University of Zurich[UZH]

A Spatial Field Decomposition Approach to Evaluate Biodiversity Indices on Dominant Scales

Roman Charles Flury & Prof. Dr. Reinhard Furrer

JSM 2019, Denver

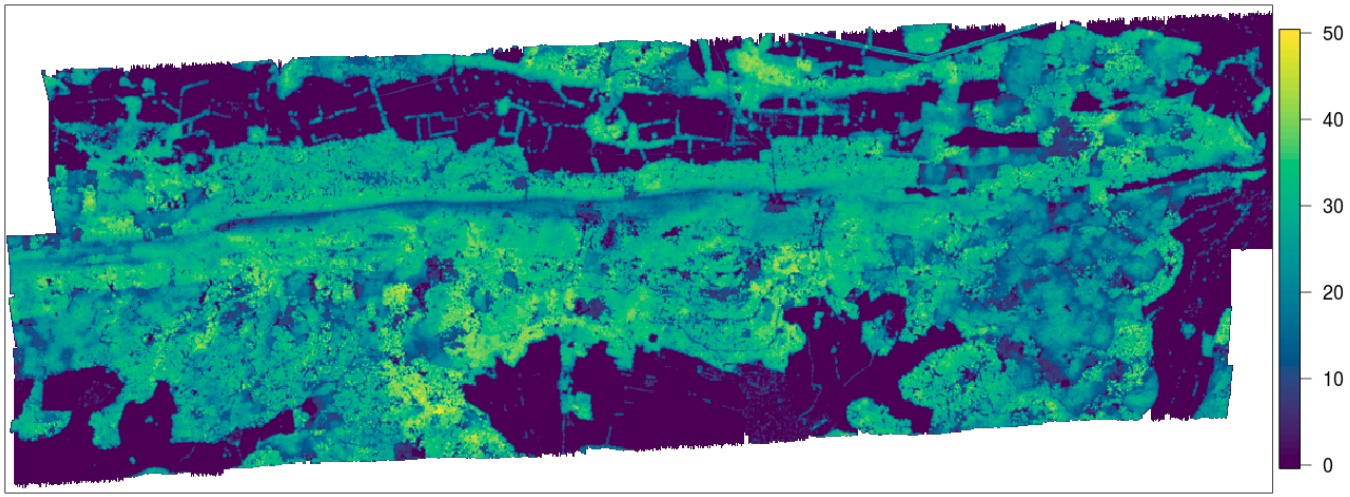
Morphological Traits

Pixel based morphological traits canopy height (*ch*), plant area index (*pai*) and foliage height diversity (*fhd*) (Schneider et al., 2017).

Google maps satellite image of beech-dominated forest on the mountain Laegeren in Switzerland.

Morphological Traits

Pixel based morphological traits canopy height (*ch*), plant area index (*pai*) and foliage height diversity (*fhd*) (Schneider et al., 2017).



Canopy height (*ch*).

the traits are

- detrended with topological variables (e.g. slope, aspect of the same area)

Ecological Context

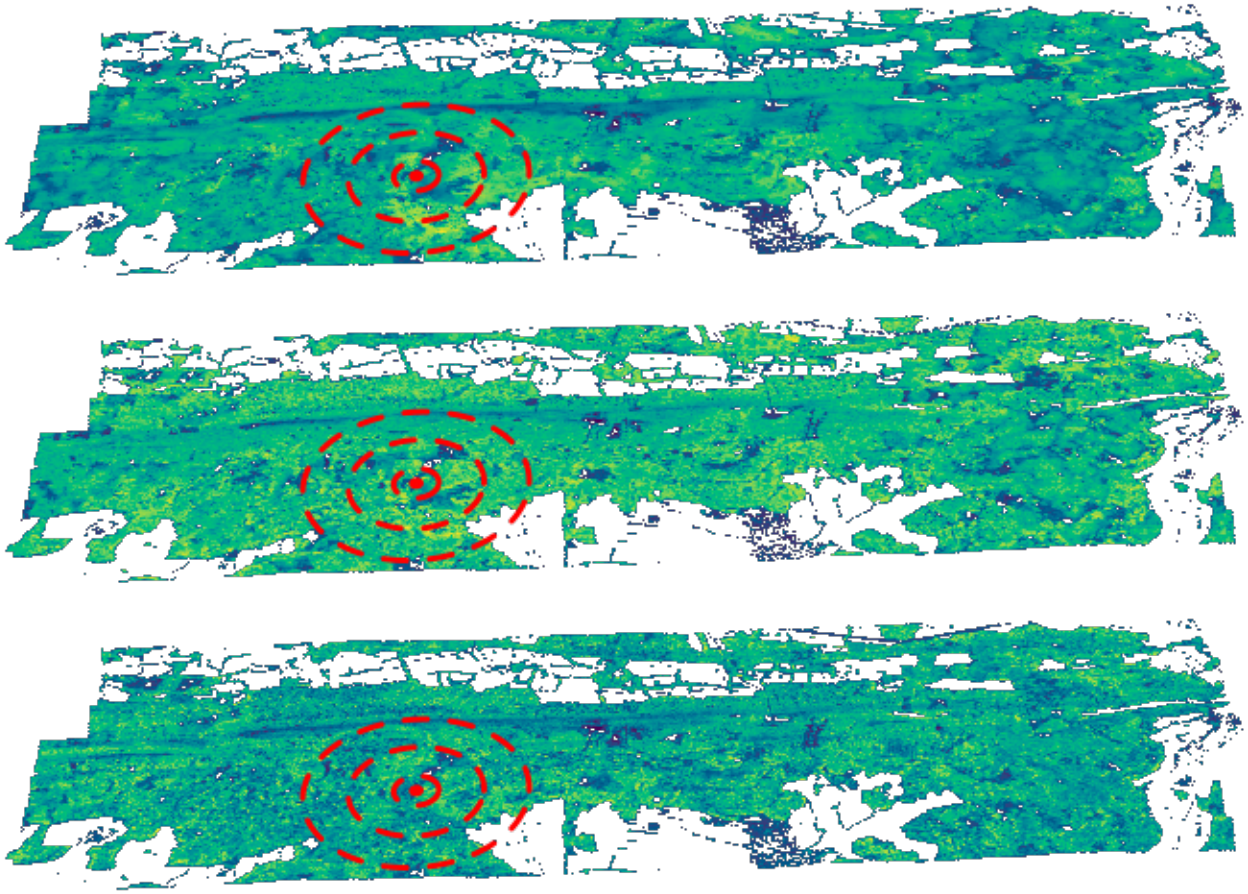
Biodiversity, a paramount performance measure of organism traits or ecosystem functioning. E.g. multidimensional functional diversity indices: functional richness, evenness or divergence, defined by Villéger et al. (2008).

These are calculated based on

- T traits, here $T = 3$: *ch*, *pai* and *fhd*
- a moving window, to subset each trait and span a T-dimensional subspace

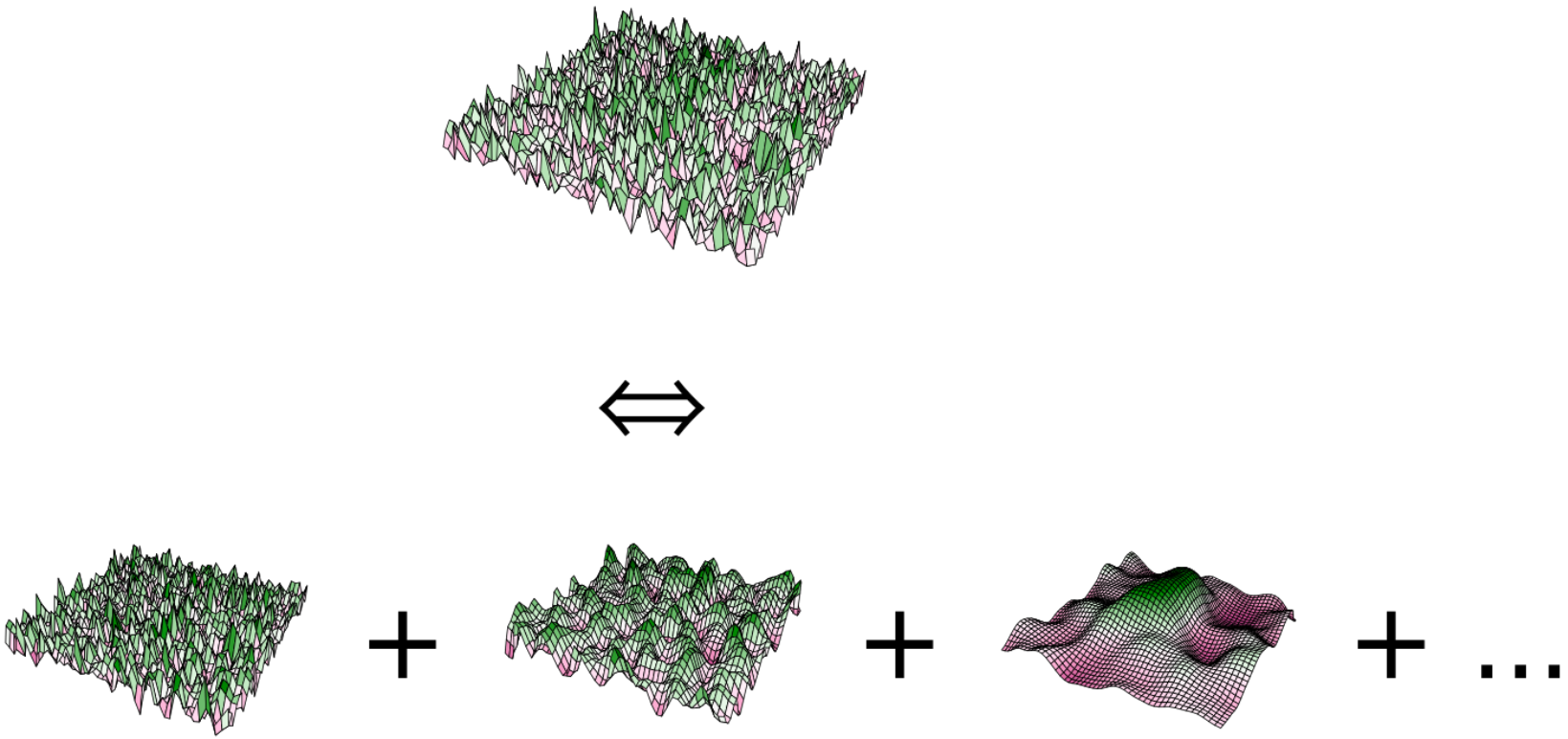
E.g. functional richness is defined as the volume of the convex hull of the points in such a subspace.

Moving Window Radius



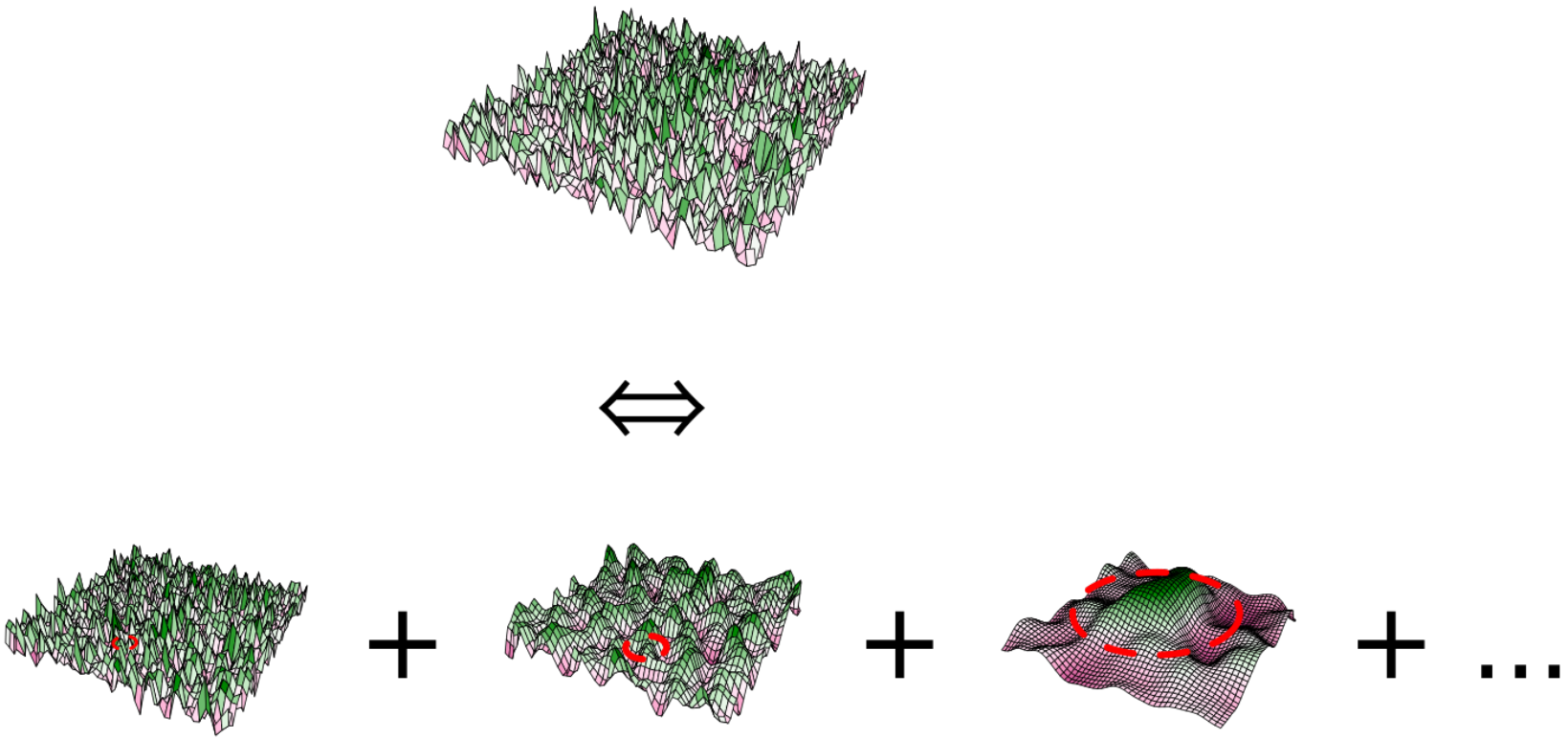
Morphological traits *ch*, *pai* and *fhd*.

Spatial Multiresolution Decomposition



Multiresolution decomposition of artificial data.

Assess Extension of Predominant Features



Radii assessment of predominant features in artificial data.

Spatial Multiresolution Decomposition

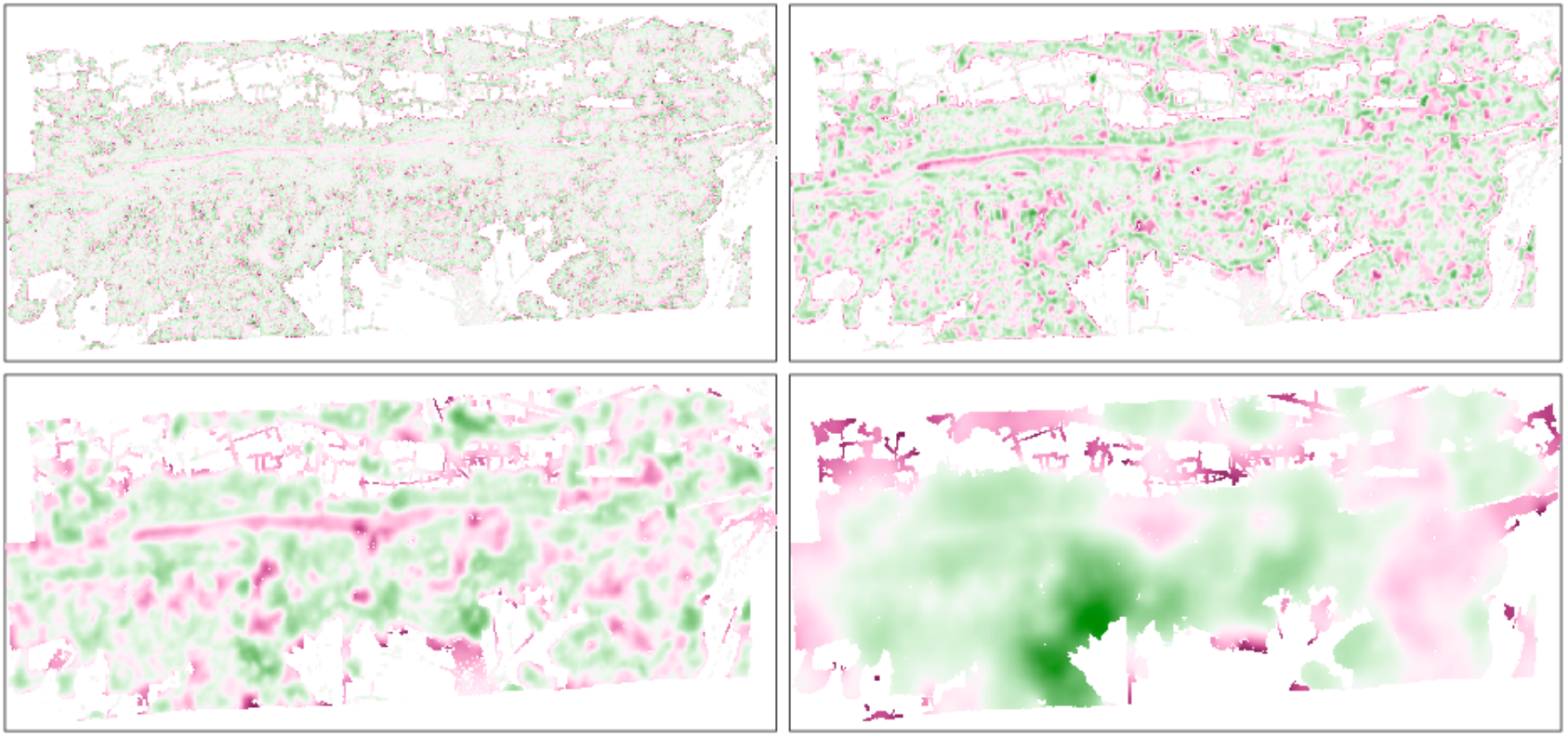
Introduced by Holmström et al. (2011):

- smooth the spatial field $\boldsymbol{x}$ on different scales using a penalty smoother $\boldsymbol{S}_\lambda = (\mathbf{I} + \lambda \boldsymbol{Q})^{-1}$
  - $\boldsymbol{Q}$ is a precision matrix modelling the spatial dependencies between the locations of $\boldsymbol{x}$
  - λ the smoothing parameter, such that $0 = \lambda_1 < \lambda_2 < \ldots < \lambda_L = \infty$
- decompose $\boldsymbol{x}$ as sum of consecutive differences of smooths

$$\boldsymbol{x} = \sum_{i=1}^{L-1} \left(\boldsymbol{S}_{\lambda_i} \boldsymbol{x} - \boldsymbol{S}_{\lambda_{i+1}} \boldsymbol{x} \right) + \boldsymbol{S}_{\lambda_L} \boldsymbol{x}$$

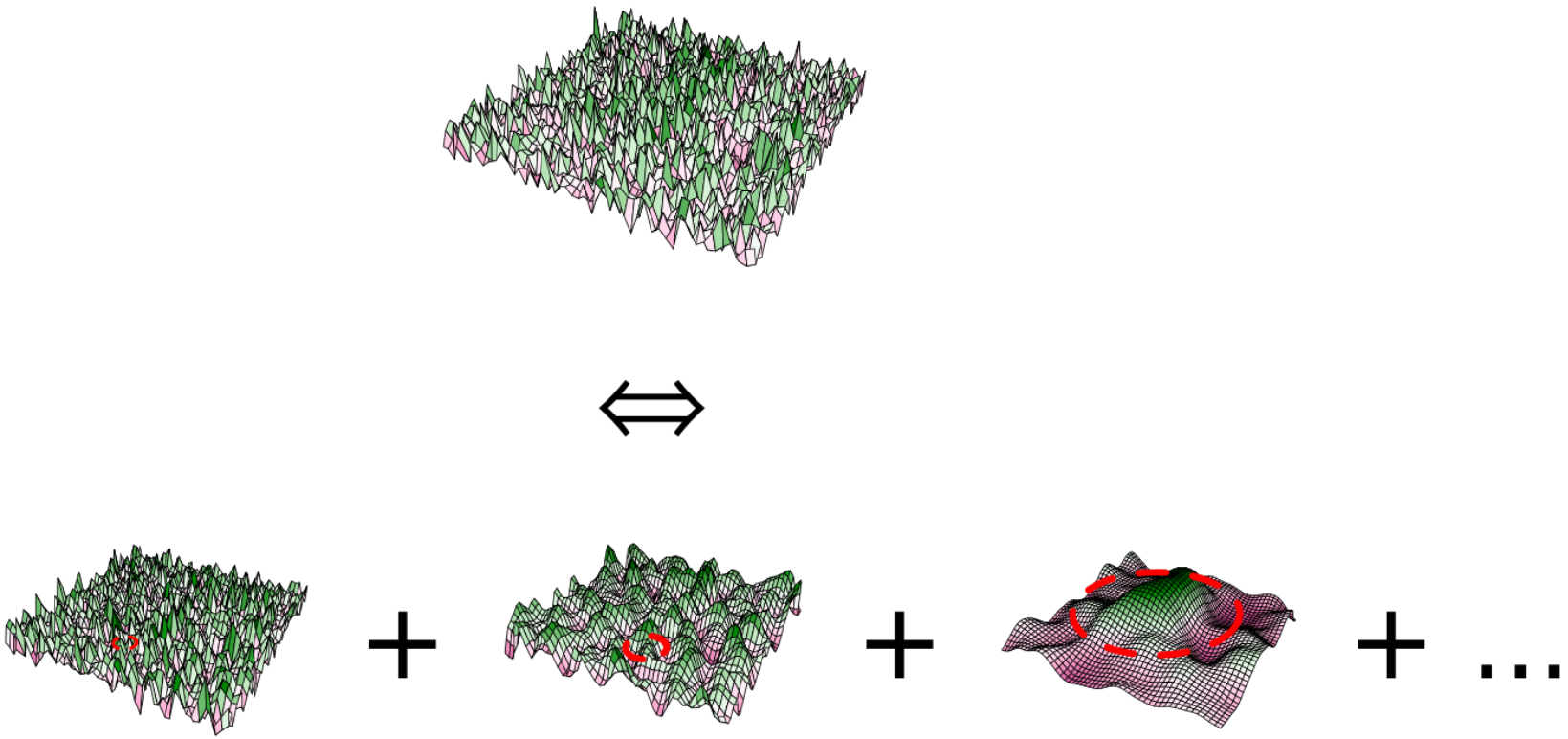
- optimal smoothing scales are chosen, such that the differences between smooths is maximal

Canopy Height Decomposition



Decomposition of *ch* with smoothing scales $\lambda_1 = 0$, $\lambda_2 = 1$, $\lambda_3 = 27$, $\lambda_4 = 860$ and $\lambda_5 = \infty$.

Assess Extension of Predominant Features



Radii assessment of predominant features in simulated data.

Feature Size Assessment

We assume

- a spatial process $\{Z(\boldsymbol{s}) : \boldsymbol{s} \in \mathcal{D}\}$, where $\mathcal{D}$ is the trait area (a subset of $\mathbb{R}^2$)
- intrinsic stationarity of $Z(\boldsymbol{s})$, i.e.

$$\mathbb{E}(Z(\boldsymbol{s_1})) \equiv \mu,$$
$$\mathrm{Var}(Z(\boldsymbol{s_1}) - Z(\boldsymbol{s_2})) = 2\gamma(s_1 - s_2)$$

  for all locations $\boldsymbol{s_1}, \boldsymbol{s_2} \in \mathcal{D}$

Thereby, 2γ denotes the variogram and γ the semi-variogram function, describing the spatial dependency between locations (Cressie, 1993).

Estimation of Variogams

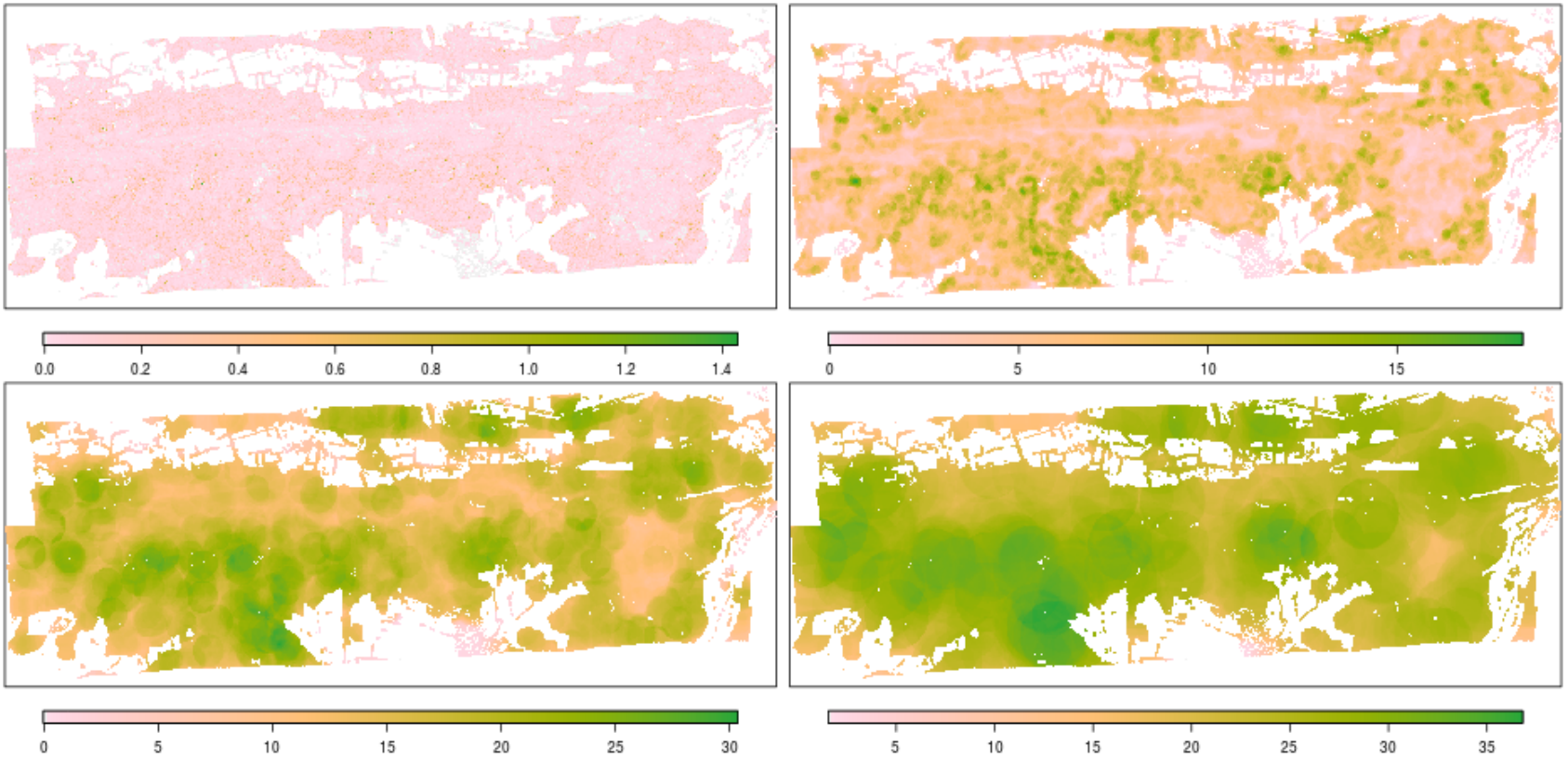
- calculation of the empirical variogram (Matheron, 1962; Cressie, 1993)
- fit a variogram function optimizing the respective parameters for different families of variograms (Pebesma, 2004; Nychka et al., 2017)
- assess the extension of scale-dependent features with the spatial data-driven range parameter

Results

range order	**expert radii**	*ch*	*pai*	*fhd*	**aspect**
1st neighbor	2	1.73	1.72	1.68	
local	10	4.68	6.89	5.71	7.80
		15.36	21.32	20.40	
global	40				45.20
		153.87	148.53	148.53	270.97

Estimated range parameters of the respective morphological traits. Expert radii were taken from Schneider et al. (2017).

Functional Richness



Functional richness, evaluated with different moving window radii. Top left: radius 2; top right: radius 7; bottom left: radius 22, bottom right: radius 46 (# grid points).

References

N. A. C. Cressie. *Statistics for Spatial Data*. Wiley, revised edition, 1993.

L. Holmström, L. Pasanen, R. Furrer, and S. R. Sain. Scale space multiresolution analysis of random signals. *Computational Statistics & Data Analysis*, 55(10):2840–2855, 2011. ISSN 0167-9473.

G. Matheron. Traité de Géostatistique Appliquée, Tome I. *Mémoires du Bureau de Recherches Géologique et Minières*, No. 14:Editions Technip, Paris, 1962.

D. Nychka, R. Furrer, J. Paige, and S. R. Sain. fields: Tools for spatial data, 2017. R package version 9.8-3.

E. J. Pebesma. Multivariable geostatistics in S: the gstat package. *Computers & Geosciences*, 30:683–691, 2004.

F. D. Schneider, F. Morsdorf, B. Schmid, O. L. Petchey, A. Hueni, D. S. Schimel, and M. E. Schaepman. Mapping functional diversity from remotely sensed morphological and physiological forest traits. *Nature Communications*, 8(1):1441, 2017. ISSN 2041-1723.

S. Villéger, N. W. H. Mason, and D. Mouillot. New multidimensional functional diversity indices for a multifaceted framework in functional ecology. *Ecology*, 89(8):2290–2301, 2008. ISSN 1939-9170.

Contact: roman.flury@math.uzh.ch; @fluryro

Slides: user.math.uzh.ch/flury/talks/19_flury_JSM.pdf