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Use of remote sensing methods in studying agricultural landscapes – a review

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Abstract

One of the advantages of remote sensing in agricultural applications lies in its ability to classify and track changes occuring over large areas. Remote sensing is commonly used for crop classification, for yield forecasts, and also for monitoring post-harvest residues and on-site meteorological conditions. Land cover evaluations are most often performed using data from multispectral optical systems of sufficient spectral resolution. To improve the spatial resolution, hyperspectral and radar data is often used. The classification accuracy of vegetation cover is influenced not only by the technical parameters of the sensors but also by the physical and biological characteristics of the vegetation that is scanned, and by the conditions in the locality. Satellite data conveniently supplies terrestrial information, and as the technologies for acquiring and processing this information are continuously improving, they have huge potential in landscape monitoring. In this paper, we summarize studies in the field of agricultural landscapes and their vegetation cover with the use of remote sensing. Methods of vegetation mapping based on the spectral behaviour of plants are discussed, and issues and factors that may affect classification are also dealt with.

Key words: Remote sensing; Land cover; Land use; Satellite data; Vegetation; Image fusion.

1. Introduction

Remote sensing data is nowadays an important source of information in many agroenvironmental studies. It is used for vegetation monitoring and for mapping land cover from a regional level to a global level (Teillet et al., 1997; Lillesand et al., 2004). Remote sensing (RS) is in general defined as the process of acquiring information about an object, area or phenomenon without being in physical contact with it (Lillesand et al., 2004; Campbell, 2002). RS is most often understood as a means of data acquisition with the use of airplanes, balloons and satellite systems, with subsequent processing and interpretation.

In connection with GIS (Geographical Information System), remote sensing may be a useful tool for classifying land cover. The accuracy of such studies is conditioned by the amount, extent and accuracy of both satellite data and

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supplementary data, and also by the classification algorithms. In satellite systems, the key parameters of the remote data are the spatial, radiometric, spectral and temporal resolution (Jensen, 2000). The classification algorithms also cover a range of possibilities..

1972 was a crucial year for vegetation research and for Earth surface research. This is when ERTS (later Landsat 1), the first satellite for research on the Earth's natural resources was put into orbit. This satellite initiated a massive development of satellite Earth sensing (Jensen, 2000). Other Landsat programme satellites followed and, in the 1980s, the French SPOT satellite system was launched, along with other systems. Recent years have seen major developments of commercial satellites that supply satellite data in various resolutions and in various combinations of spectral bands. The data is available for use in various applications (http://www.satimagingcorp.com, http://www.eurimage.com, http://www.geoeye.com). In environmental and agricultural applications and in research on land cover, satellite data enables direct repetitive monitoring of the Earth's surface. It is thus possible to detect crops and their condition throughout a season, to estimate yields (the amount of biomass), to detect changes, to monitor surface drains, to analyze soil conditions, to evaluate the spatial structure of the land cover, to classify crops into categories down to individual crop types, or to identify vegetation infested by insect pests (Franklin et al., 1995).

2. Factors influencing satellite data choice

When selecting satellite data for various purposes, we draw on specific technical parameters of the satellite measuring apparatus. Resolution is one of the most important parameters. The parameters of sensors are defined by a set of four resolution characteristics, which are decisive for their actual use.

Spatial resolution defines the size of the smallest segment (pixel) in the recorded scene. It thus defines the minimum size of an object that may be spotted and identified in the scene (Jensen, 2000). High-resolution data (1m per pixel and less in panchromatic mode) can be used for analysing the spectral response of individual crops. Data of moderate spatial resolution (generally 100–10m per pixel) is used for evaluating various types of land cover. Finally, data of low spatial resolution (1000 – 100m) is a tool for research on global changes (Lillesand et al., 2004). Spatial resolution not only defines the degree of detail that the data can express. Due to the limited capacity of the acquired data volume it also correlates inversely with the size of the scanned area.

Spectral resolution affects the amount and type of thematic information obtainable from a satellite scene (distinguishing between different types of vegetation, etc.). It defines the number and the width of the spectral intervals (bands) that are used (Jensen, 2000). A sensor is characterized not only by the number of bands but also by their position in the electromagnetic spectrum. According to the number and extent of the spectral channels, we divide RS data into panchromatic (describing the reflectance in one spectral band, usually in the visible (VIS) or near infrared (NIR) spectrum), multispectral (describing the reflectance in at least three spectral bands, which usually include the VIS and infrared (IR) part of the optical spectrum) and hyperspectral (describing the reflectance in tens to hundreds of very narrow spectral bands with a focus on differentiating very fine characteristics of the Earth's surface) (Jensen, 2000). Unfortunately, the spatial resolution is often much worse in multispectral and hyperspectral data than in panchromatic data. According to the extent of the spectral bands, Asrar (1989) divides data recordings (and subsequently also RS subject areas) into optical (including VIS 0.4 – 0.7µm, near IR 0.7 – 1.5µm and middle IR 1.5 – 3µm), thermal (3µm – 1mm) and microwave (radar) RS (1mm – 1m).

Radiometric resolution determines the value scale (gray shades) of each pixel in the scene, indicated in bits (bit/pixel). It is defined by the sensitivity of the detector and the amount of incident radiation that is recorded. The best (16bit) information about radiometric resolution is provided by the ERS and Envisat satellites, together with the Hyperion sensor, which is carried by the EO-1 satellite. The standard in most other commercial satellites with high resolution is 11bit (IKONOS, QUICKBIRD, ORBVIEW-3 etc.). Satellites with middle spatial resolution usually provide 8bit data.

Temporal resolution characterizes how often a system records data from the same area, i.e. the time interval between two subsequent revisits of the sensor (http://www.satimagingcorp.com). Geostationary satellites have the highest resolution, and are able to scan one area in minutes or tens of minutes. In satellites on polar orbits, it is possible to improve the temporal resolution significantly by turning the sensors to the sides, as in the SPOT 5 satellite. Scenes of the same area in different periods provide unique information for detecting changes such as the development of cloud systems, fires, erosion, the development of riverbeds or changes in percentage of forest cover. In such cases the temporal resolution may be the limiting factor. It may also cause problems when it is necessary to compare land covers of the same phenophase in different years (Justice et al., 1985; Xin et al., 2002). The situation is also complicated by changing cloud cover, which can make the recording unusable (Moulin et al., 1997).

The main advantage of satellite data is its ability to record a large area at one time. We can thus choose data from a wide spectrum of satellite systems that can be used for studies at local, regional as well as global levels. The size of the scene and the corresponding size of the pixel (spatial resolution) are important. Other parameters for the selection of satellite scenes may then be demanding for pre-processing and evaluation. Their price and format, or the time needed for acquisition or delivery, will be decisive.

3. Overview of available satellite systems

Land cover is most often classified and analysed by multispectral optical systems. Recently, hyperspectral and radar data has been made used of. The main RS techniques, their advantages and limitations, together with information about data prices are summarized in the report by Malthus et al. (2002).

Optical data is mostly divided into three main groups, according to spatial resolution (see above). Data with low to moderate spatial resolution, covering tens of kilometres to hundreds of metres, is used for agricultural applications, in particular for monitoring vegetation conditions and development, crop modelling and yield forecasting on a large scale. Meteorological satellites used for vegetation mapping include one of the oldest low-resolution meteorological systems, NOAA (National Oceanic and Atmospheric Administration), AVHRR, sensing in VIS, IR and three thermal bands (Campbell, 2002). VIS and IR bands are primarily used for cloud identification, but may also be used for calculating spectral vegetation indices (e.g. NDVI) and thus for estimating amounts of biomass (green matter) or the Leaf Area Index (LAI) on a global scale (Vohora, Donoghue, 2004). They may also be used for monitoring cultivated crops, the progress of phenophases (phenological phases) (Shibayama et al., 1999; Xin et al., 2002; Dymond et al., 2002), or for estimating the yield of farm products (Seiler et al., 2000).

High spatial resolution data (tens of metres) is used in a wide spectrum of applications on a regional level – e.g. for regional mapping of conditions, development and changes in landscape (land cover/land use), regional planning, city development monitoring, vegetation conditions (Zerger et al., 2009; Lelong et al., 1998; Yang et al., 2003) and development monitoring, farm land mapping and crop classification (Vancutsem et al., 2009, Rogan et al., 2008), forest condition monitoring and forest ecosystem classification (Schlerf, Atzberger, 2006), monitoring of mining, geological mapping (Nikolakopoulos, Tsombos, 2008), geomorphologic mapping, natural disaster impact mapping, etc.

One of oldest satellite systems most frequently used for agricultural purposes is LANDSAT. It provides the longest time sequence of remote sensing data (since 1972). This is why the satellites are often used for land cover classification (Oetter et al., 2000; Knorn et al., 2009) and for detecting changes in land cover/land use (Cihlar et al., 2000). The data continuity of the Landsat system is at risk because of problems with two satellites of the system on the orbit – the old Landsat 5 satellite and Landsat 7, which has sufffered damage. In addition, the thermal channel with which Landsat 5 and 7 are equipped is not planned to be included in the equipment of the LDCM (Landsat Data Continuity Mission), the satellite that is to take over the scientific challenges of Landsat 5 and 7 (Wulder et al., 2008). There are other sensors with high spatial resolution with similar parameters to Landsat – ASTER, carried by the TERRA satellite, and ALI, carried by EO-1 (Nikolakopoulos, Tsombos, 2008). ASTER provides data in even better resolution (15m) in multispectral mode, and its spectral resolution is higher than in Landsat (14 bands). This can be used in quantitative analyses such as for determining land cover types, or for monitoring vegetation and ecosystem dynamics. The ALI sensor (Advanced Land Manager) was developed for the next generation of the Landsat system, and thus has similar parameters (30m resolution). It can be used as an alternative to Landsat data in cases when it is not necessary to monitor large areas, because ALI has a much narrower scanning area (37km) than the 185 km scanning area of Landsat. Resourcesat-1 – the newest satellite of the IRS (Indian Remote Sensing) system, launched in 2003 – was intended particularly for agricultural applications. In the VIS and NIR parts of the spectrum Resourcesat-1, using a LISS-IV sensor, scans with very high resolution (5.8m). In middle IR (LISS-III), this satellite scans with resolution of 23.5m, while the width of the scanned area is 141 km. These sensors supply data useful for applications examining vegetation, such as yield assessment and crop identification. In small-scale data recording in middle IR, the AWIFS sensor with 56m resolution and width of the scanned area of 740 km is used. The SPOT satellite system (the two latest satellites, SPOT 4 and 5, are currently in operation) forms a transition between Landsat and systems with very high resolution (Ikonos, QuickBird). They may also serve as a compromise when it is not necessary to obtain data with the highest spectral resolution, such as the data supplied by the HYPERION sensor. The major advantage is that SPOT data offers a balance between scene size with high spatial resolution and relatively good spectral resolution for large areas (60x60 or 60x120 km). Thanks to the distribution of the SPOT satellites and the frequency of their scanning, an image can be obtained of any place on Earth every day (http://www.satimagingcorp.com).

The last group of optical data has very high resolution of about one metre. Satellites used for this purpose record data either only in panchromatic mode (KOSMOS, EROS, CARTOSAT-1, WorldView-1) or in a combination of panchromatic and a multispectral regime (FORMOSAT-2, IKONOS, OrbView-3, QuickBird, KOMPSAT-2 etc.). Most of the data is 11bit data; only FORMOSAT-2 provides 8bit scenes and EROS B and KOMPSAT-2 provide 10bit data (http://www.spotimage.com). Such data may be used for local-scale applications, detailed mapping, precise farming and farming activity inspection, spread vegetation mapping, soil erosion mapping, and also in many other fields (building industry, humanitarian aid, urbanistic studies and 3D city models, forestry, insurance, etc.).

Currently the highest resolution is provided by GeoEye-1 satellites (41 cm in panchromatic mode and colour images with resolution of 1.65 m), and WorldView-1 satellites of the Digital Globe company but only in a panchromatic regime with 0.5 m resolution (www.digitalglobe.com).

The ALOS satellite has provided a combination of optical and radar data since 2006. It carries two optical sensors (panchromatic PRISM, AVNIR-2 radiometer) that can scan during the day, and one radar (PALSAR) also suitable for scanning under any weather conditions and at night. The spatial resolution of panchromatic data is 2.5 m in nadir; multispectral data has resolution of 10 m, and the resolution of radar data ranges from 10 to 100 metres (http://earth.esa.int).

Obtaining data from the microwave part of the spectrum has many advantages, and for this reason the use of radar data in vegetation studies has been increasing recently (Walker et al., 2007). Scanning in long wavelengths from approx. 1 mm to 1 m (Lillesand et al., 2004) and the low frequency of microwave radiation enable radars to acquire data without being limited by cloud cover, weather conditions (based on wavelength) or nighttime. Thus this type of data complements optical data well. Based on different reflective and emissive characteristics of objects on the ground in optical and microwave parts of the spectrum, it is possible to distinguish between objects that seem to be similar in the visible part of the spectrum only. The spatial resolution of radar scenes from the older system was around 10 m and more (ENVISAT, RADARSAT-1, ERS). The resolution has been improved lately. Today, commercially available data has resolution of 1–3 metres (RADARSAT-2, TerraSar-X, COSMOSkyMED). It is not suitable to make exclusive use of radar data in vegetation mapping, but, in connection with optical data, radar data improves the resulting classification. As for low spectral resolution, it is not possible to differentiate individual types of growth; it is only possible to identify the borders of fields (Hong et al., 2007). Multitemporal radar scenes of the same area may be used for detecting changes (Simone et al., 2002).

The main advantages of hyperspectral data over multispectral data are their high spectral resolution and, above all, their continuous nature (Erives, Fitzgerald, 2005; Turner et al., 2003; Lawrence et al., 2006). For each of the pixels of the scene, it is possible to obtain a continuous spectrum, directly comparable to the field data recorded by laboratory spectrometers (Crouvi et al., 2006). So far, the only commercial satellite sensor providing hyperspectral scenes of high radiometric accuracy is Hyperion, which is carried by NASA (National Aeronautics and Space Administration) EO-1 satellite (http://eo1.gsfc.nasa.gov/).

4. Vegetation mapping

Vegetation mapping is based on knowledge of the reflectance differences between vegetation types in different intervals of the electromagnetic spectrum. The spectral behaviour of vegetation is characterised primarily by a marked increase in reflectance in the near infra-red part (0.7–1.1 µm) and very low reflectance in the visible part of the electromagnetic spectrum (0.43–0.66 µm) (Meer, Jong, 2001). The reflectance of green plants is lowest in the blue and particularly in the red part of the visible spectrum, because of the high absorption of radiation of photosynthetic pigments (Meer, Jong, 2001).

Healthy vegetation is manifested by a high increase in reflectance between VIS and NIR, which is called the “red edge”. For the purposes of comparability, the red edge is quantified as one value (red edge inflection point). Methods for calculating it are given e.g. by Meer, Jong (2001).

The spectral behaviour of plants is influenced by many factors, which may variously modify the characteristic reflectance signature of healthy vegetation: type of vegetation, inner and outer structure of vegetation, health condition of plants, water content, spatial distribution of vegetated and non-vegetated areas, leaf area index, leaf angle distribution, etc. (Jensen, 2000; Asner, 1998; Sims, Gamon, 2002). The RS of vegetation can be used for mapping changes during a growing season and also throughout the year, for monitoring abnormalities such as soil compaction, watering problems, plant stress (Lelong et al., 1998) or weed and invasive plant species distribution (Lawrence et al., 2006, Underwood et al., 2003) etc. There are various classification methods, from visual interpretation of remote scenes to automatic classification by means of various calculation algorithms.

Vegetation indices

A commonly-used vegetation mapping method is based on vegetation indices calculated from multispectral or hyperspectral data. Through vegetation indices, the main features of vegetation spectral signatures are emphasized. These indices mostly express the relation between red (600–700nm) and NIR (700–900nm) reflectance. While irradiance is strongly absorbed by chlorophyll in the visible red band, reflectance increases sharply in the NIR part of the spectrum (Meer, Jong, 2001). Reflectance is also strongly affected by water content in plants (Asner, 1998; Bowyer, Danson, 2004). The general rule is that the lower the water content, the higher the reflectance (Jensen, 2000).

The most commonly used vegetation indices are RVI (Ratio Vegetation Index), DVI (Difference Vegetation Index), LAI (Leaf area index) (Yang et al., 2007), NDVI (Normalized Difference Vegetation Index), SAVI (Soil Adjusted Vegetation Index) and Tasseled Cap (Dymond et al., 2002; Suming, Sader, 2005).

The most widespread index is NDVI, defined as (NIR–RED)/(NIR+RED) (Tucker, 1979), which is used for monitoring vegetation conditions and land cover changes. Teillet et al. (1997) present the NDVI index as an indirect tool for studying the biophysical features of vegetation and their connections to biomass distribution, LAI, primary productivity, photosynthetic radiation, CO_2 and ecological and climatic parameters. Because of different spectral (different width of the sensed bands) and spatial (different scale) resolution and radiometric processing of the data, it is not possible to make a direct comparison of NDVI calculated from data gathered by different sensors.

Bannari et al. (2006) give examples of indices used in agroenvironmental studies for mapping crop residues: Brightness Index (BI), Cellulose Absorption Index (CAI), Normalized Difference Index (NDI), Soil Adjusted Corn Residue Index (SACRI), Modified Soil Adjusted Corn Residue Index (MSACRI) and Crop Residue Index Multiband (CRIM). These indices use the NIR and SWIR reflectance values to show distinct spectral characteristics associated with the cellulose and lignin content in crop residues. However, the accuracy of these indices is usually low. They cannot distinguish a spectral mixture of different materials in the same pixel. Vegetation indices may also serve as a basis for further landscape analyses. Land Surface Emissivity is one example. It is important for surface temperature, energy balance and land cover evaluations, and also for other agroenvironmental studies. It is also used in methods for atmospheric correction. Valor and Caselles (1996) showed a relation between surface emissivity and vegetation indices (NDVI, SAVI) and other methods of vegetation cover mapping (e.g. Spectral Mixture Analysis). They also presented the Temperature/Emissivity Separation (TES) algorithm, which is used for creating land surface emissivity images, a standard product of the ASTER sensor provided by the NASA company. However, this product is not suitable for agricultural purposes because of scaling problems (Jiménez-Muñoz et al., 2006).

Data classification

There are many kinds of image classification, from traditional automatic per-pixel methods (including supervised, unsupervised and hybrid classification) to relatively new automatic machine learning methods or object classification. The aim of the classification is to find and merge objects with similar characteristics into classes that describe various sorts of objects on the Earth's surface. The most widely-used classifiers are those based on spectral behaviour (spectral pattern recognition). Other classifiers may use spatial pattern recognition or temporal behaviour of objects, as in the case of crops, where spectral and spatial parameters typically change in time (Jensen, 2000). Traditional image classification methods are based only on knowledge of the spectral characteristics of the objects of interest. They work with original bands or bands calculated by transformation of the original bands, and cannot combine data of different types (Jensen, 2000). Automatic classification methods categorize each pixel into a defined class (supervised) or a cluster (unsupervised) just on the basis of the values of the classified pixel in the processed bands, without considering the characteristics of the surrounding pixels. For this reason, this process is also called "per-pixel" or "hard" classification (Tatem et al., 2001; Zhang et al., 2008).

The use of supervised classification in many applications is limited by the choice of a suitable algorithm. Mean spectral values of various classes in distance-based classifiers, and variance in addition to probability-based classifiers as a decision rule, are therefore used (Castillejo-González et al., 2009). For angular-based classifiers (SAM, CAC), the classification decision rule based on spectral angles formed between the reference spectrum (endmembers or spectral library) and an unclassified pixel is used. SAM (Spectral Angle Mapping) is relatively insensitive to illumination and albedo effects (South et al., 2004). CAC (Cosine of the Angle Concept) incorporates in addition the length of the reference signatures, which supplies additional information to the classification. South et al. (2004) present this classifier as a method suitable for discriminating objects with a similar spectral manifestation (soil and senescent crop residues).

Unsupervised classification algorithms (e.g. K-means, ISODATA) are used to create spectrally separated categories (or spectral classes) without direct intervention of the user (Castillejo-González et al., 2009). There are more spectral classes in images with unsupervised classification than in images with supervised classification. Unsupervised classification is therefore suitable for revealing very small differences between classes of external similarity. Vancutsem et al. (2009) used the ISODATA algorithm for classifying vegetation types in a series of scenes from the SPOT Vegetation satellite. Daily data acquisition allows complete temporal characterization of vegetation.

Various types of input data can be used in machine learning algorithms (e.g. ANN, DT). It is possible to combine data from the optical part of the spectrum with radar or morphometric data generated by processing a digital terrain model. As these methods are non-parametric, normal distribution of the input data is not required.

The use of artificial neural networks (ANN) in land cover mapping is mentioned e.g. by Carpenter et al. (1999). Neural network methods may also be used for mapping land cover changes or for estimating biophysical parameters (Fernandes et al., 2004). ANN can also be used for classifying different crops or for identifying weeds (Yang et al., 2003).

Decision trees (DT) is a supervised classification method that requires extensive well-balanced training data to perform adequately. The most commonly used algorithms for land cover evaluation are the S-Plus classification tree (Rogan et al., 2008), the C4.5 classification tree, or classification and regression trees (C&RT, Hansen et al., 2000; Homer et al., 2002; Yang et al., 2003). DT methods may be used for classifying hyperspectral data, where their continuous nature allows us to find information about physical parameters (such as crop cover, crop health, soil moisture, and temperature). They can then be used in agriculture for planning operations such as fertilization, ploughing, chemical protection or treatment of crop residues.

Hyperspectral reflectance measurements may be used as a direct input into DT classifications, and provide even higher accuracy than DT based on the NDVI vegetation index (Yang et al., 2003). Lawrence et al. (2006) shows some advantages of the BCC (Breiman Cutler Classification) methods over other classification tree-based attitudes, e.g. in classifying invasive plant species.

Object-based methods for image analysis have the advantage of incorporating the spatial context and mutual relationships between objects (Blaschke, 2010). Apart from spectral information, they also use shape, texture and topological data. Conchedda et al. (2008) used these classification methods for mapping land cover and changes in land cover using SPOT XS in the Definience Professional software environment (Definiens 2006). Land cover and vegetation (locality conditions) change analysis with the use of multispectral aerial scenes analysed by object classification are presented by Walter (2004) and by Stow et al. (2008).

With the increasing amount of commercially-available data, new methods for classifying land cover in various extents are continuously developing. Land cover evaluation of large areas using the Chain classification method is presented by Knorn et al. (2009). Chain classification is a new approach to the classification of land cover on large areas. This method uses the classification of one image to train a classifier for the neighbouring images. The approach is simple, as it only requires accurate georeferencing of scenes and no atmospheric correction. Chain classification can also be used for classifying images from different sensors with different radiometric or geometric resolutions in the same chain, as long as sufficiently large overlap areas exist between them. The method has been used for forest vegetation, but is also usable for other types of vegetation cover (Knorn et al., 2009).

Problems of vegetation mapping

Problems and factors that may affect accurate vegetation cover classification are linked to technical features of the sensors and to the selection of a suitable classification method. Mapping is also influenced by the physical and biological characteristics of the locality and by the vegetation itself.

The **spectral characteristics** of crops are influenced by the chlorophyll and water content, and they therefore change in the course of the growing season. For better identification, it is beneficial to use a set of scenes acquired throughout the growing season of the studied crop. Best results for crop identification may be achieved during the phase of full vegetation development, when the influence of the soil on the spectral reflectance of the habitat is lowest. The exact time of full development, however, differs from crop to crop. The problem in crop classification linked to the differences in spectral reflectance due to uneven crop maturation and differences in the growth phase of plants within a single field or among different surfaces (caused by different date of sowing) are presented by Nellis, Tao (1999). Spectral reflectance is also influenced by soil humidity, orientation and slope of the surfaces, or elevation. Identification of crops or detection of changes on agricultural surfaces is performed by multitemporal classification (Hansen et al., 2000).

Although there are enough satellites with high spatial resolution, individual pixels may still contain more than one class (object). It such a case, **mixels** (mixed pixel/element), pixels with mixed spectral information (containing objects belonging to different spectral classes), may appear and cause accuracy problems if traditional classification methods are used. Mixels appear when the spatial frequency of the land cover classes is higher than the pixel size (Zhang et al., 2008).

Traditional “hard” per-pixel methods assign each pixel to one class. Such strict classification of mixels would lead to an information loss. Therefore, alternative methods which use “soft” classifiers have to be used for mixel classification.

These methods are called sub-pixel classifications. Mixels are divided into individual fractions (according to the number of objects), which correspond with areas outside the pixel. The fractions are then assigned to individual land cover classes (Blaschke et al., 2002). From the soft classification, a number of fraction images is gained which is equal to the number of land cover classes (Zhang et al., 2008).

An overview of sub-pixel classifications is given by Fernandes et al. (2004). The presence of mixels may cause difficulties in classifying the presence of crop residues in fields. Such residues play an important role in protecting soil against wind and water erosion. Moreover, they have many other beneficial effects on soil (soil structure improvement, increased organic matter content, a positive influence on water infiltration into soil, evaporation, temperature). They also play an important role in CO_2 fixation. Information on the amount of crop residues is also important as an input into soil erosion models. One of the methods used for distinguishing drying vegetation from soil is SMA (Spectral Mixture Analysis) (Bannari et al., 2006; Kressler, Steinnocher, 1999; Dennison et al., 2003; Arsenault, Bonn, 2005). Soil and dry vegetation appear similar in the IR part of the spectrum. Bannari et al. (2006) and Arsenault and Bonn (2005) suggested differentiating between dry vegetation (lignin and cellulose absorption features), soil and green vegetation with the use of hyperspectral data, where the continuous type of data makes it possible to detect differences in the SWIR part of the spectrum. SMA fractions are more robust than traditional vegetation indices, particularly when classifying hyperspectral data (Dennison et al., 2003). The SMA algorithm was also used by (Kressler, Steinnocher, 1999) for detecting changes in land cover from NOAA-AVHRR data.

Although data is available from commercial satellites with sufficient spectral, spatial and temporal resolution, only a small part of this data complies with all requirements for growth type identification in farming applications (Hong et al., 2007).

Image fusion, which aims to improve the information value of the resulting scene, may be a solution to this problem. Image fusion has been used extensively to provide a single image that simultaneously combines high spectral information (from multispectral or hyperspectral images) with high spatial information from panchromatic images or from radar satellites.

Available image fusion techniques (IHS - Intensity, Hue, Saturation), PCA (Principal Components Analysis), arithmetic combination based fusion, and wavelet based fusion), together with a description of them, common problems (such as colour distortion) and restrictions have been described by Zhang (2002). Simone et al. (2002) presented types of fusions and methods of radar and optical data fusion.

Combined optical and radar data can be used for more accurate classification of land cover (Hong et al., 2007) or for mapping the height of vegetation growth (Walker et al., 2007). The possibilities of improving LANDSAT scene temporal resolution by means of fusion with high temporal resolution data (1–2 days) acquired by the MODIS sensor, carried by the TERRA satellite, have been described by Hilker et al. (2009).

5. Conclusions

Differences in spatial, temporal and spectral resolution are limiting factors for the use of RS data in various applications. Unfortunately, due to technical constraints, satellite RS systems can only offer high spatial resolution combined with low spectral resolution, or vice versa. This means that a system with high spectral resolution can only offer medium or low spatial resolution. Therefore, it is necessary either to find compromises between different resolutions with respect to the application, or to utilize alternative data acquisition methods.

It is not possible to recommend one general method of data analysis, because each method offers information of a different type. On the other hand, it is possible to combine RS data, supply it with field measurements and thus improve the final information and its accuracy. Satellite scenes may supply or even substitute data for terrestrial research, as we can obtain information about large areas and about areas which are difficult to access. This can significantly decrease the costs of data acquisition. Satellite data will continue to become more available, at it will be increasingly used because of its spatial nature, and because it can be processed digitally and easily archived.

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