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Field-scale digital soil mapping of mobile zinc: Combining different digital covariates and comparing geostatistical and machine learning models

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Abstract

It is well documented that the yield of cultivated crops decreases when the amount of mobile zinc in the soil is insufficient. Digital mapping techniques are needed to identify areas with a shortage of plant nutrition elements. In the present research, data collected from the Novosibirsk region (Russia) (50 observations) were used to compare the accuracy of geostatistics (Ordinary kriging (OK)) and machine learning approaches (Lasso Regression (LR) and Random Forest (RF)) to map the concentration of mobile zinc in the upper horizon of the soils in order to determine which method generates maps more accurately. The effectiveness of vegetation indices and morphometric relief factors for digital mapping was assessed using machine learning methods. Fifteen vegetation-based indices were calculated by Landsat 8 OLI (resolution 30 m). Ten morphometric relief parameters were calculated using the digital elevation model SRTM v.3. In the determination of mapping performance of the machine learning and geostatistics techniques for soil mobile zinc, coefficient of determination (R^2), root mean square error (RMSE), and normalized root mean square error (NRMSE) were used through the k-fold cross-validation (n:10, repeated:5). The results of the three models showed that the LR model with lower RMSE (0.43 mg kg^{-1}) and NRMSE (17%) was the best for soil mobile zinc content prediction. The LR and RF models had the advantage of spreading the prediction results over a large area and can be used with fewer samples. The method of OK does not have such advantages, since a large number of samples are needed for its implementation, therefore is not economically profitable. The use of digital mapping methods in agricultural practice is justified since it allows for the management of plant production processes by detecting soil boundaries with a deficit of particular plant nutrition elements on the maps and considered to be key agronomic strategies.

Keywords: Covariates selection, Digital soil mapping, Lasso regression.

Introduction

Micronutrients play an important role in the life of all living organisms, as they affect growth and development, increase yield and product quality (Sharma et al., 2022). Among all micronutrients, zinc plays a special role, since chlorosis (gray-green spots) appears on the leaves of plants grown on soils with insufficient zinc content, after which the leaves die off, which leads to a decrease in the area of the assimilating surface of the leaves and a decrease in yield (Drobkov, 1958). When the amount of other macro- and micronutrients is sufficient for growing crops, then the loss of the crop due to a lack of zinc in the soil is not an economically beneficial event. Therefore, the use of digital mapping methods in the field of agricultural practice is justified and allows you to manage the production process of plants by identifying soil areas with a shortage of certain plant nutrition elements on maps and carrying out appropriate agronomic measures. There are many methods of digital soil mapping, but each of them has its advantages and disadvantages. The disadvantages of geostatistics include the need for a large number of test points, while machine learning methods allow you to make maps with a smaller sample. Both methods depend on georeferenced dataset; however, there is no need of spatial dependency on machine learning (Mendes et. all, 2020). The machine learning approach evaluates the spatial heterogeneity of soil properties according to the SCORPAN model using auxiliary variables, such as morphometric relief parameters calculated from digital elevation models (DEM), as well as vegetation cover parameters calculated from satellite images (Mendes et al., 2020; Kaya et al., 2022).

To understand which method builds maps more accurately, this study evaluates the accuracy of using geostatistics and machine learning to map the content of mobile zinc in the upper horizon of the soil. We have constructed maps of the content of soil mobile zinc by comparing three methods: Ordinary Kriging, Lasso Regression and Random Forest.

Material and Methods

Study area and sampling data

The study area is located in the Novosibirsk oblast (Russian Federation) in a field with a total area of 116 hectares, where 50 samples were taken from the upper soil horizon (depth 0-30 cm) with the coordinate reference of sampling sites using Garmin eTrex Vista GPS receiver. (Figure 1). The study area belongs to the forest-steppe zone with the denudational-accumulative relief.

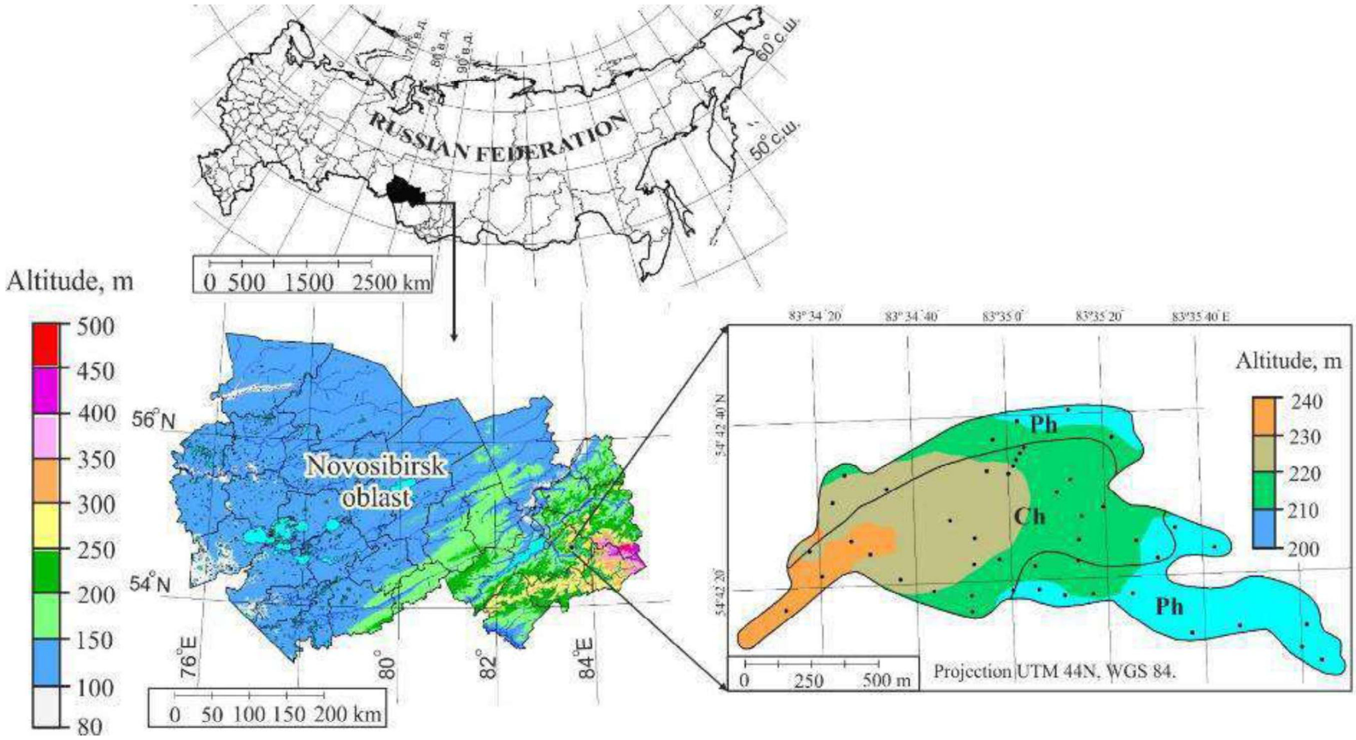

Figure 1. Location of study area with using the DEM (SRTM v.3) as background. Abbreviation: Ch – Luvic Greyzemic Chernozems (Siltic, Aric, Pachic); Ph – Luvic Retic Greyzemic Phaeozems (Siltic, Aric).

According to the international soil classification WRB (IUSS Working Group WRB, 2014), the following soils are distributed in the studied field: Luvic Greyzemic Chernozems (Siltic, Aric, Pachic) and Luvic Retic Greyzemic Phaeozems (Siltic, Aric). The soils are developed from loesslike calcareous loams. The humus content in Luvic Greyzemic Chernozems varied from 3.3 to 7.8%; in Luvic Retic Greyzemic Phaeozems from 2.5 to 5.9% (Gopp and Savenkov 2019).

Mobile form of zinc was extracted from soils samples with an ammonium acetate buffer solution (1 M CH_3COONH_4, pH 4.8), after which its concentration in the solution was determined on an atomic absorption spectrometer.

The degree of intensity of variation (CV, %) was assessed according to the scale proposed by Eliseeva and Yuzbashev (2002): CV<10 %, weak; CV from 10 to 25%, moderate; CV>25%, strong. The correlation analysis was performed using Spearman's rank correlation coefficient (*rs*) with a significance level $p < 0.05$.

Covariates used for DSM

The digital soil mapping approach is based on the SCORPAN concept (soil, climate, organisms, topography, parent material, and spatial location) (McBratney et al., 2003). The satellite-based vegetation indexes production process and all morphometric topographic variables were calculated using the System for Automated Geoscientific Analysis (SAGA) software (Conrad et al. 2015). The WGS 1984 UTM Zone 44N (EPSG :32644) system was used and all covariates used in this study were aligned to the same grid cell resolution (30 m) and extent.

Modelling process

Lasso regression and Random Forest (RF) were used to digital mapping and identify the relationship between soil mobile zinc content (mg kg^{-1}) and covariates. Besides, a linear geostatistical interpolation technique based on weighting the sums of values at adjacent sampled points, ordinary kriging was conducted.

When using LR and RF methods, the usefulness of vegetation indices and morphometric terrain parameters for digital mapping was evaluated. Vegetation indices (NDVI (Normalized Difference Vegetation Index), TVI (Transformed Vegetation Index), DVI (Difference Vegetation Index), TVI (Transformed Vegetation Index), RVI (Ratio Vegetation Index), SAVI (Soil Adjusted Vegetation Index), NRVI (Normalized Ratio Vegetation Index), TSAVI2 (Transformed Soil-Adjusted Vegetation Index), PVI (Perpendicular Vegetation Index), EVI (Enhanced Vegetation Index), MSAVI2 (Modified Soil-Adjusted Vegetation Index) were calculated by Landsat 8 OLI (resolution 30 m) by use SAGA GIS software (Conrad et al. 2015). Morphometric relief parameters (Slope, Aspect, Topographic Wetness Index (TWI), LS-Factor, Stream Power Index (SPI), Topographic Position Index (TPI), Channel Network Base Level (CNBL), Profile Curvature (PrCu), Plan Curvature (PlCu), Convergence Index (CI)) were calculated using the digital elevation model SRTM v.3. (resolution of 2"×1" arcsec at the latitude of Novosibirsk oblast, or about 35×30 m) by use SAGA GIS software.

Comparative modeling approaches were applied for different algorithms to reveal different relationships in a particular field (Wadoux et al., 2021). Conditions with high correlations between environmental variables may generally exist. Accordingly, feature selection algorithms were run in two different machine learning algorithms before modeling in this study. Lasso regression models are called as the regularized or penalized regression model (Ferhatoglu and Miller, 2022). In particular, Lasso is so powerful that it can work for multicollinearity dataset in which the number of variables (Figure 2). Before conducting random forest algorithm, the variable selection was applied with the "rfe" (recursive feature elimination) function in R core environment program (Kuhn 2020) (Figure 3). Lasso regression algorithm were conducted through the "glmnet" (Friedman et. al., 2010; Simon et al., 2011) package and random forest algorithm were conducted through the "randomForest" (Breiman, 2001) package in the R Core Environment program. The importance of the covariates used in the model were calculated using the "VarImp" and "importance" functions in R Core Environment program (R Core Team, 2022). Ordinary kriging was perfomed in Surfer 8.0 software. To evaluate the performance of three various modelling techniques used in this study, statistical criteria including coefficient of determination (R^2), root mean square error (RMSE), and normalized root mean square error (NRMSE) 10-fold cross-validation and five repeatedly calculated (Sakhaee et al., 2022).

Results and Discussion

Descriptive statistics of soil mobile zinc content are given in table 1. According to the gradations (Eliseeva, Yuzbashev, 2002), the intensity of variation was strong and amounted to 56.98%.

Table 1. Descriptive statistics of soil mobile zinc content of the current study area

Variable	Mean	SD	CV	Minimum	Median	Maximum	Skewness	Kurtosis
SI	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}		
Zn	0.93	0.53	56.98	0.34	0.73	2.87	1.79	3.22

Abbreviation: SD: Standard Deviation, CV (%): Coefficient of Variation, Zn: mobile zinc.

According to the gradations of soil mobile zinc provision (Methodological Guidelines, 2003), the studied soils are mostly low provision (less than 2 mg kg^{-1}), with the exception of insignificant areas, where the provision was average (from 2.1 to 5.0 mg kg^{-1}) (Table 1, Figure4). In these areas where the content of soil mobile zinc was higher, the values of vegetation indices (for example NDVI) were also higher (rs=0.48). At the same time, the correlation of mobile zinc with the content of clay (rs=-0.66), available phosphorus (rs=0.59), pre-sowing moisture (rs=0.44) and nitrate nitrogen (rs=0.50) was established (Gopp and Savenkov 2019). The considered soil properties can also be as a covariate for soil mobile zinc however, we tried to find such covariates only among the satellite-based remote sensing and DEM data. Figures 2 and 3 show the results of selecting the most effective covariates used in the LR and RF models.

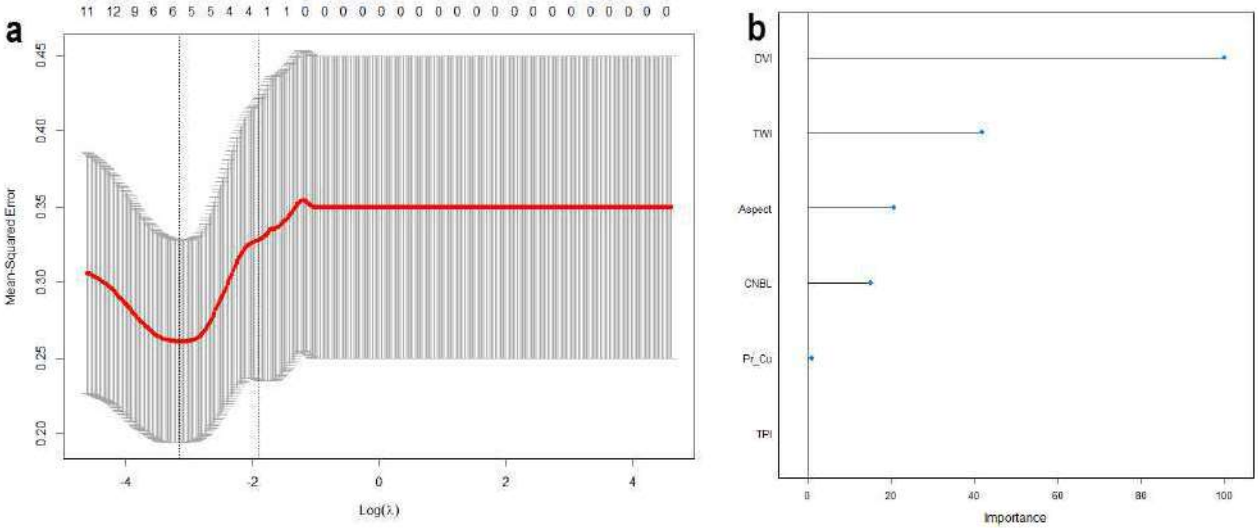

Figure 2. Lasso regression covariate selection results and importance of predictors in modelling process
Abbreviation: DVI: Difference Vegetation Index, TWI: Topographic Wetness Index, CNBL: Channel Network Base Level, Pr_Cu: Profile Curvature, TPI: Topographic Position Index.

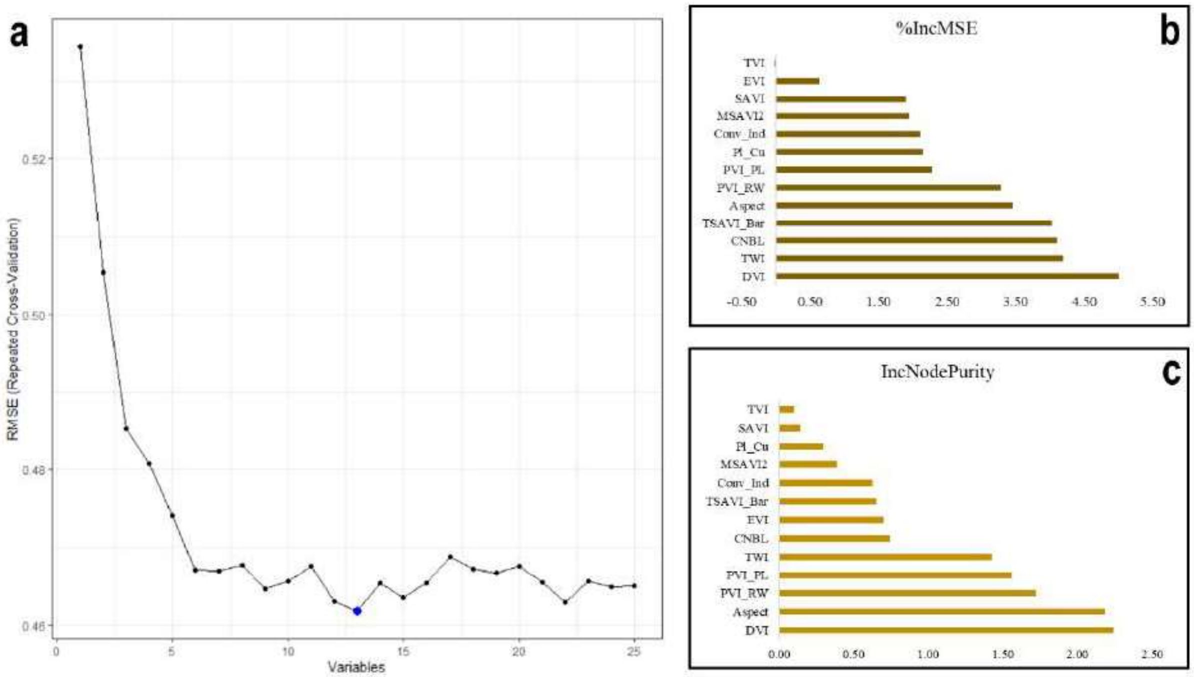

Figure 3. Random forest regression covariate selection results and importance of predictors in modelling process
Abbreviation: DVI: Difference Vegetation Index, PVI_PL: Perpendicular Vegetation Index by Perry and Lautenschlager (1984), PVI_RW: Perpendicular Vegetation Index by Richardson and Wiegand (1977), MSAVI2: Modified Soil-Adjusted Vegetation Index, TVI: Transformed Vegetation Index, SAVI: Soil Adjusted Vegetation Index, TWI: Topographic Wetness Index, CNBL: Channel Network Base Level, EVI: Enhanced Vegetation Index, TSAVI_Bar: Transformed Soil-Adjusted Vegetation by Barret and Guyot (1991), MSAVI2: Modified Soil-Adjusted Vegetation Index, SAVI: Soil Adjusted Vegetation Index, Pl_Cu: Plan Curvature, Conv_Ind: Convergence Index.

Maps constructed by three methods can be considered useful for assessing the content of soil mobile zinc (Fig. 4).

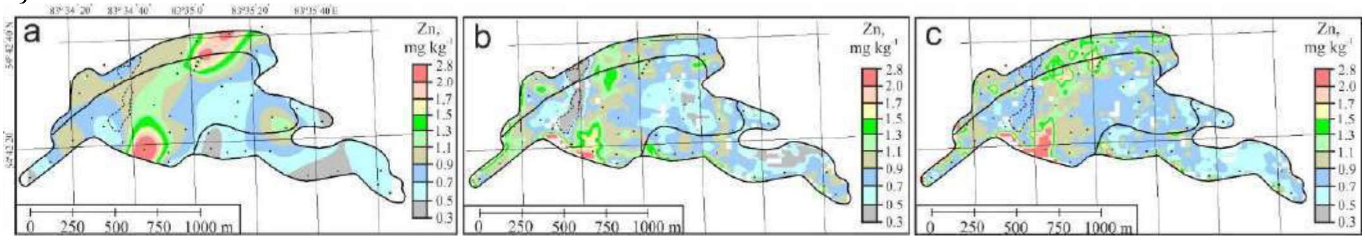

Figure 4. Soil mobile zinc content maps produced with different methods: a – Ordinary kriging; b – Lasso regression; c – Random forest. Dashed line shows crops areas that have been destroyed by the larvae of the May beetle (Melolontha).

On the maps are crops areas that have been destroyed by the larvae of the May beetle (Melolontha). In these areas, the LR model predicted lower values, while the accuracy of the map, estimated by the RMSE and NRMSE value, was the best (Tables 2). The map shows areas with an average provision of soil mobile zinc (from 2.1 to 5.0 mg kg^{-1}), which may be due to the uneven content of zinc-containing minerals.

Table 2. Performance statistics of the regression models used for predicting soil mobile zinc content

		Cross-Validation		
Variable	Model	R^2	RMSE	NRMSE
Zn	Ordinary kriging	0.29	0.49	19.3%
	Lasso regression	0.37	0.43	17.0%
	Random forest regression	0.27	0.48	19.0%

Abbreviation: R2: Determination Coefficient, RMSE: Root Mean Square Error, NRMSE: Normalize Root Mean Square Error

Conclusion

The use of digital mapping methods in the field of agricultural practice is justified and allows to manage the production process of plants by identifying soil areas with a shortage of certain plant nutrition elements on maps and carrying out appropriate agronomic measures. The results of the three models showed that the LR model with lower RMSE (0.43 mg kg^{-1}) and NRMSE (17%) was the best for soil mobile zinc content prediction. The LR and RF models have the advantage of spreading the simulation results over a large area and it can be used with fewer samples. The method of Ordinary kriging does not have such advantages. If vegetation indices are used in models of machine learning methods, then the results of modeling the content of mobile zinc will depend on the condition of crops (for example, damaged crops).

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