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Spatial variability of soil CO_2 emission in a sugarcane area characterized by secondary information

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ABSTRACT: Soil CO_2 emission (FCO2) is governed by the inherent properties of the soil, such as bulk density (BD). Mapping of FCO2 allows the evaluation and identification of areas with different accumulation potential of carbon. However, FCO2 mapping over larger areas is not feasible due to the period required for evaluation. This study aimed to assess the quality of FCO2 spatial estimates using values of BD as secondary information. FCO2 and BD were evaluated on a regular sampling grid of 60 m × 60 m comprising 141 points, which was established on a sugarcane area. Four scenarios were defined according to the proportion of the number of sampling points of FCO2 to those of BD. For these scenarios, 67 (F67), 87 (F87), 107 (F107) and 127 (F127) FCO2 sampling points were used in addition to 127 BD sampling points used as supplementary information. The use of additional information from the BD provided an increase in the accuracy of the estimates only in the F107, F67 and F87 scenarios, respectively. The F87 scenario, with the approximate ratio between the FCO2 and BD of 1.00:1.50, presented the best relative improvement in the quality of estimates, thereby indicating that the BD should be sampled at a density 1.5 time greater than that applied for the FCO2. This procedure avoided problems related to the high temporal variability associated with FCO2, which enabled the mapping of this variable to be elaborated in large areas.

Keywords: geostatistics, cokriging, ordinary kriging, cross-variogram

Introduction

Soil carbon stock is dependent on the adopted land use and agricultural practices, and minor changes in soil management lead to major changes (decrease or increase) in carbon stocks (Benbi and Brar, 2009; Boeckx et al., 2011). In 2005, the Brazilian agricultural soils were estimated to be responsible for a net emission of 192.9 Mt CO_2-eq, mainly in N_2O and CH_4 forms (Cerri et al., 2009). Positioning the contribution of soil CO_2 emission (FCO2) in this balance is a difficult task due to the large spatial and temporal variability of this important component (Teixeira et al., 2013). The temporal variability is affected mainly by soil moisture and soil temperature (Ball et al., 1999), and the spatial variability relates to soil properties that affect gaseous transport of CO_2 or O_2 inside soil (Saiz et al., 2006; Brito et al., 2010; Allaire et al., 2012).

Geostatistics enables the assessment of soil properties that exhibit spatial dependence. Ordinary cokriging (CK) uses secondary information from a covariate (BD) with a denser sampling scheme than the main variable (FCO2), provided that the variables are correlated. Although many authors have verified the spatial correlation or coregionalization between different variables (Stoyan et al., 2000; Wang et al., 2002; Prolingheuer et al., 2010), few have studied the use of this relationship to improve the quality of FCO2 spatial estimates. The estimate of soil properties by CK can be more accurate than those obtained by ordinary kriging (OK) when the cross-variogram shows dependence between two variables (Vauclin et al., 1983).

The main use of CK is where the primary variable is sampled less densely because it is either difficult to measure or it requires a costly method for its characterization, while the covariate is easily obtained by a less costly method (Deutsch and Journel, 1998). Although the method for FCO2 characterization using a portable system has been intensively used (Kosugi et al., 2007; Brito et al., 2009; Panosso et al., 2009; Brito et al., 2010; Prolingheuer et al., 2010; Panosso et al., 2011; Teixeira et al., 2011, 2012), this method is limited by the time available for evaluation. The period of FCO2 assessment in several places should be as short as possible to avoid variations between the initial and final temperatures of the evaluation period, limiting the number of sampling points. Although the BD assessment is more complex than the FCO2 assessment, there is no limitation regarding the collection period, thereby enabling BD to be measured at a larger number of sampling points. In this context, the objective of this study was to evaluate the quality of FCO2 estimates performed by OK and CK techniques when considering BD as a covariate from different sampling scenarios.

Materials and Methods

The field study was conducted in Guariba, São Paulo, Brazil (21°21' S; 48°11' W). According to Thornthwaite's classification, the local climate is defined as B1rB′4a′, which is mesothermal humid with little water stress and less than 48 % annual evapotranspiration in the summer. The soil of the area is a clayey Oxisol.

The area has been cultivated with sugarcane (*Saccharum officinarum* (L.) spp. var. SP86-155) for eight years under mechanical harvesting. At the time of study, the soil was without apparent vegetation and was covered with a large amount of crop residue (12 t ha–1) resulting from mechanical harvest performed 28 days before the experiment had started. On Jul. 13th 2010, a regular grid (60 m × 60 m) containing 141 points spaced at minimum distances ranging from 0.5 to 10 m was installed by installing PVC collars used in the FCO2 evaluation methodology (Figure 1).

Before the characterization of spatial variability, 14 points in the grid (10 % of the points) were randomly selected (Cerri et al., 2004; Teixeira et al., 2011) and defined to validate the estimation procedures. Four scenarios were defined according to the proportion between the number of sampling points of FCO2 and BD. In the first scenario (F67), 67 points (48 % of the original data) were used to provide information on the FCO2. The other scenarios considered 87 (F87), 107 (F107) and 127 points (F127) representing 62, 76 and 90 % of the original data, respectively. In all scenarios, BD was evaluated at 127 points of the sampling grid (90 % of the original data), which was used to provide supplementary information on the FCO2 spatial variation.

The FCO2 was evaluated using three portable systems (LI-COR 8100). The portable system has a chamber that measures the CO2 concentration in the captured air by means of optical absorption spectroscopy once the chamber is placed on the PVC soil collars during the field measurements. Before starting the experiment, the three machines were tested and calibrated to each other. The evaluations were performed over seven days during the mornings (8h00 – 9h30) in Julian days 195, 196, 197, 200, 201, 204 and 207 of the year 2010. A mean FCO2 was derived as a result of the average seven day assessment. After the FCO2 evaluations, undisturbed soil samples (0-0.2 m) were removed in each of the grid

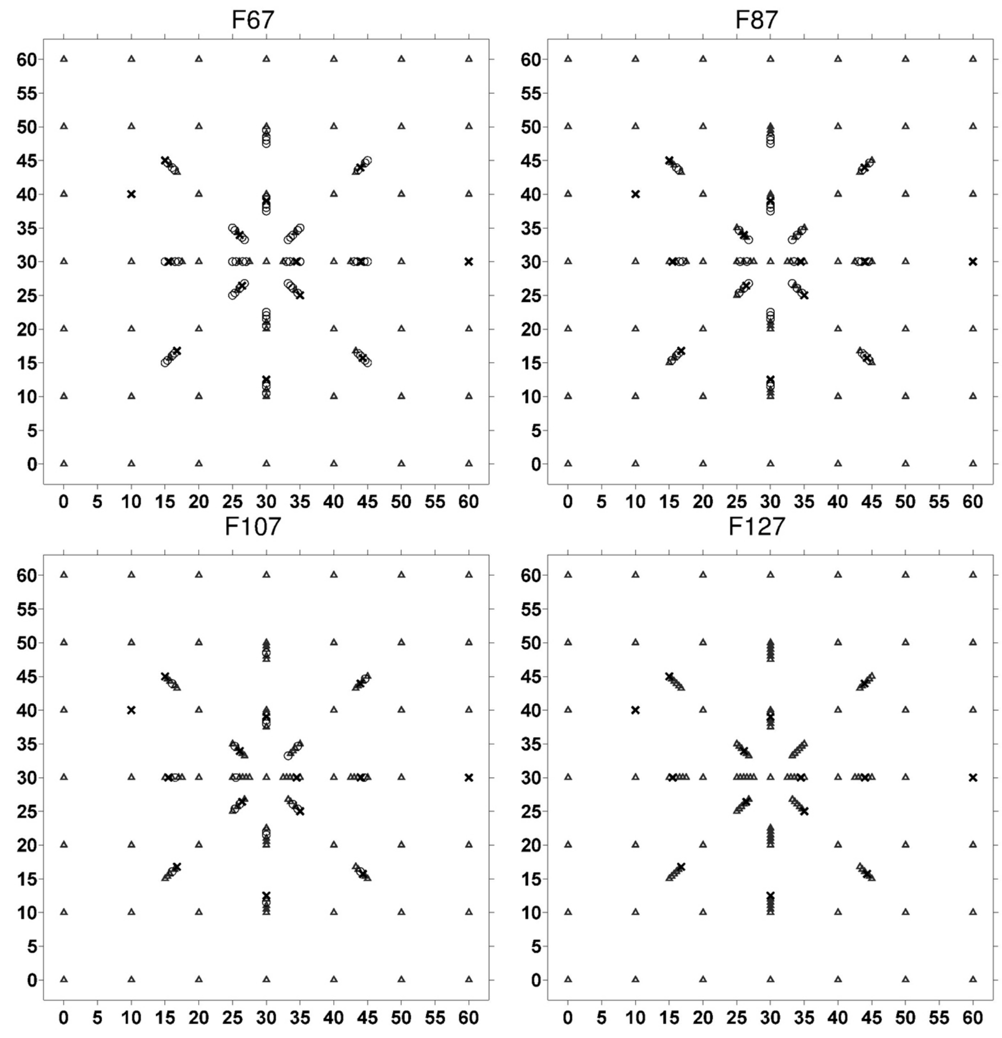

Figure 1 – Configuration sample used to collect data (FCO2 and bulk density). (▲) Places used for analysis of both properties. (○) Locations used in the evaluation of soil bulk density. (x) Places used for external validation.

points by the volumetric ring method to determine the BD (EMBRAPA, 1997).

Geostatistics provides an appropriate set of tools to assess how a property varies from place to place. This methodology allows a deeper understanding of the spatial relationship between emission and other soil properties as well as assisting in the decision-making process. By mapping the variation, areas with higher and lower emissions can be determined and indicate where different management systems would be needed to avoid further emissions and soil carbon losses.

Spatial variability was characterized by computing and modeling the experimental variogram (both auto- and cross-variograms) by the intrinsic hypothesis principle. Cross-variograms were modeled by the linear model of coregionalization to ensure the positivity of the variance of any linear combination of the variables (FCO2 and BD) (Deutsch and Journel, 1998). The experimental auto-variogram was used to determine the spatial autocorrelation of the variable (eq. 1), and was later used in the estimations performed by OK.

$$\hat{\gamma}(\boldsymbol{h}) = \frac{1}{2N(\boldsymbol{h})}\sum_{i=1}^{N(\boldsymbol{h})}[z(\boldsymbol{x}_i) - z(\boldsymbol{x}_i + \boldsymbol{h})]^2 \quad (1)$$

where $\hat{\gamma}(\boldsymbol{h})$ is the experimental semivariance at a separation distance $\boldsymbol{h}$; $z(\boldsymbol{x}_i)$ is the property value of FCO2 at the i^{th} point; and $N(\boldsymbol{h})$ is the number of pairs of points separated by the distance $\boldsymbol{h}$. The auto-variogram describes the spatial continuity or dispersion of the studied variables as a function of distance between two points in a grid.

The spatial dependence between the FCO2 and BD was estimated by means of a cross-variogram, which is estimated by the following equation (Deutsch and Journel, 1998):

$$\hat{\gamma}_{zy}(\boldsymbol{h}) = \frac{1}{2N(\boldsymbol{h})}\sum_{i=1}^{N(\boldsymbol{h})}[z(\boldsymbol{x}_i) - z(\boldsymbol{x}_i + \boldsymbol{h})][y(\boldsymbol{x}_i) - y(\boldsymbol{x}_i + \boldsymbol{h})] \quad (2)$$

where $\hat{\gamma}_{zy}(h)$ is the experimental cross-semivariance at a separation distance $\boldsymbol{h}$; $z(\boldsymbol{x}_i)$ is the value of the primary variable (to be estimated) at the i^{th} point; and $N(\boldsymbol{h})$ is the number of pairs of points separated by the distance $\boldsymbol{h}$. Note that the variogram is simply a particular case of the cross-variogram wherein the semivariance is calculated for a single property. The cross-variogram is calculated only in places where both variables (primary and secondary) are sampled simultaneously (Deutsch and Journel, 1998). Before the cross-variogram modeling, we verified the presence of coregionalization linear model, which is indicated by cross-variograms well structured and proportional to auto-variograms (Isaaks and Srivastava, 1989). More details about the cross-variogram and CK can be found in Goovaerts (1997).

The choice of the adjusted variogram model is based on the sum of squared residuals (SSRs), and the coefficient of determination (R^2), obtained by adjusting a theoretical model to an experimental variogram. In cross-validation when using either an auto- or cross-variogram, the value of the target variable at each location sampled is estimated by OK or CK, respectively. Subsequently, the estimated and observed values are compared by fitting a linear regression.

Ordinary kriging, which is the most applied geostatistical method of interpolation, is a weighted average of neighboring samples (eq. 3). The weights (λ_i) for each neighbor are determined based on adjusted variogram model (eq. 1), so that the variance of the estimates is minimized leading to a linear system of equations.

$$\hat{z}(x_0) = \sum_{i=1}^{N}\lambda_i z(x_i), \quad \text{with} \quad \sum_{i=1}^{N}\lambda_i = 1 \quad (3)$$

where $\hat{z}(x_0)$ is the estimated value of the property at point 0; N is the number of values used for prediction; λ_i is the weighting associated with each value; and $z(x_i)$ is the observed value at the i^{th} point.

If each variable exhibits spatial dependence and there is coregionalization between the variables, it is possible to use CK to estimate values (Deutsch and Journel, 1998). The CK term is used for spatial estimations using linear combinations of n values of principal attributes and m values of secondary attributes to the OK calculations. Similar to OK, CK has the same characteristics of non-bias and minimum variance estimations obtained by the development of equation 4. The CK estimations (eq. 4) are based on the auto-variogram models for each variable and on the cross-variogram model.

$$\hat{z}_{CKO}(x_0) = \sum_{i=1}^{N_1}\lambda_i z(x_i) + \sum_{j=1}^{N_2}\lambda_j y(x_j), \ \text{with} \sum_i \lambda_i = 1 \ \text{and} \ \sum_j \lambda_j = 0 \quad (4)$$

Table 1 – Descriptive statistics of soil CO_2 emission (FCO2) and soil bulk density (BD).

	Mean	SE	SD	CV	Min	Max	Skew	Kurt	AD (p)
FCO2	1.57	0.07	0.79	50.02	0.34	4.08	0.86	0.14	< 0.01
Ln(FCO2)	1.23	0.08	0.58	47.15	-0.09	2.20	-0.38	-0.25	0.21
BD	1.50	0.01	0.14	9.50	1.06	1.86	-0.25	0.39	0.35

n = 141; FCO2 = soil CO_2 emission (μmol m^{-2} s^{-1}); Ln(FCO2) = natural logarithmic transformation of soil CO_2 emission; BD = soil bulk density (g cm^{-3}); SE = standard error of mean; SD = standard deviation; CV = coefficient of variation (%); Min = minimum; Max = maximum; Skew = skewness; Kurt = Kurtosis; AD (p) = p value of Anderson-Darling normality test.

where $\hat{z}_{CK}(x_0)$ is the estimated value of the main variable (FCO2) by CK at point 0; λ_i are the weights associated with the main variable; λ_j are the weights associated with the secondary variable; $z(x_i)$ is the value of the main variable observed at the i^{th} point; and $z(x_j)$ is the value of the secondary variable observed at the j^{th} point. Cokriging should only be used when there is a correlation between the primary and secondary variables (Deutsch and Journel, 1998). Thus, Pearson's correlation analyses were performed to verify the possible correlations between the FCO2 and BD.

To assess the quality of the estimates of each method, the predicted values were subjected to external validation based on root mean square error (RMSE) of the data (Teixeira et al., 2012):

$$RMSE = \left\{ \frac{1}{n} \sum_{i=1}^{n} \left[z_{obs}(x_i) - z_{est}(x_i) \right]^2 \right\}^{0,5} \quad (5)$$

where n is the number of values used in the validation (n = 14); $z_{est}(\boldsymbol{x}_i)$ is the estimated value of the property at the i^{th} point; and $z_{obs}(\boldsymbol{x}_i)$ is the value of the property at the i^{th} point;. The RMSE index provides measures of accuracy. Thus, an index closer to 0 reflects more accurate prediction.

Subsequently, the relative improvement (RI_{RMSE}) in accuracy caused by the use of secondary information in the interpolation procedure was also evaluated using the following equation (Bourennane et al., 2007):

$$RI_{RMSE} = \frac{RMSE_{OK} - RMSE_{CK}}{RMSE_{OK}} \times 100 \quad (6)$$

where: $RMSE_{OK}$ and $RMSE_{CK}$ are the values of RMSE obtained by interpolation of values using OK and CK, respectively.

The estimates of the variogram models and from OK and CK were obtained using GS+ software (version 9.0; Gamma Software Design, 2008). Surfer software (version 9.0; Golden Software, 2009) was used for the graphs and mapping. Descriptive statistics were performed using R software (R Development Core Team, 2010).

Results and Discussion

The mean FCO2 was 12 % less than the mean reported by Brito et al. (2010) under the same soil type and culture conditions (Table 1). When evaluating the soil respiration in areas of sugarcane with different management systems, Panosso et al. (2009) observed average emission values of 2.06 ± 0.06 and 2.86 ± 0.28 μmol m^{-2} s^{-1} for green and slash-and-burn managements, respectively. The lower emission values observed in the present study may be due to higher BD values (approximately 1.5 g cm^{-3}) compared to those in other studies (Brito et al., 2009). The increased BD relates to less FCO2, as gas exchange within the soil is more difficult due to either oxygen entrance or CO_2, which is produced inside the soil and diffuses to the atmosphere. When evaluating the effect of the interaction between FCO2 and BD in three soil types (clay, silt and sand), Novara et al. (2012) found that soils with a BD of 1.1 g cm^{-3} have emissions 32 % higher than those with a BD of 1.5 g cm^{-3}.

The high FCO2 CV value (approximately 50 %) is a characteristic of this variable indicating the existence of large variability even in small areas. The FCO2 CV values in the present study were similar to the values reported by other authors in different soil types and farming systems (Kosugi et al., 2007; Brito et al., 2010; Panosso et al., 2011; Allaire et al., 2012). Although the skewness value (Table 1) was outside the recommended range (|skewness| > 1) for the realization of the natural logarithmic transformation (Kerry and Oliver, 2007), the transformation was performed in order to stabilize the semivariances and, consequently, the accuracy of estimations. Thus, the natural logarithmic transformation of FCO2, which is a procedure often adopted in soil respiration spatial analysis, was used in the present study (Stoyan et al., 2000; Kosugi et al., 2007; Panosso et al., 2009).

Table 2 – Models and parameters of the auto- and cross-variograms fitted to the soil CO_2 emission and soil bulk density data in the different scenarios evaluated.

	Models	C_0	C_0+C_1	$\lvert C_0/(C_0+C_1)\rvert$	A	R^2	SSR	Cross-validate	
								a	b
BD	Exp.	0.01	0.02	0.50	10.70	0.82	6.49E-06	0.48	0.68
F67	Sph.	0.10	0.31	0.32	31.80	0.89	3.83E-03	0.52	0.76
F67 × BD	Sph.	-1.68E-03	-0.02	0.08	18.95	0.81	3.58E-05	0.00	1.00
F87	Sph.	0.10	0.30	0.33	27.70	0.85	6.15E-03	0.56	0.78
F87 × BD	Sph.	-1.48E-03	-0.02	0.07	27.28	0.90	9.34E-01	0.00	1.00
F107	Sph.	0.11	0.32	0.34	26.47	0.89	4.98E-03	0.42	0.81
F107 × BD	Sph.	-5.11E-03	-0.03	0.17	21.49	0.86	7.12E-05	0.00	1.00
F127	Sph.	0.10	0.31	0.32	28.04	0.89	4.59E-03	0.37	0.84
F127 × BD	Sph.	-2.03E-03	-0.03	0.07	21.37	0.81	1.17E-04	0.00	1.00

C_0 = nugget effect; C_0+C_1 = sill; $\lvert C_0/(C_0+C_1)\rvert$ = degree of spatial dependence; A = range (m); a = intercept coefficient; b = slope coefficient; Exp.= exponential model; Sph.= spherical model.

Based on the classification proposed by Warrick and Nielsen (1980), BD presented a small variation characterized by the CV ratio being less than 12 % (Table 1). This homogeneity may be related to the management of sugarcane adopted in the studied area, which was based on eight years of cultivation without field reform. Although the BD presented small variability, there was a linear correlation with FCO2 in all evaluated scenarios presenting coefficients ranging from -0.26 ($p < 0.05$) to -0.34 ($p < 0.01$) for the F67 and F127 scenarios, respectively. Increased observation numbers resulted in larger coefficients of correlation with significance less than 1 % of probability because the calculation of the correlation was influenced by increasing the number of observations considered. As mentioned above, the negative coefficients indicated the inverse relationship between the FCO2 and BD.

Panosso et al. (2011) evaluated the soil respiration under sugarcane in different management systems, and they reported a correlation between the FCO2 and the interaction of BD with the rate of organic matter humification. Saiz et al. (2006) presented a multiple linear regression model using BD as the variable, combined with other environmental variables, to explain 54 % of the total variance of FCO2 under forests of *Picea sitchensis*. However, few studies have reported the influence of BD on the spatial patterns of FCO2.

Spherical (Kosugi et al., 2007; Panosso et al., 2009; Brito et al., 2010; Teixeira et al., 2011; Allaire et al., 2012) models were fitted to the FCO2 experimental auto- and cross-variograms (Table 2 and Figure 2). For the BD, the exponential model (Camargo et al., 2010) presented the best fit. The main difference between both models is that the variation associated with a spherical model has more evenly sized patches whereas those for the exponential model have a more random extent. As observed for the linear correlation, the FCO2 and BD were negatively correlated in space resulting in negative sill and nugget effect values. Stoyan et al. (2000) found positive spatial correlations among the FCO2, soil moisture and carbon content in soil in areas under forests. Prolingheuer et al. (2010) evaluated the spatial correlation between soil respiration and the respiration from the autotrophic (roots) and heterotrophic organisms in winter wheat crops, and they found a positive spatial correlation between the FCO2 and autotrophic respiration. Decreased nugget effect values were observed for the cross-variogram in relation to the auto-variogram adjusted for FCO2 in all scenarios (Table 2), which indicated that the error due to laboratory tests or sampling error was the major constituent of the residual variance overlapping that due to the microscale variability (Stoyan et al., 2000).

Table 3 – Index of accuracy (RMSE) calculated from the external validation of the different scenarios used.

	RMSE	RI_{RMSE}
F67	0.59	-
F67 × BD	0.55	6.78
F87	0.52	-
F87 × BD	0.43	17.31
F107	0.48	-
F107 × BD	0.46	4.16
F127	0.47	-
F127 × BD	0.47	0.00

(n = 14); RMSE = root mean square error (μmol m^{-2} s^{-1}); RI_{RMSE} = relative improvement (%).

The degree of spatial dependence was classified as moderate for all auto-variograms fitted to the FCO2 and BD as characterized by the following relation: $0.25 < |C_0/(C_0 + C_1)| < 0.75$ (Cambardella et al., 1994). Excepted the F107 × BD cross-variogram, all cross-variograms presented strong spatial dependence ($|C_0/(C_0 + C_1)| < 0.25$) as a consequence of the strong spatial correlation between the FCO2 and BD.

The FCO2 range values shown in Table 2 were similar to those reported by Brito et al. (2010) in different topographic positions. Allaire et al. (2012) evaluated multiscale FCO2 spatial variability in sandy soils under a corn/potato rotation, and they found range values from 24.3 and 28.5 m. Although the BD presented spatial dependence only to a distance of 10.70 m, the cross-variogram presented an average range of 22.27 m.

When considering the scenarios in the present study, small changes in the intercept and slope coefficients of the cross-validation adjustments may indicate a relative maintenance of the quality of the estimates even with the increased number of samples used. In all scenarios, the cross-variogram produced intercept and slope coefficient values close to 0 and 1, respectively (Table 2), indicating the potential use of secondary information for FCO2 spatial analysis.

The BD map shows the lowest values (< 1.52 g cm^{-3}) predominantly on the left in the same region where the highest estimated FCO2 values are shown (Figure 3). This trend confirmed the negative correlations (both linear and spatial) shown in Table 2. As the number of samples used to predict FCO2 increased, the map became more heterogeneously detailed. The F67 and F87 maps presented greater differences from those estimated by the F107 and F127 scenarios, which may have been related to the number of samples present in the central region of those maps (F107 and F127).

The digital correlation (n = 8836) of maps produced by different interpolation methods resulted in correlations ranging from 0.90 (F67) to 0.98 (F107 and F127), which indicated the high contribution of the secondary information (BD) to the primary information (FCO2). Thus, the use of secondary information in the F67 and F87 scenarios promoted greater contributions than those for the F107 and F127 scenarios. In general, the maps produced by CK were more irregular and less smoothed than those generated by OK in all scenarios (Figure 3). These results were similar to Chai et al.

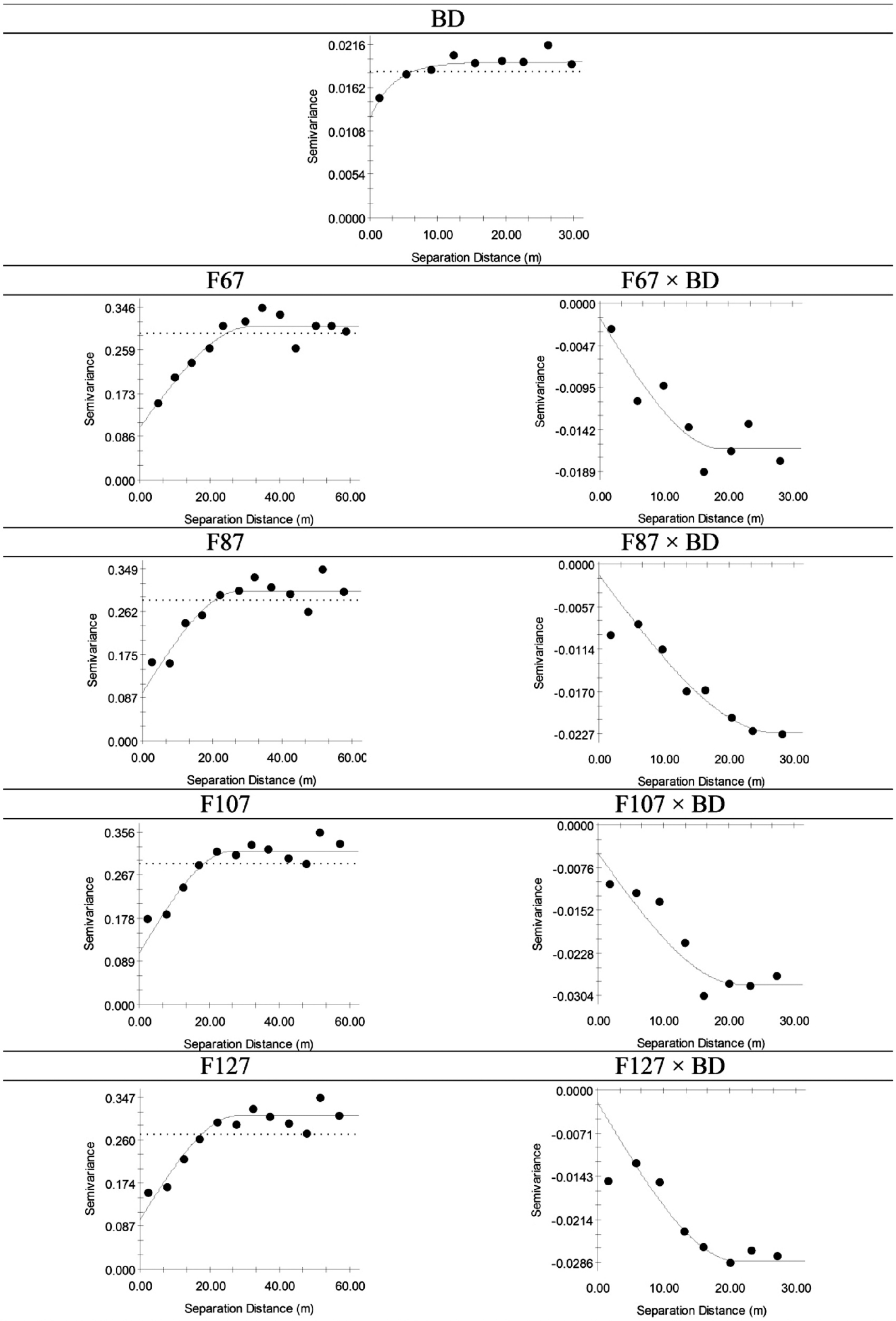

Figure 2 – Auto- and cross-variograms fitted to the soil CO_2 emission and soil bulk density data.

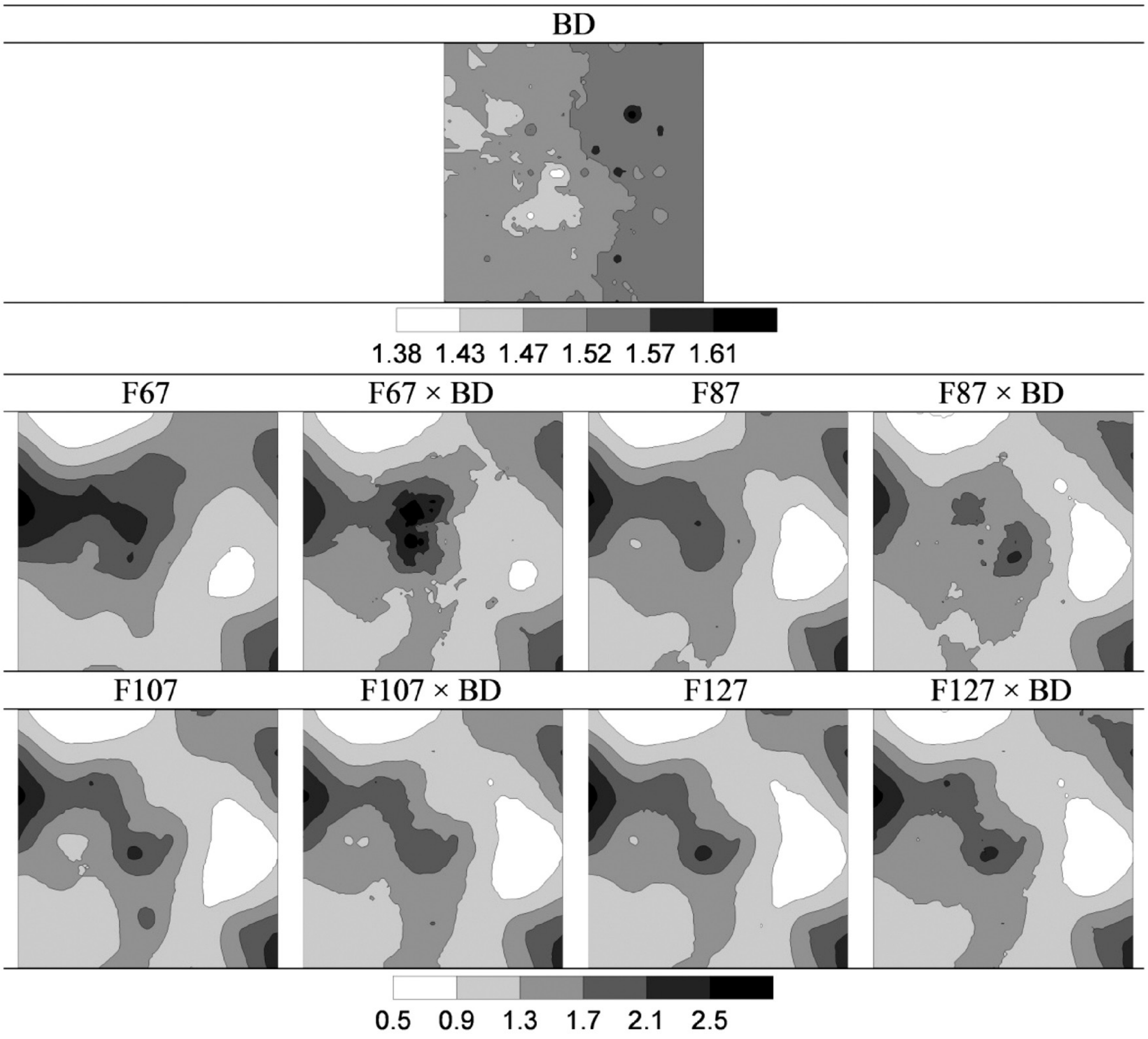

Figure 3 – Maps of the spatial pattern of the soil bulk density (g cm^{-3}) and soil CO_2 emissions (µmol m^{-2} s^{-1}) in different scenarios with and without use of secondary information.

(2007), who studied soil organic matter using elevation data as secondary information.

The quality of estimates in different scenarios was assessed by accuracy indexes (Table 3). With the increased number of observations considered in the FCO2 model, the estimation quality was improved, resulting in RMSE values closer to 0. The use of additional information regarding BD improved the predicted models only in the F107 (4.16 %), F67 (6.78 %) and F87 (17.31 %) scenarios.

In most studies, the contribution of FCO2 from agricultural soils is estimated indirectly. However, the direct quantification of FCO2 when considering the existence of spatial variability is a major task because this quantification could be integrated more accurately into inventories of greenhouse gases. Such inventories contribute to the understanding of the soil carbon balance allowing the identification of the management systems and areas that have higher potential of soil carbon storage.

FCO2 mapping by geostatistical techniques should be obtained easily and inexpensively. However, the large temporal variation of FCO2 present even in short periods (Teixeira et al., 2011) influences their characterization, thereby invalidating the mapping in large areas. The increased number of evaluation equipment partially solves the impasse however the costs of the mapping would be significantly increased. The use of data from the BD, which provides additional information to the FCO2 data, becomes a viable alternative to large area mappings because the sampling BD has no restrictions with respect to time. This methodology also has the advantage of obtaining more precise and accurate maps.

Conclusions

The use of BD provides additional information to FCO2, which is a viable alternative to large area mappings, thus resulting in more precise and accurate maps.

Increased amounts of secondary information present in locations where no primary information has been received result in greater relative improvements in CK.

The scenario with a primary (FCO2) and secondary (BD) ratio of 1.0:1.5 presented the best relative improvement in the quality of the estimates..

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