1 **Scaling impacts on environmental controls and spatial heterogeneity of soil organic carbon**
2 **stocks**

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1 **Abstract**

2   The spatial heterogeneity of land surfaces affects energy, moisture, and greenhouse gas

3 exchanges with the atmosphere. However, representing heterogeneity of terrestrial hydrological

4 and biogeochemical processes in earth system models (ESMs) remains a critical scientific

5 challenge. We report the impact of spatial scaling on environmental controls, spatial structure,

6 and statistical properties of soil organic carbon (SOC) stocks across the U.S. state of Alaska. We

7 used soil profile observations and environmental factors such as topography, climate, land cover

8 types, and surficial geology to predict the SOC stocks at a 50-m spatial scale. These spatially

9 heterogeneous estimates provide a dataset with reasonable fidelity to the observations at a

10 sufficiently high resolution to examine the environmental controls on the spatial structure of

11 SOC stocks. We upscaled both the predicted SOC stocks and environmental variables from finer

12 to coarser spatial scales (s = 100 m, 200 m, 500 m, 1 km, 2 km, 5 km, 10 km) and generated

13 various statistical properties of SOC stock estimates. We found different environmental factors

14 to be statistically significant predictors at different spatial scales. Only elevation, temperature,

15 potential evapotranspiration, and scrub land cover types were significant predictors at all scales.

16 The strengths of control (the median value of geographically weighted regression coefficients) of

17 these four environmental variables on SOC stocks decreased with increasing scale and were

18 accurately represented using mathematical functions (R^2=0.83–0.97). The spatial structure of

19 SOC stocks across Alaska changed with spatial scale. Although the variance (sill) and

20 unstructured variability (nugget) of the calculated variograms of SOC stocks decreased

21 exponentially with scale, the correlation length (range) remained relatively constant across scale.

22 The variance of predicted SOC stocks decreased with spatial scale over the range of 50 m to

23 ~500 m, and remained constant beyond this scale. The fitted exponential function accounted for

98% of variability in the variance of SOC stocks. We found moderately-accurate linear

relationships between mean and higher-order moments of predicted SOC stocks ($R^2 \sim$ 0.55-0.63).

Current ESMs operate at coarse spatial scales (50 - 100 km), and are therefore unable to

represent environmental controllers and spatial heterogeneity of high-latitude SOC stocks

consistent with observations. We conclude that improved understanding of the scaling behavior

of environmental controls and statistical properties of SOC stocks could improve ESM land

model benchmarking and perhaps allow representation of spatial heterogeneity of

biogeochemistry at scales finer than those currently resolved by ESMs.

1 Introduction

Soil organic carbon (SOC) stocks have large spatial heterogeneity globally (Todd-Brown

et al., 2013) and in the northern circumpolar permafrost region (Ping, 2013; Hugelius et al.,

2014). Achieving an accurate representation of the spatial heterogeneity of existing SOC stocks

in earth system models (ESMs) is a prerequisite for predicting future carbon-climate feedbacks

(Todd-Brown et al., 2013), given that uncertainty resulting from the distribution of SOC stocks

accounts for a large proportion of the overall uncertainty (Burke et al., 2012) in predictions of

future greenhouse gas concentrations and associated climate changes. Reliable estimates of

regional SOC stocks and their spatial heterogeneity are also essential to gaining a better

understanding of existing environmental controls of SOC stocks and their vulnerability to

changing climate (Johnson et al., 2011).

At present, large differences exist between observation-based and ESM-based SOC stock

estimates at high latitudes (Mishra et al., 2013). Several factors likely account for these

differences (Koven et al. 2013; Todd-Brown et al. 2013); the relevant factors for the current analyses are that the natural spatial variability of some environmental controls observed to affect SOC stocks are not represented in the models. One potential approach to account for spatial heterogeneity in ESMs is to incorporate the impacts of environmental controls on SOC stocks at a spatial scale consistent with the observations.

Among environmental variables, climate, topography, organisms, parent material, time, and spatial position (Jenny, 1941; McBratney et al., 2003) have widely been used to predict the spatial variability of soil properties from plot to regional scales (Thompson and Kolka; 2005; Vasques et al., 2012; Minasny et al., 2013; Mishra and Riley, 2014). At high latitudes where solar radiation and evaporation are strongly related to the geometry of the land surface (McKenzie et al., 2000), topography has been reported to play an important role in determining the level of SOC at a specific location (Jenny 1980; Birkeland, 1984; Hobbie et al., 2000). Hill slope processes, such as erosion and deposition, are related to terrain attributes, such as the soil wetness index (SWI) and sediment transport index (STI). Both the SWI and STI are strong predictors of SOC stocks and have been used extensively in digital mapping of SOC stocks at various scales (e.g., Zhu et al., 2001; Thompson et al., 2006; Adhikari et al., 2013).

Despite several global and regional studies on SOC inventories, quantitative data on the relationship between SOC stocks and the environmental controlling factors do not exist at multiple scales (Lal, 2004; Torn et al., 2009; Chaplot et al., 2010). In spatial prediction of SOC concentration and stocks, different primary and secondary topographic attributes are calculated from a digital elevation model (DEM) and used, along with other soil-forming factors such as climate, land cover type, and parent material, to predict SOC stocks across different scales (Hancock et al., 2010; Vasques et al., 2010; Kumar et al., 2012). Usually, fine-scale

1 environmental data are preferred over coarser spatial scales as they are more representative of

2 natural landscapes. However, it has also been reported that the highest scale DEMs do not

3 always produce highest accuracy in predicting soil properties and that knowledge of the

4 appropriate DEM scale for a particular landscape is important (Smith et al., 2006; Roecker and

5 Thompson, 2010). Calculated values of topographic indices of a study area differed depending

6 on the spatial scale of the DEM used (Wilson and Gallant, 2000; Thompson et al., 2001; Kienzle,

7 2004). In a recent study, Vasques et al. (2012) showed that the quality (R^2) of predicted carbon

8 stocks consistently decreased with increasing grid size of the environmental data used by the

9 models.

10   Information collected at one scale can be used to infer properties at either smaller or

11 larger scales (Beven 1995), such as when using point observations to estimate regional SOC

12 stocks, or taking areal averages of SOC stocks from ESMs and disaggregating them. The essence

13 of successful scaling is to infer the key patterns from information collected at one scale and use

14 those patterns to make inferences at another scale that maintain consistency in the desired

15 metrics across the scales (Western et al., 2002). We believe that the statistical spatial structure of

16 SOC stocks may be useful in (1) downscaling and inferring fine-scale variability from coarse-

17 scale ESM predictions; (2) model benchmarking; and (3) developing reduced order model

18 formulations relating biogeochemical processes across scales. By model benchmarking, we mean

19 using observation based scaling relationships to test the land biogeochemical representations in

20 earth system models.

21   A large literature exists on spatial scaling of soil moisture, which is a dominant control on

22 SOC dynamics and stocks. Several studies have modeled the spatial variability of soil moisture

23 patterns from relatively smaller to larger scales, and have attempted to characterize the spatial

1   structure based on system properties (Rodriguez-Iturbe et al., 1995; Peters-Lidard et al., 2001;

2   Western et al., 2002; Riley and Shen 2014; Pau et al. 2014). For some systems, soil moisture

3   spatial variance follows a power law decay as a function of spatial area (Manfreda et al., 2007),

4   although in other systems there are clear scale breaks in this relationship (e.g., Das and Mohanty,

5   2008; Joshi and Mohanty, 2010; Pau et al., 2014). Gebremichael et al. (2009) reported that, in a

6   watershed located in the Southern Great Plains of the USA, soil moisture showed scale-

7   invariance, and if the scaling parameters could be estimated from large-scale soil moisture fields,

8   it might be feasible to transform spatial soil moisture fields between scales. Despite the progress

9   made in modeling the scaling behavior of soil moisture, to our knowledge no study exists that

10   has examined the statistical structure of the scaling behavior of SOC stocks.

11   Scaling approaches might also improve prediction of the spatial structure of SOC stocks.

12   The variogram, which relates the variance of SOC stock differences between two points to the

13   distance between the two points (Webster and Oliver, 2007), is one approach to representing the

14   spatial structure of SOC stocks (Western et al., 2002). The main structural parameters of a

15   variogram are the nugget, sill, and range (Western and Bloschl, 1999; Webster and Oliver,

16   2007). A nugget shows the unexplained portion of the variance and the sill is the level at which a

17   variogram flattens and therefore represents the total variance of the variable. The nugget-to-sill

18   ratio can be used to quantify the percentage of overall variance found at a distance smaller than

19   the smallest lag interval, and to classify the spatial dependence of soil properties (Cambardella et

20   al., 1994; Mora-Vallejo et al., 2008).

21   Current ESMs operate at spatial scales larger than 50 km and use a nested subgrid

22   hierarchy approach to represent the land surface heterogeneity (Lawrence et al., 2012). ESM

23   spatial scales are becoming increasingly finer to more accurately represent the localized

features of earth systems that affect energy, water, and greenhouse gas fluxes. For example,

next generation ESMs such as those being developed by the U.S. Department of Energy

(Accelerated Climate Modeling for Energy; ACME) will have a spatial scale for the land

model of ~10 km (Bader et al., 2014). In this study, we successively increased the spatial

scale (from $s = 50$ m to 10 km) of environmental variables and used observations and

geospatial approaches to predict SOC stocks. Throughout this paper, we refer to the 'scale'

(s) as either the distance across which properties are assumed to be homogeneous or the

square root of the pixel area satisfying that criteria, and note that the terms 'scale' and

'resolution' are often interchangeable in this context. The idea was to model the change in

predicted heterogeneity of SOC stocks resulting from changing scale of the environmental

data. In this study, by the term "scaling" we mean the transfer of information about

environmental controls and statistical properties of SOC stocks from one scale to another.

We also investigated how environmental controls on SOC stocks and the spatial structure of

SOC stocks (the correlation length (range), total variance (sill), and unstructured variability

(nugget)) changed as a result of change in spatial scale of environmental variables.

2 Study approach

2.1 Soil organic carbon observations and environmental variables

We used 556 georeferenced soil profile observations by combining data from two

recently published studies of soil organic carbon stocks across Alaska (472 soil profiles from

Mishra and Riley, 2012 and 84 additional samples from a recently published database of

Michaelson et al., 2013). This database combined the U.S. Department of Agriculture's National

Resource Conservation Service's pedons with the soil pedon observations collected from the

University of Alaska Fairbanks under its northern latitudes soils program (Michaelson et al.,

1   2013). This database included measured representative soil profiles from Alaska and covered all

2   soil types at the soil suborder level (18 suborders) and all 27 major land resource areas of Alaska.

3   The observed SOC stocks showed a wide range (0.35–296 kg m^{-2}) due to varying sampling

4   depths (0.05 –4.5 m depth), various soil types with differing carbon content levels (Inceptisols to

5   Gelisols), and the large environmental heterogeneity present in the study area. About 50% of the

6   observed samples were from the 0.05 to 1 m depth interval, 41% of the samples were from the 1-

7   2 m depth interval, and the remaining samples (9%) were from the 2- 4.5 m depth interval. A

8   large number of observations had SOC stocks ≤ 50 kg m^{-2}, and about 49 samples had SOC

9   stocks greater than 100 kg m^{-2}. A majority of pedons with high SOC stocks were located in the

10   Arctic region of Alaska, which are areas with soils impacted by cryoturbation, and the majority

11   of pedons with lower SOC stocks were located in interboreal and coastal rainforests. The SOC

12   stock data has a unimodal (kurtosis, $K = 9.4$) positively skewed distribution (coefficient of

13   skewness, $S = 2$), and is unevenly distributed throughout Alaska (Fig. 1). The fine-scale (spatial

14   scale $s = 50$ m) spatially heterogeneous SOC stock estimates have uncertainty, as described by

15   the prediction errors in Mishra and Riley (2012). However, that study indicated that the SOC

16   stock estimates have reasonable fidelity with the observations withheld from the estimation

17   procedure, and therefore we believe are sufficiently accurate to be used in the scaling analyses

18   described here. As more data become available, the approaches described here to evaluate spatial

19   scaling controls can be readily re-applied.

20   We collected environmental variables of the study area from various sources. The

21   topographic attributes were derived from a digital elevation model (DEM) with a 50-m spatial

22   scale ($s = 50$ m) obtained from the U.S. Geological Survey (USGS) database (Gesch et al.,

23   2009). From the DEM, 13 topographic attributes were calculated that have been reported to be

1   useful predictors of the SOC stocks across different environmental conditions using the Spatial

2   Analyst function of ArcGIS (ArcGIS version 10.2, Environmental Systems Research Institute,

3   Inc., Redlands, CA, USA).

4   Climate data for long-term (1961−1990) average annual temperature, precipitation,

5   potential evapotranspiration (PET), and summer shortwave radiation were obtained from the

6   Scenario Network for Alaska and Arctic Planning (SNAP, 2014) database, with a spatial scale of

7    $s = 2$ km.

8   Land cover data of 60 m spatial scale ($s = 60$ m) was extracted for Alaska from the

9   National Land Cover Database (NLCD) database (Homer et al., 2007). In this study, to reduce

10   the number of categorical variables with potentially redundant information, we reclassified the

11   19 NLCD land cover types found in Alaska into 9 major categories. Thus, developed open space,

12   low intensity, medium intensity, and high intensity were classified as a developed category;

13   deciduous, evergreen, and mixed forests were classified as a forest category; dwarf scrub and

14   shrub scrub were classified as a scrub category; shrub, sedge, and moss were classified as a

15   herbaceous category; pasture and cultivated lands were classified as a cultivated category; and

16   woody and herbaceous wetlands were classified as a wetland category. In the reclassified map,

17   the category with the largest land area was the scrub category (43%), followed by forest (25%),

18   barren (8.5%), herbaceous (7%), and wetlands (7%). The remaining surface area (9.5%) was

19   under open water, perennial ice, barren land, and moss vegetation. Indicator variables for the

20   presence or absence of 7 land cover types (except open water and perennial ice) were created and

21   used in the model selection process.

22   The surficial geology data of Alaska was obtained from a USGS database (Karlstrom,

23   1964) in which the entire state of Alaska was classified into 27 different types of surficial

geology. The category with the largest land area was mountain alluvium and colluvium (22.5%),

followed by coarse rubble (19%), coastal alluvium (8.5%), glacial moraine (7%), and

undifferentiated mosaics (6%). The remaining land area (37%) was placed in the remaining

22 surficial geology types.

2.2 Spatial scaling and environmental controls

We investigated changes in environmental controls on SOC stocks at spatial scales of

100 m, 200 m, 500 m, 1 km, 2 km, 5 km, and 10 km. For this purpose, the DEM of a 50 m spatial

scale was successively aggregated to 100 m, 200 m, 500 m, 1 km, 2 km, 5 km, and 10 km using

the bilinear convolution algorithm of ArcGIS 10.2 (Fig. 2). Topographic attributes were

calculated at each spatial scale and included in predicting SOC stocks at specific scales. The land

cover types and surficial geology data were aggregated at similar scales using the nearest-

neighbors algorithm of ArcGIS 10.2 and were included in predicting SOC stocks at various

spatial scales.

Median values of the geographically weighted regression coefficients (β) of log-

transformed (natural log) SOC stock and environmental variables (that were significant at all

spatial scales) were calculated for each spatial scale. Log transformations of SOC stocks were

applied to meet the linear regression assumptions of normality and constant variance of errors.

The change in the strength of environmental controls (β's) on SOC stocks resulting from a

change in spatial scale was investigated by plotting the median values against the spatial scale at

which they were calculated. Several mathematical functions were used to represent the statistical

nature of scaling of the environmental controls on SOC stocks.

2.3 Selection of environmental predictors, prediction of SOC stocks, and variogram

modeling

We used best subset regression in SAS 9.3 (SAS Institute, 2011) to generate all possible combinations of environmental variables to predict the SOC stocks across Alaska. We used Mallows' Cp criterion to select three candidate linear models for each spatial scale for which Cp values were close to the number of predictors (Kutner et al., 2004; p.358), from which we subsequently selected one linear model for each spatial scale with uncorrelated and statistically significant environmental predictors. Presence of multicollinearity among selected environmental predictors was tested by calculating the variance influence factors (VIFs) for each of the selected variables. The VIFs for all the variables included in models selected at different spatial resolutions were < 5. High levels of multicollinearity (VIF > 10) can falsely inflate the least squares estimates (Kutner et al., 2004; O'Brien R., 2007; Gomez et al., 2013). The selected environmental predictors were then used in a geographically weighted regression approach (Mishra et al., 2012; 2014) to predict the whole profile SOC stocks across Alaska at different spatial scales using:

$$C(u_i, v_i) = \beta_o (u_i, v_i) + \sum_{i=1}^{p} \beta_k (u_i, v_i) X_k + \varepsilon (u_i, v_i)$$

where C is the SOC stock at a certain location, u_i, v_i are the geographical coordinates, X_k are the environmental predictors, p is the number of independent variables, β_o and β_k are the geographically weighted regression coefficients, and ε is the error term. We used adaptive kernel bandwidth in this study, given that the sample density varied over the study area. The optimal bandwidth was determined by minimizing the corrected Akaike Information Criterion (AICc) as described in Fortheringham et al. (2002).

1   We calculated several statistical parameters, including mean (μ), variance (σ^2), skewness

2   (S), and kurtosis (K) from the predicted SOC stocks at each specific spatial scale. The predicted

3   variances were plotted against spatial scale and a best-fit mathematical function was determined.

4   Relationships between the μ and other statistical parameters were investigated by plotting the μ

5   SOC stocks calculated at each spatial scale across Alaska versus its other statistical parameters

6   calculated at the same scale.

7   To study the change in spatial structure of SOC stocks due to spatial scaling, we

8   calculated the SOC stock variograms (Webster and Oliver, 2007) at different spatial scales:

$$\gamma(h) = \frac{1}{2n} \sum_{i=1}^{n} \{Z(X_i) - Z(X_i + h)\}^2$$

9   where $Z(X_i)$ and $Z(X_i + h)$ are the measured SOC stocks at X_i and $X_i + h$, respectively; h is the lag;

10   n is the number of paired comparisons at that lag; and $\gamma(h)$ is the semivariance. By varying h in

11   discrete steps, we obtain an ordered set of semivariances (Webster and Oliver, 1992). Suitable

12   mathematical functions were fitted to the calculated semivariance values using weighted least

13   squares (Webster and Oliver, 2007). The best-fit model parameters for each spatial scale are

14   provided in Table 2. We examined the change in correlation length (range), total variance of

15   SOC stocks (sill), and the unstructured variability (nugget) resulting from the change in the

16   spatial scales of environmental variables. A variable is considered to have a strong spatial

17   dependence if the nugget-to-sill ratio is less than 0.25; a moderate spatial dependence if the ratio

18   is between 0.25 and 0.75; and otherwise a weak spatial dependence (Cambardella et al., 1994;

19   Mora-Vallejo et al., 2008). Range, which is also referred as correlation length, is the distance at

20   which the sill is reached and represents the maximum extent of the spatial correlation between

predicted SOC stocks. The change in the spatial structure of variability of SOC stocks was evaluated using the nugget-to-sill ratio and the correlation length.

3 Results

3.1 Inferred environmental controls on SOC stocks change with scale

The set of significant environmental predictors and their individual strengths varied with spatial scale. Statistically significant environmental predictors at different spatial scales and the predicted variance of SOC stocks are summarized in Table 1. From the 13 topographic attributes, 5 attributes—elevation (meters), slope (degree), aspect (degree from north), soil wetness index (SWI), and sediment transport index (STI)—were significant predictors of SOC stocks at various spatial scales. Among land cover types, barren, scrub, herbaceous, and cultivated land covers were significant predictors. Among different climatic factors, surface air temperature and potential evapotranspiration were significant predictors. Among surficial geology types, the glacial moraine, fluvial, undifferentiated mosaic, coastal delta, and volcanic mountain types were significant predictors at various spatial scales. Among all of the environmental variables investigated in this study, only elevation, temperature, potential evapotranspiration, and scrub land cover types were significant predictors of SOC stocks at all spatial scales. In general, at finer spatial scales, controls of topographic attributes were more prominent, whereas land cover and surficial geology types were more significant predictors at coarser scales ($\geq$ 500-m spatial scale). Fewer environmental variables controlled the variability of SOC stocks at finer spatial scales, whereas the number of predictors increased at larger spatial scales.

Our results showed that the strength of the control (median geographically weighted regression coefficient across Alaska) of elevation on SOC stocks decreased by 31% as the spatial

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1   scale increased from 50 m to 1 km. Beyond this scale, we found no change in the control of

2   elevation on predicted SOC stocks (Fig. 3a). The control of temperature on SOC stocks

3   decreased with spatial scale between 50 m and 500 m and became constant at larger scales (Fig.

4   3b). The controls of elevation and temperature on SOC stocks across spatial scales can be

5   accurately modeled by using exponential functions with R^2=0.83 and 0.94, respectively. The

6   control of potential evapotranspiration decreased by 36% as the spatial scale increased from

7   50 m to 500 m, and became constant beyond 500 m (Fig. 3c). The control of potential

8   evapotranspiration on SOC stocks across spatial scales can be modeled by using an exponential

9   decay function (R^2=0.97). The control of scrub vegetation (shrubs less than 5 meters tall) on

10   SOC stocks decreased linearly (from 0.3-0.13) with scale over the range 50 m to 10 km (Fig. 3d).

11   At finer scales, scrub vegetation showed higher control on SOC stocks, which decreased by

12   about 57% as the scale increased. Despite the observed decrease in control of scrub vegetation on

13   SOC stocks due to scaling, the relationship between scrub vegetation and SOC stocks remained

14   positive. The control of scrub vegetation on SOC stocks can be modeled using a linear function

15   (R^2=0.85).

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17   **3.2 Scaling impacts on the spatial structure of SOC stocks**

18   The variogram summarizes the statistical structure of spatial variability and is known as a

19   summarizing function of the investigated property. For the predicted SOC stocks, the variograms

20   at finer-scales showed significant amount of unexplained variance (nugget) (Table 2) due to

21   measurement errors and/or microscale spatial heterogeneity not captured across the study area.

22   Both the nugget and sill decreased as the scale increased from finer to coarser spatial scales. The

23   nugget and sill decreased by 75% and 64% respectively as s increased from 50 m to 500 m and

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1   remained constant beyond 500 m scale (Fig. 4a). The relationship between these variogram

2   parameters and scale can be accurately described using exponential functions with R^2 of 0.98.

3   The correlation length of SOC stocks remained relatively constant up to about 1100 -1400 km

4   across spatial scales (Fig. 4b). The nugget-to-sill ratio of predicted SOC stocks at 50 m and 100

5   m spatial scales showed moderate spatial dependency (i.e. a nugget-to-sill ratio >25%;

6   Cambardella et al., 1994). However, strong, and relatively similar, spatial dependency (a nugget-

7   to-sill ratio ≤ 25%) was predicted for spatial scales between $s = 200$ m and s = 10 km (18–21%;

8   Table 2). These results suggest that the predicted SOC stocks show different spatial structure

9   below $s = 100$ m as compared to $s \geq 200$-m.

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11   **3.3 Statistical behavior of spatial scaling of SOC stocks**

12   We found different statistical properties in predicted SOC stocks as the spatial scale of

13   environmental variables increased. The variance of predicted SOC stocks decreased by 45% as

14   the scale increased from 50 m to 500 m and remained constant beyond 500 m (Fig. 5). An

15   exponential function based on spatial scale accounted for 98% of variability in the variance of

16   predicted SOC stocks across Alaska. These results suggest that the spatial heterogeneity of SOC

17   stocks decreases exponentially with scale until about 500 m. Beyond this scale, no change in the

18   spatial heterogeneity of SOC stocks was predicted. The higher-order moments (skewness S and

19   kurtosis K) of the predicted SOC stocks decreased as the spatial scale increased (Fig. 6a). S

20   decreased from 1.4 to 0.8 as the scale increased from 50 m to 200 m; and fluctuated between

21   1.25 and 0.74 as the scale increased further. K decreased from 5.7 to 3.6 as the scale increased

22   from 50 m to 200 m and fluctuated between 5.1 and 3.68 beyond a scale of 200 m.

We evaluated the relationships of mean SOC stocks (μ) generated at each spatial scale

with σ^2, S, and K. Within the investigated range of μ SOC stocks (45.7 to 50.4 kg m^{-2}), we found

moderately-accurate linear relationships between μ and σ^2, S, and K of predicted SOC stocks,

with R^2 values of 0.59, 0.63, and 0.55, respectively (Figs. 6 b-d). Significant negative slopes of

these relationships indicate that as μ increases the higher-order moments of SOC stock decrease,

and therefore the μ of SOC stocks can be used to predict SOC spatial heterogeneity.

4 Discussions

Soil organic carbon lies at the interface between the atmosphere and pedosphere and can

be altered at time scales relevant to climate change by anthropogenic and climatic factors. As a

result, the spatial heterogeneity of SOC stocks may affect the magnitude of greenhouse gas

fluxes from the land surface and the terrestrial carbon cycle.

Several studies have demonstrated the impact of DEM scale on calculated topographic

attributes (Thompson et al., 2001; McMaster, 2002; Smith et al., 2006; Roecker and Thompson,

2010). However, very little attention has been paid to the impact of scaling on environmental

controls and the predicted spatial heterogeneity of soil properties. We found that apparent

significant environmental controllers of high-latitude SOC stocks changed with scale. Our

findings are consistent with the results of Vasques et al. (2012), who showed inconsistent

controls of various tropical-system environmental factors in predicting SOC stocks as the scale

of environmental variables increased from 30 m to 1,920 m. Due to a lack of other scaling

studies examining the change in environmental controllers of SOC stocks, we compared our

results with findings from two studies that reported environmental controllers of SOC stocks at

two different scales. Johnson et al. (2011) reported that at the plot scale (~ 1 m^2), surface air

temperature, topographic attributes, and soil texture were primary controllers of SOC stocks

across Alaska. Similarly, Martin et al. (2011) predicted SOC stocks at 12 km scale over France,

and reported land use and clay content to be important drivers of SOC stock spatial variability.

Our results at 50 m and 10 km scales are partially consistent with these findings, showing

significant controls of temperature, land cover types, and topographic attributes on SOC stocks.

Our results showed that the strength of controls of environmental factors that were significant

decreased as spatial scale increased. The largest decrease was found in the control of scrub land

cover type, and the smallest decrease was found in the control of temperature. The rates of these

changes can be modeled using simple mathematical functions.

The scaling properties of soil moisture have been widely studied (Western and Boschl,

1999; Isham et al., 2005; Famiglietti et al., 2008; Li and Rodell, 2013). Some studies reported

that the variance of soil moisture follows a power law relationship with surface area (Rodriguez-

Iturbe et al. 1995; Manfreda et al., 2007), while others have shown non-simple scaling (Joshi and

Mohanty, 2010; Riley and Shen 2014; Pau et al. 2014). Beven (1995) pointed out that it is

unlikely that any general scaling theory can be developed because of the dependence of

hydrological systems on geological perturbations, and advocated for a disaggregation approach

to develop scale-dependent models to represent hydrological heterogeneity. These studies

suggested that further work focusing on the factors influencing soil moisture (topography,

vegetation, soil properties, and rainfall) is expected to increase understanding of the mechanisms

affecting the scaling properties of soil moisture.

Keeping these inferences in mind and that soil moisture is an important control on SOC

dynamics, in this study we used the soil-forming factors that have been documented to affect

SOC stocks to study the spatial scaling behavior of SOC stocks. However, in contrast to soil

moisture, our results show that the variance of SOC stocks follows an exponential decay with spatial scale up to about 500 m, and then remains constant thereafter. We interpreted environmental controllers on SOC stocks in an equilibrium sense; i.e., over hundreds to thousands of years these controllers are expected to be related to observed SOC stocks. However, transient responses are not expected to follow the same scaling properties, given likely changes in thermokarst formation and other hydrological and geomorphological changes at high latitudes.

The spatial structure of SOC stocks results from the spatial structure of soil-forming factors (Jenny, 1941; McBratney et al., 2003). Besides the state factors described in the Introduction, SOC stocks of Alaska and other arctic regions are also impacted by cryopedogenic features (pingos, frost boils, hummocks) and thermal surface erosion resulting from the freezing and thawing of the polygonal land surface (Tarnocai and Bockheim, 2011; Ping et al., 2008; Ping 2013). In this study, the spatial organization of predicted SOC stocks increased with spatial scale as indicated by moderately lower nugget-to-sill ratios for spatial scales >200 m. However, the correlation length remained relatively constant in the upscaled SOC stocks across Alaska.

One potential approach to represent the spatial heterogeneity of soil properties in ESMs is to relate their statistical properties to the mean state. As an analogy, several soil moisture studies investigated the relationships between soil moisture mean and higher-order statistics, such as σ^2, S, and K (Famiglietti et al., 1999; Ryu and Flamiglietti, 2005; Famiglietti et al., 2008; Li and Rodell, 2013). The results from these studies suggest that the mean of soil moisture is often related to its σ^2, S, and K, although with different functional forms depending on various system properties. Our results indicate a moderate but statistically significant linear relationship between the mean and higher-order moments of SOC stocks (i.e., σ^2, S, and K decrease linearly with the mean SOC stock within the range of mean SOC stocks investigated in this study (45.5 – 50.4 kg

m^{-2})). The strength of the linear relationship was highest between μ and S (R^2=0.63, P<0.01), and lowest between μ and K (R^2 =0.55, P<0.05). However, available observations are insufficient to determine whether the same relationship holds with dynamically changing mean SOC stocks, highlighting an area of further investigation.

Current land models integrated in ESMs, such as CLM4.5 (Lawrence et al., 2012; Koven et al., 2013; Tang et al., 2013), use a nested subgrid hierarchy approach to represent the land surface heterogeneity. In this approach the grid cells (~1° x 1°) are divided into nonspatially explicit land units (such as vegetated, lakes, urban, glacier, and crops), columns (with variability in hydrological, snow, and crop management), and plant functional types (accounting for variations in broad categories of plants and bare ground). We have shown here that this type of representation does not characterize the environmental controls and scaling properties of SOC stocks; rectifying this problem would require substantial restructuring of the model's subgrid hierarchy. One potential application of the relationships we developed in this study could be to apply them with coarse-resolution ESM results in order to generate fine-scale spatial heterogeneity parameters of SOC stocks that are more representative of the natural landscape. Currently the land models of most ESMs have a spatial scale of ≥ 50 km. In the next 5-10 years, we believe ESM land models will function much closer to the resolution we identify in our study as being representative of the SOC landscape heterogeneity (~10 km; Bader et al., 2014). As the model resolution becomes finer in next generation ESMs, datasets such as the one we describe in this study will be critical for model benchmarking. ~~Therefore our results will be directly relevant to next generation ESMs which will operate at high resolution (~10 km) (Bader et al., 2014).~~ We note that many environmental factors that we found significant at various scales are not

represented in current land models. However, representing these factors in future land model developments can improve our understanding of SOC dynamics of arctic/boreal systems.

Median values of regression coefficients of different environmental controls might change if a global or continental scale study would have been conducted. Other environmental factors which are not significant predictors of Alaskan SOC stocks might become significant in different study domains such as in temperate and tropical ecosystems. Therefore extending this kind of scaling study in larger spatial domains might produce more important information to benchmarking ESM results. We note this as a limitation to our study and recommend further work studies is required to investigate these factors in other systems and at larger spatial extents.

Soil texture has also been reported to be related to SOC stocks. To investigate the use of soil texture in our scaling study, we collected the soil texture data currently used in CLM 4.5 (Bonan et al., 2002) that was available at ~8 km spatial resolution across Alaska. However, this data has approximately one soil texture value in each Alaska ecoregion implying that the data must have been derived from a source with a much coarser spatial resolution (International Geosphere-Biosphere Programme soil dataset that had 4931 soil mapping units globally; CLM 4.5 Technical notes). Because of this limitation, we were unable to include soil texture in the current scaling study. However, if soil texture information becomes available at finer spatial scales, it could be readily incorporated in future studies using the methods described here.

5 Summary and conclusions

Understanding the spatial scaling structure of SOC stocks and their relationships with environmental factors is important for prediction of carbon-climate feedbacks under a changing climate. Here, we estimated the spatial scaling properties of environmental factors and statistical

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properties of SOC stocks. We conclude that environmental controllers of SOC stocks change

with scale, and the strength of environmental controls can be accurately modeled using simple

mathematical functions. The variance of predicted SOC stocks decreases exponentially with

scale up to about 500 m, and then remains constant thereafter. Our results showed that the mean

predicted SOC content is linearly related with its variance, skewness, and kurtosis. If the

objective of a study is to represent the spatial heterogeneity of SOC stocks resulting from

environmental factors, the prediction spatial scale should be finer than ~500 m. Similarly, the

choice of environmental predictors should be based on the intended final spatial scale of

predicted SOC stocks. Therefore, the current subgrid structure of many ESM-scale land models

does not allow for characterization of the environmental controls and scaling properties affecting

SOC stocks. The findings of this study may help to develop scale-appropriate techniques for

ESM-scale land models and ultimately reduce the existing uncertainties in carbon-climate

feedback predictions.

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Table 1: Environmental predictors and predicted variance of soil organic carbon stocks across different spatial scales. Black dots represent statistically significant (P<0.05) predictors.

Environmental Variables	Spatial Scale							
	50 m	100 m	200 m	500 m	1 km	2 km	5 km	10 km
Elevation	●	●	●	●	●	●	●	●
Slope								●
Aspect	●							
SWI	●			●			●	
STI				●				
Temperature	●	●	●	●	●	●	●	●
PET	●	●	●	●	●	●	●	●
Barren	●	●	●			●		●
Scrub	●	●	●	●	●	●	●	●
Herb						●		
Pasture						●	●	
Glacial Moraine				●	●		●	●
Fluvial				●	●	●	●	●
Undifferentiated Mosaic							●	
Coastal delta						●		●
Volcanic mountain						●	●	
Predicted variance	476.5	354	304	263	261	257	256.4	258

Table 2: Modeled variogram parameters of predicted soil organic carbon stocks at various spatial scales.

Spatial scale (m)	Nugget (Ln kg m^{-2})^2	Sill (Ln kg m^{-2})^2	Nugget/Sill (%)	Range (km)
50.00	0.12	0.45	27	1,484
100.00	0.07	0.26	27	1,094
200.00	0.04	0.20	19.5	1,126
500.00	0.03	0.16	18	1,124
1,000.00	0.03	0.15	19	1,078
2,000.00	0.04	0.17	21	1,170
5,000.00	0.03	0.16	20.5	1,174
10,000.00	0.03	0.16	19	1,129

1 **Figure Legends**

2 Figure 1. Spatial distribution of observation sites, histogram, and summary statistics of observed

3 SOC stocks across Alaska.

4 Figure 2. The spatial scaling approach used in this study. The black dot represents the location of

5 an SOC sampling site, and the rectangles denote different pixel sizes of environmental variables

6 (the rectangles do not represent exact scale).

7 Figure 3. Control of environmental factors on SOC stocks as a function of spatial scale. Each dot

8 is a median geographically weighted regression coefficient (β) for a particular spatial scale. The

9 fitted functions are: (a) Elevation $\beta = -0.0009 + 0.0003*(1-\exp(-0.0089*s)$, adjusted $R^2 = 0.83$,

10 $P < 0.004$, (b) Temperature $\beta = -0.11 + 0.037*(1-\exp(-0.012*s)$, adjusted $R^2 = 0.94$, $P < 0.001$,

11 (c) Potential evapotranspiration $\beta = 0.066 + 0.187*\exp(-0.035*s)$, adjusted $R^2 = 0.97$,

12 $P < 0.001$, (d) Scrub $\beta = 0.395 - 0.0696*s$, adjusted $R^2 = 0.85$, $P < 0.001$.

13 Figure 4. Change of variogram parameters with scale (a), and calculated variograms of log-

14 transformed predicted SOC stocks (b) at spatial scales of 50 m, 100 m, 200 m, 500 m, 1 km,

15 2 km, 5 km, and 10 km. Fitted functions are: Sill $= 0.163 + 0.763*\exp(-0.0197*s)$, adjusted $R^2 =$

16 0.98, $P < 0.001$; Nugget $= 0.032 + 0.201*\exp(-0.016*s)$, adjusted $R^2 = 0.98$), $P < 0.001$.

17 Figure 5. Variance of soil organic carbon stocks as a function of spatial scale. Each dot is

18 predicted variance of SOC stock at each spatial scale across Alaska. The fitted function is: SOC

19 variance $= 260.61 + 422.42*\exp(-0.0318*s)$, adjusted $R^2 = 0.98$, $P < 0.001$.

20 Figure 6. Higher-order moments of predicted SOC stocks as a function of spatial scale (a), and

21 relationships between predicted mean SOC stocks and its (b) variance, (c) skewness, and (d)

22 kurtosis within the range of predicted mean values of SOC stocks.
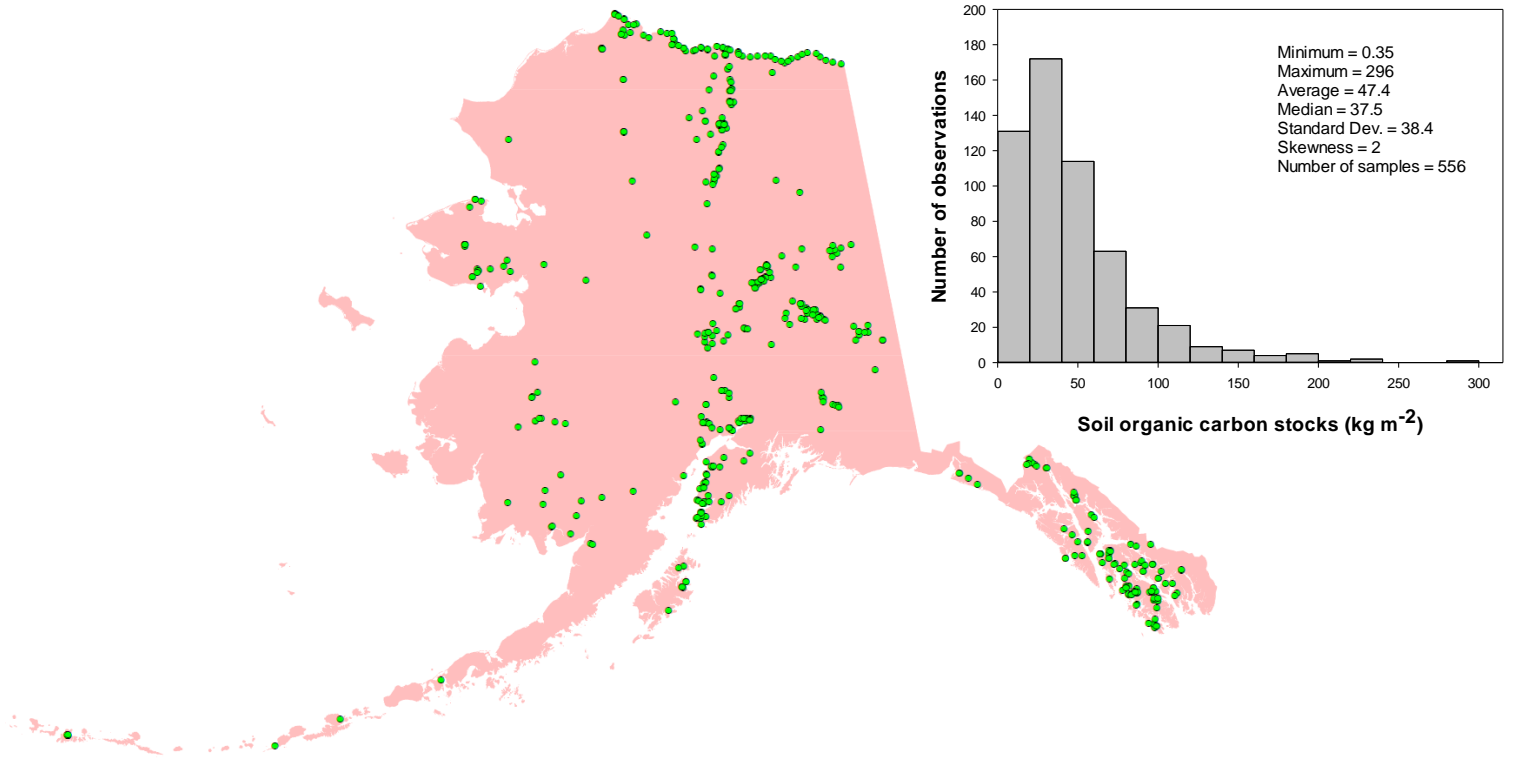
Figure 1:

| 50 | 100m | 200m | 500m | 1 km | 2 km | 5 km | 10 km |

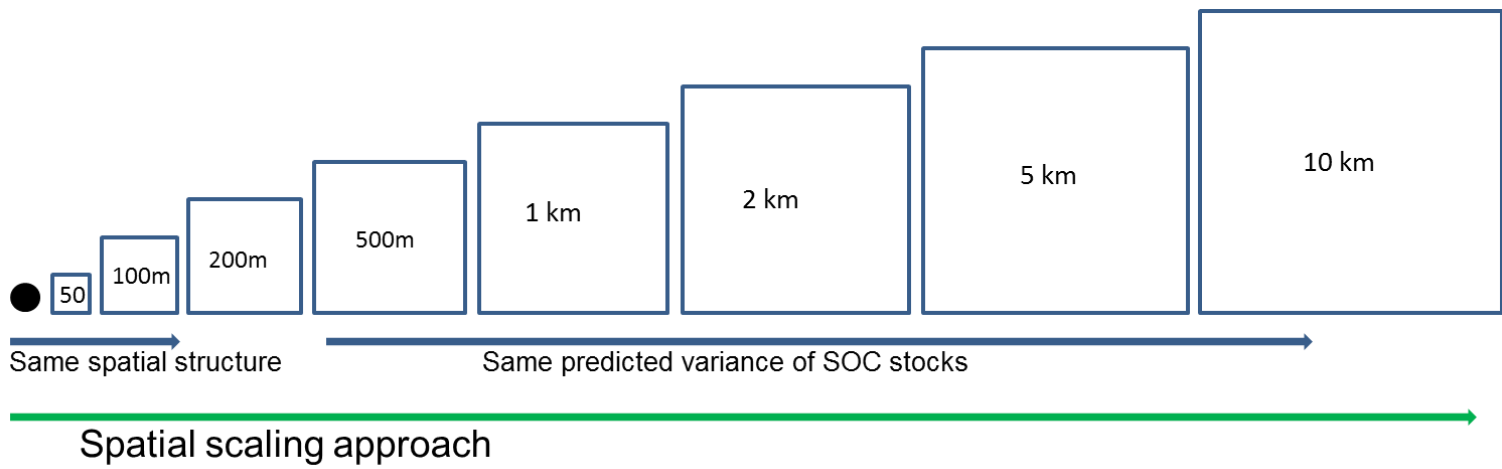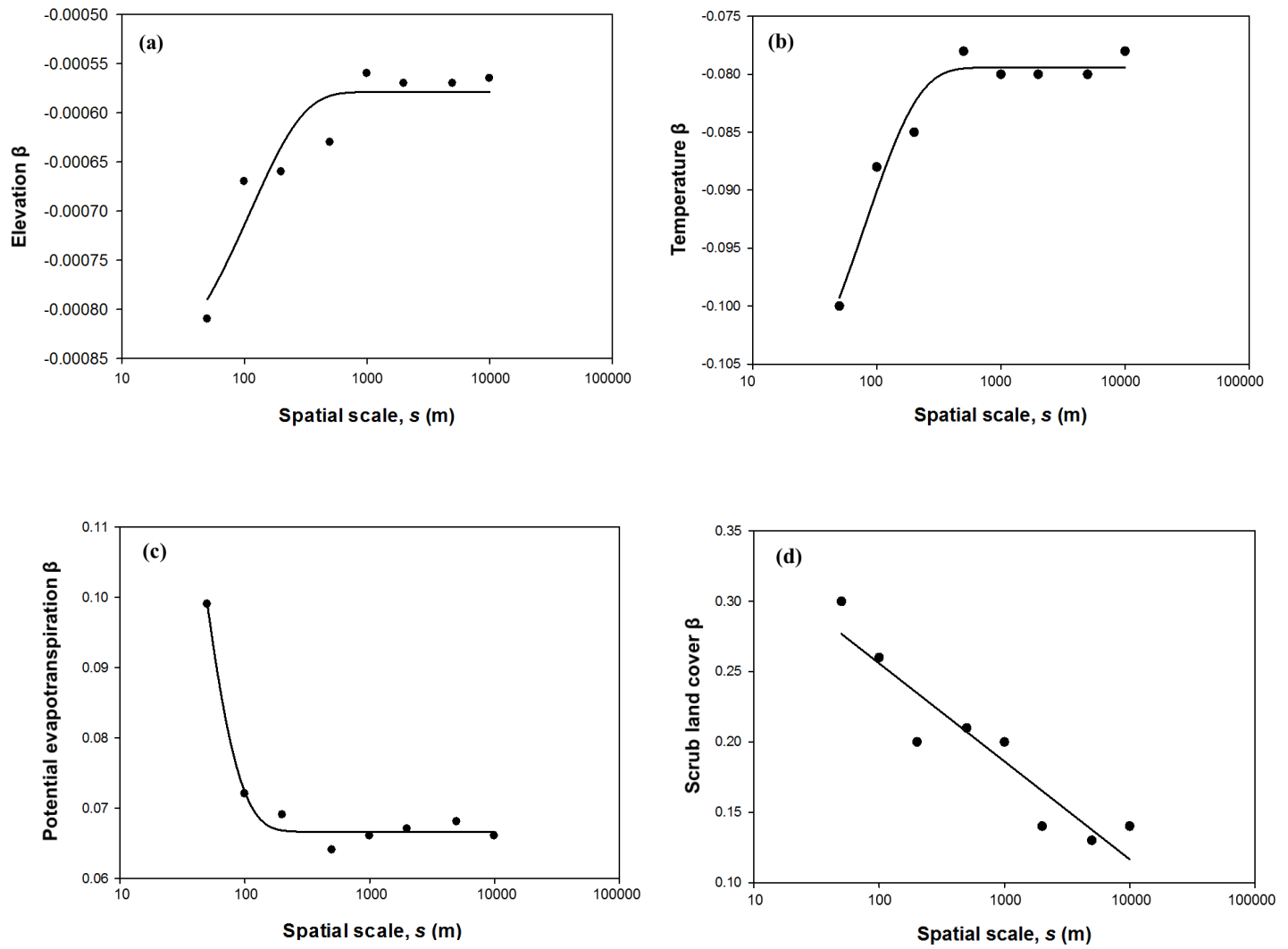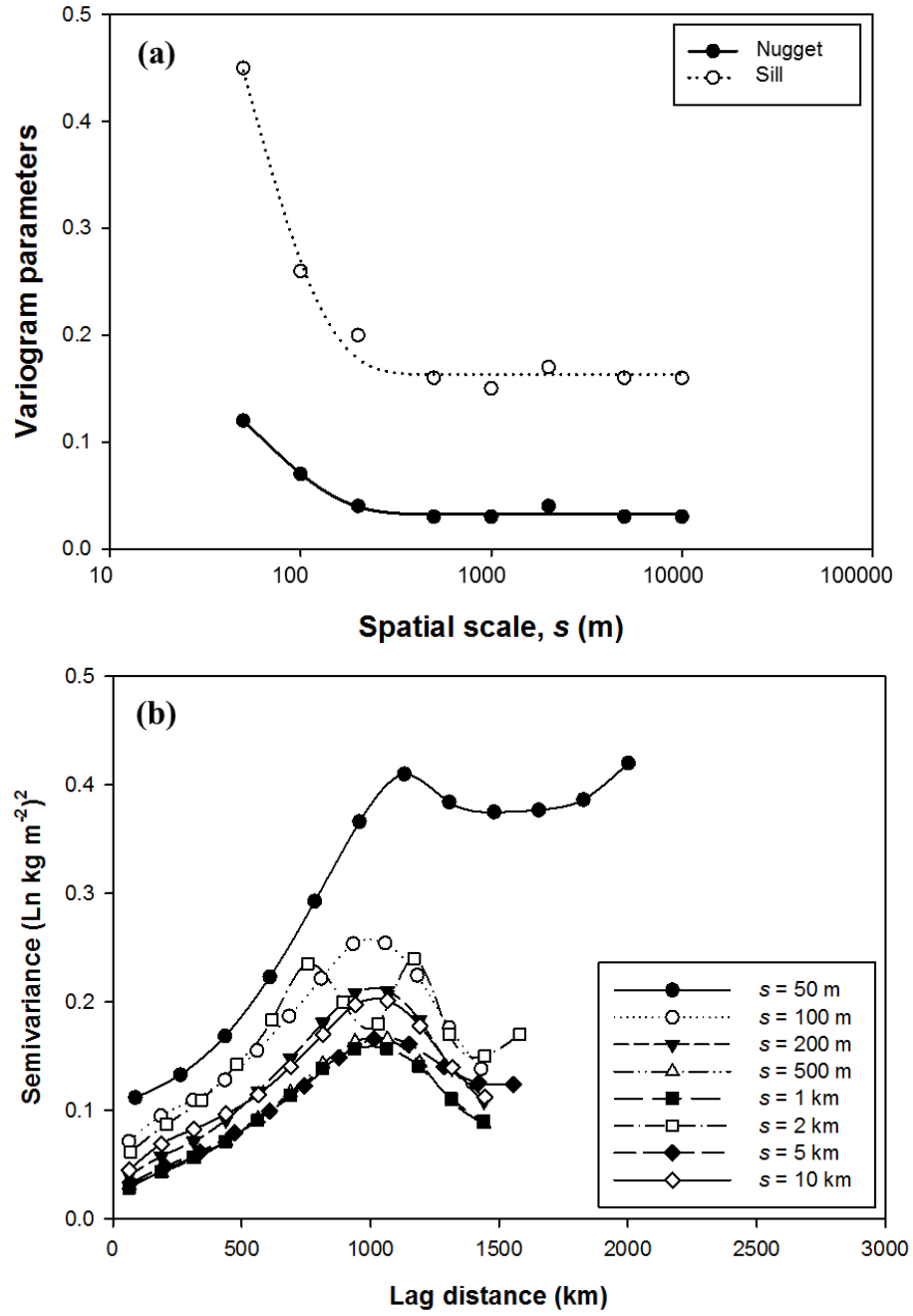Same spatial structure   Same predicted variance of SOC stocks

Spatial scaling approach

Figure 2:

Figure 3:

Figure 4:

Figure 5:

Figure 6: