SPATIAL VARIABILITY OF POTATO YIELD BASED ON FOURIER TRANSFORM

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Abstract. The influence of soil properties on spatial yield variability of potato (*Solanum tuberosum* L.) can be employed as a foundation for site-specific soil management. It is challenging to understand the mechanism of crop yield spatial variation. In this study, a Fourier transform-based spatial variation analysis method is proposed for potato yield. The current work investigated the relationship of soil properties (including texture, moisture, and nitrate-nitrogen) to the variability of potato yield on 28 ha center-pivot irrigated fields located in northwest China from 2015 to 2017. Statistics and geostatistics are applied to evaluate the spatial variability of potato yield and soil properties; correlation analysis, partial least squares regression (PLSR) and the Fourier transform-based spatial variation analysis method are applied to explore the driving factors of the spatial variability of potato yield. Compared with other soil factors, soil moisture content and potato yield had more similar spatial structure, with similar semi-variance model and parameters. A negative correlation between soil moisture content and yield has been found in the first two years. According to partial least squares regression (PLSR), soil properties can only explain 24%, 25%, and 3% of the potato yield variation in 2015, 2016, and 2017. However, the Fourier transform-based spatial variation analysis method indicated that about 80% of potato yield variation has been explained by soil texture (49%), soil moisture (30%), soil nitrate-nitrogen (10%), and other factors (10%). The contribution of multiple factors to yield spatial variation has been decomposed by the method based on Fourier transform. This method can be considered a new approach for studying spatial variation and a theoretical basis for precise field management.
Keywords: *passing structure, Fourier transform, partial least squares regression (PLSR), spectrum analysis, mixed soil*

Introduction

Crop yield can change considerably within a particular field (Van de Kerkhof et al., 2015; Khanal et al., 2017; Sharda et al., 2017). The spatial variation of yield leads to the low utilization efficiency of water resources. Evaluating the degree and driving factors of spatial variability within-field is an important consideration to achieve site-specific management. Potato (*Solanum tuberosum* L.) is the fourth most abundant food crop in China, after rice, maize, and wheat. A total of 5,815,140 ha of farmland, mostly located in the arid northwestern region of China, was used in 2016 to cultivate potato with an average yield of 17.04 t/ha. In order to apply variable rate input within a field, it is essential to understand the drivers of the spatial distribution of potato yield at field scale.

Crop yield spatial variability has been widely investigated in the literature (Florin et al., 2009; Diacono et al., 2012; Quezada et al., 2014). Several factors can cause the

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mentioned variability, including natural (soil and topography) (Green and Erskine, 2004), random (rainfall and wind) (Sharda et al., 2017), and soil management (soil tillage, seeding, irrigation and fertilization) variabilities (Warrick and Gardner, 1983; Rockström et al., 1999; Irmak et al., 2002). Earl et al. (1996) divided driving factors of yield spatial variation between those with “little control” and those with “possible control”. Factors with possible control can be manipulated in a spatially variable manner, including soil structure, available water, waterlogging, macronutrients, pH levels, trace elements, weed competition, pests, and disease. Factors with little control, including soil texture, climate, topography, and genotype. Although these factors have a great impact on crop yield variation, they are difficult to be artificially improved.

A number of researchers have reported potato yield spatial variability. The variability of soil moisture content has been proven to be similar to the spatial distribution of crop yield in many studies (Warrick and Gardner, 1983). Topography, soil texture, soil depth, soil organic matter, electricity conductivity and nutrients had also reported to be related to the spatial variation of potato yield (Redulla et al., 2002; Starr et al., 2005; Cambouris et al., 2006; Po et al., 2010; Perron et al., 2018). According to previous reports, the coefficient of variation (CV) of potato yield ranged from 0.24 to 0.32 and the variability of potato yield was classified as moderate (Cambouris et al., 2006; Taylor et al., 2018).

Geostatistical analyses have been used as a primary tool of spatial variability analysis as they can provide a relevant resource for describing and quantifying the spatial patterns of crop yield with particular reference to a potential applicability to agricultural management (Cassel et al., 2000; Bourennane et al., 2004; Mzuku et al., 2005; Ping et al., 2007; Rüth and Lennartz, 2008; Perron et al., 2018; Taylor et al., 2018) The parameters of the semi-variogram model have been used to analyze the spatial variation of yield. The ratio of nugget to sill represents the ratio of structural factors and random factors of spatial variation of yield; The variable range indicates the range of spatial autocorrelation of yield (Matheron, 1963; Cressie, 1989). If the semi-variance model of a factor is similar to that of yield, it indicates that this factor may have an impact on the spatial variation of yield (López-Granados et al., 2002; Farooque et al., 2012). However, it is difficult to evaluate the quantitative contribution of each factor to the spatial variation of yield by geostatistical analysis.

In order to evaluate the factors of spatial variation of yield, correlation analysis has been used as a supplement to geostatistical methods (Corwin et al., 2003; Van de Kerkhof et al., 2015; Uribeetxebarria et al., 2018). Generally, the factors significantly related to yield are considered to have an impact on the spatial variation of yield. Therefore, these factor has been used to define the management areas of farmland (Bakhsh et al., 2000; Diacono et al., 2012). However, in the field, many researchers have found that the correlation between crop yield and soil factors was not significant, or the significance changed remarkably in various seasons (Taylor et al., 2018; Boubou Diallo et al., 2019). Kitchen et al. (2003) employed correlation analysis to perform a systematic study on the relationship between crop yield variation (wheat, corn, and soybean) and soil properties (soil conductivity and topographic measures). They found small (mostly less than 0.2) but still significant correlation coefficients. Similar results have been reported in some research (Virgilio et al., 2007; Maestrini and Basso, 2018; Perron et al., 2018). Therefore, it is doubtful to divide farmland management zones based on such factors. In addition, even if there was a significant correlation between yield and factors, due to the correlation between soil independent variables, it is difficult to distinguish the causal factors of yield variation.

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Various methods have been also employed in this area, including multiple regression analysis (Corwin et al., 2003; Arnó et al., 2012; Gaso et al., 2019), stepwise regression method (Redulla et al., 2002; Samaké et al., 2005; Du and Noguchi, 2017), neural network model method (Irmak et al., 2006; Miao et al., 2006; Green et al., 2007), boundary line analysis method (Li et al., 2017). Kitchen et al. (2003) verified the relationship between soil electrical conductivity and corn yield with stepwise regression method. According to the results, the average value of the coefficient of determination was not significant, indicating that the measured soil properties could only explain a small part of the variation in yield. Although neural network method has been widely used to separate independent influencing factors (Green et al., 2007), it is difficult to establish an effective neural network model when the correlation coefficient between yield and factors is small.

In general, at the field scale, according to the geostatistical analysis, 30% - 90% of the spatial variation of crop yield was caused by structural (little control) factors (Cambouris et al., 2006; Rüth and Lennartz, 2008; Farooque et al., 2012). According to the current researches, soil variables can only explain a small part of the spatial variation of yield (Redulla et al., 2002). This may be due to the underestimation of the contribution of soil factors to the spatial variation of yield, which is due to the interaction between soil factors. Thus, it is necessary to study how to separate the influence of each factor on yield variation, the influence of two factor interacted on yield variation, or the influence of multi factor interacted on yield variation.

In previous literatures, when the correlation between soil attributes was significant, partial least squares regression (PLSR) was often used to analyze the contribution of soil attributes to spatial variability of crop yield (Hao et al., 2010; Ce Glar et al., 2016; Shaddad et al., 2016; Duan et al., 2020). According to Hao et al. (2010), soil properties can explain about 45% of the ethanol yield variation. Duan et al. (2020) indicated that the geographic attributes, climatic and fertilizer types exerted substantial influence on rice yield and explained 57 to 85% of the variation in rice yield.

Besides, Fourier transform may be an effective attempt. Fourier transform is one of the practical methods, which can convert signals from the 1D or 2D spatial domain to the frequency domain (Cooley et al., 1969; Nussbaumer, 1981; Bracewell and Bracewell, 1986). Fourier transform has been widely used in digital image processing (Ma, 2012; Gómez-Echavarría et al., 2020), spectral analysis (Smith et al., 1974; Allen, 1977), signal processing (Tao et al., 2006; Sejdić et al., 2011). In the field of signal processing, Fourier transform has been used to filter noise signal (Bluestein, 1970; Li et al., 2011). When the collected signal contains not only useful information but also interference information, the original signal can be decomposed into a group of frequency signals of different amplitude through Fourier transform. The effective signal, after removing the interference signal, can be obtained by the inverse Fourier transform of the modified frequency band. This is the process of filtering (Bovard, 1993).

In the study of spatial variation, the spatial distribution of crop yield can also be regarded as a signal containing interference information. The spatial distribution caused by a factor is the effective information to be extracted and the spatial distribution caused by other factors or random factors can be regarded as interference information. The interference information can be filtered and the spatial variation of yield caused by this factor can be obtained by Fourier transform.

There is a common situation that two factors A and B are not independent of each other, and both affect the spatial distribution of yield. This influence can be divided into three categories: the first is the yield distribution affected only by factor A, the second is

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the yield distribution affected only by factor B, and the third is the yield distribution affected by the interaction of factor A and B. Fourier transform can be used to separate the above three cases, which may be helpful to solve the problem, understanding the spatial variation of crop yield affected by multiple factors. In general, it is interesting to try to use Fourier transform to analyze the spatial variation of yield, and to explore a method of filtering the spectrum after Fourier transform. In order to evaluate the effectiveness of the new method, partial least squares regression should also be used to analyze the contribution of soil attributes to crop yield variation.

A Fourier transform-based spatial variation analysis method was proposed in this study and applied to spatial distribution of potato yield. Geostatistics, correlation analysis, partial least squares regression was also applied in this study. The similarity and differences of these methods were discussed. For this purpose, a commercial potato field was selected, and three years of data on yield and soil properties (texture, volumetric water content, and nitrate-nitrogen) were collected. The main goals of the current work were: (i) evaluating the spatial variability of potato yield and soil properties by statistics and geostatistics; (ii) analyzing the driving factors of the spatial variability of potato yield by correlation analysis, partial least squares regression and the Fourier transform-based spatial variation analysis method; (iii) verifying the feasibility of spatial variation analysis method based on Fourier transform and discussing its advantages and limitations.

Materials and methods

Experimental site

The current work was performed at a commercial crop field, located in the border of Mu Us Sandy Land, northwest China (38°09′N, 109°00′E, 1183 m a.s.l.), within 2015, 2016 and 2017 growing seasons. *Figure 1* shows the location of the experimental site and photos before and after soil mixing. The elevation was high in the north and low in the south (*Figure 2*). The experiment was accomplished on a 28.3-ha field, cropped with potato. The USDA/FAO textural classifications systems were applied in this study. Soil texture was sandy and was not suitable for planting before the experiment. In order to control desertification and increase cultivated land, Chinese government had implemented a project to mix sandy soil (Aeolian sandy soil) with another local soil (feldspathic sandstone). The physical and chemical properties of mixed soil were already studied (Han et al., 2012; Zhang et al., 2021). In 2014, the original Aeolian sandy soil of the study field was well mixed, for a depth of 40 cm, with 850 t/ha of feldspathic sandstone in a proportion of 5 to 1. *Table 1* shows the mechanical composition of Aeolian sandy soil and feldspathic sandstone.

After soil improvement, potato was planted in 2015, 2016 and 2017 growing seasons. *Table 2* showed soil properties, meteorological conditions and planting management in the potato field from 2015 to 2017. In addition, the variation of initial aeolian sandy soil was also measured in 2014. The sand content of the sandy soil was more than 90% and clay content was as low as 0.24%. The coefficients of variation of soil clay, silt and sand of the sandy soil were 0.53, 0.38 and 0.05 respectively. Soil organic matter, nitrate-nitrogen, and available phosphorus in the field were very poor (*Table 2*) and so potato growth mainly depended on fertilization.

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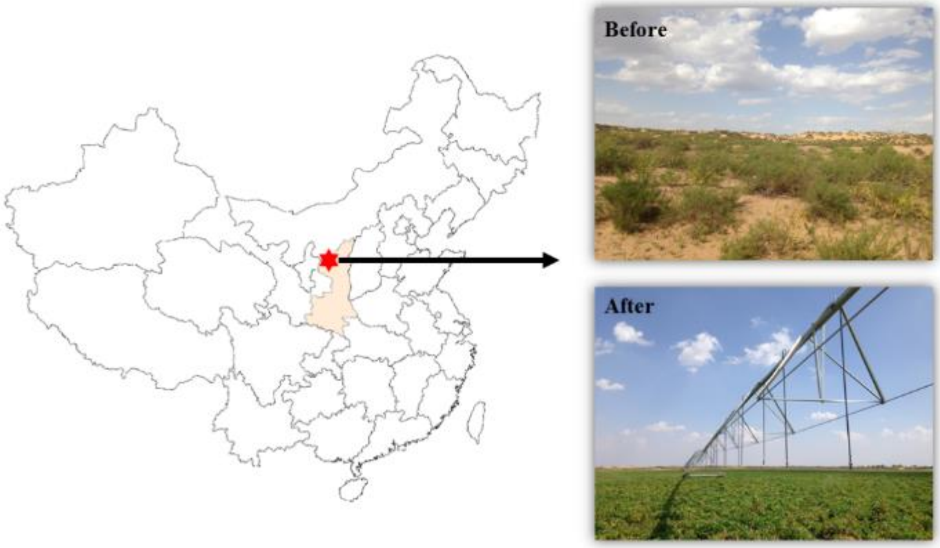

Figure 1. *Location of the experimental site in China and photos before and after soil mixing*

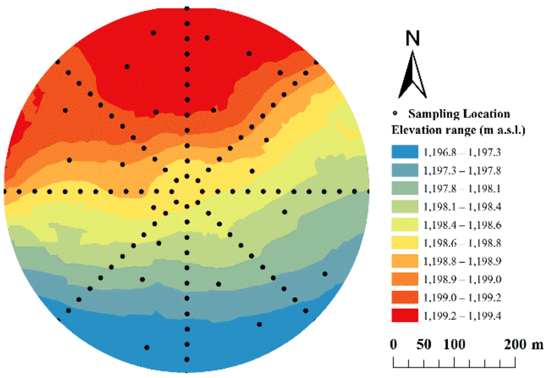

Figure 2. *Elevation map and georeferenced sampling points*

Table 1. *Composition of Aeolian sandy soil and feldspathic sandstone (%)*

Sample	Clay (<0.002mm)	Silt (0.002-0.05mm)	Sand (0.05-2mm)	Texture style
Aeolian sandy soil	0.2	4.5	95.3	Sand
Feldspathic sandstone	7.1	58.1	34.9	Silt loam

Meteorological conditions

The region where the experiment was installed generally has arid climate (BSh), according to the Köppen climate classification (Lohmann et al., 1993). The rainfalls during the growing season in 2016 and 2017 were 772 mm and 634 mm respectively, which were higher than that in 2015 (379 mm). Besides, these values were also higher than the long-term 57-year rainfall mean during the growing season (423 mm). The average temperature was higher in 2017 by 1.1°C and 2.3°C than that of 2015 and 2016, especially within the critical stage of the onset of flowering and tuber formation (July-August).

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***Table 2.** Soil properties, meteorological conditions, and planting management of the potato field*

Year	**2014**	**2015**	**2016**	**2017**
Soil properties				
Soil texture	Sandy	Loam-sandy	Loam-sandy	Sandy loam-sandy
Clay (＜0.002mm) (soil depth:0-40cm）(%)	0.24	3.09	4.30	0.60
Silt (0.002-0.05mm) (soil depth:0-40cm）(%)	4.45	32.01	27.24	9.40
Sand (0.05-2mm) (soil depth:0-40cm）(%)	95.31	64.90	68.45	90.00
Bulk density	\	1.42	1.45	1.50
Electricity conductivity (μs/cm)	\	103	362	594
Soil organic matter（g/kg）	0.08	1.04	1.82	1.85
Soil nitrate-nitrogen（mg/kg）	0.012	26.69	30	27.68
Soil available phosphorus（mg/kg）	2.68	3.15	3.25	4.28
Soil available potassium（mg/kg）	84	73.07	89	113
Plant management				
Plant area (ha)	0	28.3	28.3	28.3
Cultivar	\	Shepody	Favorita	Shepody
Growing season	\	5.1-9.25	5.1-9.1	5.1-9.22
Intra-row spacing between tuber seed pieces (cm)	\	18	18	18
Width of the ridge (cm)	\	30	30	30
Inter-row spacing (cm)	\	90	90	90
Irrigation amount (mm)	\	418	429	473
Meteorological conditions				
Rainfall (in growing stage)	\	379	772	634
Average temperature (℃)	\	20.0	19.9	20.8

Sampling

The samplings of soil and potato were done on a radial basis, with several irregular sampling points taken in some particular point. As shown in *Figure 2*, one hundred and sixteen georeferenced points were chosen from the field. The breakdown distance among the sampled regions was typically 25 m. The whole number of samples has been determined according to financial limitations and estimation precision requirements.

Crop management

The potato cultivar ‘Shepody’, a widely grown cultivar processed for chip products globally, was planted in 2015 and 2017, while another potato cultivar, ‘Favorita’, was planted in 2016. The field was a potato monoculture system with ridge tillage. The potato was sowed in early May and grown continuously under a single pass of a Valley center pivot irrigation system (E2060-G, Reinke Manufacturing Company Inc. USA) equipped with Nelson D3000 sprinkler nozzles (D3000, Nelson Irrigation Corporation, USA). The irrigation amount was 11 mm for each irrigation event, and the total irrigation amount during the entire growing period in 2015, 2016, and 2017, was 418, 429 and 473 mm, respectively. *Table 3* shows the detailed irrigation schedules. It should be noted that there was no local power supply in 2015, then the sprinkler irrigation machine was powered by a diesel engine. In order to save costs, the irrigation frequency in the first year has been lower than that in the next two years.

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Table 3. *Irrigation schedules from 2015 to 2017*

Growth Stage	Irrigation height (mm)	2015		2016		2017	
		Irrigation events	Irrigation amount (mm)	Irrigation events	Irrigation amount (mm)	Irrigation events	Irrigation amount (mm)
Germination	11	2	22	2	22	3	33
Seeding	11	5	55	6	66	6	66
Tuber formation	11	10	110	10	110	10	110
Tuber development	11	11	121	13	143	14	154
Tuber ripe	11	10	110	8	88	10	110
Whole	11	0	418	39	429	43	473

Irrigation amount distribution was measured along three years. Three buckets were placed at each sampling point (116 sampling points), with a diameter of 20 cm and a height of 15 cm. The irrigation amount was measured three times from May to June in each growing season, because the leaves of potato were small at this stage, and the distribution of sprinkler irrigation was not affected by leaf interception. The average value of 9 measurements from 2015 to 2017 represented the irrigation distribution of sprinkler irrigation machine. As shown in *Figure 3*, the amount of irrigation was higher in the radius of 200-300 m and 50 m, and lower in other areas.

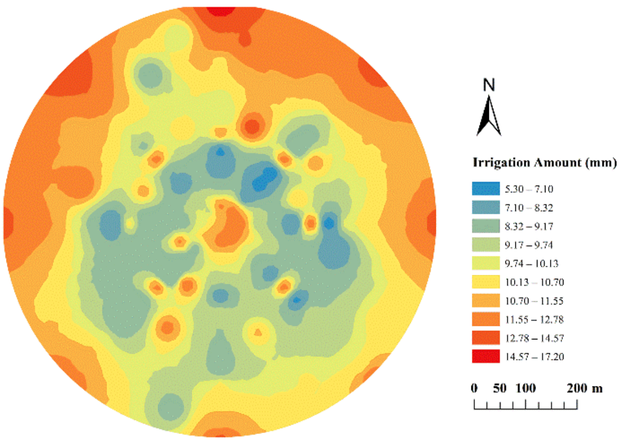

Figure 3. *Map of average irrigation amount*

Fertilizer application rates were adjusted using field mean nutrient amounts followed by present local agricultural authority guidelines. For each year, before planting, 60-75 t/ha of organic fertilizer (pig manure, with 29.5% of water, 22.8 kg/t, 28.6 kg/t P_2O_5, 28.6 kg/t K_2O, 558.4 kg/t organic matter), 225 kg/ha urea, 375-450 kg/ha diammonium phosphate and 300-375 kg/ha potassium sulfate were applied. At the budding stage, 300 kg/ha special fertilizer for potato (A sulfur based slow-release mixed fertilizer rich in medium and trace elements, N: P: K=17:17:17) were applied by center pivot irrigation system. The same plant protection plan was applied from 2015 to 2017. To avoid pests and diseases, 45 kg/ha of granular insecticide (5% phoxim) were applied before planting in each year. In order to prevent and control 28-spot lady beetles (*Henosepilachnan vigintioctopunctata*), 2.5% Deltamethrin and 70% Cyano (3-phenoxyphenyl) methyl 4-chloro-α-(1-methylethyl) benzeneacetate were used.

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Cyhalothrin and confidor were used to control aphids. In order to prevent and control the late blight, it has been prevented and treated every 7-10 days since July 15, with a total of 6 times. The insecticides were Antracol, 10% Cyanostazole SC, Amesida and DuPont Yibao, Famoxate, Redomir (Gold, MZ) and Fluazinam.

Soil texture

At each point, soil samples were collected for soil texture measuring before planting in each growing season (2015, 2016, 2017). In order to reduce the measurement error caused by testers, 2 testers (tester A and B) independently took the samples and performed the soil analysis. Three soil core samples (70 mm diameter, 52 mm height) were collected at the depth of 20 cm within a 1-m radius of each grid point by each tester. Samples were kept cool until submitted to the appropriate laboratory and air-dried, ground, and sieved through a 2 mm sieve. Soil mechanical composition of three soil core samples in each point were performed using laser particle analyzer (MasterSizer 2000, Malvern Panalytical Ltd, USA). The reliability of measurements was evaluated using the intraclass correlation coefficient (ICC). The ICC can theoretically vary between 0 and 1.0, where an ICC of 0 indicates no reliability, whereas an ICC of 1.0 indicates perfect reliability (Weir, 2005). *Table 4* shows the mean value of intraclass correlation coefficient among three years between different measurements of soil texture components. It can be seen that ICC of different measurements were higher than 0.85 indicating good reliability. The average value in each year of measurements performed by tester A and tester B were calculated and applied in the study. The USDA/FAO textural classifications systems were used to evaluate different textural classes.

Table 4. *Mean value of intraclass correlation coefficient (ICC) among three years between different measurements of soil texture components*

Soil texture components	Intraclass correlation coefficient (ICC)		
	M_{A3}	M_{B3}	A*B
Clay	0.987	0.991	0.893
Silt	0.989	0.987	0.856
Sand	0.978	0.989	0.879

M_{A3}: Three measurements collected by tester A; M_{B3}: Three measurements collected by tester B; A*B: The mean value of three measurements collected by tester A and the mean value of three measurements collected by tester B

Soil nitrate-nitrogen (NO_3–N)

From each sampling location, soil composite sample was collected three times in June, July and August in each growing season for soil NO_3–N measuring, which was composited by three soil core samples (70 mm diameter, 52 mm height) collected at the depth of 20 cm within a 1-m radius of each grid point. NO_3–N was determined according to Cawse (1967). Mean values of soil nitrate-nitrogen were employed to analyze the spectral similarity with yield for each year.

Soil moisture

A time-domain reflectometer sensor (Xi'an Bi Shui RV1, China) was employed to measure the volumetric soil water content at each sampling location at 0–40 cm depths every four days during the growing season, and a gravimetric method was adopted to

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calibrate the measured values of the volumetric soil water content during the experimental period of each year. The soil bulk density was set as the mean value of the annual measured value, which was 1.42, 1.45, 1.50, respectively. Soil moisture content was measured 35, 32, and 35 times in 2015, 2016, and 2017, respectively. The average value of soil moisture content in each year was applied in the study. Mean values of soil water content were employed to analyze the spectral similarity with yield for each year.

Soil properties

Three soil core samples (70 mm diameter, 52 mm height) were collected at three random points at the depth of 20 cm within a 1-m radius before planting in each growing season. One of samples was used for measuring soil bulk density determined according to cutting ring method. One of samples was used for measuring soil organic matter, available phosphorus, available potassium. Soil available potassium was extracted with ammonium acetate and determined by flame photometer (Shuman and Duncan, 1990). Soil available phosphorus was extracted with sodium bicarbonate solution and determined by spectrophotometer (V-T3, Yipu Instrument Manufacturing Co., LTD, Shanghai, China) (Olsen, 1954). Soil organic matter was determined according to Yeomans and Bremner (1988). Another sample was used to measure soil electricity conductivity determined by conductivity meter (DDSJ-318T, Shanghai Yi Electrical Scientific Instrument Co., LTD, Shanghai, China). The average value in each year was shown in *Table 1*.

Yield

Before the field's commercial harvest, a typical yield digs of 1 m-rows were carried out by hand at all sample points and weighed by an electronic scale (measuring range: 0.05-50 kg, measuring accuracy: 0.01 kg, Zhuoshangqi Co. Ltd., China).

Data analyses

Statistical analysis, correlation analysis and geostatistical analysis were used to evaluate the spatial variability of potato yield and soil properties. ArcGIS10.3 (ESRI, Redlands, CA, USA) was adopted to construct semi-variograms and kriged surface maps. The linear correlation coefficients ($P < 0.05$) were obtained through the Pearson's test by SPSS10.0 (International Business Machines Corporation, USA). The normal distribution estimation was performed by Shapiro-Wilks test (Abbasi, 2013). The test quantity (W) and the probability of significance (P) were calculated. When P is lower than 0.05, the data is considered as normal distribution.

Semi-variogram parameters, including the nugget (C_0), sill (C_1), and range (a), were utilized to define the spatial framework of all variables. Nugget describes the distance zero variance or the experimental error; sill defines the semi-variance amount where the semi-variogram attains the upper bound after its primary growth. It represents the maximum variance for this type of semi-variogram and indicates the overall (a priori) semi-variance of the selected region; the range defines the amount (x-axis) where a variable becomes spatially independent or the lag-distance where the semi-variogram becomes smooth. The nugget to sill ratio determines the random part significance and estimates the spatial dependence quantitatively. Nugget/sill ratios can be divided into three categories (Cambardella et al., 1994): (i) <25%, strong spatial dependence; (ii)

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25-75%, moderate spatial dependence; (iii) >75%, spatially independent or pure nugget (i.e., when semi-variograms' slopes are around zero).

Spatial variation can be described by various models (spherical, circular, etc.) fitting the semi-variograms. The best-fitting model can be selected using the highest determination coefficient and confirmed through a visual inspection. The adopted lag distance was between 5 and 12, according to the different variables considered.

Partial Least Squares Regression (PLSR)

A Partial Least Squares Regression (Garthwaite, 1994; Wold et al., 2001; Rosipal and Krämer, 2005) approach was also used to estimate the relationship between soil variables and potato yield. PLSR is a flexible method for multivariate data analysis that has been already applied in numerous previous studies (Hao et al., 2010; Mehmood et al., 2012; Shaddad et al., 2016; Duan et al., 2020). It can deal with cases when the explanatory variables are strongly correlated. In this study, significant correlations appear between soil properties.

Regression coefficients of the PLSR regression models were used to assess the influence of soil properties on potato yield in each year. It reflects both the magnitude and the direction of the influence. It represents how many standard deviations the potato yield changes for each standard deviation unit change in the explanatory variables. Values above 0 indicate positive contributions, whereas below-zero values indicate negative contributions. The determination coefficient (R^2) and mean square error (MSE) were used to evaluate the prediction accuracy of the PLSR model (Wold et al., 2001). R^2 represents the stability of the model. The closer R^2 is to 1, the better the stability and fitting of the model. MSE can test the prediction ability of the model. The smaller the MSE, the more accurate the prediction is.

A Fourier transform-based spatial variation analysis method

"Passing structure" of spatial variability

Because potato planting material is a clone, crop yield variation necessarily comes from environment. Under ideal conditions, an approximately uniform yield distribution could be considered when driving factors (including topography, soil structure, soil water content, and nutrients) were evenly distributed in the field. This study claims that variation is transmitted to crop yield step by step, from low-order factors (the factors are closer to the original variation) to high-order ones (the factors are farther away from the original variation). Low-order factors are closer to the initial variation, such as soil structure, irrigation, fertilization, while the high-order ones are farther away from the original variation, such as soil nutrient. The transmission direction can be determined through experience and scientific knowledge.

Taking potato yield as an example, the passing structure of crop yield spatial variation (*Figure 4*) has been based on soil texture, irrigation distribution, fertilization distribution, soil moisture content, soil nitrate-nitrogen (NO_3–N), and other random factors. These factors may be related to crop yield variation. Soil texture components (sand, silt, and clay) can influence potato yield more than chemical properties (Redulla et al., 2002) and so the effect of soil texture on the variation of potato cannot be ignored even for its dramatic changes in time and space in the region where the experiment was installed. Moreover, soil moisture and nitrogen were often utilized to delineate management zones due to the correlation with yield (Vrindts et al., 2005; Perron et al., 2018).

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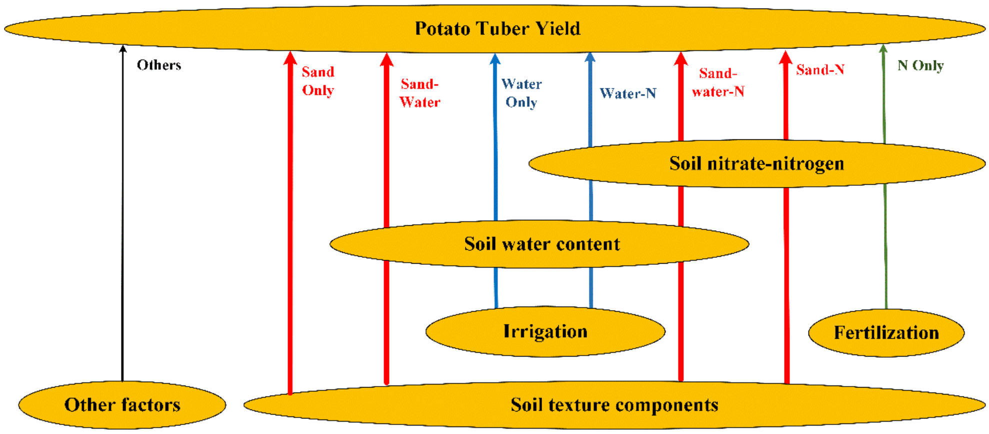

Figure 4. *Passing structure of crop yield's spatial variation*

Direction of variation transmission can be judged according to soil physics. Soil particle size distribution plays a major role in the dynamics of soil heat, water and chemicals (Marshall and Holmes, 1981; Shao et al., 2006). Soil moisture is inevitably affected by soil particle distribution. Soil nutrients are absorbed by crop roots in the form of soil solution. Thus, nutrients must be closely related to soil moisture. Some nutrients also come from the decomposition of soil particles, so it may be directly related to soil particles. Therefore, the variation can be transmitted from soil particles to soil water content, and then from water to nutrients. At the same time, the variation of irrigation or fertilization will also be transmitted to soil water and nutrients. Although the "passing structure" proposed in this paper has not been mentioned in previous studies, it is in line with the principle of pedology and soil physics.

There are four initial sources of spatial variation of yield, soil texture components, irrigation distribution, fertilization distribution, and other factors. Soil water content and soil nitrate-nitrogen were in the second and third layers, respectively. Spatial variation of yield can be decomposed into eight components based on different transmission paths. The variation of soil texture was transmitted to yield from four paths. Some variations were directly transmitted to yield (Sand Only), some variations were indirectly transmitted through soil moisture content (Sand-Water), soil nitrate-nitrogen (Sand-N), and some variations were transmitted through water and nitrogen interacted (Sand-Water-N). The effect of texture on soil water and nitrogen distribution was investigated by Li and Liu (2011). The experimental results demonstrated that layered-textural soil greatly affected water and nitrate distribution. The variation of irrigation distribution was transmitted to yield from two paths. Some variations were transmitted to yield through soil moisture content (Water Only), while some were transmitted through water and nitrogen interacted (Water-N). The variation of fertilization distribution was transmitted to yield through soil nitrogen (N-Only). The contribution of other factors or random factors to yield can be represented by other components (Others).

Due to the interaction between factors, it is challenging to determine the contribution rate of different factors to yield variation. However, according to the basic principle of Fourier transform, the interacting factors in the 1D or 2D spatial domain can be superposed in the frequency domain. Therefore, the following methods are proposed to determine the contribution rate of each component.

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Principal of Fourier transform-based spatial variation analysis method

The process of analyzing the spatial variation of crop yield by Fourier transform is divided into three parts. Firstly, the yield map is decomposed into a group of frequency bands. And then the appropriate filtering method is selected. Filtering method is used to find the frequency band representing both effective and interference information and set the amplitude of the frequency band representing interference information to zero. Finally, the filtered frequency band is transformed by inverse Fourier transform so that the yield map without interference information can be obtained.

Filtering plays an important role in spatial variation analysis. A filtering method based on spectral similarity is proposed in this study. The basic principle of this method is that spectral similarity means similar spatial distribution. The spectral similarity can be employed to determine the contribution rate of each factor to yield variation. *Figure 5* shows a schematic diagram of spatial variability analysis based on Fourier transform where the average component, soil texture component, and water component in the frequency, 1D and 2D spatial domains are shown. It should be noted that the frequency and amplitude data in the figure are not actual data and are only employed for schematic, while the other factors are not listed here. For yield, the combination of sine waves in the spectrum represents the spatial variation caused by a specific factor.

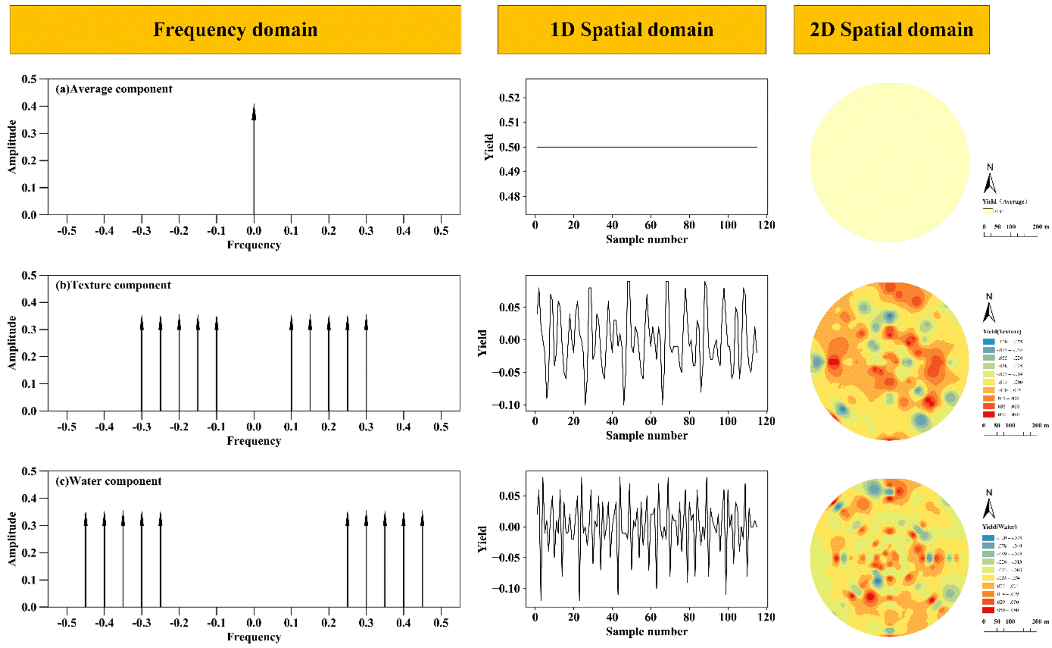

Figure 5. *Schematic diagram of spectrum analysis method based on Fourier transform*

The average component is the average yield level in 2D space, represented by the sine wave with zero frequency in the frequency domain and constant in 1D and 2D spatial domains. *Figure 5a* shows the different expressions of average yield in frequency, 1D and 2D spatial domains. First, it is easy to understand that the average yield is uniformly distributed in 2D spatial domain; secondly, the average yield is displayed as a vertical line (phase = 0) in frequency domain; finally, the average yield is displayed as a horizontal straight line in 1D spatial domain, that is, at each sampling point, the yield value remains unchanged (the abscissa in 1D spatial domain is the sampling point number). The texture

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component represents the spatial distribution of yield affected by soil texture (*Figure 5b*). In the frequency domain, it can be represented by a set of sine waves with frequencies of ± 0.10, ± 0.15, ± 0.20, ± 0.25, and ± 0.30. The 1D spatial-domain image is an oscillation curve, while the yield is higher in the local area in 2D spatial domain. The water component represents the spatial distribution of yield affected by soil water content. In the frequency domain, it can be represented by a set of sine waves with frequencies of ± 0.25, ± 0.30, ± 0.35, ± 0.40, and ± 0.45. The image in 1D spatial domain is also an oscillation curve, while the water component was distributed circularly in 2D spatial domain.

The frequency spectrum of yield is composed of zero-frequency component (i.e., average component), texture component, water component, and the other components. When the factors are evenly distributed, the spectrum only includes the zero-frequency component, while there is no spatial variation in yield. When only one factor has heterogeneous distribution, the variation is first reflected in the spectrum of the factor, and the frequency band representing the variation is then superimposed with the zero-frequency component of yield to form the yield spectrum under the influence of a single factor. When multiple factors have spatial variations, the variations are first reflected in their corresponding spectrum. Then, according to the mutual influence relationship between various factors, the spectra representing the variations are combined in a series of linear combinations and then combined with the zero-frequency component of yield to form the yield spectrum under the condition of multi-factor variation. Therefore, the spectrum similarity can be analyzed to determine the source of yield variation.

The Fourier transform is employed to obtain the frequency, amplitude, and phase of the sine wave. According to the Fourier transform principle (Rife and Vincent, 1970), frequency determines the factor’s weight on yield spatial variability; the lower the frequency, the greater the weight. The amplitude indicates the influence degree of the factor on yield spatial variability; the more relevant the amplitude, the greater the influence. The phase indicates the influence direction of the factor on yield spatial variability; the closer the phase, the more similar distribution between the factor and yield, the more significant the difference of the phase, and the more opposite distribution between them.

Analysis process

In order to determine the contribution rate of each factor to yield variation, this study compares and analyzes the frequency, amplitude, and phase of yield and soil spectrum. The detailed analysis steps are as follows:

Step 1: Constructing the input matrix of Fourier transform

It is necessary to convert the 2D spatial data into 1D spatial domain. Firstly, for each attribute, kriging interpolation was applied to obtain map. The interval between interpolation points is 25 m, as shown in *Figure 6*. The interpolation points are numbered row by row from left to right. There were 449 interpolation points in the field. Then construct a curve, take the number of sampling points as the abscissa and the corresponding yield or soil attribute of each point as the ordinate. All yield maps and soil attribute maps, in each year, generated a different curve used as input signals for Fourier transform.

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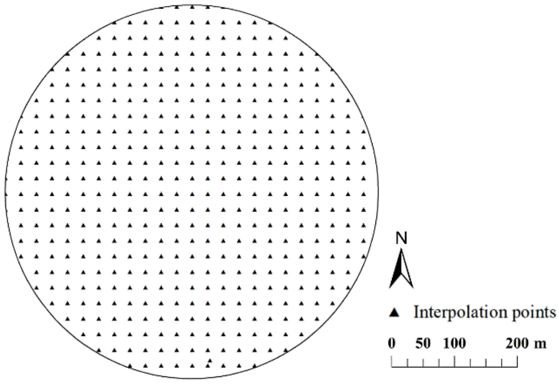

Figure 6. *Map of interpolation points*

Step 2: Fourier transform

The fast Fourier transform (FFT) is adopted (Cochran et al., 1967), where the frequency resolution is 1, and the frequency range after applying the Fourier transform is [-0.5,0.5] with a total of 898 frequency bands. The number of frequency bands is at least twice the number of interpolation points, 898 frequency bands are calculated in this study. FFT was implemented in Python 2.7, and the frequency, amplitude and phase have been stored in Excel.

Step 3: Spectrum similarity analysis

Multiple independent environmental factors can affect the spatial distribution of yield. The 1D or 2D spatial distribution of yield is composed of multiple frequency components in the frequency domain. The similarity of frequency components evaluates the contribution of factors. Phase is crucial for understanding the spatial variation. In this study, the phase similarity represents the similarity of the frequency band. Cosine similarity is one of the commonly used similarity metrics. It judges the similarity according to the cosine of the angle between two vectors. The smaller the angle, the closer the cosine value to 1, and the more similar. On the contrary, the closer the cosine value to -1, the less similar they are.

Similarity indices with phase information (S) is proposed based on the definition of cosine similarity. S is the sum of the product of cosine similarity and weight of similar frequency bands (W_i), calculated in *Eq.1* and *Eq.2*, where $\Delta\varphi_i$ indicates the phase difference of the i-th frequency band. If $\cos(\Delta\varphi_i) \geq 0.5$, the i-th frequency band is similar; if $\cos(\Delta\varphi_i) < 0.5$, the i-th frequency band isn`t similar, W_i is zero. S represents the similarity of two variables in general, varying in the interval [0,1]. If S > 0.5, the positive effect is higher than the negative one, the closer S to 1, the more similar the frequency spectrum, and the more similar spatial distribution; If S < 0.5, the negative effect is higher than the positive one, the closer S to 0, the more different spatial distribution.

$$W_i = \begin{cases} 0, & \cos(\Delta\varphi_i) < 0.5 \\ \frac{0.99^i}{\sum_{i=1}^{N/2} 0.99^i}, & \cos(\Delta\varphi_i) \geq 0.5 \end{cases} \quad \text{(Eq.1)}$$

$$S = \sum_{i=1}^{N/2} W_i \quad \text{(Eq.2)}$$

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Step 4: Contribution rate calculation

The similar frequency bands between each factor and yield are detected in step 3. Step 4 calculates the contribution rate of each factor alone or interacted to the spatial variation of yield by comparing the similarities and differences of similar frequency bands. Overlapping the similar frequency bands of two or more factors means that similar frequency bands have the same frequency. The overlapping frequency bands represent the interaction of the factors influencing the yield distribution, while the remaining frequency band represents the part where the factor independently affects the yield distribution.

Therefore, the frequency bands of eight yield components are analyzed, and the contribution rate (CR) of the components, the sum of the weight of frequency bands of each component, is calculated.

Step 5: Filtering

Filtering is used to extract the frequency band representing valid information and eliminate the frequency band representing invalid information. If you want to obtain the yield map only caused by soil sand content, you only need to keep the frequency bands representing sand only component and set the amplitude and phase of the other frequency bands to 0. The yield map only affected by sand can be obtained by inverse Fourier transform of modified frequency bands. The eight components of yield spatial variation are filtered respectively in this step.

Step 6: Inverse Fourier transform

The inverse Fourier transform is utilized to obtain the spatial distribution of eight components using modified frequency bands in each year. The average value of the components over three years is calculated and interpolated through the inverse distance interpolation method in ArcGIS 10.3 (ESRI, Redlands, CA, USA). Since the Fourier input matrix data are all dimensionless, the spatial distribution variables are also dimensionless.

Results

Descriptive statistics

Table 5 gives the descriptive statistics in tuber yield and soil properties within-field for the three years. Most variables have a normal distribution according to the Shapiro-Wilks test. A few contrasts of both yield and soil properties are notable. Yield in 2015, 2016, and 2017 were 54.17 t/ha, 54.49 t/ha, and 70.88 t/ha, respectively. It is much higher than the average potato yield of China in 2016 (17.04 t/ha). This may be attributed to standardized planting management and high-quality seed potatoes. Although the same potato cultivar, ‘Shepody’, was planted in 2015 and 2017, the yield varied considerably. The higher rainfall was obtained within May to October in 2016 (772 mm) and 2017 (634 mm), compared with that in 2015 (379 mm). This may be due to the lower rainfall and poor irrigation management in the first year after mixing soil with Aeolian sandy soil and feldspathic sandstone. Differences in potato variety and climate may lead to different tuber yield values from year to year.

According to the coefficient of variation (CV) as a measure of field stability with years, spatial yield variation was remarkable. The CV of yield in 2015 was as high as 0.41, while the minimum yield was only 19.05 t/ha, and the highest was 103 t/ha. The CV of yield

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has been reduced among years, ranging from 0.41 to 0.16. In contrast, according to Cambouris et al. (2006), the potato yield variability had an approximately fixed value in different year. The coefficient of variation ranged from 0.24 to 0.27. Although the potato was also planted in sandy loam soil, it had a lower variation of soil sand content (CV=0.03).

Table 5. *Descriptive statistics for potato tuber yield and soil properties among three years*

Year	Property	Mean	Min	Max	SD	W	P	CV（%）	Num
2015	Yield (t/ha)	54.17	19.05	103.00	22.38	0.96	>0.05	41	116
	Clay (%)	3.09	0.24	8.28	1.48	0.93	>0.05	48	116
	Silt (%)	32.01	7.23	59.27	12.37	0.96	>0.05	39	116
	Sand (%)	64.9	35.1	92.54	13.44	0.96	>0.05	21	116
	Θ_v (%)	11.47	4.58	19.81	4.35	0.99	>0.05	38	116
	N (mg/kg)	29.69	10.48	51.1	8.27	0.98	>0.05	28	116
2016	Yield (t/ha)	54.49	29.94	78.41	12.04	0.98	>0.05	22	116
	Clay (%)	4.3	1.43	8.56	1.66	0.97	>0.05	39	116
	Silt (%)	27.24	8.55	55.72	9.65	0.96	>0.05	35	116
	Sand (%)	68.45	36.12	89.49	10.77	0.96	>0.05	16	116
	Θ_v (%)	11.31	5.85	18.94	2.73	0.99	>0.05	24	116
	N (mg/kg)	30	9.58	55.56	10.58	0.99	>0.05	35	116
2017	Yield (t/ha)	70.88	43.68	107.45	11.68	0.95	>0.05	16	116
	Clay (%)	0.6	0	1.9	0.33	0.96	>0.05	55	116
	Silt (%)	9.4	3.84	15.86	2.18	0.96	>0.05	23	116
	Sand (%)	90	82.91	96.14	2.37	0.94	>0.05	3	116
	Θ_v (%)	12.31	7.91	18.45	2.51	0.99	>0.05	20	116
	N (mg/kg)	27.68	8.76	59.43	13.24	0.99	>0.05	48	116

W: inspection quantity of Shapiro–Wilk test; P: probability of significance; CV: coefficient of Variation. Θ_v: the mean value of volumetric soil water content; N: the mean value of soil nitrate-nitrogen

Regardless of the small region of the experimental plot, most soil variables' spatial and temporal variabilities were considerable. It should be noted that the soil texture components changed dramatically from 2015 to 2017. Since the clay proportion remained low, fluctuating from 0.6% to 4.3% through three years, soil texture was determined by silt and sand. After the first year, silt reduced moderately from 32.02% to 27.04%, then tumbled to 9.4% in the third year. In contrast to silt, sand increased slightly from 64.9% to 68.45% and then raised rapidly to 90.00% through three years. This may due to instability of mixed soil and the downward migration of silt (Zhang et al., 2021). Based on recent evidence, due to low organic inputs and tillage practice disturbances, continuous monoculture systems could degrade soil aggregate stability (Acosta-Martinez et al., 2004; Ma et al., 2016). It was reported that soil aggregate stability could decrease significantly in the potato monoculture system after two years of continuous cropping. Besides, the soil was mixed, while the soil aggregate was not stable in the formation process. Therefore, silt may migrate downward with high-frequency irrigation and rainfall. Since the rainfall in 2016 (772 mm) is higher than in 2015 (379 mm), this phenomenon was more noticeable after two cultivation years. However, soil texture in deeper than 40 cm had not been analyzed. The reasons for the drastic change of soil texture in depth of 0-40 cm need to be further studied.

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The CV of sand decreased considerably among years from 0.21 to 0.03, and the CV of silt also decreased from 0.39 to 0.23, while the CV of clay was higher than the others and fluctuated around 0.48. However, according to several reported studies involving spatial variation within-field, spatial variation of soil particle distribution remained fixed year by year (Casa and Castrignanò, 2008; Li et al., 2016). Meanwhile, most soil chemical and physical features had moderate variability considering the CV amounts ranging from 0.15 to 0.35. Based on the soil survey reported by Cambouris et al. (2006), the CV of clay, silt, and sand were 0.20, 0.29, and 0.03, respectively.

Similar to soil sand content, the CV of soil moisture was declined from 0.33 to 0.21. However, for nitrogen, this was not the case. The maximum nitrogen variability was observed in 2017. Since this study takes fertilization as the primary source of soil nitrogen, it is not easy to ensure the uniformity of fertilization.

Soil factors are sorted from large to small according to their CV, as clay, silt, soil water content, soil nitrate-nitrogen, and sand in 2015, clay, silt, soil nitrate-nitrogen, soil water content and sand in 2016, clay, nitrate-nitrogen, silt, soil water content and sand in 2017. It can be concluded that the clay has the maximum variability, while the variability of sand is always the smallest. This may be because the sand comes from the Mu Us Sandy Land, while the clay particles mainly come from arsenic sandstone, significantly affected by the non-uniformity of mechanical mixing.

In mixed-soil with a potato monoculture system, the spatial and temporal variabilities of soil particle distribution, water contents, and nitrogen were considerable, not conducive to the mixed-soil maturation. Further complex extended rotations can provide higher nutrient accumulation than the monoculture or short rotation (West and Post, 2002; Karlen et al., 2006). A few years after soil improvement, the plant alfalfa was suggested to accumulate organic matter and promote the soil aggregates' formation and stability.

Geostatistics analysis

The semi-variogram model of potato yield and soil variables are presented in *Figure 7*, while the best fitting model parameters are given in *Table 6*. The exponential model was the most used, that approached sill value asymptotically. Tuber yield showed moderate and non-consistent spatial dependence among three years, with the nugget-to-sill ratio decreasing from 70% to 57%. It had a more significant range value (216 m) and a lower nugget-to-sill ratio (57%) in 2017 than in the previous years, indicating that the tuber yield had stronger spatial dependence in 2017. According to the above results, there was higher soil sand content in 2017. It can be concluded that potato tuber yield may have more considerable spatial dependence in sandy soil. In contrast, according to Cambouris et al. (2006), consistent and unchanged variability in tuber yield from 1998 to 2000 can be found, with the nugget-to-sill ratio around 47%. The nugget-to-sill ratio values in the current work were higher than those obtained by Cambouris et al. (2006) and derived from the relatively less uniform soil texture at the mixed-soil site.

Soil clay content showed moderate spatial dependence among three years, with the nugget-to-sill ratio ranging from 51% to 67%. Silt and sand showed strong spatial variability in 2015 and 2016, with the nugget-to-sill ratio ranging from 15% to 25%, and showed moderate spatial dependence in 2017, with the nugget-to-sill ratio from 70% to 71%. The range of soil particles increased year by year, the range of clay increased from 90 m to 207 m, the range of silt increased from 59 m to 213 m, and the range of sand increased from 51 m to 241 m. The increase of range can also be found in soil water content, which increased from 144 m to 190 m. Soil water content showed moderate

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spatial dependence among three years, with the nugget-to-sill ratio ranging from 43% to 58%. Soil nitrate-nitrogen showed moderate spatial variability in small range, which varied from 46 m to 58 m. Compared with other soil factors, soil moisture content and potato yield had more similar spatial structure, with similar semi-variance model and parameters. Therefore, soil moisture content may affect the spatial distribution of yield.

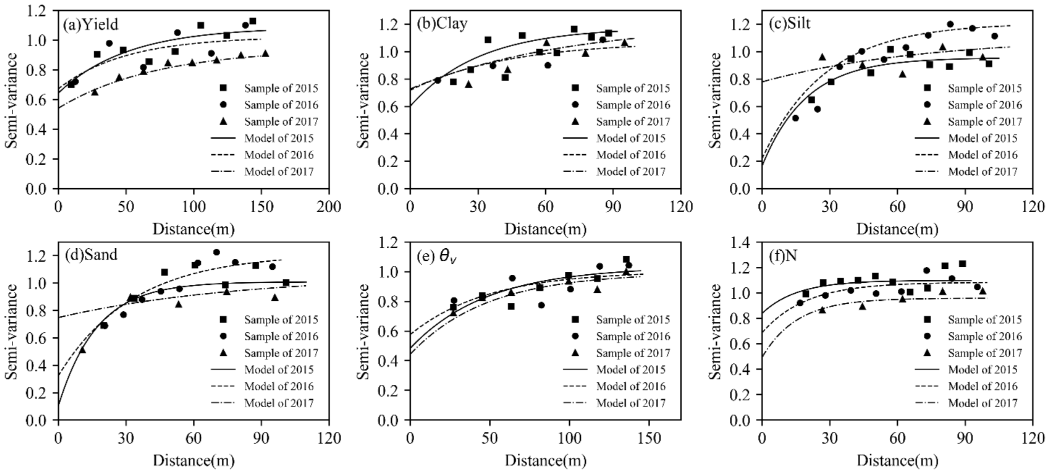

Figure 7. *Semi-variance functions of potato tuber yield and soil variables*

Table 6. *Semi-variance function model parameters of potato tuber yield and soil variables*

Property	Year	Nugget	Sill	Range(m)	Nugget/sill (%)	R^2	Num
Yield	2015	0.64	1.08	154	59%	0.86	116
	2016	0.67	1.02	148	66%	0.79	116
	2017	0.54	0.94	216	57%	0.92	116
Clay	2015	0.60	1.17	90	51%	0.75	116
	2016	0.71	1.06	129	67%	0.83	116
	2017	0.72	1.20	207	60%	0.79	116
Silt	2015	0.16	1.10	59	15%	0.89	116
	2016	0.21	1.19	89	18%	0.85	116
	2017	0.77	1.09	213	71%	0.89	116
Sand	2015	0.19	1.09	51	17%	0.87	116
	2016	0.30	1.21	99	25%	0.79	116
	2017	0.74	1.05	241	70%	0.85	116
Soil water content	2015	0.48	1.03	144	47%	0.94	116
	2016	0.57	0.99	146	58%	0.92	116
	2017	0.43	0.99	190	43%	0.90	116
N	2015	0.82	1.09	46	75%	0.81	116
	2016	0.68	1.07	58	64%	0.79	116
	2017	0.49	0.95	46	52%	0.82	116

Correlation analysis

Table 7 shows the Spearman correlation among tuber yield and soil features. Although significant correlation relationships were extracted among soil features and yield, a few contrasts can be observed between soil features and potato yield in various growing seasons. The yield was negatively and positively correlated to clay in 2015 and 2016,

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respectively. This was compatible with earlier observations (Redulla et al., 2002), indicating that correlation coefficients among potato point yield and clay were positive in one field and negative in another with different soil textures. Although soil moistures and N were negatively correlated to yield in the previous two growing seasons, this significant correlation relationship cannot be observed in 2017. Accordingly, soil texture was sandy clay loam in 2015 and 2016, while sandy in 2017. It also means that increasing soil water content and nitrogen in the sandy clay loam field decreases the potato yield. The opposite phenomenon can be observed in sandy soil. These results may be due to the less drainability and the lower soil moisture tension in the sandy clay loam soil than the sandy soil.

Table 7. *Spearman's correlation coefficient of potato tuber yield and quality with soil properties*

Property	Year	Clay	Silt	Sand	Ɵv	N
Yield	2015	-0.10*	NS	NS	-0.19**	-0.56**
	2016	0.14**	-0.16**	NS	-0.27**	-0.23**
	2017	NS	NS	NS	NS	NS

Θ_V: The mean value of volumetric soil water content; N: The mean value of soil nitrate-nitrogen; NS, Not Significant. *, **: Significand at the 0.05, 0.01 probability levels, respectively

The earlier studies confirmed the mentioned results. Saini (1976) studied the physical parameters of different soils and discovered the high correlation between the oxygen diffusion rate (ODR) and potato yield. Holder and Cary (1984) extracted a significant relation between oxygen diffusion rate (ODR) and soil moisture tension (matric potential) at the 30 and 40 cm depths. These results indicated that carried out irrigation might be excessive for potatoes in a sandy clay loam field.

Partial Least Squares Regression (PLSR)

Table 8 showed the parameters of partial least squares regression model in each year. Obviously, R^2 of the regression model in 2017 was very small, almost 0, which means that this model can hardly explain the variation of yield; R^2 in 2015 and 2016 was 0.24 and 0.25, respectively, indicating that these five factors can explain 24-25% of the yield variation. The distinction in prediction ability may be due to the difference in correlation between soil properties and potato yield in different years. MSE in the three years were relatively large, ranged from 0.08 to 0.19.

Table 8. *Parameters of partial least squares regression (PLSR) model in each year*

Year	Regression coefficients					R^2	MSE
	Clay	Silt	Sand	Ɵv	N		
2015	-0.01	0.02	0.01	-0.03	-0.13	0.24	0.19
2016	0.04	-0.02	0.01	-0.02	-0.03	0.25	0.08
2017	0.01	0.01	-0.01	0.01	-0.01	0.03	0.13

Θ_V: The mean value of volumetric soil water content; N: The mean value of soil nitrate-nitrogen; R^2: The determination coefficient of model; MSE: Mean square error of model

It can′t be ignored that the absolute values of regression coefficients of most variables were minimal in this study. It means that the independent contribution of each factor to

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yield variation was very small. Similar results had been reported in previous studies (Kitchen et al., 2003; Taylor et al., 2018; Boubou Diallo et al., 2019). These studies were carried out in the field. Although PLSR can deal with cases when the explanatory variables are strongly correlated. However, due to the complexity of the field, lower model accuracy had been obtained.

There is a puzzling question: can soil properties really explain only a small part of the spatial variation of yield? Where does the variation of yield come from? We believed that the contribution of soil factors to yield variation is underestimated due to inappropriate analysis methods.

Spectrum similarity analysis

Table 9 shows the spectrum similarity of potato yield and soil properties. In 2015, S of clay was 0.38, indicating that it has a more significant negative effect on production distribution than the positive effect. The positive effect is that the yield with higher clay content is high, and the opposite result can be deduced under the opposite conditions. The positive effect is due to clay particles' larger specific surface area, which is beneficial to water holding and nutrient adsorption capacities. The meaning of negative effect is that the yield with higher clay content is low. The negative effect could be due to poor soil aeration caused by higher water and nutrients, as reported by other studies (Saini, 1976; Ferreira et al., 2017). In 2016 and 2017, S of clay was 0.56 and 0.54 respectively, indicating that the positive effect increased compared with 2015.

Table 9. *Spectrum similarity of potato tuber yield and soil properties*

Year	Index	Clay	Silt	Sand	Θv	N
2015		0.38	0.42	0.52	0.37	0.31
2016	S	0.56	0.44	0.56	0.38	0.48
2017		0.54	0.62	0.44	0.54	0.49

S: Similarity ratio of phase in all-frequency band; Θ_v: The mean value of volumetric soil water content; N: The mean value of soil nitrate-nitrogen

In 2015 and 2016, S of silt was 0.42 and 0.44, respectively, indicating that silt has a more significant negative effect on production distribution than the positive effect. The negative effect is also due to poor soil aeration caused by sufficient water supply capacity of silt. Silt is mainly derived from arsenic sandstone in this study, whose main component is Montmorillonite. If montmorillonite encounters water, it will swell rapidly, while the soil aeration will decrease. On the contrary, the positive effect is due to the sufficient water supply of Montmorillonite. However, the negative effect decreased in 2017 (S of silt was 0.62). Unlike the silt, sand had a more significant positive effect on the distribution of production than the negative effect in 2015 and 2016 (S of sand was 0.52 and 0.56). The positive effect could be due to significant soil aeration while the negative effect could be due to poor soil water and nutrient supply. The positive effect decreased in 2017 (S of sand was 0.44).

In 2017, compared with 2015, the positive effects of clay and silt on the spatial distribution of tuber yield were increased by 16% and 20%, respectively, while the positive effects of sand were decreased by 8%. It indicates the more significant negative effect of the sand on the production distribution due to increasing the soil sand content.

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Soil aeration meets the potato growth requirements, while the water holding capacity and nutrient supply were insufficient due to the decline of clay and silt.

The S value of soil moisture content was 0.37 and 0.38 in the first two years, indicating that about 70% of the frequency band in the water spectrum has a negative effect on the yield's spatial distribution. Sufficient water causes the positive effect, while the negative effect is due to inappropriate soil aeration. In 2017, S of soil moisture content was 0.54, 17% higher than that in 2015, demonstrating the improvement in the positive effect of soil moisture content. The results reflected an unreasonable irrigation schedule in 2015 and 2016, while the irrigation amount was too much for potatoes and affected the soil aeration. Based on the previous studies, there is a parabolic relationship between potato yield and soil moisture; that is, the yield rises and then declines with the increase of moisture (Fabeiro et al., 2001). In 2017, the sand content was increased to 90%, improving the soil aeration and reducing the water holding capacity. Therefore, although the irrigation schedule has not been adjusted, the adverse effects of excessive irrigation have been reduced due to soil texture variations.

In 2015, the S value of soil nitrate-nitrogen was 0.31. The results about 70% of the frequency band had adverse effects on the yield's spatial distribution. In 2016 and 2017, S of soil nitrate-nitrogen was 0.48 and 0.49, and about 13% higher than that in 2015, indicating the increase in the positive effect of soil nitrate-nitrogen. The positive effect may be due to the sufficient nitrogen, while the negative effect may be due to the decrease of nutrient absorption caused by the unreasonable concentration of the root zone solution.

Generally, the results represented by the S value were compatible with the correlation analysis results, indicating the effectiveness of the similarity indices (S). Although some valuable results were obtained from spectral similarity analysis, due to the interdependence of the soil factors, it is not easy to explain whether the low yield is caused by soil texture, moisture, or nitrogen through spectrum similarity.

Contribution rate and spatial distribution of yield components

Figure 8 shows average of the contribution rate among three years and spatial distribution of eight components of yield spatial variability for different transmission paths. The contribution rate in different years were shown in *Table 10*.

It can be seen that soil texture components in this field caused 49% of yield variation. Among them, 16% was directly affected by soil texture components, represented by the sand component, and the other 33% was indirectly affected by soil texture components interacted with moisture (8%), nitrate-nitrogen (21%), and moisture and nitrate-nitrogen (3%), expressed by sand-water, sand-N, and sand-water-N components, respectively. Among them, the contribution rate of “sand only” and “sand-water” changed greatly with time. The contribution rate of “sand only” decreased from 0.20 to 0.08. This may be due to the improvement of sand content uniformity (CV decreased from 0.21 to 0.03). The contribution rate of “sand-N” was always low, about 0.03, while the contribution rate of “sand-water-N” was high, stable at about 0.21. This shows that these three factors mostly affect each other. This also conforms to the objective facts of agricultural research.

Based on the results, soil texture plays a crucial role in the spatial variability of potato yield in this field, especially in the first two years. Some researchers also indicated that soil texture is essential for potato variability (Cambouris et al., 2006). Therefore, improving soil texture or delineating the management zone according to soil texture was the most effective way to improve the potato yield variation in this area.

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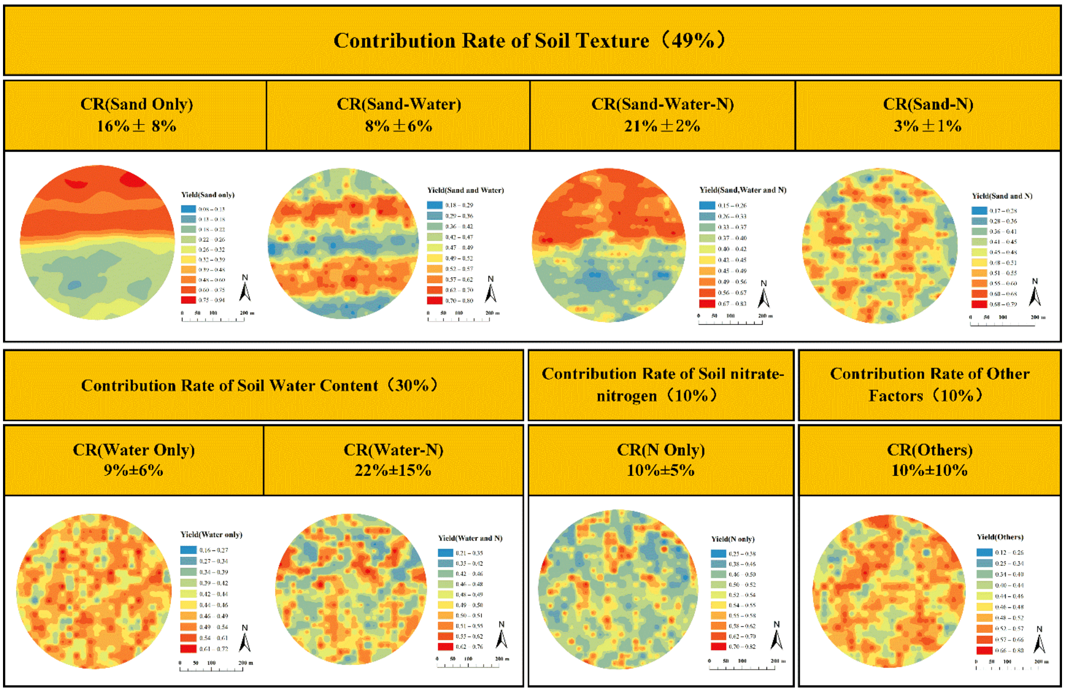

Figure 8. *Contribution rate and spatial distribution of eight components of yield spatial variability*

Table 10. *Contribution rate of eight components of yield spatial variability in different years*

Year	Sand Only	Water Only	N only	Sand and Water	Sand and N	Water and N	Sand, Water and N	Others
2015	0.20	0.03	0.09	0.02	0.03	0.36	0.21	0.05
2016	0.21	0.08	0.08	0.13	0.03	0.22	0.20	0.06
2017	0.08	0.15	0.15	0.08	0.04	0.07	0.23	0.20

The contribution rate of soil moisture content was 30%, reflecting that the soil water distribution was mainly affected by the distribution of irrigation amount, influencing 30% of the yield variation. Among them, 9% was independently affected by soil water content, while the other 22% affected the yield distribution by interacted with soil nitrate-nitrogen. Among them, the independent contribution of water increased year by year, while the contribution of “water-N” decreased year by year. This may be due to the weakening of the correlation between soil moisture and nitrate-nitrogen with the increase of soil sand content. The results reflected that the moisture distribution determined by irrigation could significantly affect the yield variation and soil texture components. Therefore, the yield variation can be reduced by improving irrigation uniformity. Another study showed that irrigation uniformity is also one of the influencing factors in yield variation (Or and Hanks, 1992).

The contribution rate of soil nitrate-nitrogen was only 10%, which means that its distribution, mainly affected by fertilization distribution, affected 10% of yield variation. Based on the previous analysis, the soil nitrogen distribution determined by soil texture components and soil water content, represented by the sum of sand-N component, water-N component, and sand-water-N component, affected 46% of yield variation. The results

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showed that soil nitrate-nitrogen distribution determined by fertilization has not a considerable effect on the yield variation. Therefore, it is not reasonable to reduce yield variation by improving fertilization uniformity.

The contribution rate of other factors or random factors to yield increased from 0.05 to 0.20. This may also be related to the decline of soil particle variation. According to the results, soil texture components, soil moisture content, and nitrate-nitrogen can explain about 80% of potato yield variation in this area, while the proportion of other factors or random variation is less than 20%. In general, the factors were ranked as soil texture components, soil water content, and nitrate-nitrogen, in descending order in terms of their contribution rates.

Discussion

Although geostatistical analysis showed that soil moisture content has a similar semi-variance model with potato yield, it was still difficult to estimate the contribution rate of water to the yield map. The results of correlation analysis showed that there is a significant negative correlation between soil moisture and yield in 2015 and 2016, and the spectral similarity analysis also showed that the impact of soil moisture on yield is mainly negative. However, the contribution rate of soil moisture content to yield has been calculated to be 39% through filtering after Fourier transform. It has been divided into three categories. 8% was the contribution of water distribution affected by soil sand content, 9% was the contribution of water distribution affected directly by irrigation distribution, and 22% was the contribution of water distribution affected by irrigation distribution and nitrate nitrogen interacted.

According to the Fourier transform-based spatial variation analysis method, about 80% of yield variation could be explained and 49% of yield variation affected by soil sand content. It was different from the results obtained through the correlation analysis, which showed that insignificant correlation could be obtained between sand and yield. Hence, the actual contribution of the texture may have been underestimated. Due to the interdependency among soil factors, the indirect effect of texture on the spatial distribution of yield could not be identified in correlation analysis and spectral similarity analysis. It was not easy to separate the influencing factors in the 1D or 2D spatial domain. Thus, soil properties had a low degree of explanation for crop variation in the literature (Kitchen et al., 2003).

In recent five years, the application of remote sensing, UAV technology and machine learning in precision agriculture has been extensively studied (Maes and Steppe, 2019; Sharma et al., 2020; Cisternas et al., 2020). The prediction accuracy of crop yield is gradually improved through data driven model or knowledge driven model. However, these studies can predict the average level of crop yield on a large scale. On a small scale, the spatial pattern of crop yield cannot be predicted, which is necessary for effective site-specific management. Trevisan et al. (2021) reported that On-farm precision experimentation can be a valuable tool for the estimation of in-field variation of optimal input rates and thus improve agronomic decisions. It pointed that it’s necessary to encourage more research on response-based input management recommendations instead of the still widespread focus on yield-based algorithms.

In this study, the contribution of multiple factors to yield spatial variation could be decomposed, and yield variation could be understood more clearly than geostatistics and correlation analysis. This method can be used to supplement the limitations of

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geostatistics. Although the spatial variation analysis method based on Fourier transform has been considered to be useful, there are some problems that need to be studied. More appropriate spectral similarity indexes and filtering methods can be tried in future research. In addition, the transmission structure of yield variation in this study only included five soil factors and three arrangements. When the number of arrangements and soil variables increases, it is still necessary to study the establishment of transmission model.

Conclusion

In this study, the spatial pattern of potato yield and soil properties has been evaluated by statistics and geostatistics; the driving factors of the spatial variability of potato yield has been analyzed by correlation analysis, partial least squares regression (PLSR) and the Fourier transform-based spatial variation analysis method. Some conclusions can be drawn.

Potato yield had substantial spatial variability, which decreased from 2015 to 2017 in the field. Similar phenomena can also be found in soil silt, clay and water content, and their coefficient of variation decreased year by year. According to geostatistics, tuber yield showed moderate and non-consistent spatial dependence among three years. Compared with other soil factors, soil moisture content and potato yield had more similar spatial structure, with similar semi-variance model and parameters.

Although significant correlation relationships were extracted among soil features and tuber yield, a smaller correlation coefficient (ranged from -0.56 to 0.14) could be obtained. And significance changed remarkably in various seasons. Similarity indices (S) has been used to explore the relationship between soil and yield. The results represented by the S value were compatible with the correlation analysis results. The negative correlation between soil moisture content and yield has been found in the first two years according to the above methods.

According to partial least squares regression (PLSR), soil properties can only explain 24%, 25%, 3% of the potato yield variation in 2015, 2016, 2017. However, according to the Fourier transform-based spatial variation analysis, soil texture components, soil moisture content, soil nitrate-nitrogen, and other factors explained 49%, 30%, 10%, and 10% of potato yield variation, respectively. The research results indicated the importance of improving the uniformity of texture and soil moisture content or delineating the management zone according to soil texture. In mixed soils, improving soil texture may help to reduce yield variability, thereby increasing economic benefits for farm managers.

The proposed method can be employed for analyzing the source of crop spatial variation in the frequency domain. Although it can separate the influencing factors and restore the transmission process of variation, it still requires further experimental verification, and the judgment criteria of similar frequency bands should be further studied.

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