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Forest Density Mapping in the Lower 48 States: A Regression Procedure

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SUMMARY

Techniques used in a project to map forest density over the conterminous United States are described. The process was based on coregistration of Advanced Very High Resolution Radiometer (AVHRR) data and Landsat Thematic Mapper (TM) data and on regression analysis of statistical relationships between the two data types. A forest density value is the percentage of forested TM cells within one AVHRR cell. The process can be used in other remote sensing projects that involve a primary, inexpensive, data set for total enumeration and a secondary, more accurate data sample. However, this process is ideally suited to AVHRR data whose characteristics (low cost and large area coverage) make the process more meaningful for large area forest mapping applications. Benefits of the forest density mapping procedure, as demonstrated by the project, include providing additional forest land information derived from subpixel measurements, aiding forest type classification, and allowing the study of density distributions of different forest types.

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INTRODUCTION

The United States Department of Agriculture, Forest Service, Southern Forest Experiment Station's Forest Inventory and Analysis (SO-FIA) research unit conducted a project to map the distribution of forest lands for the entire United States. Forest types and forest densities were mapped, and a new forest type group map for the country was produced (Powell and others, in press; Zhu and Evans 1992). This project supported the 1993 Forest and Rangeland Renewable Resources Planning Act (RPA) Assessment Update program, by which the Forest Service was required to provide statistics on current forest land and rangeland conditions.

The duration of the RPA mapping project, conducted in two phases, was from April 1991 through December 1992. In the first phase, seven Midsouth States (Alabama, Arkansas, Louisiana, Mississippi, Oklahoma, Tennessee, and Texas) were used as the test area for methodology. During the second phase, through a cooperative effort between the SO-FIA and the FIA unit in Alaska, all 50 States were mapped. Results of this project include maps, digital image files, derived data, and scientific publications.

The significance of the project may be summarized in the following four ways: (1) there is a new United States forest map, which visually depicts spatial patterns of the current distribution of forest types in the country; (2) the map provides the scientific community with much needed information on current forest resources over a large area; (3) the project produced valuable experience and identified useful methods through the applied research; and (4) the project is a key connection to other large area forest studies (e.g., those involving Mexico and boreal forests) currently being conducted at SO-FIA (Eggen-McIntosh and Zhu 1992, Evans and others 1993).

An important part of this project was a forest density map of the conterminous United States. Forest density, defined in the project as the proportion of cells (each cell was 28.5 by 28.5 meters in size) per square kilometer that was forested, was for the first time derived for the entire lower 48 States using a statistical modeling procedure. The methodology developed for constructing and using the forest density values was very important in achieving the main objective of classifying forest type groups.

Primary procedures and findings from this project have been reported in an earlier publication (Zhu and Evans 1992). The research associated with creating and using the forest density map is emphasized here, specifically, the relationships between the forest density mapping and other procedures used in the project, techniques used in creating forest density values, and analysis of some further results.

BACKGROUND

Because data from the Advanced Very High Resolution Radiometer (AVHRR) offered many advantages for large-scale land cover studies (Zhu and Evans 1992), these data were a logical choice for the RPA mapping project. However, not only was the project performed on a continental scale in terms of the extended areas to be mapped, but it also required a classification of the RPA forest type groups (table 1)—an unprecedented level of detail for AVHRR data. Precisely because of the data's characteristics, simple use of AVHRR spectral classification was considered insufficient to attain the RPA requirements; a combined

Table 1.—*Forest type groups of the conterminous United States used in assessments under the Forest and Rangeland Renewable Resources Planning Act (RPA)*

Eastern United States	Western United States
White–red–jack pine	Douglas fir
Spruce–fir	Hemlock–Sitka spruce
Longleaf–slash pine	Redwood
Loblolly–shortleaf pine	Ponderosa pine
Oak–pine	Western white pine
Oak–hickory	Lodgepole pine
Oak–gum–cypress	Larch
Elm–ash–cottonwood	Fir–spruce
Maple–beech–birch	Western hardwoods
Aspen–birch	Chaparral
	Pinyon–juniper
	Aspen–birch

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approach of well-defined procedures was deemed necessary. As a result of this necessity, this project relied on a combination of the following procedures to achieve the predefined classification goal (fig.1).

Physiographic Stratification

There have been many studies that divided a very large land area into relatively homogeneous regions based on a set of criteria. These studies included classifications of ecoregions, land surface forms, soils, potential vegetation, and land physiography. Depending on project applications, these regional divisions offer mechanisms to subset, or stratify, a large-scale data set in favor of certain variables. The purpose of geographic data stratification used in this project was to reduce spectral variations between different regional physiographic conditions and to emphasize spectral variations by local vegetation types.

When applied to a large area, such as the conterminous United States, the regional physiographic stratification was closely related to the forest density mapping objectives. Iverson and others (1989) suggested that a particular density model was valid only within a limited area. Therefore, multiple models were needed for a large region with different physiographic settings. Because of this need, the utility of regional divisions was essential to the project.

Use of Multitemporal Data

One important advantage of AVHRR data over other satellite remote sensing data is the sensor's frequent data coverage of a large area of the Earth. Multiple dates of data from a common area (multitemporal data) contain phenological information about vegetation, such as the green-up profiles (Loveland and others 1991), which can be valuable for separating different types of vegetation in a large area. Multitemporal AVHRR data were used in the RPA project, based on this premise.

To construct a multitemporal, remotely sensed data set for a large area, one encounters the problems of an increased number of spectral channels (bands) and an increased volume of data. Too many spectral channels not only add to computational difficulty but also possibly compromise classification accuracy (Coggeshall and Hoffer 1973). The normalized difference vegetation index (NDVI) channel created for each date of AVHRR data provides a good means of reducing data volume. Many large area land studies based on multitemporal AVHRR data use exclusively the NDVI channel for each date that data were collected (Loveland and others 1991). Depending on the applications, this approach may not be desirable for species discrimination because it omits two important spectral channels (the midinfrared, which is sensitive to vegetation water content, and the thermal, which measures surface temperature) from the sensor's already limited spectral range.

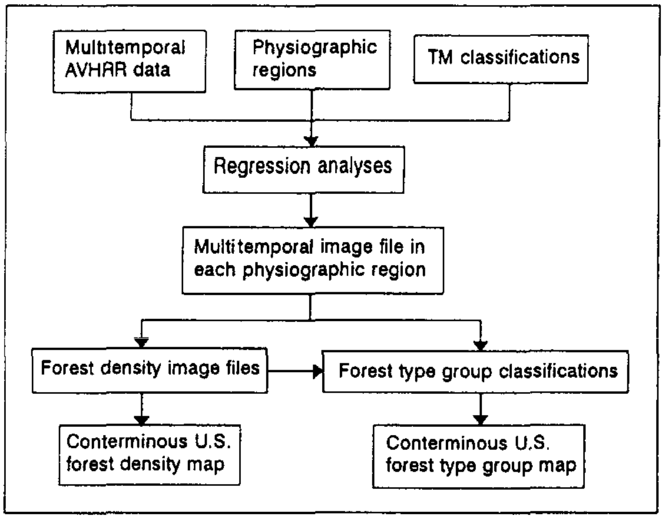

Figure 1.—*Procedures used in the Forest and Rangeland Renewable Resources Planning Act (RPA) mapping project.*

The RPA mapping project used AVHRR composites from nine dates in 1991 (table 2), selected to represent vegetation seasons in 1991 (spring, summer, and autumn). Five channels were entered for each date (regular channels 1 through 4: visible, near-infrared, midinfrared, and thermal; and the NDVI chanel); AVHRR channel 5 was closely correlated to channel 4 and was not used. Because a total of 45 spectral channels was used, it was necessary to reduce the data volume but still maintain a multitemporal data set to characterize vegetation phenology. The data reduction was guided by studying statistical relationships among dates, spectral channels, and forest cover during the forest density modeling process.

Forest Density Modeling

Modeling forest density over a large area is developed from research on resolving mixed-satellite data pixels for component terrain types. It is also related to the concept of double sampling in statistical methods. For individual pix-

Table 2.—*Periods in 1991 from which Advanced Very High Resolution Radiometer (AVHRR) biweekly composite data sets were used in the Forest and Rangleand Renewable Resources Planning Act (RPA) mapping project*

Data Set	Composite period
1	March 1–March 14
2	March 29–April 11
3	April 26–May 9
4	May 24–June 6
5	July 19–August 1
6	September 13–September 26
7	September 27–October 10
8	October 11–October 24
9	November 8–November 21

els, the level of detail and the limit of accuracy are functions of the sensor's spatial, spectral, and radiometric resolutions. When spatial resolution is coarse, such as that of AVHRR, pixels covering small objects or edges of large objects become mixed. In this respect, if the objects under consideration are forest and nonforest lands, the measure of the amount of forest per unit area (i.e., forest density) is the same as the solution for mixed-pixel components.

Solutions for pixel mixture are often derived by calibrating the coarse resolution satellite data with reference data that are based on accurate subpixel measurements. This approach assumes that the magnitude of the spectral response from a particular pixel location is correlated to the pattern of pixel mixture. The calibration models adopted can be applied to a large area containing the coarse resolution satellite data. This procedure is consistent with the double-sampling concept in which a population is sampled using an inexpensive, easy-to-get variable, and the results are adjusted using a subset of a more expensive and more dependable variable.

This modeling approach has been used for various sensor types, including both Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM) data in the early 1970's and 1980's (Gilmer and others 1980, March and others 1980). The interest in resolving pixel mixture and measuring subpixel content recently has been more focused on AVHRR data because the sensor has become widely used in large area, land cover studies. Such interest is supported by the coarse, 1-kilometer, spatial resolution and by the recognition that large area mapping at subpixel levels has great potential due to low data cost and low volume.

A number of studies describe applications of the multisource approach involving AVHRR and Landsat data (Cross and others 1991, Iverson and others 1989, Nelson and Holben 1986). These studies were conducted on limited areas and based on single calibrations. The RPA project's effort to map forest density for the entire conterminous United States using multiple calibration models was the first time this modeling approach was used on such a large scale.

METHODS

Construction of Forest Density Images

With the primary reference to Hammond's land-surface form map (1964), plus consideration of Fenneman and Johnson's physical division map (1946) and Omernik's

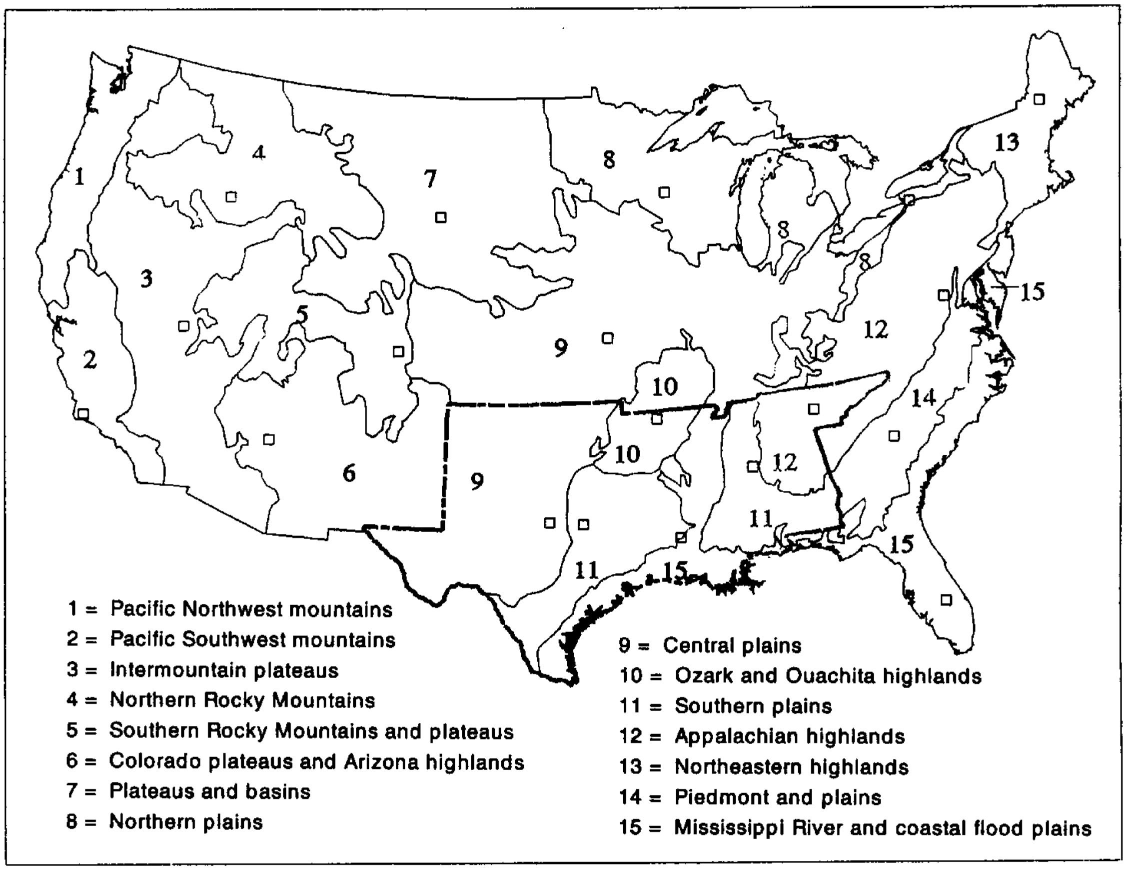

Figure 2.—*Physiographic regions and locations of the Thematic Mapper (TM) scenes. Locations of the TM scenes are identified by the abbreviations of the States in which the scenes are located. Note that the bold line outlines the seven Midsouth States used as the test areas for methodology in the first phase of the project.*

ecoregions map (1987), the conterminous United States was divided into 15 regions (fig. 2). Subsequent data processing steps were conducted within each region; results were combined to form the final images.

Landsat Thematic Mapper (TM) classified data sets (scenes and subscenes) were used as the secondary reference data to calibrate AVHRR data enumerations. At least one TM data set was acquired and classified per region; two were used in a few regions that covered extended areas or the test areas (the seven Midsouth States) used in the first phase of the project (fig. 2). The regional data partitions ensured that the calibrations were applied only to limited areas to maintain validity of each calibration. In all, 19 TM scenes or subscenes were used for this study.

The TM data used in this project had a pixel size of 28.5 by 28.5 meters. At this size, 1 AVHRR pixel (1 by 1 kilometer) corresponded to about 1,225 TM pixels. The AVHRR and TM data were coregistered to the Lambert azimuthal equal area map projection (fig. 3). A rectangular calibration window was then identified for each AVHRR/TM pair; data within this window were prepared for statistical analysis. Both size and location of the window were considered while identifying its corner coordinates on AVHRR and TM images. Window size determined the number of observations for each regression model and also affected computation time. The location of the window represented regional land cover patterns; large water bodies and clouds were avoided.

The following steps were used when preparing each TM reference data set. (1) An unsupervised classification process was used to classify the TM scenes into the local RPA forest type groups. The process usually included several iterations of a guided clustering routine and a maximum likelihood classifier. (2) Ground control points were identified and digitized from the 1:100,000 topographic maps and the spectral images. (3) The classified scene was rectified first to Universal Transverse Mercator, then reprojected to Lambert azimuthal equal area projection. (4) The subset area outlined by the calibration window was recoded so that value 1 represented all forest classes and value 0 represented all nonforest classes. (5) Pixel values of the above recoded raster subset were converted to an ASCII file. (6) Data values from every 35 lines and 35 columns (corresponding to 1 AVHRR pixel) were summarized to derive a percentage value saved to an output file.

The AVHRR spectral data were prepared for statistical analysis using the following steps: (1) each data set from a particular date was visually examined for quality problems, such as residual clouds or compositing seams, and these problem areas were noted for exclusion from subsequent analyses for each physiographic region; (2) spectral data within the window area were extracted for each date and were combined with data from other dates in a time series; and (3) pixel values were converted to an ASCII file in which spectral channels and dates were listed as columns.

Next, correlation and regression procedures were applied with the TM-determined forest percentages (the dependent variables) and corresponding AVHRR spectral values (independent variables). A simple linear model using all variables was tested. If it was found significant, i.e., p-value (model significance probability value) was less than 0.01 and model correlation coefficient (R^2) was high, AVHRR spectral bands were noted for individual performances.

The process of evaluating individual AVHRR bands included a simple correlation analysis with the forest percentage variable, a test of colinearity among the AVHRR bands, and linear models for all possible combinations of

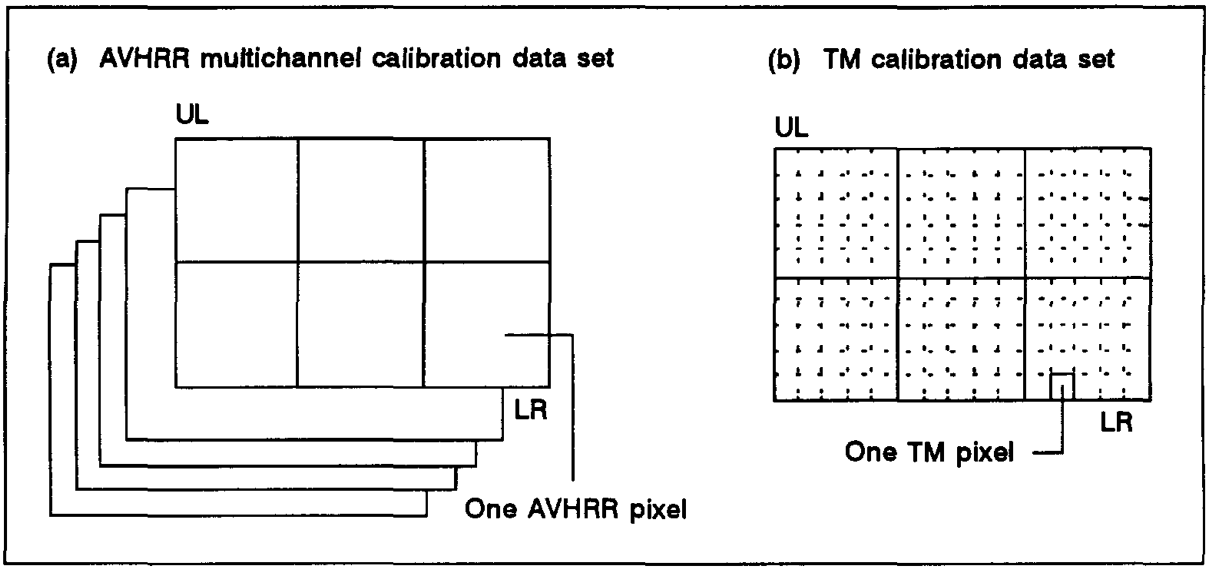

Figure 3.—*Illustration of Advanced Very High Resolution Radiometer (AVHRR) (a) and Thematic Mapper (TM) (b) calibration. Note that the two data sets have the same upper left (UL) and lower right (LR) coordinates. In this illustration, 1 AVHRR pixel contains 25 TM pixels.*

the AVHRR bands. Combination models were tested using a statistical procedure that always chose the highest R^2 among different levels of independent variable combinations. Other procedures, such as step-wise regression, were available but were not used.

Although it is true that more variables added to a model would always bring a higher R^2, it was evident in this project that the increase in R^2 was marginal after the first five to eight independent variables were chosen (fig. 4). Based on this observation, five to eight "best" AVHRR spectral bands were chosen to build a final linear model for each of the calibration windows (table A1). The increase in R^2 and dates of the AVHRR bands were examined collectively, with the correlations, colinearities, and other statistics once again considered.

If at first the simple linear regression was not significant, i.e., it had a low R^2 and a p-value higher than 0.05, second order polynomial models were tested. Normally, a curve-fitting procedure would benefit the process. However, a large number of records were usually involved in each calibration, making examination of the curve pattern difficult. The process used in this project for testing second order polynomial models was an interactive and exploratory approach in which subsets of the AVHRR bands were selectively tested. Effectiveness of polynomial models was most noticeable in sparsely forested regions, such as western Texas and much of the Great Plains prairie lands (table A1).

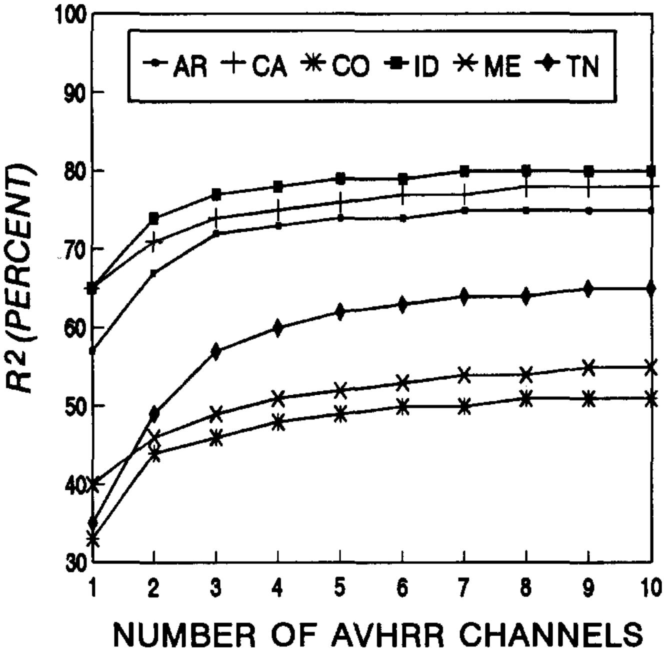

Figure 4.—*Increase in* R^2 *versus increase in number of Advanced Very High Resolution Radiometer (AVHRR) channels in each of the six selected Thematic Mapper (TM)/AVHRR regression models. Curves are indicated by the abbreviations of the States in which the models are located.*

Using the above steps, the optimal regression models were selected, and the best AVHRR bands were identified. These bands were then extracted from original dates of the AVHRR spectral data partitions and stacked together to form a multitemporal image file for each of the physiographic regions. These AVHRR multitemporal image files, identified through the regression process, were the basis for both regional forest density images and RPA forest type group classifications.

Regression parameters derived from each calibration model were applied to the AVHRR multitemporal image file to compute a predicted value, or forest percentage value, for each of the AVHRR spectral data records (pixel locations). These forest percentage values, ranging in magnitude from 0 to 100 percent, formed a forest density distribution in each physiographic region. A forest density map covering the entire lower 48 States was obtained by combining all regional density maps (fig. 5).

Use of Density Values in Forest Type Classification

The RPA forest type group classifications were conducted separately for each physiographic region based on the multitemporal image files. Due to the large areas involved, ground reference data to support class identifications were never adequate, and the forest density images provided excellent guidance for labeling the spectral classes after the unsupervised classification process. Primarily, the density values were used: (1) to mask out most of unforested land cover classes immediately after each classification; (2) to serve as one layer of ancillary information in inferring different forest type groups, particularly woodland types; and (3) to refine forest/nonforest land use patterns in individual areas during later phases of the project.

While forest type groups were identified in the spectral classifications, the extent of forest lands in the lower 48 States reflected the use of forest density modeling. In a verification process, forest lands, in terms of a percentage of all land area, in each of the 50 States were compared to 1993 RPA data. Results are listed in table A2.

Preliminary analysis of the relationships between the forest density values and individual forest type groups indicated that forest density was a useful tool to help define the extent of a forested area identified in AVHRR classifications. Because it was a tool that was used in an integrative fashion in the RPA project, no attempt was made to apply one particular density value as a threshold to all forest type groups.

Differing from the forest type group classification, the forest density map was the result of statistical models rather than classification algorithms in which human decisions were involved in deciding pixel identities. Density pixel labels were scaled values (percentages) rather than named spectral classes. Because of the differences, common classification accuracy methods using ground reference data were not suitable for assessing the forest density mapping process. Instead, the effectiveness of a density model may be indicated by a set of statistical model indicators, such as R^2 and residual scatter plots.

An example of scatter plots is shown for residual and predicted values from two selected models (fig. 6). Plotted data points were a small random sample from each of the large data files used in models. Plots a and c in the figure draw predicted forest percentage values (y axis) against actual, TM-determined forest percentage values. The plot for a perfectly fit model would display distribution between the two variables in a straight diagonal line, whereas a less effective model would have more points deviating from the line. Plots b and d are distributions of studentized residuals (residuals divided by standard errors) for which data points should fall mostly between ± 2-percent intervals and should be randomly distributed around the central axis.

DISCUSSION

A basic assumption for using the forest density mapping approach is that the spectral response received by the AVHRR sensor is proportional to the amount of forest covered by the sensor's instantaneous field of view. Further, this radiometric sensitivity to the presence of forest vegetation is not weakened during the subsequent data conversion processes (e.g., analog to digital conversion, radiometric calibration, 10 bit to 8 bit data conversion, etc.).

Thus, this approach should conceivably work best in areas where forests predominate in vegetation spectral characteristics and where interference in the unique forest spectrum by other nonforest vegetation types is minimal. For example, dense conifer forests in the Black Hills, South Dakota, should have high spectral contrast against surrounding unforested land surfaces, mostly low croplands and rangelands. Presumably, the contrast should provide a consistent difference in spectral responses from the infrared and thermal AVHRR bands. Similar results may also be found in areas that have been clearcut versus mature stands or in areas that have a mixed pattern of forest and agricultural land use.

The choice of a calibration area in a primary data enumeration (e.g., AVHRR) can affect the model in several ways. For instance, some nonforest tall vegetation cover types, such as orchard trees or tall grass/meadow shrub lands during certain seasons, may have inconsistent spectral reflectance, which will contribute to noisy data in regression. On the other hand, models developed from

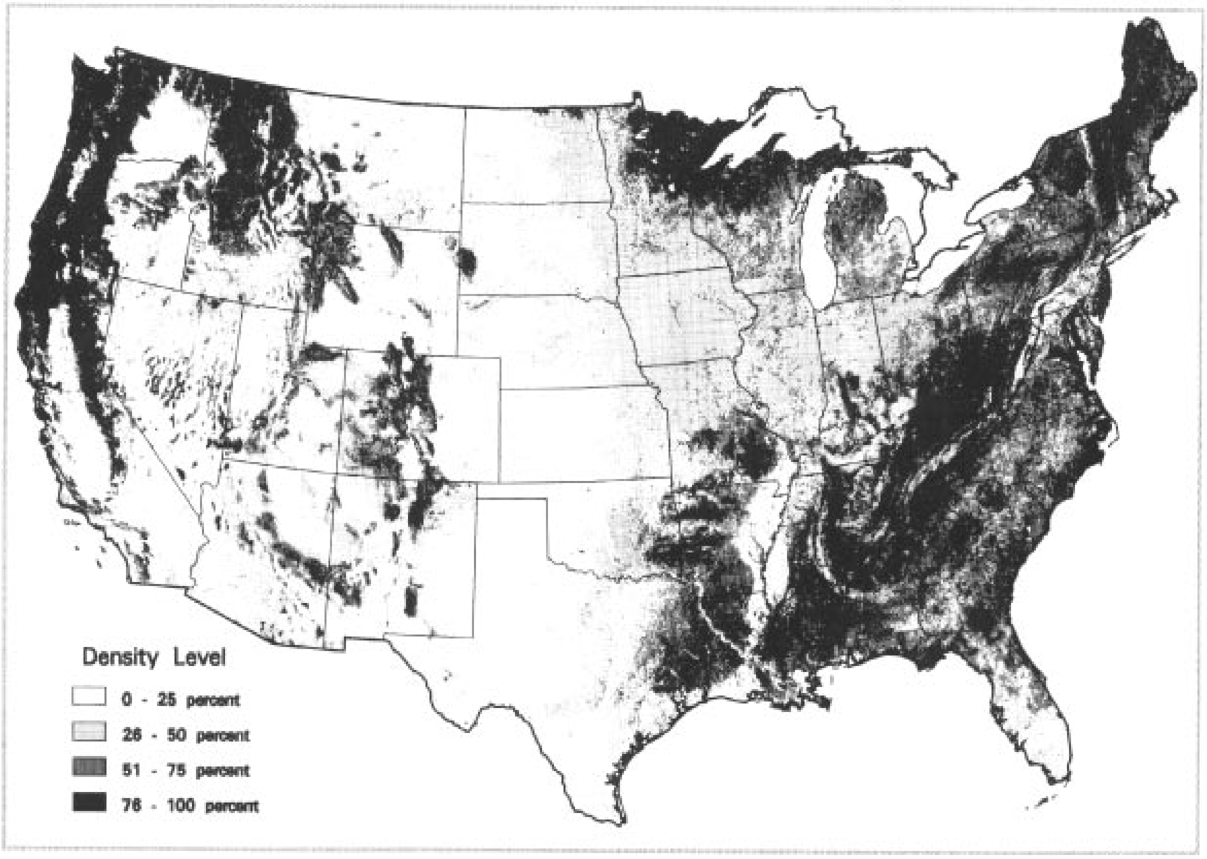

Figure 5.— *Forest density map of the conterminous United States.*

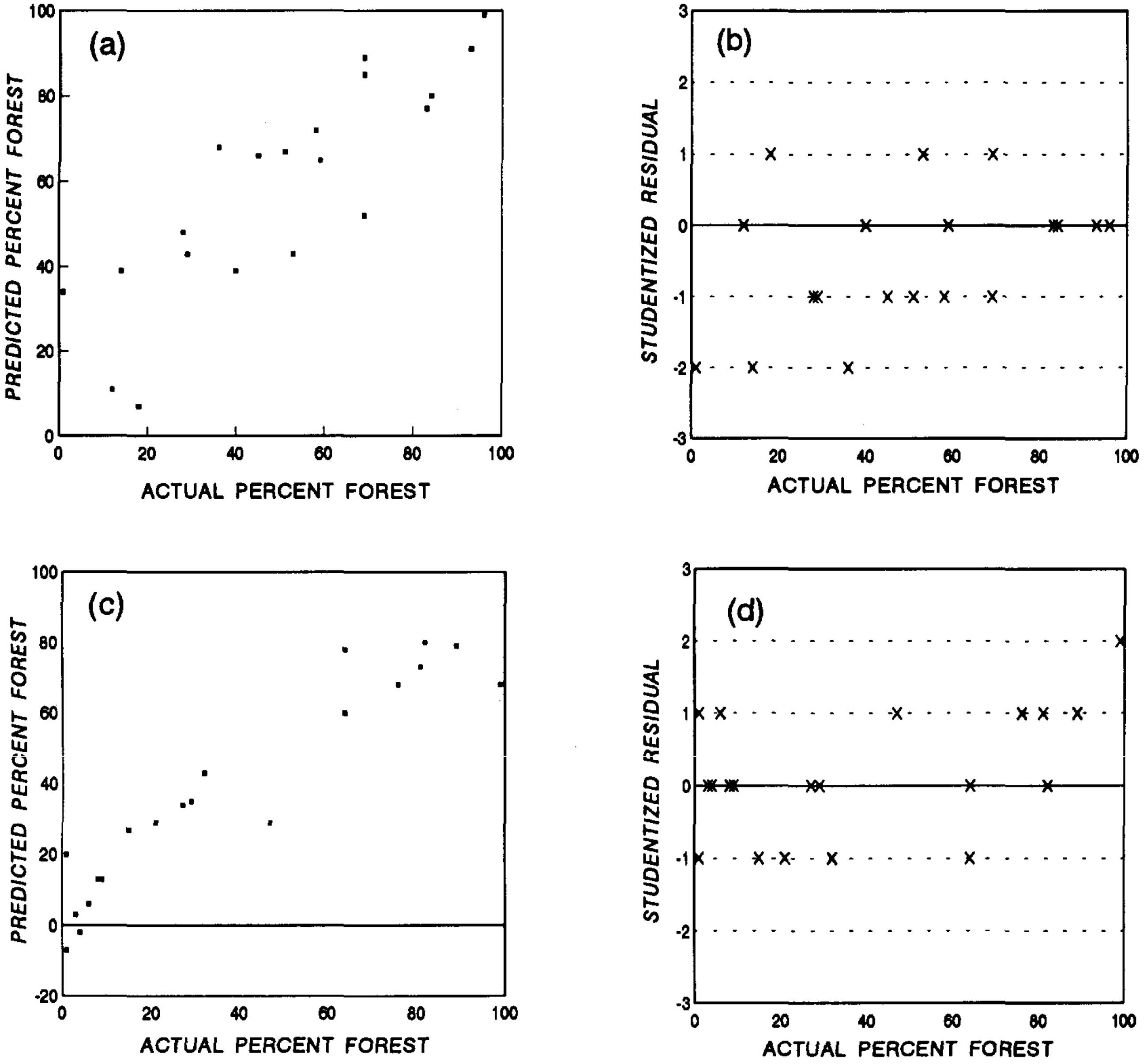

Figure 6.—*Scatterplots of two forest density regression models. Models are indicated by the abbreviations of the States in which the models are located. (See figure 2 for model locations.) For model AR, plots a and b are predicted versus actual and residual versus actual, respectively. For model SD, plots c and d are predicted versus actual and residual versus actual, respectively. Note residual values are studentized, that is, residuals divided by standard errors.*

mostly forest or mostly nonforest land covers will not be very effective due to the lack of representative samples of percentage of forest cover. To overcome these problems, one may consider using different seasonal data or other types of spectral data with improved spectral separability.

During the process of building a forest density model using the regression techniques, a number of parameters were considered in evaluating the model's effectiveness, including correlation coefficients of selected variables, p-value and R^2; R^2 is the proportion of the dependent variable's total variance that can be explained by the model. Often, there were questions of how to judge the value of R^2 and how to use it in choosing models. In this project, it was recognized that the magnitude of R^2 was affected by the different types of data involved and by many other variations (haze, change in viewing angles, etc.) inherent to a project of land observations. Given these natural variations, it would be normal to expect R^2's in this context to reach a reasonable height but not a near perfect value (i.e., close to 1), as illustrated by the range of R^2 values obtained from this project (fig. 4). Thus a minimum value of 0.50, above which a model was acceptable, was optionally set in the project. The R^2 values lower than 0.50 were considered an indication of potential systematic errors (e.g., AVHRR/TM misregistration) during the model-building process. Solutions to this problem included development and testing of polynomial models, a careful study of the calibration area to adopt a new window, and reexamination of the georectification process to make sure that no error was due to a mismatched pair of AVHRR/TM images.

Another problem that required special attention in the density mapping process was the treatment of water bodies of various sizes. Most large water bodies had consistent spectral properties (e.g., low reflectance in the near-infrared and low temperature in the thermal band), which necessarily led to forest density values around zero. However, a great deal of spectral variation existed in medium-to-small water bodies, which could result in high density values for these small (compared to AVHRR pixel size) lakes or reservoirs. Although this problem may be related to the water bodies' physical characteristics, such as sediment content, it was beyond the scope of this project. A complete water layer was created by using a water mask to overlay the forest density pixels.

Forest percentage values ranged from 0 to 100 percent as determined by classified TM pixels. Often, a regression model could cause the resulting predicted forest density values to fall out of the range limit. That is, a forest density value could be less than 0 or greater than 100 percent when a regular model was directly applied. This problem can be seen in figure 6, plot c, where negative values were predicted. If necessary, such a tendency may be prevented by using a constrained model in which specifications on the intercept and model coefficients would restrict predicted values from exceeding the a priori known value range. In this project, however, all models were unconstrained. Predicted values less than 0 were automatically converted to 0 by the digital image processing software package; predicted values greater than 100 were truncated to 100.

In future studies, the forest density mapping approach as described in this paper may be used to estimate forest acreage data. Presently, forest area estimates from AVHRR spectral classifications often yield mixed results in sparsely forested regions (e.g., the Plain States) or over small areas (e.g., a county). Because forest density is a measurement of the amount of forest at the subpixel level, it will be desirable to see how well forest density mapping can improve at this level.

CONCLUSIONS

The forest density mapping procedure described in this paper was an integral part of the RPA mapping project, which was interrelated with other processes and considerations (e.g., regional stratification, multitemporal data sets, and spectral band selection). The procedure provided a different and complementary type of information on the forest land distributions in the lower 48 States. Forest density was used as an ancillary data layer to assist in forest type group classification. It was the first time that a forest density mapping procedure was applied to such a large area and that a conterminous United States forest density map was created.

The regression analysis of AVHRR and TM data was just one approach to the mapping of forest canopy densities. The effective role it played in the RPA forest mapping project was associated with the characteristics of the two data types that were suitable for vegetation mapping of large areas. There are other methods that may be more useful for other sensor types or in other applications. It is important to realize the basic assumptions and limitations associated with each method.

There may be many other uses for the forest density map in addition to the roles played in the RPA forest type group classification. For example, one may attempt to understand differences in spatial distribution patterns of forest type groups at the landscape level by studying spatial statistics of forest density values that correspond to these forest type groups. The forest density mapping approach is also a useful tool for defining the extent of forest lands in different regions or countries, which can be important for a global change study coordinated among countries that have varying forest land definitions. Entomologists may be able to devise a contiguous canopy model based on the density map for their studies forecasting the spread of forest insects.

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Appendix

Table A1.—*Selected regression models used in the forest density mapping process*

Region	TM*	R^2	Model †
2	CA	0.71	– 489.1966 + 3.9649(AV61) – 3.7289(AV62) + 4.4256(AV65) – 1.1576(AV71) + 0.7616(AV85)
4	ID	0.79	– 60.9285 – 0.9014 (AV61) – 0.7761 (AV64) + 1.9747(AV71) – 1.5588(AV72) + 1.6517(AV75) + 0.8073(AV85)
5	CO	0. 50	– 111.3565 – 0.0662 AV32) + 0.6567(AV41)– 0.6581(AV42) + 1.7625(AV45) – 0.4679(AV53) – 0.5078(AV74) + 1.0402(AV75)
7	SD	0.85	– 551.5842 – 0.0768(AV23) – 0.2513(AV33) + 0.7059(AV35) – 0.1232(AV52) – 0.1266(AV72) + 3.5067(AV81) – 2.5331(AV82) + 4.8239(AV85)
9	KS	0.65	– 134.115 – 0.0202(AV11)(AV11) + 0.0212(AV12)(AV12) + 0.0425(AV15)(AV11) –0.0481(AV15)(AV12) + 0.0206(AV15)(AV15) – 0.0025(AV82)(AV44) – 0.006(AV84)(AV83) + 0.0101(AV85)(AV84)
9	TX	0.55	– 139.7329 + 0.0187(AV81)(AV55) – 0.0301(AV82)(AV15) + 0.0599(AV82)(AV51) – 0.0195(AV83)(AV51) + 0.019(AV85)(AV15)
10	AR	0.75	– 17.9352 – 0.5415(AV22) + 1.1951(AV55) – 1.2245(AV81) – 0.2842(AV83) – 0.8441(AV92) – 0.9099(AV94) + 1.8732(AV95)
11	MS	0.63	184.454 – 0.2563(AV12) – 0.3874(AV72) + 0.9961(AV75) – 0.7288(AV82) – 1.2555(AV83) + 0.6008(AV85)
12	TN	0.65	– 94.0381 + 1.9229(AV11) – 1.9712 (AV12) + 2.3352(AV15) – 0.2695(AV22) + 0.8202(AV55) – 1.0309(AV82) – 0.7322(AV83)
15	LA	0.63	– 547.0699 – 0.3704(AV23) + 1.4606(AV71) – 0.9514(AV72) + 1.4108(AV75) + 3.5221(AV81) – 2.8542(AV82) – 0.4498(AV83) + 4.8253(AV85)

*Thematic Mapper (TM) scenes are indicated by the abbreviations of the States in which these TM Scenes are located.

† Advanced Very High Resolution Radiometer (AVHRR) channels in the equations are designated by their data set number (see table 2) and spectral channel number (channels 1 through 4 are regular AVHRR spectral channels, channel 5 is the normalized difference vegetation index channel). For example, AV61 represents AVHRR data set 6, channel 1.

Table A2.—*Comparison of estimates of forest area percentages derived from 1993 Forest and Rangeland Renewable Resources Planning Act (RPA) Forest Inventory and Analysis survey data (FIAPF) and from the Advanced Very High Resolution Radiometer (AVHRR) forest type group map (AVPF), by State (ST)*

ST*	FIAPF	AVPF	Bias †	ST*	FIAPF	AVPF	Bias†
AL	67.65	67.86	0.21	MT	24.17	24.75	0.58
AK	35.35	28.05	–7.32	NE	1.47	1.15	–0.32
AZ	26.94	25.41	–1.53	NV	12.72	12.94	0.22
AR	53.60	51.07	–2.53	NH	86.78	88.75	1.97
CA	37.33	39.63	2.30	NJ	42.27	43.38	1.11
CO	32.14	32.71	0.57	NM	19.69	25.18	5.49
CT	58.66	58.19	–0.47	NY	61.92	64.08	2.16
DE	31.10	34.38	3.28	NC	61.83	64.20	2.37
FL	7.89	44.41	–3.48	ND	1.05	0.98	–0.07
GA	65.12	69.27	4.15	OH	30.00	31.91	1.91
HI	42.52	39.88	–2.64	OK	12.04	15.35	3.31
ID	40.82	43.94	3.12	OR	45.57	46.61	1.04
IL	11.99	12.30	0.31	PA	59.16	60.60	1.44
IN	19.34	21.16	1.82	RI	59.94	59.15	–0.79
IA	5.73	3.04	–2.69	SC	63.60	66.91	3.31
KS	2.60	1.13	–1.47	SD	3.48	3.60	0.12
KY	50.00	47.72	–2.28	TN	51.60	50.11	–1.49
LA	49.72	47.95	–1.77	TX	11.45	11.73	0.28
ME	88.76	90.04	1.28	UT	30.87	29.57	–1.30
MD	42.89	43.38	0.49	VT	76.66	74.78	–1.88
MA	63.86	64.14	0.28	VA	62.57	61.50	–1.07
MI	50.20	55.00	4.80	WA	48.07	48.90	0.83
MN	32.81	35.93	3.12	WV	78.68	75.99	–2.69
MS	56.62	59.18	2.56	WI	44.63	41.38	–3.25
MO	31.77	30.05	–1.72	WY	16.04	18.22	2.18
Mean					41.03	41.35	1.95
Standard deviation					22.76	22.92	1.47
Minimum					1.05	0.98	0.07
Maximum					88.76	90.04	7.32

*State names are alphabetized according to abbreviation.

† AVPF minus FIAPF.

Zhu, Zhiliang. 1994. Forest density mapping in the lower 48 States: a regression procedure. Res. Pap. SO-280. New Orleans, LA: U.S. Department of Agriculture, Forest Service, Southern Forest Experiment Station. 11 p.

A forest density map was produced for the lower 48 States using regression models and calibrated satellite image data.

Keywords: AVHRR, image modeling, Landsat TM, mixed pixels.

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