Characterising and evaluating Digital Soil Maps by their patterns

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Outline

1. Evaluating Digital Soil Maps – the problem

2. Patterns of soils on the landscape

3. Pattern analysis
   Continuous soil properties maps
   Class or classified maps

4. Letting the map "speak for itself"

5. Comparing maps vs. "reality"

6. On, on!

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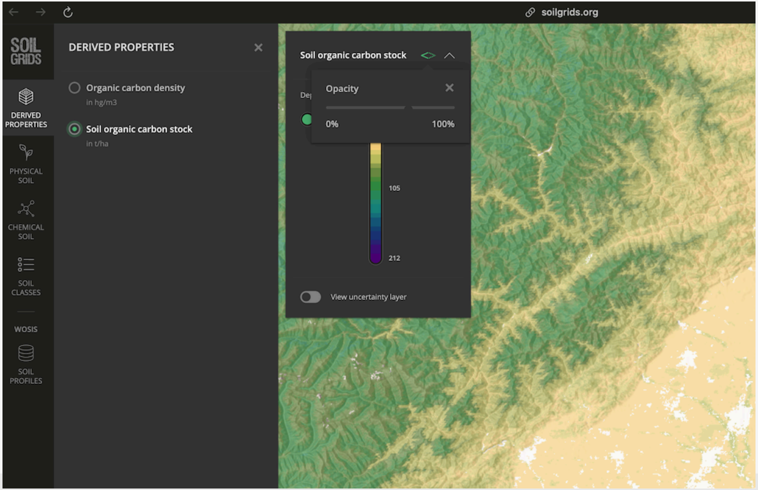
Digital Soil Mapping

Direct production of digital maps…
…of soil **properties** or **classes**…
…by machine-learning or geostatistical methods…
…from **training points**…
…and **covariates** that are surrogates for **soil-forming factors**, covering the study area.

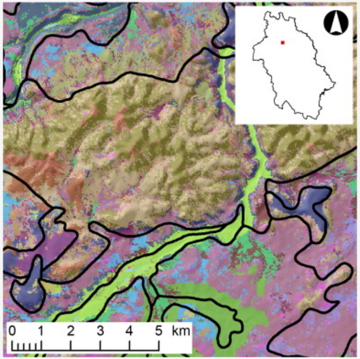
Conceptual basis (McBratney *et al.* 2013): $S = f(s, c, o, r, p, a, n) + \varepsilon$

Example DSM product: ISRIC SoilGrids v2.0



Detail; uncertainty

Example DSM product: disaggregation of legacy soil map



Most probable soil class with the original soil polygons overlaid
Source: Odgers *et al.* 2014, `doi:10.1016/j.geoderma.2013.09.024`

How have these maps been evaluated?

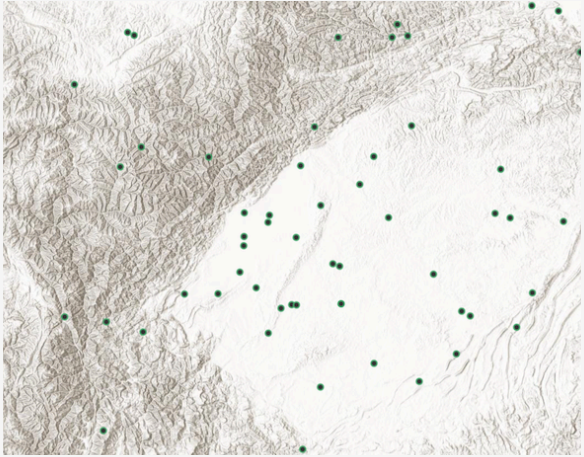
- On the basis of **test points**
  - independent test set in target area
  - out-of-bag (OOB) in bagged Machine Learning (ML) methods: members of training set, not used in one calibration
  - repeated splits into test/training of one dataset
- (pointwise) **evaluation statistics**: ME, RMSE, 1:1 R^2 (MCC, Nash-Sutcliffe Model Efficiency), gain/bias of actual regressed on observed ...

Problems with evaluation by point statistics – Internal

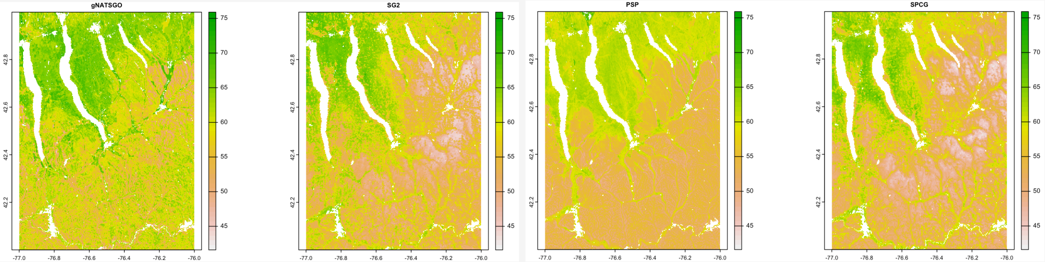
From the mapper's point of view:

1. Based on a **limited number of observations**, far fewer than the number of predictions (grid cells, "pixels").
2. Evaluating at points, but predicted value is for the grid cell (either centre or block average)
3. Evaluation points are almost never from an independent **probability sample**.
4. Cross-validation and data-splitting approaches rely on this **biased** point set.
5. **Evidence**: Different DSM approaches can result in maps with quite **similar "validation statistics" but obviously different spatial patterns**.

Example of limited evaluation points: ISRIC WoSIS



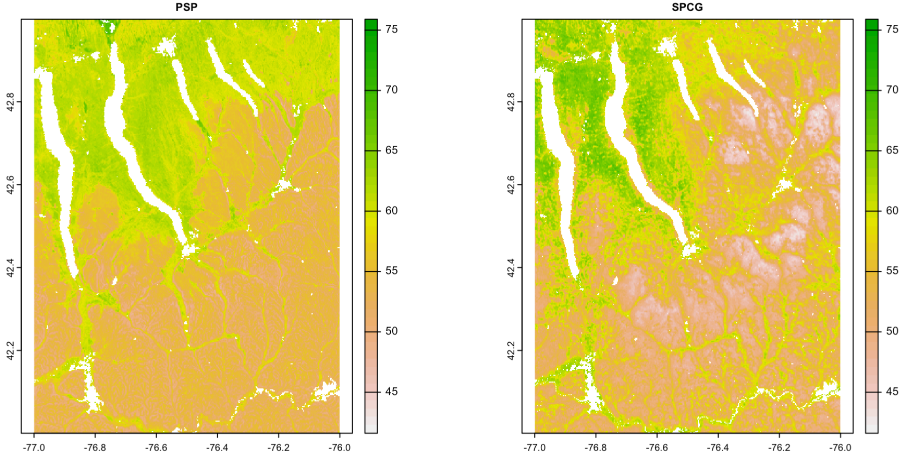
Different ML methods, covariates, points → different patterns



Central NY State (USA), pH x 10, 0-5 cm

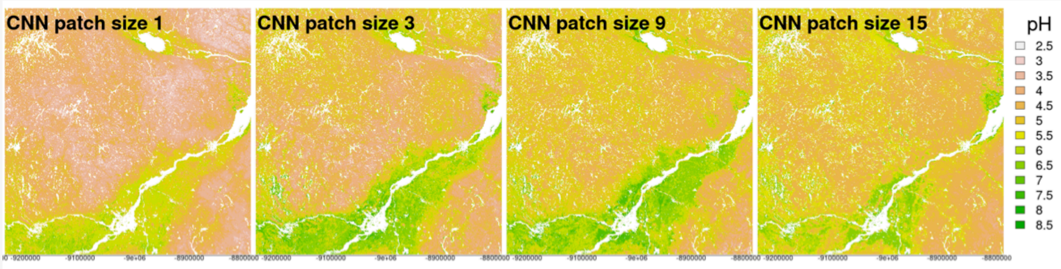
Some obvious difference in **values** but also **pattern**.

Detail



PSP
SPCG
75
70
65
60
55
50
45
42.8
42.6
42.4
42.2
-77.0
-76.8
-76.6
-76.4
-76.2
-76.0

Same ML method, covariates, points; different parameters → different patterns



Convolutional Neural Network (CNN), different window size (Giulio Genova, ISRIC)

But …almost identical evaluation statistics

product	mae	mec	rmse
RF SoilGrids	0.64	0.57	0.91
CNN patch size 1	0.73	0.48	1.00
CNN patch size 3	0.74	0.48	1.00
CNN patch size 9	0.74	0.47	1.01
CNN patch size 15	0.74	0.47	1.01

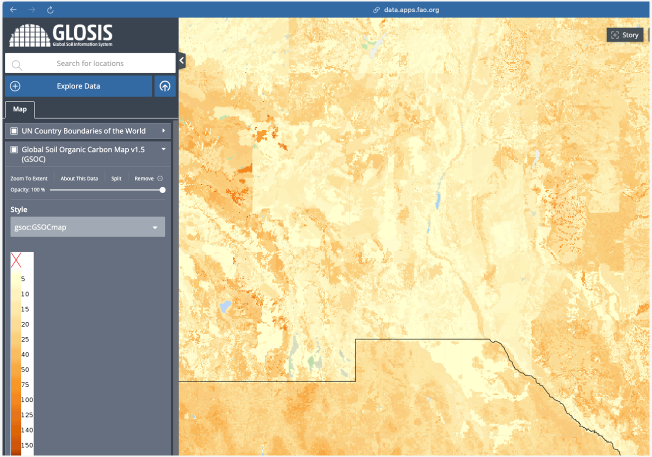
mae = Mean absolute error

mec = Model efficiency coefficient (R squared on the 1:1 line)

rmse = Root Mean Squared Error

SoilGrids $>$ CNN, but all CNN $\approx$ equal.

Different surveys, different patterns



Legacy map updated by DSM – realistic or artefact?

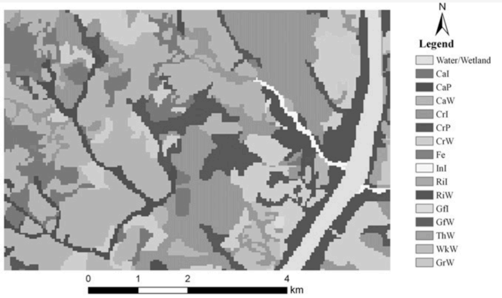


Fig. 3. The 30- by 30-m raster soil map with soil association and drainage class as the soil unit created from the 1:20,000 soil map.

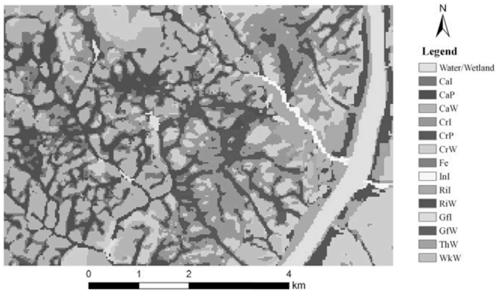
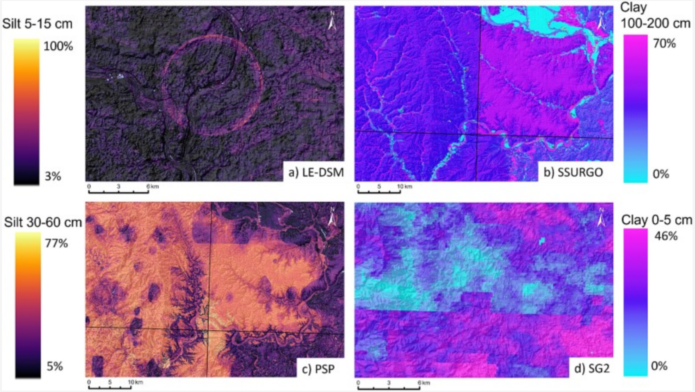


Fig. 10. The updated digital soil map using the fuzzy *c*-means–Soil Land Inference Model (FCM–SoLIM) approach.

(Yang L. *et al.* 2010)

Artefacts



(Bohn & Miller 2024)

Problems with evaluation by point statistics – External

From the map user's point of view:

1. Soils are **managed as units** at some scale, *not* point-wise.
2. Land-surface models often rely on 2D or 3D **connectivity** between grid cells.
   - Especially hydrology / chemical transport models
3. More than a century of fieldwork has shown that **soils occur in more-or-less homogeneous patches**, *not* as isolated pedons (Fridland, Boulaine, Hole ...).
4. How to understand and account for **artefacts**?

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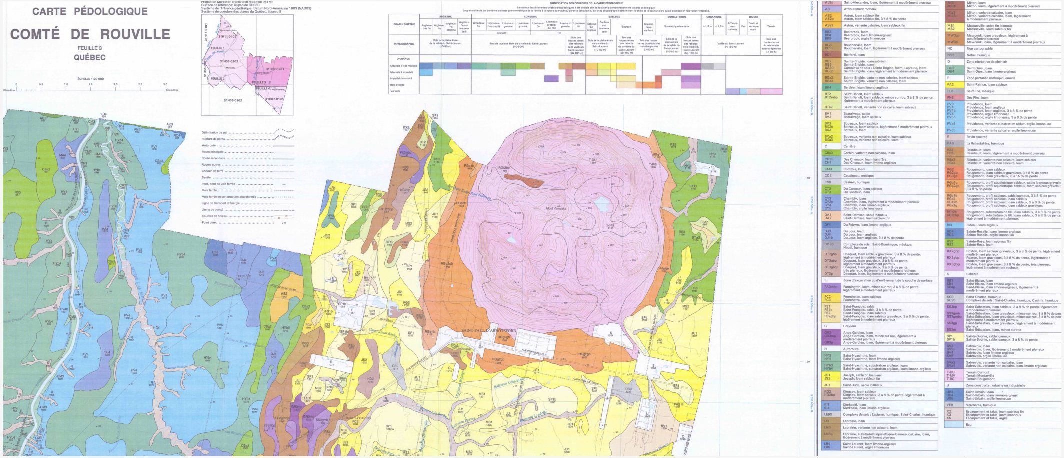
Scale of patterns of soils on the landscape

- Catena/hillside/toposequence scale
    - landscape segments
    - DSM resolution 50–250 m
    - mapping scale 1:12k - 1:62.5k
    - minimum mappable area (MMA) 0.625-10 ha
- Detailed scale within segments
    - precision agriculture
    - DSM resolution 1-10 m
    - mapping scale 1:1k - 1:4k

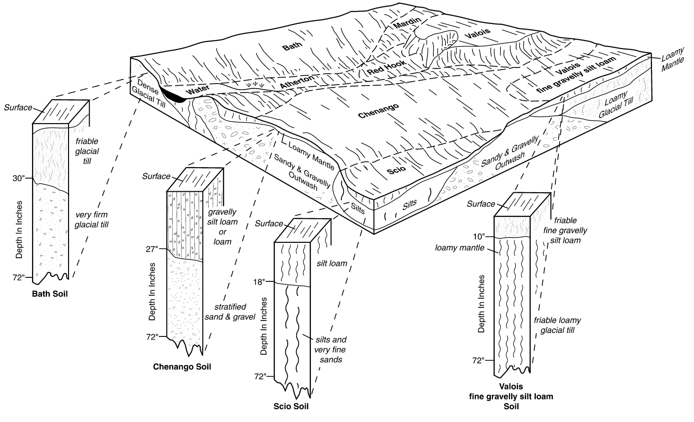
Soil-landscape polygon maps



Conceptual basis of the soil-landscape model

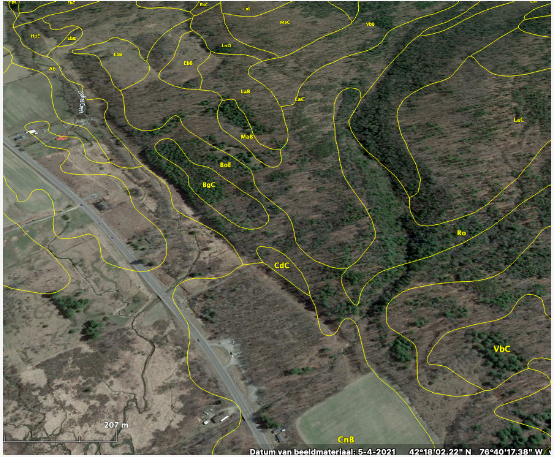
- Soilscape **segments** with different **combinations of soil-forming factors**
- Majority of heterogeneity is **between** polygons
- Identified by a **conceptual paradigm** (Hudson 1992), used for conventional mapping
- identifiable transitions (but see Lagacherie *et al.* 1996)
- **scale-independent** (??)

Soilscape segments, 1:12k – 1:24k



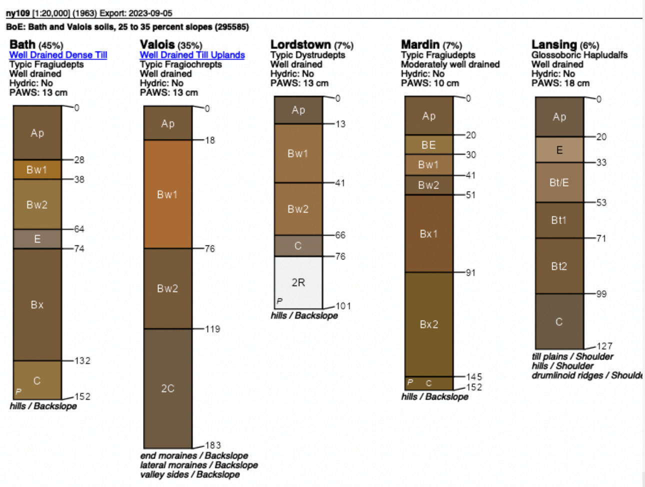
Conceptual block diagram, Otsego County NY (USA)

Detailed (1:24k) soil survey: pattern of landscape segments



centre -76°40’23” E, 42°18’10” N

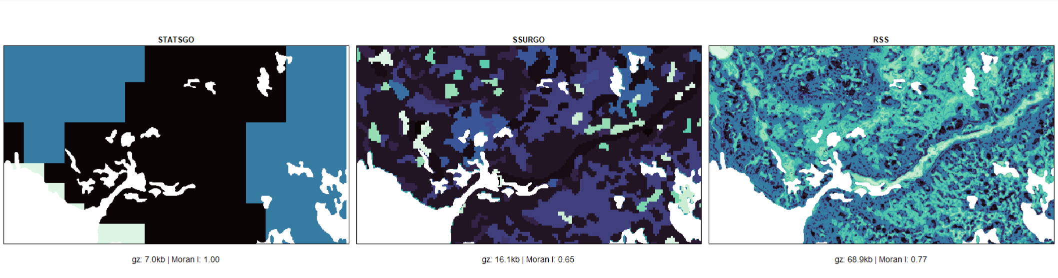
Map unit components



Field-level patterns, 1:1k – 1:4k

Wood County, Ohio (USA); `HoA`: Hoytville clay loam

Same soilscape at different resolution



source: Dylan Beaudette (NRCS)

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Pattern analysis

- Quantitative description of (spatial) patterns
- Long history in image analysis
- Applied to landscape mosaics (FRAGSTATS)
- R packages `motif`, `landscapemetrics`, `rassta` ...
- Aggregation: `superpixels`
- Stand-alone: segmentation: `geoPat`[1]

[1] https://github.com/Nowosad/geopat2

Levels of pattern analysis

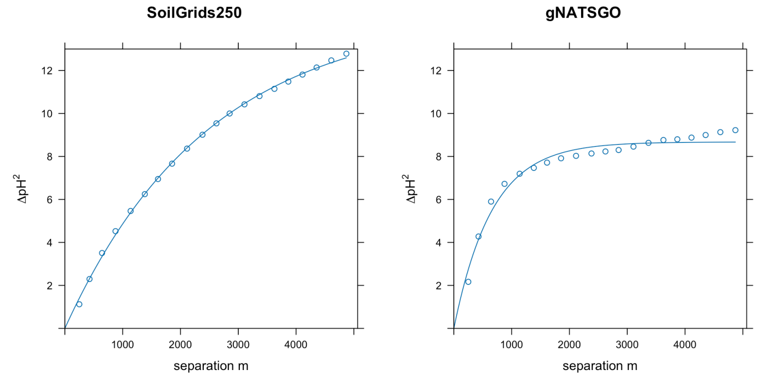
1. **Characterize** the pattern of one map
2. **Compare** patterns of several maps
3. **Evaluate** pattern with respect to “reality”
4. **Aggregate** or **Segment** map by its patterns – let the map “speak for itself”

Different methods for **continuous** and **classified** maps

Characterizing patterns – continuous soil properties

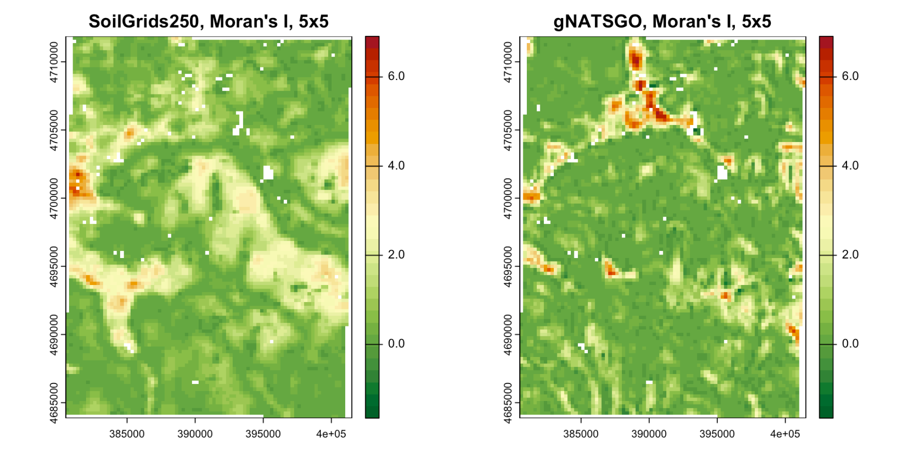
1. Variogram analysis: inherent spatial scales and variabilty, averaged over entire area
2. **Moving-window autocorrelation**: how does this vary across the DSM?
   - Shows “hot spots” of high local variability, “cold spots” of high local consistency

Variograms with fitted models



$(\mathrm{pH} * 10)^2$; interpret sill and range; gNATSGO much finer and more local structure, less smoothing

Moving-window autocorrelation

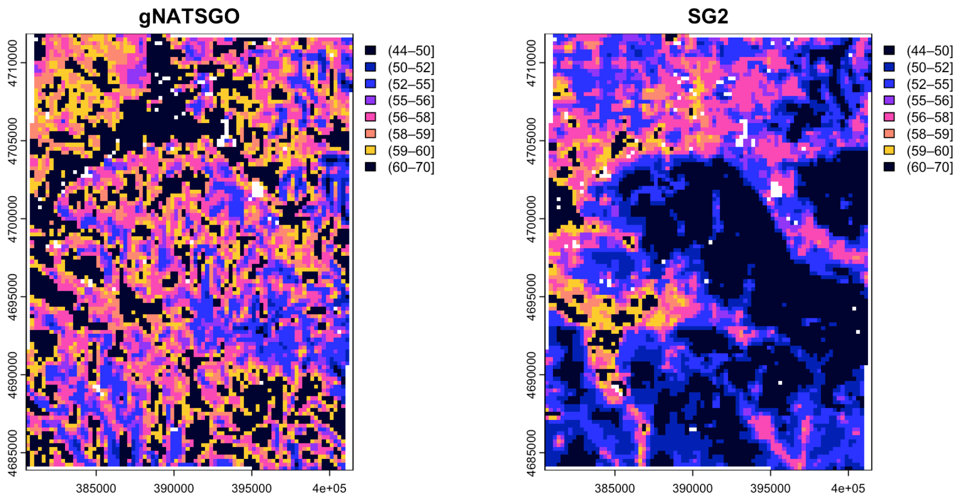


note: global Moran's *I* 1.02 (SG250), 0.68 (gNATSGO)

Characterizing patterns – classified soil properties or soil classes

- Well-known techniques from landscape ecology (FRAGSTATS)
- Select metrics that are relevant to the objective
    - here, characterizing the soil pattern
- For continuous properties must **slice** (discretize)
    - meaningful limits for an application (e.g., pH for liming recommendation), or …
    - equal-intervals, or …
    - histogram equalization

Histogram equalization in 8 classes



Some relevant metrics

- landscape aggregation index `LAI`
- mean fractal dimension `MFD`
- landscape shape index `LSI`
- Shannon diversity index `SHDI`
- Shannon evenness index `SHEI`
- Co-occurrence vector `COVE`

Metric: landscape aggregation index

This quantifies how **connected** is each class, averaged over all classes.

$$\text{LAI} = \left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{max - g_{ii}}\right)P_i\right](100)$$

where g_{ii} is the number of like adjacencies, $(\text{max} - g_{ii})$ is the classwise maximum possible number of like adjacencies of class i

Low values: classes are **scattered** over the map; **high** values: classes tend to **clump** together

Metric: mean fractal dimension

A shape metric, describing multi-scale patch complexity.

$$\mathsf{FRAC} = \frac{2 * \ln *(0.25 * p_{ij})}{\ln a_{ij}}$$

where the patch perimeters are p_{ij} in linear units and the areas are a_{ij} in square units.
This measures the intricacy of the soil pattern.

Metric: landscape shape index

This quantifies the **complexity of the patch shapes**, across the map.

$$\text{LSI} = \frac{0.25E'}{\sqrt{A}}$$

where A is the total area of the landscape and E' is the total length of edges, including the boundary.

Metric: Shannon diversity index

This measures both the number of classes and their relative abundance.
It is a measure of (1) the **legend complexity**, (2) the **(un)balance** between classes.

$$D = -\sum_{i=1}^{N} p_i \ln p_i$$

where p_i is the proportion of pixels of class $i = (1 \ldots N)$

Comparing maps with these metrics

product	ai	frac_mn	lsi	shdi	shei
gNATSGO	48.188	1.034	22.602	1.666	0.801
SG2	50.659	1.034	21.768	2.06	0.991
SPCG	58.483	1.041	18.557	1.887	0.907
PSP	47.025	1.04	23.232	1.898	0.913

Landscape metrics statistics, pH 0–5 cm (top); 30–60 cm (bottom).

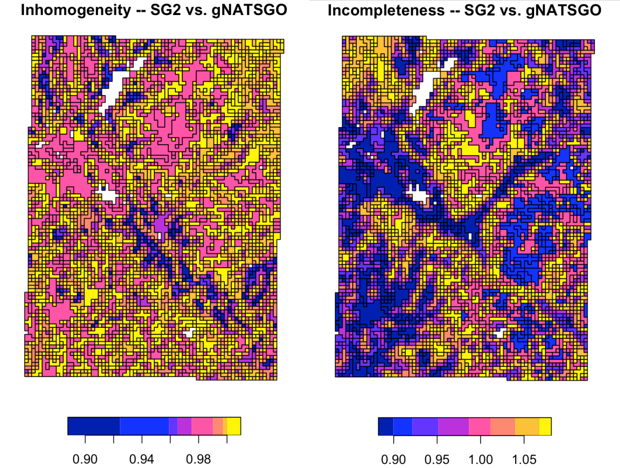
`frac_mn`: Mean Fractal Dimension; `lsi`: Landscape Shape Index; `shdi`: Shannon Diversity; `shei`: Shannon Evenness; `ai`: Aggregation Index

(Longitude -77–76°, Latitude 42–43°)

V-measure (Nowosad & Stepinski 2018)

- Compares **different spatial partitions** into classes
- Two maps could have the same **total areas** of each class, and even the same **number of polygons** within each class, and even the same **size distribution** of these polygons ...
- ...and yet be completely different in **how they partition space** into classes.
- **homogeneity**: variance of the regions within a zone, normalized by the variance of the regions in the entire domain of the **first** map
- **completeness**: variance of the zones within a region, normalized by the variance of the zones in the entire domain of the **second** map.
- $V = \frac{h \times c}{h + c}$

Comparing two maps with V-measures



Metric: Co-occurrence vector

- Summarizes the entire **adjacency structure** of a map as a normalized co-occurrence matrix: which classes are spatially adjacent to each other?
- This is a probability vector for the **spatial co-occurrence** of different classes in the map.
  - e.g., different soil classes – do we expect Histosols next to Vertisols?
  - e.g., different classes of a classified property – do we expect abrupt changes of pH class?
- The “distance” between co-occurrence vectors from two maps can be computed as a measure of the (dis)similarity between these structures

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Finding patterns by “letting the map speak for itself”

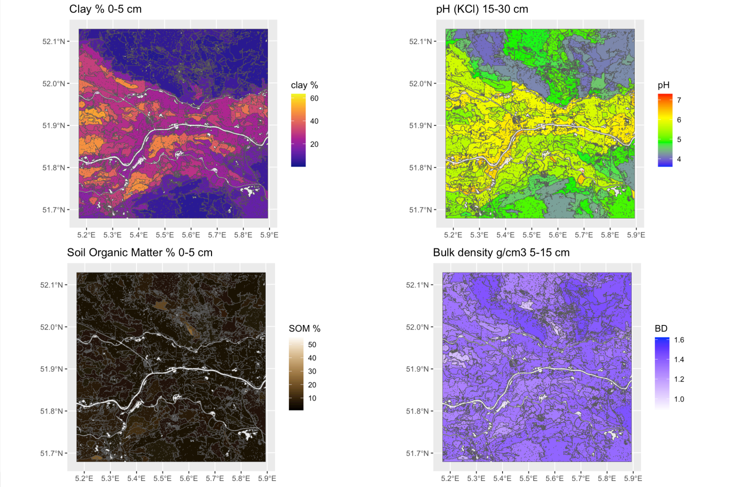
Objective: (semi-)automatically extract patterns from the map

- **Aggregation**: areas of “similar” **values** or **classes**
- **Segmentaton**: areas with “similar” internal **spatial patterns**

Aggregation

- Group grid cells ("pixels") of "similar" **values** or **classes** into "super-pixels"
- Parameters to control degree of similarity and how to measure it
- R package `supercells`

Aggregation example – BIS-4D map of NL

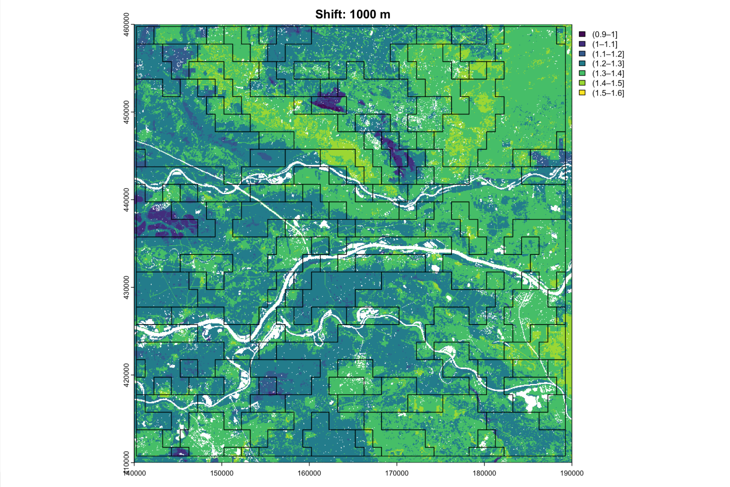


Segmentation by patterns

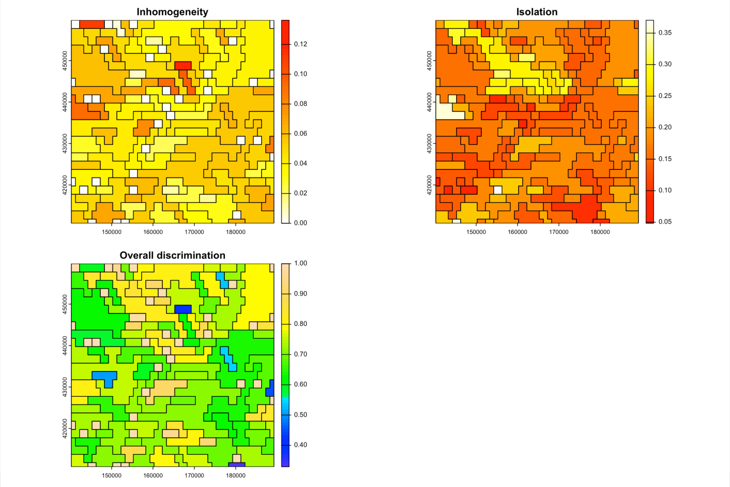
- A recent development by Nowosad[2], based on an algorithm of Jadiewicz
- Aggregates groups of pixels (size set by analyst) into polygons with a "similar enough" spatial **pattern** of classes
- The pattern of these grid cells can be considered a **meta-pattern** of the DSM product

[2] https://jakubnowosad.com/

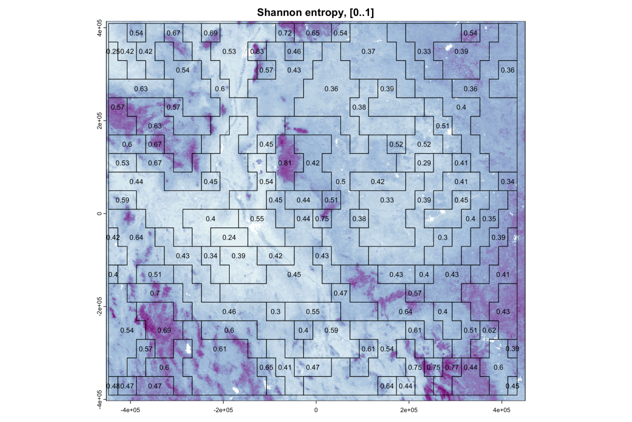
Segmentation example – bulk density of all layers, 1 km resolution



Evaluating segmentation success



Characterizing the patterns in a segment



SOC stocks predicted by SoilGrids 2.0, M’exico / USA. Centre near Alamogordo (NM)

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Comparing maps; maps vs. “reality”

- The pattern analysis applied to different maps can be compared
- The homogeneity and completeness of one map, representing the other, can be quantified
- The pattern of the **difference** map can be quantified
- But …which is closest to the actual soil pattern **at the design scale**?
- Much knowledge from traditional soil survey about actual patterns at detailed mapping scales 1:12k – 1:50k (Fridland 1974, Hole 1978)

Soil patterns as seen by traditional surveyors

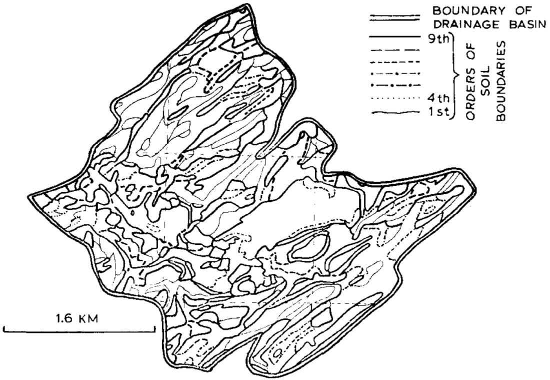


Fig. 12. Soil boundaries expressing degree of contrast between adjacent soil bodies in a fourth order drainage basin (9.8 km^2) 2 km northwest of New Berlin, Waukesha County on Woodfordian or Cary drumlinoid moraine of Wisconsin. Relief is about 73 m. Map scale was 1:15,840 (Steingraeber and Reynolds, 1971).

source: Hole (1978)

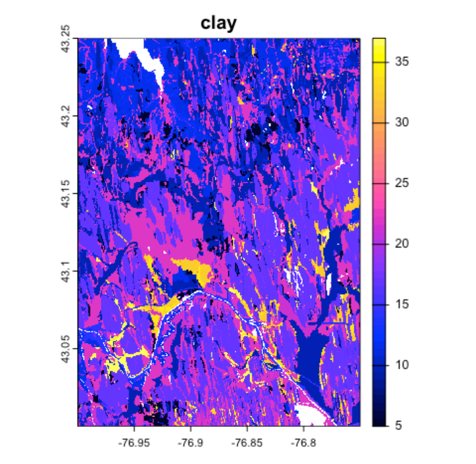
Resolution and scale

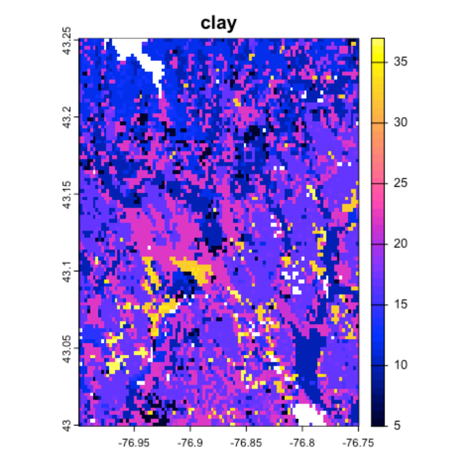
DSMaps are **gridded** at some horizontal **resolution** ("pixel size") – what is the relation to map scale?

Table 1
Suggested resolutions and extents of digital soil maps

Name	Approximate USDA survey order[a]	Pixel size and spacing[b]	Cartographic scale[b]	Resolution 'loi du quart'[c]	Nominal spatial resolution[b]	Extent[d]	Cartographic scale[b]
D1	0[e]	$<(5\times5)$ m	>1:5000	$<(25\times25)$ m	$<(10\times10)$ m	$<(50\times50)$ km	>1:5000
D2	1, 2	(5×5) to (20×20) m	1:5000–1:20,000	(25×25) to (100×100) m	(10×10) to (40×40) m	(500×500) to (200×200) km	1:5000–1:20,000
D3	3, 4	(20×20) to (200×200) m	1:20,000–1:200,000	(100×100) to (1×1) km	(40×40) to (400×400) m	(2×2) to (2000×2000) km	1:20,000–1:200,000
D4	5	(200×200) to (2×2) km	1:200,000–1:2,000,000	(1×1) to (10×10) km	(400×400) to (4×4) km	(20×20) to $(20,000\times20,000)$ km	1:200,000–1:2,000,000
D5	5	$>(2\times2)$ km	<1:2,000,000	$>(10\times10)$ km	$>(4\times4)$ km	$>(200\times200)$ km	<1:2,000,000

DSM scale effects – 20 vs. 250 m resolution gSSURGO





What will the map be used for?

- This governs the selection of grid cell size.
- The soil variability *within* the grid cell is ignored ...
  - ...for the map user ...
  - so, for the evaluator
- The **single value** of the grid cell represents the value the user will put in their "model"
- The **uncertainty** of the grid cell is the uncertainty **of that predicted value**, *not* the variance within the grid cell.

Should the DSM match the polygon map?

- Maybe DSM finds the "inclusions" within the map unit polygon
- This depends on the DSM resolution vs. minimum legible delineation (MLD) derived from the design scale
  - 0.4 cm^2 on map $\rightarrow$ ground area
  - e.g., 1:24k $\rightarrow$ MLD 2.3 ha; 1:12k $\rightarrow$ 0.576 ha
  - If 4 pixels per MLD, pixel resolution 96 m (1:24k), 48 m (1:12k)
- There is no way to check this spatially, but the proportion can be compared to estimates

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Next steps

1. Clarify concepts
2. Match metrics with soil patterns at various scales
3. Quantify match with “actual” soil pattern at various scales
4. **Still quite some confusion…**, must use the “little grey cells”

ISRIC
World Soil Information

Questions, comments, suggestions?

www: https://www.css.cornell.edu/faculty/dgr2/index.html
e-mail: david.rossiter@isric.org; d.g.rossiter@cornell.edu

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