Mapping geomorphology based on the information from existing geomorphological maps with a multiple-point geostatistics technique

Lucie Babel, Ekkamol Vannameteew* Martin Hendriks, Jasper Schuur, Steven de Jong, Marc Bierkens, Derek Karsenberg; Faculty of Geosciences, Utrecht University, the Netherlands
*corresponding author: Tel: +31302552183, E-mail: e.vannameteew@uu.nl

Introduction

Automated geomorphology mapping has shown a rapid growth over recent years due to advances in machine-learning technologies and increasing availability of digital terrain data at higher resolutions. Existing automated landform classification techniques are based on the statistical analysis of terrain attributes at a single point (e.g. clustering, regression-based methods) or between two point locations (i.e. region growing, image segmentation, variogram-based methods). These techniques are, however, incapable of capturing complex spatial patterns or reproducing the mathematical complexity of covariogram landform features, as this would require taking into account the co-variation of a larger number of spatial locations. Multiple point geostatistics (MPS) can be used to overcome these problems. This approach uses field geomorphological maps, together with the topographical data obtained from the Digital Elevation Model (DEM), as a training image, to extract topographical characteristics and autocorrelations between attributes at multiple spatial locations for different landform types. This knowledge can be used to map other areas with similar geomorphological characteristics. We explore and investigate a MPS technique, so-called the Single Normal Equation Simulation approach, or SNESIM, in geomorphological landform classification, focusing on medium-scale landforms with a dimension between 16”-10 km, such as alluvial fans, fluvial terraces, and debris slopes.

Concept

Landform class at 10-cell downstream from the central template node
- Data search template for constructing the search tree
  - DEM derivatives at the central template node
  - Height above the nearest drainage (HAND)
  - Slope gradient
  - Profile curvature
  - Slope variability
  - Flow direction
  - Outlet point

Landform class at an adjacent downstream cell of the central template point
- Landform class at 10-cell downstream from the central template point (Due to the space limit, the fourth downstream cell is highlighted here)
- Map realizations

Results

Mapping accuracy per landform classes (%)

<table>
<thead>
<tr>
<th>Landform</th>
<th>MPS</th>
<th>Rule-based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fluvial terrace</td>
<td>64%</td>
<td>81%</td>
</tr>
<tr>
<td>Fluvial fan</td>
<td>26%</td>
<td>57%</td>
</tr>
<tr>
<td>Glacis</td>
<td>9%</td>
<td>26%</td>
</tr>
</tbody>
</table>

Findings

- MPS outperforms rule-based classification
- Misclassification is only restricted to the neighbouring landforms with overlap characteristics
- Optimal training image size is between 7.5-10% of total area

Mapping quality and size of training image

- Kappa coefficient = 0.25
- Correct cells = 33.5%
- Missclassified landforms undersampled in the training image

Conclusion

- Number of attributes and class numbers per attributes cannot be too large to limit the size of search tree
- Incapable of discriminating landforms with overlap characteristics
- Underestimate or unable to map landforms undersampled in the training image

Multiple-point geostatistics

<table>
<thead>
<tr>
<th>Configuration of MPS</th>
<th>MPS</th>
<th>Rule-based</th>
</tr>
</thead>
<tbody>
<tr>
<td>37.5 DEM resolution</td>
<td>78%</td>
<td>58%</td>
</tr>
<tr>
<td>Region growing</td>
<td>92%</td>
<td>62%</td>
</tr>
<tr>
<td>Clustering</td>
<td>100%</td>
<td>78%</td>
</tr>
<tr>
<td>Path of cell visit</td>
<td>62%</td>
<td>42%</td>
</tr>
</tbody>
</table>

Abstract ID: EGU2014-12616

*Present address: Department of Geography, University of Edinburgh, Edinburgh EH8 9JU, UK.