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Remote sensing of forest cover and change assessment for carbon monitoring

Instructors: Cindy Schmidt and Pontus Olofsson (Boston University)

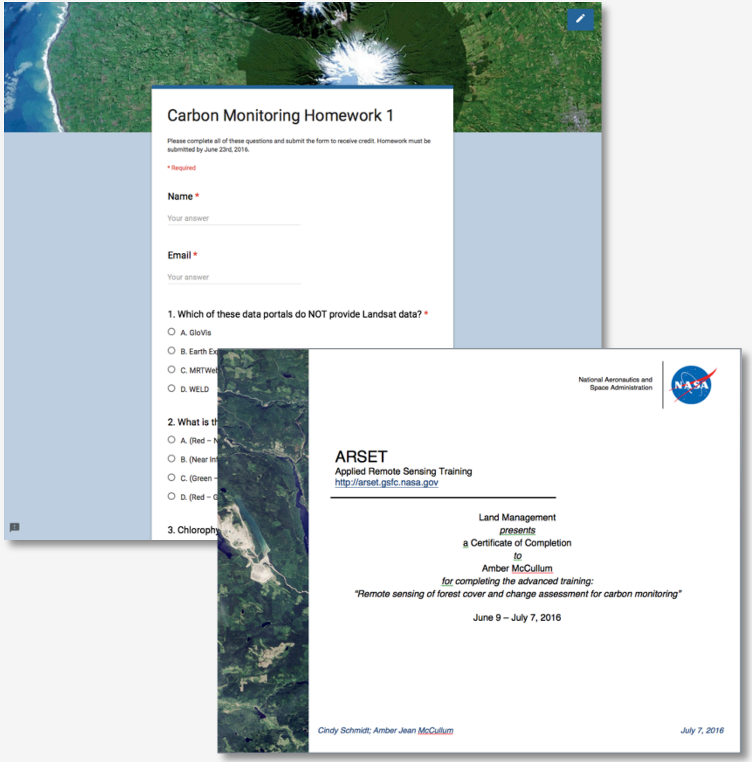
Week 4: June 30, 2016

Course Structure

- One lecture per week – every Thursday from June 9 to July 7 at 1:00-2:30pm and 10:00-11:30pm EDT(-04:00 UTC)
- Please only sign up for and attend the same session each week
  - Lectures
  - Q&A
  - Homework exercises
- Webinar recordings, PowerPoint presentations, in-class exercises, and homework assignments can be found after each session at:
  - http://arset.gsfc.nasa.gov/ecoforecasting/webinars/carbon-monitoring-2016
  - Q&A: Following each lecture and/or by email (cynthia.l.schmidt@nasa.gov) or (amberjean.mccullum@nasa.gov)

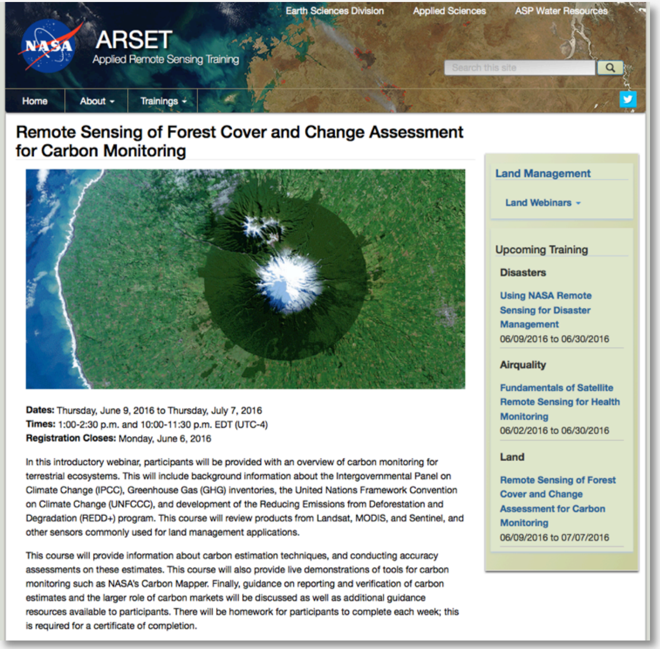
Homework and Certificates

- Homework
  - Answers must be submitted via Google Form
- Certificate of Completion:
  - Attend all 5 webinars
  - Complete all 5 homework assignments by the deadline (access from ARSET website above)
    - Week 2 HW Deadline: Today June 30^{th}
    - Week 4 HW Deadline: July 14thth
  - You will receive certificates approximately 2 months after the completion of the course from: marines.martins@ssaihq.com



Accessing Course Materials

https://arset.gsfc.nasa.gov/land/webinars/carbon-monitoring-2016


Earth Sciences Division Applied Sciences ASP Water Resources

ARSET
Applied Remote Sensing Training

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Remote Sensing of Forest Cover and Change Assessment for Carbon Monitoring

Dates: Thursday, June 9, 2016 to Thursday, July 7, 2016
Times: 1:00-2:30 p.m. and 10:00-11:30 p.m. EDT (UTC-4)
Registration Closes: Monday, June 6, 2016

In this introductory webinar, participants will be provided with an overview of carbon monitoring for terrestrial ecosystems. This will include background information about the Intergovernmental Panel on Climate Change (IPCC), Greenhouse Gas (GHG) inventories, the United Nations Framework Convention on Climate Change (UNFCCC), and development of the Reducing Emissions from Deforestation and Degradation (REDD+) program. This course will review products from Landsat, MODIS, and Sentinel, and other sensors commonly used for land management applications.

This course will provide information about carbon estimation techniques, and conducting accuracy assessments on these estimates. This course will also provide live demonstrations of tools for carbon monitoring such as NASA's Carbon Mapper. Finally, guidance on reporting and verification of carbon estimates and the larger role of carbon markets will be discussed as well as additional guidance resources available to participants. There will be homework for participants to complete each week; this is required for a certificate of completion.

Land Management

Land Webinars

Upcoming Training

Disasters

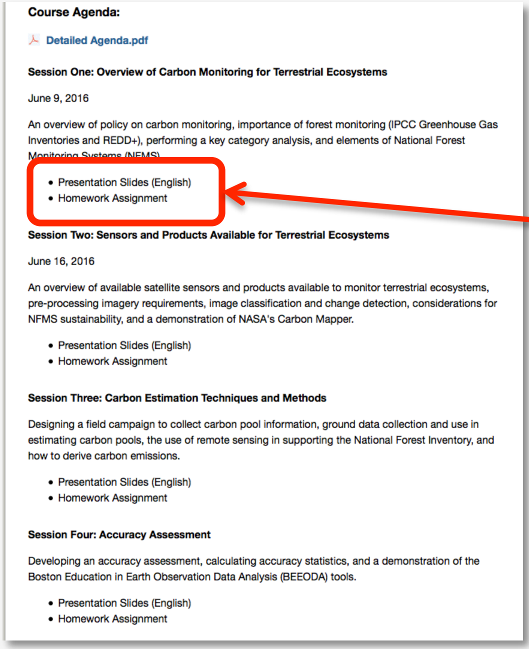
Using NASA Remote Sensing for Disaster Management
06/09/2016 to 06/30/2016

Airquality

Fundamentals of Satellite Remote Sensing for Health Monitoring
06/02/2016 to 06/30/2016

Land

Remote Sensing of Forest Cover and Change Assessment for Carbon Monitoring
06/09/2016 to 07/07/2016


Course Agenda:

Detailed Agenda.pdf

Session One: Overview of Carbon Monitoring for Terrestrial Ecosystems

June 9, 2016

An overview of policy on carbon monitoring, importance of forest monitoring (IPCC Greenhouse Gas Inventories and REDD+), performing a key category analysis, and elements of National Forest Monitoring Systems (NFMS)

- Presentation Slides (English)
- Homework Assignment

Session Two: Sensors and Products Available for Terrestrial Ecosystems

June 16, 2016

An overview of available satellite sensors and products available to monitor terrestrial ecosystems, pre-processing imagery requirements, image classification and change detection, considerations for NFMS sustainability, and a demonstration of NASA's Carbon Mapper.

- Presentation Slides (English)
- Homework Assignment

Session Three: Carbon Estimation Techniques and Methods

Designing a field campaign to collect carbon pool information, ground data collection and use in estimating carbon pools, the use of remote sensing in supporting the National Forest Inventory, and how to derive carbon emissions.

- Presentation Slides (English)
- Homework Assignment

Session Four: Accuracy Assessment

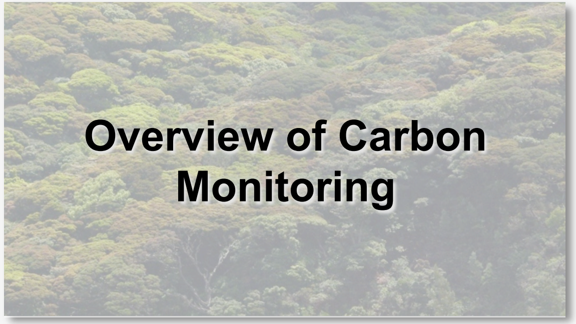
Developing an accuracy assessment, calculating accuracy statistics, and a demonstration of the Boston Education in Earth Observation Data Analysis (BEEODA) tools.

- Presentation Slides (English)
- Homework Assignment

Course materials are provided here using each specified link and will be active after each week

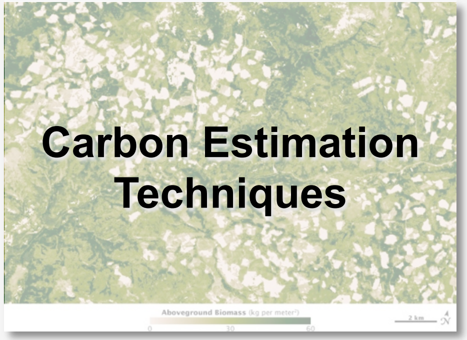
Course Outline

Week 1

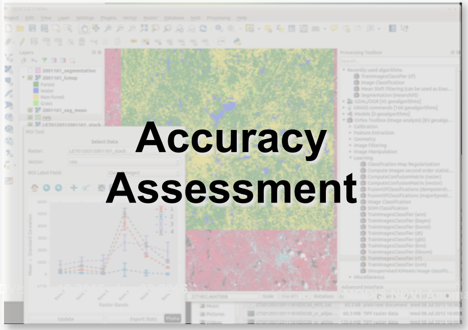


Week 2

Week 3



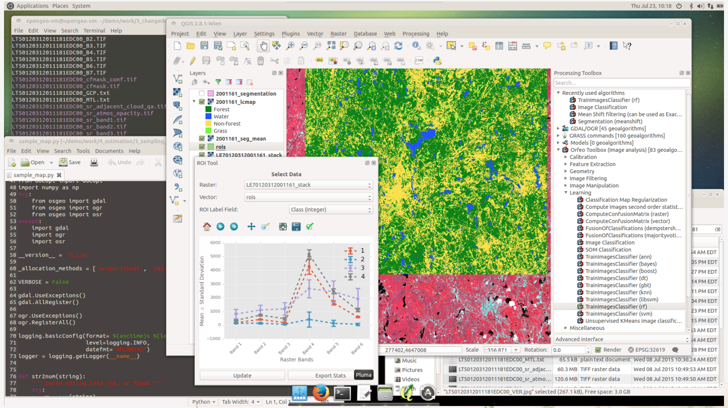
Week 4

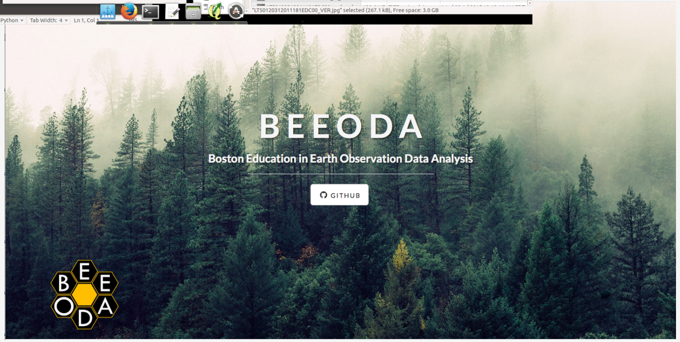


Week 5

Week 4 Agenda

- Statistical Inference according to IPCC
  - Real life example
- Terminology
  - Reference observations
  - Reference data
  - Accuracy
- Error matrices and sample counts
- Area estimators
- Case study and BEEODA
- Q&A





Example of image classifier in BEEODA tools. Photo Credit: BEEODA.

Guest Speaker: Pontus Olofsson

SilvaCarbon/NASA ARSET webinar series: Accuracy Assessment

Thursday June 30, 2016, at 1:00-2:30 p.m. EDT

Stratified estimation of area and accuracy

Pontus Olofsson (olofsson@bu.edu)

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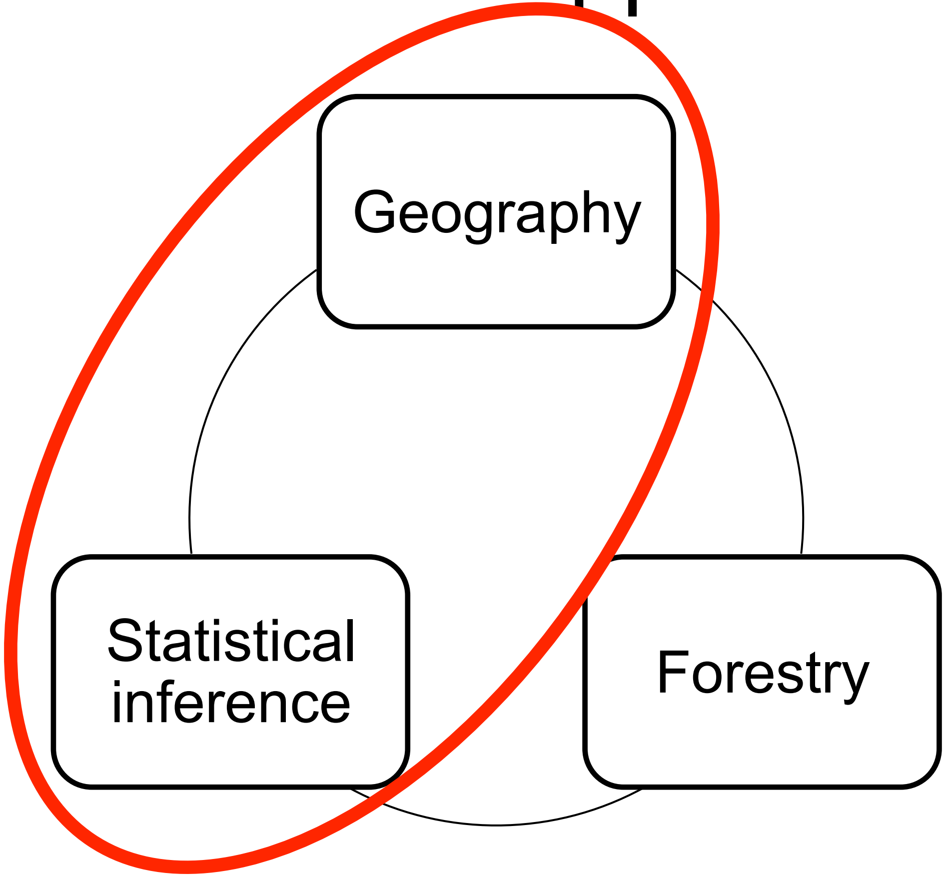
To make REDD+ happen:



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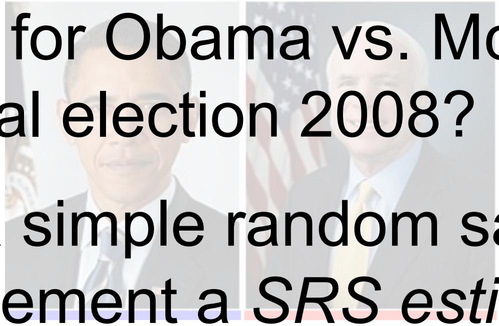
Why?

- For application to GHG inventories, the IPCC defines two good practice criteria (Penman et al., 2003):
  I. "neither *over - nor under - estimates* as far as can be judged"
  II. "*uncertainties are reduced* as far as practicable"
- Criterion I: relates to concept of *bias* – property of an *estimator* which, when applied to sample data, produces an *estimate*
- Criterion II: estimate might deviate from true value – *confidence intervals* express uncertainty of estimates

Real life example of inference

- *Statistical inference*: obtain information about a population by examining a sample – for example:
- Estimate votes for Obama vs. McCain, prior to the U.S. presidential election 2008?



- Let's assume a simple random sample (SRS) of 500 voters; we implement a *SRS estimator* to get an *unbiased estimate* of votes:

$$\hat{\mu}_{Obama} = \frac{1}{n}\sum_{i=1}^{n} y_i = \frac{1+1+0+\ldots+1}{500} = 0.51$$

Real life example of inference

- A 95% *confidence interval* (CI) means that 95% of such intervals, one for each set of sample data, include the true value.
- The interval width is related to *precision*, a measure of the *uncertainty* addressed by IPCC criterion II. A CI is calculated as the product of the standard error and the z- or t-score:

$$\hat{V}(\hat{\mu}_{Obama}) = \frac{\sum_{i=1}^{n}(y_i - \hat{\mu})^2}{n-1} = 0.003$$

$$1.96\sqrt{\hat{V}(\hat{\mu}_{Obama})} = 0.11$$

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Real life example of inference

- $\mathbb{E}$: 95% of Black voters are for Obama compared to 43% of White voters
- If we select a SRS of 100 with **70/30** White/Black voters: we expect Obama to receive *(30 × 0.95)* + *(70 × 0.43)* = ***59% of the votes***
- If we select a SRS of 100 with **95/5** White/Black voters: we expect Obama to receive *(5 × 0.95)* + *(95 × 0.43)* = ***46% of the votes***

Hence, SRS might not properly represent population – the solution is <u>stratified random sampling</u>

- If Black proportion of electorate known, we can sample each ethnic group (*<u>stratum</u>*) separately


"All the News That's Fit to Print"

The New York Times

Late Edition

VOL. CLVIII ... No. 54,485

NEW YORK, WEDNESDAY, NOVEMBER 5, 2008

$1.50

OBAMA

RACIAL BARRIER FALLS IN DECISIVE VICTORY

ONLINE

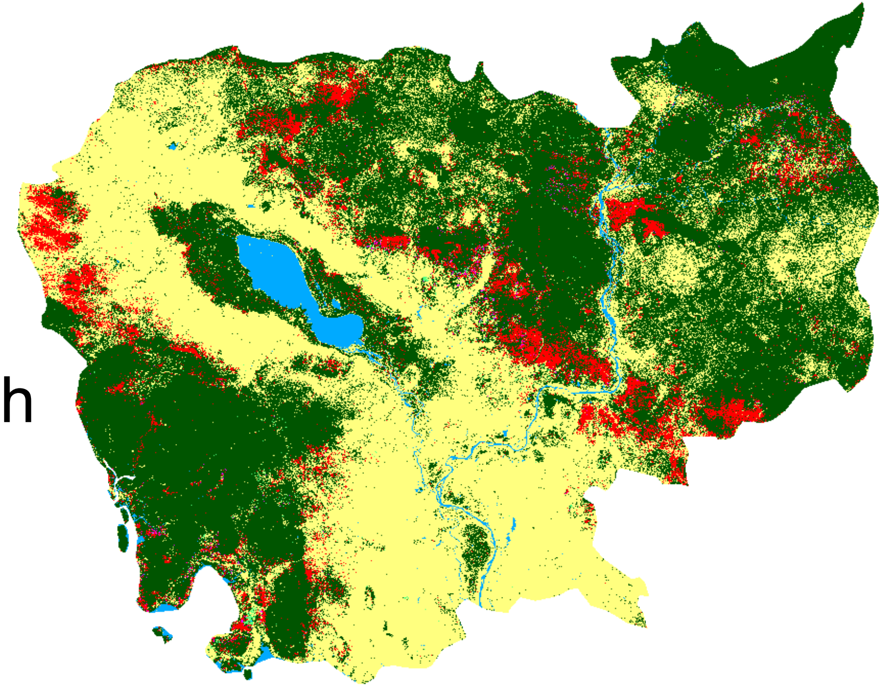
PRESIDENT-ELECT

Democrats in Congress Strengthen Grip

By ADAM NAGOURNEY

The task of estimating the number of voters planning to vote for Obama in the 2008 U.S. election...

...is not different from estimating the amount of deforestation in Cambodia 2000-2012! (Let's go through this exercise!)



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Some additional terminology

- We identify classification errors in a map by designing and implementing an *accuracy assessment*
- *Sample* the map (i.e. the population) and collect *reference observations* – best assessment of land surface condition – for each sample unit
- *Reference data*: information used to obtain reference labels
- By comparing map and reference labels – compute *estimates of area* (adjusted for classification errors) and *accuracy* (the degree to which the map corresponds to reference conditions)

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Some additional terminology

- ***Sampling design:*** Decide which elements of the map (population) to visit
  - *Where will we observe the reference condition?*
- ***Response design:*** Determine the land surface reference condition at the locations of the sample units
  - *What is the reference condition?*
- ***Analysis:*** Organize and summarize data to make inference (accuracy, area) about the population (map)
  - *And how will we use the data?*

Error matrix; sample counts; errors of omission and commission

Reference (j)

Map (i)	Forest loss	No loss	Map tot.	*Strata weights* (W_i)
Forest loss	n_{11}	n_{12}	n_{1+}	n_{1+}/n
No loss	n_{21}	n_{22}	n_{2+}	n_{2+}/n
Ref. tot.	n_{+1}	n_{+2}	n	1

$$\hat{p}_{ij} = W_i \frac{n_{ij}}{n_{i+}}$$

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Error matrix; estimated area proportions

Map (*i*)	Reference (*j*) Forest loss	No loss	Map prop.=W_i
Forest loss	$\hat{p}_{11}$	$\hat{p}_{12}$	p_{1+}
No loss	$\hat{p}_{21}$	$\hat{p}_{22}$	p_{2+}
Ref. prop.	$\hat{p}_{+1}$	$\hat{p}_{+2}$	1

$$\hat{p}_{ij} = W_i \frac{n_{ij}}{n_{i+}}$$

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Overall, User's and Prod.'s Accuracy

Reference (*j*)

Map (*i*)	Forest loss	No loss	Map prop.=W_i
Forest loss	$\hat{p}_{11}$	$\hat{p}_{12}$	p_{1+}
No loss	$\hat{p}_{21}$	$\hat{p}_{22}$	p_{2+}
Ref. prop.	$\hat{p}_{+1}$	$\hat{p}_{+2}$	1

$$\hat{O} = \sum \hat{p}_{jj} = \hat{p}_{11} + \hat{p}_{22}$$

$$\hat{U}_i = \hat{p}_{ii} \div p_{i+} = \hat{p}_{11} \div \ p_{1+}$$

$$\hat{P}_j = \hat{p}_{jj} \div \hat{p}_{+j} = \hat{p}_{11} \div \hat{p}_{+1}$$

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Area estimators

Map (i)	Reference (j): Forest loss	No loss	Map prop.=W_i
Forest loss	$\hat{p}_{11}$	$\hat{p}_{12}$	p_{1+}
No loss	$\hat{p}_{21}$	$\hat{p}_{22}$	p_{2+}
Ref. prop.	$\hat{p}_{+1}$	$\hat{p}_{+2}$	1

Bias-adjusted estimator

$$\hat{p}_{+1} = \text{map prop.} - \text{bias} = p_{1+} + (\hat{p}_{21} - \hat{p}_{12})$$

Stratified/post-stratified estimator

$$\hat{p}_{+1} = \text{sum of ref. obs.} = \hat{p}_{11} + \hat{p}_{21}$$

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Area estimators

Bias-adjusted estimator

- Unbiased for any sample size
- Known as a “difference” estimator in sampling texts
- Map classes are more efficient if map class is continuous

Stratified/Post-stratified

- Unbiased (but problem if no units from a post-stratum)
- Allows use of all map classes as post-strata
- More efficient if map classes are categorical

Example

Stratified estimation explained in Cochran (1977); Olofsson et al. (2013; 2014) illustrate implementation in geography context

Sampling Techniques

third edition

WILLIAM G. COCHRAN

Professor of Statistics, Emeritus
Harvard University

JOHN WILEY & SONS

New York • Chichester • Brisbane • Toronto • Singapore

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

ELSEVIER

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]

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ARTICLE INFO

Article history:
Received 15 February 2012
Received in revised form 23 October 2012
Accepted 26 October 2012
Available online 29 November 2012

Keywords:
Land use change
Land cover change
Carbon modeling
Uncertainty
Stratified estimation
Accuracy assessment

ABSTRACT

The area of land use or land cover change obtained directly from a map may dif
of change because of map classification error. An error-adjusted estimator of are
an accuracy assessment has been performed and an error matrix constructed.
stratified estimator which is applicable to data acquired using popular sampli
random, simple random and systematic (the stratified estimator is often label
for the latter two designs). A confidence interval for the area of land change sho
tify the uncertainty of the change area estimate. The uncertainty of the change a
the confidence interval, can then subsequently be incorporated into an uncerta
using land change area as an input (e.g., a carbon flux model). Accuracy ass
change studies should report the information required to produce the stratifi
and to construct confidence intervals. However, an evaluation of land change
2005 and 2010 in two remote sensing journals revealed that accuracy assessm
key information. We recommend that land change maps should be accompanie
that includes a clear description of the sampling design (including sample si
stratification), an error matrix, the area or proportion of area of each category a
scriptive accuracy measures such as user's, producer's and overall accuracy.
should be adjusted to eliminate bias attributable to map classification error and
timates should be accompanied by confidence intervals to quantify the samplin
area. Using data from the published literature, we illustrate how to produce er
and confidence intervals of land change areas. A simple analysis of uncertai
bounds for land change area is applied to a carbon flux model to illustrate n
the land change area estimate can have a dramatic effect on model outputs.

Remote Sensing of Environment 148 (2014) 42–57

Contents lists available at ScienceDirect

Remote Sensing of Environment

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ELSEVIER

Review

Good practices for estimating area and assessing accuracy of land change

CrossMark

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

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ARTICLE INFO

Article history:
Received 30 May 2013
Received in revised form 15 January 2014
Accepted 22 February 2014
Available online 12 April 2014

Keywords:
Accuracy assessment
Sampling design
Response design
Area estimation
Land change
Remote sensing

ABSTRACT

The remote sensing science and application communities have developed increasingly reliable, consistent, and robust approaches for capturing land dynamics to meet a range of information needs. Statistically robust and transparent approaches for assessing accuracy and estimating area of change are critical to ensure the integrity of land change information. We provide practitioners with a set of "good practice" recommendations for designing and implementing an accuracy assessment of a change map and estimating area based on the reference sample data. The good practice recommendations address the three major components: sampling design, response design and analysis. The primary good practice recommendations for assessing accuracy and estimating area are: (i) implement a probability sampling design that is chosen to achieve the priority objectives of accuracy and area estimation while also satisfying practical constraints such as cost and available sources of reference data; (ii) implement a response design protocol that is based on reference data sources that provide sufficient spatial and temporal representation to accurately label each unit in the sample (i.e., the "reference classification" will be considerably more accurate than the map classification being evaluated); (iii) implement an analysis that is consistent with the sampling design and response design protocols; (iv) summarize the accuracy assessment by reporting the estimated error matrix in terms of proportion of area and estimates of overall accuracy, user's accuracy (or commission error), and producer's accuracy (or omission error); (v) estimate area of classes (e.g., types of change such as wetland loss or types of persistence such as stable forest) based on the reference classification of the sample units; (vi) quantify uncertainty by reporting confidence intervals for accuracy and area parameters; (vii) evaluate variability and potential error in the reference classification; and (viii) document deviations from good practice that may substantially affect the results. An example application is provided to illustrate the recommended process.

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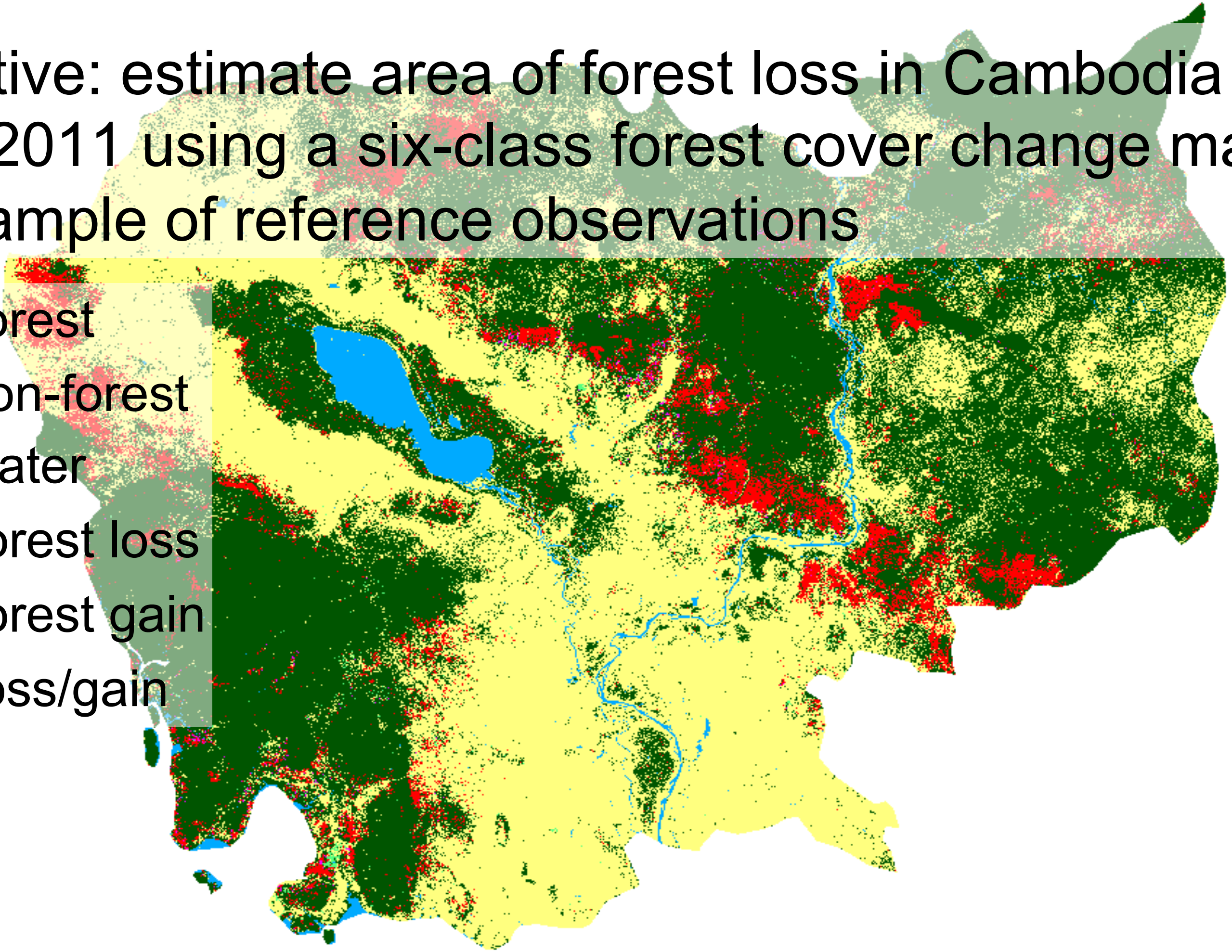
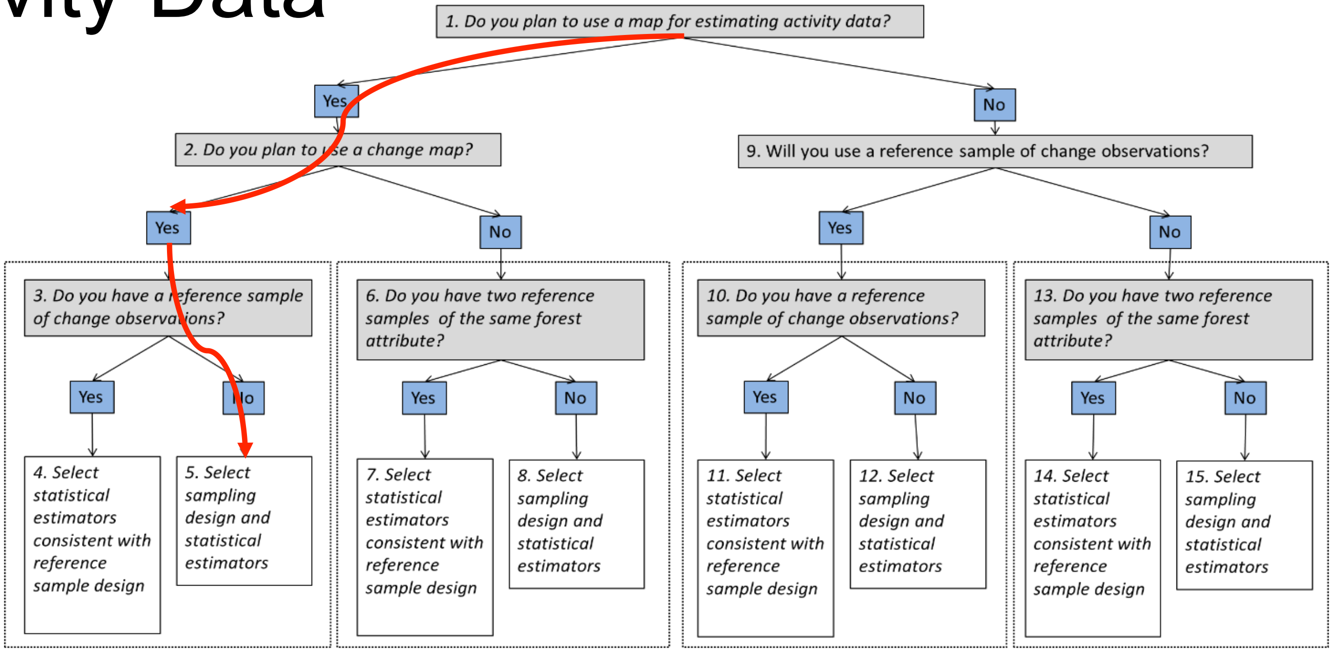
Objective: estimate area of forest loss in Cambodia 2000-2011 using a six-class forest cover change map and sample of reference observations



- 1. Forest
- 2. Non-forest
- 3. Water
- 4. Forest loss
- 5. Forest gain
- 6. Loss/gain

GFOI Methods & Guidance, inference of Activity Data



Example situation

- Objective stated: estimate area of forest loss
- Categorical change map (each pixel belong to one of 5 distinct classes)
- No reference sample in place
- Landsat and Google Earth data available

Therefore

- Preferred sampling design: *stratified random*
- Preferred area estimator: *stratified*

Steps involved in estimation

1. ***Sampling design:*** Select a random sample stratified by change map of Cambodia; determine sample size and allocation of sample to strata

2. ***Response design:*** Examine a time series of Landsat observations at each sample unit (pixel) for provision of reference labels; record date of change and confidence level (1-3)

3. ***Analysis:*** Create an error matrix and construct estimators of area with confidence interval; and calculate accuracy measures

Step 1. Design sample

Estimate total size of stratified sample:

$$n = \left(\frac{\sum W_i S_i}{S(\hat{P})} \right)^2 \text{ where } S_i = \sqrt{p_i(1-p_i)}$$

Stratum i	1 Non-forest	2 Forest	3 Water	4 Loss	5 Gain	6 Loss/gain	**Total**
Area [pixels]	82,897,900	99,763,633	5,173,728	13,251,084	732,374	474,833	**202,293,552**
Area [ha]	7,460,811	8,978,727	465,636	1,192,598	65,914	42,735	**18,206,420**
Wi [%]	40.98%	49.32%	2.56%	6.55%	0.36%	0.23%	**100%**
pi [%]	1%	1%	0%	80%	0%	0%	
Si	0.0995	0.0995	0	0.4	0	0	
S(P^) [%]				1%			

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Step 1. Design sample

- Allocate sample to strata
- Equal allocation favors estimation of User's accuracy.
- Optimal allocation for area estimation close to proportional (but need 50-100 units in target stratum)

Merging class 5 and 6 to one stratum

Stratum i	1 Non-forest	2 Forest	3 Water	4 Loss	5 Gain	6 Loss/gain	Total
Area [pixels]	82,897,900	99,763,633	5,173,728	13,251,084	732,374	474,833	**202,293,552**
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pi [%]	1%	1%	0%	80%	0%	0%	
Si	0.0995	0.0995	0	0.4	0	0	
S(P^) [%]				1%			
prop all	221	266	14	35	2	1	539
equal all	90	90	90	90	90	90	539
ni	175	200	50	75	50	0	550

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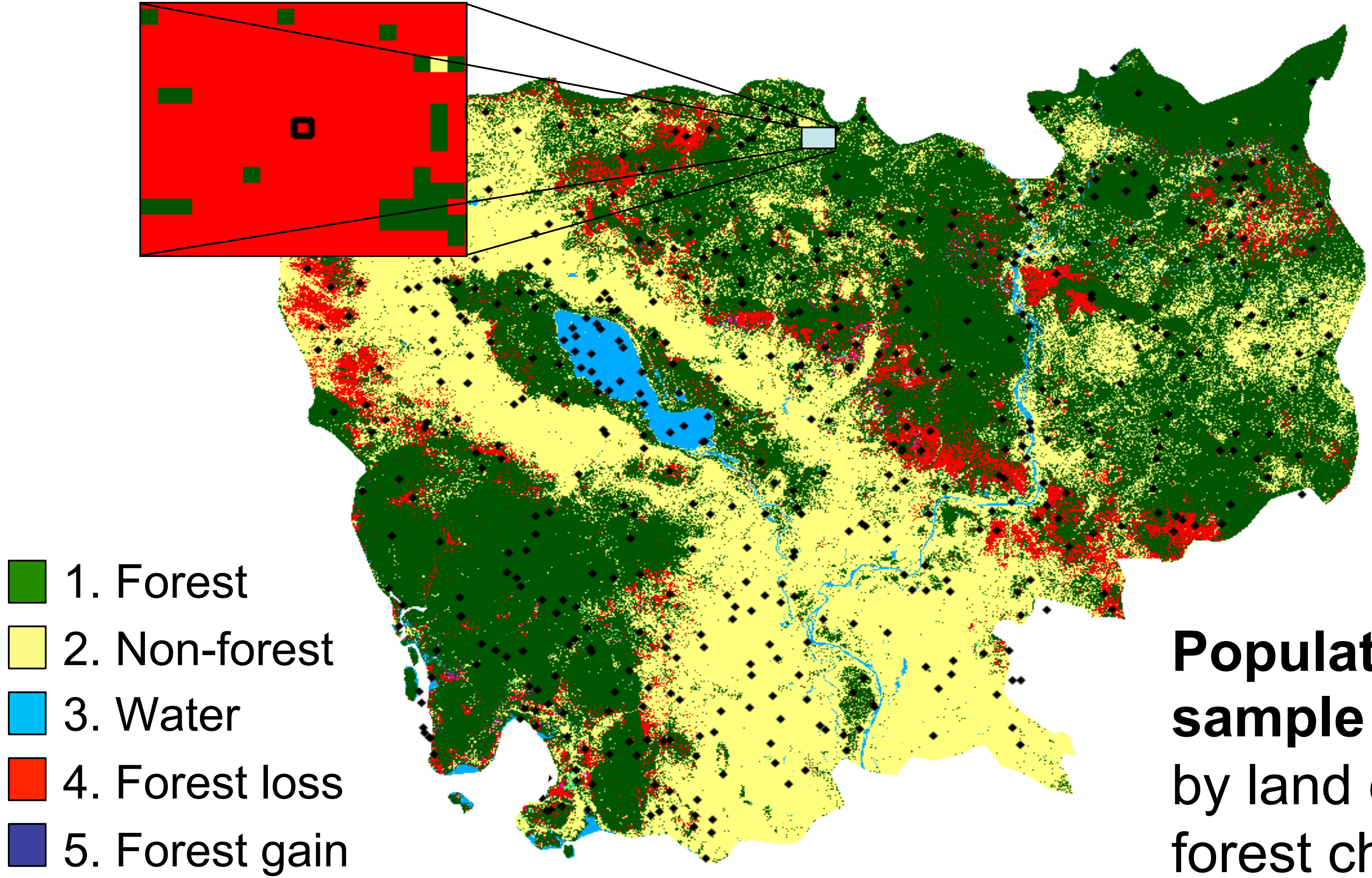
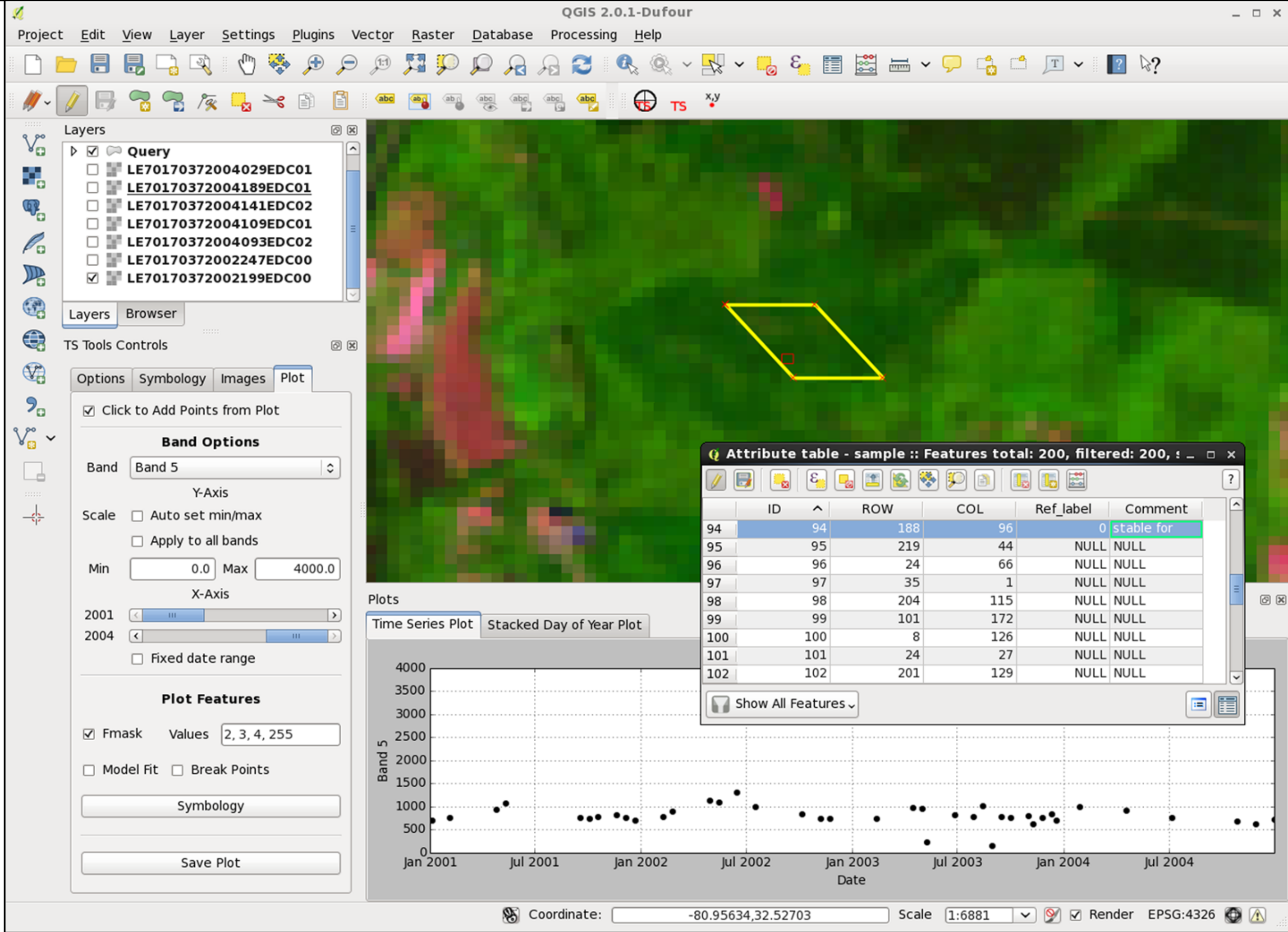


Population and **sample** stratified by land cover and forest change

Step 2. Response design

- Assess reference condition for each unit in the sample using combination of available Earth observations
- Time series of Landsat data preferred and GE imagery if available
- Three interpreters
- Three levels of confidence
- Reference labels correspond to map labels

Screenshot of QGIS with the TSTools plugin in the BEEODA virtual machine: examining time series of Landsat data for collection of reference observations



Step 3. Analysis

Construct error matrix

Sample counts

	1 Non-forest	2 Forest	3 Water	4 Loss	5 Gain	Total	Area [ha]	Wi
1 Non-forest	165	8	0	1	1	175	7,460,795	0.411
2 Forest	8	190	1	1	0	200	8,978,709	0.494
3 Water	1	0	49	0	0	50	465,631	0.026
4 Loss	5	4	0	66	0	75	1,192,591	0.066
5 Gain	7	12	0	0	31	50	108,649	0.006
Total	186	214	50	68	32	550	18,206,420	1.000

Step 3. Analysis

Can't compute by sample counts as sample is stratified – need to estimate area proportions:

$$\hat{p}_{ij} = W_i \frac{n_{ij}}{n_{i+}}$$

Sample counts

	1 Non-forest	2 Forest	3 Water	4 Loss	5 Gain	Total	Area [ha]	Wi
1 Non-forest	165	8	0	1	1	175	7,460,795	0.411
2 Forest	8	190	1	1	0	200	8,978,709	0.494
3 Water	1	0	49	0	0	50	465,631	0.026
4 Loss	5	4	0	66	0	75	1,192,591	0.066
5 Gain	7	12	0	0	31	50	108,649	0.006
Total	186	214	50	68	32	550	18,206,420	1.000

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Step 3. Analysis

We get an new error matrix expressing estimated area proportions

	1 Non-forest	2 Forest	3 Water	4 Loss	5 Gain	Total	Area [ha]	Wi
1 Non-forest	0.3873	0.0188	0.0000	0.0023	0.0023	0.411	7,460,795	0.411
2 Forest	0.0198	0.4696	0.0025	0.0025	0.0000	0.494	8,978,709	0.494
3 Water	0.0005	0.0000	0.0251	0.0000	0.0000	0.026	465,631	0.026
4 Loss	0.0044	0.0035	0.0000	0.0578	0.0000	0.066	1,192,591	0.066
5 Gain	0.0008	0.0014	0.0000	0.0000	0.0037	0.006	108,649	0.006
Total	0.412	0.492	0.028	0.062	0.006	0.412	18,206,420	1.000

A stratified area estimator of area (Cochran, 1977, Eq. 5.52) is

$$\hat{p}_{+j} = \sum W_i \frac{n_{ij}}{n_{i+}}$$

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Step 3. Analysis

- Area estimates are easily obtained for each class;
- And the standard error of $p\downarrow+j$ and a 95% CI are:

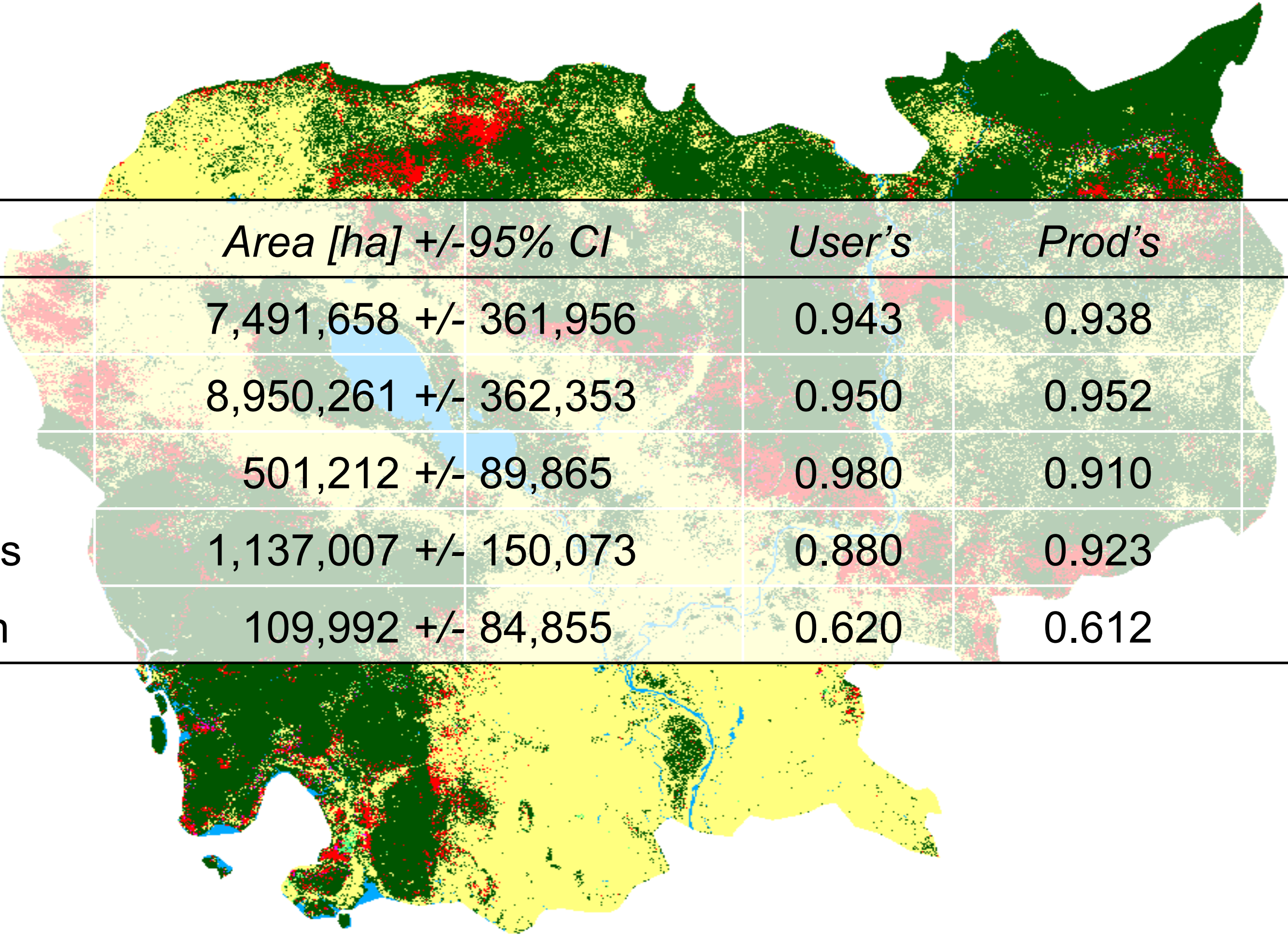
$$S(\hat{p}_{+j}) = \sqrt{\sum_{i=1}^{5} \frac{W_i \times \hat{p}_{ij} - \hat{p}_{ij}^2}{n_{i+} - 1}} \quad \text{and 95\% CI is} \pm 1.96 \times S(\hat{p}_{+j})$$

	1 Non-forest	2 Forest	3 Water	4 Loss	5 Gain	Total	Area [ha]	Wi
1 Non-forest	0.3873	0.0188	0.0000	0.0023	0.0023	0.411	7,460,795	0.411
2 Forest	0.0198	0.4696	0.0025	0.0025	0.0000	0.494	8,978,709	0.494
3 Water	0.0005	0.0000	0.0251	0.0000	0.0000	0.026	465,631	0.026
4 Loss	0.0044	0.0035	0.0000	0.0578	0.0000	0.066	1,192,591	0.066
5 Gain	0.0008	0.0014	0.0000	0.0000	0.0037	0.006	108,649	0.006
Total	0.412	0.492	0.028	0.062	0.006	0.412	18,206,420	1.000
A^ [ha]	**7,497,641**	**8,960,518**	**501,212**	**1,137,007**	**109,992**			
S(A^) [ha]	184,672	184,967	45,849	76,568	43,294			
+- 95% CI [ha]	**361,956**	**362,535**	**89,865**	**150,073**	**84,855**			
Margin of Error	5%	4%	18%	13%	77%			

Step 3. Analysis

Accuracy measures are easily calculated using the information in the error matrix. Note that accuracy must be calculated using area proportions – not sample counts!

	1 Non-forest	2 Forest	3 Water	4 Loss	5 Gain	Total	Area [ha]	Wi
1 Non-forest	0.3873	0.0188	0.0000	0.0023	0.0023	0.411	7,460,795	0.411
2 Forest	0.0198	0.4696	0.0025	0.0025	0.0000	0.494	8,978,709	0.494
3 Water	0.0005	0.0000	0.0251	0.0000	0.0000	0.026	465,631	0.026
4 Loss	0.0044	0.0035	0.0000	0.0578	0.0000	0.066	1,192,591	0.066
5 Gain	0.0008	0.0014	0.0000	0.0000	0.0037	0.006	108,649	0.006
Total	0.412	0.492	0.028	0.062	0.006	0.412	18,206,420	1.000
User's accuracy	**0.943**	**0.950**	**0.980**	**0.880**	**0.620**			
Prod.'s accuracy	**0.938**	**0.952**	**0.910**	**0.923**	**0.612**			
Overall accuracy			**0.941**					



Stratum	*Area [ha] +/- 95% CI*	*User's*	*Prod's*	*Overall*
1 Non-forest	7,491,658 +/- 361,956	0.943	0.938	0.941
2 Forest	8,950,261 +/- 362,353	0.950	0.952	
3 Water	501,212 +/- 89,865	0.980	0.910	
4 Forest Loss	1,137,007 +/- 150,073	0.880	0.923	
5 ForestGain	109,992 +/- 84,855	0.620	0.612	

Conclusions

- All maps have errors, therefore, areas obtained by pixel counting are biased – and are not IPCC-compliant!
- But maps are essential in identifying areas where land surface activities are occurring
- Unbiased estimation is a necessity
- Estimators and confidence intervals are easily computed using the information in an error matrix

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Thank You

Next Week:

Additional Guidance and Policy Perspectives