# Clustering of river profiles

## Examples from real and synthetic landscapes


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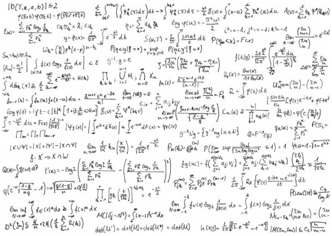
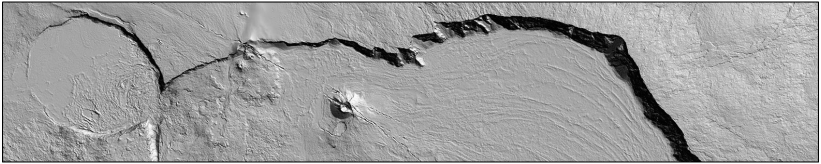
# Combining topographic data with numerical models



**1.** New theory, method, etc...

**2.** Test on a numerical model



**3.** Apply on topographic data. 1m lidar for Mauna Loa, OpenTopography

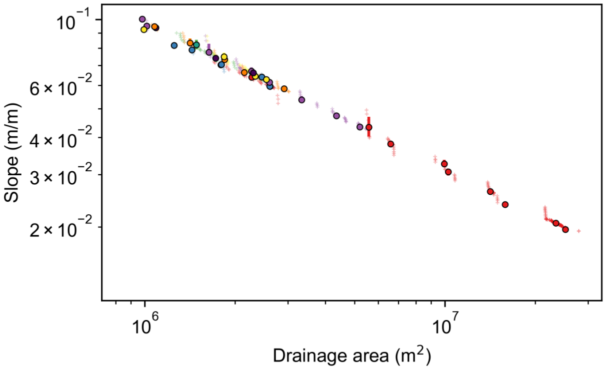

# How do landscapes respond to external forcing?

# Channel gradient

River Traligill, Northwest Highlands, Scotland



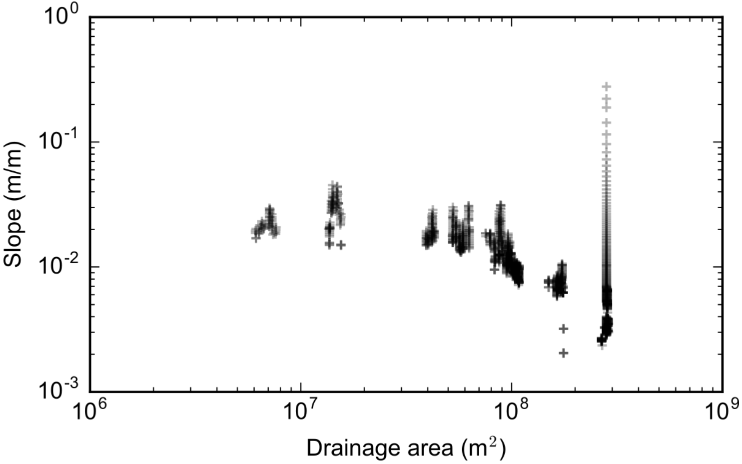
# Slope vs. drainage area




Empirical observations show a power law relationship between slope and drainage area (e.g. Morisawa, 1962; Flint, 1974)

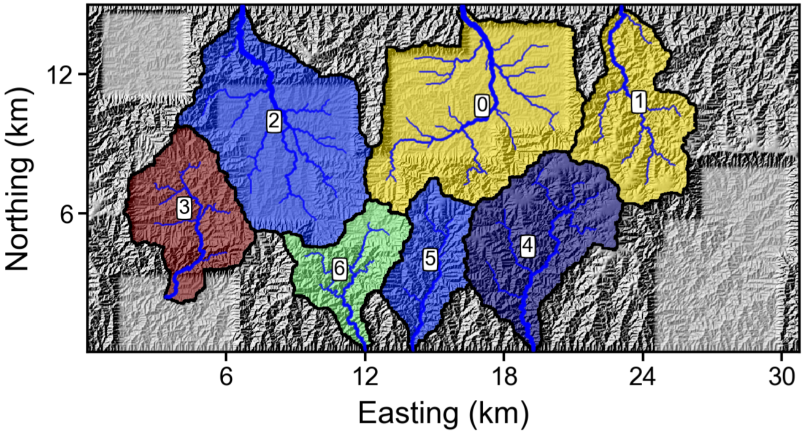
$$S = k_s A^\theta$$

# Problem 1: Data gaps and noise




Typical slope-area plot from Xi'an province, China (Mudd et al., 2018)

# Problem 2: Landscape heterogeneity



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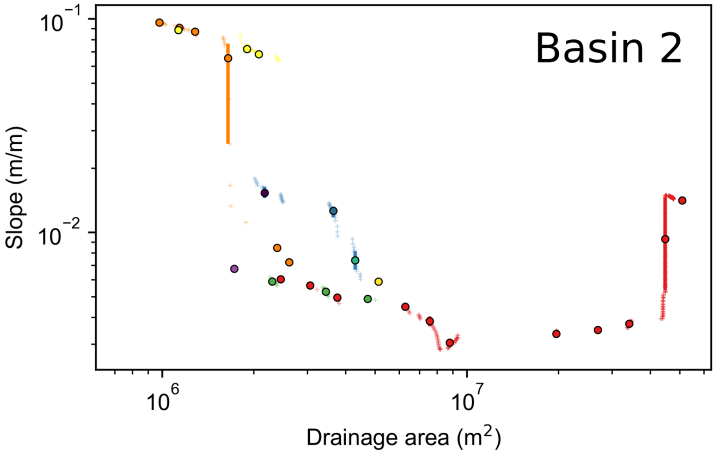

# Potential solution: clustering the river profiles

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## Separate channels with different morphology

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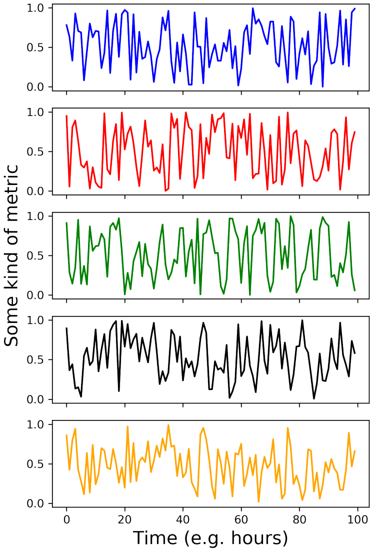
Separate channels with different morphology

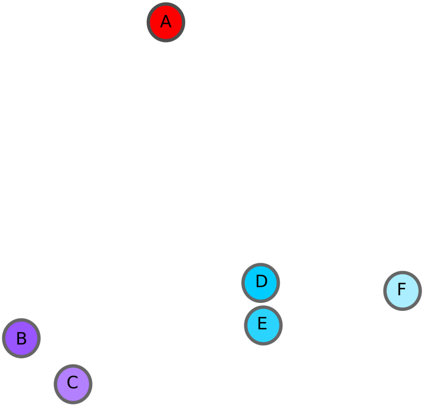
'Clean up' extraction of channel metrics, such as normalised channel steepness

# Clustering of 1D data

- Algorithms developed mostly for **time series data**
- Used in diverse fields: climate science, meteorology, geophysics, quantitative finance, economics, epidemiology, etc...



# Agglomerative clustering



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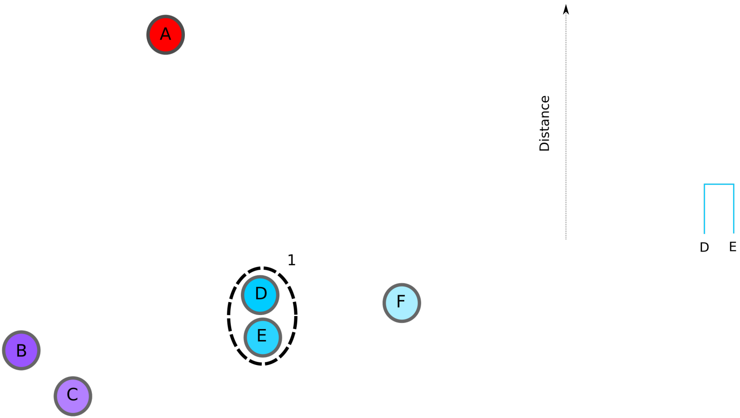

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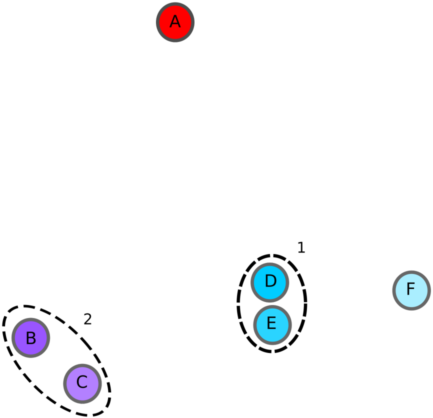


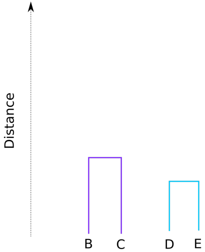

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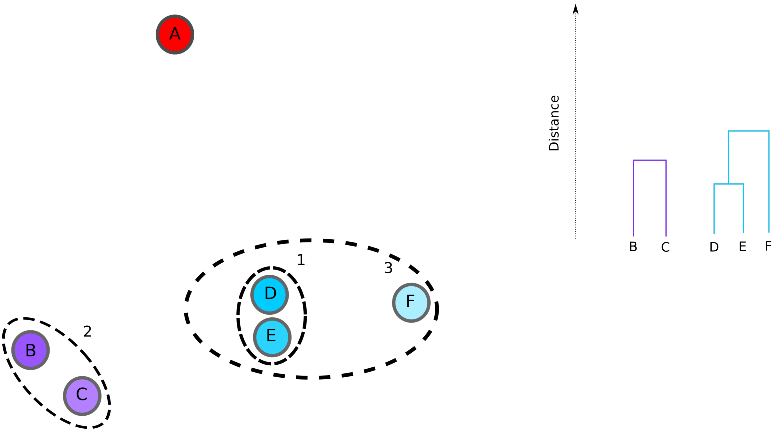

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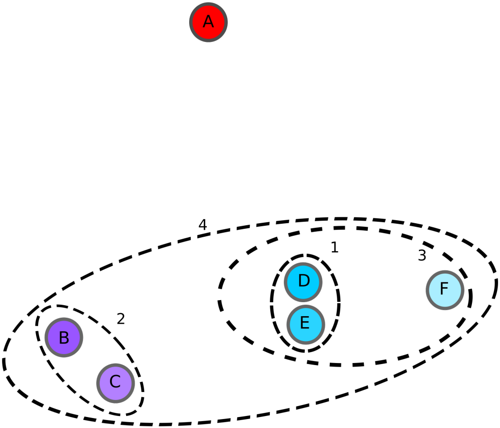


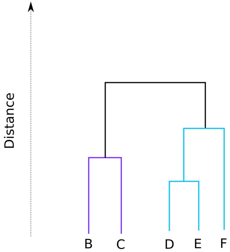

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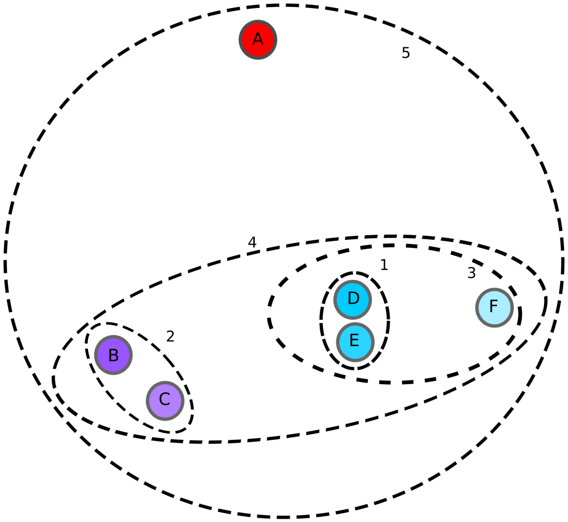
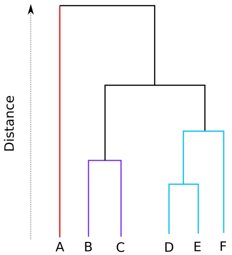
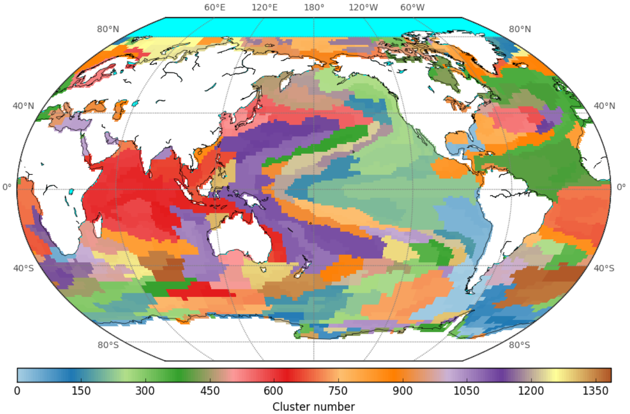


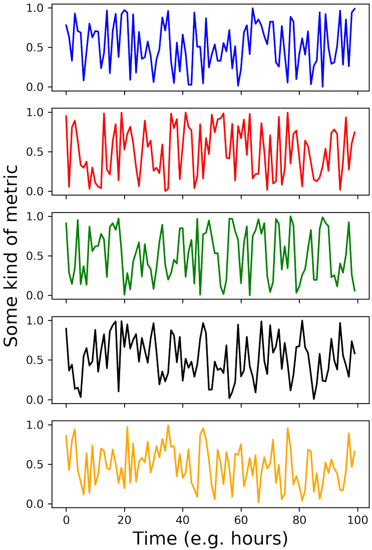



# Example from environmental context




Global clustering of time series of sea surface temperatures (Rheinwalt et al., 2017)

# Application to river profiles



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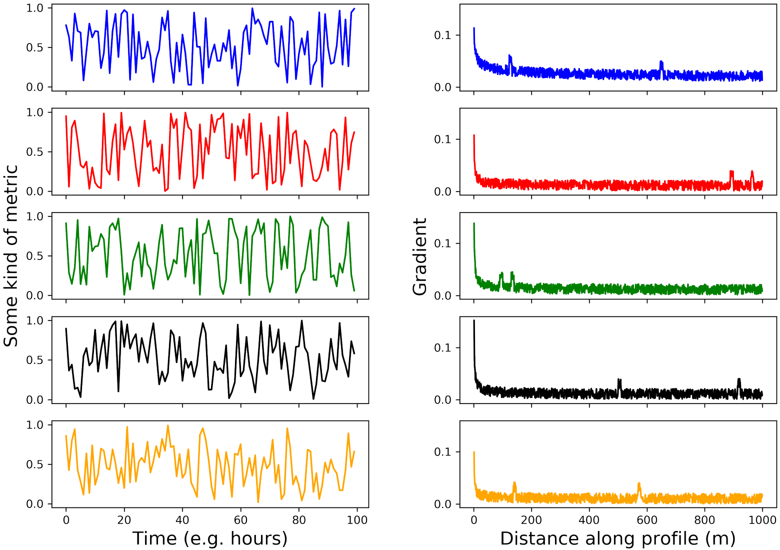
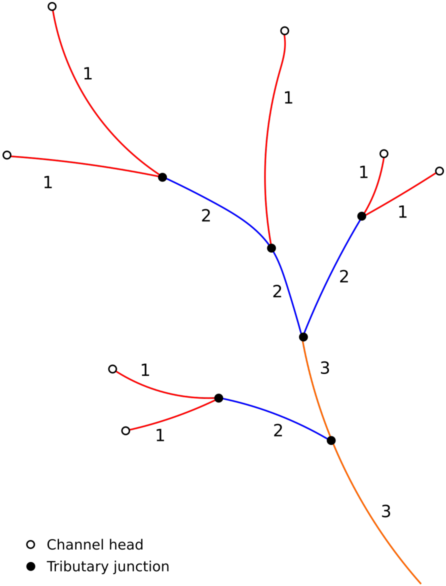
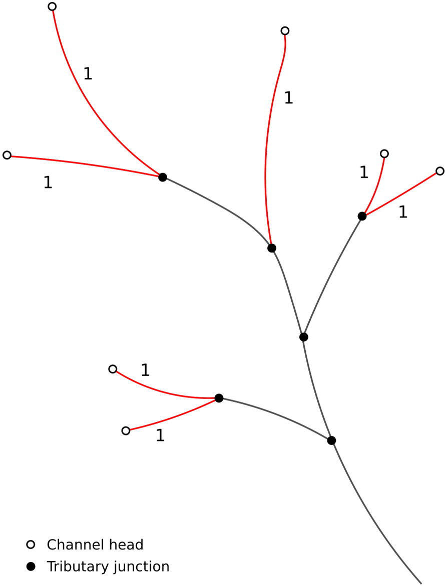


# Clustering a river network




Separate channels by stream order to ensure we are comparing channels with similar discharge/drainage area

# First order streams

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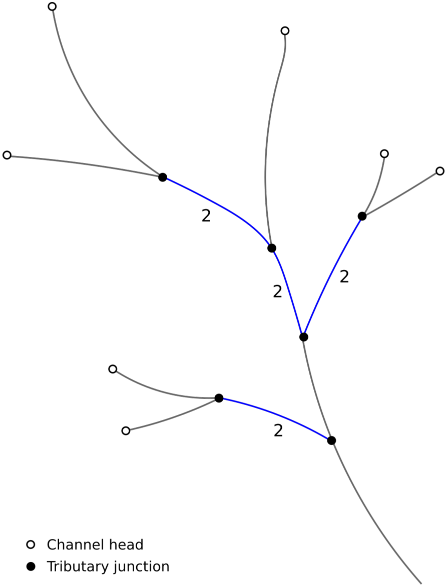
# Second order streams

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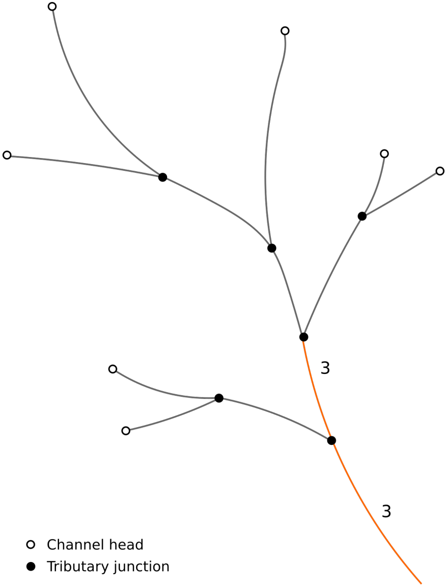
# Third order streams




Separate channels by stream order to ensure we are comparing channels with similar discharge/drainage area

# Testing the method

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## Example from a model landscape with varying lithology

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Example from Santa Cruz Island, CA

# Varying lithology

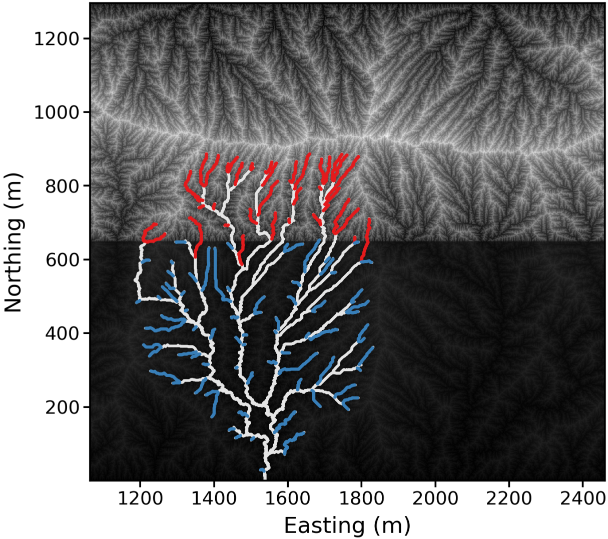
**North: harder rocks**

$K = 6.23{\times}10^{-5}$

**South: softer rocks**

$K = 3.12{\times}10^{-4}$

# First order streams



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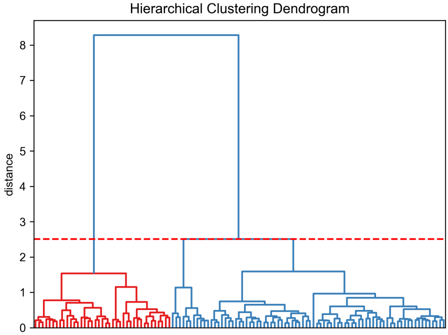
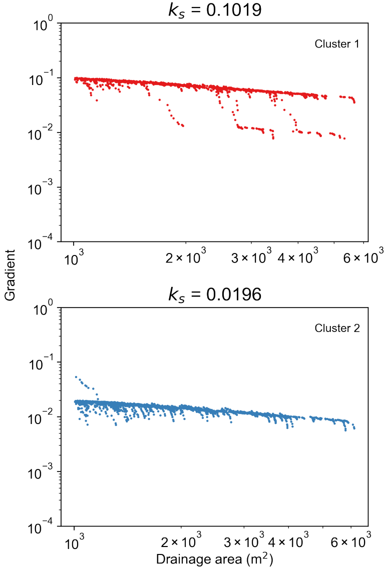
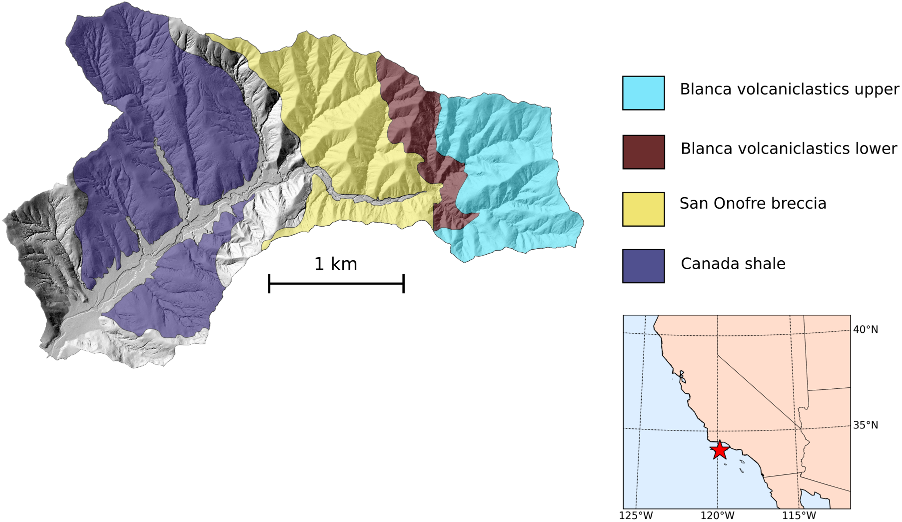


# Pozo catchment, Santa Cruz Island



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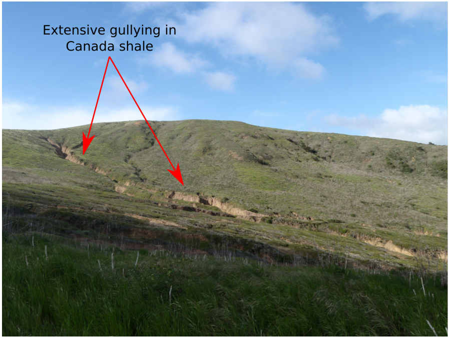
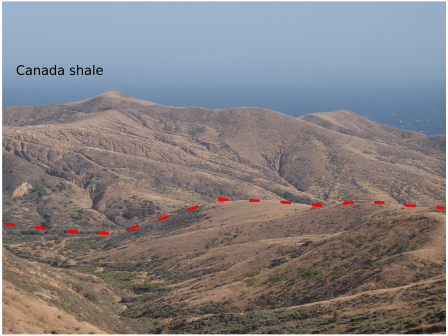



Photo credit: B. Bookhagen




San Onofre breccia

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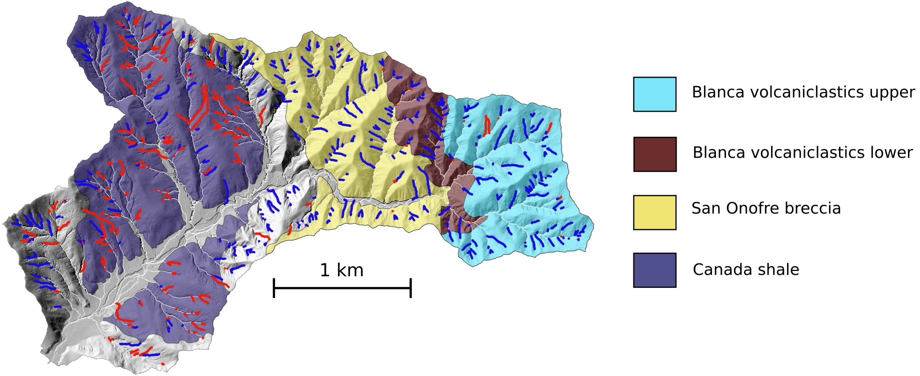

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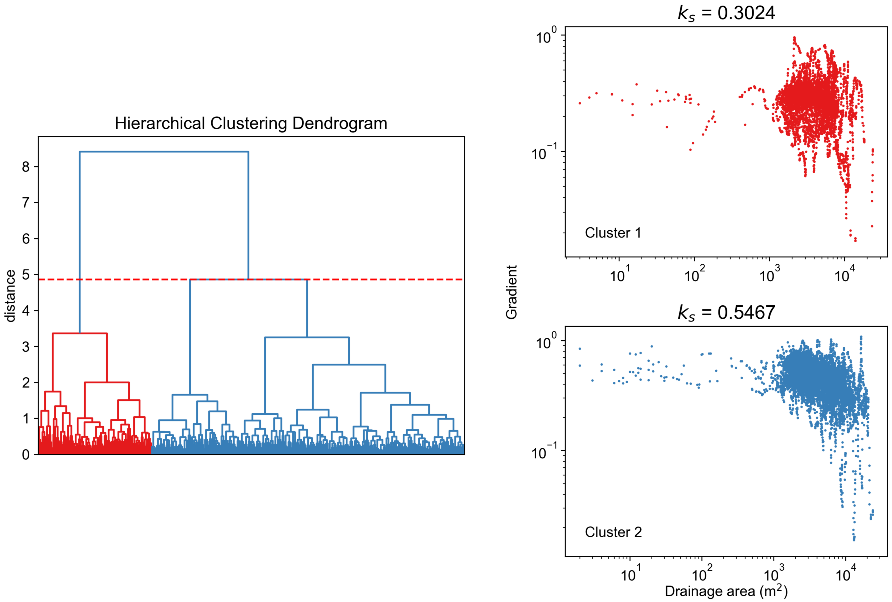
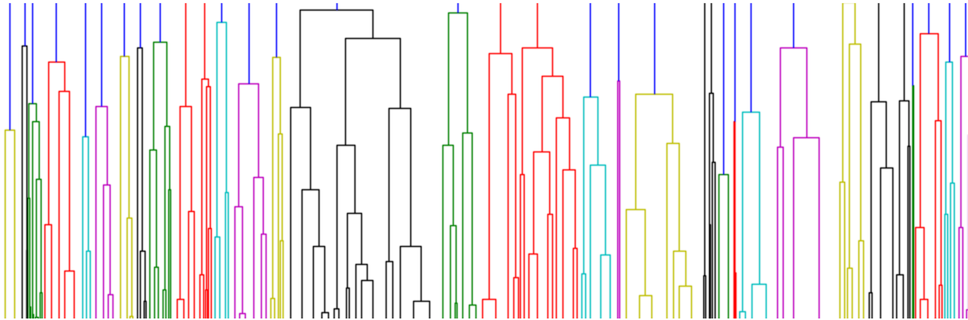


# Summary



- Clustering can be used to tackle the problem of landscape heterogeneity

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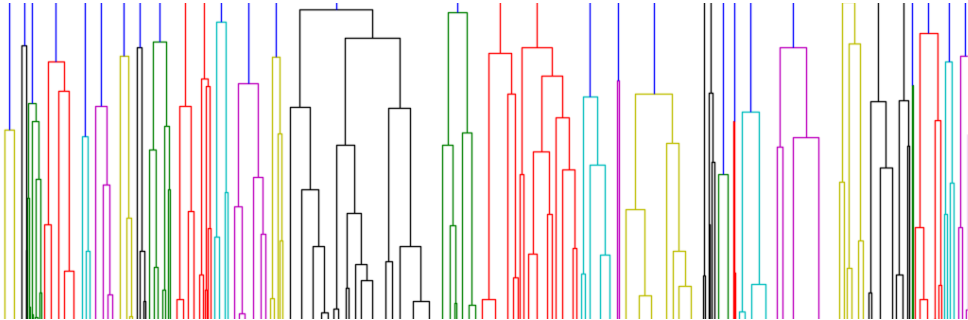

- Clustering can be used to tackle the problem of landscape heterogeneity
- Data-driven approach with few assumptions

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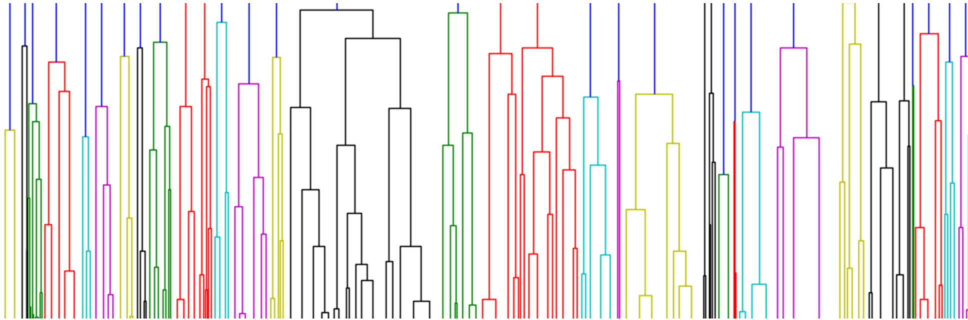

- Clustering can be used to tackle the problem of landscape heterogeneity
- Data-driven approach with few assumptions
- Potential applications: channel steepness analysis, hillslope-valley transitions, extraction of alluvial reaches, etc...

**Questions?**

# Quantifying differences

$$d = \left\| \frac{\mathbf{X} - \mathbf{Y}}{\mathbf{X} + \mathbf{Y}} \right\| \Big/ \sqrt{n}$$

$\mathbf{X}$ = Profile 1

$\mathbf{Y}$ = Profile 2

$n$ = number of points in profile

# Determining the number of clusters