The Influence of Multi-season Imagery on Models of Canopy Cover: A Case Study

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Abstract

Quantifying tree canopy cover in a spatially explicit fashion is important for broad-scale monitoring of ecosystems and for management of natural resources. Researchers have developed empirical models of tree canopy cover to produce geospatial products. For subpixel models, percent tree canopy cover estimates (derived from fine-scale imagery) serve as the response variable. The explanatory variables are developed from reflectance values and derivatives, elevation and derivatives, and other ancillary data. However, there is a lack of guidance in the literature regarding the use of leaf-on only imagery versus multi-season imagery for the explanatory variables. We compared models developed from leaf-on only Landsat imagery with models developed from multi-season imagery for a study area in Georgia. There was no statistical difference among models. We suggest that leaf-on imagery is adequate for the development of empirical models of percent tree canopy cover in the Piedmont of the Southeastern United States.

Introduction

Tree canopy cover is a primary component of ecosystems and is defined as the area covered by the vertical projection of tree crowns (Jennings, 1999). The amount and density of cover influences habitat suitability, fire behavior, aesthetics, and carbon dynamics. For example, Rollins and Frame (2006) used a map of percent tree canopy cover (Homer *et al.*, 2007) as a major component in their forest fire behavior and fuel models. Tree canopy cover is also a critical component of forest management activities (Jennings, 1999). Additionally, both forest land use definitions and forest land cover definitions are partially based on the amount of tree canopy cover present during the time of classification. For example, the definition of forest land cover used in the National Land Cover Database (NLCD) land cover mapping effort partially relies on identifying areas with at least 20 percent tree canopy cover (Homer *et al.*, 2007). Likewise, the United Nations Food and Agriculture Organization (FAO) definition of forest land use partially relies on identifying areas with at least 10 percent tree canopy cover (FAO, 2001). Because of the importance of tree canopy cover, a national map of percent tree canopy cover, across all lands, was developed as part of the 2001 NLCD (Huang *et al.*, 2001, Homer *et al.*, 2007) and a 2011 version is under development (Coulston *et al.*, 2012).

The 2001 NLCD percent tree canopy cover product is a freely available 30 m dataset. Because percent tree canopy cover is not calculable from Landsat imagery directly, empirical models were developed to predict percent canopy cover at unmeasured locations. In this case, the response variable was derived from classifying 1 m Digital Orthophoto Quarter Quadrangles (DOQQs) as either tree canopy or no tree canopy. Approximately 1 to 4 km^2 per Landsat scene were purposively sampled and classified using a classification tree (Homer *et al.*, 2004). The response, percent tree canopy cover, was then calculated on a 30 m pixel level for the sampled area. Multi-season (leaf-off, spring, leaf-on) Landsat-5 and -7 data and indices (e.g., tasseled cap), along with digital elevation models and derivatives (e.g., slope), and other ancillary information (e.g., 1992 NLCD) were used as the explanatory variables. Empirical models of percent tree canopy were then developed using regression trees based on the relationship between the response and explanatory variables.

The current effort to produce a 2011 NLCD percent tree canopy product (Coulston *et al.*, 2012) relies on a probabilistic sampling approach where a two stage sample is employed. The locations of the primary sampling units (PSUs) were identified based on a global sampling grid (White *et al.*, 1992), and within each PSU a systematic dot grid (105 points) covers a 90 m by 90 m area. Each point within the PSUs was classified using photographic interpretation of leaf-on 1 m true color or false color imagery provided by the National Agriculture Imagery Program (NAIP). This photointerpretation technique was similar to that used by Carreiras *et al.* (2006). The percent canopy cover estimates of each PSU then served as the response variable for empirical model development. The explanatory variables were leaf-on Landsat-5 imagery and derivatives, elevation and derivatives, and other ancillary data such as the 2001 NLCD land cover map. There are several notable differences between the approach used to develop the 2001 NLCD percent tree canopy cover map and the approach for the 2011 NLCD percent tree canopy cover map. The scope of this research is not to compare and contrast all the differences between the 2001 and 2011 NLCD approaches. It is rather to examine whether empirical models of leaf-on percent tree canopy cover are improved by using multi-season Landsat imagery as opposed to only leaf-on Landsat imagery as explanatory variables.

The available literature is comprised of examples suggesting that the use of multi-season imagery is appropriate, and others suggesting that using only single season imagery is appropriate for this type of application. For example, Franco-Lopez *et al.* (2001) used multi-season imagery to map forest stand density, volume, and cover type in St. Louis County, Minnesota. Hansen *et al.* (2003) used 40-day Moderate-resolution Imaging Spectroradiometer (MODIS) composites

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over the course of one year to model global tree canopy cover at 500 m. Alternatively, Carreiras *et al.* (2006) used leaf-on Landsat imagery to model tree canopy cover of evergreen oak woodlands on the Iberian Peninsula. Sen *et al.* (2011) used leaf-on imagery to quantify percent tree canopy cover of mined lands in the Appalachian Mountains in the southeastern United States. Clearly there are varying viewpoints on whether to use leaf-on or multi-season imagery for developing empirical models of percent tree canopy cover. The objective of this research is to test whether the inclusion of multi-season imagery as an explanatory variable significantly improves empirical models of percent tree canopy cover and to provide some guidance on where our results are relevant.

Methods

The study area was approximately the size of one Landsat scene covering central and northern Georgia in the southeastern United States (Figure 1). While the area was one Landsat scene in size, it covered path-rows 19-36 and 19-37 and was specifically selected to capture the south to north environmental gradient. The Piedmont was the dominant (77 percent) ecoregion (USEPA, 2011) in the study area. Land cover, based on Homer *et al.* (2007), in this ecoregion was 22 percent urban, 13 percent agriculture, and 56 percent forest cover. Much of the urban area was part of the Atlanta, Georgia metropolitan area. The Blue Ridge ecoregion covers 19 percent of the study area and was 6 percent urban cover, 5 percent agriculture cover, and 85 percent forest cover. A small percentage of the study area was classified in the Ridge and Valley ecoregion (3 percent) and the Southeastern Plains ecoregion (1 percent). The Ridge and Valley ecoregion was 14 percent urban, 22 percent agriculture and 54 percent forest cover. The Southeastern Plains ecoregion was 5 percent urban, 21 percent agriculture, and 59 percent forest cover.

Percent tree canopy cover was estimated for 4,125 sample locations (PSUs) across the study area and these estimates served as the response data. Sample locations were identified based on a 4X intensification of the USDA Forest Service Forest Inventory and Analysis sampling grid using the procedures described by White *et al.* (1992). At each PSU, a 105 point triangular-grid that filled a 90 m by 90 m (0.81 ha) area served as the basis for photo-interpretation (Figure 1). Each of the 105 points was manually interpreted as either "tree canopy" or "no tree canopy" using leaf-on 2009 NAIP (USDA,

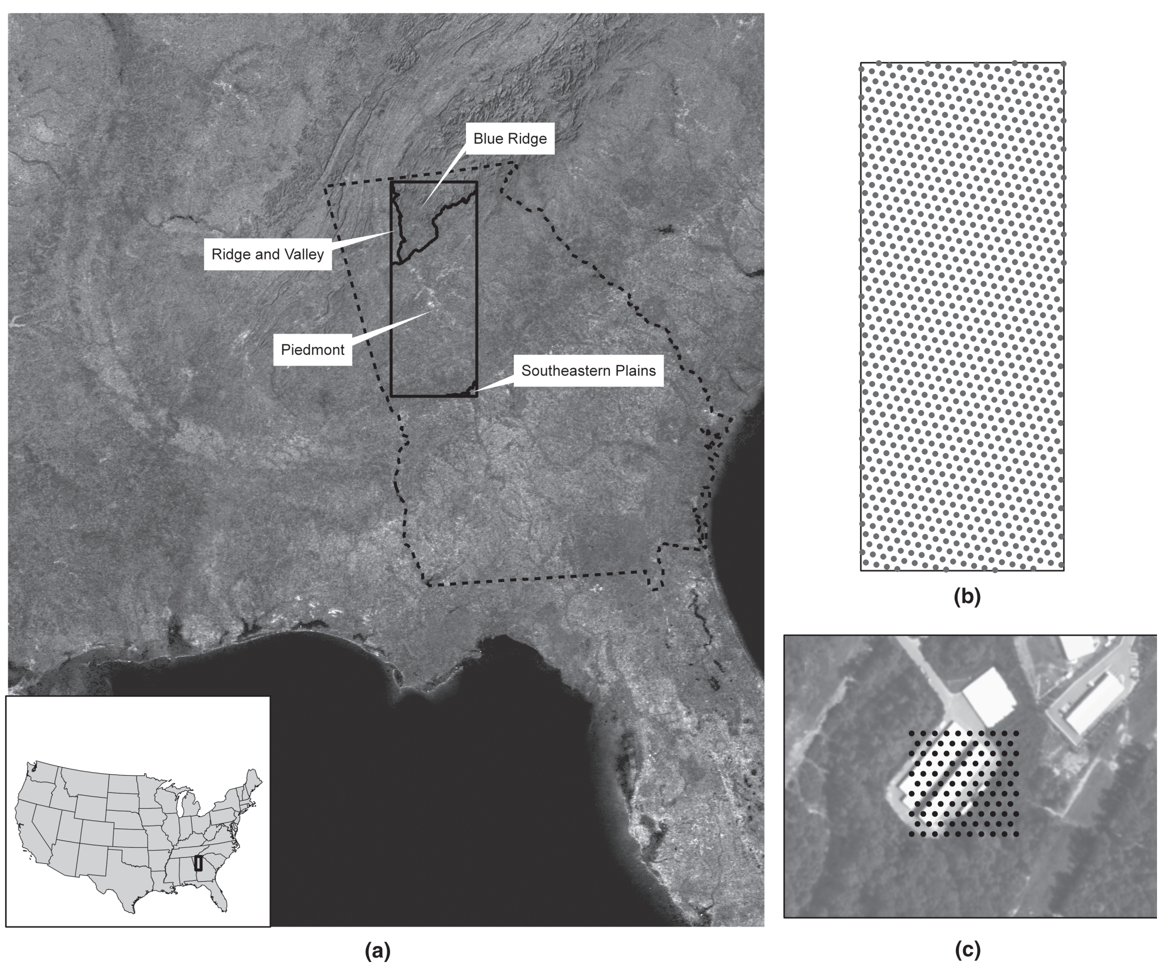

Figure 1. (a) Georgia study area, and (b) and (c) sample design. One of the four systematic samples (PSU) is displayed in (b). For each PSU a 105 point secondary sampling unit was used for photo interpretation of canopy cover (c).

2009) imagery. The overall design was considered a two-stage sampling design where the 0.81 ha area was the PSU, and each of the 105 points within the PSUs were the secondary sampling units. The design based estimators of proportion canopy cover in each PSU, mean proportion canopy cover, and the standard error of the estimate were obtained following Cochran (1977).

Landsat-5 data and derivatives (NDVI, tasseled cap), digital elevation data and derivatives (slope, aspect, sine and cosine of aspect, compound topographic index), and 2001 NLCD land cover data were used to develop the explanatory data. In total, six Landsat-5 scenes were downloaded from MRLC (2011) (Table 1). The 2001 NLCD land cover was also downloaded from MRLC (2011). Digital elevation data and derivatives were downloaded from USGS (2005). The Landsat data were already converted to top of atmosphere reflectance as described by Homer *et al*. (2004). For consistency with Coulston *et al*. (2012), the top of atmosphere reflectance was then converted to surface reflectance by dark object subtraction following the COST method (Chavez 1996). This approach assumes that there are some objects in the scene (e.g., clear water bodies and deep shadows) which have near-zero percent surface reflectance and their recorded values are conditional on atmospheric scattering which should be removed (see Song *et al*. (2001) and Schroeder *et al*. (2006) for more discussion on this topic). For modeling purposes, recall that the percent tree canopy cover was estimated for each 0.81 ha PSU. Also note that the explanatory variables (Landsat bands, vegetation indices, elevation and derivatives, and 2001 NLCD) were 30 m (0.09 ha) resolution. The response variable (percent tree canopy cover) was taken directly from the estimate for each PSU. The explanatory variables for modeling were developed by calculating the mean and standard deviation of each variable for each PSU. Because the PSU was registered to the NLCD base, the means and standard deviations for each variable were simply calculated using 3 × 3 pixel window focal statistics. In total there were 73 explanatory variables.

We used the random forest algorithm, developed by Breiman (2001), to construct empirical models of percent tree canopy cover. Random forest was chosen for consistency with Coulston *et al.* (2012) although there are other alternatives (see for example, Coulston *et al*., 2012; Walton, 2008; Sen *et al*., 2011; Homer *et al*., 2004; Hansen *et al*., 2003). Random forest is an ensemble method that uses bootstrap sampling to develop multiple models and improve prediction. Generally speaking, the random forest modeling approach is a non-parametric technique in that there are no distributional assumptions. The term "random forest" may be confusing particularly given the context of this research. "Random" in this case refers to random bootstrap resampling of the data and the term "forest" refers to an ensemble of regression trees (i.e., forest). The bootstrap is a resampling technique in which n observations from the original dataset are selected randomly, with replacement. The size of the bootstrap sample is also n but because the sampling is performed with replacement. On average only 63 percent of the observations in the original dataset will be included in a single bootstrap sample. Bootstrap approaches rely on selecting B bootstrap samples all of size n from the original data (see Efron and Tibshirani (1993) for more information). Bootstrap resampling is fundamental to developing random forest models. In the following example, adopted from Liaw and Wiener (2002), we assume that we have a dataset with n = 100 observations, and we set the forest size a priori to 500 regression trees. To construct the ensemble, we draw B = 500 bootstrap samples. The bootstrap samples are selected with replacement and each bootstrap sample has on average 63 observations (63 percent of observations). For each bootstrap sample, a regression tree is developed, but instead of determining the best split across all explanatory variables, a predetermined number of explanatory variables (for example, 5) are randomly selected and the best split among those variables is selected. Predicted values are then obtained by averaging the predictions from each of the 500 individual trees. For modeling we used the R ver. 2.12 (R Development Core Team, 2010) random forest library (Liaw and Wiener, 2002) to construct empirical models of percent tree canopy cover.

Three random forest models were developed each using 25 percent of the observations. To accomplish this, the original 4X systematic sample was decomposed using the hierarchical properties of triangular grids (White *et al*., 1992). A triangular grid can be enhanced or decomposed by factors of 3, 4, 7, or any multiplicative combinations of those factors. This property allowed us to create four systematic subsamples of the 4X grid. Subsample 1 was used to develop the multi-season model, subsample 2 was used to develop the leaf-on model, and subsample 3 was used to develop the reduced model. Subsample 4 was used as a hold-out for model comparison. This approach was used to insure that the samples were independent. The multi-season model was fit including all explanatory variables. The leaf-on model was fit based on all remaining variables after removing leaf-off and spring Landsat variables and derivatives from the model. A third model (reduced model) was based on a set of explanatory variables identified using principal components analysis on the 72 continuous variables, in addition to the 2001 NLCD. Principal components analysis is a data reduction and interpretation technique that leverages the correlation among all variables to identify orthogonal dimensions (Johnson and Wichern, 2002). Each component is a linear combination of the original variables and can be interpreted based on its eigenvector. When interpreting each component, the practitioner typically examines the magnitude of the loadings for each variable in the linear combination. Components are then interpreted as a composite value of those variables that have large absolute values of their loadings. We performed two principal component analyses: one for standardized (mean = 0, variance = 1) Landsat data and derivatives, and another for standardized (mean = 0, variance = 1) elevation data and derivatives. For each principal component analysis, the first n components that accounted for approximately 90 percent of the variation among all variables were retained for interpretation. Each component was interpreted based on the loading of each variable in the component. Of the variables that loaded high in each component, a single "representative" variable was selected based on its Pearson correlation with percent tree canopy cover.

Table 1. Landsat-5 Acquisition Dates for Leaf-on, Leaf-off, and Spring

Image	Date
Landsat-5 (path 19 row 36)	
leaf-on	24 July 2008
leaf-off	16 January 2009
spring	09 April 2010
Landsat-5 (path 19 row 37)	
leaf-on	09 August 2008
leaf-off	16 January 2009
spring	09 April 2010

The three models (multi-season, leaf-on, and reduced) were compared using the hold-out dataset. Models were examined in terms of root mean square error (RMSE), and pseudo-R^2. Pseudo-R^2 was calculated as $1 - (SS_{error}/SS_{cc})$ where SS_{error} was the sum of squared model error and SS_{cc} was the sum of squares for observed canopy cover in the hold-out dataset. We also statistically compared the three models using the Kolomogrov-Smirnov two sample test (KS) and analysis of covariance (ANCOVA). The KS was used to test for differences in the predicted canopy cover distribution among the three models and the difference between observed and predicted distributions for each model. ANCOVA was used to test for equality of slopes and intercepts in the observed versus predicted regression line. Steel *et al.* (1997) provide background on these statistical tests. We used ANCOVA to examine model differences across all land cover types as well as for forest, agricultural and urban land covers specifically. Both the KS and the ANCOVA assume that the data are independent. This was the motivating factor for fitting the three models based on independent samples and predicting canopy cover for a hold-out dataset.

Accounting for phenology is a motivating factor for using multi-date imagery to develop empirical models of tree canopy cover. Phenology is influenced by a variety of factors such as topography (Hwang *et al.*, 2011), land cover, and climate such as minimum temperature (White *et al.*, 2002). Minimum temperatures are also used to identify plant hardiness zones (USDA, 2012). Because topography and land cover were explicitly accounted for in our modeling effort, we relied on climate to indicate where our results would likely be relevant. To accomplish this, we focused on 1981 to 2010 estimates of monthly average daily minimum temperature acquired from the PRISM Climate Group (PRISM Climate Group, 2012). These data were in raster format and modeled at a spatial resolution of 30-arcseconds. We performed a Fourier regression on the monthly time series of monthly average daily minimum temperature for each pixel. Fourier regression is a common technique used to identify and model periodicity in time-series data (Brocklebank and Dickey, 1986). It has also been used to quantify phenological patterns based on vegetation indices (e.g., Brooks *et al.*, 2012; Wilson *et al.*, 2012). For our application we developed each model based on one cycle per 12 months using the following model:

$$T_m = \tau + \alpha \sin(2\pi m/12) + \beta \cos(2\pi m/12) + e$$

where T_m is the average minimum daily temperature for month m, τ is the average minimum daily temperature across months, α and β are estimated parameters controlling the amplitude and shape of the curve, and e is error. The model was parameterized for each pixel using ordinary least squares. The regression models developed within the study area were then compared to the regression models developed from outside the study area using the Wald test (see Harrell (2001) for background). For each pixel outside the study area we retained the probability that τ, α, and β were equal to the most similar τ, α, and β from within the study area.

Results

Based on the photo-interpretation of the 4X sample, the average percent canopy cover (across all 2001 NLCD land cover classes) was 66 percent (s.e. 0.53 percent) in the GA study area. The average percent tree canopy cover was 34 percent (s.e. 0.12 percent), 84 percent (s.e. 0.45 percent), and 41 percent (s.e. 0.94 percent) in the NLCD 2001 agriculture, forest, and urban land cover, respectively.

Table 2. Model Fit Statistics for Each Model

Model	RMSE	R^2
Leaf-on	15.01	0.81
Multi-season	14.02	0.83
Reduced	14.10	0.83

Principal components analysis was used to reduce the dimension of the full set of 73 explanatory variables. The results from the principal components analysis of the Landsat variable and derivatives indicated that 90 percent of the variance across all 60 variables was explained by the first 10 principal components. As expected this result suggests that there was a lot of redundant information in the Landsat-based explanatory variables. Each component was interpreted, and a single representative variable selected, based the pairwise correlation coefficient with observed percent tree canopy cover. The following Landsat based variables were retained: leaf-off TM band 3, standard deviation of spring TM band 3, standard deviation of leaf-off greenness, standard deviation of leaf-on TM band 6, spring NDVI, leaf-on NDVI, standard deviation of spring wetness, standard deviation of spring TM band 4, spring TM band 5, and leaf-off brightness. There was less redundant information in the digital elevation models and derivatives, where 90 percent of the variation across the 12 variables was explained by the first seven principal components. The final set of variables selected included: slope, aspect, sine aspect, standard deviation of slope, standard deviation of aspect, standard deviation of sine aspect, and standard deviation of compound topographic index. These ten Landsat variables and seven digital elevation variables, along with 2001 NLCD land cover, served as the explanatory variables for the reduced model.

The empirical models of percent tree canopy cover had similar pseudo R^2 s (Table 2). The R^2 for the model constructed with only leaf-on imagery was slightly lower than the multi-season model and the reduced model. The RMSE was also slightly higher for the leaf-on model as compared to the multi-season and reduced models. However, based on the KS test, all three models produced distributions that were statistically different ($p < 0.001$) than the observed distribution. Overall, the three models under-predicted the amount of no tree canopy cover and under-predicted the amount of 100 percent tree canopy cover (Figure 2). While all three models produced distributions that were significantly different from the observed distribution, there was no significant difference ($\alpha = 0.05$) among the model predicted distributions based on the KS test. Because the observed values were fixed and there was no statistical difference among model predictions, this indicated that there was no statistical difference ($\alpha = 0.05$) between RMSE and R^2 model fit statistics among models.

Typically with the ANCOVA there are two hypotheses tested sequentially. The first hypothesis is that the regression lines are parallel (i.e., the slopes are equal). If the lines are parallel, the second test examines whether they are coincident (i.e., equal slopes and equal intercepts). We used ANCOVA to test for differences between the slope and intercept of the observed versus predicted regression lines irrespective of 2001 land cover and for agriculture, forest, and urban classes individually. Overall, there was not enough evidence to reject the hypotheses that the observed versus predicted regression lines were

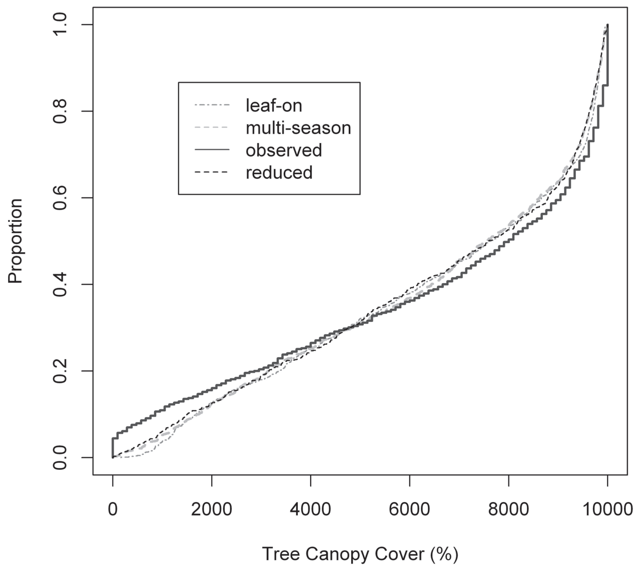

Figure 2. Cumulative distribution of observed tree canopy and predicted tree canopy cover based on the leaf-on, multi-season, and reduced models.

coincident for each of the models (multi-season, leaf-on, and reduced) (Table 3). When not considering land cover class, all three models had slopes of approximately 1 and intercepts within 0.58 percent of zero. When examining the agriculture and urban land cover classes, intercepts were generally within 3 percent of zero and slopes were close to one, but as noted earlier, there was no statistical difference among models. In general, the intercepts for all models when considering the agriculture and urban land covers were negative. This indicated over-prediction at low canopy cover as evident in Figure 3. Intuitively one would expect under-prediction at low levels of canopy cover in the forest cover classes because the intercepts for all models were greater than zero. However, the actual case was that over-prediction occurred at low canopy cover. In the case of the forest land cover classes, the slope and intercept of the observed versus predicted regression line was heavily driven by the large number of observation where both the observed and predicted canopy cover were greater than say, 80 percent. In this range, percent canopy cover was also under-predicted and because of the density of observation this caused the intercept to be positive even though the few observations with canopy cover less than say, 20 percent were clearly over-predicted by all three models (Figure 3).

To speculate on the likely applicability of our findings to other areas we relied on Fourier regression of average 1981 to 2010 monthly average daily minimum temperature for each pixel in an area surrounding our study area. The total area examined was based on seven US Geological Survey mapping zones (Homer and Gallant, 2001) (Figure 4). The per-pixel Fourier regression models, across this broader area, had R^2 ranging from 0.94 to 0.99. We examined probability that τ, α, and β were equal to the most similar τ, α, and β from within the study area using a Wald test. Based on probabilities from the Wald test, our results may be applicable to much of the Piedmont and foothills of the Southeastern United States where the probability that regression parameters were equal to regression parameters within the study area exceeded 0.95 (Figure 4). Conversely, our results may not be applicable to the outer and southern Coastal Plain of the Southeastern United States.

Table 3. Intercept and Slope of the Observed versus Predicted Line for Each Model across 2001 Land Covers, and by Agriculture, Forest, and Urban Land Covers; the Results of the Analysis of Covariance are also Provided

Land Cover	Model	Intercept	Slope
All	Leaf-on	0.00	1.00
	Multi-season	–0.50	1.01
	Reduced	0.58	1.00
	P-value	0.66	0.70
Agriculture	Leaf-on	–2.79	1.05
	Multi-season	–1.42	1.02
	Reduced	–2.41	1.08
	P-value	0.75	0.88
Forest	Leaf-on	14.59	0.84
	Multi-season	12.46	0.87
	Reduced	11.47	0.87
	P-value	0.59	0.36
Urban	Leaf-on	–1.69	1.01
	Multi-season	–2.74	1.02
	Reduced	–3.73	1.08
	P-value	0.68	0.55

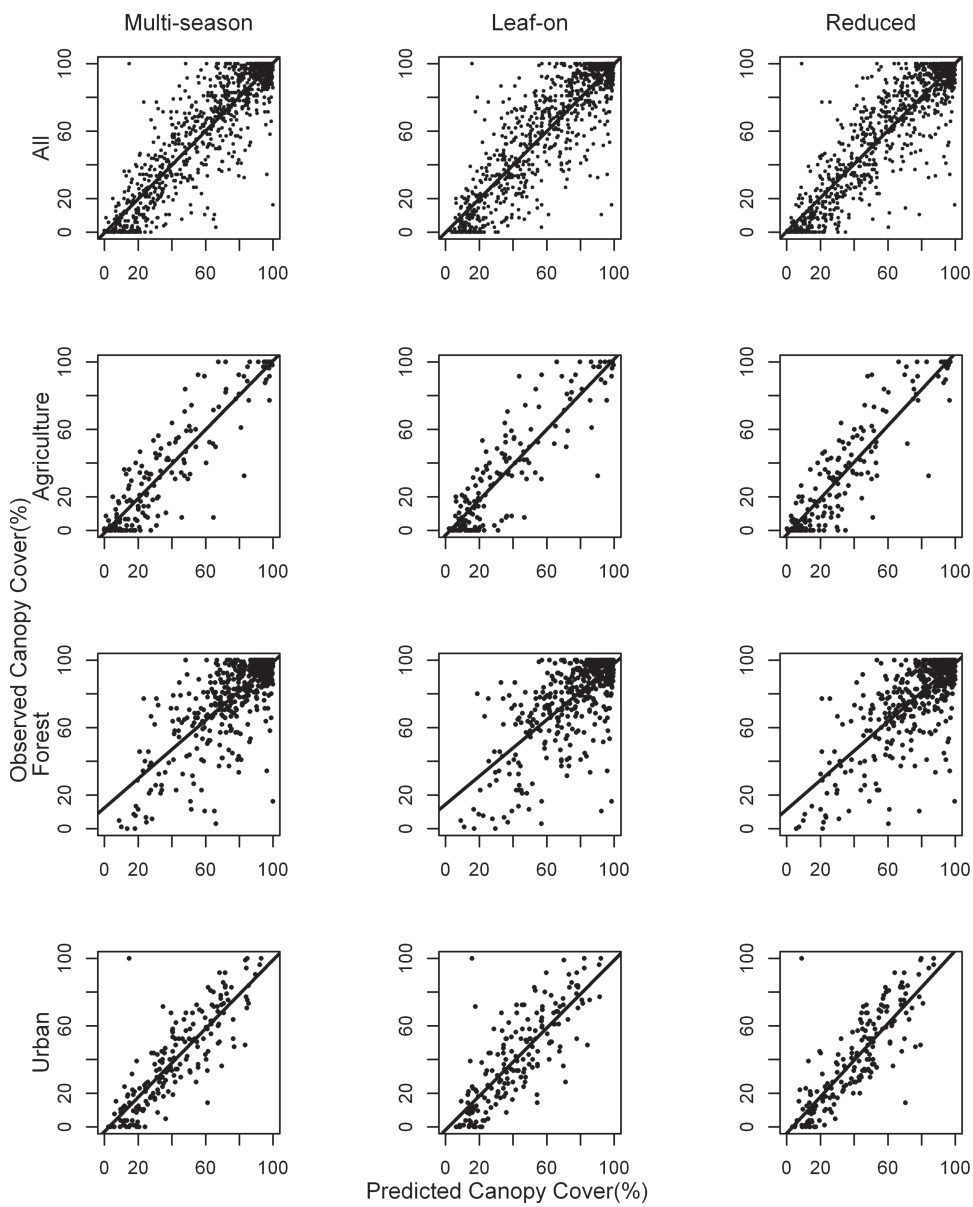

Figure 3. Observed versus predicted canopy percent canopy cover, based on a hold-out dataset, for all land cover classes, agricultural classes, forest classes, and urban classes based on the multi-season model, the leaf-on model, and the reduced model. The solid line is the observed versus predicted regression line with parameters as described in Table 3.

Discussion

The scope of this research was to identify whether using multi-season imagery as explanatory variables resulted in more accurate empirical models of percent tree canopy cover. The answer to this question lies in a discussion of model accuracy and parsimony. Generally speaking, when models are equally complex, the most accurate model is preferred and when models are equally accurate, the simplest model is preferred. This concept follows Occam's razor. In our particular case all models were equally accurate based on the KS and ANCOVA tests. The reduced model was the simplest model and the multi-season model was the most complex in terms of the number of predictor variables. However, to apply our logic to select a model, we must consider not just the number of predictor variables used in the model, but also the time invested in constructing and managing the explanatory data. Both the multi-season and the reduced model require the acquisition, storage, and processing of three times more Landsat data. Also, while the reduced model is simpler than the multi-season model, the leaf-on model is the simplest in terms of Landsat data acquisition, storage, and processing. Therefore in this case we recommend using leaf-on imagery as

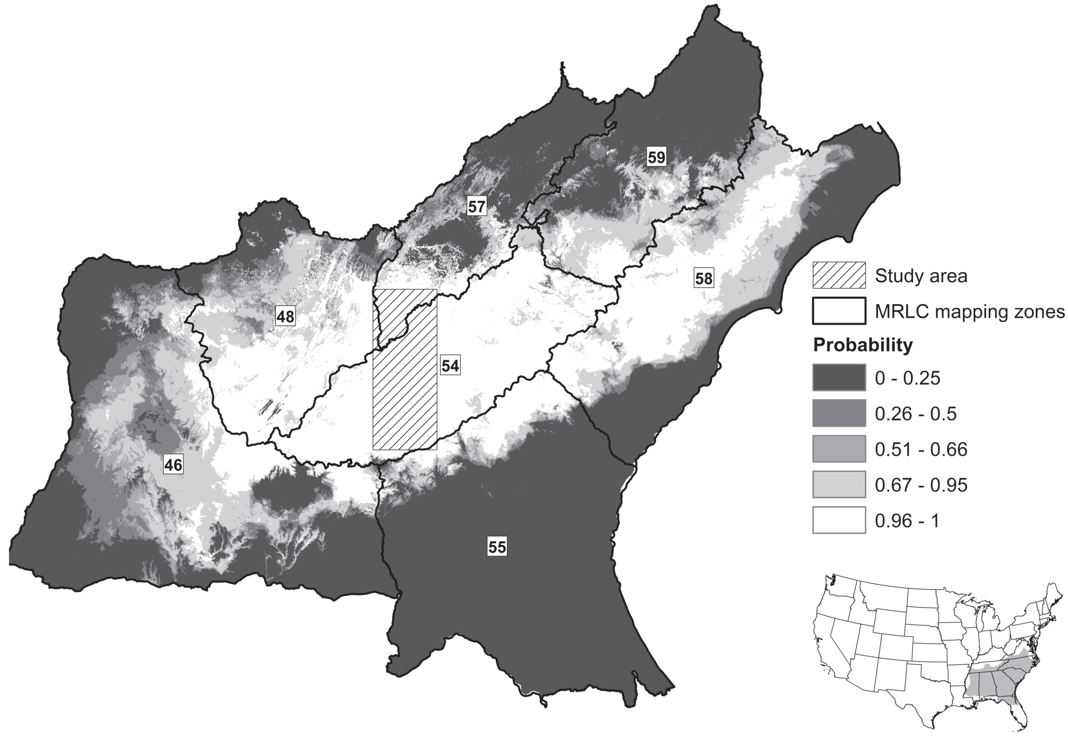

Figure 4. The probability of similar monthly minimum temperature profiles to the study area. The probabilities were from the Wald test which compared Fourier regression parameters of areas outside the study area to the most similar Fourier regression parameters from within the study area.

opposed to multi-season imagery. However, we acknowledge that this recommendation is more applicable when relatively broad geographic extents, comprised of numerous scenes, are modeled and imagery is minimally pre-processed. For smaller geographic areas, or if pre-processed imagery is available, the multi-season, leaf-on, or reduced models are all equally appropriate.

Similarity among models was expected when examining model performance irrespective of NLCD 2001 land cover class. However, we did expect to observe some marked differences in model performance particularly in agricultural areas. Hypothetically, multi-season imagery should allow for better separation between vegetative cover with distinct phenological cycles (e.g., Brooks *et al.*, 2012). This in turn should result in smaller errors for agricultural fields and residential urban areas. There are at least three plausible explanations for the similarity among models in agricultural and urban land covers. The first potential explanation is that the three date time series was not sufficiently dense, from a temporal perspective, to adequately capture the phenological profiles associated with different vegetation. The second potential explanation is that phenological differences at the pixel-level only account for a small proportion of the variability in subpixel tree canopy cover. The third potential explanation is that including land cover as an explanatory variable accounted for most of the variation in phenological cycles among various vegetative covers. However, we tested the third potential explanation by removing land cover from the empirical models. This did not yield significantly different models. The first two potential explanations are the most likely.

We used an extrapolation technique to identify other areas in the Southeastern United States where our results may be applicable. This approach assumed that average daily minimum temperature is a driver of phenology which is consistent with White *et al.* (1997) except that we used long-term averages rather than daily values. This approach was also based on the notion that phenology provides the motivation to use multi-season imagery. Phenology and modeling phenology is clearly more complex than the approach we have taken. Regardless, our goal was not to quantify phenology per se but rather to identify areas where one might expect a similar phenology, as driven by minimum temperature, and hence similar results regarding models of percent tree canopy cover when similar explanatory variables are used. We suggest that our results may be applicable to the Piedmont of the Southeastern United States. However, our results may be more broadly applicable if the reason behind our finding is that phenological differences, as defined by three seasons of imagery at the pixel-level, only account for a small proportion of the variability in subpixel tree canopy cover but this remains to be tested.

The models we developed provided reasonable results across land cover classes and for the agriculture and urban classes based on the intercepts and slopes of the observed versus predicted regression lines. However, the results for the forest land cover require more attention. As shown in Table 3, the intercept was approximately 12 percent across the three models. Upon closer examination, we observed that the density of percent tree canopy cover estimates in the 65 percent to 90 percent range were the primary driver of the slope and intercept parameter estimates in the forest land cover class

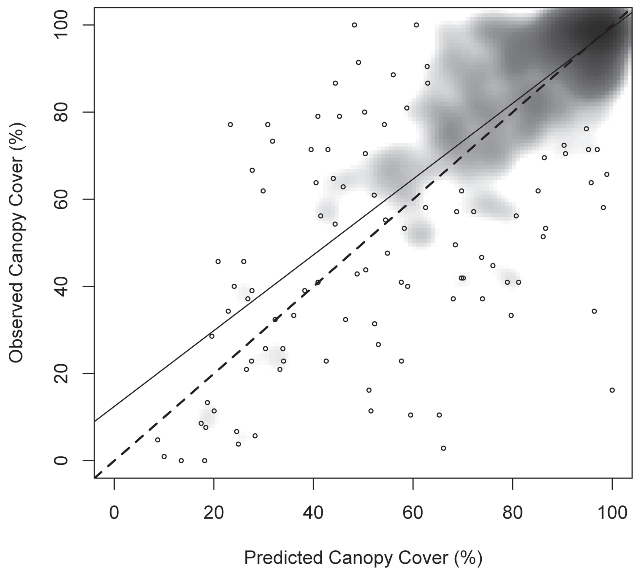

Figure 5. Smoothed scatter plot of observed versus predicted percent tree canopy cover using the multi-season model. The cloud denotes the densest part of the plot and the 100 observations in the least dense part of the scatter plot are denoted by points. The solid line is the observed versus predicted regression line using the parameters from Table 3 and the dashed line is the 1:1 line.

(Figure 5). The under-prediction in this range of canopy cover is counterintuitive to saturation issues of explanatory variables such as NDVI and may be more related to the influence of bare ground on vegetation indices as described by Sellers (1985). Given the importance of percent tree canopy cover in, for example, fire modeling applications, more research should be focused on improving the model predictions for forested areas. One potential approach is to fit separate models for each land cover class, perhaps at the Anderson Level I classification. Hypothetically this would allow for more flexibility in the model parameterization by land cover class and alleviate the underestimation at low-levels of canopy cover as described here.

There are numerous examples of model assessment techniques. Duane *et al.* (2010) and Riemann *et al.* (2010) are some recent examples. However, there are few examples of appropriate use of statistical test from either a parametric or nonparametric perspective. One of the key challenges to using statistical tests is the assumption of independent samples. In the research presented here, we overcame this issue by fitting three models using three independent samples, and predicting values using each model to a fourth independent sample. In many cases, researchers do not have enough data to take this approach. One alternative is the chi-square test for nested models (see for example, Satorra and Bentler, 2001). However, the significance of the test statistic can only be assessed when the degrees of freedom for each model can be specified. In the typical regression scenario this equates to the number of estimated parameters that a model contains. Clearly specifying the degrees of freedom for a learning based model (such as random forest or stochastic gradient boosting) is problematic, but one area of future research is to develop an approach to approximate the degrees of freedom for these types of models.

In summary, we found that empirical models of percent tree canopy cover were not significantly improved by including multi-season imagery as explanatory variables. We also found the empirical models of canopy cover based on the wise selection of 18 explanatory variables (reduced model) performed as well as models developed from 33 explanatory variables (leaf-on model) and 73 explanatory variables (multi-season model). All three modeling strategies are equally valid and we suspect that these results apply to much of the Piedmont in the Southeastern United States.

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