A STRATEGY FOR ESTIMATING TREE CANOPY DENSITY USING LANDSAT 7 ETM+ AND HIGH RESOLUTION IMAGES OVER LARGE AREAS†

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ABSTRACT

Forest cover is of great interest to a variety of scientific and land management applications, many of which require not only information on forest categories, but also tree canopy density. In previous studies, large area tree canopy density had been estimated at spatial resolutions of 1km or coarser using coarse resolution satellite images. In this study, a strategy is developed for estimating tree canopy density at a spatial resolution of 30 m. This strategy is based on empirical relationships between tree canopy density and Landsat data, established using linear regression and regression tree techniques. One-meter digital orthophoto quadrangles were used to derive reference tree canopy density data needed for calibrating the relationships between canopy density and Landsat spectral data. This strategy was tested over three areas of the United States. In general, models derived using both linear regression and regression tree techniques were statistically significant. The regression tree was found more robust than linear regression, primary due to its capability of approximating complex non-linear relationships using a set of linear equations. This strategy will be recommended for use in developing a nation wide tree canopy density data set at a 30 m resolution as part of the Multi-Resolution Land Characteristics 2000 project.

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1.0 INTRODUCTION

The Multi-Resolution Land Characteristics (MRLC) consortium was initiated in early 1990s to address the need for consistently developed national and regional land cover data (Loveland and Shaw, 1996). Through this consortium, a 1992-vintage National Land Cover Dataset (NLCD) was developed for the conterminous United States (Vogelmann et al., 2001), and a second generation National Land Cover Dataset (NLCD 2000) will be developed using 2000-vintage Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images and ancillary data. The 2000 NLCD will consist of a suite of data layers relevant to many applications, including a tree canopy density layer describing percentage of tree canopy cover within each 30 m pixel. As a continuous variable, this tree canopy density layer is proposed in addition to a land cover classification to better characterize subtle variations of tree canopy and to meet the increasing needs for continuous measures of land cover components (DeFries et al., 1995).

Previous efforts to estimate tree canopy density as a continuous variable have utilized linear spectral mixture analysis (SMA) or linear regression techniques (e.g. Iverson et al., 1989, Zhu and Evans, 1994, DeFries et al., 2000). Other techniques such as physically based models and fuzzy logics have also been explored but are probably premature for use over large areas (e.g. Li and Strahler, 1992, Baret et al., 1995, Maselli et al., 1995). A major disadvantage of SMA is that it cannot predict tree canopy density directly, because tree canopy is not a spectral end-member (Roberts et al., 1993). Both linear SMA and linear regression use linear models to approximate the relationships between spectral signal and canopy density. However, such relationships are often very complex and highly variable, especially over large areas (e.g. Ray and Murray, 1996). This is partly due to multiple scattering effects and the highly spatially variable spectra of tree canopy and other surface materials (Borel and Gerstl, 1994). This problem may be partially alleviated using non-linear regression techniques. However, many nonlinear regression techniques require prior knowledge on the nonlinear form of a relationship (Gallant, 1987), which may be spatially variable and often unknown for land cover analysis. The regression tree technique, however, may be appropriate for this purpose because it could potentially approximate complex relationships using a set of linear models, which were found more accurate than a single linear regression model (Huang and Townshend, 2001). Therefore, we propose a strategy for deriving tree canopy density at intermediate spatial resolutions using this technique. We tested its applicability over large areas in three study areas located in Virginia, Utah and Oregon of the United States.

2.0 METHODOLOGY

The overall approach of the proposed strategy consists of three key steps: deriving reference data from high resolution images, calibrating canopy density models using the derived reference data, and extrapolating the developed models spatially using 30 m resolution images (figure 1). Considering the extremely high cost of intensive fieldwork over large areas, deriving reference data from high-resolution images was common in previous studies (e.g. DeFries et al., 1997). In this study we used 1 m Digital Orthophoto Quadrangle (DOQ) images for reference data development and 30 m ETM+ images for model extrapolation.

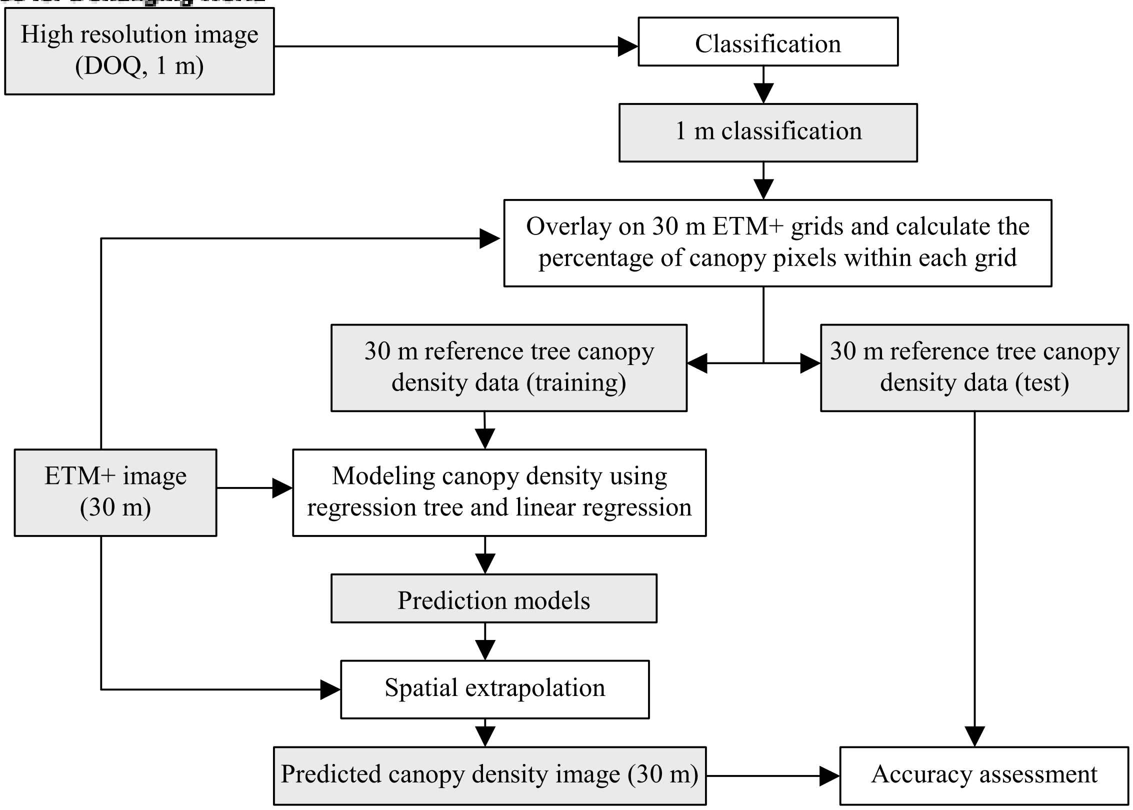


Figure 1. A flowchart of the strategy for deriving 30 m tree canopy density data. Data layers and models are in the gray boxes and operation procedures in the white boxes.

2.1 DATA AND STUDY AREAS

Three study areas were selected to evaluate the proposed strategy, each covering two ETM+ path/rows and representing a different landscape and ecological condition (table 1). For each ETM+ path/row, a summer leaf-on image and a fall/winter leaf-off image were used as model input. Improved land cover characterization using multi-temporal scenes has been reported in previous studies (e.g. Coppin and Bauer, 1994). Radiometric calibration and geometric and terrain correction of the ETM+ images were performed at the EROS Data Center of the United States Geological Survey (USGS) using standard methods (Irish, 2000). The digital number values of the six ETM+ spectral bands were converted to at-satellite reflectance according to Huang et al. (2001) in order to reduce data noise arising from changing illumination geometry. The high gain thermal band (band 9) was resampled from 60 m to 30 m and converted to at-satellite brightness temperature according to Irish (2000). These bands were used to develop tree canopy density models and to spatially extrapolate them.

Table 1. Study areas and selected ETM+ images

Location	Path	Row	Leaf-on date	Leaf-off date
Virginia	15	34	Jul. 28, 1999	Nov. 17, 1999
	16	34	Jul. 19, 1999	Nov. 8, 1999
Utah	38	31	Aug. 14, 1999	Oct. 17, 1999
	39	31	Jul. 4, 1999	Oct. 24, 1999
Oregon	45	29	Jul. 30, 1999	Dec. 21, 1999
	46	29	Aug. 22, 1999	Dec. 28, 1999

For each study area, 8 – 9 DOQ images were used for deriving reference data. Produced by the USGS, the DOQ image was scanned from color infrared or black and white panchromatic aerial photograph with high-resolution scanner[1]. The selected DOQ images over the Virginia area were color infrared, containing the green, red and near infrared bands. Those over the other two areas were black and white panchromatic. From each image a window of 1800 m by 1800 m was identified. These DOQ image windows were visually selected to capture spatial, spectral and tree canopy density variations in each area, and to avoid areas where observable land cover changes occurred between the acquisition of the DOQ and the ETM+ images. The acquisition dates of the selected DOQ images varied from late 1980s to mid-1990s. Misregistration errors between the DOQ images and the ETM+ images were generally less than 1 ETM+ pixel.

2.2 REFERENCE DATA DEVELOPMENT

Reference canopy density data were derived from classifications of the 1 m DOQ images derived using a decision tree classifier. This classification method was selected because it has several advantages over some other classifiers, including the maximum likelihood classifier and neural networks. Decision tree classifiers are fast. They can handle categorical data, and as non-parametric classifiers, are not limited by the statistical distribution of class signature (Hansen et al., 1996, Friedl and Brodley, 1997). The classification program used in this study was C5. This program recursively partitions training samples into homogeneous subsets according to a gain ratio criterion (Quinlan, 1993). For this study, three broad classes: tree canopy, non-canopy and shadow were differentiated from the DOQ images. Shadow was identified as a target class because it could not be unambiguously considered as any of the other classes in the following calculation of canopy density. Where water existed, it was also classified. Training points were visually identified from the DOQ images based on visual interpretation.

In order to increase class separability, 3×3 and 5×5 standard deviation textures were calculated according to Haralick et al. (1973). Two additional textures were derived by normalizing the standard deviations by the center pixel's gray scale value. These texture measures were not necessarily the optimal ones, but as will be discussed in section 3.3, were found useful for classifying the DOQ images. For color infrared DOQ images, the red band was used to calculate the above textures.

The initial classifications developed using the C5 program was evaluated using cross validation, a technique designed to obtain reliable accuracy estimates when only limited reference samples are available for both training and accuracy assessment. For an *N*-fold cross validation, one *N*th of the reference points are randomly selected and reserved for accuracy assessment, and the classification model is developed using the remaining points. This training and accuracy assessment process is repeated *N* times. Each time the test points are selected using a different randomization seed. The mean accuracy of the *N* experiments represents the accuracy of the classification model developed using all reference points. A 5-fold cross validation was deemed sufficient for obtaining objective accuracy estimates for classifying the DOQ images.

Because the reference data needed to be as accurate as possible, the above classifications were hand edited to correct for some misclassification

[1] Detailed information on the DOQ images is available at http://edc.usgs.gov/glis/hyper/guide/usgs_doq.

errors. Thirty-meter reference canopy density data were derived by overlaying the edited 1 m classifications on ETM+ grids and calculating the percentage of 1 m canopy pixels within each grid. Shadow pixels were ignored in the calculation, i.e., they were not counted in either the numerator or the denominator, as it was generally unable to determine the land cover type under a shadow. Each 1800m × 1800m DOQ image window resulted in a 30 m reference tree canopy density image of 60 × 60 ETM+ pixels. In order to avoid introducing any additional misregistration error, the corner coordinates of the pixels in the derived reference canopy density images were made to match those in the ETM+ images exactly.

2.3 MODEL CALIBRATION AND EVALUATION

Ideally, the training points for model calibration and test points for model evaluation need to be spatially independent. Furthermore, the test points need to be selected using a random sampling strategy in order to obtain objective accuracy estimates (e.g. Yang et al., 2001). Due to time limitations, however, the derived 30 m reference data were used for both training and validation purposes. Training and test samples were selected as follows. Each reference image of 60 × 60 ETM+ pixels was divided into 9 equal-sized blocks, six of which were randomly selected as training samples and the remaining reserved as test samples. Splitting the reference points by pixel block rather than by pixel reduced the spatial auto-correlations between training and test samples, and thus reduced possible inflation of estimated accuracy (Campbell, 1981). For each study area the training samples from all DOQ image windows were combined to form a training data set and the test samples combined to form a test data set.

For each study area, a regression tree model was established using the training data set and evaluated using the test data set. Regression tree is similar to the decision tree classifier in that it recursively splits training samples into subsets, two at each split. Instead of assigning class labels to the subsets, it develops a linear regression model for each of them. Each splitting is made such that the combined residual error of the models for the two subsets is substantially lower than the residual error of the single best linear model for the samples in the two subsets, and that the combined residual error of the split is the minimum of all possible splits (Huang and Townshend, 2001). The regression tree program used in this study was a proprietary program called Cubist[2]. This program has some advanced features, including committee model and instance model, which were not used in this study. For comparison purpose, linear regression models were also developed for each study area. All 7 ETM+ bands of both leaf-on and leaf-off images were used as model input.

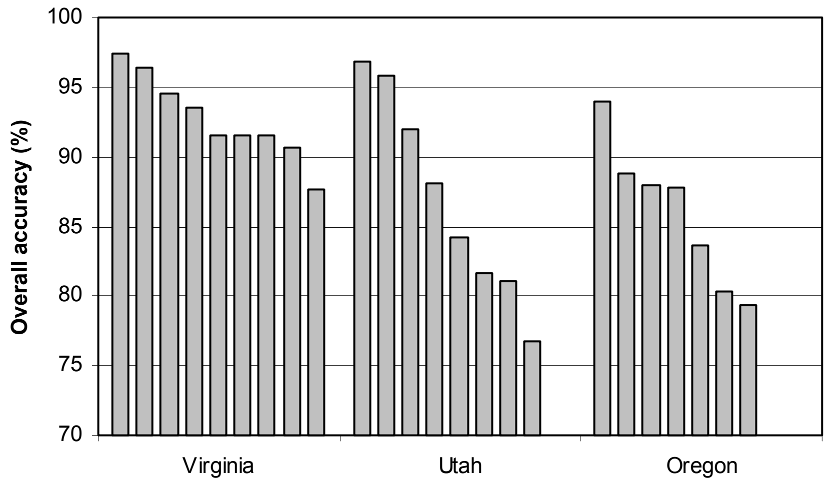
3.0 RESULTS AND DISCUSSION

3.1 CLASSIFICATION OF DOQ IMAGES

Due to time limitation, quantitative accuracy assessment was performed only on the initial decision tree classifications of the DOQ images using 5-fold cross validation. The accuracy estimates are reported in figure 2. This figure reveals the general separability of tree canopy from non-canopy surfaces in the DOQ images. The overall accuracy of decision tree classifications ranged from 75% to over 95%. Because the reference points were selected on an ad hoc basis and many of them were spatially correlated, some of the training and test points, though randomly selected, might be spatially correlated. Therefore, the accuracy estimates in figure 2 may be inflated for the initial decision tree classifications. Visual inspection of the classifications revealed some confusions between tree canopy and wet non-canopy surfaces, water and shadow, and impervious surface and agricultural land, many of which were corrected through hand editing. Therefore, the accuracy of the final classifications should be close to or better than the cross validation estimates in figure 2.

[2] Limited information on this program can be found at http://www.rulequest.com/cubist-unix.html.

Figure 2. Five-fold cross validation estimates of the accuracy for the decision tree classification of DOQ images. Each bar represents the estimated accuracy of classifying one DOQ image window.



3.2 MODELING TREE CANOPY DENSITY FROM

ETM+ IMAGES

With the reference data derived from DOQ images, relationships between tree canopy density and ETM+ spectral values were modeled using both the regression tree and multiple linear regression techniques. Model performance was measured by the mean absolute difference (*MAD*) and correlation (*r*) between predicted and actual canopy density values for the set aside test samples of each study area. *MAD* can be considered as an indication of the expected error of model predictions and *r* a measure of the generalization capability of the developed models.

Table 2 gives the *MAD* and *r* values of the developed models. In all three study areas, regression tree models had lower prediction errors than linear regression models, confirming an observation made in a previous study (Huang and Townshend, 2001). The *r* values of regression tree models were 0.06 ~ 0.15 higher than the linear regression models, suggesting better generalization capability of the regression tree models than the linear regression models. The relatively consistent *MAD* and *r* values of the regression tree models over the three different areas demonstrated the general applicability of the proposed strategy to estimating tree canopy density over large areas.

Table 2. Mean absolute difference (*MAD*) and correlation (*r*) between predicted and actual canopy density values on independent test samples. The unit of *MAD* is tree canopy density in percentage.

Study area	Regression tree model		Linear regression model	
	MAD (%)	*r*	*MAD* (%)	*r*
Virginia	11.65	0.89	13.15	0.83
Utah	9.92	0.85	10.14	0.70
Oregon	10.98	0.87	11.93	0.80

The residual errors of model predictions are mostly likely due to the complex and highly variable nature of mixings between tree canopy and non-canopy surface materials. Other sources include uncertainties in reference data and noises in the ETM+ images. The former may arise from errors in classifying the DOQ images, partial canopy cover pixels in the 1 m DOQ images, and temporal discrepancies and residual misregistration errors between DOQ and ETM+ images. With the ETM+ images being converted to at-satellite reflectance, the major noise components in those images include the impact of the atmosphere and topography on satellite signal. Modeling error will likely decrease if the uncertainties in reference data and noises in the ETM+ images can be reduced.

3.3 SOME PRACTICAL ISSUES FOR LARGE AREA APPLICATIONS

With the global coverage capability of the Landsat 7 and lowered cost of ETM+ imagery, 30 m tree canopy density data should be derivable in areas where some high resolution images are available. For operational applications of the proposed strategy over large areas, however, some practical issues need to be considered.

1. Need for high resolution images: Although only DOQ images were used in this study, any georeferenced high resolution images can be used for reference data development, provided tree canopy can be reliably separated from non-canopy surfaces. Such images do not need to be of a single data type and cover the whole study area. However, they need to be scattered spatially to ensure adequate sampling of the spectral, spatial and density variability of tree canopy over a study area. To avoid significant changes in tree canopy density as observed in high resolution images and ETM+ images, the acquisition dates of these two types of images should be as close as possible. Efforts should be made to avoid observable land cover changes between selected high resolution images and ETM+ images.

2. Use of texture in classifying high resolution images: Tree canopy exhibits unique texture patterns in high resolution images. Texture measures were found very useful for separating tree canopy from non-canopy surfaces, especially for the spectral information limited black and white images. For some black and white DOQ images we used, the overall accuracy estimated using cross validation increased as much as 10% when the texture measures were used. However, while the textures used in this study improved the classification, they were not necessarily the best for separating tree canopy from non-tree surface. The optimal texture measures for a specific type of high resolution images need to be determined experimentally.

3. Need for a conservative non-forest mask: A problem with linear regression is that a single linear model may predict a substantial amount of tree cover in a large agricultural field or water body, where little or no tree cover should be predicted. This problem should be partially alleviated using regression tree models because these models can be trained to predict zero percent canopy cover for non-forested areas without sacrificing predicting accuracy over other areas, provided those non-forested areas are well represented by the training points. However, it is impossible to represent all non-forested areas in the training points for large area applications. Therefore, both linear regression and regression tree models may over-predict tree canopy cover in some non-forested areas. A partial solution to this problem is to use a conservative non-forest mask and assign 0% canopy cover to the masked pixels. Such a mask can be created from ETM+ images using any supervised or unsupervised classification techniques. Its overall accuracy does not need to be very high. In order to avoid wrongly assigning 0% canopy cover to partially forested pixels, however, the mask must have very low commission errors, i.e., only pixels having no tree cover should be included in the non-forest mask.

4.0 SUMMARY AND FUTURE WORK

A strategy was developed for deriving tree canopy density at a spatial resolution of 30 m. This strategy relies on high resolution images for reference data development and uses regression tree and multiple linear regression to model tree canopy density from Landsat 7 ETM+ images. The applicability of this strategy was demonstrated in three areas of the United States, each of the size of the mosaic of two ETM+ scenes. The results were relatively consistent in the three study areas. The 1 m DOQ imagery proved a valuable source for deriving reference tree canopy density data. Tree canopy was separable from non-canopy surfaces using a decision tree classifier. The regression tree was found more robust than multiple linear regression for estimating tree canopy density from ETM+ images. The residual error of model prediction arises not only from the complex nature of mixings between tree canopy and non-canopy surface materials, but also from uncertainties in reference data and noises in the ETM+ images, which likely will decrease as the quality of both high resolution and ETM+ imagery improves.

With the increasing availability and decreasing cost of both high resolution and ETM+ images, the developed strategy likely will be applicable in many regions of the world. For operational applications of this strategy over large areas, however, some related issues need to be further investigated. The first relates to uncertainties in the reference data, arising from classifying high resolution images. Knowledge on how such uncertainties translate to errors in the 30 m reference canopy density data and affect the developed canopy density model and its prediction capability should provide guidelines as to what accuracy levels are acceptable in classifying high resolution images. The second issue is how to select the most relevant variables for modeling tree canopy density. In this study we used 7 ETM+ bands of two acquisition dates, which might not be an optimal set of variables for modeling tree canopy density. Using the most relevant variables for model development may lead to simpler models with better prediction capability. We will further investigate these issues in developing the tree canopy density data layer for the NLCD 2000 project.

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5.0 REFERENCES

F. Baret, J. G. P. W. Clevers, and M. D. Steven, "The robustness of canopy gap fraction estimates from red and near-infrared reflectances: a comparison of approaches," *Remote Sensing of Environment*, Vol. 54, No. 2, pp. 141-151, 1995.

C. C. Borel and S. A. W. Gerstl, "Nonlinear spectral mixing models for vegetative and soil surfaces," *Remote Sensing of Environment*, Vol. 47, No. 3, pp. 403-417, 1994.

J. B. Campbell, "Spatial correlation effects upon accuracy of supervised classification of land cover," *Photogrammetric Engineering & Remote Sensing*, Vol. 47, No. 3, pp. 355-363, 1981.

P. R. Coppin and M. E. Bauer, "Processing of multitemporal Landsat TM imagery to optimize extraction of forest cover change features," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 32, No. 4, pp. 918-927, 1994.

R. DeFries, M. Hansen, M. Steininger, R. Dubayah, R. Sohlberg, and J. Townshend, "Subpixel forest cover in central Africa from multisensor, multitemporal data," *Remote Sensing of Environment*, Vol. 60, No. 3, pp. 228-246, 1997.

R. S. DeFries, C. B. Field, I. Fung, C. O. Justice, S. Los, P. A. Matson, E. Matthews, H. A. Mooney, J. R. G. Townshend, C. J. Tucker, S. L. Ustin, and P. M. Vitousek, "Mapping the land surface for global atmosphere-biosphere models: toward continuous distributions of vegetation's functional properties," *Journal of Geophysical Research*, Vol. 100, No. D10, pp. 20867-882, 1995.

R. S. DeFries, M. C. Hansen, and J. R. G. Townshend, "Global continuous fields of vegetation characteristics: a linear mixture model applied to multi-year 8km AVHRR data," *International Journal of Remote Sensing*, Vol. 21, No. 6/7, pp. 1389-1414, 2000.

M. A. Friedl and C. E. Brodley, "Decision tree classification of land cover from remotely sensed data," *Remote Sensing of Environment*, Vol. 61, No. 2, pp. 399-409, 1997.

A. R. Gallant, *Nonlinear statistical models,* John Wiley & Sons, New York, p. 610, 1987.

M. Hansen, R. Dubayah, and R. DeFries, "Classification trees: an alternative to traditional land cover classifiers," *International Journal of Remote Sensing*, Vol. 17, No. 5, pp. 1075-1081, 1996.

R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 3, No. 6, pp. 610-621, 1973.

C. Huang and J. R. G. Townshend, "A stepwise regression tree for nonlinear approximation: applications to estimating subpixel land cover," *International Journal of Remote Sensing*, in press.

C. Huang, B. Wylie, C. Homer, L. Yang, and G. Zylstra, "Derivation of a Tasseled cap transformation based on Landsat 7 at-satellite reflectance," *International Journal of Remote Sensing*, in press.

R. R. Irish, *Landsat 7 science data user's handbook*, Report 430-15-01-003-0, National Aeronautics and Space Administration, http://ltpwww.gsfc.nasa.gov/IAS/handbook/handbook_toc.html, 2000.

L. R. Iverson, E. A. Cook, and R. L. Graham, "A technique for extrapolating and validating forest cover across large regions: calibrating AVHRR data with TM data," *International Journal of Remote Sensing*, Vol. 10, No. 11, pp. 1805-1812, 1989.

X. Li and A. H. Strahler, "Geometric optical bidirectional reflectance modeling of the discrete crown vegetation canopy: effects of crown shape and mutual shadowing," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 30, No. 2, pp. 276-292, 1992.

T. R. Loveland and D. M. Shaw, "Multiresolution land characterization: building collaborative partnerships." In *Proceedings of the ASPRS/GAP Symposium -- Gap analysis: a landscape approach to biodiversity planning,* Charlotte, North Carolina, pp 83-89, 1996.

F. Maselli, C. Conese, T. D. Filippis, and S. Norcini, "Estimation of forest parameters through fuzzy classification of TM data," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 33, No. 1, pp. 77-84, 1995.

J. R. Quinlan, *C4.5 programs for machine learning,* Morgan Kaufmann Publishers, San Mateo, California, p. 302, 1993.

T. W. Ray and B. C. Murray, "Nonlinear spectral mixing in desert vegetation," *Remote Sensing of Environment*, Vol. 55, No. 1, pp. 59-64, 1996.

D. A. Roberts, M. O. Smith, and J. B. Adams, "Green vegetation, nonphotosynthetic vegetation, and soils in AVIRIS data," *Remote Sensing of Environment*, Vol. 44, No. 2, pp. 255-269, 1993.

J. E. Vogelmann, S. M. Howard, L. Yang, C. R. Larson, B. K. Wylie, and N. V. Driel, "Completion of the 1990s national land cover data set for the conterminous United States from Landsat Thematic Mapper data and ancillary data sources," *Photogrammetric Engineering & Remote Sensing*, Vol. 67, No. 6, pp. 650-662, 2001.

L. Yang, S. V. Stehman, J. H. Smith, and J. D. Wickham, "Thematic accuracy of MRLC land cover for the eastern United States," *Remote Sensing of Environment*, Vol. 76, No. 3, pp. 418-422, 2001.

Z. Zhu and D. L. Evans, "US forest types and predicted percent forest cover from AVHRR data," *Photogrammetric Engineering & Remote Sensing*, Vol. 60, No. 5, pp. 525-531, 1994.