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Wavelet for Predicting Soil Nutrients using Remotely Sensed Satellite Images

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ABSTRACT
In country like India, where agricultural economy plays major role, understanding and tracking the soil nutrients are essential. However, the chemical analysis, which determines the nutrient contents of soil, is expensive and time consuming. Hence, we attempt to exploit remote sensing imagery for estimating them. This paper analyzes the correlation between the level of soil nutrients and wavelet decompositions of remote sensing imagery of a particular region. Four renowned wavelet transformations such as Daubechies, Symlet, Biorthogonal and Coiflet are used to represent the image in wavelet domain. Subsequently, here exploit a neural network model to predict the soil nutrient content using the principle wavelet components. Experimental analysis on the prediction accuracy and the correlation measure reveals the suitability of each wavelet transformation of remote sensing imagery in predicting the soil nutrients.

General Terms
Remote Sensing, Image Processing, Analysis.

Keywords
Soil nutrient; prediction; wavelet.

1. INTRODUCTION
Remote sensing is a prominent technology to acquire spatially distributed parameters to define both temporal and spatial properties of land surface [2] [10]. This makes ease of predicting soil nutrients, especially in agriculture based countries like India [3]. Since these methods are non-destructive and computationally efficient, they gain wide attention recently [7]. These methods acquire hyperspectral data [1, 11, 12, 18] to model the characteristics of soil nutrients, often termed as soil nutrient prediction models [16].

Generally, a soil nutrient prediction model falls in any of the three categories such as linear models, nonlinear models and integrated models [20]. Principle component regression, partial least square regression and multi-linear regression are few examples for linear models [17, 19, 22], whereas artificial neural network, locally weighted regression are examples for nonlinear models [4, 20]. Integrated or hybrid models results from the combination of two or more linear or nonlinear models or combination of both [21].

The hyperspectral data was reported to be useful, yet the complexities reside on image acquisition and processing steps have led the way for finding alternatives [8-10]. Moreover, the hyperspectral data is not consistent to define spatial variance based on soil nutrients [5, 13, 15]. Despite hyperspectral data have been used in [14], the wavelet decompositions have played crucial role to predict the biomass from temperature deciduous forest. Being motivated by this work, we attempt to study the ability of wavelet decomposed remote sensing imagery on predicting soil nutrient contents. We describe the study region and preliminary materials for the study in Section II. Section III presents the correlation analysis and the outcome, whereas Section IV presents the prediction analysis and the practical implications. Section V concludes the paper.

2. STUDY AREA AND MATERIALS
By considering four major cultivating regions of Maharashtra province - India, namely, Baggi, Ibrahimpur, Mogara and Wai, as study region from which soil samples are acquired various regions and the chemical analysis is conducted. From the chemical analysis, results determine the level of significant nutrients such as pH, electrical conductivity, carbon, phosphorous and potassium.

Meantime, by acquiring the satellite imagery of the study regions from “Google Earth”. Five image samples are acquired for every region at two different altitudes, say 500m and 1km. Hence, here obtain 10 images/ study region, which are preprocessed to remove watermarks and annotations followed by resizing them uniformly.

3. CORRELATION ANALYSIS
3.1 Methodology
The architectural view of the correlation analysis is presented in Figure 1. Our preliminary work presents more details about the correlation analysis [23]. Let $\{I\}_{N_R \times N_S} : \{I\} \supset \{I_{0.5}\}, \{I_1\}$ be the set of acquired images, where N_R, N_S, $\{I_{0.5}\}$ and $\{I_1\}$ are the number of study regions, number of samples/study region, image set acquired at 0.5km altitude and image set acquired at 1km, respectively.

The images are subjected to wavelet decomposition from its own $\Re^{M \times N}$ domain. The wavelet decompositions are accomplished using renowned wavelets such as Daubechies wavelet, Symlet wavelet, Biorthogonal wavelet and Coiflet wavelet. The transformation leads to four decomposed set constituents for i_{rs}, which can be referred as $\{A_k, H_k, V_k, D_k\} = W_k(i_{rs})$, where, A_k, H_k, V_k and D_k are the low frequency components, horizontal and vertical high frequency components and diagonal components, of k^{th} wavelet respectively, $k = 1,2,3\, and\, 4$ refers to Daubechies wavelet, Symlet wavelet, Biorthogonal wavelet and Coiflet wavelet, respectively. We consider low frequency components in this paper for the further analysis.

3D representation can be given for the extracted wavelet samples as $\{A\}_{4 \times N_R \times N_S}$. Here, $\{A\}$ is the wavelet decompositions of two different spatial representations, $\{I_{0.5}\}$ and $\{I_1\}$ and hence we fuse both the decompositions to formulate them as single representation using simple averaging method. The fused set of wavelet decompositions can be represented as $\{A^F\}:\left|A^F\right| = 4 \times N_R \times N_S / 2$.

A dimensional conversion process is applied over $\{A^F\}$ to obtain 1D array of decomposed set, termed as $\{A^{1D}\}$, using column-wise operation. Further, we reduce the dimensionality of $\{A^{1D}\}$ using principle component analysis (PCA) followed by calculating the correlation coefficient for the wavelet parameter and the output variable, i.e., soil nutrient intensity.

3.2 Findings

We have considered five principle components of wavelet descriptors to understand its correlation with soil nutrient contents. The correlation coefficients of the principle components of each wavelet descriptor on describing each soil nutrient is tabulated in Table I.

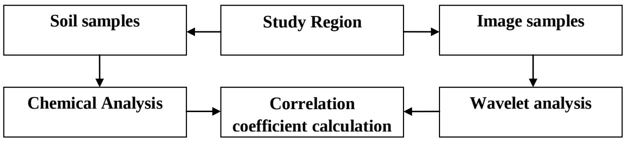

Fig 1: Architectural view of correlation analysis

Table 1: Correlation between the principle components of each wavelet and the soil nutrients.

Soil Nutrients	Principle components	Daubechies wavelet	Symlet wavelet	Biorthogonal wavelet	Coiflet wavelet
pH	1	**0.1742e-16**	0.1161e-16	**0.1742e-16**	-0.0581e-16
	2	0	0	0	0.1595 e-16
	3	0	0	0	-0.0493e-16
	4	0.0467e-16	0.0410e-16	0.0467e-16	-0.1709e-16
	5	-0.0273e-16	0	-0.0273e-16	-0.0467e-16
Electrical Conductivity	1	0.0278e-16	0	0.0278e-16	0.0278e-16
	2	-0.0509e-16	0	-0.0509e-16	-0.1019e-16
	3	-0.0945e-16	-0.0236e-16	-0.0945e-16	-0.0236e-16
	4	-0.1789e-16	**0.2619e-16**	-0.1789e-16	0.0524e-16
	5	-0.0524e-16	0.2237e-16	-0.0524e-16	-0.2237e-16
Carbon	1	0.1516 e-16	0.0505e-16	0.1516 e-16	0
	2	**0.3703 e-16**	0.2778e-16	**0.3703 e-16**	0
	3	0	-0.1288e-16	0	0
	4	0.0813 e-16	0.1190e-16	0.0813 e-16	-0.2975e-17
	5	0.0416 e-16	-0.0813e-16	0.0416 e-16	0.8129 e-17
Phosphorous	1	**0.6332e-16**	-0.6385e-16	**0.6332e-16**	0.4696 e-16
	2	0.3722e-16	-0.1837e-16	0.3722e-16	-0.2030 e-16
	3	-0.0022e-16	-0.1143e-16	-0.0022e-16	0.0336 e-16
	4	0.0424e-16	-0.2585e-16	0.0424e-16	-0.1789 e-16
	5	0.0497e-16	0.2377e-16	0.0497e-16	0.3396 e-16
Potassium	1	0.0792 e-16	0	0.0792 e-16	0
	2	0.0484 e-16	-0.2903 e-16	0.0484 e-16	-0.1935 e-16
	3	**0.0897 e-16**	**0.0897 e-16**	**0.0897 e-16**	0.0449 e-16
	4	-0.2549e-16	-0.1741 e-16	-0.2549 e-16	-0.0995 e-16
	5	-0.0497e-16	0	-0.0497 e-16	-0.0850 e-16

Table 2: Performance of wavelates on predicting the soil nutrients

Soil nutrients	pH (Actual = 7.94)		Electrical Conductivity (Actual = 0.37)		Carbon (Actual = 0.03)		Phosphorous (Actual = 23)		Potassium (Actual = 792)	
	Predicted	*Error*	*Predicted*	*Error*	*Predicted*	*Error*	*Predicted*	*Error*	*Predicted*	*Error*
Daubechies wavelet	8.213	0.273	0.59739	0.22739	**0.12313**	**0.09313**	**41.0431**	**18.0431**	1280.8913	488.8913
Symlet wavelet	8.4173	0.4773	0.31661	0.05339	0.47067	0.44067	47.0524	24.0524	**1068.7408**	**276.7408**
Biorthogonal wavelet	**7.9694**	**0.0294**	0.36249	0.00751	0.21532	0.18532	-10.1245	33.1245	402.3755	389.6245
Coiflet wavelet	8.147	0.207	**0.36832**	**0.00168**	0.35809	0.32809	53.1117	30.1117	1280.6289	488.6289

The results reveal that biorthogonal wavelet and daubechies wavelet exhibits similar performance on understanding the characteristics of soil nutrients from the images. First principle component of coiflet wavelet exhibits strong correlation with pH level, whereas the fourth and fifth components are underperforming. Cumulatively, biorthogonal and daubechies wavelets provide substantial correlation with the pH contents than other wavelets.

They also exhibit high correlation with carbon and phosphorous contents with the principle components. They share the positions with symlet wavelet on providing good correlation with potassium level. Symlet wavelet exhibits relatively average correlation with all the nutrients with less deviation. From the analysis, we can define that the daubechies and biorthogonal wavelets are suitable to maintain a substantial relationship with the soil nutrients.

4. PREDICTION ANALYSIS

4.1 Methodology

To ensure the correlation performance of the selected wavelets and their principle components, we attempt to use feedforward neural network to investigate the prediction performance. A dedicated neural network for every soil nutrient is constructed with 20 neurons in its single hidden layer.

The training library consists of $\left\{A^{1D}\right\}$ as input attributes and the nutrient level as the target variables. Levenberg-Marquardt (LM) algorithm is used to train the neural network and the Mean squared error (MSE) is set as the objective function to be minimized. Random division process is exploited to segregate the training library and hence training and validation of the neural network is performed. Test images are acquired for the same region, but from point of capturing, and applied to the neural network for predicting the soil nutrients.

4.2 Results

The actual nutrient level and the predicted level by the neural network are tabulated in Table II. The results have produced that the performance of all the wavelets are not consistent with respect to the nutrients. Daubechies wavelet performs better in predicting carbon and phosphorous content of the soil. However, it performs poorer than other wavelets, when predicting potassium and electrical conductivity of the soil. Biorthogonal wavelet dominates on predicting the pH level, whereas symlet and coiflet wavelets dominate on predicting potassium and electrical conductivity of the soil, respectively.

4.3 Discussion

When comparing the outcome of prediction analysis with that of the correlation analysis, we can identify the coinciding effect between both the outcomes. For instance, the first principle component of the daubechies and biorthogonal wavelets has correlated well with the pH level of the soil samples, as per Table I. Table II states biorthogonal wavelet has produced least prediction error for pH level. The similarities persist when studying the carbon, phosphorous and potassium contents also, except electrical conductivity. This reveals that the wavelet features that exhibit strong correlation with the soil nutrients level can help in predicting them using remote sensing imagery.

4.4 Implications

Since the results are encouraging, the challenges ahead in the chemical analysis on estimating the soil nutrients can be overcome by using remote sensing imagery. The remote sensing imagery can assist well in understanding the nature of the soil, its nutrient enrichment, their quantity, etc. This application can further assist not only in agriculture, but also for infrastructural development, urban development and other commercial proposals.

5. CONCLUSION AND FUTURE WORK

This paper reported the outcomes of both the correlation analysis and the prediction analysis on remote sensing imagery. The correlation analysis has revealed the dominating wavelets and their principle components that correlate well with the chemical report. The outcomes have been highly supported by the prediction analysis performed using neural network. By comparing the results of the correlation analysis and the prediction analysis, the wavelets that are able to correlate well with the chemical report have produced substantial prediction accuracy on the remote sensing imagery. These results are highly encouraging to use remote sensing imagery for predicting the soil nutrients and their quantity. In the future work, we have planned to consider extensive features of the remote sensing images to ensure precise prediction of soil nutrients.

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