Proc. Natl. Acad. Sci. USA
Vol. 96, pp. 9154–9158, August 1999
Ecology

Biodiversity assessment at multiple scales: Linking remotely sensed data with field information

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ABSTRACT We examine the efficacy of a scheme of multiscale assessment of biodiversity linking remote sensing on larger spatial scales with localized field sampling. A classification of ecological entities from biosphere to individual organisms in the form of a nested hierarchy is employed, such that entities at any level are differentiated in terms of their composition/configuration involving entities at the next lower level. We employ the following hierarchy: biosphere (10^{14} m^2), ecoregions (10^{11}–10^{12} m^2), ecomosaics (10^8–10^{10} m^2), ecotopes (10^3–10^6 m^2), and individual organisms (10^{-4}–10^2 m^2). Focusing on a case study of West Coast–Western Ghats ecoregion (1.7×10^{11} m^2) from India, we demonstrate that remotely sensed data permit discrimination of 205 patches of 11 types of sufficiently distinctive ecomosaics (10^8–10^{10} m^2) through unsupervised classification by using distribution parameters of the Normalized Difference Vegetation Index, with a pixel size of 3.24×10^6 m^2. At the ecomosaic scale, Indian Remote Sensing LISS-2 satellite data with a pixel size of 10^3 m^2 permit discrimination of ≈30 types of sufficiently distinctive ecotopes on the basis of supervised classification. Field investigations of angiosperm species distributions based on quadrats of 1–10^2 m^2 in one particular landscape of 27.5×10^6 m^2 show that the seven ecotope types distinguished in that locality are significantly different from each other in terms of plant species composition. This suggests that we can effectively link localized field investigations of biodiversity with remotely sensed information to permit extrapolations at progressively higher scales.

Assessing the distribution of the diversity of life forms on the earth and the efficacy of measures for their conservation is one of the major scientific challenges of the day. This is an immense task because the number of species of living organisms, one of the most appropriate measures of diversity, runs into thousands per km^2 over much of the surface of the earth and into several million for the earth as a whole (1). Moreover, the patterns of distributions of these species are exceedingly complex in space and time. Appraising species diversity in all its complexity through field investigations obviously is not a practical proposition. This can be attempted at best as an exercise focusing on some selected taxonomic groups for a representative selection of localized sampling points and must be coupled to broader-scale, more rapid sampling to facilitate extrapolation at a global scale.

Remote sensing, in particular with satellites, is an obvious tool for such broader-scale rapid sampling. The Global Biodiversity Assessment advocates its use linked to localized sampling for organizing a program of biodiversity assessment at the global level (1). However, there have not been many investigations using satellite data for assessing species diversity at more detailed and larger scales, of hundreds to tens of thousands of square kilometers. The few reports of successful applications mostly relate to mapping of temperate or boreal forest communities focusing on fairly homogeneous stands of a small number of canopy tree species (2, 3). In the far more diverse biological communities of the tropics, such stands at large scales do not occur. These areas present a challenge of an altogether different magnitude—a challenge that has not been investigated (4).

To assess species diversity at spatial scales much larger than those of individual organisms, other types of entities must be identified. Ecological systems at the scales of a few tens of square kilometers have been studied extensively as landscapes (5, 6). The elements making up such landscapes may be termed ecotopes, characterized at the spatial scale of hectares (6). If boundaries of species distributions correspond in many cases to boundaries of ecotopes (7), different types of ecotopes would differ significantly from each other in their species composition. If such ecotopes can be identified in the field on the basis of some emergent biological parameters such as vegetation structure, it is likely that they also would possess a distinctive enough spectral signature to be identifiable on the basis of remotely sensed information. Identification of a small, manageable number of different types of ecotopes that are both sufficiently distinctive in species composition and classifiable with an adequate degree of reliability on the basis of remotely sensed information then would provide an appropriate link between the landscape scale of tens of square kilometers and field assessment of species diversity at the hectare scale or lower.

However, the global scale to which this information needs to be extrapolated is still several orders of magnitude larger than the landscape scale. Therefore, we need additional emergent entities at intermediate scales to facilitate such an extrapolation. We may identify ecomosaics and ecoregions as such entities. Although no standardly accepted definitions for these exist, we propose the term ecomosaic to describe land mosaics on the scale of hundreds or thousands of square kilometers that are relatively homogeneous with respect to their composition in terms of constituent ecotopes. A few hundred adjacent ecomosaics may comprise an ecoregion (6). These ecoregions may be thought of as corresponding to biogeographic provinces or biomes such as those proposed by Udvardy (8), covering tens to hundreds of thousands of square kilometers. As defined by the World Wildlife Fund (9), each ecoregion harbors a characteristic set of species, communities, dynamics, and environmental conditions.

The proposal then is to divide the globe into a manageable number of ecoregions, e.g., a few hundred, on the basis of a system such as that proposed by the World Wildlife Fund (9). Each individual ecoregion on a spatial scale of 10^{11}–10^{12} m^2 then would be divided into a few hundred ecomosaics, on the scale of 10^8–10^{10} m^2. The ecomosaics constituting a given

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Abbreviation: NDVI, Normalized Difference Vegetation Index.

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ecoregion may be assigned to a small number, of the order of 10–100 types. Each ecomosaic type would have a characteristic composition of between 10 and 100 types of ecotopes, delineated on a spatial scale of 10^4 m^2 or hectares. Each of these types of ecotopes would be so defined as to differ from others in terms of their species composition. Because all taxa biodiversity inventories as yet are not practicable, these ecotopes would be characterized in terms of the incidence of thousands of species of particular groups such as flowering plants.

We thus propose a scheme of classification of ecological entities from biosphere through successive levels of ecoregions, ecomosaics, and ecotopes to individual organisms as a nested hierarchy. At each level the classes should be distinguished from remotely sensed data in a way that makes them significantly different from each other in terms of their composition/configuration with respect to the different types of entities at the next lower level. For instance, different types of ecomosaics should be delineated in this way to be significantly different from each other in terms of their composition/configuration with respect to ecotope types.

We report here an exercise of testing the feasibility of such a system for one particular ecoregion, that of the Western Ghats–West Coast of India.

MATERIALS AND METHODS

Study Area

The narrow strip of Indian West Coast extending over a distance of 1,600 km flanked by the hills of Western Ghats (8–21°N latitude, 73–77°E longitude) constitutes a very distinctive ecoregion, covering an area of 1.7×10^{11} m^2. This ecoregion has been categorized as the Western Ghats Moist Forest major habitat type by the World Wildlife Fund (9). Enjoying a much higher level of precipitation than the adjoining regions of peninsular India, the natural biota of the region, an island of tropical rain forest separated from the more extensive rain forest tracts of Eastern Himalayas and Southeast Asia, exhibits a high level of endemicity (10, 11). The natural biota, however, has been disturbed extensively by human interference at least over the last two millennia (12–14). The region therefore is designated as one of the world's 18 biodiversity "hot spots"—areas with high levels of biodiversity under serious threat (15). This dynamic region, recognized as a distinctive entity in biogeographic province/biome classifications (8, 16) as well as ecoregion classifications (9) and clearly evident in satellite imagery as a region with much higher levels of plant biomass compared with adjacent tracts, is an excellent choice for a case study.

Methods

Ecoregion Scale. Our largest scale of mapping for a specific ecoregion as delineated by the World Wildlife Fund (9) was based on 50 scenes from the Indian Remote Sensing satellite IRS 1B LISS 2 sensors, covering the Western Ghats and West Coast of India. All images were from the premonsoon season, mid-February to mid-June, when deciduous trees are leafless, enhancing the chances of discriminating deciduous from evergreen forests (17). Scene dates range from 1991 to 1994 depending on availability of cloud-free data in the premonsoon season. The spatial resolution of LISS-2 data is 36.25×36.25 m. Each scene covers 87×74 km, and neighboring scenes overlap to varying extents (18). Manual coregistration of images was carried out to remove overlap areas, and the scenes were pasted together to create a composite image of the total study area.

For each pixel in this composite image, we computed the Normalized Difference Vegetation Index (NDVI; ref. 19), believed to correlate well with photosynthetic vigor of vegetation, and reduce problems of interscene variability. Nonoverlapping sets of 50×50 pixels, covering 1.8×1.8 km, then were used to create a "super-pixel," which was characterized by the four distribution parameters (mean, SD, skew, and kurtosis) of the set of NDVI values of the 2,500 constituent pixels (20).

Detailed, supervised classification of large areas takes enormous effort and inputs in terms of time, manpower, and money (21). Unsupervised classification is relatively faster and less expensive, but could lead to a compromise in terms of classification accuracy (22, 23). It is, however, the only option fast enough to permit regular mapping for monitoring purposes at this scale. Super-pixel units of 1.8×1.8 km therefore were input into an unsupervised classification of the study area by using the i.cluster algorithm of the GRASS 4.1 image-processing software (24).

This classification delineated 12,164 patches belonging to 14 ecomosaic types. Several of these patches were only a few square kilometers in extent, which is very small relative to the size of the total study area. For practical purposes, about 200 patches constitute a manageable number of entities that can be studied to extrapolate information about the entire ecoregion. All patches smaller than 100 km^2 (a relatively arbitrary cut-off point) therefore were merged with the ecomosaic type most predominant in the vicinity, resulting in a total of 205 patches belonging to 11 ecomosaic types. The distribution of ecomosaic types was interpreted with reference to maps of topography, rainfall, temperature, forest cover, and agricultural land use of the Western Ghats (20).

Ecomosaic Scale. At the intermediate, ecomosaic scale of mapping, 12 landscapes belonging to 5 of 11 ecomosaic types were taken up for more detailed investigations. This limited selection was a result of logistic constraints. These landscapes range from 9 to 54 km^2 in area (Table 1). Single-date IRS 1B LISS 2 data collected in the premonsoon seasons of 1991, 1992, or 1993 were used in conjunction with ground-training information collected during the months of February–August 1995 to carry out supervised classifications of each landscape into ecotope types, by employing the maximum likelihood algorithm (19). In addition, an unsupervised classification of each landscape into the same number of ecotope types was carried out by using the i.cluster algorithm of the GRASS 4.1 software.

In August and September 1997, between 70 and 120 randomly distributed points were used to estimate the accuracy of supervised and unsupervised classification for each of the 12 landscapes. From the classified maps, patch sizes for all patches were calculated as patch area, patch shape as the ratio of patch perimeter to that of a square patch of the same area (shape index increasing as patch shape becomes less compact), and nearest-neighbor distance as distance to the nearest neighboring patch of the same ecotope type. Mean patch size, mean patch shape, and mean nearest-neighbor distance then were determined for each landscape. In addition, ecotope-type richness and Shannon's index of ecotope diversity (based on proportion of landscape area occupied by various ecotope types) were computed (5). All calculations were carried out with the help of FRAGSTATS 2.0 (25).

Whether landscapes belonging to different ecomosaic types differ significantly in parameters of ecotope structure and composition was assessed on the basis of Monte Carlo simulations. The intratype variance in ecotope parameters was computed for 7 of 12 landscapes belonging to a single ecomosaic type, type 7. These estimates were compared with those for subsets of 7 landscapes randomly assembled from the total set of 12 landscapes. This exercise was repeated 100 times. The intratype variance had to be estimated by using only the

Table 1. The area, location in terms of latitude and longitude, ecomosaic type, and accuracy of supervised and unsupervised classification for the 12 landscapes studied at the ecomosaic scale

Landscape	Area, km	Latitude, °N	Longitude, °E	Ecomosaic type	Accuracy of supervised classification, %	Accuracy of unsupervised classification, %
1	12	18°20′–23′	72°53′–55	5	91.7	64.3
2	54	14°32′–34′	74°48′–50′	10	91.5	59.4
3	31	14°25′–27′	74°33′–35′	7	86.5	56.8
4	9	13°39′–41′	75°27′–29′	7	88.5	42.3
5	29	13°28′–30′	74°59′–75°01′	9	70.3	55.1
6	39	12°58′–13°01′	75°28′–31′	7	88.8	53.9
7	30	12°39′–42′	75°36′–38′	7	85.5	54.8
8	17	11°27′–29′	75°27′–29′	7	82.1	40.5
9	20	10°54′–56′	76°34′–36′	7	83.3	31.4
10	14	10°52′–54′	76°36′–38′	7	84.6	75.4
11	32	10°07′–09′	76°41′–43′	8	70.8	30.8
12	14	8°39′–41′	77°08′–10′	9	80.7	41.3

landscapes belonging to type 7, because no other ecomosaic type was sufficiently sampled because of logistic constraints. The exercise was carried out by using structural parameters calculated from both supervised and unsupervised classifications. If the actual intratype variance in a landscape structural parameter for type 7 was less than that for a randomly assembled set of landscapes, in 95 or more of 100 simulations, then the null hypothesis that landscapes belonging to different ecomosaic types do not differ in their ecotope configuration was rejected at a 95% confidence level.

Ecotope Scale. For the most detailed ecotope spatial scale, IRS 1B LISS 2 data of March 1993 were purchased for a single landscape of 27.5 km^2 from Siddapur taluk (i.e., county) of Karnataka (altitude, 400–600 m; latitude, 14°16′–14°19′N; and longitude, 74°52′–74°54′E). This imagery was used in conjunction with ground-training information collected in November 1994 to classify the landscape into seven ecotope types: secondary evergreen forest, secondary moist deciduous forest, savanna, grassland, *Acacia auriculiformis* Forst. plantations, *Casuarina equisetifolia* L. plantations, and paddy fields (4, 26). Unsupervised classification into seven ecotope types also was carried out by using the i.cluster algorithm of the GRASS 4.1 software. During January and February 1995, 246 quadrats of 10 × 10 m were used to record the tree-layer species distributed in these seven ecotope types. Within these, subquadrats of 5 × 5 m and 1 × 1 m were used to record the angiosperm species (excluding grasses, which could not be identified accurately in the field) present in the shrub and herb layers, respectively, for all seven ecotope types. Statistical tests were carried out to determine whether ecotope types as identified by supervised classification, and by unsupervised classification, differ significantly in their species composition (4).

RESULTS

Ecoregion Scale. The patch-merging exercise resulted in the elimination of three ecomosaic types that consisted of patches less than 100 km^2 in extent, so that the resultant map of the entire ecoregion had 205 patches belonging to 11 ecomosaic types. Comparison of the distribution of each type with maps of the Western Ghats topography, rainfall, temperature, forest cover, and agricultural land use suggests that each ecomosaic type is associated with a particular climate regime, land use, and vegetational characteristics. For example, ecomosaic type 3 corresponds mainly to high-altitude complexes of stunted evergreen forests or sholas and montane grasslands, interspersed with plantations of *Eucalyptus*. Ecomosaic type 8 is present mostly on the West Coast and comprises rice, tapioca, and coconut plantations, interspersed with patches of secondary evergreen and semievergreen forest. A more detailed description of each ecomosaic type, with reference to topographic, climatic, and vegetational characteristics, can be found in ref. 20. As noted below, the 11 ecomosaic types also differ significantly from each other in four parameters reflecting their configurations in terms of constituent ecotope types.

Ecomosaic Scale. The 12 landscapes selected for more detailed ground truthing belonged to ecomosaic types 5, 7, 8, 9, and 10, which cover 66% of the ecoregion. These represent composites of evergreen–moist deciduous–tree plantation–agricultural ecotope types and support high levels of biomass and species. The more degraded and low-biomass areas of the Western Ghats and West Coast, as well as small patches of very high biomass, high-altitude evergreen forest–grassland complexes, could not be represented in this set of landscapes because of logistic difficulties.

Table 1 presents the accuracy of supervised and unsupervised classification for each landscape. As can be seen, accuracies of supervised classification range from 70 to 92% and are uniformly better than those of unsupervised classification, which range from 31 to 75%. Table 2 presents the results of the Monte Carlo simulation carried out to determine whether intratype variation in ecotope structural characteristics for the seven landscapes belonging to ecomosaic type 7 is less than that expected by chance. Whereas intratype variance in patch size for ecomosaic type 7 was not significantly lower than that of a random assemblage of seven landscapes, for supervised as well as unsupervised classification, it was lower in every 1 of 100 simulations for the other 4 structural parameters analyzed; namely, mean patch shape, mean nearest-neighbor distance, Shannon index of ecotope diversity, and ecotope-type richness. Although 12 landscapes distributed among 5 ecomosaic types do not form a sufficient sample size for rigorous statistical tests, these results suggest

Table 2. Results of the Monte Carlo simulations carried out to determine whether intratype variation in ecotope structural characteristics for the seven landscapes belonging to ecomosaic type 7 is less than that expected by chance

	Supervised classification	Unsupervised classification
Mean patch size	84*	82*
Mean patch shape	100	100
Mean nearest-neighbor distance	100	100
Ecotope diversity: Shannon index	100	100
Ecotope diversity: Richness	100	100

Values in the Table represent the number of times out of 100 that intratype variance in the structural parameter specified by the column heading, using the classification method specified by the row heading, was less than the variance for a randomly assembled set of seven landscapes. If a value is greater than 95, the null hypothesis that landscapes belonging to different ecomosaic types do not differ in their ecotope structure is rejected at a 95% confidence level.
*Value not significant at a 95% confidence level.

Table 3. An outline of the three scales of analysis, specifying the entities involved, spatial scales, units of study, and methods of study

	Ecoregion scale	Ecomosaic scale	Ecotope scale
Total area	10^{11}–10^{12} m^2	10^8–10^{10} m^2	10^6–10^7 m^2
Constituent entities	Ecomosaic types	Ecotope types	Species
No. of constituent entity types in an individual elements	11	5–9	16–116
Size of entities	10^8–10^{10} m^2	10^6–10^7 m^2	10^{-4}–10^2 m^2
Study units	Landscapes	Ecotope patches	Quadrats
Size of study units	10^7–10^8 m^2	10^3–10^6 m^2	10^0–10^2 m^2
Field level discrimination: Basis	None	Vegetation structure and composition	Morphology
Field level discrimination: Means	None	Visual observation of physiognomy and presence of characteristic species	Visual observation of morphological characteristics
Imagery based discrimination: Basis	Ecomosaic structure and composition	Vegetation structure and composition	None
Imagery level discrimination: Means	Unsupervised classification using 1.8×1.8-km resolution NDVI data	Supervised classification using 36.25×36.25-m resolution four-band IRS LISS 2 data	None

that the ecomosaic scale classification does result in classes that differ significantly in terms of the configurations of their constituent ecotopes.

Ecotope Scale. At the ecotope scale, the accuracy of supervised and unsupervised classification of the single landscape at which species diversity studies were carried out was 88% and 56%, respectively. Analysis of the data on angiosperm species distributions (excluding grasses) revealed that the seven ecotope types identified by supervised classification do differ significantly in their species composition, whereas those identified by unsupervised classification do not, at a 95% confidence level (4).

DISCUSSION

This case study of the Western Ghats–West Coast moist forest ecoregion of India thus demonstrates the feasibility of a multispatial scale methodology by employing a classification of ecological entities in the form of a nested hierarchy for assessing species diversity with the aid of satellite based remote sensors.

Table 3 summarizes the methodology and results. At the ecoregion scale, the area of 170,000 km^2 is classified by a relatively rapid and simple, unsupervised classification by using NDVI data into 11 different ecomosaic types. The smallest individual element distinguished at this scale extends more than 100 km^2. Each ecomosaic type is a complex of different types of ecotopes, whose structure is reflected in the distribution parameters of the NDVI. At the ecomosaic scale, 12 selected landscapes belonging to 5 ecomosaic types, extending over 9–54 km^2, were mapped into between 5 and 9 ecotope types each by using supervised and unsupervised classification. The smallest ecotope element that can be distinguished at this scale covers about 1/10th of a hectare. The ecotope classes are based on vegetation composition, structure, and phenology. At this scale, supervised classification provides better information on ecotope-type distribution compared with unsupervised classification. At the lowest ecotope scale, quadrats of 100 m^2 are used to sample angiosperm species distributed among different ecotope types in a landscape of 27.5 km^2. Ecotope types delineated by supervised classification harbor distinctive sets of flowering plant species; those delineated by unsupervised classification fail to do so.

Previous large-scale studies using remote sensing to assess biodiversity mainly have been carried out in temperate, relatively homogeneous, and species-poor areas (4). This exercise in the tropics explicitly investigates the linkages between information collected at such widely different spatial scales, combining remote sensing and field-based species inventories. The scheme suggested here may provide a basis for organizing programs of assessing biodiversity for other species-rich tropical areas.

We thank M. B. Naik and S. G. Patgar for helping with field data collection and S. N. Singh and M. D. S. Chandran for assistance with species identification. We have benefited greatly from discussions with U. Ghate and N. V. Joshi. J.-P. Pascal and K. S. Bawa carefully read the manuscript and made a number of most helpful suggestions. This study was supported by the Ministry of Environment and Forests and the Department of Space, Government of India.

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