

Global Soil Mapping in a Changing World

Sabine Grunwald

Acknowledgements:
GIS-Pedometrics Team, UF

Soil Story

My soil story

.... Your soil story

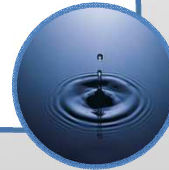
Digital Soil Mapping in a Changing World

Global climate change, land use change, population growth

Soil Gap



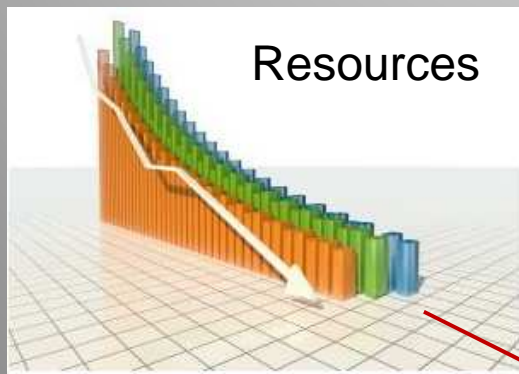
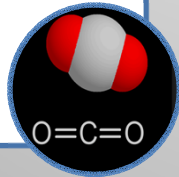
Water Gap



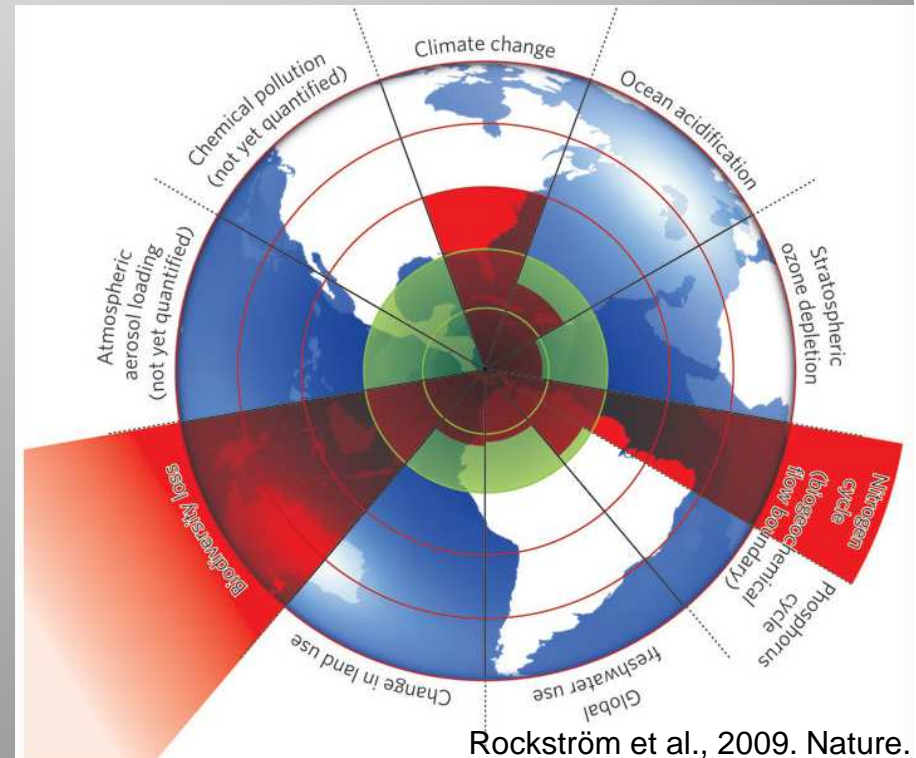
Food Gap



Soil
Carbon



Sustainability



Digital Soil Mapping (DSM)

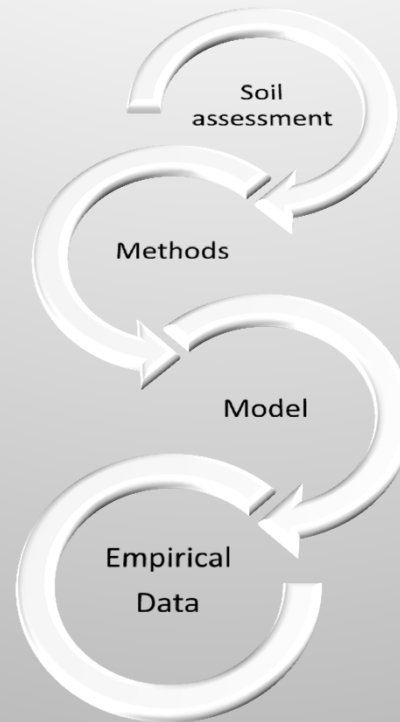


Abstraction level & complexity

High

- Sustainability
- Adaptation / mitigation potential
- Soil ecosystem services (natural capital)
- Risk / vulnerability
- Soil gaps
- Soil functions
- Soil ecosystem processes
- Soil change / evolution
- Soil properties
- Soil classes

Low



Statistical methods:

e.g. multivariate regression
Ensemble trees
Machine learning

Geostatistical methods:

e.g. kriging

Mixed/hybrid methods:

e.g. regression kriging
PTF & interpolation

Process-based methods:

e.g. simulation models

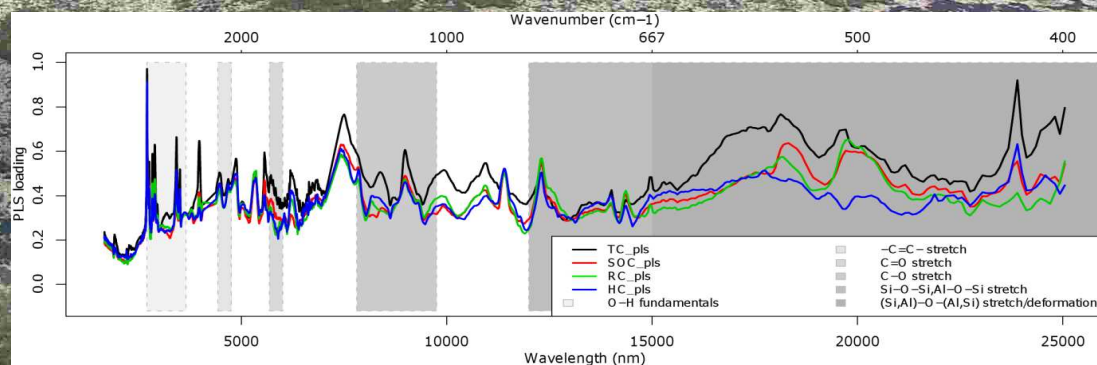
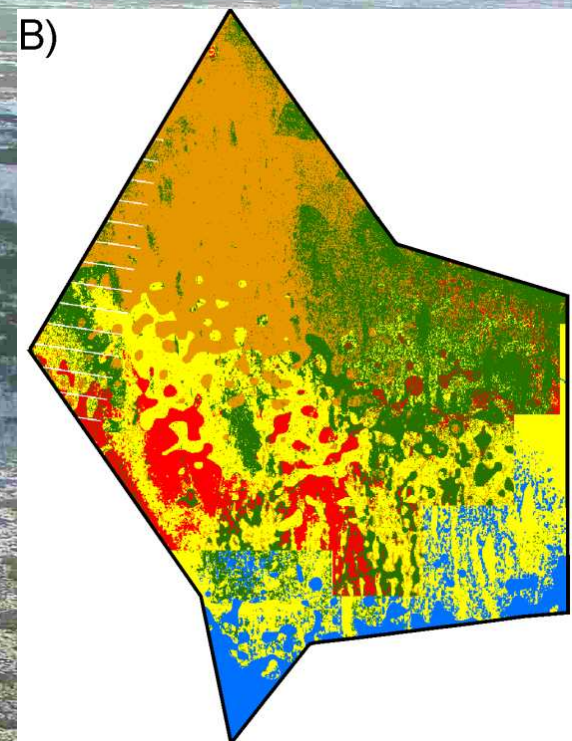
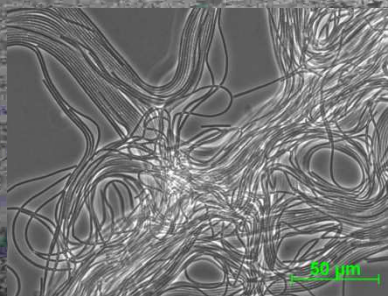
and more

What is the Purpose of Digital Soil Mapping?

- (1) *Intrinsic* knowledge: “just for the sake of knowing” (create maps)
- (2) *Extrinsic* knowledge: To address societal, complex, global issues; a changing world w/ uncertainty; we co-create soil ecosystems

Global – regional – local scales

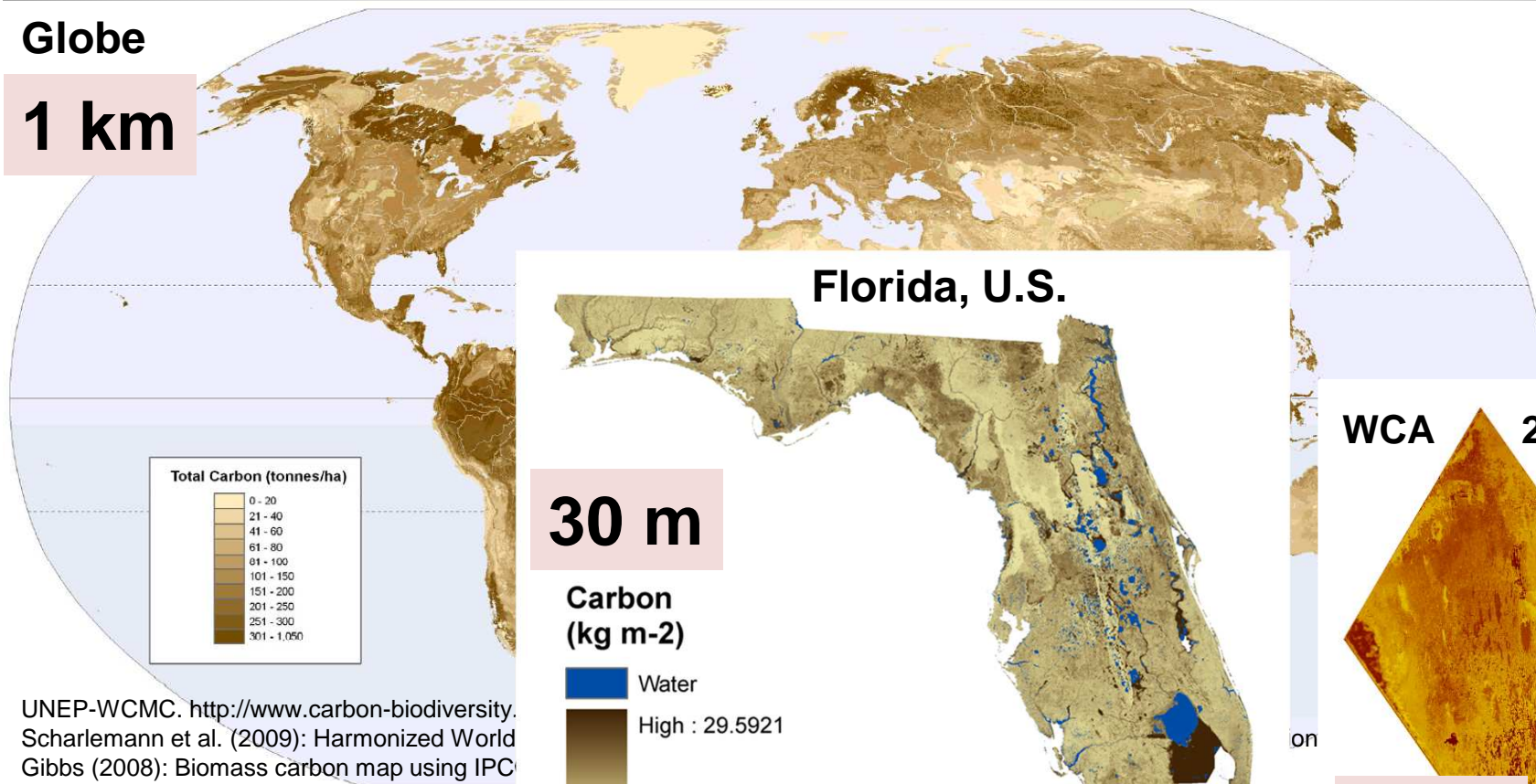
Multiple Soils Perspectives



Estimates of Carbon Stocks

Globe

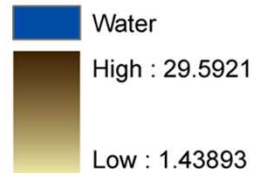
1 km



Florida, U.S.

30 m

Carbon
(kg m⁻²)

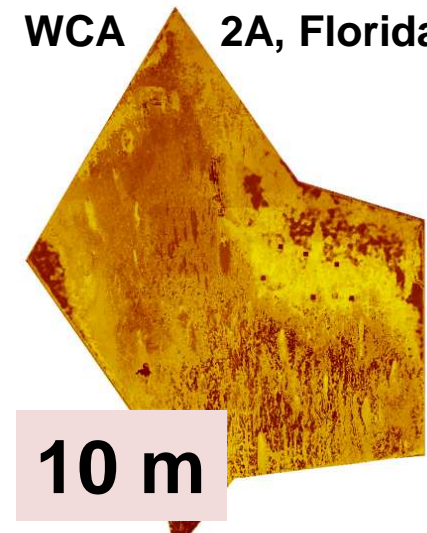


Grunwald, Myers, Harris, and Comerford. 2012.

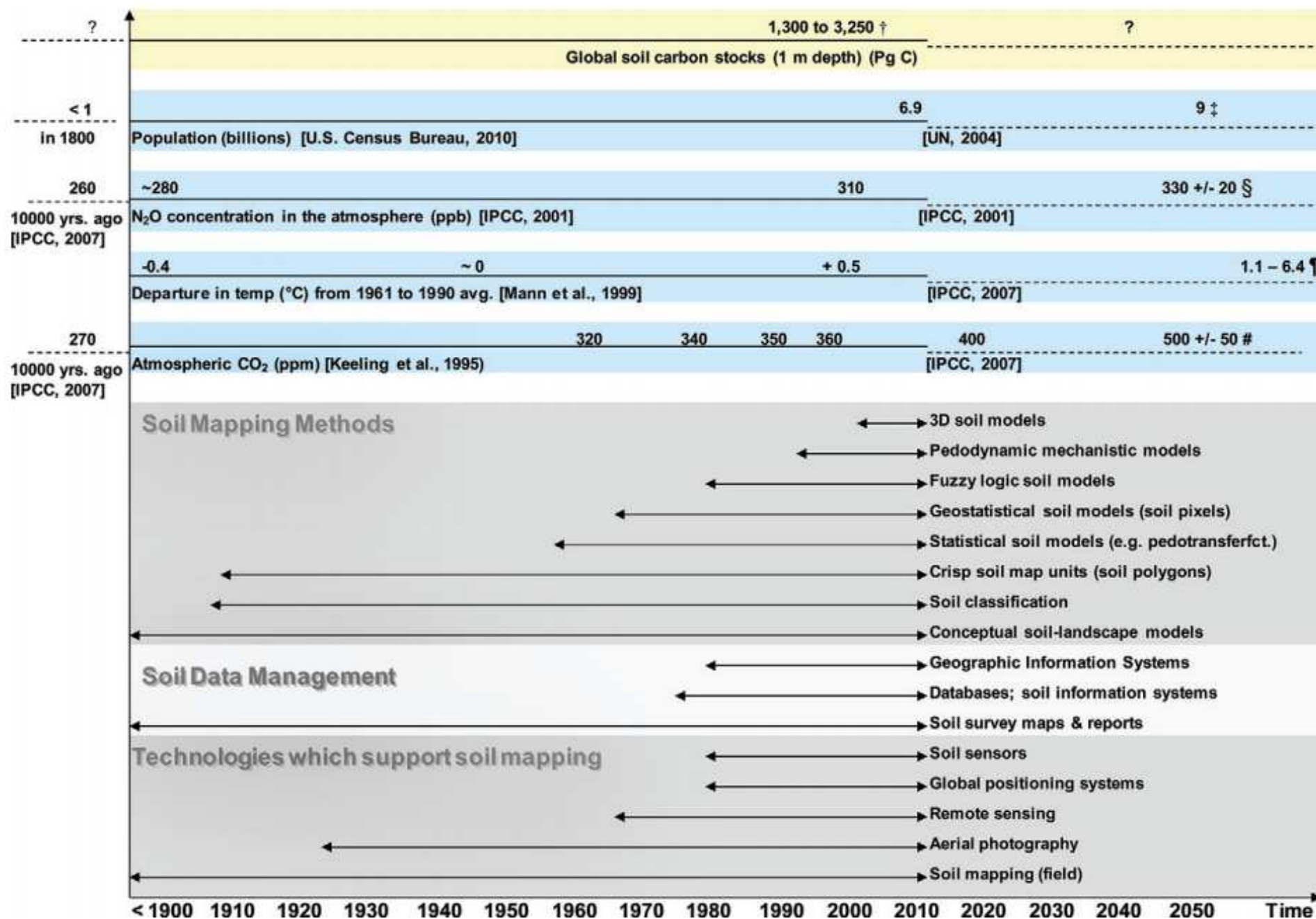
WCA

2A, Florida

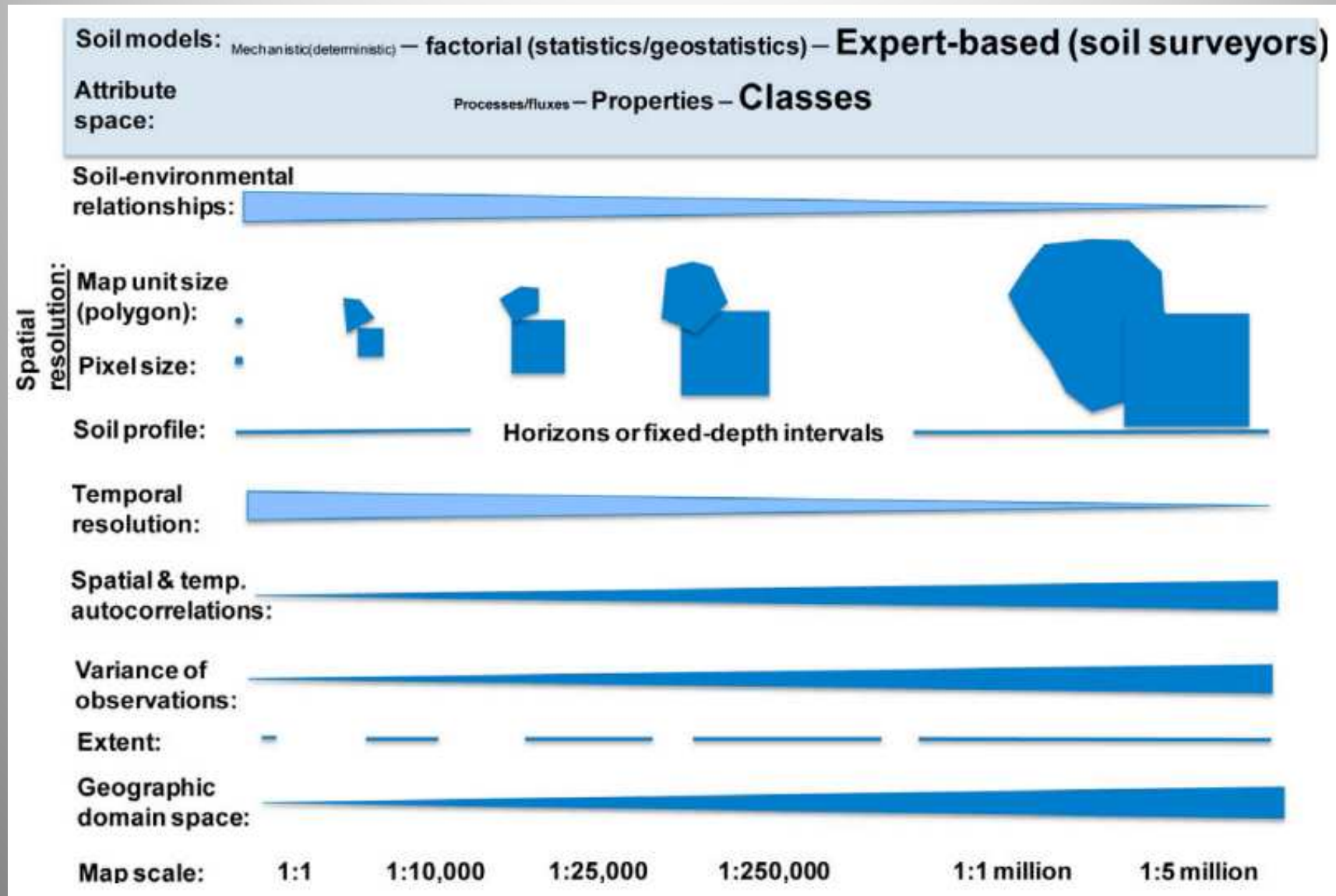
10 m



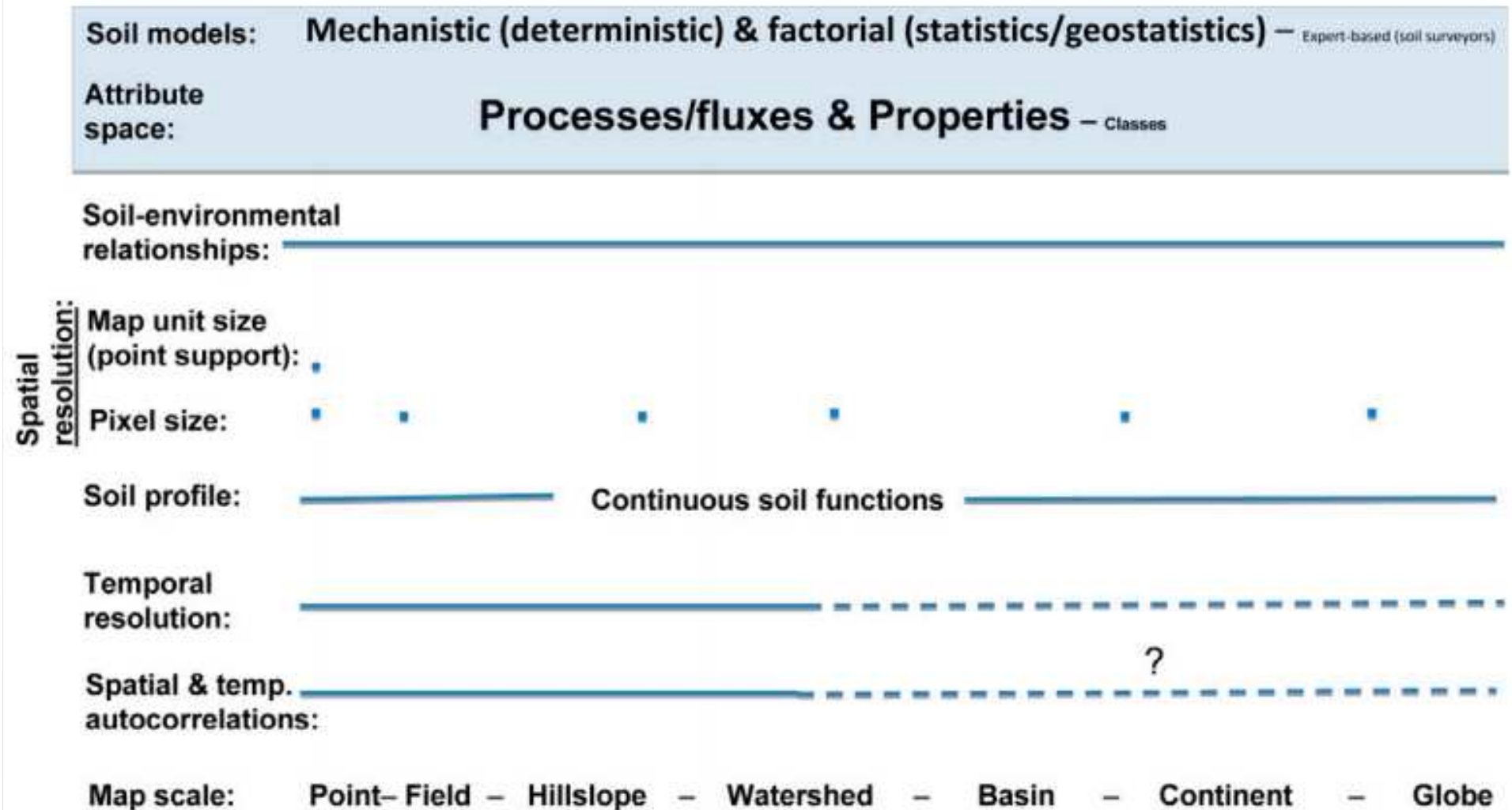
Kim and Grunwald, 2013



Overview of Phenomena of Space and Time, Distribution of Soil Properties and Processes at Escalating Spatial Scale



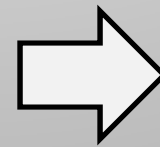
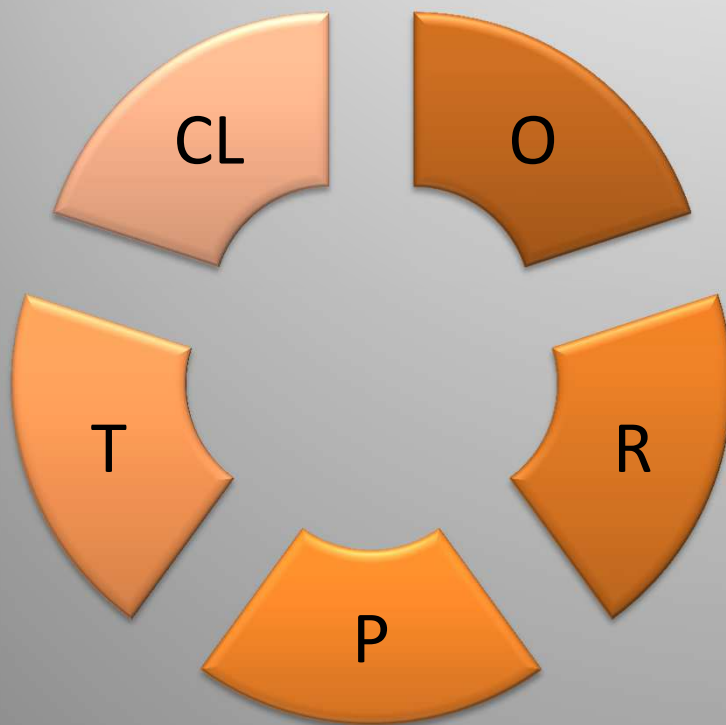
Envisioned Future of Digital Soil Mapping and Modeling



Conceptual Soil Formation Models

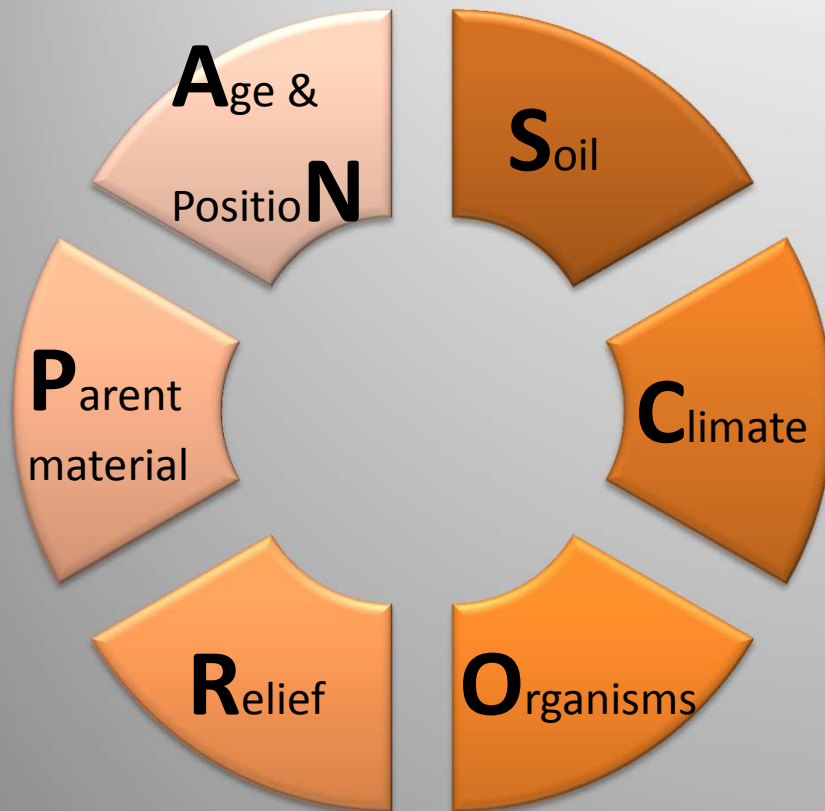
Factorial soil models:

The soil forming factors - climate (CL), organisms (O), relief (R), parent material (P), and time (T) - form soils



Jenny (1941)

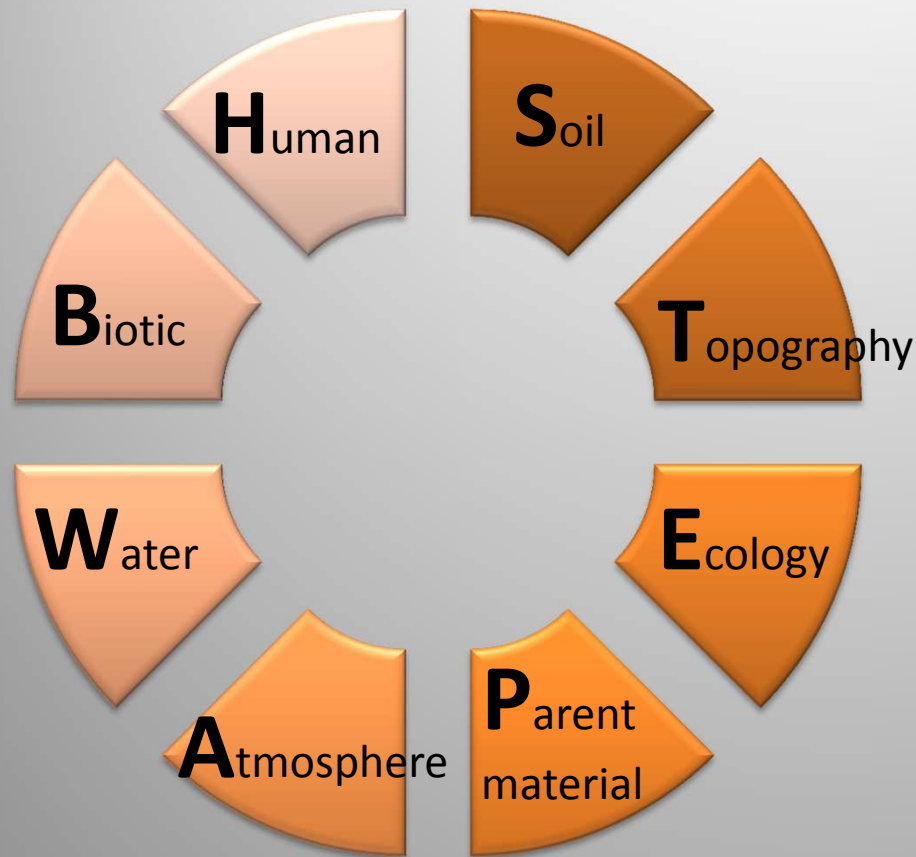
SCORPAN Model \Rightarrow Soil Properties/Classes



- Quantitative framework suited for digital soil mapping (DSM)
- Empirical model
- Factors and soil predictions are spatially-explicit (x, y) and temporally-explicit (t)

McBratney et al. (2003)
Geoderma

STEP-AWBH Model ⇔ Soil Properties/Classes



- Spatially and temporally explicit
- Additional factors (W, H)
- Accounts for time-dependent variation of STEP-AWBH variables
- Facilitates modeling of soil evolution and change
- Space-time model

Grunwald et al. (2011) SSSAJ
Thompson et al. (2012). DSM: Interactions w/
and applications for hydrogeology.

STEP-AWBH Model

Target soil property,
rate, change,
process, risk, etc.

Soil

Topography

Ecology

**Parent
material**

$$SA(z, p_x, t_c) = f \left\{ \sum_j^n S_j(z, p_x, t_c), T_j(p_x, t_c), E_j(p_x, t_c), P_j(p_x, t_c) \right\};$$

Spatially-explicit, ~stable across time

$$\int_{i=0}^m \left\{ \sum_j^n A_j(p_x, t_i), W_j(p_x, t_i), B_j(p_x, t_i), H_j(p_x, t_i) \right\}$$

Spatially-explicit + account for time-dependent variation of variables

Atmosphere

Water

Biota

Human

Soil
Depth

Pixel
w/ size x

Current (c)
time

S Factor



e.g. soil org. C
 $SA(z, p_x, t_c) =$

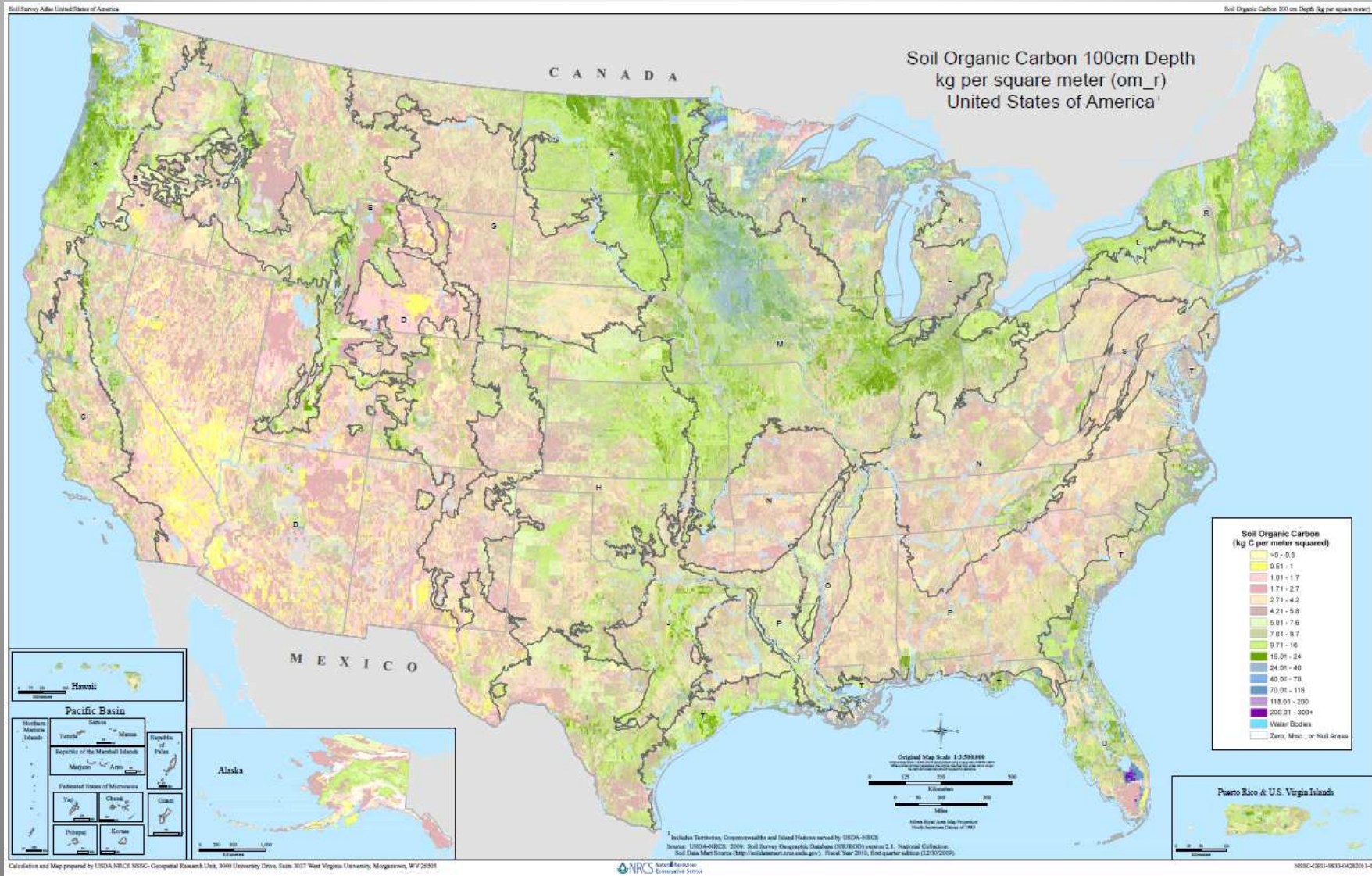


$$f\left\{\sum_j^n S_j(z, p_x, t_c)\right\}$$

Examples - How to populate the S factor:

- Soil taxonomic data (e.g., soil order, great groups)
- Soil drainage class map
- Available water storage top 25 cm
- Soil texture map (clay, silt, sand content)
- Soil organic matter map

S Factor: Historic Soil Organic C (U.S.)



Data source: Soil Survey Geographic Database (SSURGO) Soil Data Mart, NRCS

A Factor



e.g. soil org. C

$$SA(z, p_x, t_c) =$$

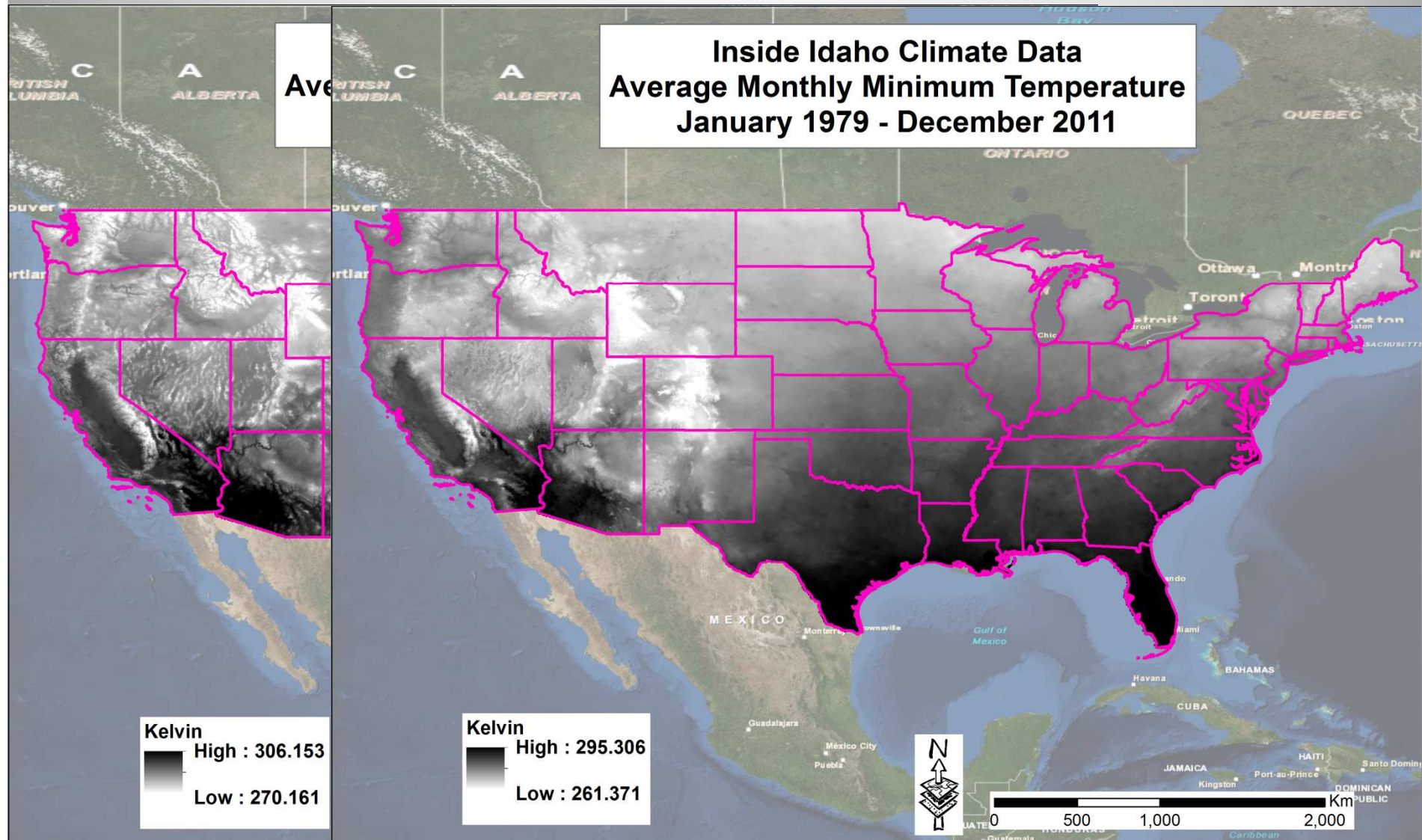


$$\int_{i=0}^m \left\{ \sum_j^n A_j(p_x, t_i) \right\}$$

Examples - How to populate the A factor:

- Long-term mean precipitation
- Aggregated precipitation during summer months
- Max. temperature last year
- Max. temperature over the past 30 years
- Daily, weekly or monthly soil moisture
- Soil moisture yearly average

A Factor: Temperature

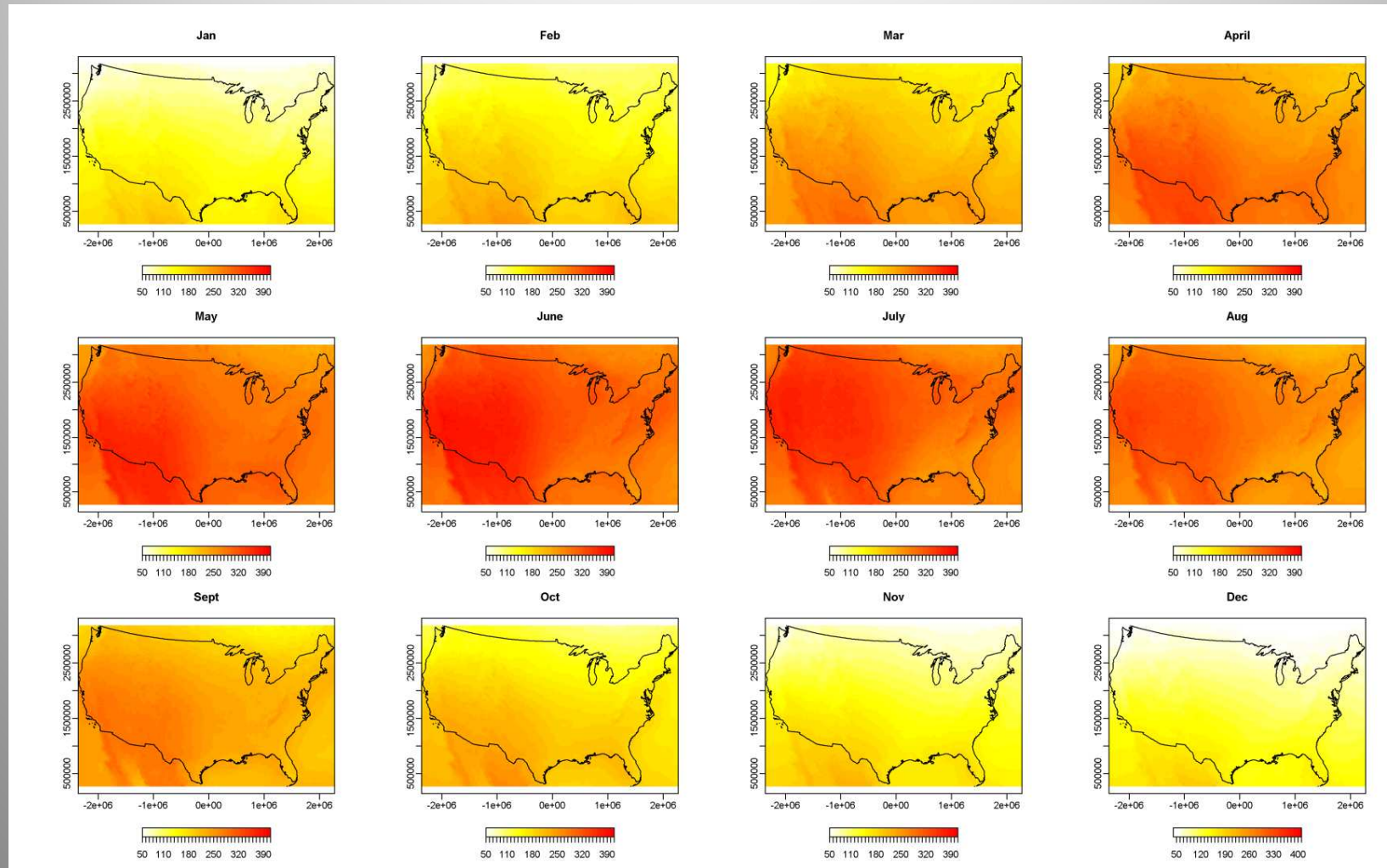


Data source: Idaho Geospatial

Spatial data extraction: R. Patarasuk (GIS-Pedometrics Team)

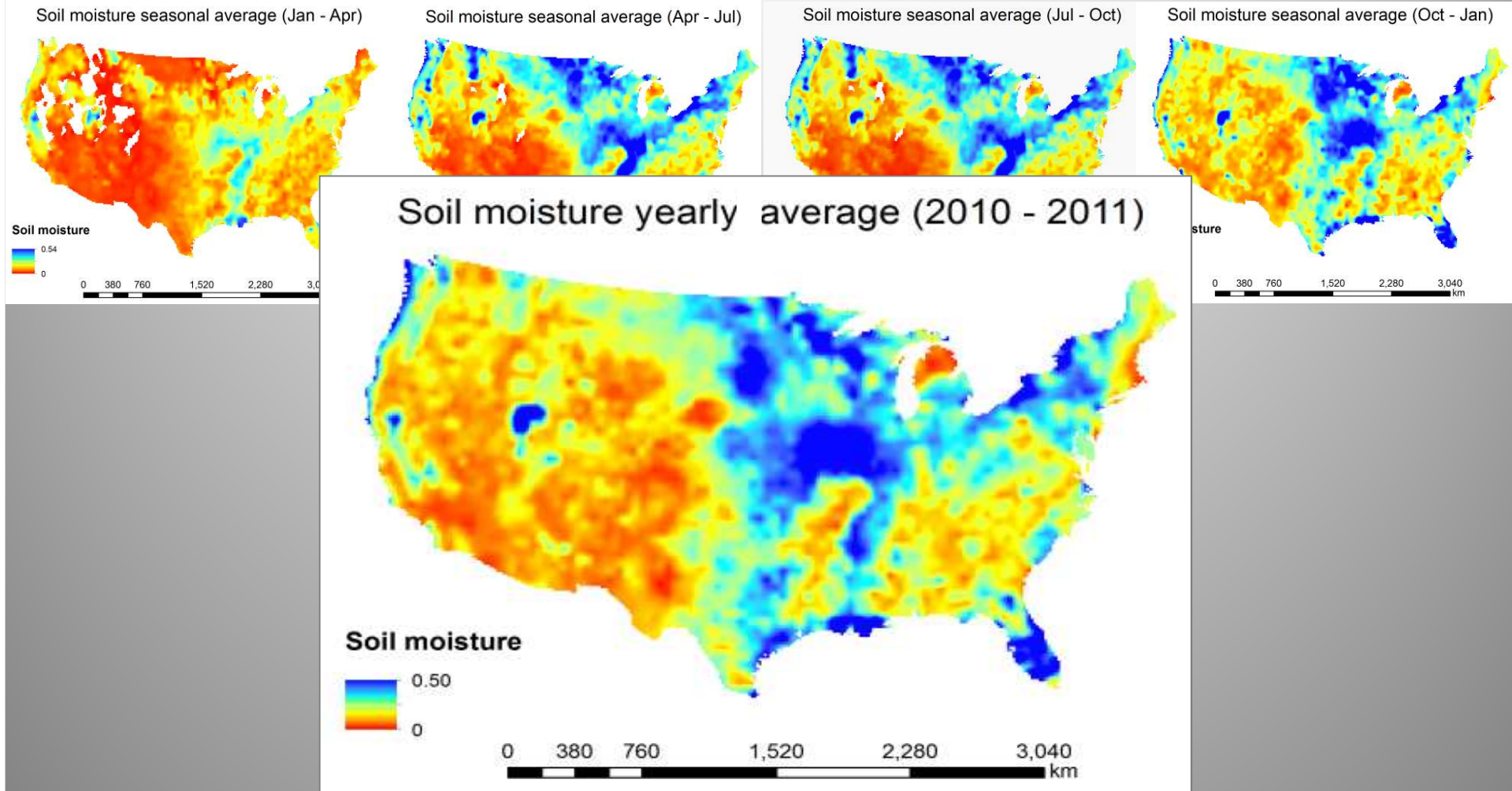
A Factor: Solar Radiation

Solar radiation – 30 yr averages for each month



Data source: North American Regional Reanalysis (NARR) – National Oceanic and Atmospheric Administration (NOAA)
Spatial data extraction: X. Xiong (GIS-Pedometrics Team)

W Factor: Soil Moisture

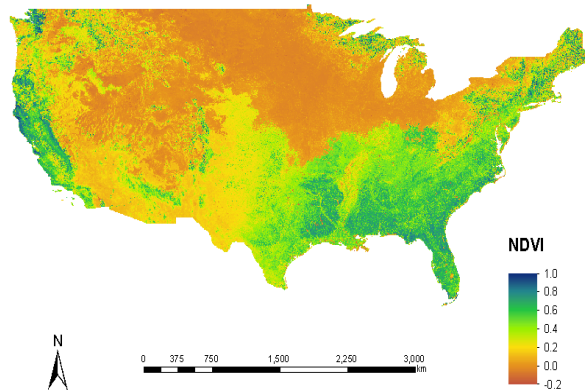


Spatial data extraction: X. Xiong (GIS-Pedometrics Team)

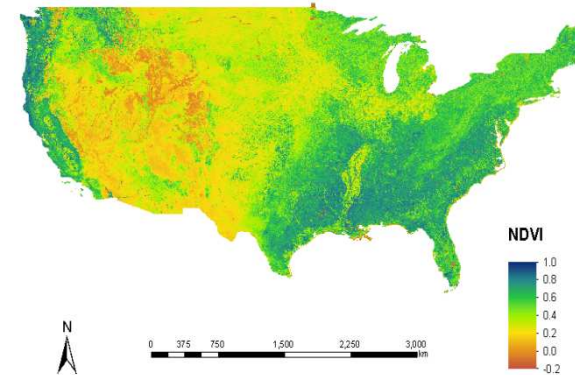
Soil Moisture Data (SMOS) (European Space Agency, ESA)

B Factor: NDVI

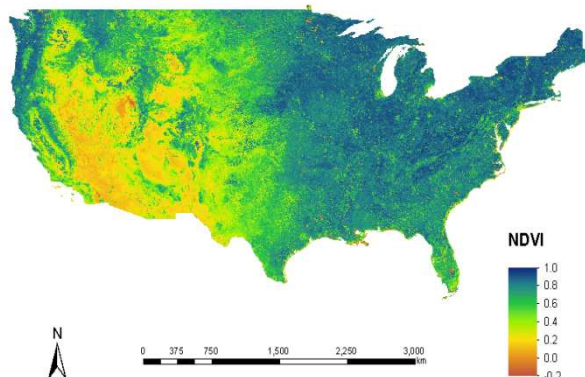
NDVI (Normalized Difference Vegetation Index)
01-01-2010



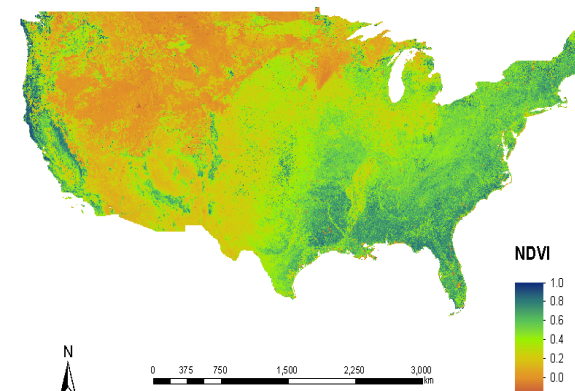
NDVI (Normalized Difference Vegetation Index)
04-07-2010



NDVI (Normalized Difference Vegetation Index)
07-12-2010

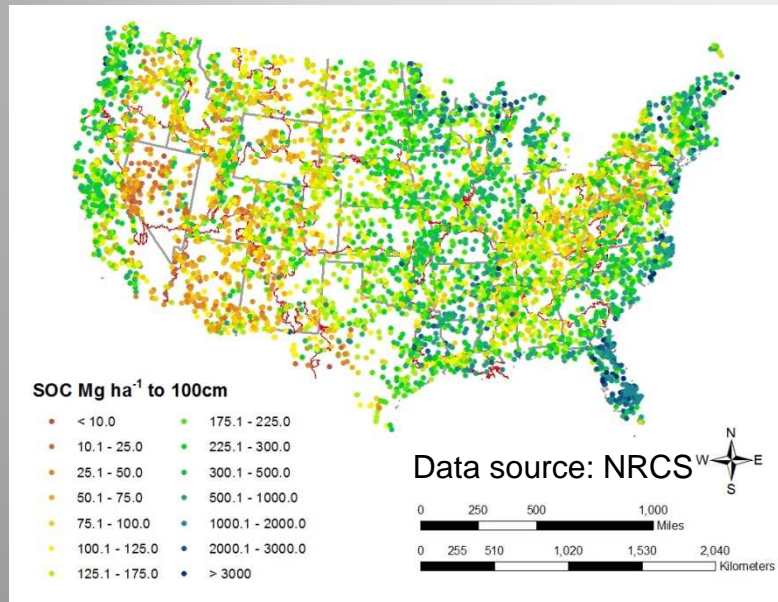


NDVI (Normalized Difference Vegetation Index)
11-17-2010



Spatial data extraction: X. Xiong (GIS-Pedometrics Team) and Y. Qiu (Geography, UF)
Data source: MODIS (NASA) Moderate-resolution Imaging Spectroradiometer

Soil Carbon Assessment across the U.S.



+

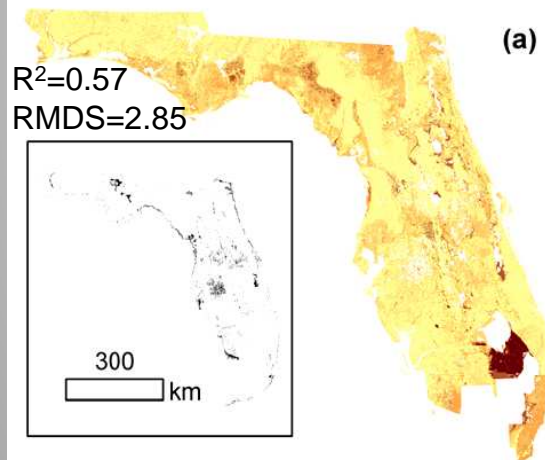
STEP-AWBH
(environmental covariates)

Soil carbon map

Soil Carbon Assessment across Florida, U.S.

(Xiong, Grunwald et al. 2013. Geoderma)

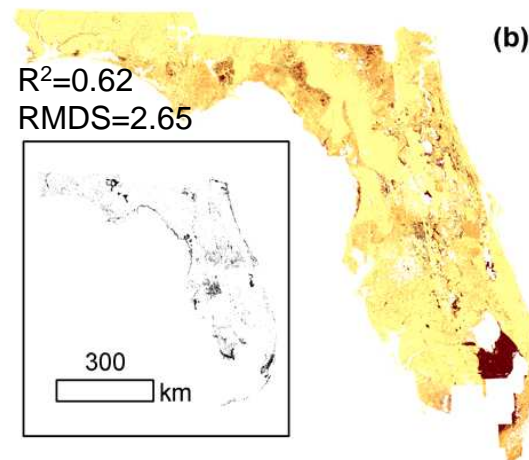
Validation results



0 50 100 200 300 400 km

Model: greedy forward random forest

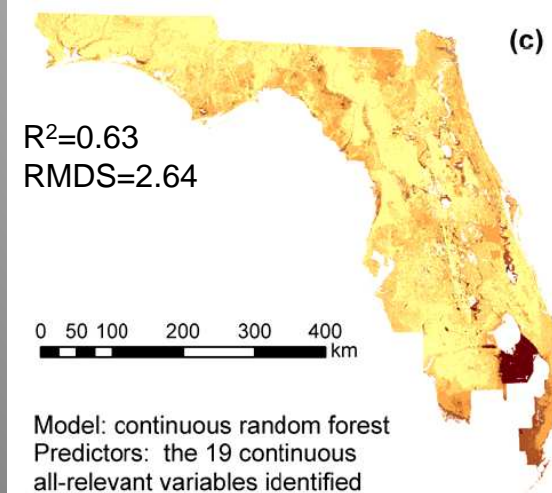
Number of categorical predictors: 3



0 50 100 200 300 400 km

Model: simulated annealing random forest

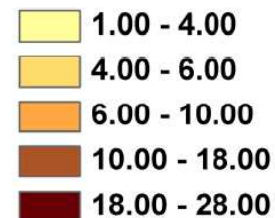
Number of categorical predictors: 13



0 50 100 200 300 400 km

Model: continuous random forest
Predictors: the 19 continuous all-relevant variables identified by Boruta algorithm

SOC at 0-20 cm (kg m^{-2})



[Grid res. = 30x30 m]



STEP-AWBH
variables = 210

Significant continuous predictor variables:

AWC (25 and 50 cm)

SOM

Soil albedo

Sand %

Slope

Dist Stream

Landsat (Bd5, Bd7, PC1, TC1)

Dry Biomass Vegetation

EVI (April)

MODIS (small NDVI peak integral)

MODIS (GPP)

MODIS (NPP)

(PrecipFeb and PrecipSept)

(PrecipAvg)

Significant categorical predictors:

LULC

VegType

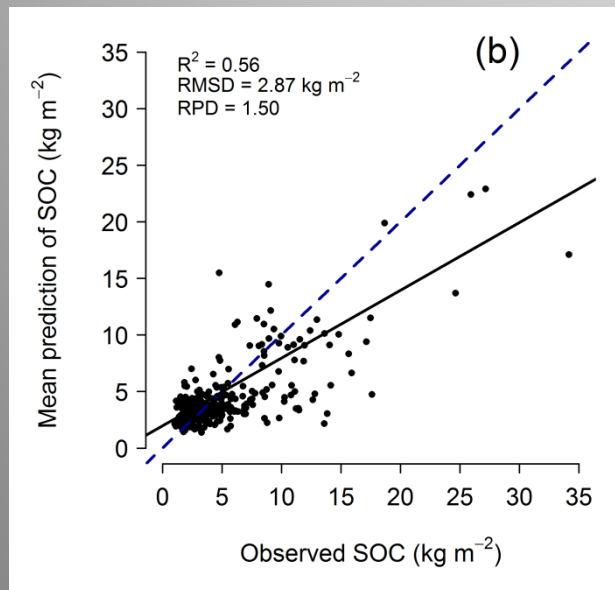
Soil Hydration

Bayesian Geostatistical Modeling of SOC with Uncertainty Assessment

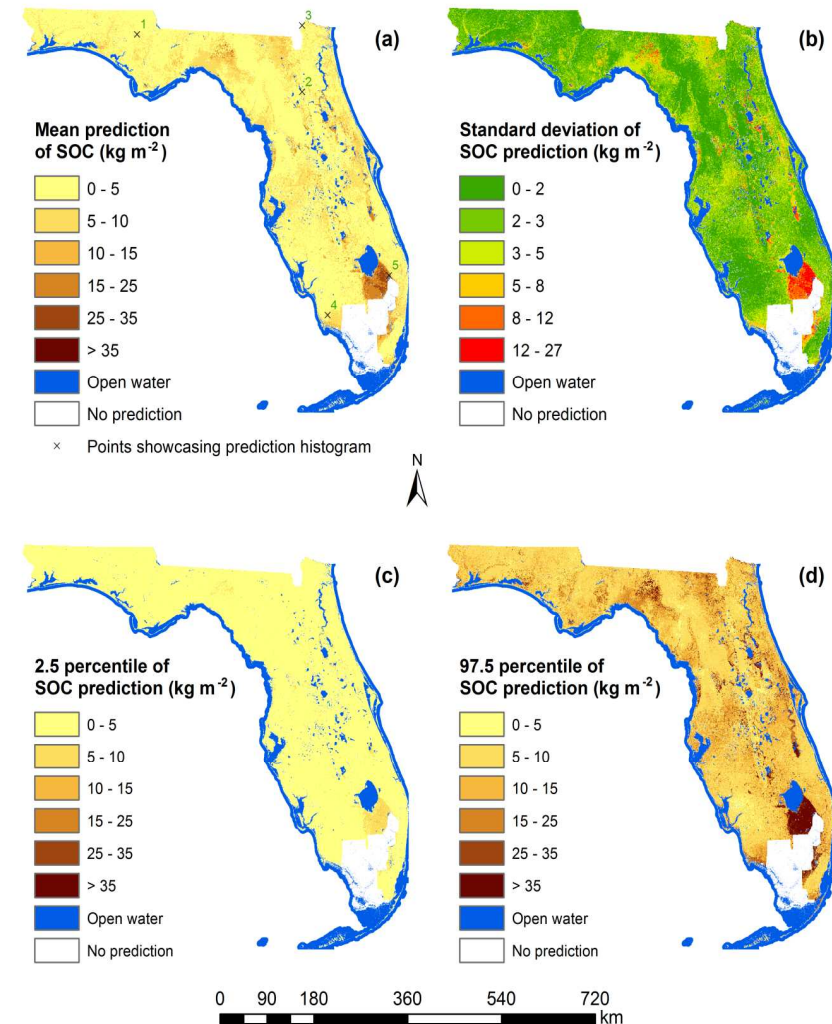
Xiong X., S. Grunwald, D.B. Myers, J. Kim, W.G. Harris, N. Bliznyuk and N.B. Comerford. 2013. Geophys. Res. Biogeosciences

Posterior mean (a), standard deviation (b), 2.5 percentile (c) and 97.5 percentile (d) of soil organic carbon (SOC) prediction at 0-20 cm depth in Florida from Bayesian geostatistical model with both fixed and spatial random effects.

(Markov Chain Monte Carlo (MCMC) simulation, after Diggle et al. 1998)



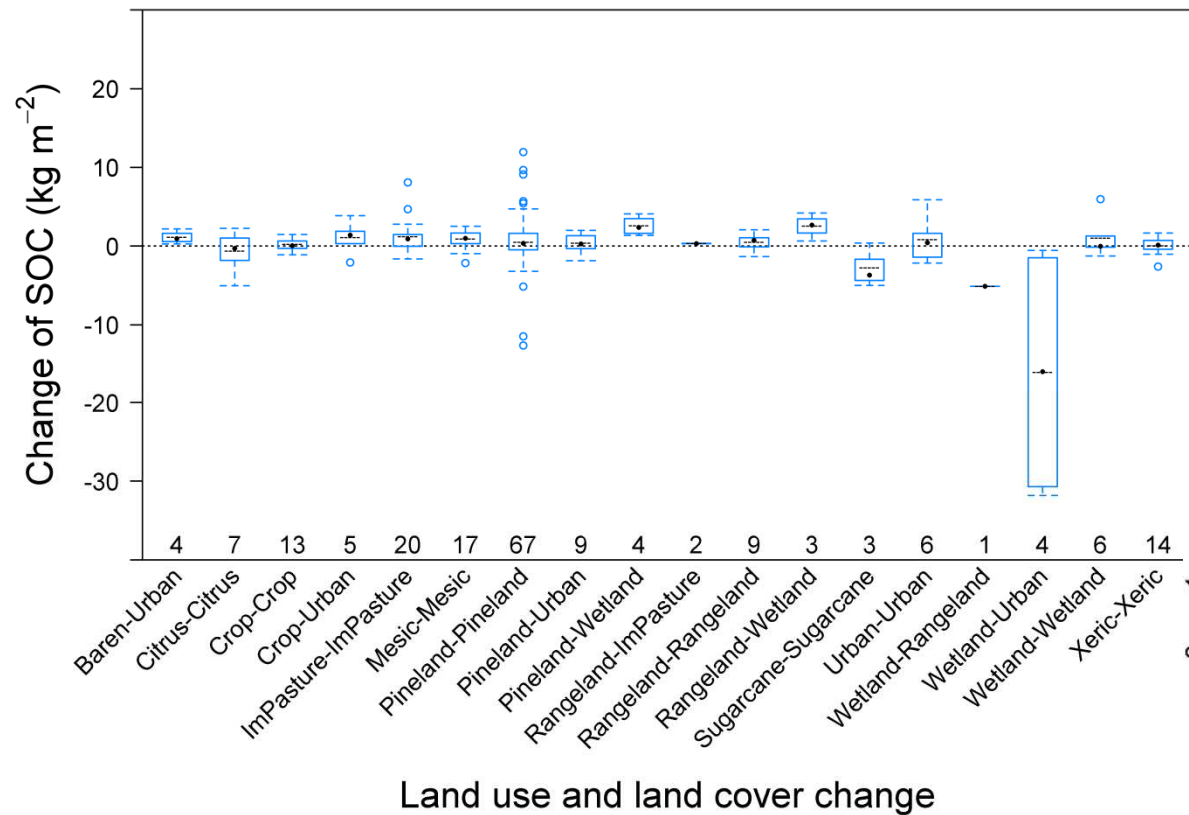
Environmental covariates: AWC, SOC (SSURGO), dry surface albedo, Landsat PC1, CTI, LAI



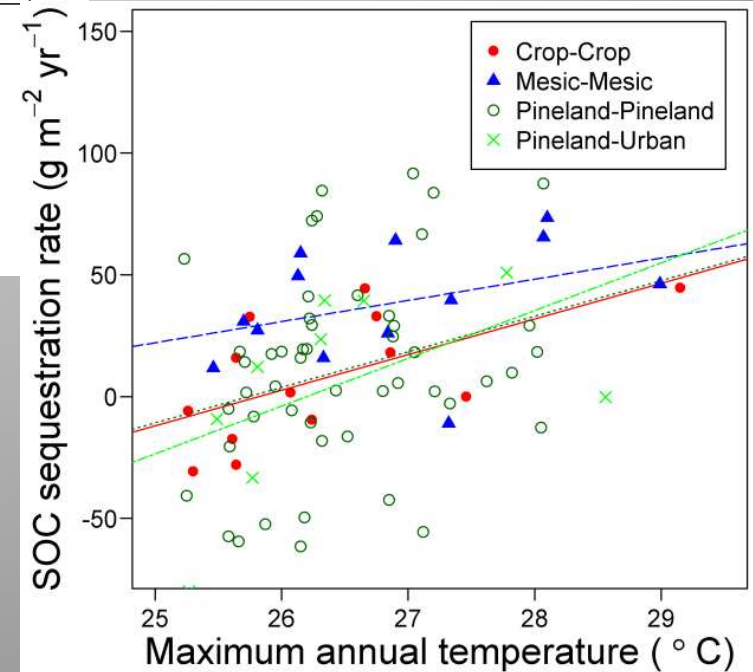
Open water: Florida vegetation and land cover data derived from Landsat ETM+ imagery. Spatial resolution: 30 m. Florida Fish and Wildlife Conservation Commission (FFWCC), 2003

Soil Carbon Change 1965 to 2010 (Florida)

(Xiong, Grunwald et al. 2013.)



N = 194

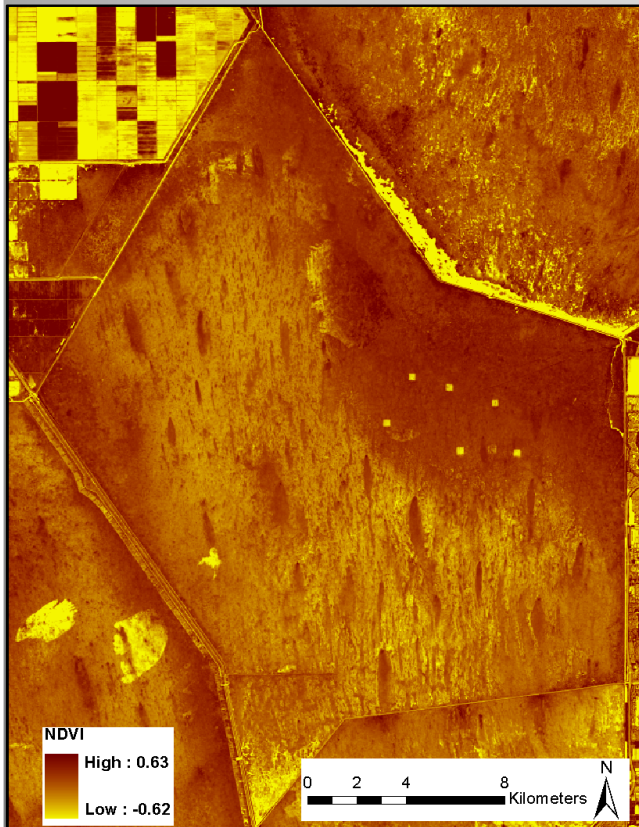


Remote Sensing Supported DSM

(Kim, Grunwald et al. 2012)

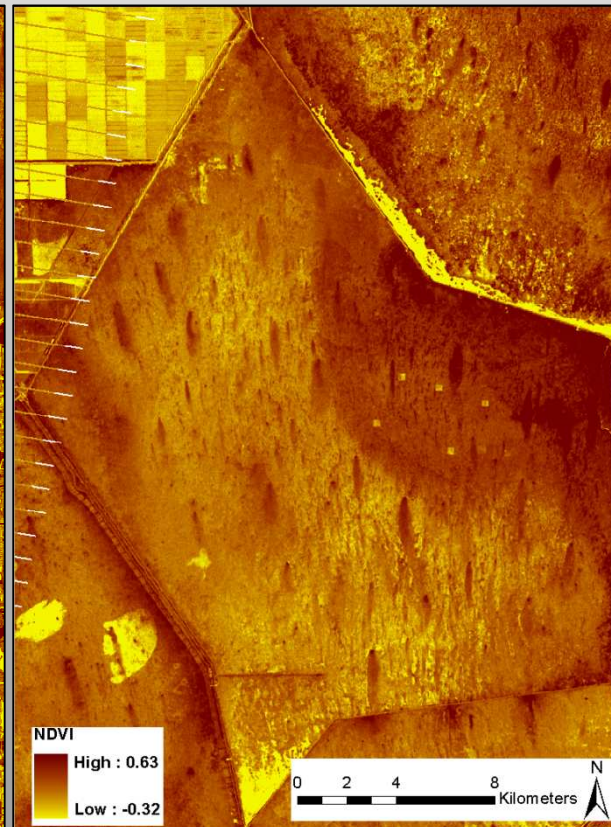
- Water Conservation Area 2A, Florida, Everglades
- Spectral indices: EVI, MSI, NDVI, NDVI green, NDWI, RSR, SR, TVI

SPOT (10 m)



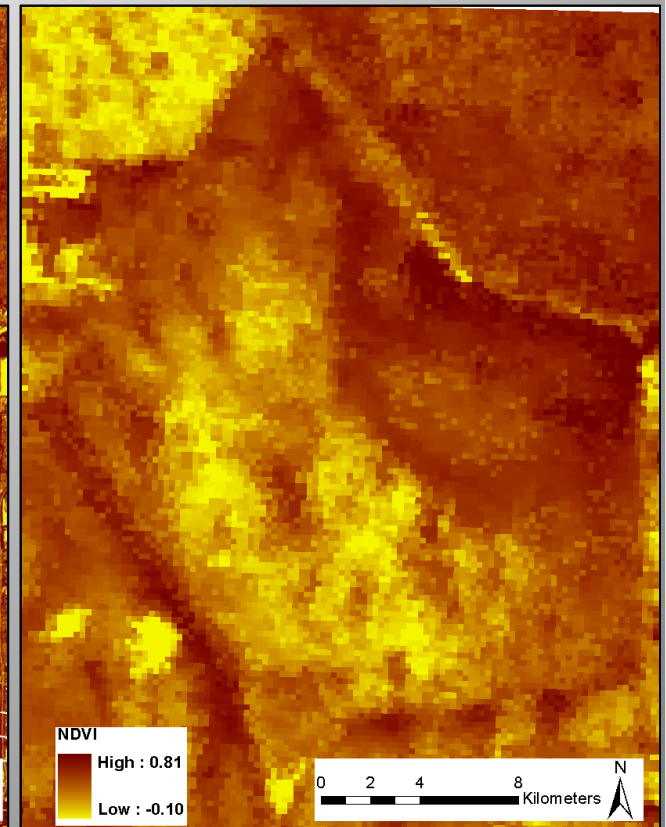
Jan. 09, 2009

Landsat ETM+ (30 m)



Feb. 16, 2010

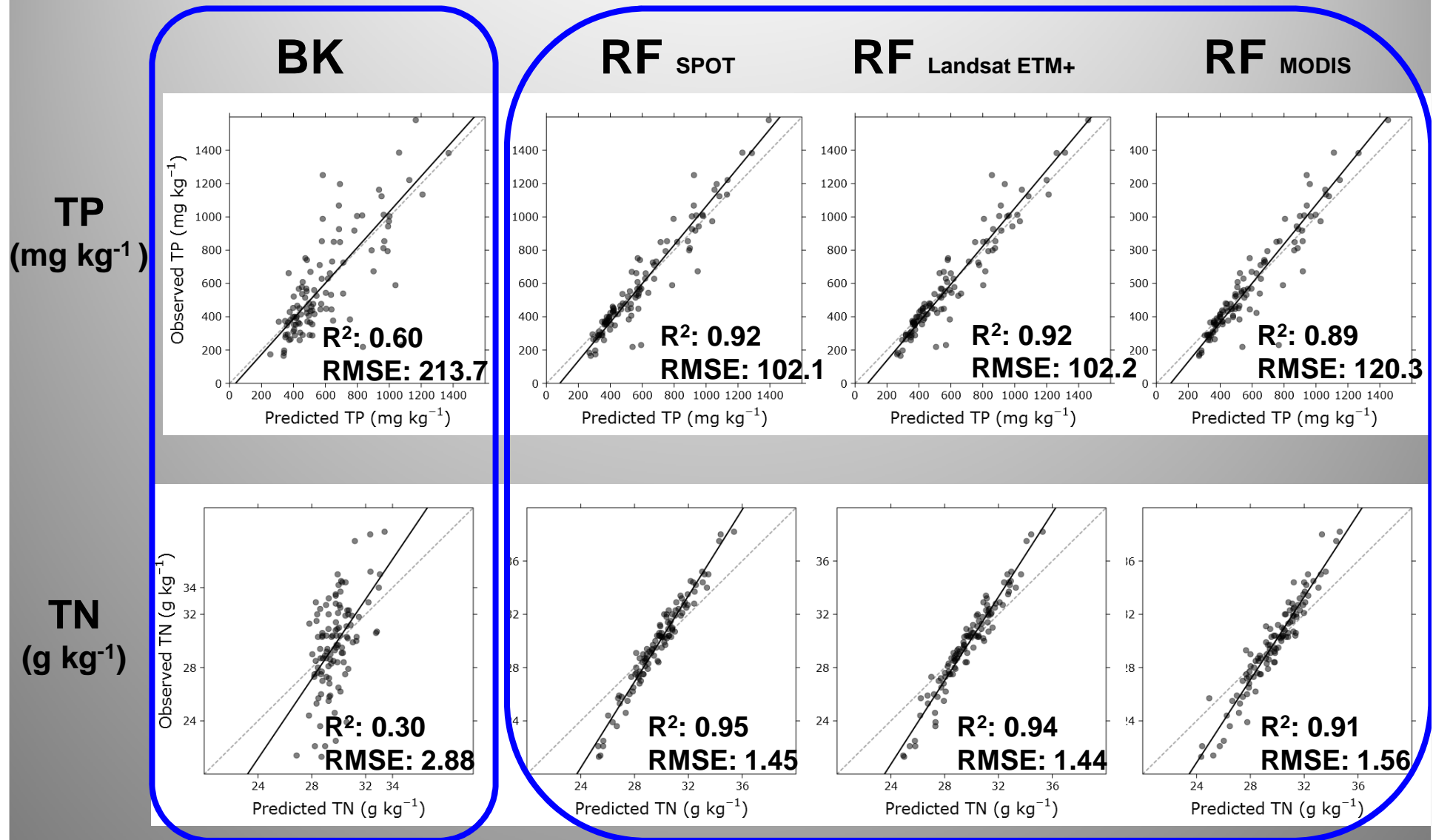
MODIS (250 m)



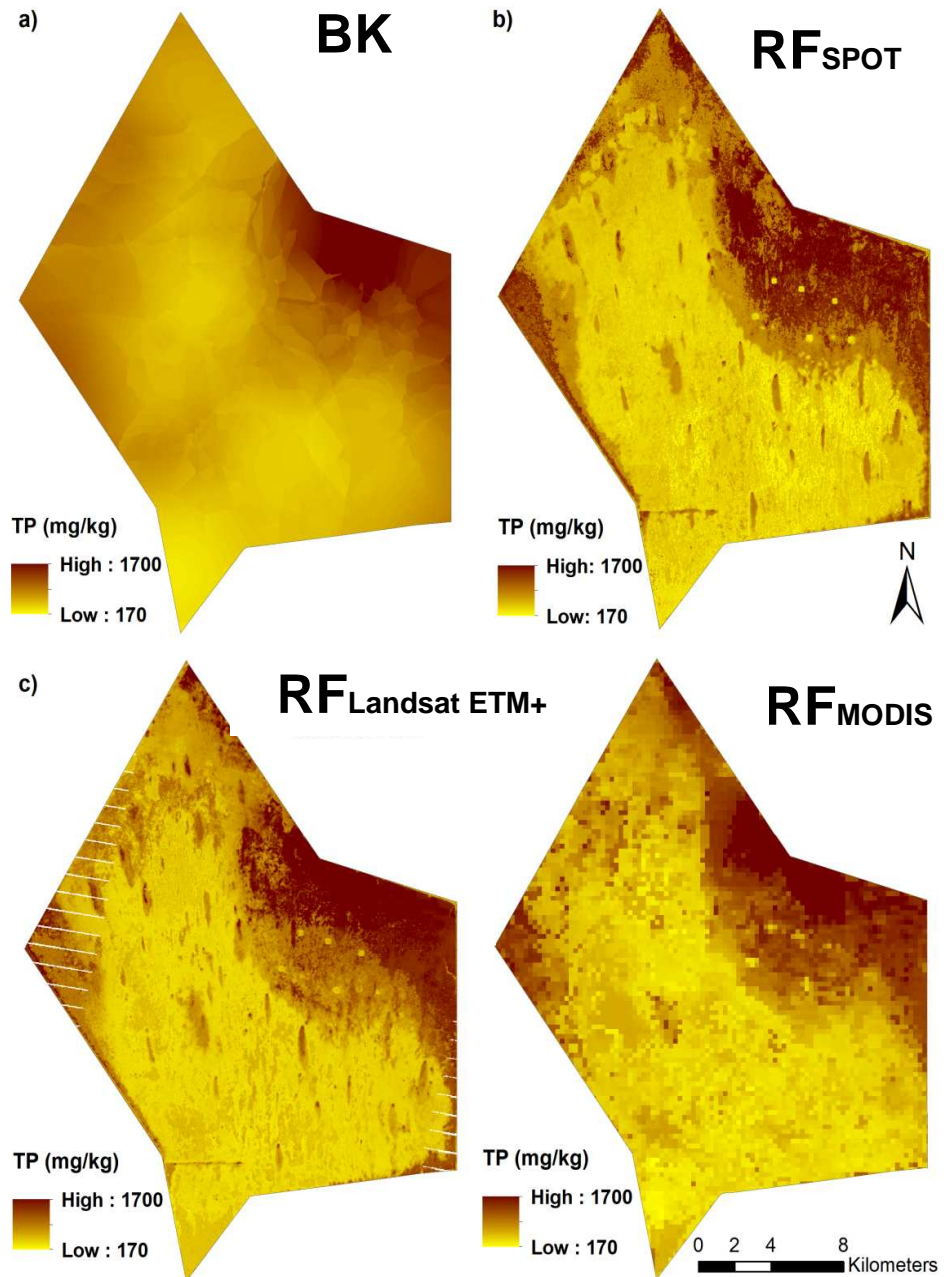
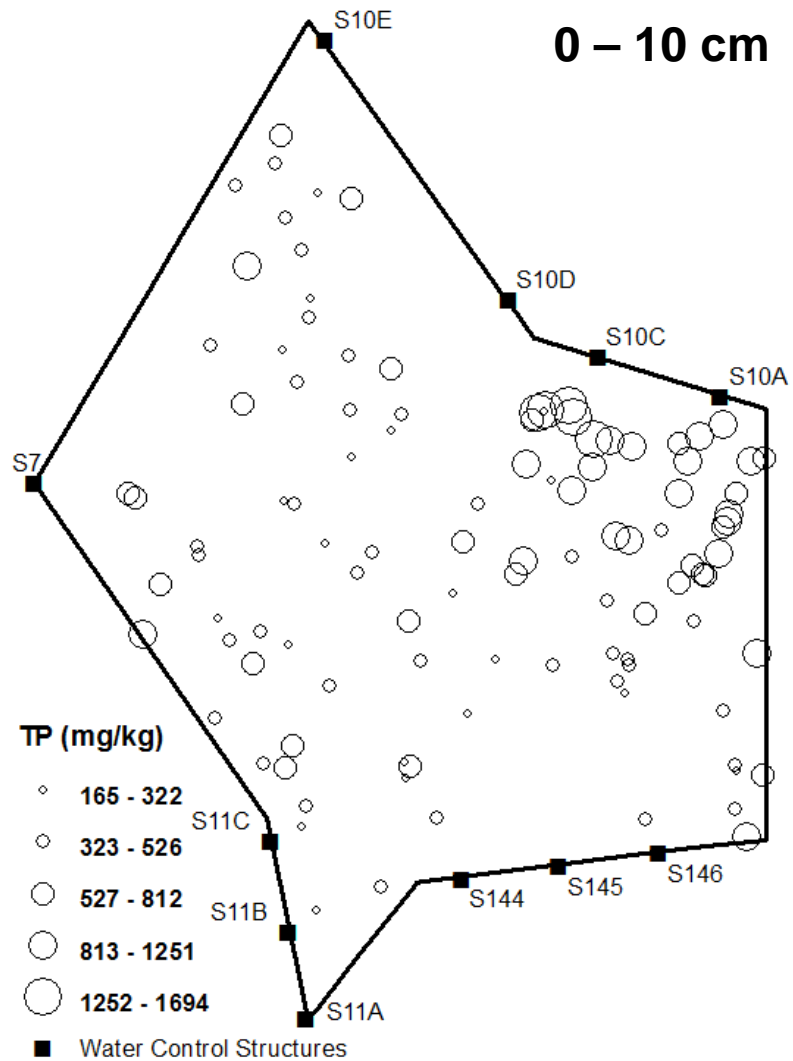
Feb. 18, 2010

Remote Sensing Supported DSM

(Kim, Grunwald and Rivero. 2013. IEEE Trans. Geosci & Remote Sensing J.)

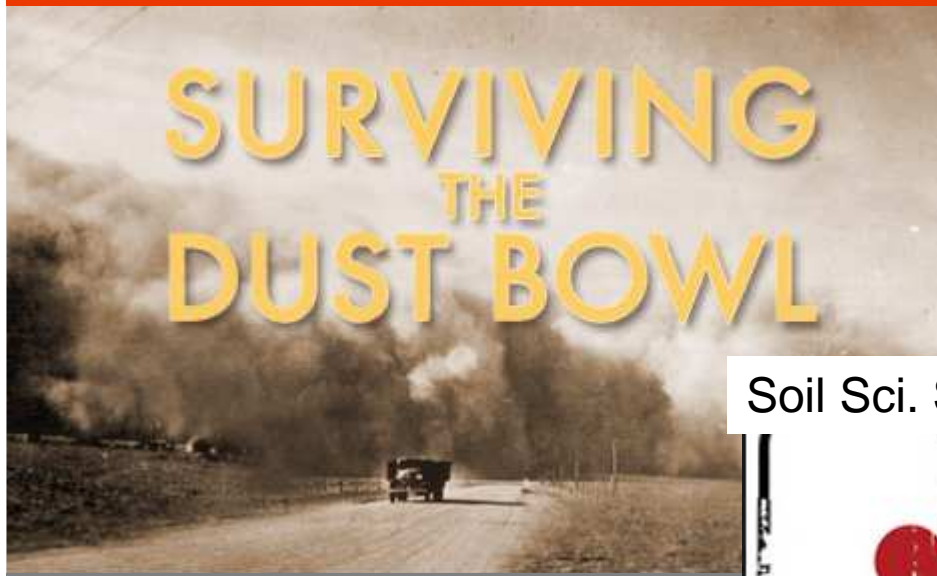


Observations (TP)



TVI, SR, and NDVI green (biotic factor) ranked high.

Soil Gaps



Soil Sci. Soc. Am.



Deep Soil Science



Human activities triggering “Global Soil Change”
(National Geographic, 2010)



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<http://soils.ifas.ufl.edu/faculty/grunwald>

