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Development of a Methodology for Predicting Forest Area for Large-Area Resource Monitoring

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Abstract

The U.S. Department of Agriculture, Forest Service, Southern Research Station, appointed a remote-sensing team to develop an image-processing methodology for mapping forest lands over large geographic areas. The team has presented a repeatable methodology, which is based on regression modeling of Advanced Very High Resolution Radiometer and Landsat Thematic Mapper data. It is a methodology that Forest Inventory and Analysis survey personnel can implement in any region or area. The term repeatable implies objectivity. Studies in the conterminous United States, Central America and Mexico, and west Texas and Oklahoma have provided valuable insights that address the subjective nature of some of the steps taken in mapping large forest areas. The team has identified seven such steps. They have reduced or eliminated subjectivity in four of the steps and identified two steps in which objectivity can be enhanced.

Keywords: AVHRR, ecoregions, FIA, Landsat, regression modeling, remote sensing.

Introduction

Lillesand and Kiefer (1987) defined remote sensing as the science and art of obtaining information about an object, area, or phenomenon. Their use of the term art raises questions about the reliability and repeatability of remote sensing. For various purposes, including compliance with the Forest and Rangeland Renewable Resources Planning Act (RPA), periodic updates of forest inventories of the United States are necessary. To help ensure those updates are accomplished, the Southern Research Station Forest Inventory and Analysis (FIA) remote-sensing team is developing methodologies that remove some of the subjectivity, or art, from the modeling process.

Zhu and Evans (1994) modeled percent forest canopy for the conterminous United States from Advanced Very High Resolution Radiometer (AVHRR) data that were based on calibration of Landsat Thematic Mapper (TM) data. In Mexico and Central America, Lannom and others (1995) made an effort to repeat and improve on their model. Current research focuses on application and additional refinement of this model in the semiarid and arid regions of Texas and Oklahoma. The evolution of a procedure to analyze AVHRR data for large-area analyses is described in this publication.

Evaluation of Procedures

Phase I—Initial Modeling Efforts for RPA

Zhu and Evans (1994) used AVHRR and TM data to model percent forest cover. The resulting maps displayed approximate percent forest cover per AVHRR pixel. Those pixels that had forest cover percentages above a certain minimum threshold value were classified by forest type. Generally, to be classified as forest, an area's within-pixel forest-cover had to be 20 percent or greater. Data for United States forest types and percent cover are now available on CD-ROM at the USDA Forest Service FIA office in Starkville, MS, and on the World Wide Web at http://www.srsfia.usfs. msstate.edu. The team has distributed about 200 of the CD-ROM's to organizations and individuals and over 25,000 of the hard-copy map *Forest Type Groups of the United States* (fig. 1). The team compared, by State, forest-area percentages derived from FIA survey data in the 1993 RPA with the AVHRR forest-type group map. They determined that forest area from the AVHRR data in the conterminous United States had been overestimated by 1.95 percent when compared to FIA survey data. Comparisons are illustrated in table 1 (Zhu 1994).

The modeling efforts used to create the *Forest Type Groups of the United States* map relied on multiple regression procedures. Regression models that were used to predict percent forest canopy were developed in part by classifying Landsat TM scenes to forest types, then aggregating those types into forest and nonforest classes. Landsat TM scenes were chosen on the basis of their location within physiographic regions. Zhu used a combination of Hammond's *Classes of Land Surface Form* and Fenneman's *Physical Divisions of the United States* to locate Landsat TM scenes (Hammond 1964, Fenneman and Johnson 1946).

Model development required that the team choose calibration windows common to both the Landsat TM and AVHRR data sets. These windows were considered to be representative of land-cover conditions within the physiographic regions. Advanced Very High Resolution Radiometer channels, channel transformations, and temporally separated channels became the independent

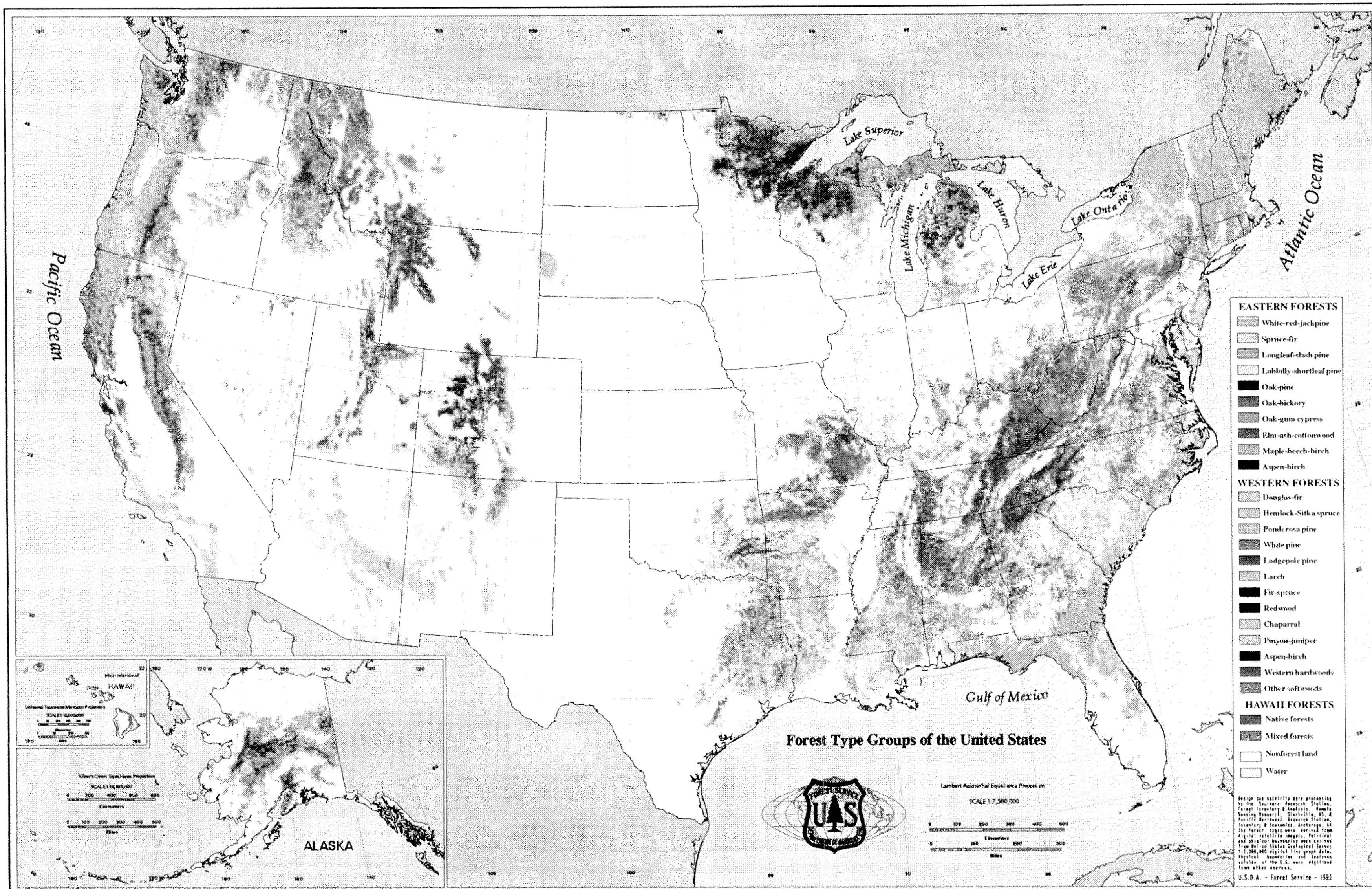

Figure 1—Forest type groups of the United States. (The color version of map is available on the World Wide Web at http://www.srsfia.usfs.msstate.edu/rpa/rpa93.htm.)

Table 1—Comparison of estimates of forest area percentages derived from 1993 Forest and Rangeland Renewable Resources Planning Act (RPA) Forest Inventory and Analysis data (FIAPF) and from the Advanced Very High Resolution Radiometer (AVHRR) forest type group map (AVPF), by State (ST)

ST[a]	FIAPF	AVPF	Bias[b]	ST[a]	FIAPF	AVPF	Bias[b]
AL	67.65	67.86	0.21	MT	24.17	24.75	0.58
AK	35.35	28.05	-7.30	NE	1.47	1.15	- .32
AZ	26.94	25.41	-1.53	NV	12.72	12.94	.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	.57	NM	19.69	25.18	5.49
CT	58.66	58.19	- .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	4.41	-3.48	NC	1.05	0.98	- .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	.31	PA	59.16	60.60	1.44
IN	19.34	21.16	1.82	RI	59.94	59.15	- .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	.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	.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	.28	VA	62.57	61.50	-1.07
MI	50.20	55.00	4.80	WA	48.07	48.90	.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	.98	.07
Maximum					88.76	90.04	7.32

[a] State abbreviations are alphabetized according to State names.
[b] AVPF minus FIAPF.

(predictor) variables. The dependent (predicted) variable was the percent forest canopy within the calibration window that was derived from the Landsat TM classification.

The selection of independent variables was based on an all-possible-combinations approach. Advanced Very High Resolution Radiometer channels and channel transformations constituted the pool of possible independent variables. The process of evaluating potential independent variables 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 the AVHRR bands. Combination models were tested, and models were chosen on the basis of highest R^2 among different levels of independent variable combinations.

Figure 2 illustrates essential steps of the modeling methodology. Statements in brackets, e.g., <Partitioning System>, denote steps at which subjective decision making must occur before the analyst proceeds to the next step. Within the methodology illustrated in figure 2, subjectivity is present at several steps, each of which will require closer

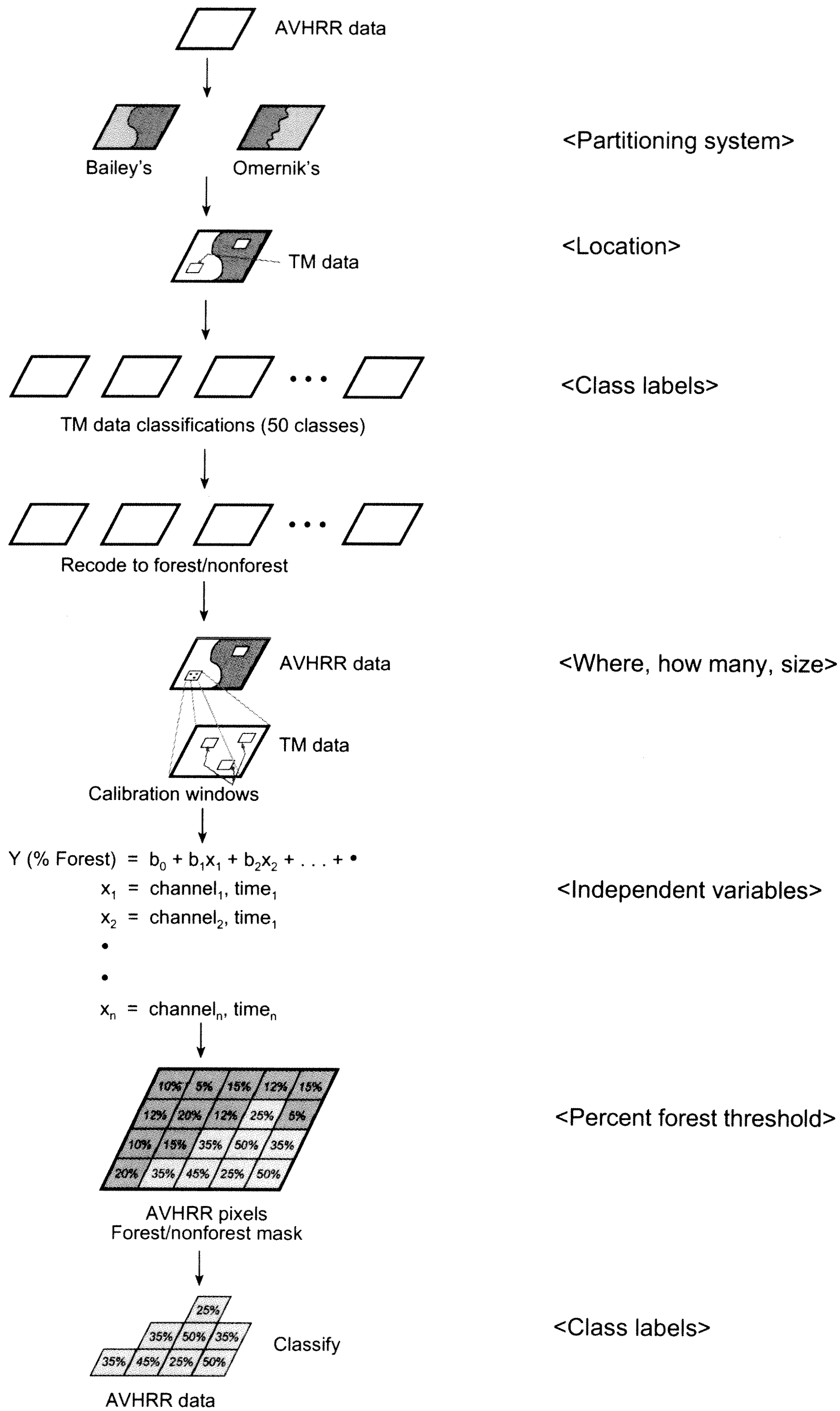

Figure 2—Essential steps of the modeling methodology.

examination: (1) choice of a landscape partitioning system; (2) location of TM scenes within the partitions; (3) class-labeling process for TM classifications; (4) number, size, and location of calibration windows; (5) independent-variable selection process; (6) choice of a percent forest canopy threshold; and (7) class-labeling process for AVHRR classification.

Choice of a landscape partitioning system—Landscape divisions may be based on changes in soils, physiography, climatic zones, elevation, and ecoregions, to name just a few. Choosing the most applicable landscape-partitioning system to determine land-cover classes and generate the digital data products necessary for study is a critical step. Jensen (1986) notes the general agreement that spectral signatures used in automated classification procedures become less representative of actual land-cover conditions when those statistical signatures are extrapolated over large distances.

Zhu (1994) used geographic data partitioning to reduce spectral variations among regional physiographic or ecosystem conditions and to emphasize spectral variations among local vegetation types. His choice of Fenneman's and Hammond's combined physiographic regions was purely subjective. He also considered using Powell's physiographic regions and Lobeck's physiographic provinces.

Location of TM scenes with partitions—Because a statistical signature becomes less representative of a land-cover class extrapolated over great distances (Jensen 1986), the analyst must carefully choose the location of TM scenes within each partition. Should TM scenes be chosen at partition boundaries, or should they be near the center of the area partitioned?

Class-labeling for TM classification—The analyst's knowledge of the geographic area and his or her access to reference imagery or photography and ground-verification information are critical. Class labeling is the assignment of names to the classes produced during the automated classification procedure. Reclassification or combinations of some classes may be necessary. Once labels have been assigned, classes are combined as forest or nonforest. At this step, distinctions between land use and land cover become important. For example, the image analyst's automated classification process may not enable differentiation between a clearcut and agricultural bare-soil conditions. If an analyst determines that an area will be replanted or allowed to revert to some natural forest condition, survey personnel in the field will classify a clear-cut as forest land. Conversely, if automated classification procedures were followed, both would probably be classified as bare soil.

Number, size, and location of calibration windows—The modeling process uses high-resolution data (TM) to predict percent forest canopy in areas for which low-resolution data (AVHRR) are available. To accomplish that, the analyst chose calibration windows over geographic areas common to both data sets. Those data serve as input for the modeling process, so the analyst chooses windows that are representative of actual land-cover conditions, as well as the number size, and location of those windows. If they are too small, TM and AVHRR coregistration errors may be a problem; if they are too large, statistical calculations may be extremely slow and file storage requirements may be difficult. The same concerns apply to the number of windows chosen to represent forest and nonforest classes. If calibration windows are too few, land-cover conditions may not be adequately sampled; if too many, performance and storage problems may occur. Therefore, the location of calibration windows should maximize information content while minimizing number and location.

Selecting independent variables—Zhu (1994) used an all-possible-combinations approach to independent variable selection. Although this is the only method guaranteed to find the best model, it requires fitting $2^k - 1$ models (k = the number of variables). Its disadvantages are computational inefficiency and the amount of time the scientist must spend assessing correlation matrices for all possible independent variable combinations. Other approaches include forward selection, backward elimination, and stepwise independent variable selection. These are automated procedures that quickly find the best possible combination of independent variables. One disadvantage of automated variable selection routines is that they are designed to give one answer without displaying the results on a large number of subset models (Myers 1990). It is also possible that the truly best model may not survive any of the automated procedures. Myers (1990) recommends automated independent variable selection when there is a large number of potential independent variables.

Choice of percent forest-cover threshold—The model produces an AVHRR image wherein each pixel represents a percentage of forest cover. Subsequent automated land-cover classifications of AVHRR data forest-type mapping are made for pixels that exceed some minimum percentage of forest cover, which the analyst chooses. Comparisons of forest-area estimates based on Zhu and Evans' (1994) work with FIA field-plot data are shown in table 1. Choice of the percent forest-canopy threshold directly affects such comparisons.

Class-labeling for AVHRR classifications—The concerns about class labeling for TM classifications (step 3) also apply to labeling AVHRR classifications. Whereas class labeling for TM classification efforts can sometimes be applied at the species level, class labeling for AVHRR classification efforts generally is applied at the major forest-type group level. The AVHRR class labeling process requires that the analyst is familiar with ecosystem processes that operated at the landscape level and also has a basic understanding of the distribution of forest-type groups associated with these processes.

Phase II—Application of Modeling Techniques in Mexico and Central America

The U.S. Agency for International Development (USAID) funded a land-cover classification study for Mexico and Central America, which provided an opportunity to replicate and improve modeling methodologies. The study resulted in valuable refinements to the modeling process.

Choice of a landscape partitioning system was subjective; therefore, no improvement was made in step 1 of the process.

The location of TM scenes was determined primarily by the availability of cloud-free imagery. In many parts of the world, persistent cloud cover prevents the acquisition of TM data in areas that are optimum for modeling purposes. Wherever possible, cloud-free TM scenes were recorded in or near the center of ecoregions, which allows the analyst to reduce problems tied to signature extrapolation. As greater geographic distances are traversed, land-cover class means and standard deviations may change. If TM scenes are acquired near the center of an ecoregion, forest-class means and standard deviations are more likely to be representative of the population for that region. However, the analyst should carefully weigh this conclusion against the appropriateness of the partitioning system for the forest or land-cover class. If time and budget constraints prevent the acquisition of a sufficient number of TM scenes to cover each ecoregion, they can be obtained between ecoregions.

The class-labeling process for Mexico and Central America points out a weakness in the methodology. Field visits to foreign countries are expensive, and reference data are often inaccurate or unavailable. Whenever possible, the analyst should closely involve an understudy expert that is familiar with local vegetation types in the TM class-labeling process. The analyst can then either classify TM scenes on location and send results to the SRS remote sensing team for modeling, or experts can travel to the data processing location.

The team tested the number, size, and location of calibration windows, although those tests were inconclusive. Mayaux and Lambin (1995) found that in tropical areas, a minimum 13 by 13 AVHRR pixel window minimizes coregistration problems. The team developed a new technique that significantly improved coregistration of calibration windows for the AVHRR and Landsat TM data sets—one that helps ensure the precise corner pixels. The ability to precisely locate corner pixels will, in turn, increase the probability of modeling success if the analyst selects numerous small calibration windows rather than a few large ones.

The team developed automated routines for importing cell values from calibration windows into the statistical software. Once cell values have been exported from the image processing system in ASCII format, these routines reformat the data into data frames appropriate to the S-Plus[2] statistical software. Although these routines do not specifically address an area of subjectivity, they indirectly impact subjective processes by enabling scientists to allocate more time to areas of subjectivity.

Stepwise independent-variable selection procedures were used for this study. Automated variable selection procedures have both strengths and weaknesses. Speed is an obvious strength of forward and backward automated selection procedures. Stepwise selection is a modification of the forward selection technique that permits reexamination of the variables incorporated into or dropped from the model in earlier steps. A partial F-test for each variable is computed as though it was the most recent variable entered. This technique is a good compromise between the calculation inefficiency of the all-possible-combinations approach; and the forward or backward selection techniques are chosen strictly on the basis of their computational efficiency.

The analyst arbitrarily chose the percent forest-canopy threshold values. Comparisons of the percent forest area map (fig. 3) with forest-cover maps (where available) formed the basis for the threshold value choice. As a result, the analyst did not reduce subjectivity at this stage in the modeling process.

Labeling of the AVHRR classifications followed conventions established for major forest-type groups in Mexico and Central America. The requirement that forest-type groups fit

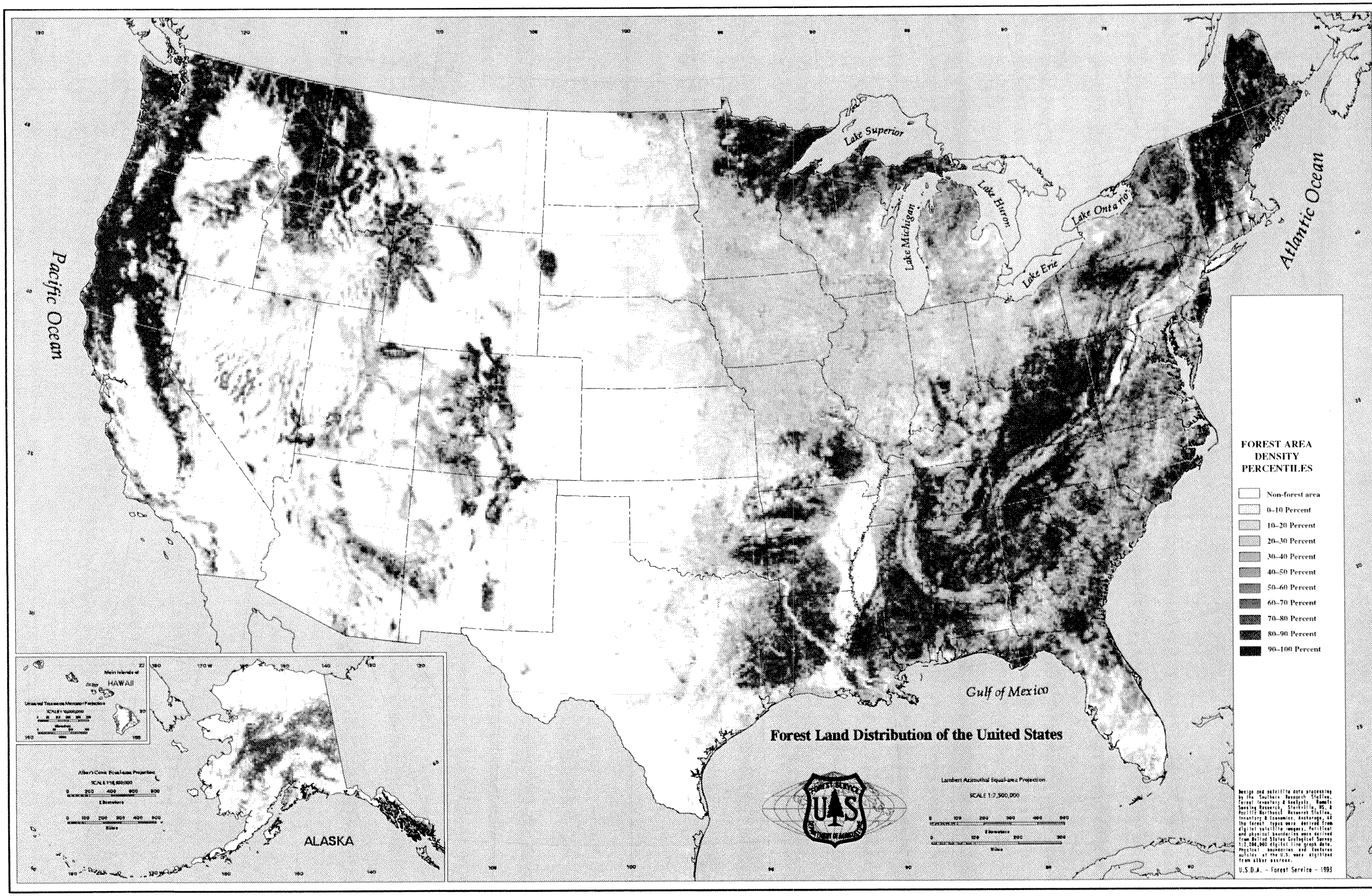

Figure 3—Percent forest area for the United States. (The color version of map is available on the World Wide Web at http://www.srsfia.usfs.msstate.edu/rpa/rpa93.htm.)

categories determined *a priori* is a major complication at this stage. Fitting the classes to predetermined categories implies that these categories (major forest-type groups) actually exist on the landscape at the AVHRR data resolution (1-km pixels).

The modeling process is now complete, and the project manuscript "Forest Mapping of Central America and Mexico with AVHRR Data," has been accepted for publication by Geo Carta International. The forest-type maps for Mexico and Central America have been completed and are available from the USDA Forest Service, Southern Research Station, 101-A G.T. Thames Drive, Starkville, MS 39759.

Phase III—Application of Modeling Techniques in the Semiarid and Arid Regions of West Texas and West Oklahoma

The SRS remote sensing team further refined the modeling process in west Texas and Oklahoma, incorporating methodological improvements made in earlier studies. The team's primary focus in this study concerned the choice of a landscape partitioning system, a choice that impacts the entire methodology. Zhu (1994) used geographic data partitioning to reduce spectral variations among regional physiographic or ecosystem conditions and to emphasize spectral variations among local vegetation types. Spectral variations among different regional conditions are minimized if the landscape partitioning system accurately reflects forest-cover conditions.

The team has completed quantitative tests of the general effectiveness of partitioning and has presented its findings at the Sixth Forest Service Biennial Conference of Remote Sensing (Cooke 1996). Calculation of Jeffries-Matusita (J-M) distances for woody and nonwoody vegetation spectral classes was the basis of the quantitative tests. The J-M test measures the distance (separation) between the means and variances of spectral classes to determine their statistical "uniqueness." The team tested pixels representing all woody and nonwoody areas within each adjacent pair of landscape partitions. In that complete enumeration of the pixel population, the team found that landscape partitioning using Bailey's ecoregions improved the distinction between woody and nonwoody vegetation. Figure 4 illustrates Bailey's ecoregions and shows the locations of TM scenes used in regression modeling. Ecosystems 315B and 315C are illustrated by red text in figure 4 as representative of partitioning effectiveness in two adjacent ecoregions. Random statistical sampling tests of the variability of the J-M divergence test results confirm the results of the partitioning tests based on the completely enumerated population (Cooke 1997). Figure 5 depicts the improvement partitioning makes in woody and nonwoody spectral class separability. Figure 6 displays results of the 1-percent random statistical tests of variability in the J-M distance test for Bailey's ecoregions 315B and 321A.

Bailey's ecoregions also were found to be more useful than Omernik's system in separating mesquite (fig. 7). These results reveal the importance of Bailey's inclusion of a climatic variable, which may account for the east-west climatic gradient that impacts plant-community distribution in Texas (Norwine and Greegor 1983).

To complete labeling for TM classifications, the team acquired land-cover information from several sources, including extensive natural color video data and National Aerial Photography Program (NAPP) stereo pairs within each TM scene. The Texas Parks and Wildlife Department supplied hard-copy maps and digital Geographic Information System (GIS) files of the "Vegetation Types of Texas." The team is still seeking analysts who have extensive knowledge of the plant communities and ecosystem processes in the study area.

Stepwise variable selection procedures were used, and tests of number, size, and location of calibration windows were performed. These tests substantiated the work of Mayaux and Lambin (1995), which indicates only marginal improvements in models using windows larger than 13 by 13 pixels.

Choice of a percent forest-canopy threshold remains a major concern in west Texas and west Oklahoma. Initial efforts have concentrated on differentiating woody from nonwoody vegetation. It is likely that field crews will be needed for determining which woody vegetation classes represent forest as defined by the Forest Service.

Phase IV—Future Modeling Improvements

Data for inventoried areas, which have been published in FIA reports and the RPA, are in agreement in most States (table 1) and indicate extremely high agreement for the areas inventoried by field crews. For prediction of forest area in regions of the United States where FIA field inventory data exist, correction of regression models by field data may be possible. However, analysts should use caution in developing correction factors; those comparing field data with remotely sensed data should only be used when the data are gathered at the same time. Ideally, the data should be collected in the same calendar year. Forest Inventory Analysis survey cycles should be taken into consideration

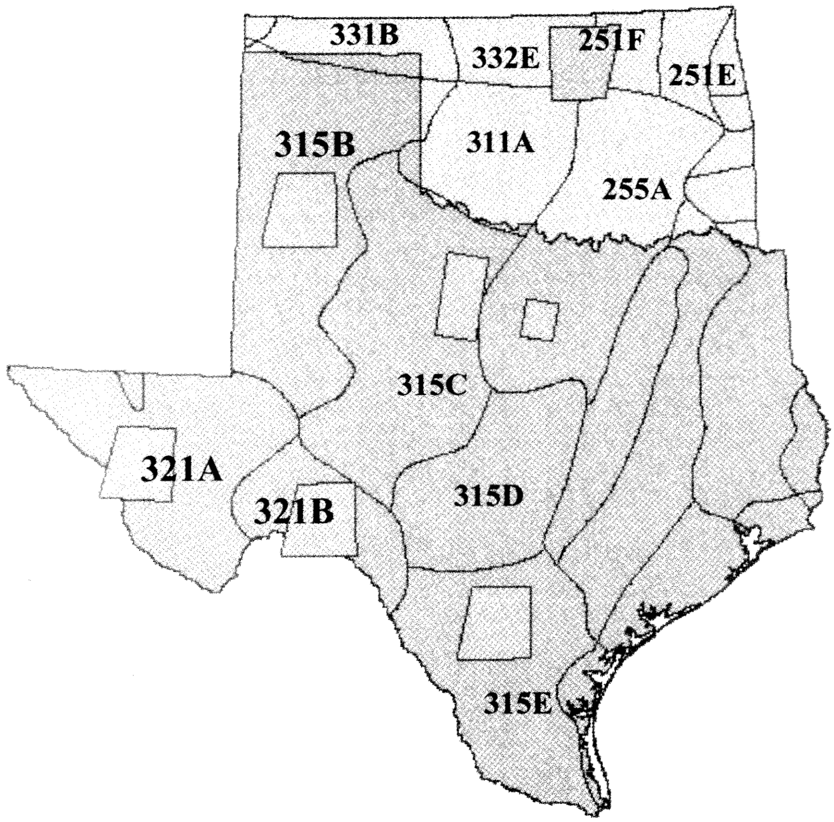

Figure 4—Bailey's landscape partitions used to test partitioning effectiveness. Boxed areas represent Landsat TM scenes used for regression modeling.

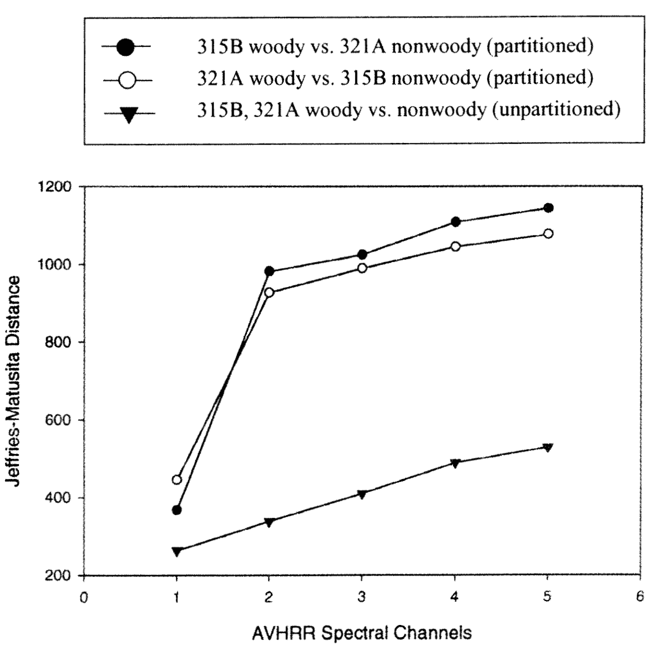

Figure 5—Mean Jeffries-Matusita separability of Bailey's adjacent partitioned ecoregions 315B and 321A versus unpartitioned ecoregions 315B and 321A combined, AVHRR data.

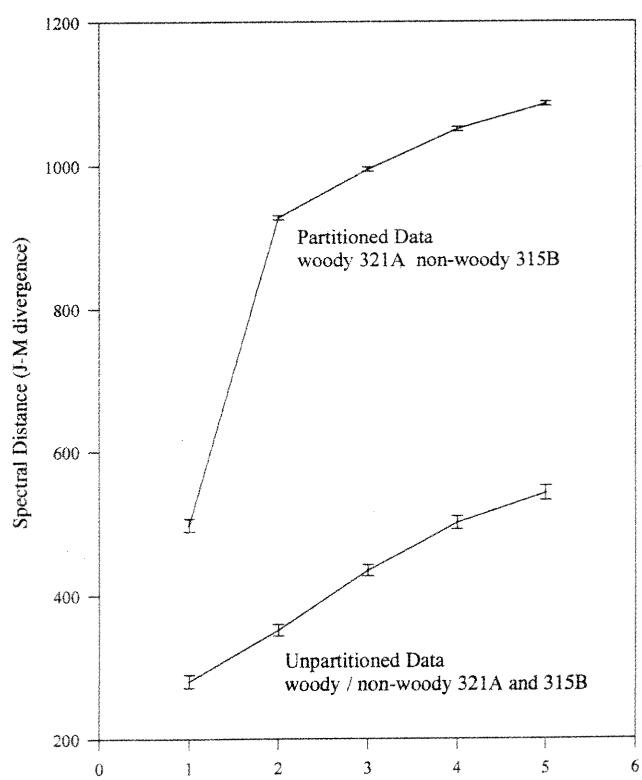

Figure 6—Means and confidence intervals for 1 percent random tests of woody vegetation within Bailey's ecoregions 315B versus nonwoody vegetation within Bailey's ecoregion 321A ($\alpha = 0.05$).

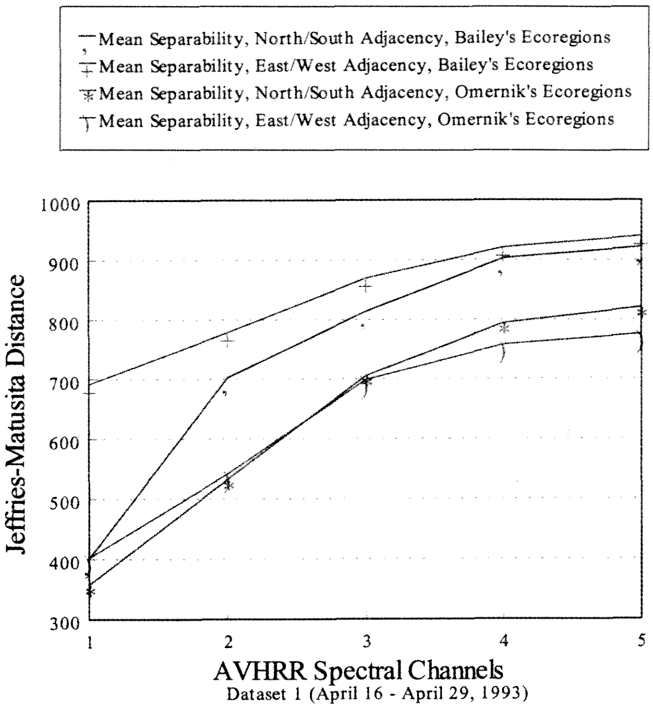

Figure 7—Mean Jeffries-Matusita separability of Bailey's ecoregions versus Omernik's ecoregions.

when the described modeling techniques are used for predicting forest area. Advanced Very High Resolution Radiometer and TM imagery should be contemporaneous with field inventories.

If data are collected at nearly the same time, correction factors can be used to make midcycle updates of forest area using the modeling methodology alone. This would ensure the best possible midcycle estimates of forest area using the AVHRR and TM modeling process. Recalculation of correction factors should be done during the next combined FIA field survey and remote sensing modeling study. If the Southern Annual Forest Inventory System (SAFIS) were implemented in all 13 Southern States, the 5-year completion cycle for each State would further facilitate calculation of those correction factors.

Accuracy Assessment Procedures—Accuracy assessment of classifications of AVHRR data for forest area and forest type employs the technique of cross validation. Calibration windows of the TM imagery that are used for modeling are considered as samples drawn without replacement. Windows from other regions of the TM data, which were not used for modeling, are used to test the model's performance. R-squared values indicate the performance of a model over an ecoregion and indirectly indicate the accuracy of the modeling results. Other sources of data may also be used for accuracy comparisons.

To test classification accuracy in estimating forest area, Lannom and others (1995) compared interpreted aerial photography with AVHRR classifications. Estimates made by photo interpreters did not differ significantly from those made through analysis of AVHRR data within calibration windows to a 1000-m cell size. Grayscale images are created from the AVHRR and TM data within the calibration windows. Visual and quantitative comparisons of the grayscale images' frequency distributions are indicative of classification accuracy. Replication of this procedure in areas for which both AVHRR and TM imagery are available—but not within the calibration windows—requires a combination of cross validation and grayscale comparisons.

Because the pixel size of AVHRR data is so large and the spectral mixing of land-cover classes within each 1000-m pixel may be extensive, field verification of those data is extremely difficult. However, field verification of TM classifications, aerial photography, and video imagery is important in validating the results of TM reference data.

Accurately located FIA plot data should be used to verify Landsat TM classifications and ancillary data sources that refine the TM classifications. Unfortunately, AVHRR/TM modeling efforts are hampered in west Texas and west Oklahoma by the absence of a field-based forest inventory.

Conclusions and Recommendations

No discussion of error or confidence intervals for estimates of forest area and type derived from this methodology is presented in this paper, nor does it imply that the removal of subjective decisionmaking will improve the accuracy of estimates. The methodology does, however, reduce subjectivity at four of seven major decision-making points; and reduction of subjectivity is possible at two others. Although reduced subjectivity does not necessarily improve the accuracy of data, a greater degree of repeatability ensures a more consistent product and facilitates comparisons across geographic regions and among data sets.

Large-area mapping projects based on modeling TM and AVHRR data would benefit from the expertise of remote sensing specialists who are familiar with the landscape and ecology of an entire FIA region.

Accuracy assessment of AVHRR classifications is difficult using traditional field methods. Nonetheless, field measurements should be used to verify Landsat TM classifications and the ancillary data used in refining those classifications.

The first phase of sampling design is based on the forest/nonforest interpretation of recent aerial photography of temporary plots that represent about 230 acres (Kelly 1991). These areas are compatible, and the AVHRR data can be used to classify the area between temporary plots. The AVHRR data are available for about $32 per year; and temporal data composites enable the monitoring of phenological changes in land-cover classes over any given time.

Forest area estimation procedures are not consistent among FIA regions. Valid comparisons of the results of this methodology for different geographic areas are compromised by this inconsistency.

Finally, what does or does not constitute forest land is an issue that cannot be resolved by remote sensing. Although data so gathered can yield information about forest canopy spectral conditions, determining forest area on multiple-use lands and within urban, semi-arid, or arid areas is problematic.

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The Forest Service, United States Department of Agriculture (USDA), is dedicated to the principle of multiple use management of the Nation's forest resources for sustained yields of wood, water, forage, wildlife, and recreation. Through forestry research, cooperation with the States and private forest owners, and management of the National Forests and National Grasslands, it strives—as directed by Congress—to provide increasingly greater service to a growing Nation.

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