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Robust quantification of riverine land cover dynamics by high-resolution remote sensing

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ABSTRACT

Floodplain areas belong to the most diverse, dynamic and complex ecological habitats of the terrestrial portion of the Earth. Spatial and temporal quantification of floodplain dynamics is needed for assessing the impacts of hydromorphological controls on river ecosystems. However, estimation of land cover dynamics in a post-classification setting is hindered by a high contribution of classification errors. A possible solution relies on the selection of specific information of the change map, instead of increasing the overall classification accuracy. In this study, we analyze the capabilities of Unmanned Aerial Systems (UAS), the associated classification processes and their respective accuracies to extract a robust estimate of floodplain dynamics. We show that an estimation of dynamics should be built on specific land cover interfaces to be robust against classification errors and should include specific features depending on the season-sensor coupling. We use five different sets of features and determine the optimal combination to use information largely based on blue and infrared bands with the support of texture and point cloud metrics at leaf-off conditions. In this post-classification setting, the best observation of dynamics can be achieved by focusing on the gravel-water interface. The semi-supervised approach generated error of 10% of observed changes along highly dynamic reaches using these two land cover classes. The results show that a robust quantification of floodplain land cover dynamics can be achieved by high-resolution remote sensing.

1. Introduction

Floodplain areas are among the most important ecosystems in terms of biodiversity, despite their low terrestrial coverage (Postel and Carpenter, 1997). A recent report (Mosselman et al., 2016) indicates that 40% of European rivers are affected by hydropower production, navigation, agriculture, flood protection or urban development, which disturb water flow, inundation, erosion and sedimentation processes that directly impact hydromorphological properties. In the last years, the concept of *habitat dynamics* has become even more relevant than *habitat heterogeneity* for supporting biodiversity in riparian areas (Haase et al., 2013; Palmer et al., 2010; Turner et al., 1993). The dynamics of the riverine environment have been studied by focusing on the water channel, of both short (Arscott et al., 2002) and long time periods, mostly using historical photography (Latterell et al., 2006) or by focusing on riparian areas (Bertoldi et al., 2011; Clerici et al., 2014). Moreover, several models of landscape evolution have been developed to provide temporal simulations of riverine environments (Coulthard et al., 2007; Crosato and Saleh, 2011; Kooistra et al., 2008; Murray and Paola, 2003; Perucca et al., 2007).

The riverscape is unique in its structure, creating a heterogeneous image composition not commonly seen in remote sensing applications. The composition of the riverscape may change strongly depending on the distance from the water channel in active floodplains (Gregory et al., 1991). Closer to the water, the land cover is very heterogeneous, representing a transitional environment that consists of, e.g., drying dead arms, gravel and sand bars, decomposing woody debris and riverine shrubs. Further from the river, the land cover exhibits more homogeneous patterns composed of riparian vegetation, floodplain to upland forest and grassland. While an ecological study would focus on

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so-called floodplain dynamics, i.e., the dynamics of ecological habitats, we use here the proxy of land cover dynamics for our study, i.e., the dynamics of land cover classes detected by remote sensing.

In a riverscape context, remote sensing technologies offer a unique point of view on the floodplain dynamics, allowing researchers to sample data at regular temporal intervals and cover large areas with less effort than traditional ground sampling approaches. Riverscape remote sensing embraces aspects of light propagation in the water body (Eugenio et al., 2015; Legleiter and Overstreet, 2012), large woody debris detection (Marcus et al., 2003; Smikrud and Prakash, 2006), species classification (Hamada et al., 2007), sandbar relocation (Bryant and Gilvear, 1999) and modeling of floodplain vegetation (Schaepman et al., 2007) or hydrology (Gleason and Smith, 2014; Güneralp et al., 2014b; Javernick et al., 2014). Riverscape remote sensing deploys a suite of technologies ranging from high-resolution to imaging spectrometry sensors.

Unmanned Aerial Systems (UAS) technologies are nowadays used for many applications requiring very high-resolution imagery. The efficiency and advantages of UAS for remote sensing purposes have been demonstrated in general (Colomina and Molina, 2014) and for specific uses such as segmentation of tree crowns in forested ecosystems (Torabzadeh et al., 2014), civil engineering structures (Siebert and Teizer, 2014) or urban vegetation mapping (Feng et al., 2015a). Specific aspects of riverscape remote sensing using UAS have been validated, including immersed topography (Feurer et al., 2008), submerged aquatic vegetation (Flynn and Chapra, 2014), hydraulic fish habitat (Tamminga et al., 2015) and hydromorphological effects of flooding (Langhammer and Vacková, 2018).

Recent developments in UAS technologies offer a new perspective on the land cover component of the riverscape. Land cover classification algorithms have been successfully developed for high-resolution imagery in various environments (Cleve et al., 2008; Myint et al., 2011; Tuia et al., 2009), including GEOBIA approaches (Kim et al., 2011). Moreover, land cover change mapping by remote sensing has been developed and applied for many years in various environments (Butt et al., 2015; Herold et al., 2002; Willis, 2015). However, few applications in the context of a riverine landscape can be found today (Demarchi et al., 2016; Güneralp et al., 2014a; Johansen et al., 2007). The main processes triggering the dynamics of riverscape habitats include fluvial geomorphic processes and ecological processes of succession, recruitment and dispersal (Knighton, 2014; Richards et al., 2002). Various classification systems are used to discriminate habitats of the riverscape (Bryant and Gilvear, 1999; Harmon et al., 1986; Woodget et al., 2017). The current study is restricted to a coarse classification of habitats including the most important land cover types, namely water, gravel, vegetation and woody debris, to ensure that the method could be applied on different sites. Finally, the chosen land cover types relate to the main geomorphic macro-units in ecological terms composed by (i) open water, (ii) bare sediment and (iii) vegetation (e.g. vegetated sediment, vegetated islands, forest).

For observing land cover dynamics in the riverscape, post-classification change mapping is suitable because of its ability to interpret changes. In general, post-classification approaches remain more popular than pre-classification change detection (Tewkesbury et al., 2015). Furthermore, processing images independently allows us to understand the underlying factors of variations by modeling statistically sensor selection, seasonality, extracted covariates (or *features*), platform design and data processing to the final land cover map at each time step. However, the error rate of a change map is linked to the product of the individual error rate of the classification maps, hindering the usability of change mapping when the error rate is higher than the actual land cover changes (Serra et al., 2003). Methods to improve the general accuracy of post-classification change mapping have been proposed to solve these issues. A direct approach consists of reducing the impact of classification errors by detecting changes before the classification step (Hussain et al., 2013). Another approach consists of using the confusion matrix of classification maps to correct the estimates of dynamics (Van Oort, 2005). Here, we focus on the second kind of approach to determine a robust dynamics estimate with respect to the classification errors.

In this study, we analyze the capabilities of UAS technologies and their associated classification processing chain to observe post-classification dynamics in the specific case of the riverscape. We aim to determine the best observer specifications and landscape features for achieving a robust quantification of riverscape dynamics. Hence, the final aim is not an improvement of raw classification accuracy, but a robust extraction of dynamics information that takes into account potential classification errors. Robustness is here understood as a stability of the quantification against classification errors due to image acquisition, image processing, vegetation status and seasonal influences. We assess the use and importance of different types of information extracted from the acquired high-resolution imagery by studying the link between classification accuracy, features used in the machine learning algorithms, the acquisition and camera parameters, and the corresponding change maps. Finally, we assess the accuracy of the whole processing chain to carry out post-classification change mapping, including a post-analysis error-adjustment (c.f. Olofsson et al., 2013).

2. Materials & methods

2.1. Study sites

The test area consisted of three hydromorphologically different reaches of two Swiss rivers in the pre-Alpine region, i.e., the Sarine (46°45′N 7°7′W) and the Sense (46°44′N 7°18′W) (Fig. 1). Both rivers are located in the region of Fribourg, in western Switzerland, and share similar climatic conditions. Hydropower considerably impacts the hydrological regime of the Sarine River, while the Sense River, near Plaffeien, is one of the last Swiss rivers with almost no anthropogenic control of the hydrological regime. The reaches represented three different land cover dynamics, i.e., a residual reach along the Sarine (almost no flow changes), a hydropeaking reach along the Sarine (frequent hourly and daily flow changes), and a natural reach along the Sense (irregular natural flow changes). The regular and frequent flow changes observed in the hydropeaking reach are due to the operation of a hydropower plant upstream of the reach. The extent of the covered areas was based on the federal inventory of floodplains of national importance (updated on 01 July 2007) issued by the Swiss Federal Office for the Environment (FOEN).

2.2. Data acquisition

We collected the UAS image data using three different cameras, each with different spectral capabilities (Table 1). The RGB camera was a standard camera Canon IXUS 125HS (Canon Manual, 2012) acquiring three wavelength bands centered at 450 nm, 520 nm and 660 nm. The red edge camera (ReGB) was a modified version of the same camera containing three bands centered at 450 nm, 500 nm and 715 nm. The red edge band of the camera was enforced by altering the red filter to a near-infrared filter. The multispectral camera (senseFly Manual, 2014) consisted of four bands centered at 550 nm (R), 660 nm (G), 735 nm (NIR1) and 790 nm (NIR2), out of which the R, G and NIR2 were used. The NIR1 band was not used because of its extremely high correlation to the NIR2 band, not providing any additional information for our land cover classes. In the case of the multispectral camera, an irradiance sensor was located on the top of the camera, which enabled the conversion of recorded radiation to reflectance quantities. While the multispectral camera was calibrated before each flight, no pre-flight or post-flight calibration was performed on the RGB and ReGB cameras. Datasets used in this study were regularly acquired throughout the year resulting in trees with leaf-on and leaf-off states. The ReGB Snow and ReGB Leaf-Off datasets corresponded to the winter acquisitions over the