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Variance-preserving mosaicing of multiple satellite images for forest parameter estimation: Radiometric normalization

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ABSTRACT

Measuring, Reporting and Verification (MRV) systems of the United Nations programme on Reducing Emissions from Deforestation and forest Degradation (REDD+) aim to provide robust and reliable data on carbon credits over large areas. Multitemporal satellite mosaics are often the only cost-effective remote sensing data that allow such coverage. Although a number of methods for producing mosaics has been proposed, most of them are dependent on the order in which tiles to normalized are presented to the algorithm and suffer from loss of input scenes' variance which can substantially reduce the carbon credits. In this study we propose a variance-preserving mosaic (VPM) algorithm that considers all images at the same time, minimizes overall error of the normalization and aims to preserve average variance of input images. We have compared the presented method with a popular relative normalization algorithm commonly used nowadays. The proposed algorithm allows to avoid iterative pair-wise normalization, results in visually uniform mosaics while maintaining also the original image variance.

1. Introduction

In model-based estimation of geographical quantities based on satellite images, regression models are built on normalized band values of image pixels. There are many applications where not only the fit of estimates to ground truthing is important, but also the fitting of variance. One such application is the Measuring, Reporting and Verification (MRV) of the United Nations programme on Reducing Emissions from Deforestation and forest Degradation (REDD+). REDD+ aims to create a financial value (carbon credits) for the carbon stored in forests, especially those of developing countries, in order to reduce greenhouse gas emissions.

One of the important steps within REDD+ is to develop a cost-effective and accurate methodology for carbon monitoring over large areas. Such methodology requires an approach that combines together ground measurements and remote sensing technologies (Angelsen, 2008). Possible remote sensing technologies that can be employed are satellite imagery, LiDAR, aerial images and radar data.

For REDD + MRV, satellite imagery has several advantages over other remote sensing technologies. Firstly, satellites provide "wall-to-wall" observations of the target area. Secondly, the price of satellite images is considerably cheaper, and even more, some of the satellite imageries, such as Landsat, can be acquired completely free of charge. And lastly, satellites offer reliable historical data. For instance Landsat delivers global images for the last four decades (Gibbs et al., 2007).

Despite many benefits satellite imagery provides, there are also challenges that should be addressed. One of them is radiometric differences between adjacent multitemporal scenes. Due to variation in acquisition conditions (e.g. solar illumination, atmospheric scattering and atmospheric absorption) the same ground object on two overlapping images can result in different spectral values (Yuan and Elvidge, 1996). Because of this, radiometrically uniform mosaics using multitemporal scenes should be created before employing satellite imagery into carbon assessment. Another challenge is the variance suppression that likely occurs during mosaicing of multiple images, whenever it is based on averaging pixel values of overlapping parts of images. REDD + MRV's credits are based on measuring the change in carbon captured in forests. If regression estimates for carbon capture are built using satellite images, suppressing the true variance of band values gets translated into suppression of change in carbon captured, and hence into a reduction of the corresponding carbon credit.

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To overcome radiometric differences between multitemporal scenes there are two approaches commonly in use: absolute and relative normalization (also called correction). The first one aims to convert pixel intensity values to true surface reflectance using *in situ* ground measurements of atmospheric properties. The main disadvantage of the method is that it is very difficult and often not possible at all to obtain atmospheric measurements (Du et al., 2002). The second one (relative normalization) uses an assumption of a linear relationship between overlapping regions of multitemporal images (Song et al., 2001). The linear relationship is constructed using pseudo-invariant features (PIFs) which represent areas of temporally constant reflectance. Substantial research has been done on this topic in past decades and researchers propose various methods for automatic PIF identification, as well as for modeling linear relationships (Hall et al., 1991; Yuan and Elvidge, 1996; Song et al., 2001; Du et al., 2002; Gibbs et al., 2007; Canty and Nielsen, 2008; Zhang et al., 2008; Liu et al., 2012).

All proposed relative radiometric normalization methods are following a common routine to normalize two scenes: identify PIFs, run regression analysis on the overlapping region and apply the coefficients found to the whole scene. If the mosaic needs to be built for a large area that is covered by many satellite images, the same routine is applied recursively pairwise, where a normalized scene becomes the reference for the next one (Du et al., 2001; Furby and Campbell, 2001; Olthof et al., 2005).

Such an approach raises several concerns. Firstly, the resulting mosaic depends on the order of the normalization and may vary significantly (Furby and Campbell, 2001). Secondly, due to the recursive manner of the approach, error propagation brings a high level of uncertainty (Olthof et al., 2005). Additionally, as regression analysis is commonly used for the normalization step, a change (loss or gain) in variance of the normalized image values is expected. The change of variance over mosaic scenes will in turn cause error to the forest parameters estimated from them (e.g. biomass, height, etc.).

To resolve these problems, we propose variance-preserving mosaic (VPM) algorithm that considers all images at the same time, minimizes overall error of the normalization and aims to preserve average variance of input scenes. In order to validate the proposed method, we compute two independent mosaics – one using an existing radiometric algorithm and the other one with the proposed algorithm. We assess the mosaics by visual inspection, by computing the variance of each scene, and by leave-one-out cross-validation of the forest parameters estimated from them.

2. Study area and data

2.1. Study area

The study area is located over the Terai Arc Landscape (TAL), along the foothills of the Himalayas in the southernmost part of Nepal, with altitude ranging from less than 100 m up to 2200 m. Influenced both by tropical and subtropical climate about half of the study area is covered by subtropical mainly deciduous forests. The dominating forest types are sal (*Shorea robusta*) terai mixed hardwood, khair-sisau (*Acacia catechu*/*Dalbergia sissoo*) and chir-pine (*Pinus roxburghii*). TAL is one of the priority landscapes in Nepal, both for the conservation of its biodiversity and the protection of the ecological services (e.g. greenhouse gas mitigation, purification of air and water) it provides.

2.2. Ground-truth data

The field data consists of 738 plots (12.6-m radius) collected in the spring of 2011. Systematic cluster sampling was used to design the locations of sample plots. As this was done for the so-called LAMP, or LiDAR-Assisted Multi-source Process for MRV, the plots are clustered as in three-stage sampling. In the first stage, a set of LiDAR blocks of 5000 hectars is randomly allocated over the whole area. In the second stage, six plot clusters are assigned in a systematic fashion on those blocks. In the third stage, eight circular sample plots are systematically placed within plot clusters. Possible spatial correlation of ground truth data resulting from plot clustering is ignored.

Diameter at breast height (DBH), height and species were measured for those trees in the plot that had DBH more than five meters. The following forest attributes for each plot were then derived from the tree-level measurements: stem count (1/ha), mean diameter at breast height weighted by basal area (cm), basal area (m^2/ha), mean tree height weighted by basal area (m), stem volume (m^3/ha), and above-ground biomass (tons/ha). For more detailed information about field measurements and equations in use reader is referred to Gautam et al. (2013).

For applying the LAMP method, LiDAR data was collected from about five percent of the whole study area in blocks. Each block was scanned with full coverage from a height of 2200 m above ground. Raw LiDAR data was classified into three categories: ground returns, vegetation returns, and errors. Digital Terrain Model was built from the ground returns and using it LiDAR data was converted from absolute elevation into distance-to-ground.

Set of 10000 circular-shaped one hectare size "surrogate plots" were calculated using original field and LiDAR data. Forest attributes were estimated for this set. Locations of the surrogate plots were selected through weighted random sampling using the inverse of the block weights applied in LiDAR block sampling (Gautam et al., 2013).

2.3. Satellite imagery

Medium and high resolution satellite images were used in this study, specifically Landsat 5 and RapidEye. The scenes were chosen so that they have as little as possible clouds and are acquired in the same growth season. All bands, but thermal infrared, were employed in this study. Table 1 represents detailed information on the images, and Fig. 1 depicts the location of the scenes over the study area. As a pre-processing step clouds and snow were identified within satellite scenes and masked out by setting their pixel values to nodata.

3. Method

3.1. VPM method

We are given a set of images $I_n,\ n = 1, \ldots, N$ that should be normalized in order to construct a uniform, variance-preserving mosaic. Each image I_i overlaps at least one neighbor I_j. We will define I_{ij} as the subset of I_i corresponding to the no-change pixels for the overlap with image I_j, and m_{ij} as the corresponding size of I_{ij}. The pixels can be identified as no-change ones in all pairwise overlaps simultaneously using well established technique (e.g. Canty and Nielsen, 2008). Obviously, m_{ij} is always equal to m_{ji}, and m_{ji} is always zero when the images I_i and I_j do not overlap.

We can describe how different two neighbor images I_i and I_j are by analyzing pixel values of their overlapped regions. We define the squared difference d_{ij} as the measure of similarity between two images over the same overlapped area:

$$d_{ij} = \sum_{m=1}^{m_{ij}} (p_m - q_m)^2, \qquad (1)$$

where p_m and q_m are pixel values of areas I_{ij} and I_{ji} respectively.