Soil & Tillage Research 156 (2016) 194–208

Contents lists available at ScienceDirect

Soil & Tillage Research

journal homepage: www.elsevier.com/locate/still

Towards mapping soil carbon landscapes: Issues of sampling scale and transferability

Bradley A. Miller[a,*], Sylvia Koszinski[a], Wilfried Hierold[a], Helmut Rogasik[a], Boris Schröder[b,c], Kristof Van Oost[d], Marc Wehrhan[a], Michael Sommer[a]

[a] Leibniz Centre for Agricultural Landscape Research (ZALF), Institute of Soil Landscape Research, Eberswalder Straße 84, 15374 Müncheberg, Germany
[b] Technische Universität Braunschweig, Institute of Geoecology, 38106 Braunschweig, Germany
[c] Berlin-Brandenburg Institute of Advanced Biodiversity Research (BBIB), 14195 Berlin, Germany
[d] Université Catholique de Louvain, George Lemaitre Center for Earth and Climate, Earth and Life Institute, 1348 Louvain-la-Neuve, Belgium

ARTICLE INFO

Article history:
Received 2 March 2015
Received in revised form 16 June 2015
Accepted 5 July 2015
Available online 22 July 2015

Keywords:
Soil mapping
Sampling design
Spatial regression
Kriging
Estimated error
Uncertainty
Spatial autocorrelation
Spatial association

ABSTRACT

The conversion of point observations to a geographic field is a necessary step in soil mapping. For pursuing goals of mapping soil carbon at the landscape scale, the relationships between sampling scale, representation of spatial variation, and accuracy of estimated error need to be considered. This study examines the spatial patterns and accuracy of predictions made by different spatial modelling methods on sample sets taken at two different scales. These spatial models are then tested on independent validation sets taken at three different scales. Each spatial modelling method produced similar, but unique, maps of soil organic carbon content ($SOC_{\%}$). Kriging approaches excelled at internal spatial prediction with more densely spaced sample points. Because kriging depends on spatial autocorrelation, kriging performance was naturally poor in areas of spatial extrapolation. In contrast, the spatial regression approaches tested could continue to perform well in spatial extrapolation areas. However, the problem of induction allowed the potential for problems in some areas, which was less predictable. This problem also existed for the kriging approaches. Spatial phenomena occurring between sampling points could also be missed by kriging models. Use of covariates with kriging can help, but the requirement of capturing the full feature space in the map remains. Methods that utilize spatial association, such as spatial regression, can map soil properties for landscape scales at a high resolution, but are highly dependent on the inclusion of the full attribute space in the calibration of the model and the availability of transferable covariates.

1. Introduction

Erosion and deposition processes redistribute large amounts of mineral soil and soil organic carbon (SOC) across agricultural landscapes (Van Oost et al., 2007). SOC dynamics at the landscape scale show fluctuations in space and time that challenge research on soil and SOC erosion (Kirkels et al., 2014). A key component for monitoring carbon dynamics in soil landscapes is converting point observations to areally extensive maps. This transition from sample points to a geographic field necessitates some type of spatial prediction. Reasons of practicality limit the quantity of points that can be sampled and fewer samples mean the map must depend more upon the spatial prediction methods (Webster and Oliver, 1990). Nonetheless, the design of sampling locations can be done strategically to optimize their utility for the spatial model. Previous studies have examined the effect of sampling distribution within the same extent (spatial domain) with respect to different modelling methods (Mueller and Pierce, 2003; Corwin et al., 2010; Schmidt et al., 2014). However, for mapping landscapes, issues of scale, representativeness, and uncertainty become increasingly important and that is the focus of this research.

Methods for spatial prediction commonly described as spatial interpolation (e.g., inverse distance weighting, kriging) rely on spatial autocorrelation (Burgess and Webster, 1980; Goovaerts, 1999; Schloeder et al., 2001). For this reason, greater sampling density increases the spatial support of the model and prediction error increases with distance away from sampling points. Similarly, because these methods are intended only for spatial interpolation, they are considered inappropriate for extrapolating beyond the extent of the sampling points.

Recognizing the utility of spatial association approaches used in traditional soil mapping (Odeh et al., 1994; McBratney et al., 2003),

* Corresponding author. Fax: +49 33432 82280.
E-mail address: miller@zalf.de (B.A. Miller).

http://dx.doi.org/10.1016/j.still.2015.07.004
0167-1987/

some varieties of kriging leverage spatial covariates to improve predictions. Examples of approaches that incorporate spatial association with spatial autocorrelation include co-kriging (McBratney and Webster, 1983; Juang and Lee, 1998) and universal kriging (Hengl et al., 2007; Li et al., 2015). The covariates used are typically more easily measured than the target variable and thus usually have better spatial coverage than samples of the target variable. However, spatial autocorrelation still has an important role in all forms of kriging. Thus kriging at the landscape scale continues to present a conflict between the size of the mapping extent and the number of observations that need to be taken to produce an adequate sample density for the desired range of uncertainty.

Approaches that rely more purely on spatial association have become more quantitative and are using more sophisticated techniques of predictor identification and spatial modelling. Some examples include spatial regression or environmental correlation (McKenzie and Austin, 1993; Moore et al., 1993), regression trees (Adhikari et al., 2014; Lacoste et al., 2014; Miller et al., 2015a), random forests (Vasques et al., 2010; Häring et al., 2012; Schmidt et al., 2014), boosting algorithms (Häring et al., 2014) and artificial neural networks (Tamari et al., 1996; Behrens et al., 2005). In contrast to spatial autocorrelation techniques' characteristic of prediction error increasing with distance from samples, spatial association techniques' error depends on the model's ability to fit equations to the full feature space using available covariates. However, spatial autocorrelation would still suggest that areas further away are more likely to be outside the feature space of the sampled area. For these reasons, studies have recommended stratification of the feature space to optimize sampling designs for models utilizing this prediction strategy (Gessler et al., 1995; Hengl et al., 2003).

Comparison of resulting maps should consider several factors. Typically maps produced by models are evaluated by error statistics for a single set of validation points, which provides a quantitative comparison. However, spatial model realizations can have similar performance metrics at the designated validation points while still representing differing spatial structures (Mueller and Pierce, 2003; Corwin et al., 2010 Adhikari et al., 2013). This aspect can have implications for the interpretation of landscape processes and the eventual use of the map, which should not be overlooked. Similarly, different combinations of sampling designs and spatial modelling methods will have different patterns of error magnitude, which can also have bearing on the suitability of the map for the desired purpose (McBratney et al., 2000). This study considers each of these criteria in its comparison of maps for $SOC_{\%}$ at multiple scales.

We focus on the attribute of soil organic carbon content ($SOC_{\%}$) in the topsoil because of its importance in monitoring and modelling carbon dynamics in soil landscapes. The highest concentrations and thus the largest storage of carbon is in the topsoil. However, $SOC_{\%}$ can be highly spatially variable, which greatly impacts the mass balance of carbon at the landscape scale. This soil property has been heavily-sampled for the CarboZALF project under different sampling designs for different research purposes. Therefore, these samples provide a unique opportunity for comparing the nature and performance of spatial modelling methods with respect to samples taken at different scales. The objective of this study is to evaluate six spatial models, built from two sample sets taken at different scales, in terms of their prediction performance as well as the distribution and reliability of their error estimations. As the spatial scales of the calibration and validation point sets are shifted, the degree of extendibility or transferability of the models is uniquely tested.

2. Methods

2.1. Study area

Situated in the Northeast German Plain, the site for this study belongs to the main experimental area of the Leibniz Centre for

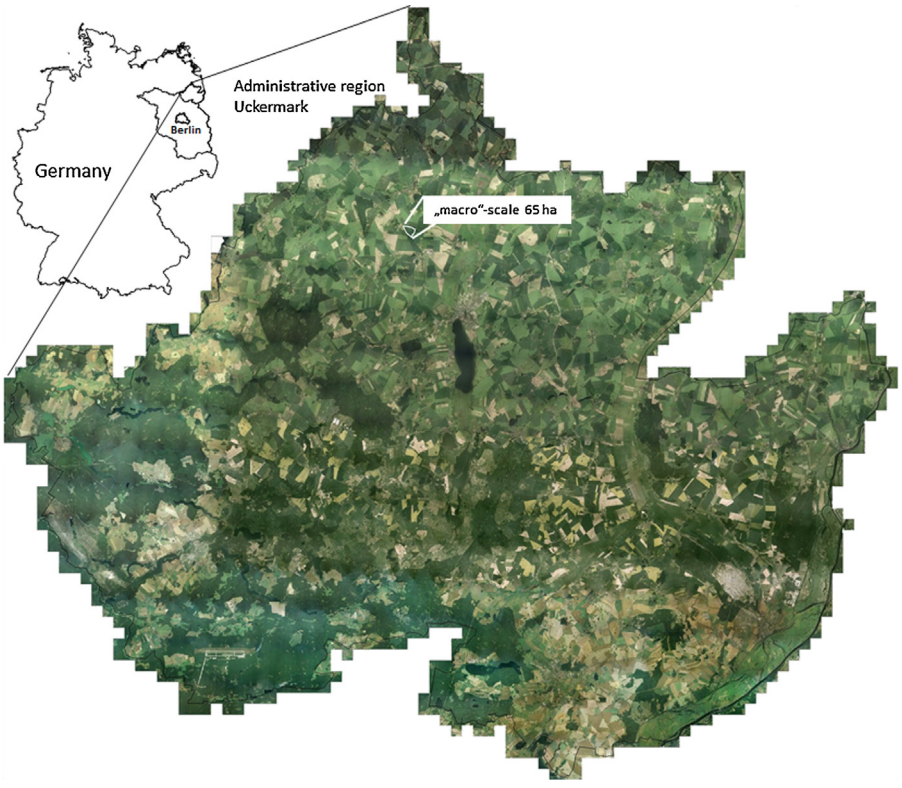

Fig. 1. Location of study area within the Uckermark district of northeast Germany.