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 maps

4. Comparing maps vs. “reality”

5. On, on!

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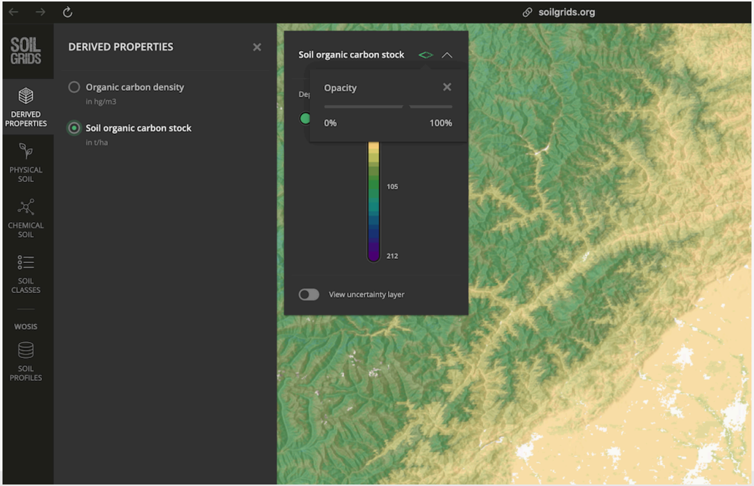
Digital Soil Mapping

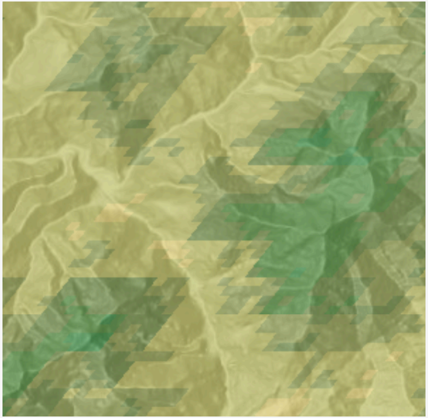
Direct production of digital maps…
…of soil **properties** or **classes**…
…by machine-learning or geostatistical methods…
…from **training points**…
…and **covariates** that are surrogates for **soil-forming factors**, covering the study area.

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

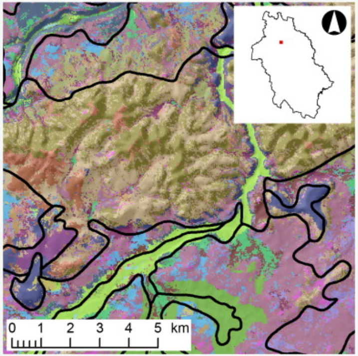
Example DSM product: ISRIC SoilGrids v2.0



Detail; uncertainty

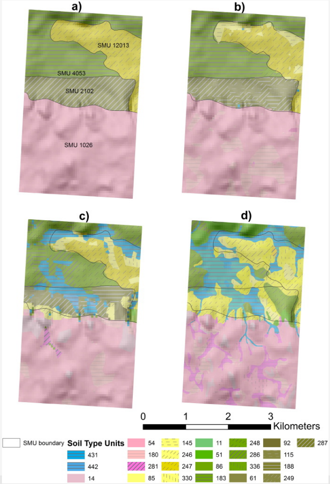


DSM with disaggregation - 1



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

DSM with disaggregation - 2



a) original 1:250,000 map
b) predictive map of Soil Type Units without soil-landscape rules for allocating STUs
c) predictive map of Soil Type Units with soil-landscape rules
d) the observed soil map

Source: Vincent *et al.*' 2018, `doi:10.1016/j.geoderma.2016.06.006`

How have these maps been evaluated?

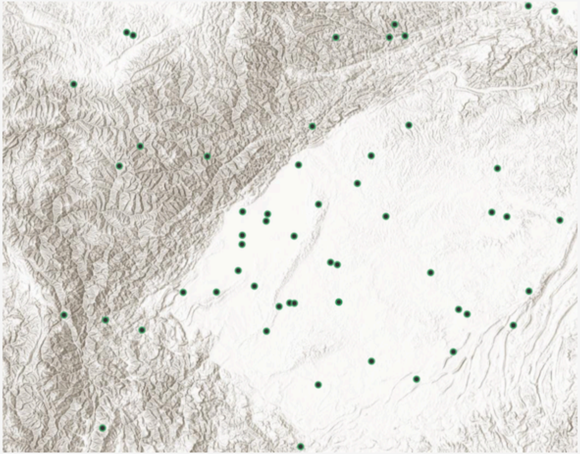
- On the basis of **test points**
  - independent test set in target area
  - out-of-bag (OOB) in bagged Machine Learning (ML) methods: members of training set, not used in one calibration
  - repeated splits into test/training of one dataset
- (pointwise) **evaluation statistics**: ME, RMSE, 1:1 R^2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

Problems with evaluation by point statistics – Internal

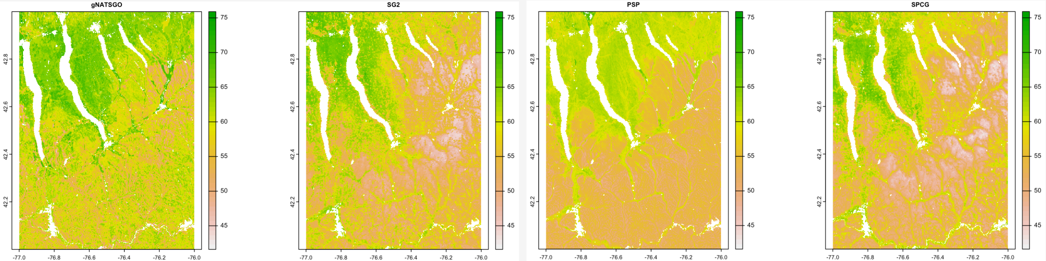
From the mapper's point of view:

1. Based on a **limited number of observations**, far fewer than the number of predictions (grid cells, "pixels").
2. Evaluation points are almost never from an independent **probability sample**.
3. Cross-validation and data-splitting approaches rely on this **biased** point set.
4. 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

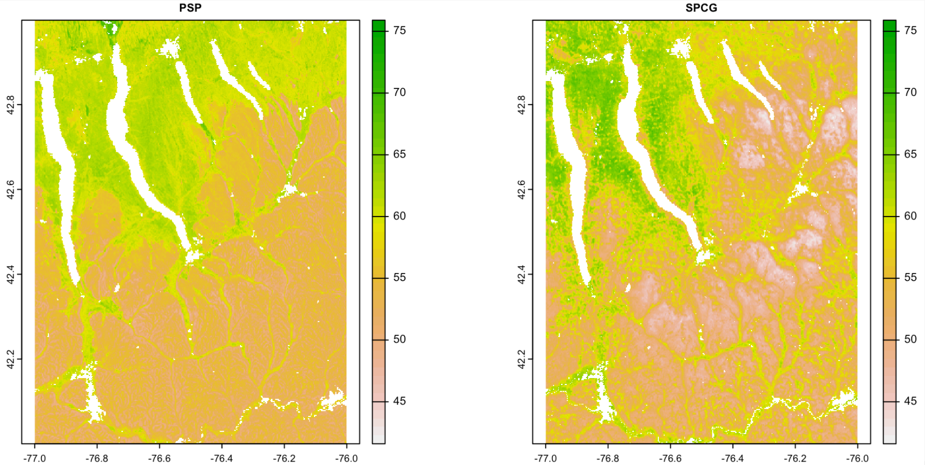


Different ML methods, covariates, points → different patterns



pH x 10, 0-5 cm

Detail



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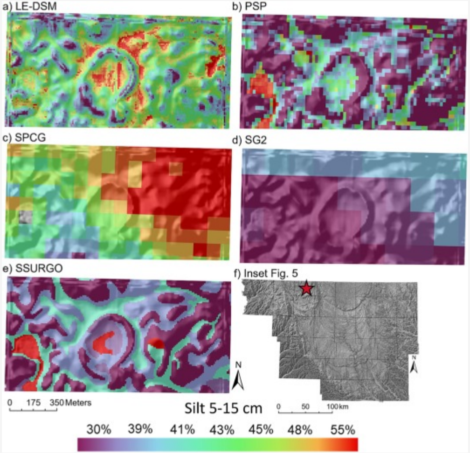
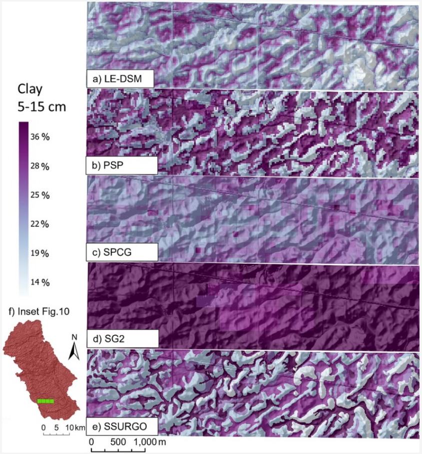
Different ML methods, covariates, points → different patterns



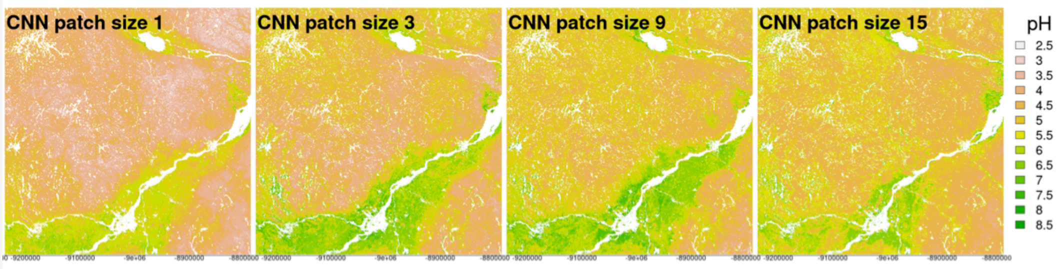
(Bohn & Miller 2024)

Different ML methods, covariates, points → different patterns



(Bohn & Miller 2024)

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



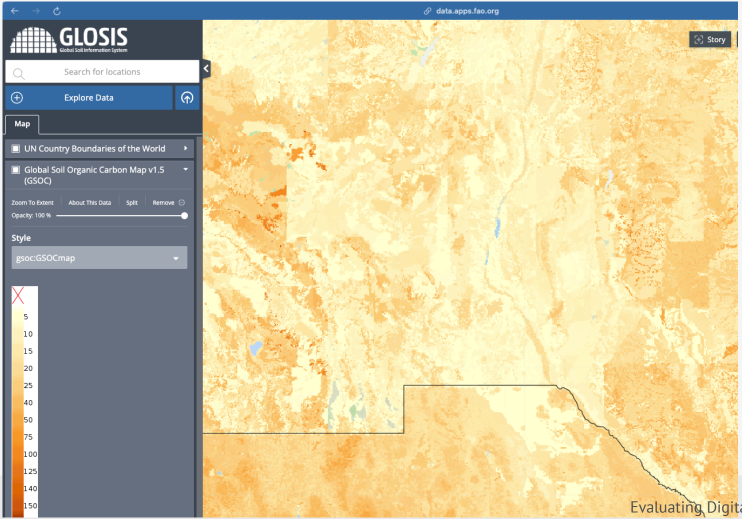
Convolutional Neural Network (CNN), different window size (Giulio Genova, ISRIC)

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

Different surveys, different patterns



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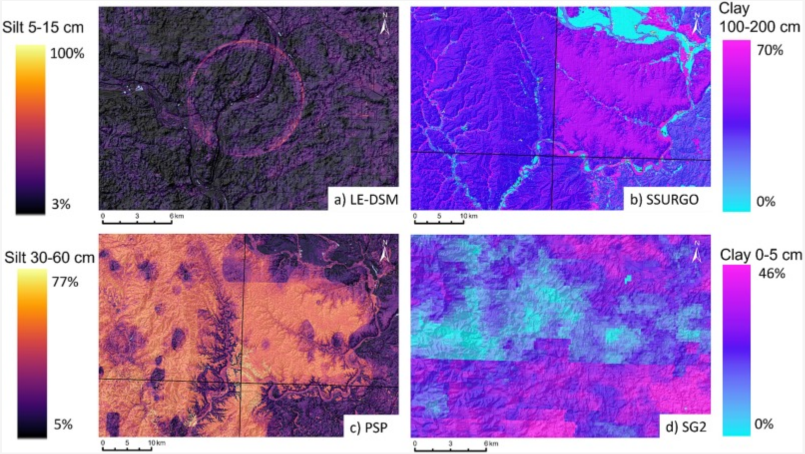
Artefacts



(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.
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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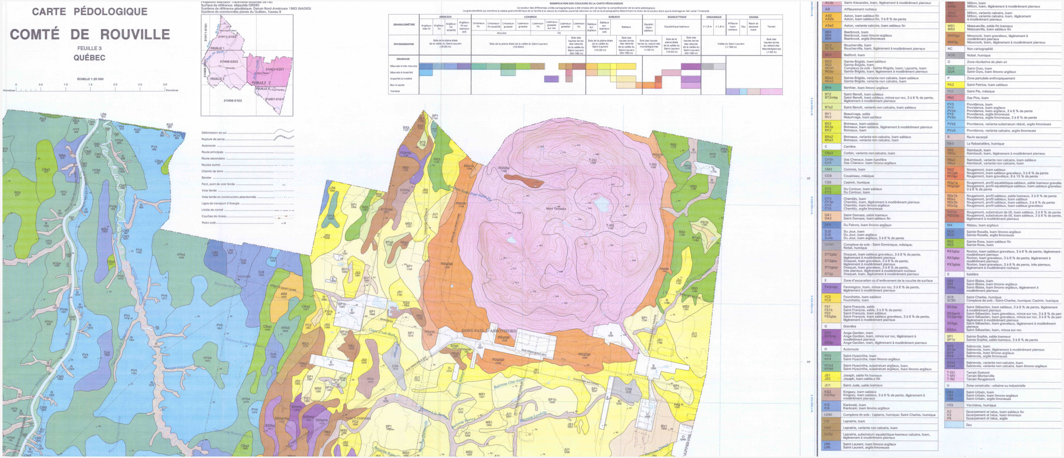
Scale of patterns of soils on the landscape

- 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

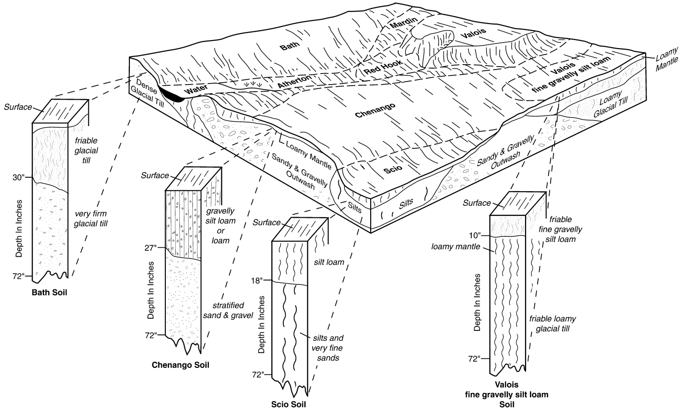
Soil-landscape polygon maps



Conceptual basis of the soil-landscape model

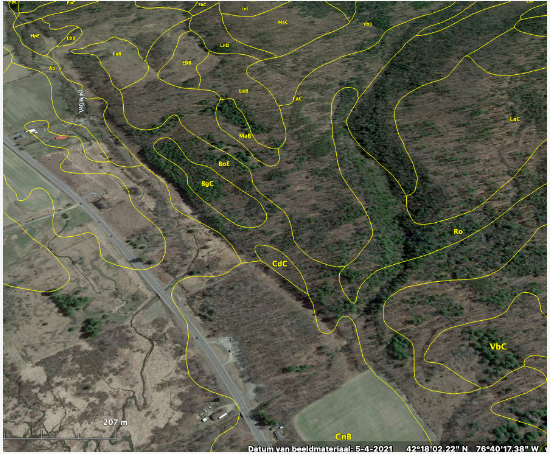
- Soilscape segments with different combinations of soil-forming factors
- Majority of heterogeneity is **between** polygons
- Identified by a conceptual paradigm (Hudson 1992)
- identifiable transitions (but see Lagacherie *et al.* 1996)
- **scale-independent** (??)

Soilscape segments, 1:12k – 1:24k



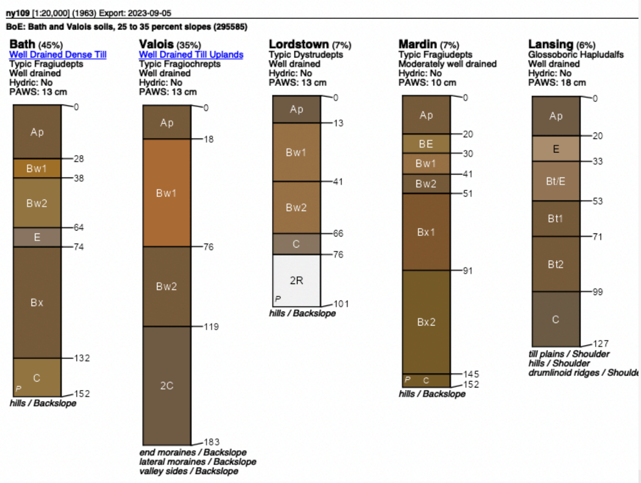
Conceptual block diagram, Otsego County NY (USA)

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



centre -76°40’23” E, 42°18’10” N

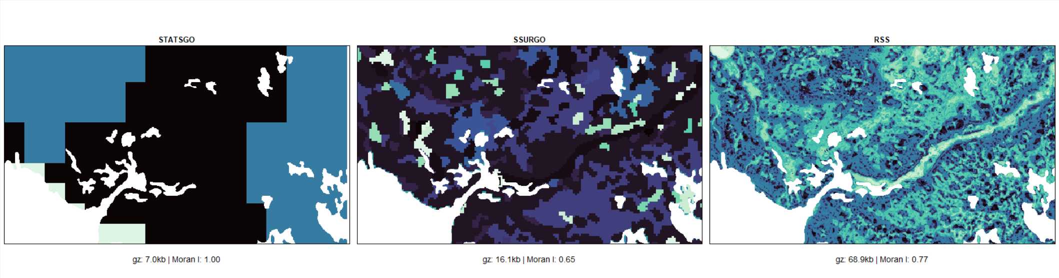
Map unit components



Field-level patterns, 1:1k – 1:4k

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

Same soilscape at different resolution

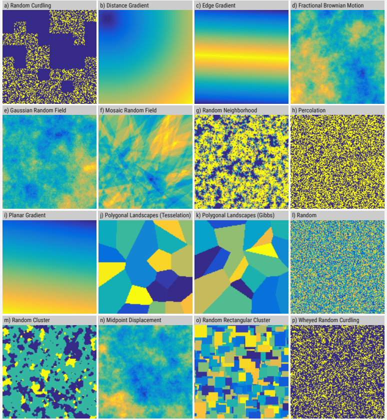


source: Dylan Beaudette (NRCS)

Are there mathematically "natural" soil patterns?

- Neutral Landscape Models (Riitters et al. 2007, 2009) for landscape ecology
  - Attempt to reproduce landscape patterns (e.g., vegetation patches) with mathematical models
  - **Do soils also occur in these patterns?**
- `NLMR`, `landscapetools` R packages (Sciani 2018)

Neutral landscapes



source: Sciaini et al. (2018)

Which “look like” soil patterns?

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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` ...
- Stand-alone `geoPat`[1]

  “GeoPAT’s core idea is to tessellate global spatial data into grid of square blocks of original cells (pixels). This transforms data from its original form (huge number of cells each having simple content) to a new form (much smaller number of supercells/blocks with complex content)”

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

Levels of pattern analysis

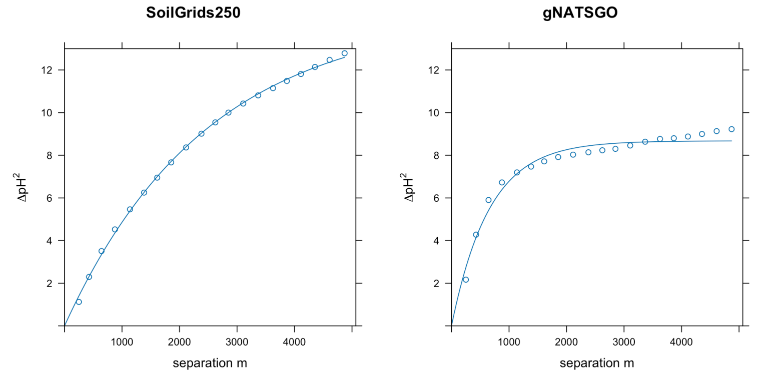
1. Characterize the pattern of one map
2. Compare patterns of several maps
3. Evaluate pattern with respect to “reality”
4. Segment map by its patterns

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

Characterizing patterns – continuous soil properties

1. Local variogram analysis: spatial scale of finest resolution
2. Moving-window autocorrelation: how does this vary across the DSM?

Variograms with fitted models



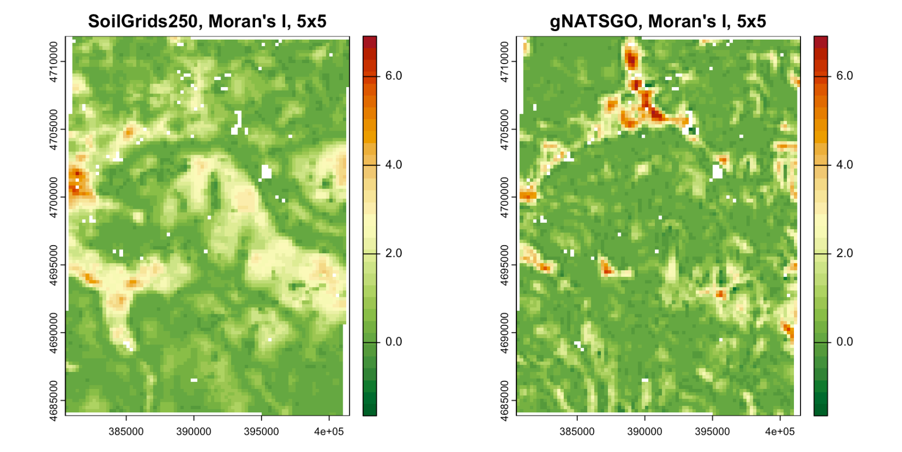
$(\text{pH} * 10)^2$; interpret sill and range

Comparing local spatial structure with fitted variogram parameters

Product	Effective range	Structural Sill	Proportional Nugget
gNATSGO	1938.00	10.32	0.00
SG2	3699.00	12.93	0.00
SPCG	6924.00	11.81	0.01
PSP	3918.00	6.50	0.02

Fitted variogram parameters, pH 0-5 cm.
Effective range in m; structural sill in $(\mathrm{pH}x10)^2$, proportional nugget on $[0 \ldots 1]$

Moving-window autocorrelation



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

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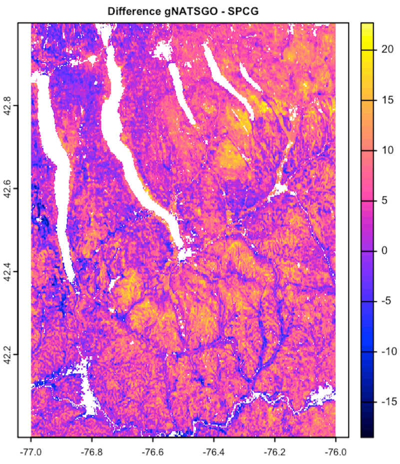
Difference map of continuous property – this also has a pattern

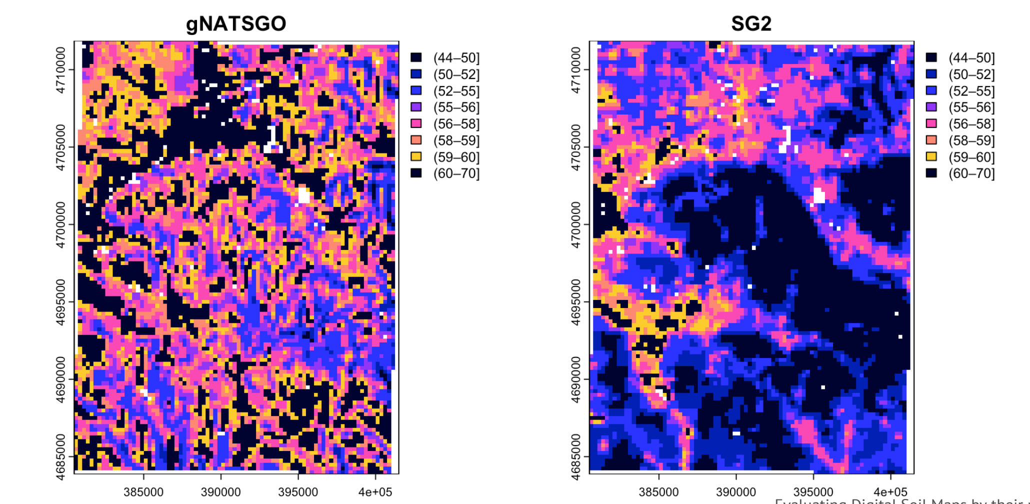


ΔpHx10

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, 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, $(\max - g_{ii})$ 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.

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

where the patch perimeters are p_{ij} in linear units and the areas are a_{ij} in square units.

Metric: landscape shape index

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

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

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

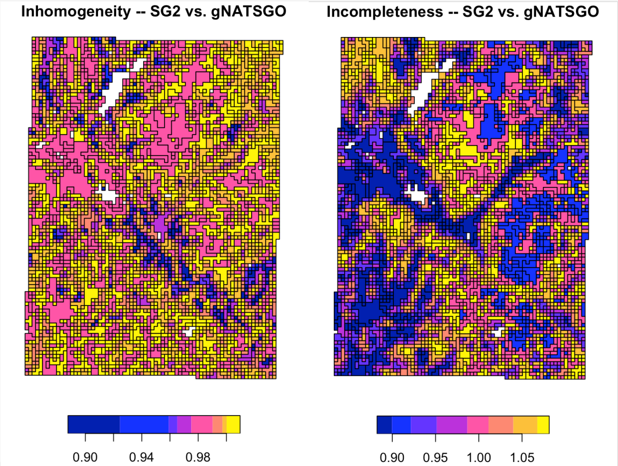
product	ai	frac_mn	lsi	shdi	shei
gNATSGO	48.188	1.034	22.602	1.666	0.801
SG2	50.659	1.034	21.768	2.06	0.991
SPCG	58.483	1.041	18.557	1.887	0.907
PSP	47.025	1.04	23.232	1.898	0.913

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



V-measure example

DSM products	V-measure	Homogeneity	Completeness
gNATSGO vs. SG2	0.0128	0.0143	0.0116
gNATSGO vs. SPCG	0.0258	0.0275	0.0243
gNATSGO vs. PSP	0.084	0.0897	0.079
SPCG vs. SG2	0.3342	0.3495	0.3201

V-measure statistics, pHx10 0–5 cm

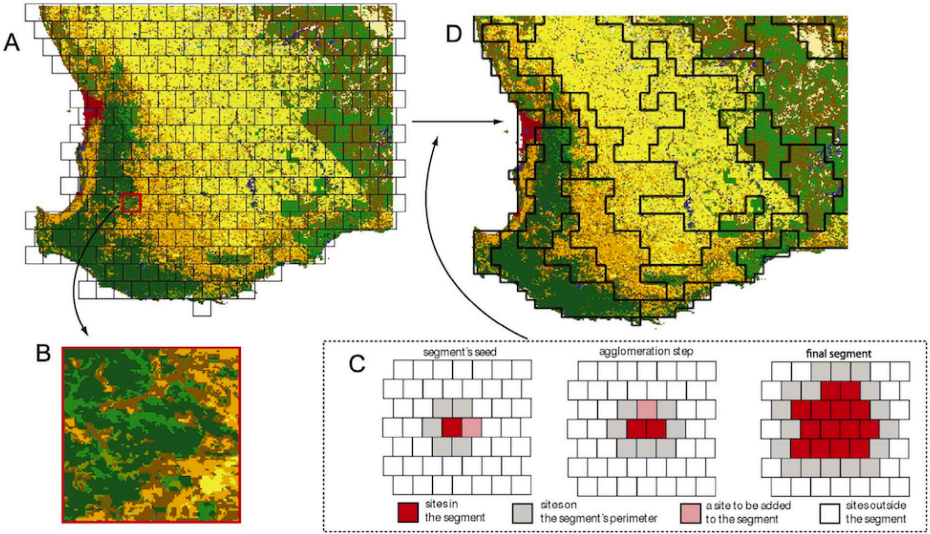
Metric: Co-occurrence vector

- 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.
- The "distance" between co-occurrence vectors from two maps can be computed as a measure of the (dis)similarity between these structures (Jensen-Shannon distance, used to compare probability distributions)

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 thse polygons could be considered a **meta-pattern** of the DSM product

[2] https://jakubnowosad.com/


A
B
C
D
segment's seed
agglomeration step
final segment
sites in the segment
sites on the segment's perimeter
a site to be added to the segment
sites outside the segment

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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

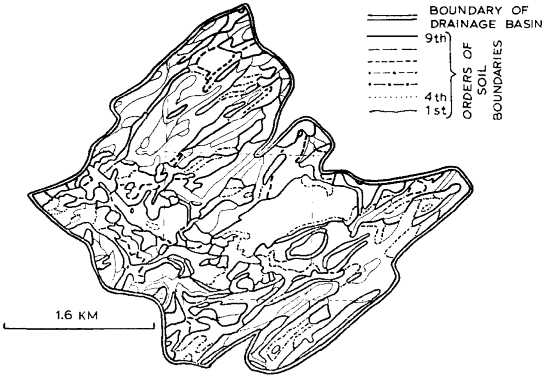


Fig. 12. Soil boundaries expressing degree of contrast between adjacent soil bodies in a fourth order drainage basin (9.8 km^2) 2 km northwest of New Berlin, Waukesha County on Woodfordian or Cary drumlinoid moraine of Wisconsin. Relief is about 73 m. Map scale was 1:15,840 (Steingraeber and Reynolds,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

source: Hole (1978)

Resolution and scale

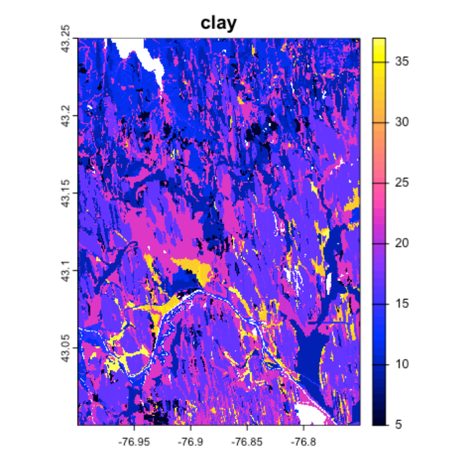
DSMaps are **gridded** at some horizontal **resolution** ("pixel size") – what is the relation to map scale?

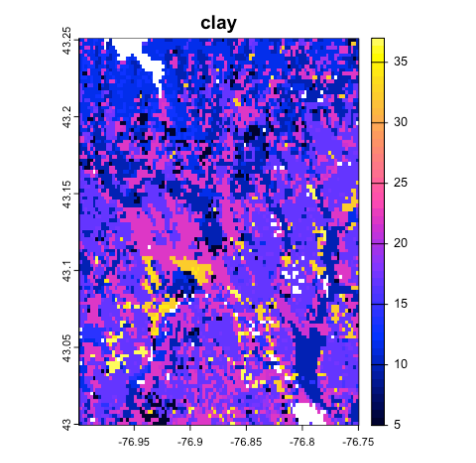
A.B. McBratney et al. / Geoderma 117 (2003) 3–52 5

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”

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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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