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Regional forest cover estimation via remote sensing: the calibration center concept

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Abstract

A method for combining Landsat Thematic Mapper (TM), Advanced Very High Resolution Radiometer (AVHRR) imagery, and other biogeographic data to estimate forest cover over large regions is applied and evaluated at two locations. In this method, TM data are used to classify a small area (calibration center) into forest/nonforest; the resulting forest cover map is then used in combination with AVHRR spectral data from the same area to develop an empirical relationship between percent forest cover and AVHRR pixel spectral signature; the resultant regression relationship between AVHRR band values and percent forest cover is then used to extrapolate forest cover for several hundred kilometers beyond the original TM calibration center. In the present study, the method was tested over two large regions in the eastern United States: areas centered on Illinois and on the Smoky Mountains on the North Carolina-Tennessee border. Estimates of percent forest cover for counties, after aggregating AVHRR pixel estimates within each county, were compared with independent ground-based estimates. County estimates were aggregated to derive estimates for states and regions. For the Illinois region, the overall correlation between county cover estimates was 0.89. Even better correlations (up to $r = 0.96$) resulted for the counties close to one another, in the same ecoregion, or in the same major land resource region as the calibration center. For the Smokies region, the correlations were significant but lower due to large influences of pine forests (suppressed spectral reflectance) in counties outside the hardwood-dominated calibration center. The method carries potential for estimating forest cover across the globe. It has special advantages in allowing the assessment of forest cover in highly fragmented landscapes, where individual AVHRR pixels (1 km^2) are forested to varying degrees.

Introduction

The concentrations of greenhouse gases in the atmosphere are increasing. A primary factor contributing to the rise in the greenhouse gas carbon dioxide is deforestation (Houghton *et al.* **1987).** It is therefore important to develop methods to assess and monitor changes in the amount of forestland.

Advanced Very High Resolution Radiometer (AVHRR) data, collected by the National Oceanographic and Atmospheric Administration (NOAA) meteorological satellites, are often used to assess

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land cover over large regions. With its 1.1 x 1.1 km pixel size and daily global coverage, AVHRR is presently the sensor of choice to assess land cover over large regions. AVHRR data have been used to monitor continental primary productivity (Tucker *et al.* 1985; Goward *et al.* 1985, 1987; Townshend and Justice 1986), rangeland condition (Sadowski and Westover 1986), and tropical deforestation (Nelson and Holben 1986; Malingreau *et al.* 1989; Graham *et al.* 1990), and to assess the potential for sequestering carbon (Iverson *et al.* 1993a). Most of these studies have used digital analyses of AVHRR data alone, augmented with visual interpretation of Landsat or other imagery. For forest cover assessment, however, such methods invite error, especially in zones with fragmented forest cover, because they generally use a binary forest classification (forest or nonforest) for each of the large 1.I x 1.1 km resolution cells of the AVHRR. For example, much of Illinois' forestland occurs in parcels of 80 ha or less and often would not appear as forest in a binary AVHRR classification (Iverson *et al.* 1989c). Similarly, in regions where deforestation follows a pattern of removing small forest patches within a closed forest matrix, an AVHRR binary classification would overestimate forest cover. In many parts of the tropical world, forests are being degraded steadily but in small areal increments; conceivably, 50 percent or more of the forest could be removed for a given AVHRR pixel without the change being detected by a binary classifier. As an example, the fragmentation of closed tropical forests, such as those in Peninsular Malaysia and other parts of continental Asia, would be difficult to detect with a binary AVHRR classification but is extremely important concerning loss of forest biomass (Brown *et al.* 1993; Iverson *et al.* 1993b). It is therefore important to detect the regions of fragmented (mixed pixels) forest and evaluate the percent forest contained within each pixel.

In this study, our primary objective was to test the utility of a forest cover detection method that creates an estimate of percent forest cover within individual AVHRR pixels rather than a binary classification. The method accomplishes this by integrating find resolution Landsat Thematic Mapper (TM) data with the coarse AVHRR data. Single date TM and AVHRR data from a small section of the region (the calibration center) were used to develop an empirical relationship between AVHRR band values and percent forest cover. This relationship was then applied to the remaining AVHRR pixels of the region. Although the work we present here was conducted over two regions in the United States where data were readily available for evaluation of the results, the method is applicable elsewhere, including the tropics. Our secondary objectives were to (1) test the proposed method on various landscapes and (2) explore the number and density of calibration centers that would be needed under different landscape conditions.

Methods

Study regions

One of the two regions selected for testing of the methodology is centered on Illinois, and the other, on the Great Smoky Mountains National Park on the North Carolina-Tennessee border (Fig. 1). In each case, an area of roughly 12,000 km^2 was selected for the calibration center. The AVHRR/forest cover relationship developed within this calibration center was then applied to a much larger surrounding region to develop regional estimates or forest cover.

Illinois andsurrounding region. Southwest Jackson County, in southwestern Illinois, was the calibration site for this region. Much of the forestland in Jackson County is contained within the Shawnee National Forest, and forests account for 54,450 ha (35.1 percent) of the county (Iverson *et al.* 1989c). The forests in this area are primarily oak-hickory on the uplands and elm-ash-cottonwood on the bottomlands. This county has one of the most diverse floras in the United States. The nonforested portion of the county is in row-crop agriculture that is interspersed with small parcels of forested land. The landscape has been seriously fragmented by human use. Since colonization by Europeans in the early 1800s, the county has lost 63 percent of its forest and 70 percent of its wetlands (Iverson and Risser 1987).

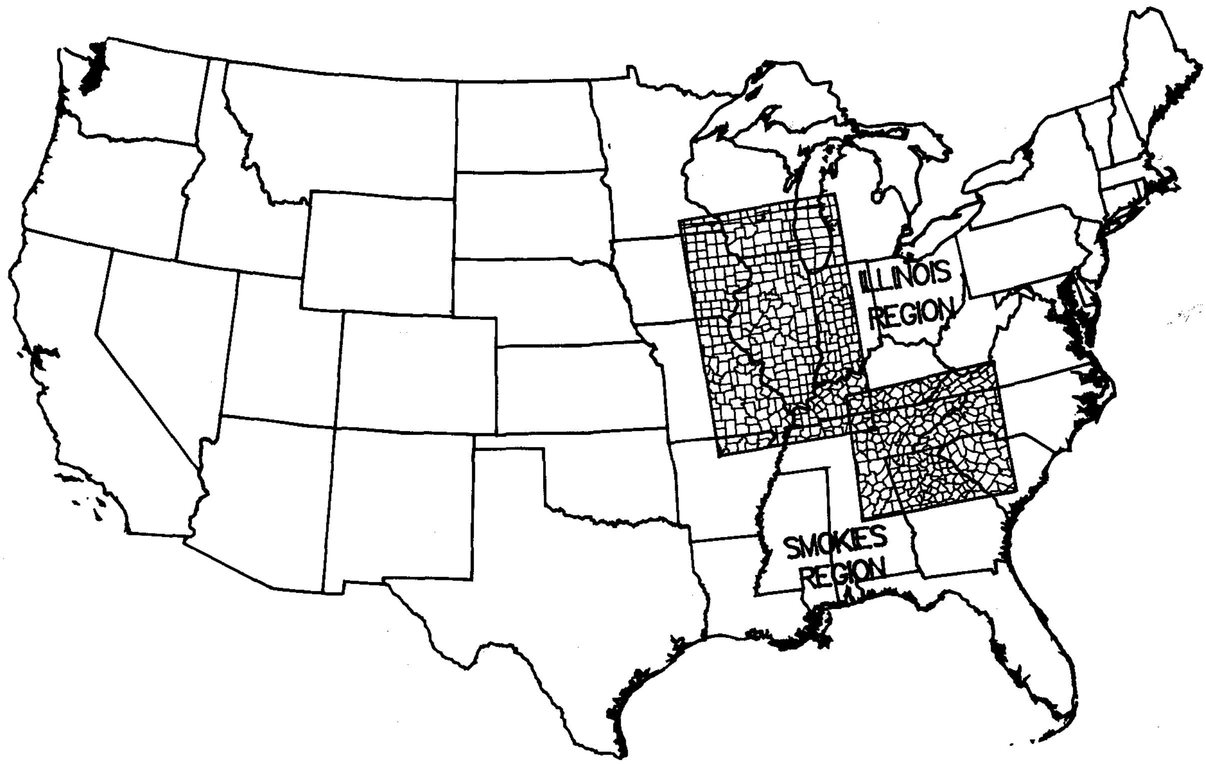


Fig. 1. Map of study areas, centered on the state of Illinois (Illinois region) and the Great Smokies National Park (Smokies region).

Smoky Mountains and surrounding region. The Smoky Mountains National Park and surrounding areas in Tennessee, Kentucky, Georgia, North Carolina, and South Carolina served as the second study region. The Cades Cove 7.5-minute quadrangle in the western part of the Smokies was selected as the calibration center. Although much of the Smokies region was at one time disturbed by logging or agriculture, about 20 percent of the area remains pristine, and the rest of the area has been left undisturbed since it became a national park in 1934 (Pyle 1985). The calibration area covers a complex set of ridges and valleys of considerable relief. A complex mosaic of vegetation types is present in this region because of moisture and elevation gradients (Whitener 1956) as well as historic disturbance patterns (Delcourt *et al.* 1986). The area has some of the most diverse vegetation in all of North America. Cove forests containing 10 or more predominant tree species occupy the sheltered mid-slope positions. On exposed low-to-middle elevation slopes, oaks, pines, black gum *(Nyssa sylvatica)*, sourwood *(Oxydendrum arboreum)*, and red maple (*Acer rubrum*) grow. Higher slopes have northern hardwood and hemlock (*Tsuga candensis)* communities, with spruce-fir *(Picea-Abies*) at the highest elevations. Outside the Park, the landscape is a mosaic of second-growth hardwood forests with numerous species, monoculture pine plantations of various ages, and agricultural fields and pastures. The dominance of pine forest increases to the south and east of the park. Within 300 km of the calibration center, one passes through at least three major physiographic provinces-the Appalachian mountains, the Piedmont, and the upper and lower coastal plain. Thus, the larger region surrounding the Smokies calibration center is extremely diverse in vegetation and topography and consequently represents a difficult test of the forest cover classification method.

Data sources

A multitude of digital data sources was combined and processed to successfully carry out and test the methodology. The analyses were performed in ARC/INFO (Environmental Systems Research Institute, Redlands, California) for most geographic information system (GIS) processes and ERDAS (Earth Resources Data Analysis Systems, Inc., Atlanta, Georgia) for image processing.

Landsat Thematic Mapper. TM data were used as high resolution **(30** m) information for the calibration centers. For southern Illinois, a July **18, 1984** scene (Path **23,** Row **34,** Quad **2)** was acquired, and for the Smokies a September **8,1984** scene (Path **19,** Row **35,** Quad **4)** was acquired. These scenes provided sufficient spectral information to distinguish forest from nonforest with confidence.

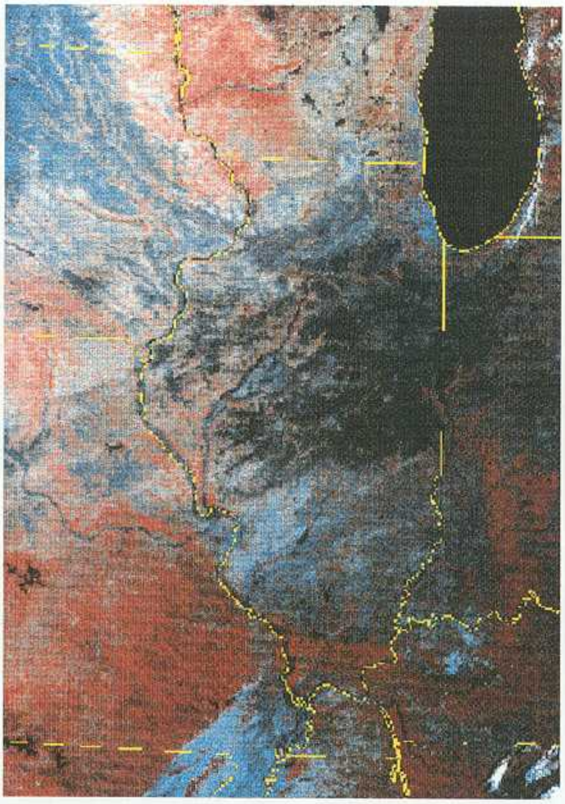
Advanced very high resolution radiometer (AVHRR). AVHRR data, with a resolution of 1.1 km, were used for extrapolating forest cover estimates across the larger regions. Georeferenced data, from June **4,1987** were acquired for a 10-state area centered on Illinois from the U.S. Geological Survey's EROS Data Center in Sioux Falls, South Dakota (Fig. 2a). For the Smokies region, data were collected on September **28, 1985** and were acquired from the National Oceanic and Atmospheric Administration (Fig. **3a).** The AVHRR data for the Smokies region were georeferenced using large lakes and grasslands dispersed within the forest matrix as ground control points. In both data sets, the selected phenological period allowed for trees to be in full leaf with most agricultural crops in a low-chlorophyll state. Therefore, there was maximum contrast between forest and nonforest classes in spectral reflectance of chlorophyll, and most of the reflected chlorophyll was due to forest leaves.

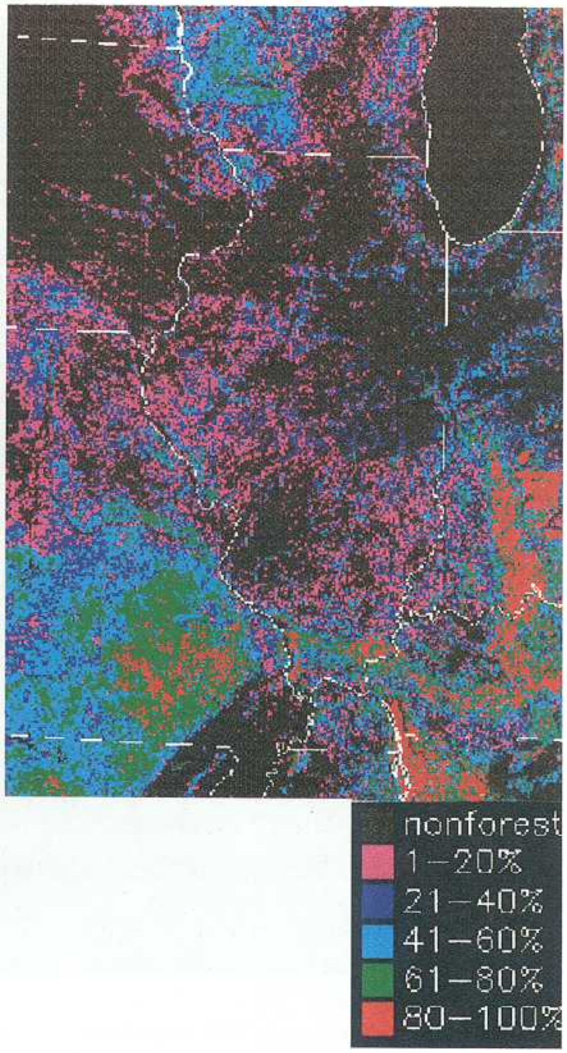
Biogeographic information. Several tabular county-level data sources were used as independent estimates of forest cover (hardwood and softwood). The U.S. Forest Service (USFS) inventory data were the primary data source for this effort. USFS data were available for the whole country (for the period through **1980)** through the Oak Ridge National Laboratory's Geoecology database (Olson ***et al.*** **1980).** A total of **428** counties, over **10** states, was used in the analysis for the Illinois region. More recent forest cover information available from later USFS inventories and not included in the Geoecology database were used for the independent estimate of forest cover for counties in Illinois (Hahn 1987), Indiana (Hanson 1987), Wisconsin (Raile 1985), and Arkansas (Hines **1988).** As an example of the accuracy of the USFS forest cover estimates at the county level, the Illinois county estimates were reported to be accurate within **4** percent (Hahn **1987).**

For the Smokies region, forest cover data for **187** counties under the jurisdiction of the Tennessee Valley Authority (TVA) were selected for testing the AVHRR model results. The TVA data were considered better than the Geoecology data because noncommercial forest lands were included in the TVA estimates and some of the data for this region within the Geoecology data base were dated.

Ecoregions map. The U.S. Environmental Protection Agency's (EPA) map of ecoregions of United States (Omernick **1987)** was used to delineate areas of ecological uniformity. The ecoregions were developed with water-resource quality as a major objective, and they are a result of the integration of many factors such as soils, climate, and potential vegetation. A digital version of the ecoregion map was acquired from the U.S. Environmental Protection Agency.

Major land resource areas map. The U.S. Department of Agriculture Soil Conservation Service's map of Major Land Resource Areas (MLRA) (U.S. Department of Agriculture **1981)** was used to delineate areas of similar land-use patterns and resources. This map is used for planning and reporting of land-resource information across the country. General soil associations account for major boundary delineations, and can be considered an integration of related factors such as





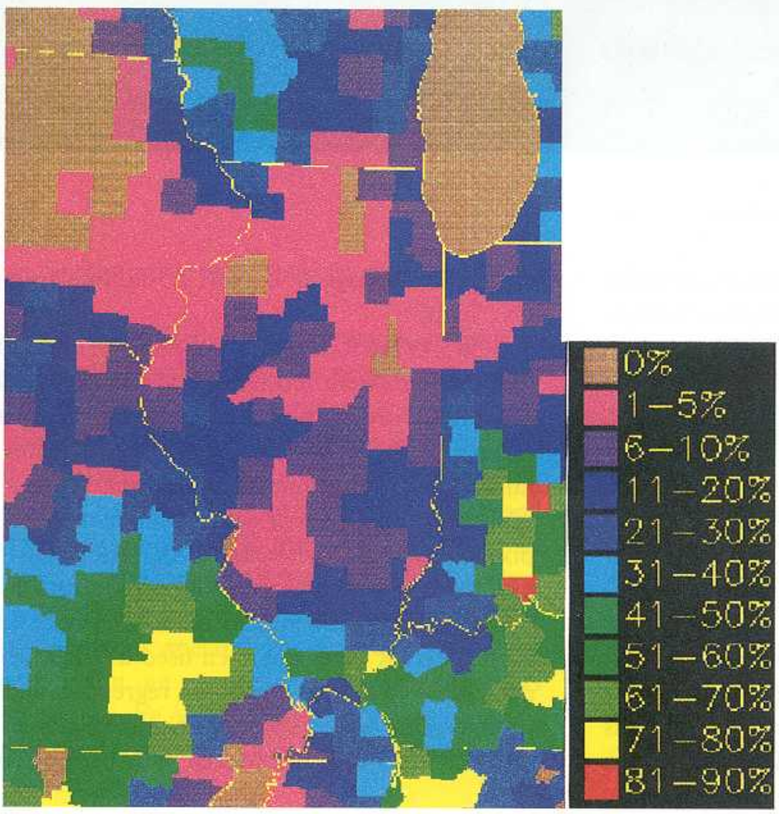


Fig. 2. Illinois region: (a) raw AVHRR image data; (b) percent forest by AVHRR pixel; (c) percent forest by county, as aggregated from AVHRR pixels.

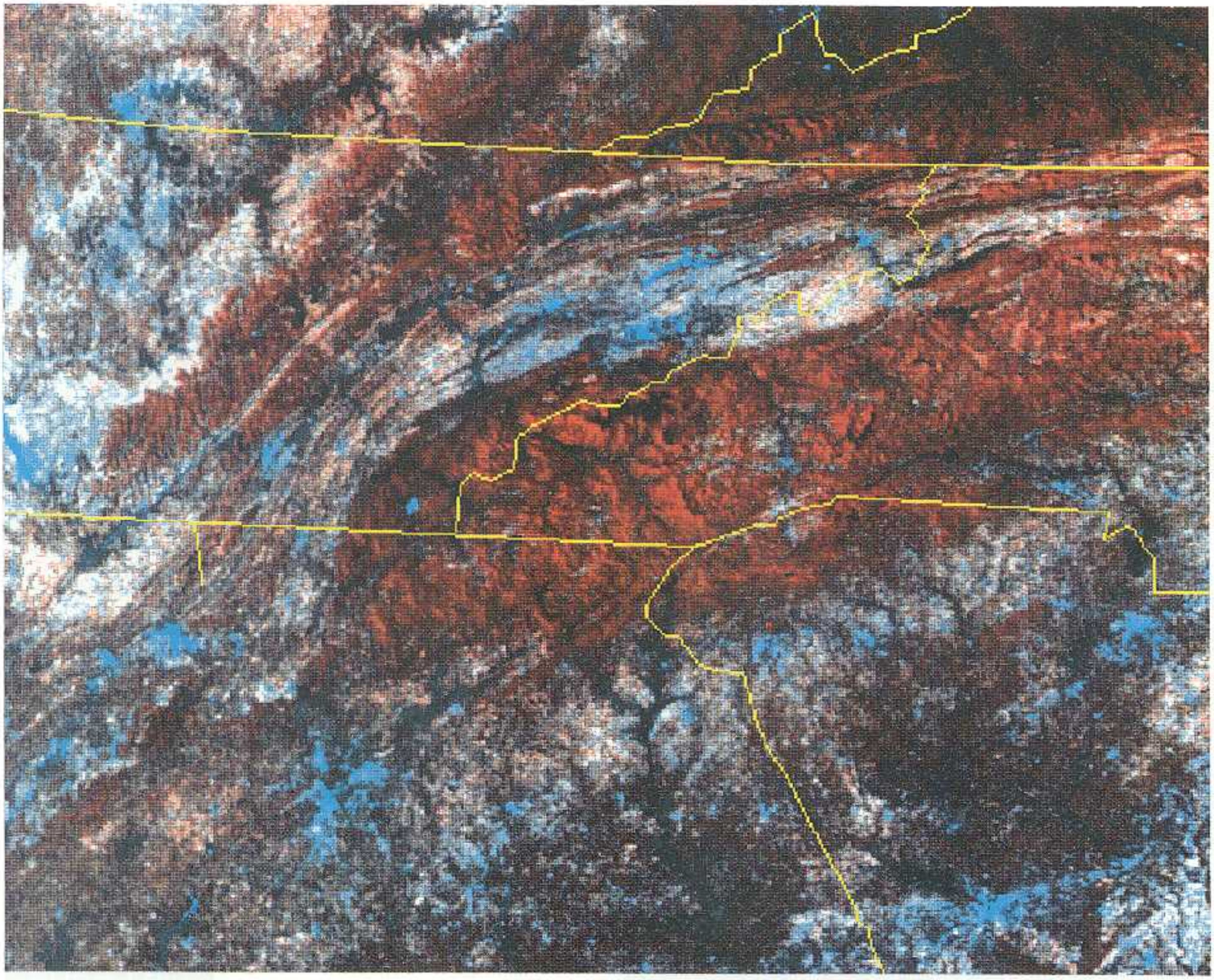


Fig. 3a. Smokies region: raw AVHRR image data.

topography and vegetation. A digital version of the MLRA map was acquired from the Soil Conservation Service.

Calibration and extrapolation

Estimates of forest cover for the two study regions were developed in three basic steps. First, the TM data were used to produce a fine resolution (30 m) binary (forest/nonforest) map of the forest cover of the calibration center. Unsupervised classification techniques were used to create the TM-generated forest cover maps. Class definitions were verified via contemporary aerial photographs and U.S. Geological Survey 7.5-minute topographic maps.

Next, AVHRR data corresponding to the calibration center were co-registered with the TM-generated forest cover map, and the number of forested TM pixels within each AVHRR pixel was tallied. For the Illinois calibration center, 154 AVHRR pixels, each of which contained 1,369 TM pixels, were used, whereas 99 AVHRR pixels were used for the Cades Cove calibration center in the Smokies. The number of forested TM pixels within each AVHRR pixel was then used as the independent variable in multiple linear regression analysis to determine which spectral characteristics of the AVHRR data most correlated with percent forest

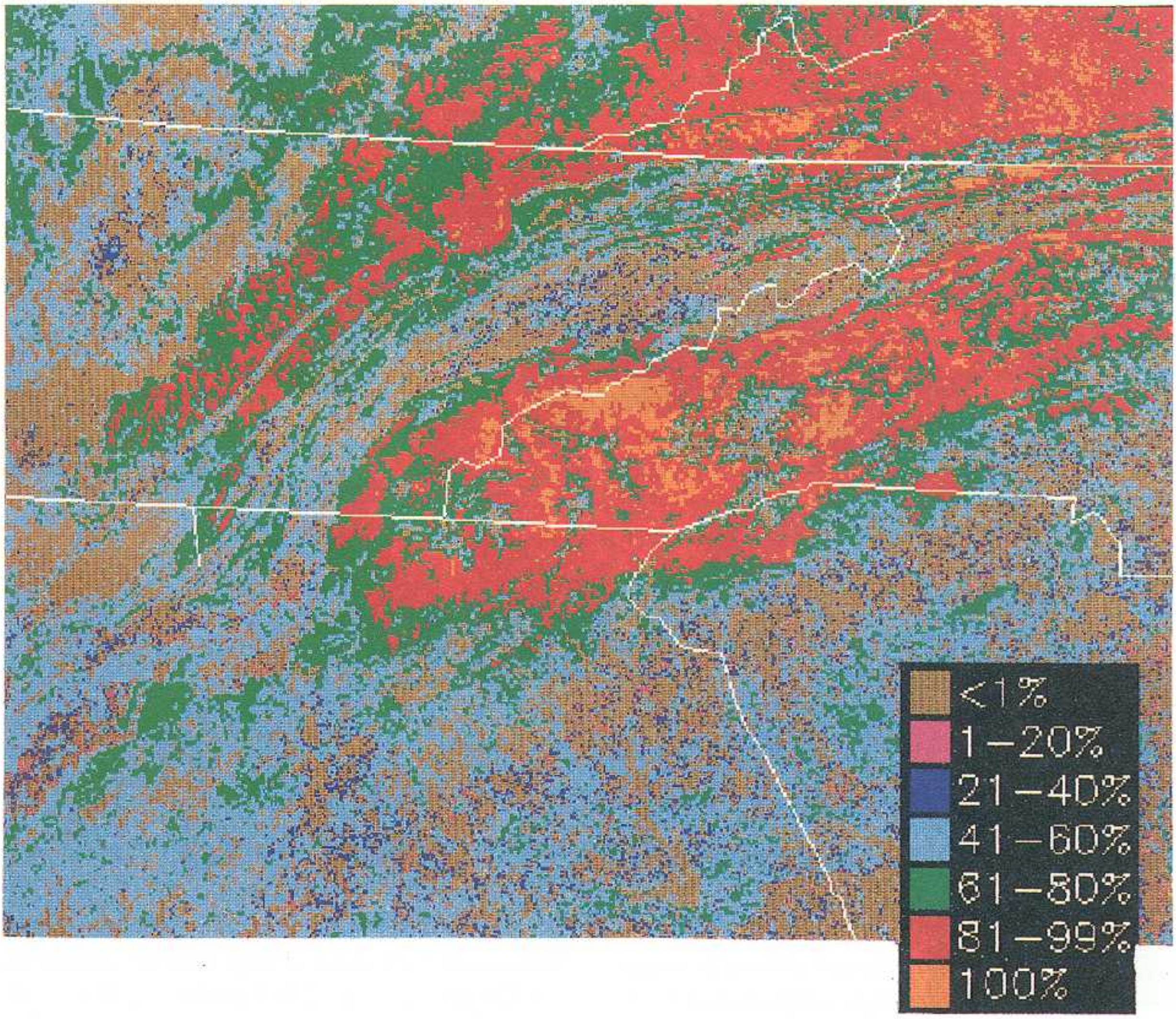


Fig. 3b. Smokies region: percent forest by AVHRR pixel.

cover. Care was used during regression analysis to avoid excessive collinearity, as provided by diagnostics within the statistical package.

Finally, the best fitting regression equation was used to extrapolate forest cover across the much larger study region. This extrapolation was based entirely on the AVHRR spectral data. Percent forest cover was estimated for each AVHRR pixel using the appropriate regression equation together with the pixel's spectral characteristics. For the Illinois region, an unsupervised classification was performed on the AVHRR data prior to this step to remove pixels containing absolutely no forest cover (*i.e.*, Lake Michigan, clouds, areas with 100 percent intensive row-crop agriculture). The resulting percent forest-cover maps were then simplified by aggregating the AVHRR pixel estimates of forest cover into percent forest-class intervals of 10 percent (*i.e.*, 0–10, 11–20, ... 91–100 percent forest). Further details on the general method can be found in Iverson *et al.* (1989a).

Validation

For each region, the estimates of percent forest cover by AVHRR pixel were aggregated to county

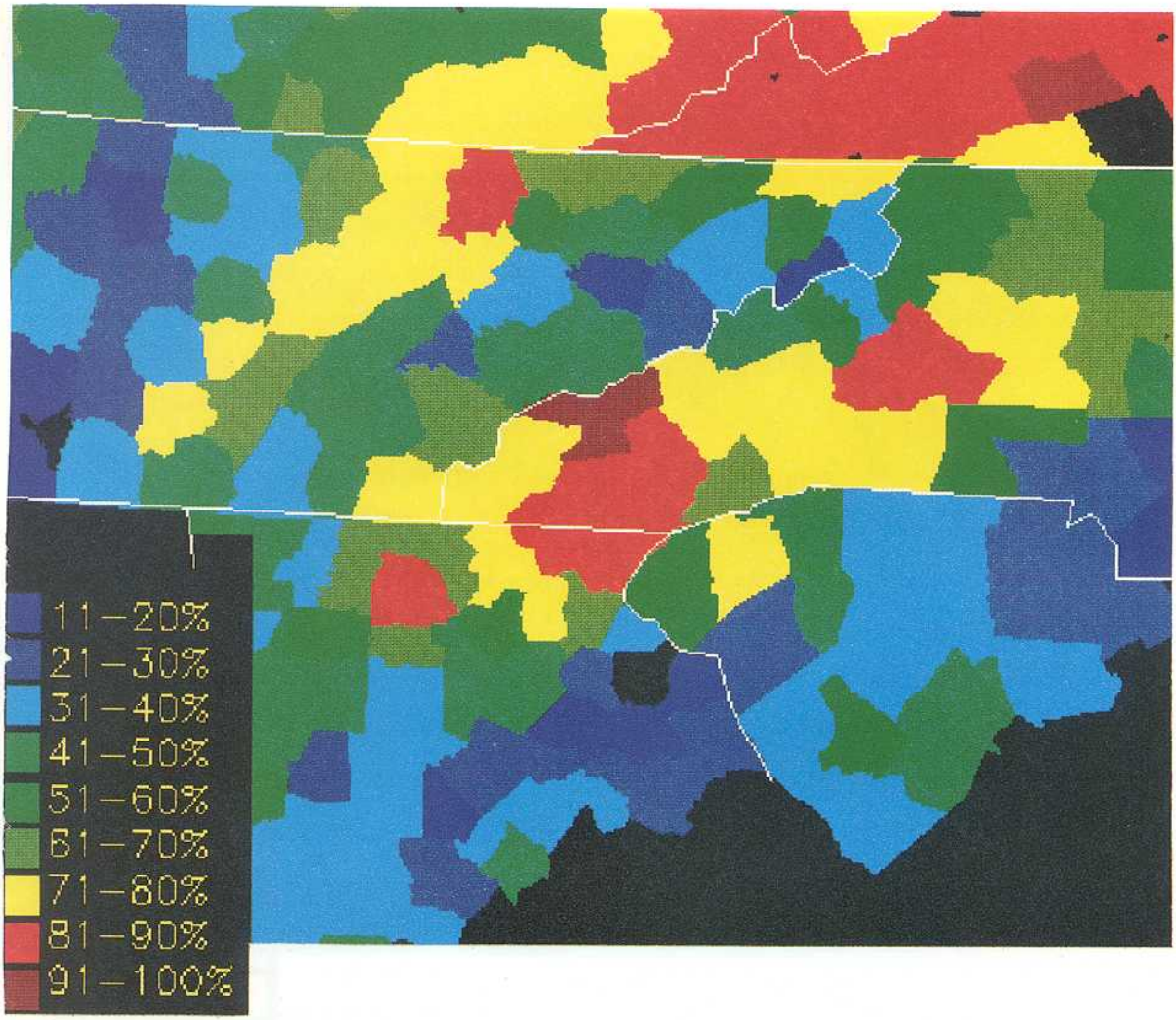


Fig. 3c. Smokies region: percent forest by county, as aggregated from AVHRR pixels.

estimates using the geographic information system. The resulting county estimates of forest cover were then compared with the USFS or TVA estimates of county forest cover. For the Smokies, estimates of hardwood versus softwood cover were considered in addition to total forest cover.

County-level forest cover estimates were aggregated by state, by distance from the calibration center (*i.e.*, 0–100, 100–200, 200–300, 300–400, >400 km from calibration center), by ecoregion (Omernick 1987), and by major land resource area (U.S. Department of Agriculture 1981). Correlations and t-tests were used to test the utility of using the ecoregions and major land resource area boundaries as a means of bounding the extrapolation. By correlating the two estimates of county forest cover within these various ways of classifying land, it was possible to assess the geographic sensitivity of the AVHRR estimates of forest cover and thus the robustness of the method. It was hypothesized that the AVHRR method should work best in ecoregions (or land resource areas) ecologically similar to those in which the calibration was developed.

Results and discussion

Calibration and extrapolation results

For each of the two calibration centers, the regression analysis revealed a significant ($p < 0.0001$) relationship between percent forest within an AVHRR pixel and some combination of AVHRR spectral bands. In Illinois, the relationship with the best fit used a linear combination of AVHRR Bands 1 (AVHRR 1) and 2 (AVHRR 2) and had an adjusted r^2 of 0.41:

$$\text{Percent forest} = 232 - 3.056\ (\text{AVHRR 1}) + 0.615\ (\text{AVHRR 2})$$

The greater chlorophyll content of forested pixels at this time of year (late spring) is evident in the regression equation, because the near-infrared band (AVHRR 2) is positively correlated with chlorophyll content.

For the Smokies region, the relationship with the best fit used an index featuring primarily thermal bands (AVHRR channels 3 and 4) and had an adjusted r^2 of 0.57:

$$\text{Percent forest} = -221.86 + 2.15\ (\text{AVHRR 4}) + 940.42\ (\text{AVHRR 3}/(\text{AVHRR 4} * \text{AVHRR 1})).$$

This relationship suggests that in the morning in late September (the time of the AVHRR satellite overpass), forested land is generally warmer and greener than nonforested land. The temperature effect is probably due to topographic effects. At the time of satellite overpass in early morning, the shadowed, mostly agricultural valleys tend to be wet and cool and the forested side slopes are warmer. This is the reverse of what is seen in the tropics during the dry season when the forested areas are cooler due to evapotranspiration and the dried-out grasslands are warmer.

The two equations were applied to the appropriate band values of each AVHRR pixel in the respective regions to generate maps depicting percent forest cover. In the map of the Illinois region, one can see the highly forested regions in the Missouri Ozarks, south-central Indiana, western Tennessee, southwestern Wisconsin, southern Michigan, and southern Illinois, along with the importance of river networks for the less forested areas (Fig. 2b). In the Smokies regions, the Great Smoky Moutains are shown as highly forested, as are most of the ridges extending west of the Smokies (Fig. 3b). The southern pine plantations to the south and east are also evident.

Validation

Maps of county forest cover were generated by aggregating pixels within a county (AVHRR county maps, Figs. 2c, 3c). Maps were also prepared from the independent **USFS** or TVA forest cover estimates (independent county maps), along with difference maps (AVHRR-derived estimate – independent estimate, for each county). The difference maps provided a graphic comparison of the two types of county forest cover estimates. Correlation and paired t-test analysis between estimates generally revealed a high correspondence (Tables 1–3). Analyzing the data by state, by distance from the calibration center, by ecoregion, and by major land resource area allowed further validation of the procedure.

Illinois and surrounding region. Correlation analysis revealed a high correspondence between the AVHRR and independent **(USFS** or TVA) estimates of county forest cover, especially in the Illinois region (Table l). Considering all 428 counties in the Illinois region, the mean county forest cover estimates were very close (24.1 percent cover for AVHRR estimate versus 23.2 percent **USFS),** while the correlation coefficient was 0.89. There was an excellent correspondence between estimates except in highly urbanized areas (relatively high numbers of trees but low amounts of commercial forest) or where there were clouds on the AVHRR data (underestimation of forest cover in AVHRR estimate). In the former case, the AVHRR estimate is probably a truer estimate of forest cover for carbon balance purposes than the **USFS** or TVA estimates which exclude such ‘forest cover’. There was some variation in the correspondence between the two estimates among states, but all states had significant correlations above **0.7** (Table 1). Some variation

Table 1. Comparison of Illinois region percent forest cover estimates, derived either from Advanced Very High Resolution Radiometer (AVHRR) data or from U.S. Forest Service (USFS) ground-based surveys.

Category	n[1]	AVHRR	USFS	P[2,3]	r[4]	P[3,5]
Overall	428	24.2	21.6	NS	0.89	**
State						
Arkansas	15	39.7	40.7	NS	0.89	**
Illinois	100	12.7	13.7	NS	0.90	**
Indiana	62	30.3	21.2	**	0.91	**
Iowa	55	4.5	4.9	NS	0.80	**
Kentucky	39	42.1	33.4	**	0.72	**
Missouri	77	32.8	32.6	NS	0.96	**
Tennessee	23	35.6	36.3	NS	0.85	**
Wisconsin	36	24.6	25.6	NS	0.79	**
Distance						
0–100 km	27	28.5	28.9	NS	0.96	**
100–200 km	70	27.4	29.9	*	0.94	**
200–300 km	96	36.1	33.0	*	0.89	**
300–400 km	82	28.1	24.4	NS	0.78	**
>400 km	153	12.1	12.4	NS	0.86	**
Ecoregion						
39 Ozark Highlands	29	28.6	24.0	NS	0.81	**
40 Central Irregular Plains	27	27.4	28.8	NS	0.87	**
47 Western Corn Belt	46	28.9	26.6	NS	0.92	**
52 Driftless Area	15	16.3	19.7	NS	0.95	**
53 Southeast Wisconsin Till Plains	18	25.2	25.4	NS	0.94	**
54 Central Corn Belt	79	25.4	23.9	NS	0.89	**
55 Eastern Corn Belt Plains	34	23.5	22.5	NS	0.92	**
56 South Michigan Till Plains	22	22.5	22.8	NS	0.78	**
71 Interior Plateau	67	20.0	20.2	NS	0.89	**
72 Interior River Lowland	61	22.1	20.9	NS	0.92	**
Major land resource area						
95 Southern Wisconsin and Northern Illinois Drift Plain	15	22.6	20.6	NS	0.85	**
108 Illinois and Iowa Deep Loess and Drift	49	21.0	20.3	NS	0.86	**
111 Indiana and Ohio Till Plain	37	29.7	26.9	NS	0.87	**
114 Southern Illinois Loess and Till	22	34.6	32.9	NS	0.90	**
115 Central Mississippi Valley Wooded Slopes	50	25.5	24.7	NS	0.89	**
116 Ozark Highlands	35	22.7	22.1	NS	0.80	**
120 Kentucky and Indiana Sandstone/Shale Hills/Valleys	24	26.7	26.6	NS	0.94	**
122 Highland Rim and Pennyroyal	30	19.5	20.8	NS	0.87	**

[1] Number of counties analyzed
[2] Significance level for difference between means
[3] NS = Not significant; * = $P<0.01$; ** = $P<0.001$
[4] Correlation coefficient for the two estimates
[5] Significance level for correlation coefficient

here can be attributed to the forest changes that have occurred in the interim between the TVA or **USFS** data collection and the 1987 AVHRR data (the independent data were collected as long ago as 1966). When evaluated by buffer distance from the calibration site, the highest r values occurred within the 0 to 100 km radius ($r=0.96$), with the correlation decreasing beyond 200 km (Table **1).** This trend is not surprising because one would expect the landscapes closest to the calibration center to be the most similar.

More interesting, however, is the correspondence between county estimates within ecological or land resource zones, because some method of selecting calibration centers will be needed to use this methodology to evaluate forest cover at continental or global scales. In the Illinois region, the Jackson County calibration center occurs in the Interior River Lowland ecoregion zone (Zone **72**), and the **62** counties within that zone had a correlation of **0.92** between the two estimates. Several other ecoregion zones, generally with dominant forest types (oak-hickory) and landscape patterns similar to the calibration site **(20–35** percent forest in a matrix of cropland), also correlated very highly (Table 1). However, the Ozark Highlands and the Southern Michigan and Indiana Till Plains zones (Zones **39** and 56, respectively), which have different landscape features and dominant forest types from the calibration site, exhibited lower correlations ($r = \mathbf{0.78-0.81}$). If additional calibration sites were used to capture the information from dissimilar ecoregions in the above-described fashion, one might expect the correlation between estimates to be even higher. Multiple calibration sites are needed especially in order to expand the extrapolation to the spatial scale of continents or eventually the entire planet. The concept of stratifying AVHRR data according to physiographic units was also emphasized by Lozano-Garcia *et al.* **(1991).** There was no significant difference (using paired t-test analysis) between the AVHRR and **USFS** mean estimates of forest cover for any of the ecoregions.

Further testing of the need for multiple calibration sites was conducted using major land resource areas (MLRA). The Jackson County calibration center straddles the Southern Illinois and Indiana Thin Loess Till Plain and the Central Mississippi Valley Wooded Slopes major land resource area zones (MLRA Zones **114** and **115,** respectively). The **72** counties contained within these zones had correlations of **0.89** and **0.90,** respectively, between forest cover estimates (Table **1).** Other MLRA zones with high correlations, such as the Central Claypan Areas, the Kentucky and Indiana Sandstone and Shale Hills and Valleys, and the Northern Illinois and Indiana Heavy Till Plain zones (MLRA Zones **113, 120,** and **110,** respectively), also tend to have forest types and landscape mosaics similar to those of the calibration center. On the other hand, the Ozarks zone (MLRA Zone **116)** had a lower correlation, presumably because of differing dominant forest types (including the inclusion of a significant proportion of spectrally dark pines) ,and other landscape features (Table 1). No MLRA zone had a significant difference between AVHRR and **USFS** forest cover means.

Smoky *Mountains and surrounding region.* A different reporting scheme was used in this region because it has considerable pine-dominated forests, whereas the calibration area was dominated by hardwood forest and had very little pine. Therefore, correlations and area estimates are reported for total forest cover, hardwood forest cover, and softwood forest cover (Tables **2–3).** For this region, significant differences existed between the AVHRR and TVA estimates of mean total forest cover (Table **2).** In all cases, the AVHRR estimates of forest cover were significantly less than the TVA estimates of total forest cover, but higher than the TVA estimates of hardwood forest cover. States with the widest discrepancy between total forest estimates, Georgia and South Carolina, also had the largest percentages of softwood forests **(39–50** percent of forests are softwood compared to less than **18** percent for the other three states). The influence of high amounts of softwood forest in Georgia and South Carolina undoubtedly contributed to an underestimation of percent forest by AVHRR because of the different spectral characteristics of pine forests. The Cades Cove calibration center is dominated by hardwood forests; therefore, the counties with sizeable quantities of softwoods would not be well represented by the calibration center. On the other hand, total forest percentages were quite well represented by AVHRR in those states containing forest types more closely related to those of the Cades Cove area. AVHRR and TVA estimates were within 8 percent of each other for North Carolina, Kentucky, and Tennessee (Table **2).**

Examination of the correlation coefficients between TVA and AVHRR county estimates of

Table 2. Comparison **of** Smokies region percent forest cover estimates, derived either from Advanced Very High Resolution Radiometer (AVHRR) data or from Tennessee Valley Authority (TVA) data.

Category	n[1]	AVHRR	Total TVA	P[2]	Hardwood TVA	Softwood TVA
Overall	190	52.2	62.6	**	38.0	14.9
State						
Georgia	50	42.9	66.7	**	29.5	26.1
Kentucky	20	57.9	60.8	NS	50.0	**5.0**
North Carolina	32	66.7	67.9	NS	44.7	11.7
South Carolina	18	38.8	69.2	**	24.0	34.5
Tennessee	57	46.8	54.9	NS	38.6	6.7
Distance						
0–100 km	28	62.3	69.4	*	41.3	11.9
100–200 km	92	53.8	66.2	**	42.3	14.1
200–300 km	67	44.2	55.0	**	30.3	17.8
Ecoregion						
65 Southeastern Plains	68	51.8	63.3	**	38.2	14.2
66 Blue Ridge Mountains	21	59.1	64.2	NS	36.1	19.0
67 Central Appalachian Ridges	30	52.6	59.4	NS	38.4	13.7
68 Southwestern Appalachians	17	48.1	59.8	NS	38.4	12.2
69 Central Applachians	18	57.2	64.5	NS	41.9	14.2
71 Interior Plateau	33	48.4	63.5	**	36.4	16.0
Major land resource area						
122 Highland Rim and Pennyroyal	15	49.3	60.8	NS	35.2	14.9
125 Cumherland Plateau and Mountains	15	48.4	61.3	NS	36.7	15.7
128 Southern Appalachian Ridges and Valleys	30	51.9	60.4	NS	40.7	12.9
130 Blue Ridge	20	64.6	65.8	NS	40.1	17.0
136 Southern Piedmont	45	52.7	61.3	*	36.0	14.3

[1] Number of counties analyzed
[2] Significance level for difference between means (NS = Not significant; * = $P < 0.01$; ** = $P < 0.001$)

average total forest cover revealed a significant relationship for the entire region, although the correlation was only 0.47 (Table **3).** The regional TVA/AVHRR relationship improved when the AVHRR cover value was compared to the TVA cover value for hardwoods only ($r = 0.58$). The negative influence of softwoods on the accuracy of the AVHRR/forest cover relationship is apparent. When the data were stratified by distance from the calibration center, we see that there is a very high correlation within 100 km of the Cades Cove calibration center ($r = 0.84$), and the relationship rapidly breaks down as one moves beyond that distance (Table **3).** In this region of extreme landscape heterogeneity, the AVHRR/forest cover relationship apparent at the calibration center cannot be considered representative of AVHRR/forest cover relationships of distant areas with differing vegetation and topography.

The ecoregions encompassing the Cades Cove calibration center, the Blue Ridge Mountains and the Central Appalachian Ridges, (Zones 66 and 67, respectively) showed the best correlations between the TVA hardwood forest cover and AVHRR forest cover estimates (Tables 2 and **3).** The 68 counties in the Southeastern Plains (Zone 65) also show a high correlation between the TVA hardwood and the AVHRR forest cover estimate. Other ecoregions in the Smokies region had lower correspondence between the TVA hardwood and AVHRR forest cover estimates, presumably because of a further departure from the conditions (forest type and landscape mosaic) present at the Cades Cove calibration center. For all six eco-

Table 3. Correlation coefficients and significance levels for AVHRR and TVA estimates of total hardwood and softwood forest cover by county.

	Correlation of AVHRR estimates to:					
Category	Total TVA	P[1]	Hardwood TVA	P[1]	Softwood TVA	P[1]
Overall	**0.47**	**	**0.58**	**	**−0.26**	NS
State						
Georgia	**0.68**	**	**0.70**	**	**−0.15**	NS
Kentucky	**0.81**	**	**0.76**	**	**0.32**	NS
North Carolina	**0.54**	*	**0.21**	**	**0.05**	NS
South Carolina	**0.08**	NS	**0.23**	NS	**−0.14**	NS
Tennessee	**0.62**	**	**0.46**	**	**0.24**	NS
Distance						
0–100 km	**0.84**	**	**0.66**	**	**0.17**	**NS**
100–200 km	**0.48**	**	**0.56**	**	**−0.31**	*
200–300 km	**0.17**	NS	**0.50**	**	**−0.21**	NS
Ecoregion						
65 Southeastern Plains	**0.55**	**	**0.63**	**	**−0.30**	NS
66 Blue Ridge Mountains	**0.62**	NS	**0.64**	*	**−0.46**	NS
67 Central Appalachian Ridges	**0.62**	**	**0.67**	**	**−0.15**	NS
68 Southwestern Appalachians	**0.20**	NS	**0.31**	NS	**−0.25**	NS
69 Central Applachians	**0.50**	NS	**0.55**	NS	**−0.32**	NS
71 Interior Plateau	**0.49**	*	**0.54**	*	**−0.16**	NS
Major land resource area						
122 Highland Rim and Pennyroyal	**0.52**	NS	**0.61**	*	**−0.27**	NS
125 Cumberland Plateau and Mountains	**0.29**	NS	**0.42**	NS	**−0.23**	NS
128 Southern Appalachian Ridges and Valleys	**0.49**	*	**0.54**	*	**−0.17**	NS
130 Blue Ridge	**0.27**	**NS**	**0.58**	*	**−0.39**	NS
136 Southern Piedmont	**0.41**	*	**0.57**	**	**−0.39**	*

[1] Significance level for correlation coefficient (NS = Not significant; * = P < 0.01; ** = P < 0.001)

regions, there was a negative relationship between the TVA softwood forest cover estimate and the AVHRR forest cover estimate component. This trend is not altogether surprising because pine forests are most likely to be cooler than hardwood forests and the AVHRR regression relationship predicted that warmer pixels would have more forest. Clearly, an additional AVHRR model, possibly developed from a winter scene where deciduous trees are in leaf-off condition, needs to be developed that considers the softwood component of forest cover in this region.

The Cades Cove calibration center was located in the Blue Ridge MLRA zone (Zone **130),** which is characterized by Appalachian oak forest vegetation, including significant pine and hemlock stands (U.S. Department of Agriculture **1981).** Just to the west of the calibration center is the border for the Southern Appalachian Ridges and Valleys zone (Zone **128),** also supporting a hardwood or mixed hardwood-pine forest vegetation (Fig. **2).** These zones, along with Southern Piedmont and Highland Rim and Pennyroyal zones (Zones **136** and **122,** respectively), all had about the same correlations of hardwood forest cover with the AVHRR estimate, though sample sizes were quite small (Table **3).**

Conclusions

AVHRR data, when calibrated with TM data, can successfully generate landscape and regional estimates of forest cover in areas of highly fragmented forest cover but fairly uniform topography and forest type such as the Illinois region. The TM calibration in effect creates a sub-pixel model that allows a level of precision not possible using AVHRR data alone. The output maps and statistical compilations are based on the percent forest contained within an AVHRR pixel, not simply a binary forest/nonforest classification of AVHRR data. As noted in the introduction, this type of calculation is very important in regions that, because of human impact or ecological factors, have some forest, but in parcels smaller than 100 percent forested within each 1 km^2 area. Depending on the forest/nonforest definitions used and the actual amount of forest on the land, an AVHRR binary classification approach may grossly underestimate or overestimate the actual amount of forestland.

Ecoregions appear to provide a reasonable basis for determining the number and location of calibration centers necessary for using the methods outlined here to develop continental or global estimates of forest cover. Ecoregion, or ecofloristic zone, maps are now becoming available for most of the world (*e.g.*, Food and Agriculture Organization 1989), so that a stratification of ecological zones could be performed before using these techniques. In both Illinois and the Smokies region, the highest correlations between AVHRR-predicted forest cover and independent estimates of forest cover occurred within the ecological zone of the calibration center, or in ecological zones of a similar nature with regard to forest type and landscape structure. For continental evaluation of forest cover, fine-resolution ecological zones (*e.g.*, ecoregions or MLRAs described here) could, based on evidence from this study, be aggregated without major loss in precision provided basic topography and forest type remain somewhat similar.

The Smokies results show that in regions where there is considerable topographic and vegetation variation, calibration centers will likely have to be fairly specific to an ecological zone or specific forest type. The AVHRR/forest cover model developed in a hardwood-dominated location of this region was obviously inadequate when the dominant forest-cover type became pine as was the case south and east of the calibration center. In zones where there are forest types with very different reflectance patterns such as hardwoods and pines in the Smokies, the AVHRR/forest cover models developed at calibration centers must be constructed to account for that variation. One approach to this problem might be addressed by developing one model using a calibration center dominated by the first vegetation type and a second model using a calibration center dominated by the second vegetation type. At either center, a wide distribution in forest cover within AVHRR pixels is desirable so that the derived regression equation is applicable to all levels of forest cover. Preferably, the first model would be insensitive to the presence of forest of the second type and the second model insensitive to the presence of forest of the first type, or the sensitivities of each model to the other vegetation type would be known and quantifiable. This might best be accomplished by capitalizing on any phenological differences between the two vegetation types. It might also be possible to do a preliminary stratification of the AVHRR data into pixels containing no forest, pixels containing the first forest type, and pixels containing the second forest type and then applying the appropriate model to the appropriate pixel type.

By relying on a network of calibration centers that represent various physiographic regions, regional and eventually global estimates of forest cover may be possible. The network could be built on established networks of ecological research sites or bioreserves (*e.g.*, Man and the Biosphere, Long Term Ecological Research). However, the calibration sites must represent the entire physiographic region and not just the best preserved portion of the region. This work was conducted in the United States because ancillary data, including the independent forest cover data used for validation of the technique, were readily available. Obviously, information concerning forest cover is more urgently needed in the tropical world. To that end, these methods are being tested in some tropical regions.

More and more information on the biosphere is being gained via remote sensing (Botkin *et al.* 1988; Cook *et al.* 1989; Iverson *et al.* 1989b; Hobbs and

Mooney 1990). The potential is great for many more gains in this area. We need to develop new quantitative methods to take advantage of these remotely sensed data to monitor a subtly changing planet. Changes in forest area and biomass are critical phenomena to monitor, and the methodology proposed here can help achieve a better picture of current conditions and trends of our world's forests.

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