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Institute of Soil Landscape Research

Issues of Sampling Scale and Transferability for Digital Soil Mapping

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Purpose

The conversion of point observations to a geographic field is a necessary step in soil mapping. Addressing issues of sustainability requires soil mapping at the landscape scale. Such an endeavor, however, needs to consider relationships between sampling scale, representation of spatial variation, and accuracy of estimated error. Also, the importance of extending information from sampled points increases with larger map extents due to limitations in practical sampling density. Therefore, the purpose of this research is to examine the ability of different spatial models to predict a soil property for a range of scales and for areas beyond the sampling extent. The accuracy of model error estimations is also tested.

Study Area

Soil organic carbon content ($SOC_{\%}$) has been intensively sampled at the CarboZALF research site under different sampling strategies for a variety of projects. This collection of data provided a unique opportunity to test the sampling scale's affect on a variety of spatial prediction methods.

Stratified randomly sampled points taken at two different scales were used as separate calibration sets. Independent sample sets taken on grids at two different scales were used for validation. The macro-scale points served as an additional validation test for the models calibrated by the meso-scale points.

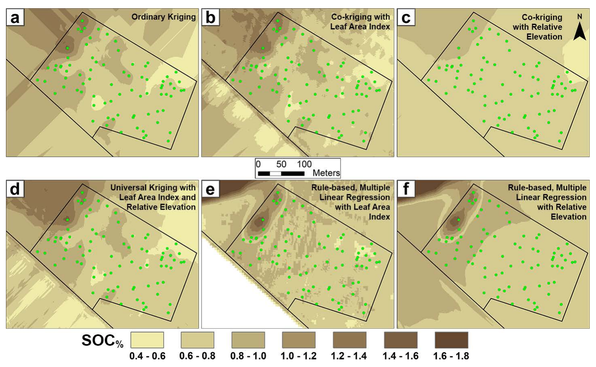
Methods

Tested spatial modelling methods included ordinary kriging (OK), co-kriging (CK) with the leaf area index (LAI), CK with relative elevation (REL), universal kriging (UK) with both of the covariates used with CK, as well as rule-based, multiple linear regression (MLR) with LAI and REL, separately. Selection of these covariates was done by Cubist as part of the MLR model construction.

Resulting Maps

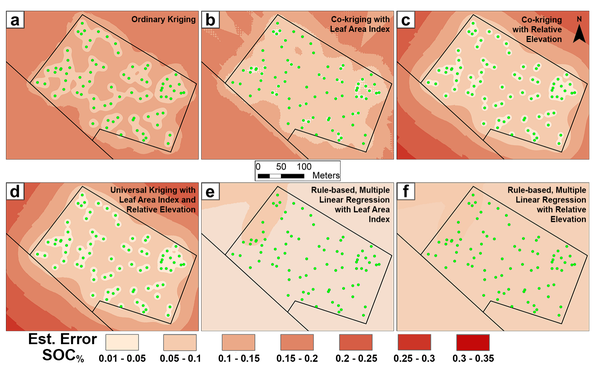
For the most part, differences in the maps highlight the known limitations of the respective modelling methods. Spatial autocorrelation methods (i.e. kriging) are not suited for predicting areas outside the sampling extent. Spatial association methods (i.e. spatial regression) require calibration on the full feature space of the area being mapped. Although this suggests that spatial regression methods have the greatest potential for transferability, greater distances from the calibration area still increase the chances of encountering problems of induction, i.e., it is difficult to predict patterns/relationships that have not been observed. However, comparison with validation points and known landscape features within these map areas demonstrated that distance is not a requirement for encountering the problem of induction.

Meso-scale



Performance (R^2)	Validation Points				
Models	Micro	Meso-All	Meso-Internal	Meso-External	Macro
a) OK	0.56	0.61	0.71	0.05	0.00
b) CK-LAI	0.57	0.60	0.71	0.03	0.03
c) CK-REL (5200m)	0.54	0.54	0.70	0.06	0.02
d) UK-LAI & REL (5200m)	0.55	0.55	0.71	0.06	0.05
e) MLR- LAI	0.59	0.55	0.61	0.28	0.34
f) MLR- REL (5200m)	0.58	0.45	0.48	0.04	0.32

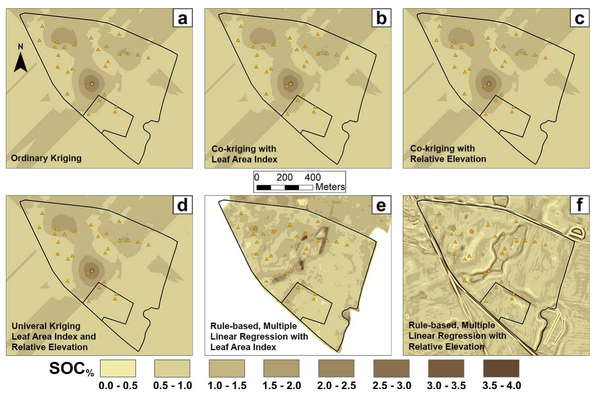
In general, all the models performed similarly at most validation scales. The notable exceptions were the stronger performance of kriging for meso-internal validation and some resilience of the MLR models in spatial extrapolation areas.



Accuracy of Error Estimation	Models					
	OK	CK-LAI	CK-REL	UK	MLR-LAI	MLR-REL
Micro Validation						
Mean Est. Error	0.096	0.066	0.057	0.056	0.085	0.093
Within Range	59%	45%	37%	34%	58%	70%
Meso-Internal Validation						
Mean Est. Error	0.098	0.067	0.058	0.056	0.078	0.090
Within Range	73%	61%	57%	54%	56%	56%
Macro Validation						
Mean Est. Error	0.160	0.149	0.262	0.259	0.084	0.092
Within Range	21%	21%	25%	25%	29%	29%

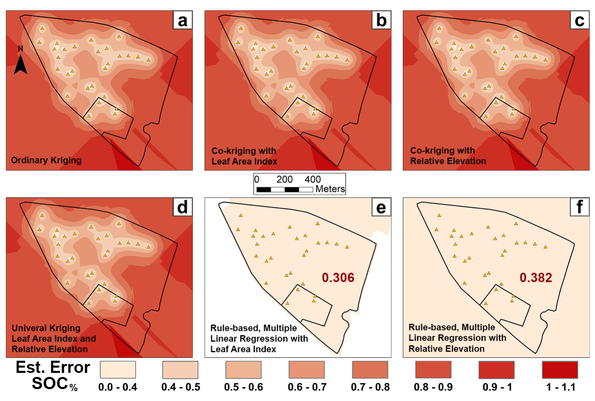
Theoretically, observed error should be within the range of the estimated error approximately 68% of the time. Kriging with covariates reduced estimated error at validation points, but those were underestimations of the observed error. As expected, more distant spatial extrapolation greatly reduced the models' ability to estimate their prediction errors.

Macro-scale



Performance (R^2)	Validation Points			
Models	Micro	Meso-All	Meso-Internal	Meso-External
a) OK	0.41	0.39	0.42	0.07
b) CK-LAI	0.41	0.39	0.43	0.06
c) CK-REL (20m)	0.41	0.39	0.42	0.07
d) UK-LAI & REL (20m)	0.41	0.39	0.43	0.06
e) MLR- LAI	*0.57*	*0.56*	*0.56*	*0.56*
f) MLR- REL (20m)	0.28	0.01	0.06	0.03

Although the models calibrated on the macro-scale points did not perform as well on the same validation points as the meso-scale models, the performance was still very similar across modelling methods. The major exception was the consistent strength of the MLR-LAI model (italics) and the greatly reduced performance of the MLR-REL model.



Accuracy of Error Estimation	Models					
	OK	CK-LAI	CK-REL	UK	MLR-LAI	MLR-REL
Micro Validation						
Mean Est. Error	0.587	0.587	0.587	0.587	0.306	0.382
Within Range	100%	100%	100%	100%	86%	90%
Meso Validation						
Mean Est. Error	0.631	0.631	0.631	0.631	0.306	0.382
Within Range	98%	98%	98%	98%	96%	76%

Error estimations by models calibrated on the macro-scale points were an order of magnitude larger than those made by the meso-scale models. However, these tended to be overestimations of the error observed at the validation points. The distribution of estimated error for the kriging models showed the expected pattern of reliance on spatial autocorrelation, but also indicated that the covariates were not very influential in those models. The estimated error for the MLR models did not vary because both models only used one rule.

Conclusion

Despite their different strategies, all spatial modelling approaches are susceptible to the problem of induction. Although standard metrics of prediction performance were generally similar across modelling methods, spatial regression showed the capability of being resilient in areas that were technically outside the sampled feature space. Although this ability is dependent on the covariates used, it can be a benefit to digital soil mapping where the problem of induction is a constant issue.

ZALF-Kernthema 1 Landscape Functioning

Verbundprojekt *(Carbon)Biogeochemistry of Landscapes*

Querschnittsprojekt *LandStructure*

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