SATELLITE BIOMODELLING: USE OF REMOTE SENSING FOR PREDICTING PLANT BIODIVERSITY

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Abstract

Conservation measures involve planned management to protect the Earth's biodiversity around the world, thus preventing exploitation, destruction, or neglect of a natural resource. Satellite data from remote sensing systems offer valuable information to ecologists for studying diversity patterns. The term 'satellite biomodelling' implies the development of models for biological interests, while integrating remotely sensed data. This paper explores how recent advances in spatial and spectral resolutions of satellite sensors can contribute to studying aspects of biodiversity, as well as discussing advantages and challenges of adopting such technologies for conservation management. A case study is also presented, developing a spatial regression model for predicting global plant diversity based on the Normalised Difference Vegetation Index (NDVI) derived from satellite data, while integrating other biophysical and environmental parameters (temperature, precipitation, and topography). This paper demonstrates that remote sensing data can offer valuable information about diversity patterns and has the potential to become an effective tool in conservation and biodiversity evaluation.

Keywords: Biodiversity; remote sensing; conservation; NDVI; satellite biomodelling

1. Introduction

The term *biodiversity* is defined as the variability among living organisms from all sources, including inter alia, terrestrial, marine and other aquatic ecosystems (CBD 1992). As rates of habitat and species destruction continue to rise, the need for conserving biodiversity has become increasingly imperative during the last decade (Wilson 1988, Kondratyev 1998). In order to design meaningful conservation strategies, there exists an urgent need to map and monitor species richness and distributions, as an important aspect of conservation and land use planning (Sala *et al.* 2000).

A first step recommended by the Convention on Biological Diversity (CBD) to prevent loss of biodiversity is the implementation of "a system for identifying and monitoring components of biological diversity, along with processes that significantly threaten its conservation" (CBD 1992). Comprehensive information on the distribution of species is required for designing effective conservation management strategies. However, ground-based surveying techniques developed by conservation biologists have traditionally been used to assess plant species richness and composition, which is difficult to implement logistically and financially at regional scales. Remote sensing (RS) technologies and the launch of many new satellite systems have made available an unprecedented number of tools with which to address such challenges (Soule and Kohm 1989, Lubchenco *et al.* 1991, Stoms and Estes 1993).

This paper critically evaluates the potential of RS technologies for developing a regional vegetation biodiversity mapping and monitoring system. The term 'biodiversity' is restricted to its most commonly used form, i.e. species diversity (Stoms and Estes 1993). The challenge of mapping and monitoring plant diversity is discussed in the following section, while direct and indirect methods of assessing plant species distributions are compared in the second section. In the third section, specific recommendations are made on how to apply such technologies for large-scale assessment of plant biodiversity. Finally, a case study of work in progress is presented with the purpose of developing a model for predicting global plant diversity based on satellite and climatic data.

2. The Importance and Challenge of Mapping Plant Diversity

Plant diversity is a major part of total biodiversity, as it forms the basis of all food webs and underpins the functioning of all ecosystems (Nagendra 2001). However, in order to know how to protect or conserve a plant species or assemblage of species, we must attain knowledge of *where* these species occur and to what extent they are distributed. Geographic variation in *species richness* (number of species in a particular area) is one of the most conspicuous patterns in biodiversity (Lennon *et al.* 2004). Cross-taxon relationships in species richness have led many conservation biologists to using species diversity of certain taxa as indicators of species diversity of other taxa (Pearson and Carroll 1999, Myers *et al.* 2000, Moore *et al.* 2003). Important questions in conservation biology now include whether species diversities of different groups of organisms are correlated and, in particular, whether plant diversity influences animal diversity. Studies have shown that the well-investigated vascular plants are comparatively well-suited to serve as indicator groups in terrestrial habitats (Gould 2000).

Relatively few studies have been carried out to survey species numbers of vascular plants on continental and global scales. The first world map of the species numbers of vascular plants was published by Barthlott *et al.* (1996), locating six diversity maxima occurring in the tropical/subtropical zones. Kier *et al.* (2005) produced the first global map of vascular plant species richness by ecoregions, identifying the Borneo Lowlands and Central and South America as species richness 'hotspots'. Such broad-scale biodiversity mapping projects have highlighted the challenges of using traditional methods of inventorying and assessing biodiversity and the possible advantages of integrating RS data for detection, mapping, and monitoring.

3. Remote Sensing Approaches for Assessing Plant Species Distributions

The potential benefits of using satellite RS to assess and monitor plant diversity were suggested by researchers over a decade ago (Soule and Kohm 1989, Noss 1990, Roughgarden *et al.* 1991, Lubchenco *et al.* 1991). Much of the available literature on RS applications for mapping and monitoring aspects of biodiversity reveal certain commonalities. Chief among these is the unique ability of satellite imagery to synoptically monitor large areas in a timely systematic and repeatable manner (Stoms and Estes 1993). The use of RS to quantify or model biodiversity components can be categorised into 'direct' and 'indirect' approaches (Table 1).

3.1 Direct remote sensing of species and species assemblages

Direct approaches are considered a first-order analysis of species occurrence, mapping the composition, abundance, and distribution of individual species or assemblages of species (Turner *et al.* 2003). In terrestrial applications, such direct observations are typically limited to the detection of larger plants (e.g. trees), or in open areas where crops, shrubs or lichens form a spatially contiguous layer of vegetation (Nagendra 2001).

Table 1. Summary of indicators of plant biodiversity that are mapped directly or indirectly by RS approaches.

Direct Approaches	Indirect Approaches
Land cover classification Species composition	Climate (i.e. precipitation, temperature, soil moisture) Topography Primary productivity (i.e. chlorophyll, fPAR) Habitat structure (i.e.vertical canopy structure)

At sub-metre spatial resolutions, direct identification of certain tree species is feasible through the detection of individual tree crowns. High resolution satellites, IKONOS and Quickbird offer multispectral imagery at resolutions of 4 m and 2.4 m, respectively, and panchromatic imagery at 1 m and 0.6 m, respectively (GeoEye 2006). Digital aerial photography likewise provides access to high spatial resolution, often as fine as 0.5 m (King 1995). However, even with fairly large plants, the spatial resolution required for identification is fairly high. For example, Biging *et al.* (1995) attempted to discriminate tree species using Landsat imagery, concluding that pixel sizes of 0.5 m were not sufficient for assigning individual tree crowns to species. However, 'ideal' pixel size will obviously depend upon the size of tree crowns, which can vary widely within as well as between species.

In tandem with increases in spatial resolution, gains in spectral resolution have offered new possibilities for direct remote sensing of biodiversity patterns, especially from the use of airborne and spaceborne hyperspectral sensors. *Hyperspectral sensors* measure reflected radiation as a series of narrow and contiguous wavelength bands, typically at 10 to 20 nm intervals including 200 or more spectral bands. Acquired spectral signatures are compared to spectral libraries, which enable improved landcover classification (Gould 2000). One application of hyperspectral imagery is the detection and mapping of invasive species. Research conducted in the Theodore Roosevelt National Park of North Dakota, USA successfully detected infestations of leafy spurge *Euphorbia esula*, using three hyperspectral sensors (Kokaly *et al.* 2002). The Hyperion instrument achieved mapping accuracies of up to 80%, but was unable to resolve infestations <500 m^2 or mixed pixels with <35% leafy spurge. Another study by Goodwin *et al.* (2005) utilised 0.8 m CASI-2 imagery to assess the capacity of spectrally discriminating individual species in a native eucalypt forest in Australia. Results indicated that the two species were sufficiently spectrally and structurally distinct to allow for mapping of individual crowns and species.

3.2 Indirect detection through remote sensing of environmental parameters

Indirect approaches use RS imagery to measure environmental variables or indicators that are known or believed to influence aspects of biodiversity (Turner *et al.* 2003). In practice, this is the most common approach of assessing plant biodiversity using RS data. It provides quantifiable elements that can be readily and repeatedly obtained and statistically related to species richness and distributions (Gontier *et al.* 2006). To examine the variety of indirect indicators used to assess plant diversity, four categories are identified in Table 1. These include climate, topography, vegetation productivity or function, and habitat suitability with respect to its spatial arrangement and structure.

In general, temperature and moisture (i.e. annual precipitation and evaporation) are two variables most often utilised in climatic analyses (Sarr *et al.* 2005). A review by Rosenzweig (1995) also identified elevation as a key biodiversity gradient when determining the diversity and distribution of plant species. In the tropics, species diversity of many plants exhibited unimodal distributions with respect to elevation, with the highest species diversity occurring at mid-elevations. Elevation has also been correlated with levels of productivity. A study by Whittaker and Niering (1975) in the Santa Catlina Mountains of Arizona, USA found a steeper decrease in productivity from high-elevation forests to mid-elevation woodlands, along with a less steep decrease from dry woodlands through desert grassland into desert. It becomes evident that various species richness-elevation patterns exist, although some may be influenced by the size of the area sampled (Rahbek 1997).

The nature of the relationship between vegetation primary productivity and species richness remains contentious. Most studies have found that species richness tends to increase linearly with productivity, suggesting that higher productivity levels lead to higher energy availability and a greater number of species and larger populations (Berry and Roderick 2002, Running *et al.* 2004). Using RS data, vegetation production can be assessed through relationships with standing biomass or foliage vigour, such as prediction of leaf area index (LAI), tree volume or biomass, or photosynthesis through the fraction of light absorbed by the vegetation (fPAR).

Vegetation indices and derivatives such as LAI and fPAR, facilitate the investigation of relationships between ground-based measures of species richness and satellite-based measures of vegetation productivity and function. Waring *et al.* (2006) utilised NDVI data over the continental USA to predict woody species richness, as measured using the USDA Forest Service Forest Inventory data, finding significant relationships between total species numbers at the ecosystem level and maximum annual NDVI. At regional levels, moderately strong correlations have been established between plant species richness and NDVI using AVHRR data in California, with the accuracy of results dependent on the season and species characteristics (Walker *et al.* 1992).

While climate and productivity have been linked to global patterns of plant diversity (Willig *et al.* 2003, Hawkins *et al.* 2003), finer-scale spatial patterns such as land use and land cover, forest structural stage and their associated spatial patterns are increasingly being investigated as potential predictors of species diversity and abundance (Fahrig 2003). In forested environments, vertical structural complexity has been linked with forest biodiversity and RS technologies have become increasingly successful at mapping and monitoring such spatial structures (Hansen *et al.* 1991, Imhoff *et al.* 1997). Lidar technology has been successfully applied to estimating elements of forest structure that were traditionally assessed by empirical techniques (Wulder 1998, Lim *et al.* 2003). Capabilities include estimating vegetation density at different heights throughout the canopy, tree or stand height characteristics, canopy closure, volume, and LAI.

4. Recommendations for a Vegetation Biodiversity Mapping and Monitoring System

Understanding regional/mesoscale patterns of ecosystem properties is imperative if we are to effectively monitor ecosystem change due to land use and climate change. Understanding regional/mesoscale biodiversity patterns is important, as it is a scale at which land use management decisions are made (Kareiva 1993, Stoms 1994, Bengtsson *et al.* 1997). It was shown previously that there are a variety of direct and indirect approaches to map and monitor biodiversity using RS. The purpose of this section is to introduce recommendations that are transferable for regional or national vegetation biodiversity monitoring systems.

This paper suggests that there are several key considerations when designing and developing a system for assessing and monitoring biodiversity using RS. First, such large area monitoring schemes should be *comprehensive* or cover as much of the geographic area as possible. The system should also be as complete as possible in characterising the vegetated terrestrial biosphere, considering both upperstorey and understorey species. Third, a monitoring system should have two initial foci, (a) an assessment of the current vegetative biodiversity across the region, and (b) a monitoring component to assess changes over time. Fourth, a monitoring system should utilise a range of available RS datasets available for the region, rather than focusing on one dataset or sensor alone. Finally, results from the system should be *scalable* – information should not only be available at regional/national scales, but also accessible at the local level. Programmes investigating vegetation biodiversity should be encouraged across a range of habitat and ecosystem types, such as forests, wetlands, agricultural lands, and marine and coastal habitats.

There is an increasing trend in the wealth of new RS data (i.e. rainfall, cloud cover, soil types), which enhance or replace information currently used to monitor and predict species distributions. The challenge now exists on what to do with all of this available data – how to analyse or utilise it for management purposes. Five types of analyses are suggested here that can potentially be used for conservation priority-setting and examining acquired RS data.

The first step suggested for any regional vegetation monitoring and mapping system is to assess the conservation status of areas within a given geographic unit. *Persistence value analyses* identify areas that are likely to have a high level of species richness that will persist over time (Turner *et al.* 2003). *Threat analyses* may involve predictive models using RS data, integrating information on human land use patterns, demographics, and infrastructure to assess future impacts on species and habitats. Such analyses are important when considering the form, timing, and sequence of conservation initiatives, as well as the level of effort required. *Representation analyses* consider the full range of plant species richness in an area in terms of habitat blocks (Duro *et al.* 2007). RS may assist in identifying which areas support the largest and most viable populations of target species or estimating which habitat blocks have the resources or conditions to support such species. Other potential analyses include *gap analysis* and *conservation feasibility analyses*, which could utilise RS data for identifying conservation priorities, while considering political, socio-economic, and cultural factors (Duro *et al.* 2007).

It becomes evident that any broad-scale vegetation biodiversity monitoring framework that encompasses a range of plant species, the mapping of indirect estimates of diversity provides the most realistic, flexible, and cost-effective approach. Should such an approach be adopted, this paper suggests focusing on four primary measures: climate and topography, vegetation function/production, habitat spatial arrangement/structure, and change detection. Monitoring these key measures through time at a regional level has the potential to provide an 'early warning system', highlighting high prioritisation areas.

In Section 3.2, climate and topography were identified as key biodiversity gradients when determining the distribution of plant species. Inclusion of information about elevation and climatic variables has been shown to improve RS landcover classification accuracies (Franklin and Peddle 1989), particularly in mountainous terrain. Elumnoh and Shrestha (2000) incorporated digital terrain information into classification of 13 plant species and classification accuracy improved 7%, particularly when discriminating lowland and highland vegetation. There also exists a strong link between vegetation productivity and species richness. Utilising RS generated estimates of fPAR could provide critical information for identifying vegetation. In particular, the MODIS sensor provides fPAR data on a monthly basis that could be used to better understand changes in vegetation habitat and production, especially for seasonal species.

A measure of habitat spatial arrangement/structure is recommended here for monitoring and mapping, referring to the heterogeneous nature of landcover or the degree of landscape or habitat fragmentation. Patch size, distribution, dispersion of patch types, contrast among patches, patch shape complexity, contagion/clumping, and corridors between patches are structural components of the landscape that can be easily quantified from RS imagery (McGarigal and Marks 1995, Urban 2005).

Change detection is the final measure recommended, stressing the importance of monitoring a site over time. This facilitates monitoring and predicting trends in the distribution of species and species assemblages in response to environmental changes (climate change, fire, floods), human impacts (roads, urban sprawl), and other disturbances. Disturbance indices have been developed utilising MODIS data that have successfully detected vegetation vigour and changes in disturbance conditions across Canada (Mildrexler *et al.* 2007).

5. Case Study: Adopting a Spatial Econometric Approach for Predicting Global Plant Diversity

Biodiversity mapping methods have been based on two basic approaches: (a) a taxon based approach, and (b) the inventory based approach (Kier *et al.* 2005). In a taxon based approach, the diversity map is the result of overlaying data on the individual taxa. In contrast, the inventory based approach, which has been used to produce global maps of the species numbers of vascular plants, is based on summary data for geographical units, such as total species or family numbers in a region. After standardisation of taxon numbers of regions of different sizes to a defined area size, diversity maps can be created in a rather short time and the centres of diversity can be delineated. Since the data structure is often strongly determined by political units, it is necessary to adjust the boundaries of diversity zones by superimposing the data with vegetation maps and datasets on physical geofactors. A GIS-based approach can be useful in order to reach a complete standardisation and reproducibility of the methodology for multiple datasets.

The world map of species richness of vascular plants presented by Mutke and Barthlott (2005) was generated with the inventory-based methodology (Figure 1). This work was produced by using more than 3,270 species richness figures for more than 2,460 different operational geographical units, such as countries, provinces, mountains, islands, national parks, and others collected on a global scale. The final map was interpolated on the basis of GIS layers of the suitable geographical units and additional data on vegetation, climate, topography, and other parameters.

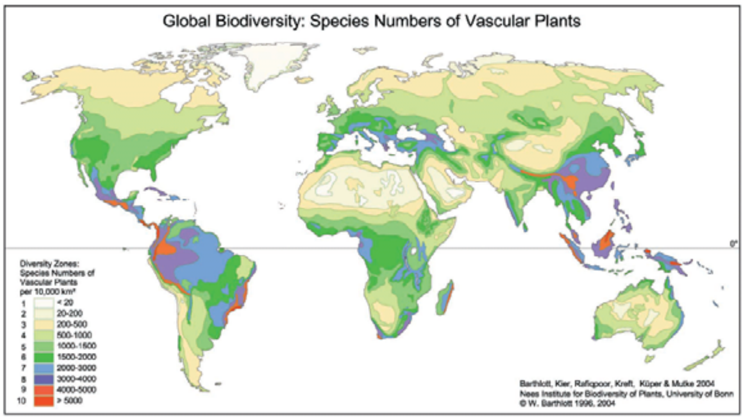

Figure 1. World map of species richness of vascular plants after Mutke and Barthlott (2005).

However, most methods that attempt to model or predict plant distributions based on environmental or climatic factors tend to ignore the spatial properties inherent to the phenomena that is being measured. If spatial autocorrelation is ignored, the model will systematically overestimate the observed values in some regions, while underestimating the observed values in other regions (Anselin 2002). *Spatial autocorrelation* exists when the value at any point in space is dependent on values in surrounding or neighbouring geographic units. That is, the spatial arrangement of values is not random. The presence of spatial autocorrelation in the residuals can be diagnosed by calculation of the Moran's I test statistic. If the presence of spatial autocorrelation in the residuals is significant, this means that the confidence limits are unrealistic (Anselin 2002). The presence of spatial autocorrelation would bias the correlation coefficient and OLS regression estimators and the precision of parameter estimates would be overestimated as the information content of the sample would be less than implied by classical theory (Messner and Anselin 2004). Spatial autocorrelation analysis enables us to assess the correlation of a variable (i.e. plant species richness) in reference to the spatial location of the variable.

The research in progress introduced in this paper involves developing a model for predicting global plant diversity based on satellite data. A spatial econometric approach is adopted by developing a spatial regression model predicting global plant diversity based on the Normalised Difference Vegetation Index (NDVI) derived from satellite data. The model also integrates selected biophysical parameters, namely temperature, precipitation, and elevation.

When estimating a spatial regression model that controls for spatial effects, the model can take the form of either a spatial lag model or a spatial error model (Anselin 2002). A *spatial lag model* implies that the geographic clustering of plant diversity is due to the influence of plant diversity in one place on plant diversity in another (neighbourhood effects). This model is consistent with some kind of diffusion, interaction, or clustering process (Mardia and Marshall 1984). In contrast, a *spatial error model* indicates that clustering reflects the influence of unmeasured variables. Spatial error model specification is usually applied when other independent variables may be statistically significant but are excluded from the model specification (Anselin 2002).

Table 2. Diagnostics for spatial dependence for global plant diversity based on NDVI, temperature, precipitation, and elevation as independent variables. Five test statistics for spatial dependence in the residuals of the OLS model are shown.

Spatial Dependence Diagnostic Test	Value	P-value
Moran's I (error)	4.658	0.00000
LM-Lag	13.535	0.00023
LM-Error	18.166	0.00002
Robust LM-Lag	3.701	0.05237
Robust LM-Error	8.332	0.00390

To determine the most appropriate model specification, diagnostics for spatial dependence were conducted, which included tests against spatial autocorrelation. Five test statistics for spatial dependence are shown in Table 2. The Moran's I test statistic proved to be highly significant ($P < 0.00000$), indicating the presence of spatial autocorrelation. However, as noted by Anselin (2002), while the Moran's I statistic has great power in detecting misspecifications in the model, it is less helpful in suggesting which model specification (i.e. spatial lag or spatial error) should be used. To this end, the Lagrange Multiplier test statistics may be used, which test for a missing spatially lagged dependent variable (LM-Lag) or error dependence (LM-Error) in order to guide the specification search.

In this analysis of modelling global NDVI, the resulting simple LM-Lag and LM-Error test statistics were both highly significant ($P < 0.001$), providing further evidence of spatial dependence. As a result, it was necessary to consider the robust forms of the statistics. The spatial regression model matching the more significant test statistic was estimated, since both Robust test statistics proved to be not significant to a certain degree. The Robust LM (lag) test statistic ($P = 0.054$) proved to be less significant than the Robust LM (error) statistic ($P = 0.004$). Therefore, the spatial error model was considered to be the most appropriate spatial regression specification for global plant diversity based on NDVI and climatic dependent variables.

The research presented here is work in progress and the model estimation results are not shown here. However, the model estimation results are expected to show which independent variables (NDVI, temperature, precipitation, elevation) have the most effect on the spatial distribution of global plant diversity. This research demonstrates the utility of remote sensing and climatic data in predicting global plant diversity. Findings are expected to support the use of remote sensing vegetation products as a potentially effective tool when predicting plant diversity patterns, which can be useful in conservation and biodiversity evaluation.

6. Conclusion

International agreements, such as the CBD, require countries to establish a means of inventorying and monitoring elements of biodiversity, and the processes that may impact them. However, conventional field-based techniques continue to dominate the mainstay of biodiversity research, although they are costly and often logistically difficult to conduct over large areas. This paper has shown that the launch of new satellite systems has provided an unprecedented number of RS tools to address such challenges.

7. References

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