



Universidade Federal do ABC

Combining RADAR and optical images with LIDAR for biomass estimation in Tropical Forests

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Workshop Improving Biomass
Estimation Methods for the
Amazon (FUNCATE/INPE)

Overview

- Biomass estimation in tropical forests
 - ✓ Importance
 - ✓ Challenges
- Remote sensing and biomass estimation
 - ✓ Optical approach
 - ✓ RADAR approach
 - ✓ LIDAR approach
- Multisensor approach for biomass estimation
- Future prospects

Tropical Forest

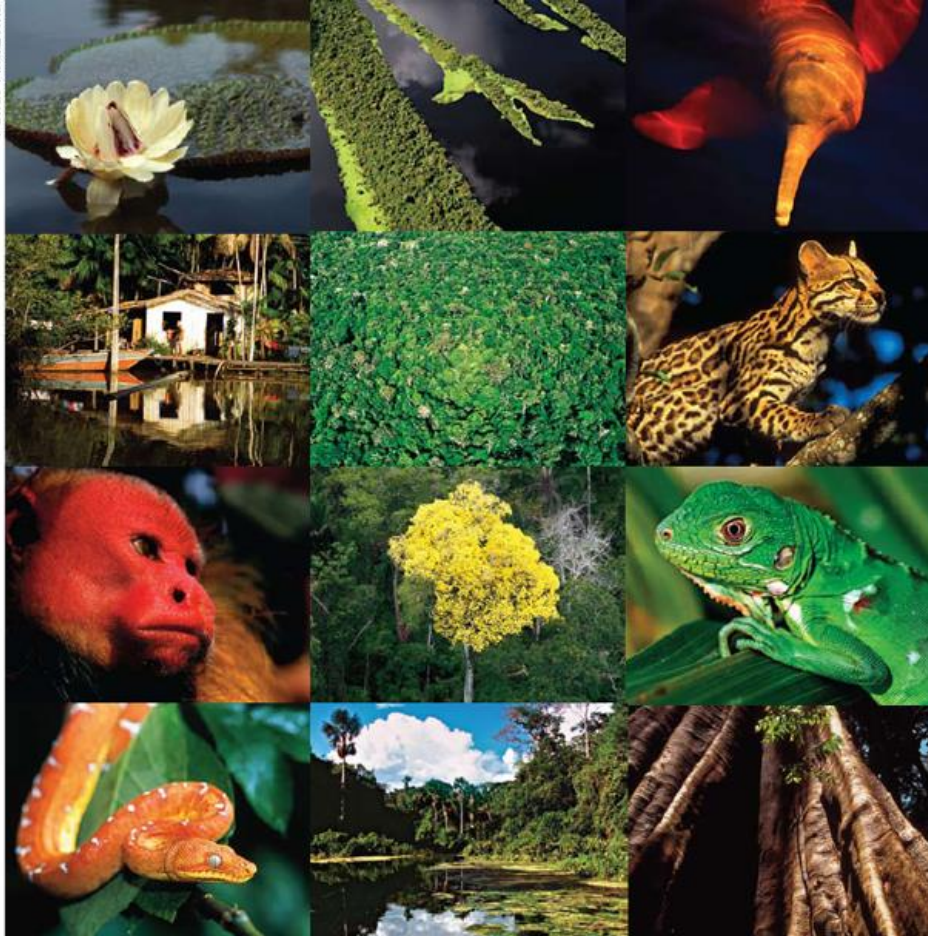
The most complex terrestrial ecosystem in the world



<https://animalcorner.co.uk/rainforests/>

Why is the Tropical Forest so important?

Fundo Amazônia



High biodiversity



- ❖ Great environmental variability
- ❖ High complexity of the relationships
- ❖ Typical ecologic processes

Why is the Tropical Forest so important?



- ❖ Has important role in the global carbon cycle: **50% of global terrestrial carbon is stored in this system**
- ❖ More than half of global gross primary productivity
- ❖ Sequester of large amounts of CO₂ from the atmosphere

Photograph: Ricardo Moraes/Corbis (The Guardian)

Why is the Tropical Forest so important?



- ❖ Sequester of large amounts of CO₂ from the atmosphere
- ↓
- ❖ CO₂ is stored in form of **Biomass**
- ↓
- ❖ Very important for initiatives like REDD (Reducing emissions from deforestation and forest degradation)

Photograph: Ricardo Moraes/Corbis (The Guardian)

Why is the Tropical Forest so important?

- ❖ Estimation of the **carbon** stock will **depend** on accurate **biomass** estimation!!!

**Biomass :
Essential Climate Variable**

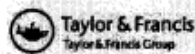
Photograph: Ricardo Moraes/Corbis (The Guardian)

The spatial distribution of forest biomass in the Brazilian Amazon: a comparison of estimates

R. A. HOUGHTON,* K. T. LAWRENCE,* J. L. HACKLER* and SANDRA BROWN†

*The Woods Hole Research Center, PO Box 296, Woods Hole, MA 02543, †Winrock International, c/o 831 NW Sundance Circle, Corvallis, OR 97330, USA

International Journal of Remote Sensing
Vol. 26, No. 12, 20 June 2005, 2509–2525



Aboveground biomass estimation using Landsat TM data in the Brazilian Amazon

D. LU

Research



Biomass Estimation

ISPRS Journal of Photogrammetry and Remote Sensing 65 (2010) 581–590

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

Journal homepage: www.elsevier.com/locate/isprsjprs



Status and future of laser scanning, synthetic aperture radar and hyperspectral remote sensing data for forest biomass assessment

Barbara Koch

Estimating biomass and biomass change of tropical forests

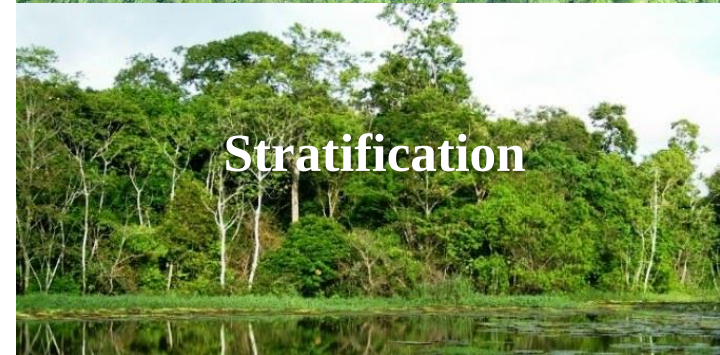
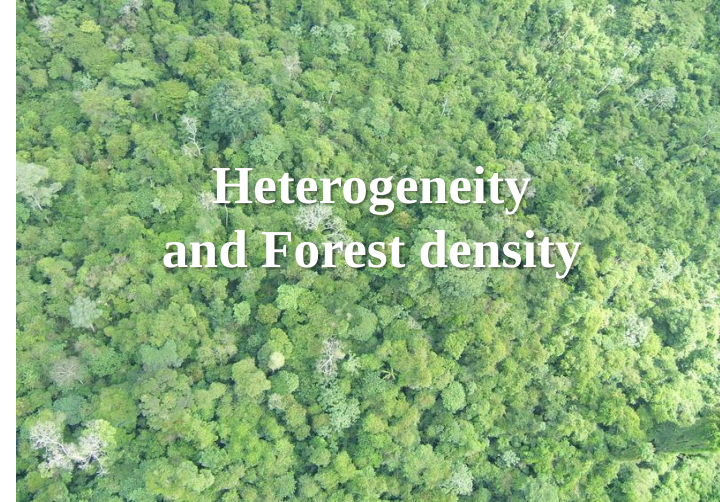
A primer

FAO
FORESTRY
PAPER

134

But there are many **challenges** to estimate the biomass of tropical forests!!

Uncertainty of
the biomass
estimation



Tropical Forest: Challenges

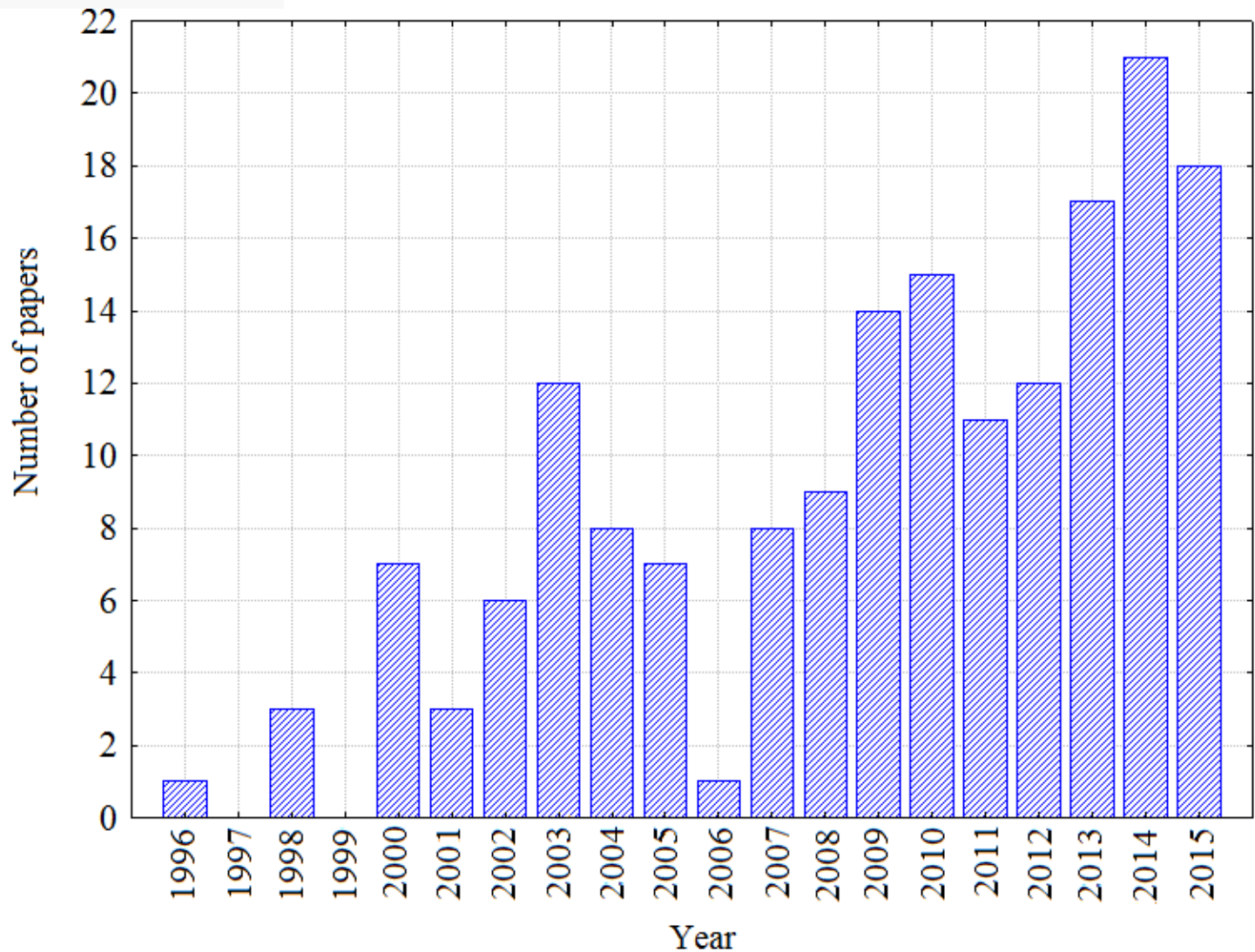
Methods and strategies

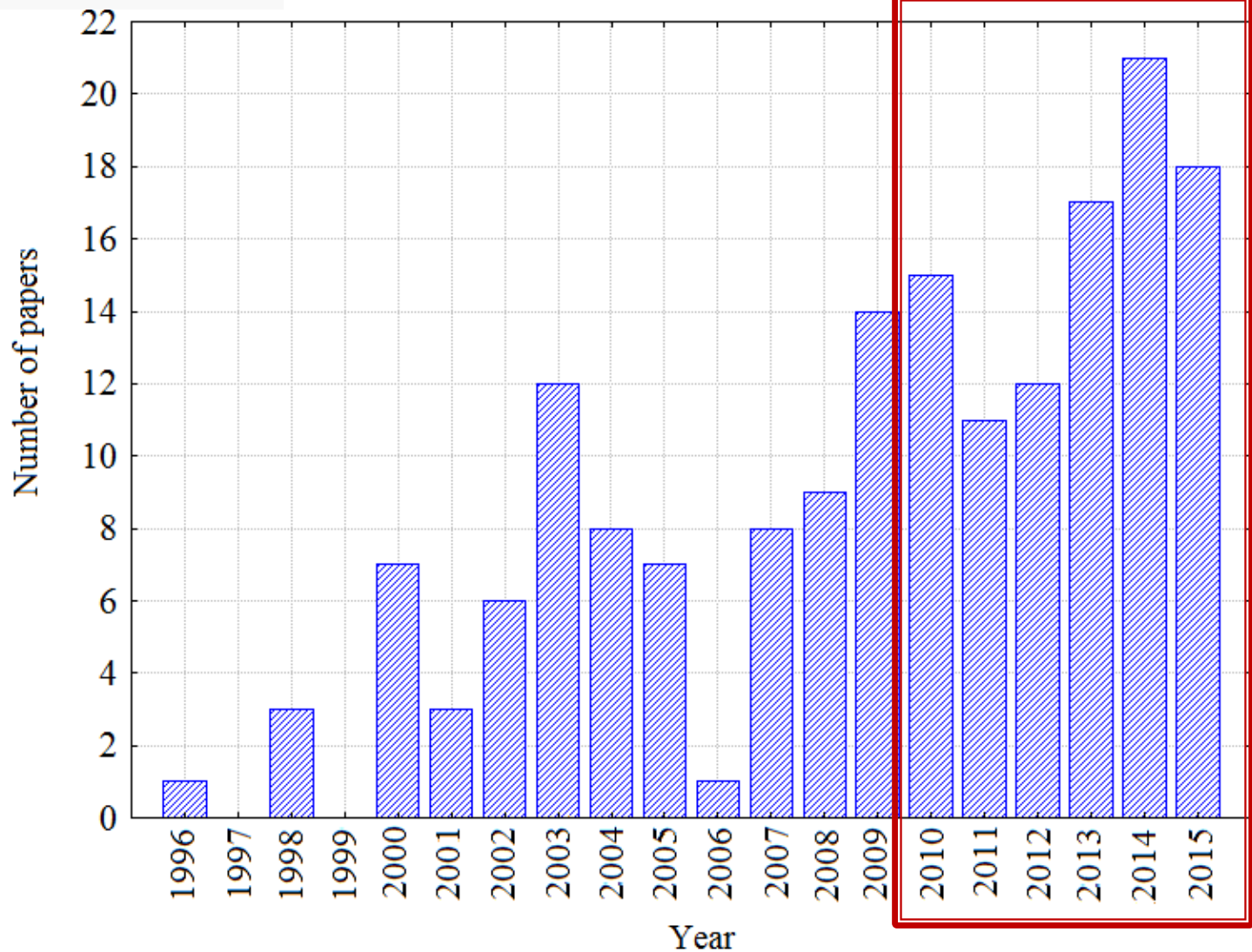


**To accurately estimate the
biomass of a complex ecosystem
as tropical forest**

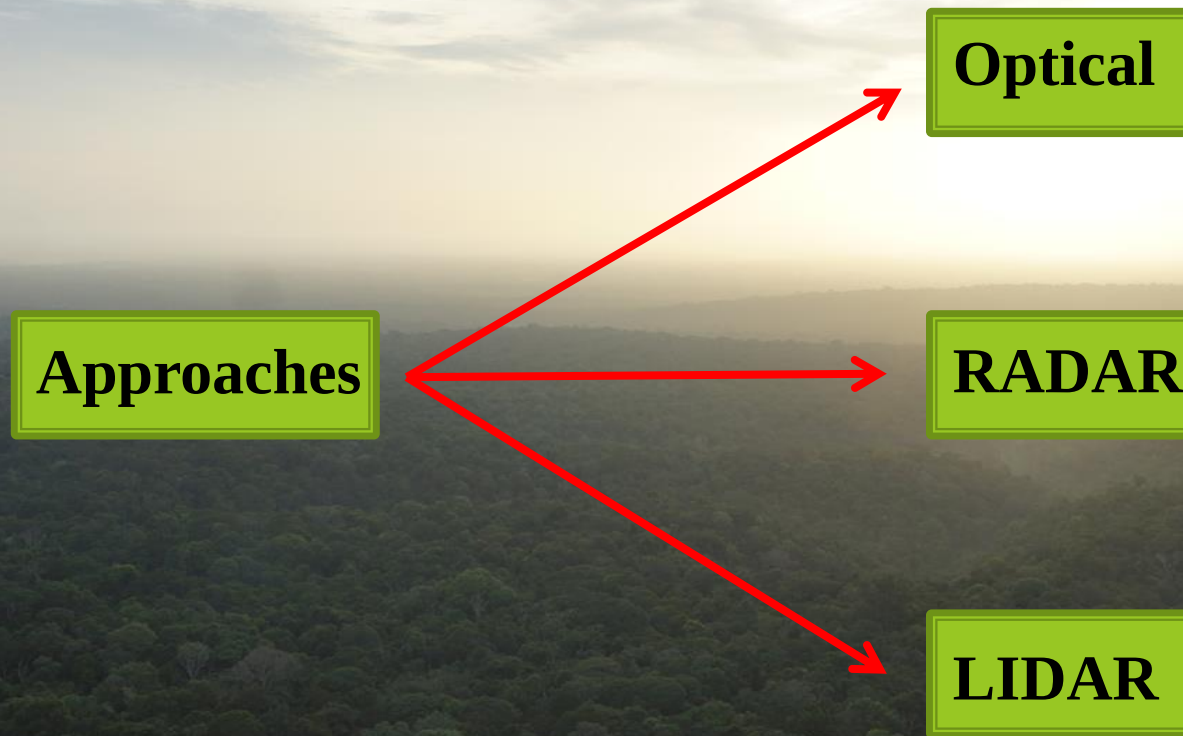


Amazon

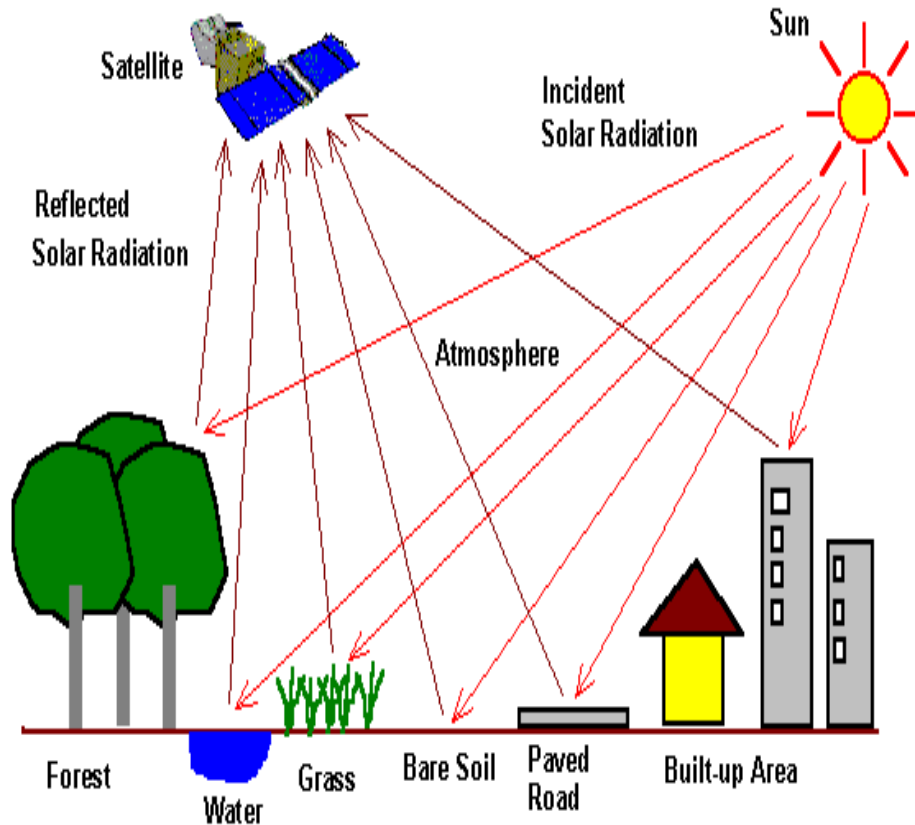
forest biomass **and** remote sensing **and** amazon

forest biomass **and** remote sensing **and** amazon

How to estimate biomass using remote sensing?



Optical Remote Sensing



❖ Passive systems → external source of energy, the sun.

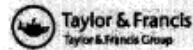
❖ The image is based on:

Spectral response of the reflected energy by the different targets and captured by the sensor

<http://www.crisp.nus.edu.sg/~research/tutorial/optical.htm>

Optical Remote Sensing

International Journal of Remote Sensing
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Aboveground biomass estimation using Landsat TM data in the Brazilian Amazon

D. LU

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Landsat has long history of data availability that have made it a primary source for biomass estimation

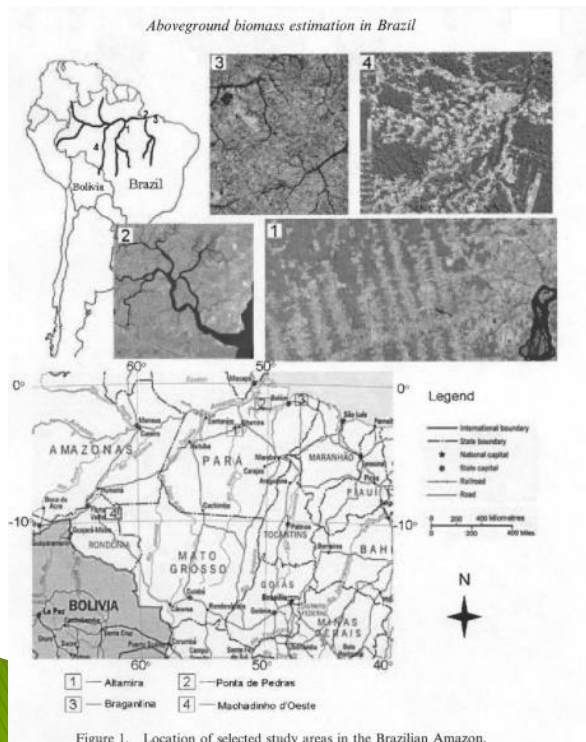


Figure 1. Location of selected study areas in the Brazilian Amazon.

Table 2. Summary of aboveground biomass estimation models using Landsat TM derived variables.

Variables	Study areas	Models	R^2	Beta Value
Spectral responses	Altamira	-49.892 - 202.045 ND54	0.404	
	Pedras*	95.196 - 5.852 TM5	0.683	
	Bragantina	68.116 - 1.832 TM4	0.701	
	Machadinho (SF)	66.772 - 1.392 TM4	0.746	
	Machadinho (MF)	102.414 - 5.496 TM5	0.158	
Textures	Altamira	89.461 - 151.495 VARTm2_9	0.708	
	Pedras*	35.109 - 6.455 KUtm3_5	0.493	
	Bragantina	21.038 - 3.766 VARTm5_15	0.304	
	Machadinho (SF)	16.462 - 0.227 VARTm4_15	0.232	
	Machadinho (MF)	13.457 + 1.929 CONtm5_19	0.392	
Combination of spectral and texture	Altamira	122.288 - 1.078 KT1 - 128.913 VARTm2_9	0.772	-0.28 (sp), -0.72 (txt)
	Pedras*	65.239 - 10.189 TM7 - 3.816 KUtm3_5	0.748	-0.58 (sp), -0.42 (txt)
	Bragantina	64.037 - 1.651 TM4 + 1.405 SKtm4_9	0.780	-0.76 (sp), 0.29 (txt)
	Machadinho (SF)	48.082 - 0.806 TM4 - 0.098 VARTm4_15	0.755	-0.71(Sp), -0.24(txt)
	Machadinho (MF)	75.331 - 4.321 TM5 + 1.789 CONtm5_19	0.498	-0.31(sp), 0.65(txt)

Note: * Ponta de Pedras; SF and MF: successional forest and mature forest; sp and txt: the variables of spectral signatures and textures; TM4, TM5, and TM7: Landsat TM bands 4, 5, and 7; ND54 is the ratio $(TM5 - TM4)/(TM5 + TM4)$; KT1: the first component from the tasseled cap transform based on Landsat TM images; VARTm_a_b: variance texture measure with TM band a and associated $b \times b$ window size; KU, SK, and CON: Kurtosis, skewness, and contrast texture measures.

Optical Remote Sensing

- Optical information is suitable for forest biomass estimation for the areas with relatively simple stand structure but does not work well for the areas with complex forest stand structure.
- So we need to combine optical datasets with other types of sensors sensing systems

Optical Approach

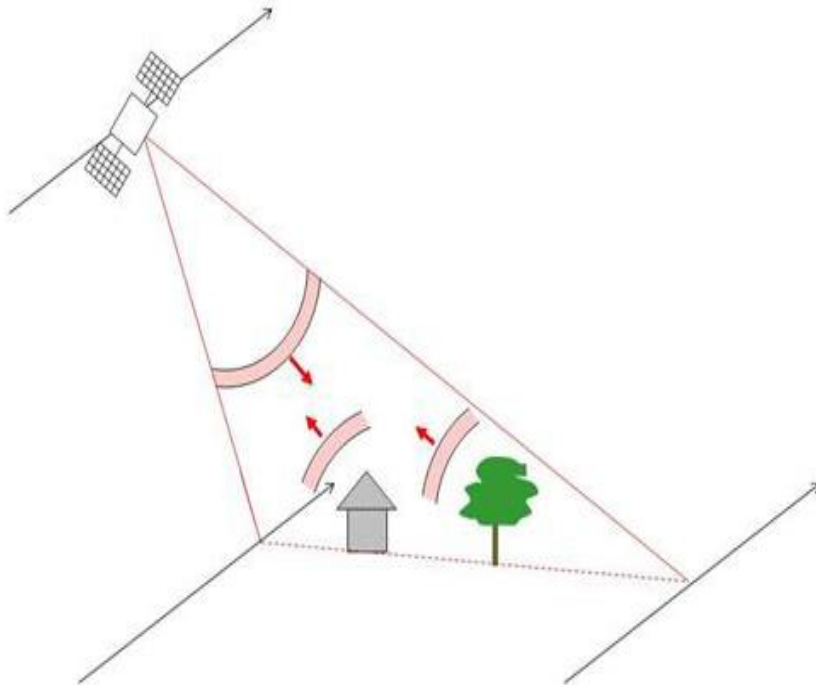
- Advantages

- ✓ Large volume of available data, long historical datasets (time series);
- ✓ The visual interpretation is more simple than other type of sensors;
- ✓ Nature of the information (physical and biochemical properties);
- ✓ Some of this data is free like the Landsat, Cbers and Rapdeye;
- ✓ Horizontal information of the forest structure.

- Limitations

- ✓ Imaging depends on the weather;
- ✓ Only provide good results in the discrimination of largely different biomass classes;
- ✓ Small changes in biomass are difficult to be detected;
- ✓ Saturation of the signal generates large uncertainty for sites with high biomass density or sites having complex forest stand structure.

SAR (Synthetic Aperture RADAR)

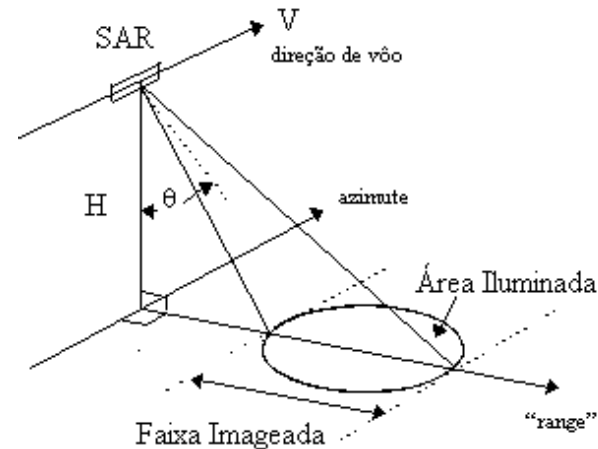


Active sensors



own energy source

❖ The sensor sends the signal in the form of microwaves that interact with the target and comes back to the sensor.



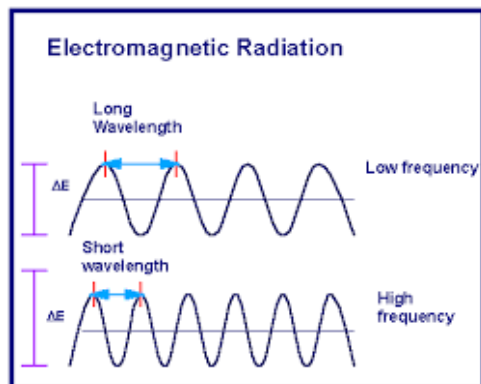
<http://www.esa.int/images/image131,4.jpg>

<http://www.dpi.inpe.br/spring/teoria/RADAR/RADAReng.htm>

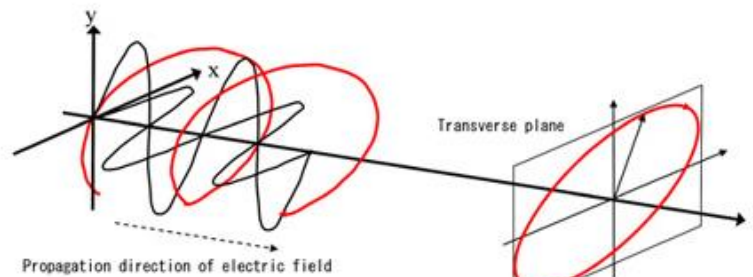
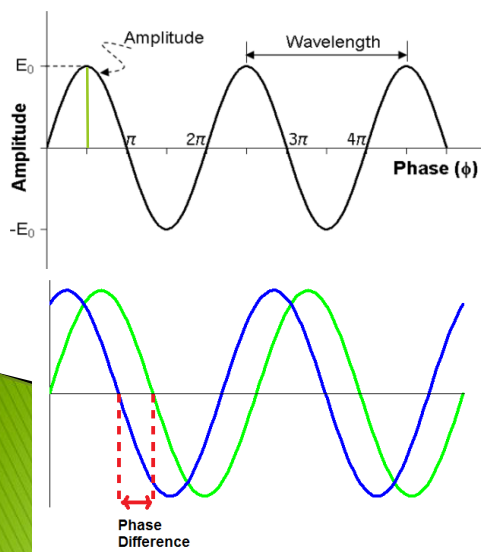
SAR (Synthetic Aperture RADAR)

Incidence Angle and Polarization

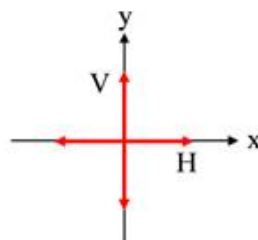
Frequency and Wavelength



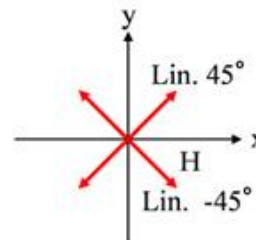
Amplitude and Phase



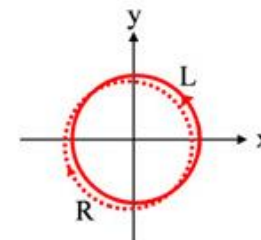
(i) Locus of an elliptically polarized wave



(a) Horizontal polarization, Vertical polarization



(b) Linear 45 degree polarization, Linear -45 degree polarization,



(c) Left circular polarization, Right circular polarization

(ii) Typical polarizations



(iii) Scattering with respect to polarization

http://www.eorc.jaxa.jp/ALOS/en/img_up/pal_polarization.htm

SAR (Synthetic Aperture RADAR)

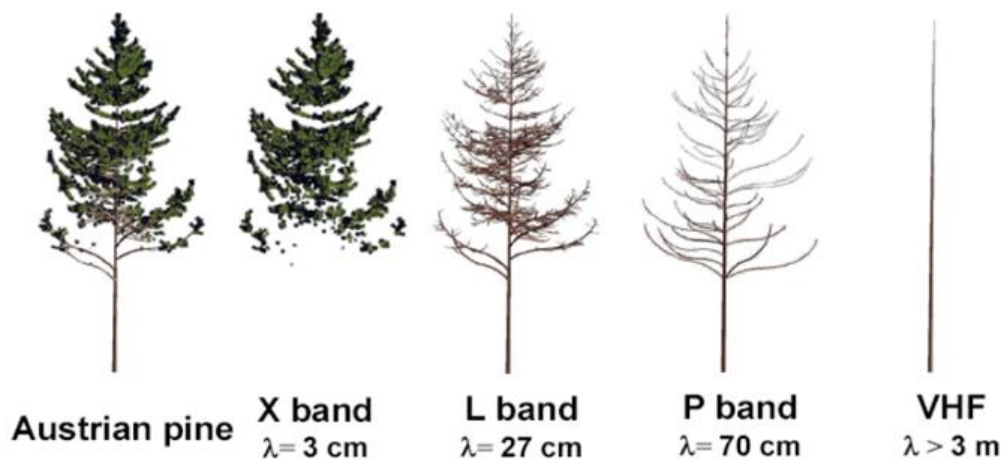
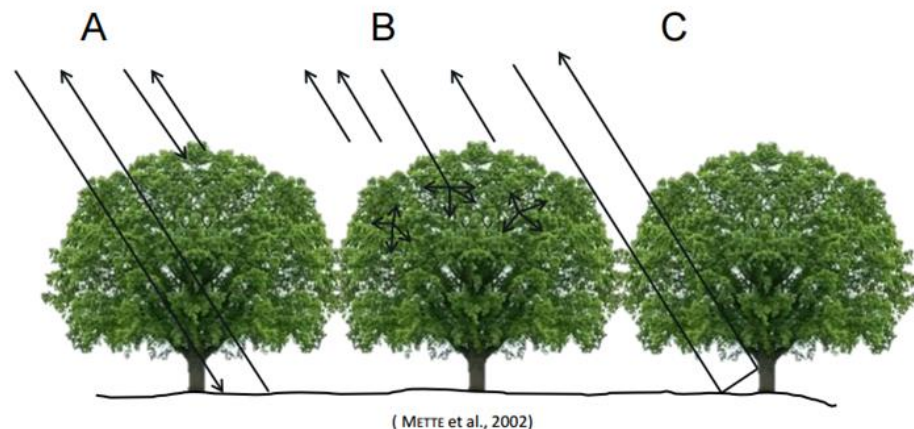
❖ This signal may interact with different parts of the forest structure by different scattering mechanisms.

❖ It can interact with the ground or only the surface of the canopy (surface scattering), or with the constituents of the canopy (volume scattering) or can interact only with soil-trunk, trunk-to-ground (double bounce scattering).

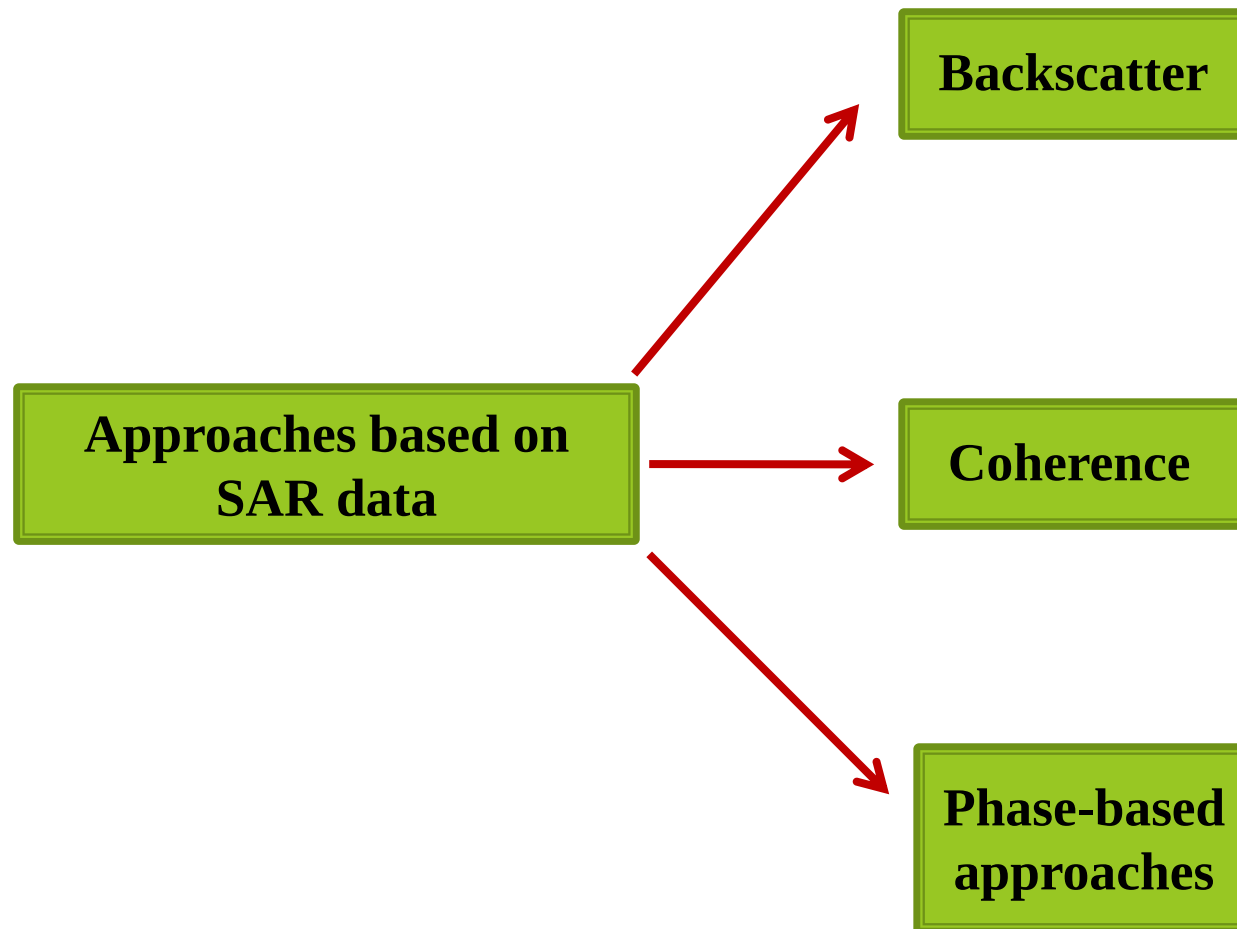
❖ SAR sensors have different penetration capabilities in accordance with the bands in which they operate.

❖ The penetration capacity increases towards longer wavelengths (X-band to P-band).

❖ Thus there are different responses of vegetation structure which have been really important in the estimation studies, quantification and monitoring of biomass in tropical forests.



Main scatterers at different frequencies (LE TOAN et al., 2001).



**Biomass mapping based
on backscatter values or
on coherence.**

Limitations

**roughness of the objects
in relation to the
wavelength**

**weather influence at
different acquisitions**

**exact
co-registration**

saturation

**Biomass mapping using
phase-based extraction
of the height.**



Limitations



**Atmospheric
decorrelation**



**Temporal
decorrelation**

Approaches based on backscatter intensities have been used to establish a relationship with biomass. However, the results show that a direct relationship with biomass is difficult to establish for areas which contain biomass greater than **40-150 Mg/ha to L-band**.

REMOTE SENS. ENVIRON. 60:1-13 (1997)
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655 Avenue of the Americas, New York, NY 10010



A Study of the Relationship between Radar Backscatter and Regenerating Tropical Forest Biomass for Spaceborne SAR Instruments

Adrian Luckman,^{*} John Baker,^{*} Tatiana Mora Kuplich,[†]
Corina da Costa Freitas Yanasse,[†] and Alejandro C. Frery[‡]

The biomass density limit of around **60Mg/ha**, above which the L-band backscatter shows no further sensitivity to increased biomass density.

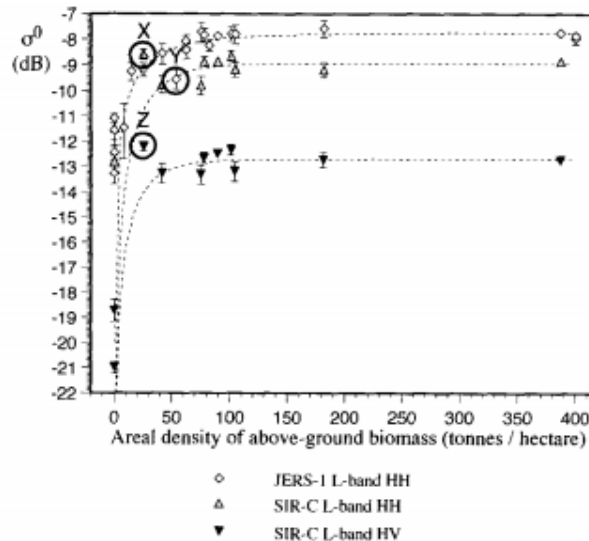


Figure 4. Backscattering coefficient versus biomass density for all L-band images studied. Sigmoid curves have been fitted to the data by least squares.

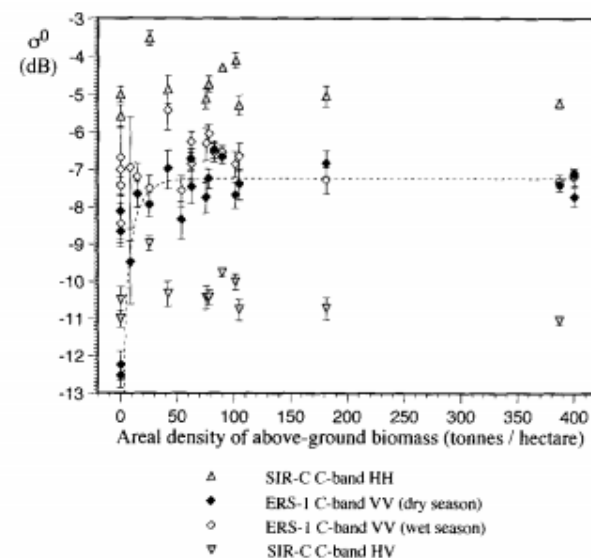


Figure 5. Backscattering coefficient versus biomass density for all C-band images studied. Sigmoid curves have been fitted to the dry-season ERS-1 data by least squares.

Today in polarimetry and interferometry there is a strong research focus not only to map deforestation and degradation as an input for biomass calculations, but also to develop better methods for **direct biomass estimation**.

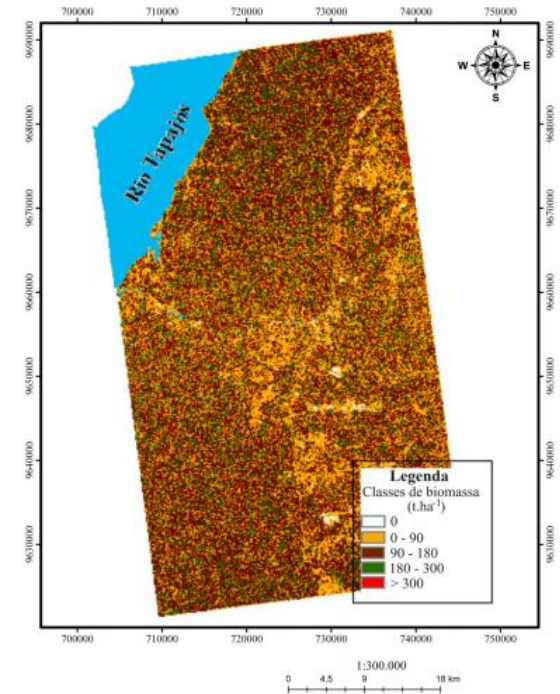
❖ Narvaes, 2010 studied the polarimetric SAR data to estimate biomass of different tropical vegetation types.

Primary and Secondary forest of Tapajós National Forest-Brazil

The explanatory variables used are composed of a range of **polarimetric attributes** considered by literature as **incoherent and coherent**, in other words, based only on the RADAR measurement of power – **amplitude data** – and additionally its **phase** information of the backscattered radiation, respectively.

Linear Multiple Regression

ALOS-PALSAR (L band), 2006, full polarimetric – HH,HV, VH, VV



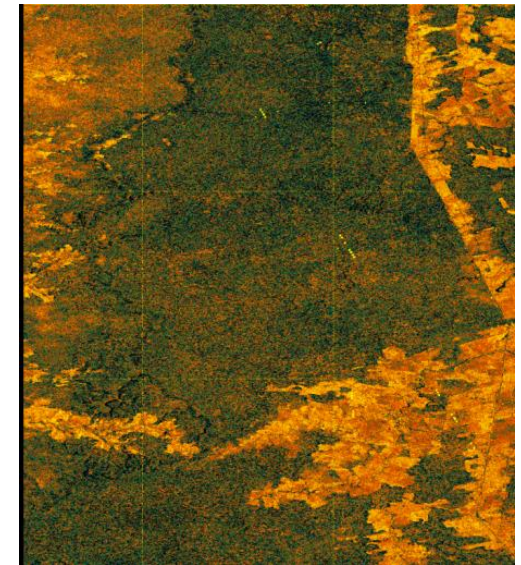
$$\text{Biomassa} = -1221,37 - 70,31 (\sigma_{HH}^0) + 1064,65 (P_V) + 6,28(\alpha_{S2}) - 2,42(\Phi_{S2}) + 3,44(\Phi_{S3}) + 6,05(\tau_m)$$

$R^2 = 0.46$
RMSE ~ 10%

Today in polarimetry and interferometry there is a strong research focus not only to map deforestation and degradation as an input for biomass calculations, but also to develop better methods for **direct biomass estimation**.

❖ Santos et al, 2014 studied the aboveground biomass of the forest successional chronosequence in a test-site of Brazilian Amazon through X- and L- band data analysis. At Tapajós National Forest - Brazil.

Verification of the capability of the **full polarimetric PALSAR/ALOS (L-band)** attributes, when combined with the **interferometric coherence (γ_i)** from the **TanDEM/TerraSAR (X-band)**, to characterize the secondary succession and to improve the AGB estimates of the chronosequence.

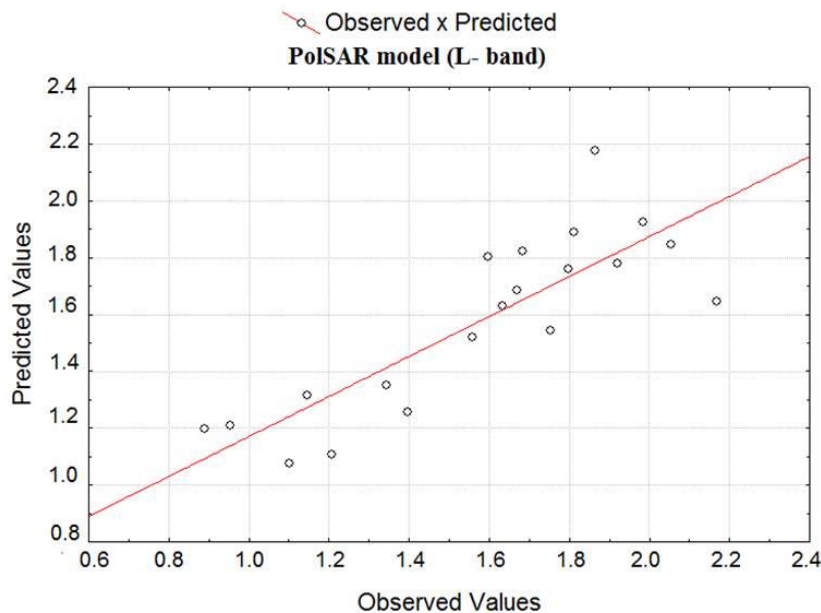


Interferometric coherence

With the joint use of HH-pol. and interferometric coherence attribute (γ_i) from TanDEM-X and PALSAR (L-band) attributes, the best regression model to estimate the biomass is expressed by:

$$R^2 = 0.70$$

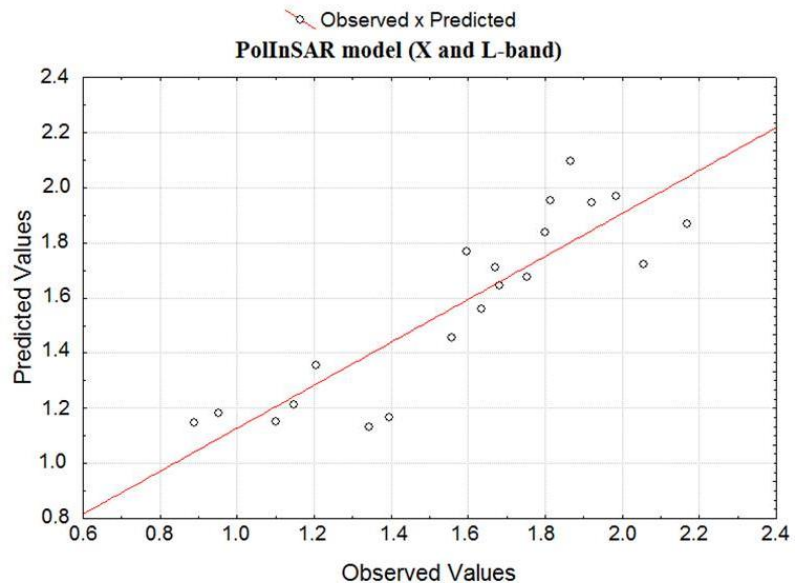
$$\log \text{AGB} = 0.701 + 5.153 * P_v - 1.454 * A$$



Estimated vs. ground-observed biomass (in log) of secondary succession for PALSAR L-band model

$$R^2 = 0.78$$

$$\log \text{AGB} = 2.963 - 2.5359 * \gamma_i + 5.26954 * P_v$$

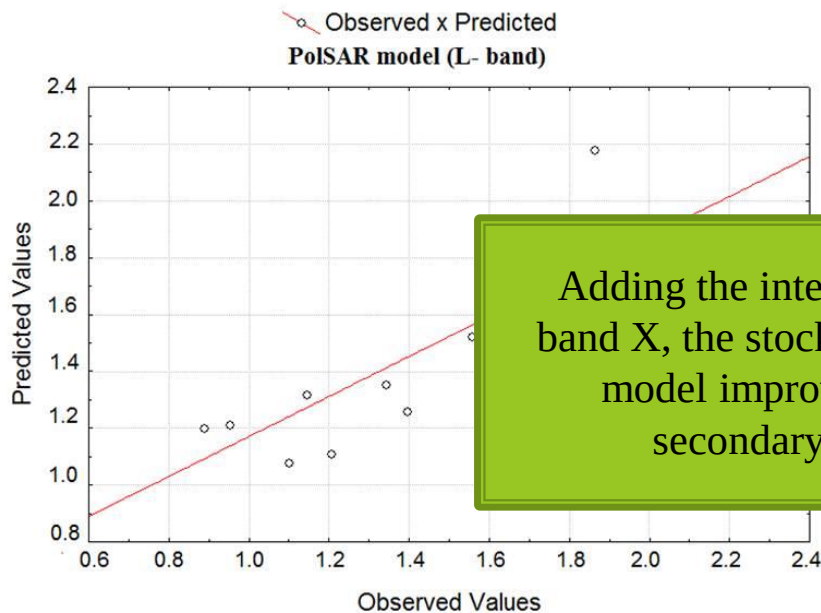


Estimated vs. ground-observed biomass (in log) of secondary succession for PALSAR combined with TanDEM X- band dataset

With the joint participation of HH-pol. of interferometric coherence attribute (γ_i) from TanDEM-X and PALSAR (L-band) attributes, the best regression model to estimate the biomass is expressed by:

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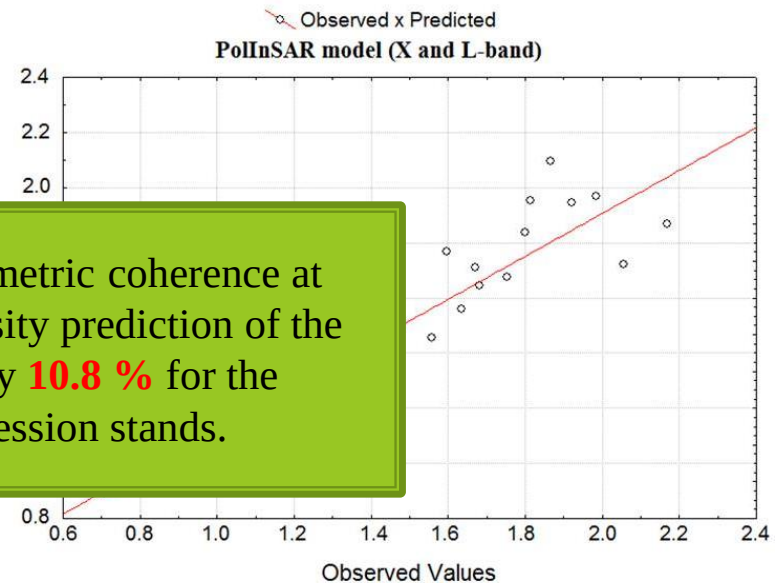
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Estimated vs. ground-observed biomass (in log) of secondary succession for PALSAR L-band model

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Estimated vs. ground-observed biomass (in log) of secondary succession for PALSAR combined with TanDEM X- band dataset

If **indirect methods** are used to estimate biomass, the most important single forest variable is the **tree or canopy height**. Only SAR interferometric techniques such as repeat pass or single pass interferometry (InSAR), polarimetric interferometry (PolInSAR) and tomography can provide this information

- ❖ Santos et al, 2004 studied the potential of dual frequency SAR interferometry (X and P bands) for biomass mapping in tropical forest. At Tapajós National Forest - Brazil.

The airborne SAR images were obtained by a system developed by AeroSensing RadarSysteme GmbH Company, that acquires both P (polarimetric) and X- band interferometric data. This radar system provides P band ($\lambda = 72$ cm), obtained with a middle frequency of 415 MHz, band-width of 70 MHz, depression angle of 45° , range resolution of 1.5 m and azimuth resolution of 0.7 m, for 1 look slant range image. The X band imagery have a pixel up to 0.5 m of ground range resolution, with HH polarization, middle frequency of 9.6 GHz and 400 MHz band-width.

Linear Multiple Regression

$$\text{biomass} = 44.965 + 13.887 \times h_{int} + 10.556 \times \sigma_{HH}$$

$$R^2 = 0.89$$
$$\text{RMSE} = 20\text{-}40 \text{ ton/ha}$$
$$\sim 10\%$$

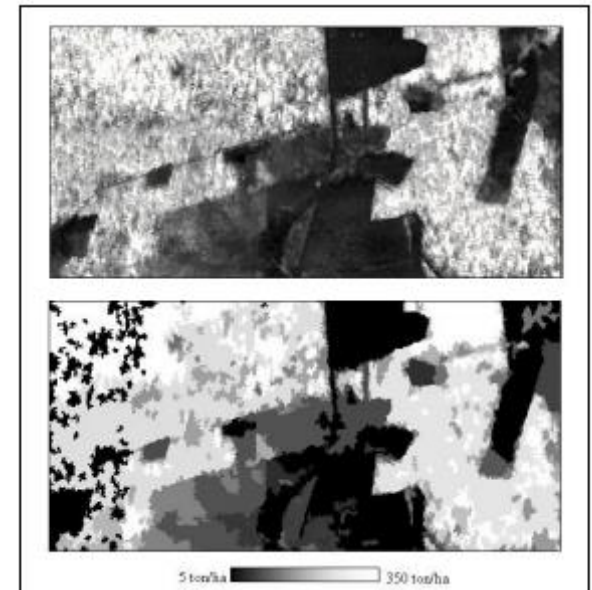
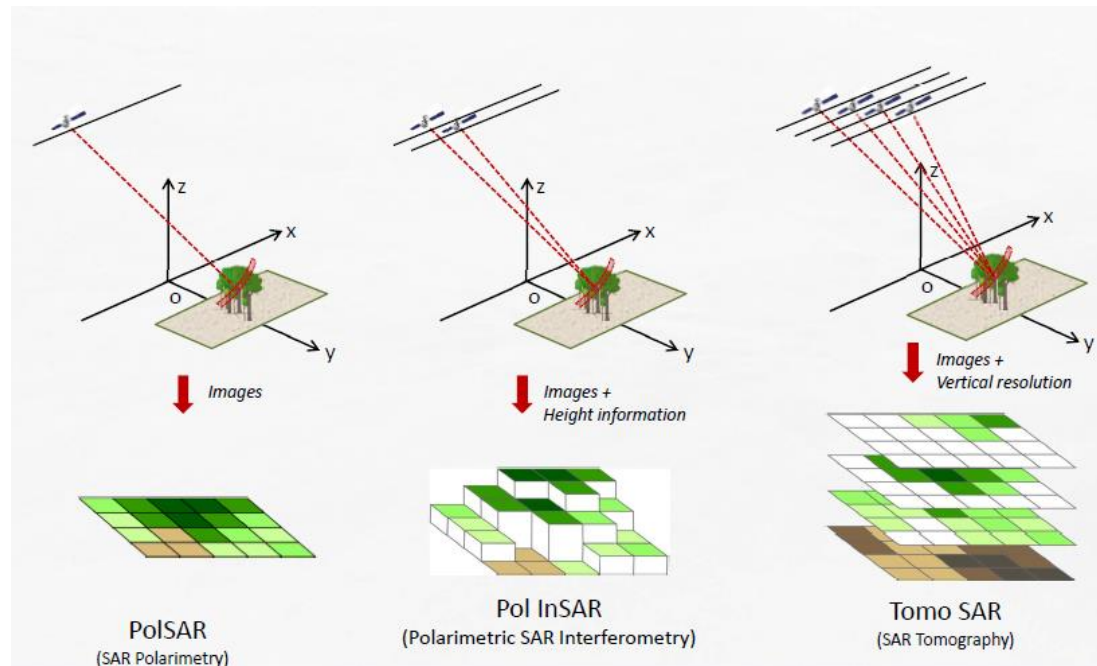


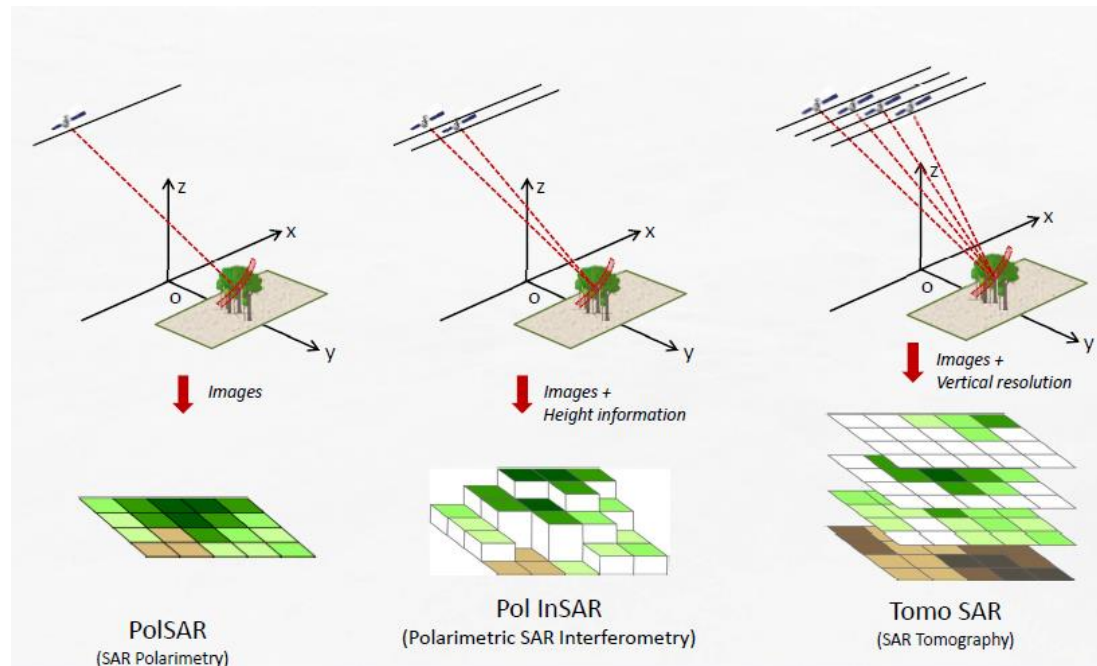
Figure 3. Section of SAR interferometric height image and biomass distribution map of land cover classes in the Tapajós region. In the above figure, the dark areas correspond to deforested areas (mainly pastures), the brightest grey levels are primary forest, intermediate variations in tone reflect forest successional stages.

A recent approach to extract forest height and stand structure from RADAR data is the use of **tomography methods**



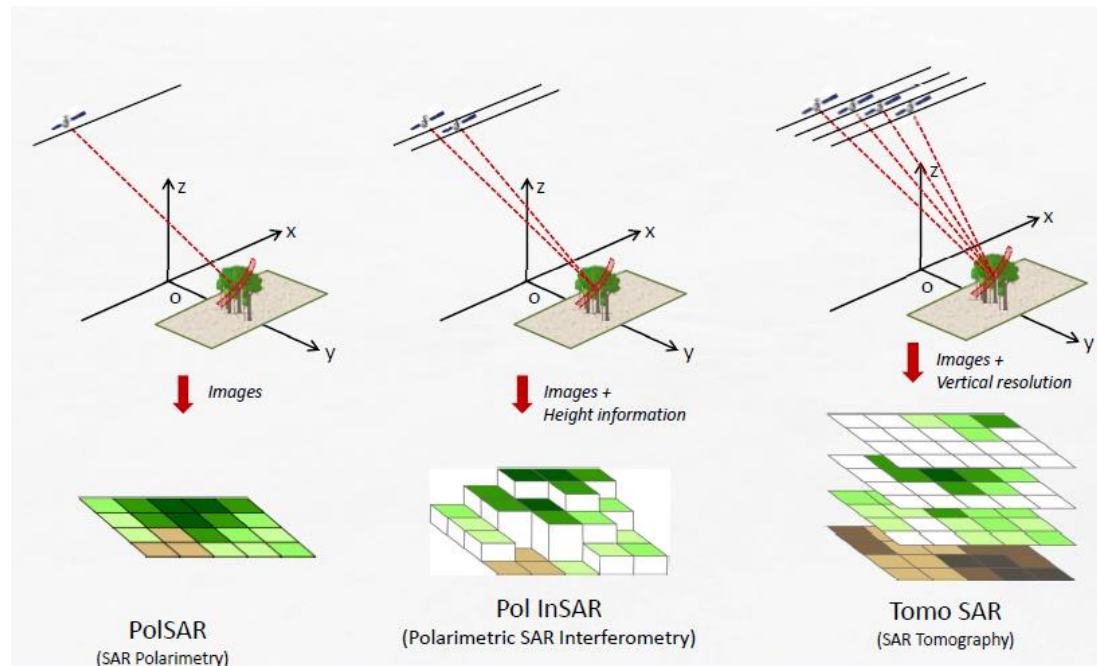
The polarimetric SAR image constituted by pixels whose polarimetric backscatter signal contains information on the surface (the ground and forest canopy).

A recent approach to extract forest height and stand structure from RADAR data is the use of **tomography methods**



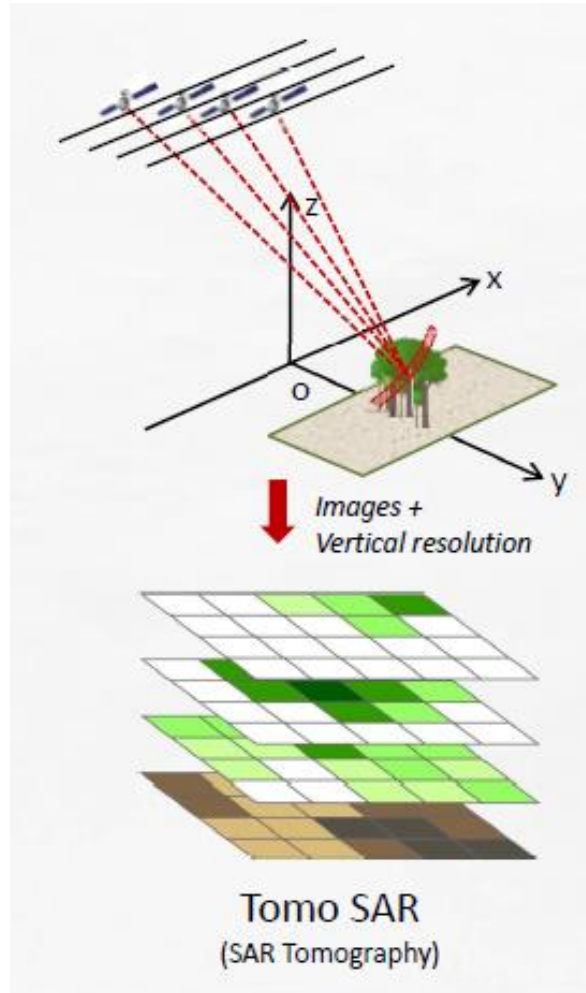
PolInSAR technique -based on two or more images in repeat pass acquisitions- combines interferometry and polarimetry to measure the canopy height.

A recent approach to extract forest height and stand structure from RADAR data is the use of **tomography methods**



With more repeat passes, SAR Tomography can analyze the distribution of the backscattering energy at different heights, thus is able to separate different targets inside the same pixel.

A recent approach to extract forest height and stand structure from RADAR data is the use of **tomography methods**



❖ There are not many investigations on the SAR tomography in tropical forest and they all are at a very early research stage.

❖ But these methods have some problems that need to be solved like that the **high intensity values within tomography images** are accompanied by considerable **side lobes and ambiguities in the normal direction**.

❖ The **suppression of the ambiguities** is one of the main **challenges** in order to improve the quality of tomography images.

A different approach SAR attributes and topography information

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Copyright © CASI
ISSN: 0703-8992 print / 1712-7971 online
DOI: 10.1080/07038992.2014.913477



Integration of Polarimetric PALSAR Attributes and Local Geomorphometric Variables Derived from SRTM for Forest Biomass Modeling in Central Amazonia

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¹*European Space Agency-ESA/ESRIN, Via Galileo Galilei, Casella Postale 64, 00044 Frascati, Roma, Italy*

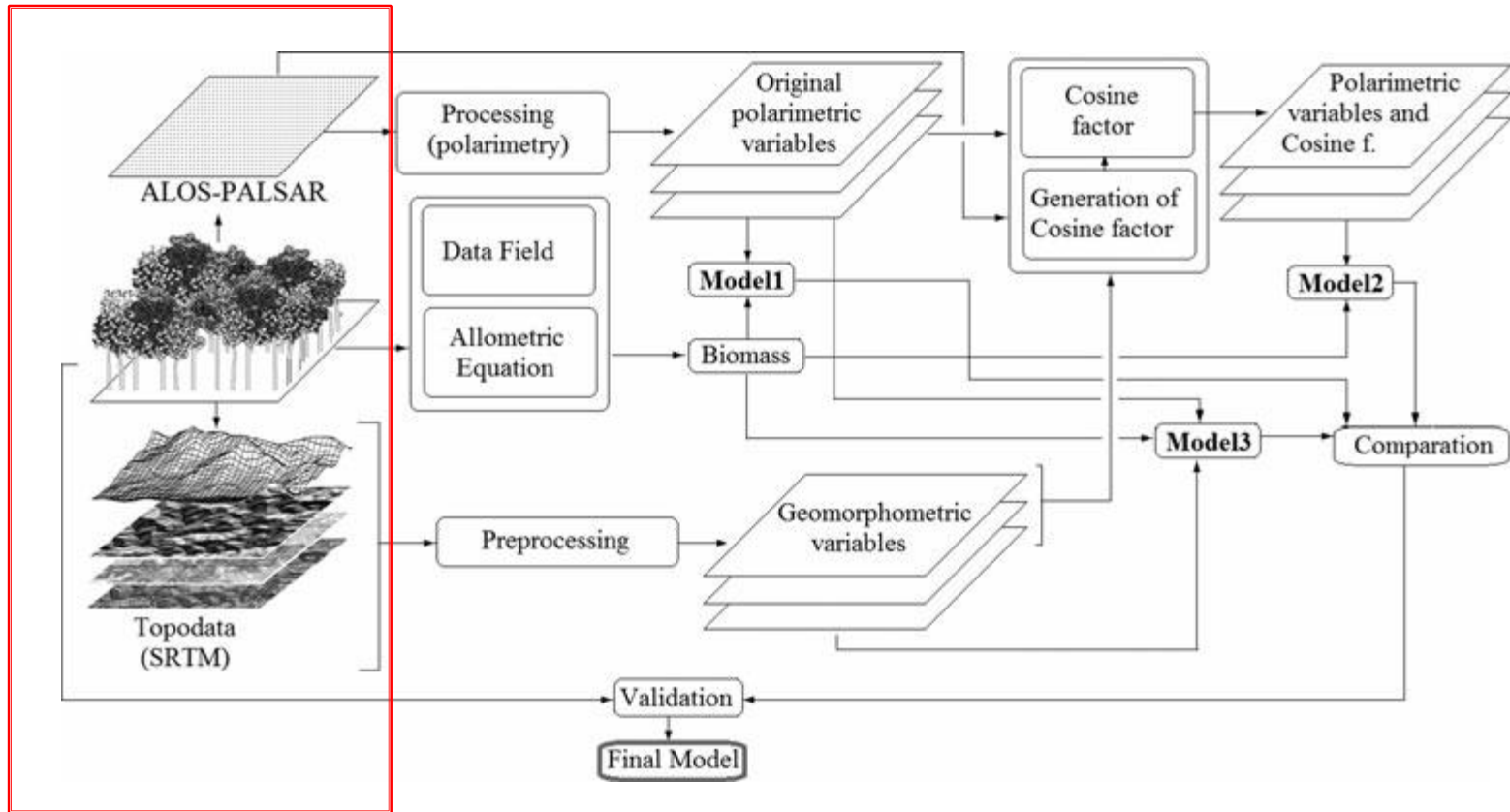
²*National Institute for Space Research-INPE, Av. dos Astronautas, 1758, CEP: 12227-010, São José dos Campos, São Paulo, Brazil*

³*Canada Centre for Remote Sensing, Natural Resources Canada, 588 Booth Street, Ottawa, K1A 0Y7, Canada*

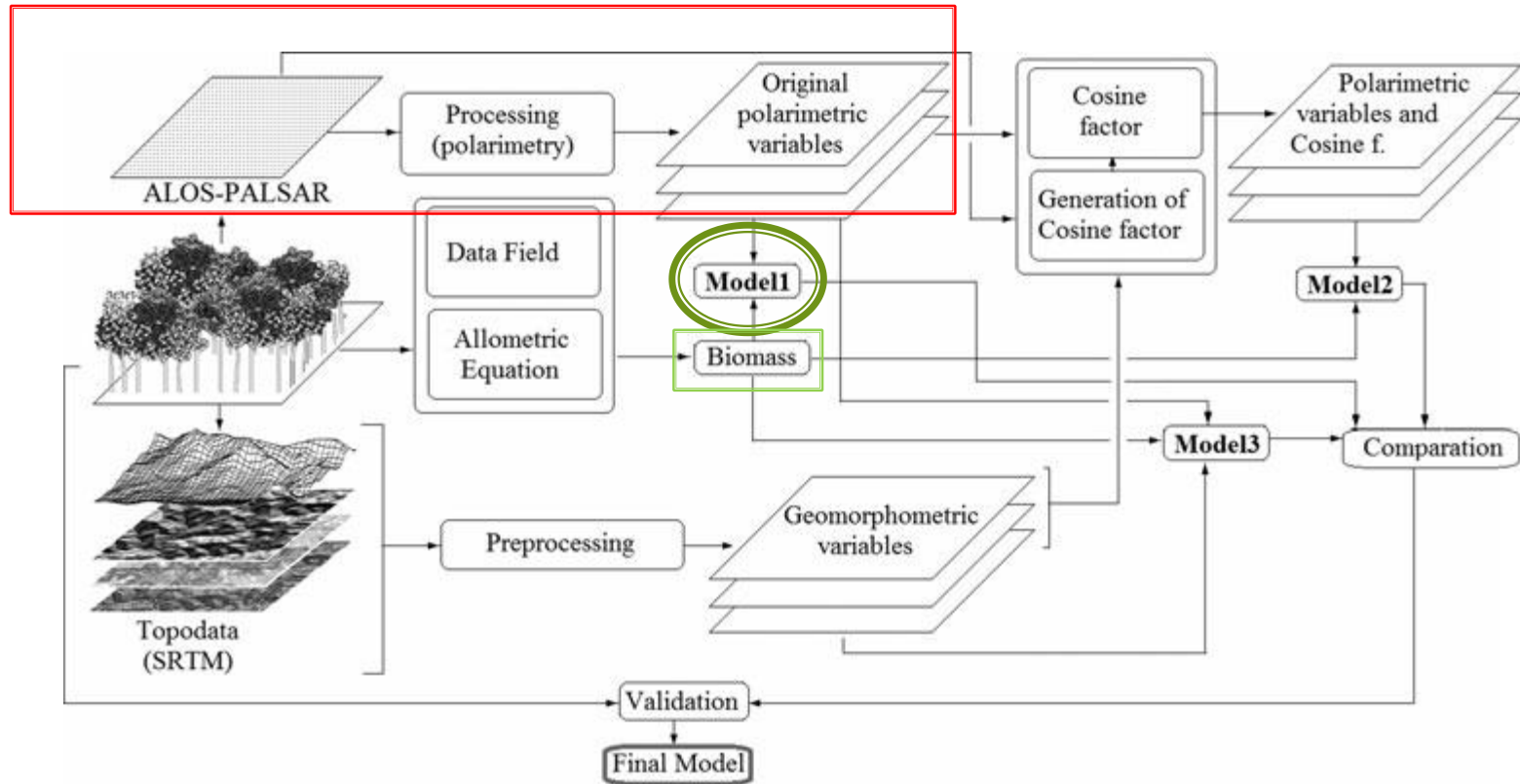
Generate a predictive model for biomass estimation in an area of central Amazonia based on the integration of coherent and incoherent polarimetric attributes originating from PALSAR and geomorphometric variables derived from SRTM.

Tapajós National
Forest

BISPO, P.C.; SANTOS, J.R.; VALERIANO, M.M.; TOUZI, R.; SEIFERT, F. M. Integration of polarimetric PALSAR attributes and geomorphometric variables derived from SRTM for forest biomass modeling in central Amazonia, *CJRS*, 2014.



BISPO, P.C.; SANTOS, J.R.; VALERIANO, M.M.; TOUZI, R.; SEIFERT, F. M. Integration of polarimetric PALSAR attributes and geomorphometric variables derived from SRTM for forest biomass modeling in central Amazonia, CJRS, 2014.

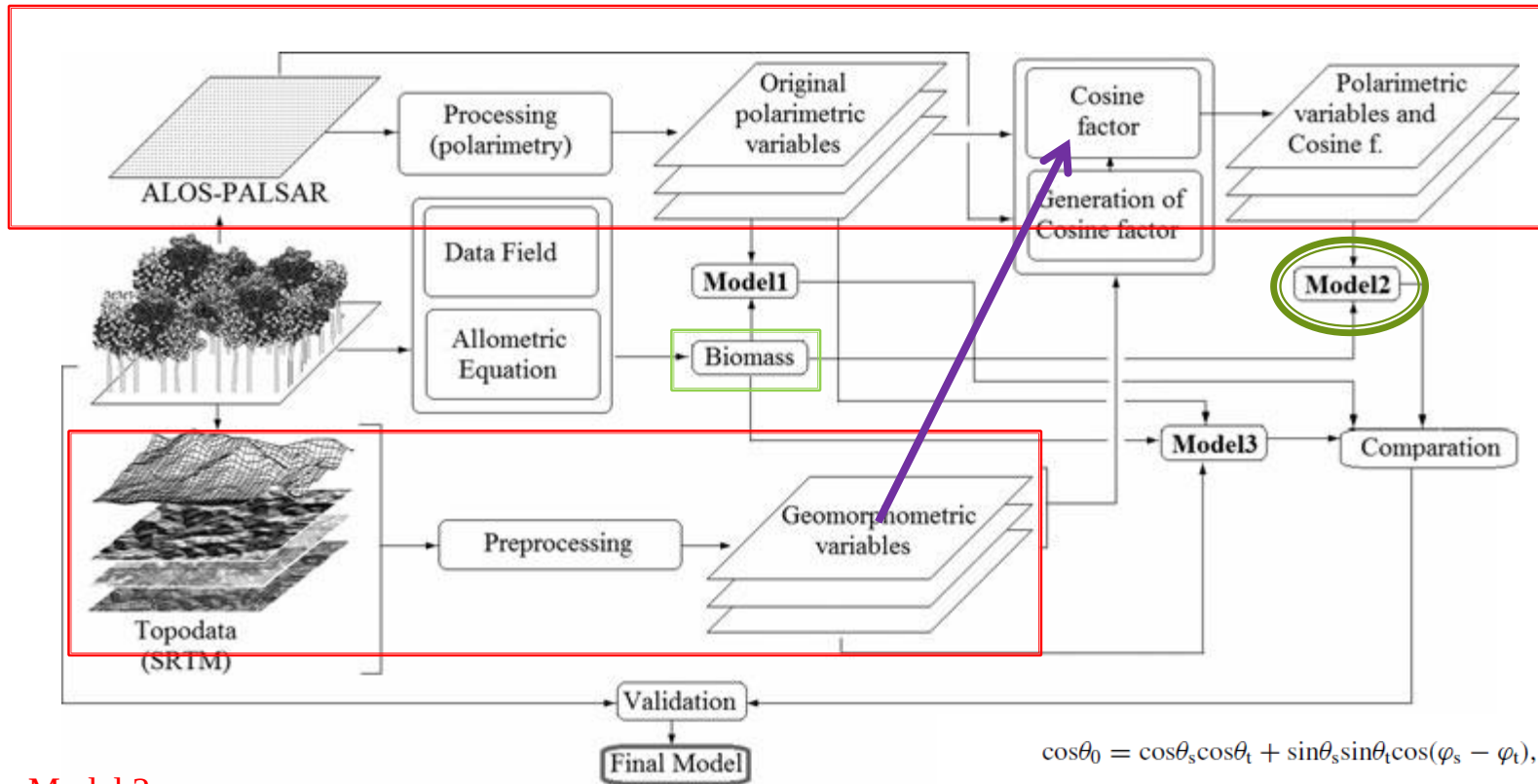


Model 1

Dependent variable: Biomass

Independent variable: Original polarimetric variables

BISPO, P.C.; SANTOS, J.R.; VALERIANO, M.M.; TOUZI, R.; SEIFERT, F. M. Integration of polarimetric PALSAR attributes and geomorphometric variables derived from SRTM for forest biomass modeling in central Amazonia, *CJRS*, 2014.



Model 2

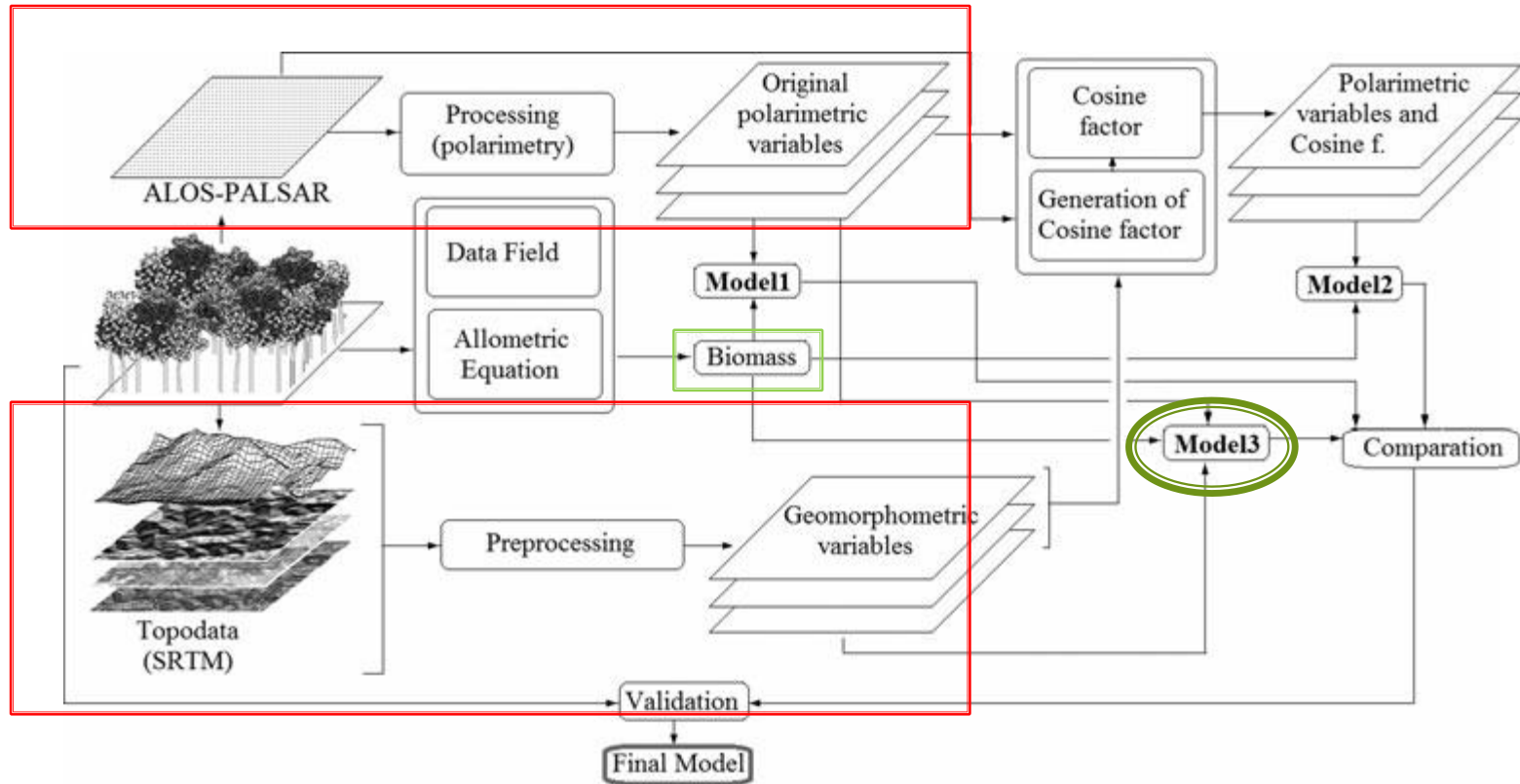
Dependent variable: Biomass

Independent variable: Polarimetric variables corrected by the cosine factor

$$\cos\theta_0 = \cos\theta_s\cos\theta_t + \sin\theta_s\sin\theta_t\cos(\varphi_s - \varphi_t),$$

where $\cos\theta_0$ is the cosine factor, θ_s is the solar zenith angle, θ_t is the zenith angle of the normal to the terrain surface (which corresponds to the slope), φ_s is the solar azimuthal angle and φ_t is the azimuthal angle of the normal to the surface (which corresponds to the slope orientation).

BISPO, P.C.; SANTOS, J.R.; VALERIANO, M.M.; TOUZI, R.; SEIFERT, F. M. Integration of polarimetric PALSAR attributes and geomorphometric variables derived from SRTM for forest biomass modeling in central Amazonia, *CJRS*, 2014.

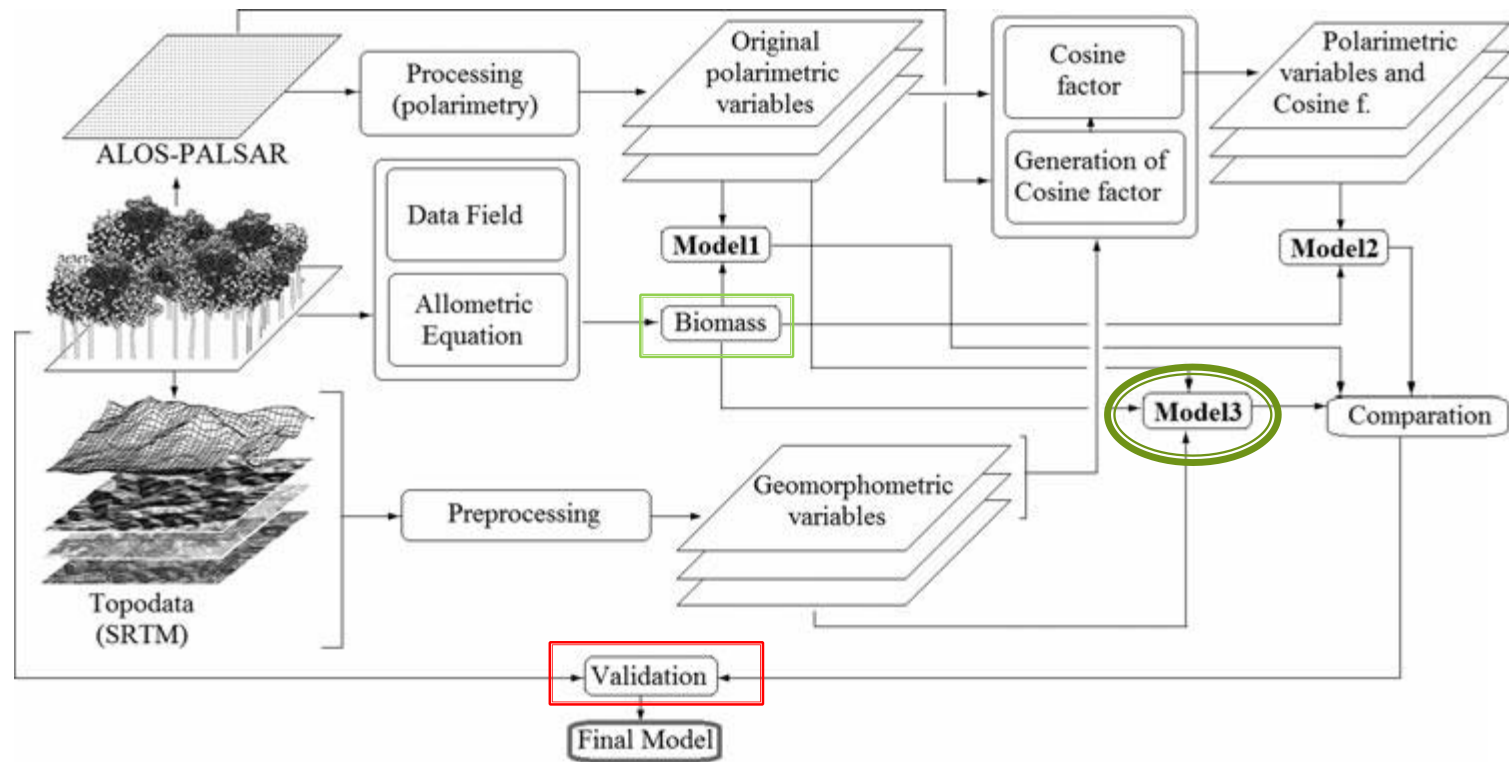


Model 3

Dependent variable: Biomass

Independent variable: polarimetric variables + geomorphometric variables

BISPO, P.C.; SANTOS, J.R.; VALERIANO, M.M.; TOUZI, R.; SEIFERT, F. M. Integration of polarimetric PALSAR attributes and geomorphometric variables derived from SRTM for forest biomass modeling in central Amazonia, *CJRS*, 2014.

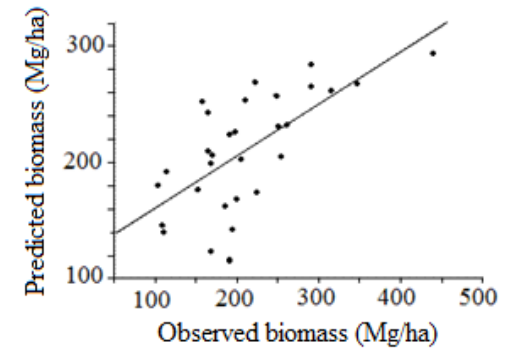
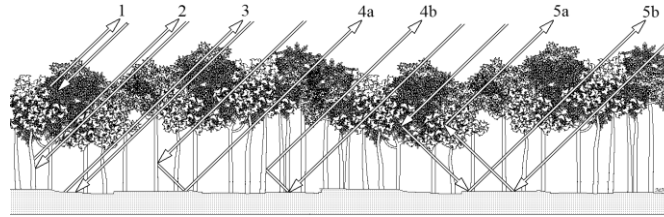


Estimated biomass from polarimetric variables (SAR):

$$BM = -191,8 - 10,595 \tau_{m1} - 11,562 \alpha_{s1} + 634,6 H - 463,9 An$$

$$r^2=0,35, p=0,004$$

$$\text{error}=54.2 \text{ Mg/ha}$$

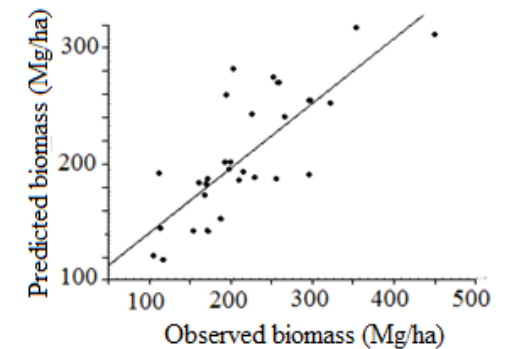
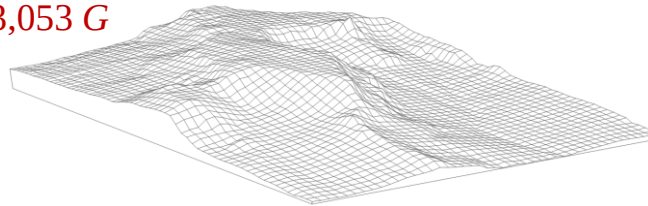


Estimated biomass from geomorphometric variables:

$$BM = -19,67 + 1,3467 h + 3,053 G$$

$$r^2=0,58, p=0,000$$

$$\text{error}= 45.80 \text{ Mg/ha}$$

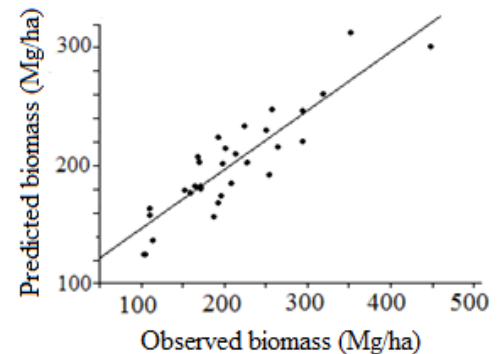
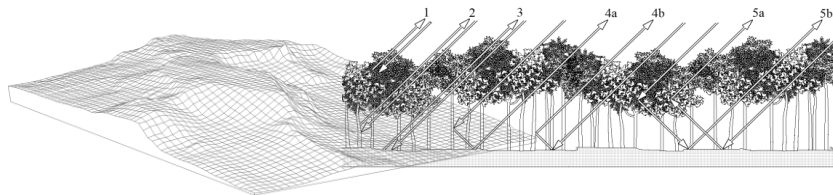


Estimated biomass from composite model:

$$BM = 31,11 + 142,01 Pv - 598,3 An + 1,465 h + 3,35 G + 0,4288 \tau_{m3} - 9,478 \tau_{m1}$$

$$r^2=0,74, p=0,000$$

$$\text{error}= 33.15 \text{ Mg/ha}$$



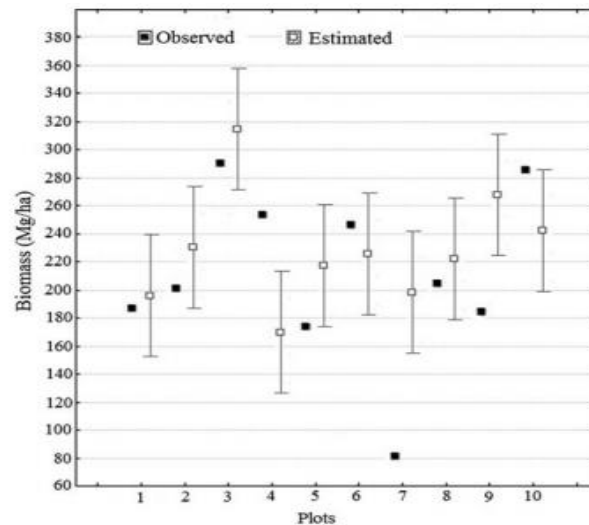
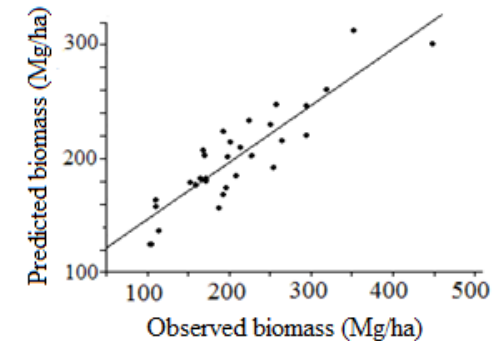
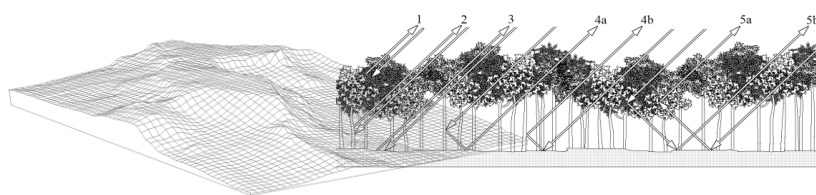
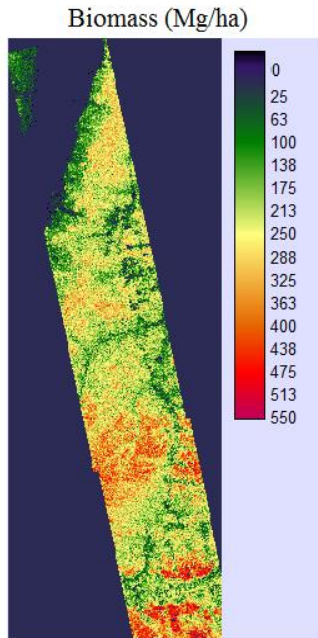
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$$r^2=0,74, p=0,000$$

$$error= 33.15 \text{ Mg/ha}$$

BM: Biomass; *Pv*: Volumetric Scattering Freeman; *An*: Anisotropy; *h*: Altitude; *G*: Slope; τ_{m3} : Third Component of Touzi Helicity; τ_{m1} : First Component of Touzi Helicity



Observed and estimated values of biomass data for the 10 sample parcels of the forest inventory. The vertical bars correspond to prediction intervals computed with a 95% confidence level.

The validation of the model used
10 independent samples.

RMSE: 42.96 Mg/ha or 20.31%.

Tapajós National Forest

Tropical-Forest Biomass Estimation at X-Band From the Spaceborne TanDEM-X Interferometer

Robert Treuhaft, Fabio Gonçalves, João Roberto dos Santos, Michael Keller, Michael Palace, Søren N. Madsen, Franklin Sullivan, and Paulo M. L. A. Graça

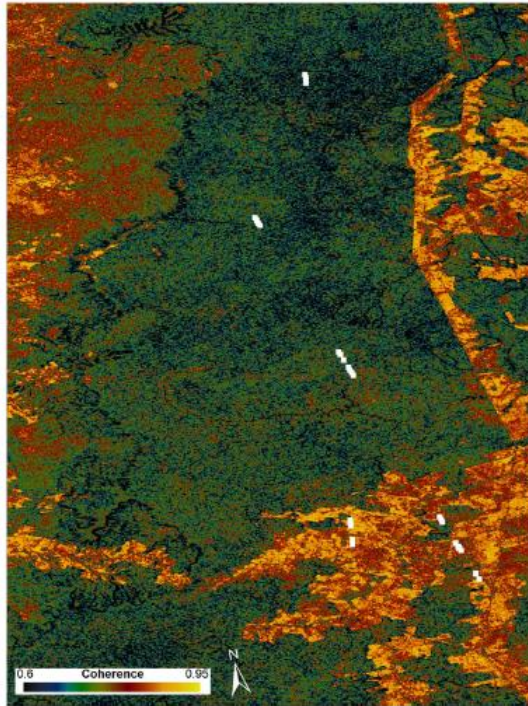


Fig. 1. InSAR Coherence from TanDEM-X, the magnitude of (1), over a 47 km (vertical) $\times$ 18 km area of the Tapajós test site. The center of the image is at 3.0114° S and 54.9900° W. The white dots indicate the locations of the 30 sites. Coherence scale is indicated along with true north. The spacecraft trajectory points downward parallel to the long side.

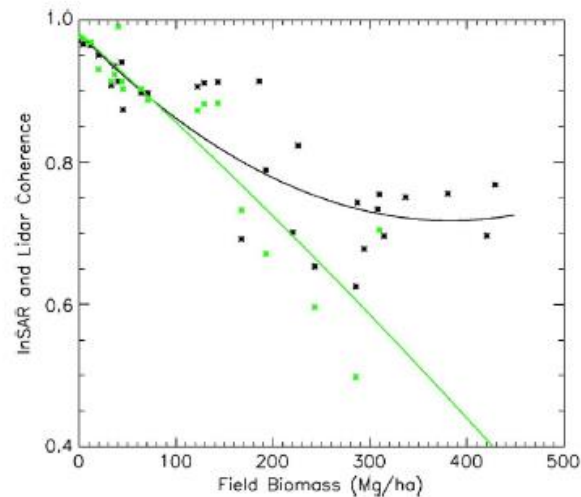


Fig. 2. InSAR coherence—magnitude of (1)—from TanDEM-X in black for 30 field locations versus field-estimated AGB. The black curve is a second-order polynomial fit of TanDEM-X coherence versus AGB. Lidar coherence—magnitude of (2)—is in green, with the green curve a second-order polynomial fit. The vertical wavelength of both InSAR and lidar is 73 m.

RMS scatters between 52 – 62 Mg-ha⁻¹, i.e., 29%–35% of the mean AGB

To assess the potential performance of AGB estimation in tropical forests from TanDEM-X complex correlations, a linear model was used for AGB for the j th stand, i.e., $B_{\text{mod}j}$. As a function of the amplitude and phase of $\gamma_{Ij}(\alpha_z)$, we have

$$B_{\text{mod}j} = a + b|\gamma_{Ij}| + c \arg(\gamma_{Ij}) \quad (4)$$

where it is understood that j runs from 1 to the number of stands. In (4), $\arg(\gamma_{Ij})$ is the phase of γ_{Ij} for the j th stand.

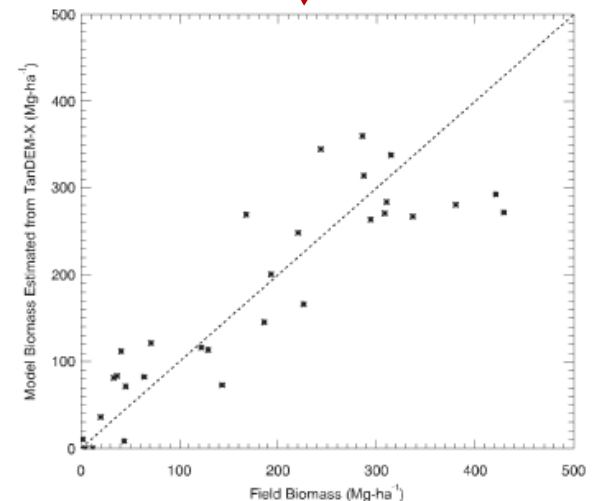


Fig. 5. Model AGB, estimated as a function of the amplitude and phase of the TanDEM-X γ_{Ij} , (4), versus field-estimated AGB. In (4), a , b , and c were estimated to minimize the reduced χ^2 in (5). The line is $y = x$.

SAR (Synthetic Aperture RADAR)

- ❖ The RADAR imagery is sensitive to forest biomass, is capable of capturing the spatial variability, and can provide estimates of aboveground biomass.
- ❖ However, because of the spatial variability of forest structure, the performance of the RADAR backscatter and height measurements are strongly dependent on the scale of observation.
- ❖ RADAR sensors at P-band in general perform better than L-band in estimating the aboveground biomass over a larger range (new mission BIOMASS)
- ❖ The overall biomass range (the so-called saturation referred to in RADAR literature) for each frequency depends on the sensitivity of RADAR, the calibration of the RADAR measurements, and the accuracy of the estimation.

RADAR Approach

- **Advantages**

- ✓ Independent from atmospheric conditions, clouds etc;
- ✓ Independent from sunlight;
- ✓ Increased penetration capacity in the targets compared to optical sensors;
- ✓ Unique nature of the information (electrical and geometrical properties);
- ✓ Vertical information of the forest structure over large areas.

- **Limitations**

- ✓ Roughness of the objects in relation to the wavelength;
- ✓ The weather influence at different data take times;
- ✓ The exact co-registration;
- ✓ Saturation;
- ✓ Temporal and atmospheric decorrelation .

Comparing the results from the studies developed in the Amazon using active sensors

Publications	Study area	Tipo de vegetação	Data	Technic	Analysis	RMSE
Santos et al 2004	Tapajós	Primary and Secondary forest	SAR P and X band	Interferometry	Multiple Regression	10%
Silva et al. (2014)	Tapajós	Secondary forest	SAR L and X band	Polarimetry and interferometry	Multiple Regression	33%
Silva et al. (2014)	Tapajós	Primary	SAR L band	Polarimetry	Multiple Regression	20%
Bispo et al. (2014)	Tapajós	Primary	SAR L band	Polarimetry	Multiple Regression	26%
Bispo et al. (2014)	Tapajós	Primary	SAR L and C band (SRTM)	Polarimetry and geomorfometry	Multiple Regression	20%
Treuhalt et al (2015)	Tapajós	Primary and Secondary forest	SAR X band	Interferometry	Fourier Transformation and Multiple Regression	29-35%

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Treuhalt et al (2015)	Tapajós	Primary and Secondary forest	SAR X band	Interferometry	Fourier Transformation and Multiple Regression	29-35%

20%

Multi-frequency RADAR imaging for the analysis of tropical forest structure in the Amazon (2016-2018)

Polyanna da C. Bispo and Heiko Balzter

- ✓ The main research goal of this project is to develop a methodology to derive information on forest structure and floristics based on the/polarimetric and interferometric variables from TanDEM-X (X band), PALSAR/ALOS (L band), Sentinel 1 (C band) integrated with geomorphometric data derived from SRTM (C band) to benefit the monitoring of forest communities, estimates of biomass and carbon stock to understand the carbon biogeochemical cycling in tropical forests which is essential in the context of global climate change.

Multi-frequency RADAR imaging for the analysis of tropical forest structure in the Amazon (2016-2018)

Polyanna da C. Bispo and Heiko Balzter

The specific research objectives (RO) are:

RO1: To determine which variables/attributes (geomorphometric and SAR variables) are related to the floristic composition and structure of forest plant communities;

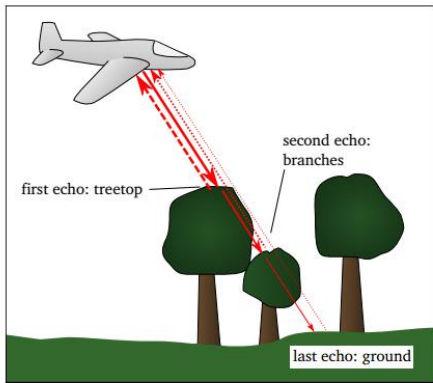
RO2: To develop a methodology to derive information on forest floristic structure from the integration of multifrequency (2 to 8 GHz) SAR data and geomorphometry;

RO3: To develop and validate a predictive model for forest structure, especially the above ground biomass and floristics based on the integration of different data sources;

RO4: To quantify the relationship between biomass and the rate of carbon stocks in tropical areas.

**Next step (after
2018) addition of
LIDAR**

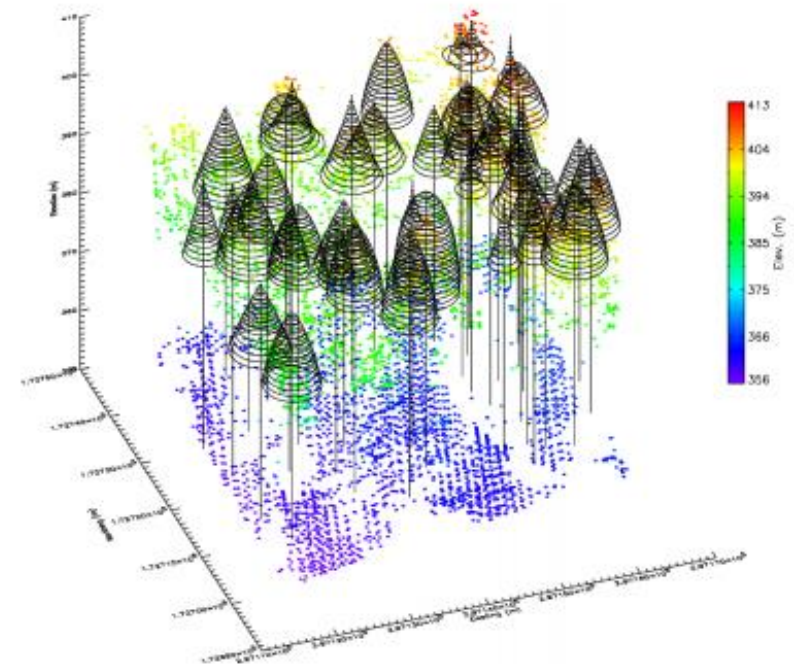
Laser Scanners (LIDAR)



Principle of range measurement by airborne laser scanning

❖ In the last couple of years, LIDAR data has become very popular for mapping forest structure attributes, particularly biomass.

Active airborne or spaceborne sensors that emit the signal and use the time for the signal to return as well as the reflectivity to estimate 3-dimensional information of the forest.



❖ Horizontal and vertical distribution of the trees constituents reflecting: leaves, branches, trunks. Powerful to estimate forest biophysical parameters such as biomass.

Andersen et al, 2002 in : ALS state of the art. (Jea Matthieu Monnet UR EMGR, Irstea 2012)

Laser Scanners (LIDAR)

- LIDAR stands as for a recent technology used to obtain direct measurements of vegetation, such as canopy height, the number of individual trees, the volume and diameter of the canopy.
- This sensor is suitable for the estimation of forest biomass as the variables that can be measured directly by LIDAR correlate with data from AGB measurements in the field.

LIDAR Approach

- Advantages

- ✓ The data can capture forest canopy height, its use has proven to offer an alternative for improvement of biomass estimation ;
- ✓ Can overcome the data saturation shortcoming of optical and RADAR data providing more robust biomass estimations ;
- ✓ Calibration and validation

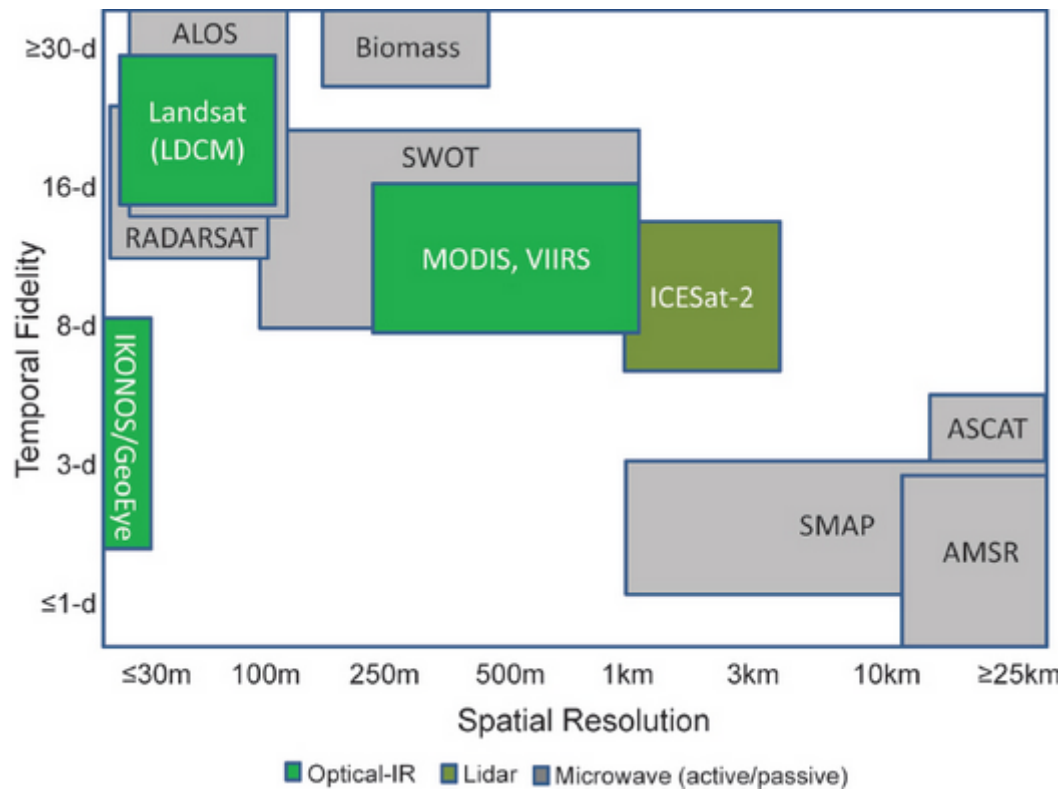
- Limitations

- ✓ High cost;
- ✓ This data alone cannot provide sufficiently accurate biomass estimation results.

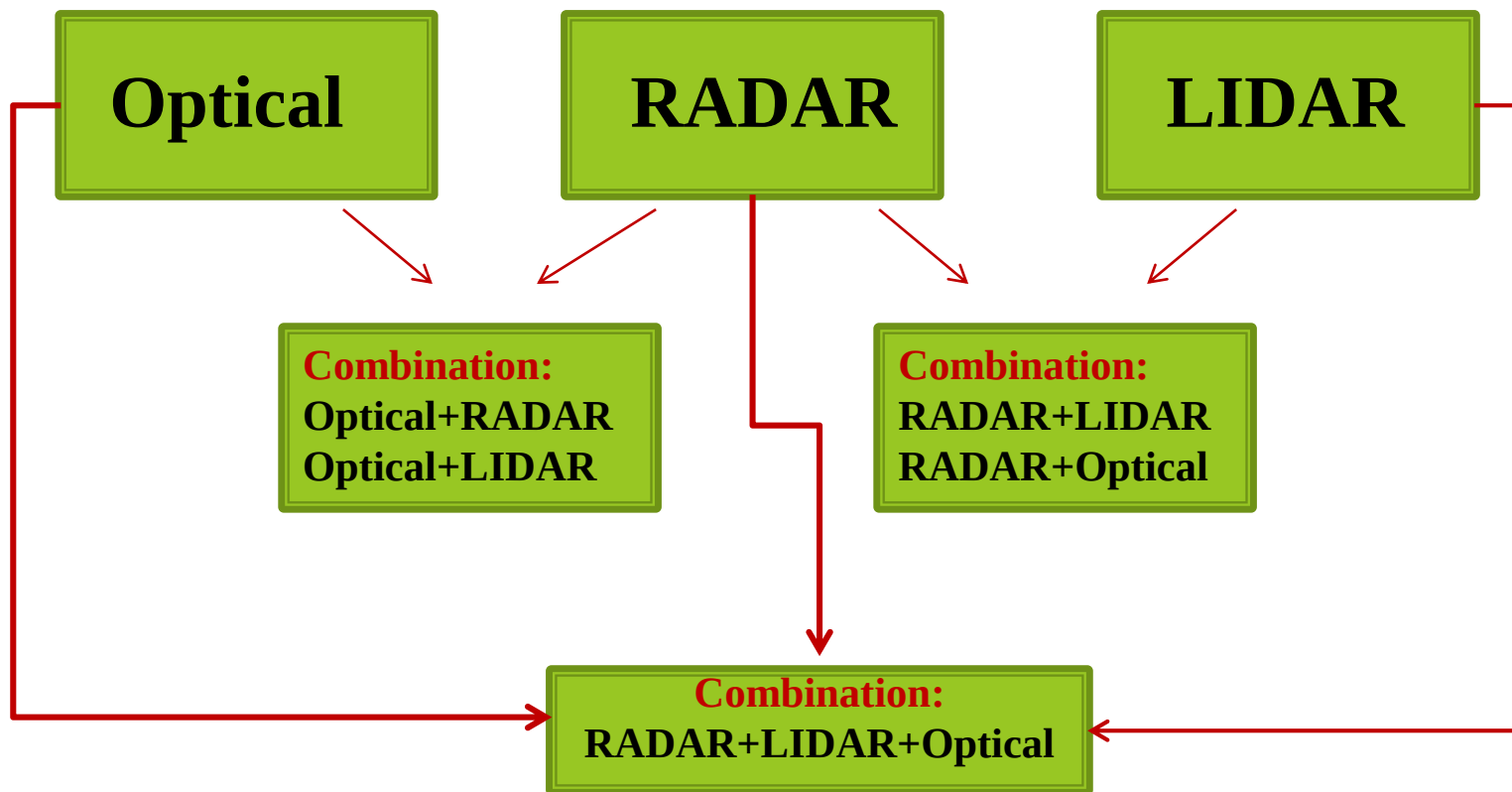
Multisensor Approach

❖ It is difficult to represent a so complex system as the tropical forest in all the dimensions, specially to the biomass estimation using just one approach

- ❖ Biomass is a three-dimensional metric
- ❖ Fusion approaches need to be developed



<http://www.nap.edu/read/18711/chapter/4>



Optical + LIDAR

Hindawi Publishing Corporation
International Journal of Forestry Research
Volume 2012, Article ID 436537, 16 pages
doi:10.1155/2012/436537

Can. J. Remote Sensing, Vol. 36, No. 2, pp. 129–141, 2010

Research Article

Aboveground Forest Biomass Estimation with Landsat and LiDAR Data and Uncertainty Analysis of the Estimates

Dengsheng Lu,¹ Qi Chen,² Guangxing Wang,³ Emilio Moran,¹ Mateus Batistella,⁴ Maozhen Zhang,⁵ Gaia Vaglio Laurin,⁶ and David Saah⁷

Integration of GLAS and Landsat TM data for aboveground biomass estimation

L.I. Duncanson, K.O. Niemann, and M.A. Wulder

- ❖ Optical data has critical limitation due to the saturation
- ❖ LIDAR can overcome the data saturation of optical data

Multisensor Approach

- ❖ In the last 20 years, both LIDAR and RADAR technology have been demonstrated to be sensitive to the vertical structure of vegetation
- ❖ While the science of acquiring remotely sensed estimates of horizontal vegetation structure has matured now considerably over the past 30 years.

- ❖ RADAR systems provide measurements of vegetation structure

- ❖ Provide spatially contiguous metrics

- ❖ Theoretical scattering models have been developed to understand and characterize RADAR signals

- ❖ Any successful estimation of height or biomass are dependent on well calibrated reference data sets

❖ With the advances of LIDAR, the vegetation height in particular can be derived from a purely remote sensing based approach

❖ LIDAR data can be used to calibrate models
predictor variables: optical and RADAR
horizontal and vertical characteristics

Table 1. Summary of studies of combined use of lidar and synthetic aperture radar (SAR) in biomass estimation. Abbreviations: above-ground biomass (AGB), digital terrain model (DTM), digital surface model (DSM), root mean square error (RMSE), airborne laser scanning (ALS).

Activity	Application	SAR Description	Results	Accuracy	References
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	AGB & canopy height in temperate forests	ALOS PALSAR polarimetry / interferometry (C- & L-band)	Adding SAR variables improves the lidar-based AGB estimation	RMSE is down to 7.1%–11.7%	Tsui et al. (2012)
	AGB in temperate forests	BioSAR cross-sections (80–120 MHz)	Tree height from lidar data improves the AGB estimation	$R^2 = 0.80$, RMSE = 21.3 t/ha (profiling) and $R^2 = 0.76$, RMSE = 24.2 t/ha (scanning)	Banskota et al. (2011)
	Forest height prediction with statistical fusion	C-band SRTM InSAR scattering phase center	Stand heights with tree height from LVIS	$R^2 = 0.71$, RMSE = 4.4 m (13% error)	Kellindorfer et al. (2010)
	Stereo radargrammetry & image pairs in boreal forests	TanDEM-X DSM [70], Terra-SAR-X image pairs in 1 m resolution [59]	More accurate large-area AGB using lidar DTM	RMSE = 57 m ³ /ha (plot level) and 25 m ³ /ha (stand level) [70]. RMSE = 41.3 t/ha [59]	Vastaranta et al. (2014) Solberg et al. (2013)
Data fusion: limited or no improvement from lidar/radar data fusion.	Forest inventory in the boreal forest zone	TerraSAR-X images	No improvement compared to lidar alone	30% error level resembling manual inventories	Holopainen et al. (2010)
	Stand level AGB + canopy height (US pine forests)	X- and P- band SAR cross-sections	Insignificant improvement compared to lidar alone	RMSE: 33.9 t/ha with lidar to 32.7 t/ha combined [42], 26.0 t/ha to 24.9 t/ha (with lidar canopy height) [71]	Nelson et al. (2007) Hyde et al. (2007)
	Stand level AGB in Sierra Nevada mixed forest	X-band inter-ferometric phase center & 10 m resolution lidar DEM	Lidar is the best sensor, addition of SAR → marginal or no improvement	RMSE = 75.3 Mg/ha with lidar alone and with lidar + InSAR, related to field-measured biomass	Hyde et al. (2006)
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	Northern hard-wood forests	L-band polarimetric SAR imagery	20 m resolution extended to large areas	AGB with RMSE down to 203.9 Mg/ha	Tsui et al. (2013)
	AGB mapping in boreal hard-wood forests	L-band polarimetric SAR imagery & passive optical image combinations	Accurate large-area AGB maps, lidar combined with SAR & optical images	Reduced errors 12%–38% (11–28 Mg/ha) from those where lidar is used with SAR or optical alone	Montesano et al. (2013)
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	AGB in tropical forests	X- and L-band SAR backscatter	Accurate large-area AGB maps	$R^2 = 0.53$, RMSE = 79 t/ha	Englhart et al. (2011)
	Plot-level bio-mass in (sub) tropical man-grove forests	C-band SRTM interferometry (90 m resolution) & ICES at GLAS	Extending lidar-based height/structure data, estimation of biomass loss	SRTM canopy height bias (–1.3 m) and estimation error (RMS = 1.9 m)	Simard et al. (2008)

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	AGB in tropical forests	X- and L-band SAR backscatter	Accurate large-area AGB maps	$R^2 = 0.53$, RMSE = 79 t/ha	Englhart et al. (2011)
	Plot-level bio-mass in (sub) tropical man-grove forests	C-band SRTM interferometry (90 m resolution) & ICES at GLAS	Extending lidar-based height/structure data, estimation of biomass loss	SRTM canopy height bias (–1.3 m) and estimation error (RMS = 1.9 m)	Simard et al. (2008)

Table 1. Summary of studies of combined use of lidar and synthetic aperture radar (SAR) in biomass estimation. Abbreviations: above-ground biomass (AGB), digital terrain model (DTM), digital surface model (DSM), root mean square error (RMSE), airborne laser scanning (ALS).

Activity	Application	SAR Description	Results	Accuracy	References
Combined lidar/SAR data: joint use of SAR and lidar in biomass models. SAR data combined with lidar DTM/DSM	AGB in tropical forests	L-band polarimetric SAR imagery	100 m resolution AGB map	±25% uncertainty	Mitchard et al. (2012)
	AGB & canopy height in temperate forests	ALOS PALSAR polarimetry / interferometry (C- & L-band)	Adding SAR variables improves the lidar-based AGB estimation	RMSE is down to 7.1%–11.7%	Tsui et al. (2012)
	AGB in temperate forests	BioSAR cross-sections (80–120 MHz)	Tree height from lidar data improves the AGB estimation	$R^2 = 0.80$, RMSE = 21.3 t/ha (profiling) and $R^2 = 0.76$, RMSE = 24.2 t/ha (scanning)	Banskota et al. (2011)
	Forest height prediction with statistical fusion	C-band SRTM InSAR scattering phase center	Stand heights with tree height from LVIS	$R^2 = 0.71$, RMSE = 4.4 m (13% error)	Kellndorfer et al. (2010)
	Stereo radargrammetry & image pairs in boreal forests	TanDEM-X DSM [70], Terra-SAR-X image pairs in 1m resolution [59]	More accurate large-area AGB using lidar DTM	RMSE = 57 m ³ /ha (plot level) and 25 m ³ /ha (stand level) [70]. RMSE = 41.3 t/ha [59]	Vastaranta et al. (2014) Solberg et al. (2013)
Data fusion: limited or no improvement from lidar/radar data fusion.	Forest inventory in the boreal forest zone	TerraSAR-X images	No improvement compared to lidar alone	30% error level resembling manual inventories	Holopainen et al. (2010)
	Stand level AGB + canopy height (US pine forests)	X- and P- band SAR cross-sections	Insignificant improvement compared to lidar alone	RMSE: 33.9 t/ha with lidar to 32.7 t/ha combined [42], 26.0 t/ha to 24.9 t/ha (with lidar canopy height) [71]	Nelson et al. (2007) Hyde et al. (2007)
	Stand level AGB in Sierra Nevada mixed forest	X-band inter-ferometric phase center & 10 m resolution lidar DEM	Lidar is the best sensor, addition of SAR → marginal or no improvement	RMSE = 75.3Mg/ha with lidar alone and with lidar + InSAR, related to field-measured biomass	Hyde et al. (2006)
	Norway spruce & pine AGB	X-band InSAR	ALS DEM improved the AGB accuracy	RMSE = 24 t/ha (spruce), 17t/ha (pine)	Solberg et al. (2010)
Upscaling: using lidar and field data as reference	Northern hard-wood forests	L-band polarimetric SAR imagery	20 m resolution extended to large areas	AGB with RMSE down to 203.9 Mg /ha	Tsui et al. (2013)
	AGB mapping in boreal hard-wood forests	L-band polarimetric SAR imagery & passive optical image combinations	Accurate large-area AGB maps, lidar combined with SAR & optical images	Reduced errors 12%–38% (11–28 Mg/ha) from those where lidar is used with SAR or optical alone	Montesano et al. (2013)
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	AGB in tropical forests	X- and L-band SAR backscatter	Accurate large-area AGB maps	$R^2 = 0.53$, RMSE = 79 t/ha	Englhart et al. (2011)
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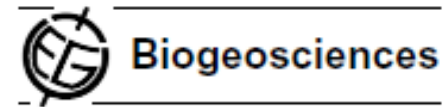
RADAR + LIDAR

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Mapping tropical forest biomass with radar and spaceborne LiDAR in Lopé National Park, Gabon: overcoming problems of high biomass and persistent cloud

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Response Variable:

Biomass derivated by the field work using alometric equation

Multiple Regression
Analysis



Biomass map limited
at 150 Mg/ha

Predictive Variables:

Terrain corrected Palsar
layers (HH, HV)

Layers:
HH
HV
RDFI
DEM

Unsupervised
Classification

Map with 40 classes
from 100 interactions

LIDAR: ICEsat
GLAS
footprints

Association of each class from
classification with biomass
average from LIDAR

**BIOMASS MAP FROM
CLASSIFICATION AND
LIDAR**

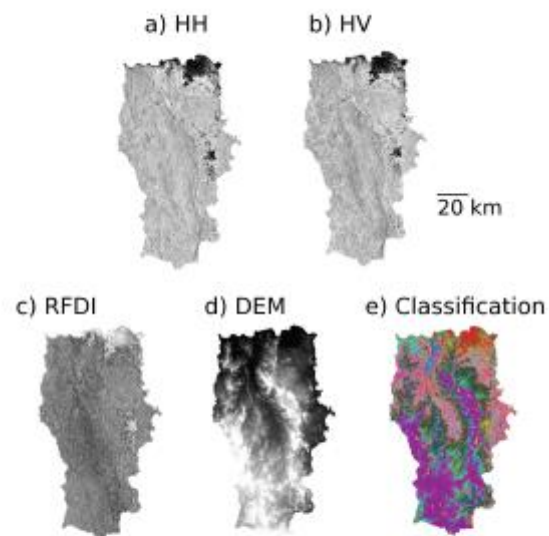


Fig. 3. Images of Lopé National Park using (a) PALSAR HH, (b) PALSAR HV, (c) Radar Forest Degradation Index (RFDI), (d) Digital Elevation Model (DEM), (e) Classified map, showing 40 classes with arbitrary colours.

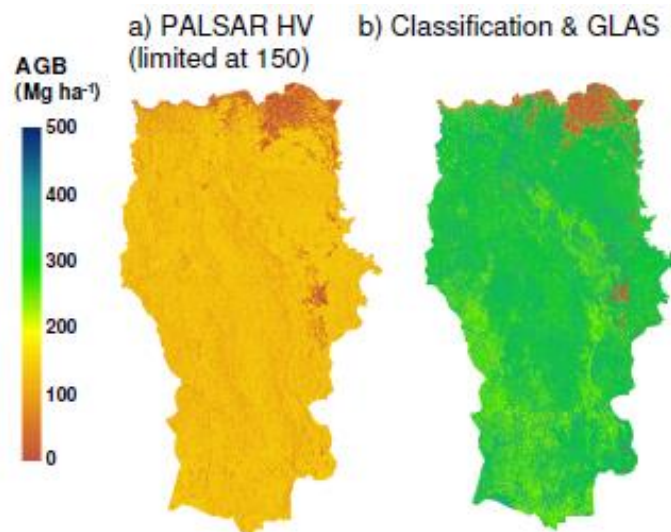


Fig. 7. Two different AGB maps for Lopé national park are displayed. (a) is for the regression with PALSAR HV, which is limited at 150 Mg ha^{-1} due to the saturation of these data; (b) is for the map produced by classifying PALSAR data and giving the 40 classes AGB values derived from GLAS footprints.

Table 2. Mean LiDAR-derived AGB in broad radar-derived biomass classes.

AGB class from PALSAR HV (Mg ha^{-1})	Mean AGB from LiDAR footprints within this class (Mg ha^{-1})	Standard Deviation LiDAR-AGB (Mg ha^{-1})	Number of LiDAR footprints
0–25	14.1	13.1	148
25–50	43.1	25.1	131
50–75	68.7	33.8	158
75–100	89.9	35.1	236
100–150	134.4	45.5	1847
> 150	297.2	102.9	4522

uncertainty = $\pm 25\%$ on
our carbon stock value for
the park.

Optical+RADAR + LIDAR



JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 115, G00E08, doi:10.1029/2009JG000997, 2010

Statistical fusion of lidar, InSAR, and optical remote sensing data for forest stand height characterization: A regional-scale method based on LVIS, SRTM, Landsat ETM+, and ancillary data sets

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Study area: region in the eastern United States
surrounding the Chesapeake Bay area

Segmentation

Predictive Variables:

SRTM, Landsat ETM+,
ancillary datasets

Random Vegetation Tree
Regression



BIOMASS MAP

Response Variable:

LIDAR LVIS (Laser
Vegetation Image Scanner)

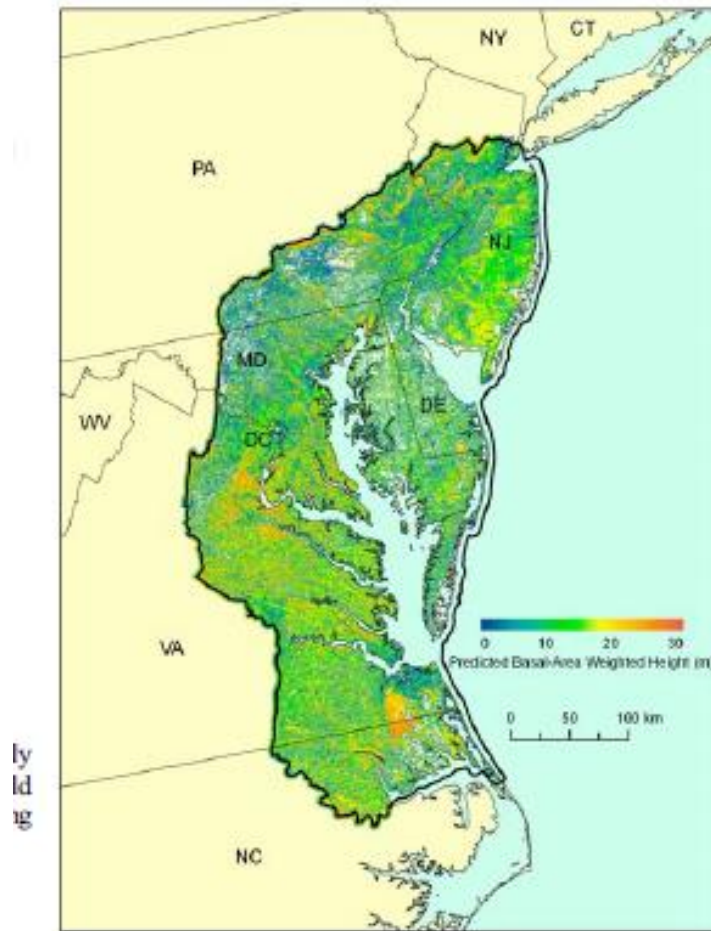


Figure 7. Predicted map of vegetation height in Mapping Zone 60 based on the remote sensing based model from lidar/InSAR/optical/slope data fusion.

Independent LVIS testing resulted in a correlation coefficient $r = 0.83$ with an RMSE of 3.0 m (9% error), independent FIA data tested with $r = 0.71$ with an RMSE of 4.4 m (13% error).

The fusion of data sets among continuous satellite measurements (optical reflectance, RADAR backscatter, interferometric height), morphometric measurements (slope, DEM height, aspect), and categorical variables (e.g., forest cover type) via random Forest-type regression trees is a viable approach to mine a range of diverse information layers which cannot easily be combined with traditional stratified regression modeling.

Future Prospects

Space LIDAR missions can be expected in the near future, such as the **ICESAT-2** and **NASA's GEDI** to be launched about 2018.

The upcoming **ESA BIOMASS (SAR)** mission will provide biomass data at a spatial scale of 100–200 m , using P band, polarimetric interferometry information, and will be launched in 2020.

LIDAR methods could replace manual field inventories in validating the LIDAR based ground reference in improving the accuracy of the large-area above ground biomass with SAR and/or optical datasets .

Future Prospects

What do we need?

Consolidate or develop new methods to improve biomass estimation in tropical forests: Amazon

Establish reference in situ network (and LIDAR data) for model calibration and result validation

Exploit synergy among the Earth Observation data

Prepare for use in C flux estimations

Where are we today?

We have available today several sensors and new sensors being launched. This will provide more information. I presented here two possibilities of use and manipulation of data from different sources.

From everything discussed today and also tomorrow in this workshop, **alternatives and new possibilities will emerge to improve the biomass estimation in the Amazon.**



An aerial photograph of a vast, dense tropical rainforest. The canopy is a thick, textured layer of green, with some areas appearing slightly more yellowish-green, possibly due to sunlight filtering through. In the background, several mountain ranges are visible, their peaks partially obscured by soft, white clouds. The sky is filled with large, billowing clouds, creating a dramatic and atmospheric scene. The overall tone is natural and serene.

THANK YOU!