EGU General Assembly 2022

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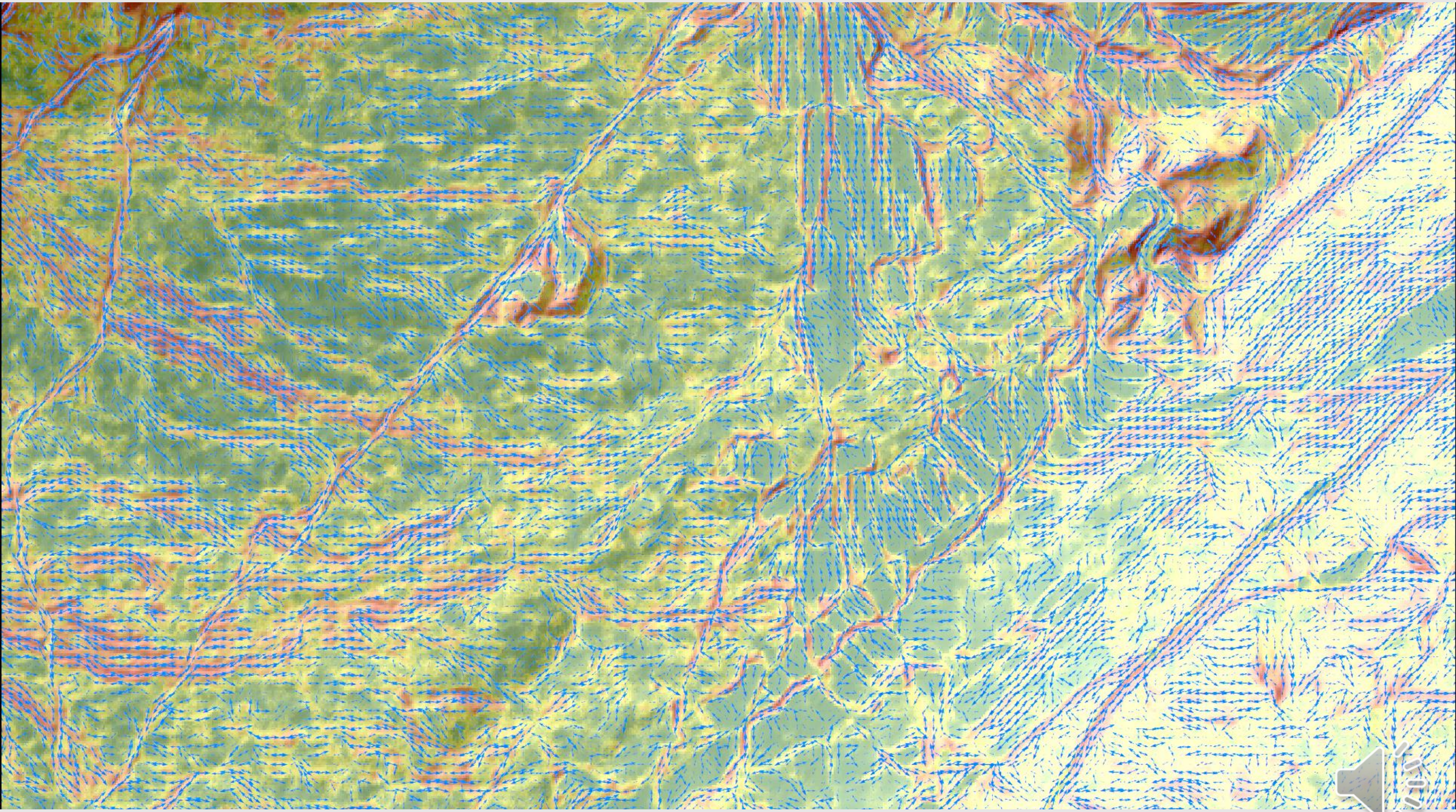
Session: GM2.8 – Advances in geomorphometry and landform mapping: possibilities, challenges and perspectives

Returning to geostatistical-based analysis of image/surface texture: from generalization to a basic one-click short-range surface roughness algorithm



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Preamble

Despite the long record of applications and the well-known and robust theoretical framework, geostatistical based image/surface texture tools have still not gained momentum in the context of geomorphometric analysis.

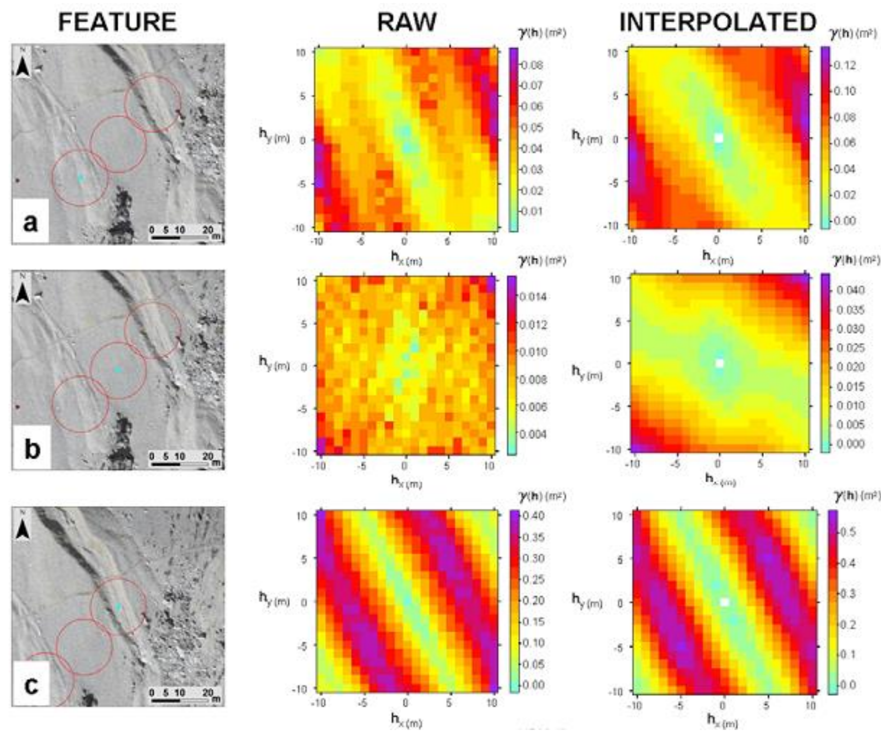
$$\gamma(\boldsymbol{h}) = \frac{1}{2\mathrm{N}(\mathbf{h})}\sum_{\alpha=1}^{N(\boldsymbol{h})}[z(\boldsymbol{u}_\alpha) - z(\boldsymbol{u}_\alpha + \boldsymbol{h})]^2 = 1/2\frac{1}{N(\boldsymbol{h})}\sum_{\alpha=1}^{N(\boldsymbol{h})}\Delta^2(\boldsymbol{h})_\alpha = 1/2 \cdot mean(\Delta^2(\boldsymbol{h}))$$

$$\Delta(\boldsymbol{h})_\alpha = z(\boldsymbol{u}_\alpha) - z(\boldsymbol{u}_\alpha + \boldsymbol{h})$$

$$\gamma(\boldsymbol{h})_p = \frac{1}{2\mathrm{N}(\mathbf{h})}\sum_{\alpha=1}^{N(\boldsymbol{h})}|z(\boldsymbol{u}_\alpha) - z(\boldsymbol{u}_\alpha + \boldsymbol{h})|^p = 1/2 \cdot mean(|\Delta(\boldsymbol{h})|^p)$$

$$\mathrm{MAD(h)} = |\Delta(\boldsymbol{h})_{\alpha=median}|$$

Variogram maps as morphology fingerprints…



Many geomorphometric studies dealing with roughness are still based on popular approaches such as vector dispersion of normals to surface or even approaches as the TRI. Unfortunately, these indexes present many drawbacks, have a limited capability to represent specific aspects of surface roughness and sometime are not easily interpretable.

One of the reasons of the limited popularity of the geostatistical-based surface texture analysis could be related to the wide range of approaches and user dependent choices that can be adopted. For example, conventional geostatistical algorithms require the derivation of a residual DEM before the calculation of roughness indices; unfortunately, the derivation of residual DTM can be obtained with different levels of smoothing and even with different smoothing approaches.

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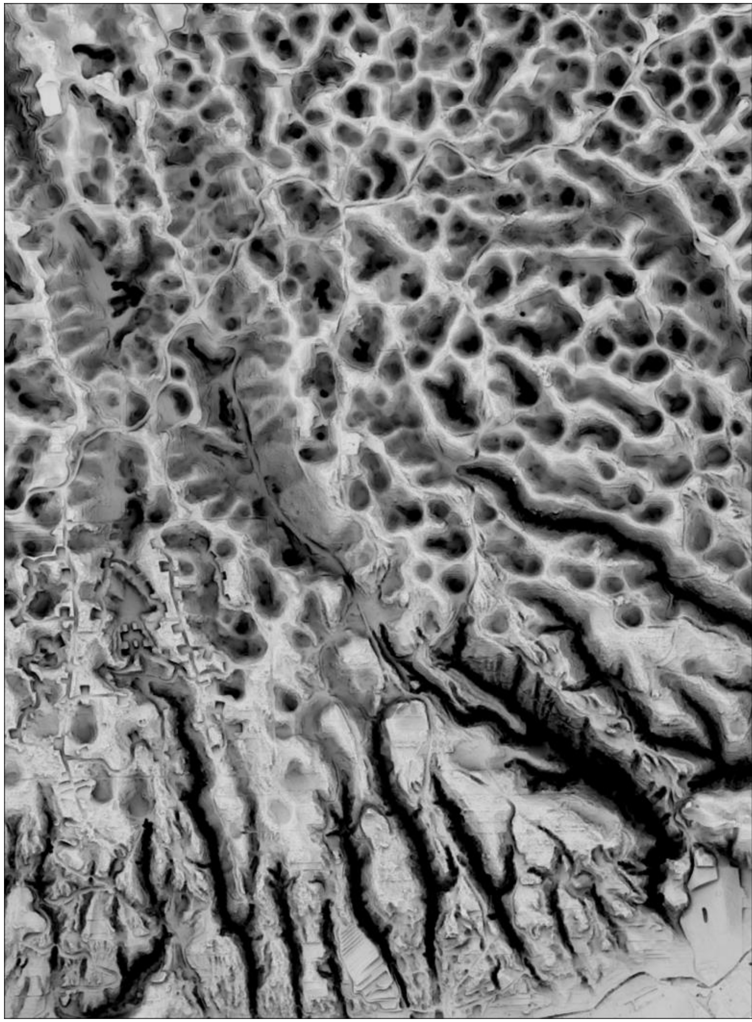
Preamble

NB$_1$: here the terms "surface texture" and "roughness" are used interchangeably !

NB$_2$: with usual 2.5D DEMs we are not analyzing true surface roughness but an "apparent roughness" according to a zenithal projection!

The wide flexibility of geostatistical roughness-based approaches, analogously to gray-level co-occurrence matrix approach, is strictly linked to the fact that surface texture is a general concept referring to wide set of aspects of surface morphology. It is unmeaningful to refers generically to a single roughness index; more realistically a wide family of roughness indexes exist. Each index highlights specific aspects of roughness at a given scale.



In one hand, the high flexibility and potentialities of the geostatistical approach represent an opportunity; on the other hand, these seem a limitation for its applicability by a wide range of users (given the general preference for, at least apparently, simpler algorithms, with less or no user-dependent choices).

NB$_3$ Geostatistical based roughness methodologies have links with other approaches used in image/surface texture analysis and pattern recognition: e.g., local binary patterns, geomorphons, etc.

The new algorithm MAD_{k2}: motivations

The algorithm can be applied considering the robust estimator MAD (also Madogram and Variogram can be used) that is conceived for working with highly nonstationary data (e.g. high resolution geomorphometric data).

MAD_{k2} has been developed with the following characteristics:

1) Minimal intervention of the user (it requires only the definition of the search window radius)
2) Calculation by default of 3 basic short-range roughness parameters: isotropic roughness, anisotropy in roughness and direction of anisotropy
3) Intuitive

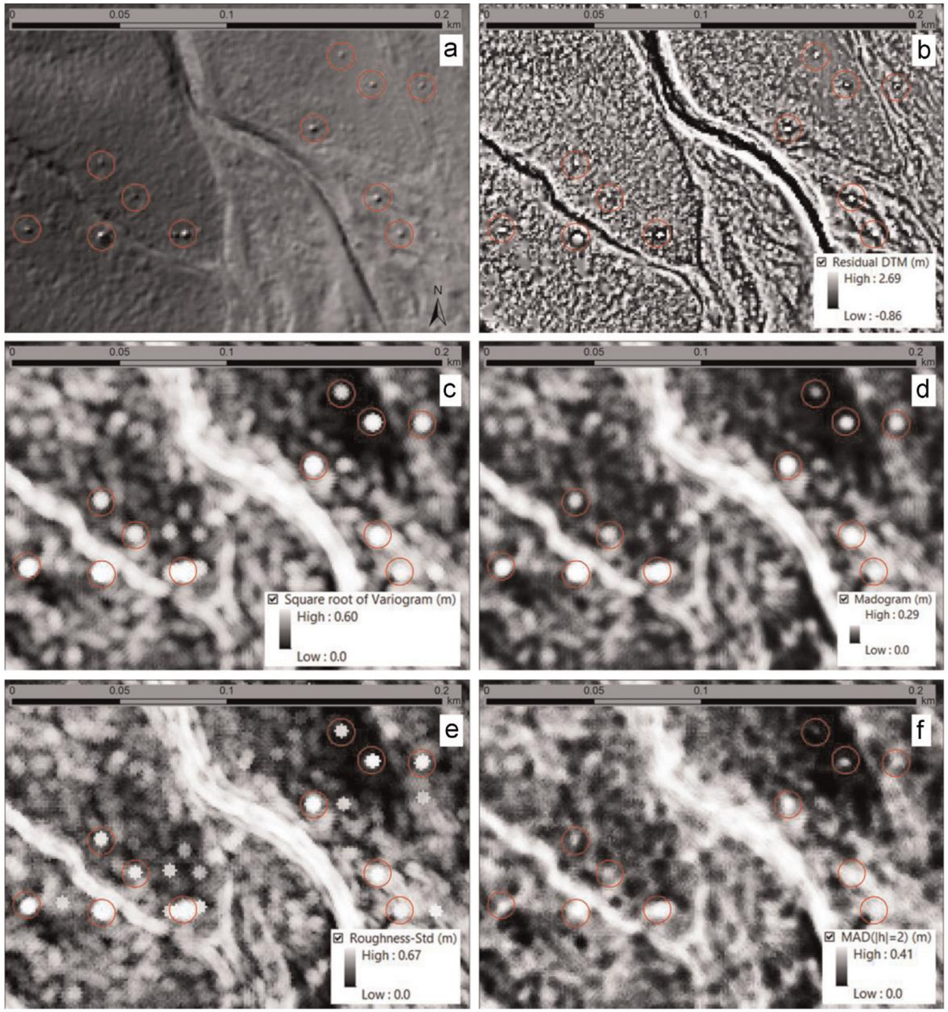
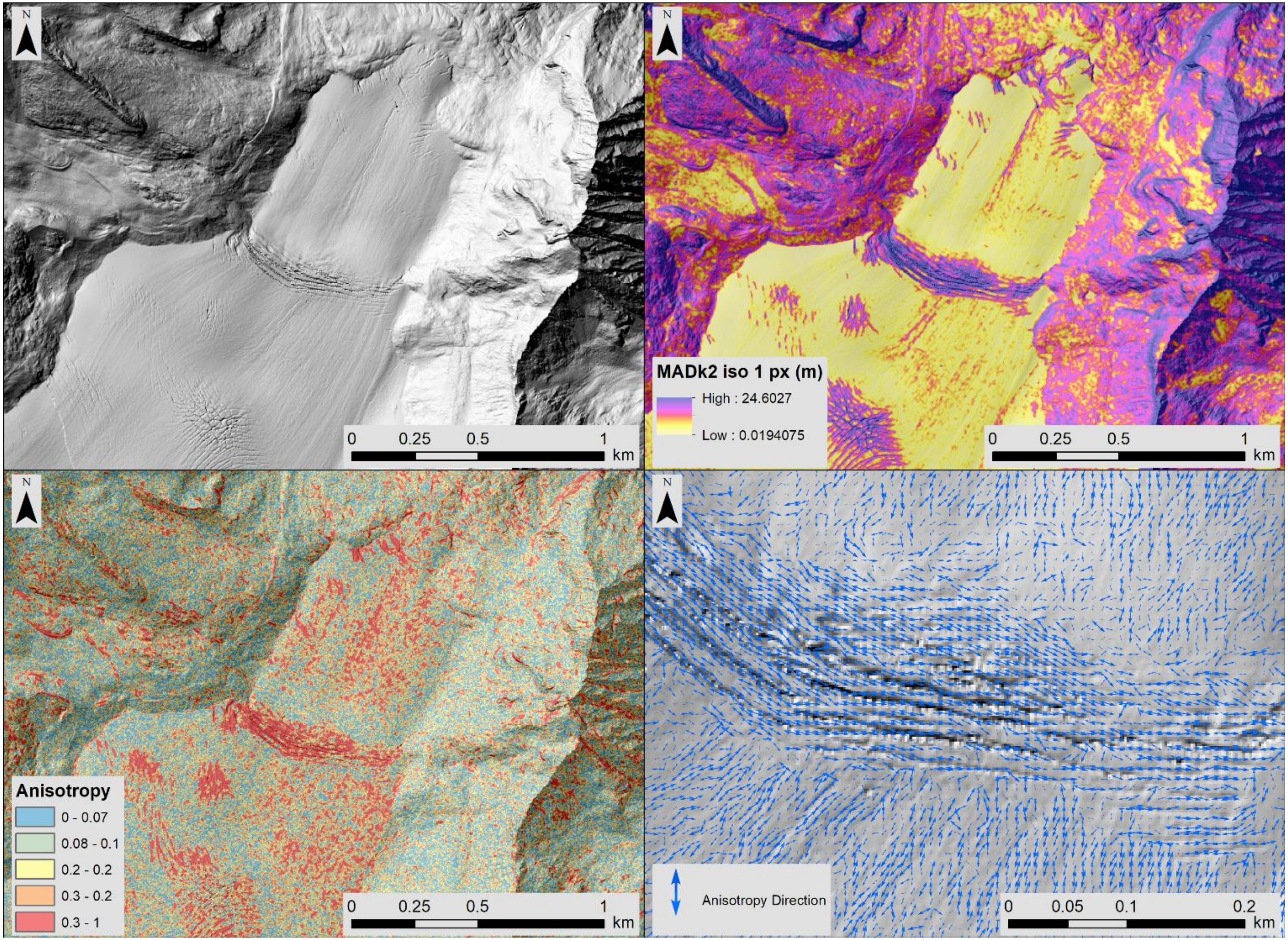


Fig. 12. Comparison of different surface texture indices for a particular portion of the area presented in Figs. 4 and 5. (a) Shaded relief (sun from 315°, altitude 45°). (b) Residual DTM. (c) Square root of the omnidirectional variogram (|**h**|=2 pixels). (d) Omnidirectional madogram (|**h**|=2 pixels). (e) $Roughness_{std}$. f) Omnidirectional MAD (|**h**|=2 pixels). The MAD-related image is less noisy and more focused; in particular, linear discontinuities are described more sharply. Moreover, in the MAD image, the smooth areas related to the presence of vegetation and lower LiDAR point densities are better outlined.

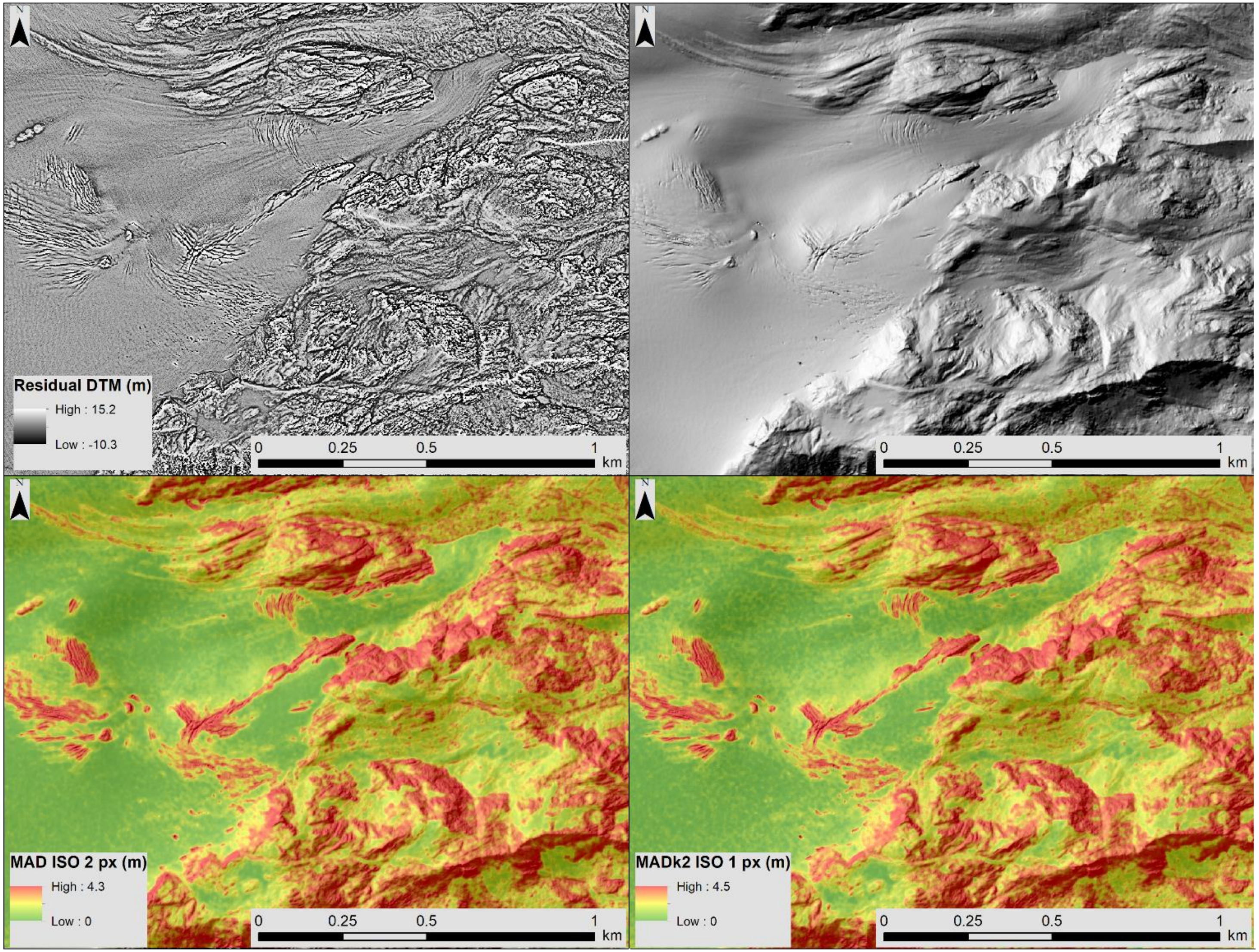
The new algorithm: 3 key aspects of roughness

Even if MAD_{k2} is focused on short-range roughness measures (i.e. lags between pixels up to 2 pixels), the algorithm returns key surface texture parameters. Among these, anisotropy represents a relevant added value.



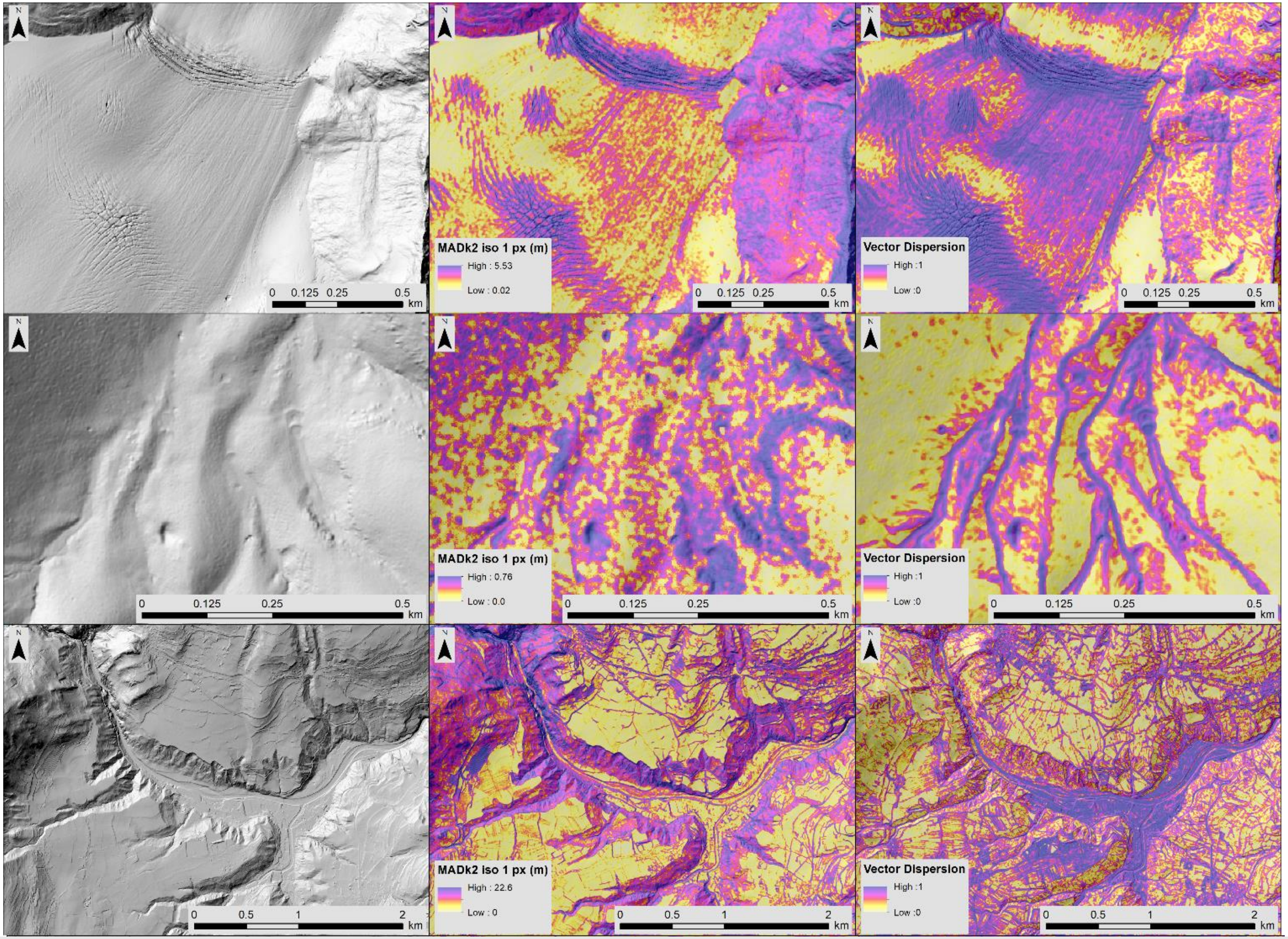
The new algorithm: a comparison with MAD

The algorithms provides similar results to MAD (well, depending on the way in which you derived residual DEM!)....but it works still better in correspondence of discontinuities...and does not require detrending.



The new algorithm: a comparison with vector dispersion of normals

Focusing on isotropic roughness indexes, the new algorithm MAD_{k2} respect to roughness based on vector dispersion is truly independent to slope and it is much more interpretable!



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Some key points

- The MAD_{k2} algorithm can be easily adapted to derive other ad-hoc roughness indexes (e.g. flow directional roughness)
- it can be deployed also for multiscale analysis adopting smoothing approaches (e.g., Trevisani 2010; Lindsay 2019)
- it is implemented in the Terra package and in phyton for ArcGis; but you can code it in any software implementing convolutional approaches (i.e. focal analysis…)

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