STUDY OF SPATIO-TEMPORAL VARIATION OF SOIL NUTRIENTS IN PADDY RICE PLANTING FARM

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ABSTRACT

It is significant to analysis the spatial and temporal variation of soil nutrients for precision agriculture especially in large-scale farms. For the data size of soil nutrients grows once after sampling which mostly by the frequency of one year or months, to discover the changing trends of exact nutrient would be instructive for the fertilization in the future. In this study, theories of GIS and geostatistics were used to characterize the spatial and temporal variability of soil nutrients in paddy rice fields in the Erdaohe farm of Heilongjiang Province, China, which located in the north of Daxing'an Mountains, has an area of nearly 36.1 million hectares for paddy rice planting. The soil samples, collected from 2009 to 2013 once a year, were sampled based on the spatial distribution of paddy rice fields, counting as 651 in 2009, 1488 in 2010, 954 in 2011, 483 in 2012, and 471 in 2013. These samples were analyzed for pH, soil organic matter (SOM), available nitrogen (AN), available phosphorus (AP), and available potassium (AK). In these measurement results, value of pH is not very variable among four years, ranging from 4.6 to 6.4 in 2009, 5.1 to 6.5 in 2010, 5.98 to 6.4 in 2011, 4.88 to 6.52 in 2012, and 4.94 to 6.21 in 2013, and the coefficient of variation (C.V. %) were 4.77, 3.73, 3.60, 4.42, 3.11 from 2009 to 2013, all of which had a weak spatial variability. Besides, the other four nutrients had a medium spatial variability, with the highest one of AK. On the other hand, for the general trend, spatial variation of soil organic matter (SOM) increased from 2009 to 2013, and decreased the rest AN, AP, AK. After calculating and comparing the spatial and temporal variation in whole farm area, variations between management regions is the second research point. To reach this aim, we chose interpolation method of kriging to generate grids for every soil test data. Among these five factors, only data of soil pH fit the normal distribution, the other four factors for several years need to be transformed for better results. Take the interpolation of AN as an example, Box-Cox transformation parameters were chosen as 0.1 in 2009, and Log transformation was used in 2012 and 2013, the temporal geographic maps revealed that in 2009, region I had the highest level of AN, and the next year most regions has the same level of AN, except for region VIII which is lower than the other six regions. In 2011, region II, IV, VI had a higher level than region I, III, V, VIII, while the next year kept the same except for region V becoming higher. Based on this study, conclusion acquired is that from 2009 to 2013, the spatio-temporal variations decreased in soil pH, AN, AP, AK, and increased in SOM. Moreover, according to the comparison of interpolation results, these five soil properties in Erdaohe farm remained not very stable in the past four years, which could implicate important significance in future research with consideration of fertilization, rice yield and other factors.

Keywords: Spatio-temporal variation, Soil nutrition, Geostatistical analysis, Semivariogram model

INTRODUCTION

Soil nutrients provide a scientific accordance in fertilizer applications, especially in paddy rice planting farms. However, soil properties not only have spatial variability, but also change with the time. It is significant to analysis the spatio-temporal variation of soil nutrients for more reasonable fertilizer applications.

A lot of work has been carried out on soils for studying the spatial dependencies of soil properties (Sun et al., 2003; Tesfahunegn et al., 2011). For example, Weijun Fu et al. studied the spatial variation of soil nutrients in a dairy farm in southeastern Ireland (Fu et al., 2010), Kelin Hu et al. studied the spatial and temporal patterns of soil organic matter in the urban–rural transition zone of Beijing (Hu et al., 2007), and Zhang Xing-Yi studied the spatial variability of nutrient properties in black soil of northeast China (ZHANG et al., 2007). However, most of the researches learned temporal variation in period of time with long intervals, neglecting the continuous changing year after year (Huang et al., 2007). In this paper, methods of statistics, geostatistics were used to study the spatio-temporal variation for data of soil pH, soil organic matter (SOM), available nitrogen (AN), available phosphorus (AP), and available potassium (AK) collected from 2009 to 2013 once a year in a paddy rice planting farm in northeast China.

MATERIALS AND METHODS

Study area

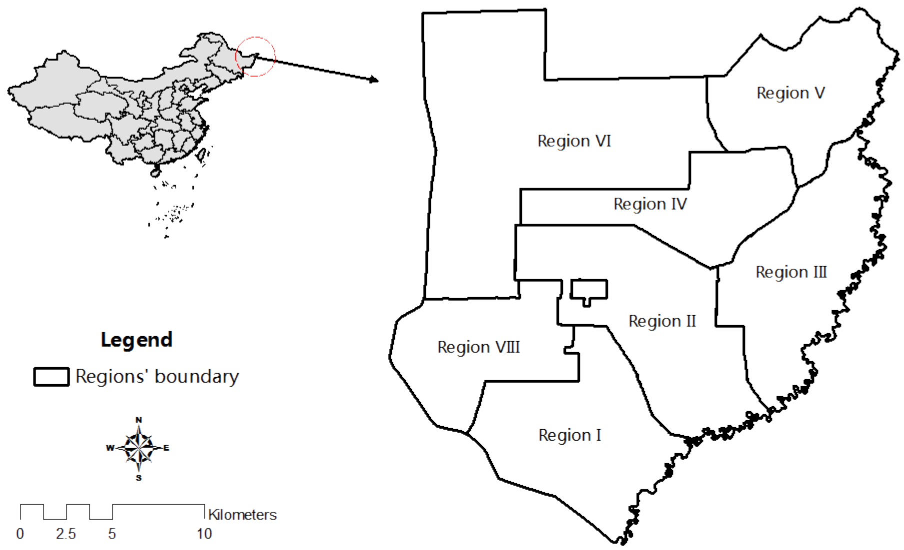


Fig.1. Location of the study area

The farm of Erdaohe located in northeast boundary of China, closed to Russia across the Ussuri River in the east, and the Heilongjiang in the north (Fig. 1). This area belongs to the Sanjiang Plain, and has a humid or semi-humid continental monsoon climate of temperate zone, which is suitable for agriculture production, especial for paddy rice planting. The total area of this farm is 534.2 kilometers, with an area of 362 kilometers for cultivated land, including 360.7 kilometers for paddy rice planting.

Soil sampling

Table 1. Soil test methods used in study area

Test item	method	Unit of test result
Soil pH	Potentiometry method (water soil ratio is 2.5:1)	——
SOM	Potassium dichromate sulfuric acid heating method	g/kg
AN	NaOH hydrolyzation diffusion method	mg/kg
AP	NaHCO3 - Molybdenumblue method	mg/kg

AK	Atomic absorption spectrophotometric method	mg/kg

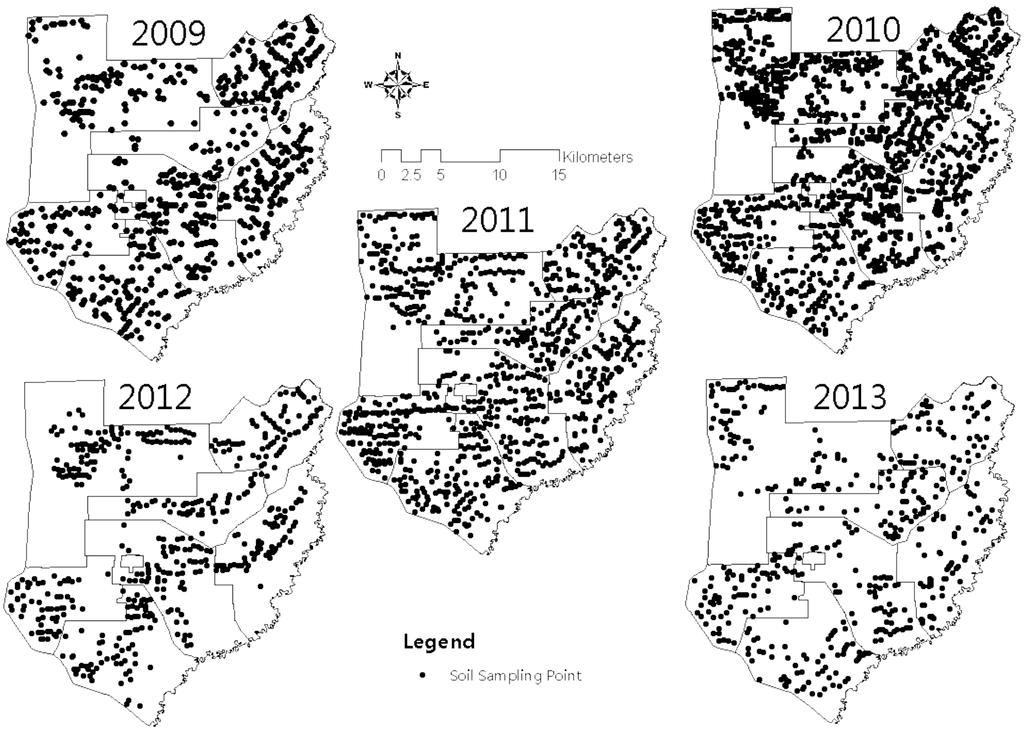


Fig.2. The distribution of sampling points from 2009 to 2013

The soil samples were collected at the depths of 0-20cm from 2009 to 2013 once year (Fig. 2). The sample time were mostly between autumn harvests and fertilizers. Generally, this work was mostly done by experienced technicians, who has a quantity knowledge of agriculture production in the sampling region. The count of sampling points are 651 in 2009, 1488 in 2010, 954 in 2011, 483 in 2012, and 471 in 2013. On the other hand, location of these points were selected according to space distribution of land parcels, soil types, land use types and experience of technicians. After sampling, soil samples were naturally dried at ventilation place and sieved to pass a 2-mm mesh after crushed. In this article, soil test results of pH, soil organic matter (SOM), available nitrogen (AN), available phosphorus (AP), and available potassium (AK) are used for spatio-temporal variation analysis, the soil test methods are listed in Table 1.

Analytical methods

Exploratory statistical analysis

In this paper, methods of exploratory statistical and Geostatistical analysis are both used to study the spatio-temporal variation of soil nutrients in this farm.

First of all, descriptive analysis indexes such as minimum (min), maximum (max), mean, median, standard deviation (S.D.), coefficient of variation (C.V.), skewness and kurtosis were chosen to achieve the summary information of soil nutrients distribution. These indexes can be divided into three different types: location, spread, and shape, which provide diverse descriptions of soil nutrients. The mean is the arithmetic average of the data. The mean provides a measure of the center of the distribution.

Besides indexes described above, Normal quantile–quantile (Q–Q) plots were produced for identification of probability and obvious outliers (extreme values). The observed values were plotted on the x-axis, and values expected for a normal distribution were plotted on the y-axis. Samples with a normal distribution cluster along a diagonal straight line (Evans et al., 2000). Meanwhile, the high or low value

outliers can be easily observed on the normal Q–Q plots, as they will be off the normal Q–Q line.

Geostatistical analysis

Geostatistics was used to describe the spatial variation of each of the soil properties measured in this study. Experimental variogram estimator is asymptotically unbiased for any intrinsic random function, however it is very sensitive to outlying values because it is based on squared differences among data. A semivariogram was determined for each microbiological parameter in order to characterize the degree of spatial variability between neighboring samples, and the appropriate model function was fit to the semivariogram. The semivariogram $\gamma(h)$ was estimated using the equation

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

(1)

Where h is the separation distance between locations x_i and x_i+h, $Z(x_i)$ and $Z(x_i+h)$ are the measured value for the regionalized variables at locations x_i or x_i+h, and N(h) is the number of pairs at any separation distance h (Burgess and Webster, 1980; Piotrowska and Długosz, 2012).

There are several models available to fit the experimental semivariogram including spherical, exponential, Gaussian, linear and power models (Goovaerts, 1999; Liu et al., 2009; Wang, 1999). On the other hand, a semivariogram consists of three basic parameters which describe the spatial structure as: $\gamma(h)=C_0+C$. Co represents the nugget effect, which is the local variation occurring at scales smaller than the sampling interval, such as sampling error, fine-scale spatial variability and measurement error. C_0+C is the sill (total variance). The distance at which the semivariogram levels off at the sill is called the range. At separation distances greater than the range, sampled points are no longer spatially correlated (Piotrowska and Długosz, 2012).

The equation of different models are described below. A spherical anisotropic model was fitted to the empirical semivariance, which is defined as:

$$\begin{cases} \gamma(h) = C_0 + C_1\left[\dfrac{3h}{2a} - (h/a)^3/2\right] & 0 < h < a \\ \gamma(h) = C_0 + C_1 & h >= a \\ \gamma(0) = 0 & h = 0 \end{cases} \tag{2}$$

Where C_0 is nugget value or the spatial variability arising from the random components like measured error and micro-scale processes, C_1 is the structural variance or the spatial heterogeneity arising from spatial autocorrelation, $C_1 + C_0$ is the sill, and A is the spatial correlation distance (or range).

Other stationary models i.e. Gaussian (Eq. (3)), exponential (Eq. (4)) and linear (Eq. (5)) equations are defined as:

$$\gamma(h) = C_0 + C_1\left[1 - \exp(-h/a)^2\right] \tag{3}$$

$$\gamma(h) = C_0 + C_1\left[1 - \exp(-h/a)\right] \tag{4}$$

$$\gamma(h) = C_0 + bh \tag{5}$$

Where C_0, C_1, h and a represent the same meanings as spherical anisotropic model, while b is slope of the semivariance line in Equation (5).

RESULTS AND DISCUSSION

Variation of soil properties in past five years

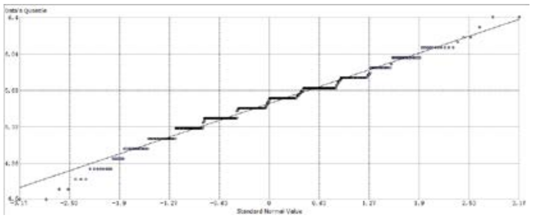
According to exploratory statistical analysis, Table 2 shows the soil nutrients determined values of minimum, maximum, mean, median, standard deviation (S.D.), coefficient of variation (C.V.), skewness and kurtosis from 2009 to 2013. First of all, considering the values of different soil nutrients described by min, max, median and mean, in the past five years, test results of pH shows a relatively inflexible constant, while the other four properties appears more variable. Among these nutrient types, except for SOM, the variation degree tested by C.V. (%) all decreased with small fluctuations in the past five year. Furthermore, a relatively small C.V. value was observed for pH data, and the relatively large C.V. values for AK data.

On the other hand, the degree of dispersion tested by S.D. shows that the sequence from high to low is AK, AN, AP, SOM, AP and pH, besides, the degree of dispersion of SOM increased significantly in recent two years. At last, skewness and kurtosis indicated the shape of distribution of soil raw data compared with normal distribution. The results showed that except for AK and several years' data of SOM and AN, the others were closest to normal distribution.

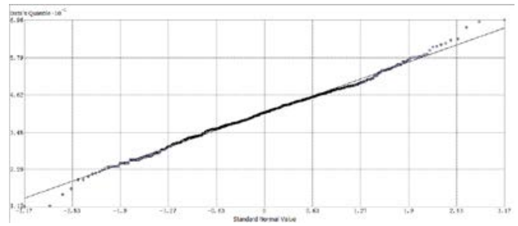
Table 2. The statistical values of soil properties.

	Year	min	max	mean	Median	S.D.	C.V. (%)	Skewness	Kurtosis
pH	2009	4.60	6.40	5.50	5.60	0.26	4.77	-0.22	3.79
	2010	5.10	6.50	5.55	5.50	0.21	3.73	0.45	3.36
	2011	4.98	6.40	5.57	5.58	0.20	3.60	0.20	3.17
	2012	4.88	6.52	5.52	5.52	0.24	4.42	0.52	4.64
	2013	4.94	6.21	5.54	5.54	0.17	3.11	-0.19	3.10
SOM	2009	11.20	69.56	40.44	40.66	8.40	20.77	0.00	3.62
	2010	17.79	59.19	39.55	44.66	6.51	16.45	-0.18	2.69
	2011	12.50	74.20	39.25	39.08	8.69	22.13	0.34	3.83
	2012	23.20	154.00	43.11	41.80	10.56	24.49	3.37	31.05
	2013	12.60	379.80	43.29	41.00	24.43	56.44	10.67	143.39
AN	2009	111.20	507.50	231.85	229.30	50.18	21.64	0.79	5.34
	2010	83.76	376.70	243.00	275.70	56.94	23.43	0.22	2.75
	2011	86.90	485.59	236.77	260.71	41.73	17.63	0.48	4.59
	2012	135.35	371.63	220.44	216.16	32.80	14.88	0.82	4.88
	2013	109.90	351.20	203.67	197.20	41.08	20.17	1.09	4.67
AP	2009	3.60	79.90	27.70	27.20	9.67	34.91	0.40	4.48
	2010	3.93	63.40	27.88	34.70	9.39	33.67	-0.20	2.72
	2011	3.57	52.09	28.44	29.39	8.58	30.16	-0.50	3.63
	2012	3.30	54.14	30.90	31.36	9.29	30.07	-0.18	3.02
	2013	3.70	66.40	30.03	30.60	9.28	30.91	-0.29	3.53
AK	2009	25.00	531.00	149.82	132.00	73.95	49.36	1.67	7.23
	2010	27.00	569.00	157.95	141.00	65.84	41.69	1.44	6.06
	2011	53.54	609.30	163.47	143.23	73.26	44.82	2.21	10.80
	2012	38.00	609.00	176.91	163.42	67.53	38.17	1.90	11.26
	2013	71.00	699.00	192.71	170.00	86.59	44.93	2.07	9.96

Normal QQ-plots analysis and data transformation



pH



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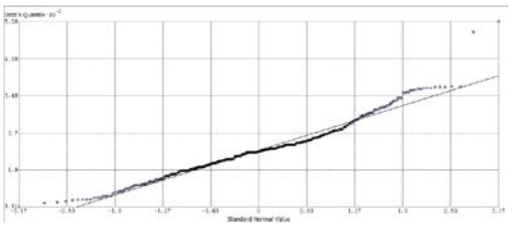

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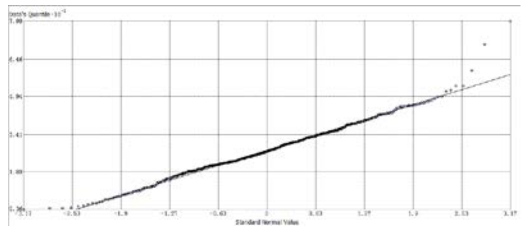

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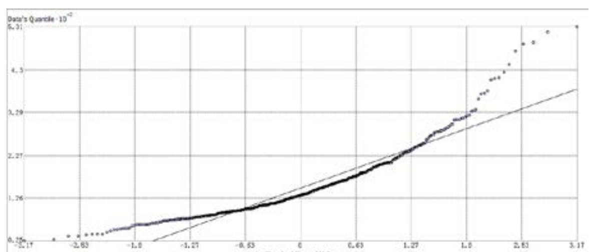


AK

Fig. 3 Normal QQ-plots of soil nutrients in 2009

Since parts of soil values did not fit the normal distribution, data Figure 3 shows the normal QQ-plots of five different soil nutrients in 2009. Besides AK values displayed a concave shape, the pH, SOM and AP values followed a near-straight line shape, which means a near normal distribution, while the AN data followed a straight diagonal line with data points nearby except for several points deviated at both ends. Normal QQ-plots of the other four years were not shown for limitation of paper length. While the analysis results found that in 2010 and 2011, soil nutrients data except AK, followed a nearly straight diagonal line just like that in 2009. And in 2012 and 2013, only pH values remained the same distribution, the others became not very accordant with that more or less.

Transformation was needed for the followed analysis. With the combination of exploratory statistical analysis and normal QQ-plot analysis, different transformation method were chosen, seen from Table 3. Figure 4 shows the Normal QQ-plots of data before and after the transformation for AK values in 2011, it is obvious that after transformation, the points were more fitted with the straight line.

Table 3. Data transformation method selected

	2009	2010	2011	2012	2013
pH	a	a	a	a	a
SOM	a	a	a	b	c(λ= -0.4)
AN	c(λ= 0.1)	a	a	b	b
AP	a	a	a	a	c(λ= 1.3)
AK	b	b	c(λ= -0.4)	b	c(λ= -0.5)

a - None transformation;

b - Log transformation;

c - Box-Cox transformation.

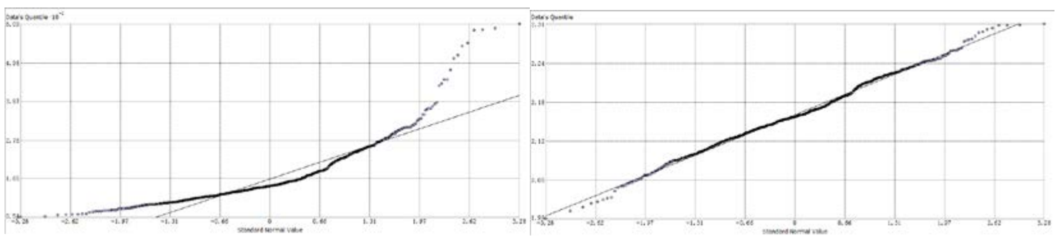
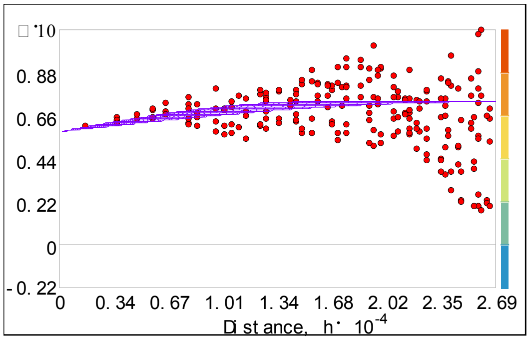


Fig. 4 Normal QQ-plots of AK raw data and transformation result Box-Cox (λ = -0.4) in 2011

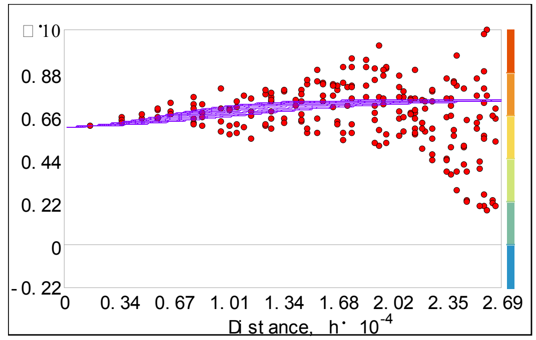
Spatio-temporal variation of different soil properties

According to the theory of geostatistical, semivariance analysis was applied to soil properties from 2009 to 2013, the results indicated that spatial autocorrelation existed for the soil properties in study area, which means spatial interpolation method of kriging could be used to predict the soil nutrients in missing data area. While the step was to choose the appropriate semivariogram model for each property and each year, Figure 5 shows the semivariogram for soil pH in 2009 (anisotropic) with different models (Spherical, Gaussian and Exponential).

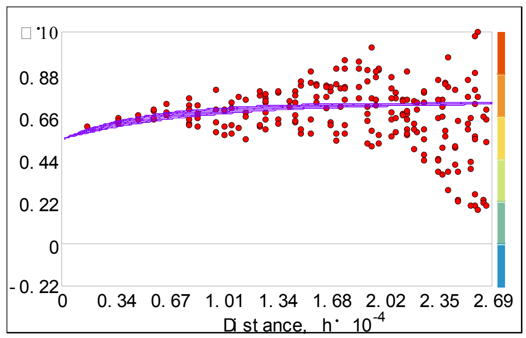
In order to select the best model for following analysis, comparison of precision for different models is needed. Table 4 offered the precision analysis results of spatial data of soil nutrients in 2009. For in condition that mean standardized closer to zero, the root-mean-square was smaller, average standard error closer to root-mean-square, and root-mean-square standardized closer to one, semivariogram model may be the most appropriate one. Based on the precision errors, the best semivariogram model for soil data collected in 2009 were: Spherical for pH and SOM, Gaussian for AN, Exponential for AP and AK.



(a) Spherical



(b) Gaussian



(c) Exponential

Fig. 5. Semivariograms of different models for soil pH in 2009

Table 4. Comparison of precision analysis among different models for soil test data in 2009

	Model	Root-Mean-Square	Average Standard Error	Mean Standardized	Root-Mean-Square Standardized
pH	Spherical	0.2482	0.249	0.003599	0.9969
	Gaussian	0.2485	0.2521	0.004238	0.9863
	exponential	0.248	0.2444	0.002406	1.015
SOM	Spherical	8.133	8.304	0.000509	0.9803
	Gaussian	8.136	8.293	0.001108	0.9823
	exponential	8.115	8.27	-0.0005942	0.9823
AN	Spherical	48.07	47.88	0.001782	1.005
	Gaussian	48.3	48.54	-0.001631	0.9986
	exponential	47.8	47.67	0.002623	1.004
AP	Spherical	9.093	9.417	-0.0001489	0.9657
	Gaussian	9.098	9.525	-0.0003632	0.9555

	exponential	8.996	9.183	0.001384	0.9798
AK	Spherical	68.57	73.67	-0.009017	0.9971
	Gaussian	68.98	75.13	-0.00288	0.9827
	exponential	68.2	72.55	-0.01263	0.9979

Table 5 displays the selected best models for each soil properties from 2009 to 2013 and their parameters. First of all, directional features were observed for the majority soil data except for SOM values collected in 2009 and 2010, which also became the special cases of range values above 25 km. The value of Nugget/Still indicates the relative size of the nugget effect among different soil properties (Trangmar et al., 1985). This value was used to define distinct classes of spatial dependence for the soil variables as follows: if the ratio was <25%, the variable was considered strongly spatially dependent; if the ratio was between 25 and 75 %, the variable was considered moderately spatially dependent; and if the ratio was >75%, the variable was considered weakly spatially dependent, which means random factors is the majority one which effected the spatial variation of soil properties (Cambardella et al., 1994).

Table 5. Semivariogram models selected for soil nutrients and parameters of each model (2009-2013)

	Year	Model	Anisot-ropic	Still	Major range(m)	Nugget	Direction	Nugget /Still
pH	2009	Spherical	Yes	0.074	25577.3	0.058	277.6	0.79
	2010	Exponential	Yes	0.036	26993.5	0.019	39	0.35
	2011	Exponential	Yes	74.571	25829.5	0.021	276.8	0.45
	2012	Exponential	Yes	42.344	26322.6	0.021	336.5	0.28
	2013	Exponential	Yes	76.740	25442.6	0.011	79.6	0.31
SOM	2009	Spherical	No	0.0491	3584.73	59.571		0.80
	2010	Spherical	No	0.0045	4148.61	41.847		0.99
	2011	Exponential	Yes	0.141	26133.4	71.409	290.7	0.93
	2012	Spherical	Yes	3263.87	25427.1	0.035	312.7	0.72
	2013	Exponential	Yes	1799.66	25493.9	0.0025	56.4	0.56
AN	2009	Gaussian	Yes	0.0217	25507.6	0.126	316.3	0.90
	2010	Exponential	Yes	0.041	25902.3	3156.4	66	0.97
	2011	Exponential	Yes	99.234	25766.3	1535.3	25.8	0.85
	2012	Exponential	Yes	97.084	25321.6	0.017	307.1	0.80
	2013	Exponential	Yes	88.399	26021.5	0.027	239.6	0.66
AP	2009	Exponential	Yes	289.06	25667.5	77.23	29.4	0.78
	2010	Exponential	Yes	768.09	26219	64.194	51	0.66
	2011	Spherical	Yes	0.227	26795.5	47.283	48.8	0.53
	2012	Exponential	Yes	0.175	26322.6	250.5	59.175	0.87

	2013	Spherical	Yes	0.003	26021.5	345.93	61.6	0.45
	2009	Exponential	Yes	0.145	26556.1	0.169	240	0.75
	2010	Exponential	Yes	0.0009	26846.3	0.101	63.2	0.58
AK	2011	Spherical	Yes	0.074	26086.2	0.0018	33.2	0.64
	2012	Spherical	Yes	0.036	25407.7	0.098	24.6	0.67
	2013	Exponential	Yes	74.571	25215.6	0.0007	46.4	0.75

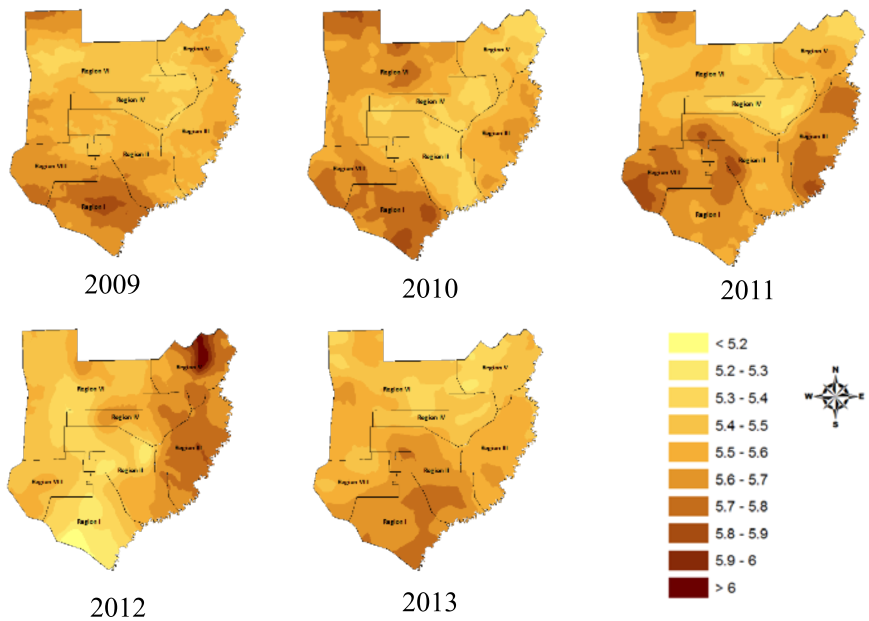


Fig. 6. Spatial distribution maps for soil pH (2009-2013)

From this table, it is clear that all of the soil properties tested in this study were not strongly spatially dependent. From 2009 to 2013, the value of Nugget/Still for each soil property decreased in overall trend, relatively, soil pH was the considered as the most strongly spatial dependent, while soil AN was the weakest one in study area.

According to the results below, interpolation method of ordinary kriging was used to predict the spatial distribution maps of soil nutrients in study area. Figure 6 shows the prediction maps for soil pH from 2009 to 2013. For the limitation of paper length, the maps of other soil nutrients were not shown in this paper.

The spatial distribution maps of soil pH shows that the soil pH in this study area were mostly acidic, or strongly acidic in some regions. From 2009 to 2011, the spatial distribution is similar in the whole area, while there was obvious changes in 2012, especially in the south area, soil pH became more acidic. Until the next year, distribution changed similar as that in 2009. For other soil nutrients, the spatial distribution remained not very stable in the five years, which probably because of the fertilization changed every year.

CONCLUSIONS

This study analyzed the spatio-temporal variation for several soil nutrients in a paddy rice farm from 2009 to 2013. Among these soil properties, data of soil pH collected all the five years followed a normal distribution, and had a relatively small C.V. values which decreased along the study five years. On the other hand, the spatial variation of soil pH increased, became more strongly spatial dependent. The others, such as soil AK, followed a log-normal distribution in 2009, 2010 and 2012, while in 2011 and 2013 followed neither normal nor log-normal distribution. Thus, data transformations were acquired for better analysis. Except for soil pH, raw data of other soil properties were transformed by log or box-cox method more or less. According to the analysis results, the spatial variation of soil pH, SOM, AN, AP and AK all increased from 2009 to 2013, while except soil pH, most of that were not strongly spatial dependent, which means the spatial variation was mostly based on random factors in this study area.

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