

# **Modeling Forest Productivity Across a Heterogeneous Landscape: A Comparison of Satellite, Geospatial, and Climate Predictors**

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Remote sensing can provide a relatively low-cost and low-impact approach to large scale assessment of forest condition and productivity over time. However, the connection between canopy spectral signatures and scalable field metrics is not well understood. To explore this relationship, we compared annual basal area increment (BAI) throughout northern Vermont and New Hampshire to a suite of vegetation indices, ancillary spatial data sets and climate variables. Our specific research questions include:

- How sensitive is the model to repeated measures?

### Model Inputs:

- 1322 tree cores across 105 plots



# Model Calibration and Assessment:

### **Preliminary Results:**

- Remote Sensing metrics alone can NOT be used to mode a heterogeneous landscape
- The addition of ancillary environmental variables improv significantly, and the addition of climate variables increa
- There was no significant difference in models developed significance between the stepwise and mixed effects app

## Conclusions:

By: Jesse Little

How well can we model forest productivity across a heterogeneous landscape using remote sensing metrics? How much do predictions improve if we include ancillary environmental variables as covariates?

**Response Variable:** Yearly Basal Area Increment measurements between 2001 and 2012 were measured for

Independent Predictor Variables: For each core sample, 108 variables from different geospatial datasets were recorded which include: remote sensing variables like MODIS NDWI (min, max, mean), ancillary data such as disturbance, and PRISM climate data like temperature(min, max, mean).

> • Because of the large number of possible predictor variables a backwards stepwise regression with a p-value threshold of 0.01 was used to identify a subset of key spatial data sets for forest productivity modeling. • Compare these results to a mixed effects model with Site ID nested in year as a random effect to determine the impact of autocorrelation across yearly metrics on model accuracy and stability. • Repeat these models with the addition of ancillary and environmental variables

	<u>Approach</u>	<u>Stepwise</u>			<u>Mixed Model</u>		
		<b>RS Only</b>	<u>RS + Site</u>	RS + Site + Climate	<b>RS Only</b>	RS + Site	<u>RS + Site + Climate</u>
el productivity across	r^2	0.006	0.14	0.269	0.01	0.14	0.269
	r^2 Adjusted	0.006	0.134	0.25	0.009	0.139	0.268
ves predictions ases accuracy further. d, their accuracy or proaches.	RMSE	6.5	6.06	5.64	0.654	6.05	5.58
	press RMSE	6.42	6.09	5.75	0.655	6.06	5.59
	AIC	8704	8528	8367	9525	8528	8360
	BIC	8720	8580	8551	9547	8584	8549
	Durban Watson						
	Autocorrelation	0.8	0.77	0.73	0.04	0.77	0.74
	DW significance	< 0.0001	<0.0001	<0.0001	<.0435	<0.0001	<0.0001
	Variable Count	1	8	33	2	9	34

Landscape scale assessments of forest productivity must include ancillary environmental and climate variables • Repeated yearly metrics do not limit model power or configuration, such that this is a viable analytical approach to modeling dendrochronological data. • This information will be used to investigate spatial and temporal patterns in forest productivity across the northeast.



