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Assessment of Geostatistical Interpolation Method for Spatial Soil Mapping in Imba-Numa watershed, Japan

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Abstract: *Spatial distribution of soil data is a current issue with which most of areas are being faced. Imba-Numa watershed, Japan, is also one among those areas which lack of spatial data of soil parameters. This study aims to generate spatially distribution of soil properties which consist of soil particles, total carbon, total nitrogen and Bulk density in Imba-Numa watershed. Three geostatistical interpolation methods: Ordinary Kriging (OK), Universal Kriging (UK), and Inverse Distance Weighting (IDW), were applied to interpolate soil properties into spatially continuous data. To evaluate the performance of methods to obtain the best method which has the minimum error, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Error Percentage (MEPE) were used. Cross Validation comparison was also used to compare and validate method. The results show that Universal Kriging with Hole-effect Model is the best method to interpolate soil parameters (except Bulk density) in Imba-Numa watershed. Due to limitation of available data, the interpolated maps could not perfectly provide the satisfactory map and consists of error, but it is still acceptable.*

Keywords: Ordinary Kriging; Universal Kriging; Inverse Distance Weighting; soil properties; Cross Validation

1. INTRODUCTION

The paper map, as a product of a traditional soil mapping, appears to be increasingly irrelevant to many users and does not have a market with land managers and policy makers at different scale (Omran, 2008). While the traditional role of soil survey is diminishing, the need of soil information becomes more important in terms of sustainable land management. Many policies required good soil information and rapid answers. We do not have enough and accurate soil data to contribute to variety of application fields from the increasing demand.

There are a lot of soil information and maps of soil which are not completed, or there is too much blank area. Widely used soil models essentially yield empirical result due to lack of good soil data (Stroosnijder, 2005). Updating soil inventories is one of the main fields where new technologies should facilitate data sampling and acquisition. New high quality soil data is needed to complement existing database and to provide spatial detail required by the users. The failure to evaluate map accuracy due to the consistency between predicted and observed attribute values for any given location within the mapped region is a recurring limitation. At present there is no consensus regarding best or most approaches to map soil properties. It was known little about performance and accuracy of different interpolation methods applied to soil properties.

Geostatistics has played an increasing role in both groundwater hydrology and petroleum reservoir

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characterization and modeling, driven mainly by the recognition that heterogeneity in petrophysical properties dominate groundwater flow, solute transport, and multiphase migration in the subsurface. Geostatistics, by transforming a spare data set from the field into a spatial map, offers a means to recreate heterogeneity to be incorporated into numerical flow and transport modeling. On the other hand, by transforming a spare data set into multiple spatial maps, it offers a means of evaluating the uncertainties on modeling due to the uncertain nature of each map.

Geostatistics often faces interpolation and estimation problems during analyzing spare data from field observations. Geostatistic is an invaluable tool that can be used to characterize spatial or temporal phenomena. Geostatistics originated from the mining and petroleum industries, starting with the work by Danie Krige in the 1950’s and was further developed by Georges Matheron in the 1960’s. In both industries, geostatistics is successfully applied to solve cases where decision concerning expensive operations are since been extended to many other fields in or related in space. The quality control is not part of standard interpolation methods. Furthermore, standard interpolation methods do not take into account the intrinsic properties of the interpolated phenomena as they only take account of the position of the measurement points. Geostatistics uses a probabilistic model to overcome these problems. Geostatistics was originally used in prospecting where it was necessary to estimate the potential of a deposit as accurately as possible using spatially dispersed sampling.

Interpolation can be undertaken utilizing simple mathematical models (e.g., inverse distance weighting (IDW), splines and Thiessen polygon), or other complex models (e.g., geostatistical method, such as kriging) (Negreiros et al., 2011). The review of comparative studies of interpolation methods applied to soil properties demonstrates that the selection of method can significantly influence map accuracy. Ordinary Kriging (OK), Universal Kriging (UK) and Inverse Distance Weighting (IDW) are ways to interpolate soil properties. Past applications of these methods have given a range of results which have not always been consistent.

The main objectives of this study are to analyze of soil parameters in Imba-Numa watershed by using statistical analysis, compare the performance of geostatistical interpolation methods (OK, UK and IDW) and to interpolate soil properties (soil particles, Bulk density, total carbon and total nitrogen) for future use.

2. METHODOLOGY

2.1 Study area

Figures This study was conducted on the Imba-Numa watershed, located in Chiba Prefecture, 30-50 km eastof Tokyo metropolitan area, Japan. The surface of the study area is 11002.24 ha with an altitude ranging from 8 to 90 meters. The population in this basin is around 767,000 people, which accounts for about 12 percent of the total population of the prefecture. It is the third biggest population basin after Biwa basin and Kasumigaura basin. Imba-Numa Lake is a former lagoon located in Imba basin. Rivers such as the Kashimagawa River, Shinkawa River, and Tagurigawa River flow into the lake, resulting in a catchment of 541.1 km^2. Valuable animals and plants inhabit the environs of the many springs that appear in the rivers feeding the lake. This lake is divided in to two parts; Northern Imba-Numa Lake and Western Imba-Numa Lake. The original shape of Imba-Numa Lake is like “W” and larger than the size of the lake nowadays. Until the 1960’s, it was 25.8 km^2, but as a result of land reclamation after the war (World War II), the lake is divided into Northern and Western Imba-Numa Lake which are connected by a narrow waterway, and the area have been reduced to less than half. Now its size is 11.55 km^2, with a mean depth of 1.7 m. However, it is still the largest lake in Chiba prefecture. Both Northern and Western Imba-Numa Lake are linked via central drainage and Imba waterway.

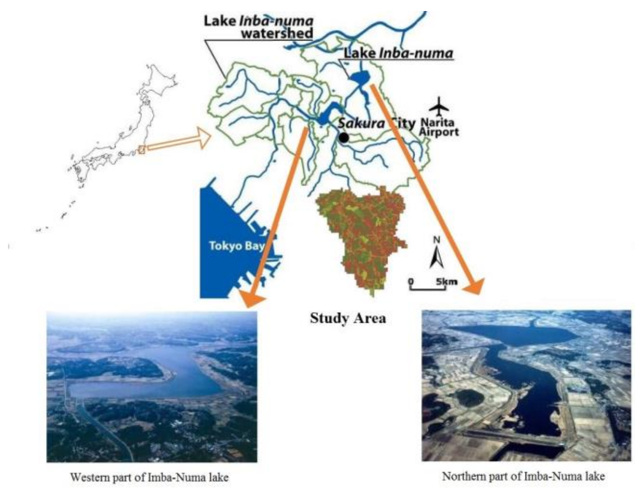


Figure 1. Study area, Imba-Numa watershed.

2.2 Soil sample and analysis

2.2.1 Soil sample data

Soil data from Japan Soil Association was used within this study. The purpose of this soil data investigation is to support to conservation in agriculture. This data consists of soil parameters including soil particles (percentage of clay, silt and sand), Total Carbon, Total Nitrogen and Bulk density.

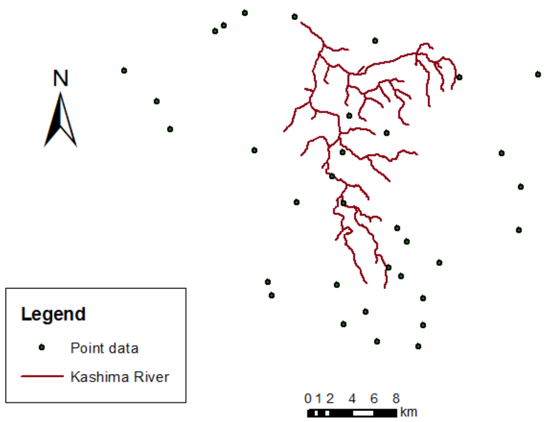


Figure 2. Map of available soil sample point data.

2.2.2 Data transformation

Unimodal and nearly symmetric distributions have many practical advantages. A single number can be used to represent the central value in the batch, because the mode, median, and arithmetic mean are practically the same. Furthermore, histogram approximates a bell-shaped normal distribution, the standard deviation is about three-fourths the interquartile range, so that it does not matter whether we use the standard deviation or the interquartile range to measure the spread.

To guarantee that soil data follows by normal distribution, data transformation method was used. A suitable model can be fitted to the transformed data making a distribution of the original data available by inverting a function of random variable. In this study, power transformation method was applied in order to transform soil parameters such as clay percentage, total carbon and Bulk density to be closer to Normal distribution. The power transform is defined as follows for non-negative data:

$$y = \begin{cases} (z^k - 1)/k & k > 0 \\ \ln(z) & k = 0 \end{cases} \tag{1}$$

where k is a real valued parameter.

2.3 Deterministic methods

Ordinary Kriging (OK), Universal Kriging (UK), and Inverse Distance Weighting (IDW) are three interpolation method which were used to interpolate soil properties in this study. IDW interpolation implements the assumption that things that are very close to one another are more influent than things that are farther apart. The optimal power is determined by minimizing the prediction error.

2.3.1 Ordinary Kriging

Ordinary Kriging (OK) is one of the most basic kriging methods. At the unsampled location x_0, Z is estimated by:

$$Z(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \tag{2}$$

where $Z(x_0)$ is the estimated value of the random variables (RV) Z at the unsampled location x_0 and λ_i are the n weights assigned to the observation points $Z(x_i)$. The weights λ_i sum to one to assure unbiased conditions and they are found by minimizing the estimation variance.

The RV $Z(x)$ can be decomposed into a trend component $m(x)$ and a residual component $R(x)$:

$$Z(x) = m(x) + R(x) \tag{3}$$

OK assumes stationarity of the mean and considers $m(x)$ to be a constant, but unknown, value. Nonstationary conditions are taken into account by restricting the domain of stationary to a local neighbourhood and moving it across the study area. The residual component $R(x)$ is modeled as a stationary RV with zero mean and under the assumption of intrinsic stationary.

2.3.2 Universal Kriging

Universal Kriging (UK) considers that $m(x)$ (Eq. (3)) is not constant, but it varies smoothly within the local neighbourhood, representing a local trend. The trend $m(x)$ is recalculated with each local neighbourhood. This trend component is modeled as a weighted sum of known functions $f_l(x)$ and unknown coefficients $a_l, l = 0, ..., L$ (Journel & Rossi, 1989):

$$m(x) = \sum_{l=1}^{L} a_l f_l(x) \tag{4}$$

2.3.3 Variogram modelling

The experimental variogram or semivariogram was calculated as a half of the squares difference between paired values to distance by which they were separated:

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left(Zs_i - Z(s_i + h) \right)^2 \tag{5}$$

where $N(h)$ is the number of pairs of data locations at distance h apart.

In practice, the average squared distance was obtained for all pairs separated by a range of distances and these average squares differences were plotted against the average separation distance. A theoretical model might be fitted to the semivariogram and the coefficient of this model could be used for kriging. In this study, we used four existing theoretical models as following:

- **Gaussian Model:**

For Gaussian model we have semivariogram expression:

$$\gamma(h) = \sigma^2\left(1-\exp\left(\frac{h^2}{L^2}\right)\right) \tag{6}$$

where variance $\sigma^2 > 0$ and $L > 0$ are two parameters of this model. Because the covariance function decays asymptotically, the range a is defined as distance $a \approx 7L/4$.

- **Exponential Model**

For Exponential model semivariogram expression is expressed by:

$$\gamma(h) = \sigma^2\left(1-\exp\left(-\frac{h}{L}\right)\right) \tag{7}$$

where the parameters are the variance $\sigma^2 > 0$ and the length parameter $L > 0$. The range is $a \approx 3L$.

- **Pentaspherical Model**

For Pentaspherical model we have semivariogram expression:

$$\gamma(h) = \begin{cases} \sigma^2\left[\frac{15}{8}\frac{h}{L} - \frac{5}{4}\left(\frac{h}{L}\right)^3 + \frac{3}{8}\left(\frac{h}{L}\right)^5\right] & \text{for } 0 \le h \le L \\ \sigma^2 & \text{otherwise} \end{cases} \tag{8}$$

where $\sigma^2 > 0$ and $L > 0$ are two parameters.

- **Hole-Effect Model**

For Hole-Effect model semivariogram expression is expressed by:

$$\gamma(h) = \sigma^2\left[1-\left(1-\frac{h}{L}\right)\exp\left(-\frac{h}{L}\right)\right] \tag{9}$$

where $\sigma^2 > 0$ and $L > 0$ are two parameters.

2.3.4 Inverse Distance weighting (IDW)

Inverse Distance Weighting (IDW) estimates values at un-sampled points by the weighted average of observed data at the surrounding points. Therefore, this can be defined as a distance reverse function of each point from neighboring points (Teegavarapu & Chandramouli, 2005). That means by using a linear combination of values at a known sampled point, values at un-sampled points can be calculated (Ly *et al.*, 2011). IDW relies on the theory that the unknown value of a point is more influenced by closer points than the points further away.

$$\hat{Z}(S_0) = \sum_{i=1}^{N} \lambda_i \times Z(S_i) \tag{10}$$

$$\lambda_i = \frac{d_i^{-p}}{\sum_{i=1}^{N} d_i^{-p}} \tag{11}$$

$$\sum_{i=1}^{N} \lambda_i = 1 \tag{12}$$

where

$\hat{Z}(S_0)$ value of prediction for location S_0

N number of measured sample points

λ_i weight assigned to each measure points

$\hat{Z}(S_i)$ neighbors to include

d_i distance between prediction and measured point

p parameter power (p > 1).

The p parameter is specified as a geometric form for weight while other specification are possible. Small power p tends to give estimated values as averages of $\hat{Z}(S_i)$ in the neighborhood, while large power p tends to give larger weights to nearest points and increasingly down-weights points further away (Lu & Wong, 2008).

2.4 Validation

The Root Means Square Error (RMSE), Mean Absolute Error (MAE) and Mean Error Percentage (MEPE) were used to calculate the averaged squared difference between the observed value and the estimated values.

- Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\varepsilon_i^2} \tag{13}$$

- Mean Absolute Error:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\varepsilon_i| \tag{14}$$

- Mean Error Percentage:

$$MEPE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\varepsilon_i}{S_0}\right)^2} \quad (15)$$

where:

- $\varepsilon_i = S_p - S_o$ that S_p and S_o represent the predicted and observed values of soil parameters respectively.
- N is the number of observation points of data set $(N = 34)$.

3. RESULTS AND DISCUSSION

3.1 Exploratory Statistics for Soil Properties

Summary statistics of soil properties is shown in Table 1 By using power transformation method, we can get the result that all soil parameters tend to follow by normal distribution. This is shown that histograms and Q-Q plot in Fig. 3 provide for visual examination of fitting to normality, but we complement the graphical procedures with some statistics to objectively confirm normality assumption.

Table 6. Summary statistics for transformed soil parameters.

Soil Data	lnClay	Silt	Sand	lnTC	TN	-lnBD
Min	1.08	4.16	28.77	0.78	0.07	0.40
1st Quartile	3.52	21.13	56.20	1.65	0.25	0.54
Median	12.38	26.99	62.53	2.72	0.29	0.64
Mean	12.38	26.18	61.44	3.01	0.32	0.73
3rd Quartile	18.65	31.08	69.07	3.43	0.35	0.89
Max	37.23	41.15	92.32	10.58	0.90	0.73
Skewness	0.87	-0.69	-0.44	1.94	1.88	1.13
Kurtosis	2.69	3.84	4.23	7.26	9.01	3.26

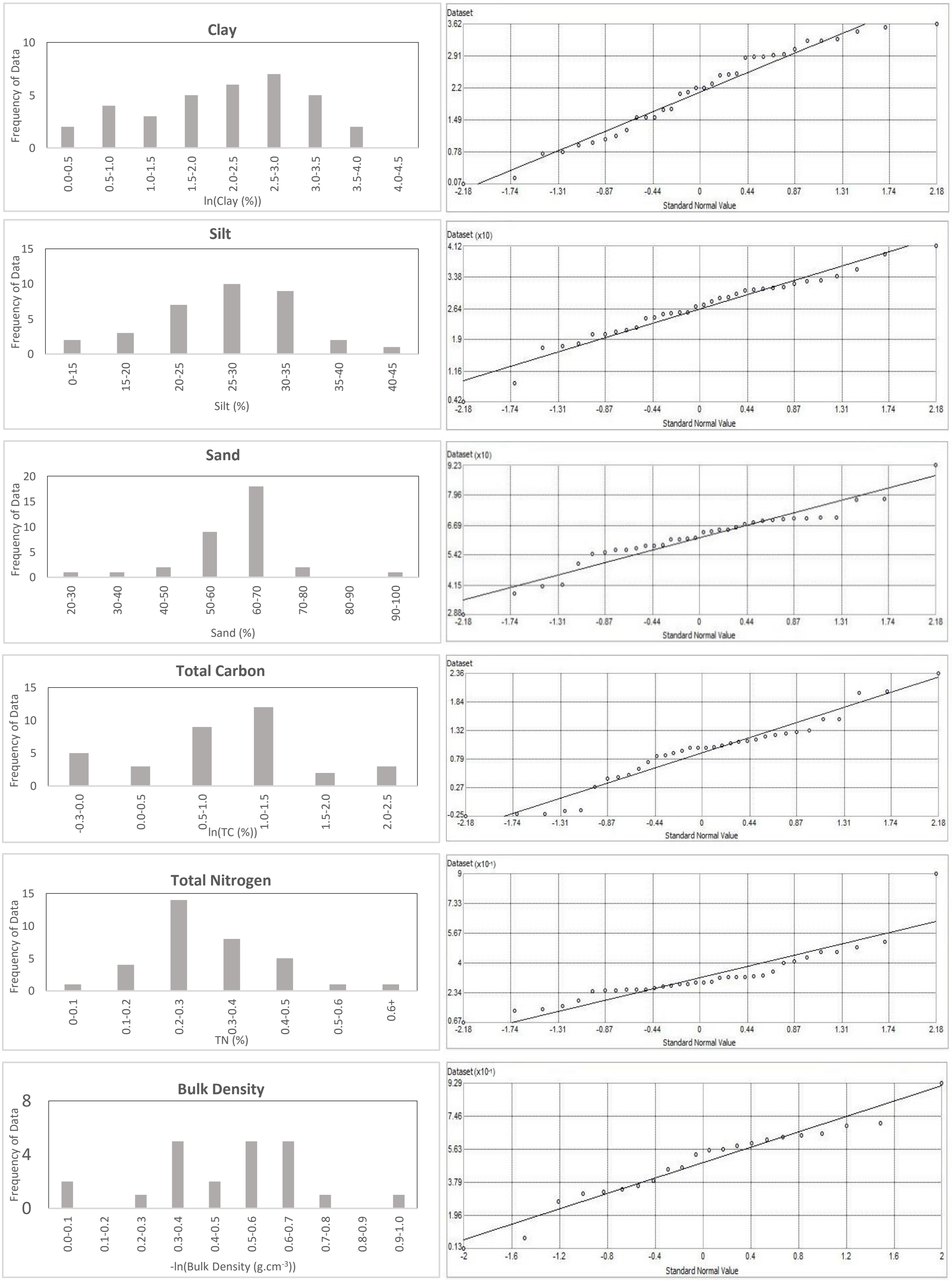


Figure 3. Histogram and Normal Q-Q plot of soil properties: clay, silt, sand, TC, TN and Bulk density.

3.2 Comparison of the Interpolated Maps by Three Methods

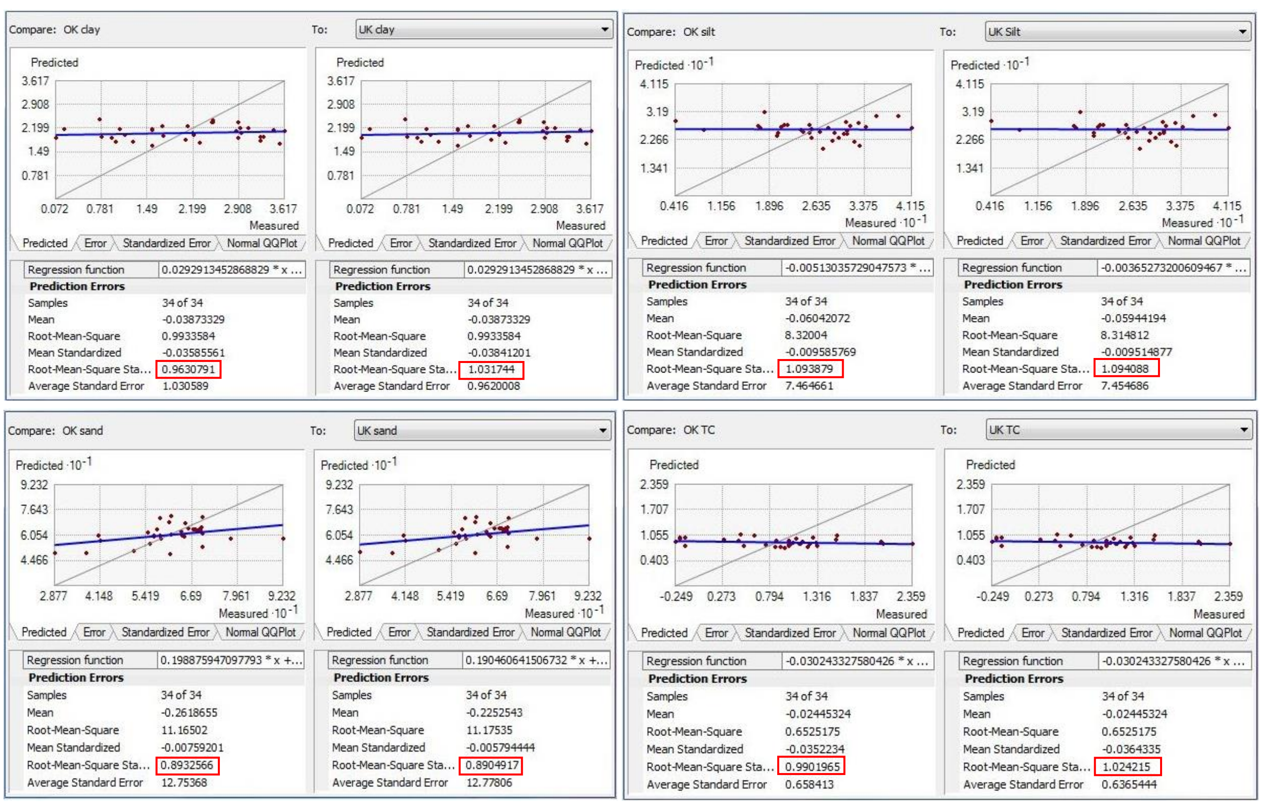
Table 2 indicates the elements of each interpolation models for OK and UK. Those elements are nugget, sill, range, and interpolated prediction errors which are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Error Percentage (MEPE). According to Table 2, Hole-effect Model contains the lowest error among RMSE, MAE and MEPE comparing to other three models: Gaussian Model, Exponential Model, and Pentaspherical Model. In short, Hole-effect Model is the best semivariogram model to show the strong spatial distribution of soil parameters.

Table 7. Data of the different interpolated methods for soil properties.

Methods	Model	Soil Properties	Nugget	Partial sill	Sill	RMSE	MAE	MEPE	Range (m)
OK	Gaussian Model	lnClay	0.961	0.053	1.013	0.9942	**0.8228**	**4.7227**	3000
		Silt	36.085	22.862	58.947	8.8467	7.1043	1.1400	800
		Sand	161.002	4.242	165.244	12.4642	8.3626	0.2763	800
		lnTC	0.370	0.061	0.431	0.6564	0.5120	2.4709	3000
		TN	0.011	0.006	0.017	0.1574	0.1079	0.8501	800
		-lnBD	0.025	0.031	0.056	0.2493	0.1968	10.1965	2000
	Exponential Model	lnClay	0.990	0.000	0.990	0.9934	0.8236	4.7322	3000
		Silt	0.000	62.291	62.291	8.7407	6.6875	1.1550	800
		Sand	88.623	91.527	180.150	11.8601	8.3294	0.2548	800
		lnTC	0.373	0.041	0.414	0.6609	0.5162	2.4799	3000
		TN	0.001	0.017	0.018	0.1614	0.1133	0.8772	800
		-lnBD	0.008	0.046	0.054	0.2510	0.2029	9.9469	2000
	Hole-effect Model	lnClay	0.990	0.000	0.990	0.9934	0.8236	4.7322	3000
		Silt	32.129	19.957	52.086	8.3200	6.5390	1.1090	800
		Sand	66.795	98.995	165.790	11.1850	8.3294	0.2548	800
		lnTC	0.404	0.000	0.404	0.6525	0.5084	2.4557	3000
		TN	0.012	0.003	0.015	0.1483	0.1011	0.8035	800
		-lnBD	0.020	0.028	0.047	0.2666	0.2114	10.3365	2000
	Pentaspherical Model	lnClay	0.990	0.000	0.990	0.9934	0.8236	4.7322	3000
		Silt	15.755	41.694	57.449	8.6707	6.7115	1.1433	800
		Sand	101.169	73.499	174.668	11.2850	8.3427	0.2511	800
		lnTC	0.378	0.035	0.413	0.6588	0.5142	2.4731	3000
		TN	0.006	0.010	0.016	0.1579	0.1099	0.8577	800
		-lnBD	0.013	0.039	0.052	0.2552	0.2047	10.1188	2000
UK	Gaussian Model	lnClay	0.862	0.000	0.862	0.9934	0.8236	4.7322	3000
		Silt	35.813	22.727	58.540	8.8504	7.1027	1.1406	800
		Sand	162.173	0.563	162.736	12.5073	8.3479	0.2779	800
		lnTC	0.363	0.027	0.390	0.6538	0.5100	2.4600	3000
		TN	0.013	0.003	0.016	0.1515	0.1019	0.8122	800
		-lnBD	0.024	0.033	0.057	0.2513	0.1984	10.2471	2000
	Exponential Model	lnClay	0.862	0.000	0.862	0.9934	0.8236	4.7322	3000
		Silt	0.000	62.264	62.264	8.7407	6.6875	1.1550	800
		Sand	96.036	80.878	176.914	11.9116	8.3340	0.2570	800
		lnTC	0.378	0.000	0.378	0.6525	0.5084	2.4557	3000

	TN	0.007	0.010	0.017	0.1549	0.1062	0.8381	800
	-lnBD	0.007	0.048	0.055	0.2514	0.2034	9.9538	2000
Hole-effect Model	lnClay	0.862	0.000	0.862	0.9934	0.8236	4.7322	3000
	Silt	31.704	20.374	52.078	8.3148	6.5288	1.1093	800
	Sand	70.405	93.904	164.309	11.1754	8.0870	0.2152	800
	lnTC	0.378	0.000	0.378	0.6525	0.5084	2.4557	3000
	TN	0.014	0.001	0.016	0.1479	0.0994	0.7933	800
	-lnBD	0.021	0.029	0.049	0.2662	0.2110	10.3279	2000
Pentaspherical Model	lnClay	0.862	0.000	0.862	0.9934	0.8236	4.7322	3000
	Silt	15.269	42.240	57.509	8.6724	6.7034	1.1438	800
	Sand	105.764	66.541	172.305	11.8694	8.3362	0.2531	800
	lnTC	0.378	0.000	0.378	0.6525	0.5084	2.4557	3000
	TN	0.011	0.005	0.016	0.1522	0.1033	0.8201	800
	-lnBD	0.012	0.041	0.053	0.2568	0.2065	10.1511	2000

The cross validation (CV) comparison was plotted to examine how well the surface model predicts an unknown value. The CV tools uses statistical measures to assess the surface models performance. Its compares measured values with the predicted values derived from the surface model. Fig. 4 shows graphical comparison between measured and predicted values. Ideally, the predicted values should be the same as the measured ones, but in reality, data points scatter along this line due to natural variation and uncertainties. Since Root Mean Square Standardized Prediction Errors for UK with Hole-effect semivariogram are close to 1.0 except Bulk Density which is a bit high value than 1.0, this indicates that its prediction accuracies have almost comparable accuracies (Diodato & Ceccarelli, 2004).



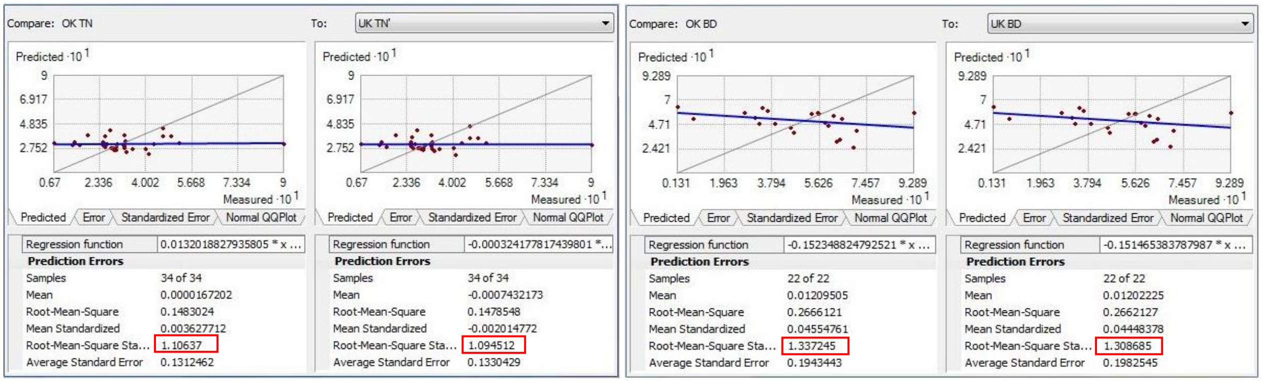


Figure 4. The cross validation comparison of soil properties: clay, silt, sand, TC, TN and Bulk density.

To compare the performance of the interpolators, we calculate Root Mean Square Error, Mean Absolute Error, and Mean Error Percentage as shown in Table 3. Table 3 shows that the differences between the OK and UK are very small. Finally, according to Table 3 and Fig. 4 Universal Kriging is ranked the first low error of prediction which is followed by Ordinary Kriging and Inverse Distance Weighting. IDW is the third accurate method because it produce the highest error among the three interpolation methods.

Table 8. Comparison of interpolation methods using RMSE, MAE, and MEPE.

Evaluation Methods	Soil Properties	OK	UK	IDW
RMSE	lnClay	0.9934	0.9934	0.9917
	Silt	8.3200	8.3148	8.3835
	Sand	11.1850	11.1754	11.9262
	lnTC	0.6525	0.6525	0.7078
	TN	0.1483	0.1479	0.1503
	-lnBD	0.2666	0.2662	0.2323
MAE	lnClay	0.8236	0.8236	0.8151
	Silt	6.5390	6.5288	6.4528
	Sand	8.3294	8.0870	8.7786
	lnTC	0.5084	0.5084	0.5561
	TN	0.1011	0.0994	0.1053
	-lnBD	0.2114	0.2110	0.1867
MEPE	lnClay	4.7322	4.7322	4.6152
	Silt	1.1090	1.1093	1.1248
	Sand	0.2548	0.2152	0.2556
	lnTC	2.4557	2.4557	2.5678
	TN	0.8035	0.7933	0.8011
	-lnBD	10.3365	10.3279	9.0832

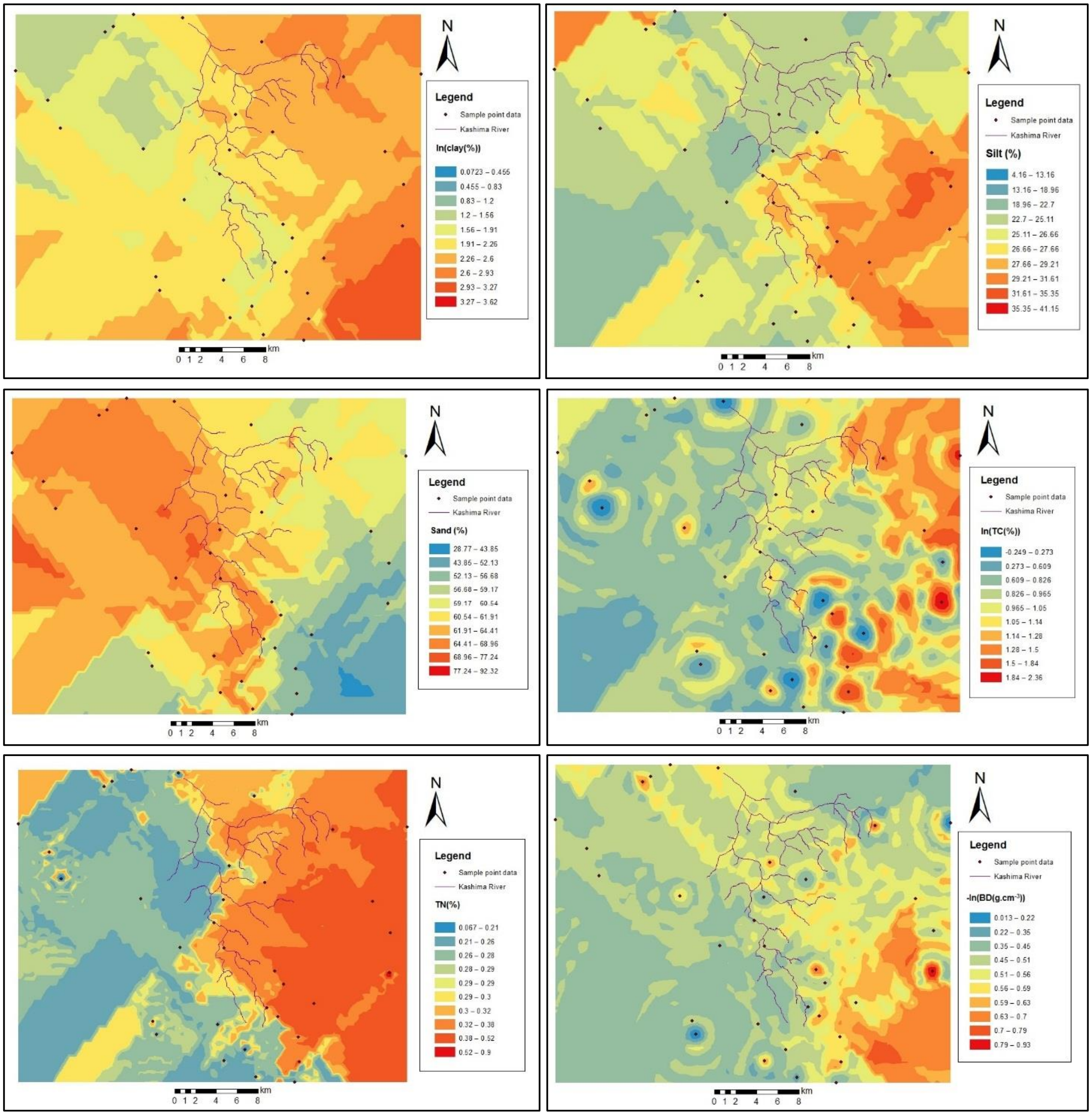


Figure 5. Interpolated map of clay, silt, sand, total carbon, total nitrogen and Bulk density.

4. CONCLUSIONS

This study is to apply Geostatistical interpolation methods to interpolate spatial pattern soil properties in Imba-Numa watershed, Chiba Prefecture, Japan. The objectives of this study was to provide information on soil properties and mapping methods which are in common use. This case study showed that UK method is more accurate than the OK and IDW for predicting the spatial pattern of soil parameters (soil particles, TC TN and BD) by using Hole-effect Model. The generally superior performance of UK is due to less prediction errors. Therefore, UK can be considered as an accurate method for interpolating soil parameters (soil particles, TC TN and BD).

The results of this study can be a key for the future research to choose the appropriate interpolation methods to generate map of soil properties. Additionally, it can help if the methodology applied in this study can also be applied to generate map of soil particles, TC, TN and BD in other area where spatial distribution of soil parameters was currently unavailable.

In this study, because of the limitation of point data of soil properties; therefore, the result of spatial distribution of soil properties were not so satisfactory and had contented high error. For the next study, to generate the better spatial distribution of soil properties, there are some recommendations:

- investigate as many points of soil parameter data as possible
- apply interpolation method with other Geostatistical interpolation software for example: SGeMS, Gslib, and other softwares because it is easier to generate geostatistics element such as semivariogram and so on.

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