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The potential of dense Landsat time series to characterize historical dynamics and monitor future disturbances in human-modified rainforests of Indonesia

Hadi[1,*] (hadi.hadi@aalto.fi), Andrey Krasovskii[2], Victor Maus[2,3], Ping Yowargana[2], Stephan Pietsch[2] and Miina Rautiainen[1,4]

[1] Aalto University, School of Engineering, Department of Built Environment, Espoo, Finland
[2] Ecosystems Services and Management (ESM) Program, International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria
[3] Institute for Ecological Economics, Vienna University of Economics and Business (WU), Wien, Austria
[4] Aalto University, School of Electrical Engineering, Department of Electronics and Nanoengineering, Espoo, Finland

1. Motivation

Forests are central in the breakthrough 2015 Paris climate agreement. It has been estimated that tropical forest conservation and restoration could provide half of the target net emission reduction. The tropical region of insular South East Asia, notably the country of Indonesia, is a global hotspot of deforestation. Satellite remote sensing is the only viable means to map and monitor the vast Indonesian rainforests, to support REDD+ Tier-3 Measuring, Reporting, and Verifying requirements and the reporting principles of consistency, accuracy, comparability, completeness, and transparency. Landsat data have the appropriate spatial resolution (30 m) to capture human influence on the forest landscape, as well as provide the longest, rigorously calibrated time series (30 years+) which can aid in estimating Reference Emission Levels and operating a National Forest Monitoring System. Previous forest change detection studies using Landsat Time Series (LTS) in Indonesia were typically based on annual or epochal composites, and thus were yet to fully exploit the dense (i.e., "all available data") LTS potential for sub-annual detection, and may miss transient changes due to the rapid vegetation regrowth. More recently, there have been significant advances in the development of dense time series algorithms. The objective of this study is to investigate the potential of using LTS data and data-driven dense time series algorithms for the detection of deforestation events at sub-annual time scales in Indonesian tropical rainforests.

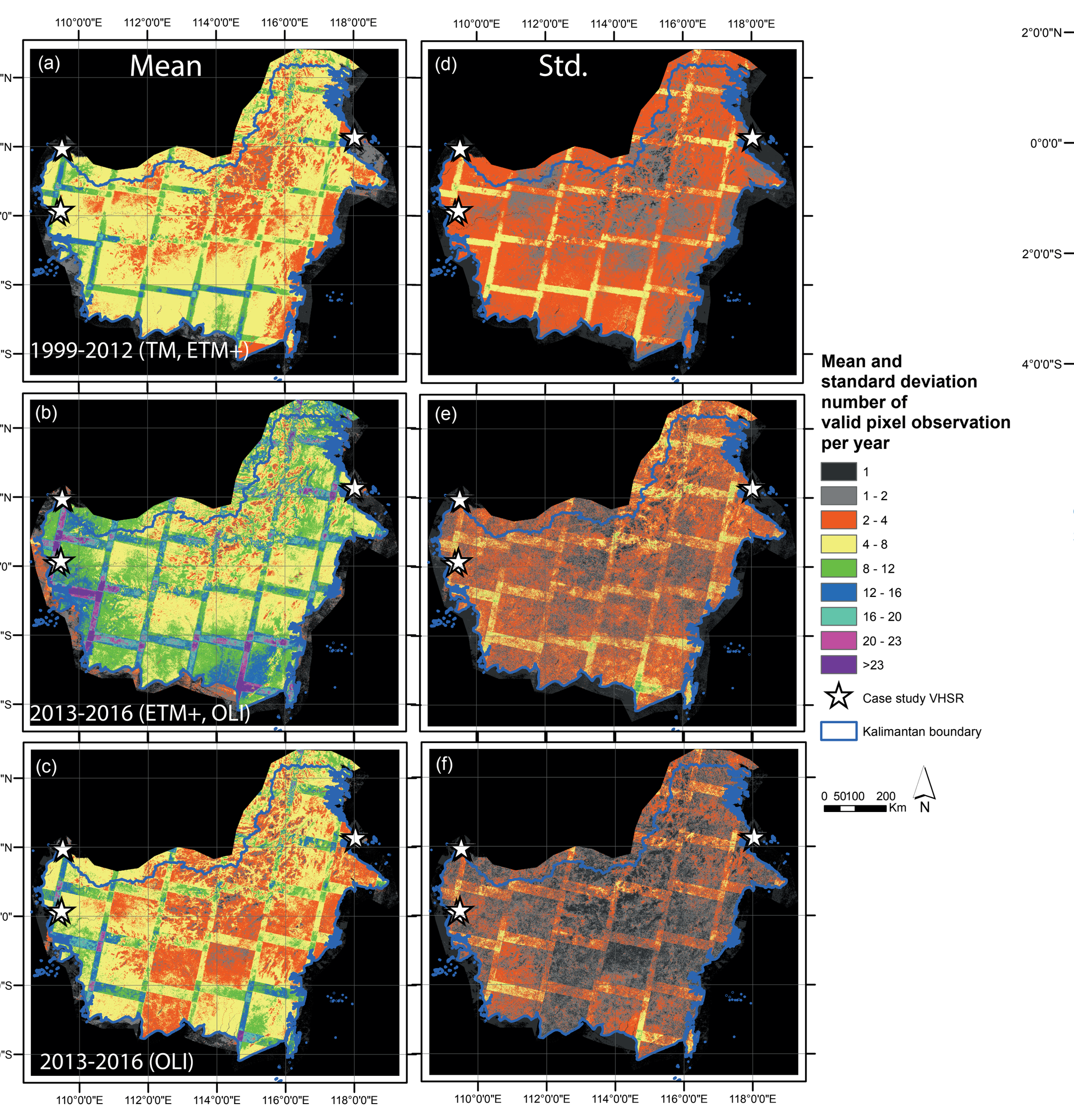
2. Satellite and reference data

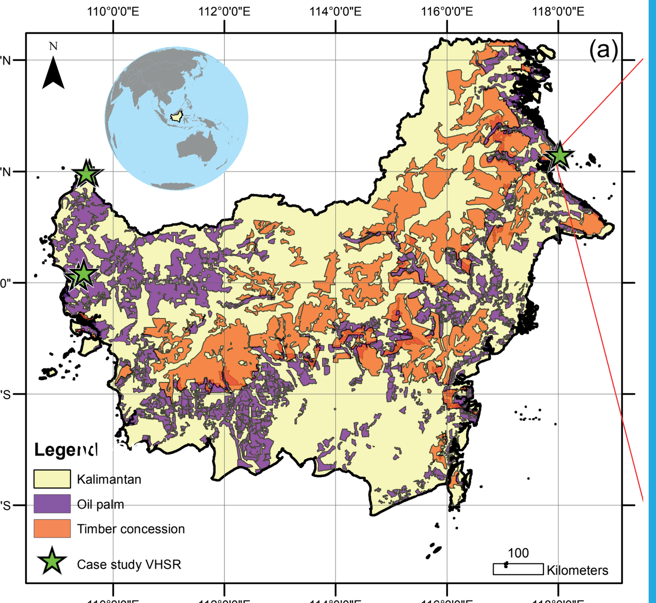
We used the cloud-based platform google Earth Engine (EE) to retrieve all available Landsat surface reflectance images in the USGS archive, including Landsat-5 TM (1984-2012), Landsat-7 ETM+ (1999-2016), and Landsat-8 OLI (2013-2016) sensors, as temporal stacks for our study locations. Clouds and shadows were masked using the CFMask product.

We used the normalized difference moisture index (NDMI) as it shows high sensitivity (most clear signal) in response to deforestation events in our study area, with signal change magnitude most visibly larger than ephemeral noise (e.g., un-masked clouds).

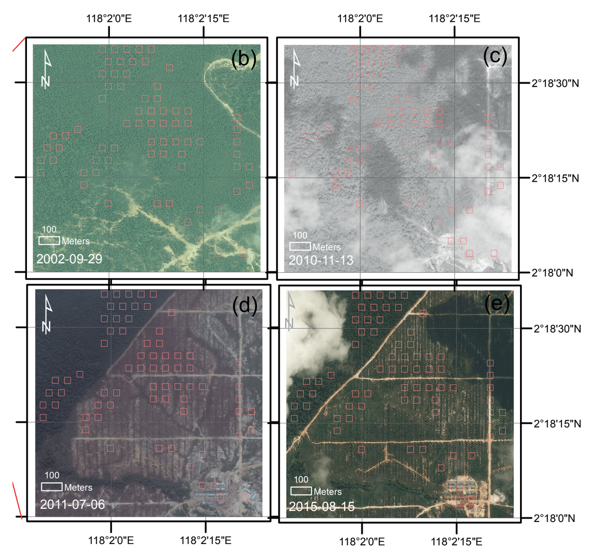
Reference sample pixels (435 samples: 227 "deforestation" samples and 208 "forest-remaining-forest" samples) were interpreted from six very high spatial resolution images obtained through Digital Globe viewing service.

Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, S.; Thau, D.; Moore, R. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment 2017, 202, 18–27

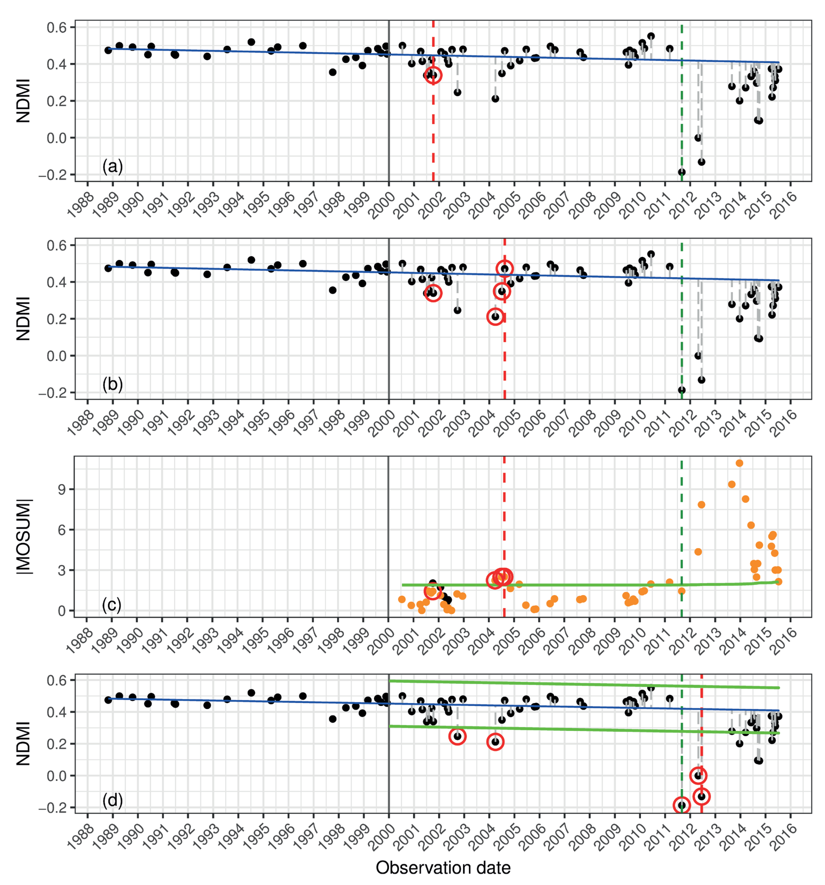




Data source: from http://www.glad.umd.edu/dataset/primary-forest-cover-loss-indonesia-2000-2012.; http://www.greenpeace.org/seasia/id/Global/seasia/Indonesia/Code/Forest-Map/en/data.html,



3. Dense time series algorithms for deforestation detection



Algorithm 1: BFAST Monitor

Fit a trend model to the history period ($t = 1, ..., n$). Monitor discrepancies (i.e., moving sum of residuals, MOSUM) between model predictions and observations in the monitoring period ($t = n+1, ..., N$). Breakpoint signalled if MOSUM (*process*) exceeds the statistical boundary.

Algorithm 2: BFAST Monitor with Consecutive Anomalies Criterion (CAC)

BFAST Monitor's statistical boundary and MOSUM updating

```
for t = n + 1, ..., N – cons + 1 do
    if process_t > boundary_t then
    flag_t = "changeFlagged"
        for j = t, ..., (t + cons – 1) do
            if all(process_j > boundary_j) and
              (T_{t+cons–1} – T_t) ≤ 2 then
                flag_{t+cons–1} = "changeConfirmed"
                flag_t = "changeFirstFlagged"
                break
            else
                flag_t = "noise"
            end if
        end for
    end for
end for
```

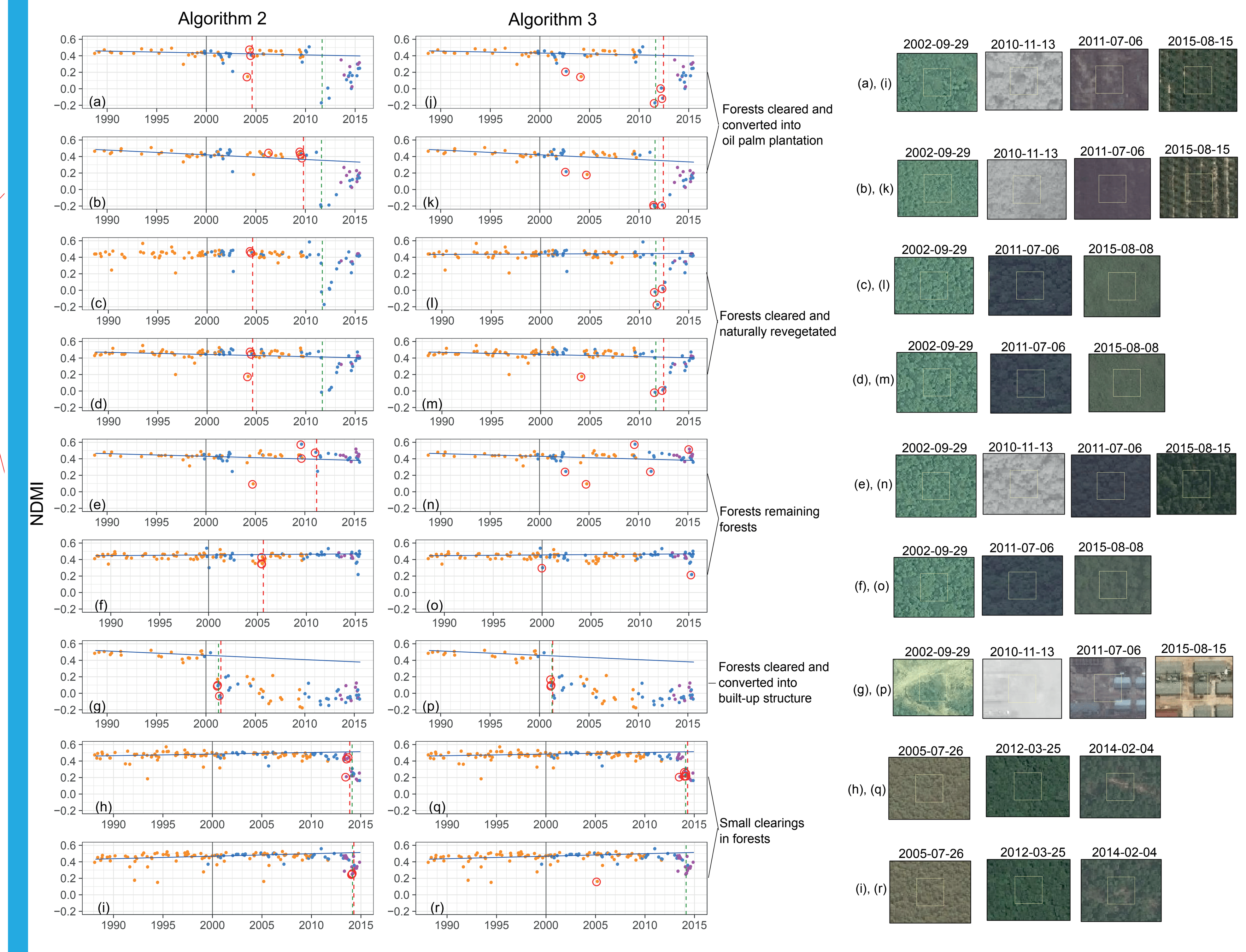
Algorithm 3: Alternative decision boundary with CAC

$$\text{boundary} = k \times \text{RMSE}_{\text{history}}$$

Verbesselt, J.; Zeileis, A.; Herold, M. Near real-time disturbance detection using satellite image time series. Remote Sensing of Environment 2012, 123, 98–108.

Zhu, Z.;Woodcock, C.E. Continuous change detection and classification of land cover using all available Landsat data. Remote Sensing of Environment 2014, 144, 152–171

4. Demonstrations of the deforestation detection algorithms



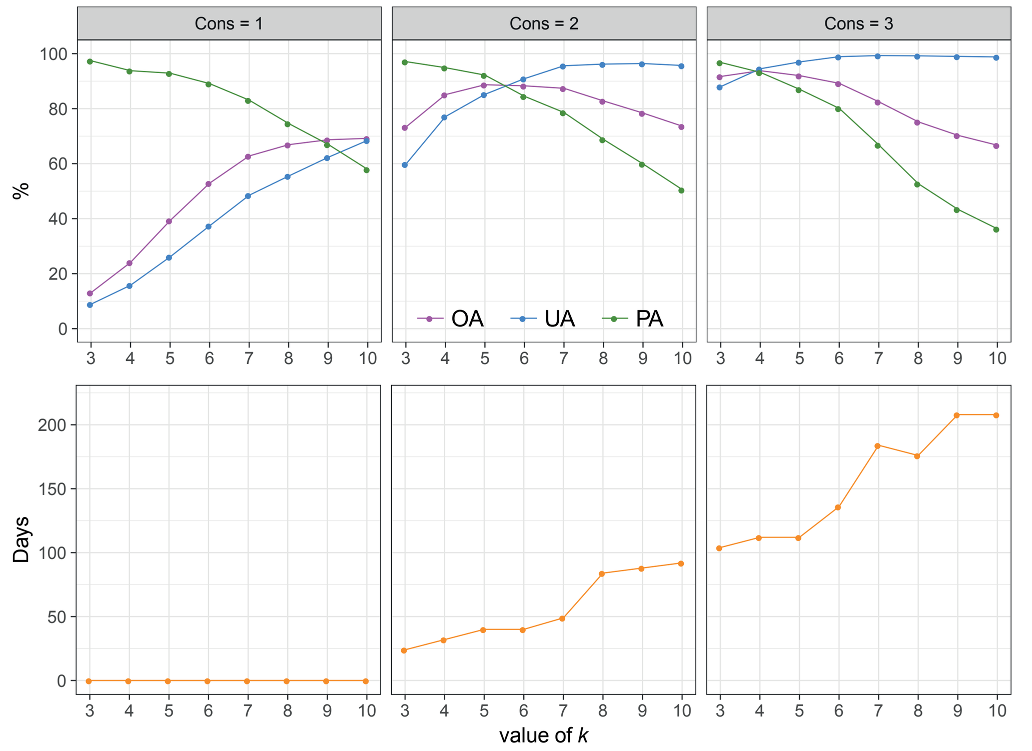
5. Spatial and temporal accuracies

Algorithm	History denoised	*cons*	*k*	update MOSUM	OA (%)	UA (%)*	PA (%)*	MTL (days)	MTL (# obs)
1	No	NA	NA	NA	43.0	32.6	100.0	24	1
1	Yes	NA	NA	NA	8.3	5.0	100.0	0	0
2	Yes	3	NA	No	15.2	9.8	100.0	128	2
2	Yes	3	NA	Yes	15.9	9.9	100.0	128	2
2	No	3	NA	No	51.7	40.3	99.3	136	3
2	No	3	NA	Yes	53.3	41.3	99.3	132	3
3	No	3	4	NA	93.8	94.5	93.2	112	2
3	Yes	3	4	NA	94.7	95.0	94.6	112	2
3	No	2	5.5	NA	88.7	87.0	89.9	40	1
3	Yes	2	5.5	NA	89.0	85.3	92.7	40	1

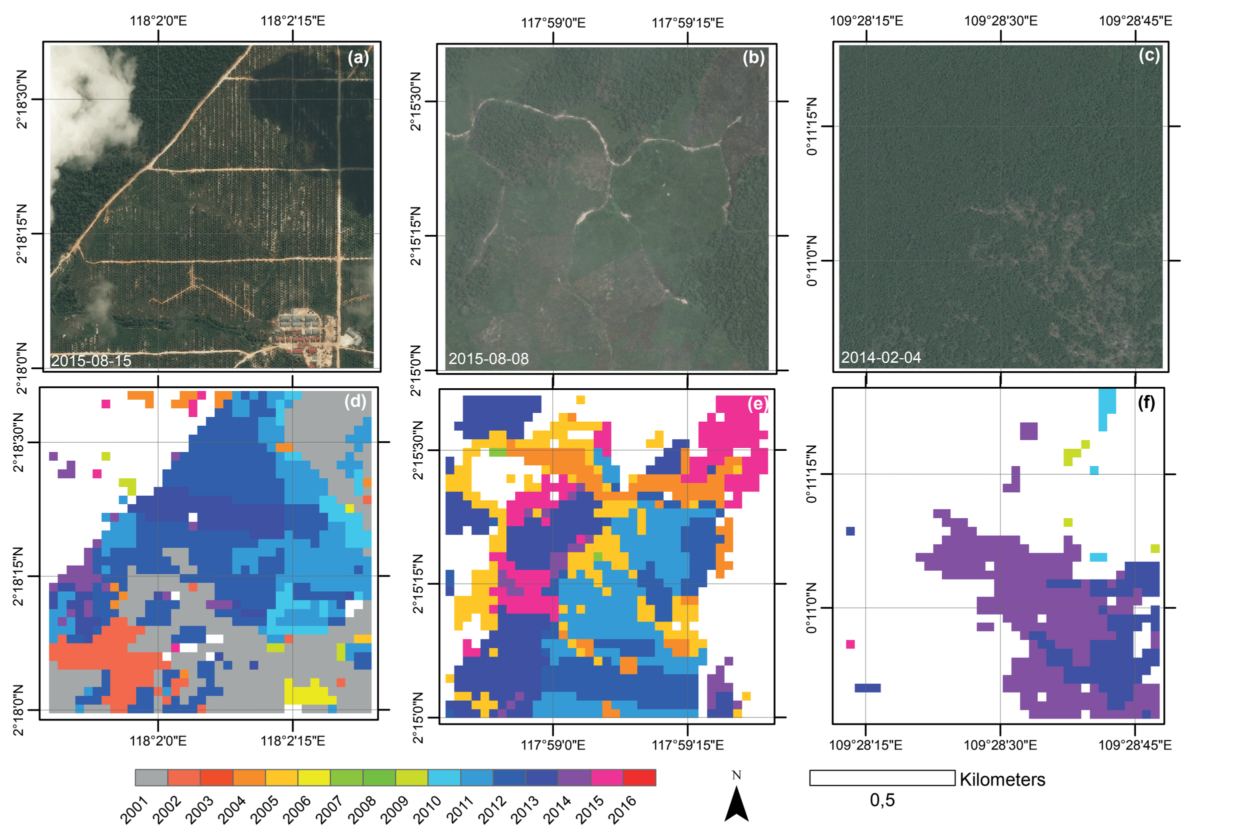
* deforestation class

Overall accuracy, $OA(\%) = 100 \times (TP + TN)/(TP + TN + FP + FN)$
User's accuracy, $UA(\%) = 100 \times (TP/(TP + FP))$
Producer's accuracy, $PA(\%) = 100 \times (TP/(TP + FN))$
Median temporal lag, $MTL = \text{median}[T_{conf}(T_{conf} \geq T_{ref}) - T_{ref}]$

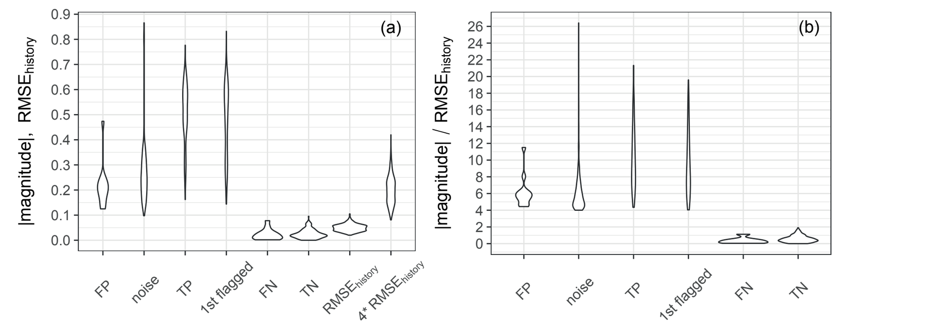
TP: true positive; TN: true negative; FP: false positive; FN: false negative; T_{conf}: confirmed date (algorithm); T_{ref}: reference date



6. Wall-to-wall assessment



7. Analysis of change magnitude



9. Outlook

- Magnitude-informed spatio-temporally adaptive *cons*.
- Publish the algorithm codes in public repository.
- Collect large reference sample representative of the larger Kalimantan area, to evaluate the robustness of the methodology for producing large area estimates and statistics.
- Investigate spectral-temporal features in dense LTS data to automate mapping of natural forests and plantations.
- Multisensor and ensemble (algorithm, indices) methods.

8. Conclusions

- Cloud-free observation density from combined TM, ETM+, and OLI sensors indicated feasibility of sub-annual deforestation mapping and monitoring.
- Frequent noise in LTS (due to remnant clouds), and its large range of change magnitude, caused high commission errors in the implemented BFAST Monitor (Algorithm 1).
- CAC improved the spatial accuracy of BFAST Monitor (in Algorithm 2); however, alternative decision boundary (Algorithm 3) dramatically improved the spatial accuracy.
- Therefore, the presented methodology based on dense LTS data and optimal Algorithm 3 is promising for use cases in which high spatial accuracy is a priority, such as carbon accounting for the purpose of REDD+ reporting.
- The temporal accuracy was not adequate for near-real-time monitoring. However, looking forward, combining Landsat data and the now fully-operational (i.e., global and systematic acquisitions realized) Sentinel-2A and Sentinel-2B will provide < 4 days revisit interval, thus potentially improves cloud-free observation density, and consequently the temporal accuracy of deforestation detection.

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