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Activity data production in Ethiopia
Lessons learned from the FRL

R. d'Annunzio, Y. Finegold, M. Gelet, A. Salis, D. Belay, W. Getachew

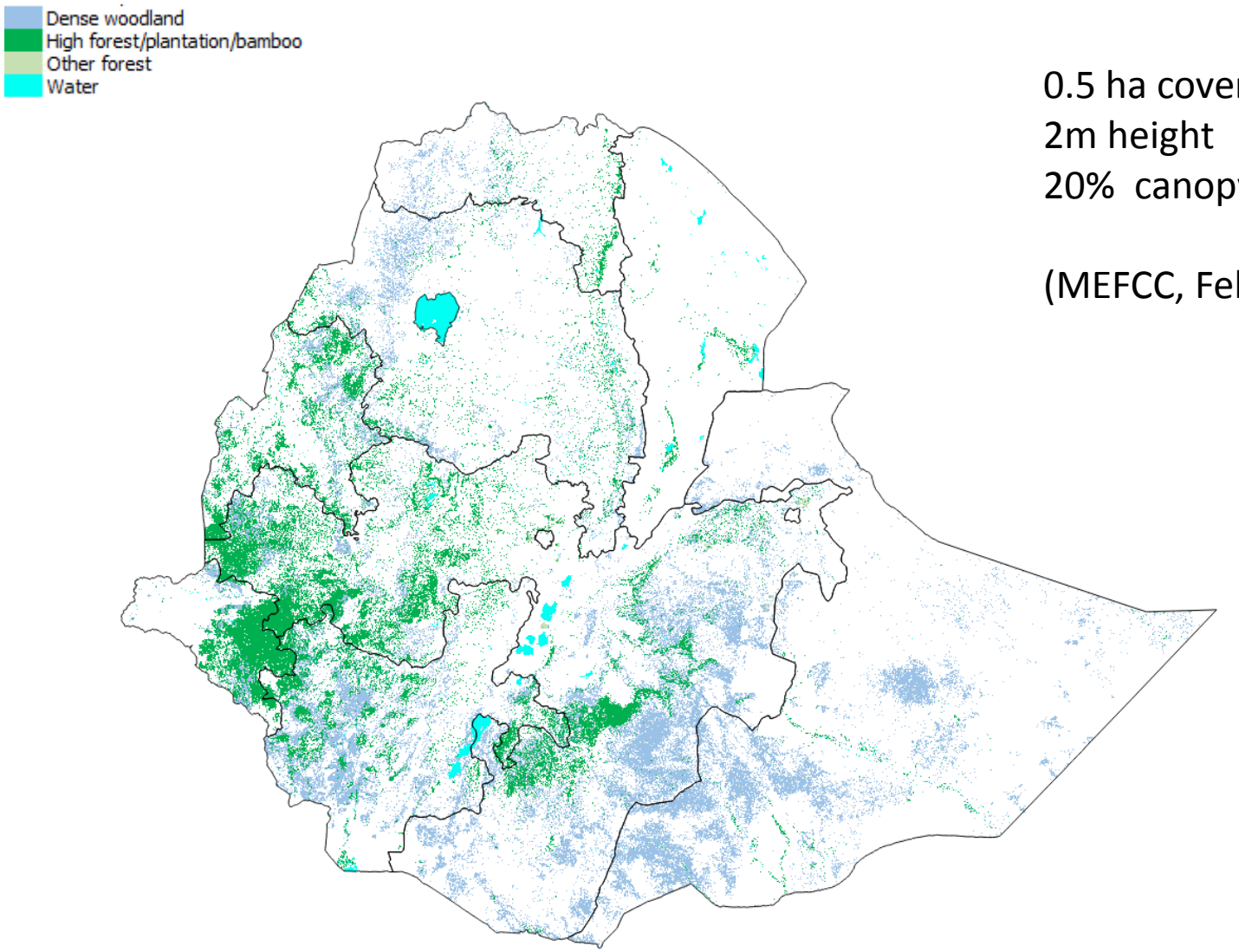
Outline

Change detection and national definition of forests in Ethiopia

Activity data production workflow

Results and lessons learned

National definition of forests



0.5 ha covered by trees
2m height
20% canopy cover

(MEFCC, Feb. 2015).

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The issue with post-classification

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

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]

Uncertainty of a given class must be inferior to the order of magnitude of change between 2 maps

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Which change detection ?

Remote Sensing of Environment 160 (2015) 1–14

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

Review

A critical synthesis of remotely sensed optical image change detection techniques

Andrew P. Tewkesbury [a,b,*], Alexis J. Comber [b], Nicholas J. Tate [b], Alistair Lamb [a], Peter F. Fisher [b]

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[b] Department of Geography, University of Leicester, Leicester LE1 7RH, UK

More research is required to identify optimum approaches for change detection

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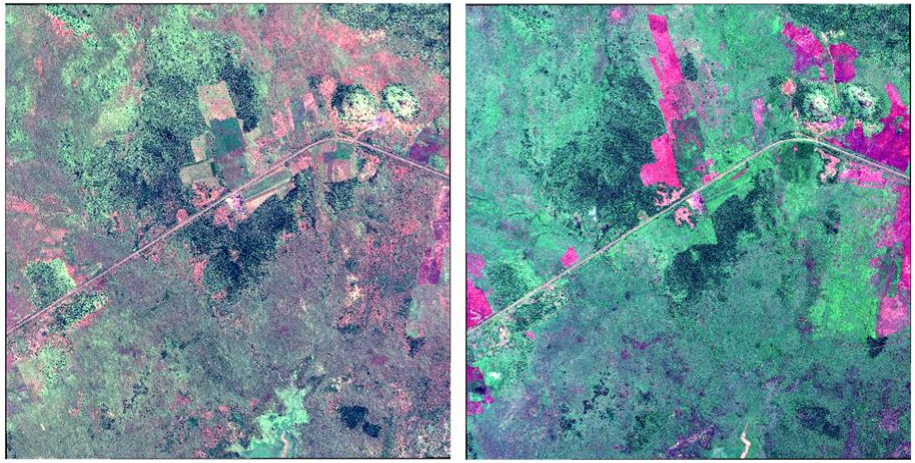
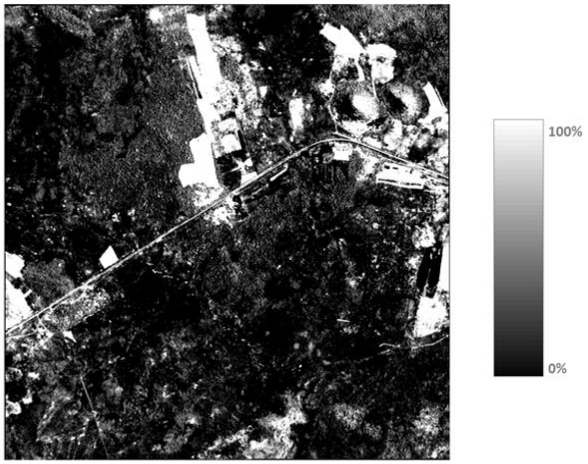
Comparison of methods

	Description	Advantages	Limitations
Layer arithmetic	Image radiance or derivative features are numerically compared to identify change.	Can be simple to implement.	Usually gives little insight into the type of change.
Post-classification change	The comparison of multiple maps to identify class transitions.	Produces a labelled change map. Prior radiometric calibration may not be required.	Errors in any of the input maps are directly translated to the change map.
Direct classification	A multi-temporal data stack is classified directly identifying both static and dynamic land covers.	Only one classification stage is required. Provides an effective framework to mine a complicated time series. Produces a labelled change map.	Classification training datasets can be difficult to construct, especially for a time series of images.
Transformation	A mathematical transformation to highlight variance between images.	Provides an elegant way to handle high dimensional data.	There is no defined thematic meaning to the results. Change may be difficult to locate and interpret.
CVA	The computation of difference vectors between analysis units giving both the magnitude and direction of change.	Gives insight into the type of change occurring.	In its raw form the change direction and magnitude may be ambiguous.
Hybrid change detection	The use of multiple comparison methods within a workflow.	Training data does not have to be collected over radiometrically stable areas.	No specific limitations.

Hybrid approach

IMAD transformation: a robust unsupervised change detection





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Available online at www.sciencedirect.com
ScienceDirect
Remote Sensing of Environment 112 (2008) 1025–1036

Remote Sensing of Environment
www.elsevier.com/locate/rse

Automatic radiometric normalization of multitemporal satellite imagery with the iteratively re-weighted MAD transformation

Morton J. Canty [a,*], Allan A. Nielsen [b,1]

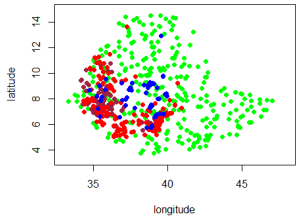
[a] Institute for Chemistry and Dynamics of the Geosphere, Jülich Research Center, D-52425 Jülich, Germany
[b] Danish National Space Center, Technical University of Denmark, Richard Petersens Plads, Building 321, DK-2800 Kgs. Lyngby, Denmark

Received 27 March 2007; received in revised form 21 June 2007; accepted 15 July 2007

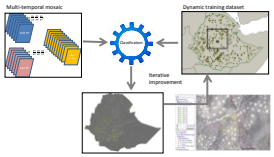
http://www2.imm.dtu.dk/pubdb/views/edoc_download.php/5362/pdf/imm5362.pdf

Adopted workflow

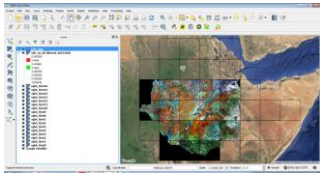
Generate training data



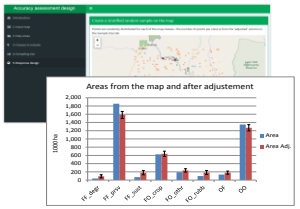
Create mosaic and run supervised change detection / classification



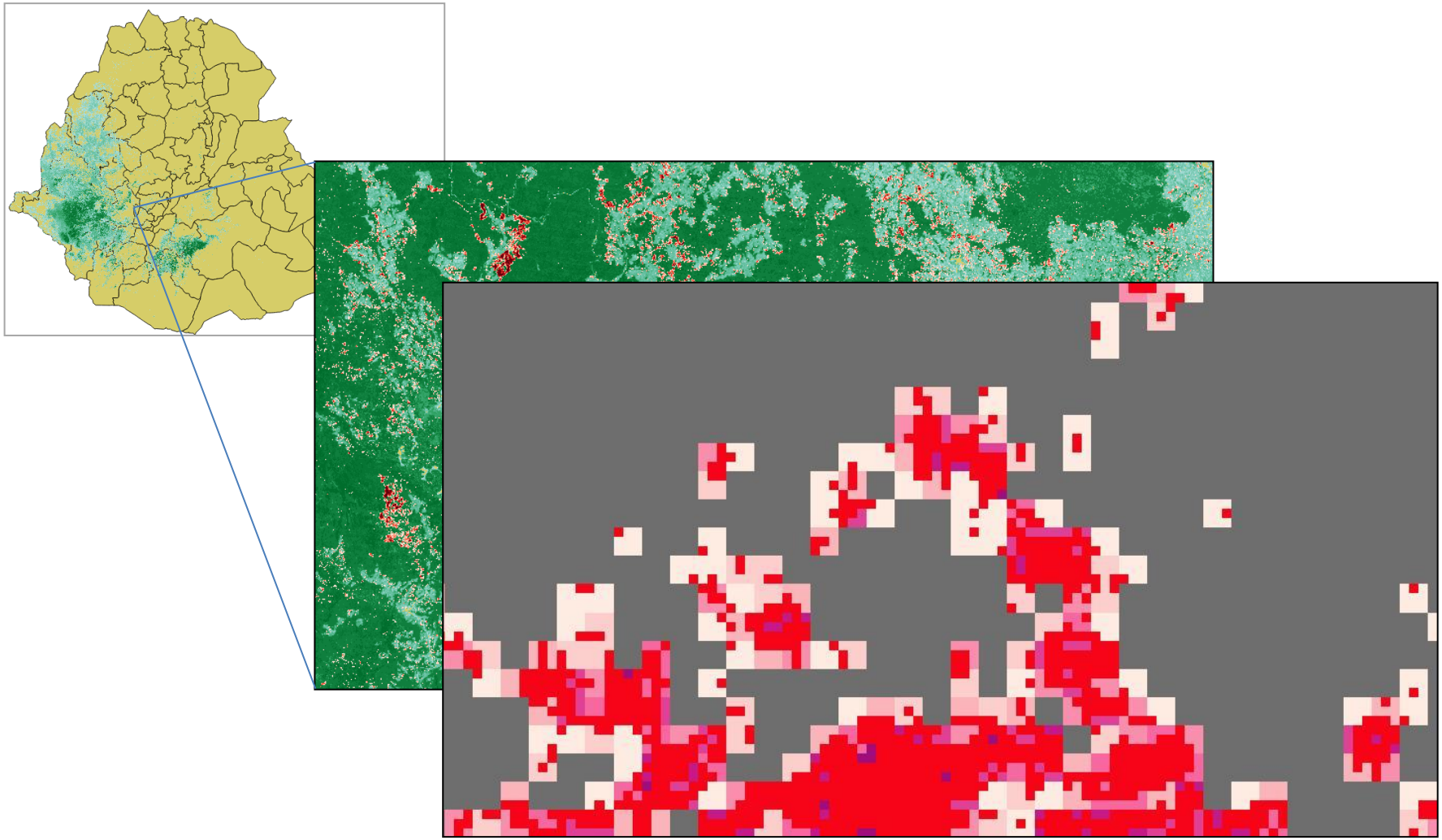
Manually edit and correct the map



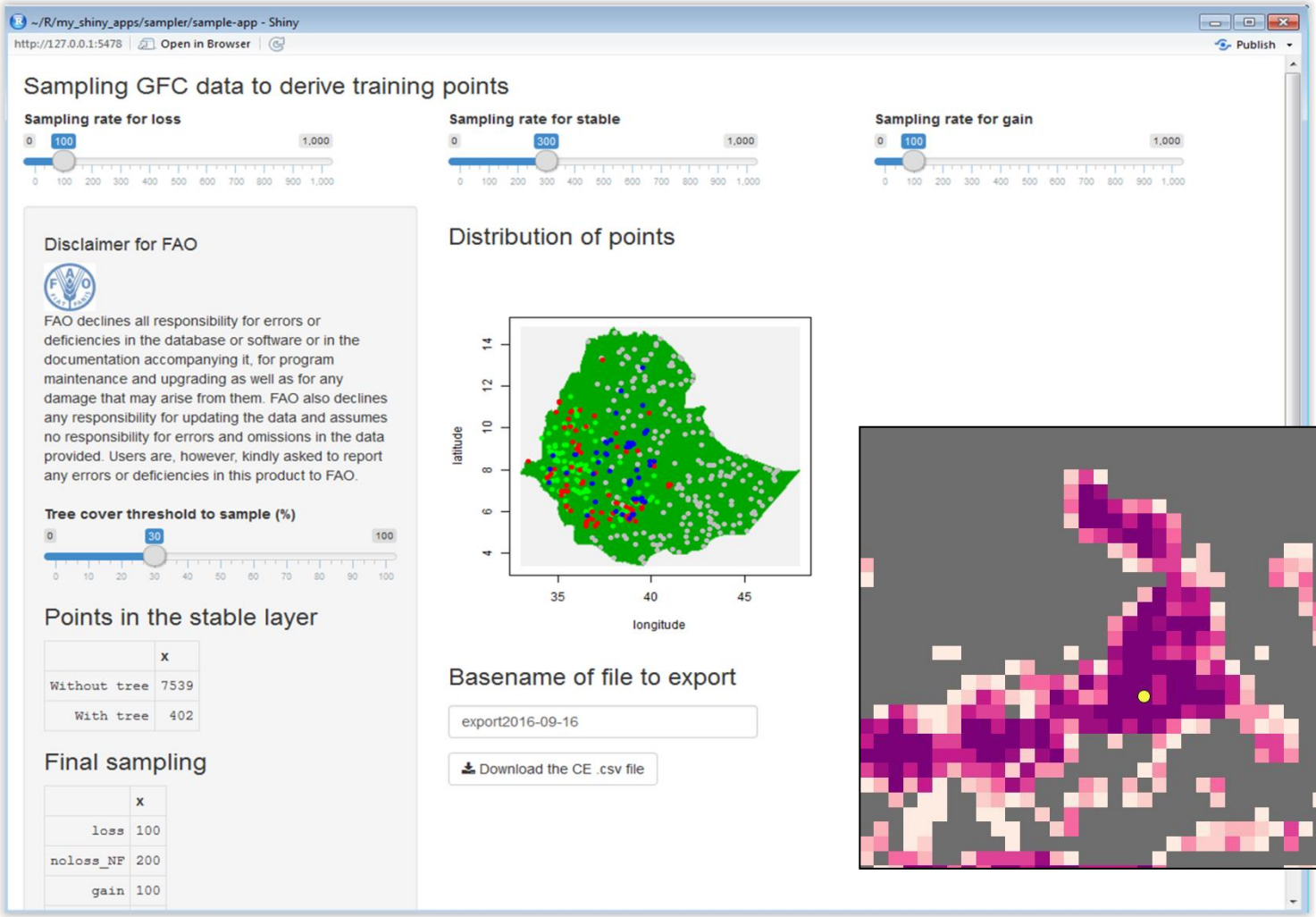
Assess accuracy and correct biases

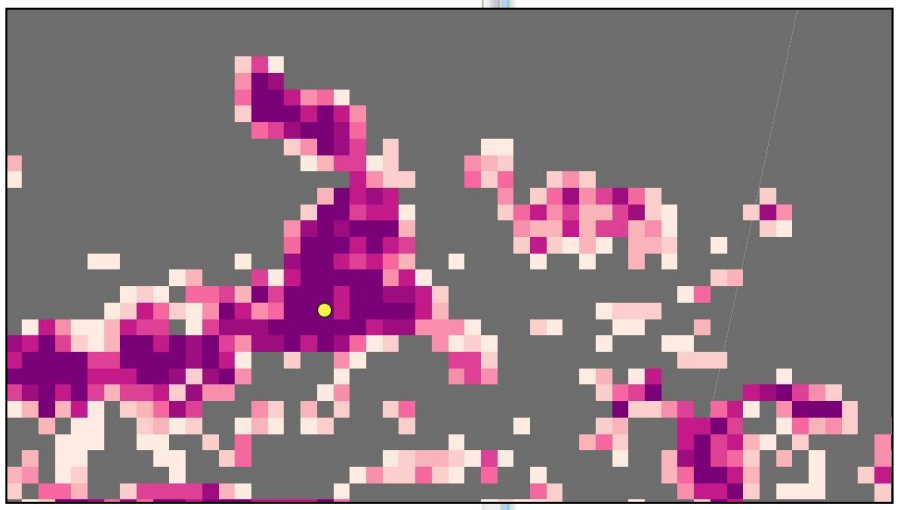


How to maximize training data validity ?

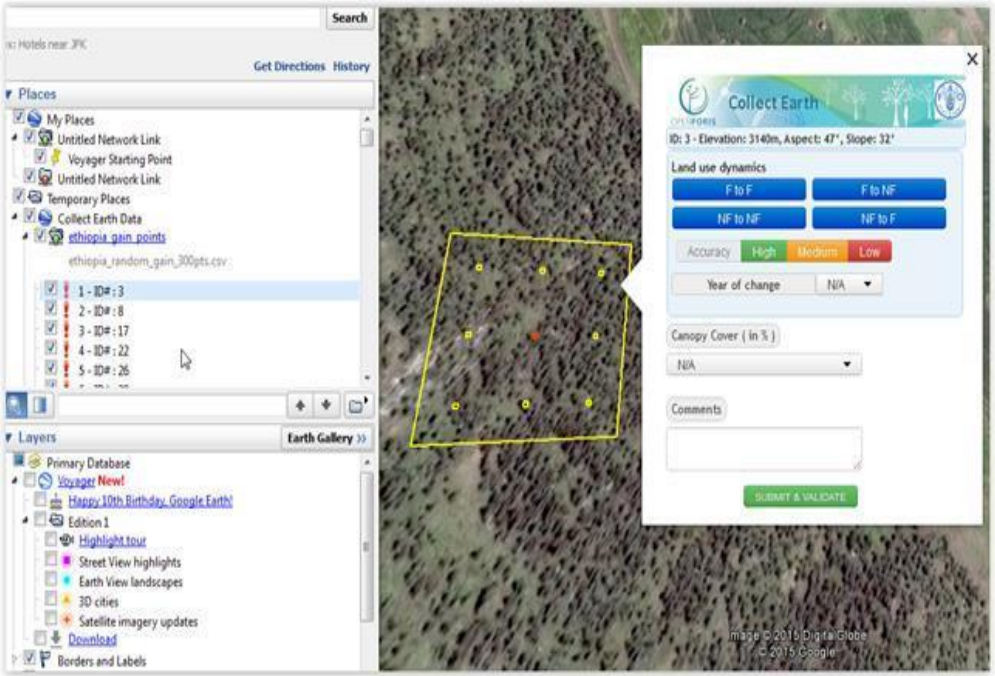


Random selection of points



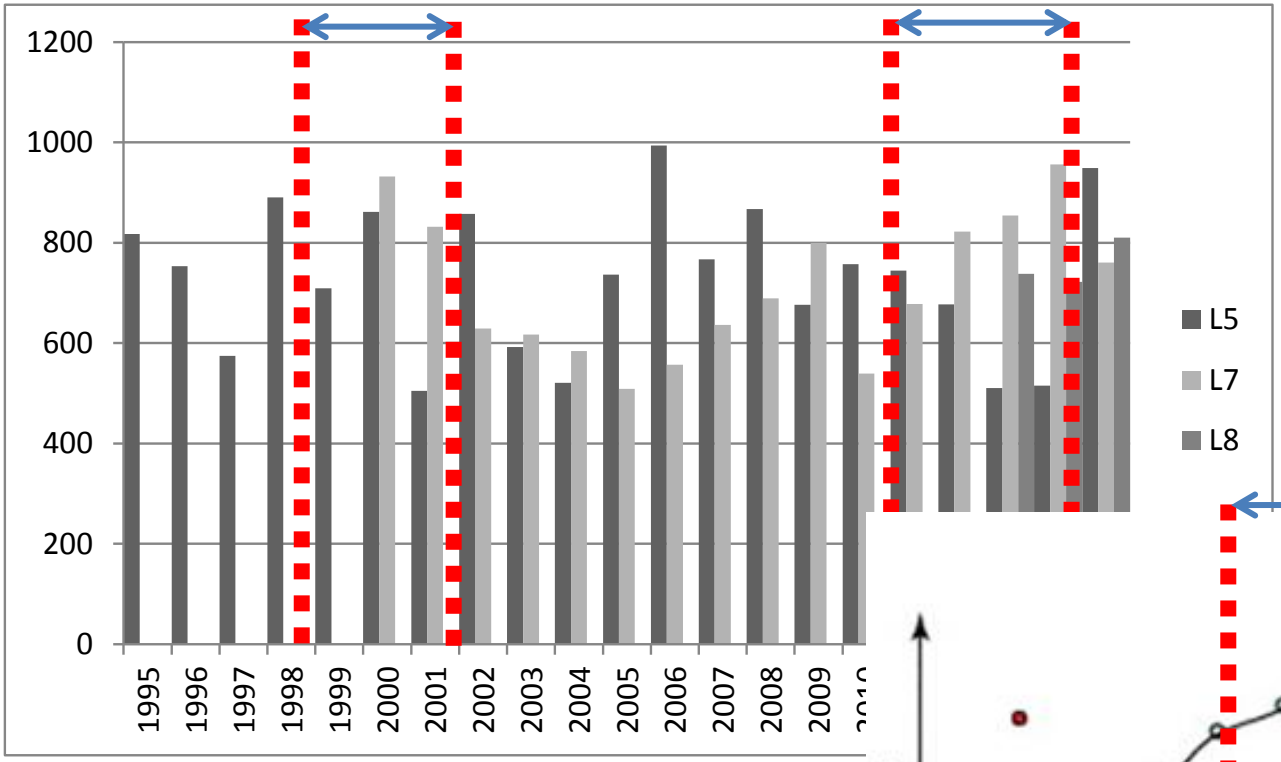


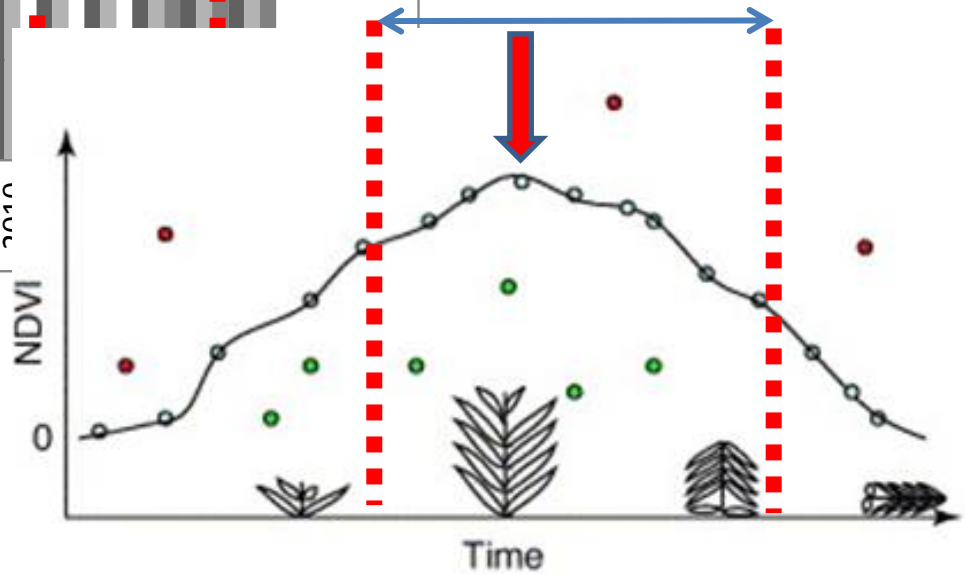
Visual checking of the training points



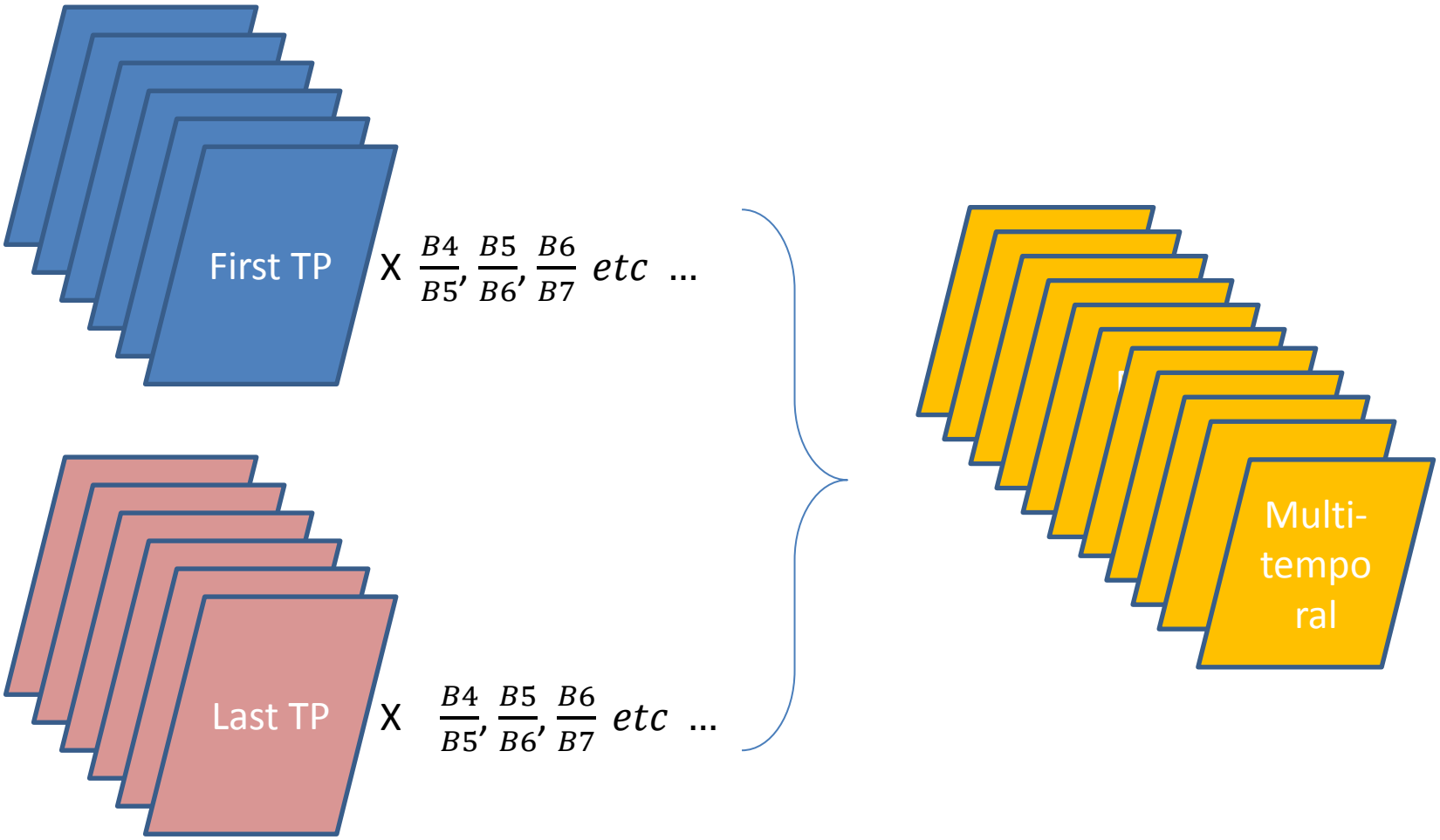
	Initial	Cleaning	Final
Stable	300	503	921
Loss	100	79	100
Gain	100	95	109

Availability of data, national parameters





Combine in a multi-temporal object



Visualize & call the training points

Scripts | Docs

Saved Scripts
- GFC_congo
- aaaaa_test
- alfonso_collect_earth
- bangladesh_tc2012
- change_2
- change_detection
- change_detection_ethiopia
- change_detection_ethiopia_1

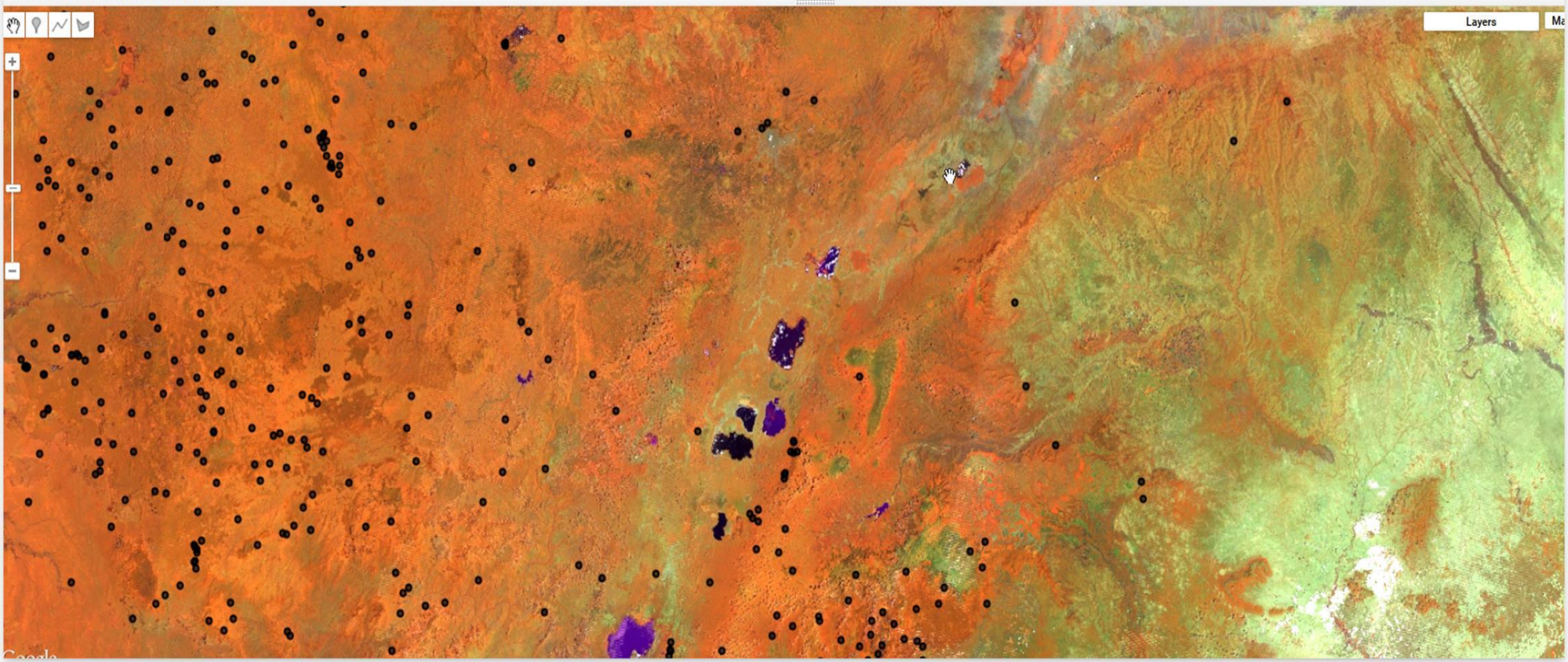
change_detection_ethiopia_1 *

Get Link | Save | Run | Reset

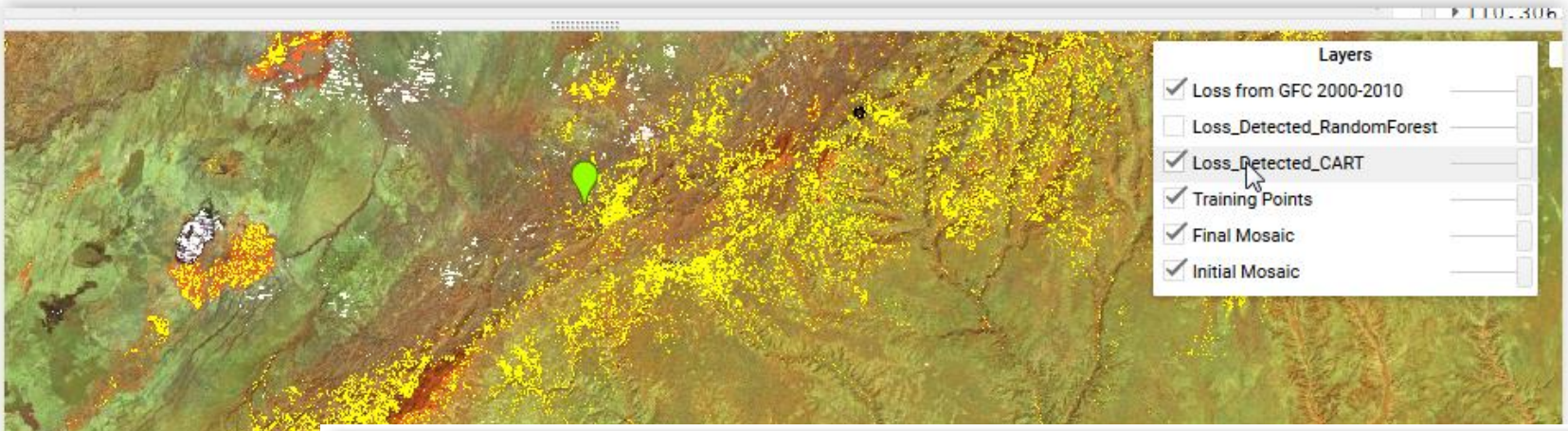
```
    'EPSG:4326',
    mosaic_final.projection().atScale(90).getInfo()['transform'],
    null,
    1,
    0,
    'Cart'
    );


// Classify the composite with the trained classifier
var classimg = mosaic_final.classify(classifier);
```

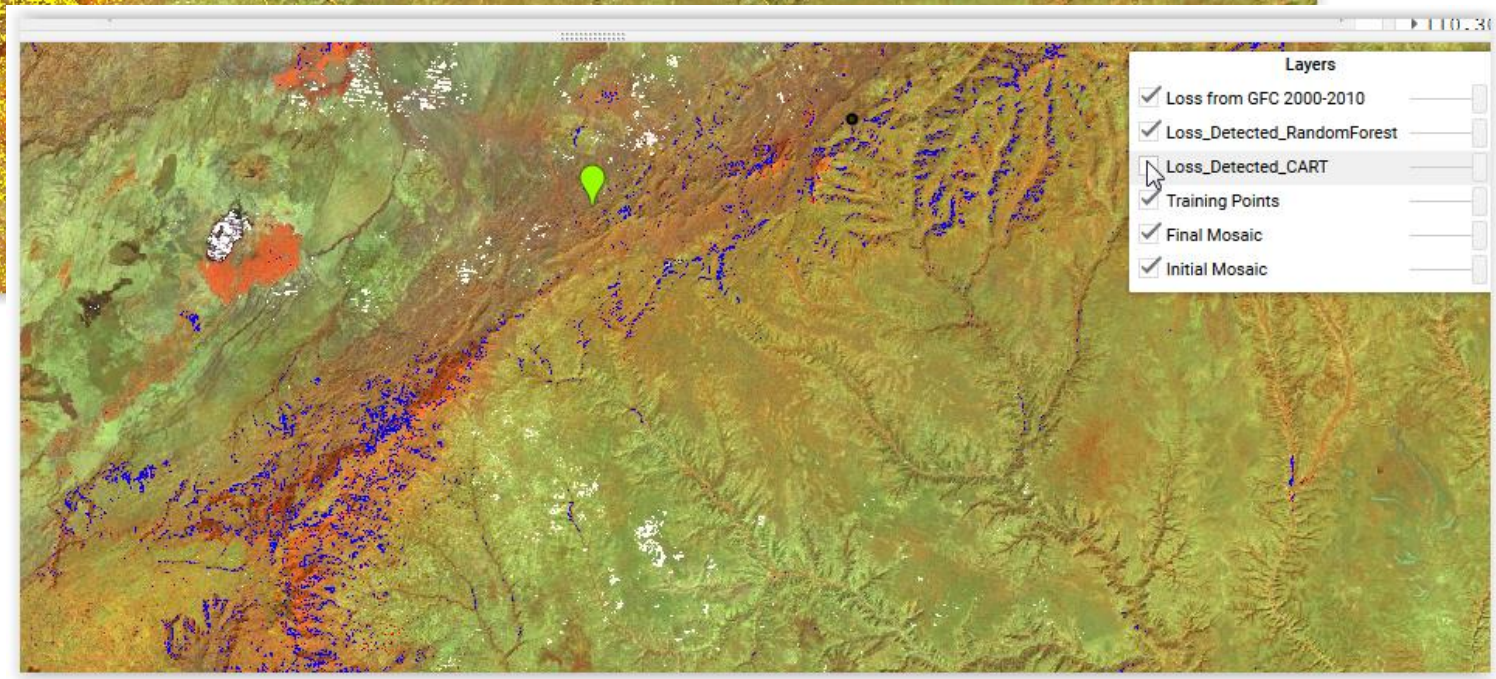
Inspector | Console | Tasks

Use print(...) to write to this console.



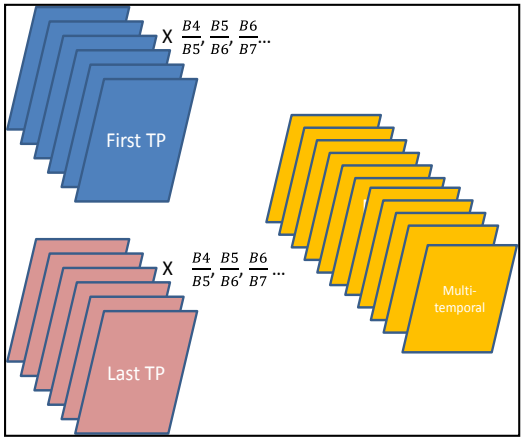
Run with different algorithms



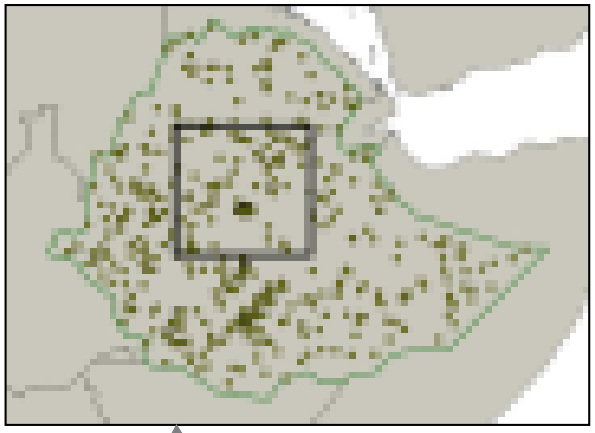


Iterative improvement

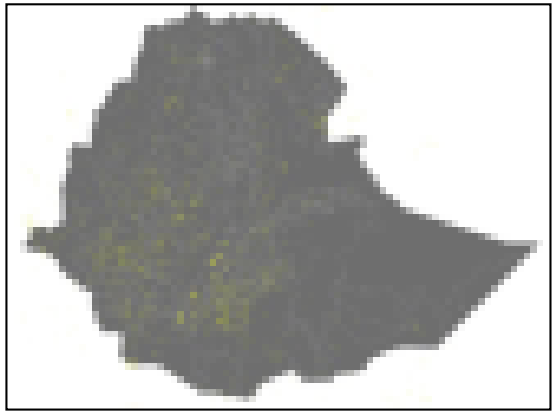
Multi-temporal mosaic



Dynamic training dataset



Iterative improvement



Not perfect but 100%
- Reproducible
- Transparent
- Sharable

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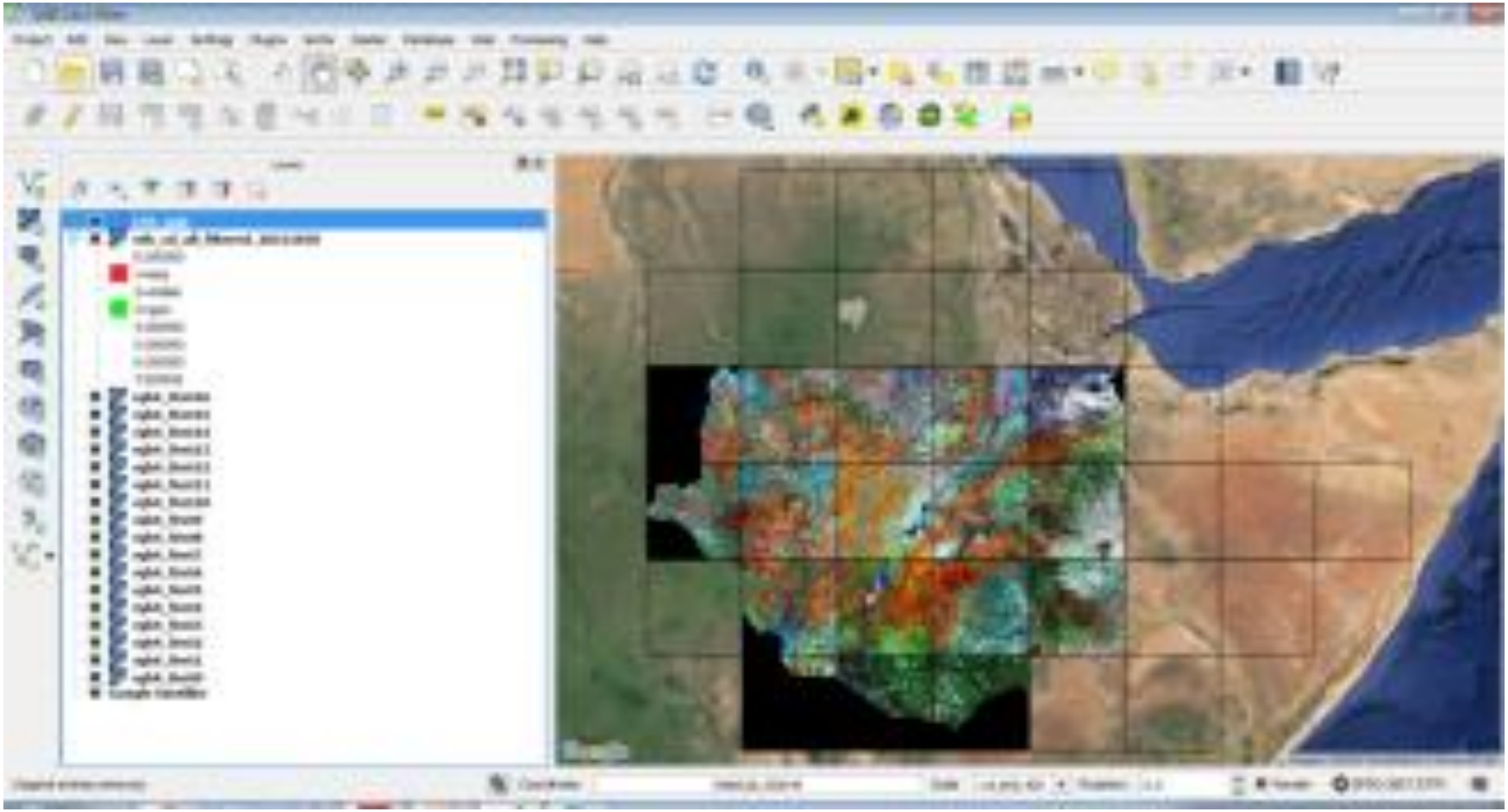
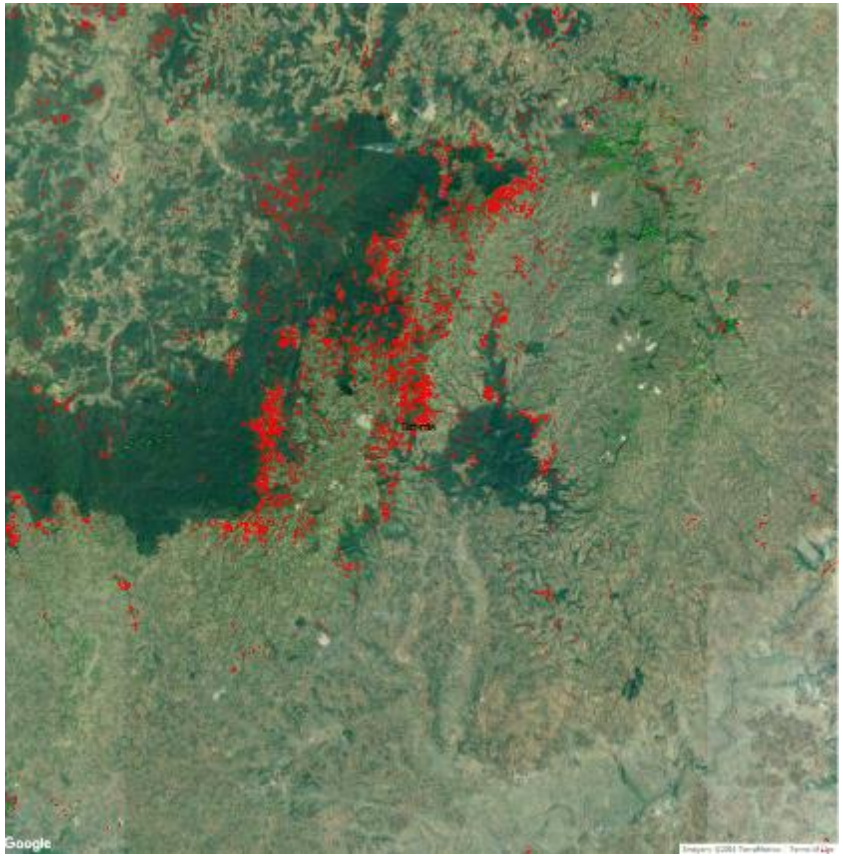
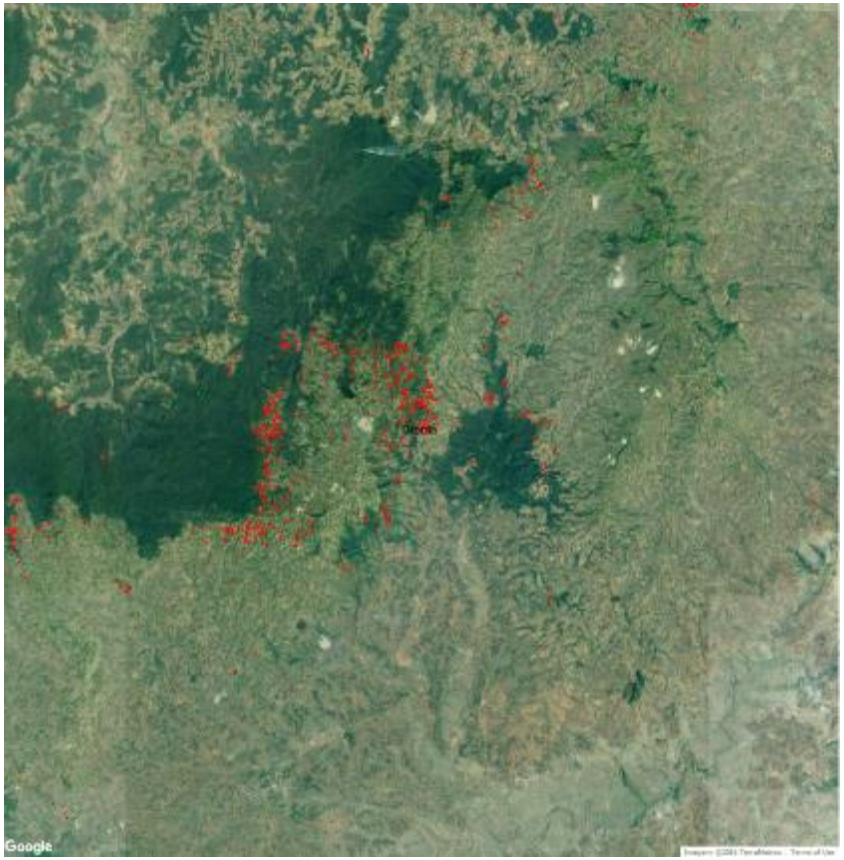
Manual correction of errors



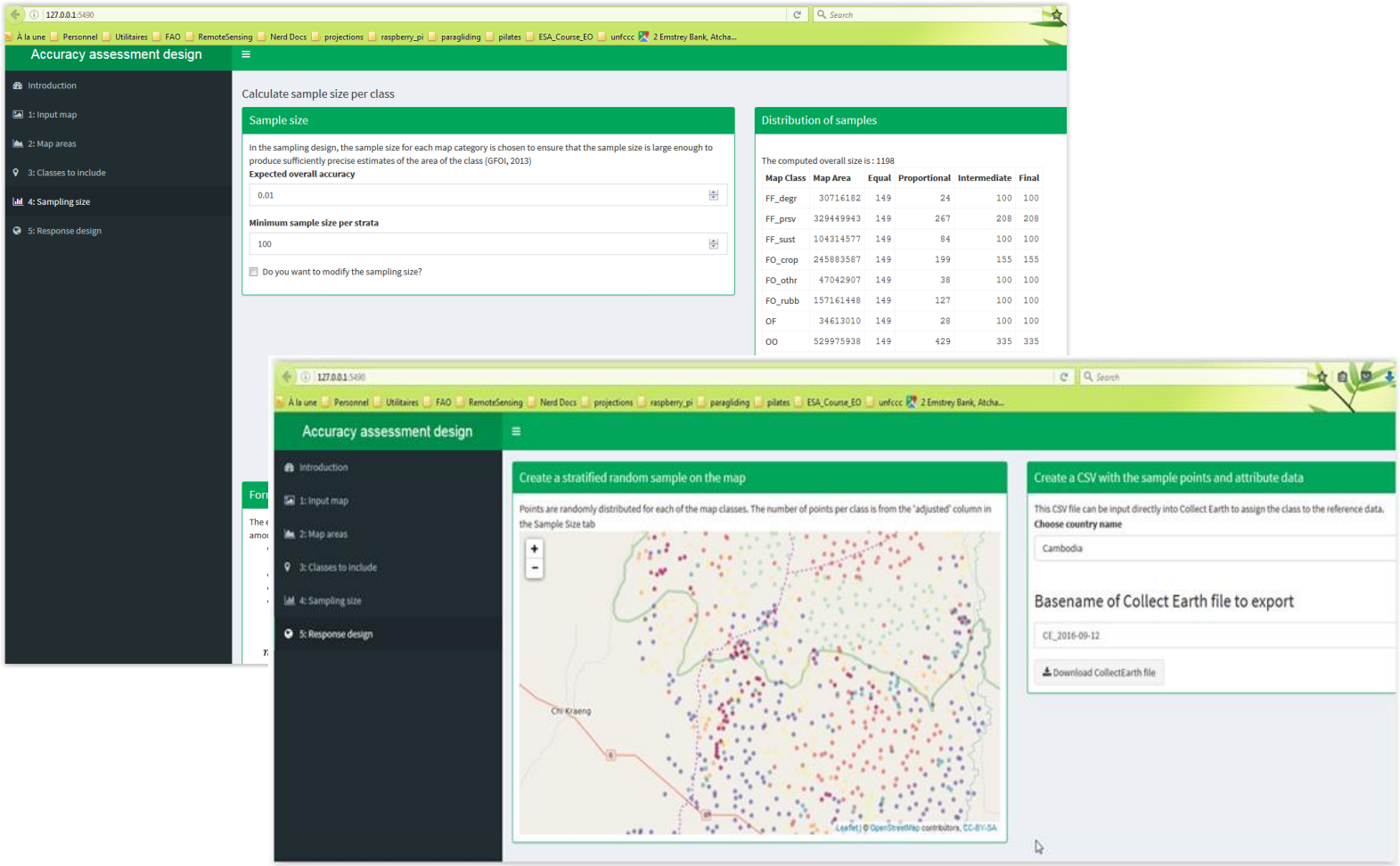
Manual correction of errors





Loss: 22% area reduction after manual corrections
Gain: 38% area reduction after manual corrections

Sampling design (see hands-on session)



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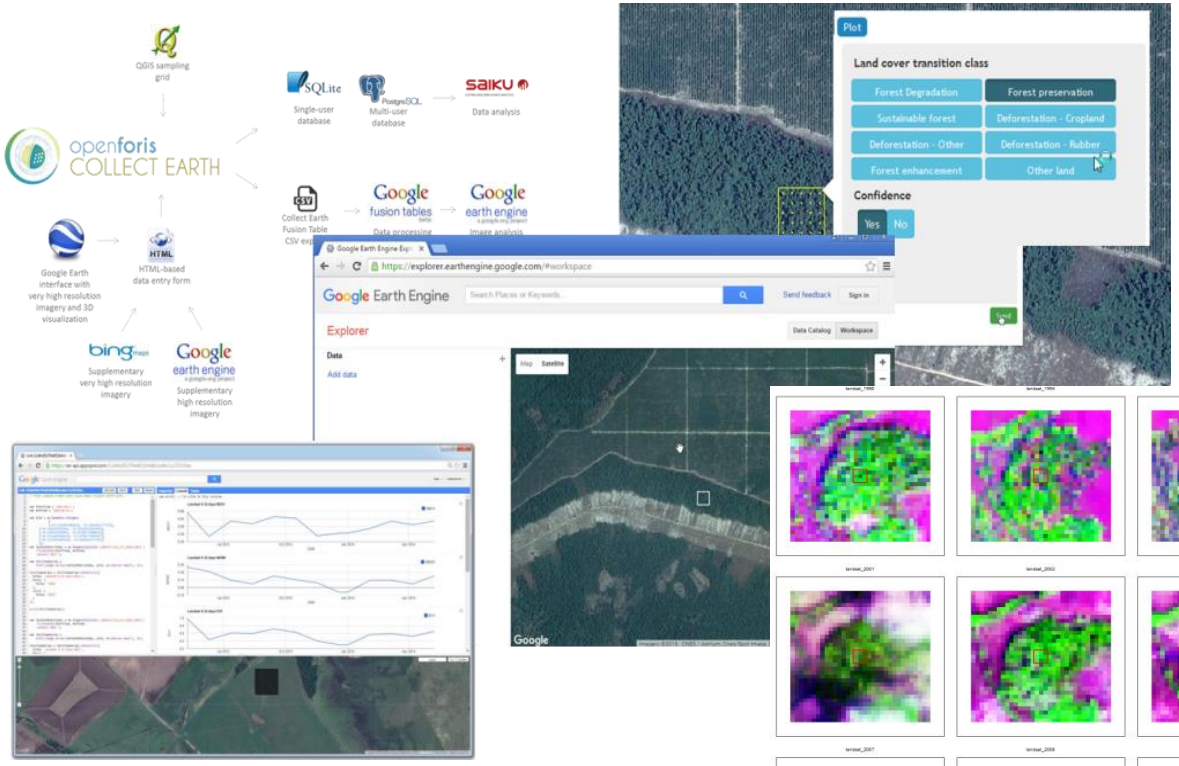
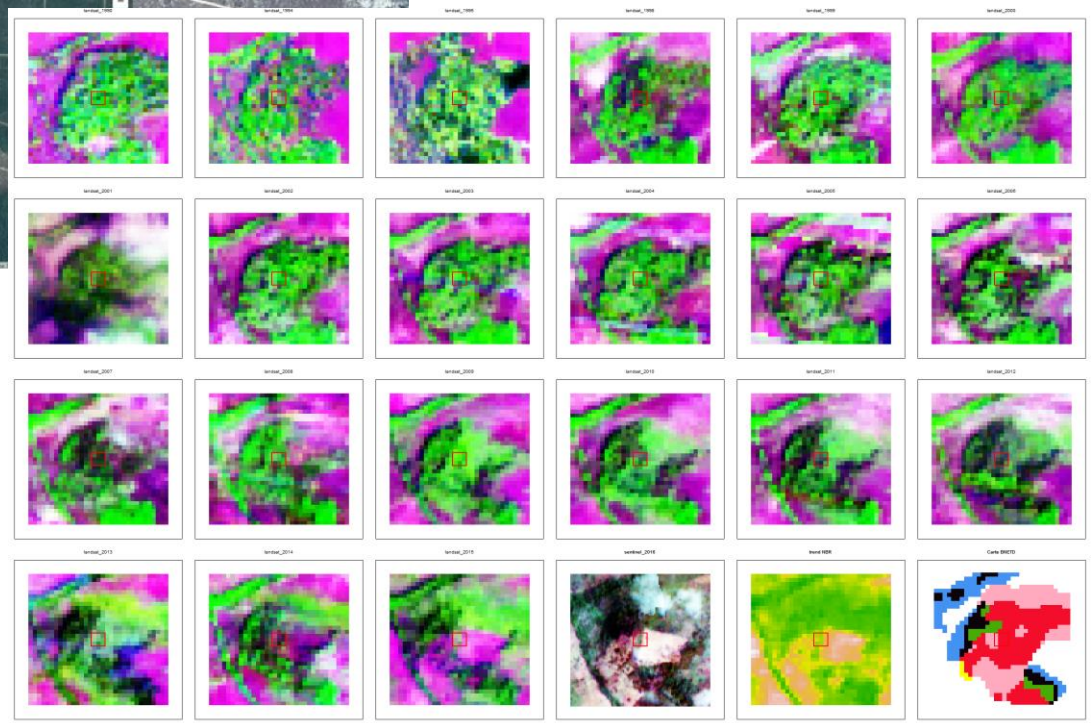
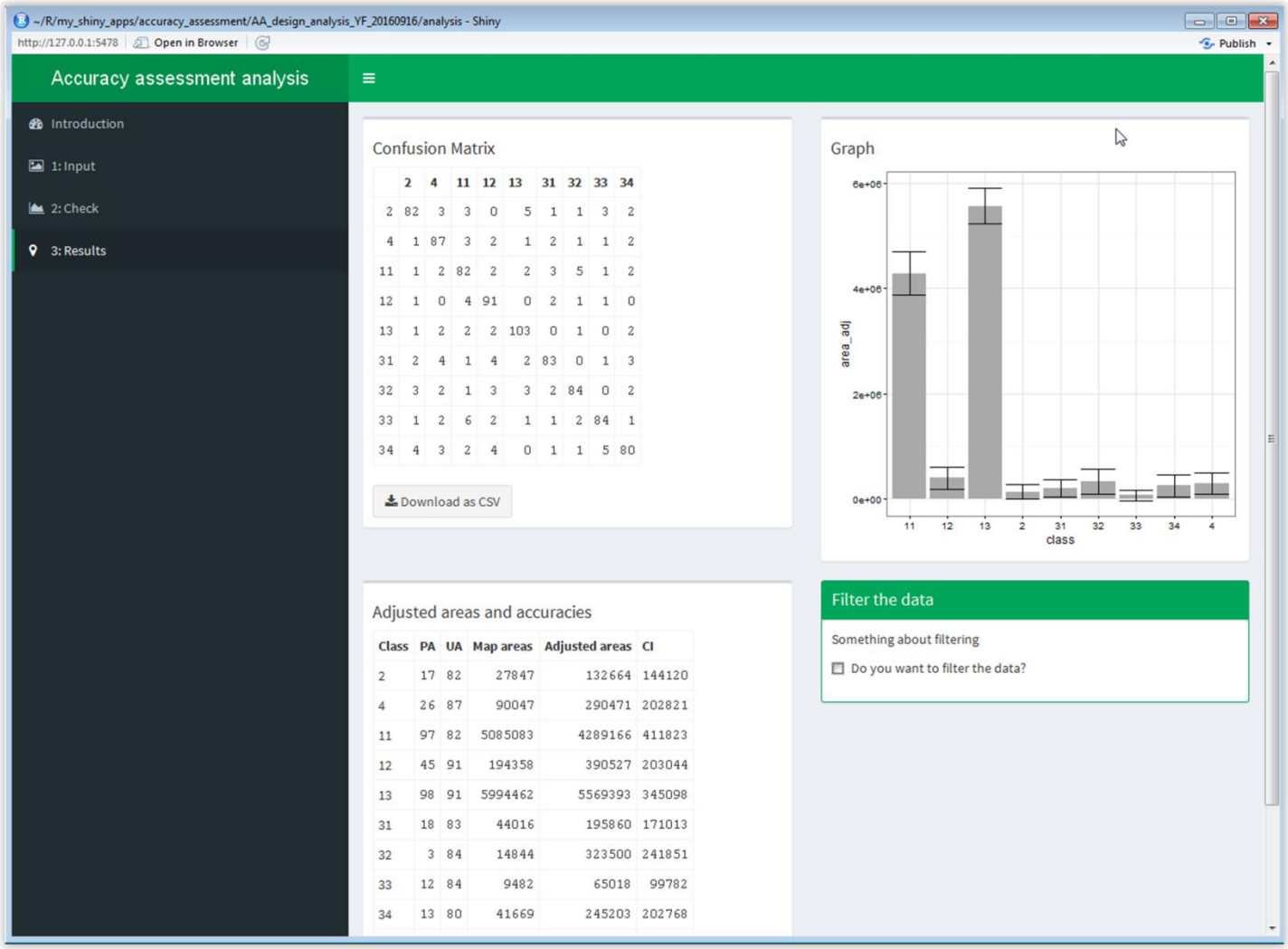
Response design





Analysis design (see hands-on session)



	2	4	11	12	13	31	32	33	34
2	82	3	3	0	5	1	1	3	2
4	1	87	3	2	1	2	1	1	2
11	1	2	82	2	2	3	5	1	2
12	1	0	4	91	0	2	1	1	0
13	1	2	2	2	103	0	1	0	2
31	2	4	1	4	2	83	0	1	3
32	3	2	1	3	3	2	84	0	2
33	1	2	6	2	1	1	2	84	1
34	4	3	2	4	0	1	1	5	80

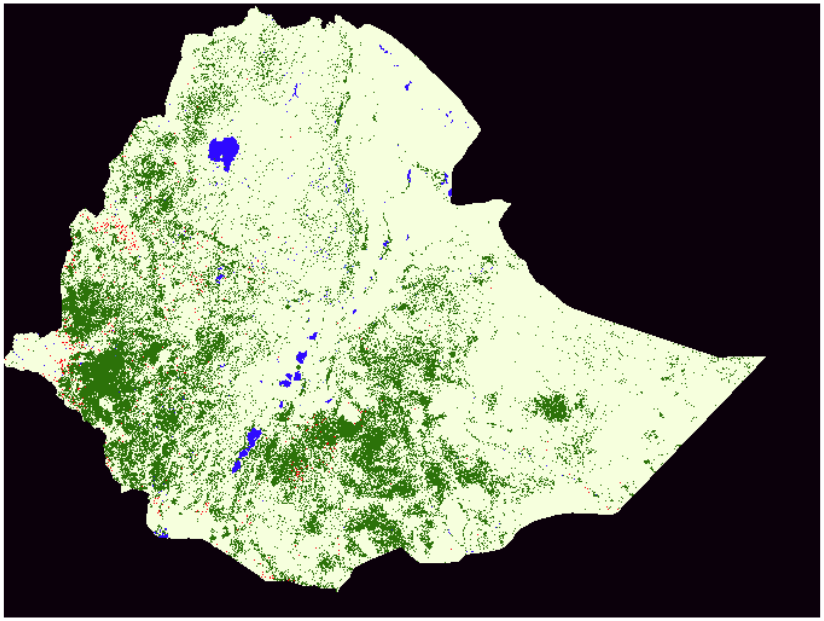
Class	PA	UA	Map areas	Adjusted areas	CI
2	17	82	27847	132664	144120
4	26	87	90047	290471	202821
11	97	82	5085083	4289166	411823
12	45	91	194358	390527	203044
13	98	91	5994462	5569393	345098
31	18	83	44016	195860	171013
32	3	84	14844	323500	241851
33	12	84	9482	65018	99782
34	13	80	41669	245203	202768

Timeframe of the process

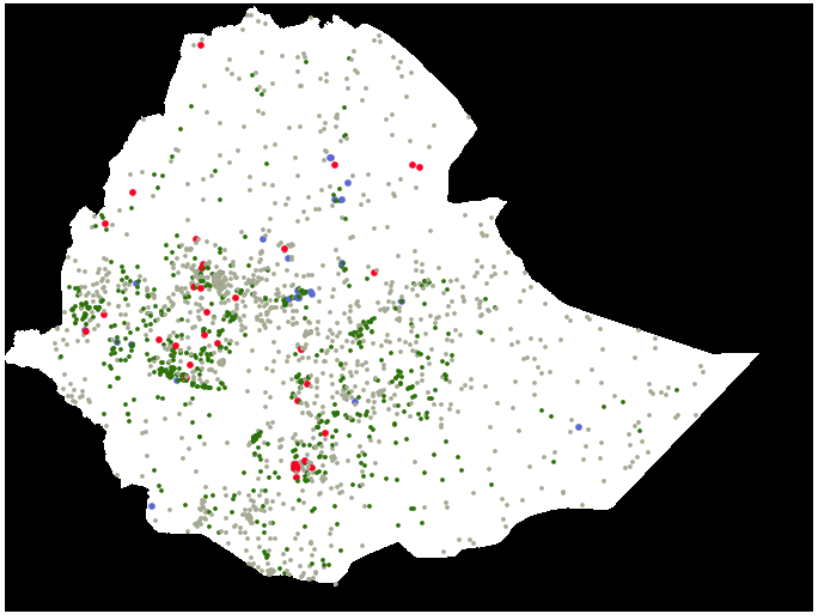
Generate training data: automatic + checking	= 2 days
Create mosaic and run supervised change detection	= 2 days
Manually edit and correct the map	= 1 month
Assess accuracy and correct bias	= 1 week

Results

Map strata



Sampling points

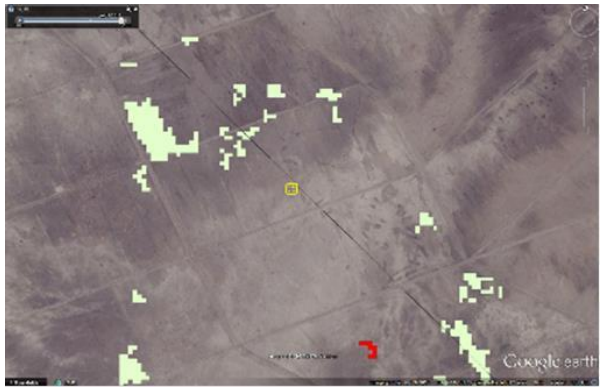


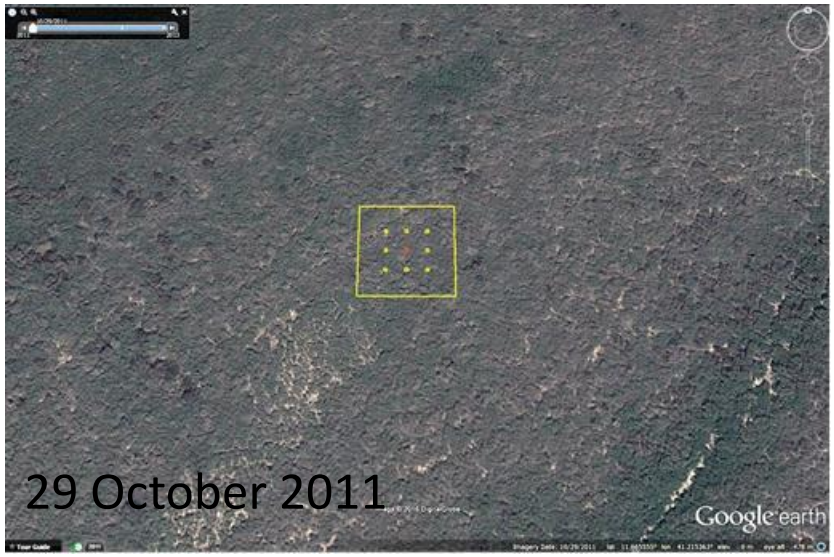
	raw	bias corrected	CI
Forest loss	372,188	1,192,559	579,471
Forest gain	39,960	246,063	216,062
Stable Forest	22,025,622	22,195,021	1,716,067
Stable non-Forest	91,975,841	90,779,968	1,794,784

Omission errors

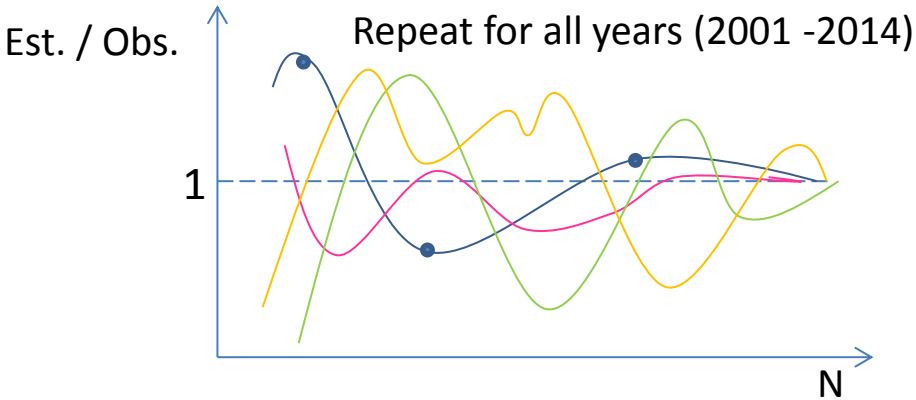
Map: Stable NF
Reference: Loss

Afar region





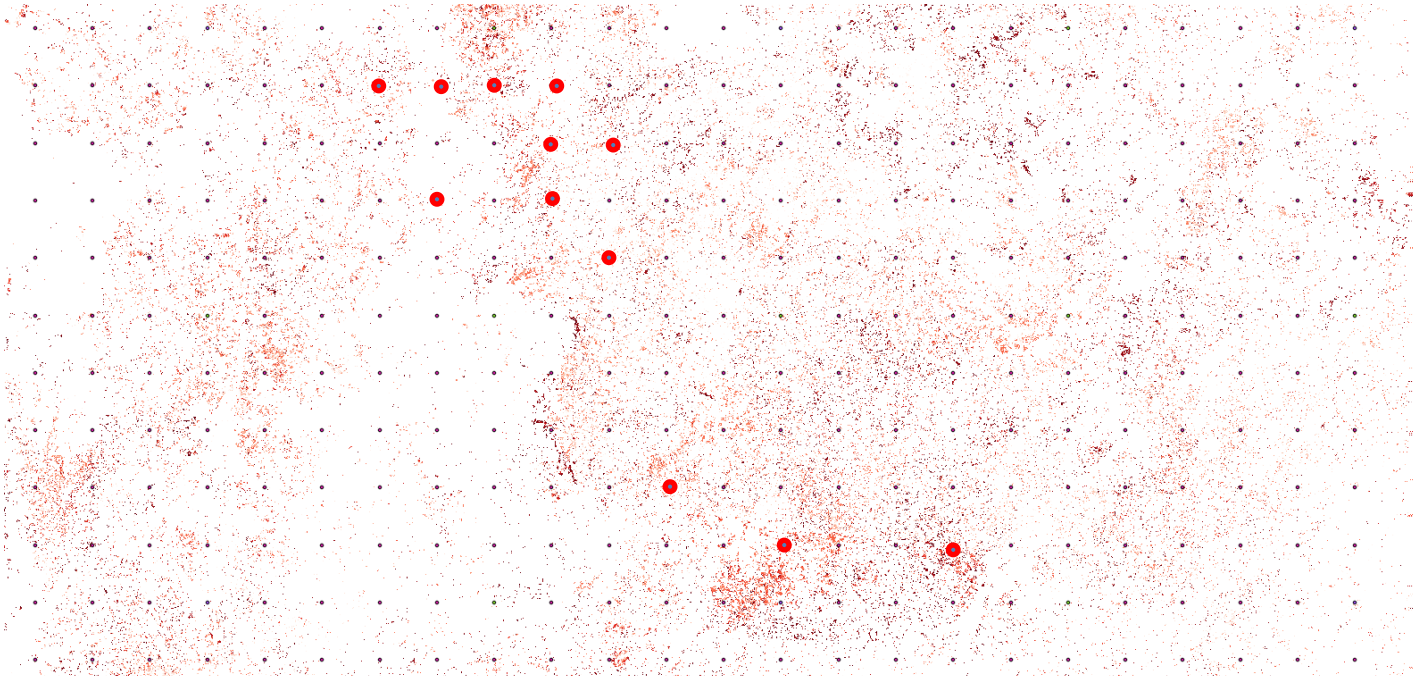
What about systematic sampling ?



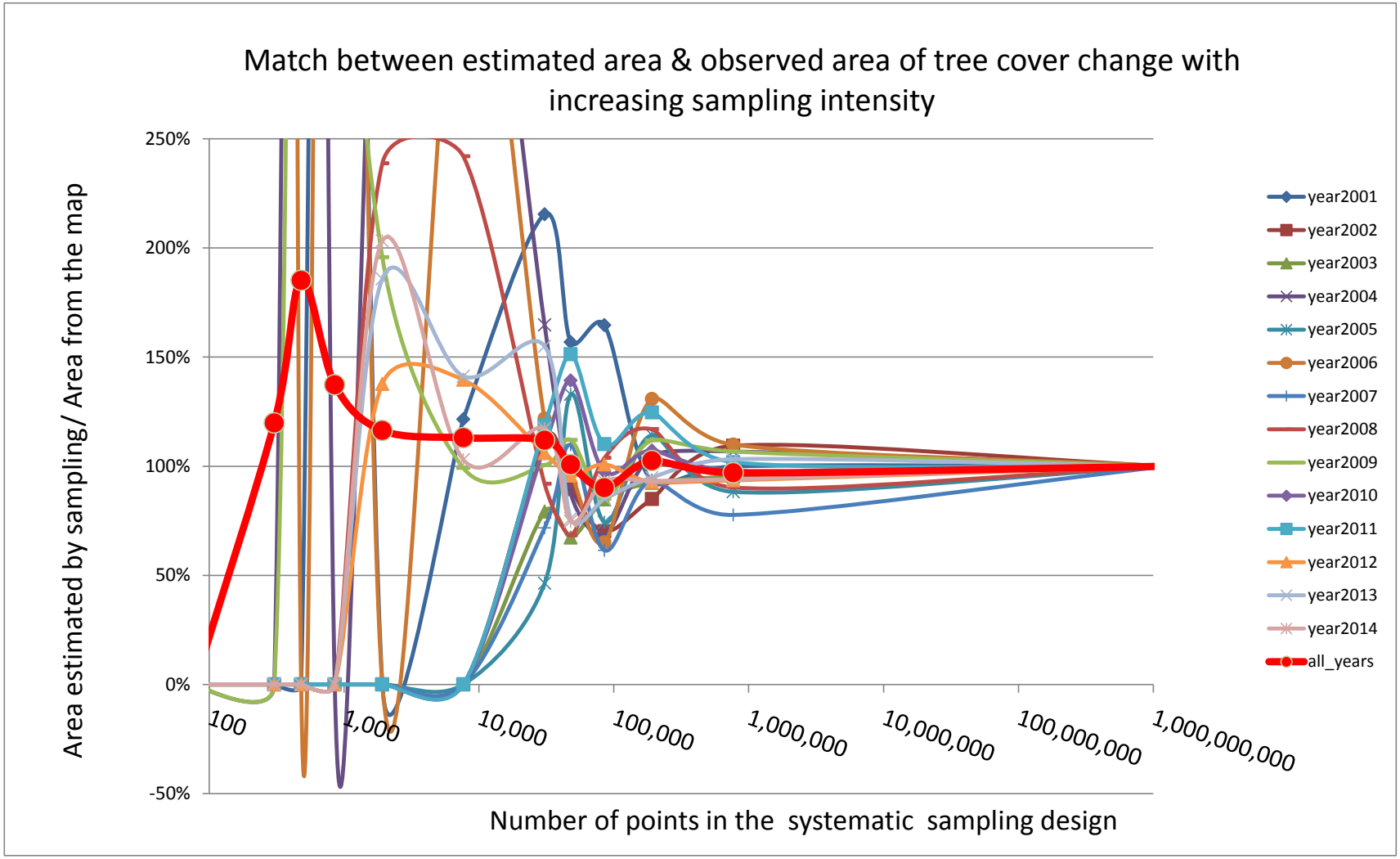
n points intersect loss

N points in total

$$Area\ Est. = \frac{n}{N} \times Total\ Area$$



Systematic sampling of GFC in Ethiopia



Lessons learned

Learning process:	first time this is EVER being done
Sensitive process:	reference data quality is CRITICAL
Compliant process:	bias-corrected estimates for BUR
Improvable process:	COMBINED approaches AREAL s.s.d ? “CALIBRATE” the RS teams