Soil maps are more than predictors at points and we should evaluate them as such

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Outline

1. Evaluating Digital Soil Maps – the problem
2. Pattern analysis
3. Letting the map “speak for itself”
4. Comparing maps vs. “reality”
5. On, on!

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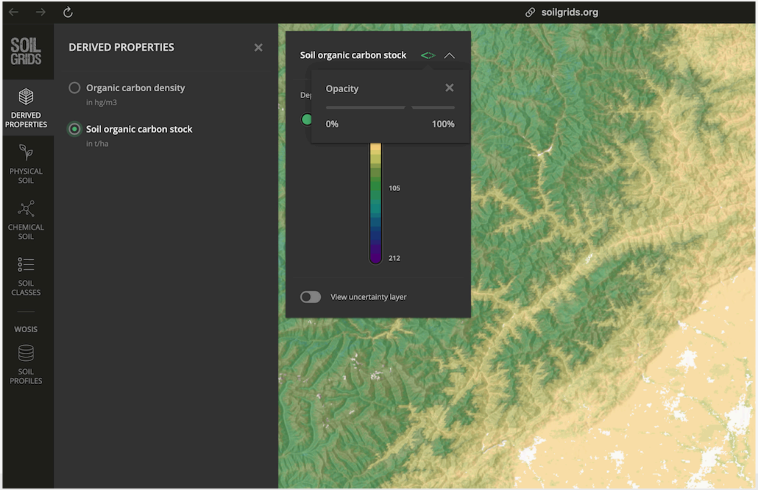
Digital Soil Mapping

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 (Poggio *et al.* 2021)



How have these maps been evaluated?

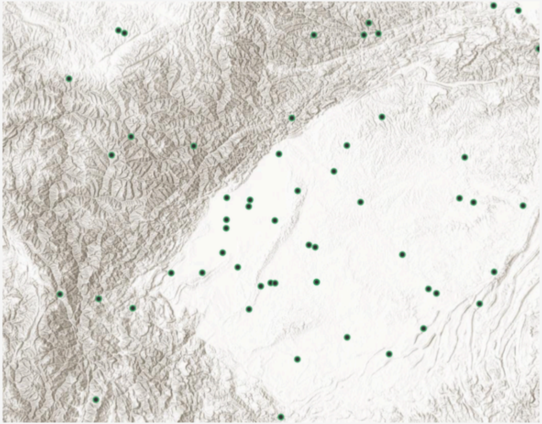
- On the basis of **test points**
  - independent test set in target area
  - cross-validation of out-of-bag (OOB) observations in Machine Learning (ML) methods
  - repeated splits into test/training of one dataset
- (pointwise) **evaluation statistics**
  - ME, RMSE
  - 1:1 R^2 (MCC, Nash-Sutcliffe Model Efficiency)
  - gain/bias of actual regressed on observed
  - ...

Problems with evaluation by point statistics – Internal

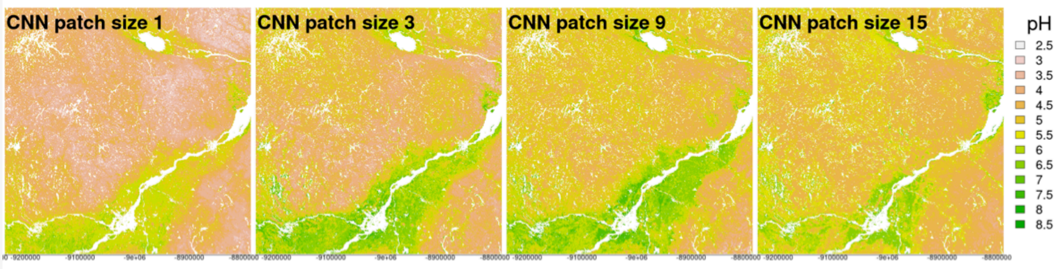
From the **mapper's** point of view:

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**.

ISRIC WoSIS: limited, non-probability evaluation points



Same ML method, covariates, points; different *parameters*



Montréal area, PQ, pH 0-5 cm

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

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

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. Fieldwork shows that **soils occur in more-or-less homogeneous patches**, *not* as isolated pedons (Fridland, Boulaine, Hole ...).
4. How to identify **artefacts** resulting from the DSM model?

Legacy map updated by DSM – realistic or artefacts?

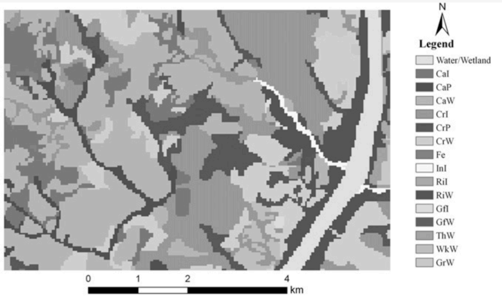


Fig. 3. The 30- by 30-m raster soil map with soil association and drainage class as the soil unit created from the 1:20,000 soil map.

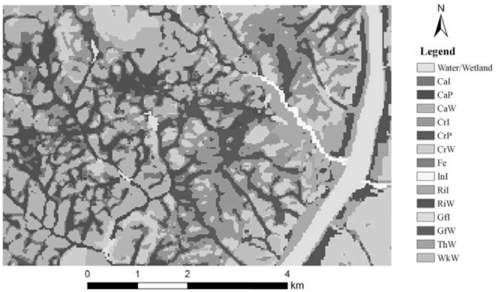


Fig. 10. The updated digital soil map using the fuzzy *c*-means–Soil Land Inference Model (FCM–SoLIM) approach.

(L. Yang 杨琳 *et al.* 2010)

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Pattern analysis

- **Quantitative** description of (spatial) patterns
- Long history in **image analysis** and **landscape ecology**
- Applied to landscape mosaics (FRAGSTATS)
- R packages `motif`, `landscapemetrics`, `rassta`, `superpixels` (**aggregation**)
- Unix program `geoPAT2`[1] (**segmentation**)

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

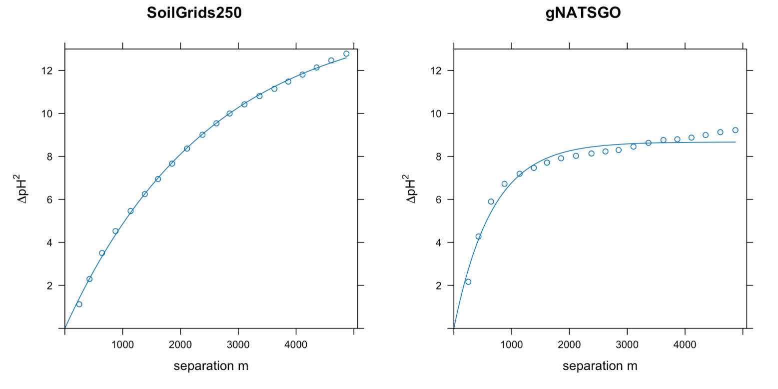
Levels of pattern analysis

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

Characterizing patterns – *continuous* soil properties

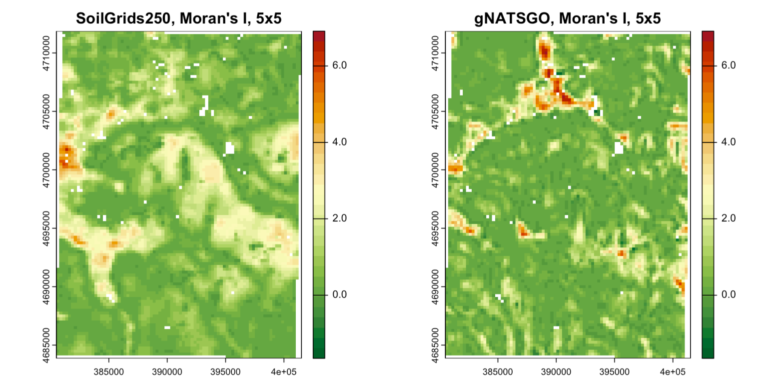
1. Variogram analysis: inherent spatial scales and variability averaged over entire map
2. **Moving-window autocorrelation**: how does this vary across the DSM?
    - Shows "hot spots" of high local consistency (high values of Moran's *I*), "cold spots" of high local variability (low values)
    - Do these correspond with perceived local variability?

Variograms with fitted models



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

Moving-window autocorrelation



high values of Moran's *I*: high local spatial correlation (consistent values)

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

Some useful metrics

- `LAI` *landscape aggregation*: index quantifies how **connected** is each class, averaged over all classes
- `MFD` *mean fractal dimension*: describes multi-scale **patch complexity**
- `LSI` *landscape shape index*: quantifies the **complexity of the patch shapes**
- `SHDI` *Shannon diversity index*: a measure of (1) the **legend complexity**, (2) the **(un)balance** between classes
- `GLCM` *Gray Level Co-occurrence Matrix*: characterizes the "texture" of a raster class map
  - **local** statistical properties of a window as it moves across the map.
- `COVE` *Co-occurrence vector*: summarizes the adjacency structure

Example 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 $i = (1 \dots N)$

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

(Evaluation area: -77—76° E, 42–43° N)

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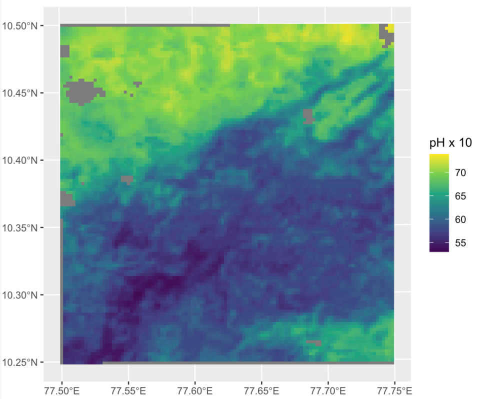
Finding patterns by “letting the map speak for itself”

- Objective: (semi-)automatically extract patterns from the map
- These can be compared to “reality”
- Methods
  - **Aggregation**: areas of “similar” **values** or **classes**
  - **Segmentation**: areas with “similar” **internal spatial patterns**

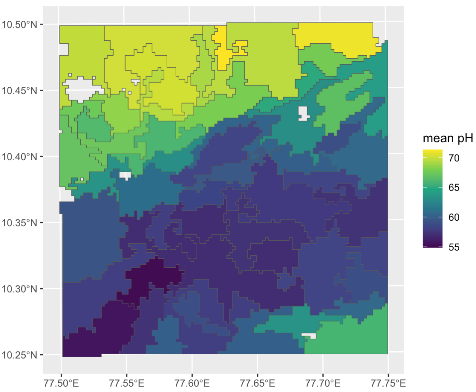
Aggregation

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

Aggregation example – pH class map of Tamil Nadu (part)



SoilGrids v.20 pH x 10 values



Supercells with mean pH x 10

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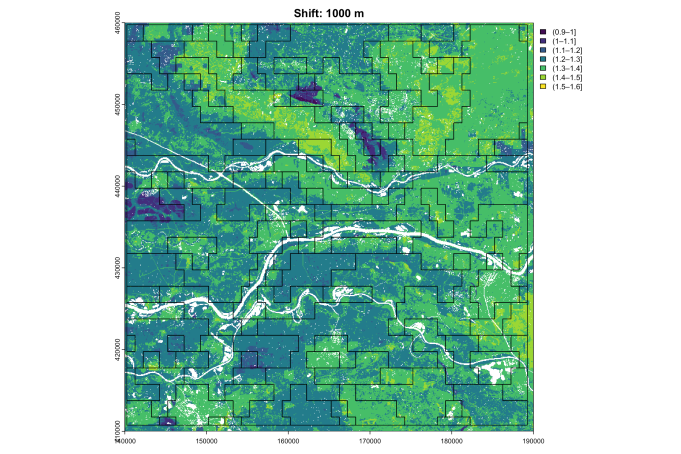
Segmentation by patterns

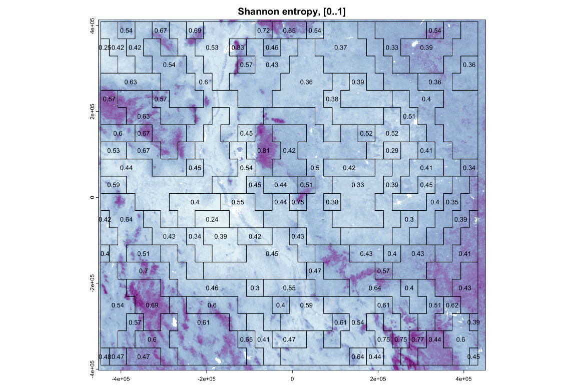
- A recent development by Nowosad[2], based on an algorithm of Jadiewicz
- Aggregates groups of pixels (size set by analyst) into polygons with a "similar enough" spatial **pattern** of classes within the polygon
    - Limitation: polygons are composed of square cells at least 10x the original grid resolution
- The pattern of these grid cells can be considered a **meta-pattern** of the DSM product

[2] https://jakubnowosad.com/

Segmentation example – BIS-4D, bulk density of all layers



Characterizing the patterns in a segment



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

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Comparing maps; maps vs. “reality”

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

Scales of soil patterns

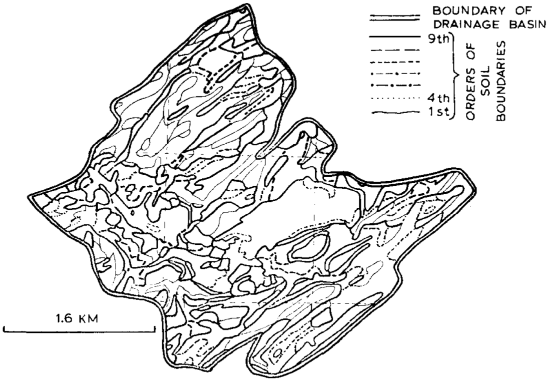
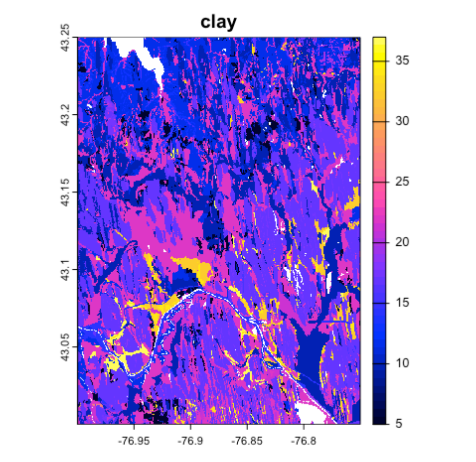
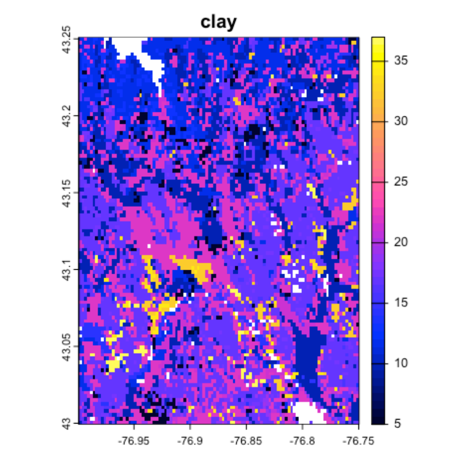


Fig. 12. Soil boundaries expressing degree of contrast between adjacent soil bodies in a fourth order drainage basin (9.8 km^2) 2 km northwest of New Berlin, Waukesha County on Woodfordian or Cary drumlinoid moraine of Wisconsin. Relief is about 73 m. Map scale was 1:15,840 (Steingraeber and Reynolds,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

source: Hole (1978)

DSM scale effects – 20 vs. 250 m resolution gSSURGO





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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. Publish paper on “letting the map speak for itself”
2. Match metrics with soil patterns at various scales and in various soil-landscapes
3. Quantify these matches

Questions, comments, ideas, suggestions?

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www: https://www.css.cornell.edu/faculty/dgr2/index.html

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