Abstract ID: EGU2014-12616

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

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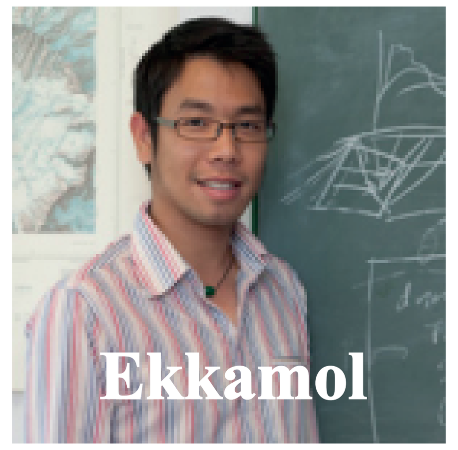
Universiteit Utrecht

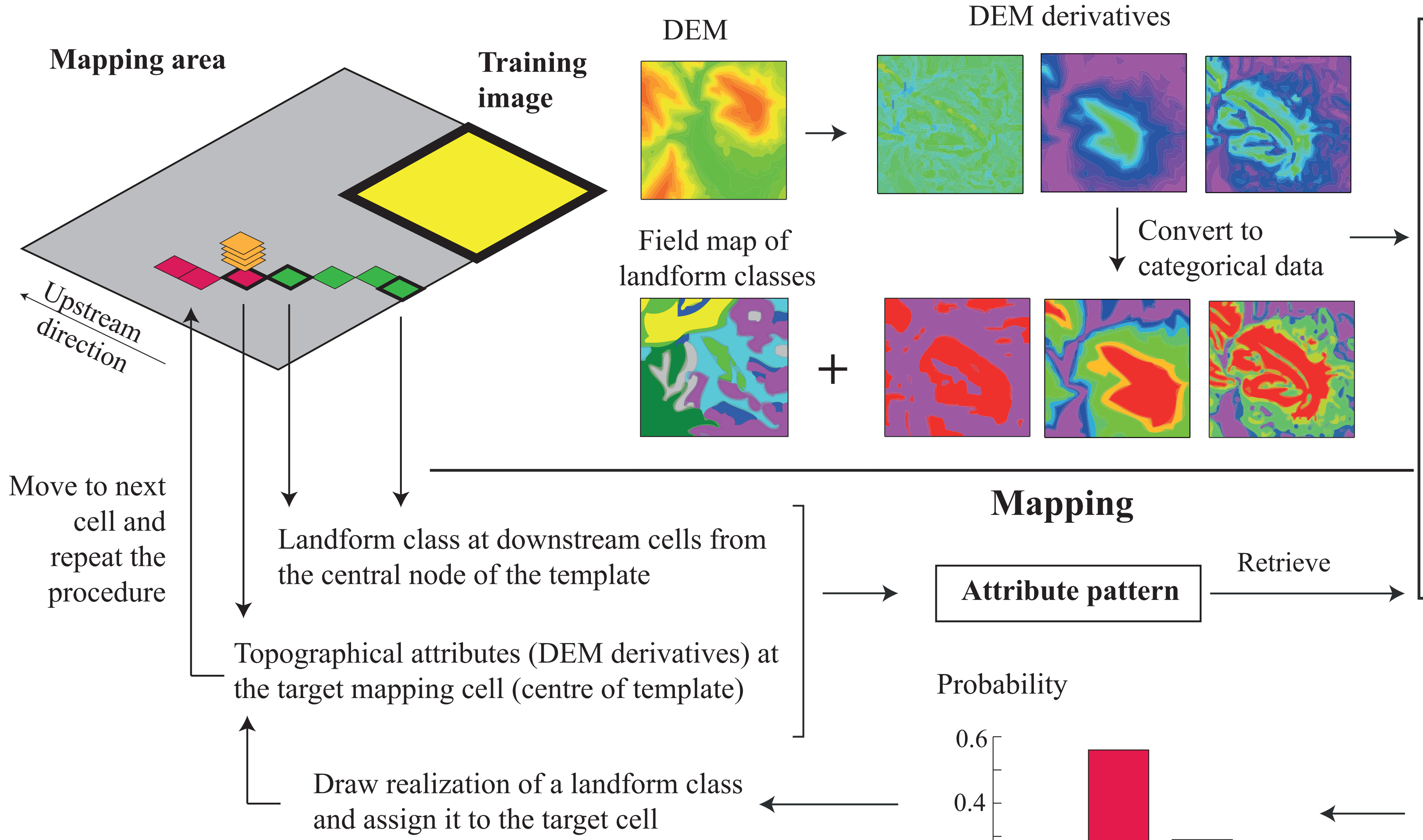
European Geosciences Union
General Assembly 2014
Vienna | Austria | 27 April - 02 May 2014

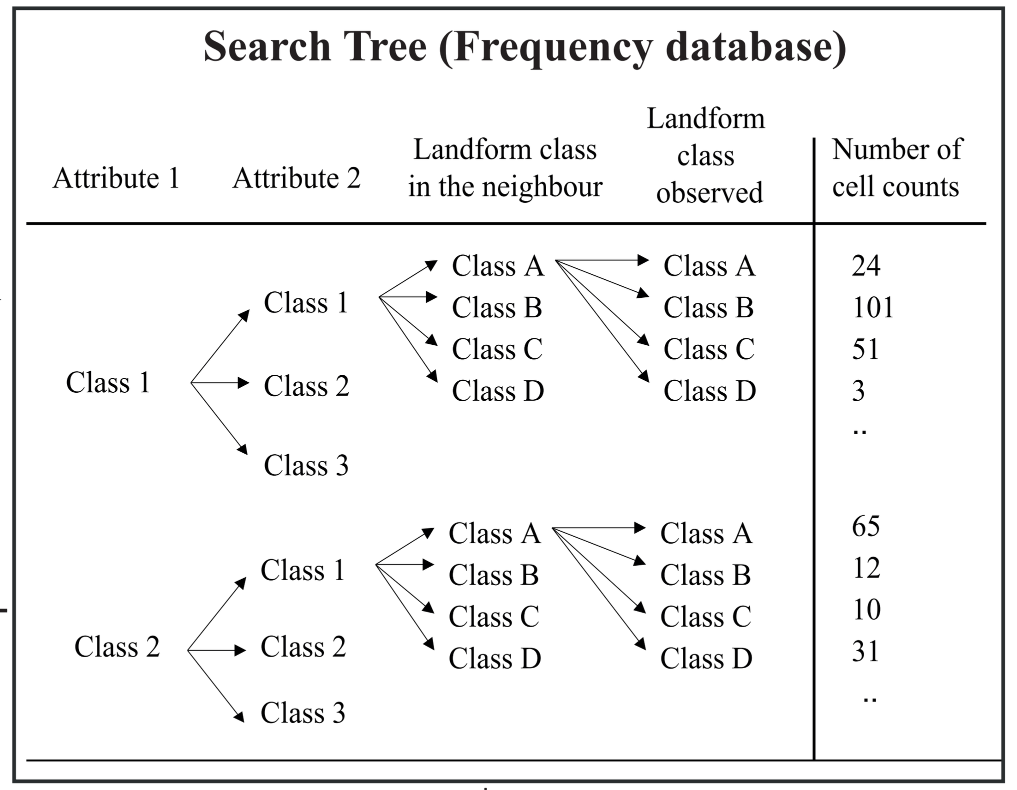


Introduction

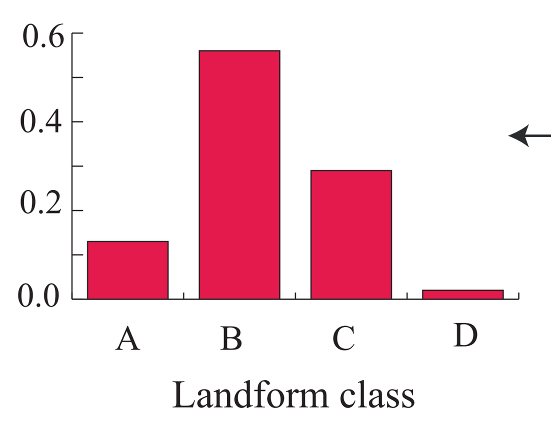
Automated landform mapping has shown a rapid growth over recent years due to advances in machine-learning technologies and increasing availability of digital terrain data at higher resolutions. Existing automated landform classification techniques are based on the statistical analysis of terrain attributes at a single point (i.e. clustering, regression-based methods), or between two point locations (i.e. region growing, image segmentation, varigram-based methods). These techniques are, however, incapable of caputuring complex spatial pattern or reporoducing the mathematical complexity of curvilinear landfrom 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 apporach 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 10^{-2}–10 km², such as alluvial fans, fluvial terraces, and debris slope.

Concept





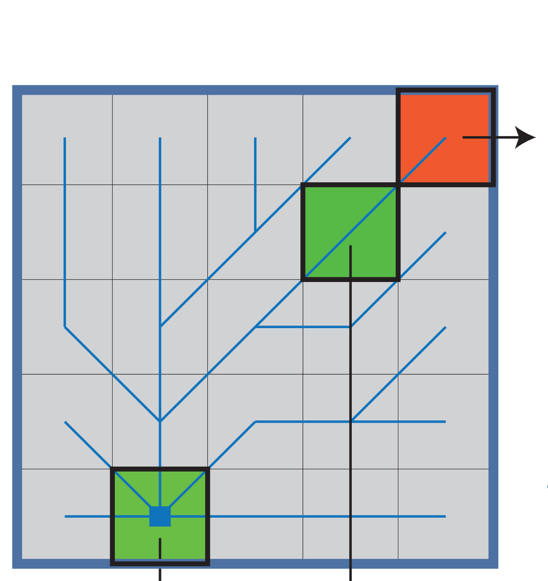
Calculate the probability distribution of landform classes coniditioned to the observed attribute pattern:



$$\text{Prob}\{I(i,g)\mid \mathbf{V}_i\} = \frac{f(\mathbf{V}_i \mid g)}{f(\mathbf{V}_i)}$$

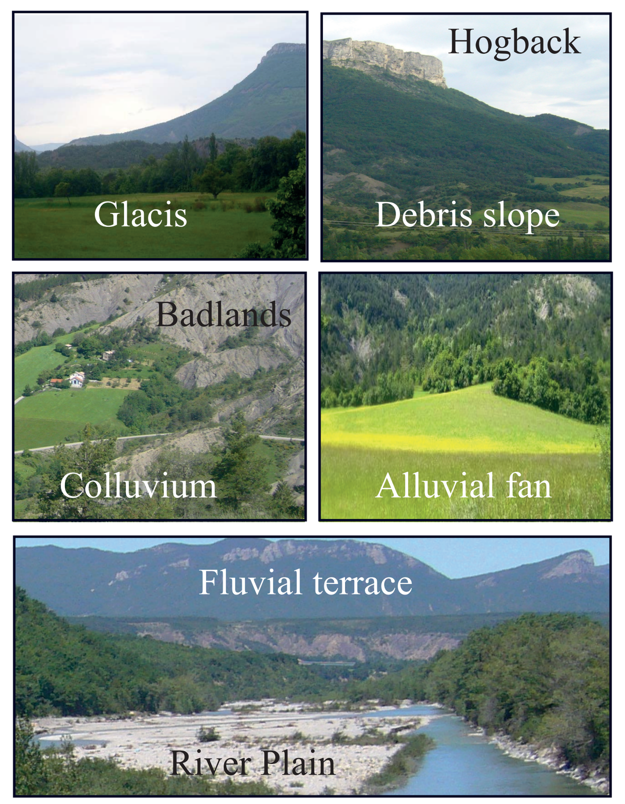
- $I(i,g)$ Event that the cell i belongs to the landform class g
- $\mathbf{V}_i$ Vector containing the attribute pattern observed at location i
- $f(\mathbf{V}_i)$ Number of cells in the training area with the attribute pattern $\mathbf{V}_i$
- $f(\mathbf{V}_i \mid g)$ Number of cells in the training area with the attribute pattern $\mathbf{V}_i$ that belongs to the landform class g

Data search template for constructing the search tree



Landform class at 10-cell downstream from the central template node (Due to the space limit, the fourth downstream cell is highlighted here).

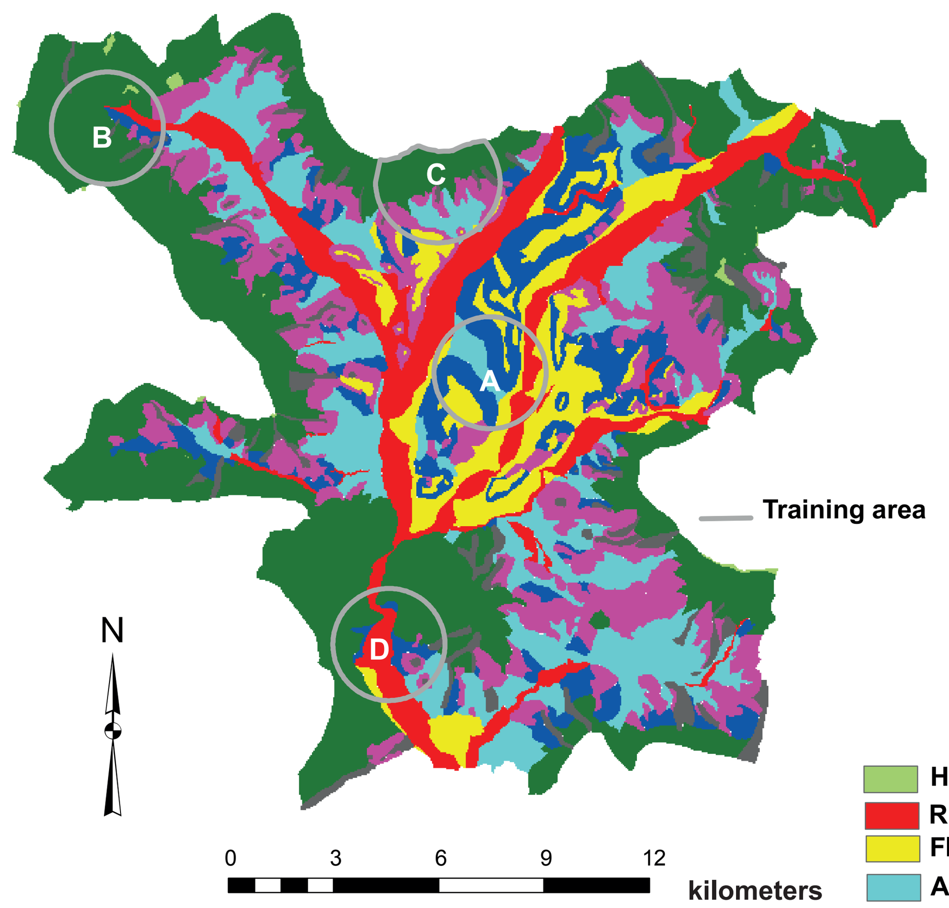
Landforms (8 classes)



- Buëch valley, French pre-Alps
- 280 km²
- 700-1800 m above m.s.l.
- Massive limestone (i.e. Calcaire Tithonique) overlying alternating layers of limestone and highly-erodible Callovian-Oxfordian marls (i.e. Terres Noires).
- Not glaciated during the Würm period.

Results

Field map of geomorphological landforms

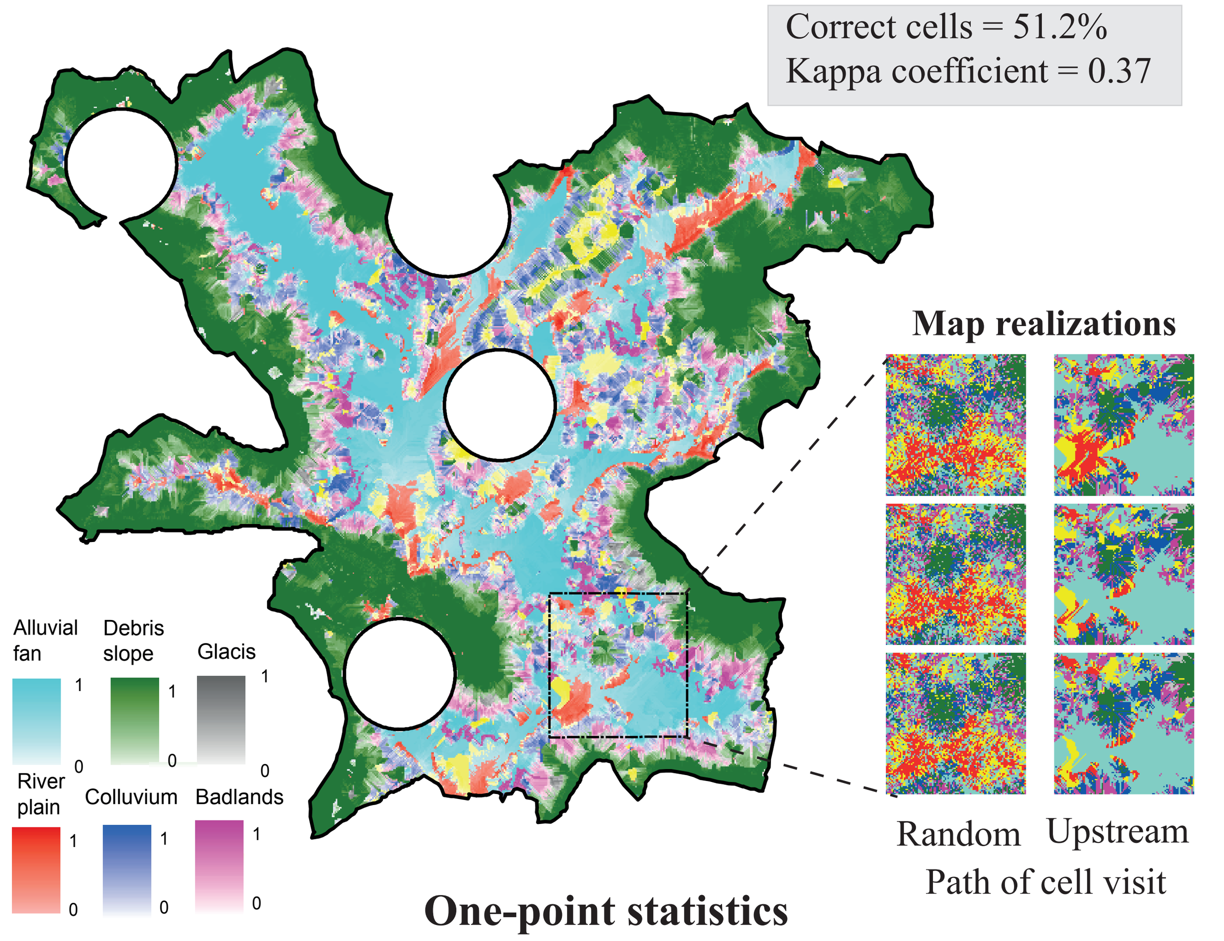


Configuration of MPS

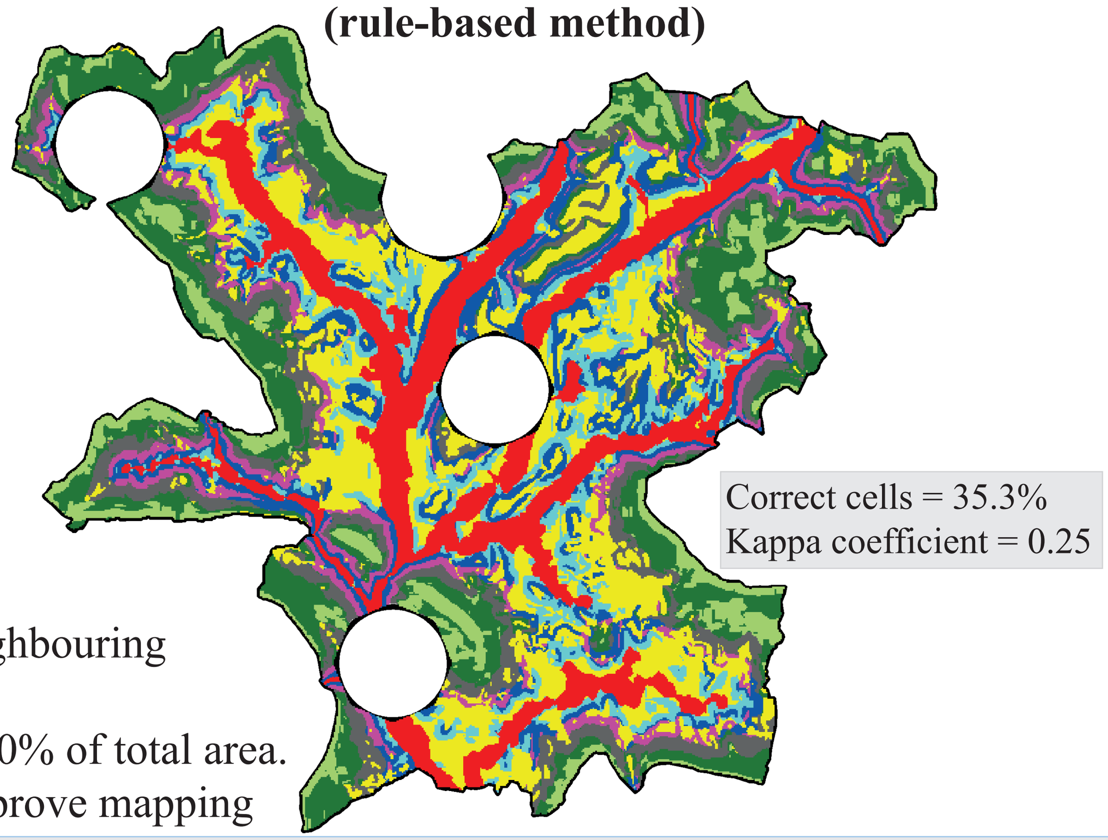
- 37.5 DEM resolution
- 7, 5, 3, 2 classes for HAND, slope, profile curvature, and slope variability, respectively.
- 4 randomly-chosen training areas, (i.e. A, B, C, D) covering 28 km² or 10% of the total area
- Path of cell visit: random and following the drainage network to the upstream direction
- Generate 35 map realizations and select the most-often occurring landform class per cells.

Automated geomorphological map

Multiple-point geostatistics



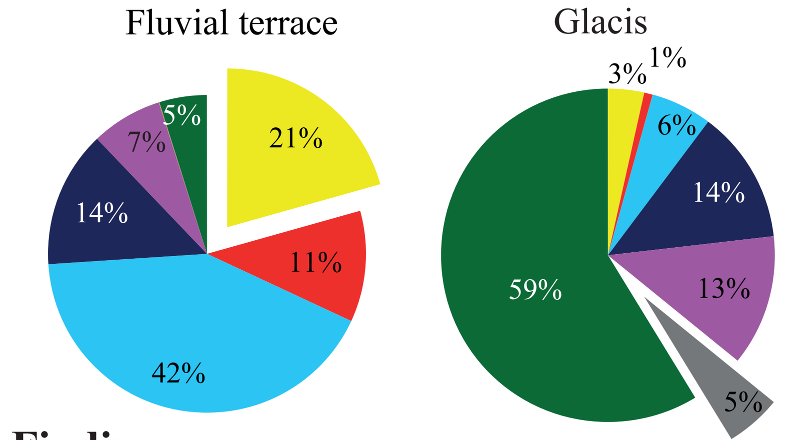
One-point statistics (rule-based method)



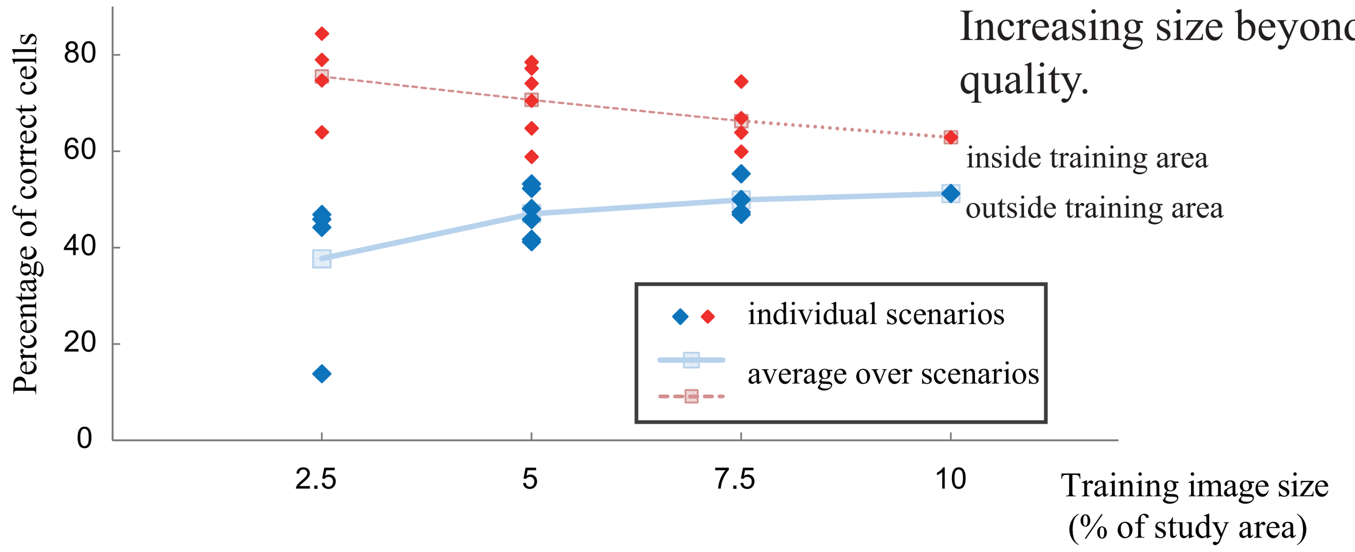
Mapping accuracy per landform classses (%)

Landform	MPS	Rule-based
Hogback	0	57.1
Fluvial terrace	20.6	42.4
River plain	26.0	81.1
Alluvial fan	57.2	18.4
Colluvium	31.6	30.7
Badlands	21.8	12.3
Glacis	5.4	22.6
Debris slope	89.1	39.9

Percentage of missclassified cells (MPS)



Mapping quality and size of training image



Findings

- MPS outperforms rule-based classification.
- Missclassification is only restricted to the neighbouring landforms with overlap characteristics.
- 'Optimal' training image size is between 7.5-10% of total area. Increasing size beyond this range does not improve mapping quality.

Conclusion

Strength

- Capable of using non-morphometric information (landform types) at multiple locations in mapping at cells of interest.
- Units mapped with correct shape and overall proportions of different landforms.
- Mapping uncertainty can be evaluated.

Weakness

- 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.