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Research paper

Simultaneous comparison and assessment of eight remotely sensed maps of Philippine forests

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A R T I C L E I N F O

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A B S T R A C T

This article compares and assesses eight remotely sensed maps of Philippine forest cover in the year 2010. We examined eight Forest versus Non-Forest maps reclassified from eight land cover products: the Philippine Land Cover, the Climate Change Initiative (CCI) Land Cover, the Landsat Vegetation Continuous Fields (VCF), the MODIS VCF, the MODIS Land Cover Type product (MCD12Q1), the Global Tree Canopy Cover, the ALOS-PALSAR Forest/Non-Forest Map, and the GlobeLand30. The reference data consisted of 9852 randomly distributed sample points interpreted from Google Earth. We created methods to assess the maps and their combinations. Results show that the percentage of the Philippines covered by forest ranges among the maps from a low of 23% for the Philippine Land Cover to a high of 67% for GlobeLand30. Landsat VCF estimates 36% forest cover, which is closest to the 37% estimate based on the reference data. The eight maps plus the reference data agree unanimously on 30% of the sample points, of which 11% are attributable to forest and 19% to non-forest. The overall disagreement between the reference data and Philippine Land Cover is 21%, which is the least among the eight Forest versus Non-Forest maps. About half of the 9852 points have a nested structure such that the forest in a given dataset is a subset of the forest in the datasets that have more forest than the given dataset. The variation among the maps regarding forest quantity and allocation relates to the combined effects of the various definitions of forest and classification errors. Scientists and policy makers must consider these insights when producing future forest cover maps and when establishing benchmarks for forest cover monitoring.

1. Introduction

Forests supply ecosystem services that are essential for human survival. However, over half of the world's forests have been lost during the last 8000 years due primarily to human activities (Bryant et al., 1997; Shimada et al., 2014). Data from FAO's global forest resources assessment show that the world's forest cover continues to decline from 4.13 billion ha in 1990 to 4.06 billion ha in 2000, 4.03 billion ha in 2005, 4.02 billion ha in 2010, and 4.00 billion ha in 2015 (FAO, 2016). Thus, the monitoring of the world's remaining forest cover is a global priority.

The Philippines is among the world's 18 mega biodiversity countries due to its diverse habitats and high rates of endemism (PAWB, 2009; BMB, 2014). The Philippines maintains 5% of the world's flora and is ranked fifth globally in terms of the number of plant species (PAWB, 2009). However, the Philippines has become one of the world's hotspots where biodiversity is threatened due to exotic species, mining and land change, especially deforestation (Myers et al., 2000; PAWB, 2009; Lasco et al., 2013; BMB, 2014). The Philippines ranks fourth on the Conservation International's list of the world's most threatened forest hotspots (Conservation International, 2011).

The forest cover of the country has been changing rapidly, declining from 90% in 1521 when Spanish colonizers arrived to 70% in 1900 and then to 22% in 1998 (ESSC, 1999). Population increase, urban growth, agricultural expansion, and timber harvesting are among the most important drivers of deforestation in the country (Kummer, 1992; Liu

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et al., 1993; ESSC, 1999; Lasco et al., 2013). Consequently, the protection, conservation and improvement of the country's remaining forests have become major concerns to the national government and to other organizations.

Numerous reforestation projects and management policies in the Philippines have emerged during the last century (Harrison et al., 2004; Lasco et al., 2013). The most recent reforestation initiative of the Philippine government is the National Greening Program (NGP). NGP's main objective was to plant 1.5 billion trees on 1.5 million hectares from 2011 to 2016 (RP, 2011). Like previous reforestation projects, the challenge lies in monitoring NGP's impact, which requires accurate baseline information.

Remote sensing is an important source of information for forest cover monitoring across various spatial and temporal scales. The advances in remote sensing technology have enabled the production of various global forest and land cover products that can serve as benchmarks for monitoring future forest cover changes. Examples of these products include the GlobeLand30 (Chen et al., 2015), the Global Tree Canopy Cover (Hansen et al., 2013), the ALOS-PALSAR Forest/Non-Forest Map (Shimada et al., 2014), and the Landsat Vegetation Continuous Fields (Sexton et al., 2013).

However, various types of remotely sensed data and various forest classification procedures can produce various estimates of forest cover. For instance, according to the GlobeLand30 estimate, the Philippines had 19.8 million ha of forest cover in 2010 (Chen et al., 2015). In the same year, the ALOS-PALSAR Forest/Non-Forest Map (Shimada et al., 2014), the Global Tree Canopy Cover (Hansen et al., 2013) (forest > 50%) and the Landsat Vegetation Continuous Fields (Sexton et al., 2013) (forest > 50%) estimated 16.8, 16.8, and 10.6 million ha, respectively. Meanwhile, the Philippine Land Cover map of 2010 produced by the National Mapping and Resource Information Authority (NAMRIA) estimated 6.8 million ha (Manuel, 2014; DENR, 2015). This muddle of estimates causes confusion and can potentially affect forest cover monitoring and forest management planning. Thus, it is necessary to assess and compare these forest and land cover products simultaneously.

Many studies have compared and assessed various remote sensing-derived global forest and land cover products. Recent ones that are closely related to this study include Yang et al. (2017), Sexton et al. (2015) and Bai et al. (2014). Bai et al. (2014) compared and assessed five moderate-resolution global land cover products covering China, circa year 2000. Their comparison of the land cover products with reference data revealed disagreement that ranges from 48% to 67%. Bai et al. (2014) hypothesize that the disagreements could have been due to differences in the satellite sensors, time points, classification algorithms, or classification schemes.

Sexton et al. (2015) assessed the agreement of eight global land cover products for the class forest in or near the year 2000. Their study revealed that areas with high forest disagreement and uncertainty are in sparsely forested regions. They also argued that the observed disagreement is due to the many definitions of the term 'forest'. The authors write that due to "different geographic and cultural backgrounds, even expert human interpreters disagree on the identification of forests in situ or in satellite images" (p. 192).

Yang et al. (2017) compared and assessed eight medium-resolution forest cover maps in 2010 on the Loess Plateau, China. The authors used Google Earth images captured around 2010 and field photos taken during 2010–2013 to interpret visually 100 forest and 493 non-forest regions. Their forest omission error intensity ranged from 7% to 48% and their forest commission error intensity ranged from 6% to 28%. The potential reasons for the observed disagreements between the forest cover maps included variation in forest definitions, data sources, and algorithms (Yang et al., 2017).

Our study builds on these previous studies as we compare and assess eight remotely sensed maps of Philippine forest cover in the year 2010 by quantifying their agreements and disagreements. Our goal is to provide insights regarding the potential sources of disagreements among the maps and to discuss the implications of such disagreements for forest cover monitoring. Our manuscript makes a unique contribution to methodology in that we have created a technique to compare multiple maps simultaneously in terms of quantity and allocation of a category, which is forest in our case.

2. Methodology

2.1. Land cover data, reclassification, and reference data preparation

We compared and assessed eight maps of forest versus non-forest of the Philippines in 2010 derived from eight remotely sensed land cover products. One of these products is the Philippine Land Cover produced by NAMRIA (Manuel, 2014; DENR, 2015), which has national coverage. The other seven products have global coverage. They are the Climate Change Initiative (CCI) Land Cover (ESA, 2017), the Landsat Vegetation Continuous Fields (VCF) (Sexton et al., 2013), the MODIS VCF (DiMiceli et al., 2011), the MODIS Land Cover Type product (MCD12Q1) (Friedl et al., 2010; Channan et al., 2014), the Global Tree Canopy Cover (Hansen et al., 2013), the ALOS-PALSAR Forest/Non-Forest Map (Shimada et al., 2014), and the GlobeLand30 (NGCC, 2014; Chen et al., 2015). Table 1 describes these products in detail.

We extracted the coverage of the Philippines from the seven global products then reclassified their original categories, including those of the national product, into two categories: forest and non-forest. Table 1 shows the reclassification procedure. The reclassification generated eight Forest versus Non-Forest maps that we call, respectively, NAMRIA30, CCI300, LANDSAT30, MODIS250, MODIS500, GTCANOPY30, ALOS25, and GLOBELAND30. The number at the end of each name indicates spatial resolution in meters.

To produce the reference data, we generated 10,000 sample points distributed randomly across the spatial extent of the Philippines. We first converted the points into a kml file, which we uploaded to Google Earth. We attempted to classify visually each point as either forest or non-forest based on a > 50% threshold at a 25 m spatial resolution, which is the smallest spatial resolution among the land cover data (Table 1). We classified a point as forest when its corresponding 25 m × 25 m grid contained > 50% tree cover based on visual interpretation and estimation. Otherwise, we classified the point as non-forest.

Some points were easier than others to make a decision concerning forest versus non-forest. Fig. 1 shows an example where the cover of points (b), (d) and (e) is clearer than of points (a) and (c). We classified 9852 of the 10,000 points, because the other 148 points were impossible to identify due to cloud cover, shadow or lack of image. Fig. 2 shows the spatial distribution of these points. Google Earth has a feature that allows the user to select images according to capture date. We were interested in 2010. However, a 2010 image was not available for some points. In such cases, we used the closest available capture date (see Fig. 2). We used these points as reference information for error assessment, thus we call this dataset REFERENCE.

2.2. Comparison and assessment of forest versus non-forest maps

We analyzed the 9852 points where each point is either forest or non-forest in each of the eight Forest versus Non-Forest maps and in the reference data: NAMRIA30, CCI300, LANDSAT30, MODIS250, MODIS500, GTCANOPY30, ALOS25, GLOBELAND30, and REFERENCE. We applied the following procedures.

First, we performed error assessment using the Google Earth data as reference. For each of the eight Forest versus Non-Forest maps, we computed for the forest category the omission disagreement, commission disagreement, and agreement. If a point is forest according to a map and non-forest according to the reference data, then the point is forest commission disagreement for that map. If a point is non-forest