Advances in global land cover research: Hybrid change detection, time series postprocessing, and spatiotemporal deep learning

Dainius Masiliūnas[1], Nandin-Erdene Tsendbazar[1], Lili Xu[3], Liam Adam[1], Rob Burger[1], Lennart Murk[1], Sven-Arne Quist[1], August Slomp[1], Qin Xu[1], Duyen Bui[1], Diego Marcos[4], Laura Cue La Rosa[1], Martin Herold[2]

1. Introduction

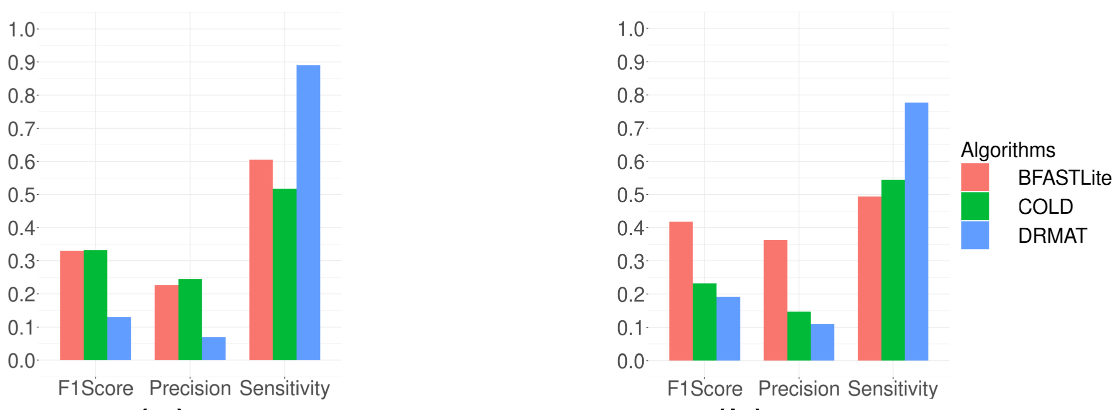
At the Laboratory of Geoinformation Science and Remote Sensing of Wageningen University, we are investigating ways to improve land cover mapping and land cover change detection techniques. Our focus is on land cover fraction time series and unsupervised change detection. There are three research directions that attempt to tackle research questions from different perspectives:

Hybrid (supervised and unsupervised) change detection

Change detection techniques reduce spurious change between land cover maps. However, the accuracy of unsupervised land cover change detection is limited to around 0.36 F_1 score. Tested solutions:

1. **BRF framework**: combine multiple unsupervised BFAST Lite outputs (break magnitude, R^2) and vegetation indices in a supervised Random Forest (RF) to predict true breaks (Xu et al. 2022).
   - Outcome: RF acts as a smart filter, spurious breaks reduced, F_1 score **increased to 0.62**.
2. Use **Random Forest directly** to detect breaks (Adam et al. 2024).
   - Outcome: RF alone increases F_1 score to **0.45**, outperforming BFAST Lite alone, but not BRF.
3. Combine outputs (magnitudes, R^2) from **multiple unsupervised change detection algorithms in RF** (Quist et al. 2023).
   - Outcome: Combined RF F_1 **decreased to 0.28**, not better than either BFAST Lite or DBEST separately, Prophet performed worst.
4. **Multivariate change detection**: use natively multivariate unsupervised change detection models or aggregate univariate outputs (Bui et al. 2025).
   - Univariate aggregation technique **achieved 0.44** F_1 score and outperformed natively multivariate models.

Summary: BRF framework worked best. Aggregating multiple univariate model outputs shows promise. Prophet and RF directly not well suited for land cover change detection.



(a) NDVI input (b) Six band input

Figure 1: Accuracy of change detection algorithms with univariate and multivariate input (Bui et al. 2025).

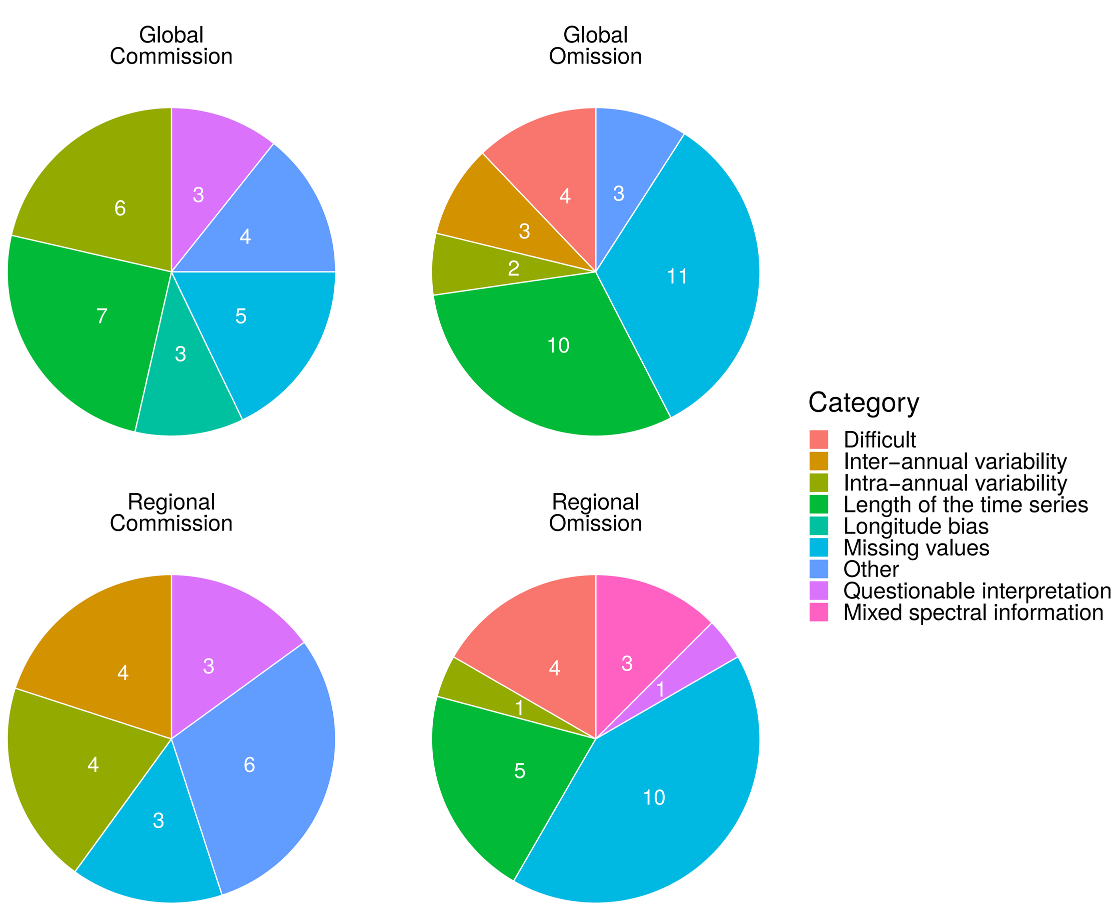


Figure 2: Categorisation of the sources of random forest based land cover change detection errors for global and regional scales. Note: some errors had multiple dominant causes and thus belonged to multiple categories. Adapted from Adam et al. (2024).

Postprocessing land cover fraction predictions

Machine learning models are used to predict land cover. Working on fractions or probabilities allows tracking gradual changes as well. Spurious change between subsequent maps can be reduced by postprocessing the time series of land cover maps. Tested solutions:

1. **Markov Chain**: optimise differences between time steps of land cover fractions (Burger et al. 2022).
   - Outcome: **reduced RMSE by 1.1** on average for yearly maps and by 6 for year-to-year change.
2. **Recurrent and temporal RF**: include previous/next time step as feature in RF (Masiliūnas et al. 2025a, in preparation).
   - Outcome: Recurrent and temporal RF increased yearly map RMSE by 2 and decreased change RMSE by only 1. They **performed worse than Markov chain** or even a linear smoother.
3. **Unsupervised change detection**: BFAST Lite used as preprocessing technique to remove noise from time series while retaining large changes (Masiliūnas et al. 2025b, in preparation).
   - Outcome: BFAST Lite **reduced change MAE** by half, but very slightly increased yearly MAE. Can be used to obtain information about LC trends.

Summary: Markov Chain and BFAST Lite reduce spurious change in LC time series. RF directly not suitable for LC time series postprocessing.

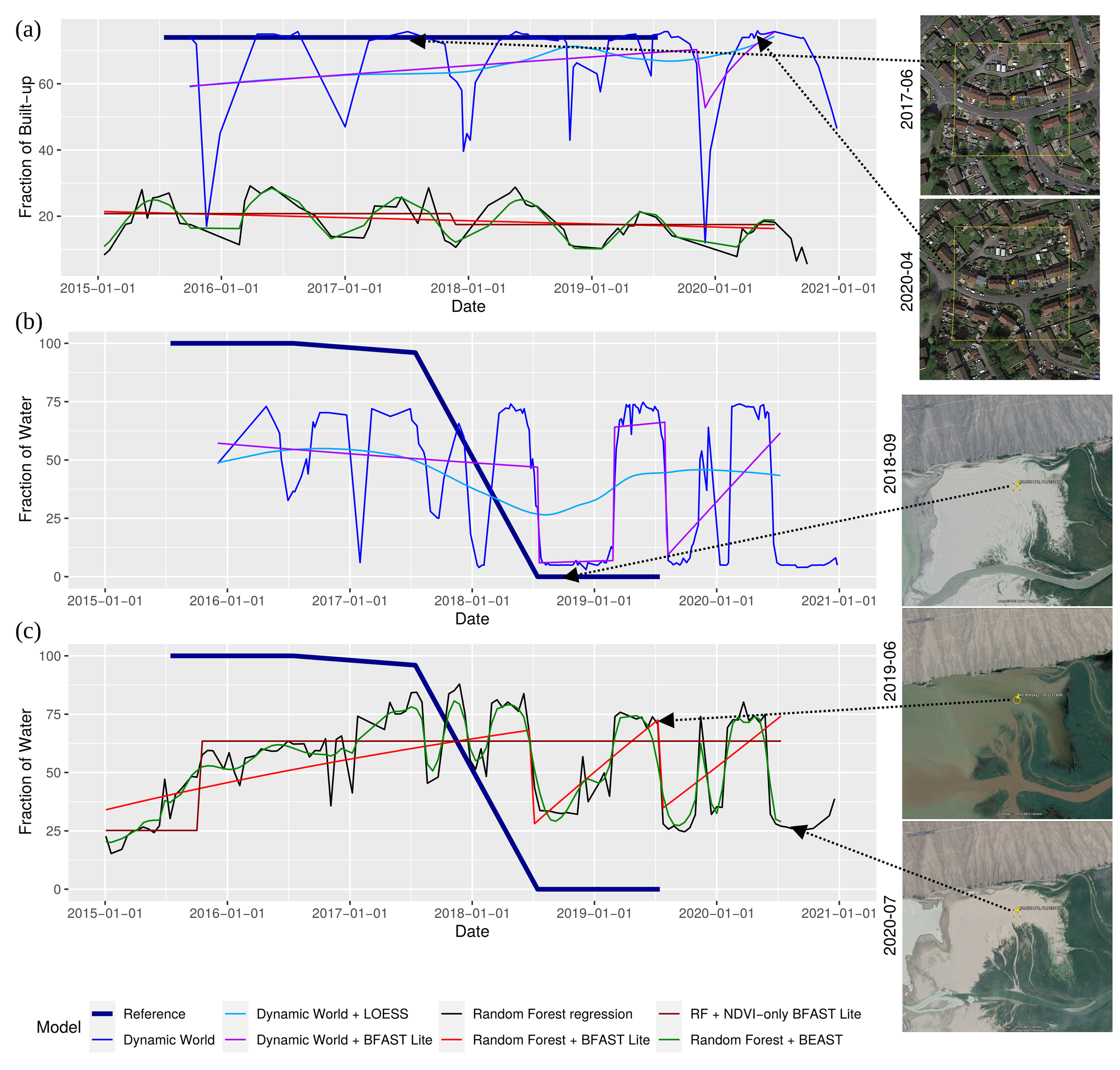


Figure 3: Examples of LC time series postprocessing. a) built-up class fraction in a suburban area of Kingswood, Bristol, UK. No change. b & c) water fraction of the Ili river draining into the Kapchagay reservoir in Kazakhstan. Water fluctuates seasonally, but relatively stable between 2015 and 2018 . Abrupt drought events happened in 2014-08, 2018-08 and 2019-08. Adapted from Masiliūnas et al. (2025b).

Improving land cover fraction predictions using machine/deep learning

Postprocessing can only help to reduce variability, but cannot solve mistakes in machine learning predictions. Ideally, postprocessing would not be needed, if the ML model was accurate enough. Tested solutions:

1. **Random Forest regression** (Masiliūnas et al. 2021).
   - Outcome: **RF outperformed** other shallow learning models (linear, lasso, multilayer perceptrons).
2. Long-Short Term Memory (**LSTM**) (Slomp et al. 2025, in review).
   - Outcome: LSTM performed **similarly** to RF, but is **less flexible** in training.
3. **3D CNN** and **2D CNN-RNN** combination (Murk et al. 2025).
   - Outcome: **3D CNN is an improvement** over a 2D CNN-RNN combination.
4. **Vision Transformer** (Xu et al. 2025).
   - **ViT is a significant improvement** over the 3D CNN (see Table 1).

Summary: ViT performed the best, but still has further room for improvement. RF has advantage of not needing spatiotemporal context to train on.

Table 1: MAE per land cover class across the studies. Classes in italic are combinations of smaller sample size classes. Adapted from Xu et al. (2025).

Model	**RF**	**LSTM**	**3D CNN**	**ViT**
Area	Global	Global	Africa	Africa
Spatial res.	100 m	100 m	20 m	20 m
Years	2015	2015–2018	2015–2018	2015–2018
Bare	6	8	17.5	11.7
Crops	6	6	19.5	15.0
Herbaceous	20	22	32.5	30.5
Shrubs	9	8	22.0	17.8
Trees	11	11	18.1	13.6
Built-up	3	3	3.0	3.0
Water	2	3	5.0	4.4

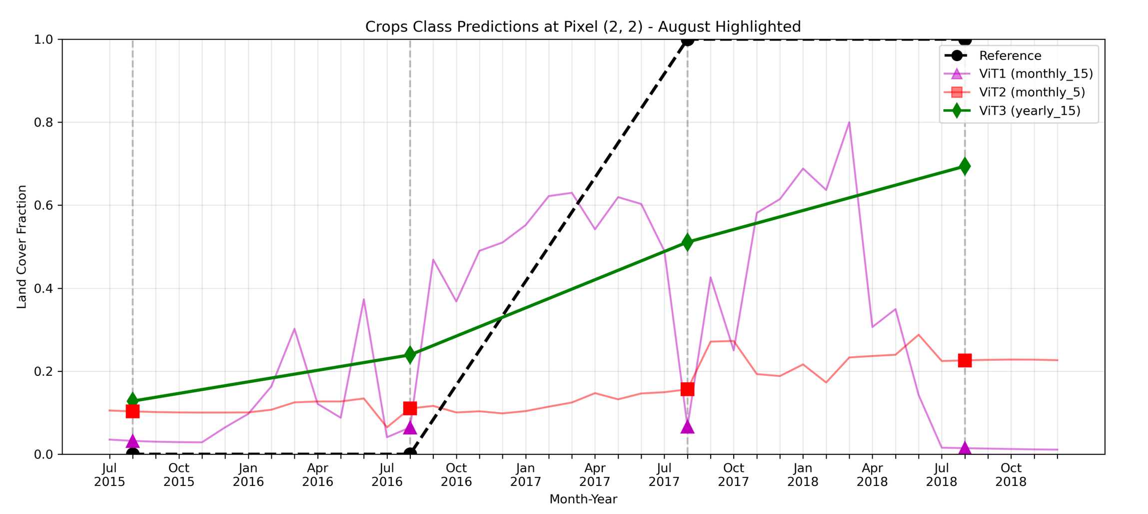


Figure 4: Line plots of the predictions of Vision Transformer models for the Crop class in Sudan, where a change in fraction was observed. Adapted from Xu et al. (2025).

Outlook

Future studies will involve more elaborate aggregation for BFAST Lite, integration with postprocessing and R SITS package, large-scale analysis of LC trends, ViT application at a large scale and the integration of high-level products to improve LC and change mapping.

Acknowledgements

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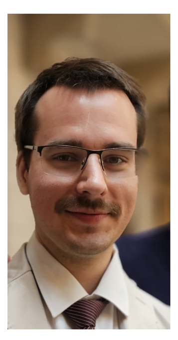
This work was partly funded by the Open Earth Monitor Cyberinfrastructure project, which has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No.101059548.



Dainius Masiliūnas
Email: dainius.masiliunas@wur.nl
LinkedIn: https://www.linkedin.com/in/greatemerald
ResearchGate: https://www.researchgate.net/profile/Dainius_Masiliunas
Laboratory of Geo-information Science and Remote Sensing, http://wur.eu/grs
P.O. Box 47, 6700 AA Wageningen

[1] Laboratory of Geo-Information Science and Remote Sensing, Wageningen University & Research, Wageningen, Netherlands
[2] Helmholtz Centre Potsdam, German Research Centre for Geosciences (GFZ), Potsdam, Germany
[3] Central China Normal University, Wuhan, P. R. China
[4] Inria, Montpellier, France

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