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Algorithms vs. surveyors: A comparison of automated landform delineations and surveyed topographic positions from soil mapping in an Alpine environment

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A R T I C L E I N F O

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A B S T R A C T

Landform delineation has long been used in digital soil mapping to infer soil-relevant information. While its potential as an environmental variable in soil parameter modeling has been investigated for various automated landform delineations, little research has been invested into the relationship between the delineation of landforms by algorithms based on digital terrain models (DTM) and the perception of landforms by the soil surveyor during field work. Five Open Source automated landform classification algorithms and a support vector machine classifier based on single terrain parameters are investigated with regard to their ability to replicate topographic position, at two different scales, as described by surveyors for soil profile sites in the Alpine environment of South Tyrol. We also analyse how the variation of parameters and cell size affects the distribution of the computed landforms. While a clear trend regarding grid cell size and window size can be observed with regard to the difference between macro and meso scale topographic positions, the overall classification accuracy regarding the different topographic position classes was less promising. Although some automated classifications partly resemble the surveyor's classification, a considerable number of issues remain to be investigated in order to explain the lack of reproducibility of surveyor position, some of which are linked to the Alpine environment of the study area. These include the dominance of the backslope position, the objectivity of the surveyor in rugged terrain under forest cover, and the fuzzy nature of classifying topographic position, especially in steep terrain. By applying a forward stepwise feature selection procedure for a model based on single terrain parameters, we show that at macro scale a regional terrain parameter (topographic wetness index) and curvatures at a coarse DTM resolution of 50 m are the most influential in distinguishing topographic position, whereas at meso scale it is the topographic position index (TPI) with a search radius of just 70 m combined with slope gradient. This study is an important first step towards consolidating topographic perception during field survey and digital terrain analysis, which, at least in Alpine terrain, still requires more investigation.

1. Introduction

Topography has always been acknowledged as an important control on the formation and, hence, distribution of soil. Schaetzl (2013) notes that by solely discussing a soil based on the description of a pit face, a soil surveyor disregards the possibly most influential factor in its formation - the landscape. Consequently, soil description guidelines for soil classification schemes require the characterization of landform and topography of soil profile sites. For instance, when following the FAO guidelines for soil description, topography is described using the four categories major landform, relative position of the site within the landscape, slope form and slope angle (FAO, 2006). Similarly, the Austrian (Nestroy et al., 2011) as well as the German soil classification and mapping manuals (Ad-hoc-Arbeitsgruppe Boden, 2006) require the measurement of slope angle and a description of the landform on which the soil profile site is located at three different scales, specifically macro, meso and micro, relative to the surrounding 100 to 500 m, 50 to 100 m and 5 to 10 m, respectively (Englisch and Kilian, 1999). The various landform and slope position descriptions are usually performed by the surveyor while at location, supported by topographic maps and possibly aerial photographs, and based on expert rule sets as well as the surveyor's mental soil landscape model.

Readily available digital terrain models (DTMs) of increasing resolution have led to research into landform modeling and the segmentation or stratification of DTMs into landform units. Approaches vary from expert-based rule sets to completely automated landform

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classifications, from supervised to unsupervised classifications, and include classifications with crisp as well as fuzzy borders. The output units may be attributed with the names of landforms as mapped by a surveyor, but can also represent elementary land units that adhere to certain geometric constraints. Similar to the information required of the soil surveyor (slope angle and landform), the input variables for DTM-based landform classifications range from local terrain variables, such as slope and curvature, to regional variables like catchment area, which further describe a profile site's position in the landscape.

An early example of the local terrain variable approach was proposed by Dikau (1988), who combined plan and profile curvature as well as the radius of curvature to create a map of form elements. Pennock et al. (1987) describe a similar landform element classification based on plan and profile curvatures. Addressing the problem of appropriate scale, Wood (1996) presented an approach based on slope and multiple curvature calculations to model 6 morphometric features, and added the possibility to calculate the terrain parameters at different scales, i.e. at different window sizes. A similar analysis with regard to curvature and slope was performed by Blaszczynski (1997). Minàr and Evans (2008) proposed a concept of elementary landforms on the basis of homogeneous areas of altitude and its derivatives, separated by lines of discontinuity.

Another branch of landform classifications applies not only local, but also regional terrain attributes (Gallant and Wilson, 2000) that include information on the surrounding area of a central pixel. Schmidt and Hewitt (2004) extended Dikau's form elements by means of fuzzy classification and introduced landscape context into the classification scheme by implementation of the TOP HAT approach (Rodriguez et al., 2002) to additionally distinguish between valleys and hills. Similarly, MacMillan et al. (2000) proposed a landform element classification based on heuristic rules and fuzzy logic. Therein, the landform elements of Pennock et al. (1987) are classified based on a semantic input model, and landscape context is added via terrain parameters that describe each cells slope position relative to its watershed. Klingseisen et al. (2008) present a landform classification based on classic local terrain attributes as well as elevation-related regional attributes. The slope class is further segmented using breakpoints in the slope profile. In a similar approach, Matsuura and Aniya (2012) also applied breakpoint detection to create subdivisions of the slope class. Hollingsworth et al. (2006) is an example for an application of regional terrain parameters in landform classification that can be linked to the hydrological regime, as they use the Static Wetness Index in their decision tree-based land unit mapping approach. Weiss (2000) proposed an automated landform classification by combining the topographic position index (TPI), which compares the elevation of a pixel to that of surrounding pixels, at large and small scale. Involving the surrounding landscape at a given search radius, r.geomorphons (Jasiewicz and Stepinski, 2013) represents a classification based on line-of-sight calculations and pattern recognition.

The previously mentioned landform classification approaches have in common that the resulting classes are attributed names, which have specific implications regarding the description or characterization of each landform element. A different approach is unsupervised classification, wherein an algorithm separates the grid cells into classes that may or may not be afterwards provided with a name attribute related to landforms. Instead of organising a map according to certain heuristic rules, unsupervised classifications create groups of grid cells that are similar with regard to certain terrain parameters, but the group boundaries are not constrained by any existing classification system. Irvin et al. (1997) compared the results of a crisp and a continuous clustering algorithm with regard to manually delineated landforms. While Adediran et al. (2004), Arrell et al. (2007) and Burrough et al. (2000) similarly applied clustering of terrain derivatives with regard to landforms, Moravej et al. (2012) based their clusters not on the terrain attributes but on their first principle components. A different unsupervised approach is that of Iwahashi and Pike (2007), who applied a nested-means partitioning algorithm to delineate terrain types or surface-form classes.

Yet another approach to landform delineation is derived from object-based image analysis (OBIA), its principles applied to geographic information science are described by Blaschke et al. (2014). It differs to the previously described approaches, as in a first step homogenous areas with regard to certain terrain parameters are segmented, which can later be aggregated and classified into landform elements. Drăgut and Blaschke (2006) classified landform elements similar to the concepts of Dikau (1988) and Pennock et al. (1987) by applying OBIA to a group of terrain parameters which has been used in many landform classification attempts, i.e. slope, plan and profile curvature, and elevation. Gerçek et al. (2011), Mashimbye et al. (2014) and Kringer et al. (2009) provide further examples of the application of OBIA to landform delineation, the latter for use in soil mapping procedures.

Geomorphologic questions may be the main subject of interest for automated landform classification, nonetheless the relationship between landforms and soil has long been of strong scientific interest, consequently leading to research into classifying landforms for soil mapping purposes (Schmidt and Hewitt, 2004; Herbst et al., 2012; Hughes et al., 2009; Barringer et al., 2008). MacMillan et al. (2000) well illustrate how different landforms can be interpreted in terms of soil formation and erosion, and the catena concept in soil science (Schaetzl, 2013) shows the importance of topographic position in pedogenesis. Many have highlighted the importance of topography as a soil forming factor especially in mountainous areas (Geitner et al., 2011b; Herbst et al., 2012). Consequently, it seems important, especially for future research, to consolidate the perception of topographic position in field soil survey on the one side and digital terrain analysis on the other, in order to advance the understanding of the interdependencies between soil and topography.

The aim of this study is to increase the understanding of the perception of landscape by soil surveyors. This is done by testing various landform classification algorithms with regard to their suitability to emulate the mental soil-landscape model of soil surveyors, especially with regard to the concept of topographic position. This testing is conducted using support vector machine (SVM) classification (Cortes and Vapnik, 1995), a supervised learning algorithm which can efficiently perform non-linear classification. A resulting map of topographic position shall serve as an additional support for soil surveyors during field work. For each classification method we also give an overview of the influence of parameter thresholds and window sizes on the number and distribution of computed landform classes to allow better understanding of how these algorithms classify DTMs. Whereas past publications presenting new landform classification approaches commonly measure the performance of their classification by visual or statistical comparison with existing thematic maps (or classifications performed by human interpretation of photo- or topographic maps for validation purposes) or by correlation with metric parameters such as soil depth, the authors deem it important to analyse the classifications performed during field work. Consequently, in this study we compare computed classifications to the topographic positions of numerous soil profile sites in South Tyrol (Italy) as mapped by soil surveyors. The Alpine environment of this research area presents an additional challenge to automated landform classification, as most previous studies have concentrated on areas suited for agriculture, thus having significantly less distinguished elevation differences as well as slope gradients.

The investigated algorithms were restricted to supervised classifications implemented in the readily available Open Source geographic information systems (GIS) GRASS GIS (GRASS Development Team, 2017) and SAGA GIS (Conrad et al., 2015). Although some classifications have been compared with the results of different algorithms, and Barka et al. (2011) compared a number of automated landform classification algorithms with regard to correlation with soil and forest units, to our knowledge there has been no systematic comparison to point