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GAPS AND OPPORTUNITIES IN THE USE OF REMOTE SENSING FOR SOIL EROSION ASSESSMENT

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Abstract. Remote sensing data provide spatial information of the Earth surface and are used, amongst various applications, for obtaining information on soil erosion parameters, such as vegetation cover, topography and soil moisture. The use of high spectral resolution information remained however limited. This paper provides an overview of common applications of remotely sensed data in soil erosion studies. We then discuss integration of high resolution spectral data in soil erosion studies, and explain and propose the use of spectroscopy of chemical elements for soil particle tracing as a method for assessment of soil erosion and deposition.
Keywords: soil erosion, remote sensing, soil particle tracing

Introduction

Land degradation and soil erosion have been studied since the 1940's, when the first concepts of detachment and transport of soil material were introduced (Ellison, 1944). Various soil erosion models have been developed to monitor and assess the severity of erosion, however the large extent of this process poses a major challenge in acquiring required input data (Jetten et al., 2003). Remote sensing is found to provide solutions for estimating some of the erosion parameters and for outlining already developed erosion features (Alatorre & Beguería, 2009; Jetten et al., 2003; Vrieling, 2006). Most research, however, focused on land cover mapping, identification of bare soil regions, and mapping soil types (Alatorre & Beguería, 2009). Different classification techniques and processing algorithms based on spectral correlation have been implemented in order to overcome some of the limitations (Chabrillat et al., 2002; Shrestha et al., 2005). Yet, the potential of using remotely sensed imagery for soil erosion studies is still not fully explored.

The aim of this paper is to provide an overview of existing applications of remotely sensed data in soil erosion studies done in the laboratory and in the field. We provide a detailed review on the methodologies that are applied on remotely sensed imagery to estimate the main parameters used as input for soil erosion models. In addition we look into soil particle tracing techniques to identify gaps, where remotely sensed data can be integrated to widen the scope of currently existing methodologies.

Satellite remote sensing as an input for soil erosion models

Observing soil erodibility over large areas has two requirements. First, there is a clear need of a holistic conceptual framework that describes how factors of erodibility such as physical soil characteristics, vegetation, topography, operate in time-space continuum. Second, the measurement technique should provide high resolution spatio-temporal data to characterize this continuum (Chappell et al., 2005). Research on soil erosion is mainly focused on the use of soil erosion models in order to measure and monitor the event. A major limitation of these models is that they are applied on small scale study area or catchment only (Nigel & Rughooputh, 2010). Methods and models for soil erosion assessment have been reviewed by Jetten et al. (Jetten et al., 2003) and later on Zhou et al. (Zhou et al., 2008). The most widely applied ones include: Universal Soil Loss Equation (USLE) (Wischmeier & Smith, 1978), its revised version (RUSLE) (Prasannakumar et al., 2012; Renard et al., 1991), the Soil Erosion Model for Mediterranean regions (SEMMED) (de Jong et al., 1999), the Water Erosion Prediction Project (WEPP) (Flanagan & Laflen, 1997), Limburg Soil Erosion Model (LISEM) (Flanagan & Laflen, 1997) as well as particle tracing techniques (Campbell et al., 1982; Chappell, 1999; Luleva et al., 2011; Sanchez-Cabeza et al., 2007; Syversen et al., 2001; Walling & Quine, 1991). A main limitation of erosion models is the fact that they are applied on small scale for particular study area or catchment (Nigel & Rughooputh, 2010).

An extensive review of satellite-based sensors that have been used in soil erosion studies was provided by Vrieling (2006). A more recent review by Goldshleger et al. (2010) looks into the use of sensors with high spectral resolution for studying three specific degradation processes- soil salinity, soil crusting and post-fire mineral alterations. The authors suggest that there is potential in the use of these data for monitoring soil erosion factors.

Efforts have been put into studying landcover and landuse change (Sobrino & Raissouni, 2000) focusing mainly on vegetation. When it comes to direct assessment of soil composition and degradation, however, the number of studies decreases. By using satellite imagery it is possible to observe only the surface soil characteristics and only when the signal is not masked by the vegetation cover (Vrieling, 2006).

The most commonly used remotely sensed data in soil erosion modeling come from Landsat TM imagery. Availability and low cost of the scenes allow long term monitoring of particular areas. The main benefit of Landsat TM sensor is the multi-temporal aspect (de Jong et al., 1999), although the low spatial and spectral resolution of the scenes present a limitation. Soil erosion parameters estimated from this imagery, including assessments of vegetation cover, outlining of bare ground, calculation of vegetation indices and rarely changes in topography, have been reviewed by Alatorre & Beguería (2009). It is important to note that the information provided by remote sensing is limited to the surface characteristics, although some statistical relationships have established between the surface and depth properties (Vrieling, 2006). Monitoring visible signs of degradation such as sheets, rills or gullys as well as physical deteriorations such as crusting, hardsetting and compaction , total erosion can be estimated over time (Boardman, 2006; Omuto & Shrestha, 2007) . Remote sensing data are used in order to measure soil erosion parameters that trigger their formation (Table 1).

Identification and mapping erosion features is performed by automated or supervised extraction of digital information based on spectral and/or structural pattern recognition (Alatorre & Beguería, 2009). Classifiers based on statistical probability functions are commonly used to allocate ground pixels to a given surface type. Based on the composition of vegetation abundance and the identification of soil degradation features, linear mixture modeling has shown useful to map land degradation (Metternicht & Fermont, 1998).

The models and techniques, used to date, in terms of studying soil related processes, have been mainly static, based on "one place- one time" events. Consequently, to accurately assess and predict soil dynamics, there is a clear need of developing new methods that integrate the spatial extent of the event, the development of the process over time, as well as the factors affecting the soil behavior.

Table 1. Key soil erosion parameters studied with remote sensing

Parameters	Sensors/Platforms	Cited Literature
Vegetation related parameters	Landsat TM, NOAA AVHRR, Spot HRV, ERS SAR, RADARSAT	Reviewed in Shoshany (2000)
- NDVI and LST *- Active Fires*	Landsat TM, HyMap* Radarsat SAR	(Asner & Heidebrecht, 2003; de Jong et al., 1999; Khawlie et al., 2002; Nicholson & Farrar, 1994; Park et al., 2004; Sharma, 2010; Shrestha et al., 2005; Shrestha et al., 2004)
- Land Cover and Ecology	AVIRIS*, Landsat TM, Spot HRV, Hyperion*	(Asner & Heidebrecht, 2003; de Jong et al., 1999; Khawlie et al., 2002)
Hydrological Variables	SPOT, Landsat TM, ASTER, Ikonos, Quickbird	Reviewed in (King et al., 2005)

-Surface Soil Moisture *-Rainfall and cloud cover*	Laboratory spectra acquired with ASD spectrometers, NOAA AVHRR- thermal bands, MODIS, SAR	(Dasgupta et al., 2007; Famiglietti et al., 1999; Haubrock et al., 2008; Kimura, 2007; Zribi et al., 2005; Zribi et al., 2003)
Topography: Slope and Morphology	ASTER, Landsat TM, LiDAR	(Betts & DeRose, 1999; de Jong et al., 1999; Evans, 2002; Hessel & Jetten, 2007)
Soil Chemistry and Physics	Laboratory spectra acquired with ASD spectrometers	(Baumgardner et al., 1985)
-Chemical Composition and Crusting	Laboratory spectra acquired with ASD spectrometers	(Ben-Dor et al., 2003; Ben-Dor et al., 2002; Shepherd & Walsh, 2002; Udelhoven et al., 2003)
- Roughness	SAR, Laboratory spectra acquired with ASD spectrometers. Suggestions* for using CHRIS, MISR, Proba	(Anderson et al., 2006; Croft et al., 2009; Moran et al., 2002)
Particle Tracers	ASD Spectrometer*	(Luleva et al., 2011)

* Limited number of sources

Soil erosion parameters

Vegetation related parameters

Vegetation cover has been widely studied with remote sensing (Shoshany, 2000), due to its distinct signature in the visible and near-infrared part of the electromagnetic spectrum. The most commondly used imagery is provided by Landsat TM and SPOT HRV, although Limited number of studies has attempted to implement hyperspectral remote sensing from HyMap (Asner & Heidebrecht, 2003; Shrestha et al., 2005). Vrieling (2006) provides an extensive review on the different satellite sensors used for detection of vegetation in soil erosion.

The bulk of research has focused on estimating Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI) and Land Surface Temperature (LST) from satellite imagery. These are used as indicators for spatial and temporal changes in soil quality (Julien & Sobrino, 2009; Nicholson & Farrar, 1994; Park et al., 2004). In their study, Troufleau & Søgaard (1998) used LST and NDVI to derive soil surface moisture status while Unganai & Kogan (1998) used standardized difference of NDVI and LST to estimate drought-prone areas in Southern Africa. In addition, Park et al. (2004) used vegetation indices to estimate the impacts of hydrologic properties. They showed that values for NDVI and LST are related to soil runoff potential. Considering that soil is classified in hydrologic soil groups, based on runoff potential and soil physical conditions, it is suggested that physical degradation can influence LST and NDVI (Omuto & Shrestha, 2007; Park et al., 2004).

Topography

Slope steepness and aspect are important controlling factors for development and formation of soil erosion (Hessel & Jetten, 2007). As stated by Smith & Clark (2005), remote sensing provides the most effective way of developing Digital Elevation and Terrain models (DEM, DTM). The main sources of such data have been reported to be ASTER and Landsat TM (Thurmond et al., 2006).

The resolution of the produced DEMs plays a crucial role. LiDAR cloud point data provide means for more accurate building of DEMs, however this usually requires great amount of time, effort and resources (Liu, 2008), limiting their use.

Soil moisture

Soil moisture content is another indicator of soil erosion. Methods applied for determining soil moisture content cannot often be extrapolated spatially due to variation over time. On the soil surface, moisture content influences the process of exchange of heat between land surface and atmosphere (Owe et al., 2001), as part of the environmental water cycle. Research focuses on potential use of infrared spectra for estimating surface soil moisture. It is known to affect spectrum shape in the visible, near infrared (VNIR) and shortwave infrared (SWIR) spectral range (350 nm and 2500 nm) (Doerr et al., 2000; Haubrock et al., 2008), where increasing moisture content leads to decreasing reflectance (Baumgardner et al., 1985; Lobell & Asner, 2002; Weidong et al., 2002). Estimations from optical measurements in the VNIR and SWIR are considered increasingly important, not only for improving existing hydrological models at different scales (Doerr et al., 2000) but also for estimation of ground cover properties.

The overtone and combination absorption bands of molecular water around 900 nm, 1400 nm and 1900 nm are indicative regions for soil moisture variability (Haubrock et al., 2008; Weidong et al., 2002). Soil moisture influences background reflectance and therefore affects quantification of soil parameters (Haubrock et al., 2008). For instance, Iron oxides, soil organic matter and Phosphorus prediction from VNIR and SWIR have been tested by Bogrekci & Lee (2006), and Galvão & Vitorello (1998), who developed calibration models for estimation of these parameters using specific bands as a function of moisture.

Problems related to estimation of surface soil moisture from spectra, are mainly related to validation of the results. A number of moisture indices have been developed, including Modified Temperature - Vegetation Dryness Index (MTVDI) (Kimura, 2007), Normalized Difference Water Index (NDWI) (Dasgupta et al., 2007), Normalized Soil

Moisture Index (NSMI) (Haubrock et al., 2008). The correlation coefficients between the certain bands and the actual moisture content, however, have not been shown to be higher than 0.71 (Haubrock et al., 2008).

MTVDI (Kimura, 2007), for instance, can be calculated from satellite-derived surface temperature, and aerodynamic minimum and maximum surface temperatures estimated from meteorological data. The main purpose of this index was to help identifying wet-edge index, by combining the MTDVI with the commonly used NDVI. The authors, however, reported lack of sufficient data for drawing strong conclusions. NDWI takes into account the bands at 860nm and 1240 nm (Dasgupta et al., 2007), however the study acknowledged uncertainties up to 66% associated with the index. The most recent one reported in the literature was introduced by Haubrock et al. (2008) (NSMI). From a systematic study over the whole spectral range from 350-2500 nm, the NSMI based on the reflectance at 1800 nm and 2119 nm has been determined to be suitable quantifier of water content for the surface. The authors claim that NSMI can be seen as a generally applicable parameter, which can be used without any a priori knowledge about the target. The index should be tested for its applicability from remote sensing data, where resolution and atmospheric effect complicate spectral measurements.

In arid regions, surface soil moisture is a dynamic variable at a relatively low level, making optical remote sensing useful for assessment of degradation. In such regions, moisture indices have great potential for rapid and efficient surface soil moisture estimations (Famiglietti et al., 1999; Khawlie et al., 2002; Zribi et al., 2005; Zribi et al., 2003).

Integration of high spectral resolution remote sensing data in studies on soils

It was shown here how satellite remote sensing data can be used as an input for soil erosion modeling. The spatial extent of these data has been explored to some degree, however most studies have used only the information in the visible and near-infrared wavelengths of the electromagnetic spectrum. There is a clear lack of studies that use spectral information from multi- and hyperspectral imagery. On one hand this could be due to the cost of multi- and hyperspectral images, and on the other hand, due to the advanced analytical techniques needed for image interpretation.

Literature covers the use of spectral data in identifying organic matter, moisture content, soil chemistry and roughness either directly (Baumgardner et al., 1985; Ben-Dor et al., 2003; Shepherd & Walsh, 2006), or indirectly through analyzing and relating factors (King & Campbell, 1994). The aim of most laboratory based studies is to establish methodologies that can be applied on remotely sensed imagery to extrapolate results in the spatial dimension. The focus is on detecting changes in soil structure, which determine the impact of degradation and regenerative processes of soil, indicating soil erosion (Chappell et al., 2005). Research efforts have been put into successfully linking soil erosion to particular soil types, where studies from the 1960s were first used (Holden, 1968). Laboratory analysis of soil spectra have also been conducted, to estimate chemical constituents and predicting crust formation (Ben-Dor et al., 2003; Udelhoven et al., 2003). Not much has been done in terms of scaling these to image data.

Silt and silt loam soils, rich in salts and poor in organic matter content, are more erodable then these characterized by high clay and organic matter content (Le Bissonnais et al., 2005). Indicative is the formation of soil crust , which decreases infiltration and causes runoff (Eghbal et al., 1996). By establishing chemical soil constituents, characteristic for silt and silt loam soils, through spectra, statistical probability of crust formation can be established and treated as a sign of soil erodibility. The challenge is to determine a method that predicts soil surface chemical properties using remote sensing techniques and to investigate ways of deriving sub-surface soil spectral information. An attempt was recently made by Ben-Dor et al. (2008), introducing an extension to an ASD spectrometer, specifically designed for sub-surface spectral measurements, while others refer to more conventional methods of implementing geophysical measurements using gamma-ray spectrometers (Tyler, 2008).

In order to implement the use of remotely sensed data for quantifying soil chemical properties, a method to separate noise caused by different atmospheric and environmental factors from actual signal, should be established. However, the transition from laboratory scale analysis through filed measurements to satellite imagery presents a challenge. As it has been pointed out by Vrieling (Vrieling, 2006) "due to the complexity of erosion processes, regional differences, and scale dependency, it cannot be expected that a standardized operational erosion assessment system using satellite data will develop in the near future".

Chemical properties of soils

It has been established that soil physical degradation is a relatively slow process (Morgan, 2005). It begins with structural deterioration culminating into soil loss through erosion after many years (Jones et al., 2003). Visible signs in the field such as rills, gullies or sediment deposits are manifestations of advanced stage of degradation. To detect early warning signs, it is important to study soil properties sensitive to the degradation. Spectral reflectance is a property of soil that integrates many functional processes influencing physical conditions (Ben-Dor et al., 2003; Shepherd & Walsh, 2006). It is sensitive to soil constituents such as Iron Oxide, Carbon content and Calcium Carbonate that influence aggregation (Baumgardner et al., 1985; West et al., 2004) and soil crust formation. Furthermore, large-area sampling for spectral reflectance is more effective compared to conventional sampling methods for laboratory analysis (Janik et al., 1998; Shepherd and Walsh, 2006).

Some efforts have been put into studying soil properties from spectra. As stated by Udelhoven et al. (2003), soil parameters are neither static nor homogenous in space and time. Costs of analytical procedures are often a limiting factor when spatial soil variability in large-scale is addressed. Reflectance spectra have been used extensively to determine variation in the Earth's surface composition (van der Meer, 2004). Soil properties derived from spectra have been studied long before the 1980s. Soil research has focused on VNIR and SWIR regions of the spectrum (Baumgardner et al., 1985) and the trend has been followed to date, with some relationships established from data in the thermal and microwave regions (Barnes et al., 2003; Yitagesu et al., 2011). The basic physical and chemical soil properties show high correlation with derivative reflectance values within the visible and short-wave infrared wavelengths (Shepherd & Walsh, 2006). Subtle differences in the spectral shape can serve as a valuable base for identifying soil properties mainly due to the fact that the soil spectra forms as a result of the overlap between absorption features of many organic and inorganic compounds (Shepherd & Walsh, 2006). According to Ben-Dor et al. (2003), changes in spectral response occur due to changes in soil albedo and soil mineralogy, where the former is strictly related to the physical soil properties, while the latter is strictly related to the chemical. Soil albedo is strongly influenced by soil color, organic matter, moisture content and iron content (Post et al., 2000).

Literature covers extensively in-situ laboratory procedures for estimating and predicting soil properties. These procedures, however, are rarely applicable to satellite imagery. As identified by Ben-Dor et al. (2002), the main limitations are that only the top few centimeters can be studied and vegetation masks the response from the soil surface.

There have been some efforts to include aerial photographs and satellite images of bare soil in order to estimate Organic Matter and Phosphorus levels. However, as pointed out by Lopez-Granados et al. (2005), these approaches were limited to linear regression with brightness values from the blue, green and near infrared bands. Chabrillat et al. (2002), suggest an improvement to these methods by stating that unlike multispectral imagery, hyperspectral remote sensing with its continuous spectrum for each pixel, enables the spectral identification of minerals, rocks, or soils at image level (Ben-Dor et al., 2002; Chabrillat et al., 2002).

Chemical soil particle tracing

As it was discussed in the previous section, data acquired with field and laboratory spectrometers have been widely applied in studies on soils in order to examine the soil chemical properties. These data and the corresponding analytical techniques, however, have not been yet integrated in studies of soil erosion, most likely because of the limited reference to soil chemical composition. One of the few lines of research that can potentially benefit from these data is the concept of chemical soil particle tracing for monitoring soil movement due to erosion.

The Cesium-137 isotope (^{137}Cs) is the most widely used chemical soil particle tracer. Soil particles move according to their size, under the influence of wind, water or gravity (Morgan, 2005). Using tracers for soil erosion originated in China, shortly after the Chernobyl incident in the late 1980s. The use of ^{137}Cs in soil erosion modeling has been identified as a very effective technique in assessing both spatial patterns and rates of soil redistribution in the landscape (Li et al., 2000). Distribution of ^{137}Cs in soil profiles at undisturbed sites shows an exponential decrease with depth while ploughed soils show uniform mixing of ^{137}Cs in the ploughed layer (Belivermiş, 2012). Although biological and chemical processes can move some amount of ^{137}Cs, the dominant factors affecting its movement within landscapes, are the same physical processes that affect the movement of soil particles to which it is attached (Warren et al., 2005). As suggested by Chappell (1999) ^{137}Cs offers the greatest potential for measuring net soil flux in semi-arid environments where soil flux monitoring is limited due to considerable spatial and temporal variability of the controlling factors. There are a number of assumptions behind the models that use ^{137}Cs distribution. Chappell (1999) explains in more detail the problems related to them. First, it is assumed that there is a spatially uniform distribution of ^{137}Cs within a climatologically uniform area. Secondly, the fixation of ^{137}Cs to the clay size fraction of different minerals is considered immediate and permanent, and the redistribution of soil corresponds to the movement of ^{137}Cs. The reasoning behind this is that Cs is rapidly adsorbed by clay particles in the surface soil and it is essentially none-exchangeable once adsorbed to the clay surfaces. The extent of adsorption and fixation of ^{137}Cs to clay particles depends largely on the clay type. Generally, ^{137}Cs is adsorbed irreversibly by micas and hydrobiotite, while morillonite, kaolinite and vermiculite hold ^{137}Cs much less strongly

A number of models developed for calculation of redistribution rates of soil have been derived from ^{137}Cs measurements and summarized by Li et al. (2000). Although Cs^{137} isotope has been extensively used to model soil redistribution, little has been reported on the integration of spectral data. Limited number of studies have attempted the use of remote sensing to map Cs^{137} net soil flux with SPOT imagery, but the results were poor (Chappell, 1998).

The limited use of spectral data in monitoring Cs^{137} distribution is mainly the fact that the chemical difference between the isotopes of Cs is very small- associated with reaction kinetics. Therefore, all isotopes behave in the exact same way and it is very difficult to determine each of them with any techniques different from laboratory based mass spectrometry. Moreover, the relatively low concentrations of the chemical prevent the formation of a distinct absorption. Anything below 3300 Bq of activity (or 1 nano gram per gram of soil) is already under the detection limit of the main analytical instruments.

Considering that Cs is an alkaline metal, its physical and chemical behavior is similar to those of Potassium (K) and Sodium (Na), extensively studied by spectral analyses. Luleva et al. (Luleva et al., 2011) suggest that K can be used as a potential alternative tracer that could be observed using soil spectral response, allowing rapid spatial mapping. Table 2 outlines the differences and similarities between the two elements, as well as the advantages and limitations of each one in their use as particle tracer. Introducing K is a soil particle tracer can introduce a number of advantages to erosion studies. The element has potential to be measured using spectral measurements which can increase the spatial representation. It has been shown that K concentrations can be quantified measured using spectral means (Luleva et al., 2011), however there is a need to test whether tracing patterns can be established spatially using spectral data.

Table 2. Differences and similarities between Cs^{137} isotope and K, for soil particle tracing

	Cs^{137}	K
Introduction to the environment	Introduced in the environment due to the Chernobyl incident in the late 1980s	Naturally occurring, but also introduced to the environment as an agricultural fertilizer.
Distribution	The even distribution of Cs is always assumed and therefore it has been a cause of debate, although some studies have provided supporting arguments based on climatological factors and study area locations (Chappell, 1999).	Although K fertilizer should be applied evenly to all agricultural fields in order to maintain optimal crop production (Jalali, 2007), the distribution of the element should be measured in order to account for natural variation.
Displacement	Radioactive Cs is assumed to move only due to erosion as it binds strongly to the soil particles.	K can be moved due to uptake by plants or by leaching.
Cost of analytical measurement	High	Low
Previously used as a tracer	Yes	No*
Detection using spectral response	No	Yes

* Part of ongoing research

Conclusions

Over the recent years, the problem of soil erosion has received much broader acknowledgement in literature. Time and effort associated with field sampling and analytical techniques due to the large scale of the event, however, still present a major limiting factor. Remote sensing provides some solutions to spatial data acquisition; however the potential of these data is not yet fully explored. General conclusion is that change detection of vegetation cover alongside with change in landuse are soil erosion parameters most widely studied with remote sensing. Landsat TM, ASTER and SPOT HRV are most frequently used, however it can be argued that the availability and price of the science determine their use, rather than sensor capabilities. There is a clear gap in the use of remotely sensed data with high spectral resolution. Chemical soil particle tracing of soil movement due to erosion is a line of research that can benefit from the development of a methodology that combines the spatial and the high spectral properties of remotely sensed data. The two upcoming international missions- Enmap, scheduled to launch in year 2013 and HyspIRI- expected to launch between year 2013 and 2016, promise to provide satellite hyperspectral data that would allow detailed and repetitive analysis of surface parameters.

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