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Requirements to develop and implement a credible and transparent MRV system

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ASEAN, Singapore, December, 12-13, 2016

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Requirements to develop and implement a credible and transparent MRV system

The long way from political decisions to practical implementation

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What I will NOT present:

• Stipulations of IPCC on MRV-systems





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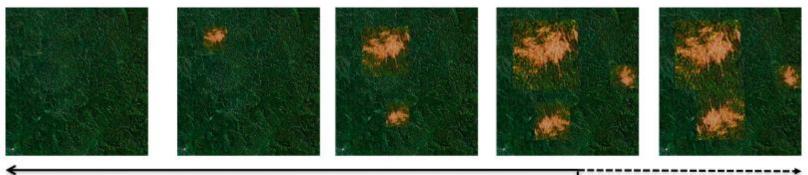
What I will present:

- Potential pitfalls in the development of MRV-methods
- Long-term implications of methodological procedures
- Warnings and possible solutions





FREL/FRL



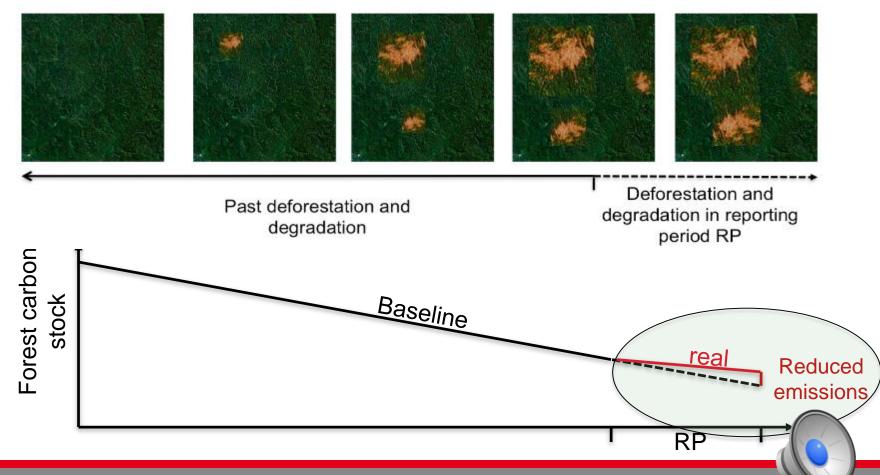
Past deforestation and degradation Deforestation and degradation in reporting period RP



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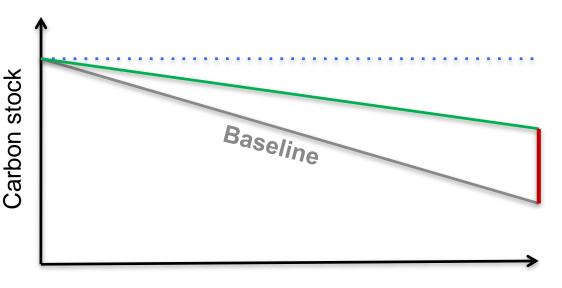
FREL/ FRL



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Accountable emission reduction



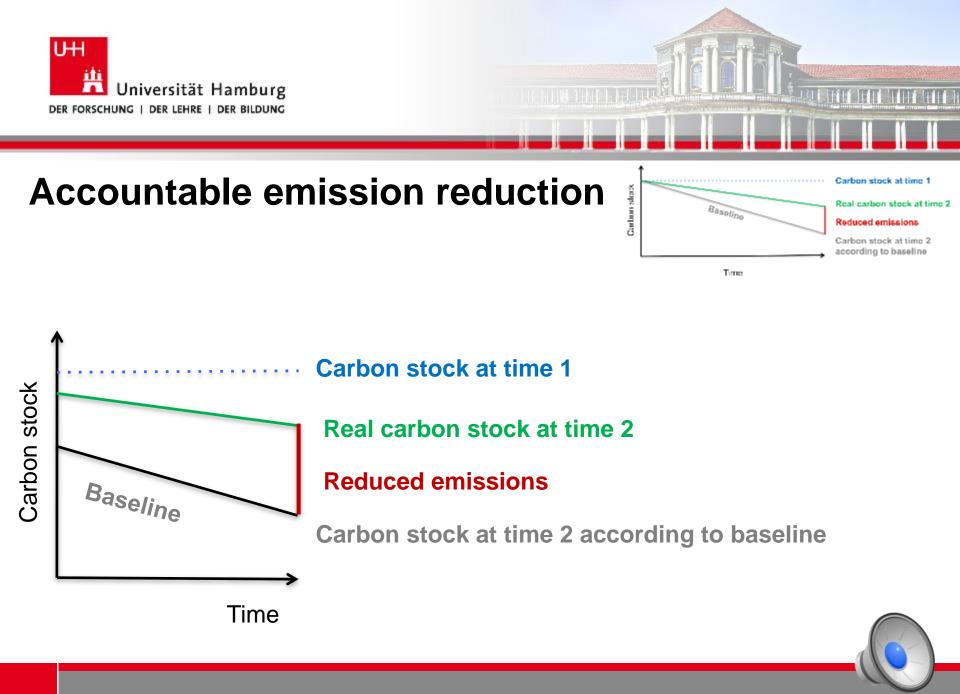
Time

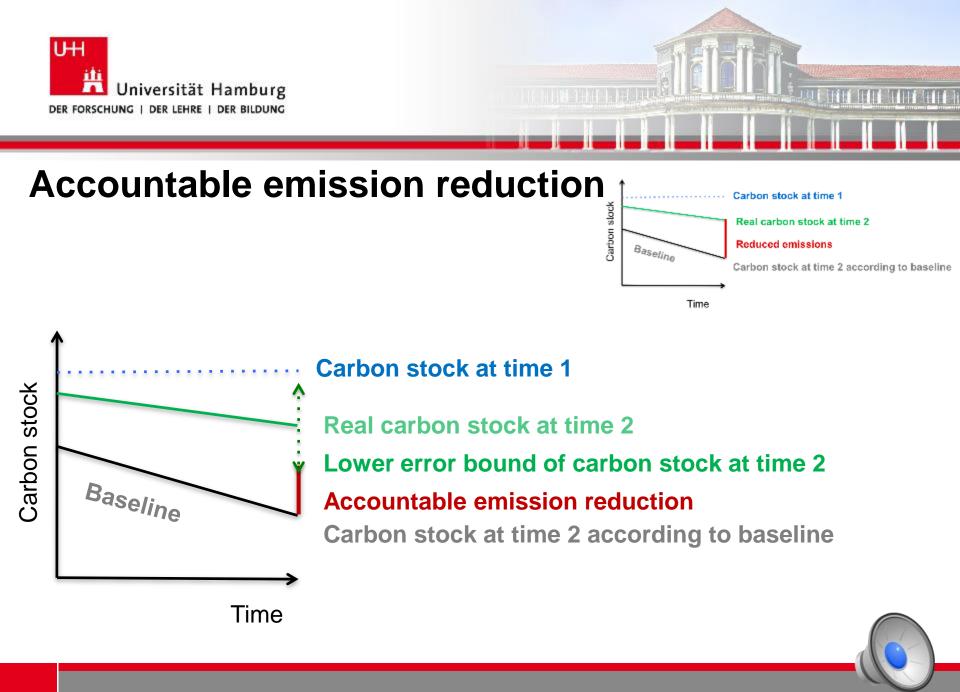
Carbon stock at time 1

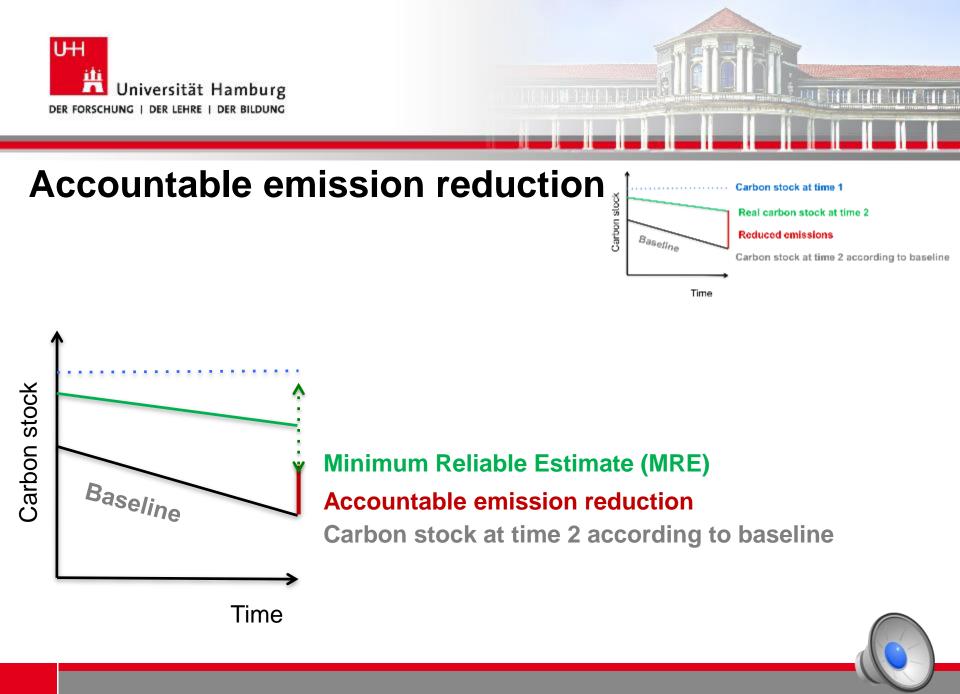
Real carbon stock at time 2

Reduced emissions

Carbon stock at time 2 according to baseline









General Aspects of Uncertainties in Emission Estimates

Uncertainties are a composite of errors arising from

• observations (statistical uncertainty), and





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Uncertainties are a composite of errors arising from

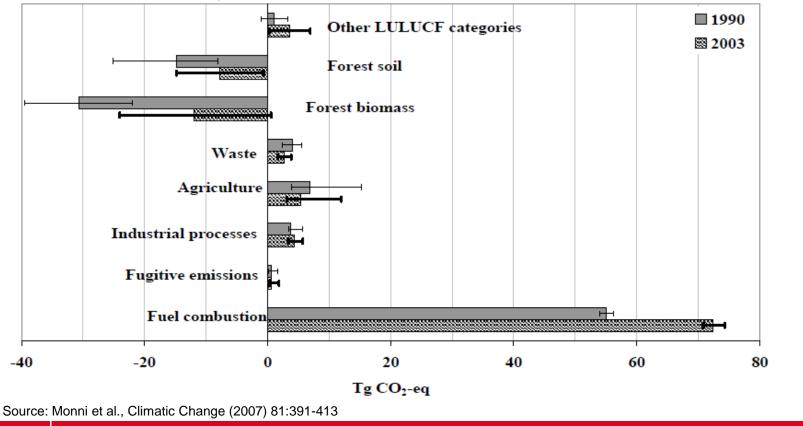
- observations (statistical uncertainty), and
- the appropriateness of models (systematic, structural, epistemic uncertainty)
- Non-statistical errors (e.g. measurement, classification, or calculation errors)





Uncertainties in GHG Emissions and Removals

National Inventory Report for Finland





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Data Sources and Uncertainties



Field assessments



Remote sensing



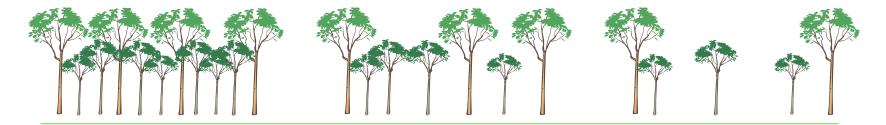
Models and analysis





Problems with monitoring forest degradation by remote sensing





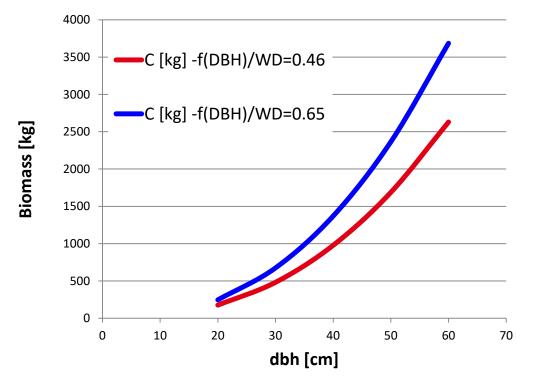
Biomass Stock time 1

Biomass Stock time 2 Not detectable by passive remote sensing Biomass Stock time 3 Detectable by passive remote sensing

Stealthy degradation => Classification errors



Estimating individual tree biomass by biomass equations



Biomass = f(dbh, WD, EF)

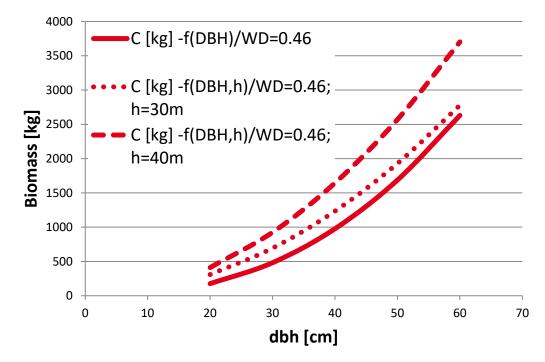
Assuming wood density (WD) of 0.46 kg/m³ vs. 0.65 kg/m³

Results for a tree with dbh=60 cm in a difference of 1055 kg (140%)

Biomass equation: Chave et al., 2014



Estimating individual tree biomass by biomass equations



Biomass = f(dbh,WD) Biomass = f(dbh,h,WD)

 $WD = 0.46 \text{ kg/m}^3$ Tree height: 30m/ 40m

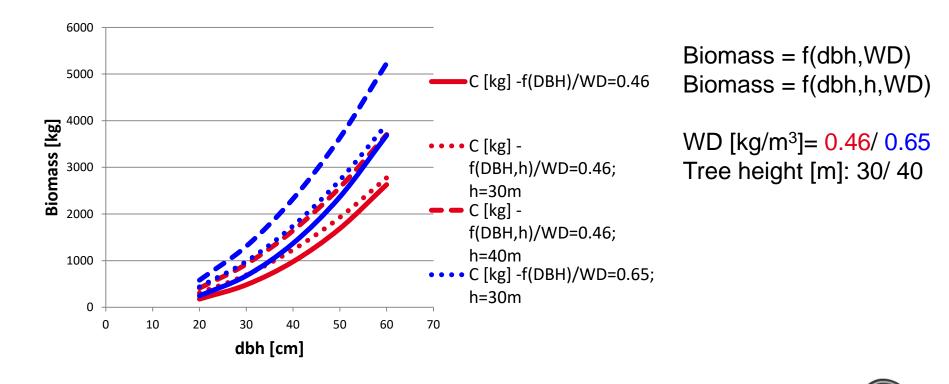
Results for a tree with dbh=60 cm in a difference of 1073 kg (141%)



Biomass equation: Chave et al., 2014



Estimating individual tree biomass by biomass equations



Biomass equation: Chave et al., 2014



How to deal with the uncertainty related to biomass functions

• Adopt a conservative estimate = principle of conservativeness





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- Adopt a conservative estimate = principle of conservativeness
- Selection of best-fitting allometric model for the respective forest types (results in ≈20 % error of tree AGB)





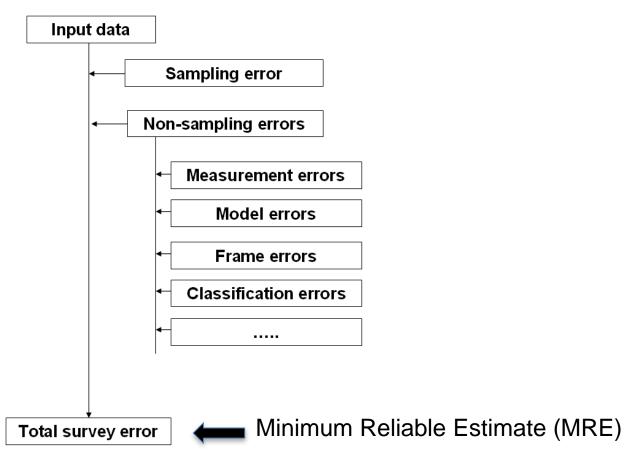
How to deal with the uncertainty related to biomass functions

- Adopt a conservative estimate = principle of conservativeness
- Selection of best-fitting allometric model for the respective forest types (results in ≈20 % error of tree AGB)
- Sampling approach
 - select a sub-sample of trees
 - on sub-sample intensive individual tree biomass assessment (e.g. accurate height measurement, stem taper, crown dimensions)
 - Update the sample with the biomass values assessed in the sub-sample



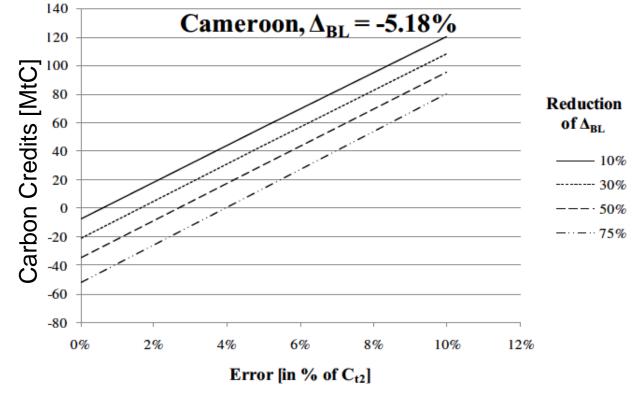


Sources of Uncertainties





The Effect of Uncertainties on Accountable Carbon Credits

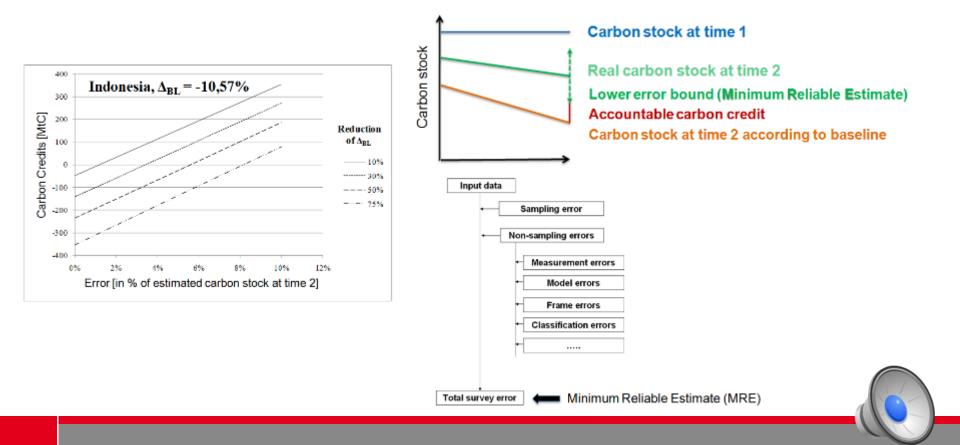


Source: Köhl et al., 2009

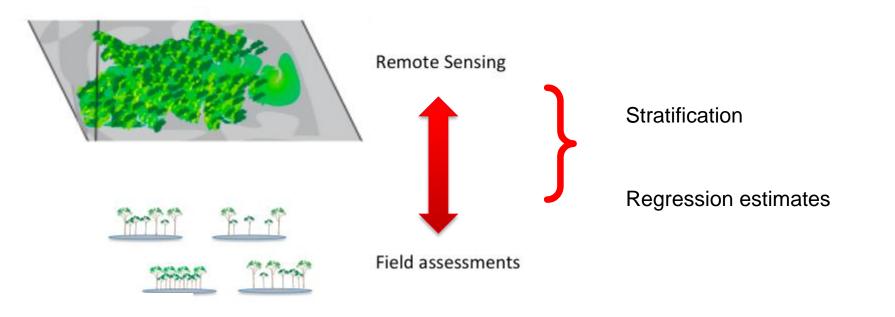
Error [in % of estimated carbon stock at time 2]



The amount of accountable carbon credits depends on the uncertainties underlying a national REDD monitoring concept

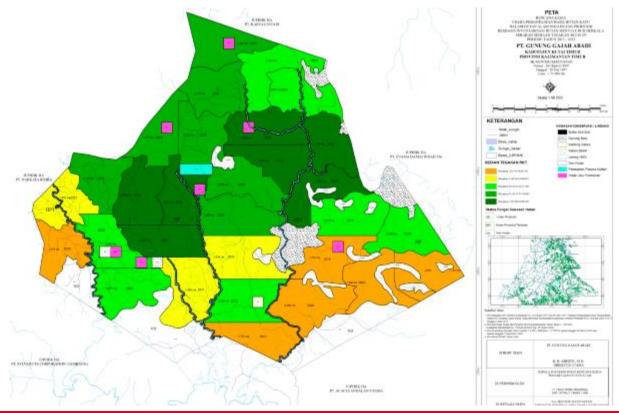








Stratification







Stratification



Stratum 1 Size [ha] Mean biomass Variance		Stratum 2 Size [ha] Mean biomass Variance		 Stratum h Size [ha] Mean biomass Variance	
Plot	Biomass	Plot	Biomass	Plot	Biomass
1	12984	1	5432	1	45232
2	23097	2	6349	2	54395
3	28358	3	4875	3	69745
					(

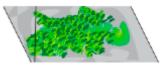


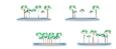
Stratification

			Siz Total	otal e [ha] biomass iance		
Stratum 1		Stratum 2			Stratum h	
Size [ha]		Size [ha]			Size [ha]	
Mean biomass		Mean biomass			Mean biomass	
Variance		Variance			Variance	
Plot	Biomass	Plot	Biomass		Plot	Biomass
1	12984	1	5432		1	45232
2	23097	2	6349		2	54395
3	28358	3	4875		3	69745



Regression estimate





Plot	Biomass	Biomass		
	Remote Sensing	Field assessment		
1	12984	18745		
2	43097	41984		
3	8358	8874		
4	30863	29734		

estimated biomass =

mean biomass field plots + ß(mean biomass all pixels – mean biomass paired pixels)

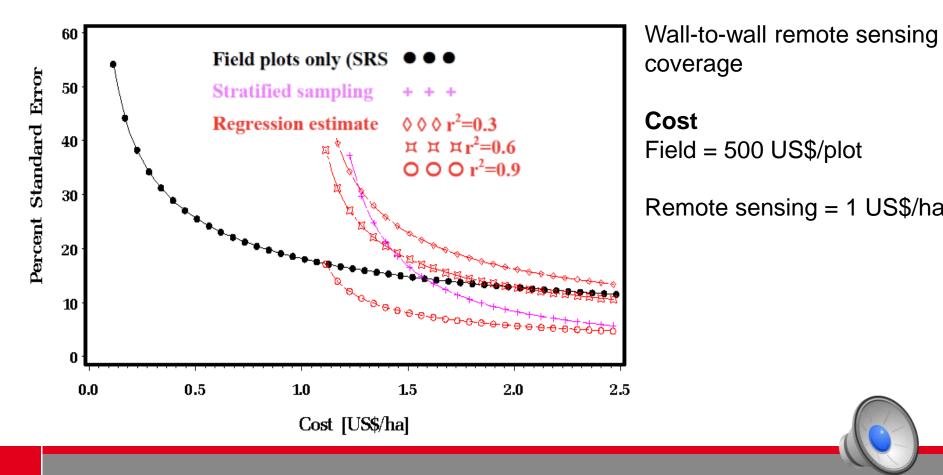
 β = regression coefficient

 r^2 = coefficient of determination = {0,...,1}



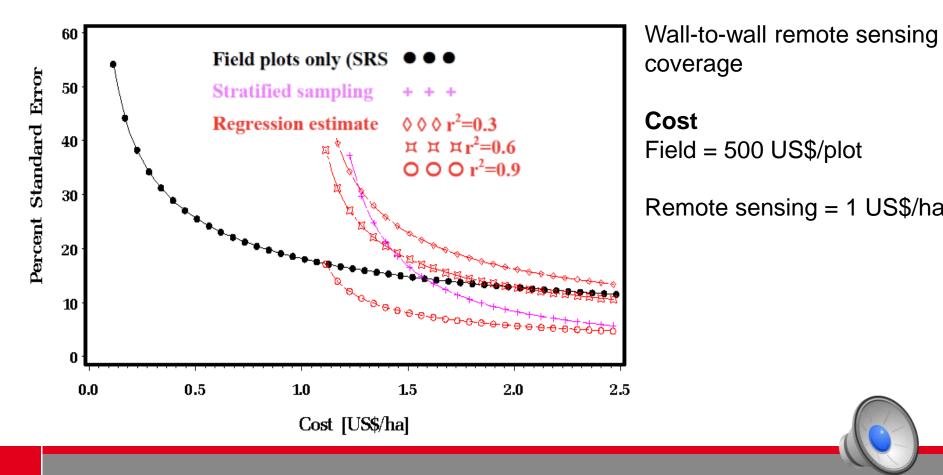


Optimal REDD+/ MRV design



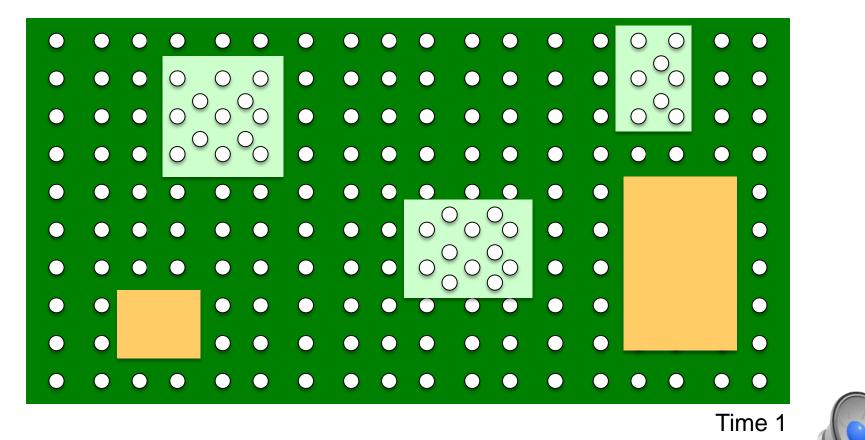


Optimal REDD+/ MRV design



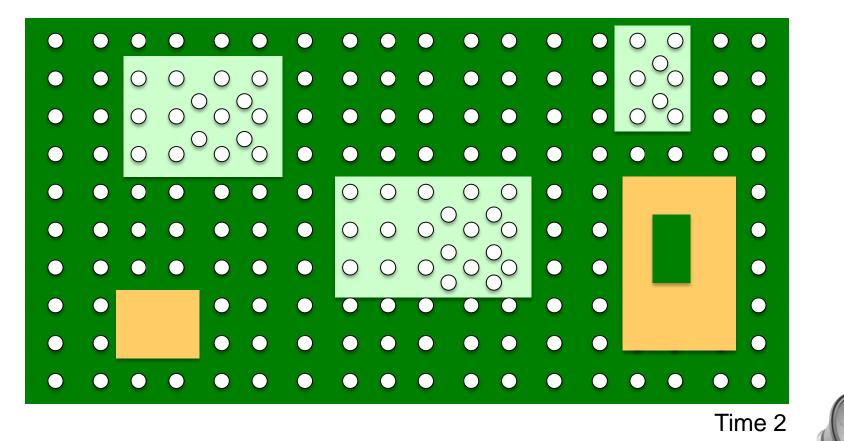


Sampling at Successive Occasions





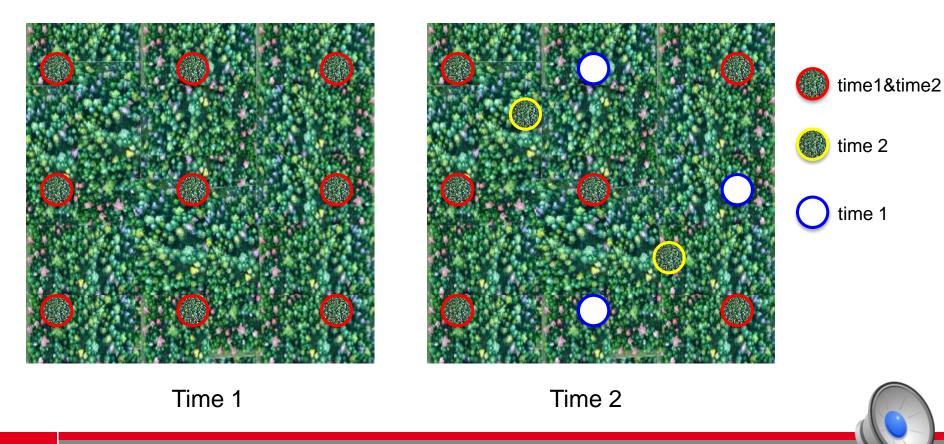
Sampling at Successive Occasions





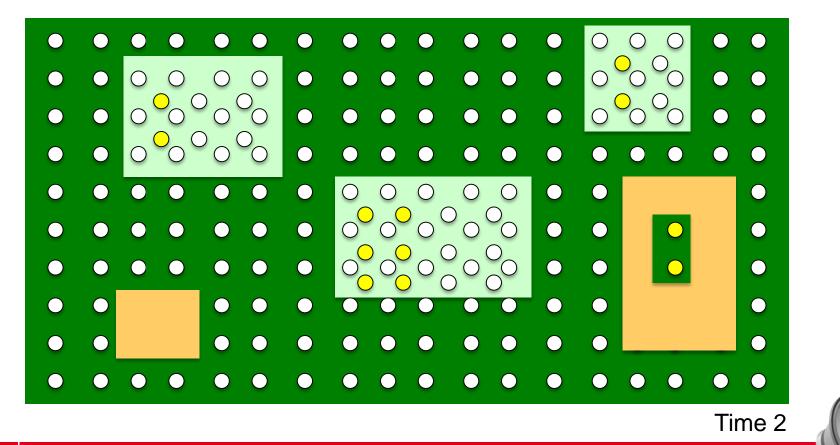


Sampling with Partial Replacement (SPR)





Sampling with Partial Replacement (SPR)





General Aspects of Uncertainties in Emissions

Uncertainties arise from different error sources

Reductions of uncertainty carry a cost



From an economic perspective a certain level of uncertainty is inevitable





Conclusion







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