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Prediction of soil chemical properties using multispectral satellite images and wavelet transforms methods

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ABSTRACT

The main aim of this paper is to develop the accurately map of soil chemical parameters were used for development of the agriculture, forestry, ecological planning, and crop yield production. Soil chemical properties analysis and forecast model was developed and validated with the Wavelet transform methods and multispectral satellite images. At the study area sites, satellite images and soil samples were collected during a similar time. Three most important soil chemical properties such as organic carbon, pH and EC were chosen to development of predication modeling based on the soil chemical information. This valuable information of parameters was analysed according to conventional methods. The observed data of soil was used for the predication modeling of soil chemical properties by MATLAB software. The identification of soil chemical properties was the subject of multi-spectral satellite images through algorithm of soil predication modeling. The real chemical characteristics of the soil are associated to wavelet transformation methods. Forecasting of soil chemical properties and this model can be given more accurate information related to soil nutrient parameters. Now a day's machine learning programming is an easy to applied on the natural resources and agriculture studies. The chemical characteristics of the soil are compared with the different spectrum wavelengths of the MATLAB program. Therefore, four wavelets models like Daubechies, Symlet, Biorthogonal and Coiflet were selected to development of predication modelling, which wavelet model can be given more accurate information with best model of the soil chemical properties. Also, the coefficient of five key components and soil-chemical values were associated in the MATLAB software. In the semi-arid regions in, India, which components have been highly correlated with soil parameters in the predicated modeling. More detailed information of soil chemical characteristics was provided by four selected wavelet models developed based on the observed data and satellite data. Prediction of soil chemical values has been identified through low and high-frequency satellite images and artificial neural network model. In this study, the neural network wavelet model was used to predicted values related to soil chemical properties in the semi-arid region. The developed two models, like polynomial and ANN, have been validated and compared to the soil chemical properties data, which models can be fitted with the study of soil chemical properties. The results of the study area can be more beneficial for development of agriculture activities, climate change approaches, crop and soil suitability planning. From the results of models have been given a fast and quickly information of soil nutrient parameters without laboratory analysis. The results of predicated values can be more helpful to precision farming related activates and soil fertility mapping to provide the farmers and agriculture scientist.

1. Introduction

In the natural resources and soils properties are one of the essential resources on the land surface and deliver an irreplaceable and various environmental average for entirely terrestrial organisms (Osman 2014; Pande et al. 2021). In order to improve the development of smart agriculture, water and ecological planning and practices, spatiotemporal assessment of soil chemical properties is necessary (Lagacherie et al., 2008). For agriculture and

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conservation factors observed on the land surface, however, rapid and reliable valuation of soil chemical characteristics has been established. Since, traditional data was obtained by field soil sampling and laboratory results (Ciampalini et al. 2015). A very efficient method of saving time using less labor has obtained by a large number of soil samples (Kumar et al. 2015;). In addition, the techniques' applications are restricted to small areas only, while measurements and estimations of soil chemical properties have been needed for landscape rulers by soil scientists, environmentalists and farm managers (Psomas et al. 2011; Yang et al. 2019). Preparing novel processes is necessary for proper soil chemicals and monitoring of climate smart villages and growing sustainable yields (Patode et al. 2017).

Remote sensing and GIS technology have very quick given the information of soil chemical parameters and an overview of larger areas (Das et al. 2015; Pande et al. 2018a). Multispectral data applications, however, viz. Due to the low, coarse spatial and spectral resolution of cloudy images masking complete indicator material or soil data frequency, the Landsat Thematic Mapper data for the calculation of soil chemical properties has been limited (Cloutis 1996; Pande et al. 2018b; Pande and Moharir, 2018). Hyperspectral images from the satellite show spectral radiance with wide, high-wavelength ranges given new learning perspectives (Castaldi et al. 2016). Hyperspectral data are also generally useful in describing the essential chemical properties of soil, such as soil texture, soil colour, soil moisture, soil erodibility, soil composition, nutrients, pH, EC and OC, etc. (Arslan et al. 2014; Shinde et al. 2020). The surface of the earth is moderately enclosed by forestry, plant and agriculture. Soil-related soil naturally co-occurs in canopy spectra with green vegetation, which contributes to a variety of vegetation and soil pixels and combined spectral signature (Yao et al. 2014; Fernández et al. 2016). In soil-related studies, entire hyperspectral data have used and integrated spectral reflectance of soil and soil-covered features reflecting the original pixels of satellite images have required (Summers et al. 2011; Bangelesa et al. 2020). The hand-held responses and approaches of agricultural bodies and plants were assessed and analyzed in the group of soil chemical properties, including soil texture, moisture, salinity, pH level, chemical structure and temperature (Lausch et al. 2013; Zhang et al. 2019).

Remote Sensing is an important method for describing both temporal and spatial properties observed from earth surface characteristics for spatially separated variables (Kneubuhler, et al. 2014; Pande et al. 2017; Pande et al. 2019). Vandana Tomar et al. 2014 studied the prediction of soil physical and chemical properties useful for special emphasis on agricultural land and ecological management in India (2014). Ustin et al. (2006) used non-destructive and well-organized computational wavelet transformation techniques, but the current view of agriculture, forestry and other areas under the climate change scenario is critical to soil health.

Wavelets convert methods and satellite data was easily classify the soil chemical properties (Xuelei Wang et al., 2010; Lihua and DetiXie, 2012; Peng et al., 2012; Liao et al., 2012; Pande, 2020d). Models for real-time monitoring of soil factors outlook for soil physical and chemical properties prediction have developed (Ines et al., 2013). Hongyan Chen et al. (2011), viz., have developed three predictive models. Useful for predicting soil chemical properties, linear, polynomial, strength, nonlinear.

Although the key component regression analysis and limited multilinear regression are very small researchers who have researched soil chemical properties via linear, nonlinear and power models (Ma et al., 2010; Dong et al., 2011; Isenstein and Park, 2014), while the ANN model, and restricted weighted regression analysis has used to predicted the soil properties values based on the non-linear model (Hongyan Chen et al. 2011; Lin Qiu et al. 2013; Jia et al. 2017). The effects of merged or hybrid models from two or more linear or non-linear models were used (Cheng-Wen et al., 2001).

Spectral reflectance from spectra protected by long wavelength or low–high frequency bands may be automatically correlated compared to the different reflectance ranges conducted by Bilgili et al. (2008). For correlating spectral reflectance information with the variable of interest, traditional statistical processes are not useful. India is the best agricultural market and plays a key role in understanding the chemical properties of the soil. India is the second largest nation in the world in terms of population. Therefore, the demand for organic or inorganic food from stockholders is very strong, but because of climate change factors, India has faced many problems for a few years. These factors influence different atmospheric factors, such as elevated CO_2 levels, temperature, drought, inadequate rainfall, and the availability of groundwater and surface water. The findings will help to improve sustainable yields, crop preparation, soil quality and salinity problems in the semi-arid region of India.

2. Study area

The study area was located in Rahuri block, Dist. Ahmednagar of Maharashtra State in the India. The mean elevation is 530 m and the latitude and longitude are between 19° 15 ' N to 19° 34′ N and 74° 23′ E to 74° 50′ E. (Fig. 1). The region was dominated by the Western Ghats' rain shadow zone in the Mula and Pravara river basins. In the study area, the farmers are familiar with sugarcane crop. Most of the agriculture land is under irrigation, in this these area farmers have cultivated land during three seasons of India but the other areas unavailability of water is not cultivated land for three seasons. As per observational records, the total study area is 20 Ha. agriculture land. In the Deccan trap formation, the entire study region is under basaltic hard rock with black soil. The mean temperature between April and May is 45° C; the minimum temperature during December and January falls to 09° C.

Because of these factors, the region is situated in the half-help region with variations of soil temperatures of average summer to winter exceeding 7 °C. The annual precipitation average is 550–650 mm. The present soils have ben formed by basaltic Deccan trap formation rocks. Therefore, six types of soil (i.e. deep black, black, alluvial, red and saline soils) are observed in the study area.

3. Methodology

More specific soil predication values were given by the adopted methodology. It is useful for selection of crops, forestry and environmental growth in semi-arid regions. Predicated data were generated and validated with observed data. Multispectral data are collected from USGS site. In this study, three soil chemical parameters such as pH, EC and organic carbon (OC) are selected and analyzed by the Department of Soil and Agricultural Chemistry, MPKV, Rahuri. Predicated the soil chemical properties values have calculated by wavelet transformation models. Using adopted models and algorithms, the real and expected values of soil properties are compared and the errors calculated, which models is best for the predication of soil chemical properties values. The same approach is as follows:

4. Field soil sampling

In this analysis, various soil samples were collected and analysis and used for predication models of soil. Similar date of soil samples from the USGS portal are obtained from multispectral data with high resolution images in the months of Sept. to Dec. of 2018. Four

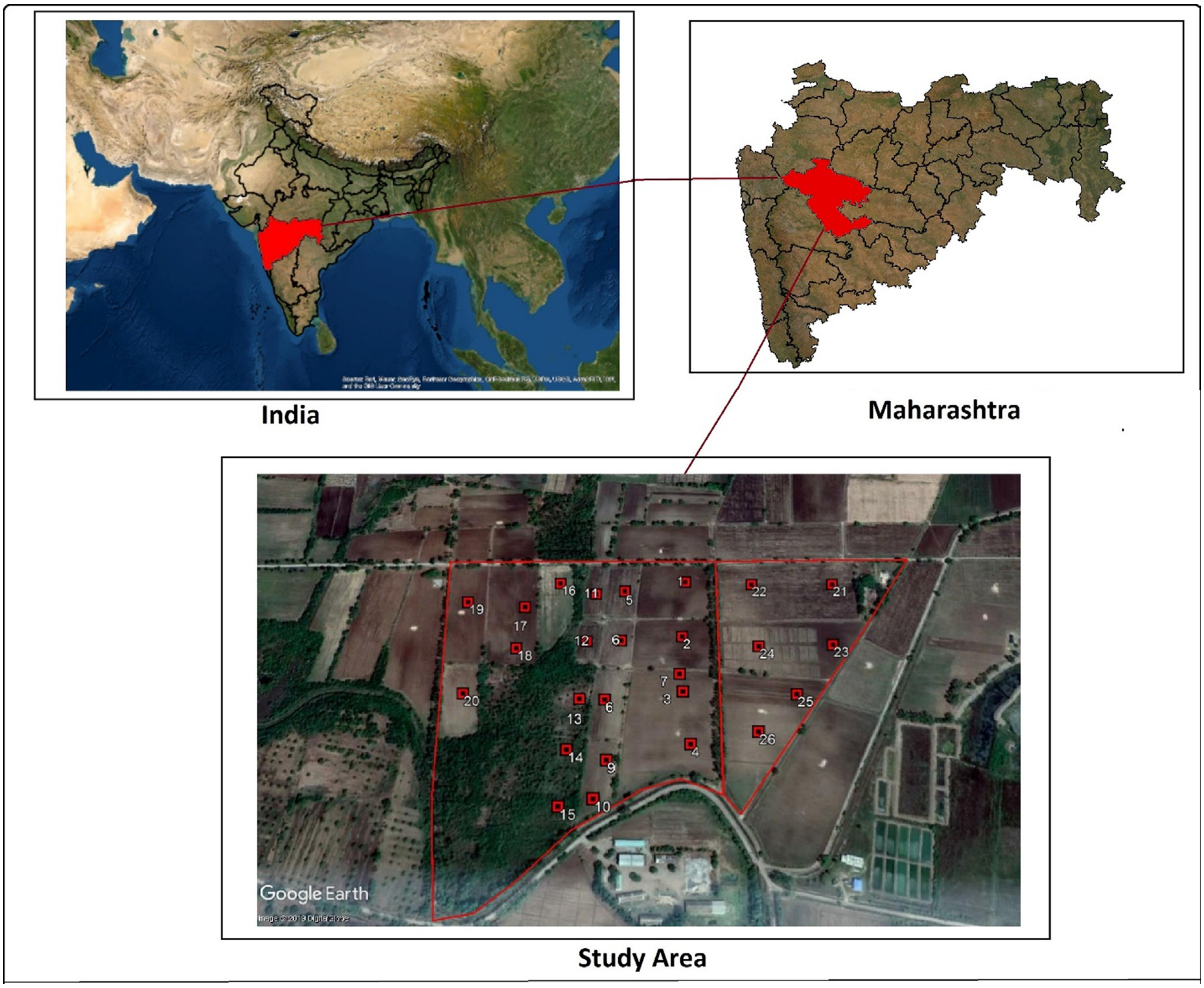

Fig. 1. Location map of study area.

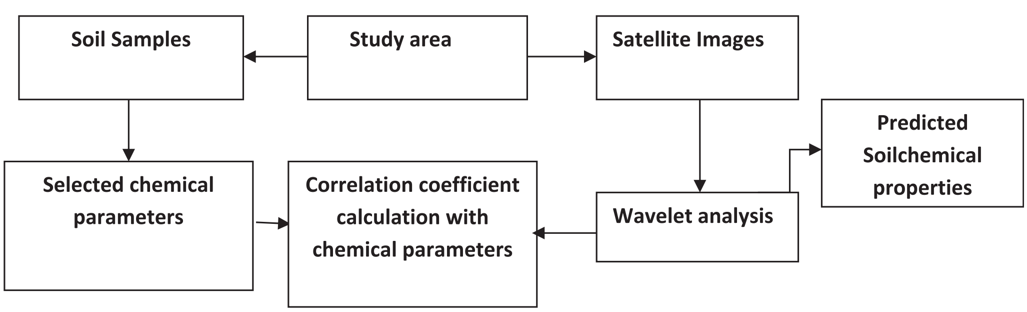

Fig. 2. Architectural flow diagram for correlation analysis and predicted soil properties.

bands, such as Red, Green, Blue and NIR, split the multispectral results. One cycle with average numbers derived for the use of spectral reflectance was composed at each soil position point and multispectral estimation. A reflectance graph with four wave reflection values was planned for multispectral measurements. In order to reduce the influence of the atmosphere due to climatic circumstances. For calibrations or coefficient correlation, satellite data has used on the observed data. The soil properties values such as soil organic carbon, pH and EC. were determined at the MPKV, Rahuri with analyzed in the Soil Chemistry department at MPKV, Rahuri respectively.

5. Statistical analysis

5.1. Correlation analysis

Data on soil properties and satellite data were compared by using PCA and wavelet transformation models. In this analysis, a total of five components were tested for the accuracy of four wavelet methods based on soil property data. These findings provide more specific information on soil parameters, but we have developed a correlation analysis equation $\{I\}_{NR\times NS} : \{I\} \supset \{I_{0.5}\}, \{I_1\}$ be the set acquired images where N_R, $N_s\{I_{0.5}\}$ and $\{I_1\}$ is shows values, total number of samples and image set developed at 0.7 km height and image set attained at 1 km, respectively. Multispectral images focus on wavelet decomposition as per this equation $\Re^{M\ XN}$. domain Multispectral images were produced using four wavelet decomposition methods, including the Daubechies wavelet, the Symlet wavelet, the Biorthogonal wavelet and the Coiflet wavelet. In the transformation of wavelets, the development of four decomposed image set components was a key role i_{rs}, which are referred to equation as per$\{A_k, H_k, V_k, D_k\} = W_k(i_{rs})$, where, A_k, H_k, V_{k2} and D_{k2} hence equation directly showed of low frequency, horizontal and vertical high frequency and diagonal components, of $_k$th wavelet methods respectively, $k = 1,2,3 and 4,$ Useful methods, such as Daubechies, Symlet, Biorthogonal and Coiflet wavelets, are used to provide more accurate predictions of soil chemical parameters in the study area. 3D representation of the extracted wavelet samples as per equation $\{A\}_{4\times NR\times NS}$ Here, $\{A\}$ is the wavelet decompositions of two different spatial representations, $\{I_{0.5}$ and $\{I_1\}$. Thus, as per extracted and decommissioned wavelets, they were formulated as a single representation using a simple averaging method. Multispectral images of the fused wavelet decomposition are shown in the following equation-1, respectively

$$\left\{A^F\right\}A^F = 4\times N_R \times N_s/2 \quad (1)$$

A dimensional conversion process has applied $\left\{A^F\right\}$ to obtain 1D array. It is decomposed sets, describe as $\left\{A^{1D}\right\}$, through column-wise operations. Further, we have been reduced the dimensionality of $\left\{A^{1D}\right\}$ with the help of principle component analysis as per estimating for correlation coefficient as per wavelet factors and output variable, i.e. soil chemical properties concentration from satellite images.

6. Statistical and validation strategy

Separation of soil samples and results from wavelet prediction and validation data sets is difficult due to the limited number of soil samples. As a result, the Leave One-Out Cross-Validation Method was used to examine the predictive capacity and stability of soil spectral models. This operation was carried out in the MATLAB and Data Analysis Toolbox. A number of studies have demonstrated the possibility of a single-out cross-validation method in estimating the model performance of the prediction models (Gao and Bai, 2015; Mikshowsky et al., 2017). For the evaluation of soil chemical properties value, the root mean square error (RMSE) and the determination efficiency coefficient (R2) have been used. These functions may be described as follows: In this study area, two validation criteria were used to determine model performance: root mean square error (RMSE) and coefficient of determination (R^2) as per Eqs. (1) and (2).

$$R2 = 1 - \frac{\sum_{i=1}^{n}(Z_i - z_i)^2}{\sum_{i=1}^{n}(Z_i - z_i)^2} \quad (2)$$

Where, n is the number of samples, zi is the measured soil chemical properties value for the sample i, zi is the predicted value, z is the mean value of the measured properties.

$$RMSE = \frac{1}{n}\sqrt{\sum (Py_i - Oy_i)^2} \quad (3)$$

Where, n is the total number of observations, py denotes estimated or predicted values of soil properties oy is the observed or actual values of soil properties

7. Results

7.1. Wavelets transforms methods (Models) performance

The results of soil prediction models were correlated with the PCA analysis (Hong et al. 2018). This outcome is presented in Table 1. Therefore, for the analysis of soil chemical predictive values were chosen to analysis of five key components. These soil values have been determined from methods of wavelet transformation that highly correlate components with soil chemical factors in the semi-arid zones. For the prediction of three major soil chemical properties, the study of correlation coefficients of the five main components of each wavelet method established these values, which are very helpful for precision farming and agricultural purposes. Too many projects on the precision agriculture, AI and remote sensing technologies are underway today (Gomez et al. 2008; Zhang et al. 2013). This research will contribute to the sustainable development of agriculture in the semi-arid zone. The results have demonstrated by the use of biorthogonal and daubechies wavelets, while the methods of transformation of wavelets and multispectral images have shown on soil characteristics data. The adopted methodology have given better accuracy compared with other soil data predication models (Gruszczynski, 2019). The first main component of the coiflet wavelet shows a strong correlation with the pH range, whereas the fourth and fifth components are not well correlated with the pH ranges (Table 1). The current research has shown a broad correlation of biorthogonals and daubechies with the pH content with other methods using MATLAB software. In the comparison with other wavelets. These other parameters show a high correlation with the EC and with the main components of organic carbon.

With a strong correlation with organic carbon levels, the symlet wavelet has provided better results. We found that the Symlet wavelet also has less variance compared to the average association with pH and EC values. Daubechies and biorthogonal wavelet techniques were adapted from the correlation coefficient analysis demonstrated to maintain a significant relationship established through MATLAB software with soil chemical properties. In Table 2, the actual and expected spectrum of soil values is present. In this analysis, the performance of the selected four wavelets was not consistent with the chemical properties of the soil. The Daubechies wavelet performs well in the soil data for predicted organic carbon values (Fig. 3).

The predicted Biorthogonal wavelet models dominates the pH range of multispectral data, while the regulation of the symlet and coiflet wavelets was calculated using multispectral data for the predicted electrical conductivity. The soil chemical parameter predicated maps were prepared using Arc GIS software (Fig. 4). For decision support systems, crop suitability sites and other agriculture approaches the land prediction map can be used. However, ANN Model predicted low-and high-frequency soil chemical properties in satellite images (Panneerselvam et al., 2021).

8. Discussion

8.1. Prediction analysis

Further analysis was calculated in order to ensure the coefficient correlation of the value of soil properties using selected four wavelet methods and thus the key components into 1 to 5. Within the MATLAB program, the neural network model was developed based on the observed soil data. The soil chemical parameters with the best output using the prediction model is observed. With 22 neurons in its single hidden layer, the neural network model was developed. It is used without soil laboratory analysis for the

Table 1
Correlation of principle components for four wavelets transform methods with soil properties.

Soil properties	Principle component s	Daubechies wavelet	Symlet wavelet	Biorthogonal wavelet	Coiflet wavelet
pH	1	0.1750e−16	0.1160e−16	0.1750e−16	−0.0580e−16
	2	0	0	0	0.1595 e−16
	3	0	0	0	0.0493e−16
	4	0.0465e−16	0.0400e−16	0.0457e−16	−0.1729e−16
	5	−0.0273e−16	0	−0.0273e−16	−0.0467e−16
EC	1	0.0277e−16	0	0.0277e−16	0.0277e−16
	2	−0.0519e−16	0	−0.0519e−16	−0.1019e−16
	3	−0.0935e−16	−0.0246e−16	−0.0935e−16	−0.0246e−16
	4	−0.1779e−16	0.2619e−16	−0.1779e−16	0.0524e−16
	5	−0.0534e−16	0.2137e−16	−0.0534e−16	−0.2137e−16
Carbon	1	−0.1416–16	0.0505e−16	−0.1416e−16	0
	2	−0.0935e−16	−0.0236e−16	−0.0935e−16	0
	3	0	0.01288e−16	–	0
	4	0.0823e−16	0.1190e−16	−0.0823e−16	−0.2975e−17
	5	−0.0426e−16	0.0813e−16	−0.0426e−16	−0.2129e−17

Table 2
Details of Prediction values and MSE Errors of Soil properties.

Soil chemical properties	pH		EC		Carbon	
	Predated	MSE Errors	Predated	MSE Errors	Predated	MSE Errors
Daubechies wavelet	8.183	0.203	0.58739	0.18739	0.11313	0.07313
Symlet wavelet	8.321	0.341	0.33654	0.06346	0.04106	0.00106
Biorthogonal wavelet	8.112	0.132	0.39241	0.00759	0.19432	0.15432
Coiflet wavelet	8.541	0.561	0.39185	0.00815	0.31709	0.27709

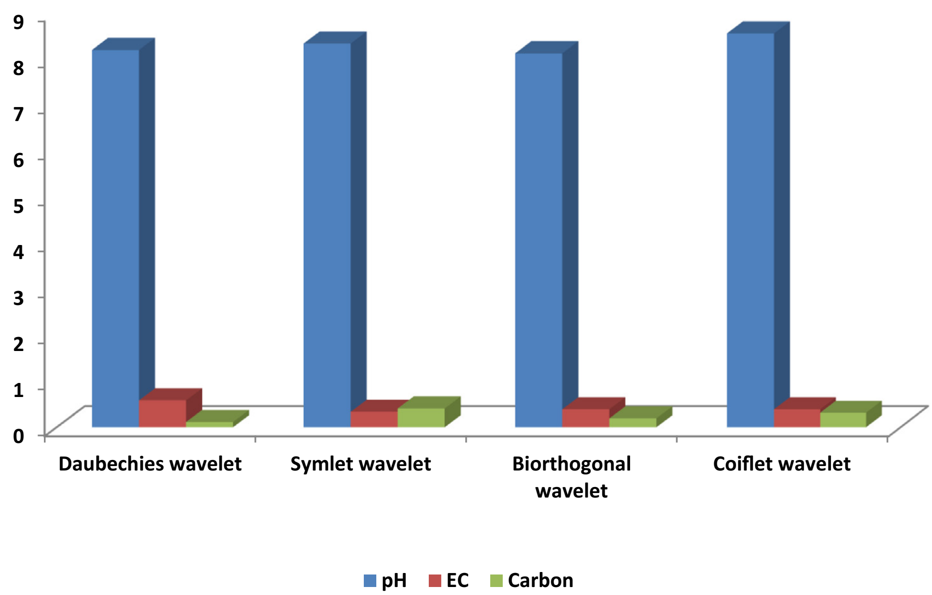

Fig. 3. Performance of selected four wavelets methods for prediction of soil properties.

prediction of soil chemical properties values. The training library consists of $\left\{A^{1D}\right\}$ as input characteristics and the soil chemical properties range as the target variables. In the development of a neural network the Levenberg Marquardt (LM) algorithm is being used to set up an objective function to be minimized in soil. The MSM is a function that can be minimized. The altered division of the training library had collapsed. The neural network model was trained and validated under the MATLAB Program on soil chemical characteristics. The numerous multispectral tested data are collected for the same territory but are useful for the neural network model from the point of reception. Models have been used to measured the predictive values for soil chemical properties (Fig. 2).

Four Models such as Daubechies, Symlet, Biorthogonal, and Coiflet were chosen in this analysis. Various soil chemical parameter values such as pH, EC and carbon were calculated using wavelet transform models with expected values such as 8.183, 8.321, 8.112, 8.541, 0.58739, 0.06346, 0.00759 and 0.07313, 0.00106, 0.15432 and 0.27709 respectively (Table 2). The key findings showed that the quality of carbon, pH and EC had the strongest and moderate association with the variance of soil chemical property values. Average standard errors were calculated through ANN model. The soil property values were contrasted with the real values of the chemical properties of the soil (Table 3). Polynomial model was validated with ANN Model results. In the soil parameters the validation has provided with more precise values.

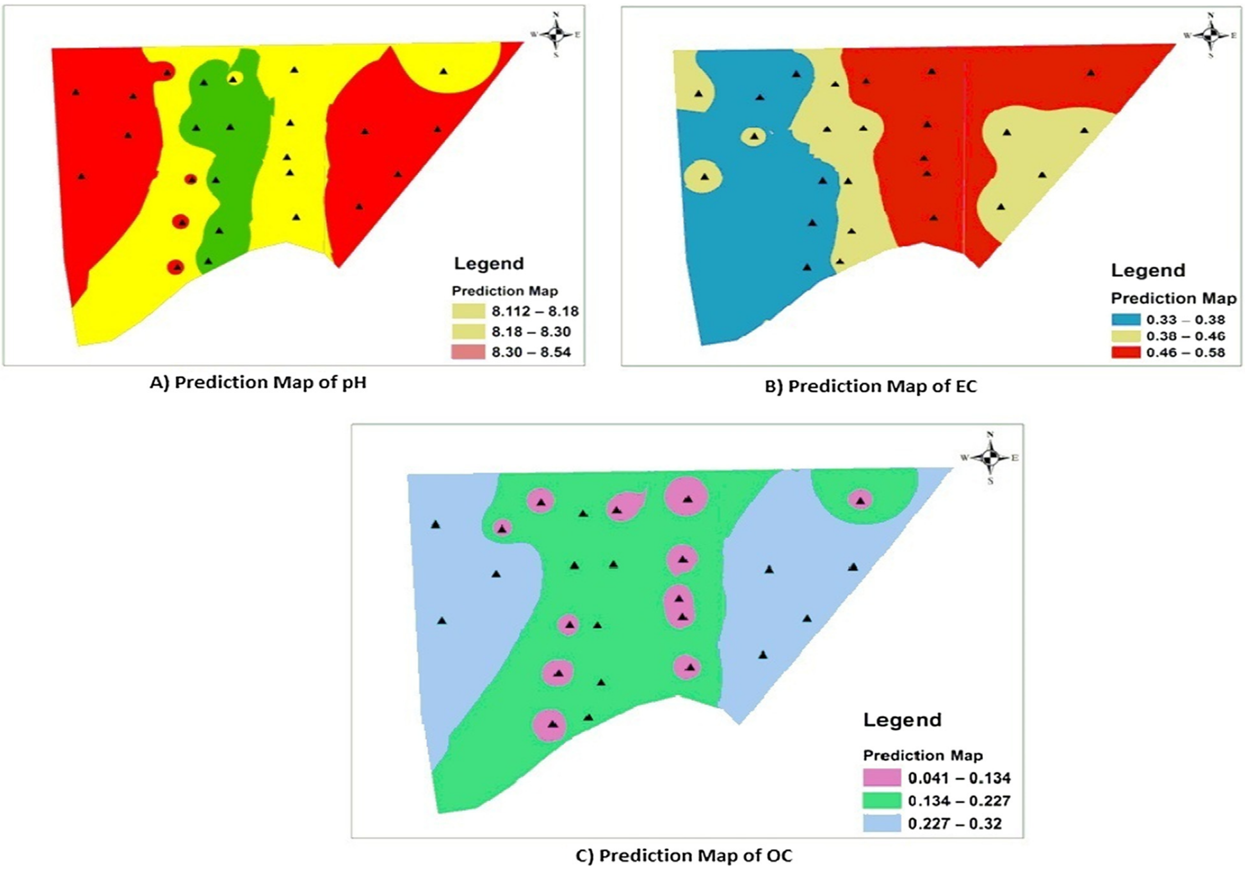

Fig. 4. Predicted maps of soil chemical properties using ANN Model in MATLAB software.

Table 3
Comparisons of observed and predicted soil properties values.

Actual pH	Predicted	Actual EC	Predicted	Actual Carbon	Predicted
7.93	8.18	0.48	0.58739	0.05	0.11313
7.92	8.321	0.4	0.33654	0.04	0.4106
7.9	8.112	0.4	0.39241	0.04	0.19432
7.98	8.541	0.38	0.39185	0.03	0.31709

9. Model performance

For validation of soil property values predicted using wavelet transforming methods, Table 4 showed two models by two output methods, two model types were selected in this study. For each model, the best model is show in cross validation. More accurately than polynomial models, created by validation criteria, ANN models have shown. The results show that the most predictable pH, EC and Carbon efficiency is achieved between the tested models using the wavelet methods. Both ANN and polynomial models have showed different variation performance to predict pH content (R^2 = 0.8313) and (R^2 = 0.8713). ANN and polynomial models' performance are not similar to predict EC content (R^2 = 0.9571) and (R^2 = 0.9871). Similar, compared to both the model's performance showed on the Carbon content (R^2 = 0.8556) and (R^2 = 0.9146).

10. Prediction accuracy

The accuracy of various established models for potential outcomes in the semi-arid region has tested in this analysis. Relative RMSE values for models have calculated (Table 4). The results showed that ANN and polynomial models were used to achieve the highest and lowest prediction accuracies for EC and pH, respectively (Fig. 5). Although the carbon content with high determination coefficients (R^2 = 0.91) was predicted by ANN models, it was also equal to high relative RMSE. When the performance of all models was calculated to predict different soil chemical properties, the RMSE values were consistent with other validation requirements for the most accurate model (Table 4). On the other hand, when the performance of the models studied was compared to the expected soil properties values, the EC content forecast was

Table 4
Results Validation R^2 and RMSE for studied models.

Soil properties	Model	R^2	RMSE	Model	R^2	RMSE
pH	Polynomial	0.8313	0.44	ANN	0.8713	0.341
EC	Polynomial	0.9571	0.0092	ANN	0.9871	0.00759
Carbon	Polynomial	0.8546	0.31	ANN	0.9146	0.4106

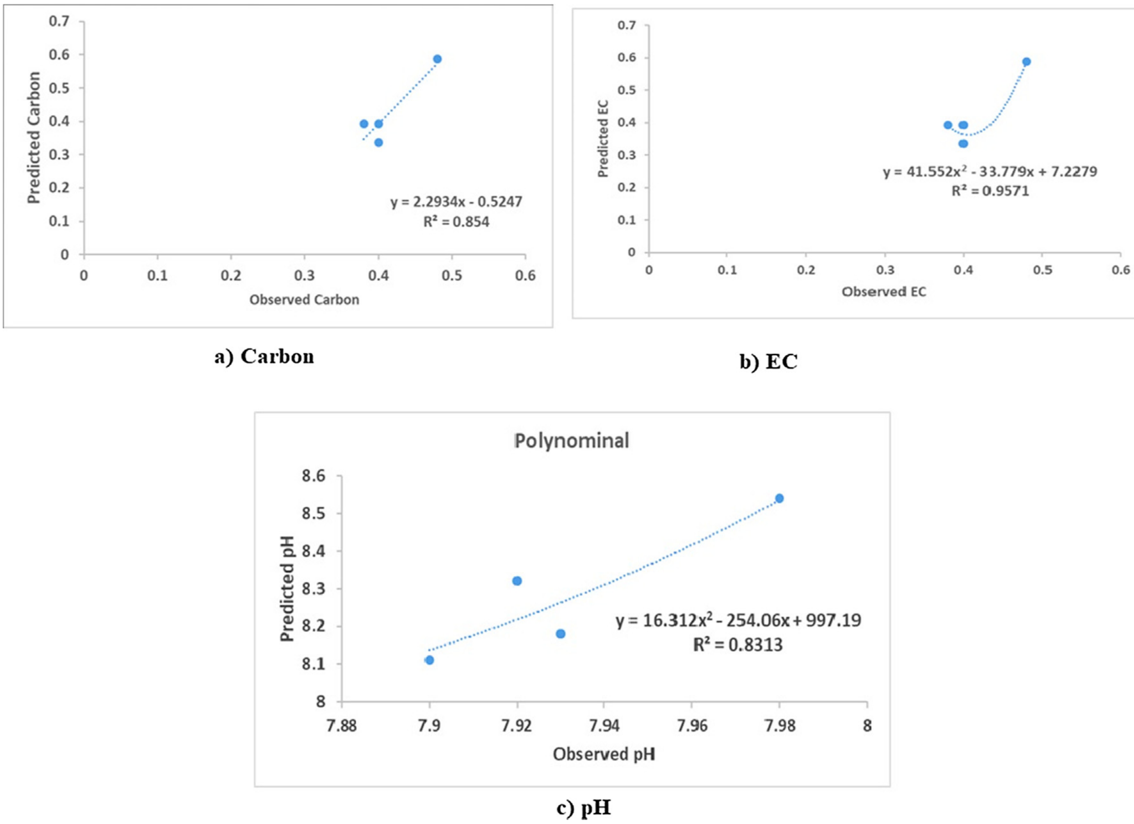

Fig. 5. Correlation of Observed and Predicted soil properties.

the lowest error (lowest relative RMSE). Mosleh et al. (2016) determined that pH, EC, and Carbon were all so accurate in the finest prediction model, but the finest prediction model for coarse fragment did not show the most precise calculation. Our research area results showed that the finest prediction model did not lead to the most reliable evaluation.

11. Conclusion

In the semi-arid area of Maharashtra in India, spatial distributions of pH, EC and carbon content were observed using the Wavelet transforming method with ANN and polynomial models. Two results of the expected soil values are validated for polynomial models. In order to predict pH, EC and carbon content, the ANN model had the highest performance and even the polynomial model had the lowest expected pH, EC and carbon content performance. Among the other wavelet transformation methods studied, the remote sensing indices showed an advantage and allowed clarification of pH, EC and carbon content variability. Validation criteria should be carefully interpreted, since the best model cannot always make the most reliable calculation can be inferred. The effects of the joint coefficient correlation analysis and the forecast analysis of soil chemical properties on multispectral images were observed in the study area results. This satellite data was useful for a better understanding of the characteristics of the soil and the improvement of its properties. The correlation analysis revealed that the dominant wavelets and their examination of key components revealed that the chemical report correlation is strong. The results are strongly supported by the prediction analysis carried out with the neural network in MATLAB software. Additional studies may also be needed to investigate and propose new environmental covariates in order to capture and spread soil variability in arid and semi-arid regions. The study area was divided into homogeneous sub-areas sampled by elevation strata and determined to be higher. Wide soil sampling is likely to increase the performance of the ANN model by wavelet methods.

Declaration of Competing Interest

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

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