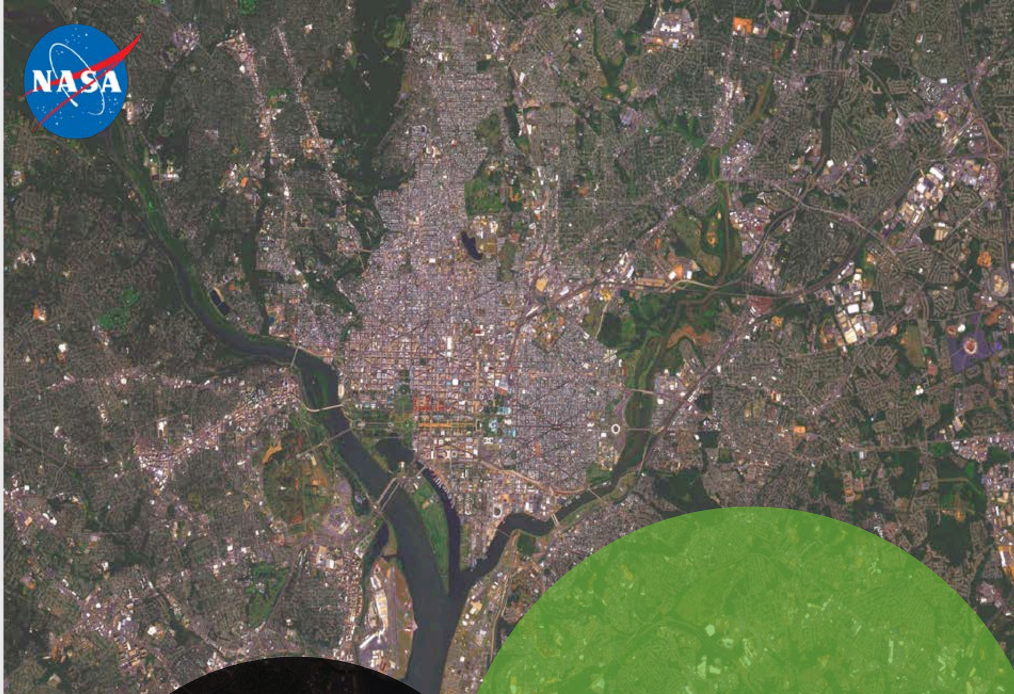
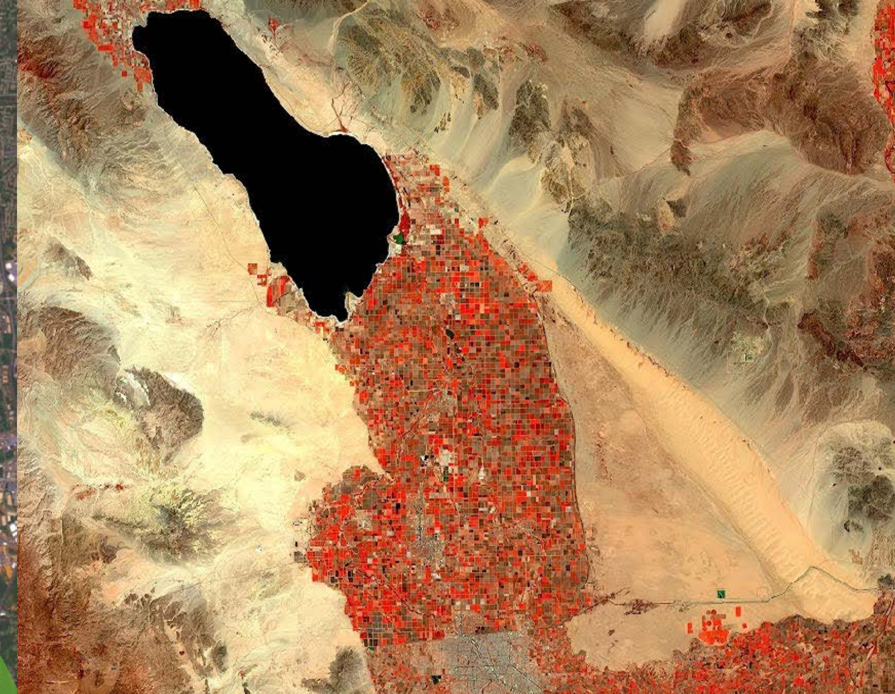




NASA Earth Exchange

Biomass Estimation Using Remote Sensing

Sangram Ganguly
Earth Science Division
NASA Ames Research Center, BAERI

October 10, 2015

NASA EARTH EXCHANGE (NEX).

OVERVIEW

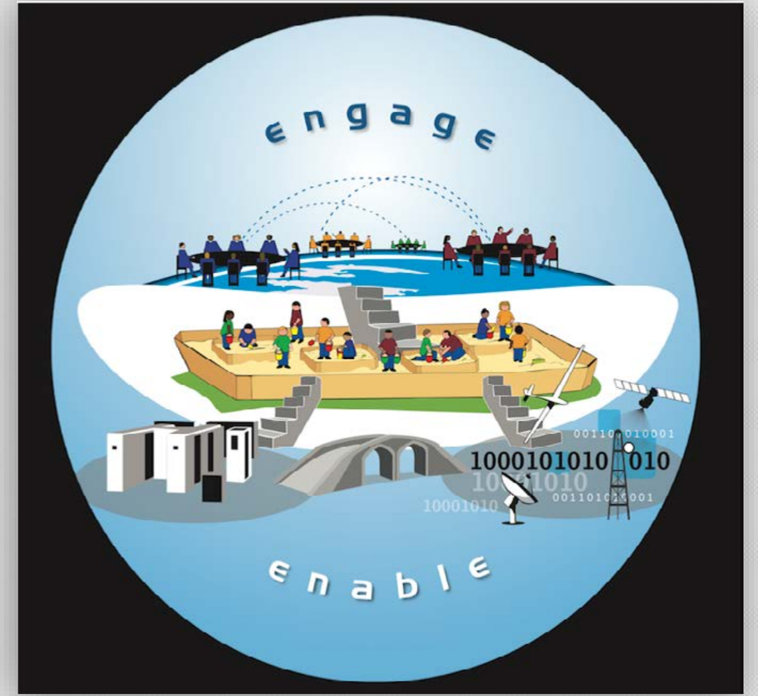
VISION

To provide "science as a service" to the Earth science community addressing global environmental challenges

GOAL

To improve efficiency and expand the scope of NASA Earth science technology, research and applications programs

+ **NEX** is virtual collaborative that brings scientists and researchers together in a knowledge-based social network and provides the necessary tools, computing power, and data to accelerate research, innovation and provide transparency.



Engage

Network,share & collaborate
Discuss & formulate new ideas
Portal, Virtual Institute

Enable

Rapid Access to data & storage
Access to computing
Access to knowledge/ workflows

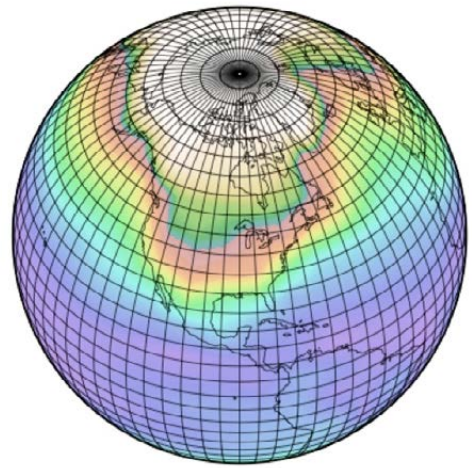
NEX Solutions

- NEX provides access to wide variety of ready-to-use data
- NEX provides the ability to bring “code to data”
- NEX offers capabilities for reproducing science through virtual machines and scientific workflows
- NEX offers state-of-the-art advanced compute capabilities

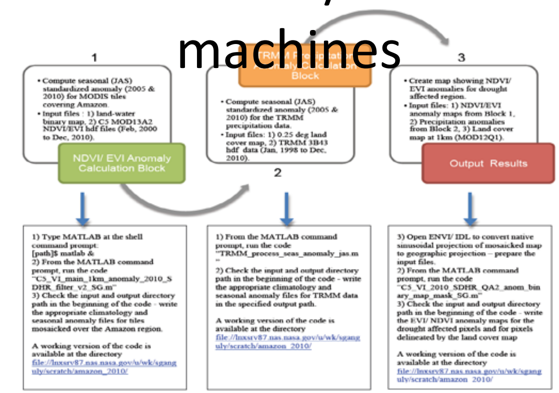
"Science As A Service"

Ready-to-use data

Ready-to-use models

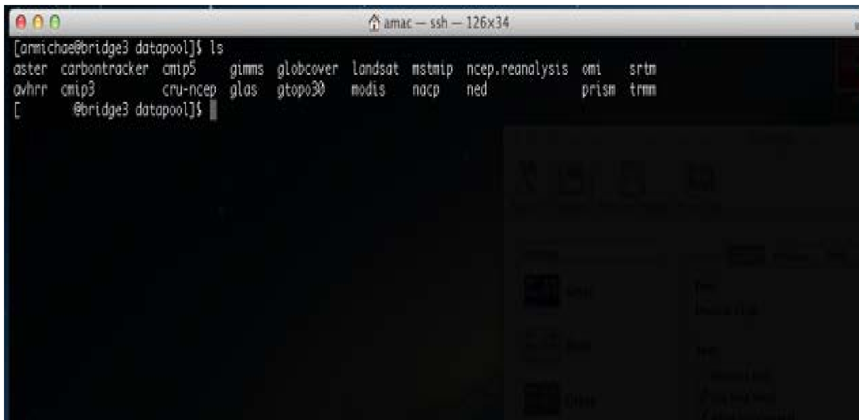


Access to workflows/virtual machines



Engage: Web portal

Enable: Terminal



NEX Specs…

Portal
- Web Server
- Database Server
- 503 Registered Members

Sandbox
- 96-core server, 264GB memory, will have 320 TB storage
- 48-core server, 128 GB, 163 TB storage

HPC
- 720-core dedicated queue + access to rest of Pleiades
- 181 users/ 44 active (153/40 last year)
- 1.3 PB storage (from 850TB)

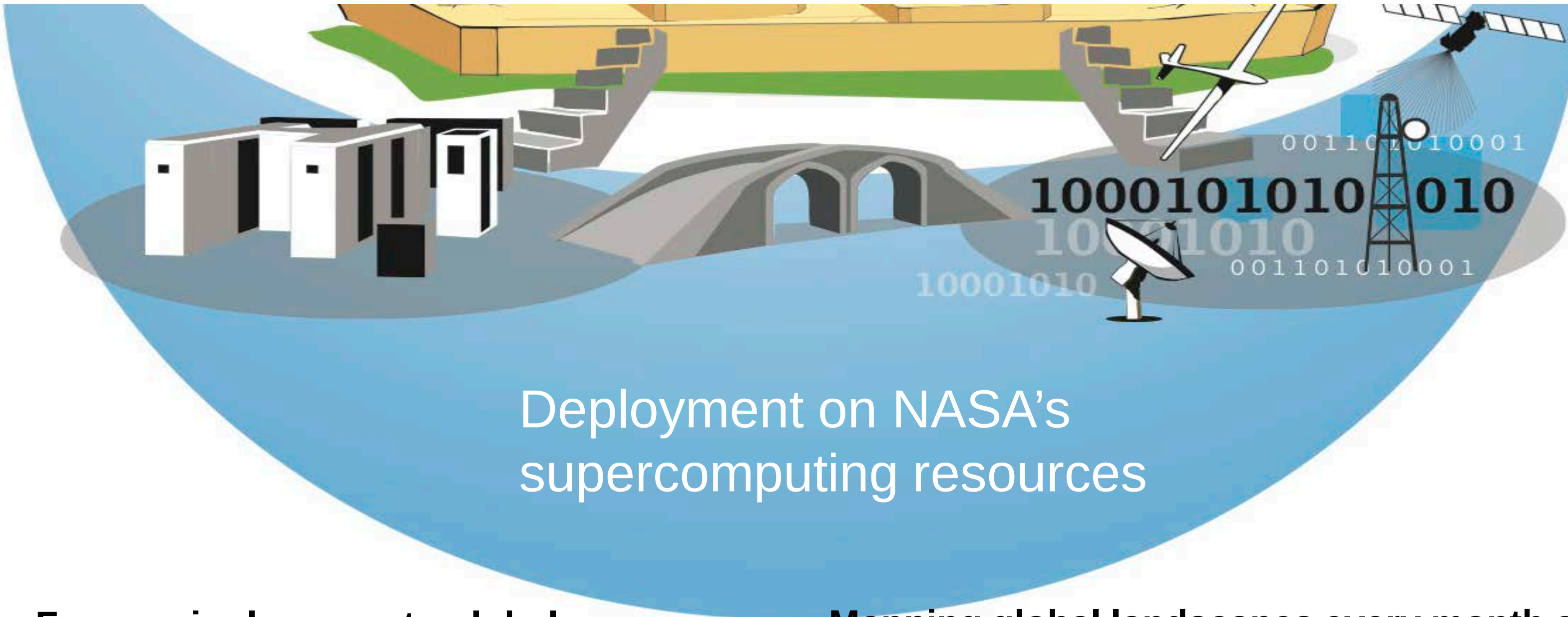
Data (>800 TB on & near-line)

Data (450 TB – constantly increasing)
- Landsat (>2M scenes)
- MODIS
- TRMM
- GRACE
- ICESAT
- CMIP5
- NCEP
- MERRA
- NARR
- GLAS
- PRISM
- DAYMET
- NAIP
- Digital Globe
- NEX-DCP30
- WELD

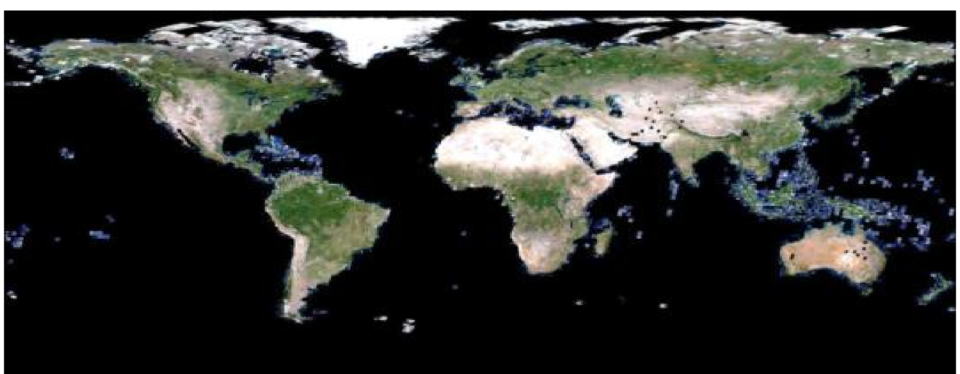
Models/ Tools/ Workflows

Model Codes
- GEOS-5
- CESM
- WRF
- RegCM
- VIC
- BGC
- CASA
- TOPS
- BEAMS
- Fmask
- LEDAPS
- METRIC

Scale it up



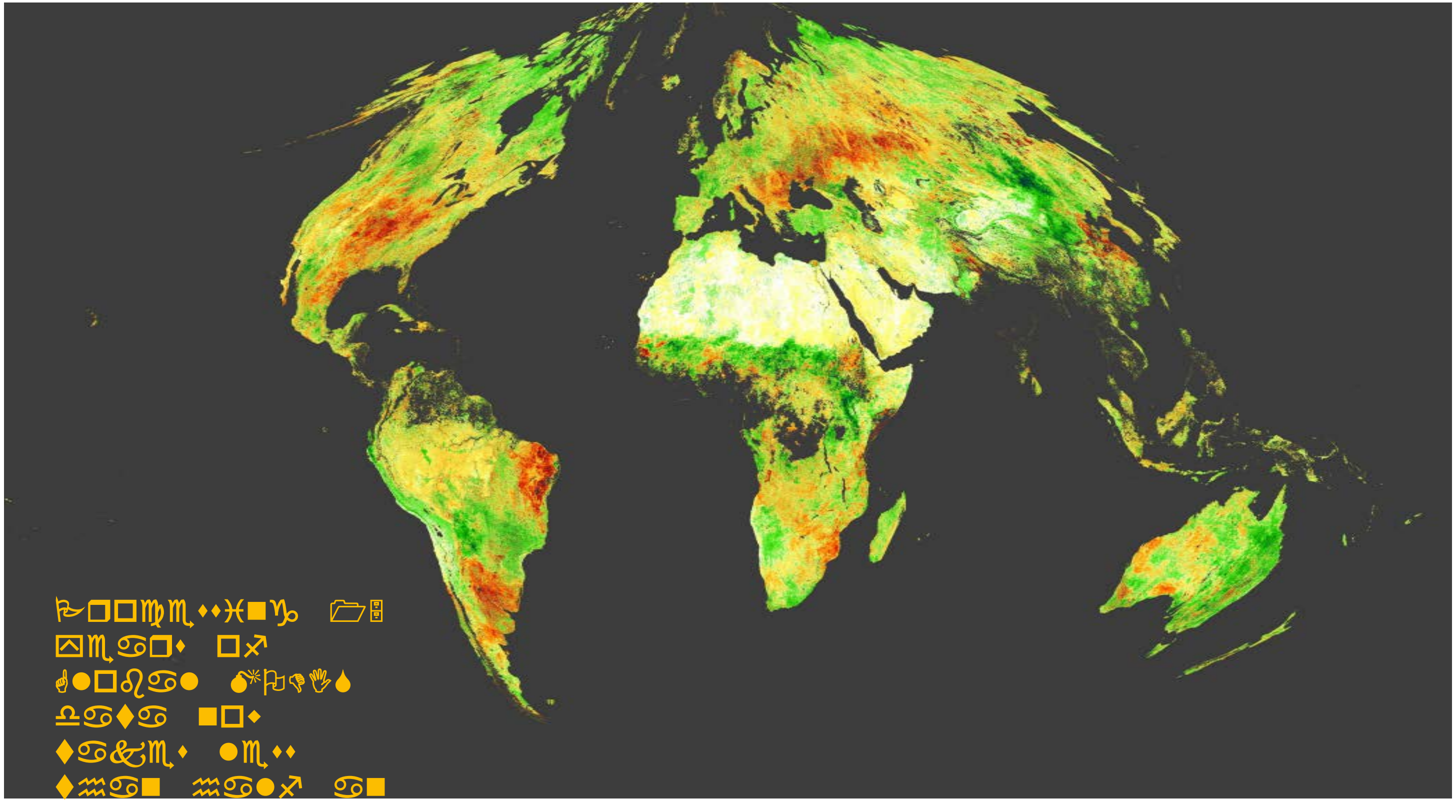
From a single scene to global



Mapping global landscapes every month at 30m

Anomaly Detection Workflow.

Global Drought Monitoring, 2012



Total # of Scenes:

- **1Million for 15 years**

Total Input Data

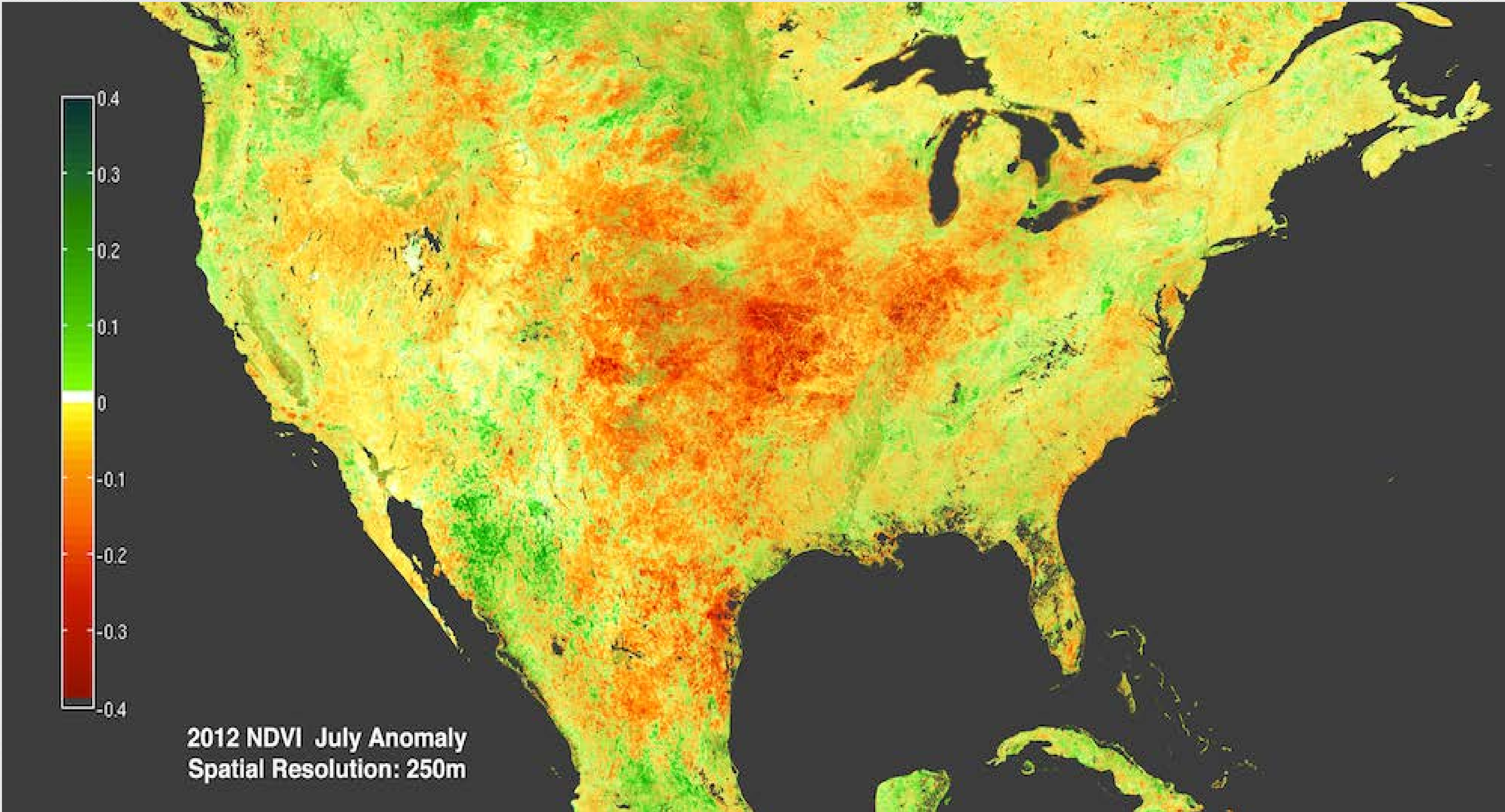
- **10 TB**

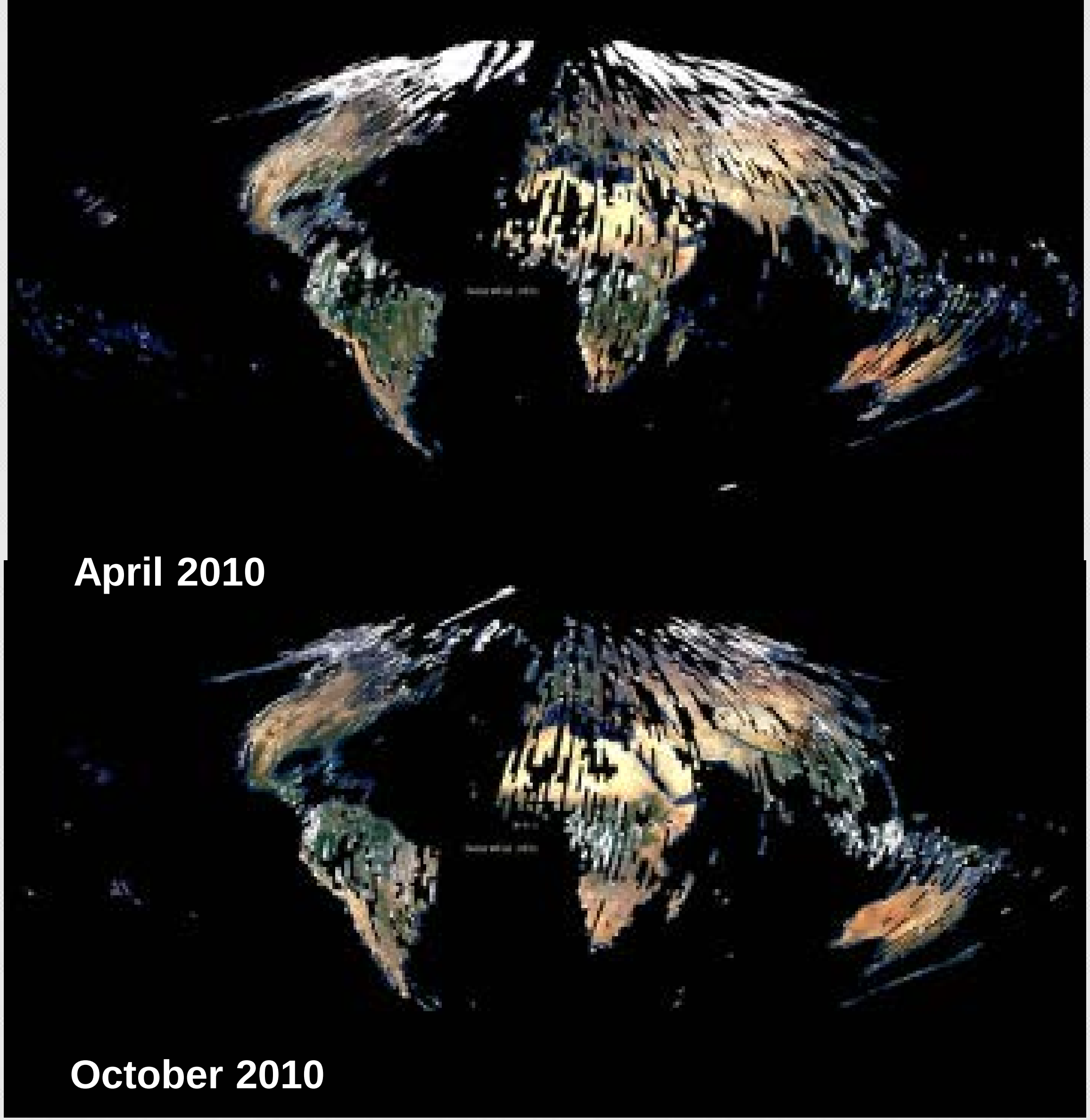
Total Output Data

- **50 TB**

Global Drought Monitoring.

2012





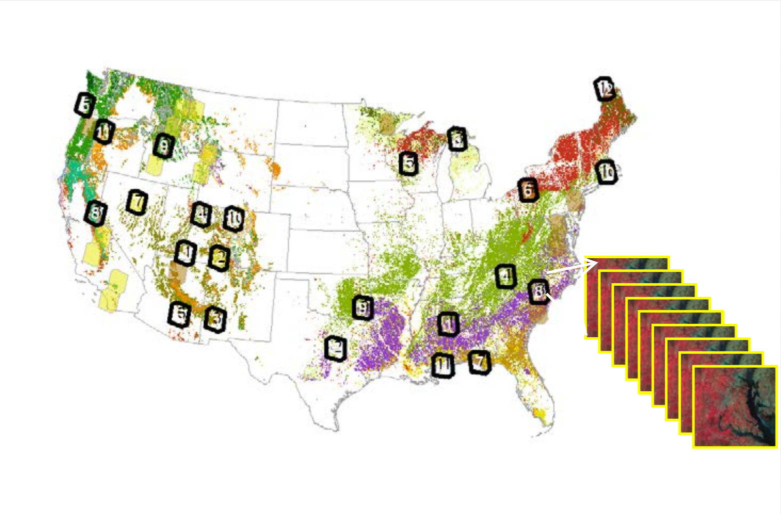
Web Enabled Landsat Data: Going Global, Roy et al.,

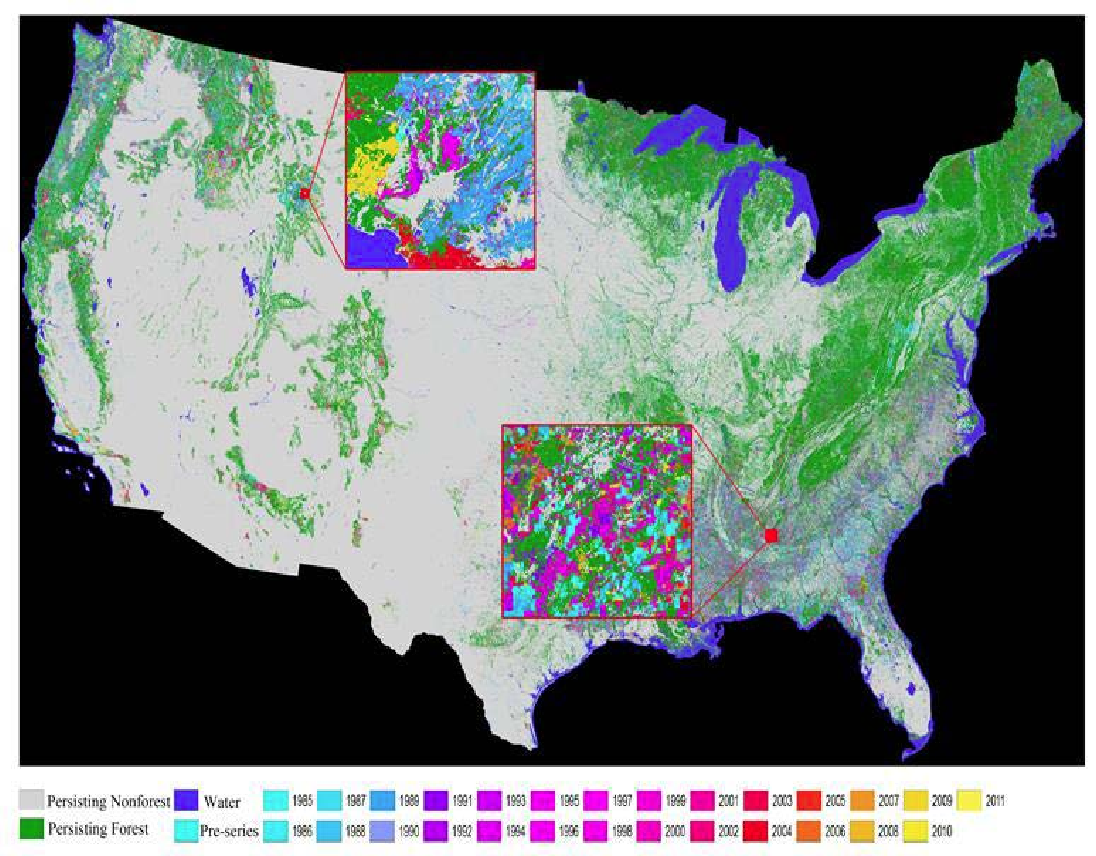
Creating Global Monthly Landsat Composites, 1999 - Present

Takes about 6,000 scenes each month using WELD system

Prototyping land products from Landsat: LAI/FPAR, Albedo

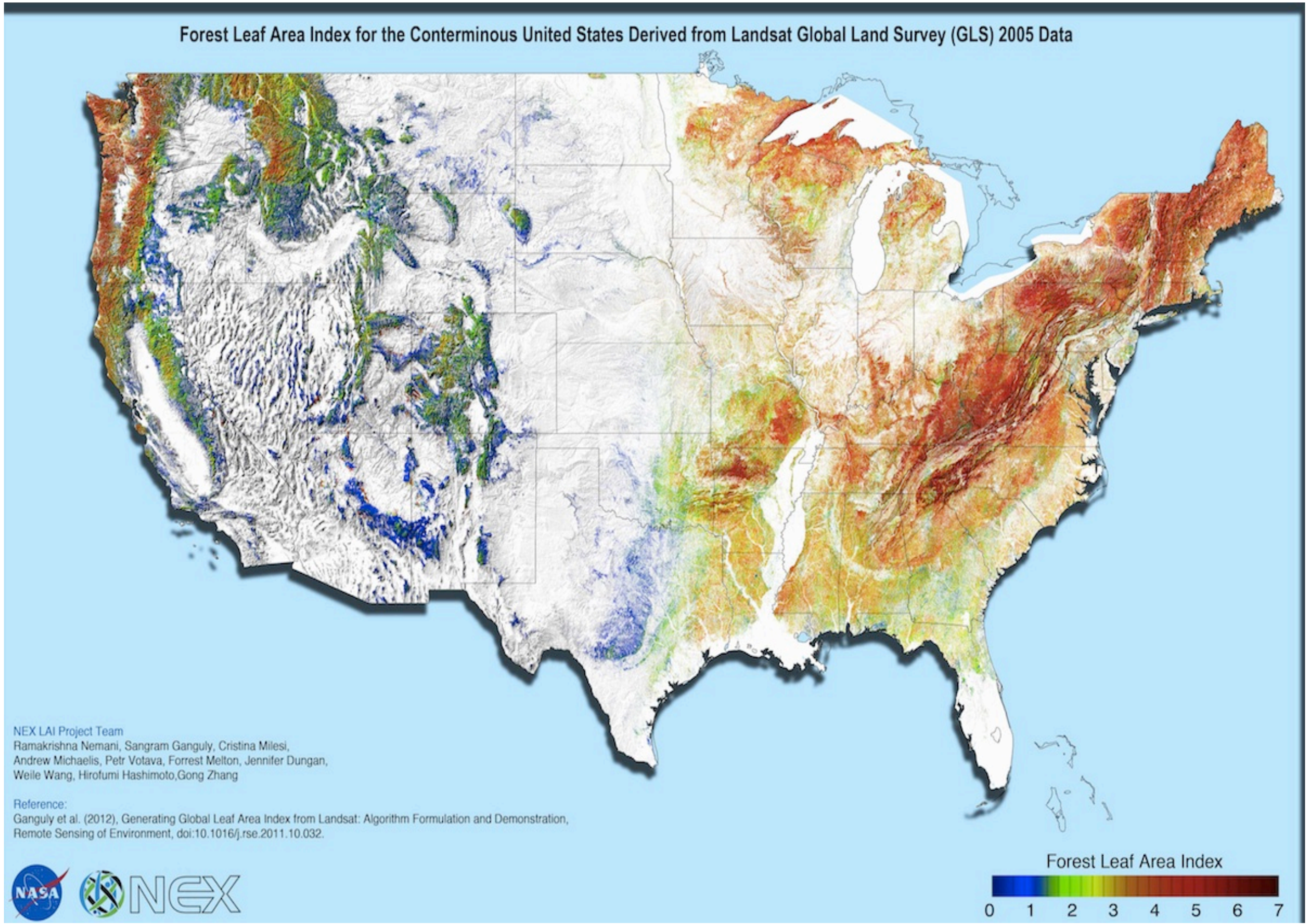
North American Forest Disturbance (NAFD, Goward et al.,)





Expanding from 23 samples to Wall-to-wall coverage Processing 96000 scenes from 1985-2010 on NEX

Historical Landsat Analysis.



Map of Leaf Area Index (LAI) generated using Landsat Thematic Mapper data and a modified MODIS LAI/FPAR algorithm

Landsat Thematic Mapper 1984-2012

Monthly composites of surface reflectances

Biophysical products such as LAI

Focus on:

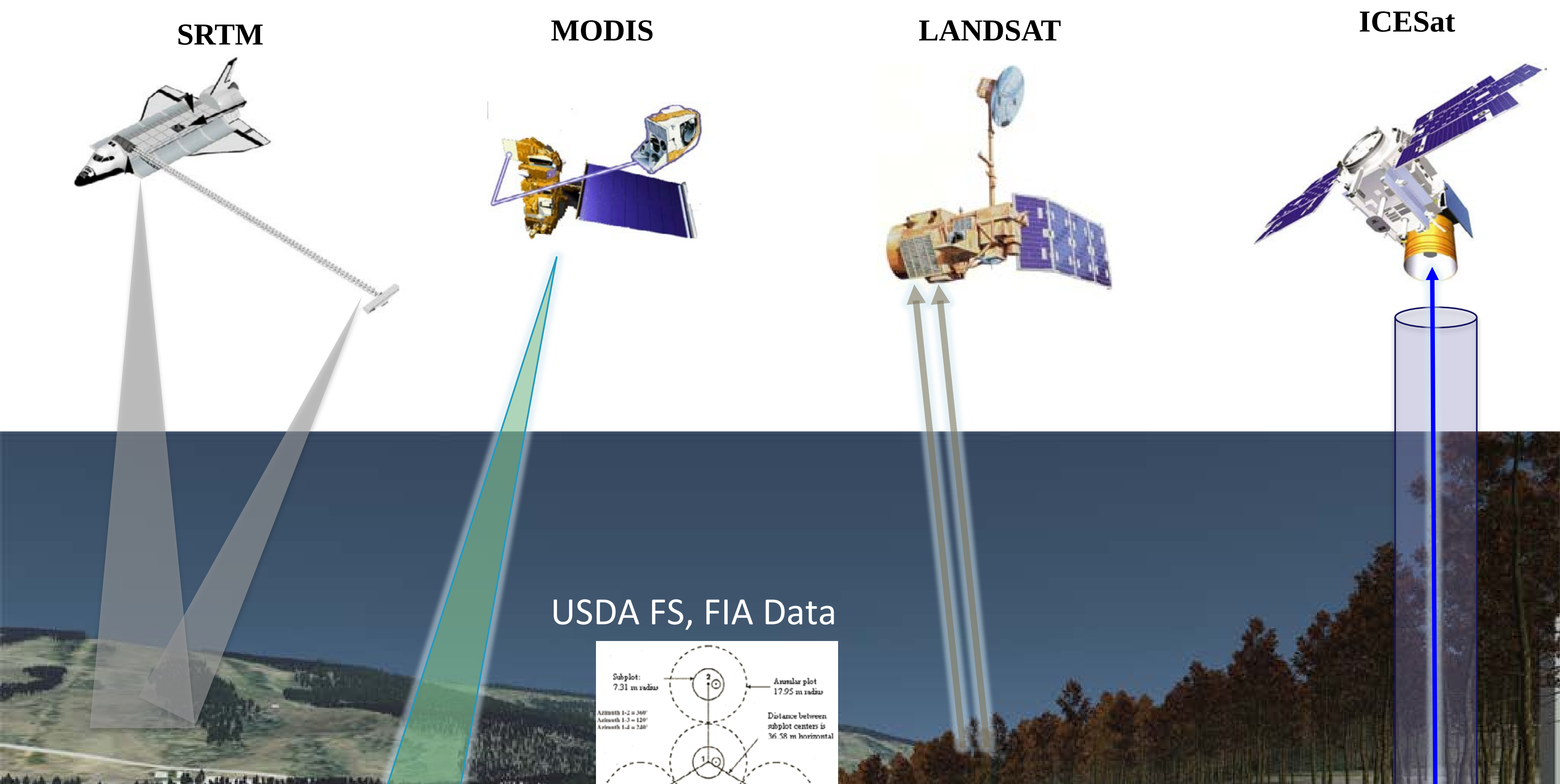
- Land cover changes
- Migration of ecosystems
- High altitude ecosystems
- Forest mortality

Carbon Monitoring System Phase I & II

Multi-sensor remote sensing-based estimation of Aboveground biomass

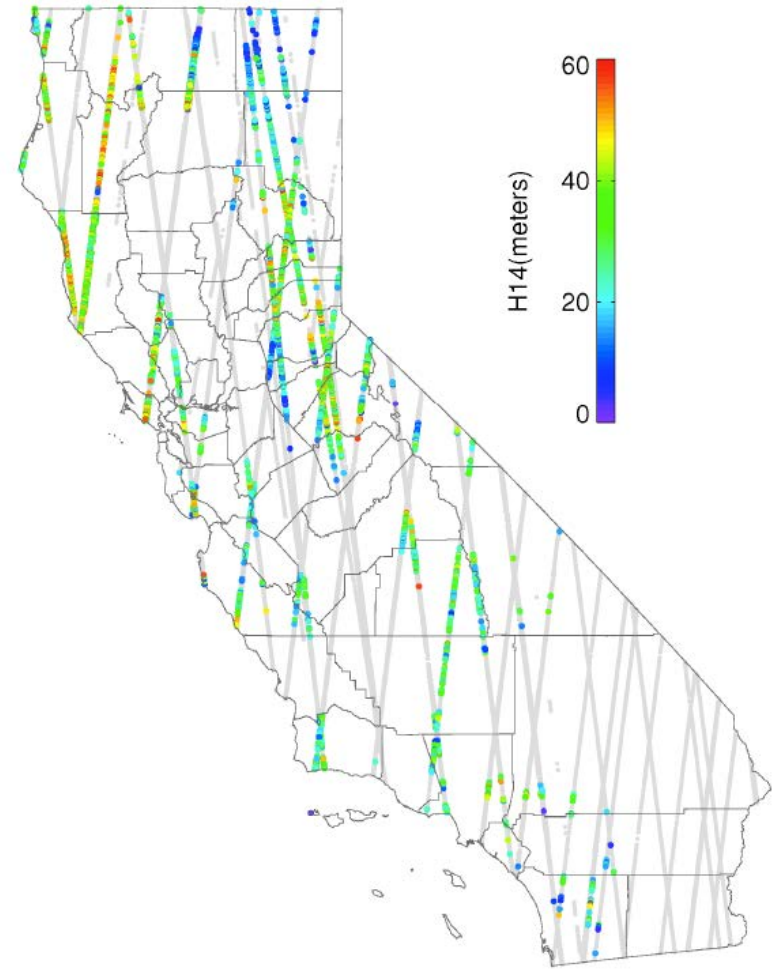
Sassan Saatchi, Sangram Ganguly, Compton Tucker, Ramakrishna Nemani, Stephen Hagen. Yifan Yu

NBCD AGB map | USFS AGB map | This study



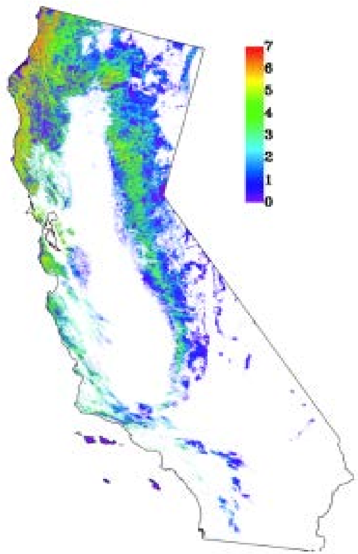
GLAS Processing

- Seasonal (May-Oct) GLA14 data selection
- Cloud free and saturation free shots selected
- (NED-ground peak) difference threshold filter
- Slope gradient filter (>0.1 = shots excluded)
- NLCD land cover map for forest delineation
- Landsat RED spectral band filter (>0.3=non forest)

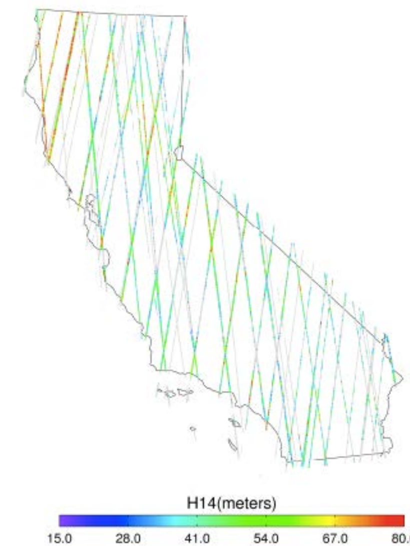


LANDSAT LAI and GLAS height

Landsat LAI



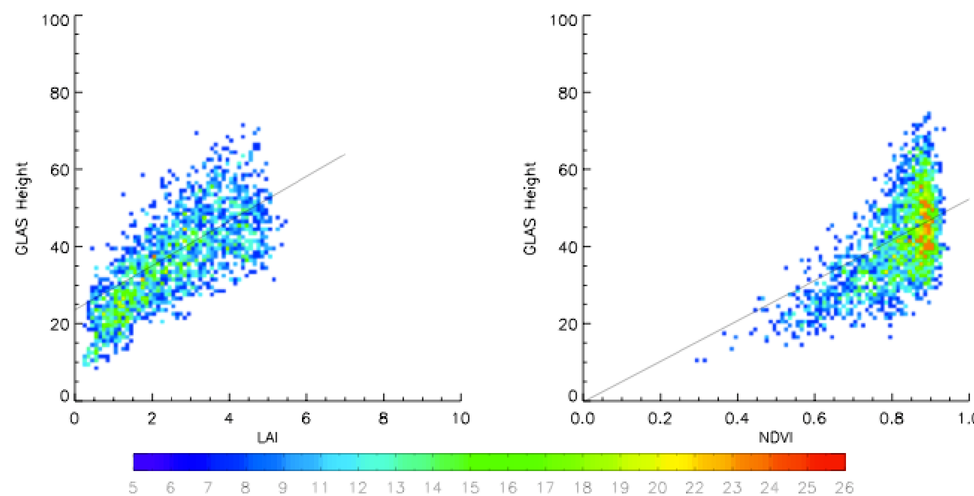
GLAS Height Metrics

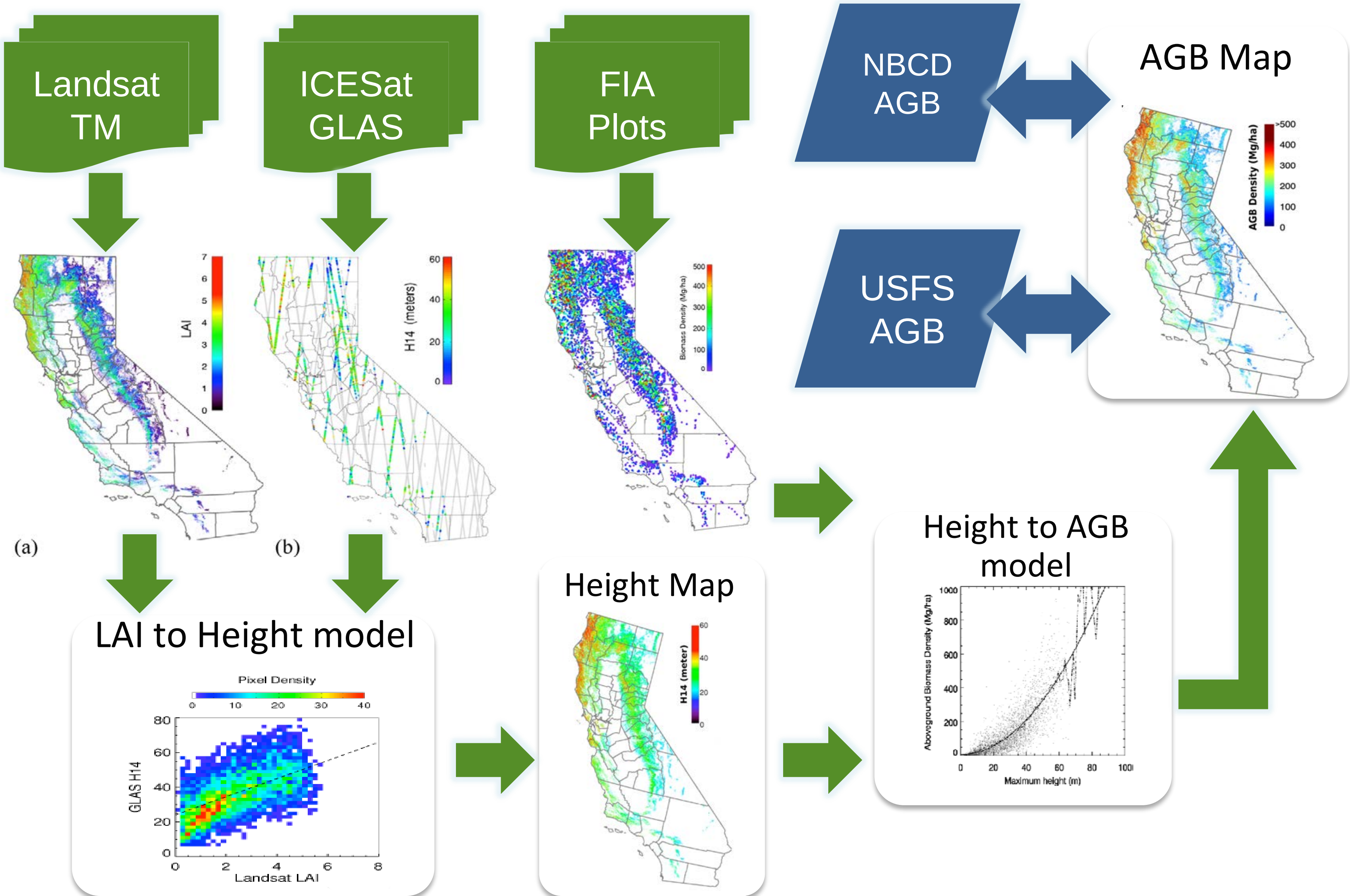


LAI-Height empirical modeling

1.Set up empirical rule between GLAS maximum canopy height (H14) and Landsat LAI nearest to the GLAS center locations.

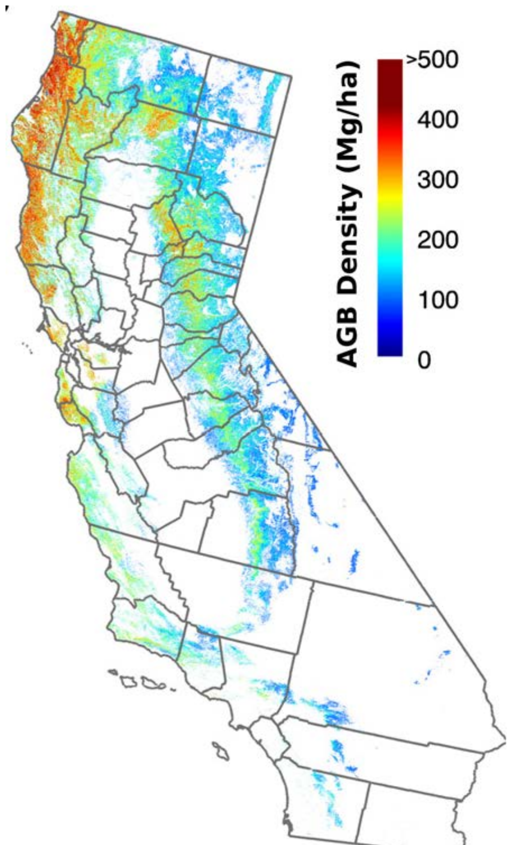
2. The total number of sample points is 8196. The fitted model is "H14 = 24.097+5.22*LAI" and the RMSE is 12.327



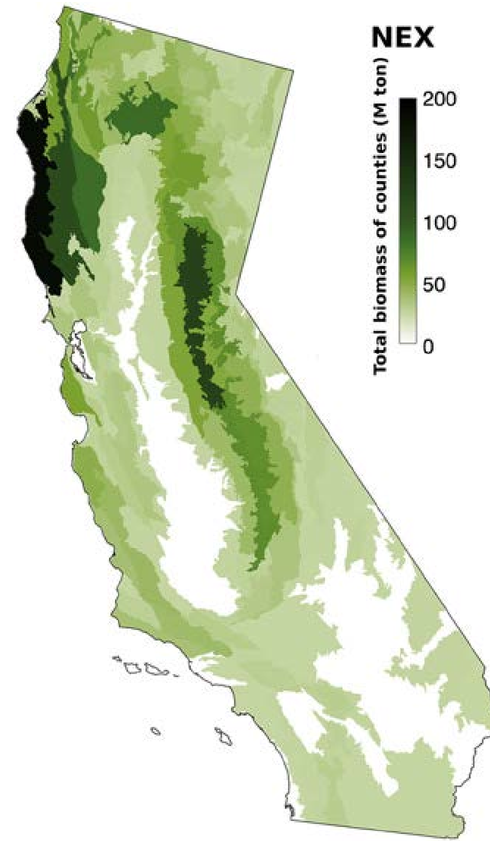


Landsat TM
ICESat GLAS
FIA Plots
NBCD AGB
USFS AGB
AGB Map
AGB Density (Mg/ha)
LAI
H14 (meters)
Biomass Density (Mg/ha)
(a)
(b)
LAI to Height model
Pixel Density
GLAS H14
Landsat LAI
Height Map
H14 (meter)
Height to AGB model
Aboveground Biomass Density (Mg/ha)
Maximum height (m)

California Forest Above-ground Biomass

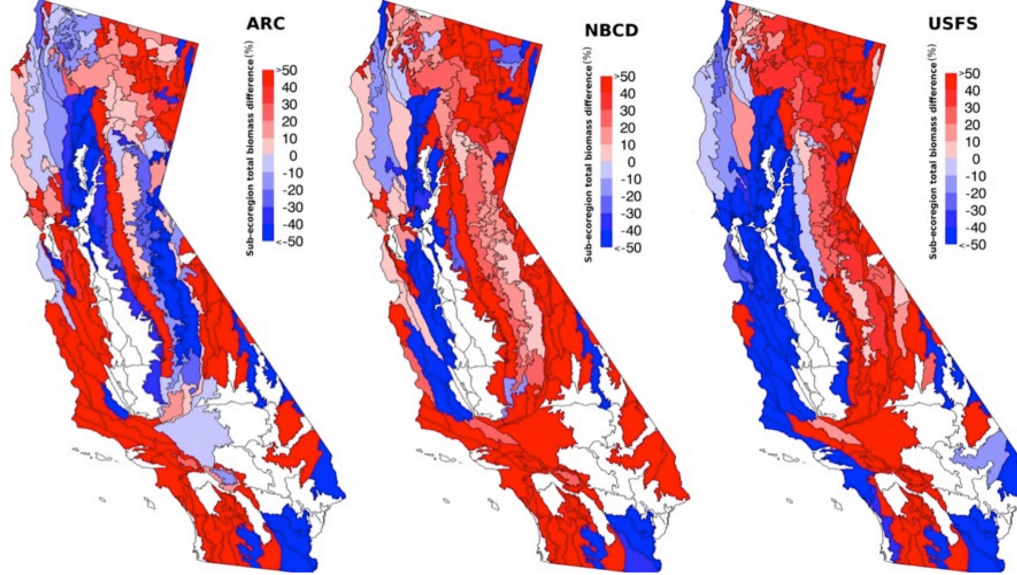


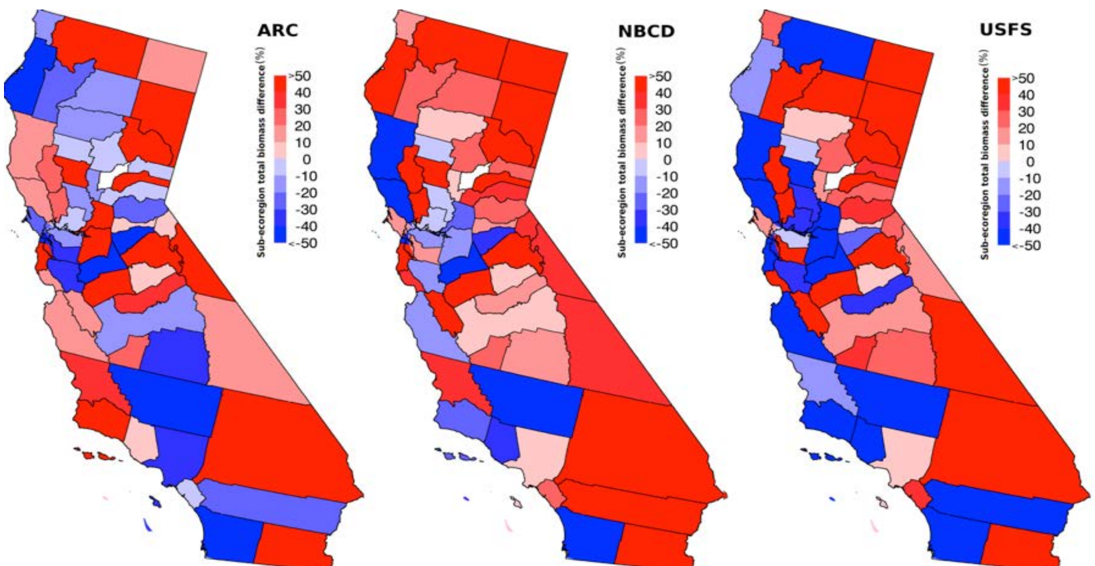
Forest AGB Density at 30-m



Total Forest AGB by sub-ecoregions

Relative Accuracy of Total Biomass by Sub-ecoregions

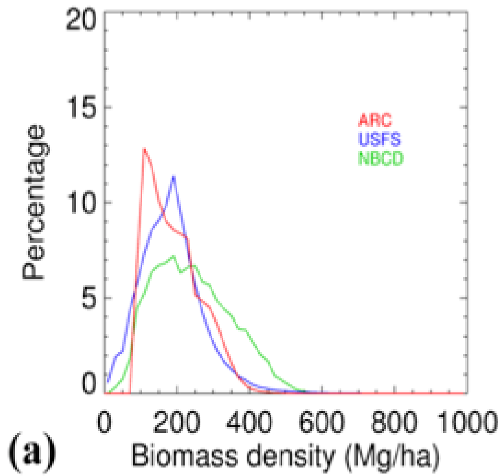




Relative Accuracy of Total Biomass by Counties

Regional AGB Validation with FIA

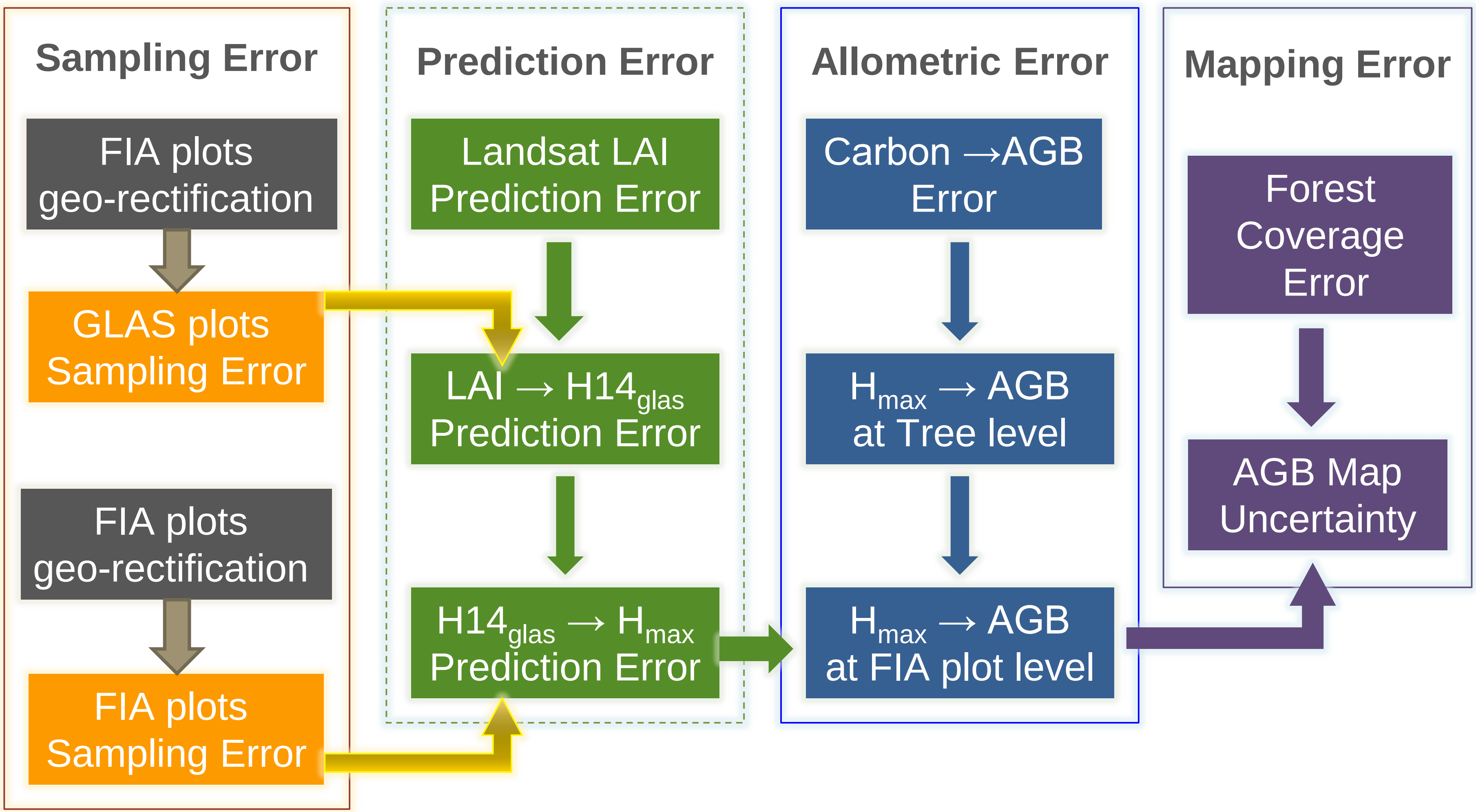
Comparison to the NBCD, USFS and FIA derived aggregated total AGB at sub-ecoregion and county levels.



Our map shows the least error from FIA estimated total biomass at county and sub-ecoregion levels.

Metrics (w.r.t. FIA)	**ARC**	**NBCD**	**USFS**
County RMSE (M ton)	8.63	11.60	14.17
Sub-ecoregion RMSE (M ton)	8.38	9.11	11.30

Uncertainty Analysis I



Uncertainty Analysis II

- We implemented a Monte Carlo error propagation model to calculate the total prediction components by assuming all errors are independent and random
  - The uncertainty in LAI to Height estimation

$$\boldsymbol{H}\hat{1}4 = \left(24.10 + 5.22 * \left(\hat{\boldsymbol{LAI}} + \varepsilon_{predict_i}\right)\right) + \varepsilon_{predict_{ii}}$$

  - The uncertainty in maximum canopy height estimation

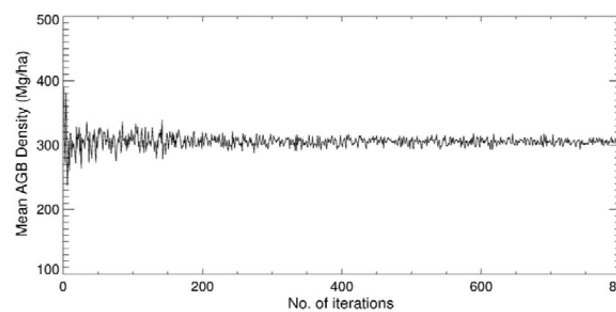
$$\hat{\boldsymbol{H}}_{\max} = \boldsymbol{H}\hat{1}4 + \varepsilon_{predict_{iii}} + \varepsilon_{samlping_{ii}}$$

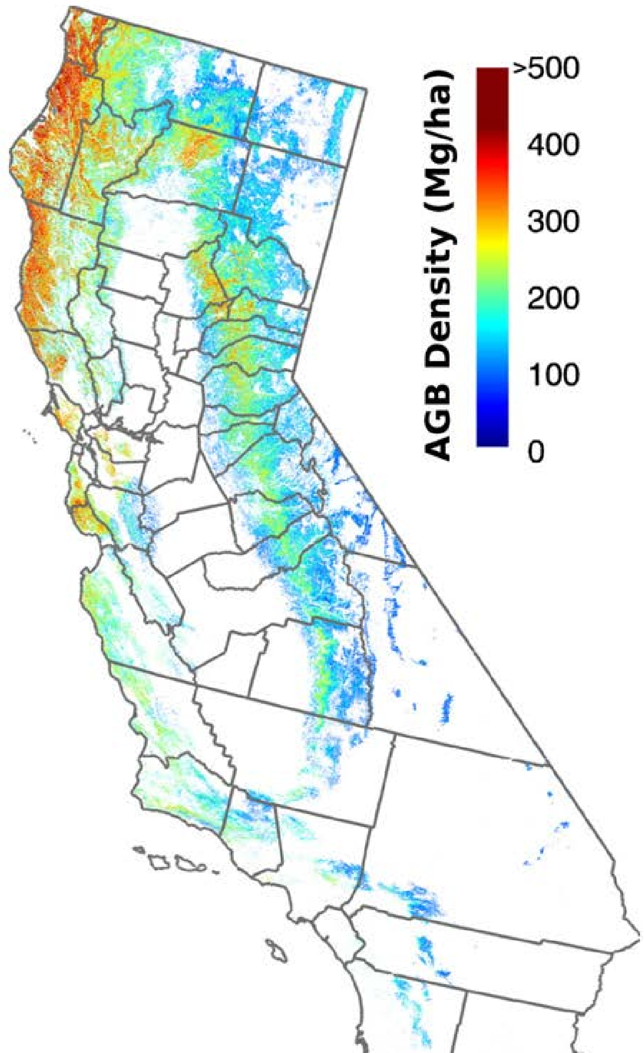
  - The uncertainty of allometric functions, sampling and forest cover

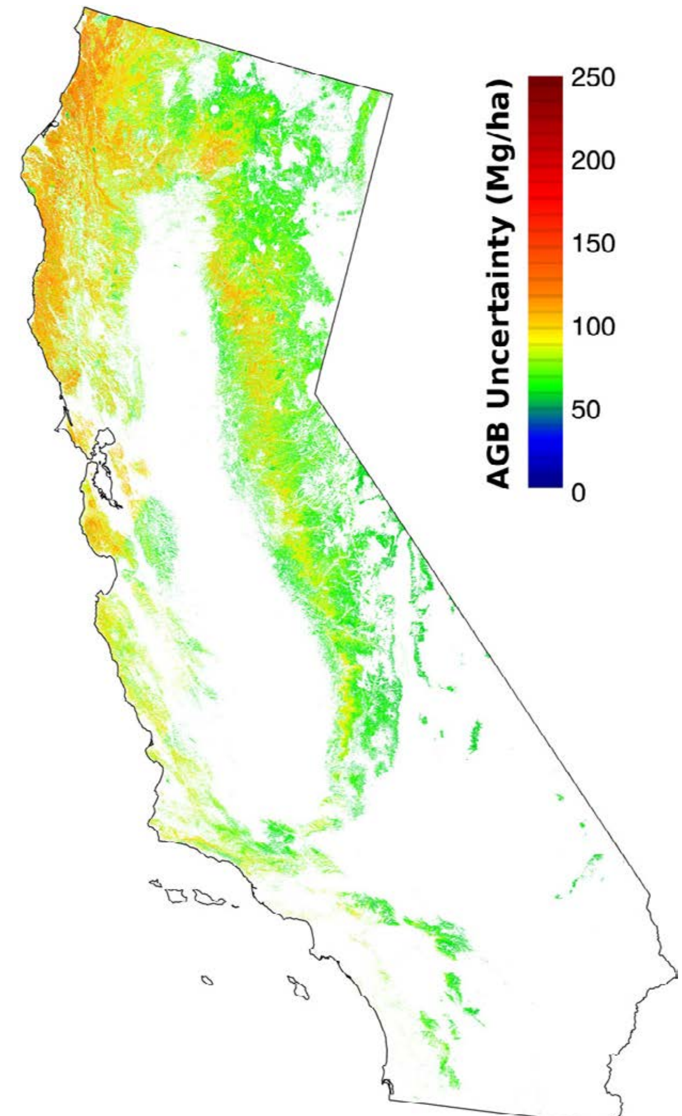
$$\boldsymbol{A\hat{G}B} = 2.39 + 0.14 \times \hat{\boldsymbol{H}}_{\max}^2 + \varepsilon_{allmetric_i} + \varepsilon_{allmetric_{ii}} + \varepsilon_{sampling_i} + \varepsilon_{coverage}$$

- The total uncertainty in RMSE
  - Iteration number = 200

$$\sigma_{\boldsymbol{A\hat{G}B}} = \sqrt{\frac{\sum_{i=1}^{n}\left(\boldsymbol{AGB_i} - \boldsymbol{A\hat{G}B}\right)^2}{\boldsymbol{n}}}$$



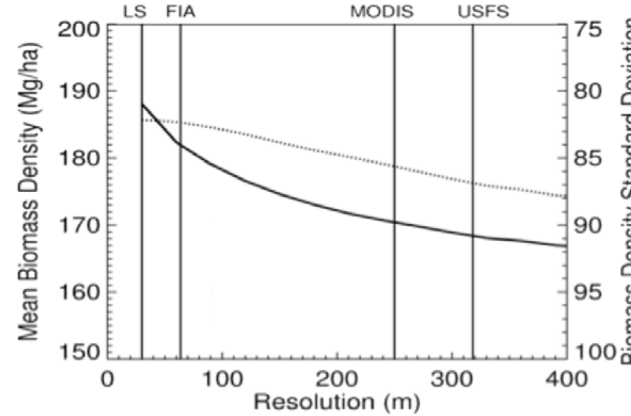

AGB Density (Mg/ha)
>500
400
300
200
100
0


AGB Uncertainty (Mg/ha)
250
200
150
100
50
0

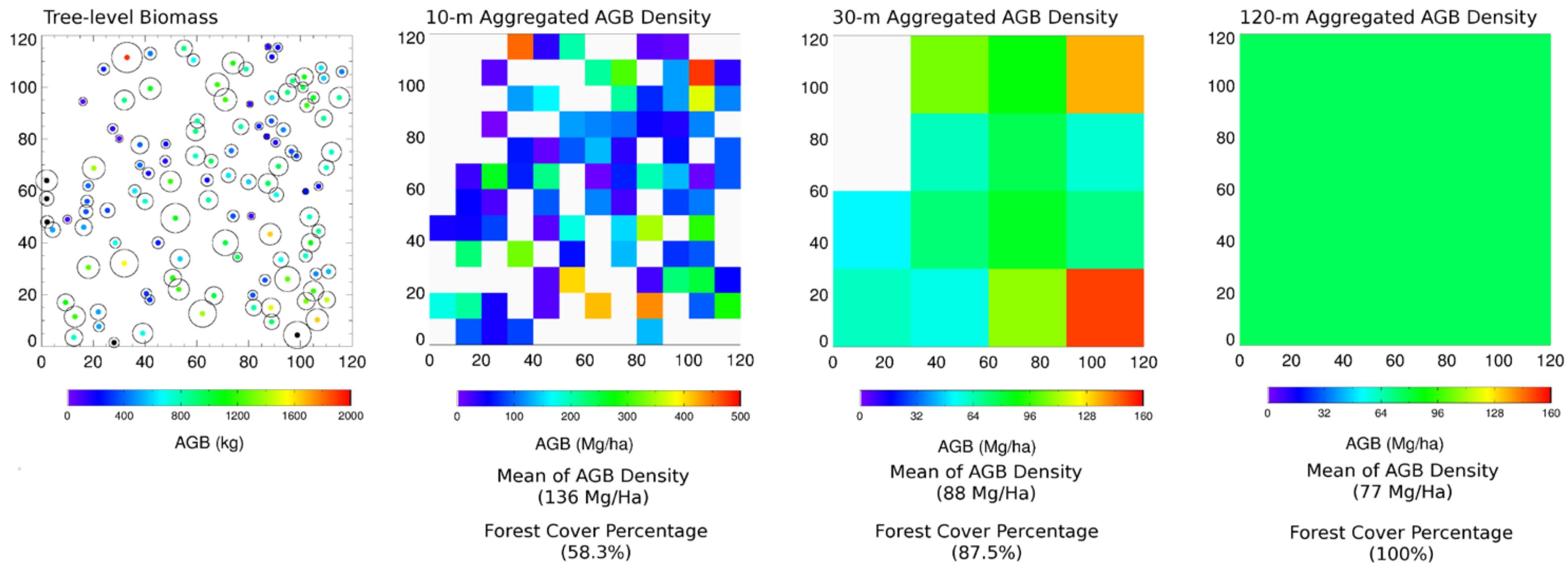
AGB density variation with scale

Scale Issues: **AGB density decrease along resolution**

•*Variation of mean biomass density and standard deviation with changes in spatial resolution. The region of interest spans a wide region of hardwood forests in California covering an area of ~5500 square miles. Both mean biomass density and standard deviation decrease along resolution*



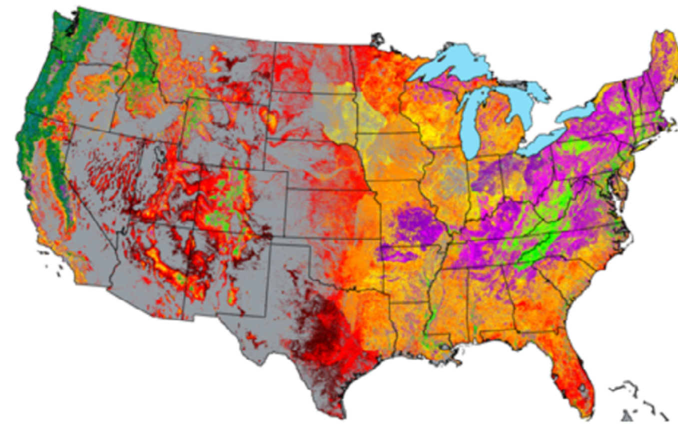
A test sample based on ground data

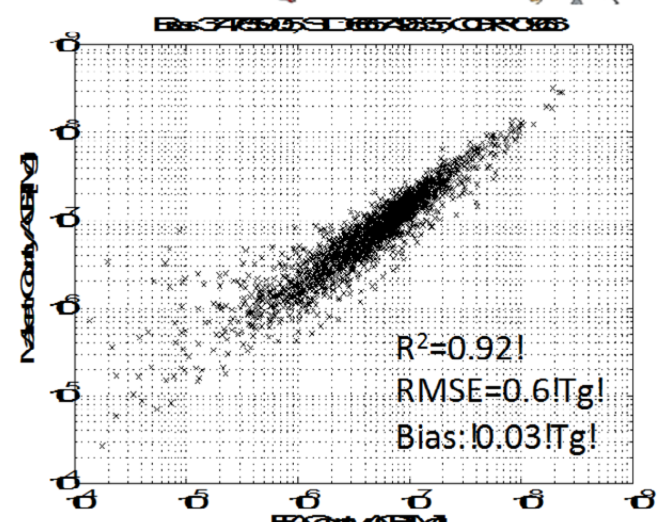


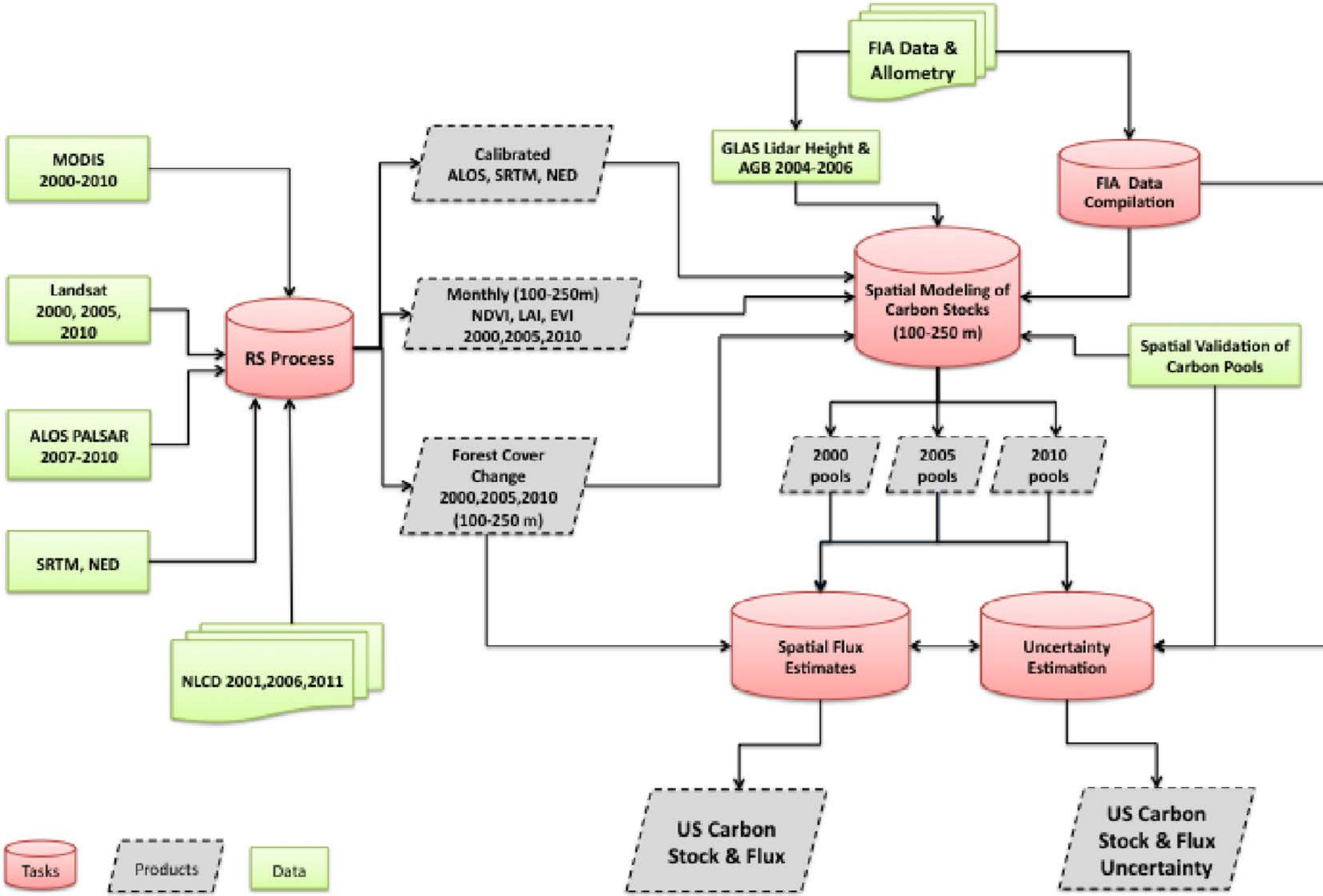
Prototyping MRV Systems Using Systematic and Spatially Explicit Estimates of Carbon Stock and Stock Changes of US Forestlands

JPL/CALTECH!
Sassan!Saatchi,!!
Alexander!Fore,!!
Ziad!Haddad!
*!
UCLA/IOES!
Yifan!Yu!
*!
NASA/AMES*!
Ramakrishna!Nemani!
Sangram!Ganguly!
Gong!Zhang!
!!
UMD*
Ralph!Dubayah!

USDA*Forest*Service**
Christopher!Woodall!
Richard!Birdsey!
Kristofer!Johnson!
Andrew!Finely!
!!
Winrock*Interna?onal,*Inc.
Nancy!Harris!
Sandra!Brown!
!
Applied*GeoSolu?ons,*LLC
William!Salas!
Stephen!Hagen!
Bobby!Braswell!
!!






FIA Data & Allometry
MODIS 2000-2010
Calibrated ALOS, SRTM, NED
GLAS Lidar Height & AGB 2004-2006
FIA Data Compilation
Landsat 2000, 2005, 2010
RS Process
Monthly (100-250m) NDVI, LAI, EVI 2000,2005,2010
Spatial Modeling of Carbon Stocks (100-250 m)
Spatial Validation of Carbon Pools
ALOS PALSAR 2007-2010
Forest Cover Change 2000,2005,2010 (100-250 m)
2000 pools
2005 pools
2010 pools
SRTM, NED
Spatial Flux Estimates
Uncertainty Estimation
NLCD 2001,2006,2011
US Carbon Stock & Flux
US Carbon Stock & Flux Uncertainty
Tasks
Products
Data

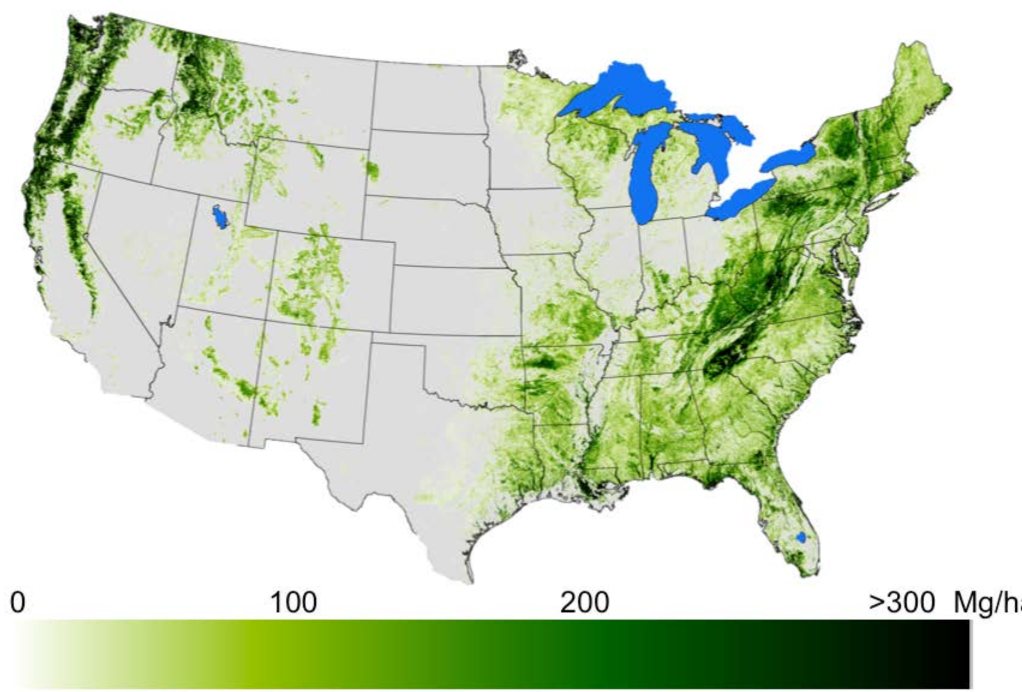
- Forestlands in the US are measured and monitored
  - Forest Inventory Analysis
  - Fire monitoring
  - Insect monitoring
  - Wind damage
  - Conversion to settlement
  - Harvest
  - Spatially explicit carbon stocks
- Create estimates of ***attribute*** carbon fluxes in US forestlands between 2005 and 2010 at ***1 ha resolution*** with ***estimates of uncertainty***.

- Spatially explicit carbon stock estimates at the 1 ha resolution
  - Above ground
  - Below ground
  - Soil
  - Dead (standing, coarse debris, fine debris, litter)
- Spatially explicit maps of disturbance (activity)
  - Annual land cover change maps across US forestland combined with
  - Maps of fire, wind, insect, forest conversion, and harvest
- Summary tables of ***carbon stock changes*** derived from FIA measurements
  - 140,000 FIA plots were measured at two time periods.
  - Allowed us to calculate ***Δcarbon*** in above/below ground carbon pools under different conditions

Carbon Stock Maps

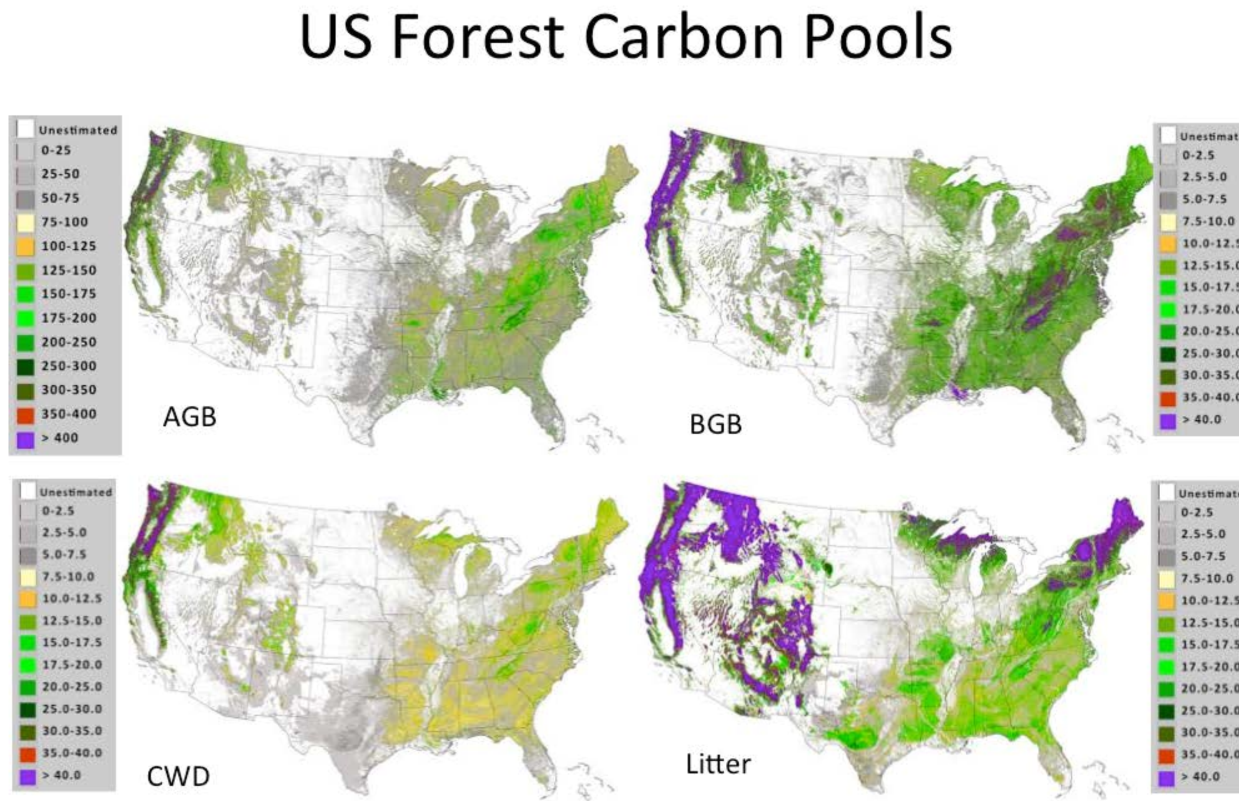
Above ground biomass

CMS Biomass Map Product



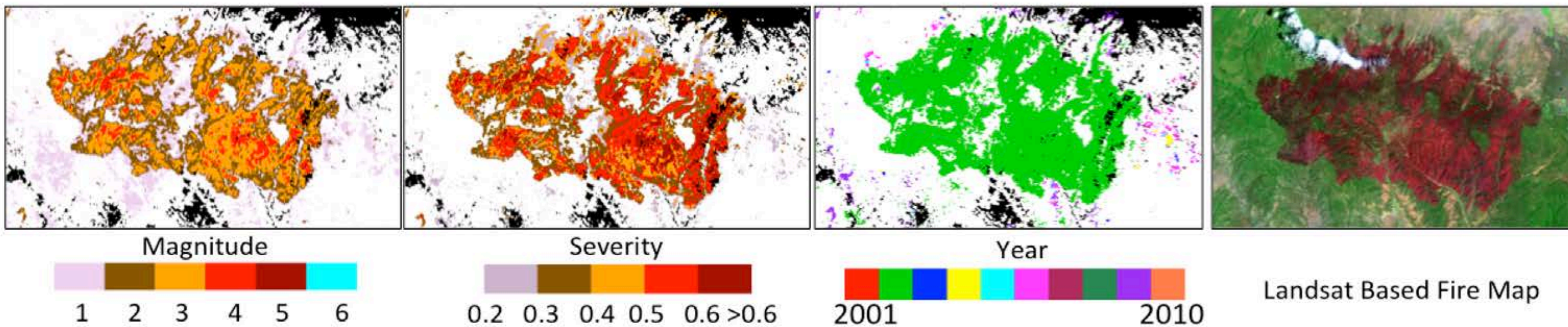
Carbon Stock Maps

- Other pools

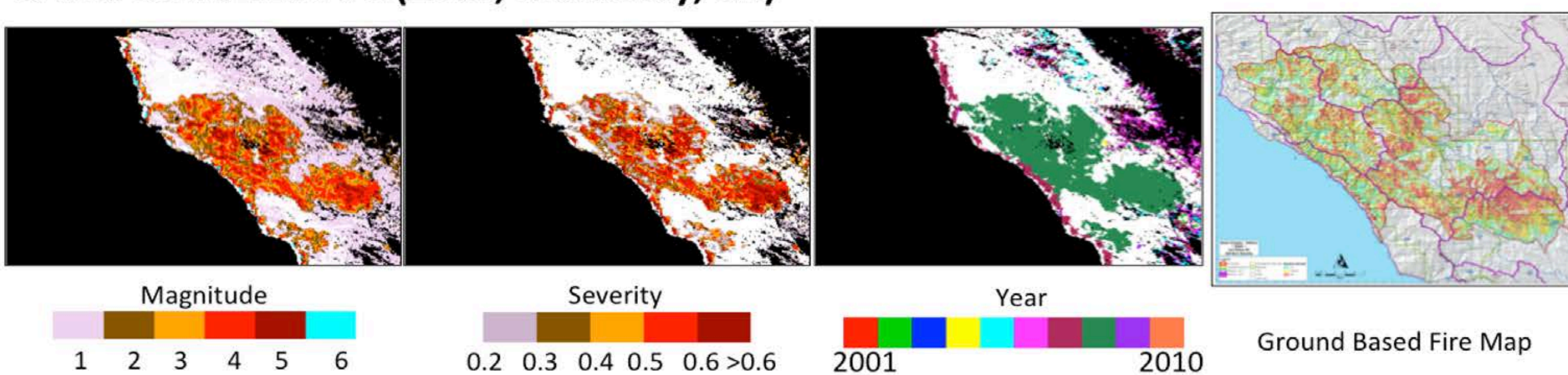


Validation of MODIS disturbance metrics with Landsat and Ground fire maps

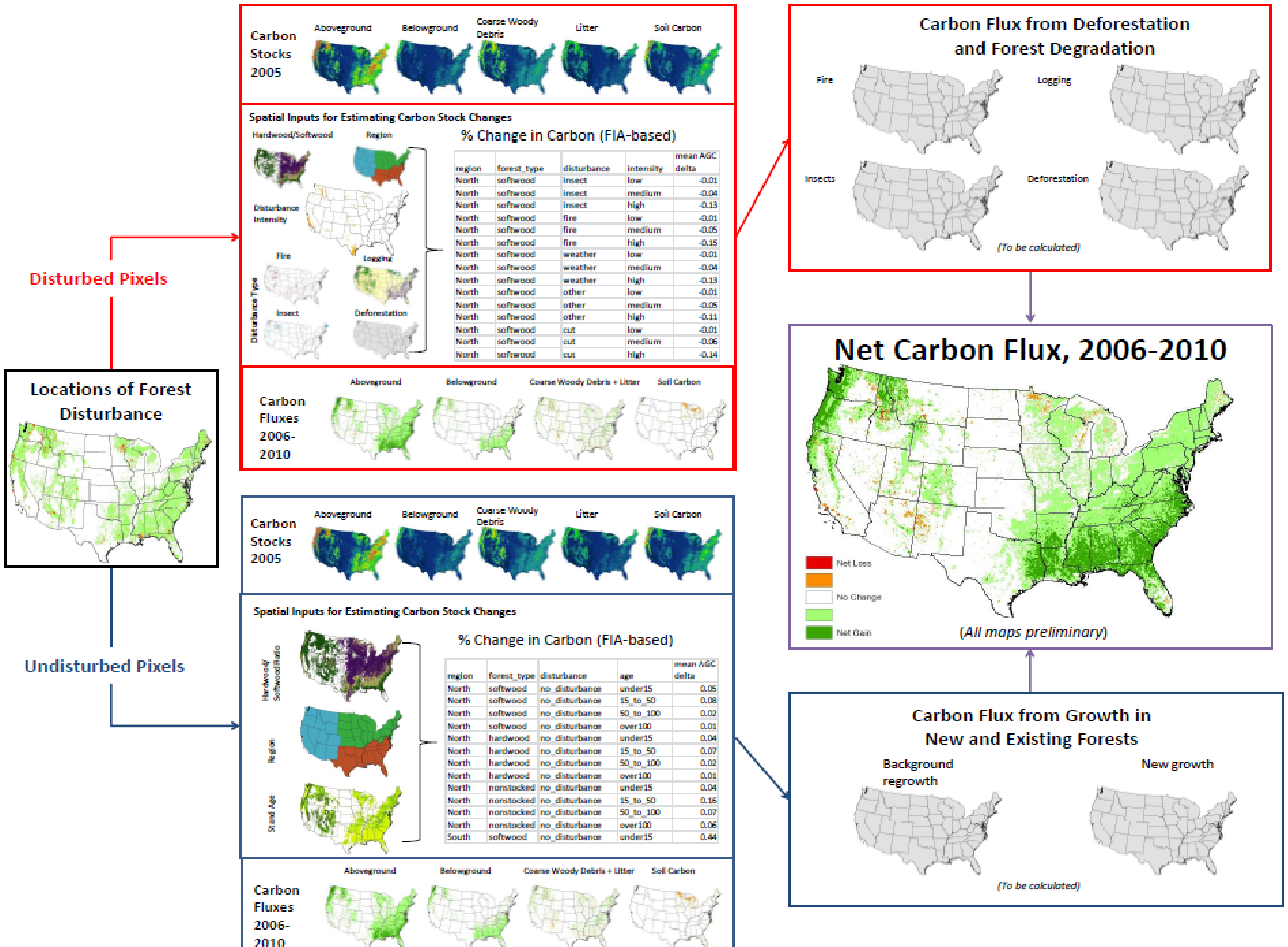
Rodeo–Chediski Fire (2002, AZ)



BASIN COMPLEX Fire (2008, Monterey, CA)



Carbon Flux Map Framework



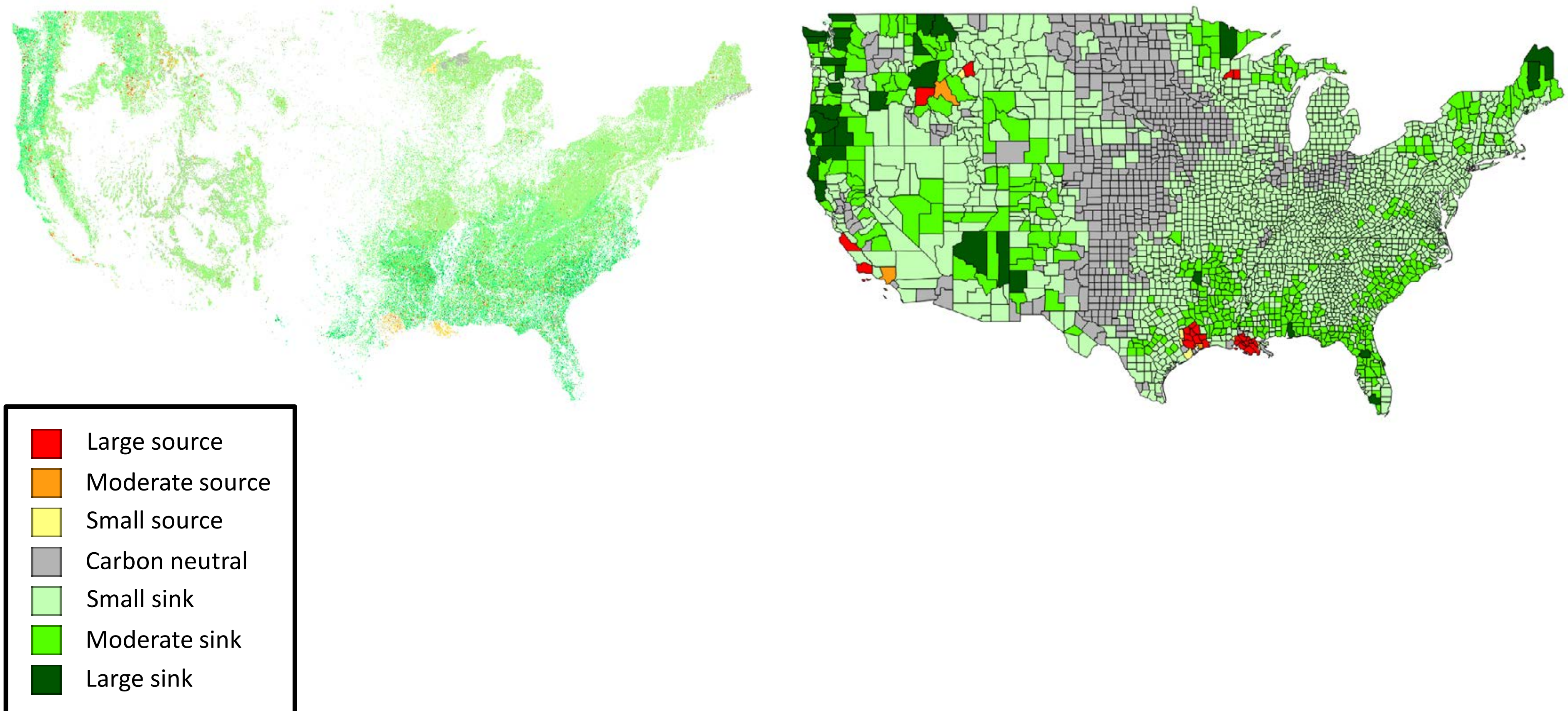
% Change in Carbon (FIA-based)

region	forest_type	disturbance	intensity	mean AGC delta
North	softwood	insect	low	-0.01
North	softwood	insect	medium	-0.04
North	softwood	insect	high	-0.13
North	softwood	fire	low	-0.01
North	softwood	fire	medium	-0.05
North	softwood	fire	high	-0.15
North	softwood	weather	low	-0.01
North	softwood	weather	medium	-0.04
North	softwood	weather	high	-0.13
North	softwood	other	low	-0.01
North	softwood	other	medium	-0.05
North	softwood	other	high	-0.11
North	softwood	cut	low	-0.01
North	softwood	cut	medium	-0.06
North	softwood	cut	high	-0.14

% Change in Carbon (FIA-based)

region	forest_type	disturbance	age	mean AGC delta
North	softwood	no_disturbance	under15	0.05
North	softwood	no_disturbance	15_to_50	0.08
North	softwood	no_disturbance	50_to_100	0.02
North	softwood	no_disturbance	over100	0.01
North	hardwood	no_disturbance	under15	0.04
North	hardwood	no_disturbance	15_to_50	0.07
North	hardwood	no_disturbance	50_to_100	0.02
North	hardwood	no_disturbance	over100	0.01
North	nonstocked	no_disturbance	under15	0.04
North	nonstocked	no_disturbance	15_to_50	0.16
North	nonstocked	no_disturbance	50_to_100	0.07
North	nonstocked	no_disturbance	over100	0.06
South	softwood	no_disturbance	under15	0.44

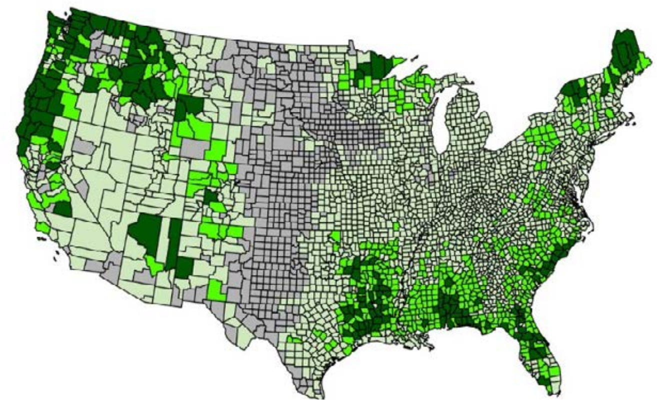
Multiple Scales

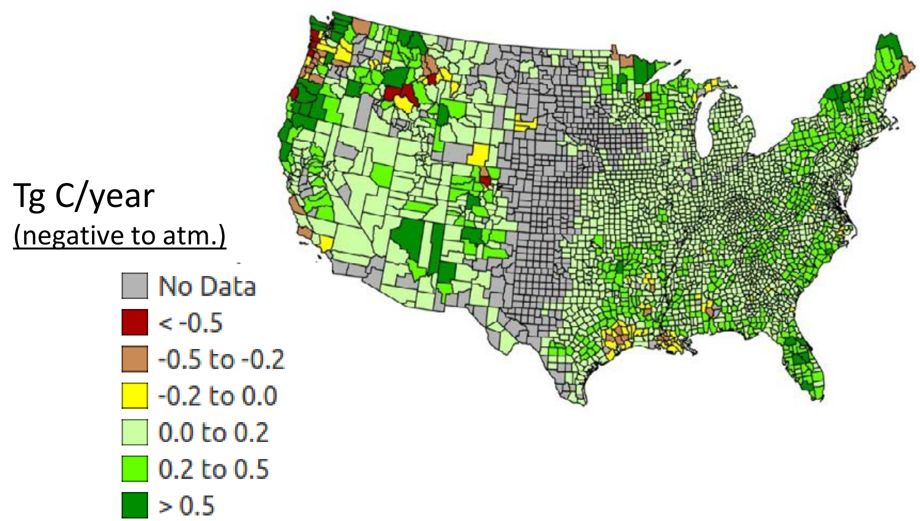


2005-2010 Carbon Flux in US Forests

- **PRELIMINARY RESULTS:**
- **Gross sequestration**: 487 Tg C/year [435-542]
- **Gross committed emissions**: 231 Tg C/year [226-250]
- **Net flux (committed)**: 256 Tg C/year (sink) [199-313]
- **Emission attribution** (% of gross emissions):
  - Harvest: 69%
  - Converted: 6%
  - Fire: 10%
  - Wind: 8%
  - Insect: 7%
  - Drought: < 1%

Gross Sequestration





Very High Resolution Satellite Image Classification

- NASA Carbon Monitoring System (CMS) NAIP Data Application
- NASA Advanced Information Systems Technology (AIST) Program Application

NAIP – Deriving Tree-cover from 1-m Imagery for CONUS.

330,000 Scenes

Need for Big Computation

60 Terabytes of Images

Big Data

7000x7000 Images

Images fed in parallel to cores in HPC

Current End-to-end Processing Time (California with 11,000 scenes) -> 48 hours

Problem and Motivation

Quality of data affected by data acquisition, pre-processing and filtering.

Significant inter-class overlaps and often hard to distinguish between classes.

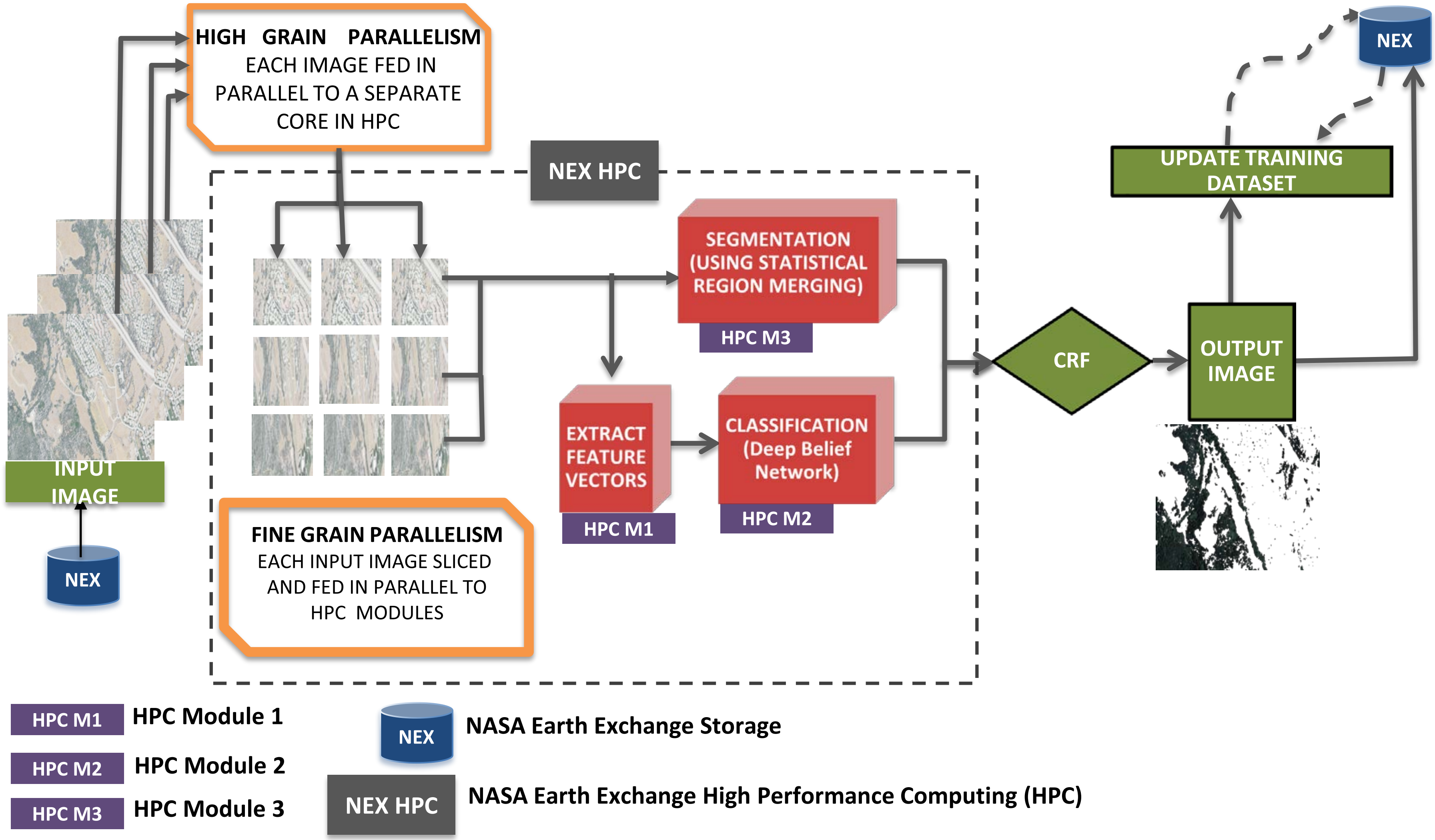
Tree cover delineation is a *hard* problem

Need to harness strong discriminative features and efficient learning algorithm.

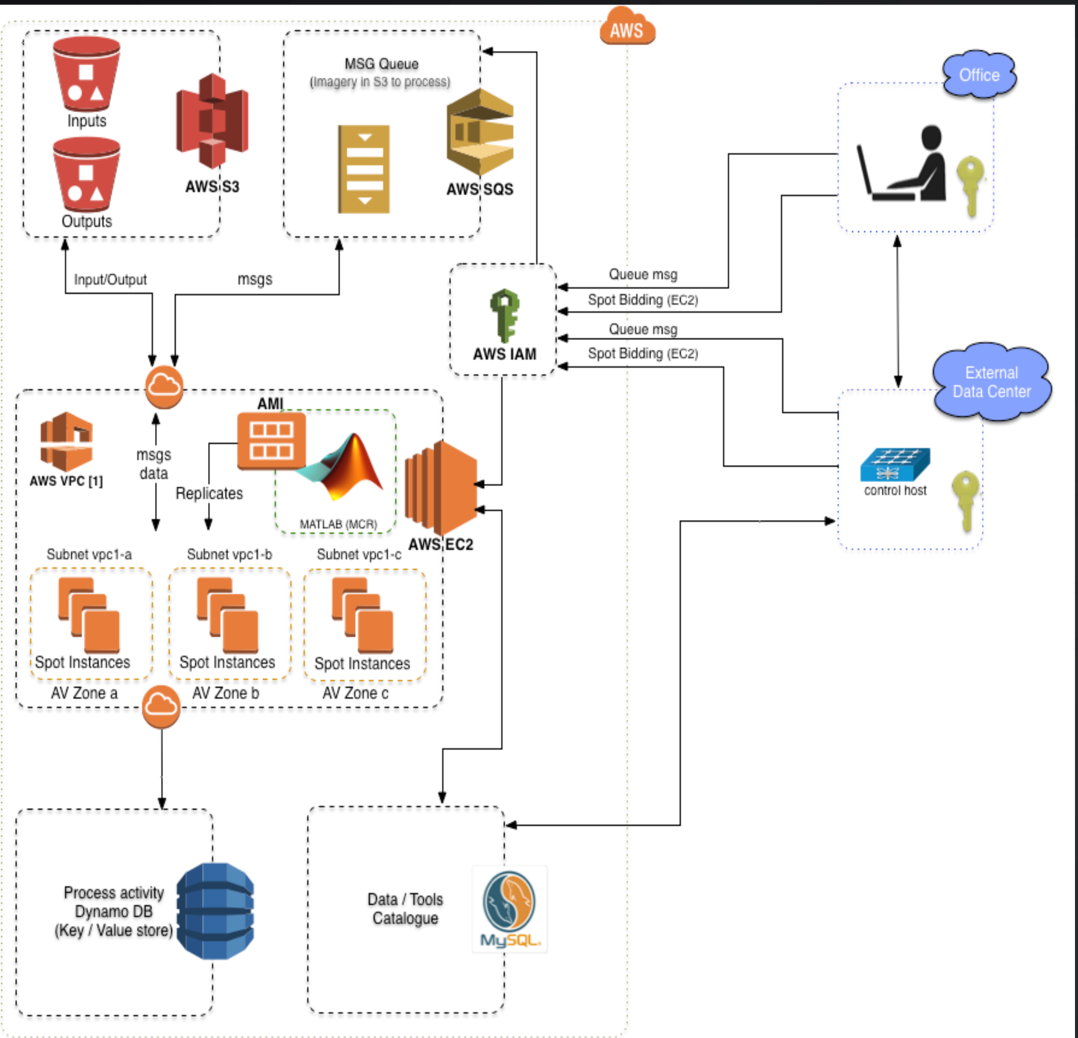
Accuracy of present algorithms is low and there is a pressing need to create high resolution land cover maps.

We create a learning framework by combining *unsupervised segmentation* and *deep learning based classification* which produces state-of-the-art results.

NAIP Processing Architecture

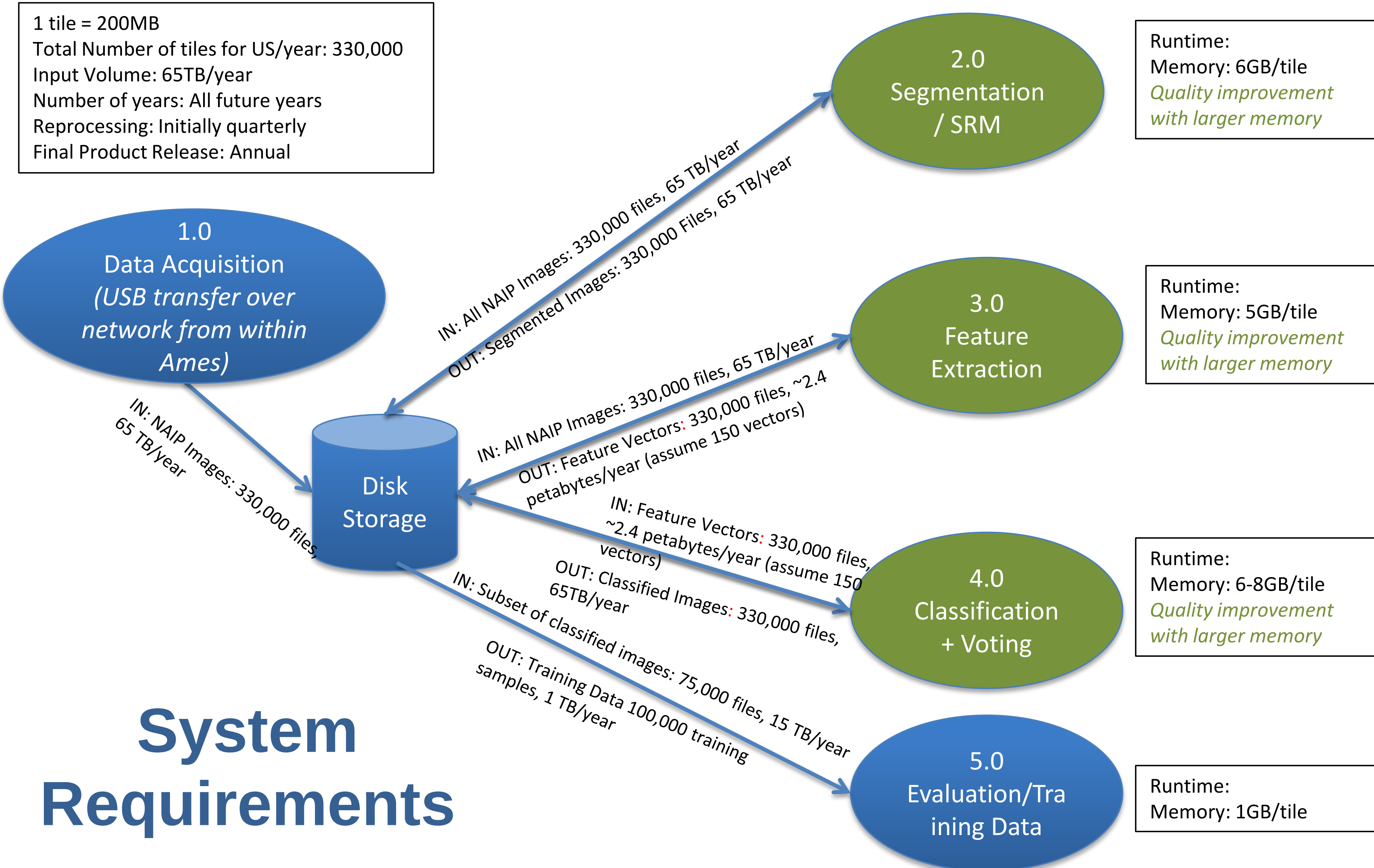


National Agriculture Imagery Program (NAIP) Example



- Configure a base set of AWS services to build the processing pipeline
- Process ~15,000 Scenes
  - ~5000 x 5000 pixels / scene
- Leveraged Spot Instances
  - 70% savings
  - Managed services
    - Spinup, process, tear down in 1 week.
- More that just computing…

System Requirements



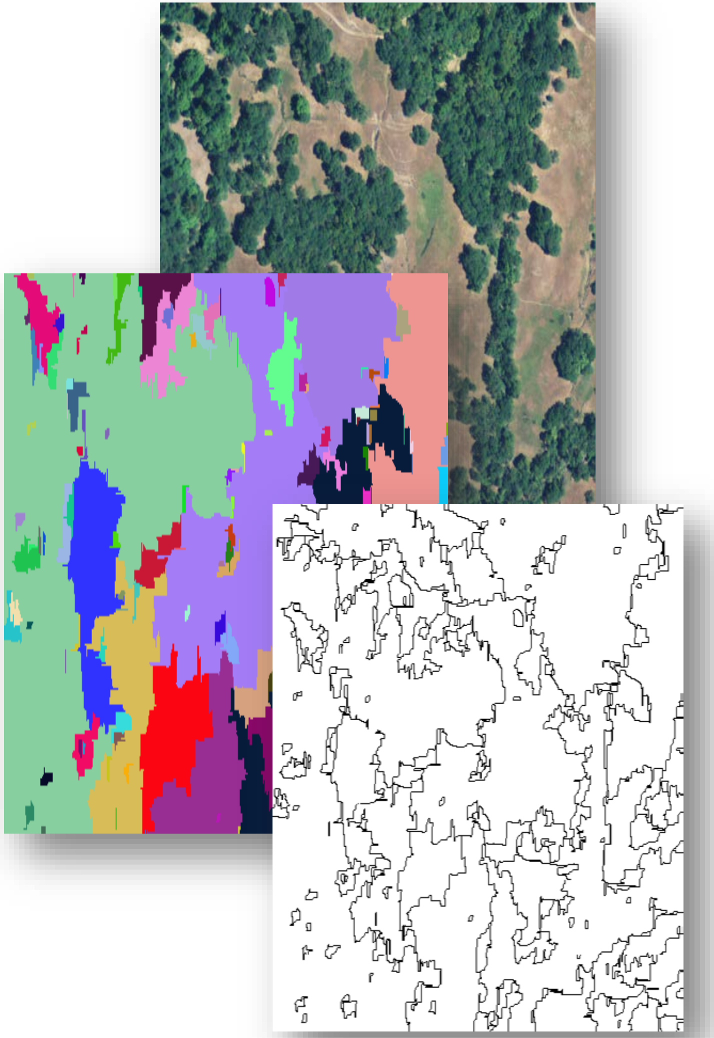
Segmentation

A segment can be considered to be any region having pixels with uniform spectral characteristics

What is a segment?

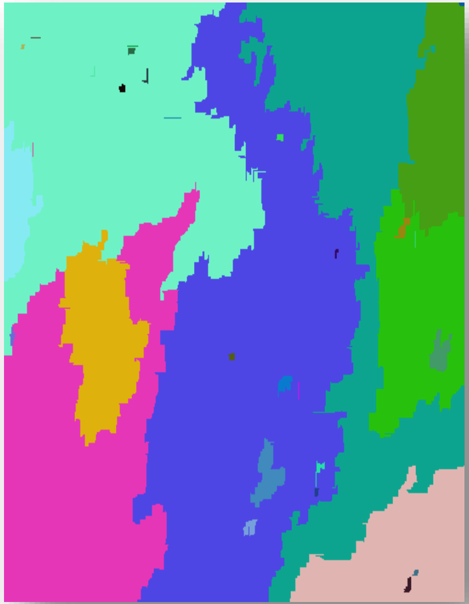
To cluster together similar looking image patches

The goal of segmentation



Segmentation using SRM algorithm

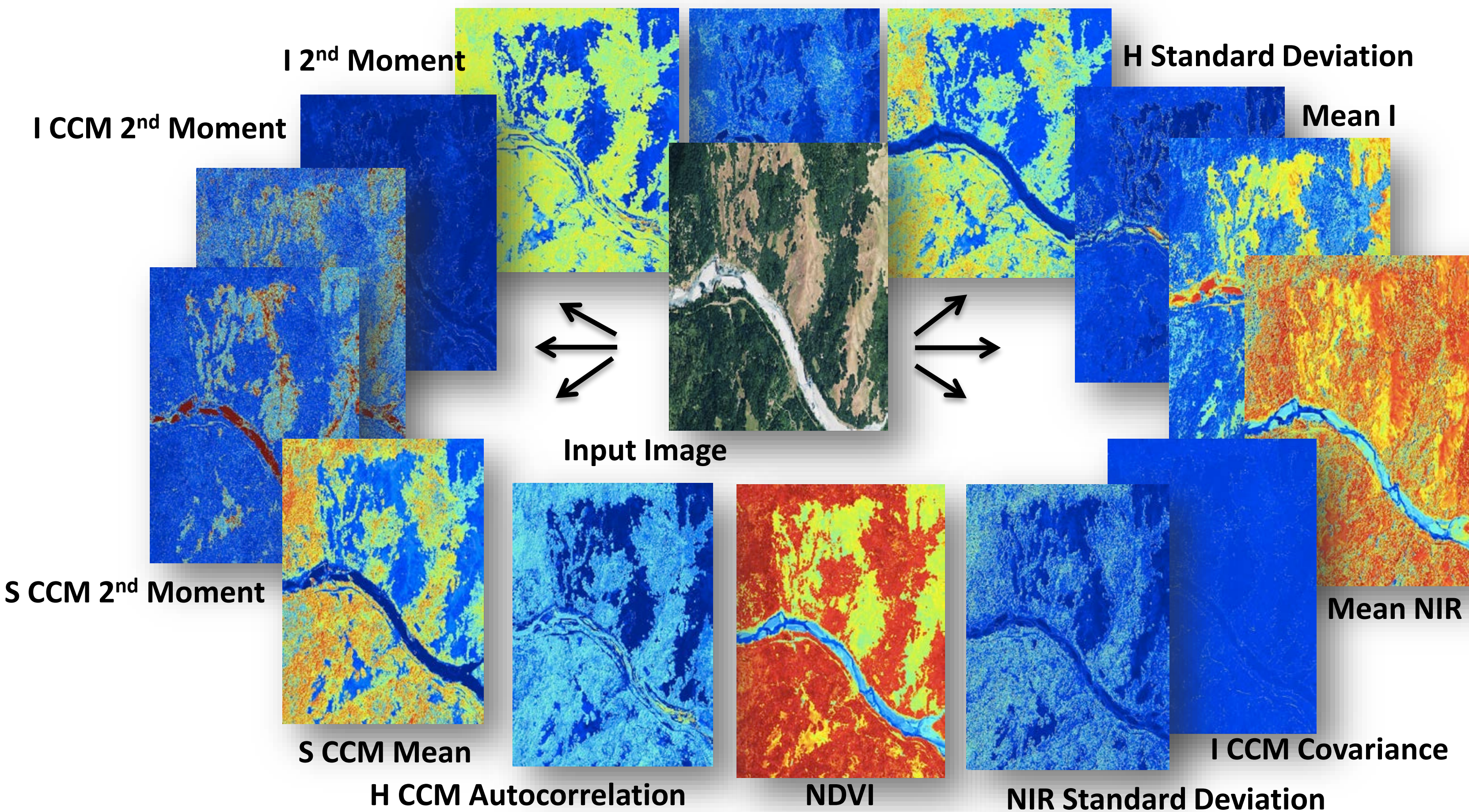
Input Image



Under-segmentation
Creates inter-class overlap within a segment

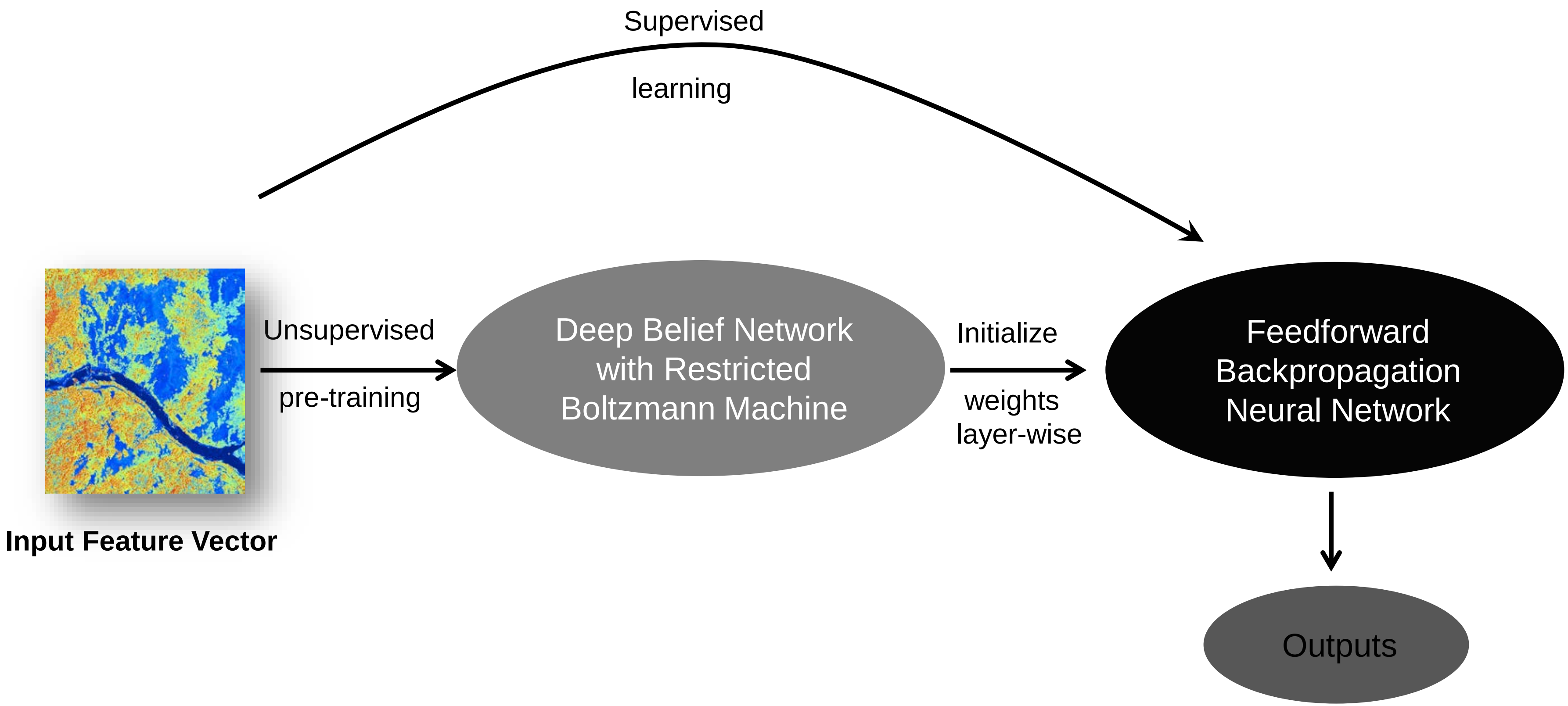
Over-segmentation
Each segment ideally contains regions belonging to a single class, no inter-class overlap

NAIP Feature Extraction Process



Multiple Features extracted from the Input Image

Learning


Supervised
learning
Unsupervised
pre-training
Deep Belief Network
with Restricted
Boltzmann Machine
Initialize
weights
layer-wise
Feedforward
Backpropagation
Neural Network
Input Feature Vector
Outputs

Learning

Unsupervised Learning using Deep Belief Network:

- ❑ Unsupervised pre-training using a Deep Belief Network (DBN) where each layer is trained using a Restricted Boltzmann Machine (RBM)
- ❑ The weights of the DBN are used to initialize the corresponding weights of the Neural Network
- ❑ A Neural Network initialized in this manner converges much faster than an otherwise uninitialized Neural Network
- ❑ Unsupervised pre-training is an important step in solving a prediction problem with petabytes of data with high variability

Learning

Deep Belief Network:

- ❑ Each layer is conditionally independent of the other
- ❑ DBN can be trained layer-wise by iteratively maximizing the conditional probability of the input vectors or visible vectors given the hidden vectors and a particular set of layer weights
- ❑ A DBN trained layer-wise with RBM can help in improving the variational lower bound on the probability of the training data under the composite learning model

Learning

Supervised Learning using Artificial Neural Network:

- ❑Fully connected Feed-forward backpropagation neural network

- ❑One input layer with 26 input neurons, three hidden layers each having 100 neurons and one output layer having one neuron.

$$\sigma(t) = tanh(t) = \frac{e^t - e^{-t}}{e^t + e^{-t}}$$

- ❑Activation function: tansigmoid (tanhyperbolic)

Neural Network (contd.)

❑Weights and biases initialized using: Deep Belief Network

❑Performance function: mean squared error (mse)

Training:

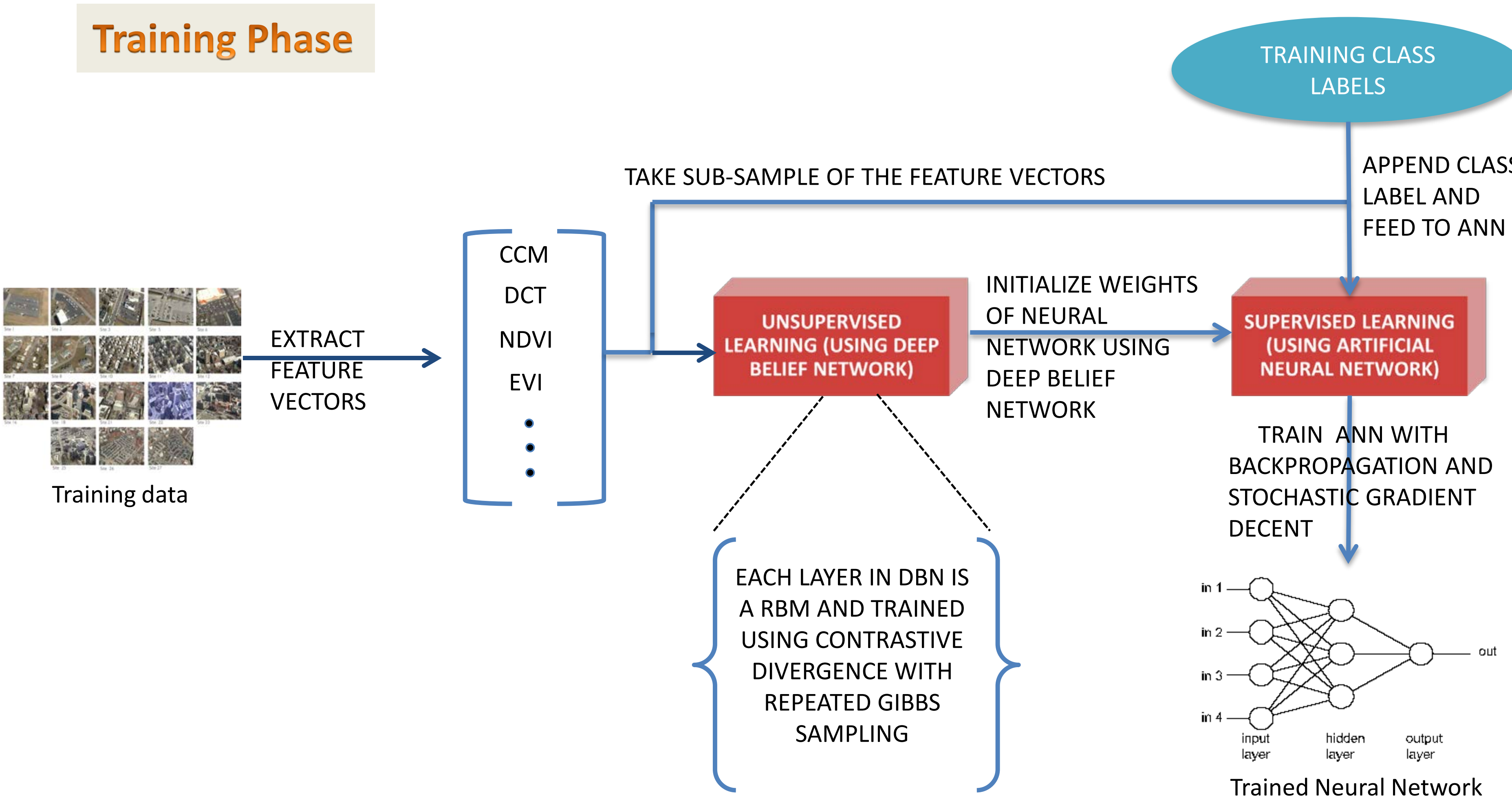
❑In the training phase around 100,000 training samples are chosen

❑Chosen randomly from a multitude of scenes having various kinds of tree-cover like urban, dense, fragmented etc.

Testing:

❑Testing involves using the trained model to generate classification maps for satellite images from the dataset on the fly.

Learning Module



Learning Module

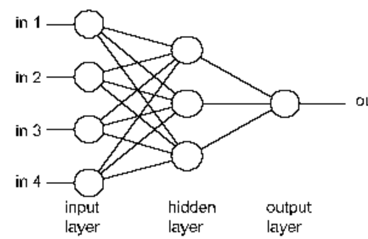
Testing/Prediction Phase

NAIP Tile

EXTRACT
FEATURE
VECTORS

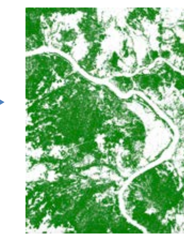
CCM
DCT
NDVI
EVI
•
•
•

NORMALIZE
DATA AND
FEED TO ANN



Trained Neural Network

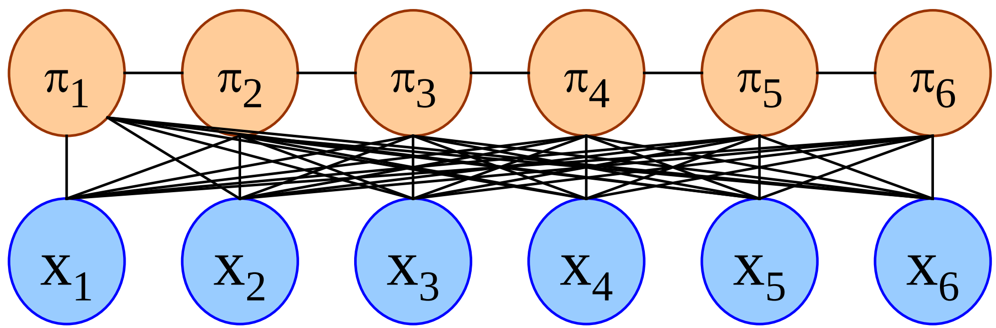
PREDICT CLASS
AND GENERATE
LABELS



CLASS MASK

Structured Prediction using Conditional Random Field

Labeling of a pixel depends not only on the feature values of that particular pixel but also on the values assumed by “neighboring” pixels.



Conditional Random Field to encode contextual information from the SRM output into the Classifier output distribution.

Experimental Results

Total scenes processed = 11095 for the whole of California

	Densely Forested	Fragmented forests	Urban areas	Overall
Total samples	12000	12000	12000	36000
Tree samples	6000	6000	6000	18000
Non-tree samples	6000	6000	6000	18000
True Positive Rate (%)	85.87	88.26	73.65	82.59
False positive Rate (%)	2.21	0.99	1.98	1.73

Comparison with National Land Cover Data (NLCD) Algorithm

Fragmented Forests:

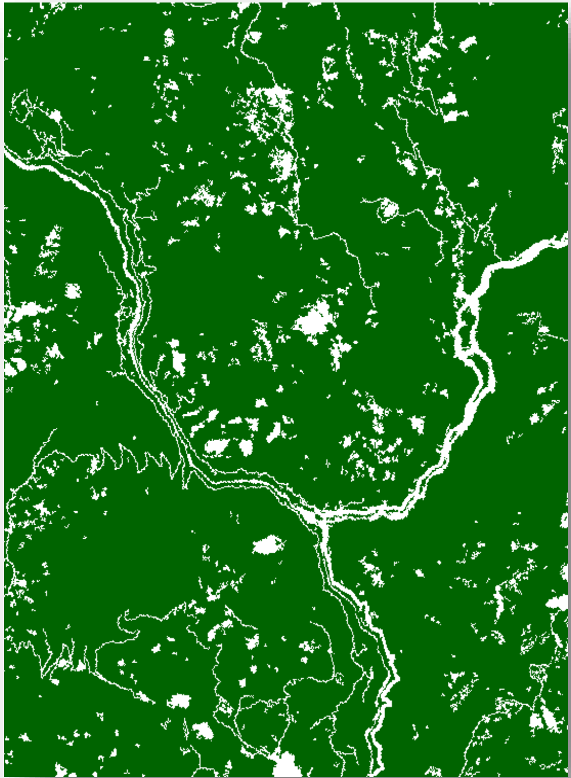
	NLCD 30-m	NAIP 1-m
Total samples	1000	1000
Tree samples	500	500
Non-tree samples	500	500
True Positive Rate (%)	72.31	87.13
False positive Rate (%)	50.8	1.9

Confusion Matrix

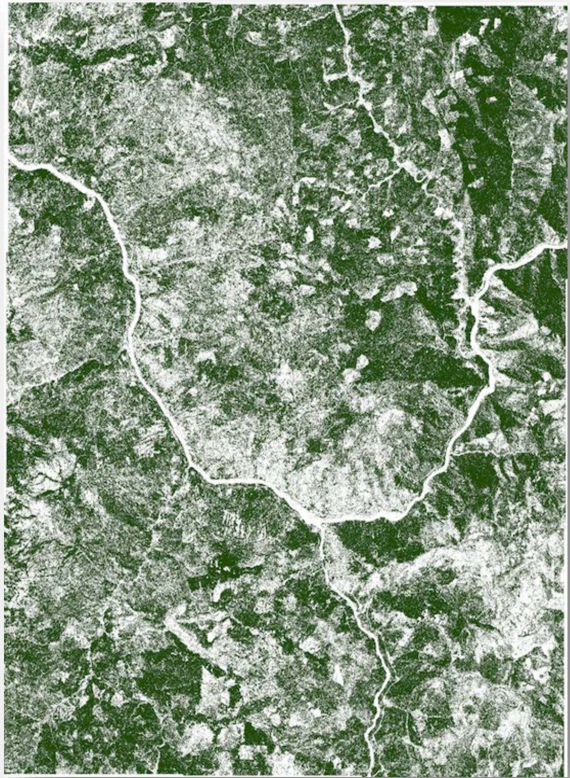
		Actual Class			
		Tree	Non-tree	Total Pixels	User's Accuracy
Predicted Class	Tree	14832	317	15149	97.9%
	Non-tree	3168	17683	20851	84.8%
	Total pixels	18000	18000	36000	
	Producer's Accuracy	82.4%	98.23%		90.31%

Comparison with NLCD

Fragmented Forests



NLCD 30-m OUTPUT



NAIP 1-m OUTPUT

Comparison with NLCD

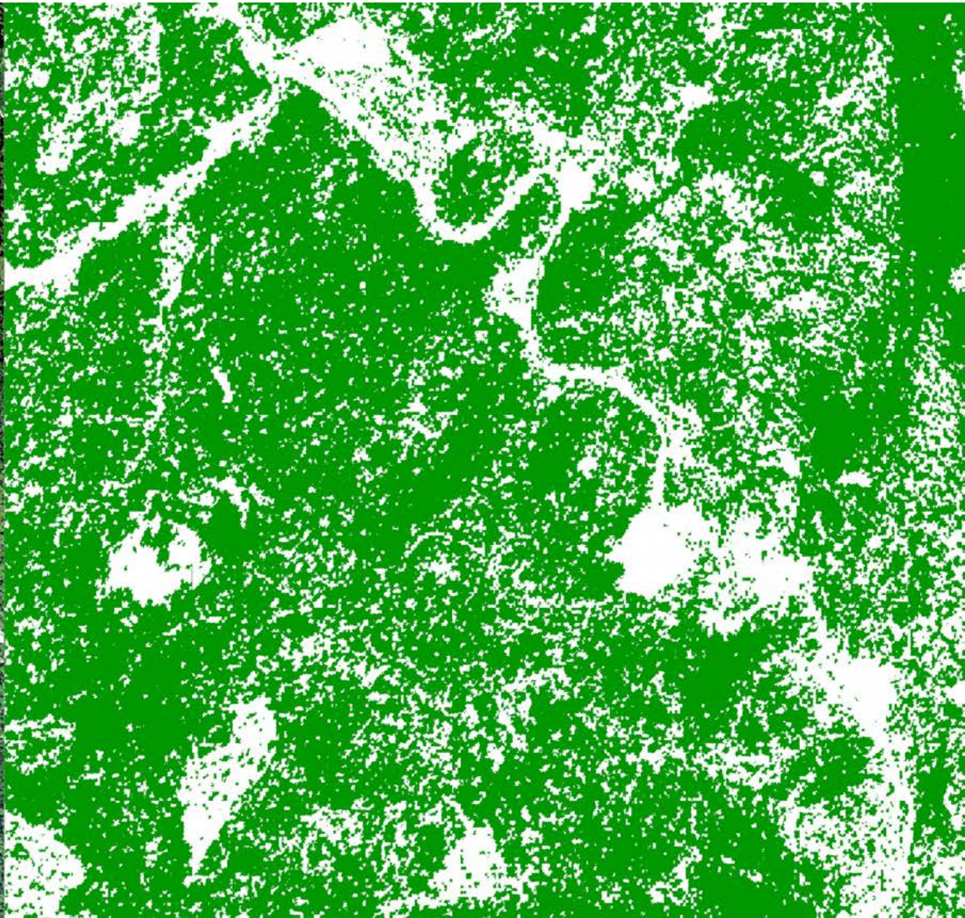
Urban Landscape

NLCD 30-m OUTPUT

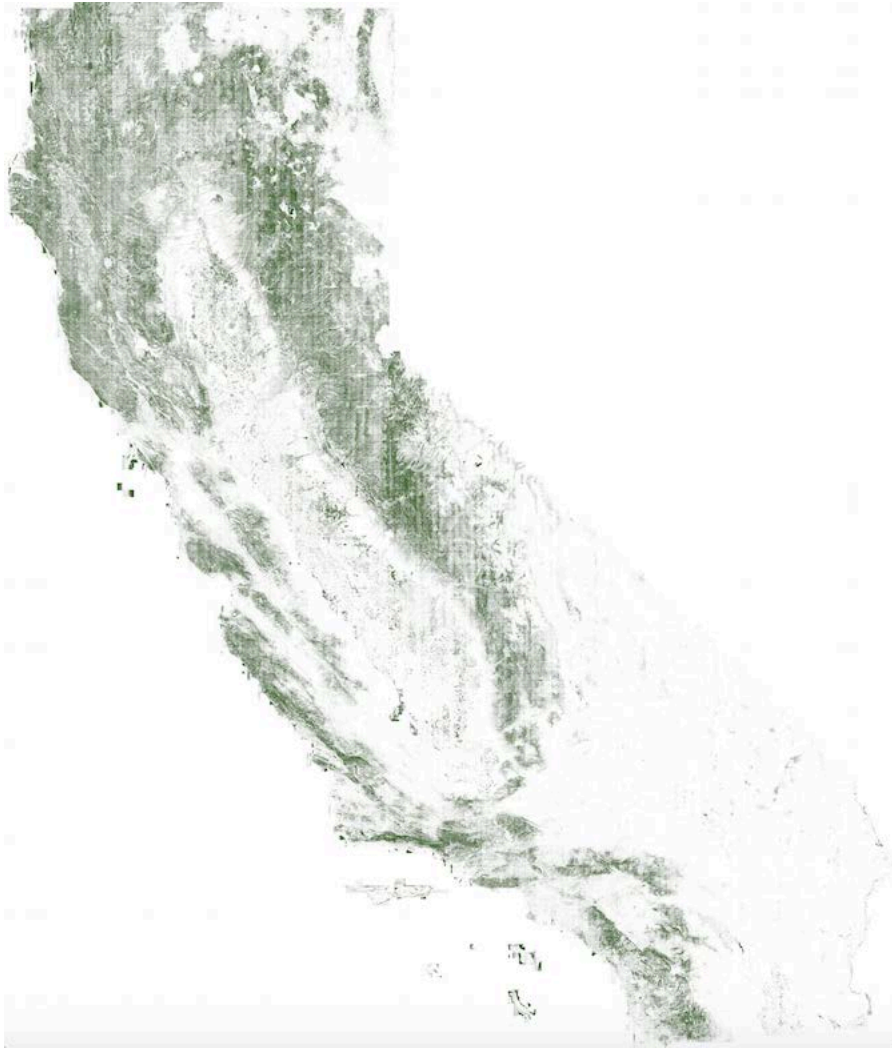
NAIP 1-m OUTPUT

San Francisco Bay Area

Yosemite

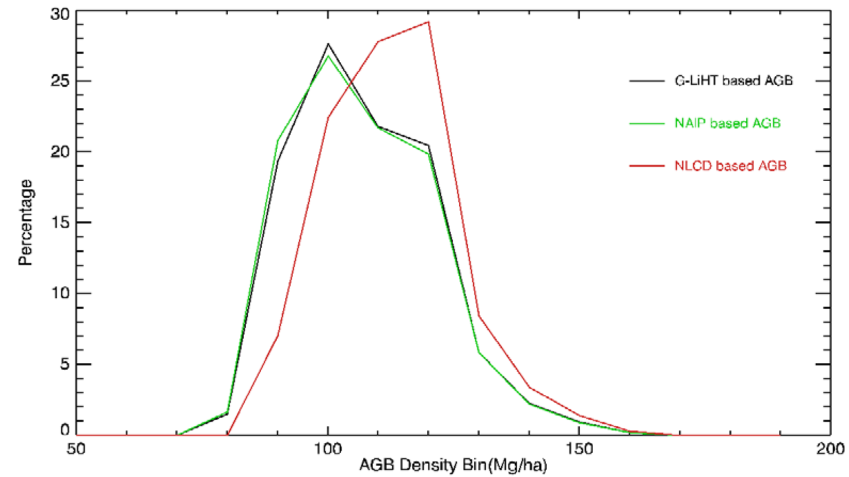


California Tree Cover Mosaic



AGB estimation based on NAIP

- We implemented a similar approach to estimate AGB from Landsat based on NAIP tree cover map.
- To test the improved AGB estimates, we estimated AGB based on the G-LiTH airborne LiDAR tree cover map and compared it to the AGB estimates based on NLCD land cover.
- Preliminary results show that improved NAIP-based AGB is close to LiDAR derived biomass.



AGB density histogram of forests near Lassen National Park, CA for calculated based on NLCD land cover map, the NAIP classified tree cover map, and G-LiTH classified tree cover map.

The forest cover and total AGB estimates based on three tree cover maps in a G-LiTH scene (S551).

	LiDAR	NAIP	NLCD
Forest coverage	87.2%	91.1%	66.9%
Total AGB (Ton)	14981	15541	11935

Attributing AGB uncertainties in tree cover estimates across sensors

- With the high resolution NAIP tree cover, we can attribute AGB uncertainties in tree cover from other coarse sensors.
- Theoretically, total forest AGB is the sum of AGB values for each forest pixel.

$$AGB_{total} = \sum_{i=1}^{n} (AGBD_i \times A_i)$$

- The total forested area can be expressed in terms of the total number of forested pixels and the area per unit pixel as: $A_{forest} = n \times A_0$

- In a similar manner, the mean AGB density for all forested pixels can be expressed as: $\overline{AGBD} = \frac{1}{n} \sum_{i=1}^{n} AGBD_i$
- The total biomass takes the form: $AGB_{total} \approx \overline{AGBD} \times \left(A_{forest} \pm \left| \frac{A_{Sensor} - A_{NAIP}}{A_{NAIP}} \right| \right)$

- The AGB uncertainties in tree cover estimates based on other sensors can be computed by Monte Carlo approach such that:

$$AGB_{total} = \overline{AGBD} \times (\tilde{A}_{forest} \pm \delta A)$$

Advantage of the Deep Belief Network based Learning Framework

- Since labeled training data is limited, we have to resort to **Unsupervised Learning**.

- **Deep Belief Networks** use unlabeled data in the first phase. Since, there are ample amounts of unlabeled data, the unsupervised learning phase is able to initialize the weights and biases of the Neural Network to a global error basin.

- Because the neural network is initialized to a global error basin, in the supervised learning phase, it requires very little training data which is well suited for our purposes since we already have limited training data.

- DBN provides the most powerful and state-of-the-art learning framework to address these problems.

Conclusion

- There is a significant correlation between Landsat LAI and Maximum canopy height derived from GLAS for forested pixels in California;
- We created a California wall-to-wall AGB density map at 30-m, based on a simple empirical model between LAI and Height along with related uncertainties;
- The regional aggregated total biomass estimates are comparable to inventory-based estimates and existing satellite derived maps at different spatial resolutions;
- The present Monte Carlo uncertainty approach is particularly useful to address AGB pixel-level uncertainties at different spatial resolutions;
- As part of NASA CMS efforts, we used different satellite-derived metrics along with machine learning methods to map CONUS Aboveground biomass at ~100m;
- The coarse spatial resolution of Land cover/Tree cover estimates contribute to a large uncertainty in AGB estimation.
- The new 1-m tree cover map derived for the whole of CONUS will considerably reduce in the uncertainties in the final biomass estimates

Relevant Publications

Zhang, G., **Ganguly, S.**, Nemani, R. R., White, M., Milesi, C., Wang, W., Saatchi, S., Yu, Y. and Myneni R. B. (**2014**), Estimation of forest aboveground biomass in California using canopy height and leaf area index estimated from satellite data, *Remote Sensing of Environment* (ForestSat Special Issue), DOI: 10.1016/j.rse.2014.01.025.

Basu, S., **Ganguly, S.,** Nemani, R. R., Mukhopadhyay, S., Zhang, G., Milesi, C., Michaelis, A., Votava, P., Dubayah, R., Duncanson, L., Cook, B., Yu, Y., Saatchi, S., DiBiano, R., Karki, M., Boyda, E., and U. Kumar **(2015)**, A semi-automated probabilistic framework for tree cover delineation from 1-m NAIP imagery using a high performance computing architecture, *IEEE Transactions on Geoscience and Remote Sensing,* vol.53, no.10, pp.5690-5708, Oct. 2015 doi: 10.1109/TGRS.2015.2428197.

Saikat Basu, Manohar Karki, **Sangram Ganguly**, Robert DiBiano, Supratik Mukhopadhyay, Ramakrishna Nemani**,** Learning Sparse Feature Representations using Probabilistic Quadtrees and Deep Belief Nets, *European Symposium on Artificial Neural Networks*, ESANN 2015.

Saikat Basu, **Sangram Ganguly**, Supratik Mukhopadhyay, Robert Dibiano, Manohar Karki and Ramakrishna Nemani, DeepSat - A Learning framework for Satellite Imagery, *ACM SIGSPATIAL* 2015.

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Ganguly, S., R. R. Nemani, G. Zhang, H. Hashimoto, C. Milesi, A. Michaelis, W. Wang, P. Votava, A. Samanta, F. Melton, J. L. Dungan, E. Vermote, F. Gao, Y. Knyazikhin, and R. B. Myneni (**2012**), Generating global leaf area index from Landsat: Algorithm formulation and demonstration, *Remote Sensing of Environment*, http://dx.doi.org/10.1016/j.rse.2011.10.032.

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