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Coupling high-resolution satellite imagery with ALS-based canopy height model and digital elevation model in object-based boreal forest habitat type classification

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ABSTRACT

We developed a classification workflow for boreal forest habitat type mapping. In object-based image analysis framework, Fractal Net Evolution Approach segmentation was combined with random forest classification. High-resolution WorldView-2 imagery was coupled with ALS based canopy height model and digital terrain model. We calculated several features (e.g. spectral, textural and topographic) per image object from the used datasets. We tested different feature set alternatives; a classification accuracy of 78.0% was obtained when all features were used. The highest classification accuracy (79.1%) was obtained when the amount of features was reduced from the initial 328 to the 100 most important using Boruta feature selection algorithm and when ancillary soil and land-use GIS-datasets were used. Although Boruta could rank the importance of features, it could not separate unimportant features from the important ones. Classification accuracy was bit lower (78.7%) when the classification was performed separately on two areas: the areas above and below 1 m vertical distance from the nearest stream. The data split, however, improved the classification accuracy of mire habitat types and streamside habitats, probably because their proportion in the below 1 m data was higher than in the other datasets. It was found that several types of data are needed to get the highest classification accuracy whereas omitting some feature groups reduced the classification accuracy. A major habitat type in the study area was mesic forests in different successional stages. It was found that the inner heterogeneity of different mesic forest age groups was large and other habitat types were often inside this heterogeneity.

1. Introduction

In boreal forests, habitat type mappings are widely used in forestry purposes but they are also valuable in conservation. In forestry, habitat type maps and other thematic maps are used e.g. for strategic analysis in forest management planning (Tomppo et al., 2008). In conservation perspective, habitat type maps can be used e.g. in mapping biodiversity patterns (e.g. Kerr and Ostrovsky, 2003; Turner et al., 2003). Habitat type mapping is often based on land use/land cover remote sensing data classification. Land cover and land use refer to biophysical surface characteristics of the Earth and land utilization respectively (e.g. Kerr and Ostrovsky, 2003; McDermid et al., 2005). Habitats, though, do not equate land cover and thus a specific approach is needed for habitat classifications (Lucas et al., 2011; McDermid et al., 2005).

Habitats are usually defined as the resources present in an area that are needed by organisms. On the other hand, habitat type is defined as a mappable land unit in which vegetation and environmental factors are fairly homogenous. However, the terms habitat and habitat type are also used interchangeably (Corsi et al., 2000). In some of the previous mapping approaches, habitat types have been mapped using only single-date satellite imagery. Yet, it has been acknowledged that mapping of detailed habitat types using only satellite imagery is challenging, since the spectral differences between different habitat types are often minor (Díaz Varela et al., 2008). To tackle this problem, multi-temporal imagery and ancillary data, such as soil map, existing land-use dataset, and digital terrain model (DTM), have been included in some of the approaches (Bock et al., 2005; Lucas et al., 2011).

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For more than a decade, object-based image analysis (OBIA) has been used in constructing habitat type or other thematic maps from remotely sensed data. It has been acknowledged that OBIA gives more robust information and higher classification accuracies than pixel-based analyses (e.g. Bock et al., 2005; Díaz Varela et al., 2008; Whiteside et al., 2011; Yan et al., 2006). OBIA combines pixels into meaningful objects which ideally mimic human perception of the analyzed image and are better representations of the landscape features. One major benefit of OBIA is that several different factors can be included into the OBIA workflow more easily and efficiently than into pixel-based analyses. These factors include several different types of data, contextual and textural information and multi-scale analysis (Benz et al., 2004; Blaschke, 2010; Bock et al., 2005). Finally, OBIA has become increasingly popular, because very high spatial resolution remote sensing data and software tools for doing OBIA have become more common (Blaschke, 2010).

So far, the main data sources in OBIA have been aerial or satellite images (Blaschke, 2010). From the spectral images, several different layers and several derived features have been used in the OBIA analyses. For instance, the usage of textural features such as the Gray-Level Co-occurrence Matrix (GLCM, Haralick, 1979; Haralick et al., 1973) is almost a standard in the OBIA analyses (e.g. Han et al., 2012; Johansen et al., 2007; Kim et al., 2009, 2011; Murray et al., 2010; Sasaki et al., 2012; Yu et al., 2006). Additionally, the promise of the wavelet features in the texture analysis has been noted also when combined with the GLCM (Arivazhagan and Ganesan, 2003; Ouma et al., 2008; Ruiz et al., 2004; Su et al., 2012; Wang et al., 2012). Wavelets have also been used in the data pattern or structure analysis (Falkowski et al., 2008; James et al., 2011; Strand et al., 2006). In this manner, Morgan et al. (2010) note that the GLCM is mainly used for a fine-scale textural analysis, whereas wavelets can extract coarse-scale patterns from the spectral images. The inclusion of different textural features in classification has produced higher classification accuracies (Han et al., 2012; Kim et al., 2009, 2011; Murray et al., 2010; Ruiz et al., 2004).

In addition to the multispectral images, several types of data have been used in the OBIA analyses. Especially, the usage of airborne laser scanning (ALS) data has become more popular (Blaschke, 2010). Yet, studies that combine ALS and spectral images in OBIA are still rather few (e.g. Arroyo et al., 2010; Breidenbach et al., 2010; Geerling et al., 2007, 2009; Ke et al., 2010; Sasaki et al., 2012; Wang et al., 2012). From ALS, the vertical and horizontal structure of vegetation or buildings, and a high-resolution DTM can be accurately quantified. Hence, ALS complements spectral images by revealing details that cannot be seen visually from above (Lefsky et al., 2002; Vierling et al., 2008). Mostly, ALS has been used for vegetation structure quantification (Antonorakis et al., 2008; Bar Massada et al., 2012; Breidenbach et al., 2010; Ke et al., 2010; Sasaki et al., 2012) but also an ALS based DTM has been in use (Bar Massada et al., 2012; Ke et al., 2010).

From the DTM, several different topographic features can be calculated, and features such as slope, aspect and curvature, are widely used in OBIA (Ke et al., 2010; Morgan and Gergel, 2010; Thompson and Gergel, 2008; Thompson et al., 2008; Yu et al., 2006). Moreover, from the DTM, different hydrological features can be calculated. One of the most used hydrological features has been topographical wetness index (TWI), originally proposed by Beven and Kirkby (1979), which has also been used in the OBIA studies (Ke et al., 2010; Morgan and Gergel, 2010; Thompson and Gergel, 2008; Thompson et al., 2008). Although many different features have been included in the OBIA studies, thorough tests of the importance of different features in classifying different habitat types are few.

1.1. Aims of the study

The main objectives in this study were: (1) Develop a working classification workflow applicable to boreal forest habitat type mapping. (2) Study, which features and layers are important in mapping different habitat types. (3) Examine the internal variation of habitat types and types' similarities with each other. Finally, we used the Finnish multisource National Forest Inventory (MS-NFI, Tomppo and Halme, 2004; Tomppo et al., 2008, 2012) as a benchmark against which we compared the results of our method.

2. Materials and methods

2.1. Used data

Our primary datasets were a multispectral 2-m resolution WorldView-2 (WV-2) satellite image and ALS data. The WV-2 image was taken by Digital Globe Inc. in July 14th 2010 and was a subarea of one scene. The spectral range of WV-2 image was 400–1040 nm and it consisted of eight bands: coastal blue (center wavelength 425 nm), blue (480 nm), green (545 nm), yellow (605 nm), red (660 nm), red-edge (725 nm), near infra-red 1 (NIR1, 835 nm), and NIR2 (950 nm). The ALS data was provided by the National Land Survey of Finland, had at least 0.5 point per 1 m^2, and was collected in May 2010. The data was delivered as point clouds, automatically classified to ground hits, low vegetation hits, low error hits, and unclassified hits. The ALS point clouds were first triangulated and after that rasterized to construct three primary layers: a DTM, a digital surface model, and an intensity layer using LAStools (rapidlasso, Gilching, Germany). Additionally, we used 20 cm resolution aerial images (orthophotos) obtained from the city of Jyväskylä taken in 2007, a 1:10,000 resolution topographic database from the National Land Survey of Finland from the year 2010, a 1:20,000 resolution digital soil map from the Geological Survey of Finland, a 1:50,000 SLICES land use database from the NLS Finland, and a 20 m resolution MS-NFI from the Finnish Forest Research Institute from the year 2009 (Tomppo et al., 2012). Datasets and preprocessing are explained in more detail in Räsänen et al. (2013).

2.2. Study area and field work

We studied a 15 km^2 rural area southwest of the city of Jyväskylä divided into three sub-areas (Fig. 1). A part of the study area was classified into 26 different habitat or land-use types (Table 1) which were mapped with the help of field work and aerial imagery during June–July 2011. Three meadows that were mapped during the summer of 2010 were included into the analysis as well as a sand pit that was digitized using visual interpretation of WV-2 imagery. These data were included into the analysis since they were extremely close to the training dataset and because there were few meadows inside the training dataset. The field work covering in total 7 km^2 consisted of 632 patches in three contiguous sub-areas inside our study area (Fig. 1). The field work area was used for the training of the classifiers and for the classification accuracy assessments. The study area and the field work are explained in detail in Räsänen et al. (2013).

2.3. Habitat type classification system

Our habitat type classification system included natural, semi-natural and man-made habitat types. The classification system was based on the work by Rossi and Kuitunen (1996) and was modified to make it useful with remotely sensed data. Rossi and Kuitunen (1996) used habitat types as surrogates for potential