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Editorial

Editorial for Special Issue: "Remote Sensing of Forest Cover Change"

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Forests play a critical role in the global carbon budget, either acting as a sink of carbon from growth processes (e.g., regrowth, afforestation, reforestation) or releasing carbon to the atmosphere via disturbances such as deforestation and degradation [1]. Therefore, it is of the utmost importance to have a good understanding of the distribution and magnitude of all processes leading to forest cover change.

Data obtained from Earth Observation (EO) platforms are critical in providing a systematic and temporally resolved assessment of forest cover change. The current availability of long-term Landsat data and the launch of Sentinel-1 and Sentinel-2 constellations are fostering the development of improved methods to characterise forest cover change. Furthermore, advances on high performance and cloud computing, machine learning, high-quality temporal datasets (e.g., Landsat collection 1), as well as the development of datacube formats, are increasingly facilitating the analysis of forest cover change and the temporal dynamics of forest biophysical parameters.

In this special issue, most studies used data acquired by optical sensors to characterise forest disturbances over a range of biomes. Rengarajan and Schott [2] provide a very interesting evaluation of the interoperability of Landsat 8 Operational Land Imager (OLI) and Sentinel-2 Multispectral Instrument (MSI) data, taking into account different sensor characteristics and environmental conditions and their implications for time series analysis. They simulated a deciduous forest canopy and estimated Landsat 8 OLI and Sentinel-2 MSI responses according to different sensor configurations and modelled atmospheres and its impacts on normalised difference vegetation index (NDVI) products. They concluded that the uncertainty in NDVI products generated from both sensors could be impacted by several factors and reach quite high values. Mainly as a consequence of not correcting for atmospheric effects (40%), not compensating for different spectral response curves (20%), view angle differences (40%) and solar zenith angle differences (10%). Langner et al. [3] presented an approach to monitor forest canopy disturbance in evergreen forests of continental Southeast Asia based on temporal differences of a modified normalised burn ratio (NBR) index applied to Landsat 8 data. The method to discriminate disturbance from no disturbance was validated using very high-resolution optical imagery and resulted in detection rates of 46–52%. Hassan et al. [4] used Sentinel-2 MSI imagery and a machine learning algorithm to quantify the territorial expansion of Rohingya refugee settlements in Bangladesh. The overall classification accuracy was 95% in 2016 and 2017 when discriminating four classes: Forest, refugee camp, non-forest and water bodies. The comparison of the two land cover maps showed a net growth rate of the area occupied by refugee camps in the order of ~800%. Silva et al. [5] used Landsat data, census information, and landscape metrics to assess large-scale land use and land cover change over an area of agricultural expansion in the Brazilian Atlantic Forest in two separate periods: 1995–2006 and 2006–2013. Independent validation resulted in overall accuracies of 83%

(1995–2006) and 84% (2006–2013), with the transition non-forest to planted forest showing classification errors of 46% and 74% in 1995–2006 and 2006–2013 respectively, mostly from misclassification as planted forest (1995–2006) or forest remnants (2006–2013). Forest cover increased 18% between the two periods, mostly as conversion from non-forest to planted forest and conservation of planted forests. Housman et al. [6] used Landsat or MODIS data to generate forest disturbance products to improve the detection of areas impacted by insects and diseases and compared against existing products relying on surveys (Insect and Disease Survey programme) or coarse resolution imagery (MODIS Real-Time Forest Disturbance programme). The overall accuracy for all products ranged from 72% to 93% in the Southern New England site and 63% to 79% in the Rio Grande National Forest area. However, omission and commission errors of the change class ranged from 5-86% and 28-70%, respectively, in the Southern New England study area and 16-93% and 13-63%, respectively, in the Rio Grande National Forest region. They concluded the differences amongst products were not statistically significant. Chen et al. [7] used a time-series of Landsat images (1987–2015) over Hainan Island (China) to identify the establishment year of rubber plantations. They generated maps of plantation start year with a root mean square error of 2.34 yr and 0.54 yr at pixel and plantation scale, respectively. Rubber plantations from the mid-1980s were established mainly over old rubber plantations; although, croplands and evergreen forests were also significantly converted to plantations. McCarthy et al. [8] used a combination of aerial photos, Landsat and WorldView-2 images to assess forest decline in the Big Bend region of Florida's Gulf of Mexico coast (USA) since the early 1980s. Results show a forest decline of 0.6% in the period 1982-2003 but increasing to 7.4% between 2010 and 2017. They were able to track this decline to acute cold snap events since 2010, which leveraged existing stress factors such as sea-level rise and saltwater intrusion.

Two studies dealt with mapping forest disturbance using Synthetic Aperture Radar (SAR) data. Berninger et al. [9] estimated forest aboveground biomass (AGB) over Kalimantan (Indonesia) in 2007, 2009, and 2016 using Sentinel-1 (C-band SAR), Advanced Land Observing Satellite (ALOS) Phased Array L-band SAR (PALSAR) and ALOS-2 PALSAR-2 (L-band SARs). Validation results of the individual AGB maps showed a root mean square error (RMSE) ranging between 53 t/ha and 57 t/ha (relative RMSE = 31–38%) and absolute bias in the range 5–10 t/ha, with the latter highly dependent of the AGB class but clearly showing overestimation for AGB values up to 250 t/ha and underestimation for AGB values above 250 t/ha. The authors mapped forest disturbance by comparing AGB maps at several time steps (2007–2009, 2009–2016 and 2007–2016). Bouvet et al. [10] used Sentinel-1 C-band SAR data in a highly innovative way to detect forest loss. The authors based their method on the assumption that SAR shadow forms at the border of a deforested area, which could be tracked by analysing high-frequency time series of Sentinel-1 data. The method was tested and validated in an evergreen rain and seasonal deciduous forest region in Peru with a detection rate of 80% (using pixel count statistics).

The articles published in this special issue cover a wide range of topics on the field of forest cover dynamics such as disturbance mapping, biomass change and forest health, using innovative approaches to study the rich information content of EO time-series datasets. It also stresses the potential as well as the challenges of EO data to monitor the different forest ecosystem dynamics efficiently and transparently.

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