Temporally-dense, high-resolution LAI estimation using multi-sensor fusion

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Project at a Glance

- **Objective:** Create a 30 m resolution map of LAI at a 2-week interval for a study-site in the NC piedmont.
- **Method:** A novel multi-sensor fusion approach blending Ikonos, Landsat and MODIS imagery.
- Texture is a surrogate for canopy structure and is a complimentary estimator to spectral indices.
- Multiple regression using multiple SVI and texture measures can leverage complimentary information.
- AIC based model-selection can reveal alternative, *good* models.
- Our model is simple to apply and successful in producing reasonable maps of LAI at an arbitrary temporal resolution.

Motivation

Ecosystem process simulations on local- to regional-scales require high spatial and temporal resolution maps of LAI to achieve reliable simulation results. The tradeoff between achievable spatial and temporal resolutions from remote sensing platforms has stimulated research into multi-sensor fusion models. We propose a novel method of LAI estimation which combines complimentary information from remotely sensed imagery spanning three orders of magnitude in spatial resolution. Texture information from high-resolution Ikonos imagery and spectral information from moderate resolution Landsat TM imagery is used to capture the fine-scale spatial variability in LAI, and coarser resolution MODIS data is used to extract the temporal signal of phenological change. This study demonstrates that the use of multiple SVI as well as texture information can significantly improve LAI estimation when compared with conventional approaches. We used the model to construct 30 m spatial resolution LAI maps at a 2-week interval for a study-area in the NC piedmont. The model is simple to run, not data intensive, and produces reasonable estimates of the time evolution of LAI throughout a growing season.

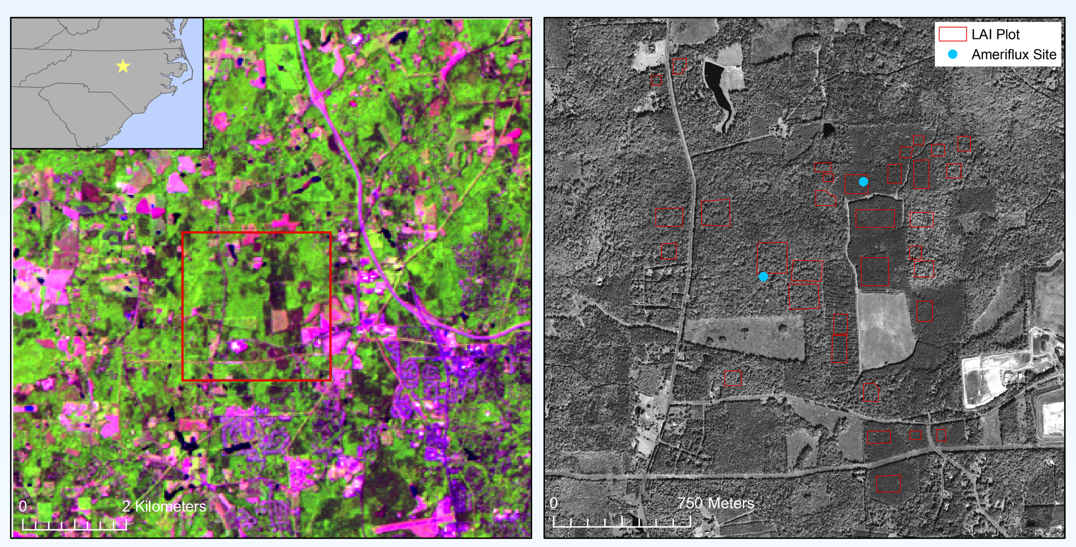

Figure 1: Left Panel: May, 19 2009 Landsat TM composite of study-area (10 km x 10 km extent of Ikonos image). Right Panel: The Duke Forest research area where ground-observations of LAI were made. Sampling plots are shown on the panchromatic Ikonos image.

Model Overview

Separate empirical models for conifer and deciduous forest types are fit to ground observations using a combination of spectral and spatial information from Landsat and Ikonos imagery and used to generate a map of maximum LAI (Eq. 3). A deciduousness parameter is calculated (Eq. 6) and used to mix LAI contributions from conifer and deciduous vegetation within a given pixel (Eq. 1). A phenological function (Eq. 4 and 5) is used to adjust an individual pixel's LAI between it's minimum and maximum values for an arbitrary day, t, during the growing season (Eq. 2).

$$\mathrm{LAI(t)} = (1-\Omega)\mathrm{LAI}_c(t) + \Omega\mathrm{LAI}_d(t) \tag{1}$$

$$\mathrm{LAI}_{c,d}(t) = \mathrm{LAI}^{min}_{c,d} + f_{c,d}(t)\left[\mathrm{LAI}^{max}_{c,d} - \mathrm{LAI}^{min}_{c,d}\right] \tag{2}$$

$$\mathrm{LAI}^{max}_{c,d} = \beta_0 + \beta_1\mathrm{SVI}_1 + \beta_2\mathrm{SVI}_2 + \beta_3\mathrm{TEX} \tag{3}$$

$$f_{c,d}(t) = \mathrm{MODSVI}_{c,d}(t) \rightarrow [0,1] \tag{4}$$

$$\mathrm{MODSVI}_{c,d}(t) = \left(\frac{1}{1+e^{a-bt}} - \frac{1}{1+e^{a'-b't}}\right) g + h \tag{5}$$

$$\Omega = \frac{\mathrm{NDVI}_{summer} - \mathrm{NDVI}_{winter}}{\mathrm{NDVI}_{summer} + \mathrm{NDVI}_{winter}} \rightarrow [0,1] \tag{6}$$

Empirical LAI Model

We use two innovative techniques to fit an empirical model to ground measured LAI: 1) we utilize image texture from high-resolution imagery to compliment multiple SVIs in a multiple regression framework, and 2) we adopt the information theoretic criteria approach to model selection. Ground-based estimates of effective LAI were obtained for a mixture of homogenous evergreen and deciduous plots ($n = 33$) using indirect optical techniques (LAI-2000). Field campaigns were conducted in late June and July of 2009. Landsat TM imagery was obtained to coincide with the field collections and atmospherically corrected using a dark-object subtraction approach with downwelling diffuse radiation calculated using 6S.

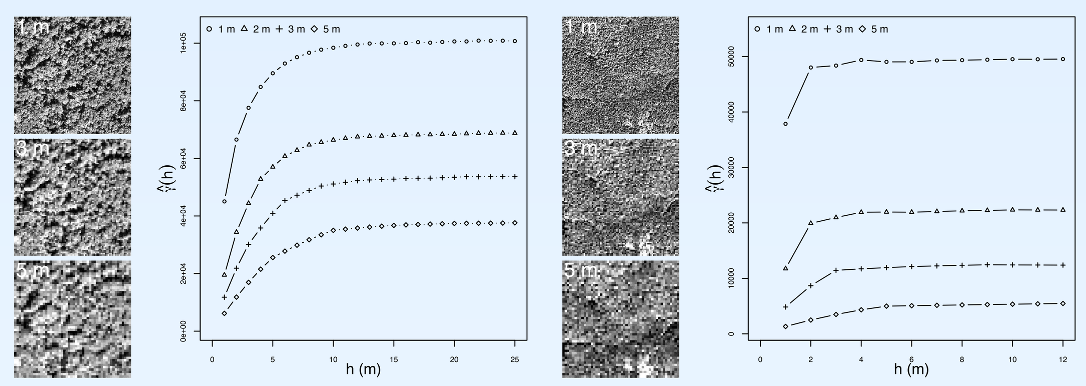

Figure 2: Semivariograms for deciduous (left) and pine (right) calculated at four spatial resolutions on 250x250 pixel samples from the Ikonos image. The effect of regularization is to lower the overall variance in the sample (sill) and increase the range. Note the significantly smaller spatial scale of the pine spatial pattern.

Eight multiple regression models were proposed to fit the observed LAI data. We allowed models to have two SVI predictors, the first being either the simple ratio (SR), or reduced simple ratio (RSR), and the second being either the structural index (SI), or enhanced vegetation index (EVI). Additionally, half of the models included a texture predictor (VAR). We chose to use a first-order measure of image texture, windowed variance, although alternatives such as GLCM features have also demonstrated effectiveness in estimating canopy structure. We determined the window size based on empirical semivariograms at various pixel resampling sizes (Fig. 2) as well as images of windowed variance over the study area (Fig. 3). The models were fit and ranked via AIC (Table 1). Texture information leads to a significant improvement in estimating deciduous LAI, whereas conifer LAI is best predicted using SVI alone (Fig. 4).

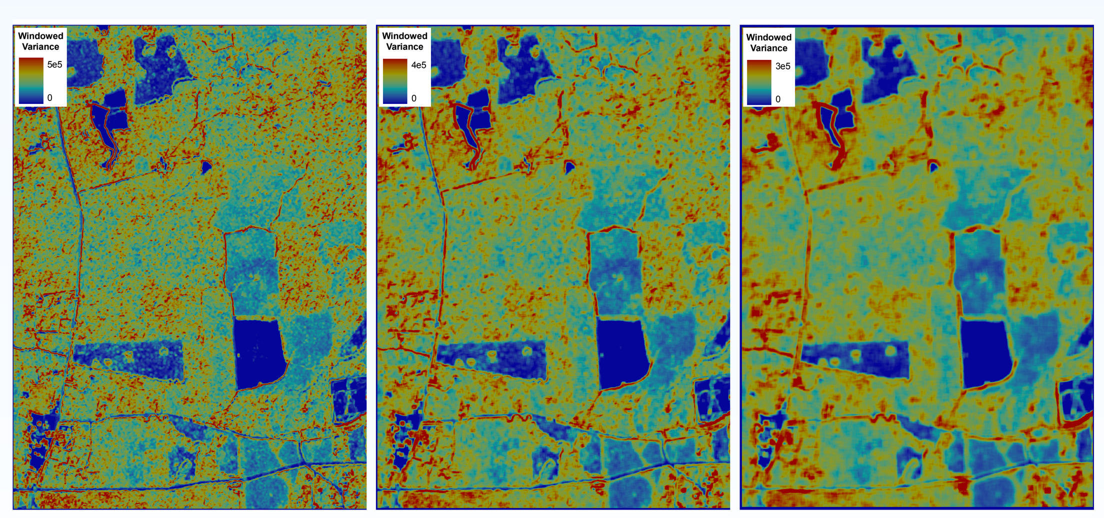

Figure 3: Variance calculated on 1 m spatial resolution Ikonos panchromatic image at three window size: 13, 21 and 33 pixels. Note the differences in color-scale for each.

Table 1: Candidate models ranked by AICc and associated parameter estimates. All models have effective LAI (L_e) as the dependent variable. Sig: ***: <0.001, **: <0.01, *: <0.05, ·: <0.1

Model	Parameters						Rank	AICc	AIC Weight	R^2
SEV	SR_c	SR_d	EVI_c	EVI_d	VAR_c	VAR_d	1	87.4	0.71	0.73
	1.0e1***	2.9·	-1.0e2***	-4.8e1*	-1.6e-5	1.1e-4**				
REV	RSR_c	RSR_d	EVI_c	EVI_d	VAR_c	VAR_d	2	90.0	0.20	0.71
	5.2***	1.7	-3.0e1*	-1.8e1*	-3.2e-5	9.6e-5**				
SE	SR_c	SR_d	EVI_c	EVI_d			3	92.5	0.05	0.61
	1.0e1***	4.3e-1	-1.0e2***	-8.3						
RE	RSR_c	RSR_d	EVI_c	EVI_d			4	93.7	0.03	0.59
	5.1***	2.0e-1	-3.4e1*	-3.7						
RS	RSR_c	RSR_d	SI_c	SI_d			5	100.4	<0.01	0.50
	1.3	4.8e-1	3.7	0.7						
RIV	RSR_c	RSR_d	SI_c	SI_d	VAR_c	VAR_d	6	101.1	<0.01	0.59
	3.3	-1.8e-1	8.3e-1	-2.2	-5.5e-5	6.0e-5				
SIV	SR_c	SR_d	SI_c	SI_d	VAR_c	VAR_d	7	101.5	<0.01	0.59
	-1.2e-1	-4.6e-1	7.4**	2.4e-1	-3.6e-5	6.8e-5·				
SI	SR_c	SR_d	SI_c	SI_d			8	189.8	<0.01	0.33
	1.7***	2.0e-1·	8.3e-1**	-6.2e-2						

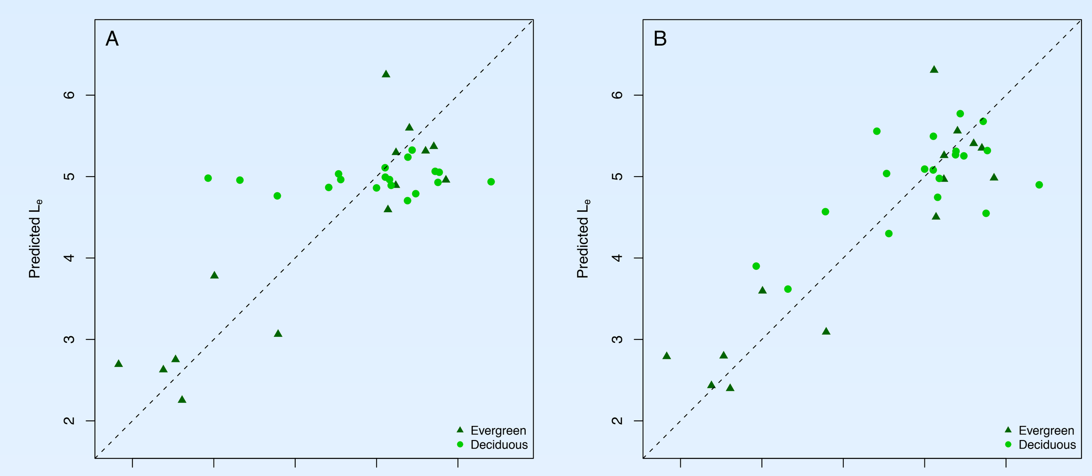

Figure 4: Comparison of observed and predicted L_e using models SE (A) and SEV (B). Model SEV contains a texture estimator which leads to a significant improvement in model fit for deciduous stands.

Phenology

We fit the difference logistic function (Eq. 5) to MODIS NDVI. The VI Reliability Index was used to limit calculations to reliable pixels only, and the MOD12 Landcover product (Type 1) was used to construct separate time-series of deciduous and evergreen vegetation. Daily mean values of NDVI were calculated by using the Composite DOY product. Further filtering was necessary to remove outliers and dates for which there were less than 20 pixels available for calculation of the mean (Fig. 5). The resulting time-series were fit using weighted nonlinear least squares methods where the weights are determined as the reciprocal of the sample mean (i.e., N_i/σ^2). It was found that the evergreen and deciduous time-series had identical temporal trajectories, so we use the deciduous model for both evergreen and deciduous LAI estimation.

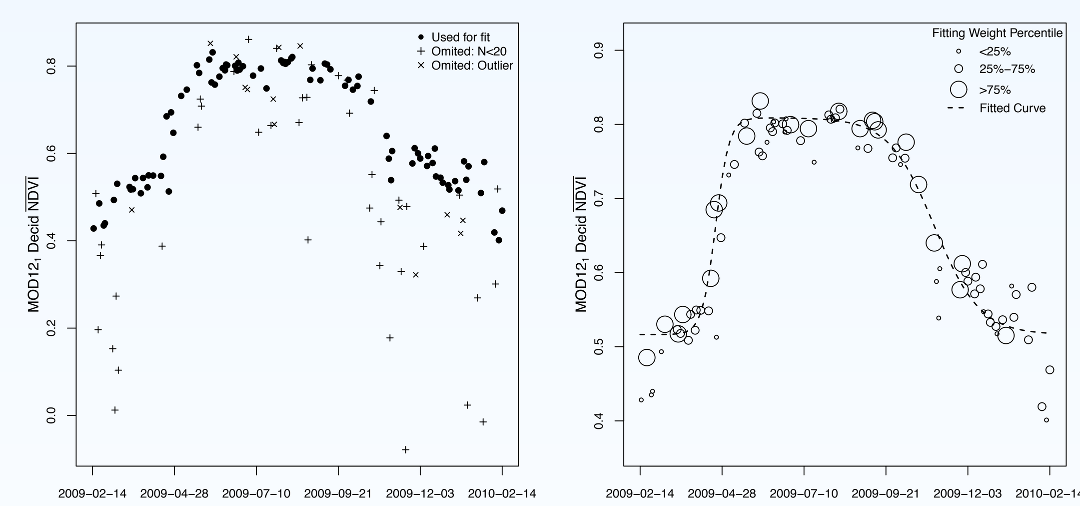

Figure 5: Left panel: Mean NDVI for MOD12Q1 Type 1 Deciduous forests indicating points omitted from fitting procedure by outlier detection (Tukey IQR method) or too few pixels used in calculation. Right panel: Full range of fitted data. Point sizes indicate the relative weight used in the nonlinear least squares fit. Dashed line is fit.

Results

We used the full model to estimate maps of LAI at a 2-week interval for the study-area. Fig. 6 shows four such maps at select temporal intervals. Two Ameriflux sites within the study-area have a daily record of LAI for deciduous and conifer plots. We compared these records to our daily estimates of LAI at these plots (Fig. 7). Our model does a good job of capturing both the temporal trend as well as the magnitude of LAI at these plots. However, for the deciduous stand, we note a longer senescence period for our model than is indicated by the ground observations. This is likely due to understory herbaceuous and evergreen vegetation which becomes visible to the satellite sensor as the overstory canopy sheds its leaves.

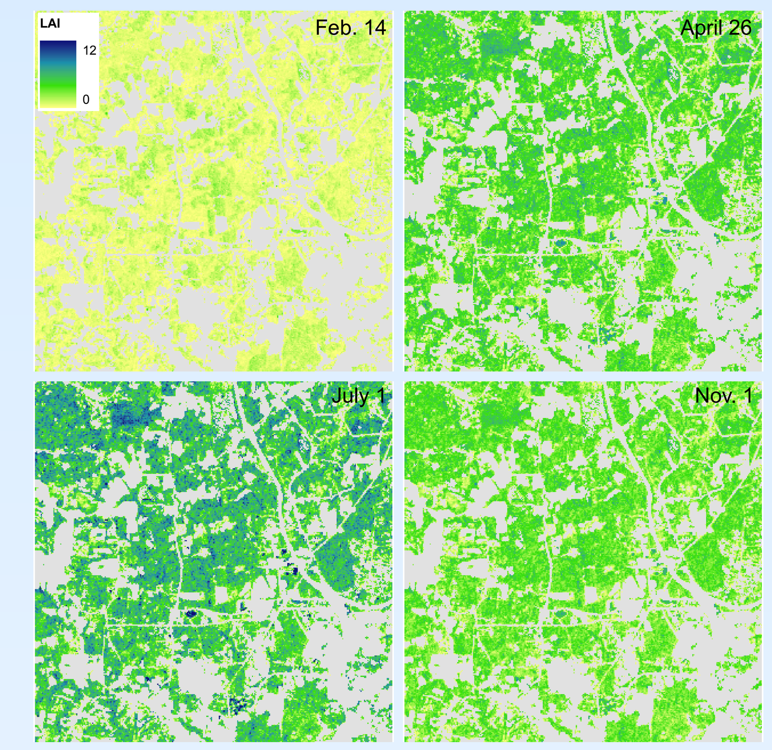

Figure 6: LAI map of the study area at four select dates throughout the growing season. Minimum, green-up, peak and senescence phases of the vegetation are depicted.

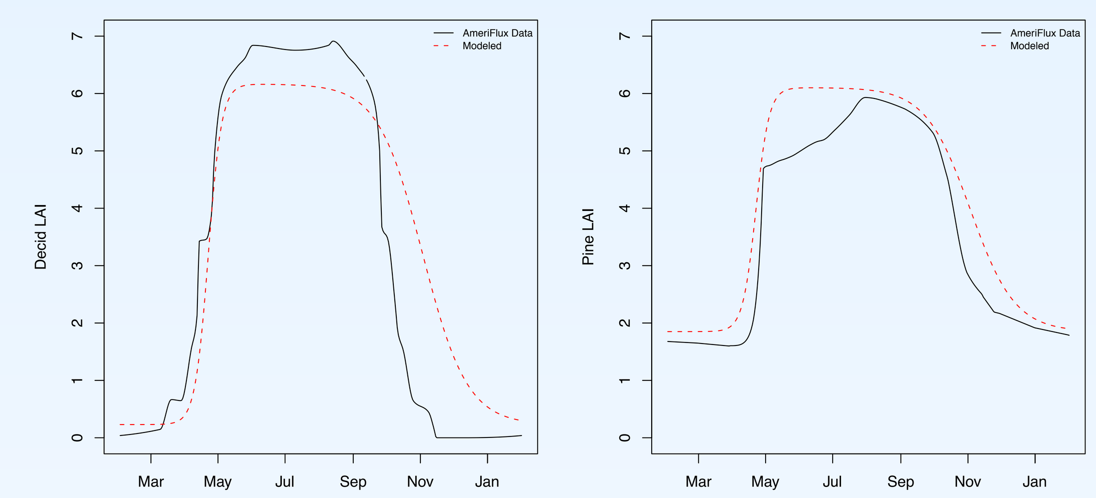

Figure 7: Validation data from Duke Ameriflux towers.

Conclusions and Future Directions

- We demonstrate that texture indices lead to significant improvements in the estimation of LAI, particularly for deciduous vegetation. Texture acts as a surrogate for canopy structure and contains information about crown size and stocking density. We show that empirical variograms on representative textures are useful for determining texture parameters such as window size and resampling resolution.
- The successive filtering steps we applied to MODIS NDVI 16-day composites allow for the extraction of smooth time-series suitable for determining stable parameters of phenological functions. That evergreen and deciduous time-series were temporally identical indicates that there is a substantial amount of mixed or misclassified pixels in the MOD12 landcover product, and that it may be unsuitable for this application.
- Overall, our method represents a very simple method for fusing complimentary remote sensing information from three distinct spatial resolutions. This method has demonstrated its effectiveness in representing the magnitude and temporal signature of LAI production.
- Future improvements should focus on improving the phenological time-series data by using improved landcover classifications. Additional validation, particularly in mixed stands, will improve confidence in our modeling approach.