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Application of Geospatial Technology in Assessment of Spatial Variability in Soil Properties: A Review

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Authors' contributions

This work was carried out in collaboration among all authors. Author HK designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors AK and BS managed the analyses of the study. Author RB managed the literature searches and critically revised the final draft of MS as per style of CJAST. All authors read and approved the final manuscript.

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Review Article

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ABSTRACT

Under the changing climatic scenarios, sustaining agricultural production and enhancing input use efficiency is highly crucial to ensure food security in future. As crop productivity is considerably affected by soil characteristics such as soil organic carbon (SOC), nutrient availability, pH, salinity and soil moisture etc., thus their spatial variability needs to be assessed for site-specific and more efficient management. RS, GIS and GPS can be used quite successfully for assessing spatial variability in these properties. Recently with the advent of highly sophisticated sensors, it is possible to assess various soil properties by observing spectral reflectance in different wavelength bands and computing various spectral indices from the data recorded through satellite remote sensing. Spectral reflectance in different wavelength bands viz. visible, thermal and microwave etc. along with different spectral indices computed from spectral reflectance viz. normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), modified soil adjusted vegetation index (MSAVI), ratio vegetation index (RVI), soil moisture index (SMI), normalised difference water index (NDWI) and normalized difference salinity index (NDSI) etc. are used to retrieve different soil

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properties from satellite data. Similarly, various spatial interpolation techniques viz. inverse distance weighting (IDW), ordinary kriging (OK), radial basis function (RBF) and empirical bayes kriging (EBK) etc. are used for spatial interpolation of various soil characteristics. A critical review concluded that geospatial techniques can be used successfully for retrieval and spatial interpolation of various soil properties, which can be highly beneficial in site specific management leading to improved input use efficiency and sustained agricultural productivity for future food security.

Keywords: Remote sensing; GIS; GPS; spatial variability; soil properties.

1. INTRODUCTION

Soil is a dynamic entity with distinct chemical, physical, biological and mineralogical attributes that ceaselessly differ over time and space Rogerio et al., [1]. Geospatial technology provide better alternatives to conventional traditional methods, as they can cover large regions with information on spatio-temporal variations in soil properties Mohammed et al., [2]. Such spatio-temporal variation accounts for the soil heterogeneity which tends to occur both at small and large scale within the soil Cambardella and Karlen, [3]; Feng et al., [4]. The heterogeneity may be either due to intrinsic soil forming factors influencing differentially during the pedogenic processes or extrinsic factors such as tillage, irrigation, crop rotation and land degradation etc. Further, the type of vegetation, geomorphic elements and landforms also contribute towards gradual increase in the soil variability Buol et al., [5]. Salviano [6] first presented the spatial variability of soil properties as affected by long term soil erosion. Thus, the monitoring and quantification of soil variability is important to comprehend the various land use and soil management systems. Recently, various methods have been proposed to retrieve different soil properties from remote sensing data Mohammed et al., [7].

Evaluation and analysis of soil properties is the main application of geospatial technology in agriculture. Efficient monitoring of soil nutrient contents from geospatial technologies is very for farmland soil productivity, sustainable agricultural development and food security Peng et al., [8]. Remote sensing involves extraction of useful information from images and other forms of pictorial representation of an object captured from a distance. Both digital and analog satellite data is used to prepare small scale soil resource maps representing various soil sub-groups and their association Manchanda et al., [9]. Various soil properties can be easily determined from remote sensing techniques. For instance, surface soil moisture can be estimated based on NDVI and land surface temperature (LST). NDVI is estimated from reflection of red and near infrared region, whereas LST is determined from thermal emission Amato et al., [10]; Hammam and Mohamed, [11]; Rahimzadeh-Bajgiran et al., [12].

The information on the spatial distribution and soil moisture content is very important in hydrological applications and precision farming in addition to climate change analysis and meteorology etc. Pasolli et al., [13]. Remote sensing techniques are extremely helpful in soil moisture estimation and soil mapping. Remote sensing provides the data on surface soil moisture content, giving information about the amount of moisture in the soil that further helps to decide the type of crop to be grown in the soil. From soil mapping, farmers may come to know about the sites with requirements of fertilizer or irrigation for any crop. This is highly beneficial for farmers involved in precision agriculture Sinha et al., [14]. Geographical information system (GIS) and remote sensing have potentially exposed accelerated, spatio-temporal and repetitive, synoptic view, thus providing newer possibilities of estimating various soil properties. Therefore, assessing spatial variability distribution of various soil properties is crucial for assessing rates of ecosystem processes Schimel et al., [15], understanding how ecosystem works Townsend et al., [16] and effects of future land use changes on availability of nutrients Kosmas et al., [17].

2. ADVANTAGES OVER CONVENTIONAL METHODS

Assessment of spatial variability in soil properties is possible through scientific survey of soil that renders an accurate and scientific repertoire of various soils, their nature, type and extent of distribution to facilitate the prediction regarding the distinct characteristics and potentialities possessed by such soils. Apart from this, it also generates information about terraces, landform and vegetation etc. The timely and reliable information on soils is essential for the execution of efficient management strategies for sustainable agriculture. Precision agriculture includes accurate analysis of various soil properties at field scale. Soil being one of the major factors influencing the growth and yield of plants and various other processes in agriculture, its properties should be determined with immense accuracy to benefit the crop planning and requirement, hence affecting growth and yield.

The traditional approaches of estimation of soil properties such as sampling are known to have less accuracy as some sites in the field may remain unsampled leading to inaccurate results and hence poor planning. However, in the recent times, remote sensing techniques along with geographic information system (GIS) and global positioning system (GPS) have gained the attention of agricultural scientists throughout the world to fill such gaps in conventional methodologies. The advent of highly sophisticated hyperspectral sensors have made it possible to monitor various soil properties viz. pH, salinity, alkalinity, moisture and nutrient status etc. using satellite data. In addition to this, GIS and GPS are major parts of geospatial technology. Geographic information system is a framework that makes it possible to capture and analyze the spatial and geographic data whereas GPS (originally NAVSTAR) is satellite based radio-navigating system. While analyzing any type of soil properties, GIS is used to create soil database. The attribute data are linked with spatial data in GIS. GPS,on the other hand, is used to locate different soil sampling locations, thus helping growers to develop maps portraying fertility variations throughout the fields, so that one can vary crop inputs in field based on GIS maps or real-time sensing of crop conditions (Fig. 1).

This technology is being used quite successfully in precision agriculture as it involves accurate analysis of various soil properties at field scale. Precision Agriculture deals with site-specific management of the agricultural inputs to improve yields and input use efficiency. Soil sensing and mapping is one of the most important improved management technologies included in precision agriculture. For soil sampling, some representative soil samples are collected and analysed. These samples exhibit spatial variability. A global positioning system (GPS) receiver with a data logger measures the soil sample and GIS generates a map that is further processed in addition to other spatially varying layers. This approach is often termed as a map-based method. Whereas, other sensors that are used without a GPS receiver belong to real time system Morgan and Ess, [18]. The most important soil sensors used for measuring spatial and temporal characteristics of soil parameters include electrical, electromagnetic, acoustic, mechanical, optical, radiometric,electrochemical and pneumatic sensors Adamchuk et al., [19]. Geospatial technologies used in this type of farming are important to understand the spatio-temporal features of the soil. This helps in site-specific management and optimization of resources. A large number of researchers, soil scientists and farmers make the potential use of remote sensing and geographical information system as an important component of precision farming Liaghat and Balasundram, [20] to increase crop productivity, input use efficiency and profitability.

3. HISTORICAL DEVELOPMENT

Bushnell [21] explained the efforts made in the 1920s by using aerial photographs to depict the boundaries of different soil series. Relationships between soil properties and remotely sensed data have been mainly examined from the reflective region of the electromagnetic spectrum (0.3 to 2.8 μm) and some in the microwave and thermal bands. The differences in iron content, texture and organic matter content are related to various spectral responses in the reflective spectrum Stoner and Baumgardner, [22]. Soil albedo is highly correlated to reflectance-based data Post et al., [23]. Predictive equations have been developed from reflectance data over tilled fields to estimate silt, sand and/or clay content Suliman and Post, [24]; Coleman et al., [25].

Henderson et al. [26] observed strong correlation between visible wavelengths (0.425 to 0.695 μm) and organic matter in soils with the same parent material, whereas, this relationship could be affected by Fe and Mn-oxides for soils with different parent materials.In this case, better predictions of organic carbon content was made by the use of middle infrared bands. White salt crust represented salt-affected soils, which had higher NIR and visible reflectance Rao et al., [27]. This spectral response, however, cannot always be used for identification of saline soils, because salt-crusted soils must have NIR and visible properties similar to soils with high sand contents. The salt-affected soils can be better differentiated by including thermal data Verma et al., [28] and L-band microwave data Sreenivas et al., [29]. Bbased on the spectral reflectance of soil, many spectral indices have been devised for retrieval of soil properties using geospatial techniques (Table 1).

Soil properties that can be deduced from crop response include soil nutrient deficiencies McMurtrey et al., [30]; Bausch and Duke, [31], salinity Wiegand et al., [32], and soil moisture availability Colaizzi et al., [33]. Wiegand et al. [32] made use of SPOT HRV imagery and airborne digital videography in conjunction with plant and soil samples for quantification and mapping of electrical conductivity. Colaizzi et al. [33] studied the relation between crop water stress index (CWSI) and soil water depletion. Wildman [34] illustrated the relation between crop patterns in color-infrared (CIR) photos and soil type in irrigated fields. Soil organic matter (SOM) is known to have good correlation with NIR and visible reflectance Stoner and Baumgardner, [22]. Sudduth and Hummel [35] made a portable spectrophotometer for the purpose of acquiring NIR soil reflectance data at various narrow-band wavelengths and were able to predict SOM with different soil types and moisture contents. Thus, with the recent advancements in the field of geospatial technology, many research studies have been carried out to estimate various soil properties (Fig. 2).

3. ASSESSING SOIL PROPERTIES WITH GEOSPATIAL TECHNIQUES

3.1 Organic Matter

Soil organic matter is a very crucial factor which not only influences the crop production, but also affects soil color and quality Zomer et al., [51]. The derivation of soil organic matter is from plant residue Allison, [52]. Soil is the most essential source of carbon in the world Swift, [53]. Soil organic carbon (SOC) affects the agricultural productivity and contains about 75% of Total Carbon (TC) pool of terrestrial ecosystem. Large amount of SOC leads to enhanced crucial ecosystem functions, soil quality, nutrients, soil structure, nutrient supplies for soil microbial fauna and water holding capacity. Increasing SOC levels are responsible for better crop production due to improved plant available water holding capacity of soil, better plant nutrient level, availability and storage as well as enhancement of soil physical properties Lal, [54].

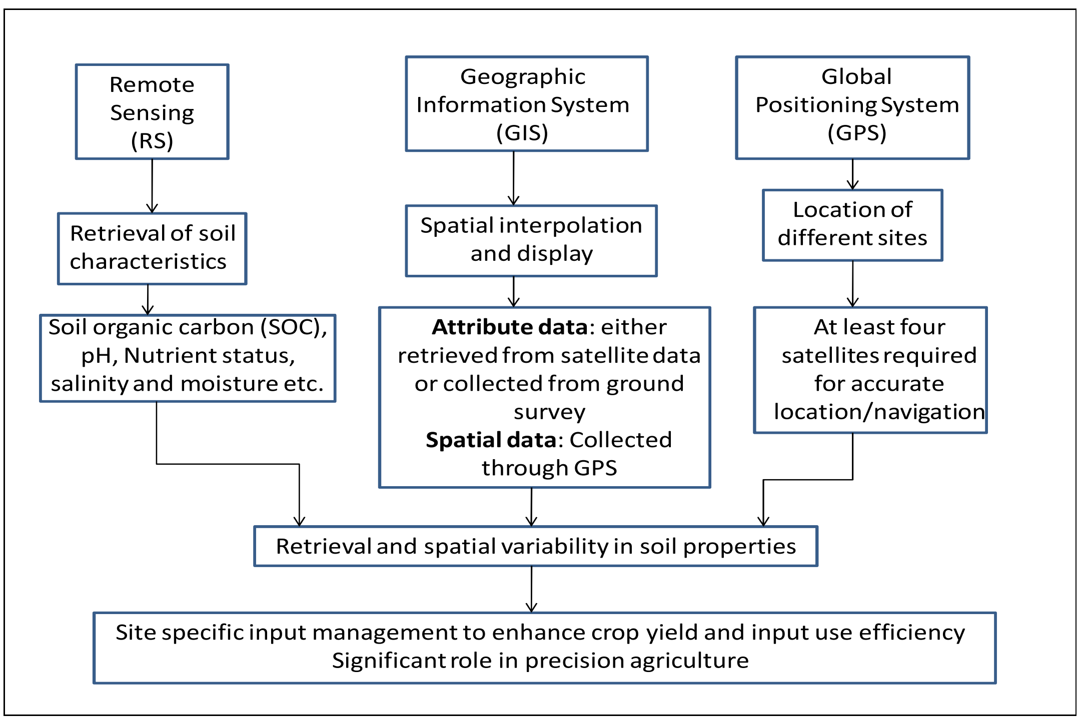

Fig. 1. Role of geospatial techniques in retrieval and spatial variability assessment of soil properties

Table 1. Different spectral indices used for assessing soil properties through remote sensing

Soil property	Vegetation index	Formula	References
Soil organic matter	Modified Soil Adjusted Vegetation Index (MSAVI)	$\frac{NIR-Red}{NIR+Red+L}(1+L)$	Qi et al., [36]
	Normalised Difference Vegetation Index (NDVI)	$\frac{NIR-R}{NIR+R}$	Rouse et al., [37]; Tucker, [38]
	Ratio Difference Vegetation Index (RDVI)	$\frac{NIR-R}{(NIR+R)^{0.5}}$	Roujean and Breon, [39]
	Modified Non Linear vegetation Index (MNLI)	$\frac{(p^2NIR-pR)(1+L)}{(p^2NIR+pR+L)}$	Gong et al., [40]
Soil moisture	Soil Moisture Index (SMI)	$\frac{(LST_{max}-LST)}{(LST_{max}-LST_{min})}$	Mohamed et al., [2]
	Soil Moisture Index (SMI)	$\frac{(LST_{min}-LST)}{(LST_{max}-LST_{min})}+1$	van Leeuwen, [41]
	Moisture Stress Index (MSI)	$\frac{MidInfrared}{NearInfrared}$	Zakir M, [42]
	Normalised Difference Water Index (NDWI)	$\frac{(NIR-MidIR)}{(NIR+MidIR)}$	Zakir M, [42]
	Soil Moisture Index (SMI)	$\frac{TS_{max}-LST}{TS_{max}-TS_{min}}$	Ghazali et al., [43]
Soil salinity	Normalised Difference Vegetation Index (NDVI)	$\frac{NIR-R}{NIR+R}$	Ghazali et al., [43]
	Ratio Vegetation Index (RVI)	$\frac{NIR}{R}$	Major et al., [44]
	Normalised Difference Salinity Index (NDSI)	$\frac{(R-NIR)}{(R+NIR)}$	Khan et al., [45]
	Enhanced Vegetation Index (EVI)	$\frac{2.5(NIR-R)}{(NIR+R+L)\times(1+L)}$	Liu and Huete, [46]
	Soil Adjusted Vegetation Index (SAVI)	$\frac{(NIR-R)}{(NIR+R+L)\times(1+L)}$	Huete, [47]
	Salinity Index (SI)	$\sqrt{BLUE}\times\sqrt{R}$	Khan et al., [45]
	Salinity Index (SI1)	$\sqrt{G}\ X\ \sqrt{R}$	Khan et al, [45]

Geostatistical techniques have been widely used to map SOC content. Digital signatures are identified using various satellite imagery band combinations. Different slopes, soils, and land use categories have different amount of SOC content which can be analyzed using the GIS and RS techniques. Till date many geostatistical techniques were used to analyse the spatial distribution of SOC Kumar et al., [55,56]. But, classical statistics could not give accurate results because some areas remained unsampled. As a result, geostatistics has come out to be an appropriate method of ex3ecuting soil properties Saito et al., [57]; Liu et al., [58]; Behera and Shukla, [59].

Different researchers had different opinions about the various interpolation techniques for analysing the spatial variability of soil organic carbon. Earlier researchers applied geospatial techniques Wei et al., [60]. Zare-mehrjardi et al. [61] described that ordinary kriging (OK) and co-kriging to be better than inverse distance weighting (IDW) method. Robinson and Metternicht [62] used kriging, IDW and Radial basis function (RBF). Pang et al. [63] reported that ordinary kriging to be the best technique. Hussain et al. [64] reported that Empirical Bayes kriging (EBK) as best method for estimation of total dissolved solids (TDS) in water. Bhunia et al.[49] showed that OK interpolation method was better than geo-statistical and deterministic methods, whereas IDW method depicted the most results. Kumar et al. [48] presented an equation involving the use of NDVI to evaluate the organic carbon content. The NDVI reflects the measure of vegetation condition and amount Velmurugan and Carlos, [65].

Table 2. Various geospatial techniques used for assessment of soil properties

Sr. no.	Soil properties studied	Data / tools used	Advantages / limitations	References
1.	Soil organic carbon (SOC)	IRS P-6 satellite LISS III sensor	Estimated SOC using geospatial methods and relation of SOC with NDVI and soil pH. However, further research is required by incorporating long-term multi-factor experimental design for other environmental variables.	Kumar et al., [48]
2.	Sloi salinity, moisture and pH	Landsat-8	Soil pH was successfully estimated, but improvement in extraction methods required to explain uncertainties of relation of soil pH with moisture, salinity and temperature. But spectral and spatial resolution of Landsat-8 data is limited, thus other data with better properties should be considered.	Ghazali et al., [43]
3.	Soil moisture	Radar Sentinel-1 and Landsat-8 optical and thermal band data	Spatial pattern of crops grown should also be considered as soil moisture is related with type of crops grown.	Mohamed et al., [2]
4.	Soil organic carbon (SOC)	GIS, GPS, Spatial interpolation techniques viz. Inverse distance weighting (IDW), Local polynomial interpolation (LPI), Radial basis function (RBF), Empirical bayes kriging (EBK) and ordinary kriging (OK)	OK was found superior over other methods whereas IDW gave worst results	Bhunia et al., [49]
5.	Soil moisture	Landsat 4,5,8 satellites, Thematic mapper	Successfully predicted moisture percent of areas where *insitu* measurements are not available.	Zakir, [42]
6.	Soil salinity	Ikonos and Landsat-5 (3 visible bands (1,2&3), 2 NIR (4&5) and 1 MIR (7) band, ERDAS Imagine 8.7	Provided accurate methodology for estimating soil salinity using geospatial techniques.	Eldiery et al., 2008
7.	Soil moisture	GIS, Interpolation methods viz. inverse distance weighting, kriging, co-kriging	Co-kriging generated the most accurate soil moisture map	Gharechelou et al., [50]
8.	Soil salinity, pH and nutrient	Landsat 5 TM, GIS	Examined relation between soil salinity level and soil reaction as well as , and factors affecting soil properties (Na and K contents, land inclination)	Gloweinka et al., 2016

3.2 Soil pH

Soil pH is a very important soil property as it affects various chemical, physical and biological characteristics of soil and other plant growth processes. The soil analysis done by Denton et al. [66] showed that pH had no notable difference ($p < 0.05$) at two depths i.e. 0–20 cm and 20–40 cm and three locations, which were plotted and interpolated with the help of kriging interpolation algorithm methods. Ghazali et al. [43] collaborated the soil data obtained from survey and laboratory with Landsat 8 satellite images to formulate multiple regression model named the soil pH Index (SpHI). The results of these models showed 4.49–7.59 of soil pH, 4.66 in bare soil model and 6.62 in paddy leaf model. According to Goto [67], soil pH gradually increased from initial value of 5.5. Pittman et al. [68] carried out regression analysis between the field data and pixel value of Landsat 8 bands. The models developed were used to calculate soil pH by carrying out the accuracy assessment.

3.3 Soil Nutrient

Assessment of soil nutrient status using geospatial technology is of paramount importance for soil productivity, agricultural sustainability and food security Peng et al., [8]. The vegetation spectral response is used to deduce various soil conditions such as nutrient differences, water-holding capacity and eroded locations. McMurtrey et al. [30] used laser-induced fluorescence (LIF) and passive reflectance measurements in the laboratoryand observed differences in maximum intensity of fluorescence at 440 nm, 680 nm and 780 nm which came out to be related to different levels of N fertilization in corn. Krishan et al. [69] used soil probe to collect soil samples and a small wooden rod for the removal of soil core from the tube. Detailed micro and macro nutrients such as Calcium carbonate ($CaCO_3$), pH, EC (dsm^{-1}), organic carbon (%), nitrate, potassium, phosphorous, iron, manganese, copper andzinc were measured by Orion iron electrodes using general procedure to observe the soil nutrients behavior. The map was scanned and geo-referenced using ArcGIS software. The layout of the map was prepared with latitude and longitude for better understanding and more information. Similarly, Peng et al. [8] introduced a GA-BPNN method to improve the estimation accuracy of soil nutrient contents.

3.4 Soil Moisture

Spatial variability in soil moisture is influenced by complex interaction of various environmental factors viz. land use, topography, soil properties, precipitation, radiation and vegetation etc. De Benedetto et al., [70]; Yao et al., [71] that vary immensely over time, thus rendering high temporal variability apart from the spatial one. Therefore, it is tremendously important to estimate not only the total amount of water present in the soil but also its spatial and temporal distribution within the soil. This is achieved through the application of geoscientific tools. Newly emerging technologies in remote sensing such as thermal infrared, optical, passive and active microwave (with high penetration potential) have increasingly widened the concept of land surface and other associated parameters. Thermal infrared/ thermal imaging radar(TIR) and optical sensors have a wide coverage and produce fine spatial resolution. Nevertheless, the surface penetration is minimum and the measurements are often obstructed by clouds and vegetation, which weakens its relationship with the soil moisture. The microwave sensors, on the other hand with a higher penetration potential up to 5 cm, are not affected by the clouds. Hence, they can be effectively used to produce higher spatial and temporal resolutions under all weather conditions with improved physical basis.

The estimation of soil moisture is drawn from scattered point measurements occurring at discrete intervals. Also, the procurement of precise soil moisture measurements, designs and locations of soil samples encompasses a crucial step. For this, spatial interpolation and geospatial techniques act asmost practical tools Marin et al., [72]; He et al., [73]; Diana et al., [74]. The application of GIS provides a full-fledged package of tools including geo-ecological monitoring, mapping, evaluation and ultimately the spatial analysis e.g, merging, filtering and overlaying etc. This effectively exposes the spatial interactions between several physical attributes of soil viz. type of soil, geology, vegetation cover etc. Grunwald et al., [75]; Kevin et al., [76]; Harahsheh and Tateishi, [77].

Various researchers have produced soil moisture measurements using Land Surface Temperature (LST) and soil reflectance Haas, [78]; Wang et al., [79]; El-Zeiny and Effat, [80]. Further, moisture of surface soil can be calculated from Normalized Difference Vegetation Index (NDVI) and land surface temperature (LST) or simply their integration called as triangle method Zeng et al., [81]; Petropoulos et al., [82]. These methods are based on thermal emissions or surface reflectance thus, forming the thermal and optical remote sensing Amato et al., [10]; Rahimzadeh-Bajgiran et al., [12]; Hammam and Mohamed, [11]. Koparan [83] employed optical remote sensing and synthetic aperture radar (SAR) to predict the total soil moisture.

Gillreath-Brown et al. 2019 developed the Soil Moisture Proxy Model (SMPM) which is a geospatial soil moisture model that processed the topographic and other soil variables to compute soil moisture potential over a watershed. In an experimental study by Gharechelou et al. [50], several geospatial processing techniques were used to collaborate various geo-environmental layers viz. land use, rainfall, soil type, geology, topography etc. into homogeneous land unit area (LUA) map. The LUA sampling and geostatistical interpolation techniques (e.g. Inverse distance weighting (IDW), co-kriging and kriging) resulted in the most accurate soil moisture database and map in the arid region. Likewise, van Leeuwen [41] took use of Medium Resolution Imaging Spectroradiometer (MODIS) in addition to data products to generate index maps of soil moisture. The products were NDVI and LST, both of which were based on vegetation Satellite index and daily moderate resolution LST. The soil moisture maps hence generated enabled the constant monitoring of spatial and temporal soil moisture variation across a larger area. Moreover, soil moisture as a parameter can be used to obtain useful information on drought and flood indicators when successfully merged with pedological, climatological, meteorological and other geomorphological databases.

3.5 Soil Salinity

Heavy salinization of soil is one of the most usual land destruction processes that deteriorates the overall productivity of crops. The substantial amount of salts adversely influence the crop growth, soil health and water quality which leads to poor agricultural sustainability, environmental health and eventually the economic viability Zhu et al., [84]; Corwin et al., [85]. It is complex process that relies upon various factors such as soil type, land cover, climate, topography, type of vegetation, soil management practices, hydraulic conductivity, groundwater level, quality of irrigation water, etc. Wang et al., [86]; Ma et al., [87]. In agricultural fields, soil salinity exhibits wide variability both spatially and temporally. Therefore, for improvised application of various soil reclamation practices and subsequent prevention of salinization requires adequate and in-depth information on spatial and temporal characteristics of soil salinity. Traditionally, soil salinity has been assessed through extraction of in situ soil samples and their analysis in the laboratory to determine the electrical conductivity. However, since dense sampling is needed for adequate characterization of the spatio-temporal variability, such soil sampling methods are relatively time- consuming and expensive Brunner et al., [88]; Dehaan and Taylor, [89]. On the contrary, the use of modern geospatial technologies, solute transport models and geophysical sensors Farifteh et al., [90] have potentially outperformed the conventional methods. These professional techniques offer comparatively rapid assessment and mapping of soil salinity. The geophysical sensors are progressively used for rapid and cost-effective quantification of the electrical conductivity Nosetto et al., [91].

The remote sensing techniques have been increasingly implemented for monitoring and mapping the soil salinity. Multispectral data such as Landsat, SPOT, IKONOS, QuickBird and the Indian Remote Sensing (IRS) series of satellites, as well as hyper-spectral data such as EO-1 Hyperion and HyMap, are highly useful in detection and mapping of soil salinity Farifteh, [92]; Weng et al., [93]; Teggi et al., [94]; Koshal, [95]; Dehni and Lounis, [96]; Setia et al., [97]; Dwivedi et al., [98]. Soil salinity can be detected from remote sensing data using different direct and indirect indicators. The direct indicators include the visible salt layer on the soil surface whereas the indirect indicators are halophytes growing in the salt challenged soil. As remote sensing makes use of electromagnetic radiations reflected from target areas to produce detailed information regarding the Earth’s surface. Therefore, depending upon this concept, the remote sensing is used to study the spectral reflectance from the thick salt encrustations present on the soil surface. For instance, Schmid et al. [99] observed the strong spectral reflectance of soil crusts in the visible and near-infrared region.

Singh and Sirohi [100] demonstrated that in reflectance from salt surface is higher than the non-saline surface, which was further confirmed by Rao et al. [27]. Nevertheless, complications arise when the salt crusts and efflorescence integrate with other soil components viz. organic matter, vegetation, high soil moisture, soil texture etc. and as such are not visible. Moreover, Metternicht and Zinck [101] revealed that the surface roughness or color of salt crust possibly interfere the reflectance in the visible and NIR range. In such conditions, the direct method may result in imprecise measurements both in space and time scales Metternicht and Zinck, [101]. But, the visible presence of halophytes on the soil surfaces interestingly serve as an indirect indicator of the soil salinization, thereby, making it practicable to detect, monitor and mapthe salt affected areas. However, the spectral features of vegetation differ with diverse environments such as type of soil, vegetation cover and type etc. under normal conditions, unhealthy or poor vegetation with lesser photosynthetic activity, leads to lowered near infrared reflectance (NIR) and augmented visible reflectance from the salt stressed plants Allbed et al.,[102]; Wang et al., [103].

Hence, based on the observation of this pattern, various vegetation indices (VIs) including Soil Adjusted Vegetation Index (SAVI) and Normalized Differential Vegetation Index (NDVI) or simply Salinity Index (SI) and Normalized Difference Salinity Index (NDSI) are used by several researchers to detect and map soil salinity. Other crop/vegetation indices include Ratio Vegetation Index (RVI), the Green Vegetation Index (GVI), Soil Brightness Index (SBI) and the Wetness Index (WI). These have been extensively used in experimental studies on soil salinity Alhammadi and Glenn, [104]; Zhang et al., [105]; Wang et al., [106]. Advantages of remote sensing data include wide coverage, cost-effective, rapid and timely provision of soil salinity maps in addition to multispectral image with medium to high resolutions Allbed and Kumar, [107]; Metternicht and Zinck,[101].

El Bastawesy and Ali [108] also applied GIS/RS techniques for the salinity assessment and problem of rising groundwater. Wang et al. [109] estimated the soil salinity of agricultural oasis at catchment scale. For over four decades, the potential of GIS and RS was combined to analyze the spatial changes in various soil attributes viz. electrical conductivity (EC) and exchangeable sodium percentage (ESP). The experimental study highlighted that the ESP and EC showed spatial deviation with drainage and soil depths giving rise to huge decline in the soil salinity Güler et al., [110]. Choubey [111] analyzed the extent of salinization and water table rise using remote sensing in Gujarat, India.

Solute transport model is based on the concept of water flow modeling. Its calibration requires vast data and various other parameters viz. solute transport parameters, soil hydraulic parameters, and initial and boundary conditions, which are commonly attained from in-fieldobservations and GIS/RS data (field to regional scale). However, the model resolution intensively depends upon the resolution of input datathus, necessitating the integration of several different approaches for the full -fledged comprehension of spatial and temporal features of soil salinity Metternicht and Zinck, [101]; Aldabaa et al., [112]. The combined use of remote sensing and GIS techniques are relatively more advantageous than used singly Gossel et al., [113]. These combined approaches were developed for multi-perspective and more comprehensive understanding. Ren et al., [114] applied the integrated approach and conducted soil sampling at multiple scales, then the spatial data was processed and analyzed using GIS/RS and finally the details of sail salinity dynamics were further quantified through solute transport model.

4. CONCLUSION

This review highlighted that advances in the field of geospatial technology have enabled the assessment of spatial variability in soil characteristics at regional scale from satellite data. Various spectral indices have been devised for retrieval of different properties of soil from spectral reflectance data, which are able to estimate various properties quite accurately. Hyper spectral remote sensing and various spatial interpolation techniques have lead to assess spatial distribution of soil characteristics so precisely. Such techniques can be used successfully for retrieval and spatial interpolation of various soil properties, which can be highly beneficial in site specific management leading to improved input use efficiency and sustained agricultural productivity for future food security.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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