ACCURACY ASSESSMENT OF BIOMASS AND FORESTED AREA CLASSIFICATION FROM MODIS, LANDSAT-TM SATELLITE IMAGERY AND FOREST INVENTORY PLOT DATA

Dumitru Salajanu, Forester
Dennis M. Jacobs, Research Forester
USDA Forest Service
Forest Inventory and Analysis
4700 Old Kingston Pike
Knoxville, TN 37919
dsalajanu@fs.fed.us
djacobs@fs.fed.us

ABSTRACT

The objective of this study was to determine how well forest/non-forest and biomass classifications obtained from Landsat-TM and MODIS satellite data modeled with FIA plots, compare to each other and with forested area and biomass estimates from the national inventory data, as well as whether there is an increase in overall accuracy when pixel size (spatial resolution) decreases. A subset of 1049 inventory plots (100% forested, 100% non-forested) was used to classify the land cover and model the biomass in 20 counties of East Kentucky. Forest inventory data have been further subdivided into two datasets containing 100% forested/non-forested, and only 100% forested plots. Separately, each of these two datasets was used in a decision tree modeling process applied to Landsat-TM, MODIS satellite data, and ancillary data to classify the land cover and model the forest biomass. The satellite, ancillary, and plot data have been processed in See5 and Cubist software. Classification results from trials with Landsat-TM and MODIS show that overall classification accuracy for the percent of pixels correctly classified (%PCC) increased from 85.9% to 89.9%. Classifications from Landsat-TM and MODIS modules show an increase in biomass and forest area when compared to forest inventory estimates, but Landsat-TM module performed better. Comparison between classified forest area with MODIS and Landsat-TM, forest area shows a 2.9% increase. The forest/non-forest single layer classification from each trial was used to mask out non-forested areas for the forest biomass classification. Accuracy of modeled forest biomass was compared with plot data estimates of forest biomass. Biomass obtained from Cubist models with 100% forested forest inventory plots and Landsat-TM images, when compared to the biomass from the published plot data estimates, show a difference less than 2.5%.

INTRODUCTION

Satellite image data from sensors with different spatial and spectral resolution have been used in many land cover/use classifications. Satellite remote sensing is an important tool for forest management and for surveying vast areas of forestland. Forest type classifications have been derived from an assortment of satellite data sensors with a variety of spatial and spectral resolutions. Results varied according to the classification algorithm, site location, number of classes used in each classification, etc.

Spectral and spatial resolutions were the primary elements that dictated classification accuracy and what could be achieved (Ma, 1985; Ma and Olson, 1989; Chavez et al., 1991; Salajanu, 1992; Lunetta et al., 1998).

Improvements in technology and classification algorithms allow ancillary data (slope, soil type, vegetation indices, merged information from sensors with different resolutions, etc.) to be incorporated into the original satellite data as new channels. Classification accuracy has improved when the original spectral channels have been combined with ancillary data as additional channels in the classification process (Ricchetti, 2000; Chavez, 1986; Borry et al, 1990; Pellemans et al, 1993; Vogelmann et al 1998; Salajanu and Olson, 2001). In the last few years, classification and regression tree analyses have been implemented in several software programs and were used in many remote sensing applications (Huang and Jensen, 1997; Lawrence and Wright, 2001; Cooke and Jacobs, 2005).

The inventory design of the Forest Inventory and Analysis National Program of the United States Department of Agriculture Forest Service (FIA) requires annual measurements on a portion of all land in order to form rotating

panels. The Southern States strive for a 20% sample each year as part of a 5-year cycle. Forest inventory plot data are used as ancillary information when modeling the forest biomass, and classifying forest types and forest area.

The main objective of this study was to determine whether decreasing pixel size provides significant increase for the overall accuracy of forest/non-forest and forest biomass classifications from Landsat-TM, and Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery modeled with 100% forested/non-forested FIA plots from a complete 5-year cycle of FIA data.

STUDY AREA

The test site for this study encompasses a large portion of the USGS mapping zone 53, which covers 20 counties in East Kentucky. The test site consists of a large diversity of landforms and land cover/use types such as forests, agricultural lands, strip mines, open spaces, highly developed areas (apartments complexes, commercial/industrial areas), low developed areas that includes single-family units, bodies of water and wetlands. Hardwoods forests are the dominant forest type followed by the mixed hardwoods-conifers and conifer species. Hardwoods forests consist of mixed broadleaf species throughout the area.

FOREST INVENTORY AND ANALYSIS PLOTS

The national inventory design of the Forest Inventory and Analysis program requires annual measurements on a proportion of all lands and 5-year reports. The field plot design consists of four subplots approximately 1/24 acre in size, and are used to collect data on trees with a diameter at breast height of 5 inches or greater (Figure 1). Each subplot contains a microplot of approximately 1/300 acre in size. Microplots are used to collect information data on seedlings and saplings.

An attempt is made on all forested plots to collect coordinates with a Global Positioning System (GPS) receiver at the center subplot. Some non-forest plots may have GPS coordinates, but some do not. Hence, not all of the plots used in the study have accurate GPS coordinates. For this study, a subset of 1049 plots (850 forest/81%, 195 non-forest/18.6%, and 4 water/0.4%) was filtered from a complete 5-panel dataset of Kentucky for mapping zone 53. This subset includes all of the 100% forest and 100% non-forest plots.

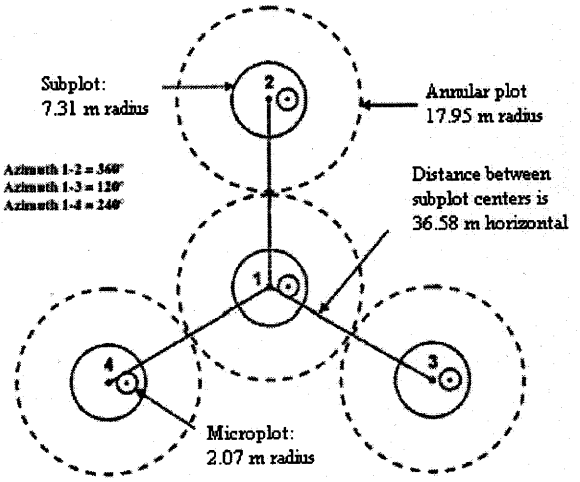


Figure 1. FIA field plot design.

DATA BASE DESCRIPTION

Satellite images from two different satellite sensors, Landsat-TM and MODIS were used to model forest/non-forest cover and forest biomass of the study area. The database consists of raster and vector data that fall within the USGS mapping zone 53. Mapping zone 53 used in this study consists of two different sets of data. One data set contains 269 layers of data (49 are MODIS): a large number of ancillary and remote sensing layers re-sampled to a spatial resolution of 250 meters and projected to the Albers Equal Area projection. Multitemporal MODIS satellite data have been acquired during the spring, summer, and fall of 2001, 2002, and 2003, while Landsat-TM was acquired in 1999. The other set contains 221 layers of data (6 are Landsat-TM). The six Landsat-TM layers have replaced the MODIS layers in the first data set. Landsat-TM layers were projected to the Albers Equal Area projection and the ancillary layers have been re-sampled to 30 meters spatial resolution. These data sets were used to model the forest biomass and forest/non-forest land cover.

The data layers in Table 1 either existed as 250-meter resolution data or were re-sampled to 250-meters and projected to Albers Equal Area projection by personnel at the USFS Remote Sensing Applications Center in Salt Lake City (RSAC). The database contains continuous and categorical variables.

Table 1. List of Layers Used to Map Forest, Non-forest and Forest Biomass.

Database Layers Description
MODIS 32 day composite imagery between 2001 and 2003
Conus MODIS32-2001097 - Bands 1 to 7
Conus MODIS32-2001193 - Bands 1 to 7
Conus MODIS32-2002129 - Bands 1 to 7
Conus MODIS32-2002225 - Bands 1 to 7
Conus MODIS32-2002257 - Bands 1 to 7
Conus MODIS32-2002321 - Bands 1 to 7
Conus MODIS32-2003161 - Bands 1 to 7
Conus Bailey's Ecoregions image layer
MODIS Vegetation Indices Layers
Conus EVI- 2002097 image
Conus EVI- 2002225 image
Conus EVI- 2002321 image
Conus NDVI- 2002097 image
Conus NDVI- 2002225 image
Conus NDVI- 2002321 image
MODIS Vegetation Layer: MODIS –percent tree cover image
Reflectance layers from spring, summer and fall of 2002
Conus Reflectance – 2002097 – Bands 1 to 7
Conus Reflectance – 2002225 – Bands 1 to 7
Conus Reflectance – 2002321 – Bands 1 to 7
NLCD layers;
Conus NLCD – Percent conifer forest image
Conus NLCD – Percent deciduous forest image
Conus NLCD – Percent mixed forest image
Conus NLCD – Percent shrub land image
Conus NLCD – Percent woody wet land image
Terrain information; Conus dominant aspect, Conus mean elevation, stream density
Conus MODIS fire points from 2001 and 2002
Soil data layers; available water capacity, permeability, soil bulk density, soil ph, soil plasticity, soil porosity, rock volume and soil texture.
USGS mapping zone images
Precipitation – annual and for each month
Temperature layers – averages, minimum and maximum temperatures.

DATA MINING – CUBIST AND SEE5

Cubist and See5 are regression tree software used to create decision tree classifications (forest/non-forest map) and models for modeling continuous variables (forest biomass). See5 was used to classify/model categorical variables, forest, non-forest and water, while Cubist was used to model the biomass continuous variable. Two files are essential for running Cubist or See5, and several others are optional. The first essential file is the names file that lists the names and describes the classes and attributes/predictors, as shown below (Table 2).

Table 2. Names File Description.

```
FNF
FNF: 1, 2, 3, 4.
awc-250m.img-band1: continuous.
bdgrid-250m.img-band1: continuous.
conus-dvi-2002225.img: continuous.
conus-evi-2002097.img: continuous.
conus-modis32-2001097-albers.img-band1: continuous .
us_ppt01_jan.img: continuous.
us_ppt02_feb.img: continuous.
us_ppt03_mar.img: continuous.
us_tavg301_albers.img: continuous.
us_tavg302_albers.img: continuous.
us_tavg303_albers.img: continuous.
usgs_mapping_zones.img: 0, 54, 58, 59.
ustmax01_albers.img: continuous.
ustmax02_albers.img: continuous.
:
:
attributes excluded:
conus_modis32_2001097_albers.img_band5.
conus_modis32_2001193_albers.img_band5.
```

The first row/entry in the name file is the attribute (forest/non-forest, biomass) that contains the target value to be classified/ modeled based on values of the other predictors. Predictors contained in the name file are continuous or defined by numeric values. The final entry in the name file specifies if a predictor is included or excluded from the classifier/model. The second essential file is the data file that provides information on the training data used to construct the decision tree model. The entry for each case consists of one or more lines that give the values for all the predictors. A comma separates the values and the entry terminates with a period (http://www.rulequest.com). The test file is one of the optional files, and it is used to evaluate the performance of the classifier/model. There are several ways for assessing model predictive ability such as; collection of new data to check the model and its predictive ability, comparison of results with earlier empirical results, and use a holdout sample when a data set is large to check the model performance. In this study FIA, plot data have been split randomly 60% and 40% into data training and test files. Test file has the same structure as data file.

FOREST NON-FOREST CLASSIFICATION

There are several types of algorithms and methods to classify satellite data, such as supervised and unsupervised classification, neural network, decision tree, etc. The decision tree algorithm in See5 was used for this study. A subset of 100% forested/non-forested plots was selected from a complete 5-year cycle of FIA data. These data were used to produce two datasets containing a) Landsat-TM satellite data (30 m), 100% forested/non-forested plots and ancillary data; b) MODIS satellite data (250 m), 100% forested/non-forested plots and ancillary data. Separately, an iterative decision tree modeling process was applied to each of these two datasets to classify the land cover into forest, non-forest, and water. See5 cannot process geographic information system data (GIS) or remote sensing layers. Prior to the data mining process, satellite, ancillary and plot data for each dataset was processed with tools developed at the Remote Sensing Applications Center (RSAC) in Salt Lake City for ERDAS Imagine to convert remote sensing and GIS layers to See5 and Cubist data file formats.

The "Prepare FIA Data for Cubist/See5" tool extracts geospatial image information using FIA points. The program then creates three data files for See5 and three for Cubist (data file, name file, and test file), and randomly selects a dataset to be set aside for accuracy assessment. Once the name, data, and test files have been produced,

See5 program is used to create decision tree models. See5 offers several options (rulesets, boost) to build a decision tree model, and each option produces a different type of classifier/decision tree based on the way it is constructed.

The boosting option set to ten trials, was the only one used in this study to model the forest/non-forest categorical variable. The boosting option was selected because it creates several classifiers/decision trees. Each classifier/decision tree produced by boosting option will be different from the previous. Each decision tree tries to correct the prediction error from the previous decision tree. This process continues for a pre-determined number of trials. Data file from each dataset (with TM and MODIS) was used in See5 to create forest/non-forest (fnf) decision tree models. Forty percent of the data were set-aside in each data set for accuracy assessment. A sample of the output file from the See5 software program (Table 3) reports classification errors based on a confusion matrix produced for both training and test datasets.

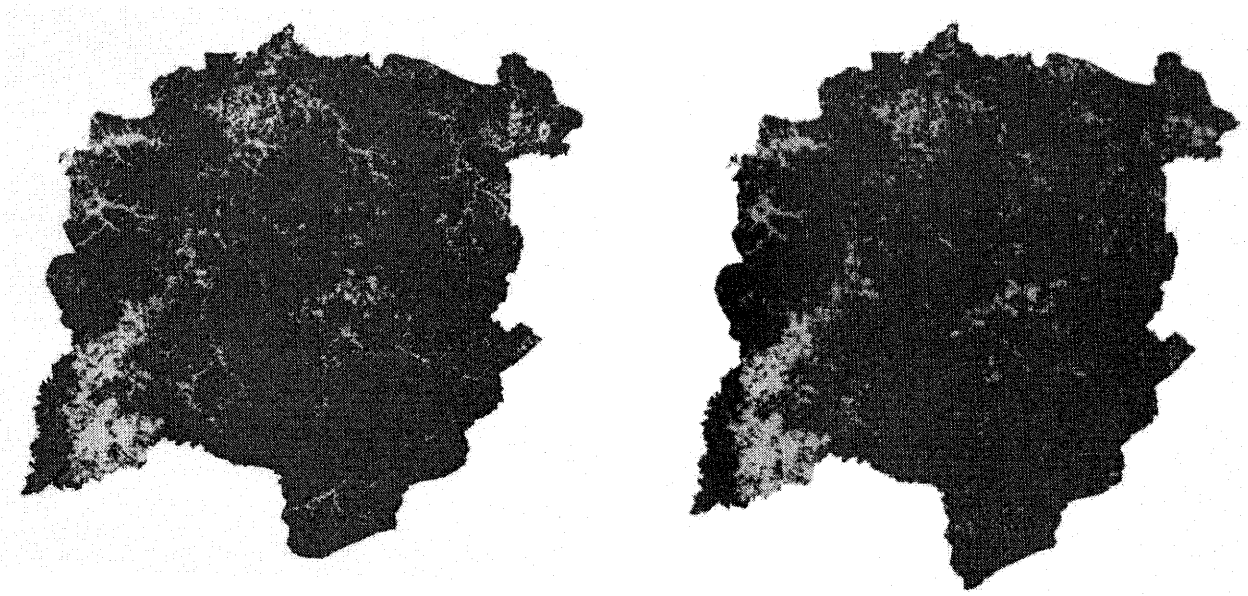
Table 3: Sample of the See5 output showing the misclassifications from Landsat-TM.

```
Options:
    10 boosting trials
Class specified by attribute `fnf'
Trial 9: Decision tree:
SubTree [S1]
conus_tm6_albers.img_band6 <= 1: 4 (9.1)
conus_tm6_albers.img_band6 > 1:
:...conus_tm3_albers.img_band3 <= 14:
SubTree [S2]
conus_reflectance_2002321.img_band4 > 507:
conus_reflectance_2002321.img_band4 <= 507: 1  (254.9/22.2)
:...conus_modis_percent_tree_cover.img > 80.56: 2 (13.6/5.8)
   conus_modis_percent_tree_cover.img <= 80.56:
     :...us_ppt04_apr.img <=10467: 2  (36.6/11.6)
        us_ppt04_apr.img > 10467:  1  (14.5 )
  conus_tm3_albers.img_band3 > 14:
    bdgrid_30m.img_band10 > 2.64:  1  (42.3/14)
    :...conus_modis_percent_tree_cover.img > 67.852: 1 (18.4/4.3)
       conus_modis_percent_tree_cover.img <= 67.852:
Evaluation on training data (464 cases):        Evaluation on test data (308 cases):
Trial        Decision Tree                      Trial        Decision Tree
     Size      Errors                                Size      Errors
  0    15    24( 5.2%)                        0      15     54(17.5%)
  1    11    65(14.0%)                        1      11     60(19.5%)
  2    12    48(10.3%)                        2      12     45(14.6%)
  3    22    49(10.6%)                        3      22     59(19.2%)
  4    19    39( 8.4%)                        4      19     71(23.1%)
  5     9    37( 8.0%)                        5       9     50(16.2%)
  6    23    52(11.2%)                        6      23     53(17.2%)
  7    15    65(14.0%)                        7      15     94(30.5%)
  8    14    44( 9.5%)                        8      14     42(13.6%)
  9     9    47(10.1%)                        9       9     51(16.6%)
  boost       9( 1.9%)  <<                    boost         31(10.1%)
(a)  (b)  (c)  (d)  (e)  classified as        (a)  (b)  (c)  (d)  (e)  classified as
                         (a): class 0                                   (a): class 0
     377                 (b): class 1              248   10             (b): class 1
       9   73            (c): class 2               19   29             (c): class 2
                         (d): class 3                                   (d): class 3
                      5  (e): class 4                1    1             (e): class 4
```

The See5 decision tree model was used in the "Apply See5 Results Spatially" tool developed for ERDAS Imagine by RSAC to spatially model the entire forest/non-forest area. The classification tree obtained from

boosting was used in the Apply See5 software module to model forest non-forest and water classes as a function of the modeling dataset for each sensor. The final product is a single layer forest/non-forest image map (predicted output image) with values representing the variables (forest/non-forest) that were modeled (Figure 2) and a confidence image that shows spatial distribution of the correct and misclassified areas. Confidence values range from zero to one. A value of or near one indicates a more confident prediction for forest area, while values near zero show a confident prediction for non-forest area.

Pixels classified as forested have been converted to hectares and total forested area from each sensor was compared to each other and to the total forest land area (U.S. Survey acres converted to hectares) reported in the Forest Resources of the US, 2002 report (Smith et. al. 2004).



a) b)

Figure 2. Forest non-forest classification from a) Landsat-TM and b) MODIS images.

BIOMASS CLASSIFICATION

The procedure for preparing the data for Cubist and classifying/modeling the forest biomass is similar to the forest/non-forest classification procedures for See5. Before modeling forest biomass, a forest mask was produced for each sensor (Landsat-TM and MODIS). Classified forest maps from Landsat-TM and MODIS have been used to mask non-forested area.

Forest biomass estimates (total dry weight) from FIA plot data and hundreds of continuous predictor layers were used in Cubist to produce biomass predictor models. Cubist, like See5, offers several options (rules alone, let Cubist decide, etc.) to build decision tree models. A model consists of a collection of rules. Two of the several available options in Cubist were used to produce decision tree biomass models – "rule alone" and "committee of 5 members." Committee option, like boosting in See5, creates several rule-based models. Each member of the committee predicted a value for a class and the members' predictions have been averaged into a final prediction. There were five committee members and each member of a committee model tries to correct the predictions of the previous member (www.rulequest.com). A biomass model was produced for each sensor using complete forested/non-forested FIA plots. For each data set, a random sample of 40% of the data was set aside for accuracy assessment and the remaining 60% was used to build the model. For each sensor data, several iterations of decision-tree biomass models were performed and analyzed. With each step, predictor layers poorly correlated with the biomass estimates were excluded during the next iteration. The Cubist output file (decision tree model) reported the errors (average and relative error), and the correlation coefficient for both training and test data sets.

Forest biomass models obtained for each sensor were used in the ERDAS Imagine tool "Apply Cubist Results Spatially" to create a spatial biomass image map (predicted image) with predicted values representing the biomass variable and an error image file showing the predicted misclassifications.

RESULTS AND DISCUSSIONS

Forest/non-forest land cover was classified for the 20 county study areas in East Kentucky using satellite information from two different sensors (MODIS and Landsat-TM), ancillary and FIA plot data. A set of single condition plots, and the See5 option of boosting with 10 trials were used to classify the land cover into forest, non-forest and water. Results of these trials are summarized in Table 4, 5, and 6. Classification results from See5 showed an increase in overall classification accuracy (%PCC and Khat %) from Landsat-TM data compared to MODIS. Classification accuracy assessments were performed using three different methods. The first method is based on analysis of a contingency table produced by the See5 program for the 40-percent set-aside data set (Table 4). This test was used to evaluate the predictive ability (validation) of the selected model. Overall classification accuracy shows that Landsat-TM prediction model performs better (89.94%) than MODIS predictive model (85.92%). Predictive models from both sensors perform relatively poor in detecting the non-forest land cover, while the two water plots were each misclassified as either forest or non-forest. Table 4 summarizes the producer, user, Khat, and overall accuracy (%PCC) for each sensor type obtained from classifications with single condition (100% forested/non-forested) FIA plots.

Table 4. Classification accuracy of forest/non-forest from test data.

Sensor Type	Percent of Forest/nonforest	Khat %	Overall %PCC	Producer accuracy %			User accuracy %		
				Forest	Non-forest	Water	Forest	Non-forest	Water
Landsat-TM	100% forest /non-forest	59.88	89.94	96.12	60.42		92.54	72.50	
MODIS	100% forest /non-forest	50.84	85.92	95.49	50.60		87.84	73.68	

The second method used in accuracy assessment is based on analyses of contingency tables obtained from overlaying FIA forest/non-forest plots on the classified image (Table 5). Information from each contingency table shows how well FIA plots were correctly classified in each class, as well as the number of misclassified plots. The assessed classification accuracy ranges from 61.9% to 98.5%. The overall accuracy is 94.8% for the Landsat-TM and 92.6% for the MODIS data. According to user, producer, Khat, and overall accuracy (Table 5) the Landsat-TM model performed better in modeling (classifying) each land cover class than the MODIS model. Both producer and user accuracy show a much higher classification accuracy of forest class than for non-forest and water classes. The low percent discrimination of non-forest cover type may be due to the presence of narrow mountain streams and roads as well as single-family housing units and small open spaces that are modeled as forest. The Z test proposed by Cohen (1960), was used to test for significant differences between the two land cover classifications. The results show that there is a significant difference between the classification accuracy of the two sensors at 90% significance level ($Z=1.79 > 1.64$).

Table 5. Classification accuracy of forest/non-forest from FIA plots overlaid on the modeled output.

Sensor Type	Percent of Forest/nonforest	Khat %	Overall %PCC	Producer accuracy %			User accuracy %		
				Forest	Non-forest	Water	Forest	Non-forest	Water
Landsat-TM	100% forest /non-forest	78.94	94.82	98.47	75.31	66.67	95.54	89.71	100
MODIS	100% forest /non-forest	68.09	92.61	98.25	61.90		93.35	86.67	

The third approach used for assessing classification accuracy of the forest/non-forest models was to compare outputs of area to the published FIA numbers (Table 6). Forest inventory mapmaker web-application version 2.1

has the most recent biomass and forest area estimates (Miles, Patrick D. January 19, 2007). Pixel area classified as forest was converted to hectares and compared to the total FIA forest area estimates, converted from acres to hectares.

Results in Table 6 show an increase of 5.71% in forested area model with Landsat-TM data, and respectively 8.75% increase in forested area modeled by MODIS data as compared to forested area from FIA data.

Table 6. Comparison of MODIS and Landsat-TM classifications with published inventory forested area.

Sensor Data	Land cover	Area (ha)	FIA (ha)	Difference (+/-)	Percent (%)
Landsat-TM	Forest	1,470,128	1,390,665	+ 79,463	5.71
	Non-forest/water	215,050	295,886	- 80,836	27.32
	Total land	1,685,178	1,686,551	- 1,373	0.08
MODIS	Forest	1,512,392	1,390,665	+ 121,727	8.75
	Non-forest/water	174,438	295,886	- 121,448	41.04
	Total land	1,686,830	1,686,551	+ 279	0.02

Map-based estimates of forest area from Landsat-TM compare relatively well with FIA forested area when only single condition plots (100% forest, 100% non-forest) are used in the model. The forest classification obtained from MODIS image (100% forest and 100% non-forest plots) overestimate forest area by 8.75% when compared to FIA estimates. Forest non-forest classifications obtained from each sensor were used to mask out the non-forested area and retain a forested area mask. This forest area mask was then used as the area over which forest biomass was modeled using the same geospatial predictors. Models developed from each sensor have been applied to their corresponding predictor dataset to produce forest biomass predictions on a pixel-by-pixel basis. An output of the predicted biomass map distribution obtained from Landsat-TM is shown in Figure 4. The decision tree models developed to model forest biomass varied in their ability to predict plot level biomass and the results show variation of the total biomass from one sensor to another. The MODIS biomass model overestimated forest biomass by 8.87% when compared to FIA estimates, and estimated 6.23% greater total biomass than that provided by the Landsat-TM biomass model. However, the Landsat-TM model provided a biomass estimate that was less than 2.5% greater than FIA estimates (Table 7).

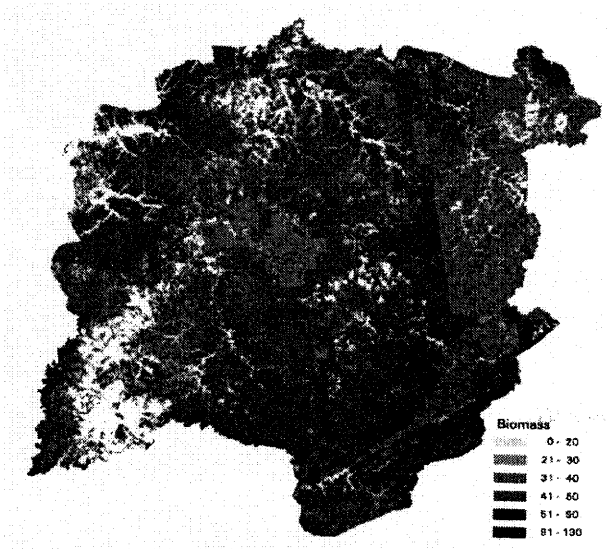


Figure 4. Predicted biomass from Landsat-TM for East Kentucky (dry tons/ac).

Table 7. Comparison of modeled biomass with FIA estimates (total dry weight).

Satellite sensor	Classified/modeled biomass (dry-tons)	FIA forest biomass (dry-tons)	Error %
Landsat - TM	188,378,078	183,804,593	2.49
MODIS	200,124,616	183,804,593	8.87

An analysis of the predicted biomass values show that both Cubist models overestimated biomass for the FIA plots containing low amounts of biomass, and underestimated biomass for plots with high biomass values.

CONCLUSIONS

This dataset is a part of a product developed with the intent of using a full five-year cycle of FIA plot data.

Accuracy of the forest/non-forest map is a very important factor when modeling the correct forest area for forest biomass.

Based on the work described, Landsat-TM performed relatively better than MODIS in both forest area determination and biomass modeling.

Biomass classifications provide information not only on the total amount of estimated biomass, but also information on how forest biomass is spatially distributed throughout the forested landscape. The spatial pattern allows a visual assessment of biomass distribution below the county level to help analysts understand where there are areas of high and low forest biomass.

Although classification accuracies suggest that both models under-predicted the amount of non-forest area, MODIS was more adversely affected, due to its larger cell size, by the presence of small-area fragmentation (narrow mountain roads and streams) and single-family housing units much more than the Landsat-TM model.

FIA plot information ties See5 and Cubist models to actual FIA plot measurements on the ground.

Even though the overall classification accuracies between the two sensors are not particularly disparate, each is nonetheless significant and thus meaningful when used in different forest applications. Results suggest that FIA plot information can provide good results in classifying large areas of land cover.

REFERENCES

Borry, F. C., B. P DeRoover, R. R. DeWulf, and R. E. Goossens (1990). Assessing the value of monotemporal SPOT-1 imagery for forestry applications under Flemish conditions. *Photogrammetric Engineering and Remote Sensing*, 56(8):114–1153.

Chavez, P .S., Jr. (1986). Digital merging of Landsat TM and digitized NHAP data for 1:24,000 scale image mapping. *Photogrammetric Engineering and Remote Sensing*, 52(10):1637-1646.

Chavez, P. S Jr., S. C. Sides, and J. A. Anderson (1991). Comparison of three different methods to merge multiresolution and multispectral data: Landsat TM and SPOT panchromatic. Photogrammetric

Cohen, Jacob, (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, 20(l):37-40.

Conner, R. C., T. Adams, B. J. Butler, W. A. Bechtold, T. G. Johnson, S. N. Oswalt, G. Smith, S. W. Wolf, and C.W. Woodall (2004). *The state of South Carolina's forests*, 2001, pp. 67.

Cooke, W. H., D. M. Jacobs (2005). Rapid classification of Landsat TM imagery for phase 1 stratification using the automated NDVI threshold supervised classification (ANTSC) methodology. In: *Proceedings of the fourth annual forest inventory and analysis symposium*, 2002 November 19–21 New Orleans, LA. Gen. Tech. Rep. NC-252. St. Paul, MN: U.S. Department of Agriculture, Forest Service, North Central Research Station, pp. 81-86.

Guo, X., K. P. Price, and J. Stiles (2003). Grasslands discriminant analysis using Landsat TM single and multitemporal data. *Photogrammetric Engineering and Remote Sensing*, 69(11):1255–1262.

Homer, C., C. Huang, L. Yang, B. Wylie, and M. Coan (2004). Development of a 2001 national land-cover database for the United States. *Photogrammetric Engineering and Remote Sensing*, 70(7):829–840.

Lawrence, R. L., and A. Wright (2001). Rule-based classification system using classification and regression tree (CART) analysis. *Photogrammetric Engineering and Remote Sensing*, 67(10):1137–1142.

Lunetta, R.S., J. G. Lyon, B. Guindon, and C. D. Elvidge (1998). North American landscape characterization dataset development and data fusion issues. *Photogrammetric Engineering and Remote Sensing*, 64(8):821-829.

Ma, Z., and C. E. Olson Jr. (1989). A measurement of spectral overlap among cover types. *Photogrammetric Engineering and Remote Sensing*, 55(10):1441-1444.

Miles, Patrick D. (2007). Forest inventory mapmaker web-application version 2.1. St. Paul MN: U.S. Department of Agriculture, Forest Service, North Central Research Station.

Pellemans, A. H. J. M., R. W. L. Jordans, and R. Allewijn (1993). Merging multispectral and panchromatic SPOT images with respect to the radiometric properties of the sensor. *Photogrammetric Engineering and Remote Sensing*, 59(1):8 –87.

Ricchetti, E. (2000). Multispectral satellite image and ancillary data integration for geological classification. *Photogrammetric Engineering and Remote Sensing*, 66(4):429–435.

Salajanu, D., and C. E. Olson Jr. (2001). The significance of spatial resolution: Identifying forest cover from satellite data. *Journal of Forestry*, 99(6):32-38.

Salajanu, D., and D. M. Jacobs (2006). The effect of using complete and partial forested FIA plot data on biomass and forested area classifications from MODIS satellite data. In: *Proceedings: American Society for Photogrammetry and Remote Sensing 2006 annual conference*, May 1-5, 2006. Reno, Nevada. Bethesda, MD: American Society of Photogrammetry and Remote Sensing.

Skidmore, A. K., B. J. Turner, and E. Knowles (1997). Performance of a neural network: Mapping forests using GIS and remotely sensed data. *Photogrammetric Engineering and Remote Sensing*, 63(5):501-514.

Smith, W. B., P. D. Miles, J. S. Vissage, and S. A. Pugh (2004). Forest resources of the United States, 2002. Gen. Tech. Rep. NC-241. St. Paul MN: U.S. Department of Agriculture, Forest Service, North Central Research Station, pp. 137.

Volgemann, J. E., T. Sohl, and S. M. Howard (1998). Regional characterization of land cover using multiple sources of data. *Photogrammetric Engineering and Remote Sensing*, 64(1):45-57.

Wayman, J. P., R. H. Wynne, J. A. Scrivani, and G. A. Reams (2001). Landsat TM-based forest area estimation using iterative guided spectral class rejection. *Photogrammetric Engineering and Remote Sensing*, 67(10):1155–1166.