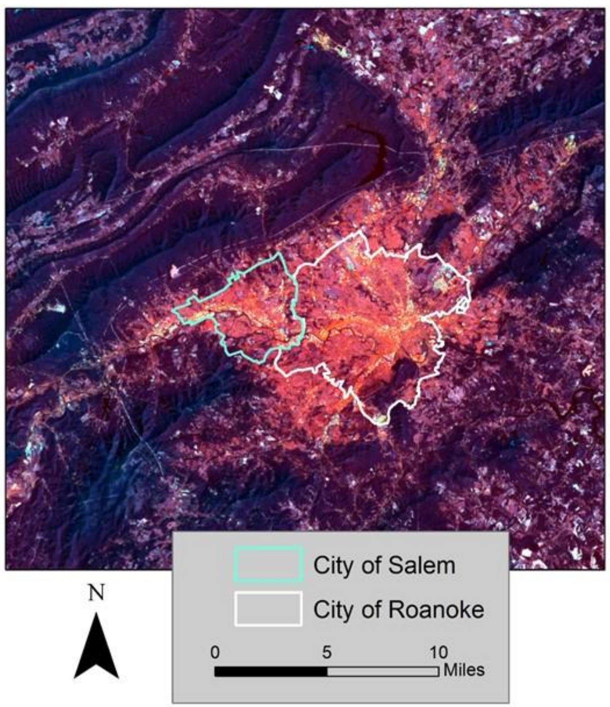
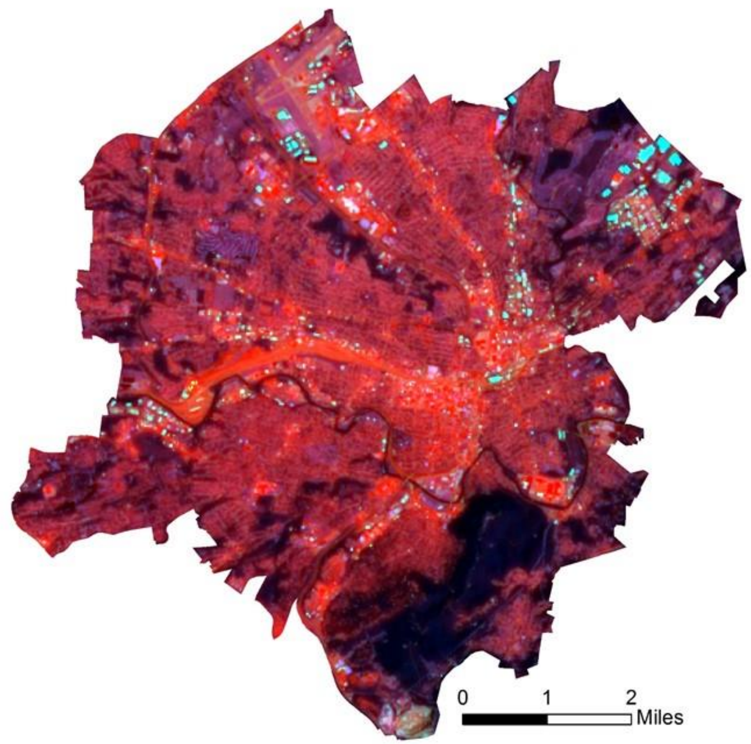
Urban Temperatures– *why didn't we use Landsat ?*

James B. Campbell

Tammy Parece, Jie Li, & David Carroll





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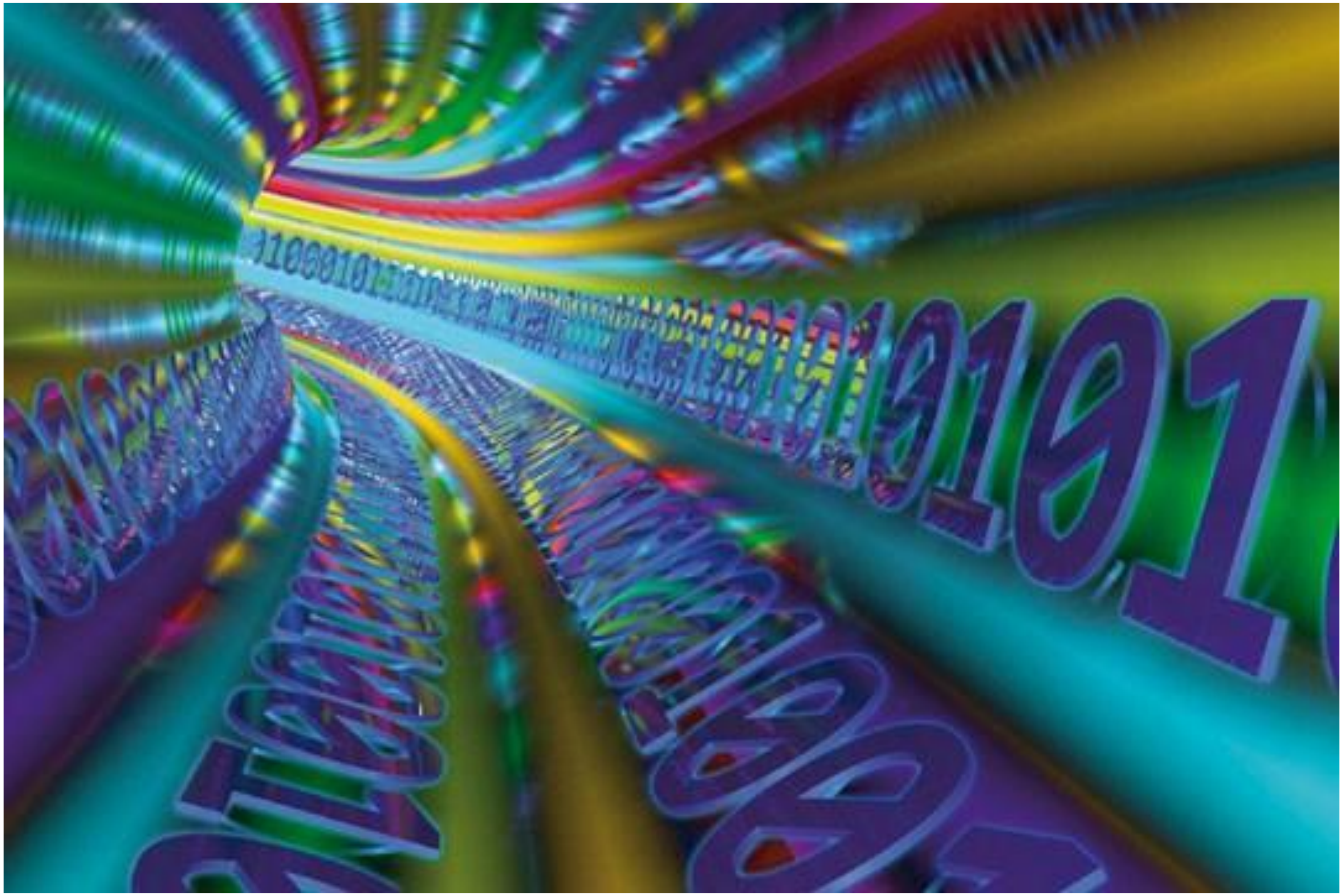
Urban Temperatures– *why didn't we use Landsat ?*



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Tammy E. Parece, Jie Li, James B. Campbell, and David Carroll. "Assessing Urban Landscape Variables' Contributions to Microclimates," *Advances in Meteorology*, vol. 2016, Article ID 8736263, 2016. doi:10.1155/2016/8736263

Hindawi

Research Article

Assessing Urban Landscape Variables' Contributions to Microclimates

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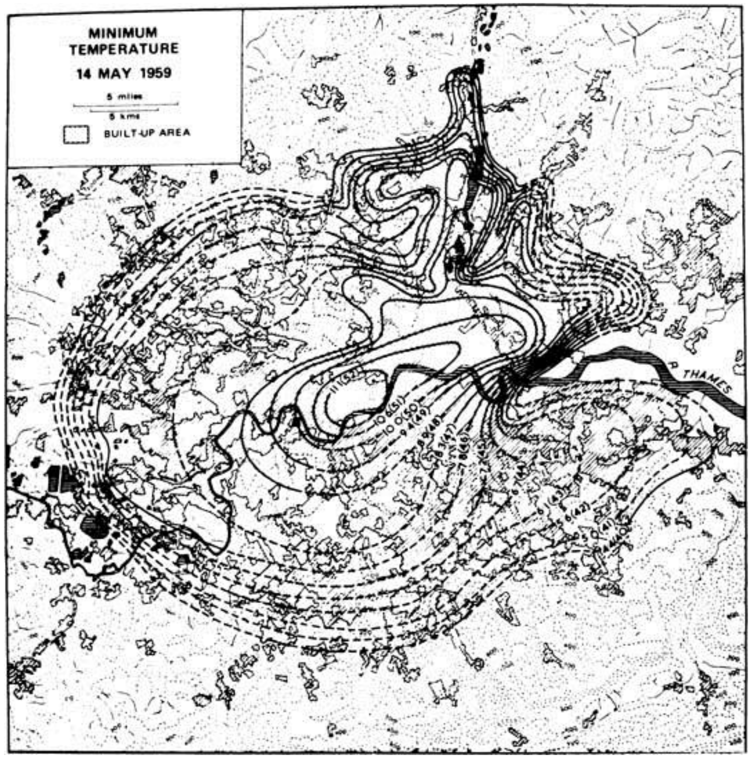
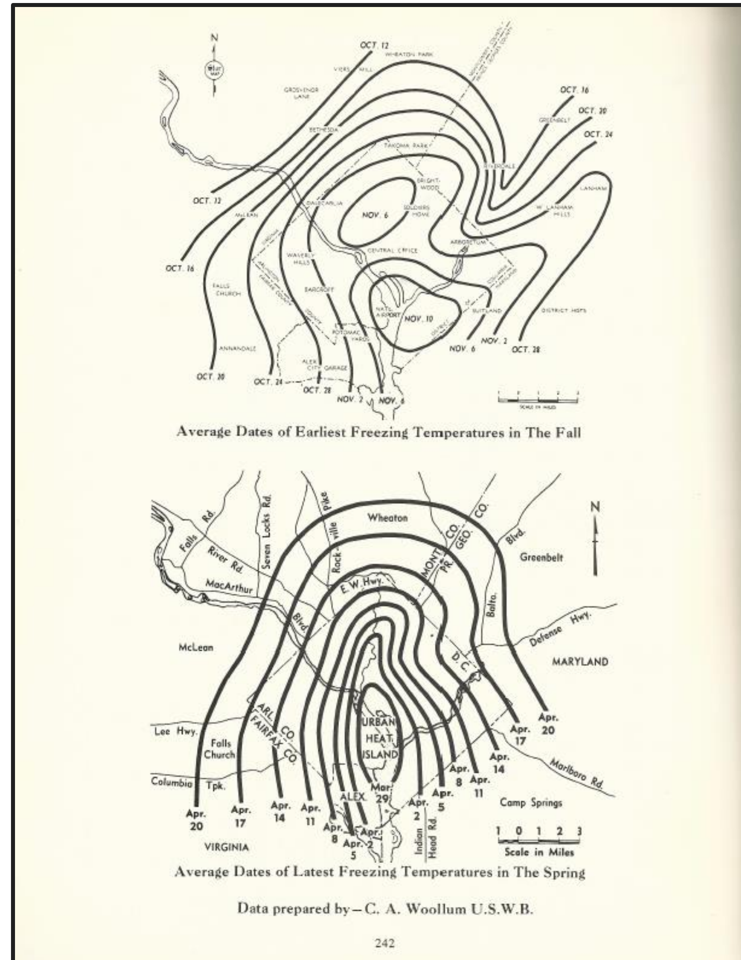
Academic Editor: Stefania Bonafoni

The well-known urban heat island (UHI) effect recognizes prevailing patterns of warmer urban temperatures relative to surrounding rural landscapes. Although UHIs are often visualized as single features, internal variations within urban landscapes create distinctive microclimates. Evaluating intraurban microclimate variability presents an opportunity to assess spatial dimensions of urban environments and identify locations that heat or cool faster than other locales. Our study employs mobile weather units and fixed weather stations to collect air temperatures across Roanoke, Virginia, USA, on selected dates over a two-year interval. Using this

temperature variation within the urban landscape



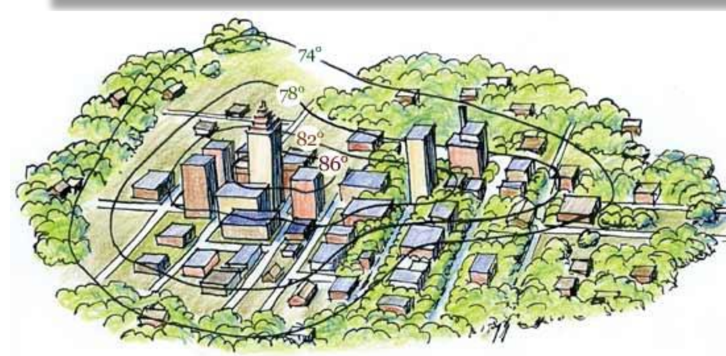


Average Dates of Earliest Freezing Temperatures in The Fall

Average Dates of Latest Freezing Temperatures in The Spring

Data prepared by—C. A. Woollum U.S.W.B.

242



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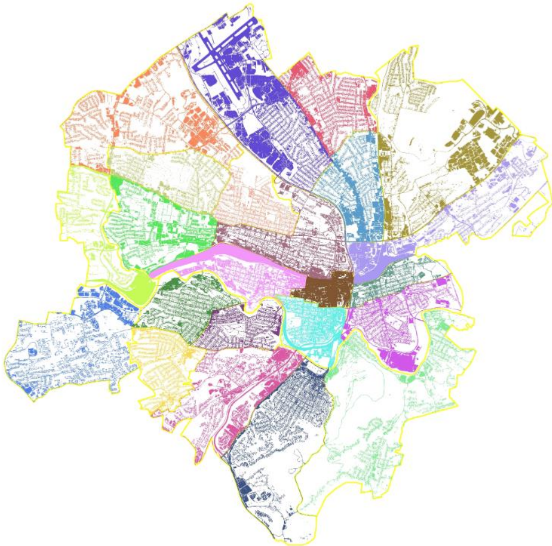
Data & Analysis – short version

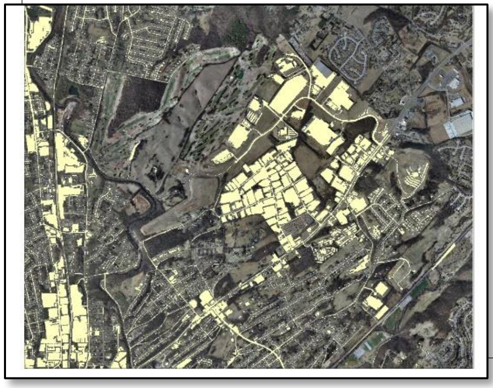


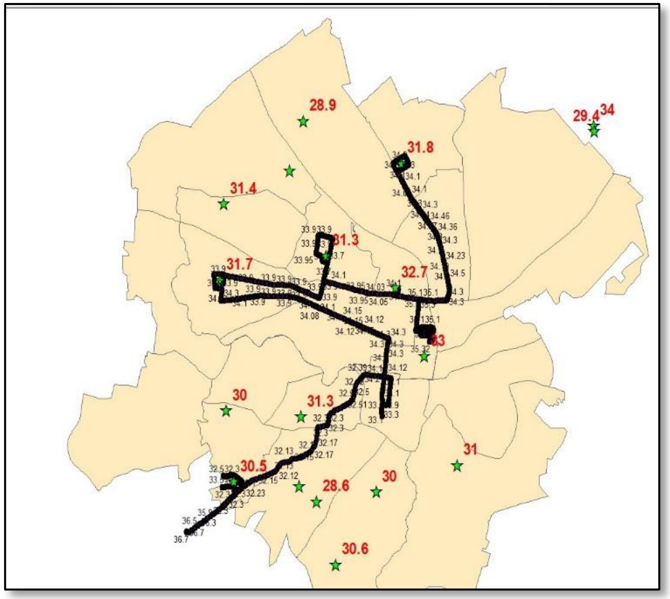
Mobile temperature collection
Landscape variables
- impervious surfaces
- relief
- aspect
- elevation
- canopy cover

Scaled to 30m cells

Extrapolation
- Kriging & Random Forest

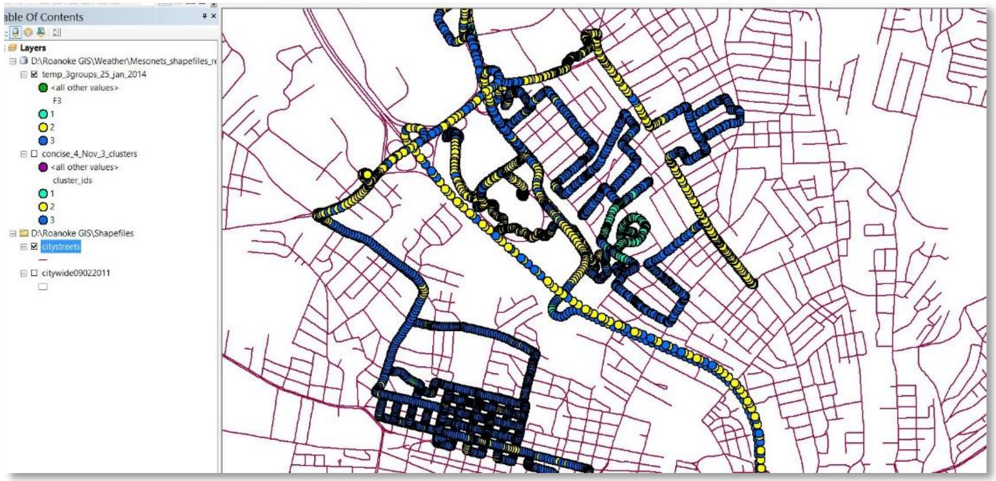
Reserve 10% of observations for accuracy assessment



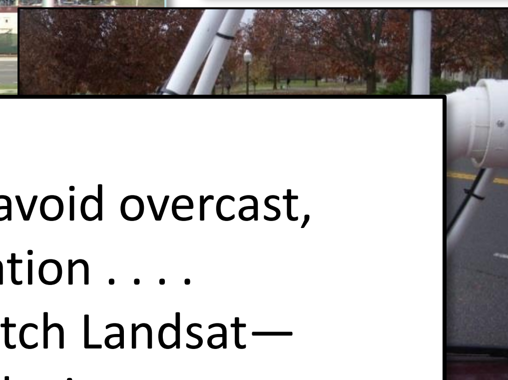


this study: 19 models

mobile air temperature data collection

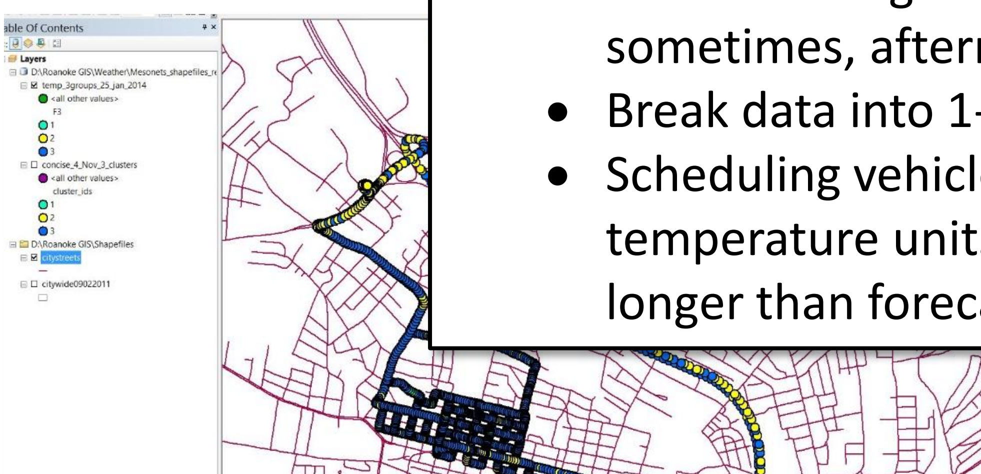


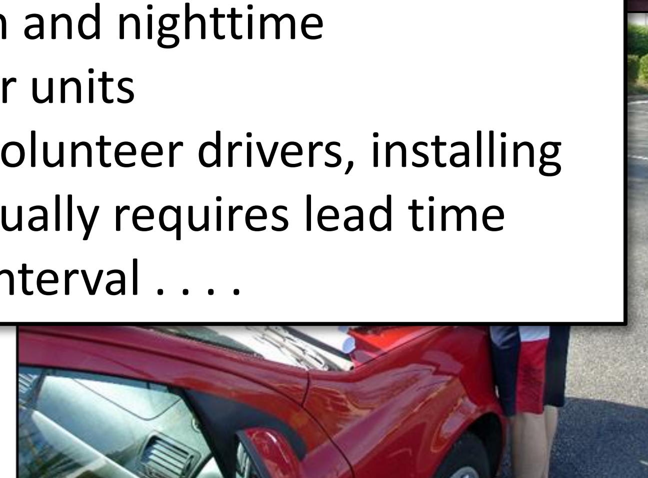
mobile air temperature data collection



Mobile temperature collection:

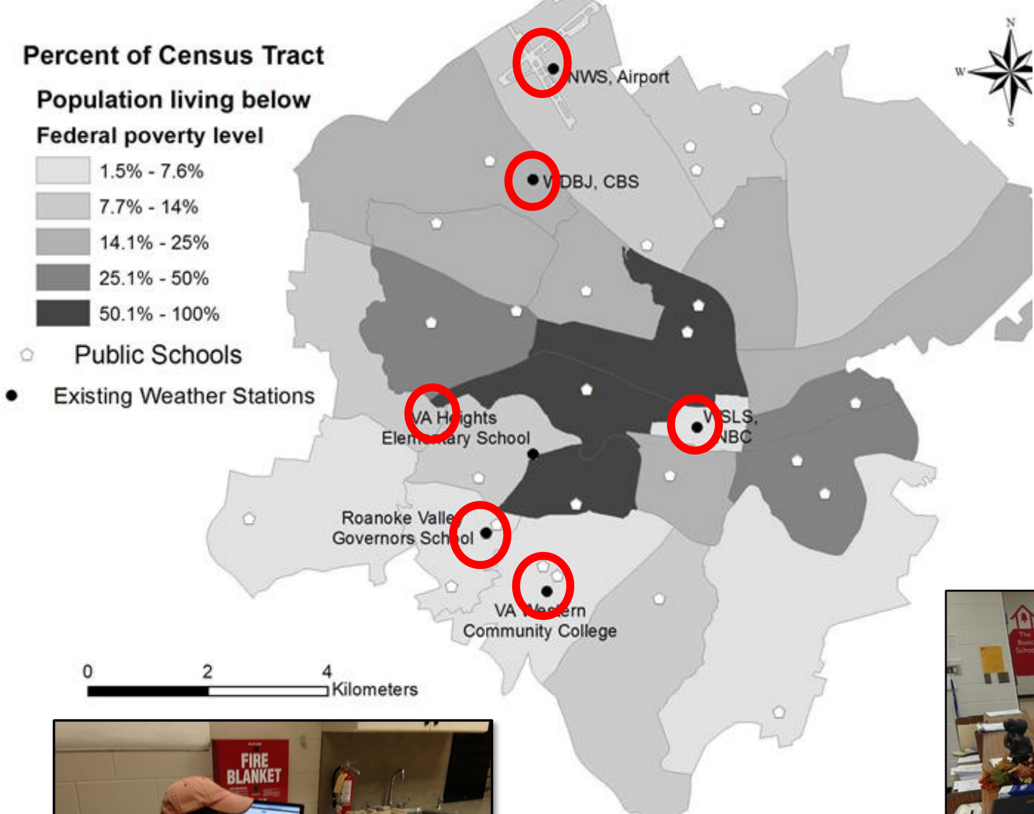
- Select calm, clear, forecast -- avoid overcast, wind, frontal activity, precipitation . . . .
- Drive morning schedule to match Landsat—sometimes, afternoon and nighttime
- Break data into 1-hour units
- Scheduling vehicles, volunteer drivers, installing temperature units, usually requires lead time longer than forecast interval . . . .



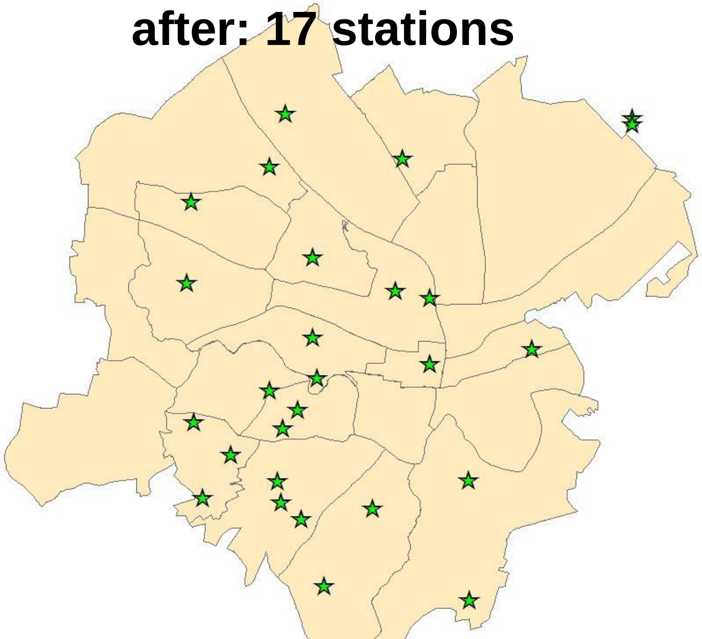


expanding Roanoke's fixed station network

before: 6 stations

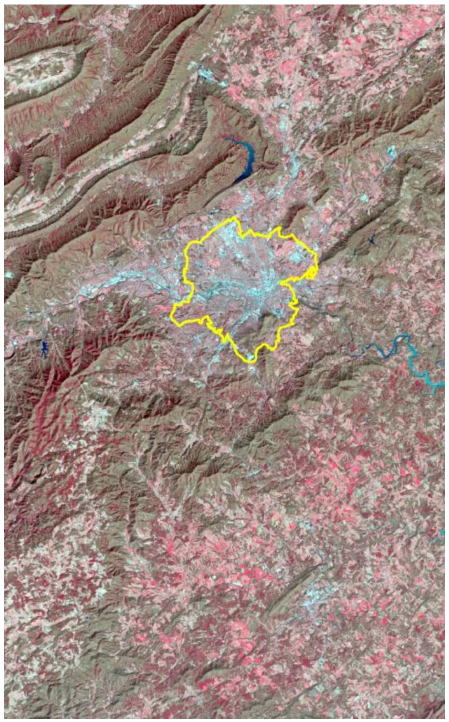


after: 17 stations

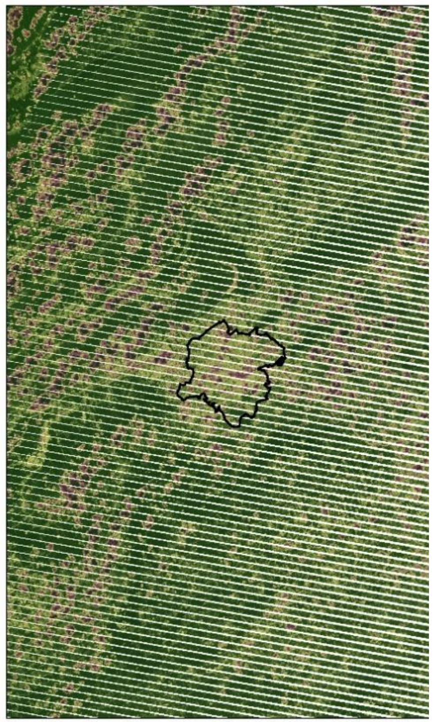


Matching data collection to Landsat schedule

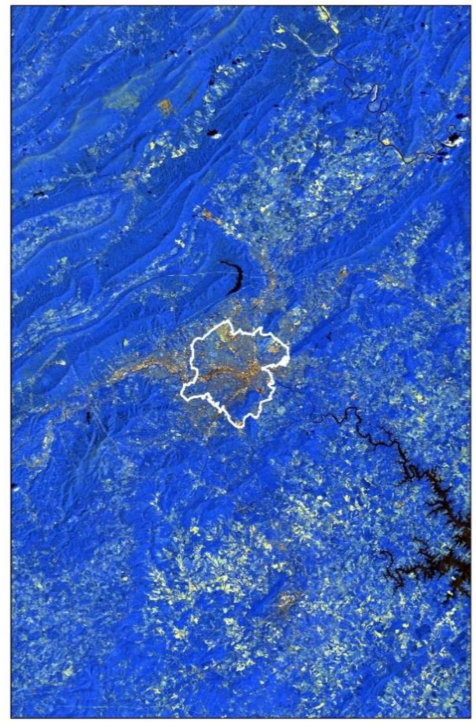
Roanoke is positioned at the western edge of Path 16, so in 2013 & 2014, it was (theoretically) possible to collect three scenes in one week (weather permitting).



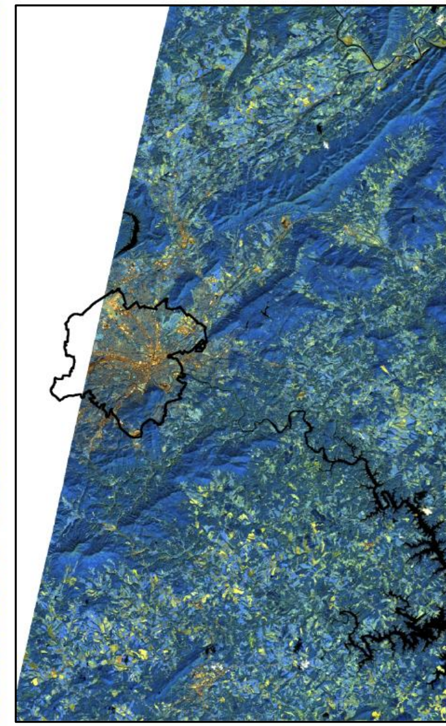
Landsat 5 TM (Path 17, Row 34)



Landsat 7 TM, SLC-off (Path 17, Row 34)



Landsat 8 OLI (Path 17, Row 34)

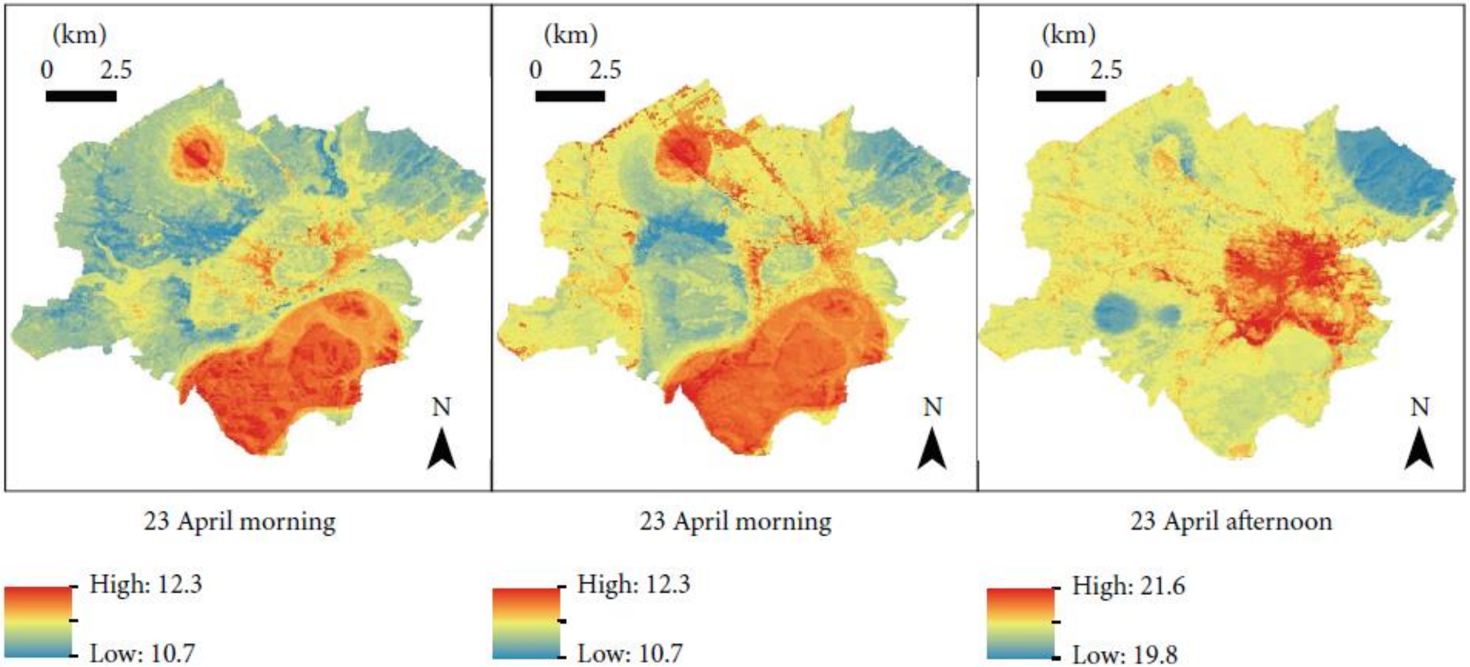


Landsat 8 OLI (Path 16, Row 34)

some results

23 April 2013

morning temperatures	morning temperatures lag -1	afternoon temperatures



Key variables: IS, elevation, basis temperature (varies w/time of day)
Accuracy: landscape metrics explain 60% - 90% of temperature variation

comparison with similar strategy

Hart & Sailor (2009), Portland, OR

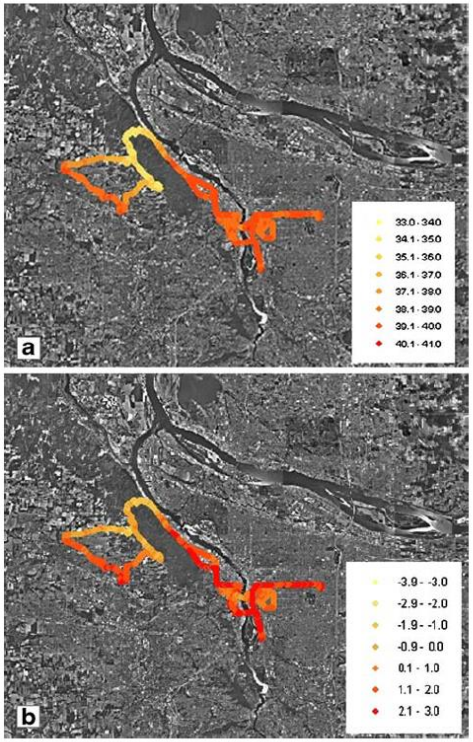


Fig. 5 a Temperatures measured (the legend shows temperatures in degrees Celsius) and b UHI magnitude (the legend shows temperatures in degrees Celsius) during an afternoon vehicle traverse on 26 June 2006

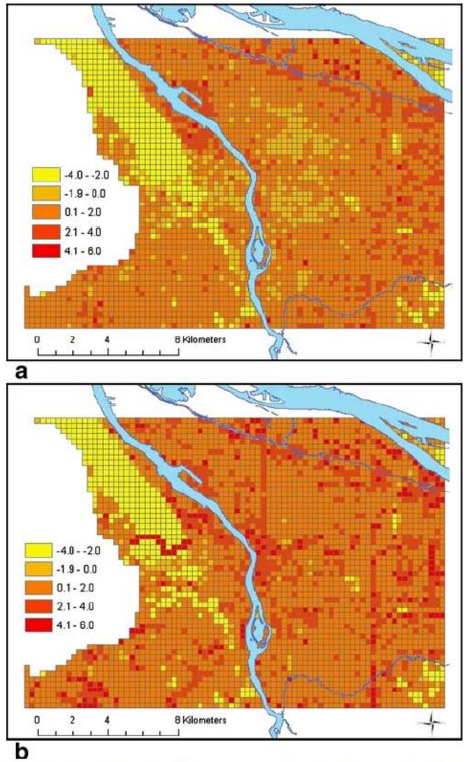


Fig. 7 Grid values of UHI intensity produced using tree-structured regression models (UHI magnitude is in °C) for a weekend daytime UHI, and b weekday daytime UHI

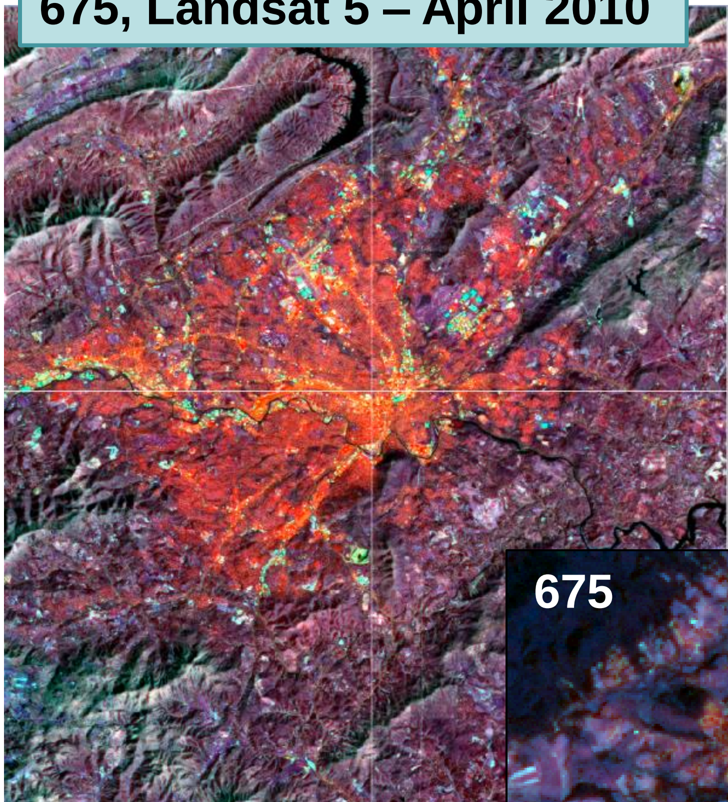
Mobile temperature collection
Landscape variables

Vegetation cover
Canopy cover
Impervious surface
Loose surface cover
Land use
Bldg floor space
Length of roads

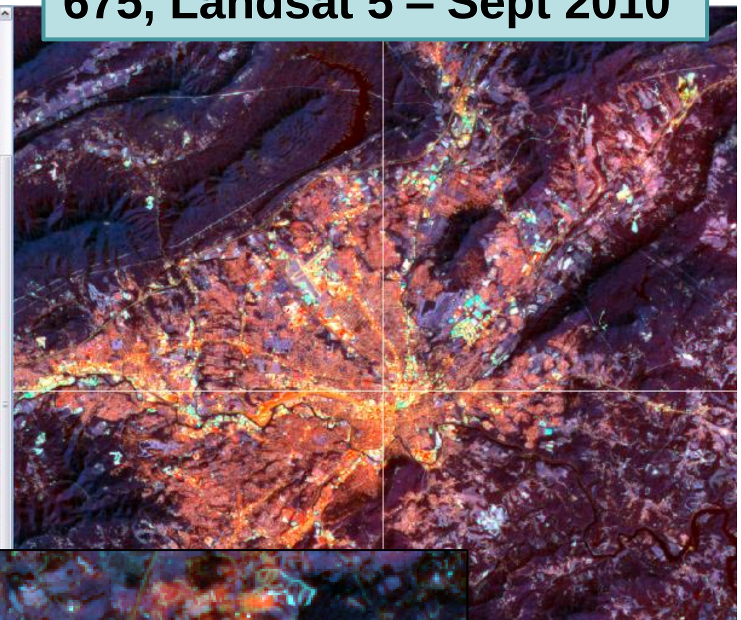
300 m grid cells

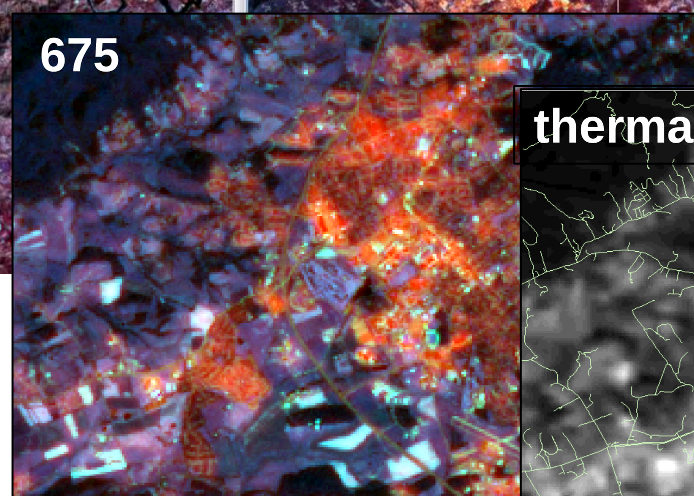
Hart, Melisa, and David J. Sailor. 2009 "Quantifying the influence of land-use and surface characteristics on spatial variability in the urban heat island." ***Theoretical and Applied Climatology*** 95(3):397-406. Feb, 2009 clear, calm weather, with solar heating several days in succession.

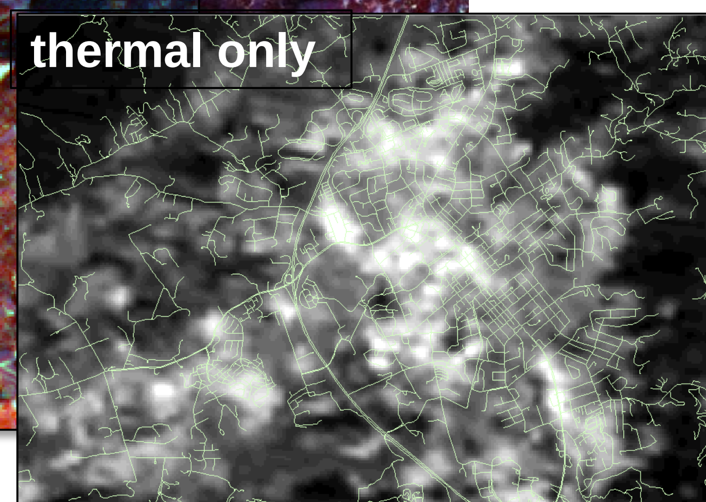
675, Landsat 5 – April 2010



675, Landsat 5 – Sept 2010







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Peter Sforza

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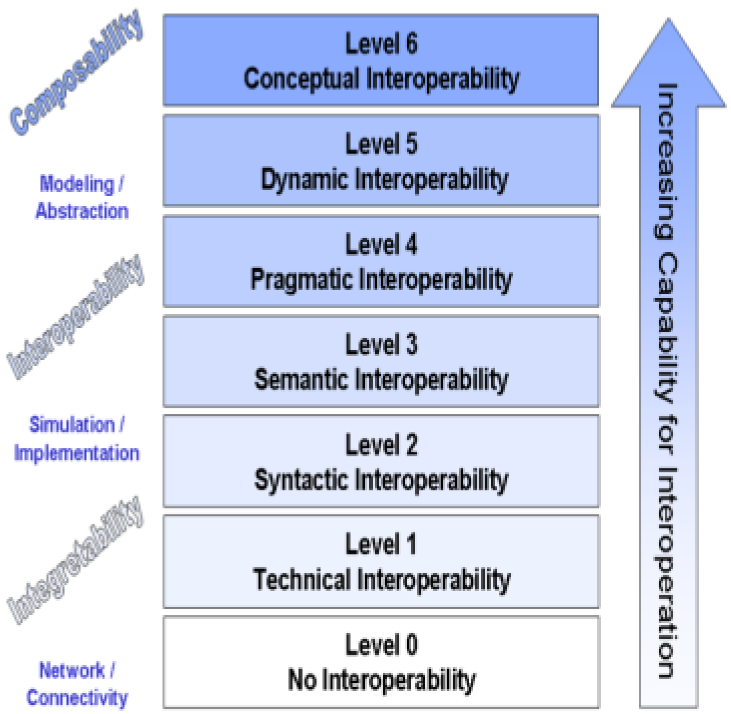
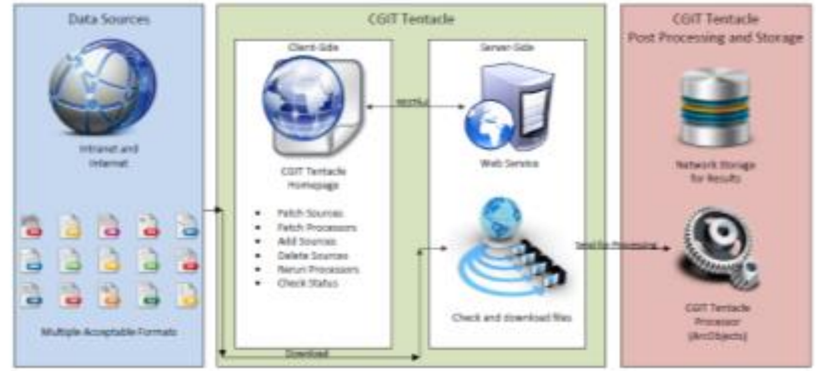
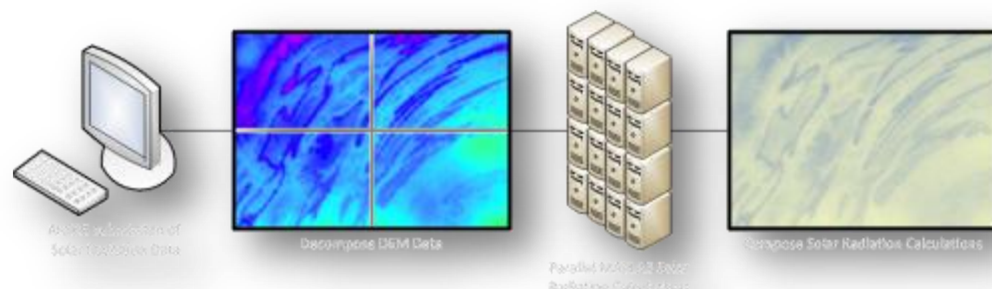
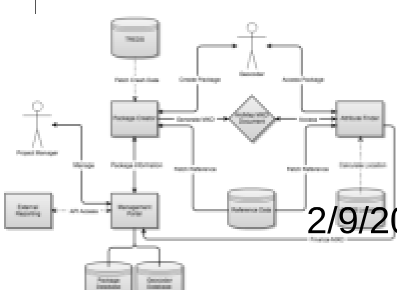
Research Infrastructure

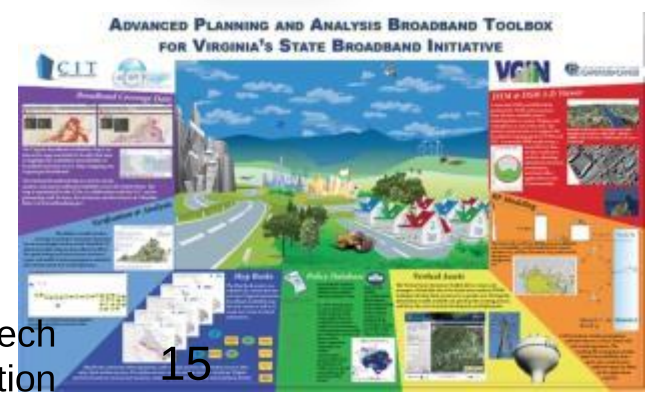
Source	Name	URL	Last Updated	Recurrence	Status	Action
1	US Drought Monitor	http://drought..	06/05/2012 7:00:00 AM	Weekly		Delete



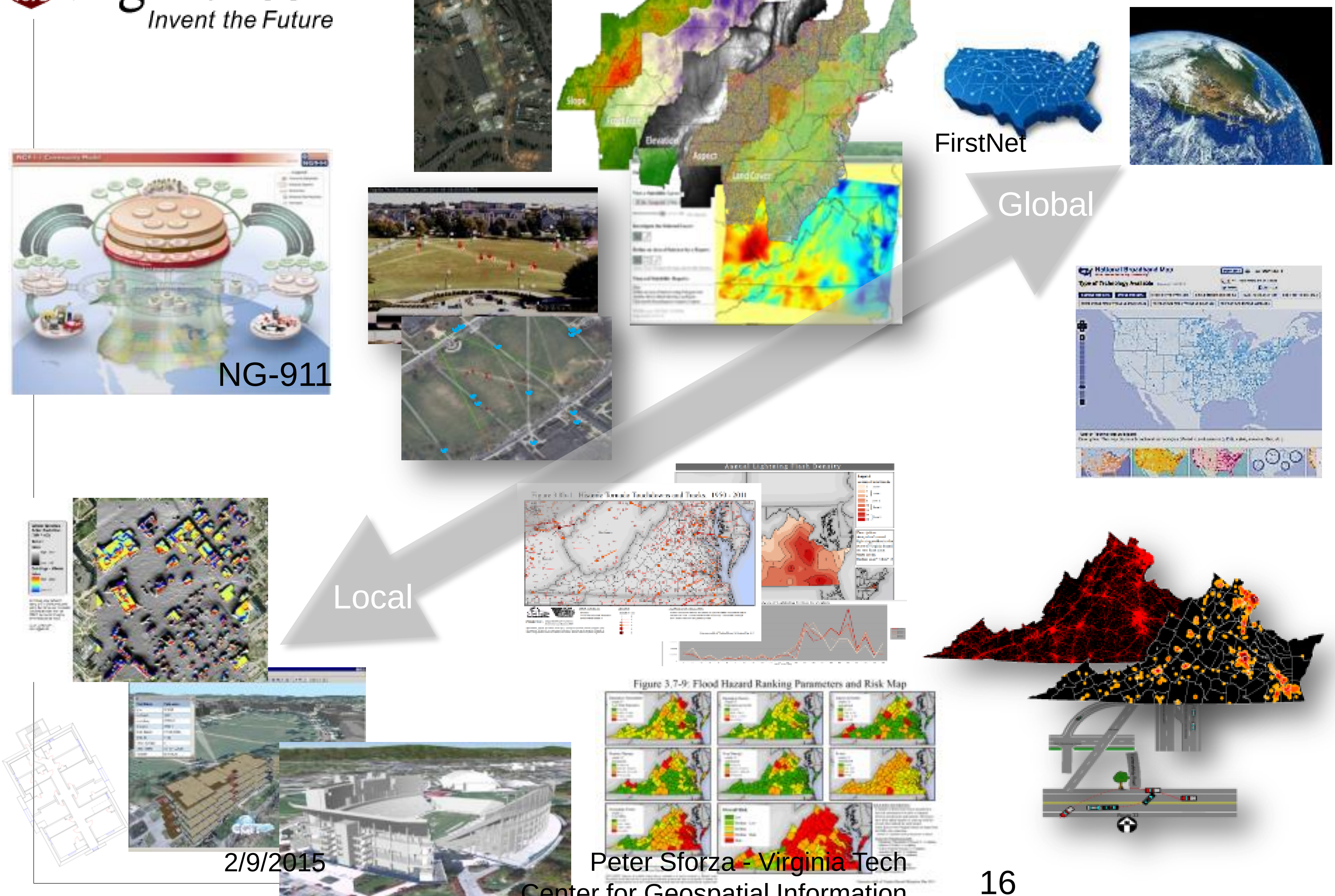








Research Examp



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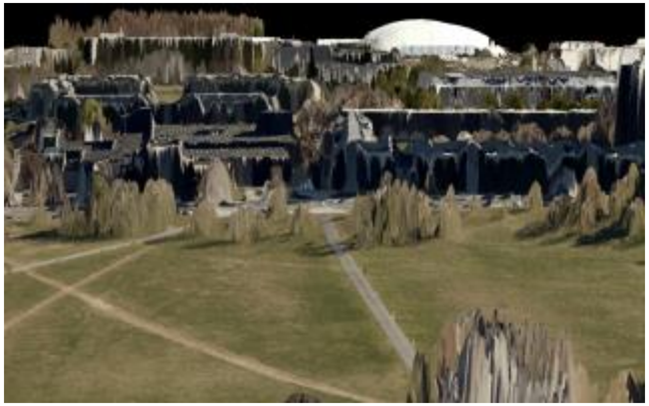
New Statewide Digital Surface Model (DSM) for Virginia from LiDAR and Photogrammetry



- Proposed by VT-CGIT and VGIN to support development of 3D Spatial Data Infrastructure and the Advanced Broadband Analysis and Planning Toolbox for the Commonwealth of Virginia Broadband Mapping Initiatives
- A digital surface model (DSM) is a digital representation of all natural and artificial features that are visible on the surface of the earth. It includes exposed ground and above –ground features, such as vegetation, buildings and other cultural features. It is useful in geospatial analysis and applications that require line-of-sight, viewshed or vegetation analysis. Applications of DSM data are found in telecommunications, forestry, community planning and renewable energy.
- A statewide DSM for the Commonwealth will be created to support wireless broadband mapping efforts such as vertical assets identification and wireless broadband propagation modeling. The statewide seamless DSM will also provide the basis for analysis and visualization that may support policy and business investment decisions related to broadband and communications infrastructure in the Commonwealth of Virginia.
- As a part of the final product deliverable, a qualitative accuracy assessment will be performed by the DSM developer. This assessment will conform to the National Standard for Spatial Data Accuracy (NSSDA) http://www.fgdc.gov/standards/projects/FGDC-standards-projects/accuracy/part3/chapter3

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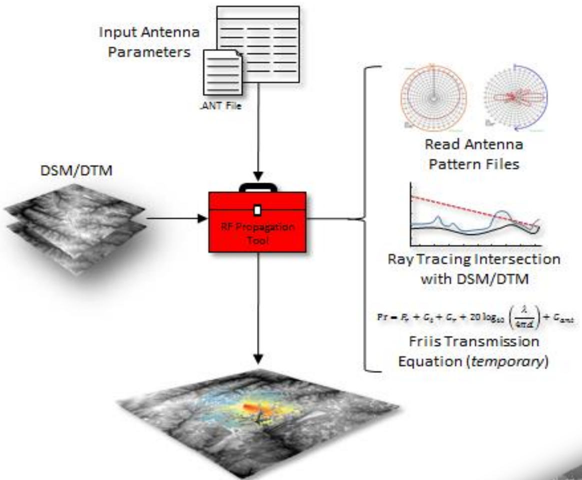
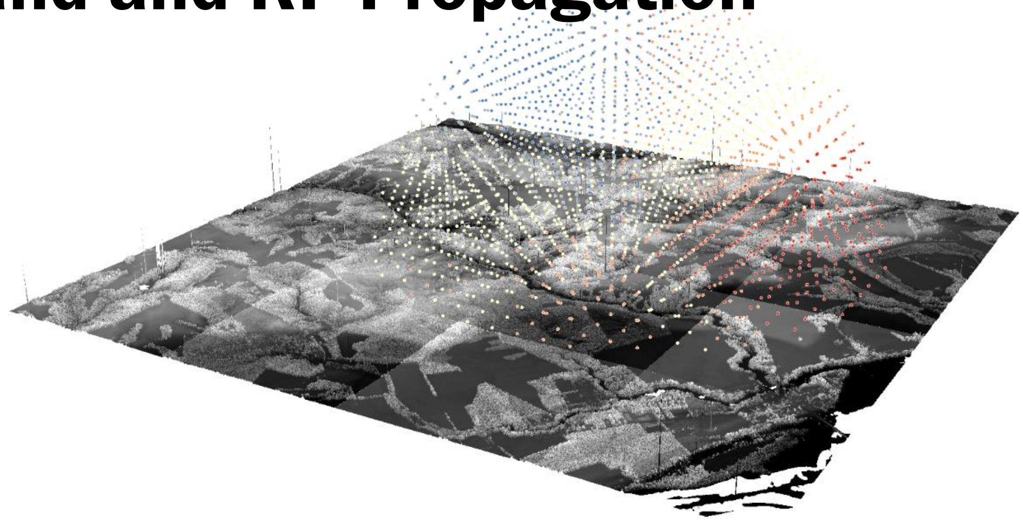
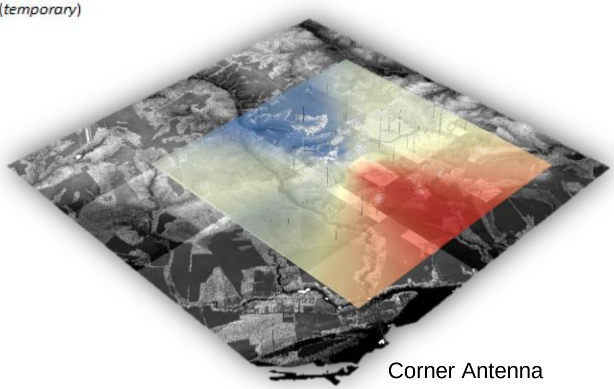
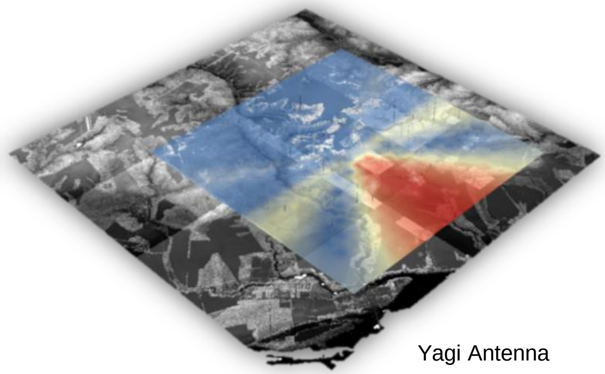
3D Virginia:
Statewide Broadband and RF Propagation





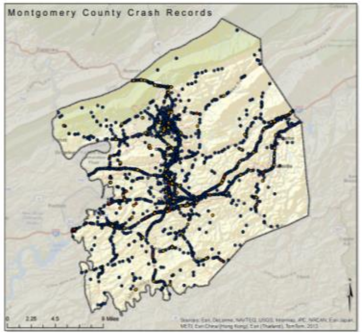


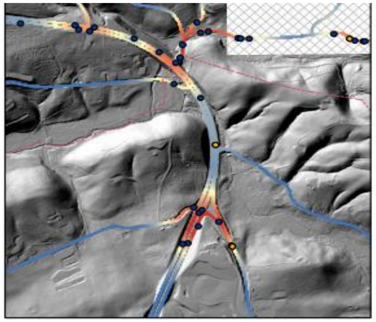
Corner Antenna



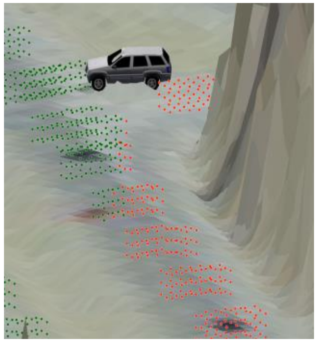
Yagi Antenna

3D Virginia:
Statewide DMV Crash Record Analysis





CGIT has developed automated methods for real-time DMV crash records, with a total of 566,232 crash locations processed in the Commonwealth of Virginia from January 1, 2011 through September 29, 2015.



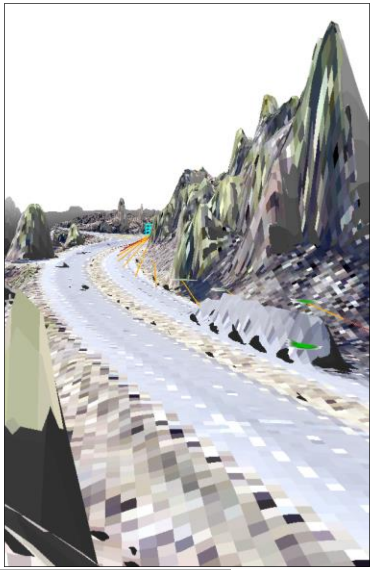
All Crash Locations
Number of Vehicles
5
4
3
2
1

Single Car Crashes
Fatal
Serious Injury
Minor Injury / Property Damage

Data is based on located police reported crash records from 2011, 2012, and 2013 (prelimanary data).

Sample Location: US-460 (Pandapas Pond Road), between the intersection of US-460 and US-460 BUS and the intersection of US-460 and Fortress Drive. Also including Coal Bank Hallow Road.

Virginia Department of Motor Vehicles Highway Safety Office
Data use restricted under US Code-23USC409



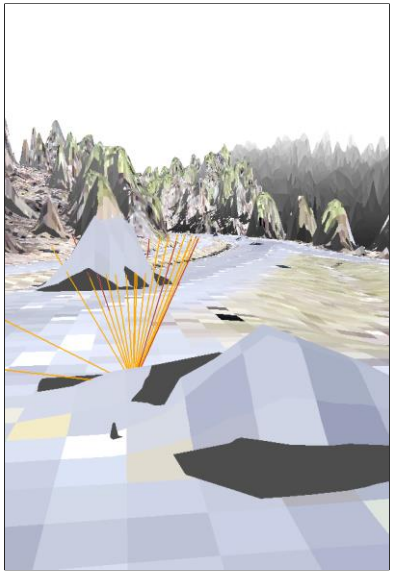
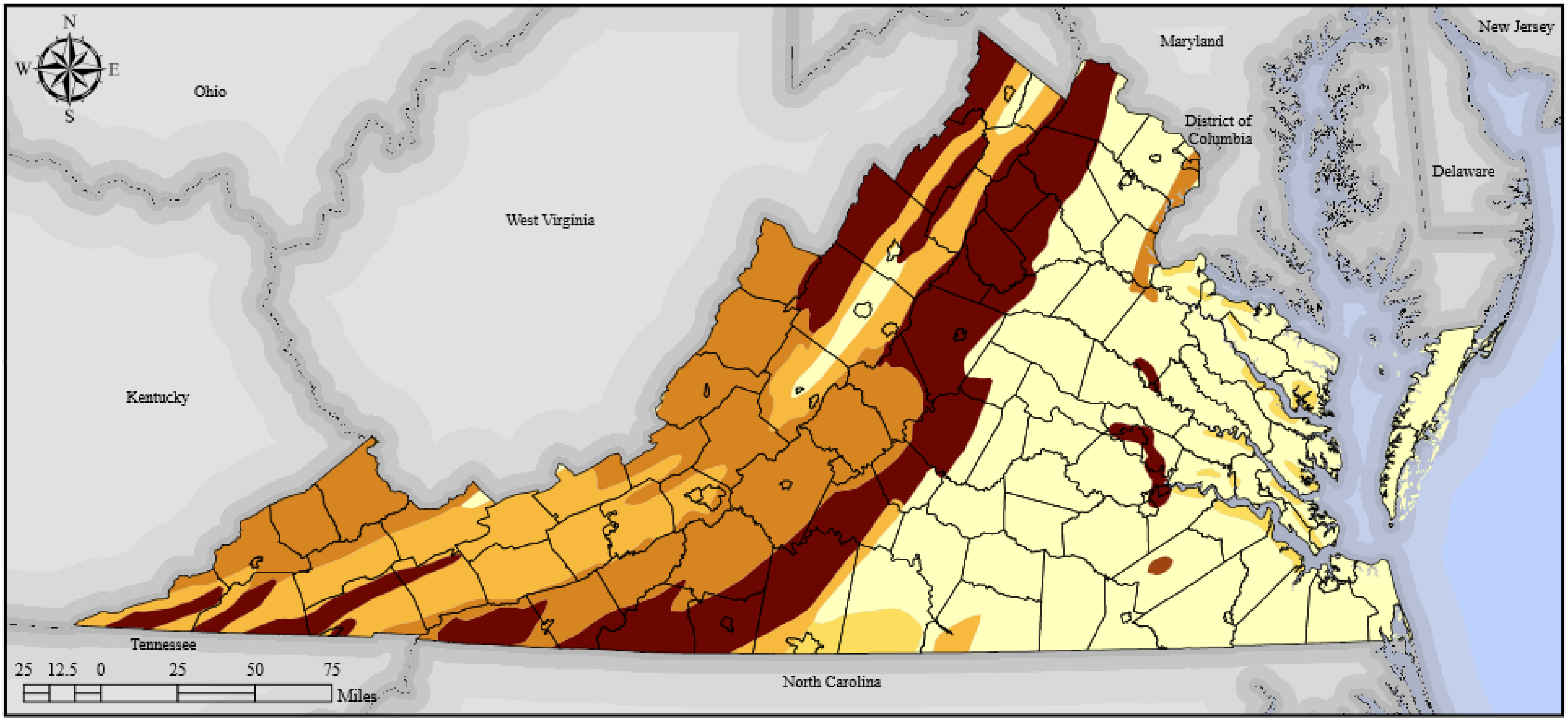


Figure 3.12-1: Landslide Incidence and Susceptibility



PROJECTION: *VA Lambert Conformal Conic North American Datum 1983*

DISCLAIMER: Majority of available hazard data is intended to be used at national or regional scales. The purpose of the data sets are to give general indication of areas that may be susceptible to hazards. In order to identify potential risk in the Commonwealth available data has been used beyond the original intent.

DATA SOURCES:

USGS NLHP
VGIN Jurisdictional Boundaries
ESRI State Boundaries

LEGEND:

Landslide Categories

- High Susceptibility & Moderate Incidence
- High Susceptibility & Low Incidence
- High Incidence
- Moderate Susceptibility & Low Incidence
- Moderate Incidence
- Low Incidence

HAZARD IDENTIFICATION:

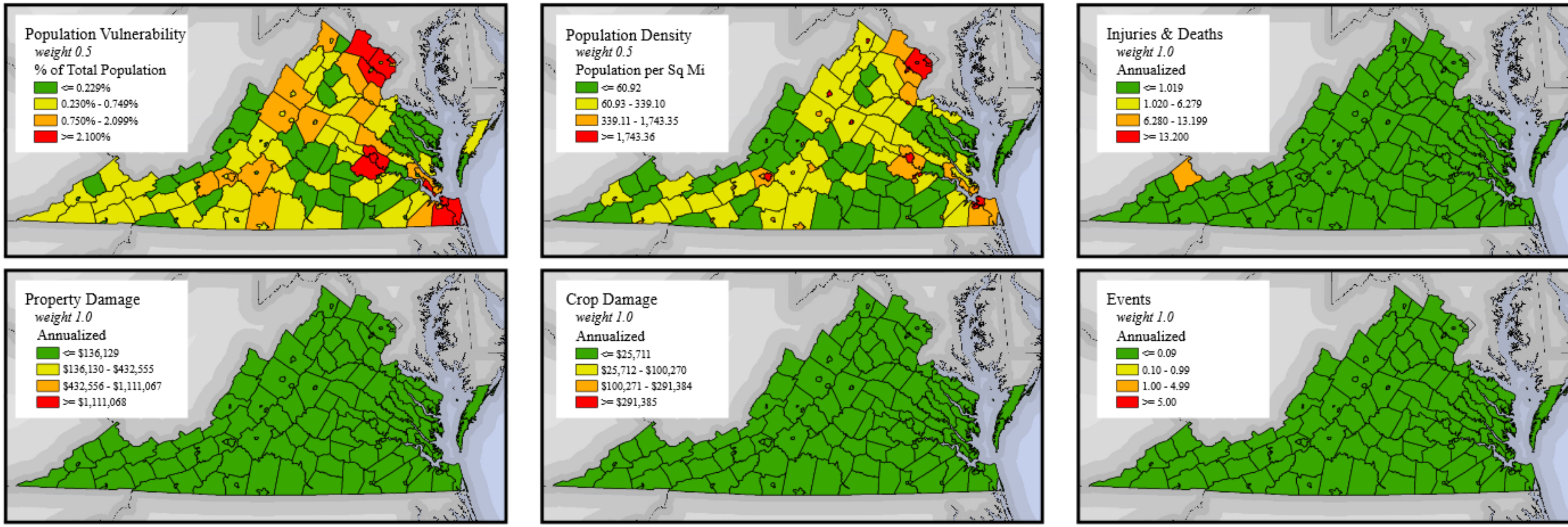
The Landslide Incidence and Susceptibility map layer shows areas of landslides and areas susceptible to future landsliding. Areas where large numbers of landslides have occurred and areas which are susceptible to landsliding have been delineated in this layer.

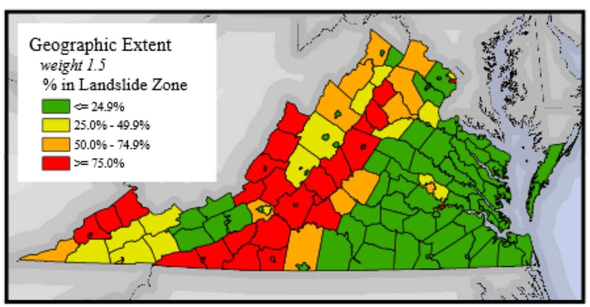
Landslides are defined to include most types of gravitational mass movement such as rockfalls, debris flows, and the failure of engineered soil materials.

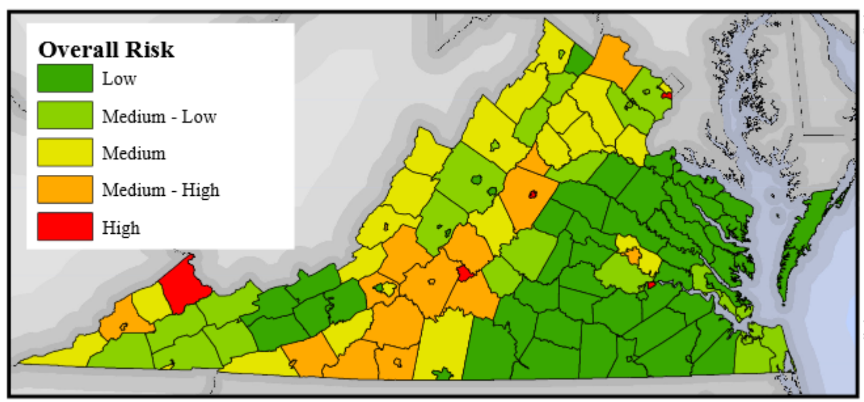
Commonwealth of Virginia Hazard Mitigation Plan 2013

VirginiaTech

Figure 3.12-3: Landslide Hazard Ranking Parameters and Risk Map







HAZARD RANKING:

A number of factors have been considered in this risk assessment to be able to compare between jurisdictions and hazards. The factors have been added together to come up with the overall total ranking for each hazard. Some factors were weighted based on imput from the HIRA sub-committee.

Section 3.5 explains each of the factors in detail.

Factors & Weighting Include:

- Population Vulnerability & Density 0.5 weighting
- Injuries & Deaths 1.0 weighting
- Crop & Property Damage 1.0 weighting
- Annualized Events 1.0 weighting
- Geographic Extent 1.5 weighting

DATA SOURCES:

CGIT Ranking Methodology
VGIN Jurisdictional Boundaries
ESRI State Boundaries

PROJECTION: *VA Lambert Conformal Conic*
North American Datum 1983

N W E S

DISCLAIMER: Majority of available hazard data is intended to be used at national or regional scales. The purpose of the data sets are to give general indication of areas that may be susceptible to hazards. In order to identify potential risk in the Commonwealth available data has been used beyond the original intent.

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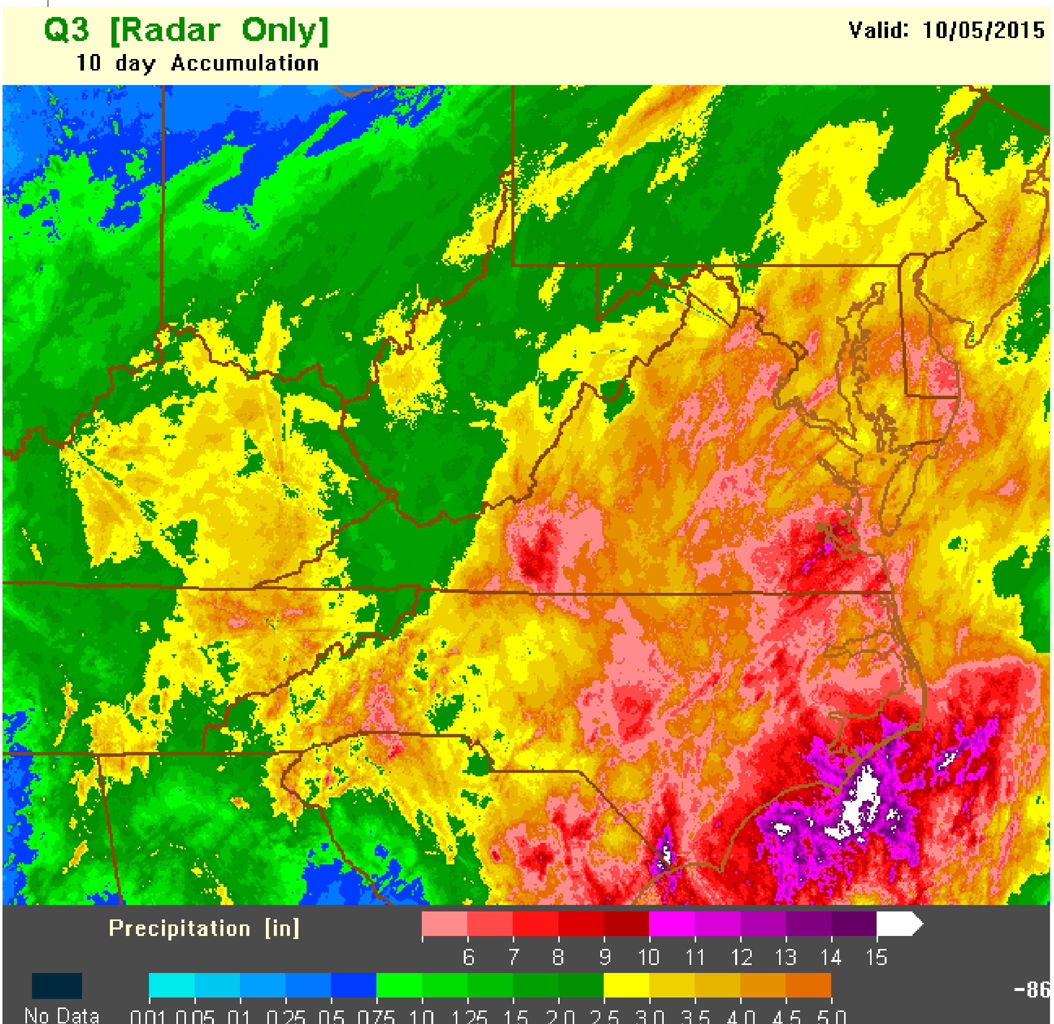
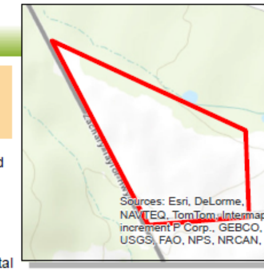
BigData for Real-Time Landslide Risk



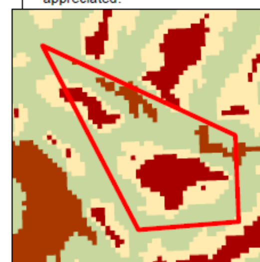
Topographic Features



Elevation in feet

Maximum	823
Average	800
Minimum	768

Elevation has a profound influence on the minimum and maximum temperatures in a vineyard, particularly in hilly and mountainous terrain. Because frosts and freezing temperatures can so dramatically reduce vineyard profitability, elevation is one of the most - perhaps the most - important features of vineyard site suitability. The physics of topographic effects on air temperature are well documented (Geiger, 1966) and its horticultural significance generally well appreciated.



Slope

The change in elevation over a horizontal ground distance, is expressed here as a percent. Gentle to moderate slopes are best-suited for vineyard production as they protect against damaging frosts (Wolf & Boyer, 2009). Cold air has a higher density than surrounding air, causing it to sink with gravity and move downhill. As a result, vineyards planted on slopes at higher elevations benefit from fluid cold air drainage away from vines and the resulting warm air displacement upwards.

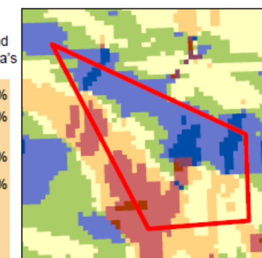
0% - 2%	Poorly Suited
2% - 5%	Fairly Well-Suited
5% - 15%	Well-suited
> 15%	Poorly Suited

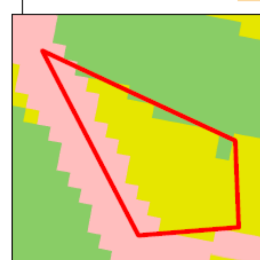
Minimum	0.02	%
Average	4.05	%
Maximum	14.22	%

Aspect

Aspect describes the direction a slope faces, which relates to the sun angle and amount of sunlight that reaches the ground. According to Dr. Tony Wolf, Virginia's State Viticultural specialist (p.16), aspect is one of the least influential factors related to a vineyard's overall suitability; however, choosing a site with a favorable aspect can enhance grape taste and facilitate efficient disease and pest management.

Northern 315° to 45°	North-facing	16.3%
	Northeastern-facing	25.9%
Eastern 45° to 135°	East-facing	9.0%
	Southeast-facing	21.7%
Southern 135° - 225°	South-facing	15.7%
	Southwest-facing	8.1%
Western 225° - 315°	West-facing	1.4%
	Northwest-facing	1.8%





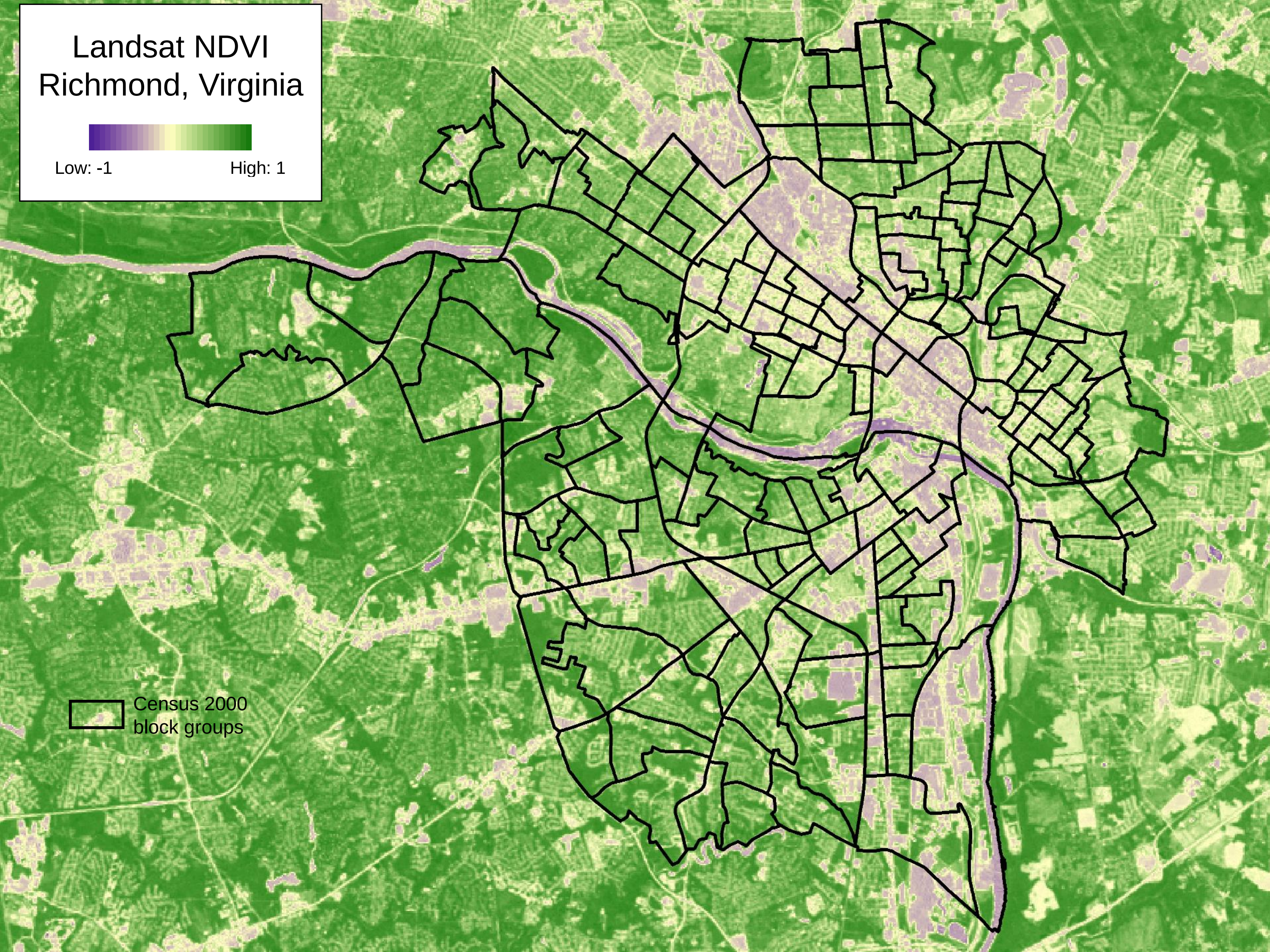
Land Cover

The Multi-Resolution Land Characteristics Consortium National Landcover Database (NLCD 2006) is a land cover classification that was generated using Landsat imagery.

Open Water	Barren Land	Grassland/Herbaceous
Open Space	Deciduous Forest	Pasture/Hay
Developed-Low Density	Evergreen Forest	Cultivated Crops
Developed-Med. Density	Mixed Forest	Woody Wetlands
Developed-High Density	Shrub/Scrub	Herbaceous Wetlands

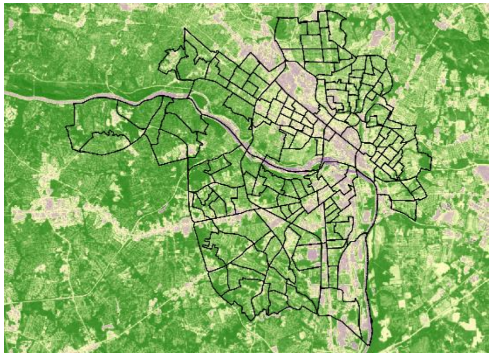
Report Generated by: http://vmdev.cgit.vt.edu/ECVineyards

Report generated 2014-01-31 11:44:09


Landsat NDVI
Richmond, Virginia
Low: -1
High: 1
Census 2000
block groups

NDVI zonal statistics

(for a specific scene-polygon combination)



Block Group ID	517600603002
Scene Name	LT50150342008162EDC00
Min NDVI	-0.0710
Max NDVI	0.5252
Mean NDVI	0.1532
Std. Dev. of NDVI	0.1298

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Phenology:

Vegetation phenology, the study of the timing of recurring vegetation cycles such as canopy emergence and senescence, has emerged recently as an important focus for ecological research because that the phenological state of vegetation significantly affects exchanges of heat, mass, and momentum between the Earth's surface and the atmosphere (Weber 2001, White et al. 2002, Jolly et al. 2005). Through measuring phenological variability especially at large scale, it provides considerable promise to address important questions in global modeling, monitoring, and climate change (Reed et al. 1994, Schwartz & Reiter 2000, Chen et al. 2001, Jenkins et al. 2002, Beaubien et al. 2003, Debeurs & Henebry 2005,).

Phenology applications:
1.Phenology model can provide spatial and temporal continuous phenology maps over large areas. The temporal and spatial variation in vegetation growth and activity can be quantified.
2.Phenological metrics include: start of green-up, start of brown-down, end of green-up, end of brown-down, Maximum NDVI, NDVI value at green-up, brown-down and Maximum NDVI, and Integral NDVI during growing season for each year.
3.Monitoring vegetation phenology is fundamental to understanding the consequences of a changing climate for the biosphere because phenological events represent the response of plants to the recent local climate.
4.Phenological information is important in monitoring all aspects of ecosystems and is essential to understanding the dynamics of plant communities, which of course impact animal populations as well.
5.Phenology data can be used to characterize land cover, and to monitor changes in vegetation associated with events such as fire, drought, land use conversions, climate fluctuations, and directional climate change and land management practices.
6.Phenology data can support decision making in fields as diverse as epidemiology, medicine (pollen warnings for allergy sufferers), forensic studies, tourism, and wildlife management.
7.Leaf phenology affects the terrestrial carbon cycle, exchanges of heat, water, mass, and momentum between the Earth's surface and the atmosphere.
8.It is crucial to account for phenology to accurately simulate seasonal cycle in coupled biosphere/atmosphere climate models, in terrestrial biogeochemical cycle models, and in vegetation dynamics models.

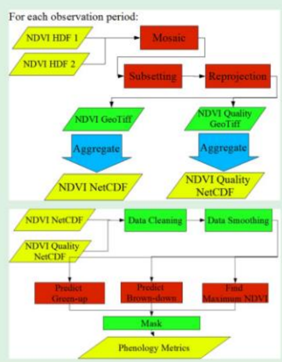
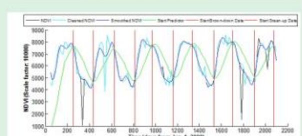
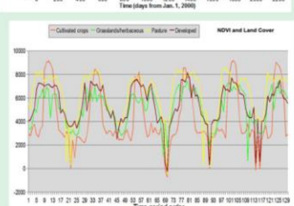


Table 1. NDVI metrics and their definition

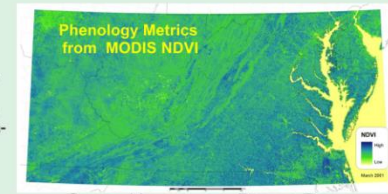
Metrics	Definition
Temporal NDVI metrics	
Time of start of green-up	The time point where the smoothed time-series data crossed the backward moving average in an upward direction and remained above it for the greatest sustained increase in NDVI
Time of end of green-up	The time point where the smoothed time-series data crossed the forward moving average in a downward direction and remained above it for the greatest sustained decrease in NDVI
Time of maximum NDVI	The time point where the cleaned time-series data has the maximum NDVI
Time of start of brown-down	The time point where the smoothed time-series data crossed the backward moving average in a downward direction and remained below it for the greatest sustained decrease in NDVI
Time of end of brown-down	The time point where the smoothed time-series data crossed the forward moving average in an upward direction and remained above it for the greatest sustained decrease in NDVI before the cross point
NDVI-value metrics	
Value of start of green-up Value of end of green-up Value of maximum NDVI Value of start of brown-down Value of end of brown-down	NDVI-value of corresponding time point
Time-integrated NDVI value	The cumulated area under the smoothed time-series data between the time of start of green-up and the time of end of brown-down

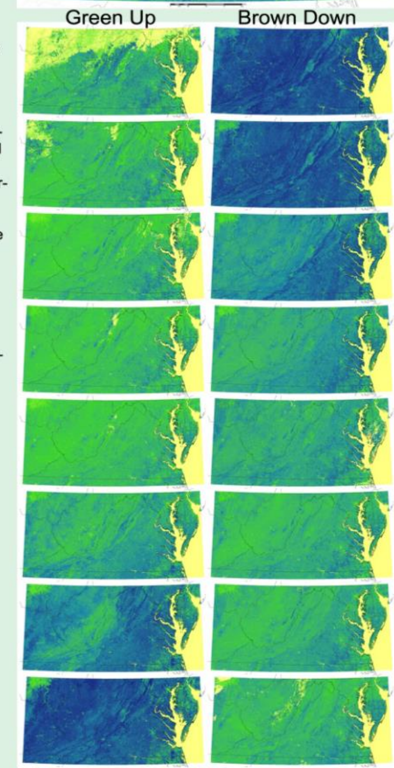
Temporal NDVI metrics	Year	Land cover type: Developed	Deciduous forest	Evergreen forest	Mixed forest	Grassland/herbaceous	Pasture	Cultivated crops	Wetlands
StartGreenup	2001	79±10	88±11	101±23	91±15	84±14	79±18	88±31	91±27
StartGreenup	2002	84±29	87±12	101±30	88±16	87±16	80±29	100±48	89±42
StartGreenup	2003	75±16	83±12	94±26	87±16	79±13	75±17	81±35	79±30
StartGreenup	2004	80±13	82±8	93±15	83±11	80±9	77±13	86±26	90±19
StartGreenup	2005	80±13	83±9	94±17	87±13	80±9	80±15	90±31	89±23
StartGreenup	Globe*	80±11	85±7	96±14	87±9	82±7	78±10	89±25	87±17
StartBrowndown	2000	239±29	251±17	250±29	250±20	249±21	242±33	244±35	244±29
StartBrowndown	2001	247±26	252±14	261±26	251±18	250±18	246±22	253±24	255±23
StartBrowndown	2002	240±39	255±19	259±35	253±21	248±29	238±41	248±47	248±39
StartBrowndown	2003	236±28	249±14	250±29	246±18	243±18	239±26	245±29	238±27
StartBrowndown	2004	245±21	251±12	252±17	248±14	249±17	244±22	248±21	245±17
StartBrowndown	2005	233±17	246±9	242±13	244±11	240±14	233±19	238±22	242±13
StartBrowndown	Globe*	240±24	250±11	252±21	248±13	246±16	240±23	245±24	245±19
EndGreenup	2001	154±30	144±16	166±35	145±18	149±21	150±26	172±28	158±34
EndGreenup	2002	174±43	148±21	177±47	152±26	158±36	175±44	194±36	164±47
EndGreenup	2003	144±26	142±13	155±26	146±15	141±17	146±28	165±28	150±28
EndGreenup	2004	146±27	137±13	151±27	140±16	142±20	150±31	165±26	149±27
EndGreenup	2005	135±14	138±10	143±10	140±11	133±12	133±16	153±15	146±13
EndGreenup	Globe*	151±25	142±9	158±24	144±11	144±17	151±25	168±22	153±19
EndBrowndown	2000	350±22	343±28	365±39	343±33	351±26	352±21	349±33	356±33
EndBrowndown	2001	347±23	340±22	358±35	341±26	355±21	342±25	327±40	340±32
EndBrowndown	2002	344±24	343±18	348±36	344±25	346±20	345±28	338±33	335±37
EndBrowndown	2003	352±21	340±17	363±30	344±22	351±16	351±18	347±34	353±33
EndBrowndown	2004	355±20	341±21	365±30	345±26	355±18	356±21	345±40	353±31
EndBrowndown	Globe*	350±18	341±16	359±26	343±20	351±15	349±16	341±28	347±23
MaxNDVI	2000	187±47	186±44	207±54	194±48	195±43	191±48	206±42	197±48
MaxNDVI	2001	194±46	177±39	195±54	176±44	187±40	185±42	209±38	197±45
MaxNDVI	2002	208±61	184±43	199±66	188±46	191±53	198±60	206±58	183±62
MaxNDVI	2003	175±43	169±40	172±60	171±47	170±37	172±42	199±45	180±44
MaxNDVI	2004	185±43	167±31	188±36	167±30	177±37	178±40	200±32	185±34
MaxNDVI	2005	179±42	173±38	185±37	176±37	173±39	172±39	198±32	192±36
MaxNDVI	Globe*	188±45	176±35	191±47	179±39	182±38	183±42	203±35	188±38





MODIS satellite data pre-processing and processing procedures with definitions and resulting metrics. Graphs show NDVI for single pixels by land cover type.





MODIS 250-meter 16-day composite NDVI timeseries visualization for green-up from winter to spring (left column) and brown-down from fall to winter (right column). This project demonstrated integrated data download, data processing and key phenology metrics production for automatically characterizing phenology phenomena at regional scale.

Current efforts in vegetation phenology research are summarized at www.MapSeasons.net, a website launched by VT Geography faculty members Dr. Kirsten De Beurs and Peter Sforza in 2008.

http://www.MapSeasons.net/

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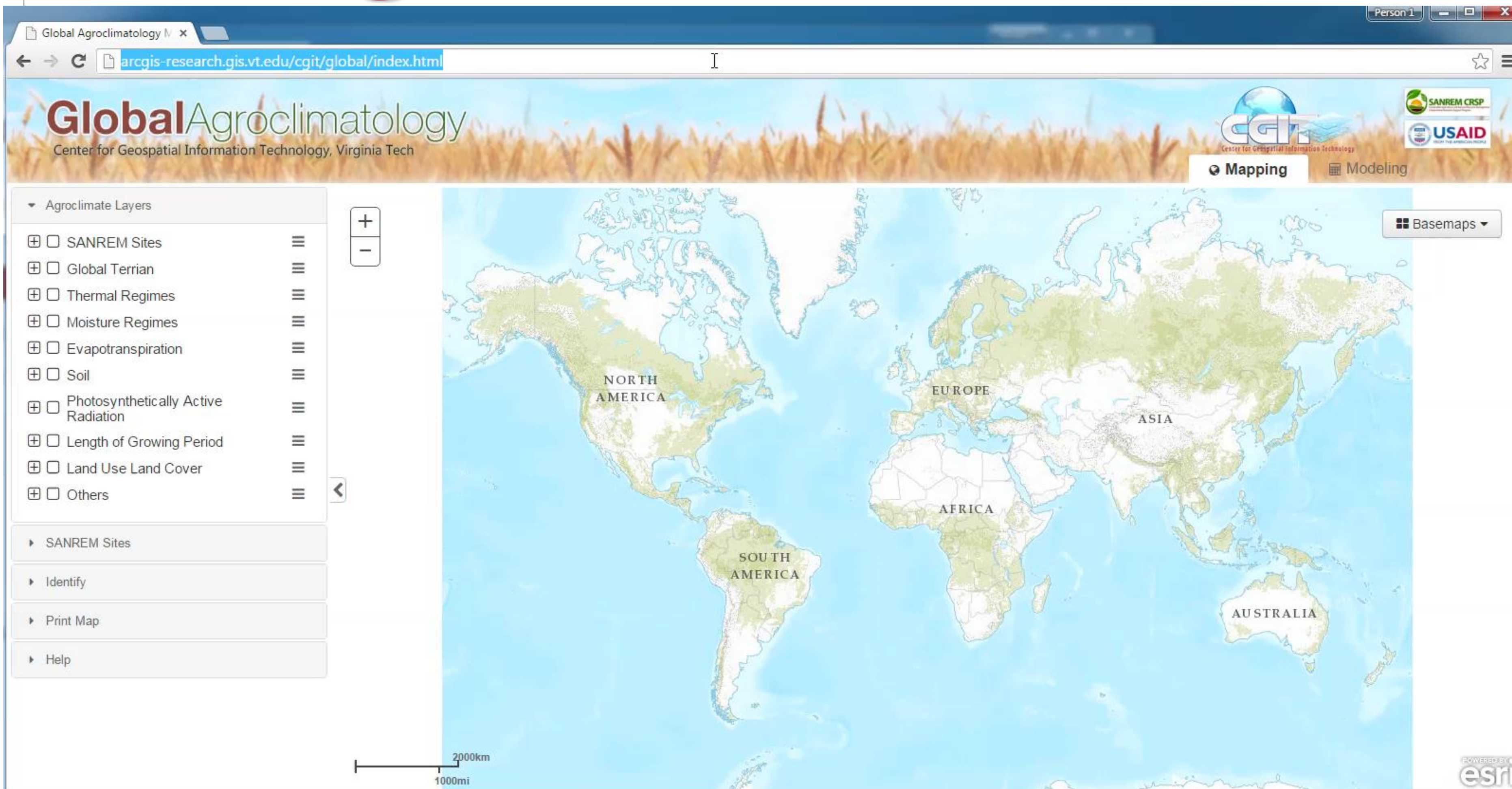
Global Agroclimate

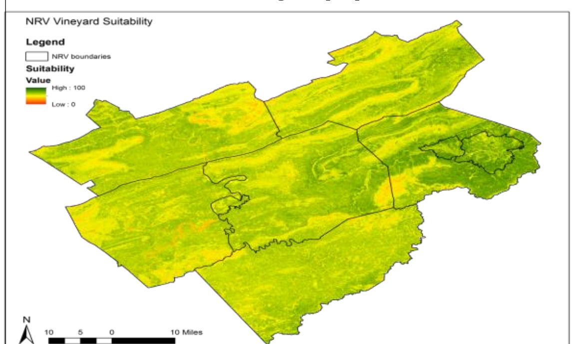
http://arcgis-research.gis.vt.edu/cgit/global/index.html



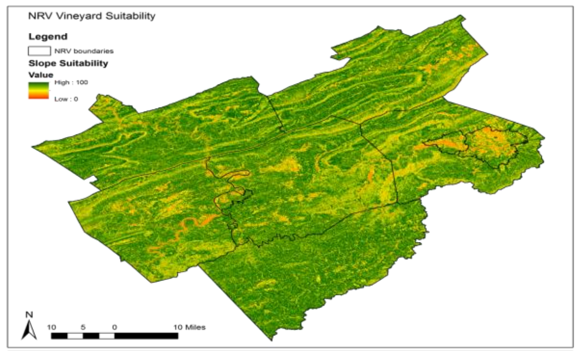
Site Suitability

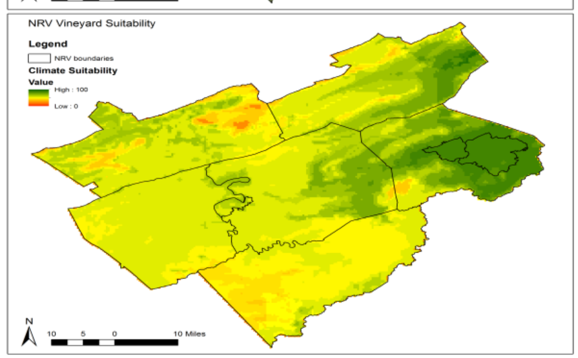
$$S = \sum_{i=1}^{n} (w_i \times C_i) \times \prod_{j=1}^{m} R_j$$

Suitability (S)

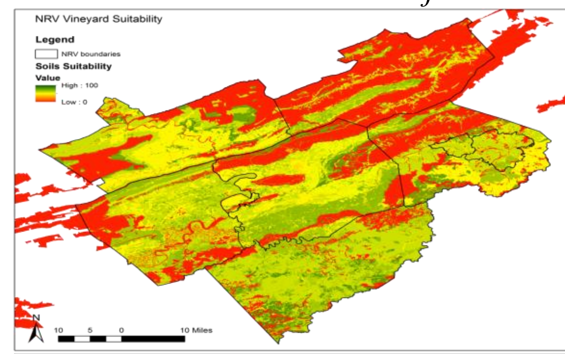


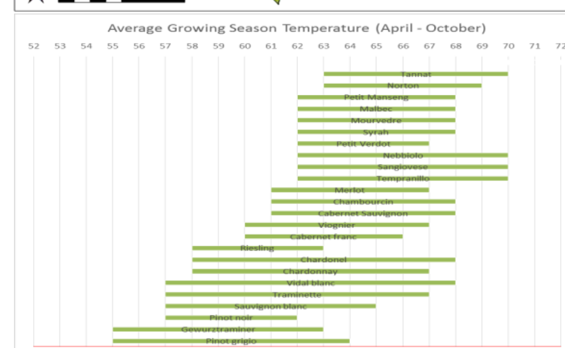
Weighted Criteria ($w_i \times C_i$)



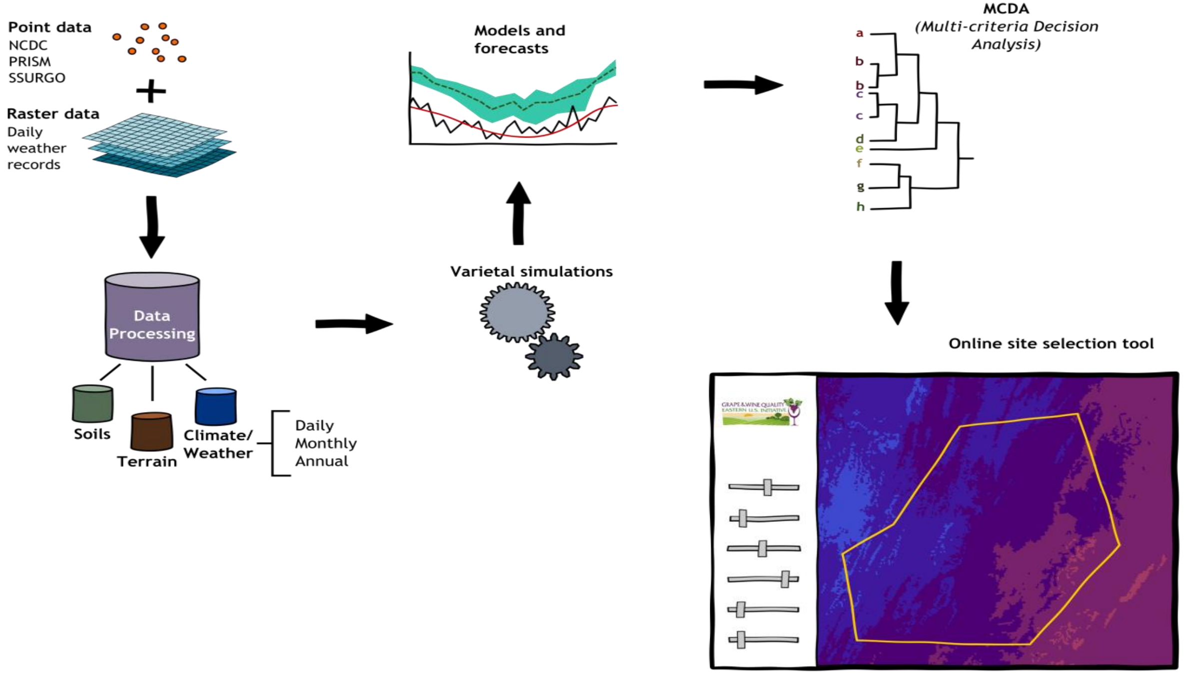


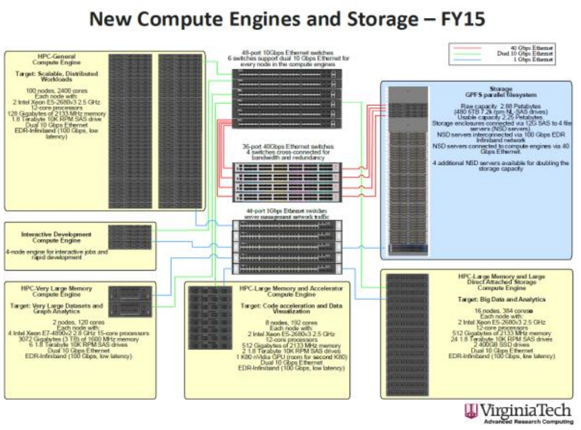
Restrictions (R_j)





Current Research at CGIT: Vineyard Site Assessment and Simulation of Grape Varieties in Virginia and the Eastern U.S.





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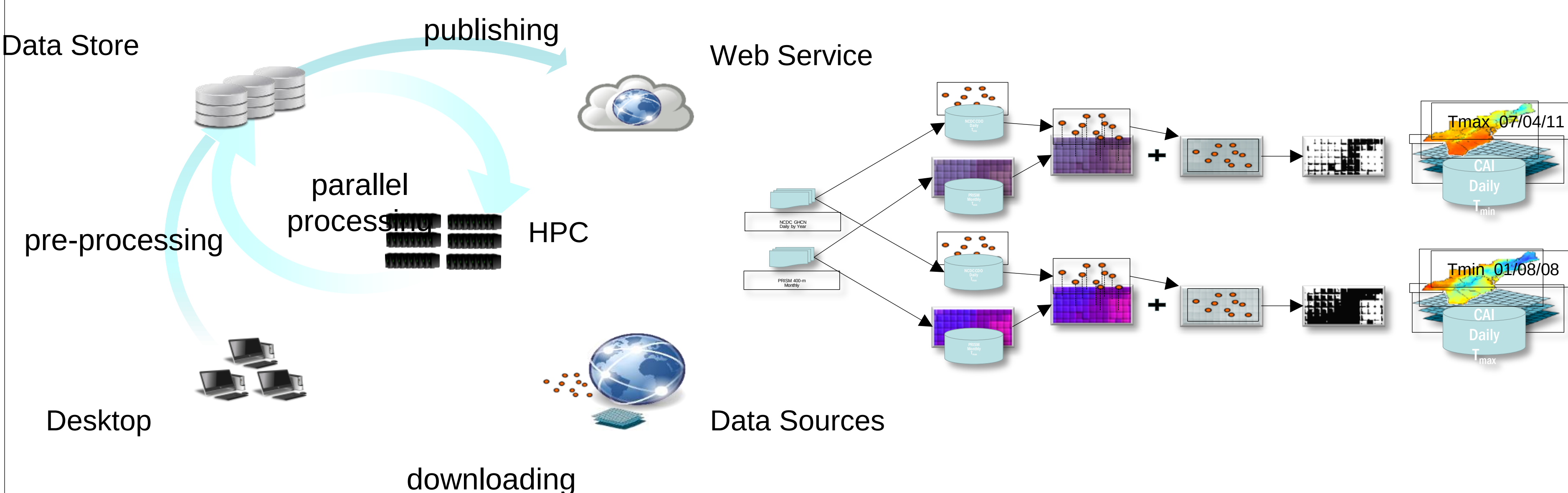
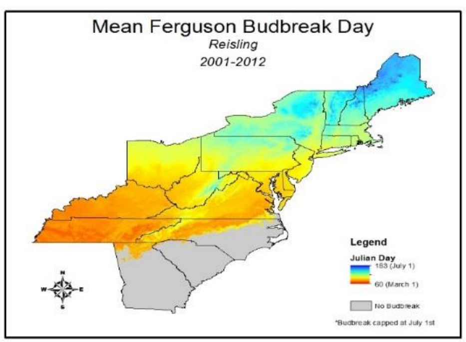
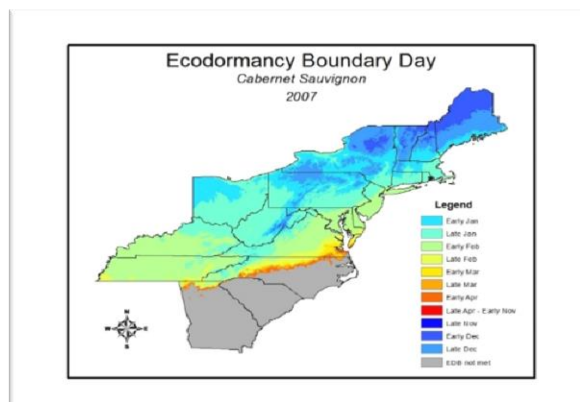
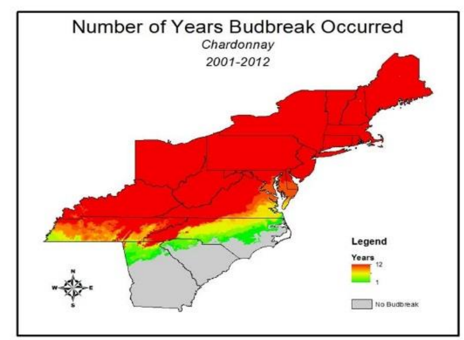
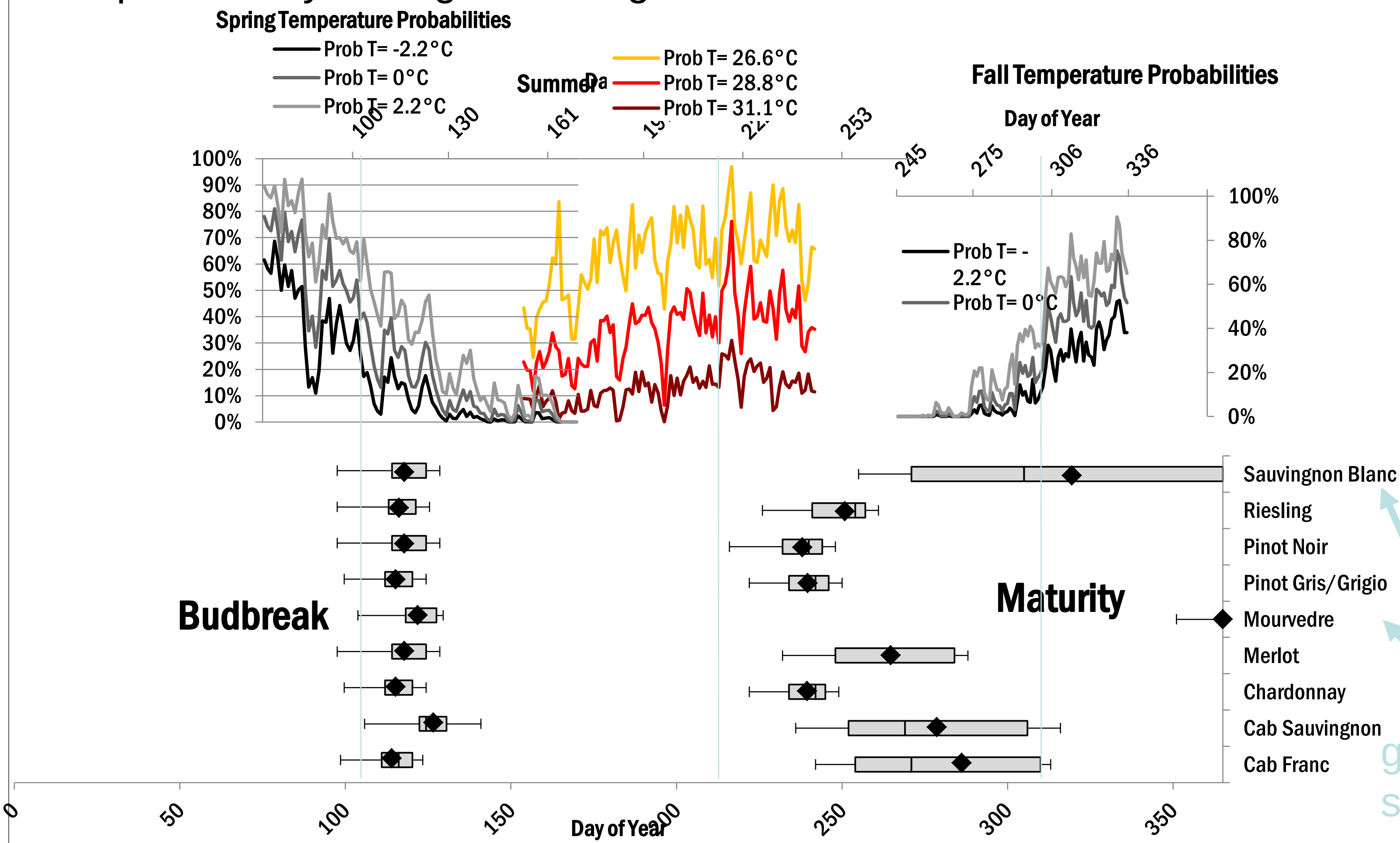








Concept for analysis of growth stage x weather interaction



growing season is too short for these varieties at this site

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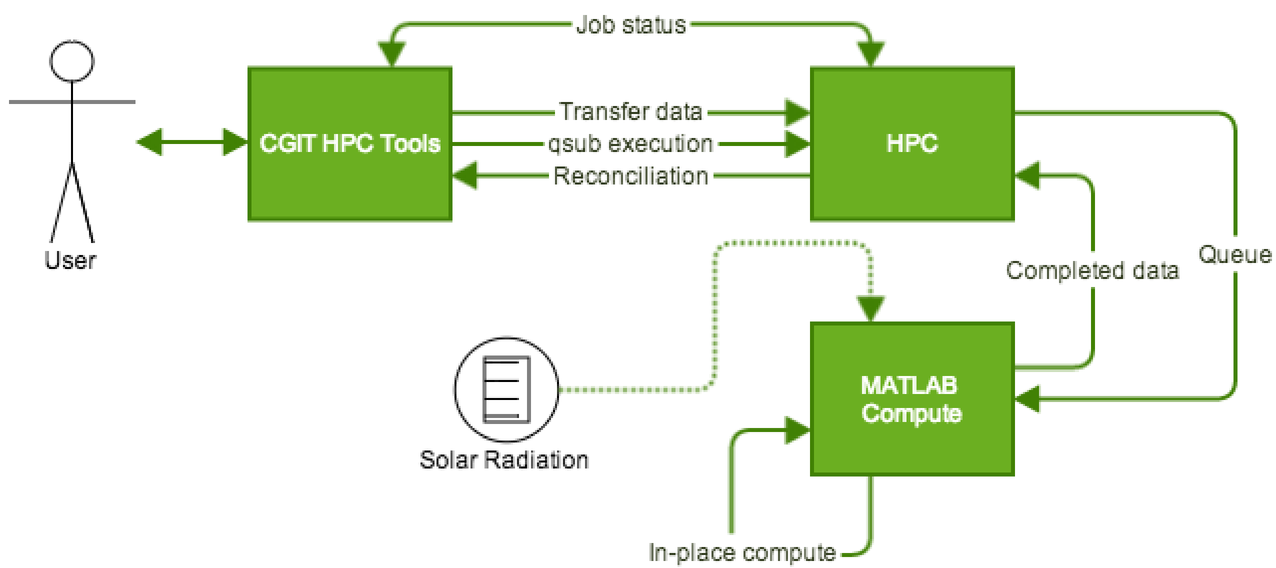
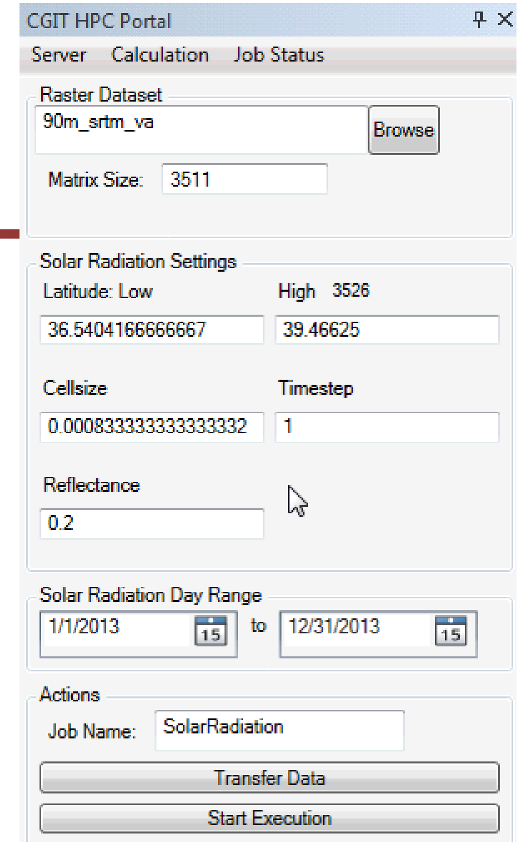
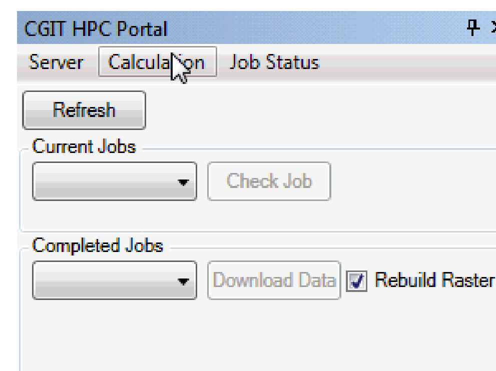
Implementation Overview

- Read and extract raster metadata
- Split raster grid-wise and convert to ASCII GRID
- Transfer data to ARC staging
- Execute qsub job to queue MATLAB computation
- Retrieve job ID and status
- Reconcile and regenerate complete raster







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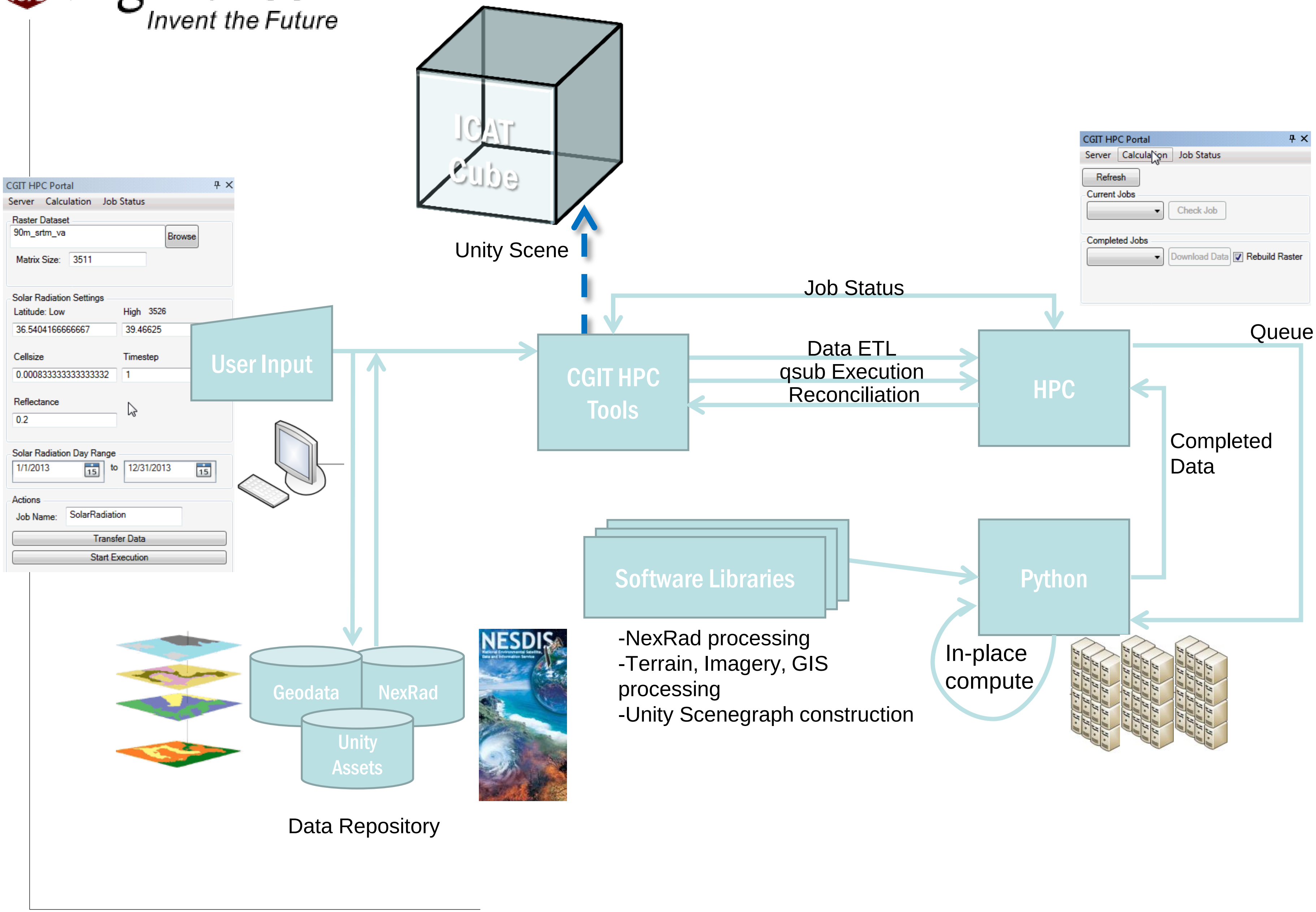
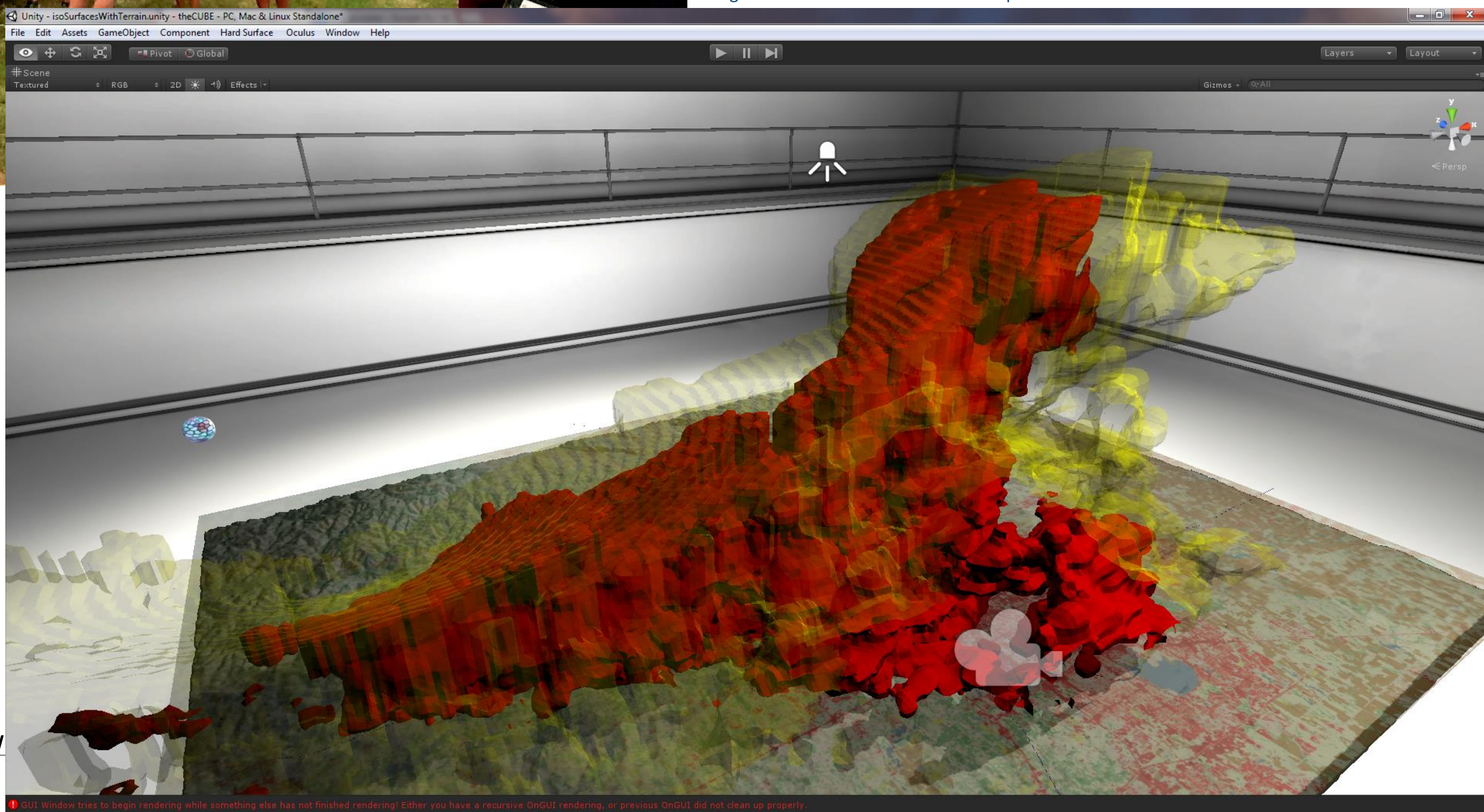


Virginia Tech ICAT Scientific Visualization Moore, OK Tornado

a. Dave Carroll – Instructor of Meteorology
b. Bill Carstensen – Professor of GIS
c. Drew Ellis – Professor of Meteorology
d. Kenyon Gladu – undergraduate student in Meteorology
e. Peter Sforza – Director of the Center for Geospatial Information Technology
f. Trevor White – Graduate student in Business Information Technology (but presently transferring to Geography)
g. Run Yu – PhD. student in Computer Science



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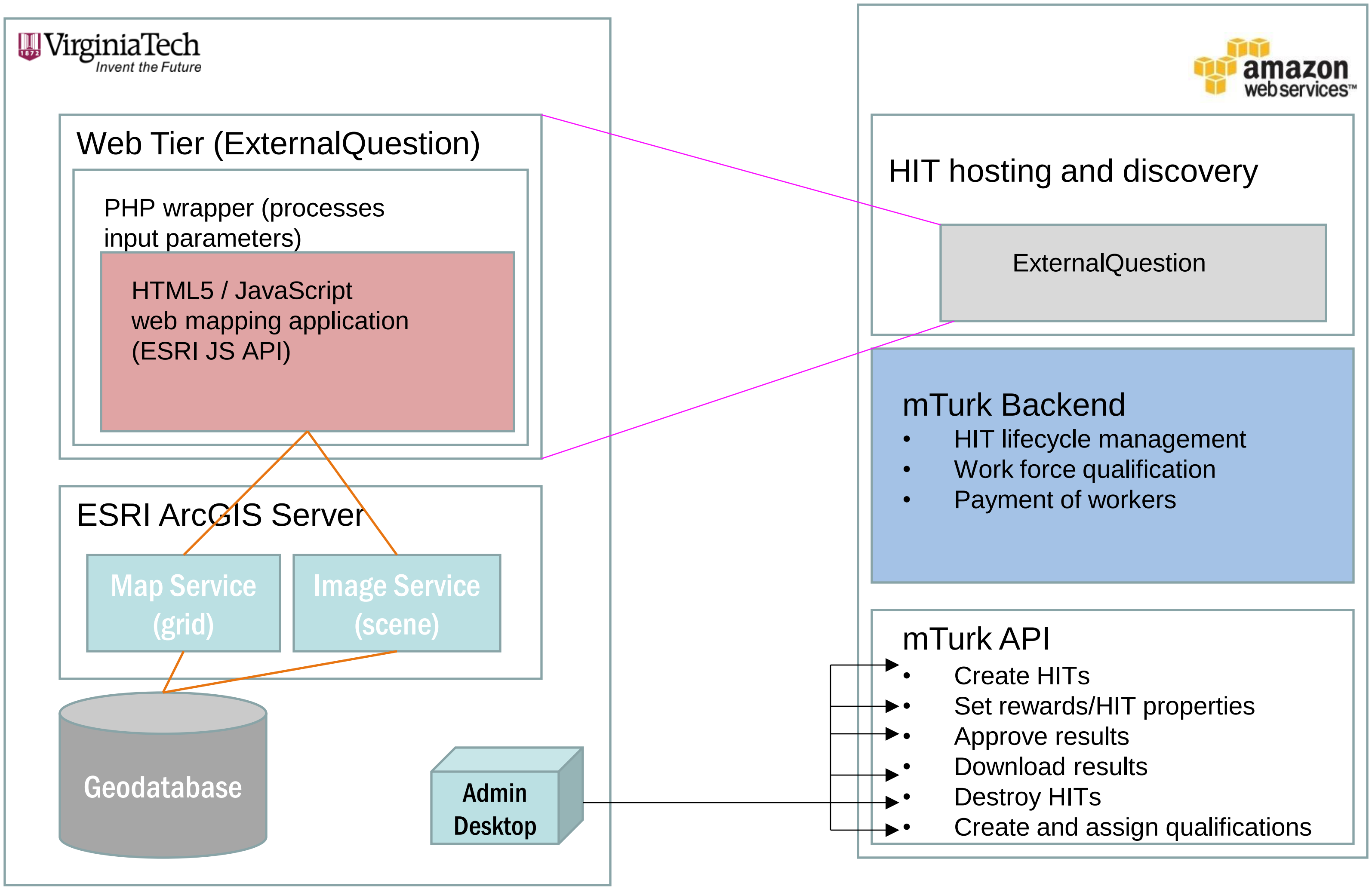
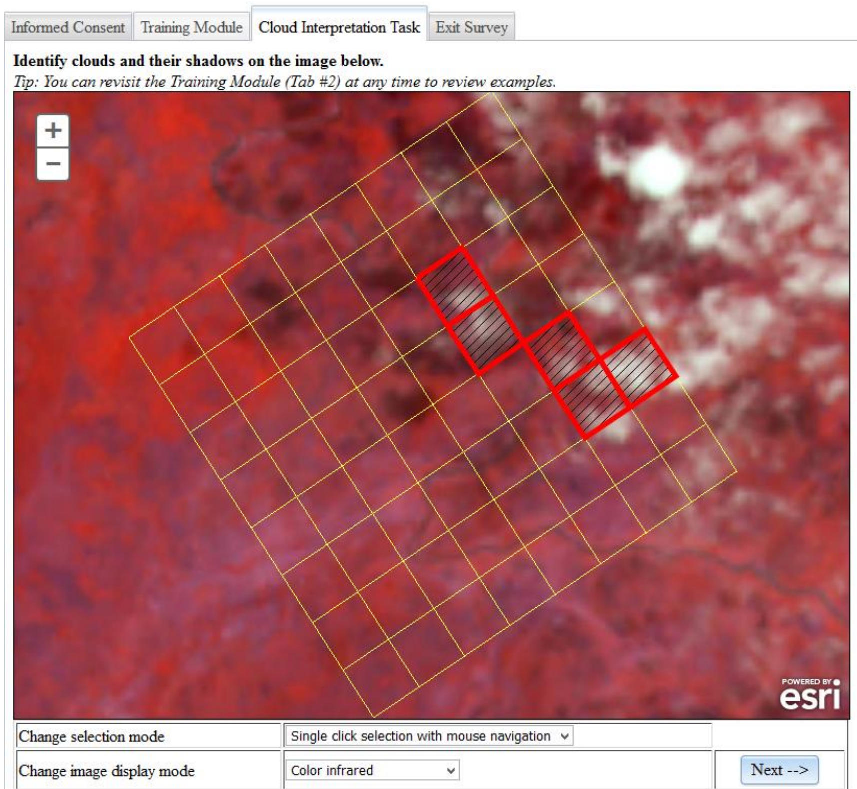
Integrating ESRI ArcGIS Server and Amazon Mechanical Turk to facilitate human image interpretation

Seth Peery, Sr. GIS Architect
Virginia Tech Information Technology

System Design



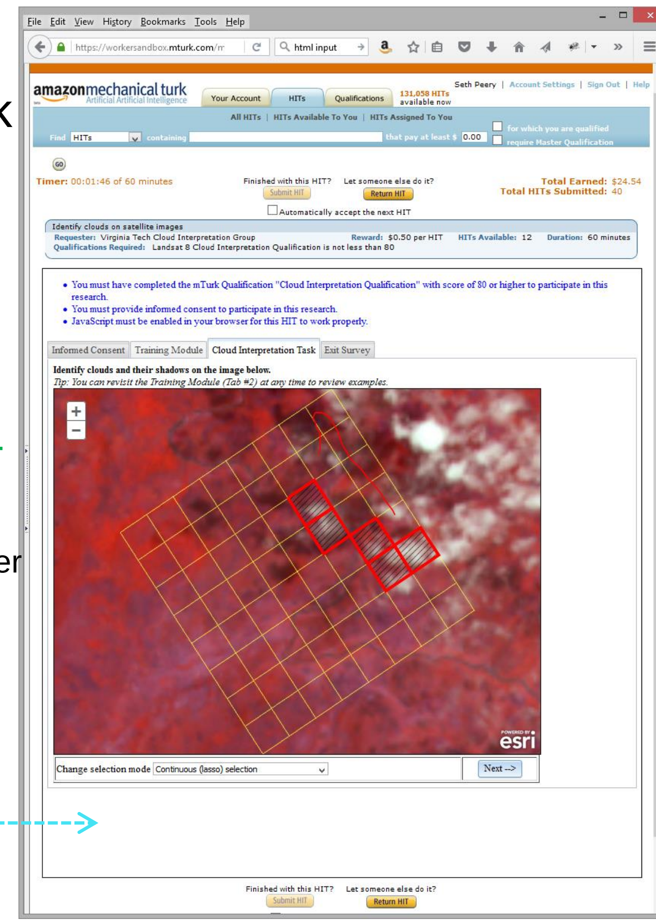
The Human Intelligence Task (HIT)



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}

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Research to date

- Collaboration with applied economists
- Objectives
  - Find optimal wage for this type of work
  - Determine practical work units (human attention span)
  - Evaluate accuracy of human interpreters
  - Comparison to automated methods

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Article

Cloud-Sourcing: Using an Online Labor Force to Detect Clouds and Cloud Shadows in Landsat Images

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Academic Editors: Chandra Giri and Prasad S. Thenkabail

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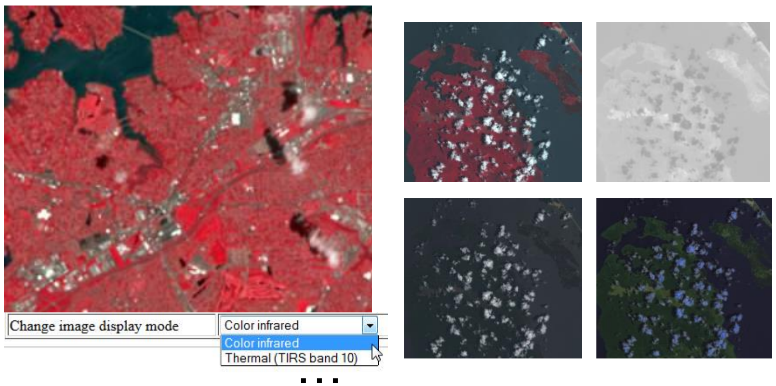
Abstract: We recruit an online labor force through Amazon.com's Mechanical Turk platform to identify clouds and cloud shadows in Landsat satellite images. We find that a large group of workers can be mobilized quickly and relatively inexpensively. Our results indicate that workers' accuracy is insensitive to wage, but deteriorates with the complexity of images and with time-on-task. In most instances, human interpretation of cloud impacted area using a majority rule was more accurate than an automated algorithm (Fmask) commonly used to identify clouds and cloud shadows. However, cirrus-impacted pixels were better identified by Fmask than by human interpreters. Crowd-sourced interpretation of cloud impacted pixels appears to be a promising means by which to augment or potentially validate fully automated algorithms.

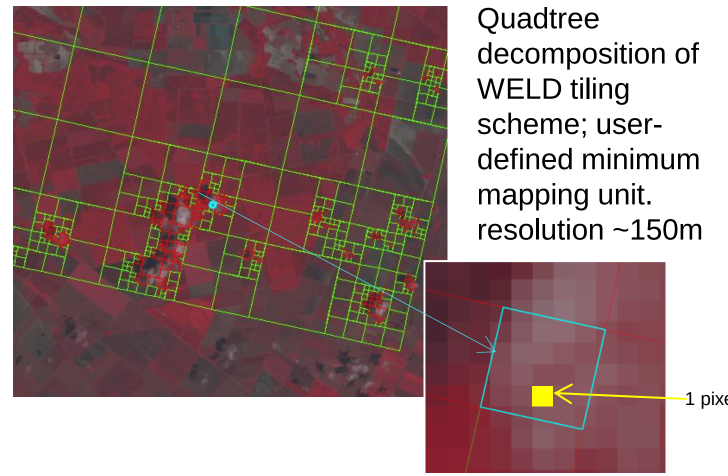
Keywords: cloud interpretation; satellite images; Mechanical Turk; economic experiment

Methodological Considerations

1) Band combinations

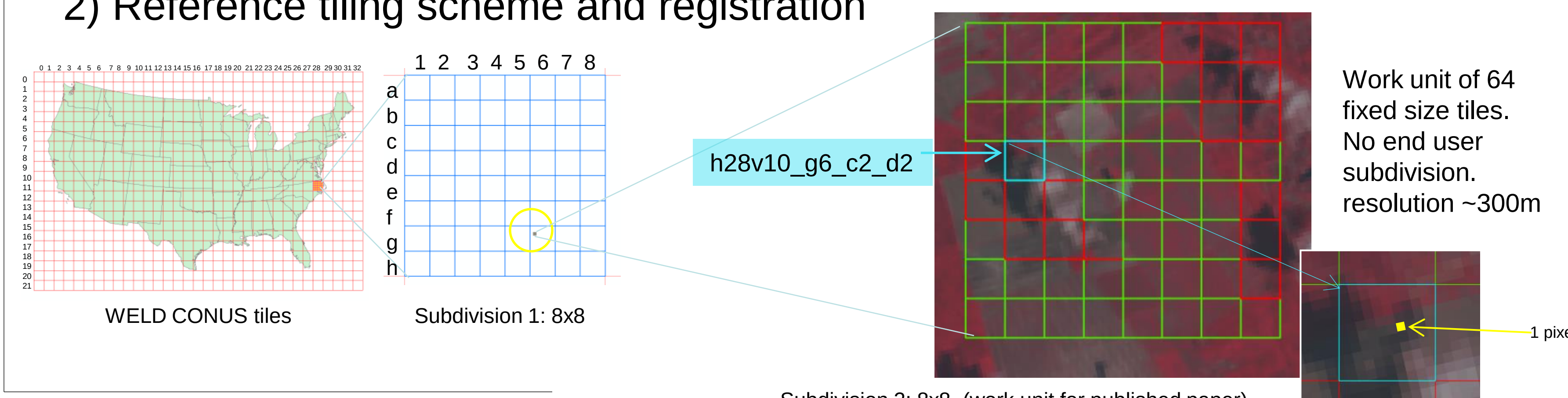


3) Minimum mapping unit



Quadtree decomposition of WELD tiling scheme; user-defined minimum mapping unit. resolution ~150m

2) Reference tiling scheme and registration



Work unit of 64 fixed size tiles. No end user subdivision. resolution ~300m

Subdivision 2: 8x8 (work unit for published paper)

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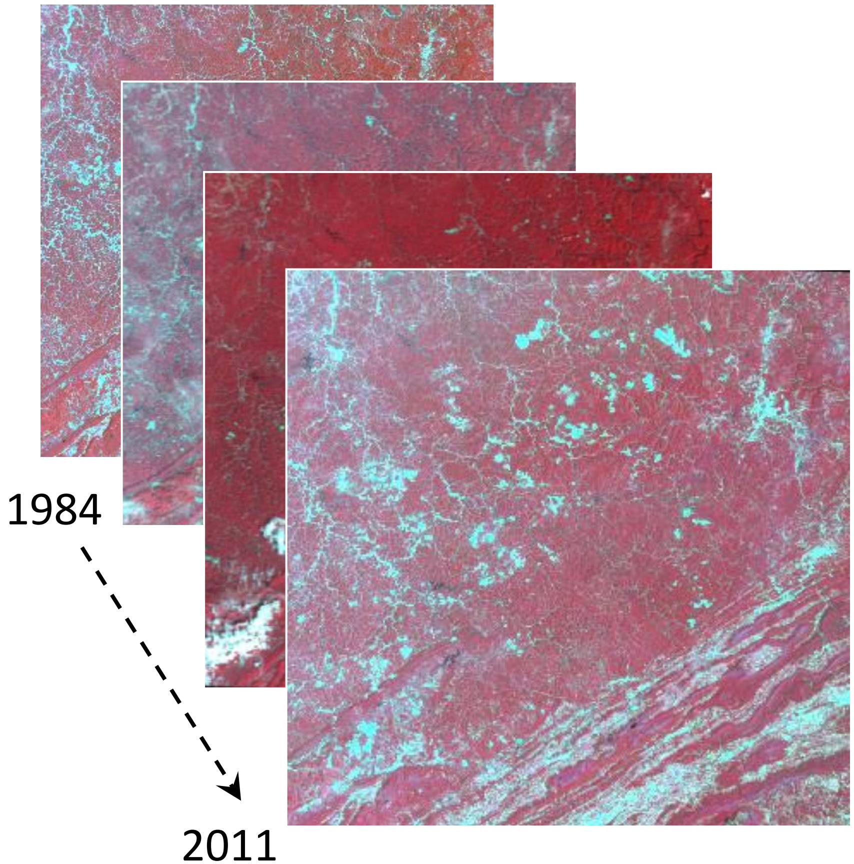
Delineation of Surface Coal Mining History in Appalachia Using Landsat Imagery



Presenter:
C.E. Zipper[‡]

and J. Li,[†] P.F. Donovan [‡], R.H. Wynne[§], A.J. Oliphant[§]

[†] China University of Mining and Technology;
[‡] Crop and Soil Environmental Sciences, Virginia Tech
[§] Forest Resources and Environmental Conservation, Virginia Tech

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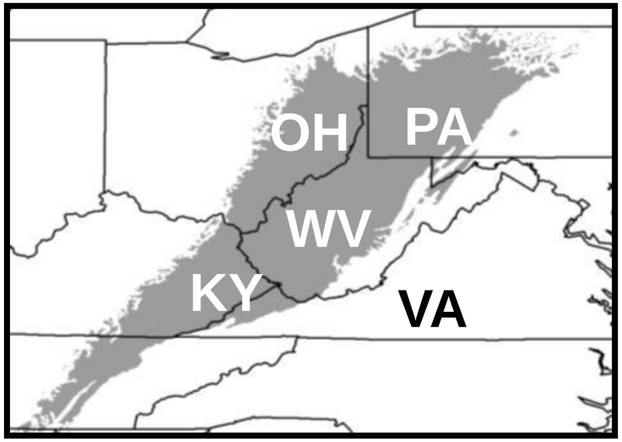
Problem: Significant land base in eastern USA mined and reclaimed under SMCRA. Where is it? What are its properties? What are cumulative effects of Appalachian mining?



Appalachian coalfield

Coal surface mining disturbance

Mined land reclaimed

Research Goals

Prepare inventory of land mined under SMCRA in southwestern Virginia’s Appalachian coalfield by mining date, so as to characterize the progressive nature of landscape change over the period of study.

Develop method that can be applied in other areas.

Apply data product to improve understanding of environmental impacts and recovery processes.

Research Methods

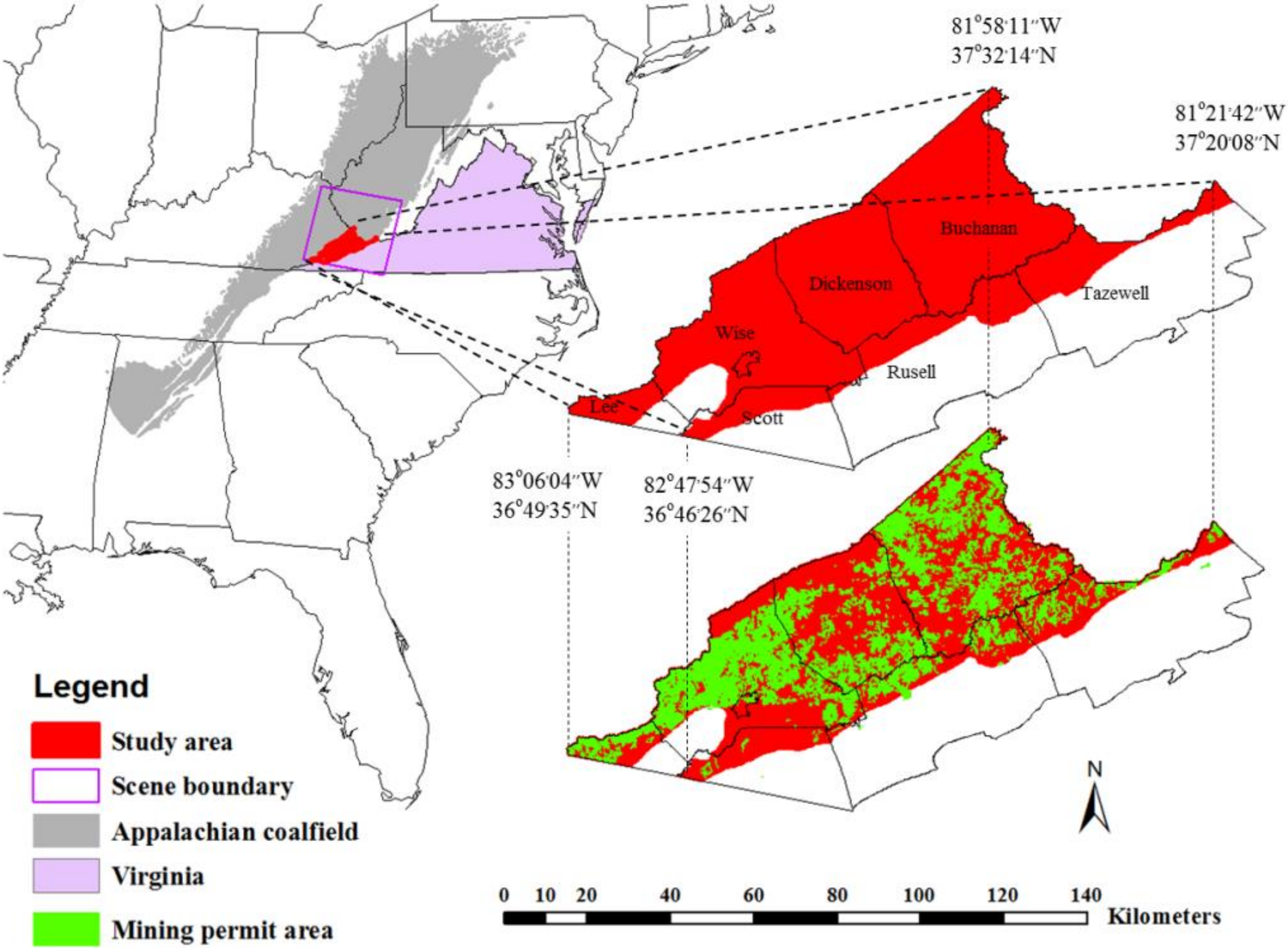
1. Acquire leaf-on Landsat TM/ETM+ images (Path 18, Row 34): 1 per year, 1984-2011. Process†, georectify, and "stack."

2. Obtain ancillary data to assist classification:

- ✓ Virginia DMME mine permit database,
- ✓ High-resolution aerial imagery (NAIP)
- ✓ National Land Cover Database (NLCD).

3. Produce and classify Training & Validation data:

✓**PV:** Persisting vegetation, vegetated for each image
✓**EM:** "Ever mined", mined within the image sequence
✓**OD:** Other disturbances, with subclasses



81°58′11″W
37°32′14″N
81°21′42″W
37°20′08″N
Buchanan
Dickenson
Tazewell
Wise
Rusell
Lee
Scott
83°06′04″W
36°49′35″N
82°47′54″W
36°46′26″N
Legend
Study area
Scene boundary
Appalachian coalfield
Virginia
Mining permit area
N
0 10 20 40 60 80 100 120 140
Kilometers

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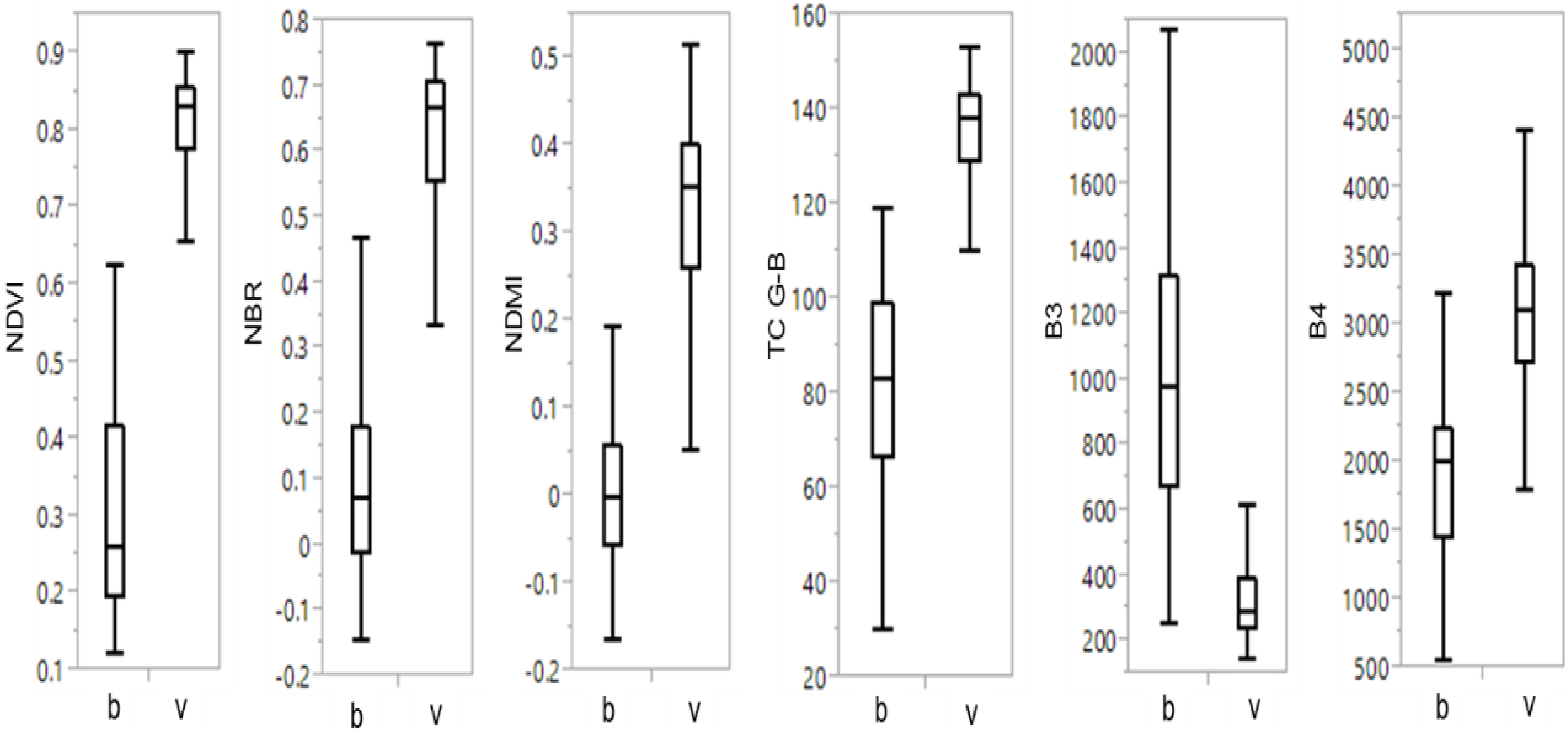
4. Using training data and 2008 image: Select vegetation index for use (b= bare, v = vegetated); define bare-ground threshold.



NDVI works best!

Normal-ized burn ratio

Normalized difference moisture index

Tassled cap greeness-brightness difference

Landsat Band 3

Landsat Band 4

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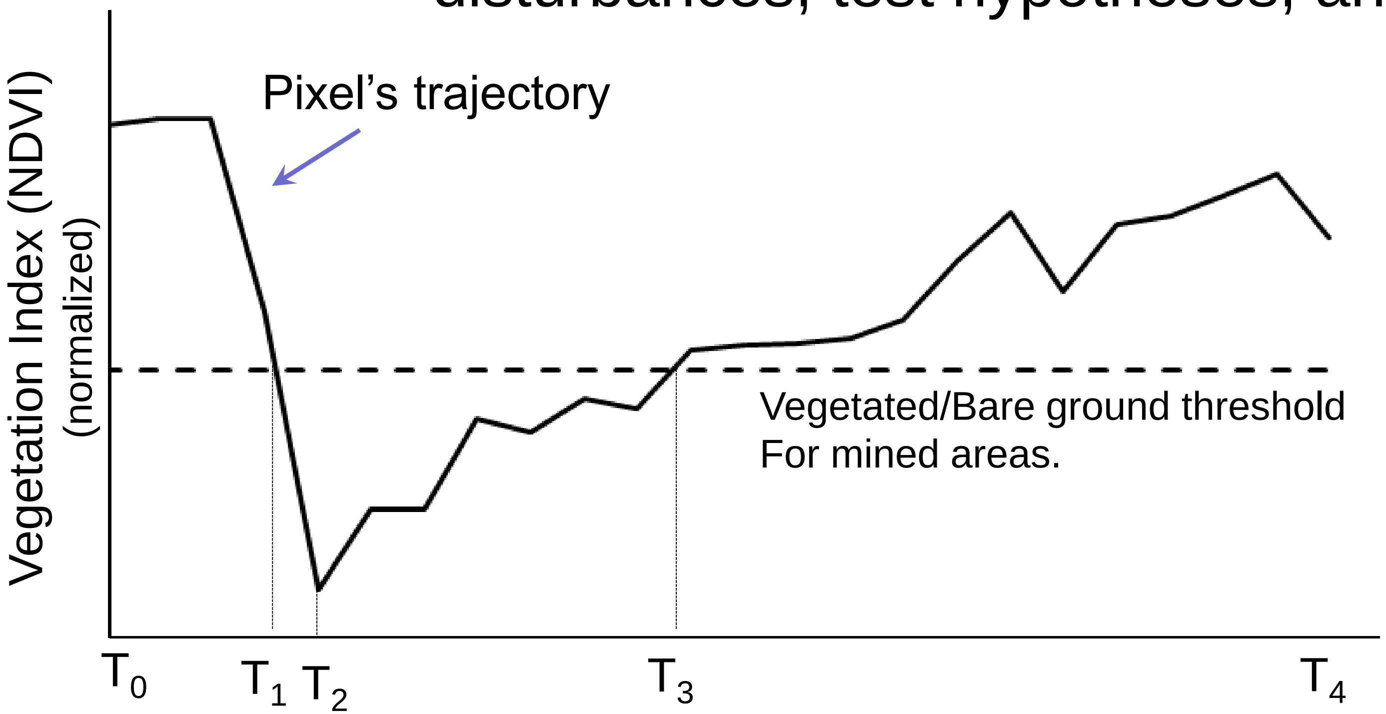
5. Analyze "spectral trajectory" to identify disturbances, test hypotheses, and classify.



Classes:

PV: persisting vegetation

EM: Ever mined

OD: Other disturbances

: Hypotheses are:

i. Minimum *NDVI* for mined lands (EM) will generally be lower than the minimum *NDVI* for non-mining disturbances);

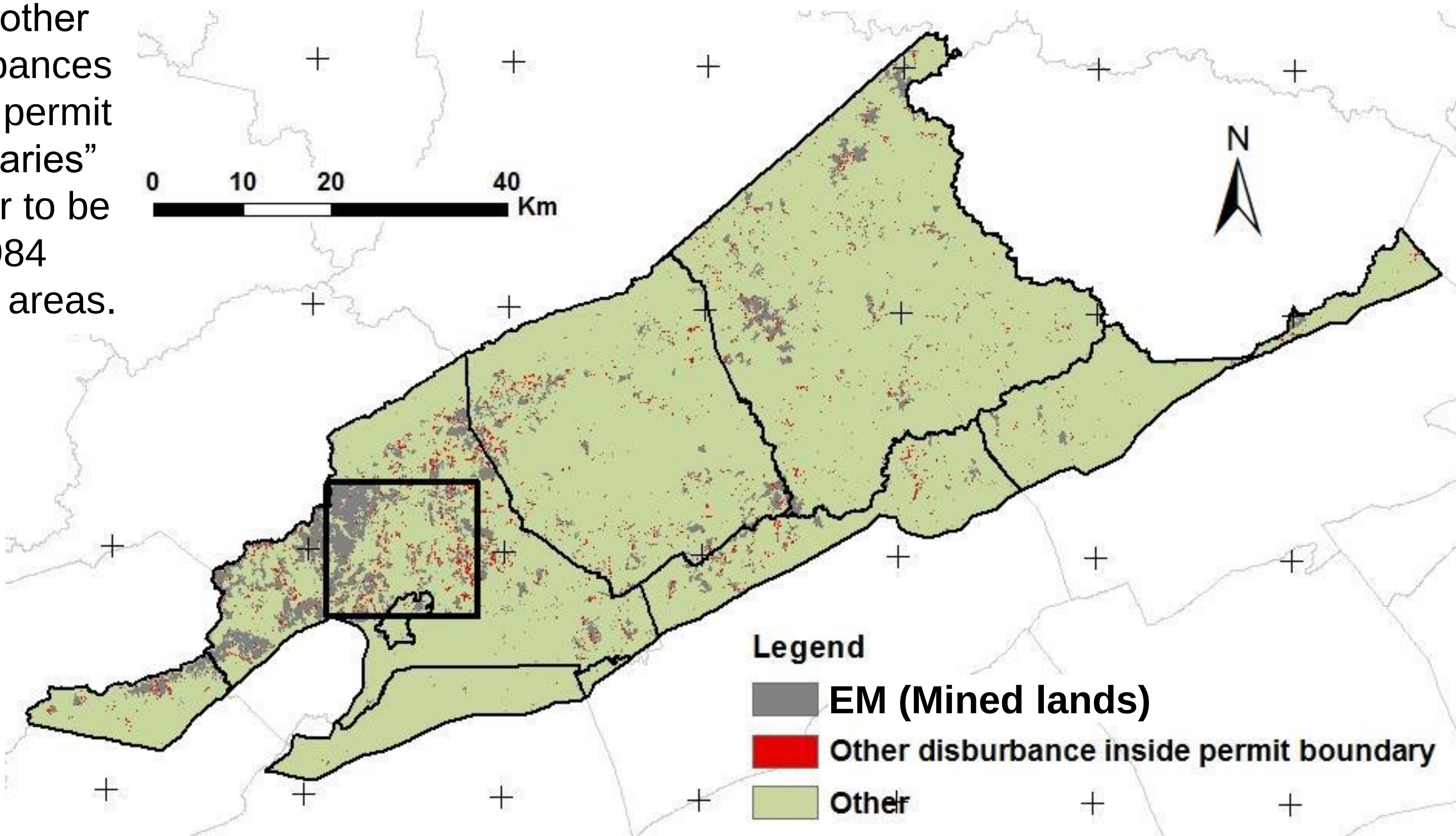
ii. Standard deviation of *NDVI* after disturbance will be greater for mined lands than non-mining disturbances.

Results

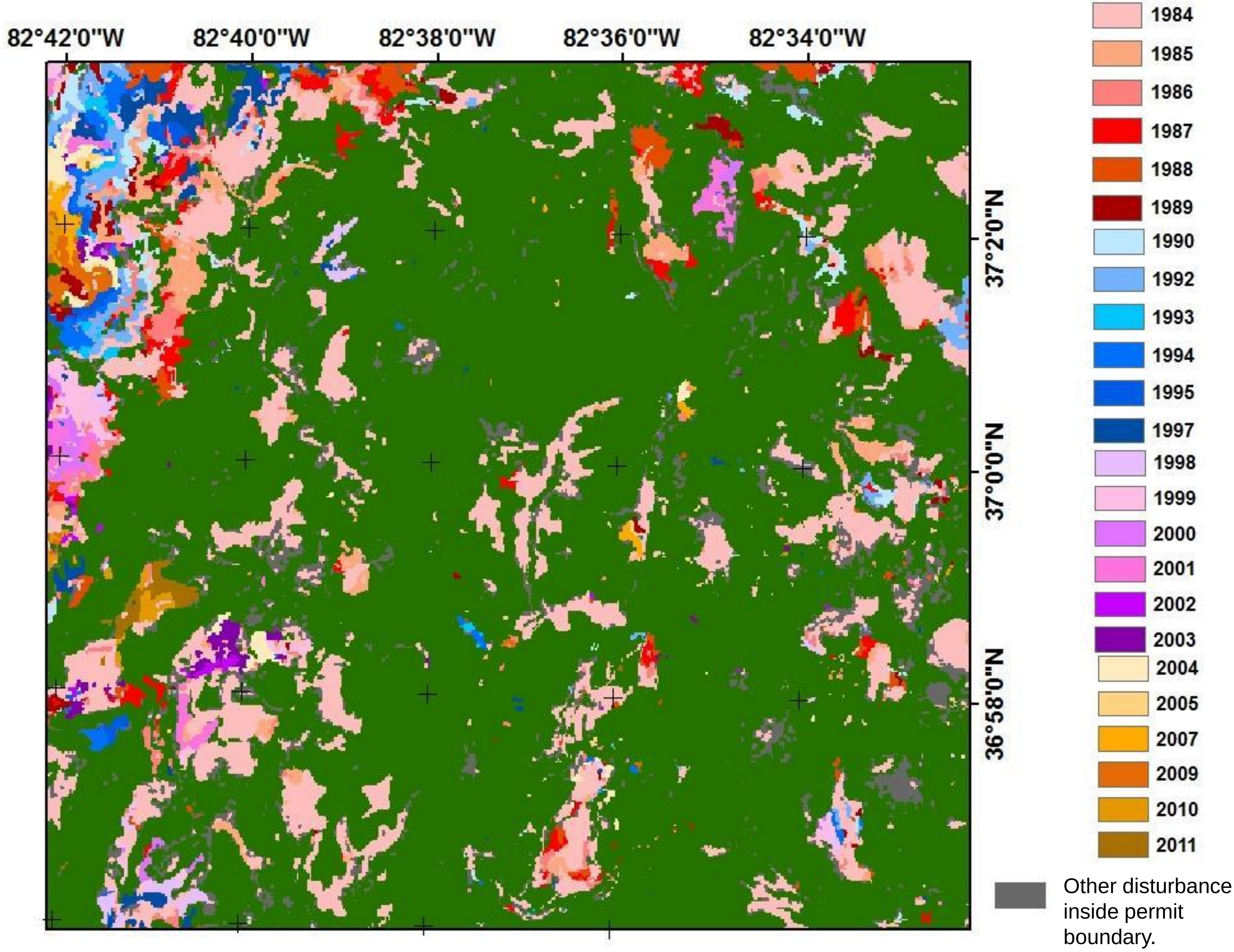
Accuracy assessment: 95% overall

(Users Accuracy = 95.4%; Producers accuracy: 93.3%)

Most "other disturbances inside permit boundaries" appear to be pre-1984 mined areas.



Primary errors: Polygon edges; narrow, linear mining features; where cloud contamination increased time intervals.


82°42'0"W
82°40'0"W
82°38'0"W
82°36'0"W
82°34'0"W
37°2'0"N
37°0'0"N
36°58'0"N
1984
1985
1986
1987
1988
1989
1990
1992
1993
1994
1995
1997
1998
1999
2000
2001
2002
2003
2004
2005
2007
2009
2010
2011
Other disturbance inside permit boundary.

Applications

- Terrestrial
- Aquatic

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Terrestrial Application

A.J Oliphant: "Mapping *Elaeagnus umbellata* on Coal Surface Mines using Multitemporal Landsat Imagery" M.S. Thesis

Method: Classify AO cover on mined land by "age" using 8 Landsat images, 7 bands & 7 indices per image.

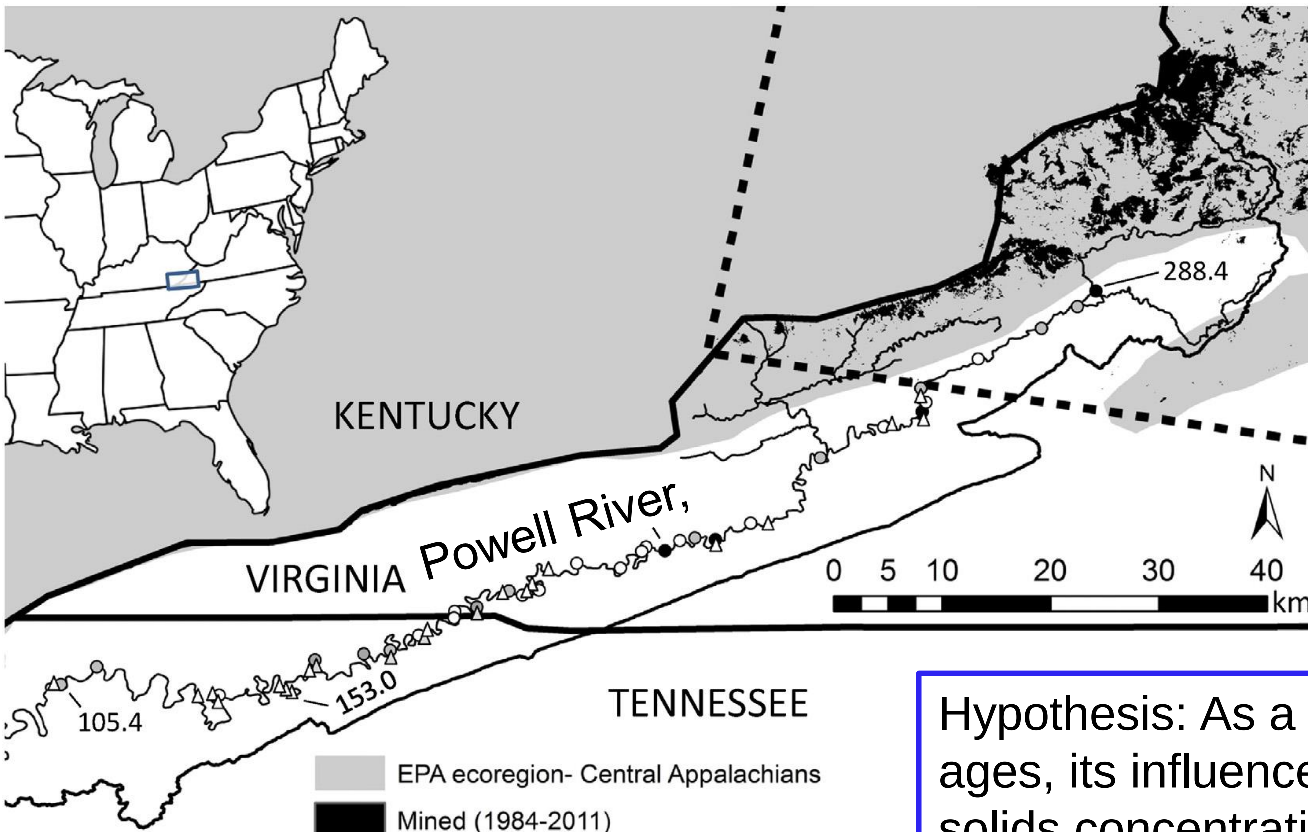
Results:
AO is a major component of vegetative cover on ~15% of lands mined 2001 and earlier.

Lands mined 2002 - 2011:
Fraction of lands classified AO increases with the amount of time that has past since mining.

Non-Native Invasive – Autumn Olive (AO)

Aquatic Application

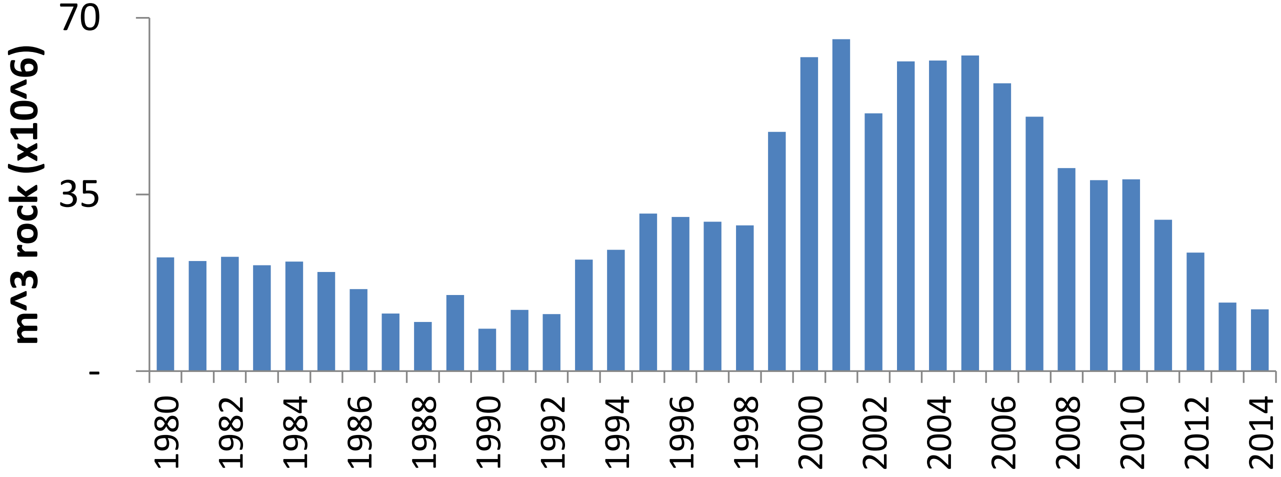
“ Spatial and temporal relationships among watershed mining, water quality, and freshwater mussel status in an eastern USA river” CEZ et al. Sci. Tot. Environ. 2016

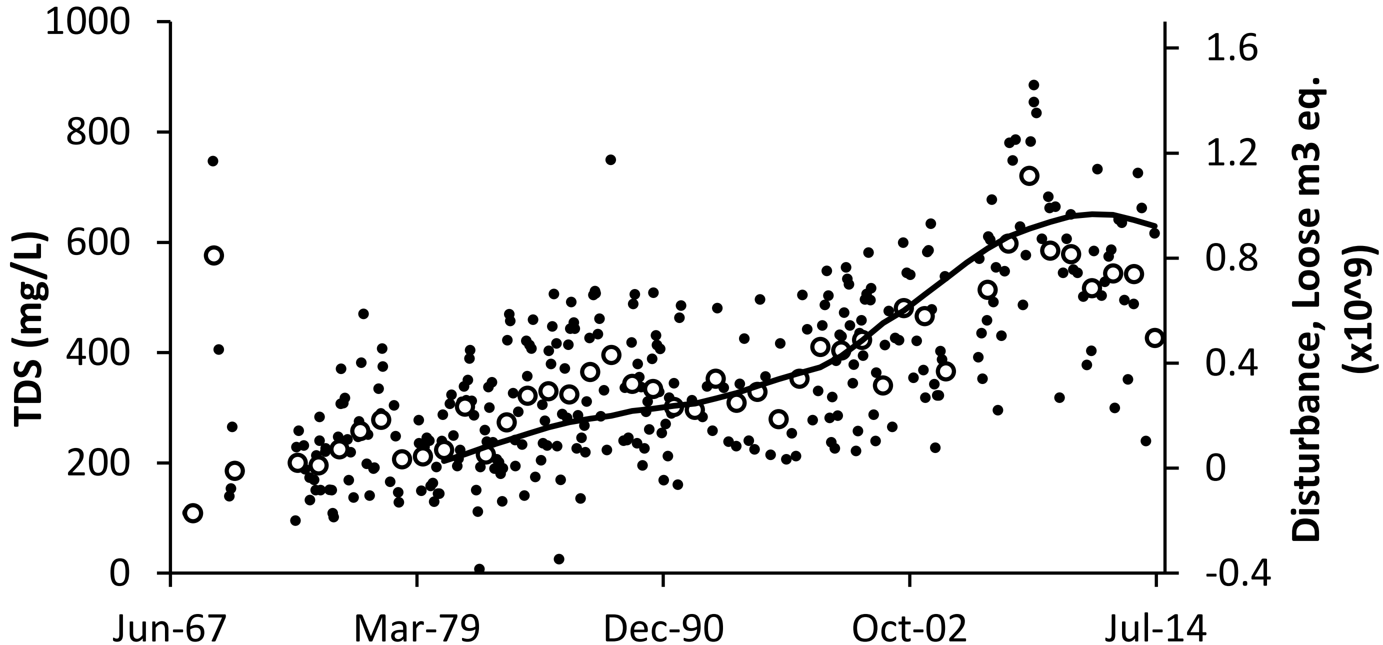


Hypothesis: As mining disturbance expands continues through time, total dissolved solids (TDS) concentrations in draining stream water increase.

Hypothesis: As a mining disturbance ages, its influence on total dissolved solids concentrations of the river or stream draining the watershed will decline

Estimated annual geologic disturbance in watershed (assuming even proportions to annual land disturbance & coal production)





TDS at Big Stone Gap, Virginia DEQ monitoring data, 1967 – 2014, and cumulative decay-weighted geologic disturbance (black line).

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Conclusions

Time-series analysis of Landsat TM/ETM+ imagery was well suited for the task of identifying surface coal mining locations, and quantifying mining disturbances over a broad area by approximate date of initial disturbance.

The resulting data can be applied to aid understanding of (i) environmental impacts due to mining disturbance, and (ii) recovery processes as they occur over extended time periods

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North Carolina State University · Virginia Polytechnic Institute and State University · Universidad de Concepción

Use of LAI Derived from Landsat for Silvicultural Decision in Southern Pine Plantations

Thomas Fox
The Honorable Garland Gray Professor of Forestry
Director, Forest Productivity Coop

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Forest Productivity Cooperative

- A partnership among, Virginia Polytechnic Institute and State University, North Carolina State University, and the Universidad de Concepción and forest industry and landowners
- 55 Industry Members that own > 30 million acres of pine and eucalyptus plantation in Southern US and Latin America

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NC STATE UNIVERSITY

Universidad de Concepción

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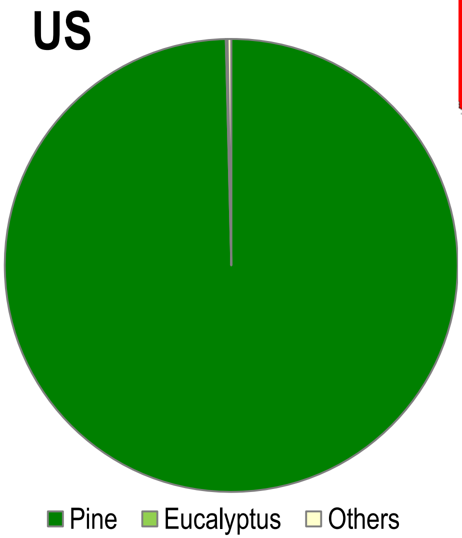
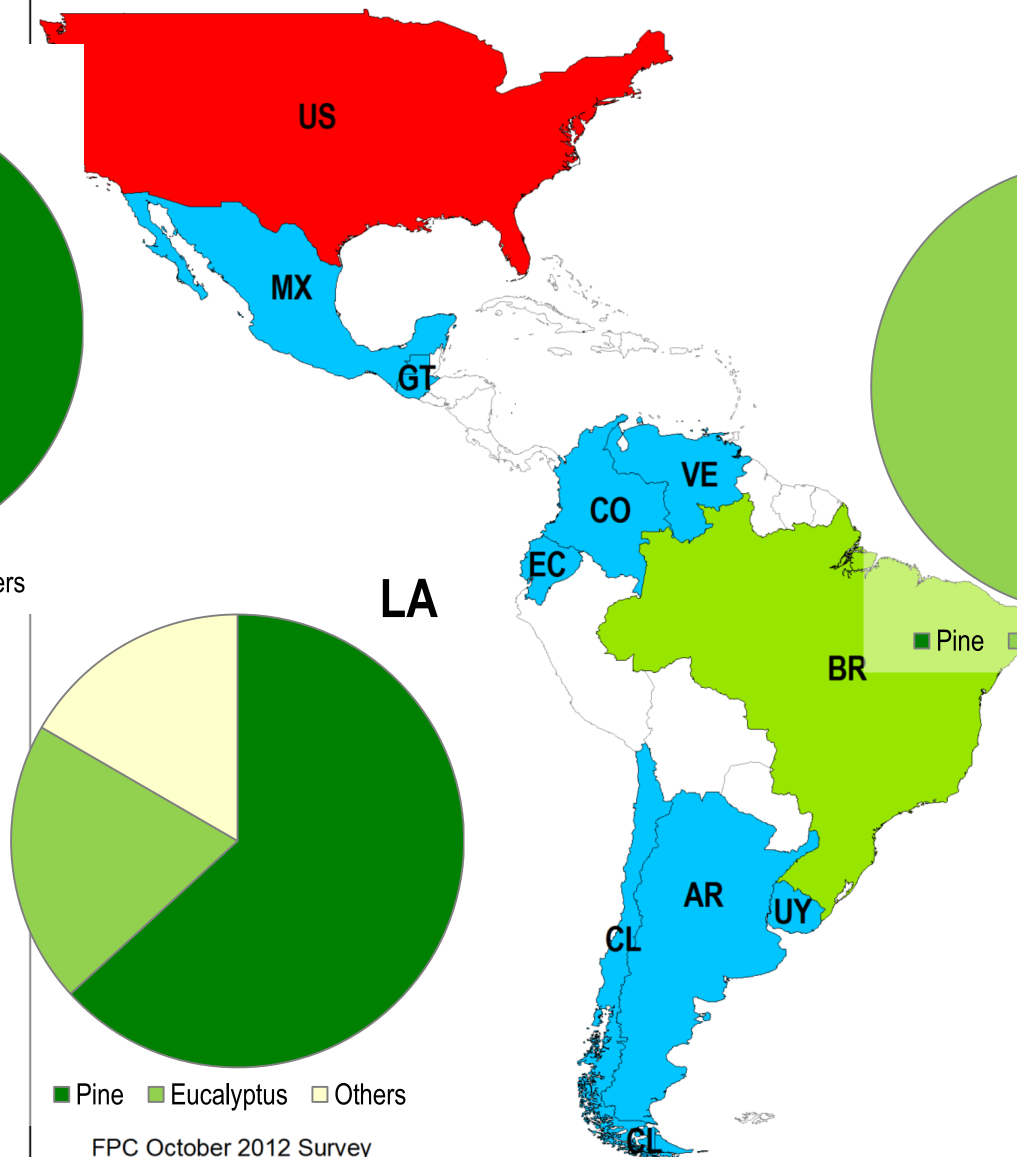
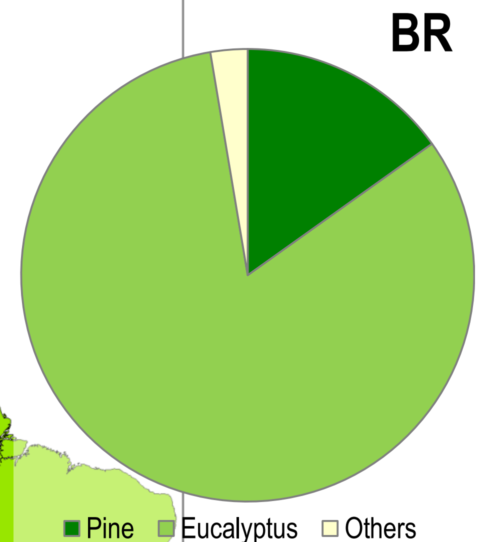
FOREST PRODUCTIVITY COOPERATIVE
North Carolina State University · Virginia Polytechnic Institute and State University · Universidad de Concepción







FPC October 2012 Survey

Percentage of Forest Type per Region

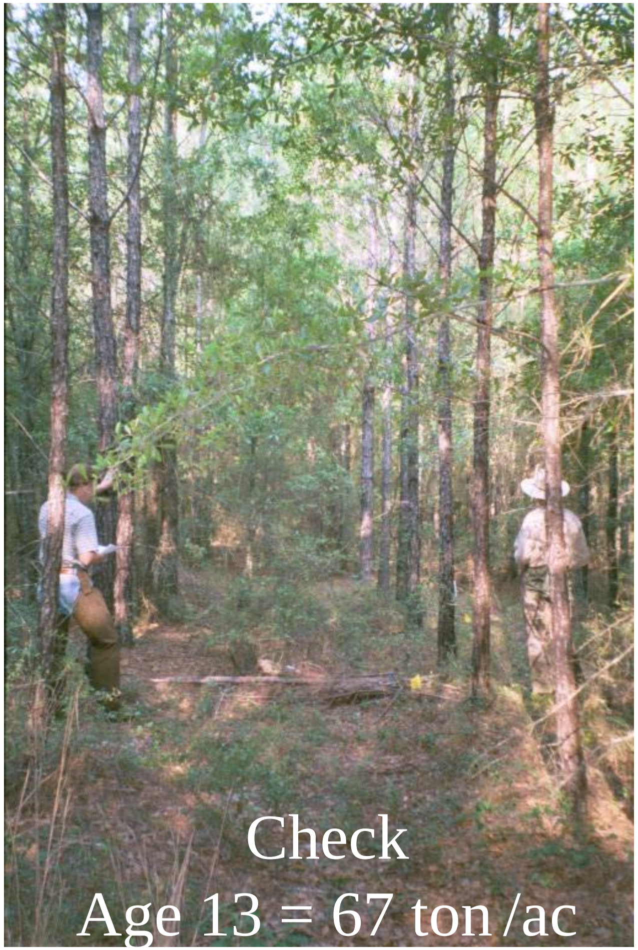
Goal is to Increase Productivity, Profitability, and Sustainability of Planted Forests Through Use of Site Specific Silvicultural Treatments

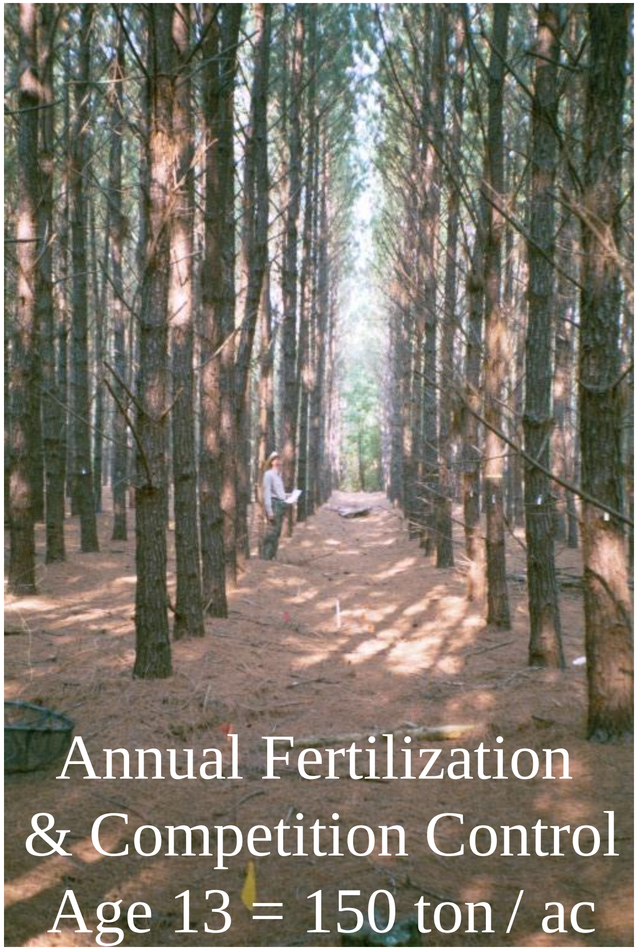
Fertilization

Weed Control

Elite Genotypes

Impacts of Intensive Management on Growth of Loblolly Pine in Southeast Georgia

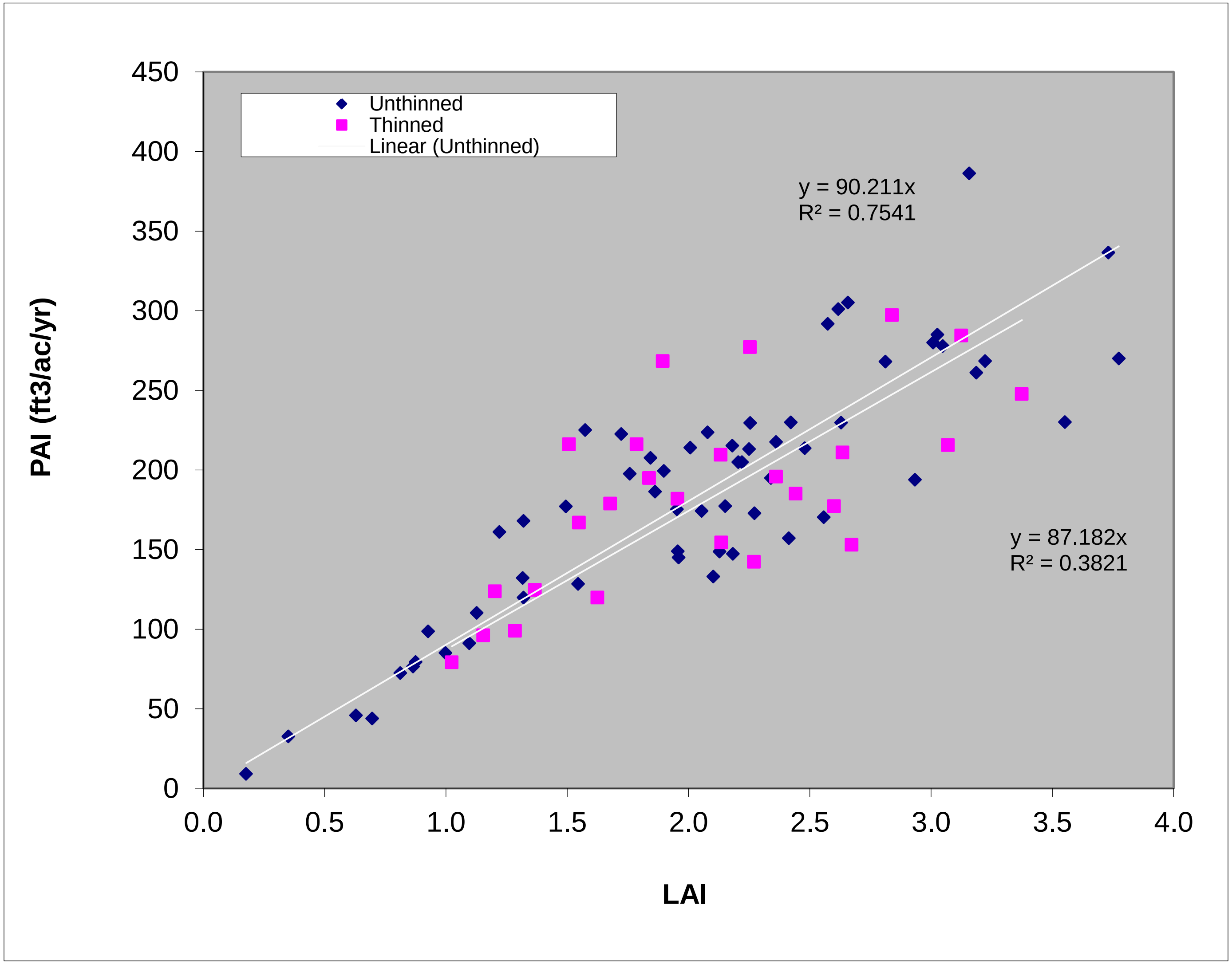




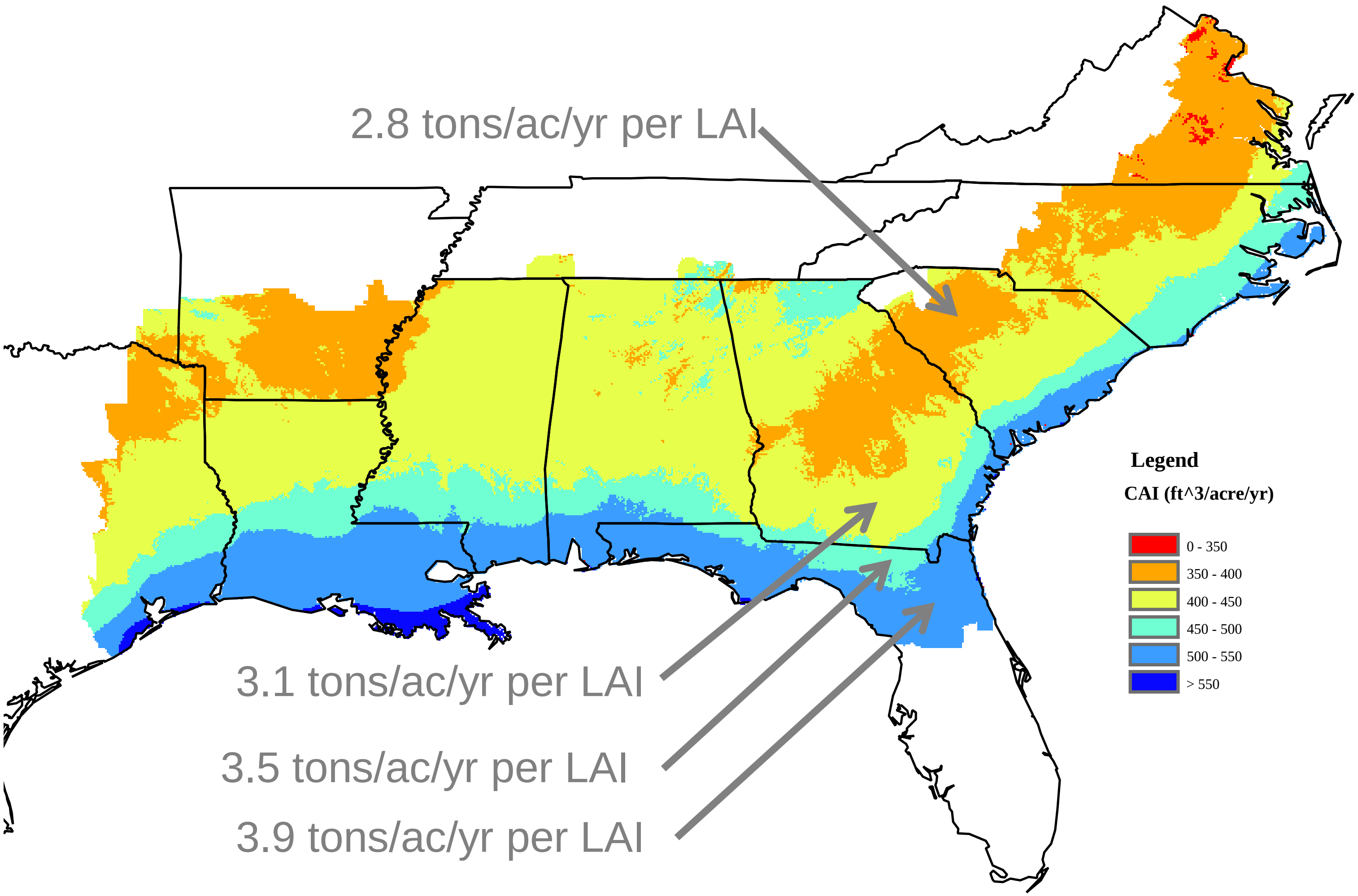
Poor Growth in Stands with Low LAI

Rapid Growth in Stands with High LAI

LEAF AREA VS PERIODIC ANNUAL INCREMENT IN LOBLOLLY PINE



Model Estimates of Growth Efficiency of Loblolly Pine



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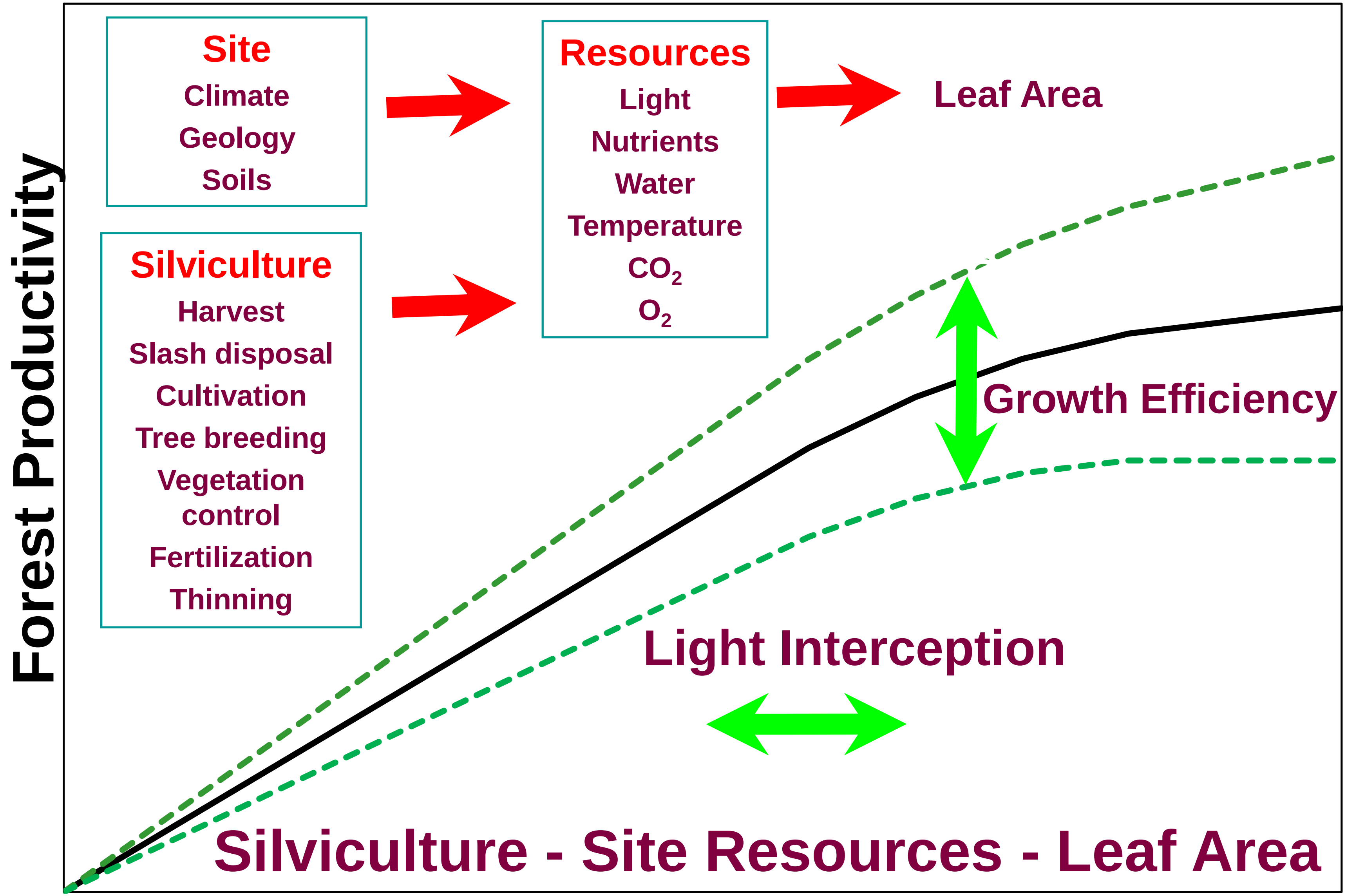
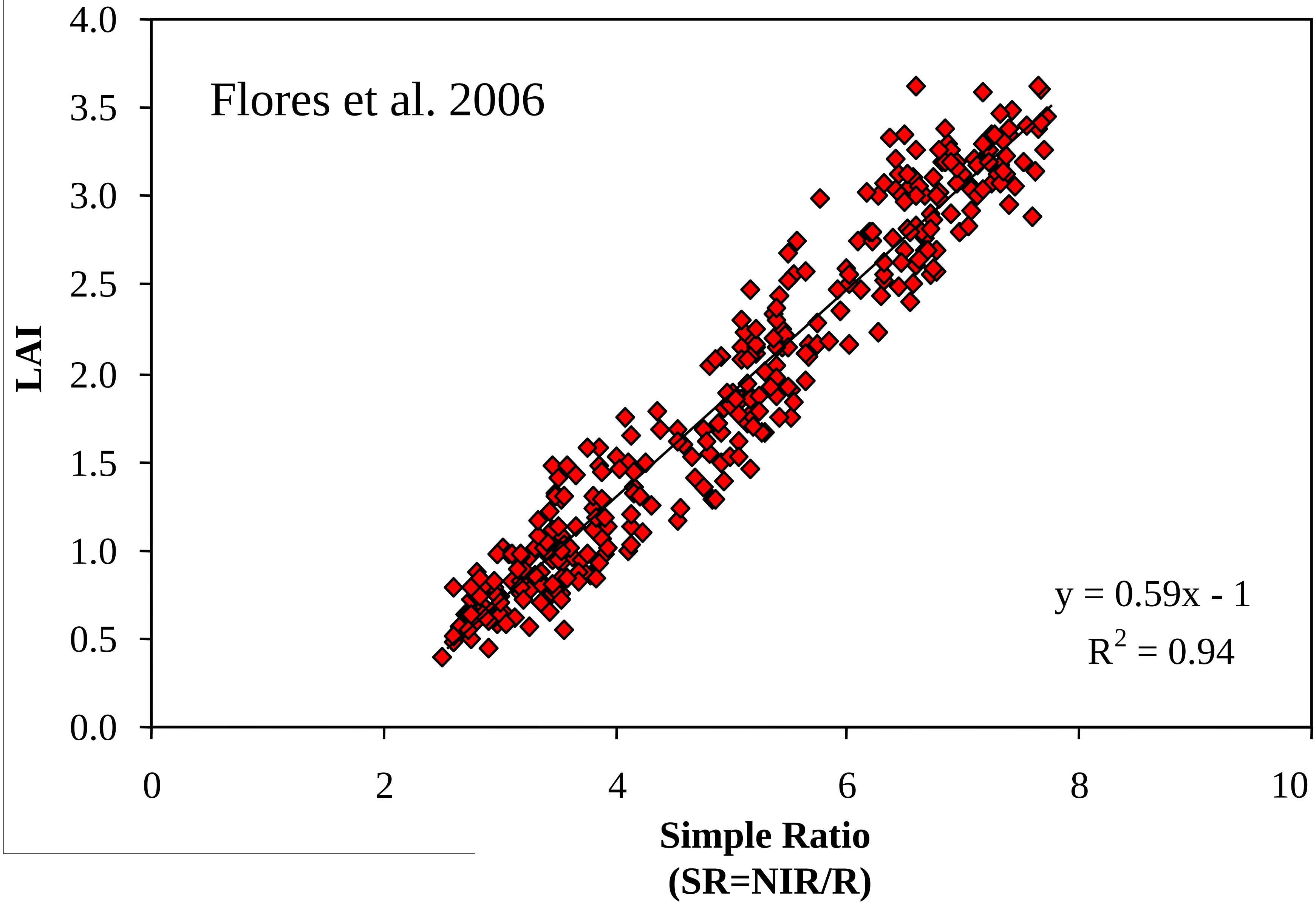


Landsat as a Tool to Determine Leaf Area

Remote Sensing Estimation of LAI Using Landsat Imagery



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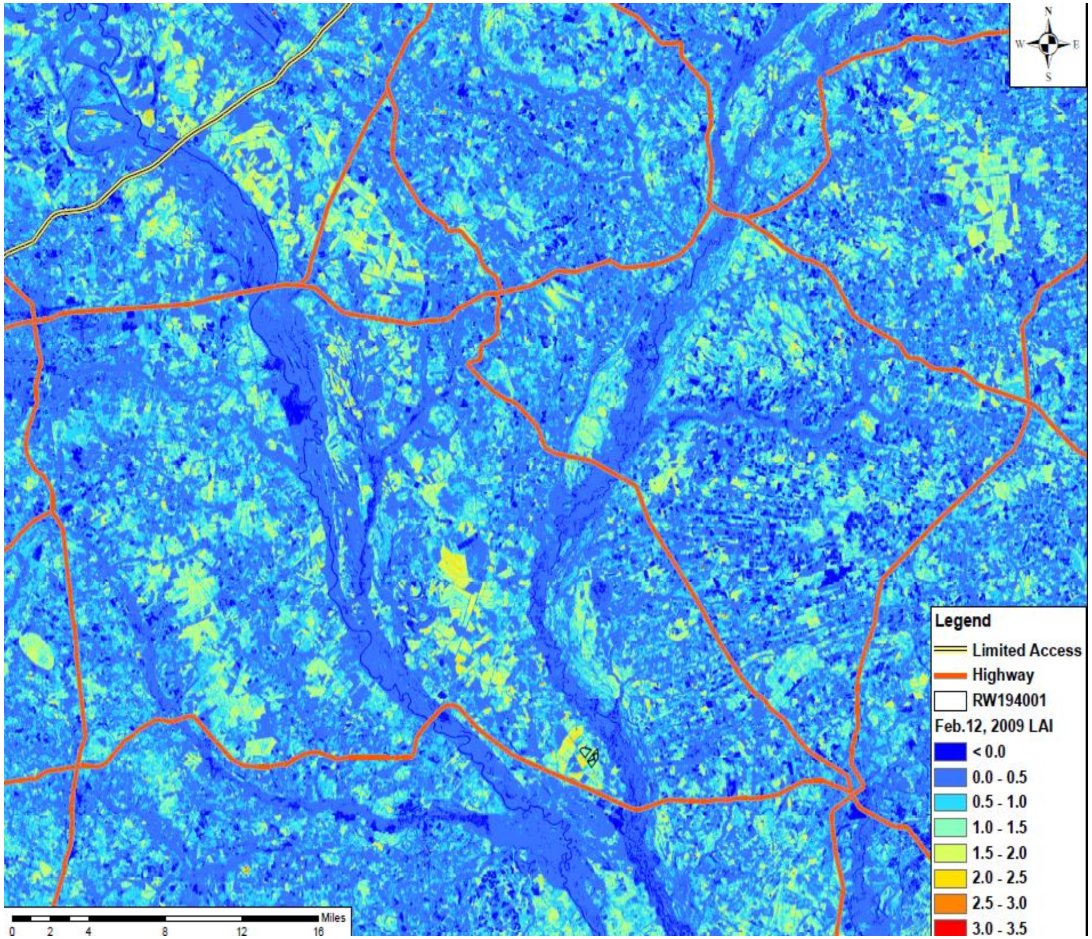
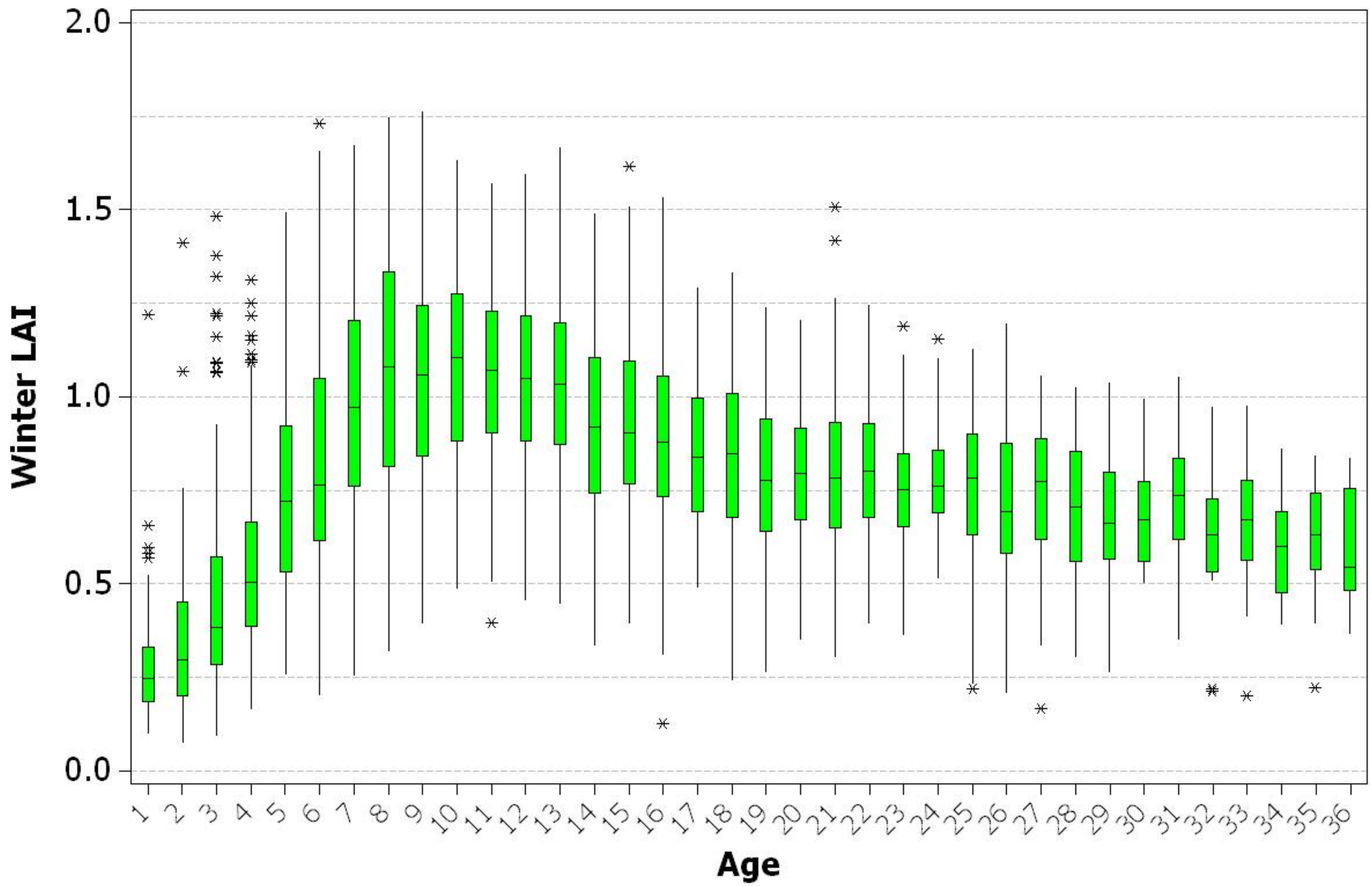
Winter Leaf Area in South Carolina



LAI versus Age of Loblolly Pine Plantations in Alabama



LAI is based on Flores et al. 2006 equation which uses TOA reflectance

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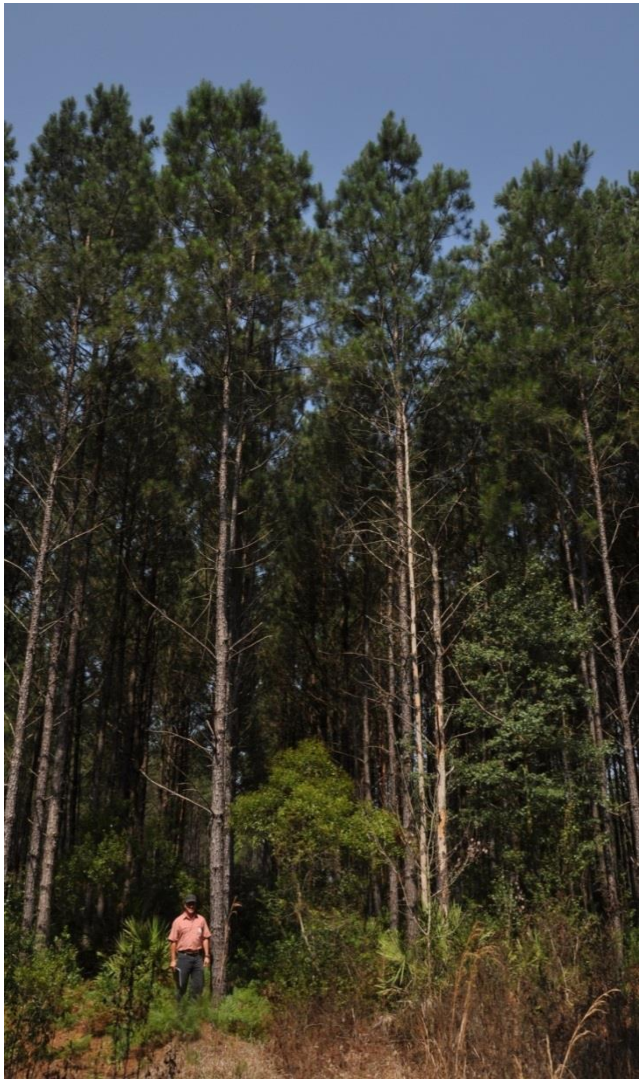
FERTILIZATION

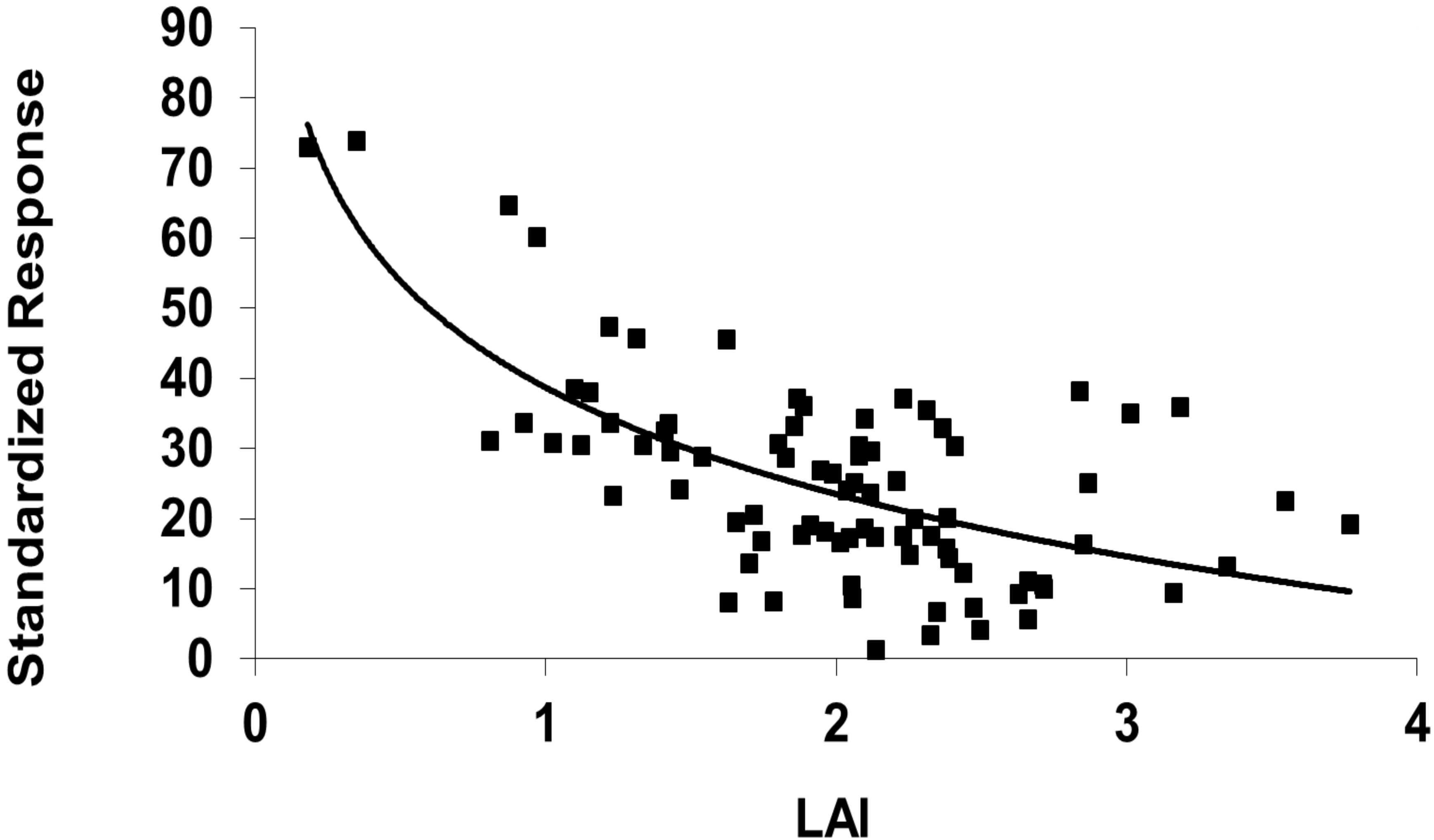
11 Year Fertilizer Response in Loblolly Pine in Southeast Georgia

Control



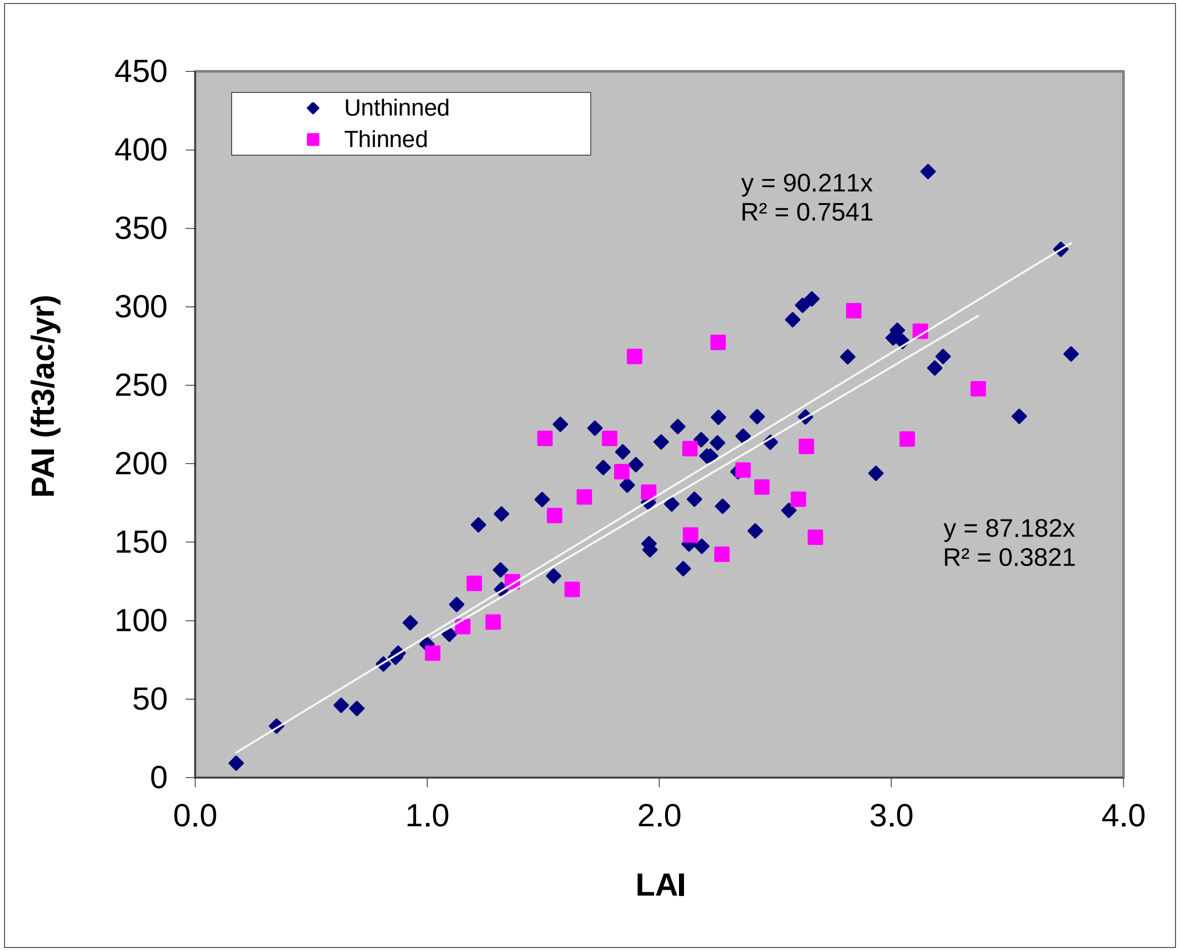
Fertilized

LAI Impact On Standardized Fertilizer Response



LEAF AREA VS PERIODIC ANNUAL INCREMENT IN LOBLOLLY PINE

Loblolly Pine
Growth Efficiency
3 tons/ac/yr per
Unit LAI



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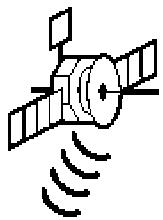
Technology for Precision Silviculture Prescriptions



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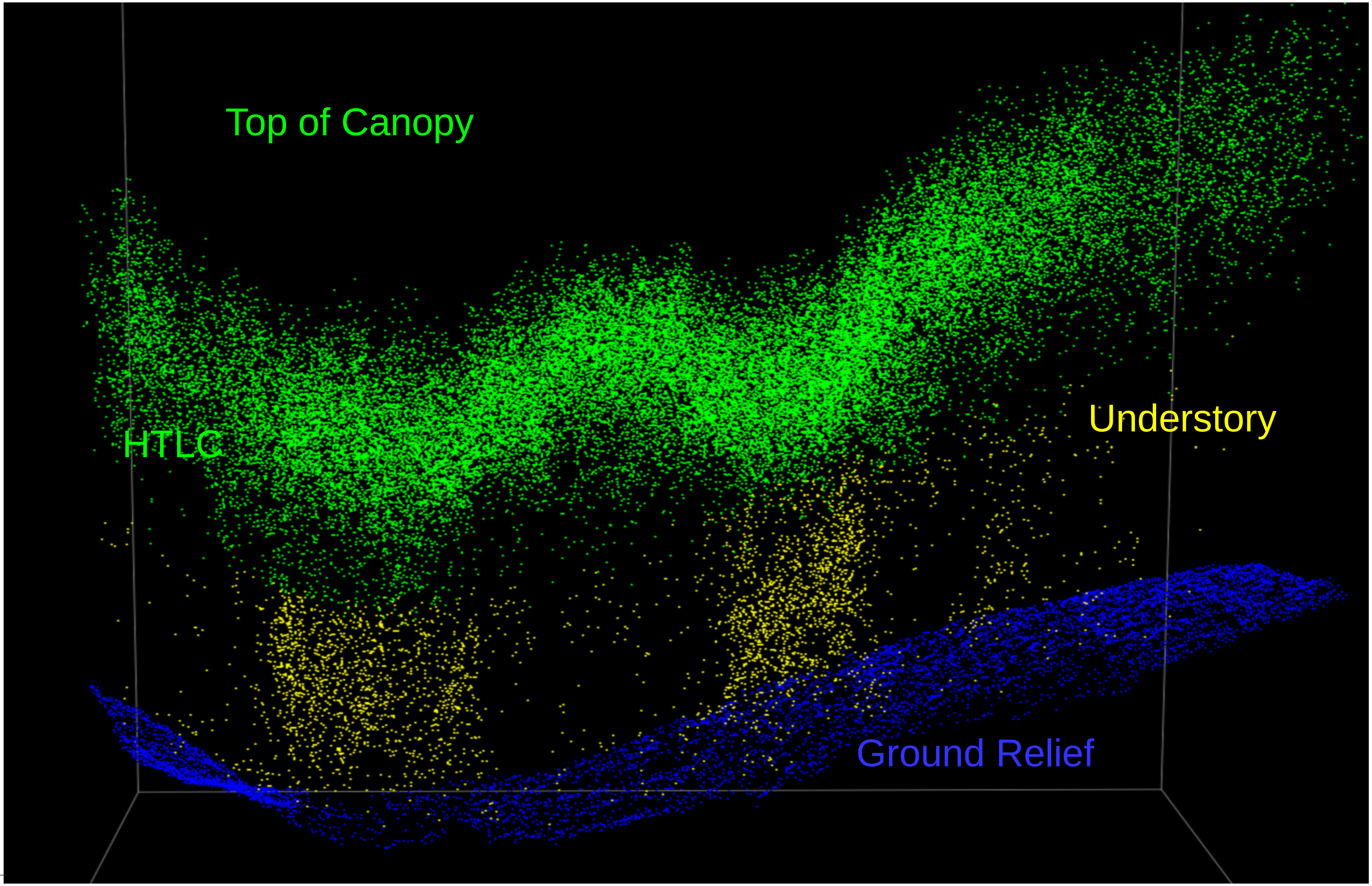
Precision Plantation Silviculture
Site Specific Treatments

Problems with LAI estimation in Stands with Evergreen Understory

Lidar Profile at RW18 in South Hill, VA



Questions

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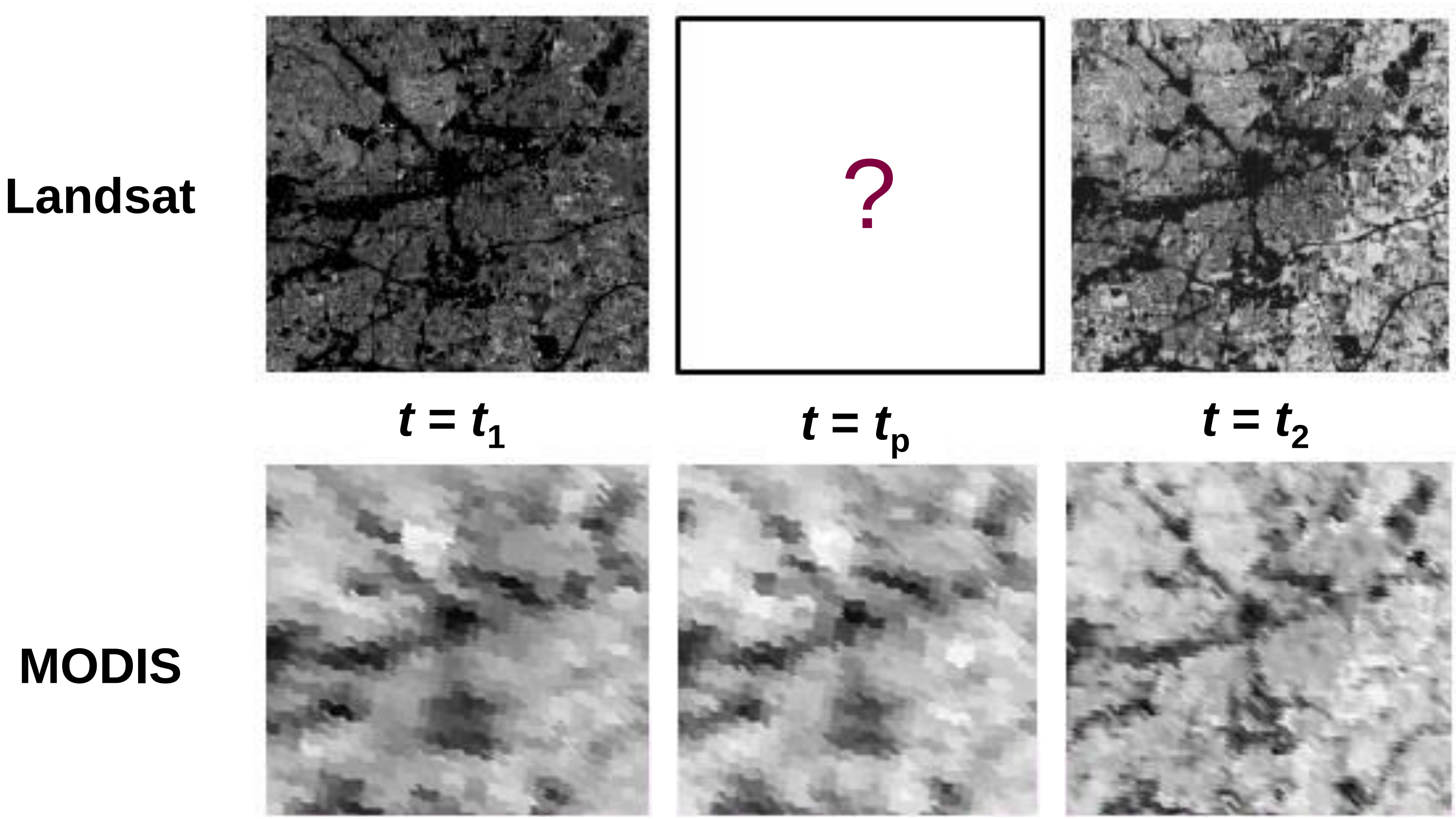
Landsat – MODIS Wavelet-based Fusion Model

Sherin Ghannam, PhD student, IGEP group

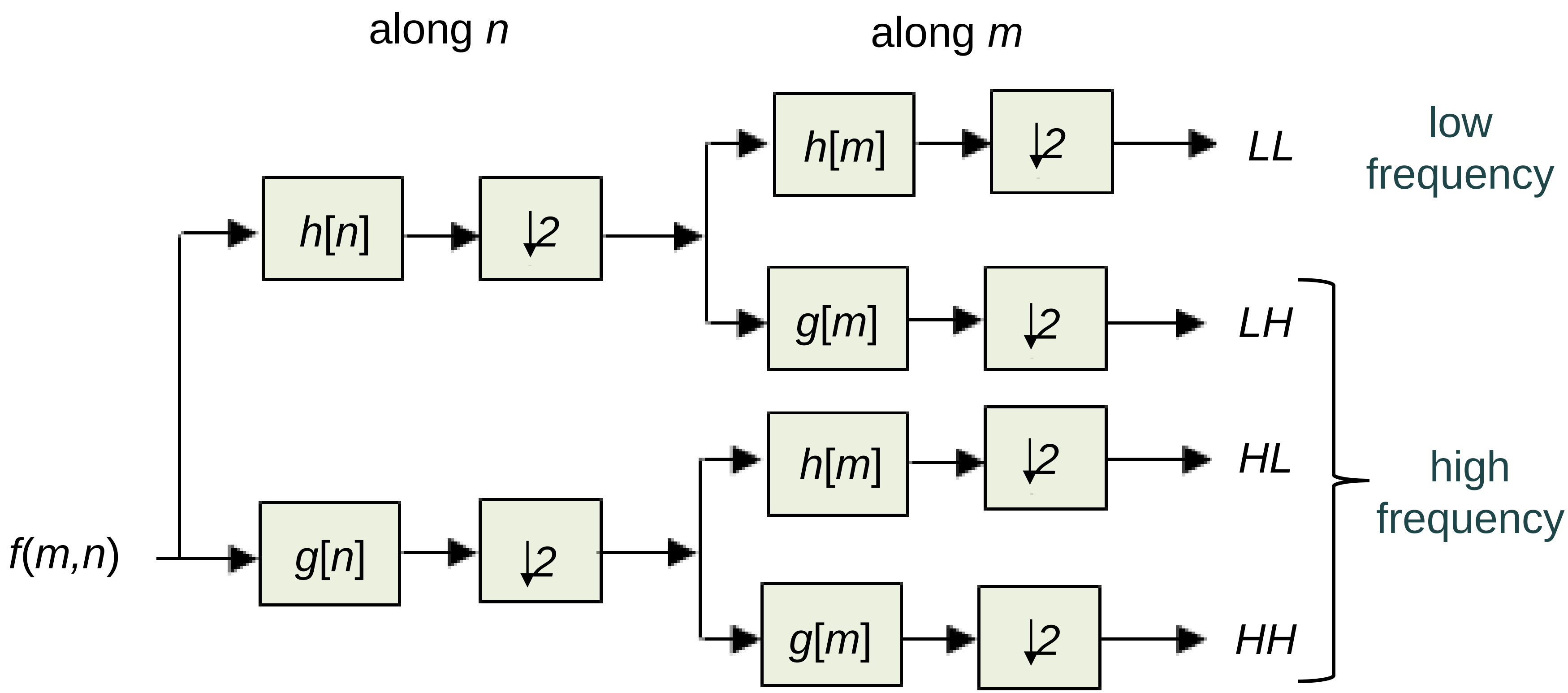
Spatial and temporal resolution tradeoff



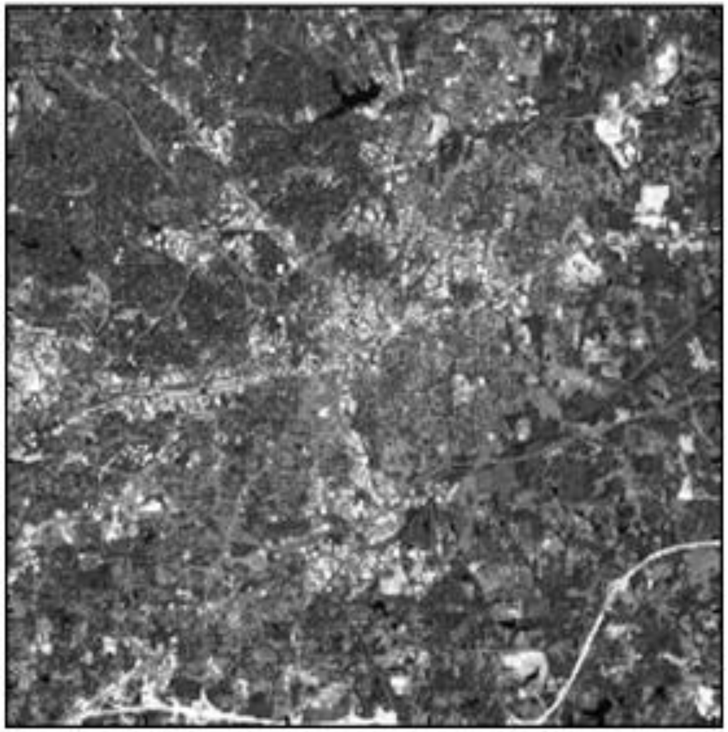
Transform based + reconstruction based fusion techniques

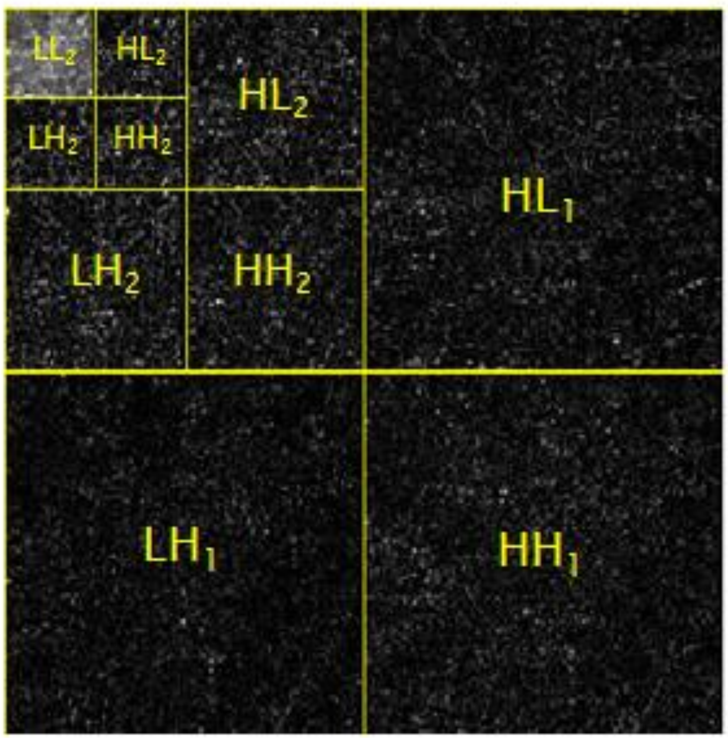
STRONG
TOGETHER

Multiresolution analysis by wavelet decomposition:

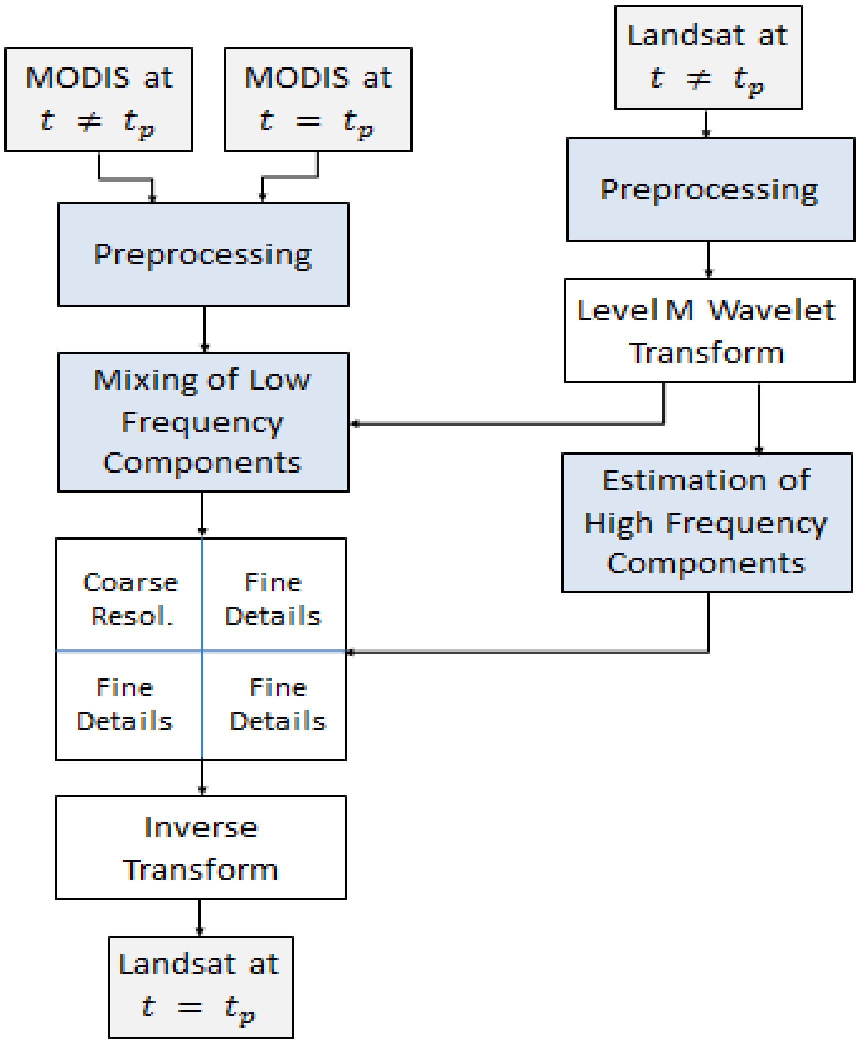


3 level wavelet decomposition

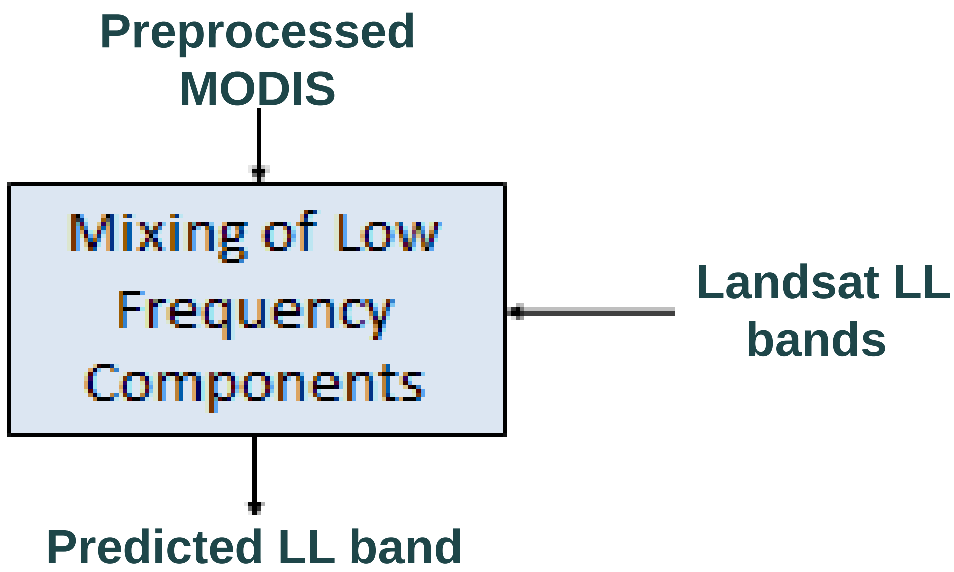




Proposed model

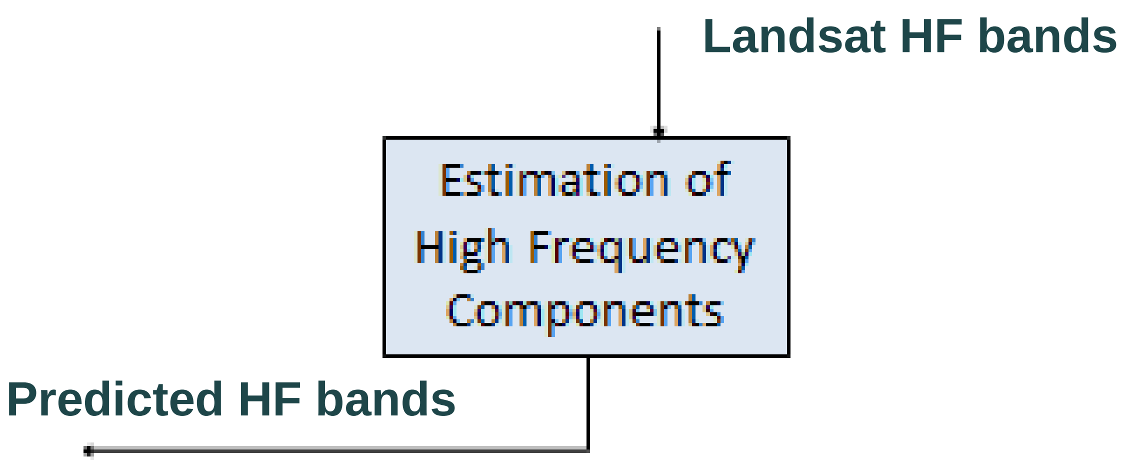


Low frequency prediction



$$L_a(x_i, y_j, t_p) = \sum_{k=1}^{K} W_{ijk} \times L_a(x_i, y_j, t_k) + \sum_{k=1}^{K} a_k \times \; W_{ijk} \times (M(x_i, y_j, t_p) - M(x, y, t_k))$$

High frequency prediction



$$L_d(x_i, y_j, t_p) = \sum_{k=1}^{K} W_{ijk} \times L_d(x_i, y_j, t_k)$$

Weighting function

$$a_k = B \times r_{nk} \qquad B = 2^n$$

$$S = \left\{ \frac{L_a(x_i, y_j, t_k)}{B \times M(x_i, y_j, t_k)} |_{0<i\leq M, 0<j\leq N} \right\}$$

$$r_k = median\,(S)$$

$$r_{nk} = \frac{r_k}{\sum_{k=1}^{K} r_k}$$

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Weighting function

$$S_{ijk} = |L_a(x_i, y_j, t_k) - r_{nk} \times M(x_i, y_j, t_k)|$$

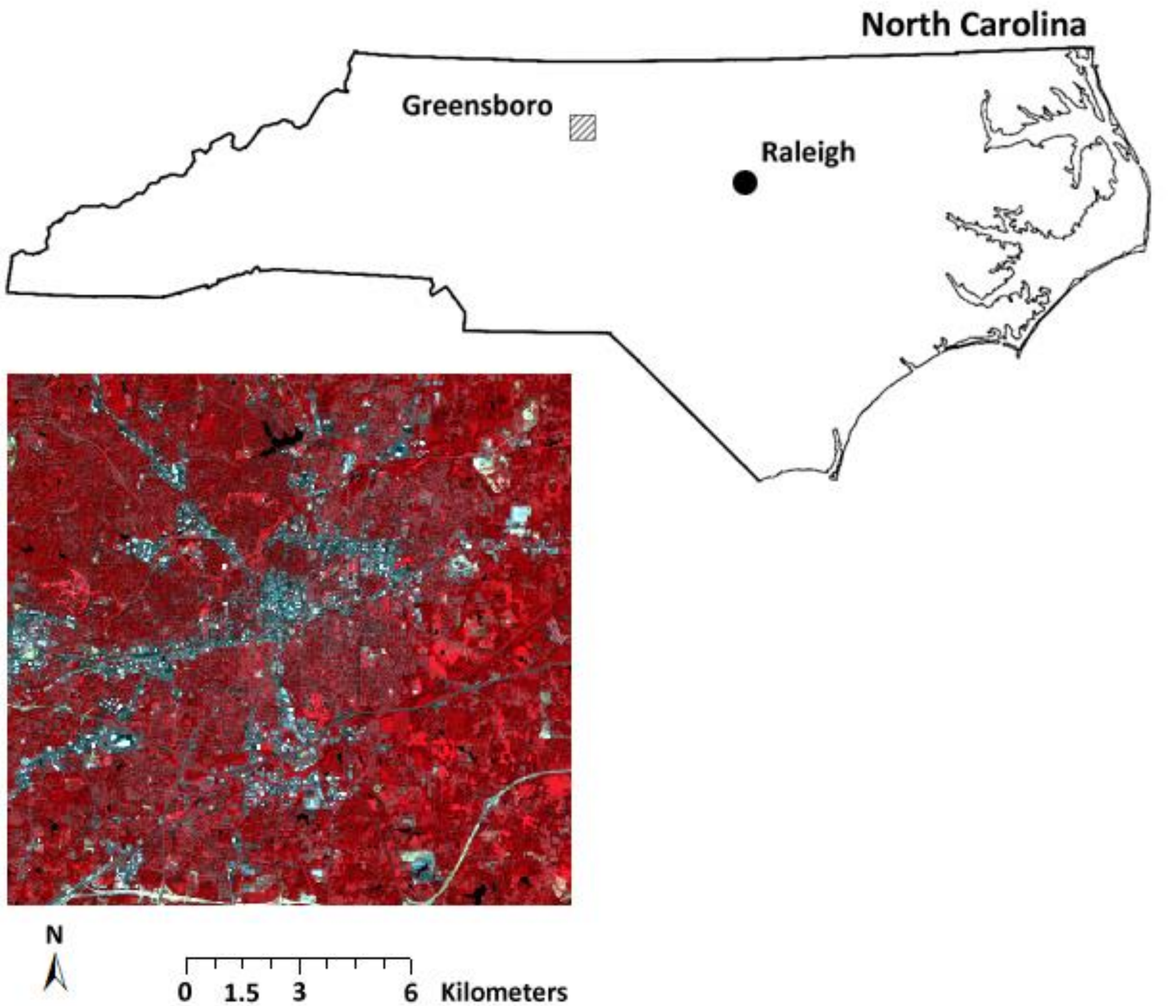
$$T_{ijk} = |M(x_i, y_j, t_k) - M(x_i, y_j, t_p)|$$

$$D_k = |t_p - t_k|$$

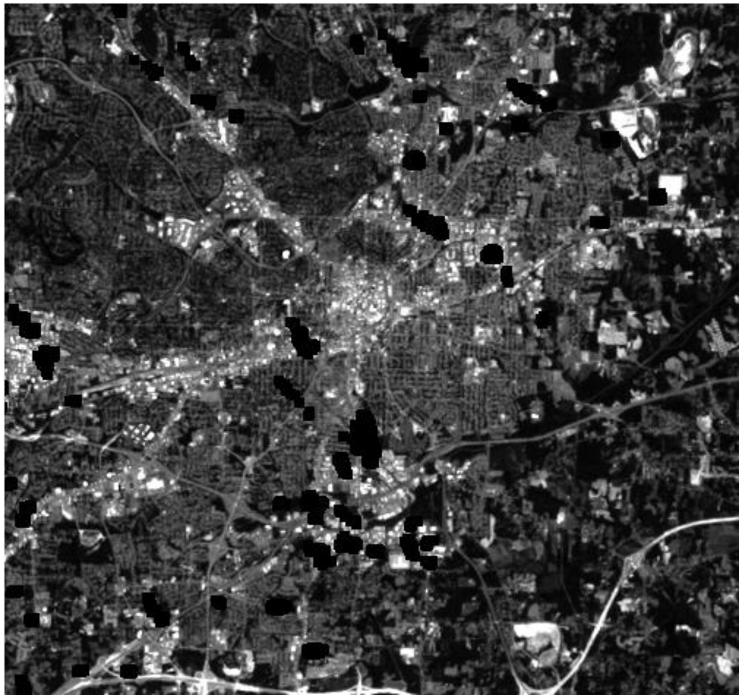
$$C_{ijk} = S_{ijk} \times T_{ijk} \times D_k$$

$$W_{ijk} = (1/C_{ijk}) / \sum_{k=1}^{K} (1/C_{ijk})$$

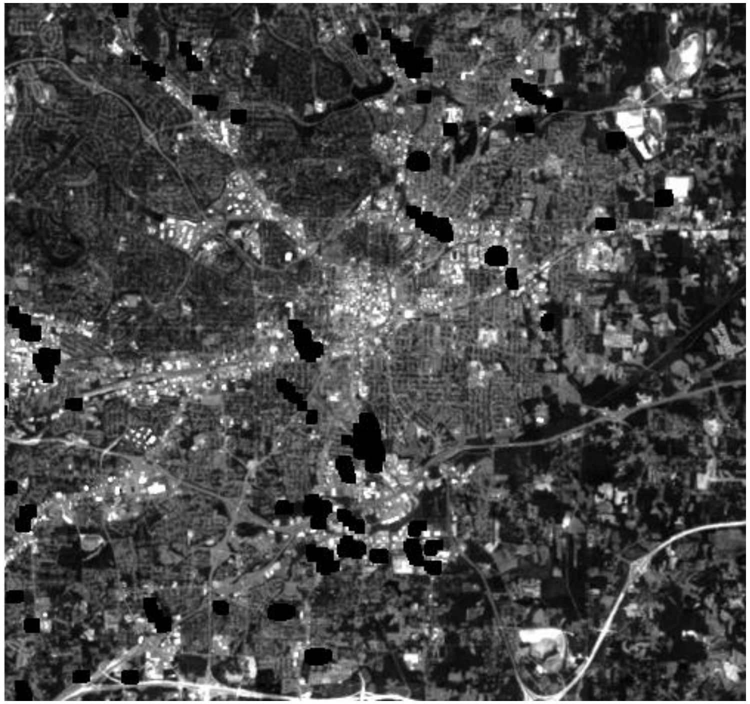
Study area



Results: May 24, 2002



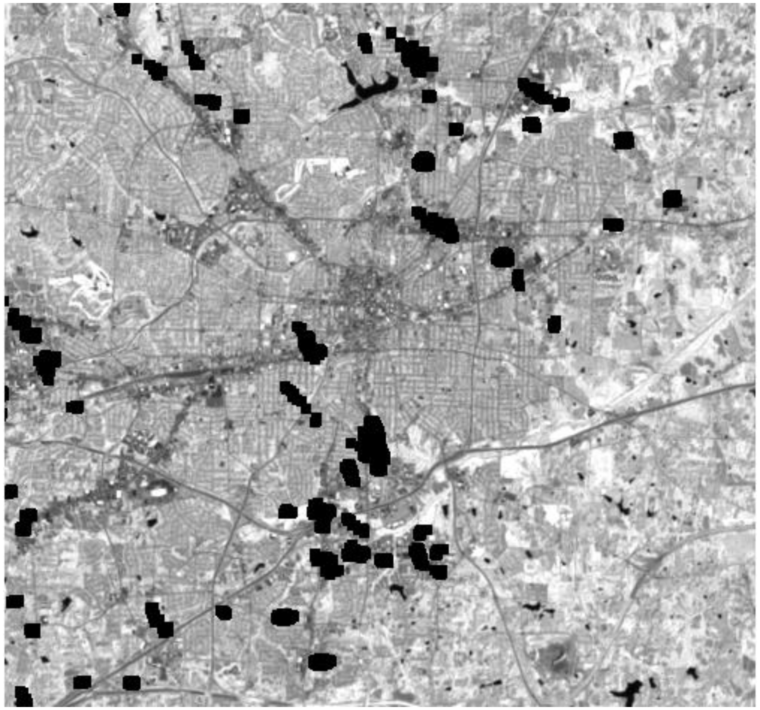
Actual red band image



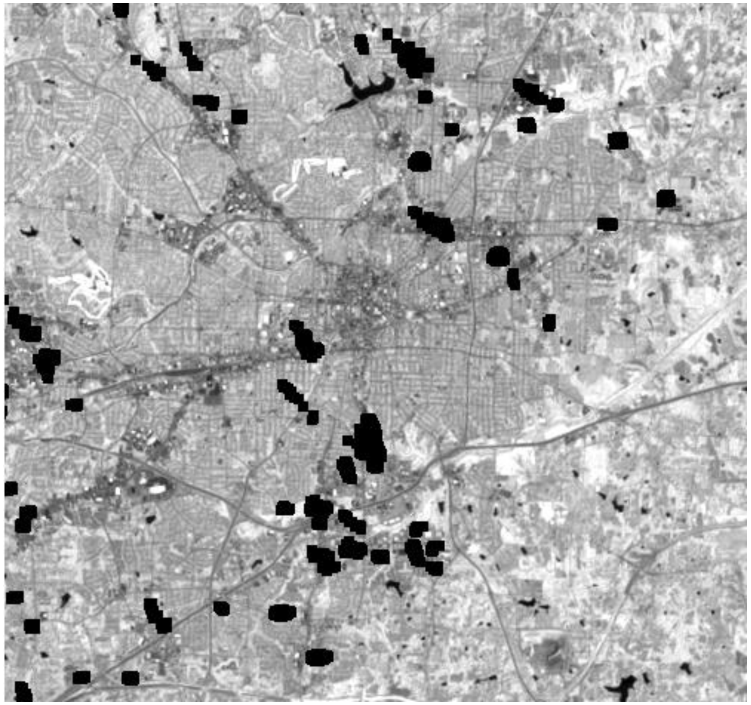
Predicted red band image

$R^2 = 0.7819$

Results: May 24, 2002



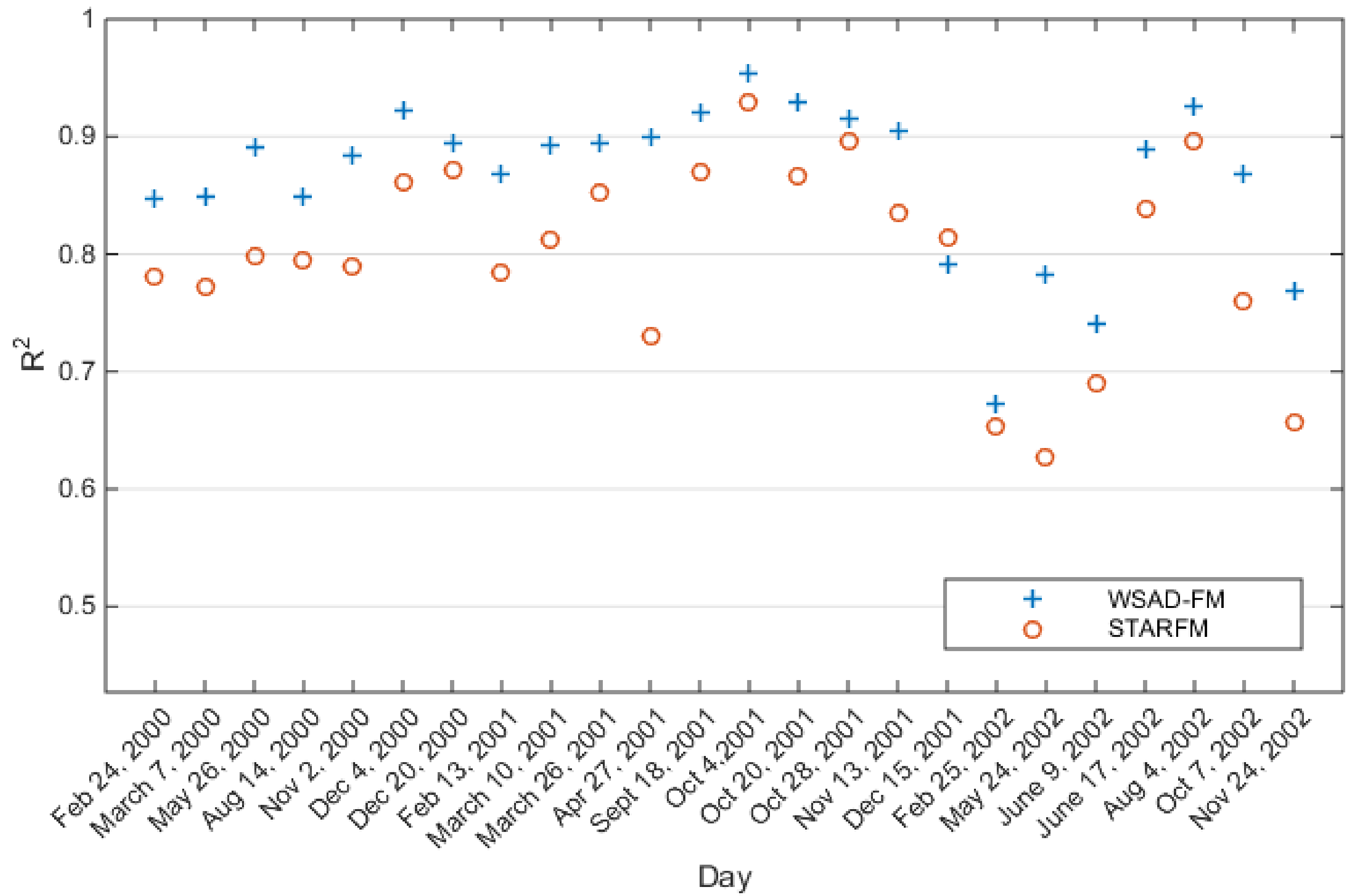
Actual near-infrared band image



Predicted near-infrared band image

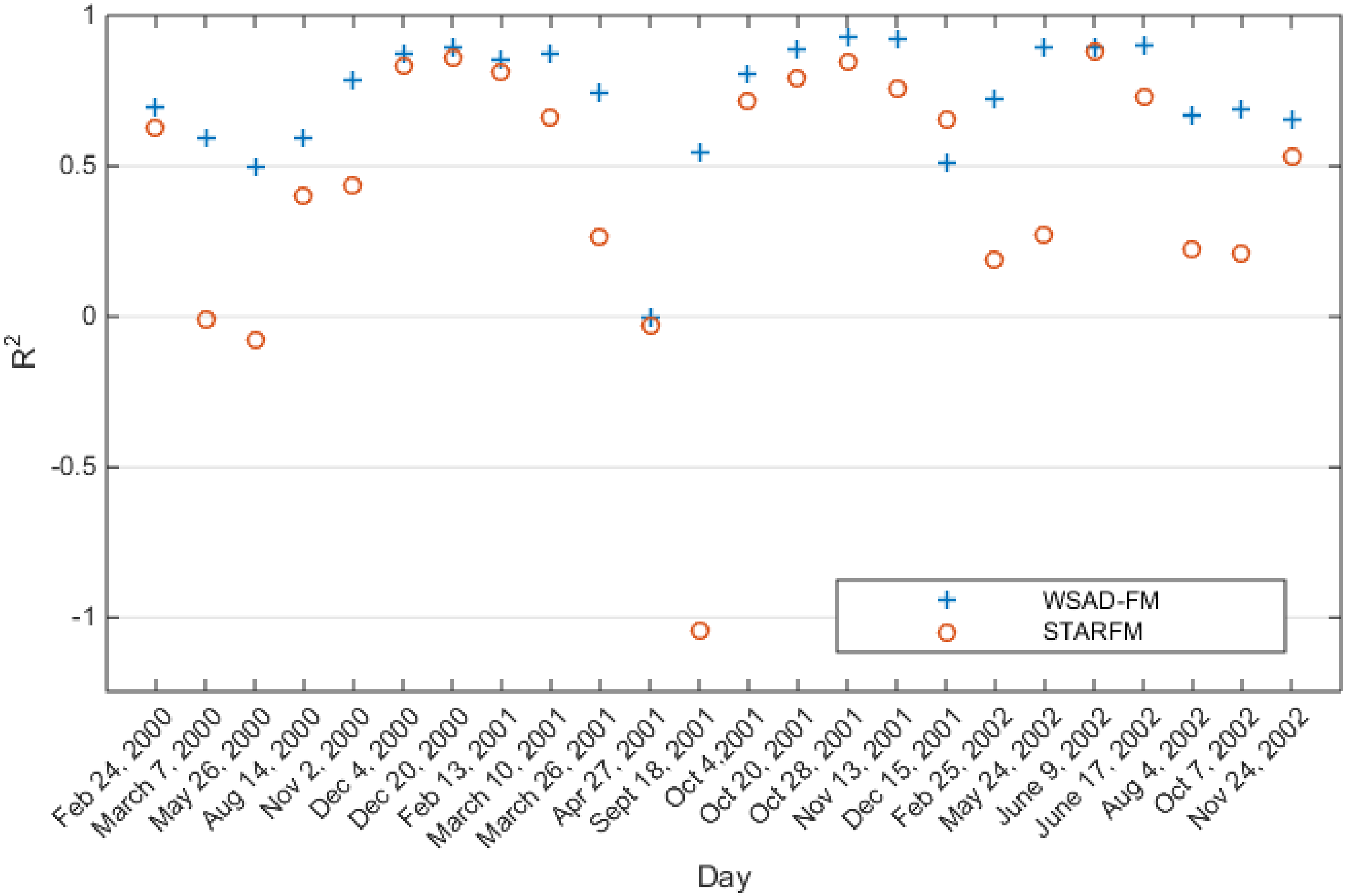
$R^2 = 0.8972$

Results : red band
(prior-posterior base images)

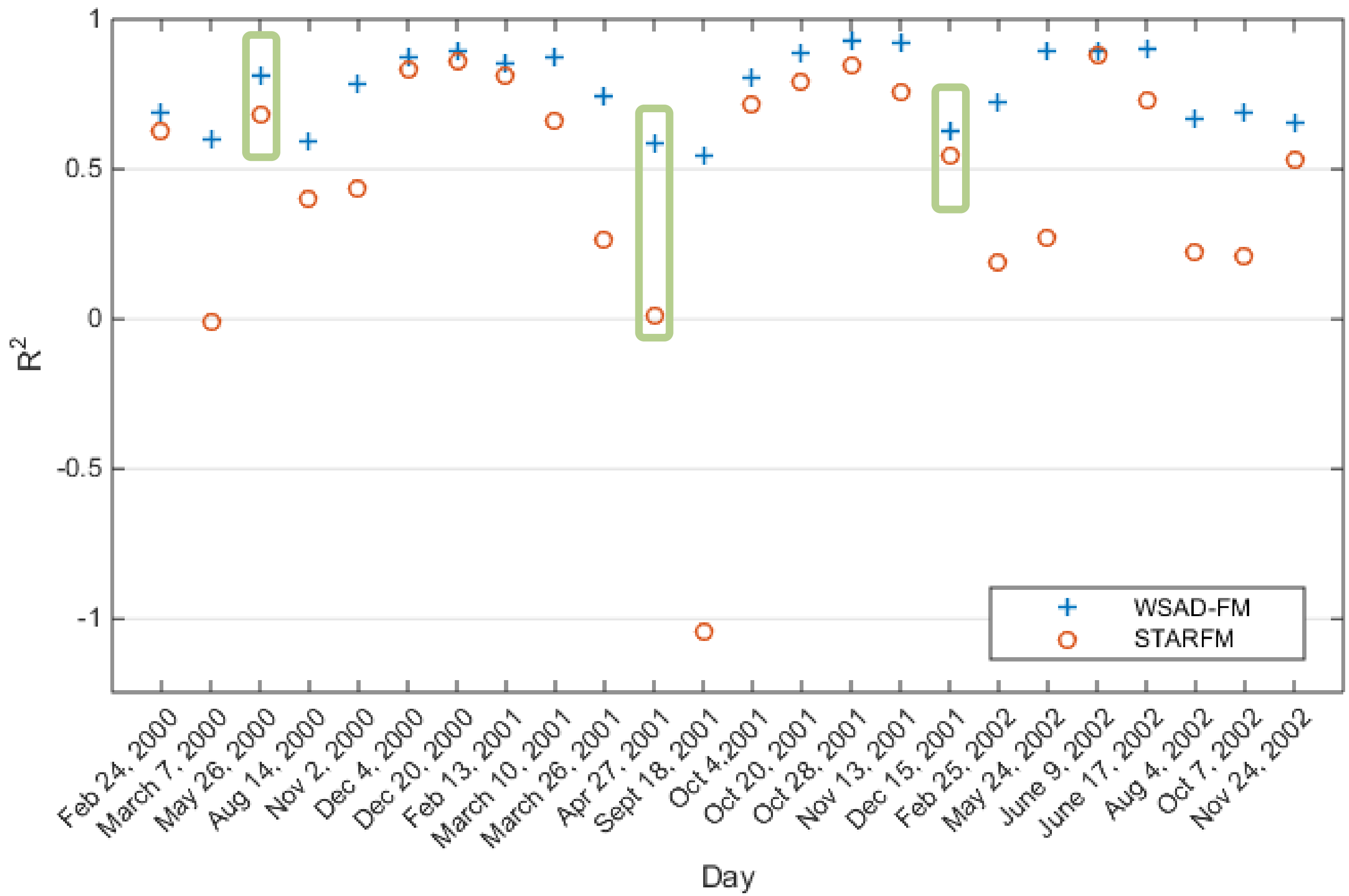


Results: near-infrared band

(prior-posterior base images)



Results: near-infrared band
(nearest base images across years)



Thanks

sghannam@vt.edu

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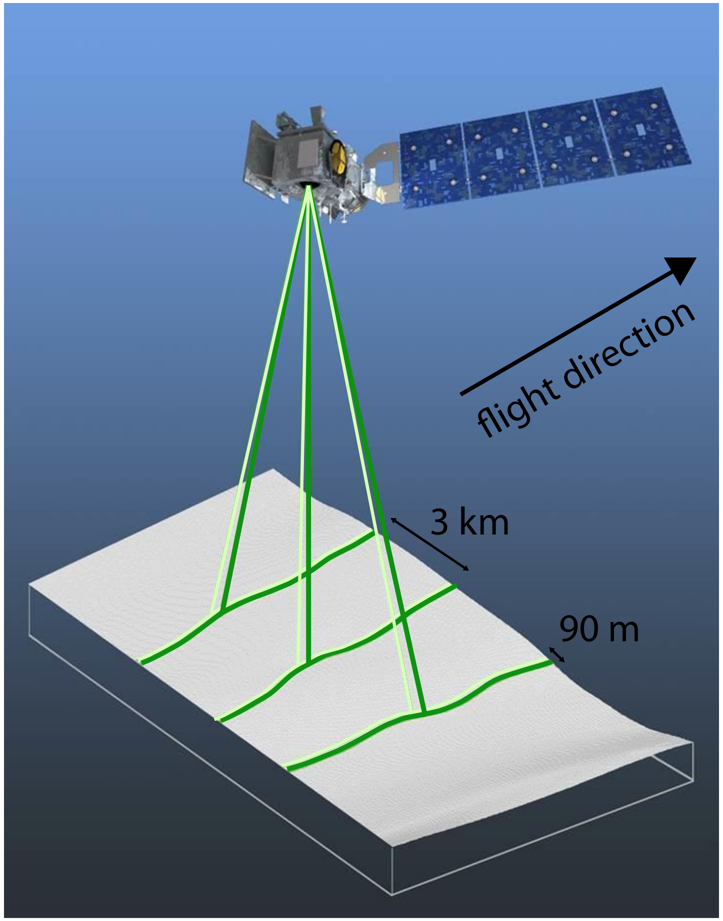
Automatic Surface Extraction from Photon Counting LiDAR in Preparation for ICESat-2

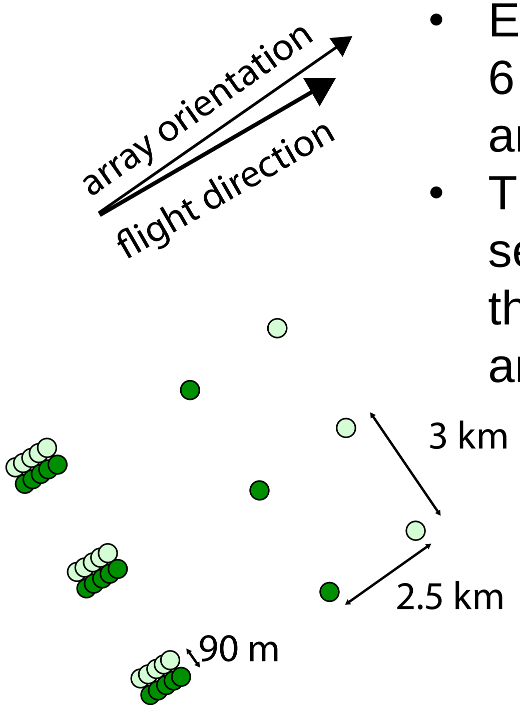
Mahmoud Awadallah

Motivation

- **ICESat (2003 – 2009):**
  - Full waveform: Geoscience Laser Altimeter System (GLAS).
- **ICESat-2 (to be launched in 2017):**
  - Photon-counting: Advanced Topographic Laser Altimeter System (ATLAS).

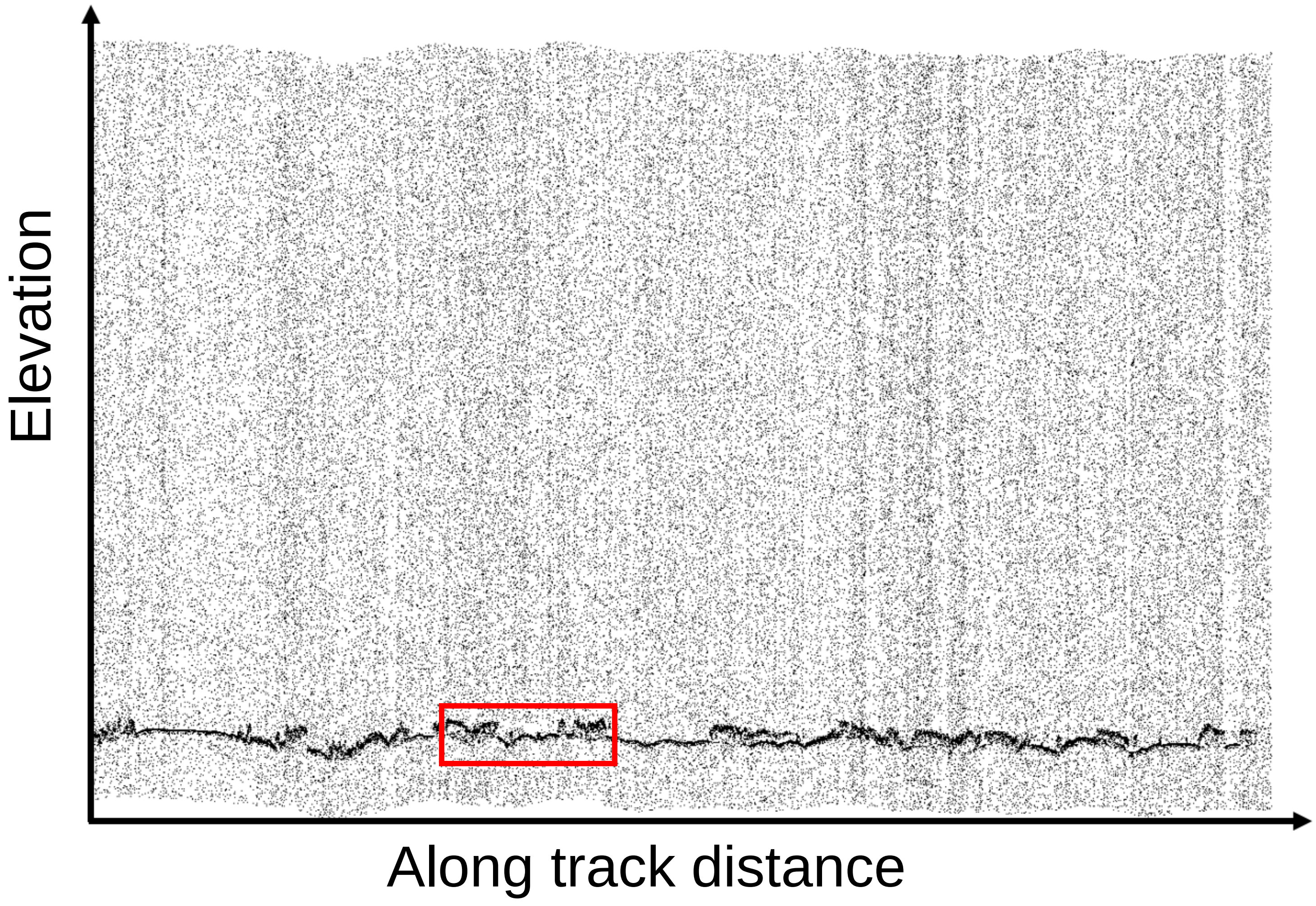
ATLAS



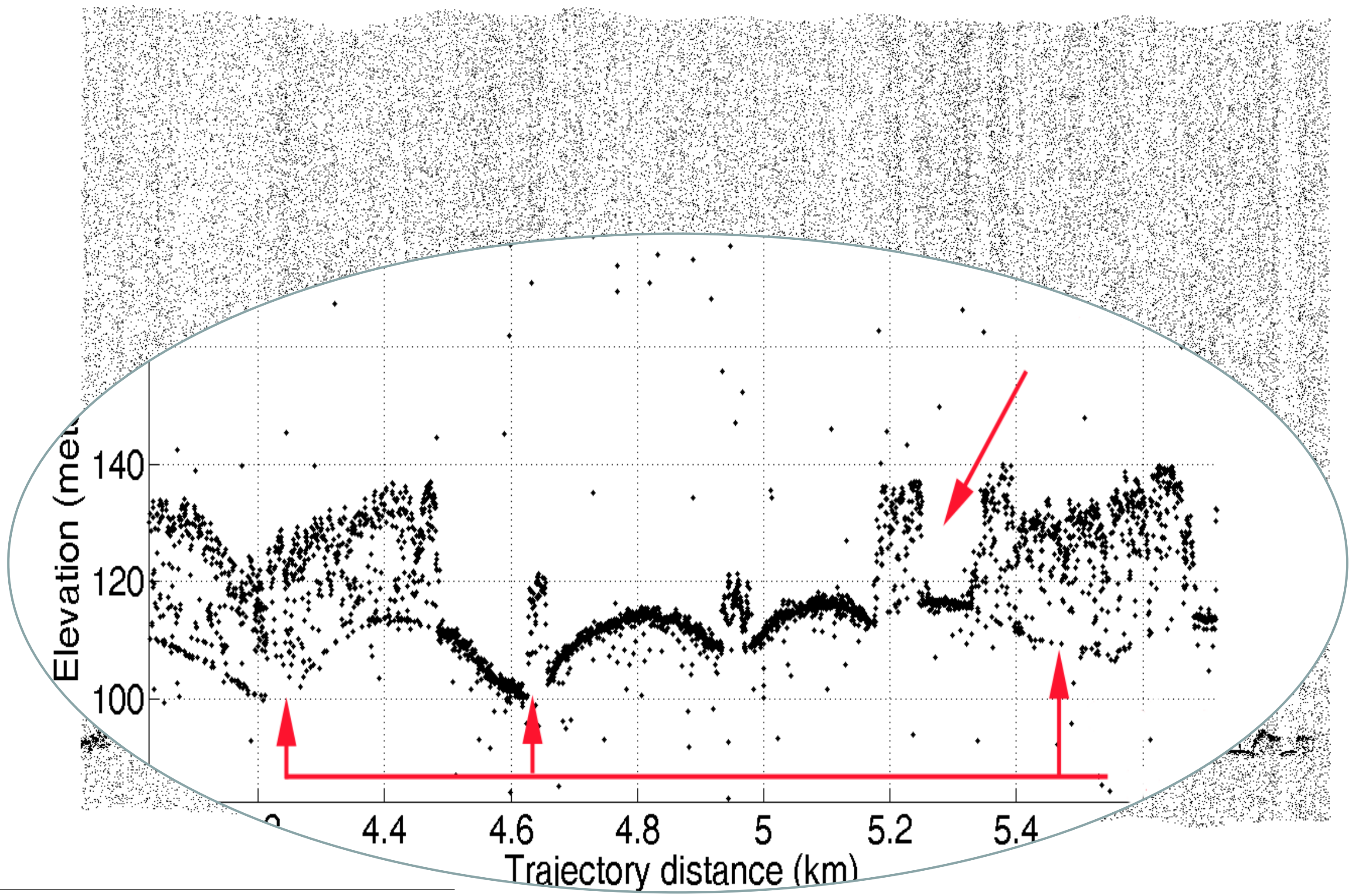


- Transmits green (532 nm) laser pulses at 10 kHz
- Footprint diameter 14 m
- Each laser pulse is split to 6 individual beams, arranged in three pairs.
- The beam pairs are separated by ~3.3 km in the across-track direction, and the strong and

M-ATLAS example



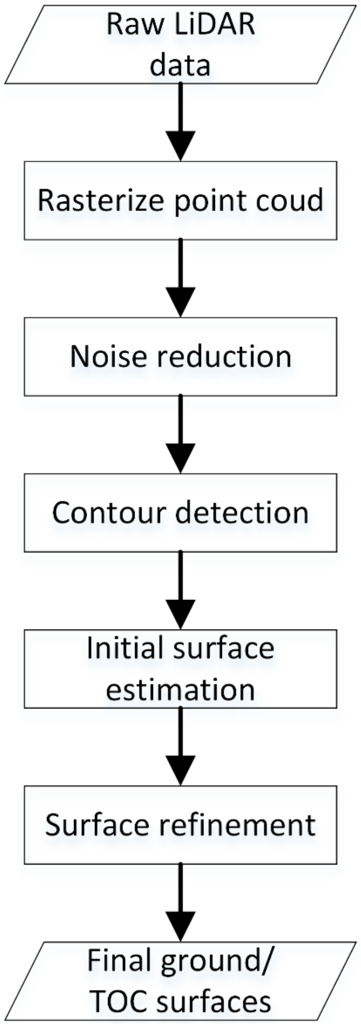
M-ATLAS example



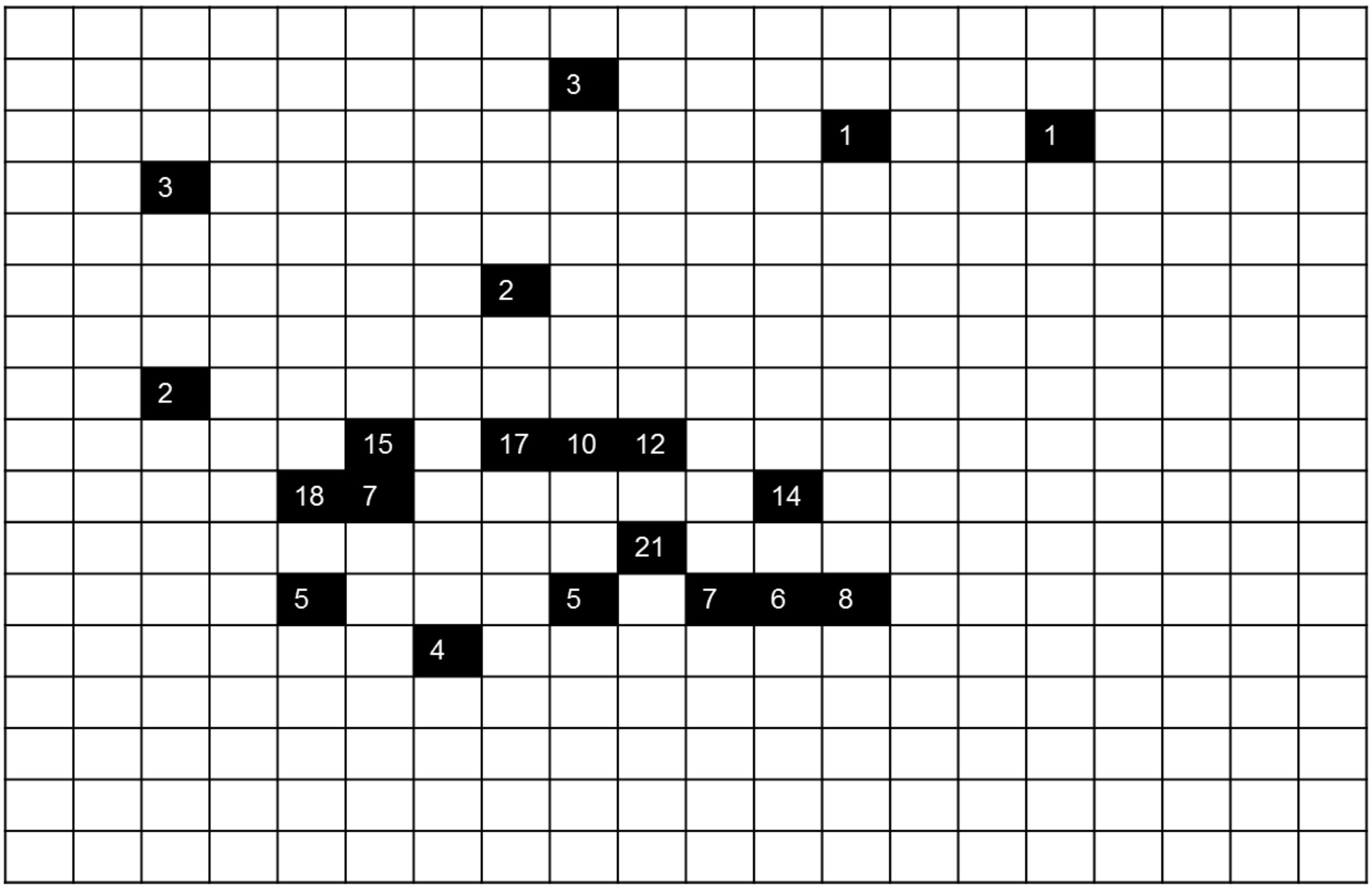
Datasets

- Sigma Space MPL (Micropulse Photon-Counting LiDAR)
- MABEL (Multiple Altimeter Beam Experimental LiDAR)
- M-ATLAS
- SIMPL (Slope Imaging Photon-counting Multi-polarized LiDAR)

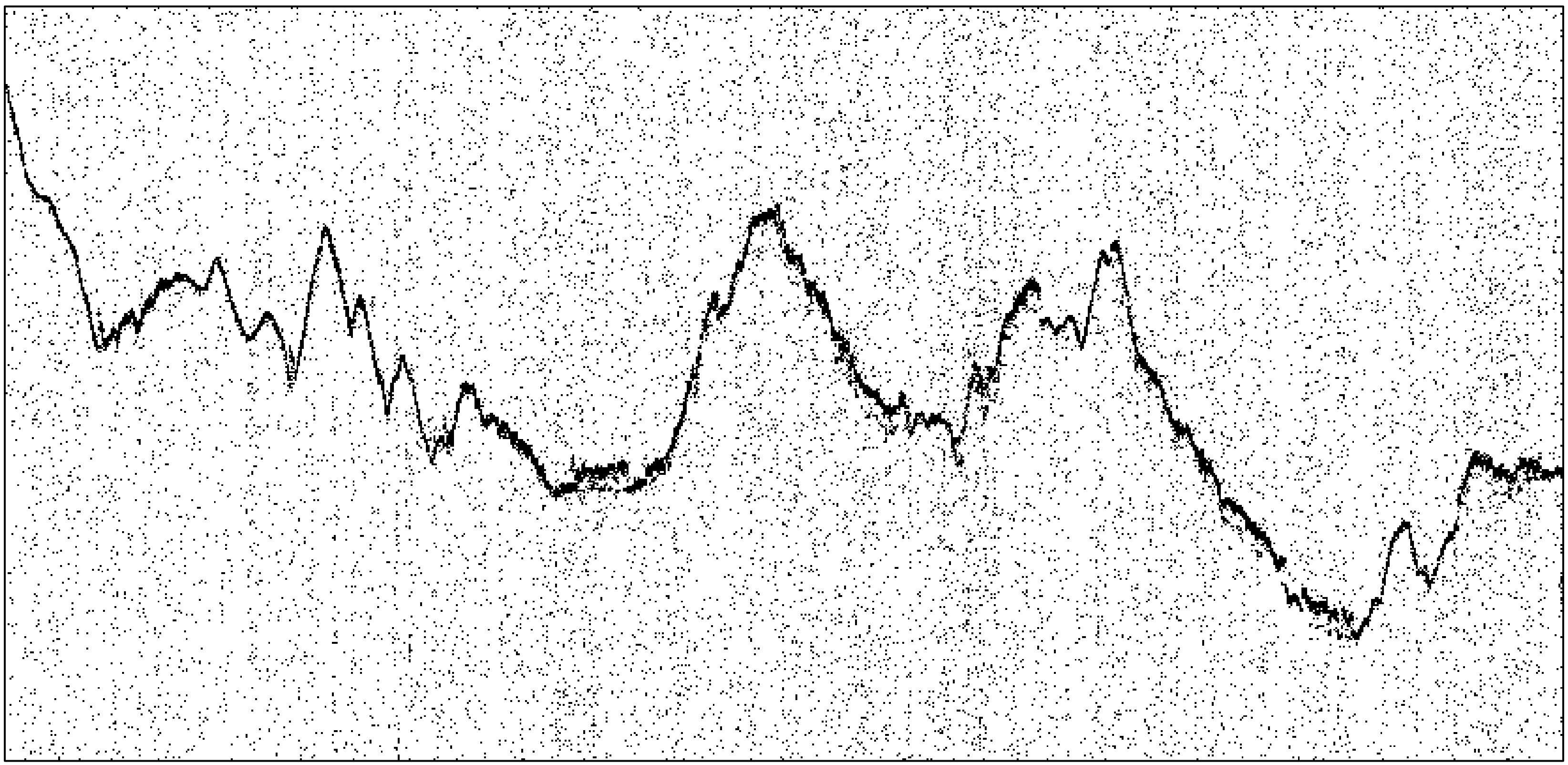
Algorithm flowchart



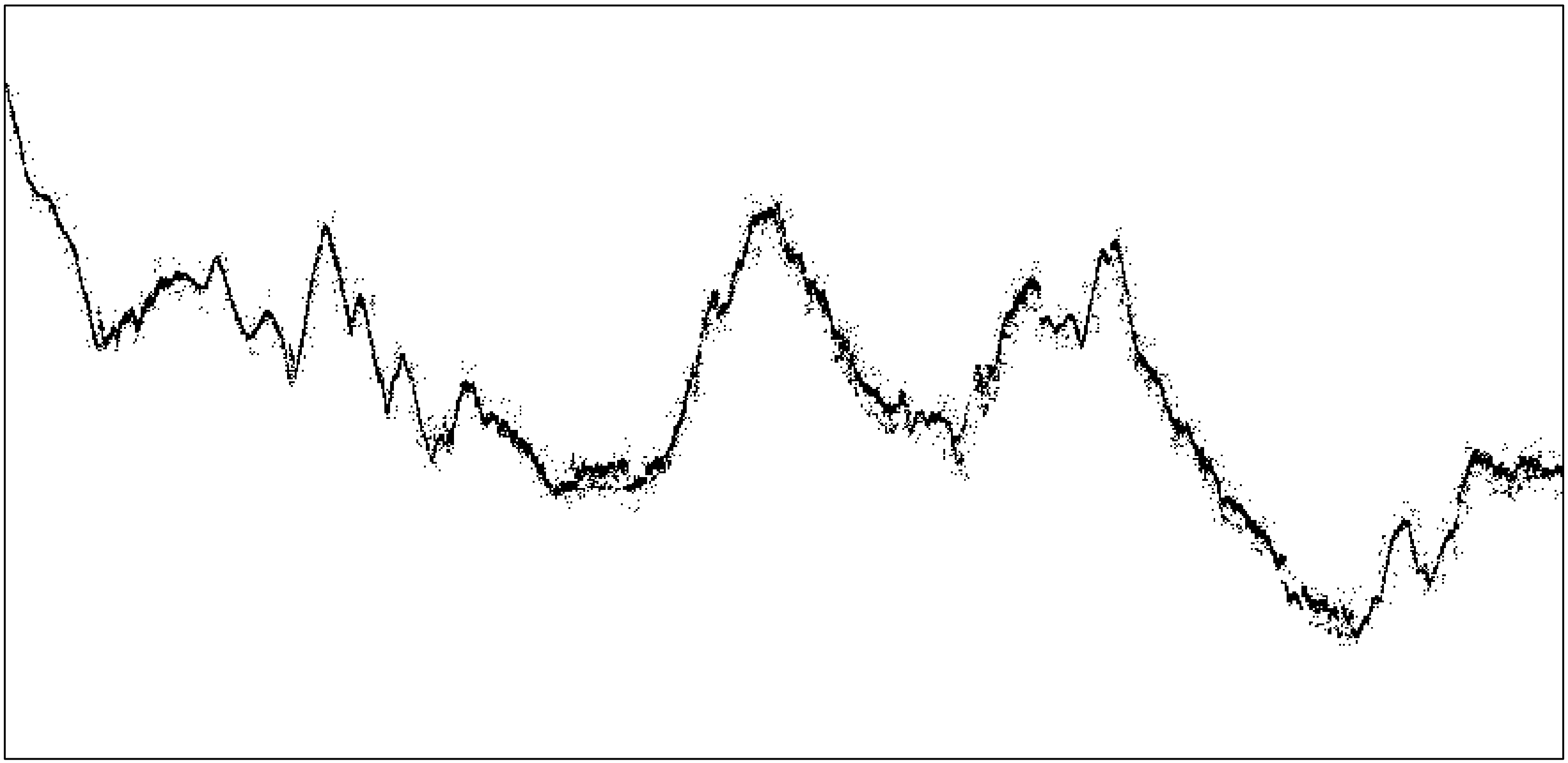
Rasterization



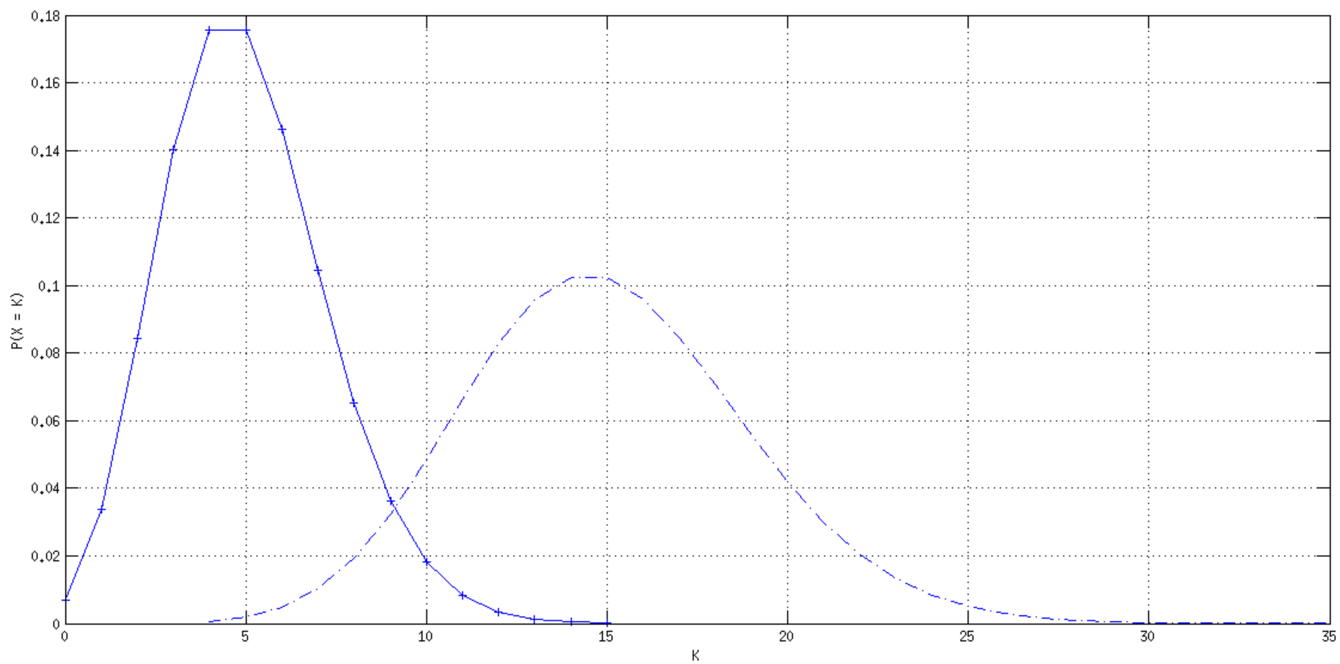
Noise reduction



Histogram noise reduction

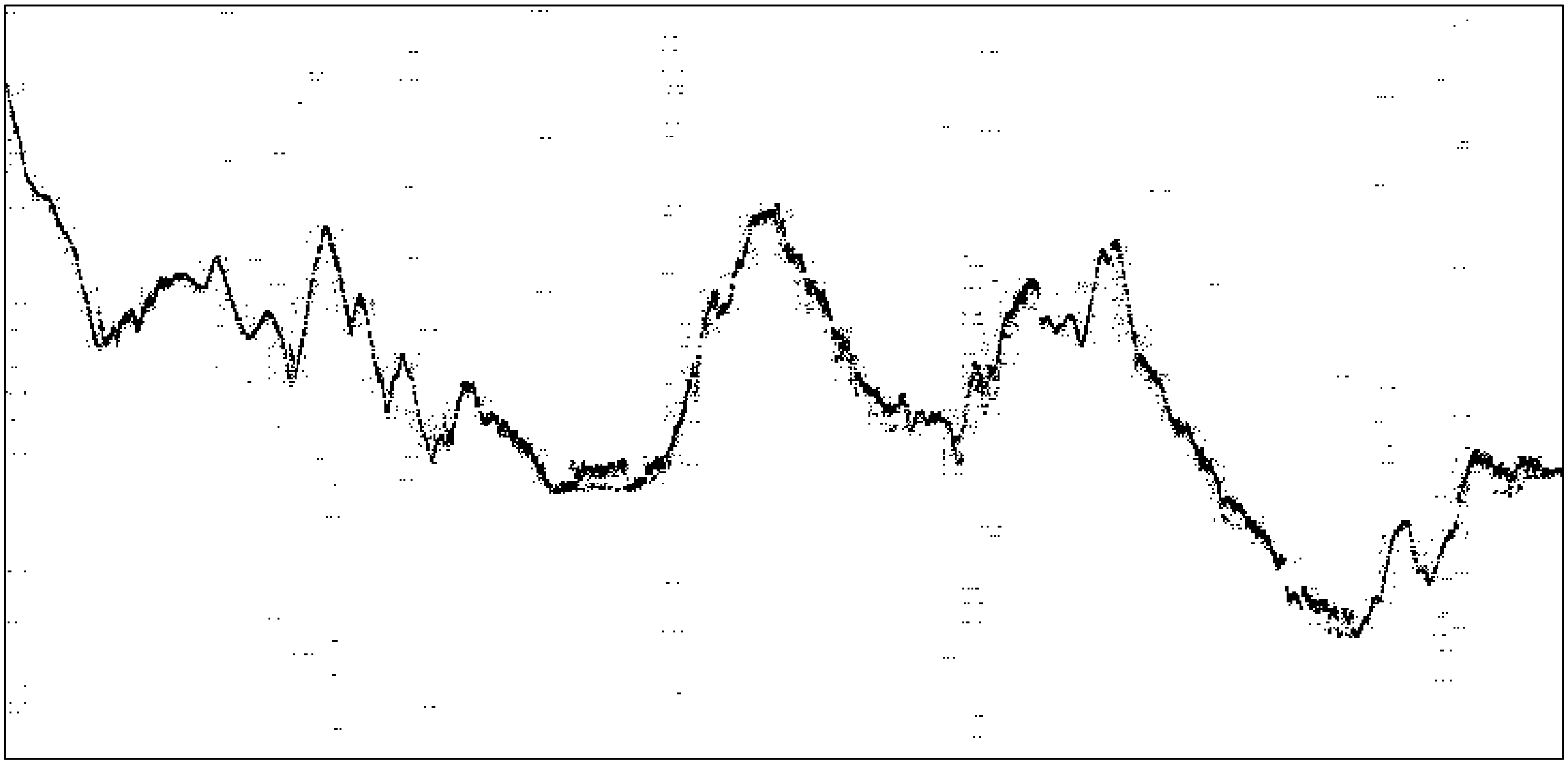


Bayesian noise reduction

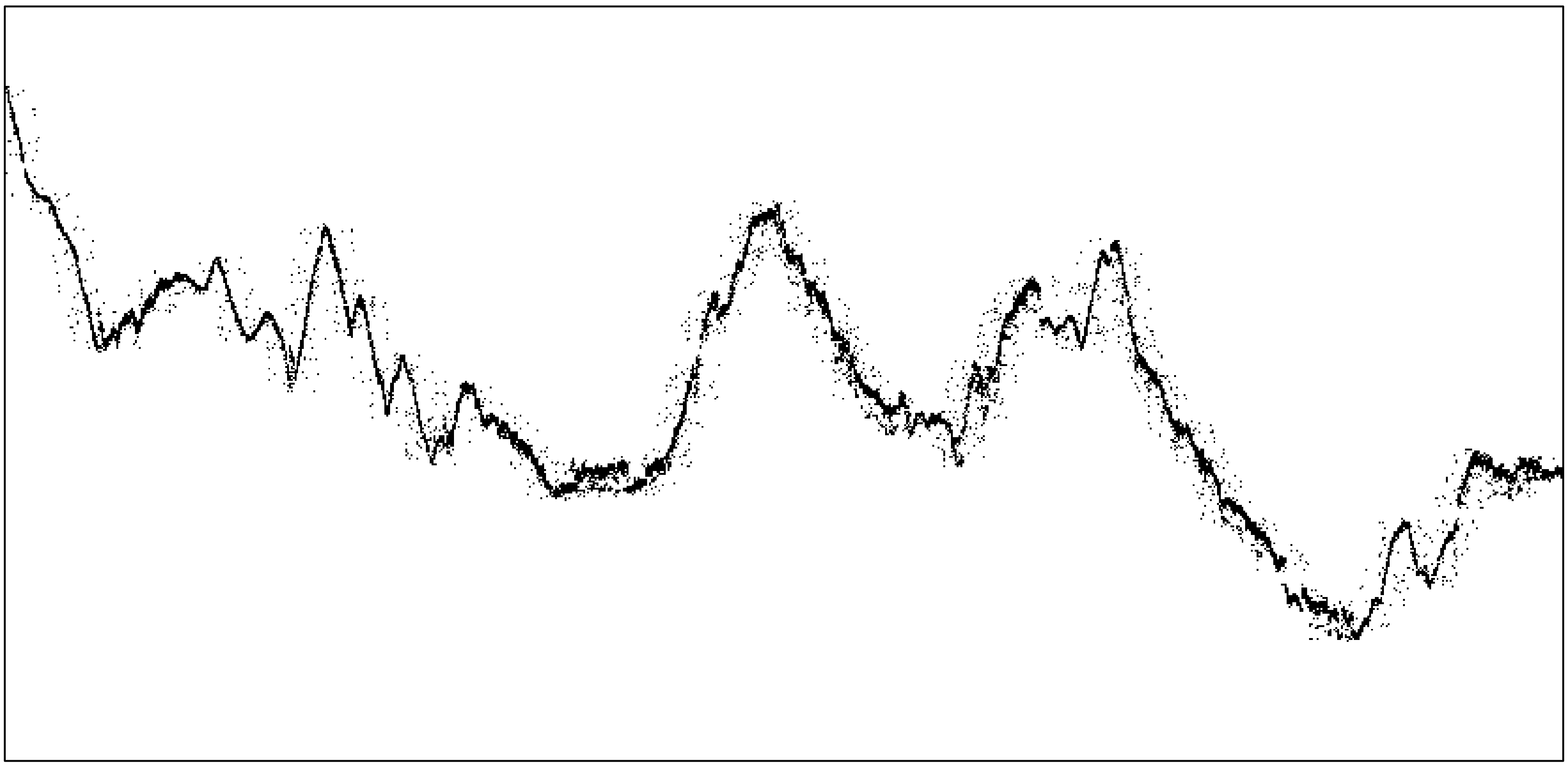


- $P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}$
- $likelihood\ ratio = \frac{\lambda_2^k\, e^{-\lambda_2}}{\lambda_1^k\, e^{-\lambda_1}}$

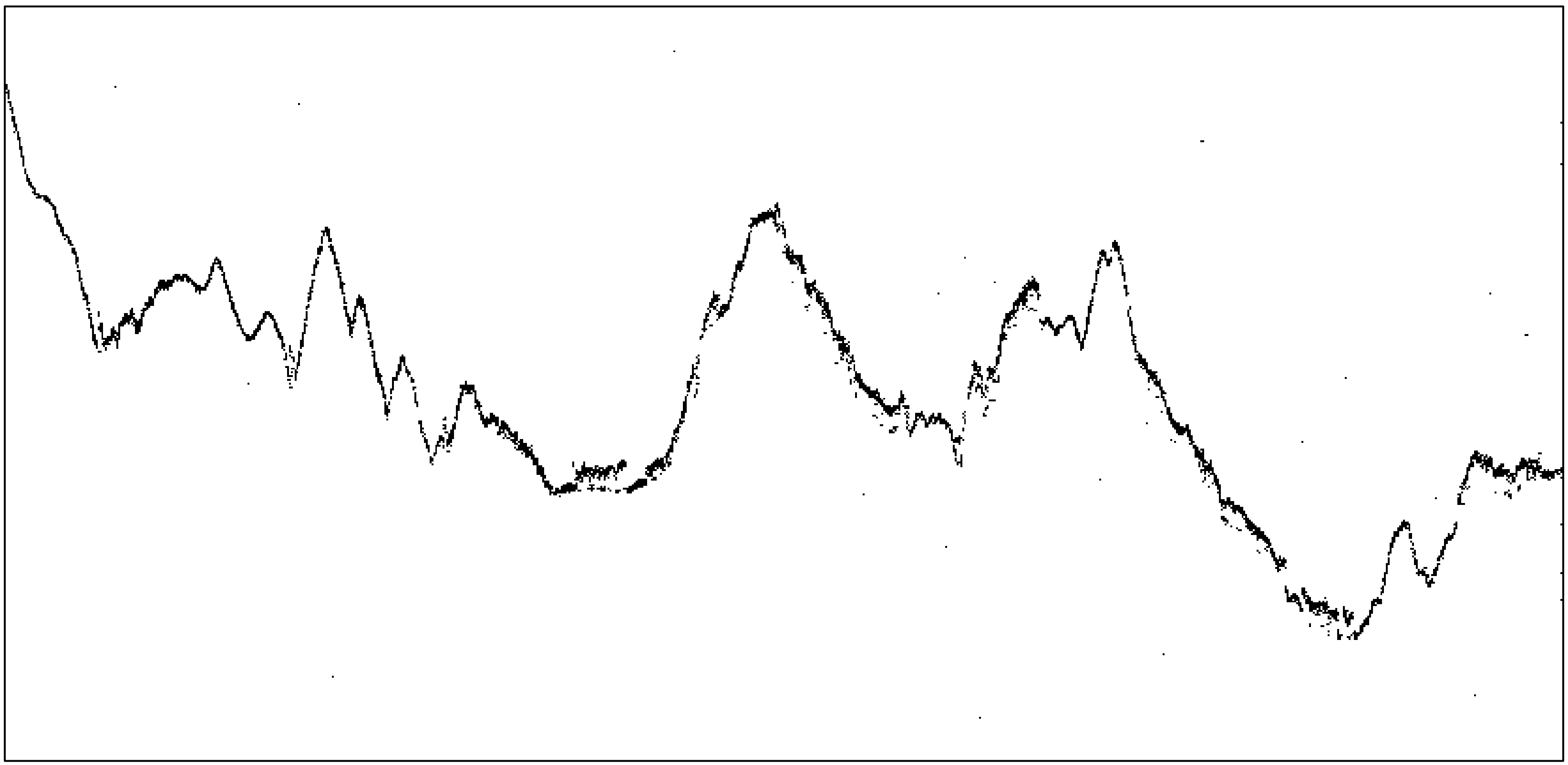
Bayesian noise reduction



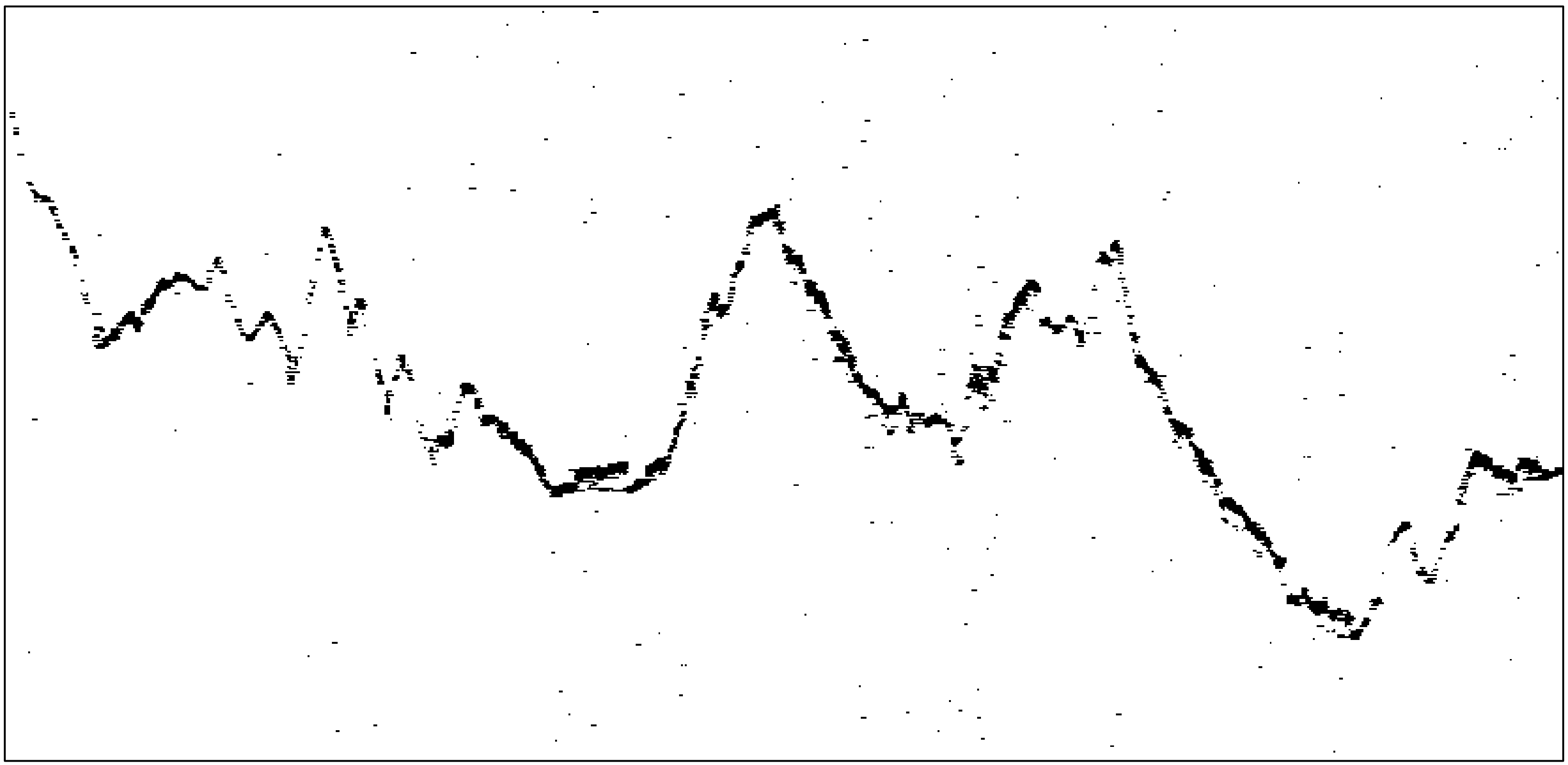
Wiener filter



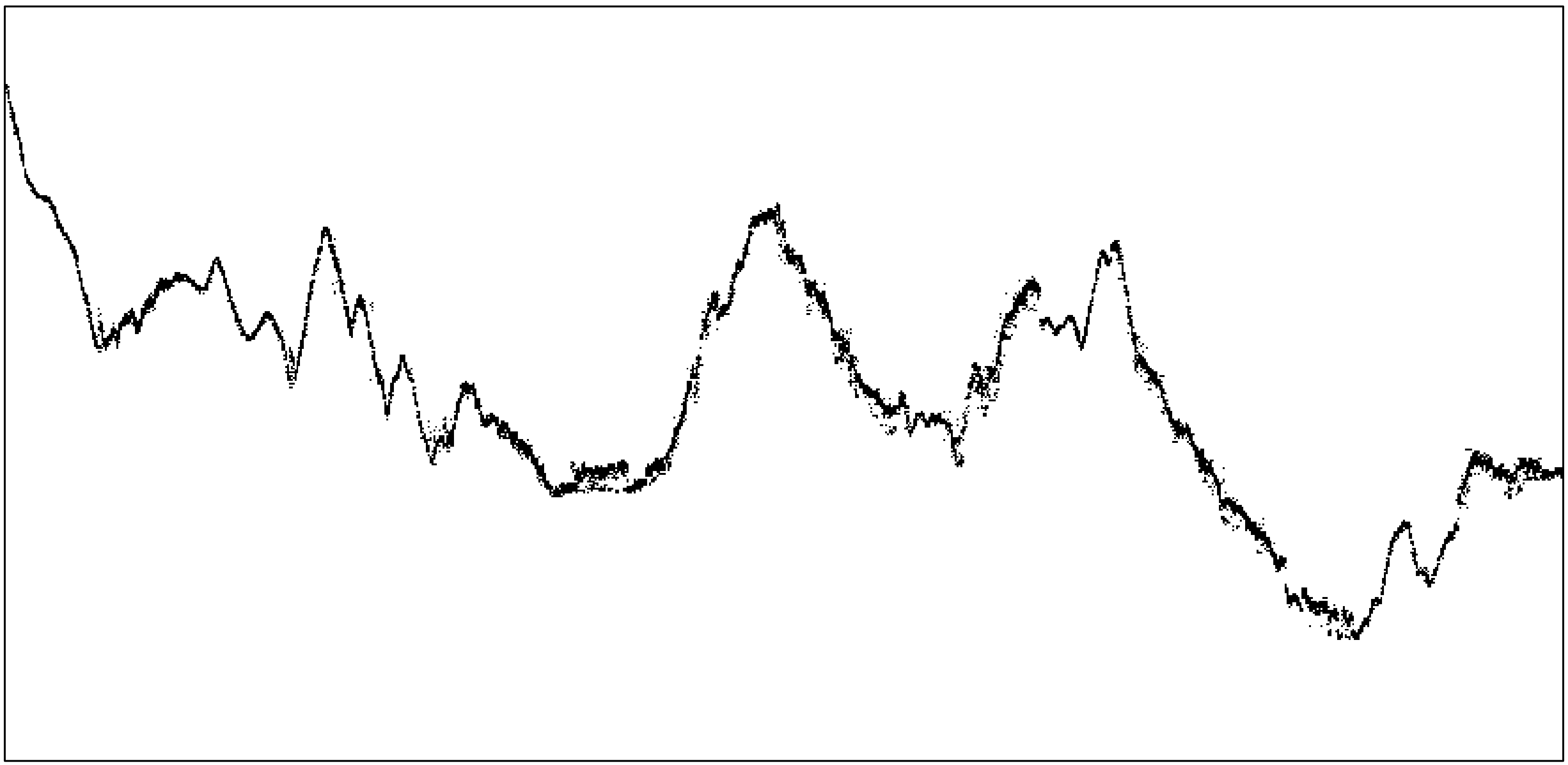
Morphology



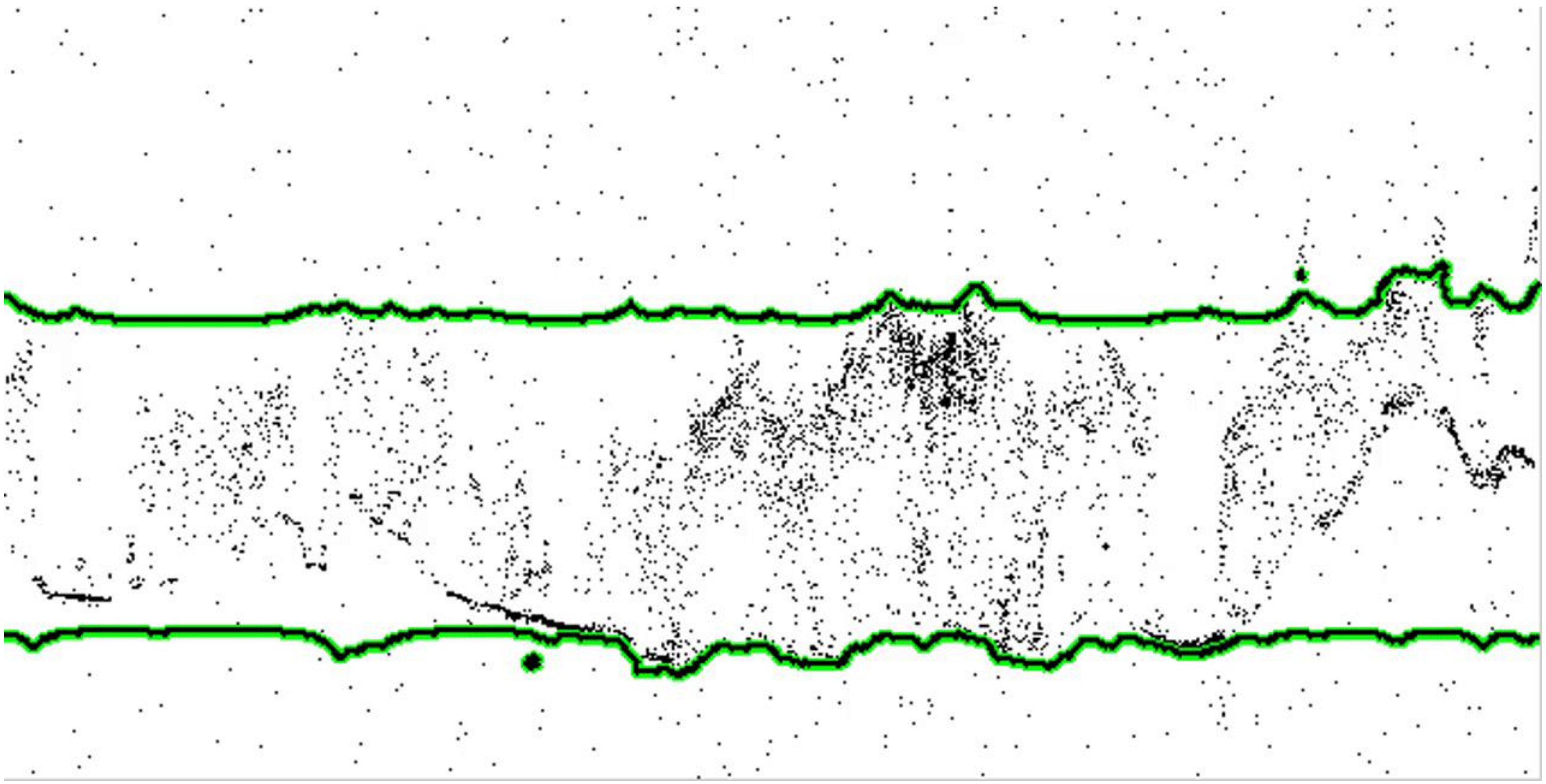
Median filter



Majority voting



Contour detection



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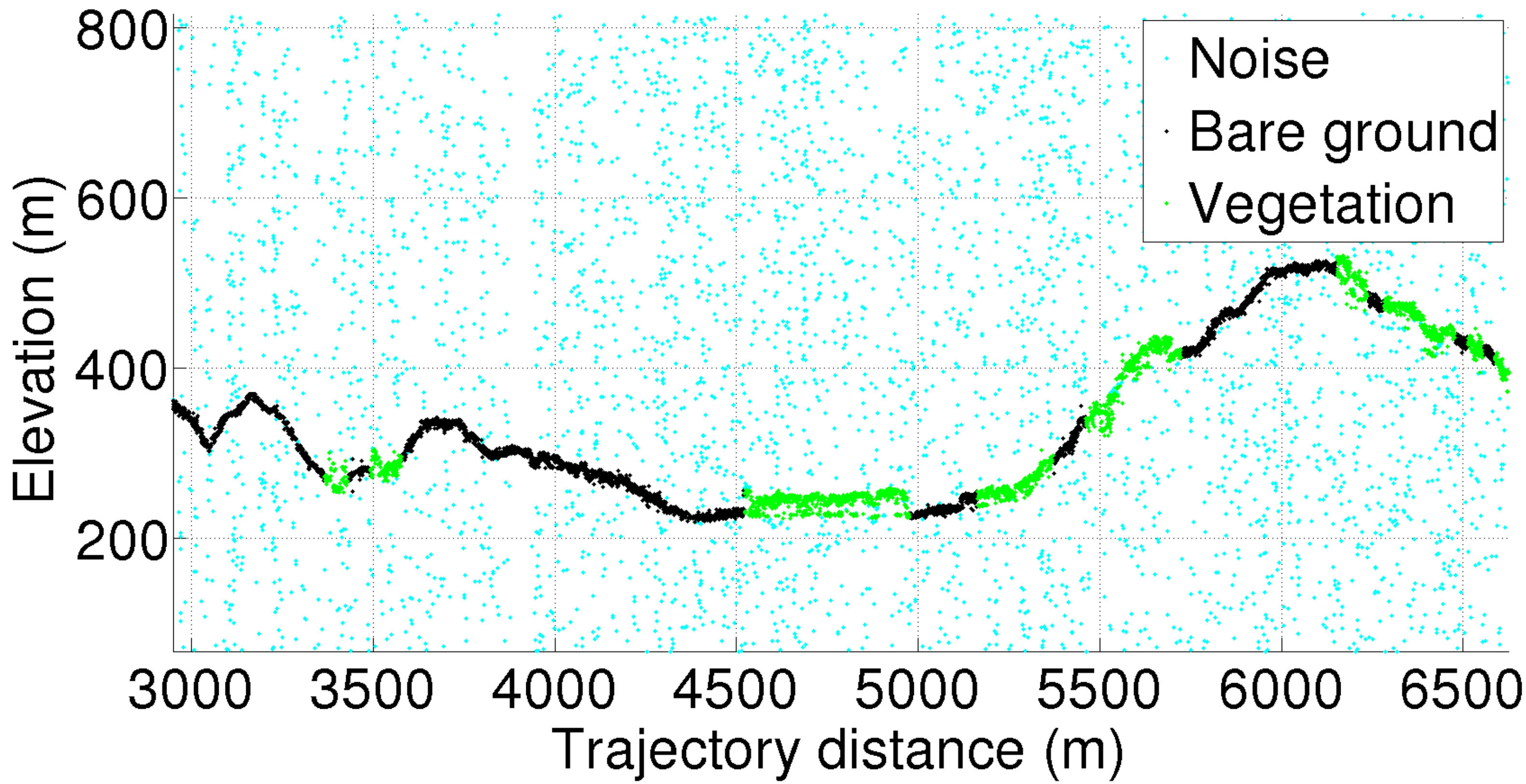
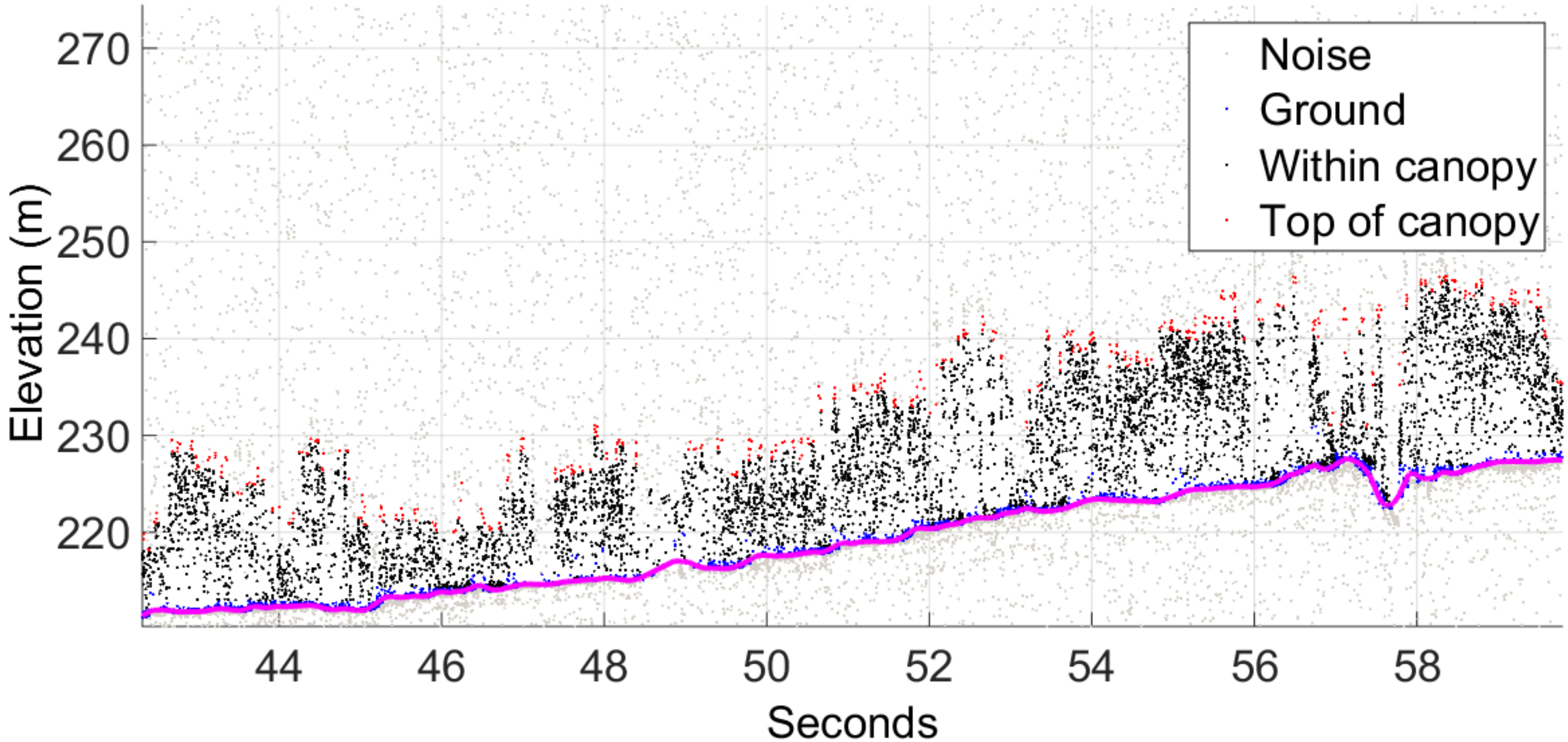
Area classification

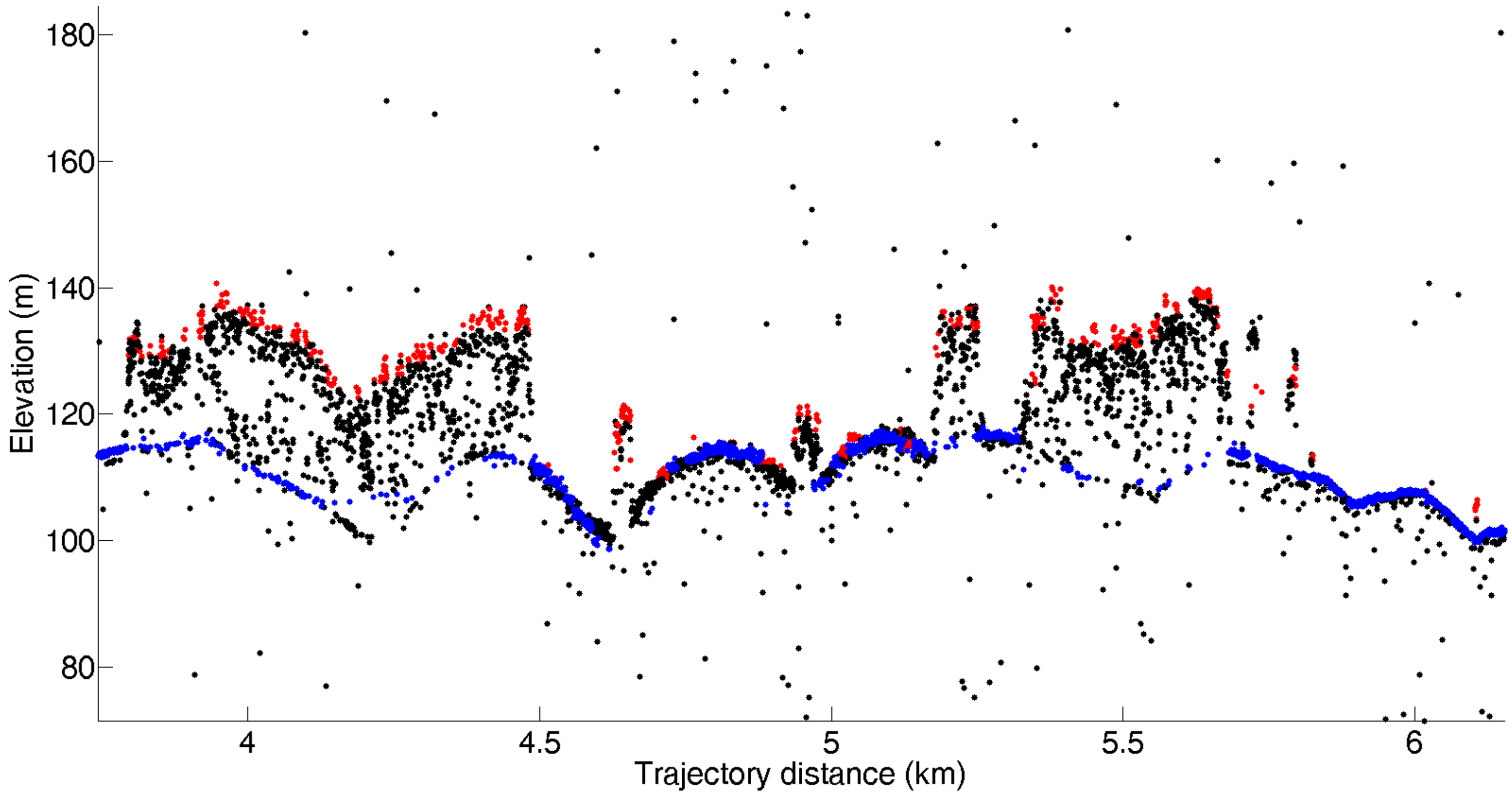
Locally weighted scatterplot smoothing (LOWESS) regression method



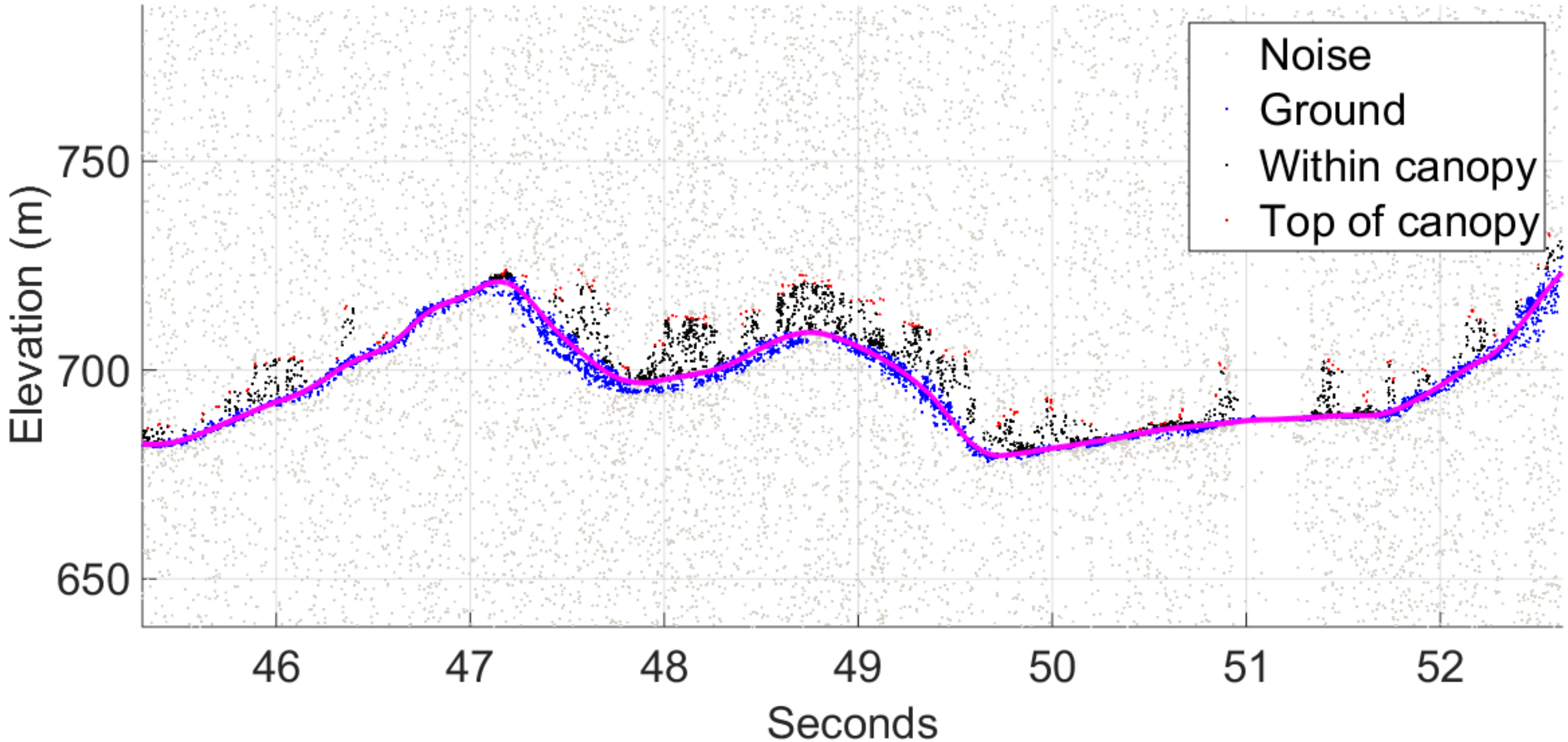
Example result



Example result



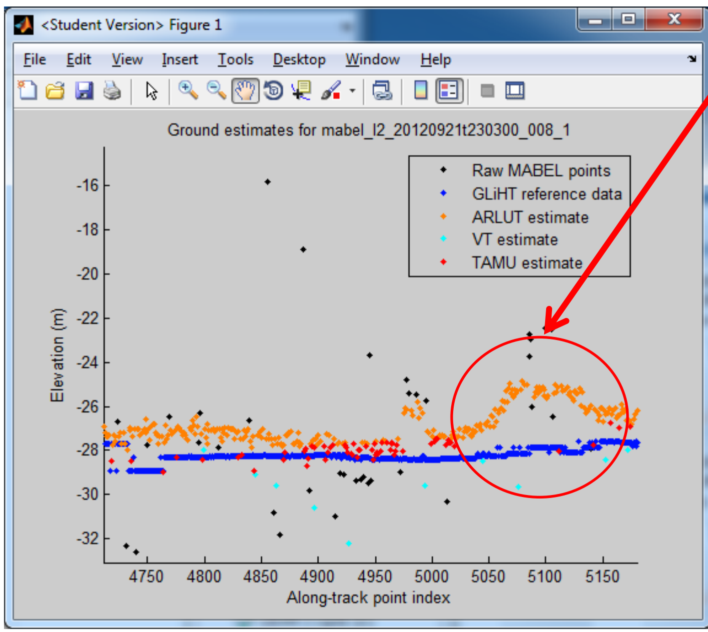
Example result

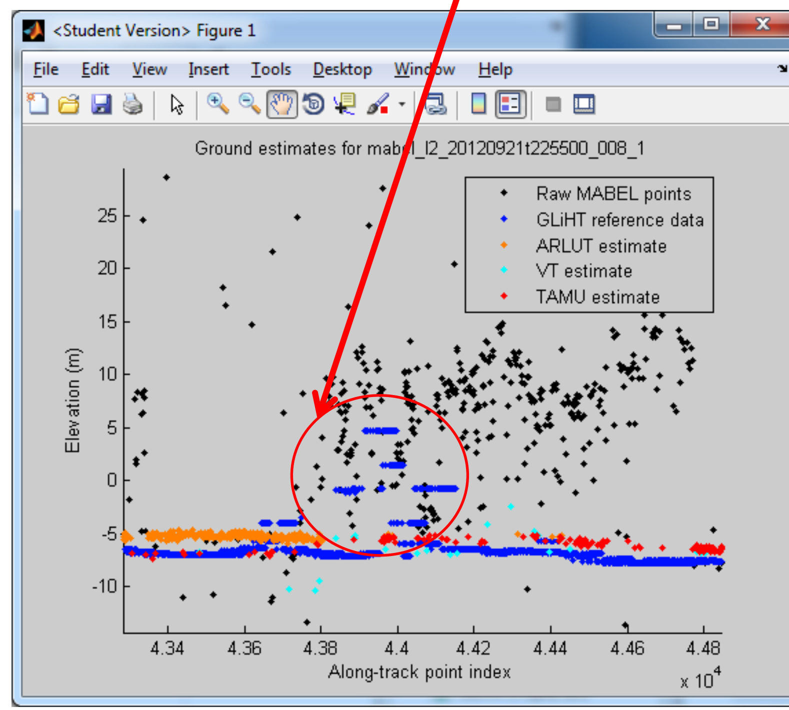


Validation (G-LiHT?)

Hill clipped in G-LiHT DTM

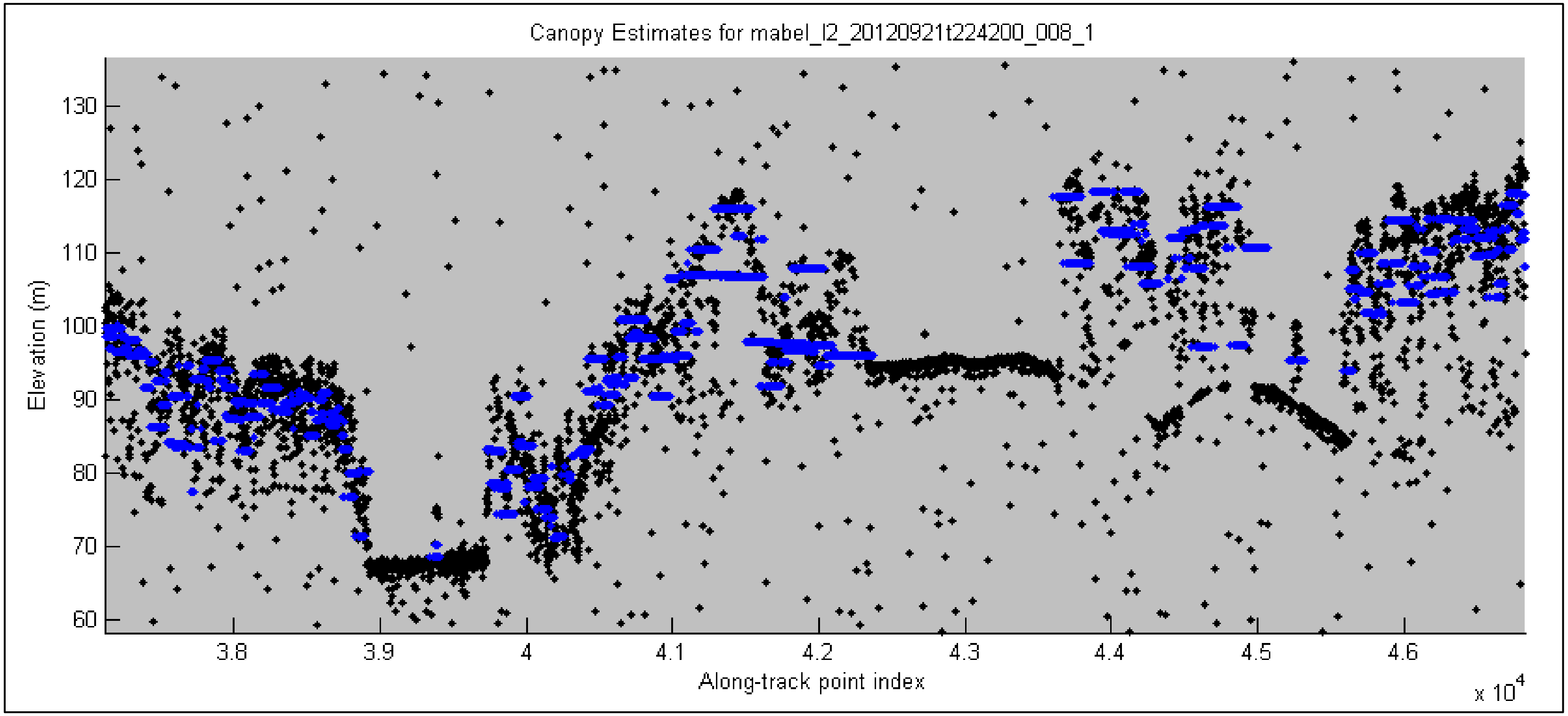
Vegetation not removed in G-LiHT DTM





From Amy Neuenschwander

Validation (G-LiHT?)



From Amy Neuenschwander

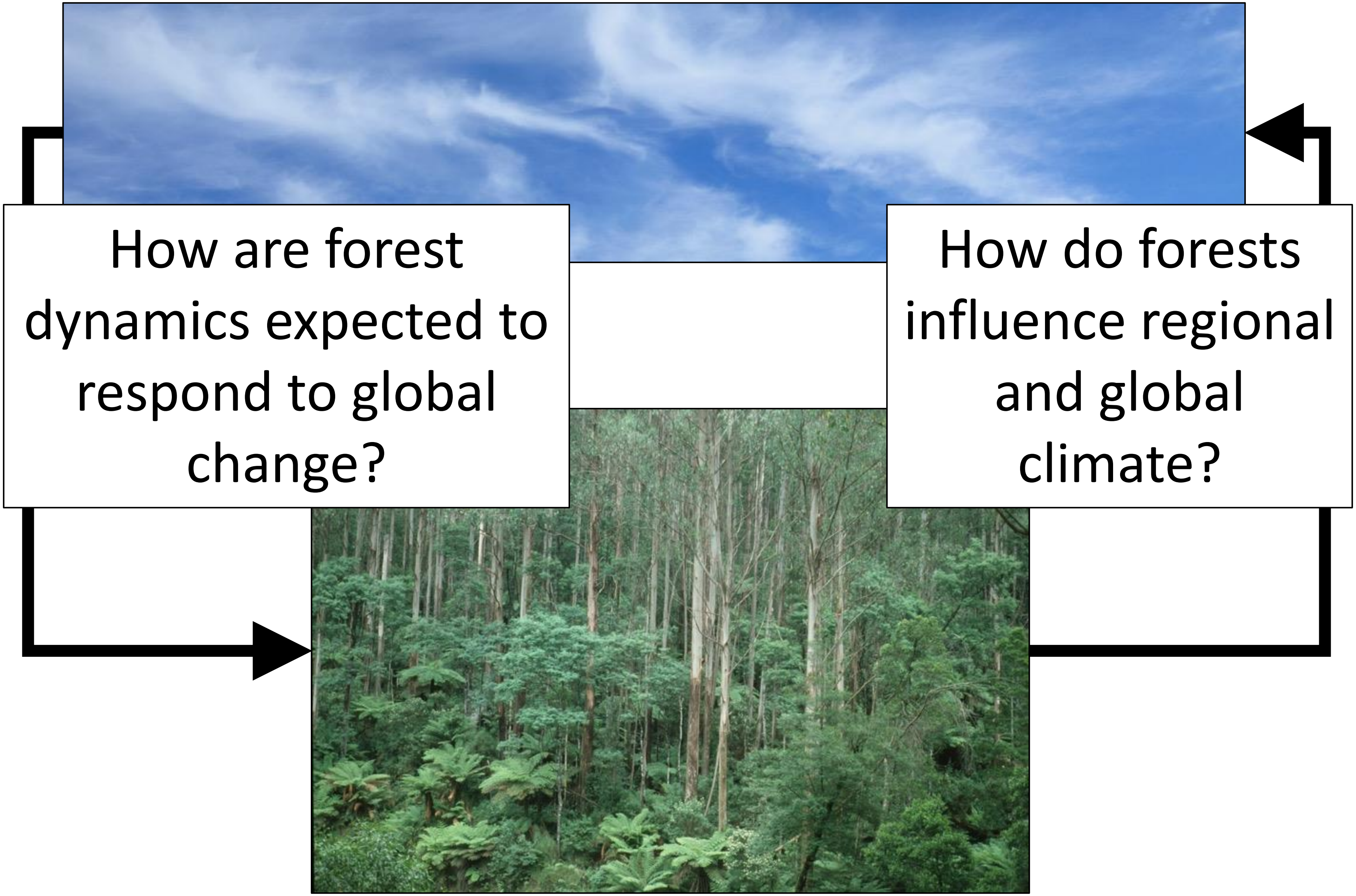
Thank you

Forecasting the Forests of the Future

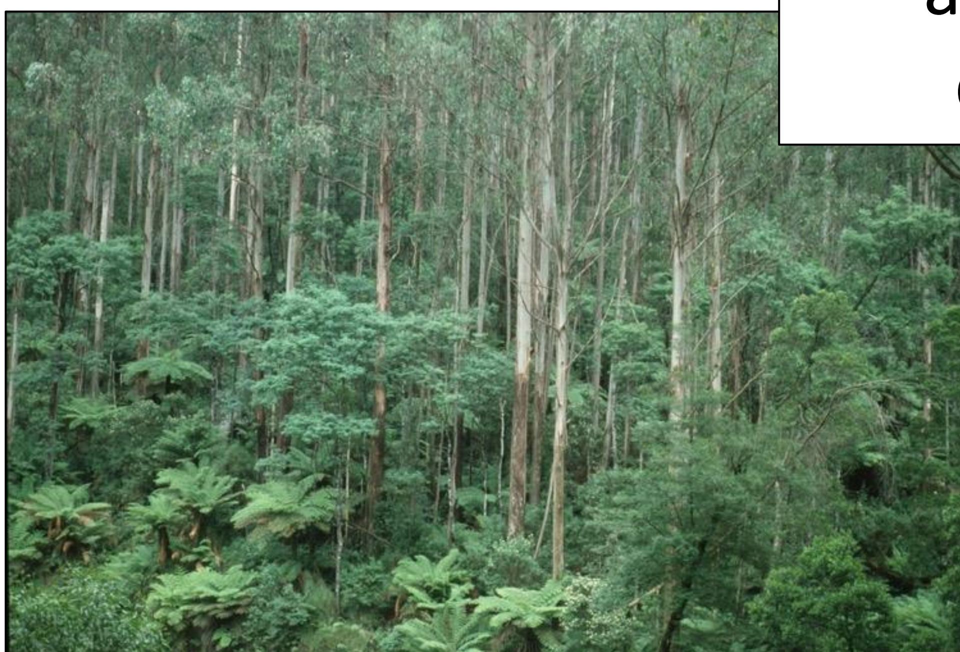
R. Quinn Thomas

Forest Resources and Environmental Conservation

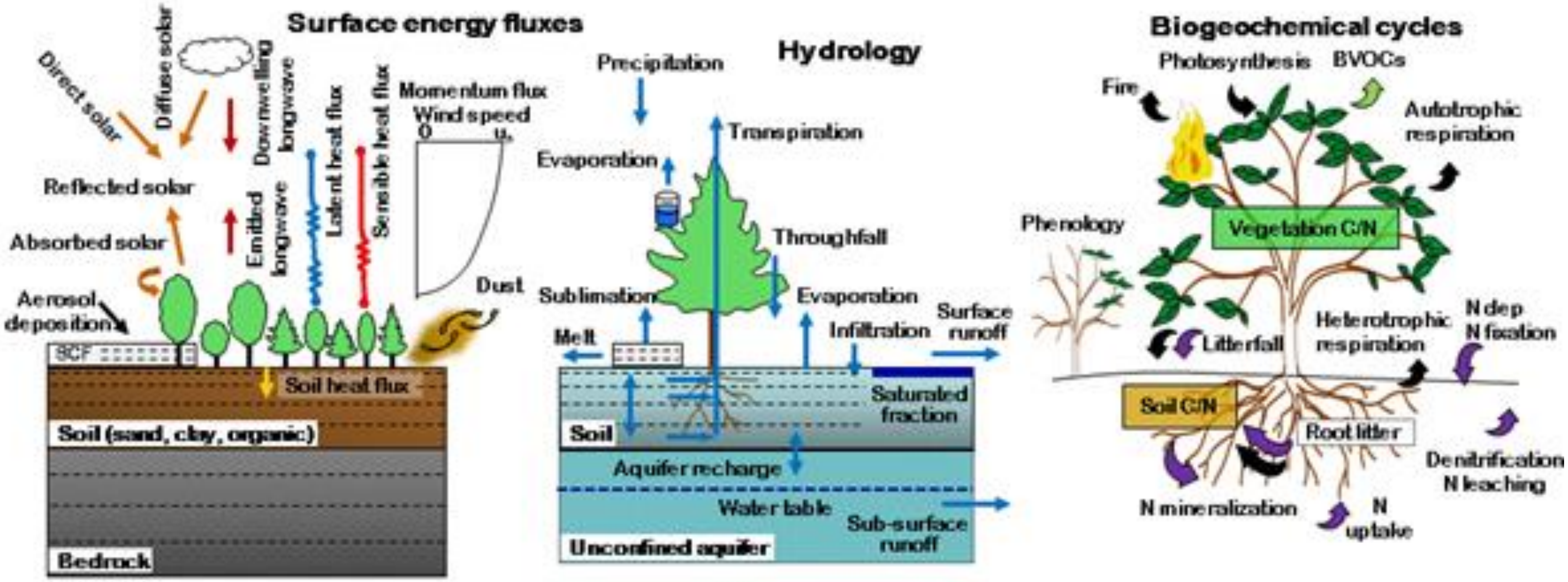
Virginia Tech College of Natural Resources and Environment


How are forest dynamics expected to respond to global change?
How do forests influence regional and global climate?

How do forests influence regional and global climate?

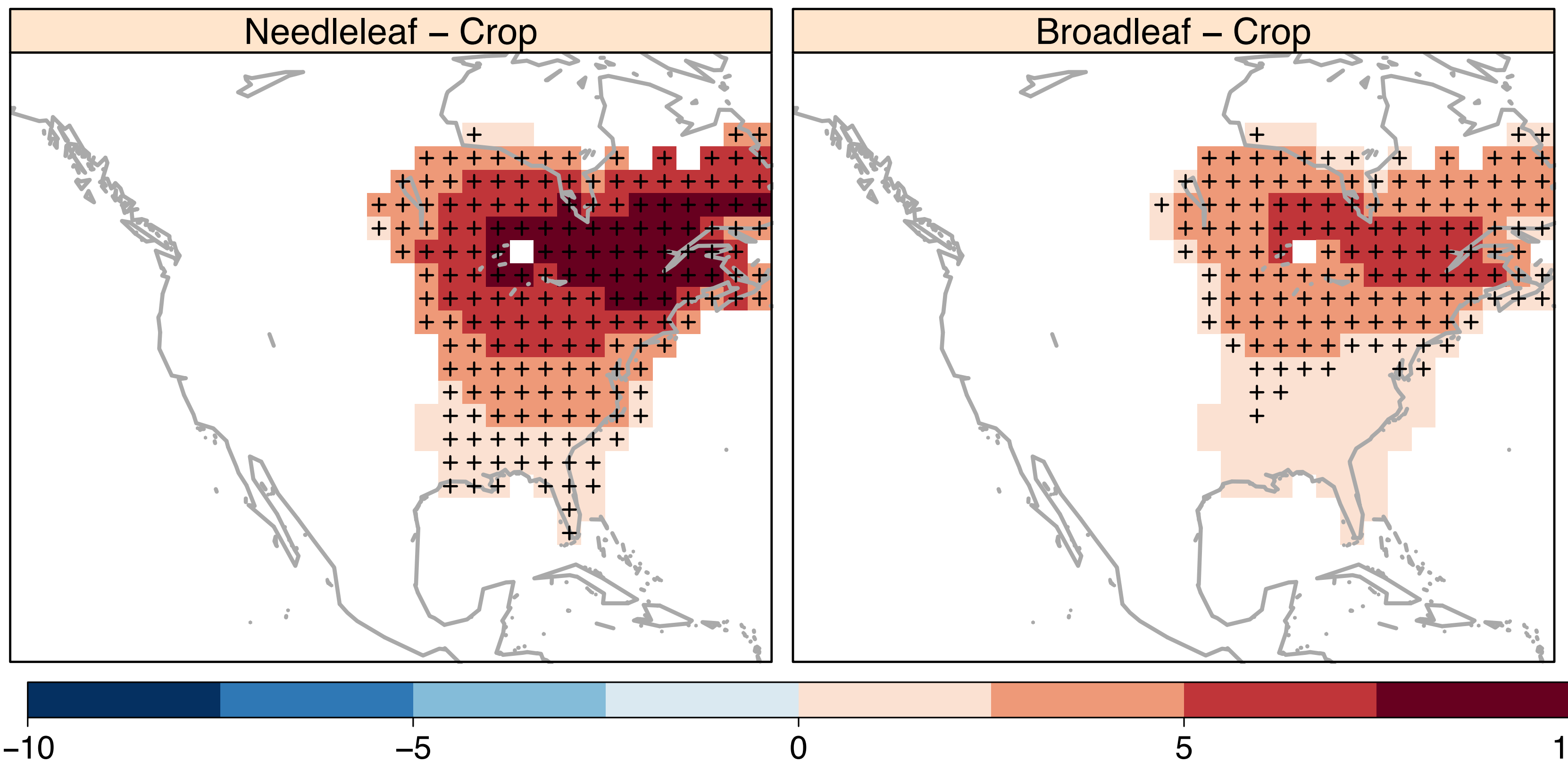


Earth System Modeling



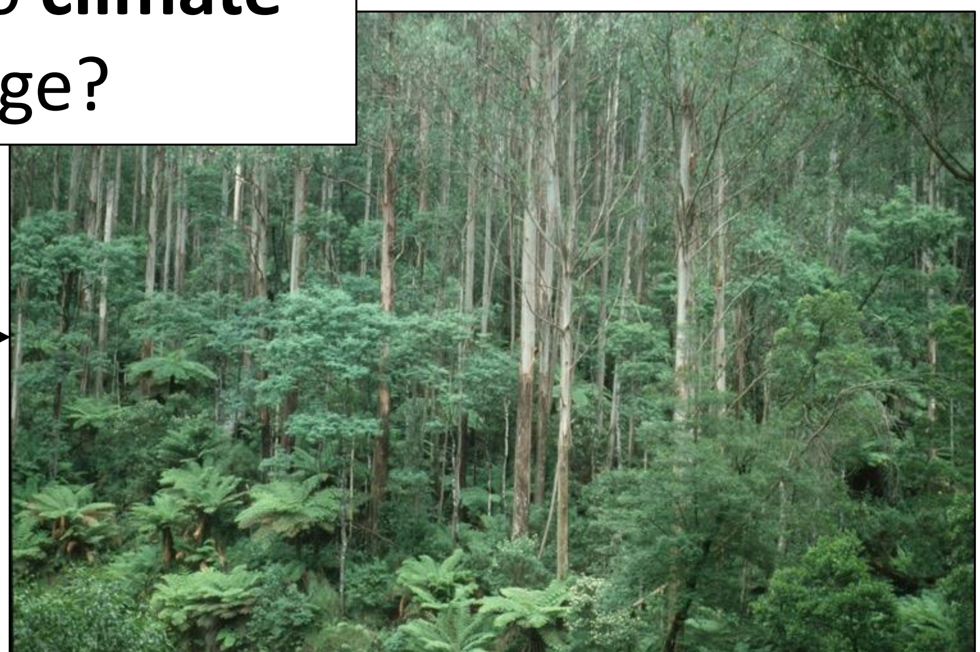
ipcc
WMO UNEP
INTERGOVERNMENTAL PANEL ON
climate change

Afforestation influence on climate



Ben Ahlswede
M.S. 2015, Ph.D.

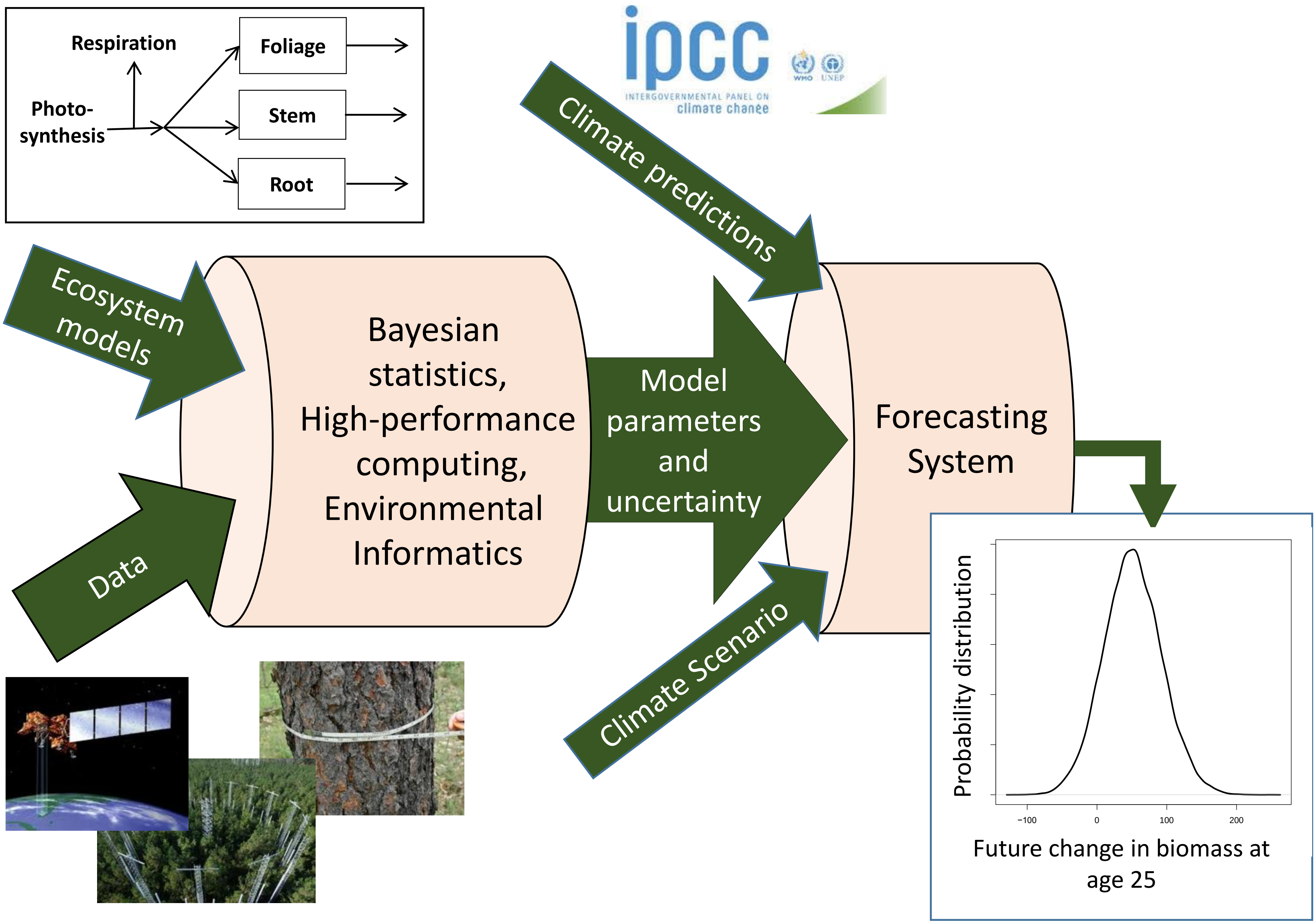
How are forest dynamics expected to respond to **climate** change?



“Study the past, if you would divine the future.”
- Confucius

"Build and parameterize a model that is consistent with past research and quantify uncertainty to forecast future forests"

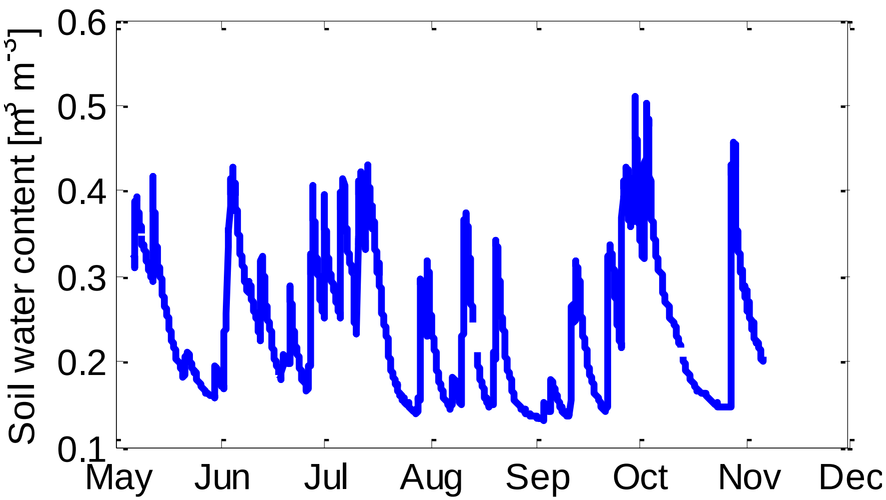
- iConfucius v2


Respiration
Photo-
synthesis
Foliage
Stem
Root
ipcc
INTERGOVERNMENTAL PANEL ON
climate change
WMO
UNEP
Climate predictions
Ecosystem
models
Data
Bayesian
statistics,
High-performance
computing,
Environmental
Informatics
Model
parameters
and
uncertainty
Forecasting
System
Climate Scenario
Probability distribution
−100
0
100
200
Future change in biomass at
age 25

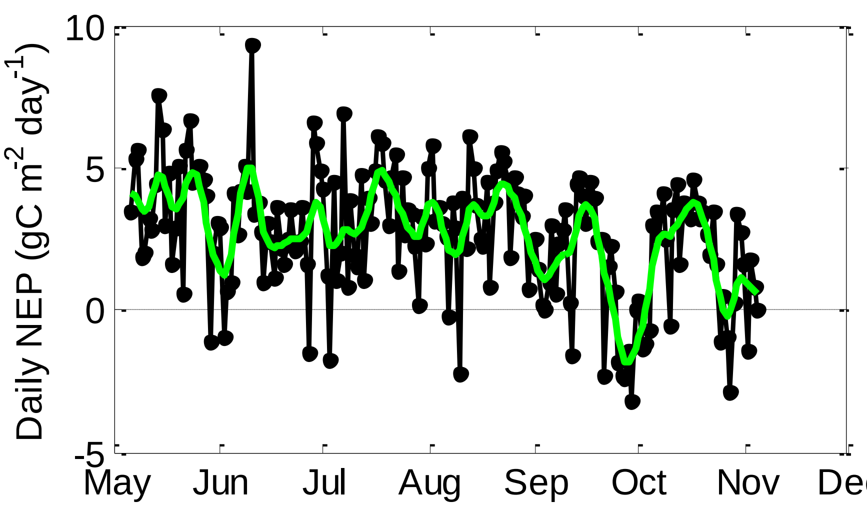
Sweet Briar - Virginia Tech Flux Tower

Dr. Tom O'Halloran

Forest response to environmental variation



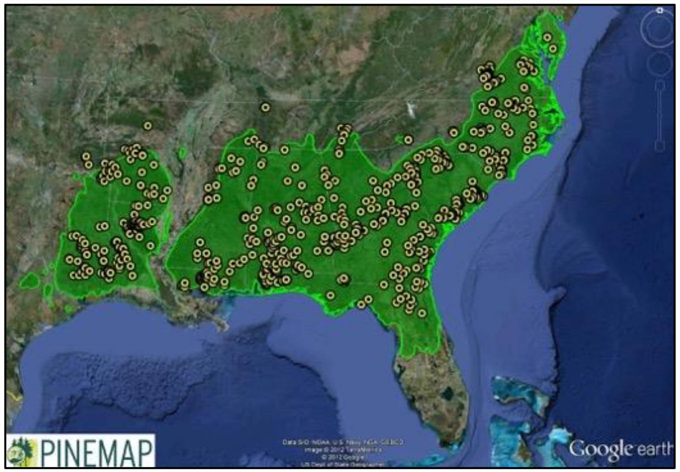
Ameriflux: US-SBC



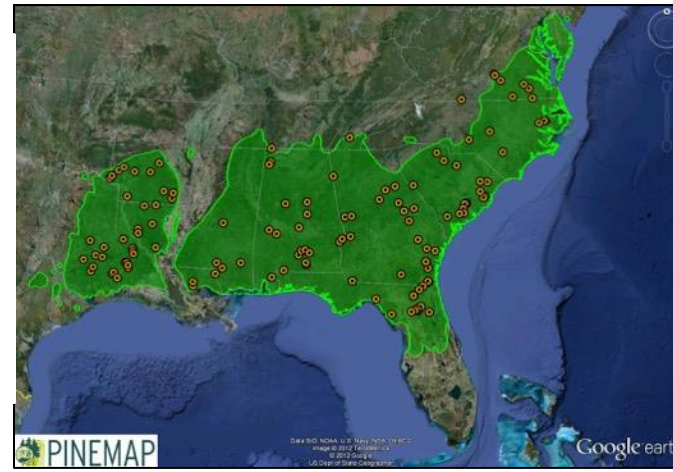
sbc-**lars**.blog.sbc.edu

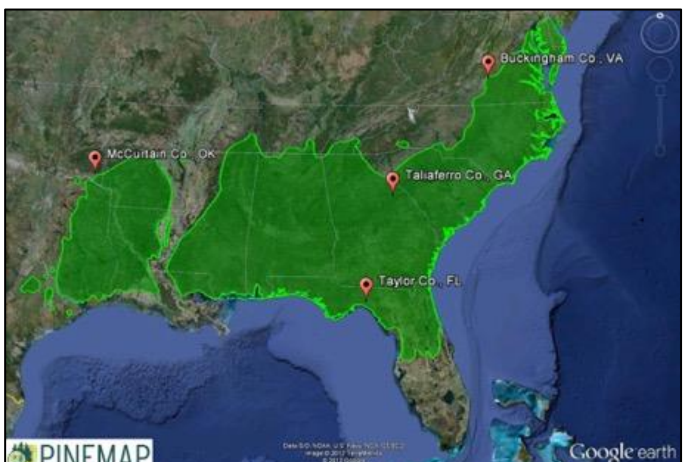
PINEMAP www.pinemap.org

Pine Integrated Network: Education, Mitigation, and Adaptation Project



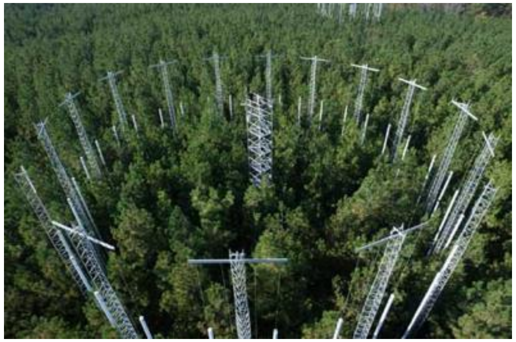
Climate gradients
Nutrient addition
<u>University-Industry Cooperatives</u>
(e.g., FPC & FMRC)
1979-present





Nutrient x Drought Factorial
(30% rain exclusion)

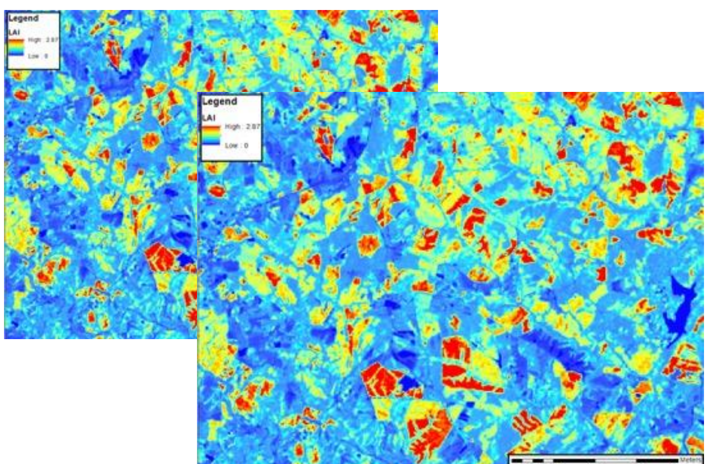
Other data in the region



Duke CO_2 Experiment
(Higher CO_2)

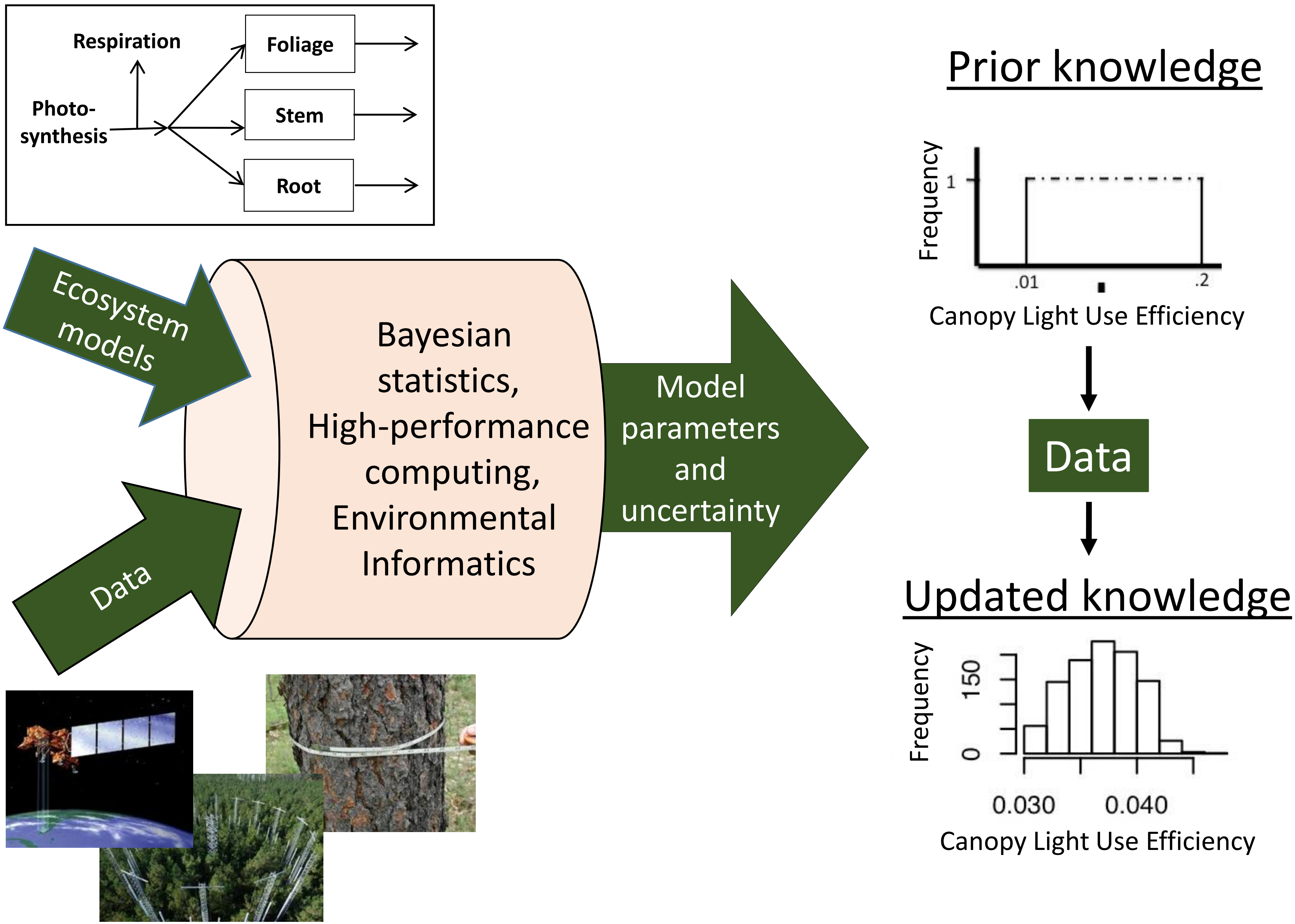
NC2 Ameriflux Tower
(Inter-annual climate sensitivity)

Duke Ameriflux Tower
(Inter-annual climate sensitivity)



Time-series Leaf Area Index (Landsat)
Climate gradients

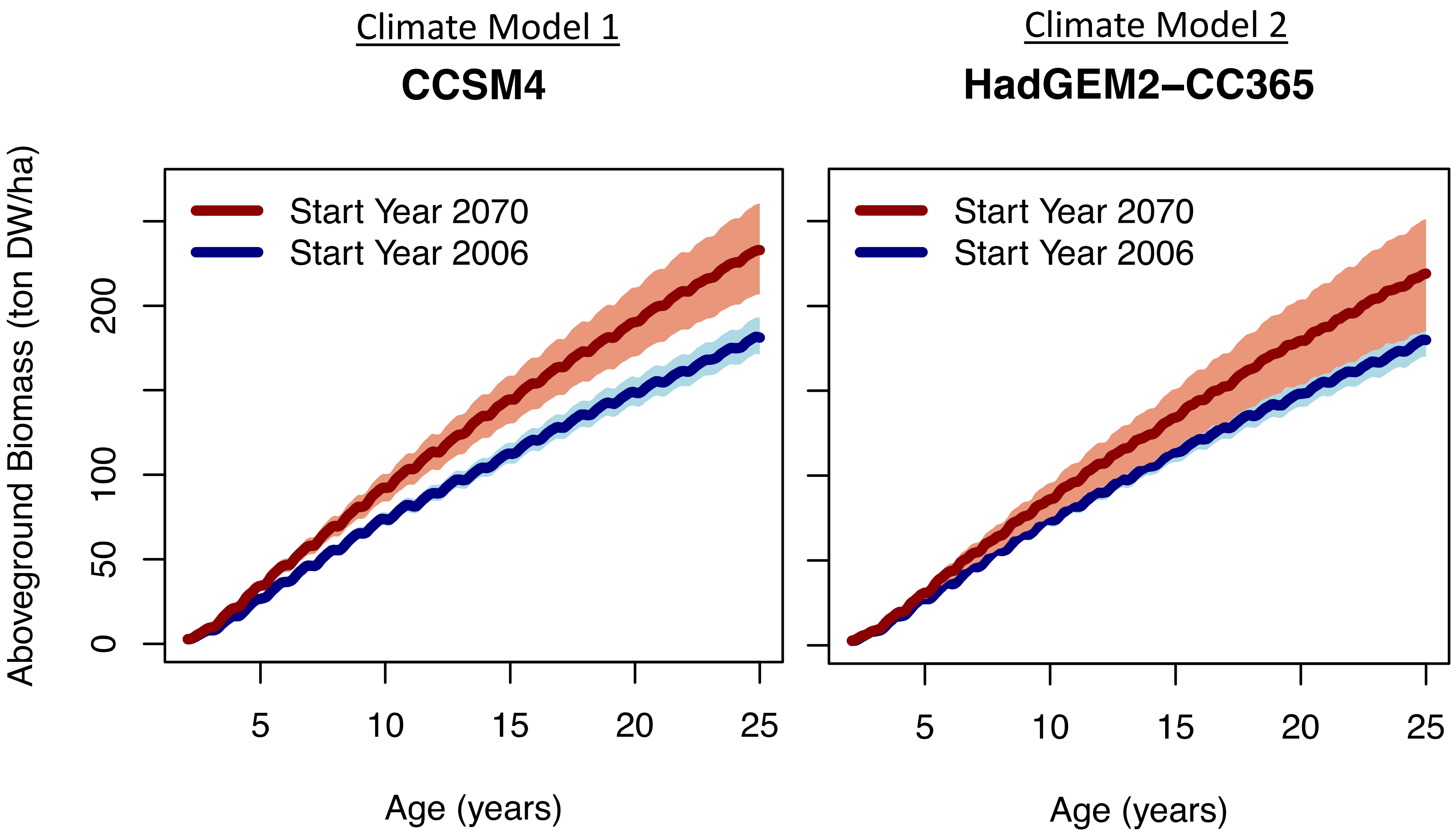
Courtesy of Images Dr. Christine Blinn



Respiration
Foliage
Photo-
synthesis
Stem
Root
Ecosystem
models
Data
Bayesian
statistics,
High-performance
computing,
Environmental
Informatics
Model
parameters
and
uncertainty
Prior knowledge
Frequency
1
.01
.2
Canopy Light Use Efficiency
Data
Updated knowledge
Frequency
0
150
0.030
0.040
Canopy Light Use Efficiency

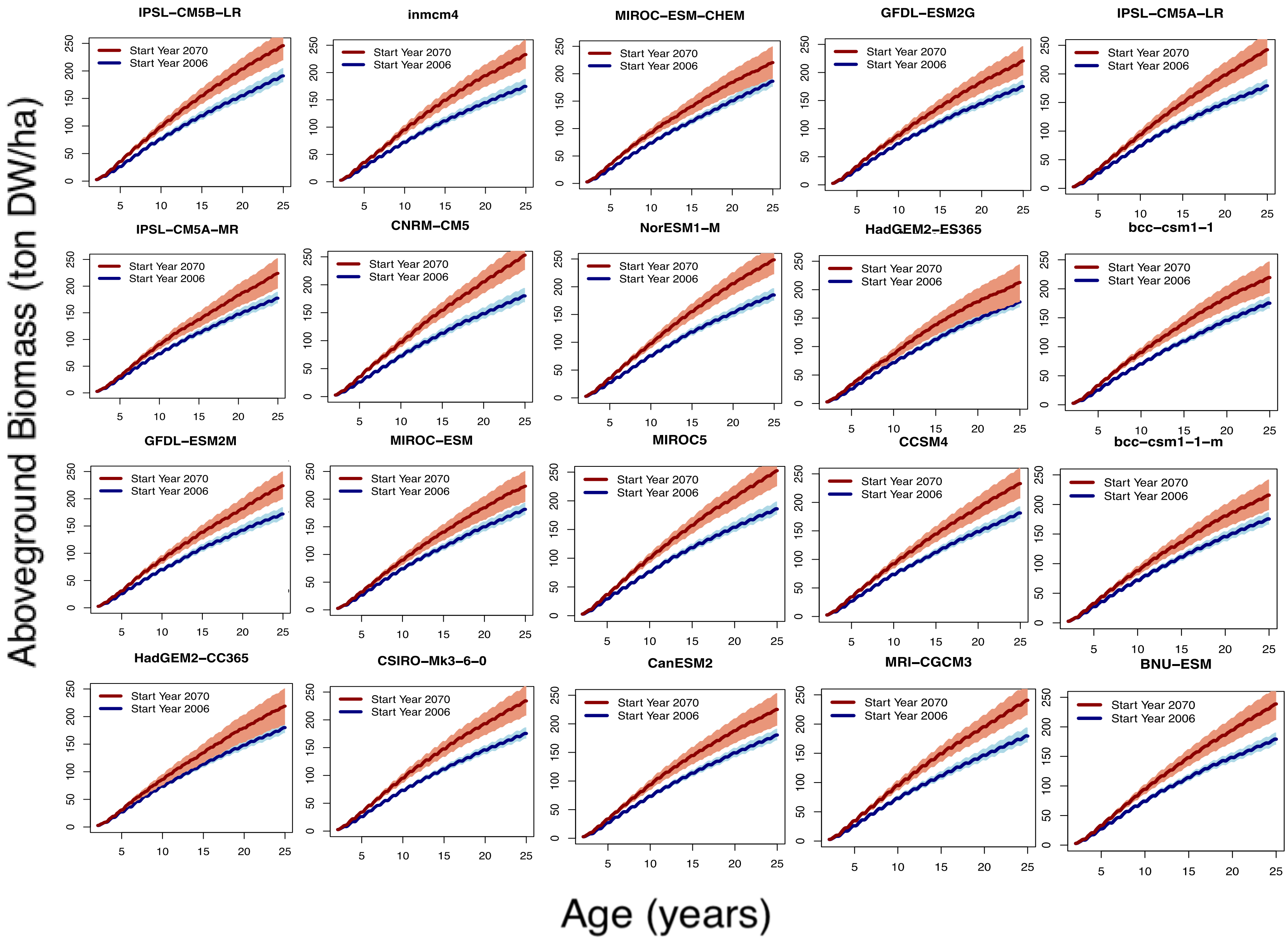
Forecasts

Annika Jersild
M.S. Student

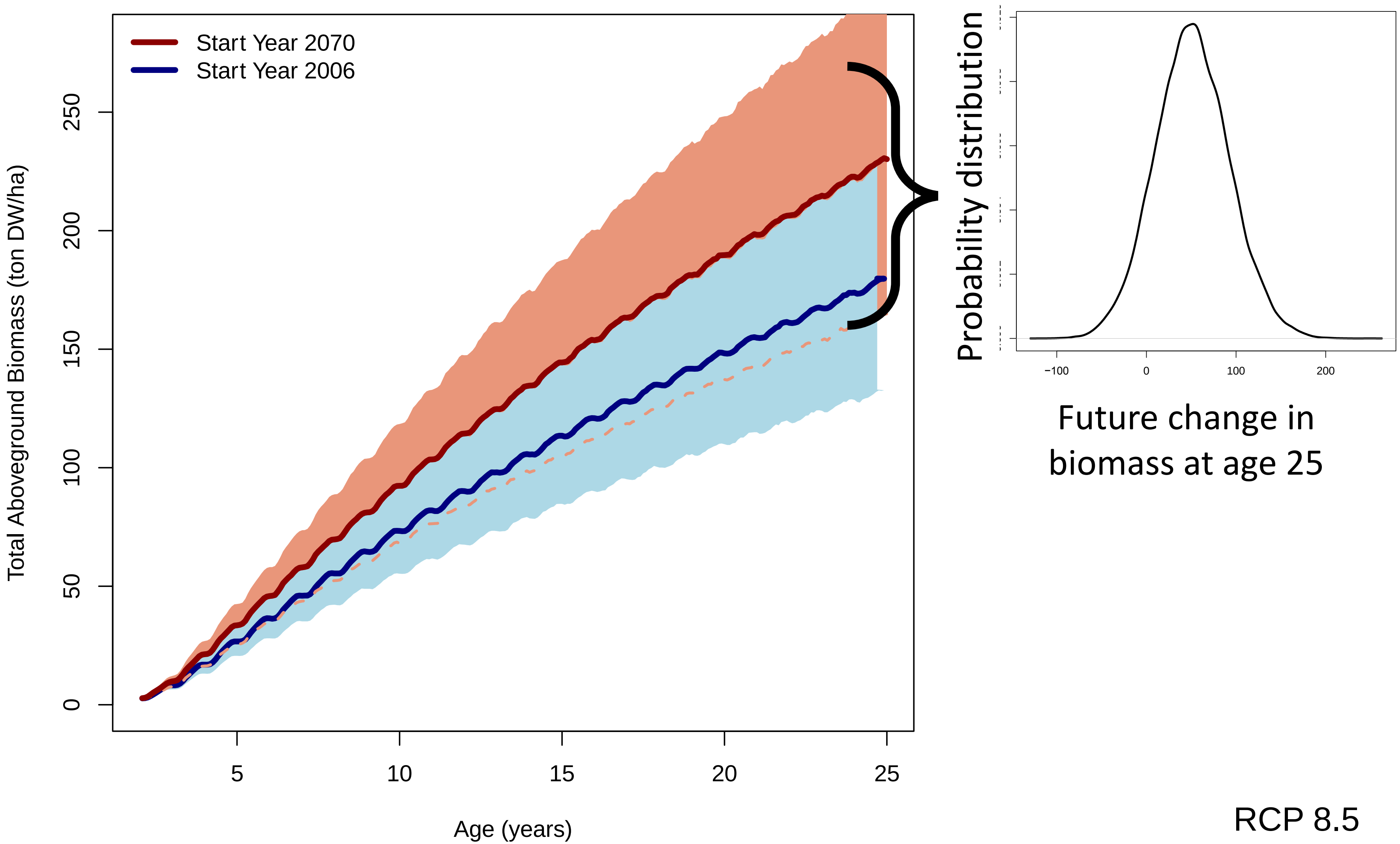


RCP 8.5

20 different climate models



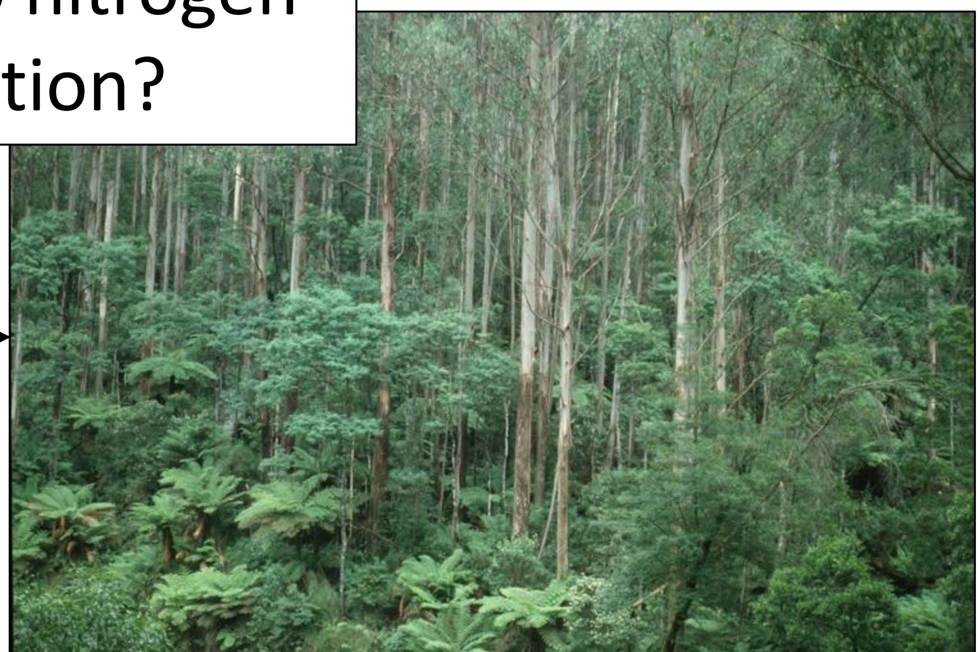
Full integration of uncertainty



Future change in biomass at age 25

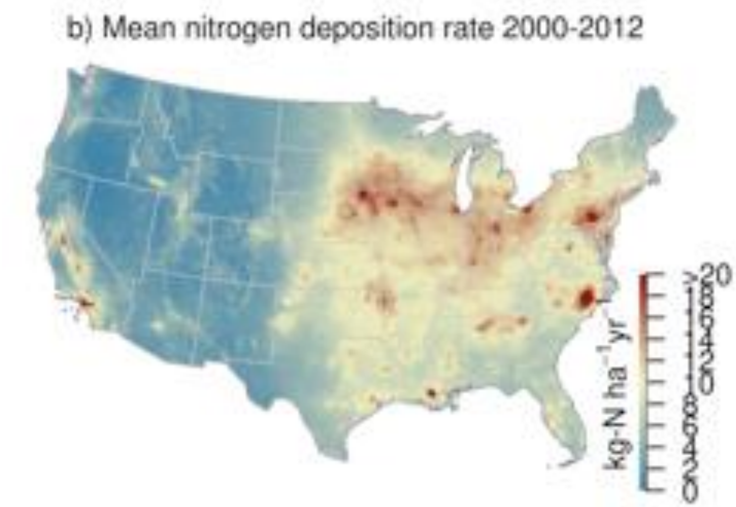
RCP 8.5

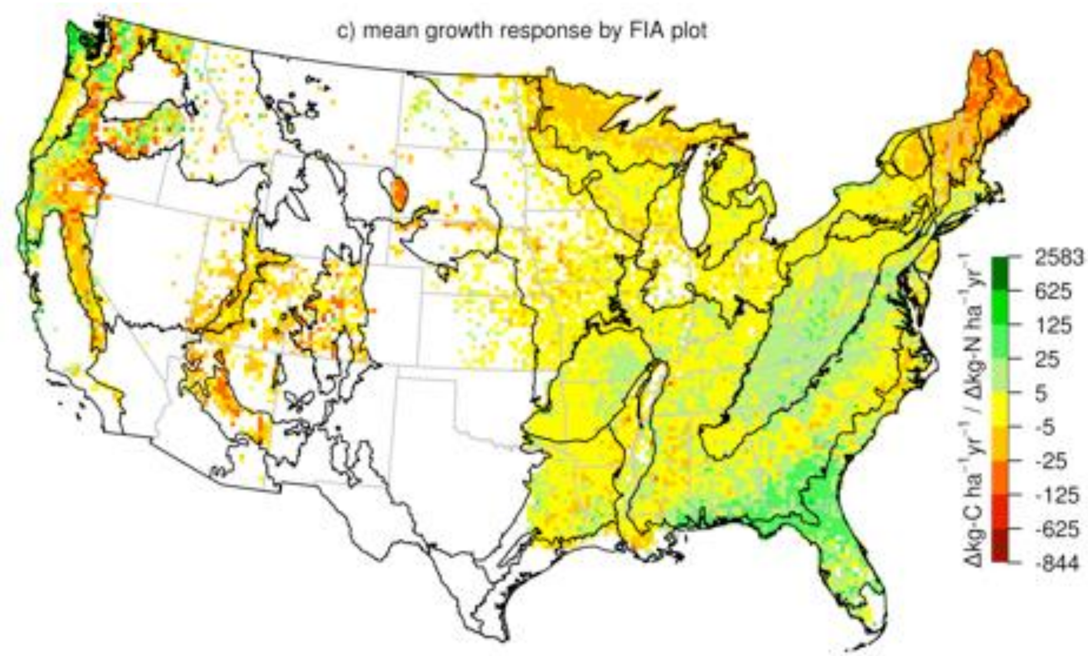
How are forest dynamics expected to respond to nitrogen deposition?



Tree growth response to N deposition

Dr. Kevin Horn, Post-doc





U.S. Forest Service Inventory and Analysis Data

Carbon response to additional nitrogen deposition

USDA

United States Department of Agriculture
National Institute of Food and Agriculture

FOREST SERVICE
U S
DEPARTMENT OF AGRICULTURE

USGS
science for a changing world

EPA
United States
Environmental Protection
Agency

VT
Global Change Center

Forest Productivity &
Forest Modeling Research
Cooperatives

University Libraries Services

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Personnel

Consultation Services

- College Librarian for Natural Resources & Environment
- Government Documents & Maps Librarian
- Geospatial Data Consultant
- Research Data Consultant
- Data Curator

Administration

- Associate Dean for Research & Informatics
- Assistant Director for Data Services

Traditional Services

College Librarian for Natural Resources & Environment

- Collection Management
- Instructional Services
- Research Assistance

Other Services

- Interlibrary Loan
- Off campus access & troubleshooting

New services

- Port ** (GIS) ***
- Publishing

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Conference Support

Government Documents & Maps Librarian
Geospatial Data Consultant Collection

Search ogis.org.vt.edu:

Search Go

- Researchers & Staff
- GIS Labs & Facilities
- Research Projects
- Annual VT GIS Research Symposium
- UCGIS
- Maps, Cartographic Data

Maps Librarian
Bruce Obenhaus
540-231-6181
2005 Newman Library

GIS specialist
Ed Brooks
540-231-9225

2015 GIS and Remote Sensing Research Symposium

April 10, 2015 | 1:00 - 5:00 pm
Virginia Tech, Newman Library Multipurpose Room (first floor)

GIS
Office of Geographic Information Systems and Remote Sensing Research

2015 Program

1:00 – 1:30	**Geospatially Enabling Decision Making.** Kathleen Hancock, PE, PhD VT Via Department of Civil and Environmental Engineering.
1:30 – 2:00	**UAV Solutions: A New Tool to Quickly Obtain Precise 2D and 3D Maps at Low Operational Costs.** Chris Robson, Caron East, Inc.
2:00 – 2:30	**Break. Opportunity to network and view posters.**
2:30 – 3:00	**Atmospheric Sampling Challenges and Opportunities using Small Unmanned Aircraft Systems.** Craig Woosley, Ph.D., VT Department of Aerospace & Ocean Engineering.
3:00 – 3:30	**The Integration of Small Unmanned Aircraft Systems into the National Airspace System… and Beyond.** R. Lance Nuckolls, Unmanned Aircraft Systems Integration Office, Federal Aviation Administration.
3:30 – 4:30	**Poster Session and social.**
4:30	**Poster awards and closing remarks**

Sponsor Acknowledgements
The Virginia Space Grant Consortium (VSGC)
VirginiaView
Interdisciplinary Remote Sensing PhD Program

VIRGINIA SPACE GRANT CONSORTIUM
VIRGINIA VIEW
VirginiaView.net

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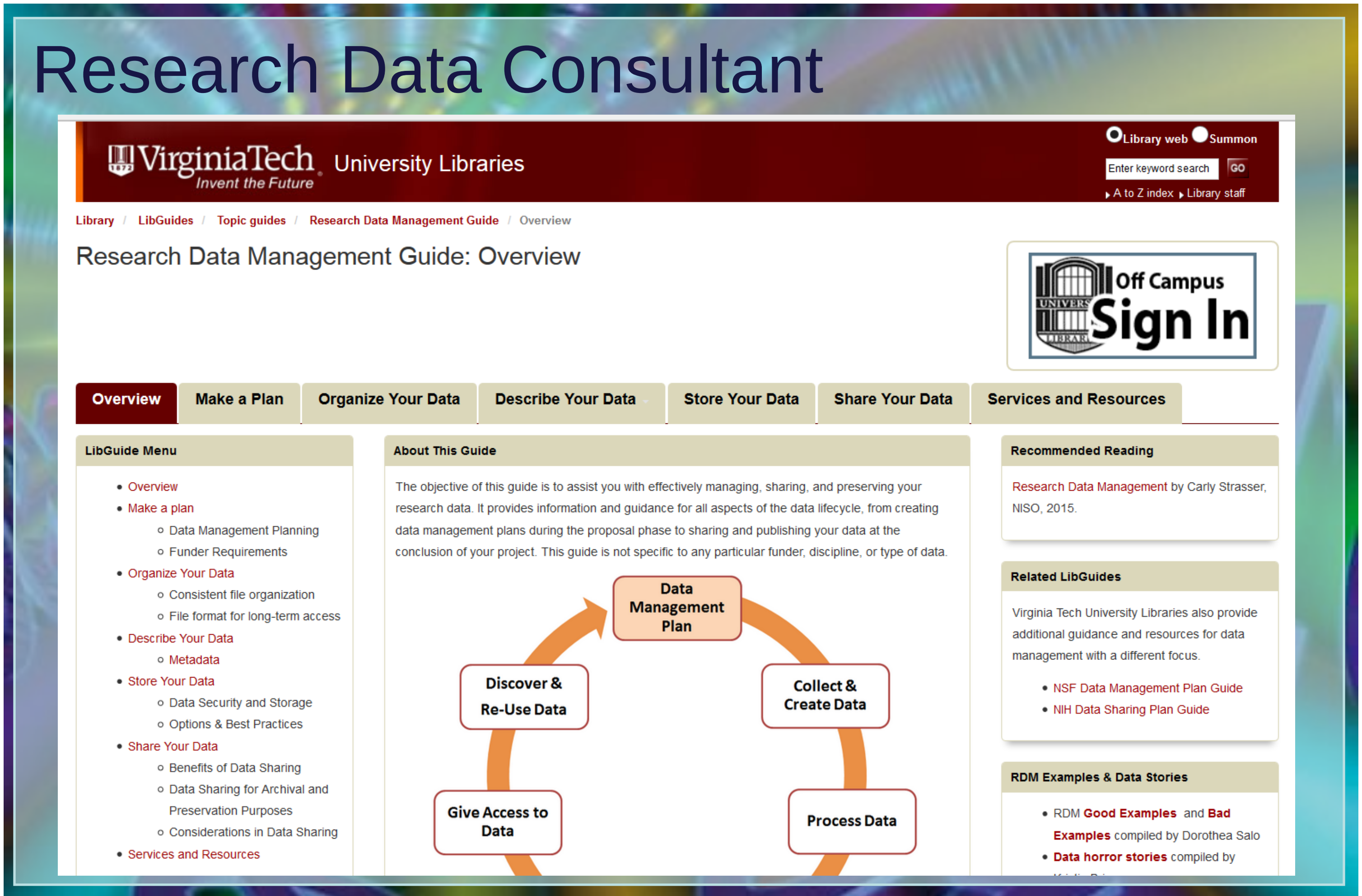
Data Services – Grant Mandates



Data Services – Project Support

Data Curator

- Workflow development for curation of our geospatial data collection
- consulting with faculty on curation issues and collecting datasets for the data repository.

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Other Initiatives

Institutional Repository ***

- Electronic Theses/Dissertations (ETDs)
- Research
    - Articles ***
    - Algorithms/Scripts ***

Publishing Support ***

- Open Access
    - Subvention Fund

Data Repository (forthcoming)

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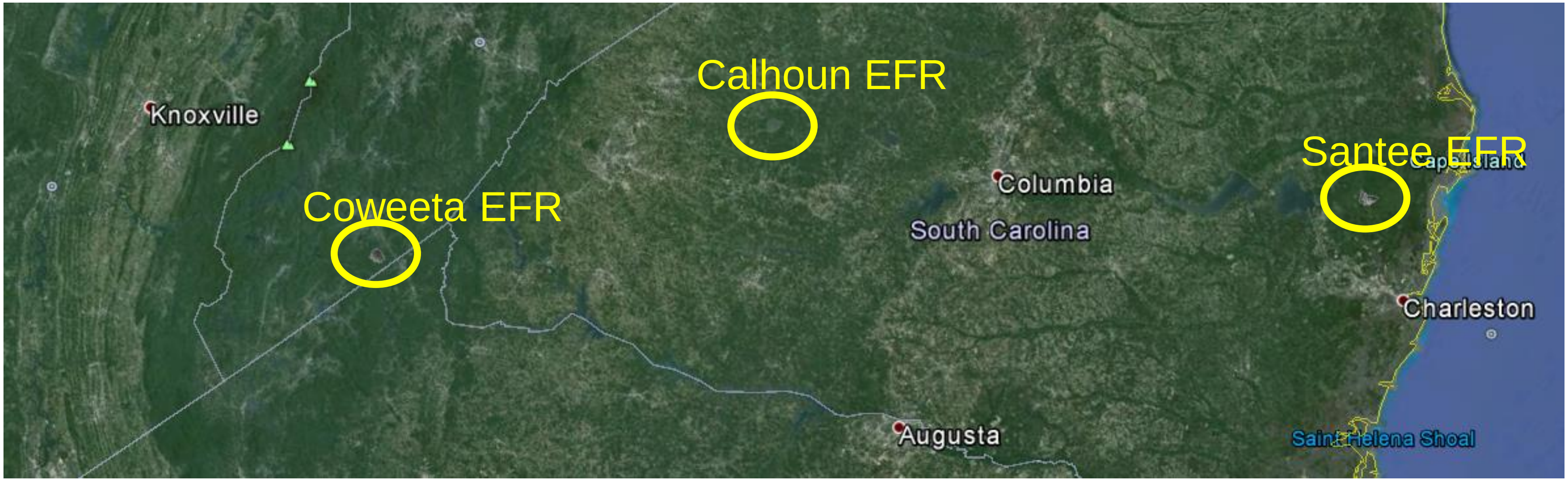
Research Projects Using Landsat

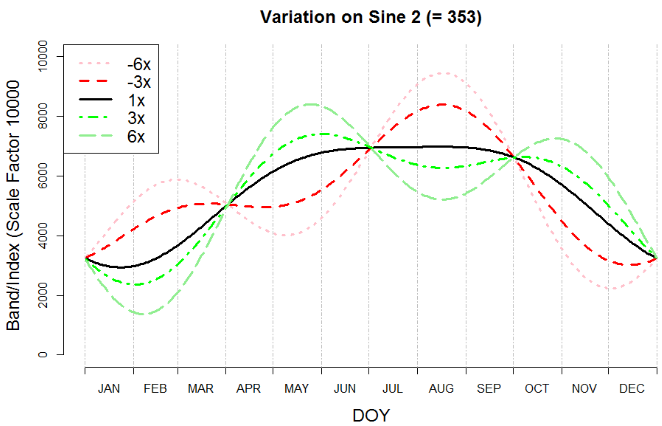
Evan Brooks

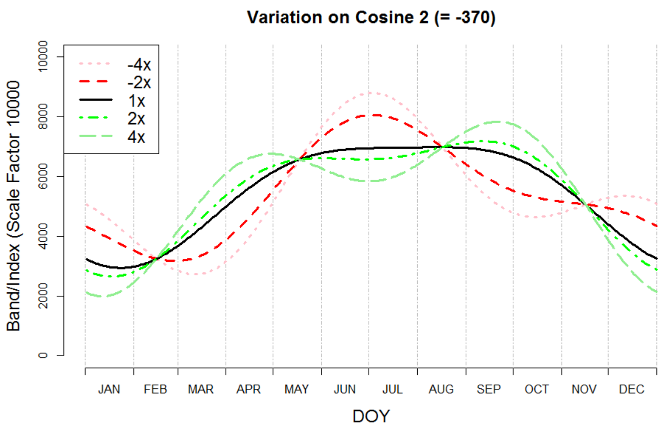
EFR Maps

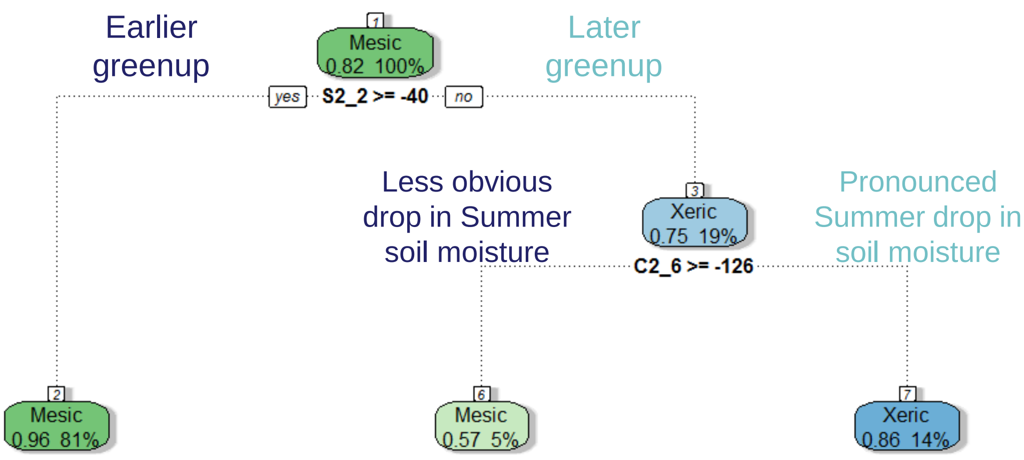
- Harmonic regression coefficients used as predictors in a conditional random forests model to make a wall to wall map of forest variables from EFR intensified plots



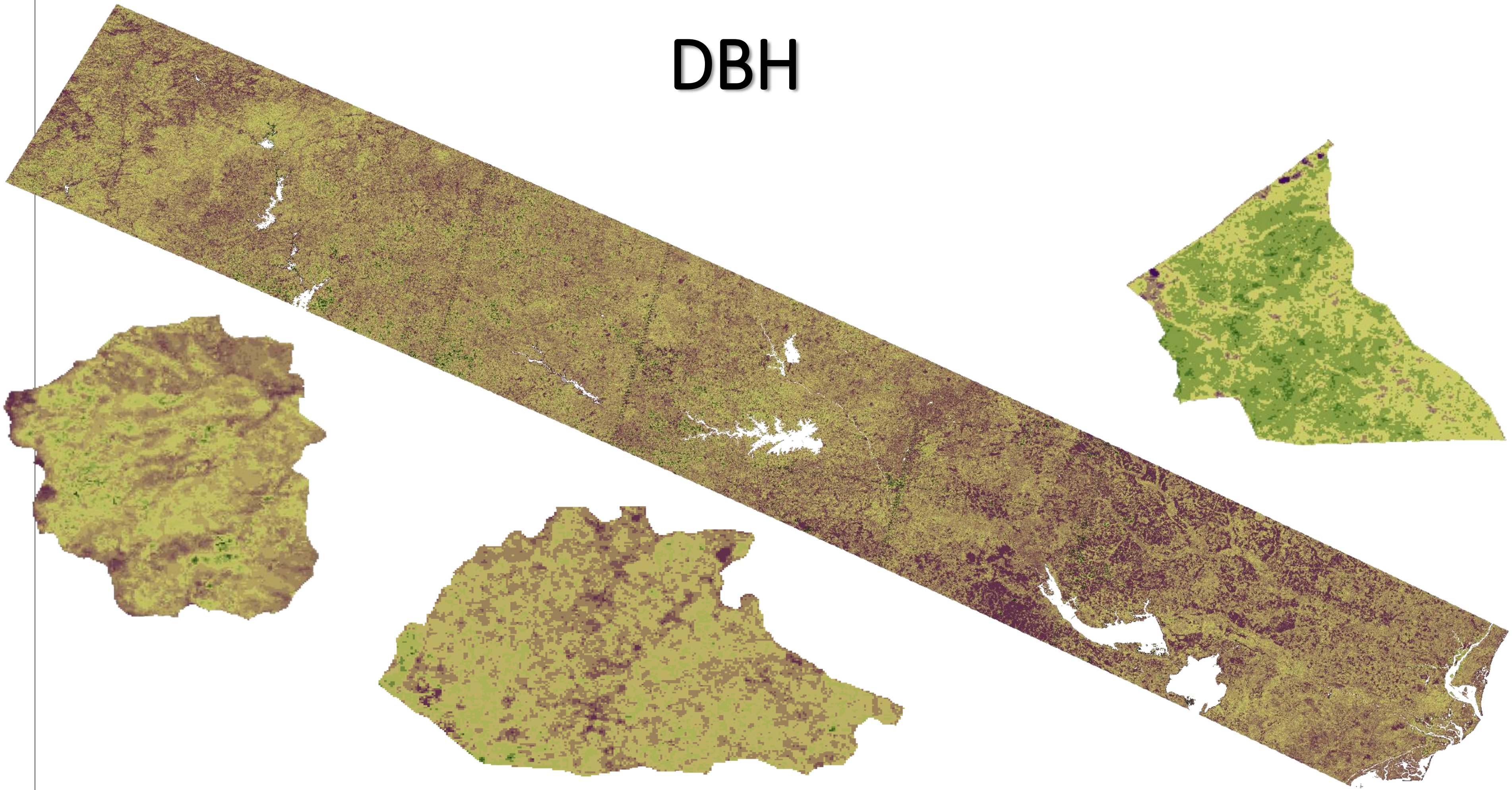
EFR Maps


Variation on Sine 2 (= 353)
-6x
-3x
1x
3x
6x
Band/Index (Scale Factor 10000
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC
DOY


Variation on Cosine 2 (= -370)
-4x
-2x
1x
2x
4x
Band/Index (Scale Factor 10000
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC
DOY

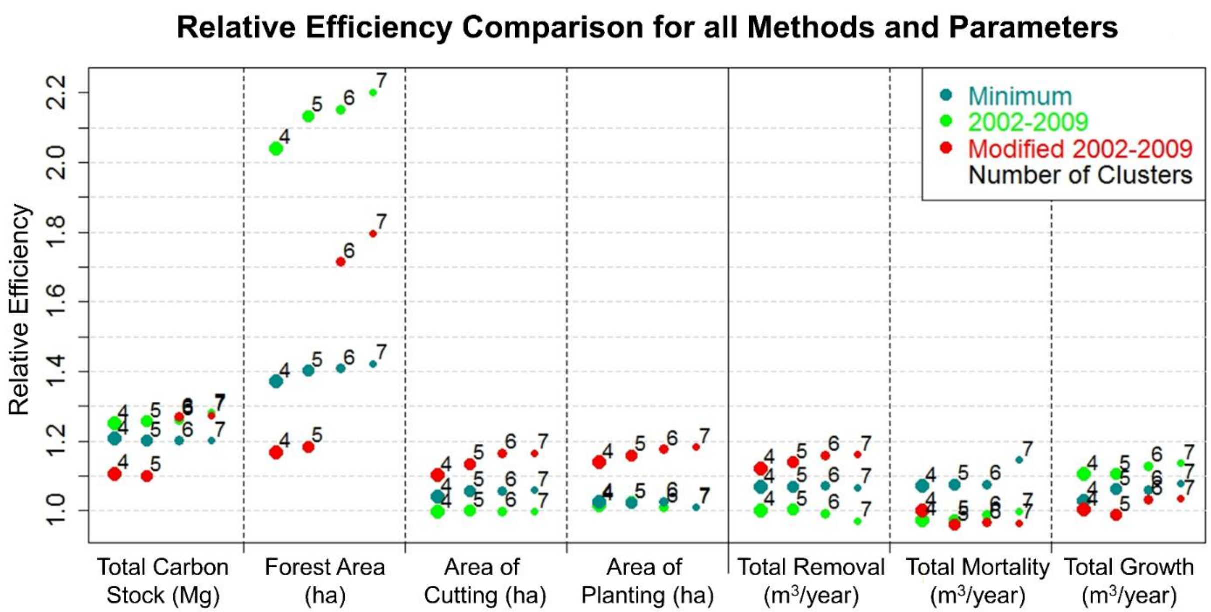

Earlier greenup
Later greenup
1
Mesic
0.82 100%
yes
S2_2 >= -40
no
Less obvious drop in Summer soil moisture
Pronounced Summer drop in soil moisture
3
Xeric
0.75 19%
C2_6 >= -126
2
Mesic
0.96 81%
6
Mesic
0.57 5%
7
Xeric
0.86 14%

DBH



Post-Stratification

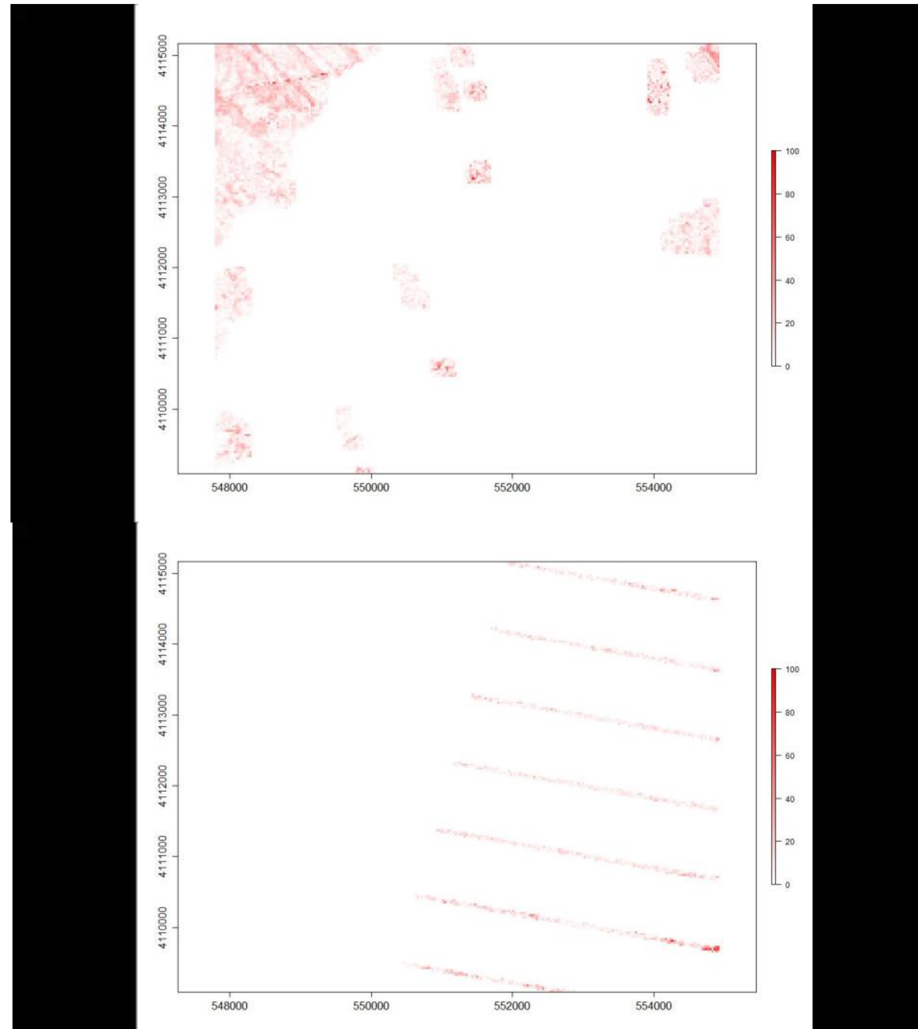
- **Using harmonic regression coefficients to build maps for post-stratification of FIA Phase 2 plots**
  - Refined version undergoing continued review in *Remote Sensing of Environment*



Source: Brooks, E. B., Coulston, J. W., Wynne, R. H., and Thomas, V. A. "Improving the precision of dynamic forest parameter estimates using Landsat." *Remote Sensing of Environment* (in review).

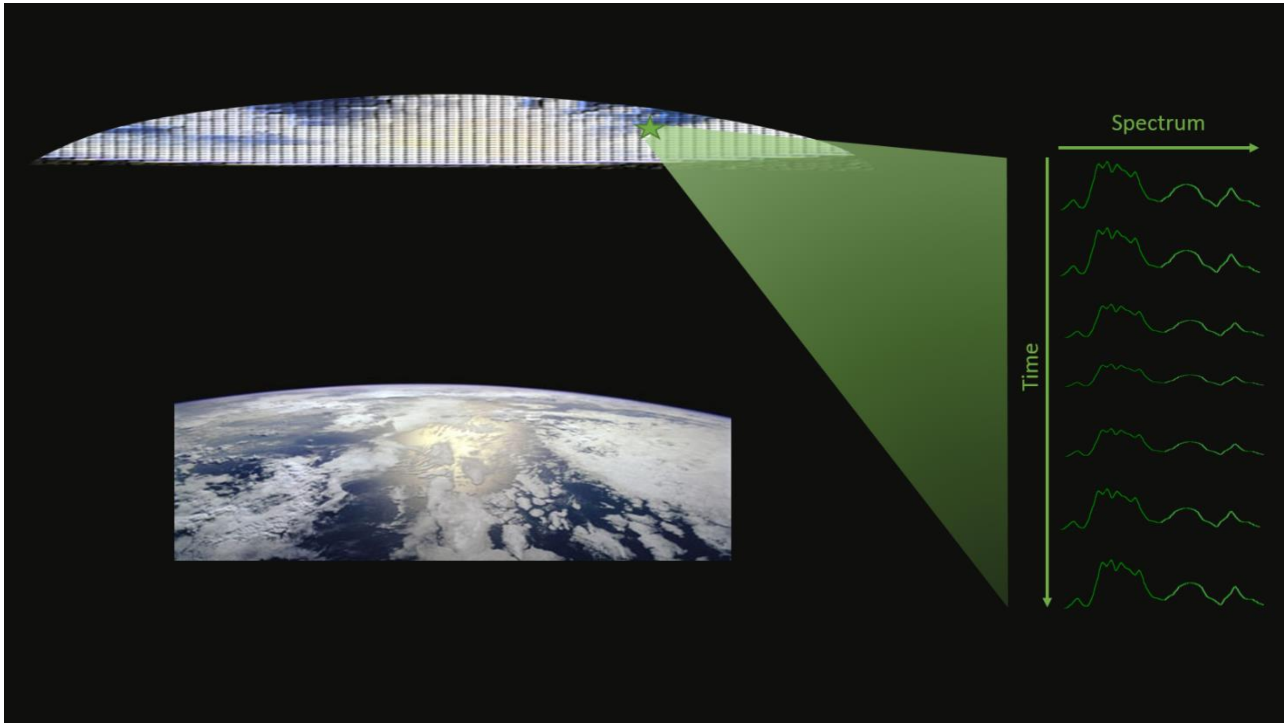
Window Regression

- Testing the applicability of WR in destriping ETM+ data and filling in cloud-masking gaps
  - Initial results suggest mean absolute percentage error of ~15%, varying by band
  - Paper submission pending (*Remote Sensing*)



Stack Archives (Starchives)

- **EWMACD implemented successfully on Hadoop via starchive architecture**
  - Fortran version also employed on standard binary format using NewRiver



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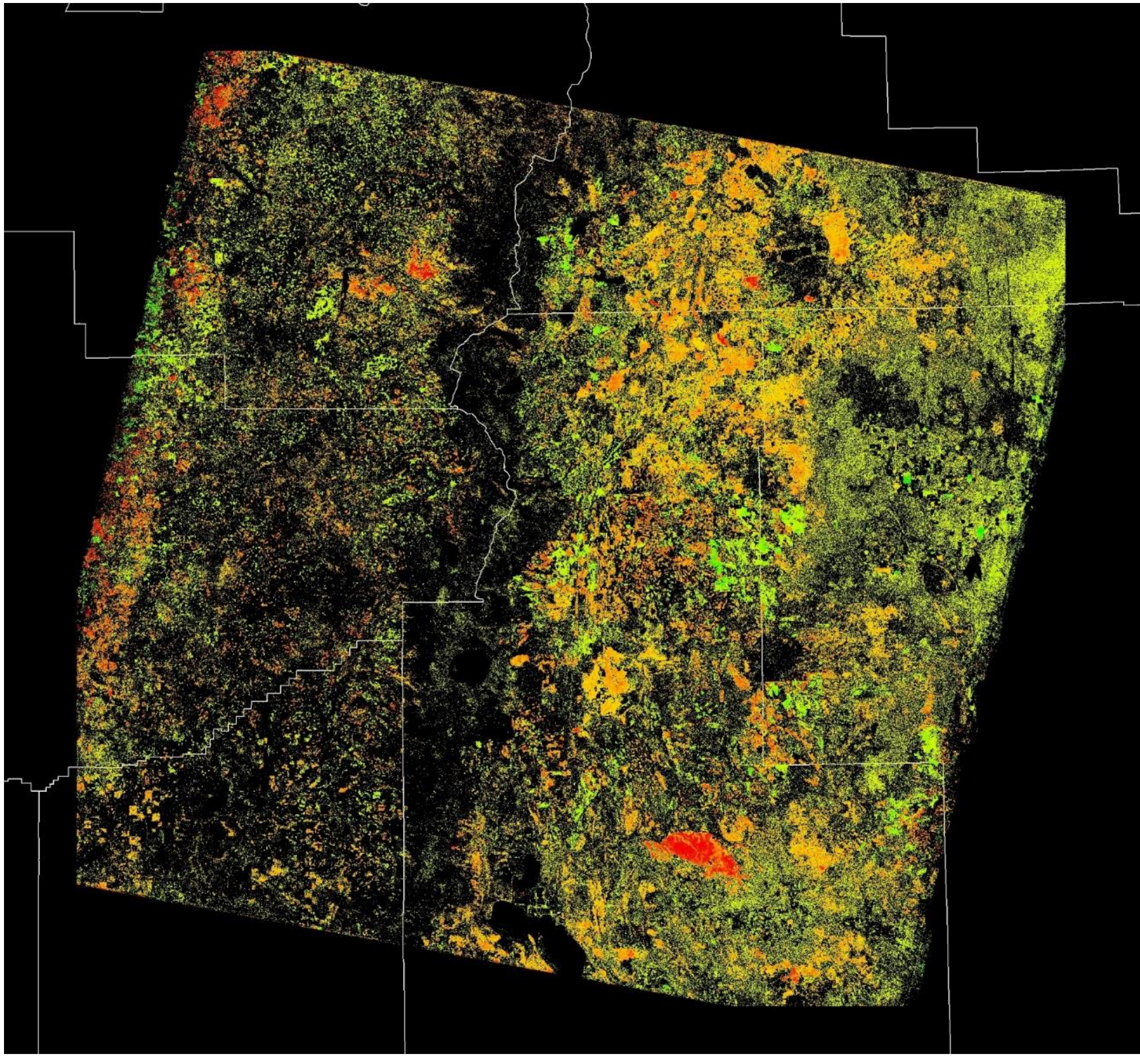
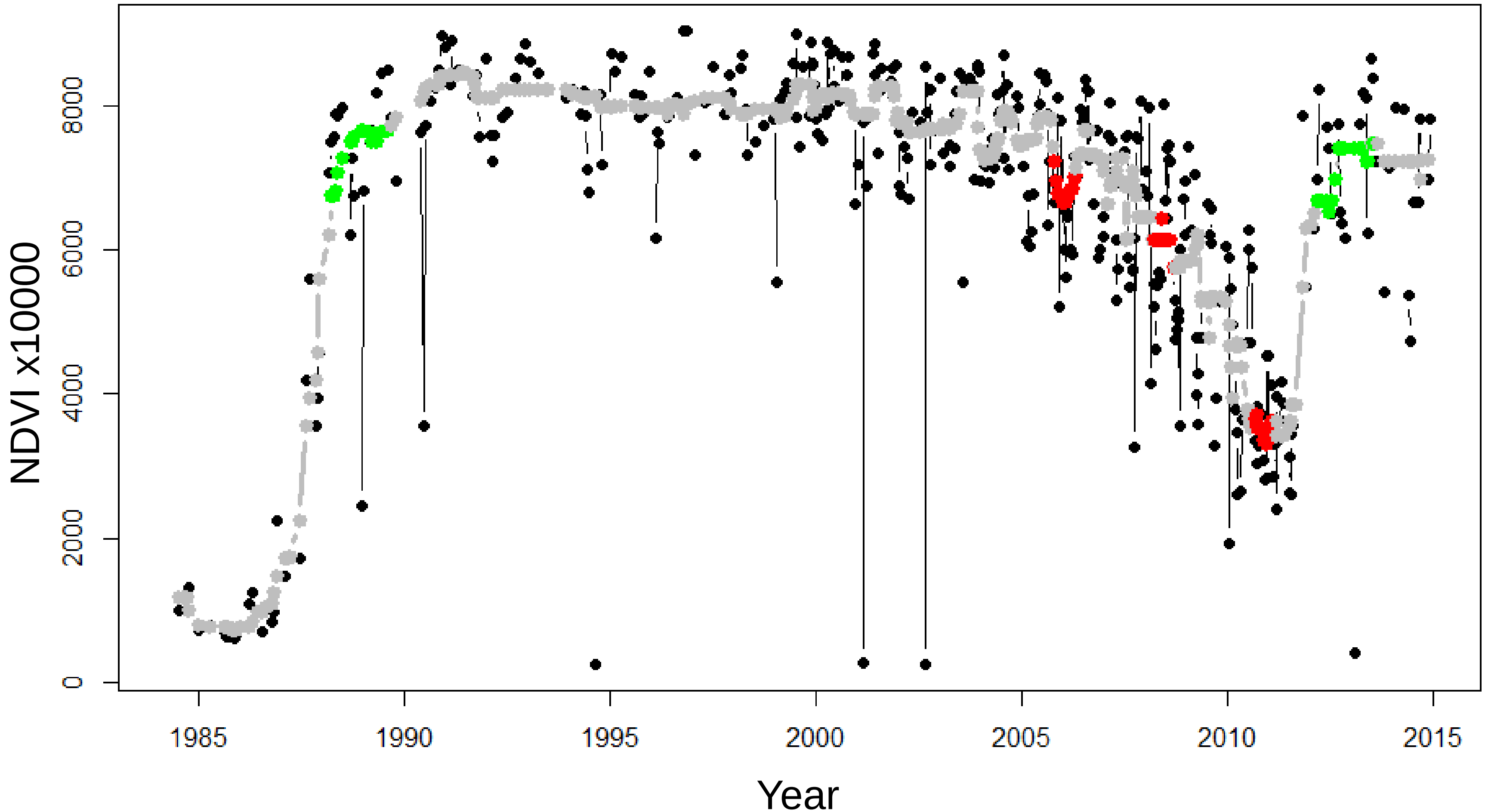
EWMACD/LCMS

- Completed processing for pilot study (six scenes, full TM history)
  - 45/30 shown
- Accuracy comparable to other LCMS base learners
  - Will use TimeSync reference data to tune EWMACD for improved agreement



EWMACD/Updates



EWMACD/Projects

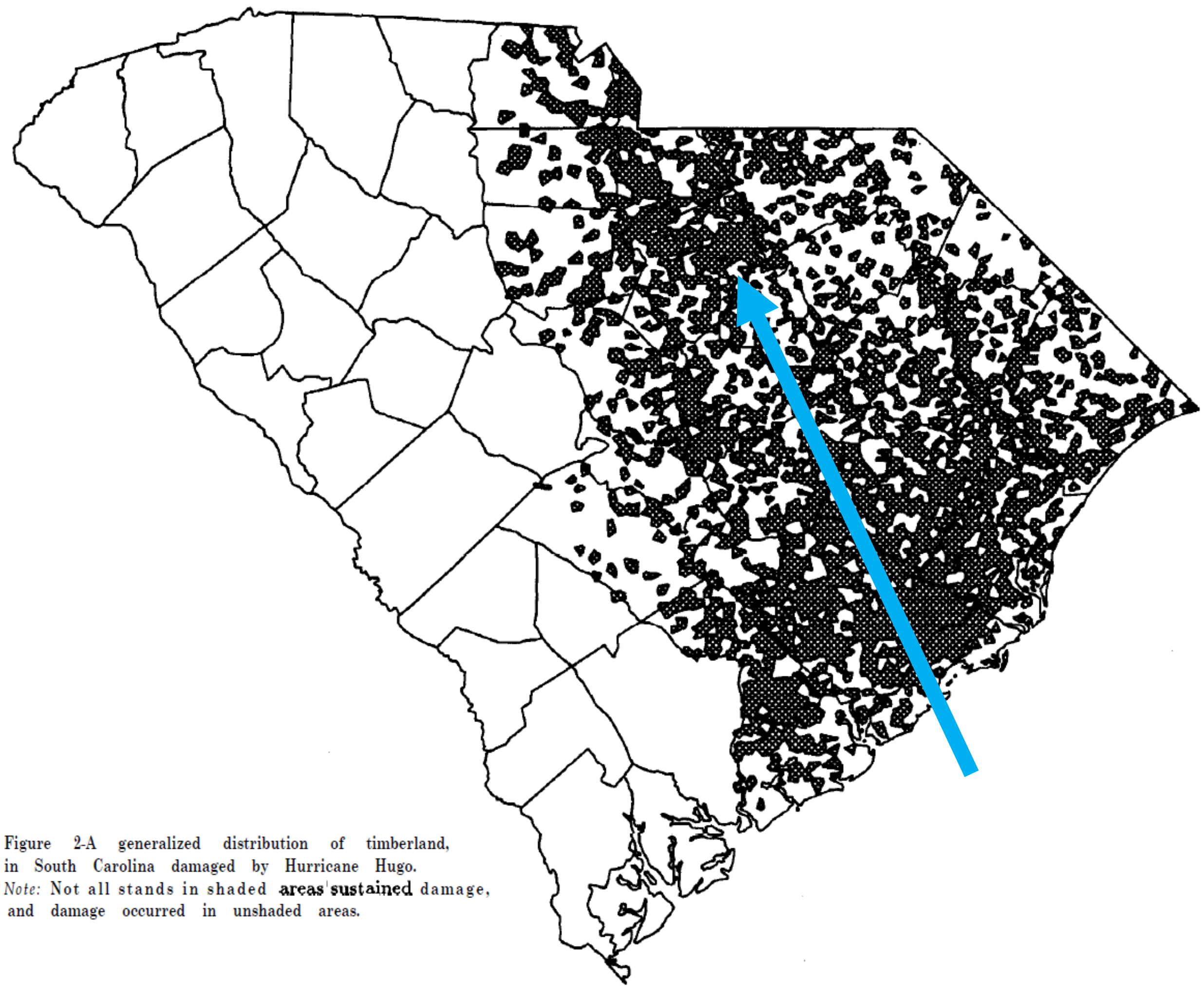


Figure 2-A generalized distribution of timberland, in South Carolina damaged by Hurricane Hugo.
Note: Not all stands in shaded areas sustained damage, and damage occurred in unshaded areas.

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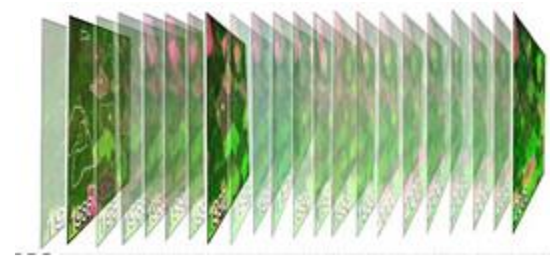
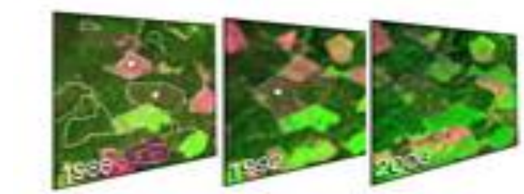
Landsat Images: Algorithms for Trend and Change Detection

Rishu Saxena, Prof. Layne Watson, and Prof. Randy Wynne

Introduction



- Given: The time series of the band values from a stack of satellite images of a region take over time.
- Change detection is our primary focus:
  - How do we design algorithms?
  - Can we distinguish stable vegetation cycles from harvest, occurrence of fire, volcanic activity, or any other stress in that region?
- Scalability is an inevitable issue:
  - Algorithms must be scalable on the available hardware both temporally as well as spatially.



Motivation

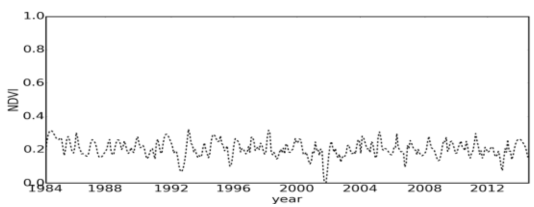
Model-Map on Oregon   EWMACD on Oregon   SHAPES on Oregon

- Different algorithms give different results!!!

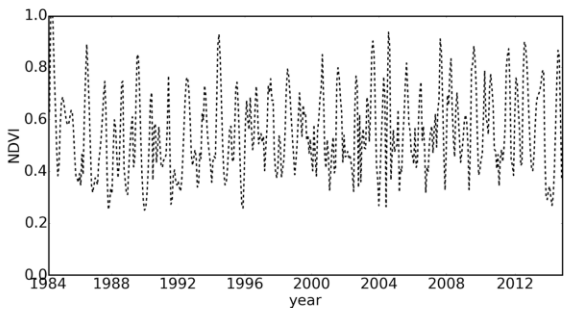
Examples of time series

Signals from remote sensing	Signals from different disciplines

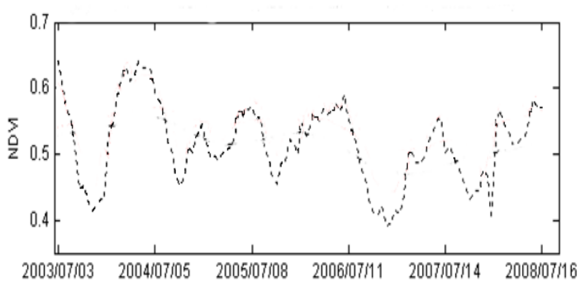
**Orego
n**



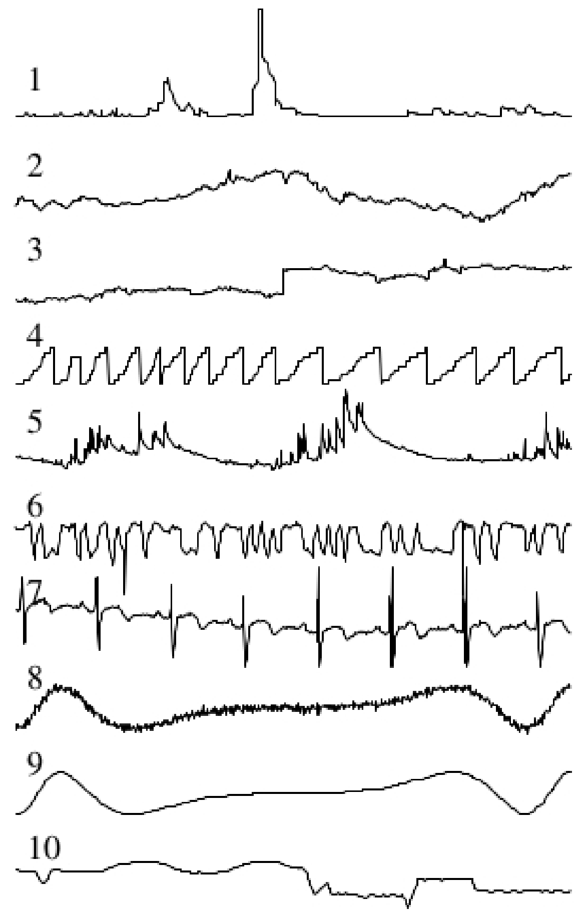
**South
Carolin
a**



**Australi
a
Woodlan
ds**



Radio waves
Exchange Rates
Tickwise II
Tickwise I
Water level
Manufacturing
ECG
Noisy sine cubed
Sine cubed
Space shuttle



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State-of-the-art

Algorithms in Remote Sensing	Segmentation approaches in general time series literature
• BFAST (2009) • VCT (2009) • Model Map (2009) • LandTrendR (2010) • MIICA (2011) • EWMACD (2012) • VeRDET (2014) • CCDC (2014) • SHAPE-SELECT-FOREST (2015)	• Kernel regression methods • Top-down approach • Bottom-up approach

Remote sensing vs. the broader picture

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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

Our approach

We believe that developing an algorithm that combines algorithms that

- already exist, but
- differ in terms of the phenomena they capture,

will adequately address the problem of analyzing time series coming from anywhere across the globe.

Question: How do we combine different algorithms?

Our 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.
Eg. Random Forests.	Eg. (i) Introsort for sorting, (ii) Brent's method for root finding.	Eg. Root finding algorithm in NAPSS (uses secant method with requisite tests).

Our approach

Construction of a polyalgorithm:

- Initial choice of basic algorithms.
- Rough synthesis of polyalgorithm and strategy.
- Refinement of numerical analysis procedures and development of new procedures for unforeseen situations.
- Reorganization of the polyalgorithm to improve efficiency.
- Refinement of error control and accuracy measures.
- Extensive testing and refinement.

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Scalability

Data storage, transfer and processing are computationally challenging. Parallel and high performance computing is indispensable. We have run experiments on

- Honeybadger: a Hadoop cluster at VT.
  - We used one compute node, which is a 2.3 GHz AMD Opteron CPU, with 16 cores and 64 GB of main memory.
  - Running EWMACD (python) on one image stack (600 GB) takes about 10 hours.
- Newriver: a 134-node system at VT.
  - We used one compute node, which is a 2.5GHz Intel Xeon(R) CPU, with 24 cores and 264GB of main memory.
  - Running EWMACD (Fortran) on one image stack (21 GB) takes about 7 minutes.
  - Detailed specifications at: https://secure.hosting.vt.edu/www.arc.vt.edu/computing/newriver/

Summary

- Different currently existing algorithms give different results for trends and change in land usage and land cover.
- In this project, we are
  - studying time series algorithms available in remote sensing community as well as in the broader time series analysis literature,
  - sorting out the unique ones, and
  - developing strategies to combine them into a single algorithm, a polyalgorithm, so as to best suit the remote sensing community.
- Ongoing work: We are currently
  - developing fortran code base.
  - exploring OpenMP and MPI implementations of all our codes along with the use of databases for efficient storage and access.

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Acknowledgements

- Dr. Evan Brooks, Prof. Valerie Thomas, Dr. Christine Blinn, for all the opportunities, discussions and other resources.

- ARC personnel at Virginia Tech for supercomputing resources.

Thanks!!

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Advanced Research Computing

Mission

Advanced Research Computing (ARC) provides centralized support for research computing by building, operating and promoting the use of advanced cyberinfrastructure at Virginia Tech. ARC delivers a **comprehensive ecosystem consisting of advanced computational systems, large-scale data storage, visualization facilities, software, and consulting services**. ARC provides education and outreach services through conferences, seminars, and scientific computing courses. ARC seeks to help **maximize research productivity** at Virginia Tech through interdisciplinary collaborations that connect researchers to new opportunities in computing and data driven research as they occur. By fostering strategic partnerships with the public and private sector, ARC serves to cultivate an entrepreneurial spirit around advanced computing infrastructure as a platform for collaboration and helps secure the position of Virginia Tech as a leader in education and research.

ARC Personnel

- **Associate VP for Research Computing: Terry Herdman (herd88@vt.edu)**
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  - Srijith Rajamohan (srijithr@vt.edu)
  - Open Searches: Computational and Data Scientists
- Systems and Software Engineer: Open Searches
- Visualization and Virtual Reality Systems Specialist - Lance Arsenault

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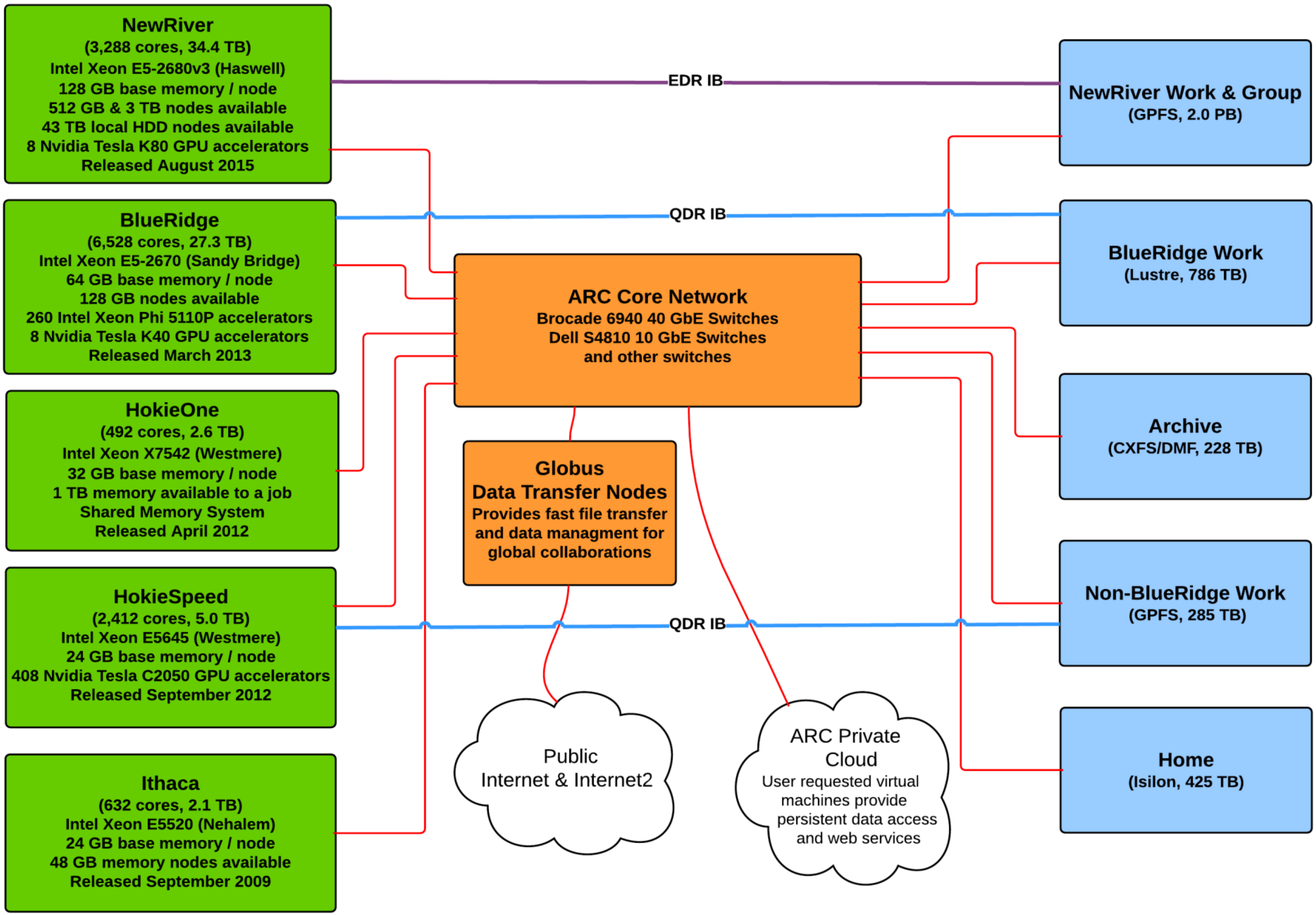
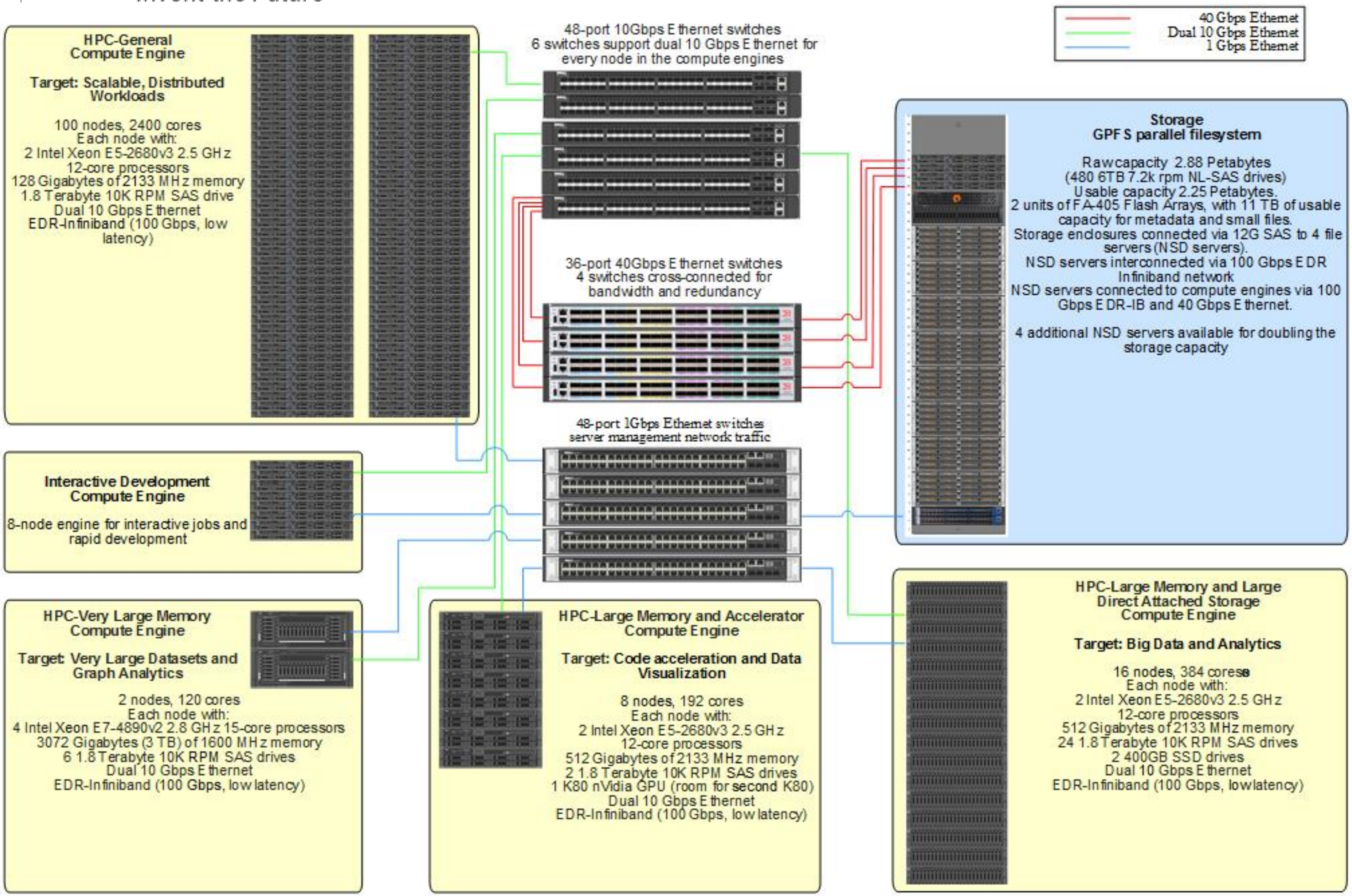
ARC Cyberinfrastructure



NewRiver



40 Gbps Ethernet
Dual 10 Gbps Ethernet
1 Gbps Ethernet
HPC-General Compute Engine
Target: Scalable, Distributed Workloads
100 nodes, 2400 cores
Each node with:
2 Intel Xeon E5-2680v3 2.5 GHz 12-core processors
128 Gigabytes of 2133 MHz memory
1.8 Terabyte 10K RPM SAS drive
Dual 10 Gbps Ethernet
EDR-Infiniband (100 Gbps, low latency)
48-port 10Gbps Ethernet switches
6 switches support dual 10 Gbps Ethernet for every node in the compute engines
36-port 40Gbps Ethernet switches
4 switches cross-connected for bandwidth and redundancy
48-port 1Gbps Ethernet switches
server management network traffic
Storage
GPFS parallel filesystem
Raw capacity 2.88 Petabytes
(480 6TB 7.2k rpm NL-SAS drives)
Usable capacity 2.25 Petabytes.
2 units of FA-405 Flash Arrays, with 11 TB of usable capacity for metadata and small files.
Storage enclosures connected via 12G SAS to 4 file servers (NSD servers).
NSD servers interconnected via 100 Gbps EDR Infiniband network
NSD servers connected to compute engines via 100 Gbps EDR-IB and 40 Gbps Ethernet.
4 additional NSD servers available for doubling the storage capacity
Interactive Development Compute Engine
8-node engine for interactive jobs and rapid development
HPC-Very Large Memory Compute Engine
Target: Very Large Datasets and Graph Analytics
2 nodes, 120 cores
Each node with:
4 Intel Xeon E7-4890v2 2.8 GHz 15-core processors
3072 Gigabytes (3 TB) of 1600 MHz memory
6 1.8 Terabyte 10K RPM SAS drives
Dual 10 Gbps Ethernet
EDR-Infiniband (100 Gbps, low latency)
HPC-Large Memory and Accelerator Compute Engine
Target: Code acceleration and Data Visualization
8 nodes, 192 cores
Each node with:
2 Intel Xeon E5-2680v3 2.5 GHz 12-core processors
512 Gigabytes of 2133 MHz memory
2 1.8 Terabyte 10K RPM SAS drives
1 K80 nVidia GPU (room for second K80)
Dual 10 Gbps Ethernet
EDR-Infiniband (100 Gbps, low latency)
HPC-Large Memory and Large Direct Attached Storage Compute Engine
Target: Big Data and Analytics
16 nodes, 384 cores
Each node with:
2 Intel Xeon E5-2680v3 2.5 GHz 12-core processors
512 Gigabytes of 2133 MHz memory
24 1.8 Terabyte 10K RPM SAS drives
2 400GB SSD drives
Dual 10 Gbps Ethernet
EDR-Infiniband (100 Gbps, low latency)

Software

- **Bioinformatics**: BLAST/BLAST+, CUDASW++, Trinity, Mothur, QIIME
- **Code Development**: Boost C++ Libraries, CMake, CUDA, FFTW, GCC,
GNU Scientific Library (GSL), Haskell, HDF5, Intel, Java, MAGMA, Intel-MKL, OpenMPI, PETSc, PGI, Python, Subversion, TotalView, Valgrind, netcdf, Mvapich, Allinea
- **Computational Fluid Dynamics**: ANSYS Fluent, OpenFOAM
- **Electronic Structure/DFT**: Quantum ESPRESSO, VASP, WIEN2k
- **Evolutionary Biology**: BEAGLE, BEAST, MrBayes, OpenBUGS
- **FEM**: ABAQUS, ANSYS, LS-DYNA, OpenSees
- **Mathematics**: GAUSS, MATLAB
- **Molecular Dynamics**: GROMACS, LAMMPS, NAMD, Amber
- **Quantum Chemistry**: Gaussian, NWChem
- **Statistics**: GAUSS, MATLAB, R, CPLEX
- **Visualization**: ParaView, Ensight, Visit, VMD, VTK, Fieldview, Tecplot

Access / Usage

ETX
NewRiver offers web browser-based access to interactive nodes. This interface provides faster, more interactive access to graphical user interfaces than standard X11 forwarding (e.g. ssh -X). ETX will automatically load balance users between the eight interactive nodes.

To access it, use a web browser (e.g. Firefox or Safari, not Chrome) to go to

http://newriver.arc.vt.edu

Globus
From www.globus.org - “Globus gives researchers everywhere access to a fast, powerful data management service that’s easy to use. Simply fire off a transfer request and walk away, or share big datasets directly from your existing storage with just a few clicks — and when you need to make your data available to others, let our data publication service guide you.”

Search endpoints for => Virginia Tech - ARC

Questions???

See www.arc.vt.edu

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An Alternative View

Of Forest Biogeochemistry and Ecophysiology

Val Thomas, B. Strahm, K. Britt, B. Cook

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Some big picture questions

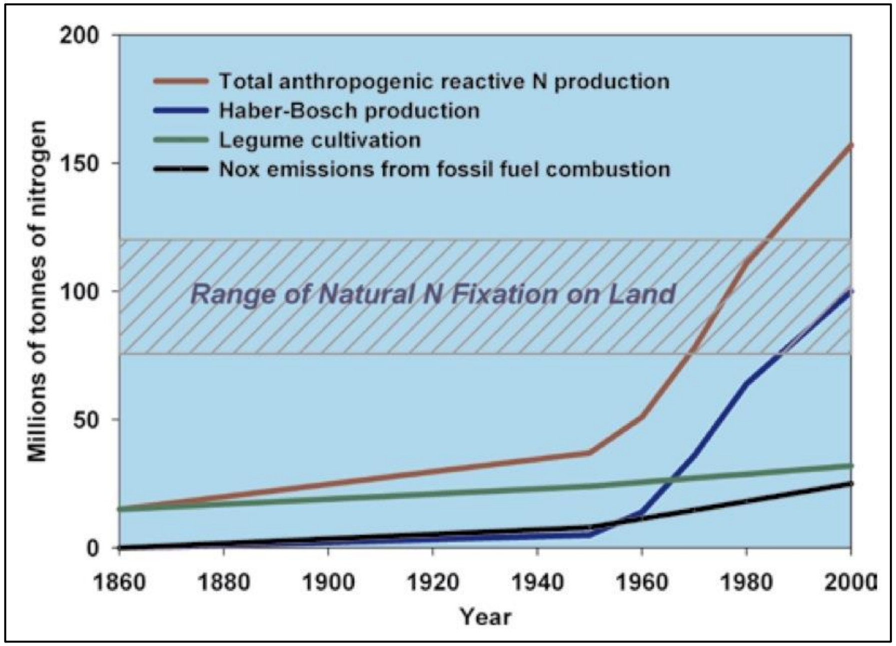
- How does forest structure relate to canopy physiology, and what drives changes in these relationships across geographic and environmental gradients?
  - How will forests respond to existing and future pressures?
- How can these processes be measured/monitored with remote sensing?
  - Forest biogeochemistry
  - Forest structure/crown architecture
  - Forest growth, disturbance, recovery
  - Biodiversity

Lidar
Imaging Spectroscopy

Multitemporal data
(Landsat and other)

Eg: Long-term research goal

- **Prediction of where and when forest ecosystems will:**
  - buffer anthropogenic alterations to the N cycle through N retention
  - or be susceptible to increased N and lose it to the surrounding environment
    - e.g., leaching to aquatic systems, etc..



UNEP and WHRC, 2007

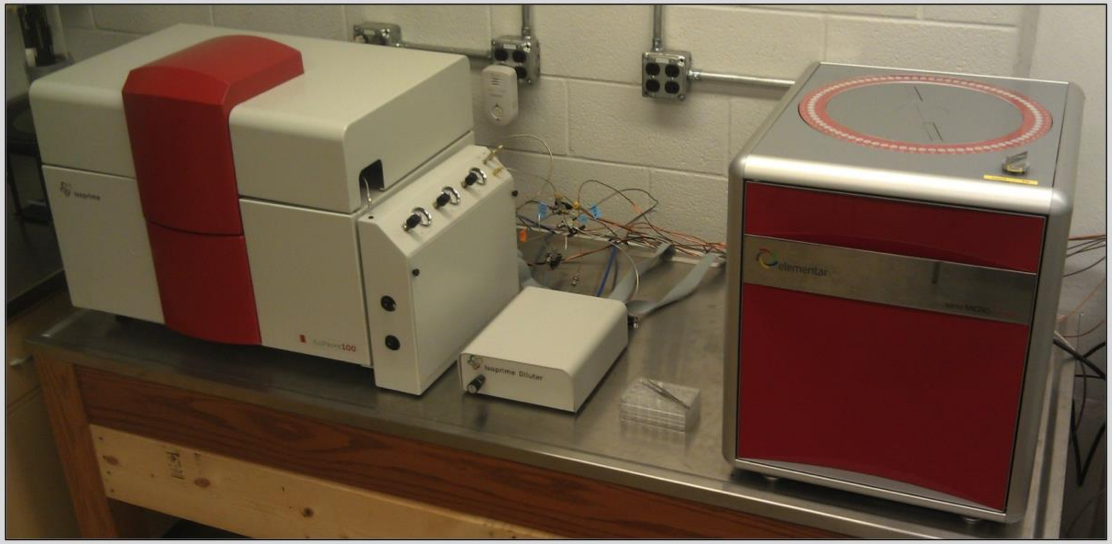
Nitrogen Retention

- $\delta N = {}^{15}N/{}^{14}N$

- Foliar = $\delta^{15}N_{Fol}$
- Soil = $\delta^{15}N_{Soil}$
- Enrichment Factor (EF) =

  $\delta^{15}N_{Fol} - \delta^{15}N_{Soil}$

Isotope Ratio Mass Spectrometer (IRMS)



$$\text{Air} = \frac{^{15}N}{^{14}N} = \frac{0.366\%}{99.634\%} = 0.0036765$$

Study area

- 20 Hardwood Plots
  - 38 large trees to sample major species
- 10 Loblolly pine plots
- Foliar and soil samples collected

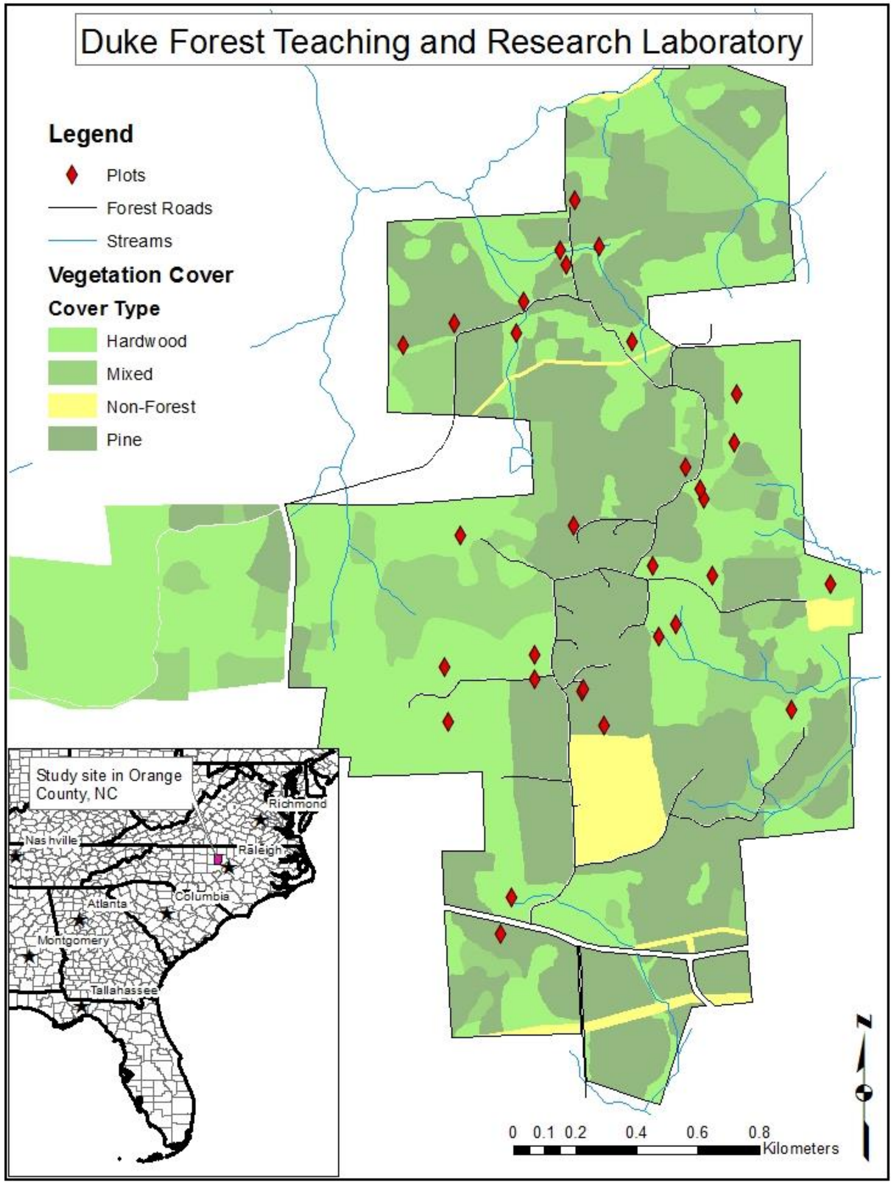
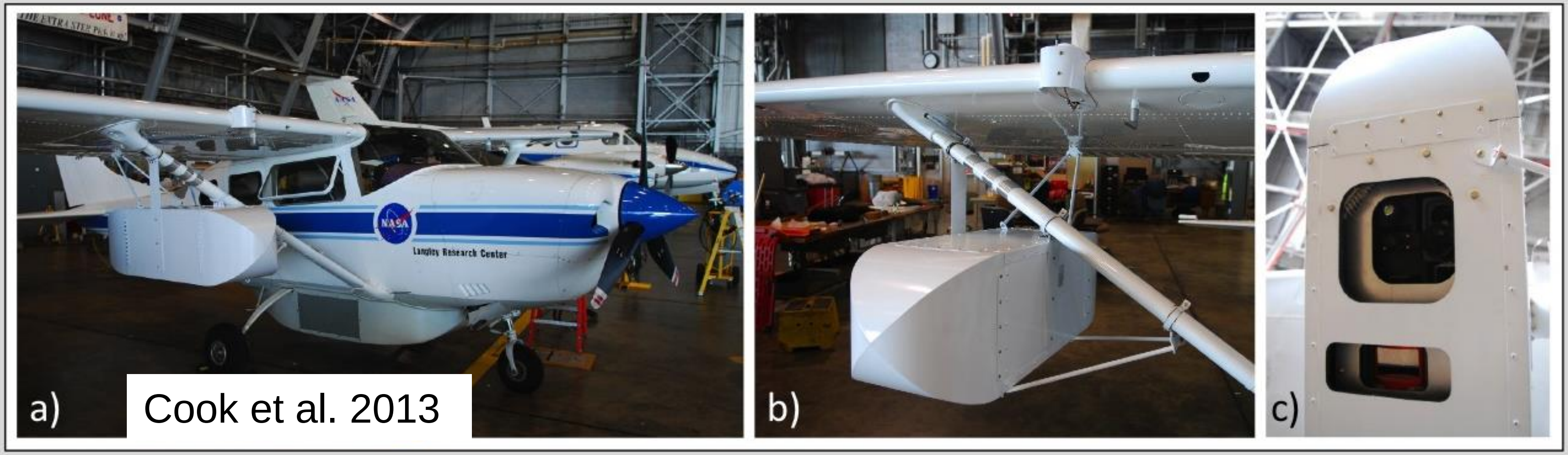


Image Acquisition

- September and October, 2014 - G-LiHT (NASA)
  - airborne scanning lidar and imaging spectroscopy
    - 10 cm footprint at an altitude of 335 m
    - 0.3 mrad beam divergence angle
    - VNIR spectroscopy data



Cook et al. 2013

Laboratory Analysis

- Foliar:
  - %N, $\delta^{15}N$, enrichment
  - C:N, %C, Al, B, Ca, Fe, K, Mg, Mn, Na, P, Zn
  - Chl_a, Chl_b, Chl_{a+b}, $Chl_{a/b}$, carotenoids
- Soil:
  - %N, $\delta^{15}N$, enrichment,
- Tree:
  - Species, DBH, Crown width (NS/EW)

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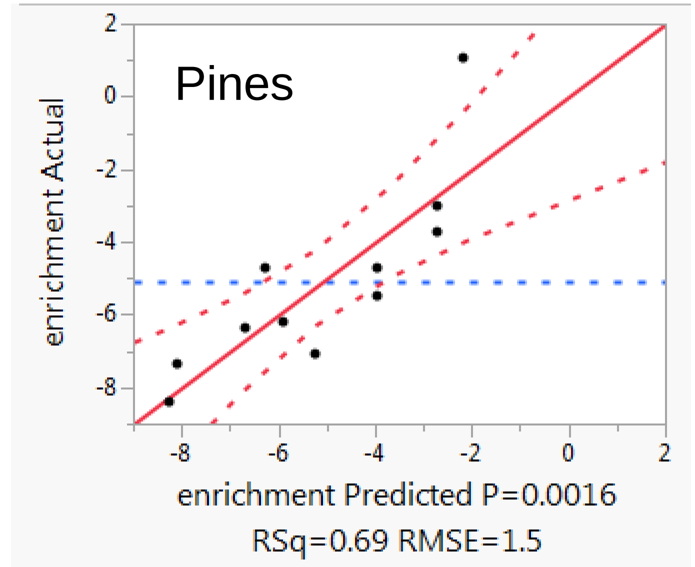
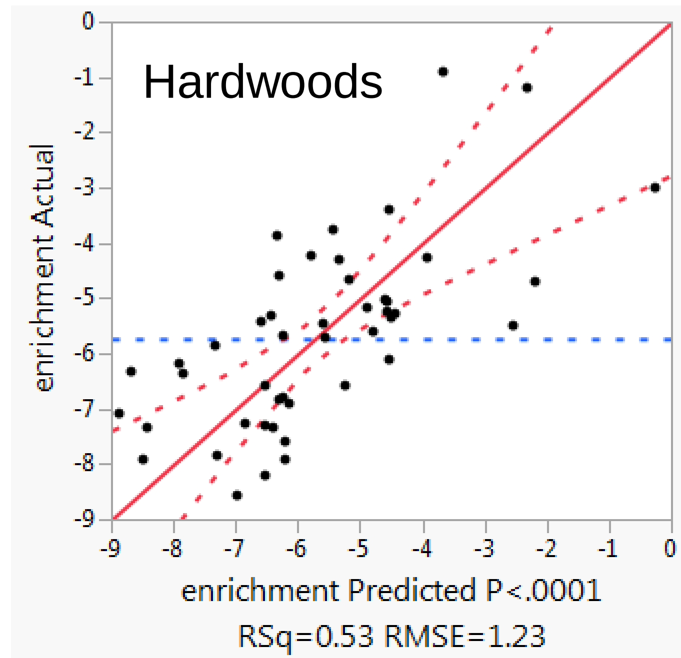
Some findings

- %N in the soil is a stronger driver of nitrogen retention than %N in the foliage
- %N in the soil is strongly correlated to foliar isopotic N

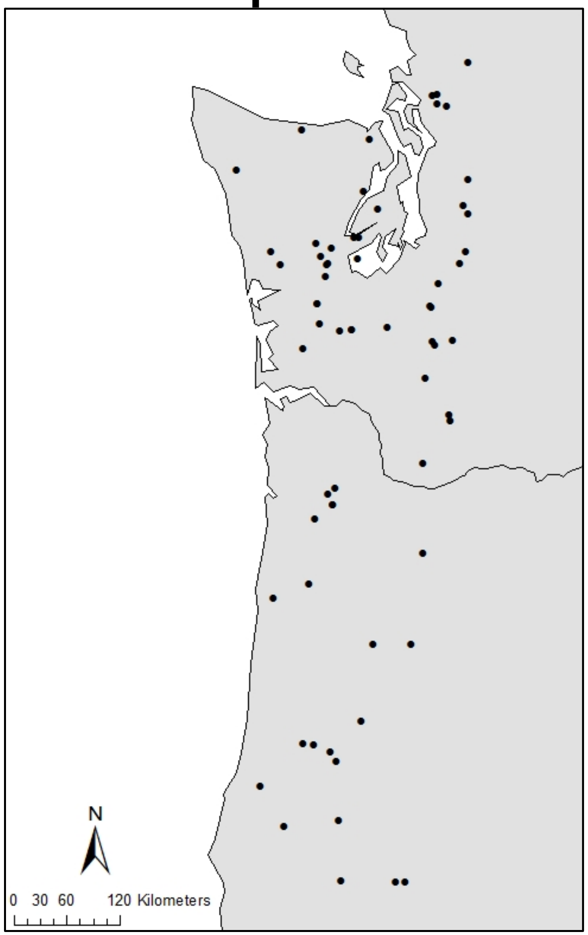
- Lidar metrics of canopy structure related to height and biomass are predictors of ecosystem nitrogen retention
  - Suggests Landsat-derived growth response may provide valuable insights



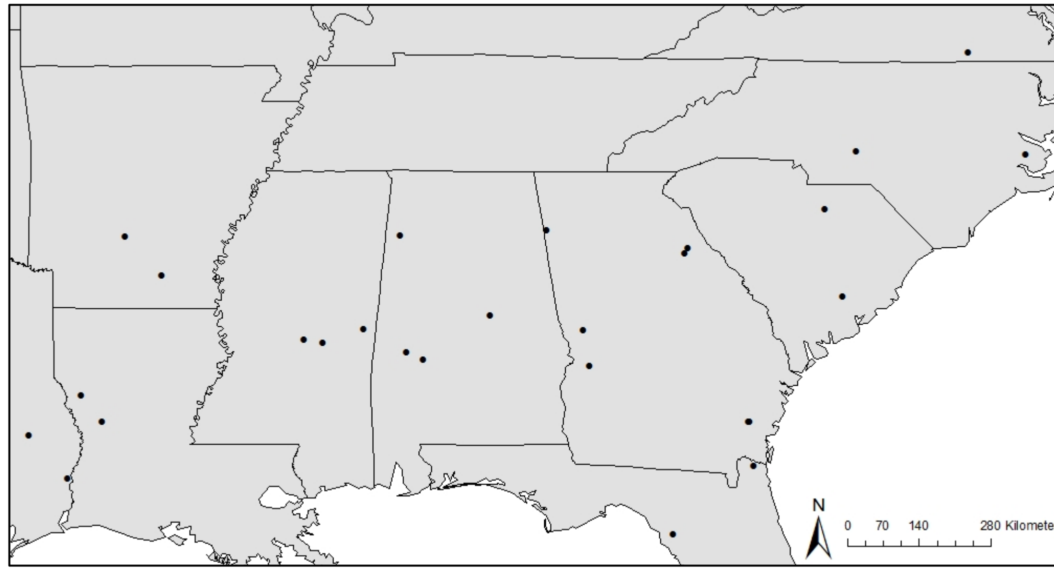


Future Work

Pacific Northwest Stand Management Cooperative



Forest Productivity Cooperative



- Incorporate foliar biochemical response and hyperspectral data to improve discrimination across species.
- Derive and incorporate response metrics from Landsat time series at our measured sites