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Remote Sensing And Gis Techniques for Sustainable Land Resource Management And Planning

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Abstract: The primary role of remote sensing in land management and planning is to provide information concerning the physical characteristics of the land which influence the management of individual land parcels, assessment of the extent of land degradation, intensity of urban sprawl and the allocation of lands to various uses (LULC). These physical characteristics have typically been assessed through aerial photography, which is used to develop resource maps and to monitor changing environmental conditions over years. Many newly emerging uses of remote sensing involve optimum use of digital images obtained from satellites for various land resource related applications. Digital imagery offers the potential for computer-based automated map production, a process that can significantly increase the amount and timeliness of information available to land managers and planners. Remote sensing in land planning and management involve geographic information systems, which store resource information in a geocoded format. Geographic information systems allow the automated integration of disparate types of resource data through various types of spatial models so that with accompanying sample groundtruth data, information in the form of thematic maps or aerially aggregated statistics can be produced. Key issues confronting the development and integration of geographic information systems into planning pathways are enhancement, quality assessment and classification of digital images, automated techniques for combining both quantitative and qualitative types of data in information-extracting procedures, and the compatibility of alternative data storage modes.

Keywords: Remote Sensing, Land Degradation, Land Resource Management, Image Enhancement, Change Detection, Urban Sprawl, Shannon Entropy.

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I. INTRODUCTION

Land degradation with respect to salt accumulation and urban sprawl are genuine ecological issue. Elevated concentrations of soluble salts at surface or near surface soil horizons are a major problem with severe world wideeconomic and social consequences. Excessive salt concentration in soils accelerates land degradation processes and decrease crop yields and agricultural production. Increased salt concentrations lead also to other major soil degradation phenomena such as soil dispersion, scaling and crust formation and structural changes, which result in unstable and compact soil (De Jong, 1994). Monitoring and predicting soil water and salt space-time distribution of water–saving irrigation and salt land are significant in ensuring a sustainable development of the agricultural sectors. Consistent and early stage identification of soil salinization process as well as assessment of extent and degree of severity are vital in terms of sustainable land management, especially in areas with rapidly increasing population densities which require agricultural intensification and land use changes (Frenkel&Meiri, 1985).As a response to the challenge of rapid pace of urbanization and lack of reliable data for environmental and urban planning, especially in the developing countries proper estimation of land use and land cover and urban sprawl expansion is necessary.

In India soil salinity and sodicity is a severe environmental hazard which increasingly impact crop yields and agricultural production and also impedes several socio – economic aspects. To keep track of changes in salt affected soil and anticipate further degradation, monitoring is needed so that proper and timely decisions can be made to modify the management practices or undertake reclamation and rehabilitation. Keeping the above problem in mind there is the need for the generation of an effective and time saving soil management system. Furthermore, understanding and quantifying the magnitude, extent and pattern of salt affected soil variability in space and time are necessary in defining cost effective management zones and in managing variability in a site specific way. These steps can lead to better land use pattern and high crop yields.

The discussed issues together with the advances in the field of data acquisition are the motivation for developing robust modeling techniques for detecting salt-affected areas. Robust approaches should have predictive capabilities based on establishing empirical relationship between soil physico/chemical properties and soil reflectance and must be applicable to non-surveyed areas having geographical conditions similar to known salt affected areas.Satellite remote sensing has been shown to be a particularly valuable tool owing to varying spectral signatures for obtaining relevant data on soil in the irrigated area. Monitoring salt concentration in soil means first identifying on satellite data the spots where salts concentrate and secondly, detecting the temporal and spatial changes in this occurrence

Irrigation induced water logging and salinization are highly dynamic conditions, which vary widely in time and in space. The development of reliable, easy-to-use remote sensing methods for monitoring and mapping of water logging and salinity conditions in irrigated areas would give the concerned countries a very valuable tool in the combat of salt control of irrigated land. Apart from this integration of remotely sensed data, geographic information system (GIS), and spatial statistics is also useful for modeling large-scale variability to predict the distribution, presence of native plant species as well as soil characteristics and other socio-economic condition owing to the impact of salt affected soil. An important development over the past quarter century has been the deployment of a range of Earth-observing satellites, along with rapid improvements in computing power to support the analysis of space – based imagery. Now that these technologies have been in place for a significant period of time, we may review how they have been integrated into land monitoring practice and, importantly, exploited by decision makers.

Timely, accurate and reliable information on land resources with respect to their potentials and limitations is a prerequisite for sustainable development. Satellite remote sensing data comprise essentially a faithful record of the reflected or emitted electromagnetic radiation from a given segment of earth's surface (Rao, 1998). Satellite remote sensing data by virtue of synoptic view at a regular interval hold a great promise in providing such information in a timely and cost effective manner. Remote sensing capabilities have evolved rapidly over the past quarter century with development of new satellites and sensors, information management technologies, and image interpretation techniques. Most importantly, the spatial and spectral resolution of imagery has been enhanced, enabling interpreters to discern more attributes of a land from a given scene. It is now widely accepted and demonstrated by many researchers such as Bendor et al (2002); Dehaan and Taylor (2003); Farifteh et al (2006); that remote sensing and geographical information system (GIS) technology provide essential tool for the required assessment and systematic observation on land resource. Remote sensing could be designed to support sustainable soil and land management and in modeling and projections at a variety of scales based on a common understanding of biophysical and ecological principals. GIS could provide a real tool in analysis, updating, retrieval and modeling etc. that help us in improving our understanding about land, their impact on crop, their realistic planning, operation and management on sustainable basis, impact of urban sprawl on land resources.

Image Enhancement And Quality Assessment

Digital enhancement of an image is essentially improving the analysis and interpretability of images for various land resource related applications like LULC mapping, change detection, urban sprawl, vegetation cover etc.It plays an imperative part in digital image processing (Terai and Goto 2009). Accurate identification & verification of objects is frequently needed for various applications related to natural resource management, with high precision (Khandizod and Deshmukh 2014), image enhancement plays a vital role in it. Image enhancement aims at modifying attributes of an image to make it more suitable for a given task and for specific observer (Maini and Agrawal 2010). Image and data fusion has been investigated over the past two decades using various combinations of remote sensors. Image fusion methods generates higher spatial resolution MS images by combining low resolution multispectral (MS) images to high resolution panchromatic (PAN) images. Number of image fusion methods have been developed and used for the enhancement of the image for various land resource applications. Most of these fusion techniques while improving the spatial resolution alters the spectral properties of the MS image (Alparone et al. 2004, Ehlers et al. 2010). Therefore, one major issue when developing image fusion is to improve the spatial resolution while retaining the spectral consistency (Matsuoka et al. 2016).

Image fusion applications related to land use land cover mapping date back to the 1980s. Haydn et. al. (1982) were among the first to use the Intensity- Hue – Saturation (IHS) transformation based image fusion procedure, in which the panchromatic image is substituted with the intensity produced via IHS transformation of the original multispectral image. Harris et al. 1990, described how to use IHS fusion method in integrating Radar with diverse types of image such as Landsat TM, airborne geophysical and thematic data. Chavez et al. 1991, compared IHS with principle component analysis (PCA) and other fusion methods by merging the information contents of the Landsat TM and SPOT panchromatic image. It was claimed that IHS method distorts the spectral characteristics of the data the most. Schetselarr 2001, modified the IHS transform and presented a new method that preserves the spectral balance of the multispectral image data and modulates the IHS coordinate uniformly. The method takes the limits in the representation of color of the display device into account, which aids in compromising the amount and spatial distribution of the over-range pixels against contrast in intensity and saturation. There are other improvements about IHS such as using wavelet (Nuñez et al., 1999; King and Wang, 2001; Chibani and Houacine 2003, Bin et al. 2010).

Hallada& Cox (1983) used the Brovey transformation – based fusion algorithm, whereby there is division of each multispectral band by the intensity image obtained from the multispectral bands and multiplication of the result by the original panchromatic image. Chavez (1986) fused TM data with National High Altitude Photography program (NHAP) data, and later with panchromatic data (Chavez & Bowell, 1988) using the High-Pass Filtering (HPF) fusion algorithm. The multiplicative fusion algorithm, described by Crippen (1989), multiplies each multispectral band by the panchromatic image to produce the fused image. Li et al (1995) and Chipman et al. (1995) were among the first to use discrete wavelet transformation (DWT) in image fusion in the 1990s. Chavez et al. 1991, used principal component analysis to merge six Landsat TM bands and SPOT data and concluded that the color distortion in the fusion result of PCA method is less than the result acquired by IHS fusion method.Chibani and Houacine 2003, investigated the use of the nonorthogonal (or redundant) wavelet decomposition in image fusion and concluded that this method is better for image fusion than the standard orthogonal wavelet decomposition. Zhu 2010, have presented image fusion based on wavelet and rough set for better classification.

Teggi et al. 2003, presented a fusion method which combines the principal component analysis and “à trous” wavelet and applied it to a pair of images acquired by Thematic Mapper (TM) and IRS-1C-PAN sensors. González-Audícana et al. 2004, presented a new fusion alternative, which uses the multiresolution wavelet decomposition to extract the details and principal component analysis to inject the spatial detail of the high resolution image into the low resolution multispectral image. There are other improvements about PCA such as integrating PCA with high pass filtering (Metwalli et al. 2010)

Several indices also proved beneficial for image enhancement in terms of land resource applications like NDVI, NDSI, NDWI, NDBI etc. (Somvanshiet.al., 2012).Vegetation indices have advantage of reducing effect of solar irradiance, atmospheric influence and spectral contribution of soils to vegetation (Girard and Girard, 2003). Knipling (1970); Viollieret al. (1985); Rouse et al. (1974); Tucker (1979) and Perry and Lautenschlager (1984) applied physical and physiological based ratio for the reflectance of visible and near infrared radiation from vegetation. Vegetation indices have been applied for crop yield estimation and modeling by Singh et al. (2005); Ray et al. (2005); Manjunath and Potdar (2004); Deosthali and Akmanchi (2006); Mukherjee and Sastri (2004) and Badarinathet al. (2004). Comparison of vegetation indices has been done by Jaishankeret al. (2005).

The spatial variation of an image is an important parameter for image interpretation. By manipulating spatial distribution of the radiance value of an image, it is possible to highlight certain features, for better interpretability of the image for various applications related to land resource management. Enhancement is essentially required for the images which are blurred and contain noise. Thus spatial filtering methods are widely accustomed enhancing the images by reducing the noise (Makandar and Halalli, 2015). Spatial filtering modifies the value of a pixel on the basis of the values of the neighboring pixel, reducing the noise of the image. Duda and Hart (1973); Lee (1981); Frost et al. (1982) and Schowengerdt (1983) applied spatial filtering for image enhancement.

Statistical quality measures are required for assessing the quality of enhanced images. The measures could be either qualitative or quantitative. Qualitative measures are normally used for enhancing the visual interpretability of the image, due to the limitation of human eyes. However, quantitative measures are more desirable in mathematical modelling(Somvanshi et. al., 2017). Reflecting the need for quality evaluation of the enhanced images, many image quality measures have been developed. Li et al (2010) investigated 27 quality measures and classified them into five categories based on the similarities of the measures using hierarchical clustering. Image quality measures can either be subjective or objective. Subjective quality measures evaluate the quality of image by using histogram based on human observance while, evaluation using objective quality measures is based on statistical parameter. However, Subjective quality measure is time consuming, inconvenient expensive and varies from person to person; therefore objective image quality measure is more preferable (Khandizod and Deshmukh 2015).

Quality assessment is a key issue in the image enhancement process in order to compare the quality of the enhanced images as well as the performance of the approach used. Attempts to establish a protocol for quality assessment have been published (Wald et al. 1997, Vrabel 2000; Wald and Ranchin 2002). Quality assessment Indicators that are most commonly used to evaluate enhancement results are the mean value and standard deviation, the mean gradient i.e. the contrast between the detailed variation of pattern on the image and the clarity of the image (Choi et al. 2003), the spectral and simple two-dimensional correlation (Bretschneider and Kao 2000, Sanjeevi et al. 2001), the root mean square error (RMSE) (Bretschneider and Kao 2000, Beaulieu et al. 2003), the universal quality index (Aiazzi et al. 2004), and the peak signal-to-noise ratio (PSNR) (Li et al. 2004).

Image Classification And Change Detection

Duda and Canty (2002) applied different types of unsupervised classification algorithms on multispectral satellite data for land cover classification. Xiuwanet al. (1999) attempted land cover classification by combining unsupervised algorithm and training data. Steele and Redmond (2001) applied a method for improving land cover mapping. The digital classification techniques were well demonstrated by Lillesand and Kiefer (2004).

B'ardossy and Sammaniego (2002) have applied Fuzzy rule-based classification on remotely sensed digital image data. Lucas et al. (2007) used rule-based classification of multitemporal satellite imagery for habitat and agricultural land cover mapping. Ji (2002) and Ibrahim et al. (2002) did Fuzzy modeling and classification for realistic representation of vegetative characteristic. Kalita and Devi (2002) have used fuzzy supervised classification of remotely sensed image in the presence of untrained classes using Neural Network. Tapia et al. (2005) have optimized sampling schemes for vegetation mapping using fuzzy classification. Shalanet al. (2003) have reported fuzzy classification to depict a more appropriate land cover in an area where classes were generally mixed.

Neural Network classification has been applied by Augusteijn and Folkert (2002) for identification of ground cover. Artificial Neural Network applications have been demonstrated by Kavzoglu and Mather (2002) for feature selection. Hu and Hwang (2002) described advantage of artificial neural network application over statistical regression techniques in classification. Murthy et al. (2002) have applied Artificial Neural Network and maximum likelihood algorithm for classification of paddy on multi-temporal digital images. Artificial Neural Network for hierarchical classification of multi-date WiFS images was also conducted by Kannan et al. (2002). Chitroub (2005) executed a neural network model that was performed on standard PCA and its variants directly from the original remote sensing data. Benediktssonet al. (1990) applied neural network approaches verses statistical method in classification of remote sensing data. Bischofet al. (1992) have used neural network classification on multi spectral Landsat images. Chlorophyll-A concentration was estimated using an artificial neural network based algorithm with Oceansat-1OCM data by Nagamani et al. (2007).

Mannan and Roy (2003) have been demonstrated application of crisp and fuzzy algorithms to the classification of multi-spectral IRS image and found fuzzy method showing accurate results in comparison to other. Foody (2005) has derived thematic classification accuracy through confusion matrices. Hrol and Akdeniz (2005) made an application based on Mixture Distribution models for the pre-field classification method and assessed classification accuracy. Janseenet al. (1999) presented vegetation monitoring on reliability aspects with high-resolution remote sensing images. Campbell (2002) demonstrated spatial correlation effects upon accuracy of supervised classification of land cover. Accuracy assessment through error matrix analysis was done by Sharma and Bren (2005).Hixon et al. (1980) evaluated several schemes for classification of remotely sensed data. Land use and land cover change, as one of the main driving forces of global environmental changes, is central to the sustainable development debate. Kant et al. (1997) assessed micro level landuse changes using remote sensing data.

Land use and land cover are distinct yet closely linked characteristics of the Earth's surface. Land use affects land cover and changes in land cover affects land use. A change in either however is not necessarily the product of the other. Changes in land cover by land use do not necessarily imply degradation of the land. However, many shifting land use patterns driven by a variety of social causes, result in land cover changes that affects biodiversity, water, trace gas emission and other processes that come together to affect climate and biosphere (Riebsame et. al, 1994). The changes in land cover occurs even in the absence of the human activities through natural processes where as land use change is the manipulation of land cover by human being for multiple purposes food, fuelwood, timber, fodder, litter, medicine, raw materials and recreation. So many socio-economic and environmental factors are involved for the change in land use and land cover.

In order to use land use optimally, it is not only necessary to have the information on existing land use land cover but also the capability to monitor the dynamics of land use resulting out of both, changing demands of increasing population and forces of nature acting to shape the landscape. Conventional ground method of land use mapping are labor intensive, time consuming and are done relatively infrequently. These maps soon become outdated with the passage of time, particularly in a rapid changing environment.

According to olorunfemi (1983), monitoring changes and time series analysis is quite difficult with 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 interval of time. In case of inaccessible region this technique is perhaps the only method of obtaining the required data on a cost and time effective basis.

Applications of remote sensing and GIS for change analysis of landuse/ landcover have been done by Gosh et al. (1996); Xiuwan (2002). Tirkeyet al. (2005) demonstrated use of remote sensing and GIS to track temporal changes in Mumbai coastal area. Land damage assessment and change detection analysis have been and GIS offers a wide scope in detection of land cover changes over period of time. Zhang et al (2014) used remote sensing data in the national landuse change program of China. Digital change detection techniques based on multi-temporal and multi-spectral remotely sensed data have demonstrated a great potential as a means to understanding landscape dynamics – detect, identify, map and monitor differences in land use and land cover patterns over time, irrespective of casual factors (Jensen, 1996). Recent improvements in satellite image quality and availability have made it possible to perform image analysis at much larger scale than in the past. Change detection is an important process in monitoring and managing natural resources and urban development because it provides quantitative analysis of the spatial distribution of the population of interest. Macleod and Congation (1998) listed four aspects of change detection which are important when monitoring natural resources: (i) Detecting the changes that have occurred (ii) Identifying the nature of the change (iii) Measuring the area extent of the change (iv) Assessing the spatial pattern of the change.

A wide variety of digital change detection techniques have been developed over the last two decades. Coppin & Bauer (1996) summarize eleven different change detection, these include Mono temporal change delineation, Delta or post classification comparisons, Multi-dimentional temporal feature space analysis, Composite analysis, Image differencing, Multi-temporal linear data transformation, Change vector analysis, Image regression, Multi-temporal biomass index, Background subtraction and Image rationing.Pandy and Nathawat in 2006 inferred that land use land cover pattern in the area are generally controlled by agro – climatic conditions, ground water potential and other geological factors, which are very important in developing a land resource management scheme.Daniel et al, 2002 in their comparison of land use land cover change detection methods, made use of 5 methods viz; traditional post – classification cross tabulation, cross correlation analysis, neural networks, knowledge – based expert systems, and image segmentation and object – oriented classification. They observed that there are merits to each of the five methods examined, and that, at the point of their research, no single approach can solve the land use change detection problem.

BhagawatRimal (2011), studied the urban growth and land use/land cover change of Pokhara sub-metropolitan city Nepal, they concluded that urban accessibility is vitally responsible for the development of urbanization. Population growth, migration, political instability, economic opportunities, centralized plans and policies of the government, accessibility of physical infrastructure, globalization are some of the major causes of the high level of urbanization in Nepal. In this study Markov chain model has been used to predict future changes based on the rate of past change in IDRISI GIS. M. Harika et.al. (2012), studied the Land use/land cover change detection and urban sprawl analysis. They observed that the Vijayawada, Hyderabad and Vishakhapatnam are the three urbanized and rapidly growing cities of Andhra Pradesh, they also observed that the future area may increase. The increased urbanization may have several impacts on infrastructure, energy use and economy of the country.

The study of land use change referred to as change detection and the growth of urban centers have gained prominence in the recent years. This is partly due to the fact that there is an increasing need for proper land use planning to control various urban problems. Remote sensing techniques are of immense practical use for resources evolution and environmental. In fact, it has emerged as the most efficient and effective way to obtain large amounts of timely accurate information about terrain. Urban land use change monitoring compared, using high-resolution remote sensing technology to monitor more efficient time saving, saving a lot of manpower, material resources and time, improve the urban land use database building and database and update efficiency. The growth of city without planning will lead to create many complex urban problems. Basic amenities such as water, electricity, sewage etc. in this context.

Urban Sprawl And Shannon Entropy

Urbanization is considered as the most influential drivers of land use and land cover change in human history associated with growth of populations and economy (Weng, 2001). The rapid pace of world's urban population growth, especially in developing countries, is one of the major challenges for governments and planning agencies. The inevitable outcomes from this process are the spatial expansion of towns and cities beyond their limits and into their suburbs and peripheries in order to accommodate the growing urban population, which is referred as urban sprawl (Hassan et. al., 2016). Urban areas and their spatial extension are needed to minimize wasteful use of non-renewable resources, to avoid the disruption of the ecosystem equilibrium, to reduce social inequities, and to promote inclusive and sustainable development (Burgess and Jenks, 2002). A major concern with the urban sprawl and LULC change is associated with negative environmental, social and economic impacts (Buiton, 1994; EEA, 2006; Hasse and Lathrop, 2003). Need for large scale urban expansion results in encroachment of surrounding natural land parcels such as, agricultural fields, forest lands and wetlands (Xu et. al., 2001). Therefore, effective planning to achieve a more sustainable urban form are crucial for urban planners and policy makers.

Since urbanization is an unavoidable process, efforts can be made to direct it in the most proper way by urban land use planning so as to protect the natural resources and the needs and rights of the people (Soffianian et al., 2010). Hence, accurate mapping of urban environments and monitoring urban growth is becoming increasingly important at the global level (Guindon and Zhang, 2009). Over the last few decades, the exacerbation of these issues not only has led to rising new approaches to achieving a more sustainable urban form such as smart growth and compact city (Ewing, 1997; Kushner, 2002; Shaw, 2000; Jenks and Dempsey, 2005), but also new methods and techniques have been developed to monitor and analyze urban sprawl phenomenon and its consequences. The conventional surveying and mapping techniques are expensive and time consuming for the estimation of urban growth, hence statistical techniques along with remote sensing and GIS have been used as an alternative for urban growth studies (Yeh and Li, 2001; Sudhira et al., 2004; Punia and Singh, 2011). GIS and remote sensing techniques has largely proved to be effective and valuable tools for mapping, monitoring and estimating urban sprawl and LULC change over a time period (Yeh and Li, 1997; Masser, 2001; Jat et al., 2008; Belal and Moghanm, 2011; Butt et al., 2015; Dadras et al., 2015). These tools are also effective in cost and time related barriers (Epsteln et al., 2002; Haack and Rafter, 2006).

In the past few years, significant research has been carried out on the use of satellite data and GIS for measuring urban growth patterns using Shannon entropy approach (Sudhira et al., 2004; Joshi et. al., 2006; Sun et al., 2007; Sarvestani et al., 2011). Shannon's entropy is based on information theory. Shannon's entropy acts as an indicator of spatial concentration or dispersion and can be applied to investigate any geographical units. It is a metric calculation technique whereby spatial variation and temporal changes of growth areas are taken into account statistically to measures urban sprawl patterns (Gar-On Yeh et al., 1998). It can also specify the degree of urban expansion by examining whether the land development is dispersed or compact (Lata et al., 2001).

Since most of the districts near the metropolitans in India are situated at the heart of fertile agricultural regions, understanding and monitoring the urban growth and LULC change is crucial and would be helpful for the city planners and policy makers to direct future developments and for environmental management (Sudhira et al., 2004; Knox, 1993; Simmons, 2007). Accordingly, this paper aimed to indicate and monitor urban spatial expansion patterns and land use change in the Gautam Buddha Nagar (GBN) district of Uttar Pradesh, India based on spatial forms of urban sprawl. Also, future directions and growth patterns of the city by 2031 are estimated.

Remote Sensing Of Agricultural Land Resource

Saha, Kudrat and Bhan (1990) used digital classification of TM data in mapping salt affected and surface waterlogged lands in India, and found that these salt-affected and waterlogging areas could be effectively delineated, mapped and digitally classified with an accuracy of about 96 per cent using bands 3, 4, 5 and 7. Interesting studies have been done for salinity detection using microwave brightness and thermal infrared temperature synergistically in recent years.

Salt – affected soils are widespread over the world. In India, the problem of salinity and alkalinity increases every year as a result of secondary salinisation. The spatial variability of salt affected soil over the landscape is exceedingly delicate and controlled by a variety of factors such as parent material, permeability, table depth, groundwater quality, topography, irrigation, drainage, rainfall and humidity (Douaiket. al., 2008). Salt-affected soils occur in the states of Uttar Pradesh, Gujarat, West Bengal, Rajasthan, Punjab, Maharashtra, Haryana, Orissa, Delhi, Kerala and Tamil nadu. The total extent is estimated to 7 million hectares. Almost 2.8 million hectares of salt-affected soils are present within the Indo-Gangetic alluvial plain occupying parts of Punjab, Haryana, Uttar Pardesh, Delhi, Bihar and Rajasthan states (Abrol and Bhumbla, 1971).

Salt degrades agricultural land causing the decline in the productivity of plants and thus leading to the loss of agricultural yields (Patel et al., 2009). Knowing when, where and how salinity and sodicity may happen is very critical to the sustainable development of any irrigated production framework. Ground-based measurement of EC and pH is generally accepted as the most efficient method for quantification of soil salinity and sodicity respectively (Norman et. al.,1989). These traditional methods of measuring soil salinity are expensive, tedious and need extensive human resources for land surveying and mapping. Moreover, the dynamic nature of salt affected soil in space and time makes it more difficult to use conventional methods for comparison over large area (IDNP, 2003). In recent decades, there has been a far reaching use of remote sensing information to map soil salinity and sodicity, either directly from bare soil or indirectly from vegetation, in a real - time and cost effective way at different scales (Metternicht and Zinck, 2008). Spatial modelling, which is the use of numerical mathematical statements to simulate and predict real phenomenon and processes, has followed several methodologies for evaluating and predicting soil salinity and sodicity. Several approaches has been used for spatial modelling till date, few of them are Artificial Neural Network (Akramkhanov and Vlek, 2012), Regression Tree (Taghizadeh-Mehrjardiet. al., 2014), Fuzzy Logic (Malinset.al.,2006), Generalized Bayesian Analysis (Douaiket. al., 2004), Geostatistics (eg. Kriging, Cokriging, Regression Kriging) (Tajgardanet. al., 2010) and Statistical Analysis (regression, ordinary least square) (Judkins and Myint , 2012).

Bouaziz et al. (2011) reported moderate correlations between EC and spectral indices using a linear spectral unmixing (LSU) technique to enhance the prediction of salt-affected soils using MODIS data. They also revealed that the use of LSU improve the correlation. Bannari et al (2008) proposed the Soils Salinity and Sodicity Indices (SSSI) using EO-1 ALI 9 and 10 spectral bands which offers the most significant correlation with the ground reference (EC) and proved efficient to predict different spatial distribution classes of slight and moderate saline and sodic soils.

A regression model based on image enhancement techniques (spectral indices, Principal Components Analysis (PCA) and Tasseled Cap Transformation (TCT)) have also been extensively used to predict soil salinity and to improve the characterised variability of salinity. Jian-li et al. (2011) used a Landsat Enhanced Thematic Mapper Plus (ETM+) image using a decision tree methodology to focus the key variables to be utilized for classification and extraction of salinized soil using principal component analysis (PCA). Their study uncovered that the PC3 was the best band to distinguish territories of extremely salinized soil while the blue spectral band from the enhanced thematic mapper plus sensor (TM1) was the most appropriate to recognize salinized soil by identifying salt-tolerant vegetation. Afework (2009) built a reliable model to predict soil salinity in the Metehara sugarcane farms in Ethiopia by relating EC to the Normalized Difference Salinity Index (NDSI) using linear regression.

It creates the impression that the utilization of statistical methods and spectral transformation as often as possible have a great result for upgrading the extracting of soil information from spectra. Janik et al. (2009) compared the performance of PLSR analysis for the prediction of a variety of soil chemical and physical properties from their MIR spectra using a combination of PLSR and neural networks (NN). Cozzolino and Moron (2003) utilized modified partial least squares regression (MPLS) and first derivative transformation of the reciprocal reflectance to analyse soil samples for silt, sand, clay, Ca, K, Mg, Cu and Fe. Principally, PLSR is the most frequently used statistical spectral treatment technique for soil analysis. Recently, Judkins and Myint (2012) found that Landsat band 7, Transformed Normalized Vegetation Index (TNDVI) and Tasselled Cap 3 and 5, derived from TCT, provided high correlation to the variation in soil salinity. Combining these spectral variables into a multiple linear regression model enabled them to predict and map spatial variation levels of salt affected soil efficiently (AmalAllbedet. al., 2014).

Thus, predicting the inconsistency of salt affected soil and mapping its spatial distribution are becoming even more important in order to execute or maintain effective soil reclamation programs that diminish or avoid future increase of salt in soil.

II. CONCLUSION

An increasingly useful application of GIS is the development of Land Information System, which provides upto date records of land tenure, land values, landuse, ownership details etc. in both textural and graphic formats. In such a system, the land parcel is the principal unit around which the collection, storage and retrieval of information operate. The information contained in a cadastral system makes it possible to identify the extent and level of development and management of land to make effective plans for the future. With the availability of high-resolution data from different satellite, it is helpful in generating information in greater details and facilitate updating of existing records. They also serve as useful inputs in prioritizing implementation of area development plans and effective monitoring.Sustainable land management technologies require reliable and repetitive information on the current status and utilization potential of natural resources. Satellite remote sensing data in conjunction with collateral data proved to be very effective in meeting these requirements. Geographic Information system (GIS) served as a very effective tool in the storage, manipulation, analysis, integration and retrieval of information. The synergistic use of these front line technologies helped to evolve an ‘action plan’ which was quite useful in planning for sustainable management of land resources.

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