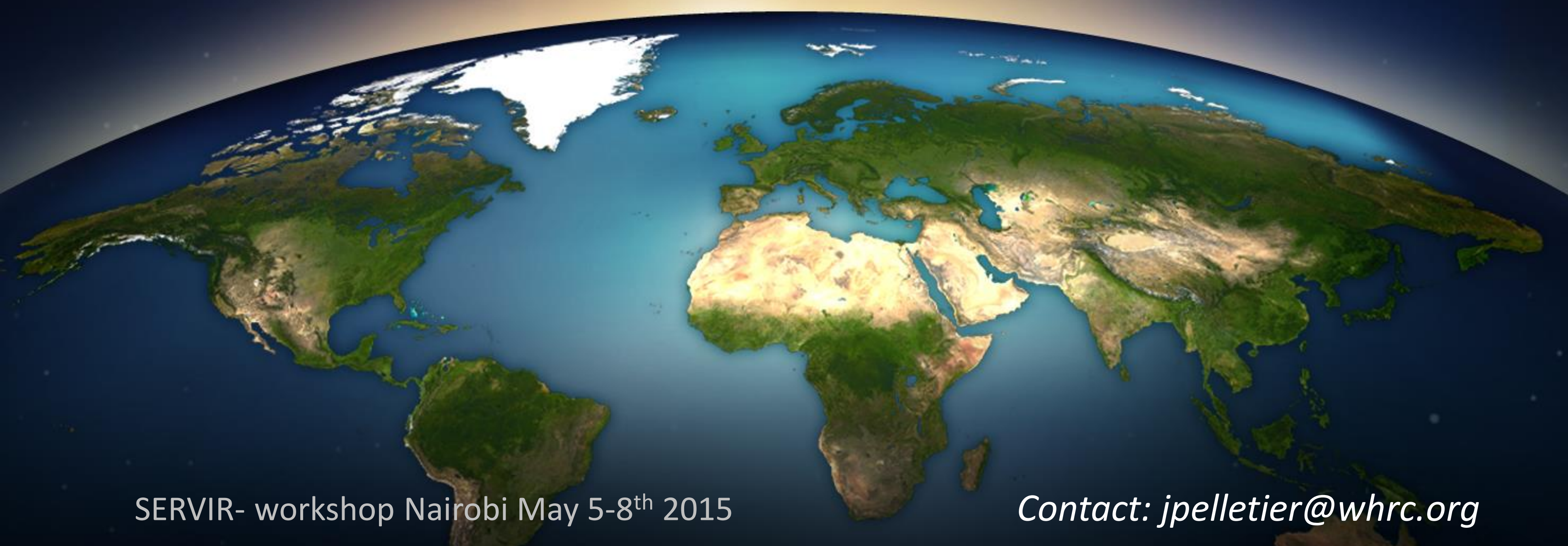
Forest carbon assessment for REDD+ in the East & South Africa SERVIR region

"Filing the gap between Carbon Science and policy"

Dr. Scott Goetz – Dr. Johanne Pelletie r- Dr. Patrick Jantz   Woods Hole Research Center, MA-USA
Ned Horning American Museum of Natural History, NY-USA
Dr. Nadine Laporte, NASA SERVIR-Science Team, USA



SERVIR- workshop Nairobi May 5-8th 2015

Contact: jpelletier@whrc.org

SERVIR GLOBAL

THE WOODS HOLE RESEARCH CENTER

USAID FROM THE AMERICAN PEOPLE

NASA

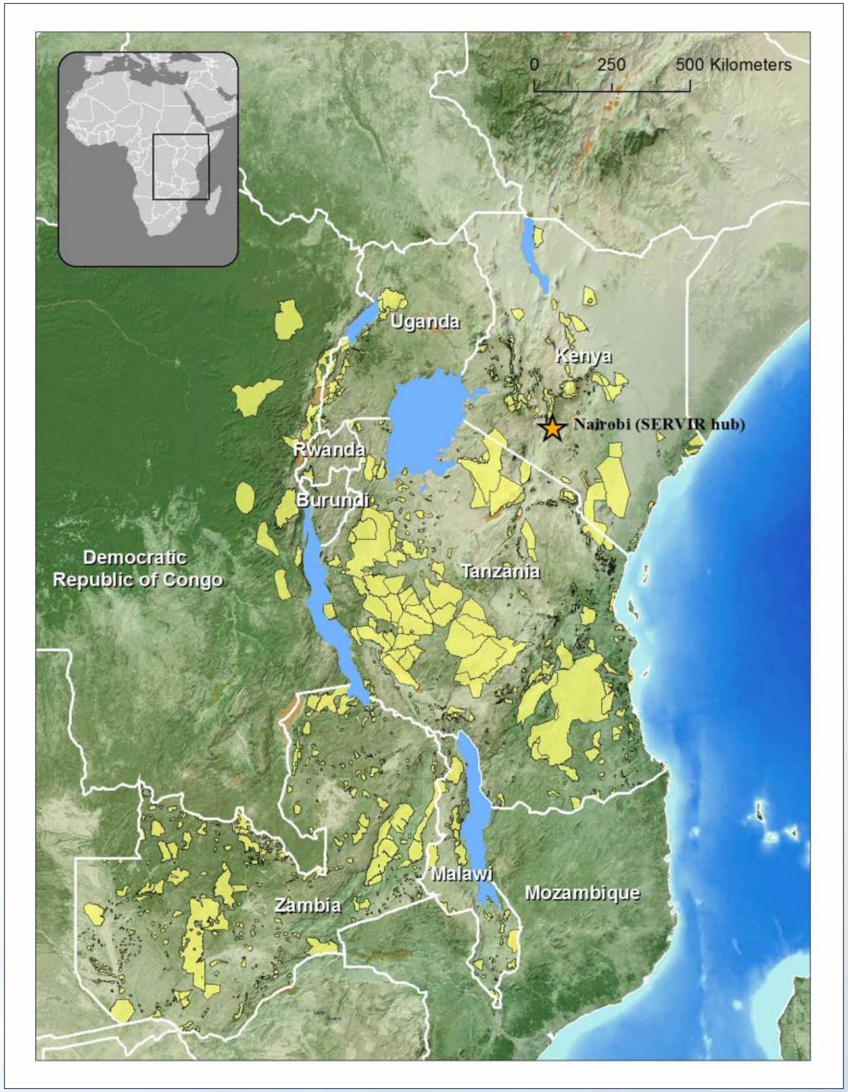
Forest Carbon Assessment for REDD+ in the East & South Africa SERVIR Region

THE WOODS HOLE RESEARCH CENTER

Objectives

Our **Project demonstrates** how NASA Earth science products and derived models can assist East African countries, including the DR Congo, with their terrestrial carbon assessment and forest conservation strategy. The main focus of the project is:

- **Establishing forest carbon stock baselines and trends**, assessing historical and current carbon emissions from deforestation and degradation *(Gov/NGOs/Universities)*
- **Identifying corridors of high forest carbon stock** to be preserved and potential areas to be replanted in order to connect parks and protected areas and sustain biological diversity. *(Science WHRC-Implementation GOV/NGOs)*
- **Training and building capacity** in the use of maps, tools and models to be developed as part of this project *(SERVIR Hub, AMNH, JGI partners)*



Our project is assisting countries with developing strategies for reducing emissions from deforestation and forest degradation (REDD) to effectively decrease forest-based emissions.

USAID FROM THE AMERICAN PEOPLE

THE WOODS HOLE RESEARCH CENTER

SERVIR

Introduction to GHG and uncertainty estimation

WORK PLAN:

1. Uncertainty in GHG estimation and in the REDD+ context:
   - Sources of uncertainty
   - IPCC principles
   - MRV in the REDD+ context
2. Components of uncertainty in GHG from land-use/cover change:
   - Land-cover change data (Activity data)
   - Biomass estimation (Emission Factors)
   - Accounting (or modelling) approach
3. Estimating uncertainty (IPCC approach)
   - Tier 1: Error propagation
   - Tier 2: Monte Carlo Method
4. Exercise in R

Uncertainty in GHG estimation and in the REDD+ context

United Nations
Framework Convention on
Climate Change

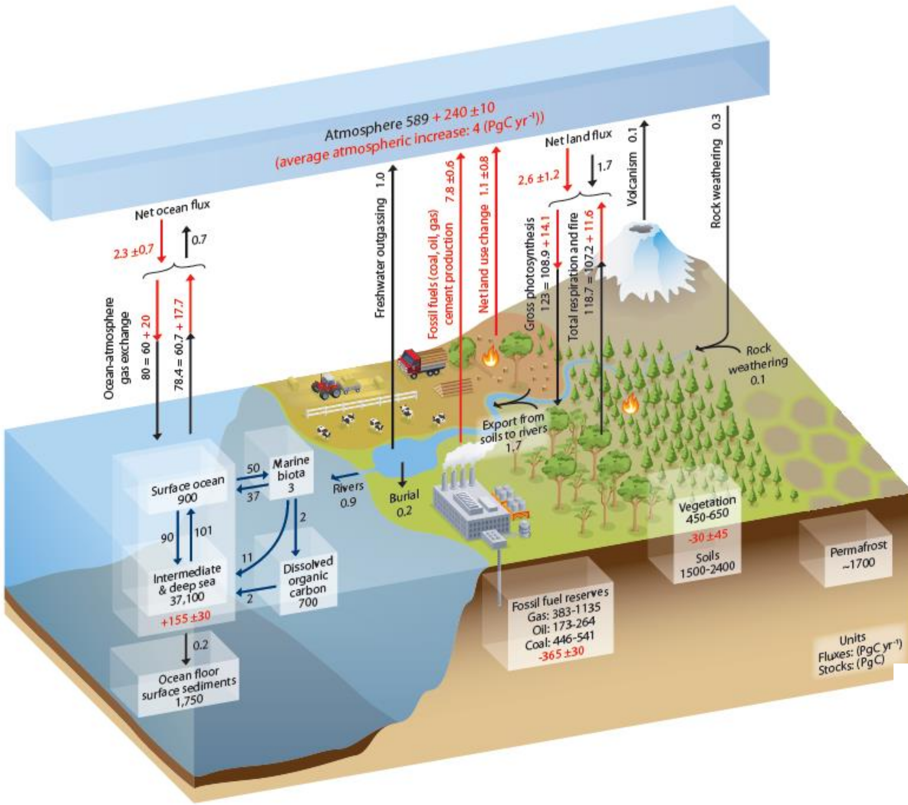
PARIS2015
UN CLIMATE CHANGE CONFERENCE
COP21·CMP11

- First objective "*to stabilize GHG concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system*"

Uncertainty in GHG estimates can hinder the fulfillment of this objective

- Are we on the global target 2 C degrees?
- Are countries meeting their pledged emission reduction targets?
- Are carbon trading systems working as well as they should for the climate?

Sources of emissions & uncertainty



6-17% of global emissions

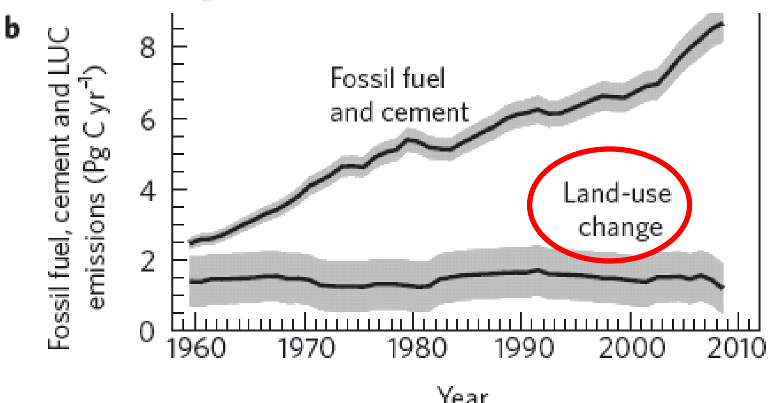
IPCC AR5

Fossil fuel:

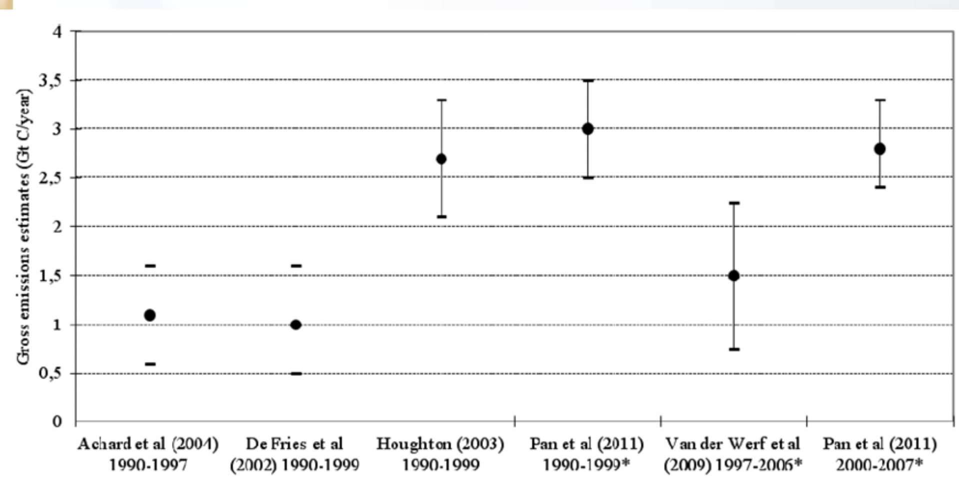
7.8 ±0.6 Pg/yr

Land Use Change:

1.1 ±0.8 Pg/yr



Le Quéré *et al.* Nature Geoscience (2009)



Bucki et al. Environmental Research Letters, 2012

Uncertainty in GHG estimation and in the REDD+ context

- ## Policy requirements

UNFCCC: parties are encouraged, but not obliged, to report on uncertainty in their national GHG inventory

Kyoto Protocol: GHG inventory uncertainty is monitored, but it is not regulated, which means that there are no rules to limit or discount foruncertainty when evaluating compliance.

***

- ## Market requirements

Carbon trading: UNFCCC does not provide compulsory instructions on how uncertainty must be addressed, and uncertainty is generally ignored (Marland et al. 2009).

BUT NOT FOR LONG

Five estimating and reporting principles:

Transparency: All the assumptions and the methodologies clearly explained time

Consistency: The same methodologies and consistent data sets are used along time

Comparability: Estimates of emissions and removals should be comparable among parties

Completeness: Estimates should include—for all the relevant geographical coverage—all the agreed categories, gases and pools

Accuracy: Estimates should be systematically neither over nor under the true value, so far as can be judged, and that *uncertainties* are reduced so far as is practicable

Calculating carbon emissions

The general approach for calculating carbon emissions:

Emissions = Activity data (AD) X Emission Factor (EF)

Activity data refers to the area of forest change (in hectare), e.g., forest converted to grassland or forest converted to cropland,

Emission factor relates to the carbon stock change estimations per unit of activity (in carbon per hectare).

For Emission Factors

Gain-Loss Method based on estimates of annual change in biomass from estimates of biomass gain and loss

Where:

- ΔCB = annual change in carbon stocks in biomass
- ΔCG = annual increase in carbon stocks due to biomass growth
- ΔCL = annual decrease in carbon stocks due to biomass loss

***

Stock-Difference Method which estimates the difference in total biomass carbon stock at time t2 and time t1

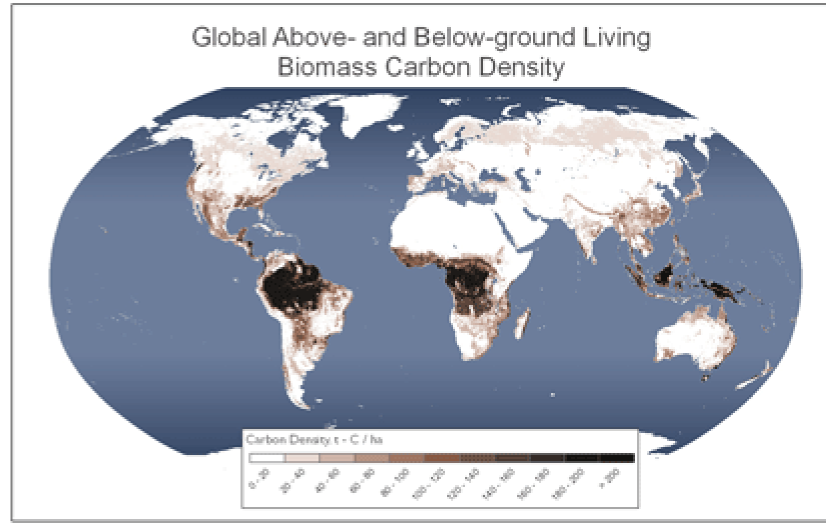
- Where:
  - ΔC = annual carbon stock change in the pool, tC/yr
  - $C_{t\,1}$ = carbon stock in the pool at time t1, tonnes C
  - $C_{t\,2}$ = carbon stock in the pool at time t2, tonnes C

Tier approach for emission factor

Level of methodological complexity:

Tier 1: Uses IPCC default parameters

Tier 2: Requires some country-specific carbon data



Tier 3: Uses highly disaggregated national data of carbon pools and assesses any change in pools through repeated measurements and/or modeling.

Approaches for activity data

Approach for activity data: Area change
1. total area for each land use category, but no information on conversions (only net changes)
2. tracking of conversions between land-use categories (only between 2 points in time)
3. spatially explicit tracking of land-use conversions over time

GOFC-GOLD, 2012

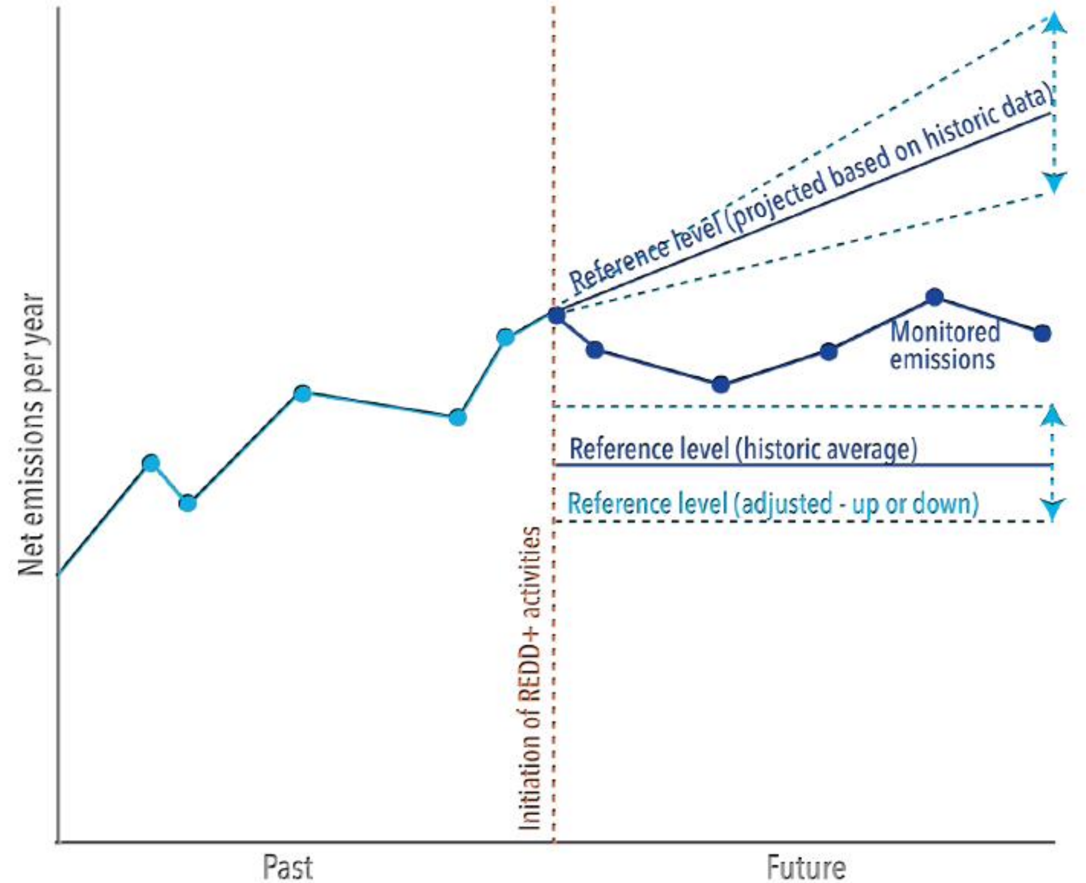
Approach 2 and 3 are likely to be required for REDD+ for traceability

REDD+ decisions on REL or RL

Forest Reference Emission Levels or Reference Levels

Basic criteria:

- Benchmarks, expressed in tonnes of carbon dioxide equivalent per year, for assessing each country's performance in implementing REDD+ activities;
- Most be consistent with GHG national reporting for LULUCF;
- Take into account historic data and adjust to national circumstances (are flexible);
- Develop in a step-wise approach;



Chagas et al. Climate focus, 2013

- Will be technically assessed and countries need to submit details about the procedure taken on a voluntary basis.

REDD+ decisions on accuracy and reporting

COP 15 -Copenhagen

SBSTA Decision CP.15 1.d) (ii) Provide estimates that are transparent, consistent, as far as possible accurate, and that reduce uncertainties, taking into account national capabilities and capacities

COP 19 - Warsaw

Annex to **Decision 13/CP.19 (**Warsaw Framework)

(c) The extent to which the information provided was **transparent, complete, consistent and accurate, including methodological information, description of data sets, approaches, methods, models,** if applicable, **and assumptions used**

Inception of REDD+

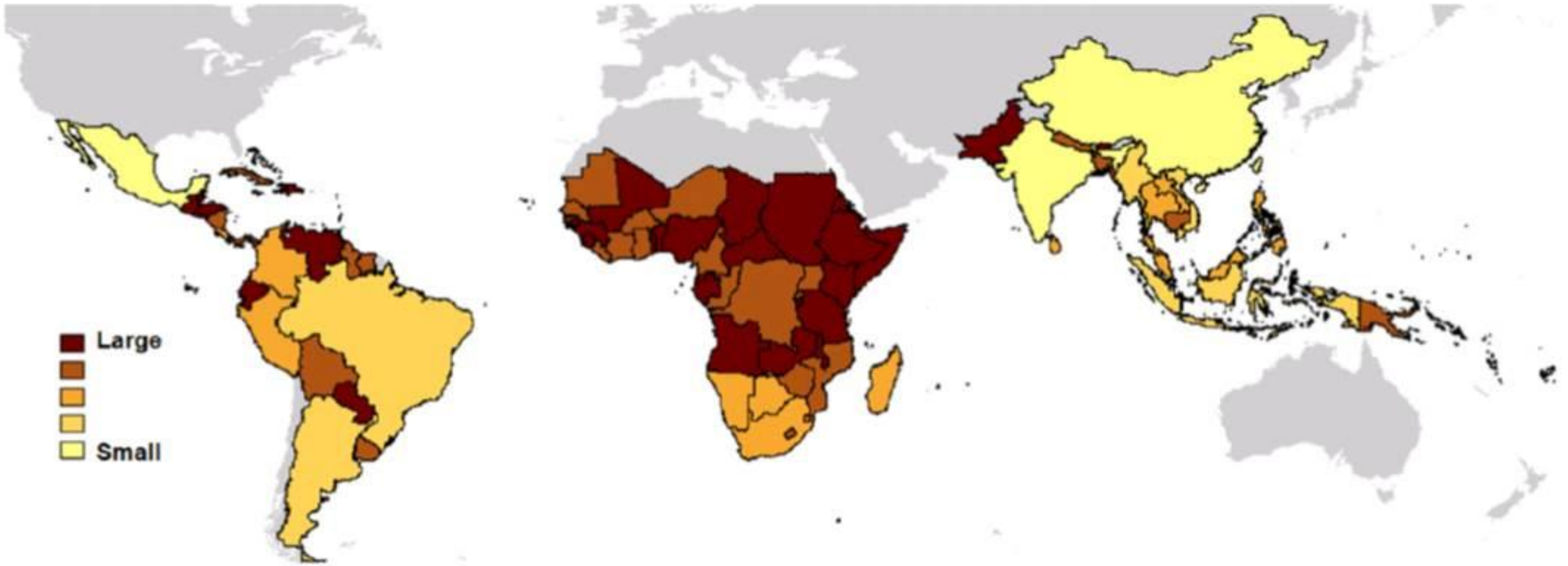
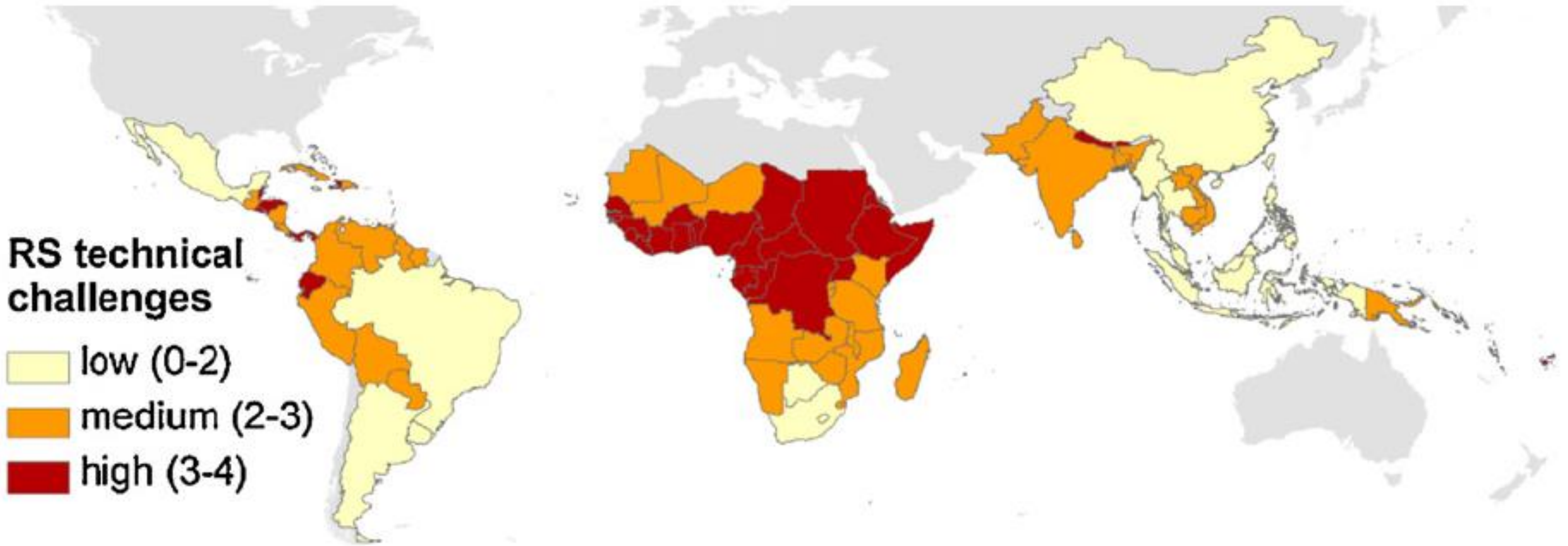


Figure: Spatial distribution of the capacity gap for different countries analyzed.

Herold, M. GOFC-GOLD project and University of Jena, 2009)

- *"the majority of non-Annex I countries have limited capacity in providing complete and accurate estimates of GHG emissions and removals from forests"* (UNFCCC, 2009)

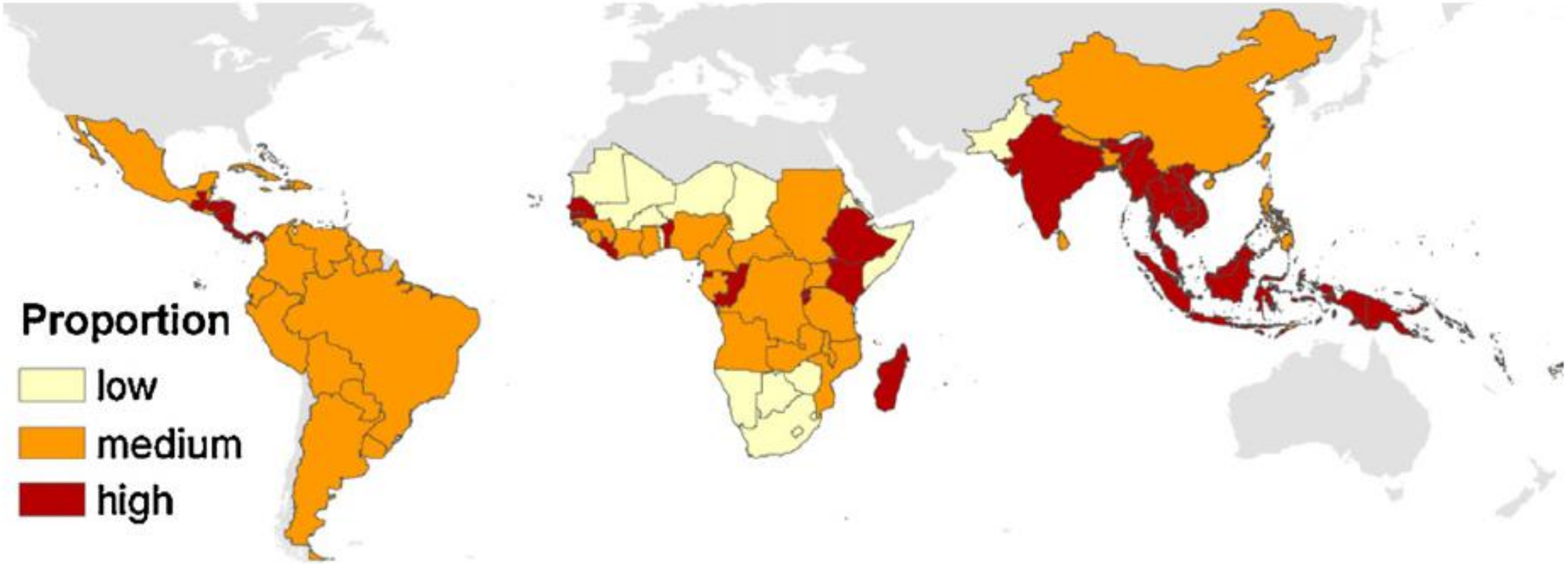
Challenges with Activity data



Forest area change monitoring capacity

Romijn et al. , Environmental Science & Policy, 2012

Challenges with Emission Factors



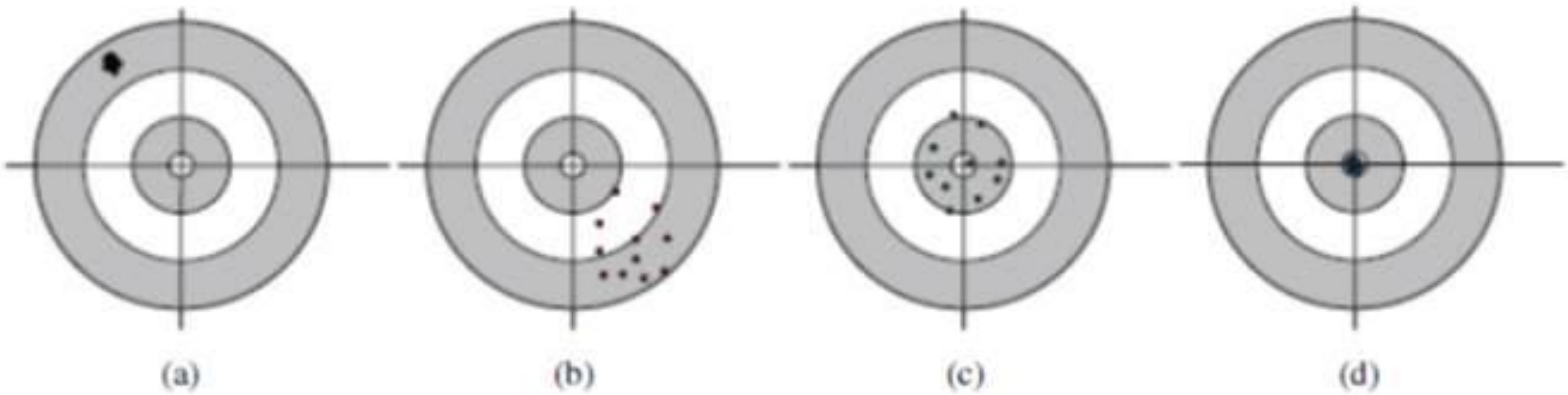
Proportion of forest (tree cover >40%) with high soil carbon content (>15 kg/m2/m) present a challenge due to lack data

Romijn et al. , Environmental Science & Policy (2012)

Causes of uncertainty

- Lack of completeness
- Model:
  - Simplification of the ‘real world’
  - Interpolation
  - Extrapolation
  - Alternatives formulation of the model
  - Model inputs
- Lack of data
- Lack of representativeness of data
- Statistical random sampling error
- Measurement error
- Misreporting or misclassification
- Missing data

Illustration of accuracy and precision

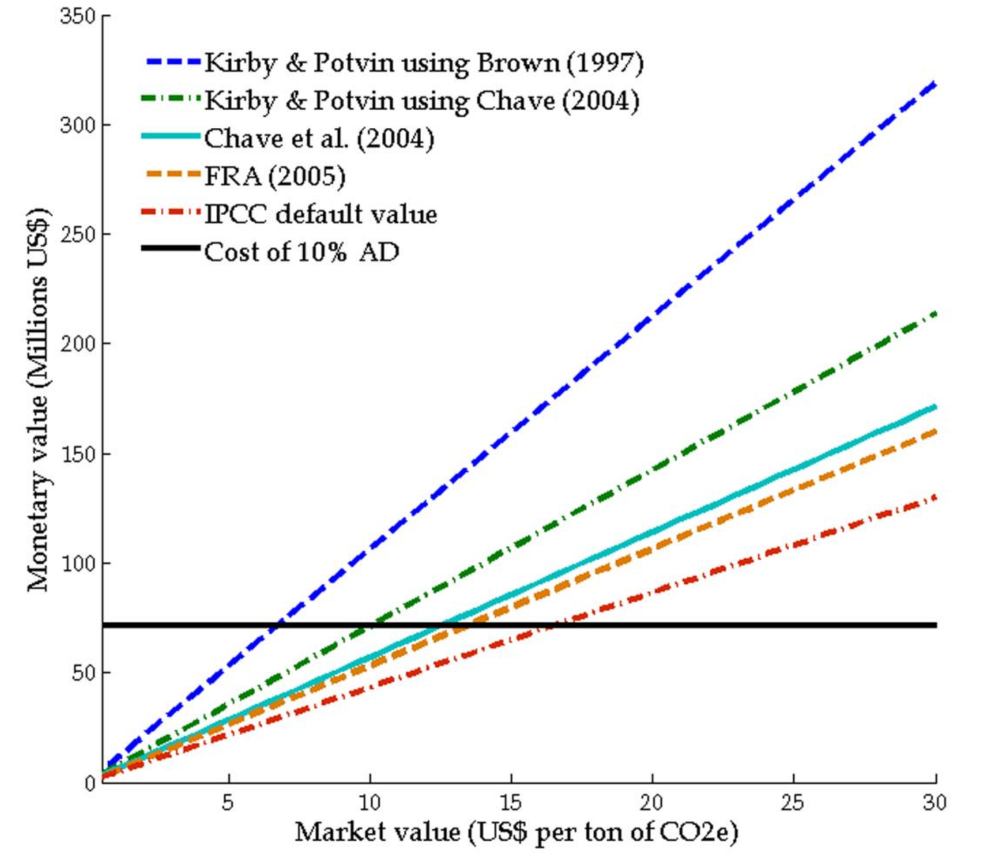


(a) inaccurate but precise;
(b) inaccurate and imprecise;
(c) accurate but imprecise;
(d) precise and accurate.

IPCC guidelines (2006, chap 3)

Why does uncertainty matter?

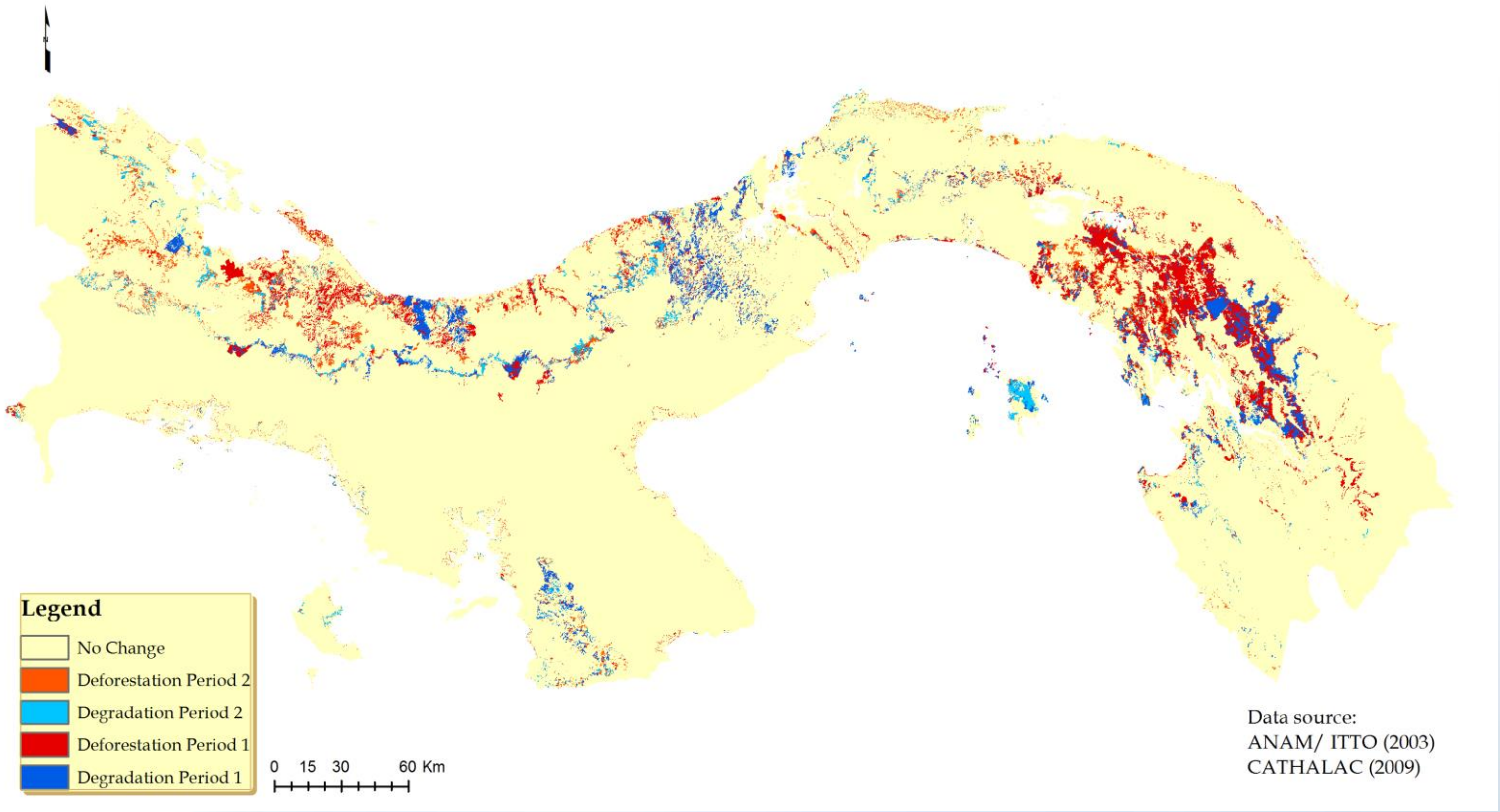
Large uncertainties surround estimates of C stocks and emissions. They have financial implications.



Pelletier et al. Forest Policy and Economics (2012)

Case study for Panama

Credible emission reductions from REDD+



Pelletier et al., Climatic Change (2015)

Dealing with uncertainty upstream or downstream?

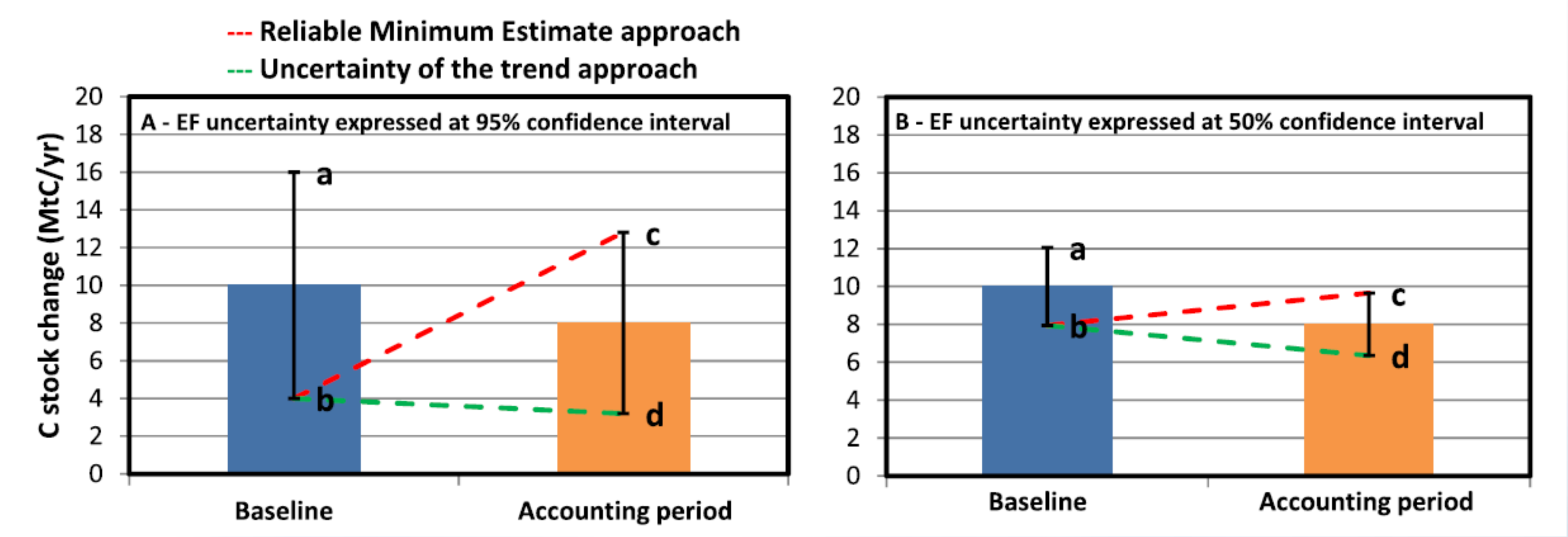
Upstream: *Before emission reduction accounting*

One approach to reduce uncertainties prior to carbon accounting, through ‘upstream’ investments in improved forest monitoring technologies and techniques.

Dealing with uncertainty Upstream or downstream?

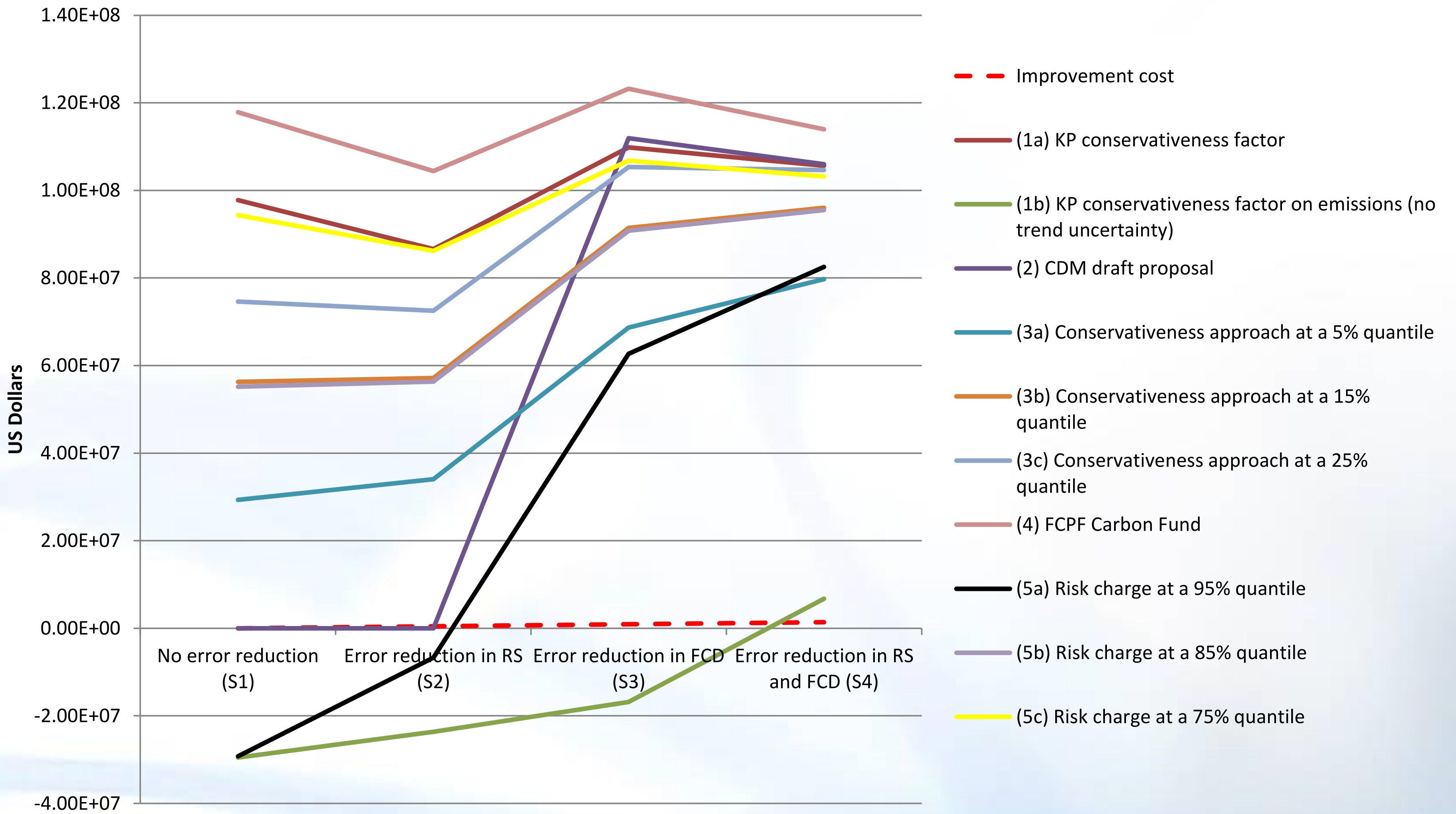
Downstream: *After emission reduction accounting*

- Discounting approaches under funds or market: the use of an adjustment or crediting rules used *a posteriori* of the carbon accounting that would reduce the risk of overestimating emission reductions or removals.



Grassi et al. Climatic Change (2013)

Dealing with uncertainty Upstream or downstream?



Forest monitoring improvement costs represents less than 2% of potential carbon credits

Elements of discussion:

- What are the main sources of error or uncertainty on emission and removals estimation that you can identify through your work?

Group discussion (15 min.)/ report in plenary (15 min.)

COMPONENTS OF UNCERTAINTY

1. Land-Cover Change and Land-use dynamics
2. Carbon stock and change (from forests to other land uses)
3. Accounting of emissions and removals (modelling approach)

DIAGNOSIS OF UNCERTAINTIES

Example from Panama:

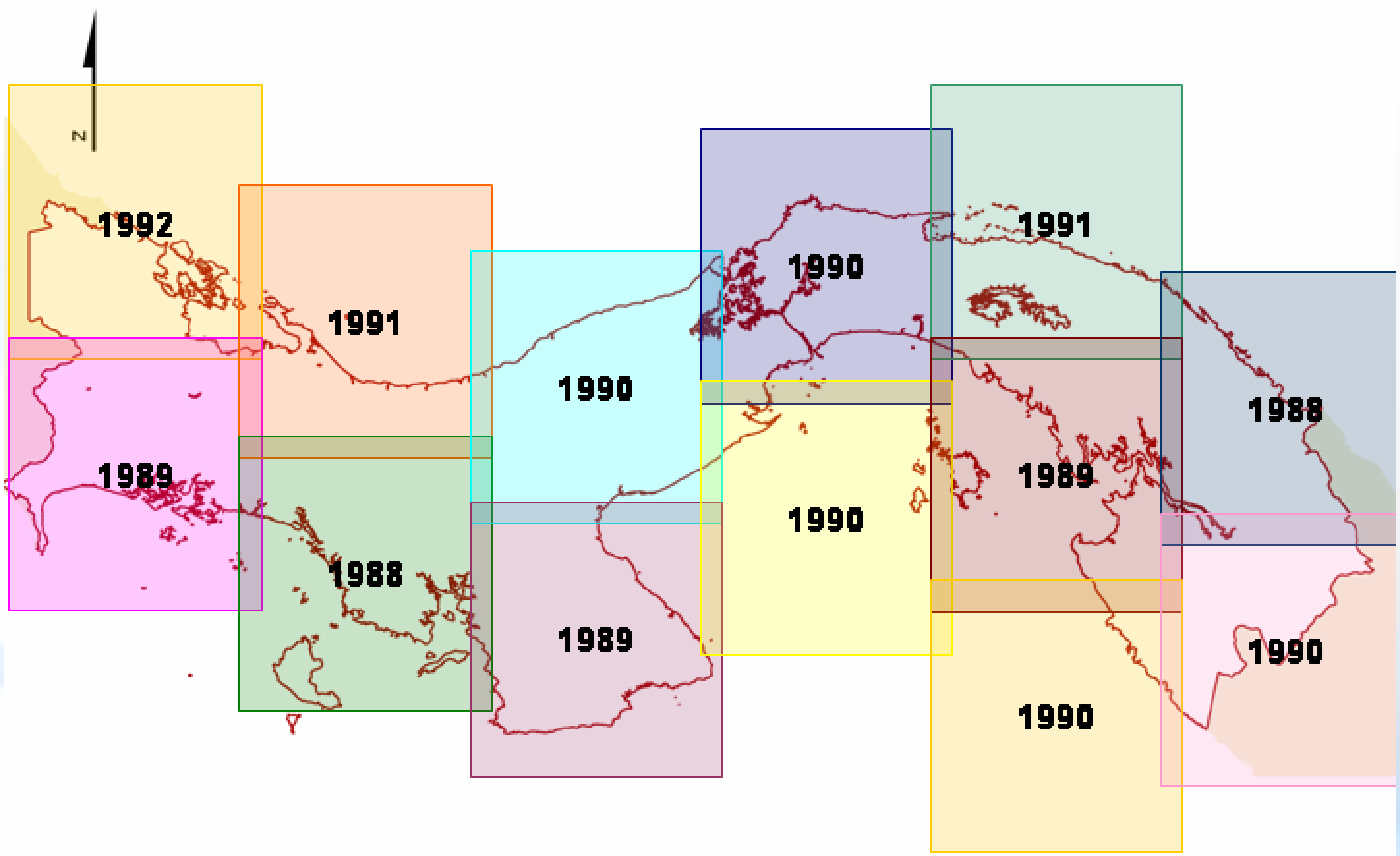
	Uncertainty
Mature forest C density	**54.5%**
Fallow C density	22.4%
Deforested area classification	2.2-19.1%
Snapshot effect	19.3%
Quality of land cover map	15.6-35.2%

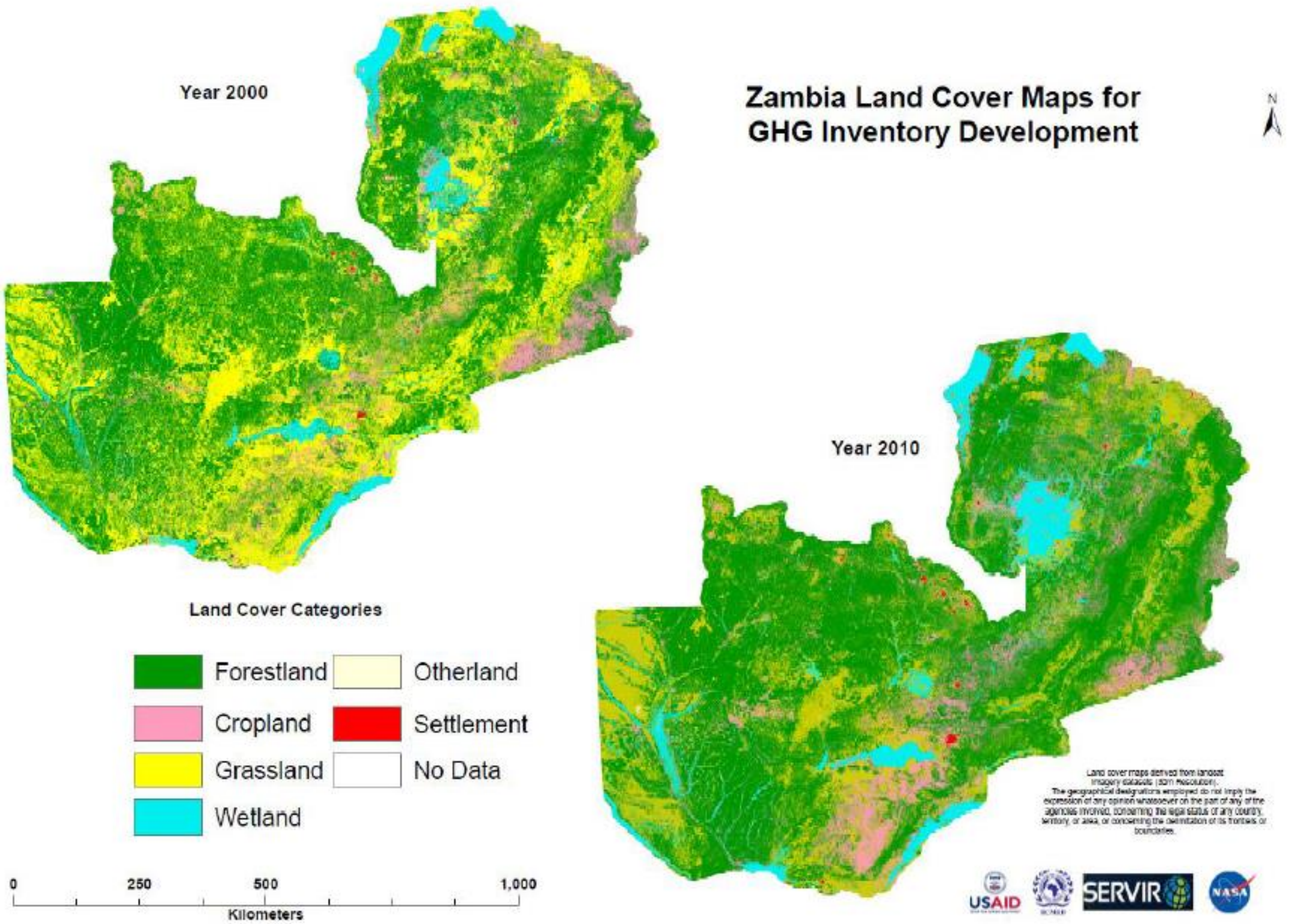
Pelletier, J., Ramankutty, N., Potvin, C. Environmental Research Letters (2011)

LAND-COVER MAP QUALITY

15.6 to 35.2 %

Map based on a mosaic of multi-year satellite images / Low availability of usable satellite imagery

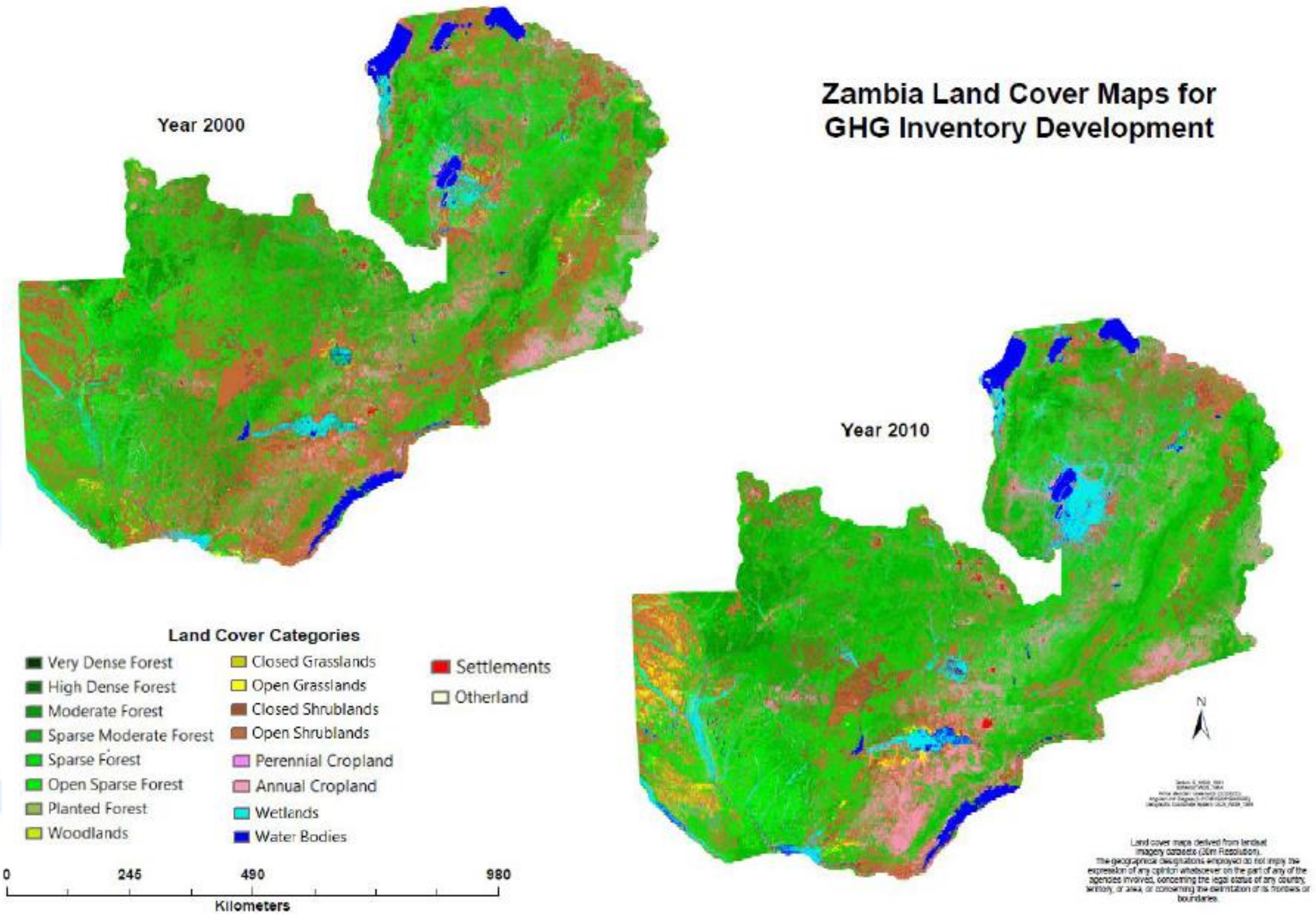




Zambia Scheme 1, Land Cover maps

The Woods Hole Research Center

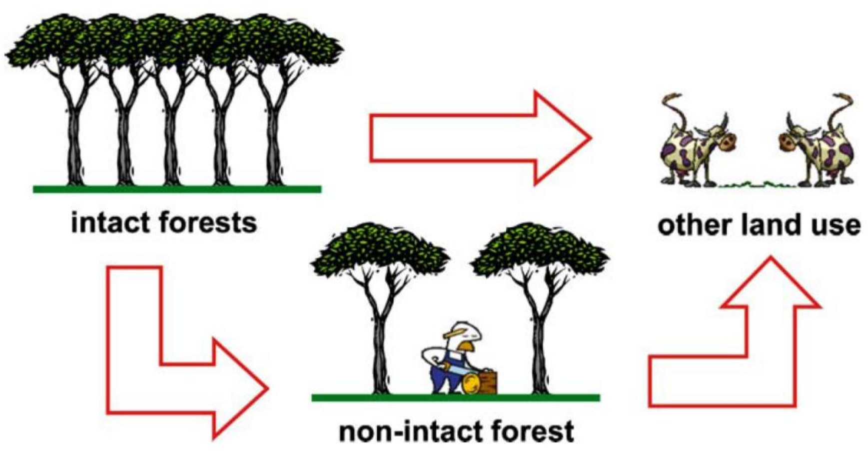
NASA



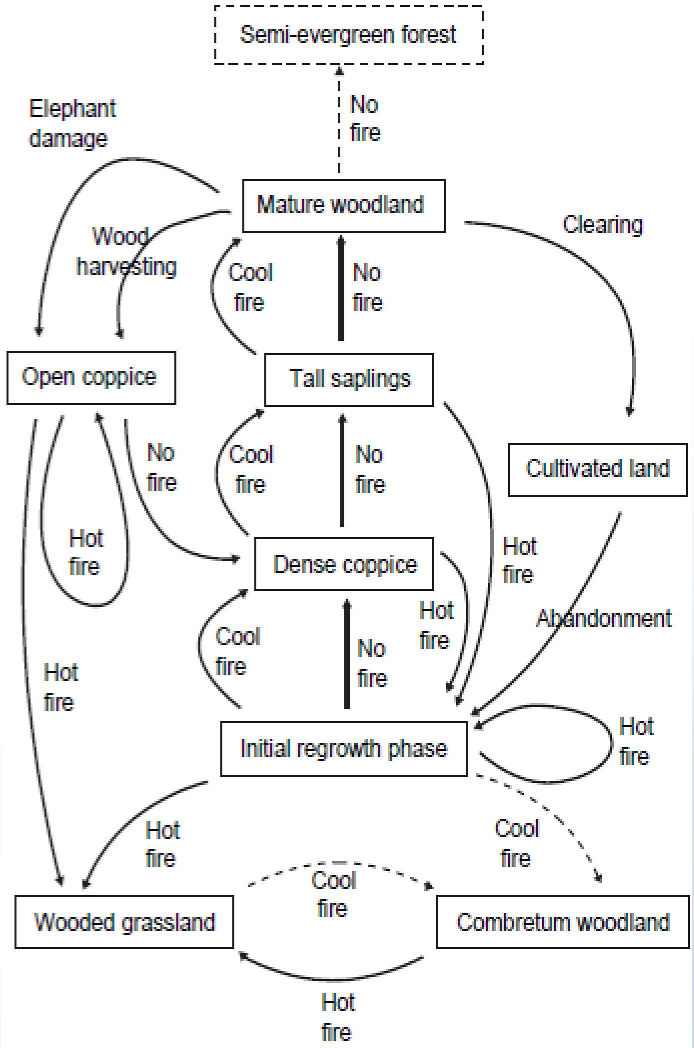
Zambia Scheme 2, Land Cover maps

Land-use dynamics

- More complex dynamics in the Miombo woodlands



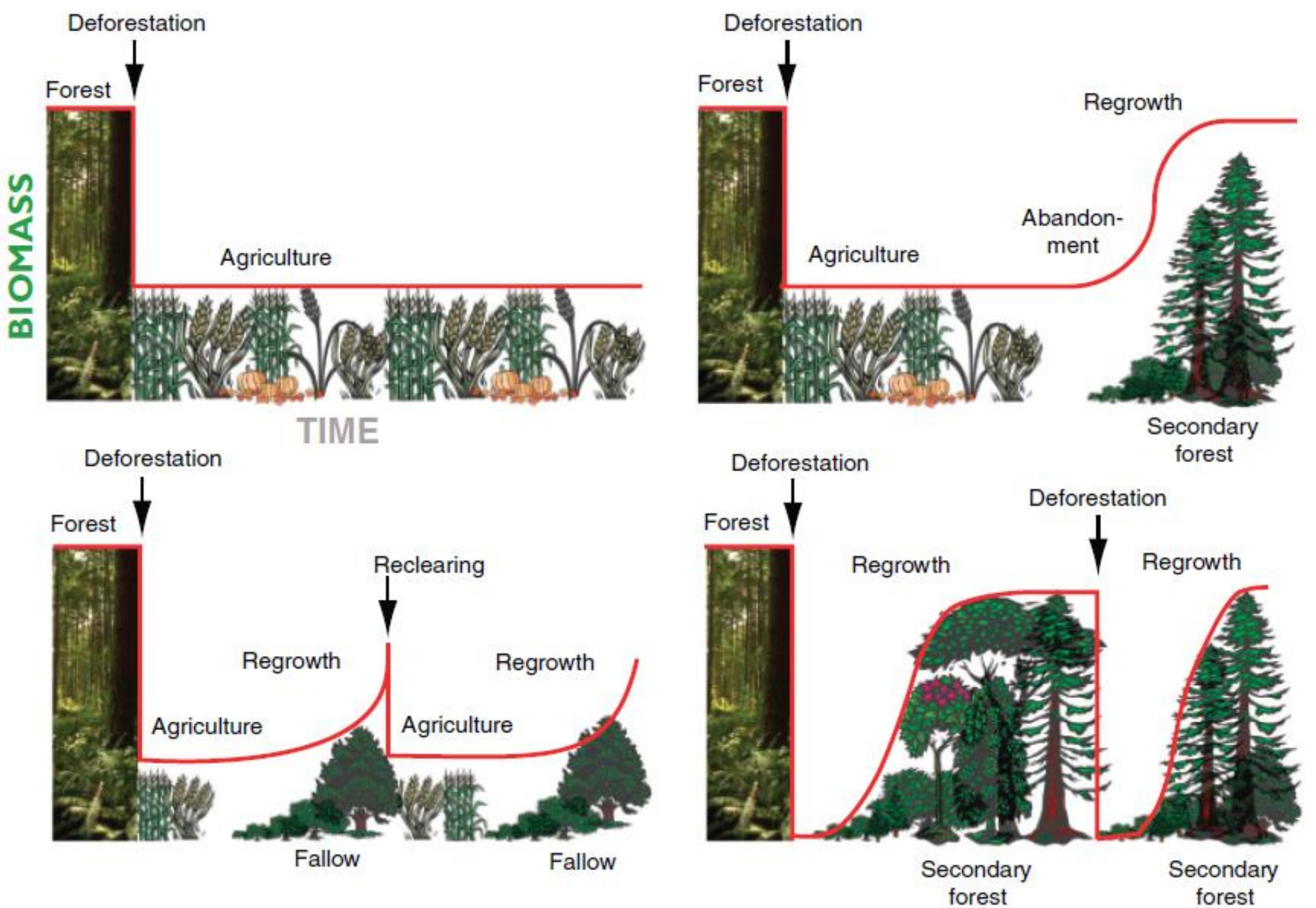
Mollicone et al., Climatic Change (2007)



Frost, in Campbell, Miombo in Transition (1996)

Land-use dynamics

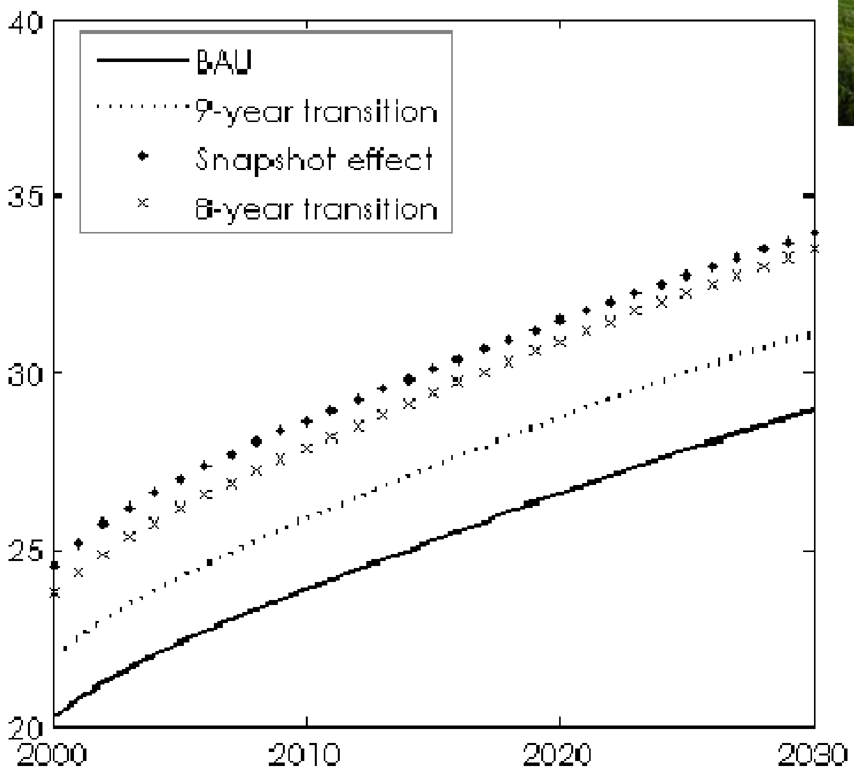
Different pathways of carbon dynamics following deforestation



Ramankutty et al. Global Change Biology (2007)

Land cover change: SNAPSHOT EFFECT

Long time interval between two maps/Lack of knowledge on land-cover dynamics

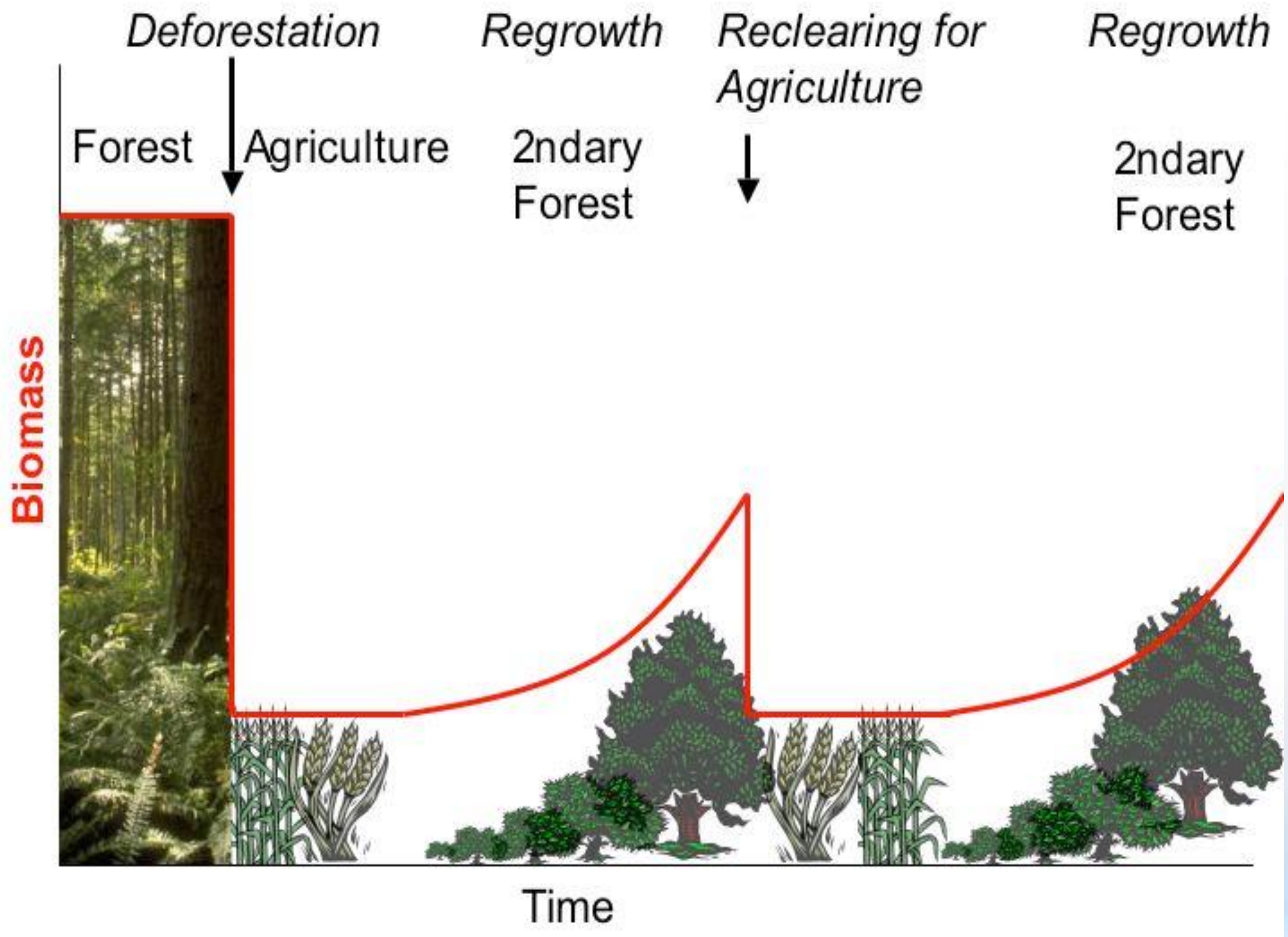


19.3 %

PROBLEMS MONITORING SHIFTING CULTIVATION

Overestimating:

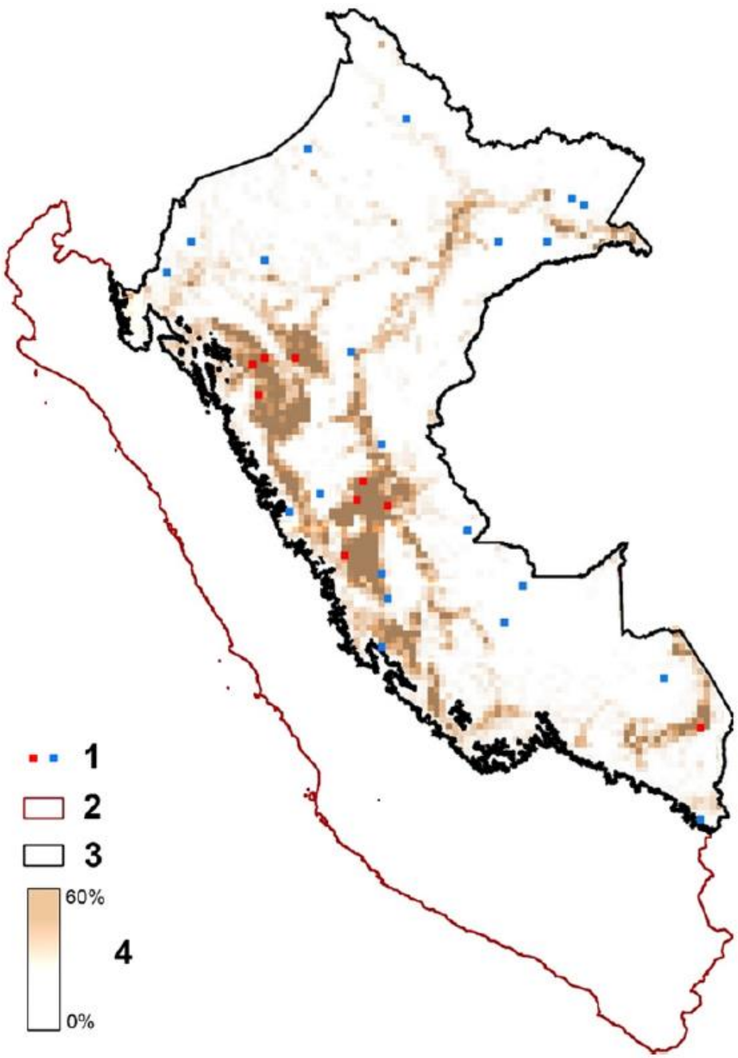
- Emissions of new deforestation
- Removals from forest regrowth



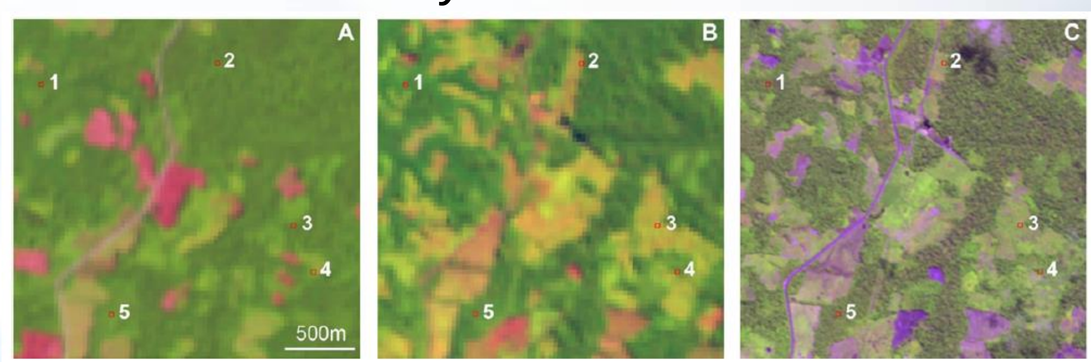
From Ramankutty *et al.*, Global Change Biology (2007)

Assessing accuracy of land change

- Sampling design:
  - Strata
  - Cluster sampling
  - Systematic vs random selection
- Response design
- Analysis:
  - Estimating accuracy, area and uncertainty



Stratified sampling design



Point-based validation

Potapov et al., Environmental Research Letters, 2014

Assessing accuracy of land change

Table 3

Error matrix of sample counts (n_{ij}) constructed from the accuracy assessment sample of a change map by Jeon et al. (in press). Class 1 is deforestation, and classes 2 and 3 are no change classes of forest (class 2) and non-forest (class 3). Map categories are the rows while the reference categories are the columns.

Class	1	2	3	Total	Map area [ha]	W_i
1	97	0	3	100	22,353	0.013
2	3	279	18	300	1,122,543	0.640
3	2	1	97	100	610,228	0.348
Total	102	280	118	500	1,755,123	1

Olofsson et al. Remote Sensing of Environment, 2013

Calculating standard error:

$$S(\hat{p}_{\cdot 1}) = \sqrt{\sum_{i=1}^{3} W_i^2 \frac{\frac{n_{ij}}{n_{i\cdot}}\left(1-\frac{n_{ij}}{n_{i\cdot}}\right)}{n_{i\cdot}-1}} = ((0.013^2 \frac{\frac{97}{100}\left(1-\frac{97}{100}\right)}{99} + 0.64^2 \frac{\frac{3}{300}\left(1-\frac{3}{300}\right)}{299}$$

$$+0.35^2 \frac{\frac{2}{100}\left(1-\frac{2}{100}\right)}{99})^{\frac{1}{2}} = 0.00613.$$

Standard error of the adjusted area estimate:

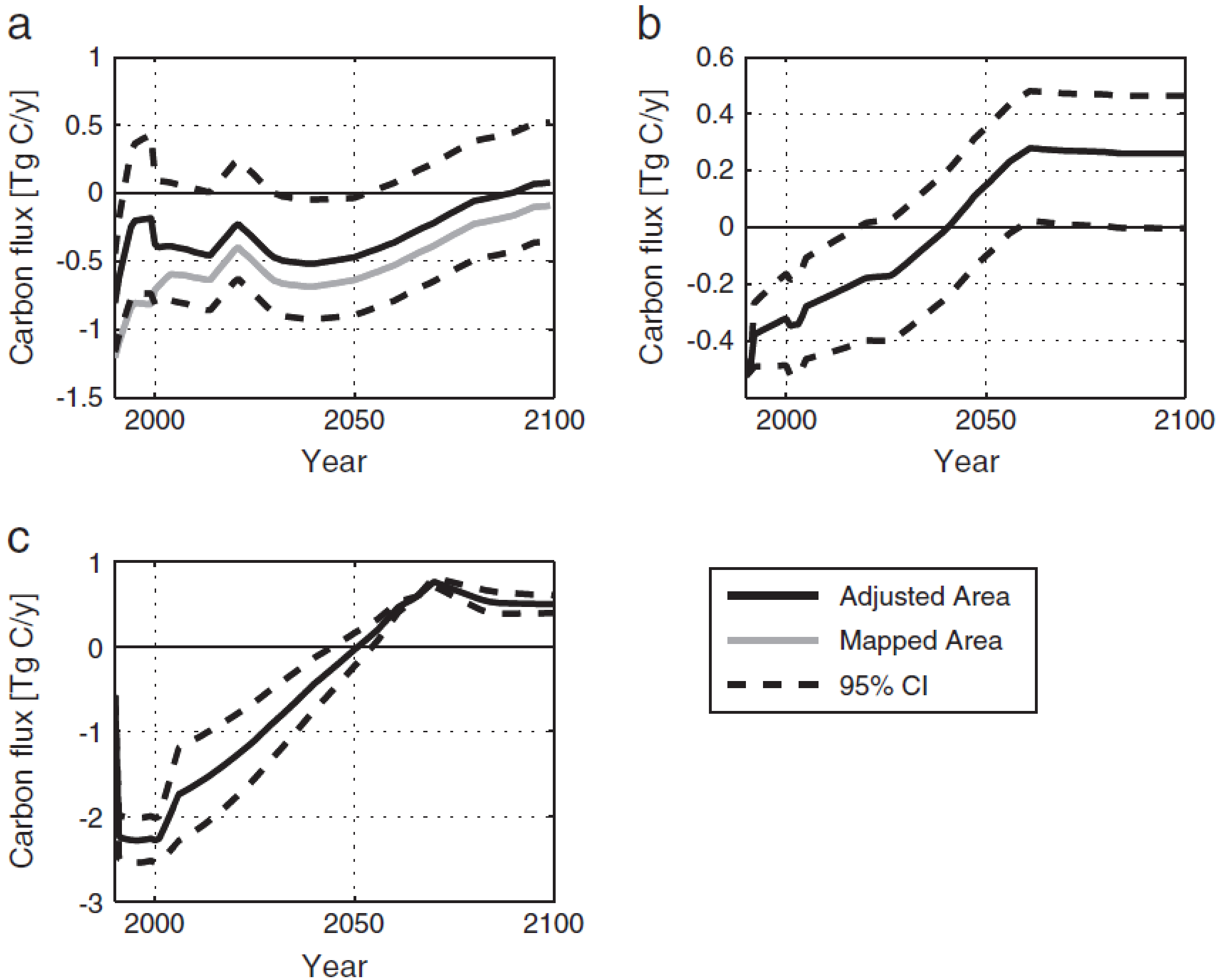
$$S\left(\hat{A}_1\right) = A_{tot} \times S(\hat{p}_{\cdot 1}) = 1,755,123 \times 0.00613 = 10,751 \text{ ha}$$

A final land change area estimate with margin of error (at 95% CI):

$$\hat{A}_1 \pm 2 \times S\left(\hat{A}_1\right) = 45,651 \pm 21,502 \text{ ha}.$$

The confidence interval quantifies the uncertainty associated with the sample-based estimate of the area of deforestation.

Assessing accuracy of land change

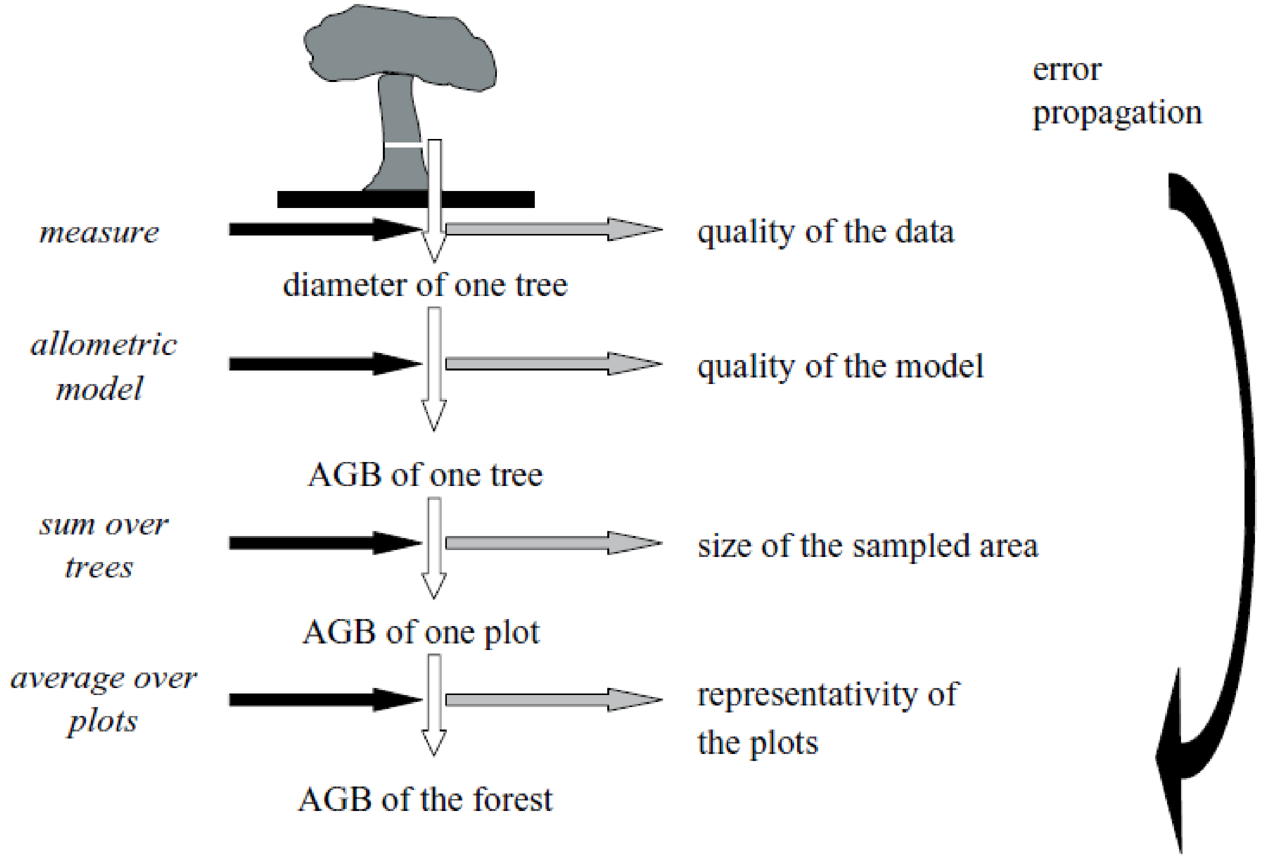


The true area of deforestation could be as low as 241,149 ha or as high as 67,153 ha at 95% level of confidence.

Large impact on emission estimates but rarely available.

Olofsson et al. Remote Sensing of Environment, 2013

Biomass estimation: error propagation



Chave et al. Phil. Trans. R. Soc. Lond. B, 2004

Biomass estimation: error in measurements

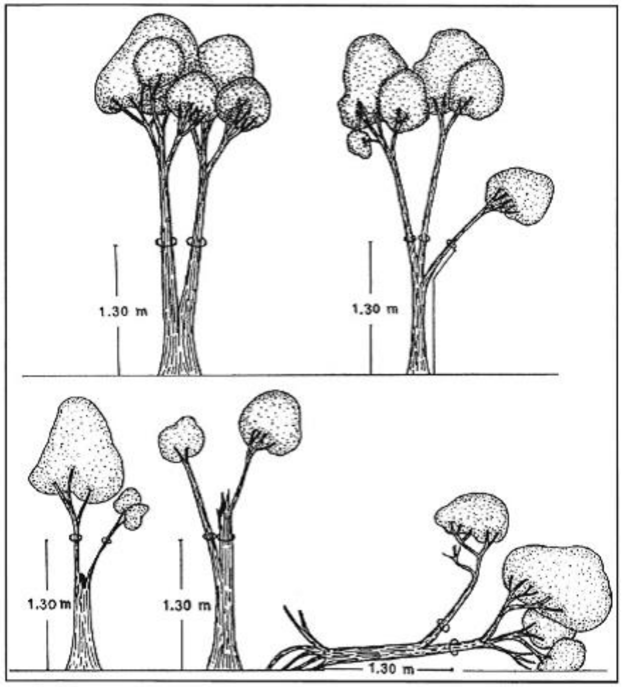
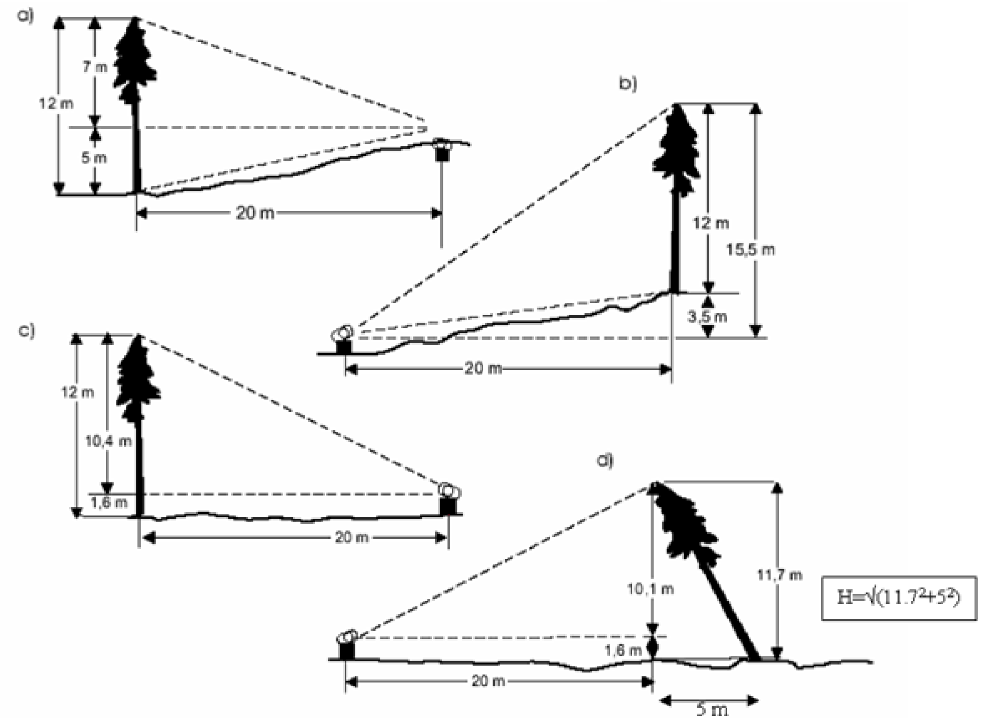


Fig. 2.2.6. Measurement of multiple stems. Any fork between the base and 1.3 m counts as a second stem, and must be measured 1.3 m from the base of the tree.



Biomass estimation: error in measurements

WOOD DENSITY to parameterize allometric models vary with the age of the tree, growth conditions, intraspecific but mostly interspecific

- Can be downloaded from repository:

1. http://datadryad.org/resource/doi:10.5061/dryad.234
2. http://db.worldagroforestry.org/wd/

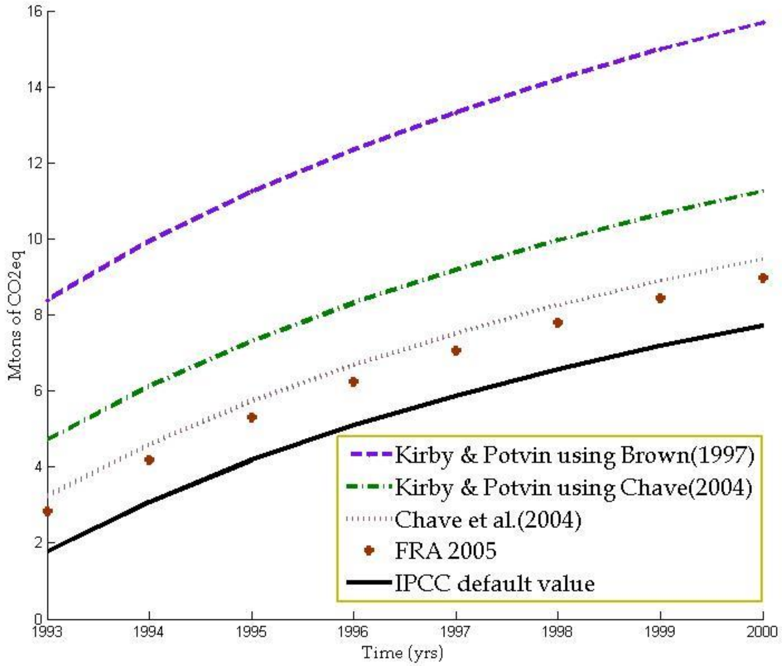
- The variability in wood density can be included in uncertainty analysis

Biomass estimation: allometric models

- Improved allometric models

Tissue type		Number of samples per tree
Trunk		15
Branches		10
Twigs		10
Flowers		10
Leaves	Small	10
	Medium	10
	Large	10
Coarse Roots		10
Fine Roots		10
Total:		95

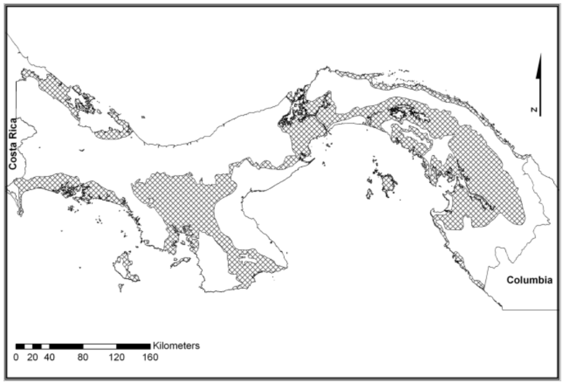
Biomass estimation: allometric models



Different allometric equations, Same inventory data

MATURE FOREST C DENSITY

No standardized methodology and error-prone allometric equations



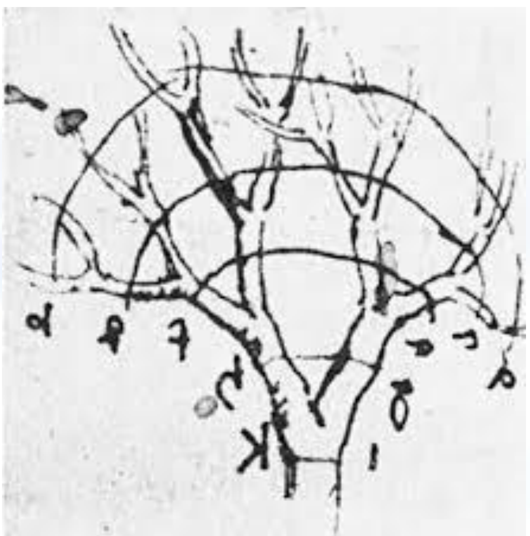
Moist tropical forest

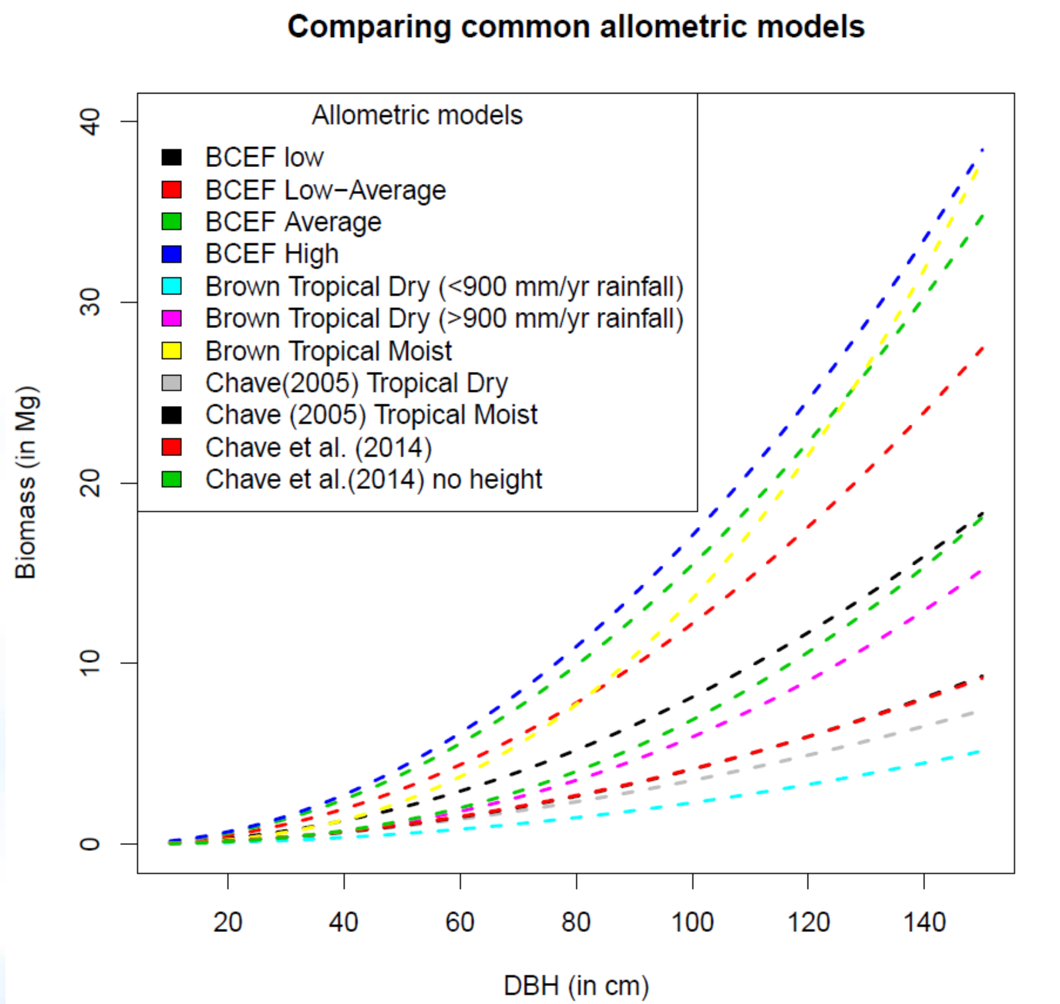
Pelletier, J., Kirby, K.R., Potvin, C., Forest Policy and Economics (2012)

Biomass estimation: allometric models

Example for Zambia

Using pan-tropical generalized allometric models



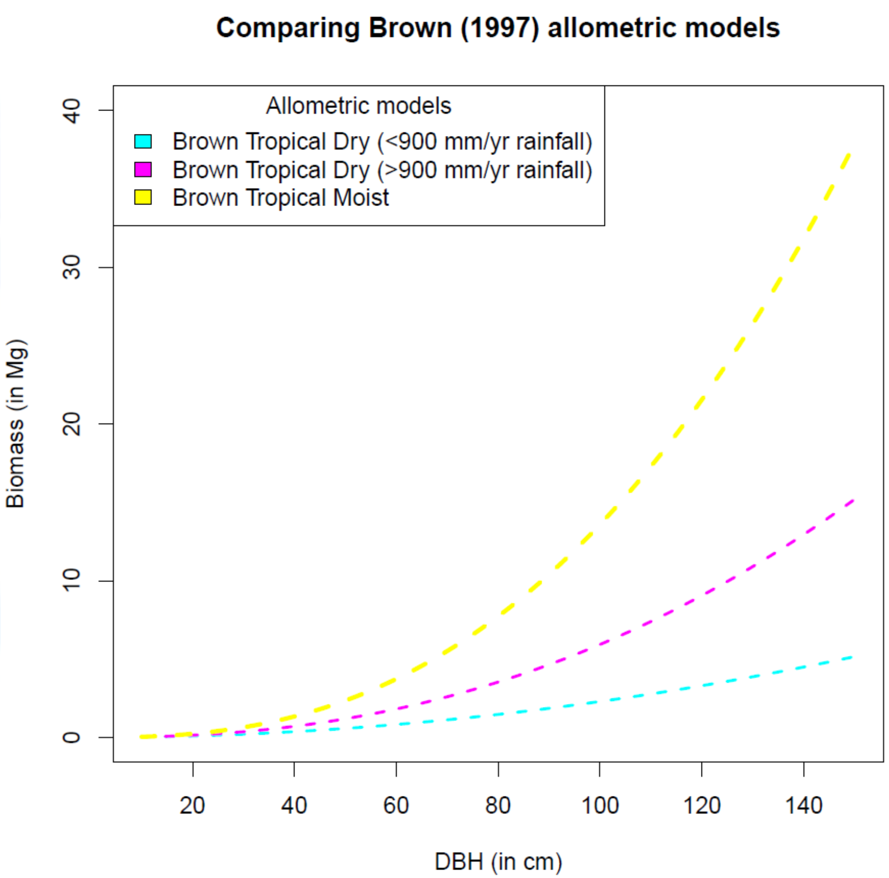


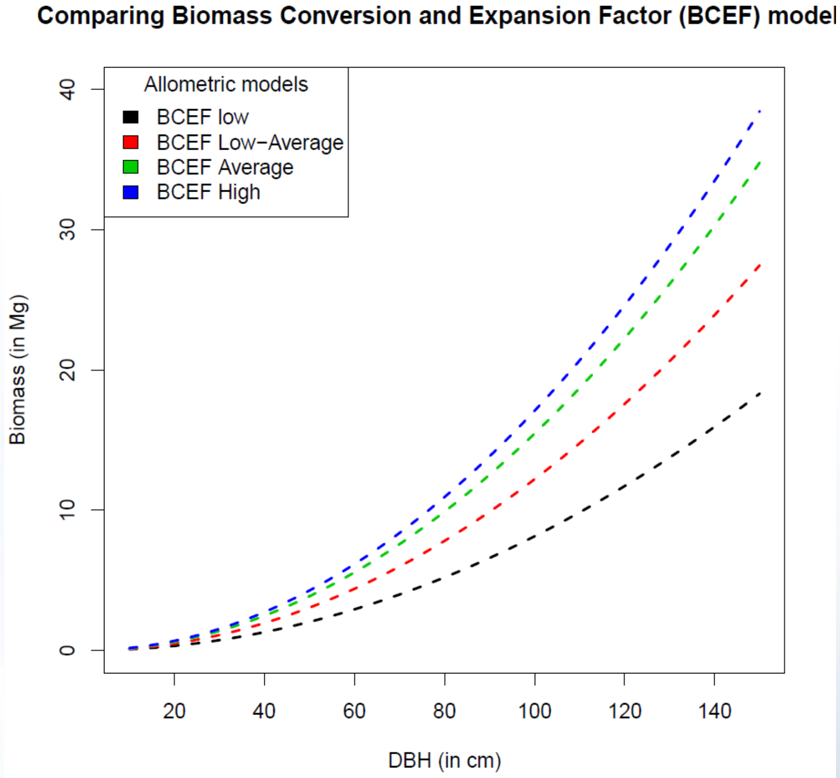
Pelletier et al. (in prep)

Biomass estimation: allometric models

Example for Zambia

BIOMASS EXPANSION AND CONVERSION FACTORS





BROWN (1997) ALLOMETRIC EQUATIONS:

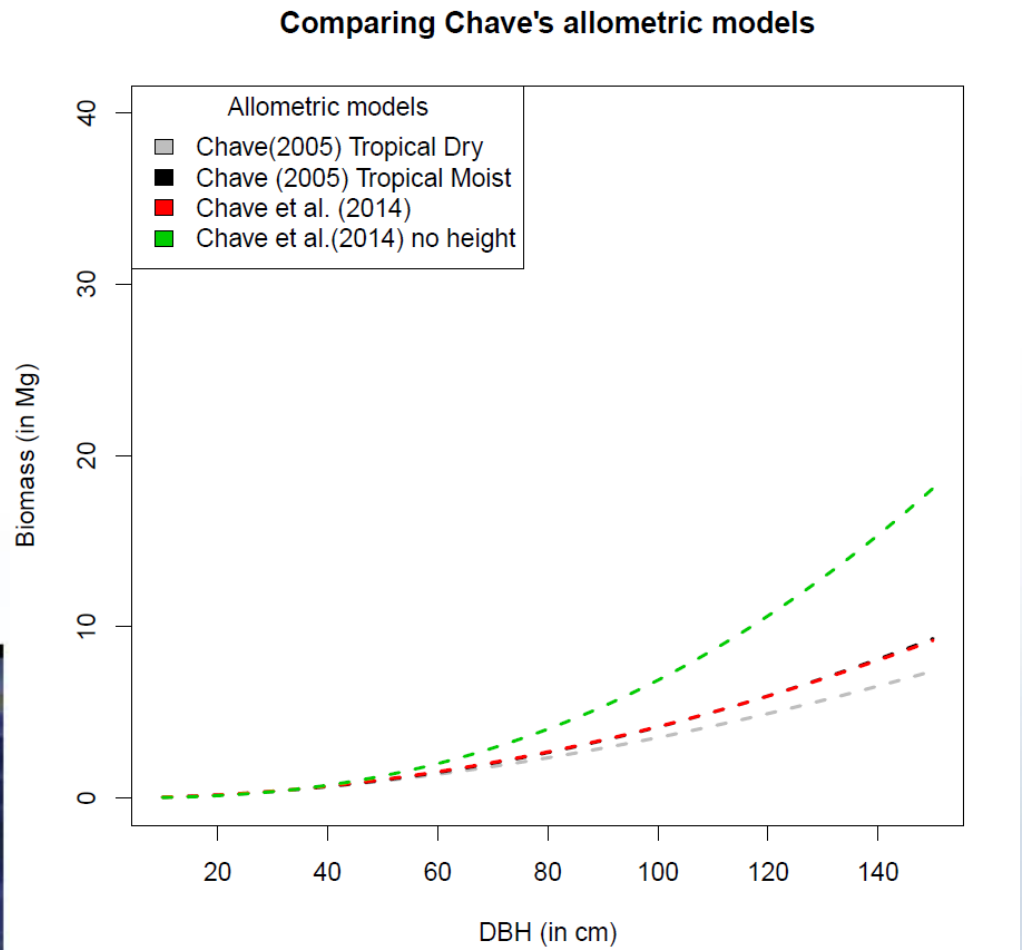
- Based on a limited sample size
- Applicable to different forest types
- No height measurement

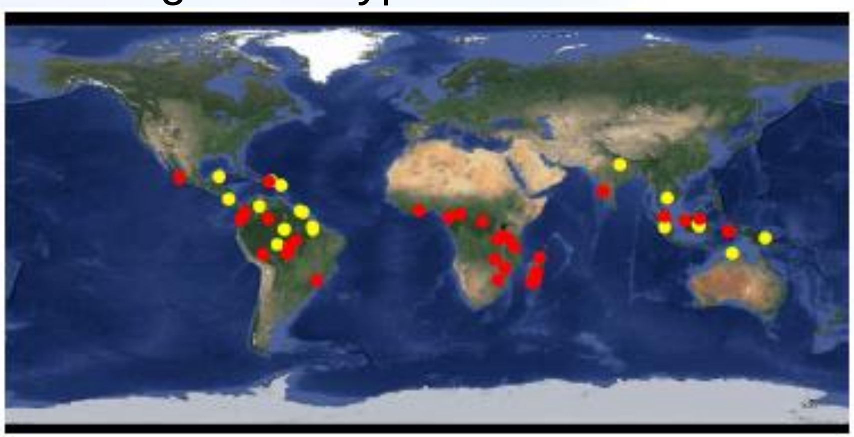
Biomass estimation: allometric models

Example for Zambia

BEST PAN-TROPICAL ALLOMETRIC MODELS

- With height measurements
- Without height measurements
- Based on the destructive sampling of 4004 trees ≥ 5 cm DBH, spanning a range of climatic conditions and vegetation types





Yellow circles: 20 sites included in 2005 eq.
Red circles: 38 new sites included in 2014 eq.

CHAVE et al. 2005 & 2014 ALLOMETRIC EQUATIONS

Database of harvested trees is available at: http://chave.ups-tlse.fr/pantropical_allometry.htm

Global database on tree allometry

- GlobAllomeTree database: *For Assessing volume, biomass and carbon stocks of trees and forests*.

GlobAllomeTree

Assessing volume, biomass and carbon stocks of trees and forests.

Home | About | Data | Software | Documents | Contributors | jopel

Equations

Your current search

Export Results

Equations found: 59

Keyword | Kenya | clear

Keyword | Identification | Taxonomy | Location | Components | Input/Output | Allometry | Reference

Search allometric equations by keyword. This searches accross several text fields.
Example searches: Acacia, Zambia, Bellefontaine, Glutinosum, rainforest

Keyword: Kenya

Search

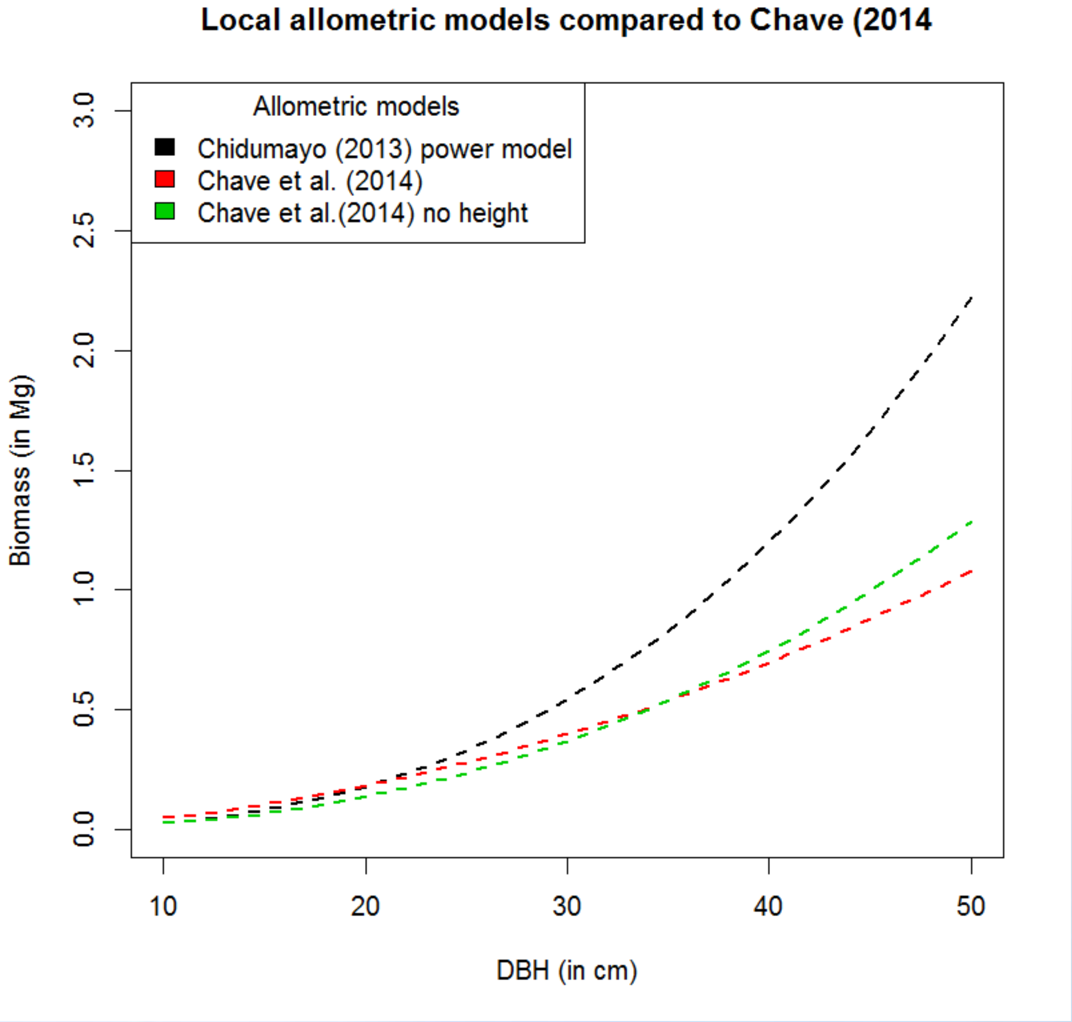
Id	Equation	Genus	Species	Country	Components	Output	Biome (FAO)	Aut
1136	-1.0899+2.4937*log(H)	Rhizophora	mucronata	Kenya	L	Biomass	Tropical moist deciduous forest	Kair
1143	-1.4295+0.9154*log(DBH*H)	Rhizophora	mucronata	Kenya	Rb	Biomass	Tropical moist deciduous forest	Kair
1314	0.134*DBH+0.0579*DBH^2+0.317*H	Tarchonanthus	camphoratus	Kenya	Bd Bg Bt T	Biomass	Tropical mountain system	Kiru
1319	1.8069*DBH^2.5628	Rhizophora	mucronata	Kenya	L	Biomass	Tropical moist deciduous forest	Kiru
1119	-1.301+2.4044*log(DBH)	Rhizophora	mucronata	Kenya	Rb	Biomass	Tropical moist deciduous forest	Kair
1121	0.3703+0.2708*log(DBH)	Avicennia	marina	Kenya	Bd Bg Bt	Biomass	Tropical moist deciduous forest	Kair
1126	0.1862-0.3740*log(DBH)	Ceriops	tagal	Kenya	L	Biomass	Tropical moist deciduous forest	Kair
1133	-0.9905+2.3918*log(H)	Rhizophora	mucronata	Kenya	Rb	Biomass	Tropical moist deciduous forest	Kair
1138	-1.4413+1.4267*log(DBH*H)	Rhizophora	mucronata	Kenya	Rb	Biomass	Tropical moist deciduous forest	Kair
1140	-0.6275+0.8088*log(DBH*H)	Rhizophora	mucronata	Kenya	B T	Biomass	Tropical moist deciduous forest	Kair
1145	-0.5761+0.4968*log(DBH*H)	Rhizophora	mucronata	Kenya	B T	Biomass	Tropical moist deciduous forest	Kair

http://www.globallometree.org/

Biomass estimation: allometric models

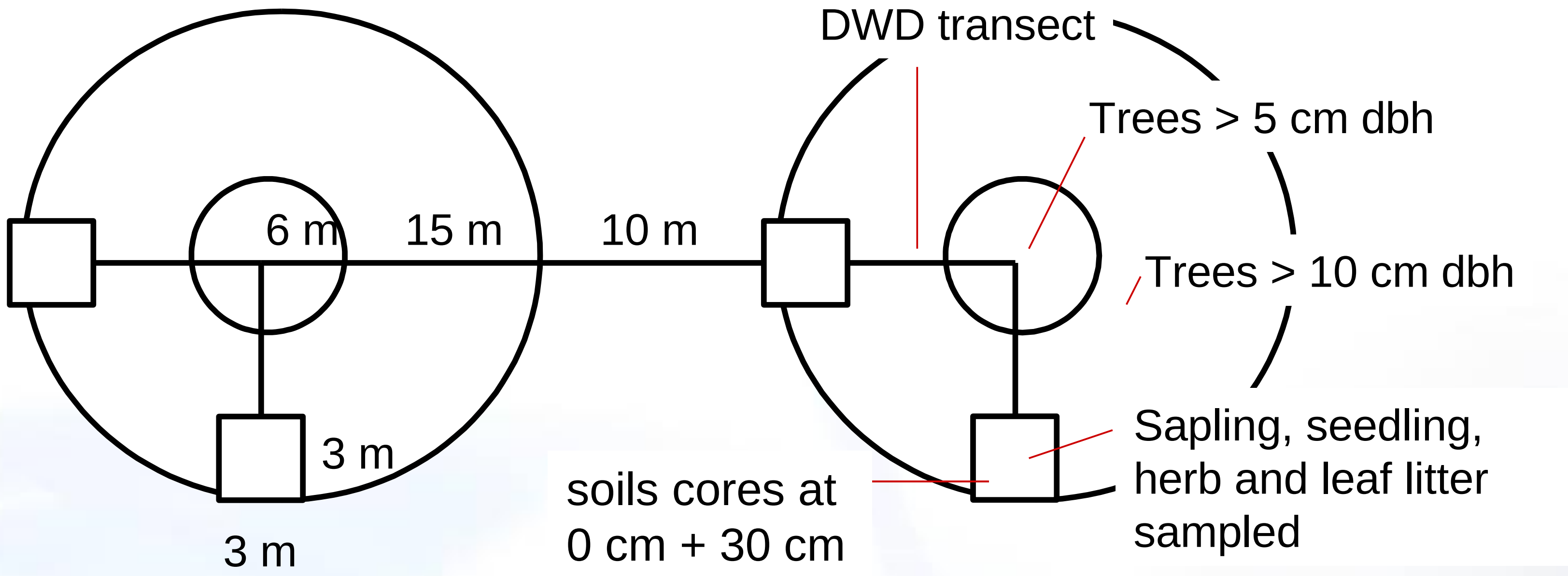
Example for Zambia

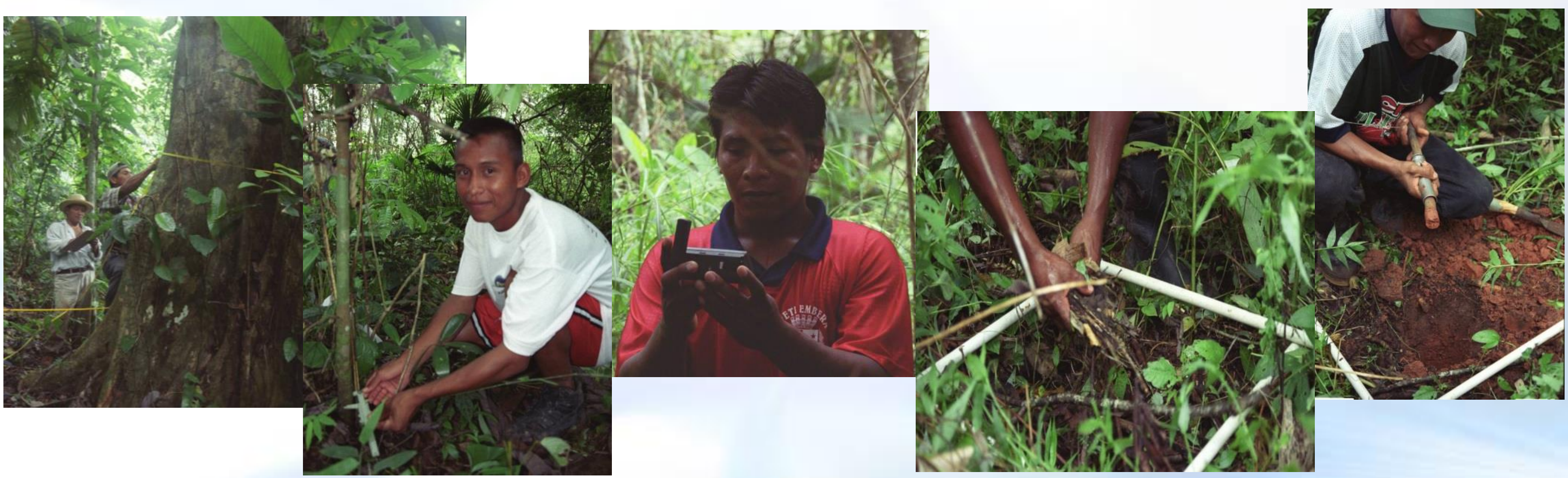
- Chidumayo (2013)
- Destructive sampling of 113 trees between 2-39 cm dbh.
- Miombo woodland



Biomass estimation: sampling design

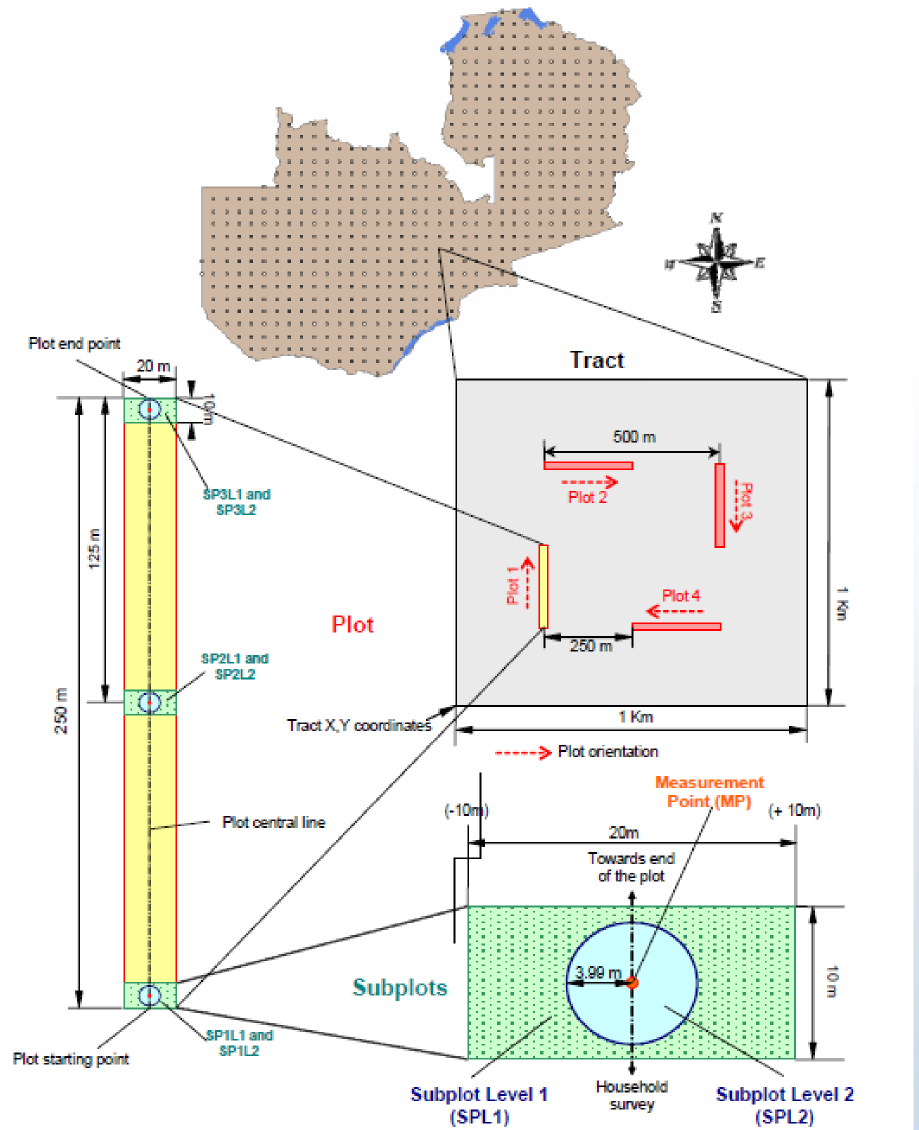
Area of each sub-plot: 707 m^2





Biomass estimation: sampling design

- Size of the plots
- Systematic or stratified random design



ILUA I, Field Manual, 2005-2008

Plot size (Chave et al., 2004):

sub-plot size (m)	number of plots	s.d.	skewness	kurtosis
10×10	5000	385.08	5.42	47.05
20×20	1250	187.64	2.57	10.62
25×25	800	149.44	1.88	5.34
20×50	500	119.52	1.54	3.47
50×50	200	77.55	0.57*	−0.24**
100×100	50	42.01	−0.06**	−0.12**

With plots of 50X50m and greater, a normal distribution is obtained
The standard deviation is reduced.

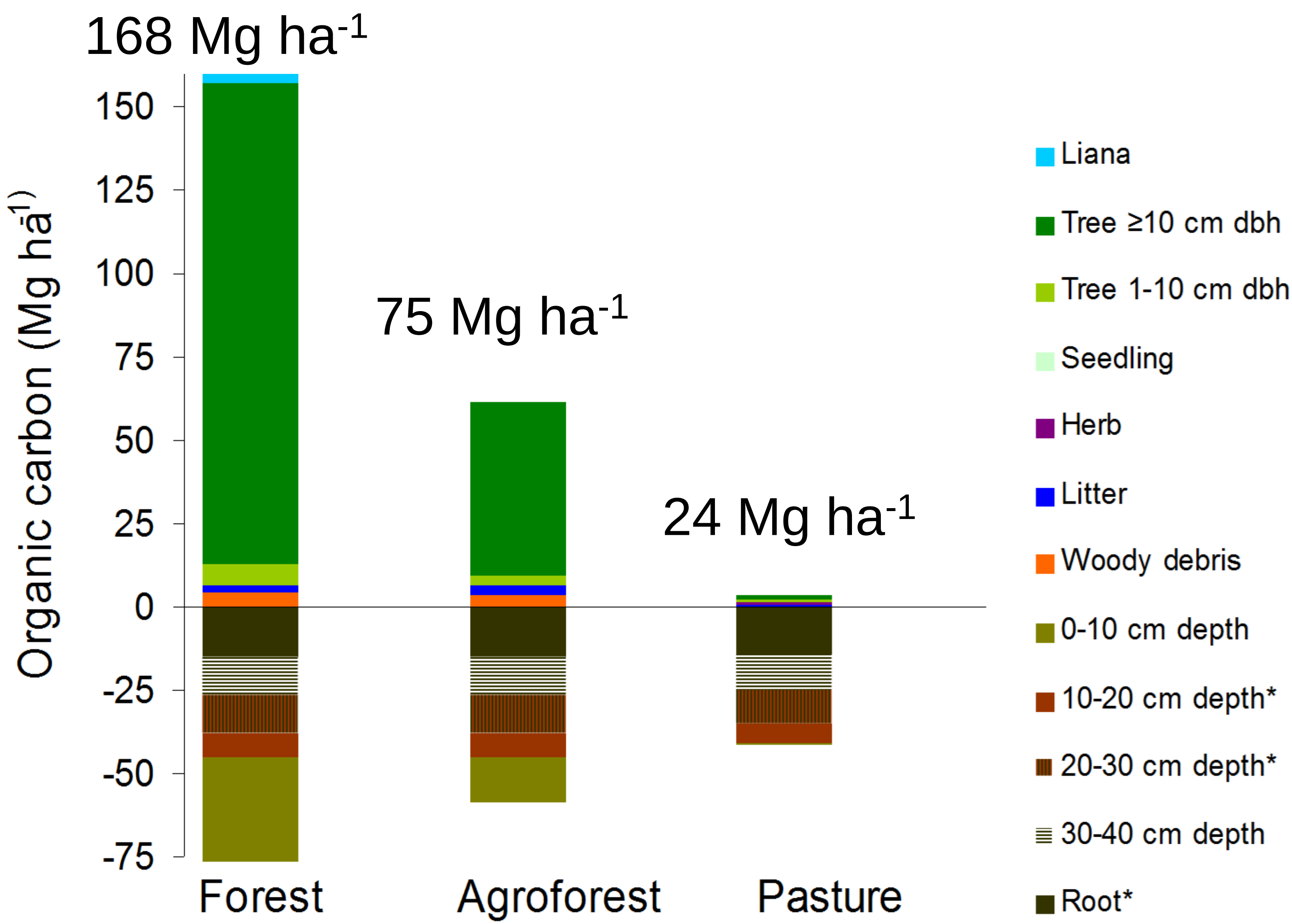
Biomass estimation: the effect of each component

Summary of the sources of error in the AGB estimation of a tropical forest

error type		s.e.m. (percentage of the mean)	type of data
1. tree level error	trees > 10 cm diameter	48	BCI plot—pan-tropical allometric model
	trees < 10 cm diameter	78	
2. allometric model	before ρ correction	22	BCI plot—eight allometric models
	after ρ correction	13	
	after large tree correction	11	BCI plot—pan-tropical allometric model
3. within-plot uncertainty	0.1 ha plot	16	
	0.25 ha plot	10	
	1 ha plot	5	
4. among-plot uncertainty		11	Marena plots—pan-tropical allometric model
total	50 1 ha plots, after ρ and large tree corrections	24	—

Chave et al. *Phil. Trans. R. Soc. Lond.* B (2004)

Five carbon pools



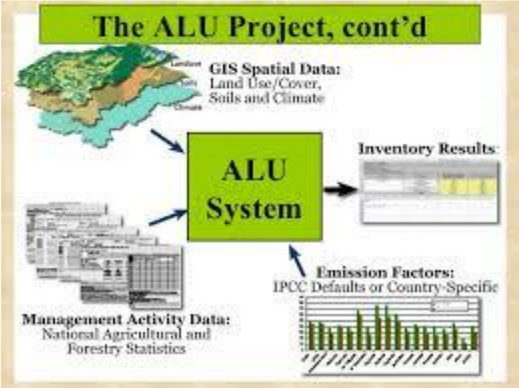
Kirby and Potvin, Forest Ecology and Management (2007)

Error in the modelling approach

Difference approaches exist to estimate:

- » Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3) ;
  https://www.nrcan.gc.ca/forests/climate-change/13107

- » ALU software: Agriculture and Land Use National Greenhouse Gas Inventory Software;



http://www.nrel.colostate.edu/projects/ALUsoftware/

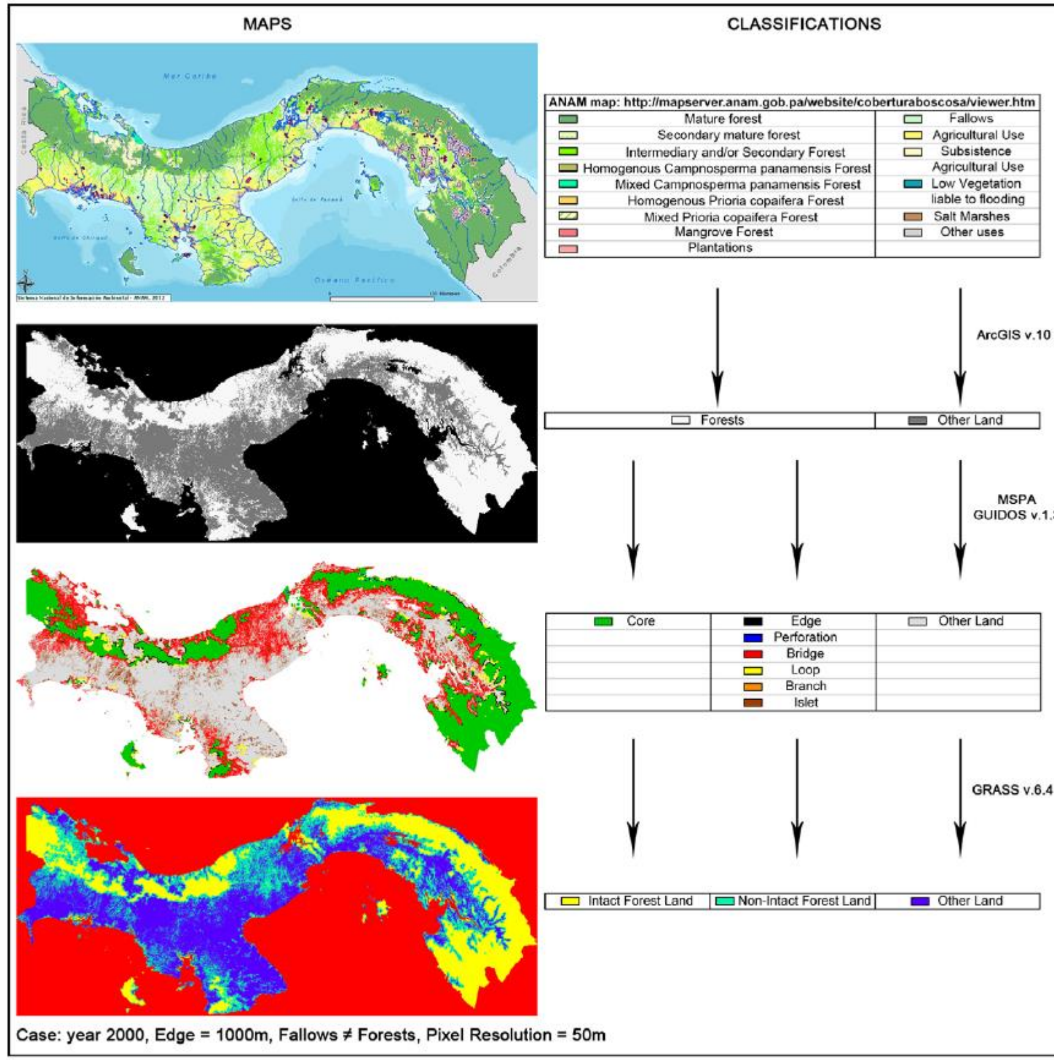
- » OpenForis, FAO
  http://www.openforis.org/

Error in the modelling approach

Testing a proposed accounting approach:

Bucki *et al* (2012)
Simplified approach to provide robust performance indicators for REDD+ using default emission factors

with Panama as a case study



Pelletier, J, et al, Environmental Research Letters, 2013

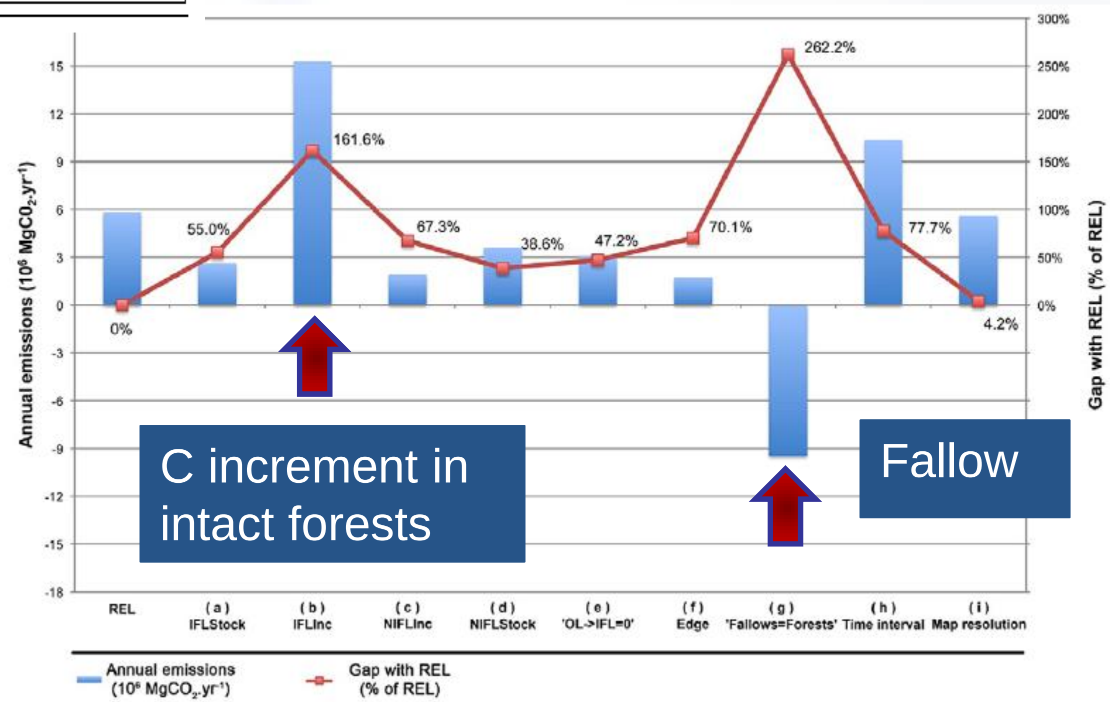
Error in the modelling approach

	IFL 2000	NIFL 2000	OL 2000
(a)			
IFL 1992	2829 (1374)	311 (207)	239 (173)
NIFL 1992	133 (175)	521 (846)	300 (182)
OL 1992	73 (161)	396 (224)	2596 (1156)
(b)			
IFL 1992	−7.77 (9.43)	11.65 (9.03)	17.49 (7.53)
NIFL 1992	−4.97 (3.85)	−4.53 (3.93)	10.69 (4.62)
OL 1992	0	−16.72 (6.09)	0
(c)	Forest conservation	**Forest degradation**	**Deforestation**
	Enhancement of carbon stocks	Sustainable management of forests	**Deforestation**
	Enhancement of carbon stocks	Enhancement of carbon stocks	-

THE MATRIX APPROACH

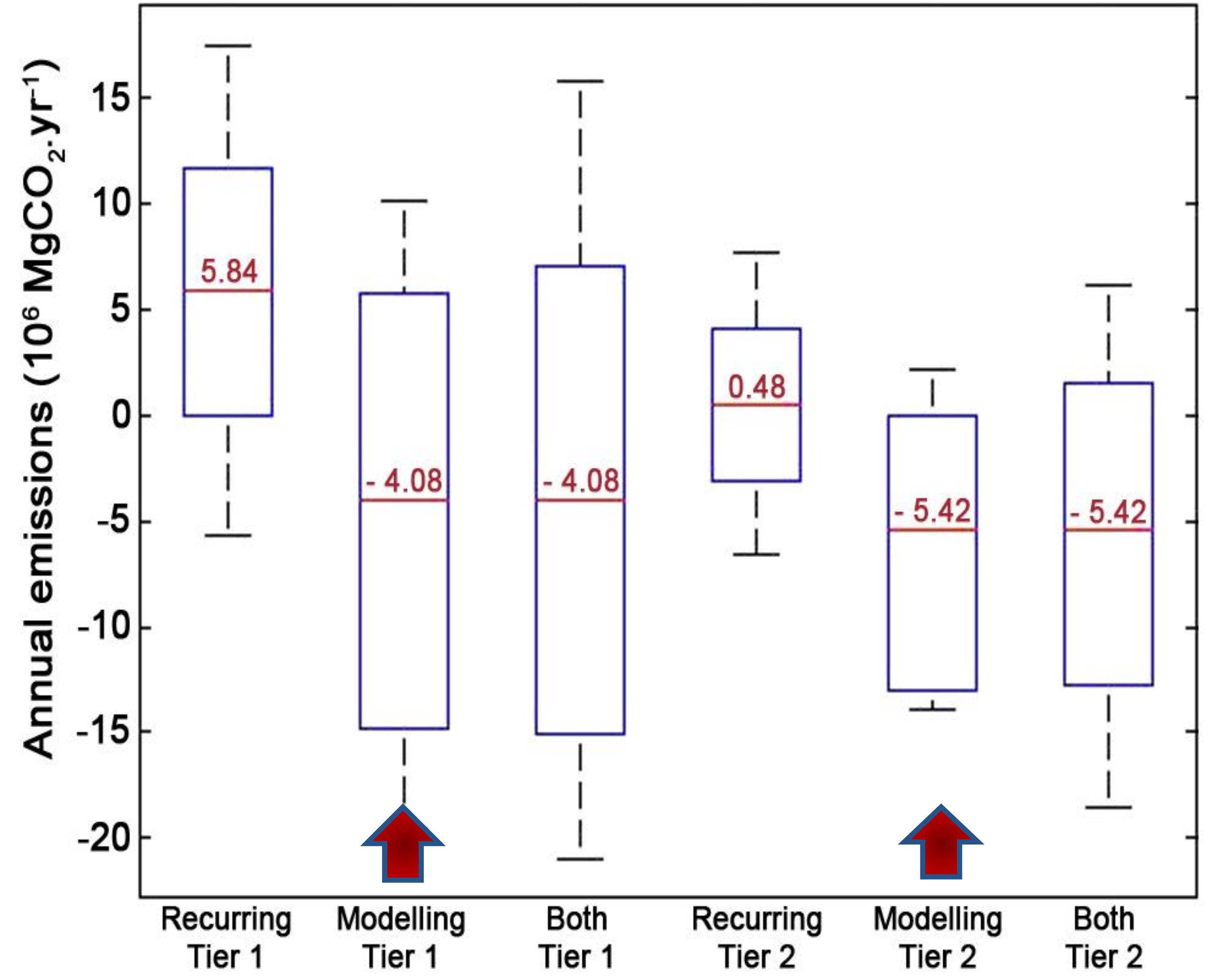
Difference between MODELLING and RECURRING (data) sources of error

- Models are based on different sets of assumptions
- Testing the impact of those assumptions is important



Pelletier et al. ERL, 2013

Error in the modelling approach



Major problem for comparability between countries

Modelling error dominates over recurring sources

Methods to combine uncertainty

Uncertainty analysis:

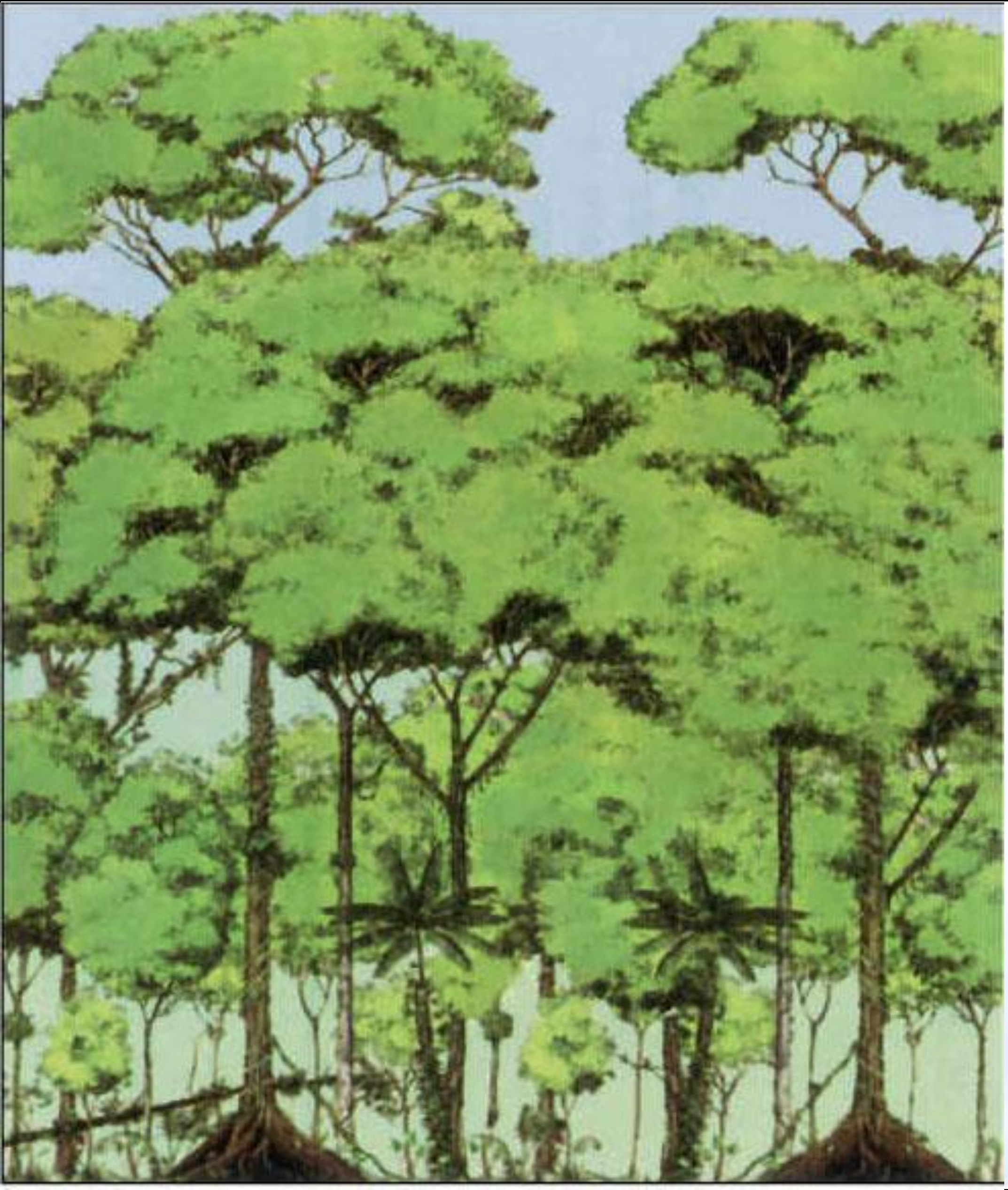
- Determine the uncertainties around the different components in activity data and emission factor (Mean, Standard deviation, Minimum, Maximum value.
- **Combine** uncertainties around different components to provide an overall uncertainty estimates

2 approaches are proposed by the IPCC:

TIER 1: Error propagation

TIER 2: Monte Carlo method

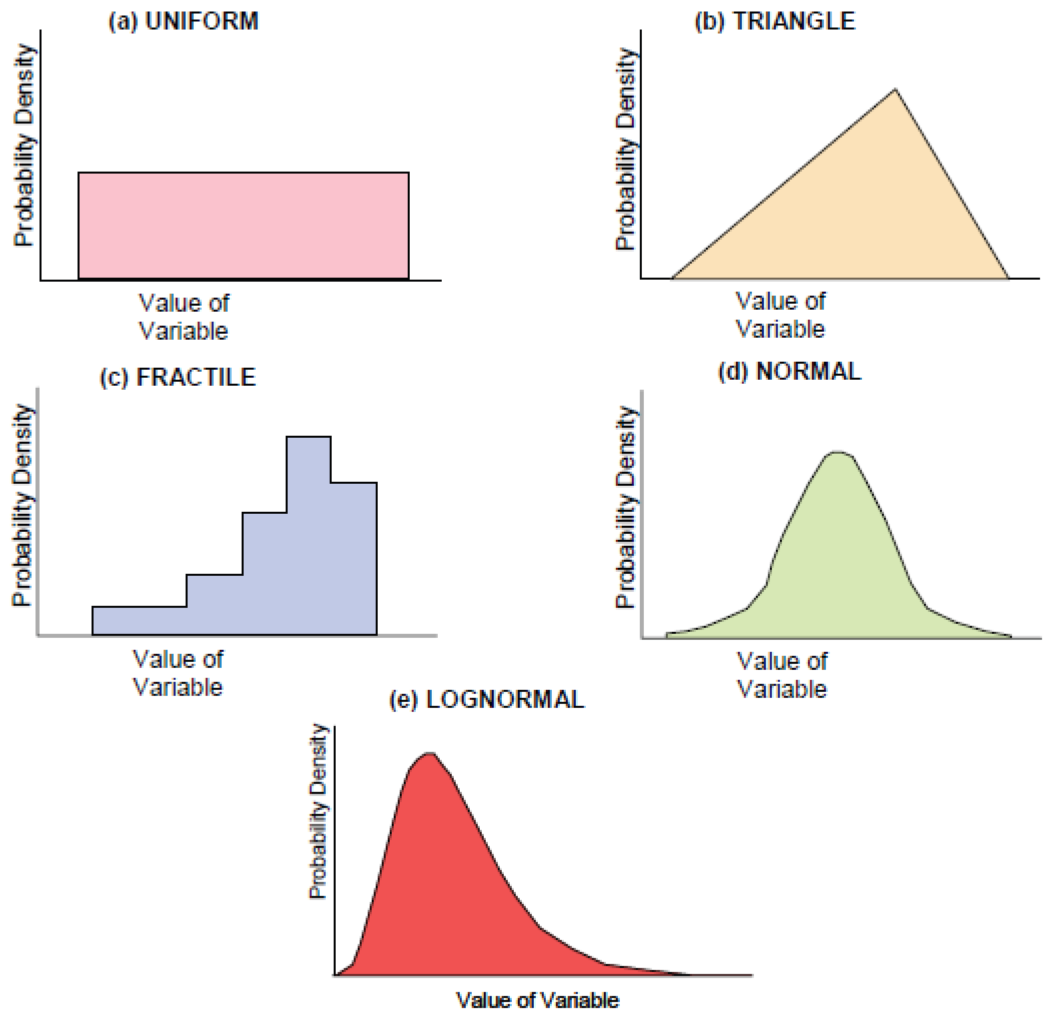
Benefits of conducting uncertainty analysis



- Identify key parameters to your estimate
- Prioritize data collection where most needed
- Cost-effective investment in forest monitoring

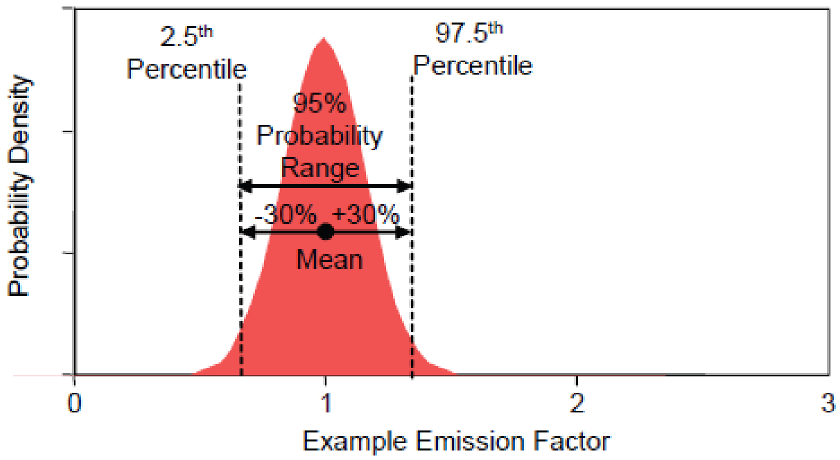
Representing variables

- Example of commonly used probability density function models

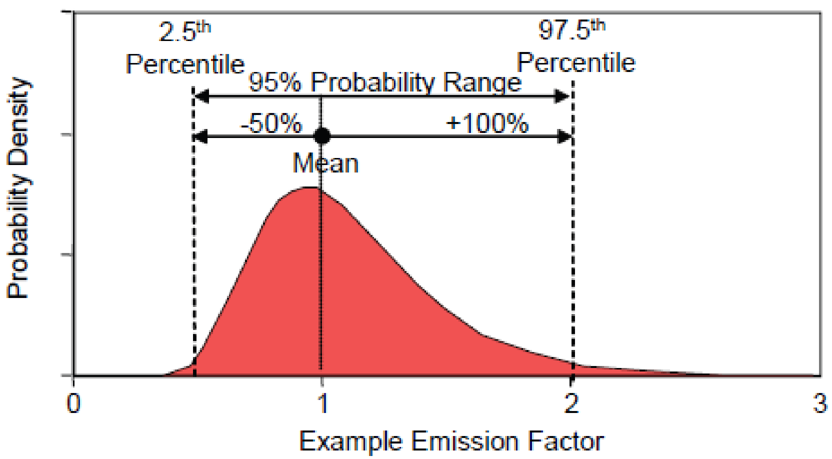


Symmetric vs Asymmetric distribution

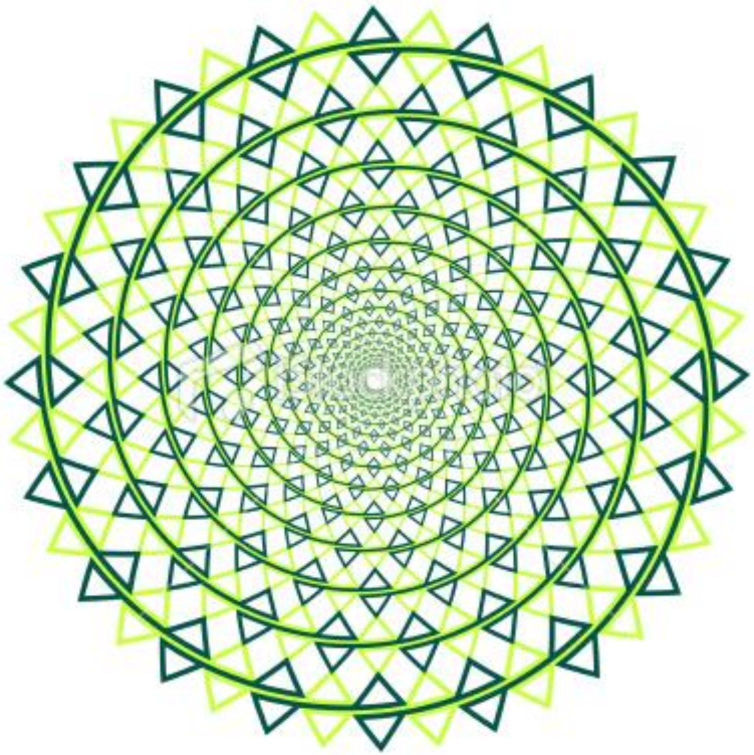
(a) Example of a symmetric uncertainty of ±30% relative to the mean



(b) Example of an asymmetric uncertainty of -50% to +100% relative to the mean, or a factor of two



IPCC approach to estimate uncertainty



Tier 1: Error propagation

- Simple approach (Spreadsheet)
- Requires the mean and standard deviation of input data
- Assume small error
- Doesn’t deal well with large or asymmetric uncertainty
- Doesn’t deal well with correlations or covariances

IPCC approach to estimate uncertainty

Tier 1: Error propagation

Type	Example	Standard Deviation (σ_x)
Addition and subtraction	x = a + b – c	$\sigma_x = \sqrt{\sigma_a{}^2 + \sigma_b{}^2 + \sigma_c{}^2}$
Multiplication and division	x = a x b/c	$\frac{\sigma_x}{x} = \sqrt{\left(\frac{\sigma_a}{a}\right)^2 + \left(\frac{\sigma_b}{b}\right)^2 + \left(\frac{\sigma_c}{c}\right)^2}$

In practice for multiplication and division, it is usually simplest to convert all of the uncertainties into percentages before applying the formula

These equations assume that the quantities a, b, etc. have errors which are uncorrelated and random

IPCC approach to estimate uncertainty

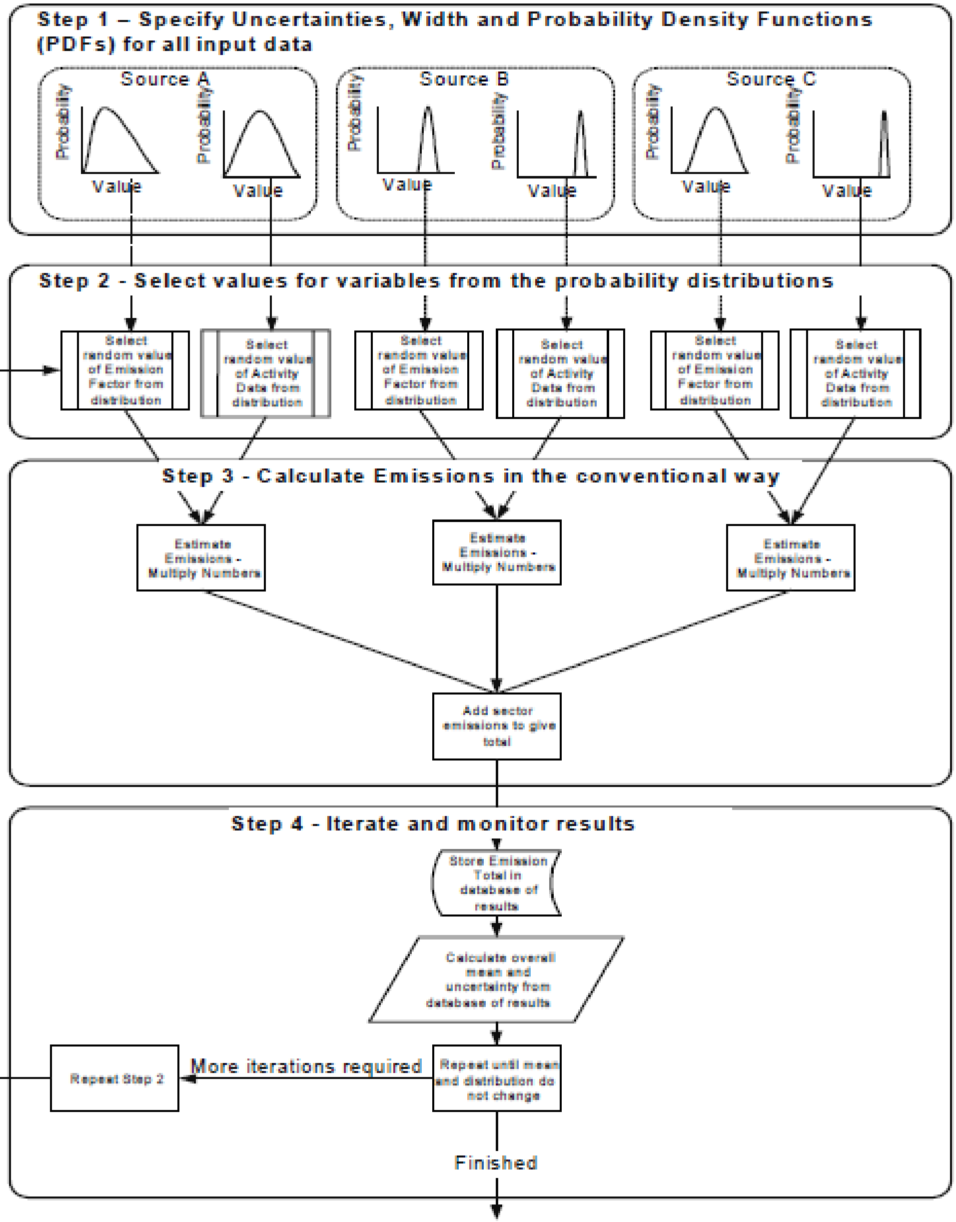
Tier 2: Monte Carlo analysis

Good for large and asymmetric errors

Take into account correlations easily, e.g. Dependencies of data coming from the same datasets (emission factors)

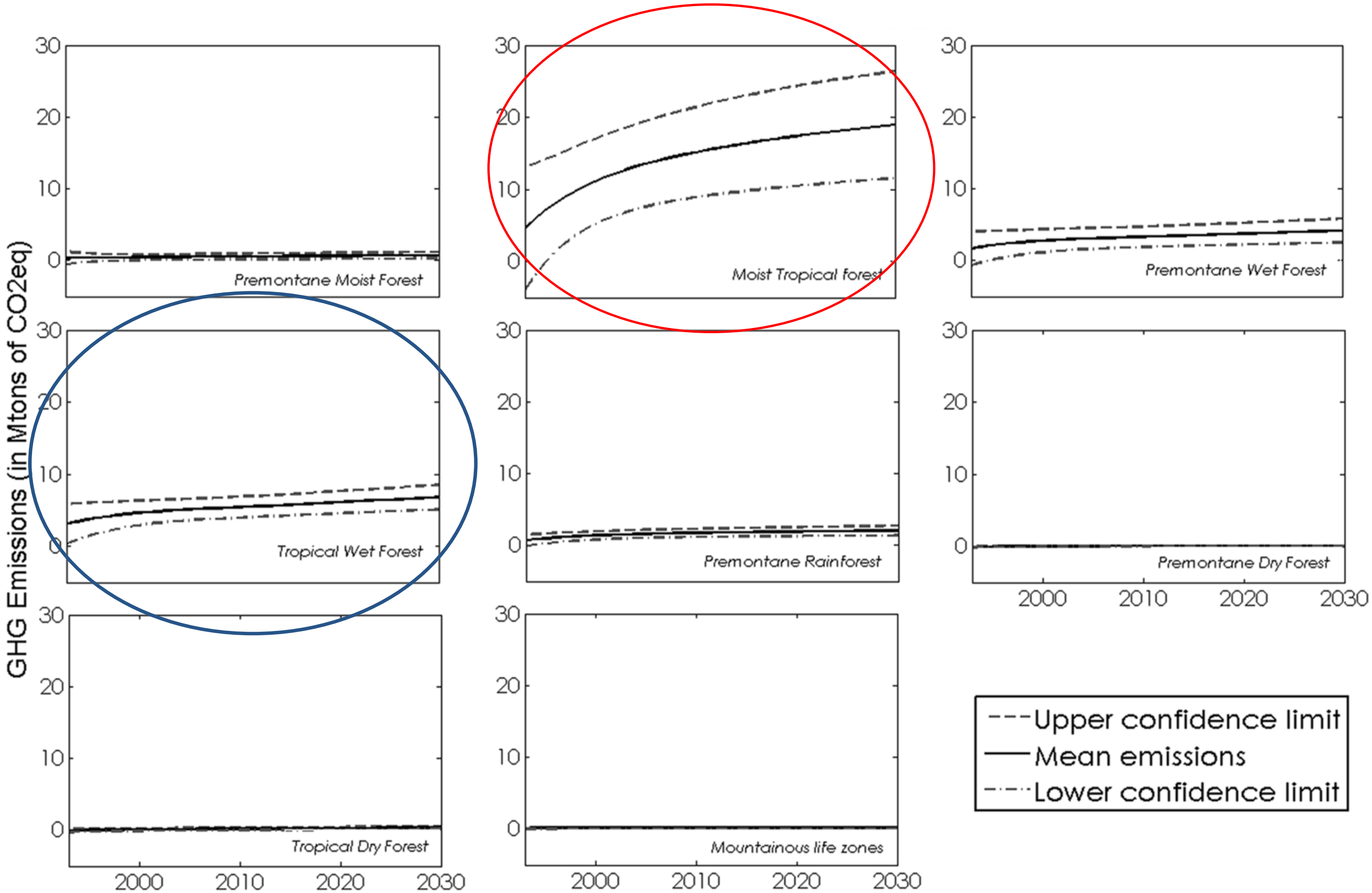
Illustration of Monte Carlo Method

Need to choose a distribution your input variables



IPCC guidelines (2006), chap. 3

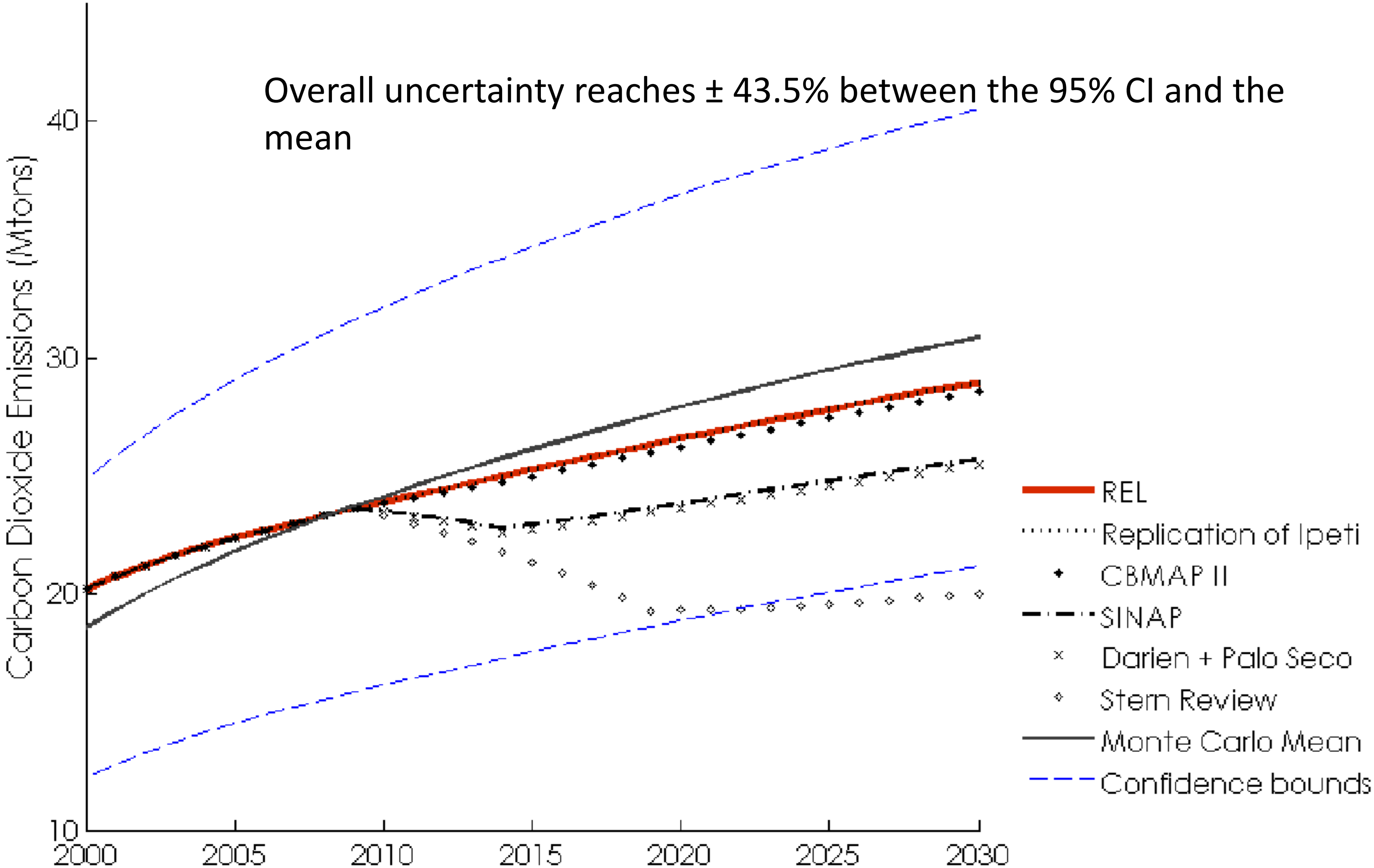
MONTE CARLO UNCERTAINTY ANALYSIS



Pelletier, J., Ramankutty, N., Potvin, C. Environmental Research Letters (2011)

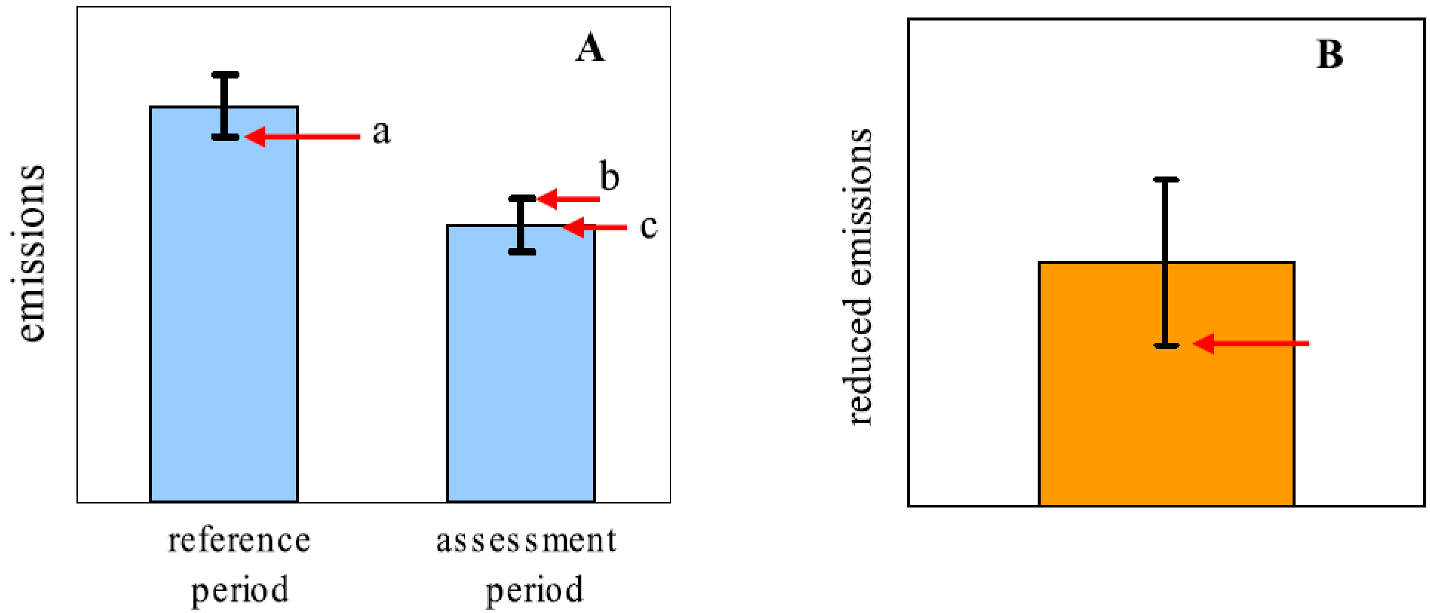
COMPARING SCENARIOS TO THE OVERALL UNCERTAINTY

Overall uncertainty reaches ± 43.5% between the 95% CI and the mean



Pelletier, J. *et al* (2011)

Trend Uncertainty



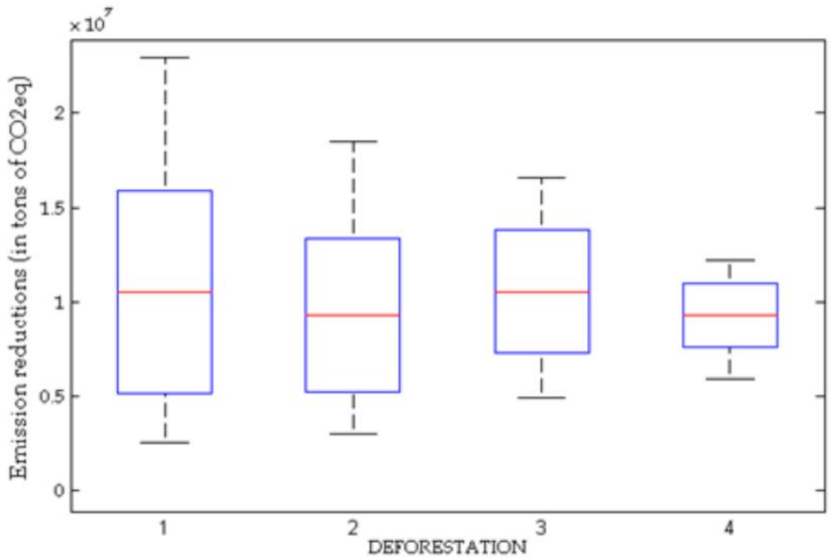
Approach A: Evaluate uncertainties of both the reference and the assessment period

Approach B: Uncertainty of the difference of emissions between the reference and the
assessment period

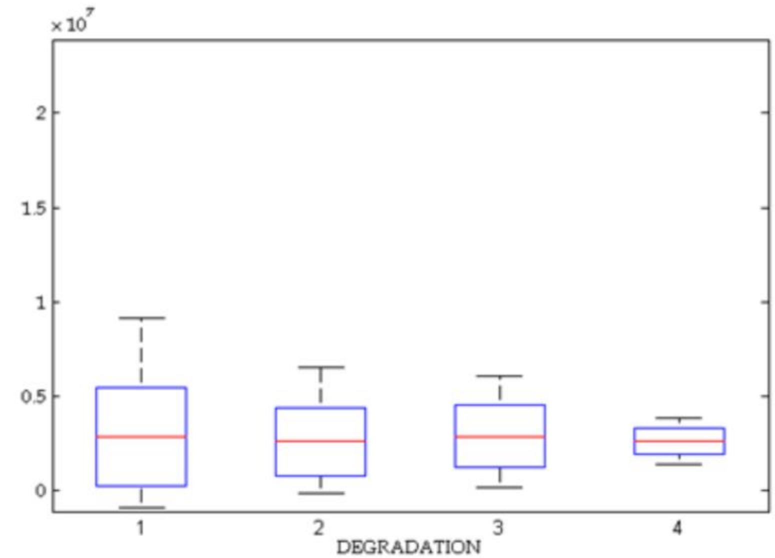
Grassi et al. Environmental Research Letters, 2008

On Emission reductions

DEFORESTATION



DEGRADATION



	1= No Error reduction			2=Error reduction in RS			3=Error reduction in FCD			4=Error reduction in RS and FCD		
	Deforestation	Degradation	Overall	Deforestation	Degradation	Overall	Deforestation	Degradation	Overall	Deforestation	Degradation	Overall
5% percentile	2.52	-0.94	2.93	2.99	-0.12	3.40	4.90	0.14	6.87	5.95	1.38	7.97
25% percentile	6.05	0.67	7.46	5.95	1.12	7.25	8.10	1.56	10.54	8.19	2.07	10.46
Mean	10.52	2.87	13.39	9.28	2.59	11.86	10.52	2.87	13.39	9.28	2.59	11.87
75% percentile	13.56	4.28	17.35	11.65	3.64	15.11	12.87	4.03	16.10	10.57	3.09	13.42
95% percentile	22.92	9.14	29.71	18.48	6.53	24.40	16.57	6.07	20.51	12.18	3.87	15.48
CV of SD on emission reductions	63.4%	116.8%	65.6%	53.4%	82.3%	56.9%	32.9%	63.2%	30.4%	19.2%	29.4%	18.4%

Implementing Monte Carlo approach in R

Asante!

REDD+ negotiations

COP 11 Montreal 2005: Kick-off REDD Negotiations

COP 13 Bali 2007: **Definition of eligible REDD+ activities**
(Decision 1/.13 1.(b) (iii) in FCCC/CP/2007/6/Add.1: Bali Action Plan)

AWG-LCA: REDD+ Finance

COP 15 Copenhagen 2009: **most recent IPCC GL & Guidance, Drivers analysis**
(Decision 4/.15 in FCCC/CP/2009/11/Add.1)

COP 16 Cancun 2010: **Key elements** (National Strategy, REL, National Forest Monitoring System for MRV, Safeguards monitoring), **phased approach, 7 safeguards** (FCCC/CP/2010/7/Add.1 Cancun Agreements),

COP 17 Durban 2011: **FREL/FRL modalities, safeguards reporting**
(Decision 12/CP.17 in FCCC/CP/2011/9/Add.2)

COP 18 Doha 2012: **REDD+ policy approaches and positive incentives**
(Agreed outcome pursuant to the Bali Action Plan)

*COP 19 Warsaw 2013: "**Warsaw Framework for REDD-plus**"*

- Modalities for national forest monitoring systems
- Modalities for measuring, reporting and verifying
- Guidelines and procedures for the technical assessment of FREL/FRLs
- Addressing the drivers of deforestation and forest degradation
- The timing and the frequency of presentations of the summary of information on safeguards

- Work programme on results-based finance
- Coordination of support for the implementation of activities in relation to mitigation actions in the forest sector

GFOI, Global baseline date acquisition strategy, 2014