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Satellite remote sensing for water erosion assessment: A review

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Abstract

Water erosion creates negative impacts on agricultural production, infrastructure, and water quality across the world. Regional-scale water erosion assessment is important, but limited by data availability and quality. Satellite remote sensing can contribute through providing spatial data to such assessments. During the past 30 years many studies have been published that did this to a greater or lesser extent. The objective of this paper is to review methodologies applied for water erosion assessment using satellite remote sensing. First, studies on erosion detection are treated. This comprises the detection of erosion features and eroded areas, as well as the assessment of off-site impacts such as sediment deposition and water quality of inland lakes. Second, the assessment of erosion controlling factors is evaluated. Four types of factors are discussed: topography, soil properties, vegetation cover, and management practices. Then, erosion mapping techniques are described that integrate products derived from satellite remote sensing with additional data sources. These techniques include erosion models and qualitative methods. Finally, validation methods used to assess the accuracy of maps produced with satellite data are discussed. It is concluded that a general lack of validation data is a main concern. Validation is of utmost importance to achieve regional operational monitoring systems, and close collaboration between the remote sensing community and field-based erosion scientists is therefore required.

Keywords: Review; Land degradation; Soil erosion; Remote sensing; Modelling; Validation

Contents

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1. Introduction

Soil erosion by water is the most important land degradation problem worldwide (Eswaran et al., 2001). Although some authors question its impact on global food security (Crosson, 1997; Lomborg, 2001) soil erosion creates strong environmental impacts and high economic costs by its effect on agricultural production, infrastructure and water quality (Lal, 1998; Pimentel et al., 1995). Furthermore, erosion results in emission of soil organic carbon to the atmosphere in the form of CO_2 and CH_4, causing impact on global warming (Lal, 2004). Global warming in turn is expected to increase erosion rates (Nearing et al., 2004). A proper assessment of erosion problems is greatly dependent on their spatial, economic, environmental, and cultural context (Warren, 2002).

Water erosion is controlled by climatic characteristics, topography, soil properties, vegetation, and land management. Detachment of soil material is caused by raindrop impact and drag force of running water. Detached particles are transported by overland flow (sheet- or interrill erosion) and concentrated flow (rill erosion) and deposited when flow velocity decreases (Lal, 2001). Gullies can develop as enlarged rills, but their genesis is generally more complex, involving sub-surface flows and sidewall processes (Bocco, 1991).

To control water erosion, biophysical measures need to be implemented at the field, hillslope or watershed scale. However, allocation of scarce conservation resources and development of policies and regulations require erosion assessment at the regional scale. An important limitation for this task is data availability and quality (Van Rompaey and Govers, 2002). Remote sensing provides homogeneous data over large regions with a regular revisit capability, and can therefore greatly contribute to regional erosion assessment (King and Delpont, 1993; Siakeu and Oguchi, 2000).

Traditionally, remote sensing has been used for soil erosion research through aerial photo interpretation both for detecting erosion features (e.g. Bergsma, 1974; Jones and Keech, 1966) and obtaining model input data (e.g. Morgan and Napela, 1982; Stephens et al., 1985). Starting in 1972 with the launch of Landsat-1, satellite imagery has become increasingly available to the scientific community.

During the past 30 years many studies have been published that fully or partially applied satellite imagery for soil erosion assessment in many different ways. The objective of this paper is to provide an overview of methodologies applied for water erosion assessment using satellite remote sensing. It focuses on erosion processes related to surface run-off and gullying. Although important sensor development has taken place during the past years using airborne systems, which are of interest to erosion research (e.g. laser altimetry, hyperspectral remote sensing), this paper focuses only on satellite-based applications. Mainly peer-reviewed journal articles are treated, with a few exceptions. The review addresses (1) erosion detection, (2) the assessment of erosion controlling factors, and (3) data integration for erosion mapping.

2. Satellites and sensors applied in erosion research

A large number of earth observation satellites has orbited, and is orbiting our planet to provide frequent imagery of its surface. From these satellites, many can potentially provide useful information for assessing erosion, although less have actually been used for this purpose. This section provides a brief overview of the spaceborne sensors applied in erosion studies. More recent satellites (e.g. SPOT-5, CBERS) and future satellites (e.g. ALOS, SMOS) that are of potential interest are not discussed here. The sensors can be divided in those measuring reflection of sunlight in the visible and infrared part of the electromagnetic spectrum and thermal infrared radiance (optical systems), and those actively transmitting microwave pulses and recording the received signal (imaging radars).

Optical satellite systems have most frequently been applied in erosion research. The parts of the electromagnetic spectrum covered by these sensors include the visible and near-infrared (VNIR) ranging from 0.4 to 1.3 μm, the shortwave infrared (SWIR) between 1.3 and 3.0 μm, and the thermal infrared (TIR) from 3.0 to 15.0 μm. Table 1 summarises sensor characteristics of the systems used.

Table 1
Overview of optical satellite sensors applied in erosion research

Satellite	Sensor	Operation time	Spatial resolution	# Spectral bands	Spectral domain
Landsat-1,2,3	MSS	1972–1983	80 m	4	VNIR
Landsat-4,5	TM	1982–1999	30 m	6	VNIR, SWIR
			120 m	1	TIR
Landsat-7	ETM	1999–present	15 m	1	VNIR
			30 m	6	VNIR, SWIR
			60 m	1	TIR
SPOT-1,2,3	HRV	1986–present	10 m	1	VNIR
			20 m	3	VNIR
SPOT-4	HRVIR	1998–present	10 m	1	VIS
			20 m	4	VNIR, SWIR
IRS-1A,1B	LISS-1	1988–1999	72.5 m	4	VNIR
	LISS-2		36.25 m	4	VNIR
IRS-1C,1D	PAN	1995–present	5.8 m	1	VNIR
	LISS-3		23.5 m	3	VNIR
			70 m	1	SWIR
Terra	ASTER	1999–present	15 m	3	VNIR
			30 m	6	SWIR
			90 m	5	TIR
NOAA/ TIROS	AVHRR	1978–present	1.1 km	5	VNIR, SWIR, TIR
IKONOS	Panchromatic	1999–present	1.0 m	1	VNIR
	Multispectral		4.0 m	4	VNIR
QuickBird	Panchromatic	2001–present	0.61 m	1	VNIR
	Multispectral		2.44 m	4	VNIR

Landsat is still among the widest used satellites, partly because it has the longest time series of data of currently available satellites. The first satellites of the Landsat family were equipped with the Multispectral Scanner (MSS), having four bands at 80-m resolution. Later Landsat satellites had the Thematic Mapper (TM) and the Enhanced TM (ETM) sensors onboard with improved resolution and more spectral bands. The SPOT (Système Pour l'Observation de la Terre) series of satellites started acquiring data in 1986 with the HRV-sensor (High Resolution Visible). The HRV-sensor has a 10-m panchromatic mode and a three-band 20-m resolution multispectral mode. SPOT-4 flew the HRVIR-sensor (High Resolution Visible Infrared) on which a SWIR band was added. The Indian Remote Sensing Satellites (IRS) 1A and 1B both have two sensors called LISS-1 and LISS-2 (Linear Imaging and Self-Scanning Sensor), which are identical except for a two times higher spatial resolution on LISS-2. IRS 1C and 1D also have an identical payload being a 5.8-m resolution panchromatic camera (PAN) and a 23.5-m resolution multispectral sensor called LISS-3. ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) is one of the sensors onboard the Terra satellite. It has 14 spectral bands of which several are situated in the SWIR and TIR regions. One near-infrared (NIR) band looks both nadir and backward creating stereo-view from a single pass. IKONOS and QuickBird are both high-resolution satellites, with a spatial resolution in panchromatic mode of 0.61 and 1.00 m respectively, and 2.44 and 4.00 m in multispectral mode. AVHRR (Advanced Very High Resolution Radiometer) has five bands in 1.1-km resolution and has been flown on many platforms, including TIROS-N (Television Infrared Observation System) and several NOAA-satellites (National Oceanic and Atmospheric Administration).

The start of spaceborne imaging radar instruments was in 1978 with the SAR (synthetic aperture radar) onboard SEASAT, operating in L-band (23.5-cm wavelength) during 105 days only. For erosion studies, only five SAR sensors have been applied, which were flown on ERS-1 and 2, JERS-1, RADARSAT-1, and ENVISAT respectively. In 1991 ERS-1 was launched with the Active Microwave Instrument (AMI) onboard operating in C-band (5.7-cm wavelength). The SAR image mode of AMI acquired data at 30-m resolution. ERS-2 flies the same instrument and has been operational from 1995 till present. JERS-1 (Japanese Earth Resources Satellite) flew an 18-m resolution L-band SAR (23.5-cm wavelength), recording data from 1992 to 1998. RADARSAT-1 has acquired C-band SAR data since 1995 and has the possibility of using a variety of incidence angles (between 20° and 49°) and different resolutions (between 10 and 100 m). The Advanced SAR (ASAR) onboard ENVISAT, launched in 2002, also has the possibility of using several incidence angles (between 15° and 45°). Besides, its C-band SAR can transmit and receive radar pulses both in horizontal and vertical polarization, which refers to the plane in which the electromagnetic wave is propagating. Spatial resolutions of ASAR are approximately 30 m, 150 m, or 1 km, depending on the mode used.

Furthermore, a number of short-duration Space Shuttle flights have flown earth-observation instruments. Only two of them have been used for erosion studies, being MOMS-2, and SIR-C/X-SAR. MOMS-2 (Modular Optoelectronic Multispectral Scanner) is an optical sensor that was flown in 1993. It has four multispectral bands in the VNIR range at 13.5-m resolution, a panchromatic band having 4.5-m resolution, and two panchromatic stereo bands (backward and forward looking) at 13.5-m resolution. SIR-C/X-SAR is a joint instrument consisting of SIR-C (Shuttle Imaging Radar-C) and X-SAR, which was flown two times in 1994. SIR-C provided multi-polarization L- and C-band SAR imagery and X-SAR simultaneously X-band (3.1-cm wavelength) mono-polarized SAR imagery with approximately 30-m resolution.

3. Erosion detection

Satellite data can be applied to directly detect erosion or to detect erosion consequences. Direct detection has been achieved through identification of individual large erosion features, discrimination of eroded areas, and assessment of erosion intensity based on empirical relations. Detectable effects include the damage occurred due to major erosion events, and the sedimentation of reservoirs.

3.1. Detection of erosion features and eroded areas

Although the mapping of erosion features is an important application of aerial photography, the limited spatial extent of the features often inhibits its detection using satellite imagery. Spatial resolutions such as offered by Landsat and SPOT imagery can at best be applied for identification of individual large and medium sized gullies (Langran, 1983; Millington and Townshend, 1984) and do not allow gully growth analysis with sequential imagery (Bocco and Valenzuela, 1993). For large gullies in Central Brazil, Vrieling and Rodrigues (2004) found that optical ASTER imagery provided better description of gully shape than ENVISAT ASAR data, when compared to a QuickBird image. With the current availability of high-resolution satellites such as IKONOS and QuickBird, options for detecting and monitoring individual small-scale features have increased, although not yet reported in literature.

Instead of detecting individual erosion features, satellite data have been effectively applied for assessing eroded areas. Extensive areas suffering gully erosion (i.e. badlands) have been mapped with visual interpretation techniques on optical image composites of different sensors (e.g. Bocco et al., 1991; Dwivedi et al., 1997b; Kumar et al., 1996). In some cases erosion classes could be separated based on vegetation cover derived as well from visual interpretation

(Dwivedi and Ramana, 2003; Sujatha et al., 2000) or vegetation and topographic characteristics derived from additional data sources (Yuliang and Yun, 2002). The delineation of eroded areas on multi-temporal images allowed an assessment of its increase (Fadul et al., 1999; Sujatha et al., 2000). Karale et al. (1988) performed a bi-temporal comparison using aerial photos and Landsat TM imagery. Although a clear increase of eroded lands was found, aerial pictures allowed for a better differentiation of ravine types than satellite imagery.

An alternative for visual interpretation techniques is the automatic extraction of eroded lands from satellite imagery. Servenay and Prat (2003) applied an unsupervised classification algorithm to multispectral SPOT HRV data to distinguish four stages of erosion. Floras and Sgouras (1999) used the maximum likelihood classifier after principal component analysis of Landsat TM imagery to separate one erosion class. Bocco and Valenzuela (1988) applied the same classifier for multispectral Landsat TM and SPOT HRV images to discern several erosion and vegetation classes. They found that the higher resolution SPOT data performed better in classifying eroded areas, but that the larger number of spectral bands of Landsat TM resulted in a better classification of land cover and land use. Dwivedi et al. (1997a) also found that SPOT HRV was better in classifying eroded lands than Landsat TM and MSS, but they did not use all TM bands for classification. Metternicht and Zinck (1998) performed a maximum likelihood classification on Landsat TM, and on the combination of Landsat TM with JERS-1 SAR data. They achieved highest classification accuracy using the combination of both images.

Besides classification techniques, direct correlation between erosion and spectral reflectance values sometimes permits the detection of erosion and the mapping of its intensity. Price (1993) found high correlation between reflectance values of single Landsat TM bands, especially band 4 (NIR), and erosion rates for pinyon-juniper woodlands. Erosion rates were determined from the distance between the ground level and a string that was stretched between the base of two adjacent tree trunks, assuming a stable surface level at the trunks. For arid rangelands in Australia, Pickup and Nelson (1984) successfully distinguished eroding, stable, and depositional areas using the data space defined by the 4/6 and 5/6 band ratios of Landsat MSS imagery (corresponding to green/NIR and red/NIR respectively). They stressed that the method is dependent on the relation between erosion status and vegetation cover, and is not suitable for humid climates. Pickup and Chewings (1988) used the same approach in combination with autocorrelation functions to predict changes in patterns of erosion and deposition. Beaulieu and Gaonac'h (2002) describe a more complex method involving Fourier scaling and multifractal analysis of Landsat TM and ERS-1 SAR imagery, which allowed for separating eroding surfaces in Ethiopia.

Changes of surface states can supply direct information on erosion occurrence. A great variety of methods for change detection from satellite imagery exists (Coppin et al., 2004). Studies that relate changes merely to soil properties will be described in Section 4.2. Albedo differences between different Landsat MSS passes allowed identification of soil degradation and erosion areas in arid and semi-arid environments of the USA (Frank, 1984a,b; Robinove et al., 1981). Dhakal et al. (2002) showed that the methods of spectral image differencing, principal component analysis, and spectral change vector analysis on bi-temporal Landsat TM imagery all resulted in a proper detection of erosion and flooded areas resulting from an extreme rainfall event, when compared to a field survey of affected and non-affected areas.

Repeat-pass SAR interferometry is a special change detection technique (Massonnet and Feigl, 1998; Rosen et al., 2000). It uses the amplitude and phase information of two SAR scenes having a very similar viewing geometry and a certain time lag. Although digital elevation model (DEM) extraction and slight deformation measurements are among the application areas, derived interferometric coherence imagery has most potential for erosion detection. Coherence between two radar signals is high when the land surface characteristics are very similar on both recording dates. Random surface changes as caused by erosion result in temporal decorrelation. Spatial decorrelation effects due to differences in satellite paths can be partly accounted for using the ratio between two coherence images (Lee and Liu, 2001). However, vegetation and soil moisture changes are also a major cause of decorrelation (e.g. Vrieling and Rodrigues, 2004; Wegmüller et al., 2000), which confines erosion detection with coherence imagery to (semi-)arid environments. In Mediterranean sites, ratio coherence imagery derived from ERS SAR data has been effectively applied to detect erosion (Lee and Liu, 2001; Liu et al., 2001, 2004). For an extreme glacier flooding event in Iceland, Smith et al. (2000) applied interferometric decorrelation to assess unstable areas that were related to erosion and deposition. Wegmüller et al. (2000) separated erosion classes in the Death Valley (USA) using coherence imagery in combination with backscatter values. A relation was found between erosion activity and degree of coherence. In spite of erosion detection possibilities, most authors stressed the need to integrate coherence imagery with additional spatial data, like optical imagery, because of the multiple causes of temporal decorrelation.

For extreme events, the extraction of multi-temporal DEMs using SAR interferometry offers possibilities to assess erosion and deposition volumes, as demonstrated by Smith et al. (2000). They created DEMs from pre-flood and post-flood interferometric ERS tandem pairs, and by subtraction they were able to assess volumes of erosion and deposition. Because of height accuracy DEM subtraction is limited to areas that experience at least 4-m net erosion or deposition.

3.2. Detection of erosion consequences

Erosion is a process that transports soil particles. At downstream locations, both the transport and the deposition of soil material often cause undesired effects. Izenberg et al. (1996) determined the loss of agricultural land due to the extreme flooding of the Missouri River in 1993 with Landsat TM and SPOT HRV imagery. Thickness of deposited sand could be assessed with SIR-C L-band, as field data revealed a correlation between the sediment thickness and vegetation on deposition areas. Khan and Islam (2003) used multi-temporal Landsat data to investigate the dynamics of the Brahmaputra-Jamuna River, which is greatly influenced by the heavy sediment load originating from erosion in the Himalayas. However, most studies that have applied satellite imagery to assess erosion consequences focus on reservoirs and lakes, where sediments create important economic and ecological impacts.

Sedimentation volumes have been estimated for Indian reservoirs using multi-temporal IRS LISS-2 and LISS-3 imagery (Goel and Jain, 1996; Goel et al., 2002; Jain et al., 2002). Images were selected of a year with maximum variation in the reservoir water level. For different image dates, water-spread areas at varying depths were extracted using simple classification algorithms. Reservoir capacity was then calculated with geometric equations and compared with the original capacity to determine sedimentation volumes. A drawback of the approach is that capacities can only be determined in the water fluctuation zone. Comparison with a hydrographic survey showed a slight overestimation of sedimentation rates, which was attributed to confusion between water and land pixels at the reservoir periphery (Jain et al., 2002).

Erosion influences the water quality of downstream lakes and reservoirs. The suspended sediment concentration is the most important water quality parameter for erosion studies (Ritchie and Schiebe, 2000). Reflectance from surface water in the visible and infrared domain is positively influenced by suspended sediments (Ritchie et al., 1976). Many studies found significant relationships between in situ determined suspended sediment concentration of inland water bodies and atmospherically corrected spectral reflectance derived from satellite remote sensing data, such as Landsat (e.g. Carpenter and Carpenter, 1983; Harrington et al., 1992; Nellis et al., 1998), IRS LISS-1 (e.g. Choubey, 1998), and multispectral SPOT HRV (e.g. Chacontorres et al., 1992). The optimal wavelength to determine these relations depends on the sediment concentration (Curran and Novo, 1988; Ritchie and Cooper, 1991), but often used spectral bands are between 500 and 800 nm (within VNIR range). Because sediment characteristics, like texture and colour, influence the water reflection (Han and Rundquist, 1996; Ritchie et al., 1989), developed empirical relationships are not easily transferable to other regions where erosion entrains different sediment types. To increase transferability, Schiebe et al. (1992) developed a theoretically derived exponential equation for a wide range of sediment concentrations, which also attempted to account for chlorophyll and algal influences. However, until present a universal equation does not exist, and most models of suspended sediment are site-specific (Liu et al., 2003). Detailed reviews of remote sensing for water quality assessment, including suspended sediments, are provided by Dekker et al. (1995), Ritchie and Schiebe (2000) and Liu et al. (2003). A combination of suspended sediment equations and a remote sensing based identification of water bodies across the landscape was proposed by Ritchie et al. (1987) to assess areas with high soil erosion rates, and concentrate soil conservation efforts. However, practical applications of this approach have not been found in literature.

4. Erosion controlling factors

Most remote sensing studies of soil erosion concentrated on the assessment of erosion controlling factors. Especially soil and vegetation attributes have often been determined with satellite data, and to a lesser extent topography and management. Here, only studies that determined these attributes in relation to erosion processes are treated. The climate factor is not discussed, as no satellite applications were found in literature for assessing rainfall characteristics in erosion studies. Rainfall gauges are generally used for this purpose, although Mannaerts and Saavedra (2003) propose the use of large-scale precipitation data derived from the Tropical Rainfall Measuring Mission (TRMM), which is the first satellite system with a precipitation radar.

4.1. Topography

To study the effect of topography on erosion, landforms have been discriminated on the basis of visual interpretation of e.g. Landsat image composites (Khan et al., 2001; Mitchell, 1981). However, current spatial erosion models nearly always require DEM input for the assessment of slope characteristics. Traditionally such DEMs have been obtained from contour lines on topographic maps, or less frequently from stereo aerial photography. Nowadays, various options exist to extract good quality DEMs (vertical accuracy <20 m) from satellite data, such as stereo optical imagery provided by SPOT and ASTER (Toutin and Cheng, 2003) or SAR imagery (Toutin and Gray, 2000). SAR interferometric processing of the Shuttle Radar Topography Mission (SRTM) data provided readily available DEMs for land areas between 60° northern and 57° southern latitude (Rabus et al., 2003).

Few researchers have applied DEMs derived from satellite data for erosion studies. Khawlie et al. (2002) calculated slope gradient from an ERS SAR interferometric DEM. Also ERS SAR interferograms, an interferometric product obtained before the DEM construction step, have been used directly for slope extraction (Liu et al., 2000).

SPOT HRV derived DEMs were used to aid visual interpretation of erosion features (Bishop and Shroder, 2001) and to extract slope and topographic curvatures (Haboudane et al., 2002). Stereo-data of MOMS-2 allowed DEM extraction and subsequent calculation of slope length and gradient (Reusing et al., 2000). Applications of ASTER and SRTM derived DEMs for erosion studies have not been found yet in peer-reviewed literature, although it is probable that this already happens at the institution level.

4.2. Soil

Soils differ in their resistance to erosion, which is a function of a range of soil properties such as texture, structure, soil moisture, roughness, and organic matter content. The susceptibility of soil to erosion agents is generally referred to as soil erodibility (Lal, 2001). Soil classifications are often used to account for spatial differences in erodibility. Important factors on the basis of which soils can be classified include soil properties, climate, vegetation, topography, and lithology. These factors can be potentially mapped with satellite remote sensing (McBratney et al., 2003). Especially optical satellite imagery has been used for soil mapping, mainly through visual delineation of soil patterns (Dwivedi, 2001). To use visual interpretation techniques, detailed knowledge on the relationship between observable terrain characteristics and the occurrence of soil units is required. Such knowledge can be formalized in clear criteria, like those used for the creation of the Soils and Terrain digital databases SOTER (Van Engelen and Wen, 1995; Van Lynden and Mantel, 2001). Soil classification by visual interpretation of optical satellite imagery has been used to assess differences in soil erodibility (Reusing et al., 2000; Sharma and Singh, 1995). The relation between soil classes and erodibility was determined using equations of Wischmeier and Smith (1978).

Wang et al. (2003) used the same equations to determine erodibility in the field. The obtained erodibility values were extrapolated to the whole sampling region using two geostatistical methods, collocated co-kriging and joint sequential co-simulation. Within these methods, Landsat TM band 7 allowed for reproducing the spatial variability of the erodibility. The success of this mapping must be contributed to the existence of a clear link between natural vegetation and soil types in the studied area. When this link is clearly present, spatial variability of erodibility will probably be better represented than when assigning erodibility values to a soil classification.

Topsoil characteristics influence the soil surface colour, and thus spectral reflectance curves. Significant relationships were found between soil colours defined by the Munsell system and optical satellite imagery (Escadafal, 1993; Singh et al., 2004). Various soil properties affect the soil's spectral reflectance, such as soil texture, organic matter content, moisture content, iron oxides and soil minerals (Barnes and Baker, 2000; Dwivedi, 2001; Escadafal, 1994). This can be a limitation for the study of one particular property, but surface states may be classified when one or more topsoil properties affect its spectral reflectance. These surface states can then be related to runoff and erosion potential using field measurements (Gardner and Duffy, 1985). Surface state conditions that are important for erosion are surface crusting and the uncovering of subsoil. Crusted soil can sometimes have distinct spectral properties as compared to uncrusted soil, due to an increase in clay particles at the soil surface, and a decrease of surface roughness (Ben-Dor et al., 2003; Escel et al., 2004), but this is largely dependent on the crust type and soil type. Satellite applications using this relation for erosion assessment are limited to analysis of crust dynamics of bare soil surfaces for Northern France with multi-temporal SPOT HRV imagery (King et al., 1989; Mathieu et al., 1997). Apart from crusting, the gradual uncovering of subsoil by erosion also results in detectable spectral changes. When these changes are well known, optical satellite data allows spatial and temporal assessment of erosion status (Latz et al., 1984; Pelletier and Griffin, 1985, see also Section 3.1).

A difficulty in measuring topsoil reflectance with satellite data is the disturbing influence of vegetation, which greatly limits satellite-based soil studies for temperate and humid areas, unless agricultural practices leave the soil bare periodically. To separate the soil from the vegetation signal, a common used technique in (semi-)arid environments is linear spectral unmixing (Adams et al., 1986; Smith et al., 1990). In this technique, spectral reflectance signatures are modelled as a linear combination of a few prototype spectra, called endmembers. It is assumed that the spectral variation in remote sensing images is caused by mixtures of a limited number of surface materials, which have sufficient spectral contrast, allowing their separability. As long as the number of endmembers does not exceed the number of spectral bands minus one, a unique solution is obtained for the relative endmember abundance per pixel. Disturbing influences for soil assessment as caused by vegetation and shade can thus be accounted for (Adams et al., 1989; Hill, 1993). Knowing the regional soil types and their respective climax and degradation forms in combination with their spectral characteristics, spectral unmixing allows erosion assessment (Hill et al., 1995a). When the top layer of the soil is removed by erosion, the volume of organic matter and iron oxides decreases, and gradually rock becomes visible at the surface (De Jong et al., 1999). Hence, spectral unmixing has been used for erosion status mapping with Landsat TM imagery (e.g. De Jong et al., 1999; Haboudane et al., 2002; Hill and Schütt, 2000; Metternicht and Fermont, 1998). Changes in erosion status were analyzed with multi-temporal imagery for a site in Greece and showed an increase of erosion between 1985 and 1990 (Hill et al., 1995a,b).

Soil properties that can be assessed with SAR systems are surface roughness, soil moisture, and texture (Ulaby et al., 1978, 1979). Although many studies addressed the soil moisture assessment by SAR, satellite-based assessment is still very complicated (Walker et al., 2004). Even at locations with bare soil, there is a confusing influence of surface roughness conditions and soil moisture on radar backscatter (Davidson et al., 2000) and the two effects cannot be separated without additional information (Colpitts, 1998). Nevertheless, several authors claimed success in representing spatial and temporal soil moisture variability when good land use information is available (e.g. Löw et al., 2004; Quesney et al., 2000). For erosion studies, few authors have used SAR to assess roughness and moisture properties. To identify run-off risks in vineyards in southern France, Remond et al. (1999) identified the periodic and stable surface roughness of agricultural areas with multi-temporal ERS-1 imagery. Baghdadi et al. (2002) classified surface roughness to determine run-off potential of bare soils in northern France. They found that RADARSAT-1 imagery with a high incidence angle (47°) performed better for roughness classification than images with incidence angles of 39° (RADARSAT-1) and 23° (ERS-1).

4.3. Vegetation

Vegetation cover provides protection of the soil against erosion processes. To account for vegetation in erosion assessments, a cover and management factor (C-factor) has often been used. The C-factor is defined as the ratio of soil loss from land cropped under specified conditions to the corresponding clean-tilled continuous fallow (Wischmeier and Smith, 1978). In many regions of the world, vegetation cover shows a high temporal dynamics. Long-term dynamics relate to e.g. land use conversions or gradual depletion of resources. Short-term dynamics are caused by rainfall characteristics, and by human activities such as crop harvesting or burning practices. Many satellite remote sensing studies of soil erosion focus on the assessment of vegetation cover. These studies need to account somehow for the temporal variation, and consequently image timing is highly important, although not always sufficiently highlighted. Depending on the purpose of the study, sometimes a mono-temporal assessment can be sufficient. However, especially for physically based models (see Section 5.1) careful matching of satellite imagery with rainy periods and crop development is required, which demands a time series of remote sensing images to account for seasonal variability (e.g. Cyr et al., 1995).

Land use classification is often used to map vegetation types that differ in their effectiveness to protect the soil. After classification, a qualitative ranking of vegetation types is made, or C-factors are assigned from reported values in literature (e.g. Morgan, 1995; Wischmeier and Smith, 1978). In most cases seasonal crop dynamics are accounted for within the classification, because an average annual C-factor is assigned. For erosion studies, land use classification has been performed with optical satellite systems through visual interpretation of image composites (e.g. Khan et al., 2001; Mati et al., 2000; Sharma and Singh, 1995) or automated classification approaches. The most common ones are unsupervised classification, in which pixels are grouped according to their relative spectral similarity (e.g. Feoli et al., 2002; Jakubauskas et al., 1992) and supervised classification, where pixels are allocated to predefined classes that are generally established based on ground-truth data (e.g. Jürgens and Fander, 1993; Millward and Mersey, 1999; Pelletier, 1985). The mentioned classification techniques can also be combined. Folly et al. (1996) performed a visual interpretation of a Landsat TM composite to classify main cover types. Subsequently a fine-tuning within each class was achieved with a supervised classification. Several authors applied hybrid unsupervised–supervised approaches (e.g. Bhuyan et al., 2002; Fraser et al., 1995; Vaidyanathan et al., 2002). Due to seasonal changes of some vegetation classes, classification of multi-temporal imagery can improve the classification accuracy (Müschen et al., 2001). Details on the accuracy assessment of land use classifications are given by Foody (2002). Although SAR systems allow land use classification (e.g. Brisco and Brown, 1998) and other classification approaches exist such as neural networks (e.g. Miller et al., 1995), no studies were found in literature that relate this to erosion assessment.

To decrease the influence of classification errors and account for within-class variability, direct linear regression has been performed between image bands or ratios and C-values were determined in the field. For agricultural lands in New Brunswick, Canada, good relationships were obtained between C-values and band ratios of NIR to red reflection (Cihlar, 1987; Stephens and Cihlar, 1982). In a mixed savannah–woodland landscape in Texas, Gertner et al. (2002) found a high correlation between Landsat TM band ratio 3/4 (red over NIR) and vegetation attributes. They mapped C-factors with the technique of joint sequential co-simulation, in which the band ratio accounted for the spatial variability of vegetation attributes (secondary variable), while field data provided the attribute values (primary variable). In the same study area, Wang et al. (2002) used Landsat image ratio (TM3 + TM7/TM4), which gave higher correlation with directly calculated C-values from the field. Wang et al. (2003) applied Landsat TM band 7 as a secondary variable, because they jointly mapped erodibility and C-values, for which band 7 gave optimal correlation. While comparing different C-factor mapping techniques for this area, joint sequential co-simulation with a Landsat TM image outperformed classification, regression of C-values against image ratios, collocated co-kriging, and co-simulation without a Landsat TM image (Wang et al., 2003, 2002).

Vegetation indices are a specific class of spectral band ratios. A wide range of such indices exists. Often they exploit the fact that green vegetation has high reflectance in the NIR and low reflectance in the red part of the spectrum. A common index is the normalized difference vegetation index (NDVI), which is defined as the NIR reflection minus red reflection divided by the sum of the two (Tucker, 1979). NDVI has been used directly as an indication of the protective cover of vegetation (Gay et al., 2002; Jain and Goel, 2002; Liu et al., 2000; Thiam, 2003) or was related to vegetation cover with regression analysis (Bhuyan et al., 2002; Symeonakis and Drake, 2004; Zhang, 1999). De Jong (1994b) concluded that the relationship between Landsat derived spectral indices and vegetation attributes was quite poor for Mediterranean France, but he still applied the NDVI for *C*-factor estimation in later works (De Jong et al., 1999; De Jong and Riezebos, 1997). Such poor relationships can also partly be explained by the methodological difficulties in precisely assessing the proportional vegetation cover in the field (Hill et al., 1995a; Zhou et al., 1998). Due to seasonal variability it is often highly important for which date a vegetation index is calculated, and for most environments a carefully chosen time series of satellite images is required to reliably estimate the vegetative soil protection (e.g. De Jong et al., 1999).

Main problems with indices like the NDVI are the effect of soil reflectance (Escadafal, 1994, Section 4.2) and the sensitivity to the vitality of the vegetation (De Jong, 1994b; Frederiksen, 1993). To account for soil reflectance, several soil adjusted vegetation indices have been developed, like the transformed soil adjusted vegetation index TSAVI (Baret and Guyot, 1991). Cyr et al. (1995) showed that TSAVI performed better for the assessment of low vegetation covers than NDVI. Negative TSAVI values have been related to potentially degraded areas (Flügel et al., 2003; Hochschild et al., 2003). However, soil adjusted indices have difficulty in accounting for spatially variable soil types (Hill et al., 1994a). The main vegetation vitality effects are during early growth stages, when thin vegetation covers are often overestimated by vegetation indices due to intense chlorophyll activity, and during vegetation senescence when vegetation indices usually decrease even when the cover remains the same (Cyr et al., 1995). For erosion processes, vegetation condition is of minor importance however, as senescent vegetation offers the same protection to the soil as vigorous vegetation. To improve the detection of dry vegetation, Bonn et al. (1997) proposed to combine SWIR and NIR reflection in a soil adjusted crop residue index (SACRI). Spectroradiometer studies support the use of SWIR reflection for separating crop residue from soils (e.g. Daughtry et al., 2004; Nagler et al., 2000). French et al. (2000) showed that senescent vegetation can be distinguished from bare soil using TIR emissivity in combination with NDVI, which is currently possible with the ASTER sensor on the Terra satellite. Bhuyan et al. (2002) avoided vegetation indices for separating wheat-stubble areas, but related ground data on crop residue to classes obtained by unsupervised clustering instead.

Linear spectral unmixing is an alternative technique for assessing the vegetation cover (see Section 4.2). This technique is mainly used in (semi-)arid environments, where it has the advantage that different soil characteristics within a scene can be accounted for. Using the green vegetation spectrum as an endmember, spectral unmixing permits an estimation of percentage green cover (e.g. De Jong et al., 1999; Haboudane et al., 2002; Hill, 1993). In this way, Zhang et al. (2002) determined green vegetation cover at different spatial scales using aerial photographs, Landsat TM and AVHRR imagery. Ma et al. (2003) related the derived vegetation cover from unmixing Landsat data to the *C*-factor using a log-linear relation. To account for distinct spectral properties of vegetation types, Paringit and Nadaoka (2003) automatically retrieved the vegetation endmember from a field-survey based land use map before applying the unmixing procedure, assuming no mixing of vegetation types per pixel. Hill et al. (1995a,b) proposed that possible endmembers can include non-photosynthetic vegetation, like senescent vegetation or leaf litter. Bonn et al. (1997) stated that for such vegetation, SWIR spectral bands are required, and thus Landsat TM is more appropriate than SPOT (HRV) satellites. Asner and Heidebrecht (2002) effectively assessed non-photosynthetic vegetation cover with spectral unmixing. To assess the protection effect to erosion of crop residues, Biard and Baret (1997) proposed the algorithm CRIM (crop residue index multiband) which is based on spectral unmixing of soil and residue spectra. Using field radiometric measurements, they achieved better estimates for residue cover with CRIM than with the vegetation index SACRI. As the crop residue spectrum tends towards the soil spectrum with progressive aging, the residue fraction can best be determined soon after harvest. Using Landsat data, CRIM also performed better than indices like SACRI in assessing maize and wheat residue fractions on clayey and silty soils in Quebec (Arsenault and Bonn, 2005).

4.4. Conservation practices and tillage

Especially in agricultural areas, conservation practices such as contouring, strip cropping, or terracing, reduce soil losses. The effectiveness of such practices is often analyzed with a support practice factor (*P*-factor), defined as the ratio of soil loss with the practice applied and up- and downslope cultivation (Wischmeier and Smith, 1978). *P*-values have been assigned to land use classes that were derived from a classification of remote sensing imagery, using literature values (Lee, 2004) or expert opinion (Bhuyan et al., 2002) for practices that commonly occur for the land use class in the studied area. Interpretation of aerial photographs allows the detection of many conservation measures, but with coarse resolution Landsat MSS data this becomes problematic (Langran, 1983). Nevertheless, Pelletier and Griffin (1985) managed to successfully detect several conservation measures with Landsat MSS and TM imagery. Still, there have been few studies on the detection of conservation practices with satellite remote sensing.

An exception to this is the detection of tillage practices with satellite imagery. Tillage practices differ in their effect on surface roughness and amount of crop residues, which forms the basis of their detection (see also Sections 4.2 and 4.3). Image timing is very important, because tillage operations are performed during a specific time of the year. DeGloria et al. (1986) performed visual interpretation of 5-year Landsat MSS data to monitor land under conventional and conservation tillage practices in California. Various authors used logistic regression techniques to separate tillage practices in Landsat imagery (Bricklemyer et al., 2002; Gowda et al., 2001; Van Deventer et al., 1997). Although several band combinations were used in the different studies, all authors included TM band 5 (SWIR), which has been related to crop residue (Section 4.3).

In temperate regions, cloud cover restricts acquisitions of optical imagery at the time of tillage. Therefore, SAR data has been used for assessing tillage, mainly because the radar return is dependent on surface roughness. To assess the effect of autumn tillage on erosion in Norway, ERS-1 SAR imagery allowed a good separation of grain stubble and ploughed fields, whereas SPOT HRV imagery performed worse (Leek and Solberg, 1995; Solberg, 1992). Using RADARSAT imagery, McNairn et al. (1998) separated classes with different erosion potential based on the effect of residue cover and tillage operations on radar return. They stress that multi-temporal or multi-polarization SAR imagery is required for effective class separation. As radar return depends on other factors than those affected by tillage, such as soil moisture and vegetation density, assessment of tillage practices is not always straightforward. For example, effects of tillage row direction on radar backscatter have found to be as significant as the differences between tillage implements for grain stubble fields (Brisco et al., 1991). Moran et al. (2002) demonstrated that integration of optical and SAR imagery provides more information on tillage and other surface characteristics than the separate analysis of both data sources.

5. Data integration for erosion mapping

Many rationales exist for the mapping of soil erosion. A first step in erosion mapping is the definition of clear objectives on the type of assessment, the extent of the region, the spatial integration level, and temporal aspects. A general used level of spatial integration is a pixel, but also hydrological catchments may be used. Temporal aspects refer to the assessment of either past, actual, or predicted erosion, to events versus long-term averages, and to the mono- versus multi-temporal assessment.

Remote sensing data assist erosion mapping through direct erosion detection (Section 3) or through the use of erosion controlling factors (Section 4). With detection, multiple explanations may exist for certain image characteristics, which could be accounted for with additional data sources. Using erosion controlling factors, a framework for integrating the different factors is required to map erosion. In many cases, only one factor (e.g. vegetation) is assessed with satellite imagery, and other factors are derived from additional data. The choice for a specific integration method depends highly on the mapping objectives. A common way of integrating erosion controlling factors is through the use of erosion models, although other more qualitative approaches exist. Such qualitative approaches may include erosion detection results within the framework. To assess the accuracy of the produced maps, validation with independent data is required, which can be obtained from field measurements, surveys, and high-resolution imagery.

5.1. Erosion models

A large number of erosion models exists, which can be divided in empirical models and physically based models (Morgan, 1995). Empirical models have a statistical basis, whereas physically based models intend to describe the acting processes on a storm event basis. Nevertheless, many models contain both empirical and physically based components. A recent review of several current erosion models is provided by Merritt et al. (2003). Satellite imagery has the potential to provide regional spatial data for several input parameters of erosion models (e.g. King and Delpont, 1993; Pelletier, 1985). However, most published studies merely use optical satellite data to assess the vegetation component (see Section 4.3). Additional spatial data is generally extracted from rainfall gauges, readily available soil maps and DEMs, topographic maps, aerial photographs, and field measurements. Conservation practices are sometimes considered, but usually assumed not present.

The most widely used model is the Universal Soil Loss Equation (USLE), which is an empirical model assessing long-term averages of sheet and rill erosion, based on plot data collected in eastern USA (Wischmeier and Smith, 1978). The USLE and adapted versions (RUSLE: Renard et al., 1997; MUSLE: Smith et al., 1984) have been applied to various spatial scales and region sizes in different environments worldwide. USLE applications in which satellite imagery accounted for the vegetation component have been performed for a small hydrological catchment of about 2.5 km^2 in size (Jürgens and Fander, 1993), areas between 10 and 100 km^2 (Fenton, 1982; Fraser et al., 1995; Lee, 2004; Millward and Mersey, 1999; Reusing et al., 2000), between 100 and 500 km^2 (Anys et al., 1994; Baban and Yusof, 2001; Bonn et al., 1997; Cihlar, 1987), large watersheds of more than 10,000 km^2 (Cerri et al., 2001; Ma et al., 2003; Mati et al., 2000), the country scale for Morocco (Gay et al., 2002) and to the European scale (CORINE, 1992; Van der Knijff et al., 2000). Most of these studies have not sufficiently realized that in different environments empirical relationships of the USLE may not be valid. Besides, the model is developed for evaluating sheet and rill erosion on short slopes. In larger regions also other erosion processes and deposition occur, which are not included in the USLE. Furthermore the data applied in these studies generally have a low spatial resolution (30 m to 1 km), which greatly affects soil loss estimates (e.g. Schoorl et al., 2000). Ideally, the spatial scale of a model is in balance with the various erosion processes that occur in a specific region (Favis-Mortlock et al., 1996). These considerations also concern the application of other models, as many studies fail to provide a clear rationale why a specific model is selected.

The only model which was developed with the intention to be used with satellite data is the Soil Erosion Model for Mediterranean regions SEMMED (SEMMED: De Jong, 1994a). It is based on the Morgan et al. (1984) model, but modifications were made to model the erosion process in a spatially distributed approach and to enable the input from satellite imagery and DEMs. SEMMED uses optical imagery to assess the crop cover factor (same as USLE *C*-factor) and the rainfall interception factor of vegetation at different moments. Multi-temporal Landsat TM imagery and additional data sources allowed the application of SEMMED to the Ardèche Province in France (De Jong and Riezebos, 1997), to a small watershed (12 km^2) in the same area, and to a 4200-km^2 watershed in Sicily, Italy (De Jong et al., 1999). Although the model yields quantitative values, De Jong and Riezebos (1997) recommend to use model outcomes in a qualitative sense, thus to assess the spatial erosion pattern.

Other models that have been used in combination with satellite data include the Thornes model (Thornes, 1985), the Agricultural Nonpoint Source Pollution model (AGNPS: Young et al., 1989), and the Areal Nonpoint Source Watershed Environment Response Simulation model (ANSWERS: Beasley et al., 1980). The Thornes model was applied with satellite-derived vegetation cover information at the continental scale for assessing annual erosion rates, both in a multi-scale approach with remote sensing data of different resolutions (Zhang et al., 2002), and in a multi-temporal approach using AVHRR NDVI data (Symeonakis and Drake, 2004). The AGNPS model was used for predicting soil loss from several watersheds (33–1223 km^2) within Kansas State (USA) employing a land use map derived from satellite data (Bhuyan et al., 2003, 2002). ANSWERS allowed for the prediction of soil loss at the outlet of three watersheds (320–1020 km^2) in the arid zone of northwest India (Sharma and Singh, 1995). Landsat TM data was used here to assess landform, drainage, soil, land use, and land cover. Paringit and Nadaoka (2003) compiled their own physical model from existing equations using a Landsat image to derive vegetation parameters. A combination of models was used by Flügel et al. (2003) for a 4400-km^2 catchment in South Africa. They first delineated terrain units having homogeneous process dynamics with aerial photography and a Landsat TM image. Depending on the relative importance of sheet and rill erosion versus gully erosion, the RUSLE and a gully erosion model were applied to estimate sediment yields.

5.2. Qualitative methods

Drawbacks of erosion models are the fixed data requirement, and the fact that models are developed for a certain region, scale, and specific processes. Often erosion rates are not required, but merely an indication of the spatial distribution of erosion, e.g. for conservation prioritization. Therefore, qualitative erosion mapping approaches have been developed, which are adapted to regional characteristics and data availability. Resulting maps usually depict classes ranging from very low to very high erosion or erosion risk. There is no standard method for qualitative data integration, and consequently many different methods exist. However, common features are the classification of considered erosion controlling factors in discrete classes and the application of a decision rule to combine the classes. Factor selection and decision rules are generally based on expert judgment, or on the author's personal knowledge of the regional erosion processes.

The most basic qualitative approach is to assign weights to spatial units expressing the erosion intensity. This way, Khan et al. (2001) assigned a weighting to visually delineated units from a Landsat TM image. Multiplication with a sediment delivery ratio allowed the contribution of each watershed to sedimentation at a reservoir downstream. Instead of directly assigning weights to units, separate weights can be assigned to different erosion controlling factors according to their importance in the occurring erosion processes. Erosion risk has subsequently been determined from factor weights by summation (Jain and Goel, 2002; Shrimali et al., 2001), averaging (Vrieling et al., 2002), and using hierarchical decision rules to combine the weights (Haboudane et al., 2002). Simple if–then decision rules were applied by Hill et al. (1994b) to combine soil status and vegetation cover information layers derived from spectral unmixing of Landsat TM data. The resulting index is related to erosion occurrence. Multi-temporal comparison of this index derived from images acquired in the same season but during different years would allow the assessment of further erosion, stability, or recovery (Hill et al., 1995b).

For semi-arid Spain, Liu et al. (2000, 2004) used multi-temporal SAR interferometric decorrelation images to detect candidate pixels for erosion. Areas vulnerable to rapid erosion were determined by applying fuzzy logic and multi-criteria evaluation to Landsat-derived lithology and vegetation information, and slope calculated from a SAR interferogram. Where the candidate pixels and vulnerable areas coincided, rapid erosion was expected. However, erosion on agricultural land cannot be accounted for with this approach. For a semi-arid part of Bolivia, Metternicht (1996) applied fuzzy logic to determine the degree of membership of a particular pixel to considered factors, including slope, landscape position, vegetation cover, rock fragments, reddish soil, and whitish soil, derived from a DEM, a geopedologic map, and spectral unmixing of

Landsat TM data. The membership functions were translated to five classes from very low to very high expressing the erosion hazard. If–then decision rules subsequently combined the ranges for the different factors.

5.3. Validation

To evaluate the performance of a specific erosion mapping method and its predictive value, validation of resulting maps with independent data is required. Validation implies an assessment of the accuracy of the representation of spatial erosion patterns, and of erosion rates in the case of quantitative results. Obtaining spatial validation data for assessing the accuracy of erosion maps is a complicated task. Two major issues play a role: first, the considerable investment of time and money required to understand, assess and possibly quantify the local erosion processes; and second the difficulty of extrapolating local observations to larger areas (Stroosnijder, 2003). For example, a common measurement technique for quantification purposes is the collection of runoff and sediments from bounded plots. However, plot size has a considerable impact on measured sediment concentrations (Chaplot and Le Bissonnais, 2000) and results from plot replications can show high variation, which stresses the need for long-term measurements (Nearing et al., 1999). Several good summaries of field techniques for erosion assessment and measuring exist (e.g. Ciesiolka and Rose, 1998; Hudson, 1993; Loughran, 1989; Morgan, 1995). Here we will focus on techniques applied for validation in remote sensing studies of erosion.

From the reviewed literature, it is striking that many studies have not or only slightly addressed the issue of validation. Some merely related the acquired range of quantitative erosion rates to measured or predicted values from literature, and were satisfied when values correlated (e.g. De Jong, 1994a; Reusing et al., 2000; Zhang et al., 2002). However, reported values of erosion rates should be treated carefully, as was pointed out by Boardman (1998). De Jong and Riezebos (1997) performed an internal validation of the SEMMED model, using a Monte Carlo approach to compute the effect of various sources of uncertainty on the model outcome. They found a large uncertainty in soil loss predictions, although the error contribution of remotely sensed vegetation parameters was relatively small.

Erosion measurements were seldom used for validating satellite-based erosion assessments, which is partly due to the high time and labour requirement to perform these measurements. Techniques that have been used include soil loss measurements from bounded plots (Mati et al., 2000); runoff measurement and sampling to determine sediment concentrations at the outlet of a watershed (Sharma and Singh, 1995); the assessment of sediment concentrations at the outlet using optical turbidity sensors (Paringit and Nadaoka, 2003); and the evaluation of sediment accumulation in a reservoir through successive bathymetry campaigns (Bonn et al., 1997).

The common output of satellite-based erosion assessment is a spatial map, which ideally requires validation at several locations. The above-mentioned measurements cannot be easily repeated at many locations. Spatial validation may however be done with Cesium-137 measurements that were used by Bonn et al. (1997) to determine areas of erosion and deposition. More common though are erosion surveys, in which rill dimensions are measured (Cerri et al., 2001; Mathieu et al., 1997), or which are limited to a visual field estimation of erosion risk based on observed features and erosion factors that depend on the study region (e.g. Dwivedi et al., 1997b; Metternicht and Zinck, 1998; Millward and Mersey, 1999).

Besides erosion measurements and surveys, interpretation of high-resolution remote sensing imagery can also be used for validating erosion maps. Aerial photographs have been used to locate evidence of erosion or deposition, and this information provided good correlation with a data space defined by two Landsat MSS band ratios (Pickup and Chewings, 1988; Pickup and Nelson, 1984). Current availability of high-resolution satellites provides similar possibilities as aerial photography in detecting erosion features and thus providing validation data. Panchromatic QuickBird imagery was used to evaluate the potential of detecting and delineating large gullies with optical and SAR satellite imagery (Vrieling and Rodrigues, 2004).

6. Conclusions and recommendations

This review has shown that satellite remote sensing can contribute to erosion assessment in many ways. The effectivity of most methodologies presented largely depends on site characteristics. For semi-arid areas, many interesting techniques such as SAR interferometry and spectral unmixing of optical data were applied to assess erosion status. However, these techniques will only work under specific conditions and cannot be transferred easily to more humid environments. In these environments, satellite applications were mostly limited to the assessment of vegetation class and cover. Recent and future satellite missions will continuously provide new possibilities for erosion research and assist in filling current gaps. Some of the major observation-related gaps are (1) the automatic detection of individual erosion features like gullies or medium-sized rills; (2) the accurate assessment of senescent vegetation cover in different environments; (3) the spatial and temporal evaluation of rainfall characteristics; (4) precise mapping of soil properties and soil moisture in a wide range of environments.

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. Furthermore the required erosion assessment type depends largely on the regional context and the intended use. Therefore no recommendations can be made for one single technique or a set of methods in erosion assessment. Instead, it is recommended for any erosion study that intends to use satellite data, to first thoroughly evaluate what are the observables that may be derived from different types of satellite imagery for the region and the scale required. For most cases, empirical relations will have to be developed, and thus field data on the variable to be observed is needed. Promising methods that deserve special attention and require additional testing include: (1) SAR interferometric decorrelation for erosion detection; (2) evaluation of differential suspended sediment across water bodies in a landscape; (3) the use of geostatistics for soil erodibility or C-factor mapping; and (4) spectral unmixing of optical data to assess soil and vegetation status.

Satellite-derived vegetation information has been the most important input for erosion mapping approaches. For simple empirical models generally one well-timed image is sufficient, but for process-based models multi-temporal imagery is often needed to account for seasonal variability of vegetation cover. Qualitative erosion mapping methods are more flexible than models and can easily incorporate other satellite-derived information. For erosion mapping and monitoring, it is recommended to use qualitative approaches in the case that no model is available that was developed or tested in the region under study. Unless merely a quick identification of erosion risk is envisaged, a proper validation of presented results is always required, which currently is not or poorly done in many studies. Validation is essential for identifying methods that allow accurate mapping and monitoring of erosion. Long-term erosion field measurements and detailed field surveys are indispensable for this purpose, although costly and time-consuming. Close collaboration between the remote sensing community and field-based erosion scientists is therefore required, and accordingly forms the key towards achieving regional operational erosion monitoring systems.

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