Recent Remote Sensing Innovations and Future Direction

Co-Authors: 2016 NLCD Tree Canopy Science Team

Virginia Tech: V.A. Thomas, R. Wynne, J. Derwin, E. Brooks, R. Saxena

USDA Forest Service: G. Liknes, J. Coulston, K. Megown, G. Moisen, C. Toney, K. Schleeweis

RedCastle Resources: M. Finco, R. Benton, and B. Ruefenacht

Seminar Outline

- Introduction
  - Science Team Research Questions
    - Do time time series approaches improve tree canopy cover modeling?
    - How has US canopy cover changed from 2011-16?
- Methods
- Results
- Lessons learned to date
- Other innovations and future directions

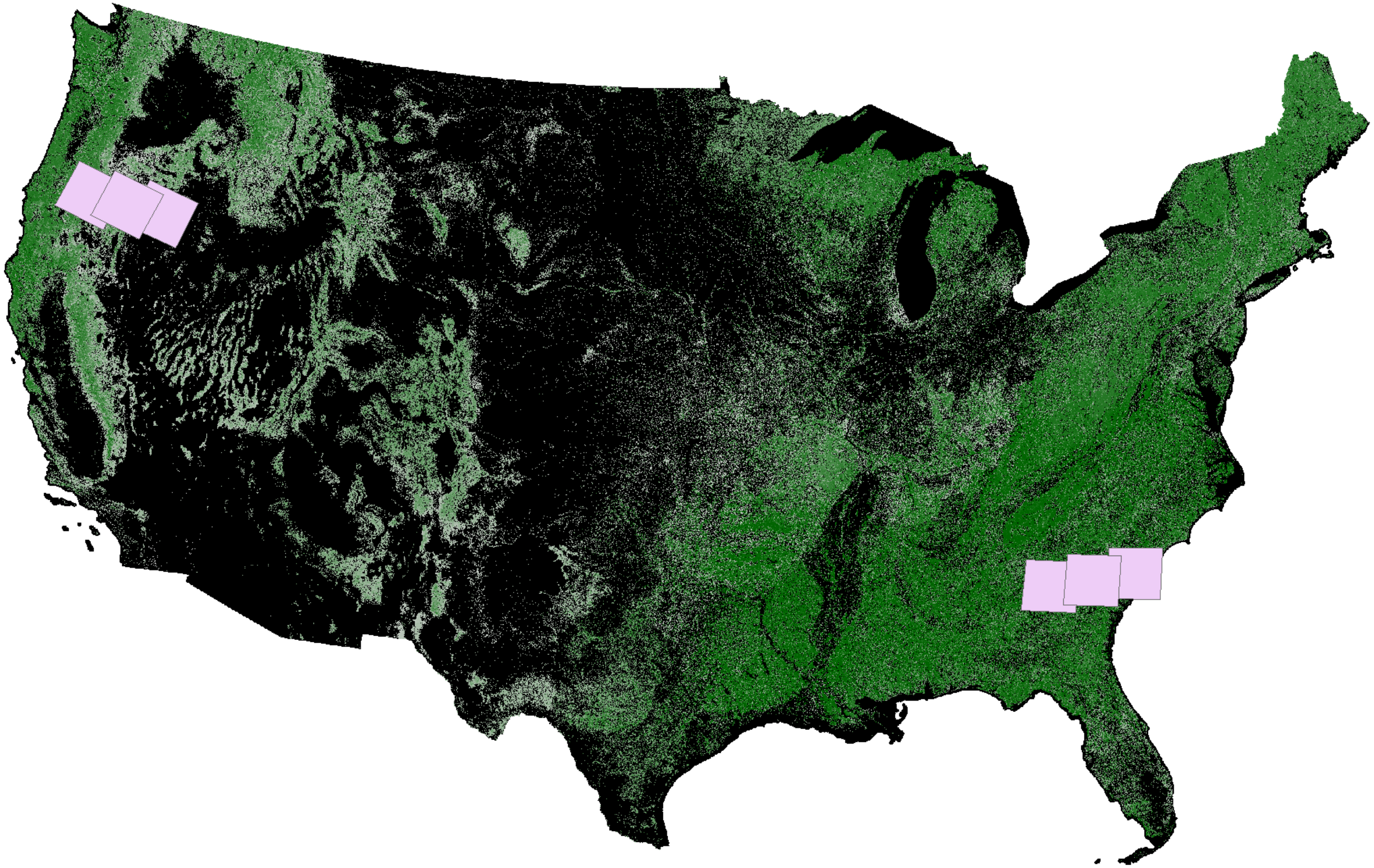
Do time series approaches help us to predict/map tree canopy cover?

Percent tree canopy from 0-100%
With associated pixel-level uncertainty
Responsibly deal with change

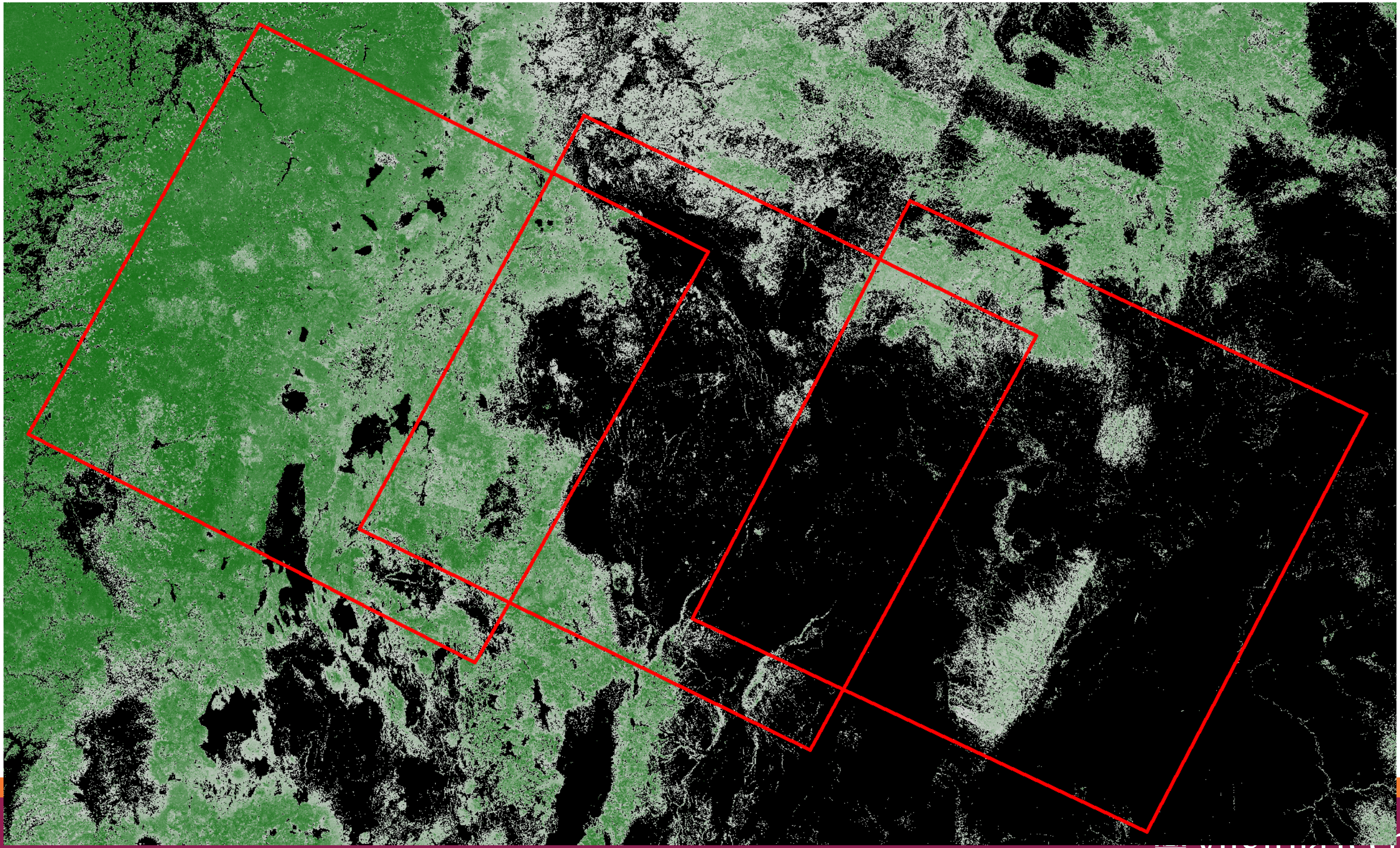
Why would we want to use time series for TCC?

- Understand the dynamics of the system
- Can provide insight into the type of change
  - Understand drivers
- Examine trends within the time period

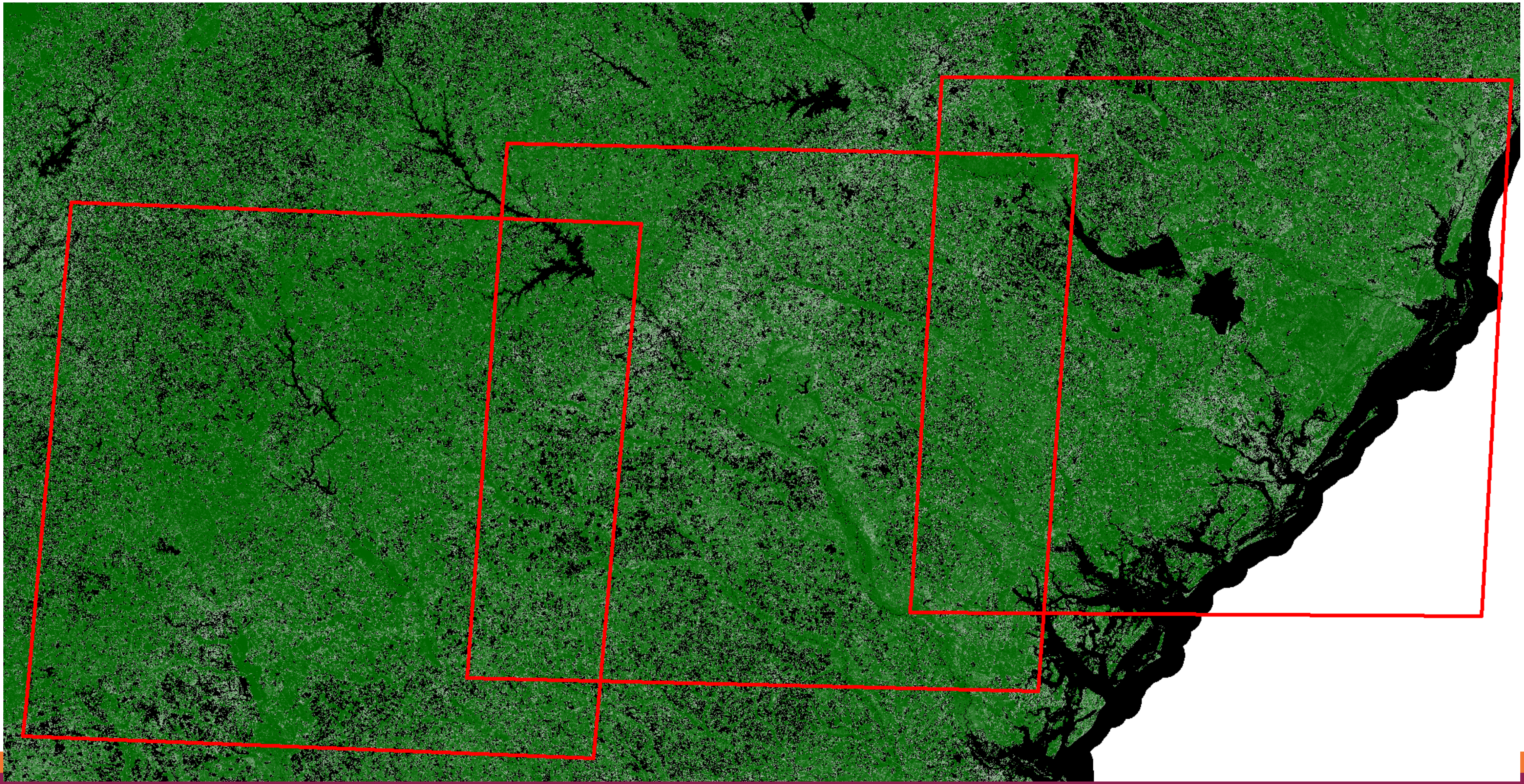
Study Area



2011 Product - West



2011 Product - Southeast



How can we get the “Static” product?

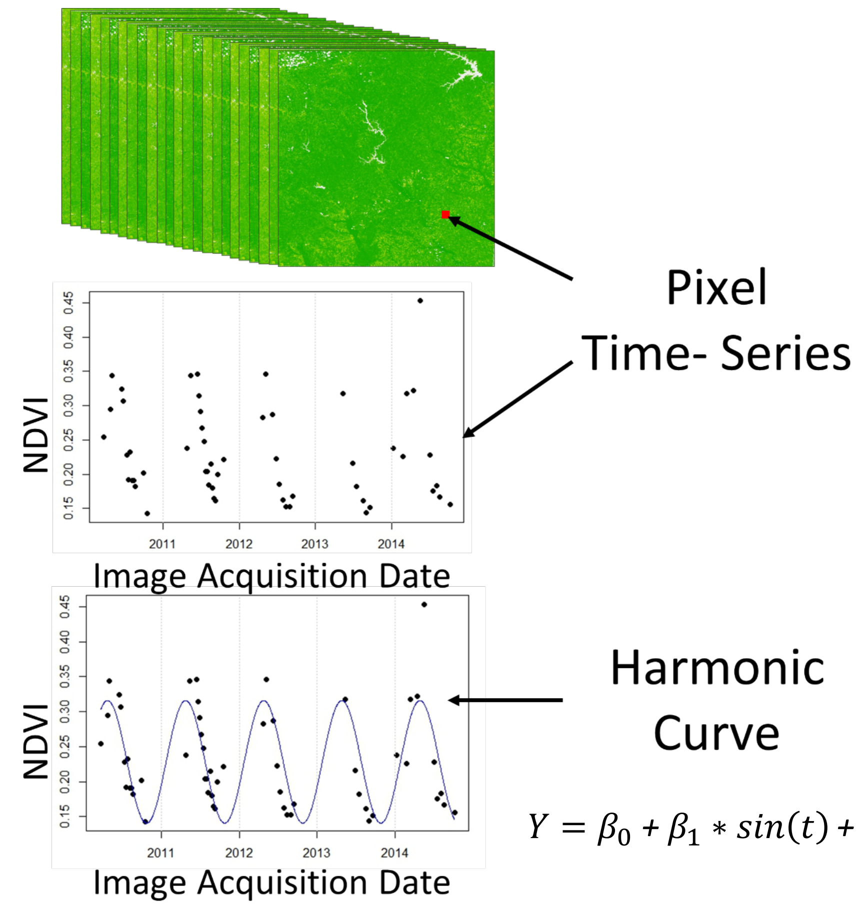
i.e., 2016 Tree Canopy Cover

2 Main Approaches

- 1.) Use the same approach as for the 2011 product
- 2.) Exploit the time series data around the year of interest
  - For 2011: use data from 2010, 2011, and 2012
  - Use newly developed (published) Landsat time series algorithms
    - Harmonic regression, EWMA, Shapes, etc.

Time Series Variables

- NDVI, SWIR 5, SWIR 7 images from 2008-2014
- Constant, 1 Sine Coefficients, 1 Cosine Coefficients
- 9 bands, if all data are used



$$Y = \beta_0 + \beta_1 * sin(t) + \beta_2 * cos(t)$$

RSAC Variables

Aspect_Mean_T1
Aspect_Std_T1
Cos_Aspect_Mean_T1
Cos_Aspect_Std_T1
Sin_Aspect_Mean_T1
Sin_Aspect_Std_T1
Baileys_Sec_fmaj_T1
DEM_30m_Mean_T1
DEM_30m_Std_T1
X2001_LC_fmaj_T1
L_med_comp_Mean_b1_T1
L_med_comp_Mean_b2_T1
L_med_comp_Mean_b3_T1
L_med_comp_Mean_b4_T1
L_med_comp_Mean_b5_T1

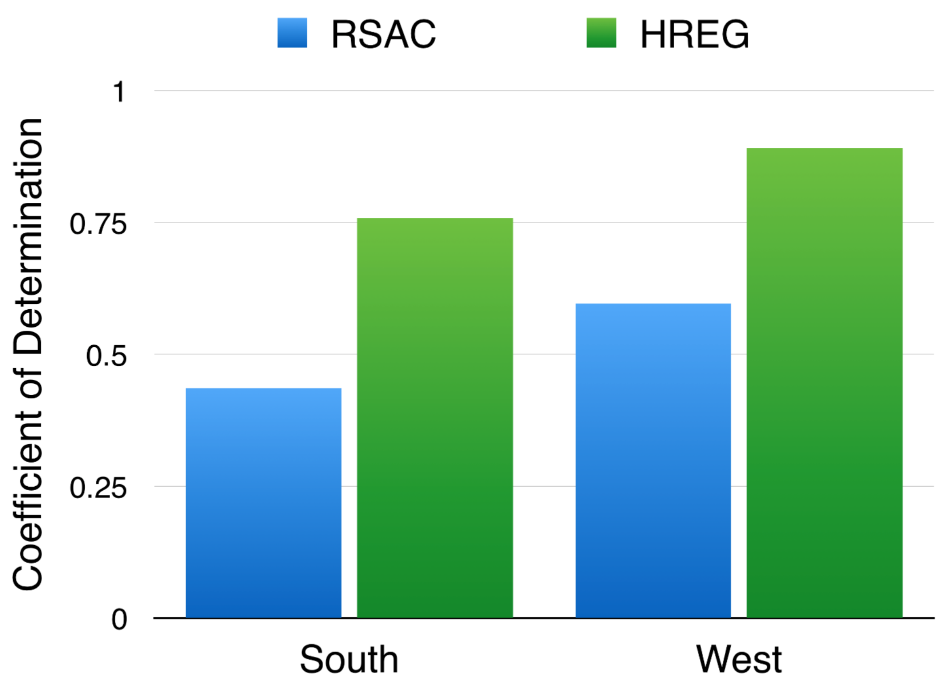
L_med_comp_Mean_b7_T1
L_med_comp_Std_b1_T1
L_med_comp_Std_b2_T1
L_med_comp_Std_b3_T1
L_med_comp_Std_b4_T1
L_med_comp_Std_b5_T1
L_med_comp_Std_b7_T1
NDMI_Mean_T1
NDMI_Std_T1
NDVI_Mean_T1
NDVI_Std_T1
Tcap_Mean_b1_T1
Tcap_Mean_b2_T1
Tcap_Mean_b3_T1
Tcap_Mean_b4_T1

Tcap_Mean_b5_T1
Tcap_Mean_b6_T1
Tcap_Std_b1_T1
Tcap_Std_b2_T1
Tcap_Std_b3_T1
Tcap_Std_b4_T1
Tcap_Std_b5_T1
Tcap_Std_b6_T1
X2001_PctCC_Mean_T1
X2001_PctCC_Std_T1
Slope_Deg_30m_Mean_T1
Slope_Deg_30m_Std_T1
X11_LC_fmaj_T2

43 bands, if all are used

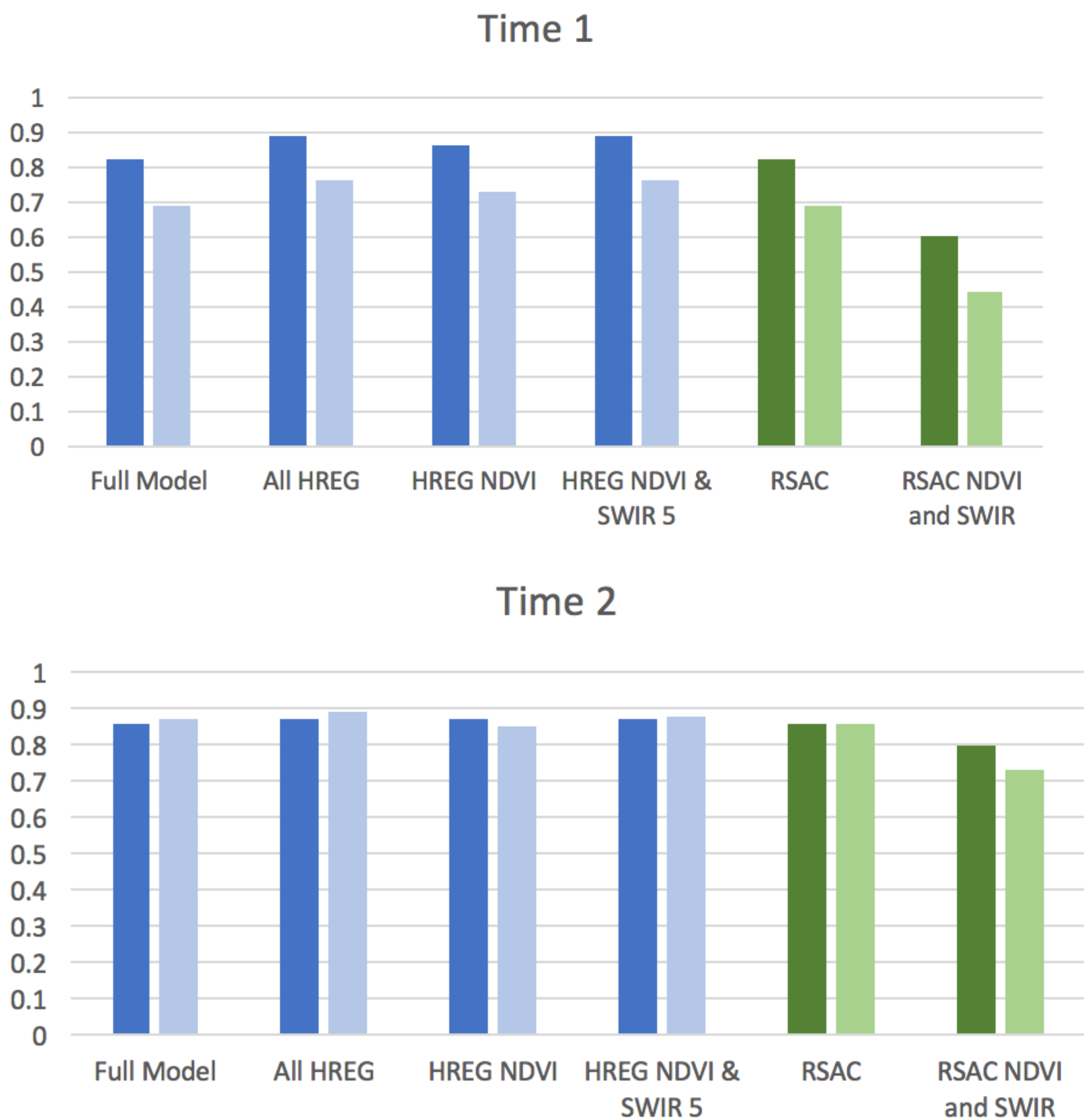
Table 3 :Landsat Acquisition Information			
Path/Row	Number of Bands	Sensors	Date Range
16/37	199	Landsat 5, 7	2009-2014
17/37	199	Landsat 5, 7	2009-2014
18/37	198	Landsat 5, 7	2009-2014
43/30	235	Landsat 5, 7	2008-2014
44/30	236	Landsat 5, 7	2008-2014
45/30	237	Landsat 5, 7	2008-2014

Harmonic regression clearly outperforms median composite for "Head's Up" comparison



SWIR 1, SWIR 2 & NDVI

Heads up comparison between time series (Green) versus the 2011 approach (Blue)



- Not much difference if all data are used.
- Time series regression models much simpler.

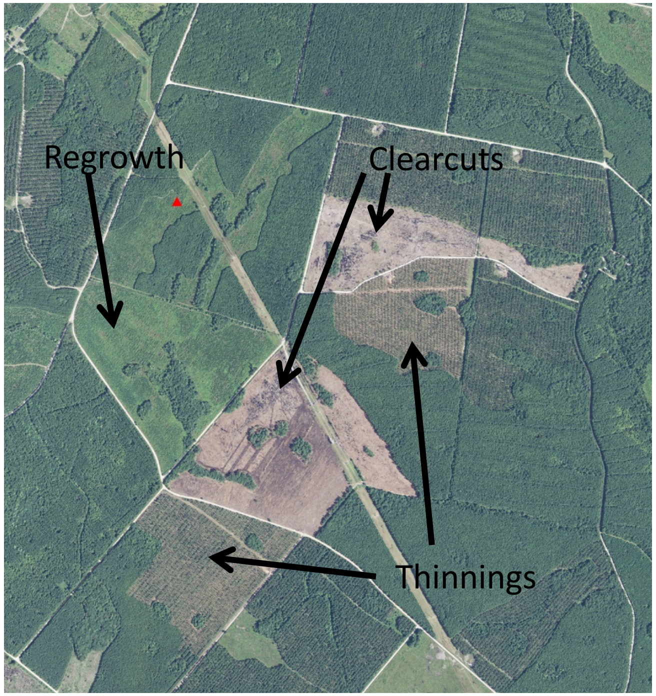
How can we get change?

4 Main Change Detection Approaches

- Indirect change
  - Time 2 – Time 1
- Direct change
  - separate models for T1, T2, and change
- Stratified direct change
  - Use time series algorithms to flag likely change
    - Fit separate models for change/no change areas
- Multivariate regression approaches
  - Where by definition T2-change = T1

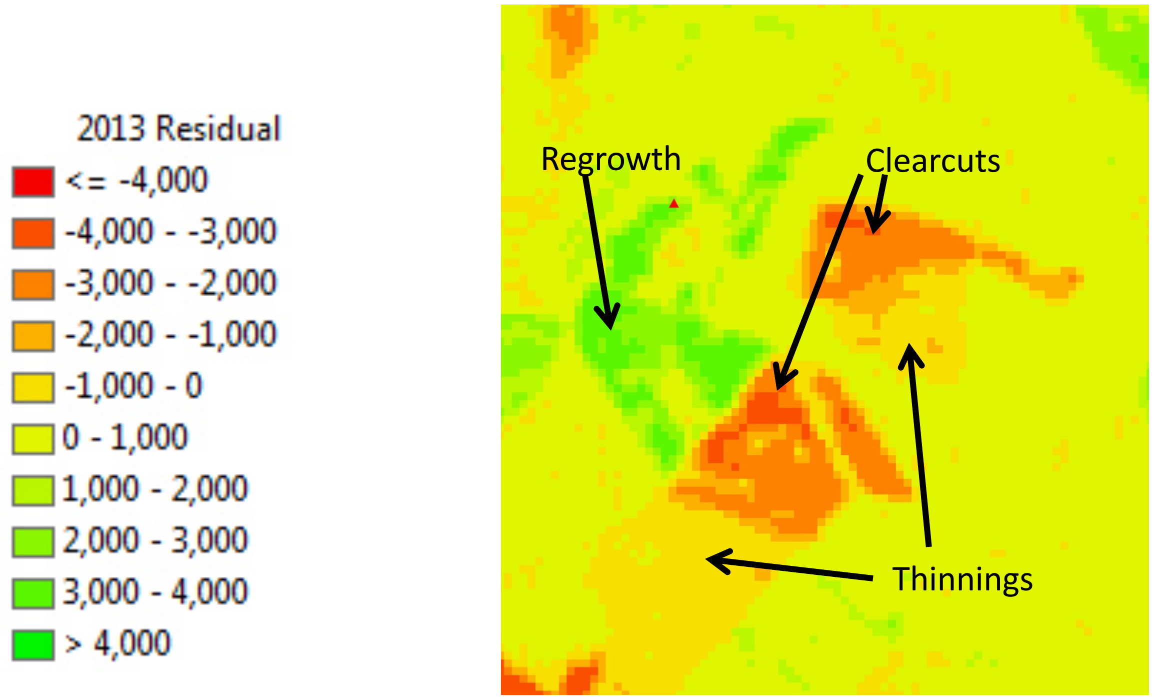
% Canopy Cover Example – NAIP

2011 NAIP



2013 NAIP

Harmonic Regression Residuals Show the growth and loss



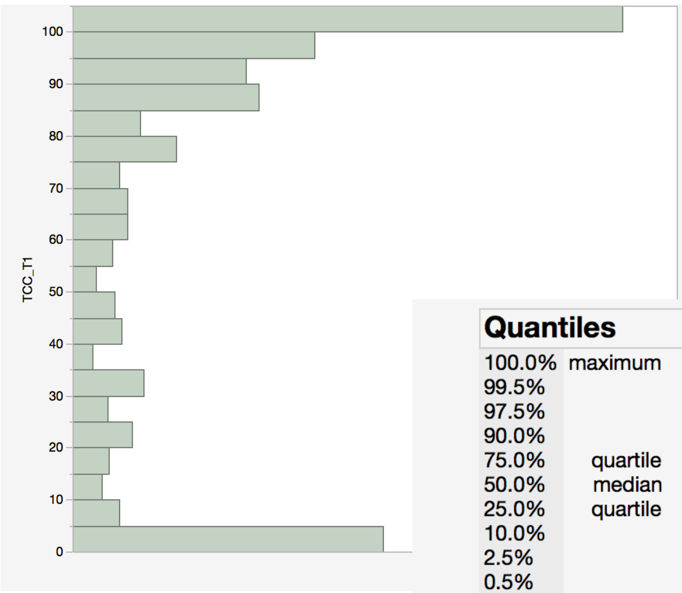
2013
Mean Residuals

Challenges for modeling change for TCC project

1. Time period is relatively short
   (2010-2013 or 2009-2013)
2. Not much change in the PI data

Distributions of the PI Data

Time 1



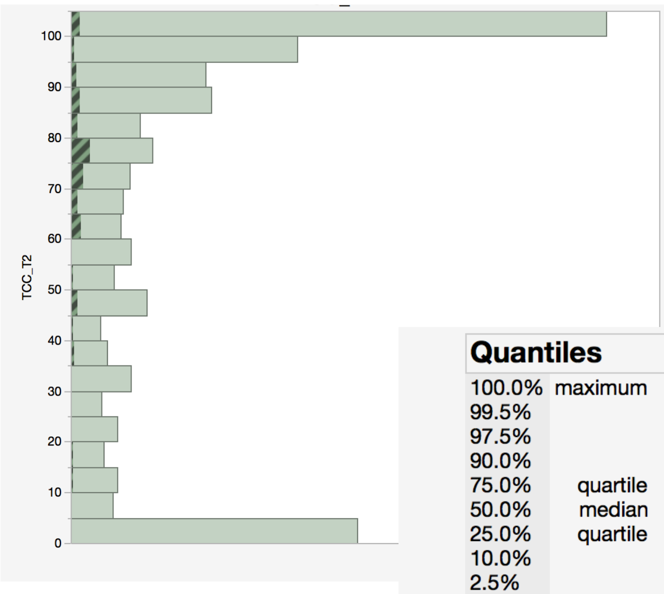
Quantiles

100.0%	maximum	100
99.5%		100
97.5%		100
90.0%		100
75.0%	quartile	99.1
50.0%	median	86.2
25.0%	quartile	33
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	66.922258
Std Dev	37.13669
Std Err Mean	1.0546111
Upper 95% Mean	68.991279
Lower 95% Mean	64.853237
N	1240

Time 2



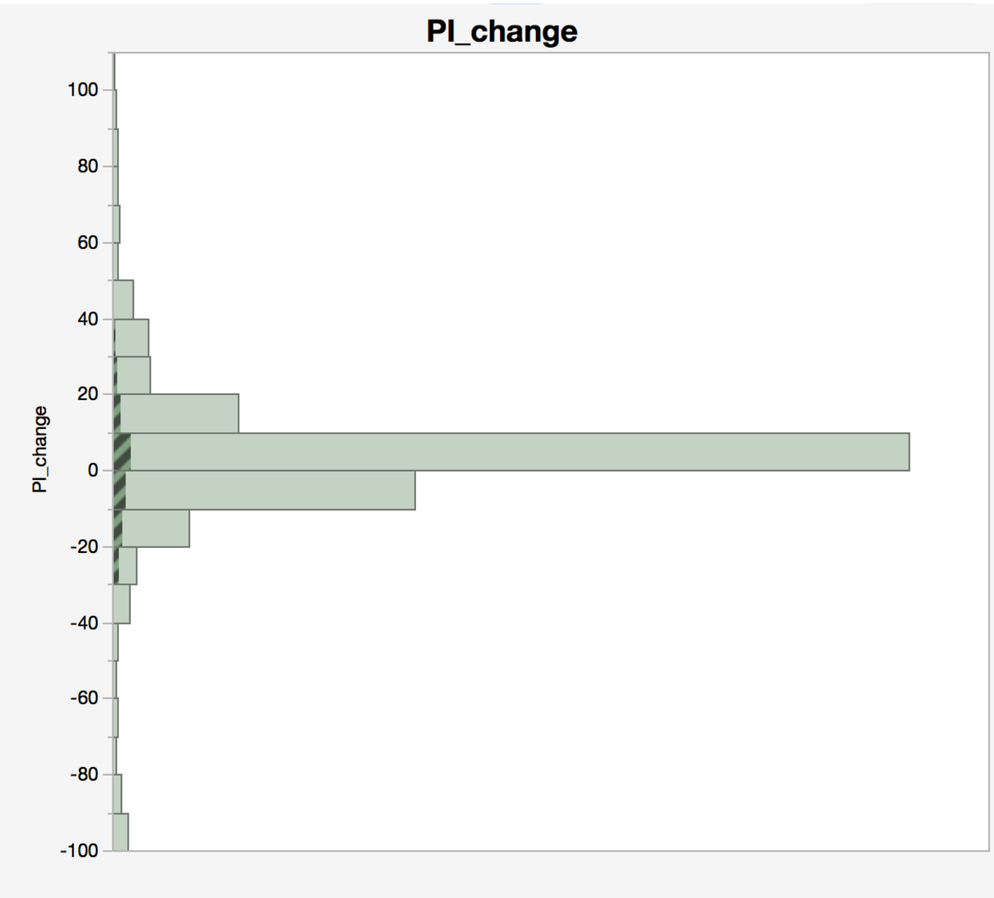
Quantiles

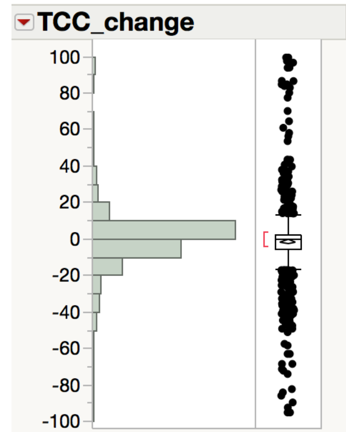
100.0%	maximum	100
99.5%		100
97.5%		100
90.0%		100
75.0%	quartile	100
50.0%	median	83.5
25.0%	quartile	34.9
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	65.905645
Std Dev	36.835601
Std Err Mean	1.0460608
Upper 95% Mean	67.957891
Lower 95% Mean	63.853399
N	1240

Change from the PI Data





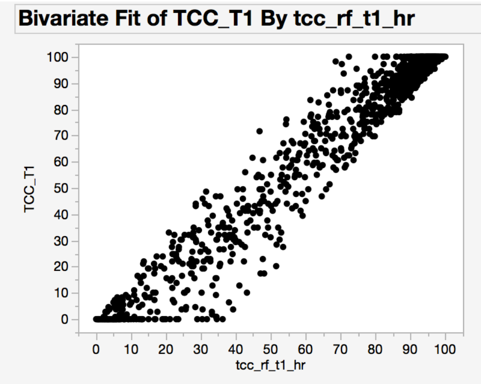
Quantiles

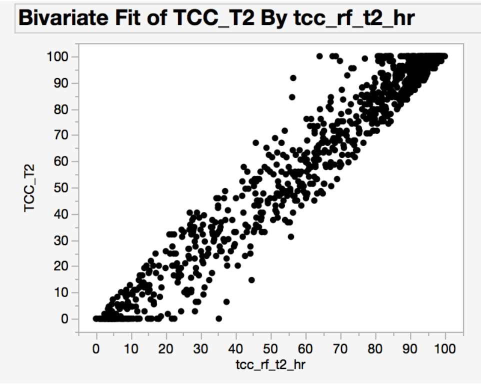
100.0%	maximum	99.1
99.5%		95.7735
97.5%		39.475
90.0%		10.1
75.0%	quartile	1.9
50.0%	median	0
25.0%	quartile	-5.5
10.0%		-16.5
2.5%		-43.235
0.5%		-85.147
0.0%	minimum	-95.4

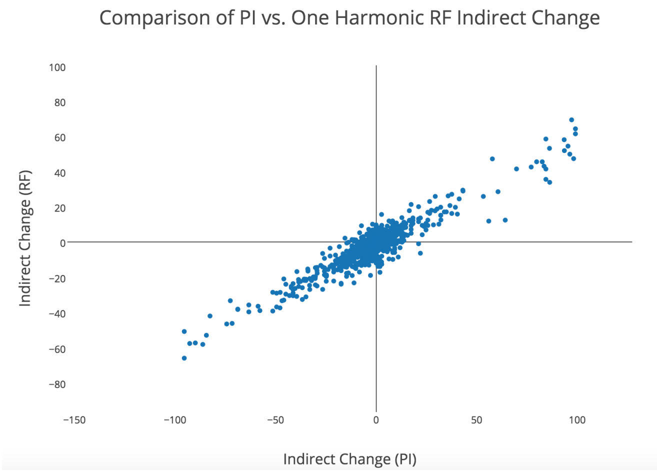
Summary Statistics

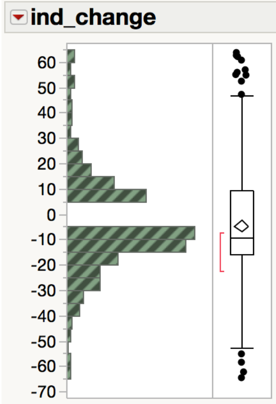
Mean	-1.487724
Std Dev	19.388261
Std Err Mean	0.5803724
Upper 95% Mean	-0.348979
Lower 95% Mean	-2.626469
N	1116

Indirect Change, HREG models









Quantiles

100.0%	maximum	63.6
99.5%		62.8575
97.5%		53.875
90.0%		20.5
75.0%	quartile	9.2225
50.0%	median	-9.13
25.0%	quartile	-15.95
10.0%		-27.6
2.5%		-44.05
0.5%		-63.0475
0.0%	minimum	-64.6

Summary Statistics

Mean	-4.714401
Std Dev	21.353245
Std Err Mean	1.1683976
Upper 95% Mean	-2.416031
Lower 95% Mean	-7.012772
N	334

Ability to Predict Change

- Direct Change, incorporating HR residuals
  - R^2 = 0.7 for west
  - R^2 = 0.53 for south
- PI data does not contain much change (n=1240)
  - T2 mean = 66%
  - T1 mean = 67%
- Sample number very low in areas of high change, limiting any model's ability to capture it (3% of plots -- 40 -- with plus or minus 65% change
- Maps of change look good, qualitatively (both direct and indirect)
  - But absolute accuracy, spatially, is unknown

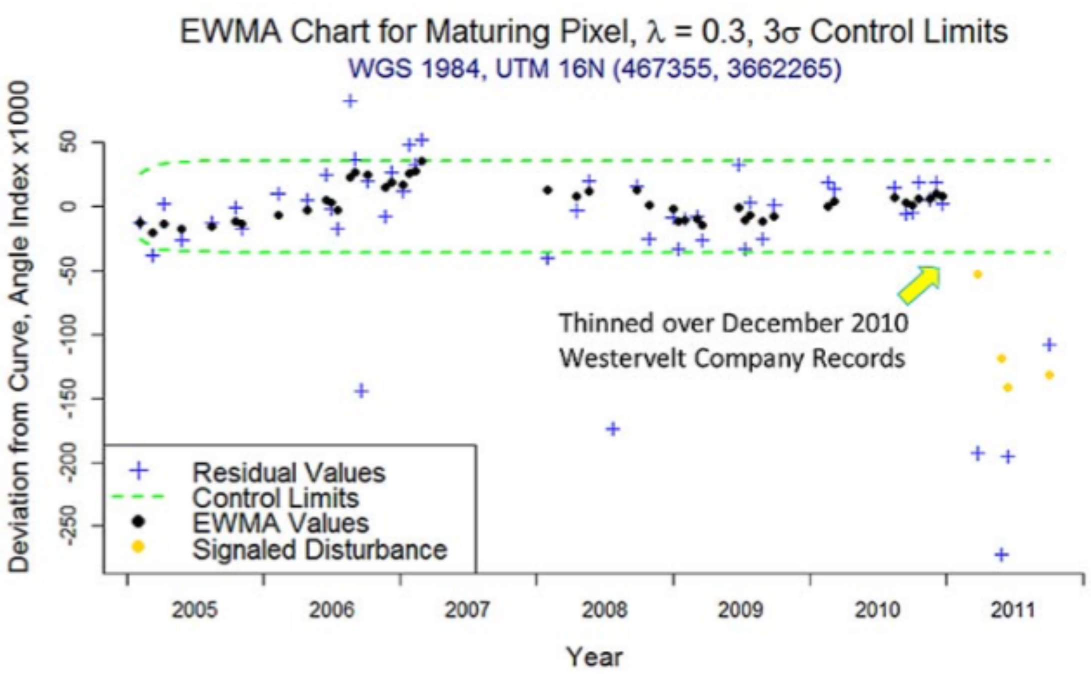
Using change detection algorithms to stratify for change

State-of-the-art

Algorithms in Remote Sensing	Segmentation approaches in general time series literature
• **EWMACD**, CCDC, SHAPE-SELECT-FOREST	• Kernel regression methods
• LandTrendR, VeRDET	• Top-down approach
• Model-Map, **BFAST**, MIICA, VCT	• Bottom-up approach

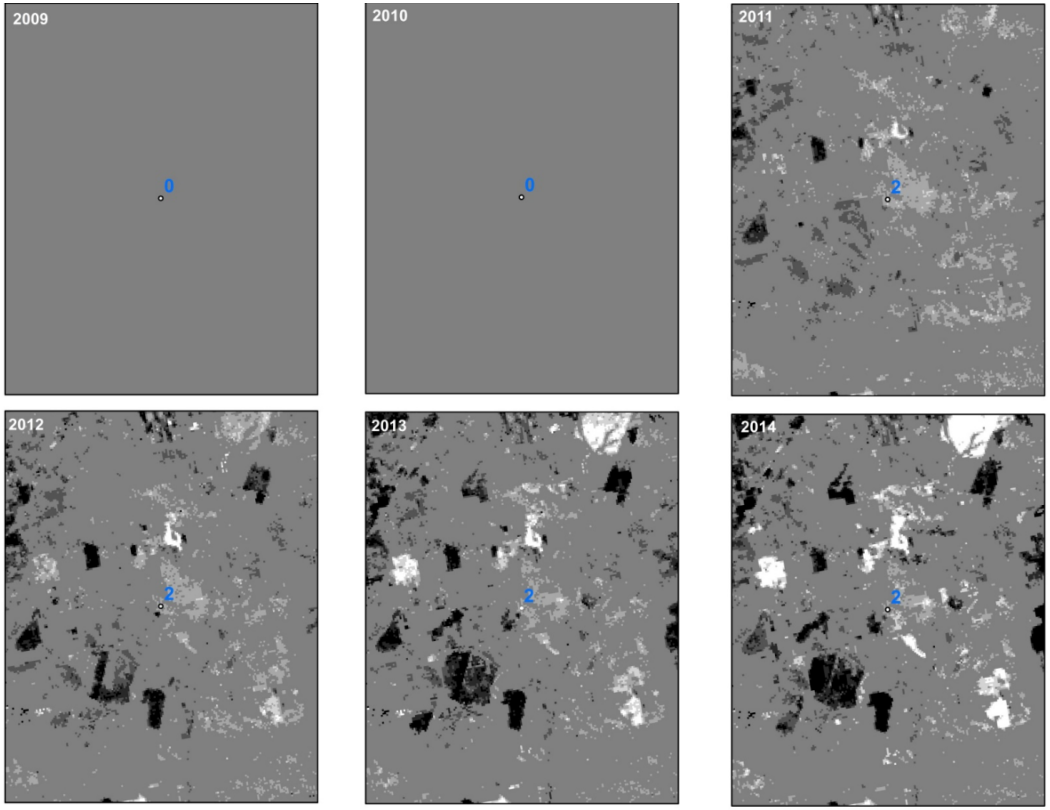
Remote sensing vs. the broader picture

Flagging Persistent Change



Harmonic Regression, Brooks, et al., 2014

“Zoomed-in” NDVI Change Flags: 2009-2014



Change models for the Southeast

Southern Analysis (1355 records)

	Change Flag	N	Pseudo R2	RMSE
EWMA change flag (2009-2014)	All EWMA	300	0.61	21.5
	NDVI-EWMA	171	0.64	25.1
	SWIR5-EWMA	227	0.62	22.7
	SWIR7-EWMA	196	0.60	24.8
	NDVI&SWIR5	**285**	**0.63**	**21.5**
	NDVI&SWIR7	247	0.65	21.7
	SWIR5&SWIR7	256	0.60	22.6
Shapes disturbance (2009-2016)	All Shapes	537	0.33	16.9
	Shapes-NDVI	473	0.31	18.0
	Shapes-DNBR	126	0.18	20.5
	Shapes-B5	340	0.22	18.8
	Shapes –B7	104	0.05	22.6

1. Growth and loss can be modelled together.

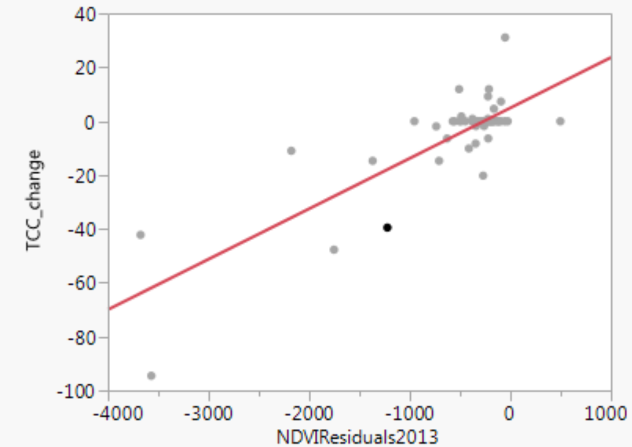
2. Improvements over direct change models.

West

- Growth and loss must be modeled separately
- Models are strong, but not enough change PI points to feel confident.

West-flaggednegativechange - Fit Y by X of TCC_ch...

Bivariate Fit of TCC_change By NDVIResiduals2013



Linear Fit

Linear Fit

TCC_change = 4.9569995 + 0.0187236*NDVIResiduals2013

Summary of Fit

RSquare	0.659807
RSquare Adj	0.655016
Root Mean Square Error	8.860614
Mean of Response	-3.30959
Observations (or Sum Wgts)	73

Lack Of Fit

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	10811.299	10811.3	137.7052
Error	71	5574.244	78.5	Prob > F
C. Total	72	16385.543		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	4.9569995	1.25369	3.95	0.0002*
NDVIResiduals2013	0.0187236	0.001596	11.73	<.0001*

Multivariate Regression (ENN) for Change

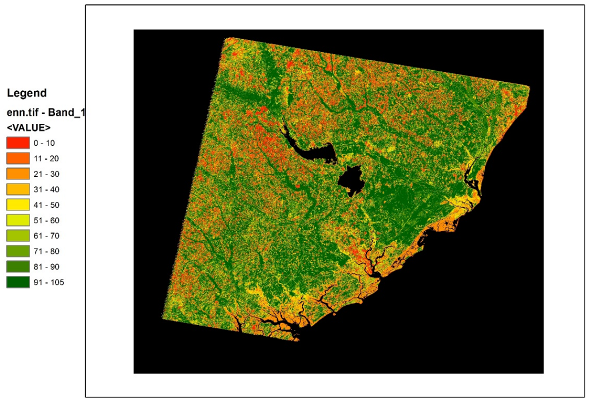
	Time 1		Time 2		Change	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
All Points, EWMA change as a variable	0.79	17.6	0.80	17.1	0.37	16.0
"No Change" Points	0.81	16.7	0.81	16.5	--	--
"Change" Points	0.62	23.7	0.66	21.3	0.59	27.9

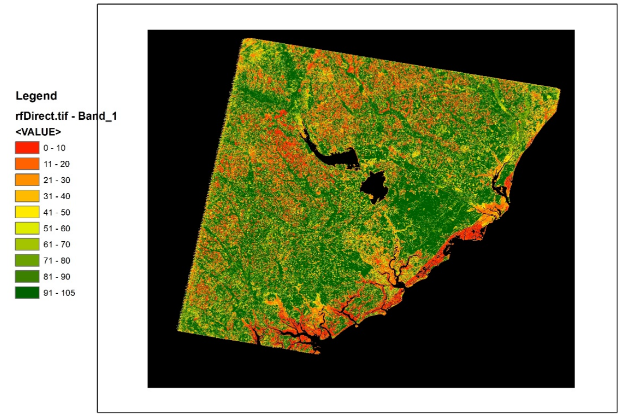
Advantage? T2-change = T1

Multivariate (ENN)

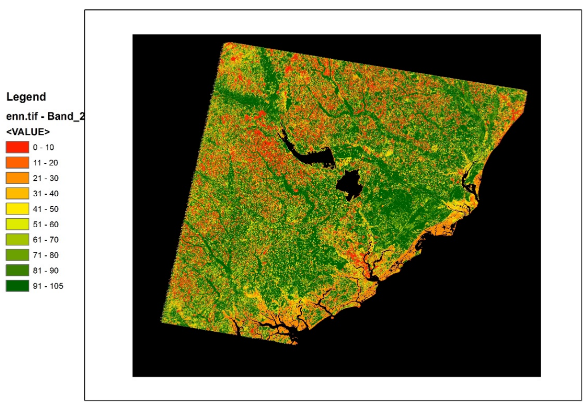
Direct Change

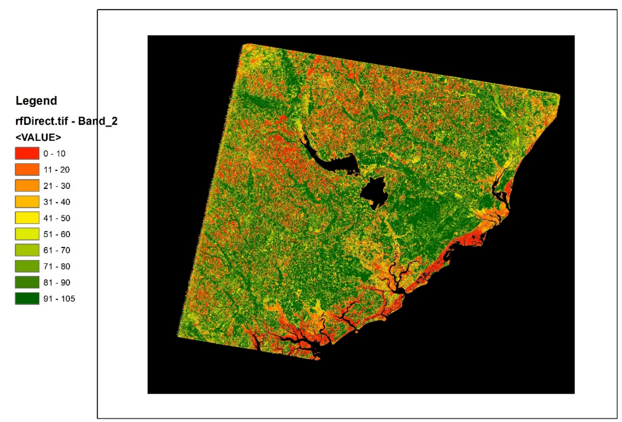
Time 1





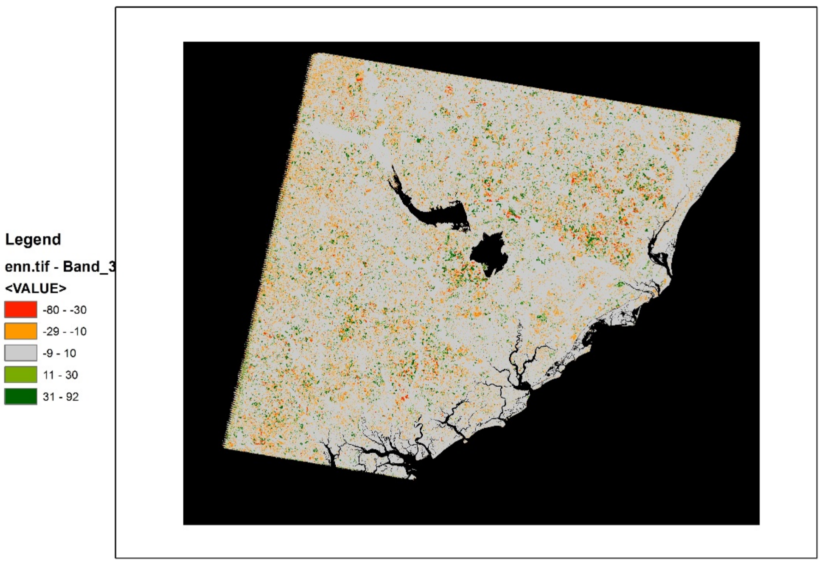
Time 2



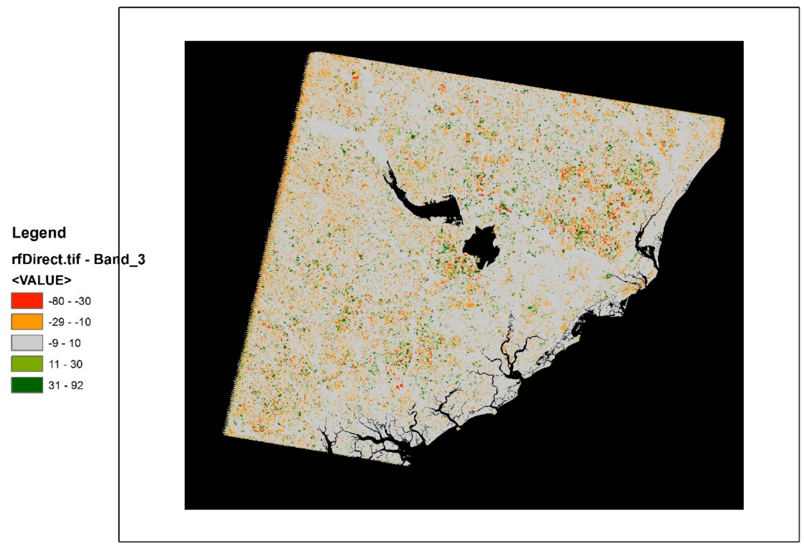


Change looks as expected

Multivariate change



Direct change



Other Approaches

Polyalgorithm

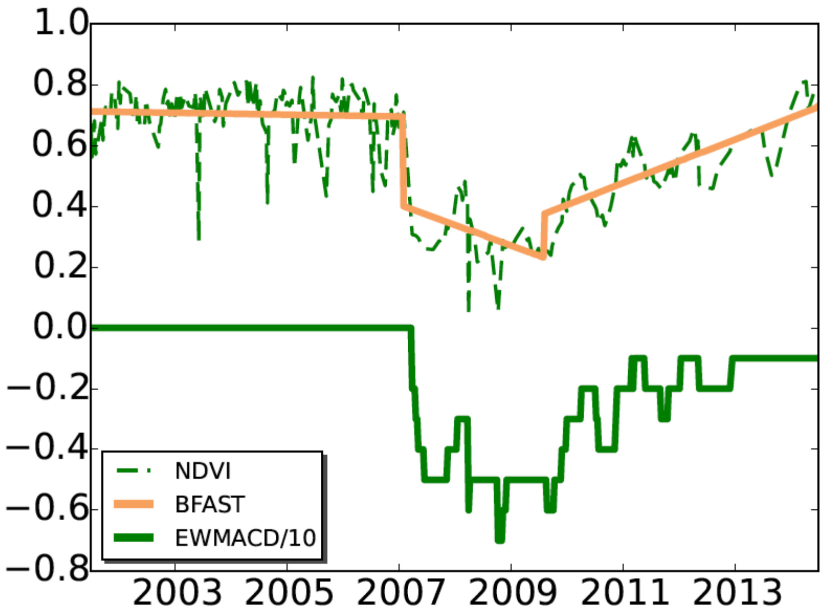
Tree height indicators: Lidar & Photogrammetric point clouds

Crowdsourcing

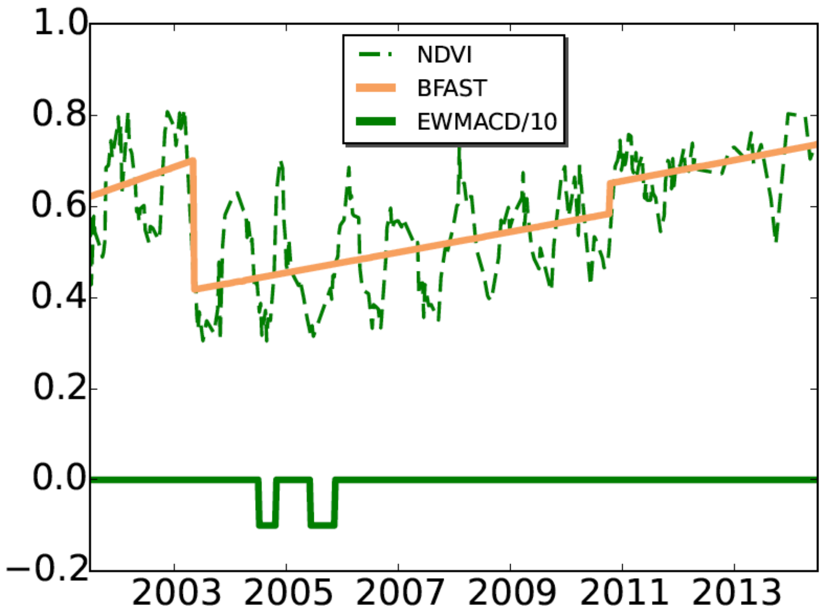
Our polyalgorithm approach

Combining multiple algorithms:

Ensemble	Hybrid	Polyalgorithm
Contains multiple learners called base learners. Base learners are generated from training data by a base learning algorithm which can be decision tree, neural network or any other kind of learning algorithm.	Combines two or more different algorithms that solve the same problem, either choosing one (depending on the data), or switching between them over the course of the algorithm.	*Collection* of several algorithms that strives to satisfy certain objectives as it determines which particular algorithm to use in a given scenario.
e.g. Random Forests, LCMS	e.g. (i) Introsort for sorting, (ii) Brent's method for root finding.	e.g. Root finding algorithm in NAPSS (uses secant method with requisite tests).



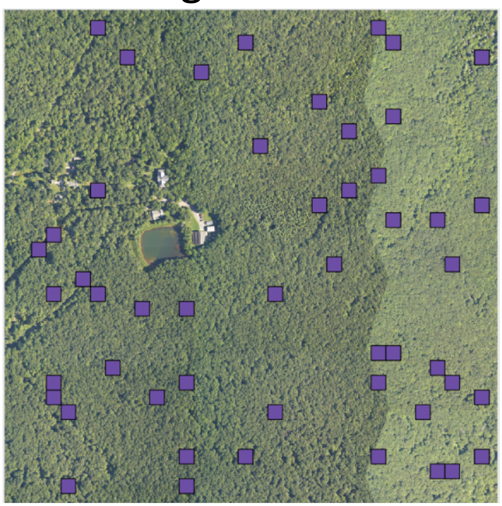
Forest → Scrubs/shrubs
TCC(2009)=93.6, TCC(2013)=87.2



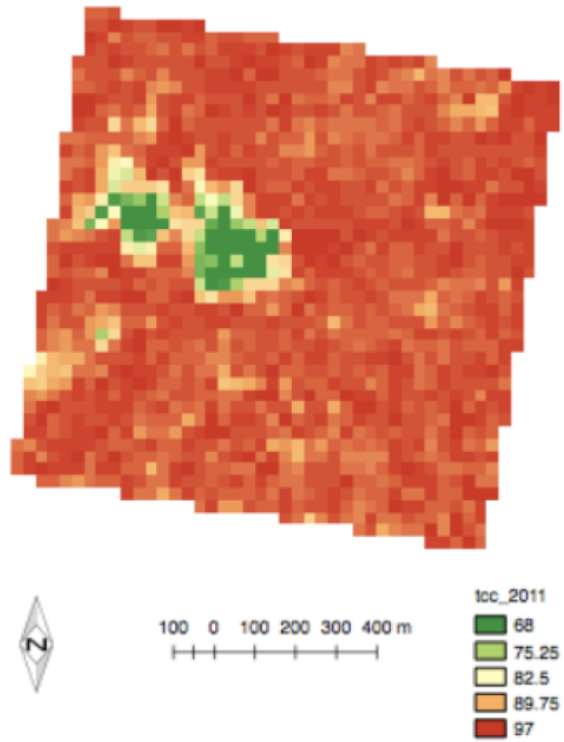
Forest → Scrubs/shrubs
TCC(2009)=54.1, TCC(2013)=9.2

Correlation of lidar to TCC

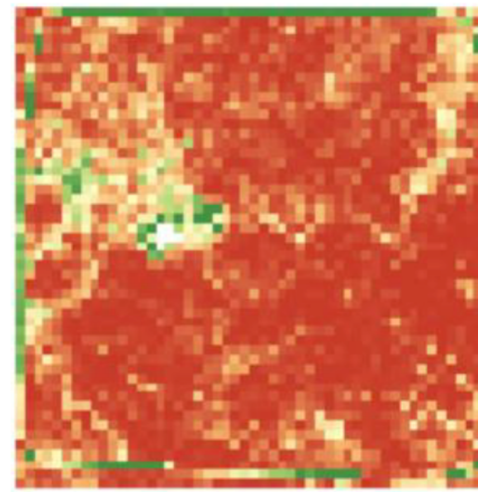
Mountain Lake
Biological Station



2011 TCC



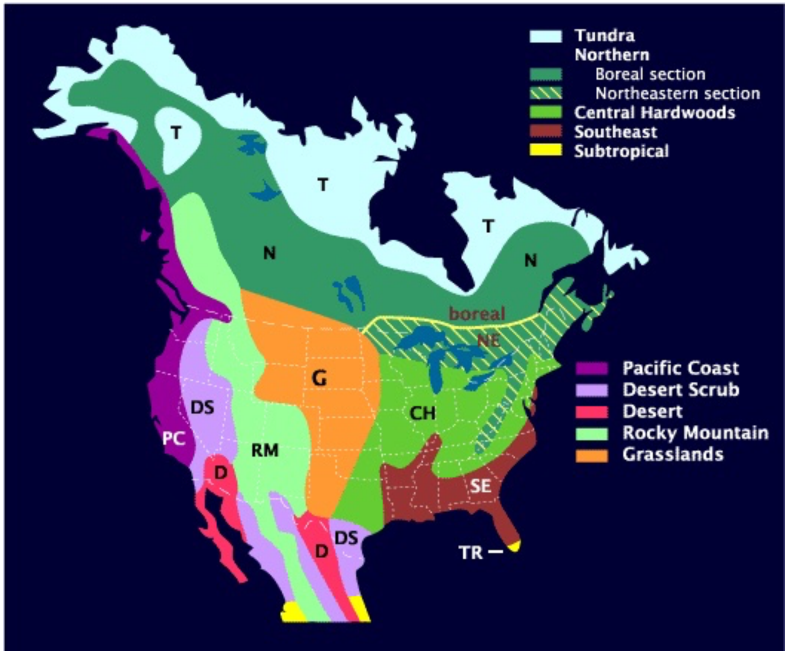
30m lidar model of TCC



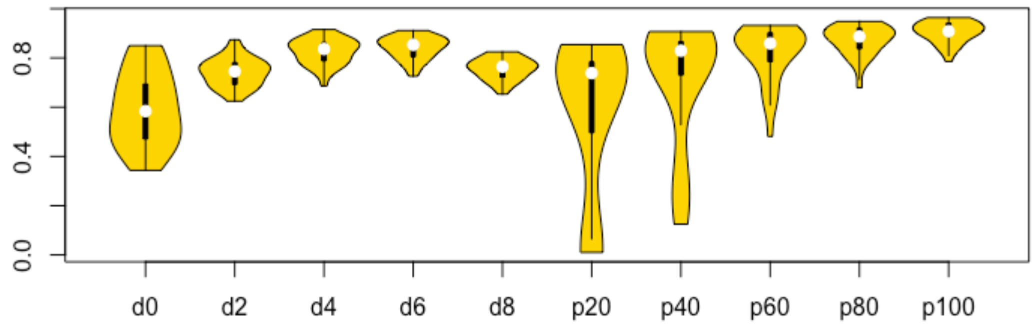
TCC = 64.7 + 0.34PFRAM
$R^2 = 0.88$

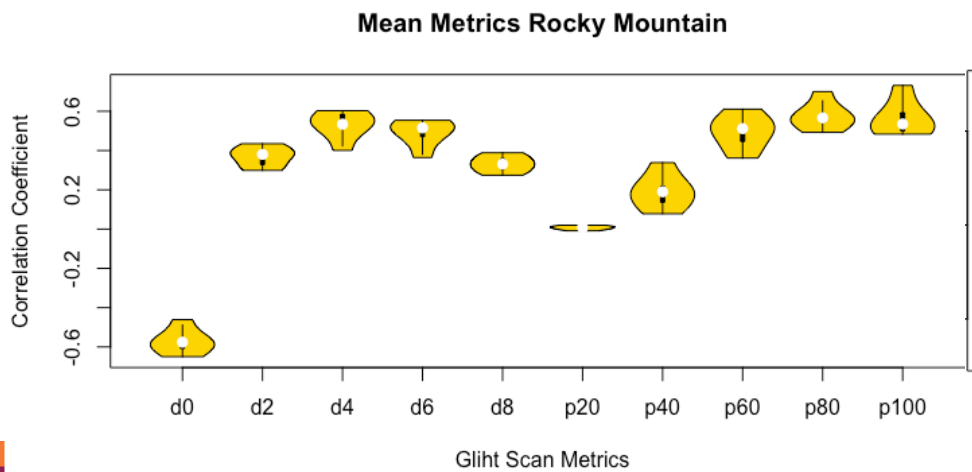
P. Corey Green, 2017

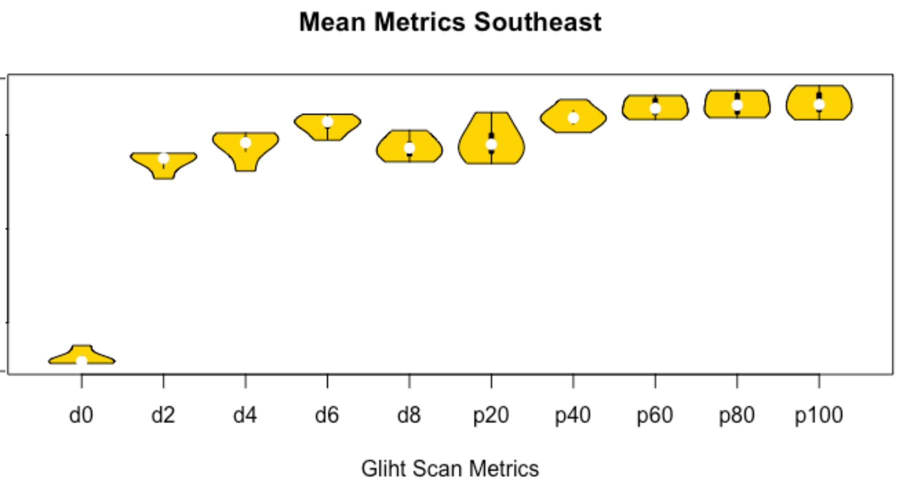
Lidar



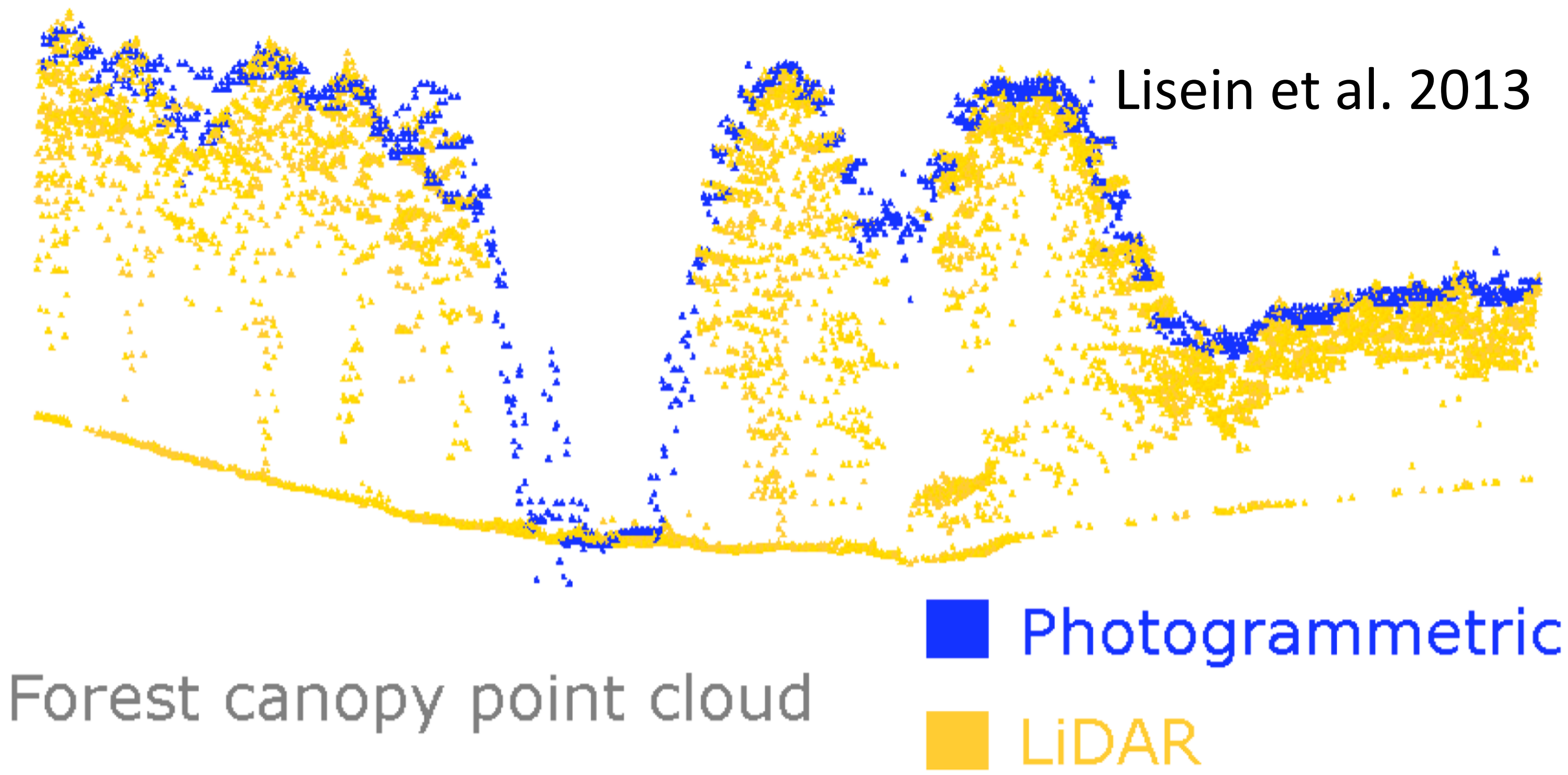
All regions (280 acquisitions)



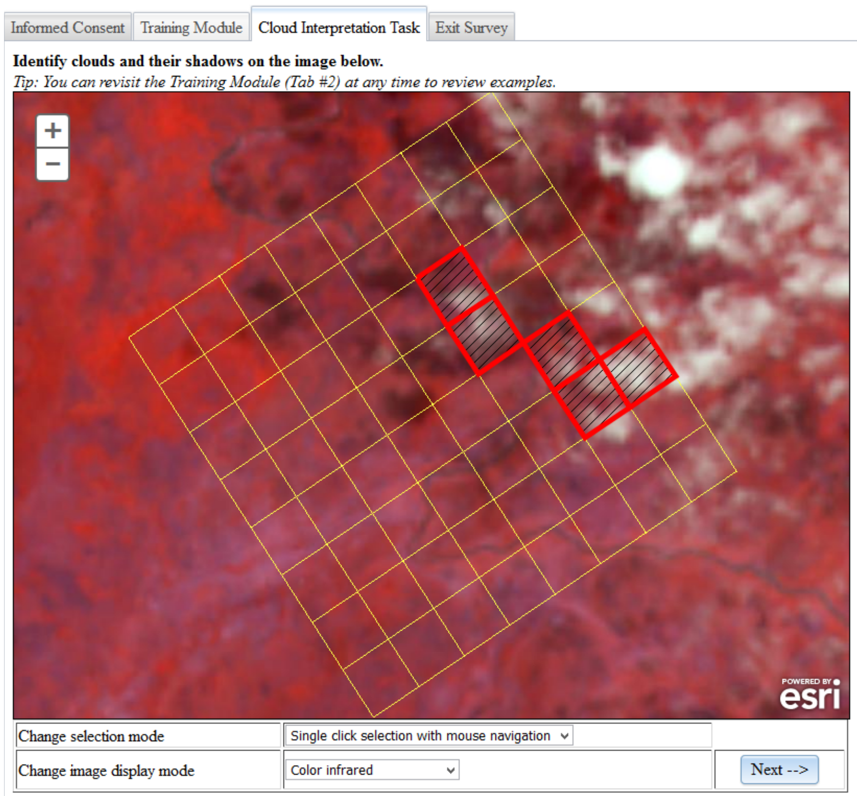




Photogrammetric Heights Could be used instead of lidar



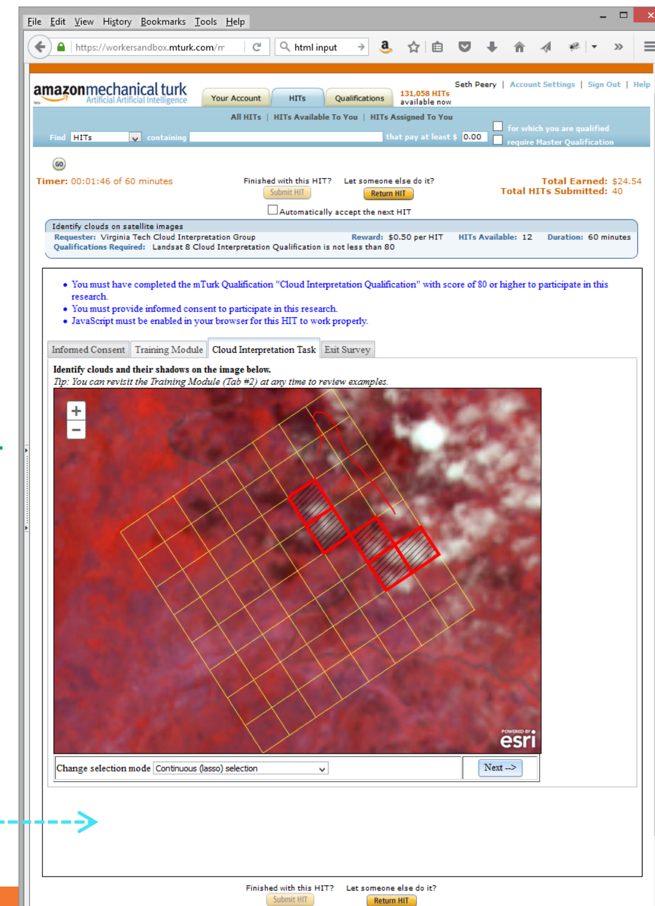
Developing Crowd-Sourced PI Chips



VT←→ mTurk

ExternalQuestion

ESRI ArcGIS Server
JS API App
located at VT



p092r086_c1 : 2	p092r086_b1 : 2	p092r086_a1 : 2
p092r086_c2 : 2	p092r086_b2 : 2	p092r086_a2 : 2
p092r086_c3 : 2	p092r086_b3 : 2	p092r086_a3 : 2
p092r086_c4 : 0	p092r086_b4 : 0	
p092r086_c5 : 0	p092r086_b5 : 0	
p092r086_c6 : 0	p092r086_b6 : 0	
p092r086_c7 : 0	p092r086_b7 : 0	
p092r086_c8 : 0	p092r086_b8 : 0	

Cloud impacted tiles are returned to mTurk, as {ID:interp code}

Crowdsourcing Response Variable

Concluding Thoughts I

- Multivariate regression (T2 – change = T1) best for direct models of change
  - Random forest, ENN, etc.
- Larger number of repeat PI samples, across multiple forest types, needed for robust modeling of change
  - Crowdsourcing could be valuable here
- Multitemporal approaches are needed for direct modeling of change

Concluding Thoughts II

- Lidar data clearly ideal for TCC estimation or, more likely, given coverage, improved training
- High resolution orthoimagery (e.g., NAIP, sensu Ganguly et al.) can be used for TCC training (classification chips and crowdsourcing) and estimation
  - incorporation of DSM with programmatic changes will improve separation from shrubs or other non-tree vegetation

Questions?

V.A. Thomas: thomasv@vt.edu

R.H. Wynne: wynne@vt.edu