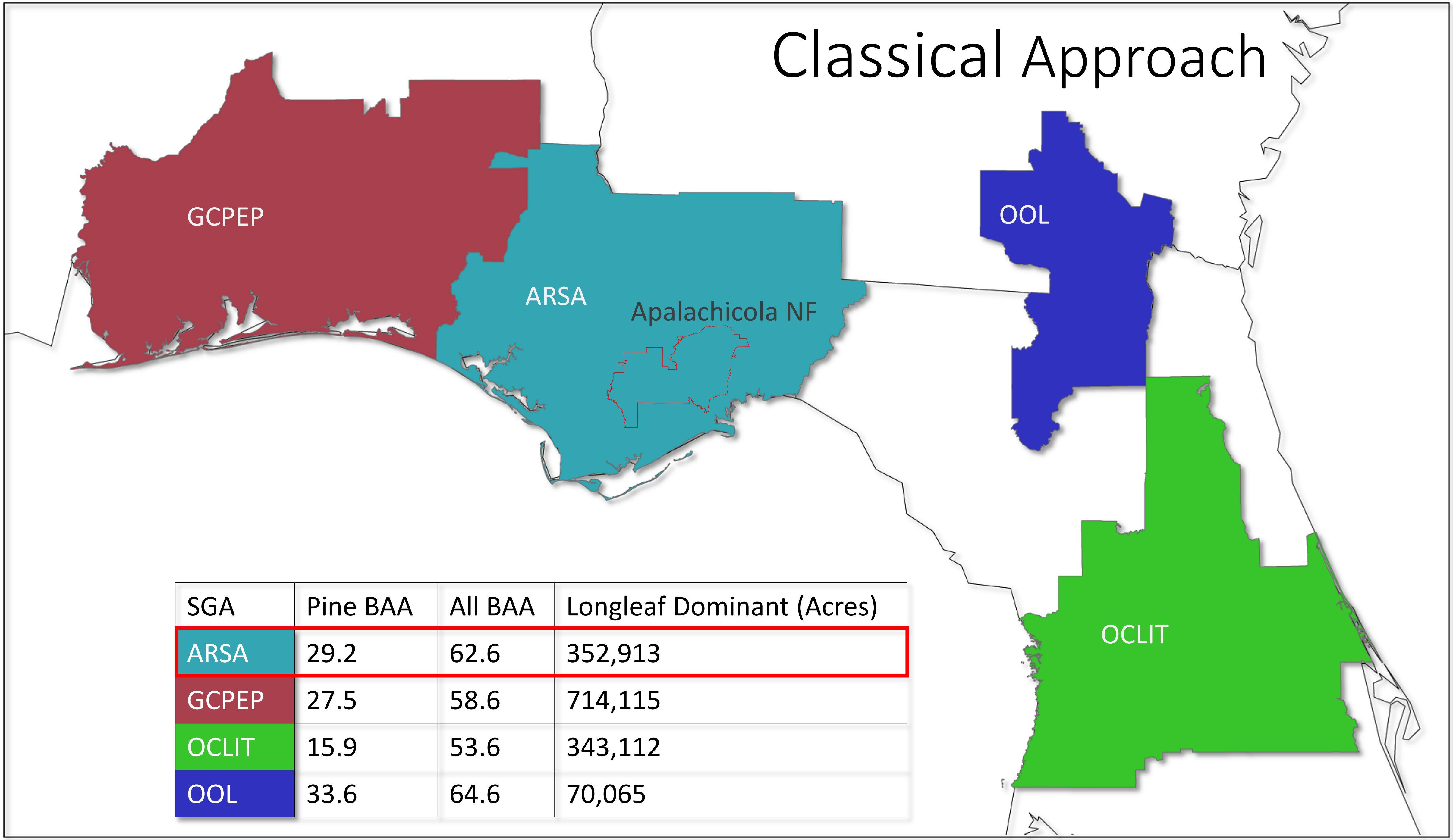
ESTIMATING CHARACTERISTICS OF FORESTS IN THE APALACHICOLA REGION USING REMOTELY SENSED IMAGERY AND FIELD SAMPLES

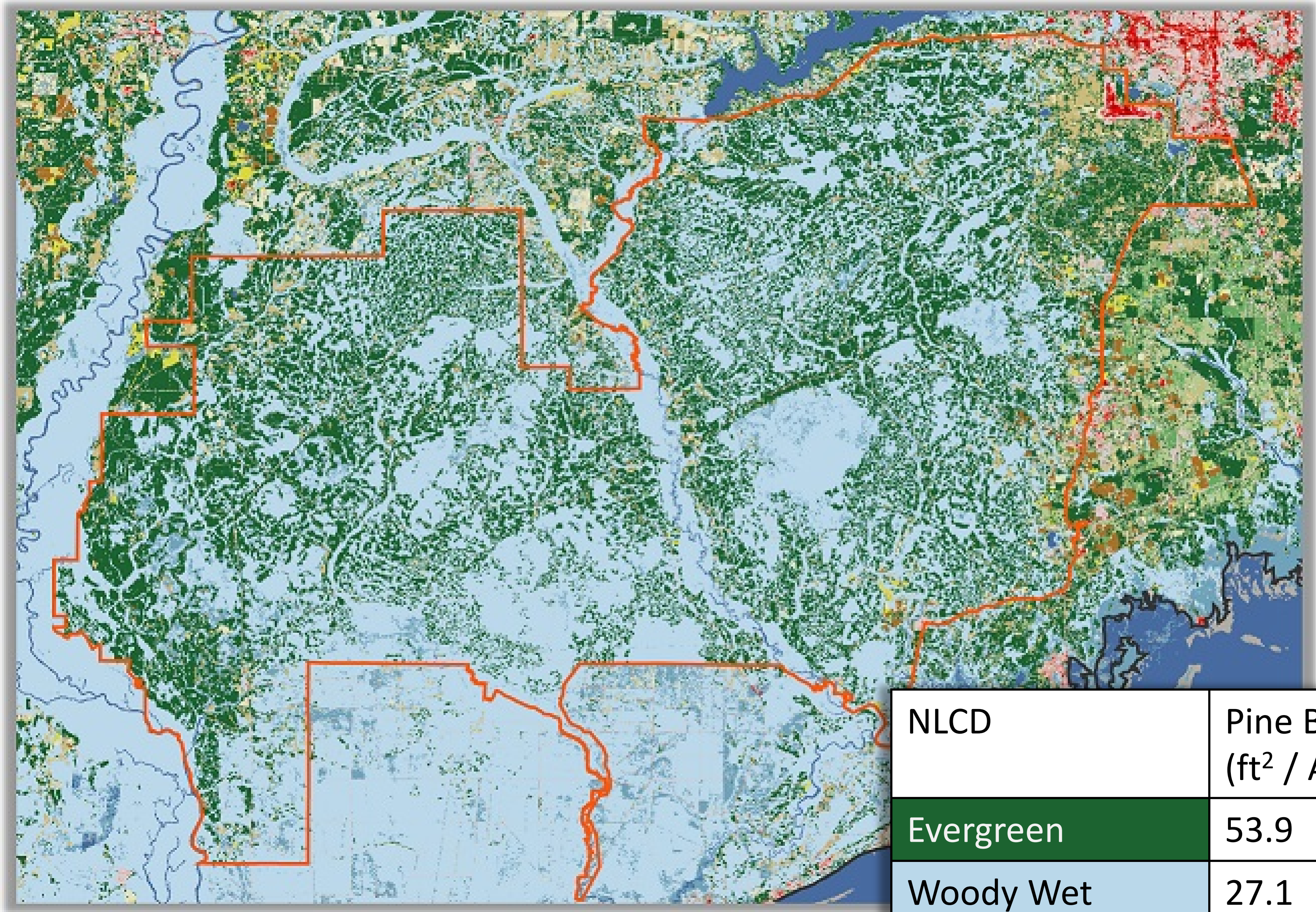
John Hogland, Nathaniel Anderson, Jason Drake, Paul Medley, David Affleck, and Joseph St. Peter

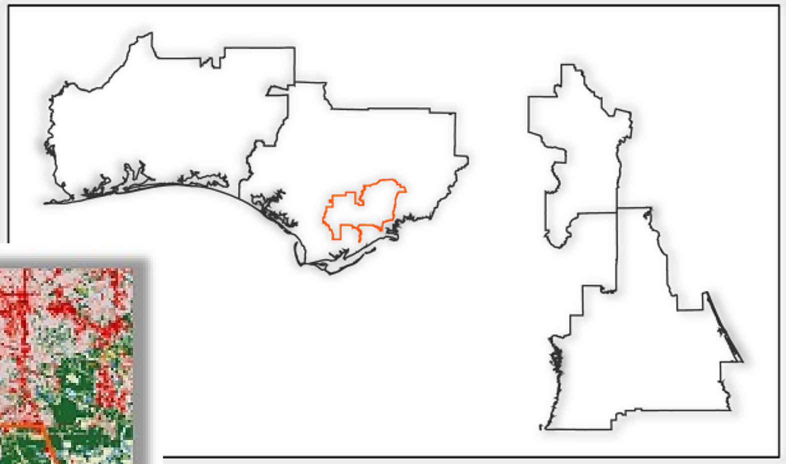
Classical Approach



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

22,400,000 acres

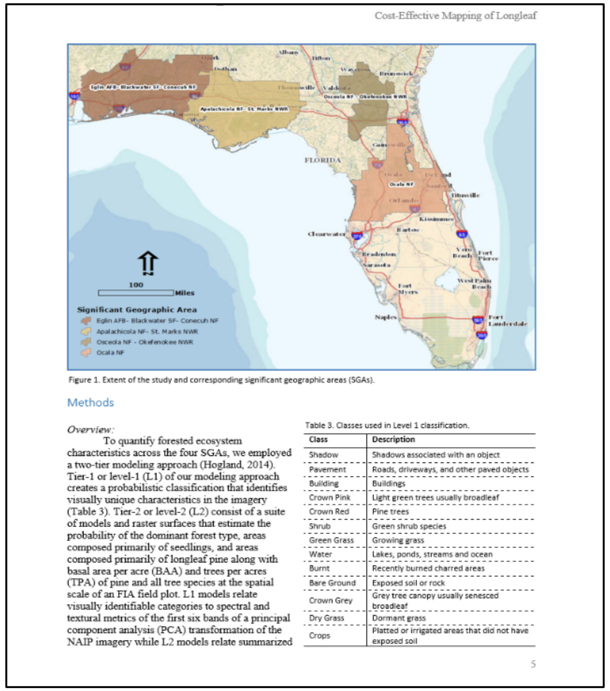

Cost-Effective Mapping of Longleaf

Figure 1. Extent of the study and corresponding significant geographic areas (SGAs).

Methods

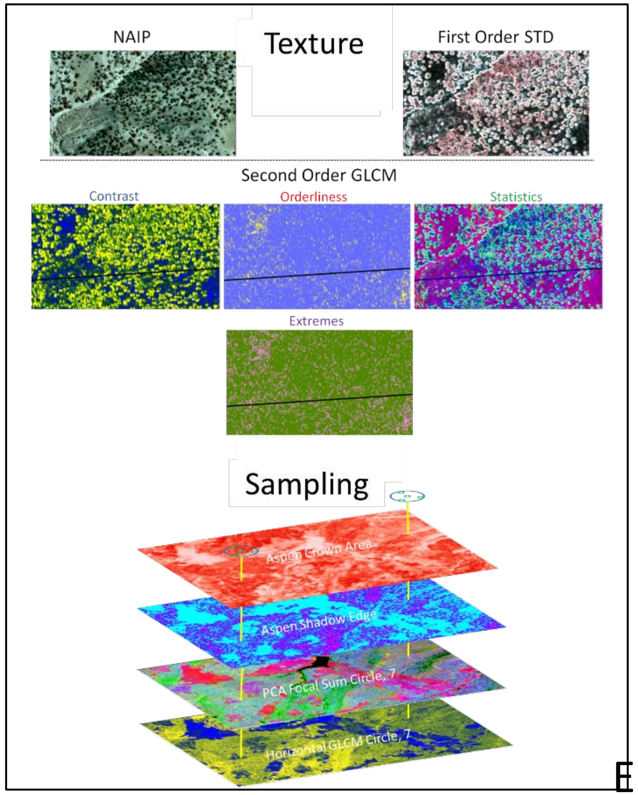
Overview.
To quantify forested ecosystem characteristics across the four SGAs, we employed a two-tier modeling approach (Hogland, 2014). Tier-1 or level-1 (L1) of our modeling approach creates a probabilistic classification that identifies visually unique characteristics in the imagery (Table 3). Tier-2 or level-2 (L2) consist of a suite of models and raster surfaces that estimate the probability of the dominant forest type, areas composed primarily of seedlings, and areas composed primarily of longleaf pine along with basal area per acre (BAA) and trees per acres (TPA) of pine and all tree species at the spatial scale of an FIA field plot. L1 models relate visually identifiable categories to spectral and textural metrics of the first six bands of a principal component analysis (PCA) transformation of the NAIP imagery while L2 models relate summarized

Table 3. Classes used in Level 1 classification.

Class	Description
Shadow	Shadows associated with an object
Pavement	Roads, driveways, and other paved objects
Building	Buildings
Crown Pink	Light green trees usually broadleaf
Crown Red	Pine trees
Shrub	Green shrub species
Green Grass	Growing grass
Water	Lakes, ponds, streams and ocean
Burnt	Recently burned charred areas
Bare Ground	Exposed soil or rock
Crown Grey	Grey tree canopy usually senesced broadleaf
Dry Grass	Dormant grass
Crops	Platted or irrigated areas that did not have exposed soil

5

Preprocessing



Papers


International Journal of Geo-Information

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Article

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

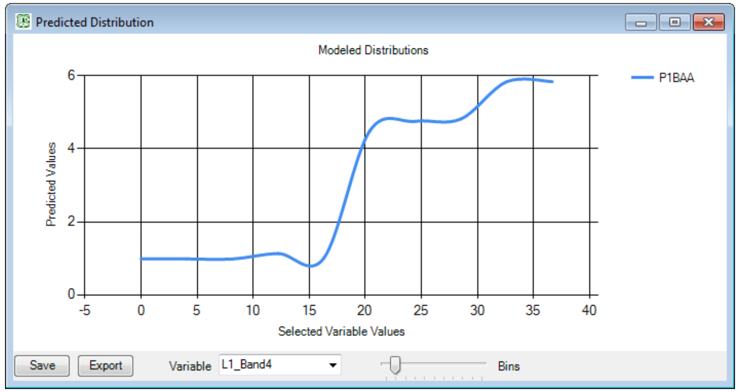
John Hogland, Nathaniel Anderson, Joseph St. Peter, Jason Drake and Paul Medley

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) aerial imagery across broad extents. Our findings support 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.

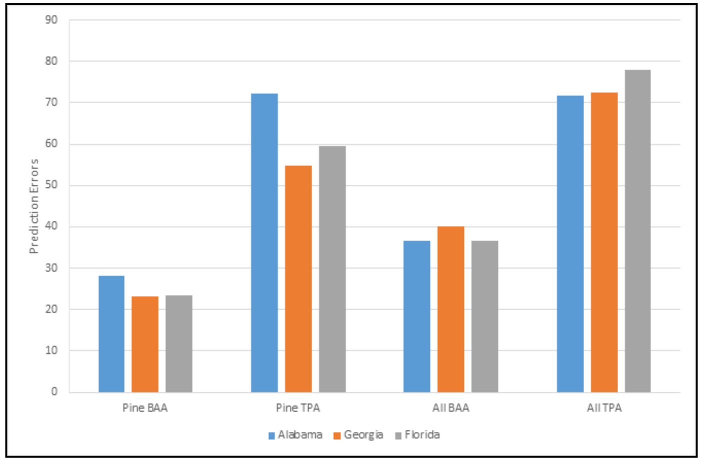
Keywords: NAIP; FIA; remote sensing; forest measurements

1. Introduction

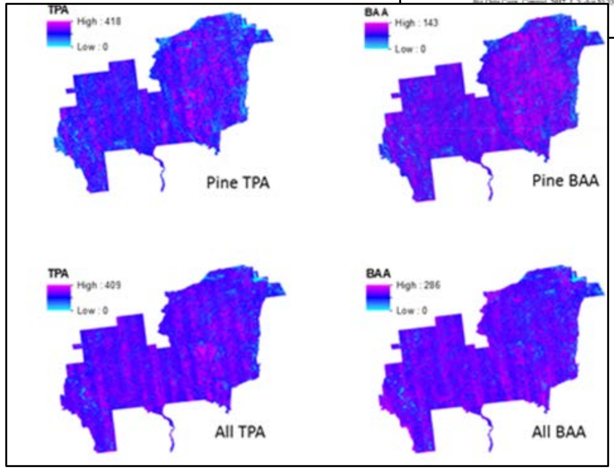
Modeling



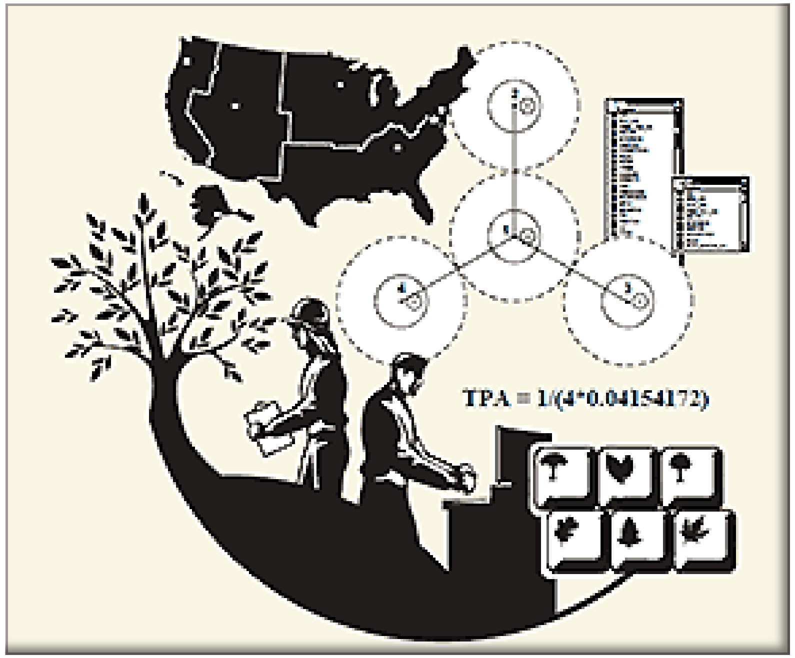
Error



Spatial Outputs



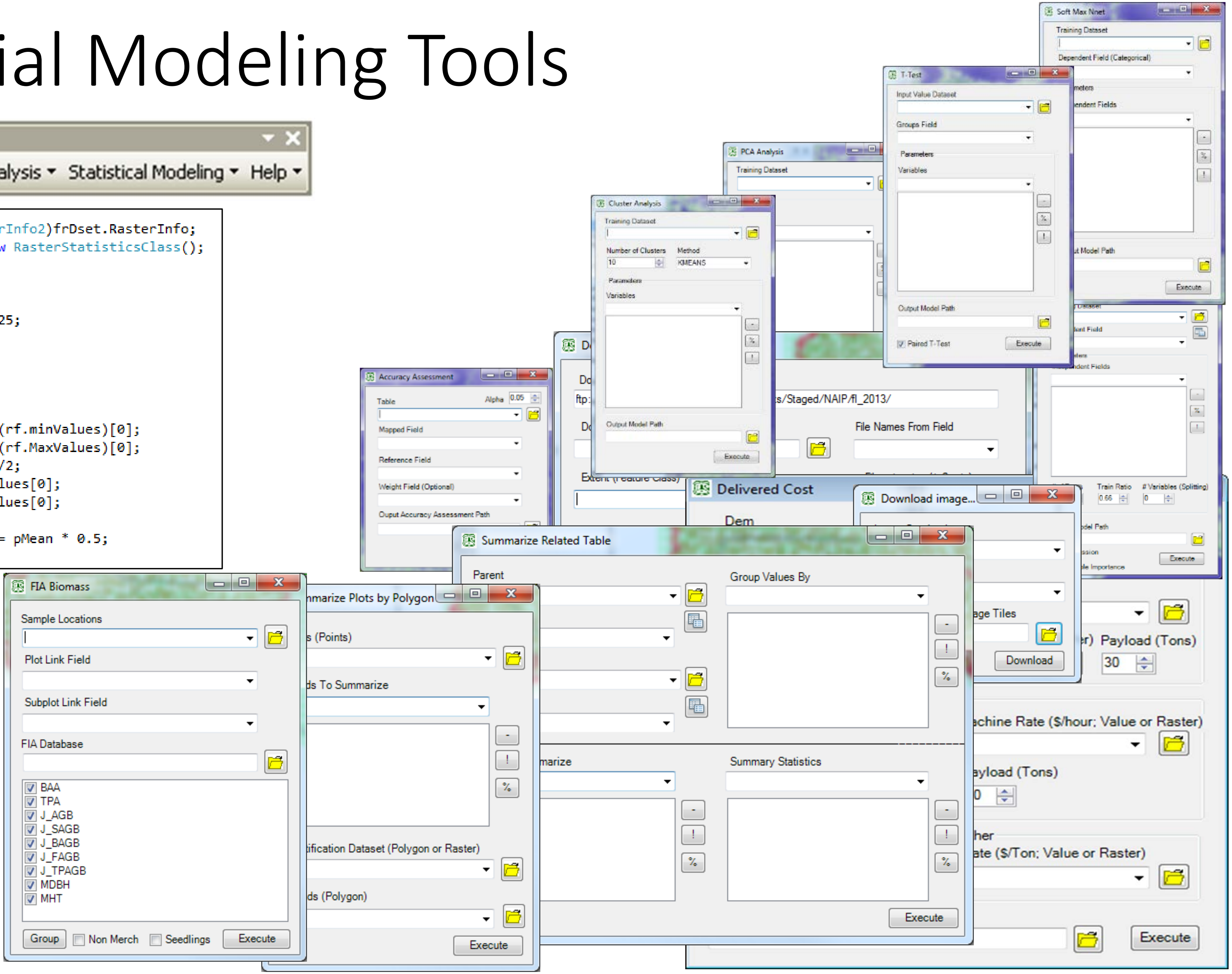
How It Works



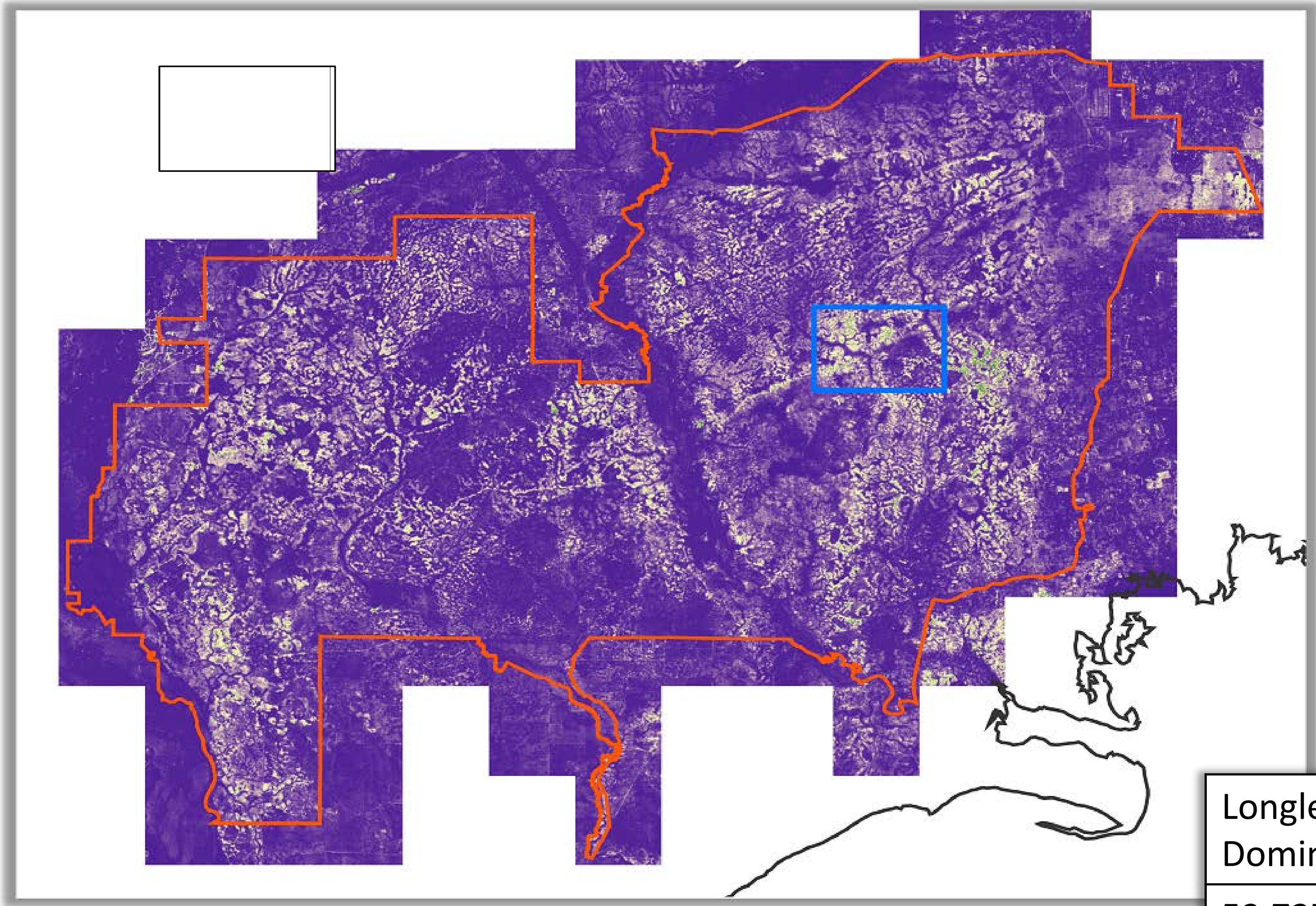

ADF *2008*

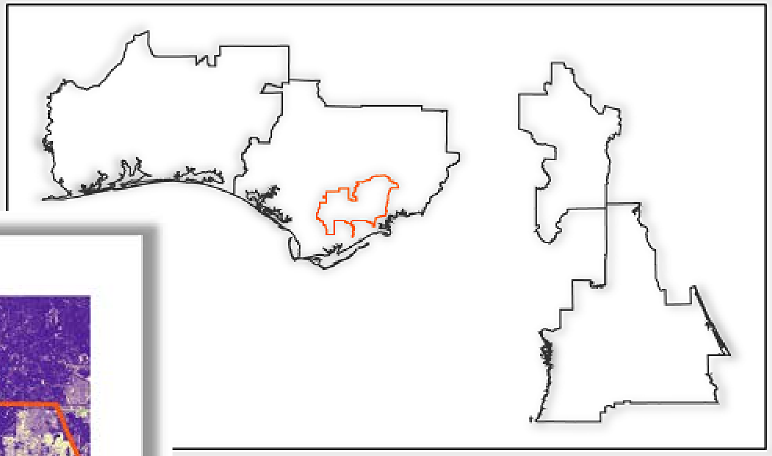
Improved Spatial Modeling Tools


```
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.Regression)
{
    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;
}
```



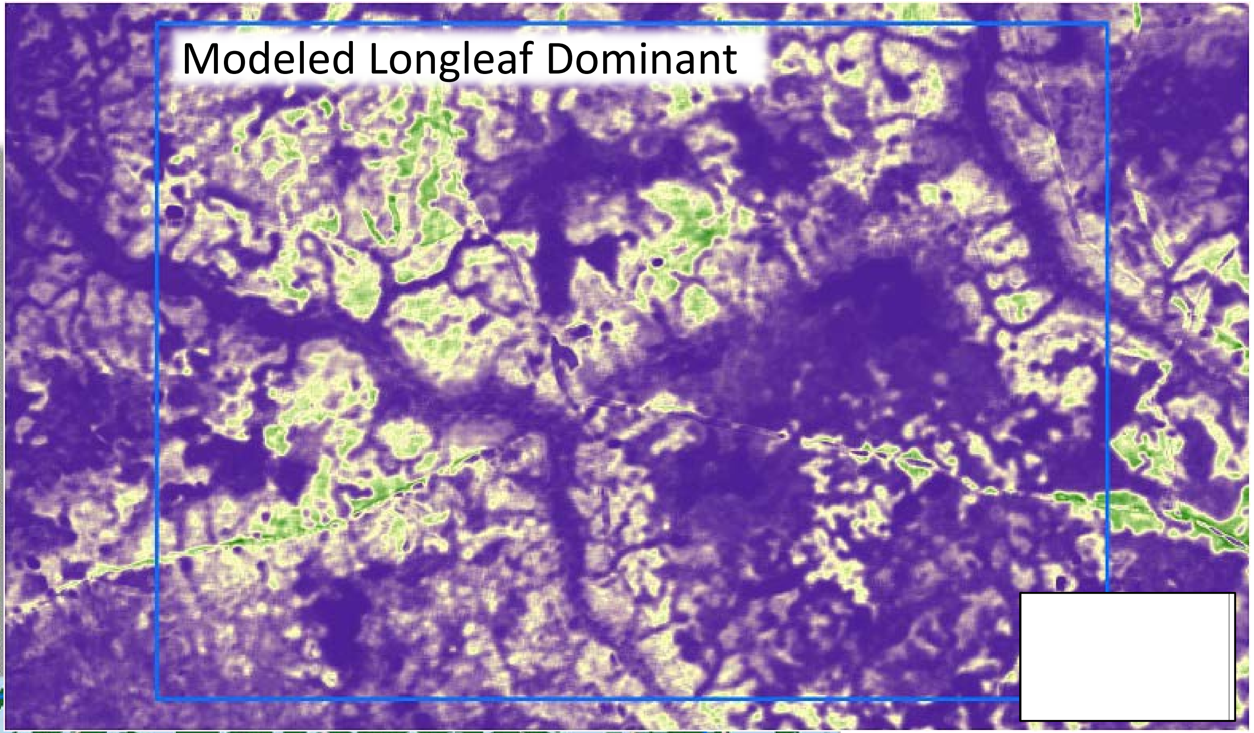
Modeled Estimates

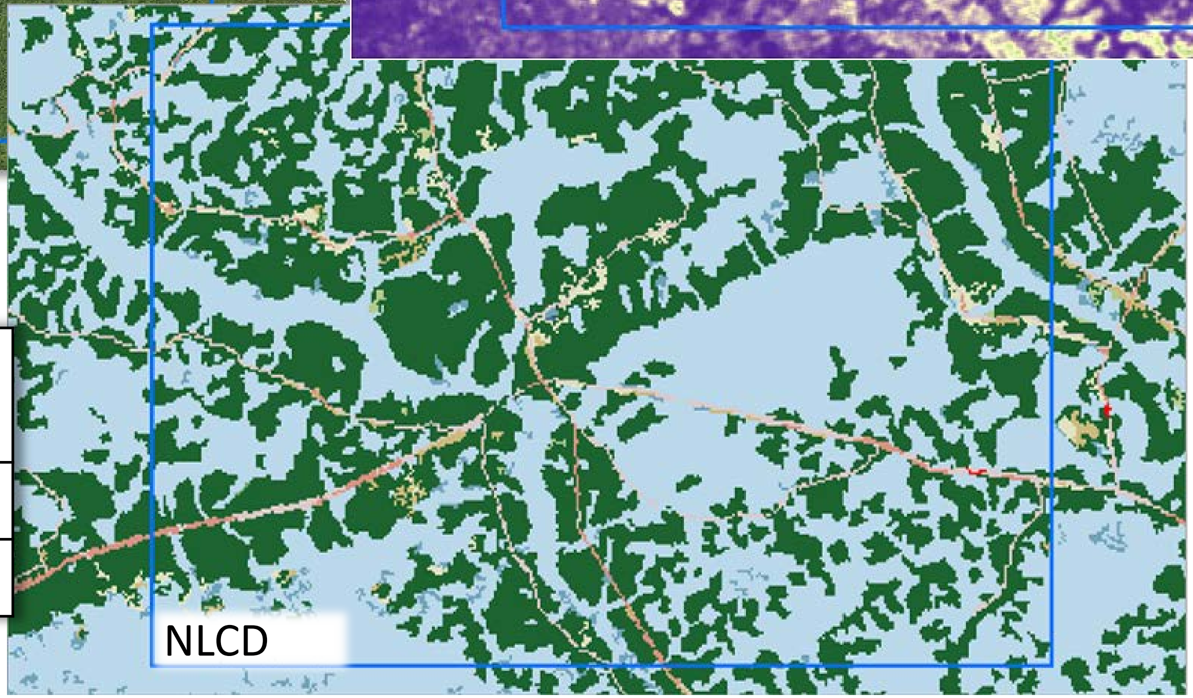




Longleaf Dominant (Acres)	Lower 95% CL	Upper 95% CL
52,737	45,271	60,202

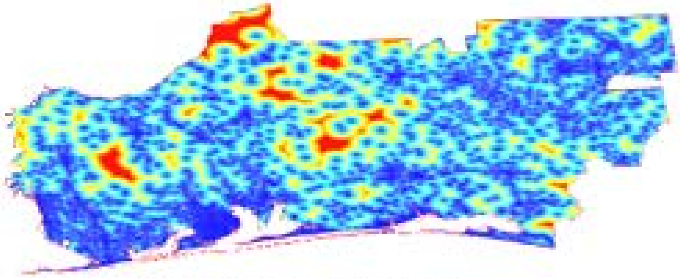
Comparison (30 miles^2)



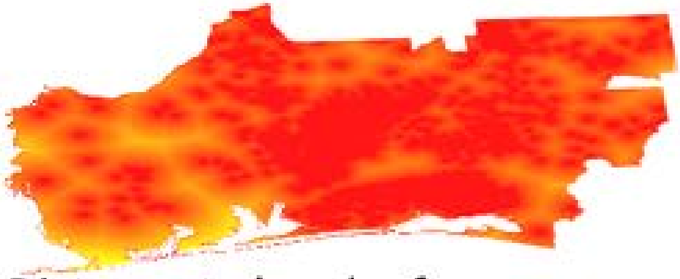


NLCD Class	Pine BAA	All BAA	Longleaf Dominant
Evergreen	53.9	73.5	26,158
Woody Wet	27.1	92.9	8,847

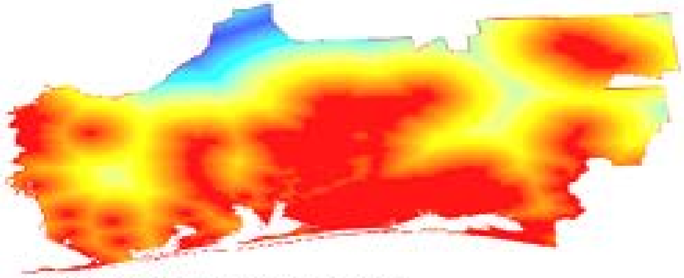
Restoration Prioritization



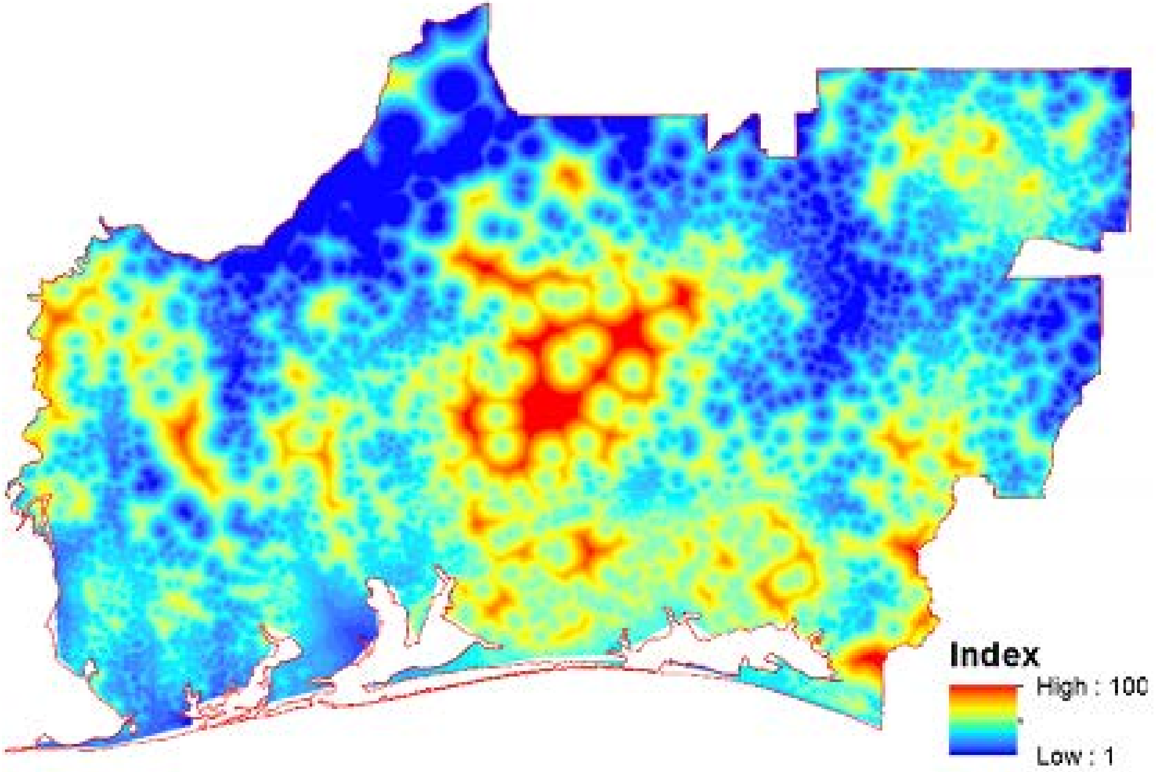
Distance from urban



Distance to longleaf

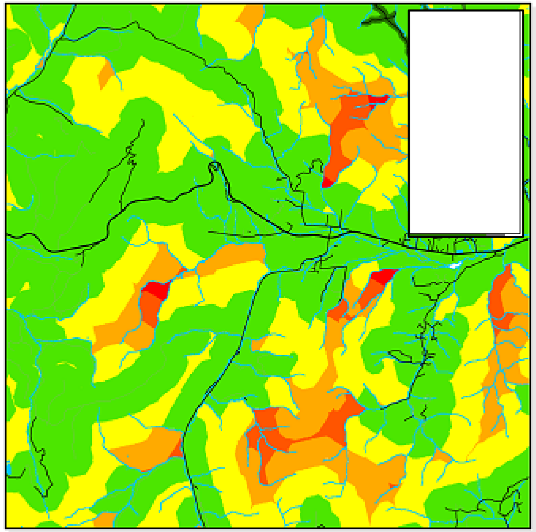


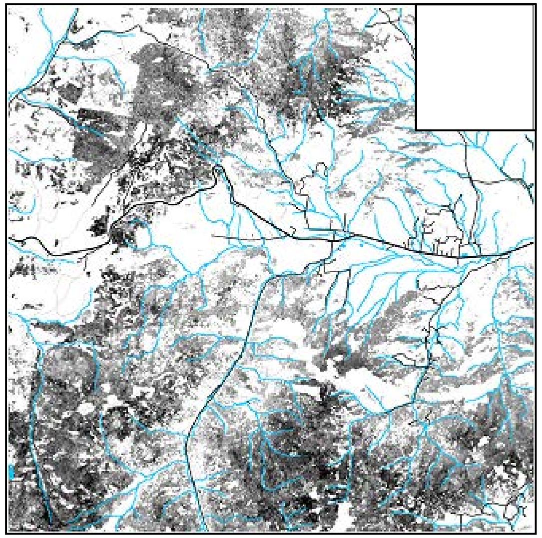
Distance to public

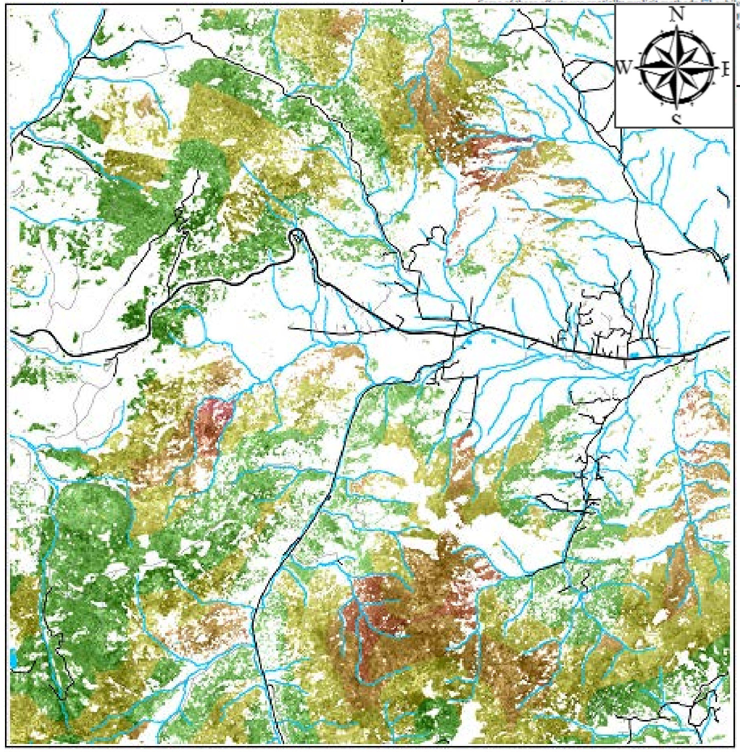


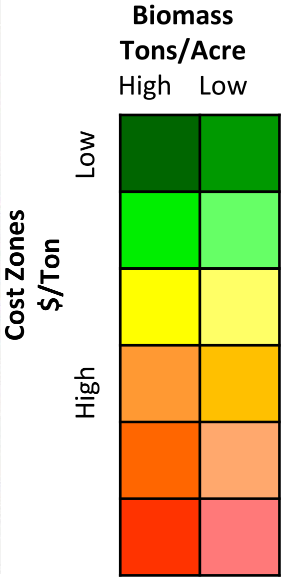
Restoration hotspots

Utility

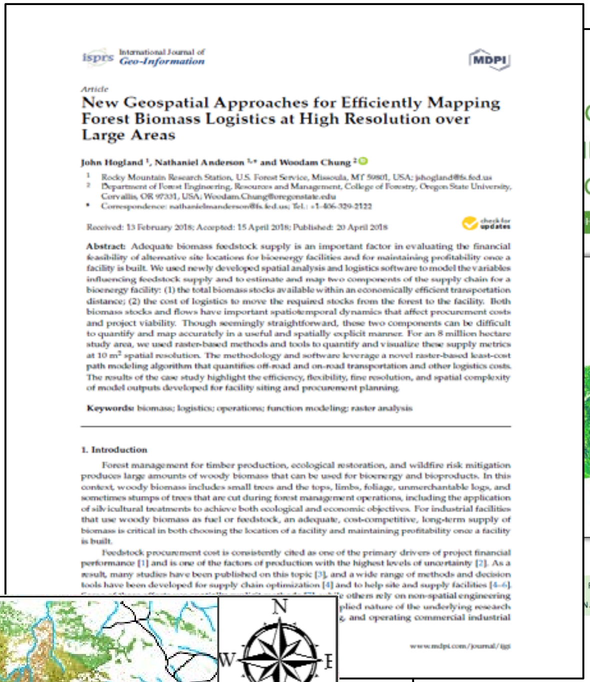








Papers & Tutorials



International Journal of Geo-Information

MDPI

Article

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

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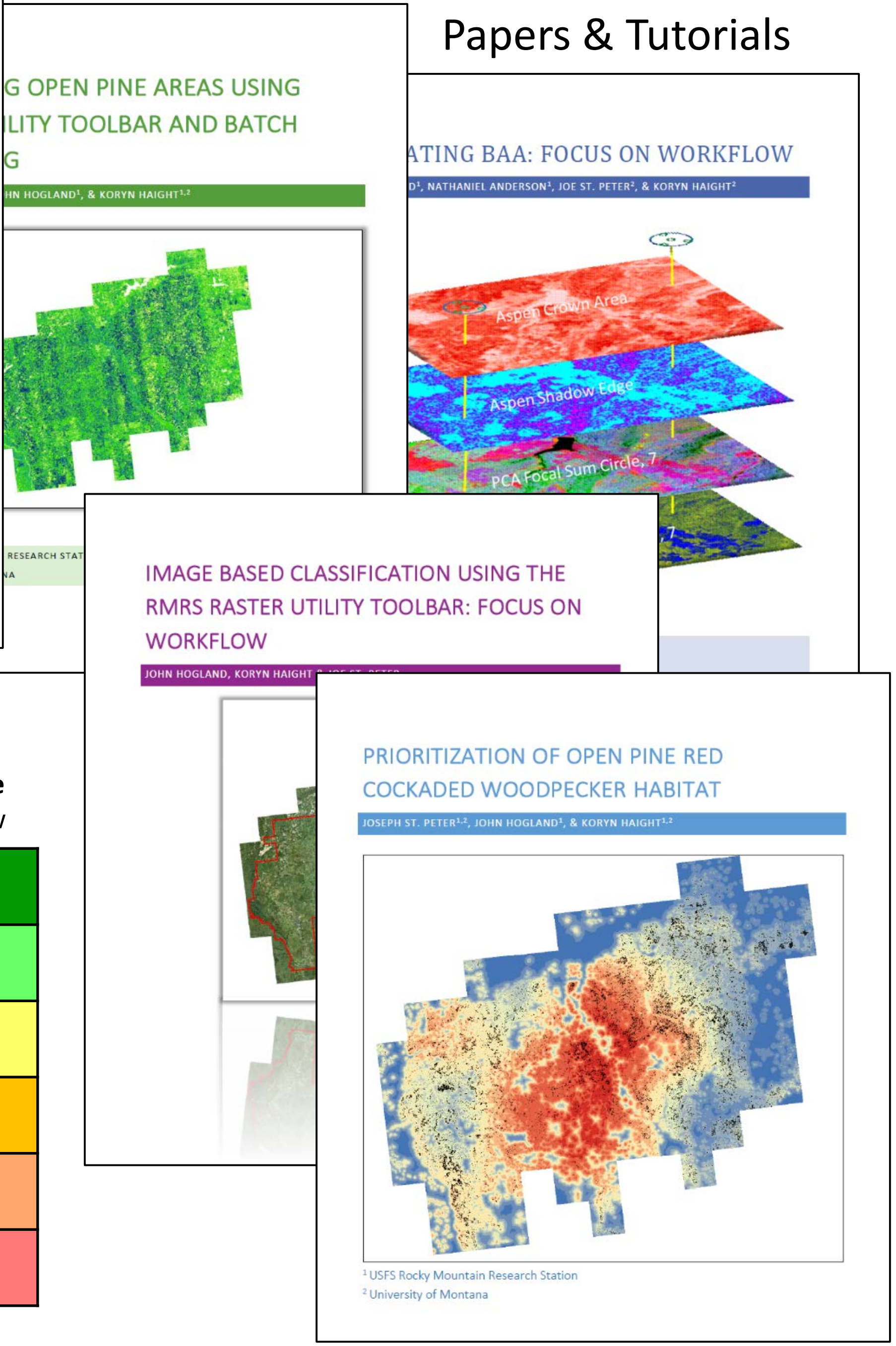
Abstract: Adequate biomass feedstock supply is an important factor in evaluating the financial feasibility of alternative site locations for bioenergy facilities and for maintaining profitability once a facility is built. We used newly developed spatial analysis and logistics software to model the variables 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 m^2 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

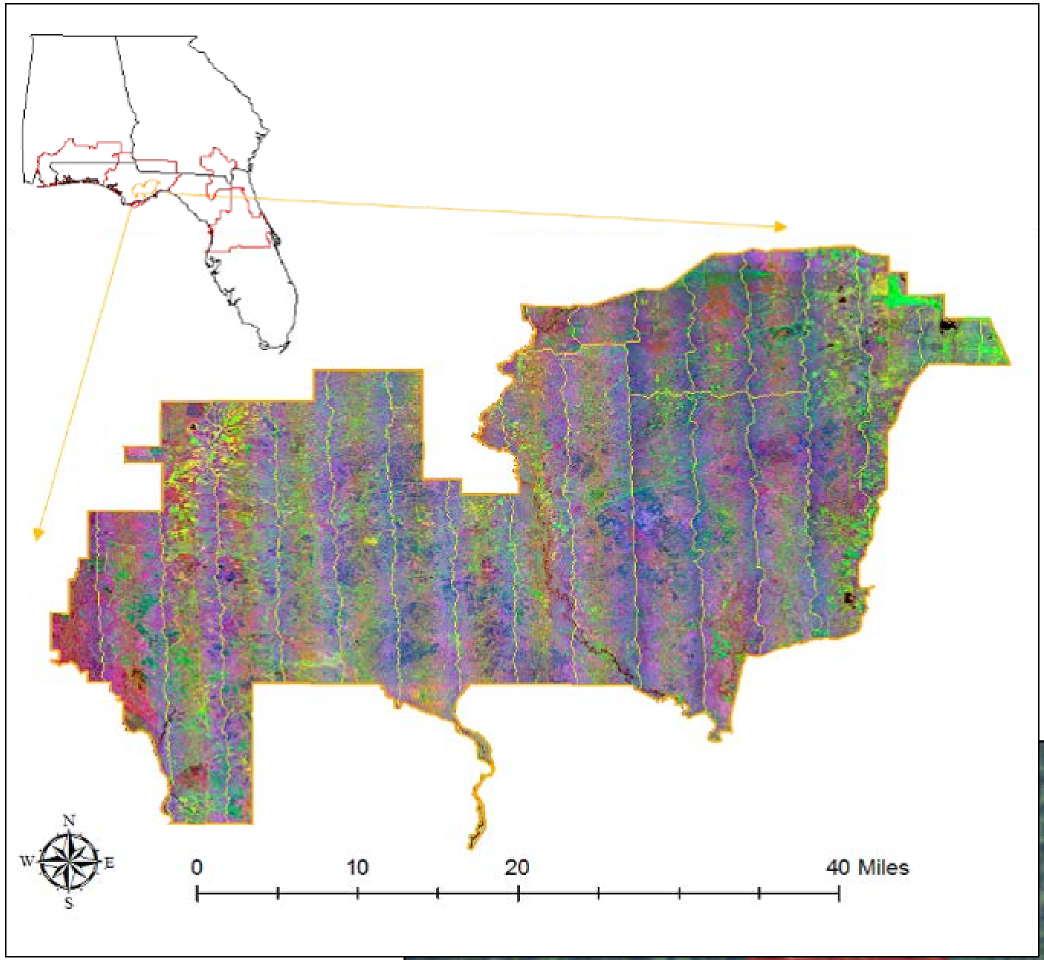
Forest management for timber production, ecological restoration, and wildfire risk mitigation produces large amounts of woody biomass that can be used for bioenergy and bioproducts. In this context, woody biomass includes small trees and the tops, limbs, foliage, unmerchantable logs, and sometimes stumps 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 in both choosing the location of a facility and maintaining profitability once a facility is built.

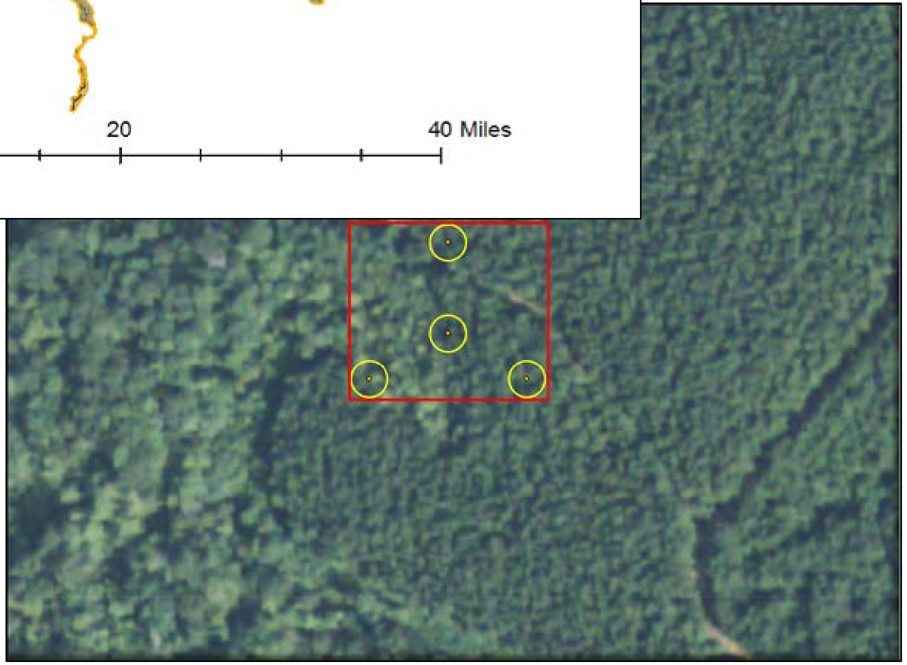
Feedstock procurement cost is consistently cited as one of the primary drivers of project financial performance [1] and is one of the factors of production with the highest levels of uncertainty [2]. As a result, many studies have been published on this topic [3], and a wide range of methods and decision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



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

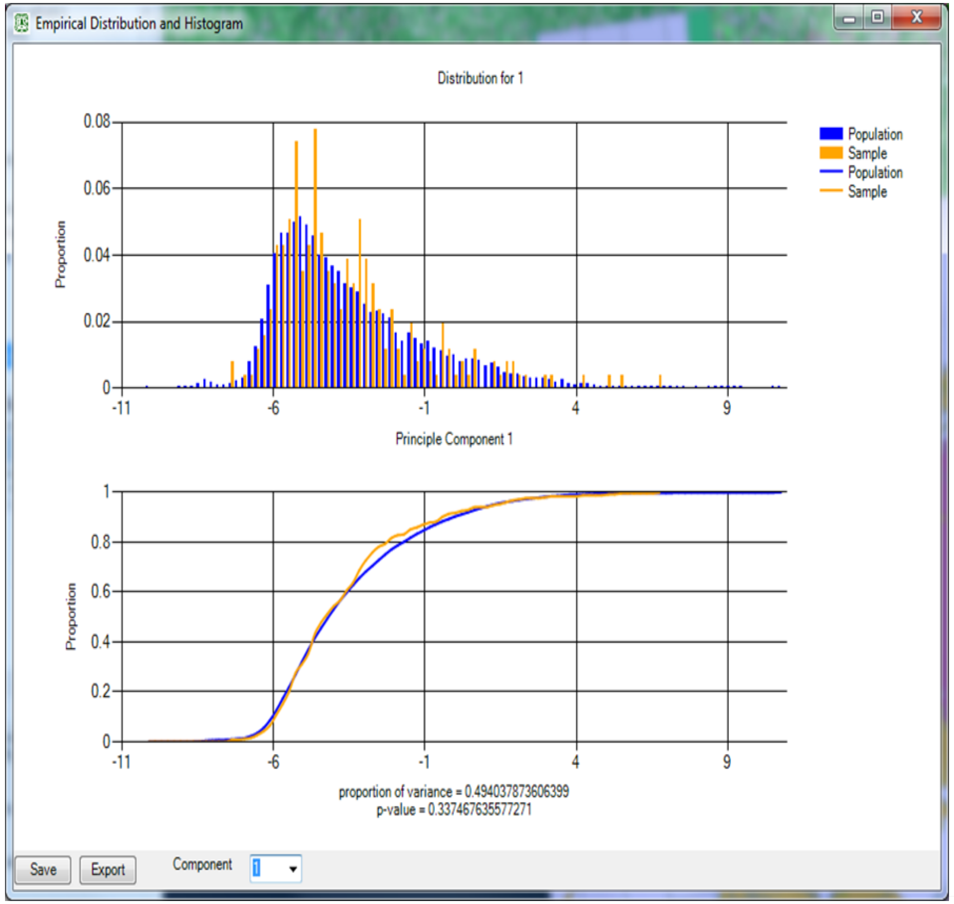
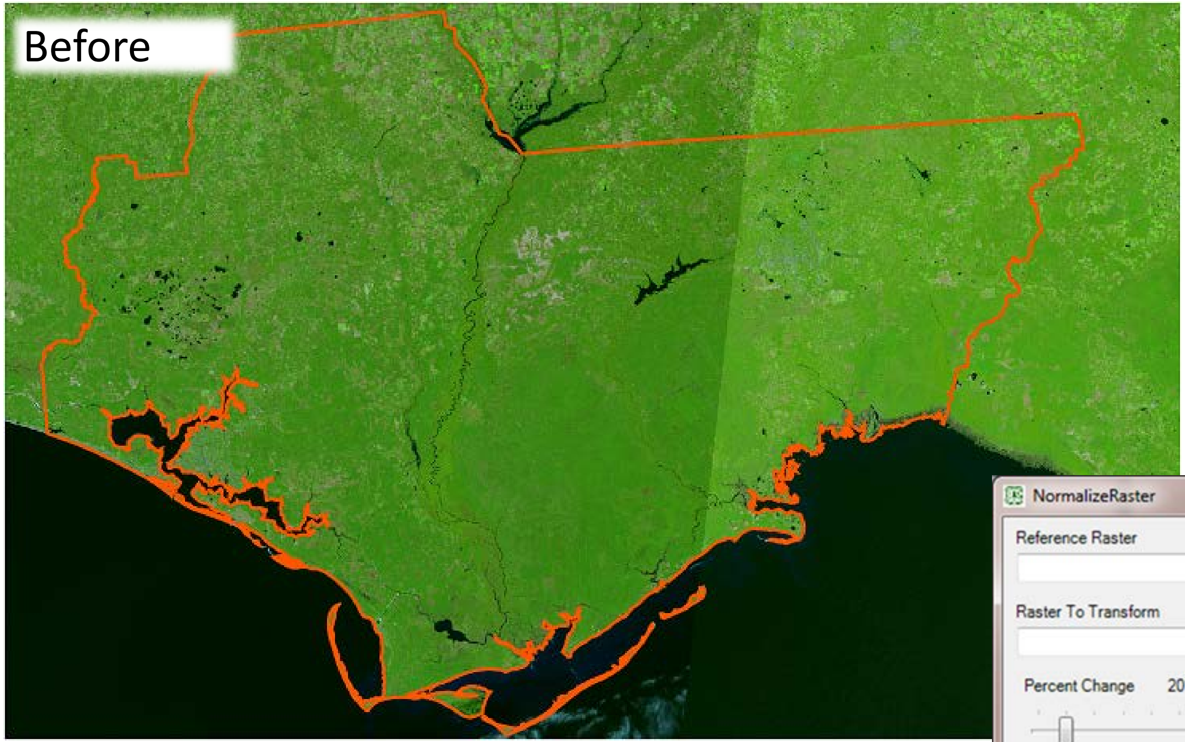
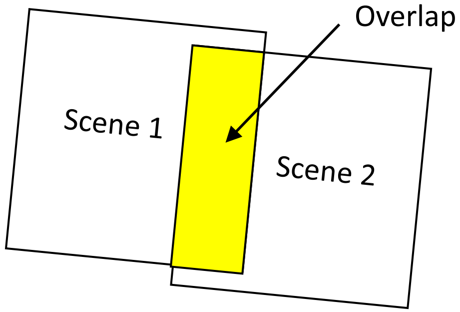
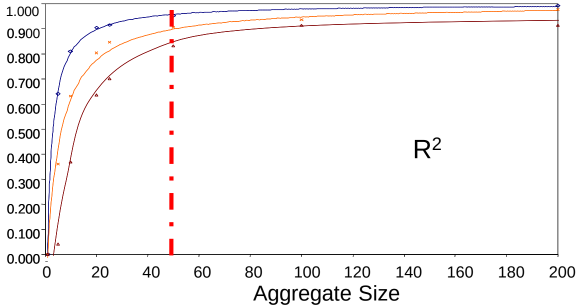
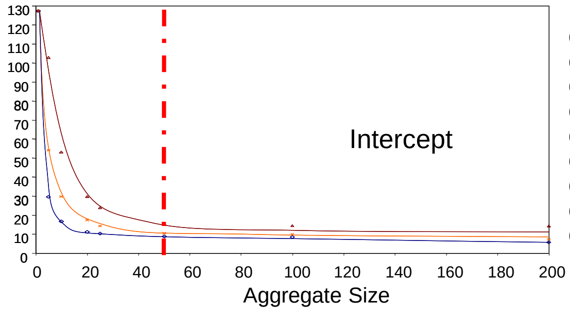


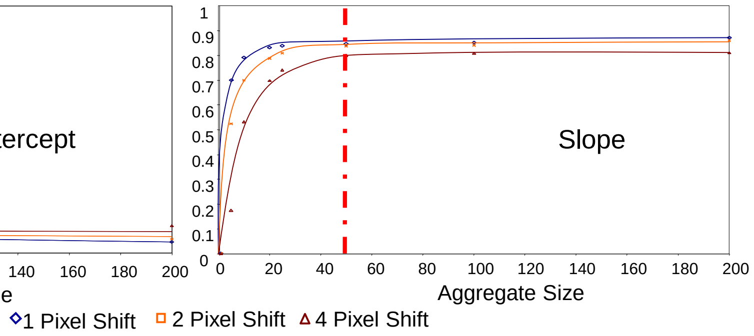
Image Normalization

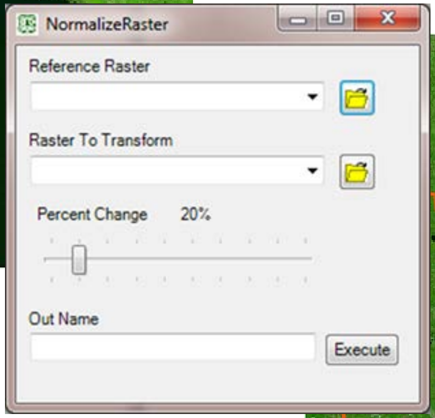


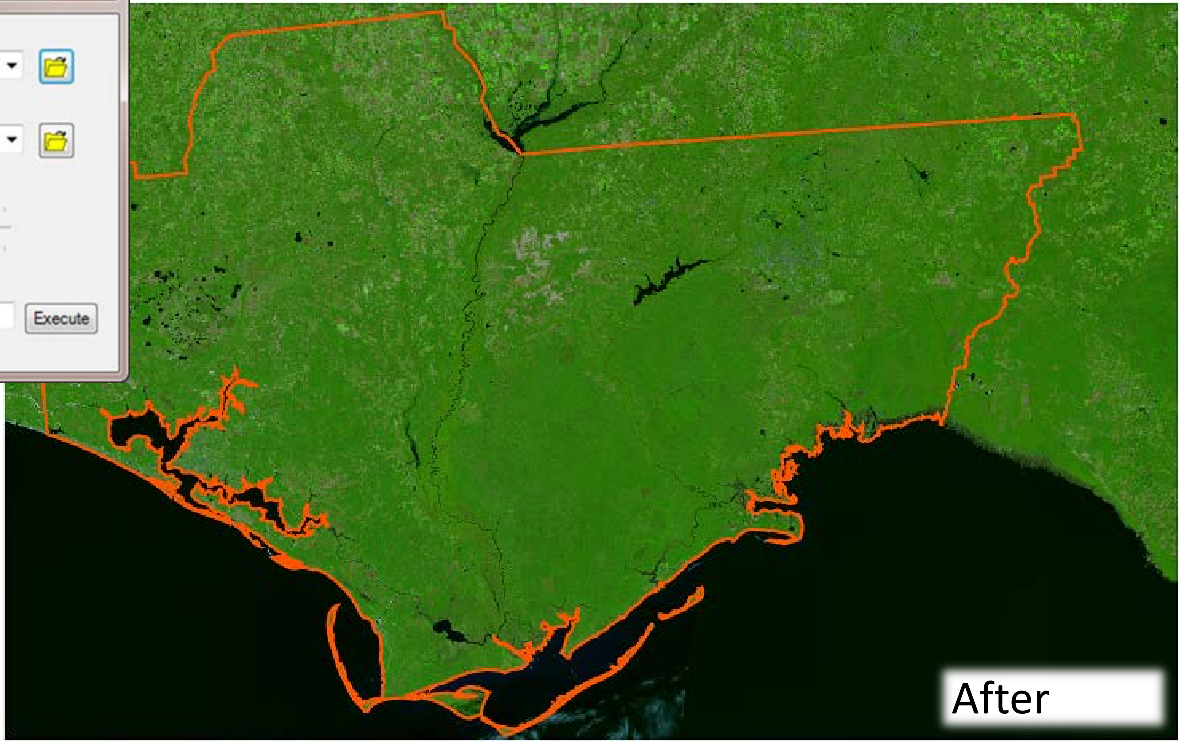












Aggregation size

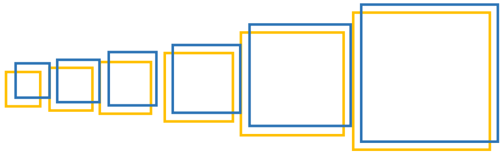
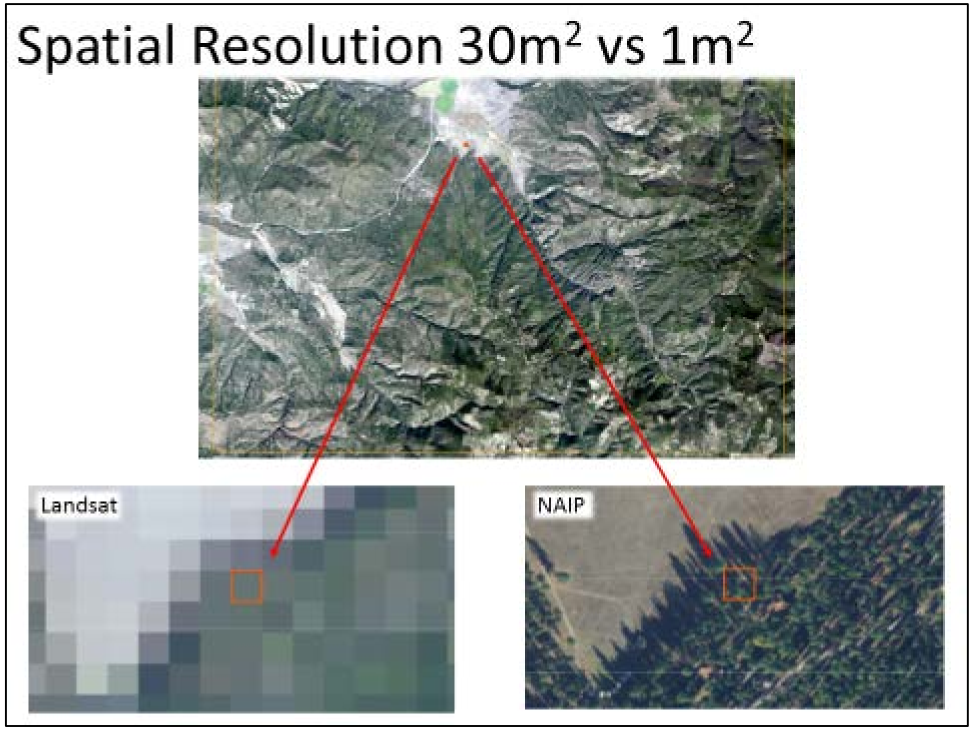
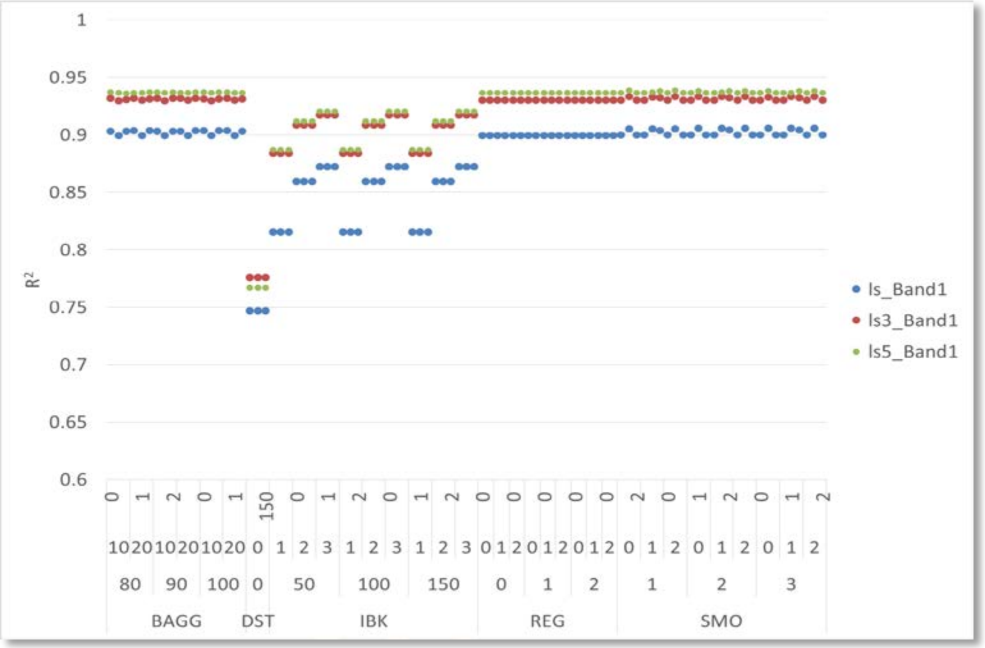
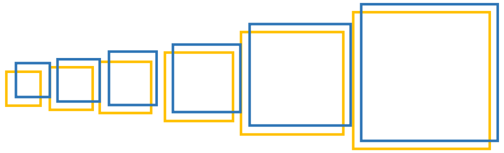


Image Normalization NAIP



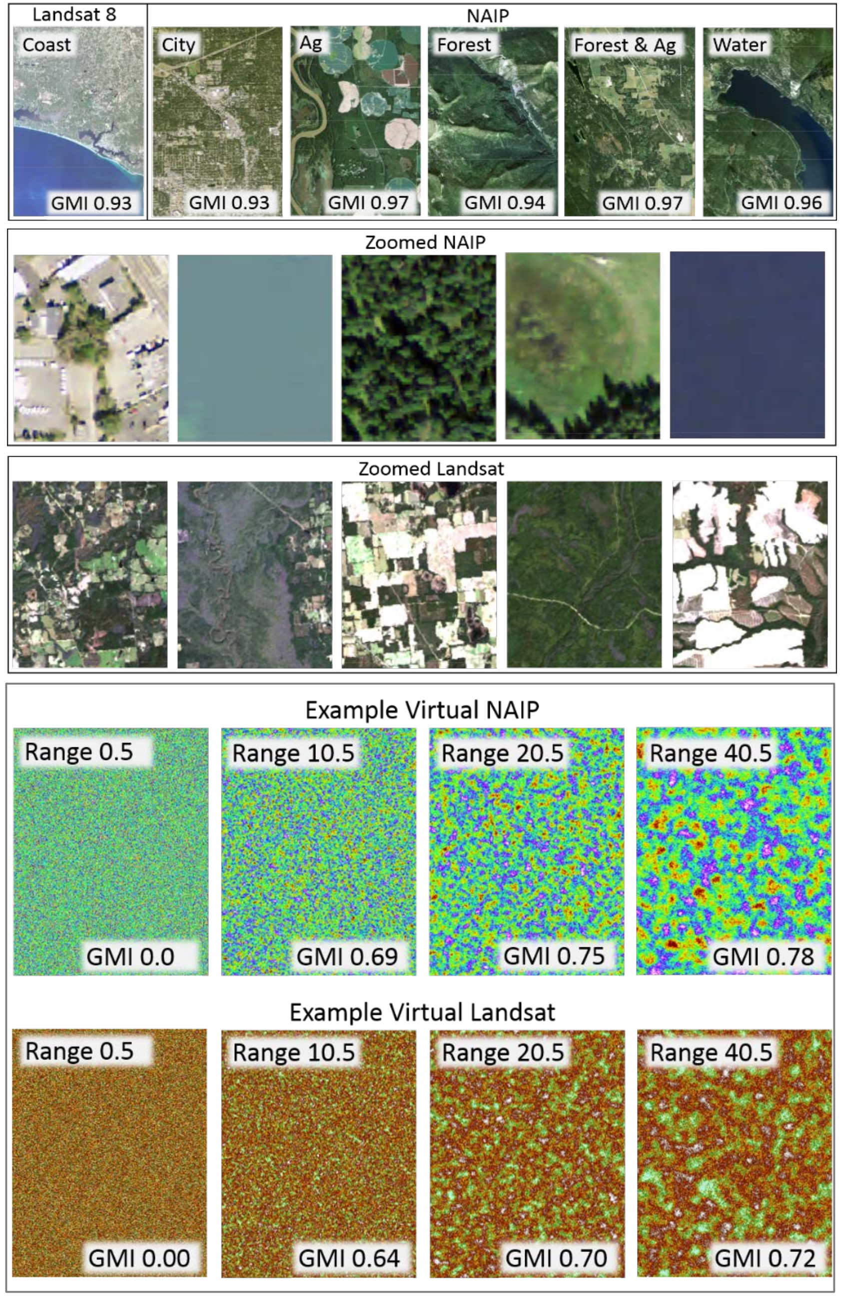


Aggregation size 

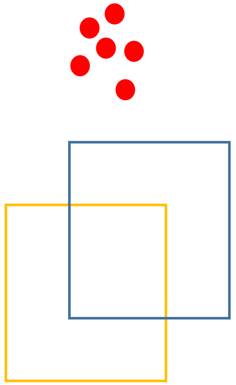
Plot Protocol & Co-registration Errors:

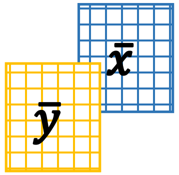
NAIP Shift GPS & Image (8m, 6m)

Simulations



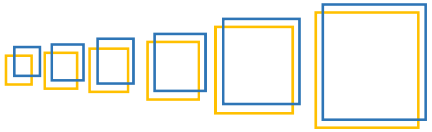
- 6 real images and 19 virtual images
- 200 locations
- 2 random shifts
  - GPS (7 m)
  - Image (NAIP: 6 cells, Landsat: 2 cells)
- Extract spectral values
- Regress against one another
- Record intercept, slope, RMSE and R^2
- Repeated (1-100 cells)





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

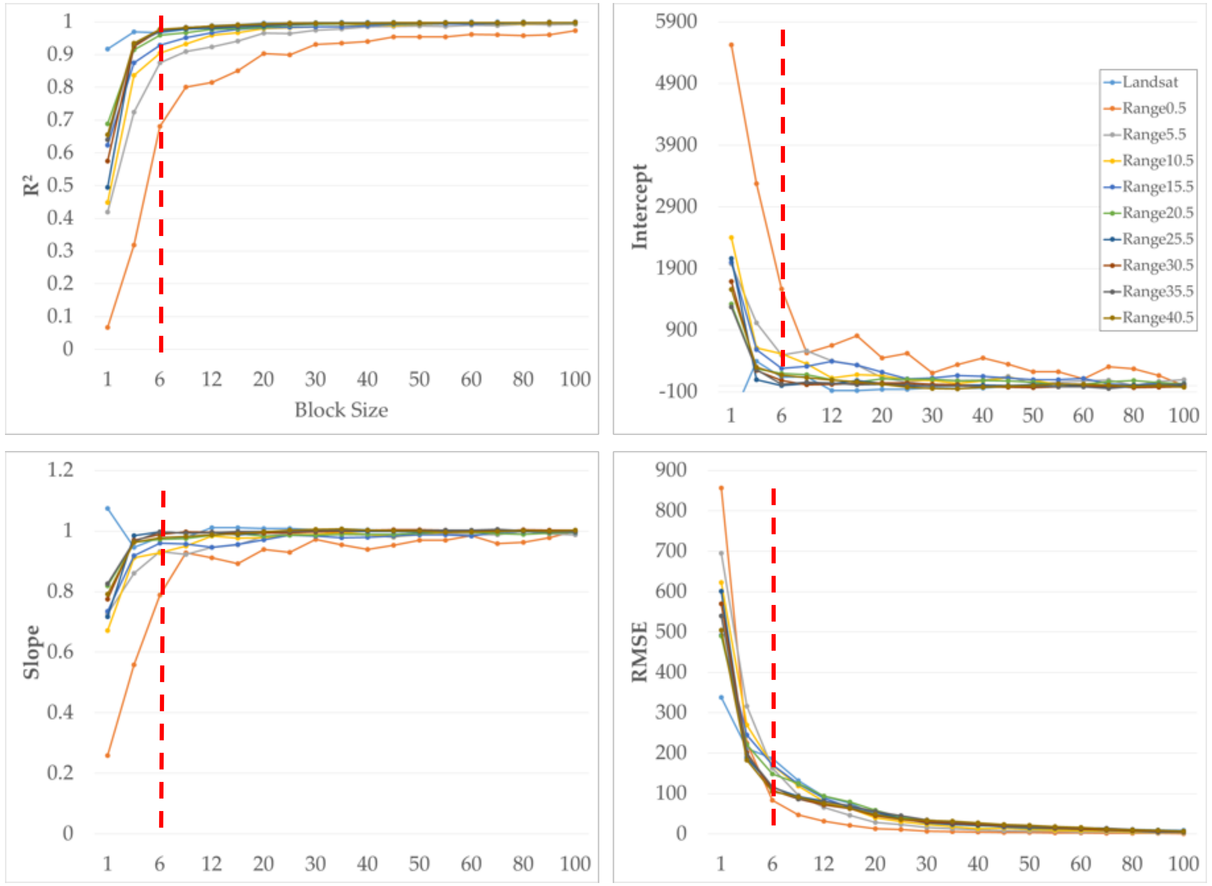
Record



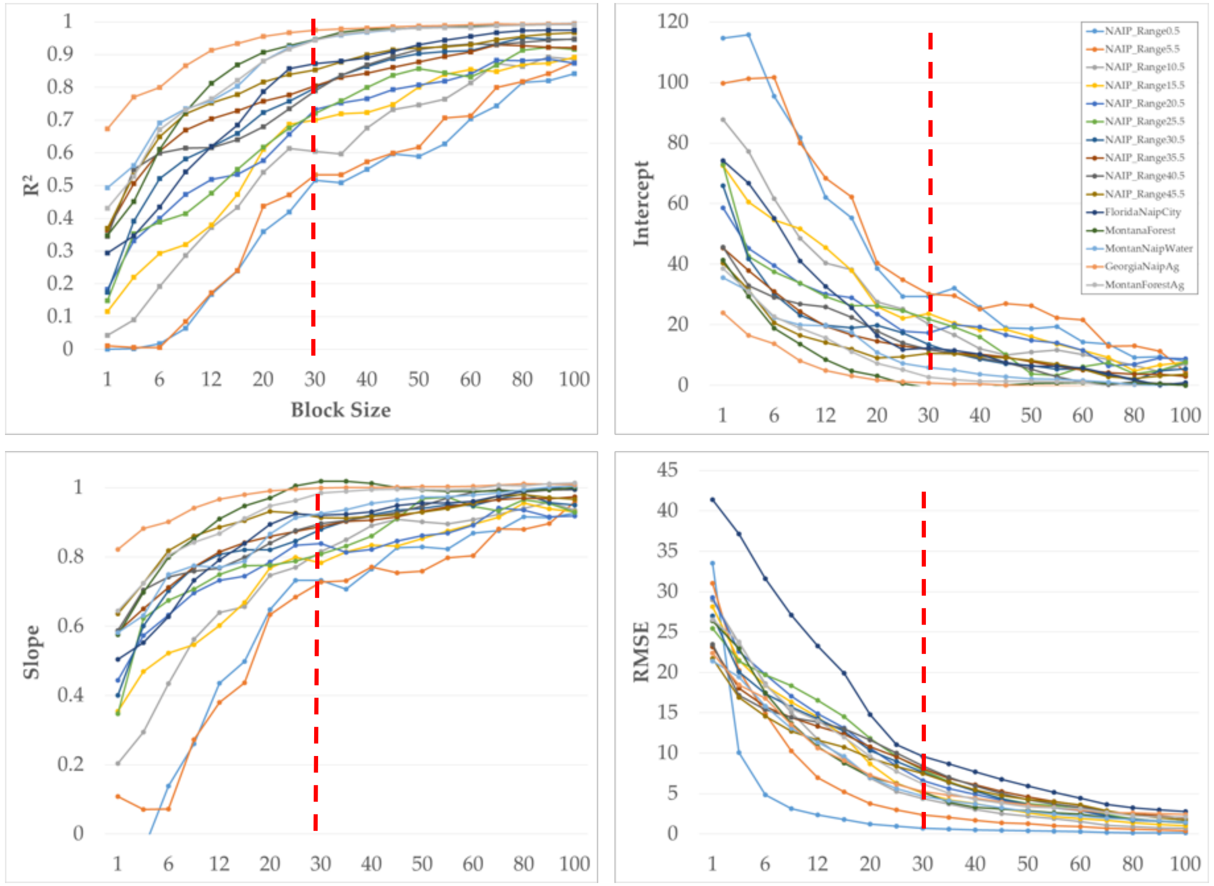
Results: Co-registration

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

Landsat



NAIP

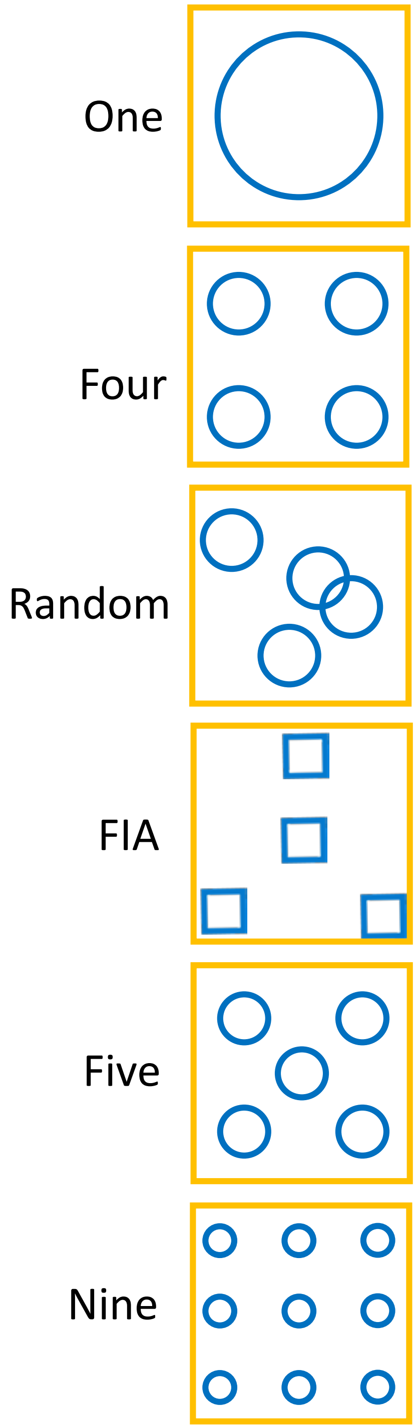


Plot Protocol & Co-registration errors

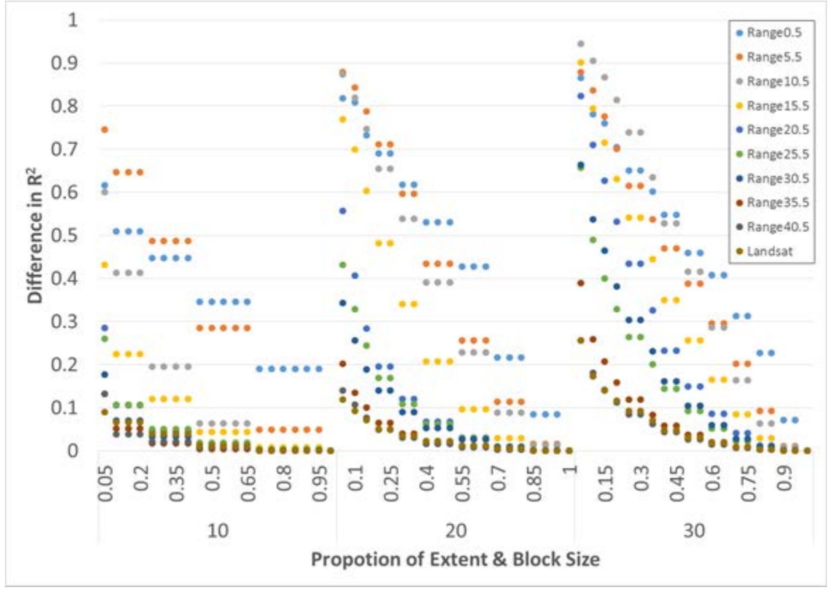
- Given extent, what sampling intensity and spatial layout

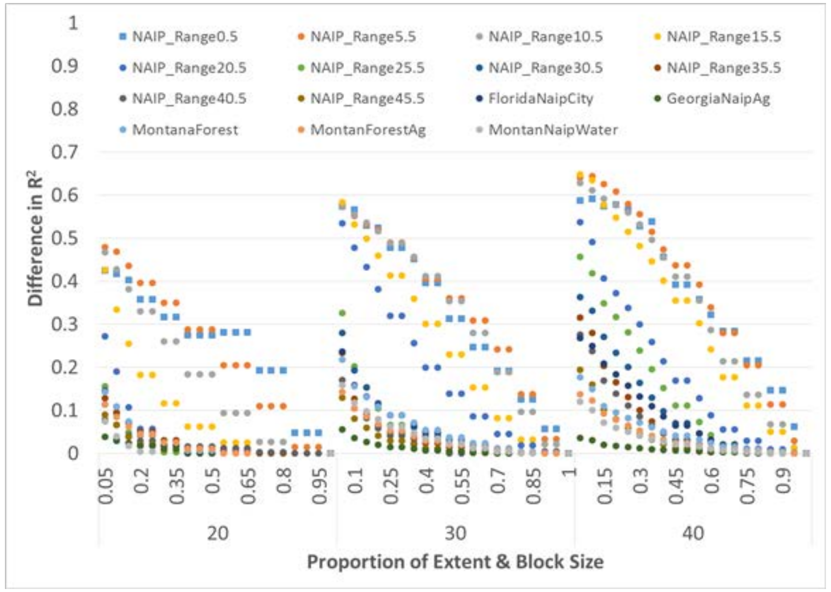
- Layouts
  - 1 big plot
  - 4 subplots one in each corner
  - 4 subplots randomly placed
  - 4 subplots based on FIA protocol
  - 5 subplots one in the center one in each corner
  - 9 subplots equally spaced out within the extent

- Intensity
  - 5-100% area inventoried

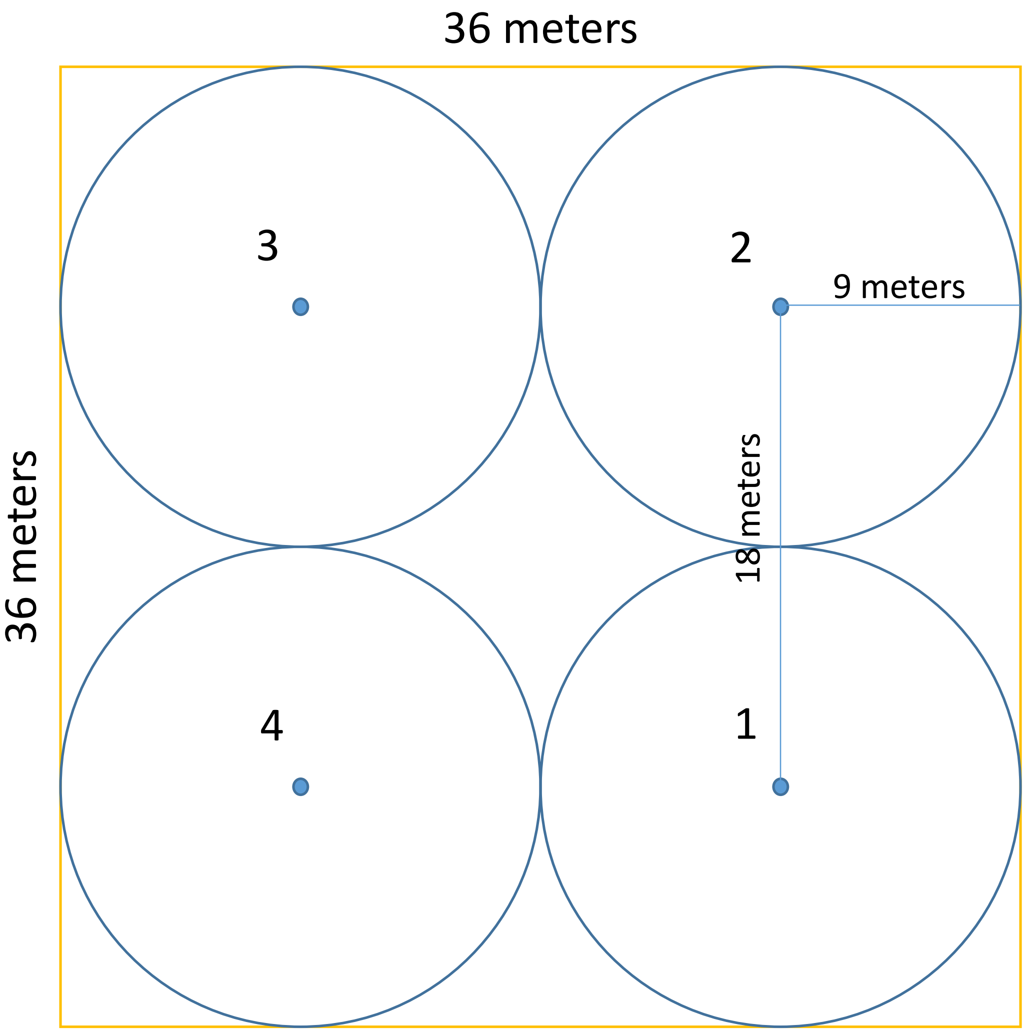


Results: Plot\Subplot Layout



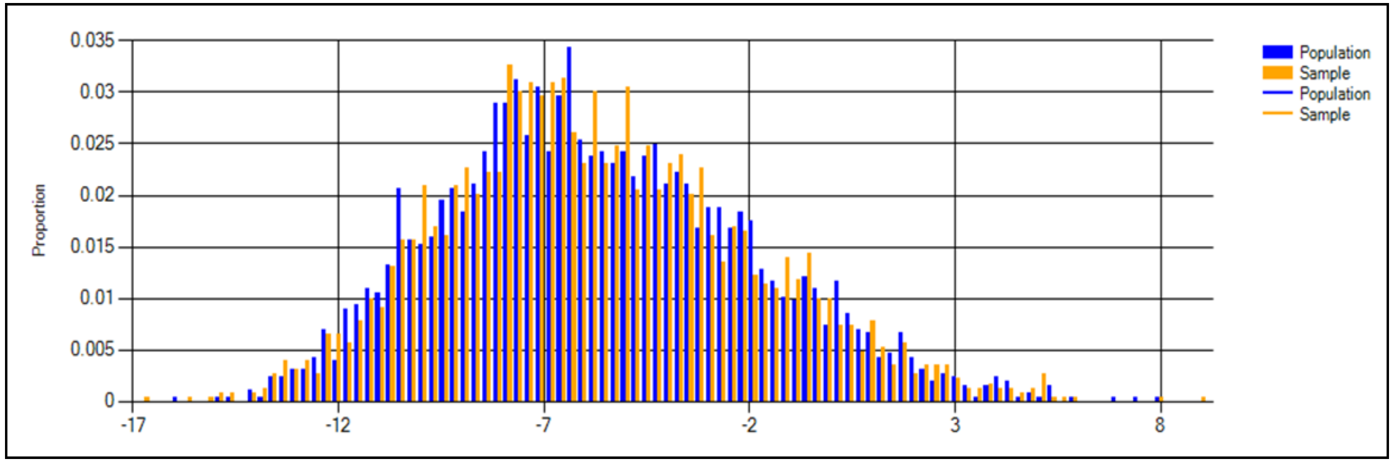


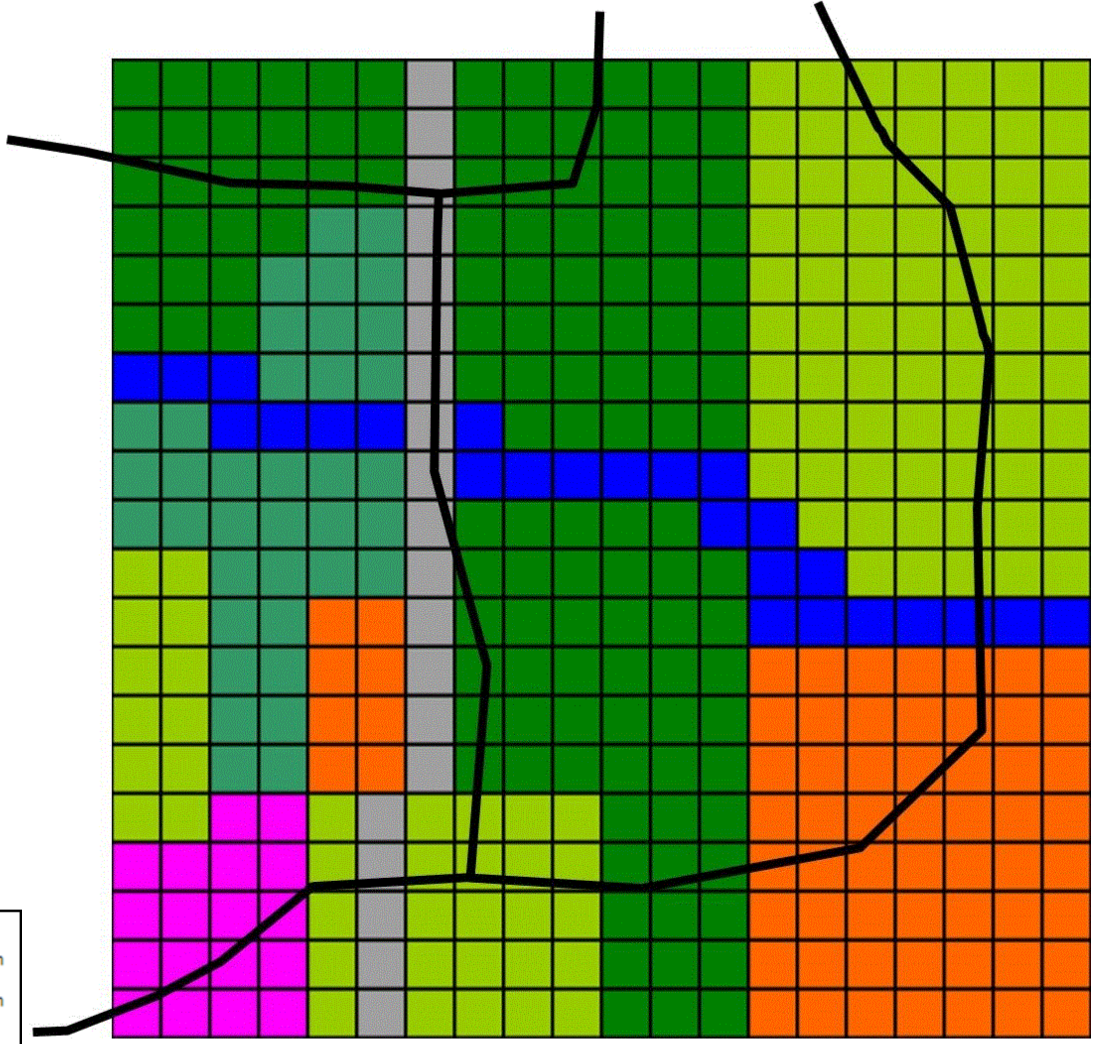
- Plot data
  - GPS location Subplot1
    - 20 positions (Averaging)
    - HDOP < 5
    - 3D mode
    - DGPS if possible
  - Picture
- Subplot data
  - Last Burn
  - % CWD
  - % Herb
  - % Saw
  - % Broad
  - % Bare
  - % Pine
    - Tree
      - DBH > 2”
      - Species
      - Status
      - Count



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





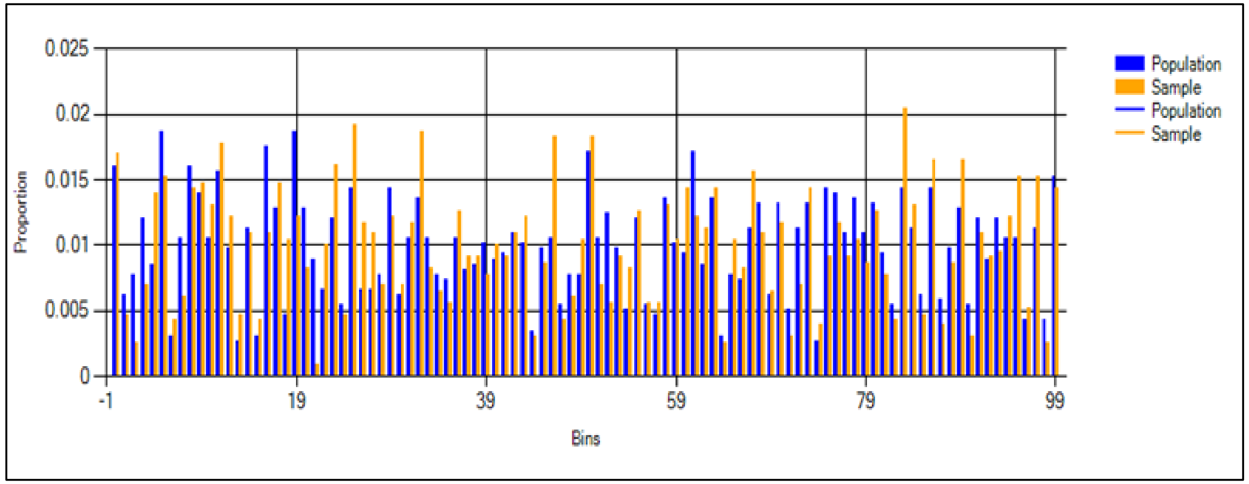
How

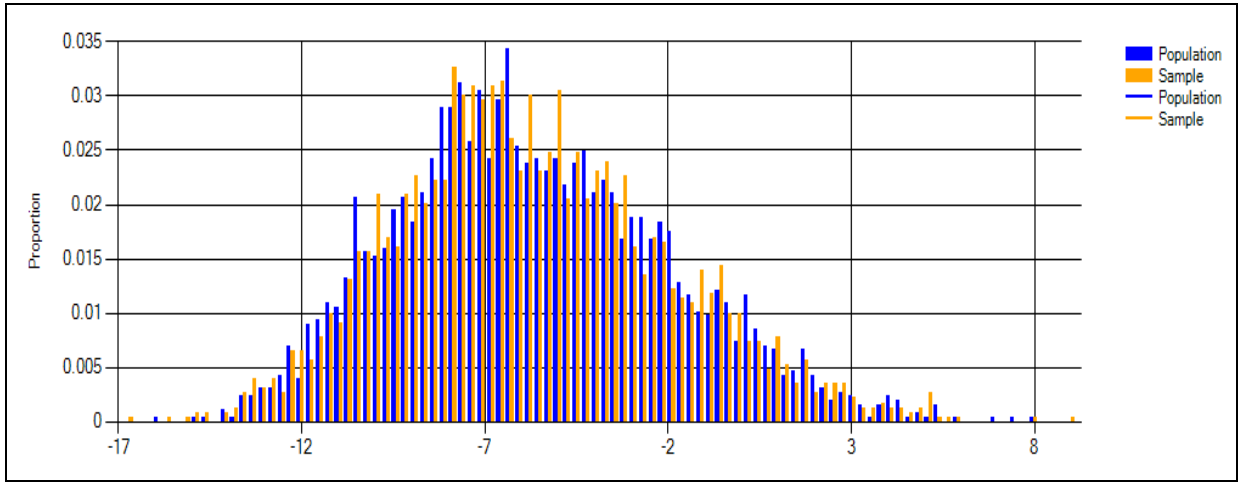
$$d = \max_x \left| f_{n1}(x) - f_{n2}(x) \right|$$

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

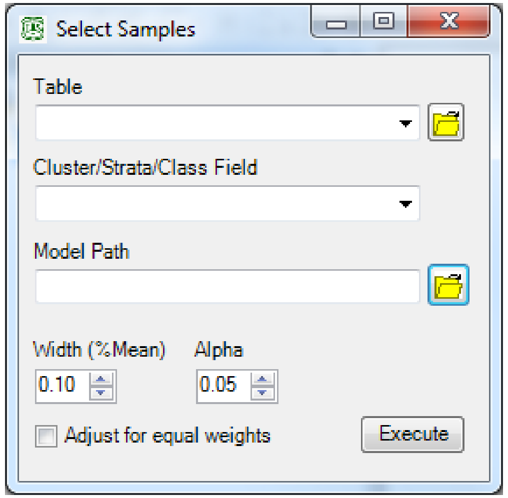
$$\overline{wKS} = \sum_{i=1}^{k} KSstatistic_i * \lambda_i$$

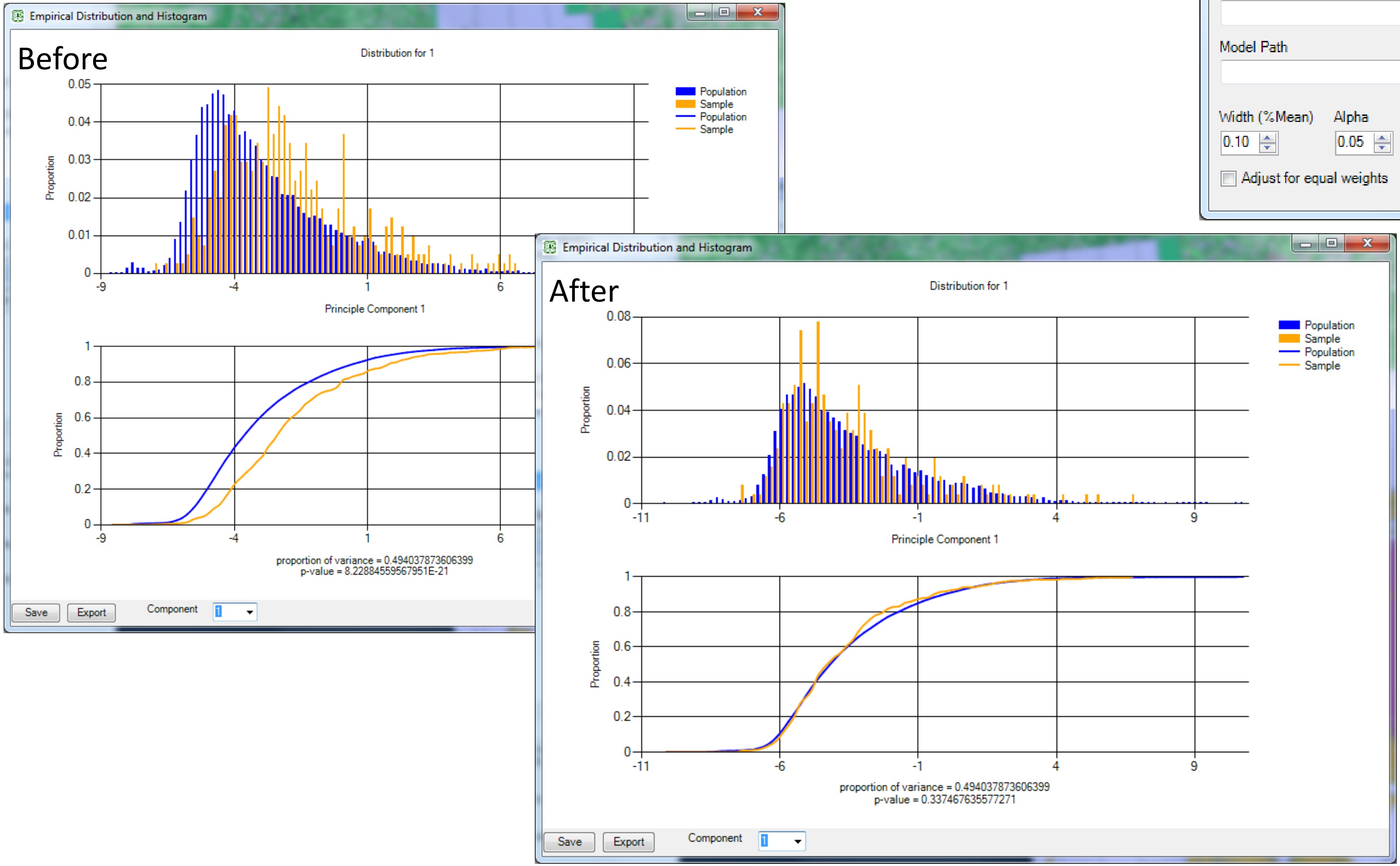
- Develop a methodology to determine if the values of a sample match the natural population distribution
  - Multivariate Kolmogorov-Smirnov (K-S) test
- Partition predictor variables into cluster space
- Randomly select locations within predefined inexpensive areas to match frequency distribution of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

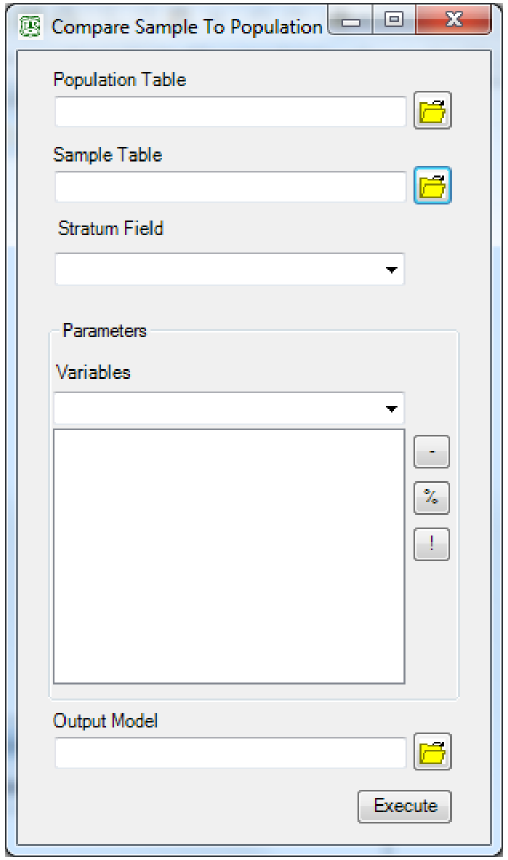




Results: Sample Design

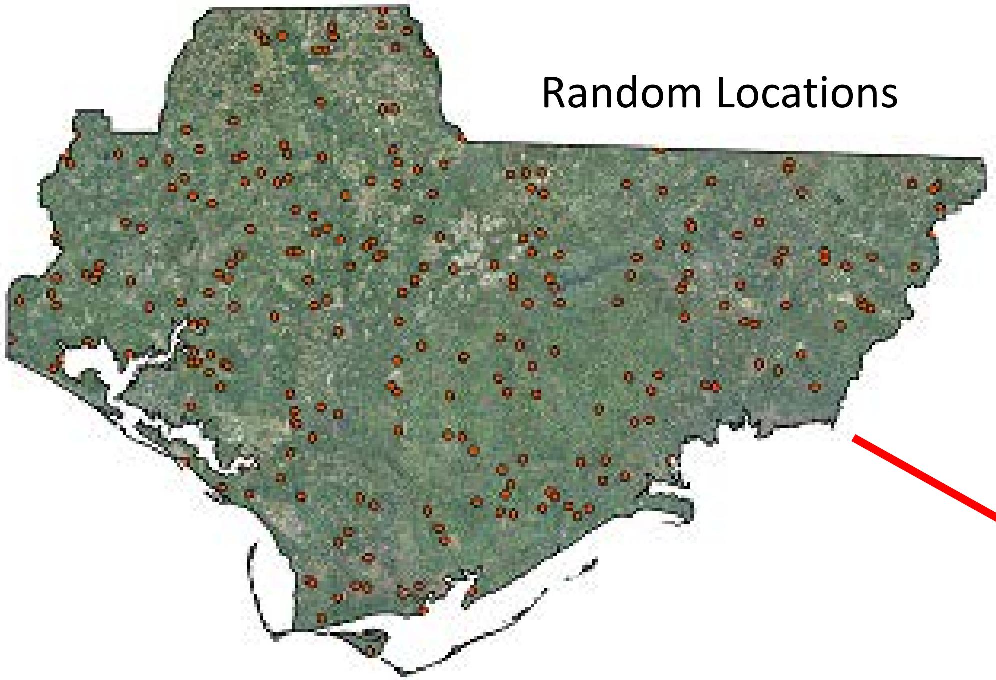




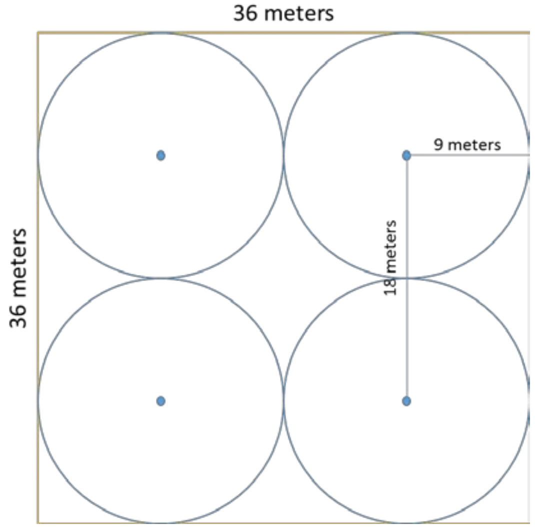


Results: Field Plots

Random Locations

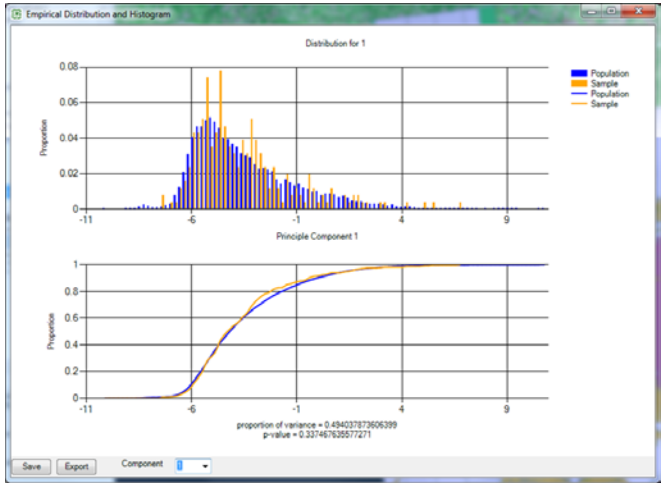


Practical

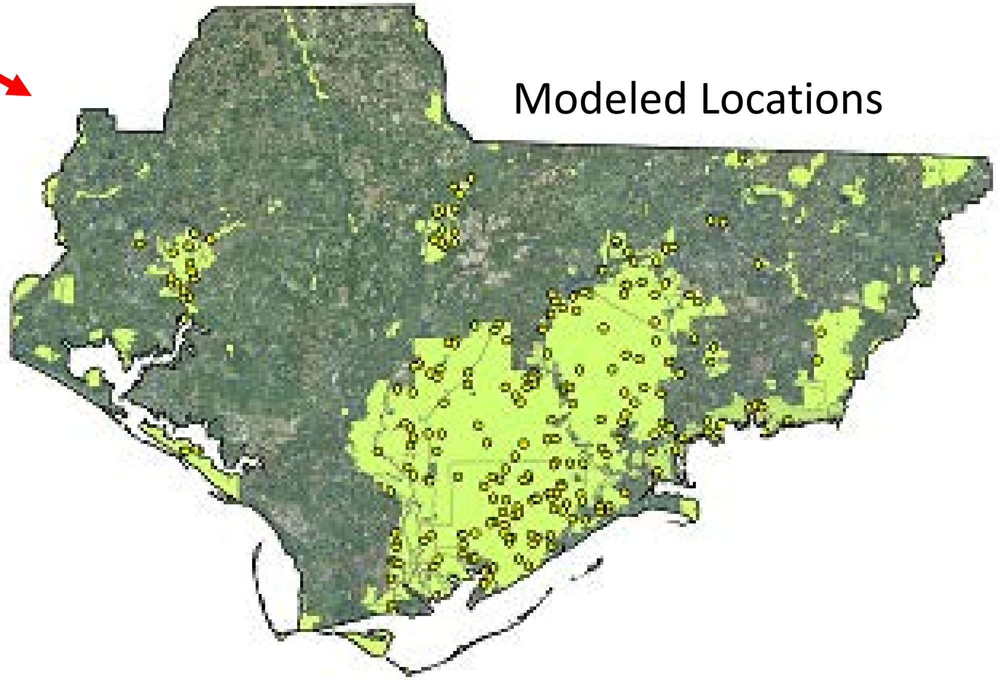


Integrated

Natural Distribution

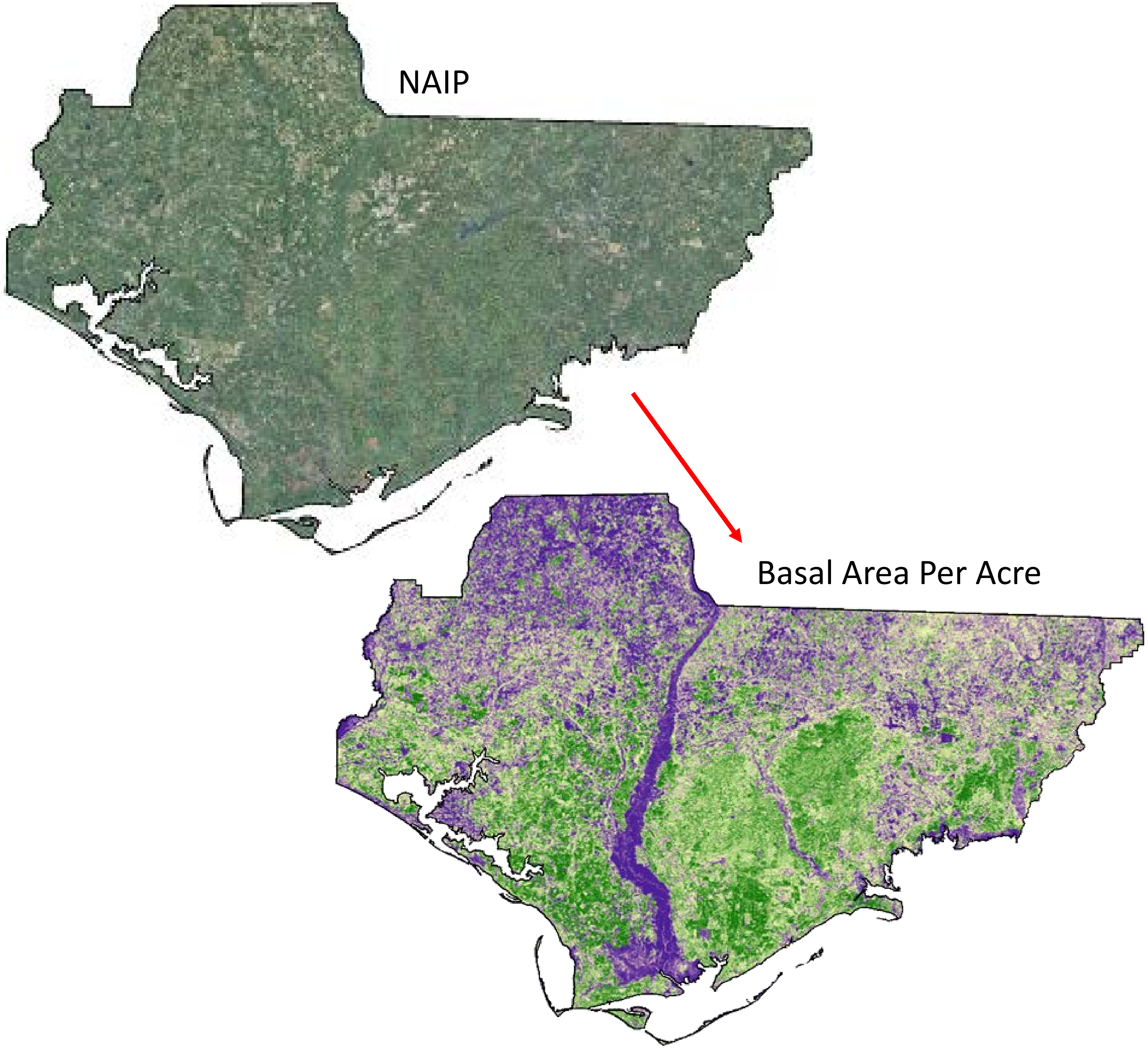


Modeled Locations

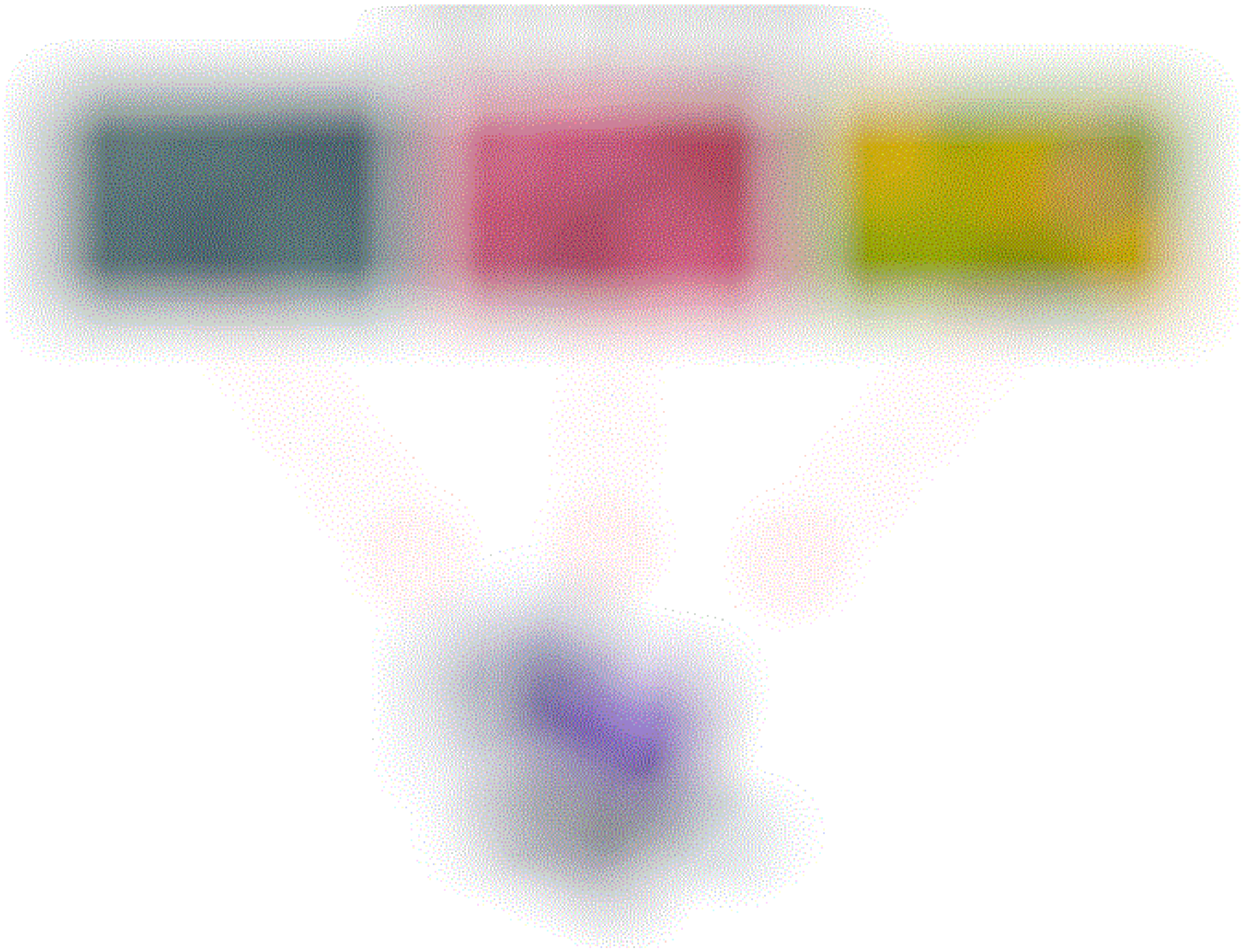


Next Steps

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



Questions ?



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