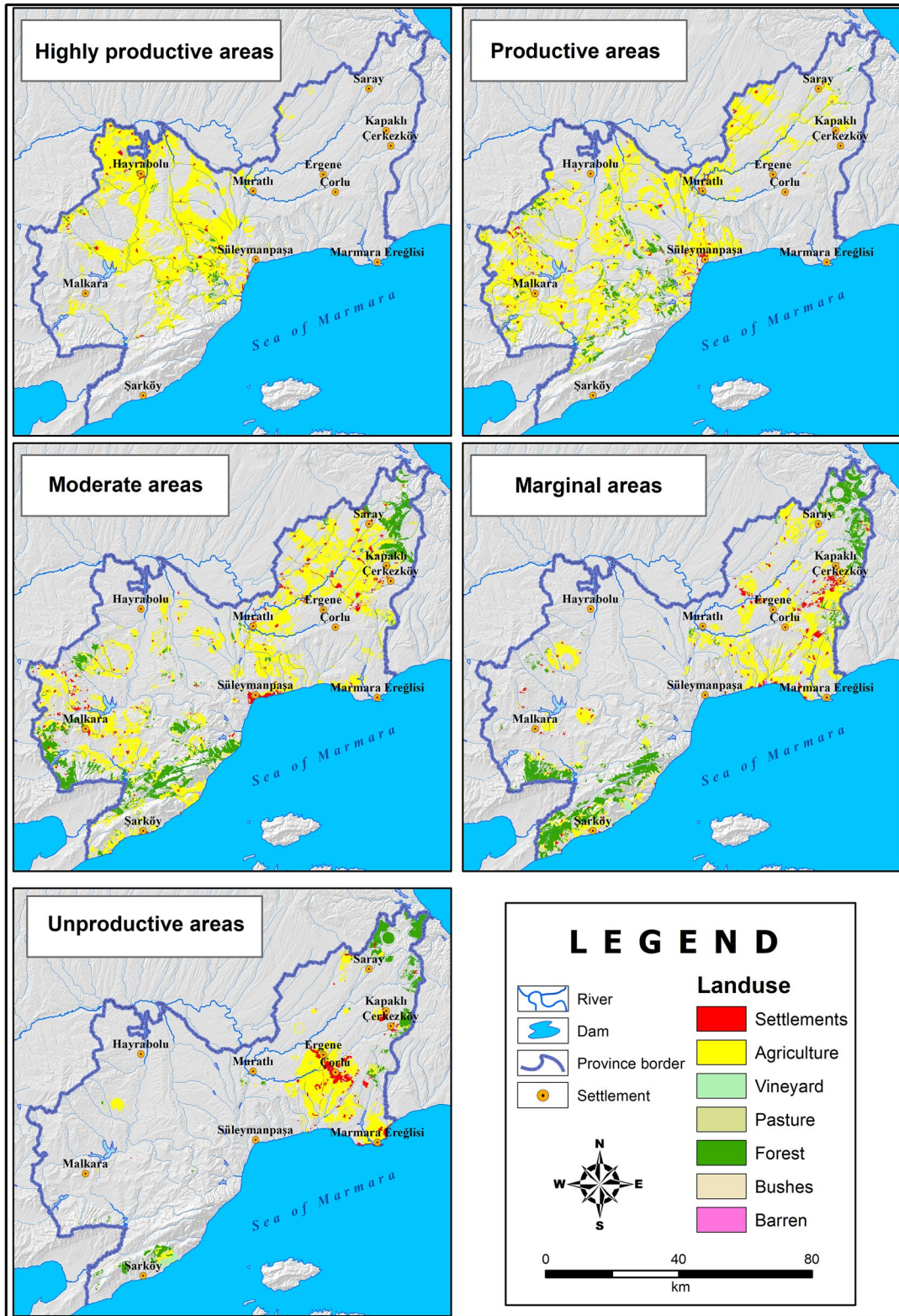


Fig. 4 Distribution of productivity classes overlapped with current land use classes

Table 7 The relationship between the productivity and average yield of grains and fruits

Productivity value is between 0 and 1 where 0 indicated least productive and 1 indicated most productive areas

Productivity class	Productivity value	Minimum	Maximum	Mean (%)
Grains				
<i>Highly productive</i>	0.65–1.00	27,758.80	52,463.05	28.51
<i>Productive</i>	0.60–0.65	16,667.34	52,471.85	22.98
<i>Moderate</i>	0.55–0.60	16,667.06	51,153.44	18.84
<i>Marginal</i>	0.50–0.55	11,553.32	44,341.47	15.87
<i>Unproductive</i>	0–0.50	11,207.22	33,568.44	13.79
Fruits				
<i>Highly productive</i>	0.65–1.00	737.68	5526.40	13.85
<i>Productive</i>	0.60–0.65	737.01	5727.63	22.39
<i>Moderate</i>	0.55–0.60	482.53	5745.91	25.93
<i>Marginal</i>	0.50–0.55	252.16	5745.04	22.23
<i>Unproductive</i>	0–0.50	235.04	3418.70	15.60

to the hydrogeological environment and the conditions offered by the lithological units underground. Although hydrogeologically favorable, the environmental conditions are dominant in the study area due to the impermeable or semi-permeable lithological structure in the northern and southern parts of the provincial lands containing low to medium groundwater. Irrigation water comes predominantly from surface water in the northern and southern areas.

Another important factor found to be affecting the ALSA is the climate variables. Agricultural procedures evolve and adapt to the dominant climate factors. Many agricultural activities in the area are vulnerable to the impact of climate change. The study area is under the influence of Marmara (transitional) climate conditions (Sahin & Cigizoglu, 2012). Mainly due to the variations in temperature and precipitation, the non-irrigated agricultural production varies annually (West, 2019). The mean annual temperature is 13.4 °C and the mean annual precipitation is 586.36 mm depending on the local climate characteristics. While coastal areas offer a humid and hot climate, Ergene Basin has more continental climate conditions. The increase in evaporation in the dry season causes the need for irrigation. This water requirement is met by irrigation from surface waters. This situation causes a significant change in the distribution of the greening period of vegetation in the study area (Ozsahin & Eroglu, 2018). In the northern areas, the greening period of the vegetation varies usually between 180 and 240 days.

One of the most dynamic factors affecting the temporal and spatial variability of ALSA is the human

impact. Human practices are of great importance in terms of management and usage of agricultural areas (Tasan & Demir, 2017). Agricultural reports indicate that approximately 80% (49,583 ha) of the province is suitable for agriculture. However, only 64% (39,667 ha) of this land is used for agricultural activities, where 25,527 farmers are active workers (Agriculture Report, 2019; Farmer Registration System Report, 2019). The aforesaid records indicate that 198,692 ton of fertilizer and 635 ton of agricultural pesticides are used on 305,300 parcels of the land. The parcels are generally 10–50 ha in size. Therefore, while human influence on agricultural productivity in the study area increases with the use of fertilizers and pesticides, it also has a reducing effect with misuses of the lands as well as by dividing the parcels into smaller parts (Kontgis et al., 2019; Kremer & DeLiberty, 2011). This situation is due to the socio-economic characteristics of the study area, regardless of natural conditions (Ozsahin & Eroglu, 2017).

The results of the model indicate that some products show better yield in different productivity classes. Grain yield is higher in the *highly productive* class (28.51%) and lower in the *unproductive* class (13.79%). On the other hand, the fruit yield is higher in the *moderate* class (25.93%) and lower in the *highly productive class* (13.85%). These findings suggest that while a strong correlation exists between the spatial distribution of grain yield and the productivity classes, the situation is quite different for fruit yield. Besides, needs for minerals, water, and climate conditions are varied dramatically depending on the type of fruit. The study area has a negligible number

of orchards compared to grains. Thus, the results of the model might be skewed if used for fruit productivity. Therefore, it would be more appropriate to use the model in determining suitable areas for grains rather than in any other agricultural suitability.

In general, model validation can be considered as satisfactory if $NSE > 0.50$ and $RSR < 0.70$, and if PBIAS is 25% for streamflow, 55% for sediment, and 70% for N and P (Moriassi et al., 2007). The high maximum and minimum values and variances of NSE, RSR, and PBIAS presented in [calibration and validation](#) are due to variation of agricultural land use in the province (see Fig. 3). For validation, the data obtained in the form of district averages differ in each district as the agricultural land availability varies. This causes the high variance of NSE, RSR, and PBIAS presented in [calibration and validation](#). It is plausible to obtain different results if the study is conducted only in agricultural areas. However, in the present study, besides the agricultural lands in the districts, other land use classes were also examined. The reason for this is to detect all suitable and unsuitable land uses in the study area. As seen in Table 6, the existence of *productive* classes in land use classes other than agricultural areas (pasture, forest, and settlements) suggests that some of the productive lands in the study area are misused or not used at all.

The model projection indicated a linear decrease of agricultural use from *highly productive* to *marginal* classes. Agriculture is the most common in the *highly productive* class. However, the remaining portion of the *productive* area is subject to further research and evaluation. On the other hand, a high percentage of the *unproductive* lands appear to be used for agriculture in the study area. This situation could be related to the fact that the study area is located in fertile land in general, in which wide agricultural activities are spread throughout the area. This situation might lead the local governments and the policymakers to designate the entire land for agriculture. Thus, agricultural activities in *marginal* and *unproductive* areas may represent a misuse of land and cause various environmental problems. Therefore, the agricultural activities in the study area should be performed only in *highly productive*, *productive*, and *moderate* classes. Depending on the demand for agricultural products, it also might be beneficial to use marginal class in some cases.

Conclusion

In this study, a spatial model developed for ALSA for agricultural productivity has been introduced and applied using the GIS-MCDA technique. The model was applied to the entire land use types to determine the most suitable lands for agricultural productivity. The results indicate that a significant portion of the lands, which are used for settlement and other uses in the study area, is in fact suitable for agricultural production. The model also indicates that the *highly productive* and *productive* classes are in the northwestern part, while *marginal* and *unproductive* classes are in areas where settlement and industrial activities are concentrated. In addition, the relationship between productivity and the current land uses indicates that agriculture in the study area should be cultivated only in *highly productive*, *productive*, and *moderate* classes. However, the study model offers advantageous conditions only to determine grain agriculture. For other types of agricultural uses, it is uncertain how it might result; therefore, more research is encouraged. The model performance rating indicates a high NSE and RSR range and acceptable PBIAS values. In addition, it has been determined that modeling the interrelation between the parameters with correct methods and techniques is important for a better assessment of land suitability for better agricultural productivity. In this way, more productive lands can be identified, and more accurate decisions can be made in spatial site selection to prevent unsuitable land use.

Since cultivation areas are limited and cannot be expanded to increase agricultural production, the outcomes of this study suggest that the existing agricultural areas should be protected, and sustainable agriculture practices should be applied. Sustainable and productive agricultural production is essential to meet the grain needs of the rapidly increasing population. Otherwise, unsustainable agriculture might result in food security problems in the near future for societies that provide a significant part of their food from grains. This study indicates that with better land use planning and the application of modern agricultural techniques, it is possible to increase the productivity of grains. Focusing on solving current problems of agriculture, in a supportive nature, this study provides

precise spatial information about the consistency and reliability of the findings. Nevertheless, more research is encouraged to ensure that agriculture would reach the desired place in terms of production and sustainability Table 8.

Author contribution EO conceived and designed the analysis, collected the data, and performed the analysis. MO contributed to data and analysis, wrote the paper, and other contributions.

Data availability On demand.

Code availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

Appendix

Table 8 Ratio of factors and variables affecting agricultural productivity

Main factors	Variables/units	Classified as	Rating
Topography (F1)	Altitude (V1) (m)	<-100	1
		100–250	0.75
		250–500	0.5
		500->	0.25
	Slope (V2) (%)	0–2	1
		2–4	0.75
		4–6	0.50
		6–12	0.25
		12->	0
	Aspect (V3) (direction)	Flat	1
		S	0.75
		W-E	0.50
		N	0.25
Landforms (V4) (major landforms)	Plain	1	
	Plateau	0.50	
	Mountain	0	

Table 8 (Continued)

Main factors	Variables/units	Classified as	Rating
Soil (F2)	Depth (V5) (cm)	<-30	0
		30–60	0.25
		60–90	0.5
		90–120	0.75
		120->	1
	Texture (V6) (%)	C-SC-SiC	0
		SCL-SiCL	0.25
		CL-SiL-SL	0.5
		LS	0.75
		L	1
Drainage (V7)	Very poor	0	
	Poor	0.25	
	Moderate	0.5	
	Good	0.75	
	Very good	1	
Erosion (V8)	Very low	1	
	Low	0.8	
	Moderate	0.6	
	High	0.4	
	Very high	0.2	
Reaction (V9) (pH)	<-6.5	0	
	6.5–7	1	
	7->	0	
Lime (V10) (%)	<-5	1	
	5->	0	
Salinity (V11) (%)	0.01–0.03	1	
	0.03–0.05	0	
Electric conductivity (V12) (μS/cm)	<-200	1	
	200->	0	
Cation exchange capacity (V13) (me/100 g)	10.66–25	0	
	25–47.13	1	
Organic matter (K14) (%)	<-3	0	
	3->	1	
N (V15) (ppm)	<-750	0	
	750->	1	
P (V16) (ppm)	<-8	0	
	8–25	1	
	25->	0	

Table 8 (Continued)

Main factors	Variables/units	Classified as	Rating
Seeds (F3)	K (V17) (ppm)	<-110	0
		110-290	1
		290->	0
	Ca (V18) (ppm)	<-1150	0
		1150-3500	1
		3500->	0
	Mg (V19) (ppm)	<-160	0
		160-480	1
		480->	0
	Fe (V20) (ppm)	<-4.5	0
		4.5->	1
	Zn (V21) (ppm)	<-0.7	0
		0.7->	1
	Mn (V22) (ppm)	<-14	0
		14-50	1
		50->	0
	Cu (V23) (ppm)	<-2	0
		2->	1
	Seed yield (V24) (kilogram per decare)	<-200	0
		200-300	0.3
		300-400	0.7
		400->	1
	Grain yield (V25) (kilogram per decare)	<-20,000	0
20,000.01-30,000		0.3	
30,000.01-40,000		0.7	
40,000.01->		1	
Fruit yield (V26) (kilogram per decare)	<-1000	0	
	1000.01-2000	0.25	
	2000.01-3000	0.5	
	3000.01-4000	0.75	
Grain production (V27) (ton)	<-100,000	0	
	100,000.01-200,000	0.25	
	200,000.01-300,000	0.5	
	300,000.01-400,000	0.75	
	400,000.01->	1	

Table 8 (Continued)

Main factors	Variables/units	Classified as	Rating
	Vegetable production (V28) (ton)	<-15,000	0
		15,000.01-30,000	0.25
		30,000.01-45,000	0.5
		45,000.01-60,000	0.75
		60,000.01->	1
	Fruit production (V29) (ton)	<-10,000	0
		10,000.01-20,000	0.25
		20,000.01-30,000	0.5
		30,000.01-40,000	0.75
		40,000.01->	1
Irrigation (F4)	Distance to water sources (V30) (m)	0-100	1
		100.01-250	0.75
	Groundwater depth (V31) (m)	250.01-500	0.5
		500.01-1000	0.25
Climate (F5)	Hydrogeology (V32)	1000.01->	0
		Permeable zone	1
	Temperature (V33) (°C)	Semi-permeable zone	0.5
		Impermeable zone	0
Precipitation (V34) (mm)	<-13	0	
	13->	1	
Solar radiation (V35) (h/min)	<-550	0	
	550->	1	
Vegetation period (V36) (day)	<-6.5	0.5	
	6.5->	1	
Human (F6)	Number of farmers (V37) (person)	<-300	0
		300->	1
		<-100	0
		100-250	0.5
		250->	1

Table 8 (Continued)

Main factors	Variables/ units	Classified as	Rating
Land use (V38)		Settlements	0
		Agricultural areas	1
		Vineyard and garden	0.8
		Pastures and grasslands	0.6
		Shrubs area	0.4
		Forest area	0.2
		Artificial surfaces	0
		Land capability classes (V39)	Class I
		Class II	0.9
		Class III	0.8
		Class IV	0.6
		Class V	0.4
		Class VI	0.2
		Class VII	0.1
		Class VIII	0
		Fertilizer (V40) (kilogram)	
10,000,000.01–20,000,000	0.25		
20,000,000.01–30,000,000	0.5		
30,000,000.01–40,000,000	0.75		
40,000,000.01–47,321,136	1		
Pesticide (V41) (kilogram per liter)		5915.01–50,000	0
		50,000.01–100,000	0.25
		100,000.01–150,000	0.5
		150,000.01–200,000	0.75
		200,000.01–213,779,0781	1
Land tenure (V42) (per decare)		0.32–1.000	1
		1000.01–2500	0.75
		2500.01–5000	0.5
		5000.01–7500	0.25
		7500.01–8186	0

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