Land Quality Index for Paddy (Orzya sativa L.) Cultivation Area based on Deep Learning Approach using Geographical Information System and Geostatistical Techniques

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Land Quality Index for Paddy (Orzya sativa L.) Cultivation Area based on Deep Learning Approach using Geographical Information System and Geostatistical Techniques*

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Abstract

Many fields in Turkey have suitable ecological conditions for rice production and its per hectare yield is usually above the global average.

However, because of such as unstable fertilization, lack of nutrients, and irrigation, the production amount cannot meet the consumption amount when soil properties are not considered. This case entails Republic of Turkey to be a rice-importing country. The present study was conducted to on a 1,763-hectare field in the province of Çorum, Osmancık district, which is one of the most significant rice fields in Turkey. The main purpose of this study is to determine land quality classes for rice (Oryza sativa L.) production based on Geographic Information System (GIS) and the deep learning approach. Deep learning is a popular technique for image processing and data analysis with procuring results and great potential. This technique has recently been used extensively in precision agriculture applications. In the study, Feedforward Neural Networks (FNN), a basic deep learning model, was used. It is used 15 different physicochemical properties (pH, EC, lime, OM, depth, slope, HI, HA, clay, silt, sand, N, P, K, and Zn). Using this parameters soil types was classified and regression analysis (index, efficiency, NAI, and SQI) was performed by deep learning. In the study, using the index, efficiency, NAI, and SQI soil parameters as network outputs caused different performance levels in models. Therefore, different models were suggested for each network output. R2 values are at an acceptable level for predicting parameters (index: 91.14%, efficiency: 87.50%, NAI: 87.54%, and SQI: 87.54%). A success rate of 88% is achieved in classifying "class" information. It has been shown that deep learning can be used successfully in predicting soil parameters and identifying land quality classes. In addition, identified land quality classes have been confirmed by field study. As regards research results, a significant positive relationship was found between land quality classes and yield using Statistical methods. In addition, according to field validation study, rice yield was significantly affected by the land quality classes which was at a $\boldsymbol{p < 0.001}$ level. The highest product yield was achieved in ($\mathbf{7197}\ \boldsymbol{kg\ ha^{-1}}$ in S1 class), ($\mathbf{5032}\ \boldsymbol{kg\ ha^{-1}}$ in S2 class), and then ($\mathbf{3572}\ \boldsymbol{kg\ ha^{-1}}$ in S3 class).

Keywords: Paddy,Orzya sativa L.,deep learning,precision agriculture,mapping.

1 Introduction

Rice, a warm climate grain (Oryza sativa L.) is the main food source for 50% of the world's population [1]. In addition, rice is the most produced grain in the world and has the most cultivation area after wheat [2]. Most of the rice produced in the world is grown in tropical and subtropical regions. According to FAO data, rice production is made on a field of 167.13 million ha; total production is 782 million tons, the average yield is 4678.9 kg ha-1. According to the latest FAO data, the total rice cultivation area is 120.14 thousand ha, production is 940 thousand tons, and yield is 7824.4 kg ha–1 in Turkey [3]. Although rice cultivation is conducted in all geographical regions in Turkey, 56.0% of the total rice area is in the Thrace-Marmara region, 36.5% in the Black Sea region, and 7.5% in other regions [4]. In terms of human nutrition, the fact that rice is rich in amino acids and that its protein content is much higher compared to other grains demonstrates that it is an important grain. In addition, lysine and threonine content found in small amounts in many plants and they are 4% for rice [5, 6]. Considering different scenarios derived from climate change models, food security is the most pressing issue in densely populated developing countries [7]. A great effort has been exerted to meet the nutritional needs of the growing population in developing countries in terms of achieving consistent high yield rates [8]. In addition, the specification and classification of plant diseases are one of the most vital methods for early-stage intervention to increase yield [9]. It also ensures the ecological sustainability of soil types, which is one of the important components in both the economic and terrestrial ecosystem, as well as the use of produce considering land needs, its management, yield, and increase in quality [10]. Therefore, important studies have been conducted on soil and land quality index approaches in recent years. However, the concepts of land and soil are often mistaken for each other. The land encompasses a broader concept of describing the climate, topography, and hydrology. Therefore, the soil is one of the core elements of the land [11, 12]. Identifying land quality is actually a difficult process. Because the relationships between land quality and yield are quite complex. The reason for the complex relationship is between the physical, chemical, biological properties of the soil and other factors. Many researchers are conducting studies to search the relationships between physical, chemical, and biological properties of soil types and yield [11, 13–17]. While it is possible to assess land quality by directly conducting land testing, several modal approaches such as comparative assessment, dynamic assessment, and land quality index (LQI) can be used indirectly. Since direct approaches are generally expensive, labor-intensive, and time-consuming, modal approaches are used more often [18]. LQI approach was used in rice land assessment. In this approach, the land quality index assessment process, which usually starts with the creation of a data set, is graded by giving score ratios according to the severity of limiting plant growth on indicators with different units [19]. In addition, the possibility of the deep learning system, which had never been used before in rice land quality studies, was investigated.

Deep learning is a modern and popular technique for image processing and data analysis with promising results and great potential [20]. Deep learning, which has been successfully applied in various fields, has recently been used in precision agriculture applications [21]. To give an example of these studies, computer-aided diagnosis (CAD) systems, using Artificial Intelligence, was used in order to accurately identify diseases and pests affecting small farmers' production and to help understand the severity of symptoms, as well as allowing any farmer with access to a smartphone to benefit from expert knowledge in a practical and cost-effective manner [22, 23].

Azizi et al. [24] used CNN, a deep learning method, to classify soil clusters while they used VggNet16, ResNet50, and Inception-v4 trained models to train CNN. The ResNet50 produced very good accuracy (98.72%). It has shown that Deep learning can be used in classifying soil clusters. Esgario et al. [23] used deep learning to classify biotic stress in coffee and to estimate its severity. The ResNet50 produced high accuracy rate (95.24%). The study has demonstrated that deep learning can be a convenient tool to assist both experts and farmers in identifying and measuring biotic stresses in coffee plantations. Pederian et al. [25] used deep learning to predict soil properties from regional spectral data. The study in which they used CNN showed that it could be reduced by 87% compared to PLS, a traditional method. Moreover, Padarian et al. [26] used deep learning for digital soil mapping. In the study, they predicted soil carbon in deeper soil layers with a high accuracy rate. The researchers demonstrated that deep learning can be used in weed identification with an accuracy rate of 92.89% using CNN and K-means feature learning [27].

The decrease in land quality due to intensive rice cultivation threatens the sustainability of rice agriculture in the Çorum-Osmancık region. In the present study, it is necessary to identify detailed rice land quality classes and to map their spatial distributions in order to perform sustainable rice agriculture practices. To this end, the possibility of using the deep learning technique, which has become increasingly important in recent years, within the rice land quality index model, accompanied by geographic information systems and geostatistics, has been investigated, and a high correlation rate has been achieved with obtained data, resulting from field verification studies.

2 Material and Methods

2.1 Study area

The study area is located within the boundaries of Çorum- Osmancık district, in the Kızılırmak Valley of the Western Black Sea region, and between the coordinates 652000-659000E-W and 4528000-4536000N-S (WGS84, Zone 36 UTM-m). The study area covers approximately 1,763 ha and is between 399-480m above sea level (Figure 1).

The study area is located in a transition area between the Black Sea and Central Anatolian climate regimes and falls into the semi-arid climate class. According to Çorum Osmancık meteorological station data [28] (1960-2019, DMI), average annual precipitation, temperature, and potential evapotranspiration values are 340.1 mm, 13.6 mm, oC, and 782.43 mm respectively. Summer months are much warmer compared to winter months (the warmest month is July (24.9oC); the coldest month is January (1.9oC) while the maximum average annual precipitation was recorded in June with 42.2 mm. According to Newhall simulation model [29], soil temperature and moisture regimes are Mesic and Dry Xeric, respectively (Figure 2).

The region is surrounded by Ilgaz Mountains, which extend through the east-west direction, from the west and by its extensions and Köroğlu Mountains from the south. The geological structure of these mountainous areas in the region is generally composed of Paleozoic metamorphic rocks. There are also Eocene flysch and volcanic fields sporadically. The wide valley bottom plains through which Kızılırmak (the Halys river) flows, makes up alluvial deposits belonging to the Quaternary period. Generally, rice is grown on soil formed on these alluvial deposits.

The study area is mostly flat or slightly inclined (0.0-2.0%). A total of eight soil series have been identified in the study area. Dengiz et al., [30], defined 29 mapping units according to the digital soil map they created (Figure 3).

2.2 Methods

2.2.1 Soil sampling and indicator selection

The field study was carried out in 2011, and a total of 246 soil samples, disturbed and undisturbed sampling from the surface (0-30 cm), were taken from the grit points (400 m x 400 m) formed on the soils where Vertiso, Entisol, and Inceptisol soil types were distributed. Soil sampling was conducted especially in the autumn after the harvest, in order to avoid the effects of soil management processes such as fertilization and irrigation during the rice-growing period. The coordinates of points where soil samples were taken were recorded in the field using a handheld GPS (global positioning system) instrument. Each mapping unit (land mapping units) defined with its unique soil and land properties significantly affects the suitability of the determined land utilization type to the land. Therefore, it is necessary to identify the land needs of each land utilization type for a successful and sustainable agricultural practice.

The land utilization type investigated in this study is rice. Some literature sources were examined in order to identify the land needs of rice and soil physicochemical and topographic indicators required for the model [31–38]. The development of the rice plant depends on the physical and chemical conditions of the soil type that affect the plant root system and affects the ability to grow efficiently. Therefore, Moron (2005) stated that the indicators used in soil quality identification should be sensitive enough to track changes and be easily measured and interpreted. The gradient and clay content of soil types are of critical importance for rice cultivation lands. Hence, soil types with high clay content are given high scores in terms of the suitability of soil types to rice cultivation [18]. In addition, many researchers [39–41] stated that high clay content was much more suitable for rice cultivation due to further restricting the percolation of water through the profile, excess water, and nutrient holding capacity. In identifying land suitability classes for rice cultivation, the topographic factor, especially the gradient degree, plays an effective role in the homogeneous distribution of water in the pan and changing in the physicochemical properties of the soil. Kikuta et al., [42] concluded that the gradient has a significant effect on the development and yield of the rice plant. Aldababseh et al., [43] stated in land quality index studies that soil depth was an important indicator due to the fact that it was a water and nutrient reservoir as well as providing a good plant root development. The organic matter content of the soil directly affects the soil quality and sustainable soil fertility as well as plant cultivation. In addition to providing basic nutrients and energy sources for microorganisms, organic matter also plays an important role in improving many physical and chemical properties in the soil. Moreover, the EC, pH, and CaCO3 contents in the soil, as well as the adequacy of the nutrient element in the soil regarding rice cultivation, significantly affect yield and quality [44–46]. Fourteen quality parameters fall into two different main categories for the rice land quality index model (LQIR). These are i-) Nutrient Availability Index (NAI) (including nitrogen, phosphorus, potassium, and zinc content in the soil), ii-) soil quality index (SQI) (including slope, soil depth, bulk density, clay, silt, sand, hydraulic conductivity (HC), organic matter, electrical conductivity (EC), lime-CaCO3, and soil reaction-pH (Table 1). Table 1 shows the analytical protocols used.

Table 1 Analytical Protocol measurements for indicators.

Indicators	Unit	Protocol	Reference
Soil quality indicators			
Soil Depth	cm	From soil map	Dengiz et al. (2009)
Slope	%	From DEM	Dengiz et al. (2009)
BD	$gr\ cm^{-3}$	Undisturbed condition	Blacke and Hartge, 1986
HC	$cm\ h^{-1}$	Undisturbed and saturated condition	Oosterbaan (1994)
OM	%	wet oxidation method (Walkley-Black) with potassium dichromate ($K_2Cr_2O_7$)	Nelson and Sommers 1982
pH	1:2.5	(w:v) soil-water suspension	Soil Survey Staff (1996)
EC	$dS\ m^{-1}$	(w:v) soil-water suspension	Soil Survey Staff (1996)
$CaCO_3$	%	Scheibler calsimeter	Soil Survey Staff (1993)
Nutrient availability indicators			
$NaHCO_3 - P$	$mg\ kg^{-1}$	the molybdophosphoricblue method	Kacar B (2016)
Total N	%	Kjeldahl	Bremner and Mulvaney (1982)
NH4OAC–K	$mg\ kg^{-1}$	Ammonium acetate extraction, flame spectrometry detection	Soil Survey Staff (1992)
DTPA–Zn	$mg\ kg^{-1}$	DTPA extraction, AAS detection	Kacar B (2016)

2.2.2 Land quality index and rating assignment

The rice grows in an environment rich in water. During the growth season, temperature must be equal or greater than 22°C. Rooting depth is at least 50 cm, and the plant can be grown in soil with pH requirements of 4.5 to 8.5. Optimum cultivation can be achieved in a heavily textured soil type with an impermeable layer, 45-150 cm below the surface. In this way, water loss is minimized. The rice plant likes soil that is deep, clayish, and rich in plant nutrients and organic matter, as well as being medium resistant to salt [47].

Land quality indicators and factor ratings normally employed in physical land assessment were used to compile information on the study area (Table 2). The identification of rice land quality index consists of nutrient availability index and soil quality index. The following formula is used to identify the nutrient availability index [13].

$$NAI = N \times P \times K \times Zn \tag{1}$$

where; NAI is the Nutrient Availability Index, N is total nitrogen (%), P is available phosphorous ($mg\ kg^{-1}$), K is available potassium ($mg\ kg^{-1}$), and Zn is available zinc ($mg\ kg^{-1}$). The following formula is used in soil quality index (SQI) [48].

$$SQI = Cy \times Si \times Sa \times D \times F \times P \times G \times S \times K \times H \tag{2}$$

Where; Cy is clay, Si is silt, Sa is sand, D is soil depth, F is slope, P is bulk density, G is hydraulic conductivity, S is soil salinity or exchangeable sodium percentage (ESP), K is lime ($CaCO_3$) content, and H is soil reaction (pH).

Each indicator was scored with a ratio value between 0.2 and 1.0. The result of the analysis on the indicator takes a value of 1.0 if it has the most suitable condition for rice cultivation, and 0.2 if it has the most unfavorable condition. The indicator takes a value between 0.2 and 1.0 according to the severity of limiting rice growth. The spatial information of both descriptive indicators on the nutrient availability index and descriptive indicators on the soil quality index were obtained from land mapping units and surface soil samples. In order to identify the land quality index value for rice, the following formula was used [13, 36].

$$LQI_R = NAI \times SQI \tag{3}$$

Where; LQI_R is the Land Quality Index, NAI is the Nutrient Availability Index, and SQI is the Soil Quality Index. The above-mentioned formula is applied to each soil sample.

As a result, the higher the point value is, the higher the suitability of land is for the specified Land Utilization Type. Rice land quality classification according to Dengiz [13] is given in Table 3.

For the purpose of model verification, for each quality class in the study area, two years in random blocks trial pattern using 12 paddy varieties (Şumnu, Osmancık-97, Gönen, Beşer, Durağan, Halilbey, 7721, Karadeniz, Kızılırmak,

Table 2 Factor rating of land quality indicators for rice cultivation.

Land quality indicator			Factor rating			
	Diagnostic Factor	Unit	1.0	0.8	0.5	0.2
			> 0.60	0.40-0.60	0.10-0.40	< 0.10
			$NAI = N \times P \times K \times Zn$			
I. Nutrient Availability Index (NAI)	TN	%	> 0.2	0.1-0.2	< 0.1	-
	P	$mg\ kg^{-1}$	> 25	10-25	< 10	-
	K	$mg\ kg^{-1}$	> 60	30-60	< 30	-
	Zn	$mg\ kg^{-1}$	> 07	0.5-0.7	< 0.5	-
II. Soil Quality Index (SQI)	$SQI = Cy \times Si \times Sa \times D \times F \times P \times G \times S \times K \times H$					
Texture	Clay-Cy	%	> 50	40-50	25-40	< 25
	Silt-Si	%	< 25	25-40	40-50	> 50
	Sand-Sa	%	< 30	30-45	45-50	> 50
Depth (D)		xm	> 50	25-50	15-25	< 15
Topography (F)			Flood plain or	Low terrace or	Middle terrace or	High terrace/ mountain or
	Land form or Slope	%	0-2%	2-4%	4-6%	$> 6\%$
Bulk Density (P)	BD	$gr\ cm^{-1}$	$< 1,40$	1,40-1,45	1,45-1,60	$> 1,60$
Hydraulic conductivity (G)	HC	$cm\ h^{-1}$	< 0.5	0.5-2.0	2.0-6.25	> 6.25
Electric Conductivity (S) or ESP		dS/m	0-3.1	3.2-4	4.1-5	> 5.1
	EC	%	10	10-20	> 20	> 20
Organic matter (O)		%	> 3	3-1,5	1,5-0,5	$< 0,5$
Lime (K)	CaCO3	%	0-5	5-15	15-20	> 20
Soil reaction (H)	pH	-	5.5-7.3	7.4-7.8 5.1-5.5	7.9-8.4 4.0-5.0	>8.4 <4.0

Table 3 Land quality index value for rice cultivation.

Definition	Suitability Class	Land Quality Index Value
Highly Suitable	S1	1.00-0.250
Moderate Suitable	S2	0.250-0.100
Marginally Suitable	S3	0.100-0.025
Unsuitable	N	<0.025

Koral, Neğiş and Aromatik) field trial was carried out. In the experiment where the strewing planting method was applied, parcel yields were obtained by removing the edge effect so that the plot size was $4 \times 4 = 16\ m^2$ and the harvest area was $3 \times 4 = 12\ m^2$ [49]. ANOVA and $LSD_{0.05}$ were done for the grain yields. In addition to that, in order to gain values of basic descriptive statistics' parameters, IBM SPSS Statistics 23v. program was used [50].

2.2.3 Deep Learning and Algorithms

Classification and estimation is a skill that a person has learned and used multiple times throughout their life. The network depth is determined by the number of layers. Previously used neural networks only had one or two hidden layers; however, deep models may have a hundred layers [51]. In many cases, the network contains fully-linked layers placed near the model output. These layers are used to classify pre-tagged input data or to perform numerical prediction [21]. Multiple linking between layers generates a large number of parameters. These parameters are usually initialized with random values.

2.2.4 Architecture of deep learning and tools

Despite the differences in deep learning architectures with their unique features, they all share the same aim that is to reduce the complexity of model and increase the accuracy [23]. The Tensorflow library, developed by Google for deep learning, is a calculation process that takes a node for each tensor and presents it as a tensor after performing the defined operation [52]. Our model in the present study is trained on Google Colaboratory [53], a free Jupyter notebook environment operating on the cloud. Keras [54] backend (Python Deep Learning library) is used as a deep learning package with Tensorflow. Python 3 programming language was used to implement the deep model. In addition to many libraries required to implement deep learning algorithms, Numpy, Pandas, and MatPlotlib libraries were used. Feedforward Neural Networks (FNN), a basic deep learning method was used [51]. In prepared FNN layers, the Sequential model, which provided a flat layer stack, the most common model type in which each layer had one input tensor and one output tensor, was used [55]. Dense layers were most commonly used in sequential models [56].

In this research, the models are presented in Table 4. Fifteen different physicochemical properties (pH, EC, lime, OM, depth, slope, HC, BD, clay, silt, sand, N, P, K, and Zn) of soil types investigated in the study were chosen as input layer parameters in the deep learning system. The ReLU (Rectified Linear Unit) activation function, which is a widely used system in identifying the activation status of neurons in models as well as offering a computational advantage, was used in the study. RMSprop, based on gradient descent, was used as the optimization method. The learning rate was chosen as 0.001. That one may eliminate the uncertainty caused by network randomness, fixed seed data were input at the beginning of the program.

2.2.5 Training, Test and Validation

In the present study, the dataset was divided into education (80%) and test (20%) sets. In addition, 20% of the training set was chosen as validation data. In deep neural networks the learning is based on gradient descent algorithm and back propagation approach. The cross entropy cost function is used for classification evaluation. After the cost function is calculated, the derivative of

Table 4 Deep learning regression (RM1, RM2, RM3) and classification models (CM1, CM2).

Models	Input Layer	Hidden Layer	Output Layer	Trainable parameters
RM1	Dense: 15	Dense: 30 Dropout: 20% Dense: 45 Dropout: 20%	Dense: 1	1.921
RM2	Dense: 15	Dense: 64 Dropout: 20% Dense: 128 Dropout: 40%	Dense: 1	9.473
RM3	Dense: 15	Dense: 64 Dropout: 20% Dense: 64 Dropout: 20% Dense: 128 Dropout: 20%	Dense: 1	13.633
CM1	Dense: 15	Dense: 64 Dropout: 20%	Dense: 4	5.444
CM2	Dense: 15	Dense: 32	Dense: 4	7.044

this function is assessed on weights. While performing regression, MSE (Mean squared error) loss function was used.

2.2.6 Performance metrics

During network training, the cases where the models provided the minimum cost function value for the validation set (weight set) were recorded. Then, these recorded models were assessed using the test dataset. In the classification study, the results were compared in terms of Confusion Matrix and Accuracy (ACC). In the regression study, results were assessed in terms of RMSE and R^2. To evaluate the proposed deep learning algorithms the accuracy metric was used (Equation 4):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

Where TP, TN, FP and FN are true positive, true negative, false positive, and false negative, respectively [57].

2.2.7 Interpolation analyses

Interpolation techniques are used in expressing and mapping the changeability of values on investigated properties depending on the distance [58, 59]. If data do not have normal distribution before mapping, transformations are made according to relevant properties. In the formation of the distribution map, Inverse Distance Weighting (IDW), Radial Basis Function (RBF), and Kriging methods were used and the mapping process was conducted in the ArcGIS program environment.

The "Geostatistical Extension" feature of the ArcGIS program uses root-mean-square error (RMSE) of the estimation and standardized mean error of estimation in generated maps. If the mean error of the estimation is close to 0 and the standardized root-mean-square-error of the estimation is close to 1 on the map, the accuracy rate of this map can be assessed [60].

IDW, the most commonly used interpolation models used in identifying the spatial distribution of rice land quality index (LQI_R) value for each point defined within the study area and from RBF (spline) deterministic and stochastic models (also known as Kriging) models such as ordinary, universal, and simple Kriging models were used. It was observed that different comparison methods were considered in the literature in terms of choosing the most suitable one among models that is the one providing the closest results to measured values, in order to investigate the relationship between measured values and estimated values in model comparisons [61]. The most commonly used methods, in general, are square-root-mean-error (RMSE) and mean absolute error (MAE) methods. RMSE was chosen for this study. 15 models used for forming a spatial distribution map of LQI_R on the interpolation were (Inverse Distance Weighting-IDW; 1, 2, 3, Radial Basis Function-RBF; Thin Plate Spline-TPS; Completely Regularized Spline (CRS); Spline With Tension (ST), and Ordinary, Simple, and Universal Kriging models. The method that provided the lowest square-root-mean-error-value was assessed as the most suitable method. The following formula was used to calculate the square-root-mean-error.

$$RMSE = \sqrt{\frac{\sum(z_{i*} - z_i)^2}{n}} \tag{5}$$

Z_i: refers to the estimated value, Z_{i*} measured value, and n the number of samples.

3 Result and Discussion

3.1 Soil physico-chemical characteristics

Descriptive statistics of some physico-chemical properties of soil samples are shown in Table 5. When examining changes in some of the study area's physico-chemical properties in terms of the coefficient of variation (CV), it can be seen that the soil properties examined are highly variable.

Wilding et al [62] and Mulla and McBratney [59] reported that when the CV is lower than 15%, variability is classified as low; when it is between 15% and 35%, it is classified as moderate; and when it is greater than 35%, it is classified as high. In this sense, variables of pH has low CV. On the other hand, the variables of HC, sand, EC and AvP, AvK, AvZn and OM content had a high level of variability. Main characteristics of the alluvial land and soils which are being widely classified as fluvent sub order of Entisol order often shows large variations in their features such as textural or organic matter distribution over short distances [63].

Furthermore, in the study area, the distributions of physico-chemical quality indicators show different distributions in terms of the skewness and kurtosis

Table 5 Descriptive statistics of some physicochemical properties of soil samples.

Indicators	Mean	SD	CV (%)	Variance	Min.	Max.	Skewness	Kurtosis
Clay (%)	53.34	1.21	25.23	181.04	23	67	-0.11	-0.84
Silt (%)	27.15	0.53	21.82	35.08	21	43	1.71	1.41
Sand (%)	19.52	1.26	71.94	197.13	6	55	1.09	1.32
BD ($gr\ cm^{-1}$)	1.35	0.02	15.42	0.04	0.88	1.88	0.63	-0.31
HC ($cm\ h^{-1}$)	1.28	0.17	144.6	3.43	0.11	5.93	1.47	1.69
pH	7.76	0.04	5.37	0.42	7.14	8.82	1.79	1.33
EC (dS/m)	6.62	0.46	78.02	26.65	1.14	17.15	-0.83	0.74
$CaCO_3$ (%)	9.73	0.27	30.47	8.79	3.04	15.97	1.02	-0.19
OM (%)	2.57	0.16	69.34	3.18	0.81	8.08	5.56	2.60
TN (%)	0.13	0.004	31.07	0.002	0.054	0.337	8.86	2.15
P ($mg\ kg^{-1}$)	18.88	0.69	40.98	59.88	6.67	52.22	2.38	1.19
K ($mg\ kg^{-1}$)	38.19	2.306	67.25	659.81	11.9	257.15	44.77	5.80
Zn ($mg\ kg^{-1}$)	2.36	0.26	122.7	8.42	0.31	19.65	13.45	3.29

coefficient. It is possible to comment on whether the data shows a normal distribution by looking at the kurtosis and skewness values in data that are not suitable for the normality test or in cases where you cannot perform the test [64, 65]. In this study, clay, silt, sand, BD, HC, pH, EC, and $CaCO_3$ shows normal distribution.

3.2 Regression with Deep Learning (DNN) on Randomly Selected Data, Independent of Soil Classes

Parameters on the dataset are clearly grouped into different soil classes. During deep learning, training and test dataset were randomly selected without considering class information. The results obtained in this way are below.

In Figure 4, the regression estimation of the "index" parameter using DNN is conducted. A R^2 value of 86.07% was achieved for RM2 after 1,500 epochs on the test dataset. R^2 values on the test conducted for other network models: RM1 77.77%, RM3 85.61%. The number of network parameters in Model 1 was insufficient, the number of network parameters in RM2 was at the optimum level, and the large number of network parameters in RM3 caused overfitting. Therefore, higher estimation was achieved with the network trained using RM2. The error rate decreased as the number of epochs increased. There was not much change after approximately 250 epochs.

According to results obtained in regression estimation using DNN on the "yield" parameter in Figure 5, an R^2 value of 86.61% was obtained on the dataset after 1,000 epochs for RM3. R^2 values for other network models on the test: RM1 81.88%, RM2 79.61%. A high accuracy rate in estimation is obtained as the number of parameters increases on the network. Therefore, RM3 had the highest R^2 value. The error rate decreased as the number of epochs increased. After approximately 50 epochs, the training error continues to decrease; however, validation error decreases in a slower fashion.

According to results obtained in regression estimation using DNN on the "NAI" parameter in Figure 6, an R^2 value of 84.53% was obtained on the dataset after 1,000 epochs for RM2. R^2 values for other network models on the test: RM1 81.74%, RM3 81.07%. The number of parameters in RM2 provides the best estimation success rate for NAI. It also provides a high accuracy rate in the NAI estimation in the other two models. The error rate decreased as the number of epochs increased. There was not much change after approximately 200 epochs.

According to results obtained in regression estimation using DNN on the "SQI" parameter in Figure 7, an R^2 value of 87.80% was obtained on the dataset after 1,500 epochs for RM3. R^2 values for other network models on the test: 83.83% for both RM1 and RM2. Therefore, RM3 had the highest R^2 value. The error rate decreased as the number of epochs increased. There was not much change after approximately 200 epochs.

In the study, using the index, efficiency, NAI, and SQI soil parameters as network outputs caused different performance levels in models. Therefore, different models were suggested for each network output. All R^2 values obtained are at an acceptable level for the estimation of the index, yield, NAI, and SQI parameters.

3.3 Regression using Deep Learning (DNN) on Randomly Selected Data, Dependent on Soil Classes

During deep learning, training and test dataset were randomly selected depending on the soil class information. The results obtained in this way are given in Table 6.

In this sense, selecting samples, considering class information, yields healthier results.

Table 6 R^2 results of Deep Learning on Randomly Selected Data Dependent/Independent of Soil Classes.

	train		test		model	
	Ind.	Dep.t	Ind.	Dep.	Ind.	Dep.
Index	88.70%	91.49%	86.07%	91.14%	RM2	RM2
Productivity	87.23%	88.29%	86.61%	87.50%	RM3	RM3
NAI	89.02%	89.00%	81.74%	87.54%	RM2	RM1
SQI	89.50%	91.09%	87.80%	87.54%	RM3	RM2
Mean	88.61%	89.97%	85.56%	88.43%		

3.4 Soil classification using deep learning

In Figure 8, the results obtained from 1,000 epochs are given when CM1 is used to classify the "class" information. A performance rate of 96.97% for training and 80.00% for testing was achieved. Classifying properties generated an error in Class 0. 56% of Class 0 samples are classified as Class 3 errors.

In Figure 9, the results obtained from 1,000 epochs are given when CM2 is used to classify the "class" information. A performance rate of 95.96% for training and 88.00% for testing was achieved. Classifying properties generated an error in Class 0. 33% of Class 0 samples are classified as Class 3 errors.

The accuracy rate obtained on the test dataset was higher in CM2. Therefore, CM2 should be used in soil classification study.

3.5 Land quality assessment and model verification

In order to form a distribution map of LQI_R values for each point identified by the deep learning system, 15 semivariogram models were applied and the model comparison obtained for RMSE values is given in Table 7. In table 7, the lowest RMSE value was found to be 0.1095 and the Completely Regularized Spline model, belonging to the Radial Basis Function, was identified. Moreover, in Table 3, a distribution map of the LQI_R map, consisting of 4 classes, was formed (Figure 10).

Table 7 Cross validation according to different interpolation models.

Criteria	Inverse Distance Weighing IDW			Radial Basis Function RBF		
	1	2	3	TPS	CRS	ST
LQIR	0.1171	0.1120	0.1098	0,1169	0.1095	0.1096

Criteria	Kriging Ordinary			Simple			Universal		
	Gau.	Exp.	Sph.	Gau.	Exp.	Sph.	Gau.	Exp.	Sph.
LQIR	0.1109	0.1101	0.1101	0.1123	0.1114	0.1109	0.1109	0.1102	0.1101

According to results obtained in the study, it was found that 64.9% of the total land was distributed between suitable (S1) and medium-suitable (S2) classes for rice cultivation while 26.5% was in the marginal class (S3). In addition, a very small part of this land (8.6%) was found to be unsuitable for paddy cultivation. The lands that were found to be unsuitable for rice cultivation were the At.1 mapping unit, belonging to Adatepe soil series classified as Vertic Calcixerept, with shallow soil depth and high slopes, Boztepe (Bz.1) classified as Vertic Haploxerept, and Bz.2 soil series. The marginal suitability class in terms of land quality is on Dağmatoğlu, Çengeldüzü, Yücekyazısı and Kumbaba soil series which are respectively classified as Aquic Haploxerept, Vertic Xerefluvent, and Typic Haploxeret including mapping units Dc.2, Dc.3, Cd.1, Yc.3 and Kb.1 mapping units which were respectively classified as Aquic Haploxerept, Vertic Xerefluvent, and Typic Haploxeret on Dağmatoğlu, Çengeldüzü, Yücekyazısı and Kumbaba soil series. The most important limiting feature of these soils is their salinity and coarse texture.

In order to test the model verification, a field trial study was conducted for two years in classes belonging to different rice land quality indices identified within the study area. The yield values of all rice varieties were affected by their location. Mean yield values for S1-class, S2-class, and S3-class were found to be 7,197, 5,032, and 3,572 $kg\ ha^{-1}$ respectively. The difference between S1 and S3 was found to be 3,624 $kg\ ha^{-1}$. The highest yield was obtained in S1 class Beşer and Osmancık-97 varieties with 8,166 and 8,078$kg\ ha^{-1}$ respectively while the lowest yield was obtained in S3 suitability class in Kızılırmak variety with 1,505 $kg\ ha^{-1}$ (Tablo 8). According to statistical analysis, the grain yields were significantly affected by the land suitability class (LSC) and LSC also affected varieties differently (ANOVA, P ¡ 0.001).

Table 8 Grain yields ($kg\ ha^{-1}$) of rice varieties cultivated in the Çorum-Osmancık district of Turkey ($LSD_{0.05} = 2.07$).

Suitability Classes	Variety	Max.	Min.	SD	Mean*
S1	Osmancık-97	8100	8053	17	8078 a
	Neğiş	6135	6015	50	6060 e
	Aromatik	7740	7536	77	7652 b
	Beşer	8365	8002	133	8166 a
	7721	7400	7190	88	7269 c
	Halilbey	7897	7500	165	7748 b
	Gönen	6695	6490	91	6558 d
	Karadeniz	6800	6695	43	6759 d
	Kızılırmak	7840	7368	208	7679 b
	Koral	6310	6140	70	6245 e
	Durağan	7185	6922	100	7036 c
	Şumnu	7383	6940	177	7116 c
S2	Osmancık-97	6150	6045	42	6087 b
	Neğiş	4345	3830	173	4085 h
	Aromatik	2780	2280	210	2595 ı
	Beşer	6260	6230	11	6247 ab
	7721	5730	5605	53	5650 c
	Halilbey	6560	6525	53	6480 a
	Gönen	4800	4550	108	4712 g
	Karadeniz	5485	5140	128	5332 d
	Kızılırmak	4135	3825	110	3990 h
	Koral	4955	4870	36	4923 fg
	Durağan	5405	5030	134	5232 de
	Şumnu	5130	4950	72	5058 ef
S3	Osmancık-97	4475	4240	100	4390 b
	Neğiş	2505	2305	78	2423 g
	Aromatik	1805	1645	68	1703 h
	Beşer	4357	3830	185	4079 cd
	7721	4318	4063	87	4187 bcd
	Halilbey	5930	5463	179	5662 a
	Gönen	3830	3275	212	3513 f
	Karadeniz	4515	4155	149	4291 bc
	Kızılırmak	1657	1244	174	1505 ı
	Koral	4063	3873	73	3954 de
	Durağan	4075	3650	166	3827 e
	Şumnu	3375	3302	25	3339 f

Results of the $LSD_{0.05}$ comparison test are provided in Table 7. For the S1 class, the ranking of rice varieties for decreasing grain yield was Beşer ¿ Osmancık ¿ Halil Bey ¿ Kızılırmak ¿ Aromatik ¿ 7721 ¿ Şumnu ¿ Durağan ¿ Karadeniz ¿ Gönen ¿ Koral ¿ Neğiş. As for the S2 class, Halil Bey had the highest yield, whereas Aromatik had the lowest yield. In addition, Kızılırmak also had the lowest grain yield for the S3 class. According to grain yield, Beşer, Osmancık-97 and Halil Bey were the 3 best varieties, whereas Aromatik, Kızılırmak, and Neğiş were the 3 worst varieties. According to the results, the most suitable class was determined S1 for growing high grain yield, with the S2 and S3 classes following it.

4 Conclusion

Rice is an important food product globally, and a plant with special ecological needs for areas where it will be grown. However, rice ecosystems are currently facing numerous problems such as wrong rice production systems, unsuitable land, and soil conditions, water scarcity, biotic and abiotic stresses. For this reason, a spatial model study was conducted based on a multi-criteria assessment and deep learning approach using GIS in order to identify land quality areas for rice. Considering the land quality distribution for rice, most of the land (64.9%) was found to be suitable for rice cultivation while very few (8.6%) were found to have low land quality, which is unsuitable for rice agriculture. The data obtained in the study in order to identify the performance rate of the deep learning approach were assessed using this approach. Deep learning is a neural network that contains more parameters compared to artificial neural networks that provide a hierarchical representation of data through various processes. Thus, it provides a wider learning ability and higher performance. Agriculture 4.0 applications, including deep learning, have stood out in agricultural research. The decrease in soil quality due to intensive rice cultivation threatens the sustainability of rice agriculture in the Çorum-Osmancık region. Land quality classes, which are an important factor in agricultural production, have been prioritized in this study, and different physicochemical soil properties have been chosen as input parameters in order to conduct a regression analysis and classification using deep learning. It was found that the selection of training and test samples in the dataset, considering class information, produced high-performance results in estimating soil parameters and identifying land quality classes for rice.

Ethical Approval and Consent to participate

Not applicable.

Consent for publication

We give our consent for the publication.

Availability of supporting data

We save our data on the CoLab platform. Datum can be accessed with the permission of the authors upon request.

Competing interests

The authors declare no conflicts of interest.

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Authors' contributions

N.S., M.S.O. and O.D. conceived of the presented idea. H.A., M.S.O. and O.D. developed the theory and performed the computations. N.S. and M.S.O. realized the deep neural networks. S.S., O.D. and M.S.O. supervised the findings of this work. All authors discussed the results and contributed to the final manuscript. All authors reviewed the manuscript.

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Not Applicable

Conflicts of interest

The authors declare no conflicts of interest.

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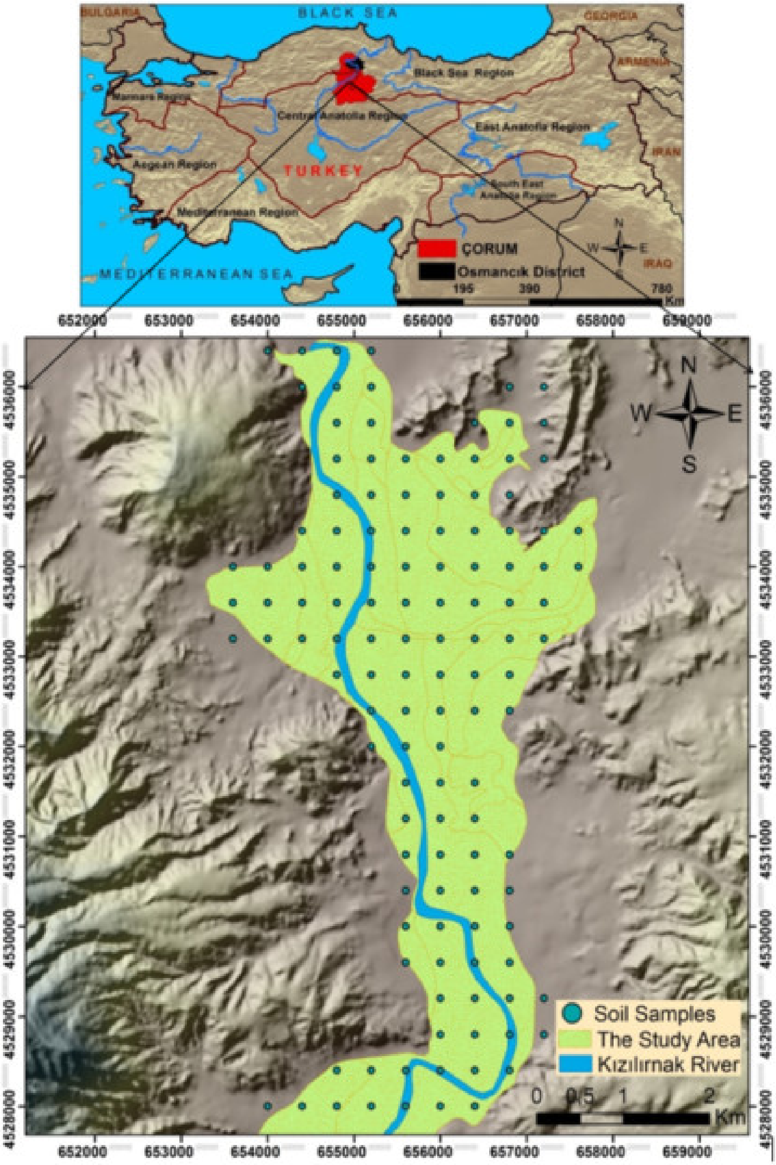

Fig. 1 Soil sample pattern and location map of the study area

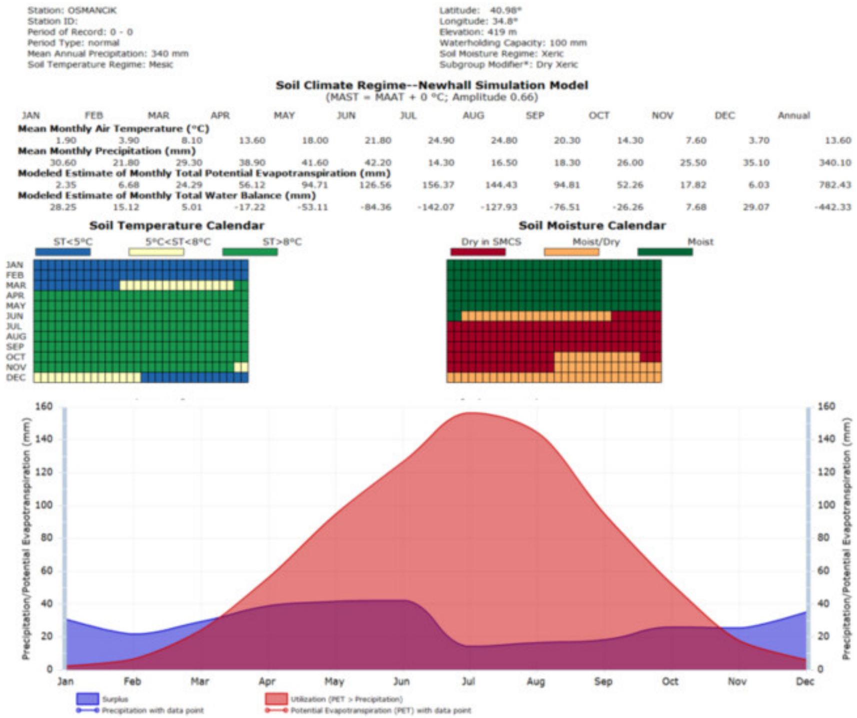

Fig. 2 Soil moisture and temperature regimes diagram

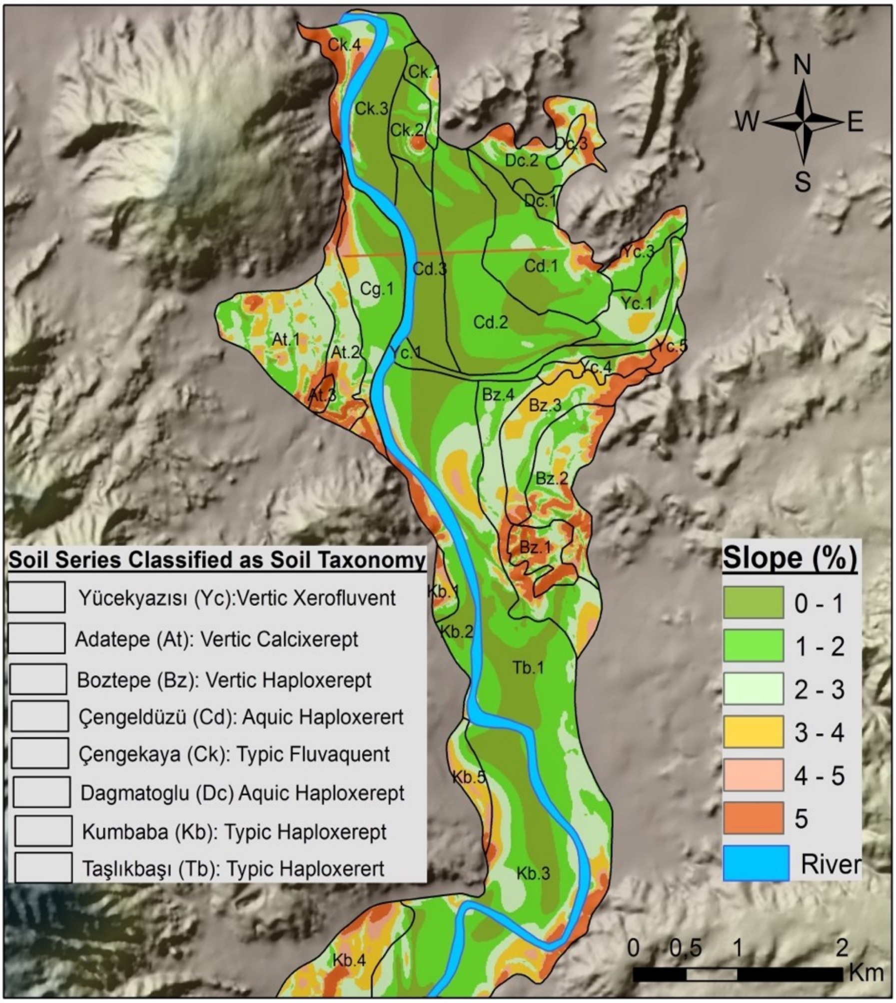

Fig. 3 Slope and soil map of the study area

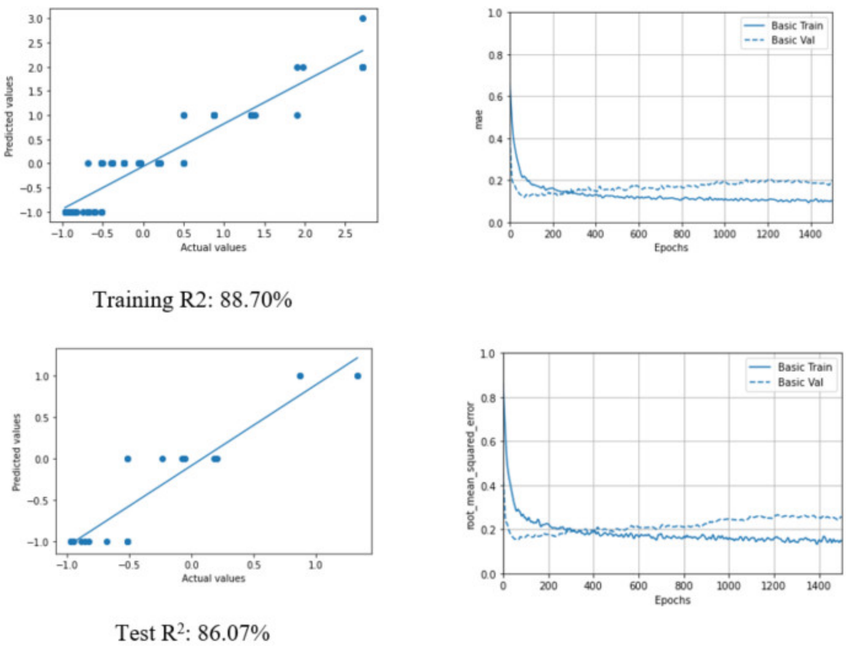

Fig. 4 R^2 and error (MAE and RMSE) graphics obtained from RM2 network used for training and test data on the “index” parameter

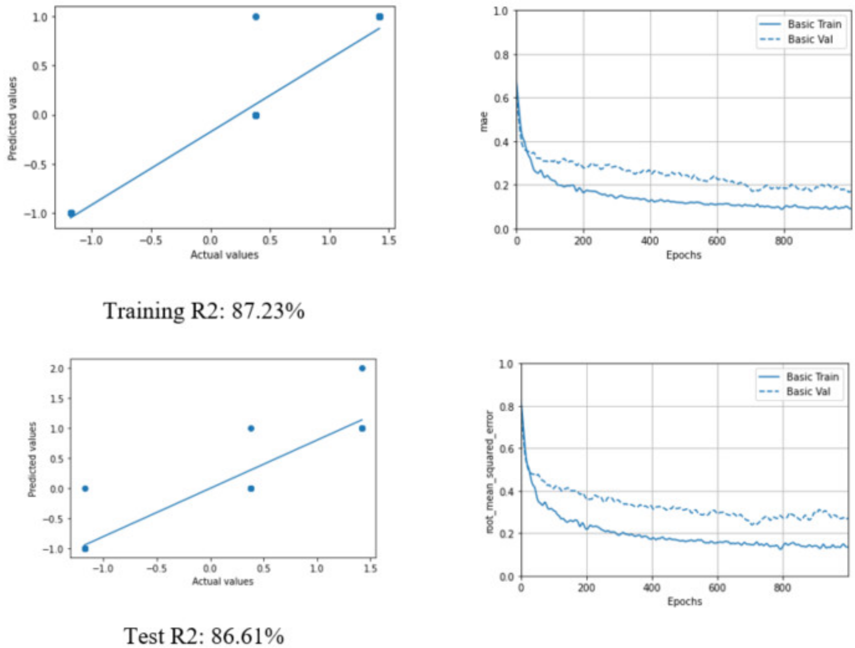

Fig. 5 R^2 and error (MAE and RMSE) graphics obtained from RM3 network used for training and test data on the "yield" parameter

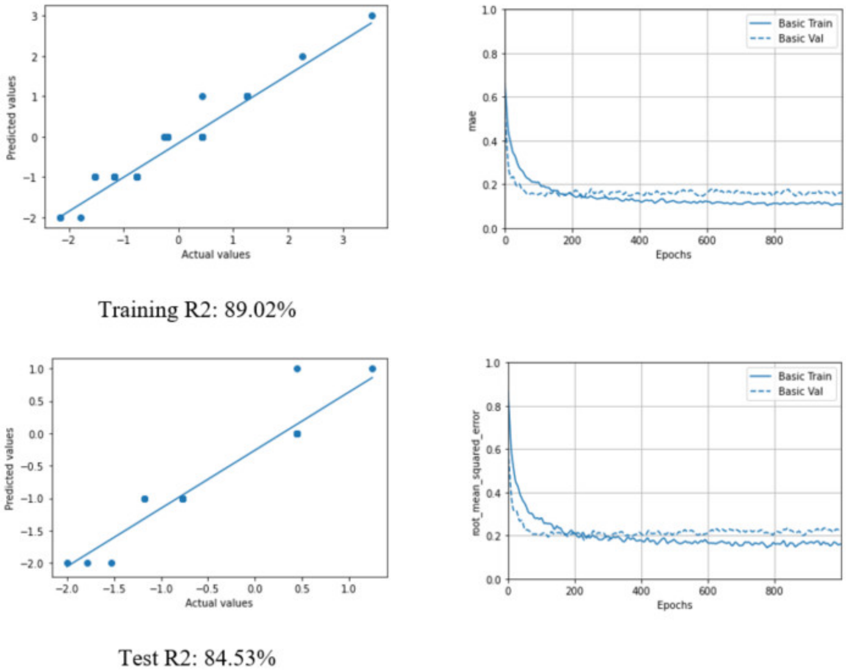

Fig. 6 R^2 and error (MAE and RMSE) graphics obtained from RM1 network used for training and test data on the "NAI" parameter

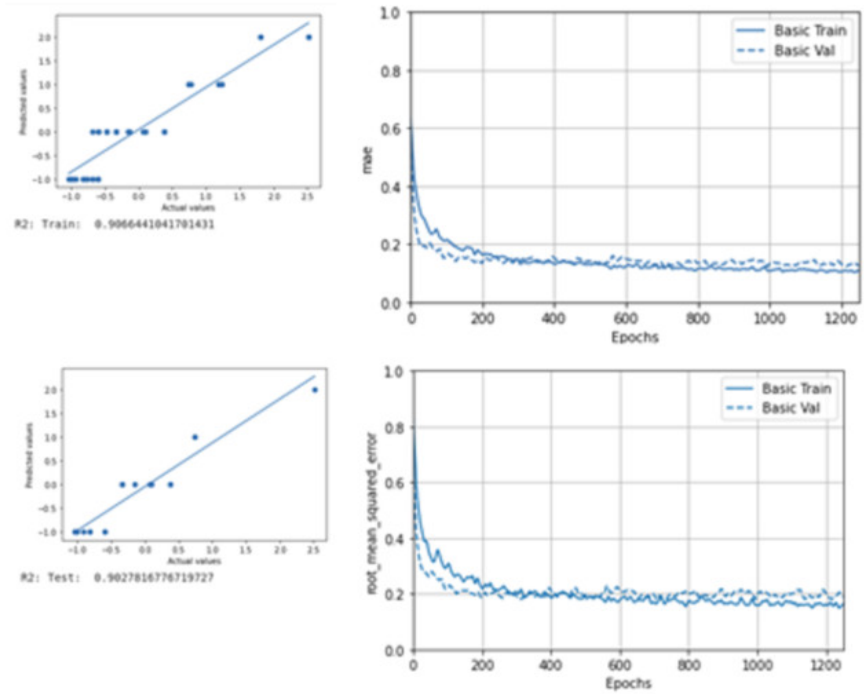

Fig. 7 R^2 and error (MAE and RMSE) graphics obtained from RM3 network used for training and test data on "SQI" parameter

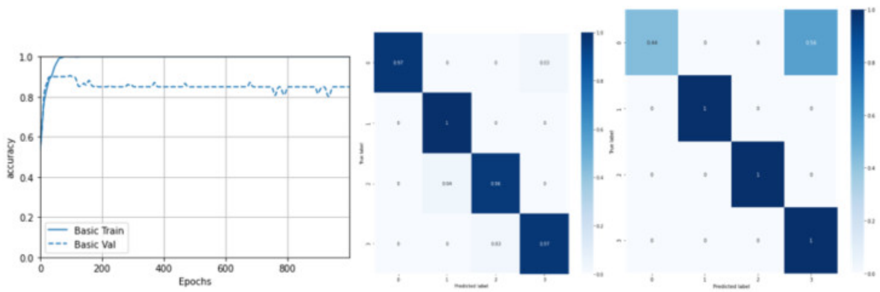

Fig. 8 Graphic of Accuracy and Confusion matrix for training and test data for CM1

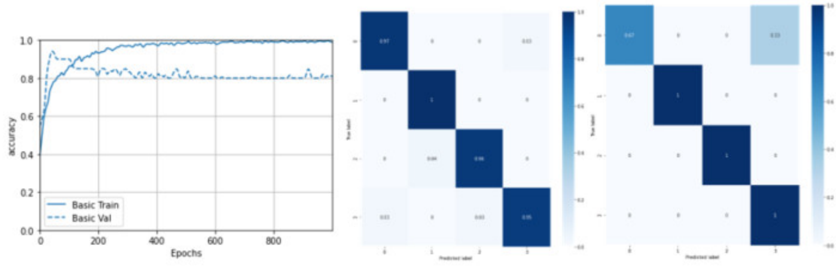

Fig. 9 Graphic of Accuracy and Confusion matrix for training and test data for CM2

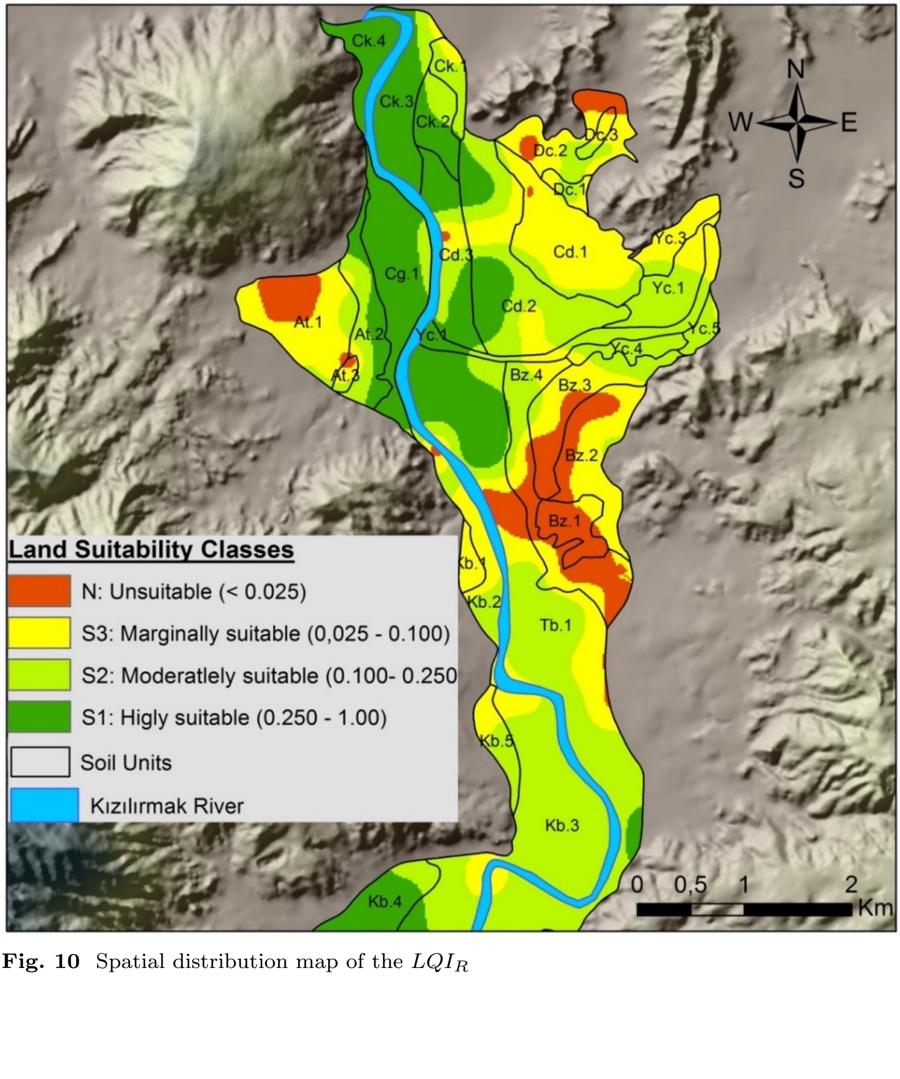

Fig. 10 Spatial distribution map of the LQI_R