Supplementary material

SM Methods

N_2O flux equation

Emission fluxes were calculated based on the accumulation of N_2O gas [$\mu gN_2O\ m^{-2}\ h^{-1}$] per each chamber during the 20 – min sampling time by equation SM 1:

$$F_{N2O} = \frac{\Delta C \times M_{N2O} \times V_{ch} \times 60 \times f}{V_m \times A_{ch} \times t_{20}} \quad \text{(SM 1)}$$

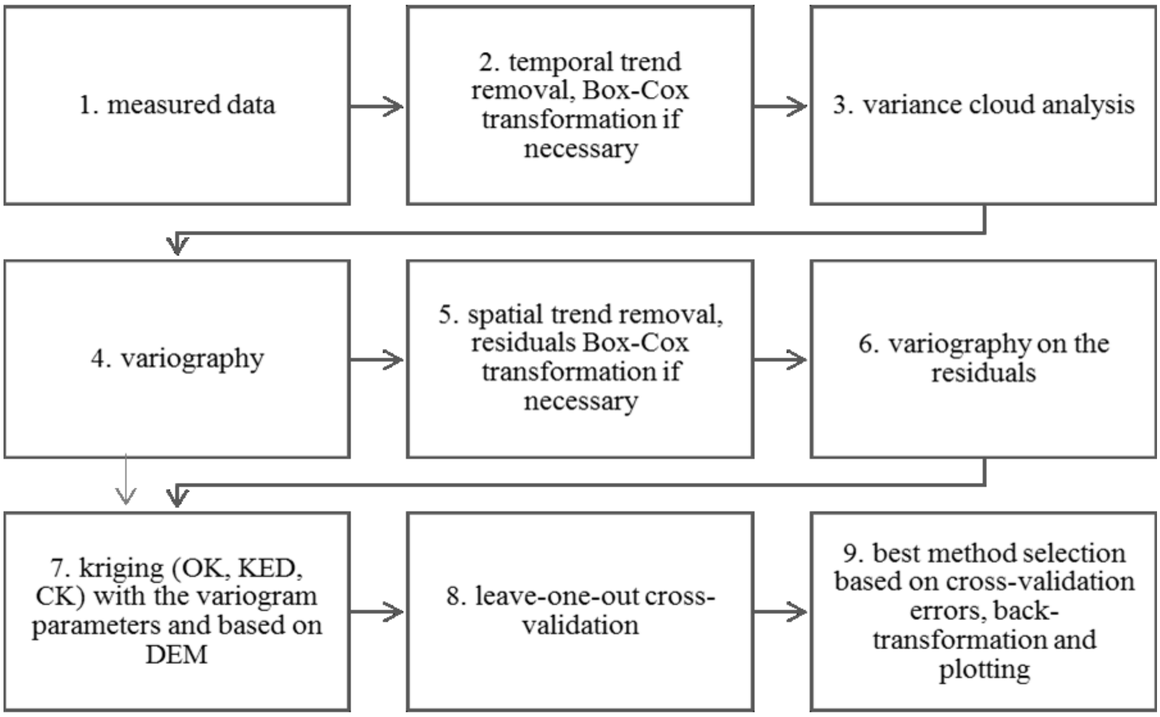
where ΔC is the difference in mixing ratios [ppb] in chambers at the end and start of samplings, M_{N2O} is the molecular weight of N_2O, V_{ch} is the volume of the chambers [4×10^{-4} m^3], 60 is the time conversion factor for hour [$min\ h^{-1}$], f is the factor taking into account the residual pressure in the evacuated tubes, V_m is the molar volume – 24 liters at laboratory temperature [t = 20 °C] during measurements –, A_{ch} is the surface of soil covered by chambers [80 cm^2], t_{20} is the sampling time [20 min].

Correlation of background factors from different campaigns

SOC and TSN data sampled in Oct-2012 in the grazed treatment were used as a background for that day but the Oct-2014 data from the grazed and mowed treatments were used for the other datasets because of the slight modification of the sampling positions mentioned in the main text. We found statistically significant positive correlation between the two sampling dates' (Oct-2012 and Oct-2014) SOC and TSN data ($p<0.01$ for both) for the grazed site, so joining the datasets was justified.

Spatial data processing

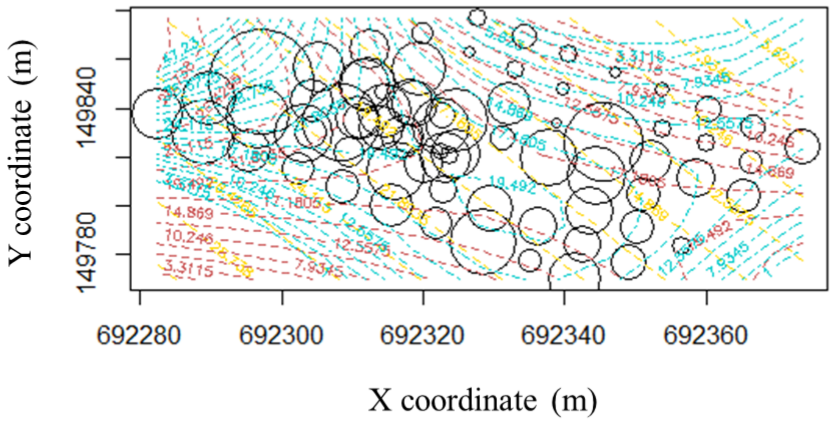
The data analysis consisted of the steps summarized in Supplementary material (SM) Figure 1.



SM Figure 1. Steps of the spatial data processing.

Variography

Spatial patterns of the variables were investigated by variograms, cross-variograms and kriging. Raw data were often non-normally distributed and were affected by elevation (micro-relief topography) or temporal trends (the latter was suspected in T_s and R_s datasets, because these variables may change rapidly within a few hours). In the presence of temporal trends linear detrending of the data against time was applied (2nd step, SM Figure 1). In case of non-normality data were normalized by the Box-Cox power transformation (Fox and Weisberg 2011; Meyer and others 2014; R Core Team 2014) prior to geostatistical analysis. Variogram and cross-variogram analysis was done on normally distributed data after excluding outliers by variance cloud analysis (Pebesma 2004) (3rd step, SM Figure 1). In case of spatial (elevation) trends, when either the autocorrelation length was larger than allowable (larger than half of the maximum lag distance: Rossi and others 1992; Stein and Ettema 2003), or sill was not found in variography (4th step, SM Figure 1), surface detrending was done by fitting 1st, 2nd and 3rd order polynomial trend surfaces by using the least squares method (Venables and Ripley 2002; Vieira and others 2010)(5th step, SM Figure 1, SM Figure 2). Similarly to Vieira and others (2010), the simplest detrending polynomial was chosen when a stable sill had already been found for the residuals. After detrending, residuals were retained for further analysis. Residuals were also normalized, if necessary (5th step, SM Figure 1), and variography was repeated (6th step, SM Figure 1). The variogram parameters from variography in the 4th or 6th steps of the data processing were used in kriging (7th step, SM Figure 1, see the different types below). Kriging results were evaluated using the leave-one-out cross validation (8th step, SM Figure 1, (Oliver and Webster 2014)). The best kriging method was selected on the basis of the cross validation errors and data were back-transformed to the original scale for mapping (9th step, SM Figure 1).



SM Figure 2. Example of spatial detrending of the Oct-2012 N_2O dataset from the grazed plot. Circles are proportional to the N_2O flux, dashed lines represent trends (1st order: yellow, 2nd order: red, 3rd order: cyan) in space.

All variables were standardized to zero mean and unit variance before variography and kriging to facilitate comparison of different variables (Katsalirou and others 2010).

Semivariance (γ(h)) was calculated as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{n} \left[z(s_i) - z(s_i + h) \right]^2 , \qquad \text{(SM 2)}$$

where *z(s)* is a data value at a particular location, *h* is the average separation distance between data pairs, and *N(h)* is the number of data pairs separated at a distance of *h* (Dale 1999).

Gaussian, exponential and spherical models were fitted to the experimental semivariances against lag distance.

Gaussian:

$$\gamma(h) = y_0 + c\left(1 - e^{\left(\frac{-h^2}{a_0^2}\right)}\right) \qquad \text{(SM 3)}$$

Exponential:

$$\gamma(h) = y_0 + c\left(1 - e^{\left(\frac{-h}{a_0}\right)}\right) \qquad \text{(SM 4)}$$

Spherical:

$$\gamma(h) = y_0 + c\left[1.5\frac{h}{a_0} - 0.5\left(\frac{h}{a_0}\right)^3\right] \quad ;\text{if } h < a \qquad \text{(SM 5)}$$

$$\gamma(h) = y_0 + c \quad ;\text{if } \dot{h} \geq a$$

In the models, h is the lag distance, a is the autocorrelation length (the distance at which the variogram reaches a plateau or, in the case of models with an asymptotic plateau, at which the variogram reaches its 95%, and is calculated from a_0 as $a=a_0\times3$ in the case of the exponential model, $a=a_0\times3$^0.5 in the case of the Gaussian model, and $a=a_0$ in the case of the spherical model), y_0 is the variance resulting from measurement errors and smaller scale processes ('nugget effect') and c is the structural variance. The following model parameters were also used in the subsequent analysis: ($y0+c$) or '*sill*', the total sample semivariance; *psill*, the ratio of structural variance and total variance, expressed as a percentage.

The criterion for model selection was the residual sum of squares (SSErr). The goodness of model fit was quantified by the Nash–Sutcliffe model efficiency coefficient (ME), which is calculated similarly to the coefficient of determination, but ranges from -∞, indicating a better prediction of the observed values by the mean than by the model to 1, which points to a perfect match of the observed and modelled data. Only fits with ME≥0.5 were accepted. Cross-variograms were used to investigate the spatial correlation of two variables. Cross-semivariance $y_x(h)$ was calculated from normally distributed variables, but without trend removal as follows:

$$\gamma_x(h) = \frac{1}{2N(h)} \sum_{i=1}^{n} \left[z(s_i) - z(s_i + h)\right]\left[z(r_i) - z(r_i + h)\right], \qquad \text{(SM 6)}$$

where $z(s)$ and $z(r)$ are the two investigated variables. In contrast to direct variograms, cross-variograms could become negative, indicating that the two variables are negatively correlated in space and their patterns change inversely (while the value of the driver variable increases in space, that of the dependent variable decreases). Positive values indicate positive spatial correlation, i. e. joint/linked change (while the value of the driver variable increases the dependent variable also increases, that is the driver has a controlling effect on the dependent variable) in space, while values close to zero indicate that they change independently in space. The same theoretical models were fitted to the cross-variances as to the semivariances, and the same set of variogram parameters (*y0, c, sill, psill, a and ME*) were obtained. Furthermore, as surface trends were not removed, we complemented the cross-variogram analysis, with linear model (Pebesma 2004) to be able to describe the spatial correlation between the pairs of variables if the cross-variogram was unbounded (not saturated/did not reach sill). Linear model reflects the changes of the variables without spatial threshold.

Kriging

Kriging is an interpolation technique for the estimation of the values of a variable at unsampled locations, based on the measured values in the neighbourhood and the variogram parameters. Three types of kriging methods were investigated (then one of them was selected)(Pebesma 2004) on SWC, T_s, R_s, AGB and N_2O data. For ordinary punctual kriging (OK), those variograms with ME>0.5 values were used, the ones which had already been found to be the best fitting models from exponential, Gaussian and spherical. The kriging neighbourhood was set to the autocorrelation length of the variogram in question (Goslee 2006), and 7 to 25 nearest data (Oliver and Webster 2014) within this range were used for the estimation. Universal kriging or kriging with external drift (KED) is a technique when the values of the sparsely measured target variable at unsampled locations are estimated on the basis of a high resolution auxiliary variable. In our study the DEM of the study plots was used as the auxiliary variable. Here, the autocorrelation length of the residual variograms (fitted on the residuals' - received after subtracting the correlation with ALT from the measured variable - semivariances) and the 7 to 25 nearest points were set as kriging neighbourhood. Finally, ordinary co-kriging (CK) is a technique when the high resolution auxiliary data is used for the estimation on the basis of fitting a linear model of co-regionalization on the experimental semivariances of the target variable and the auxiliary data (here: ALT) and on their cross-semivariances. CK was performed on a reduced spatial resolution (Plant 2012) DEM (one tenth of the original DEM data was used) because of computational limits. (The kriged maps by this method are patchy due to this data reduction, cf. Figure 4).

For the evaluation of the kriging methods leave-one-out cross-validation was performed. The procedure consisted of a series of estimations by omitting the observed data one by one and predicting their values by kriging. The following error estimates were used to compare the different kriging methods' goodness:

- normalized root mean square error (nRMSE):

$$nRMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} / ((\max(y) - \min(y)), \qquad \text{(SM 7)}$$

where y is the variable in question, y_i is one observed value of the variable at a given position, $\hat{y}_i$ is the estimated value for the given position by the kriging method when the point has been omitted from the dataset, n is the number of observations.

– mean squared deviation ratio (MSDR), because we could compare the goodness of the three methods on the same dataset and choose the method with MSDR closest to 1. This comparison allowed us to assess the importance of the auxiliary variable in the estimation.

$$MSDR = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2/var_{kr}, \qquad \text{(SM 8)}$$

where the parameters are the same as in SM 7, and var_{kr} is the kriging variance.

– and with regard to prediction bias: the closer the mean error (meanERR) to zero, the better the prediction is. Its negative values mean over-estimation, whereas its positive values mean under-estimation by the method.

$$MeanERR = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n}, \qquad \text{(SM 9)}$$

with the same parameters as SM 7.

When the spatial estimation was not successful either due to non-normality of the datasets, ME<0.5 for the variogram fitting, occurrence of smaller autocorrelation length for the variogram than the grid scale (10 m), or large deviation between predicted (kriging) and measured values (the average of the estimated values by the best kriging method differed more than 100% from the average of the measured data) due to e. g. large nugget variance, we used inverse distance weighting (IDW) interpolation method (Baddeley and others 2015) before mapping. IDW estimates the values of a variable at unsampled locations on the basis of neighbouring data values in such a way that the closer the measured data position is to the unsampled location, the more influence (weight) it will have on the estimation. (Presence of the random measuring positions allowed us to use this method, rather than simply the linear interpolation.)

SM Results

Spatial co-patterns and temporal persistence of the driving variables

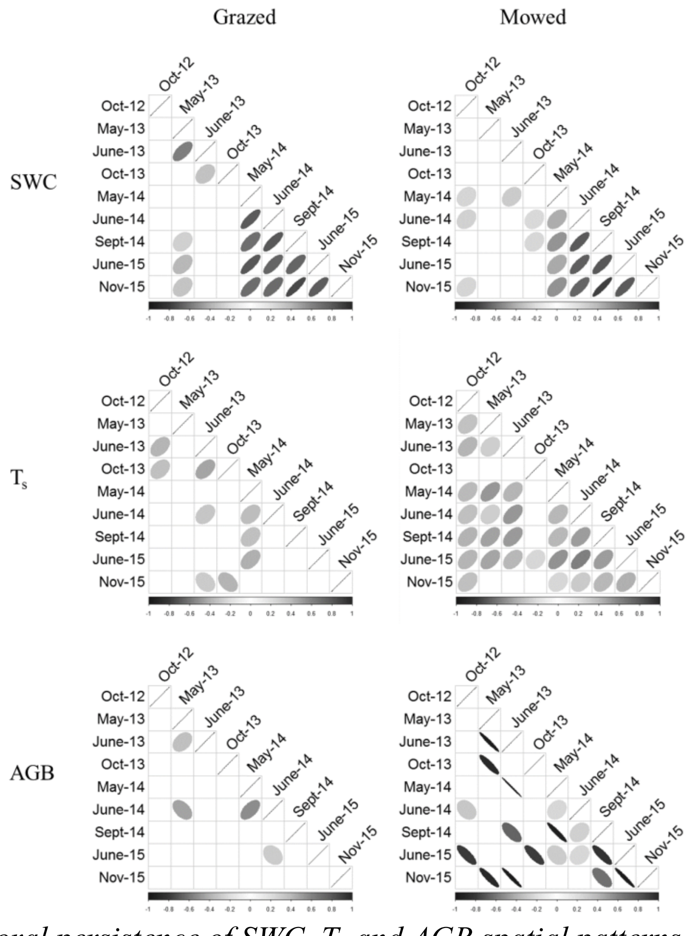
The autocorrelation lengths of ALT were similar between 45-59 m and 36-52 m in the grazed and mowed plots, respectively (depending on the spread of positions actually taken into account) despite the slight topographic differences. We found that the direct variograms of SOC had 30 and 40 m and TSN had 20 and 40 m autocorrelation lengths in the grazed and mowed plots, respectively. The cross-variogram autocorrelation lengths for ALT-SOC/TSN negative spatial correlations were around 40 m for both treatments.

Descriptive statistics and variogram model parameters of the driving variables, SWC and T_s and those of AGB can be found in SM Tables 1, 2 and 4, while sign of the spatial correlation between all possible variable pairs (based on the cross-variogram analysis) can be found in SM Table 6.

SWC had 43±17.7 m autocorrelation length on average in the grazed plot (SM Table 1) and was negatively linked to ALT with 53.6±5.5 m average cross-variogram autocorrelation length. At the mowed plot nugget variograms occurred 8 times out of 10, indicating homogeneity at the study scale and the average autocorrelation length was more than 60 m for the successfully fitted datasets. The SWC-ALT cross-variograms had 53.8±6.3 m average autocorrelation length for the whole study period. The spatial pattern of SWC in the mowed plot showed larger scales than the background variables (ALT, SOC, TSN), while scales were more similar in the grazed treatment.

T_s (detectable in 6 cases in both plots, SM Table 2) generally showed smaller autocorrelation length than SWC with 27.3±14.3 m and 32.9±15.4 m on average for the grazed and mowed plots, respectively. In most of the cases SWC and T_s were negatively correlated in space, while T_s-ALT spatial correlations were generally positive except for autumn occasions in the grazed plot when the spatial patterns of SWC and T_s changed jointly (two campaigns), while ALT and T_s changed inversely (three campaigns).

The pattern of AGB (SM Table 4) showed 29.7±12.7 m and 33±21.7 m average autocorrelation lengths in the grazed and mowed plots, respectively. Concerning the spatial correlations, we found joint AGB-SWC patterns (except for one autumn datasets from the grazed plot again), while AGB-T_s and AGB-ALT patterns correlated negatively. Correlation between AGB and SOC/TSN was rarely detectable in the grazed plot, while joint patterns were found in 7 out of 9 cases in the mowed plot. The hypothesized joint spatial changes of AGB and R_s in space were detected in 3 out of 9 cases in both plots.



SM Figure 3. Temporal persistence of SWC, T_s and AGB spatial patterns for the grazed and for the mowed plots, represented by significant rank-correlations (p<0.05) between measuring campaigns. The darker the colour, the more stable the pattern is, while directionality of the symbols represents the sing of the correlation, positive or negative.

The non-parametric rank correlations showed relatively strong persistence of SWC patterns for the second part of the investigated period (SM Figure 3), quite similarly for both the grazed and mowed plots. This period corresponded to the year with levels of precipitation higher than the average and in the following years. For T_s (SM Figure 3) a relatively stable pattern was characteristic in the mowed plot along the study, while low persistence and negative correlations could also be detected in the grazed one. AGB was the least stable among the variables (SM Figure 3) with practically no temporal persistence except for a few cases in the second part of the study period when the average AGB was slightly larger than in the first part (SM Table 4). However, we found high occurrence rates of negative correlations in the mowed plot between consecutive measuring occasions or between measurements being distant in time.

SM Table 1. Average (mean, %), standard deviation (sd), coefficient of variation (cv, %), minimum (min, %) and maximum (max, %) as well as the best variogram model and the model parameters, the nugget variance (y0), the structural semivariance (c), the total sample semivariance (y0+c, or 'sill'), the ratio of structural variance and total variance, expressed as a percentage (psill), autocorrelaion length (a, m) and the goodness of model fit (ME) for the grazed and mowed plots' SWC data by measuring campaigns.

date	transect	mean	sd	cv	min	max	model	y0	c	sill	psill	a	ME
Oct-2012.	SWC grazed	16.49	5.03	30.50	4.10	25.7	Sph	0.38	0.84	1.22	68.85	55.67	0.97
May-2013.		14.73	4.39	29.80	3.60	23.3	Sph	0.43	0.77	1.2	64.17	62.76	0.98
June-2013.		14.19	5.67	39.96	4.10	30.6	Sph	0.06	0.96	1.02	94.12	19.6	0.98
Oct-2013.		14.07	3.69	26.23	6.60	22.3	Exp	0	1.05	1.05	100	21.92	0.96
May-2014.		16.16	4.39	27.17	7.10	26.2	Gau	0.65	0.56	1.21	46.28	47.86	0.87
May-2014 (N_2O)		20.31	4.93	24.27	9.50	30.1	Sph	0.34	0.89	1.23	72.36	56.66	0.97
June-2014.		14.60	4.38	30.00	6.10	26.2	Exp	0.03	1.3	1.33	97.74	64.88	0.84
Sept-2014.		23.25	6.49	27.91	9.00	35.5	Sph	0.22	0.95	1.17	81.2	46.84	0.98
June-2015.		7.92	2.60	32.83	3.60	15.4							
Nov-2015.		16.96	5.61	33.08	6.60	27.2	Sph	0.13	0.91	1.04	87.5	21.61	0.99
Oct-2012.	SWC mowed	15.31	6.02	39.32	2.20	29.20							
May-2013.		13.97	4.33	31.01	2.70	25.20							

June-2013.	14.06	5.03	35.78	5.10	31.60	Gau	0.85	0.34	1.19	28.57	71.75	0.54
Oct-2013.	10.48	4.14	39.45	3.10	22.80							
May-2014.	15.47	4.36	28.17	5.10	26.70							
May-2014 (N_2O).	13.96	4.15	29.73	7.10	25.70							
June-2014.	12.38	4.77	38.52	3.60	27.70							
Sept-2014.	18.77	7.38	39.31	8.10	37.50							
June-2015.	6.42	2.65	41.28	2.70	13.90							
Nov-2015.	11.05	6.11	55.29	3.60	28.70	Gau	0.71	0.6	1.31	45.8	68.9	0.88

SM Table 2. Average (mean, %), standard deviation (sd), coefficient of variation (cv, %), minimum (min, %) and maximum (max, %) as well as the best variogram model and the model parameters, the nugget variance (y0), the structural semivariance (c), the total sample semivariance (y0+c, or 'sill'), the ratio of structural variance and total variance, expressed as a percentage (psill), autocorrelaion length (a, m) and the goodness of model fit (ME) for the grazed and mowed plots' T_s data by measuring campaigns.

date	transect	mean	sd	cv	min	max	model	y0	c	sill	psill	a	ME
Oct-2012.		16.93	1.25	7.37	14.40	20.2							
May-2013.		21.03	0.99	4.71	19.10	25.2	Sph	0.84	0.19	1.03	18.45	48.45	0.97
June-2013.		19.28	1.27	6.61	17.20	22.4							
Oct-2013.		17.11	0.63	3.68	15.86	18.92							
May-2014.	T_s	20.72	1.56	7.52	17.40	24.5							
May-2014 (N_2O).	grazed	19.84	0.71	3.58	17.70	21.6	Sph	0.72	0.3	1.02	29.41	40.62	0.85
June-2014.		20.05	0.92	4.59	17.77	22.27	Sph	0	1.07	1.07	100	24.68	0.92
Sept-2014.		15.78	0.50	3.17	14.22	17.14	Exp	0	1.09	1.09	100	21.6	0.78
June-2015.		26.51	1.51	5.70	22.71	30.94	Exp	0	1.02	1.02	100	11.43	0.64
Nov-2015.		10.48	0.21	2.00	10.04	11	Gau	0	1.05	1.05	100	16.89	0.96
Oct-2012.	T_s	14.47	0.76	5.27	12.90	17.10							
May-2013.	mowed	22.16	1.10	4.96	19.50	25.70	Exp	0.44	0.62	1.06	58.49	46.11	0.94

June-2013.	19.79	1.04	5.26	17.00	22.40	Sph	0	1.07	1.07	100	21.55	0.99
Oct-2013.	17.03	0.61	3.58	15.80	18.90	Gau	0	0.99	0.99	100	12.28	0.91
May-2014.	19.89	1.25	6.29	17.17	22.35							
May-2014 (N_2O).	19.58	1.17	5.98	12.70	22.00							
June-2014.	21.13	2.02	9.54	8.72	25.70							
Sept-2014.	15.80	0.69	4.37	13.90	17.20	Sph	0.76	0.31	1.07	28.97	39.67	0.96
June-2015.	26.69	2.24	8.39	21.70	31.60	Sph	0.13	1.2	1.33	90.23	51.87	0.99
Nov-2015.	10.63	0.34	3.20	9.90	11.80	Sph	0.65	0.37	1.02	36.27	25.89	0.98

SM Table 3. Average (mean, %), standard deviation (sd), coefficient of variation (cv, %), minimum (min, %) and maximum (max, %) as well as the best variogram model and the model parameters, the nugget variance (y0), the structural semivariance (c), the total sample semivariance (y0+c, or 'sill'), the ratio of structural variance and total variance, expressed as a percentage (psill), autocorrelaion length (a, m) and the goodness of model fit (ME) for the grazed and mowed plots' R_s data by measuring campaigns.

date	transect	mean	sd	cv	min	max	model	y0	c	sill	psill	a	ME
Oct-2012.		6.10	1.41	23.11	3.66	10.16	Exp	0.2	0.85	1.05	80.95	24.97	0.92
May-2013.		9.40	2.33	24.70	2.97	14.58	Sph	0.64	0.41	1.05	39.05	29.65	0.79
June-2013.		5.60	1.85	33.04	2.08	11.17	Sph	0.27	0.68	0.95	71.58	19.12	0.85
Oct-2013.		5.47	1.22	22.30	3.27	8.01	Gau	0.71	0.32	1.03	31.07	20.87	0.8
May-2014.	R_s grazed	8.50	1.57	18.47	4.48	14.84	Sph	0.62	0.35	0.97	36.08	24.44	0.84
June-2014.		10.28	1.97	19.16	6.52	15.9	Sph	0.3	0.66	0.96	68.75	18.54	0.91
Sept-2014.		7.35	1.82	24.76	4.60	16.7	Gau	0.72	0.43	1.15	37.39	55.47	0.88
June-2015.		9.89	2.52	25.48	4.88	17.2	Sph	0.41	0.66	1.07	61.68	26.97	0.93
Nov-2015.		2.44	0.60	24.59	1.17	3.88	Sph	0.71	0.33	1.04	31.73	45.81	0.9
Oct-2012.		4.06	1.08	26.60	1.45	6.63	Gau	0.24	0.77	1.01	76.24	11.33	0.62
May-2013.	R_s mowed	10.28	2.29	22.28	5.24	15.40	Exp	0	1.01	1.01	100	11.27	0.55
June-2013.		7.38	1.94	26.27	2.53	12.50	Sph	0.78	0.32	1.1	29.09	40.11	0.93

Oct-2013.	5.15	0.88	17.09	3.41	7.77	Gau	0.89	0.19	1.08	17.59	66.59	0.79
May-2014.	9.50	1.84	19.36	5.81	14.30							
June-2014.	9.28	1.81	19.56	5.97	13.40							
Sept-2014.	7.98	1.63	20.43	5.24	15.40	Sph	0.57	0.45	1.02	44.12	34.25	0.88
June-2015.	7.52	2.36	31.38	3.41	14.02	Exp	0.24	0.96	1.2	80	52.43	0.98
Nov-2015.	2.09	0.75	35.89	0.88	4.10	Sph	0	1.09	1.09	100	25.91	0.98

SM Table 4. Average (mean, %), standard deviation (sd), coefficient of variation (cv, %), minimum (min, %) and maximum (max, %) as well as the best variogram model and the model parameters, the nugget variance (y0), the structural semivariance (c), the total sample semivariance (y0+c, or 'sill'), the ratio of structural variance and total variance, expressed as a percentage (psill), autocorrelaion length (a, m) and the goodness of model fit (ME) for the grazed and mowed plots' AGB data by measuring campaigns.

date	transect	mean	sd	cv	min	max	model	y0	c	sill	psill	a	ME
Oct-2012.	AGB grazed	2.26	1.39	61.50	0.45	6.7							
May-2013.		2.03	0.97	47.92	0.41	5.04							
June-2013.		3.50	1.80	51.43	0.48	11.33	Exp	0.71	0.31	1.02	30.39	28.73	0.91
Oct-2013.		1.82	0.76	41.76	0.46	3.71	Exp	0	1.01	1.01	100	18.27	0.89
May-2014.		3.07	1.60	51.96	0.72	10.5							
June-2014.		1.02	0.80	78.99	0.16	4.65							
Sept-2014.		3.55	1.96	55.21	0.73	8.68	Sph	0	1.09	1.09	100	16.76	0.8
June-2015.		3.38	1.90	56.21	0.52	12.1							
Nov-2015.		5.20	2.33	44.81	1.11	10.84	Sph	0.05	1.07	1.12	95.54	18.69	0.83
Oct-2012.	AGB mowed	3.35	1.42	42.39	0.50	7.65	Gau	0	0.95	0.95	100	17.98	0.79
May-2013.		2.93	1.25	42.66	0.47	7.13							
June-2013.		3.89	1.83	47.04	0.80	9.33	Gau	0.8	0.33	1.13	29.2	60.76	1

Oct-2013.	1.52	0.70	46.14	0.38	3.11							
May-2014.	3.15	1.22	38.73	0.80	6.75	Sph	0.64	0.31	0.95	32.63	26.48	0.93
June-2014.	1.43	0.86	59.72	0.33	5.36							
Sept-2014.	5.43	2.17	39.96	1.80	12.67	Sph	0.73	0.35	1.08	32.41	59.66	0.83
June-2015.	4.76	2.28	47.90	1.19	13.18	Sph	0.75	0.31	1.06	29.25	21.29	0.91
Nov-2015.	4.99	3.03	60.72	1.63	18.92	Gau	0	1.02	1.02	100	12.01	0.96

SM Table 5. Average (mean, %), standard deviation (sd), coefficient of variation (cv, %), minimum (min, %) and maximum (max, %) as well as the best variogram model and the model parameters, the nugget variance (y0), the structural semivariance (c), the total sample semivariance (y0+c, or 'sill'), the ratio of structural variance and total variance, expressed as a percentage (psill), autocorrelaion length (a, m) and the goodness of model fit (ME) for the grazed and mowed plots' N_2O flux data by measuring campaigns.

date	transect	mean	sd	cv	min	max	model	y0	c	sill	psill	a	ME
Oct-2012.	N_2O	9.04	8.3	92.3	-7.32	38.91	Sph	0.55	0.53	1.08	49.07	39.2	0.97
May-2014 (N_2O).	grazed	8.62	15	171	-21.4	64.84							
Oct-2012.	N_2O	6.79	9.8	144	-10.4	31.7	Sph	0.44	0.5	0.94	53.19	18.37	0.9
May-2014 (N_2O).	mowed	9.53	11	112	-14.7	37.5							

SM Table 6. Sign of the spatial correlations between variable pairs on the basis of the cross-variogram analysis for the grazed and mowed plots' measuring campaigns (n in blue cells: negative, p in red cells: positive). (It has to be noted that we had only one SOC, TSN and ALT datasets.)

	Grazed										Mowed									
Date	Oct-2012	May-2013	June-2013	Oct-2013	May-2014	May-2014 (N_2O)	June-2014	Sept-2014	June-2015	Nov-2015	Oct-2012	May-2013	June-2013	Oct-2013	May-2014	May-2014 (N_2O)	June-2014	Sept-2014	June-2015	Nov-2015
SWC-T_s	n	n	n	p		n		p	n		n		n	n					n	
SWC-R_s						-	p	p	p				p	p		-	p		p	
SWC-AGB	n	p	p			-		p	p				p			-	p		p	
SWC-ALT		n	n	n	n	n		n	n				n	n			n		n	
SWC-N_2O	p																			
SWC-SOC	p	p	p	p		p	p	p	p				p	p	p	p	p		p	
SWC-TSN	p	p	p	p	p	p	p	p	p				p	p	p	p	p		p	
T_s-R_s				p		-		p	n		n	n	n		n	-			n	
T_s-AGB			n			-							n	n		-			n	
T_s-ALT		p		n		p		n		n	p	p	p	p	p		p	p	p	
T_s-N_2O											p									
T_s-SOC	n						p				n	n	n	n	n			p	n	
T_s-TSN	n							p			n	n	n	n	n				n	
R_s-AGB			p	p		-			p				p			-		p	Pp	
R_s-ALT				n		-		n	n	n	n	n	n	n		-	n	n	n	

R_s-N_2O						-										-				
R_s-SOC	p			p		-	p	p	p		p	p	p	p		-	p	p	p	p
R_s-TSN	p			p		-	p	p	p	p	p	p	p	p		-	p	p	p	p
AGB-ALT		n	n	n		-		n					n	n	n	-		n	n	
AGB-N_2O	n					-					p					-				
AGB-SOC			p			-					p	p	p	p	p	-		p	p	
AGB-TSN			p			-					p	p	p		p	-		p	p	
N_2O-ALT	n																			
N_2O-SOC	p																			
N_2O-TSN																				
SOC-ALT	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n
TSN-ALT	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n	n
SOC-TSN	p	p	p	p	p	p	p	p	p	p	p	p	p	p	p	p	p	p	p	p

Kriging methods selected for interpolation

We compared the goodness of kriging estimates based on the root means square error and the mean squared deviation ratio (MSDR) values (see SM: Kriging) before plotting. The best method for a given variable was selected for each measuring occasion then the mean error (meanERR) was checked for bias. We found the meanERR to be relatively low in almost all cases (SM table 7). The general pattern was very diverse (SM Table 8): the best estimate was given 17, 27 and 7 times ordinary kriging (OK), universal kriging (KED) and ordinary co-kriging (CK), respectively, while kriging was not applicable in further 29 cases out of 80. In these 29 cases inverse distance weighting (IDW) estimates were used before plotting. Differences between the arithmetic mean and the estimated mean were generally small for abiotic variables (absolute values for the normalized difference <0.1: SM Table 8, arithmetic means: SM Tables 1-5) and larger for biotic variables.

SM Table 7: nRMSE, MSDR and meanERR of R_s and N_2O kriging estimates (when adequate variograms were found and kriging was successful) for the grazed and mowed plots' measuring campaigns.

		Grazed			Mowed		
		nRMSE	MSDR	meanERR	nRMSE	MSDR	meanERR
Oct-2012.		0.21	1.87	-0.01	0.23	1.34	0.07
May-2013.		0.20	0.90	-0.02	0.27	1.51	0.00
June-2013.		0.20	0.84	0.00	0.19	0.96	-0.02
Oct-2013.		0.25	1.08	0.00	0.20	0.94	-0.01
May-2014.	R_s	0.16	0.95	0.02			
June-2014.		0.20	1.42	-0.01			
Sept-2014.		0.19	1.00	-0.01	0.19	0.95	0.02
June-2015.		0.17	1.08	0.01	0.19	1.58	-0.01
Nov-2015.		0.17	1.01	-0.01	0.18	1.23	0.02
Oct-2012.	N_2O	0.19	1.03	-0.01	0.19	0.76	0.00

SM table 8. Relative difference between the arithmetic mean of the measured data and the average of the estimated values (estimated-measured)/estimated) (kriging estimates: black letters with blue, green and yellow background for the OK, KED and CK predictions, respectively, IDW estimates: grey letters).

Sampling dates	SWC		T_s		R_s		AGB		N_2O	
	Grazed	Mowed	Grazed	Mowed	Grazed	Mowed	Grazed	Mowed	Grazed	Mowed
Oct-2012.	-0.01	-0.03	0.00	0.00	-0.07	0.12	0.00	-0.02	-0.23	-0.42
May-2013.	0.04	0.00	-0.03	-0.04	-0.08	0.12	0.05	0.02		
June-2013.	0.03	0.02	0.00	-0.07	-0.28	0.15	0.40	-0.28		
Oct-2013.	0.08	-0.02	0.00	0.00	-0.02	-0.08	-0.03	0.02		
May-2014.	0.01	-0.01	0.00	0.00	0.00	0.01	0.00	0.21		
May-2014 (N_2O)	0.07	0.00	0.00	0.00					-0.09	0.03
June-2014.	0.08	0.00	-0.05	0.00	-0.02	0.00	-0.06	-0.03		
Sept-2014.	0.03	-0.01	0.00	-0.05	-0.05	-0.02	0.44	-0.05		
June-2015.	0.01	-0.03	0.00	-0.10	-0.17	-0.01	-0.05	-0.06		
Nov-2015.	0.08	0.16	0.00	-0.02	-0.14	0.23	-0.03	-0.07		

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