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Unmasking the story behind forest carbon flux: an integrated remote-sensing based approach

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Forest biomass carbon sinks will be critical for achieving the goal of CO₂ neutrality under the Paris Agreement, by the middle of the century (UNFCCC 2015). Robust measurement, reporting and verification of carbon fluxes is necessary to monitor the implementation of the Paris Agreement. Global Carbon emissions from deforestation and land use change were estimated to be 1.3 ± 0.7 GtC yr⁻¹ on an average during 2007–16, accounting for about 12% of all CO₂ emissions (GCP 2017). The magnitude of CO₂ emissions, its dynamics and the uncertainty involved makes it imperative to establish reliable methods to account for carbon stocks and fluxes in forests. This letter (Kennedy et al 2017) represents an integrated approach for improved live forest biomass flux accounting in temperate forests in the western United States, which helps quantify such a flux.

In this letter, the authors describe a comprehensive system by which both live biomass flux and probable causes are identified over a multi-decadal period for the western United States region. To review briefly, the method broadly operates at the scale of forest change patches (e.g. a clearcut). One aim is to assign each such patch to a definite change event. For this, as a first step, a predictive framework is built by which several variables associated with a change patch (including remote sensed spectral data and change patch shape index values) are used to predict the nature of the change event (clear-cut, fire, insect attack, etc). Such a model is realized using a large training dataset created by human interpreters. In parallel, another statistical model based on the nearest-neighbour technique is formulated, where each pixel on the forest landscape can be linked to a forest plot that is its ‘best look-alike’. Once this is done, the biomass of that ‘look-alike’ plot is assigned to the pixel. At the end of these two exercises, they have estimated both the per-pixel forest biomass values and the change agents over the study area and over several decades.

A distinctive and central aspect of this work is the ability to attribute the change in biomass of a forest patch to a particular change agent. The study has attempted an assessment of the major factors contributing to biomass flux over the entire study area (approximately 48 000 km²) (see figure 1). The dominance of forest management activities can be discerned, although some interesting trends are seen in other agents. For example, in the case of fire, the study seems to pick up increasing western US wildfire trends reported previously (Westerling et al 2006). An assignment of a change agent would be immensely useful for a comprehensive understanding of forest change dynamics and for assessing the impact of differing policy and management regimes on the flux in the aboveground biomass pool. A spatially explicit biomass change map (the where and why of biomass flux, here the why is the change agent label generated), which would be extremely useful to regional-level forest managers, can also be generated (see figure S3 in the article and Kennedy et al 2015). The utility of such maps lies in the fact that the 30 m grain size used brings out stand-level and intra-stand trends, which makes possible operational forest management planning and policy optimization. Currently methods that tightly connect the observed magnitude of change with the change agent are lacking hence, the work described in Kennedy et al is very topical.

Uncertainties in the methodology are estimated using an ensemble approach, where variations in output for varying values of parameters used in the algorithms involved are analysed. A notable advantage of the approach outlined is that the results are purely ‘observation based’, with no intervening mechanistic models (and their associated uncertainties such as those with parameters used or process representation).

Another interesting aspect of this work is the use of a well-researched modelling approach, by which the authors map a distinct forest plot on each and every pixel on the landscape. This is done using the
non-parametric nearest neighbour approach, which has recently emerged as an useful and intuitive method within the international forest inventory community (McRoberts et al 2010). The fact that this method is non-parametric and hence makes no assumptions about underlying distributions and that it can be easily extended to multivariate prediction are some advantages that makes such a technique appealing for forest variable prediction. Although this methodology has its flaws (especially when some forested conditions are under-represented in the plot data), there is the possibility of extending the plot level ‘gold standard’ data quality over the entire region of mapping. Indeed, the estimates of biomass are shown to be quite robust against reference data ($r^2 = 0.82$). Hence, one can think of going beyond biomass and mapping more complex forest parameters (such as measures of biodiversity) over the landscape (Woodall et al 2011). Of course, for this to work in a robust way, a much richer set of predictor attributes (e.g. data from other sensors, proximity variables) would be required to better prediction accuracy (Asner et al 2017).

To conclude, this article presents an interesting and comprehensive system to spatially track live forest carbon dynamics in temperate forests. Adoption of such a forest monitoring system to plot data-poor regions (e.g. Brazil and Southeast Asia) will be a challenge. In such regions, for the nearest-neighbours methodology, it would be hard to find representative plots for each pixel in the landscape. That is, the prediction of an entire region could depend on one or a few plots, which describes a high-variance solution (Hastie et al 2013). The monitoring methods will also contribute to the Tier—3 methods of the IPCC GHG Inventory Guidelines, which are being currently updated. This approach also strongly motivates the need to densify the forest plot network, as the system effectively ‘maps’ such plot information over the whole landscape. There may be scope for scaling up such a system to larger levels (e.g. national), once challenges with more heterogeneous forest conditions and detection of subtle changes have been adequately addressed.

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References

Anon Global Carbon Project (GCP) 2017 (www.globalcarbonproject.org/)
Asner G P, Martin R E, Knapp D E, Tupayachi R, Anderson C B, Sinca F, Vaughn N R and Llactayo W 2017 Airborne laser-guided imaging spectroscopy to map forest trait diversity and guide conservation Science 355 385–9
Hastie T, James G, Tibshirani R and Witten D 2013 An Introduction to Statistical Learning with Applications in R (New York: Springer)
Kennedy R E, Ohmann J, Gregory M, Roberts H, Yang Z, Bell D M, Kane V, Hughes M J, Cohen W and Powell S 2018 An empirical, integrated forest biomass monitoring system Environ. Res. Lett. 13 025004
Kennedy R E, Yang Z, Braaten J, Copass C, Antonova N, Jordan C and Nelson P 2015 Attribution of disturbance change agent from Landsat time-series in support of habitat monitoring in the Puget Sound region, USA Remote Sens. Environ. 166 271–285
McRoberts R E, Tomppo E O and Naesset E 2010 Advances emerging issues in national forest inventories Scand. J. Forest Res. 25 368–81
UNFCCC 2015 Adoption of the Paris Agreement (http://unfccc.int/resource/docs/2015/cop21/eng/09r01.pdf)

Westerling A L, Hidalgo H G, Cayan D R and Swetnam T W 2006 Warming and earlier spring increase western US forest wildfire activity Science 313 940–43

Woodall C W, Amacher M C, Bechtold W A, Coulston J W, Jovan S, Perry C H, Randolph K C, Schulz B K, Smith G C and Tkacz B 2011 Status and future of the forest health indicators program of the USA Environ. Monit. Assess. 177 419–36