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Satellite remote sensing for soil mapping in Africa: An overview

Olivier Dewitte
European Commission – Joint Research Centre (JRC), Italy

Arwyn Jones
European Commission – Joint Research Centre (JRC), Italy

Hicham Elbelrhiti
Institut Agronomique et Vétérinaire Hassan II, Morocco

Stephanie Horion
European Commission – Joint Research Centre (JRC), Italy

Luca Montanarella
European Commission – Joint Research Centre (JRC), Italy

Abstract
The protection and the sustainable management of soil resources in Africa are of paramount importance, particularly in the context of the uncertain impact of climate change and the increasing pressures of human activities. From the perspective of a policy-maker interested in topics such as food security and land degradation in Africa, this situation requires up-to-date and relevant soil information at regional and continental scales. To provide timely and reliable information on soils at synoptic scales, moderate and coarse spatial resolution satellite data offer many possibilities. The paper reviews how a range of multispectral, thermal infrared, passive microwave and active microwave spaceborne sensors can be used in the delineation of soil units, as well as in the assessment of some of their key properties and threats to soil functions from pressures such as water and wind erosion, landslides and salinization. The paper shows that remotely sensed data can be used for mapping soils in Africa but often need to be combined with ancillary data and field observations in order to be effective. Remote sensing is shown to be a key component of the emerging discipline of digital soil mapping.

Keywords
Africa, digital soil mapping, landslides, moderate and coarse resolution satellite imagery, regional and continental scales, remote sensing, soil erosion, soil mapping, soil threats

I Introduction

Soils are at the interface between topography, climate and biology (Dietrich and Perron, 2006; Legates et al., 2011) and their formation occurs over long periods of time, in some cases taking several thousands of years (Targulian

Corresponding author:
Olivier Dewitte, European Commission – Joint Research Centre (JRC), Via E. Fermi, 2749 - TP 280, Ispra, 21027, Italy
Email: olivierdewitte@yahoo.com

and Krasilnikov, 2007). They are also one of the fundamental components for supporting life on the planet and for regulating climate (Batjes, 1996; Lal, 2004; Millennium Ecosystems Assessment, 2005a; Palm et al., 2007).

Over the last decades increased pressure on the environment has led, particularly in the African continent, to the misuse and mismanagement of land. In turn, these pressures have resulted in the degradation of soils (e.g. acidification, salinization, organic depletion, compaction, nutrient depletion, chemical contamination, landslides, and erosion) and many of the services that they provide (Lal, 2009; Millennium Ecosystems Assessment, 2005b; UNEP, 2007; Vlek et al., 2008). Once degraded, soil resources are not renewed easily, at least in human timescales, and established evidence links land degradation to famine, social upheaval, the loss of biodiversity and climate change, both as cause and effect (Gisladottir and Stocking 2005).

For a sustainable utilization of the available natural resources, particularly in the context of the uncertain impact of climate change and the increase in pressure from human activities, the availability of up-to-date and relevant soil information for Africa is crucial (Palm et al., 2010; Sachs et al., 2010; Sanchez et al., 2009; UNEP, 2007).

In that context, the European Commission's Joint Research Centre (Institute for Environment and Sustainability) together with ISRIC – World Soil Information, the Food and Agriculture Organization of the United Nations (Land and Water Development Division) and scientists from the European Soil Bureau Network and the Africa Soil Science Society are developing the Soil Atlas of Africa. The Atlas aims to compile existing information on different soil types in easily understandable maps (regional to continental scales) covering the entire continent of Africa. While aiming to raise awareness of the importance of soil in Africa, the Atlas intends to show the variety of soil characteristics across the continent, illustrate the patterns of several key soil properties at continental and national scales and provide specific maps to highlight areas under or vulnerable to threats such as soil erosion and salinization, for example.

However, the Atlas, like other studies, highlights that current knowledge about the conditions and trends of African soils is highly fragmented and outdated. Indeed much of the information on soil in Africa has been derived from surveys carried out up to 50 years ago when data on many of the key issues currently affecting soil (e.g. carbon sequestration, biodiversity, heavy metal contamination) were not collected, and some soil properties may have changed (e.g. pH, organic carbon) over time. Moreover traditional soil mapping is a time-consuming and labour-intensive process and it is not a priority for many African countries.

At regional and continental scales (i.e. the target scales of the Atlas) the collection of information on the spatial and temporal variations in soil properties and characteristics in relatively short periods of time has the potential to be of interest for a diversity of users ranging from politicians and decision-makers to land managers and modellers.

Especially in Africa, such soil data are directly applicable to food security planning (Lal, 2004, 2009), flood alleviation and risk assessment (Thiemig et al., 2010) and water management (García-Ruiz et al., 2011). The early identification of soil water deficits over large areas can be proxies for the onset of drought and desertification conditions (Karnieli and Dall'Olmo, 2003; Mishra and Singh, 2010). The accurate observation of soil conditions can result in potentially great economic and social benefits.

Correct characterization of soil is also a critical parameter in the accuracy of numerical models of the atmosphere used in weather prediction, climate projections and land-atmosphere gaseous exchange (Cox et al., 2000; Mörner and Etiope, 2002). Significantly more carbon is stored in the world's soils than is present in the atmosphere or vegetation (Batjes, 1996; Davidson and Janssens, 2006) and changes in soil condition can have a large effect on the global carbon budget (Bellamy et al., 2005; Van Oost et al., 2007). The monitoring of soil conditions is important for the assessment of these global issues (Batjes, 1996, 2008; Jones et al., 2005). It is also a crucial parameter for the applications of geoengineering options such as biochar (charcoal or black C) for enhancing the land carbon sink to mitigate global climate change (Lenton and Vaughan, 2009; Verheijen et al., 2010).

To collect this information, satellite imagery recorded by medium to coarse resolution sensors could provide a unique instrument allowing a regular and synoptic coverage of soil resources at a continental or regional level.

A number of in-depth reviews have been dedicated to the application of remote sensing to the mapping of soil and related issues such as erosion, salinity and landslides (Anderson and Croft, 2009; Ben-Dor, 2002; Dwivedi, 2001; Joyce et al., 2009; Kääb, 2008; Metternicht and Zinck, 2003; Metternicht et al., 2005, 2010; Mulder et al., 2011; Vrieling, 2006). They have demonstrated a significant increase in the efficiency of conventional soil survey methods when remotely sensed data are used (Dwivedi, 2001; McBratney et al., 2003; Mulder et al., 2011; Vrieling, 2006). However, these reviews do not focus specifically on the collection of data over large areas with a relatively high frequency and the African context of data scarcity is barely addressed. In addition, rather than sweeping across the whole range of soil characteristics, they usually focus on a very specific issue such as soil moisture or soil erosion for which they provide an in-depth analysis.

Rather than replicating previous work, this paper focuses on the potential to update medium- to small-scale soil maps (regional to continental extents) using data acquired from moderate to coarse resolution spaceborne remote sensing systems. This paper assesses the capability of remote sensing to provide information on the state, characteristics and threat to soil in a manner comparable to traditionally collected information. In particular, the paper reviews the possibilities of spaceborne based remote sensing systems that are relevant for soil unit delineation, soil properties assessment and mapping soil threats, with specific examples for soil erosion by water, soil erosion by wind, landslides, and salinization.

II Radiative properties of soils and satellite sensors

Remote sensing is the process of inferring surface parameters from distant measurements of the upwelling electromagnetic radiation from the land surface (Schmugge et al., 2002).

The radiation reflected or emitted by soil varies according to a range of chemical and physical characteristics of the soil matrix (Anderson and Croft, 2009; Barnes et al., 2003; Mulder et al., 2011; Schmugge et al., 2002; Tang et al., 2009). This makes it possible to discriminate between different soil surfaces when looking at specific wavelengths or combination of spectral bands. It is also possible to infer the properties of a known soil surface from variations in the measured radiation.

For the reflected solar radiation, the most important characteristics of a soil that determine its reflectance properties are (Jones and Vaughan, 2010; Mulder et al., 2011; Stoner and Baumgardner, 1981):

- Moisture: increasing soil moisture content decreases the reflectance in the water absorption bands but also in the remaining bands due to the internal reflections within the water film covering the soil particles; thus wet soils appear darker (less reflective) than dry soils;
- Organic matter: increasing organic matter content gives darker (less reflective) soils;

- Texture: sandy soils are more reflective than clay soils;
- Surface roughness: decreases in surface roughness slightly increase reflection: an example is the development of soil crust;
- Iron content: increasing the content of iron oxide corresponds for many soils to a change in colour towards their characteristic brick-red colour, which implies an increased reflection ion in the red and a decrease in the green (Ben-Dor, 2002).

The thermally emitted radiance from any soil surface depends on two factors: (1) the surface temperature, which is an indication of the equilibrium thermodynamic state resulting from the energy balance of the fluxes between the atmosphere, surface and the subsurface soil; and (2) the surface emissivity which is the efficiency of the surface for transmitting the radiant energy generated in the soil into the atmosphere (Schmugge et al., 2002). While the emissivity of heavily vegetated surface is relatively uniform and close to one, the emissivity of exposed soils is highly variable and generally varies with wavelength (Jones and Vaughan, 2010). The emissivity is conditioned by temperature, the chemical composition, surface roughness, and physical parameters of the surface, e.g. moisture content. For example, emissivity increases with surface roughness. This increase in emissivity can be attributed to the increase in the soil surface area that interfaces with the air and thus can transmit the upwelling energy (Schmugge et al., 2002).

To make a quantitative estimate of the surface temperature we need to separate the effects of temperature and emissivity in the observed radiance. The satellite radiometers that record the radiation emitted reaching the sensor measure what is commonly called a 'brightness temperature'. Brightness temperature is the apparent temperature of an object based on the assumption that the object in question radiates as a black body and therefore its brightness may be related to its temperature. Once it is corrected considering the impact of surface emissivity, brightness temperature, which is less than the true kinetic temperature (that measured with a thermometer), can be regarded as an estimate of the land surface temperature (Jones and Vaughan, 2010; Schmugge et al., 2002).

The thermal emission in the infrared is used for surface temperature and in the microwave for soil moisture (Schmugge et al., 2002). The backscattering radiation from active microwave sensors depends mainly on both surface roughness and moisture content (Anderson and Croft, 2009).

However, it has to be noted that some limitations exist in mapping soil from remotely sensed data as some of the following problems can occur.

- Identifying, categorizing and mapping soils can be a complex procedure which in many cases is based on soil properties that are not even visible to the naked eye and require field or laboratory analyses (e.g. pH).
- Soil is a complex three-dimensional body. The majority of remote sensing systems only characterize the surface or, in optimum conditions, shallow depths of soils (Schmugge et al., 2002; Tang et al., 2009). In many cases, the surface characteristics may not be representative of the deeper soil body (e.g. soil organic carbon concentration decreases with depth).
- Soil properties can vary dramatically both spatially and temporally within a small area.
- The upper surface can be subject to frequent alteration by tillage, precipitation, erosion, crusting and other surface processes.
- Vegetation coverage obscures most soils for most or all the time. Soil subjected to arable cultivation will be exposed after ploughing. Soil under natural vegetation may never be exposed.
- The signal recorded by sensor is the result of a combination of several soil properties

(which are frequently interlinked). Such mixtures often mask the signal from a feature under investigation.
- The spectral resolution of sensors is not suitable for mapping soil characteristics (i.e. not covering diagnostic regions of the spectrum, focused on observing vegetation).

Still, remote sensing derived observation of the soil surface, soil surface variation, and partially obscured soil surfaces can be used to infer soil properties. A wide variety of spaceborne sensors have been used to map soil (Anderson and Croft, 2009; Dwivedi, 2001; Joyce et al., 2009; Kääb, 2008; Metternicht and Zinck, 2003; Metternicht et al., 2005, 2010; Mulder et al., 2011; Vrieling, 2006).

Soil maps at regional and continental extents are usually produced at scales of 1:1,000,000 or smaller which equates roughly to a spatial resolution of about 1 km or coarser (McBratney et al., 2003). Reconnaissance mapping for continental and regional studies is often carried out to derive typical values of a subject matter over large areas (Jones and Vaughan, 2010). In the context of providing timely and reliable information on soil characteristics at regional to continental extents in Africa, such scales equate well to data acquired to moderate and coarse spatial resolution sensors.

In addition, moderate and coarse resolution sensors provide more frequent coverage than high resolution sensors such as the Landsat Thematic Mapper (TM). The higher frequency represents a specific advantage for characterizing soil conditions according to management practices and weather-related incidents. This helps assess daily or weekly variation in surface conditions and improves the methods for the delineation of soil units, the estimation of soil properties and the assessment of soil threats such as soil erosion by water and by wind and landslides. Moreover, McBratney et al. (2003) and Hengl (2006) show that when producing maps at scale 1:1,000,000, analysing data at a resolution finer than 100–200 m does not bring any effective additional information to the final product compared to the effort needed to process the data.

Several spaceborne sensors have been applied, or are potentially suitable, for regional and continental soil mapping in Africa; see the ITC database of satellites and sensors (http://www.itc.nl/research/products/sensordb/searchsat.aspx), Sharing Earth Observation Resources (http://directory.eoportal.org/d_rbt.php?type=30700000) and 'The Earth Observation Hand book' by the Committee on Earth Observation Satellites (http://www.eohandbook.com).

While this paper focuses only on the use of data from satellite-based sensors that deliver spatial data at resolutions suited to mapping large areas at small scale or coarse resolution, more detailed mapping can be carried out using airborne systems characterized by higher spatial and spectral resolutions (e.g. imaging spectrometers, LiDAR, microwave) for specific sites (Ben-Dor et al., 2009). While such systems offer the soil surveyor the advantage of customer control over the acquisition time and spatial detail, they are not discussed in this text as data acquired by high resolution sensors for regional and continent-wide surveys are extremely costly to acquire, generate an enormous data volume and are limited to low frequencies of data acquisition.

The following sections are based on the information provided in the ITC database of satellites and sensors (http://www.itc.nl/research/products/sensordb/searchsat.aspx), Sharing Earth Observation Resources (http://directory.eoportal.org/d_rbt.php?type=30700000), and 'The Earth Observation Handbook' by the Committee on Earth Observation Satellites (http://www.eohandbook.com). These sources provide an overview on the sensors that can be applied to derive soil characteristics at regional and continental scales from moderate and coarse resolution satellite data. The aim is to give potential end users the general outlines of remote sensing data that can be used to map soil characteristics in Africa and to provide some guidance on the choice of an appropriate technique for specific applications.

III Remote sensing for soil unit delineation and soil properties assessment

1 Soil unit delineation

Remote sensing can provide detailed information on the distribution of soil bodies. The delineation of surface soil patterns through the visual interpretation of aerial photographs has been used for several decades in traditional soil survey (Dwivedi, 2001). Broad differences in soil patterns (predominantly changes in colour or texture) can also be visualized on coarser resolution imagery although placing precise boundaries in complex areas is problematic. However, the use of visual interpretation techniques relies heavily on the skills of the interpreter and an understanding of the relationships between the observable terrain characteristics and the soil units. Such an interpretation may be formalized by rules and criteria such as those adopted for the creation of the World Soils and Terrain Digital Databases (SOTER) at a scale of a 1:1,000,000 (Van Engelen and Wen, 1995; Van Lynden and Mantel, 2001).

More automated delineations have been successfully performed through, for example, surface albedo measurements, soil albedo being the soil property that is most directly correlated to reflectance-based data (Post et al., 2000). Tsvetsinskaya et al. (2002) derived surface albedo statistics at 1 km resolution for the arid areas of northern Africa and the Arabian Peninsula from MODIS (MODerate Resolution Imaging Spectroradiometer) imagery and related them to soil groups and rock types based respectively on the legend of the FAO Soil Map of the World (FAO/UNESCO, 1971–1981) and geological maps. Similar work was carried out by Zhou et al. (2003) for northern Africa in which relationships between MODIS surface albedo and ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) broadband emissivities were analysed. Using the FAO soil map legend as a guide, Prigent et al. (1999) produced a map of the sand dune fields in the Sahara derived from the Special Sensor Microwave/Imager (SSM/I) brightness temperatures.

However, remotely sensed data, even for the arid areas, are not reliable enough to support totally automatic soil delineation algorithms. Broad spectral channels and medium to coarse spatial resolutions mean that surface roughness and particularly the presence of vegetation can mask the main soil characteristics (Anderson and Croft, 2009; Dobos et al., 2000; Schmugge et al., 2002). Yet remotely sensed data can be used as complementary data and/or provide indirect support to the delineation of soil units. These complementary data are frequently interlinked.

Techniques for soil delineation or mapping as reported in the preceding text can also be applied to directly or indirectly identify some soil properties. For example, topsoil characteristics can influence the soil surface colour, and thus the spectral reflectance. Singh et al. (2004) established a relationship between soil colours defined by the Munsell system and a Normalized Difference Vegetation Index (NDVI) derived from AVHRR (Advanced Very High Resolution Radiometer), which in turn could be applied to map soil properties such as organic matter and soil moisture.

2 Soil properties and characteristics

Key soil functions are governed by a few critical properties such as texture, pH, organic matter content and soil moisture levels. Some parameters are virtually impossible to assess from remotely sensed data. There are no reliable examples of remote sensing providing reliable assessments of parameters such as cation exchange capacity, base saturation, pH, porosity, etc. This is due to the complexity of assessing a three-dimensional body on the basis of surface characteristics that lack strong spectral signatures.

The best results for soil property identification have been performed with sensors that deliver data at a high spatial resolution (e.g. optical air and spaceborne remote sensing, SAR and airborne hyperspectral remote sensing) that is inappropriate for large area mapping in a short period of time (Barnes et al., 2003; Ben-Dor et al., 2009; McBratney et al., 2003; Metternicht and Zinck, 2003; Rahman et al., 2008; Vrieling, 2006). For example, Salisbury and D'Aria (1992) and Breunig et al. (2008) managed to estimate the particle size of soil using a combination of visible, near-infrared and thermal-infrared ASTER data to minimize the effects of soil properties other than texture.

Nevertheless, some researches have established links between soil properties and remotely sensed data that have (or could be) proved to be efficient at a regional scale. An analysis of the albedo and macroscopic surface roughness with the MISR sensor (Multi-angle Imaging Spectro Radiometer) with a resolution of 250 m permitted the retrieval of information about the structure and the composition of the surface material and the nature of the dune formations in Chinese deserts (Wu et al., 2009). White and Eckardt (2006) used multispectral MODIS imagery to map carbonate distribution over the Makgadikgadi Basin, Botswana. They validated their results with soil property estimates from Landsat ETM+ and laboratory analysis of field samples. Odeh and McBratney (2000) have extracted regional scale topsoil clay content information from AVHRR data and related vegetation indices in combination with a few ground measurements.

Soil moisture can be considered as a critical but complex soil characteristic as it varies with meteorological or climatic fluctuations and affects atmospheric, geomorphic, hydrologic and biologic processes. The dispersive and cohesive properties of soil moisture also make it an important variable in regional climatic analyses, landscape change through weathering, runoff generation, mass wasting and sediment transport (Legates et al., 2011). In Africa (where drought can lead to very acute food security issues), soil moisture is a key soil property that needs to be monitored closely. However, the current networks of ground stations providing in situ data such as rainfall amounts are too sparse and non-reliable to be used for soil moisture modelling at continental scale (WMO, 2006). In that context, the retrieval of soil moisture by remote sensing is definitely an effective alternative.

Soil moisture conditions are closely related to the hydraulic properties of the soil, which are defined by the soil type. The main factors which affect the accuracy of the soil moisture determination include vegetation cover, soil properties (density and texture) and surface roughness (Anderson and Croft, 2009; Barnes et al., 2003; Barrett et al., 2009; Schmugge et al., 2002; Tang et al., 2009).

A diversity of quantitative methods (indices, statistical models, physical models) can be applied to a range of satellite sensors to retrieve soil moisture information (Wigneron et al., 2003). Microwave measurements have been demonstrated to provide reliable daily soil moisture data for the whole globe (Gruhier et al., 2010; Prigent et al., 2005; Wigneron et al., 2003). Retrieval of soil water content information from microwave measurements is based on the large dielectric difference between water and the other soil components which in turn influences temperatures (and emissivities) and backscattering coefficients from passive and active microwaves sensors, respectively. Estimates of soil moisture have been obtained from passive sensors such as SMMR (Scanning Multichannel Microwave Radiometer) (Vinnikov et al., 1999), SSM/I (Prigent et al., 1998), AMSR–E (Advanced Microwave Scanning

Radiometer – Earth Observing System) (Draper et al., 2009) and TRMM TMI (Tropical Rainfall Measurement Mission Microwave Imager) (Bindlish et al., 2003), and from active microwave sensors such as the AMI (Active Microwave Instrumentation) scatterometer carried by the ERS satellite (Prigent et al., 2005; Wagner and Scipal, 2000; Wagner et al., 2007) and the ASCAT (Advanced Scatterometer) on METOP-A (Bartalis et al., 2007). Soil moisture has also been retrieved from visible and thermal images from the VISSR (Visible and Infrared Spin Scan Radiometer) on board the Meteosat satellite (Verstraeten et al., 2006; Wagner et al., 2007).

In addition to those sensors, vegetation indices derived from MODIS or AVHRR have also been used to estimate the root-zone soil moisture (Wang et al., 2007) or to assess the relationship between soil moisture and vegetation conditions (Gilabert et al., 2002; Sandholt et al., 2002). Wang et al. (2007) conducted experiments allowing retrieved soil moisture characteristics to be retrieved using NDVI from MODIS. Their research was carried out in three sites representing two types of vegetation (shrub and grass) and two types of climate conditions (semi-arid and humid). They showed that time series of soil moisture taken at several soil depth and NDVI (eight-day composite in 250 m resolution) during a four-year period allowed correlation to be done. However Gilabert et al. (2002) showed that in areas where vegetative cover is low (i.e. <40%) and the soil surface is exposed, differences in reflectance characteristics from the soil in the red and near-infrared channels (e.g. from moisture or mineralogy) can result in misleading estimates. Indeed a thick layer of foliage can totally obscure the soil surface from observation. Even partial vegetation cover can seriously affect the estimation of soil moisture levels.

Although most of the sensors used to extract soil moisture have a spatial resolution lower than those used to derive the other soil characteristics at the regional and continental scale, they have much better temporal resolutions. This allows effective time series to be produced, which may be useful in many applications. For example, the Soil Water Index (SWI), used for soil moisture, is obtained by filtering the surface soil moisture time series with an exponential function (Wagner and Scipal, 2000). The index is particularly useful for monitoring changes in soil water content over time, and is unsuitable to quantify the soil water content (Wagner and Scipal, 2000; Wagner et al., 2007).

Surface temperature measurements can be derived from sensors such as the AVHRR (Lakshmi et al., 2001; Pinheiro et al., 2006). In their study, Pinheiro et al. (2006) developed a six-year daily, daytime and nighttime NOAA-14 AVHRR based land surface temperature (LST) data set over continental Africa for the period 1995 through 2000. They used an algorithm to determine LST values that requires as input values of surface emissivity in AVHRR channels 4 and 5 (TIR). For that, they developed continental maps of emissivity using an ensemble approach that combines laboratory emissivity spectra, MODIS-derived maps of herbaceous and woody fractional cover, and the FAO Soil Map of the World (FAO/UNESCO, 1971–1981). Other measurement of surface temperature can also be derived from HIRS/2 (High Resolution InfraRed Sounder) on board the NOAA TOVS (TIROS Operational Vertical Sounder) (Lakshmi et al., 2001), SEVIRI (Spinning Enhanced Visible and Infra-Red Imager) on board the geostationary satellite MSG (Meteosat Second Generation) (Jiang et al., 2006) and MODIS (Wan and Li, 1997). Surface temperature can be correlated with soil moisture and can serve as an indicator of it (Prigent et al., 2005; Singh et al. 2004).

Surface emissivity has also the potential to be used to infer soil properties. In view of improving satellite data assimilation, Yan and Weng (2011) have developed a microwave land emissivity library from AMSU-A (Advanced

Microwave Sounding Unit) retrievals according to the desert soil type. The soil type is specified using the soil texture classes provided in FAO Soil Map of the World (FAO/UNESCO, 1971–1981).The data are classified into seven types: sand, loamy sand, sandy loam, loam, sandy clay loam, clay loam, and clay. These emissivity spectra in the library offer the mean emissivity spectral feature versus soil type, and thus they could be applicable for retrieval algorithms. In a similar manner to the use of the FAO soil map, Pinheiro et al. (2006) estimated the AVHRR band emissivity of each soil type of Africa.

Most of the studies on the determination of soil organic matter (SOM) with remote sensing have been performed at plot scale and are based on products derived from ground-based or airborne high resolution and hyperspectral systems (Barnes et al., 2003; Gomez et al., 2008; Uno et al., 2005). Unfortunately, spaceborne versions of such systems are not yet operational. However, it has been shown that Medium Resolution Imaging Spectrometer Instrument (MERIS) could be used as an alternative to conventional field surveys to provide SOM estimates at regional as well as global level. In a laboratory study the potential of the MERIS spectral resolution proved to be sufficient to predict significant variations in soil organic matter content at these scales (Boettcher et al., 2005). Estimations of topsoil organic matter at regional scale could also be made through the analysis of soil colour (Singh et al., 2004), dark soils typically containing more soil organic matter than pale soils (Viscarra Rossel et al., 2006a).

3 Validation

The validation of remotely sensed estimates of surface variables is a critical component of any remote sensing study. Many surface parameters such as surface temperature, soil moisture and surface emissivity contain large uncertainties. Thus, it is important to quantify these uncertainties in order to improve soil mapping as well as advance the assimilation of satellite data (Moradkhani, 2008). Soil parameters are indeed needed in prediction systems for weather, climatology and ecosystems, for example, and their uncertainties can degrade data impacts (Yan and Weng, 2011).

A common approach to check the accuracy or validity of remotely measured values is to compare them against ground measurements (e.g. Draper et al., 2009; Gruhier et al., 2010; Prigent et al., 2005; Vinnikov et al., 1999). In some cases, soil samples are analysed in the laboratory for practical reasons (e.g. White and Eckardt, 2006), but this analysis on soil cannot replace in situ measurement (e.g. de Rosnay et al., 2006).

There is often a mismatch between the scales at which ground reference data are collected and scale of the remote sensing data or the scale of the required outputs. This mismatch can relate both to the spatial scale and the temporal scale of the observations. For example, field instrumentation for measuring soil characteristics usually provides point observations while satellite images have km-scale resolution (Gruhier et al., 2010). In addition, for the same instrumentation there is often a temptation to use high-frequency data collection (minutes or hours) when the process of interest may operate over seasonal or longer timescales (de Rosnay et al., 2006).

Solutions to this mismatch problem depend on the application, but a usual approach is to adopt a sampling strategy (e.g. a stratified procedure) (Jones and Vaughan, 2010). The choice of sampling strategy is difficult as many details need to be considered carefully for each situation, bearing in mind both statistical and practical considerations. For example, the sample needs to be truly representative of the whole area, particularly because in large images (e.g. AVHRR) there is often a gradient of illumination or view angle across the image that can have substantial impact on the classification.

In many cases, measurements are scale dependent and modelling is often required to scale up (aggregate) small spatial- or temporal-scale field observations to the larger areas that are needed if we are to link effectively with km satellite data (de Rosnay et al., 2009). In the case of validation of km-scale satellite estimates (e.g. soil moisture), validation remains a difficult task (Gruhier et al., 2010).

It might be not technically feasible to use field measurements, particularly when the region of interest is vast with non-homogeneous soils and land use. In such a case, the validation relies on ancillary data. For example, in their study of the Indus Basin with AMSR-E data at a resolution of 25 km, Cheema et al. (2011) evaluate the soil moisture by comparing it against spatial data derived for rainfall from the TRMM satellite and seasonality of vegetation from SPOT-Vegetation. For Africa, the use of ancillary data is very often the only realistic option for the validation of remotely sensed data.

IV Remote sensing for soil threats analysis

The term 'threat' has been defined by JTC1 (2004) as 'a natural phenomenon that could lead to damage, described in terms of its geometry, mechanical and other characteristics. The threat (danger) can be an existing one (such as a creeping slope) or potential one (such as a rockfall)'. Soil threats are being increasingly related to a wide range of human activities. Threats are complex and their extent can be local, regional and even continental. They can be interlinked and when they occur simultaneously, their combined effects tend to increase the problem. For example, the occurrence of landslides on unstable slopes can modify the characteristics of the soil where it occurs and subsequently its resistance to water erosion (Lin et al., 2006). Such threats can induce soil degradation if they cause soil to lose the capacity to carry out its ecosystem and environmental functions. In the subsequent sections of this paper, only the soil threats that can be detected and analysed at regional and continental scales are presented (erosion by water and wind, landslides, salinization).

1 Soil erosion by water

Soil thickness depends on the balance between the production and erosion and for soil to persist the rate of replenishment must be equal to or greater than that of erosion (Heimsath et al., 1997). Soil erosion by water is seen as one of the most widespread forms of soil degradation and, as such, poses potentially severe limitations to sustainable development in Africa. In many arable areas (where the land is ploughed), erosion rates average 1–2 orders of magnitude greater than rates of soil production, erosion under native vegetation, and long-term geological erosion (Montgomery, 2007; Verheijen et al., 2009).

A visual detection of individual geomorphic features related to soil erosion by water is very limited or even impossible. The limited spatial extent of those features, even for the largest gullies, inhibits their detection using low-spatial resolution satellite imagery (Millington and Townshend, 1984; Vrieling, 2006). Satellite data could possibly be applied to visually delineate eroded areas such as badlands (Kumar et al., 1996; Sujatha et al., 2000), but at medium to coarse spatial resolutions (lower than 100–200 m) their automatic extraction is more problematic and difficult (Alatorre and Begueria, 2009; Le Roux et al., 2007; Vrieling, 2006).

Estimates of soil properties provide necessary information that may serve as proxies to predict soil erosion. For example, soil texture and the size of particles have a significant role in erosion potential (Salisbury and D'Aria, 1992), while variations in soil moisture have the ability to affect strongly regional runoff patterns (King et al., 2005; Verstraeten et al., 2006). Soil erosion implies the removal of topsoil and the subsequent decrease in organic matter content, which can be assessed in the analysis of soil colour and albedo (Singh et al., 2004, 2006). The analysis of changes of the surface states allows spatial and temporal assessment of erosion status.

Soil erosion processes are generally limited by vegetation cover. Soil erosion is exacerbated by surface disturbance and compaction that reduce the soil hydraulic conductivity and break down soil aggregates (Sidle et al., 2006). Therefore, the identification of the characteristics (or the absence) of the vegetation cover and its dynamics can help in the assessment of soil erosion (Vrieling, 2006). Land-use classification is often used to map vegetation types in relation to their effectiveness to protect the soil, but the identification of vegetation types can hardly be done with coarse spatial resolution data (Vrieling, 2006). However, a direct indication of the protective role of the vegetation can be obtained through the use of vegetation indices such as NDVI (Gay et al., 2002; Thiam, 2003) or the determination of the green vegetation cover with a linear unmixing technique (Zhang et al., 2002) that separates the soil component from the vegetation signal (Adams et al., 1986).

Wildfires can have a significant impact on soil properties, often leading to an increase in soil erosion vulnerability before geomorphological stability is re-established through the regrowth of vegetation (Shakesby and Doerr, 2006). Over the past decades, various spaceborne sensors have been widely used for active fire detection, burnt area (or fire scar) mapping and fire potential danger. Examples include the use of AVHRR (Barbosa et al., 1999; Pu et al., 2004), SPOT VEGETATION (Tansey et al., 2004, 2008), TRMM Visible and Infrared Scanner (VIRS) (Giglio, 2007), MODIS (de Klerk, 2008; Giglio et al., 2003; Justice et al., 2002) and MSG-SEVIRI data (Amraoui et al., 2010).

Changes in vegetation patterns can be done directly through the near real-time monitoring of forest and bush fires (Lambin and Ehrlich, 1997; Langner and Siegert, 2009). Forest clearance (or deforestation), for which fire is sometimes used, also increases the potential for soil erosion (Sidle et al., 2006). Multitemporal analyses of data provided by sensors such as MERIS (Seiler and Csaplovics, 2008), SPOT VEGETATION (Carreiras et al., 2006), MODIS (Langner and Siegert, 2009; Perera and Tsuchiya, 2009) and AVHRR (Giri et al., 2003; Thiam, 2003) allow an assessment of these land-cover changes.

2 Soil erosion by wind

Wind erosion is a degradation process that affects large areas in Africa and in particular the northern desert regions. The Sahara is one of the largest dust-producing regions in the world and includes the dustiest place on Earth, the Bodele Depression, Tchad (Engelstaedter et al., 2006; Goudie, 2008; Prospero et al., 2002). Wind erosion can be increased after wildfires (Shakesby and Doerr, 2006) and the thinning of semi-arid forests (Whicker et al., 2008). Wind erosion is a significant issue in areas affected by drought where protective vegetation cover is reduced and water bodies dry up. In some very arid places, wind erosion is the only active erosion process. Direct links between sources of dust emission and soil erosion induced by wind action have been established (Bullard et al., 2008; Lee et al., 2009).

A variety of primary and derived data sets have allowed the determination of the spatial and temporal variability of dust emissions from different surfaces. Effective use has been made of the Nimbus 7 Total Ozone Mapping Spectrometer (TOMS) Absorbing Aerosol Product (Prospero et al., 2002; Washington et al., 2003), the Infrared Difference Dust Index (IDDI) from the Meteosat IR-channel (Legrand et al., 2001), the MODIS, MISR and Clouds and the Earth's Radiant Energy System (CERES) instruments on board Terra (Zhang and Christopher, 2003). The MODIS instrument, also carried by the Aqua satellite, is widely used in dust studies as it provides information twice a day on dust aerosol concentrations in the atmosphere (Baddock et al., 2009; Bullard et al., 2008; Koren and Kaufman, 2004). Such data have been used to provide reliable detections of hot spots of dust emission through qualitative image interpretation (Lee et al., 2009; Washington et al., 2006) and more elaborate image analysis (Baddock et al., 2009; Bullard et al., 2008).

3 Landslides

The possibilities and limitations of remote sensing in the inventorying and the monitoring of landslides are very similar to those detailed for the analysis of soil erosion features produced by water. Landslides are triggered by rainfall and also by earthquakes, sometimes in combination. The occurrence of landslide generally increased after clearance of the forest canopy and wildfires (Shakesby and Doerr, 2006; Sidle et al., 2006). For the largest events, their impact on the landscape can be detected through disrupted or absent vegetation cover, anomalous with the surrounding terrain. For instance, Zhang et al. (2010) were able to detect large landslides triggered by the 2008 Wenchuan Earthquake (Sichuan, southwestern China) with MODIS-derived multitemporal NDVI imagery at a spatial resolution of 250 m and topographic slope threshold derived from SRTM (Shuttle Radar Topography Mission) elevation data. However, the detection of landslides remains difficult at low spatial resolutions.

However, remote sensing can be applied to determine factors that control landslides. At the global scale, Hong et al. (2007) used controlling factors derived from remotely sensed data such as SRTM and MODIS to compute a susceptibility to landslides occurring. This index was used in conjunction with satellite-based precipitation information from the NASA TRMM-based Multi-satellite Precipitation Analysis (TMPA) system to potentially detect areas with significant landslide potential due to heavy rainfall (Hong et al., 2006). Ray and Jacobs (2007) found a strong relationship between landslide events, AMSR-E surface soil moisture measurements and TRMM rainfall data, which opens interesting perspectives for mapping landslide susceptibility at regional or global scales (Ray and Jacobs, 2008; Ray et al., 2010).

4 Salinization

Salinization, which can be a natural process, is often associated with irrigated areas where low rainfall, high evapotranspiration rates, soil chemistry or soil textural characteristics lead to an increase in the concentration of salts in the soil.

Remote sensing has been widely used to detect and map salt-affected areas. The presence of salt in the topsoil affects the surface reflectance characteristics. High salt concentrations can be identified by the existence of characteristic vegetation type and growth which is controlled by salinity or by the presence of bare soils with salt efflorescence and crust where vegetation is unable to grow (Metternicht and Zinck, 2003). In a similar manner to vegetative indices, soil scientists have developed normalized difference ratios models and threshold values to map salt-affected soils. For example, Nield et al. (2007) developed a Normalized Difference Ratio to map gypsum- and sodium-affected soils using Landsat 7 ETM. But these mapping methods are not really adapted for low-resolution data sets (Metternicht and Zinck, 2003; Spies and Woodgate, 2005). The assessment of the expansion of salt-affected soils and potential salinization risk should be feasible with the use, as proxies, of measurements of soil moisture and land-use/cover changes (e.g. Li et al., 2007; Sujatha et al., 2000).

The detection of irrigated areas has been carried out many times, from the analysis of MODIS (Ozdogan and Gutman, 2008; Thenkabail et al., 2005) and SPOT VEGETATION (Kamthonkiat et al., 2005) data and notably through NDVI and similar indices.

5 Other soil threats

Other threats are affecting soils, such as soil sealing, soil loss of organic matter, decline in biodiversity, contamination and compaction. They can also be assessed through remotely sensed data and procedures similar to those referred above. However, not many examples can be found in an African context.

Soil sealing is the covering (i.e. sealing) of soil by artificial surfaces such as asphalt and concrete. Soil sealing may also result in soil compaction and soil contamination together with a decline in soil biodiversity and soil functions (Scalenghe and Marsan, 2009). Soil sealing is strongly related to urban expansion (e.g. Scalenghe and Marsan, 2009) which can be detected from sensors such as AVHRR, VEGETATION and MODIS imageries (Budde et al., 2004; Schneider et al., 2003).

Losses in soil organic matter are due to several factors such as the conversion of grasslands, forests and natural vegetation to arable land. Intensive arable farming, the overuse of nitrogen fertilizer, overgrazing, soil erosion and forest fires are all management factors that can lead to a reduction in levels of soil organic matter levels (Mills and Fey, 2004).

Remote sensing provides also knowledge of factors (both controlling and triggering) that are required for modelling the hazard related to soil threats (King et al., 2005; Le Roux et al., 2007; Metternicht et al., 2005; Vrieling, 2006; Webb and McGowan, 2009).

V Remote sensing and digital soil mapping

Many of the examples shown in this paper demonstrate that the use of remote sensing imagery for mapping soil properties can be problematic if used in isolation. The use of ancillary data, field observations and laboratory analysis are important approaches for inferences about soil and especially for validation procedures. Examples of important ancillary data sets include topography, vegetation type, climate and lithology, some of which can be derived from high resolution satellite and airborne sensors. Several digital mapping resources are available for the whole Africa (Table 1).

Topography data can be obtained from the SRTM mission and the ASTER DEM. Data on vegetation can be obtained from the GlobCover land cover products at 300 m resolution derived from the MERIS sensor of Envisat and covering two periods: December 2004–June 2006, and January–December 2009 (Arino et al., 2008). Other vegetation products are the USGS Global Land Cover Characteristics map based on 1 km AVHRR observations between April 1992 and September 1993 (Loveland et al., 2000), and the Global Land Cover (GLC) 2000 developed by using 1 km resolution satellite data acquired by the VEGETATION instrument on board the SPOT 4 satellite (Mayaux et al., 2004). The VEGETATION instrument was also used to produce the global, multi-annual (2000–2007) burnt area product (Global VGT burnt area product 2000–2007) at 1 km resolution (Tansey et al., 2008). The first global map of irrigated lands was generated by Siebert et al. (2005; updated by Siebert et al., 2007) and combines heterogeneous information on the location of irrigated areas with information on the total irrigated area from national and international sources. The International Water Management Institute (IWMI) released the Global Irrigated Area Map (GIAM) circa 1999 (Thenkabail et al., 2009). The data set was produced using AVHRR data augmented with additional information from SPOT VEGETATION, Japanese Earth Resources Satellite (JERS-1), SRTM elevation and climatic data. A set of global climate layers (climate grids) with a spatial resolution of 1 km is provided by the WorldClim project (Hijmans et al., 2005). Observed climate data

Table 1. Examples of pan-African digital mapping resources

Type of data	Source	Online access
Topography	SRTM Digital Elevation Model	http://earthexplorer.usgs.gov
	AfSIS Africa Soil Information Service	Hydrologically Corrected/Adjusted SRTM Digital Elevation Model (AfrHySRTM) and derivatives – http://www.africasoils.net/data/rsdownload
	ASTER Digital Elevation Model	http://www.gdem.aster.ersdac.or.jp
Land cover/land use	USGS Global Land Cover Characteristics	http://edc2.usgs.gov/glcc/glcc.php
	Global Land Cover 2000	http://bioval.jrc.ec.europa.eu/products/glc2000/glc2000.php
	GlobCover land cover products	http://ionia1.esrin.esa.int
	Global VGT burnt area product 2000–2007	http://bioval.jrc.ec.europa.eu/products/burnt_areas_L3JRC/GlobalBurntAreas2000-2007.php
	Global Irrigated Area Map (GIAM)	http://www.iwmigmia.org/info/main/index.asp
Climate	WorldClim – Global Climate Data	http://www.worldclim.org

from the period 1950–2000 have been interpolated to derive monthly precipitation, temperature and 19 other bioclimatic variables. Variables for future conditions, based on IPPC assessments, are also available.

In a wider context, remote sensing is complementary to the emerging field of digital soil mapping (DSM). DSM attempts to predict soil properties through the use of mathematical and statistical models that combine information from soil observations with information contained in correlated environmental variables. DSM frequently requires indirect information from remote sensing systems (Hansen et al., 2009; McBratney et al., 2003; Minasny et al., 2008; Mulder et al., 2011; Palm et al., 2007). For example, Dobos et al. (2000) used AVHRR data as covariates together with topographic parameters derived from SRTM DEM for small-scale prediction of soil classes in Hungary. They proved that the classification accuracy of the model was improved significantly over the case when only AVHRR data was in the model. In this study, the use of spectral imagery for the spatial prediction of soil properties was based on the spatial relation between existing soil data (SOTER database) and the observed patterns in the imagery. A similar approach was applied for mapping soil organic matter in Hungary by applying a regression kriging approach to a battery of covariates derived from MODIS, SRTM DEM and a database of georeferenced soil profiles evenly distributed all over the country (Dobos et al., 2005). Symeonakis and Drake (2004, 2010) used NDVI vegetation data, digital soil maps and a digital elevation model to estimate the erosion in sub-Saharan Africa. Ballantine et al. (2005) mapped landforms across the whole of North Africa by applying spectral unmixing algorithms to MODIS imagery, landform maps being a predictor of soil types.

Another example of the use of DSM to assess soil properties in Africa is the Africa

Soil Information Service, or AfSIS (http://africasoils.net). AfSIS is the African node of a new global soil-mapping consortium (Globalsoilmap.net) initiated by the Digital Soil Mapping Working Group of the International Union of Soil Sciences (IUSS) that aims to make a new digital soil map of the world using state-of-the-art and emerging technologies for soil mapping and predicting soil properties at fine resolution (Sanchez et al., 2009). The key properties selected by these projects are: organic carbon content, granulometry (clay, silt, and sand contents) and content of coarse fragments, pH, cation exchange capacity, bulk density and available water capacity. Since January 2009, AfSIS has been aiming to collect and generate various inputs or covariates to predict these soil properties. Remotely sensed data are a key issue in this project. AfSIS has produced large-area mosaics of radiometrically calibrated, orthorectified Landsat MSS, TM and ETM+ images. It has also developed SRTM terrain model derivatives (e.g. terrain units, slopes, curvatures, contributing areas, compound topographic and erosion/deposition indices and watershed delineations). In addition, mosaics of radiometrically corrected MODIS and AVHRR images are now being produced and the AfSIS team is currently compiling the ASTER Global Digital Elevation Model (GDEM) at a spatial resolution of 30 m for the African continent, and will be running analysis and quality checks on this during the course of the next few months. While prediction methods are now being developed within AfSIS, the main issue remains in the acquisition of environmental covariates, legacy data and additional ground observations.

VI Perspectives

Remote sensing for soil mapping can now be considered as a stable operational tool that provides regular and high-quality information about the surface of the planet. Future perspectives for mapping soils require three considerations.

1 The development of sensors that are specifically suited to identify soil characteristics

One of the technical limitations to the extraction of chemical and physical soil properties has been the radiometric characteristics of spaceborne sensors. Many earth observation systems have been targeting responses from the atmosphere, the oceans or vegetative surfaces, often with rather broad bandwidths. Such configurations often miss or even mask out characteristic and soil-specific electromagnetic absorption or reflectance features (Goetz et al., 1985). Imaging spectrometers acquire data in tens or even hundreds of very narrow spectral channels allowing detailed spectral signatures to be extracted from objects. Experimental applications of airborne imaging systems have shown that detained soil characteristics such as clay mineral content, mineral composition, salt content, pH, organic matter levels and cation exchange capacity can be extracted directly from observations of bare surfaces or through chemical conditions in the overlying vegetation cover (Ben-Dor et al., 2006; Dehaan and Taylor, 2002; Lagacherie et al., 2008; Uno et al., 2005). While sensors such as MODIS and MERIS have demonstrated the application of spaceborne spectrometer data to map soil characteristics, the spectral characteristics of these sensors are still significantly below airborne systems (e.g. MODIS has 36 channels, while the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) collects data in 224 contiguous spectral channels from 400 to 2500 nm). The spaceborne Hyperion instrument (242 contiguous spectral bands from 400 to 2500 nm, 30 m of spatial resolution) shows promising perspectives in the development of sensors of high potential for soil mapping applications (Gomez et al., 2008).

While LiDAR systems are being used increasingly for topographical mapping, the use of airborne LiDAR data to develop field-scale topographic indices as a proxy near-surface soil conditions has been limited (Anderson et al., 2006; Tenenbaum et al., 2006). In addition, very limited use has been made of spaceborne LiDAR systems (e.g. the laser altimeter on NASA's ICESat mission) to generate soil data over large extents.

In addition, global measurements of the soil moisture present at the Earth's land surface will be made by the European Soil Moisture and Ocean Salinity (SMOS) mission (Panciera et al., 2009; Wigneron et al., 2003) from 2009 and Soil Moisture Active Passive (SMAP) mission scheduled for launch in the 2014–2015 timeframe (Entekhabi et al., 2010).

The Committee on Earth Observation Satellites (CEOS) agencies estimates tens of new satellite missions will be launched and operational by 2015 (http://database.eohandbook.com).

2 The correlation between data collection and remote sensing techniques

There is a need to collect current soil data to improve accuracy and performance of satellite imagery and validate more complex issues such as soil organic carbon and greenhouse gas fluxes, for example.

To this end the collection of spectral libraries on soil attributes with proximal sensing offers good perspectives (Brown et al., 2006; Clark et al., 2003; Viscarra Rossel et al., 2010, 2011). The use of statistical and chemometric analysis of these spectroscopic data allows to derive a wide variety of soil attributes such as pH, organic carbon, clay, silt, sand, cation exchange capacity and electrical conductivity, for example (Brown et al., 2006; Viscarra Rossel et al., 2006b). A major initiative of collection of spectral data that is worth mentioning is the spectral library currently developed by AfSIS (http://www.africasoils.net/data/spectral-libraries) which will provide a valuable resource for research and applications for sensing soil of Africa.

The development of techniques comparing a remotely sensed observed spectrum (unknown) to libraries of spectra of well-characterized materials is proving to be efficient in the identification of surface characteristics (Clark et al., 2003). However, as pointed out by Mulder et al. (2011), advances in proximal sensing to detect soil characteristics have evolved much faster than in remote sensing and a technology gap still has to be bridged. In order to make optimal use of all data sources available, future researches have to focus on the improvement of the integration of proximal and remote sensing using scaling based approaches.

3 The development of new models and software algorithms

A limitation to remote sensing of soil is the fact that sensors actually only measure incoming radiation and not directly soil properties. It is up to the user of the data to infer soil characteristics by how they affect the reflectance or emittance of radiation. Consequently, models or proxies must be developed that predict soil condition. In sparsely vegetated areas, spaceborne measurements have proved to be relevant to the successful extraction of soil characteristics. In densely vegetated areas, soil data acquisition typically relies on indirect retrievals such as NDVI and other vegetation indices. However, these indices are developed to increase the information on vegetation characteristics (pattern, phenology) and tend to eliminate the influence of soil background reflectance. There is thus a need to develop models and software algorithms that consider this information.

One approach has been the development of spectral unmixing algorithms that break down the signal of individual pixels to the component surfaces. Such tools can be used to highlight the spectral characteristics of bare surfaces by removing the vegetation component (Asner and Heidebrecht, 2002). While showing much promise, more research is required to test the assumptions underlying such decomposition models. Due to the heterogeneity of landscapes and the spatial resolution of the imagery it is often difficult to find pure pixels representing soil or bare rock. Advanced unmixing tool methods, such as Tetracorder (Clark et al., 2003) are needed to extract subpixel soil and rock composition. Tetracorder identifies materials by comparing a remotely sensed observed spectrum (the unknown) to a large library of spectra of well-characterized materials, but using several innovations to maximize accuracy and performance.

Given the range of spaceborne systems that have acquired data of the Earth's surface over the last 30 years, a poorly investigated issue is the fusion of information from diverse imaging systems, often with very differing radiometric characteristics and view angles. While challenging, data fusion offers tremendous potential for soil-related studies through time series analysis of bare ground and through the development of novel models that utilize the bidirectional reflectance characteristics of soil under different illumination conditions.

VII Conclusions

This brief overview has demonstrated the relevance of data acquired by several moderate and coarse spatial resolution satellite sensors for mapping soil characteristics at regional and continental scales in Africa. Specifically, the overview provides insight into remotely sensed based mapping methods for the identification of soil properties and delineation of soil units as well as for highlighting areas that are vulnerable to, or are experiencing, various soil threats such as soil erosion by water and by wind, landslides and salinization.

Remote sensing is shown as being a key component of the emerging discipline of digital soil mapping. This integrated research offers a lot of new perspectives for the mapping of soils where both remote sensing and DSM are beneficial to each other.

We show that remote sensing approaches have the capability to provide a better picture of the state of soil in Africa, which is of paramount importance for the protection and the sustainable management of their resources. In addition to the scientific aspect that such information represents, this picture is also helpful for soil scientists to inform and educate the general public, policy-makers, land managers and other scientists of the importance and global significance of soil. It provides additional data and tools to equip decision-makers with the knowledge necessary to formulate effective soil use and practices policy. This is particularly true of the soils in Africa where the dramatic consequences of the failure to sustainably use soil has led to desertification, famine, civil unrest and human suffering, often on a tragic scale.

Entekhabi et al. (2010) concluded that improved soil monitoring at global scales will improve our understanding of the linkages between the water, energy and carbon cycles. It will also lead to improvements in estimation of global water and energy fluxes at the land surface, weather and climate forecasts, flood and drought monitoring, predictions of agricultural productivity, and quantification of net carbon flux in landscapes. There are also applications in human health and national security.

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