Discovering the Dutch Mountains: an Experiment with Automated Landform Classification for Purposes of Archaeological Predictive Mapping

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This paper reports an experiment with automated landform classification methods for archaeological predictive modelling purposes. The aim was to find out if these new techniques can produce geomorphological maps that are useful to archaeologists, save time, and provide a more objective interpretation of the landscape. It is concluded that object-based image analysis is a suitable technique, but it needs further development before it can be applied more widely.

Keywords: geomorphometry, predictive modelling, object-based image analysis

1. Introduction

Archaeologists routinely rely on geomorphological maps to predict the location of archaeological sites and to understand their location in the landscape. In the Netherlands, the availability of nation-wide LiDAR-based DEMs has highly increased the level of detail of the available information on landform. The mapping techniques used are however still the same as they were in the 1960s: visual interpretation of elevation maps and aerial photographs is combined with field visits to draw the maps. A classification system developed in the 1970s (TEN CATE and MAARLEVELD, 1977), using an amalgam of geomorphometric and geomorphogenetic criteria, is used to perform landform classification. This procedure is subjective and highly time-consuming, to the effect that high-resolution DEMs have only been 'translated' into geomorphological maps for some parts of the country (KOOMEN and MAAS, 2004), and are still only available at a 1:50,000 scale in order to guarantee compatibility with the older mapping. Archaeologists however are also interested in the small detail that is visible at the 1:10,000 scale since the location of archaeological sites often seems to be tied to relatively minor elevation differences and small landscape units. Therefore, they tend to create more detailed geomorphological maps of their own made for predictive mapping purposes.

In this paper, we will report an experiment with automated landform classification methods for archaeological purposes. The aim was to find out if these new techniques can produce geomorphological maps that are useful to archaeologists, save time, and provide a more objective interpretation of the landscape.

2. Geomorphometry and automated landform classification

Geomorphometry is a branch of the geo-sciences that is relatively young. It uses quantitative methods and techniques to characterize the earth's surface from digital elevation models (see www.geomorphometry.org). It is especially concerned with the quantification of surface form parameters and the extraction of landscape features from DEMs. Geomorphometric methods are attractive to many disciplines, including soil science, hydrology, ecology and archaeology. Until recently however, archaeologists have not given it much attention.

Archaeologists have been using DEMs for a long time. They are probably among the most avid users of the high-resolution LiDAR-based elevation models that are increasingly available in many parts of the world. These images are however, in most cases, treated as if they were aerial photographs. Hillshading and colour manipulation will be about the only analytical tools that many archaeologists use when studying these images. They will identify and delineate objects of interest (archaeological features and/or landform units) by means of visual inspection and manual digitizing. More advanced methods of landform characterization usually do not represent the earth's surface in a way that allows for easy archaeological interpretation. For example, the multi-scalar landform classification routines available in LandSerf (www.landserf.org) have attracted some interest as additional parameters to analyse and predict archaeological site location (LÖWENBORG, 2009; KAY and WITCHER, 2009) but do not seem very well suited as tools to interpret and classify individual landforms.

A relatively new branch of geomorphometry however, automated landform classification, offers the potential to quickly create highly detailed landform maps for large areas. Most published case studies consider mountainous areas and seem to be reasonably successful in delineating broad landform categories like plateaus, different types of hills, slopes and valleys (MACMILLAN and SHARY, 2009). In order to see whether these new approaches might also be used to effect in a relatively flat landscape, an experiment was carried out with two different techniques for automated landform classification: the unsupervised nested means method described by IWAHASHI and PIKE (2007), and object-based image analysis (DRĂGUŢ and BLASCHKE, 2006). These were then compared to a visual interpretation of the DEM. The study area chosen is a 12x16 km area in the vicinity of the village of Someren, located approximately 25 km to the south east of the city of Eindhoven in the Netherlands. Elevations in this area range between approximately 15 and 30 meters above sea level. The available DEM is a LiDAR-based elevation model at a resolution of 5x5 m obtained from the Dutch Ministry of Transport, Public Works and Water Management (Actueel Hoogtemodel Nederland or AHN).

3. The unsupervised nested means approach

The unsupervised nested means method is based on the classification of three separate landform parameters that can be obtained with standard GIS routines. These are

sloping	convex	elevation high
		elevation low
	concave	elevation high
		elevation low
flat	convex	elevation high
		elevation low
	concave	elevation high
		elevation low

Table 1: *Possible outcomes of the unsupervised nested means classification (modified after IWAHASHI and PIKE, 2007).*

slope, the local *convexity* in a 3x3 neighbourhood, and a parameter called *texture*, which is the median value of the elevation in a 3x3 neighbourhood, and is used as a measure for the roughness of the terrain. The texture parameter did not provide very clear landform patterns in the study area. Therefore, it was decided to replace this parameter with a measure of relative elevation, the mean elevation within a 250 m radius.

Each of the parameters used can be sliced into two classes, below and above the mean value encountered for the whole study area. These sliced parameters can then be combined through overlaying into 8 classes (table 1). When executing this approach in the study area, it quickly became clear that the high resolution of the DEM created a lot of noise in the classification. The 5x5 m DEM was therefore smoothed and then resampled to a 25x25 m resolution. The smoothing was done using a mean circular filter within a 5 cell neighbourhood.

The method has the clear advantage of being extremely simple to execute and is independent of the elevation range encountered in a study area. It resulted in relatively clear patterns for ridges, but less so for valleys and depressions (figure 1). Increasing the neighbourhood size for the calculation of relative elevation changes the scale at which the features become visible. At the downside, the method highly simplifies landform categories.

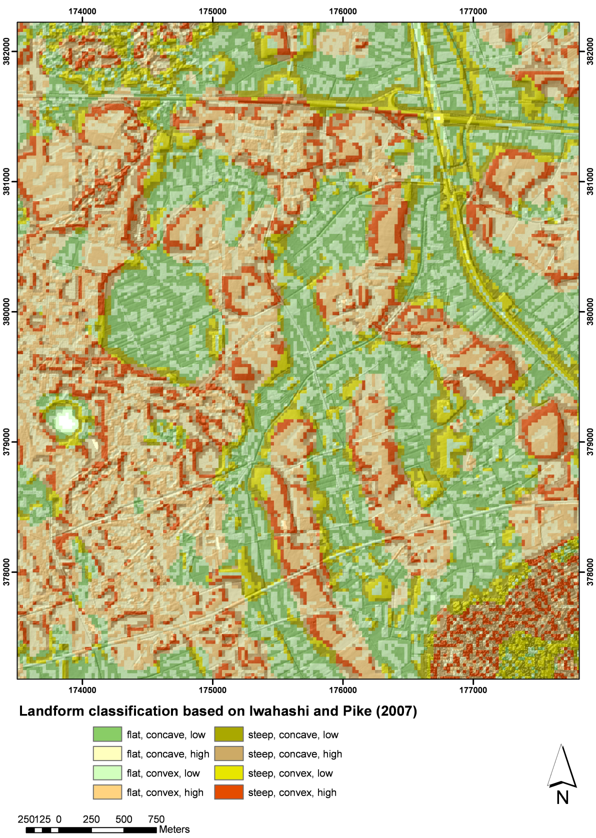

Figure 1: *Landform classification based on the unsupervised nested means approach.*

4. Object-based image analysis (OBIA)

Object-based image analysis was originally developed for medical imagery and remote sensing purposes. It is a method that can be applied for recognition and/or classification of landforms (DRĂGUŢ and BLASCHKE, 2006). It creates image objects through the aggregation of pixels into discrete regions that are homogeneous with regard to their spatial and spectral characteristics by means of image segmentation (BAATZ and SCHÄPE, 2000; RYHERD and WOODCOCK, 1996). The method described by (DRĂGUŢ and BLASCHKE, 2006) is not very well suited for flat areas as it largely depends on the classification of hill-slope profiles. Therefore, we adapted this method to landform classification in flat areas.

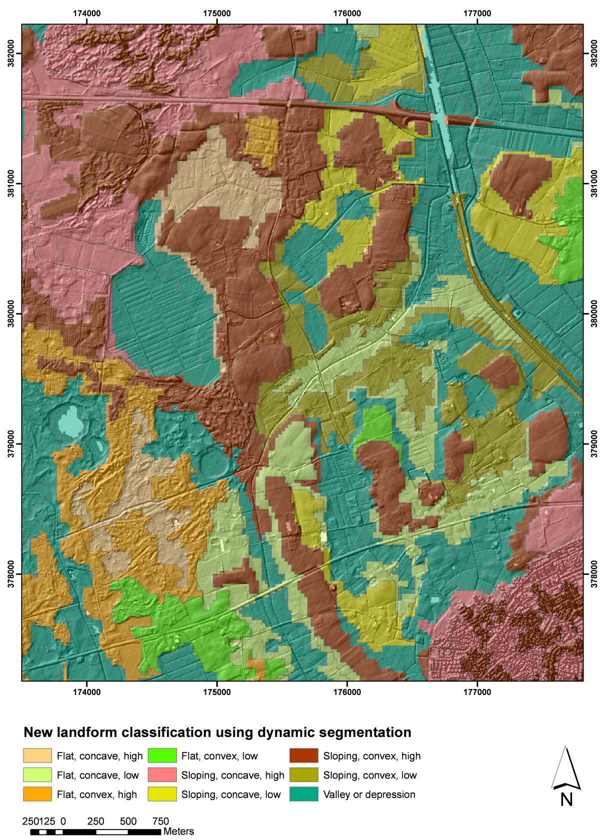

Figure 2: *Landform classification based on multi-resolution segmentation of the smoothed DEM, using elevation, slope and curvature.*

The multi-scale pattern of elevation was explored with the aid of the Estimation of Scale Parameters (ESP) tool, designed as a customized algorithm for the Definiens Developer® suite by DRĂGUŢ *et al*. (2010). It calculates the local variance (LV) (WOODCOCK and STRAHLER, 1987) of object heterogeneity within a scene. The ESP tool iteractively generates image-objects at multiple scale levels (with different values of the scale parameter used for segmentation) in a bottom-up approach, and calculates the LV for each scale. Variation in heterogeneity is explored by evaluating LV plotted against the corresponding scale level. The thresholds in rates of change of LV indicate the scale levels at which the image can be segmented in the most appropriate manner, relative to the data properties of the scene.

The 5x5 m DEM was smoothed and re-sampled to 25x25 m and slope and curvature layers were derived from this. Elevation, slope and curvature were used as input layers in eCognition Developer 8. Elevation information was used as input for segmentation, while the other two layers provided information for classification only.

The multi-scale pattern of elevation was explored with the aid of the ESP tool, with the following parameters: increment of 1, starting at 1. For this dataset, the first threshold is located at a scale parameter of 6, visible as a small step in the decay curve of the rate of change of local variance. This value of the scale parameter was used to perform the segmentation of the elevation layer, without considering shape information (shape = 0). The 965 segments thus obtained represent relatively homogeneous areas in terms of elevation (figure 2) and were further employed as building blocks for the classification, using the logic followed for the unsupervised nested means classification.

High and low regions were separated based on a ratio between the mean elevation value of a segment and the mean elevation value of segments in a radius of 2.5 km. This value was established using a trial-and-error approach. Ratio values above 1 classify high areas. For each region so classified, flat and sloping areas were classified based on the first quartile of slope values as averaged within the segments. The threshold value obtained for this area was 0.41 degrees.

Concave and convex areas were classified with a threshold of 0 in curvature values as averaged within segments. Valleys were classified based on a ratio between the mean elevation of the target segment and the mean elevation of all its neighbour segments. The threshold was given by a standard deviation lower than -0.5, which in this area was -0.36 m.

Discussion

Our objective was to compare two methods for automatic landform classification. The unsupervised nested means method produced a detailed classification of slopes, plateaus and depressions, but also included much 'noise' that is difficult to interpret. It cannot be considered good enough for archaeological purposes. The classification produced by the OBIA approach however shows that automated landform classification can get close to producing interpretable and correct landform maps of relatively flat areas at the scale that archaeologists are used to deal with. It is also very quick; whereas manual digitizing took almost 10 days, setting up an OBIA classification is a matter of hours, and transferring it to other regions will even be quicker. An additional benefit of the approach is that it can detect the presence of various man-made features in the area.

There are however a few issues that need closer attention before these methods can be applied more widely.

The segmented images still need interpretation. While the method used allows us to determine that a certain area is lower than its neighbouring segments and is flat, this does not mean that it is always correctly recognized as a valley or depression by the software. We are dealing with difficult classification issues here that not just include geomorphometric knowledge. We need to be aware that these new techniques may not just replicate geomorphological maps, but also allow us to target specific landforms of interest to archaeologists. However, in order to achieve this we need to establish a conceptual framework based on expert knowledge to define these landforms in such a way that these can be translated into formal, quantitative rules.

For further development of OBIA methods we also need to consider the software used. It seems that the remote sensing community is less involved in developing open source software than the GIS community. Yet, the availability of these methods to the relatively small-sized scientific community of archaeology should not be hampered by lack of finances or closed source programme code.

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