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Dublin, Ireland, June 14, 2018

Establishing Google Earth Engine as a platform for estimation of map accuracy and area

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Background

Why estimate areas?

- **Strength** of remote sensing: enables wall-to-wall coverage
- **Weakness**: results are never perfect! Impact of errors potentially severe[1] – if map errors unknown, map is just a **"pretty picture"**[2]
- Classification **errors** in map ⇒ mapped areas wrong ⇒ **sample-based, unbiased estimation** of areas required[1]
- Also, requirement of **IPCC Good Practices** for UNFCCC and REDD+ reporting of land change[3]

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[1] Olofsson et al. (2014), *Remote Sensing of Environment*, vol. 129
[2] McRoberts (2011), *Remote Sensing of Environment*, vol. 115
[3] GFOI (2016), *Methods and Guidance from GFOI, 2nd edition*

Sampling- or design-based estimation

- Common examples: political polls, disease prevalence, market research, factory quality control, etc.
- Basic idea: drawing inference for population parameters by analyzing a probability sample selected from the population[1]
- Design-based estimation is attractive from remote sensing perspective but underutilized[2]

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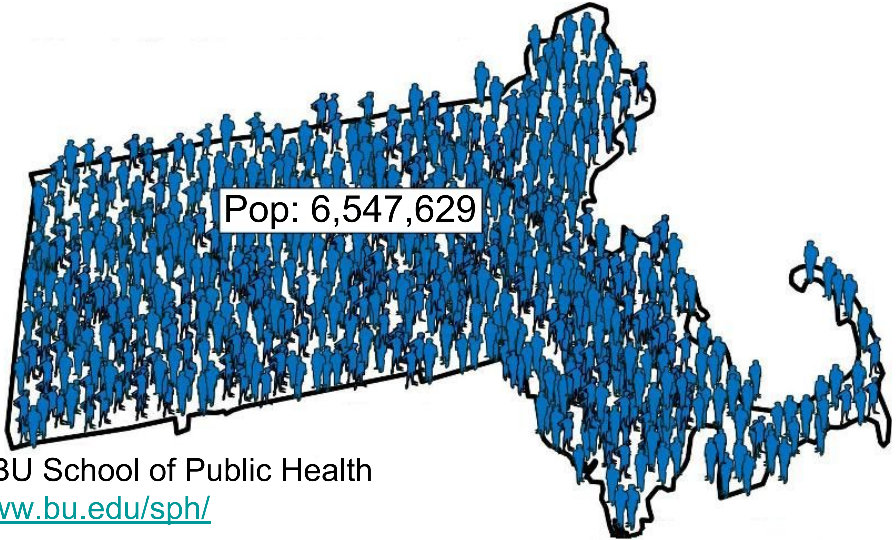
[1] Cochran (1977), *Sampling Techniques, 3rd edition*
[2] Olofsson et al. (2013), *Remote Sensing of Environment*, vol. 129

Public health example[1]

- Unknown population parameter (θ): mean blood pressure in Mass.
- Task: Provide an estimate of unknown population parameter (θ*)
- Population: Massachusetts residents in 2010



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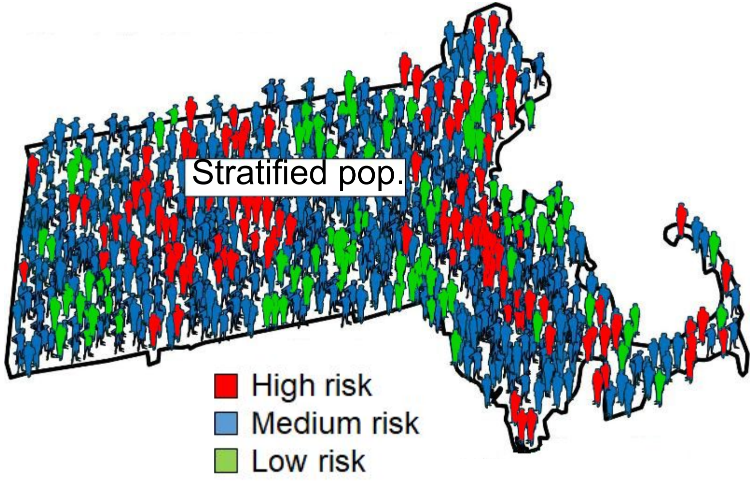
[1] From BU School of Public Health
http://www.bu.edu/sph/

Public health example[1]

1. Sampling design: stratified random sampling because strata can be constructed that differ in risk based on age, race, income (census data)
2. Response design: measure blood pressure [mm Hg] of people selected in (1) (i.e. sample units)
3. Analysis: apply stratified estimator[2] to sample data



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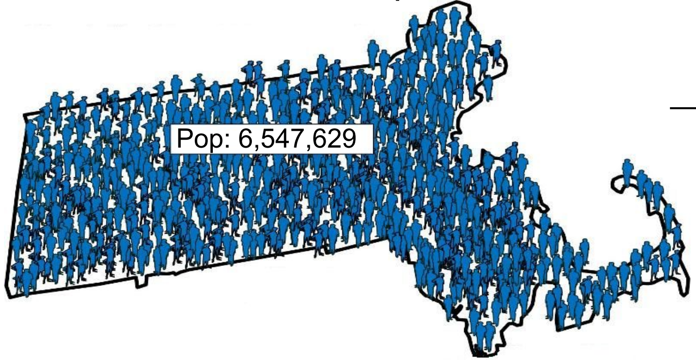
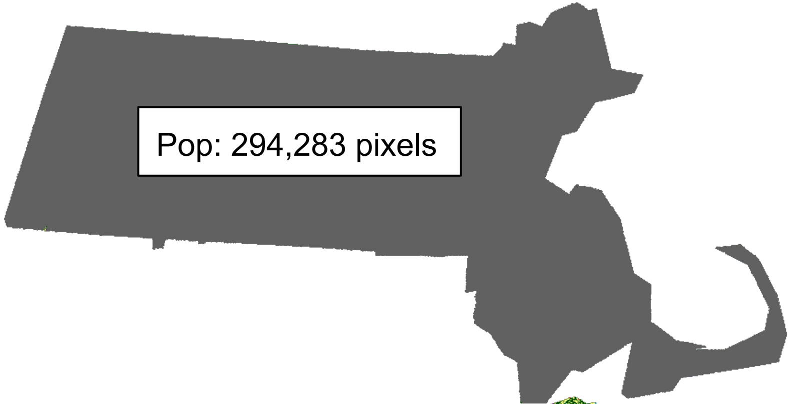
[1] From BU School of Public Health http://www.bu.edu/sph/
[2] Cochran (1977), *Sampling Techniques, 3rd edition*

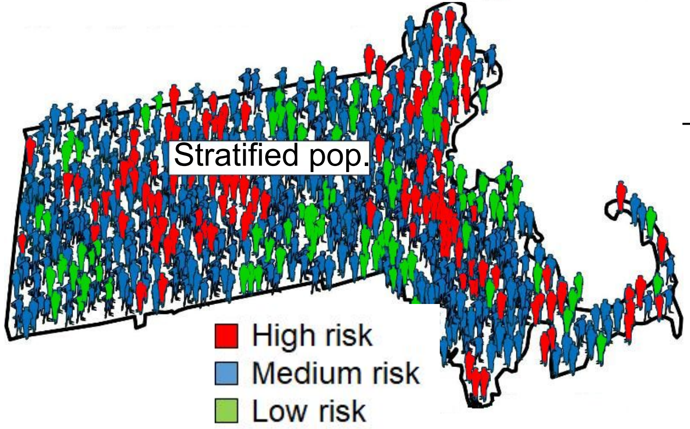
Remote sensing equivalent

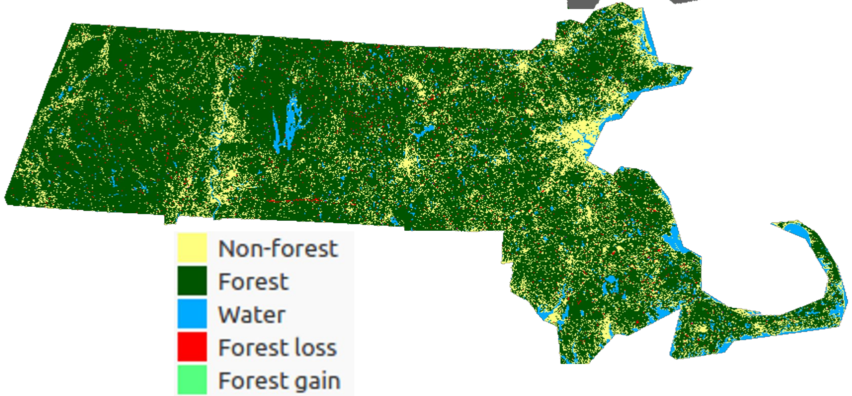
Estimate mean blood pressure in 2010

Estimate area of deforestation 2000-2018

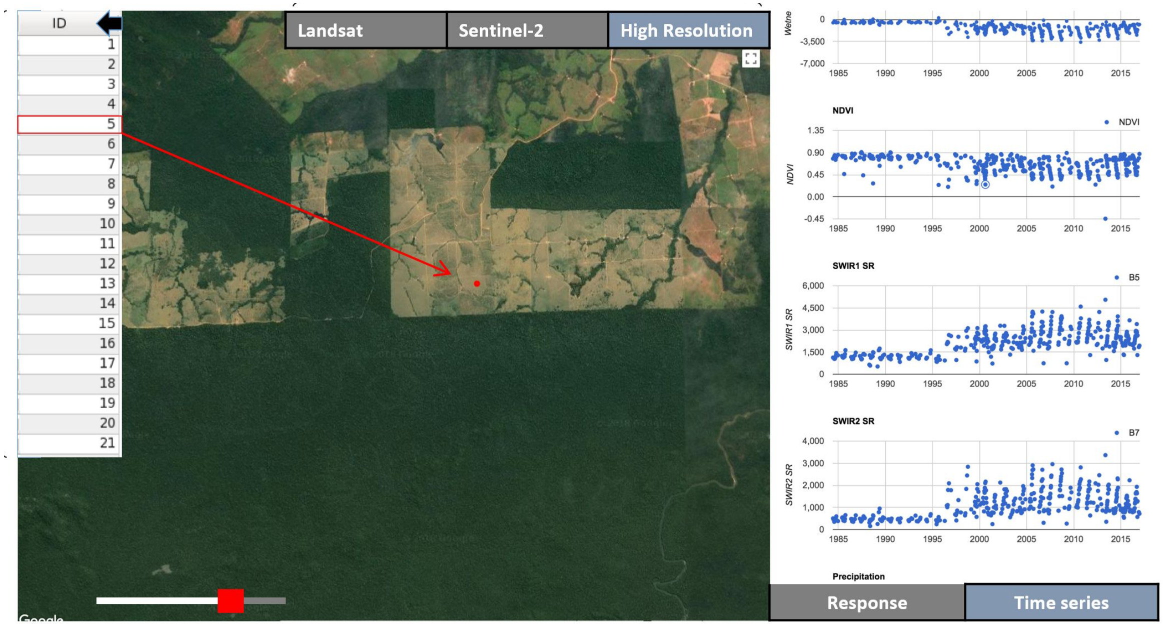








Remote sensing equivalent



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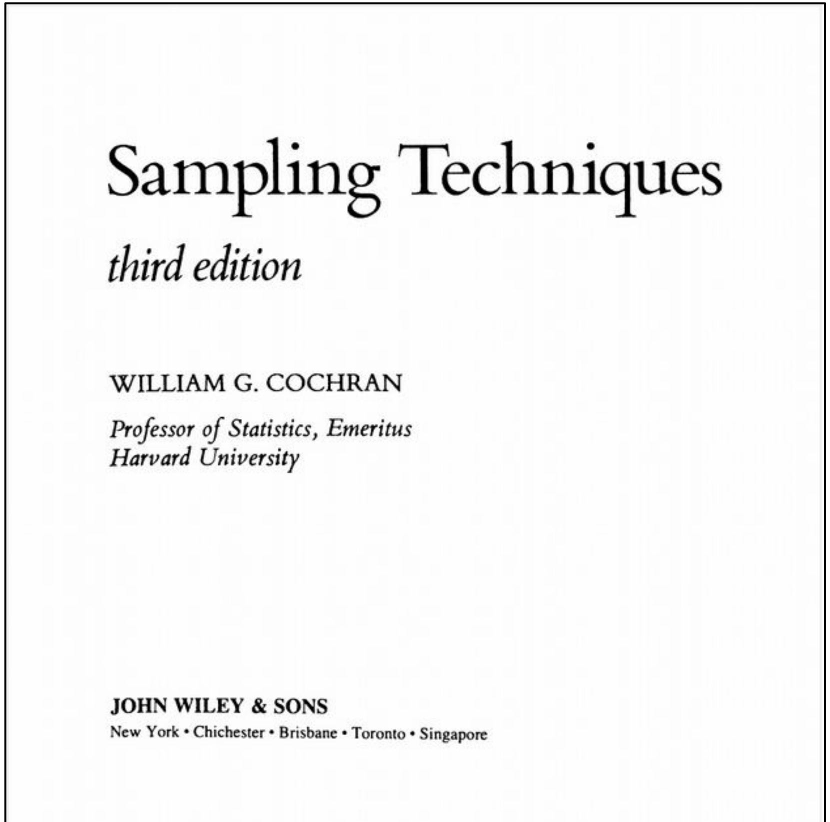
Evolution

Underlying theory (no maps or RS)



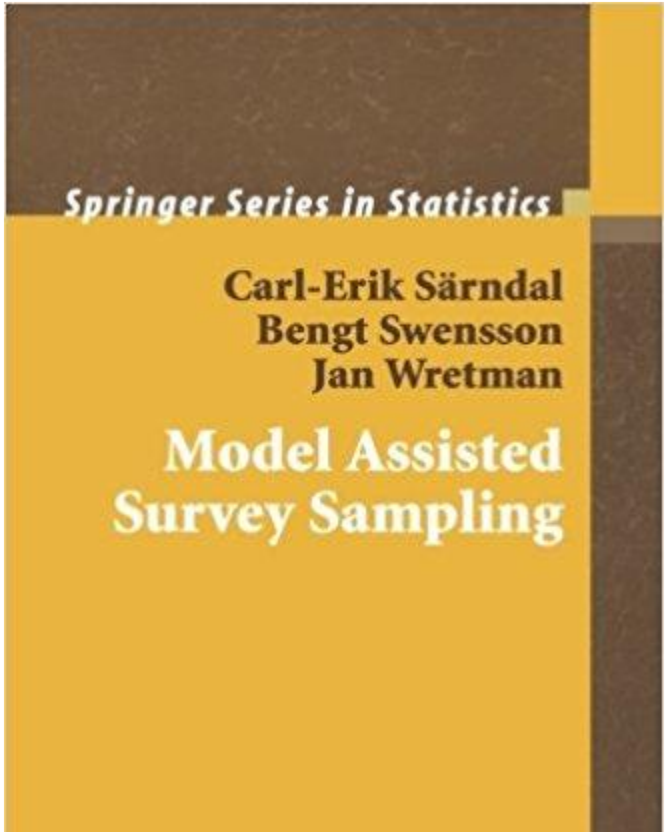
Sampling Techniques

third edition

WILLIAM G. COCHRAN

Professor of Statistics, Emeritus
Harvard University

JOHN WILEY & SONS
New York • Chichester • Brisbane • Toronto • Singapore



Sampling-based estimation in RS context

Remote Sensing of Environment 115 (2011) 715–724

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Satellite image-based maps: Scientific inference or pretty pictures?

Ronald E. McRoberts

Remote Sensing of Environment 129 (2013) 122–131

Contents lists available at SciVerse ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

5th most cited RSE paper since 2013

Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation

Pontus Olofsson [a,*], Giles M. Foody [b], Stephen V. Stehman [c], Curtis E. Woodcock [a]

Remote Sensing of Environment 132 (2013) 202–211

Contents lists available at SciVerse ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Estimating area from an accuracy assessment error matrix

Stephen V. Stehman *

Remote Sensing of Environment 148 (2014) 42–57

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

3rd most cited RSE paper since 2013

Review

Good practices for estimating area and assessing accuracy of land change

Pontus Olofsson [a,*], Giles M. Foody [b], Martin Herold [c], Stephen V. Stehman [d], Curtis E. Woodcock [a], Michael A. Wulder [e]

Remote Sensing of Environment 128 (2013) 299–314

Contents lists available at SciVerse ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Model-assisted estimation of change in forest biomass over an 11 year period in a sample survey supported by airborne LiDAR: A case study with post-stratification to provide "activity data"

Erik Næsset [a,*], Ole Martin Bollandsås [a], Terje Gobakken [a], Timothy G. Gregoire [b], Göran Ståhl [c]

International Journal of Remote Sensing, 2014

Vol. 35, No. 13, 4923–4939, http://dx.doi.org/10.1080/01431161.2014.930207

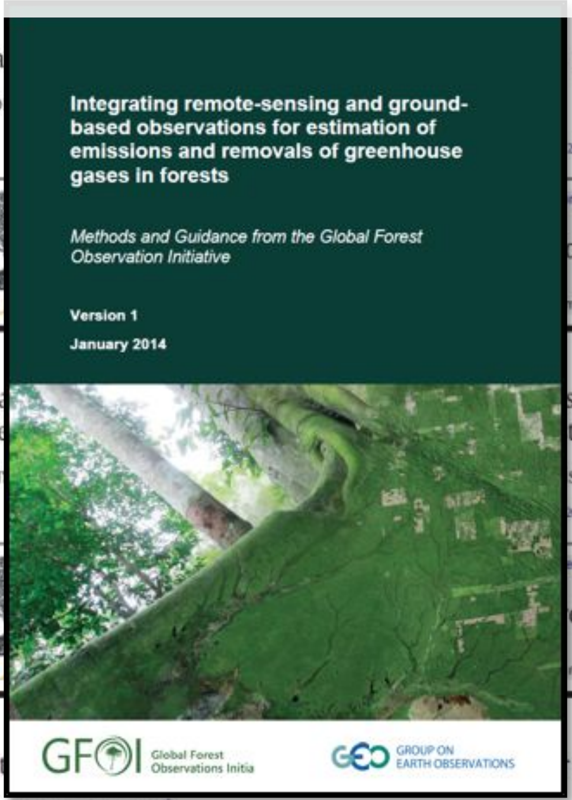
Taylor & Francis

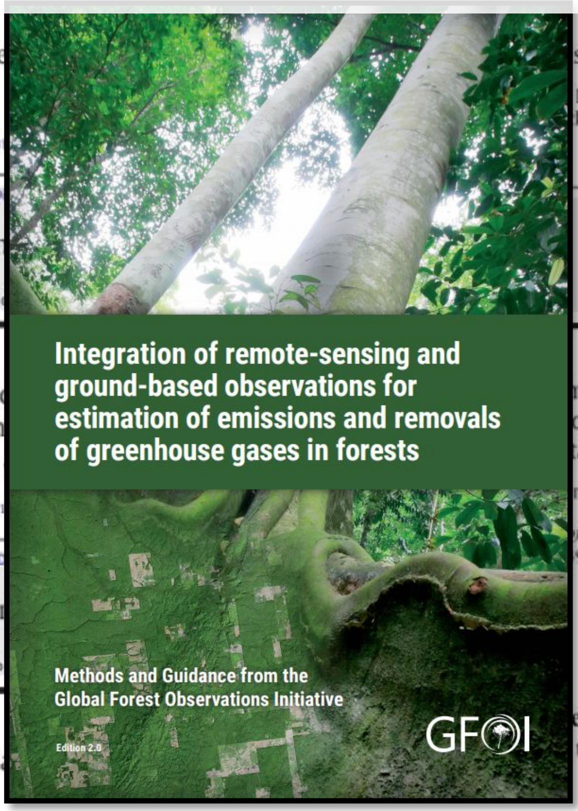
TECHNICAL NOTE

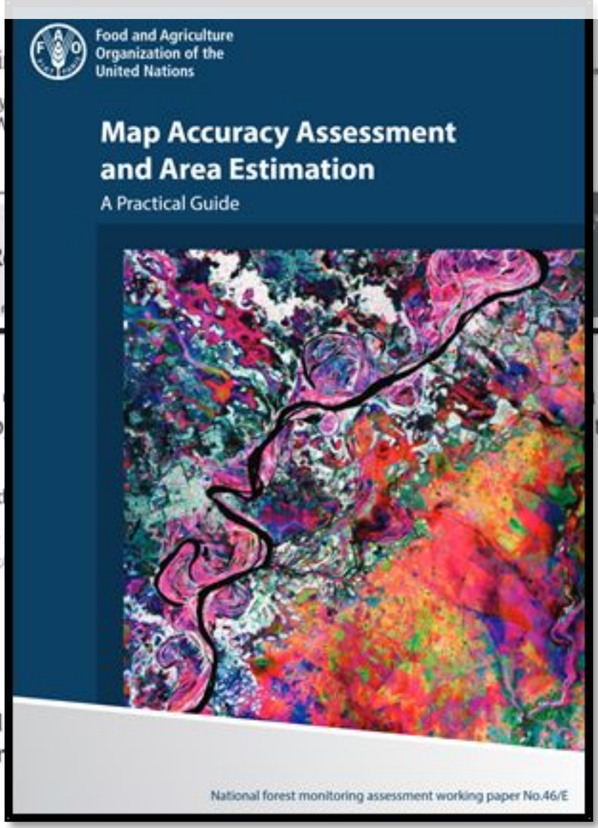
Estimating area and map accuracy for stratified random sampling when the strata are different from the map classes

Stephen V. Stehman*

International guidance







Role of Earth Engine

Sample data are essential!

- Estimating land change difficult and often associated with **high uncertainty** ⇒ prevents REDD+ payments
- The variance of an estimate is $V(\theta^*) = s^2 \div n$
- Hence, a larger sample ⇒ less uncertainty, but collecting sample data is **costly and time consuming**
- High res. data + Landsat time series powerful but requires large data quantities – **bottleneck**

Providing access to high res. data and Landsat time series for any location in the world *without having to download and process* the data would be *game-changer* – GEE, potential to provide such a solution

GEE, becoming important platform for satellite data processing and map-making – providing support for estimation of map accuracy and area in accordance with published literature would increase *credibility*, *visibility* and *usage*

Estimation application in Earth Engine

1. Sampling Design: Strata? Cluster? Simple or systematic selection? Sample size? Users guided through decisions based on objectives and situation; generate sample.

2. Response Design: observe of reference conditions at sample locations; Landsat time series + all available high res. imagery, most powerful reference dataset to date.

3. Analysis: construct unbiased estimators for area and accuracy estimation, including confidence intervals of estimates. Users guided through decision.

4. Spatial representation: this is still a topic of research but we hypothesize that pixel-level error and uncertainty will become a topic of great importance in the near future

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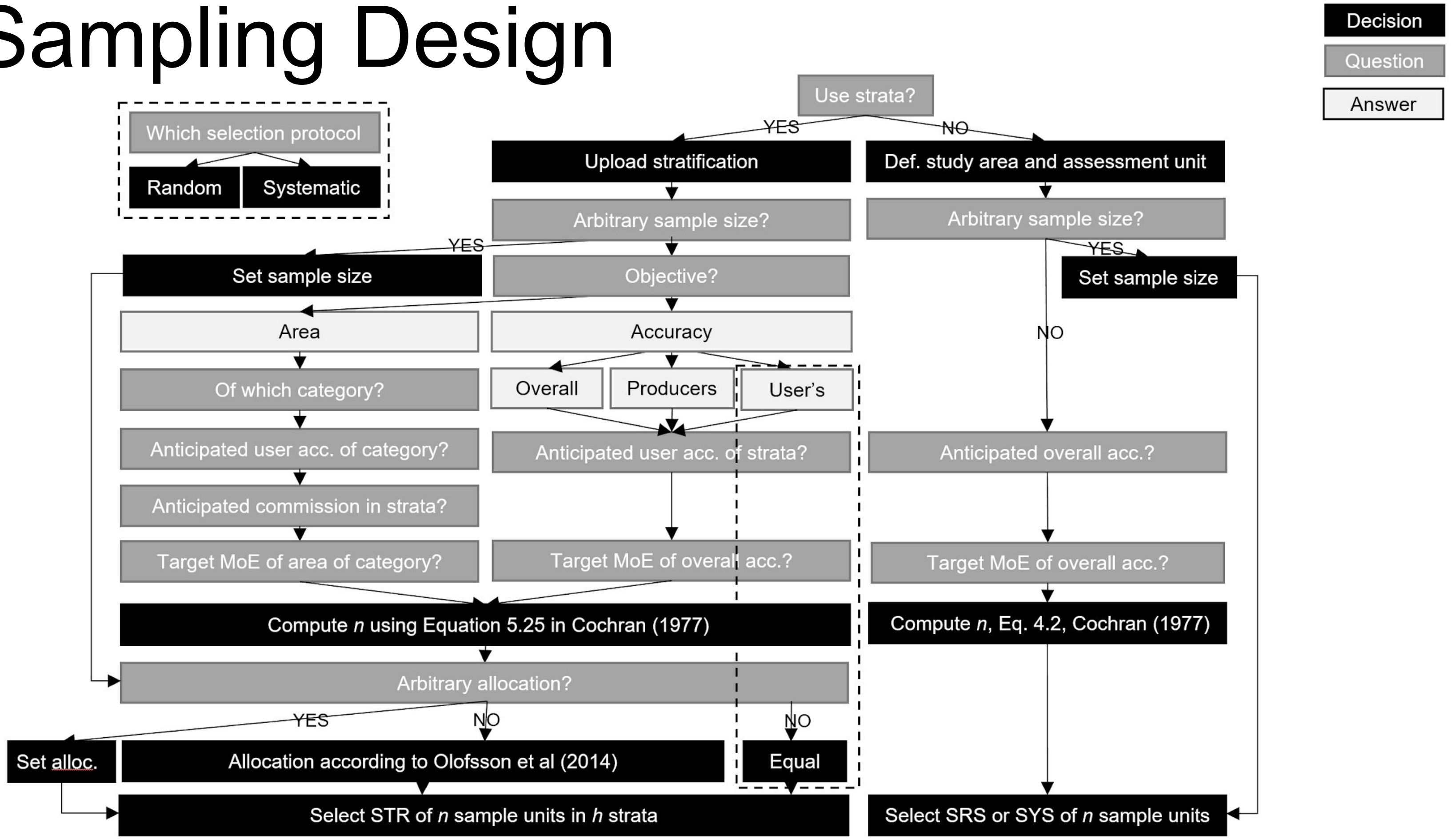
1. Sampling Design

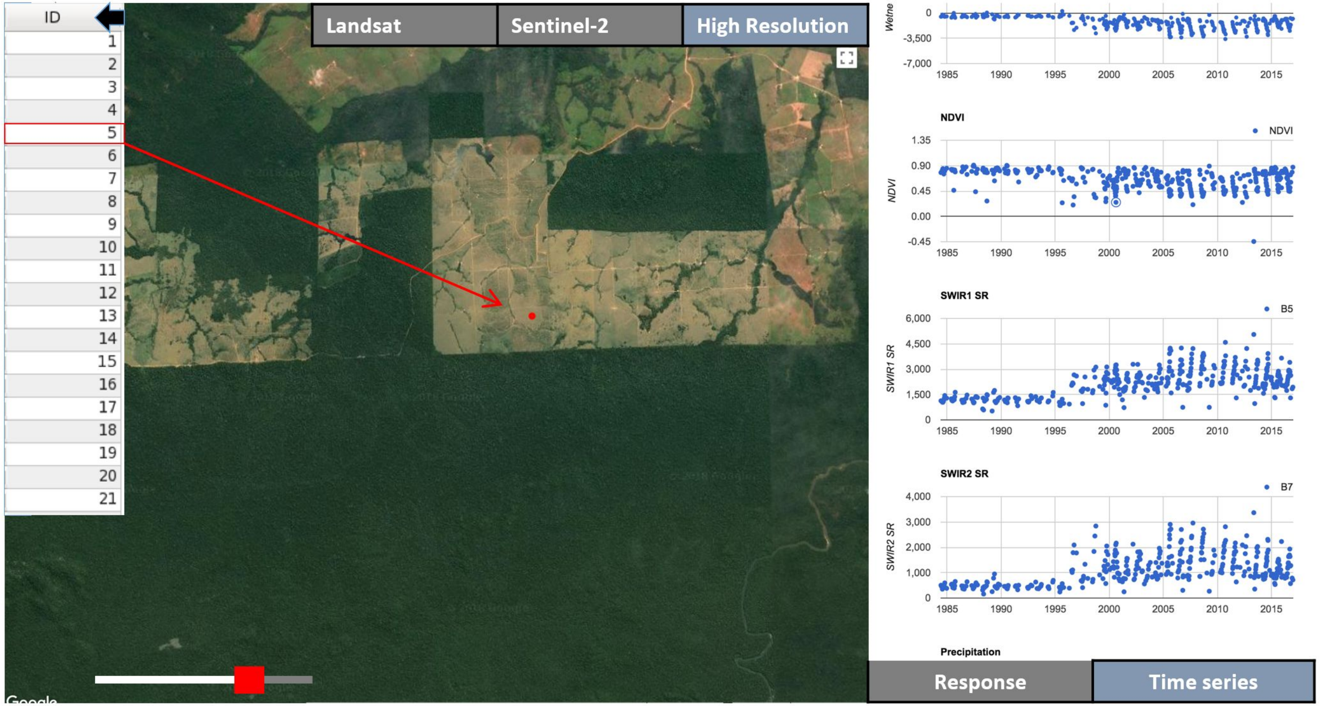


*Tree not complete; does not include cluster sampling and buffering of target categories (this looks messy but will be cleaner when implemented in a GUI!)

2. Response Design

Toggle between reference imagery to display

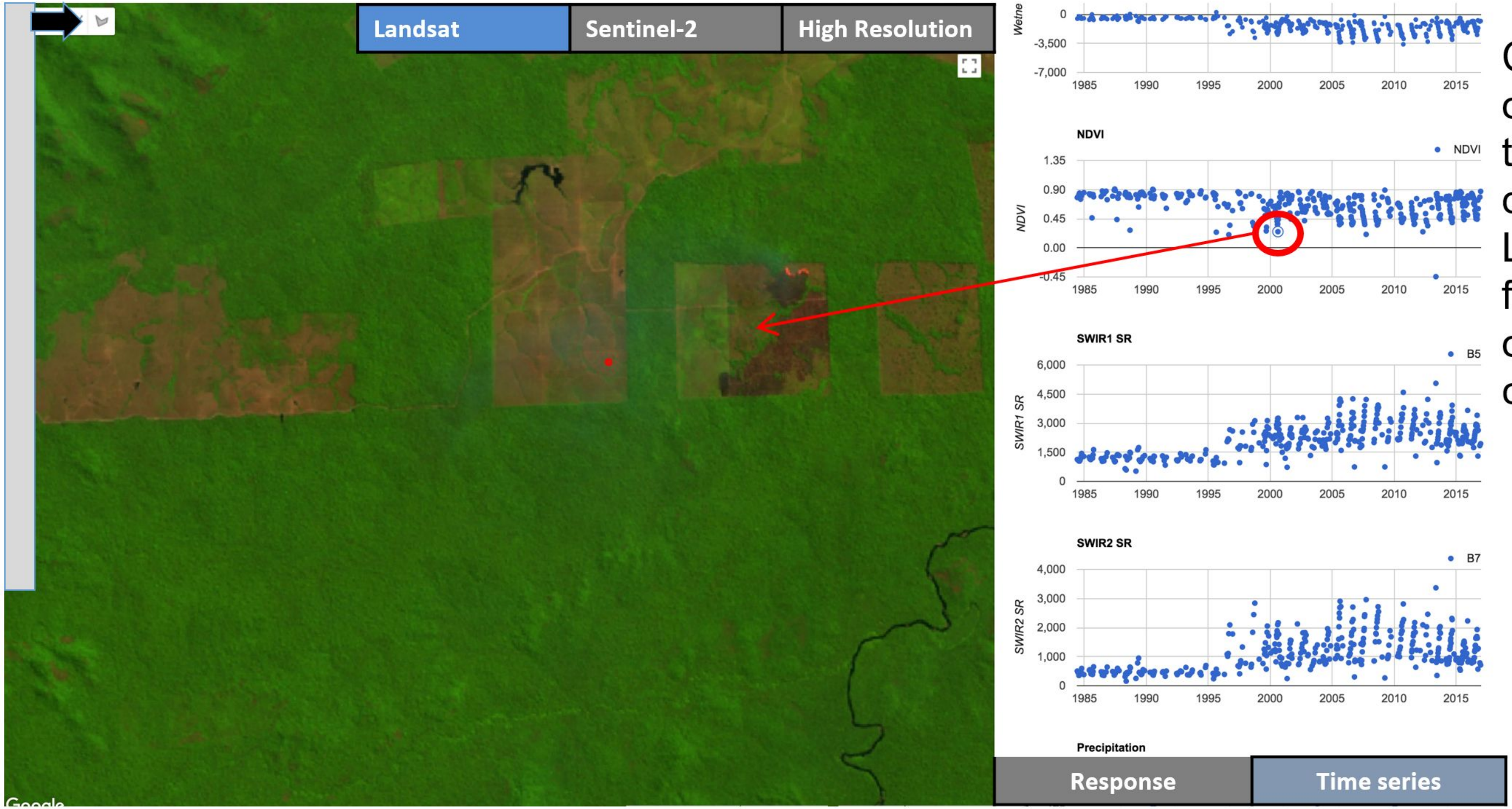
Select unit from sample generated in (1)



Date slider to select high resolution imagery from Google Earth

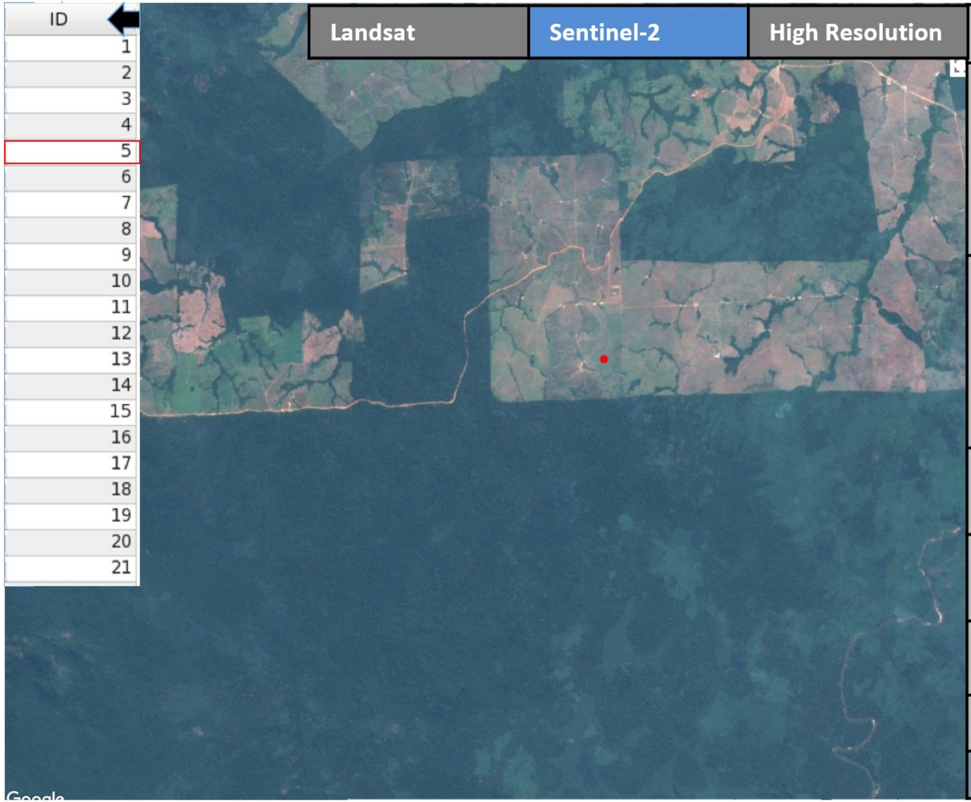
Toggle between Landsat time series and response for selected sample unit

2. Response Design



Click on observation in time series to display the Landsat image from which observation come

2. Response Design



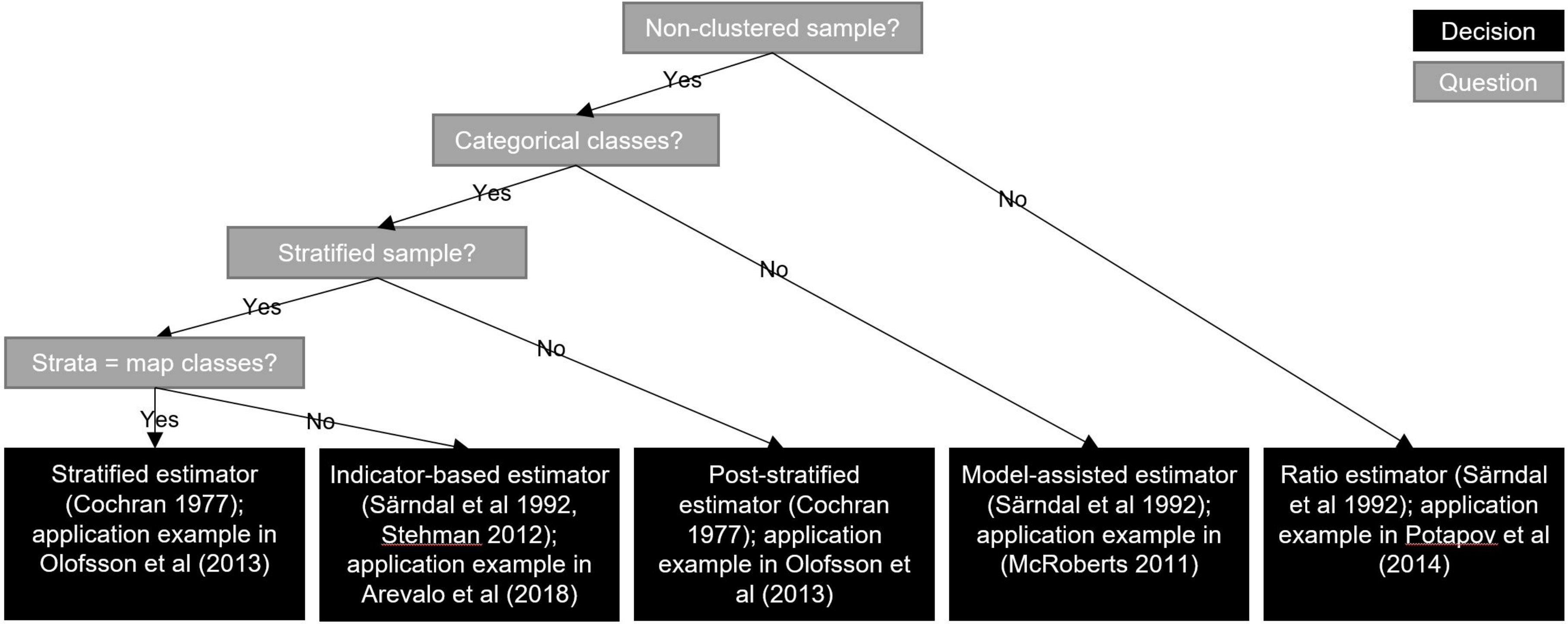
Sample unit ID = 5	
Reference label code (1=forest loss 2 = forest gain 3 = stable forest 4 = stable non-forest)	1
Reference label name (“Forest loss” “Forest gain” “Stable forest” “Stable non-forest”)	Forest loss
If change, date of change	Dec. 1995
Confidence 1-3 (3 = most confident)	3
Comment	[Enter text]

Save response

Response | Time series

Toggle to response dialog to record reference label for selected sample unit – the response categories are defined by user

3. Analysis (decision tree to assist in selection of appropriate estimator)



3. Analysis (suggested output of analysis of sample data)

Error matrix expressed in sample counts

Map		Reference: *Defor*	*F gain*	*Stable f*	*Stable n-f*	Total	A_m [ha]	W_h
Map	*Defor*	66	0	5	4	75	18,000	0.020
Map	*F gain*	0	55	8	12	75	13,500	0.015
Map	*Stable f*	1	0	153	11	165	288,000	0.320
Map	*Stable n-f*	2	1	9	313	325	585,500	0.645
	Total	69	56	175	340	640	900,000	1

Error matrix expressed in estimated area proportions

Map		Reference: *Defor*	*F gain*	*Stable f*	*Stable n-f*	Total	A_m [ha]	W_h
Map	*Defor*	0.0176	0.0000	0.0013	0.0011	0.020	18,000	0.020
Map	*F gain*	0.0000	0.0110	0.0016	0.0024	0.015	13,500	0.015
Map	*Stable f*	0.0019	0.0000	0.2967	0.0213	0.320	288,000	0.320
Map	*Stable n-f*	0.0040	0.0020	0.0179	0.6212	0.645	585,500	0.645
	Total	0.0235	0.0130	0.3175	0.6460	1	900,000	1

Estimates of area and accuracy with 95% confidence intervals

	Deforestation	*Forest gain*	*Stable forest*	*Stable non-forest*
Estimated area [ha]	21,158	11,686	285,770	581,386
95% CI of area [ha]	± 6,158	± 3,756	± 15,510	± 16,282
User's accuracy [-]	0.88	0.73	0.93	0.96
95% CI of user's [-]	± 0.07	± 0.1	± 0.04	± 0.02
Prod.'s accuracy [-]	0.75	0.85	0.93	0.96
95% CI of prod. [-]	± 0.21	± 0.23	± 0.03	± 0.01
Overall accuracy [-]	0.95			
95% CI of overall [-]	± 0.02			

Possible ways forward

- You (Google) build it with our domain help
- We build it with your technical help
- Communal effort (TimeSync, IDEAM, UMD, FAO, GOFC-GOLD, etc.)
- *It matters less to us how it gets implemented than its functionality*

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Questions to the audience

- How many of you envision the need to estimate areas? Estimate accuracy?
- Would you use a tool like this?
- Do you feel you have the capacity to design a sample for specific objectives? To construct the appropriate estimator?
- Which tools are you currently using for estimation?

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