An automatic approach of prototype-based fuzzy slope position inference method

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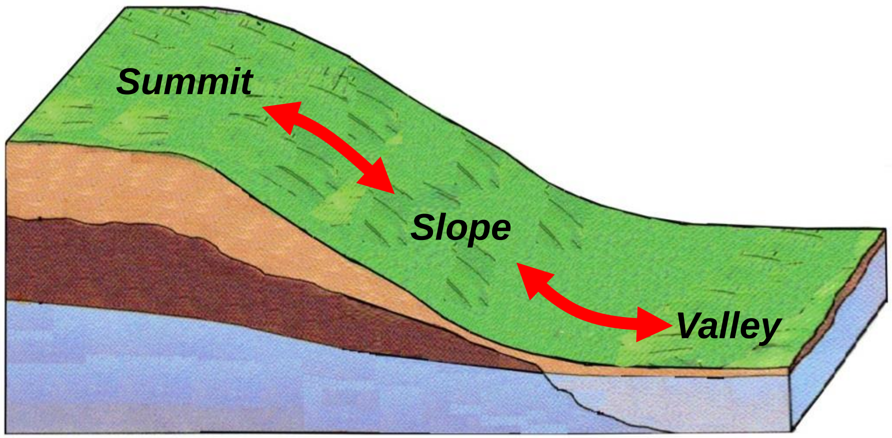
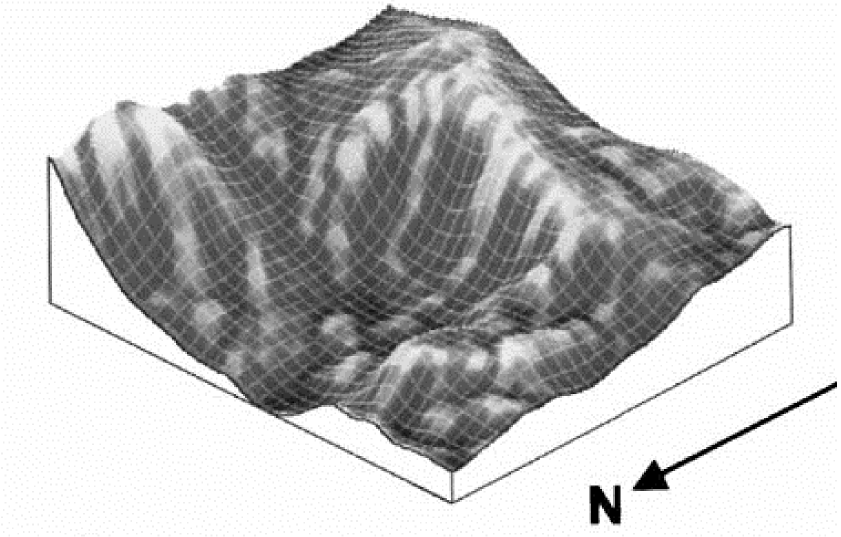
Contents

1 Background & Research question

- Spatial gradation information of slope positions is important for terrain-related geographical or ecological modeling (Deng, 2007).
- The so-called fuzzy slope positions use fuzzy membership values (or similarities) to quantify the spatial gradation.



Gradation of slope positions in reality



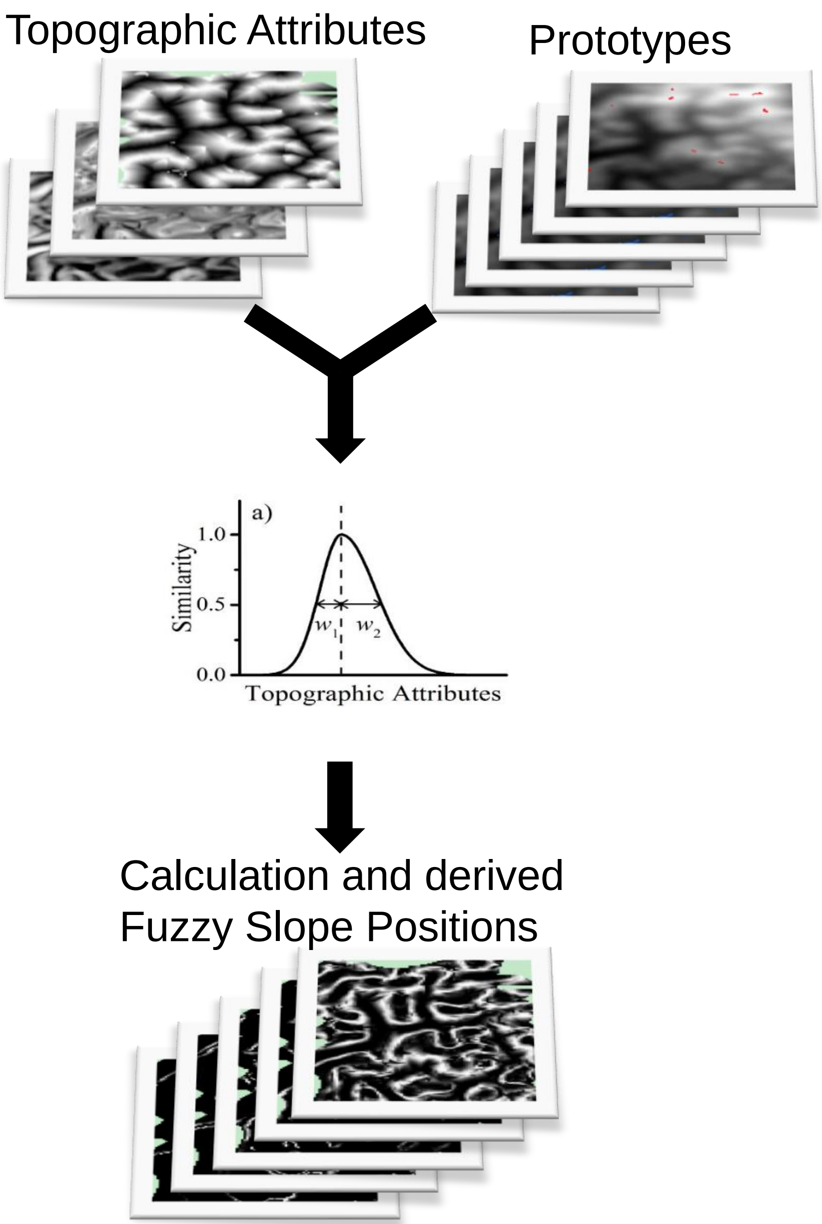
Similarity of being a divergent shoulder slope (MacMillan *et al*., 2000)

1 Background & Research question

Existing methods can be classified into two categories

Category	Basic idea	Disadvantages
Cluster-based (e.g., Burrough *et al*., 2000; Irvin *et al*., 1997)	Fuzzy clustering on topographic attributes set	1. The cluster number 2. Lack of spatial information 3. Difficult to interpret each cluster 4. Inability for low frequency
Classification-based	Predefined classification system, and user-assigned explicit rules on attribute domain (e.g., MacMillan *et al*., 2000; Schmidt and Hewitt, 2004)	1. Ignore spatial information 2. May lack of physical meaning 3. Require formalized knowledge
	Prototype-based definition, fuzzy inference on both attribute and spatial domain (Qin *et al*., 2009)	1. Extensive user intervention 2. Compute-intensive

1 Background & Research question



- Preparing topographic attributes set, *tedious*
- Extracting typical locations as prototypes, *knowledge-based*
- Determining parameters of fuzzy inference, *subjective and knowledge-based*
- Serial computing implementation, *time-consuming*

Not easy to use!

1 Background & Research question

How to automatically perform the prototype-based method reasonably and efficiently

2 Basic ideas

Automation of preparing topographic attributes set

- Selected based on physical meaning (e.g., MacMillan *et al*., 2000; Pennock *et al*., 1987; Schmidt and Hewitt, 2004)
- Often similar (e.g., Miller and Schaetzl, 2015; Qin *et al*., 2009)
- Existing DTA algorithms

Automation of extracting prototypes (typical locations)

- Overlaying all topographic attributes by corresponding value ranges
- Value ranges can be determined by fuzzy membership function types
- Common knowledge and specific knowledge derived by data mining

Automation of determining parameters for fuzzy inference

- Simply determined or calculated based on the fuzzy membership function type.

2 Basic ideas

Automation of preparing topographic attributes set

Automation of extracting prototypes (typical locations)

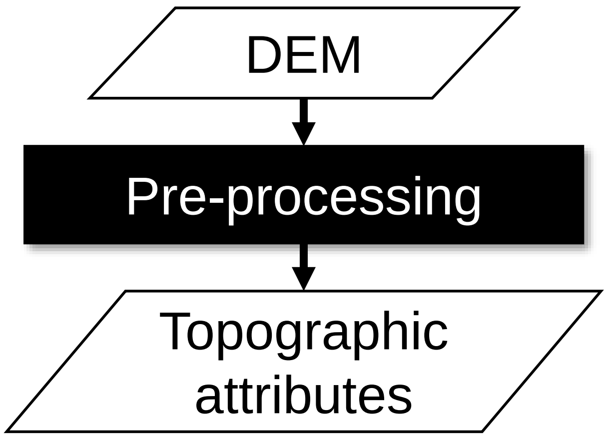
Automation of determining parameters for fuzzy inference

The entire workflow is able to be automated

based on **common domain knowledge** and **data mining**.

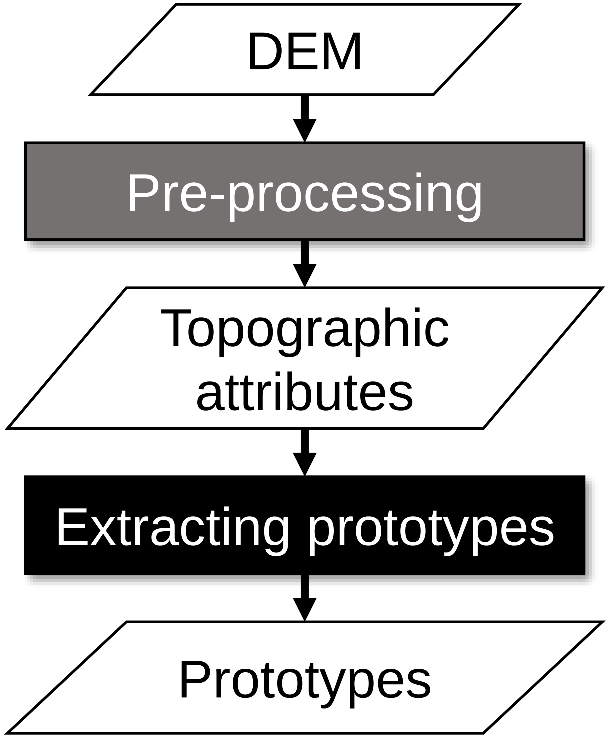
3 Method & Implementation

Take the five basic slope positions system (Qin *et al*., 2009) as an example

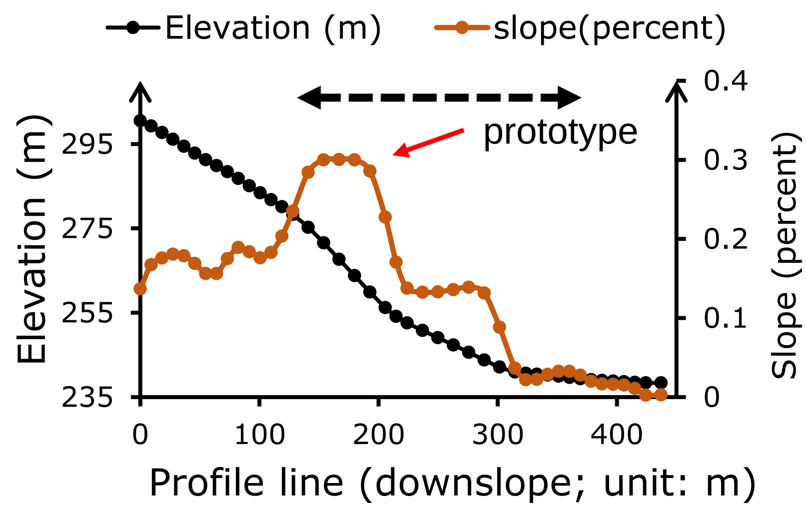


- Topographic attributes set
  - Regional attribute: **R**elative **P**osition **I**ndex (Skidmore, 1990)
  - Local attributes: profile curvature, slope gradient, elevation.
- Algorithms are speeded up by parallel computing based on MPI (Tarboton, 2014)

3 Method & Implementation



- Common domain knowledge:

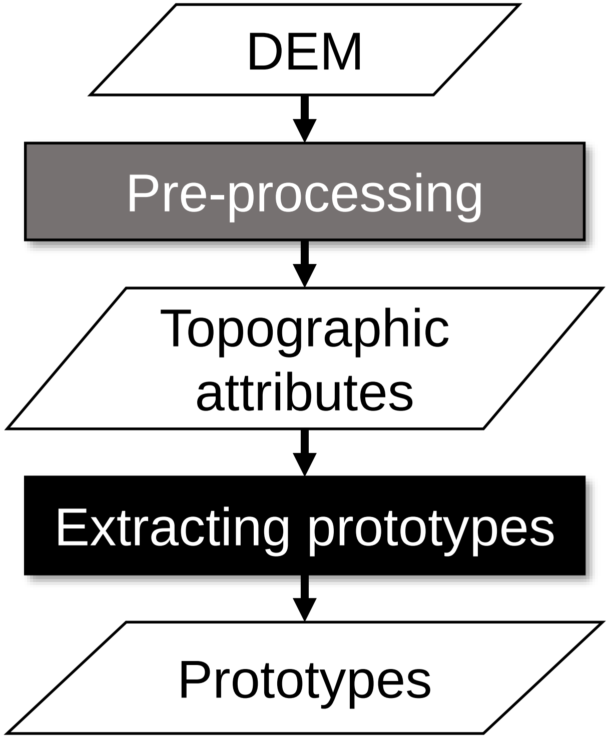


s-shaped

Slope position	**RPI**	**Profile Curvature**	**Slope**	**Elevation**
Ridge	S	S	Z	S, or N
Shoulder slope	Bell	S	Bell	N
Backslope	Bell	Bell	S	N
Footslope	Bell	Z, or Bell	Z, or Bell	N
Valley	Z	B	Z	N

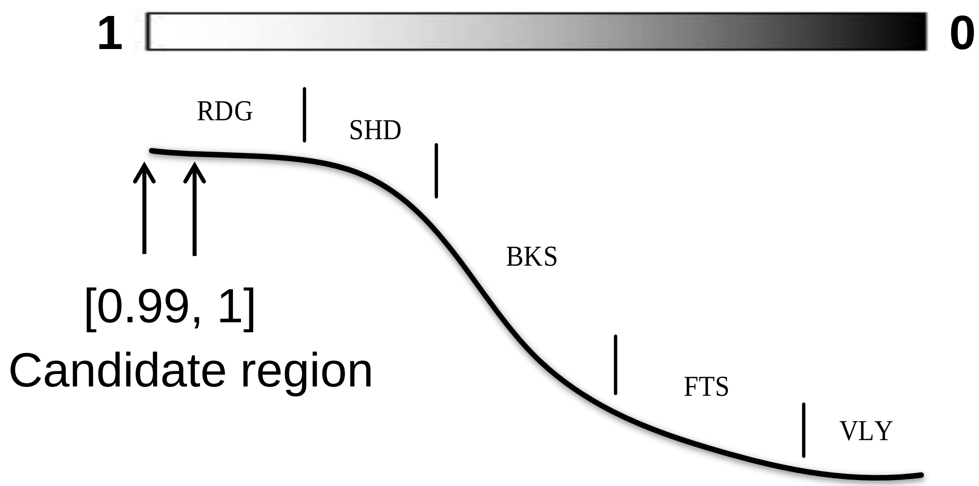
(based on Qin *et al*., 2009, 2012)

3 Method & Implementation

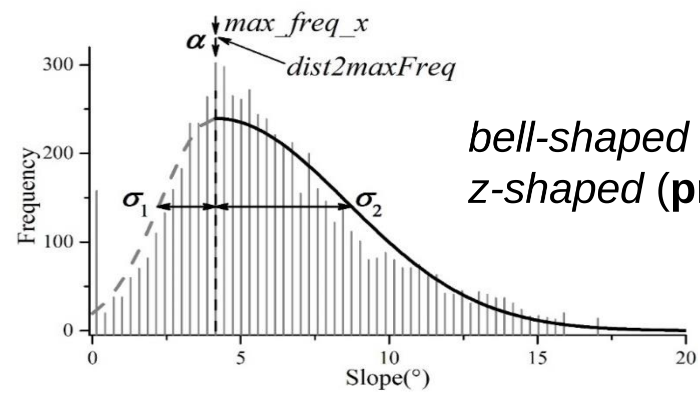


- Specific knowledge by data mining:

Regional topographic attribute



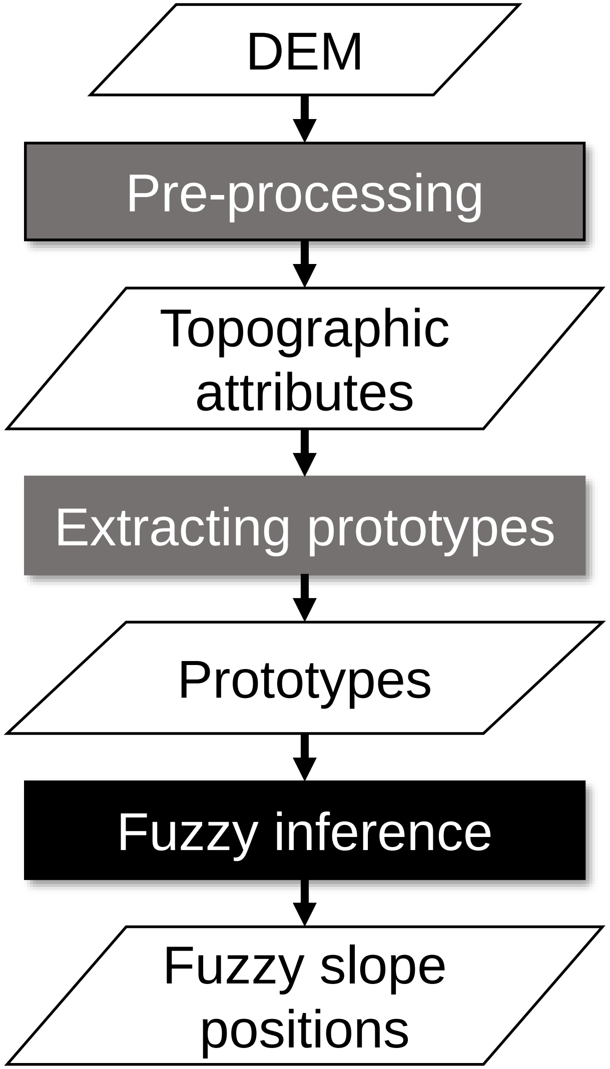
Five basic slope positions (Wysocki *et al*., 2000)



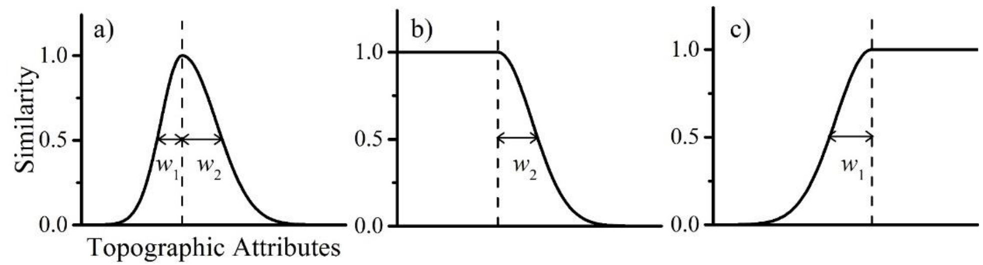
bell-shaped
z-shaped (**preferential**)

Frequency distribution of slope and the fitted bi-Gaussian mixture model

3 Method & Implementation



- Simply determined by the corresponding fitted Gaussian model or calculated by topographic attributes



Three types of fuzzy membership function:
(a) *bell-shaped*; (b) *z-shaped*; and
(c) *s-shaped*.

$$w_i = \sqrt{2}\sigma_i, \quad when\ k_i = 0.5 \quad (i = 1, 2)$$

3 Method & Implementation

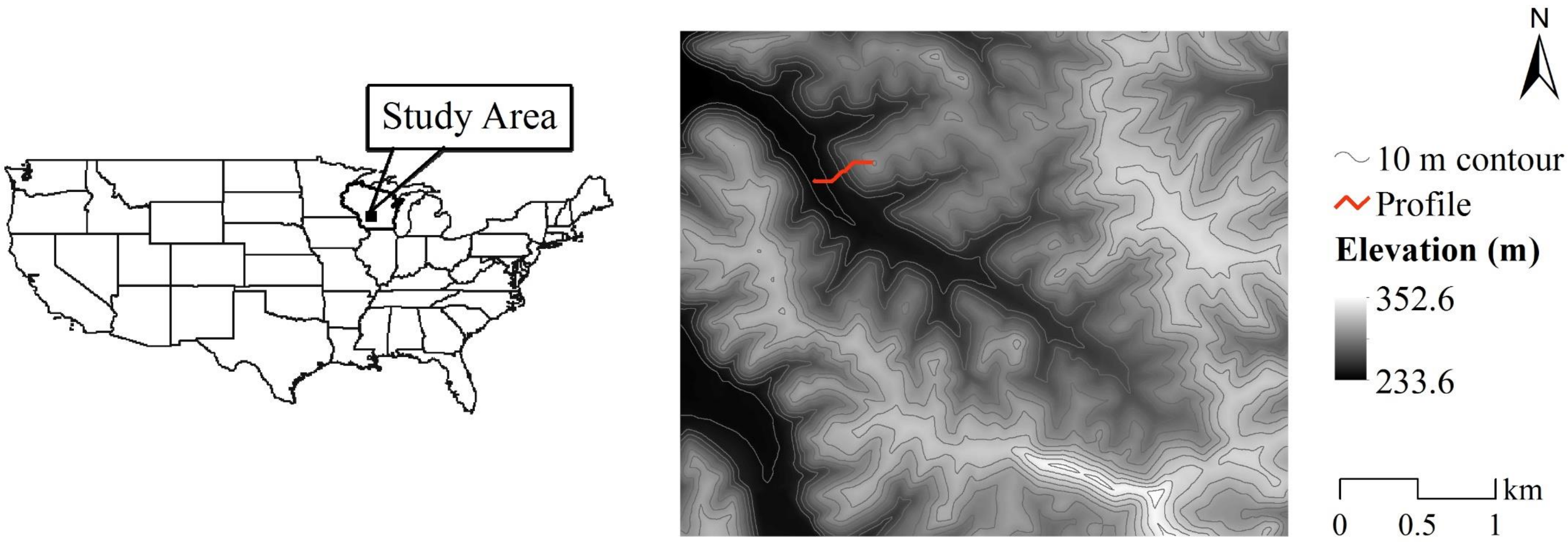
An automated, configurable, and parallelized workflow is implemented

- Automated workflow
- The only required input is the gridded DEM
- The workflow is configurable for experienced user
- Parallel computing based on MPI

Open source: https://github.com/lreis2415/AutoFuzSlpPos

4 Case study

- A small watershed (~12.7 km^2) . The resolution of DEM is 30 *ft* (~9.14 m)
- Elevation ranges from 233.6 to 352.6 m with an average of 290.8 m
- Maximum slope was 35.5° with an average of 9.7°



Map of the Pleasant Valley in southwestern Wisconsin, USA.

4 Case study

Test conditions…

- A Linux cluster with one management node and four computing nodes, GCC 4.8.4, MPICH 3.1.4, and Python 2.6.6
- The proposed approach was executed with default settings

Evaluation aspects…

- Reasonable of the derived fuzzy slope positions
  1. Estimated parameters for prototypes and fuzzy inference
  2. Spatial distribution of fuzzy slope positions
  3. Compared with Qin *et al*., (2009)
- Computational efficiency

4 Case study

Estimated parameters for prototypes

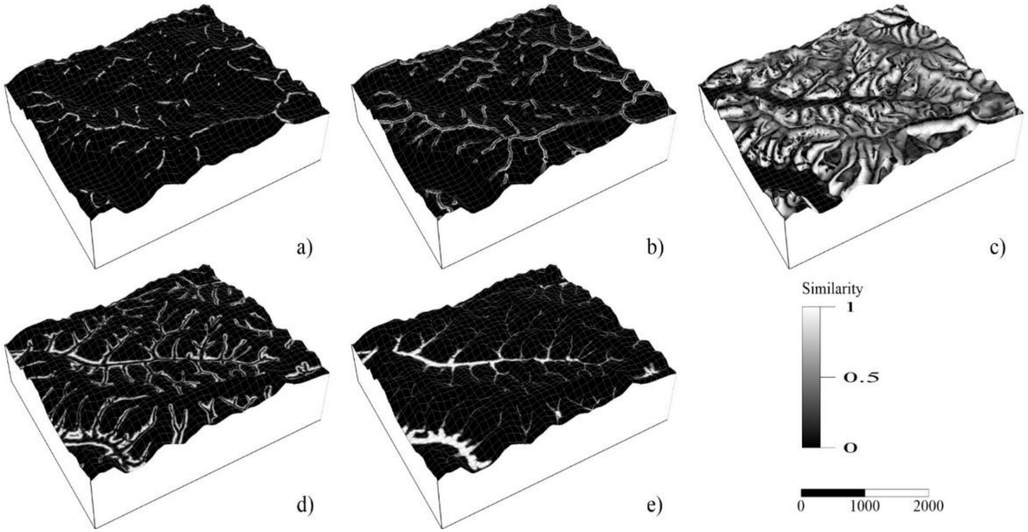
	RPI	Prof. curvature ($\times 10^{-3}$ m^{-1})	Slope (°)	Prototypes number
Ridge	≥ 0.99	≥ 4.25	≤ 6.59	794
Shoulder slope	[0.9, 0.95]	≥ 2.67	[3.4, 8.92]	1529
Backslope	[0.5, 0.6]	[-1.0, 1.95]	≥ 11.86	4088
Footslope	[0.15 0.2]	[-2.25, 0.89]	[3.58, 10.58]	2714
Valley	≤ 0.1	[-3.25, 0.49]	≤ 3.15	4984

Estimated parameters for fuzzy inference on attributes

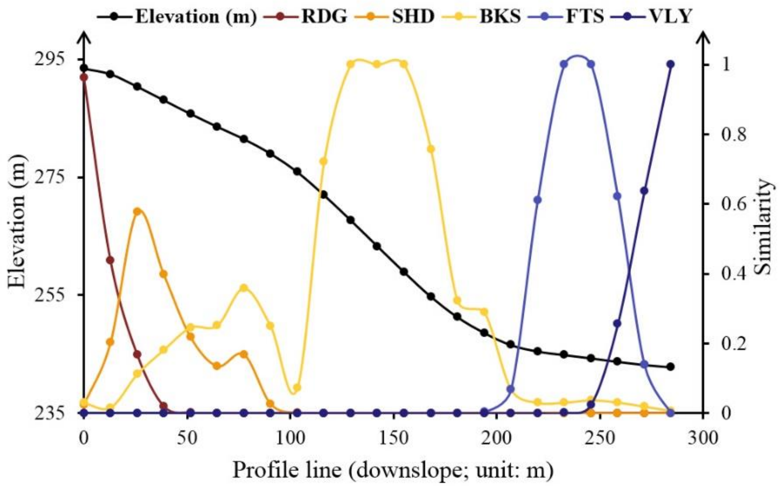
	RPI	Prof. curvature ($\times 10^{-3}$ m^{-1})	Slope (°)
Ridge	S: $w_1 = 0.05$	S: $w_1 = 7.28$	Z: $w_2 = 5.12$
Shoulder slope	B: $w_1 = w_2 = 0.04$	S: $w_1 = 4.6$	B: $w_1 = 2.64$, $w_2 = 6.39$
Backslope	B: $w_1 = w_2 = 0.3$	B: $w_1 = 2.58$, $w_2 = 2.41$	S: $w_1 = 7.22$
Footslope	B: $w_1 = w_2 = 0.05$	B: $w_1 = 3.1$, $w_2 = 2.14$	B: $w_1 = 4.51$, $w_2 = 5.87$
Valley	Z: $w_2 = 0.1$	B: $w_1 = 5.32$, $w_2 = 1.68$	Z: $w_2 = 5.29$

4 Case study

Spatial distribution of fuzzy slope positions



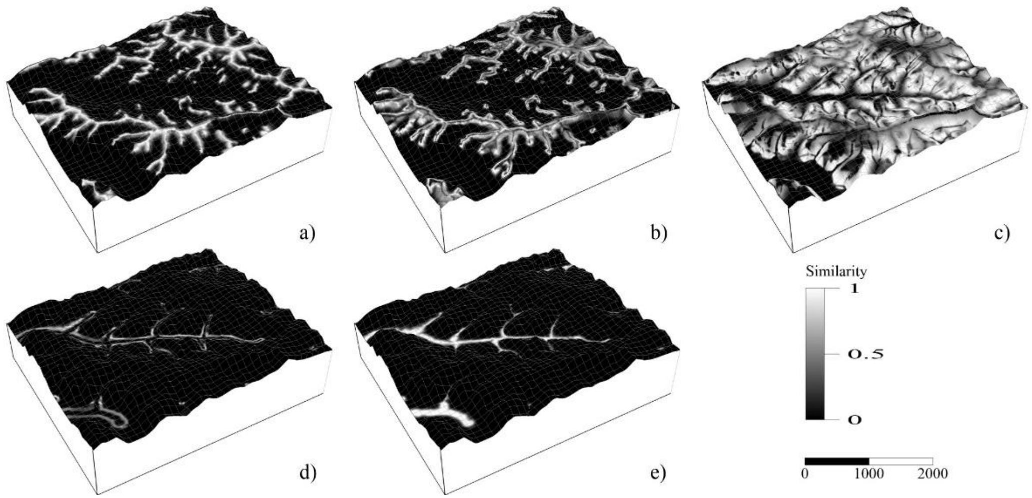
(a) ridge; (b) shoulder slope; (c) backslope; (d) footslope; and (e) valley.



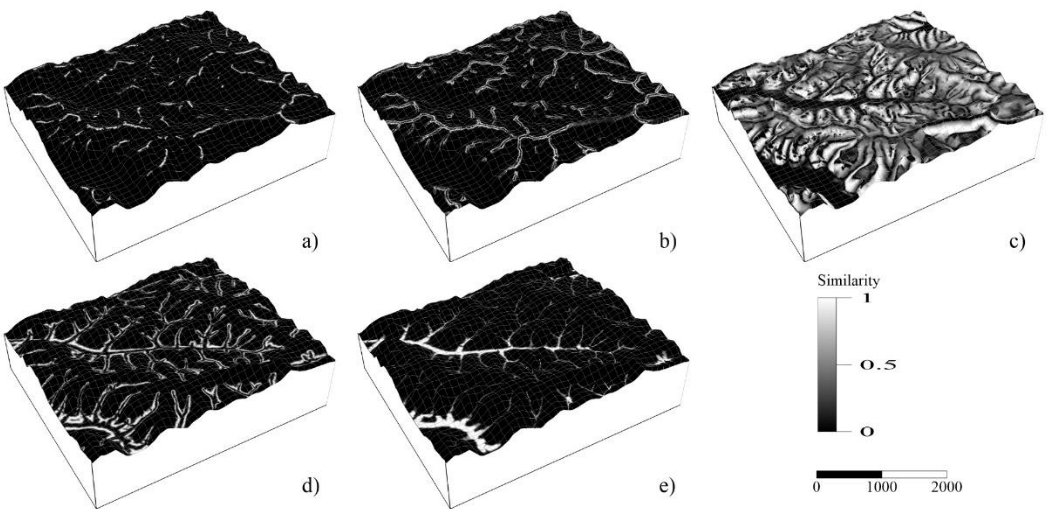
Similarity curves for the five slope positions along the longest profile

- Slope positions gradually transit from top to bottom of a hillslope
- Relative low similarity appear in the transition regions

4 Case study



Qin *et al*., 2009



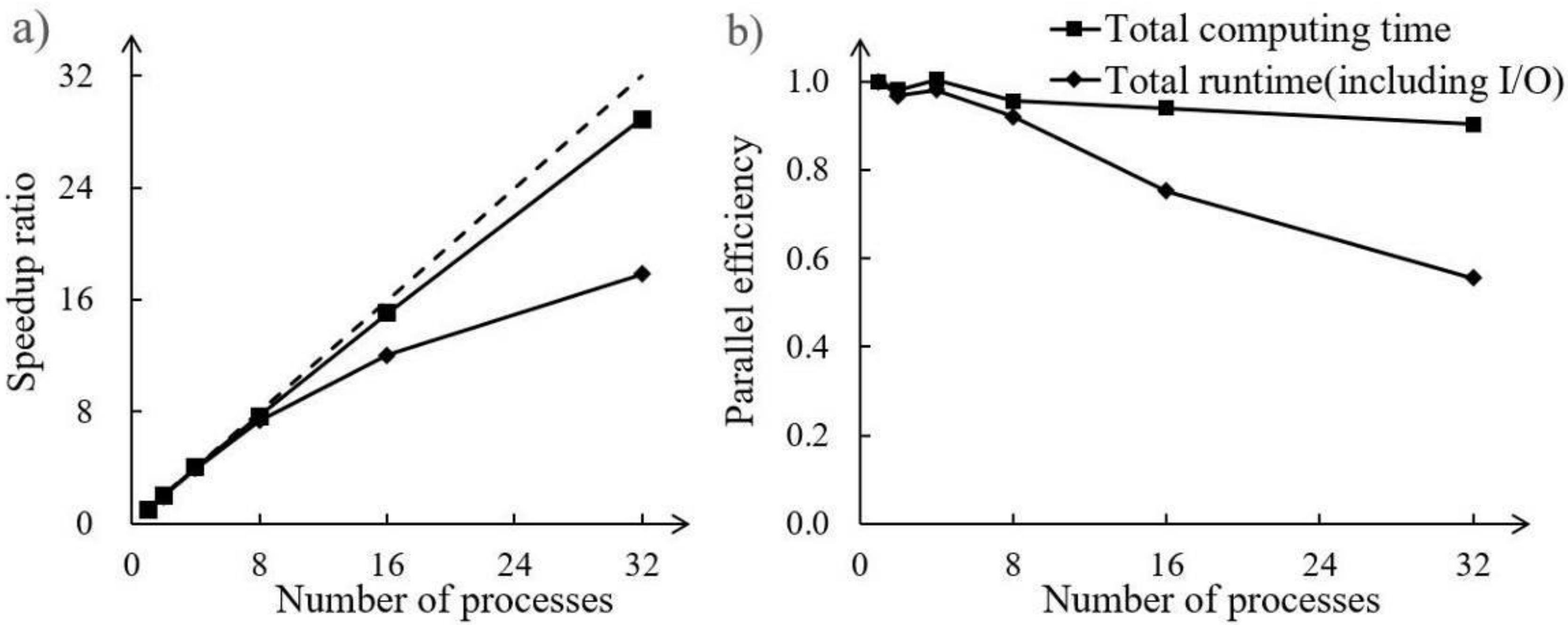
The proposed approach

Compared with Qin *et al*., (2009)

- The two results are generally consistent.
- The proposed approach derived a more detailed spatial patterns.
- The patterns are largely dependent on regional topographic attributes.

4 Case study

Computational efficiency



Speedup ratio (a) and parallel efficiency (b) of the proposed approach in the case study (total computational time excluding I/O time; total runtime including I/O time).

5 Summary

- An automatic approach to prototype-based derivation for fuzzy slope positions is proposed.
  - Only one required input data, i.e., gridded DEM
  - Reduce extensive user intervention
  - Speed up by parallel computing
- The basic idea in the proposed approach is potentially useful for automation of other similar geospatial analysis methods.

Thanks for your attention!

Question?

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https://zhulj.net

https://github.com/lreis2415/AutoFuzSlpPos

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