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Advanced remote sensing technologies for tracking landscape changes and environmental conditions

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Abstract

The integration of cutting-edge remote sensing technologies, biophysical principles, and advanced spatial statistics enables innovative landscape analysis across various spatial and temporal scales. Traditional approaches relied on classification methods and indices derived from multi-spectral imagery to assess landscape degradation. However, modern techniques can extract biophysical indices like leaf area index and canopy chemistry from satellite imagery. Long-term remote sensing archives (e.g., Landsat, AVHRR) facilitate retrospective studies of landscape changes and trajectories. Recent advancements in sensors and analysis techniques, such as sub-pixel classifications and continuous fields, have improved the accuracy of variable retrieval (e.g., Albedo, chlorophyll concentration). These developments enable powerful monitoring tools for land use/cover change detection, leading to a better understanding of landscape dynamics and the mapping of previously unexplored features. However, a trade-off exists between high spatial and high temporal resolution depending on the platform used.

Keyword: Remote Sensing; Spatial Statistics; Landscape Analysis; Biophysical Principle; Temporal Resolution

1. Introduction

Landscape research increasingly utilizes remotely sensed data to analyze patterns, gradients, and trajectories of landscape elements and properties. This introduction covers aspects of remote sensing relevant to landscape research, with a focus on ecological applications rather than data processing. We highlight the broad possibilities of using such data and the challenges of integrating remotely sensed data with landscape and field data. Three main purposes for incorporating satellite or airborne imagery into landscape-oriented ecological research are identified: (a) pattern recognition for classification or mapping of landscape and surface objects, (b) developing, mapping, or visualizing continuous representations of surface properties, and (c) monitoring landscape trajectories and detecting changes in

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both discrete and continuous features at the landscape scale. Historically, pattern mapping through classification has been a powerful tool for management and habitat-related analyses. Landscape ecology has significantly progressed from simple remote sensing to improved abilities to characterize patterns, analyze their formation and change over time, and evaluate their implications for populations, communities, and ecosystem processes (Turner et al. 2001). Additionally, landscape-scale ecological research often focuses on analyzing gradients and how gradual changes in important variables influence the response and behavior of species (Austin 2002; Austin and Smith 1989; Collins et al. 1993), ecosystems (Chapin et al. 2002; Likens et al. 1977; Pomeroy and Albert 1988), or urban growth (Herold et al. 2003; Klostermann 1999). Ecological theory is thus heavily influenced by these analyses, and the development of statistics closely follows these requirements. Consequently, both the classification of images and the derivation of indices and continuous fields from the same imagery can significantly advance landscape research in an ecological context.

1.1. Remote Sensing Principle

Remote sensing has emerged as a valuable tool in landscape ecological research, enhancing the recognition of patterns, the analysis of the state and trajectories of landscapes, and the recognition of landscape properties. Combined with Geographical Information Systems (GIS), biophysical principles, and modern spatial analysis methods, remote sensing enables powerful retrieval and interpretation of landscape patterns and processes at various spatial and temporal scales. Here, we briefly introduce the most important characteristics of remote sensing for ecologists working at a landscape scale. Remote sensing is based on the principles of sampling images of the Earth's surface and atmosphere from a large distance, usually from aircraft or satellites, and recording the reflected electromagnetic radiation from the Earth's surfaces and objects. This can be done passively, by recording ground-reflected solar illumination (in the visible, thermal, or microwave range), or actively, by recording reflectance and emissions from a source projected from the same platform to the Earth's surface.

The most widely used remote sensing platforms in landscape ecology are passive systems that scan the visible and near-infrared parts of the spectrum (e.g., 400–1000 nm). The effectiveness of detecting and recording reflected radiation stems from the fact that ground objects selectively reflect and/or absorb incoming radiation.

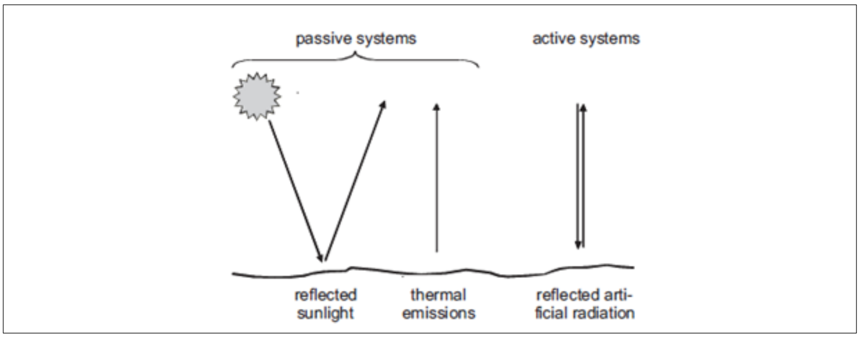

Figure 1 Examples of the flow of radiation and remote scanning of reflections and emissions

Objects on the Earth's surface reflect incoming energy at varying intensities along different wavelengths depending on their surface properties. By comparing the intensity of incoming versus reflected radiation, it is possible to distinguish ground objects and infer their nature. For instance, green leaves reflect sunlight more in the green and near-infrared wavelengths while absorbing red and blue wavelengths, which are utilized for photosynthesis, making the leaves appear green. The high infrared reflection and low red reflection have led to the development of various vegetation indices to map vegetation greenness on Earth's surface (Huete et al., 1997; Payero et al., 2004). While remote sensing is employed in diverse fields such as atmospheric sciences and oceanography, this discussion primarily focuses on terrestrial landscape ecology applications. Most digital remote sensing instruments capture electromagnetic energy by collecting photons, converting them to electrons, and storing them as digital numbers. The initial raw image lacks true Earth coordinates and a metric coordinate system, necessitating extensive processing for further analysis. This processing includes geo-registering the images to the Earth's surface in a defined projection and calibrating the digital numbers into meaningful physical units. After atmospheric correction, which adjusts for trace gases and aerosols, the radiance is converted to ground reflectance. Ground reflectance is a standardized unit used for multi-temporal and cross-sensor analysis (Jensen, 2004). Various atmospheric correction methods have been developed to manage this normalization process. The level of processing required varies by application. Some vegetation indices can be derived from original brightness values rather than percent reflectance, as they rely on ratios rather than absolute data values. Generally, better and more consistent results are achieved when images are meticulously processed for registration and radiometric correction (Schlaepfer & Richter, 2002).

1.2. A History OF Platform

Remote sensing began with the first aerial photographs taken from balloons, eventually transitioning to powered aircraft (Cohen & Goward, 2004). These early images were visually analyzed for various applications. This method saw significant advancements during World War I and further matured in World War II. During the Cold War, remote sensing became a standard for espionage, necessitating high spatial resolution to accurately interpret and identify ground targets. The launch of the ERTS-1 satellite, later renamed Landsat, marked the beginning of a new era in civilian remote sensing. The Multispectral Scanner (MSS) on this satellite captured reflected electromagnetic energy in four distinct spectral bands, enabling researchers to map vegetation distributions. These images covered large areas (185 x 185 km) at an 80-meter resolution and provided global coverage every 18 days. The fourth Landsat platform introduced the Thematic Mapper (TM), which offered improved calibration and recorded energy across seven spectral bands, ranging from visible to thermal wavelengths. The Enhanced Thematic Mapper continued this legacy with better calibration and additional spectral bands, maintaining a continuous record of the Earth's surface for over three decades, a trend that is expected to continue.

Another significant civilian sensor is the Advanced Very High Resolution Radiometer (AVHRR) on the NOAA satellite platform, which scans the entire Earth daily at a spatial resolution of 1.1 km, later enhanced to measure five spectral bands. The choice of spectral bands for surface reflectance measurement is crucial for developing ecological applications, even though some satellites were initially designed for other purposes. New multispectral and hyperspectral sensors for space and aircraft are being developed, covering bands from visible light to thermal infrared and microwaves to detect various surface, water, and atmospheric properties (Ustin et al., 2004). A variety of sensors on satellites and aircraft now exist, each with specific spatial, temporal, and spectral (radiometric) resolutions designed to meet particular application requirements. Recent platforms like NASA's EOS TERRA and AQUA, and ESA's ENVISAT, carry multiple sensors relevant to landscape-level ecology. Data from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, for example, are available online, either for free or for a nominal fee, and are fully processed for immediate use in landscape research. Landsat (MMS/TM) sensors continue to play a dominant role in regional scale applications. Cohen and Goward (2004) highlighted four main reasons for this: affordability, extensive (+30 years) time series, ideal spatial resolution for regional management (±30 m), and the availability of critical spectral domains for landscape research in the visible (VIS), near infrared (NIR), and shortwave-infrared (SWIR) ranges.

The sensor concept of Landsat and subsequent sensors like SPOT, IRS, ASTER, and the earlier NOAA-AVHRR, originated from understanding that photosynthesis utilizes only a portion of the light spectrum. Red and near-infrared (NIR) bands are particularly effective in distinguishing vegetation patterns. This makes the Landsat sensor ideal for pattern recognition, gradient mapping, and detecting land changes. Numerous ecologically relevant indices, such as the "Tasseled Cap" which includes brightness, greenness, and wetness values, are derived from Landsat data. Additionally, various vegetation, soil, and geological indices have been developed from Landsat using simple ratios like NIR/RED and the Normalized Difference Vegetation Index (NDVI), which indicate green leaf mass, specific leaf area, or chlorophyll content.

The NOAA AVHRR sensor, initially designed for meteorological purposes, was first used by Compton J. Tucker of the U.S. Geological Survey to explore its ecological applications. Tucker discovered that the NDVI concept could be applied to AVHRR with modifications (Tucker et al., 1985). This sensor, similar to Landsat, offered several advantages: it is free of charge, has over 30 years of data, has an ideal grain size for continental to global analyses (~1.1 km), and includes critical spectral domains for landscape research in the visible and NIR ranges. While AVHRR has lower spatial and radiometric resolution, its high temporal resolution (daily) compensates for this. This high temporal resolution allows AVHRR to identify vegetation and other surface patterns and detect global climate change effects by linking these patterns with climate variables (Zhou et al., 2001; Nemani et al., 2003).

1.3. Pattern Recognition and Image Classification

Classification of remotely sensed imagery with the purpose of obtaining thematic maps of the landscape is one of the main activities related to landscape oriented remote sensing. Supervised (with prior knowledge of the classes to be obtained) and unsupervised (based on statistical clustering without prior knowledge of the classes to be obtained) classification have both been used. In applications relevant to landscape ecological research, both supervised and unsupervised classifications are appropriate, but they differ with respect to the goal. The first approach aims at classifying an image based on a predefined classification scheme. Such efforts are usually appropriate if a pre-defined schema is necessary to solve associated scientific of management questions. The second approach is used mainly as an exploratory analysis tool in order to objectively find pattern at the landscape scale. By this, finer nuances of the landscape pattern may be found that are not known prior to the analysis. The principle task resulting from unsupervised classifications is to associate the obtained classes with meaningful ecological descriptions. Both approaches have long been used to generate vegetation maps from single- to multi-scene images for the purpose of mapping, or for the derivation of additional ecological or conservation information. While classifications using a single scene may be comparably easy to achieve, doing the same from multi-scene mosaicked imagery (or even more so when combining scenes through time) presents many additional difficulties.

Many different classification approaches are in use for the GAP program, where scientists usually have to face the problem of classifying complex vegetation pattern across comparably large spatial scales, which requires the simultaneous processing of a large number of Landsat scenes. Most often, though, scenes are first mosaicked together and corrected for atmosphere effects, either directly using e.g., the ATCOR method or indirectly, using pseudo-invariant features (Hall *et al.* 1991, Jensen 2004). An initial unsupervised classification generates spectral classes for which field data is collected to discriminate vegetation types in a post-classification stage that share similar spectral, but dissimilar ecological properties. Statistical rules are then applied in order to optimize this post-classification processing.

1.4. Characterization and Mapping of Continuous Gradients

One of the most powerful approaches in ecological research is to map gradients first and classify later (if necessary), meaning that many aspects of nature are hidden if objects are classified first, and then described in terms of properties later. Thus, properties and characteristics of landscapes or ecosystems should better be described directly as gradients that own various behaviors in space and time. Two advantages arise from this approach; (a) any property can be mapped and monitored at its proper spatial and temporal scale and spatial dimension, and (b) the detection of change (of a property) is directly observable from multitemporal image analyses, and not restricted to the change of classes. One example for this is the monitoring of forest resources using thematic change detection procedures. In this situation, binary maps are generated to delineate forests from non-forests, and change detection is based on the analysis of subsequently derived forest/non-forest maps. This inherits an initial cation scheme. Once calibrated, we can only detect change if a pixel in a classified image switches between forest and non-forest. Gradual changes are not observable. If pixels are comparably large and if the thematic classification of an image includes many cover classes, then change detection becomes even more difficult and error prone. This is due to the mixed nature of the landscape classified, with few pure pixels available only.

One solution to this is to monitor the forest or tree cover fraction directly. Represented as a continuous layer, we can monitor the change in forest resources more directly, for finer gradual change. We need only to consider the uncertainty of the continuous map as a source of error for change detection. The approach described above has resulted in the concept of land cover and vegetation continuous fields (DeFries *et al.* 1999; Hansen *et al.* 2002, 2003) at the global scale as an alternative to a fixed classification scheme (Belward *et al.* 1999; Fried In general, the representation of continuous fields relies on three basic approaches, though they are often mixed (Pickup *et al.* 1993); (a) derivation of indices from band combination, (b) development of continuous layers by using statistical regression techniques and a set of training data, and (c) resolving linear (spectral) mixture models (Smith *et al.* 1990) to map the fraction of classes per pixels for which a spectral signature is available. The first approach (a) is most often used, and we discuss it with more detail below. The second approach (b) was introduced above, and one example of continuous field calibration is presented for a study area in the European Alps below. The third approach (c) is conceptually similar to approach (b). The difference is that in the last approach, pure classes are calibrated spectrally, and then mixtures are derived from spectral gradients between the spectra of pure classes. The combination of bands to derive indices is often preferred over other approaches, because it tends to give satisfactory results without rigorous atmospheric correction, especially when single scenes from one time step only are used. On the contrary, most other problem.

1.5. Trade OFF Resolution

Three types of resolution are relevant to remote sensing data: spatial resolution (grain), temporal resolution (frequency), and spectral resolution (detail). Additionally, sensors differ in the sensitivity in recording electromagnetic energy. Any sensor available combines characteristics of these three domains, but no existing sensor is optimal in more than two of the three domains (Fig. 2). Despite ever increasing computational power, these general tradeoffs in resolution remain, likely due to the limited downlink capacity. For model development, similar tradeoffs have been proposed (Levins 1966), and the consequences seem largely similar. In model building, general theory says there is no single model possible that optimizes precision, generality and reality simultaneously. Thus any model has advantages or disadvantages with respect to the 3 possible characteristics. With respect to sensors, this means that the goal of a study largely determines the selection (or combination) of suitable sensors for a project.

High spatial resolution is one aspect, which traditionally has been important. It is helpful primarily for pattern recognition through image interpretation, classification and segmentation.

Usually, high resolution sensors show low temporal resolution, but in the case of airborne systems, they may also provide high spectral resolution (AVIRIS, HYMAP, ROSIS, see e.g. Kötz *et al.* 2004). Modern high resolution images (e.g. IKONOS) are thus well suited to be linked with historical air photography for change detection (Herold *et al.* 2003).

1.5.1. Classification

- pattern recognitions, textural and
- structural analyses, regional scales

1.5.2. Biophysics & -chemistry

- Physical & chemical properties
- small spatial scales,

1.5.3. Change detection

- gradient mapping, phenology,
- continental to global scales

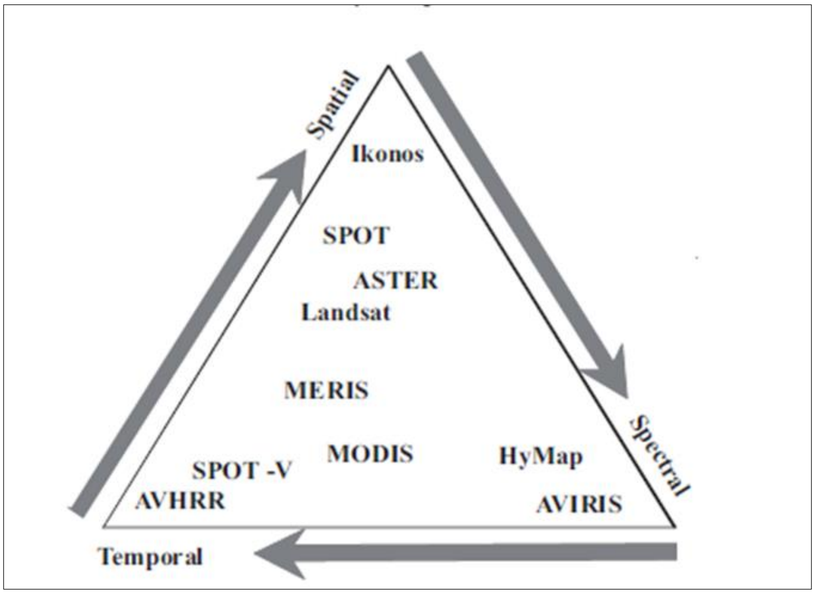

Figure 2 A classification based on resolutions. No sensor simultaneously optimizes high resolution of more than one property among spatial (grain), temporal (frequency) and spectral (detail) resolution**.**

High spectral resolution is instrumental in detecting a variety of bio-physical and bio-chemical properties, such as foliar nitrogen or lignin content (Serrano et al., 2002), and characteristics of leaves or soil (Daughtry et al., 2000; Dawson et al., 2003; Haboudane et al., 2002; Jacquemoud et al., 1995; Zarco-Tejada et al., 2000). It also aids in assessing dry plant matter and various soil properties (Shepherd and Walsh, 2002). This level of detail facilitates the mapping of vegetation properties, including individual plant species, which is challenging with low spectral resolution. Such data hold promise for scaling eco-physiological properties from small plots to larger landscapes, effectively bridging the gap between field data and coarse spatial resolution imagery like MODIS or AVHRR for model calibration and initialization.

High temporal resolution is typically provided by coarse grain space-borne imagery, such as AVHRR, MODIS, and to a lesser extent, MERIS. The AVHRR and MODIS sensors are crucial for continental and global scale analyses, enabling the scaling of physiological and biological processes to evaluate ecosystem changes (Myneni et al., 1998, 2001; Nemani et al., 2003), detecting land cover changes (Langevin and Stow, 2004; Stow et al., 2004), and characterizing basic land cover patterns needed for global resource assessments and process modeling (Running et al., 2004). The high temporal resolution also supports phenological studies (Duchemin et al., 2002; Moulin et al., 1997; Myneni et al., 1997; Zhou et al., 2001) and rapid assessments of natural hazards such as fires, floods, or droughts (San-Miguel et al., 2000). Despite their lower spatial resolution, these sensors achieve nearly cloud-free global imagery by compositing 8–10 day sequences under optimal atmospheric conditions. Integrating these composites over time allows for the analysis of annual phenological patterns and helps distinguish vegetation types that are challenging to separate spectrally on a single date. This high temporal frequency is vital for successfully differentiating needleleaf and broadleaf tree cover fractions in vegetation continuous fields (Schwarz et al., 2004).

The Southwestern Gap Analysis Project (GAP)

Traditional image classification and feature extraction from remotely sensed imagery has consistently fused imagery with ancillary data such as elevation, slope, aspect, and moisture indices, surface geology, soils, or climate. This is particularly true when large landscapes are being mapped.The tradeoffs in resolution described in this paper are consistent for remotely sensed imagery. However, new techniques and improved sensor engineering are pushing these limits. Another common tradeoff in the application of remote sensing to landscape level mapping is the concept that increasing extent requires decreasing spatial and thematic resolution. Commonly, continental and global mapping efforts focus on low resolution level mapping is the concept that increasing extent requires decreasing spatial and thematic resolution. Commonly, continental and global mapping efforts focus on low resolution area mapping commonly use sensors of higher spatial resolution (1–5 m) and a expanded thematic legend. The challenge to remote sensing is to therefore expand extent and increase resolution. The Gap Analysis Program administered through the Biological Resources Division of the U.S. Geological Survey (USGS-BRD) seeks to map land cover and wildlife habitat at scales appropriate to wildlife studies and usable to land managers and researchers. The Southwestern Gap Analysis Project that covers the states of Arizona, Colorado, Nevada, New Mexico, and Utah is considered a regional effort covering an area roughly 1/5 the size of the conterminous U.S. It has mapped land cover at relatively fine resolution

(30 m) and relatively fine thematic scale (>110 thematic classes). This project utilized three seasonal dates of Landsat Enhanced Thematic Mapper imagery (spring, summer, and fall) over the entire region (240 images) combined with topographic data and landform to map land cover (Fig. 3). These spatial data were trained with approximately 90 000 field data

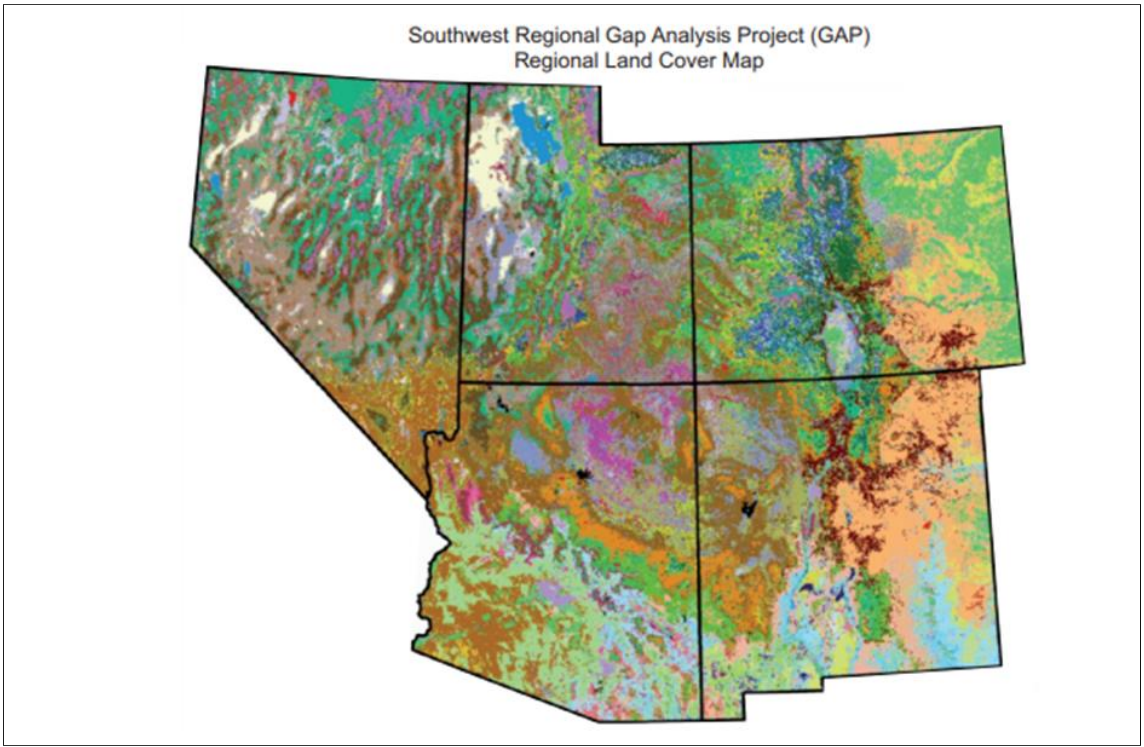

Figure 3 Soutwestern GAP regional land cover map. The map distinguishes >110 land cover types, classified from 240 multi-temporal Landsat TM images (3 seasons) across the states of Nevada, Utah, Colorado, New Mexico and Arizona. Colors represent individual cover types**.**

This effort underscored the need for the fusion of imagery and ancillary data, and the importance of field training to drive statistical classification tree models that developed the mapping rules. We have mentioned the importance of ecological theory to help drive classification models. This effort utilized ancillary data known to predominantly drive land cover distribution in this region (topography and landform). Other ancillary data such as surface geology and soils were also explored, but were found to be heavily correlated to the derived topography and landform layers. Therefore, while classification tree models allow for the inclusion of multiple predictor variables, this study found that a minimal set of quantitatively derived landscape descriptors coupled with spectral information effectively mapped land cover. In this case knowledge of the driving variables in the local ecosystem, coupled with field measures, effectively developed the ecological associations at a quantitative level rather than utilizing existing ecological theory which was more generalized and developed over time by observation and study

Disentangling climate and grazing effects upon productivity: a spatio-temporal analysis

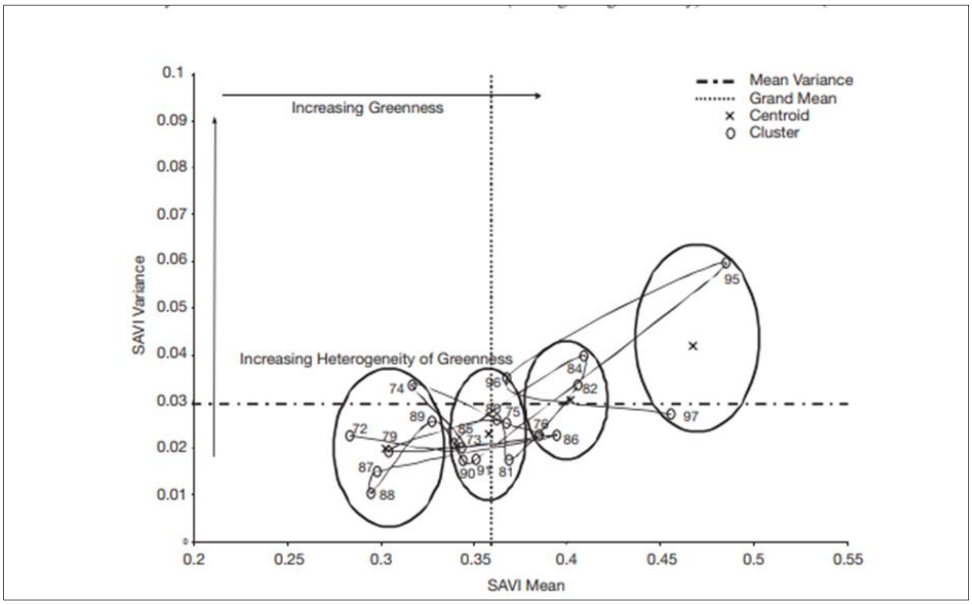

Figure 4 The SAVI mean-variance analysis from 1972 to 1997 (numbers indicate years, e.g. “95” = 1995) for the sagebrush-grassland community on Deseret Land and Livestock Company ranch**,**

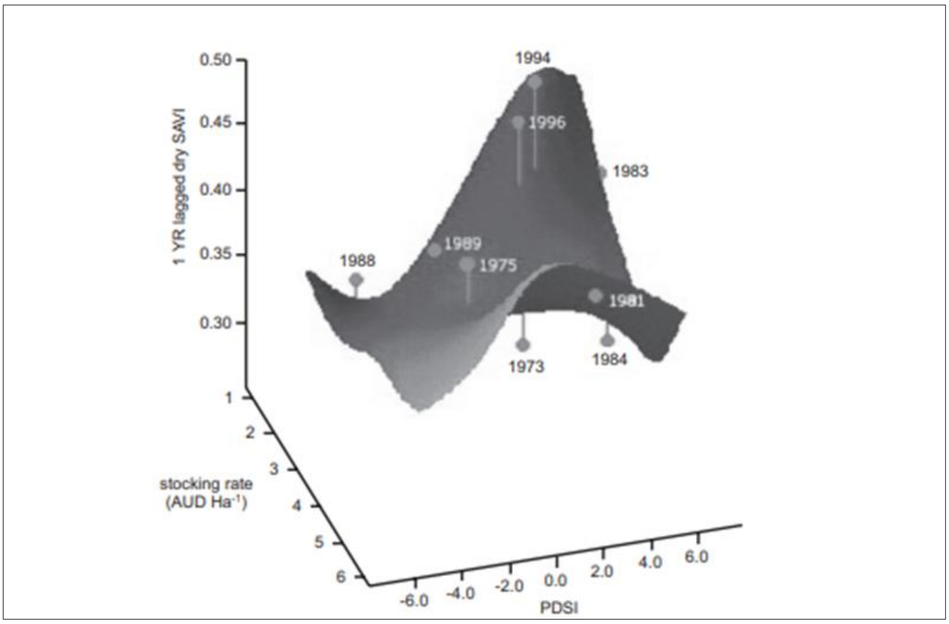

Figure 5 The one-year lagged soil-adjusted vegetation index (SAVI) response surface with respect to grazing (AUD Ha−1 = Animal unit days per area; expressing stocking rate) and climate (PDSI = Palmer

Time series of TM data were processed using a relative atmospheric correction based on temporally invariant features (Jensen 2004) prior to converting the images to SAVI. In water-limited systems, such as the Great Basin cold desert in Utah, the expectations are low vegetation index (VI) mean and variance during drought periods and high VI mean and variance during wet periods (Hanley 1979). Such system cycling between two states is labeled a limit cycle attractor (Hanley 1979). Higher variance during wet periods is hypothesized to be a function of landscape heterogeneity manifest as differences in soil texture and its effects on soil moisture availability for vegetation productivity (Fernandez-Illecs *et al.* 2001). Hanley (1979) hypothesized that sagebrush steppe vegetation response is primarily constrained by grazing and wet and drought climatic episodes. Mean-variance analysis (Pickup and Foran 1987) confirmed Hanley's hypothesis by indicating that sagebrush steppe is a limit cycle attractor, with two main states of SAVI (vegetation abundance) during wet and dry periods (Fig. 4). The wet periods are signified by the presence of two very strong El Niño events (in 1983 and 1997) and a 1988 La Niña event: the Great North American Drought (Trenberth *et al.* 1988), respectively. Secondly, the sagebrush steppe landscape's overall SAVI trajectory was increasing non-linearly from 1972 to 1997, due primarily to the very strong El Niño events (Washington-Allen *et al.* 2003). One year lagged SAVI was found to be linearly correlated ($r = 0.62$, $p = 0.006$) with the Palmer Drought Severity Index (PDSI, a regional-scale measure of soil water availability) and nonlinearly correlated ($r = 0.63$, $p = 0.04$) with grazing using a first order difference ordinary least-squares regression of climatic factors (Washington-Allen *et al.* 2003; Fig. 5).The surface generated in Figure 5 is a combination of the linear and non-linear responses. Finally, after landscape level impacts induced by repeated droughts in 1977, 1986 to 1991, vegetation recovery from these catastrophic episodes appears to be aided by very strong El Niño events, a finding that presents land managers with an opportunity to exploit this natural subsidy (Holmgren and Scheffer 2001).

1.6. Calibrating continuous fields across scales of spatial resolution

One way of conserving small scale spatial information within images of coarse spatial resolution (see also Lischke *et al.* 2007) is to map the distribution of the small scale entities as proportions per pixel of the coarse resolution image. The cover of trees, grass, snow, or open water on the ground may be of varying spatial dimension, though certain objects such as individual tree crowns usually cover areas significantly smaller than 1 hectare. While high resolution imagery allows for mapping broader cover types covering the full pixels, this becomes non-trivial at coarser spatial resolution, since naturally such pixels consist of a mixture of several cover types (Schowengerdt 1996). One alternative is to map fractions of cover types, also termed continuous fields (De Fries *et al.* 1999; Hansen *et al.* 2002

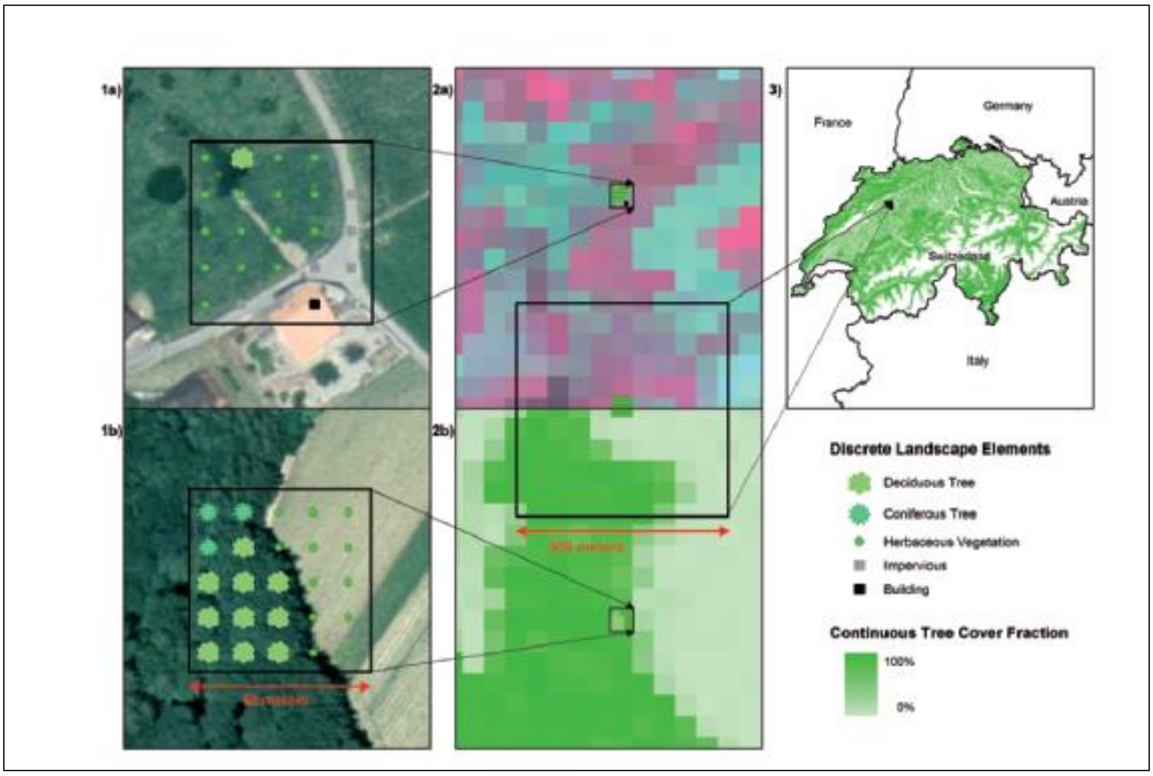

Figure 6 Predictive up-scaling of land cover information from high spatial resolution (50 cm) aerial photosin (1a,b) to medium resolution (50 m) Landsat TM data (2a,b), and finally to moderate resolution (500 m)

MODIS data in (3). Discrete landscape elements are mapped at local scale (Swiss National Forest Inventory sampling sites, 1a,b). Fraction of Tree Cover as derived from these sampling sites is then applied to medium resolution multi-temporal TM data (2a; Landsat composite) using a GLM model to produce spatially continuous fraction of tree cover (2b) at Landsat scale. The model allows map can serve as training data for high temporal MODIS reflectance data using GLMs. Direct calibration of1 to 3 – however – is not possible. E. Zimmermann *et al.* cover across the whole TM scene. When aggregating the TM scene to moderate (500 m) resolution, each pixel as a linear mixture of known end members. We propose here another solution by hierarchically calibrating multi-temporal Landsat TM data from field plot data, then

based on Generalized Linear Models (Schwarz *et al.* 2004; Schwarz and Zimmermann 2005), which are an ideal statistical tool to cope with linear and non-linear mixtures and distributions (Fig. 6). Besides the statistical calibration, the method is highly similar to the derivation of vegetation continuous fields available as global data sets based on MODIS (500 m) and AVHRR (1.1 km) reflectance data (De Fries *et al.* 1999; Hansen *et al.* 2002, 2003).

Imaging spectroscopy for mapping biophysical and -chemical ecosystem properties

Imaging spectroscopy deals with the simultaneous and continuous acquisition of a large tral features caused by the complex absorption and scattering processes at the Earth surface, which can be analyzed to improve the scientific understanding of ecosystem functioning and properties (Asner *et al.* 2000; Ustin *et al.* 2004).

The spectral reflectance of a vegetation canopy, provided by air or spaceborne imaging spectrometers, is known to be primarily a function of the foliage optical properties, the canopy structure, the background reflectance of understory and soil, as well as the illumination conditions and viewing geometry). The complex radiative transfer within a canopy governing the signal recorded by imaging spectrometers can be described by physically based radiative transfer models (RTM), which take into account the above mentioned factors (Goel and Thompson 2000; Kimes *et al.*2000).

During a large field campaign in the Swiss National Park, in summer 2002, DAIS 7915 and ROSIS imaging spectrometer flights were carried out along with intensive ground measurements of the vegetation properties (Fig. 7).The study site represents an inner-alpine valley covered by boreal sub-alpine forest (dominating species: *Pinus montana* ssp. *arborea,* average altitude 1900 m a.s.l.). Canopy structure was described by two canopy analyzers LAI2000 and hemispherical photographs following well known methods for the characterization of heterogeneous canopies such as coniferous

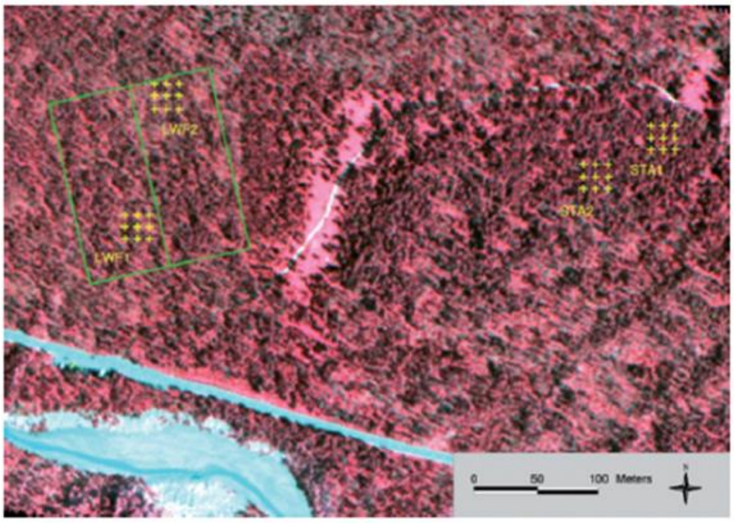

Figure 7 Airborne imaging spectrometer data over four core test sites in the Swiss National Park (crossesindicate the sampling points). The image composite represents geo-coded and atmospherically corrected data of the spectrometer ROSIS in spatial resolution of one meter resolving the heterogeneity of the observed forest.

The Long-term Forest Ecosystem Research site of WSL where forest stand characteristics are acquired is indicated by the green rectangle.

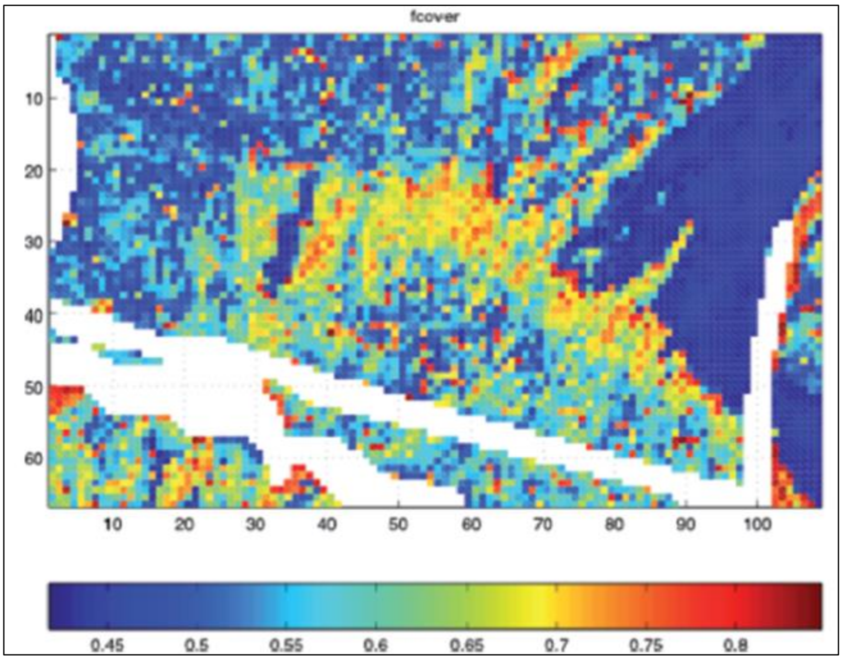

Figure 8 Map of fractional tree cover, as example of the derived biophysical and -chemical properties in the Swiss National Park.

1.7. Guidelines for Linking Field Sampling with Remotely Sensed Data

One of the key issues for linking field and other data with remotely sensed imagery is accuracy and scale. This linkage is a prerequisite to calibrate any image for further processing. Any geo-registered image has a certain amount of positional error, which usually is tested against grain. An image is considered well geo-registered if the error is below the side length of one pixel. Field data is nowadays often geo-located by GPS, which on average is of high spatial accuracy. However, we may see positional uncertainties that are significant with respect to pixel size in mountainous terrain, within forests, or in comparison with imagery of small grain (e.g. IKONOS, airborne). If, for example, field data and image both have a positional accuracy of +/– 0.5 pixel size, then in most cases the point may not be within the pixel it is sampling. The second problem associated with linking field data with remote sensing imagery is the spatial extent of the field plots and the grain of the image cover on the ground. Are they of similar extent? Both uncertainty and scale have important implications for sampling and analysis.

Field data collection needs to take the spatial resolution of images into account: a plot size well below one pixel seriously reduces the statistical power of any analysis. If spatial heterogeneity of the spectral response of the surface is high, small plots may represent the reflectance and derived indices of the sampled pixels. This leads to the recommendation that sample plots should be close to one pixel in size, or larger than one pixel. If sampled plots are smaller than one pixel, averaging multiple smaller scale measures per pixel may lead to significantly increased power when relating to image pixels (White *et al.* 1997). Another consideration is that of the high spatial autocorrelation present in these images. In this case adjacent pixels influence the spectral response of neighboring pixels. Therefore samples should be located in areas consisting of small pixel groups (e.g. 3x3 pixels) that are relatively uniform in spectral response. This will ensure an accurate sampling of the spectral response of the target and provide a buffer for spatial errors associated with rectification errors or GPS precision.

If positional uncertainty is comparably high, then we recommend considering: (1) averaging the spatial dimension covered by the field sampling by either sampling larger plots relative to pixel size, or by allocating the plots spatially nested to sample the heterogeneity within the spatial domain larger than one pixel. As an alternative to (2), one could calibrate a finer resolution image first, and use this as an input to calibrate the coarser resolution image.

Figure 9 illustrates the problem of linking field data with remotely sensed imagery where both have considerable positional uncertainty: the bold circle in the middle represents the center pixel with similar registration error. It is obvious that not all of the points fall within any of the rectangle, and with respect to plot area around these centers (see upper left in figure) it is even worse. Increasing the sample size by sampling plots along radii, as illustrated by the four transects, is one possibility to cope with this problem on the ground. Averaging pixels in a neighbor hood helps to cope with the positional uncertainty of the image as well.

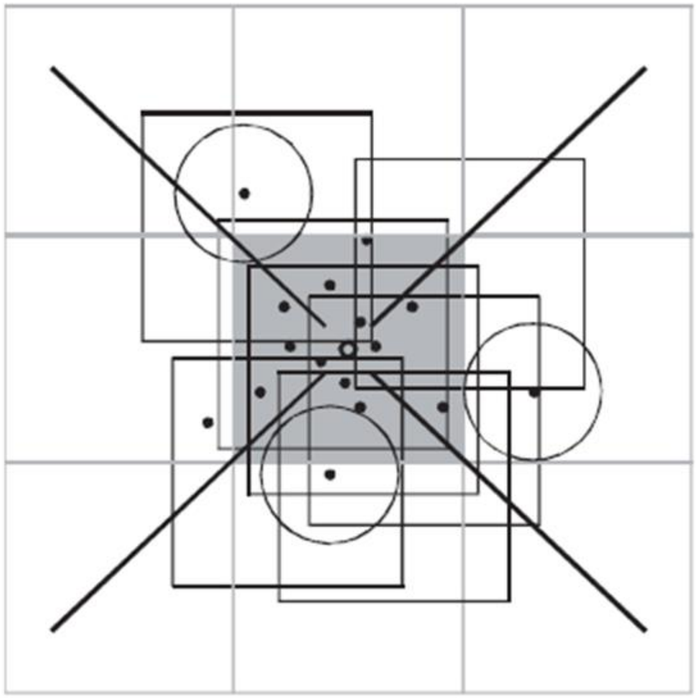

Figure 9 Issues of positional accuracy and scale. The grey rectangle represents a perfectly geo-located pixel, the bold circle is the true positions of one field plot. Open rectangles represent various possible pixel positions that on average have an error of below 0.5 pixel dimension and the small dots represent true positions of additional field plots. The open circles illustrate plot-related positional uncertainties of similar dimension as for the pixels for three plots. Sampling larger spatial domains (along e.g. transects) and averaging neighboring pixels may help to improve linking field data and imagery that have considerable positional error

1.8. Validation and error analysis

In 1993 Ustin *et al.* stated that validation is perhaps the most overlooked aspect in remote sensing (Ustin *et al.* 1993).While this may have been true back in 1993, this is certainly no longer the case. Still, it is a major challenge to clearly test pattern or gradients derived from remotely sensed imagery thoroughly. Sound statistical tests require the data to be independent and not used for calibration. In the case of remotely sensed imagery, this is not trivial.

There are three different ways to comply with this prerequisite: (1) use a spatially random sample of calibration/test data within the domain of an image, split it into two subsamples, one for calibration, and one for validation; (2) take a random sample of calibration in one area of the image and another random sample in a different area of the image for validation; (3) take a random sample of calibration data from one source, then take a second random sample for validation using a different source. A random sample is usually without replacement and may include any form of strategic- Schwarz and Zimmermann 2005). Where the calibration and test data are not directly measurable but come from models as well, it is important to test for pseudo-errors as a result of uncertainty in the validation data set. A second, independent source for validation is a calibration data if complex gradients need to be sampled. Here, a sound theory of the links.

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Friedman *et al.*. Where the calibration and test data are not directly measurable but come from models as well, it is important to test for pseudo-errors as a result of uncertainty in the validation data set. A second, independent source for validation is a more secure approach (e.g. Schwarz et al. 2004). This is often a problem when models are derived or enhanced using coarse resolution imagery. For example, it is usually not feasible to directly assess tree cover fraction on the ground on a 1 km2 basis. Thus, some method of scaling is involved to generate calibration and test data sets (often using higher resolution imagery, or DEM-based GIS modeling). This is certainly a viable approach, but requires attention with respect to statistical inference. Besides the analysis of accuracy, the assessment of errors or uncertainty, and its spatial distribution is an important task (Bastin et al. 2002; Tian et al. 2002). Often, errors are not randomly distributed across a processed image, as for instance in an image classification exercise (Congalton 1988; Foody 2002), which may have a variety of reasons (see Foody 2002 for a discussion). Users may benefit from a more detailed analysis of the errors and its statistical and geographical characteristics and distributions. Various approaches have been proposed for such error analyses (Foody 2002), including extrapolations from the training data set (Steele et al. 1998), analyzing magnitude within partitioned classes (Foody 2000), using geostatistical (Kyriakidis and Dungan 2001) or regression modeling approaches (Leyk and Zimmermann 2004). Conclusions Remote sensing is a powerful tool for a wide array of applications. In landscape research, it is very useful for mapping pattern and gradients, though in most cases, remotely sensed imagery is combined with other sources in order to solve scientific and management problems (GIS, field data, etc.). In this latter case, it is important to realize that many aspects of traditional ground-based studies can be adapted, while remotely sensed imagery cannot. Susan Ustin and co-workers (1993) conclude that in order to make the best use of remotely sensing, a new ecological paradigm seems necessary which is consistent with the spectral data. There is still insufficient – though growing – knowledge on how to link spectral response with biophysical and bio-chemical pattern, dynamical processes and small scale mixtures of ecological and landscape features on the ground. We believe that such a paradigm has to additionally respect grain and frequency at which pattern and processes can be observed. For example, when it comes to calibration or testing landscape level models where remotely sensed imagery is involved, then we are bound to the grain of such images. Careful planning is necessary to collect field and other data at a resolution that makes optimal use of reflectance data. Otherwise, uncertainty and scale mismatch inhibit successful analyses (e.g. Turner et al. [2004] for testing ecological models; Woo [2004] for hydrological applications). On the other hand, using ecological theory and sound ecological understanding is necessary to optimally use, calibrate, or process imagery for environmental research at a landscape scale. Otherwise, models or calibrated features might show unexpectedly high or spatially structured residuals, which clearly have an ecological explanation. In many cases, this also means the incorporation of modern regression techniques, consistent with the quest to calibrate bounded, skewed, or saturated response shapes. Finally – although not touched in this chapter – the best processing of remote sensing imagery is needed to enable the detection of pattern and gradients at repeatedly high precision. In practice, this means that remote sensing experts and landscape researchers need to collaborate closely, in order to make the best progress in landscape and environmental research. N. E. Zimmermann et al. m

2. Conclusions

Remote sensing is a powerful tool for a wide array of applications. In landscape research, it is very useful for mapping pattern and gradients, though in most cases, remotely sensed imagery is combined with other sources in order to solve scientific and management problems (GIS, field data, etc.). In this latter case, it is important to realize that many aspects of traditional ground-based studies can be adapted, while remotely sensed imagery cannot.

Susan Ustin and co-workers (1993) conclude that in order to make the best use of remotely sensing, a new ecological paradigm seems necessary which is consistent with the spectral data. There is still insufficient – though growing – knowledge on how to link spectral response with biophysical and bio-chemical pattern, dynamical processes and small scale mixtures of ecological and landscape features on the ground.

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Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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