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REGULAR ARTICLE

Spatial and temporal variation of soil moisture in dependence of multiple environmental parameters in semi-arid grasslands

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Abstract Grazing of grasslands changes soil physical and chemical properties as well as vegetation characteristics, such as vegetation cover, species composition and biomass production. In consequence, nutrient allocation and water storage in the top soil are affected. Land use and management changes alter these processes. Knowledge on the impacts of grazing management on nutrient and water fluxes is necessary because of the global importance of grasslands for carbon sequestration. Soil water in semi-arid areas is a limiting factor for matter fluxes and the intrinsic interaction between soil, vegetation and atmosphere. It is therefore desirable to understand the effects of grazing management and stocking rate on the spatial and temporal distribution of soil moisture. In the present study, we address the question how spatio-temporal soil moisture distribution on grazed and ungrazed grassland sites is affected by soil and vegetation properties. The study took place in the Xilin river catchment in Inner Mongolia (PR China). It is a semi-arid steppe environment, which is characterized by still moderate grazing compared to other regions in central Inner Mongolia. However, stocking rates have locally increased and resulted in a degradation of soils and vegetation also in the upper Xilin River basin. We used a multivariate geostatistical approach to reveal spatial dependencies between soil moisture distribution and soil or vegetation parameters. Overall, 7 soil and vegetation parameters (bulk density, sand, silt and clay content, mean weight diameter, mean carbon content of the soil, vegetation cover) and 57 soil moisture data sets were recorded on 100 gridded points on four sites subject to different grazing intensities. Increasing stocking rates accelerated the influence of soil and vegetation parameters on soil moisture. However, the

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correlation was rather weak, except for a site with high stocking rate where higher correlations were found. Low nugget ratios indicate spatial dependency between soil or plant parameters and soil moisture on a long-term ungrazed site. However, the effect was not found for a second ungrazed site that had been excluded from grazing for a shorter period. Furthermore the most important soil and vegetation parameters for predicting soil moisture distribution varied between different grazing intensities. Therefore, predicting soil moisture by using secondary variables requires a careful selection of the soil or vegetation parameters.

Keywords Soil moisture · Multivariate geostatistics · Spatial dependency · Grazing · Grassland

Introduction

Grassland ecosystems cover 30–40% of the global land surface. According to White et al. (2000), soils and vegetation of grassland ecosystems retain approximately 35% of the terrestrial carbon (C) stocks. Global warming and a change in land use management may alter the C storage and sequestration capacity of these ecosystems. More intensive agricultural usage or an increase in sedentary pastoralism promotes the degradation of grasslands (Sneath 1998), e.g. by a decrease in rain use efficiency (that is, the ratio of net primary productivity to precipitation) (Le Houérou 1984; Noy-Meir 1985), changes in plant composition, and an increase in wind and water erosion (Gao et al. 2002; Li et al. 2005; Hoffmann et al. 2008a). This will in turn increase the release of C into the atmosphere and amplify global warming (Schlesinger et al. 1990; Ojima et al. 1993). Although the world's grasslands have been identified as an important component of the global C cycle and hence influence the global climate, the spatial extent of grasslands is decreasing due to ongoing grassland degradation and the conversion to croplands which is accompagnied by a decrease in C content (White et al. 2000).

Humans strongly influence grassland ecosystems through pastoralism and tillage. Turning from nomadic to sedentary pastoralism changes the local grazing management, which in turn affects the carrying capacity of grasslands. However, the effects of grazing on key environmental variables such as C, nitrogen (N) and water storage in grasslands remain ambiguous. Milchunas and Lauenroth (1993) and Schuman et al. (1999) show that vegetation composition and biomass production are negatively affected by grazing. In contrast, compared to ungrazed systems, total C and N stocks in vegetation and soils in grazed grassland systems remain stable or are relocated from vegetation into soil pools. Giese et al. (2009) found no clear effect of grazing on root and shoot decomposition rates. In contrast, other studies show a clear impact of grazing on C and N storage in soils and vegetation as well as on water fluxes. Steffens et al. (2008) report that grazing causes a significant decrease of the total C, N and sulphur (S) concentrations in the soil followed by a decreased ecosystem performance. Also, the belowground net primary productivity decreases under grazing and affects the water and nutrient allocation through plants (Gao et al. 2008).

Traditionally, the grasslands of Inner Mongolia were grazed in a nomadic or semi-nomadic way and in equilibrium with the natural productivity of this ecosystem. Since the 1950s, herdsmen were forced to give up their nomadic way of life and settle in small villages or individual farms (Sneath 1998). At the same time, livestock numbers increased (Kawamura et al. 2005). Great parts of the region are now grazed continuously. While nomadic pastoralism was based on sustainable grazing management, permanent settlements with locally high stocking rates pose a high grazing pressure on the steppe regions. Reported effects of high grazing pressure comprise a shift in vegetation composition and cover (Tong et al. 2004), changes of soil physical and chemical properties (Krümmelbein et al. 2006; Zhao et al. 2007; Steffens et al. 2008; Hoffmann et al. 2008b), higher erodibility of soil by wind and water (Gao et al. 2002; Hoffmann et al. 2008b), alteration in carbon sequestration and in the release of greenhouse gases (Liu et al. 2007; Holst et al. 2008).

Soil moisture controls the evolution of vegetation cover and patterns, above and belowground biomass production, soil erodibility, as well as the C and N soil turnover processes. Soil moisture may be highly variable over time and space. Soil moisture storage is affected by topography, vegetation patterns and soil texture, to name only a few, and soil moisture distribution is governed by the interaction of these factors (Grayson et al. 1997; Western et al. 1999; Cantón et al. 2004). The spatial distribution of soil moisture and the degree of connectivity indicate where preferential flow pathways may be generated. The evolution of soil moisture patterns differ depending on wet or dry conditions. Western et al. (1999) show that soil moisture patterns tend to be more organized under wet conditions (organized patterns) than under dry conditions (unorganized patterns), indicating that the factors controlling soil moisture vary under different soil moisture conditions. Soil properties and vegetation characteristics vary spatially and hence influence soil moisture storage and the evolution of soil moisture patterns spatially and temporally. Results from previous studies suggest that a spatially distributed approach is necessary to fully understand the plant-soil-water interaction at different scales and to eliminate biased results due to a too small number of samples.

As pasture management affects soil and vegetation properties, different grazing management might not only lead to changes in soil moisture storage, but also affect the factors influencing the spatial distribution of soil moisture patterns. Soil moisture is a key variable governing processes in the vadose zone which influence matter fluxes at the plant-soil interface. Hence, it needs to be clarified how grazing alters these processes not only quantitatively, but also how it affects the spatial expression and dependencies of these processes. Therefore, the effect of stocking rate on soil and vegetation characteristics, their interaction and their spatial variability influencing the spatio-temporal evolution of soil moisture need to be analyzed. Multivariate geostatistics is a tool to explore the spatial dependencies of interacting variables. The technique evolved from univariate geostatistics, which quantifies the spatial correlation of a single variable that is spatially distributed. The resulting variogram function indicates the degree of variability as subject to spatial separation. It can be used to interpolate the data to unsampled locations (Heuvelink and Webster 2001; Webster and Oliver 2001; Wackernagel 2003; Lark 2003).

With this paper, we aim to clarify the spatial dependency of soil moisture and its driving soil and vegetation factors as subject to stocking rate. Cross-variograms for soil and vegetation parameters have been discussed by Steffens et al. (2009) in detail, so we concentrate on spatial dependencies of soil moisture and soil/vegetation parameters in this paper. A multivariate statistical and geostatistical approach was used to test our central hypotheses:

(1) there is a correlation of soil and vegetation indicators that govern the soil moisture distribution at different stocking rates,
(2) the correlation between these parameters and soil moisture is dependent on soil moisture conditions: the higher the soil moisture, the better are the correlations, and
(3) spatio-temporal correlations between soil and vegetation parameters and soil moisture exist, and differ between grazing intensities.

Material and methods

Study area

The study took place on experimental sites in the Xilin river catchment, located 500 km north of Beijing in the Autonomous Region Inner Mongolia (PR China). The sites are located at approximately 43°33′ N, 116°40′ E (Fig. 1). Climate in the catchment is semi-arid continental with a mean annual precipitation of about 340 mm and a mean temperature of 0.7°C (data from 1982 to 2006 provided by Inner Mongolian Grassland Ecosystem Research Station IMGERS). Precipitation shows a marked seasonality with 70–80% of the annual precipitation during the vegetation period from May to September. The mean annual temperature amplitude ranges from −23°C (winter) to +18°C (summer). The climate favours a steppe environment with a natural potential *Stipa grandis* and *Leymus chinensis* vegetation and calcic Chernozems (Tong et al. 2004; Steffens et al. 2008). The number of permanent settlements and the number of livestock increased during the last decades (Kawamura et al. 2005), causing increased grazing pressure on the steppe ecosystem and degradation of soil and vegetation (Tong et al. 2004).

To assess the effect of stocking rate on the spatial distribution of soil properties, vegetation characteristics and soil moisture, and the interaction and influence of these on each other, a geostatistical sampling approach was followed on four sites with different grazing management. Two grazed sites represented different stocking rates expressed in sheep units SU per hectare and year (1 SU is 1 ewe and 1

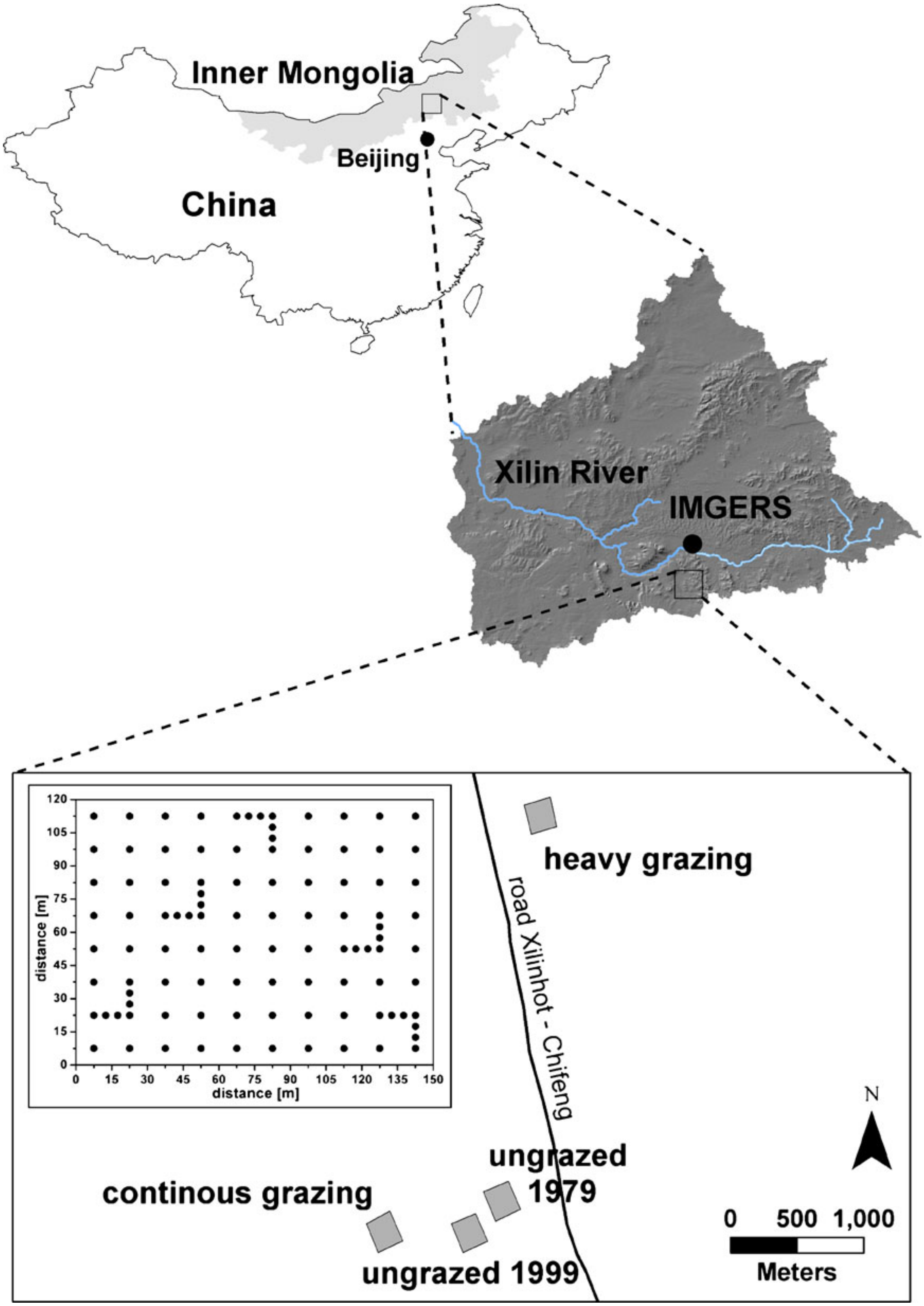

Fig. 1 Location of sampling sites at the Inner Mongolian Grassland Ecosystem Research Station (IMGERS)

lamb): heavily grazed (HG) with a stocking rate of 2.0 SU ha^{-1} a^{-1}, and continuously grazed (CG) with a stocking rate of 1.2 SU ha^{-1} a^{-1}. The selection of experimental sites was done in cooperation with IMGERS, which also provided information on stocking rates. The two ungrazed sites have been fenced and excluded from grazing for different periods: ungrazed since 1979 (UG79), and ungrazed since 1999 (UG99). The HG and CG grazing sites are grazed all year round, although at different frequencies between winter and the vegetation period in summer. The sites were grazed daily during the vegetation period. During winter, grazing occurs less frequent and is only done in addition to hay feeding. HG and CG represent different, typical types of grazing management practiced in the Xilin catchment.

Sampling design

A geostatistical sampling grid was set up on each of the four sites with a total of 100 points per site (Fig. 1). Each grid covers an area of 105×135 m with a regular point spacing of 15 m (80 points) and five nested areas with a 5 m spacing (20 points). Soil moisture in the upper 0.06 m was measured a total of 57 days on each grid during the vegetation period from 2004 to 2009. The measurements were taken with a hand-held soil moisture probe (ML2x theta probe, Delta T Devices Ltd, Cambridge UK). The measurement days were chosen to capture rainfall events and subsequent drying of the soil, i.e. soil moisture was measured after precipitation and the following days. In dry periods with no precipitation, soil moisture was measured less frequently. Bulk density, soil texture, mean weight diameter (MWD), mean C content and vegetation cover were sampled in June and July 2004 at all sites with the exception that for CG, no data on vegetation cover and MWD is available. At each grid point, three soil samples from the upper 0.04 m of the soil were taken with stainless steel cylinders (100 cm^3) and bulked. Bulk density was calculated by dividing the mass of the oven-dry soil by the core volume. Mean C content was analysed by dry combustion on a Vario Max CNS element analyser (Elementar Analysensysteme GmbH, Hanau) (Steffens et al. 2008). Soil texture was measured by wet sieving for the fractions between 63 and 2000 μm, followed by the pipette method for smaller fractions. MWD was calculated by

$$MWD = \sum_{i=1}^{n} x_i w_i \tag{1}$$

X_i is the mean diameter of the texture class and w_i represents the percentage of this texture class (Hillel 1998). MWD allows a comparison among the different particle size fractions of an aggregate. Vegetation cover was visually estimated from top view within a 1 m^2 rectangular. Further description of the survey and analysis of the soil and vegetation parameters is given in Hoffmann et al. (2008a), Schneider et al. (2008), Steffens et al. (2008) and Steffens et al. (2009). Annual measurements of soil and plant properties were not feasible in the frame of the study. However, the soil properties and the relative difference in vegetation cover between the sites are assumed to be stable over the study period from 2004 to 2009. Soil and vegetation data analysed in 2004 were used for correlation and covariance analysis with soil moisture data sampled between 2004 and 2009. Descriptive statistics of the parameters used for the analysis are given in Table 1.

Exploratory data analysis

We investigated the relationships between soil moisture and various soil and plant parameters at each point over 57 days (number of soil moisture sampling days). Correlation coefficients were calculated for every day at all sites resulting in 57 correlation coefficients for each of the parameters. To determine whether the influence of each soil parameter between different soil moisture conditions (dry: < 0.1 m^3 m^{-3}, moist: 0.1–0.2 m^3 m^{-3}, wet: > 0.2 m^3 m^{-3}) varies, we regressed the correlation coefficients with the mean soil moisture at each site. To check whether soil properties changed during the study period from 2004 to 2008, we analyzed whether correlations between soil moisture and soil parameters changed.

Geostatistical analysis

The relation of data points in dependency of their separation was explored by a geostatistical analysis. The analysis was done in the environment of the

Table 1 Overview over measured soil and vegetation parameters used for the multivariate (geo-) statistical analysis (compiled from Steffens et al. 2008, 2009; Hoffmann et al. 2008a)

	Ungrazed since1979 (UG79)	Ungrazed since 1999 (UG99)	Continuously grazed (CG)	Heavily grazed (HG)
Stocking rate (sheep units ha^{-1} a^{-1})	0	0	1.2	2.0
Bulk density [g cm^{-3}]	0.94	1.09	1.17	1.28
Texture [mg g^{-1}]				
Sand	491	467	494	681
Silt	349	370	334	209
Clay	161	163	171	110
Mean weight diameter [mm]	131	109	–	100
C [mg g^{-1}]	31.0	25.5	23.0	17.0
Vegetation cover [%]	76	68	–	69

software R (R Development Core Team 2004) and the implemented geostatistic package GSTAT (Pebesma and Wesseling 1998).

The spatial dependency of sampling points separated by lag distance h is given by the experimental variogram. It is expressed by the semivariance $\gamma(h)$ at a given lag h (Webster and Oliver 2001; Wackernagel 2003):

$$\gamma(h) = \frac{1}{2N}\sum_{i=1}^{N}\{z(x_i) - z(x_i + h)\}^2 \quad (2)$$

where $z(x_i)$ is a sample z at location x_i, and N is the number of data pairs. A variogram function is fitted to the experimental variogram to explore the spatial dependence of the samples. The maximum semivariance is called the *sill*. Unless the semivariance increases linearly and does not flatten, the sill marks the distance (*range*) at which no further spatial correlation exists. High sill values indicate high variance within the data set, and the range determines the directional degree of spatial variation. A semivariance > 0 at lag=0 (the *nugget*) indicates that small scale variation of the sampled entity exists which has not been captured by the measurements. In case no spatial correlation of the data exists, the variogram is entirely flat (nugget variogram). To explore the degree of spatial dependency, the ratio of nugget semivariance to total semivariance (that is, the nugget ratio) can be calculated. Low numbers (i.e. < 0.25) indicate that nugget semivariance is low compared to overall semivariance and hence spatial dependency of the variables, whereas high nugget ratios (i.e. > 0.75) indicate no spatial dependency due to small-scale variability overlaying a signal at larger scale (Cambardella et al. 1994). Geostatistics is used to explore the variation and spatial dependency of spatially distributed data. The variogram function can be used for kriging interpolation to generate predictions for unsampled locations within the sampling extent.

Because more than one variable has been sampled, a multivariate geostatistical approach was used to identify the driving factors which lead to a specific spatial distribution of soil moisture. Thus, the spatial dependency of soil moisture content and the soil and vegetation parameters can be explored in order to explain soil moisture patterns and soil moisture variability. In correspondence to the univariate semivariance analysis, the cross-variogram gives the correlation of two variables depending on their separation from each other:

$$\gamma_{ab}(h) = \frac{1}{2N}\sum_{i=1}^{N}\{z_a(x_i) - z_a(x_i + h)\} \times \{z_b(x_i) - z_b(x_i + h)\} \quad (3)$$

where $\gamma_{ab}(h)$ is the cross-semivariance at lag h for two different variables a and b (Wackernagel 2003). $\gamma_{ab}(h)$ values were binned at lag h, and the model fit was weighted according to the number of data pairs available. I.e. the modelled cross-semivariogram is more accurate at bins with a higher number of data pairs. The fitting was done using a spherical model as this provided best results with respect to mean squared error. A positive spatial relation of the two variables is given when $\gamma_{ab}(h)$ increases with increasing lag, whereas decreasing $\gamma_{ab}(h)$ indicates an inverse spatial relation of the two variables. Cross-variograms were computed for all 57 soil moisture sampling dates and all measured soil and vegetation parameters. As not all data can be presented in this paper, data for 17-08-2004 is shown as an example.

Results

Exploratory data analysis

The range of the correlation coefficients for all sampling dates is displayed in Fig. 2. Almost all correlations are weak (correlation coefficient <= 0.4). No significant correlation was observed at the continuously grazed sites (CG) and the ungrazed sites (UG) while at the heavily grazed sites (HG) the correlation coefficients between soil moisture content and bulk density, mean soil C content and texture parameters where somewhat higher. However, strong correlations (correlation coefficient >=0.75) as expressed by the 95% percentile could only be found for silt on the HG site. On all other sites, neither strong correlations nor differences between the soil conditions exist. In the wetness classes dry, moist, and wet, correlations between soil moisture and soil properties did not change significantly in the course of the study period (data not shown). Soil properties on the experimental sites obviously did not change significantly in the course of the 6 years of the study period and we therefore assume that effects on soil moisture storage are neglectable.

The coefficient of determinatation, intercept, slope, *p*-value and significance of daily soil moisture versus correlation coefficient at each site and for each parameter are listed in Table 2. The results show only weak goodness-of-fits for all linear models. Highest R^2 values (>30%) are mainly found on HG, i.e. for sand, silt, clay and mean C, and also on UG99 for bulk density, clay and mean C. Large slope values indicate that different soil moisture conditions affect the significance of soil and vegetation parameters on the variation of soil moisture content. Large slope values (>|2|) only exist on HG sites, i.e. for MWD, sand and silt. As descriptive statistics and regression analyses cannot satisfactorily explain the observed variations of soil moisture content in space and time, we conducted a multivariate geostatistical approach to better explain our observations.

Multivariate geostatistics

The fitted cross-variograms for 17-08-2004 are given in Fig. 3. For most variable pairs, cross-semivariances are positive, and they increase with increasing lag on this date. However, some variable pairs show decreasing cross-semivariances with increasing lag. This is in particular true for bulk density and mean C on the CG site, and for sand on the HG site. Other variable pairs show a nugget-type cross-variogram, i.e. no changes of the cross-semivariance with increasing lag, as for clay and silt on the CG site and for silt on the UG99 site. The cross-variograms for vegetation cover are scattered and do not show an increasing or decreasing trend with increasing lag. Increasing cross-variances indicate that the spatial variability of the respective parameter is positively related to the spatial variability of soil moisture, and that spatial structures between each of the two variables exist. Cross-variograms calculated from soil properties show a more pronounced spatial dependency than those calculated from vegetation cover. Also, cross-variograms for UG79 and HG provide more clear information on spatial dependencies of the variables than those for UG99 and CG. On UG79 and UG99, spatial dependency was found up to a lag distance of approximately 15–20 m for almost all coregionalized variables indicating a spatial correlation of soil moisture and the respective variables at this distance. From separations greater than 20 m the influence of the variables on soil moisture is weak. Although a correlation up to a lag of 20 m is indicated by the shape of the fitted cross-variogram functions, the spatial dependency of some coregonalization pairs is obscured by high nugget values. For example, on UG99, the cross-variograms for bulk density and sand show high nugget values and only a relative small sill. Thus, small scale variation might have more influence than the spatial dependency of the coregionalization variables on a larger scale. Furthermore, cross-variograms for vegetation cover on UG99 and UG79 are scattered, and do not indicate spatial dependency at all. Cross-variograms of the two grazed sites CG and HG have a more heterogeneous appearance. On CG, spatial dependency of mean C and bulk density is apparent up to approximately 30 m.

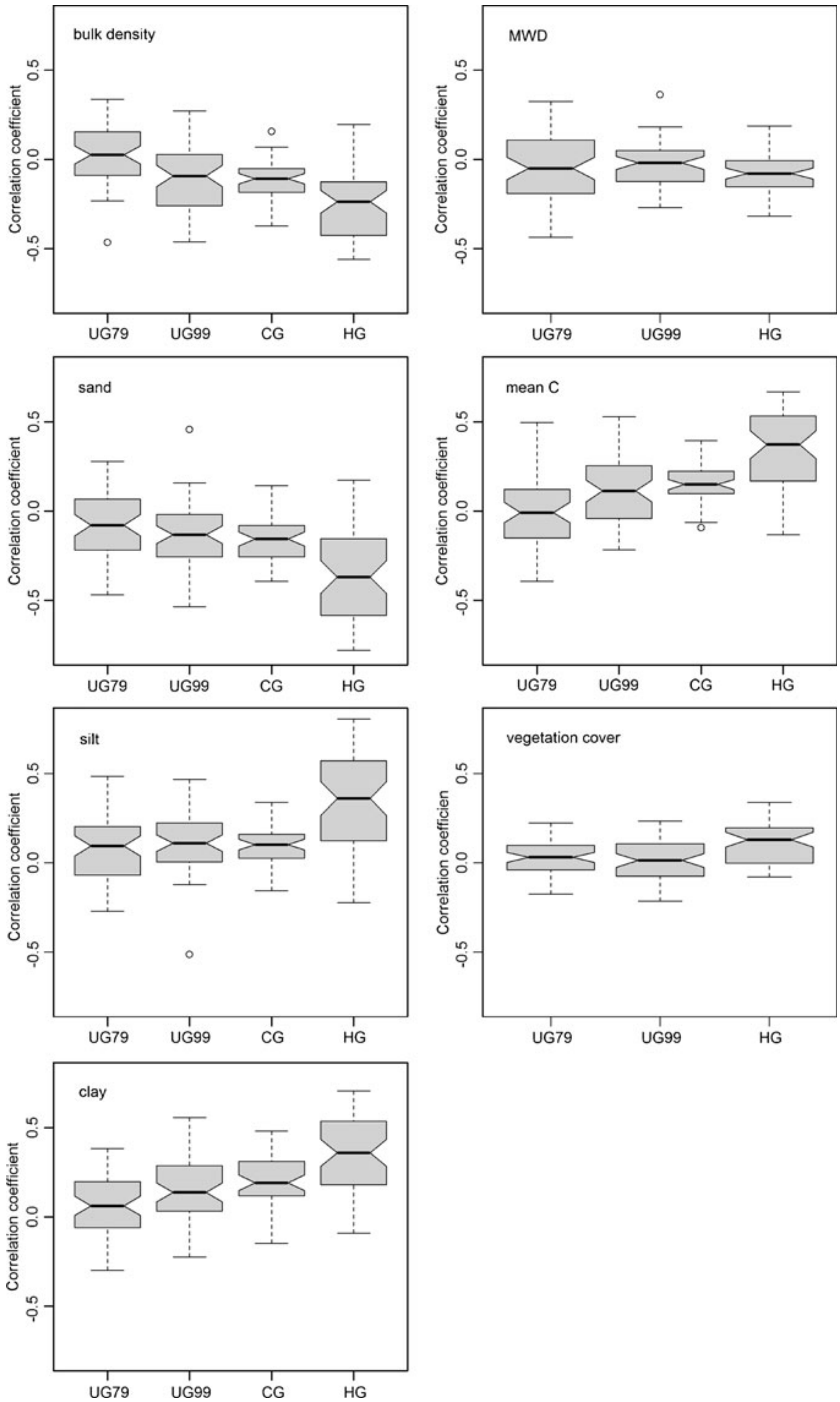

Fig. 2 Boxplots of correlation coefficients at each site for soil moisture and every soil and vegetation parameter. The boxplots summarize the correlations for each of the 57 soil moisture sampling dates. (*MWD* mean weight diameter, *mean C* mean soil carbon content) *Black bars* represent the median, notches the 95% confidence interval, and length of the box the interquartile range, i.e. the 25th and 75th quartile. *Whiskers* show the largest and lowest extremes if there are no outliers, or else, the largest and lowest observation depicted by *circles*. Outliers are observations that are >1.5 times away from the interquartile range

However, semivariance decreases with increasing lag, which indicates that the spatial extent of the sampling does not fit the scale of the spatial dependency of the coregionalization variables. The cross-variograms of sand, silt and clay content have a nugget shape. Hence, no spatial structure is apparent. On HG, the cross-variograms of sand, silt, clay, and mean carbon content are not bounded, i.e. the maximum range of the spatial

Table 2 R^2, intercept, slope, *p*-value, significance of daily soil moisture versus correlation coefficient for all soil and vegetation parameters and stocking rates

Soil/vegetation parameter	UG79	UG 99	CG	HG
Bulk density				
R^2	0.089	0.421	0	0.241
Intercept	0.097	0.129	−0.13	−0.113
Slope	−0.543	−1.4	0.016	−1.282
p−value	0.0238	0	0.9363	1e−04
Significance	0.5	0.001	ns	0.001
Mean weight diameter				
R^2	0.159	0.001	–	0.153
Intercept	0.092	−0.033	–	−0.149
Slope	−0.908	0.037	–	0.581
p−value	0.0021	0.8431	–	0.0032
Significance	0.01	ns	–	0.01
Sand				
R^2	0.147	0.264	0	0.368
Intercept	0.05	0.038	−0.158	−0.099
Slope	−0.86	−1.073	−0.014	−2.241
p−value	0.0032	0	0.9475	0
Significance	0.01	0.001	ns	0.001
Silt				
R^2	0.114	0.187	0.02	0.385
Intercept	−0.038	−0.022	0.07	0.067
Slope	0.75	0.847	0.18	2.334
p−value	0.0101	8e−04	0.3251	0
Significance	0.05	0.001	ns	0.001
Clay				
R^2	0.189	0.333	0.007	0.322
Intercept	−0.074	−0.044	0.212	0.146
Slope	0.914	1.193	−0.152	1.766
p−value	7e−04	0	0.5571	0
Significance	0.001	0.001	ns	0.001
Mean C				
R^2	0.096	0.485	0.002	0.329
Intercept	−0.107	−0.127	0.169	0.143
Slope	0.616	1.53	−0.057	1.736
p−value	0.0193	0	0.7718	0
Significance	0.05	0.001	ns	0.001
Vegetation Cover				
R^2	0.002	0.066	–	0.272
Intercept	0.032	−0.047	–	0.013
Slope	−0.047	0.331	–	0.817
p−value	0.7581	0.0536	–	0
Significance	ns	0.1	–	0.001

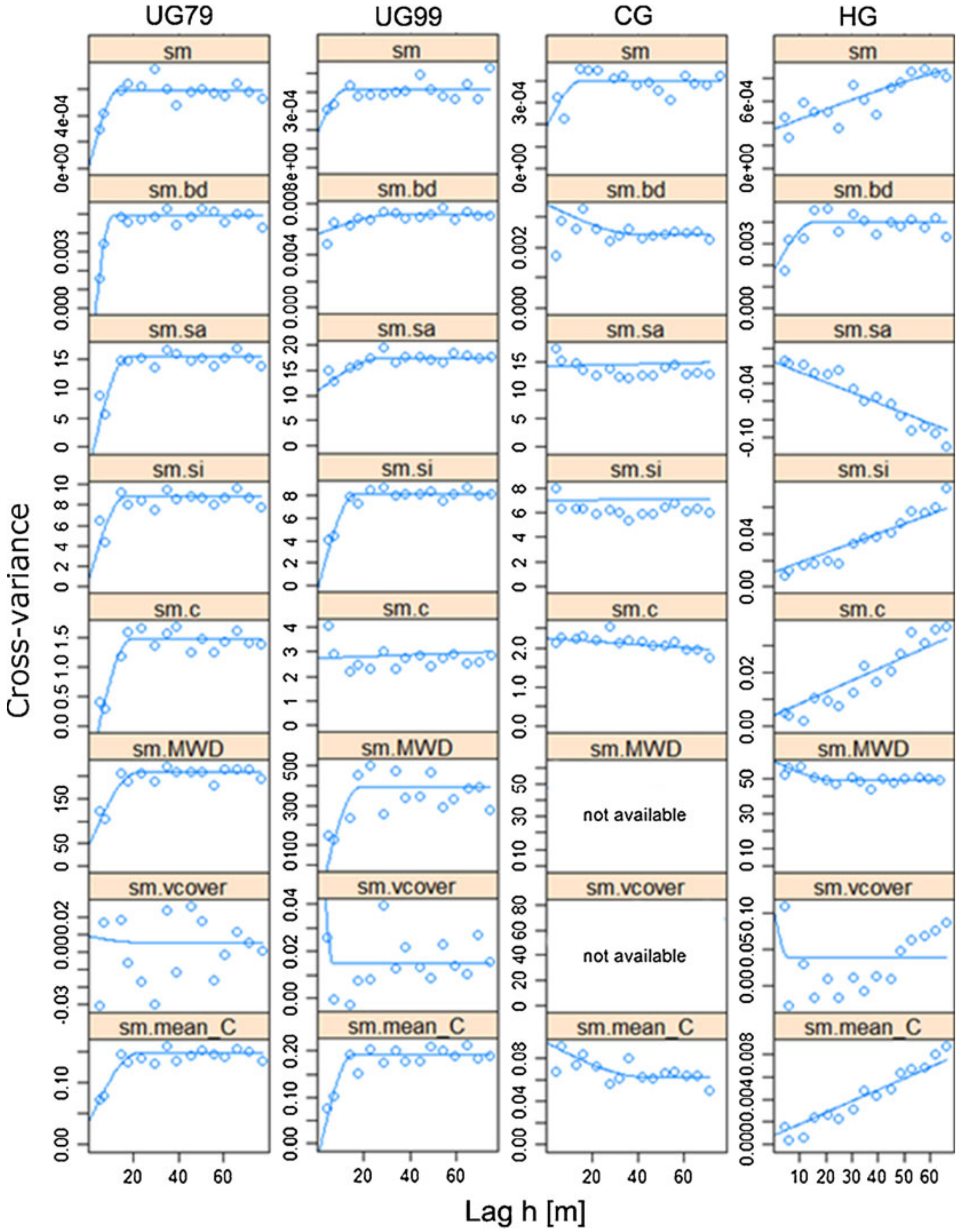

Fig. 3 Fitted cross-variograms of UG79, UG99 and HG for 17-08-2004. (*sm* soil moisture, *bd* bulk density, *sa* sand, *si* silt, *c* clay, *MWD* mean weight diameter, *vcover* vegetation cover, *mean_C* mean soil carbon content)

correlation was not captured by the sampling design. This also holds true for the cross-variogram of vegetation cover, although an outlier at a small lag distance does not allow a linear fit, i.e. unbounded function, to the experimental cross-variogram. Although no termination of the fitted function is visible, spatial structures, indicated by a flattening and a subsequent rise of the cross-variogram, are apparent at a lag of approximately

20–30 m for mean C, clay, silt, and sand. In contrast to most other cross-variograms of HG, the cross-variogram for bulk density is bounded with a range lag of approximately 20 m.

Nugget ratios on the CG site show highest values for sand, silt, clay, and mean carbon content (Fig. 4). This implies that spatial dependency of the coregionalized variables is low, i.e. small scale variability and heterogeneity of the cross-variogram obscure spatial dependencies on this site. Nugget ratios are lowest on UG79 in general, but no clear trend exists, i.e. no consistently high or low nugget ratios can be identified for UG99 and HG. On UG99, nugget ratios are high for bulk density, sand and silt content, while they are low to moderate for the other variables. On HG, nugget ratios of the different variables show high variation, and also the amplitude as indicated by the extent of the boxplots varies greatly. Only on UG79, nugget ratios of the coregionalized variables remain at a low to moderate level. It is interesting to note that nugget ratios on UG79 are lower for the coregionalized variables than for the univariate soil moisture semivariogram model alone (upper left corner). The nugget ratios shown in Fig. 4 imply that spatial dependency of the different coregionalized variables differs among the sites, with the CG site showing lowest spatial dependency as expressed by high nugget ratios.

The boxplots of range values as given in Fig. 5 provide a more unambiguous picture of the spatial dependencies and the differences between the four sites. Range values on HG show highest variability for all cross-variograms over the soil moisture sampling period, while range values on the other sites show a much lower amplitude. Also, the boxplots provide a temporal summary of range values for HG. Range expands beyond the extent of the sampling site for all variables except MWD and bulk density. This confirms the results of the cross-variograms presented in Fig. 3. Most cross-variograms for HG were linear and not bounded. Compared to the high amplitude of range values over the study period on HG, range values remain relatively stable and much smaller on all other sites. I.e., maximum spatial dependency of the coregionalized variables is already reached within the boundary of the respective sampling site. Notably, range values for bulk density are low (upper right graph) on all sites.

Discussion

In general, only weak correlation of soil and vegetation parameters and soil moisture exists. This is in contrast to Zhao et al. (2007) who reported significant and often stronger correlations between soil moisture content and various soil physical parameters. However, their investigation was based on three single and selected observations, whereas our analyses were based on a much larger database and a full range of existing soil moisture conditions. The degree of correlation increases along the grazing gradient with lowest correlations on the two ungrazed sites. The results show that single soil or vegetation parameters can not be used to predict soil moisture or soil moisture variability with the exception of HG where highest correlations occur.

Correlation coefficients change depending on soil moisture conditions (dry, moist, wet), but the effect remains weak and no strong regression can be found between correlation coefficients and soil moisture status. Again, HG stands out as it shows larger slopes and the correlation coefficients show dependency on soil moisture conditions, i.e. correlation coefficients increase or decrease from dry to wet conditions. This supports the concept of organized and unorganized soil moisture patterns by Western et al. (1999) which states that the factors influencing soil moisture distribution vary depending on soil moisture conditions. It is interesting to note that the concept only holds true for the HG site, but not for the other sites with moderate and no grazing. Due to constant grazing at high stocking rates, HG is the most homogenized site, whereas CG and, most of all, UG99 and UG79 show more patchy structures regarding vegetation distribution and top soil variability (Steffens et al. 2008). The patchy structure on the latter three sites may cause different soil and vegetation composites at the sampling points which in consequence results in non-uniform effects on soil moisture storage. In contrast, uniform soil and vegetation characteristics on HG lead to uniform effects on soil moisture storage. This assumption is partly confirmed when looking at the soil moisture maps published by Schneider et al. (2008) using Kriging methods. Here, soil moisture variability is more heterogeneous at the two ungrazed sites as compared to the grazed sites, especially at moist to wet soil moisture conditions.

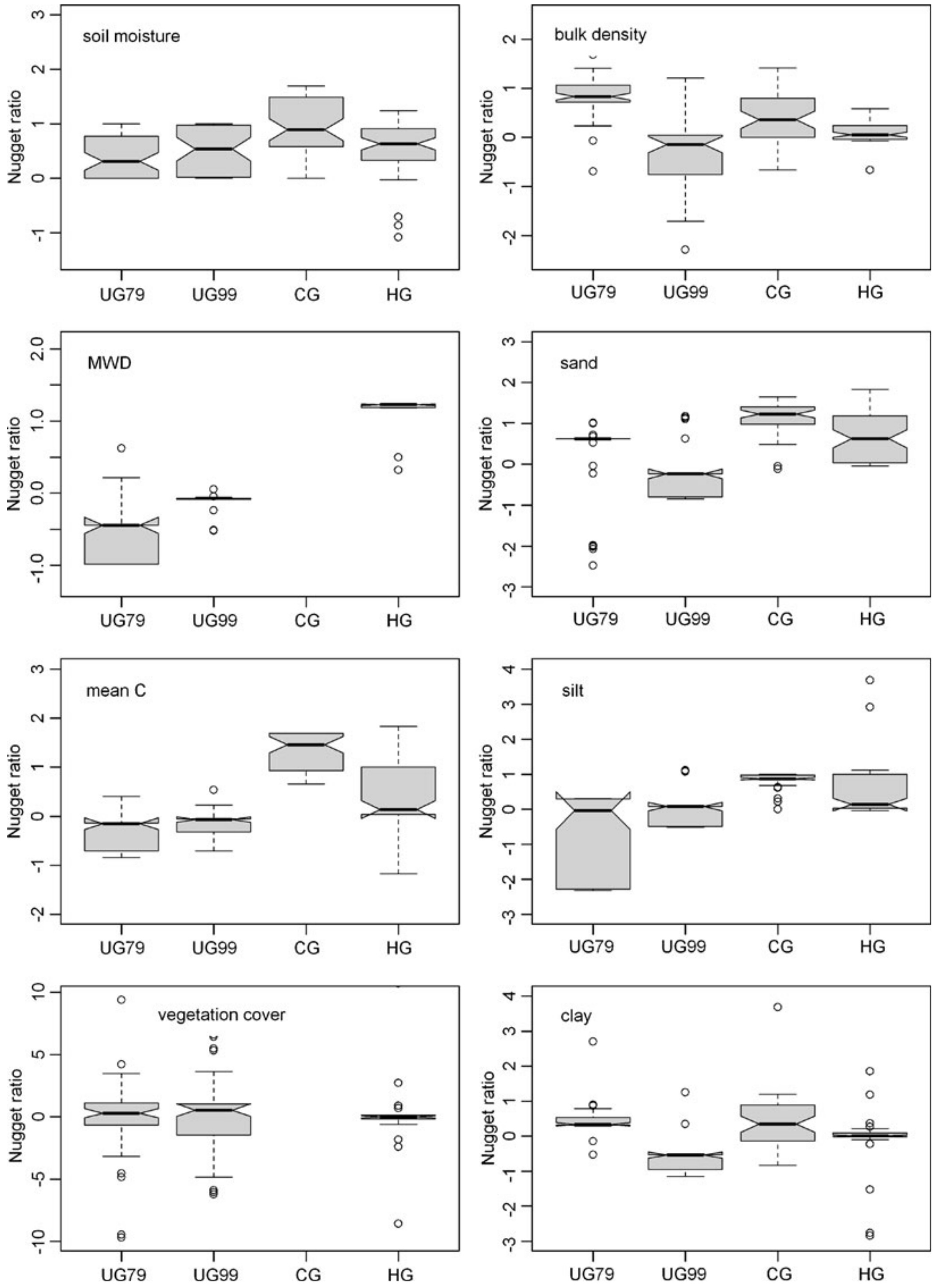

Fig. 4 Boxplots with nugget ratio values of the cross-variograms for all soil and vegetation parameters on the for experimental sites. Nugget ratio = nugget semivariance/total semivariance. (*sm* soil moisture, *bd* bulk density, *sa* sand, *si* silt, *c* clay, *MWD* mean weight diameter, vegetation cover, *mean C* mean soil carbon content). *Black bars* represent the median, notches the 95% confidence interval, and length of the box the interquartile range, i.e. the 25th and 75th quartile. *Whiskers* show the largest and lowest extremes if there are no outliers, or else, the largest and lowest observation depicted by *circles*. Outliers are observations that are >1.5 times away from the interquartile range

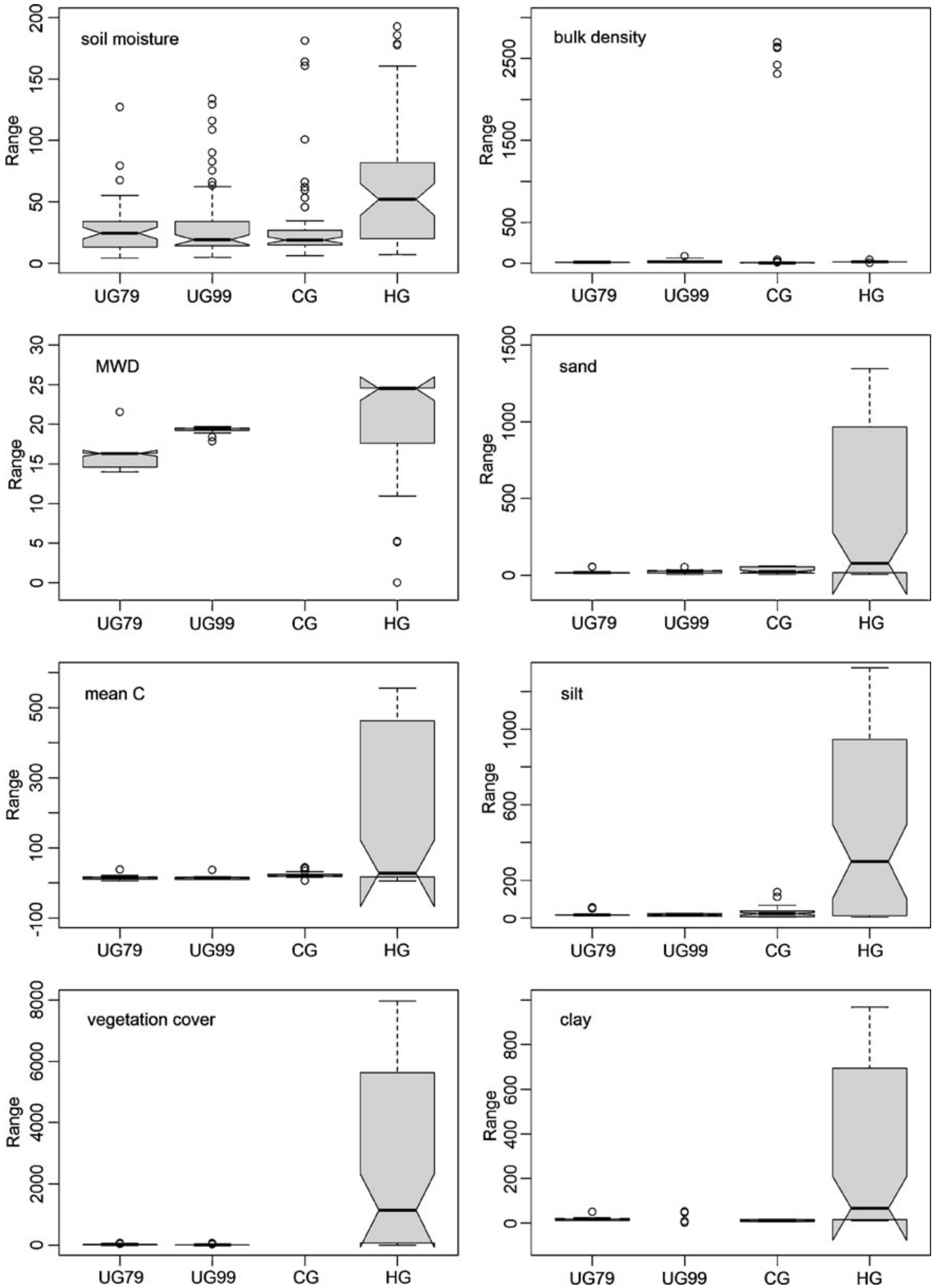

Fig. 5 Boxplots with range values of the cross-variograms for all soil and vegetation parameters on the for experimental sites. For figure details and description see Fig. 4

Given that no clear relationship between soil or vegetation parameters and soil moisture can be derived, the prediction of spatial soil moisture patterns is not feasible with simple correlation models alone. The correlation analysis did not show high correlations between the sampled variables for most sites. Spatial dependency between soil properties and soil moisture is highest, whereas it is weaker between vegetation cover and soil moisture. This might be due to the fact that soil and vegetation properties were only sampled in the beginning of the study period. Although we assume that the vegetation cover relative to the other sites is the same, the interannual precipitation and temperature regime may have obscured the interpretation of the vegetation data. Moreover, vegetation is prone to more rapid interannual changes, whereas we consider the soil properties to remain rather stable throughout the study period.

The results of the multivariate geostatistical analysis suggest that spatial dependency exists between soil moisture and soil and vegetation parameters, but the expression of these dependencies varies between the four sites. High nugget values and nugget ratios as found for the cross-variograms for CG indicate that the spatial relation between soil moisture and the soil parameters is very noisy and that spatial relation of, e.g., soil moisture and mean C content or bulk density can be found already at smaller distances (<5 m) than covered by the geostatistical sampling scheme we used. High nugget ratios also indicate that no or only weak spatial dependence exists between any of the coregionalysed variables analysed for the CG site. On the other hand, low nugget ratios as partly found for the other sites show that the spatial dependency of soil moisture and the soil or vegetation parameter is not noisy, i.e. the semivariance in the cross-variogram is not bound to a nugget effect alone. In contrast to UG99, nugget ratios on the long-term ungrazed site UG79 are higher, in particular for bulk density and sand content. The values indicate that spatial dependency of the coregionalized variables is lower on UG79 than on UG99. The results indicate that on UG79, more heterogeneous patterns of soil and vegetation properties evolved since enclosure than on UG99 with a much shorter enclosure period. However, nugget ratios are not decreasing linearly from ungrazed to the two grazed sites, CG and HG. I.e. nugget ratios on the CG site are higher then on the UG99 site. This contrasts with the assumption that grazing induces the homogenization of soil and vegetation properties, and hence, reduces small scale variability. However, nugget ratios from CG to HG decrease, indicating less small scale variation along with higher stocking rates. Although there is no linear trend in nugget ratios from UG79 to HG, there is an increase in small scale variability with a) increasing duration of enclosure for ungrazed sites and b) with decreasing stocking rate for grazed sites.

The question arises if the different expression of small scale variability between grazed and ungrazed sites indicate different states of equilibrium and non-equilibrium conditions in the two systems. The question at which point grassland systems are at equilibrium has been raised by Fernandez-Gimenez and Allen-Diaz (1999), Fuhlendorf et al. (2001), and Briske et al. (2003), to name only a few. The non-linearity of nugget rations from ungrazed to grazed sites suggest that there might be a tipping point between ungrazed and grazed systems, which changes the (small scale) variability of soil and vegetation properties and hence influences spatio-temporal soil moisture evolution. This is not clear through the interpretation of spatial soil moisture distribution using a univariate geostatistical approach. Here, nugget ratios indicate high nugget semivariance and low spatial dependency. However, when secondary variables are included with the interpretation, the nugget ratios indicate spatial dependency of the coregionalized variables despite high spatial variability of soil moisture patterns and noisy semivariogram models as found by Schneider et al. (2008) for UG79.

Although spatial dependencies for the long-term enclosure, UG79, can be clearly depicted, effects on HG at the other end of the grazing gradient remain ambiguous. Nugget ratios for mean C, clay content and bulk density are low and indicate that the variables spatially correlate with soil moisture distribution. On the other hand, values for MWD, sand and silt are higher. Hence, only selected soil properties seem to be appropriate predictors for soil moisture distribution.

On UG79, UG99 and CG, range values are in general low, whereas they are higher on HG and also exhibit a much higher span of range values. This indicates that spatial dependency of the coregionalized variables is higher on HG, and that maximum correlation length can be found at larger separation compared to the other sites. As some of the cross-variogram models for HG are linear and not bounded, spatial dependency obviously stretches beyond the extent of the sampling grid. The homogenized structure of the site may result in a spatially structured influence of soil and vegetation parameters on soil moisture distribution. On the other hand, mixed patterns on the other sites favor a mixed signal of spatial dependencies. Correspondingly, Gómez-Plaza et al. (2001) and Cantón et al. (2004) show that the distribution of vegetation patterns is influencing soil moisture patterns. Hence, stocking rate does influence the expression of spatial dependencies between soil or vegetation properties and soil moisture. However, from our data we can not identify a single best predictor variable for soil moisture distribution, as these vary among the sites.

Conclusions

We applied a multivariate geostatistical approach to reveal the influence of soil and vegetation properties on spatio-temporal soil moisture distribution. Although correlation coefficients between soil and vegetation properties and soil moisture change slightly under dry, moist or wet soil moisture conditions, only weak or moderate regressions exist. Hence, a clear allocation of soil or vegetation properties influencing soil moisture variability is not feasible. The analysis shows that prediction of spatial dependencies between two spatially distributed variables and the prediction of soil moisture with secondary data is not straightforward or possible with one parameter for different grazing intensities. To predict soil moisture distribution, the secondary variable needs to be chosen carefully as from our data, the most influencing soil and vegetation parameter differ between the different grazing sites. Coming back to our initial hypotheses, we can state that (1) spatio-temporal soil moisture variability is governed by a set of environmental (soil and vegetation) parameters. The distribution of soil moisture can not be predicted by a single parameter, and the determining parameters change between different grazing intensities. (2) The degree of correlation between soil and vegetation parameters and soil moisture is only weakly affected by dry, moist or wet soil moisture status. I.e. there is only weak correlation of soil moisture and soil or vegetation properties under wet conditions (as discussed by Grayson et al. (1997) and Western et al. (1999)), and highest correlations occur on HG. (3) Spatio-temporal correlations between soil and vegetation parameters and soil moisture were found for some sites. However, spatial dependencies of the coregionalized variables changed between the sites, which prevented the identification of a single soil or vegetation parameter to explain soil moisture variability. We observed a change in spatial dependencies between the two ungrazed sites on the one hand, and between the two grazed sites, on the other hand. However, there was no linear change in spatial dependencies of the coregionalized variables from ungrazed to grazed sites. In particular, soil properties at the long-term enclosure (UG79) might express more stable conditions which result in more pronounced effects on soil moisture patterns than on UG99. On CG and HG, grazing might result in homogenization of soil and vegetation properties. This is particular visible for the HG site with higher stocking rate, while effects on CG are less pronounced.

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