Recreation and terrain effect on the spatial variation of the apparent soil electrical conductivity in an urban park

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Introduction

Urban ecosystems provide a combination of ecosystem services such as provisioning, regulating, and habitat cultural services (Brouwer et al., 2013). Soils of urban parks influence carbon and nitrogen pools and fluxes (Raciti et al., 2011). The topsoil layer, forest litter, and vegetation cover have the key function of preventing soil erosion (Zuazo & Raciti, 2013). Urban soils and vegetation are very different from natural ones due to the recreation impact (Levin et al., 2017). Recreation is an important cultural ecosystem service and is able to significantly affect soil heterogeneity and vegetation functioning. This study investigated the role of the relief and tree stand density in the apparent soil electrical conductivity variation within an urban park. The most suitable variogram models were assessed to evaluate the autocorrelation of the regression models. The map of the spatial variability of apparent soil electrical conductivity was built on the basis of the most suitable variograms. The experimental polygon was located in the Botanical Garden of Oles Honchar Dnipro National University (Dnipro City, Ukraine). The experimental polygon was formed by a quasi-regular grid of measurement locations located about 30 m apart. The measurements of the apparent electrical conductivity of the soil in situ were made in May 2018 at 163 points. On average, the value of soil apparent electrical conductivity within the investigated polygon was 0.55 dSm/m and varied within 0.17–1.10 dSm/m. Such environment predictors as tree stand density, relief altitude, topographic wetness index, and potential of relief to erosion were able to explain 48% of the observed variability of soil electrical conductivity. The relief altitude had the greatest influence on the variation of soil electrical conductivity, which was indicated with the highest values of beta regression coefficients. The most important trend of the electric conductivity variation was due to the influence of relief altitude and this dependence was nonlinear. The smallest values of the soil electrical conductivity were recorded in the highest and in lowest relief positions, and the largest values were detected in the relief slope. Recreational load can also be explained by the geomorphology predictors and tree stand density data. These predictors can explain 32% of the variation of recreational load. The variogram was built both for the soil apparent electrical conductivity dataset and for the residuals of the regression model. As a result of the procedure of the models’ selection on the basis of the AIC we obtained the best estimation of the variogram models parameters for the electrical conductivity and for the regression residuals of the electrical conductivity. The level of recreation was correlated statistically significantly with the apparent soil electrical conductivity. The residuals of regression models in which geomorphological indicators and tree stand density were used as predictors have a higher correlation level than the original variables. The soil electrical conductivity may be a sensitive indicator of the recreation load.

Keywords: recreation; soil electrical conductivity; variogram; Matern model; digital elevation model.

It has been proposed to categorize the soils of anthropized areas according to the ecosystem services they provide in urban areas (Morel et al., 2014). Urban green spaces support conservation of the biodiversity in urban areas (McKinney, 2006; Lepczyk et al., 2017). The heterogeneous microenvironment structure of parks promotes the preservation of natural vegetation (Sarah et al., 2015; Gritsan et al., 2019). It has been shown that the measurable biological indices may be applied for assessment of ecological, environmental-regulating, and productive functions of urban soils (Vasenev et al., 2012). Soil biota has a considerable utility for estimation of the ecological potential of urban soils (Matsev et al., 2017). The diversity of soil biota is important to many environmental functions such as water depollution, biochemical cycles, fertility and carbon storage (Guil-land et al., 2018). The variability of soil properties of urban parks affects the growth and development of plants (Pregitzer et al., 2016). Significant variation of the soil properties was found in a distance gradient of measurements taken around selected individual trees affecting the quality and quantity of understory vegetation in park forest stands (Sikorski et al., 2013). The variability of soil properties promotes the maintenance of biodiversity in urban areas (McKinney, 2006). The apparent soil electrical conductivity (ECA) is a useful and express measure of soil variability (Corwin et al., 2003; Yorkina et al., 2018). This index is related to soil properties affecting ecosystem primary production (Corwin & Lesch, 2005). The characterization of soil spatial variability using ECAs may be used for...
soil quality assessment (Corwin, 2005). The spatial variability of the apparent soil electrical conductivity was modeled on the basis of regression dependencies from remote sensing predictors (Zhukov et al., 2016).

The principal issue of the ecological modeling is the precise assessment of the spatial variability of soil properties (Shit et al., 2016). An inverse distance weighting or ordinary kriging are the effective approaches for interpolation of the spatial patterns of soil properties (Uygur et al., 2010; Göğ et al., 2017; Tang et al., 2017). The efficiency of predicting spatial variability of soil properties was proposed to be improved by a combination of regression and spatial interpolation (Hengl et al., 2004). This approach was called regression-kriging (Kumar et al., 2012; Peng et al., 2013; Mondal et al., 2017). Regression-kriging is one of the most popular, practical and robust hybrid spatial interpolation techniques for modeling of the soil distribution patterns at multiple scales in space and time (Keskin & Grunwald, 2018).

The objectives of this study were (a) to investigate the role of the relief and tree stand density in the apparent soil electrical conductivity variation within an urban park, (b) to assess the most suitable variogram models to evaluate the autocorrelation of the regression models, and (c) to map spatial variability of the apparent soil electrical conductivity.

Methods

The experimental polygon was located in the Botanical Garden of Oles Honchar Dnipro National University (Dnipro City, Ukraine) (Fig. 1).

The climate at the experimental polygon is temperate-continental. According to statistics from 1998 to 2018, the average yearly precipitation was approximately 565 mm. The average temperature was the highest in August at 25.7 °C, while the lowest was in January at -10 °C. There were two soil types within the experimental polygon: calcic chernozem (siltic, Ukrainian) are characterized by lack of flexibility (Stein, 1999). As an alternative, one can consider the Matern variogram class of models (Matern, 1986). Matern models have considerable flexibility for modeling the spatial covariance and are able to describe a wide variety of local spatial processes. Based on this, the Matern model is proposed to be used as a general approach for the simulation of soil properties (Minsay & McInturff, 2005). Matern isotropic covariance function has the form (Hanscock & Stein, 1993; Stein, 1999):

$$\gamma(h) = \frac{1}{2\pi^2} \frac{h^\nu}{\kappa^{\nu+1}} \kappa^n$$

where $h$ is the separation distance; $\kappa$ is modified Bessel function of the second kind of order $\kappa$ (Abramowitz & Stegun, 1972), $\gamma$ is the gamma function, $\varphi$ is the range parameter ($\varphi > 0$), which measures how fast correlation decays with distance; $\nu$ is the smoothness parameter. The Matern model has a high flexibility compared with traditional geostatistical models in view of the smoothing parameter $\kappa$. When the parameter $\kappa = 0.5$, the Matern model fully corresponds to an exponential model. When $\kappa \rightarrow \infty$, the Matern model corresponds to a Gaussian model. If $\kappa = 1$, it corresponds to a Whittle’s function (Whittle, 1954; Webster & Oliver, 2001; Minsay & McInturff, 2005). If the range parameter $\nu$ is large ($\nu \rightarrow \infty$), then the spatial process is approximated by the power function when $\kappa > 0$, and a log function or de Wijs function if $\kappa \rightarrow 0$ (de Wijs, 1951, 1953). The spatial dependence level (SDL) or nugget to sill ratio is an indicator of the strength of the spatial autocorrelation (Cambardella et al., 1994; Sun et al., 2003; Zhukov et al., 2019a, b).

Regression kriging is a spatial interpolation technique that combines a regression of dependent variables on predictors with kriging of the prediction residuals (Hengl et al., 2004):

$$\hat{y}(x) = \beta \mathbf{x} + \hat{\epsilon}(x)$$

where $\beta$ is the fitted deterministic part, $\hat{\epsilon}(x)$ is the interpolated residual. Thus, the first part of the right-hand side of the equation represents the regression and the second part represents the kriging of the residual.

To measure the accuracy of differential entropy maps we use cross-validation procedure and consequently we compute normalized root
mean squared error (NRMSE), mean error (ME) and mean squared deviation ratio (MSDR) (Vašát et al., 2013). Mean squared error (RMSE) was calculated as follows:

$$ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} $$

Normalized root mean squared error (NRMSE) was calculated as follows:

$$ NRMSE = \frac{RMSE}{\mu - \bar{y}} $$

Mean squared deviation ratio (MSDR) was calculated as follows:

$$ MSDR = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{y_i - \hat{y}_i}{\mu - \bar{y}} \right)^2 $$

where $$y_i$$ is a prediction of the variable $$Y$$; $$x_i$$ is a measure of that variable; $$n$$ is the number of records; $$\sigma^2$$ is a kriging variance. The smaller the NRMSE values, the more accurate the map. The MSDR indicates whether the variance of measured data is well reproduced with the kriging interpolation and ideally it equals to 1 (Vašát et al., 2013). The R-squared of the regression between observed and predicted after cross validation test influence on the variation of soil electrical conductivity, which was indicated with the highest values of beta regression coefficients. The to-

Recreational load can also be explained by the geomorphology predictors and tree stand density data. These predictors can explain 32% of the variation of recreational load. As in the case with soil electrical conductivity, the relief altitude was shown to be a leading predictor. The tree stand affected the recreation. This effect was non-linear. The most favourable park areas for recreation occupied the places with moderate tree density stands. Areas of the park with too dense tree stands or with too sparse tree stands were less attractive for recreation. The negative correlation between recreational load and topographic wetness index indicated that the areas of the park with a tendency to waterlogging were less attractive for recreation.

**Table 1**

| Parameter                          | Mean ± st. error | Median | Minimum | Maximum | Coefficient of variation, % |
|------------------------------------|------------------|--------|---------|---------|-----------------------------|
| Apparent electrical conductivity (ECₐ), dSm/m | 0.55 ± 0.01 | 0.54    | 0.17    | 1.10    | 34.35                       |
| Recreation loading, %              | 49.14 ± 2.50    | 43.27   | 0.00    | 100.00  | 65.04                       |
| Tree stand density, the number of tree trunks counted within a 5-m radius | 2.90 ± 0.17 | 3.00    | 0.00    | 8.00    | 75.73                       |
| Relief altitude (DEM), meter       | 144.9 ± 0.06    | 146.00  | 133.80  | 153.20  | 3.20                        |
| Topographic wetness index (TWI), ununits | 7.64 ± 0.13   | 7.15    | 5.81    | 12.76   | 22.16                       |
| Potential of relief to erosion (LS-factor), ununits | 0.65 ± 0.03 | 0.66    | 0.03    | 1.32    | 50.06                       |

The predictors were able to explain 48% of the observed variability of soil electrical conductivity (Table 2). The relief altitude had the greatest influence on the variation of soil electrical conductivity, which was indicated with the highest values of beta regression coefficients. The topographical wetness index and LS-factor were found to be the statistically significant predictors of the soil electrical conductivity variation. The tree stand density was not a statistically significant predictor of the soil electrical conductivity on the spatial level investigated.

**Table 2**

| Predictors | Soil apparent electrical conductivity | Recreation loading |
|------------|--------------------------------------|--------------------|
| Parameter  | R² = 0.48, F = 26.3, P < 0.001 | R² = 0.32, F = 13.6, P < 0.001 |
| Tree density (Tree) | 0.22 ± 0.21 | 0.29 | 0.87 ± 0.21, P < 0.005 |
| TWI² | 0.07 ± 0.20 | 0.73 | -0.70 ± 0.20, P < 0.005 |
| Relief altitude (DEM) | 18.80 ± 3.42 | <0.01 | -15.43 ± 3.93, P < 0.005 |
| DEM² | -18.53 ± 3.44 | <0.01 | 15.61 ± 3.95, P < 0.005 |
| Topographic wetness index | 0.60 ± 0.07 | <0.01 | -0.16 ± 0.08, P 0.04 |
| LS factor | -0.17 ± 0.08 | <0.01 | -0.11 ± 0.09, P 0.25 |

The variogram was built both for the soil apparent electrical conductivity dataset and for the residuals of regression model (Fig. 3). The nugget effect was searched in first stage of the assessment of the best values of variogram model parameters for fixed values of Kappa = 2 and the starting value of Phi = 7 m (Fig. 4). The variation of soil electrical conductivity was characterized by the much smaller spatial dependence than the variation of regression model residuals in terms of the AIC criterion (Fig. 4a). An increase in the fixed values of the nugget effect was accompanied by a monotonic growth of the optimal value of variogram range parameter when Kappa parameter was fixed (Fig. 4b). In the next stages the parameters that were found to be optimal in the previous stage were selected as starting parameters. An experimental increase of Kappa parameter for electrical conductivity demonstrates the existence of optimal value, which is equal to 1.5 (Fig. 5). The AIC change is monotonomous with the increase of the Kappa parameter for variogram of the residuals of regression, indicating its best value, which approaches to ∞.

As a result of the conducted procedure we obtained the best estimation of the variogram models parameters for the electrical conductivity

**Fig. 2.** The spatial variation of recreation loading within the studied polygon according to Strava Global data (www.strava.com): data were rescaled to a range: 0 – no loading; 100% – the maximum loading
and for the regression residuals of the electrical conductivity (Table 3). The parameter \( \phi \) and the practical range were found to be much greater for OK than for RK. In turn, the spatial component of the variation characterized by an index of SDL is much higher for RK than for OK. The optimal value of the Kappa parameter \((\text{Kappa} \to \infty)\) for OK of the Matern model turns it to the Gaussian model.

The parameter \( \phi \) and the practical range were found to be much greater for RK than for OK. The optimal value of the Kappa parameter \((\text{Kappa} \to \infty)\) for OK of the Matern model turns it to the Gaussian model.

The dependence of \( \text{AIC} \) criterion on the Matern nugget values \((a, \text{fixed Kappa = 2}, \text{the initial value of } \phi = 7)\) and the estimated value of the \( \phi \) with fixed values of the nugget-effect \((b): a \text{ – } x\text{-axis is the fixed value of the nugget-effect represented for comparability by the SDL value, } \%; y\text{-axis is the AIC values for ordinary kriging (left axis)} \text{ and for regression-kriging (right axis); for ordinary kriging the AIC has a minimum in } x \text{ (nugget) = 0.0103 (corresponding SDL = 27.2%), for regression-kriging the AIC has a minimum in } x \text{ (nugget) = 0.0028 (corresponding SDL = 9.6%).}

The dependence of \( \text{AIC} \) on the model parameter Kappa \((\text{Kappa} \to \infty)\) for regression-kriging (Fig. 5). The more precise reproduction of the electric conductivity variations is in the case of RK, as indicated by the higher value of the MSDR statistic.

**Table 3**

Descriptive and geostatistical parameters of the apparent electrical conductivity variation

| Parameters          | Ordinal kriging (OK) | Regression-kriging (RK) |
|---------------------|----------------------|-------------------------|
| Mean, dSm/m         | 0.56                 | 0.71                    |
| \( \phi \), m       | 17.26                | 5.30                    |
| Practical Range, m  | 81.90                | 38.70                   |
| Sill                | 0.03                 | 0.03                    |
| Nugget              | 0.01                 | 0.001                   |
| SDL, %              | 27.23                | 9.61                    |
| Kappa               | 1.50 \( \to \infty \) |                         |
| Regression \( \text{R}^2 \) | –                  | 0.48                    |
| NRMSE               | 0.18                 | 0.08                    |
| MSDR                | 0.55                 | 0.72                    |

Cross validation \( \text{R}^2 \) was also performed (Fig. 6). The more precise reproduction of the electric conductivity variations in the case of RK, as indicated by the higher value of the MSDR statistic.

**Note:** \( \phi \) – variogram range (the distance at which the theoretical variogram curve reaches its maximum as the range); Practical Range – the value at which the variogram reaches 95% of the asymptote; Sill – the difference between the asymptote and the nugget; Nugget – the intercept of the variogram model curve; SDL – nugget to sill ratio as an indicator of the strength of the spatial autocorrelation; Kappa – Matern model smoothing parameter; Regression \( \text{R}^2 \) – adjusted \( \text{R}^2 \) of the regression model with terrain and tree stand variables as predictors; NRMSE – normalized root mean squared error; MSDR – mean squared deviation ratio.

The level of recreation was correlated statistically significantly with an apparent soil electrical conductivity (Fig. 7). However, as was shown earlier, both of these parameters were dependent on the geomorphology predictors. The residuals of regression models in which geomorphological indicators and tree stand density were used as predictors have a higher correlation level than the original variables.

**Discussion**

The soil electrical conductivity is an express parameter which can be easily measured in large quantities for the spatial analysis. It can be used as a direct indicator of the soil condition including the influence of recreational load (Özcan et al., 2013; Sarah et al., 2015). Also, information on soil electrical conductivity can be used to design an optimal placement of test polygons for the spatial modeling of the other soil and ecological properties whose number of samples is limited due to the complexity of carrying out field studies (Siqueira et al., 2016). The results obtained indicated an important role of relief predictors for explanation of the spatial variability of soil electrical conductivity. The most important trend of the electric conductivity variation was due to the influence of relief altitude and this dependence was nonlinear. The smallest values of the soil electrical conductivity were recorded in the highest and in lowest relief positions, and the largest values were detected in the relief slope. It should be noted that the highest or lowest relief positions were the most favourable for recreation. The soil properties and herbaceous vegetation characteristics were revealed to be affected by human activities. In turn, the above characteristics were affected by natural factors mainly in the microenvironments which were subjected to low levels of recreation loading (Sarah et al., 2015). The litter layer and soil organic horizon are most significantly affected by recreation (Amrein et al., 2005; Brygadyrenko, 2015; Faly et al., 2015). The litter layer and soil organic horizon are most significantly affected by recreation (Amrein et al., 2005; Brygadyrenko, 2015; Faly et al., 2017; Faly & Brygadyrenko, 2018). Recreation leads to soil compac-
tion (Özcan et al., 2013) and reduces the grass cover and litter layer, resulting in a deteriorating water regime of soils (Oral et al., 2013), which may be manifested as a reduction of the soil electrical conductivity. This interpretation also explains the fact that we have not found the statistically significant influence of the tree stand density on the soil electrical conductivity. This is due to the fact that a significant recreational load is characteristic for areas both with dense tree stand and for areas without forest cover. This result confirms the assumption that the soil electrical conductivity may be a sensitive indicator of the recreation load.

Conclusion

The recreation load and apparent soil electrical conductivity (\(\alpha\)) and correlation between residuals of regression models of recreation and apparent soil electrical conductivity with geomorphological characteristics and tree stand density as predictors: \(\alpha - \text{absciss}\) axis is a recreation load (%), ordinate axis is an observed electrical conductivity (dSm/m); \(\beta - \text{absciss}\) axis is the residuals of regression model of recreation load (%), ordinate axis is the residuals of regression model of apparent soil electrical conductivity (dSm/m).

A positive relationship between the soil electrical conductivity and the topographic wetness index and a negative relationship with LS-factor are logical. These predictors are factors in the variation of the soil electrical conductivity, which form the natural background of this indicator. It is obvious that the estimation of the recreational component in the variation of the soil electrical conductivity is possible after extraction of the underlying variability of this indicator induced by the relief factors.

The variation of soil electrical conductivity is characterized by the presence of a significant spatial component. Heng et al. (2004) introduced the process of using the regression-kriging (RK) method for spatial prediction of soil variables. The ordinal kriging and regression-kriging comparison indicates that the relief predictors contribute to the formation of a large-scale component of the spatial variation of soil electrical conductivity. An extraction of the influence of relief predictors after regression procedure allows one to obtain a fine-scale component variation of the soil electrical conductivity with a much larger spatial autocorrelation. That is why regression-kriging allows one to produce a more detailed map of the spatial variation of soil electrical conductivity. The knowledge of the precise mathematical form of the variogram enables one to predict the soil properties on a local or regional level (Minsay & McBratney, 2005). The procedure for searching the best variogram model parameters based on the AIC has shown that the Gaussian model is the best for the regression residuals. There is not any suitable model from the set of the traditional models for OK, so the Matern model with the parameter Kappa = 1.5 is the most appropriate model.

Fig. 7. Correlation between recreation load and apparent soil electrical conductivity (\(\alpha\)) and correlation between residuals of regression models of recreation and apparent soil electrical conductivity with geomorphological characteristics due to other environmental factors. This procedure also has an impact on the geostatistical characteristics of the spatial pattern of the apparent soil electrical conductivity. The traditional variogram models are not suitable for spatial modeling of the apparent soil electrical conductivity. The Matern model is the most flexible and allows one to obtain a more accurate model of the spatial process. The variogram of the residuals of regression model of apparent soil electrical conductivity with geomorphological properties and density of tree stand as predictors is characterized by a smaller practical range, which also indicates a possible recreational component of the formation of spatial patterns of this indicator.

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