Chapter

Use of Geoinformatics Techniques for the Assessment and Mapping of Soil Salinity: Concepts and Applications

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Abstract

Irrigated agriculture has a major impact on the environment, especially soil degradation. Soil salinity is a critical environmental problem, which has great impact on soil fertility and overall agricultural productivity. Since, soil salinity processes are highly dynamic, the methods of detecting soil salinity hazards should also be dynamic. Remote sensing data are modern tools that provide information on variation over time essential for environmental monitoring and change detection, as they also help in the reduction of conventional time-consuming and expensive field sampling methods, which is the traditional method of monitoring and assessment. This chapter thus reviewed the concepts and applications of remote sensing, GIS-assisted spatial analysis and modelling of the salinity issue in irrigation fields. Generally, compared to the labour, time and money invested in field work devoted to collecting soil salinity data and analysis, the availability and ease of acquiring satellite imagery data and analysis made this concept very attractive and efficient.

Keywords: soil salinity, empirical model, salinity model

1. Introduction

Since civilization, irrigation has enabled societies to produce sufficient food, as irrigated agriculture has contributed immensely to increased food production and improved quality of life for millions over the past years [1]. According to Thomas [2], irrigation represents an alteration of the natural conditions of the landscape by extracting water from an available source, adding water to fields where there was hitherto little or none, and introducing man-made structures and features to extract, transfer and dispose water, while achieving the main objective of providing plants with sufficient moisture. All methods of irrigation are prone to affect the environment negatively if not properly managed. Surface irrigation methods could lead to waterlogging, which degrades the plant root environment and thus leads to increase in soil salinity and erosion [3]. In addition, the sprinkler method may lead to soil structure destruction due to impacts of water drops and crust formation on the soil [4]. The realisation of the adverse effects, the need to avoid them and to ensure long-term benefits of projects led to the concept of sustainability. Thus this chapter critically reviewed the concepts and applications of geoinformatics techniques for the assessment and mapping of soil salinity.

2. Irrigation and agricultural soils

Irrigation development and practices have been observed to have adverse impacts on the physical and chemical properties of soil and the environment in general. According to Amdihun [5] some of the adverse impacts of irrigation schemes on soils include salinisation, alkalization, waterlogging, soil pollution and soil acidification. These have adverse effects on sustainable soil productivity, especially if not regularly monitored and assessed. Soil salinity is a major environmental factor limiting productivity of agricultural lands and has been observed as a major adverse effect of irrigation. It has been known to cause destruction of many agricultural projects [6]. The application of irrigation water even when considered to be of excellent quality is a major source of soluble salts and leads to input of salts onto the soil. According to Sharma and Rao [7], these accumulated soluble salts content in the soil is called soil salinity and they cause land degradation and affect food production resulting into toxicity to sensitive crops at high concentration. This problem does not only reduce agricultural productivity but also has a consequential effect on the livelihood strategies of small farmers [8]. Although salinisation is a natural process, which accompanies irrigation practice, proper irrigation management can prevent salt accumulation by providing adequate drainage to leach soluble salts from the soil and constantly lower the water table. Tsutsi's [9] study reported that about 2.1 million ha of irrigated land in Central Asia is affected by salinisation and nearly 1.0 million ha of land has been abandoned to prevent further soil degradation. A study by Stockle [1] indicated that about one-third of the irrigated land in the major irrigation countries of the world is already badly affected by salinity. The estimates showed that 13% of the irrigated lands in Israel, 20% from Australia, 15% from China, 50% from Iraq and 30% from Egypt have been affected by salinity. In India alone, Singh [10] reported that 3.4691 million ha of land has been seriously affected by salt. The effect of salinity on irrigated lands was documented by Surujmia [11] as shown in **Table 1** for top five irrigation countries in the world in the mid-1980s.

2.1 Soil salinity

The United States Department of Agriculture (USDA) according to Richards [13]defined electrical conductivity of the saturation extract of soil (ECe), pH of the saturated soil paste (pH) and exchangeable sodium percentage of the soil (ESP) of saline soils as ECe more than 4 dS/mat 25°C, pH less than 8.2 and ESP less than 15.

Country	Area damaged Million ha	Share of irrigated land damaged %
India	20.0	36
China	7.0	15
United States	5.2	27
Pakistan	3.2	20
Soviet Union	2.5	12
Total	37.9	24
World	60.2	24

Source: Surujmia [11] (adapted from Postel [12]).

Table 1.
Irrigation land damaged by salinity in the mid-1980s.

He also defined sodic soils having pH more than 8.2 and ESP of 15 or more. Based on USDA classification, ECe may be high for salts capable of alkali hydrolysis, while saline-sodic soils have pH greater than 8.2 at 25°C, ECe greater than 4 dS/m and the ESP greater than 15. These soils are often formed due to a combined process of salinisation and sodification. Thomas [14] classified salt-affected soils according to EC (electrical conductivity), SAR (Sodium Adsorption Ratio) and pH of the soil extract (**Table 2**).

2.2 Soil salinity assessment

Saline fields can be simply identified by the presence of spotty white patches of precipitated salts. Such precipitates usually occur in elevated or non-vegetated areas, where water evaporates and leaves salt behind.

2.2.1 Field measurement

Soil salinity is measured on the field by its electrical conductivity (EC). The SI unit of EC is dS/m and is measured with hand-held conductivity meter. Soil salinity on a large scale is mapped with an electromagnetic (EM) conductivity meter [15]. **Table 3** gives the criteria for soil salinity and sodicity measurement.

2.2.2 Geoinformatics techniques

Salinity is a dynamic process and to assess the extent of salinity, modelling is often required. Geoinformatics approach is a modern technique, which involves the combinations of global positioning system (GPS), satellite remote sensing data (SRS) and geographical information system (GIS) modelling tools. Geoinformatics involves the acquisition, processing, analysis and management of geographic or spatial information. Spatial information is concerned with knowing what (object) is where (space) and when (time). Data are usually collected using techniques such as GPS, remote sensing, orthography, total station and the use of the more traditional surveying equipment such as theodolite, level. Among these techniques, the newer and more prominent of them are the GPS and remote sensing [16].

	EC (mmhos/cm)	pH	SAR
Saline soil	>4	<8.5	<13
Sodic soil	<4	8.5–10	>13
Saline-sodic soil	>4	<8.5	>13

Source: Thomas [14].

Table 2.
Classification of salt-affected soils.

Key to degree of salinity/sodicity	Salinity ECe (dS/m)	Sodicity pH	ESP
Slight	4–8	8.2–9.0	<15
Moderate	8.25	9.0–9.8	15–40
Strong	>25	>9.8	>40

Source: Adapted from Ojo [15].

Table 3.
The criteria for soil salinity and sodicity.

2.2.2.1 Global positioning system (GPS)

GPS is a satellite positioning and navigating system technology that continues to gain wide usage and applications worldwide. Input of data directly on the field this way, saves time and greatly facilitates subsequent processing. The GPS data logger permits direct interfacing with GIS, the data base management system (DBMS) for spatial analysis [17].

2.2.2.2 Geographical information system

A computer system for the input, editing, storage, maintenance, management, retrieval, analysis, synthesis and output of geographically referenced or spatial information is defined as a GIS [18]. Ojo [15] stated that GIS is a tool used to analyse and interpret the remotely sensed data. It can also be used for the analysis and interpretation of physically collected data as well. A model is a representation of reality; models can help understand, describe or predict how things work in the real world. According to ESRI [18], there are two types of models, namely those that represent the objects in the landscape (representation models) and those that attempt to simulate processes in the landscape (process models). Representation models describe the objects in the landscape, such as buildings, streams or forest, while process models describe the interaction of the objects that are modelled in the representation model. Process models include suitability modelling, distance modelling and hydrological modelling [15].

2.2.2.3 Satellite remote sensing (SRS) concepts

Monitoring environmental changes is quite difficult with the traditional method of surveying. In recent years, satellite remote sensing techniques have been developed, which have proved to be of immense value for preparing accurate land use/land cover maps and monitoring changes at regular intervals of time [19]. This technique, in cases of inaccessible region, is the only method of obtaining the required data on a cost- and time-effective basis. In this technique, a remote sensing device records reflective response, which is based on many characteristics of the land surface, including natural and artificial cover. In addition, an interpreter uses the element of tone, texture, pattern, shape, size, shadow, site and association to derive information about land cover. It is often believed that no single classification could be used with all types of imagery and all scales as information about change is necessary for updating land cover maps and the management of natural resources and such information may be obtained by visiting sites on the ground and or extracting it from remotely sensed data [20]. Change detection is defined by Singh and Dwivedi [21] as the process of identifying differences in the state of an object or phenomenon by observing it at different times. Monitoring and managing natural resources and urban development is an important change detection process because it provides quantitative analysis of the spatial distribution. Detecting the changes that have occurred in the process involved identifying the nature of the change, measuring the area extent of the change and assessing the spatial pattern of the change [22].

3. SRS application for mapping of salt-affected soils

Application of satellite remote sensing for surveying and mapping of salt-affected areas began with the use of photography (black and white). The relatively bright appearance provides the information about salinity due to the efflorescence of salt crust [21]. The aerial photographs have been used to delineate units based on the combination of geomorphologic differences and differences in greytones. Attempts were also made to relate the differences in the greytones with the salt content [23]. In addition, indirect features like landscape may help to identify the problems of soil salinity. Relative elevation is one of the most evident landscape features in relation to salinity and moisture provided by saline and shallow groundwater table. Satellite remote sensing (SRS) data are modern tools that provide information on variation over time essential for environmental monitoring and change detection in mining areas [24–26]. SRS also helps in the reduction of conventional, time-consuming and expensive field sampling methods, which are the traditional methods of monitoring change detection [27–29]. Dehaan and Taylor [30] used field-derived spectra of salinized soils and vegetation as indicator of irrigation-induced soil salinisation for identification of saline soil regions. In a study using spectral un-mixing method in snow cover estimation, NOAA-AVHRR data was used to examine the ability of real times now cover estimation at sub-pixel level [15]. Also, Okin and Roberts [31] showed the used of multiple end member spectral mixture analysis (MESMA) in retrieving information about soil. He showed that MESMA is capable of mapping soil surface types even when vegetation type cannot be reasonably retrieved. McGwire et al. [32]compared linear mixture model based on calibrated atmospherically corrected hyper spectral imagery to show its relative ability to measure small differences in per cent green vegetation cover for the areas of sparse vegetation in arid environments. Metternicht and Zink [33] reported that multi-temporal optical and microwave remote sensing can significantly contribute to detecting temporal changes of salt-related surface features. Bastiaanssen [34] reported the IWMI review of different RS applications for water resources management. According to him, bands in the near- and middle-infrared spectral bands give information on soil moisture and salinity [35, 36]. A salinity index based on greenness and brightness indicating leaf moisture influenced by salinity, with classical false colour composites of separated bands or with a computer-assisted land-surface classification can be used to identiy salinized and cropped areas [37–40]. In order to detect soil salinity anomalies, some studies used the brightness index appearing at high levels of salinity with TM bands 5 and 7 as the best in showing the physiological conditions of a crop while, TM bands 3 and 4 are better suited to describing overall crop development [40–43]. Most of these studies were based on multispectral scanner (MSS) and thematic mapper (TM) data because the Satellite Probatoire d'Observation de la Terre (SPOT) and Indian *Remote Sensing* Satellite (IRS)'s sensors used have no bands greater than 1.7 mm. In another study by Joshi and Sahai [44], they discovered that TM with an accuracy of 90% for soil salinity mapping was better than MSS, which has 74% accurate. Thus, comparing the accuracy of TM, MSS, and SPOT, TM was found to be the best multispectral radiometer for soil-salinity mapping and thus TM was better in application [45].

3.1 SRS applications in different countries

Johnston and Barson [46] found that the application of SRS in Australia for the identification of saline areas was most successful during peak vegetation growth and also in other periods but salinized areas with low fractional vegetation cover could not be distinguished from areas that were bare because of overgrazing, erosion or ploughing. However, Siderius [47] concluded the opposite, that is, salinity is best seen at the end of irrigation or the rainy season when the plots are bare. In another study by Johnston and Barson [46] on SRS applications in Australia, they found that discrimination of saline areas was most successful during peak vegetation growth. It was also discovered that salinity was best expressed at the end of the irrigation or rainy season with bare plots. In a study in Punjab, India by Venkataratnam [48] using MSS images of pre-monsoon, post-monsoon and harvest seasons to map soil salinity, he concluded that the spectral curves of highly and moderately saline soils change considerably during the annual cycle, which significantly complicates the time-compositing procedure. In another study by Vincent et al. [40] in Pakistan, which was based on a classification-tree procedure, the first treatment was to mask vegetation from non-vegetation using normalised difference vegetation index (NDVI). Thereafter, the brightness index was calculated to detect moisture and salinity on fallow land and abandoned fields. His approach was suitable for locating blocks that had malfunctioning drainage networks and that were based on these two classes; the levels of soil salinity could be mapped with an accuracy of 70%. Areas of high salinity were 66% accurate and non-saline areas were 80% accurate. Goossens and Ranst [49] as reported in Salman [50] analysed the beginning, middle and end of the growing season in the western Nile Delta and concluded that single image may be suitable for detecting severely salinized soils, but more gradations can be determined using temporal images.

Different studies by researchers on direct observations on bare soils and indirectly by vegetation cover as reported by IDNP [51] showed that for the visible part of the spectrum, the soil reflectance of salt cover areas was found to be prominent. The bands in the middle infrared gave information of moisture content, because they are often associated with salt content differences. The report depicted that lack of vegetation or scattered vegetation and highly salt-affected soil surfaces make it possible to directly detect salt on the surface. The main factors affecting the reflectance are the quantity and mineralogy of salt, moisture, colour and roughness as indicated by ground observations and radiometric measurements as the evaluation of soil surface remains under the influence of external factors such as ground water quality, variation of depth, wetting/drying cycles and wind. Metternicht and Zinck [52] through their study stated that the main factors affecting the reflectance are the quantity and mineralogy of salts together with soil moisture, soil colour and terrain roughness, which in turn are controlled by different combinations of salts and type of soil surface, texture and organic matter content as measured with ground observation and radiometric measurement in the visible and near infrared wavelengths.

The SPOT spectral data, soil morphological, physical and chemical properties when analysed showed that many surface and some subsurface soil properties were significantly correlated. The ratio of the values in red and infrared band seems to be a better technique to employ when subsurface soil properties are of interest using brightness index, which has proved to be a more useful spectral parameter if surface soil properties are to be extracted from satellite data. The near and middle infrared bands give reasonable information on soil moisture and salinity [36]. The spectral behaviour of salt-affected soils when compared to normal cultivated soils showed relatively high spectral response in visible and near infrared regions as the new ratio is immune to colour variations and provides an indication of leaf water potential. Because the vegetation cover modifies the overall spectral response pattern of salt-affected soils especially in the green and red spectral bands, strongly saline-sodic soils were found to have higher spectral response as compared to moderately saline-sodic soils.

Spatial resolution has significant effect on enhancing the identification of salt-affected soils and crops. Steven et al. [53] stated that based on some past research in comparing the accuracy of TM, MSS and SPOT, they found TM to be the superior multispectral radiometer for soil salinity mapping and that digital classification techniques can also help in improving the identification and mapping of salt-affected soils or crops. According to Salman [50], excess soil moisture can cause a change in soil colour and a change in soil reflectance properties being detected by remote sensing and accumulation of organic matter; soil colour is generally darker in poorly drained areas than well-drained soils. The visible bands in Landsat-MSS data can be used to identify this colour. Baber [54], as cited in IDNP [51], pointed out that colour infrared photography could indicate drainage problems by soil moisture saturation or plant stress. Shallow water tables exhibit an increase in surface moisture, which can be detected from visible reflectance and microwave emissivity.

3.2 SRS Landsat and other sensors

With the launching of the Landsat Satellite 1972, researchers began to use satellite data for monitoring mining activities in different parts of the world [23]. The applicability of Landsat imagery for monitoring soil-salinity trends was tested in two areas of Punjab and Sindh, India using black-and-white mosaics of Landsat MSS band 5 at a of scale 1: 250,000 during the months of March, April and December, thereafter were visually interpreted and compared with surface salinity maps of the same scale. As reported by WAPDA [55]. Sahin et al. [56] used three Landsat geo cover datasets from 1970 to 2000 to detect temporal changes in the Zonguldak coal test field. Landsat MSS was discovered for the identification of broad land cover changes of the Western part of Horqin steppe, Inner Mongolia Autonomous Region [57]. Landsat images were used for studying land use dynamics and soil degradation in Tamduong district of Vietnam by van Trinh et al. [58]. Landsat data from 1976 to 2002 were used to detect changes in land cover in the Yazd-Ardakan basin, Iran [59]. The analysis of land cover change of the Oil Sands Mining Development in Athabasca, Canada was carried out by Latifovic et al. [60] using information extraction method applied to two Landsat scenes. Vegetation and brightness indices derived from SPOT XS were used to classify salinity for vegetative and non-vegetative areas by Vidal et al. [61] and Tabet [62]; the results were used to identify highly saline and non-saline areas. Cialella et al. [63] used the combined GIS/RS approach for predicting soil drainage classes that does not focus on soil salinity, but can be modified for salinity detection using airborne NDVI data, digital elevation data and soil types. The problem of spectral similarity where the dull-white tones of salt-affected and sandy soils have been difficult to distinguish was studied by Verma et al. [64] by combining the TM false colour composite (FCC) bands 2, 3 and 4 with thermal data at 10.4–12.5 mm to solve it. Salt-affected soils in Etah, Aligarh, Mainpuri and Mathura districts were classified into S1: <10% of the salt-affected area, S2: 10–30%, S3: 30–50%, S4: 50–75% and S5: >75%, using the integrated approach to image interpretation. It was discovered that data between March and first week of April were significantly better because of maximum contrast. The standard deviation and correlation coefficient values of TM data were used to compute a statistical parameter called the optimum index factor (OIF) in order to identify the most appropriate three-band combination of Landsat TM reflective-band data for identifying salt-affected soils [65]. Three bands combination of 1, 3, and 5 was found to be the best in terms of information content. The validation of results revealed a mixed relationship between rankings obtained from OIF values and estimated accuracy. The potential of image transformations such as principal-component analysis (PCA), rationing and image differencing to detect changes in extent and distribution of salt-affected soils using Landsat MSS data for 1975 and 1992 to study the alluvial plains of Uttar Pradesh was demonstrated by Dwivedi and Sreenivas [66]. Results indicated that the third principal component, image differencing and rationing of the first two bands provided substantial information about behaviour of salt-affected soils over time in the two periods. A synergistic approach to map salt-affected surfaces, combining digital image classification with field observation of soil-degradation features and laboratory determinations was carried out by Metternicht and Zinck [33]. In order to obtain the highest separability between salt- and sodium-affected soils, Landsat TM bands 1, 2, 4, 5, 6 and 7 were combined to result in an overall accuracy of 64% while for some soils 100% accuracy was obtained. To compare differences in salt-affected and waterlogged lands before and after implementation of the SCARP-1 programme, Chouchri et al. [67] used aerial photographs from 1953 to 1954 and 1976. Their study concluded that the waterlogged areas had decreased in extent but had often become saline and that large areas with salt-affected soils were still out of cultivation leaving only small patches of slightly saline soils under cultivation. Dean et al. [68] used processed satellite images for change detection in order to monitor expansion of mining activity and its progressive reclamation and to support environmental management, monitoring and sustainable development reporting of the Shell Canada and Albian Sands mine operations in northern Alberta, Canada. Therefore, data collected by the MSS and TM will continue to be used as a historical global database [69], but updated and newer sensors with greater spectral/temporal resolution will allow even more precise land cover classification.

3.2.1 Radiometric correction

Many studies have shown the wide application of Landsat images being used for land cover mapping and the creation of vegetation inventories at different spatial scale information on the earth's surface characteristics [70, 71], despite the existence of limitations in the use of Landsat data for multi-temporal studies because of problems in obtaining homogeneous time series. Efforts have been made in the past to reduce non-surface noise in Landsat images and to calibrate the sensor to correct radiometric trends [72] and reduce the influence of topography [73, 74]. According to Schroeder et al. [75], other studies have shown that the application of accurate sensor calibrations and complex atmospheric corrections does not guarantee the multi-temporal homogeneity of Landsat datasets because complete atmospheric properties are difficult to quantify, and simplifications are commonly assumed. There are many protocols proposed in pre-processing multi-temporal Landsat datasets [76]; these protocols are geometric correction, calibration of the satellite signal to obtain top of the atmosphere radiance, atmospheric correction to estimate surface reflectance, topographic correction and relative radiometric normalisation between images obtained on different dates. Prior to geometric processing, radiometric processing is recommended to be done, since this re-sampling step generally *smoothens* the dataset [77]. Some studies have analysed the role of complete radiometric correction protocols in processing multi-temporal Landsat data when a number of different vegetation processes are of interest. Their results found out that land classification and forest succession serve as a function of the radiometric correction applied [75, 78]. Radiometric correction and geometric correction processes are required to obtain accurate time series of Landsat imagery.

3.3 Soil salinity digital analysis and modelling

The process of delineation of salt-affected soils under bare condition and cropped condition using remote sensing investigation has enabled the soil salinity analysis, mapping and modelling. A brightness index is meant to detect high levels of brightness appearing at high levels of salinity; thus salinity index based on greenness and brightness that describes leaf moisture as influenced by salinity salinized and cropped areas can be identified with classical false colour composites of separated bands, or with a computer-assisted land surface classification [39, 40]. The unique patterns of geomorphologic shapes are thought to be helpful in discriminating the salinisation process from a physiographic perspective. A review by

Salman [50] stated that the application of remote sensing in contextual classifier for soil salinity mapping with a built GIS to link the location of the irrigation feeders and drainage master canals in the western Nile Delta with digital elevation data and satellite classifications is possible. He stated that the distance of field from the main irrigation canals, as well as to the field elevation difference with the main irrigation canals are considered proportional to soil salinity risks. In order to classify three different stages of waterlogging according to simple supervised procedure, TM bands 2, 3, 4, 5, 6 and 7 were used. Salinity can be detected through its impact on the vegetation and vegetation index is a common spectral index that identifies the presence of chlorophyll. A few vegetation indices have been proposed. In the study by Richardson et al. [79], an inverse relationship was observed between reflectance and salinity, as salt content induces less plant cover (decreasing of density, LAI and height) and sometimes slight salt deposition on surface associated with vegetation has similar reflectance as that of normal cropped area. Salt-tolerant plants are good references of salinity level on salt marshes but require good calibration. Contrasted associations of vegetation and bare soils can be more useful for salinity detection than individual surface types. RS information can be improved and modelled when it is integrated with other tools or platforms, for which a GIS is an appropriate tool.

3.3.1 Multi-criteria decision evaluation

Decision theory is concerned with the logic by which one arrives at a choice between alternatives [80]. The recommended alternatives vary from problem to problem. They might be alternative actions, alternative hypotheses about a phenomenon, alternative objects to include in a set and so on. Resource allocation decisions are also prime candidates for analysis with a GIS. Indeed, land evaluation and allocation are the most fundamental activities of resource development [81]. To meet a specific objective, several criteria are to be evaluated. Such a procedure is called Multi-criteria evaluation [82, 83]. One of two procedures most commonly achieves multi-criteria evaluation (MCE). A pair-wise comparison method has been used for the development of weights of the factors in the salt-affected soil analysis. The technique described and implemented in IDRISI is that of pair-wise comparisons developed by Saaty (1997) in the context of a decision-making process known as the Analytical Hierarchy Process (AHP). The first introduction of this technique to a GIS application was that of R*ao* et al. [84]; the procedure was developed outside the GIS software using a variety of analytical resources. In Saaty's technique, weights of this nature can be derived by taking the principal eigenvector of a square reciprocal matrix of pair-wise comparisons between the criteria. Purevdorj et al. (1998) listed the current available methods to assess and model land vegetation cover and biomass from remotely sensed data into three basic methods: spectral mixture models, calibrated cover-radiance relationships and vegetation indices approaches.

3.3.2 Spectral mixture modelling

Linear and non-linear are the two types of mixture modelling. Linear mixture modelling assumes that each field within a ground pixel contributes an amount characteristic of the cover type in that field to the signal received at the satellite sensor and is proportional to the area of the cover type. The use of linear mixture method for modelling soil salinity is difficult because the location of pure end member for the green cover component. Non-linear mixing modelling occurs when radiation transmission occurs through one material and second reflectance occurs from other materials, or there are multiple reflections within or between materials;

thus a non-linear mixing model is needed to be generated to deal with this situation. According to Kimes and Nelson [85], non-linear models are more accurate in some circumstances, but certain non-linear curves or forms should be learned before application.

3.3.3 Cover-radiance relationships

To investigate the relationship between field collected canopy cover data and radiance data, cover-radiance relationship approach is required. Sensor data, such as Landsat TM, MSS and SPOT, are best suited to medium spatial resolution satellite since they require accurate measurement of vegetation cover on the ground covering the same area. This approach has been used in many earlier studies [86–89]. Problems with comparing satellite data and ground measurement include the accuracy of estimating a large area and the efficiency of the model for describing the canopy condition.

3.3.4 Vegetation indices

A vegetation index is a common spectral index that identifies the presence of chlorophyll. Various crop indices have been derived using the fact that chlorophyll strongly absorbs the light energy in the red part and highly reflects in the near infrared part. Research for specific analyses proposed number of vegetation indices [79]. As salt content induces less plant cover, an inverse relationship is observed between reflectance and salinity [79]. Salt-tolerant plants are good references of salinity level on salt marshes but require good calibration. Contrasted associations of vegetation and bare soils can be more useful for salinity detection than individual surface types. Although the soil profile cannot be evaluated on remotely sensed imagery, spectral characteristics of the earth surface features that are indicative of subsurface conditions can be analysed. Because satellite multispectral data denote changes that aid in locating mapping units, they hold great promise for soil surveys and land use planning. Some relationships have been established between soil properties and spectral data; while most of these properties have been from the surface soil, subsurface properties that influence some surface characteristics were considered. Both subsurface and surface conditions are regarded as plant canopy parameters while soil conditions are affected by genetic factors though satellite sensors observe only the ground surface. Therefore, when satellite imagery depicts a pattern based on a different spectral response, it is not unreasonable to attempt some inferences about subsurface soil patterns as limited attempts have been made in the past to identify the waterlogging and soil salinity problems using remote sensing techniques. Therefore, several studies were attempted to develop a methodology for diagnosis of waterlogging and soil and green vegetation have different modes of reflectance characteristics. The mixture of soil, green vegetation and shade in the pixels makes remote sensing of land cover a challenge but red and near infrared have been found to be good at detecting green vegetation [88]. Therefore, most vegetation indices make use of the red and near infrared portions of spectral reflectance. The selection and suitability of a vegetation index is generally determined by its sensitivity to the characteristics of interest [87, 90]. Frequently used vegetation indices include simple ratio (SR), normalised difference salinity index (NDSI), normalised difference vegetation index (NDVI), soil-adjusted vegetation index (SAVI), enhanced vegetation index (EVI), green vegetation index (GVI) and transformed soil adjusted vegetation index (TSAVI) [71, 91]. These indices are not complete without the support of field-collected information.

3.4 Hybrid method: SRS data, field data and GIS tool

The identification and mapping of saline soil is a combination of visual interpretation of photographs, digital analysis of false colour composite (FCC) and digital analysis of surface radiation and vegetation index methods. Ground truth information for calibration and validation is used to consolidate the methods. The combined use of field and spectral data termed hybrid method is highly encouraged as studies have shown that there are high correlations between variation of field-collected variables of vegetation canopy and spectral variation [92–94].

4. Conclusion

This work depicted the concepts and applications in the use of geoinformation techniques for the assessment, mapping and modelling of soil salinity as it relates to irrigated agriculture. It has been shown that the application of RS and GIS combined with field data can be used for mapping and modelling of soil surface salinity in order to generate simple models that can be interpreted in physically meaningful maps in accordance with the subject paradigms. The studies of the use of Landsat TM and ETM+ to map and model soil surface salinity confirmed by the findings of Dimyati [95], Lewis [96] and Goossens et al. [45] that there are close relationships between field data and spectral data and that TM and ETM+ have high detection accuracy compared with MSS and SPOT. The process of mapping and modelling of salinity is necessary for updating land cover maps and the management of natural resources as suggested by Xiaomei and Ronqing [20] since irrigation-induced salinity results in environmental, social and economic impacts of greater damage than benefit to the area [97]. Therefore, maps and models development on salinity are of great importance to planners in monitoring the consequences of land use change and in predicting future changes. Conclusively, a hybrid approach with the combination of supervised classification based on field visits to adjust the parameters is being considered at field salinity levels. Also, since Landsat sensor detects only the salinity on the surface of the soil and gives no detailed idea about the conditions below the surface, the use of overlaying salinity methods using advanced sensors like SPOT, hand-held hyper or aircraft-mounted spectrometer should be applied to increase the accuracy of detection.

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