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BFAST Lite for detecting land cover change using time series of estimated land cover fractions

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1. Introduction

- Global land cover (LC) maps are useful, and periodic updates to them are essential for many applications, including climate and land management.
- A machine learning model output for one year will differ for another year due to changes in surface reflectance, even if there is no real LC change.
- Change detection algorithms help, but are limited to proxy information, such as vegetation indices, which are not always relevant for a given class.
- Traditional LC maps cannot express gradual change processes. Emerging LC fraction mapping techniques (e.g. as in Masiliūnas et al. 2021a) can solve this challenge.

2. Objectives

Combine global dense LC fraction predictions with a change detection algorithm, to:

- Smooth the time series of LC fractions, reducing spurious change;
- Retain sudden transitions, such as flooding or deforestation;
- Track multi-year trends, such as forest degradation or reforestation.

3. Input data, methods and validation

We used the entire archive of Landsat 8 30 m surface reflectance as an input (see Figure 1). It was preprocessed and used as an input to a Random Forest regression model, which outputs fractions of each class for every 16 days. The model is trained on over 138 000 locations globally with LC fractions interpreted by experts at IIASA for the year 2015.

Next, the newly developed BFAST Lite change detection algorithm (see `https://github.com/bfast2/bfast` and Masiliūnas et al. 2021b) was applied on the time series of LC fractions obtained in the previous step (see Figure 1). Results are validated with over 153 000 LC fraction data points covering the whole globe for the years 2015-2019.

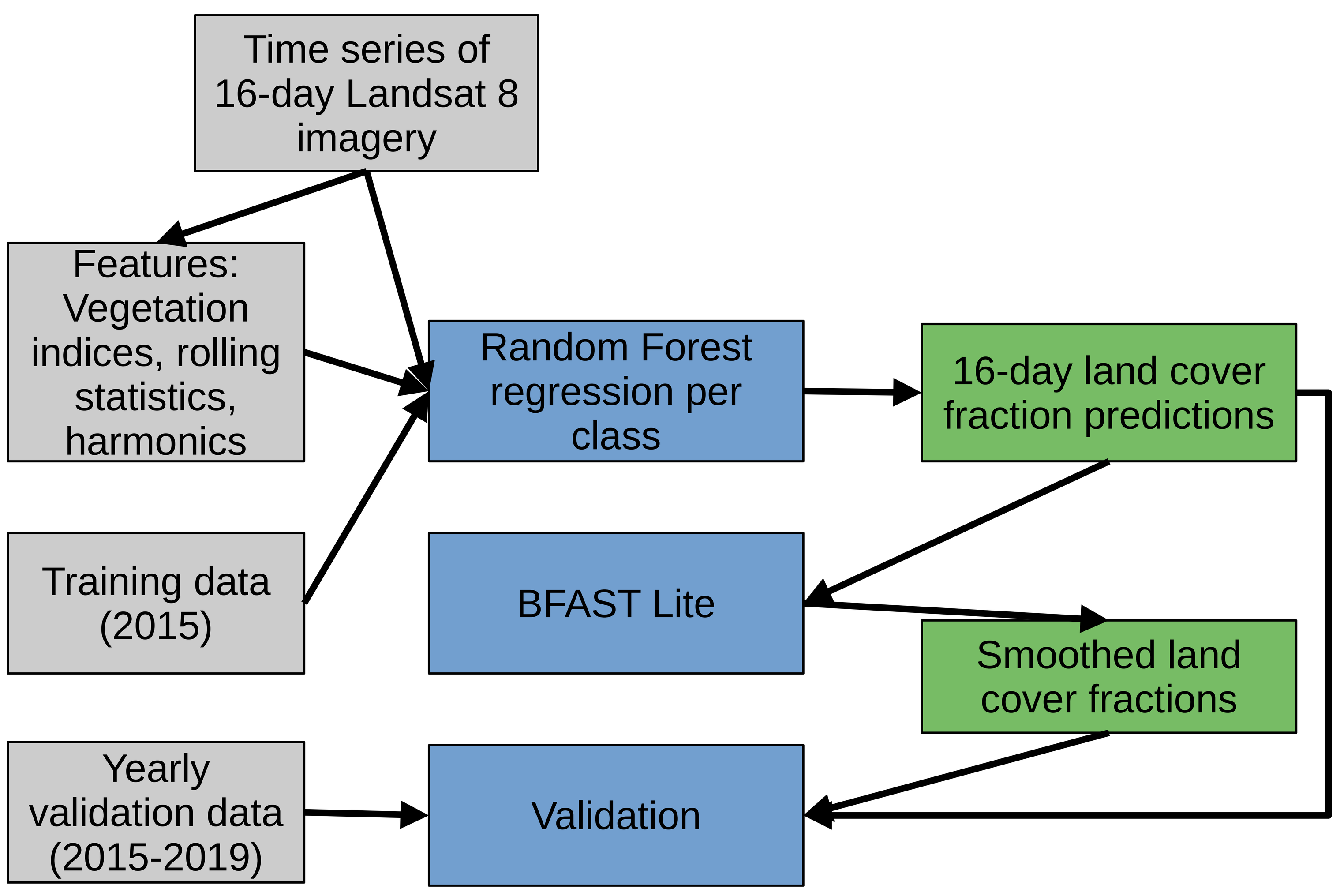

Figure 1. Workflow of the dense LC mapping processing chain. Grey: input data, blue: process, green: output.

4. Preliminary results

- Dense Random Forest LC fraction predictions without postprocessing are more accurate than the traditional workflow of yearly predictions, updated only after breaks detected in NDVI using BFAST Lite.
- The result shows more stable multi-year trends and allows LC fraction trend analysis and mapping (see Figure 2).
- Using dense LC fraction predictions from Random Forest as input into BFAST Lite leads to further improvements in mapping accuracy, especially if BFAST Lite parameters are tuned (see Figure 3).

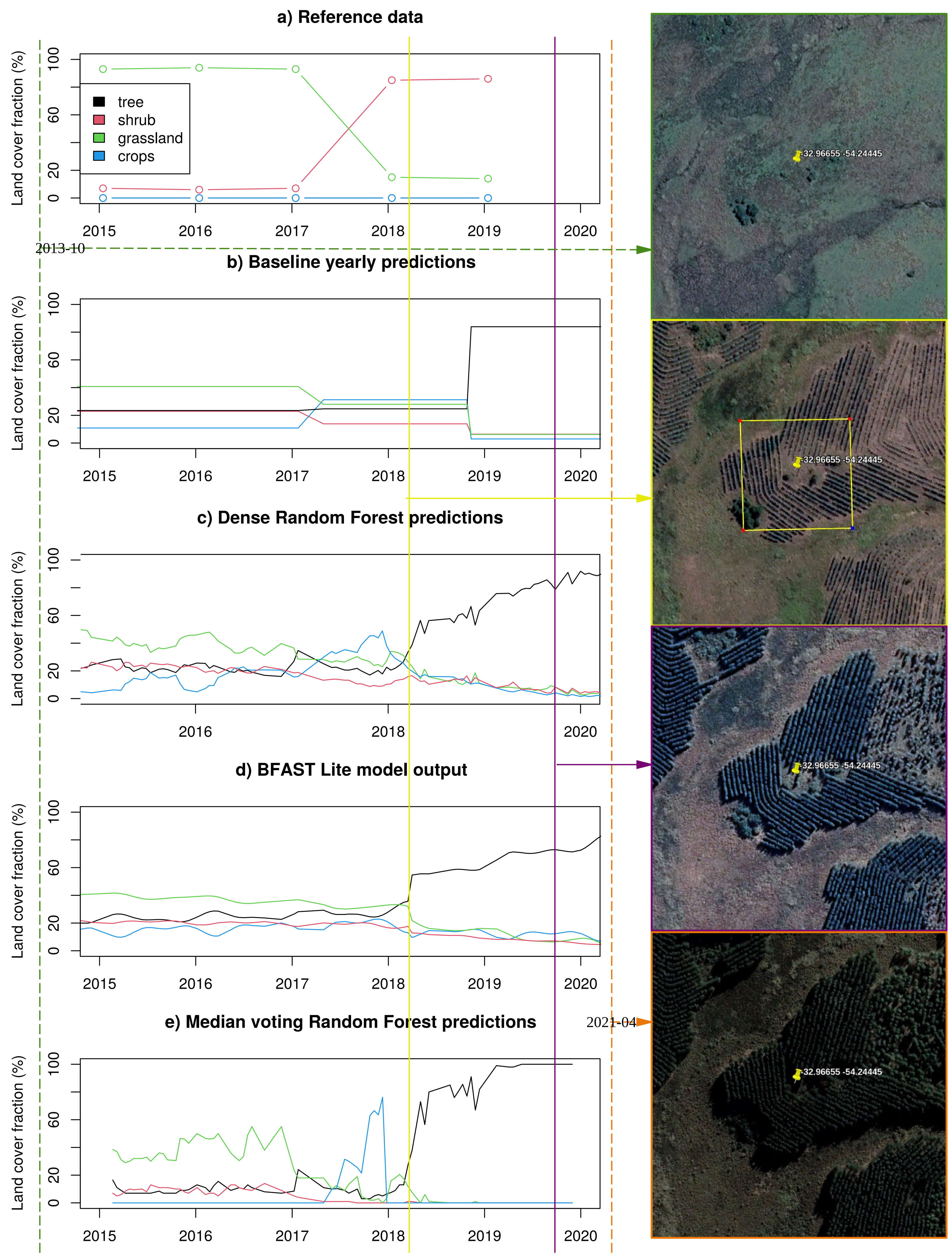

Figure 2. An example time series of land cover change: Pampas grasslands replaced by a *Eucalyptus* plantation in Uruguay. Left: time series of reference data and the tested models. Right: Google Earth imagery taken at the indicated time on the time series (first and last image: before and after the period of interest). The yellow box indicates the sample site size (100 x 100 m).

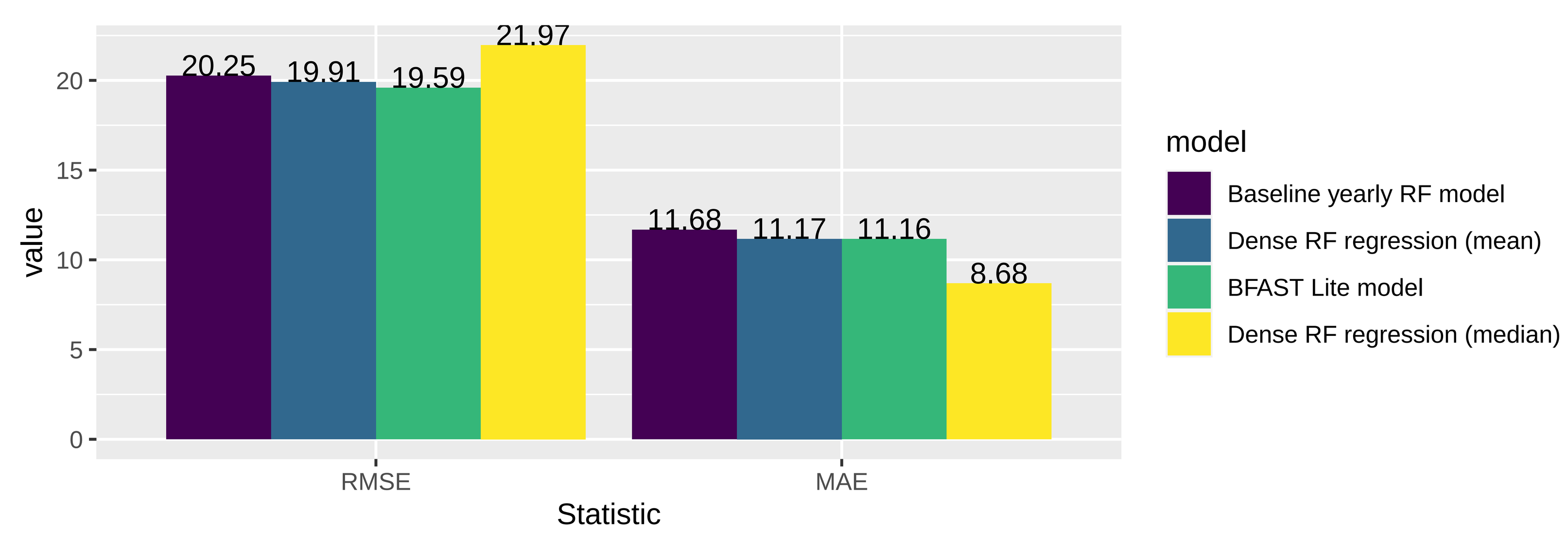

Figure 3. Validation statistics of the models shown in Figure 2.

5. Discussion

- BFAST Lite model output not only stabilises and smooths the dense LC fraction input, but also allows quantifying LC trends.
- Further research is needed to determine optimal model parameters and test the accuracy of a derived LC transition map.
- A combination with a deep learning approach could further improve results by taking the spatial context into account.

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