Review Article

MACHINE LEARNING TECHNIQUES FOR SOIL PROPERTIES MAPPING

Abstract

The aim of this review article is the estimation of Soil Nutrients and relating the spectral signatures to that of the Laboratory reference Measurements utilizing CART analysis. Sustainable agriculture aims at the controlled or precise soil fertility interventions based on spatial soil information. The profound advancements in the remote sensing and geospatial techniques provides the means of determining the spatial coverage and variability of the soil properties through the survey and image data incorporated in the mapping procedures ~~(~~i.e.~~)~~ Digital Soil Mapping. Soil moisture content at varying levels influence the crop growth and decides the yield of the crops, as crops require~~s~~d water at critical crop growth stages. ~~-~~Machine learning techniques provides the means of optimized model calibration when compared to that of the conventional geostatistical or statistical approaches.

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Keywords: G~~g~~eostatistical technique, Machine learning techniques, CART analysis, soil properties mapping

INTRODUCTION

The demand for q~~Q~~uantitative and spatial information on the soil properties among ~~others,~~others has increased the research of the soil properties assessment. The major worldwide concern in the twenty-first century is the ever-increasing population, and food security must be considered in this context. By 2025, total food demand in developing countries will have increased by almost 150 percent. To meet the food requirements and demand of the increasing population, agricultural productivity must be scaled to the present average through sustainable agriculture.

Sustainable agriculture aims at the controlled or precise soil fertility interventions based on spatial soil information. The spatial information of various soil properties can aid the crop growers at critical decision making and helps in implementing policies for increasing the agricultural productivity and also the livelihood of the small-scale farmers. The conventional means of estimating physical and chemical properties of the soils through soil sampling and laboratory analyses are highly remotes sensed data through its extractable soil spectral information, large spatial coverage and temporal consistency helps in mapping of the remote location that are inaccessible(Forkuor et al., 2017).

This eliminates the drawbacks in the traditional method of assessment and provides a venture for non-destructive sampling procedures. Though the spatial variability (i.e.) non-uniformity or heterogeneity associated with the soil properties can be included through Digital soil mapping, the process is always constrained by the within-site variability. The variability is accounted by the several natural processes influenced by the factors such as climate, soil type, land use etc., The within-site variability can be excluded by the use of variable rate technology which facilitates the precision agriculture. Precision agriculture tends to the site-specific needs of the soil and the crop through the remote sensing and geospatial techniques, DEM and other climatic variables (John et al., 2020).

Similarly, the hazards of soil erosion and its associated land degradation can be time consuming and expensive when the mapping is done at regional or national level. The profound advancements in the remote sensing and geospatial techniques provides the means of determining the spatial coverage and variability of the soil properties through the survey and image data incorporated in the mapping procedures (i.e.) Digital Soil Mapping. The

predicted through the soil properties assessments. Soil erosion is the removal of the top portion of the soil which leads to the associated nutrient leaching and land degradation. Though soil erosion is associated with that of the climatic parameters such as wind speed, temperature,

precipitation etc., a number of soil physical properties such as porosity, soil aggregate stability, permeability, texture, structure and chemical properties such as soil organic matter and Calcium carbonate equivalent were also considered responsible (Alexakis et al., 2019).

The Heavy metal assessment in the soil also provides an insight of the contaminants that degrade or retard the quality and the biological properties of the soil. In this context, most of the estimation of the soil spatial information is facilitated through the model calibration employing several of the remote sensed image variables, spectral information, climatic and environmental variables. The major limitations in any of the model calibration is the selection of the spectral variable or bands(Gomez et al., 2008).

Earlier, the use of geostatistical framework was prevalent in the spatial prediction of the soil information, which is a linear combination of the environmental covariates and spatial auto_correlated residuals and the prediction at unobserved location estimated through interpolation technique. The geostatistical models are considered for its assumptions on spatial variations and the uncertainty associated with the prediction measures. Conversely, the geostatistical models have several limitations which affects the model fit and the prediction accuracy. The limitations include the stationarity of the residuals, increase in the parameter estimated and the increased computational load due to the increased sample size. As an alternative, Machine learning approaches are employed for their increased efficiency when compared to the geostatistical

Unlike geostatistical models, machine learning techniques are void of assumptions and can process a large number of parameters.As conventional models (Geostatistical and statistical) are model-oriented and the predictive accuracy depends on the assumptions that makeup the model whereas machine learning techniques aredata-driven and the predictions are made from the predictive model calibrated using an error-minimization process. This makes the model calibrated through the machine learning techniques more accurate than conventional models (McBratney et al., 2003).

Several of the machine learning techniques have been utilized in much of the literatures as a comparative analysis and each technique have been scrutinized for its efficiency over other. The physical and the chemical soil properties are reviewed for its efficient mapping techniques, inter__correlation among the properties and the machine learning methods adopted for each of the mapping methodologies are detailed in the following.

SOIL PROPERTIES

The soil physical and the chemical properties that characterize the soil fertility and their inter correlations or influence over other soil properties are discussed. Important soil physical and chemical parameters or properties and their processes are depicted in the Table 1.

Soil Physical Properties

The fine movement of the air, water and the uptake of the nutrient by the plants are determined by the soil physical properties.

models. "*Machine learning techniques refer to a large class of non-linear data-driven algorithms employed primarily for data mining and pattern recognition purposes, and now frequently used for regression and classification tasks in all fields of science*"(Wadoux et al., 2020).

Table 1. Some of the important soil properties and its associated soil processes

Soil Property	**Soil Processes**
Soil structure	Aggregation, organic matter turnover,retention, and transportation of water and chemicals
Porosity	Plant available water capacity, soil crusting, aeration, water entry
Infiltration	Soil water availability and movement,leaching of nutrients, erosion
Bulk density	Soil structural conditions, compaction
Available water	Field capacity, permanent wilting point,water flow
pH	Soil acidification, salinization, soil structural stability, biological and chemical activitythresholds
Electrical conductivity	Plant and microbial activity thresholds,leaching of salts, soil structure decline, salinization
Plant available N, P, and K	Availability of nutrients for plant uptake, losses from the soil–plant system
Soil organic matter	Organic matter storage and quality, plantresidue decomposition, metabolic activity ofsoil organisms, mineralization–immobilization turnover, microbial activity, nutrient supply
Total soil C and N	C and N mass and balance,

Physical properties of the soil affect the germination, soil erosion processes. The germination capability of the seed is determined by the water holding capacity i.e., soil moisture of the soil considering other parameters at their optimum standards. Similarly, several of the physical properties contributes to the soil erosion process as specified. (Abd-Elmabod et al., 2017).

Soils are differentiated based on the soil particle size and are classified into textural classes of sand, slit, clay and loamy soils. Based on the relative portion of each of the classes, the soils are classified (Jat et al., 2018). Soil Texture is an essential physical property that drives the crop management and production. The particle size associated with a particular textural class is depicted in the table 2.

Through pedotransfer functions, the property that is closely associated with the any of the textural class can be quantified approximately (Schaap & Leij, 1998). The absorption peak of the high clay content particularly of those of smectitic mineralogy has the capability to shrink and resulting in the formation of large cracks and fissures when dry. Thus, the soil with high shrink-swell potential is difficult to manage when dry. Soil structure is yet another important physical property which is determined by the soil management practices, environmental factors and other soil properties. It is an important indicator of the soil and determines the porosity, infiltration erodibility, C accumulation and other processes (Jat et al., 2018). The soil structure is a measure of soil structure stability which refers to the ability of the soil particles to resist disruption when outside forces are applied. Since, Soil structure is strongly affected by the amount of organic matter, any changes in the soil organic content will affect the structure of the soil which results in lower infiltration rates, increased run-off etc., Similar to that of the soil texture, soil structure can be used as an influencing variable or factor of other correlating soil property (Boruvka et al., 2002).

soil structure, nutrient supply.

Adapted from Jat, Mangi L., Clare M. Stirling, Hanuman S. Jat, Jagdish P. Tetarwal, Raj K. Jat, Rajbir Singh, Santiago Lopez-Ridaura, and Paresh B. Shirsath. "Soil processes and wheat cropping under emerging climate change scenarios in South Asia." Advances in Agronomy 148 (2018): 111-171.

Soil moisture content at varying levels influence the crop growth and decides the yield of the crop, as crop requires water at critical crop growth stages. A saturated soil will have a soil moisture tension of about -0.001 bars or less which requires less energy for a plant uptake. At field capacity the moisture will be available between -0.05 and -0.33 bars and on the other hand when the plant requires much energy (15 bar pressure) to extract the water the situation is called as wilting point (Adab et al., 2020).

The air necessary of the crop growth and the water storage are determined by the porosity and the pore size distribution of the soil. Soil porosity influences the soil aeration capacity and the soil water holding capacity and other soil physical indices. It also determines the root development and the soil enzyme activities. The soil infiltration capacity is related to that of the soil structure and texture as specified. (Jat et al., 2018). The soil infiltration capacity determines erodibility and surface run-off but can significantly change over the time, use and management. Bulk density of soil refers to the state of soil compaction, aeration and infiltration. Bulk density is inversely proportional to that of the soil organic matter (Pittman & Hu, 2020).

Table 2. Particle size of the respective textural classes

Textural Class	Particle Size (Diameter)
Sand	2 to 0.2 mm
Slit	0.2 to 0.002 mm
Clay	< 0.002 mm

Source: Adapted from Abd-Elmabod, Sameh K., Antonio Jordán, Luuk Fleskens, Jonathan D. Phillips, Miriam Muñoz-Rojas, Martine van der Ploeg, María Anaya-Romero, Soad El-Ashry, and Diego de la Rosa. "Modeling agricultural suitability along soil transects under current conditions and improved scenario of soil

to be affected by the climatic drivers. Soil pH affects a wide range of soil biological and chemical properties from salinization and soil nutrient availability. Intensive rainfall conditions lead to the leaching of the soil nutrient properties resulting in acidification as dictated by the buffering pools existing in soils.

The extent of leaching and evaporation will depend on the degree of change in rainfall and temperature. Electrical conductivity of the soil is indirectly associated with the soil structural properties specifically in the sodic soils. Sorption capacity and the cation exchange capacity in response to the high rainfall content, low organic content of the soils leads to low cation exchange capacity, in turn increases the leaching of the base ions. Cation Exchange capacity of the soil also influences the some of the major cations such as Mg, Ca, K and immobilization od the Al and Mn content of the soil (Jat et al., 2018).

Soil organic carbon is an important soil health indicator and helps in the improved soil structure formation. Moreover, the effect of SOC on other properties and ecosystem functioning requires less precision. Climatic factors usually influence the quantity of the SOC in the soil (i.e.) Humid and Cool Temperatures increases the content of the SOC and vice versa. Although major influential factors that affect the SOC are climatic drivers and environmental variables, other soil properties were also used as a measure such as Soil Structure, Porosity, aggregate stability, pore *factors." In Soil mapping and process modeling for sustainable land use management, pp. 193-219. Elsevier, 2017.*

Soil Chemical Properties

Most of the chemical properties of the soil is influenced by the climatic parameters or drivers that affect the soil organic matter, carbon and nutrient cycling which in turn affects the crop productivity. The soil pH and EC are also likely

impact on the soil reflectance spectra. B. W. Murphy *et al.*, 2015).Total Nitrogen and Total Phosphorous in the soil are fixed through the natural biochemical processes. But the recalcitrant of OM and phosphorous adsorption by Sesquioxide has a larger effect on the total availability of the N and P in the soil (Wang et al., 2012). The TN and TP, when compared to other soil nutrients has a considerable effect on the soil productivity. Moreover, SOC cycle, Clay and slit content of the soil have a strong correlation or influence over the SOC cycle.(Liu et al., 2013).

The Total Potassium in the soil favours the several physiological function of the plant such as stomatal opening and closure, translocation of sugars and starch, enzyme activation, respiration and ATP production. The availability of the TP is influenced majorly influenced by the soil moisture content (Goldberg, 1989). The micronutrients such as Ca, Mg, Fe and Al has a significant role in determining the soil fertility and has a strong influence over the physical properties (Gao et al., 2019). Flocculated clay facilitate by the Calcium ions favours the stabilization of the soil by promoting the aggregation of the soil. Ca ions ha more affinity for exchange site resulting in the aggregation (Norton, 2013). Decreased Mg ions has its effect on plants by limiting the formation of chlorophyll, activation of the enzyme and decreased quality and yield of crops. The levels of Mg and Ca ions are affected by the increased soil acidity facilitating an increased Aluminium exchange sites. (Yan & Hou, 2018).

connectivity and the clay mineralogy that affect soil affect the SOC storage. (Jat et al., 2018).

The effect of SOM has a strong influence over other physical properties only at the top soil level till 10 or 20 cm at the most. Though the effect and prevalence of the SOM is limited, SOM is considered critical as most of the agricultural activities takes place at the top soil level. The increased SOM of the soil will have a negative

formation of the absorption peak at a particular wavelength. Almost most of the estimation of the soil chemical properties for digital soil mapping are made through the model calibration of the significant bands. Collectively, some of the Soil textural classes and soil mineral composition that greatly influences the spectral properties of the soils and forms a prominent absorption peak at wavelengths are depicted in Table 3.

Table 3. Absorption peaks associated with some of the soil properties

Soil Properties	Absorption Peak (Bandwidth)
Clay (kaolinite, montmorillonite and illite)	2200nm
Calcium Carbonate	2340nm
Hematite (Iron)	550, 630 and 860 nm
Goethite (Iron)	480, 650 and 920 nm
Liquid water and O-H bonds	1400 and 1900 nm

Source: Adapted fromGomez, Cécile, and Phillipe Lagacherie. "Mapping of primary soil properties using optical visible and near infrared (Vis-NIR) remote sensing." In Land surface remote sensing in agriculture and forest, pp. 1-35. Elsevier, 2016.

MACHINE LEARNING TECHNIQUES

The requirement and the application of the machine learning techniques have increased

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The effects of Al and Fe ions includes stabilizing clay minerals by decreasing coagulation and has a significant effect on the soil physical properties(Behnood, 2018). Increased Ca, Al and Fe content in the soil leads to the formation of the absorption peak in the soil reflectance spectra (Goldberg, 1989). The effect of each of the chemical properties has a profound change in the spectra either through the overall decrease in the reflectance or through the

exponentially in the past decade. The increased availability of the remote sensed data and many of the open-sources algorithms lead to the increased adoption of the ML techniques. *"Machine learning techniques refer to a large class of non-linear data-driven algorithms employed primarily for data mining and pattern recognition purposes, and now frequently used for regression and classification tasks in all fields of science."* The use of Machine learning techniques in calibrating the predictive models have been employed in the Digital Soil Mapping

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or Pedotransfer functions and in the analysis of the soil Vis-NIR Spectra. The machine learning techniques can be divided into shallow and Deep Learning Techniques.(Wadoux et al., 2020)

Shallow learning may be referred to as learning methods that have been adopted before 2005 and "Deep learning itself is a branch of machine learning, which can be understood as neural networks with multiple hidden layers. Compared with shallow learning-based applications, deep learning models require large amounts of training data. Furthermore, the structures of the network have a great impact on the performance of the deep learning models." (Xu et al., 2021). The percentage of the literature that have been adopted machine learning approaches in the recent years is depicted in the Figure 1.

The most often used Machine learning approaches used in soil property analysis are depicted in the Table 5 in the majority of the literature evaluated. Binary Trees (BT), Support Vector Machines (SVM), Nave Bayes (NB), Artificial Neural Networks (ANN), Cubist Regression (CB), Principal Component Regression (PCR), Partial Least Square Regression (PLSR), Least-Square SVM (LS-SVM), Extreme Learning Machines (ELM), Ordinary Least Square Estimation (OLSE), Ant Colony Optimization-interval Partial Least Squares (ACO-iPLS (CNN). (Trontelj ml & Chambers, 2021).The advantages and disadvantages of the major Shallow and deep learning techniques are depicted in the Table 4.

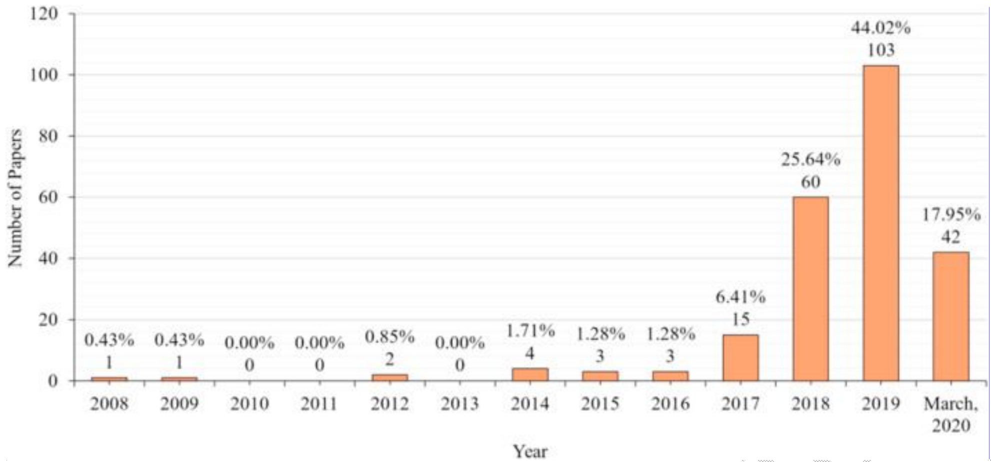

Figure 1. Percentage of literature adopted machine learning approaches over the years Source: Xu, Yayin, Ying Zhou, Przemyslaw Sekula, and Lieyun Ding. "Machine learning in construction: From shallow to deep learning." Developments in the Built Environment (2021): 100045.

Table 4. Advantages and disadvantages of major machine learning techniques implicated.

Method	**Advantages**	**Disadvantages**
Regression	Low computation time Performs well with large datasets Reduce data dimensionality Provide a feature selection Easy to implement	Do not deal with nonlinear problems over-fitting may occur
DT	Can be effectively applied for the nonlinear problem Performs well with large datasets In built feature selection procedure Easy to implement	Over-fitting may occur Non-robust to small dataset changes Input parameters, such as nods numbers, need to be defined manually
SVM	Can be effectively applied for the nonlinear problem Performs well when data dimensionality is greater than the number of samples Low risk of the over-fitting	Non-robust to small dataset changes Is not suitable for large datasets, where data dimensionality is smaller than number of samples Effective kernel function is not easy to define Large computational time for large datasets Different impact of the weights parameters that is not easy to visualize their impact Needs adaptation for multi-class problems Not easy to implement

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NB	Can be effectively applied for the nonlinear problem Low computation time Suitable for multi-class problems Effective for small training datasets Easy to implement Robust to small dataset changes Probabilistic predictions can be obtained	Assigning zero probability to a categorical variable is not available and loss of accuracy
RF	Can be effectively applied for the nonlinear problem May be applicable to soils under a great variety of environments Act to reduce bias Performs well with large datasets Overfitting is less common Accommodate random inputs and random features Can be used for classification as well as for regression	Had difficulty predicting high and low laboratory measured values, underestimating and overestimating them, respectively Number of trees need to be defined manually Long computation time Large computational power is required due to the large amount of the trees created by the algorithm
NN	Can be effectively applied for the nonlinear problem Effective in many applications Defined fault tolerance that makes classification more robust Robust to small dataset changes Can perform in parallel without affecting the system	Effective architecture parameters need to be defined manually and classes are translated to respective numeric values Require large computation power and training dataset Weights are assigned randomly, so as to acquire high accuracy, the process of training the data must be iterative The duration of the network is unknown

Source: Chambers, Olga. "Machine Learning Strategy for Soil Nutrients Prediction Using Spectroscopic Method." Sensors 21, no. 12 (2021): 4208. (NB – Naïve Bayes; RF- Random Forest; SVM – Support Vector Machine; NN- Neural Networks; DT – Decision Trees.

Shallow Learning

Shallow learning techniques requires and prior insight of the data that are to be learned. Different types of Shallow learning techniques that have been developed are 1. Supervised, 2. Unsupervised and 3. Reinforcement Learning. Supervised learning recognizes the pattern and optimizes the model based on the user-defined training datasets while Unsupervised learning recognizes the pattern purely based on the prediction i.e., patterns are determined based on the clustering techniques.Some of the supervised learning that were considered as a foundation were Logistic Regression, Perceptron and kNN. While than fully connected neural networks where each input feature is connected to each neutron in a fixed way. Two popular deep Recurrent Neural Networks (RNNs) types of are LSTM and GRU (gated Recurrent Units). GRU is used when the datasets are smaller and LSTM is used for larger datasets (Xu et al., 2021).

MAJOR MACHINE LEARNING METHODS IMPLICATED

Support Vector Machine

Vapnik (1999) introduced the SVM principle. SVM is distinguished by its ability to minimize

Perceptron undoubtedly laid the foundation for machine learning algorithms, they were fragmented and unstructured before the publication of the Decision Tree algorithm. A standardized algorithm concerning unsupervised learning includes Principal Component Analysis (PCA), kernel PCA and t-SNE. K-mean, EM, mean shift and spectral clustering are typical clustering algorithms (Xu et al., 2021). Reinforcement learning is typically avoided because of its trial-and-error method of model optimization resulting in the computational load and fitting errors.

Deep Learning

Though most of the Deep learning methods adopted in the Soil property mapping and estimations are less, model calibration through deep learning has evident significancewhen compared to the shallow learning methods.

Deep learning methods incorporates the neural networks and back_propagation is considered foundation as the earlier artificial neural networks are considered insignificant due to their inability to train multilayer neural networks. Currently, two major network structures used in deep learning are CNNs and RNNs. CNNs are considered significant for the digital image processing from spectral feature detection and classification because of their less parameter estimation and entire image processingrather

the algorithm's structural error (i.e.) an ideal separating hyperplane for distinguishing classes that overlap but are not linearly separable. It was created for classification purposes, but it can also be used to solve regression problems. There are two types of SVM models: classification and regression (Elisseeff & Weston, 2001). To solve data categorization challenges, classification models are utilized. Forecasting difficulties are solved using regression models. The SVM has the benefit of being extremely effective in high-dimensional spaces (Zhang et al., 2020).

Random Forest

Breiman (2001) combined the bagging approach (Breiman, 1996) with random 20 variable selection to create random forest (RF). The aim was to combine a group of "weak learners" to build a "strong learner." For each RF tree, bootstrap sampling is employed, and the binary split data criteria for regression and classification tasks are distinct. (Zhang et al., 2020). The general premise of group training is that it improves the accuracy of other trained models, which is related to the principle that ensemble models are more accurate than solo models (Yousefi et al., 2021).

The use of RFs has the advantage of allowing ensembles of trees to be employed

5. Machine Learning Techniques Used in the Soil Properties Mapping: Literatures Reviewed

Table 5. Some of the Machine Learning Techniques used in the Soil Properties Mapping (Literature reviewed)

S.NO	Machine Learning Technique	Study area	Property estimated	Best ML feature selected	Validation measure used	Reference
1.	ELM, PLS and BPNN	Morocco	SOC and TN	ELM	R^2, RMSE and RPD	Reda et al. (2019)
2.	RF	North east	STN	RF	R^2 and	Zhang et al. (2019)

		China			RMSE	
3.	SVM, BRT and RF	Switzerland	SOC and C:N ratio	BRT	R^2, RMSE and MAE	Zhou et al. (2021)
4.	RF and SVM	Eastern Tunisian Atlas	soil texture	RF	OA	Bousbih et al. (2019)
5.	CNN - LucasCNN, LucasResNet, LucasCoordConv and RF	Europe	soil texture	LucasCoordConv	OA, AA, Kappa	Riese and Keller (2019)
6.	ANN- Back propagation	Northwestern province of Qazvin	STP		Fitted vs original plot	Keshavarzi et al. (2015)
7.	RF	Canada	Bulk Density and Soil Carbon		MAE and R2	Pittman and Hu (2020)
8.	PLSR, Cubist Regression, LS-SVM and ELM	Middle-lower Yangtze Plain	SOM and pH	ELM	R^2, RMSE and RPIQ	Yang et al. (2019)
9.	MLR, RFR, SVM and SBG	South-western Burkina Faso	Sand, silt, clay, cation exchange capacity (CEC), soil organic carbon (SOC) and nitrogen	RFR	R^2, sMAPE and RMSE	Forkuor et al. (2017)
10.	KNN, MLP, RF,SVM,XGB ,ALR,CLR and ILR	Northwest of China	soil texture and Soil Particle Size Fractions	RF and XGB	R^2, MAE, RMSE, AD and STRESS	Zhang et al. (2020)
11.	MLR, RF, SVM, cubist regression and ANN	Calabar, Cross River State	SP and SN	RF	RMSE, MAE and R^2	John et al. (2020)
12.	MLR and RF	Morocco	Soil Aggregate	Both methods provided the same estimates	R^2 and RMSE	Bouslihim et al. (2021)
13.	boosted BRT, RF and SVM	Northwestern China	STN	BRT and RF	R^2, MAE and RMSE	Zhou et al. (2019)
14.	RF, EN , SVM and ANN	Iran	Soil Moisture	RF	Nash–Sutcliffe efficiency value	Adab et al. (2020)
15.	PCR, PLSR, LS-SVM and CB	Germany	Soil Moisture, Soil Total Nitrogen and Soil Organic	LS-SVM for OC, CB for N	RMSEP and RPD	Morellos et al. (2016)

			content			
16.	ANN, RF PLSR and CB	Brazil	Environmental vulnerability	CB for OC, PLSR for N	-	Costa et al. (2020)
17.	PLSR, BPNN and GA-BPNN	Guangdong, China	Total Nitrogen, Total phosphorus and total potassium	GA-BPNN for N, P, K	RRMSE	Liu et al. (2013)
18.	PLS and SVR	Anhui, China	Soil Available Potassium content	SVR for available K	R^2 AND RMSE	Jin et al. (2020)
19.	LS-SVM and PLSR	Zhejiang, China.	Total Nitrogen, Total phosphorus and total potassium	LS-VM for N, P and K	RMSEP	Shao and He (2011)
20.	OLSE, RF and ELM	LUCAS Soil (23 countries)	Soil total Nitrogen	ELM for N	R^2, RMSEP, RPD	Wang et al. (2020)
21.	AOC-iPLS, RF and RF-SVM	Xinjiang Uyghur Autonomous Region, China	Soil organic carbon (SOC)	RF-SVM for OC	R^2 and RMSE	Ding et al. (2018)
22.	PLSR, SVM, RF, ANN and DL	Czech Republic	selected PTEs (Cr, Cu, Pb, Zn, and Al) in forest organic horizons	ANN for Cr and Al	R^2 and RMSE	Gholizadeh et al. (2020)
23.	PCR, PLSR, LS-SVM, BP-NN	Qingdao Fushan Mountain foothills, Qingdao Zaoshan Mountain farmland, and Qingdao Licun River	total carbon (TC), total nitrogen (TN), total phosphorus (TP), total potassium (TK), available nitrogen (AN), available phosphorus (AP), available potassium (FK), and slowly available	BPNN and LS-SVM for different nutrients	R^2, RMSEP, RPD	Li et al. (2019)

			potassium (SK)			
24.	SVM and 13 ANN models	-	Soil Nutrient	GRNN for nutrients	Prediction accuracy through fitting	Li et al. (2014)

without the need for pruning. Furthermore, since RF is indifferent to the range of values, it is generally resistant to overfitting and does not require standardization or normalization. The number of trees (ntree) and the number of features randomly sampled at each split need both be changed for the RF model (mtry). (Zhou et al., 2020). This modeling technique is commonly used in soilmapping investigations because it can assess the importance of variables, is resistant to overfitting, and produces consistent and reliable results (Wiesmeier et al. (2019); Yang et al. (2019)).

Artificial Neural Networks

Artificial neural networks have shown good performance in predictive modeling and forecasting, as well as nonlinear and impermanent time series of processes where there is no definite answer and clear relationship to detect and explain them. The multilayer perceptron model is the most commonly used ANN model (MLP). To learn and train the network, the MLP requires a well-understood output; this sort of neural network is known as a supervised network. MLP creates a model that plots the input to the output using training data, and then uses the model to predict the outputwhen the outcome is unknown. This model is sometimes used in place of a feed-forward network. (John et al., 2020). The training of the weight matrix characterizes an ANN model with a feed-forward network. The weights are randomly assigned to appropriate ranges and then adjusted using various training processes (Pachepsky et al. (1996); Schaap et al. (1998)). Different approaches, such as gradient descent (GD), Levenberg–Marquardt (LM), and Conjugate Gradient, are used to reduce error in feed forward networks (CG). Back propagation (BP) is based on the gradient descent (GD) algorithm, which is relatively stable when using a modest learning rate but has sluggish convergence properties (Farjam et al., 2014)

K – Nearest Neighbor

The K-nearest neighbor (KNN) classifier is a simple non-parametric classifier that labels unknown instances based on the known instance (Cover & Hart, 1967). K-nearest training set vectors (k) were identified for the test set, and maximum summed kernel densities of 5 were computed for classification. Continuous variables can also be predicted using the average

values of K nearestneighbors for regression. The maximum value of k (kmax), the distances between the nearest neighbors (distance), and the types of a kernel function are all parameters of KNN (kernel). (Zhang et al., 2020).

Cubist Regression

The cubist model is as a rule-based

out over years. So far affordable alternatives using different statistical studies have been universally employed in estimating soil properties.

Various statistical approaches have been used to translate the spectral information to those quantified soil properties, and to develop spectral models for soil properties model which is an extension of the M5 tree model. (Quinlan, 1992). The structure of the cubic regression model contains a MLR models coupled with a conditional component acting as a decision tree. The simplification of the model is done by eliminating or pruning the rules. The key advantage of the cubist system is that it allows you to add additional training committees and enhance the weights to make them more balanced (Kuhn and Johnson (2013); Quinlan (1992); Wang and Witten (1997)). The cubist model includes boosting with training committees (typically more than one), which is comparable to the approach of "boosting" by constructing a sequence of trees with changed weights successively (John et al., 2020).

MACHINE LEARNING IN MAPPING METHODOLOGIES:

The soil properties estimation and mapping were employed majorly based on two methodology or applications

1. Spectral based modelling and Mapping,
2. Digital Soil Mapping

Spectral Based Modelling and Mapping

The extractable soil information from that remote sensed image data or Vis-NIR Spectroscopy have been utilized in the recent research for mapping of the soil properties. The evaluation and estimation of the numerous soil properties employing hyperspectral remote sensing (Vis-NIR or MIR Spectroscopy and Hyperspectral remote sensing) have been carried

studies have been implicated regarding the estimation of several soil properties such as Nitrogen (N), phosphorus (P), potassium (K), electrical conductivity (EC), cation exchange capacity (CEC), Iron (Fe) content, soil moisture content, carbonates and hydraulic properties. Usually, two major approaches are considered for the hyperspectral band selection 1, Using a specific absorption band. The absorption band characterization. Hyperspectral Data are usual rich in information but the processing associated with the data is usually a bit complicated and poses several challenges considering the data complexity, information redundancy, modelling accuracy and high correlation between the spectral bands (i.e.) High collinearity. Considering the above-mentioned vulnerabilities and disadvantages, an attempt is made to develop a methodology in order to identify the Bands of particular wavelength that corresponds or correlates with the soil nitrogen properties (Gomez et al., 2008).

Once spectrum reflectance is known and a relationship between the spectral feature and soil characteristic is known a priori, the specificity allows for the assessment of various soil nutrients. As a result, spectral fingerprints are frequently regarded as inherent soil features that differ amongst soils. Das et al. (2015) also defined that the soil reflectance is a confluence of the responses of the electromagnetic radiation from different soil factors referred to as chromophores Essentially, physical (particle size and sample geometry) and the chemical (moisture content, organic matter, clay minerals and iron oxides) chromophores contributes to the spectral characteristics of the soil under study. The spectral reflectance of soil increases exponentially as particle size decreases, with the increment being rapid below 0.4 mm diameter. As the roughness of the soil surface increases with increase in the particle size, more energy is trapped in the inter-aggregate gaps, resulting in poorer reflectance (Sadeghi et al., 2018). The soil spectra can be utilized for the estimation of the soil primary properties and many number of

out the best bands obtained, by utilizing approaches such as Regression Trees, Regression, Instance Based Methods.

Though several of the statistical analysis have been used for the spectral band selection and are validated through MLR, the MLR models are always associated with the error in the form of outliers, over or under fitting of the variables

Comment [WU4]: Do alignment the paragraph specific to a property that have been identified is tabulated in the Table 2. The area of the selected absorption band is considered as the explanatory variable to estimate the response value**.** 2. full spectra. Each spectral band value is an explanatory variable to estimate the response value (Gomez & Lagacherie, 2016).

With the advent of the various mathematical and Statistical methods, research has been entitled more on quantitative prediction with reflectance spectroscopy of various soil constituents, most of which have absorptions within Vis-NIR spectralregion, such as water, Organic Matter, Carbonates. Because of the intercorrelations among these spectral constituents, even spectrally featureless (without any specific absorption bands) soil properties such as Cation Exchange Capacity, pH and Phosphorus can be estimated indirectly.

(Bajcsy & Groves, 2004) discussed methodology incorporating various mathematical and statistical procedures for optimal band selection from the hyperspectral data. As the high collinearity and information redundancy is concerned, the best band selection process is a bit complicated. Thus, a methodology is implicated by separating the techniques of Band Selection into Supervised and Unsupervised Band Selection Procedures. In Unsupervised Band Selection Procedures, the several approaches (i.e.) Information Entropy, Contrast Measures, Correlation, Derivative Analysis, PCA, etc., have been utilized for best band selection. Based on the Bands selected from the Unsupervised Band Selection Procedures, Supervised Band Selection is performed by training data sets in order to filter and the multicollinearity associated with the if the variables selected. Hence, most of the literatures recently have adopted ML based variable selection and modelling. The literatures also have shown a better performance of the ML model over statistical models. Several of the literature reviewed determined the efficiency of the RF method and Generic Algorithm for the model selection.

(Gmur et al., 2012) studied soil samples were for its attributes by a field-based analysis of spectroradiometer providing spectral range from 400-1000nm. Ranking is done in order to find out the similarities and differences within the replicated soil series and other soil series. Further, the statistical analysis and classification is done based on Regression Trees.

Regression Trees are formed keeping the spectral responses as the independent variable and the respective Soil Nutrient concentrations (i.e.) Nitrogen, Carbon, Carbonate and organic matter as dependent variables. The ultimate aim of the study is estimation of Soil Nutrients and relating the spectral signatures to that of the Laboratory reference Measurements utilizing CART analysis. The spectral analysis of the SOC and Total Nitrogen is done utilizing three ML approaches ELM, PLS and BPNN. The spatial estimation is made utilizing the ML approached with or without variable selection measures. The External Learning Machine approach provided the best estimate for the SOC and Total Nitrogen. (Reda et al., 2019).

Digital Soil Mapping

The term "digital soil mapping" refers to the use of geospatial technology for mapping soils (DSM). The construction of geographically referenced soil databases based on quantitative correlations between spatially explicit other or previously measured attributes of the soil at a point; (2) c: climate, climatic properties of theenvironment at a point; (3) o: organisms, including land cover and natural vegetation; (4) r: topography, including terrain attributes and classes; (5) p: parent material (6) a: age, or the passage of time; (7) n: location, either spatially environmental data and measurements taken in the field and laboratory is known as digital soil mapping (McBratney et al., 2003). The progress of the digital soil mapping followed four different transformations. 1. From small areas to larger areas. 2. From simpler landscapes to complex landscapes 3. From 2D to 3D digital soil mapping 4. agricultural management besides ecosystem management (ZHANG et al., 2017)

In a nutshell, digital soil mapping refers to the geographic prediction of soil parameters based on model calibration. The science and art of soil surveying have greatly advanced thanks to the availability and accessibility of geographic information systems (GIS), global positioning systems (GPS), remotely sensed spectral data, topographic data derived from digital elevation models (DEMs), predictive or inference models, and data analysis software (Boettinger et al., 2010).

Conventional soil mapping includes the statistical and geostatistical modelling. The used of inference models to predict the soil parameters or properties in Geodatabase makes the DSM more advantageous over the conventional soil mapping. Besides the use of data mining, statistical analysis and machine learning approaches have enhanced the accuracy of the soil mapping (Wadoux et al., 2020).

The Generic framework has been implicated by the Generic framework McBratney et al. (2003). For regions where soil resource information is lacking, the scorpan SSPFe (soil spatial prediction function with spatially autocorrelated errors technique is applied. "The seven predicted scorpan factors, which are a generalization of Jenny's five factors, are as follows: (1) s: soil,

CONCLUDING REMARKS

From the literature reviewed, trends of different machine learning techniques

or geographically.

The derived SCORPAN factors of Jenny 1941, are essentially used for the mapping various soil attributes. Several of the methodologies have been implemented for deriving data layers respective to a particular factor (Avello).

Several of the authors have implicated Random Forest based machine learning methods and also compared the efficiency of the each of the major Machine learning methods. In most of the comparative analysis, RF has been considered uniquely efficient when compared to other machine learning and MLR technique. (Zhang et al. (2019);Bousbih et al. (2019); Zhang et al. (2020); John et al. (2020); Bouslihim et al. (2021); Zhou et al. (2021); Adab et al. (2020)).The comparison and the best ML algorithms selected were depicted in the Table 5. Some of the literatures have implemented ANN-Back Propagation means of classification and CNN means of soil properties estimation(Keshavarzi et al., 2015).

In most of the cases the default tuning methodology provided are sufficient considering the application used for the Digital soil Mapping. The parameter optimization is usually performed in order to increase the model calibration accuracy(Jat et al., 2018). The model validation is usually performed by comparing the fitted variable to that of the original data. The most popularly used measures of validation are R2 and RMSE values. Based on the validation parameters the efficiency of the model calibrated can be determined.

implemented in the mapping methodologies have been depicted. Machine learning techniques provides the means of optimized model calibration when compared to that of the conventional geostatistical or statistical approaches. Though most of the researches have used shallow learning approaches for the soil properties estimation, deep learning neural networks were also implicated in much of the literatures. Thus, the important highlights of the Machine learning in Soil properties mapping includes,

1. Compared to the conventional means of mapping procedures through geostatistical or statistical approach, Machine learning approaches are considered efficient.

2. Many of the approaches in soil properties estimation (i.e.) Digital Soil Mapping, Pedotransfer functions and spectral based mapping approaches are shifting from the geo-statistical or statistical modelling to Machine learning approaches.

3. In most of the soil properties estimation procedures, Random Forest method have been considered efficient through many of the comparative analysis.

4. From parameter optimization or tuning in the DSM to variable selection in the spectral based hyperspectral mapping, Machine learning tools have been utilized for its qualitative detection.

Through increased research in this concern, the means of rapid mapping of properties and optimization of the band selection methodologies specific to a soil parameter can be standardized.

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