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# Spatial Variability and Geostatistical Mapping of Selected Soil Properties in Mt. Wakakusa Grassland of Japan

**Khairun N. KAMARUDIN[1], Mayu TOMITA[1,2], Keiko KONDO[1] and Susumu S. ABE[1]***

[1] Faculty of Agriculture, Kindai University, Nara, Japan
[2] Graduate School of Life and Environmental Sciences, Kyoto Prefectural University, Kyoto, Japan

## Abstract
Mt. Wakakusa in Central Japan is a semi-natural grassland which has been maintained by repeated application of prescribed burnings of vegetation for more than 500 years. We assessed the spatial variability of selected soil properties and constructed their distribution maps using a geostatistical method to provide spatial information on soil resource for sustainable land management in this grassland. All the examined soil properties showed intermediate (coefficient of variation [CV] = 10%-90%) or high (CV > 90%) variability, except for the soil pH (CV < 10%), suggesting that the precision soil management approach is recommendable in the study site. The variogram analysis revealed that all of the soil properties, except for the electrical conductivity with a very weak spatial dependency (nugget-to-sill [N/S] ratio > 0.75), showed a very strong or moderately strong spatial dependency (N/S ratio ≤ 0.50), which might occur under the strong influence of intrinsic factors such as the inherent soil quality. The soil maps constructed by the ordinary kriging method helped in understanding the distribution patterns of the examined soil properties and identifying specific locations with signs of degradation and pollution. These spatial distribution patterns should be considered when developing a sustainable soil management strategy in Mt. Wakakusa grassland.

**Discipline:** Agricultural Environment
**Additional key words:** ordinary kriging, prescribed burning, semivariogram, spatial dependency

## Introduction

Mt. Wakakusa (otherwise known as Mt. Mikasa) is a hilly grassland (peak=342 m above sea level [a.s.l.]) located in Nara City, known as an imperial capital of Japan in the 8th century (710-794 A.D.). This grassland has been maintained at least for 500 years through repeated prescribed burnings of dead grasses (History of Nara Park Editorial Committee 1982), displaying a contrasting landscape with neighboring Mt. Kasuga (known as Kasugayama Primeval Forest; peak=498 m a.s.l.), which is mainly covered by an evergreen broadleaf forest due to the protection for more than 1,000 years (History of Nara Park Editorial Committee 1982). These (semi-)natural assets are located within Nara Park, which has some historic shrines and temples such as the Kasuga Grand Shrine, and the Todaiji and Kofukuji Temples, registered as the core architectures of the UNESCO's World Heritage Site "Historic Monuments of Ancient Nara." Aside from Mt. Kasuga, registered as part of the given World Heritage Site, Mt. Wakakusa, assigned as its buffer zone, attracts more than a hundred thousand tourists and citizens to visit for recreational purposes every year (Nara Prefecture 2014). Therefore, this grassland requires a sustainable management strategy and conservation measures.

Some environmental issues in Mt. Wakakusa, caused/accelerated mainly by the frequent disturbance by visitors and browsing by sika deer (*Cervus nippon*), a wildlife that widely inhabits in Nara Park (Torii & Tatsuzawa 2009), have been a concern among park rangers but they often face difficulty in taking necessary interventions against the issues due to the lack of survey information on this grassland ecosystem. Most of the previous studies had a focus on the vegetation and reported on decreased vegetation coverage (Takahashi & Maenaka 1977) and invasion of alien plants (e.g., *Sapium sebiferum*) (Maesako et al. 2007). In contrast, there have been only a few documents that assessed soil resource in Mt. Wakakusa despite the fact that park rangers have been aware of soil degradation such as soil erosion and slope collapse, and that our preliminary

*Corresponding author: e-mail ishi5ro@hotmail.com
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survey uncovered surface soil compaction (bulk density > 1.2 g cm$^{-3}$) and high accumulation of phosphorus (P) (>100 mg P kg$^{-1}$ by Bray No. 2 method) in some spots within Mt. Wakakusa. However, none of these degradation issues have been mentioned in the previous soil survey report by Tamura et al. (2001) because this survey was done by a classical (standard) soil survey method and thus investigated only one soil profile prepared on a middle slope of Mt. Wakakusa (specific location is unknown) with little consideration of soil spatial variability. The lack of information on soil spatial variability has been hampering the building of an appropriate management strategy for this grassland and may lead to inaccurate evaluation of the capacity to support its ecosystem services.

Considering the above given situations, there is a certain need for spatial distribution information on soil resource in Mt. Wakakusa, which can help policy makers and park rangers to sustainably manage and/or efficiently rehabilitate Mt. Wakakusa's grassland ecosystem suffering from gradual degradation. In this regard, information on spatial variability of soil properties is of particular interest because it helps the installation of site-specific (precision) management practices of soil resource in this grassland. Herein, soil spatial variability can be assessed by geostatistics, a subset of statistics specialized in the analysis and interpretation of geographically referenced data (Hengl 2007). The geostatistical approach also allows prediction of the soil properties in space and construction of soil maps over the target area based on the spatial characteristics determined from a limited number of soil samples. Thus, it is very convenient in areas that require conservation such as that of Mt. Wakakusa, where minimum ecological disturbance during the field survey is desired or where exhaustive sampling cannot be done due to limitations in time and cost (Bekele & Hudnall 2006).

In the present study, therefore, we aimed to examine the spatial variability of selected chemical properties of the surface soils (0-5 cm) and their spatial distribution patterns in Mt. Wakakusa grassland. Herein the spatial characteristics of these soil properties were examined by variogram analysis, while the mapping was achieved by the kriging method. Through these approaches, we provide the spatial information on the soil resource to help develop a sustainable ecosystem management strategy and evidence-based intervention measures for natural resource conservation in Mt. Wakakusa grassland.

## Materials and methods

### 1. Site description

The study site is located in Mt. Wakakusa, Nara, Japan (34°41′N, 135°51′E) and is situated under a humid temperate climate, classified as *Cfa* in the Köppen-Geiger classification system, having a mean annual precipitation of about 1,300 mm and a mean annual temperature of approximately 15°C over the past 30 years (1986-2015) (Japan Meteorological Agency 2017). The climax vegetation in this area is an evergreen broadleaf forest as seen in Mt. Kasuga (Maesako et al. 2007, Abe et al. 2019), neighboring Mt. Wakakusa, that has been protected for more than 1,000 years (History of Nara Park Editorial Committee 1982). More than 1,000 sika deer inhabit Nara Park (Nara Deer Protection Foundation 2015) due to protection for religious reasons (Torii & Tatsuzawa 2009), and a previous survey (Torii et al. 2007) suggests that the current population density of sika deer (i.e., 20-30 heads km$^{-2}$) in Nara Park has already exceeded a threshold density (10 heads km$^{-2}$) and can change the local vegetation. For instance, it is well known that some unpalatable plant species to sika deer (e.g., *Pieris japonica*, *Hypolepis punctata*, *Urtica thunbergiana*, and *Perilla frutescens*) are widely seen in Nara Park (Nanami et al. 1999, Torii & Tatsuzawa 2009). The soils in this site are generally classified as Brown Forest Soils in a Japanese Soil Classification System (Obara et al. 2015) or Inceptisols (suborder: Udepts) in the US Soil Taxonomy (Soil Survey Staff 2014), originating from Mikasa Andesite (andesite lava with andesitic tuff and dolerite dike) of the Middle Miocene era (Geological Survey of Japan 2000).

Mt. Wakakusa is a semi-natural grassland (ca. 30 ha) where *Miscanthus sinensis* and *Zoysia japonica* predominate (Takahashi & Maenaka 1977). This grassland has been maintained due to prescribed burnings of vegetation over the centuries. The history of prescribed burnings in Mt. Wakakusa probably extends back to the 13th century according to a historical document (History of Nara Park Editorial Committee 1982). In recent years, the prescribed burnings have been performed on the 4th Saturday of January; this burning event attracts more than a hundred thousand people every year (Nara Prefecture 2014). Although the efficiency of vegetation burning varies due to the weather conditions, the remaining vegetation if any is usually burnt in the following days to insure burning of the entire vegetation across Mt. Wakakusa.

Mt. Wakakusa has a rolling topography with three peaks (Fig. 1): first (270 m a.s.l.), second (308 m a.s.l.), and third (342 m a.s.l.). The first and third peaks are located in the southwestern and northeastern parts of Mt. Wakakusa, respectively, while the second peak is situated in-between. Both first and third peaks are the main locations where the visitors enjoy a short rest or leisure activities. There are major recreational trails (see Fig. 1) in addition to several minor tracks across Mt. Wakakusa.

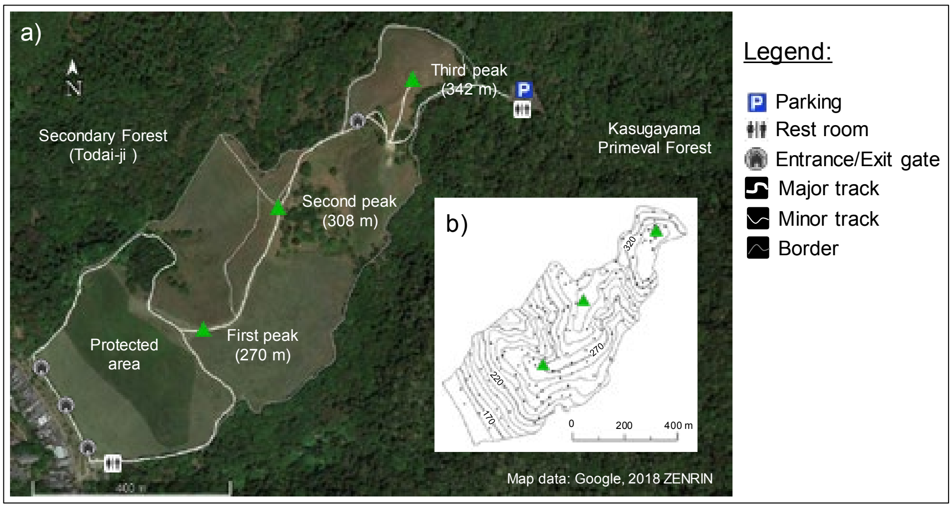


**Fig. 1. Map of the study site and soil sampling design**
a) Recreational trails and facilities on a Google Earth$^{TM}$ image, b) distribution of sampling points on a contour map

There is a 1.1 ha protected area of vegetation (190-250 m a.s.l.) in the southwestern slope of the first peak in which the protection fence was installed in 2000 to optimize the growth of *M. sinensis* for the prescribed burning event.

**2. Field survey and soil sampling**

A field survey was carried out from October to November 2014. A non-aligned block sampling design was used to capture variation over the study site. The border of Mt. Wakakusa was drawn based on a satellite image survey using Google Earth$^{TM}$. A grid of 10 m × 10 m was set up over the study area. The sampling grids were randomly selected, but excluded grids having major trekking paths and leisure facilities, and thus geo-referenced soils were collected from 147 grids out of 3,015 in total (coverage: 4.9%) using a handheld GPS receiver (GPSmap 60CSx; Garmin Ltd., KS). The coordinates were overlaid on a satellite image obtained from Google Earth$^{TM}$ to observe the two-dimensional distribution of the sampling points. In the present study, all coordinate references were projected in Universal Transverse Mercator Zone 53.

At each of the sampled grids, the above-ground biomass and litter layer (if present) was carefully removed before sampling, and the soil samples were taken from the topsoil (0-5 cm in depth) in triplicate within a radius of 3 m using a stainless-steel cylinder (internal volume: 100 $cm^3$) to prepare a composite sample. The composite samples were subjected to air-drying, grinding using a mortar and a pestle, and sieving (mesh size: 2 mm) for the laboratory analysis.

**3. Laboratory analysis**

The soil pH and electrical conductivity (EC) were measured in distilled water at the solid:liquid ratio of 1:5. The organic carbon (OC) and total nitrogen (TN) were simultaneously determined by an NC analyzer (Sumigraph NC-22A; Sumika Chem. Anal. Serv. Ltd., Tokyo, Japan). Here, all carbon in the studied soil was considered to exist thoroughly in organic forms because the soil pH measured in 1 M potassium chloride was lower than 5.5 in all the samples. The available P (Av-P) was extracted with 0.03 M ammonium fluoride and 0.1 M hydrochloric acid according to Bray & Kurtz (1945) and was determined by the molybdenum blue method (Watanabe & Olsen 1965). Exchangeable bases (calcium, magnesium, potassium, and sodium, hereafter referred to as Ex-Ca, Ex-Mg, Ex-K, and Ex-Na) were extracted with 1 M ammonium acetate buffered at pH 7, and their concentrations were determined by atomic absorption spectrometry (Z-2300; Hitachi Tech., Co., Tokyo, Japan). Exchangeable acidity (Ex-Ac) was measured by alkaline titration after the extraction with 1 M potassium chloride. The effective cation exchange capacity (ECEC) was calculated by the summation of the exchangeable bases and acidity, whereas the base saturation (BS) was defined here as the ratio of the sum of the exchangeable bases to ECEC in percentage. In the present study, the result for Ex-Na is not presented because Ex-Na was found in negligible amounts (0.06 ± 0.02 $cmol_c$ $kg^{-1}$), although Ex-Na was used to calculate ECEC and BS.

**4. Exploratory data analysis**

The statistical software R version 3.5.1 (R Development Core Team 2018) was used to perform exploratory data analysis, including the descriptive statistics of each soil variable such as normality (by the

Shapiro-Wilk test) with skewness (normality = 0) and kurtosis (normality = 0), mean absolute deviation (MAD), coefficient of variation (CV), and Spearman's rank correlation coefficients. Here, CV shown in percentage was categorized as low (CV < 10%), intermediate (CV = 10%-90%), and high (CV > 90%) following the classification by Cobo et al. (2010).

As the geostatistical analysis requires data with a normal distribution (Olea 2006), non-normally distributed variables ($P < 0.01$) were transformed to logarithm, square-root, or logit to attain/approximate normal distribution (Hengl 2007). Herein, the best transformation method to each soil variable was chosen based on the highest probability of distribution. Aside from the original data sets inherently showing normality (i.e., pH, EC, OC, TN, and Ex-K), the transformed data sets (i.e., Av-P, Ex-Ca, Ex-Mg, Ex-Ac, ECEC, and BS) were used for the variogram analysis.

Most of the examined soil variables had some extremes that can be identified as outliers due to the following criteria: the mean plus/minus 3 times standard deviation (SD) and the median plus/minus 2.5 times MAD (Leys et al. 2013) for normally and non-normally distributed data, respectively (Table 1). The outliers were often removed from the data set prior to the geostatistical analysis because they could inflate the sample variance and could distort the semivariogram, which often results in misleading views of the true situations (Oliver & Webster 2014). However, in this study, we intended to keep all outliers in the data set so that the semivariogram construction and subsequent kriging could uncover degraded and/or polluted spots in the study area.

**5. Variogram analysis**

Prior to the semivariogram construction, all the data sets were standardized using the following equation (Alfons 2016):

$$z = \frac{(x - \bar{x})}{SD} \qquad (1)$$

where $z$ is a standardized parameter, $x$ is an original (measured) data, and $\bar{x}$ is the mean of a data set. Herein, the original and transformed data sets were used for the normally ($P \geq 0.01$) and non-normally ($P < 0.01$) distributed data sets, respectively. The standardization allows a fair comparison among the variables with different units and/or different scales in the variogram analysis (Cobo et al. 2010).

Following the recommendation by Oliver & Webster (2014), a classical variogram estimator (Matheron 1965) was applied to the soil variable without any outliers:

$$\hat{\gamma}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(i) - z(i+h)]^2 \qquad (2)$$

where $n(h)$ is the number of paired comparisons at lag $h$, and $z$ is the standardized (measured) values of a target variable at the locations $i$ and $i + h$, respectively. On the other hand, the semivariograms for the examined soil variables with outliers were obtained using a robust variogram estimator (Cressie & Hawkins 1980), as recommended by Oliver & Webster (2014):

$$\hat{\gamma}_{CH}(h) = \frac{\left\{\frac{1}{2n(h)} \sum_{i=1}^{n(h)} |z(i) - z(i+h)|^{\frac{1}{2}}\right\}^4}{0.457 + \frac{0.494}{n(h)} + \frac{0.045}{n^2(h)}} \qquad (3)$$

**Table 1. Descriptive statistics of the examined soil properties at the study site**

| Variable | Unit | Mean | Median | Max. | Min. | SD† | MAD† | CV† | Skewness | Kurtosis | Normality‡ | Outliers |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| pH | — | 5.4 | 5.4 | 6.2 | 4.7 | 0.3 | 0.3 | 5.4 | −0.03 | −0.64 | 0.21 | 0 |
| EC | mS $m^{-1}$ | 4.8 | 4.8 | 7.2 | 3.0 | 0.9 | 0.8 | 17.8 | 0.07 | −0.46 | 0.20 | 0 |
| OC | g $kg^{-1}$ | 39.0 | 39.3 | 59.0 | 14.2 | 8.5 | 7.4 | 21.9 | −0.23 | 0.12 | 0.20 | 0 |
| TN | g $kg^{-1}$ | 2.9 | 2.9 | 4.4 | 1.1 | 0.6 | 0.5 | 21.9 | −0.18 | 0.24 | 0.11 | 0 |
| Av-P | mg $kg^{-1}$ | 31.0 | 14.1 | 304.9 | 3.6 | 54.1 | 11.0 | 174.5 | 3.47 | 11.99 | *** | 21 |
| Ex-Ca | $cmol_c$ $kg^{-1}$ | 6.0 | 5.0 | 19.5 | 0.7 | 3.3 | 2.6 | 54.8 | 1.43 | 3.11 | *** | 8 |
| Ex-Mg | $cmol_c$ $kg^{-1}$ | 3.1 | 2.8 | 11.9 | 0.3 | 1.8 | 1.6 | 57.2 | 1.25 | 3.39 | *** | 3 |
| Ex-K | $cmol_c$ $kg^{-1}$ | 0.7 | 0.7 | 1.5 | 0.2 | 0.3 | 0.3 | 37.6 | 0.42 | −0.13 | 0.03 | 0 |
| Ex-Ac | $cmol_c$ $kg^{-1}$ | 2.0 | 1.4 | 7.6 | 0.1 | 1.8 | 1.6 | 87.8 | 1.07 | 0.39 | *** | 8 |
| ECEC | $cmol_c$ $kg^{-1}$ | 11.9 | 11.2 | 32.5 | 4.7 | 4.0 | 3.5 | 34.0 | 1.79 | 5.76 | *** | 6 |
| BS | % | 79.9 | 87.4 | 99.6 | 19.8 | 19.2 | 15.1 | 24.1 | −1.10 | 0.28 | *** | 17 |

† Abbreviations: SD = standard deviation; MAD = median absolute deviation; CV = coefficient of variation

‡ *** indicate a significant level of $P < 0.001$.

where the denominator is a correction factor based on the assumption that the underlying process to be estimated has normally distributed differences over all lag distances (Webster & Oliver 2007). This estimator, known as one of the robust estimators against outliers (Mingoti & Rosa 2008), was selected from among the recommended robust variogram estimators by Oliver & Webster (2014) because of its better accuracy compared to the others (i.e., Dowd 1984, Genton 1998) (data are not shown here). We also confirmed that the standardized semivariograms constructed by the classical (Matheron 1965) and robust variogram estimators (Cressie & Hawkins 1980) earned similar shapes in terms of nugget, sill, and range when applied to the data sets with normal distribution but without outliers (i.e., pH, EC, OC, TN, and Ex-K) (data are not shown here). This means that understanding the comparative differences in spatial characteristics among the examined soil variables is possible even though two different variogram estimators, i.e., the classical (see Eq. (2) above) and the robust ones (see Eq. (3) above), were applied based on the presence of outliers in the present study.

Whichever equation, i.e., Eq. (2) or (3), was adopted for the construction of the semivariograms, half of the maximum sampling distance was used as an active lag distance according to a recommended manner (Olea 2006), and the number of point pairs of each bin ($n \geq 102$) was greater than the minimum number of point pairs ($n = 30$-$50$) required for the variogram analysis (Journel & Huijbregts 1978, Chilès & Delfiner 2012) and was desirable in terms of statistical reliability at each distance class (Rossi et al. 1992). All the data sets were fitted by simple regression (low-order polynomials) to check for the presence of any trend, and were confirmed to have no trends and thus to satisfy the assumption of stationarity (Oliver & Webster 2014) in this study. Anisotropy was not considered in the present study because an isotropic characterization of spatial dependence is more recommendable when the number of samples is limited (Davidson & Csillag 2003). The spherical model was fitted to all examined variables because having the same model further facilitates comparisons among variables (Cambardella et al. 1994, Davidson & Csillag 2003, Cobo et al. 2010), although the exponential model exhibited slightly better fits (based on the lower residual sum of squares (RSS)) for Ex-Ca, Ex-Mg, and ECEC than the spherical model.

In the semivariogram, the nugget, sill, and range are used to refer to the semivariance value at a zero lag distance, the semivariance value at which the semivariogram levels out, and the lag distance of the semivariogram that attains the sill, respectively (Chilès & Delfiner 2012). Here, the nugget indicates the differences between the observed values at short distances due to errors in measurement and/or small-scale variability (Oliver & Webster 2014). As a point pair of measurement becomes increasingly separated in space from each other, the dissimilarity of the measurement between the paired points becomes larger until it reaches the sill. The range defines the region of influence or spatial correlation distance of a measured value. The spatial dependency was evaluated based on the four categories of the nugget-to-sill (N/S) ratio: very strong (<0.25), moderately strong (0.25-0.50), moderately weak (0.50-0.75), or very weak (>0.75) by following Cobo et al. (2010).

**6. Geostatistical map construction**

The spatial interpolation was performed over the 10 m × 10 m grids. As all data sets did not have any trends in the present study (Oliver & Webster 2014), the ordinary kriging method (Matheron 1965) was applied for the interpolation following the instruction by Hengl (2007). As recommended by Oliver & Webster (2014), the number of the nearest observations within neighborhood was set out to 7 to 25. Here, the non-standardized data sets were used to prepare the soil maps by interpolation and thus all transformed data were back-transformed in advance as spatial prediction is preferable to present in the original scale (Oliver & Webster 2014).

The leave-one-out cross-validation was performed for each model of the data set in order to evaluate and validate the accuracy of the model estimator (Wang & Shi 2017) based on the mean error (ME) and root mean squared prediction error (RMSE) (Hengl 2007), defined as follows:

$$ME = \frac{1}{n}\sum_{i=1}^{n}\left(z(i) - z^{*}(i)\right) \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(z(i) - z^{*}(i)\right)^{2}} \quad (5)$$

where $n$ is the number of validation samples, and $z$ and $z^*$ denote the observed and predicted values, respectively. Here, ME and RMSE indicate the total prediction bias of the interpolation and the precision and accuracy of the prediction, respectively (Wang & Shi 2017).

In the present study, all geostatistical analyses were performed using the R package *gstat* (Pebesma 2004).

## Results

**1. Exploratory data analysis**

The results from the exploratory statistics are presented in Table 1. In this paper, hereafter, the representative value of each data set is given as a mean plus/minus SD and a median plus/minus MAD for normally distributed and non-normally distributed data, respectively. In general, the soils in the study site had a moderately acidic reaction (ave.: pH = 5.4 ± 0.3) and moderate levels of OC (ave.: 39.0 ± 8.5 g $kg^{-1}$) and TN (ave.: 2.9 ± 0.6 g $kg^{-1}$). Moreover, moderate levels of Av-P (med.: 14.1 ± 11.0 mg $kg^{-1}$), exchangeable bases, i.e., Ex-Ca (med.: 5.0 ± 2.6 $cmol_c$ $kg^{-1}$), Ex-Mg (med.: 2.8 ± 1.6 $cmol_c$ $kg^{-1}$), and Ex-K (ave.: 0.7 ± 0.3 $cmol_c$ $kg^{-1}$), ECEC (med.: 11.2 ± 3.5 $cmol_c$ $kg^{-1}$), a high level of BS (med.: 87.4% ± 15.1%), and low levels of EC (ave.: 4.8 ± 0.9 mS $m^{-1}$) and Ex-Ac (med.: 1.4 ± 1.6 $cmol_c$ $kg^{-1}$) were observed in the study site. The Av-P content showed the highest variability at the widest range from 3.6 to 304.9 mg $kg^{-1}$ (CV = 174.5%). In contrast, the soil pH varied in the narrowest range (4.7 to 6.2) with a low variability (CV = 5.4%). The remaining soil variables showed intermediate variability at the CV range of 17.8% to 87.8%.

The normality test revealed that the pH, EC, OC, TN, and Ex-K followed a normal distribution ($P \geq 0.01$), while the others (Av-P, Ex-Ca, Ex-Mg, Ex-Ac, ECEC, and BS) showed a non-normal distribution ($P < 0.01$). In particular, Av-P had a very positively skewed (skewness = 3.47) and highly leptokurtic (kurtosis = 11.99) distribution, making its mean (31.0 mg $kg^{-1}$) much greater than its median (14.1 mg $kg^{-1}$). For the other soil variables, Ex-Ca, Ex-Mg, and ECEC had a positively skewed (skewness = 1.25-1.79) and leptokurtic (kurtosis = 3.11-5.76) distribution. A mesokurtic distribution (kurtosis = 0.28-0.39) was found for Ex-Ac and BS, although the former had a positively skewed (skewness = 1.07) distribution but the latter showed a negatively skewed (skewness = −1.10) distribution.

Table 2 presents the Spearman's rank correlation coefficients among the soil properties examined in this study. Organic C was found to have a very strong and positive correlation with TN, and these two showed a strong positive correlation with EC as well. A very strong or strong positive correlation was also observed between all pairs among the soil pH, Ex-Ca, Ex-Mg, ECEC, and BS, although these parameters showed moderate positive correlations with Ex-K. On the contrary, these variables showed negative correlations with Ex-Ac from a moderate to a very strong extent. In the same line, Av-P had a weak but significantly negative correlation with pH, Ex-Ca, Ex-Mg, ECEC, and BS.

The transformation of the non-normally distributed data sets to either form of logarithm, squared root, or logit allowed BS to attain normal distribution ($P \geq 0.01$) without outliers (Table 3). Also, Ex-Ca, Ex-Mg, and ECEC showed a normal distribution ($P \geq 0.01$) after the transformation, but these transformed data sets still contained outliers (though all the outliers were situated close to the threshold value). In contrast, Ex-Ac became free of outliers but did not gain a normal distribution ($P < 0.01$) due to the transformation. The data set which cannot approximate the normality by any means (Av-P and Ex-Ac in the present study) is not uncommon in the geochemical and environmental studies (Reimann & Filzmoser 2000). As a result, the data sets which inherently have a normal distribution without outliers (i.e., pH, EC, OC, TN, and Ex-K) as well as those free from outliers after the transformation (i.e., Ex-Ac and BS) were subjected to the classical variogram estimator (see Eq. (2) above). On the other hand, the robust variogram estimator (see Eq. (3) above) was applied to the transformed data sets of Av-P, Ex-Ca, Ex-Mg, and ECEC, which still had outliers after

**Table 2. Spearman's rank correlation coefficients among the examined soil properties at the study site**

| Variable | pH | EC | OC | TN | Av-P | Ex-Ca | Ex-Mg | Ex-K | Ex-Ac | ECEC | BS |
|---|---|---|---|---|---|---|---|---|---|---|---|
| pH | 1.00 | | | | | | | | | | |
| EC | $0.03^{ns}$ | 1.00 | | | | | | | | | |
| OC | $-0.08^{ns}$ | $0.70^{***}$ | 1.00 | | | | | | | | |
| TN | $-0.15^{ns}$ | $0.69^{***}$ | $0.95^{***}$ | 1.00 | | | | | | | |
| Av-P | $-0.39^{***}$ | $0.28^{***}$ | $0.22^{**}$ | $0.33^{***}$ | 1.00 | | | | | | |
| Ex-Ca | $0.80^{***}$ | $0.05^{ns}$ | $0.09^{ns}$ | $0.06^{ns}$ | $-0.24^{**}$ | 1.00 | | | | | |
| Ex-Mg | $0.64^{***}$ | $-0.01^{ns}$ | $-0.03^{ns}$ | $-0.09^{ns}$ | $-0.41^{***}$ | $0.80^{***}$ | 1.00 | | | | |
| Ex-K | $0.47^{***}$ | $0.27^{**}$ | $0.22^{**}$ | $0.18^{*}$ | $0.09^{ns}$ | $0.55^{***}$ | $0.47^{***}$ | 1.00 | | | |
| Ex-Ac | $-0.95^{***}$ | $-0.12^{ns}$ | $0.00^{ns}$ | $0.05^{ns}$ | $0.30^{***}$ | $-0.81^{***}$ | $-0.60^{***}$ | $-0.39^{***}$ | 1.00 | | |
| ECEC | $0.52^{***}$ | $-0.06^{ns}$ | $-0.01^{ns}$ | $-0.05^{ns}$ | $-0.31^{***}$ | $0.82^{***}$ | $0.90^{***}$ | $0.49^{***}$ | $-0.46^{***}$ | 1.00 | |
| BS | $0.95^{***}$ | $0.09^{ns}$ | $0.01^{ns}$ | $-0.04^{ns}$ | $-0.34^{***}$ | $0.90^{***}$ | $0.73^{***}$ | $0.47^{***}$ | $-0.97^{***}$ | $0.63^{***}$ | 1.00 |

***, ** and * indicate a significant level of $P < 0.001$, $< 0.01$ and $< 0.05$, respectively; ns denotes not significant ($P \geq 0.05$).

**Table 3. Descriptive statistics of the non-normally distributed data sets after transformation**

| Variable | Transform | Mean | Median | Max. | Min. | Skewness | Kurtosis | Normality[†] | Outliers |
|---|---|---|---|---|---|---|---|---|---|
| Av-P | Logarithm | 1.2 | 1.2 | 2.5 | 0.6 | 1.12 | 1.03 | *** | 9 |
| Ex-Ca | Logarithm | 0.7 | 0.7 | 1.3 | −0.2 | −0.46 | 0.82 | 0.03 | 1 |
| Ex-Mg | Square root | 1.7 | 1.7 | 3.5 | 0.5 | 0.22 | 0.30 | 0.31 | 1 |
| Ex-Ac | Logarithm | 0.1 | 0.2 | 0.9 | −1.1 | −0.40 | −0.73 | *** | 0 |
| ECEC | Logarithm | 1.1 | 1.0 | 1.5 | 0.7 | 0.32 | 0.96 | 0.16 | 1 |
| BS | Logit | 0.8 | 0.8 | 2.4 | −0.6 | 0.12 | −0.67 | 0.22 | 0 |

[†] *** indicate a significant level of $P < 0.001$.

the transformation, in order to downplay the effects of the existing outliers on the shape of the semivariogram (Mingoti & Rosa 2008). However, the data sets which did not approximate the normal distribution (Av-P and Ex-Ac) and those which still had outliers even after the transformation need careful interpretation in the geostatistical analysis because the skewed distribution and the existing outliers distort and/or inflate the semivariance and affect the shape of the semivariogram (Mingoti & Rosa 2008, Oliver & Webster 2014).

**2. Variogram analysis**

The experimental semivariograms of all the soil variables examined in the present study were well fitted by the spherical model with an RSS of less than 0.003, and their nuggets, sills, and ranges in the semivariograms varied from 0.11 to 0.85, from 0.90 to 1.09, and from 139.7 to 216.9 m, respectively (Fig. 2, Table 4). Among the theoretical semivariograms prepared in this study, only EC showed a nearly pure nugget effect (N/S ratio = 0.81). As a result, Av-P, Ex-Ca, Ex-Mg, and ECEC had a very strong spatial dependency, as indicated by the N/S ratio lower than 0.25. In contrast, a very weak spatial

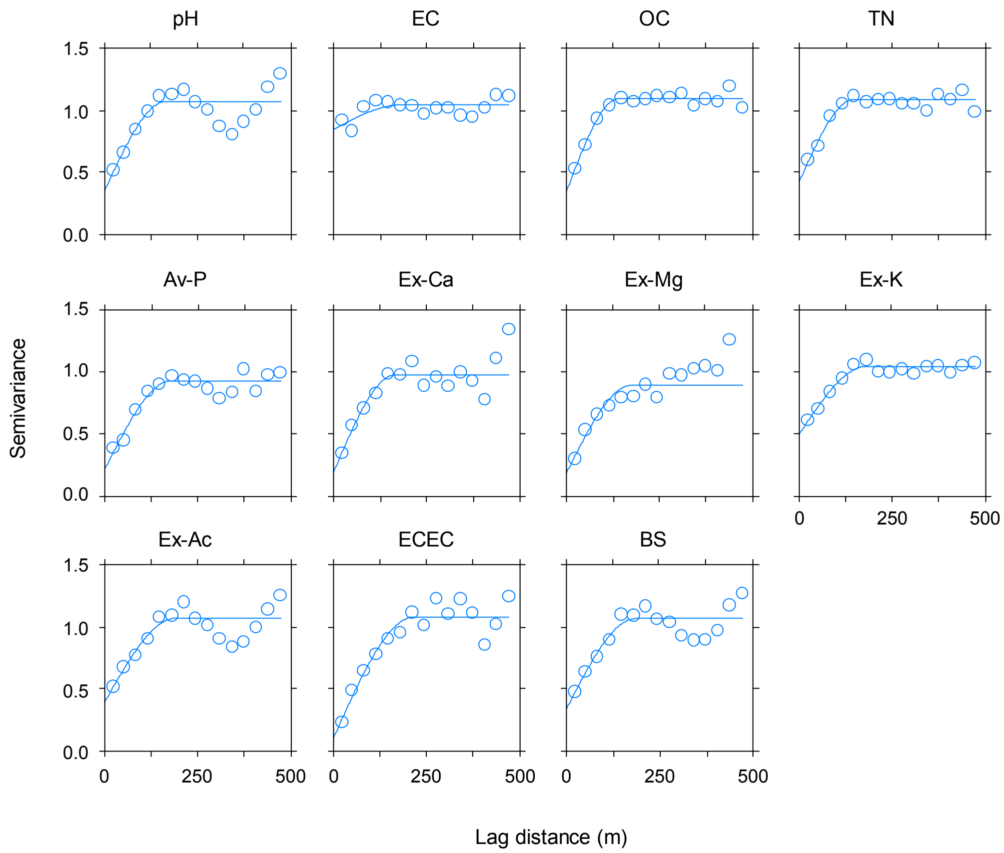


**Fig. 2. Standardized experimental (circles) and theoretical (lines) semivariograms for the examined soil properties at the study site**

**Table 4. Model parameters of standardized theoretical semivariograms (with the spherical model) for the examined soil properties at the study site**

| Variable | Transform | $R^{2†}$ | RSS† | Nugget (Co) | Sill (Co+C) | Range (m) | N/S ratio [Co/(Co+C)] | Class‡ | Cross-validation | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | ME† | RMSE† |
| pH | — | 0.85 | $1.32E^{-03}$ | 0.36 | 1.08 | 164.2 | 0.33 | MS | $4.03E^{-03}$ | 0.77 |
| EC | — | 0.00 | $2.18E^{-03}$ | 0.85 | 1.05 | 183.2 | 0.81 | VW | $-1.37E^{-03}$ | 0.96 |
| OC | — | 0.99 | $9.82E^{-05}$ | 0.34 | 1.09 | 139.7 | 0.31 | MS | $-1.19E^{-02}$ | 0.88 |
| TN | — | 0.94 | $4.26E^{-04}$ | 0.43 | 1.09 | 146.5 | 0.39 | MS | $-9.17E^{-03}$ | 0.88 |
| Av-P | Logarithm | 0.90 | $9.94E^{-04}$ | 0.22 | 0.93 | 178.0 | 0.24 | VS | $-8.10E^{-03}$ | 0.69 |
| Ex-Ca | Logarithm | 0.90 | $1.18E^{-03}$ | 0.19 | 0.98 | 166.1 | 0.20 | VS | $-8.02E^{-03}$ | 0.74 |
| Ex-Mg | Square root | 0.81 | $2.90E^{-03}$ | 0.19 | 0.90 | 174.9 | 0.21 | VS | $-4.65E^{-03}$ | 0.74 |
| Ex-K | — | 0.95 | $2.71E^{-04}$ | 0.50 | 1.04 | 179.7 | 0.48 | MS | $-6.47E^{-03}$ | 0.90 |
| Ex-Ac | Logarithm | 0.83 | $1.37E^{-03}$ | 0.40 | 1.07 | 189.7 | 0.38 | MS | $-3.04E^{-03}$ | 0.79 |
| ECEC | Logarithm | 0.92 | $1.58E^{-03}$ | 0.11 | 1.08 | 216.9 | 0.10 | VS | $-1.11E^{-02}$ | 0.77 |
| BS | Logit | 0.89 | $1.10E^{-03}$ | 0.34 | 1.07 | 185.4 | 0.32 | MS | $6.65E^{-04}$ | 0.75 |

† Abbreviations: $R^2$ = coefficient of determination; RSS = residual sum of square; ME = mean error; RMSE = root mean square error.
‡ Spatial dependency class: VS − very strong (<0.25); MS − moderately strong (0.25-0.50); MW − moderately weak (0.50-0.75); VW − very weak (>0.75).

dependency (N/S ratio > 0.75) was observed in EC. The other variables, i.e., pH, OC, TN, Ex-K, Ex-Ac, and BS showed a moderately strong spatial dependency with the N/S ratio between 0.25 and 0.50. None of the variables were categorized into the moderately weak dependency (0.50-0.75).

### 3. Geostatistical mapping

Table 4 shows the results from the leave-one-out cross-validation test. Low or very low ME ($-1.19E^{-02}$ -$4.03E^{-03}$) and RMSE (0.69-0.96) indicate that the models developed in the present study are relatively unbiased in interpolation and that the accuracy of the models is generally acceptable to predict the soil properties for making soil maps. Although Av-P had a highly skewed distribution (with outliers) and its transformed data set was still skewed with the presence of outliers, the accuracy of the prediction model (RMSE = 0.69) was the highest among the examined soil properties. In contrast, soil EC, which originally had a normal distribution without any outliers but had the lowest accuracy of the developed model (RMSE = 0.96) with the highest nugget (0.85) and N/S ratio (0.81).

The interpolation maps of the examined soil properties allowed us to visually understand the spatial distribution pattern of the examined soil properties in the study site (Fig. 3). The lower pH values were found around the peaks and along ridges (>250 m a.s.l.) where recreational places and trekking paths exist, while the higher values were seen in the valleys and slopes including the protected area. Somewhat similar distribution patterns to pH were found for Ex-Ca and BS, but a contrast distribution pattern was seen for Ex-Ac. This means that the contents of exchangeable bases (Ex-Ca, Ex-Mg, and Ex-K) and ECEC tended to be higher in the valley areas than the peaks and ridges in contrast to the content of Ex-Ac. The maps of OC and TN looked very similar to one another. Here, the smallest amounts of OC and TN were found in the sloping area at the east of the second peak. The third peak and in the middle (220 m a.s.l.) of the protected area also showed relatively small amounts of OC and TN. In contrast, the highest amounts of OC and TN were observed on a gently sloping area at the western part of the second peak (270-300 m a.s.l.). The map of Av-P revealed that a large amount of Av-P (>100 mg $kg^{-1}$) distributed around the peaks and along the major trail between the first and second peaks (>240 m a.s.l.).

## Discussion

The moderately acidic reaction and moderate levels of OC, TN, Av-P, and exchangeable bases found in the surface soil (0-5 cm in depth) at the study site (Table 1) were generally consistent with those reported by Tamura et al. (2001). However, considering that most of the soil characteristics have intermediate to high variability (CV > 10%), sustainable soil management in Mt. Wakakusa grassland needs to take soil spatial variability into account. In particular, the Av-P content showed the highest variability (CV = 174.5%) and had many outliers (n = 21;

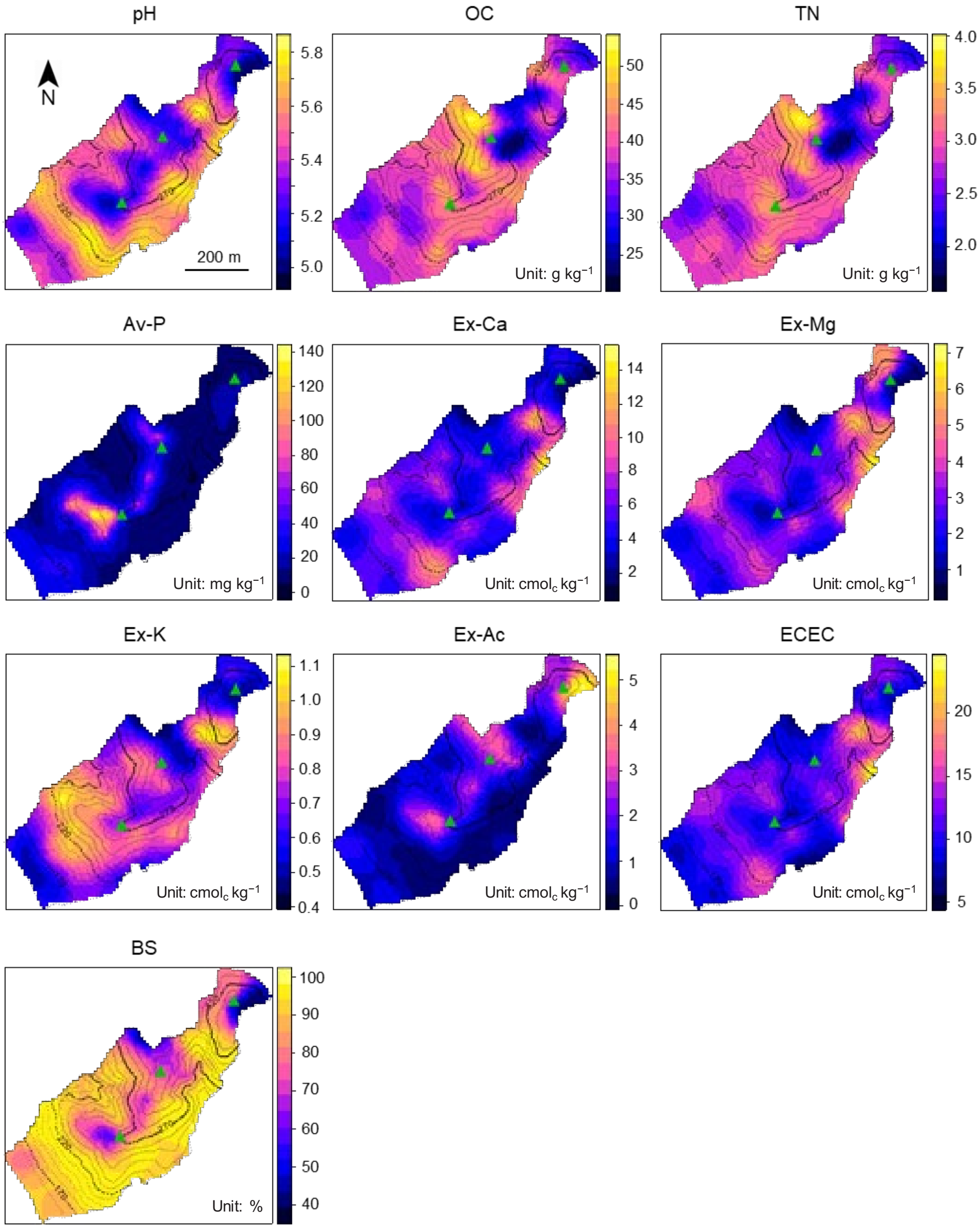


**Fig. 3. Interpolation maps of the examined soil properties at the study site**
Lines and triangular symbols in each map denote contours and peaks, respectively.

14.3% of the data set), although the majority of the soil samples analyzed in the present study were found to have a low Av-P content (<20 mg kg$^{-1}$) with a median of the data set of 14.1 mg kg$^{-1}$, reflecting its highly skewed (skewness = 3.47) and leptokurtic (kurtosis = 11.99) distribution. These results indicate that there are some hot spots with high accumulation of P in available forms to the plants (see Fig. 3) and highlights the importance of the precision management approach in Mt. Wakakusa grassland. Another advantage of understanding soil variability (and spatial characteristics) has been reported by Kamarudin et al. (2019); the geostatistical approach to estimate the surface soil (0-5 cm) OC stock in Mt. Wakakusa grassland yielded a better estimation accuracy compared to the classical survey method, which relied on a few soil profile data with little consideration to soil variability (e.g., Matsuura et al. 2012). Kamarudin et al. (2019) uncovered that the classical approach, if calculated based on the soil survey data by Tamura et al. (2001), resulted in 21% overestimation of the surface soil OC stock compared to the geostatistical method. On the other hand, in contrast to Av-P, the soil pH varied in the narrowest range (4.7 to 6.2) with the lowest variability (CV = 5.4%). However, this is not surprising because the pH value itself is shown in the logarithmic scale and the proton concentrations in the present data set differ more than 30 times between the minimum (4.7) and the maximum values (6.2). Therefore, the range and CV of the soil pH value need cautious interpretation when compared with those of the other variables.

It is generally accepted that the strong spatial dependency of soil variables can be controlled by intrinsic factors such as inherent soil quality (e.g., soil texture and mineralogy), while the weak spatial dependency can be generated by extrinsic factors such as management practices (e.g., Cambardella et al. 1994, Cobo et al. 2010, Shahidin et al. 2018). Based on this accepted theory, the very strong and moderately strong spatial dependencies found for most of the examined soil variables (i.e., pH, OC, TN, Av-P, Ex-Ca, Ex-Mg, Ex-K, Ex-Ac, ECEC, and BS) in the present study (Table 4) suggest that the soil spatial characteristics in Mt. Wakakusa have formed predominantly under the influence of intrinsic factors, especially those related to the soil forming process. Herein, one of the major influences can derive from the topography, as indicated by the preferential distribution of the exchangeable bases in the valley compared to the surrounding ridges and slopes (see Fig. 3). The topographic effect was also indicated by the distribution patterns of ECEC and Ex-Ac. The accumulation of exchangeable bases would reduce the Ex-Al content and would result in the higher pH and thus an increase in the cation exchangeable capacity (ECEC as well) of the soil (Brady & Ray 2007). This trend was observed through the significantly strong correlations between the relevant parameters, i.e., pH, Ex-Ca, Ex-Mg, Ex-K, Ex-Ac, and ECEC (Table 2).

On the other hand, as stated above, Mt. Wakakusa is a semi-natural grassland maintained by prescribed burnings. The burning practice is a significant human intervention and is considered one of the major extrinsic factors affecting soil properties in this grassland ecosystem. In fact, Abe et al. (unpublished data) reported that the prescribed burnings over the past 500 years in this grassland resulted in decrease in organic C content (approximately 50%) and enhanced pH (from 4 to 5) associated with increased contents of Ex-Ca and Ex-Mg (4-10 times) in the topsoil (0-10 cm). These results suggest the great impact of the prescribed burning on the soil chemical properties. However, the very strong and moderately strong spatial dependencies (N/S ratio $\leq 0.50$) found in most of the examined soil variables (all but EC) suggest the little impact of the prescribed burning on the spatial dependency of the soil chemical properties in the study site. Based on these situations, it is also suggested that the very weak spatial dependency (N/S ratio $> 0.75$) seen for EC is attributed to spatial autocorrelation in the shorter distance than our sampling intervals. However, further study is needed to confirm these findings through the comparison of the soil spatial dependency with the neighboring Mt. Kasuga forest reserve, which has been protected from human disturbance (in particular from logging and hunting) for more than 1,000 years (History of Nara Park Editorial Committee 1982).

The map constructed for Av-P uncovered areas with very high Av-P contents (>50 mg $kg^{-1}$) such as the area around the first peak where the visitors take a rest frequently and the area along the major trekking pass between the first and second peaks (see Figs. 1 and 3), which might indicate the anthropogenic addition of P at the study site. Also, we highly suspect that the sika deer (as an extrinsic factor) contributed to Av-P accumulation in the study site through deposition of feces, which contain a large amount of P. This suspicion is supported by the findings from our preliminary survey: some areas having high contents of Av-P in the surface soil were observed in Mt. Kasuga forest reserve which were protected from human activities (Kamarudin et al. unpublished data). However, as stated earlier, the very strong dependency of Av-P suggests that the distribution pattern of Av-P is predominantly affected by intrinsic factors. Therefore, based on spatial autocorrelation information, human interventions (e.g., prescribed burning and tourism/leisure activities) and the dense inhabitation by sika deer are not likely the cause of Av-P accumulation in Mt. Wakakusa. The impact of sika deer on the soil Av-P is not yet supported by sufficient scientific information and further study is crucial in this regard.

The very strong correlation found between OC and TN is commonly seen in well-drained soils (e.g., Abe et al. 2007, Umami et al. 2019). As a result, the maps of OC and TN had a certain similarity to one another. As reported by Kamarudin et al. (2019), the impact of the deer browsing on the vegetation was evident because vigorous growth and thus large biomass production of *M. sinensis* in the protection area were observed during the field survey and also visibly confirmed by Google Earth™ image, where a darker color in the protected area than in the surrounding non-protected area was visible (Fig. 1). However, the impact of the deer on soil resource was not clear in the present study because both the OC and TN contents in the soils of the protected area were found similar to or even slightly lower than those in the surrounding unprotected area (see Fig. 3). This result is in conflict with the recent findings by Fukushima et al. (2017), who documented the higher contents of C and N in the soil under *M. sinensis* grassland protected by deer-exclusion fences compared to that in the surrounding unprotected (unfenced) area under deer-browsing pressure. These conflicting results indicate the significant impact of the prescribed burning on the soil organic matter; the prescribed burning can eliminate the positive impact of enhanced biomass production through deer exclusion on the amount of soil organic matter. In fact, Abe et al. (unpublished data) revealed that repeated application of prescribed burning following land use change (from a primary evergreen broadleaf forest to a semi-natural grassland) would reduce the soil OC level up to one half of its original level, although a single application of prescribed burning would not change the soil OC content to a significant extent in the *M. sinensis*-dominated grasslands of Japan (Yamamoto et al. 2002, Toma et al. 2010). As seen for OC distribution, the lowest TN content (<2.0 mg $kg^{-1}$) observed in the area between the second and third peaks at 260-300 m a.s.l. could be caused by slope collapse and soil erosion on the steep slope area. In contrast, the soil on a gentle slope area around the second peak at 270-300 m a.s.l. had the highest TN content (<4.0 g $kg^{-1}$).

Among the soil variables examined in the present study, EC had the largest measurement error and/or error arising from the uncontrolled fitting over distances shorter than the shortest lag (Oliver & Webster 2014), as indicated by the highest nugget value (Table 4). Also, based on the highest N/S ratio and the nearly pure nugget effect (flat semivariogram; see Fig. 2), EC was the only variable that showed very weak spatial dependency among the examined variables. Due to such uncertainty and the spatial independency in our sampling scale, we faced the difficulty of preparing an interpolation map for EC which has an acceptable prediction accuracy. However, spatial structure may exist at lower resolution (shorter distance) than our sampling scheme (Davidson & Csillag 2003, Cobo et al. 2010). In fact, the cross-validation test revealed the lowest prediction accuracy (RMSE = 0.96) of the model developed for EC among the examined soil variables (see Table 4). In this regard, we found that the higher nugget and N/S ratio resulted in the lower prediction accuracy with the higher RMSE, as indicate by the significantly positive correlation between RMSE and nugget (R = 0.82, $P < 0.001$, n = 11) and RMSE and N/S ratio (R = 0.80, $P < 0.001$, n = 11). For this reason, we did not exhibit the interpolation map of EC in the present paper. Finding no spatial dependency for some soil parameters is not unusual, as the degree of dependency can vary as a function of the soil property, location, and survey scale (Garten et al. 2007). On the other hand, the relatively strong and positive correlations found between EC and OC, and EC and TN (Table 2) suggest a positively interacting relationship of EC with soil organic matter, which is often seen in many other soils (e.g., Abe et al. 2007, Umami et al. 2019). In any case, the EC level at the study site is very low (<7.2 mS $m^{-1}$; see Table 1) and does not need much care upon grassland management in Mt. Wakakusa for the moment. With respect to such a soil variable showing low spatial dependency with high N/S ratio, a map with better accuracy can be prepared through a shorter distance of soil sampling scale to capture a shorter-range variability (Davidson & Csillag 2003) and/or if the measurement error is simply eliminated (Oliver & Webster 2014).

Last but not least, we should mention the appropriate sampling intervals that will allow better planning of the sampling design in the future study. In this regard, the semivariogram range can provide useful information (Table 4) because it indicates the limit of spatial correlation (Oliver & Webster 2014) depending on the spatial interaction of soil processes affecting each property at the sampling scale (Trangmar et al. 1986). It is known that the semivariogram range often varies among the measured parameters, which may reflect variable intrinsic and extrinsic factors (Cambardella et al. 1994, Shahidin et al. 2018). In case of Mt. Wakakusa, the semivariogram range variability among the examined soil properties may occur under the strong influence of intrinsic factors related to the soil formation process such as topography (e.g., Garten et al. 2007), and the impact of extrinsic factors such as the prescribed burning practice (e.g., Boerner & Brinkman 2005) and the dense population of sika deer (e.g., Liu et al. 2016) were much less pronounced. The preferable distance of sampling can be referred to as that allows the collection of spatially independent (free of spatial autocorrelation) samples (Rossi et al. 1992); thus, the distance that exceeds the semivariogram range is considered appropriate, though spatial dependency usually differs with the sampling scale (Cambardella et al. 1994). The semivariograms constructed in the present study indicate that sampling intervals longer than 139-217 m are recommended in Mt. Wakakusa, though the samples for EC can be taken randomly as a nested sampling (Webster & Oliver 2007) because these variables showed very weak spatial autocorrelation. On the other hand, if the intention of the sampling is to characterize again the spatial variability within the study site, a sampling distance of less than 183 m is recommended to capture shorter-range variability (Cobo et al. 2010), though a shorter distance than the sampling distance used in the present study would be preferable for EC.

## Conclusion

In the present study, the geostatistical approach was used to assess spatial variability of selected chemical properties of surface soils (0-5 cm) and to develop interpolation maps of these examined properties to provide spatial information on soil resource in Mt. Wakakusa grassland. The major findings of this study are summarized as follows:

1. The examined chemical properties of the surface soils (0-5 cm) had intermediate spatial variability (CV = 17.8%-87.8%), except for the pH, which had a low variability (CV = 5.4%) as originally shown in the logarithmic scale and Av-P which showed the highest variability (CV = 174.5%) with many outliers (>41.6 mg $kg^{-1}$; n = 21);

2. Very strong or moderately strong spatial dependency (N/S ratio ≤ 0.50) found in all the examined soil properties except for EC can be predominantly generated by intrinsic factors related to inherent soil quality (e.g., soil texture and mineralogy);

3. Soil spatial dependency was much less controlled by extrinsic factors such as prescribed burning, tourism/leisure activities and browsing by sika deer that widely inhabit the study site;

4. Very high contents of Av-P as shown by the outliers (>41.6 mg $kg^{-1}$) found around the first peak and the major trekking pass between the second and third peaks might be attributed to sika deer through the deposition of feces.

The given spatial variability and distribution pattern of soil chemical properties should be considered upon sustainable land management in Mt. Wakakusa grassland.

Further research is needed to investigate the spatial distribution pattern of grass species, in particular those of invasive alien plants such as *S. sebiferum*, which has been increasingly invading Mt. Kasuga forest reserve (Maesako et al. 2007) as well as Mt. Wakakusa grassland (based on our field observation and interview with the park rangers), in relation to those of the soil properties at the study site.

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