

# Applications of Remote Sensing and GIS in Soil Science

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**Abstract:** Soil plays a very crucial role in supporting ecosystems and human civilization. Besides being a non-renewable and valuable resource, it has high variability in its properties and behaviour all over the World. Soil survey helps to prepare inventory of different kinds of soils and extent of distribution for the prediction of their characteristics and potentialities. Such knowledge is required for making better utilization of soils in a sustainable way. Traditional soil survey techniques are time consuming, labour intensive and costly. Recent advancements in computer and information technology have brought new techniques of soil resource mapping. Remote sensing (RS), Geographical Information System (GIS) and Global Positioning System (GPS) are such techniques for analysis the different features of soils over space and time. Present paper describes the role of RS, GIS and GPS technologies for mapping and characterizing soils at various scales. The spectral behaviour of soil and its components, which is fundamental to deriving information from RS data is also discussed.

**Keywords:** RS, GIS, GPS, Soil studies, Suitability mapping, Soil Moisture, Soil texture, Soil Erosion and Conservation.

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## INTRODUCTION

Soil plays a very crucial role in supporting ecosystems and human civilization. Besides being a non-renewable and valuable resource, it has high variability in its properties and behaviour all over the World. Non-judicious exploitation of resources by mankind has not only resulted in the depletion of finite land resources but also deteriorated their performance. All the production systems have their base in soil, so it is very much important for us to know its properties, extent and spatial distribution. Sustenance of ecosystem depends on soil (Gessler, 1996). Thus, characterization and mapping of soils and their interpretation is of great significance. For this, one has to evaluate the quantity as well as quality of resources based on accurate baseline information and methods (Laake, 2000). Soil survey helps to prepare inventory of different kinds of soils and extent of distribution for the prediction of their characteristics and potentialities (Mandal and Sharma, 2005). Such knowledge is required for

making better utilization of soils in a sustainable way. Traditional soil survey techniques are time consuming, labour intensive and costly. Recent advancements in computer and information technology have brought new techniques of soil resource mapping. RS, GIS and GPS are such techniques for analysis the different features of soils over space and time (Yeung and Lo, 2002; Shrestha, 2006).

These geospatial tools are very valuable for preparation of soil resource inventory at local to global scales. RS provides spatially explicit, digital data representing the surface features of earth that can be pooled with digitized maps in GIS for efficient characterization and analysis of vast amounts of data. In natural resource management, satellite RS along with GIS can be very much useful. According to Karla *et al.* (2010), RS integrated with GIS database can enhance data collection and interpretation for soil survey in much lesser time and with lesser expenses as compared to

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conventional methods. The high precision and synoptic coverage of RS data and GIS analysis protocols have made soil mapping very effective tool in managing the soil resource and environment (Srinivasan, 1988).

## RS FOR SOIL STUDIES

RS is a process by which one can draw inference about the surface properties of soils from measurements of electromagnetic (EM) radiation emitted or reflected from the land surface. The nature of this radiation emitted or reflected from the surface varies with the physical and chemical characteristics of the soil matrix (Anderson and Croft, 2009; Mulder *et al.*, 2011). For this reason, it is possible to study soil properties and processes and differentiate between various soils using the measured radiation (Dewitte *et al.*, 2012).

RS systems can be divided into passive and active based on the light source used. In passive RS, such as in imaging spectrometers and multispectral instruments visible, near-infrared (VNIR), shortwave infrared (SWIR), thermal infrared (TIR), and microwave portions of EM spectrum are used. On the other hand, most of the active sensors use the microwave portion. There are four types of sensors for passive remote sensing. These are optical multispectral sensors (land use and mineralogical studies), optical imaging spectroscopy sensors (retrieving soil properties like mineralogical composition, Fe-oxides, organic matter), optical TIR sensors (soil temperature estimation), and passive microwave sensors (soil moisture estimation). In active remote sensors, there are synthetic aperture radar (SAR) sensors (soil moisture, texture and salinity estimations), radar scatter meter sensors (soil moisture estimation), and LiDAR sensors (terrain analysis).

Based on the platform, RS could be ground based, air-borne or space-borne. Air- and space-borne sensors provide greater area coverage as compared to the ground-based sensors. RADAR and passive microwave systems mainly provide soil related data at regional- or catchment-scale. Airborne systems (LiDAR, multi-spectral and hyperspectral) can monitor at finer spatial resolutions. They can also identify variables like

mineralogy, moisture, elevation etc. Proximal sensing (PS) like laboratory laser profiling works at the finest spatial scale in assessing soil parameters (Jester and Klik, 2005).

Interpretation of RS data is very important if proper inference regarding soil properties has to be drawn. During interpreting the RS data, one should keep in mind the general limitations of RS techniques. There are some issues regarding the spatial and temporal resolution of air- and space-borne observations. Generally, polar orbiting satellites have revisiting times varying from days to weeks based on their observation geometry, orbital and energy constraints and downlink capacity. Intensity of the acquired radiation and measuring distance affect the spatial resolution. Spatial resolutions of passive microwave sensors are in tens of km, whereas that of optical airborne sensors ranges from cm to m. Remotely sensed data require many corrections due to geometric, topographic, atmospheric and radiometric effects. In case of soils, vegetation coverage and presence of lichens can hamper investigations by optical sensors. Spectral signatures of these items should be masked before interpreting the data. But, such masking leads to incomplete coverage of the study area. Majority of the RS data only denote the surface properties or of shallow soil depths, which may not represent the deeper layers.

In optical and microwave remote sensing techniques, much advancement has emerged recently. This advancement made possible the study of many soil parameters like mineralogical composition of soils, soil texture, soil moisture, soil organic C, soil salinity, Fe content, carbonates, erosion and finally digital soil mapping (DSM). For land use planning at different levels, soil maps at various scales are needed. With increase in scale, availability of information increases. For soil maps on 1:250,000 or smaller scale, coarse resolution data obtained from IRS LISS-I, AWiFs and LANDSAT-MSS sensors can be used. For 1:50,000 scale soil maps medium resolution data collected by LANDSAT TM, IRS LISS-II and SPOT-MLA are useful. Detailed characterization of soil resources on 1:10,000 or larger scale can be done from IRS-P6 (LISS-IV sensor), Cartosat-1 and Cartosat- 2 and IKONOS data (Dwivedi, 2001).

## **GIS FOR SOIL STUDIES**

GIS can be defined as a collection of tools for gathering, storing, retrieving at will, transforming and displaying spatial data from real world for predetermined purposes (Burrough, 1986). It consists of four software function, viz. input, storage, manipulation and output of spatial information. The GIS system is so designed that huge amount of spatially distributed data from different sources can be fed to it. GIS can store information obtained from satellite data and topographical maps. GIS enables efficient and effective manipulation of non-spatial and spatial data for mapping and characterization of soils (Star *et al.*, 1997). Using GIS, one can avoid problems related to data integration caused by various geographic units from diverse data sets.

The primary objective of GIS is to transform raw data into new information through overlay or other operations to support decision-making. Use of GIS has increased widely in recent years. Its applications have expanded very fast in accordance with developments in RS to provide infrastructure for the study of complex spatial problems in better ways (Asadi *et al.*, 2012). Various authors have reported the applications of GIS in soil resource inventory (Dwivedi 2001.), soil suitability assessment (Velmurugan and Carlos, 2009), land capability classification (Panhalkar, 2011), land productivity assessment (Patil *et al.*, 2010) and quantification of soil loss (Reddy *et al.*, 2004).

## **APPLICATIONS OF REMOTE SENSING AND GIS IN SOIL RELATED STUDIES**

### **Soil Survey**

Enhancement in GPS capability and its bonding with GIS has increased the aptitude of collecting more accurate spatial and temporal data for soil survey, thus has revolutionized the entire process. Panhalkar (2011) reported the use of GPS for collection of training site data and ground trothing of classified datasets. The geographic coordinates link the information from the field to the corresponding area on the satellite image, which in turn leads to classification and interpretation. In combination with metadata, coordinates are saved which can be examined with the help of GIS and image processing tools (Reddy *et al.*, 2012).

The surface features on satellite imagery provide sufficient information for correct delineation of boundaries. This can be effectively achieved by systematic interpretation of satellite data (Velmurugan and Carlos, 2009). Preliminary traversing of the study area can be done with the help of topo-sheets and satellite images prior to actual fieldwork (Natarajan *et al.*, 2009). Information gathered from various satellite data when referenced with that of GPS can be used to suggest management strategies (Liaghat and Balasundram, 2010). Combination of GPS and GIS has made possible site-specific farming to be developed and implemented. Such techniques enable the linking of real-time data collection with accurate position information, resulting better manipulation and analysis of large volume of geo-spatial data (Barnes *et al.*, 1998). Hand held GPS can be used to locate representative soil profiles and examination of morphological properties. Details of the location can then be transferred to GIS for creating thematic maps. Soil spatial variations can be easily depicted in GIS maps with the help of point marking based on overall uniformity of soil properties. Huge volume of spatial information can be well managed with the surface and overlay analysis abilities of GIS (Ekanayaki and Dayawansa, 2003). Based on land use, soil texture, slope, land capability classification (Ali, 2008), soil resource mapping (Velmurugan and Carlos, 2009), land degradation maps (Wang *et al.*, 2006) have been done in the past.

### **Soil Suitability Mapping**

Optimal use of land resources for stable and sustainable agricultural production requires prior knowledge about the suitability of soils for various activities (Ekanayake and Dayawansa, 2003). Due to the development of fine resolution satellite imagery and GIS techniques, soil suitability mapping has become less expensive and more efficient. This approach assumes that climate, land use, topography and soil attributes continuously vary with space (Lagacherie and McBratney, 2007). Such approach gives spatial information that can be easily analysed and represented using GIS. Land suitability maps have been prepared using IRS-P6 LISS III (Mustafa *et al.*, 2011) and soil suitability maps using Multi criteria evaluation, Quick Bird (60cm) and LISS-IV data (Ceballos-Silva and Lopez-Blanco, 2003).

## Soil Erosion and Conservation

Soil erosion severely affects many parts of the world in terms of land degradation and deterioration of environment. It affects soil fertility, water quality, agriculture productivity, and also reservoir capacity (Demirci and Karaburun, 2011; Xu *et al.*, 2013). Appropriate information is necessary for selection of suitable, technically sound, and economically effective measures for conservation of soil and water. Formulation of holistic measures for soil conservation and water harvesting requires accurate and timely information on the natural resources (Renard *et al.*, 1997). Some reports suggested conservation measures *viz.* contour bunding, contour trenching, levelling of gullies etc. using LISS IV satellite data for conservation of resources at the parcel level (Chandrashekhar and Govindappa, 2009; Kumaraswami *et al.*, 2011). To conserve soil moisture and avert soil erosion, vegetation walls were suggested after using combined high resolution satellite data of LISS III and PAN. In a similar way, percolation tanks and check-dams have been advocated at different areas across farm ponds and streams to preserve water (Singh and Singh 2009, Sankar *et al.*, 2012). Some workers reported the use of contour trenching, contour bunding, gully levelling etc. as conservation measures employing LISS IV satellite data (Chandrashekhar and Govindappa 2009; Kumaraswami *et al.*, 2011).

## Mineralogy

Spectral images of bare in-situ soils and rocks can be used to determine the mineralogical composition of the surface. Different minerals can be distinguished from the differences in the spectral signatures in VNIR to TIR range. Such estimations require fine spectral resolution of airborne or space-borne data. High spatial resolution is also helpful in minimizing the mixing effects of different spectra from land covers. Due to high spectral and spatial resolution, images from air-borne sensors (*e.g.* AVIRIS, HyMAP) are very much appropriate for such task (Green *et al.*, 1998). For estimation of weathering stage of soil, SiO<sub>2</sub> and Al<sub>2</sub>O<sub>3</sub> have been mapped from AVIRIS data (Galvao, 2008; Bedini *et al.*, 2009). Combinations of multispectral satellite data have also been employed to estimate mineral compositions. For instance, Landsat TM data and ASTER data have been used in synergy to

differentiate mineral types based on ASTER and lithological variation based on Landsat TM. ASTER Geoscience Products have also revealed similar results (Cudahy, 2012). Spectra in TIR region can discern minerals like quartzites, silicates, carbonates in rocks. Spectral libraries having signatures of many minerals are available in several institutes.

The ASTER spectral library version 2.0 is one of such libraries that has over 2400 spectra of minerals, rocks, vegetation and manmade materials in the range of 0.4 to 15.4  $\mu\text{m}$  (Baldrige *et al.*, 2008). Another such library is USGS Spectral Library that has a large variety of mineral spectra (Clark *et al.*, 2007). Algorithm based expert systems like PRISM and Tetracorder tool can be used for soil and terrain mapping. These systems compare spectra of unknown materials with reference spectra of materials with known composition. From all over the world, spectral properties of soil minerals and land cover types are listed in the USGS library, which allows the identification and characterization of unknown materials through spectroscopic studies (Kokaly, 2011).

## Soil Texture

Soil texture, in routine analysis, is determined from relative proportions of sand, silt and clay estimated by tedious and time consuming procedures, while in RS, specific absorption characteristics are used to differentiate quartz-rich soils from clay-rich ones (Figure 1).

Hydroxyl groups of clay minerals typically absorb radiation at 2.2  $\mu\text{m}$ ; ASTER bands 5 and 6 can capture this feature and give SWIR Clay Index (Chabrilat, 2002). Thermal bands from 8 to 9.5  $\mu\text{m}$  can be used to detect quartz due to the occurrence of reflectance peak of silica in this EM range; this correspond to ASTER bands 10 and 14. Thermal IR bands 10 and 14 along with ASTER SWIR bands 5 and 6 have been used to separate bright sandy soils and dark clayey soils from non-photosynthetic vegetation on a limited scale, but presence of organic matter affects the accuracy (Breunig *et al.*, 2008). Multispectral imagery from ASTER can also be used for determination of broad textural classes with the help of principal components analysis (PCA) (Apan *et al.*, 2002). However, in most of the cases, multispectral sensors are not suitable to gather

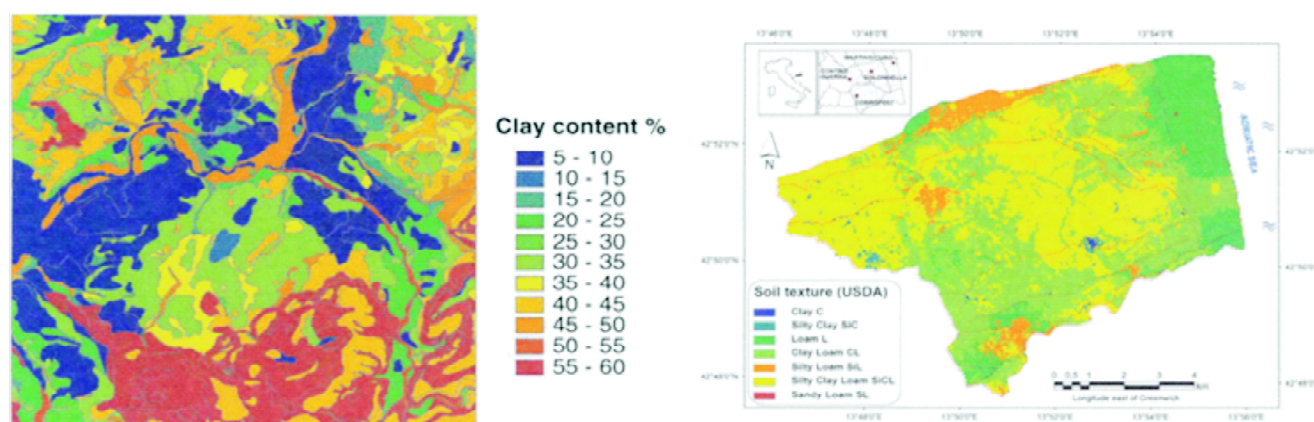


Figure 1: Nominal clay content (%) for distinct soil units based on predictions using Bayesian belief networks (Left). Soil texture based on regression kriging (Right).

necessary information for soil texture estimation. Multiple linear regression (MLR) or partial least-square regression (PLSR) can be used to retrieve soil texture from PS data. Though these methods showed promising results in soil texture prediction, they cannot give accurate results beyond the extent of calibration (Minasny *et al.*, 2008; Mulder *et al.*, 2011). Radar data have also been used to retrieve soil texture, though in a much lesser extent than optical imagery. From dielectric constant obtained from backscatter data of ERS-2 SAR, Singh and Kathpalia (2007) retrieved soil texture along with moisture and roughness using Genetic Algorithm based empirical modelling.

### Soil Moisture

Soil moisture is a crucial component in land-atmosphere interactions (Pielke, 2001). It plays an important role in hydrology, environmental sciences and agriculture. In earlier days, watershed studies have used soil moisture data retrieved from microwave observations like Special Sensor Microwave Imager (SSM/I) (Lakshmi, 1998). Wagner *et al.*, (2013) retrieved soil moisture from Advanced Scatter meter (ASCAT) and reported its main features and applicability. Dielectric constant of dry soil differs from that of water. Based on this, soil moisture content can be determined from the backscatter data obtained from microwave RS.

There is an index called Soil Water Index (SWI) that considers ERS/ASAR along with METOP data to get temporal resolution of one day for each 1 km space (Figure 2) (Wagner *et al.*, 2007).

The index is mainly useful to detect temporal changes in soil moisture content, but not suitable for quantification of soil moisture content (Wagner *et al.*, 2007). Paulik *et al.*, (2014) reported poor correlation between in situ soil moisture data and SWI data. The passive microwave Soil Moisture and Ocean Salinity satellite gives a global coverage at 1 km spatial resolution and 3 to 5 days' temporal resolution. The predicted surface soil moisture (0-3 cm) is expected to be precise to within 4% soil moisture content on volume basis (Panciera, *et al.*, 2009).

Based on reflectance data in SWIR portion of EMS, soil water have been estimated by imaging spectroscopy indices (Haubrock *et al.*, 2008). Nonetheless, presence of vegetation has limited the retrieval accuracy of most algorithms. Spengler *et al.*, (2013) could remove this problem by taking into account the vegetation-cover interference of up to 75%. There is another way of estimating soil moisture that relies on energy balance models. Studies on such approaches have been conducted on plots to local scale and generated spatio-temporal predictions for evapotranspiration in connection with soil moisture. Among various models of soil moisture estimation based on RS data, the most popular are

1. SEBAL (Soil Energy Balance) that aggregates contributions from soil and vegetation to estimate ET (Bastiaanssen *et al.*, 2005);
2. TSEB (Two-Source Energy Balance) that separates soil from vegetation (Aly *et al.*, 2007); and

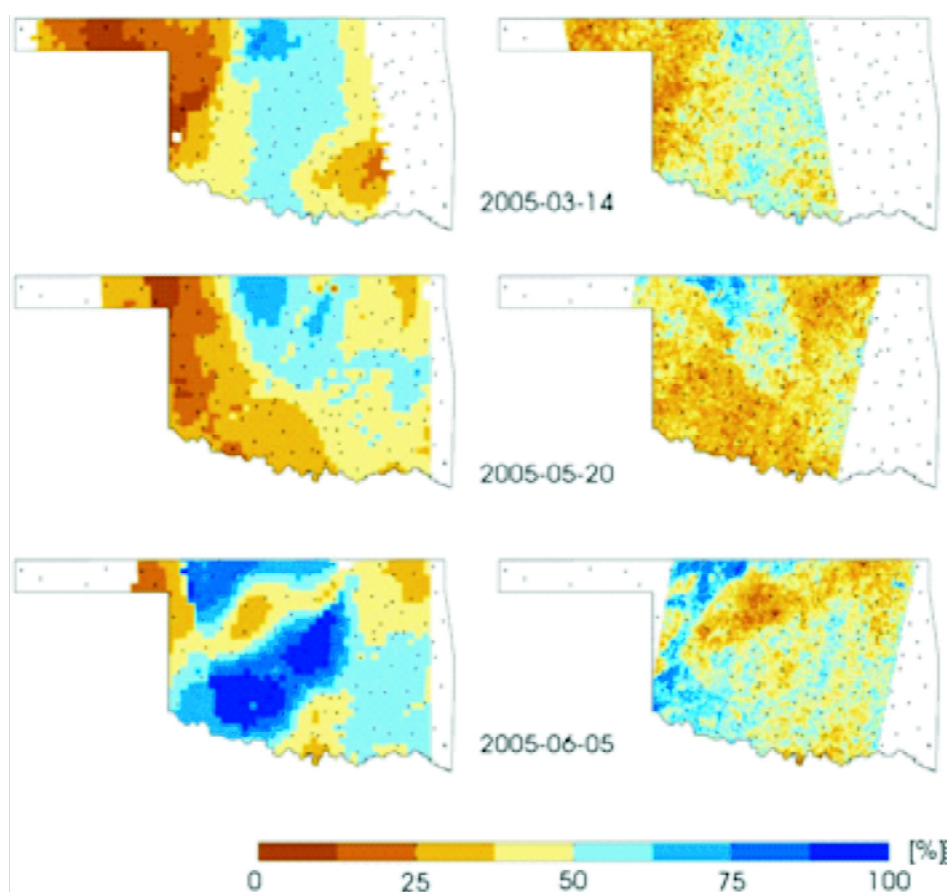


Figure 2: Surface soil moisture maps of Oklahoma retrieved from ERS scatterometer in a 50 km spatial resolution (left) and ASAR GM measurements in 1 km spatial resolution for three different dates in spring 2005 (right).

- SEBs (Surface Energy Balance System) that estimates surface evaporation and turbulent atmospheric fluxes using optical and thermal regions of EMS (Van Der Kwast, 2009).

From the interactions of soil moisture with vegetation and land surface temperature, soil water downscaling algorithms have been derived (Mallick *et al.*, 2009). Other types of algorithms rely on soil evaporation efficiency model and have been used to downscale SMOS soil moisture (Merlin *et al.*, 2011; Merlin *et al.*, 2012) and AMSR-E soil moisture (Fang and Lakshmi, 2013). Based on Normalized Difference Vegetation Index, Land Surface Temperature and brightness temperature, an algorithm has been developed to differentiate SMOS soil moisture (Piles *et al.*, 2009), AMSR-E soil moisture (Kim and Hogue, 2012). A different category of models chains active radar data with passive radiometer observations. Earlier works have also employed L-band microwave radar observations with passive microwave radiometer

data for disaggregating soil water (Das *et al.*, 2011; Piles *et al.*, 2011).

### Soil Organic C

Soil organic C (SOC) is the key factor indicating fertility and plant growth and to a negotiable extent, affects CO<sub>2</sub> concentration in atmosphere. It makes soil healthy and maintains productivity. Faster, more practical, precise and less expensive methods are needed to better characterize and monitor SOC changes (Izaurrealde *et al.*, 2013). Proximal soil sensing gives many tools to build a multi-sensor system to competently determine the organic C stock of soil profiles (ViscarraRossel *et al.*, 2011). For instance, gamma radiometers, electromagnetic induction sensors, and precise global navigation systems can produce multivariate secondary information to design sampling strategies and map soil C (Miklos *et al.*, 2010). Soil visible–near infrared (vis–NIR) spectroscopy can be used to measure soil organic C in the laboratory and in situ in the field.

Before we can start measuring with sensors however, we need to know where to sample. Locations can be selected by probability sampling (random sampling with known inclusion probabilities) or by non-probability sampling, giving rise to two widely used philosophies: the design- and the model-based approaches (Papritz and Webster, 1995; de Gruijter *et al.*, 2006). In the design-based approach, the source of randomness of an observation is the random selection of the sampling sites. In the model-based approach, randomness originates from a random term in the model of the spatial variation, which is added to the model because our knowledge of the spatial variation is imperfect. Thus, probability sampling is a requirement for the design-based approach, whereas it is not for the model-based. Choosing the most suitable approach depends, amongst other, on the motivation (Brus and de Gruijter, 1997). For example, the design based approach might be more suitable if the aim is to obtain estimates of the 'global' mean or total stock and their accuracies for an area, whose quality is not dependent on the correctness of modelling assumptions. The model-based approach might be preferable if we want to produce a 'local' map of the soil organic C stock in the area. However, deciding which approach to use is often more complicated because the design based approach can also be used for estimation of local means, and the model-based approach can be used for global estimation.

### Soil Salinity

In arid and semi-arid areas, scarce precipitation cannot maintain a regular percolation of rainwater through the soil leading to accumulation of salts at the surface affecting soil structure and land suitability. Based on dielectric constant of soil, microwave RS can sense salinity (Aly *et al.*, 2007). Soil salinity classes have been successfully derived on a local scale (< 500 km<sup>2</sup>) with the C-, P-, and L-bands of airborne and space borne radar systems; best results are obtained using L-band data as longer wavelengths are more effective in penetrating soil and vegetation than higher frequencies (Lasne *et al.*, 2008). Salt scalds and severely salinized soils exhibit additional absorption features at 680, 1180 and 1780

nm. These help in recognizing minerals, such as bassanite, gypsum, and polyhalite, which can be used as salinity indicators. At 2200 nm, when samples are more saline hydroxyl features become less pronounced. Using RS on a local scale (<104 km), broad salinity classes can be mapped with ASTER (Melendez-Pastor *et al.*, 2010), HyMAP (Dehaan and Taylor, 2003), Landsat TM and ALI imagery - the latter two using the Salinity Index and the Normalized Salinity Index (NSI) (Odeh and Onus, 2008). Weng *et al.*, (2008) were able to discriminate five classes of saline soils with Hyperion data for an area of about 1200 km<sup>2</sup>. Alternative methods for mapping saline areas are based on detecting the presence of salt scalds and halophytic vegetation. However, the spectral resolution must be high in order to detect the different vegetation types.

### Soil Degradation

Imaging spectroscopy enables the assessment of important soil erosion variables, such as water content and surface roughness (Haubrock *et al.*, 2008). Furthermore, spectroscopic data can be used to map post-fire soils and pin point water repellent soil areas that tend to be potentially highly erodible (Lewis *et al.*, 2004). The spectral difference between severely eroded soils and intact topsoil has previously been used to map surface erosion processes. In a study area in southern France, various soil erosion states have been identified based on the ratio between developed substrates and components of the parent material. Their corresponding end-member spectra were subsequently used to parameterize a spectral mixture model to map the spatial extent of soil erosion. The results highlighted that different erosion levels could be mapped with an accuracy of about 80%, which proved superior to applying the approach of Landsat-TM imagery (Hill *et al.*, 1995). Another approach to assess soil erosion and soil degradation status is based on quantitative estimates of specific soil chemical properties. In a study area in south-eastern Spain imaging spectroscopy data have been used to identify SOC concentrations indicating soil deposition and erosion states; high SOC concentrations in sediment sinks provide favourable soil conditions, owing to

their higher infiltration and water retention capacity, better aggregation, and increased nutrient availability; the corresponding source areas represent active erosion and transport zones with low organic carbon concentrations (Hill and Schütt, 2000).

In the event of a collapsed dam for mine tailings in southern Spain in 1999 the heavy metal contamination of soils was explored using HyMAP imaging spectroscopy data (Figure 3). Based on chemical and spectroscopy analysis of soil samples, prediction of heavy metals (As, Cd, Cu, Fe, Hg, Pb, S, Sb, and Zn) was achieved by stepwise MLR analysis and an artificial neural network approach. It was possible to predict six out of nine elements with high accuracy, using this approach. The best coefficients of determination ( $R^2$ ) between the

predicted and chemically analysed concentrations were As, 0.84; Fe, 0.72; Hg, 0.96; Pb, 0.95; S, 0.87; and Sb, 0.93, respectively. Results for Cd (0.51), Cu (0.43), and Zn (0.24) were not significant (Kemper and Sommer, 2002). In addition to the PS analysis, a Variable Multiple Endmember Spectral Mixture Analysis (VMESMA), (García-Haro *et al.*, 2005) was used to estimate the sludge abundance derived from the HyMap data. Furthermore, the analysis of residual pyrite-bearing material could be used to assess acidification risk and the distribution of residual heavy metal contamination. This assessment was based on an artificial mixture experiment and derived simple stoichiometric relationships. As a result, the spatial sludge abundance distribution and associated heavy metals could be used to assess the acidification potential and to plan counteracting

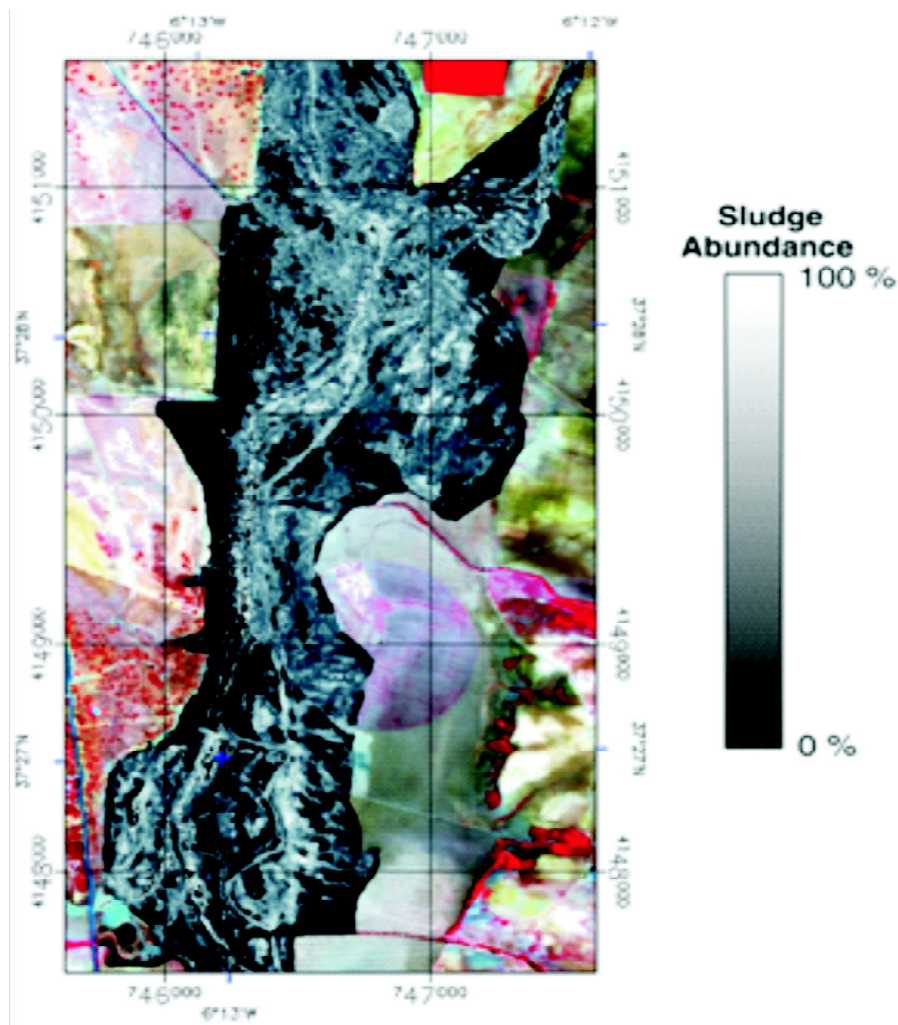


Figure 3: Sludge abundance map based on HyMap data from 1999 in Aznalcollar, Spain. The sludge affected area (black background) is superimposed on the HyMap false color image.



remediation measures (Kemper and Sommer, 2002). In summary, it can be concluded that the reflectance properties of soils enable the assessment of various contaminants in their environment and that imaging spectroscopy technology proved to be promising for that purpose.

## CONCLUSION

In summary, remote sensing provides data

1. supporting the segmentation of the landscape into rather homogeneous soil-landscape units whose soil composition can be determined by sampling or that can be used as a source of secondary information,
2. allowing measurement or prediction of soil properties by means of physically-based and empirical methods, and
3. supporting spatial interpolation of sparsely sampled soil property data as a primary or secondary data source.

Emerging technologies like high resolution satellite data can be utilized successfully for deriving the spatial and temporal agricultural information at micro level. Organizing the satellite derived spatial data and ground observations and non-spatial attribute data, in a remote sensing, GPS and GIS environment, would be highly desirable to facilitate the sustainable development of the specific region. The advent of high resolution satellite data in recent years has considerably contributed for better management of resources, as it gives mere real time information and repetitive basis which is important for monitoring.

The resources particularly soil and land needs not only protection and reclamation but also a scientific basis for the management on a sustainable manner so that the changes proposed to meet the needs of development are brought without diminishing the potential for their future use. Depending on the suitability of agro-ecological areas for alternative uses based on the detailed information, optimum way can be suggested taking into account the socio-economic conditions of the farming community and political will. The review on application of high resolution remote sensing data in conjunction with GPS and GIS shows that

soil resource mapping and their characterization is cost and time effective for their efficient management and use on sustainable basis.

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