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Spatial mapping of soil respiration using auxiliary variables. A small scale study

A talajlégzés térbeli heterogenitásának vizsgálata segédváltozók segítségével

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ABSTRACT

Soil respiration is a significant contributor to the global emissions of CO_2 and is governed by many soil factors. Reliable estimates of CO_2 emission on different scales (e.g., field, regional level) are hard to obtain due to the expressed spatial and temporal variability of the CO_2 flux. This study aims to investigate the spatial variability of CO_2 flux and soil properties in soybean cropland on Fluvisols (Croatia). The field measurements and soil samples were taken in a regular sampling grid (2 × 2 m) with 44 points in total and the spatial variability was assessed using the kriging and cokriging techniques. The soil CO_2 flux showed relatively high spatial heterogeneity, ranging from 0.03 mg/m²s to 0.40 mg/m²s. The soil organic matter content (SOM), soil water content (SWC), and soil temperature (ST) had the lower variability ranging from 2.09% to 2.52%, from 27.7% to 46.8%, and from 13.7 °C to 18.2 °C, respectively. The spatial dependence was high for CO_2 flux and ST, moderate for SOM, and low for SWC. The incorporation of the auxiliary variables increased the precision of the estimations for CO_2 flux, SOM, and SWC. Kriging was the most accurate method for the spatial prediction of ST. The SWC was associated as the most important factor of the CO_2 fluxes, indicated by their significant negative correlation, and the highest increase of the prediction precision during spatial modeling. However, more robust co-variates should be incorporated in future models to further increase the precision.

Keywords: soil properties, CO_2 emission, spatial variability, GIS

ABSZTRAKT

A talajlégzés, melyet számos talajtulajdonság befolyásol, jelentősen hozzájárul a globális CO_2 emisszióhoz. A CO_2 emisszió különböző léptékű, megbízható becslése nehéz, annak nagyfokú térbeli és időbeli változékonysága miatt. Kutatásunk célja a CO_2 kibocsátás és különböző talajtulajdonságok térbeli változékonyságának vizsgálata egy horvátországi szója ültetvényben, Fluvisol talajon. Az *in-situ* méréseket, valamint a talajminták gyűjtését egy 2x2 méteres rácsháló 44 pontjában végeztük el, a térbeli változékonyság kimutatásához krigelést és kokrigelést használtunk. A talaj CO_2 kibocsátása relatív nagy térbeli változékonyságot mutatott, az értékek 0.03 és 0.40 mg m^{-2} s^{-1} között alakultak. A talaj szerves anyag tartalmának (SOM), nedvesség tartalmának (SWC) és hőmérsékletének (ST) változékonysága kisebb volt, ezek értékei 2.09 és 2,52%, 27.7 és 46.8%, valamint 13.7 és 18.2 °C között változtak. A talaj CO_2 kibocsátását nagymértékben meghatározta a mérési pontok térbeli helyzete, a SOM közepes, az SWC pedig alacsony térbeli függést mutatott. A segédváltozók modellbe való beépítése növelte a CO_2 kibocsátás, valamint a SOM és a SWC becslésének pontosságát. A SWC volt legnagyobb hatással a CO_2 kibocsátás alakulására, e két változó között negatív szignifikáns összefüggést találtunk, valamint ez okozta a legnagyobb növekedést a becslés pontosságában a térbeli modellezés során. A továbbiakban robusztusabb segédváltozó adatsorok felvétele szükséges a pontosság növelése érdekében.

Kulcsszavak: talajtulajdonságok, CO_2 emisszió, térbeli változékonyság, GIS

INTRODUCTION

Soil respiration contributes to the global emission of CO_2 at a rate of 20-38% (Boone et al., 1998) and is recognized as the main natural carbon efflux to the atmosphere. Since soils represent the largest terrestrial carbon reservoir, the investigations of CO_2 emissions from the soils have been widely studied topic in land uses like croplands (Allaire et al., 2012; Bogunovic et al., 2020; Dencső et al., 2021), permanent plantations (e.g., Chamizo et al., 2017; Bogunovic et al., 2019), forests (e.g., Poblador et al., 2017; Hawthorne et al., 2017) or grasslands (e.g., Zhao et al., 2017; Hörtnagl et al., 2018; Ammann et al., 2020). Several studies indicated that agricultural land emits the highest amount of CO_2 from the soil, significantly higher than CO_2 released from grasslands (pastures) or forest lands in humid continental (Kurganova et al., 2003), maritime (Aslam et al., 2000), humid subtropical (Iqbal et al., 2008) or dry summer climates (Mariscal-Sancho et al., 2010). This highlights the importance of comprehension of the mechanism of soil respiration in agricultural land use and the global carbon cycle. Temporal variation of soil respiration is exhaustively studied subject on all texture soil types: clay (e.g. Kurganova et al., 2003; Iqbal et al., 2008), sand (e.g., Poblador et al., 2017), sandy-loam (Hawthorne et al., 2017), silty loam (e.g., Aslam et al., 2000; Buragienė et al., 2019), silty clay (e.g., Bogunovic et al., 2020) and loam (e.g., Dencső et al., 2021). These studies indicated that the high temporal variability of soil CO_2 flux is closely related to the variation of the soil moisture and temperature. However, the spatial pattern of soil respiration is a significantly more complex issue as it is influenced by the crop type (Bilandzija et al., 2016), microbial biomass (Chaplot et al., 2015), texture (Chantigny et al., 2016), compaction (Bogunovic et al., 2017), air porosity (Buragienė et al., 2019), soil organic matter content (Girkin et al., 2019), or crop management such as fertilization (Zang et al., 2016), tillage (Tóth et al., 2018), and manure or biochar application (Horel et al., 2018). All of these influencing factors differ on small, medium, and large scales in agroecosystems, enhancing the spatial heterogeneity of soil respiration. Previous reports indicated moderate spatial variability of CO_2 flux with a coefficient of variability between 35 and 80% (e.g. Mendonca et al., 2011; Allaire et al., 2012; Rowlings et al., 2012; Teixeira et al., 2012).

To ensure the estimation precision of the CO_2 emissions, it is necessary to study the spatial pattern of soil respiration and create accurate maps. The geostatistical analyses have been used for the evaluation and description of the spatial variability of CO_2, mostly, the kriging method for the spatial estimations (e.g., Brito et al., 2010; Konda et al., 2010; Mendonca et al., 2011). However, other sophisticated multivariate methods were also used in the international research (e.g., Ren et al., 2011; Allaire et al., 2012; Leon et al., 2014; Fóti et al., 2016) depending on the individual study goals and different methods of the results acquisition. These works contributed to the comprehension of the link between soil CO_2 emissions and the auxiliary variables (e.g., soil properties). The use of auxiliary variables has been shown as an advantage for the CO_2 emission estimations during the modeling. Accurate maps are essential for reporting precise agro-ecosystem CO_2 budgets. The scarcity of reliable estimates of spatial CO_2 variability in a field scale hampers general estimates on the regional or country levels, especially in the Croatian agro-ecosystems, where such research has not been implemented. Moreover, croplands in Croatia have been under extensive environmental stress in the past several decades due to the extreme weather (Marković et al., 2015; Bernat et al., 2015) and intensive land management (Bogunovic and Kisic, 2017; Jug et al., 2019) which continuously decreases organic carbon in the soils below threshold limit (Durdevic et al., 2019) through increased soil emission of CO_2 (Bilandžija et al., 2016; Bogunovic et al., 2020). Therefore, this research aims to: (i) assess the correlations among soil properties and CO_2 flux; (ii) characterize the variability and spatial distribution of CO_2 flux and soil properties; (iii) evaluate model accuracies of the kriging and co-kriging techniques; and (iv) present the estimation model for the accurate production of the site-specific field CO_2 budgets maps. The knowledge of the spatial pattern of CO_2 emissions could be used as an important tool for the determination of the conservation practices in a given area.

MATERIALS AND METHODS

Study site, climate and soil

The research was conducted at Šašinovec (45°50' N; 16°11' E; 120 m a.s.l.), Croatia (Figure 1). The climate of the study area is the temperate humid climate (Cfb), according to Köppen (1900). The mean annual temperature is 12.2 °C, ranging from 1.5 °C in January to 23.3 °C in July (2011-2018). The long-term average annual precipitation is 918.9 mm (2011-2018), while in 2019 it was 1147.5 mm (Brezinščak and Bogunović, 2021). Soil is silty clay loam Fluvisol (World Reference Base for Soil Resources, 2015). Soil is slightly alkaline (pH_{KCl} 7.49), with a low organic matter content (2.1%), rich in available phosphorus (249 mg/kg), available potassium (214 mg/kg), and total nitrogen (0.20%).

Experimental design, measurements, sampling and laboratory work Statistical analyses and data transformation

Measurements of CO_2 flux and soil sampling were performed on a 2 m × 2 m grid (44 points in total). Measurements were carried out in September 2019 after the soybean (*Glycine max* L. Merr) harvest. The location of the investigated field and the sampling design is shown in Figure 1. Precise georeferencing of the measurement locations was ensured by using GeoExplorer GeoXH 6000 (Trimble, USA) with 10 cm accuracy in real time. At each sampling point, the soil respiration (CO_2 flux) was determined using in situ infrared gas analyzer EGM-5 (PPSYSTEMS, USA). Disturbed soil samples (0 – 10 cm depth), and measurements of soil water content (SWC), and soil temperature (ST) were collected and measured in close vicinity of each CO_2 flux measurement point. The volumetric SWC (0 - 10 cm depth) was determined using the HYDROSENSE II probe (CAMPBELL SCIENTIFIC, USA) with an accuracy of 3% and a resolution of < 0.05%. Soil TS (0 – 10 cm depth) was determined using the STP-2 soil temperature probe (PPSYSTEMS, USA) with an accuracy of ±0.3 °C at 25 °C. Soil samples were dried, milled, sieved, and homogenized to determine the SOM content using Walkley and Black (1934) method.

Statistical analyses and data transformation

Descriptive statistical properties like mean, median, minimum, maximum, standard deviation, coefficient of variation, skewness, and kurtosis were analyzed. Histograms and probability plots were created to analyze the data distribution and potential outliers using Statistica 12.0 for windows (StatSoft, Tulsa, USA). Outliers in dataset distribution can have a negative consequences on the accuracy and semivariogram interpretation, thus some raw data were tested and transformed when necessary using logarithmic (log) and Box-Cox (BC) transformations to satisfy normality assumptions using the Kolmogorov–Smirnov (K–S) test. The normality of the datasets is desirable since possible dataset asymmetry can have important implications on interpolation methods performance (Bogunovic et al., 2014). The Pearson correlation coefficient was calculated to examine the correlation between the studied properties. Significant correlations were considered at a $P<0.05$. Statistical analyses of correlations were performed with Statistica 12.0 for windows (StatSoft, Tulsa, USA).

After data error detection, the spatial continuity structure of investigated properties was analysed employing experimental variograms using the data developed to identify the spatial continuity of CO_2 flux, SOM, SWC, and ST. Directional variograms and variogram maps for the detection of anisotropies are included in analyses. Since the sampling/measurement points were spaced 2 m, a unit lag of 2 m was used for the calculation of the omnidirectional and directional variograms, while the directional variograms were calculated along different directions with an azimuth step of 5 °. The best-fit variogram model was selected mainly visually, but taking into account the lowest nugget to sill ratio and the highest range of spatial dependence. In the case of ambiguities between more variogram model shapes, the one with the lowest mean root square error in the next step of cross-validation was selected (Pereira et al., 2015). Ordinary kriging and partially heterotopic (more information can be found in Ceddia et al., 2015) co-kriging as geostatistical techniques were tested to map the spatial variability of CO_2 flux, SOM, SWC, and ST.

Figure 1. Study site and experimental design

The quality of the final spatial prediction maps was evaluated by the root mean square error (RMSE) as outpost after means of leave-one-out cross-validation diagnostics. Spatial analysis was carried out and maps generated by using ArcGIS 10.1 (ESRI, Redlands, California).

RESULTS AND DISCUSSION

Normality tests, descriptive statistics and correlations among properties

To analyze data error detection in original data, datasets normal probability plots and histograms were created (Appendix A). With exception of the CO_2 flux, all investigated properties showed normal distribution, obtained by low skewness, kurtosis, and the K-S test (Table 1). Several extremely high values were observed in the CO_2 flux (Figure A1) at a sampling points located close to the border of the field. Apart from these extremes in the CO_2 flux dataset, a small number of other measurements deviated at both ends. However, skewness of CO_2 flux could be an indicator of spatial non-stationarity. Therefore, the CO_2 flux dataset was subjected to log and Box-Cox transformations to minimize skewness and kurtosis as seen in Table 1. Performed transformations normalize distributions (Figure A1), decrease skewness, and coefficient of variation (CV) and pass the K-S test. For modeling purposes, Box-Cox transformed CO_2 flux data was used. Soil water content, ST, and SOM show almost symmetrical distribution by a small skewness. According to the K-S test, all three properties followed a normal distribution.

Soil CO_2 flux ranged from 0.03 to 0.40 mg/m²s. The mean CO_2 flux of all measurements in the investigated field was 0.12 ± 0.09 mg/m²s¹ (Table 1). The value of CV for soil CO_2 flux in the investigated area revealed its moderate variability (according to Zhang et al., 2007). The values of CV in the studied cropland were consistent with those observed for similar croplands (e.g., La Scala Jr et al., 2000; Brito et al., 2010; Allaire et al., 2012; Teixeira et al., 2012). The SWC varied in a wide range from 27.7% to 46.8%. The mean value was high with 41.0% indicating wet conditions (according to Csorba et al., 2011) in the soil during field investigation. The studied soils had a low to moderate variability of SWC since the CV was on the edge of two classes with a value of 10.4. The ST ranged from 13.7 °C to 18.2 °C with an average value of 15.3 °C. The average content of SOM was 2.29% (Table 1) indicating the potential limitations of these soils for intensive agricultural production. According to Loveland and Weeb (2003) in the temperate areas, 3.4% of SOM content in the soil is the threshold below which soil of the studied area is considered degraded. Therefore, future management should apply agro-technical practices such as no-tillage, organic fertilization, proper residue management, wide crop rotations, which could disable further decline of SOM in soils (Pereira et al., 2018; Dekemati et al., 2019). The CV value of SOM content revealed low variability with CV 4.3%. With the exception of soil CO_2 flux, the data was relatively homogenous. Low variability in SWC, ST, and SOM datasets could be explained by the small-scale study on land with similar geomorphological conditions. Moreover, these soil properties were also characterized by their smaller heterogeneity in addition to the other soil properties (e.g. soil nutrients). Other studies also reported moderate variability of SOM (e.g., Bogunovic et al., 2014), and low variability of SWC (e.g., Zhang et al., 2013) and ST (e.g., Bicalho et al., 2014) in croplands. Although the present study does not contain the data for soil physical properties, it is very likely that CO_2 flux heterogeneity is derived by diversity in soil porous system. Moreover, the small area covered by present methodological device used in this work enhances the uncertainty in CO_2 flux measurement and their spatial heterogeneity. The soil system may vary significantly in intensively managed croplands (Mzuku et al., 2005; Duffera et al., 2007; Wang and Shao, 2013; Barik et al., 2014) like in the present one used for this study.

The correlation coefficient results are shown in Table 2. Soil CO_2 flux was negatively correlated with SWC. The correlations between CO_2 flux and SWC were expected to be significant since several studies showed strong evidence of CO_2 flux dependency on the soil water status (Allaire et al., 2012; Bilandžija et al., 2016; Dencső et al., 2021). However, in our study, the interrelation between CO_2 and SWC was negative, likely due to the extremely wet soil conditions. A similar interrelation is already reported in excessively wet vineyard soils in the same climatic conditions (Bogunovic et al., 2019).

Table 1. Univariate statistics (n=44) for CO_2 flux (mg/m²s), soil water content (SWC, %), soil temperature (ST, °C) and soil organic matter content (SOM, %)

Variable	Mean	Median	Min	Max	SD	CV	Skew	Kurt	K-S P
CO_2 flux	0.12	0.10	0.03	0.40	0.09	70.7	1.698	2.339	<0.05
Log CO_2 flux	-0.99	-1.02	-1.49	-0.40	0.26	-26.4	0.541	-0.212	>0.20
Box-Cox CO_2 flux	-3.74	-3.75	-6.95	-1.10	1.37	-36.7	0.042	-0.373	>0.20
SOM	2.29	2.27	2.09	2.52	0.10	4.3	0.523	0.630	>0.20
SWC	41.0	40.8	27.7	46.8	4.26	10.4	-0.762	0.470	>0.20
ST	15.3	15.2	13.7	18.2	1.17	7.6	0.608	-0.342	>0.20

Abbreviations: Min = minimum; Max = maximum, SD = standard deviation; CV = coefficient of variation; Skew = skewness; Kurt = kurtosis, K-S = Kolmogorov - Smirnov

A linear correlation between soil respiration and SWC was confirmed at low water contents, and when moisture increased, the dependency became non-linear, which was similar to the findings of Faimon and Lang (2018). Other variables identified only weak insignificant interrelations. Such results confirm previous findings, which stated that the SWC has a more pronounced effect on the spatial pattern of CO_2 flux, while the impact of the ST is lower (Fóti et al., 2016). The absence of a significant correlation between CO_2 and SOM could be attributed to the extremely low variations of SOM in the studied field. Other study confirmed a similar pattern (Bicalho et al., 2014).

Table 2. Correlations among the studied variables. n.s., not significant at a P>0.05. Significant at a *P<0.05. Note: CO_2 flux were Box-Cox transformed

	CO_2 flux	SOM	ST	SWC
CO_2 flux	-			
SOM	0.294204 n.s.	-		
ST	0.012544 n.s.	0.128679 n.s.	-	
SWC	-0.605550*	-0.036903 n.s.	0.123745 n.s.	-

Abbreviations: SWC - soil water content, ST - soil temperature and SOM - soil organic matter content

Spatial distribution of investigated properties

The parameters for variogram models are presented in Table 3 and the best-fitted variogram for CO_2 flux, SOM, SWC, and ST are shown in Figure 2. The analysis of the variogram maps and the directional variograms did not reveal the presence of evident anisotropies only in the case of SWC. Other tested properties (CO_2, SOM, and ST) recorded directional differences which indicate differently increased variogram values at different directions. The longest range of spatial dependence for CO_2, SOM, and ST was found in directions 39, 139, and 13, respectively (Table 3). The exponential model provided a better reproduction of the shape of the experimental variograms calculated with the CO_2, SOM, and SWC data (Figure 2a, b, c). On the other hand, the spherical model closely fitted the experimental variogram calculated for ST (Figure 2d). The case of the ST variogram model indicated an almost linear decrease in correlation with the distance up to the range, where it stabilized to the sill. The exponential and spherical models were often chosen as the best-fitted models for the studied variables in other studies (La Scala Jr. et al., 2000; Konda et al., 2010; Allaire et al., 2012).

Variograms (Table 3) indicate that the importance of the nugget effect varied from 0.006 at SOM to 16.33 at SWC, suggesting that important variability in these two properties was either not spatial or the actual sampling scheme is inappropriate disabling the observation of small-scale variability indicated by nugget. On the contrary, the nugget effect was not recorded for soil CO_2 flux and ST indicating the absence of sampling errors in the current sampling scheme. Following the classification of Cambardella et al. (1994), the CO_2 flux and ST with nugget/sill ratio of 0.00 showed strong spatial dependence. This result is in contrast with previous studies, indicating that CO_2 had no spatial dependence or weak spatial dependence (e.g. Ishizuka et al., 2005; Konda et al., 2010). This discrepancy is probably caused by the relatively small-scale area of the present study on geomorphologically and pedologically uniform terrain. Moreover, long-term application of the agricultural practices (e.g. tillage, fertilization) in the investigated soils

Table 3. Best-fitted variogram models of CO_2 flux, soil organic matter (SOM), soil water content (SWC) and soil temperature (ST) and corresponding parameters. Note: CO_2 flux were Box-Cox transformed

Property	Model	Nugget	Range (m)	Direction	Sill	Nugget/Sill
CO_2	Exponential	0.00	17.04	39	0.008	0
SOM	Exponential	0.006	8.16	139	0.010	65.74
SWC	Exponential	16.33	24.00	-	18.026	90.62
ST	Spherical	0.00	5.77	13	0.831	0

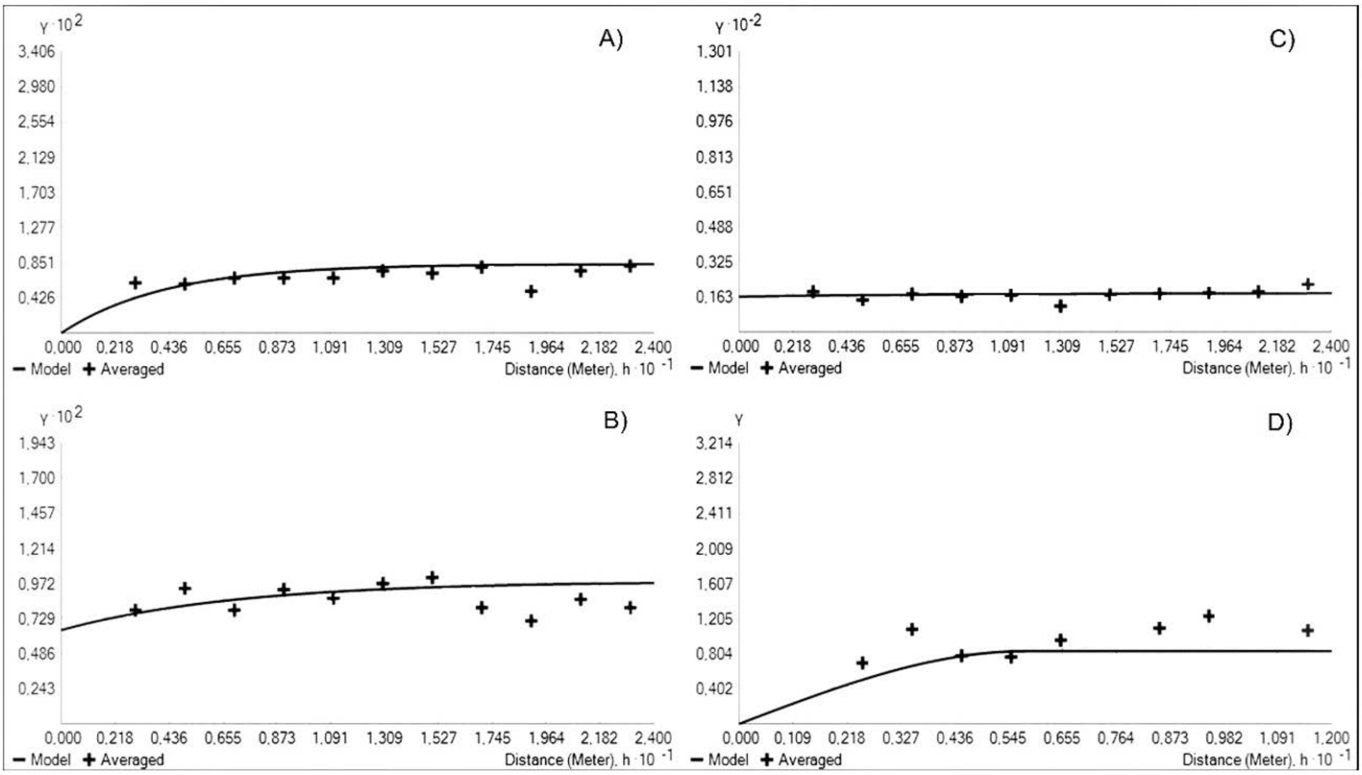

Figure 2. Semivariogram analysis, a) CO_2 flux, b) soil organic matter, c) soil water content and d) soil temperature

significantly homogenized their properties in contrast to the forest soils often characterized by different geomorphological conditions and different scales of CO_2 measurement research. The SOM and SWC with a 65.74 and 90.62 nugget/sill ratio showed a moderate and a weak spatial dependence, respectively. The shortest range of spatial autocorrelation was found for the ST content (5.77 m). The SOM and CO_2 were spatially correlated at ranges of 8.16 m and 17.04 m, respectively, while soil SWC had the highest range of 24.00 m. The ranges of all investigated parameters were much wider than the sampling interval of 2 m indicating sufficient sampling design in the present spatial statistical study (Kerry and Oliver, 2004).

The leave-one-out cross-validation was performed to evaluate the quality of the maps and to derive accuracy diagnostics connected to prediction errors during geostatistical interpolation modeling (Table 4). Among the tested geostatistical techniques, the most accurate technique for soil CO_2 flux was the co-kriging technique with the use of the SWC as an auxiliary variable. Moreover, using CO_2 flux as an auxiliary variable resulted

Table 4. Summary statistics of the accuracy of the tested geostatistical techniques. The most accurate method is shown in bold

Property	Technique	RMSE
CO_2 flux	Ordinary kriging	0.0775
	Co-kriging SOM	0.0793
	Co-kriging SWC	**0.0745**
	Co-kriging ST	0.0905
SOM	Ordinary kriging	0.0966
	Co-kriging CO_2	**0.0953**
	Co-kriging SWC	0.0983
	Co-kriging ST	0.0995
SWC	Ordinary kriging	4.2820
	Co-kriging CO_2	**3.0751**
	Co-kriging SOM	4.2824
	Co-kriging ST	4.2824
ST	**Ordinary kriging**	**0.5725**
	Co-kriging CO_2	0.7261
	Co-kriging SOM	0.6519
	Co-kriging SWC	0.7881

Abbreviations: RMSE – root mean square error; SOM – soil organic matter; SWC – soil water content; ST – soil temperature

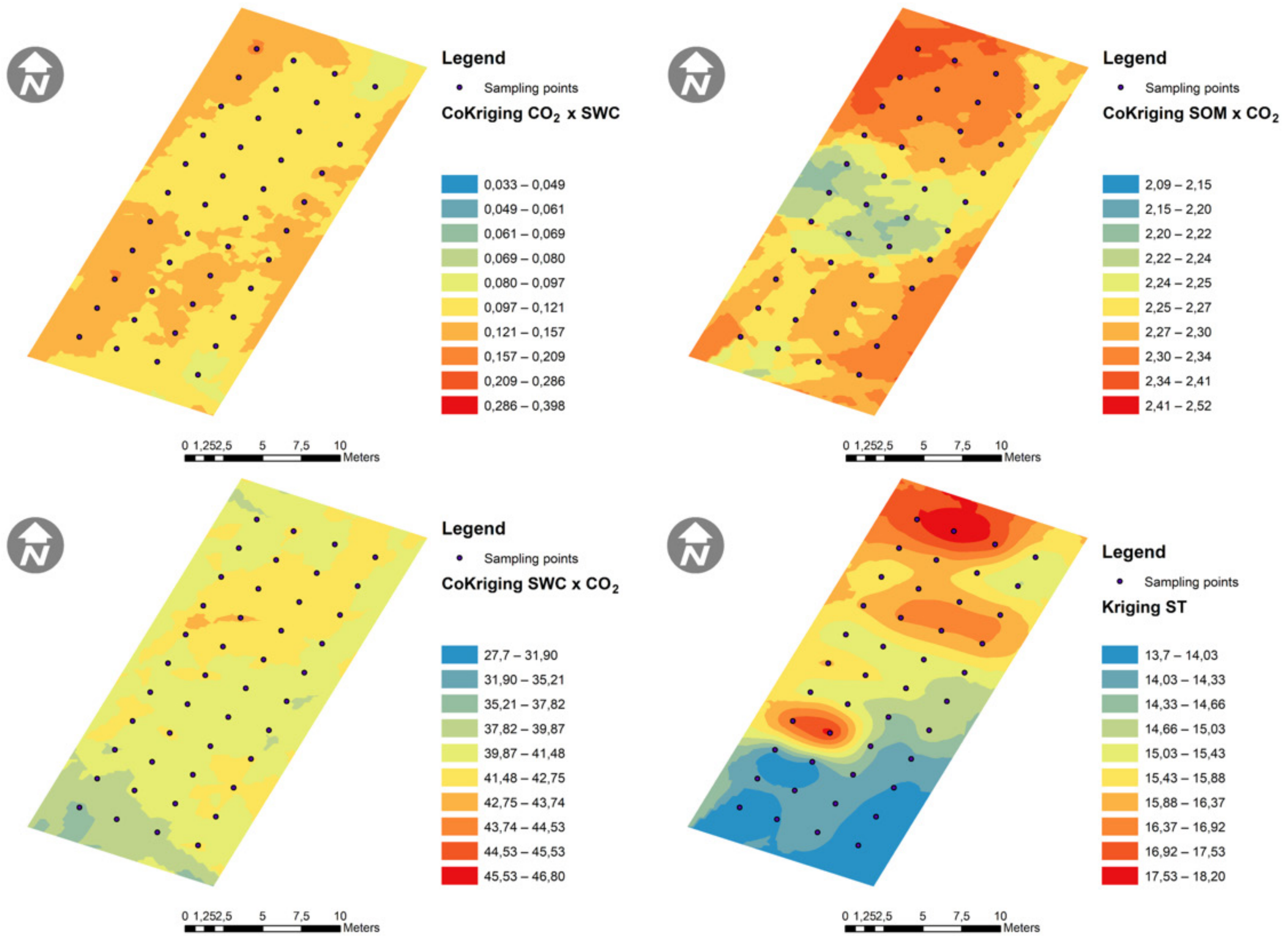

Figure 3. Spatial distribution maps according to the most accurate techniques: soil CO_2 flux (mg/m^{2}s), CoKriging CO_2 × SWC; SOM (%), CoKriging SOM × CO_2; SWC (%), CoKriging SWC × CO_2; and ST (ordinary kriging). Note: CO_2 flux dataset with Box-Cox transformed data

in the most accurate predictions for SOM and SWC. On the contrary, the most accurate method to estimate the ST was ordinary kriging. The use of auxiliary variables did not improve the predictions in this case. The maps produced from the most accurate techniques are shown in Figure 3. The geostatistical interpolation comparison is an important step to minimize the prediction error by choosing the most accurate interpolator. Many other researchers highlighted this step as a crucial step for the final decision making (e.g., Pereira et al., 2015; Durdevic et al., 2019). However, in the present study, the tested geostatistical methods revealed different results, as was expected. During modeling, several auxiliary variables resulted in decreased accuracy of the predictions in addition to the kriging technique, while few of them showed the increase of the prediction (Table 4). Such contradictions during the modeling could be attributed to the nature of interrelations between modeled variables. Often, auxiliary variables are not highly correlated with the variable of interest, as they do not show improvement or a decrease during the co-kriging modeling (Ceddia et al. 2015; Guan et al., 2017). Nevertheless, the proper choice of the auxiliary variables could improve estimation, reduce sampling costs, and provide accurate information for decision-makers of environmental monitoring.

CONCLUSIONS

At the investigated field, the spatial variability was high for the CO_2 flux and low for soil water content, soil temperature, and soil organic matter. Despite that, the

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use of spatial statistics enabled us to characterize the spatial variability at the field scale of all the measured soil properties. The spatial variability models indicate smaller ranges of spatial autocorrelation for soil temperature and soil organic matter. Soil temperature and soil organic matter did not appear to be related to the spatial variability of CO_2 emission. On the other hand, the soil water content was clearly associated with this variability. The spatial accuracy of the CO_2 flux prediction on the field scale was the highest with the soil water content as a co-variable. The results indicate the importance of testing the correlations between CO_2 flux and other potential drivers before geostatistical modeling. Future works should be adopted on a larger scale, using a temporal pattern as a factor and more robust co-variates during modeling.

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APPENDIX A

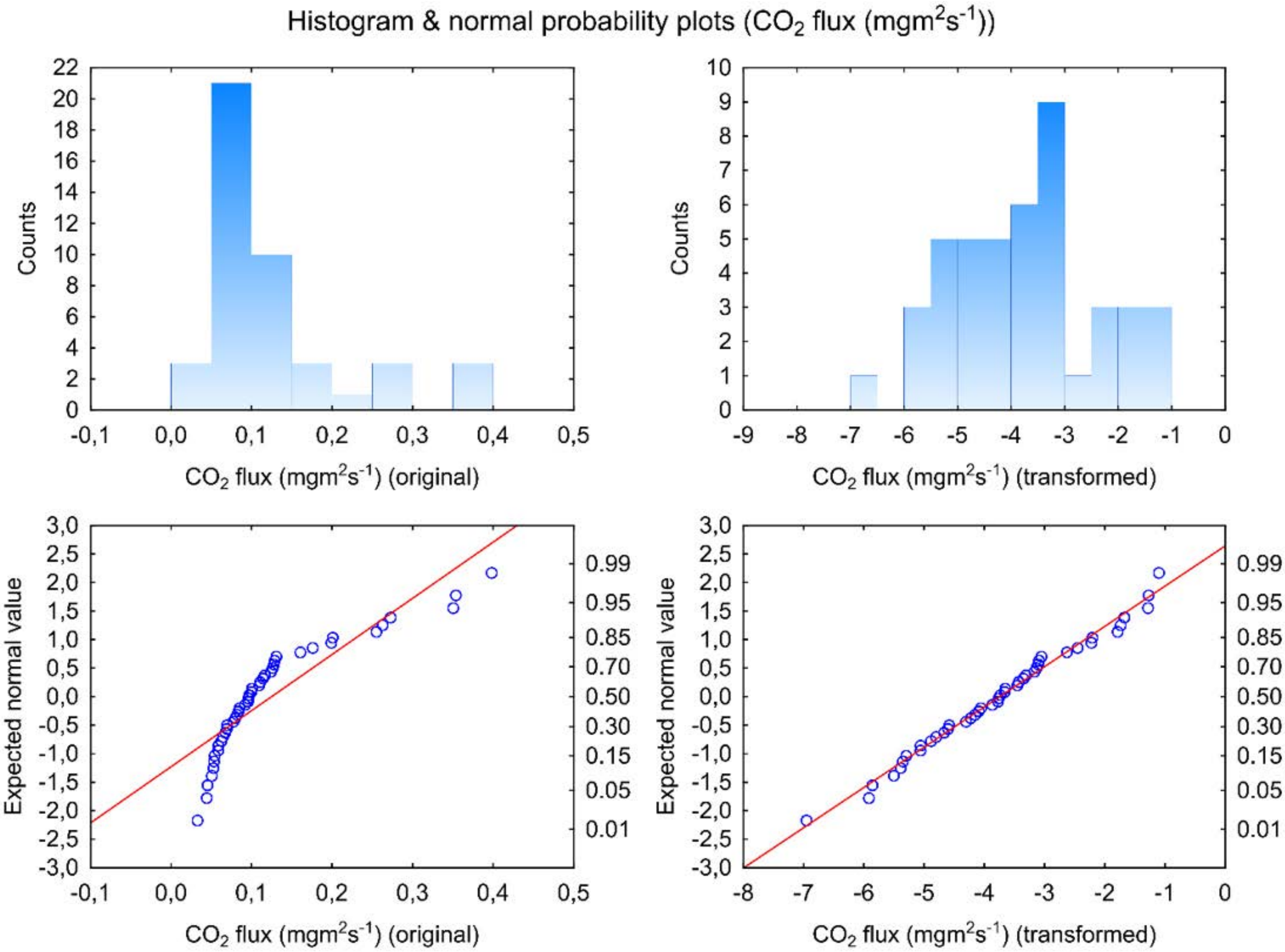

Figure A1. Histograms and probability plots of CO_2 flux original (left) and transformed (right) datasets

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