AIRBORNE MAPPING OF WATER RETENTION CAPACITY OF LIGHT SANDY SOIL

Elza Kovács[*], Annamária Szalóki[*], Péter Burai[**], János Tamás[*]

[*]University of Debrecen, Centre of Agricultural and Technical Sciences, Faculty of Agronomy, Department of Water and Environmental Management, H-4032 Debrecen, Böszörményi 138.
[**]Károly Róbert College, Institute of Natural Resources Management and Rural Development, H-3200 Gyöngyös, Mátrai 36.
email: ekovacs@gisserver1.date.hu

Abstract
Soil, as one of the most important natural resources, is affected by several soil tillage practices, which are often applied in rates following certain soil parameters. However, where soils are heterogeneous in space and time soil information data sampled at densities that reflect the scale of spatial variability is required for the development of soil maps and decision support strategies.
The aim of the study was to assess the representativeness of some sampling strategies, based on statistical analyses for the different sampling methods and supporting technologies; in particular, to evaluate three alternative sampling strategies, (A) classic average samples, (B) grid based random point samples, and (C) method based on hyperspectral remotely sensed data classification at dedicated wavelength, to find the lowest variance of the estimates associated with an optimal number of sampling points, based on soil chemical and physical properties, such as plasticity index according to Arany, capillary rise ability test and pH.

Keywords: soil sampling strategy, hyperspectral remote sensing

INTRODUCTION

Soil has been surveyed on a national basis in many countries, for a broad variety of planning purposes. However, soil maps specific for (map updating and upgrading of pedotransfer functions) do not form adequate sources of information for planning and evaluating land use and for many other soil-related activities at regional scale (Visschers et al., 2007).

Nowadays, the sustainable agriculture, an innovative, integrated and internationally standardized approach aiming to increase the efficiency of resource use and to reduce the uncertainty of decisions, is globally recognized as a potentially viable means of meeting the future demands on balancing agricultural productivity, economic stability, resource utilization, degradation, and environmental impacts (Birkás et al., 2006; Schellberga et al., 2008). Soil resource management is one aspect of sustainable agriculture that is needed to overcome limitations in economical sources, while maintaining or enhancing environmental quality (Corwina et al., 2006). Use of precision farming technologies requires better understanding of soil variability in physical, hydraulic and chemical properties (Bocchi et al., 2000, Jolánkai and Németh, 2002). As part of the decision-making process, the choice of a suitable sampling strategy is crucial to the interpretation of the results (Orl´oci, 1988). However, a wide number of different guidelines on soil sampling is recommended, at international level. The evaluation of different sampling approaches requires well characterised tools stable in time (Wagner et al., 2000).

Measurements of soil physical and hydraulic properties are time-consuming and expensive. In addition, a large number of measurements are necessary to quantify their space-time variability. Reliable measurement of these properties is confounded by the extreme spatial heterogeneity and inherent nonlinearity of soil characteristics. Therefore, it is desirable to develop simplified methods to characterize soil media properties over large areas (Chang et al., 2000, Summers et al., 2009).

Remote sensing data are also useful in helping to define management units. Remote sensing offers the potential for identifying fine scale spatial patterns in soil properties across a field, and optimizing soil sampling strategies to quantify those patterns (Németh et al., 2004).

Gomez et al. (2006) as summarized in research in environmental monitoring, modelling and precision agriculture need good quality and inexpensive soil data. Hence we need the development of more time- and cost-efficient methodologies for soil analysis. Visible and near infrared reflectance (vis–NIR) spectroscopy is a physical non-destructive, rapid, reproducible method that provides inexpensive prediction of soil physical, chemical and biological properties according to their reflectance in the wavelength range from 400 to 2500 nm.

The aim of the study was to assess the representativeness of the sampling strategies, based on statistical analyses for the different sampling methods and supporting technologies; in particular, to evaluate three alternative sampling strategies, (A) classic average samples, (B) grid based random point samples, and (C) method based on hyperspectral remotely sensed data classification at dedicated wavelength, to find the lowest variance of the estimates associated with an optimal number of sampling points, based on soil chemical and physical properties, such as plasticity index according to Arany, capillary rise ability test and pH.

MATERIAL AND METHODS

Site Description and Sampling Strategies

The study area is located at Debrecen-Pallag (lat. 47°29’N, long. 21°39’E) region East Hungary. The soil type in the area is acidic sandy soil with thin interstratified layers of colloid and sesquioxide accumulation, poor in clay, nutrient and humus (Nagy et al., 2006). The use of different soil sampling strategies and techniques may affect the results obtained from the analysis of samples collected in the same area (Wagner et al., 2001). For the investigation, 57 surface soil samples were taken, in order evaluate different sampling methods, the effectiveness of classical, grid-based random and method based on hyperspectral remotely sensed data classification at dedicated wavelength.

The data set of the first sampling was used the classical methods. At sampling sites, a total of 11 soil cores were taken to a depth of 20 cm at 5 m intervals on a grid measuring 100 m×100 m and with the centre point of the grid at the sample location. The samples were taken from the upper 0-20 cm layer of the soil and according to the Hungarian sampling standard.

The second sampling strategy included random grid-based point sampling with grid of 100 m×100 m, and additional samples were taken by using increased sampling density, for the validation calculations.

The evaluation of the potential of hyperspectral reflectance data in defining representative sample number based on the same data set as for grid-based attributes’ analyses.

Hyperspectral data analysis

Hyperspectral remotely sensed data were processed by using ENVI software. The objective of the statistical analysis was to identify the spectral regions contributing to predict the chosen soil properties, and to determine under what uncertainty the reflectance spectra could be used for the prediction. Multiple linear regression for the specification of the relationship between a response variable (Y) and a set of dependent variables (X) were carried out according to Summers et al. (2009). For the best correlated band selection, multiple stepwise regression at 5% significant level was used, while, to identify the most informative wavelength range, the Principal Component Analysis was applied. The reference data were collected at the time of the flight.

Sample preparation and measurement of soil physical and chemical parameters

All soil samples were air-dried at ambient temperature. Soil samples were sieved to remove stones and plant debris, and mixed thoroughly to obtain a representative sample. After drying they were passed through a 2 mm mesh sieve (Zhang et al., 2008). For the characterisation of the soil the following soil parameters were determined: (1) The mechanical composition was determined by the plasticity index according to Arany, which quantifies the amount of water in cm^3 added to 100 g air-dry soil sample to obtain a yarn (upper limit of plasticity).(2)The pH of each subsample were measured potentiometrically by first preparing suspensions of each mine waste sample in deionised water (1 : 2.5 w/w), allowing each to equilibrate for 24 h at room temperature before measurement, and (3) The samples used for the capillary rise ability test were tubular samples with thin walls (5 mm) and thick walls (10 mm) and were all 1350 mm long. The capillary rise height was measured 5 hours intervals by visual observation.

Statistical and geo-statistical analysis

As summarized in Bocchi et al. (2000), the first step in soil characterization is to record the main properties and then seek plausible explanations for their distributions in the light of the statistical analysis. The analytical data were processed using a classical statistical approach to test the normality of data distribution.

The development of computational resources coupled with the development of geostatistical prediction methods have allowed the possibility of mapping soil by considering different kinds of secondary information (Kerry and Oliver, 2003). In order to provide an improved prediction map, the soil variables were interpolated using the ordinary kriging method, a univariate interpolation method based on a weighting scheme widely used in soil science to estimate the unknown primary variable at unsampled location as a linear combination of neighbouring observations (Webster and Oliver, 2001). Taking into consideration different sampling sizes 11, 22 and 33 samples randomly selected and using ordinary kriging interpolation, the spatial distributions of the soil physical properties from the different methods were evaluated.

RESULTS

Soil properties

Debrecen and surrounding area is characterized by sand soil type. Comparison between the measured and predicted soil properties demonstrate similar patterns and value ranges for the soil properties examined. The upper limit of plasticity according to Arany (KA) varies between 25-28, which describes soil texture and thus indicates that the soil in question is sand (Füleky and Vicze, 2007).The percentage of clay in the samples ranges from 25% to 30%, corresponding to the sand texture. In addition, the capillary rise ability test of value shown slight variability, as the value of the capillary water ranged between 20 and 40 (20). Considering pH, the study area is typically slightly acidic, however, there are outliers in the highly acidic region (pH = 4.11) despite that the area considered is only 11 ha, and the soil tillage practice applied is uniform.

Descriptive statistics

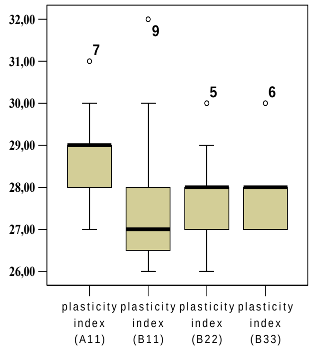
Table 1 shows descriptive statistics of the soil parameters. The variability of variance for all sampling approaches changed very slightly, very similarly to the variability in standard deviation resulting from the small-scale heterogeneity. As the sample size was increased, the decrease in degree of variance and standard deviation were directly proportional. The raw data follow neither normal nor lognormal distribution confirmed by Kolmogorov–Smirnov test. The most heavily skewed parameter was calculated for pH for random data set with sample number 22, having a skewness of 2.08 and kurtosis of 5.19; while, the capillary rise for average sampling showed the least difference from normal distribution for skewness.

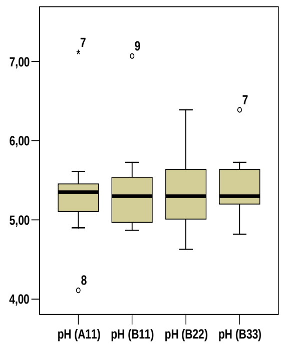
Table 1

Descriptive statistics of soil parameters

	Sample size	Mean	Median	S.D.	Variance	Kurtosis	Skewness	Min	Max
(A)	11								
pH		5,34	5,35	0,71	0,511	4,43	1,18	4,11	7,12
plasticity index		28,72	29	1,10	1,218	0,69	0,65	27	31
capillary rise		33,8	33	2,35	5,563	-0,78	0,599	31	38
(B)	11								
pH		5,38	5,3	0,63	0,4	5,19	2,08	4,87	7,07
plasticity index		27,6	27	1,85	3,45	2,22	1,56	26	32
capillary rise		31,6	31,5	4,37	19,11	0,646	0,24	24	40
(B)	22								
pH		5,37	5,3	0,57	0,32	2,64	1,42	4,63	7,07
plasticity index		27,6	27	1,52	2,33	1,92	1,29	26	32
capillary rise		30,2	30,5	4,51	20,41	0,70	-0,22	20	40
(B)	33								
pH		5,36	5,3	0,49	0,24	3,26	1,48	4,63	7,07
plasticity index		27,4	27	1,36	1,87	2,8	1,41	26	32
capillary rise		30,7	31	4,11	16,94	0,76	-0,38	20	40

In accordance with the information demonstrated by the descriptive statistics (Table 1), box-and-whisker plot describing median, lower and upper outliers, and lower and upper quartiles (Fig.1-3) (Paul et al., 1998) also reveals that average sampling strategy results in data showing almost lognormal distribution hiding hot spots at the site, while in case of point samples, extreme values can also be detected. For the latter strategy, box-and-whisker plot also confirms, that the optimal sampling number is 11, since taking into consideration even 22 points, the variance does not show significant difference for any investigated parameter, thus, variability for attributes can be well-estimated in case of a representative data set N=11.





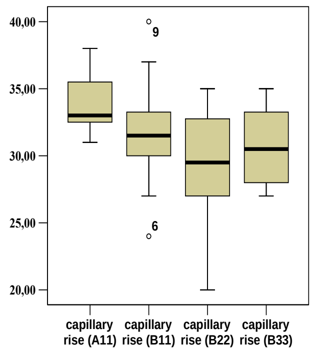


Fig1.Statistics for plasticity index Fig2.Statistics for pH Fig3.Statistics for capillary rise

Fig.4-6 presents spatial distribution of capillary rise, pH, and plasticity index for the grid based random point sampling method for different sample densities.

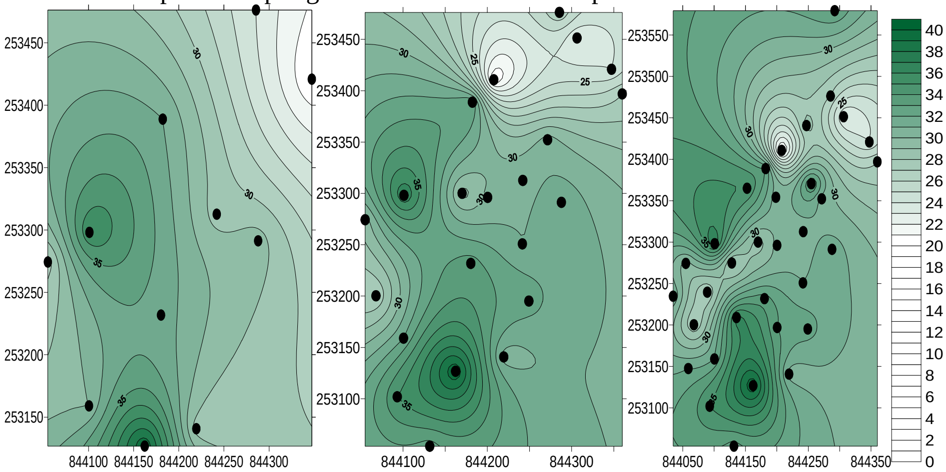


Fig. 4: Spatial distribution for capillary rise in cm, for different sample densities

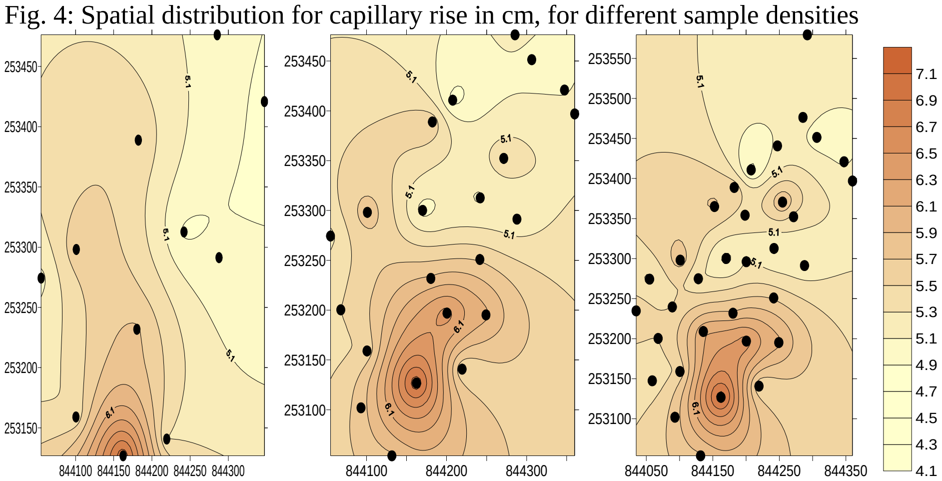


Fig. 5: Spatial distribution for pH for different sample densities

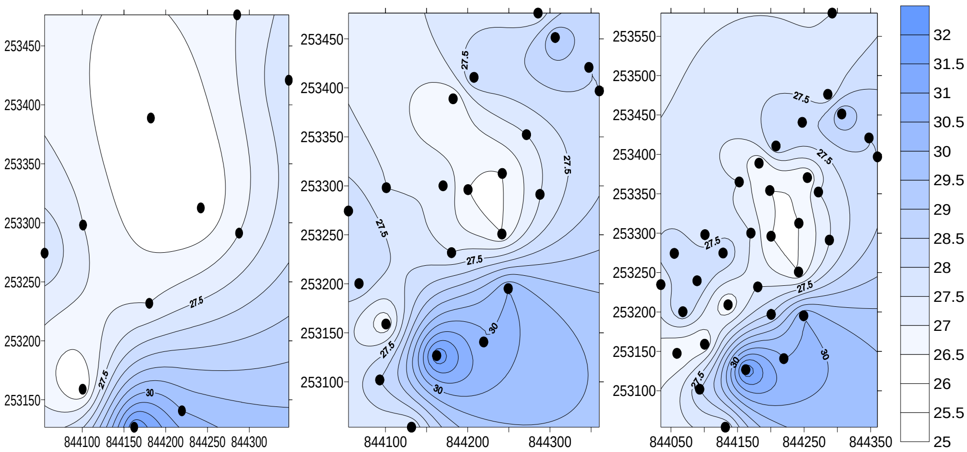


Fig. 6: Spatial distribution for plasticity index for different sample densities

Distribution maps also demonstrate that increasing sample size results in increasingly detailed information on the investigated parameters, in space, however, even for 11 measured data, informative and representative maps can be generated revealing the main spatial trends.
Since reflectance is a property, which is derived from the inherent spectral behaviour of each soil component, when hyperspectral remotely sensed reflectance data are analysed and their relation to soil condition is investigated, it is useful to identify the parameter to which the technique is mostly sensitive. Considering three parameters, only relationship between plasticity index and reflectance measured was statistically proved, though the determination coefficient is low, only 0.30, even in this case. For the others, significant relation for any bands could not be proved. Iterative series generated by regression calculation correlated best with band B116 of wavelength 908.78 nm, in the near-infrared range (Fig.7). Subsequently, Principal Component Analysis (PCA) also confirmed very weak correlation for the other soil physical properties and individual bands.

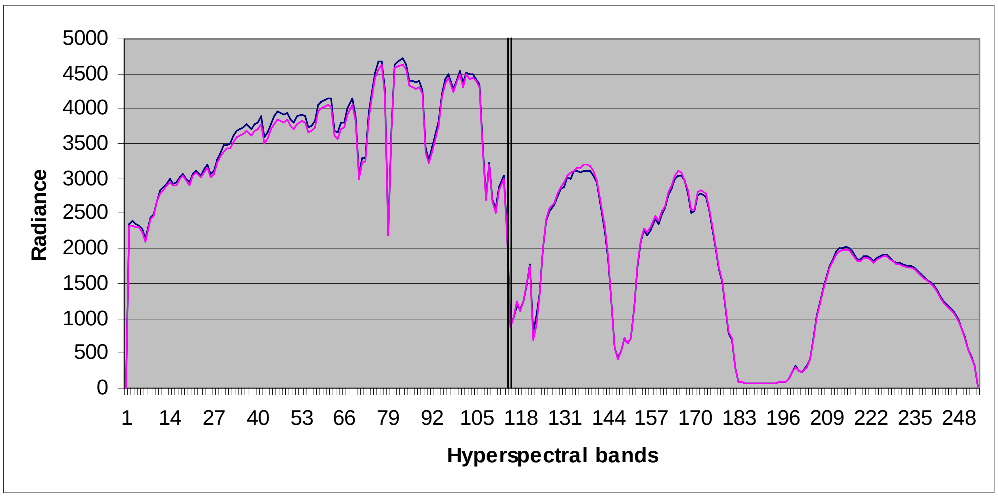


Fig. 7: Hyperspectral reflectance data most sensitive to Arany plasticity index

However, more detailed data set being more variable would provide better results even for capillary rise, as reflectance is expected to be in relation to soil moisture. Considering pH, sensitivity of reflectance has not been studied, yet, though sensitivity to calcite mostly abundant in soils having neutral pH may be informative, as well. Cohen et al. (2005) also suggested that NIR spectroscopy could be used as a rapid analytical tool for soil quality assessment and soil management. Furthermore, low costs of sample evaluation would allow high spatial and temporal resolution for routine monitoring across large areas, which may greatly reduce management uncertainty.
In addition, according to Lopez-Granados et al. (2005), the maps from kriged estimates showed that combination of geostatistical techniques and digital data from aerial photograph were accurate enough to improve the identification of soil management zones, which is the first step for site-specific management. However, they examined several soil parameters in relation to the methods simple linear regression and regression equations for ordinary kriging estimates, e.g. pH, organic matter, sand, clay, silt, phosphorus, potassium and found poor statistically proved relations to the reflectance data. The ordinary kriging, exhibited the highest R^2 since it does not take into account the secondary information and only uses the primary soil variable, and compare the simple linear regression, where higher predictions errors were obtained.

CONCLUSIONS

The aim of the study was to assess the representativeness of the sampling strategies, based on statistical analyses for the different sampling methods and supporting technologies.

Among the investigated sampling strategies, average and random grid-based, approaches that use to geostatistical techniques such as kriging and box-and-whisker plot showed smoothing effect on hot spots at the classic average sampling strategy.

Considering representativity, N=11 samples were proved statistically representative for the study area the spatial distribution maps also demonstrate that increasing sample size results in increasingly detailed information on the investigated parameters, in space, however, even for 11 measured data, informative and representative maps can be generated revealing the main spatial trends.

Though several results suggest the applicability of hyperspectral remote sensing in spatial analysis of soil condition, in this case, where variability was small, relationship between any sensitive band and any considered soil physical or chemical data could not be proved.

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REFERENCES

1. Birkás M., Dexter, A. R., Kalmár T., Bottlik L. 2006. Soil qualiy-soil condition-production stability, Cereal Res Communications, 34, 1, 135-138.
2. Bocchi, S., Castrignan`o, A., Fornaro, F., Maggiore, T. 2000. Application of factorial kriging for mapping soil variation at fieldscale. Eur. J. Agron. 13, 295–308.
3. Chang , D. H., Islam, S., 2000. Estimation Of Soil Physical Properties Using Remote Sensing And Artificial Neural Network. Remote Sens. Environ. 74, 534–544.
4. Cohen, M.J., Prenger, J.P., DeBusk, W.F. 2005. Visible-Near infrared reflectance spectroscopy for rapid, non-destructive assessment of wetland soil quality. Journal of Environmental Quality 34, 1422–1434.
5. Corwina, T.D.L., Lescha, S.M., Osterb, J.D., Kaffkac, S.R. 2006. Monitoring management-induced spatio–temporal changes in soil quality through soil sampling directed by apparent electrical conductivity. Geoderma 131, 369-387.
6. Filep Gy. 1995. Talajtani vizsgálatok. Egyemi segédlet (In Hungarian), 1-156.
7. Füleky Gy., Vicze M., 2007. Soil and archaeological evidences of the periods of the tell development of Százhalombatta-Földvár. Atti Soc. tosc. Sci. nat., Mem., Serie A, 112.
8. Gomez, C., Rossel, V. R. A., McBratney A.B. 2008. Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: An Australian case study. Geoderma 146, 403–411.
9. Govaerts, P. J., Somers, T., Offeciers, F. E., 1998. Box and whisker plots for graphic presentation of audiometric results of conductive hearing loss treatment. Otolaryngology - Head and Neck Surgery 118, 892-895.
10. Jolánkai M., Németh T. 2002. Precíziós növénytermesztés (Crop responses induced by precision management techniques), Acta Agronomica Hungarica, 50, Supplementum 173-178 pp.
11. Kerry, R., Oliver, M., 2003. Variograms of ancillary data to aid sampling for soil surveys. Precision Agric. 4, 261–278.
12. López-Granados, F., Jurado-Expósito, M., Peña-Barragán, J.M., García-Torres, L. 2005. Using geostatistical and remote sensing approaches for mapping soil properties. European Journal of Agronomy 23, 279-289.
13. MSZ 21470-1:1980. Environmental protection. Testing of soils. Sampling. (Hungarian Standard, in Hungarian)
14. Nagy P.T., Holb, I.J. 2006. Study On The Macronutrient Content Of Apple Leaves In An Organic Apple Orchard**.** J. Cent. Eur. Agri 7:2, 329-336.
15. Németh T., Harnos Zs. és Neményi M. 2004. Precíziós növénytermesztés – a hatékonyság növelése és a környezetterhelés csökkentése. Biotechnológiai és Agrárgazdasági Fejlesztések. Nemzeti Kutatási és Technológiai Hivatal, Budapest, 67-76.
16. Orl´oci L. 1988. Community organization: recent advances in numerical methods. Can. J. Bot. 66, 2626-2633.
17. Schellberga, J., Hill, M., Gerhards, R., Rothmund, M., Braun, M. 2008. Precision agriculture on grassland: Applications, perspectives and constraints. Europ. J. Agronomy 29, 59–71.
18. Summers, D., Lewis, M., Ostendorf, B., Chittleborough D. 2009. Visible near-infrared reflectance spectroscopy as a predictive indicator of soil properties. Ecological Indicators, *in print*
19. Visschers , R., Finke, P.A., Gruijter Alterra J.J. 2007. A soil sampling program for the Netherlands. Geoderma 139, 60–72.
20. Wagner, G., Lischer, P., Theocharopoulos, S., Muntau, H., Desaules, A., Quevauviller, Ph. 2001. Quantitative evaluation of the CEEM soil sampling intercomparison. Sci. Total Environ. 264, 73–101.
21. Webster, R.,Oliver, M., 2001. Local estimation or prediction: kriging. In: Geostatistics for Environmental Scientists. John Wiley and Sons, England, 149–191.
22. Zhang, C., Fay, D., McGrath, D., Grennan, E., Carton., O.T. 2008. Statistical analyses of geochemical variables in soils of Ireland. Geoderma 146, 378–390.