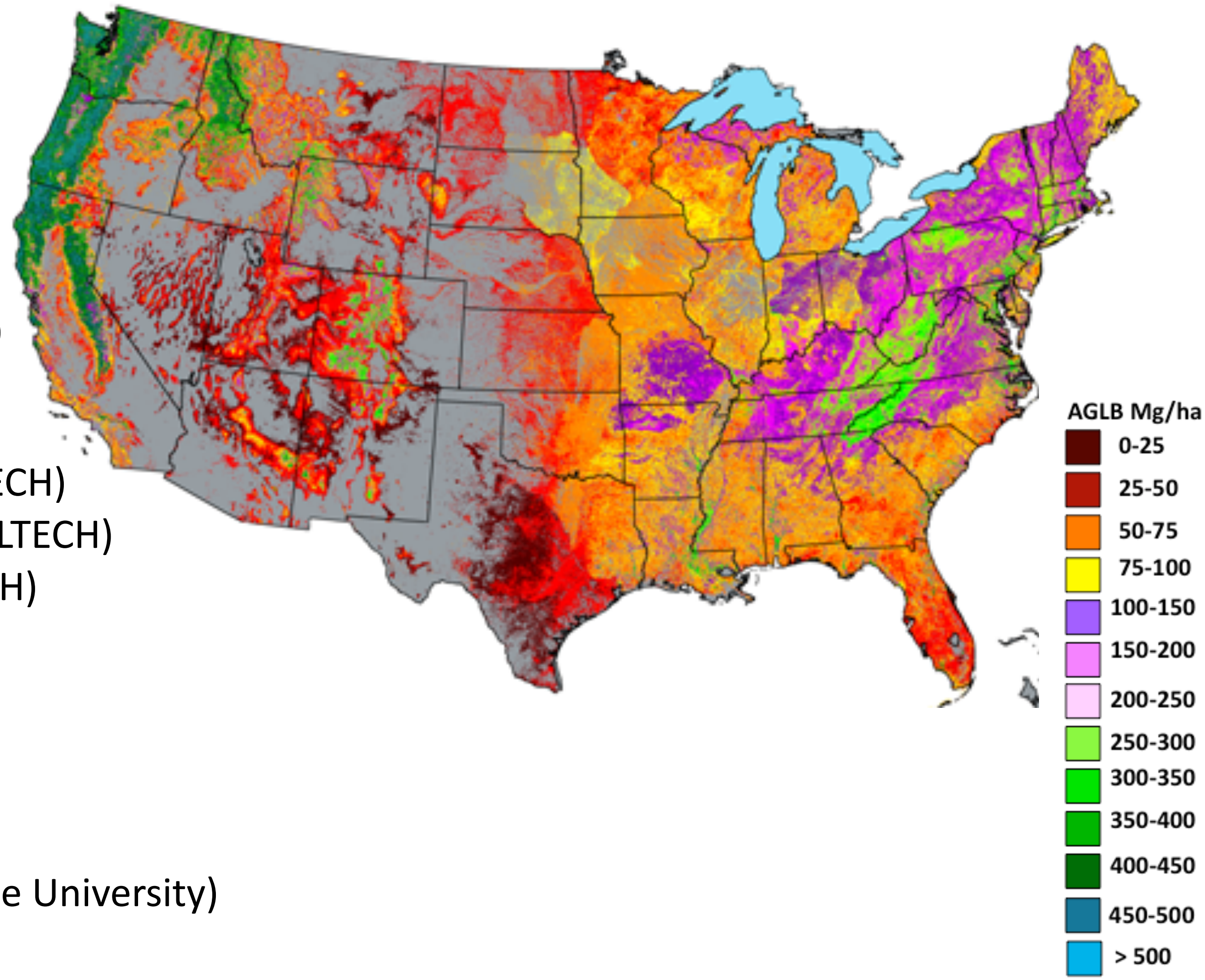
# A Specially Refined and Temporally Constrained Approach to Estimate Regional and Continental Scale Vegetation Carbon Stock





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# Carbon Monitoring System
# Biomass Pilot Project

**<u>Objectives</u>:**

❖ **Develop prototype data products of national biomass (and carbon storage/ change) that can be assessed with respect to how they meet the nation's need for monitoring (also reporting and verification) of carbon inventories.**

❖ **Demonstrate our readiness to produce a consistent global biomass/carbon stock distribution using the existing *in situ* and satellite observations to meet the monitoring (MRV) requirements.**

**<u>Outline:</u>**

❖ National Data Processing Activities

❖ Development of Methodology

❖ Regional Results and Products

❖ Validation and Uncertainty Analysis

# Terrestrial Biomass Pilot Project

**<u>Goal</u>:**

**Provide geospatially explicit, consistent estimates of aboveground terrestrial vegetation biomass and carbon storage for the U.S. by combining advanced satellite products with ground observations and evaluate how well these estimates meet the nation's need for monitoring carbon storage and changes in carbon storage.**

**<u>Objectives</u>:**

- **Develop prototype data products of national and global biomass (and carbon storage/change) that can be assessed with respect to how they meet the nation's need for monitoring (also reporting and verification) of carbon inventories.**
- **Demonstrate our readiness to produce a consistent global biomass/ carbon stock distribution using the existing *in situ* and satellite observations to meet the monitoring (MRV) requirements.**

# Terrestrial Biomass Pilot Project

<u>Objectives for Near-Term (first ~18 mos.)</u>:

❖ **Estimate aboveground biomass by combining data from several different satellites with ground data.**

❖ **Assess the accuracy of derived estimates by using Forest Inventory and Analysis (FIA) and other high-quality forest carbon/biomass inventory data.**

❖ **Produce a continental U.S. map of above-ground biomass, fully mapping errors and uncertainties**

❖ **Evaluate the likely improvements that could be achieved using data from future missions.**

❖ **Demonstrate how well biomass can be quantified with high-quality remotely sensed data taken at fine spatial resolution for selected sites representative of U.S. forest types and conditions.**

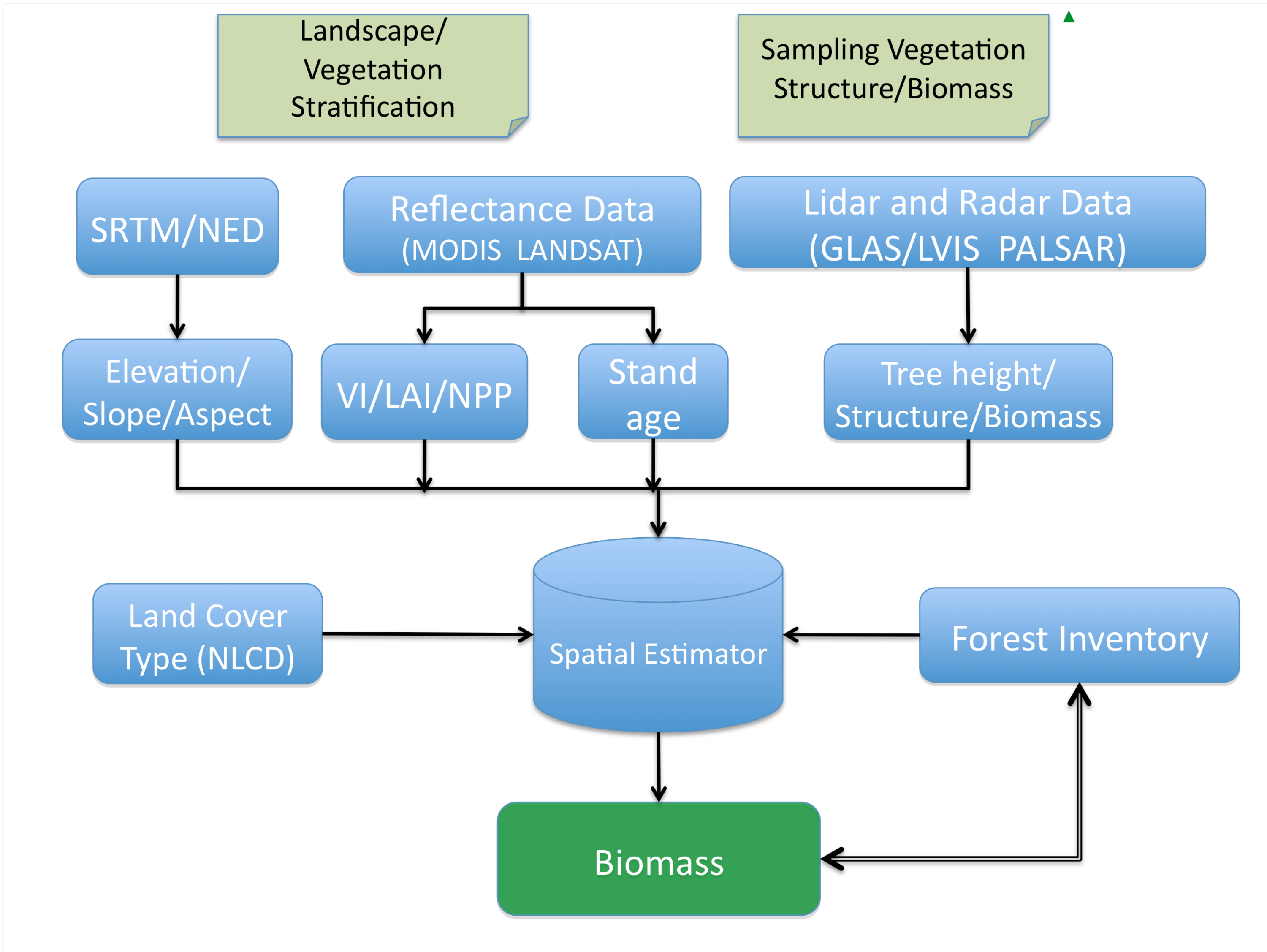
❖ **Develop the steps for a global forest biomass product.**

→ **A best possible product with what we have available now . . .**

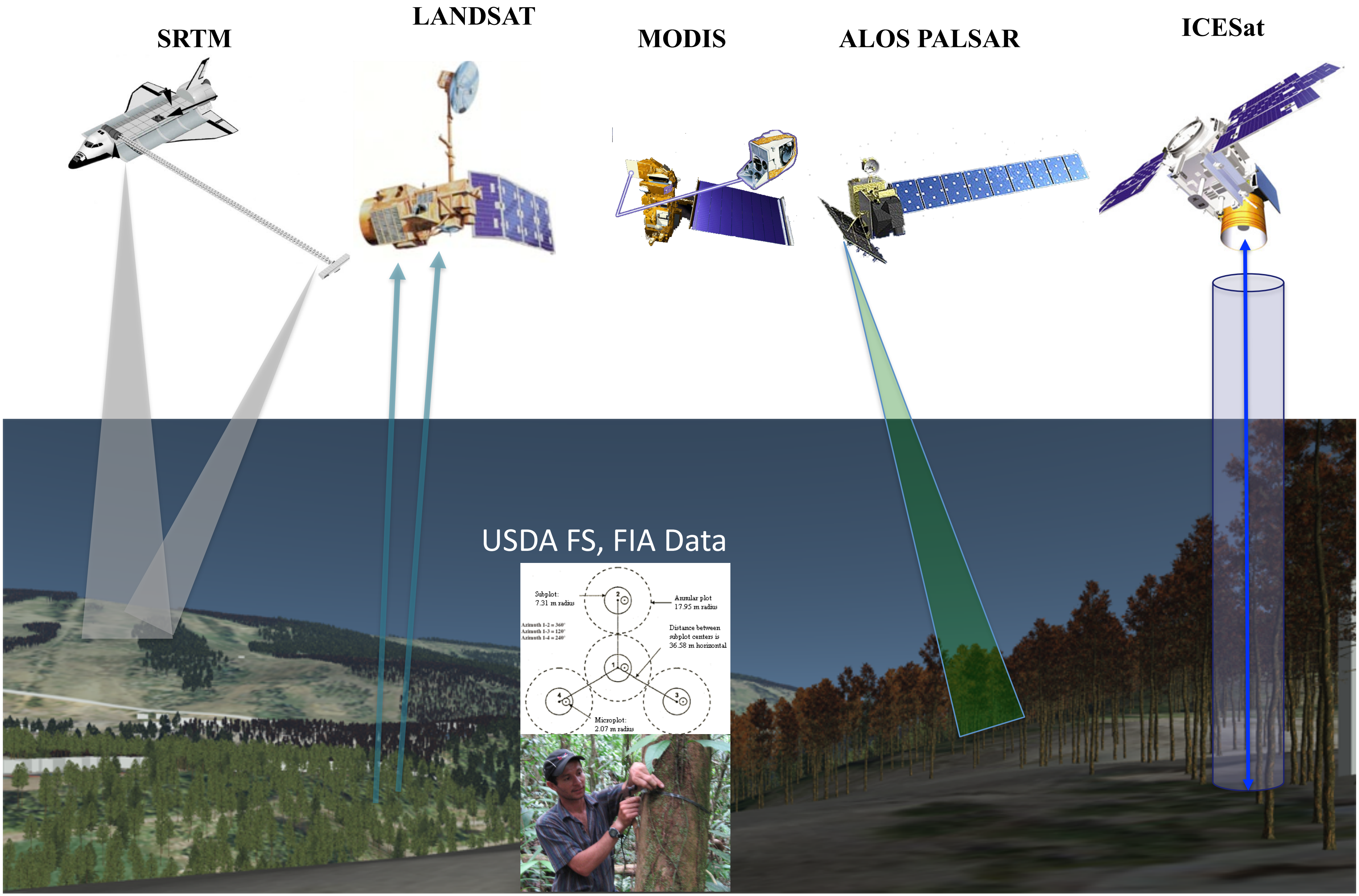
# Mapping Biomass

- Forest biomass varies over the landscape as a result of several factors: Production (photosynthesis) Consumption (respiration), mortality, recruitment, harvest, and herbivory.
- Forest biomass changes as a result of factors such as: succession, silviculture, harvesting, clearing, natural disturbance (pest, fire, wind, etc.), and climate pollutants.
- Forest biomass is a useful measure to assess variations of structural and functional attributes over a wide range of environments that can be used in models.
- Environmental variables (soil, climate, and topography) do not predict forest biomass accurately.
- Systematic statistically designed sampling can provide regional and national scale carbon stock and changes, but it cannot be applied everywhere (e.g. tropics) and as frequently as needed.

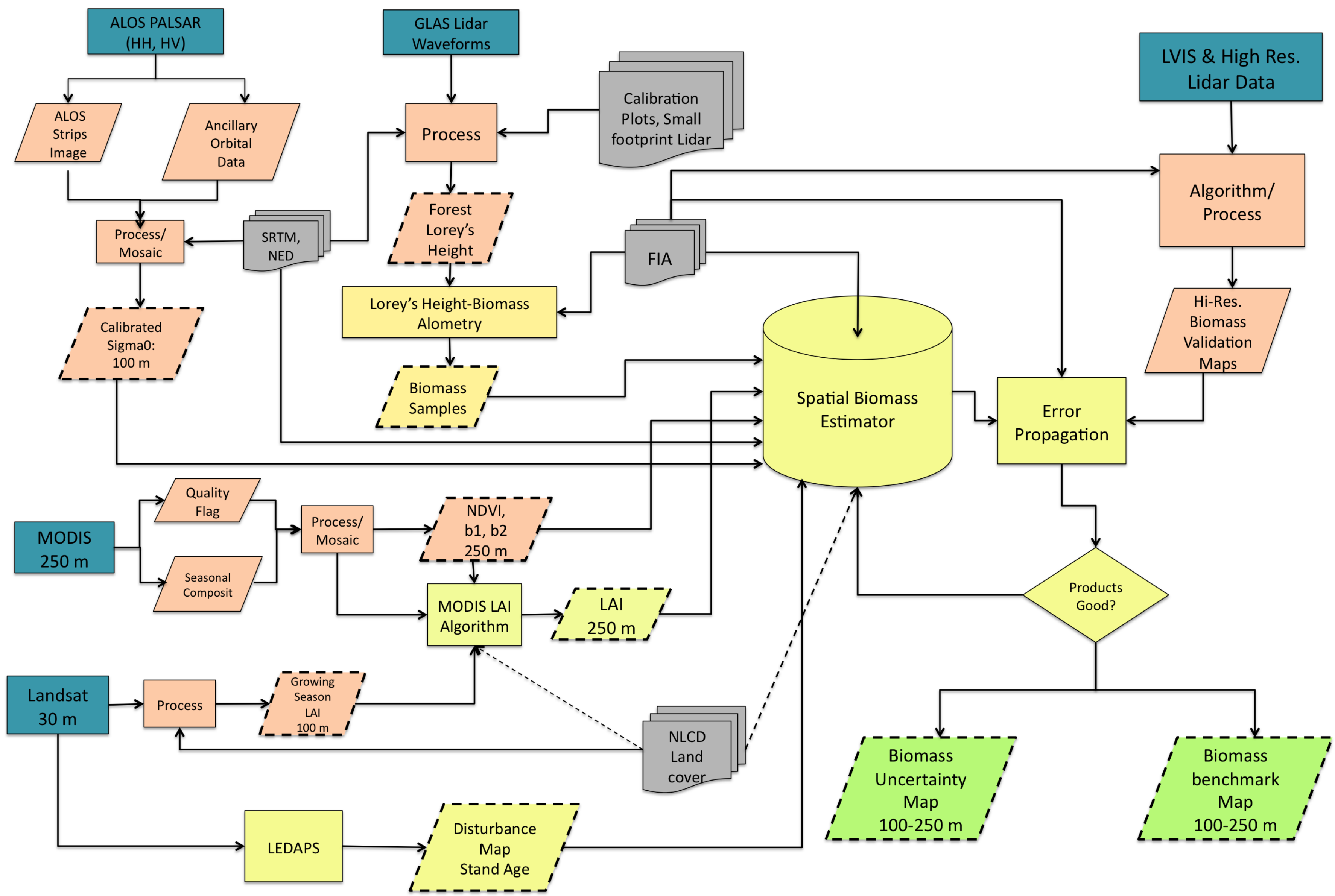
# Terrestrial Biomass Pilot Project: Methodology



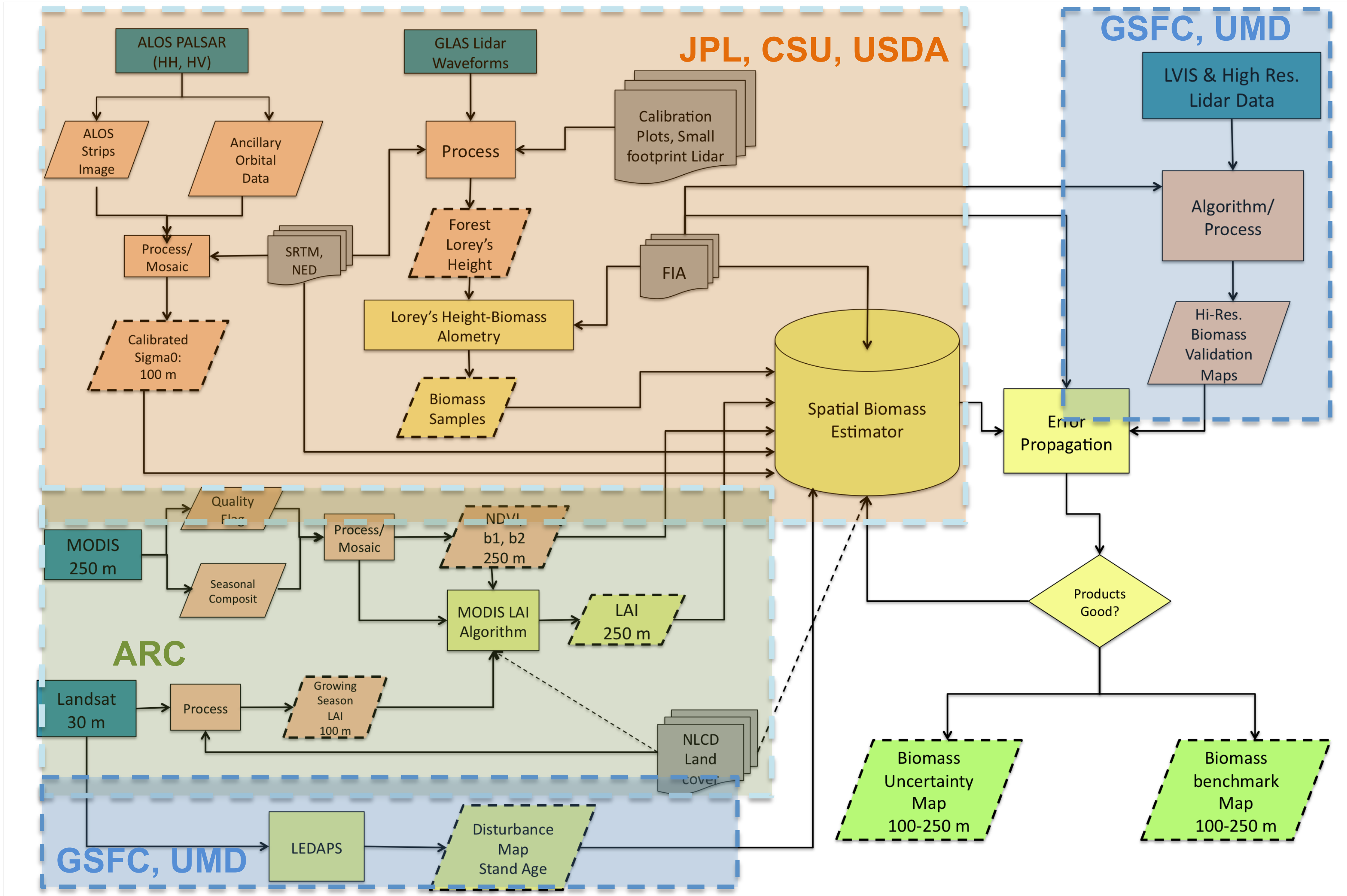
# Satellite and In Situ Observations



# Work Plan


ALOS PALSAR (HH, HV)
GLAS Lidar Waveforms
LVIS & High Res. Lidar Data
ALOS Strips Image
Ancillary Orbital Data
Process
Calibration Plots, Small footprint Lidar
Algorithm/ Process
Forest Lorey's Height
Process/ Mosaic
SRTM, NED
FIA
Hi-Res. Biomass Validation Maps
Lorey's Height-Biomass Alometry
Calibrated Sigma0: 100 m
Spatial Biomass Estimator
Biomass Samples
Error Propagation
Quality Flag
Process/ Mosaic
NDVI, b1, b2 250 m
MODIS 250 m
Seasonal Composit
MODIS LAI Algorithm
LAI 250 m
Products Good?
Landsat 30 m
Process
Growing Season LAI 100 m
NLCD Land cover
Biomass Uncertainty Map 100-250 m
Biomass benchmark Map 100-250 m
LEDAPS
Disturbance Map Stand Age

# Work Plan



JPL, CSU, USDA
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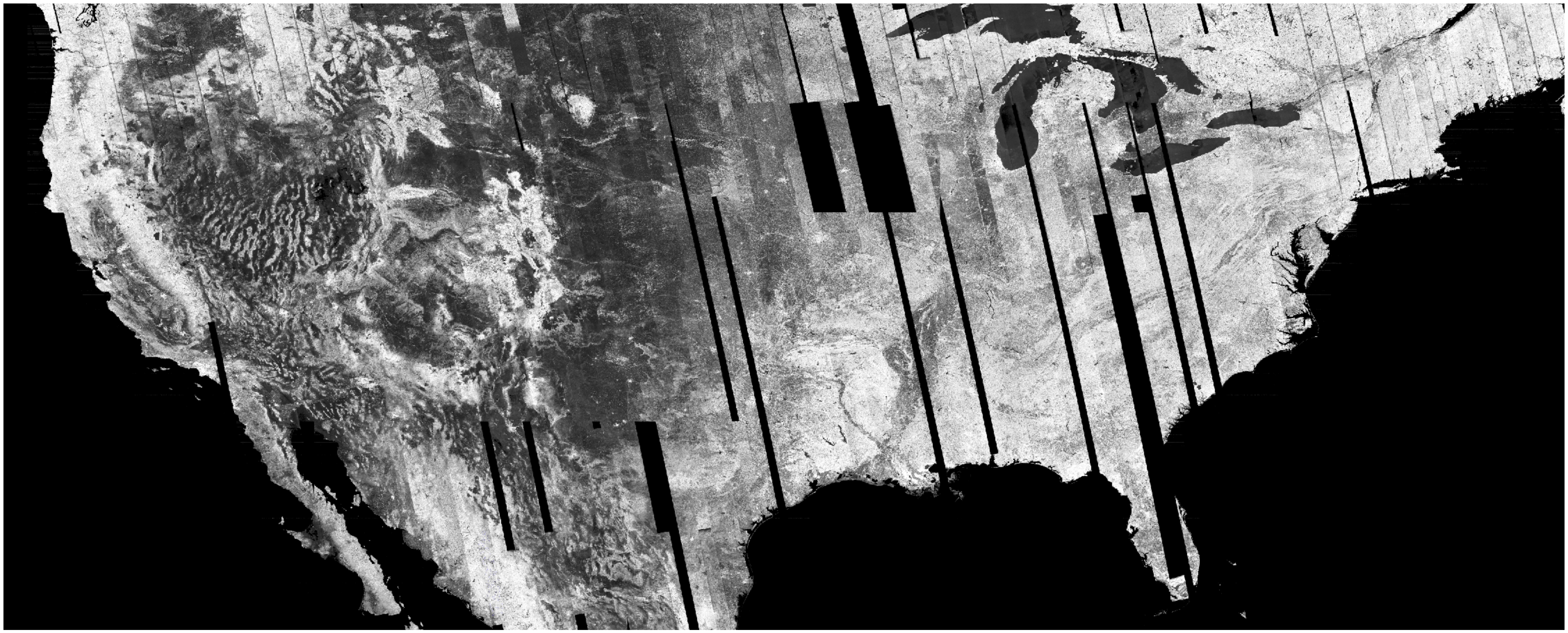
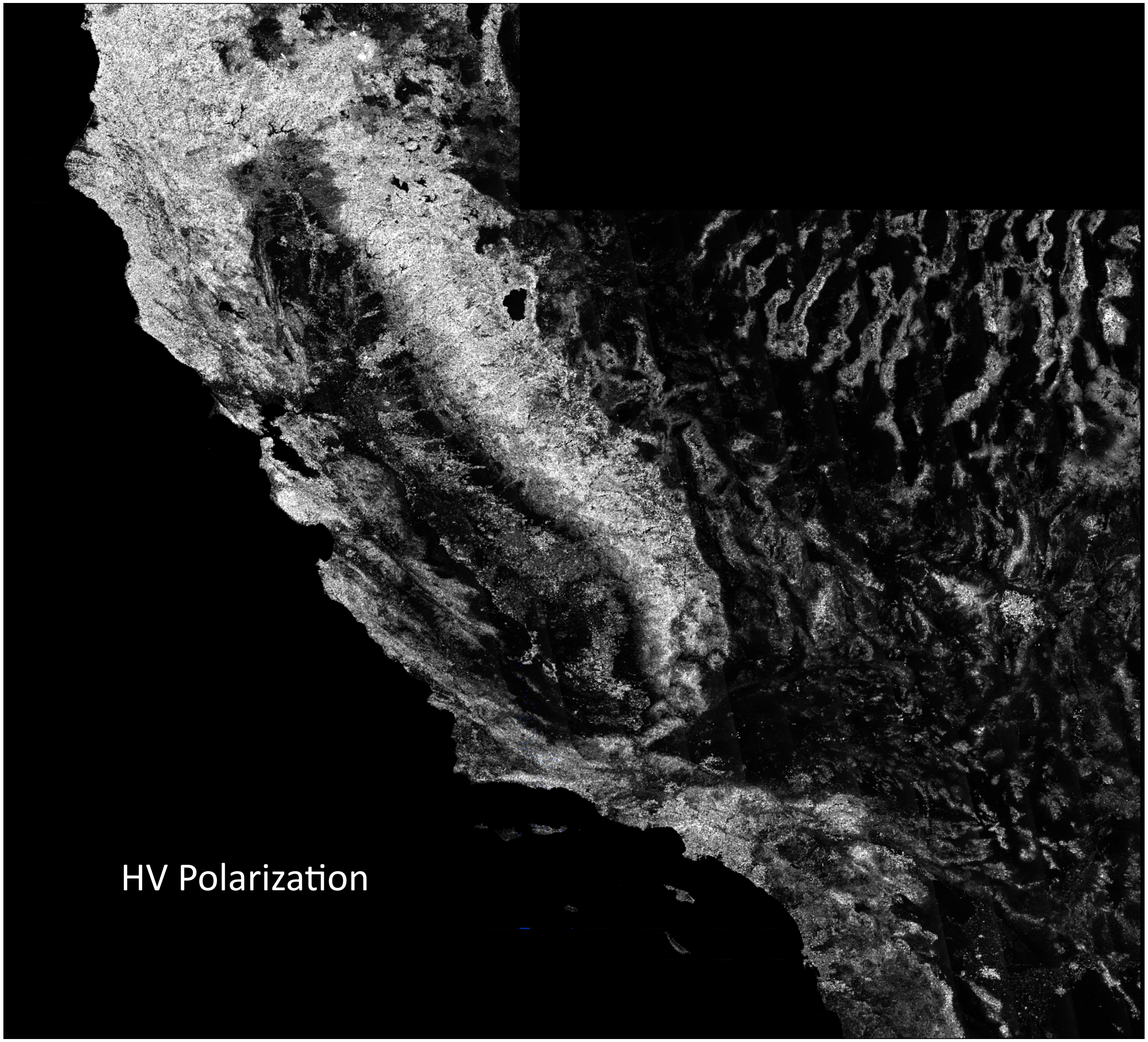
GSFC, UMD
LEDAPS
Disturbance Map Stand Age

# Continental HH US mosaic full resolution: 90 m

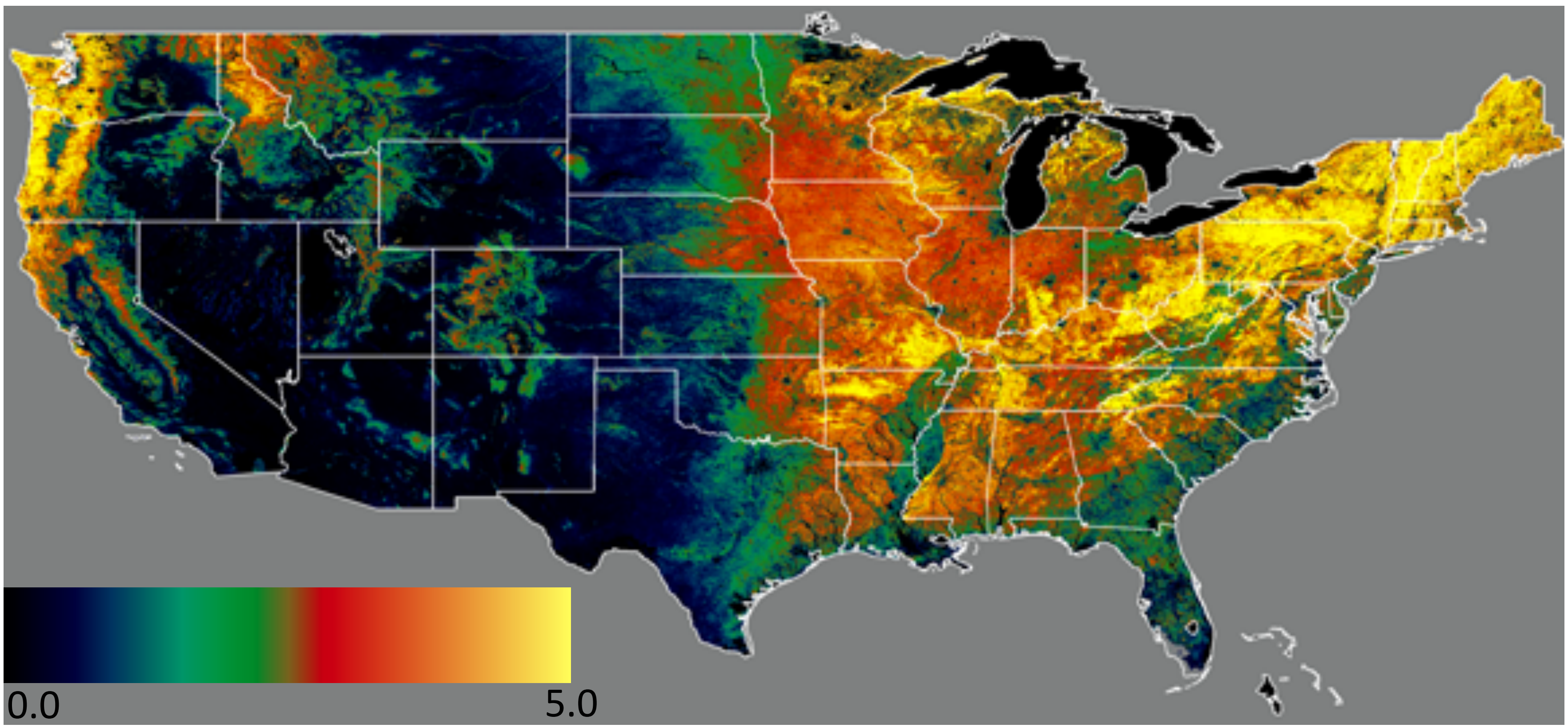


Above 40 degrees, ALOS observations switch from every orbit to every other orbit. There is less overlap between images, and some banding at edge is introduced.


HV Polarization

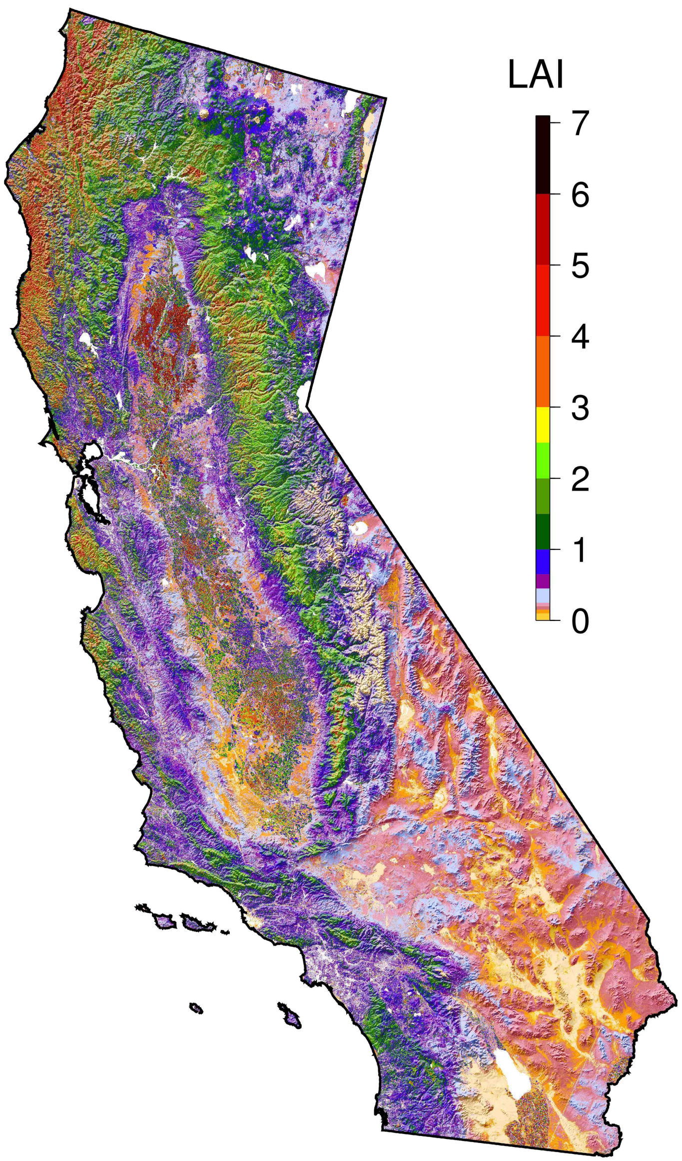
# 250-m LAI derived from MODIS

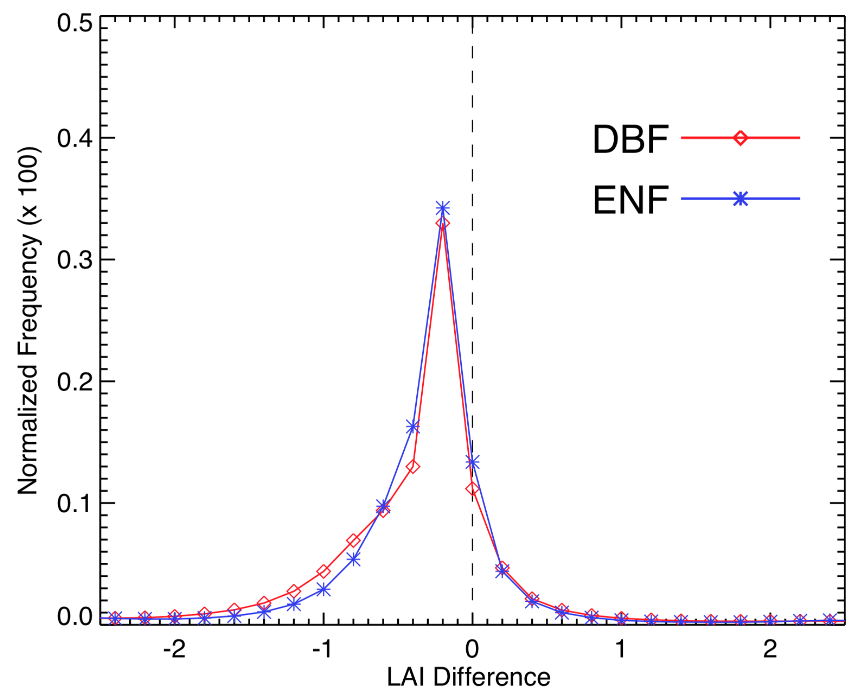
- MODIS monthly LAI Mosaic is provided at 250 m resolution
- Three years (2004-2006) of MODIS data were processed to improve image quality
- LAI estimation was implemented using the NLCD land cover map.




MODIS Summer Mean LAI (2004-2006)

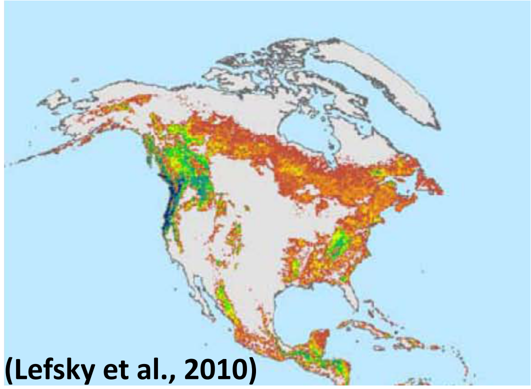
# 30-m LAI derived from Landsat and NLCD



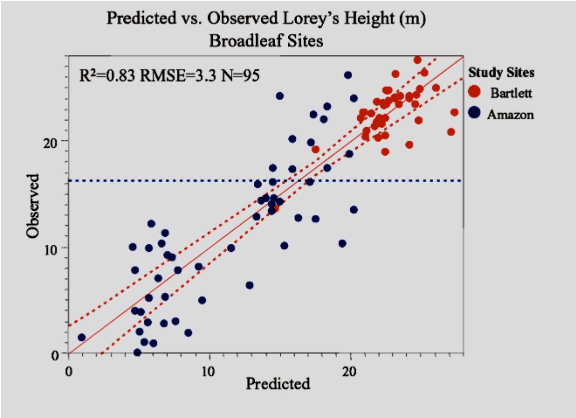



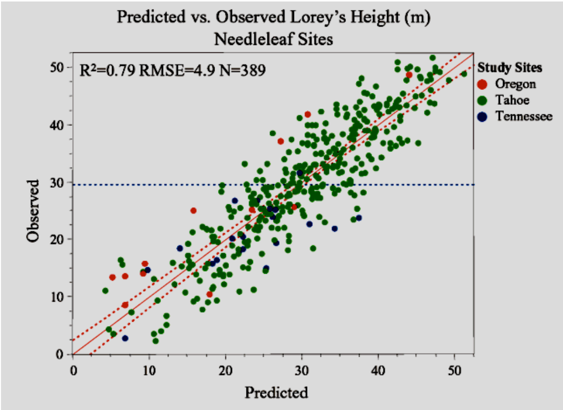

LAI difference between a 3-band inversion and 2-band inversion for pixels classified as DBF and ENF for California. The NLCD 2001 map is used to classify the forest pixels.

# ICESAT GLAS Forest Height Metric

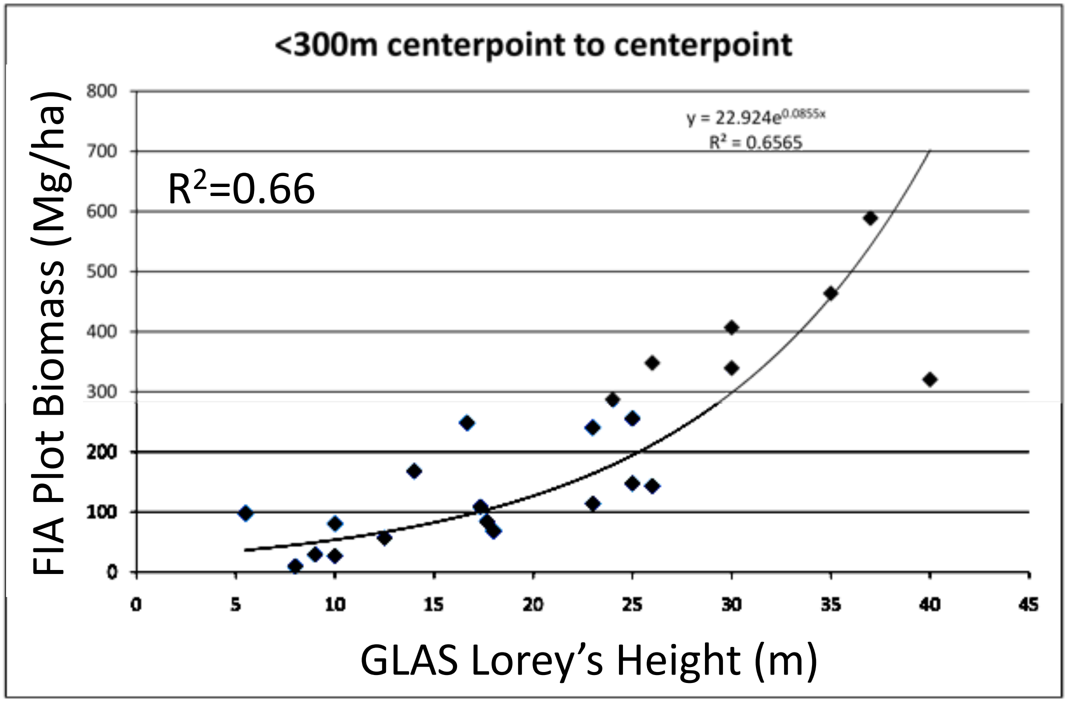



$$H_{lorey} = \frac{\sum_{i=1}^{N} BA_i h_i}{\sum_{i=1}^{N} BA_i}$$ : basal area weighted height (crown weighted height)




GLAS Validation (Sean Healey, USDA)

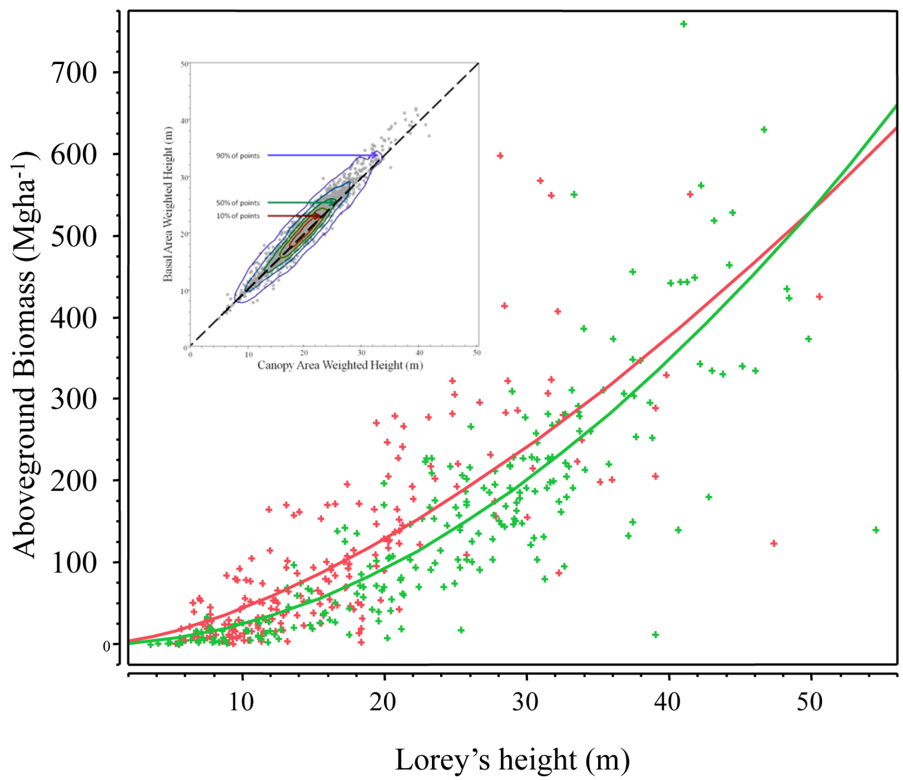


# Lorey's Height Biomass Allometry

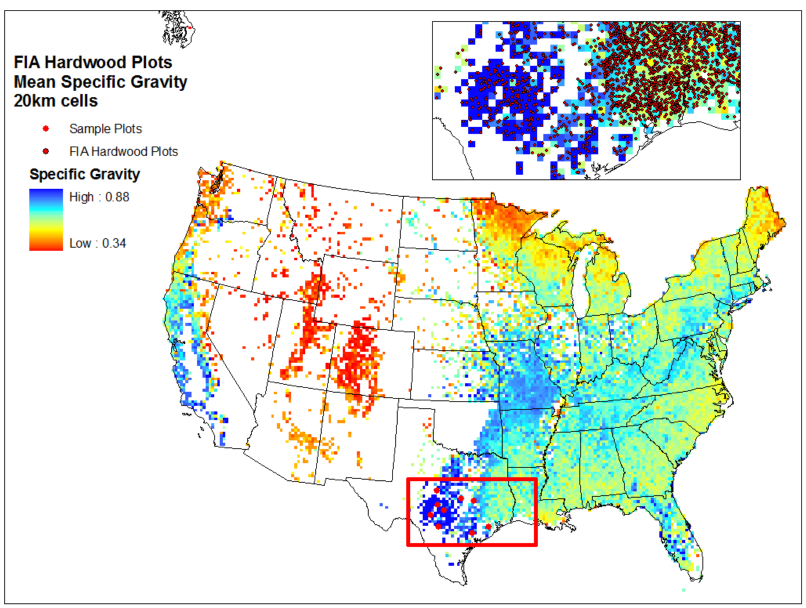
At this time, we are estimating aboveground biomass stratified by softwood and hardwood composition (for dominant individuals)

Lefsky et al. Unpublished

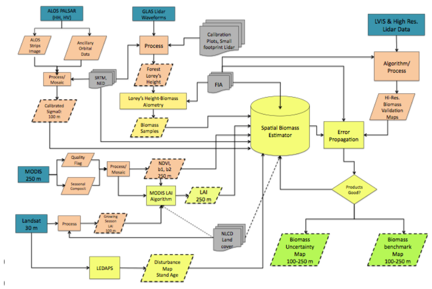
AGB (Softwood)=$0.3177*H^{1.898}$
AGB (Hardwood)=$1.179*H^{1.539}$

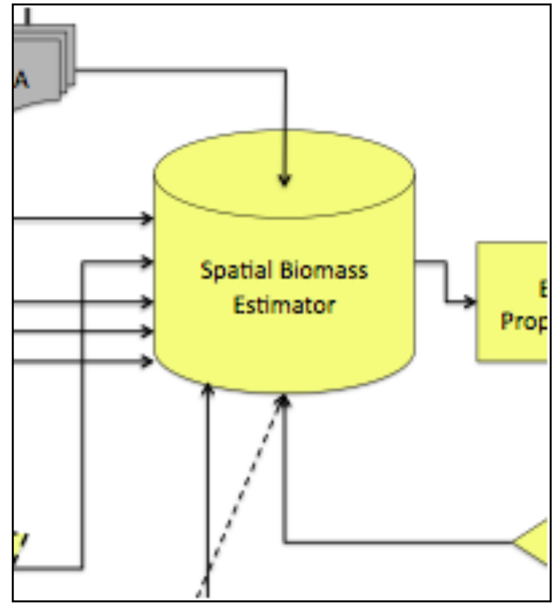



Wood Density Correction of Allometry



# Spatial Biomass Estimator





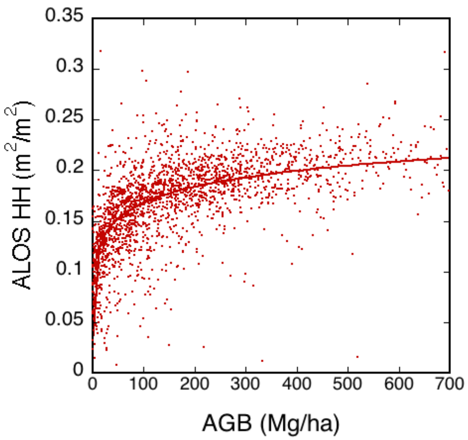

- Parametric Models:
  - Multivariate Regressions:

    AGB = *f* (*VI, SAR, SRTM*)

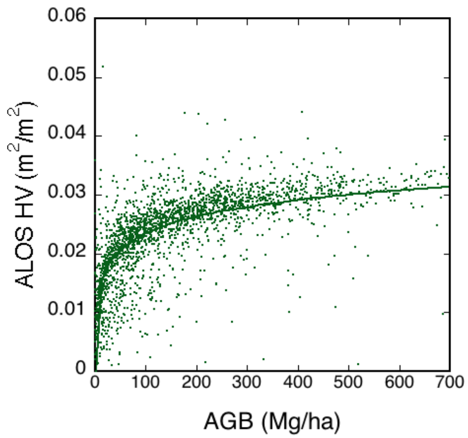
- Non Parametric Models:
  - Coloring by numbers (use of land cover maps)
  - **Image Segmentation Approach (Lefsky et al., 2010; Mitchard et al., 2011)**
  - **Decision Rule, Random Forest (Saatchi et al., 2007; Kellndorfer et al., 2010)**
  - **Maximum Entropy Approach (Saatchi et al., PNAS 2011)**

# Parametric Model

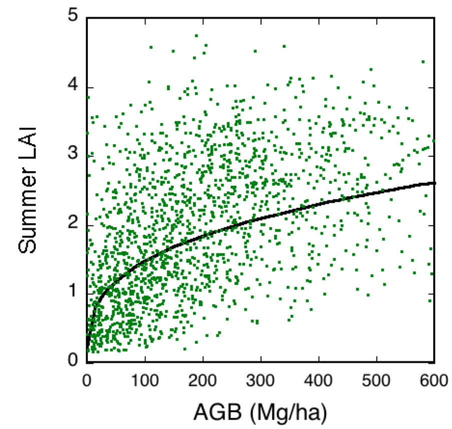
PALSAR HH



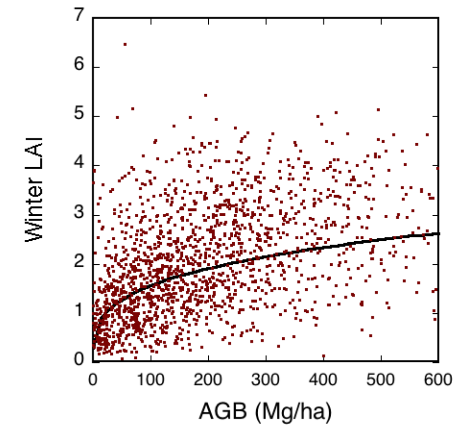

PALSAR HV

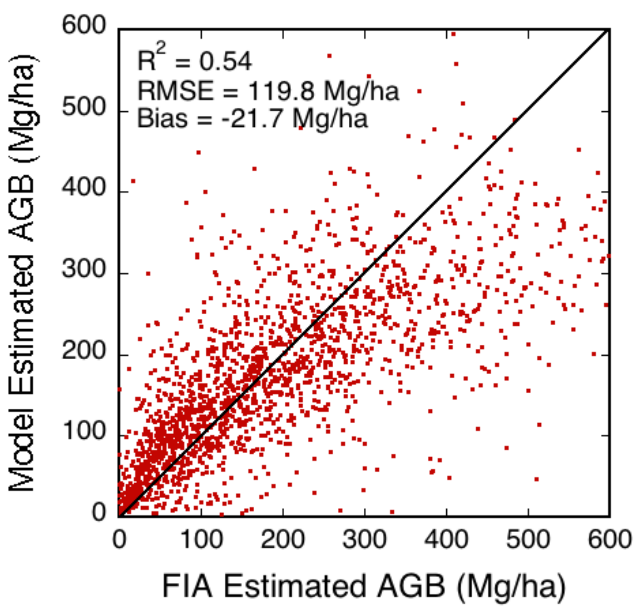



LAI Summer



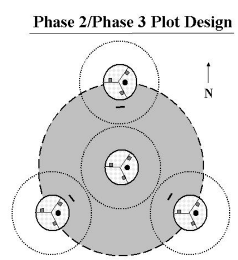

LAI Winter




$$AGB^{\lambda} = a_0 + S\sum_{i=1}^{N} a_i X_i^{\beta_i}$$

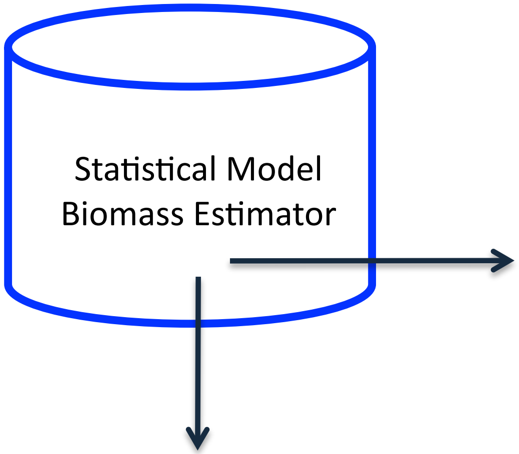
$$X = \{HH, HV, SRTM - NED, LAI_{S1}, LAI_{S2}, LAI_{S3}, LAI_{S4}, Slope\}$$




FIA Plot (< 0.1 ha)

Spatial Resolution or Remote Sensing Data ( 0.81 ha)

# Maximum Entropy Model




1. A probabilistic framework
2. Develop incomplete empirical probability distribution based on the occurrences
3. Approximate with a probability distribution of maximum entropy
4. Use environmental variables as constraints
5. A rule classifier to produce forest biomass map

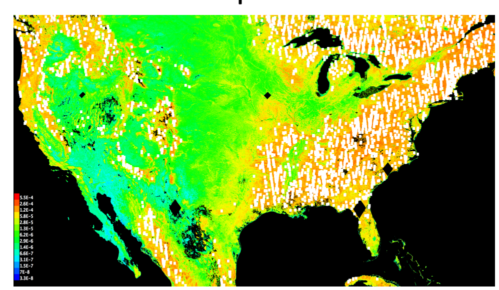
$$H(\hat{\pi}) = \sum_{x \in X} \hat{\pi}(x) \ln \hat{\pi}(x)$$

$\hat{\pi}(x)$ : emperical distribution at points x (plot location)

$H$ is maximized over feature space defined by f(x)

f : satellite image or environmental variable

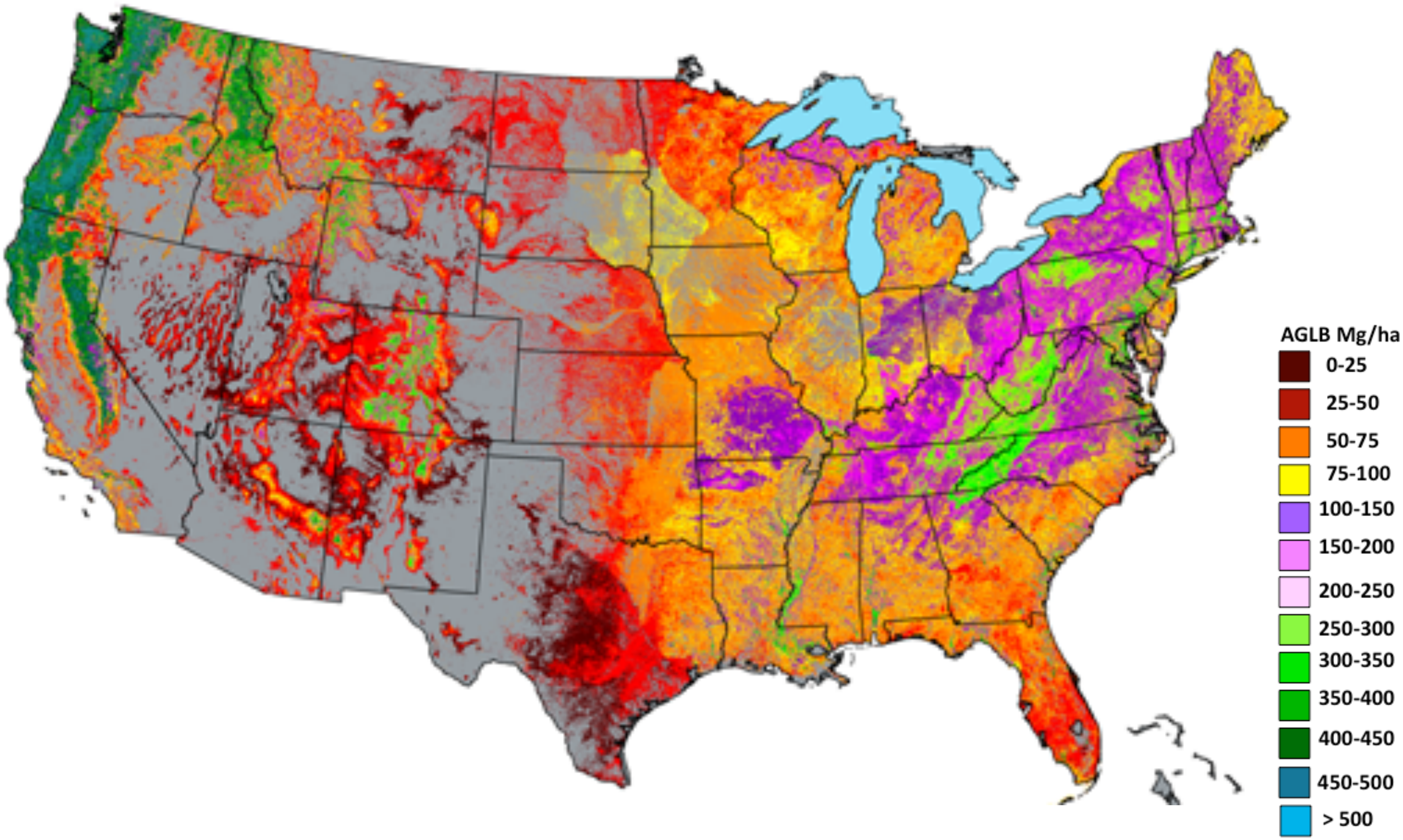
Sample Probability Space



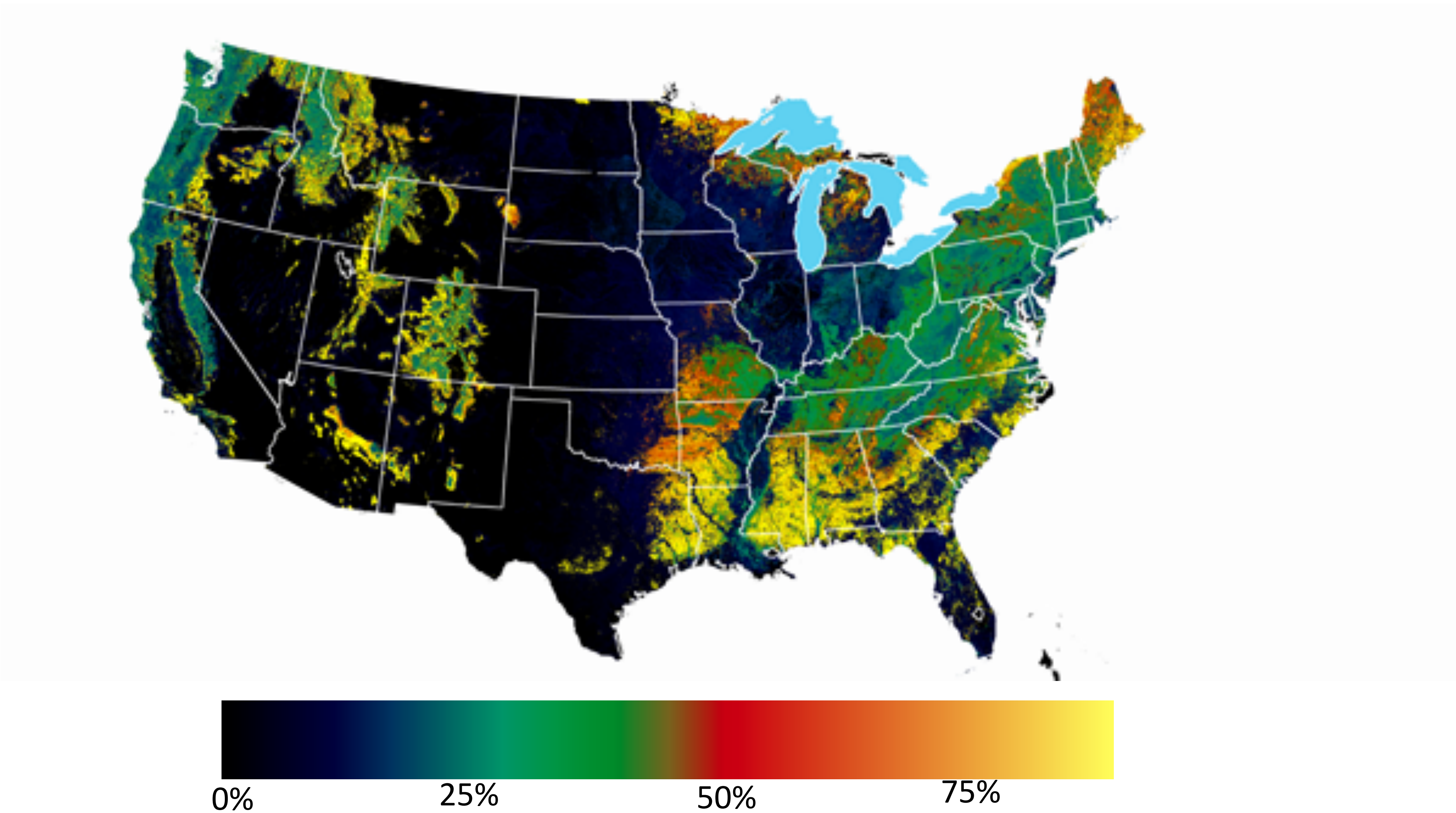
$$\hat{B} = \frac{\sum_i^N B_i P_i^n}{\sum_i^N P_i^n}, \quad for \quad n = 1,2,3,\ldots\ldots\ldots$$

$$\sigma = \sqrt{\frac{\sum_i^N (B_i - \hat{B})^2 P_i}{\sum_i^N P_i}}$$

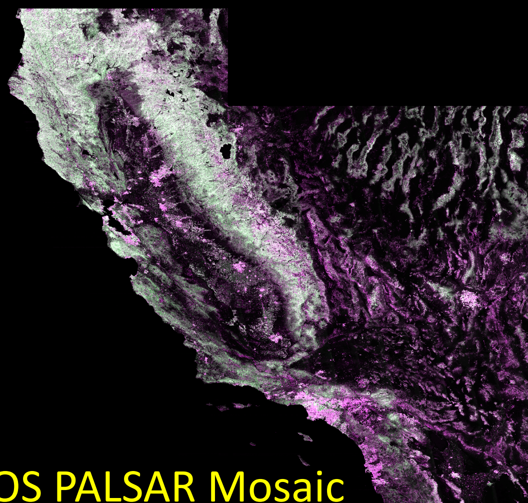
# National Biomass Estimation
# 250 m (6.25 ha) Spatial Resolution



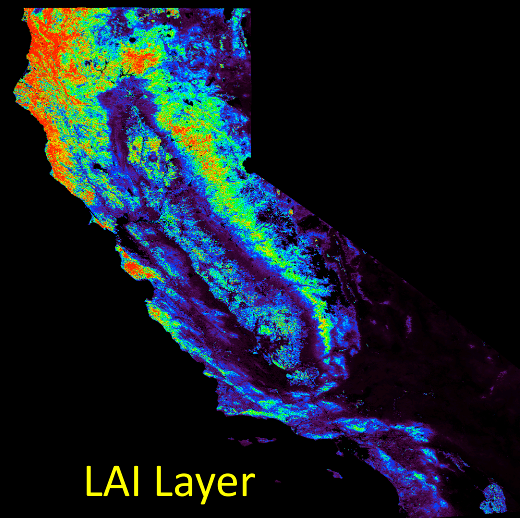
# National Biomass Estimation Uncertainty
# 250 m Spatial Resolution



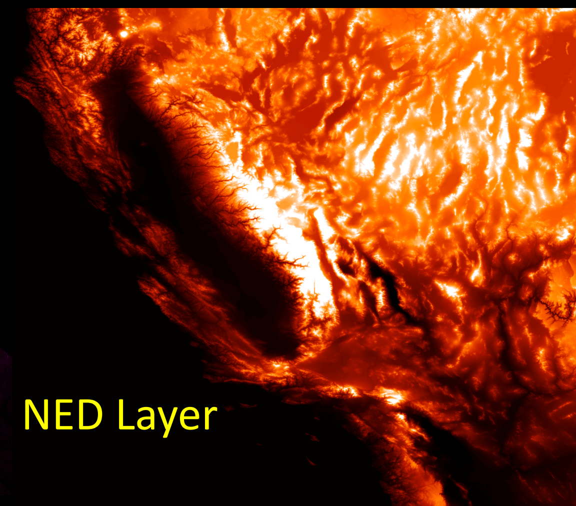
# Non-parametric Model Implementation



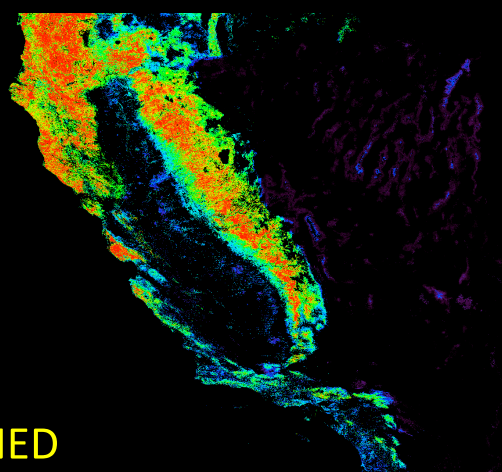
ALOS PALSAR Mosaic
(HH-red & blue, HV-green)



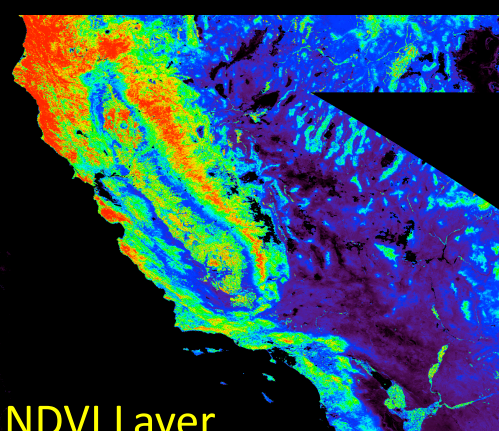
LAI Layer



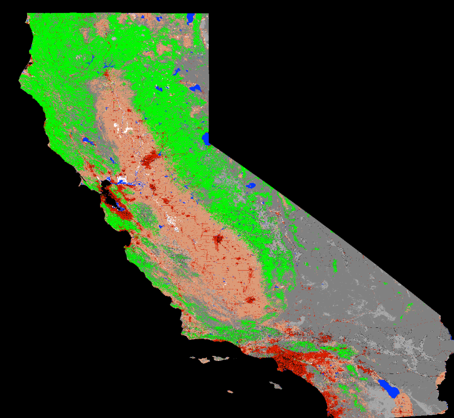
NED Layer



SRTM-NED



NDVI Layer



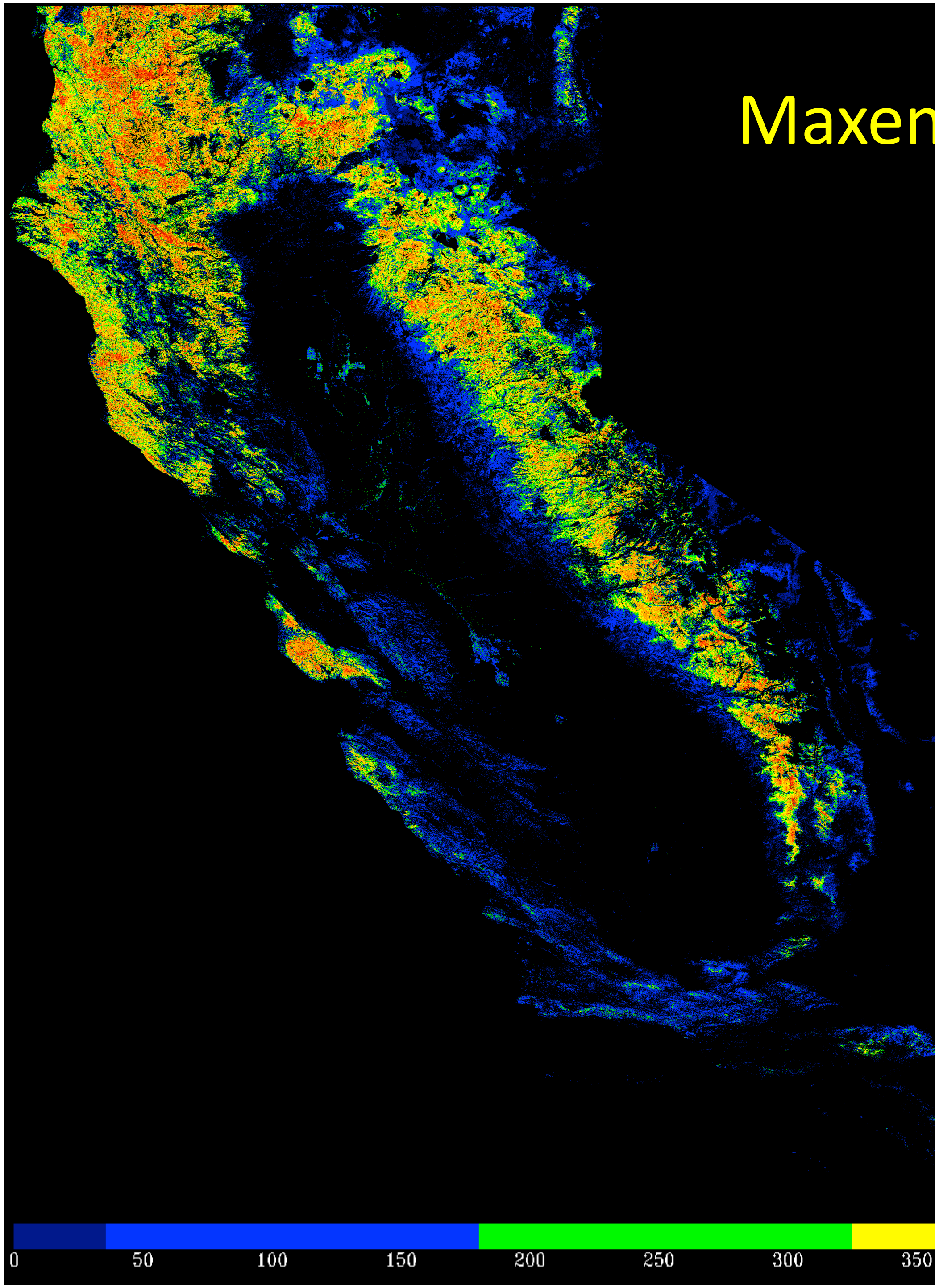
NLCD Layer

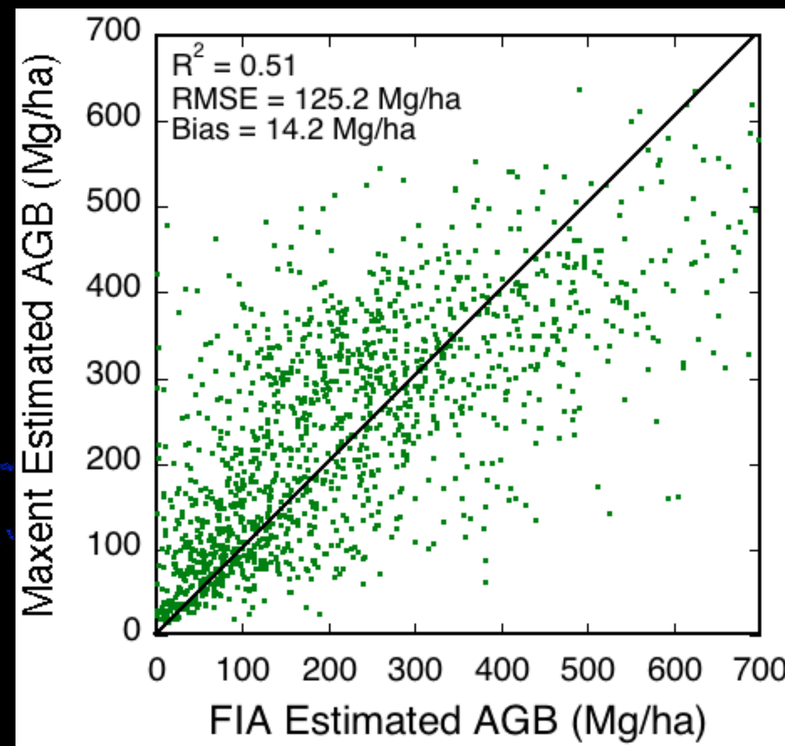
# NLCD Homogeneity Index

- Resample NLCD 2006 to 3 and 8 arcsecond pixel size
  - Use majority rule to determine class of aggregate pixel
  - Create a layer which has the number of unique NLCD classes found within this pixel
- Create a new samples spreadsheet containing only FIA samples where there was one unique class in the pixel.
  - Significant reduction in the data
  - Should we train with this data, or only validate with this data?

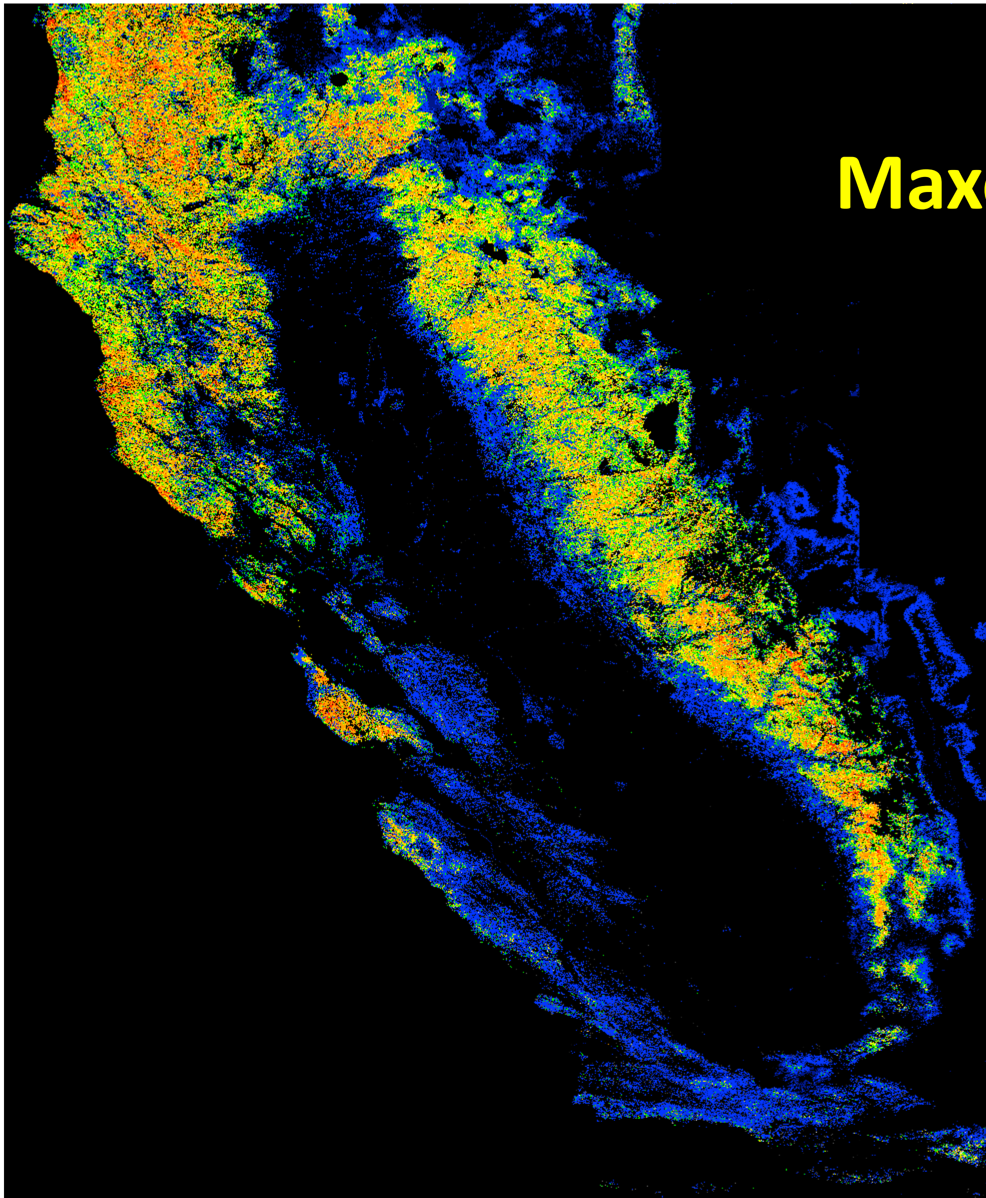
| Class agb | # Fia Plots in class | Unique nlcd In 3 sec pixel | Unique nlcd In 8sec pixel |
|---|---|---|---|
| 0 | 62 | 29 | 10 |
| 12.5 | 307 | 142 | 54 |
| 37.5 | 236 | 117 | 49 |
| 62.5 | 219 | 114 | 40 |
| 87.5 | 183 | 88 | 35 |
| 125 | 288 | 150 | 77 |
| 175 | 238 | 128 | 66 |
| 225 | 206 | 130 | 70 |
| 275 | 157 | 108 | 62 |
| 325 | 109 | 74 | 47 |
| 375 | 84 | 56 | 35 |
| 425 | 70 | 53 | 37 |
| 475 | 55 | 45 | 32 |
| 500+ | 120 | 94 | 65 |

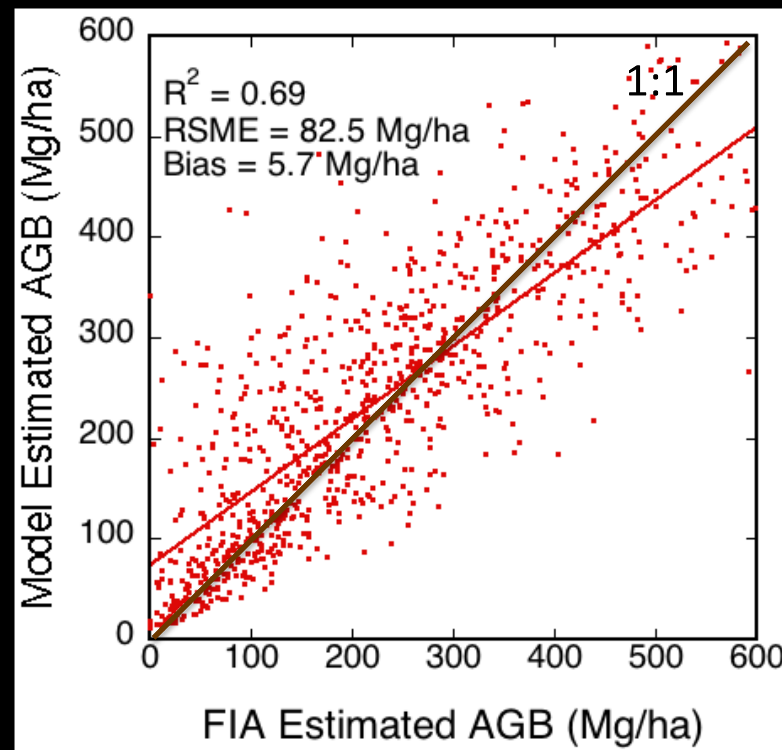
# Maxent Product at 8 arcsec

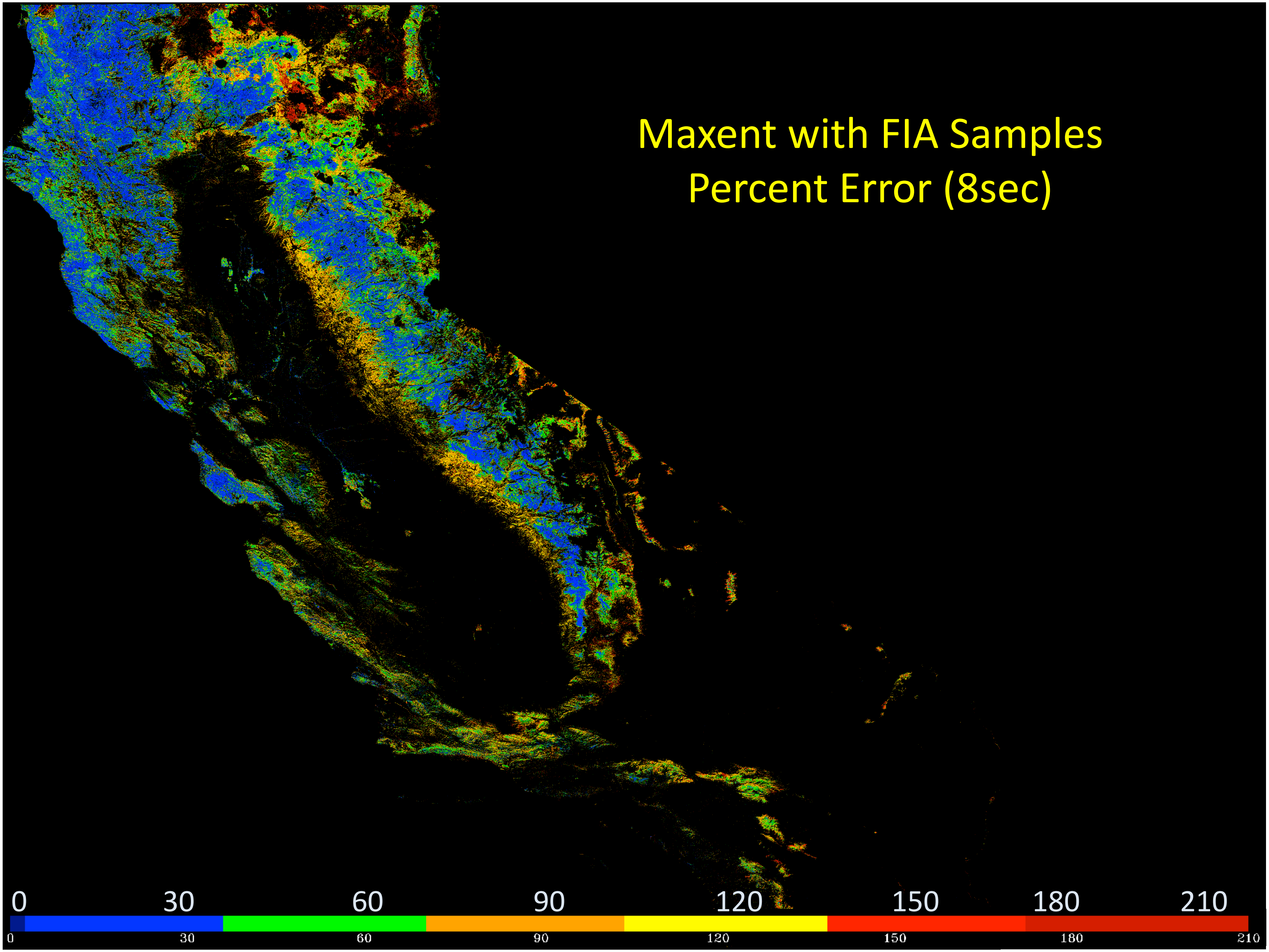


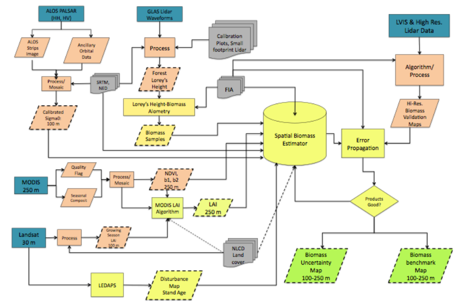
# Maxent Product at ~ 90 m

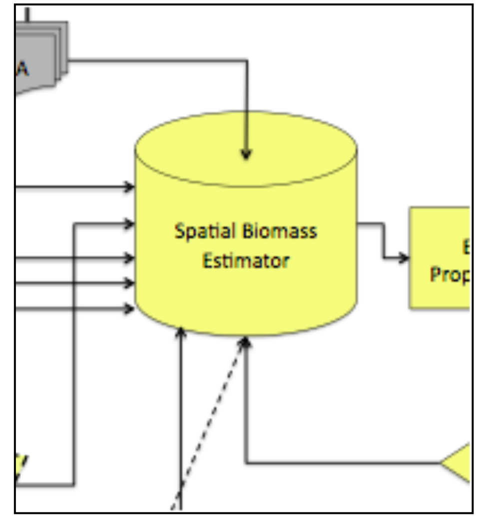






Maxent with FIA Samples
Percent Error (8sec)
0
30
60
90
120
150
180
210

# Sensitivity of Estimator to Errors



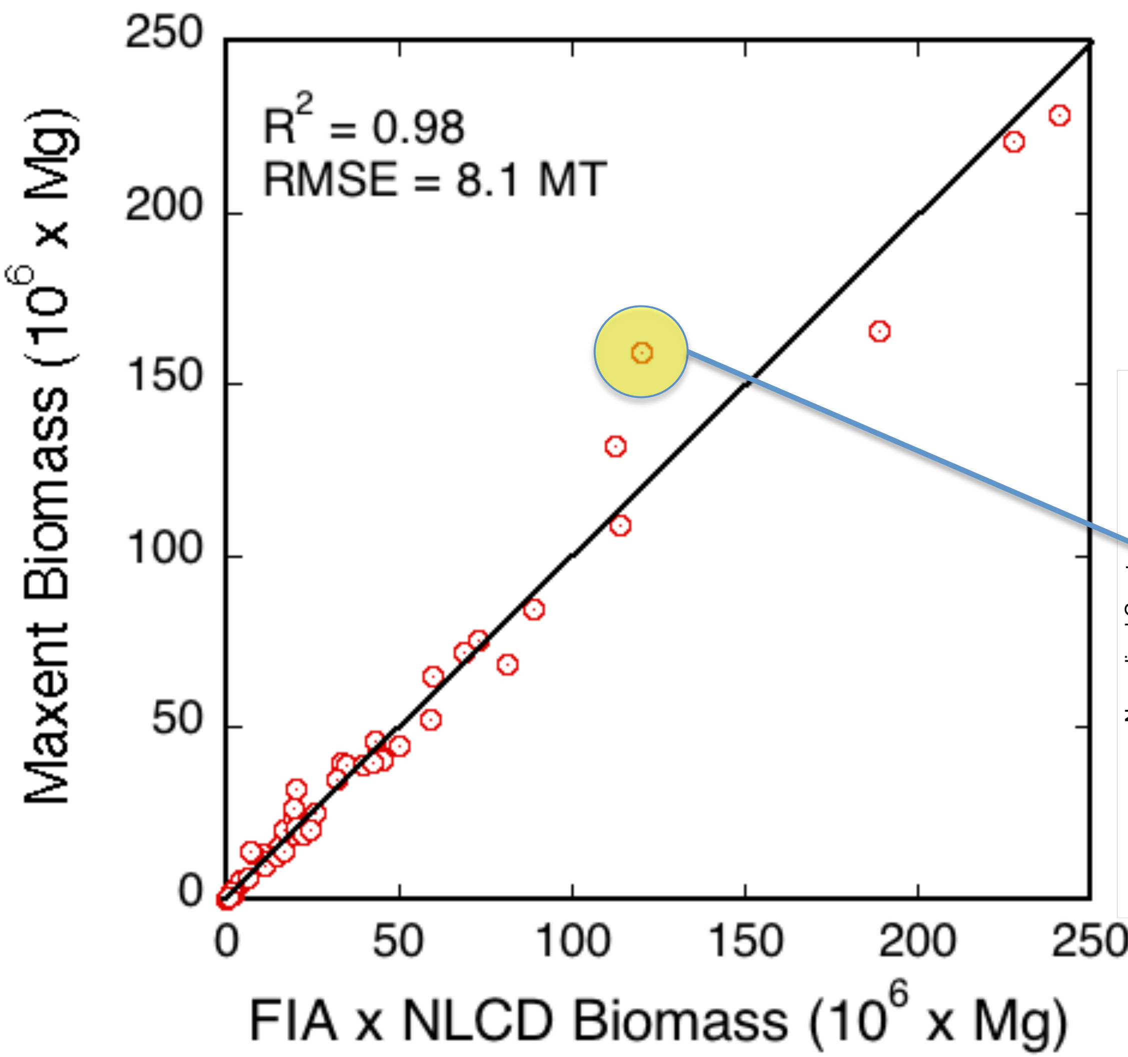



- Added random noise to:
  - ALOS HH, HV
  - LAI (spring, summer, fall, winter)
- Used a KP-style noise model:
  - X* is the noisy version of X.
  - n(0,1) is a sample from a Gaussian distribution with unit variance and zero mean.
  - I tried α = 0.2 and 0.3

$$X^{*} = X\left[1 + \alpha * n(0,1)\right]$$

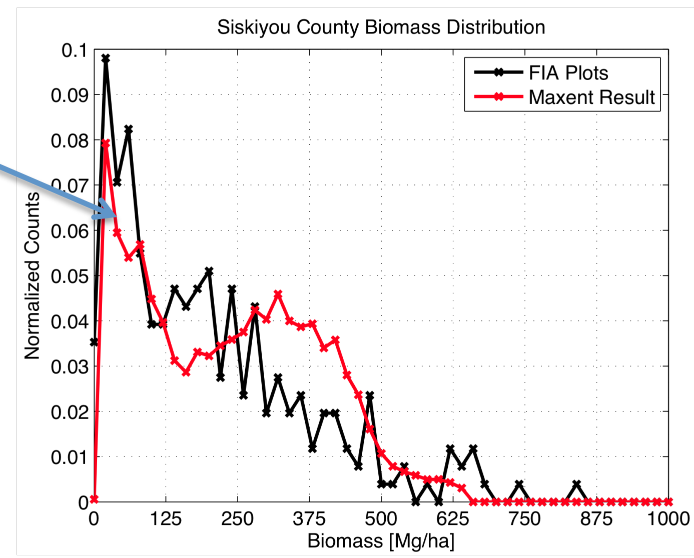
| | r2 | bias | rms |
|---|---|---|---|
| **no noise** | 0.46 | 8.50 | 135.60 |
| **alos hh; 0.2** | 0.47 | 9.70 | 134.80 |
| **alos hh; 0.3** | 0.47 | 8.40 | 133.90 |
| **alos hv; 0.2** | 0.46 | 9.20 | 135.20 |
| **alos hv; 0.3** | 0.47 | 8.50 | 134.40 |
| **lai fall; 0.2** | 0.46 | 8.80 | 135.30 |
| **lai fall; 0.3** | 0.48 | 9.50 | 133.30 |
| **lai spring; 0.2** | 0.48 | 8.30 | 133.10 |
| **lai spring; 0.3** | 0.46 | 7.20 | 135.30 |
| **lai summer; 0.2** | 0.46 | 8.00 | 135.60 |
| **lai summer; 0.3** | 0.48 | 7.90 | 133.10 |
| **lai winter; 0.2** | 0.47 | 7.10 | 134.60 |
| **lai winter; 0.3** | 0.45 | 8.40 | 136.20 |

# Validation at the County Scale

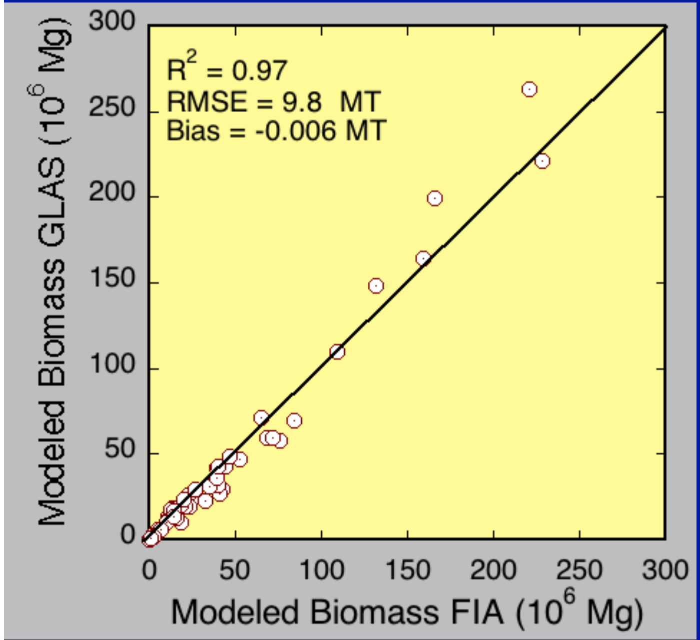


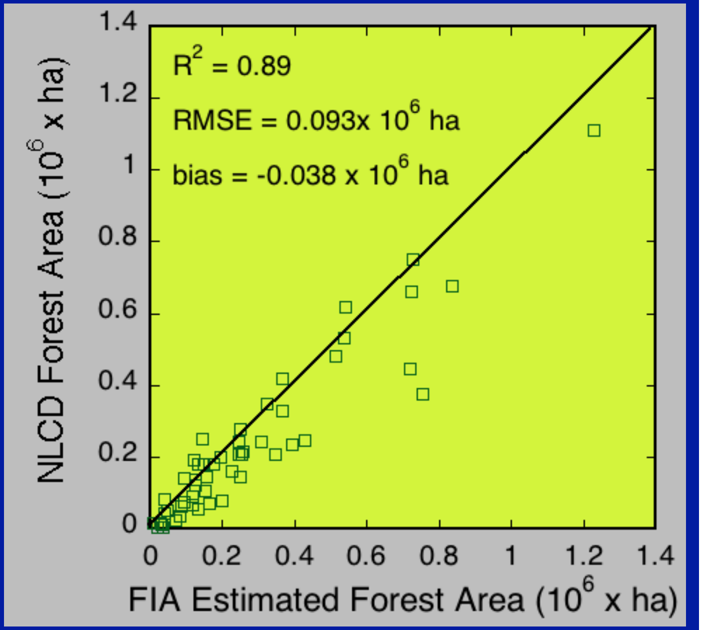

Sources of Error:

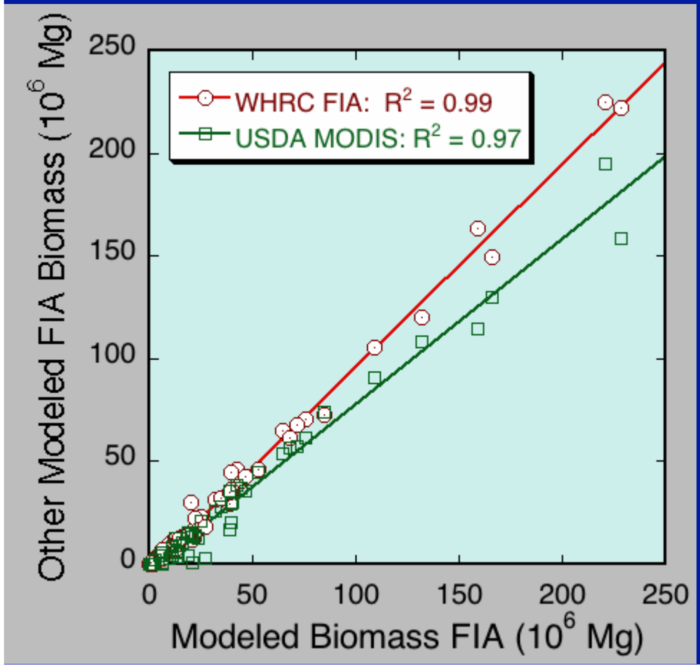
1. Forest Area Estimate
2. Maxent Prediction
3. FIA sub-sampling error

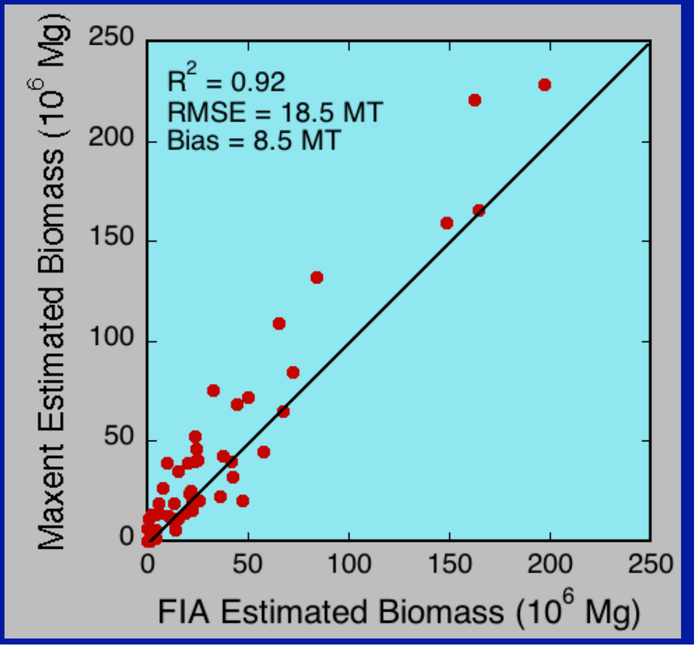


# Validation at County Level



# Summary

1. Combination of Lidar and satellite imagery can be used to model biomass distribution
2. Higher spatial resolution of 1-ha is the best to reduce errors associated with surface heterogeneity and smaller plot size
5. Large errors and small bias exists at pixel scale biomass estimation
6. Aggregated results on the US County scale agrees with the FIA data.
7. Uncertainty in biomass estimation is a function of methodology, location of plot data, allometry, forest area
8. The accuracy at county scale appears to be enough to estimate biomass changes at the annual scale, but needs to be verified.