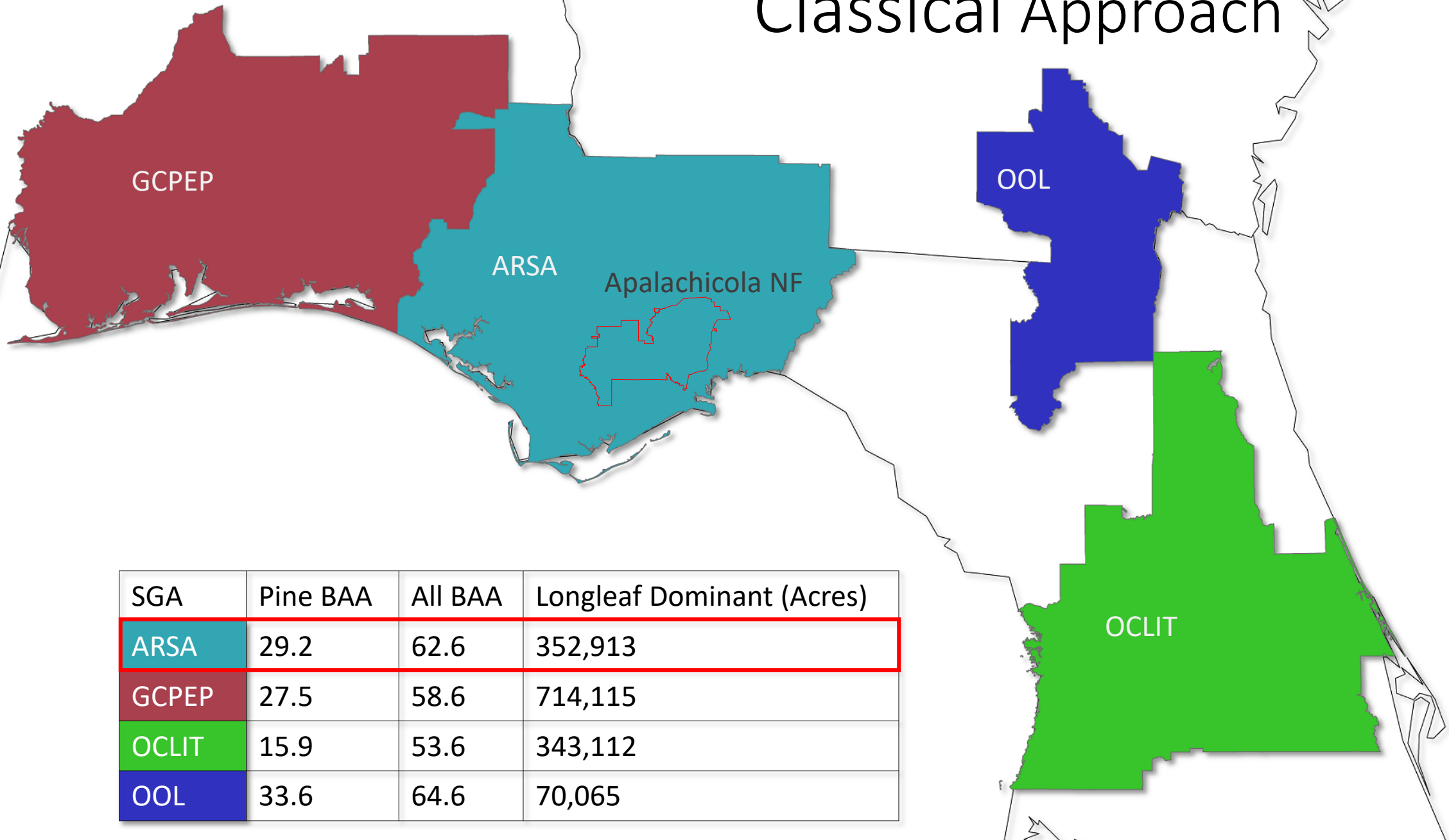




ESTIMATING CHARACTERISTICS OF FORESTS IN THE APALACHICOLA REGION USING REMOTELY SENSED IMAGERY AND FIELD SAMPLES

John Hogland, Nathaniel Anderson, Jason Drake, Paul Medley, David Affleck, and Joseph St. Peter

Classical Approach



GCPEP

ARSA

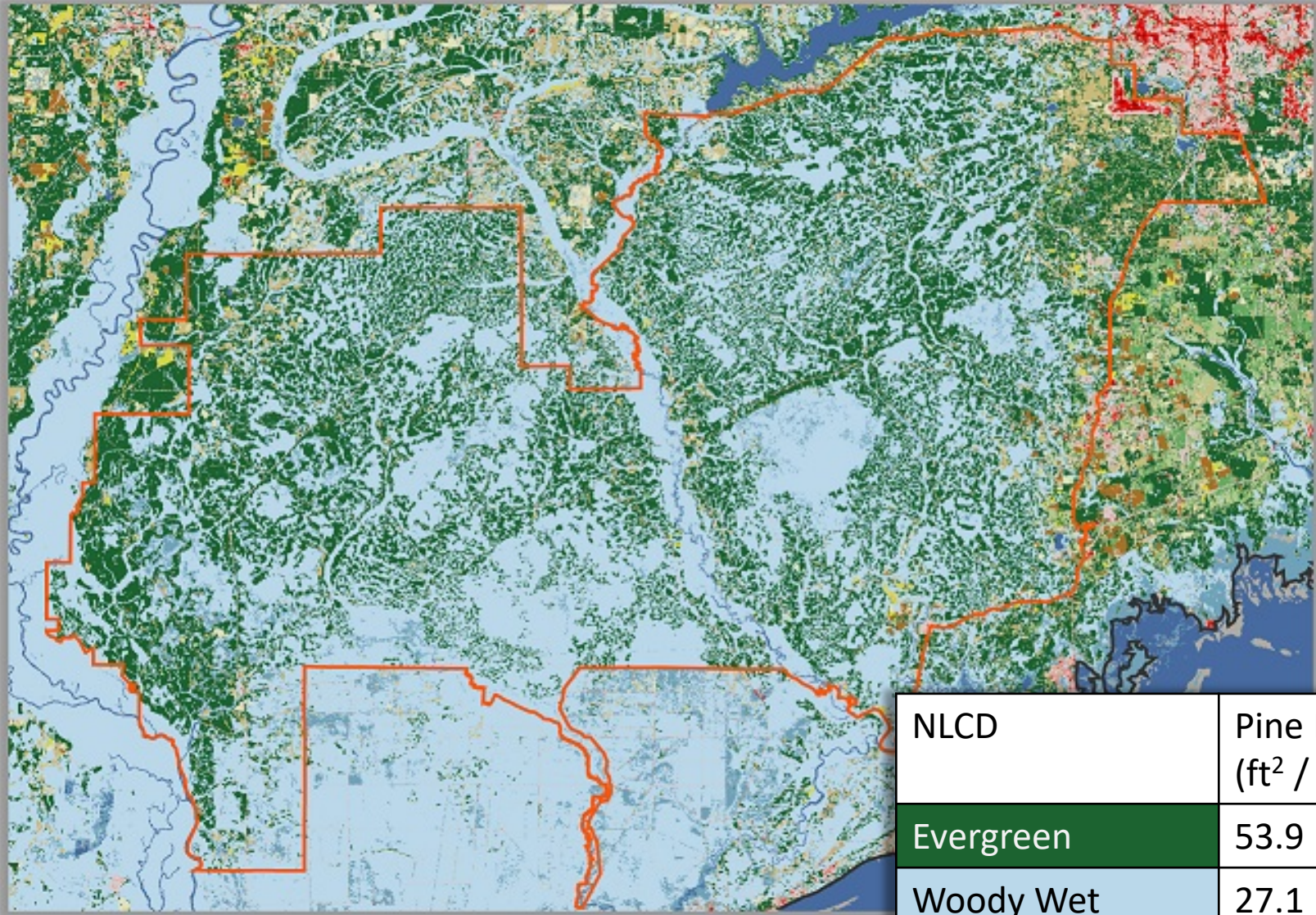
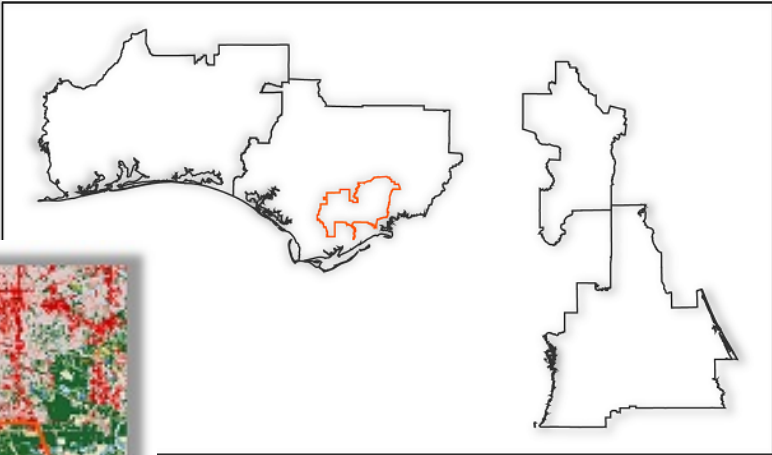
Apalachicola NF

OOL

OCLIT

SGA	Pine BAA	All BAA	Longleaf Dominant (Acres)
ARSA	29.2	62.6	352,913
GCPEP	27.5	58.6	714,115
OCLIT	15.9	53.6	343,112
OOL	33.6	64.6	70,065

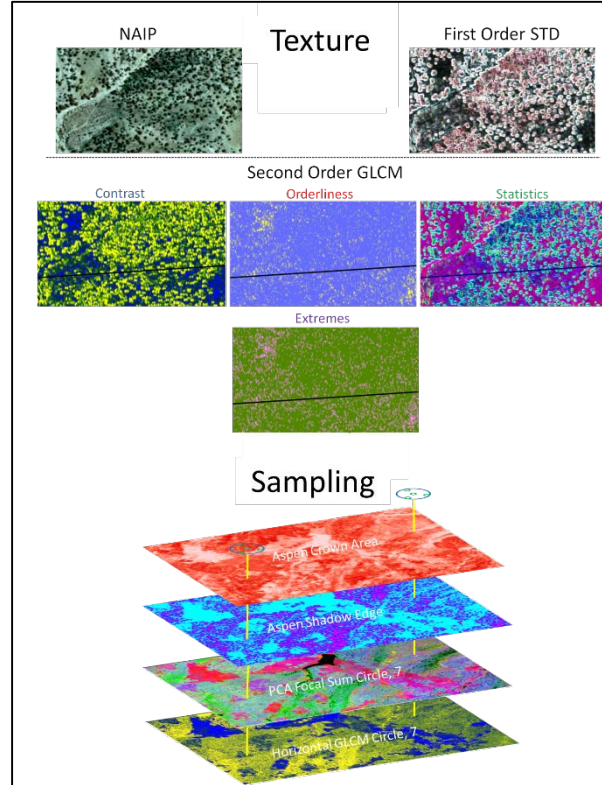
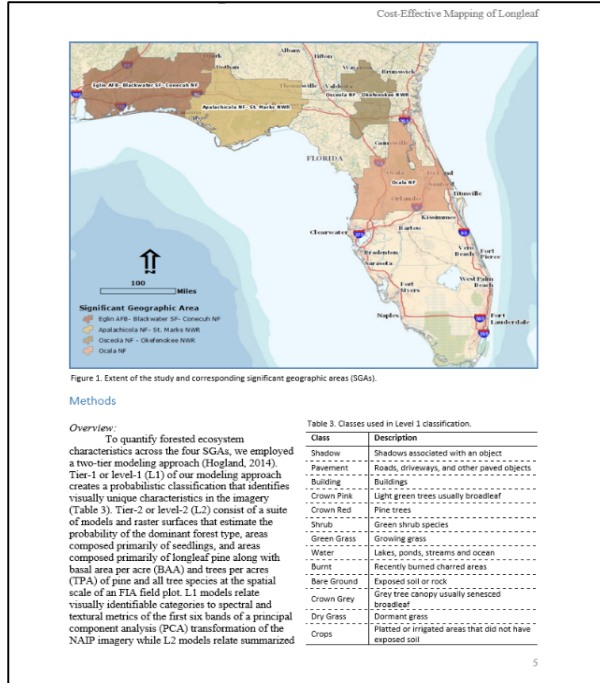
Classical Estimates (Stratified by NLCD)



NLCD	Pine BAA (ft ² / Acre)	All BAA (ft ² / Acre)	Longleaf Dominant (Acres)
Evergreen	53.9	73.5	26,158
Woody Wet	27.1	92.9	8,847

Alternative Approach Preprocessing

22,400,000 acres



Mapping Forest Characteristics at Fine Resolution across Large Landscapes of the Southeastern United States Using NAIP Imagery and FIA Field Plot Data

John Hogland ^{1,*}, Nathaniel Anderson ¹, Joseph St. Peter ², Jason Drake ³ and Paul Medley ³

¹ Rocky Mountain Research Station, U.S. Forest Service, Missoula, MT, 59801 USA; nathanielanderson@fs.fed.us

² College of Forestry and Conservation, University of Montana, Missoula, MT, 59801 USA; jstpete@fs.fed.us

³ U.S. Forest Service, Tallahassee, FL, 32321 USA; jasondrake@fs.fed.us; pmedley@fs.fed.us

* Correspondence: jhogland@fs.fed.us; Tel.: +1-406-329-2138

Received date; Accepted date; Published date

Abstract: Accurate information is important for effective management of natural resources. In the field of forestry, field measurements of forest characteristics such as species composition, basal area, and stand density are used to inform and evaluate management activities. Quantifying these metrics accurately across large landscapes in a meaningful way is extremely important to facilitate informed decision-making. In this study, we present a remote sensing based methodology to estimate species composition, basal area and stand tree density for pine and hardwood tree species at the spatial resolution of a Forest Inventory Analysis (FIA) program plot (78 m by 70 m). Our methodology uses textural metrics derived at this spatial scale to relate plot summaries of forest characteristics to remotely sensed National Agricultural Imagery Program (NAIP) imagery across broad extents. Our findings quantify strong relationships between NAIP imagery and FIA field data. On average, models of basal area and trees per acre accounted for 43% of the variation in the FIA data, while models identifying species composition had less than 15.2% error in predicted class probabilities. Moreover, these relationships can be used to spatially characterize the condition of forests at fine spatial resolutions across broad extents.

Keywords: NAIP; FIA; remote sensing; forest measurements

1. Introduction

Forest management is a complex, integrated process that combines multiple objectives to accomplish a predefined set of goals as they relate to forested lands [1]. Since the United States National Forest Management Act of 1976, the federal definition of forest management has expanded well beyond timber management to include economic and social goals as components of management choices, the consideration of broader multiple use management challenges, and the need to quantitatively justify forest management plans and decisions [1]. This expansion in scope fundamentally changed not only the values for which forests are managed, but also how managers justify forest management decisions, emphasizing the need for effective, information-driven natural resource planning for diverse values in broad spatial, ecological, social, and economic contexts.

For forests of varying ownership, complexity, size, and extent, forest plans guide management activities and steer civilization to meet both private and public objectives and goals. Effective development and implementation of those plans require knowledge of the biotic and abiotic conditions of a forest and an understanding of how such factors interact and change within the context of the objectives and goals defined [2,3]. To gain an understanding of the existing structure and composition of forests, practitioners have been implementing well-established measurement

Probabilistic Land Cover Classifications in the States

Nathaniel Anderson ¹, Jason Drake ² and Paul Medley ³

¹ University of Montana, Missoula, MT, USA; janderson@fs.fed.us

² U.S. Forest Service, Missoula, MT, USA; jdrake@fs.fed.us (J.H.); jasondrake@fs.fed.us (J.D.); pmedley@fs.fed.us (P.M.)

* Correspondence: jhogland@fs.fed.us

Received date; Accepted date; Published date

Abstract: Probabilistic land cover classification provides valuable information for prioritizing management and land use decisions. Current regional scale land cover geospatial data at a coarse resolution is too coarse to provide the necessary spatial resolution to inform management decisions. This paper describes a methodology that is software to create a land cover classification over a large area at a fine (1 m) spatial resolution. This methodology uses components derived from National Agricultural Imagery Program (NAIP) imagery, visually classified locations, and a soft-margin neural network to produce classification surfaces at 1 m resolution across broad extents (billions of acres) with less than 10% average error in modeled class probabilities. This methodology and the tools used in this study constitute a framework for probabilistic land cover classification that can be applied across large extents of land and open source software and publicly available.

Keywords: NAIP; remote sensing; neural networks; high resolution analysis

Remote sensing process that assigns classes to geographic locations is typically conducted on a per-cell basis and is often unsupervised. In unsupervised classification raster cells in supervised classification an analyst assigns a subset of [1]. Land cover classifications are versatile and often used in planning [2] studies of landscape change [4] and land use change [5]. Land cover classifications are frequently used to inform [6], forest restoration [7], fire risk mitigation [8], and land cover classification datasets, relevant objectives such as [10] or determining the number of impervious surfaces [11]. Land cover classifications can also be used as a component of more complex analyses of landscape characteristics [12] and can be used to describe

Improving the Efficiency of Spatial Data from Remote Sensing

Moscow, MT 59801 USA; nathanielanderson@fs.fed.us

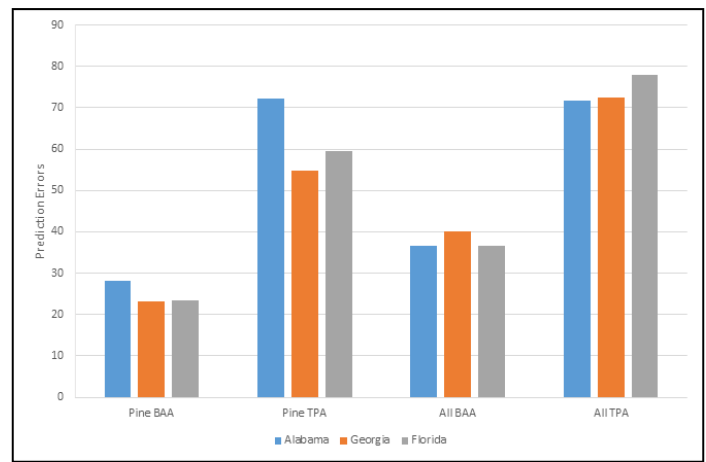
Received: 13 July 2017

Accepted: 13 July 2017

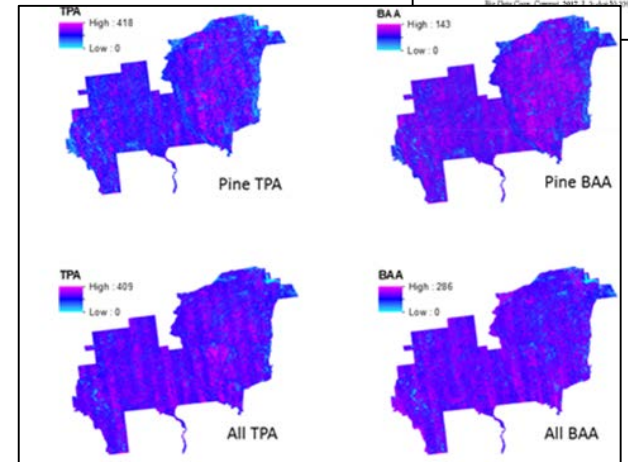
Published: 13 July 2017

Remote sensing of geographic information systems (GIS) can require substantial processing time and storage requirements. To address these limitations, multiple coding libraries and have applied those however, have recognized the inefficiencies associated with used to implement such analyses. In this paper, spatial models and demonstrate a novel approach to the problem, we introduce a new coding library that streamlines and uses lazy evaluation to facilitate a wide range of procedures within a new GIS modeling framework. Our results show a 64.3% reduction in processing time and a 45% reduction in storage requirements. In an applied case study, processing time was reduced from 2247 h to 488 h and a reduction in storage requirements was achieved.

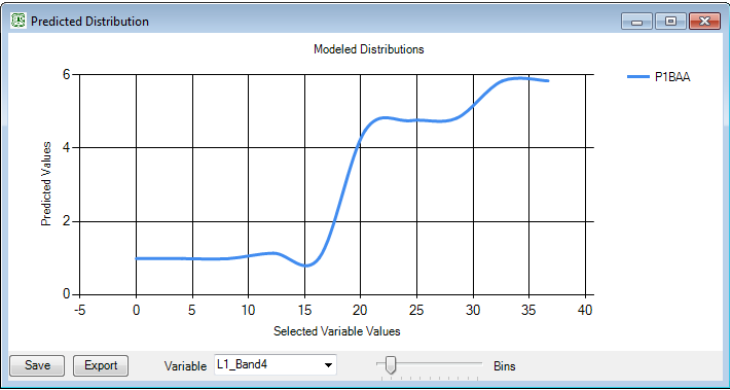
Error



Spatial Outputs



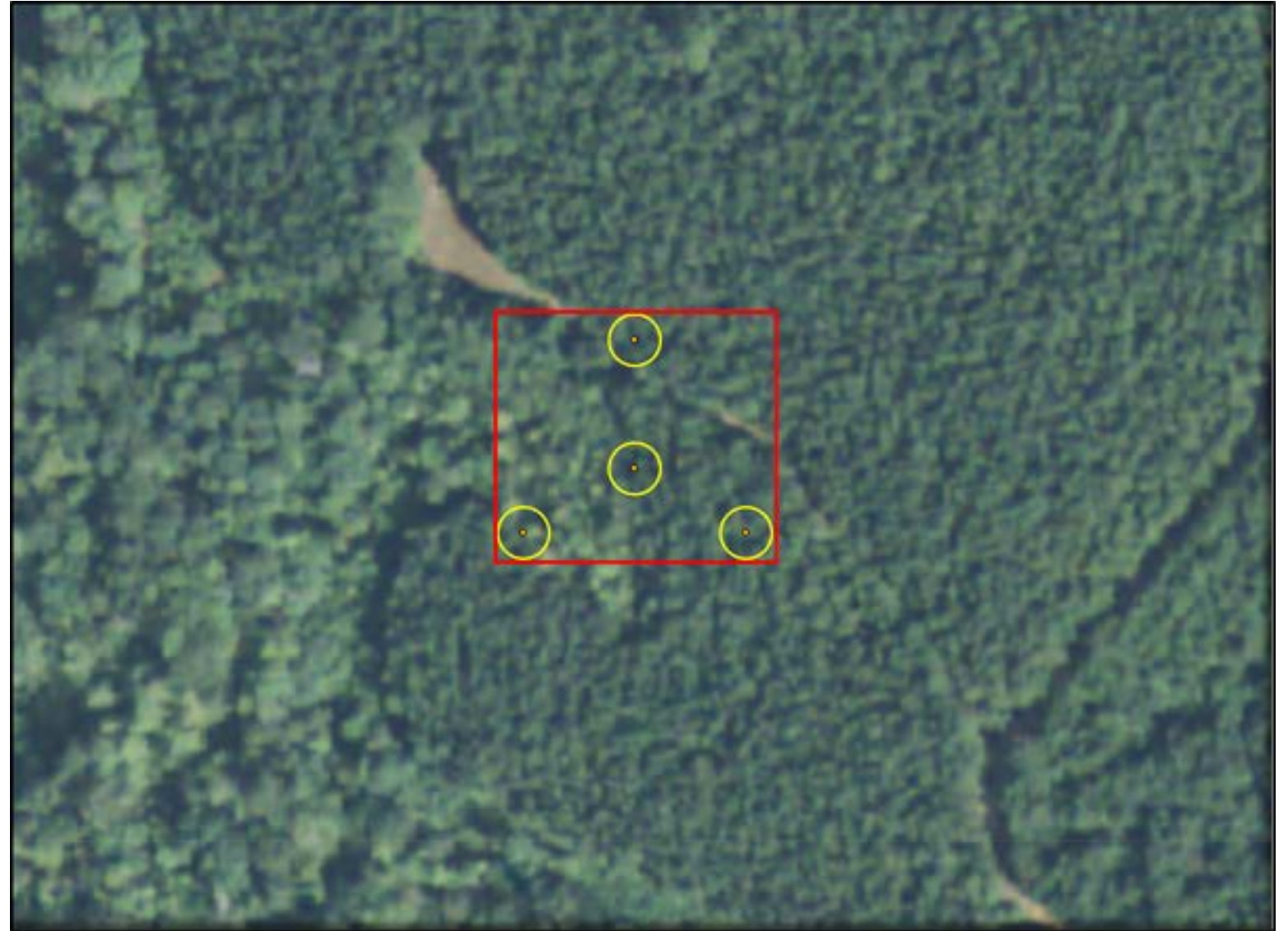
Modeling



How It Works



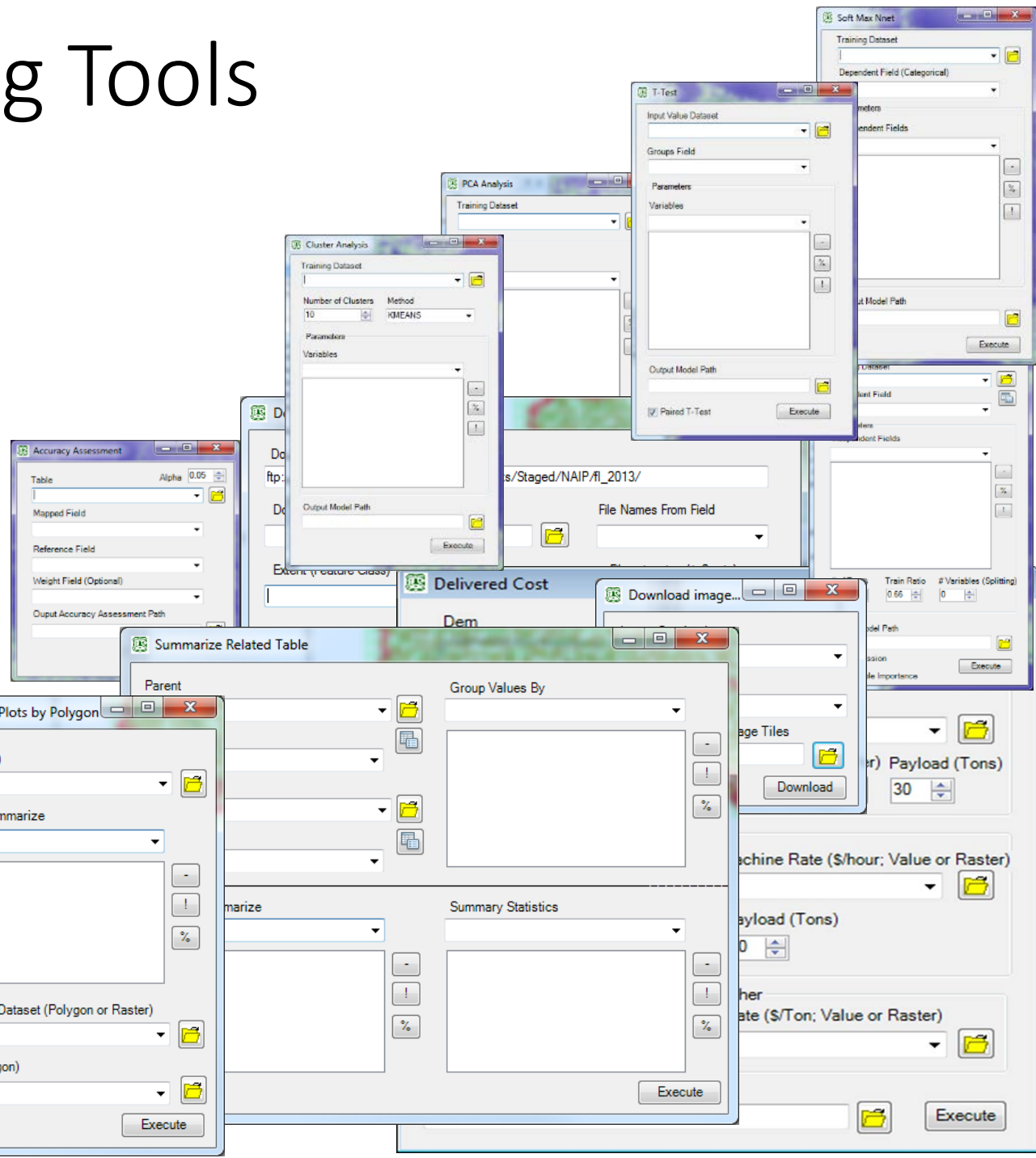
ADF 2008



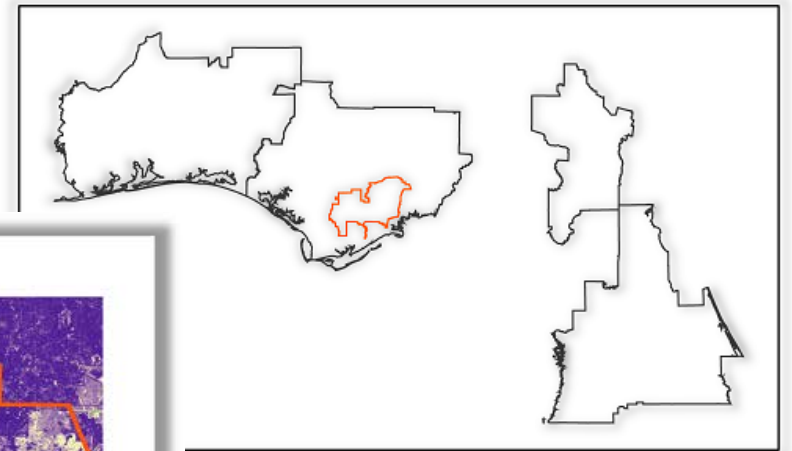
Improved Spatial Modeling Tools



```
IRasterInfo2 rsInfo2 = (IRasterInfo2)frDset.RasterInfo;
IRasterStatistics rsStats = new RasterStatisticsClass();
rsStats.Mean = 0.5;
rsStats.Maximum = 1;
rsStats.Minimum = 0;
rsStats.StandardDeviation = 0.25;
rsStats.SkipFactorX = 1;
rsStats.SkipFactorY = 1;
rsStats.IsValid = true;
if (rf.Reggression)
{
    double pMin = rf.computNew(rf.minValues)[0];
    double pMax = rf.computNew(rf.MaxValues)[0];
    double pMean = (pMax-pMin)/2;
    rsStats.Maximum = rf.maxValues[0];
    rsStats.Minimum = rf.minValues[0];
    rsStats.Mean = pMean;
    rsStats.StandardDeviation = pMean * 0.5;
}
```

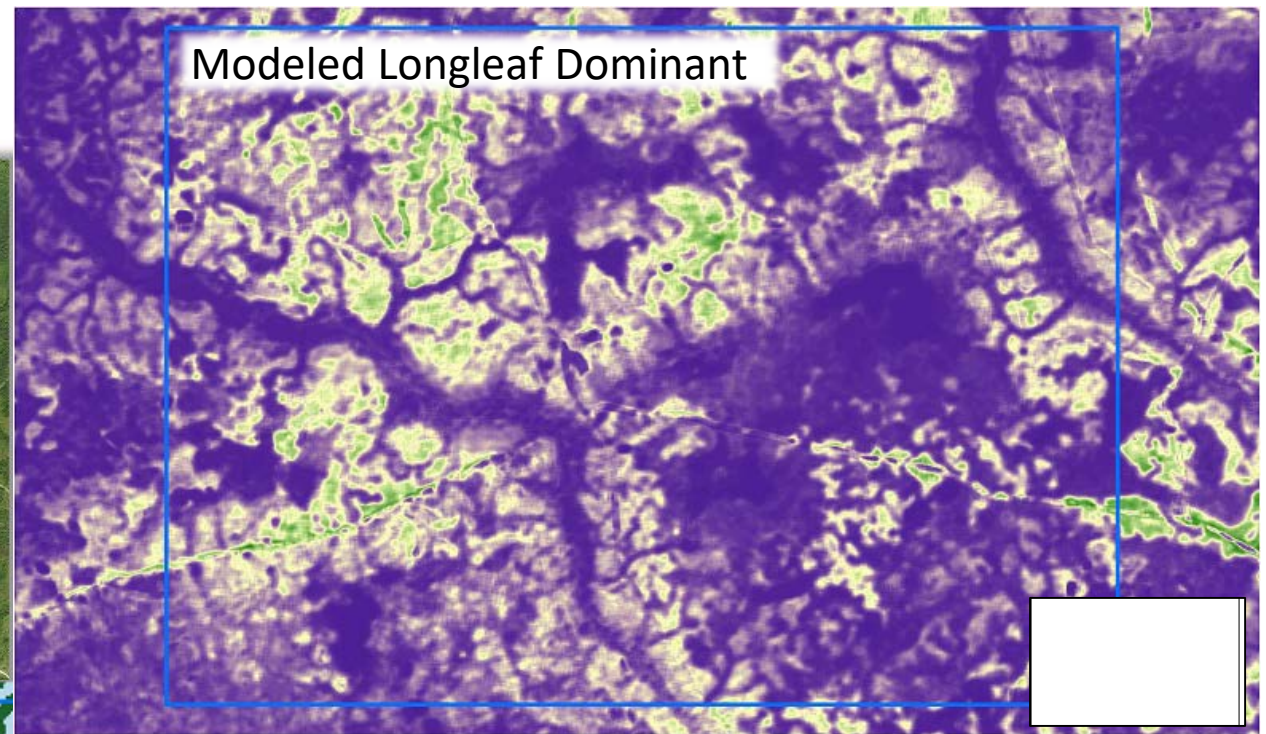


Modeled Estimates



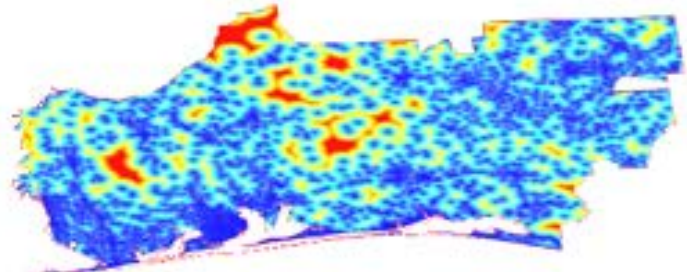
Longleaf Dominant (Acres)	Lower 95% CL	Upper 95% CL
52,737	45,271	60,202

Comparison (30 miles²)

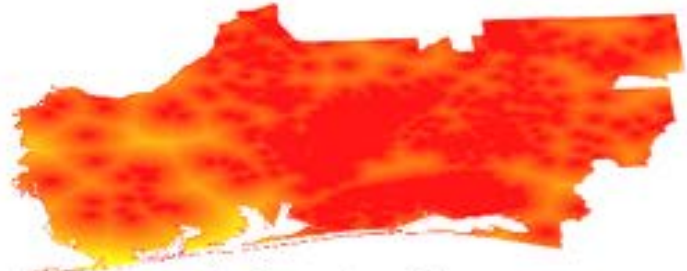


NLCD Class	Pine BAA	All BAA	Longleaf Dominant
Evergreen	53.9	73.5	26,158
Woody Wet	27.1	92.9	8,847

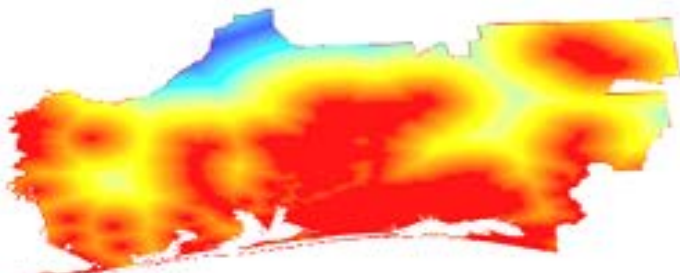
Restoration Prioritization



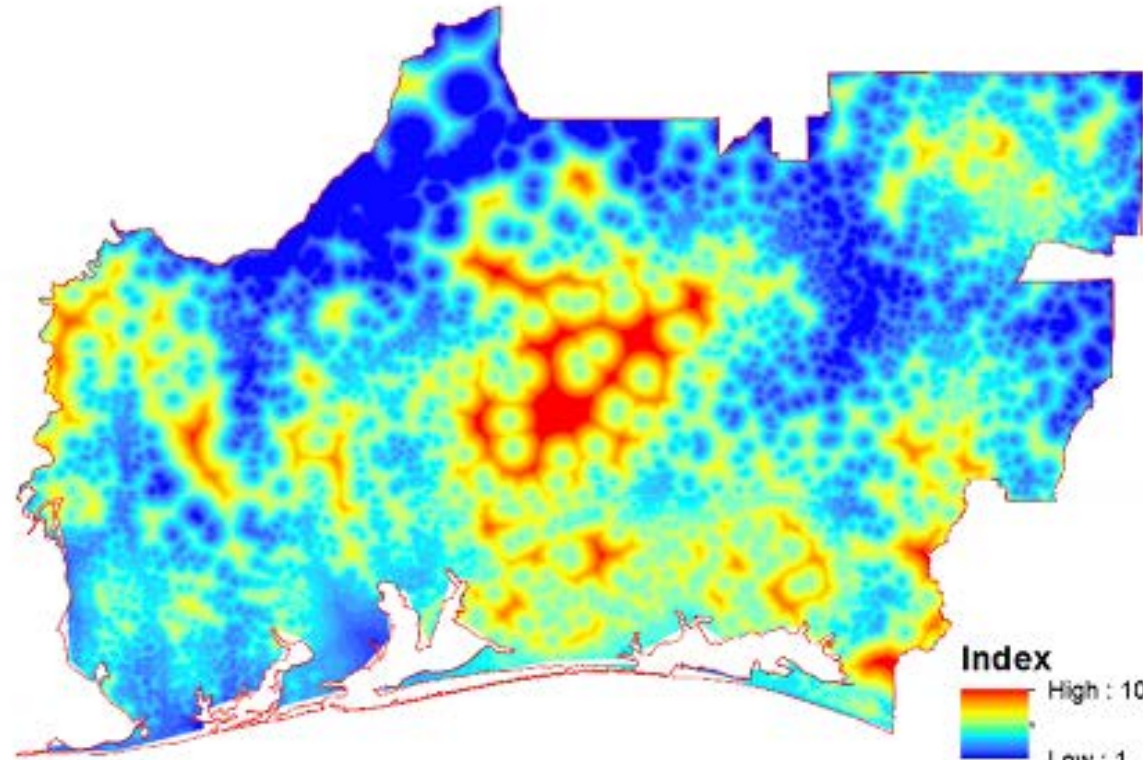
Distance from urban



Distance to longleaf

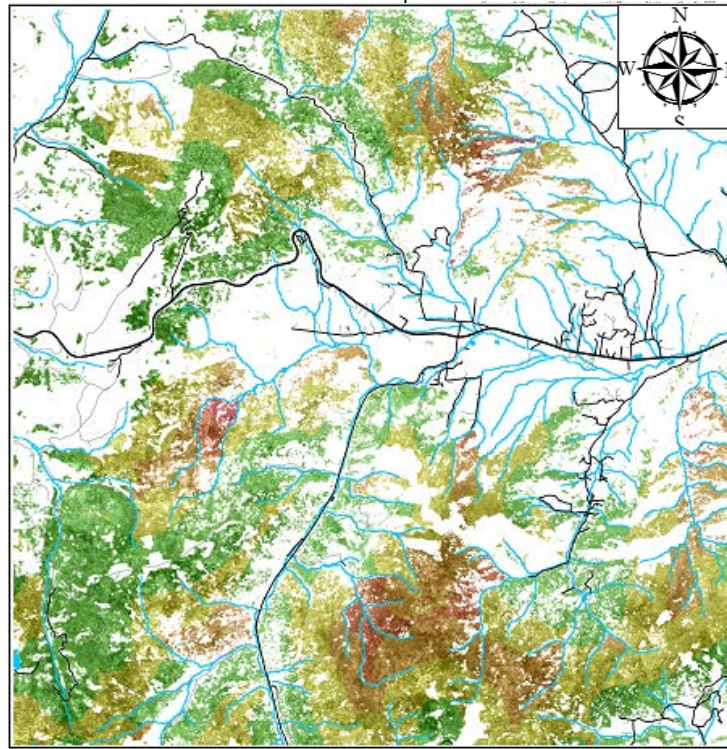
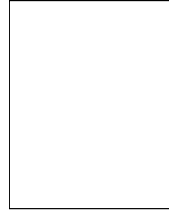
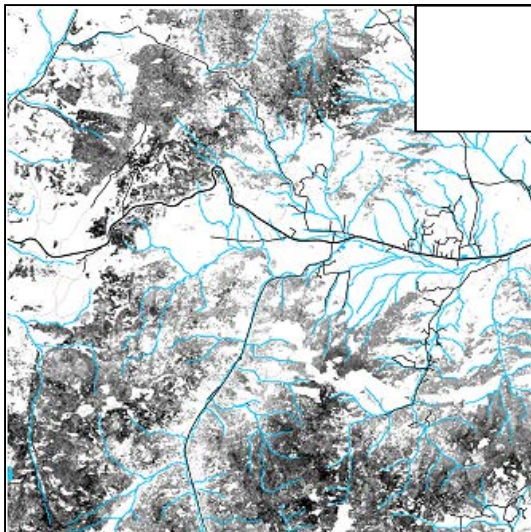
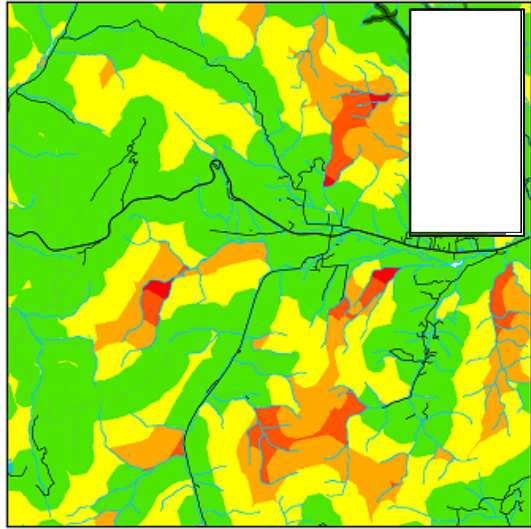


Distance to public



Restoration hotspots

Utility



International Journal of Geo-Information

Article
New Geospatial Approaches for Efficiently Mapping Forest Biomass Logistics at High Resolution over Large Areas

John Hogland¹, Nathaniel Anderson^{1,2} and Woodam Chung¹

¹ Rocky Mountain Research Station, U.S. Forest Service, Missoula, MT 59801, USA; johogland@fs.fed.us
² Department of Forest Engineering, Resources and Management, College of Forestry, Oregon State University, Corvallis, OR 97331, USA; Woodam.Chung@oregonstate.edu
 * Correspondence: nathanielanderson@fs.fed.us; Tel.: +1-406-329-2122

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Abstract: Adequate biomass feedstock supply is an important factor in evaluating the financial feasibility of alternative site locations for bioenergy facilities and for maintaining profitability once a facility is built. We used newly developed spatial analysis and logistics software to model the variables influencing feedstock supply and to estimate and map two components of the supply chain for a bioenergy facility: (1) the total biomass stocks available within an economically efficient transportation distance; (2) the cost of logistics to move the required stocks from the forest to the facility. Both biomass stocks and flows have important spatiotemporal dynamics that affect procurement costs and project viability. Though seemingly straightforward, these two components can be difficult to quantify and map accurately in a useful and spatially explicit manner. For an 8 million hectare study area, we used raster-based methods and tools to quantify and visualize these supply metrics at 10 m² spatial resolution. The methodology and software leverage a novel raster-based least-cost path modeling algorithm that quantifies off-road and on-road transportation and other logistics costs. The results of the case study highlight the efficiency, flexibility, fine resolution, and spatial complexity of model outputs developed for facility siting and procurement planning.

Keywords: biomass; logistics; operations; function modeling; raster analysis

1. Introduction
 Forest management for timber production, ecological restoration, and wildfire risk mitigation produces large amounts of woody biomass that can be used for bioenergy and bioproducts. In this context, woody biomass includes small trees and the tops, limbs, foliage, unmerchantable logs, and sometimes stumps of trees that are cut during forest management operations, including the application of silvicultural treatments to achieve both ecological and economic objectives. For industrial facilities that use woody biomass as fuel or feedstock, an adequate, cost-competitive, long-term supply of biomass is critical to both choosing the location of a facility and maintaining profitability once a facility is built.

Feedstock procurement cost is consistently cited as one of the primary drivers of project financial performance [1] and is one of the factors of production with the highest levels of uncertainty [2]. As a result, many studies have been published on this topic [3], and a wide range of methods and decision tools have been developed for supply chain optimization [4] and to help site and supply facilities [4–6].

Others rely on non-spatial engineering-based nature of the underlying research, and operating commercial industrial

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OPEN PINE AREAS USING RASTER UTILITY TOOLBAR AND BATCH PROCESSING

JOHN HOGLAND¹, & KORYN HAIGHT^{1,2}

RESEARCH STATION

IMAGE BASED CLASSIFICATION USING THE RMRS RASTER UTILITY TOOLBAR: FOCUS ON WORKFLOW

JOHN HOGLAND, KORYN HAIGHT

PRIORITIZATION OF OPEN PINE RED COCKADED WOODPECKER HABITAT

JOSEPH ST. PETER^{1,2}, JOHN HOGLAND¹, & KORYN HAIGHT^{1,2}

¹ USFS Rocky Mountain Research Station
² University of Montana

PAPERS & TUTORIALS

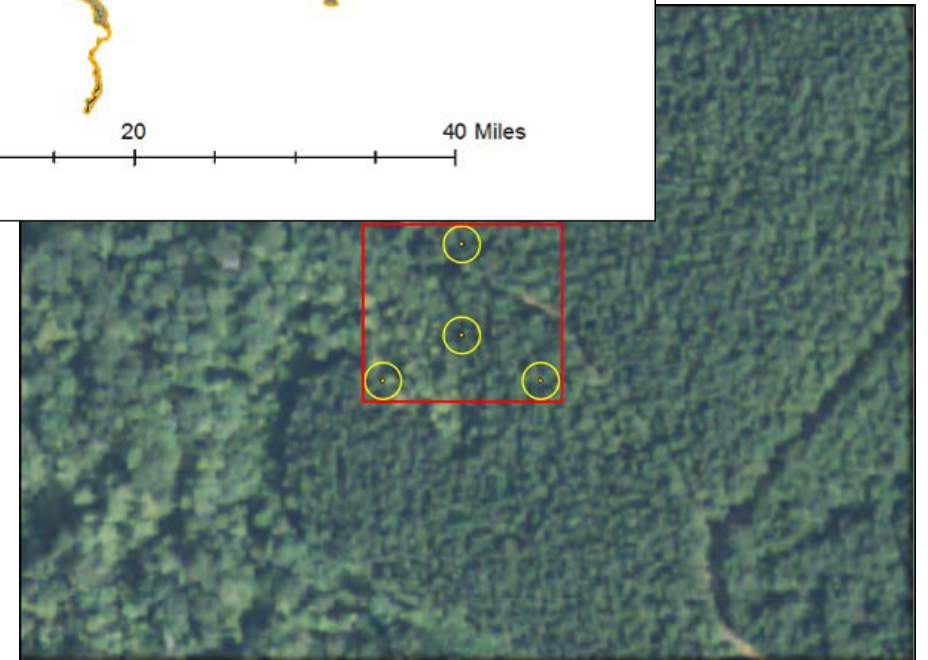
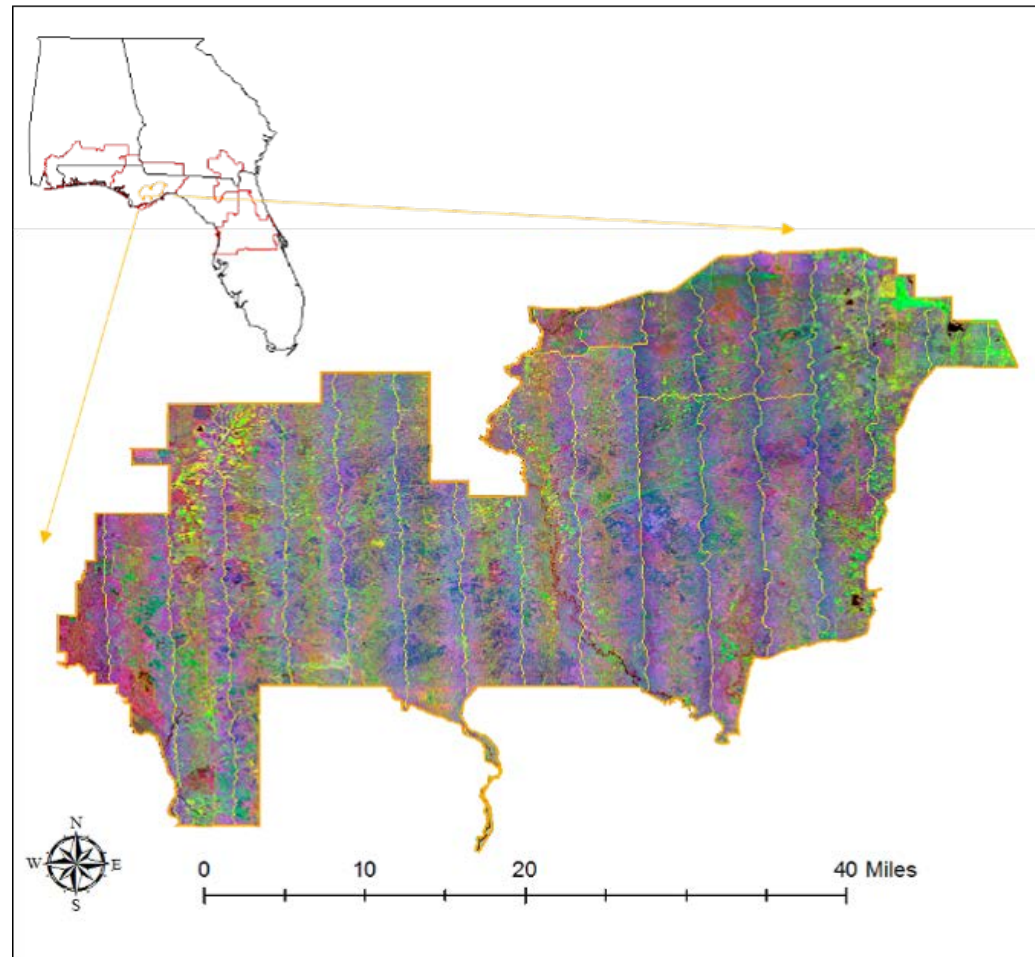
MAPPING BAA: FOCUS ON WORKFLOW

JOHN HOGLAND¹, NATHANIEL ANDERSON¹, JOE ST. PETER², & KORYN HAIGHT²

Aspen Crown Area
 Aspen Shadow Edge
 PCA Focal Sum Circle, 7

Challenges

- Imagery
 - Dates\Resolution\Preprocessing
- Plot Protocol
 - Layout
 - Size
 - Sampling intensity
 - Small trees
- Co-registration errors
 - GPS
 - Imagery



Improving Base Information

- Imagery Normalization
 - Improve radiometric normalization
- Co-registration error
 - Quantify impact
 - Correct for bias
- Plot Protocol
 - Design layout to related to imagery
 - Types of information
- Sample Design

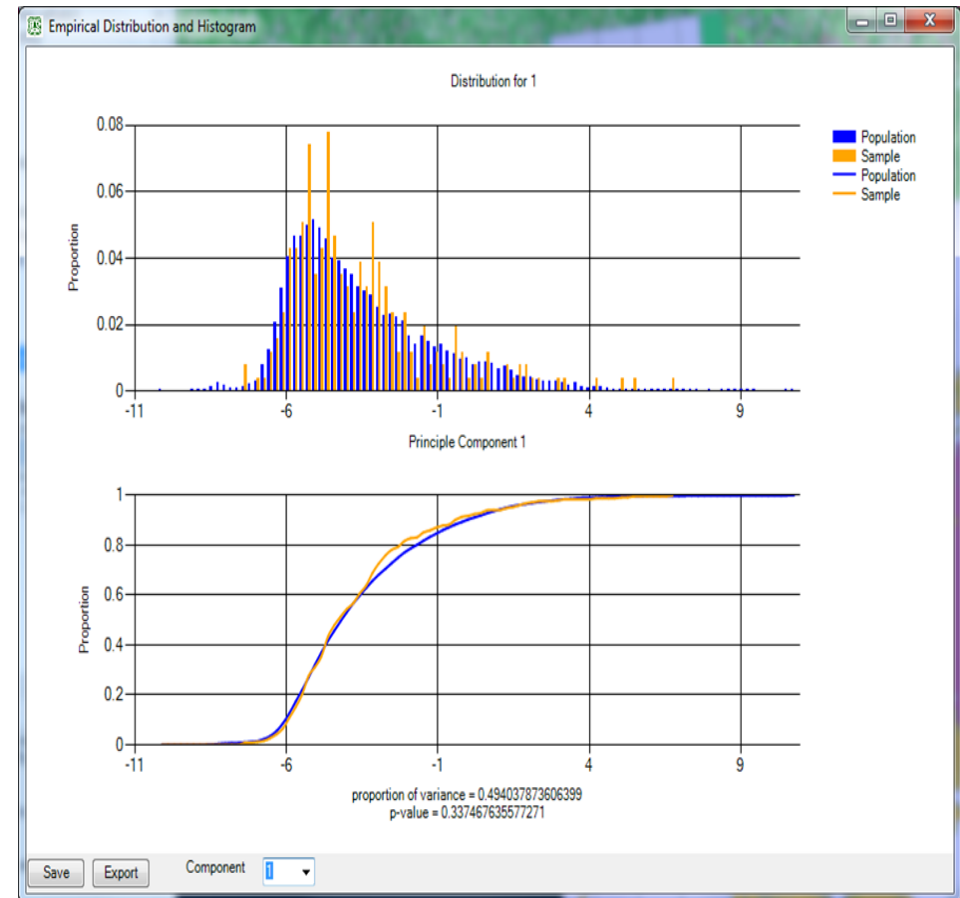
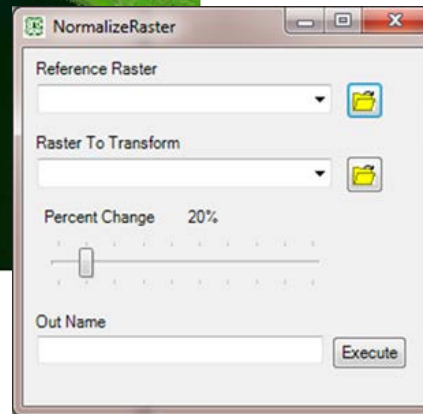
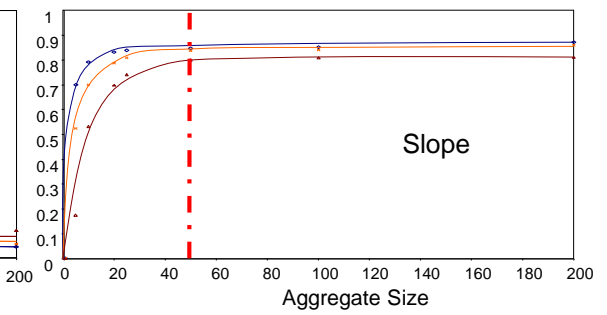
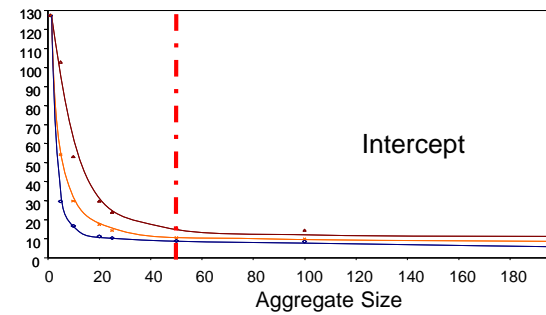
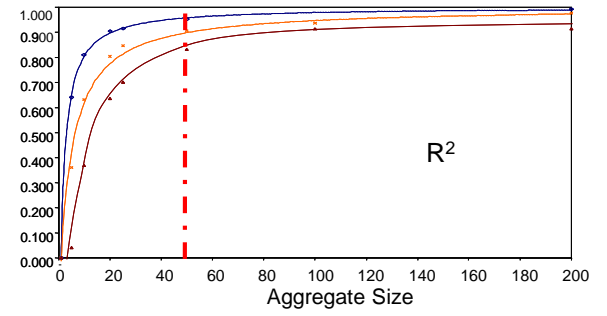
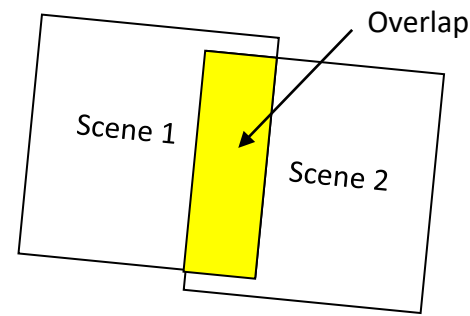
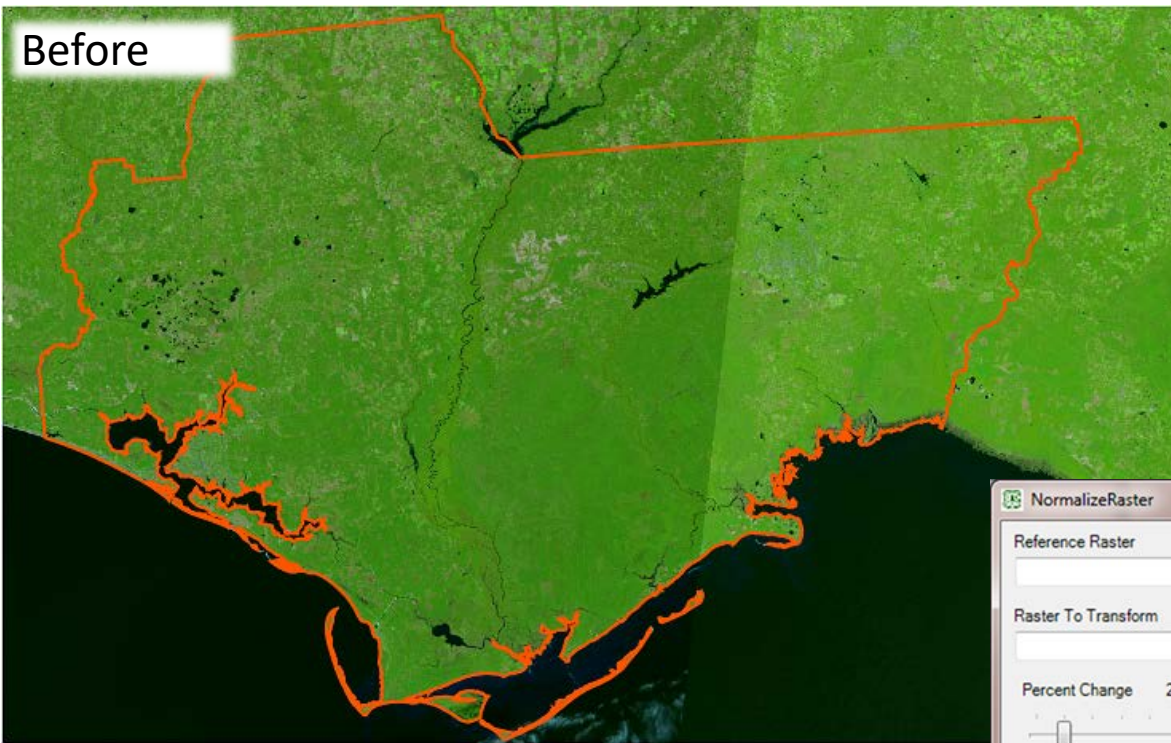


Image Normalization



Aggregation size

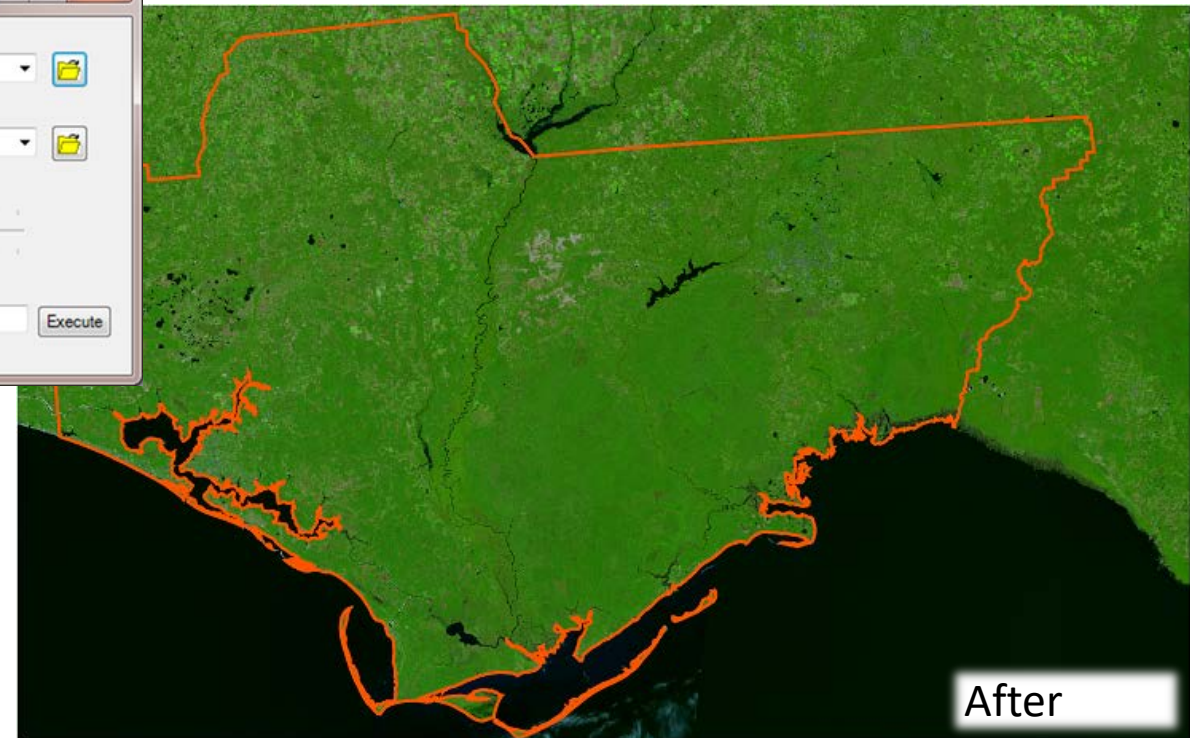
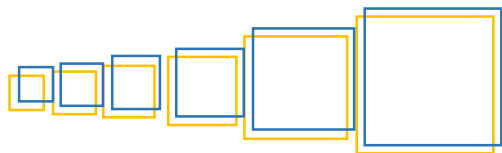
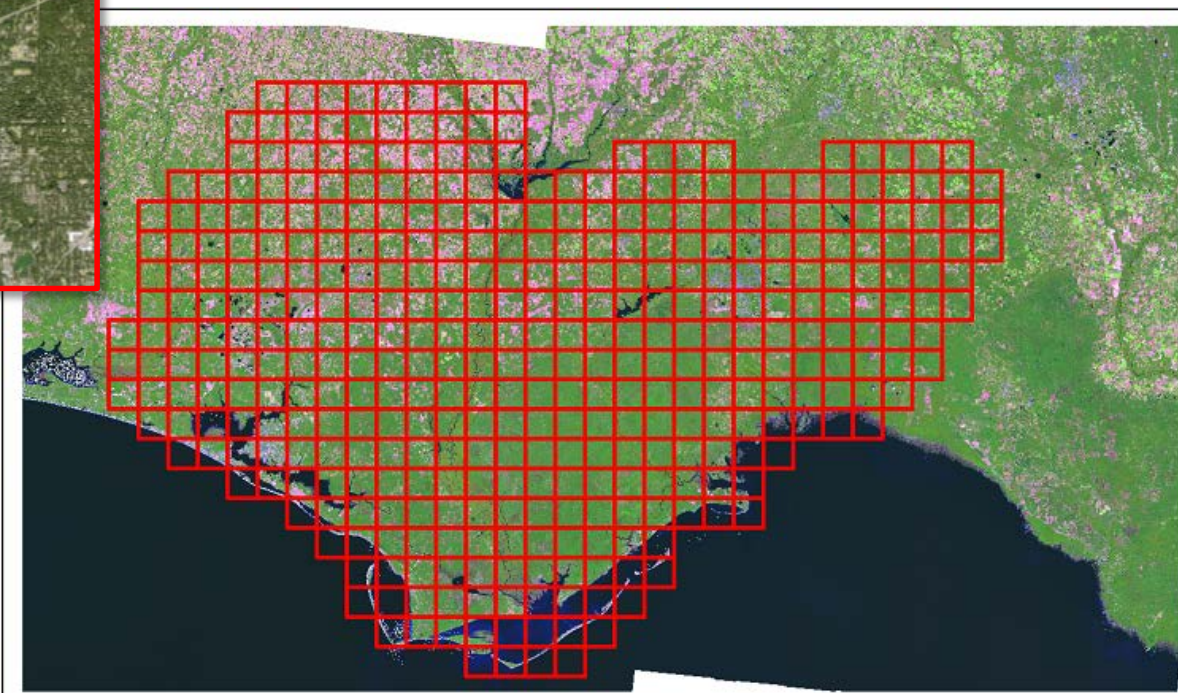
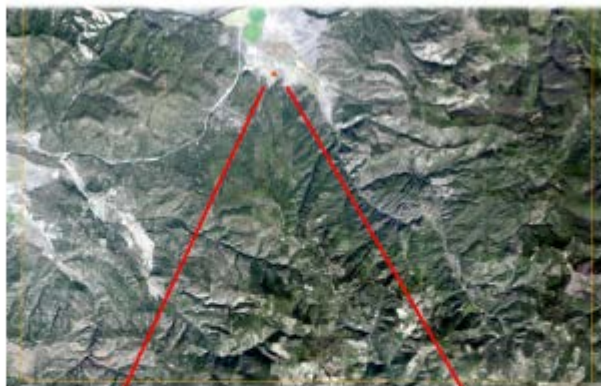
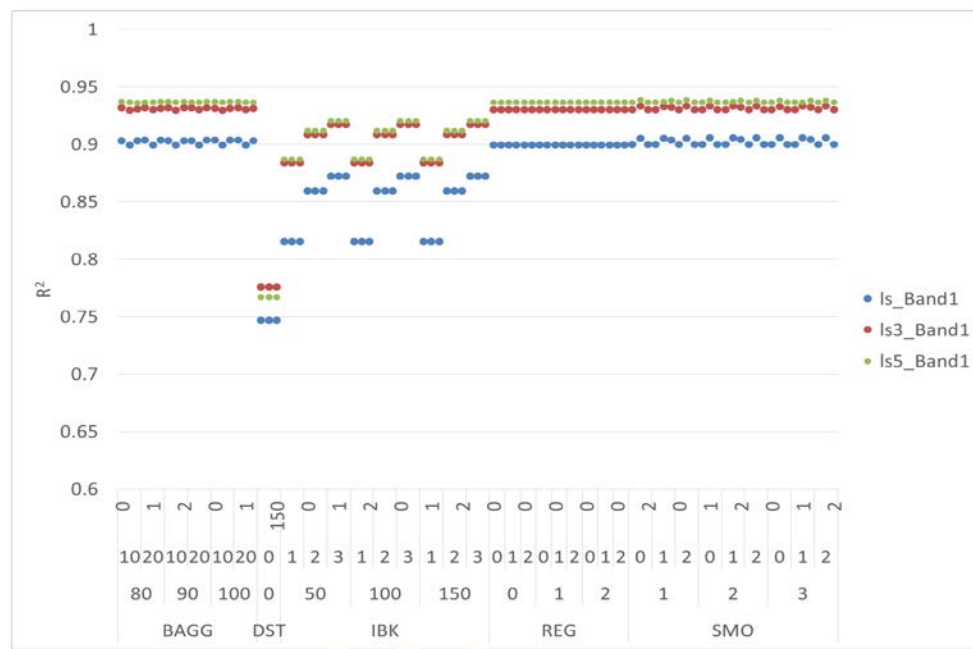
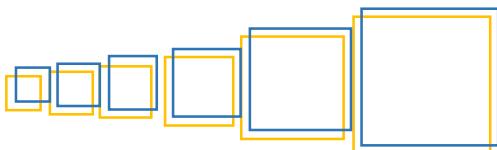


Image Normalization NAIP

Spatial Resolution 30m² vs 1m²



Aggregation size

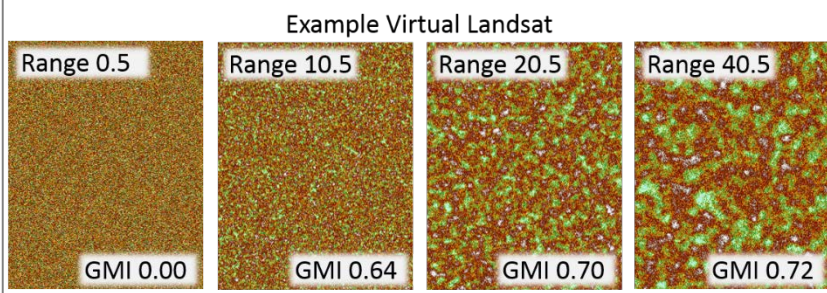
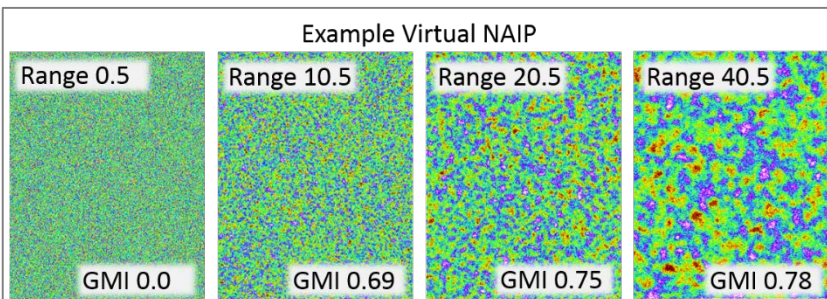
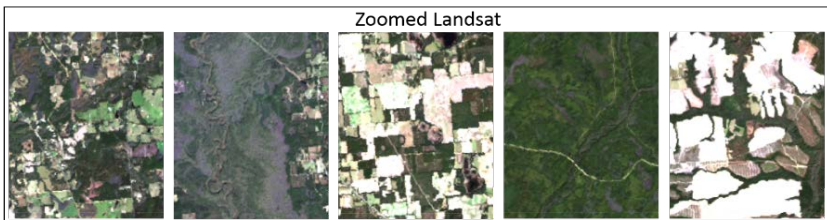
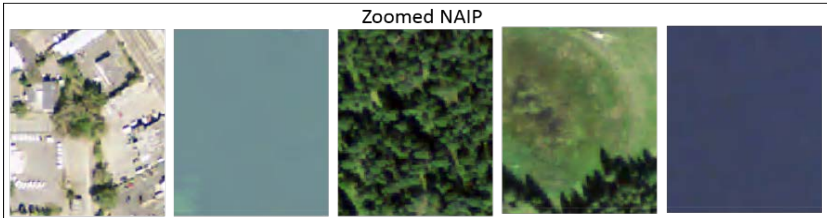
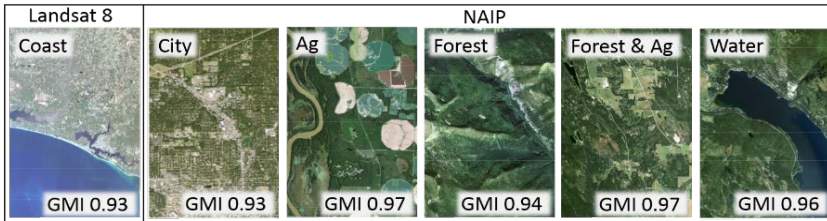


Plot Protocol & Co-registration Errors:

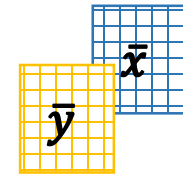
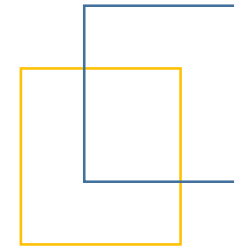
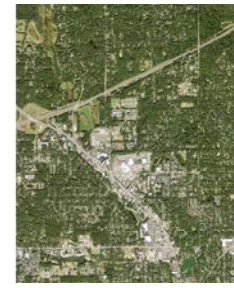
NAIP Shift GPS & Image (8m, 6m)



Simulations

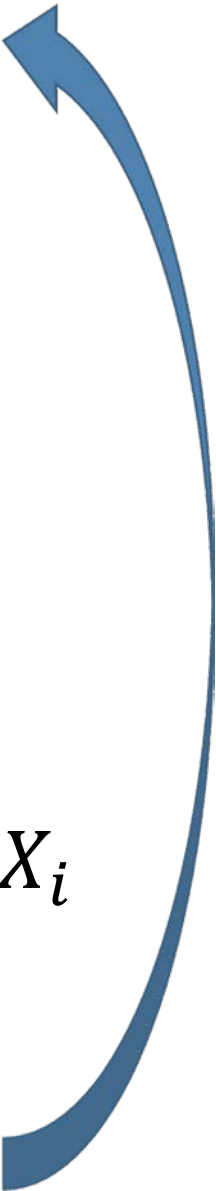
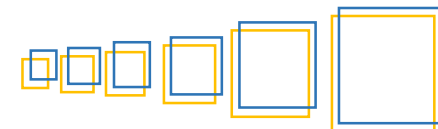


- 6 real images and 19 virtual images
- 200 locations
- 2 random shifts
 - GPS (7 m)
 - Image (NAIP: 6 cells, Landsat: 2 cells)
- Extract spectral values
- Regress against one another
- Record intercept, slope, RMSE and R^2
- Repeated (1-100 cells)



$$Y_i = \beta_0 + \beta_i X_i$$

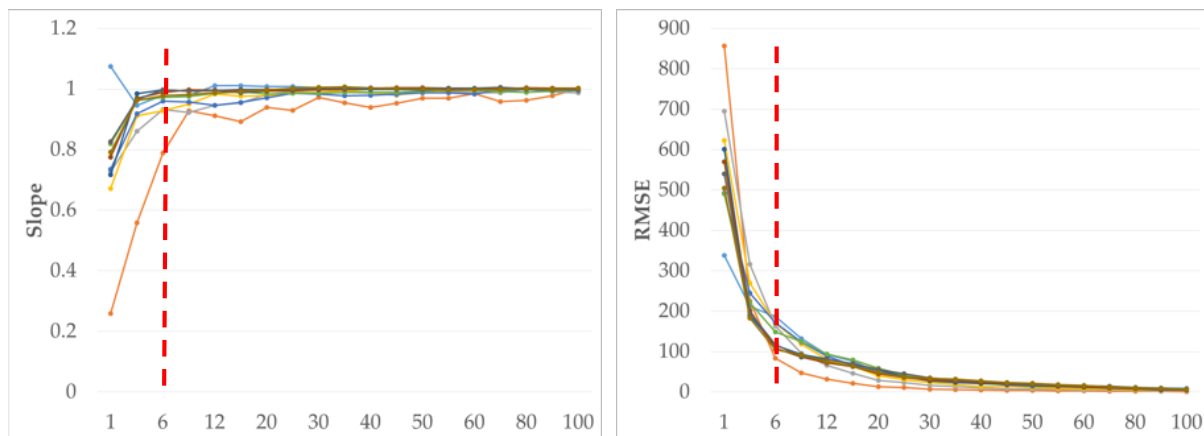
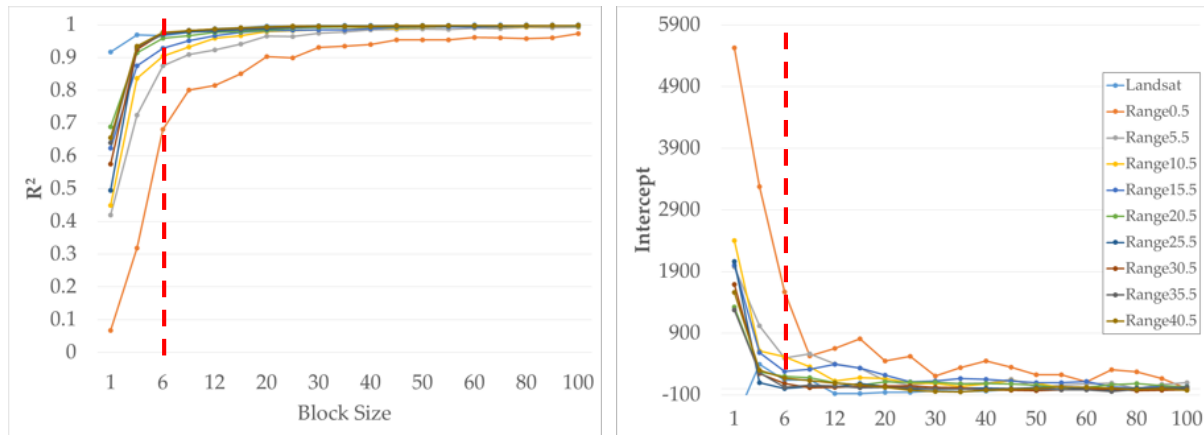
Record



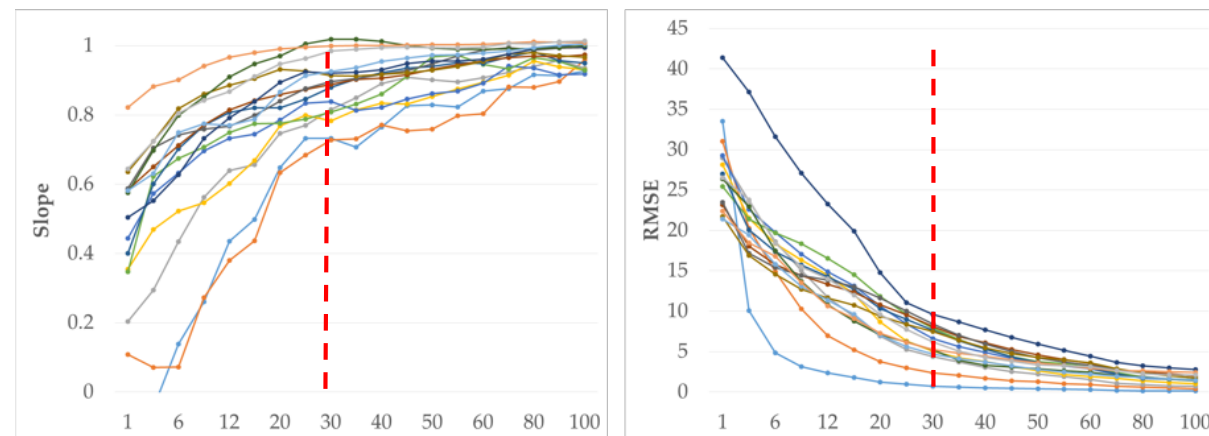
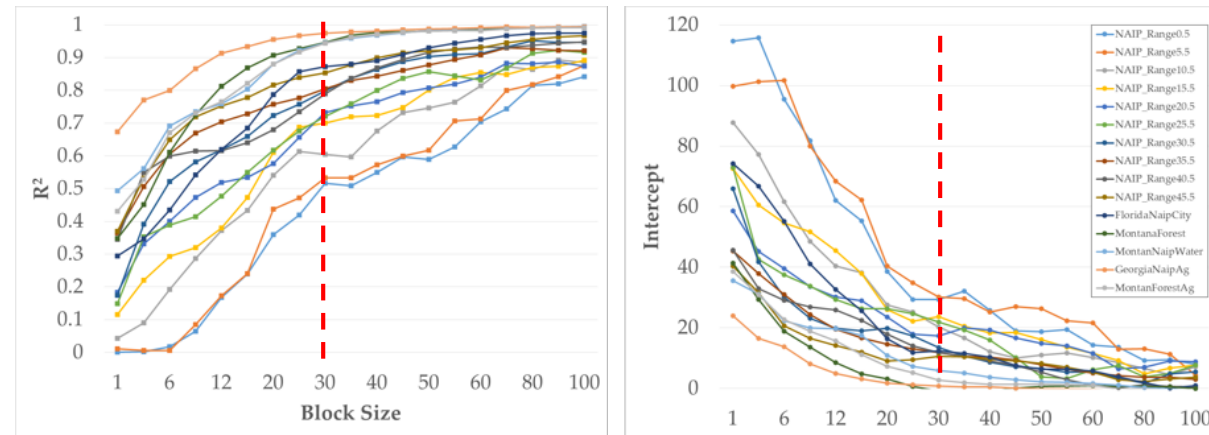
Results: Co-registration

$$\ln\left(\frac{R^2}{1-R^2}\right) = \ln(\text{overlap}) + GMI + \ln(\text{overlap}) * GMI$$

Landsat



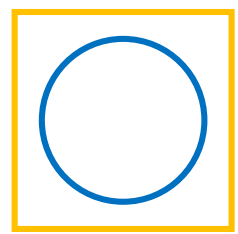
NAIP



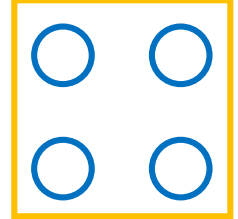
Plot Protocol & Co-registration errors

- Given extent, what sampling intensity and spatial layout
- Layouts
 - 1 big plot
 - 4 subplots one in each corner
 - 4 subplots randomly placed
 - 4 subplots based on FIA protocol
 - 5 subplots one in the center one in each corner
 - 9 subplots equally spaced out within the extent
- Intensity
 - 5-100% area inventoried

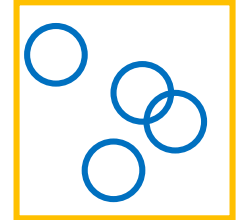
One



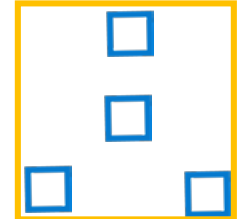
Four



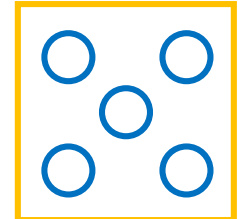
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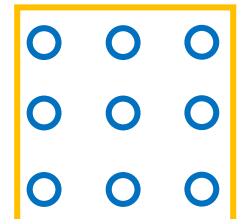
FIA



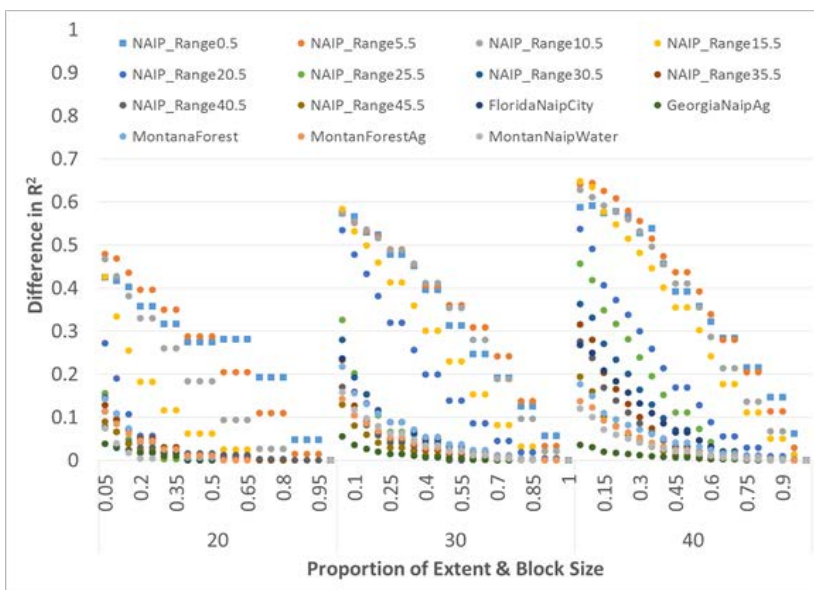
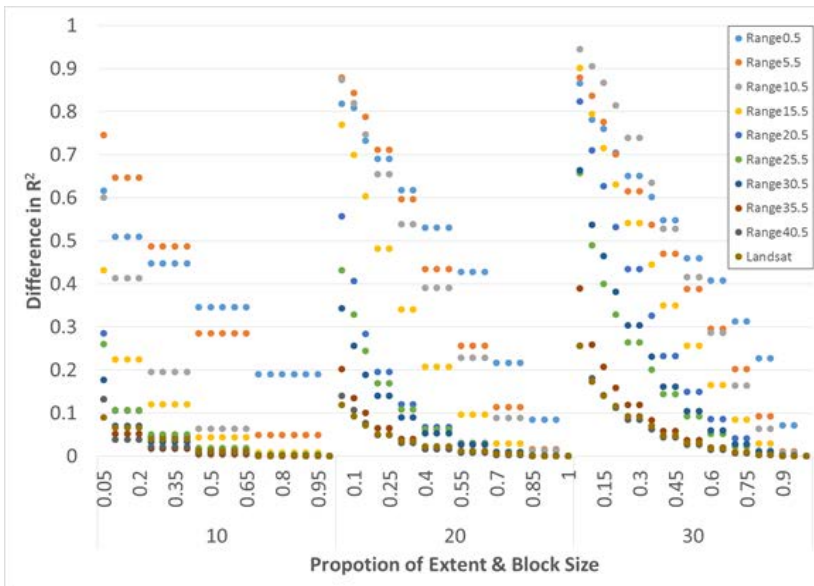
Five



Nine



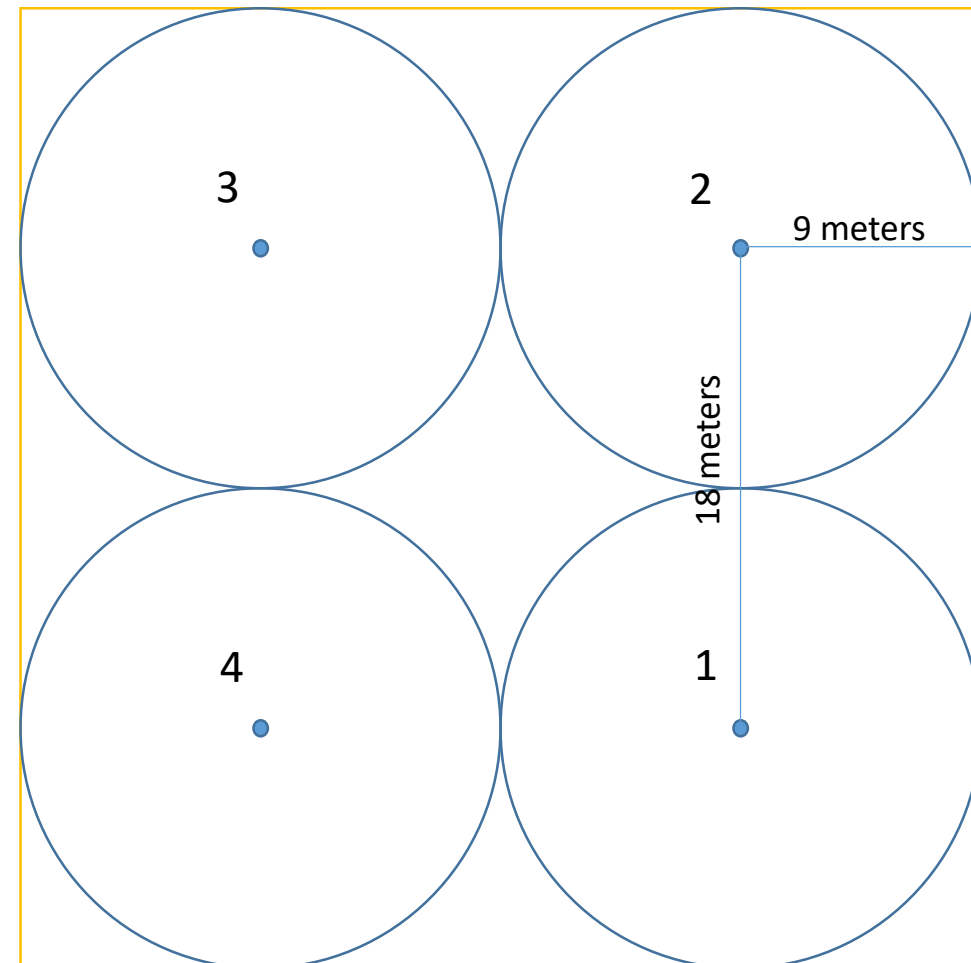
Results: Plot\Subplot Layout



- Plot data
 - GPS location Subplot1
 - 20 positions (Averaging)
 - HDOP < 5
 - 3D mode
 - DGPS if possible
 - Picture
- Subplot data
 - Last Burn
 - % CWD
 - % Herb
 - % Saw
 - % Broad
 - % Bare
 - % Pine
 - Tree
 - DBH > 2"
 - Species
 - Status
 - Count

36 meters

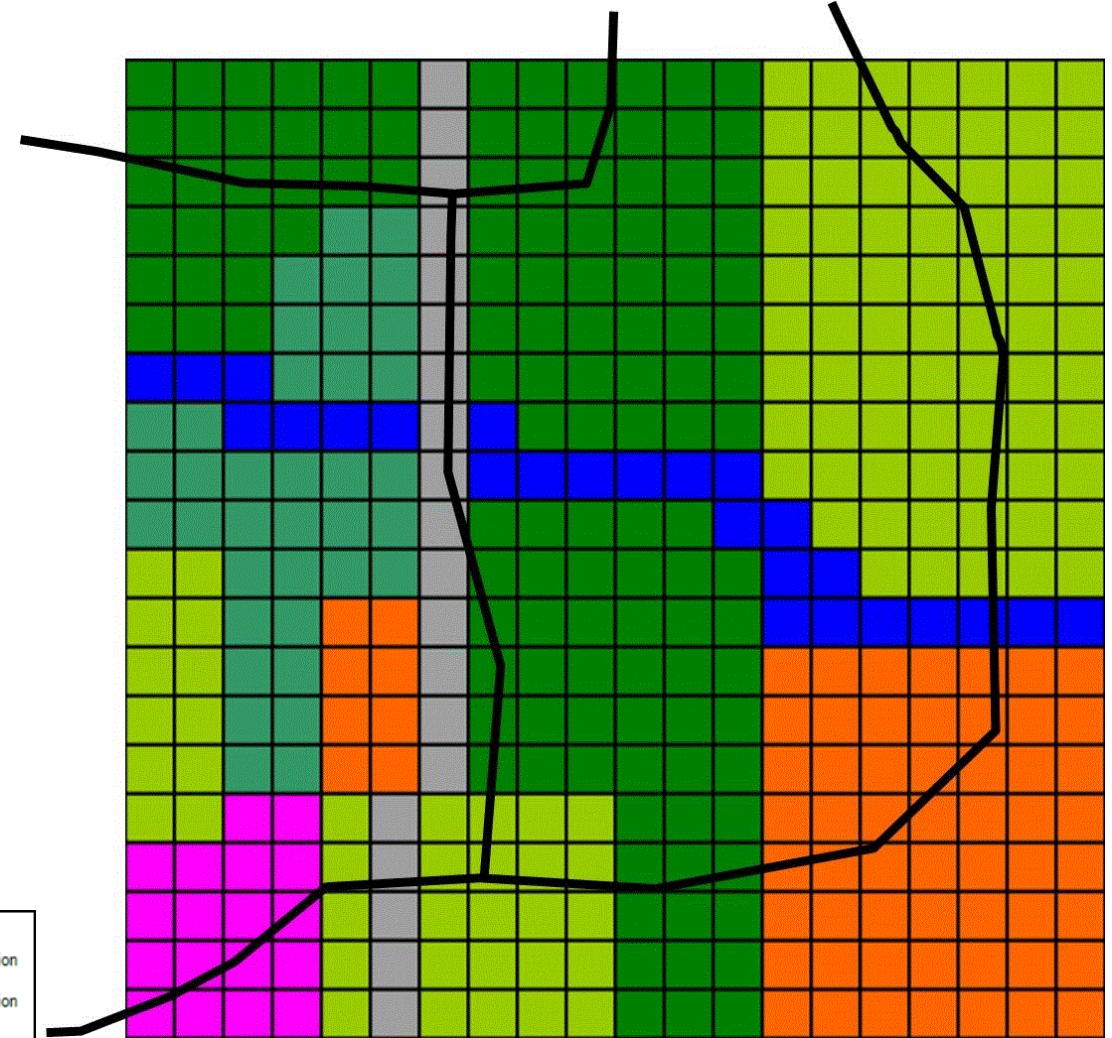
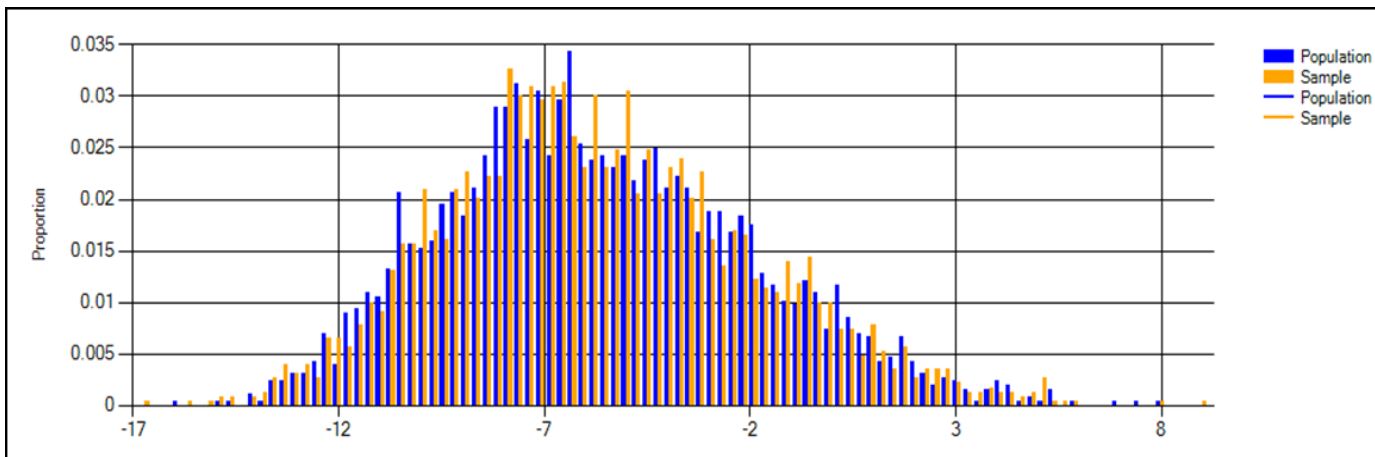
36 meters



Sample Design

- Modeled sampled design

- Partition population
 - Inexpensive and costly locations
- Describe the distribution of predictor variables for the population
- Select sample units that minimize the number of expensive samples while matching the population's predictor variables distribution



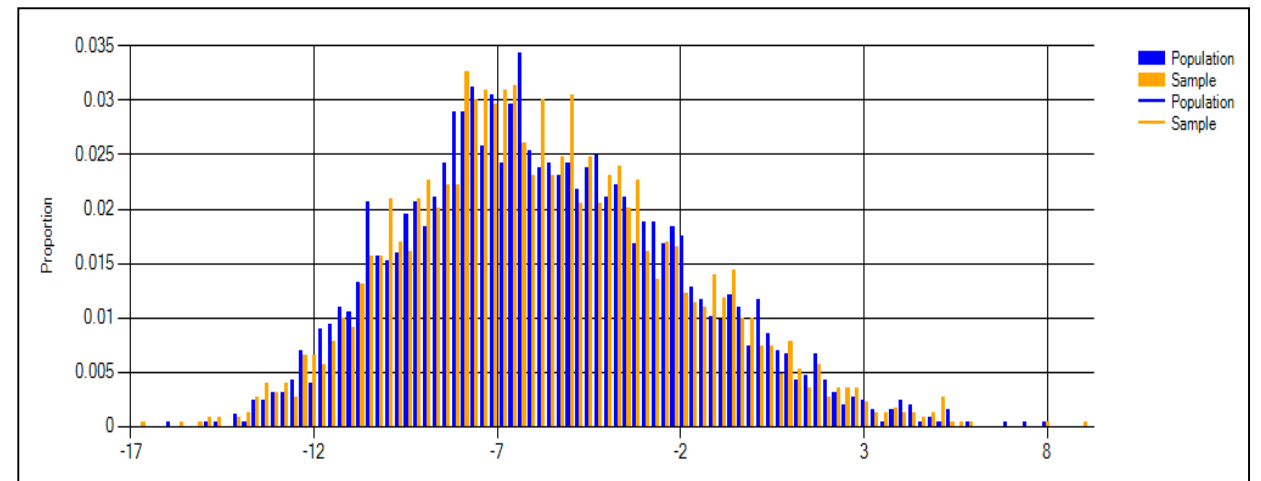
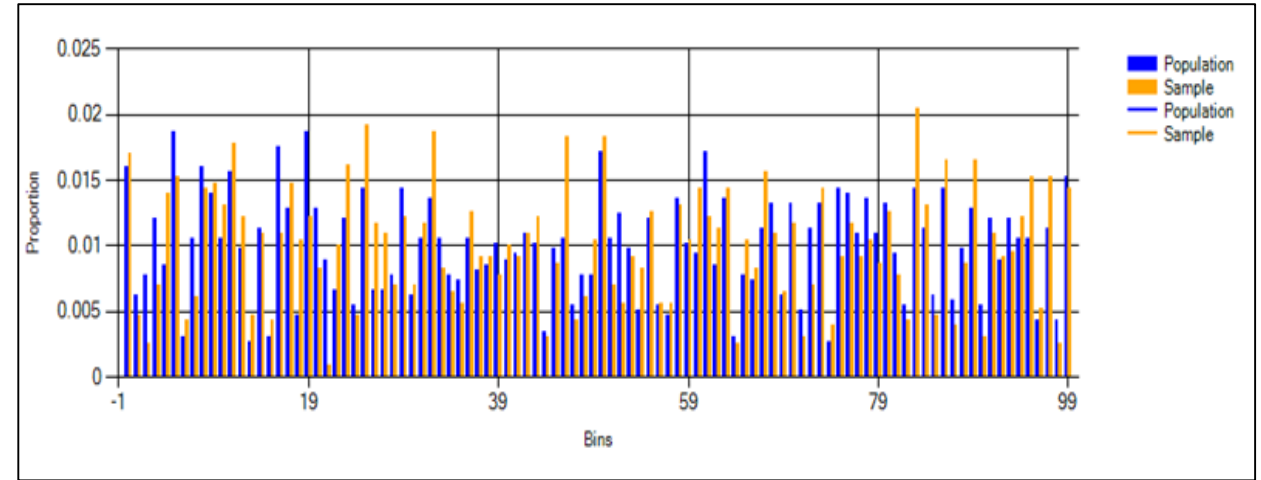
How

$$d = \max_x |f_{n1}(x) - f_{n2}(x)|$$

$$f_n(x) = \frac{1}{n} \sum_{i=1}^n I(x_i \leq x)$$

$$\overline{wKS} = \sum_{i=1}^k KSstatistic_i * \lambda_i$$

- Develop a methodology to determine if the values of a sample match the natural population distribution
 - Multivariate Kolmogorov-Smirnov (K-S) test
- Partition predictor variables into cluster space
- Randomly select locations within predefined inexpensive areas to match frequency distribution of the population clusters
- Test the distribution of predictors variables



Results: Sample Design

Select Samples

Table:

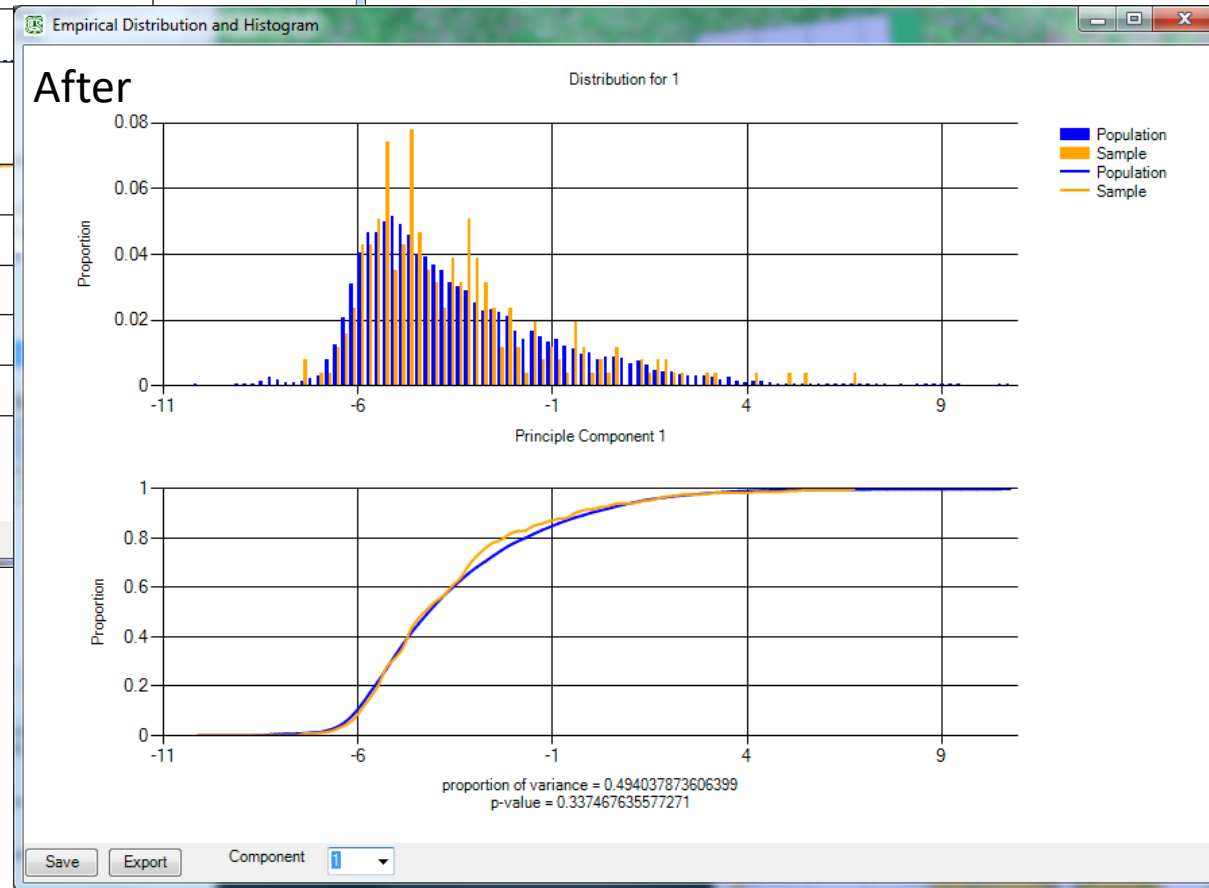
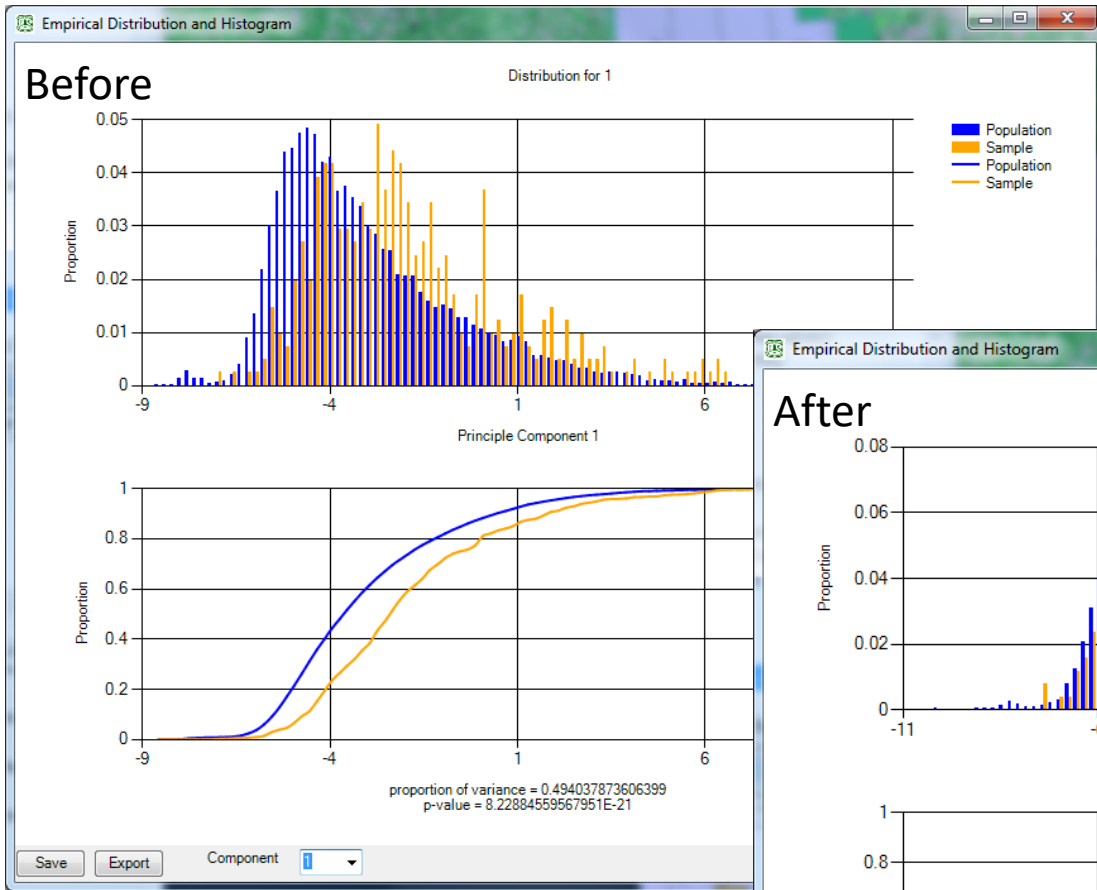
Cluster/Strata/Class Field:

Model Path:

Width (%Mean): Alpha:

Adjust for equal weights

Execute



Compare Sample To Population

Population Table:

Sample Table:

Stratum Field:

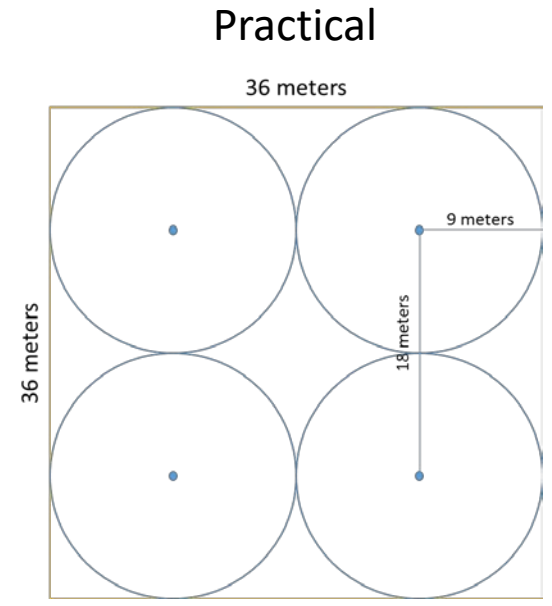
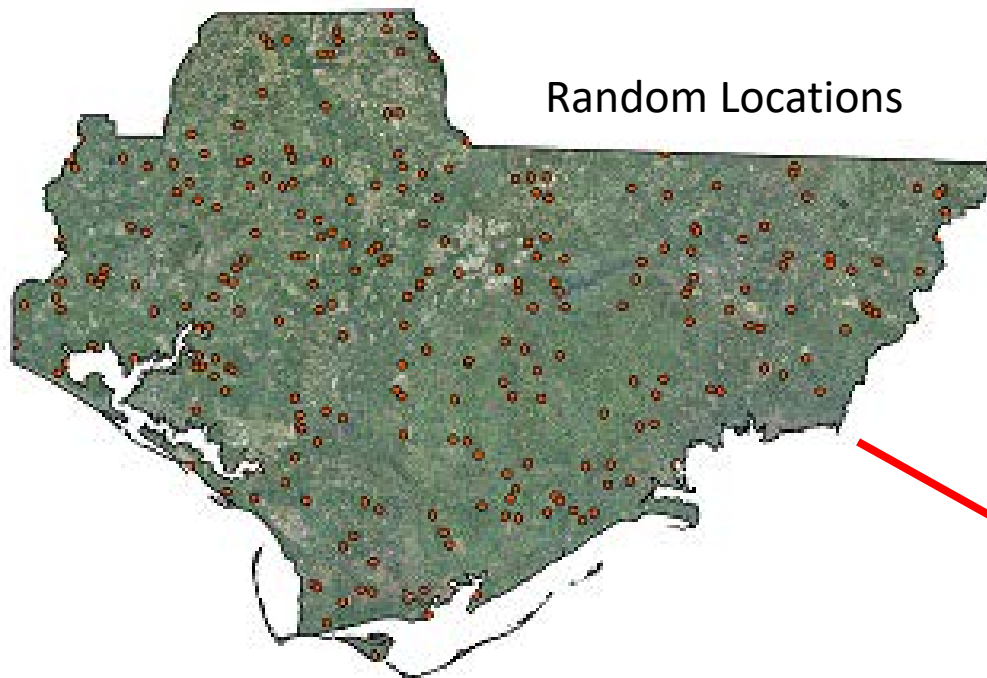
Parameters

Variables:

Output Model:

Execute

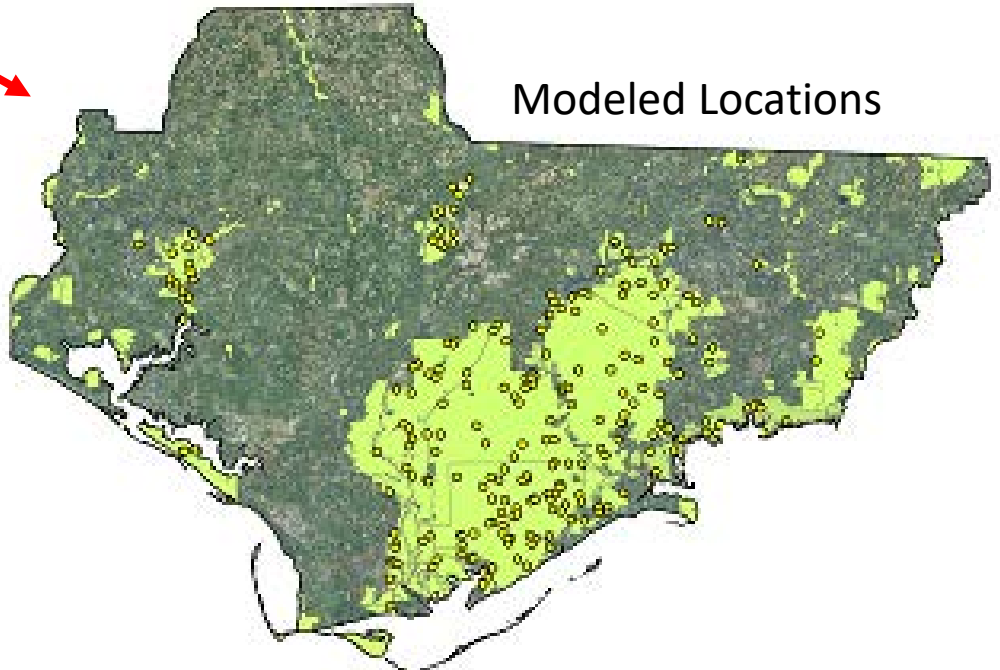
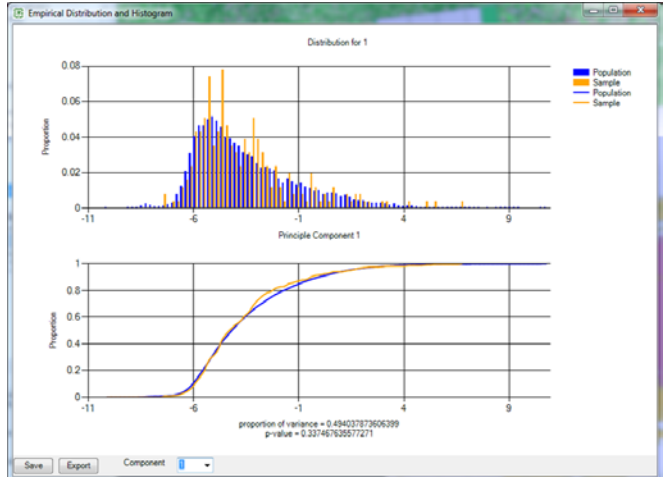
Results: Field Plots



Integrated

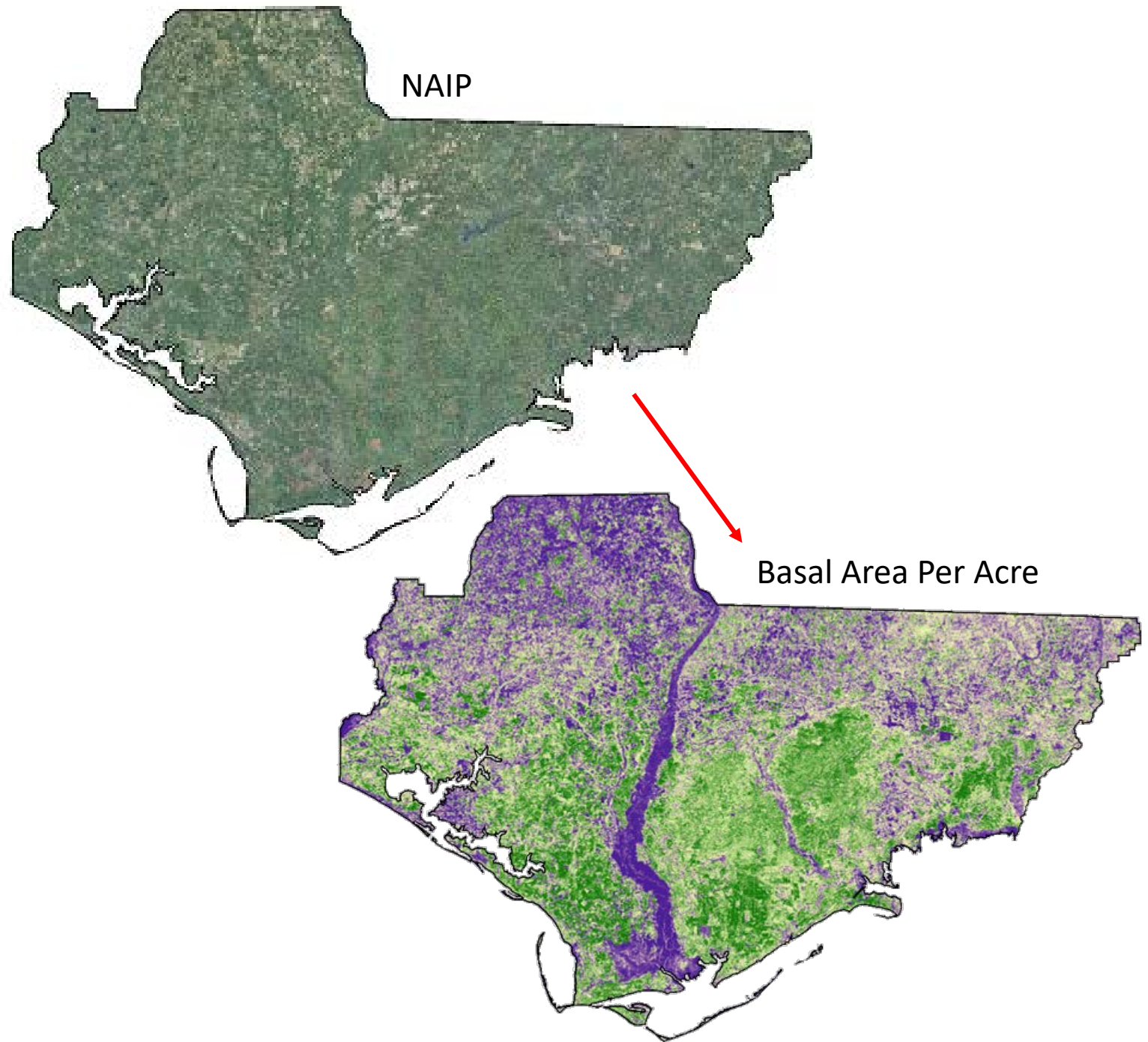


Natural Distribution



Next Steps

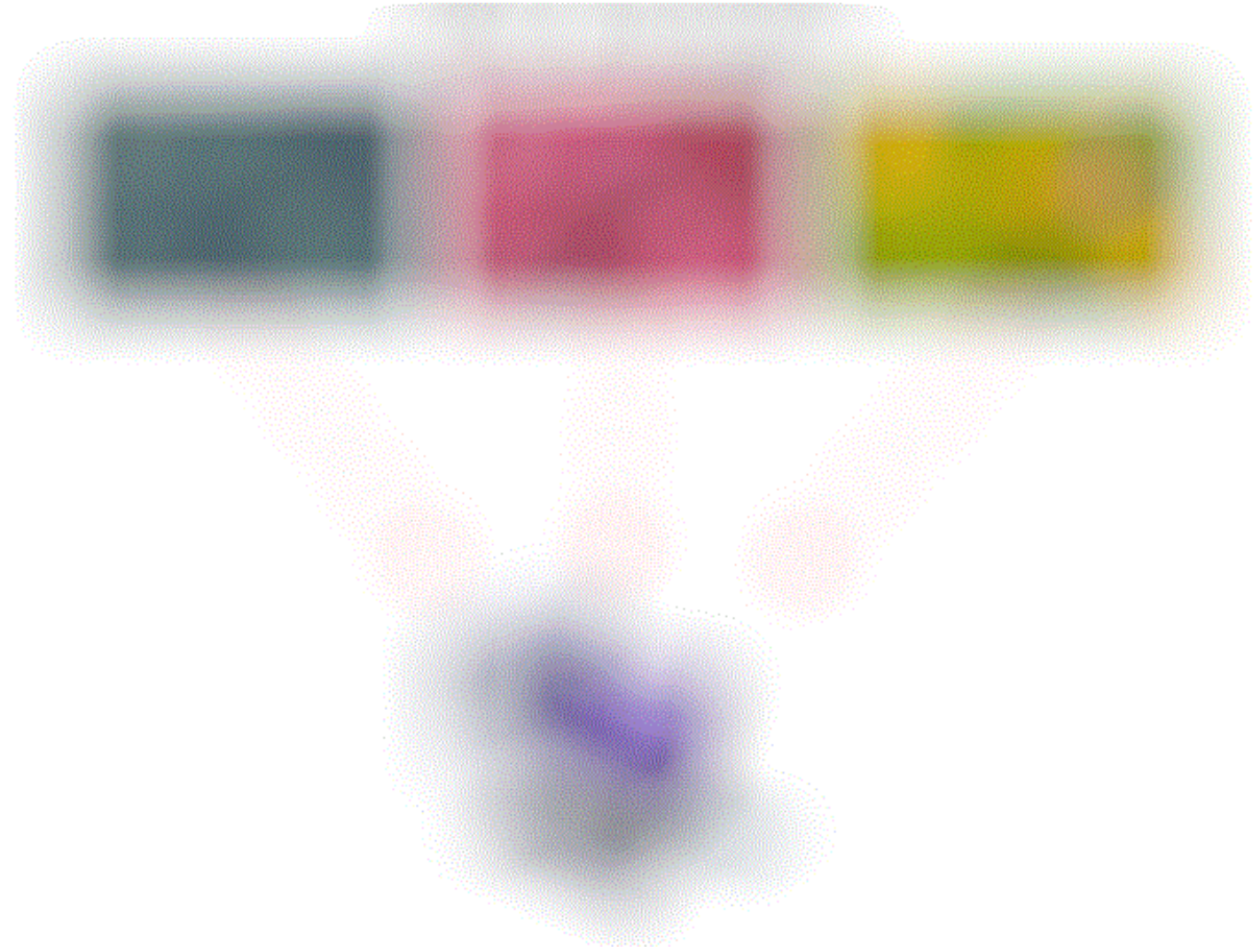
- Normalize NAIP imagery
- Build predictive surfaces
- Summarize plot data
- Build models and outputs
- Compare predictions



Questions



John Hogland, Biological Scientist
Rocky Mountain Research Station
800 East Beckwith Missoula, MT 59801
Phone: (406) 329-2138
email: jshogland@fs.fed.us



RMRS Raster Utility Website: <http://www.fs.fed.us/rm/raster-utility/>

