Gabon's Forests...

Mapped and **Monitored** to reduce climate change

Mapping and Monitoring Carbon Storage: Fusion of Ground and Space Measurements

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[1]University of Leeds

[2]Jet Propulsion laboratory, NASA/ University of California, Los Angeles

[3]Government of Gabon

Fusing ground and space measurements

- What can ground data tell us about carbon stocks and change over time?
- What can satellite data tell us about carbon stocks and change over time?
- What can a fusion of both tell us?

Tropical Forests and Climate Change

- Changing land-use and forest degradation are the cause of 10-20% of anthropogenic carbon emissions; ~1.5 Pg C yr^{-1} (Van der Werf et al. 2009, *Nature Geoscience*).

- Conversely, tropical forests absorb 10-15% of all human-induced emissions of carbon; 1.3 Pg C yr^{-1} (Lewis et al. 2009, *Nature*)

What can ground-based direct measurements tell us?

- Calculate carbon storage in a defined area to:
  - Allow ‘painting by numbers’
  - Calibrate remote sensing product outputs
  - Validate remote sensing product outputs
- Monitor changes that satellites can’t
- Provide measurements of IPCC pools that satellites can’t, e.g.
  - Litter
  - Coarse woody debris

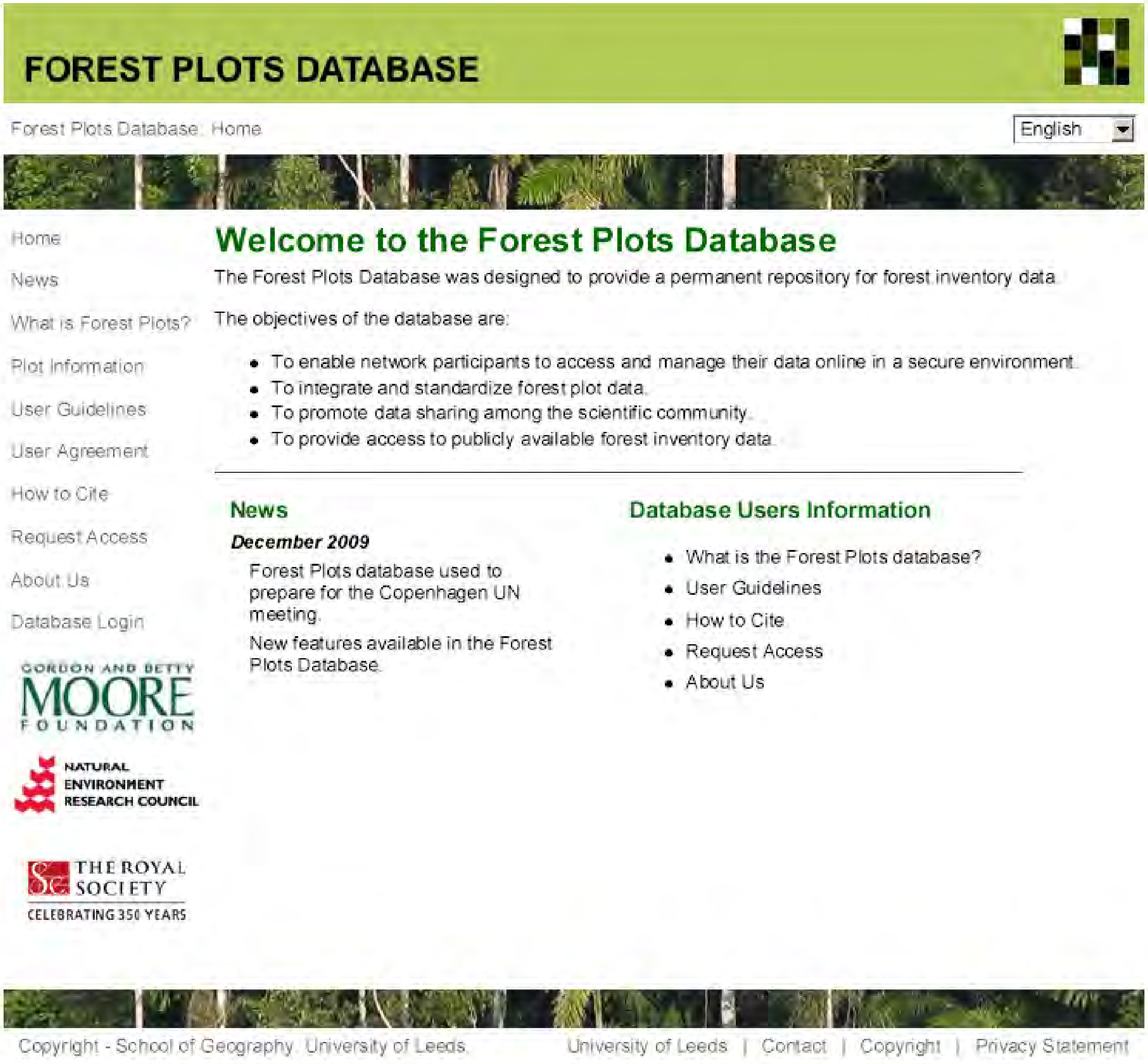
Obtaining aboveground live tree carbon (plot) data

- Define area, measure, map, indentify all trees >threshold size, often 10 cm diameter

- Note: not technically difficult except botany, but easy to get wrong

- Exact methods have converged over time, see RAINFOR, CTFS, AFRItron, TEAM networks of plots

Check, manage and process the data



FOREST PLOTS DATABASE

Forest Plots Database Home

English

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About Us
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GORDON AND BETTY MOORE FOUNDATION

NATURAL ENVIRONMENT RESEARCH COUNCIL

THE ROYAL SOCIETY CELEBRATING 350 YEARS

Welcome to the Forest Plots Database

The Forest Plots Database was designed to provide a permanent repository for forest inventory data.

The objectives of the database are:

- To enable network participants to access and manage their data online in a secure environment.
- To integrate and standardize forest plot data.
- To promote data sharing among the scientific community.
- To provide access to publicly available forest inventory data.

News

December 2009

Forest Plots database used to prepare for the Copenhagen UN meeting.

New features available in the Forest Plots Database.

Database Users Information

- What is the Forest Plots database?
- User Guidelines
- How to Cite
- Request Access
- About Us

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FOREST PLOTS DATABASE

Terrains forestiers de base de données: Accueil > Mon Parcelles

Français

- Accueil
- Accords
- Mon Parcelles
- Requête Bibliothèque
- Import Terrain
- Terrain Métadonnées
- Terrains publics
- Public Query Library
- All Plots
- Admin
- Aider
- Déconnexion

Filtre

Plot Code	Terrain commercial	Pays	Continent
ASN-02	Asenanyo F.R. 2	GHANA	Africa
ASN-04	Asenayo	GHANA	Africa
ASU-01	Asukese F.R. 1	GHANA	Africa
ASU-02	Asukese Plot 100	GHANA	Africa
BIS-01	Bissombo Plot 1	CAMEROON	Africa
BIS-02	Bissombo Plot 2	CAMEROON	Africa
BIS-03	Bissombo Plot 3	CAMEROON	Africa
BIS-04	Bissombo Plot 4	CAMEROON	Africa
BIS-05	Bissombo Plot 5	CAMEROON	Africa
BIS-06	Bissombo Plot 6	CAMEROON	Africa
BOR-05	Bonsa River 05	GHANA	Africa
BOR-06	Bonsa River 06	GHANA	Africa
BUD-17	Budongo Plot 7 >10 cm dbh, 76-92	UGANDA	Africa
BUD-27	Budongo Plot 7 >20 cm dbh, 39-92	UGANDA	Africa
CAM-01	Campo Ma'an 1	CAMEROON	Africa

FOREST PLOTS DATABASE

Terrains forestiers de base de données: Accueil > Mon Parcelles

Français

Individual passwords to view or view and edit data, or make data public to registered users

Automated error checking of data

Automated checking of valid species names from African flowering Plants database, including synonymy

Integrated wood mass density database

Integrated height data when available, or specify height-diameter relationship for a plot or group of plots

Percolates uncertainty in allometric equations

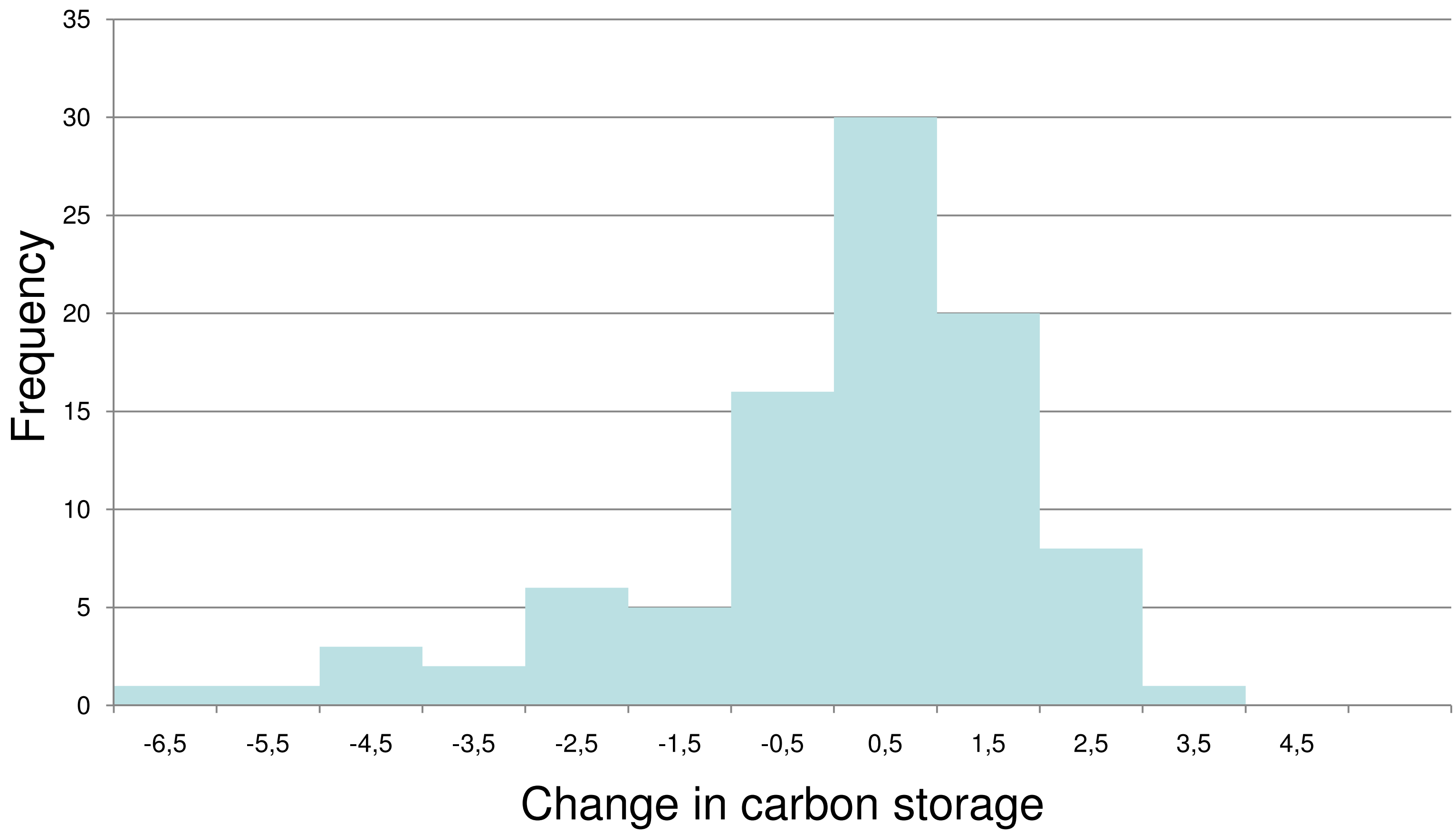
Carbon storage value per plot with one click, download to excel

CAM-01 Campo Ma'an 1 CAMEROON Africa

Ground-based measurements across the Congo Basin

- 240 plots (forest and woody savanna)
- DRC, Cameroon, Central African Republic, Republic of Congo, Equatorial Guinea, Gabon
- Mean area 1.3 ha
- Mean above-ground carbon storage, 198 Mg C ha^{-1}.
- 122 multi-census plots

www.afritron.org



Plots incr: +0.80 Mg C ha yr^{-1} (95% CI, 0.4-1.1; n = 94)

Congo basin carbon sink: 0.19 Pg C yr^{-1} (95% CI, 0.11-0.23)

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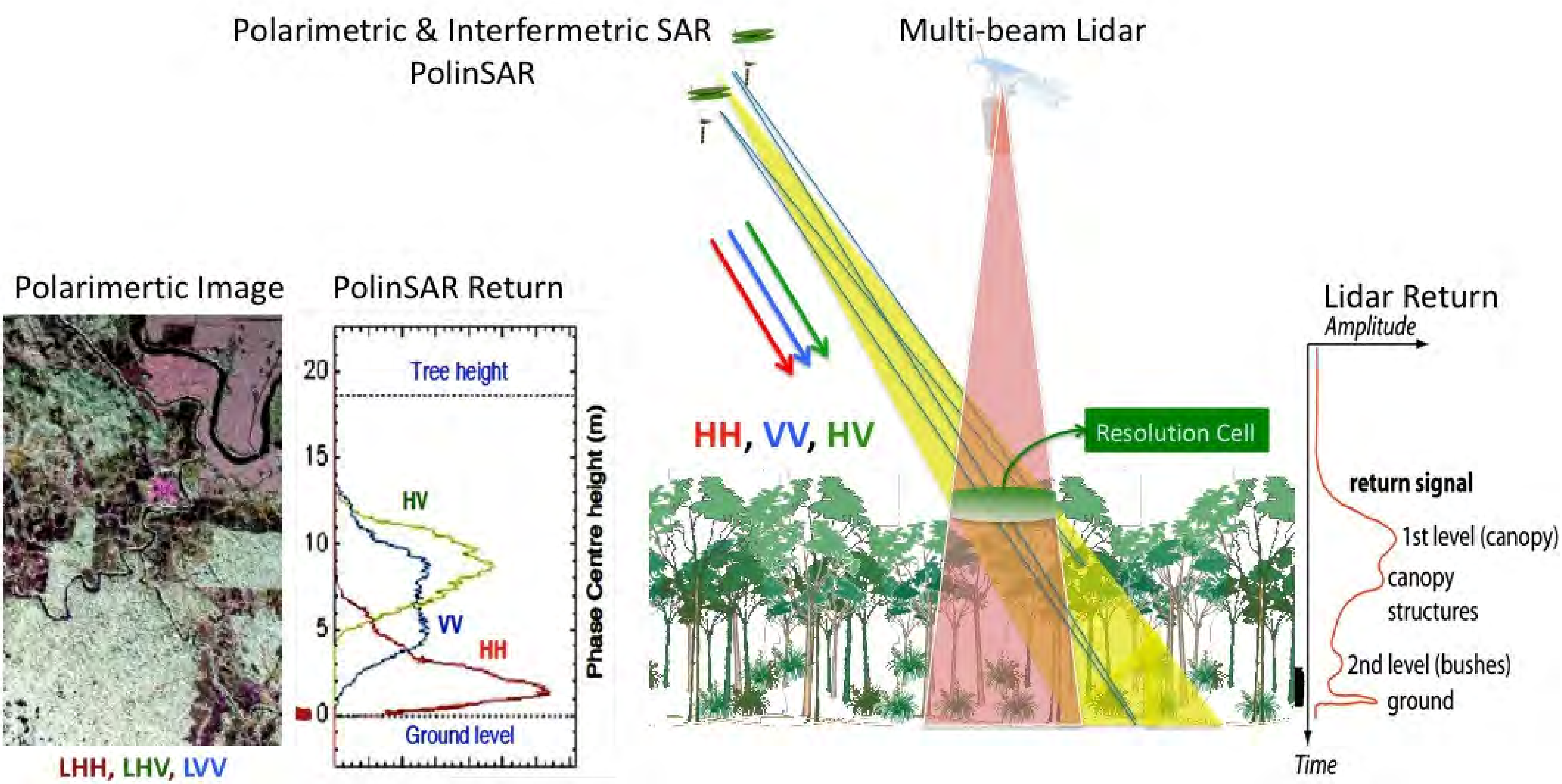
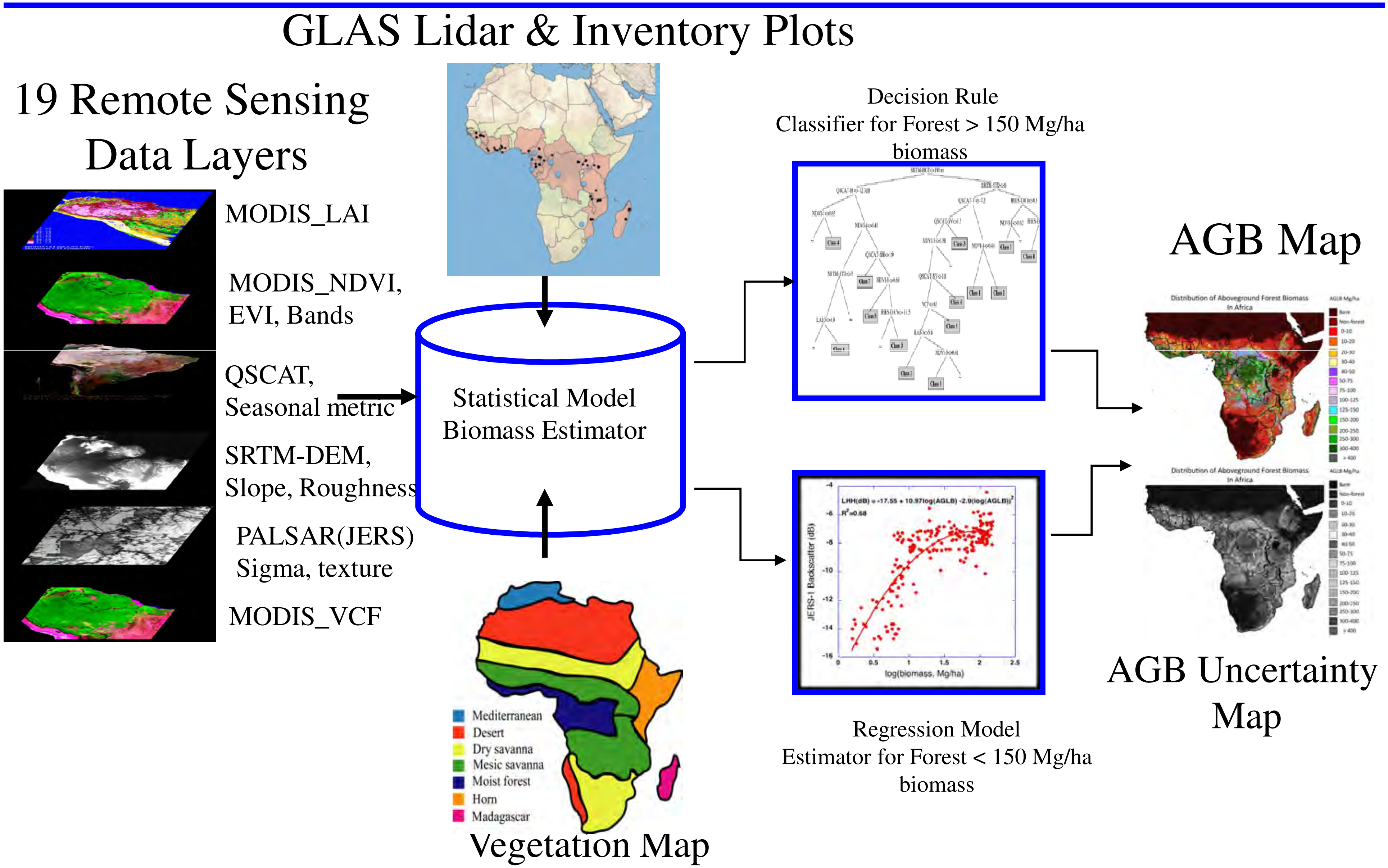
Measuring Forest Biomass from Space



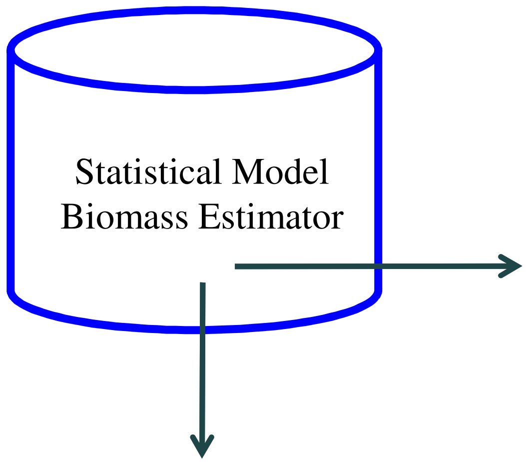
DESDynl & BIOMASS Missions
Forest Carbon of 2020

Current State-of-the-art
Forest Carbon of 2010

Integrative Approach to Map Biomass Distribution at 500-1000 m resolution



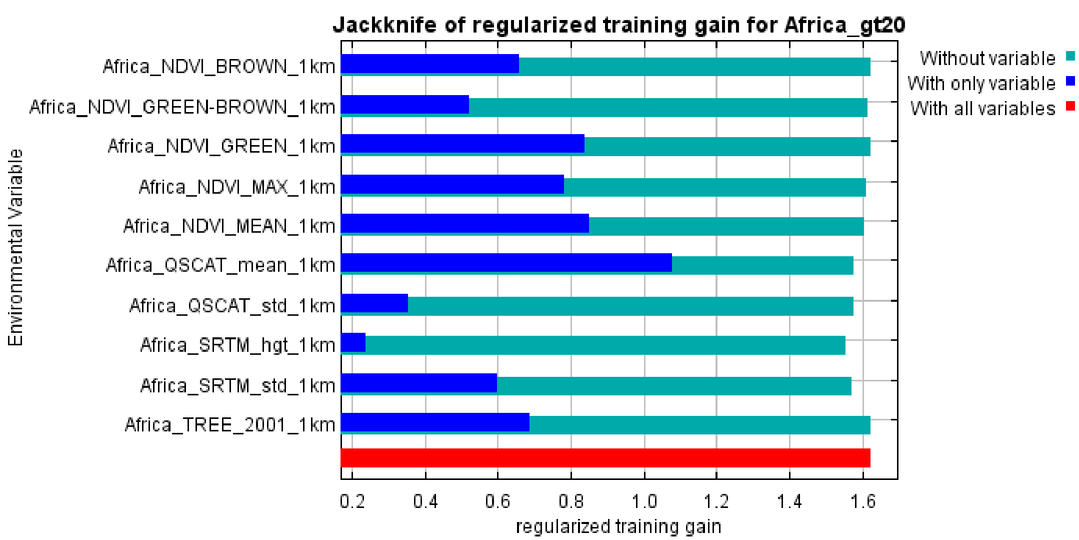
Integrative Approach to Map Biomass (Cont.)

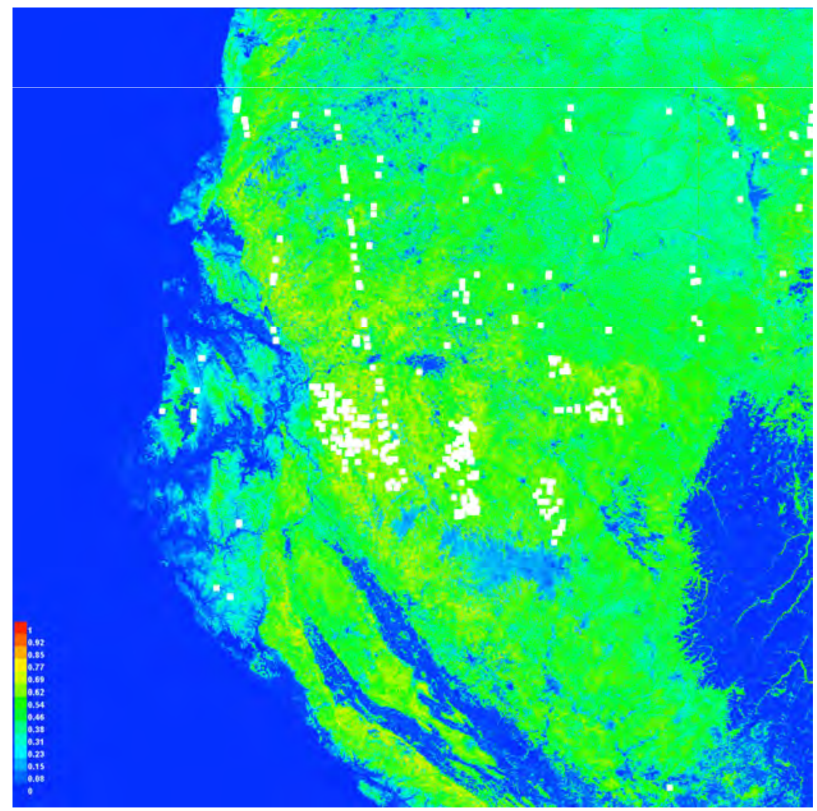


1. A probabilistic framework
2. Develop incomplete empirical probability distribution based on the occurrences
3. Approximate with a probability distribution of maximum entropy
4. Use environmental variables as constraints
5. A rule classifier to produce forest biomass map

Maximum Entropy Estimation Model

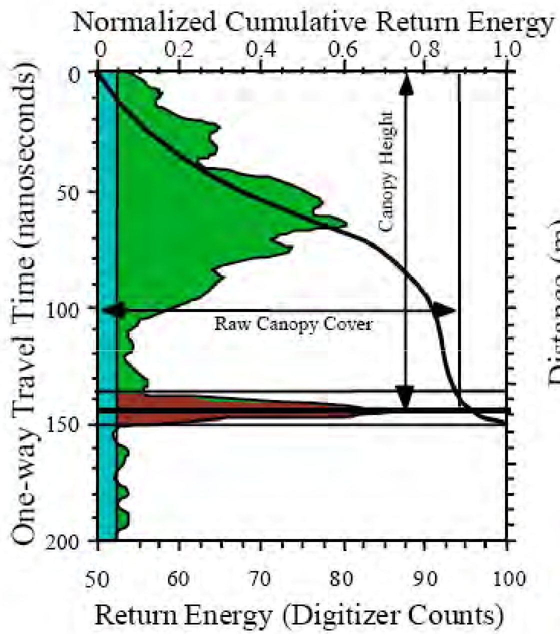
$$H(\hat{\pi}) = \sum_{x \in X} \hat{\pi}(x) \ln \hat{\pi}(x)$$

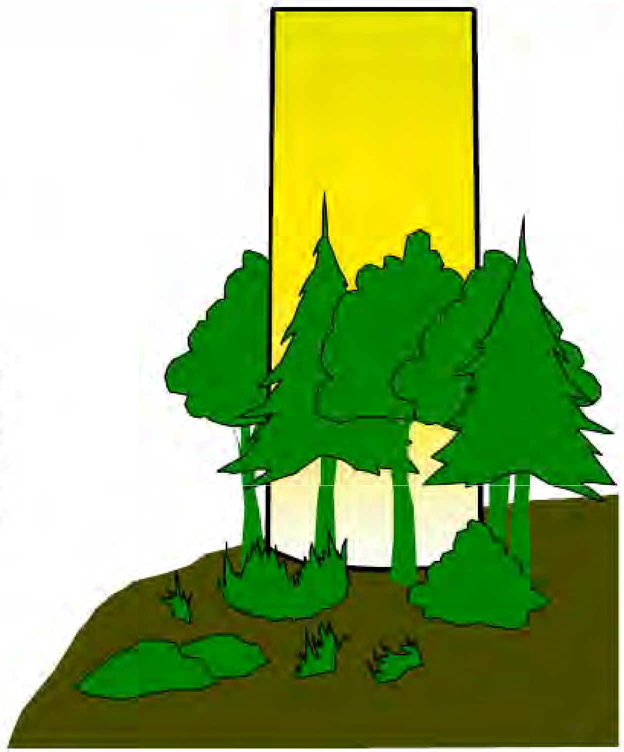


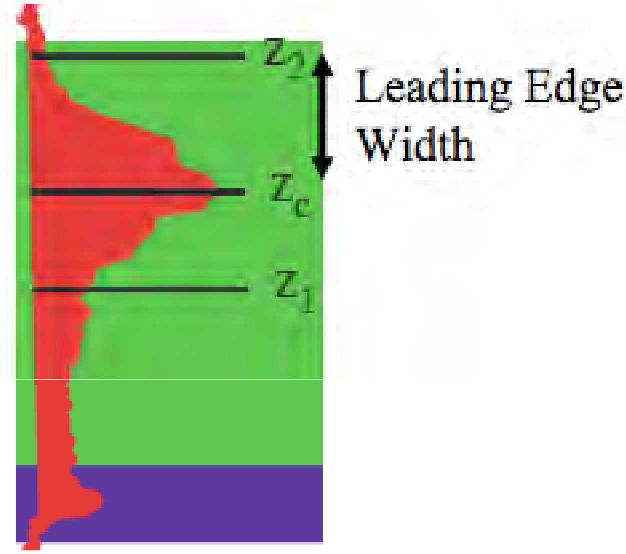


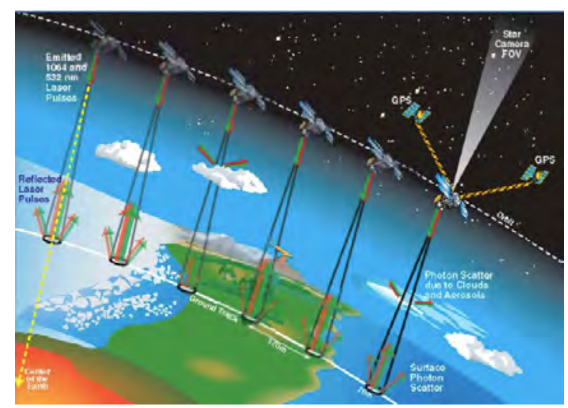
ICESAT GLAS Lidar Measurements
Forest Height

Waveform recording lidar

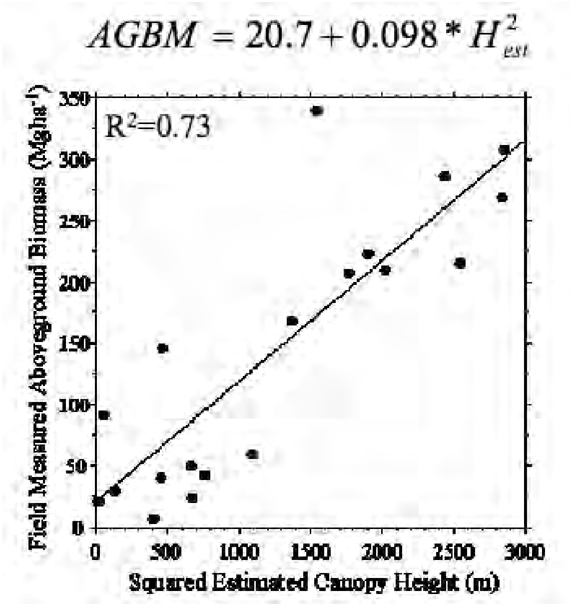






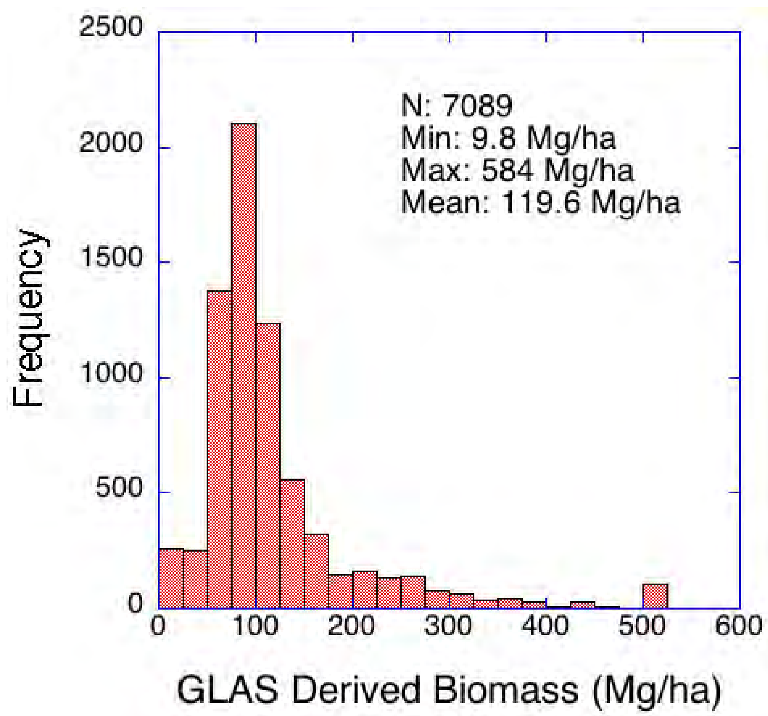


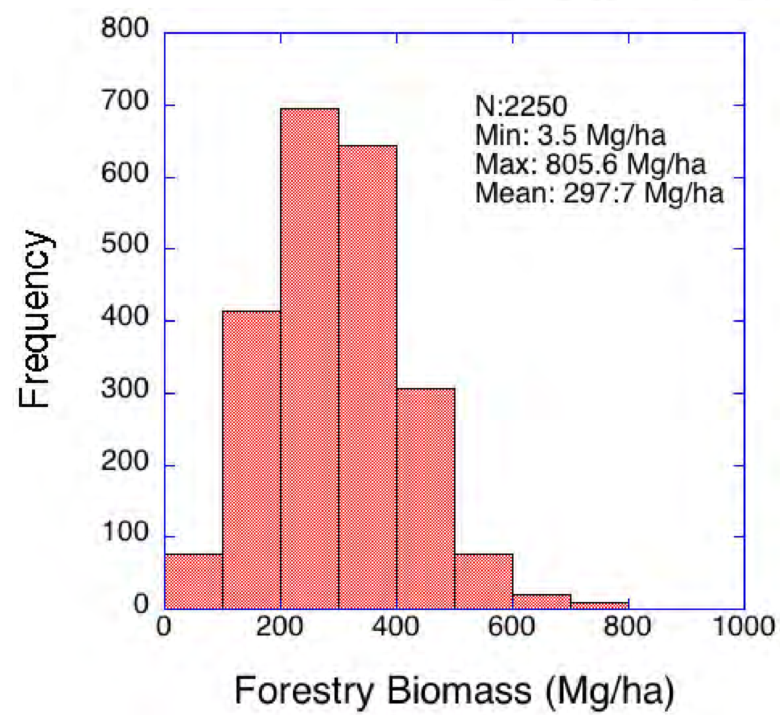
Mapping Forest Above Ground Biomass
Gabon, Circa 2000



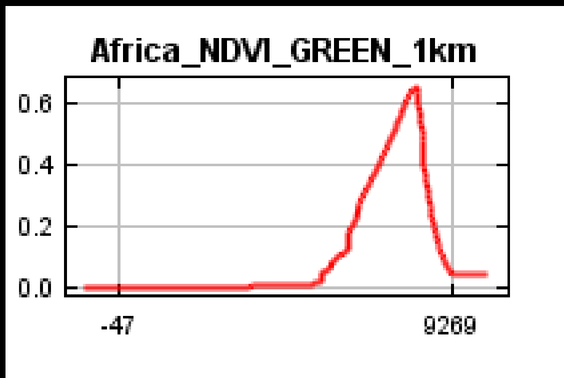
Input Biomass Data:

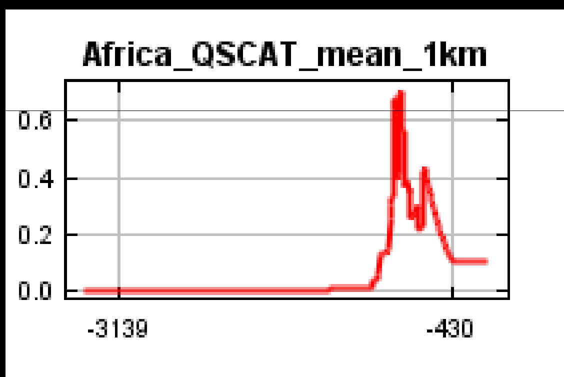
139 scientific inventory plots (0.1- 1.0 ha)
2250 forestry inventory plots (0.3 ha)
7089 ICESAT GLAS Derived Biomass

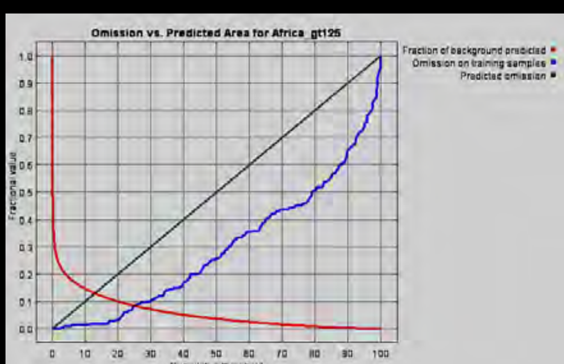




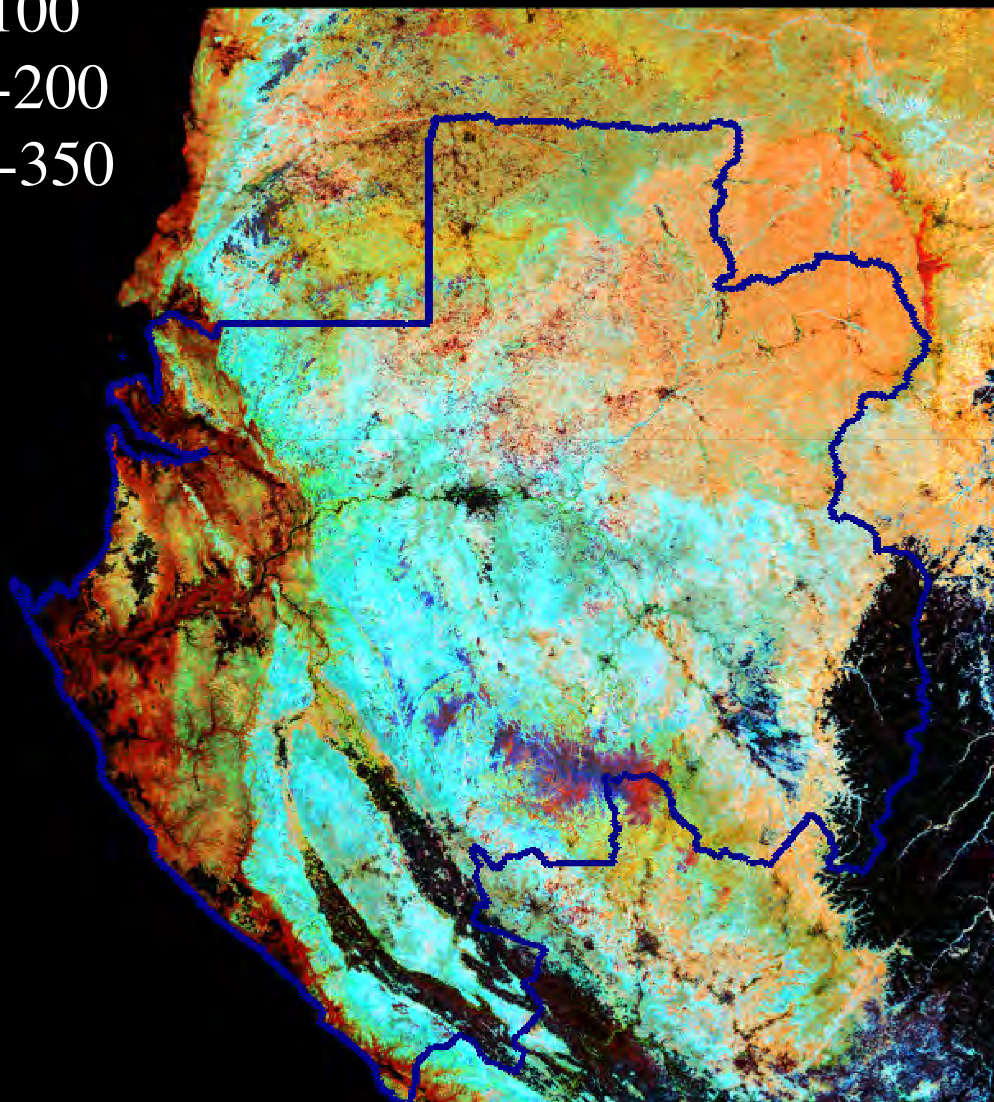
Maximum Entropy Probabilistic Predictions of Biomass



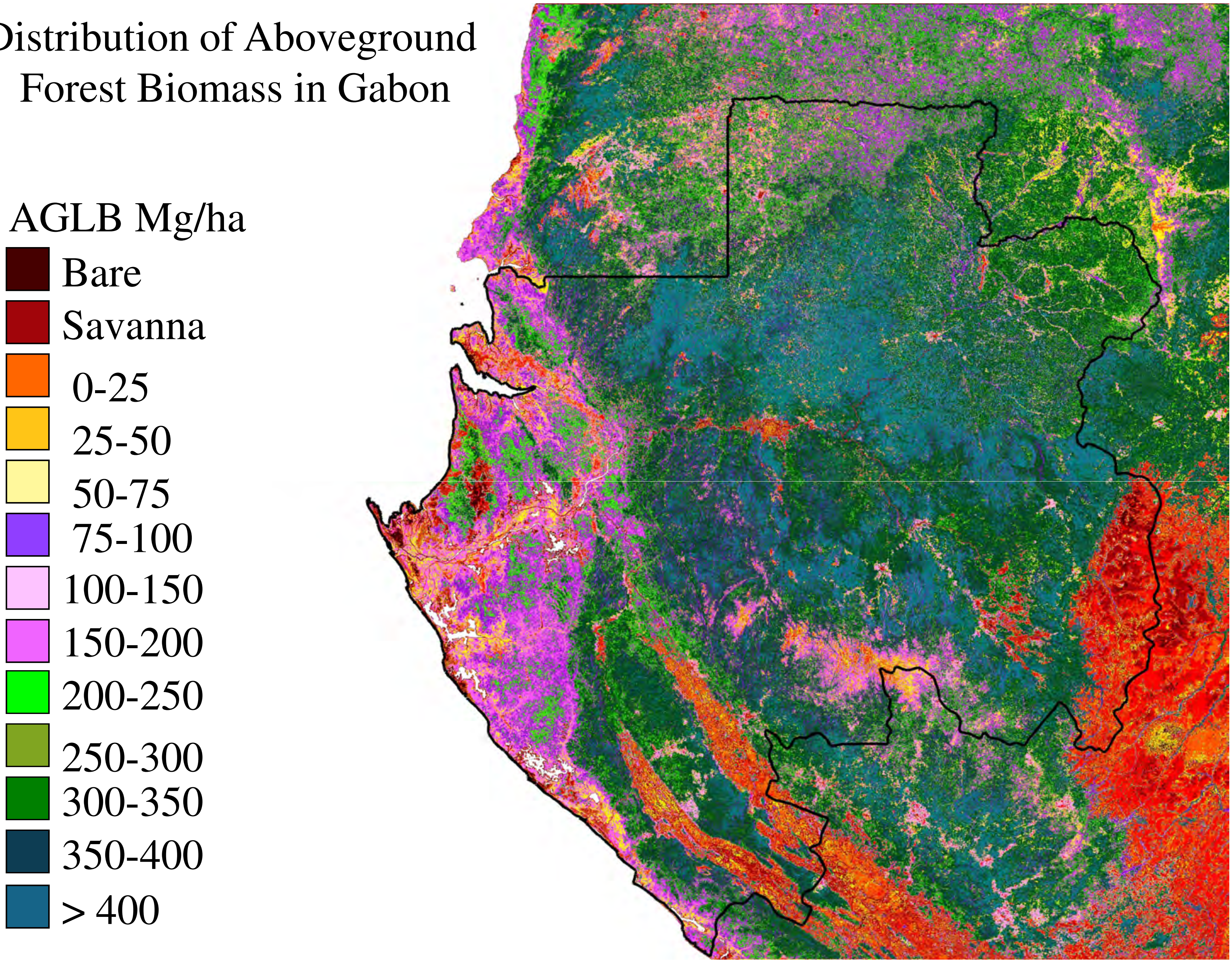




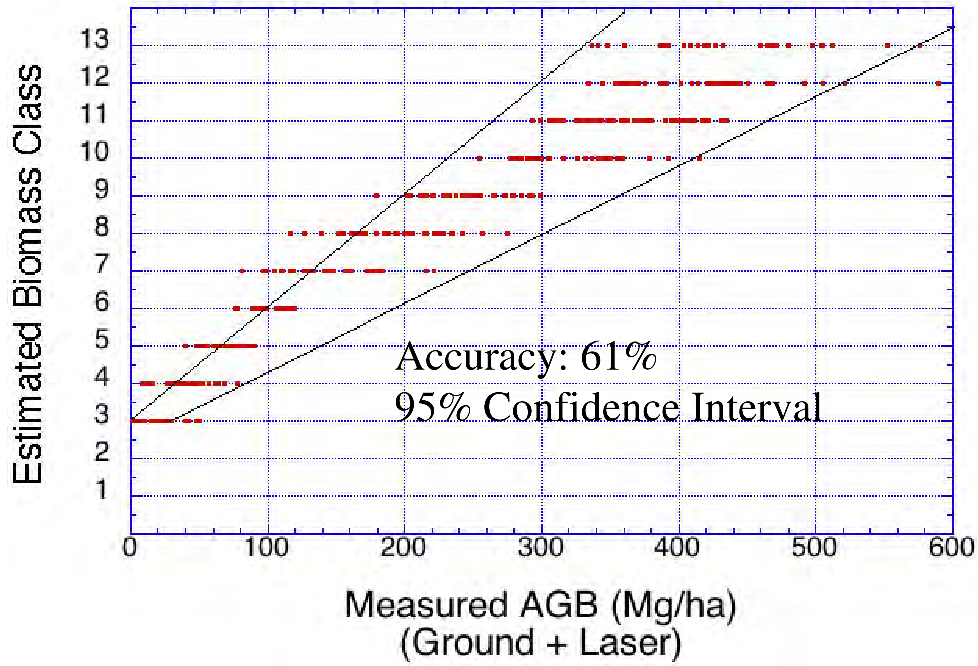
Red: 75-100
Grn: 150-200
Blue:300-350

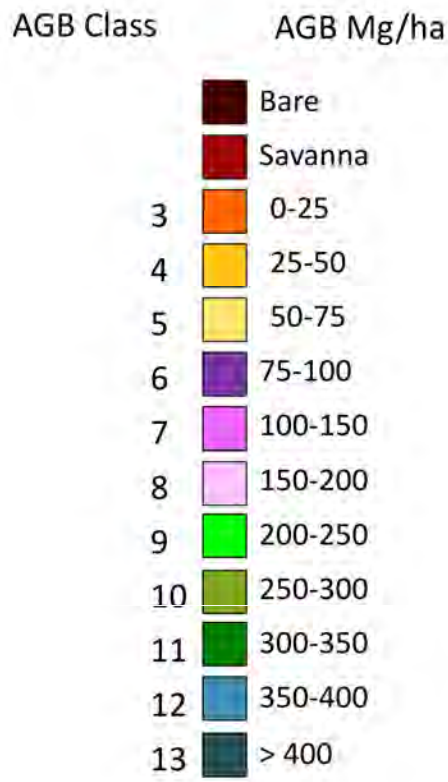


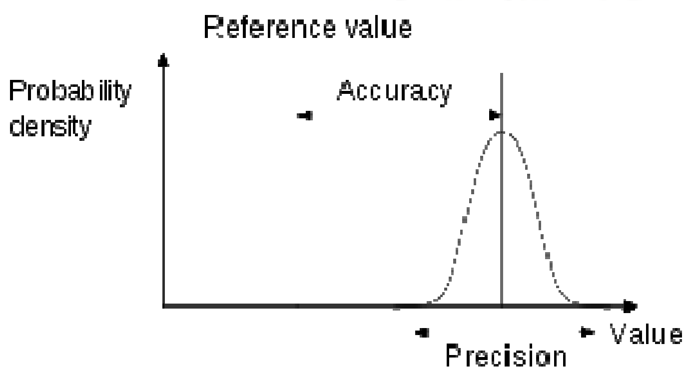
Distribution of Aboveground Forest Biomass in Gabon



Accuracy Assessment







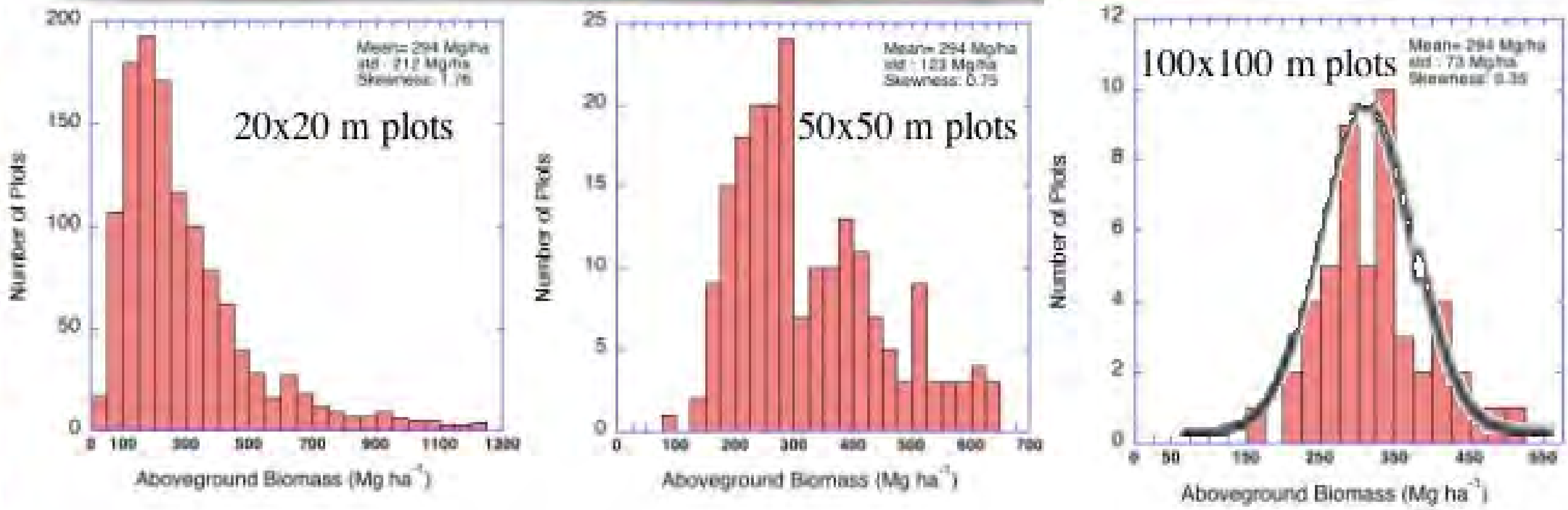
Country name	AG carbon	BG carbon	Total carbon
Gabon	3,318,669,136	856,388,067	4,175,057,202
Gabon (20% random error)	3,317,345,723	829,336,430	4,146,682,153
National Error Estimates	**2.86%**	**3.26%**	**3.2%**

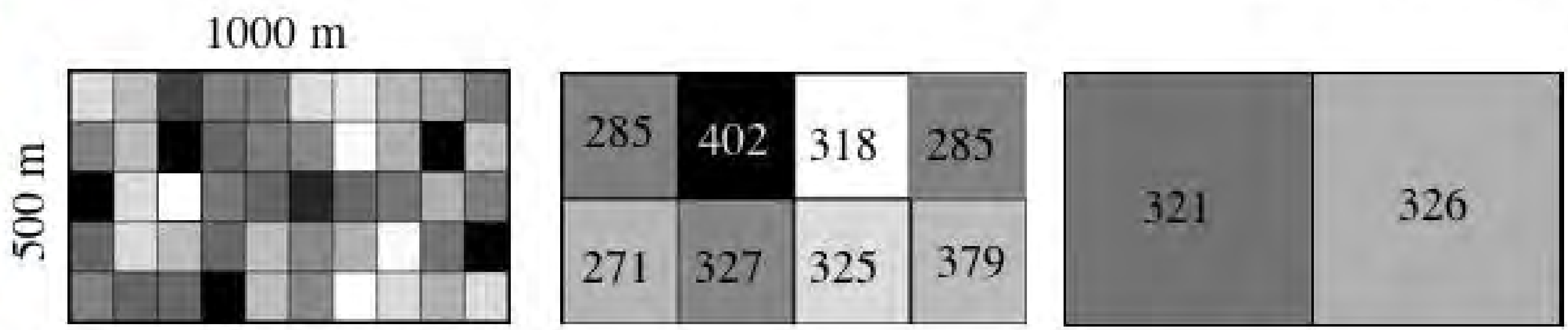
Sources of Errors

- Statistical extrapolation (Maxent, Random Forest, multiple regression, etc.) has large errors when sensitivity to AGB is low.

- Plot level inventory (small plots) & biometry
- Conversion of forest height to biomass (no allometry exists)
- Time differences in ground and satellite observations
- Spatial scale of analysis
- Errors in plot location vs satellite pixel

Spatial Variation of Forest Biomass





100 m Resolution | 250 m Resolution | 500 m Resolution

Forest Biomass of 50-ha plot in Barro Colorado, Panama

$\Delta C = AGB \times \Delta A$ Deforestation

$\Delta C = \Delta AGB \times A$ Small scale disturbance or Recovery

Using $< \mathrm{AGB} >= 294\mathrm{Mg/ha}$, $\Delta A = 1$ ha, $\Delta C = 294\,Mg$

However, $150\mathrm{Mg} < \Delta \mathrm{C} < 495\mathrm{Mg}$

DESDynI

Improvements in Estimates of Land-Based Emissions

Sassan Saatchi (UCLA-NASA/JPL),

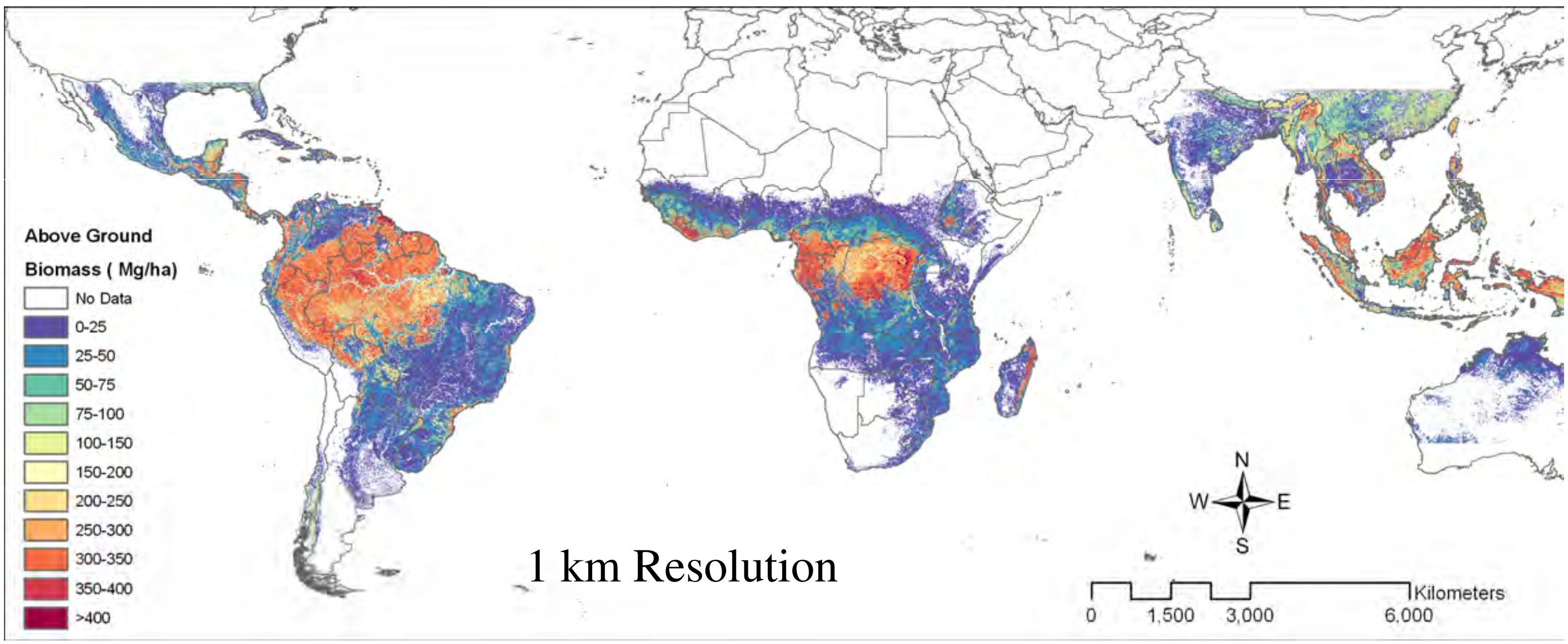
Nancy Harris, Silvia Petrova and Sandra Brown (Winrock International)

William Salas and Stephen Hagen, Applied Geosolutions

Fred Stolle and Lauriane Boisrobert (WRI)

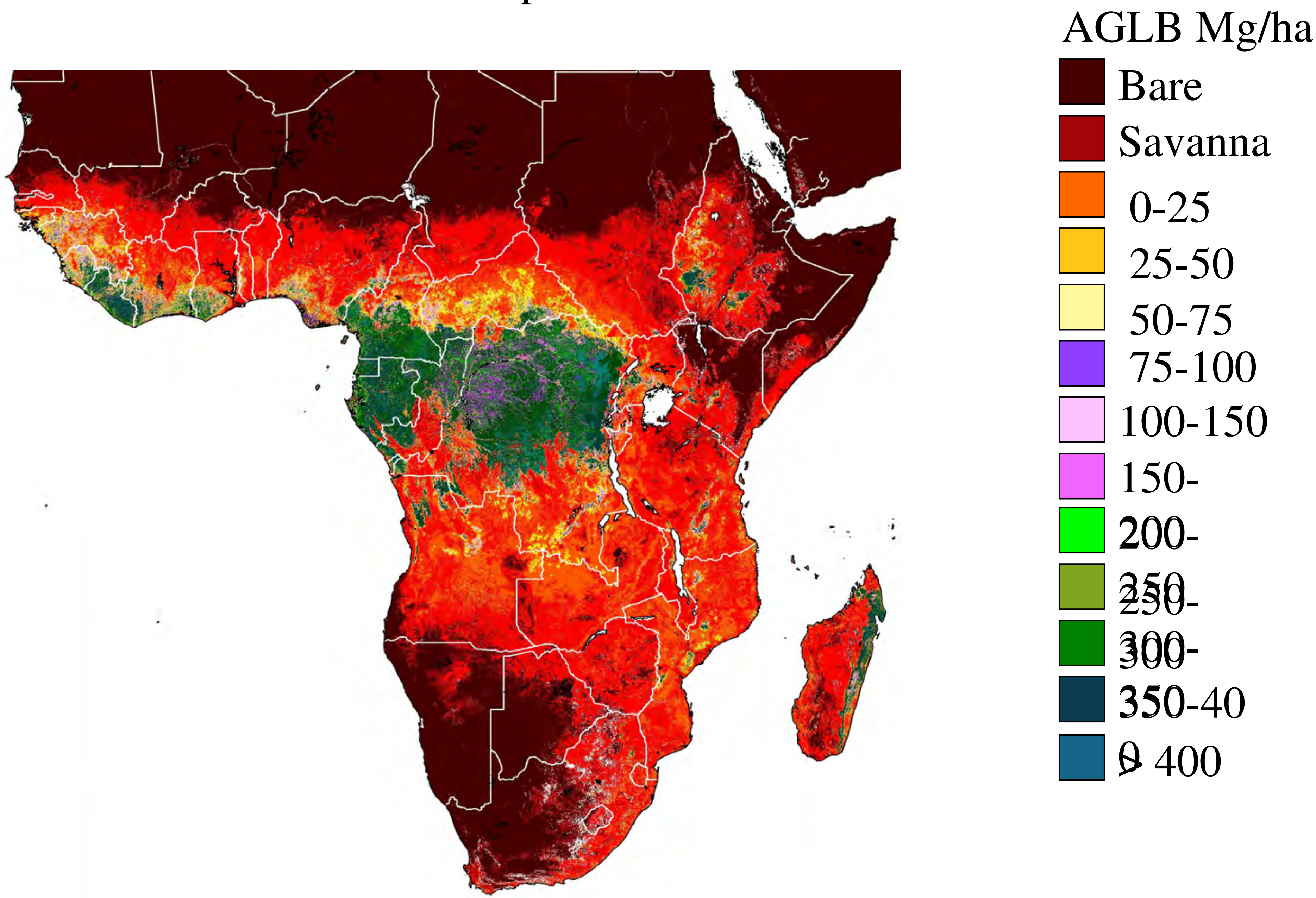
Matt Hansen (South Dakota State University)

Pan-tropical Estimates of Aboveground Biomass

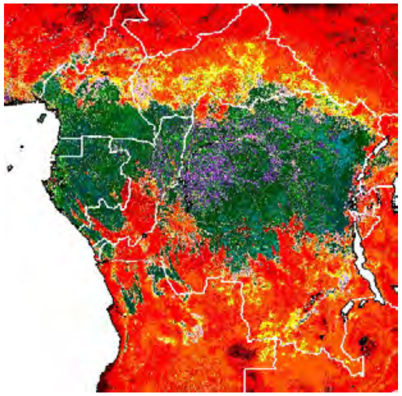


1. Ground Inventory plot data (4,087 plots)
2. GLAS lidar data (150,449 points): height converted to biomass using allometric equations
3. Nineteen satellite layers (1 km resolution)

Distribution of Aboveground Forest Biomass
In Tropical Africa



Total Carbon in Central African Forests
Circa 2000



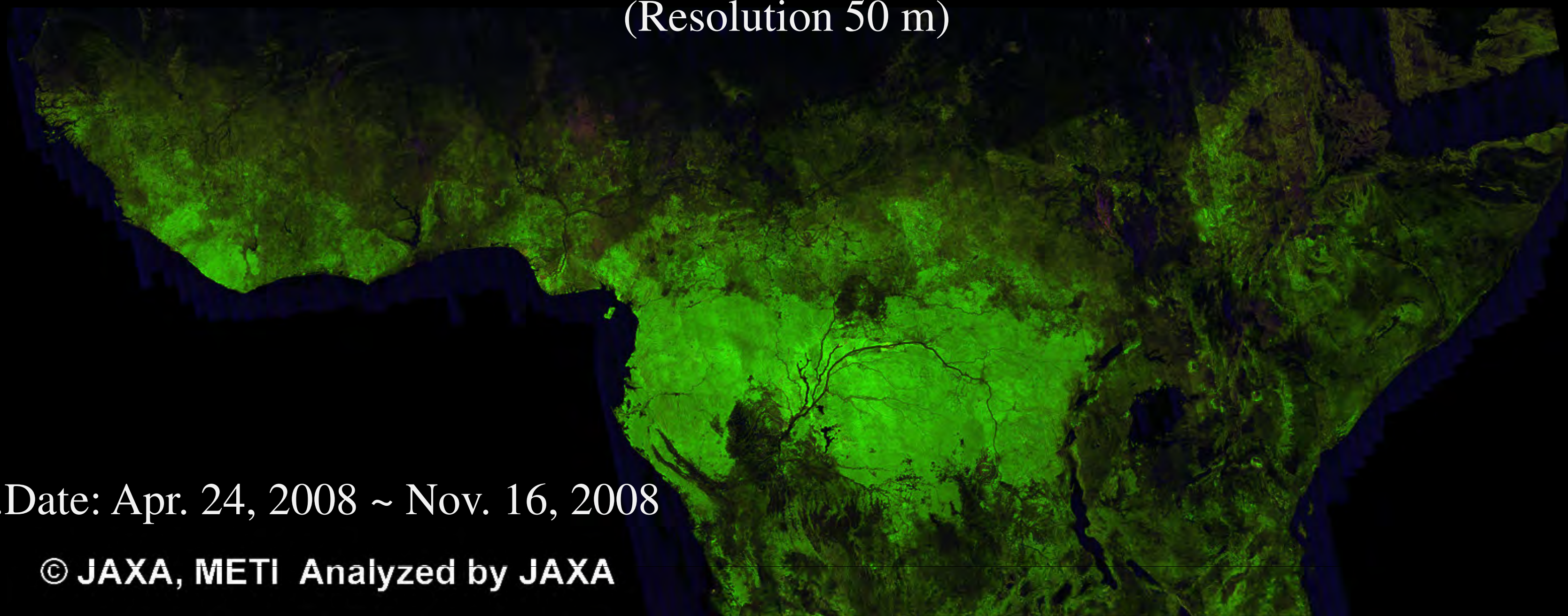
Total Carbon stocks in 2000 Forest (t C)

Country name	AG carbon	BG carbon	Total carbon
Cameroon	3,611,198,768	941,777,346	4,552,976,114
Central African Republic	1,743,934,051	492,015,859	2,235,949,910
Democratic Republic of the Congo	19,309,925,377	5,079,793,670	24,389,719,048
Equatorial Guinea	377,419,446	97,367,759	474,787,206
Gabon	3,318,669,136	856,388,067	4,175,057,202
Republic of Congo	2,984,524,266	783,744,793	3,768,269,059
Sao Tome and Principe	8,518,697	2,214,747	10,733,443
Total (t C)	**31,354,189,741**	**8,253,302,239**	**39,607,491,981**
Total (Gt C or Pg C)	**31**	**8**	**40**

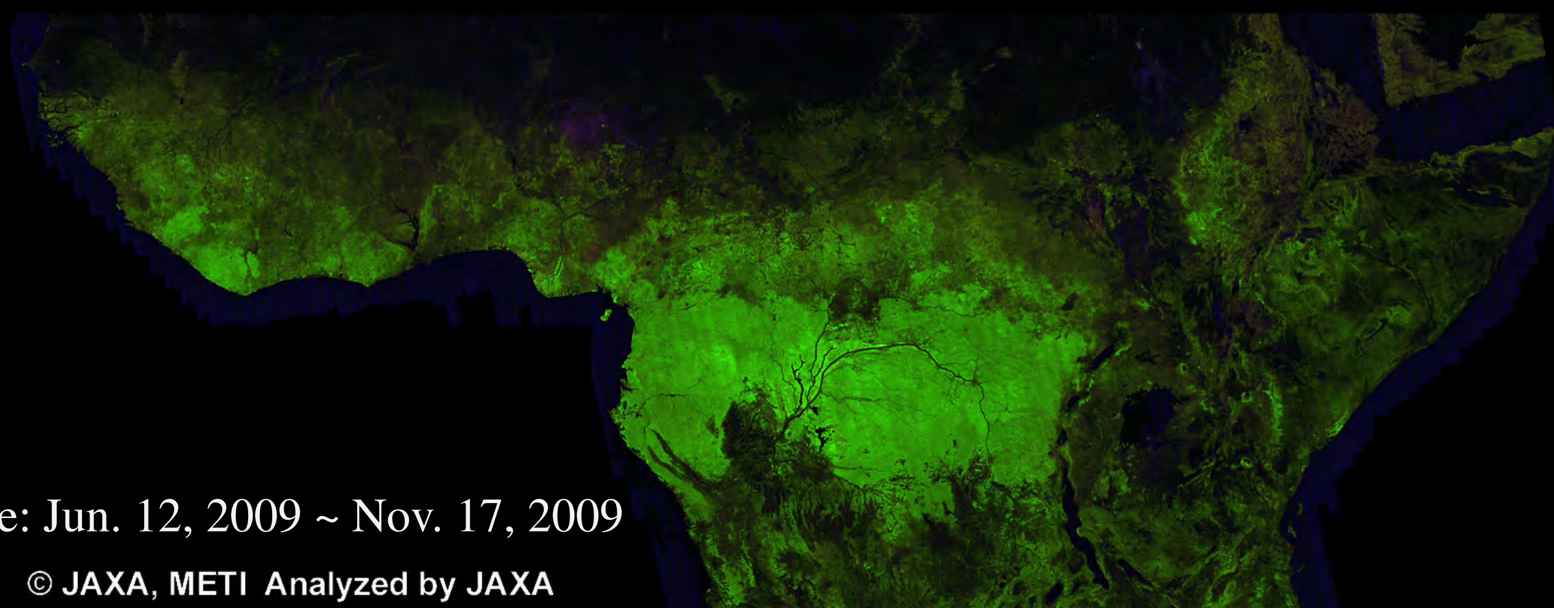
Future Work
Test Driving Prototypes

ALOS PALSAR Central Africa Mosaic

(Resolution 50 m)

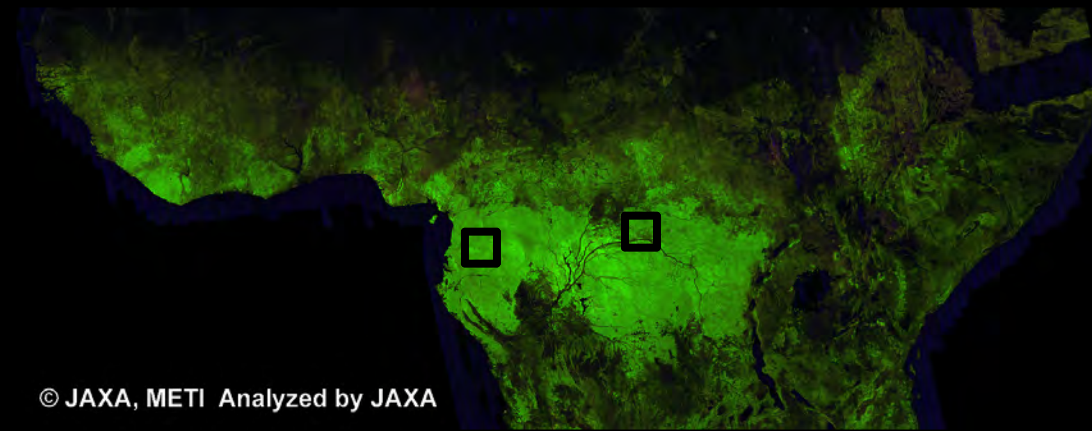


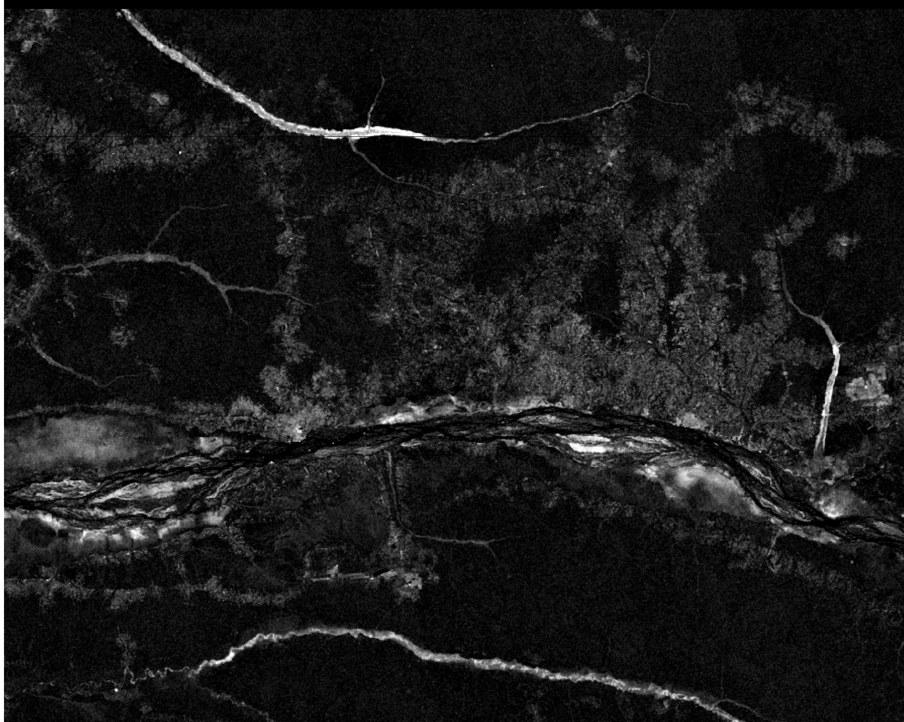
Obs.Date: Apr. 24, 2008 ~ Nov. 16, 2008

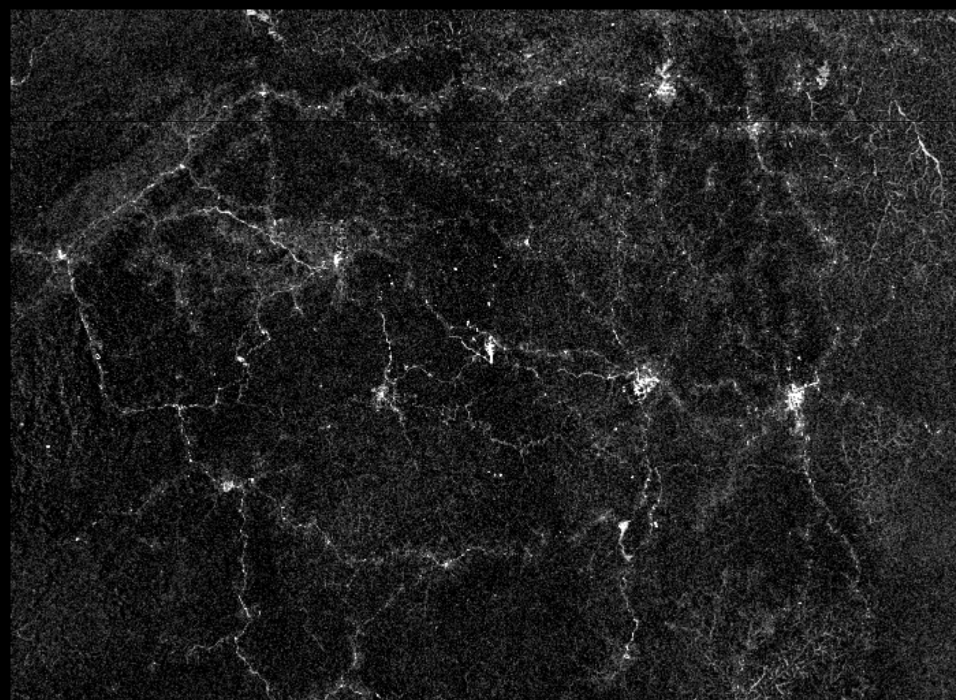


Obs.Date: Jun. 12, 2009 ~ Nov. 17, 2009

LHH
LHV
LHV Texture



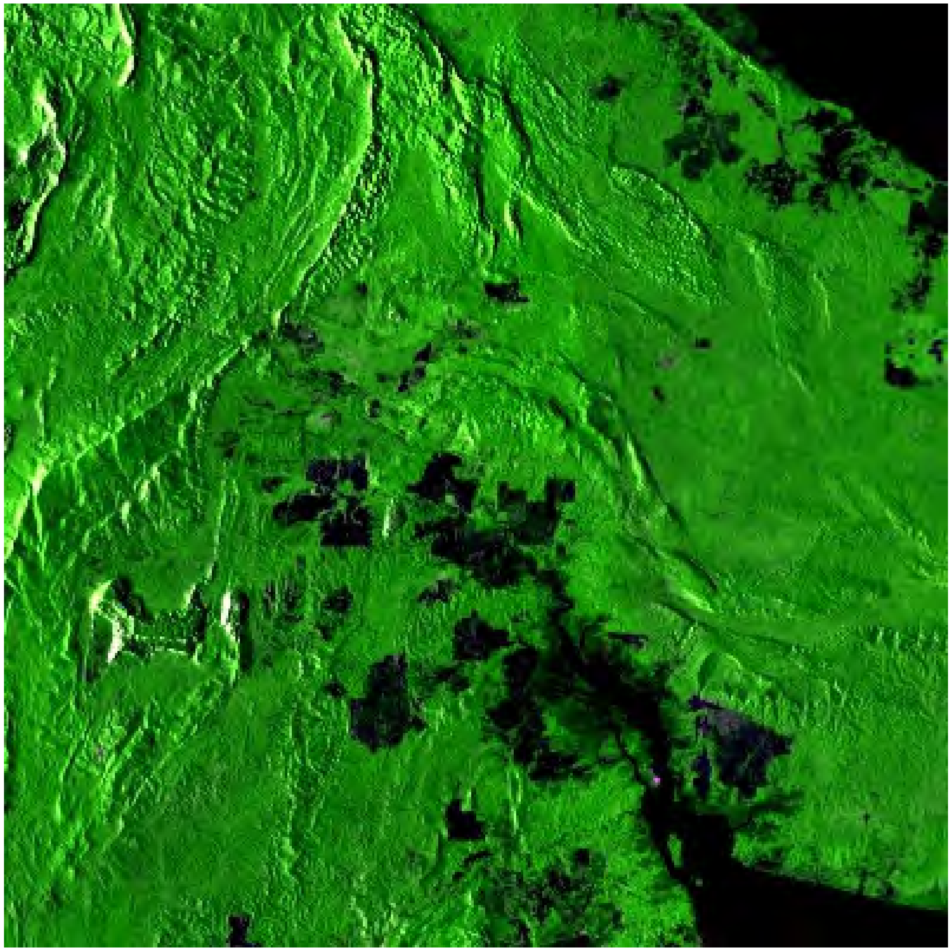




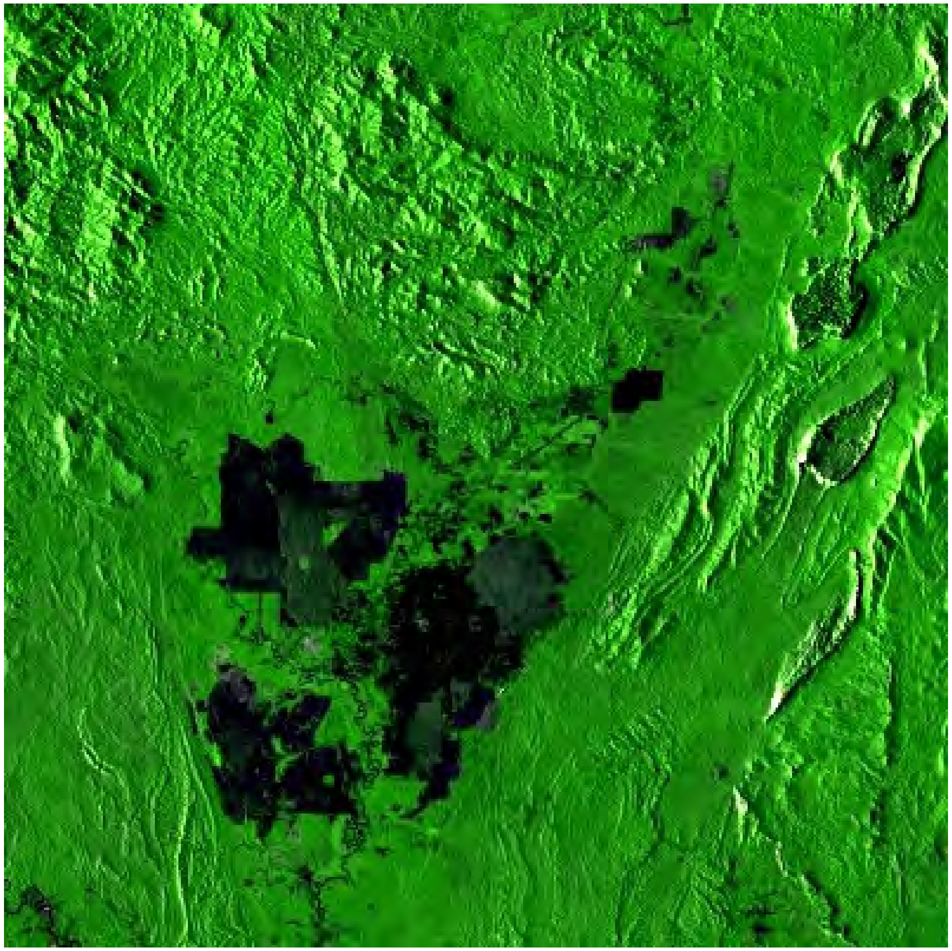
Radar Degradation Index

Monitoring Deforestation and Forest Degradation

2007

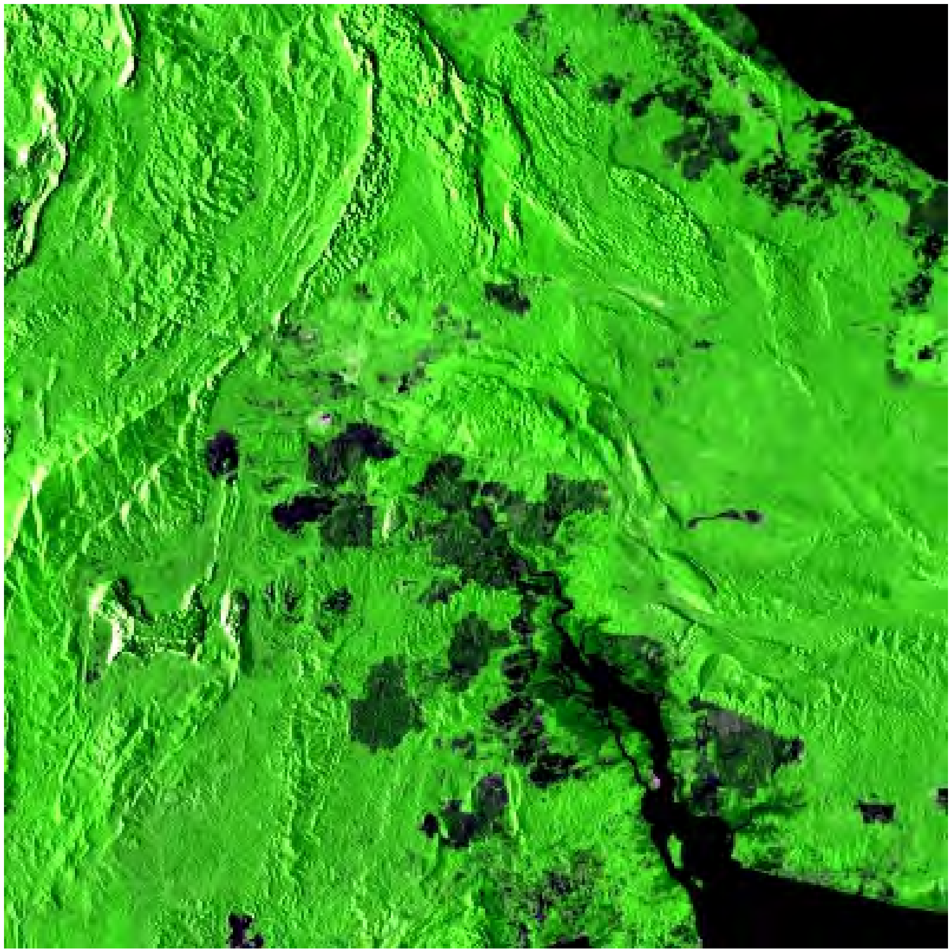


2007

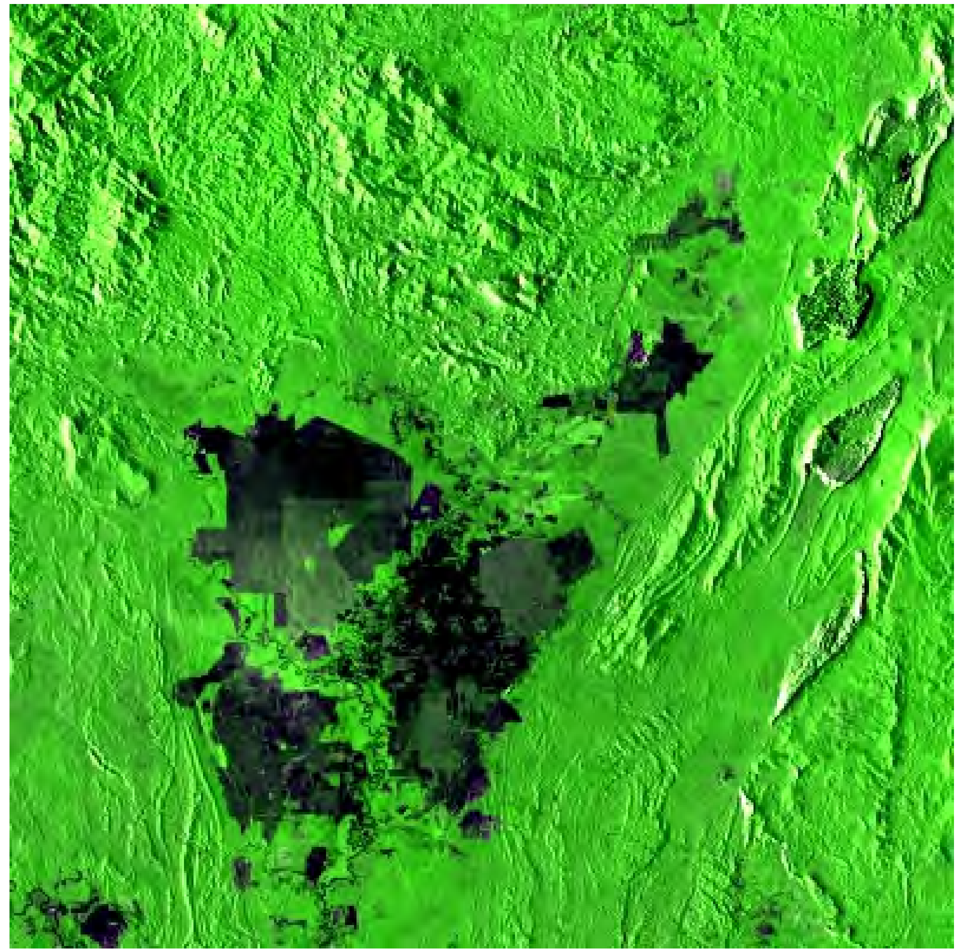


Monitoring Deforestation and Forest Degradation

2008

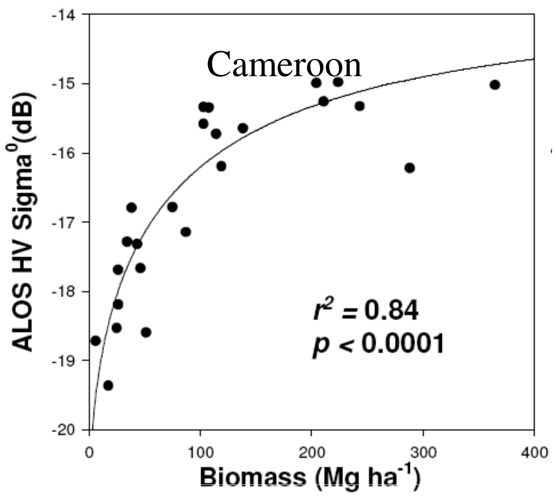


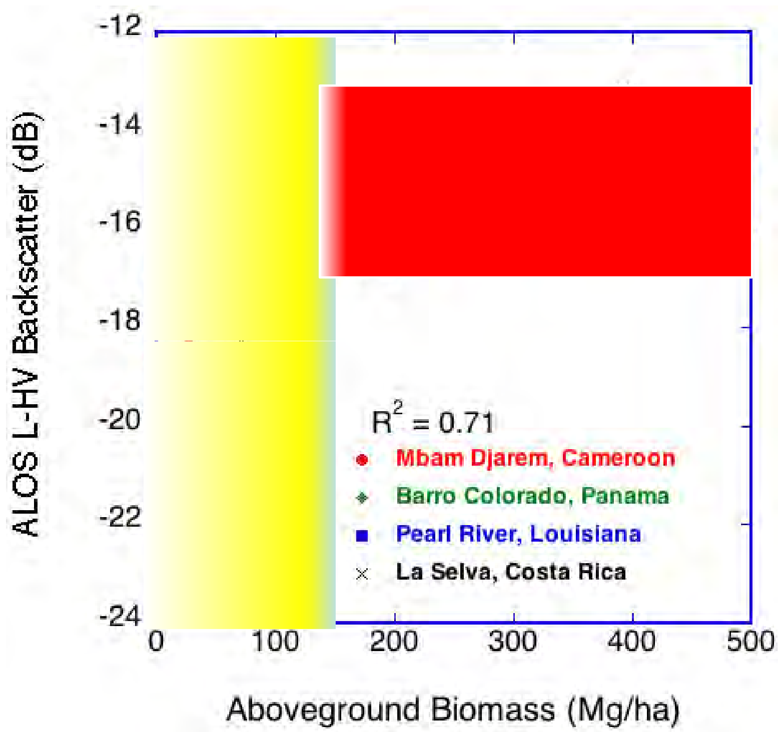
2008

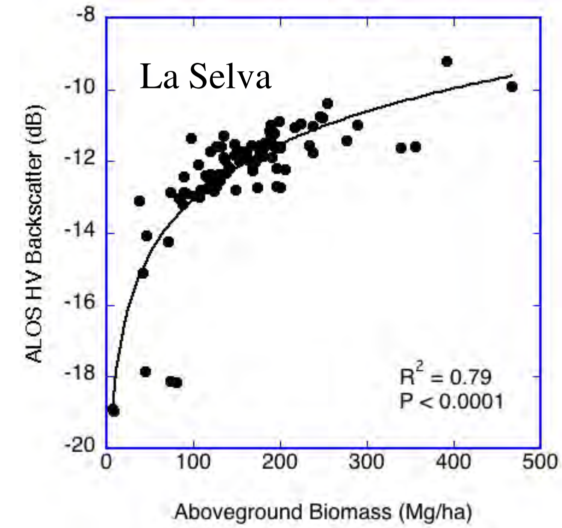


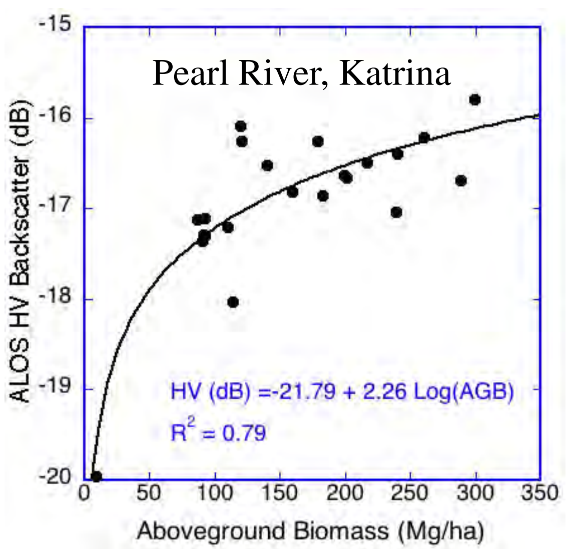
ALOS PALSAR L-HV Sensitivity to AGB

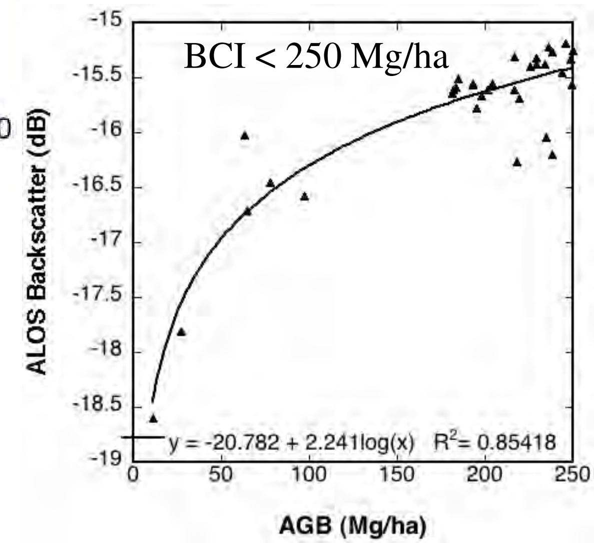
$$LHV\ (dB) = -22.5 + 3.0 Log(AGB)$$

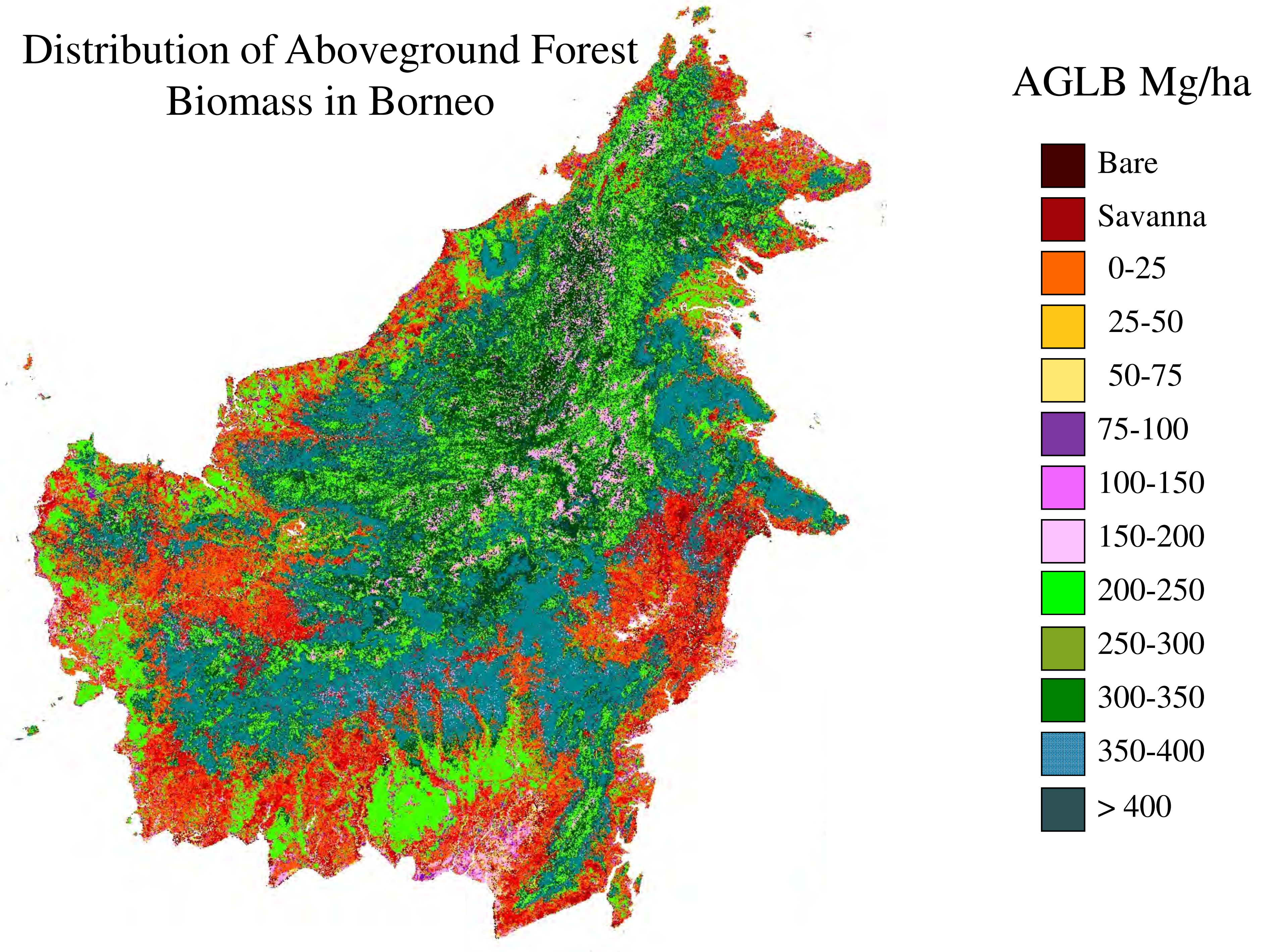




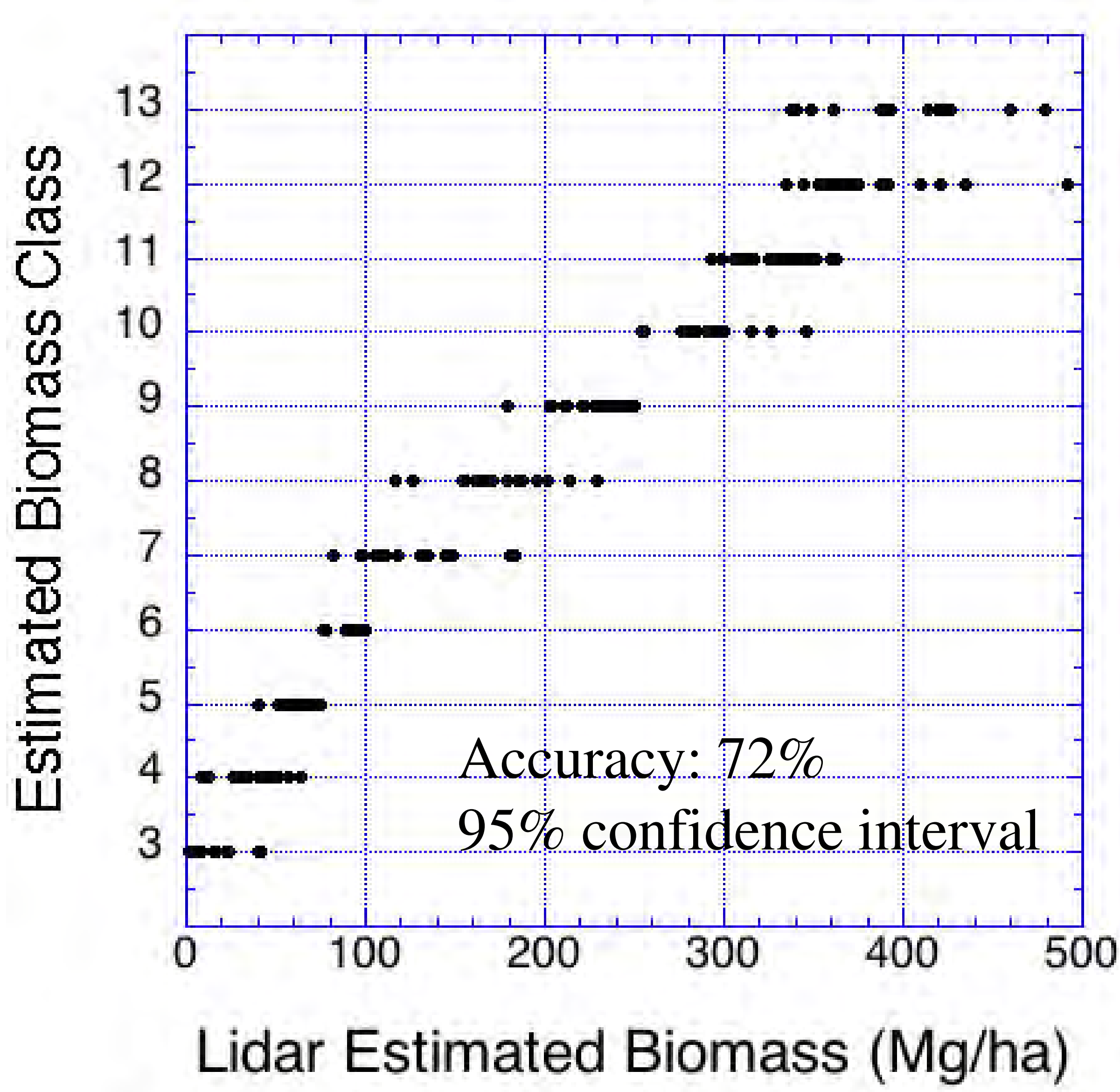






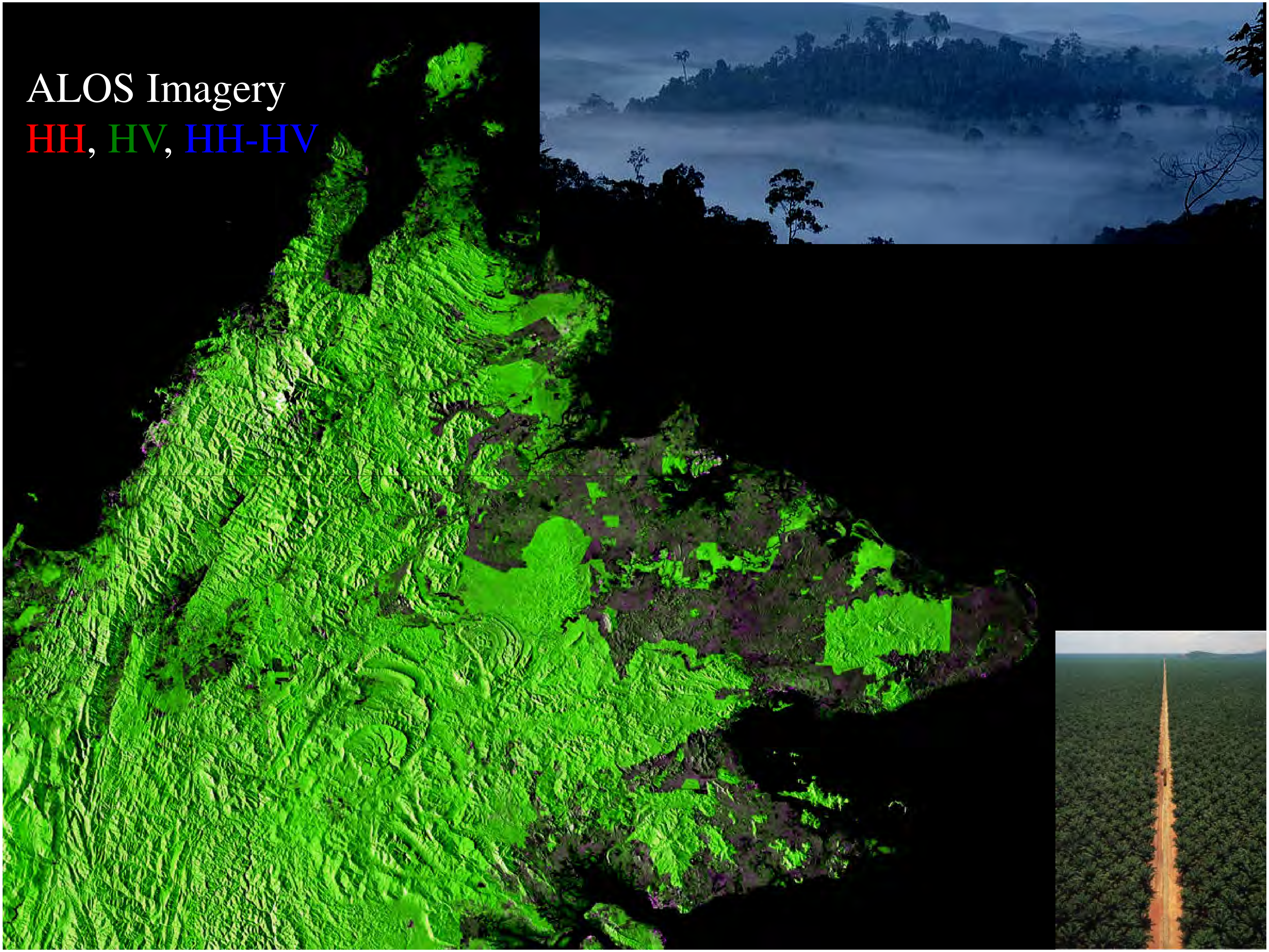

Distribution of Aboveground Forest
Biomass in Borneo
AGLB Mg/ha
Bare
Savanna
0-25
25-50
50-75
75-100
100-150
150-200
200-250
250-300
300-350
350-400
> 400

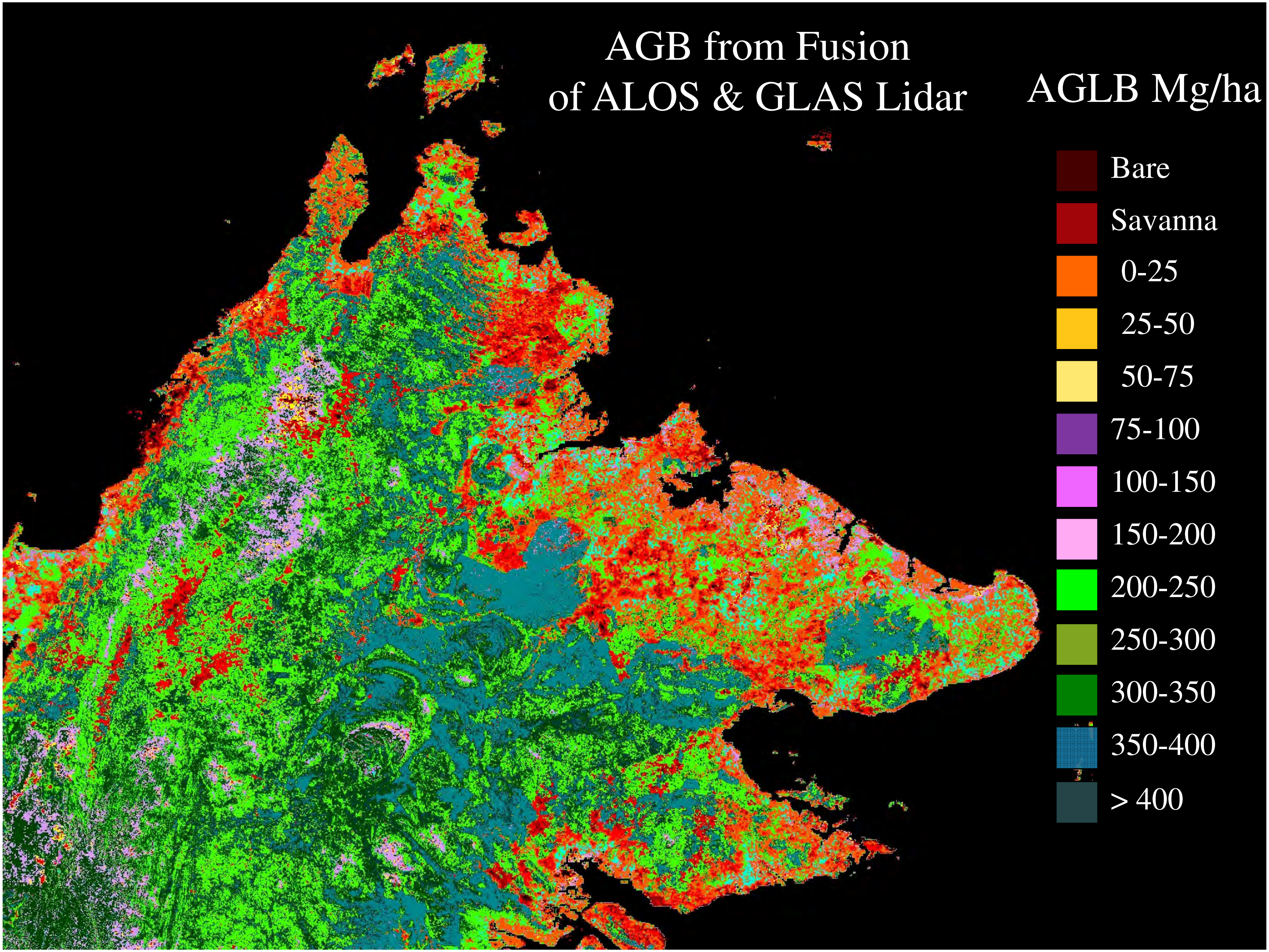
Assessment of Biomass Class Accuracy



AGB Class	AGB Mg/ha
	Bare
	Savanna
3	0-25
4	25-50
5	50-75
6	75-100
7	100-150
8	150-200
9	200-250
10	250-300
11	300-350
12	350-400
13	> 400

ALOS Imagery
HH, HV, HH-HV




AGB from Fusion
of ALOS & GLAS Lidar
AGLB Mg/ha
Bare
Savanna
0-25
25-50
50-75
75-100
100-150
150-200
200-250
250-300
300-350
350-400
> 400

SUMMARY

Ground and Satellite Data Fusion has the potential of providing global distribution of aboveground biomass

L-band PALSAR can measure forest disturbance and recovery at 100 m spatial resolution. Seasonality of moisture and phenology will impact the estimation.

National level estimation can be achieved at reasonable accuracy However, spatial accuracy is variable.

Standardizing and increasing inventory plots will improve accuracy of biomass distribution

New allometry is required for tropical forests with consideration of spatial scales of satellite data.