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Estimating deforestation in tropical humid and dry forests in Madagascar from 2000 to 2010 using multi-date Landsat satellite images and the random forests classifier

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ABSTRACT

High resolution and low uncertainty deforestation maps covering large spatial areas in tropical countries are needed to plan efficient forest conservation and management programs such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation). Using an open-source free software (R, GRASS and QGis) and an original statistical approach combining multi-date land cover observations based on Landsat satellite images and the random forests classifier, we obtained up-to-date deforestation maps for the periods 2000–2005 and 2005–2010 with a minimum mapping unit of 0.36 ha for 7.7 M hectares, i.e. 40.3% of the tropical humid forest and 20.6% of the tropical dry forest in Madagascar. Uncertainty in deforestation on the maps was calculated by comparing the results of the classification to more than 30,000 visual interpretation points on a regular grid. We assessed accuracy on a per-pixel basis (confusion matrix) and by measuring the relative surface difference between wall-to-wall approach and point sampling. At the pixel level, user accuracy was 84.7% for stable land cover and 60.7% for land cover change. On average for the whole study area, we obtained a relative difference of 2% for stable land cover categories and 21.1% land cover change categories respectively between the wall-to-wall and the point sampling approach. Depending on the study area, our conservative assessment of annual deforestation rates ranged from 0.93 to 2.33%$\cdot$yr^{-1} for the humid forest and from 0.46 to 1.17%$\cdot$yr^{-1} for the dry forest. Here we describe an approach to obtain deforestation maps with reliable uncertainty estimates that can be transposed to other regions in the tropical world.

1. Introduction

Assessing changes in tropical forest cover is a challenging research and operational topic that addresses issues like climate change, biodiversity conservation and sustainable ecosystem management. Global net loss of forest area has been estimated at 5.2 million hectares per year between 2000 and 2010 (FRA, 2010) and, according to the most recent studies (Baccini et al., 2012; Harris et al., 2012), is responsible for 10% to 25% of anthropogenic greenhouse gas (GHG) emissions to the atmosphere. Tropical deforestation is a major contributor to GHG emissions because of the extent of forest being cleared each year and because of the high carbon stock per unit area (Achard et al., 2010). The REDD+ mechanism (Reducing Emissions from Deforestation and Forest Degradation) in the United Nations Framework Convention on Climate Change (UNFCCC) aims to encourage developing countries to slow down deforestation through a compensation mechanism. This mechanism requires accurate, transparent, and cost-effective GHG measurement and monitoring systems (Olander, Gibbs, Steininger, Swenson, & Murray, 2008). Despite well established guidelines provided by the international scientific community (GOFC-GOLD, 2010; IPCC, 2006), improvements in remote sensing techniques and data availability are still necessary to provide more accurate and cost-effective estimates of forest change.

1.1. Techniques for estimating deforestation over large forest areas

Recent reviews of methods used to estimate deforestation highlight two different methods of monitoring large areas of forest: the exhaustive mapping of forest extent (also known as the “wall-to-wall” approach) or point sampling (Achard et al., 2010; GOFC-GOLD, 2010;

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Hansen & Loveland, 2012). The wall-to-wall approach uses satellite images (such as Landsat (Harper, Steininger, Tucker, Juhn, & Hawkins, 2007: Gutman et al., 2005), AVHRR (DeFries et al., 2002), MODIS (Freidl et al., 2002) or MERIS (Bicheron et al., 2008)) to map the full extent of forest and changes in forest area through hybrid techniques that combine automated digital segmentation and/or classification with visual interpretation (GOFC-GOLD, 2010, Rasi et al., 2012) or fully automated techniques (Hansen et al., 2008; Huang et al., 2009; Potapov et al., 2012). Point sampling approach consists in identifying partial but representative land cover observations through ground surveys or through visual interpretation of satellite images to estimate forest and deforestation extent over the entire area (Rasi et al., 2012; Steininger, Godoy, & Harper, 2009).

Point sampling reduces the operational cost of exhaustive analysis of a large number of satellite images, while improving the thematic accuracy of (for example) regrowth or degradation assessment by focusing on small areas (Achard et al., 2002; Duveiller, Defourny, Desclée, & Mayaux, 2008; FRA, 2010; Rasi et al., 2011; Stach et al., 2009). However, the accuracy of point sampling is closely linked to the quality of the sampling design (Steininger et al., 2009) and does not enable the production of deforestation maps of the entire forest area. Such maps are however required to target conservation efforts and to allow consistent spatial analysis of deforestation (Vieilledent, Grinand, & Vaudry, 2013).

Classical wall-to-wall land cover change analysis implies pairwise image comparison. This method of detecting change has been widely used (Harper et al., 2007; Stach et al., 2009) and provides useful transition matrices describing change from one land category at date 1 to another land category at date 2 (Duveiller et al., 2008; Huang et al., 2009). But when two single date maps are used in combination to derive land cover change, individual errors will be multiplied if errors on the two maps are assumed to be independent (Fuller, Smith, & Devereux, 2003). This seriously undermines the accurate detection of subtle change in forest area, and it is consequently recommended to combine satellite images acquired at many different dates in a single analysis that identifies change directly (GOFC-GOLD, chap. 2.6, 2010). In other words, supervised classification is performed on stacked images acquired at many different dates. This technique allows seasonal variations and vegetation dynamics to be taken into account (Pennec, Gond, & Sabatier, 2011). For instance, slash-and-burn plots may subsequently have a different cover (a permanent crop, fallow, secondary regrowth) and secondary forest, forested fallow and intact forest may be confused depending on the selected date. Thus, increasing the number of dates using time series of satellite images reduces the uncertainty associated with land cover change classification.

1.2. Classification algorithms

Open access to the 20-year Landsat archive (called the Landsat Global Land Survey Program) has greatly reduced the cost and facilitated the processing of large time series for the estimation of land cover change (Hansen & Loveland, 2012). Given that multi-date satellite images are needed to reduce the uncertainty associated with land cover change classification, the usual parametric classification algorithms (such as classification by maximum likelihood) may not be appropriate for the classification of combined multi-date images because of the heterogeneous spectral signature of land cover categories over large areas. To overcome this problem, data mining and machine learning techniques (including neural networks, decision trees, support vector machines and ensemble classifiers) have recently emerged in remote sensing, making it possible to deal with complex land cover status and dynamics. Such algorithms are efficient because they do not rely on the data distribution assumption (e.g. normality), are able to handle noisy observation (Breiman et al., 20010), and can be efficiently applied to large complex datasets if supported by sufficient training data (Rodriguez-Galiano, Ghimire, Rogan, Chica-Oimo, & Rigol-Sanchez, 2012). Among these algorithms, the random forests (RF) classifier has already provided interesting results in several studies using satellite images. For instance, Schneider (2012) reported that RF outperformed maximum likelihood classifier and was better than a support vector machine classification based on accuracy assessment and visual interpretation of the resulting maps. Previous RF applications include land cover classification using Modis data (Aide et al., 2012; Clark, Aide, Grau, & Riner, 2010), Landsat data (Gislason, Benediktsson, & Sveinsson, 2006; Lawrence, Bunn, Powell, & Zambon, 2004; Rodriguez-Galiano et al., 2012; Schneider, 2012) or hyperspectral data (Ham, Chen, Crawford, & Gosh, 2005), digital soil mapping (Grimm, Behrens, Märker, & Elsenbeer, 2008) and forest biomass mapping (Baccini et al., 2012).

1.3. Accuracy assessment of land cover change

Accuracy assessment must be associated with deforestation maps, as some authors consider errors in land cover change to be the main source of error in estimates of GHG emissions (Harris et al., 2012; Pelletier, Ramankutty, & Potvin, 2011). A common approach for accuracy assessment implies computing an error matrix from independent ground survey observations or from visual interpretation of high resolution images to quantify class specific accuracies and overall map accuracy. A probability based sampling design is required for the accurate error estimation of land change categories (Stehman, 2009). Assessing a land cover map is known to be difficult, but assessing land cover change maps is even more challenging (Hansen & Loveland, 2012) mainly due to the difficulty in obtaining accurate land cover change reference datasets (Foody, 2010). Field surveys of historical change are tricky since they involve questioning people with a deep knowledge of the plot's history (e.g. the landowner). Ground truth observation via remote sensing is also constrained by the availability and resolution of the images. Another problem with change detection assessment is the extent of the change. Fuller et al. (2003) estimate that “small to medium scale changes requires levels of precision in mapping which are near impossible to achieve […] unless it (the survey) is tailor made and rigorously applied to the recording of change”. For all these reasons, accurate assessment of land cover change is not a trivial task and requires particular attention.

1.4. Objectives

Madagascar is universally recognized for its high level of biodiversity and endemism (Goodman & Benstead, 2005). The biodiversity is mainly located in its tropical forests. In the last 50 years, Madagascar has experienced a dramatic loss of forest (Harper et al., 2007) due to traditional slash and burn, pasture extension, charcoal production, illegal logging of precious wood, and mining activities, with consequences for both biodiversity conservation and GHG emissions. To curb deforestation, Madagascar is highly committed to the implementation of the REDD+ program through both the development of REDD+ pilot projects at regional scale and policy decisions at national scale. Previous work on land cover and land cover change mapping has provided valuable insight into vegetation status (Mayaux, Gond, & Bartholomé, 2000; Mayaux, Bartholomé, Fritz, & Belward, 2004; Moat & Smith, 2007) and dynamics (Harper et al., 2007). However these insights cannot be used directly since the definition of forest varies widely among studies and does not provide sufficient levels of information (a resolution of 1 km or a minimum mapping unit of 2 ha) for the detection of subtle change. Using Madagascar as a case study, we first used the RF algorithm to map land cover change using a 10-year time series of Landsat TM satellite images covering large forest areas. Second, we calculated up-to-date annual deforestation rates for the period 2000 to 2010, and third, we assessed the accuracy of forest cover change using more than 30,000 visual interpretation points on a regular grid. The specific aim of this study was to develop a transparent and cost-effective methodology to obtain reliable deforestation maps associated with