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Applications of remote sensing to conservation of forest ecosystems

Abstract: At regional to global scales the only feasible way to monitor the world's forests is through remote sensing. The use of coarse-grain remote sensing techniques for measuring deforestation and fragmentation at regional and global scales in combination with new developments such as neural network classification promises to improve the accuracy of forest extent measurements. The use of techniques such as seasonality in AVHRR data to enable finer differentiation of forest type is still proving problematic and relies on may require improvements in sensor technology before becoming feasible. The improvement in remote sensing techniques, sensor technology and the growing emphasis on conservation are bringing forest ecologists and remote sensing scientists together for the first time. Applications of fine-grain remote sensing techniques to conservation of biodiversity, assessment of protected areas and species protection show that fine-grain remote sensing is underused in conservation of forest ecosystems.

Keywords: satellite imagery, remote sensing, tropical forests, environmental monitoring, conservation.

Introduction

Forests currently cover approximately 30 percent of the land area of the planet (Foody, Lucas et al. 1997). Estimates suggest that deforestation is occurring at a rate of between 15-17 millions ha per year, predominantly because of human-induced land-use changes. Over 45 per cent of the Earth's original forests have been cleared during the past century (United Nations 1992). These human-induced changes in forest extent and condition impact biodiversity, climate, biochemical cycles and economic development (Malingreau, Achard et al. 1995).

It is vital to protect forests, particularly tropical forests, because they contain the majority of the planet's land-based species. Nature's products support such diverse industries as agriculture, cosmetics, pharmaceuticals, pulp and paper, horticulture, construction and waste treatment. In addition, forests regulate the global atmospheric cycles that make biological life possible on earth (United Nations 1992).

Satellite based remote sensing is probably the only way to inventory the change in global forest ecosystems and prioritise and assess the success of conservation efforts. In this paper I consider remote sensing techniques being used to monitor the state and rate of change of forest ecosystems and the innovative ways this information is being applied to promote the conservation of the world's forest ecosystems.

Techniques for remote sensing forest ecosystems

Difficulties in monitoring forest ecosystems

Monitoring forest ecosystems at regional to global scales is largely focused on course spatial resolution remote sensed imagery. Fine spatial resolution sensors such as Landsat TM (30m spatial resolution) are unsuitable for large-scale sensing of forests because their 'temporal resolution' is too low. Landsat doesn't sample each area of the world's tropical forest frequently enough to guarantee up-to-date, cloud-free imagery for entire regions (Malingreau, Achard et al. 1996).

In one study of an area of 100x100km of tropical forest on the Ivory Coast, just ten Landsat (TM or MSS) images with less than 10% cloud cover were available between 1972 and 1990 (Chatelain, Gautier et al. 1996). Among these, only four were actually available. At the same time Ivory Coast was experiencing deforestation rates peaking at 6.5 percent per year. Additionally, the cost of using fine resolution imagery to map forest extent over an entire region such as West Africa would be prohibitive. Rapid change in land use, high cloud cover in tropical areas and the need to map changes in land use over large areas effectively restricts the mapping of global forest extent to coarse spatial resolution systems such as the NOAA AVHRR (Foody, Lucas et al. 1997). The rapid revisit time of AVHRR improves the probability of regularly obtaining cloud-free imagery and allows multiple images to be combined into a 'mosaic' to eliminate cloud.

However, the low spatial resolution of AVHRR makes classification of forest extent problematic because each pixel represents 1.21 km^2 on the ground. Estimates of land cover classifications based on this imagery are often inaccurate because each pixel may represent two or more land cover classes. Some studies have shown that extent of forest cover may be underestimated because of this problem while other image classifications tend to overestimate forest extent (Foody, Lucas et al. 1997).

Neural network classification

Several solutions have been proposed to reduce errors in classification of forest extent. One promising technique involves using a feed-forward artificial neural network to classify fractional pixels. A fractional pixel is a proportional class coverage estimate. For example, a pixel might be classified as 60% forest and 40% pasture. The forest extent for an image is found by summing the forest extent for each pixel over the entire image area. Using an artificial neural network for classification involves establishing a network of weights between interconnections in the network and being able to compute the error between a pixel's output classification and its known classification. The network of weights is initially set to random values and the output error is fed backward into the inputs in each of many iterations of the classification function. The network of weights is adjusted to tend toward minimising the output classification error. The final 'trained' network can then be used to classify pixels of unknown class membership.

Foody, Lucas et al. (1997) used this technique to classify tropical forest cover from AVHRR imagery of a 3000 km^2 region in Mato Grosso, Brazil. The landscape was a mix of tropical forest, rivers and patches of agricultural land. A Landsat TM scene was used to train the neural network analyses of AVHRR imagery and test the accuracy of classification by the neural network.

Table 1. Estimates of the extent of each class across the test site. The neural network extent is derived by summing the fractional components of each pixel. The standard classification is derived by assigning each pixel to the dominant class then calculating the extent. For each, the difference from the Landsat TM derived extent is provided in brackets. Partial reproduction from (Foody, Lucas et al. 1997)

Class	Areal extent (%)		
	Landsat TM	Neural network	Standard classification
River	6.71	9.39 (+2.68)	0 (-6.47)
Pasture	23.35	19.02 (-4.33)	20.20 (-3.15)
Forest	69.93	71.58 (+1.65)	79.79 (+9.86)

These results show that using a neural network to classify fractional pixels can significantly improve classification of tropical forest extent from AVHRR imagery.

The NDVI and the TREES project

There are several other techniques that can be used to improve AVHRR based classification. Though the forest/non-forest classification of land cover is very important for global-scale mapping of vegetation there are times when more precise classifications are needed. The seasonality of a forest relates to whether the remotely sensed imagery changes from season to season. An area of forest may show a continuum of signal amplitudes from "evergreen" to a fully seasonal pattern and this information can help to classify forest type (Malingreau, Achard et al. 1996).

The Normalized Difference Vegetation Index (NDVI) is the most useful derived information from AVHRR for forest classification(Malingreau, Achard et al. 1996). The NDVI is formed in terms of the ratio of the difference between the visible and near infrared bands and shows a sharp response between forest and non-forest areas. The TREES project, established in 1990, is a joint collaboration between the European Union and the European Space Agency. It specific objectives include the compilation of a pan-tropical forest map with a scale of 1:1,000,000 (Malingreau, Achard et al. 1996). The five classes of land cover used are dense and fragmented evergreen forest, dense and fragmented seasonal forest and non-forest. The TREES project makes use of NDVI and seasonality to classify AVHRR imagery.

The TREES project demonstrates two common techniques used to determine the accuracy of classification procedures from remotely sensed imagery. The first technique is comparison with other datasets. The second technique is comparison with higher resolution imagery.

The TREES project regional forest cover of South-east Asia was validated against the World Conservation Monitoring Centre (WCMC) database of global forest cover using Thailand as the test site (Malingreau, Achard et al. 1996). When aggregated to simple forest/non-forest classes there was, a relatively poor, 70 percent correspondence between WCMC conventionally derived thematic maps and TREES classifications.

The TREES project regional forest cover map was also validated against high resolution Landsat TM imagery for an area of the Thailand/Myanmar border (Malingreau, Achard et al. 1996). A direct comparison between pixels was not possible due to imprecise geo-referencing and scale differences between the imagery but qualitative classifications were found to be much better than with conventional WCMC maps.

Another objective of the TREES project was to assess the usefulness of new sensors for tropical forest mapping, in particular the Synthetic Aperture Radar (SAR) flown aboard the ERS-1 satellite (Malingreau, Achard et al. 1996). The project demonstrated the unique value of radar imagery for remote sensing in areas consistently covered by cloud and in combining the radar imagery with more traditional optical remote sensing data sources.

Applying results to conservation

Climate change predications

Imagery showing change in global forest extent, primarily through deforestation and biomass burning, is a primary input into global atmospheric models being developed to predict the effect of climate change.

However, the value of a particular area of forest as a carbon sink and the amount of carbon dioxide released by conversion of that forest area to alternate land use is a complex issue. The strength of a forest area, as a carbon sink or source when burned, depends on the age and composition of the forest. A regenerating tropical forest typically absorbs more carbon dioxide in its growth phase than a mature forest, which may have no net carbon dioxide uptake(Foody, Palubinskas et al. 1996). Furthermore, different guilds of plant species have very different carbon dioxide responses. A study near Manaus, Brazil has shown that Landsat TM imagery can be used to accurately classify tropical forests at different regenerative stages (Foody, Palubinskas et al. 1996). However, it seems likely that resolving the subtleties of these issues will have to await the development of global-scale sensors with higher spatial and spectral resolution than AVHRR.

Assessing the success of protected areas

More than 12,700 protected areas have been established around the world, accounting for 13.2 million km^2 or 8.81% of Earth's land surface (Liu, Linderman et al. 2001). Protected areas are a key strategy used to conserve biodiversity from human activities. Remote sensing is being used to determine how successful protected areas are at mitigating human impact.

A study of fragmentation and deforestation inside and outside of protected areas in the Sarapiqui region of Costa Rica showed that protected areas were dramatically curtailing the rate of deforestation (Sánchez-Azofeifa 1998). Landsat MSS images from 1976 and Landsat TM images from 1986, 1991 and 1996 were overlayed with land status information showing National parks and private conservation areas. The deforestation and fragmentation rates within national parks remained below .56% over the twenty-year study and decreased further towards the end of the period. Deforestation rate declined from 1.7% to 1.4% over the period in private conservation land. Outside protected areas deforestation rates were between 3.6% and 3.2% and the number of forest fragments increased from 537 to 1231 in 1996 (Sánchez-Azofeifa 1998).

A similar study in the Guiglo-Taï region in south-western Ivory coast used aerial surveys from 1956, Landsat MSS images from 1974 and 1984 and a Landsat TM image from 1990 (Chatelain, Gautier et al. 1996). The area of study included part of the 350,000ha national park of Taï, the largest tropical forest reserve in West Africa. In 1968, the Ivory Coast government built a road into the southwestern region and population began to increase in this previously sparsely populated area. Imagery shows that between 1974 and 1990 approximately 79 percent of the unprotected forest within the study area was eliminated (Chatelain, Gautier et al. 1996). Dramatic forest/non-forest delineation between protected and unprotected areas is visible on the 1990 remote sensed imagery showing that protected areas are working effectively. However, the final six-year period of the study, 1984-1990, has shown that protected areas are also beginning to be penetrated. It seems likely that as population and pressure for resources increases so will deforestation of protected areas.

A contrast to the above conclusions, that legal protection prevents loss of habitat, is found in Wolong nature reserve in Sichuan province, southwest China (Liu, Linderman et al. 2001). Created in 1975 the reserve covers approximately 200,000ha and is home to 10% of the wild panda population. A comparison was made between land cover inside the reserve and within a 3km wide border around the reserve (62,656ha) where habitat is not protected. Corona photographs from 1965, Landsat MSS imagery from 1974 and Landsat TM imagery from 1997 were used to assess change in habitat status in the reserve over time. The images were geo-referenced and validated using 250 ground-truth plots and differential GPS. Imagery was classified based on a forest/non-forest pixel assignment and degree of fragmentation was used to assess the habitat suitability of each area for giant pandas.

The rates of habitat loss inside the reserve were lower than those outside the reserve between 1965 and 1974, before the reserve was created. However, after the designation of reserve status, the rates of habitat loss and fragmentation inside the reserve unexpectedly and dramatically increased to levels that were similar to or higher than those outside the reserve. Local people in the reserve were the direct driving force behind the destruction of the forest and of panda habitat. To better understand the effectiveness of protected areas and develop more feasible policies, it is essential to integrate remotely sensed ecosystem properties with human population, behaviour, and socio-economics (Liu, Linderman et al. 2001).

Species conservation

Remote sensing is being applied to protecting umbrella species such as the jaguar, *Panthera onca*, in Sierra de Tamaulipas, an isolated mountain system in Northern Mexico (Ortega-Huerta & Medley 1999). Land cover was classified from a Landsat TM image and compared with the frequency distribution of jaguar sightings. Jaguar sightings showed significant association with tropical deciduous and oak forests between 400m and 900m in altitude. From this information it was possible to assess the fragmentation of high-potential jaguar habitat and prioritize conservation of land parcels that promoted regional contiguity of jaguar habitat (Ortega-Huerta & Medley 1999).

Biodiversity assessment

The convention on biological diversity, signed in Rio de Janeiro, Brazil in 1992, states that nations joining the convention must identify the components of biological diversity and monitor activities that may have adverse impacts on this diversity (United Nations 1992). Remote sensing is an important technique for measuring global biodiversity in forest ecosystems. At the local scale remote sensing is beginning to deliver structural information about forest stands such as the nature of the canopy surface, the layering within the canopy and even individual tree identification (Innes & Koch 1998). Now this information is being linked with ecological species information derived from ground sampling to give estimates of species richness and distribution over much larger scales than previously available.

One such example is the Sango bay area, comprising some 30km by 100km of swamps, grasslands, cultivated land and forests, bordering Lake Victoria in Uganda (Fuller, Groom et al. 1998). Landsat TM images from 1990 were used to map the land cover of Sango bay. Four hundred field sites were visited to collect data to be used as training samples and fourteen different land cover classes were identified. For each land cover class identified, five sites were chosen and a detailed survey of plant species was conducted in a 20x50m quadrat within each site. Biological diversity ratings were determined for each site by species richness, the total number of species and ranked by species uniqueness based on the number of sites at which the species occurred. The biodiversity value then supplanted the land cover map to produce a biodiversity map. Policy makers use this map to assess conservation options and determine optimal policies in the Sango bay area.

Discussion

The use of coarse spatial resolution systems, particularly AVHRR, has been a valuable tool for measuring the forest extent and the rate of change in extent. New techniques, such as neural network classification, promise to improve the accuracy of global forest maps produced from AVHRR data. However difficulties in identifying specific types of forests, even with the help of techniques such as seasonality analysis, limit the operational use of AVHRR to forest/non-forest classification.

Improvements in sensor technology such as the use of SAR imagery, the new Moderate Resolution Imaging Spectroradiometer (MODIS) instrument launched in 1999 and other vegetation sensors due to come online in the near future are likely to greatly improve the accuracy of global forest mapping.

Fine spatial resolution systems such as Landsat TM are able to provide valuable information on local scale deforestation and fragmentation. This information can be used to make measurements of ecosystem properties and correlate these properties with 'invisible' properties such as biodiversity and species distribution that are important to conservationists. There are still few studies in the literature extrapolating local, ground-based observation of 'invisible' ecosystem properties over a much wider scale by correlating them with satellite observed forest classes.

New sensor technology such as high spectral resolution sensors are becoming available and promise the ability to detect individual guilds of tree species, canopy structure and even soil properties (Martin, Newman et al. 1998). The increasing emphasis on monitoring the state of the world's forest environment, the development of new sensor technology and the new techniques for applying remote sensing of forests to conservation is likely to make this a burgeoning area of research in the near future.

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