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Tropical land use land cover mapping in Pará (Brazil) using discriminative Markov random fields and multi-temporal TerraSAR-X data

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ABSTRACT

Remote sensing satellite data offer the unique possibility to map land use land cover transformations by providing spatially explicit information. However, detection of short-term processes and land use patterns of high spatial–temporal variability is a challenging task.

We present a novel framework using multi-temporal TerraSAR-X data and machine learning techniques, namely discriminative Markov random fields with spatio-temporal priors, and import vector machines, in order to advance the mapping of land cover characterized by short-term changes. Our study region covers a current deforestation frontier in the Brazilian state Pará with land cover dominated by primary forests, different types of pasture land and secondary vegetation, and land use dominated by short-term processes such as slash-and-burn activities. The data set comprises multi-temporal TerraSAR-X imagery acquired over the course of the 2014 dry season, as well as optical data (RapidEye, Landsat) for reference. Results show that land use land cover is reliably mapped, resulting in spatially adjusted overall accuracies of up to 79% in a five class setting, yet limitations for the differentiation of different pasture types remain.

The proposed method is applicable on multi-temporal data sets, and constitutes a feasible approach to map land use land cover in regions that are affected by high-frequent temporal changes.

1. Introduction

The Brazilian Amazon is the largest area of tropical rain forest shared by a single country. In the last decades it has become increasingly threatened by large scale deforestation, forest degradation, and the expansion of agriculture (Davidson et al., 2012; Lapola et al., 2014). They affect the Earth's ecosystems and ecosystem services far beyond the boundaries of the original region, and can influence the climate directly at local and even regional scales (Foley, 2005; Vitousek, 1997). Thus, detailed knowledge and information on land use and land cover (LULC) offers valuable input for decision support and environmental monitoring systems.

Remote sensing satellite data offers the unique possibility to generate consistent LULC maps over large areas at a temporally high resolution. Mapping of LULC change in the Amazon is predominantly achieved by analyzing multi-spectral remote sensing data (INPE, 2015; Wulder et al., 2012; Hansen et al., 2013). However, a limitation of the analysis of multi-spectral remote sensing data is imposed by its dependency on cloud-free conditions. These are rare in tropical regions and in general not met during wet season (e.g. Rufin et al., 2015; Müller et al., 2015). Synthetic aperture radar (SAR) data can overcome these problems and various studies demonstrate the potential for mapping LULC and their changes (Pfeifer et al., 2016; Qi et al., 2012; Bovolo and Bruzzone, 2005), also in the context of deforestation and related processes (Sarker et al., 2013; Reiche et al., 2015; Englhart et al., 2011; Almeida-Filho et al., 2009). Such mapping approaches become even more attractive due to recent missions with increased repetition rates, higher spatial resolution (e.g. TerraSAR-X and Sentinel-1), as well as better data availability, e.g., by virtue of the Copernicus data policy (Aschbacher and Milagro-Pérez, 2012). TerraSAR-X and the Sentinel-1 constellation guarantee cloud free coverage within 11 and 6 days respectively, while the repetition rate of the Sentinel-2 constellation (5 days) and Landsat-8 (16 days) might be affected by clouds.

Although the classification accuracy of SAR data can be limited in direct comparison to multi-spectral data, various approaches exist to increase the mapping accuracy. These include the integration of one-pass interferometry (Schlund et al., 2013), contextual spatial information derived from texture parameters or segmentation (Cutler et al.,

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2012; Sarker et al., 2013; Schlund et al., 2013; Waske and van der Linden, 2008), or the utilization of multi-temporal or multi-sensoral data (Reiche et al., 2013; Stefanski et al., 2014a; Waske and Braun, 2009). Although limitations of short wavelength SAR data for the classification of dense vegetation are well documented (e.g. Kumar and Patnaik, 2013), various studies have highlighted the potentials of this data for LULC mapping (e.g. Schlund et al., 2013; Qi et al., 2015, 2012; Uhlmann and Kiranyaz, 2014; Khatami et al., 2016; Sonobe et al., 2014), e.g. by utilization of multi-temporal data, modern classification algorithms, or spatial context. Multi-temporal data sets are generally more adequate when classes can be characterized by clearly defined temporal signatures, e.g. caused by differences in the phenology of crops, land use management, or seasonal cycles (Blaes et al., 2005; McNairn et al., 2009). While the single classification of a multitemporal data set might be useful for study sites without or long-term changes (Waske and Braun, 2009; Stefanski et al., 2014b), it might be limited for study sites with temporally high-frequent changes in land cover, e.g. slash-and-burn activities, at arbitrary points in time. Recent studies have shown great potentials to tackle these problems by time series analysis of multispectral data (Zhu and Woodcock, 2014), but SAR speckle and quick succession processes still pose difficult challenges using such methods, especially if very long time series are often not available.

In the context of multi-temporal data analysis, a main drawback is often the assumption of non changing land cover during the investigation period. Consequently, temporally dynamic LULC, such as slash-and-burn activities or transitions between clean and shrubby pasture, are neglected. Various studies emphasize the usage of an adequate classification approach to ensure a high mapping accuracy (Liu et al., 2006; Waske and Benediktsson, 2007; Waske and Braun, 2009). Especially the integration of spatial information by means of region-based classification or spatial features such as texture lead to a gain in accuracy. In addition, Markov Random Fields (MRFs) are a promising approach to integrate spatial context (Moser et al., 2013; Moser and Serpico, 2013; Liu et al., 2006). MRFs are employed to model prior knowledge about neighborhood relations within the image, called spatial relations, but can also be extended to describe relations of the same area but at different acquisition dates (temporal relations). Since the early 1990s, approaches based on MRFs have been utilized in remote sensing for various purposes (Bouman and Shapiro, 1994; Xie et al., 2002; Tran et al., 2005; Solberg et al., 1996). Liu et al. (2008) use locally variant transition models to account for spatial heterogeneity and have applied the model on subsets of two Landsat scenes from 1990 and 2001. More recently, Wehmann and Liu (2015) have adapted an integrated kernel as proposed by Moser and Serpico (2013), and used Iterative Conditional Modes (ICM) as optimization technique with spatially-variant transitions for classifying Landsat data. Hoberg et al. (2015) apply multi-temporal Conditional Random Fields to regularize annual remote sensing imagery from different high resolution scales (IKONOS, RapidEye, Landsat) over the course of five years.

With the emergence of efficient probabilistic classifiers over the last decade, standard MRFs have been extended to discriminative MRFs (Kumar and Hebert, 2003), and turn out to be increasingly useful to optimize land cover classifications (Moser and Serpico, 2010; Tarabalka et al., 2010; Voisin et al., 2013). Liu et al. (2006) highlight the advantages of utilizing non-parametric, probabilistic Support Vector Machines (SVMs, Platt, 1999) over a maximum likelihood classifier. However, although many remote sensing studies highlight the positive capabilities of MRFs, only few studies aim on using MRFs for landscape-scale mapping with multi-temporal data sets (e.g. Cai et al., 2014; Wehmann and Liu, 2015; Olding et al., 2015), for example, to map forest cover change (Liu et al., 2006, 2008). If multi-temporal data sets are available, MRFs can also be used to optimize the corresponding maps by considering predefined spatial–temporal inter-dependencies between neighboring pixels, which are stored in transition matrices.

We present a novel framework for classification of a TS-X time series using discriminative MRFs and Import Vector Machine (IVM), a probabilistic, discriminative, non-parametric classifier. Each scene is separately classified using IVM, afterwards MRFs are utilized in an independent step to post-regularize the classification map. We chose IVMs over commonly used probabilistic SVMs, since they have proven to offer a more reliable probabilistic output (Zhu and Hastie, 2005; Roscher et al., 2012a,b). For MRF optimization we choose Loopy Belief Propagation (LBP) over ICM as this method has been shown repeatedly to yield higher accuracies (Szeliski et al., 2006; Andres et al., 2010a). Few studies have utilized LBP in the field of remote sensing (Li et al., 2013), and as a novelty we integrate LBP into a multi-temporal setting.

The presented framework aims on the classification of each individual acquisition, and thus enables mapping of high frequency spatial–temporal LULC patterns. In contrast to related studies, we use a multi-temporal MRF model on SAR data to detect short-term transitions within one season and Loopy Belief Propagation (LBP) for inference.

The overall goal of this research is focused on two objectives: (i) to map LULC in a tropical setting with short-term processes, by adapting recent MRF methods, and (ii) to assess the potential for LULC mapping using time-series image data of short wavelength SAR. The specific objective is to map LULC in Pará, Brazil, where transformations of forest to pasture are the major driver of deforestation. Pasture management in the study region tends to fall into one of two categories: long-term processes of intensively managed pasture land (pasto limpo), or short-term processes of episodically managed pasture land with a high degree of successive dynamics (pasto sujo). Pasture management in general is characterized by slash-and-burn processes resulting in sudden changes in LULC.

2. Study area and data

2.1. Study area

The study area lies in the Northern part of the Novo Progresso municipality (southern Pará state, Brazil), and is intersected by the BR-163 highway in the Southwest 1. The BR-163 is accompanied by fishbone structures indicative of deforestation (Ahmed et al., 2013; Coy and Klingler, 2014). A major driver of deforestation in the study area is the transformation of forests into pasture land. The climate in the study region is characterized by a wet and a dry season. While the dry season, between June and September, sees abrupt land cover changes in the form of large scale burning and clear cuts, the wet season is defined by gradual regrowth, yet deforestation rates over the wet season are on the rise.

2.2. Remote sensing data

The data base for the study consists of five TS-X strip map scenes with 5 m × 5 m spatial resolution (Table 1). All images are ordered in single-look complex format, comprising different VV-VH and HH-HV polarization at an incidence angle of 37.75°, and cover a swath of roughly 50 km × 15 km (5663 × 11,856 pixels). Data is calibrated and processed according to common procedures (see Section 2.2). Preprocessing in the context of this study includes all necessary steps before random sampling of training and test data is performed. After

Table 1
Scenes utilized in this study. All scenes were collected over the same area using the same incidence angle.

Date	Polarization
2014-06-08	VV-VH
2014-06-30	HH-HV
2014-07-22	VV-VH
2014-08-24	VV-VH
2014-09-04	HH-HV