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Introduction

PERSPECTIVE

1

2

3

It is estimated that 12%-20% of global greenhouse gas emissions in the 1990s and 2000s was from forest loss, primarily in the tropics, and estimates of the amount of CO₂ emitted to, and sequestered from, the atmosphere show large differences and high levels of uncertainty (Van der Werf et al 2009). Accurately estimating and accounting for changes in forest cover over time, and relating this to forest carbon stocks is essential for understanding and mitigating the impacts of climate change and is the basis for carbon-based payments for ecosystem service (PES) schemes such as the Amazon Fund (for the Brazilian Amazon) or UN-REDD+ (Reducing Emissions from Deforestation and forest Degradation, fostering conservation, sustainable management of forests and enhancement of forest carbon stocks) for developing countries where measuring, reporting and verification (MRV) of tropical forest cover is an essential component. Although care is needed in establishing what is meant by the term forest for mapping purposes (for example, determining the area, crown cover or height of trees that constitute a forest) and determining the appropriate minimum mapping unit for identifying forest loss, especially with selective or small-scale logging, the primary mechanism through which countries monitor their forest cover is through remote sensing methods (GFOI 2016).

Forest monitoring via remote sensing

Global Earth Observation datasets are particularly useful for detecting changes in forest canopy cover over time and are of obvious importance for comparing forest cover and estimating biomass globally and, potentially, for individual countries. For example, some independent studies of forest change from 2000–2010 find broad agreement with the Global Forest Watch (GFW) maps for humid tropical countries which is based on the data published in Hansen *et al* (2013) and used by Kim et al (2014) and Sannier et al (2016). In this context, if the global maps and alert systems are sufficiently accurate, they could be used as a basis to quantify forest loss at a national-scale or provide a way to measure performance of projects that aim to reduce forest loss. However, the recent publication by Milodowski et al (2017) finds that for the Brazilian Amazon, estimates of forest loss from global products differ from each other and from regional and local scale data used for national reporting obligations. Milodowski et al (2017) show that this is not only due to the resolution of the products, but also due to biases caused by different styles of ground-based disturbance affecting different products in different ways, which affect both estimates of spatial extent and timing of change.

Spatial extent of forest loss and tracking change

Milodowski *et al* (2017) show that the coarse-resolution (500 m) FORMA twice-monthly deforestation alerting system is less accurate at detecting forest loss than finer resolution global products such as GFW and the national-scale forest monitoring system for Brazil, PRODES (Projeto de Monitoramento do Desmatamento na Amazônia Legal por Satélite) which in this study are both based on 30 m pixel size data, when compared with 5 m RapidEye optical imagery. This is expected as the resolution of the product dictates the spatial accuracy with which forest loss can be determined. However, Milodowski et al (2017) also show that all three global products tested perform better at identifying deforestation in the Brazilian state of Rondonia, which is characterised by large-scale clearances, than in Acre, where deforestation is driven by selective logging and small-scale clearances along access tracks with fishbone characteristics where disturbances are less than 10-2 ha, even though these disturbances are within the resolution of the product (with GFW having the smallest minimum mapping unit). This shows that the same product can give different estimates of forest loss depending on the type of clearance mapped. The authors suggest that deforestation in areas characterised by small-scale disturbances could therefore be underestimated by as much as 50%. Milodowski *et al* (2017) have highlighted an important result given the investment made by Brazil in PRODES and DETER (Sistema de Detecção do Desmatamento em Tempo Real na Amazônia) to actively monitor forest clearing in the Brazilian Amazon.

Of particular relevance to the Milodowski et al (2017) paper is a study in the neighbouring country of Guyana which shows that the GFW maps for the year 2000 (Hansen et al 2000) overestimates the total forest area across the country when the same definitions of forest land (30% tree cover) in the two datasets are compared. This is because the GFW tree cover for the year 2000 is estimated from 500 m pixel size MODIS data. This contrasts with the GFW annual forest loss and gain maps (based on Landsat data) which underestimate change when compared against Guyana's national forest change maps produced by the Guyana Forestry Commission that are based on careful manual interpretation of RapidEye (5 m) multispectral imagery. While it is possible to calibrate the year 2000 GFW forest cover map for local conditions, this can only be done in the unusual circumstance that high quality map data are available to cross reference. The conclusion is that, if used uncritically, the GFW global product will systematically underestimate forest loss (and probably gains) in countries with large areas of forest cover, and low levels of deforestation and where small-scale disturbances account for a large proportion of the loss (Guyana Forestry Commission 2014).

Thus both studies show that Earth Observation datasets with pixel sizes smaller than 30 m may be needed to map forest loss accurately in areas where the loss is driven by small-scale disturbances.

An important contribution of the Milodowski *et al* (2017) paper is to demonstrate the value of time series of high resolution (RapidEye) images that allows tracking of activity events rather than simply creating static maps representing conditions at any given point in time. Such analysis allows characterisation of gradual and continuous change activity leading to better attribution and understanding of the drivers of deforestation (GFOI 2016, Kennedy *et al* 2014).

Reference data and definitions

A critical component of any comparative assessment is the need for appropriate reference data (Olofsson *et al* 2014). It is often the case that reference data itself contains errors and is not a 'gold standard'. Therefore, a key methodological issue raised by Milodowski *et al* (2017) relates to the availability of suitable reference data in order to obtain an unbiased assessment of the accuracy of forest change estimates. If mapping is based on fine resolution data such as RapidEye, then good practice dictates that its accuracy should be assessed using (usually sample) reference data of equal or higher quality and that may not be easily obtained or acquisition may be logistically difficult and costly. It is likely that information on uncertainty of forest loss and forest degradation estimates and rates of change that is normally derived from accuracy assessments will become an essential part of UN REDD+ reporting requirements (GFOI 2016).

In the context of performance-based PES schemes such as REDD+, activity data may be associated with particular definitions. The GFW data does not take into account specific country forest definitions and does not distinguish tropical forests from plantations (Tropek et al 2014). For example shifting cultivation and other types of forest degradation that designate as forest are mapped as forest loss in the GFW maps. This can result in an overestimation in forest change and possible carbon emissions estimates from deforestation. As Milodowski et al (2017) point out, country-specific definitions may operate with different mapping criteria with some activities being recorded below the minimum mapping unit of 0.09 ha that they associate with GFW maps. It is important to emphasise that when detecting change in land or forest cover it is not sufficient to map change in land use, which is needed for consistency with IPCC policies and guidance, and to make the distinction between deforested areas and areas such as shifting cultivation where crown cover has been removed but the designation of forest land use remains.

Conclusion

Milodowski et al (2017) draw on data from a number of Earth observation sensors and it is important to note that archives of imagery other than MODIS and Landsat will grow in future as other satellite missions develop. The value of RapidEye is highlighted in their paper and in future those tasked with forest monitoring will be able to have a choice of optical image data that includes a mix of free data from missions such as Landsat and Sentinal-2 and from commercial providers. Synthetic aperture radar (SAR) data has not been used routinely in performance-based PES schemes but research with the latest generation of fine resolution SAR sensors (e.g. CosmoSkyMed, PALSAR-2) shows much promise as it has the potential to provide a stationary time series because of cloud penetrating capabilities and the fine spatial resolution sensors are likely to enhance change detection especially when combined with optical data (GFOI 2016). The uncertainties observed in estimates of forest carbon stocks by Milodowski et al (2017) and others demonstrates the urgent need for improved Earth observation tools and services to support climate change policy development and to underpin robust carbon-based PES schemes.

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