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Geoinformatics as a Tool for Appraisal of Salt-Affected Soils—A Review

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ABSTRACT

Geoinformatics is application of information technology for study and management of earth resources. It comprises of remote sensing (RS), global positioning system (GPS) and geographic information system (GIS). Salt-affected soils are soils on which most crops cannot make normal growth owing to the presence of excessive soluble salts in the soil solution (saline soils), the presence of exchangeable sodium on surface of the soil particles (sodic soils) or both (saline-sodic soils). Remote sensing has been widely used to detect and map salt-affected areas, since thousands of medium to high resolution imageries from the earth surface are available. In practice, most of these studies have focused on severely saline areas and have given less attention to the detection and monitoring of slightly or moderately affected areas. The major constrain is related to the nature of the satellite images, which do not allow extracting information from the third dimension of the 3-D soil body e.g., where salts concentrate in subsoil. Solute transport modelling is another technique which is used to predict the salt distribution in the subsoil. Remote Sensing and GIS techniques can be extremely useful in accurate mapping and quantification of waterlogged area and salt-affected soils, thereby, helping in preparing a sound database required for taking up various reclamative and preventive measures. Multi-temporal satellite images for continuous monitoring of the waterlogging and salinity dynamics by following integrated analysis of spatial and non-spatial data parameters in Geographical Information System (GIS) are of paramount importance for decision making. The confusions that arise between the effects of salt stress and water stress are removed followed by seasonal application of the Geo-statistical analysis with the Geo-modelling approach and monitoring the variation of the electrical conductivity in the salt affected soil. Out of two modelling approaches used to map soil properties, MARS (multivariate adaptive regression splines) as a non-linear model, exhibited better estimation for all mapped soil properties than PLSR (partial least squares regression), particularly overcoming the deviations occurring between the predicted values and the measured soil values at higher ranges indicating that MARS and PLSR models coupled with ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) spectra are promising tools for estimating and mapping soil properties.

Keywords: Geoinformatics, salt-affected soils, satellite images, multivariate adaptive regression splines, partial least squares regression

INTRODUCTION

Salt affected soils are caused by unnecessary accumulation of salt typically most pronounced at the soil surface. Salt is often derived from geological formations featuring shale, marl, limestone, sylvite, gypsum, and halite. In addition, salts can be transported to the soil surface by capillary action from brackish water tables and accrued due to evaporation. They can also accumulate as a consequence of anthropogenic activities such as fertilization or oil production (Aldabaa *et al*. 2015). Soil salinity is generally measured via electrical conductivity (EC) in soil saturated paste (EC_p), its liquid extract (EC_e), or using different soil to water suspensions (Sonmez *et al*., 2008). Various dynamics processes are involved in salt-affected soils, therefore, the problem of detection, monitoring and mapping of these soils is known to be a difficult subject. However, recent advances in the application of remote sensing technology in mapping and monitoring degraded lands, especially in salt-affected soils, have shown great promise for enhanced speed, accuracy and cost effectiveness (Khan *et al*., 2005).

The ability of space platforms to provide synoptic view of the area makes remote sensing a unique tool for rapid and timely monitoring of earth resources and delineation of salt-affected soils. A wide variety of satellite remote sensing data from multi temporal Landsat – TM & ETM are now available to earth resource scientists for generating information for detection spectral salinity. The combination of remote sensing with the Geographical Information System (GIS) is used for variety data to delineate salt affected soil. The most commonly used technique for a salinity index is the computation of different indices and ratio images using infrared and visible spectral bands in the electromagnetic spectrum (Dehni and Lounis, 2012). Many studies have described and assessed salt-affected soils using satellite, airborne video imagery and land radiometric techniques. A major challenge of remote sensing is to detect different levels of soil salinity and sodicity (Fraser and Joseph, 1998). Several authors demonstrated the advantage of combining data from remote sensing with ground-based geochemical measurements (Bishop and McBratney, 2001; Bouaziz *et al*., 2011; Carre and Girard, 2002). One of the major remote sensing techniques used to monitor crucial environmental problems like salinization is the linear spectral unmixing (LSU) method. It is widely used to estimate the number of reference materials (also called end members), their spectral profiles and their fractional abundances (Bioucas-Dias and Figueiredo, 2010).

To map saline soils, different direct and indirect methods have been developed. Besides detecting altered soil optical properties, salt induced roughness changes and/or modified plant growth pattern can be detected (Szilagyi and Baumgardner, 1991; Dehaan and Taylor, 2003). For the analysis of altered soil optical properties, various analytical techniques have been developed. Methods encompass monovariate regressions to multivariate approaches. Recently, partial least squares regression (PLSR) has been extensively used for quantitative analysis of reflectance spectra (Haaland

and Thomas, 1988). Keeping in view the aforementioned facts, the topic, Geoinformatics as a tool for appraisal of salt affected soils was reviewed.

Application of remote sensing in delineation of salt affected soils

Singh and Srivastav (1990) reported that the salt-affected and waterlogged areas can be detected using microwave radiometers operating at L-band. The brightness temperature shows characteristic variation over salt-affected and waterlogged areas. However, microwave radiometers operating in the frequency range 0.1-1.5 GHz provide a promising solution to map coastal areas. In view of the utility of low-frequency microwave radiometers, satellite-borne radiometers operating within this frequency range should be developed with smaller antenna size for mapping salt-affected and waterlogged areas on a global scale.

Dwivedi *et al*. (2001) adopted the approach 'intensity–hue–saturation (IHS) transformation', with subsequent supervised classification using per-pixel maximum likelihood classifier, for mapping salt-affected soils in the Indo-Gangetic alluvial plains of northern India. The IHS transform was applied for merging high-spatial resolution panchromatic data of the IRS-1C (5.8 m) sensor with low resolution multispectral data of the LISS-III (23.5 m) and LISS-II (36.5 m) sensors. The IRS-1C and LISS-III data without any transformation ranked last in terms of overall accuracy. After transformation using the IHS approach, accuracy figures for LISS-II, LISS-III and IRS-1C, and LISS-III hybrid data were 89.5%, 85.9% and 81.5%, respectively.

Dwivedi (2002) reported that due to waterlogging and subsequent salinization the productive land is gradually becoming unproductive. Application of remote sensing technology in mapping and monitoring degraded lands, especially salt-affected soils, has shown great promise of enhanced speed, accuracy and cost effectiveness since space-borne multispectral data by virtue of providing synoptic view of a fairly large area at regular intervals, offer immense potential for generating information on degraded soils.

Bhatt *et al*. (2004) reported that remote Sensing and GIS techniques can be extremely useful in accurate mapping and quantification of waterlogged area and salt-affected soils, thereby, helping in preparing a sound database required for taking up various reclamative and preventive measures.

Farifteh *et al*. (2006) ascertained the salt concentrations in soils from measured reflectance spectra by using partial least squares regression (PLSR) and artificial neural network (ANN). The results of PLSR analyses suggested that an accurate to good prediction of EC can be made based on models developed from experiment-scale data ($R^2 > 0.81$ and RPD (ratio of prediction to deviation) > 2.1) for soil samples salinized by bischofite and epsomite minerals. For field-scale data sets, the PLSR predictive models provided approximate quantitative EC estimations ($R^2 > 0.8$ and RPD = 2.2) for grids 1 and 6 and poor estimations for grids 2, 3, 4 and 5. The salinity predictions from image-scale data sets by PLSR models were very reliable to good (R^2 between 0.86 and 0.94 and RPD values between 2.6 and 4.1) except for sub-image 2 ($R^2 = 0.61$ and RPD = 1.2). The ANN models from experiment-scale data set revealed similar network performances for training, validation and test data sets indicating a good network generalization for samples salinized by bischofite and epsomite minerals. The RPD and the R^2 between reference measurements and ANN outputs of these models suggest an accurate to good prediction of soil salinity ($R^2 > 0.92$ and RPD > 2.3). For the field-scale data set, prediction accuracy was relatively poor ($0.69 > R^2 > 0.42$). The ANN predictive models estimating soil salinity from image-scale data sets indicated a good prediction ($R^2 > 0.86$ and RPD > 2.5) except for sub-image 2 ($R^2 = 0.6$ and RPD =1.2). The results showed that both methods had a great potential for estimating and mapping soil salinity.

Mongkolsawat and Paiboonsak (2006) established the soil salinity potential with the objective of providing a spatial distribution of severity classes of soil salinity. Based on the sources and mechanisms regarding salt-affected areas, the creation of GIS data layers was performed to be used for overlay modelling with defined criteria.

Rodriguez *et al*. (2007) reported that Landsat images supply sufficient information on different aspects of the physical environment necessary to determine the distribution of salt-affected soils. It is quite possible to predict with high degree of probability the development of saline soils but their precision classification is not possible due to the fact that they are generally associated with other soil groups.

Elnaggar and Noller (2010) reported that the development of a soil salinity map additionally using decision-tree analysis (DTA) successfully distinguishes between the five classes of salinity used in the USA and elsewhere. Contrary to traditional remote-sensing data, DTA proved to be an efficient, useful approach for mapping soil salinity over large areas as DTA not only incorporates several environmental variables that significantly influence the development of soil salinity but also the spectral properties of the soil surface. The use of surficial geology, terrain and landform map layers, especially those developed using high-resolution Interferometric Synthetic Aperture Radar (IFSAR), Digital Elevation Models (DEMs), significantly enhances delineations of map classes. Using this technique significantly enhances the productivity and the accuracy of soil salinity mapping compared to conventional mapping methods especially in remote inhospitable areas.

Singh *et al*. (2010) reported that there is uncertainty linked with the information of SAS, indicating that the expert knowledge generated must be amalgamated to update database at various scales using new and existing satellite data in optical, radar, and hyperspectral imaging adapted to soil salinization processes. However, improved accuracies may be accomplished by examining sampling strategies for training and testing data. The strategies must include landform patterns and other spatial data for analysis of emerging salinity/alkalinity.

Ting-Ting and Bin (2010) studied the impact of anthropogenic land uses on salinization in the Yellow River Delta using a new RS-GIS statistical model. Based on RS-GIS system, three sub-region models (LF, ST and LU) were created to normalize salinity heterogeneity. The predicted land salinity was served as the response variable in models. Twelve explainable variables were elaborately selected as input into the models. The conventional OLSR model was compared simultaneously to validate performance of SAR model. SAR model fitted better the OSLR model because spatial autocorrelation in soil salinity was well dealt with. Two agricultural activities, salt tolerant crop plantation and fertilization were ameliorative to salinization to most models. The most effective agricultural alleviation occurred in moderately saline sub-regions, such as LF_ floodplain, ST_ soil II and LU_ wasteland to farmland, which may benefit by the development of farm forests and farm ponds.

Zhang et al (2010) ascertained the salinity of Yinchuan Plain using China-Brazil Earth Resources Satellite (CBERS)-02B image at a pixel resolution of 19.5 m to extract saline soil distribution map in April 2007 in Yinchuan Plain, and used CBERS-02B image to extract arable land distribution map August 2007. Moreover, by Geographic Information System (GIS), the distribution information of saline soil information was obtained by overlaying saline soil distribution map and arable land map. The total area of arable land is 300,100 hm2 with 41.75% of the total arable land area, non-saline arable land area of 125,300 hm^2, salt-affected arable land area of 174,800 hm^2 with 58.25% of the total arable land area. The slightly salt-affected arable land area is 67,500 hm2, moderately salt-affected arable land area 58,700 hm^2, and heavily salt-affected arable land area 48,600 hm^2. The causes that led to soil salinity include the high groundwater table, serious leakage of irrigation canals, insufficient irrigation and poor drainage, etc.

Bilgili *et al*. 2011 reported that the quality of estimations of soil EC_e with hyperspectral Visible and Near Infrared Reflectance Spectroscopy (VNIRS) was improved by constructing different calibration models for the soil groups with different types of salt minerals and using the reflectance obtained from oven dried samples after applying spectral pretreatment methods such as continuum removal. The estimation quality was poor for samples containing gypsum, but was greatly improved after these samples were removed. Multiple Adaptive Regression Splines (MARS) provided better estimations for EC_e than the commonly used Partial Least Square Regression (PLSR) method, providing the best cross validation R2 and Ratio of Prediction to Deviation (RPD) values of 0.86 and 2.7, respectively. Combining the information obtained from topographical data and reflectance spectroscopy improved the estimation of EC_e modestly. The classification tree method was moderately successful in distinguishing saline and non saline soils based on reflectance spectra. Hence, VNIRRS has potential for use in soil salinity assessment, but factors such as texture and mineral content make estimations complicated.

Zhang *et al*. (2011) used China HJ−1B satellite remote sensing data to investigate the saline soil distribution in Yinchuan Plain in 2009 by combining with texture features using support vector machine classification. The results showed that severe saline soil area 53000 km^2, moderate saline soil area of 46,300 km^2 and mild saline soil area of 150,500 km^2. The saline soil distribution rule is as follows: severe salinization of soil mainly distribute in the northern, moderate saline soil in the in the central region and mild salinization mainly in the south of the Yinchuan Plain.

Chernousenko, *et al*. (2012) reported that GIS technologies offer new possibilities for the creation of digitized thematic maps, as they ensure good matching of different cartographic materials including digital elevation models and satellite imagery after their georeferencing and the transformation of different projections into a common projection. This makes it possible to delineate the soil landscapes more accurately. However, they found that salt affected soils in Khakassia occupy relatively small areas that cannot be properly shown on small scale soil maps.

Dehni and Lounis (2012) reported that multi temporal images of LANDSAT (1987, 2002 and 2009) proved very useful to identify and delineate saline / sodic soils, since, surface accumulated white or, white bluish salt crusts are good indicators for the detection and correlation of salinity throughout dry season. Moreover, satellite remote sensing data provides real time information of these lands which proved an effective analytical tool for estimating salt affected areas and crops affected by salinity.

Nwer *et al* (2013) developed a model to map soil salinity using Remote Sensing (RS) and Geographic Information Systems (GIS) which consists of a number of phases, salinity detection using RS data, site observations, correlation and verification, and validation. Multi–temporal Landsat-7 ETM image (Enhanced Thematic Mapper) acquired in 2000 and 2002 were used to detect coastal saline areas. GIS was used to integrate the available data and information, design the model, and to create different maps. The correlation between the salinity maps developed from visual interpretation of remote sensing data, and site observations showed that the saline areas delineated using remote sensing data fits with those delineated using site observations data. It was concluded that ground truth coupled with RS data and GIS techniques are powerful tools in detecting salinity at different levels in arid conditions. Moreover, the model can be adopted elsewhere in similar areas that experience salinization problems.

Arnous and Green (2015) ascertained that changes to land-cover caused by human activities - particularly irrigated agriculture and land reclamation as well as urban expansion - will lead to a serious deterioration in the environment through waterlogging and salinization presenting future difficulties for any sustainable development. In addition; the existence of natural factors such as areas of low-lying land, topographic depressions, and rising water tables will increase the threat of waterlogging and salinization. Therefore, remote sensing and GIS tools and techniques have been found to outperform more traditional methods for assessing the impact of soil salinity and waterlogging, thereby providing extremely useful, informative, and professional rapid assessment techniques for monitoring and accurate mapping and the quantification of waterlogged areas and salt-affected soils.

Nawar *et al*. (2015) ascertained that out of two modelling approaches used to map soil properties, MARS (multivariate adaptive regression splines) as a non-linear model, exhibited better estimation for all mapped soil properties than PLSR (partial least squares regression), particularly overcoming the deviations occurring between the predicted values and the measured soil values at higher ranges indicating that MARS and PLSR models coupled with ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) spectra are promising tools for estimating and mapping soil properties.

Spectral properties of salt affected soils

Rao *et al*. (1995) reported that saline and saline-sodic soils reflect relatively more incident light energy than normal soils in the visible and near-infrared regions of the electromagnetic spectrum. However, strongly saline-sodic soils have higher spectral response when compared to strongly saline soils, while moderately saline-sodic soils show relatively lower spectral response when compared to strongly saline soils. Therefore, the separation of strongly saline-sodic soils from those having a moderate salinity/sodicity problem is useful in deciding the gypsum requirement and subsequent leaching operation, since soils with higher magnitude of sodicity need more gypsum or other reclamants. Moreover, the presence of vegetation cover modifies the spectral response of saline and saline-sodic soils. Seasonal variation in the spectral behaviour of soils due to variation in the solar elevation angle is another modifier that needs to be studied carefully in order to utilize remote sensing data efficiently for mapping and monitoring saline and saline-sodic soils.

Khan *et al*. (2005) reported that the two most desirable solutions producing the best results for assessing saline lands using LISS-II sensor data were the selection of third channel due to its significant higher spectral reflectance compared to other wavelength ranges, and the NDVI or NDSI indices, that are same in their absolute values. However, the main difficulty in retrieval of salt-affected areas from satellite data is to distinguish between ‘Salt’ and ‘Town’ classes which can be overcome using up-to-date topographic maps to get information about the settlement/urban area boundaries and excluding it after vectorizing from the calculation process while monitoring salt-affected soils.

Farifteh *et al*. (2007) ascertained that spectral similarity measures can be used as diagnostic indicators to differentiate salt affected soil spectra, since absolute reflectance, absorption strength and spectral angle proportionally deviate with salt concentration in soils. Comparison between results of deterministic and stochastic spectral matching techniques showed that the deterministic techniques are advantageous, because all the spectral aspects causing variations contribute to the calculated similarity values. However, the results of the hierarchical numerical classification method applied to spectral similarity values confirm that the spectral variations in salt-affected soils are sufficient to provide bases for aggregation in classes that are in agreement with standard international salinity classes as defined by the US salinity laboratory. Furthermore, the wavelengths in the near infrared and shortwave infrared regions contain the most crucial information and can be used as a guideline to select diagnostic wavebands to discriminate between salinity classes based on spectral reflectance.

Elnaggar and Noller (2010) reported that salt-affected areas may be overestimated when mapped using only spectral signatures.

Bouaziz *et al*. (2011) used spectral indices to characterize soil salinization features and patterns. They applied Linear Spectral Unmixing technique (LSU) to improve the prediction of soil salinity and extracted eighteen indices from the MODIS Terra data. A moderate correlation was found between electrical conductivity and the spectral indices. However, an improvement occurred in most of the correlations after LSU method was applied.

Avadhesh (2012) ascertained that salt affected soils had a high spectral value in red and near infrared bands. The analyses of digital numbers (DN) of the three classes that is normal, moderate and severe from the satellite data for the month of March were studied. The crop spectral values were examined in green, red and infrared bands. It was observed that in crop affected by severe salinity had a maximum mean DN value of 124.32 in the red band. The crop affected by moderate salinity had a mean DN value of 114.48. The spectral value (DN value) of crop affected by moderate/severe salinity was found to be substantially higher in the red and infrared bands.

Wang *et al*. (2012) developed an exponent reflectance model to estimate soil salt contents under various soil moisture conditions based on a control laboratory experiment on the two factors (soil salinity and soil moisture) to soil reflectance. They examined Na_2SO_4, NaCl, Na_2CO_3 with wide soil salinity (0% to 20%) and soil moisture (1.75% to 20%) (In weight base) levels for their effects on soil reflectance through a model based approach. Furthermore, moisture resistant but salt sensitive bands of reflected spectra were identified for the model before applying them to inversely estimate soil salt content. It was found that high R^2 of 0.87, 0.79, and 0.66, and low means relative error of 16.42%, 21.17%, and 27.16% for NaCl, Na_2SO_4 and Na_2CO_3, respectively.

Abbas *et al*. (2013) reported that using supervised classification of satellite images maximizes likelihood with an overall accuracy of about 90%, since, the accuracy measures were built on overall accuracy and the reliability for assessing the quality of maps was made from the supervised classification of the remotely sensed data. Moreover, they ascertained that different spectral reflectance in visible and near-infra red spectrum by satellite data.

Pankova (2015) reported that the methods of fast diagnostics of soil salinization on the basis of electrical conductivity values must be applied more actively, since, it is necessary to develop new methods of the identification and assessment of soil salinization with due account for the soil cover patterns. Therefore, the monitoring of soil salinization should be organized on the basis of remote sensing materials; the results of their interpretation should be confirmed by field observations.

CONCLUSION

There is consensus in the literature that traditional methods for studying salt-affected soils are not adequate due to the high costs and labour required. Cost effective and timely approaches are needed to enhance the quantitative analysis of soil salinity, mapping and modelling for improved monitoring. The use of broadband sensors for studying salt-affected soils is not satisfactory due to limited spectral information. Hyperspectral remote sensing is promising to overcome the limitations of broadband sensors. The use of hyperspectral remote sensing for monitoring salt-affected soils still warrants more investigations. The use of land components delineated by object based image analysis from DEM's has good potential for mapping saline soils. The integration of land components and spectral reflectance of vegetation/crops to study saline soils as soil properties are theoretically uniform within land components is promising. Hence, investigations on the value of using terrain attributes to identify saline prone areas should be conducted.

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