WAGENINGEN
UNIVERSITY & RESEARCH

Improving global land cover fraction change mapping using temporal deep learning

August Slomp[1], Dainius Masiliūnas[1], Nandin-Erdene Tsendbazar[1]

Background

- Land cover monitoring is increasingly important due to climate change and human activity.
- Conventional products use discrete classes, which can oversimplify heterogeneous areas and reduce accuracy.
- Land cover *fractions* represent each pixel as class proportions, better capturing spatial *and* temporal variability: they enable change quantification.

Objective

Robust fraction time series mapping.

- Current methods produce inconsistent fraction time series or oversimplify change dynamics.
- Temporal deep learning and dense time-series modelling remain underexplored.
- This study compares LSTM models with RF and Markov Chain baselines using land cover fraction time series at annual and 16-day resolutions.

Related work

This study built upon the following research:

1. **Land cover fraction modelling with machine learning** (Masiliūnas et al. 2021).
   - Outcome: Highest overall accuracy was achieved using RF.
   - But: RF treats each time step independently, and uncertainty may cause the time series to fluctuate.
2. **Land cover fraction post-processing with Markov Chain** (Burger et al. 2022).
   - Outcome: The Markov Chain consistently improved the overall and per-class accuracies of the RF predictions.
   - But: Markov Chain penalises dissimilarity and oversimplifies actual change.

Data and methods

Land cover fraction data were used to train and test the models (Figure 1). Fractions were calculated over a 100-m by 100-m grid, with information on 7 classes: bare land, cropland, grassland, shrubs, trees, built-up and inland water.

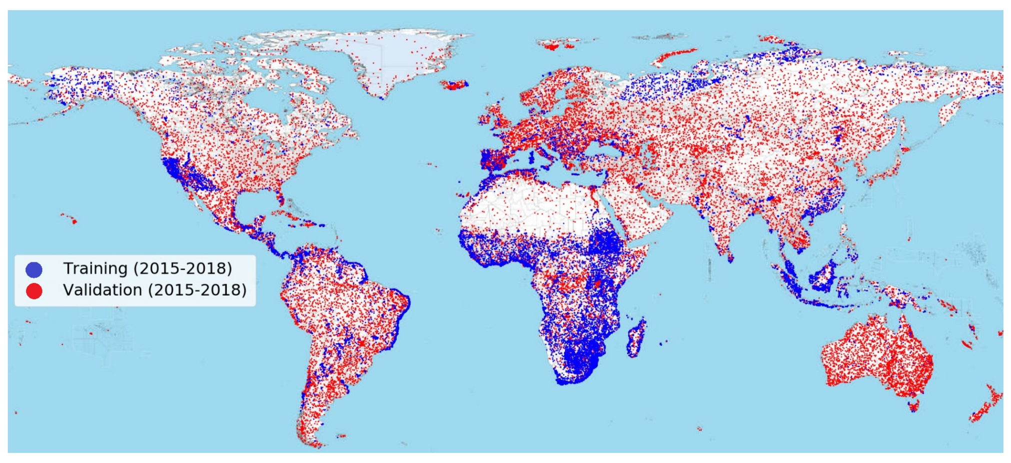

Figure 1: Data consisted of yearly (2015-2018) land cover fraction records from 60,000+ sample sites worldwide.

LSTM and RF models were trained to predict annual and dense land cover fractions. RF predictions were post-processed by LSTM (PostLSTM) and Markov Chain models (Figure 2).

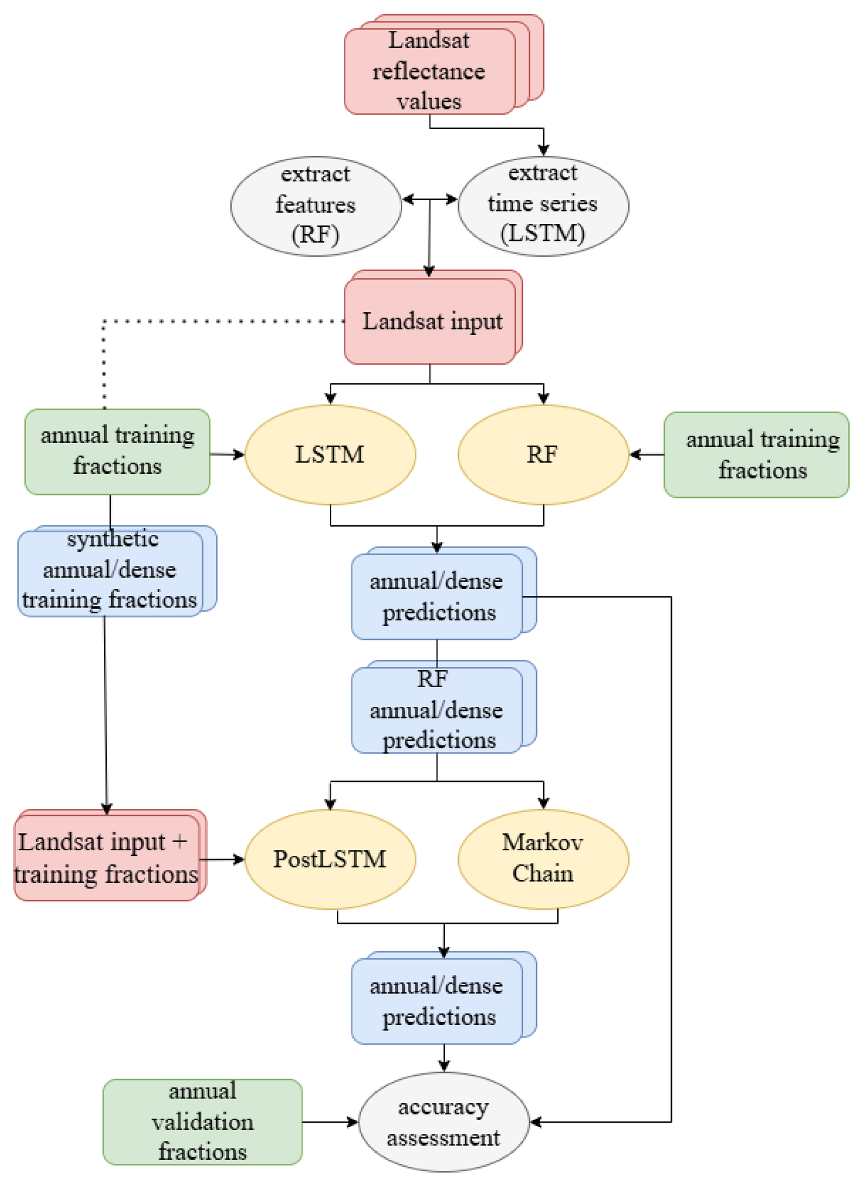

Figure 2: Workflow of this study.

Results and discussion

The RF models outperformed the standalone LSTM models. Due to fluctuating RF predictions, RF combined with PostLSTM models achieved the highest yearly Overall Accuracy (OA) (>67%) (Figure 3).

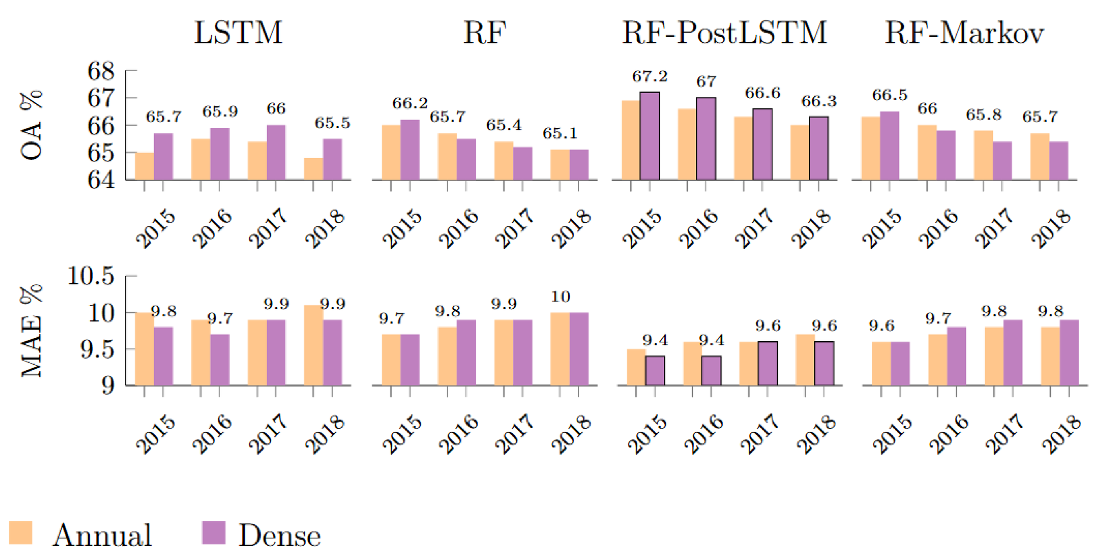

Figure 3: Results on all sample sites.

- The standalone LSTM models outperformed the RF models when considering land cover classes with predicted or validated fractions above 1% (Figure 4). However, using median-voting, RF handled zero-inflation better: for ~90% of the data, three or fewer classes were present, and for ~40%, only one.

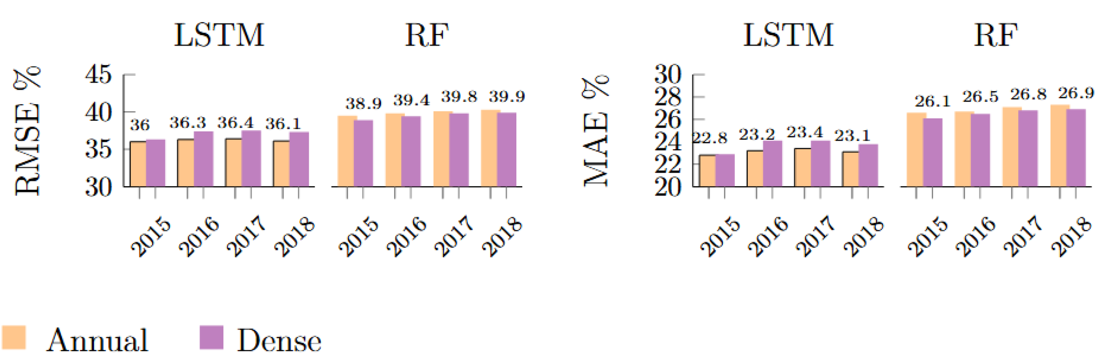

Figure 4: Errors of the LSTM and RF models, accounting only for classes that were either predicted or reported to have a fraction of at least 1%.

- Unlike the Markov Chain models, The PostLSTM models stabilised time series while preserving actual change (Figures 5 and 6).
- Dense time series gave LSTM models only a slight edge, whereas for the RF and Markov Chain models, the dense and annual models achieved similar yearly OA. In this study, only yearly reference data was available, which inhibited the models from learning intra-annual characteristics. Nonetheless, dense models have potential and can provide better defined information (Figures 3, 5, and 6).

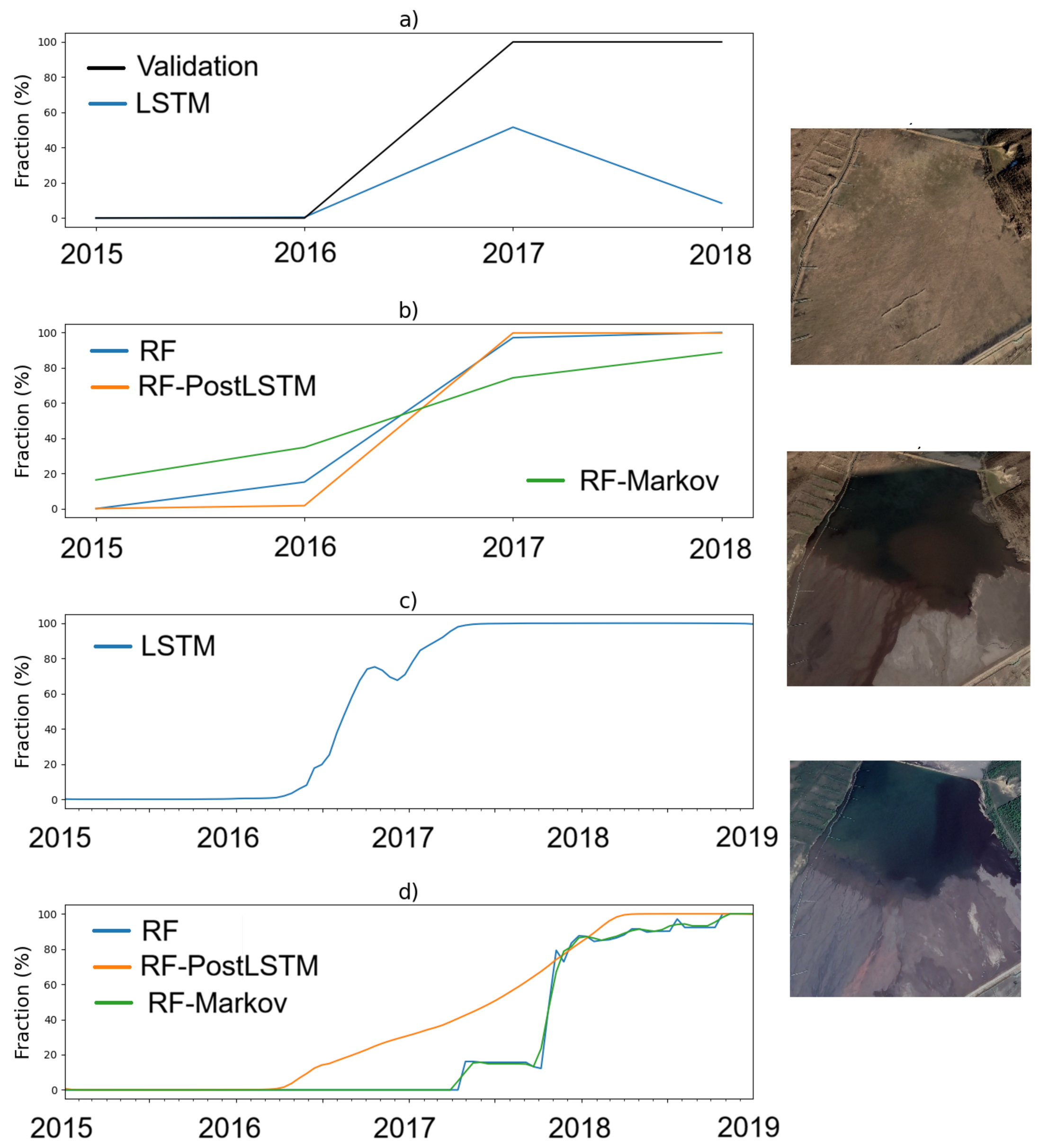

Figure 5: Results on an inundated sample site. The upper satellite image was taken on January 2, 2017, with only grassland; the middle image was taken on March 20, 2017, and the lower image was taken on April 15, 2017, showing the same sample site but almost fully flooded.

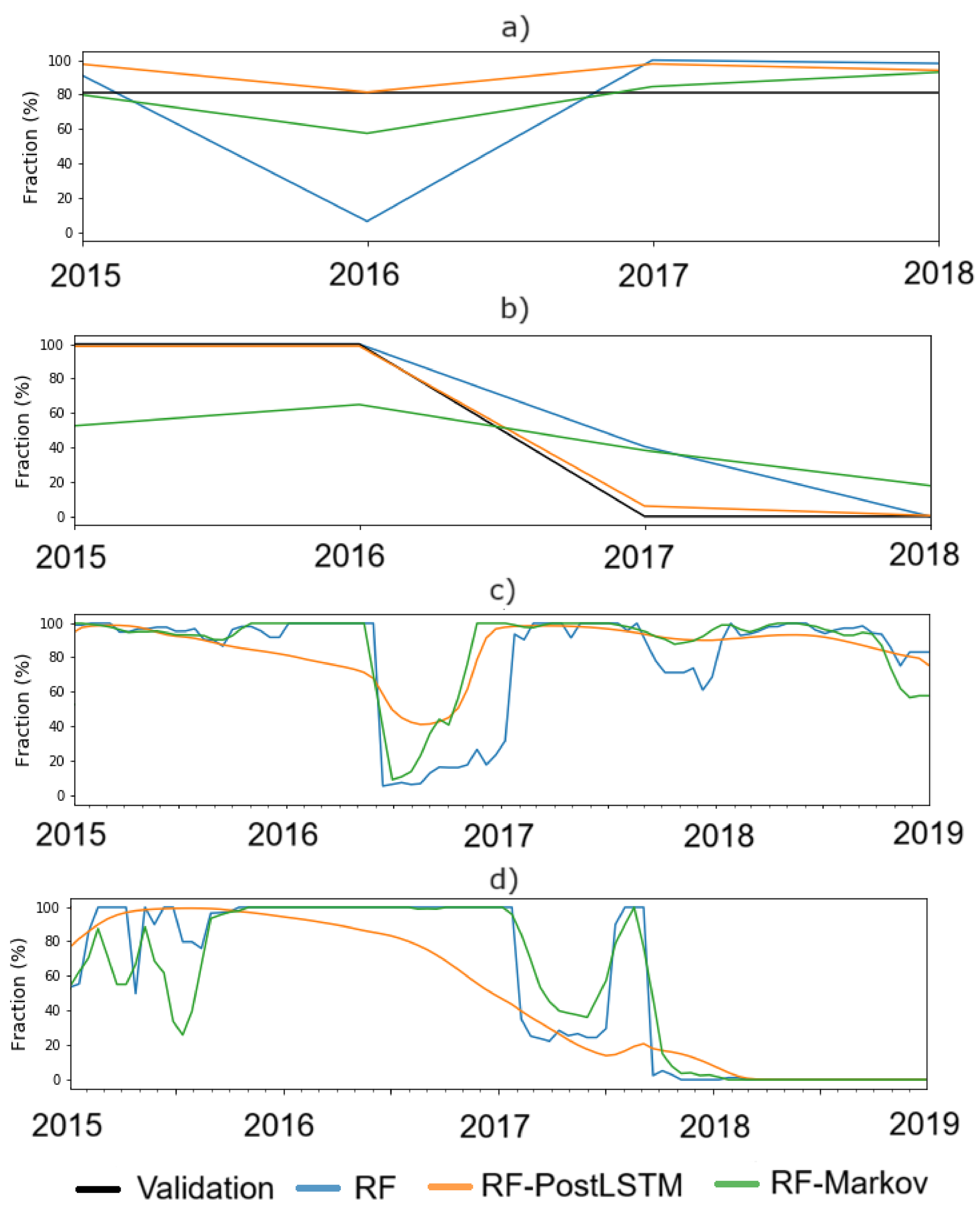

Figure 6: Predicted trees class fraction time series of a sample site with no change (a and c, of the same sample site) and with change (b and d, of the same sample site) by RF, RF-PostLSTM and RF-Markov models.

Future outlook

- Intra-annual land cover fraction reference data.
- Advanced optimisation and model architectures, such as CNN and (Vision) Transformers.
- Change detection algorithm, e.g., BFAST.
- Other satellite and ancillary data.

August Slomp
Email: augustslomp@gmail.com
LinkedIn: https://www.linkedin.com/in/august-slomp-2533b328b/
Waardenburg Ecology, www.waardenburg.eco
4101 CK Culemborg

[1] Laboratory of Geo-Information Science and Remote Sensing, Wageningen University & Research, Wageningen, Netherlands

LinkedIn - GitHub

Slomp, A., Masiliūnas, D., & Tsendbazar, N.-E. (2025). Improving global land cover fraction change mapping using temporal deep learning. International Journal of Applied Earth Observation and Geoinformation: ITC Journal, 144(104927), 104927. doi:10.1016/j.jag.2025.104927