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Random Forest with semantic tie points for classifying landforms and creating rigorous shaded relief representations

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A B S T R A C T

In this study, we tested Random Forest (RF) with semantic tie points to classify discrete landforms, which would be ultimately useful for increasing the accuracy of shaded relief representations. We therefore focused our efforts on the following landforms: rock outcrops, screes, alluvial fans and low relief areas.

A characteristic of RF, which makes it a good algorithm for geomorphological mapping, is its ability to generate thousands of classification trees. Each tree provides a classification and the value classified by the majority of the trees is the final output of the algorithm. Furthermore, having multiple classifications provides a measure of uncertainty. This is very important because it gives practitioners an idea of areas where the method is less accurate, which would require more effort in terms of sampling or surveying.

This method was applied in two mountainous areas of Switzerland, the first where we trained and calibrated it and the second where we used it for classification. The results were validated using existing geomorphological maps, and they show that this method can obtain good training accuracy with a relatively small starting dataset. Moreover, both calibration and classification present a percentage of agreement with existing geomorphological maps of over 70%. Some geomorphological classes, alluvial fans and screes, present a classification accuracy that is lower than the calibration, which is in line with previous tests found in the literature. However, for other classes, i.e., rock outcrops and low relief areas, the accuracy increases, suggesting that this method can be employed extensively and relatively securely for these landforms.

1. Introduction

Advances in remote sensing have increased the availability of high-resolution digital elevation models (DEMs). These data can be extremely useful for environmental studies, but they need processing in order to provide insights regarding the evolution of the landscape. According to Jasiewicz and Stepinski (2013), two fundamentally different approaches are available to obtain these insights: shaded relief maps and the classification of landforms and landform elements.

With shaded relief maps, the analysis is carried out by a cartographer, who is able to recognise and highlight all the important features in the landscape. This implies a certain amount of terrain generalization, standardised by Imhof (1982), which is necessary to reduce visual complexity by removing unwanted details and accentuating key landforms. The problem with this technique is that it is highly subjective and the resulting map can be changed considerably depending on the skill, experience and style of the cartographer (Leonowicz et al., 2010). However, automatic relief shading, even though it is faster and cheaper to perform, is generally considered inferior to manual shading, particularly in mountain landscapes (Jenny, 2001). The reason is evident in medium- and small-scale relief shading, where high DEM resolutions create excessive levels of detail that obscure the macrotopography and decrease the readability of the map, thus reducing the amount of information that can be discerned from it (Leonowicz et al., 2012).

With the second approach, the analysis is performed by classifying landforms and landform elements. Several methods exist in the literature to achieve this objective in a quantitative and automatic way (for a review see Smith et al., 2011). These can be classified into two main categories: unsupervised and supervised. The first generally aims at identifying morphometric classes from particular combinations of derivatives, using the ‘geometric signatures’ approach first proposed by Pike (1988). It includes methods based purely on land surface parameters (LSP; e.g. Pike, 1988; Dikau, 1989; Wood, 1996; Weiss, 2001; Florinsky, 2002; Jasiewicz and Stepinski, 2013) or methods based on clustering (e.g., Zadeh, 1965; Irvin et al., 1997; Burrough et al., 2000; MacMillan et al., 2000; Robinson, 2003; Deng et al., 2006). The second category relies on training samples to determine key landform features that are then used to classify wider landscapes; these methods are

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referred to as supervised classifications. This includes object-based image analysis methods (van Asselen and Seijmonsbergen, 2006; Anders et al., 2011; Seijmonsbergen et al., 2011) and geostatistical algorithms (Brown et al., 1998; Brenning, 2005; Brenning et al., 2007; Marmion et al., 2008).

In this research, we used Random Forest (RF, Breiman, 2001) to perform the geomorphological classification. RF is a particular form of supervised classification that is already widely used in the scientific community for different topics, such as digital soil mapping (e.g., Grimm et al., 2008; Wiesmeier et al., 2011), ecology (e.g. Prasad et al., 2006; Cutler et al., 2007), and chemistry and biology (Svetnik et al., 2003; Díaz-Uriarte and De Andres, 2006). It is also popular in the remote sensing community (e.g. Ham et al., 2005; Pal, 2005; Chan and Paelinckx, 2008) because it can generate a reliable classification of multiple features and is robust against noise (Gislason et al., 2006). Moreover, RF is able to weight predictors, giving a classification of the relative importance of each of them during the training phase. In addition, because RF creates several hundred regression trees, it can be used to determine the local uncertainty in each classified pixel of the target raster, potentially helping to identify areas where a more detailed analysis is needed.

RF is relatively new to geomorphology. Marmion et al. (2008) tested several statistical and geostatistical algorithms aiming at classifying periglacial landforms in Finland. They reported that RF had the best calibration performance, but it was among the worse for classification accuracy. Stumpf and Kerle (2011) tested RF for classifying landslides and obtained prediction accuracies between 70% and 80%. These are contradictory results and it may be interesting to test RF in classifying other landforms to determine its ability to provide a way to create a classified geomorphological map quickly and cheaply. In this work, we focused on landforms deemed important for shaded relief mapping, i.e. rock outcrops, screes, alluvial fans and low relief areas.

Supervised algorithms such as RF generally require numerous training samples to achieve their maximum potential. By looking at previous examples, the number of training samples varies widely. Grimm et al. (2008) used 165 training locations over an area of 15 km^2 for predicting soil carbon; Wiesmeier et al. (2011) used 120 samples to map the same soil property over an area of 3600 km^2. However, remote sensing classifications are generally performed with many more training locations. For example, Gislason et al. (2006) used more than a thousand samples for land cover mapping (the authors did not specify the extent of the study area), and Cutler et al. (2007) used more than 8000 observations for an ecological classification covering an area of 220 km^2.

The need for many training samples is certainly a drawback for the use of supervised classifications in geomorphological studies. In particular, if no other sources of information exist for the study area, the training locations need to be digitised manually from remotely sensed images and this can be a tedious task (Montoya-Zegarra et al., 2013). In this work, we proposed the use of a technique recently developed by Montoya-Zegarra et al. (2013). The technique is based on the use of neighbouring data (semantic tie points) to enlarge the training dataset while keeping the number of training locations to a minimum.

Based on the brief literature review above, we demonstrate two things in this work: 1) by including semantic tie points, we can decrease the size of the training dataset required to perform a classification with RF, while keeping the accuracy at high levels; and 2) the decrease in accuracy of RF from the calibration to the classification areas, as identified by Marmion et al. (2008), is highly dependent on the type of landforms.

We tested this method in two areas of Switzerland. In the first area, we selected a limited number of training samples and then calibrated the algorithm by classifying a subset of the area. Subsequently, we shifted our attention to another area with different geomorphological characteristics and, using the same training model as before, we tested the possibility of employing this method extensively.

2. Materials and methods

2.1. Procedure

This research was divided into the following three steps:

– Supervised methods require training. We started by testing the method over an area where no previous geomorphological data were present. In this situation, the user needs to create a training set by identifying locations where the presence of a particular landform is certain. The optimal number of samples is obtained by looking at the internal RF validation.
– The method is subsequently calibrated by classifying a subset of the training area.
– The test ends with the use of the algorithm to perform a classification in an external area. This validates the methodology and verifies if it can be extensively employed.

2.2. Training set

Supervised techniques rely on training to achieve good classification accuracy. In this study, as we assumed that no prior geomorphological data were available, the user needs to provide a limited set of locations where the presence of a particular landform is certain. In this way, the algorithm can be trained by analysing the relationships between each landform and the predictors, such as geomorphometric variables and data derived from aerial images.

The accuracy of supervised algorithms is directly proportional to the dimension of the training set; the more cases you have, the more accurate the classification is. However, manually extracting lots of training points can be time-consuming. For this reason, we tested a newly developed methodology for the object-based classification of aerial images based on semantic tie points (Montoya-Zegarra et al., 2013). These are neighbouring cells around the training point. The user selects a location where the presence of a landform is certain, and the algorithm automatically samples 25 cells around that location (on a 5×5 cell window), extracting predictors that are then associated with the same landform. This way we can obtain a significantly higher number of predictors, while avoiding the process of labelling all of them.

By including these locations, we can increase the number of predictors associated with each training location. This should also increase the training accuracy by allowing the algorithm to be trained with more cases. Moreover, by including semantic tie points, we can decrease the impact of DEM noise, which may seriously affect the accuracy of machine learning algorithms, particularly in low relief areas (Cavazzi et al., 2013).

2.3. Classification trees and Random Forest

This experiment is based upon the classification of the landscape into major landforms, which are generally characterised by particular predictor patterns (e.g., Pike, 1988; Iwahashi and Pike, 2007). The complex evolution of the landscape in the two study areas implies that it is very difficult to find clear morphometric signatures for each landform. For this reason, we tested classification trees that provide a statistical way to find patterns that can help with the geomorphological classification.

Classification trees, such as the popular CART (Breiman et al., 1984), are trained on a set of locations for which geomorphological classes can be compared with a set of predictors. These algorithms were developed with the purpose of finding patterns between landforms and predictors. These patterns can then be used to determine the geomorphological classification in areas where we do not have any direct observation. Classification trees achieve this objective by splitting the dataset according to rules that maximise the variance between subsets. Each split of the data is performed by testing different combinations of predictors