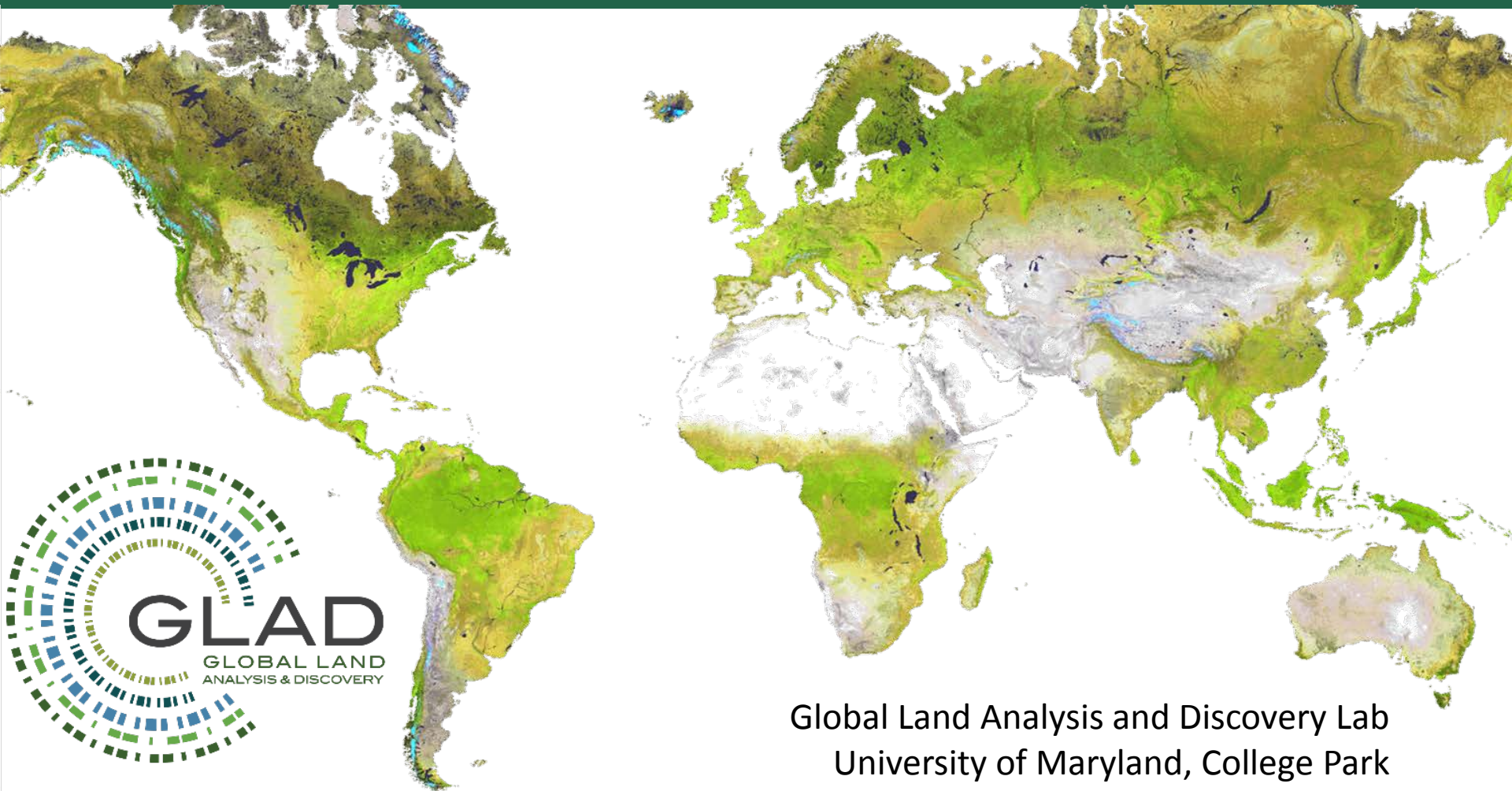
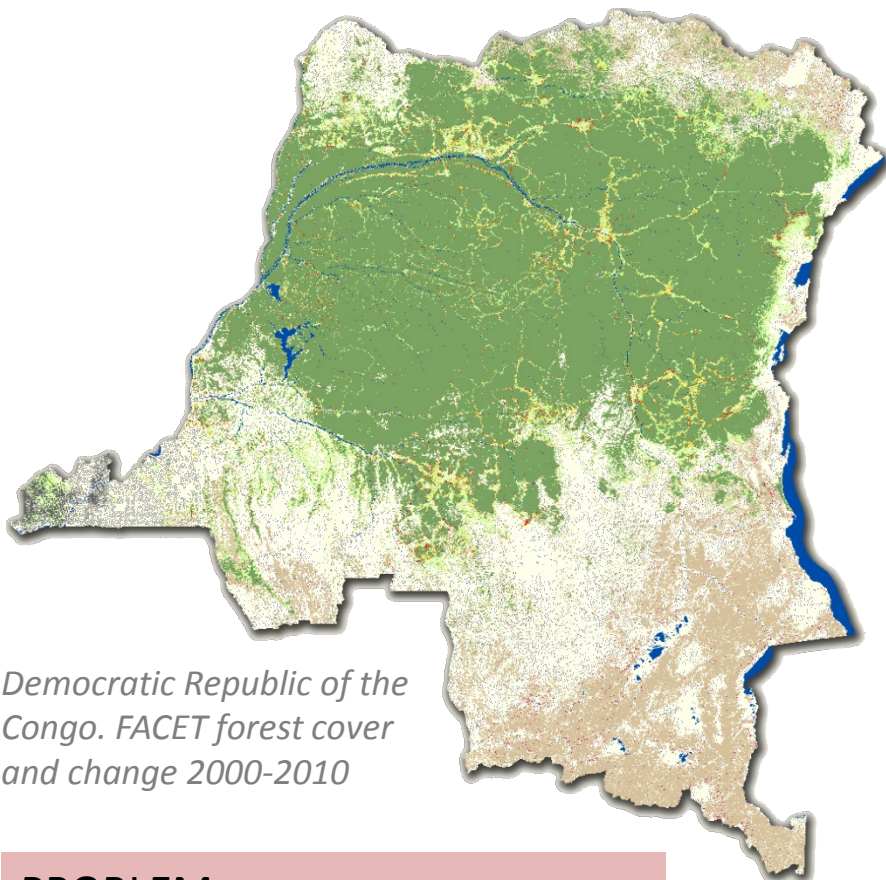


Estimating Tree Cover Area and Change Using Sample-based Analysis



Statistical Sampling

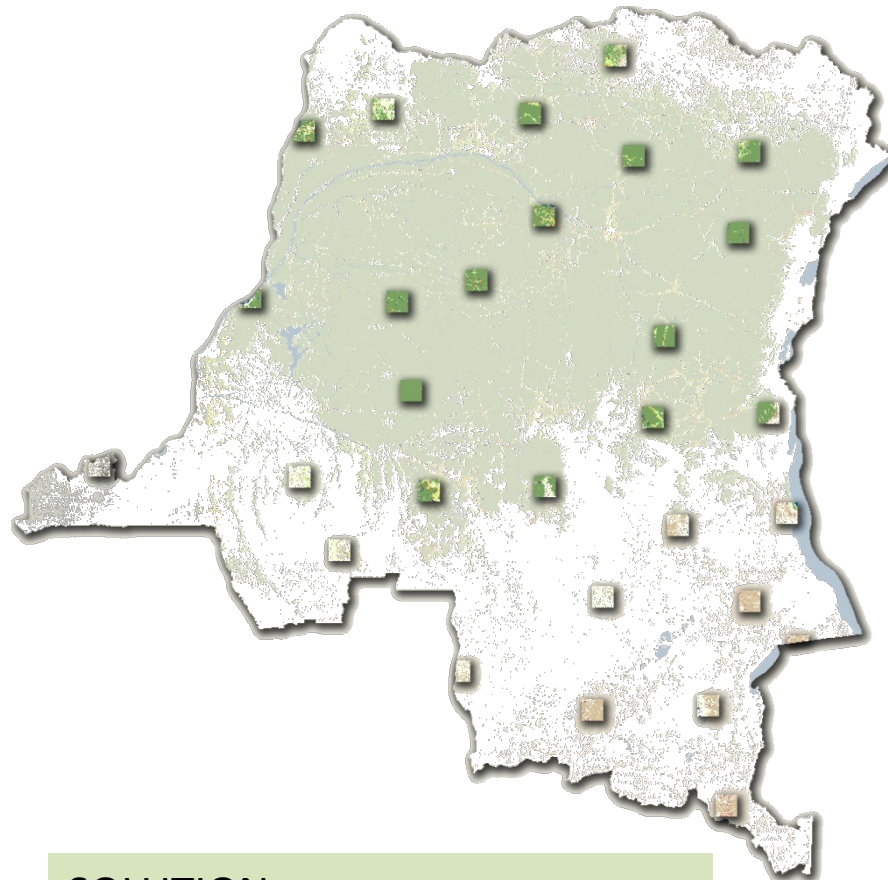
Spatially exhaustive (wall-to-wall) mapping



PROBLEM

All maps produced using remotely sensed data have errors, which bring bias to the areas calculated from the map

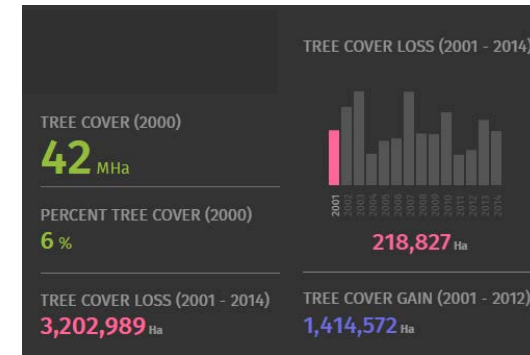
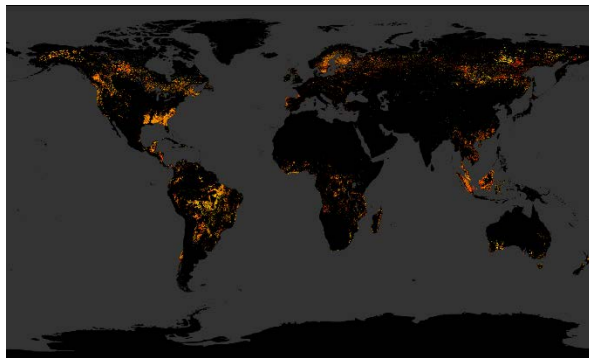
Statistical sampling



SOLUTION

Reference sample data can be used to produce an unbiased estimate of area of map classes with known uncertainty (Olofsson et al. 2013, 2014)

Wrong way



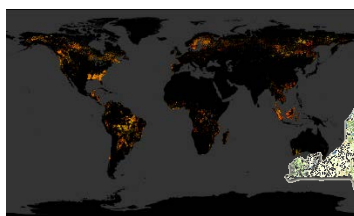
Global forest extent and change products provides spatially consistent, wall-to-wall data...

However:

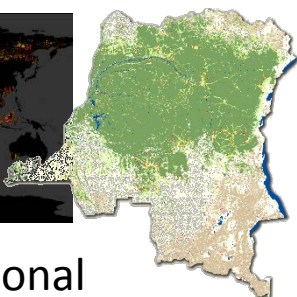
- All maps derived from remotely sensed data contain errors due to data limitation, classification/change detection algorithm limitation, analyst errors and bias, etc.
- Errors on the global overview maps usually introduce bias in area estimations. Most of the overview maps provide “conservative” estimates of rare classes, i.e. they underestimate forest change.
- The global map errors may be spatially biased (e.g. due to different characterization model sensitivity within different environments).
- The uncertainty of classification may not be estimated from the map alone.

Statistical Sampling

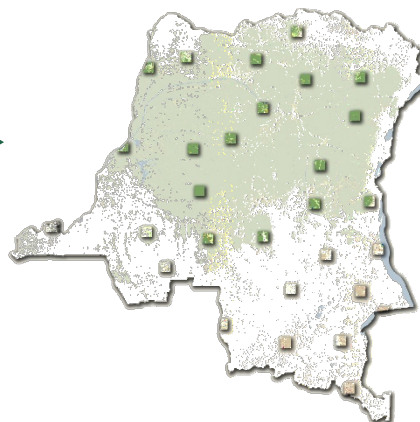
Good practice



Global or national
wall-to-wall TC change maps



Statistical
sampling



Sample-based:

- Map accuracy
- Area
- Uncertainty

Spatially exhaustive (wall-to-wall) maps

- Provide information on spatial allocation of forest cover and change.
- Allow sampling design/area estimation with improved efficiency and precision.
- Global maps may have limitations and should be substituted with regional/national maps when possible.

Sample-based assessment (reference sample data)

- Provides highest quality determination of the forest cover and change conditions per sample unit
 - Serves as reference data for map **accuracy assessment**.
 - Allows **unbiased area estimation** with known **uncertainty**.

Probability sampling allows to:

- Quantify map accuracy (Overall, User's, Producer's).
- Estimate “true” (unbiased) areas of mapped classes.
- Estimate uncertainty of the mapped classes area.
- Perform value-added thematic analysis based on visual sample interpretation (e.g. differentiate various types of forest or forest disturbance).

Primary stages of sampling assessment:

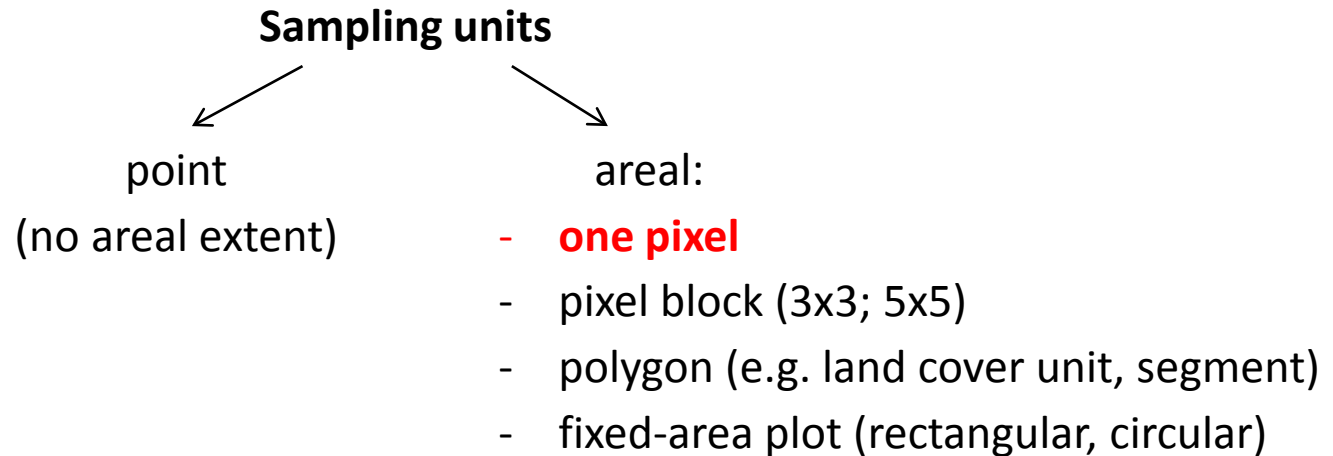
- 1. The sampling design:** how to select the reference sample.
- 2. The response design:** how to determine the “ground truth” for each observation in the reference sample.
- 3. The estimation and analysis protocol:** how to estimate area and uncertainty and quantify the accuracy of the map.

Basic principles of sampling design for TC/TCC assessment

- The **entire area of analysis** should be included into sampling frame.
- Samples should be allocated using **probability sampling** (e.g., randomly). Spatial autocorrelation does not usually affect sample-based estimates. Random allocation is preferred in most cases.
- Samples should **NEVER** be used as classification training.
- Samples should be **in sufficient number** (typically large) to reduce the uncertainty of accuracy metrics. For stratified sampling, at least 100 samples per strata is recommended.
- The number of samples is not correlated with the total population (number of pixels in the map). Only the **total number of samples drives the precision**, not the fraction of the area sampled.
- Each valid sample should have map data and reference data.

Sampling design

Sampling unit



Considerations when choosing sampling unit:

- Cost/time of deriving reference value;
- Sensitivity to location error (boundary pixels and polygons);
- Ability to retain identity under map revisions (e.g. map polygons may change in case of a map reclassification).

Stehman and Czaplewski (1998): “No consensus exists on which sampling unit is best, and it is unlikely that any one sampling unit is optimal for all applications”

Sampling design

Sampling design – the protocol by which the reference sampling units are selected

Probability sampling:

all sampling units have nonzero
inclusion probability



statistically valid estimates can be
computed

Examples of probability sampling designs:

- Simple random
- Systematic
- Stratified random
- Stratified systematic
- Cluster random
- Cluster systematic
- Stratified random cluster
- Stratified random systematic

Nonprobability sampling:

inclusion probabilities for the samples
can not be defined



should not be used for the accuracy
assessment or area estimation

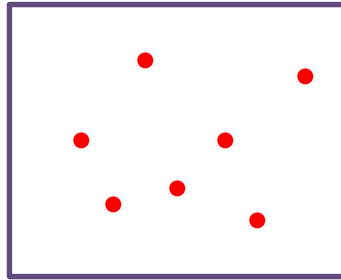
Examples of nonprobability sampling:

- Purposefully selecting training data for a supervised classification;
- Selecting reference samples from conveniently accessible sites;
- Using available aerial photography or high resolution imagery.

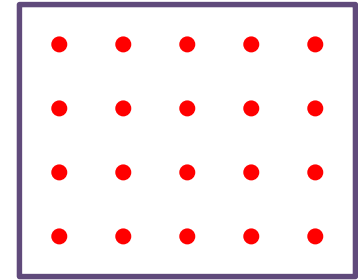
Sampling design

Common probability sampling designs

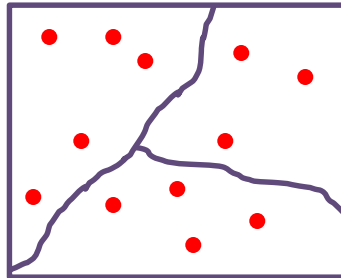
1. Simple random



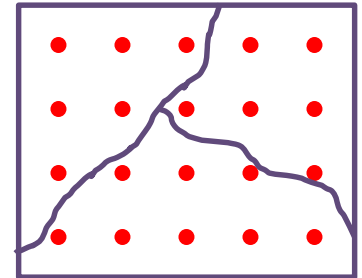
2. Systematic



3. Stratified random

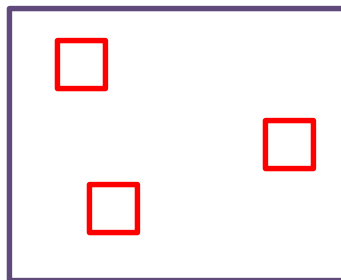


3. Stratified systematic



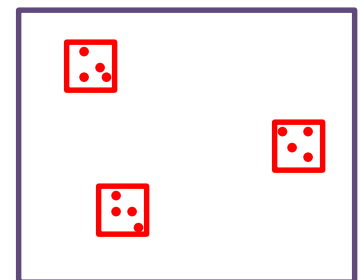
4. Cluster random one-stage

Reference data obtained for all pixels in the block (cluster)



4. Cluster random two-stage

Reference data obtained for a sample of pixels in the block (cluster)



Sampling design

Test data:

PRODES Landsat-mapped
forest cover loss 2000-2005



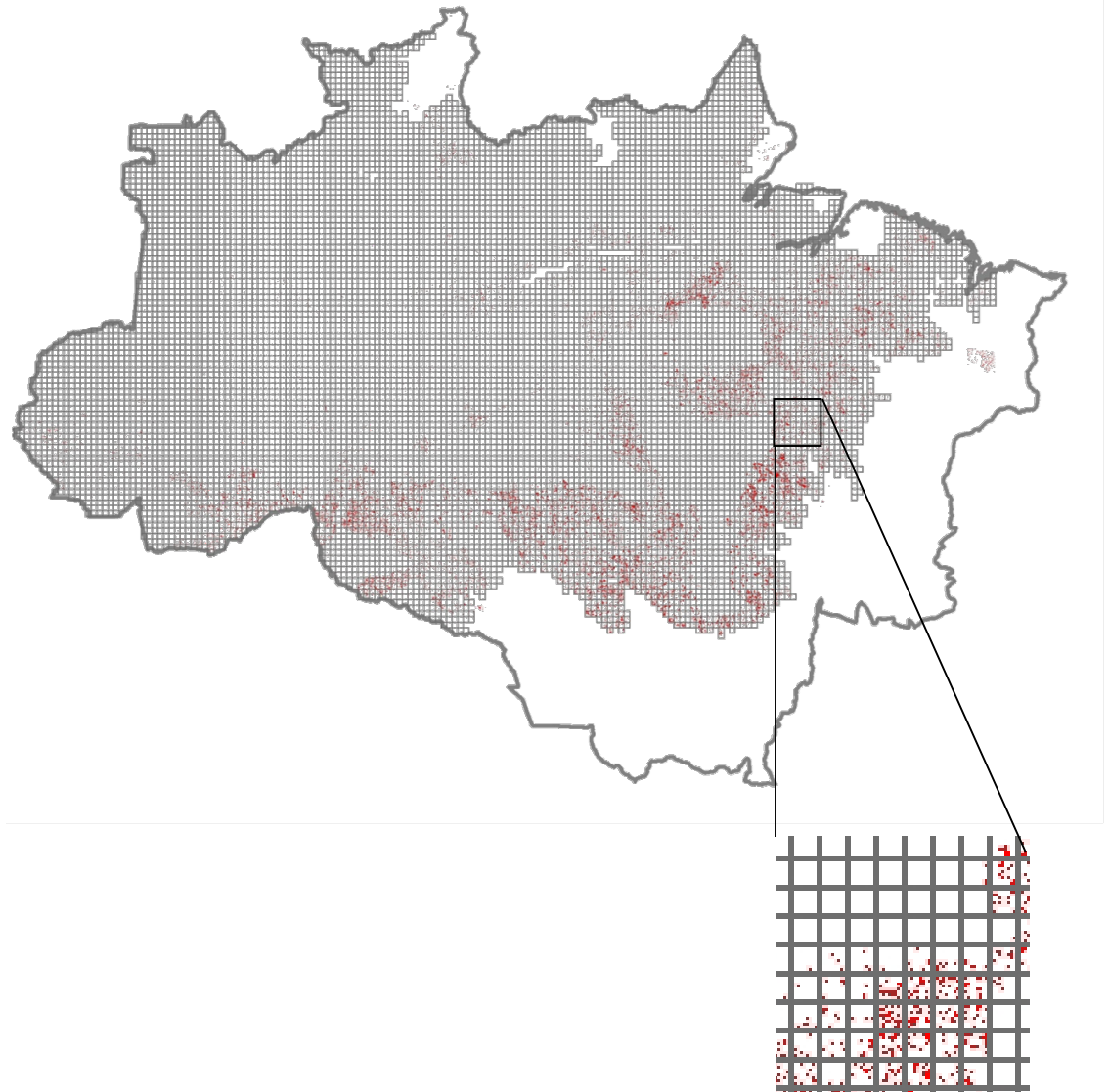
Sampling design

Test data:

PRODES Landsat-mapped
forest cover loss 2000-2005

Sampling frame:

18.5x18.5km sample blocks

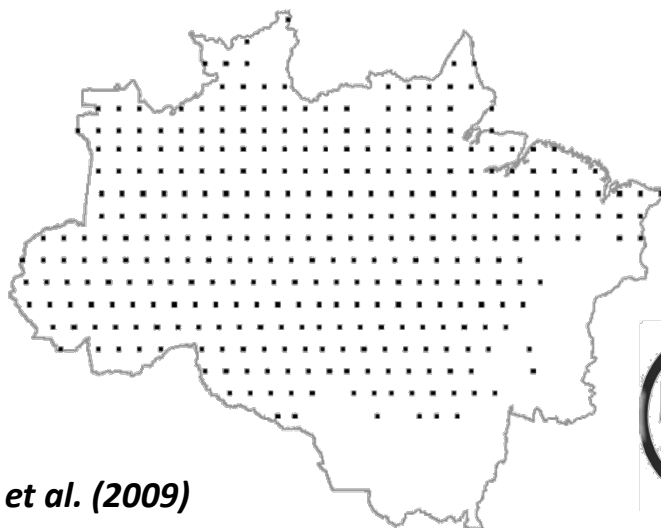


Sampling design

Random sampling



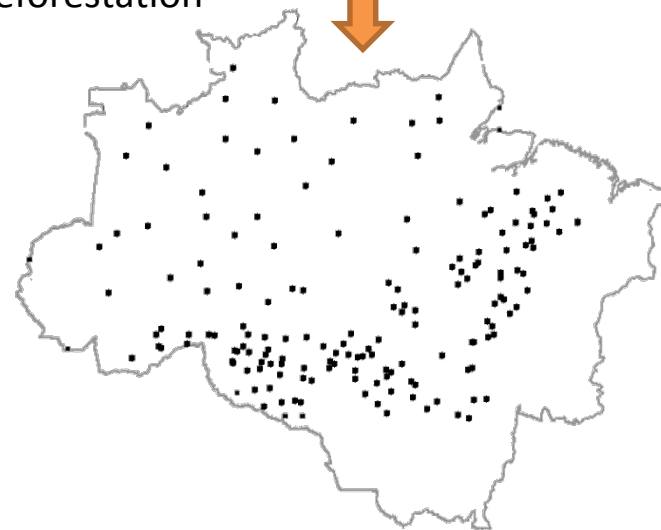
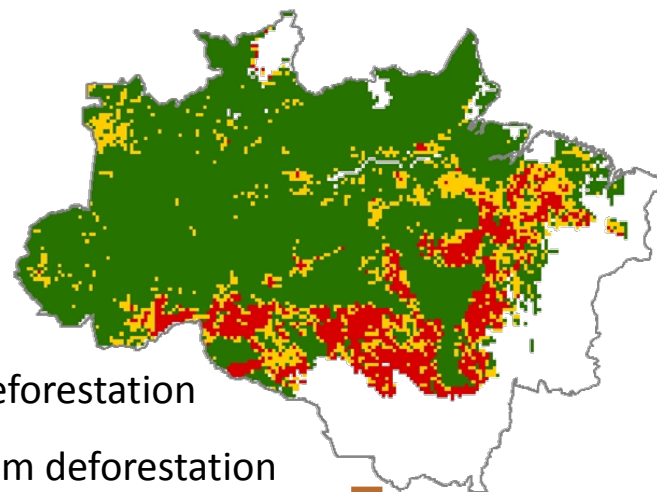
Systematic sampling



Stratified sampling

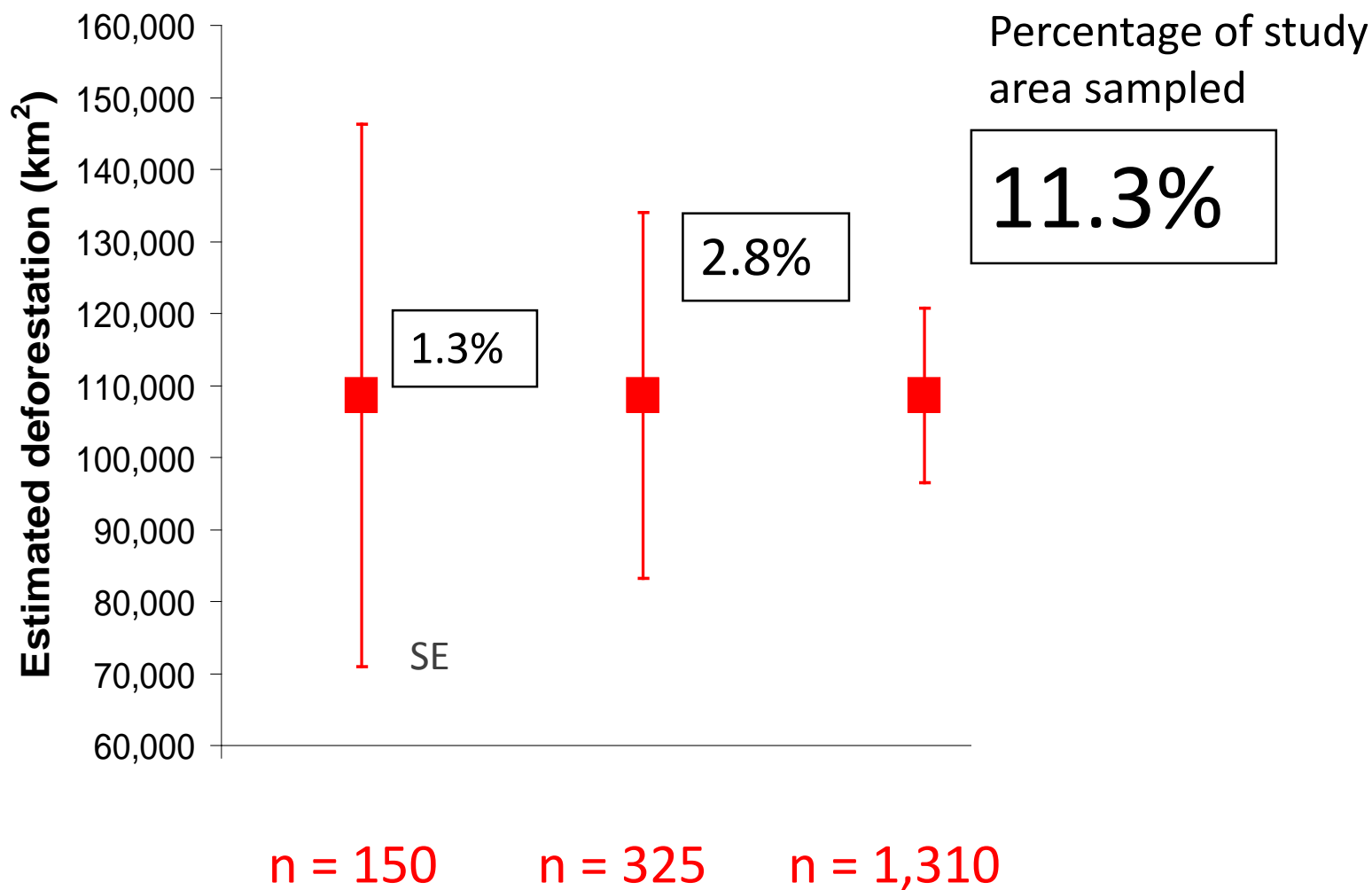
MODIS strata

- low deforestation
- medium deforestation
- high deforestation



Sampling design

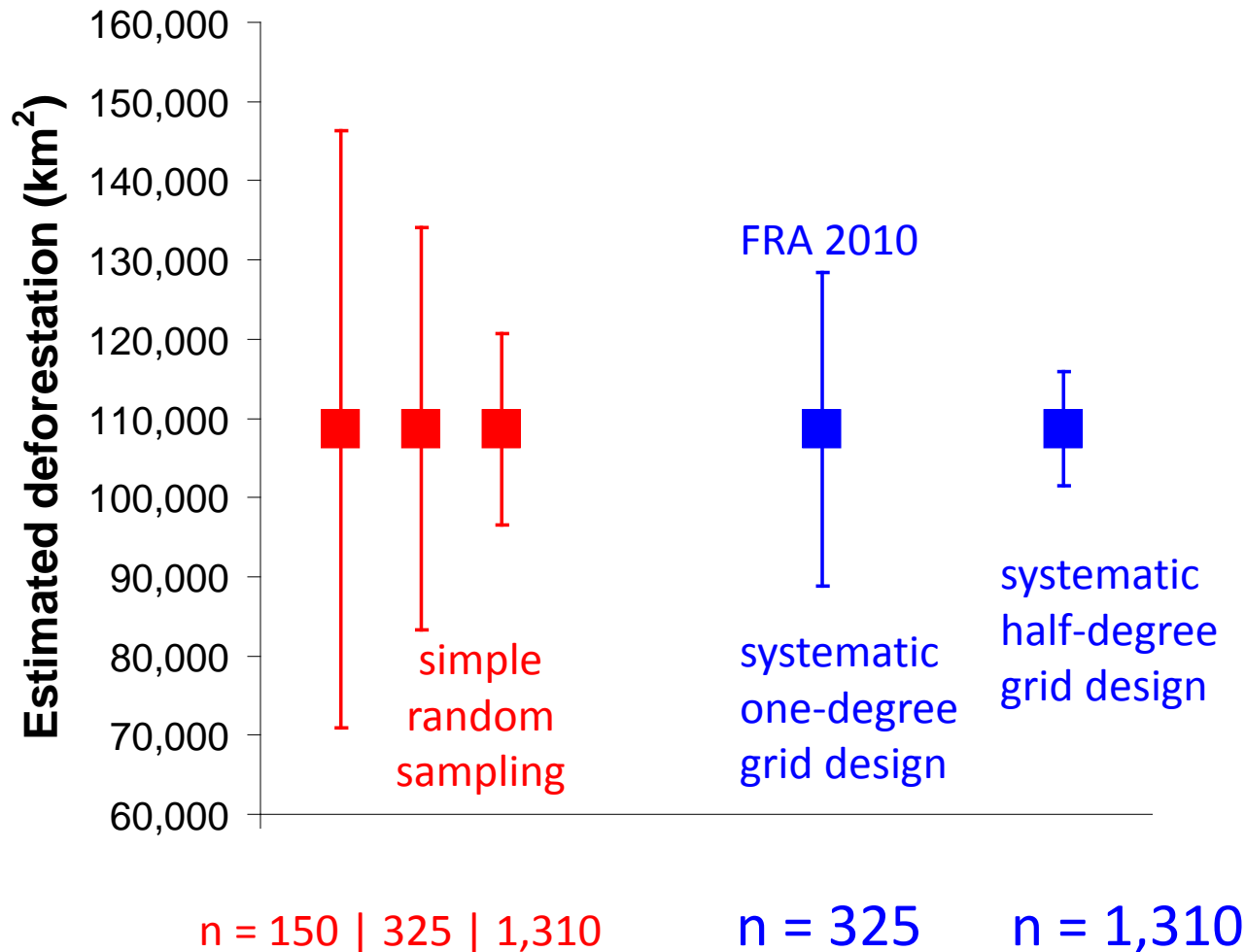
Random sampling



Sampling design

Random

Systematic sampling

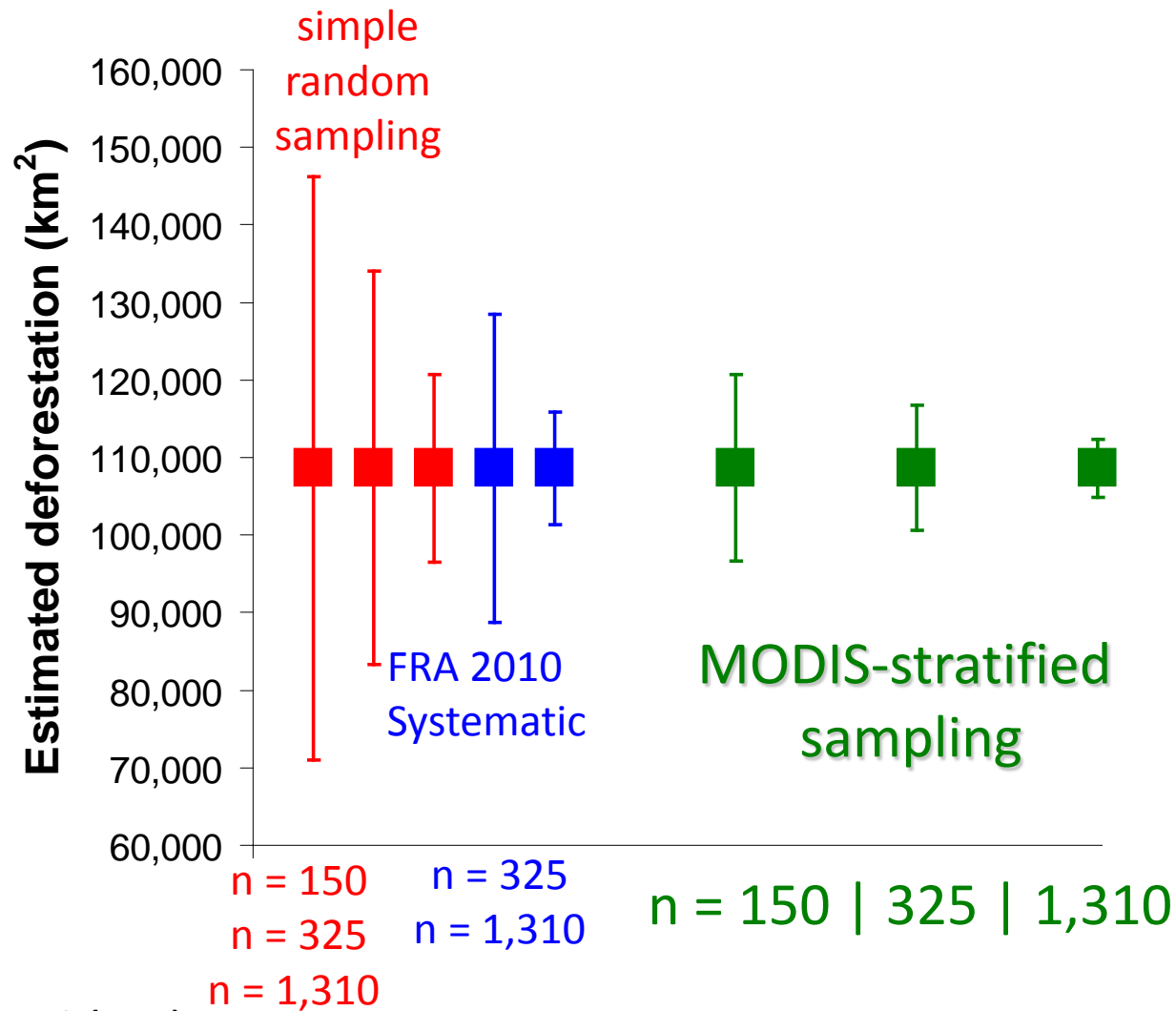


Sampling design

Random

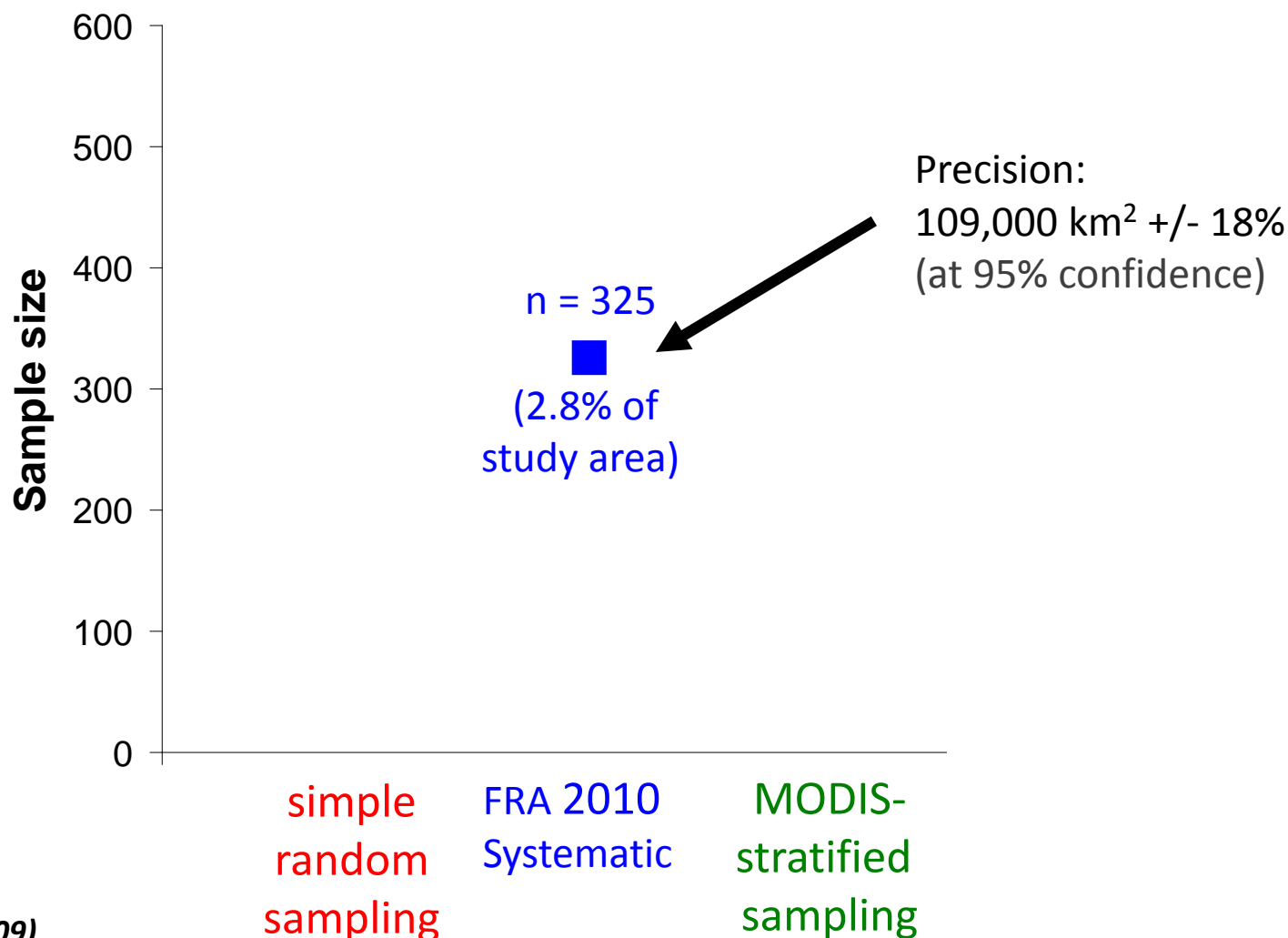
Systematic

Stratified sampling



Sampling design

Sample size needed to achieve precision of FRA 2010
(systematic one-degree grid design)



Sampling design

Common probability sampling designs

From Stehman (2009):

Table 4. Relative strengths and weaknesses of basic sampling designs according to desirable design criteria. The criteria are: *C1*) probability sample, *C2*) practical, *C3*) cost, *C4*) spatial balance, *C5*) precise estimates of class-specific accuracy, *C6*) ability to estimate standard errors, and *C7*) flexible to change in sample size. The rating symbols are ●=strength and ○=weakness; absence of a symbol indicates the design is ‘neutral’ with regard to that criterion. See also section 5.4 in text.

Design	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C4</i>	<i>C5</i>	<i>C6</i>	<i>C7</i>
<i>D1</i> : Simple random	●	●	○	○	○	●	●
<i>D2</i> : Systematic	●	●	○	●	○	○	○
<i>D3</i>: Stratified (land cover) random	●	●	○	○	●	●	●
<i>D4</i> : Stratified (land cover) systematic	●		○		●	○	○
<i>D5a</i> : Stratified (spatial) random ($n_h=1$)	●	●	○	●	○	○	
<i>D5b</i> : Stratified (spatial) random ($n_h>1$)	●	●	○		○	●	●
<i>D6</i> : Stratified (spatial) systematic	●	●	○	●	○	○	○
<i>D7</i> : Cluster random	●		●	○	○	●	
<i>D8</i> : Cluster systematic	●		●		○	○	○
<i>D9</i>: Stratified random cluster	●		●	○			
<i>D10</i> : Stratified systematic cluster	●		●			○	

Olofsson et al. (2014):

Stratified random sampling is a recommended “good practice” sampling design

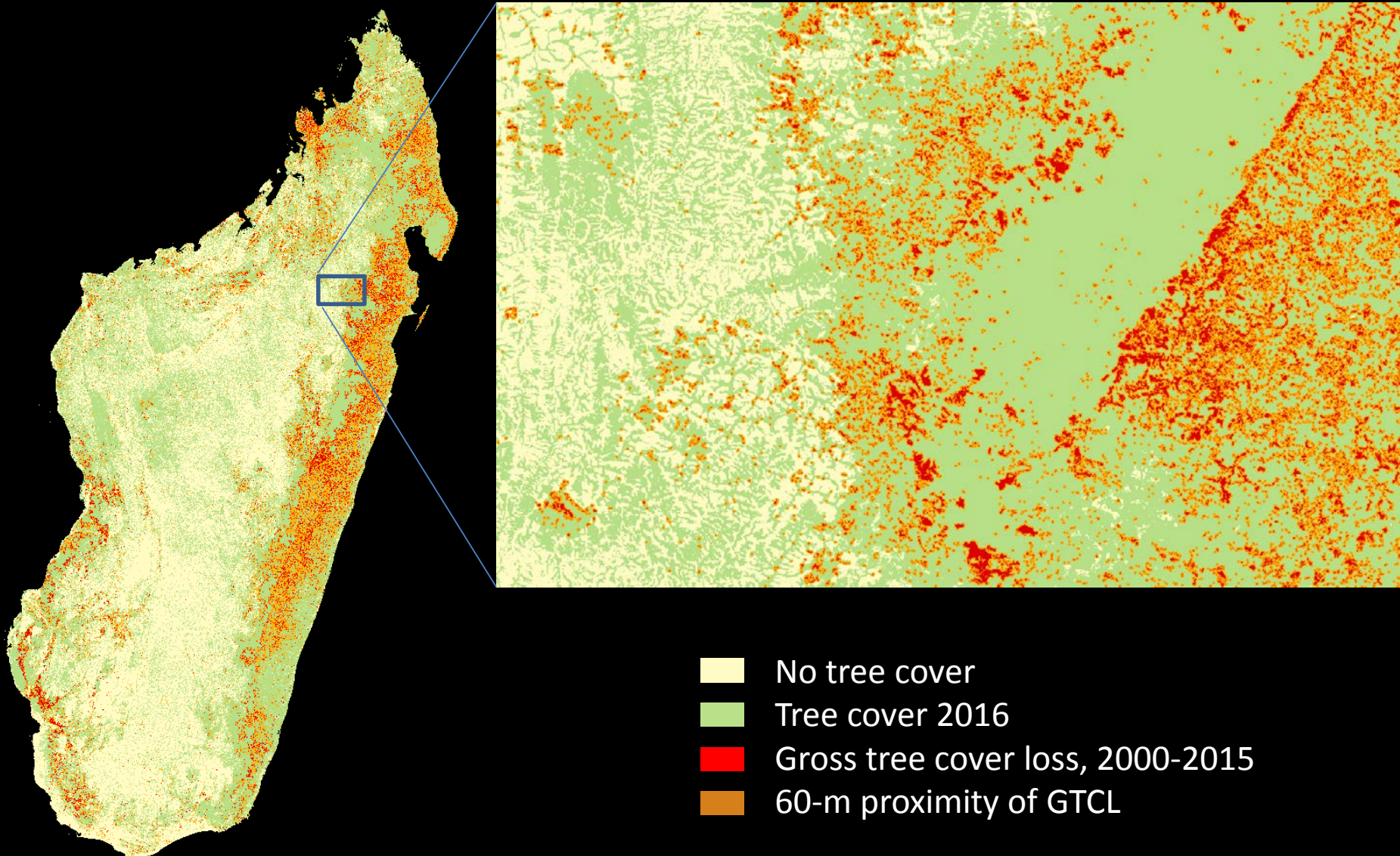
Sampling design

Principles of stratified random sampling design

- Assign all pixels to groups (strata). Strata should represent areas with low variability of the measured quantity (e.g. forest change). Alternatively, “natural” strata may be used (e.g. land-cover classes). In this case, however, stratification may not have effect on the uncertainty of the estimate.
- The large number of strata will require large number of samples and will complicate accuracy and area estimation. If required, post-strata may be added later to characterize specific regions or land cover types.
- Specify sample size for each stratum. Equal, proportional, or other allocations may be used. Ensure that rare classes (strata) appear in the sample. Sample may be added later to strata which contribute most to the overall uncertainty.

Sampling design

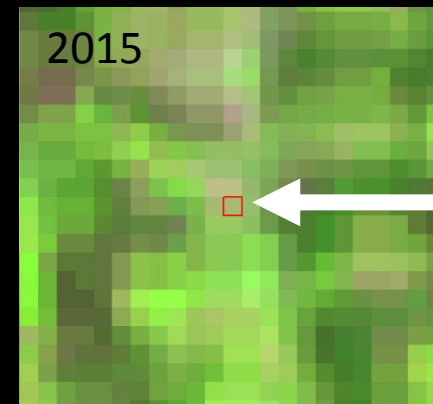
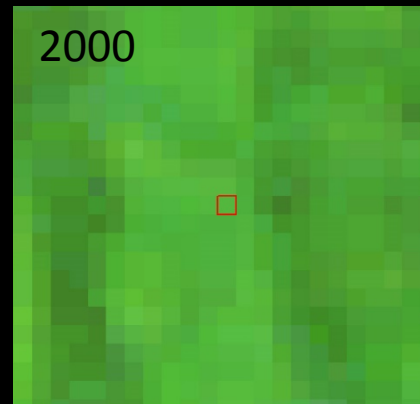
Sampling design to quantify tree cover change in Madagascar, 2000-2015



Sampling design





Sampling design to quantify tree cover change in Madagascar, 2000-2015

Stratum	area, ha	count, 30x30m pixels	% total	Total samples	Training goal
No loss / no trees	25,141,547	348008206	43	200	50
No loss / tree cover	23,815,964	327272139	40	800	150
Loss 2001-2015	2,658,505	36480651	4	1000	150
Buffer around loss	7,528,648	103251036	13	1000	150
<i>Total</i>	<i>59,144,663</i>	<i>815012032</i>		<i>3000</i>	<i>500</i>



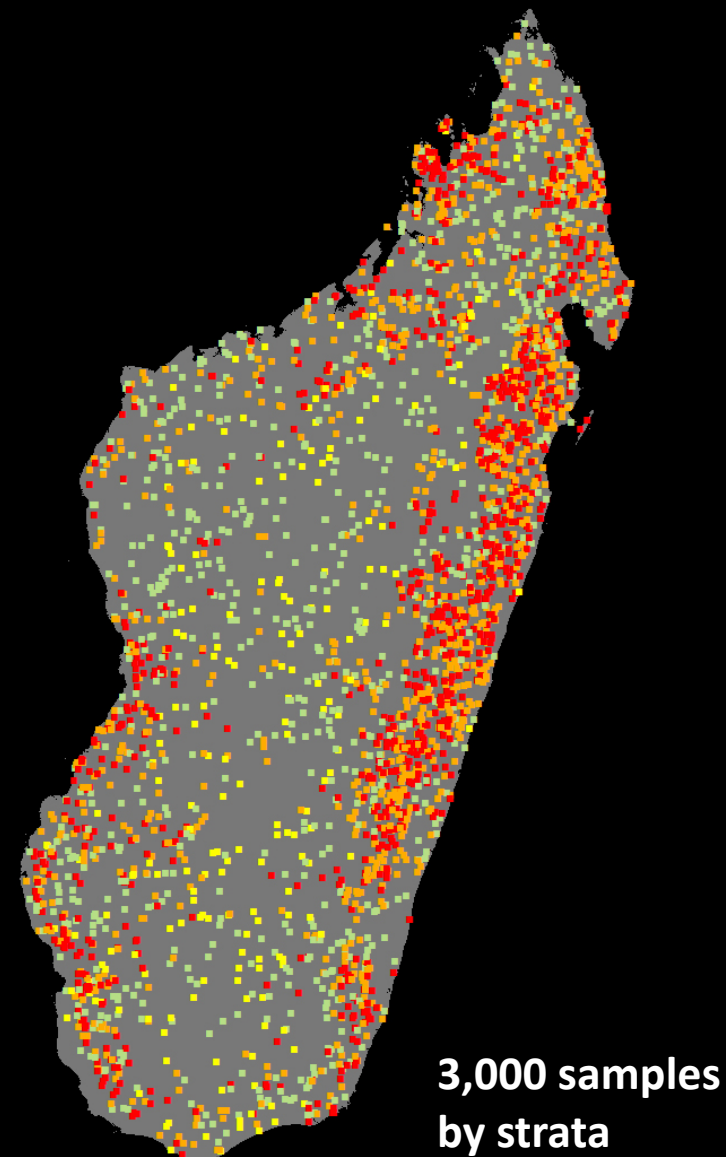
Sample
(30x30 m)

3,000 samples





-  No tree cover
-  Tree cover 2016
-  Gross tree cover loss, 2000-2016
-  60-m proximity of GTCL

Sampling design

Sampling design to quantify tree cover change in Madagascar, 2000-2015



Stratum	area, ha	count, 30x30m pixels	% total	Total samples	Training goal
No loss / no trees	25,141,547	348008206	43	200	50
No loss / tree cover	23,815,964	327272139	40	800	150
Loss 2001-2015	2,658,505	36480651	4	1000	150
Buffer around loss	7,528,648	103251036	13	1000	150
<i>Total</i>	<i>59,144,663</i>	<i>815012032</i>		<i>3000</i>	<i>500</i>

-  No tree cover
-  Tree cover 2016
-  Gross tree cover loss, 2000-2016
-  60-m proximity of GTCL

Response design

Reference classification should be:

- Of higher quality than what was used to create the map (e.g. high resolution imagery to validate Landsat-based map);

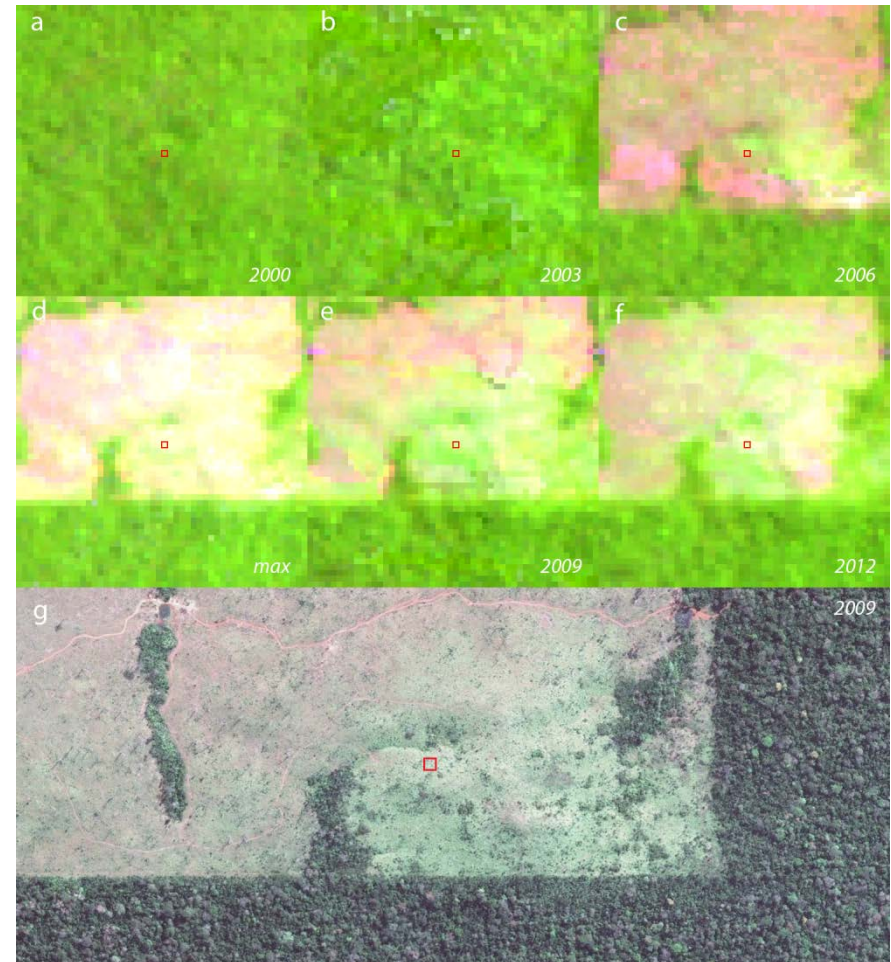
OR

- Created in a more accurate way, if the same data were used for both the map and reference classifications (e.g. visual interpretation of Landsat time-series to validate Landsat-based map derived using supervised classification).

Reference labeling protocol and rules for defining agreement between reference and map should be established prior to validation

Possible sources of error in reference classification:

- Geolocation errors (spatial mismatch between reference data and map)
- Interpretation uncertainty (interpreter error in the assignment of reference class and difference between interpreters)



Mato Grosso, Brazil

from Olofsson et al., 2014

Response design

Collecting sample (reference) data

Field data collection steps

1. Define sample locations (i.e. allocate samples randomly within the entire area, or within accessible area).
2. Develop efficient plan for visiting sites and contingencies for unreachable sites.
3. Use GPS (satellite images, on-line and off-line maps) to find pre-determined reference sites.
4. Use explicit definitions of the classes to insure that reference data are consistent



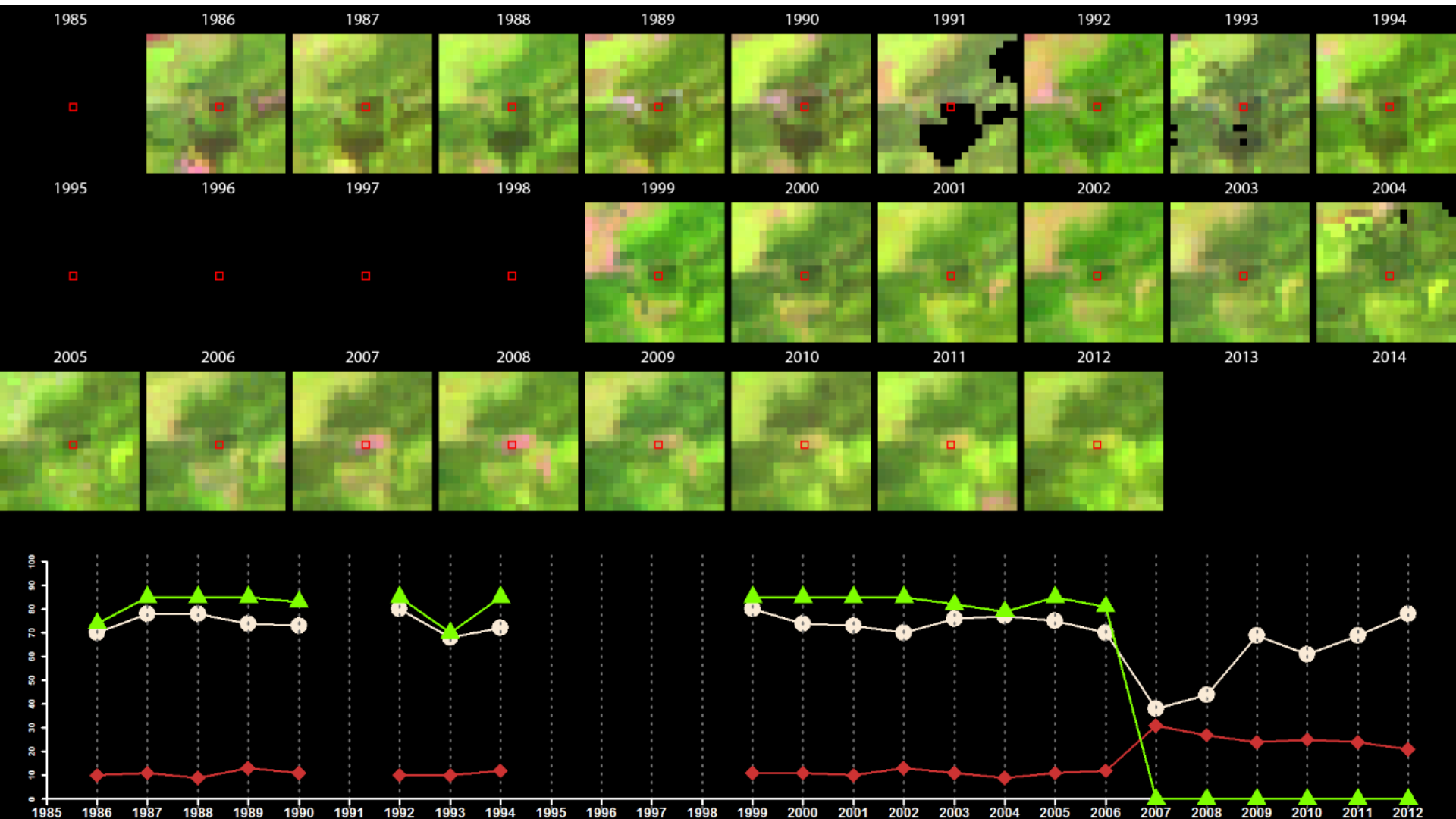
Response design

Collecting sample (reference) data



Using high-resolution images

Response design



Landsat annual time-series as reference data

Response design

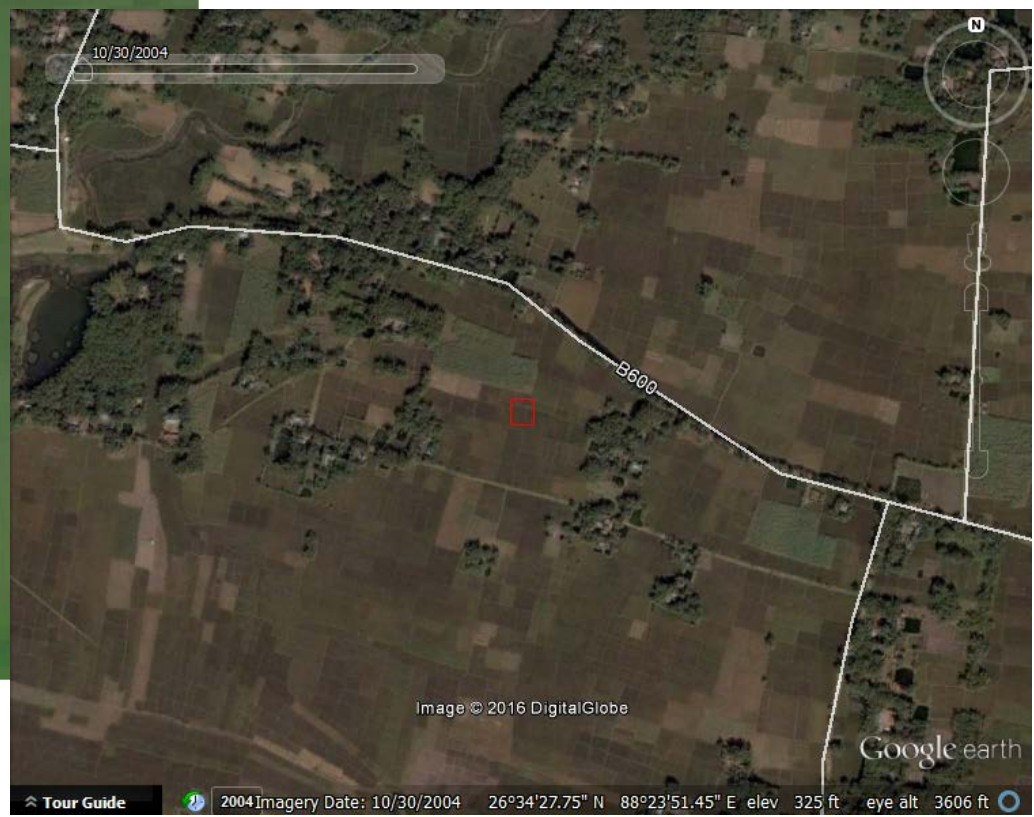
[Return to Index <<](#)

Sample 1 [Google Earth KML](#)

[>> Next](#)

[Return to Index](#)

Reference data: Forest 2000



Response design

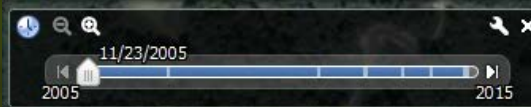
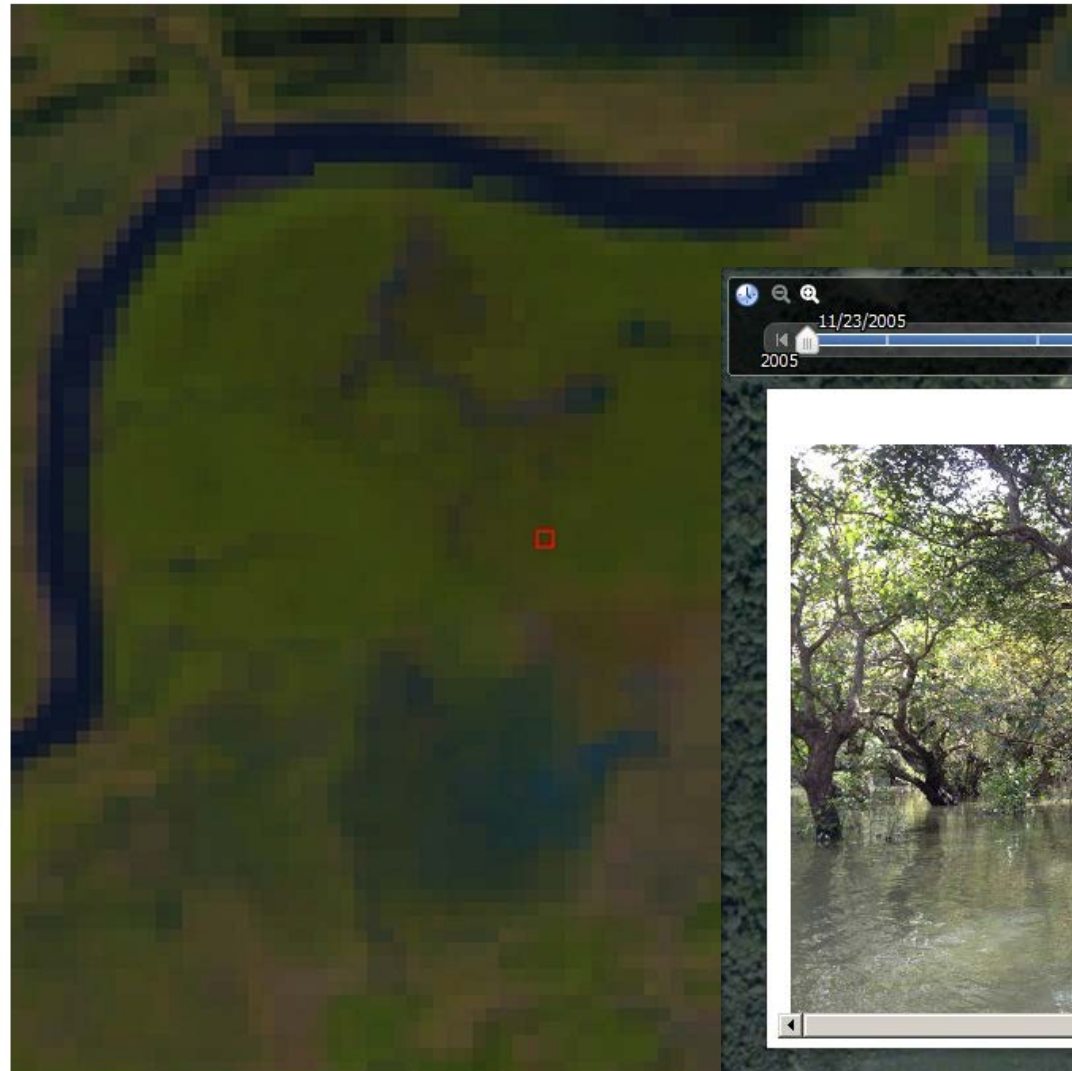
[Back <<](#)

Sample 119 [Google Earth KML](#)

[>> Next](#)

[Return to Index](#)

Reference data: Forest 2000



[By farzanahsn](#)
[Fly to this photo's location](#)
[Misplaced?](#)
[Inappropriate](#)
[Comment it](#)

[Panoramio](#)
[Upload your photos](#)

Image © 2016 DigitalGlobe

Google earth

[Tour Guide](#)

2005 Imagery Date: 11/23/2005 25°00'37.76" N 91°55'27.97" E elev 43 ft eye alt 1762 ft

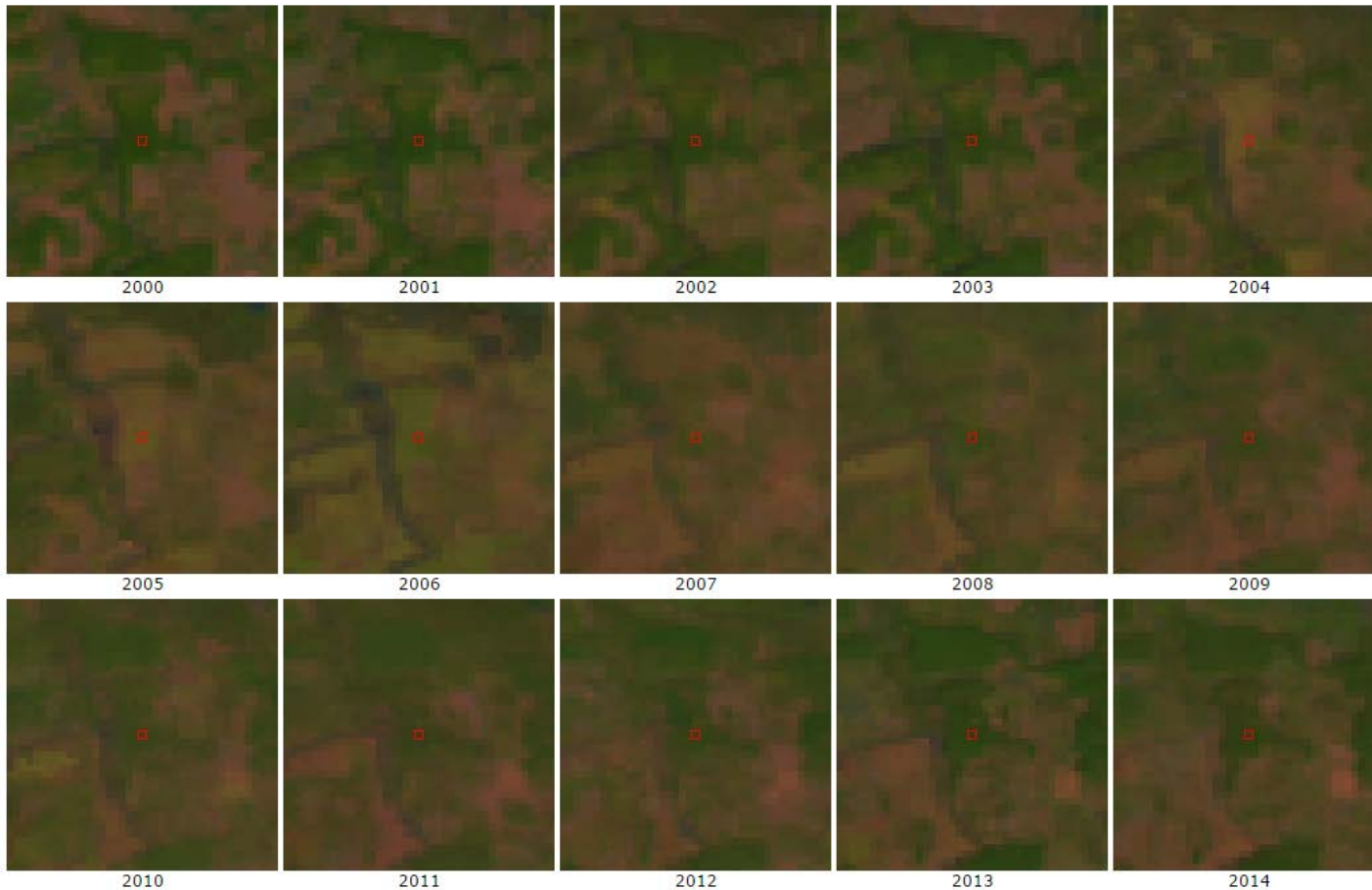
Response design

[Previous <<](#)

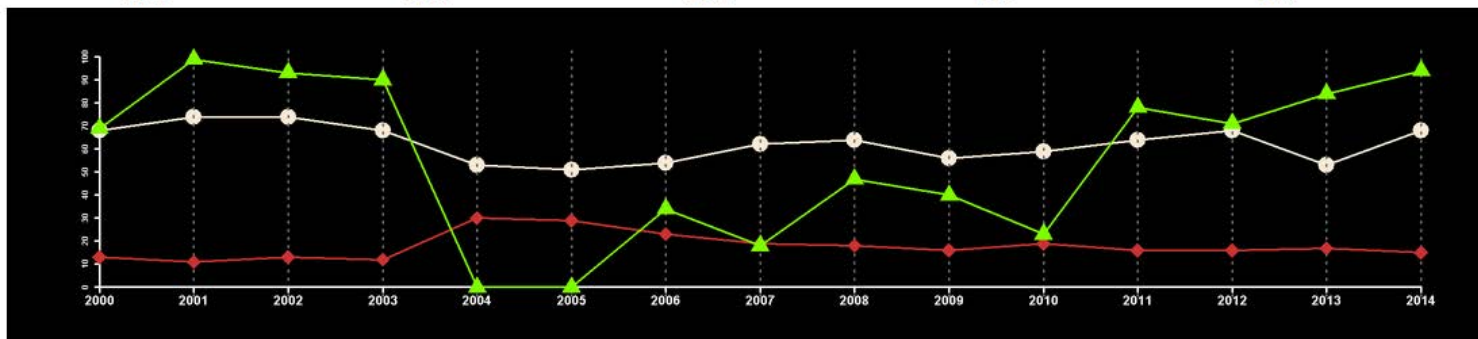
Bangladesh loss Sample 45 [Google Earth KML](#)

[>> Next](#)

[Return to Index](#)



Reference data
Forest loss



Annual min NDVI
Annual max SWIR
reflectance
Annual Tree Canopy
Cover

Response design

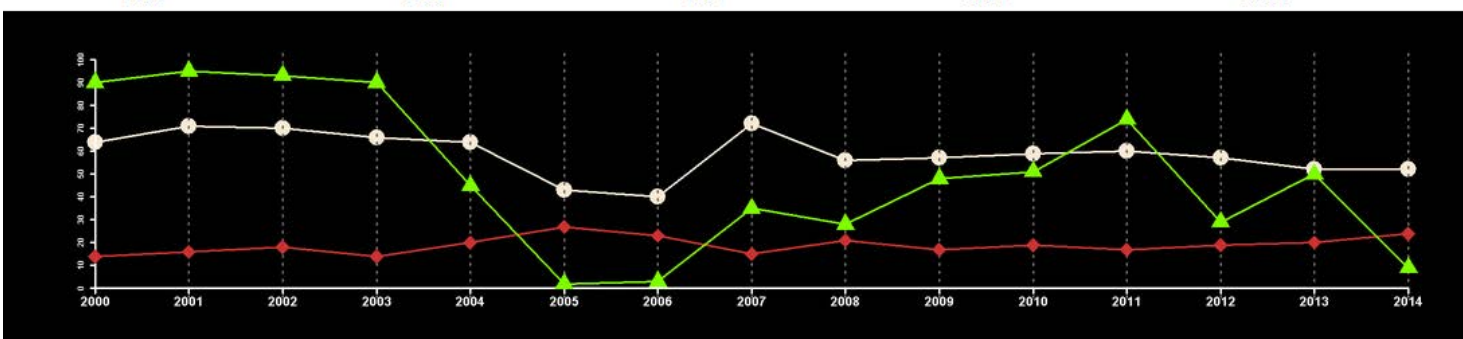
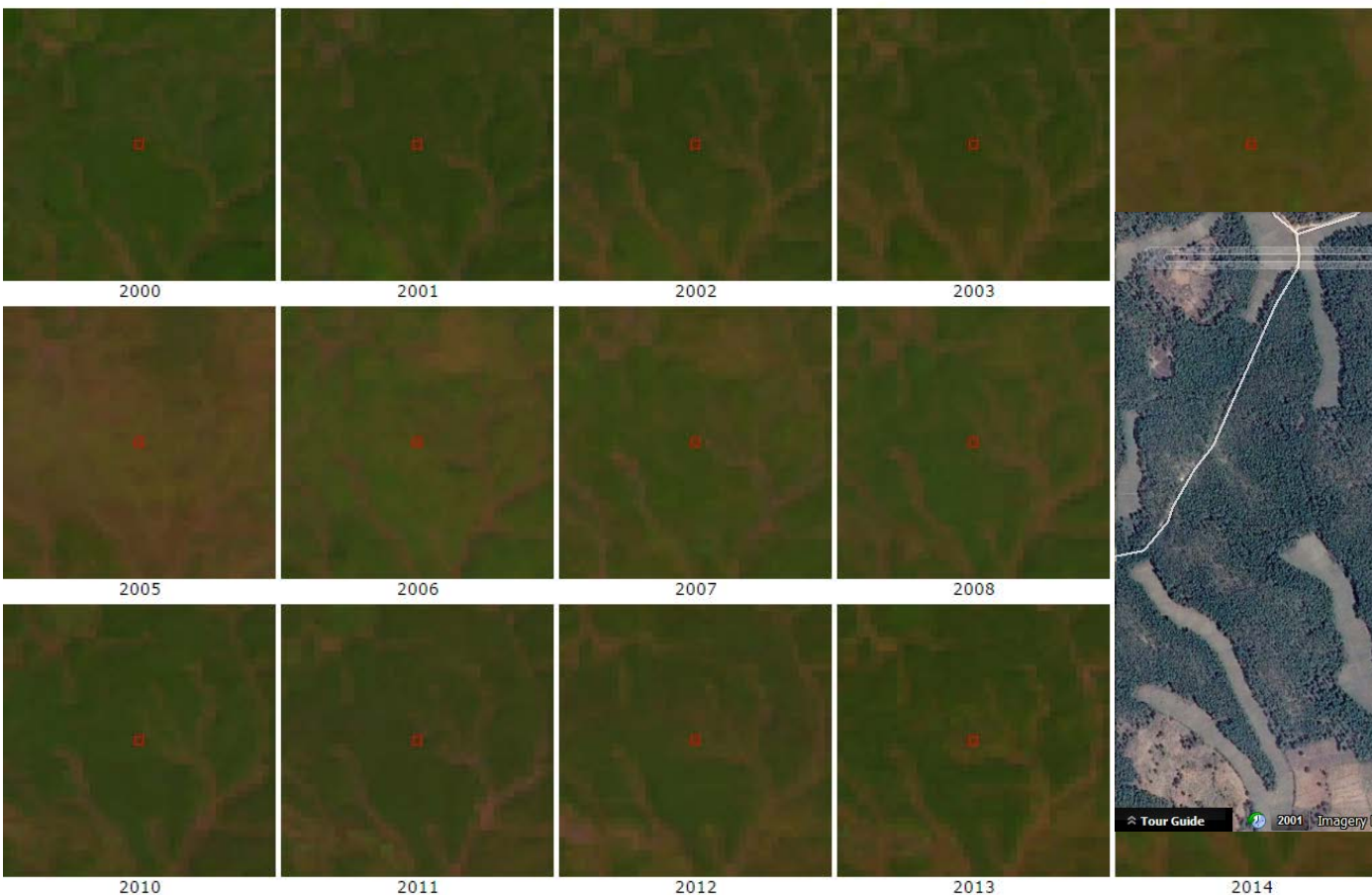
[Previous <<](#)

Bangladesh loss Sample 197 [Google Earth KML](#)

[>> Next](#)

[Return to Index](#)

Reference data
Forest loss

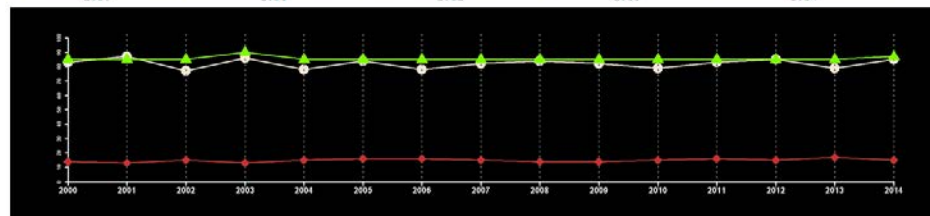
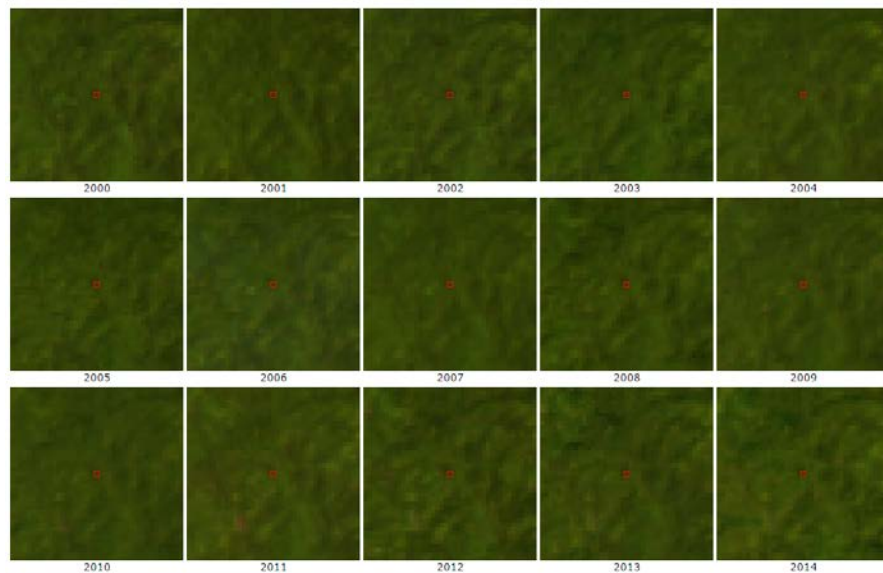


Annual min NDVI
Annual max SWIR
reflectance
Annual Tree Canopy
Cover

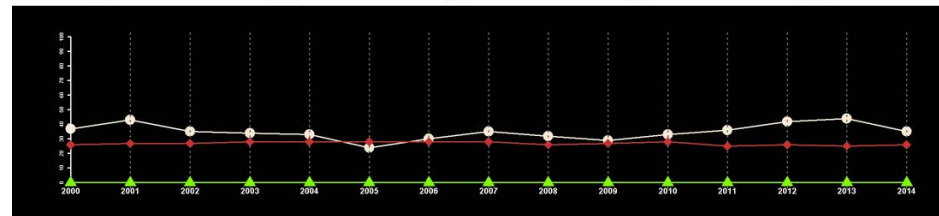
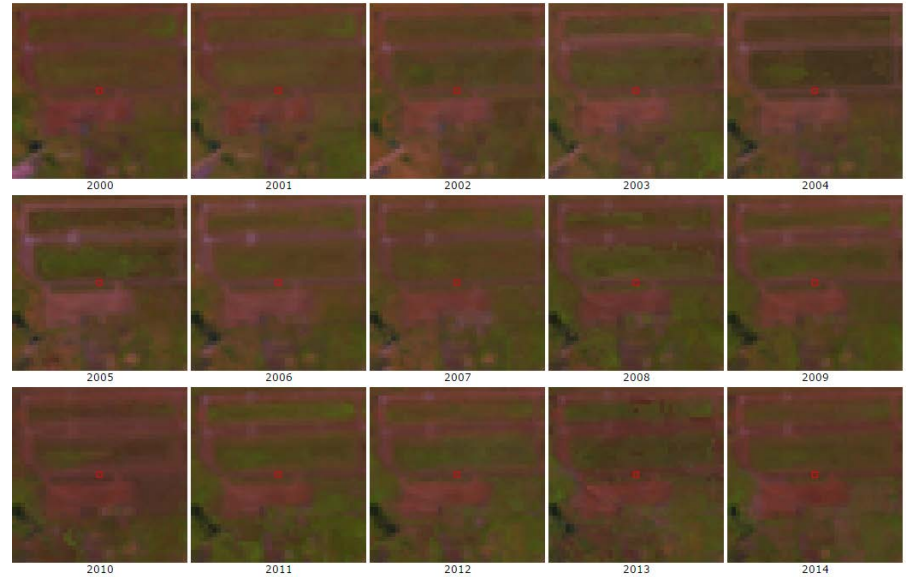
Response design

Reference data

[Sample 13 <<](#) [Vietnam Sample 14 Google Earth KML](#) [>> Sample 15](#) [Return to Index](#)



[Sample 258 <<](#) [Vietnam Sample 259 Google Earth KML](#) [>> Sample 260](#) [Return to Index](#)

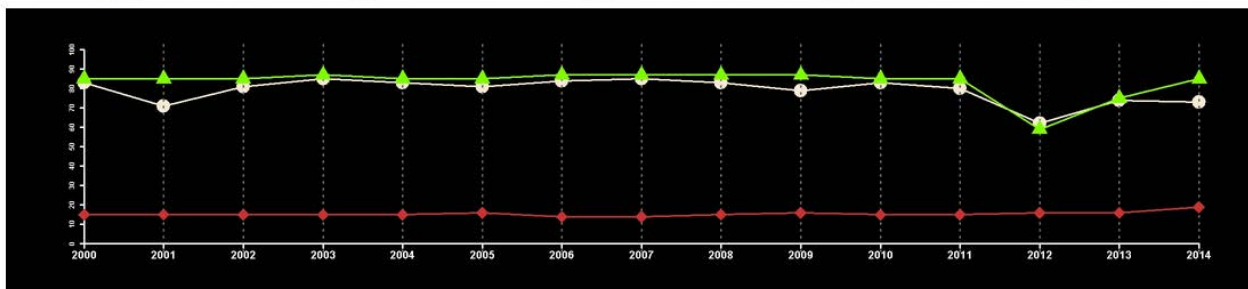
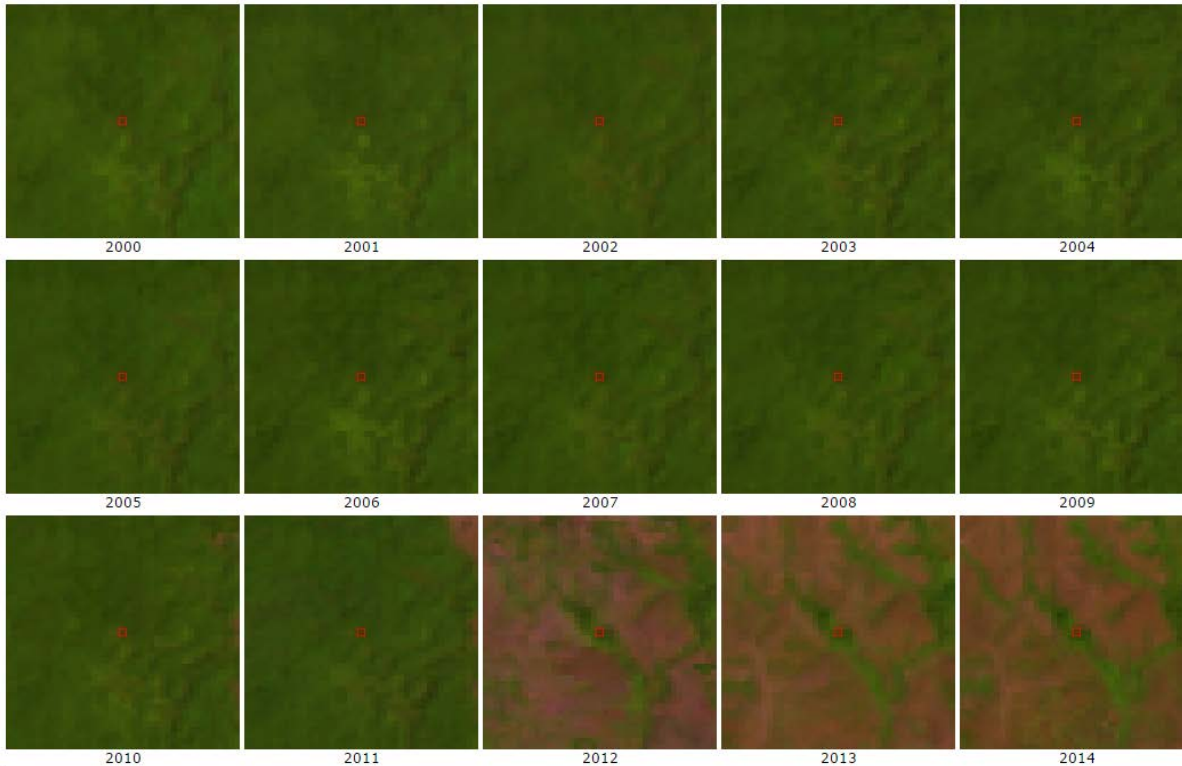


Annual min NDVI
Annual max SWIR
reflectance
Annual Tree Canopy
Cover

Response design

Reference data

[Sample 400 <<](#) [Vietnam Sample 401 Google Earth KML](#) [>> Sample 402](#) [Return to Index](#)



Google Earth (TM) Data



2000



2012

Response design

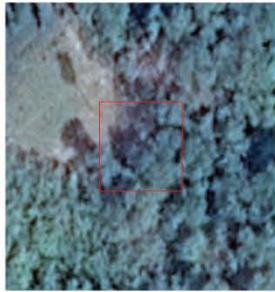
Tree canopy cover loss samples

Sample 1

2004



2014



Sample 2

2002



2011



Sample 3

2004



2014

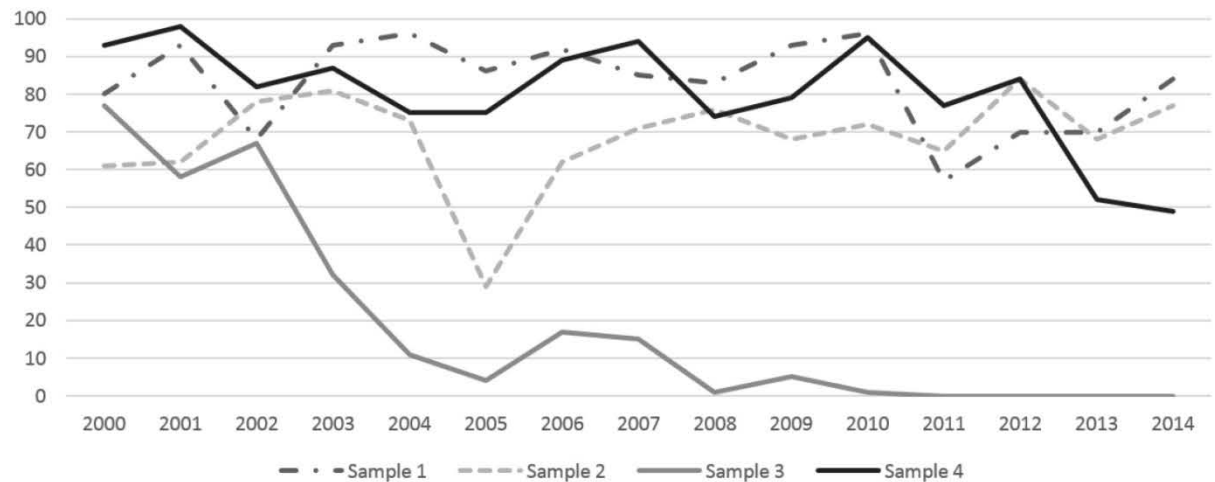


Sample 4

2009



2013



Response design

Tree canopy cover gain samples

Sample 1

2000



2014



Sample 2

2003



2013

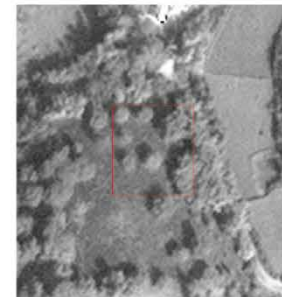


Sample 3

2007



2012

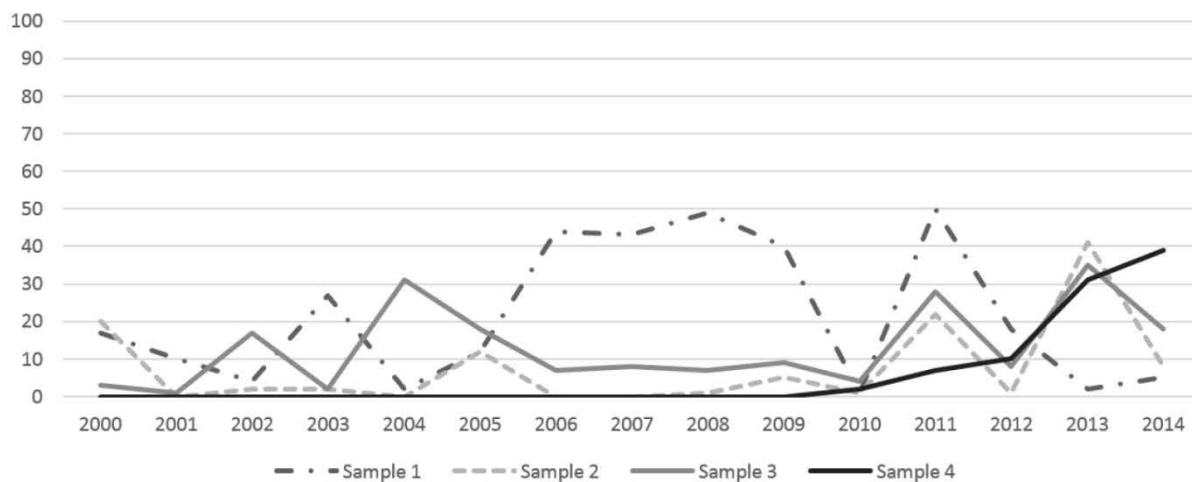


Sample 4

2004



2014



Probability sampling allows to:

- **Quantify map accuracy (Overall, User's, Producer's).**
- Estimate “true” (unbiased) areas of mapped classes.
- Estimate uncertainty of the mapped classes area.
- Perform value-added thematic analysis based on visual sample interpretation (e.g. differentiate various types of forest or forest disturbance).

Accuracy Assessment

All maps derived from remotely sensed data **have errors**

(from data limitations, analyst biases, classification process)

Errors of commission
(false positive)

Errors of omission
(false negative)



Landsat-based forest map



Map: non-forest
Reference: forest



Map: forest
Reference: forest



Map: non-forest
Reference: non-forest



Map: forest
Reference: non-forest

Accuracy Assessment

Confusion matrix (or error matrix) summarizes the relationship between the two sources of information (e.g. map and reference sample point data).

	Reference	
	Forest	Non-forest
Map		
Forest	True positive	False positive (error of commission)
Non-forest	False negative (error of omission)	True negative

→ Full population (wall-to-wall) reference data are usually absent, so a reference sample has to be used instead

Confusion matrix outputs:

- Quantification of map uncertainty:
 - Overall accuracy
 - User's accuracy (represent commission error)
 - Producer's accuracy (represent omission error)
- Estimation of the "true" area of mapped classes.

Accuracy Assessment

Accuracy measures

Overall accuracy represent the percent of correctly mapped sample points of total number of sample points.

$$OA = \frac{\text{Number of correct plots}}{\text{total number of plots}}$$

User's accuracy is a measure of the **commission error**. This statistic indicates the probability of how well the classified sample represents what is found on the ground.

$$UA = \frac{\text{Number correctly identified as a given map class}}{\text{Number claimed to be in that map class}}$$

Producer's accuracy is a statistic that specifies the probability of a ground reference data being correctly classified and it is a measure of the **omission error**. This statistic is calculated because the producer may want to know how well an area can be classified.

$$PA = \frac{\text{Number correctly identified test sites}}{\text{Number actually in that class}}$$

Accuracy Assessment

Accuracy measures

Map	Reference	
	Forest	Non-forest
Forest	True positive (TP)	False positive (FP) (error of commission)
Non-forest	False negative (FN) (error of omission)	True negative (TN)

- Overall accuracy
- User's accuracy (represent commission error)
- Producer's accuracy (represent omission error)

$$\text{Overall accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} * 100\%$$

$$\text{User's accuracy (for forest class)} = \frac{\text{TP}}{\text{TP} + \text{FP}} * 100\%$$

$$\text{Producer's accuracy (for forest class)} = \frac{\text{TP}}{\text{TP} + \text{FN}} * 100\%$$

Accuracy Assessment

Some causes of poor accuracy

Classification limitation

- Insufficient classification training
- Classes not separable (with chosen algorithm/parameters)

Data limitation

- Spatial scale of remote sensing instrument does not match classification scheme
- Classes are not separable using the spectral data used
- Insufficient data correction (e.g. atmospheric effects)
- Data pre-processing and correction introduce artifacts precluding correct classification (overcorrection)

Incorrect reference data

- Positional error
- Field identification error
- Mixed pixel
- Confused land cover with land use

Probability sampling allows to:

- Quantify map accuracy
(Overall, User's, Producer's).
- **Estimate “true” (unbiased) areas of mapped classes.**
- **Estimate uncertainty of the mapped classes area.**
- Perform value-added thematic analysis based on visual sample interpretation (e.g. differentiate various types of forest or forest disturbance types).

Area Estimation

- Sample-based analysis provides the best available reference data. Sample-based data is most suitable for national-scale area estimation for LC/LU and change classes.
- Unlike map, sample data provides unbiased estimation of class areas with known uncertainty (precision).
- The same approach used for accuracy analysis (confusion matrix) is suitable for class proportion estimation.
- Availability of the complete map may be beneficial to sample-base analysis:
 - It may be used for stratification to increase sampling efficiency and estimate precision
 - It may be used in the form of regression estimator to increase area estimation precision

Area Estimation

from Cochran, 1977

Stehman, 2013

Simple random sampling

Area calculation

Proportion of class i from total sampling area:

$$p_i = \frac{n_i}{n}; \text{ where } n_i - \text{number of samples, identified as class } i$$

n – total number of samples

Area of class i :

$$A_i = A_{tot} \times p_i; \text{ where } A_{tot} - \text{total sampling area}$$

Variance calculation

If sampling units are

Points
(infinite sampling population)

$$V(p_i) = \frac{p_i(1 - p_i)}{n}$$

Areal units (pixels, blocks)
(finite sampling population)

$$V(p_i) = \frac{p_i(1-p_i)}{n} \frac{(N-n)}{(N-1)}$$

where N – total number of sampling units in the population

Standard Error calculation

As a proportion from total area:

$$SE(p_i) = \sqrt{V(p_i)}$$

In units of area:

$$SE(A_i) = A_{tot} \times \sqrt{V(p_i)}$$

Area Estimation

from Cochran, 1977

Olofsson, 2013

Stehman, 2013

Stratified random sampling

Mean proportion of class i in stratum h :

$$\bar{p}_{ih} = \frac{\sum_{u \in h} p_u}{n_h}$$

Sampling units – pixels

$p_u = 1$ if a pixel is identified as class i ,
and $p_u = 0$ otherwise
 n_h – number of samples in stratum h

Proportion of class i from total area:

$$p_i = \sum_{h=1}^H \frac{N_h}{N} \bar{p}_{ih}$$

N_h – total number of pixels in stratum h
 H – number of sampling strata
 N – total number of pixels in the sampling region

Area of class i :

$$A_i = A_{tot} * p_i$$

A_{tot} – total sampling area

Variance calculation

$$V(p_i) = \sqrt{\sum_{h=1}^H \left(\frac{N_h}{N} \right)^2 \frac{\bar{p}_{ih} (1 - \bar{p}_{ih})}{n_h - 1}}$$

Standard Error calculation

As a proportion from total area:

$$SE(p_i) = \sqrt{V(p_i)}$$

In units of area:


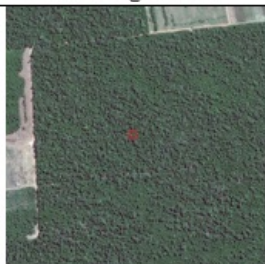
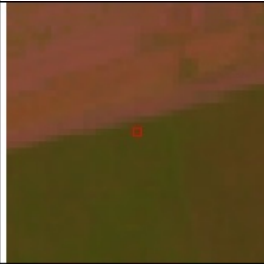
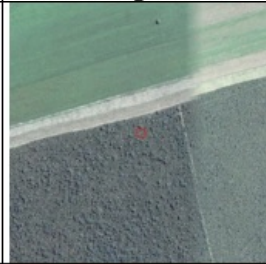



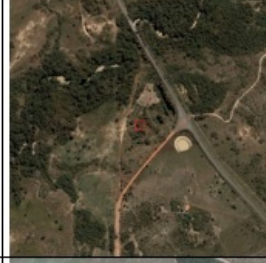


$$SE(A_i) = A_{tot} \times \sqrt{V(p_i)}$$

Probability sampling allows to:

- Quantify map accuracy
(Overall, User's, Producer's).
- Estimate “true” (unbiased) areas of mapped classes.
- Estimate uncertainty of the mapped classes area.
- **Perform value-added thematic analysis based on visual sample interpretation (e.g. differentiate various types of forest or forest disturbance).**

Value-added Analysis

Pre-disturbance forest type

Pre-disturbance vegetation type		Pre-disturbance Landsat	Pre-disturbance high resolution imagery from Google Earth™	Pre-disturbance vegetation type		Pre-disturbance Landsat	Pre-disturbance high resolution imagery from Google Earth™
Dense (>60% canopy cover) tropical forests	Primary			Woodlands (40-60% canopy cover) and parklands (10-40% canopy cover)	Natural (primary)		
	Secondary				Secondary		
				Forest plantations and other tree crops			

Value-added Analysis

Proximate causes of forest loss in Brazil

Cropland conversion



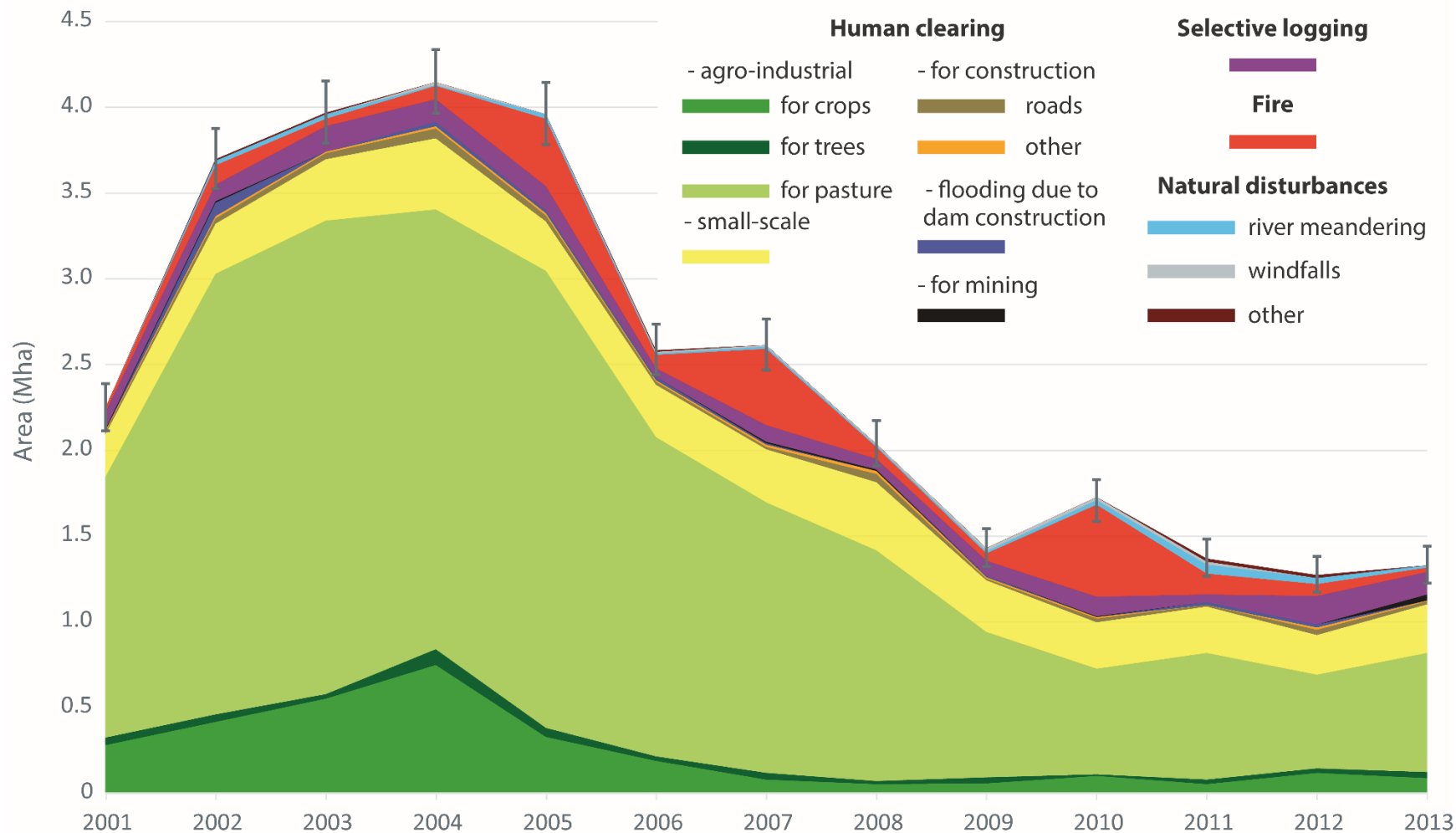
Selective logging



Construction

Value-added Analysis

Annual tree cover loss in BLA by disturbance cause



Area (Mha)

Primary forests

Natural (primary) woodlands

Secondary forests and woodlands, and plantations

Human clearing

Selective logging

Fire

Natural disturbances

Year	Primary forests	Natural (primary) woodlands	Secondary forests and woodlands, and plantations	Human clearing	Selective logging	Fire	Natural disturbances
2001	1.5	0.2	0.5	0.1	0.1	0.1	0.1
2002	2.3	0.3	0.9	0.1	0.1	0.1	0.1
2003	2.7	0.4	0.9	0.1	0.1	0.1	0.1
2004	2.6	0.6	0.9	0.1	0.1	0.1	0.1
2005	2.3	0.3	0.9	0.4	0.1	0.1	0.1
2006	1.5	0.2	0.8	0.6	0.1	0.1	0.1
2007	1.4	0.2	0.7	0.5	0.1	0.1	0.1
2008	1.2	0.1	0.6	0.4	0.1	0.1	0.1
2009	0.7	0.2	0.5	0.4	0.1	0.1	0.1
2010	0.6	0.1	0.4	0.5	0.1	0.1	0.1
2011	0.6	0.2	0.4	0.2	0.1	0.1	0.1
2012	0.5	0.1	0.4	0.2	0.1	0.1	0.1
2013	0.6	0.2	0.4	0.1	0.1	0.1	0.1

Value-added Analysis

Sample interpretation legend (to be discussed)

Year 2000

- Tree cover (yes/no or percent of the pixel)
- Forest type (primary/secondary/plantation/agroforestry or forest/woodland/shrub)

Change 2000-2016

- Tree cover loss (yes/no or percent of the pixel)
- Date of the (first) disturbance event
- Disturbance type (logging, plantation rotation, conversion (outcome), landslide, fire)

Year 2016 land cover outcome (in case of disturbance)

- Tree cover restoration (yes/no or percent of the pixel)
- Forest type or land cover type

For all samples

- Certainty (overall or each category)
- Boundary (edge) pixel (separate for tree cover 2000 and change)

Good practice recommendations and step-by-step calculation guidelines:

1. GFOI (2014) Integrating Remote-Sensing and Ground-Based Observations for Estimation of Emissions and Removals of Greenhouse Gases in Forests: Methods and Guidance from the Global Forest Observations Initiative Version 1 (January 2014) (Geneva, Switzerland: Group on Earth Observations)
2. Olofsson P., Foody G.M., Stehman S.V., Woodcock C.E. Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment* 129, 122-131 (2013)
3. Stehman S.V. Estimating area from an accuracy assessment error matrix. *Remote Sensing of Environment* 132, 202-211 (2013)
4. Stehman, S. V. Estimating area and map accuracy for stratified random sampling when the strata are different from the map classes. *International Journal of Remote Sensing* 35.13 (2014)

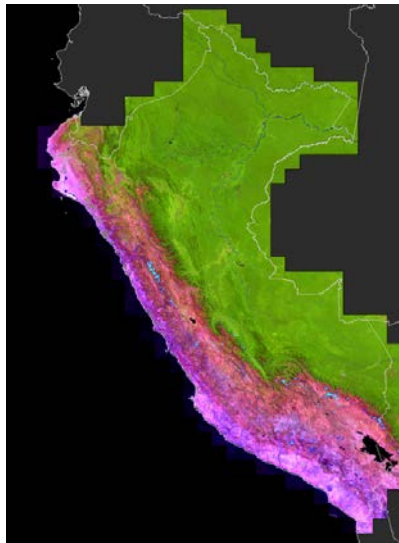
General principles of sampling design:

1. Cochran W.G. *Sampling Techniques*. New York: Wiley (1977)
2. Stehman S.V. and Czaplewski R.L. Design and analysis for thematic map accuracy assessment: fundamental principles. *Remote Sensing of Environment* 64, 331-334 (1998)
3. Stehman S.V. Sampling designs for accuracy assessment of land cover. *International Journal of Remote Sensing* 30 (20), 5243-5272 (2009)
4. Stehman S.V. Impact of sample size allocation when using stratified random sampling to estimate accuracy and area of land-cover change. *Remote Sensing Letters* 3 (2), 111-120 (2012)

Peru REDD+ project example

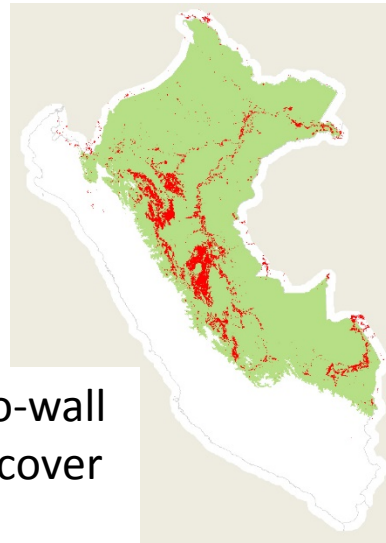
Example of wall-to-wall mapping and sample-based validation in Peru

1



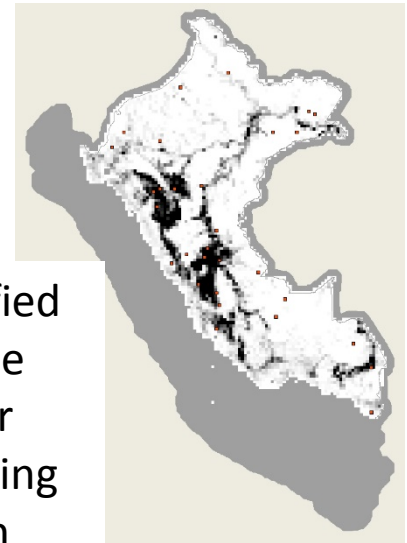
Landsat data
composites
and metrics

2



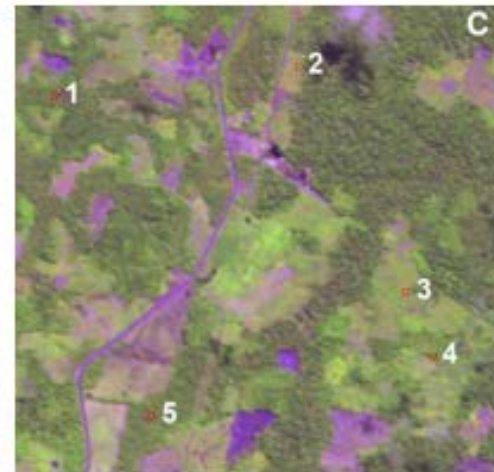
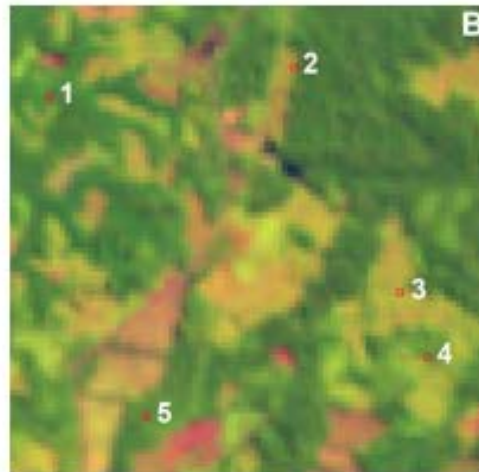
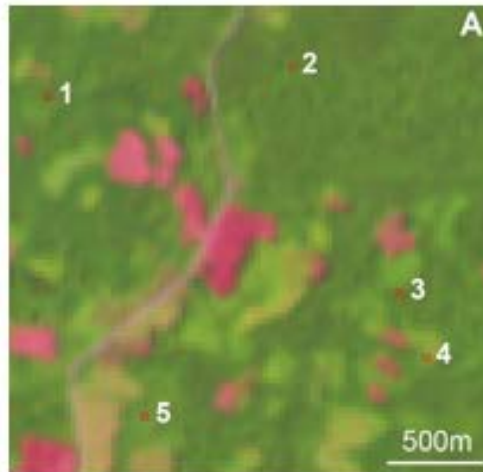
Wall-to-wall
forest cover
loss

3



Stratified
2-stage
cluster
sampling
design

4



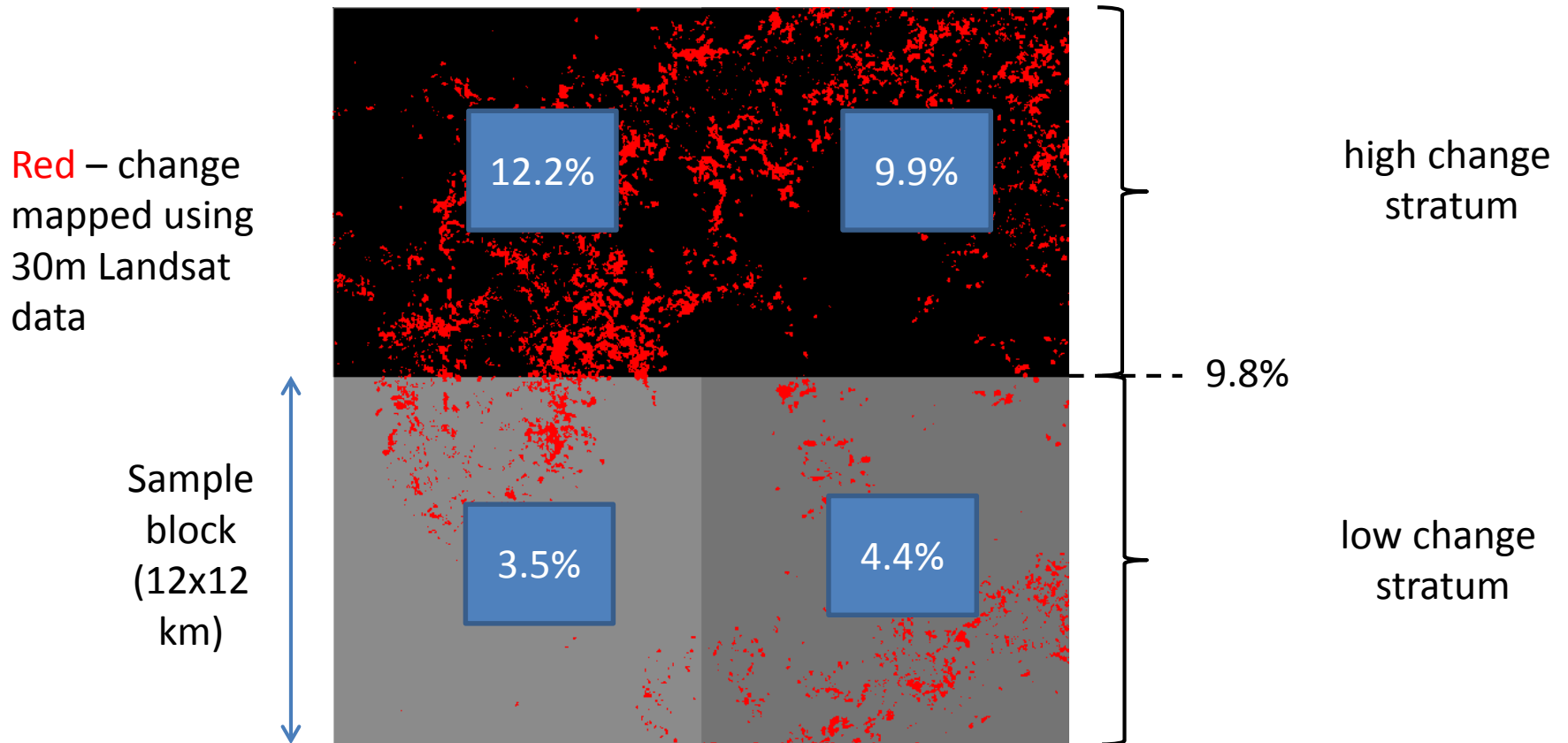
Individual sample block analysis (2-stage clustered sampling design)

Peru REDD+ project example

Sampling frame

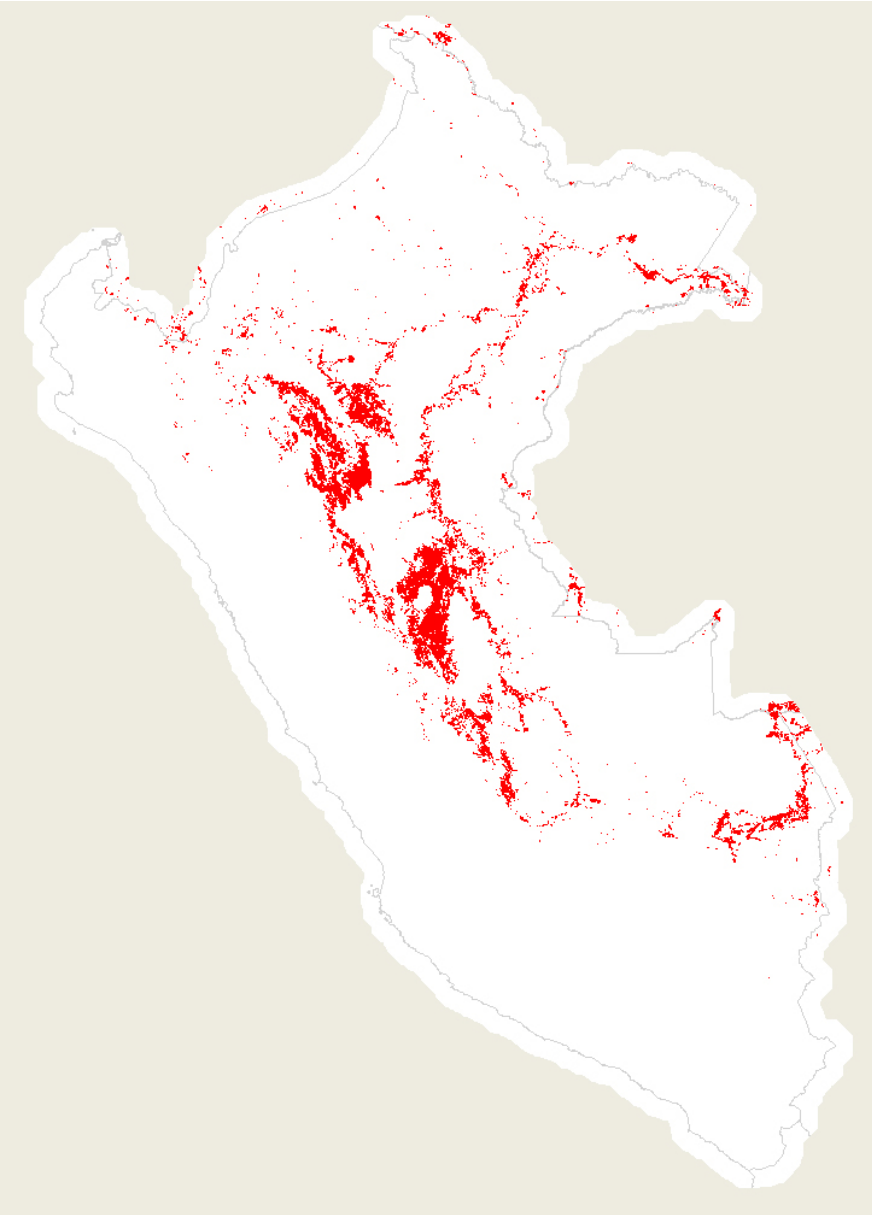
Two-stage cluster sampling:

1. 12x12 km blocks (30 RapidEye scenes)
 2. 100 random points within a block
1. Stratified random sampling, based on proportion forest cover change within a block:



Peru REDD+ project example

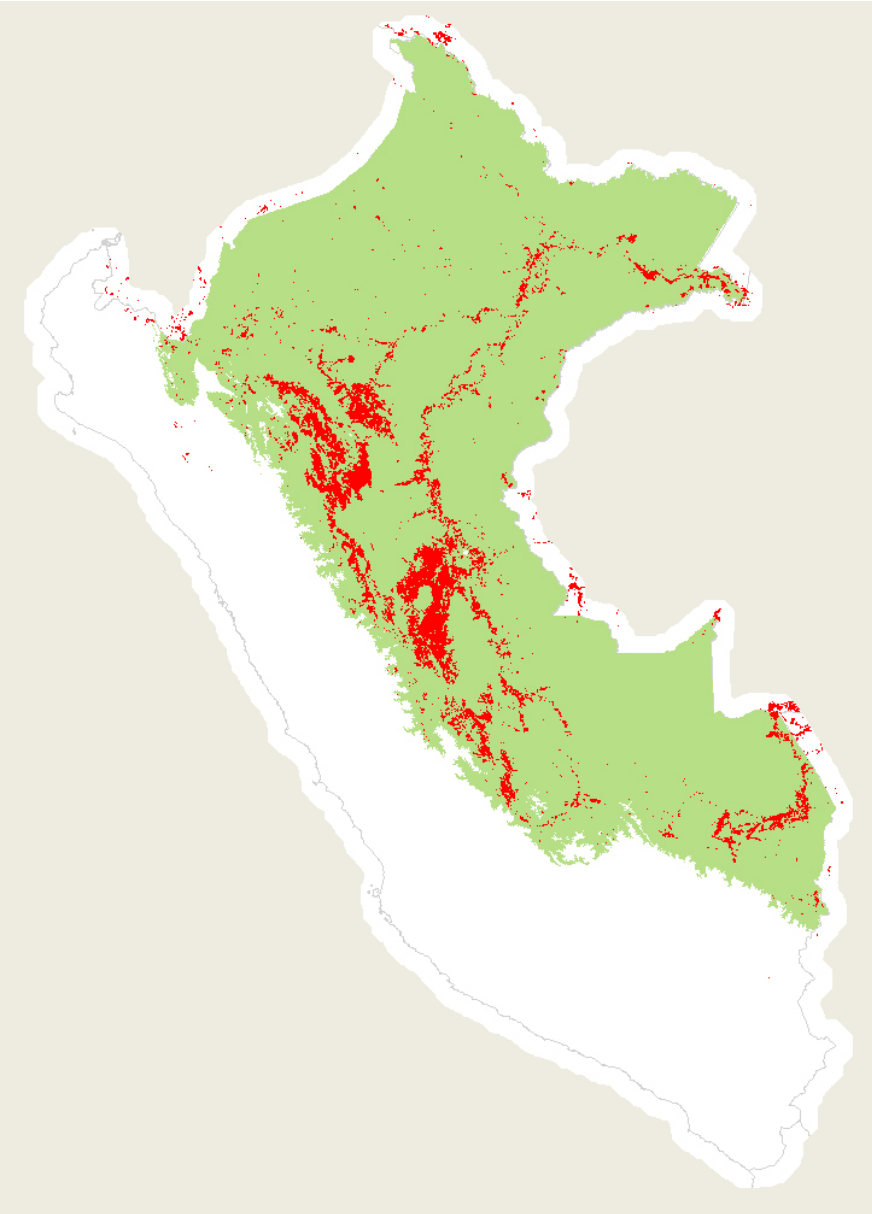
Forest cover loss mask at 30m, 2000-2011



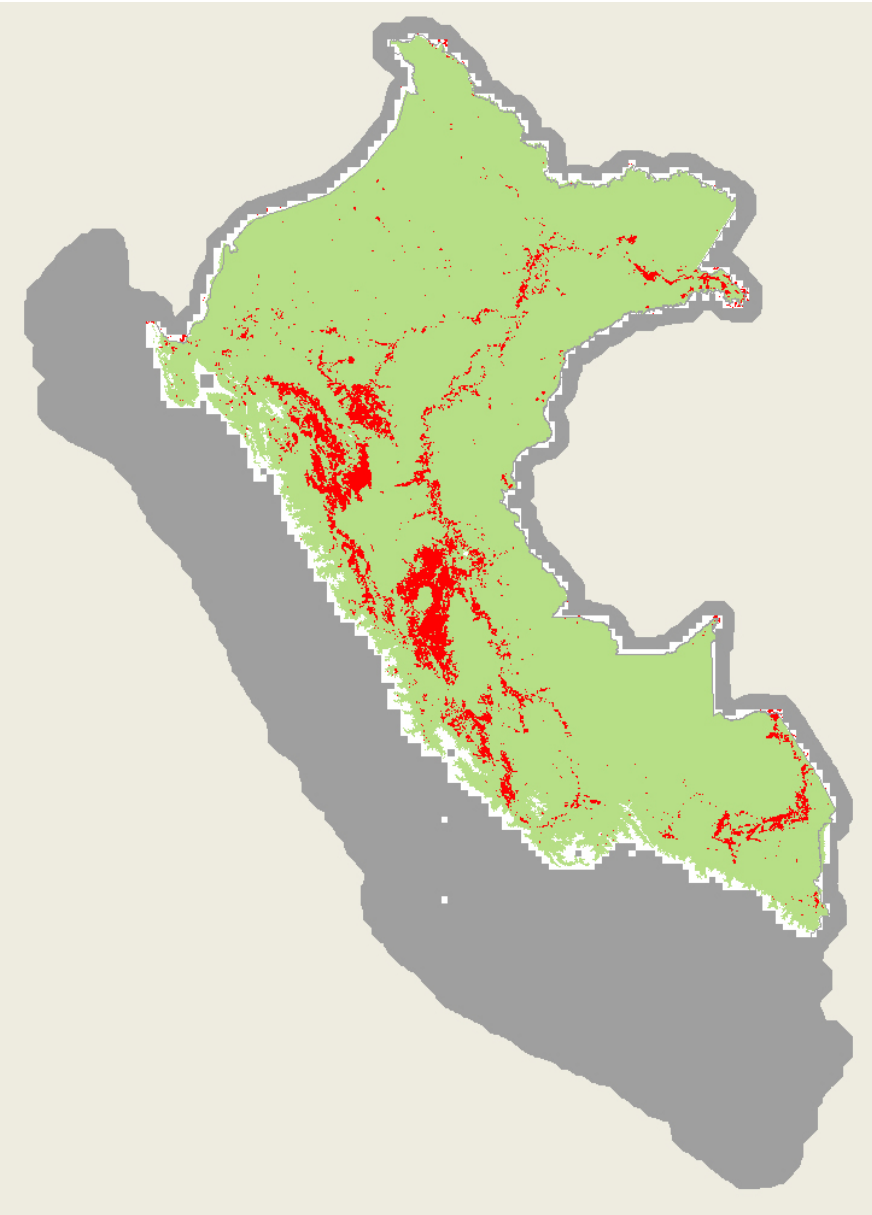
Peru REDD+ project example

Forest cover loss mask at 30m, 2000-2011

Humid tropics mask, 2000



Peru REDD+ project example

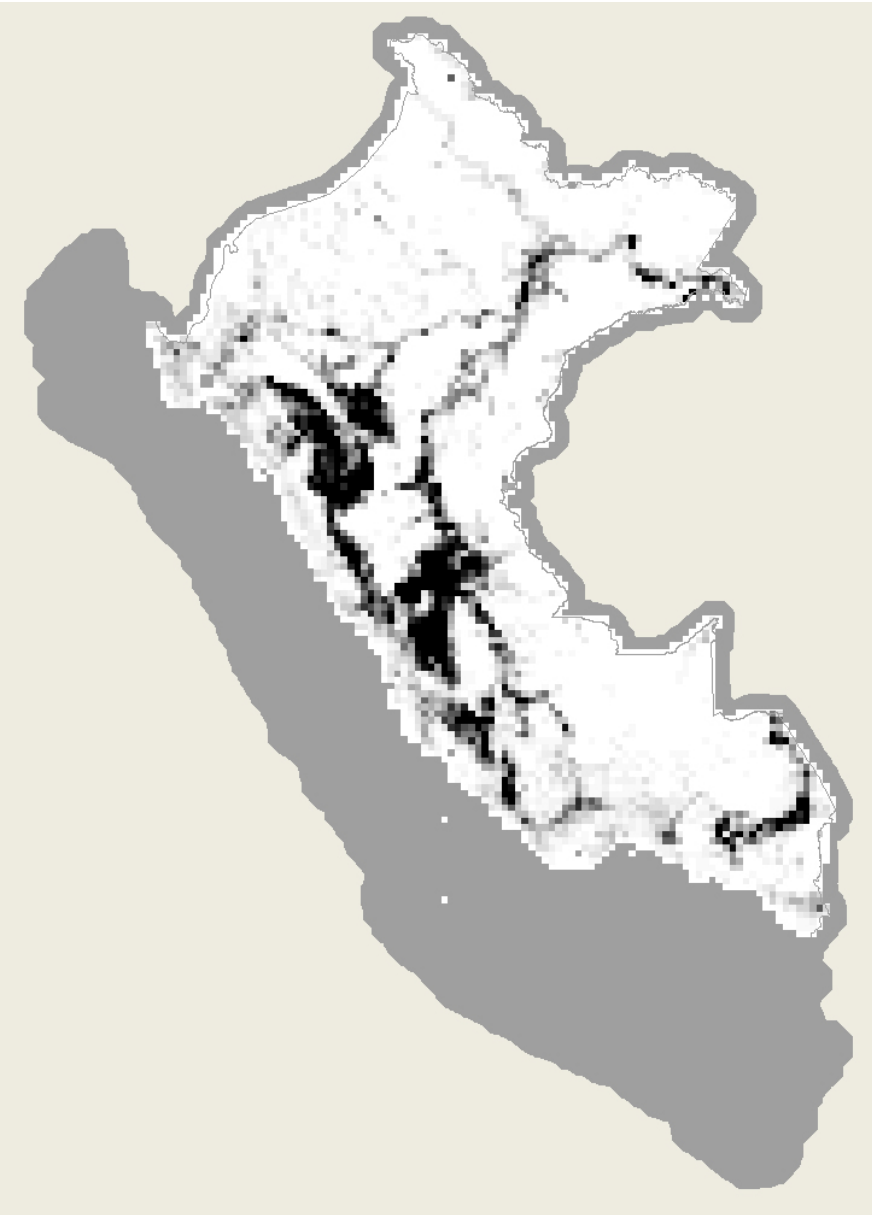


Forest cover loss mask at 30m, 2000-2011

Humid tropics mask, 2000

Sampling frame. Blocks with any proportion of forest mask are shown. Blocks with <40% forest mask were excluded from sampling.

Peru REDD+ project example



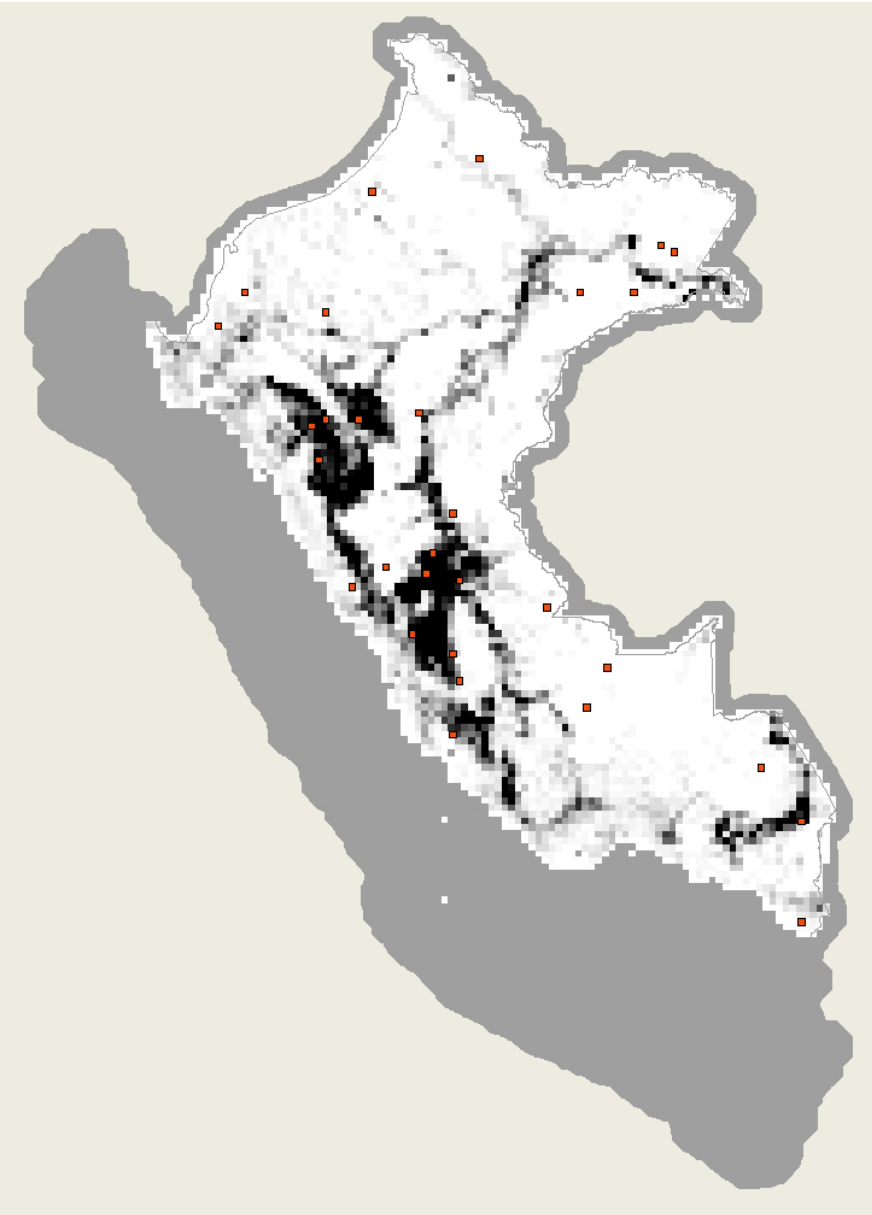
Forest cover loss mask at 30m, 2000-2011

Humid tropics mask, 2000

Sampling frame. Blocks with any proportion of forest mask are shown. Blocks with <40% forest mask were excluded from sampling.

% forest loss per 12x12 km sample block within sampling frame.

Peru REDD+ project example



Forest cover loss mask at 30m, 2000-2011

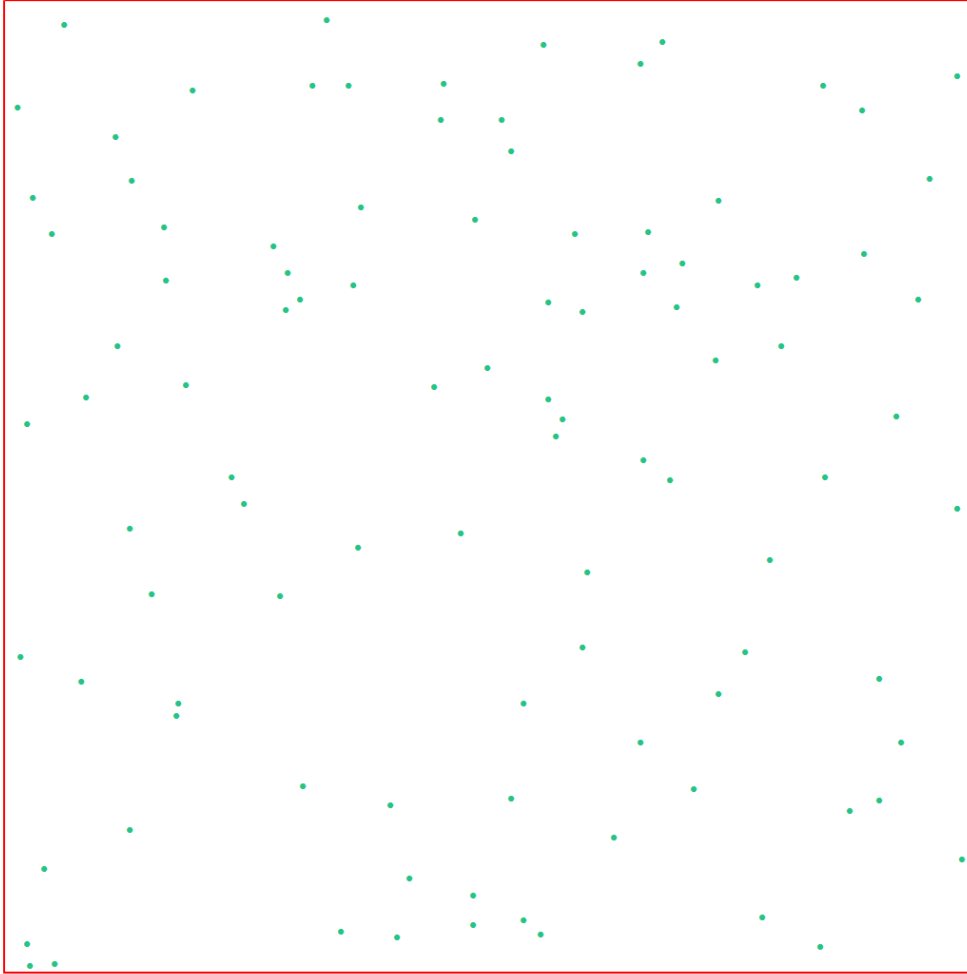
Humid tropics mask, 2000

Sampling frame. Blocks with any proportion of forest mask are shown. Blocks with <40% forest mask were excluded from sampling.

% forest loss per 12x12 km sample block within sampling frame.

Selected sampling blocks (30 total)

Peru REDD+ project example



Sample block with 100 random
sample points (Landsat pixels)

Peru REDD+ project example



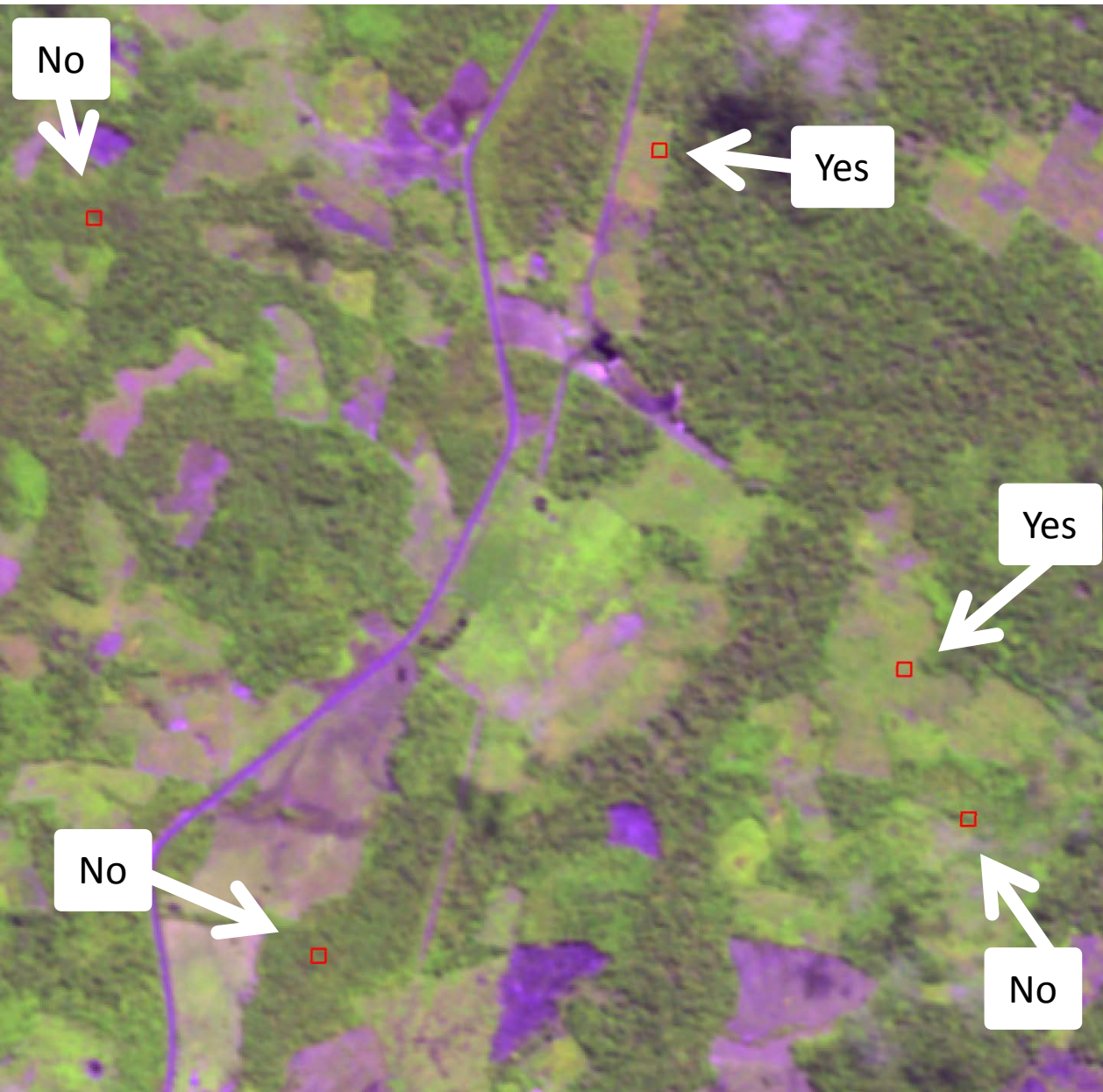
Sample points (pixels) over
year 2000 Landsat image

Peru REDD+ project example

Sample points (pixels) over
year 2011 Landsat image



Peru REDD+ project example

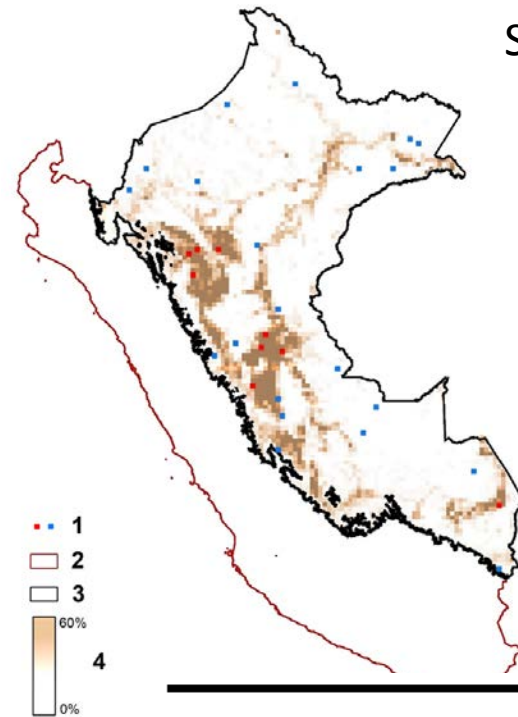


Sample points
(30m pixels) over year
2011 RapidEye image

Peru REDD+ project example

Stratified 2-stage cluster sampling design

*** For stratified sampling design we use not the number of samples, but the proportion of total sample area**



Confusion matrix for gross forest cover loss validation

		Reference			
		No change	Forest loss	Total	User's accuracy (SE)
Map	No change	97.990 *	0.465	98.455	99.5% (0.2%)
	Forest loss	0.120	1.426	1.546	92.2% (1.9%)
	Total	98.110	1.891	100.00	—
Producer's accuracy (SE)		99.8% (0.1%)	75.4% (2.5%)	Overall accuracy (SE)=99.4% (0.2%)	