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Making dense land cover products more consistent and meaningful using BFAST Lite postprocessing

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1. Introduction

- Due to the increase in satellite missions and computing capabilities, frequently updated land cover (LC) maps such as Google Dynamic World (Brown et al. 2022) are an emerging trend.
- There is great potential to track gradual changes and degradation when fraction (Masiliūnas et al. 2021a) or probability data is used.
- The LC map production chain consists of a base machine learning classifier/regressor and an optional postprocessing step (see Figure 3).
- Traditionally postprocessing is either omitted (e.g. Google Dynamic World), or is done using a change detection algorithm with NDVI as input (e.g. Copernicus Global Land Cover 100m).
- Omitting postprocessing results in a lot of spurious change, using NDVI may result in missed land cover change for classes it is not sensitive to.

2. Objectives

We propose the use of the change detection algorithm BFAST Lite (Masiliūnas et al. 2021b) as a postprocessing step that takes LC fractions/probabilities as input. We compare raw predictions with postprocessed ones using NDVI-based change detection, BFAST Lite with fractions as input, and a simple LOESS smoother.

3. Input data, methods and validation

We applied BFAST Lite (see `https://github.com/bfast2/bfast`) on LC fractions derived from a Random Forest regression model trained using the whole Landsat 8 archive at over 138 000 locations globally, and also we applied it on Google Dynamic World class probabilities, based on Sentinel-2. We validated the results using an independent validation set of over 153 000 LC fraction data points for 2015-2019 globally. See Figure 3 for the workflow.

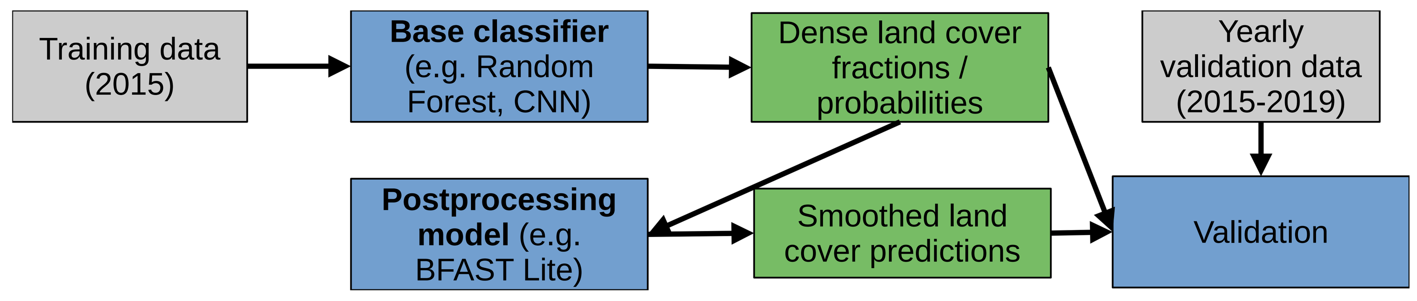

Figure 3. Processing chain for dense LC mapping. Grey: input data, blue: process, green: output.

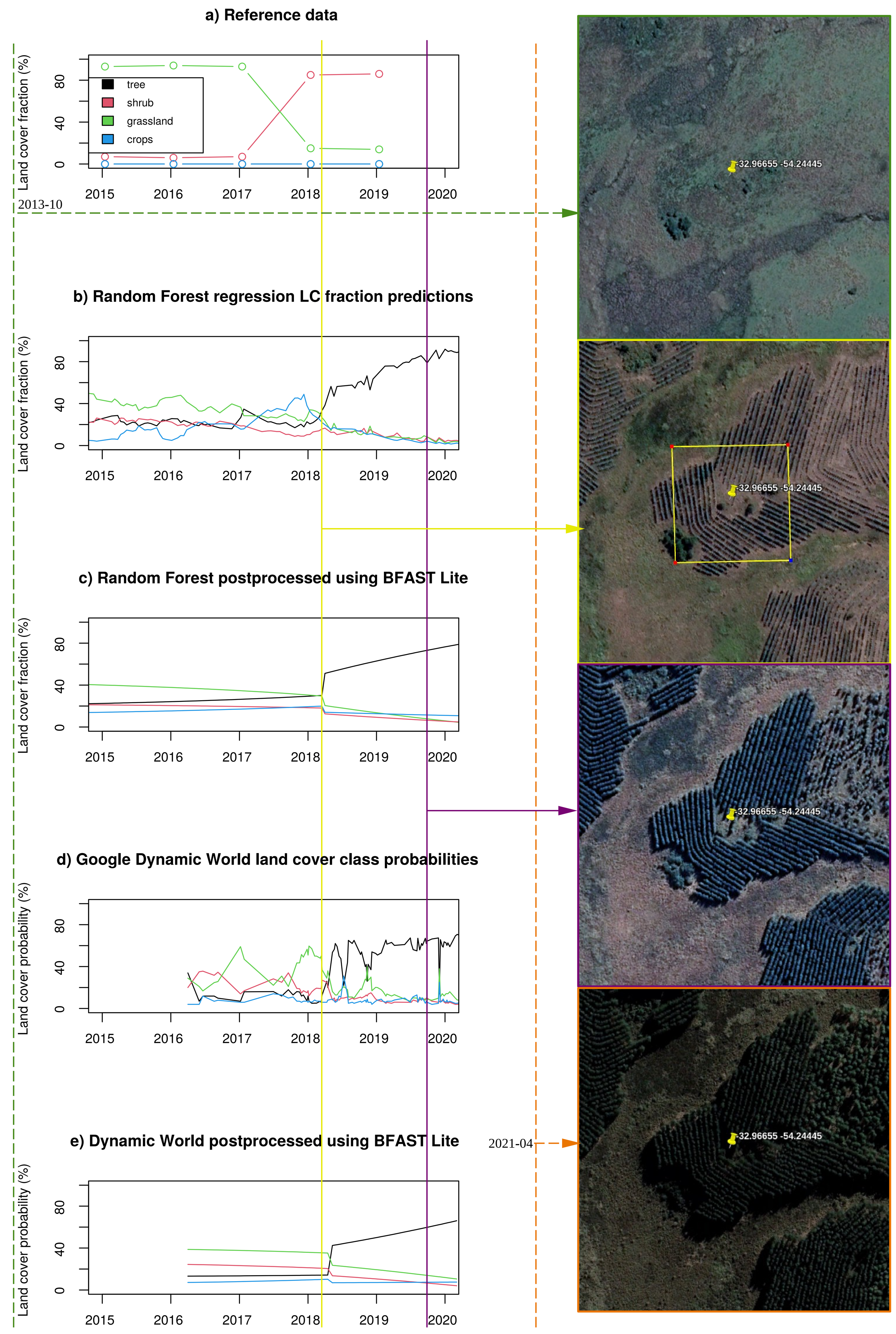

Figure 4. An example time series of land cover change: Pampas grasslands replaced by a *Eucalyptus* plantation in Uruguay. Left: time series of reference data and some of the tested models. Right: Google Earth imagery taken at the indicated time on the time series (first and last image: before and after the period of interest). The yellow box indicates the sample site size (100 x 100 m).

4. Results

- Applying any of the postprocessing techniques resulted in improved LC consistency, lower noise in the time series (see figure 4), and lower LC change error (see figure 1). Postprocessing also reduces the amount of spurious LC transitions (commission; see figure 2).
- BFAST Lite achieved lowest overall MAE in LC change, for both Google Dynamic World and Random Forest regression output (see figure 1).
- The choice of classifier had a larger effect on the map and change errors compared to the choice of postprocessing technique.

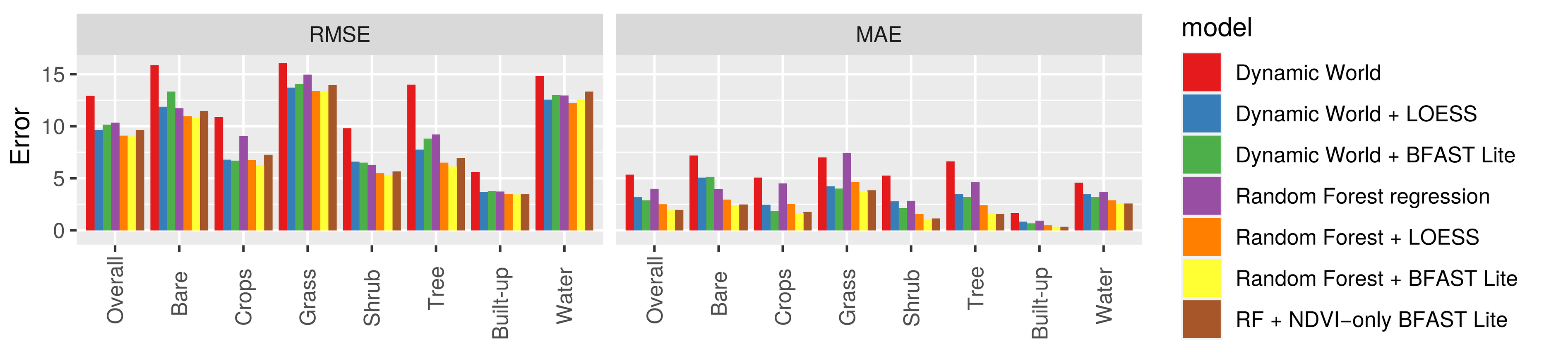

Figure 1. Validation statistics of the models shown in Figure 4. RMSE: overall root mean squared error, MAE: overall mean absolute error, compared to yearly reference data.

a) Random Forest

From 2015 \ To 2019	Trees	Shrubs	Grass	Crops	Built-up	Bare	Water
Water	94	55	−63	121	17	−9	−55
Bare	57	60	114	100	−32	−1528	−36
Built-up	32	24	34	29	−374	20	23
Crops	280	127	243	196	9	100	92
Grass	284	87	−1238	223	−19	157	−163
Shrubs	131	343	46	113	3	57	66
Trees	−508	124	212	268	18	7	115

b) Random Forest + BFAST Lite

From 2015 \ To 2019	Trees	Shrubs	Grass	Crops	Built-up	Bare	Water
Water	74	43	−115	103	11	−52	252
Bare	42	42	54	81	−41	−1210	−88
Built-up	20	15	19	21	−302	12	14
Crops	177	75	117	801	−1	73	70
Grass	129	24	−956	117	−39	81	−226
Shrubs	72	567	−5	80	−7	35	50
Trees	−626	71	82	198	6	−4	84

Fraction sum: 300, 200, 100, 0, −100, −200, −300

Figure 2. Transition matrix of LC between the years 2015 and 2019, relative to reference data, in number of sample sites. Positive numbers indicate overestimation, negative numbers indicate underestimation.

5. Discussion

- BFAST Lite proved to be a viable and versatile postprocessing algorithm that not only smooths the time series of land cover, but also provides more semantic details, e.g.: change events can be attributed to class change, magnitude of change is in intuitive fraction units, multi-year trends in LC can be quantified, etc.
- To further improve LC transition accuracy (figure 2), a rules-based algorithm, such as Markov Hidden Model, could be useful to rule out very unlikely transitions.

6. References

Brown, C.F., Brumby, S.P., Guzder-Williams, B. et al. Dynamic World, Near real-time global 10 m land use land cover mapping. Sci Data 9, 251 (2022). `https://doi.org/10.1038/s41597-022-01307-4`

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