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Partial Least Squares Regression for Determining Factors Controlling Winter Wheat Yield

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ABSTRACT

Wheat (*Triticum aestivum* L.) yield is influenced by many independent factors including precipitation, fertilization, soil nutrients, and crop variety. Due to high correlations of these factors, it is difficult to analyze their relative importance on wheat yield. This study quantified the effects of independent factors on wheat yield and identified the most important control factors through a long-term experiment on the Loess Plateau, China. The experiment consisted of 17 treatments, including five different levels of N and P fertilizer. Partial least squares regression (PLSR) was used to evaluate the factors on wheat yield in four variety groups- Qinmai4 (1985–1986), Changwu131 (1987–1996), Changwu134 (1997–2015), and 31-yr planting across the three varieties (1985–2015). Variable importance in projection (VIP) value revealed that N fertilizer had the greatest effect on wheat yield in all four groups (VIP = 1.266–2.313). The second most important factors were climate factors for Qinmai4 (VIP = 1.060), precipitation (February, annual, and fallow season) for Changwu131 (W_1 = 0.335–0.351, VIP = 1.381–1.474), and soil nutrients (total nitrogen [TN], soil organic matter [SOM], and available potassium [AK]) for Changwu134 (W_1 = −0.231–0.514, VIP = 1.084–2.317). When tested across varieties, TN and SOM were the second most important factors for 31-yr planting (W_2 = 0.455 and 0.313; VIP = 1.908 and 1.370, respectively). These results indicate that PLSR can reveal the control factors on wheat yield in the study area and provide a reference tool for analyses in other crops or areas.

Core Ideas

- Importance of factors on wheat yield was tested by partial least squares regression.
- Nitrogen fertilizer was the most important factor on wheat yield in all four groups.
- Climate factors, precipitation, and soil nutrients were also major control factors.
- Partial least squares regression is a useful tool to reveal the control factors on wheat yield.

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To meet growing demand for food and feed, global food production is expected to increase by 60 to 110% between 2005 and 2050 (Pradhan et al., 2015). Wheat is the third most-produced cereal crop in the world, and therefore improving its yield may be important in dealing with the increase in global population and decrease in arable land resources (Lu and Fan, 2013; Tilman et al., 2011). Wheat yield is influenced by various factors such as climate conditions, soil properties, crop variety, and field management (Hu et al., 2016). Assessing the relative importance of different factors on wheat yield is essential for sustainable agriculture.

Wheat yield increases can be attributed to a combination of precipitation, temperature, variety, fertilizer, planting duration, and other management practices (Carew et al., 2009; Chen et al., 2015). Wheat yield responses have been related to the interaction between water and N, in which higher uptake of N is critical for capturing the benefits of additional summer water (Sadras et al., 2012). Temperature, especially accumulated temperature, has been shown to impact crop growth, including the phenological development of wheat (Salazar-Gutierrez et al., 2013). A study found that two durum wheat varieties produced different grain yields at the Tal Amara Research Station in the central Bekaa Valley of Lebanon under rain-fed conditions; however, the effect of variety on yield was less than those of irrigation and N (Karam et al., 2009). Yang et al. (2011) found that soil organic C and wheat yields significantly increased under long-term fertilization

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Abbreviations: AK, available potassium; AP, available phosphorus; AnP, annual precipitation; C_1, Changwu131; C_4, Changwu134; FSP, fallow-season precipitation; GDD, growing degree days; GSP, growing-season precipitation; P_1, January precipitation; P_2, February precipitation; P_3, March precipitation; P_4, April precipitation; P_5, May precipitation; P_6, June precipitation; P_7, July precipitation; P_8, August precipitation; P_9, September precipitation; P_{10}, October precipitation; P_{11}, November precipitation; P_{12}, December precipitation; P_2O_5, phosphorus pentoxide; PLSR, partial least squares regression; Q_4, Qinmai4; RC, regression coefficient; Rs, total radiation solar; R_{max}, astronomical solar radiation; SOM, soil organic matter; TN, total nitrogen; TP, total phosphorus; VIF, variance inflation factor; VIP, variable importance in projection.

with chemical fertilizers (N, P, and K) with or without manure. Owing to the high correlations of different factors, it remains difficult to identify the most important control factors affecting wheat yield and assess their relative long-term contributions.

Many researchers approach this problem using single-correlation analyses or multiple regressions with stepwise-selection techniques between wheat yield and its control factors (Carew et al., 2009). Kraaijvanger and Veldkamp. (2015) found that with management practice, altitude, and N fertilizer as inputs, a linear regression model explained 56% of the total variance on wheat grain yields of 16 selected farmer groups of wheat in Tigray, northern Ethiopia. Awan et al. (2015) used a multivariate analysis to determine characteristics for grain yield selection in wheat. A canonical correlation analysis was used by Qian et al. (2009) to describe the joint variability of water-related indices associated with regional spring wheat yields. These studies enable researchers to understand the complex ways in which climate, soil, and management influence wheat yield. However, these statistical approaches face difficulties when control factors are highly correlated, as this can result in redundancy (Fang et al., 2015). Therefore, caution must be taken in the analysis of control factors on wheat yield, particularly when establishing relationships between wheat yield and its control factors using the above metrics (Nuttall et al., 2003).

Using techniques based on multivariate statistical projections can overcome the limitations of traditional multivariate regression approaches when presented with multi-collinear and noisy data (Shi et al., 2013). An example is PLSR, which combines and generalizes features from principal component analysis and multiple linear regression (Abdi, 2010). The PLSR was used to analyze chemical data in the early 1980s, and its use has increased since then (Carrascal et al., 2009). Zhang et al. (2015) found that PLSR can provide an unbiased view of the relationship between the predictors and the response variables. However, the use of PLSR in the study of crop yields has mostly been restricted to predicting the effects of leaf area index and wavelength on the growth of winter wheat (Li et al., 2016; Sharabian et al., 2014). It is unclear whether PLSR can be used to quantify the relative importance of other factors including climate conditions, soil properties, crop variety, and field management on wheat yield.

The semiarid Loess Plateau is a large rain-fed region in China, where crop yields are mainly controlled by precipitation and fertilizer, and to a lesser extent by field management, soil properties, and crop variety (Fan et al., 2005; Guo et al., 2012; Liu et al., 2013). On the basis of previous studies, further research is needed to quantify the exact contributions of these factors to wheat yield in this region. Using PLSR to evaluate the control factors on wheat yield can eliminate the colinearity between independent variables and therefore accurately quantify the relationship between independent and dependent variables.

In this study, we evaluated the effects of climate, fertilizer, soil nutrients, and crop variety on winter wheat yield by examining their relative importance in a long-term experiment on the Loess Plateau, China. The objectives of this study were to quantify the effects of different factors and identify the most important control factors affecting winter wheat yield. Addressing these objectives will improve the understanding of how different factors affect wheat yield and help select appropriate variables to predict the yield in a semiarid region.

MATERIALS AND METHODS

Experimental Site and Design

The long-term experiment started in September 1984 at the Key State Agro-ecological Experimental Station in Changwu County, Shaanxi Province, China (35°12′ N, 107°40′ E; 1220 m a.s.l.), in the southern part of the Loess Plateau (Wei et al., 2006). Based on climate data from 1984 to 2015, annual mean precipitation at the site is 574.6 mm, annual mean fallow season precipitation (July–September) is 310.8 mm, and annual mean temperature is 9.5°C. Records indicate that the experimental site has been cultivated with winter wheat for several centuries. The soil is classified as an aridic and loamy Cumulic Haplustoll (Heilu soil in the Chinese taxonomic system) developed from loessial deposits (Wei et al., 2006). The surface soil (0–20 cm) at the start of the experiment in 1984 contained 24% clay (<0.002 mm), 13.0 cmol kg^{-1} cation exchange capacity (CEC), 10.5 g kg^{-1} SOM, 0.8 g kg^{-1} TN, 37 mg kg^{-1} alkaline dissolved N, 0.7 g kg^{-1} total phosphorus (TP), 3.0 mg kg^{-1} available phosphorus (AP), and 129.3 mg kg^{-1} available potassium (AK). The surface soil had a pH of 8.3, and electrical conductivity of 110 µs cm^{-1}. In September 2014 before sowing, the soil pH reached 8.25 to 8.38, with 11.29 to 14.01 g kg^{-1} SOM, 0.85–1.04 g kg^{-1} TN, 4.14–43.02 mg kg^{-1} AP, and 123.17 to 158.15 mg kg^{-1} AK in the 17 different treatments. These physicochemical properties were analyzed using standard soil testing procedures (Bao, 2000).

The effects of fertilizers on winter wheat yield were tested in the long-term experiment consisting of 17 different treatments, including five levels of N (urea, 46% N) and P (calcium triple superphosphate, 46% phosphorus pentoxide (P_2O_5); Table 1) in different combinations. Experimental plots (5.5 by 4.0 m) were arranged at random in a complete block design, with three replicates. Fertilizers were broadcast on the soil surface as a basal dressing and plowed into the top 20 cm of soil in mid-September each year. Varieties of winter wheat changed over time. Here

Table 1. Fertilizer levels in the long-term experiment.

Treatment†	N	P_2O_5
	kg ha^{-1}	
CK	0	0
P_{90}	0	90
P_{180}	0	180
$N_{45}P_{45}$	45	45
$N_{45}P_{90}$	45	90
$N_{45}P_{135}$	45	135
N_{90}	90	0
$N_{90}P_{45}$	90	45
$N_{90}P_{90}$	90	90
$N_{90}P_{135}$	90	135
$N_{90}P_{180}$	90	180
$N_{135}P_{45}$	135	45
$N_{135}P_{90}$	135	90
$N_{135}P_{135}$	135	135
N_{180}	180	0
$N_{180}P_{90}$	180	90
$N_{180}P_{180}$	180	180

† CK: unfertilized control; P_n: application of *n* kg ha^{-1} P_2O_5; N_m: application of *m* kg ha^{-1} N; and N_mP_n: application of *m* kg ha^{-1} N plus *n* kg ha^{-1} P_2O_5.

we selected three varieties that have been widely planted in the area historically: Qinmai4 (Q_4) in 1984 and 1985 (sowing time), Changwu131 (C_1) in 1986 to 1995 (sowing time), and Changwu134 (C_4) in 1996 to 2014 (sowing time). A fourth group was formed by a combination of Q_4, C_1, and C_4, namely 31-yr planting across the three varieties. The plots were harrowed, and winter wheat was sown at 180 kg seeds ha^{-1}, with 20-cm intervals between rows. Sowing took place in late September each year and the crop was harvested in half of each plot (11 m^2) by hand at the end of the following June. The plots were not irrigated and were plowed to a depth of 20 cm in July. The field was then left fallow from July to September to store water for the next sowing. Crop cultivation and field management, including pest and weed control, followed local farming practices.

Wheat was harvested each year from the central half of each plot when the aboveground biomass reached physiological maturity in July. The grains were oven-dried at 60°C for 48 h and then weighed for dry weight (precision: 0.01 g).

Data Collection and Processing

Climate data were obtained from the Changwu Meteorological Station, approximately 2 km from the experimental site. Precipitation in the experimental site was classified as growing-season precipitation (GSP), fallow-season precipitation (FSP), and annual precipitation (AnP) based on the winter wheat growing season. The GSP falls during the crop season from October to the following June. The FSP falls between successive crops from July to September. The AnP is the sum of GSP and FSP. Growing degree days (GDD) was calculated with accumulated daily mean temperature above 0°C during the wheat growing period (Fan et al., 2015). Total radiation solar (Rs) was calculated according to the Angstrom empirical equation (Angstrom, 1924):

$$\mathrm{Rs} = \mathrm{R}_{max} (a_s + b_s \times n/n') \qquad [1]$$

where Rs is the total radiation solar (MJ m^{-2}), R_{max} is the astronomical solar radiation (MJ m^{-2}), a_s and b_s are empirical coefficients, given by the FAO as $a_s = 0.25$ and $b_s = 0.50$ for the Loess plateau, n is the duration of sunshine hours according to the meteorological station, and n' is the number of hours between sunrise and sunset, which is longitude and latitude dependent.

Prior to analysis, variety as a categorical variable was converted to a "dummy" variable, namely a numerical variable that usually represents a binary categorical variable. In the experiment, there were three varieties, Q_4, C_1, and C_4. Here we used "1" for Q_4 and "0" for the other varieties in 1985–1986 (harvesting time), "1" for C_1 and "0" for the other varieties in 1987 to 1996 (harvesting time), and "1" for C_4 and "0" for the other varieties in 1997 to 2015 (harvesting time).

Partial Least Squares Regression Analysis

The PLSR is an extension of multiple regression analysis which evaluates the effects of linear combinations of several predictors on a response variable (Carrascal et al., 2009; Fang et al., 2015; Shi et al., 2013; Zhang et al., 2015). This technique can be used to determine the relationship between two sets of variables, the matrix $Xm \times n$, which consists of m variables (columns) and n objects (rows), and a response vector $Yn \times 1$.

The PLSR identifies a few linear combinations of the original x values that describe most of the inherent variable. Here PLSR was conducted using wheat yields for Q_4, C_1, C_4, and 31-yr planting across the three varieties as the dependent variables, and fertilizer, climate factors, and soil nutrients as the independent variables. In this study, we performed PLSR analysis according to Shi et al. (2013).

Cross-validation was used to determine the number of significant PLSR components and computed using

$$Q^2 = 1.0 - \mathrm{PRESS/SS} \qquad [2]$$

$$Q^2_{cum} = 1.0 - \mathrm{p}\ (\mathrm{PRESS/SS})_a \ (a = 1, 2 \ldots m) \qquad [3]$$

where Q^2 is the fraction of the total variation in the dependent variables that can be predicted by the component, Q^2_{cum} is the cumulative Q^2 over all the selected PLSR components, PRESS is the prediction error sum-of-squares, SS is the residual sum of squares, and m is the number of PLSR components. The model exhibits good predictive ability when Q^2_{cum} is greater than 0.5. Not all variables need to be included in a PLSR model and redundant variables can lead to PLSR models with low statistical significance. To obtain an optimal model, a simulation was performed using the PLSR model with all predictor variables, followed by a series of simulations in which PLSR analyses were performed, each with a variable eliminated. The PLSR model exhibiting the largest Q^2_{cum} was selected as the optimal PLSR model.

Root mean square error of prediction (RMSEP) was calculated to provide useful information for calibrating and developing the regression model, using the following equation:

$$\mathrm{RMSEP} = \sqrt{\frac{\sum_{i=1}^{n} (y_{i,\mathrm{predicted}} - y_{i,\mathrm{measured}})^2}{n}} \qquad [4]$$

where n is the total number of data, and $y_{i,\mathrm{predicted}}$ and $y_{i,\mathrm{measured}}$ and represent the simulated and measured values, respectively.

The relationship between wheat yield and its control factors was inferred from the weight and the regression coefficient (RC) of individual factors in the group comprising the most explanatory components (Carrascal et al., 2009; Fang et al., 2015; Shi et al., 2013; Zhang et al., 2015).

The variable importance in projection (VIP) was calculated to quantify the importance of a predictor for the independent variables according to Mehmood et al. (2012):

$$\mathrm{VIP}_j = \sqrt{p \sum_{a=1}^{m} \frac{SS_a (w_{aj} / \|w_a\|)^2}{\sum_{a=1}^{m} SS_a}} \qquad [5]$$

where p is the number of variables, SS_a is the sum of squares explained by the ath component. Hence, the weight of VIP_j is a measure of the contribution of each variable according to the variance explained by each PLSR component where $(w_{aj} / \|w_a\|)^2$ represents the importance of the j-th variable. Higher VIP values correspond to greater relevance for the dependent variable. Factors with VIP > 1 are considered to be important predictors, whereas those with VIP < 1 are of minor importance (Onderka et al., 2012).

The coefficient of variation (CV) was calculated using (Chloupek et al., 2004):

$$\mathrm{CV}\ (\%) = 100 \times \mathrm{SD/Mean} \qquad [6]$$

where SD is the standard deviation, and Mean is the average value of each variable used in the PLSR model, for example, wheat yield, AnP, FSP, and so on. CV > 100% indicates high variation, 10% < CV < 100% indicates moderate variation, and CV < 10% indicates low variation (Wang et al., 2016).

Data were analyzed using SIMCA-P Demo 11.5 (Umetrics, Malmö, Sweden) and SPSS 18.0 (SPSS Inc., Chicago, IL).

RESULTS

Multi-Collinearity Diagnosis between Precipitation and Wheat Yield

In the multi-collinearity diagnosis, significant collinearity was found between precipitation and wheat yield. The correlation coefficients showed zero tolerance for AnP, GSP, and FSP in most cases. For variety Q_4, the tolerance was zero for all of the variables. For variety C_1, the variance inflation factor (VIF) value was highest for P_9 (17.348), followed by FSP (13.907), P_3 (9.013), and P_5 (5.232); VIFs ranged from 1 to 5 for the other variables. For the variety C_4 and 31-yr planting, VIFs for all of the variables ranged between 1 and 5 (Table 2).

Wheat Yield and Relevant Factors for Four Groups

Statistics for wheat yields and relevant factors for 1985 to 2015 are shown in Table 3. The yield was highest for variety Q_4 (3542.8 kg ha^{-1}), followed by C_4 (3100.8 kg ha^{-1}) and 31-yr planting across all varieties (2906.8 kg ha^{-1}); the variety C_1 produced the lowest yield (2411.1 kg ha^{-1}). The CV of the yield was moderate in the four groups, ranging from 37.31% (Q_4) to 55.77% (C_1).

With regard to climate factors, both AnP and FSP were highest for variety C_4 (593.08 and 332.7 mm, respectively), and the lowest levels were found for variety C_1 (537.03 and 271.13 mm, respectively). These two factors had moderate CVs in the four groups, being lowest for Q_4 (14.8 and 26.02%) and highest for C_1 (24.55 and 41.62%). The GSP ranged from 260.38 mm (C_4) to 285.25 mm (Q_4), with a low to moderate CV (2.94–22.68%). Monthly precipitation was generally high in June, July, August, and September, while low levels were found in December, January, and February. The CVs of monthly precipitation were high in November, December, and January (62.07–107.06%) and low to moderate in other months (3.10–77.81%). The CV of GDD and Rs were less than 10% in the four groups.

With regard to fertilizers, the mean N and P_2O_5 were 90 kg ha^{-1} for all of the four groups, with a moderate CV of 66.44 to 66.75%. As for soil total nutrients, the highest TN and SOM were found for variety C_4 (0.88 and 11.65 g kg^{-1}, respectively); both factors were lowest for variety Q_4 (0.8 and 10.25 g kg^{-1}, respectively). The CVs of TN and SOM were generally low in the four groups, that is, 3.14 to 9.01% and 4.99 to 12.55%, respectively. Regarding soil available nutrients, the highest AP and AK were found for variety C_4 (23.41 and 135.12 mg kg^{-1}, respectively), and both factors appeared to be the lowest for variety Q_4 (7.01 and 130.53 mg kg^{-1}, respectively). The AP had a moderate CV of 56.67 to 76.26%, while the CV of AK was less than 10% in the four groups.

Q^2_{cum} in the Partial Least Squares Regression Analysis

In the PLSR analysis, the prediction error decreased while Q^2_{cum} increased with an increasing number of components (Table 4). For variety Q_4, the maximum Q^2_{cum} was obtained with two components. The first two components cumulatively explained 83.4 and 94.3% of the total variance on the yield. For variety C_1, the maximum Q^2_{cum} was obtained with five

Table 2. Multi-collinearity diagnosis indexes for precipitation factors used in the analysis.

	Q_4 (1985–1986)		C_1 (1987–1996)		C_4 (1997–2015)		31-yr planting (1985–2015)	
Variable†	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
AnP	0	–	0	–	0	–	0.211	4.749
GSP	0	–	0	–	0	–	0	–
FSP	0	–	0.072	13.907	0	–	0	–
P_7	0	–	0	–	0.704	1.420	0.343	2.916
P_8	0	–	0	–	0.393	2.545	0	–
P_9	0	–	0.058	17.348	0.593	1.687	0.347	2.883
P_{10}	0	–	0.306	3.268	0.246	4.065	0.378	2.643
P_{11}	0	–	0	–	0.528	1.892	0.626	1.597
P_{12}	0	–	0	–	0.726	1.376	0.739	1.354
P_1	0	–	0.358	2.793	0.291	3.431	0.650	1.538
P_2	0	–	0.203	4.915	0.493	2.027	0.615	1.627
P_3	0	–	0.111	9.013	0.424	2.360	0.515	1.941
P_4	0	–	0.554	1.806	0.569	1.759	0.780	1.282
P_5	0	–	0.191	5.232	0.339	2.953	0.409	2.444
P_6	0	–	0.247	4.043	0.487	2.052	0.522	1.915

† Q_4: Qinmai4; C_1: Changwu131; C_4: Changwu134; VIF: Variance inflation factor; AnP: Annual precipitation; –: infinite; GSP: Growing-season precipitation; FSP Fallow-season precipitation; P_7: July precipitation; P_8: August precipitation; P_9: September precipitation; P_{10}: October precipitation; P_{11}: November precipitation; P_{12}: December precipitation; P_1: January precipitation; P_2: February precipitation; P_3: March precipitation; P_4: April precipitation; P_5: May precipitation; P_6: June precipitation.

Table 3. Basic statistics for selected variables.

Variable†	Units	Q_4 (1985–1986)			C_1 (1987–1996)			C_4 (1997–2015)			31-yr planting (1985–2015)		
		Range	Mean	CV %	Range	Mean	CV %	Range	Mean	CV %	Range	Mean	CV %
Yield	kg ha^{-1}	1575–6089.3	3542.8	37.31	341.3–6319.5	2411.1	55.77	425.3–8181.8	3100.8	47.87	341.25–8181.8	2906.8	50.71
AnP	mm	500.3–673.1	586.7	14.80	318.4–784.3	537.03	24.55	435.8–890.5	593.08	18.70	318.4–890.5	574.59	20.80
FSP	mm	223.4–379.5	301.45	26.02	140.2–516.2	271.13	41.62	152.4–608.8	332.7	30.55	140.2–608.8	310.82	34.70
GSP	mm	276.9–293.6	285.25	2.94	178.2–320.4	265.9	14.78	172.8–367.6	260.38	22.68	172.8–367.6	263.77	19.61
P_7	mm	50–91.5	70.75	29.47	18.2–202.4	96.7	54.15	15.3–225.6	114.03	46.51	15.3–225.6	105.65	49.93
P_8	mm	75–78.6	76.8	2.36	20.7–246.7	119.14	53.47	17.4–312	107.44	60.77	17.4–312	109.24	58.05
P_9	mm	98.4–209.4	153.9	36.24	4.2–100.4	55.29	52.24	26.6–217.5	111.23	47.08	4.2–217.5	95.94	57.48
P_{10}	mm	38.8–84.8	61.8	37.40	20.3–69.9	43.35	35.26	12.4–114.6	45.07	67.24	12.4–114.6	45.59	57.65
P_{11}	mm	0.3–12.8	6.55	95.89	0.5–36.7	16.67	62.07	0–70.4	18.22	101.57	0–70.4	16.96	94.08
P_{12}	mm	0.7–18.3	9.5	93.09	0–17.2	5.9	91.11	0–18.4	4.05	107.06	0–18.4	5	105.76
P_1	mm	0.9–4.3	2.6	65.71	0–17	6.8	78.78	0–28.2	8.11	91.20	0–28.2	7.33	91.35
P_2	mm	2.8–3.1	2.95	5.11	0.7–25.4	12.09	66.81	0–24.3	11.31	61.91	0–25.4	11.02	67.70
P_3	mm	11.1–27.1	19.1	42.09	8.7–53.6	33.06	42.23	1.7–41.5	19.85	53.52	1.7–53.6	24.06	54.92
P_4	mm	25.8–37.7	31.75	18.83	9–83.1	35.36	66.17	3.4–99.2	36.20	71.26	3.4–99.2	35.64	68.01
P_5	mm	14.9–117.1	66	77.81	8.9–89.3	44.09	58.51	3.5–130.4	53.53	58.38	3.5–130.4	51.29	62.12
P_6	mm	50.7–119.3	85	40.55	30.3–97.8	68.58	33.34	9.2–194.7	64.05	68.39	9.2–194.7	66.86	56.89
GDD	°C	1874.6–1918.9	1896.8	1.17	1839–2032.5	1956.8	3.44	1873.8–2164.7	2042.3	3.70	1839–2164.7	2005.3	4.28
Rs	MJ m^{-2}	3290.5–3830.7	3560.6	7.62	3331.6–3828.7	3560.3	4.75	3400.2–4036.5	3860.7	3.81	3290.5–4036.5	3744.4	5.89
N	kg ha^{-1}	0–180	90	66.75	0–180	90	66.49	0–180	90	66.46	0–180	90	66.44
P_2O_5	kg ha^{-1}	0–180	90	66.75	0–180	90	66.49	0–180	90	66.46	0–180	90	66.44
TN	g kg^{-1}	0.72–0.85	0.80	3.14	0.70–0.88	0.79	4.90	0.66–1.14	0.88	8.49	0.66–1.14	0.85	9.01
SOM	g kg^{-1}	8.52–11.01	10.25	4.99	8.52–11.63	10.00	5.91	9.26–15.5	11.65	11.86	8.52–15.5	11.03	12.55
AP	mg kg^{-1}	3–19.33	7.01	76.26	3.02–41.23	14.43	56.67	3.33–69.65	23.41	57.36	3–69.65	19.46	65.34
AK	mg kg^{-1}	123.16–140.55	130.53	2.84	123.16–144.95	132.45	3.31	112.65–171.75	135.12	7.88	112.65–171.75	133.96	6.63

† Q_4: Qinmai4; C_1: Changwu131; C_4: Changwu134; AnP: Annual precipitation; GSP: Growing-season precipitation; FSP Fallow-season precipitation; P_7: July precipitation; P_8: August precipitation; P_9: September precipitation; P_{10}: October precipitation; P_{11}: November precipitation; P_{12}: December precipitation; P_1: January precipitation; P_2: February precipitation; P_3: March precipitation; P_4: April precipitation; P_5: May precipitation; P_6: June precipitation; GDD: growing degree days; Rs: total radiation solar; P_2O_5: phosphorus pentoxide; ; TN: total nitrogen; SOM: soil organic matter; AP: available phosphorus; AK: available potassium.

components, which cumulatively explained 55.0 to 78.9% of the total variance on the yield. Adding the sixth component to the model did not substantially improve the description of the contributions to the variance. For variety C_4, the maximum Q^2_{cum} was obtained with four components, which cumulatively explained 62.7 to 71.3% of the total variance on the yield. When tested across varieties (31-yr planting), the maximum Q^2_{cum} was obtained with nine components, which cumulatively explained 43.5 to 65.1% of the total variance on yield. Adding more components to the PLSR model did not substantially improve the percentages of variance explained.

Weights in the Partial Least Squares Regression Analysis

The first two components explained much higher variance in wheat yield than the other components (Table 4). Thus, we illustrated the first two components of factors on the yield in Fig. 1. Precipitation appeared to be a major factor for the yield of varieties C_1 and C_4. For variety C_1, the first component was dominated by AnP, FSP, P_8, and P_2, with the weights of 0.351, 0.336, 0.318, and 0.335, respectively. For variety C_4, the weights of FSP, GSP, and P_8 reached −0.355, 0.307, and −0.458, respectively, in the second component. When tested across varieties (31-yr planting), the weight of GDD reached −0.359.

There was a general pattern that N fertilizer and TN generally dominated the yield, whether across or within varieties. For variety Q_4, the weights of these two N factors reached 0.751 and 0.471 in the second component, respectively. For variety C_1, the weights of N reached 0.618 in the second component, while TN reached 0.479 in the second component. For variety C_4, the weight of N reached 0.509 and 0.421 in the first two components, while TN reached 0.514 in the first component. When tested across varieties (31-yr planting), the weight of N reached 0.444 and 0.620 in the first two components, respectively, while TN reached 0.455 in the first component. Moreover, SOM dominated the yield within varieties C_1 and C_4, or across varieties in the 31-yr planting. For variety C_1, the weight of SOM reached 0.366 in the second component, and for variety C_4, reached 0.316 in the first component. When tested across varieties (31-yr planting), the weight of SOM reached 0.313 in the first component, and the weights of AK, Q_4, and C_4 reached −0.350, 0.369, and −0.308, respectively.

Variable Importance in Projection and Regression Coefficient in the Partial Least Squares Regression Analysis

Although the weights indicate how important individual factors are for the yield, variable importance in projections (VIPs) and regression coefficients (RCs) can provide a more convenient and comprehensive expression of the relative importance of the

Table 4. Summary of the partial least square regression (PLSR) model for wheat yield.

Group	R^2†	Q^2	Component	Percent of explained variability in *Y*	Cumulative explained variability in *Y*	RMSEP	Q^2_{cum}
				%	%	kg ha^{-1}	
Q_4 (1985–1986)	0.944	0.935	1	83.4	83.4	539.04	0.833
			2	10.9	94.3	316.13	0.937
			3	0.1	94.4	313.27	0.935
C_1 (1987–1996)	0.789	0.772	1	55.0	55.0	902.27	0.548
			2	15.1	70.1	735.08	0.697
			3	4.48	74.6	677.73	0.736
			4	2.91	77.5	637.74	0.761
			5	1.41	78.9	617.38	0.772
			6	0.39	79.3	611.61	0.77
C_4 (1997–2015)	0.714	0.706	1	62.7	62.7	897.37	0.626
			2	5.45	68.2	829.11	0.679
			3	2.16	70.4	800.40	0.698
			4	0.98	71.3	787.01	0.706
			5	0.26	71.6	783.39	0.705
31-yr planting (1985–2015)	0.651	0.639	1	43.5	43.5	1101.67	0.434
			2	16.0	59.6	932.15	0.594
			3	1.86	61.4	910.46	0.612
			4	1.19	62.6	896.32	0.622
			5	0.94	63.6	884.97	0.629
			6	0.70	64.3	876.46	0.635
			7	0.34	64.6	872.23	0.637
			8	0.25	64.9	869.11	0.638
			9	0.23	65.1	866.27	0.639
			10	0.07	65.1	865.41	0.638

† R^2: the fraction of the total variation of dependent variables explained by the optimal partial least square regression model; Q^2: the fraction of the total variation of dependent variables that can be predicted by the optimal partial least square regression model according to the cross-validation; RMSEP: root mean square error of prediction; Q^2_{cum}: the cumulative fraction of the variation of dependent variables that can be predicted by overall partial least square regression components according to the cross-validation; Q_4: Qinmai4; C_1: Changwu131; and C_4: Changwu134.

factors. Figures 2 and 3 show the VIPs and RCs for each factor in the yields of the individual varieties and across all varieties. The highest VIP was found for N (VIP = 1.266, RC = 0.234), followed by climate factors (VIP = 1.060, RC = −0.052); other factors had VIPs < 1 for variety Q_4.

For variety C_1, the highest VIP value was found for N (VIP = 1.56, RC = 0.344), followed by P_2, AnP, FSP, P_8, TN, P_7, P_1, P_{12}, Rs, and SOM (VIP > 1). For variety C_4, the VIP values for TN, N, SOM, AK, P_{Nov}, and P_2O_5 were greater than 1. When tested across all varieties (31-yr planting), the VIP values for N, TN, SOM, C_4, AnP, C_1, FSP, and Q_4 were greater than 1.

All factors within the individual varieties and across all varieties had different RCs, but only a subset had VIP > 1. Variables with VIP < 1 were of minor importance.

DISCUSSION

Wheat yield is influenced by precipitation, temperature, radiation, fertilization, soil properties, crop variety, and field management, among other factors (Basso et al., 2010, 2012; Diacono et al., 2012). The dryland region of China's Loess Plateau is an easily eroded area, where wheat yield is affected by even more factors (Li and Huang, 2008). In the present study, we used PLSR as an efficient tool to evaluate the relative importance of various factors on winter wheat yield in the semiarid Loess Plateau region.

The results of the correlation and multi-collinearity analyses showed that many factors were co-linear, particularly AnP, FSP, and GSP (Table 2). The variables with VIF > 10 (e.g., FSP and P_9) should be handled properly due to multi-collinearity, and the variables with VIF of 5 to 10 (e.g., P_3) had high correlations for C_1 (Akinwande et al., 2015). These factors were therefore automatically eliminated in the multivariate linear regression, and we were unable to determine the effects of these parameters on wheat yield. However, previous studies have shown that wheat yields are positively correlated with AnP in the semiarid Loess Plateau region and depend heavily on soil water stored from FSP in a continental monsoon climate (Fan et al., 2005; Guo et al., 2012; Liu et al., 2013). With regard to the monthly precipitation, P_9 provides favorable conditions for seed germination and thus affects wheat yield indirectly, whereas P_5 mainly plays a role in winter wheat yield at the heading and anthesis stages on the Loess Plateau, China (Huang et al., 2004). Since March is the turning green and erecting stages of

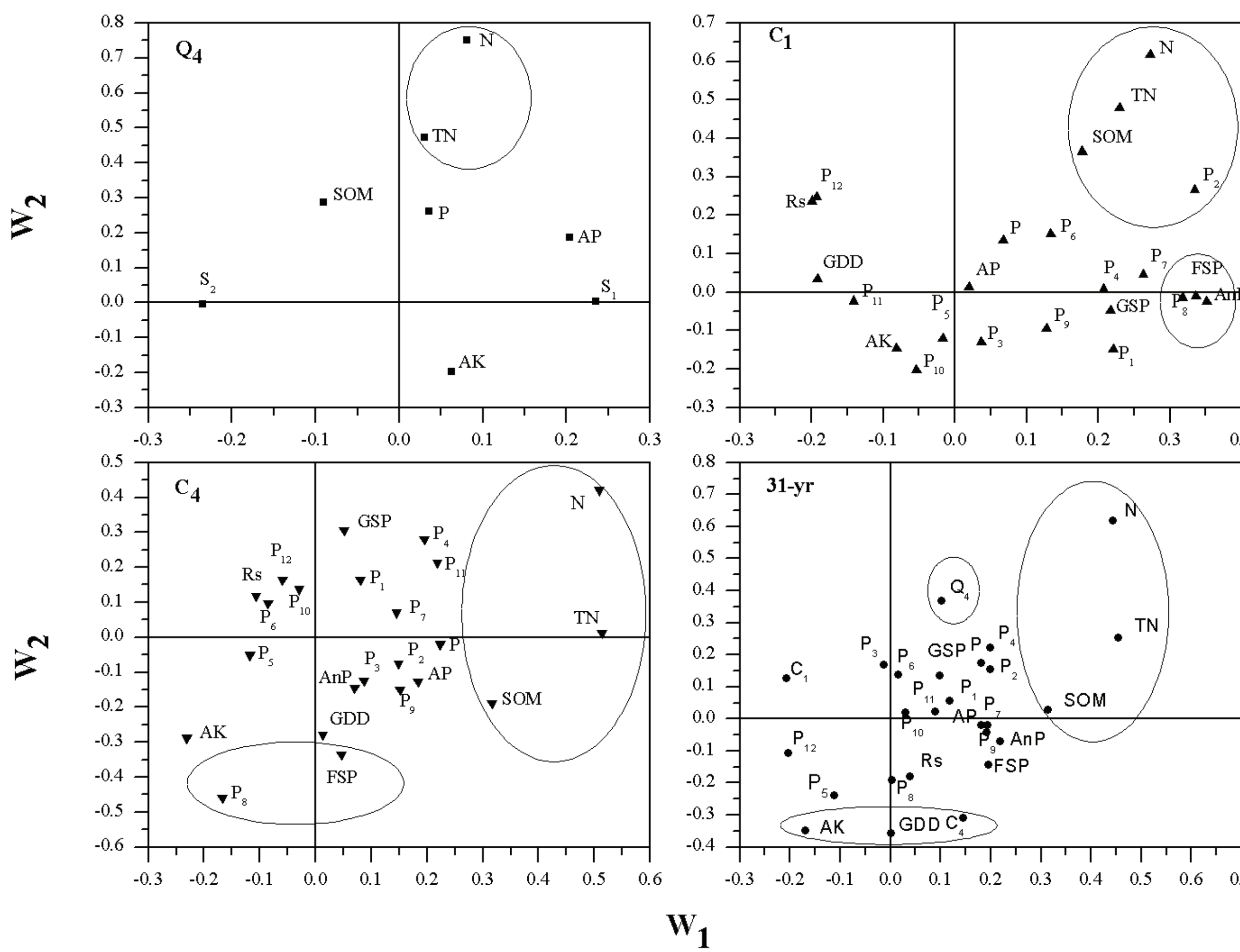

Fig. 1. Weight plot for the first and second principal components of wheat yield in four groups. AnP: Annual precipitation; FSP: fallow-season precipitation; GSP: growing-season precipitation; P_1: January precipitation; P_2: February precipitation; P_3: March precipitation; P_4: April precipitation; P_5: May precipitation; P_6:June precipitation; P_7: July precipitation; P_8: August precipitation; P_9: September precipitation; P_{10}: October precipitation; P_{11}: November precipitation; P_{12}: December precipitation; GDD: growing degree days; Rs: total radiation solar; P_2O_5: phosphorus pentoxide; TN: total nitrogen; SOM: soil organic matter; AP: available phosphorus; AK: available potassium; Q_4: Qinmai4; C_1: Changwu131; and C_4: Changwu134. S_1: P_2, P_3, P_6, and P_{10}; GDD; and Rs. S_2: P_1, P_4, P_5, P_7, P_8, P_9, P_{11}, and P_{12}.

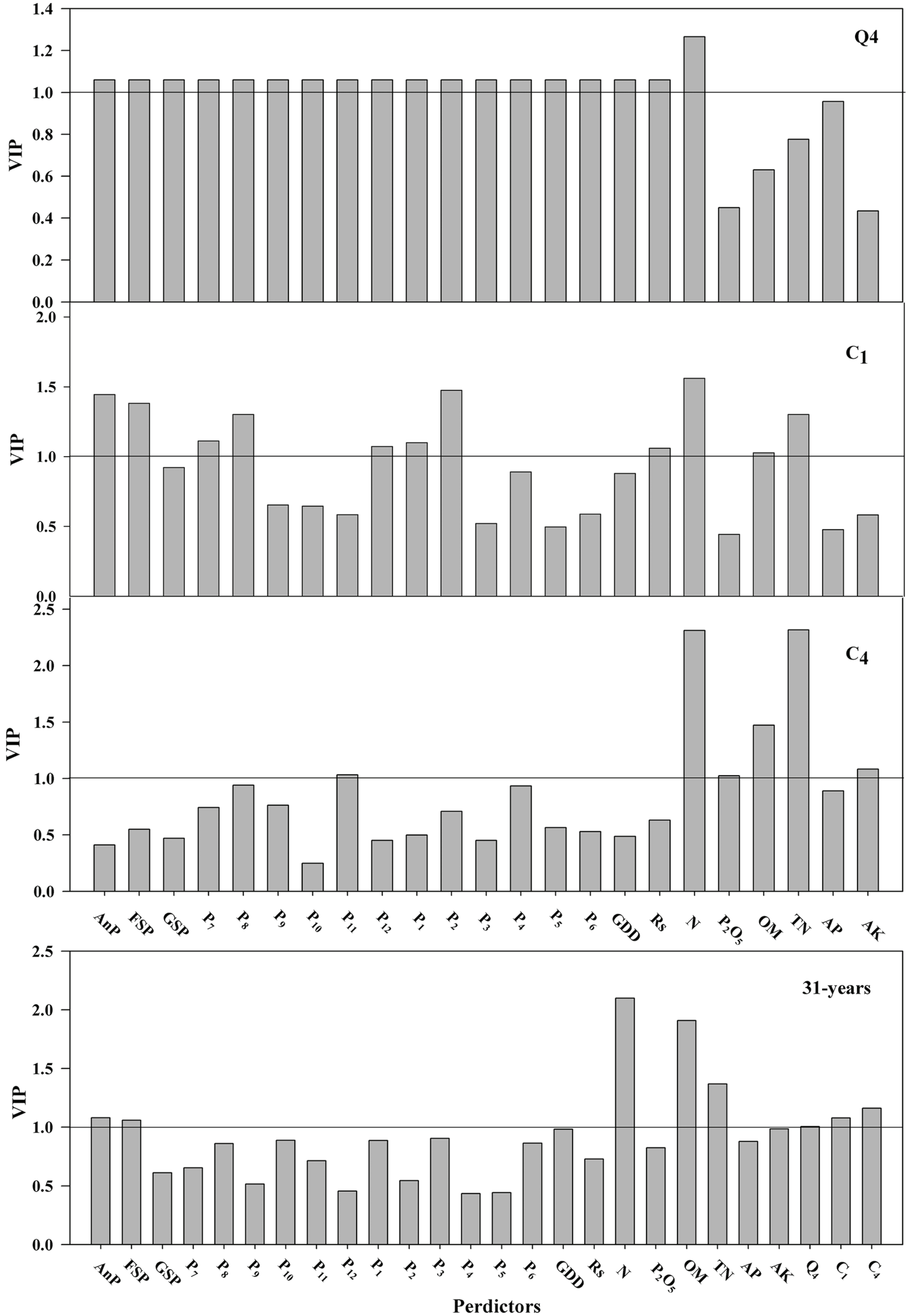

Fig. 2. Variable importance in projection (VIP) for each predictor. AnP: Annual precipitation; FSP: fallow-season precipitation; GSP: growing-season precipitation; P_1: January precipitation; P_2: February precipitation; P_3: March precipitation; P_4: April precipitation; P_5: May precipitation; P_6: June precipitation; P_7: July precipitation; P_8: August precipitation; P_9: September precipitation; P_{10}: October precipitation; P_{11}: November precipitation; P_{12}: December precipitation; GDD: growing degree days; Rs: total radiation solar; P_2O_5: phosphorus pentoxide; TN: total nitrogen; SOM: soil organic matter; AP: available phosphorus; AK: available potassium; Q_4: Qinmai4; C_1: Changwu131; and C_4: Changwu134.

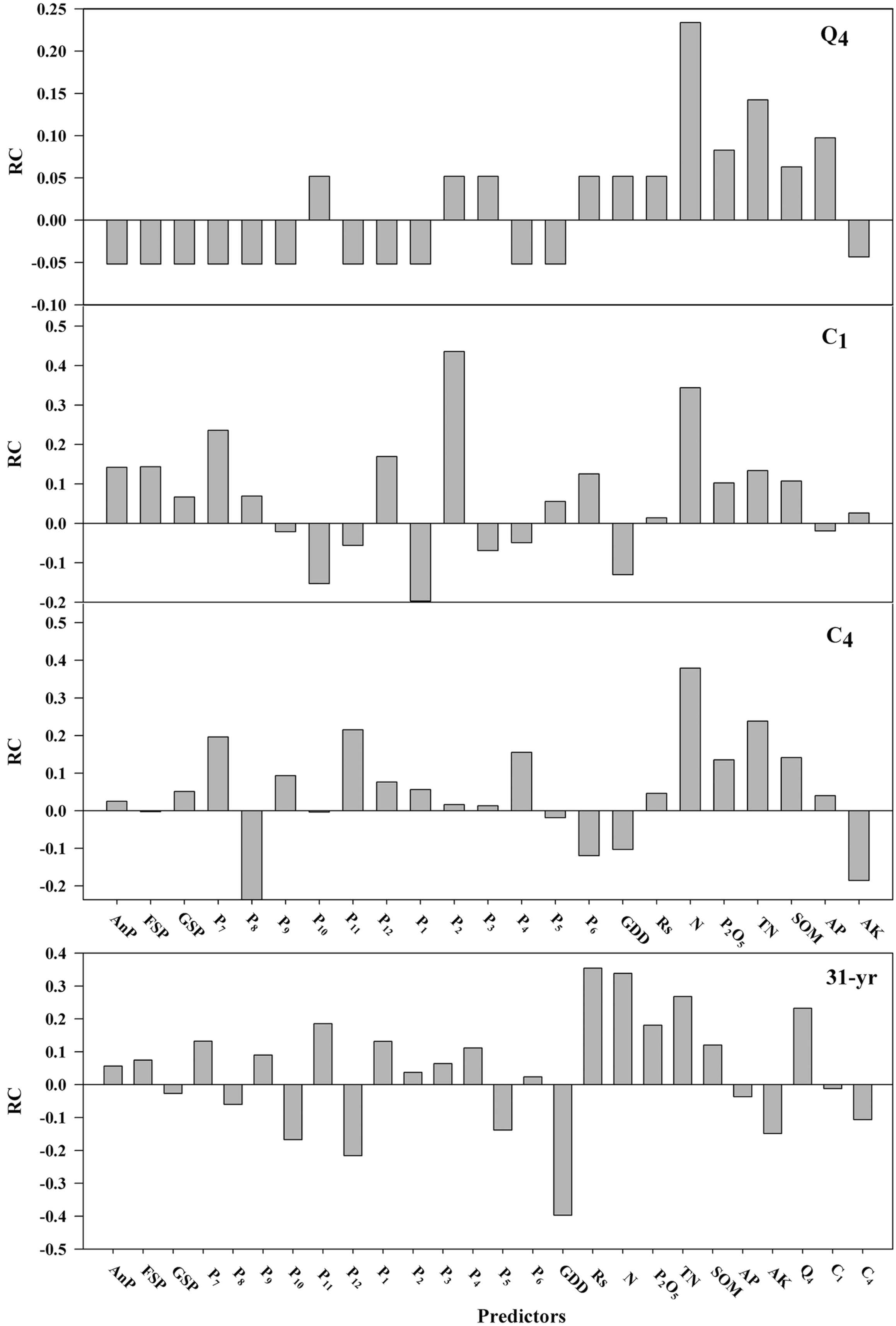

Fig. 3. Regression coefficient for each predictor. AnP: Annual precipitation; FSP: fallow-season precipitation; GSP: growing-season precipitation; P_1: January precipitation; P_2: February precipitation; P_3: March precipitation; P_4: April precipitation; P_5: May precipitation; P_6: June precipitation; P_7: July precipitation; P_8: August precipitation; P_9: September precipitation; P_{10}: October precipitation; P_{11}: November precipitation; P_{12}: December precipitation; GDD: growing degree days; Rs: total radiation solar; P_2O_5: phosphorus pentoxide; TN: total nitrogen; SOM: soil organic matter; AP: available phosphorus; AK: available potassium; Q_4: Qinmai4; C_1: Changwu131; and C_4: Changwu134.

winter wheat, P_3 has a positive correlation with winter wheat yield in a mountain area of Ningxia, China (Shan et al., 2012). For analysis of these factors on winter wheat yield, we should select an appropriate method such as PLSR, which can eliminate the colinearity between independent variables and therefore accurately quantify the relationship between independent and dependent variables.

Based on the PLSR analysis, we found that FSP and P_8 were important factors (|weight| > 0.3) for yield of varieties C_1 and C_4. Meanwhile, both AnP and FSP played important roles in wheat yield (VIP > 1) within varieties Q_4 and C_1, as well as across varieties in the 31-yr planting. P_{11} played an important role for C_4. Precipitation is the sole source of soil water in a rain-fed cropping system and is a major factor in determining the optimum fertilization treatment (Huang et al., 2003). Dai et al. (2016) and He et al. (2016) found that increased rainfall harvest during the fallow season is important for winter wheat yield in the next growing season. During this period, 50 to 60% precipitation typically occurs and the specific amount impacts the germination of the wheat, which is known to affect the yield (He et al., 2016). The minor role of AnP and FSP in the yield of variety C_4 may be due to soil nutrient accumulation under different fertilizer treatments, which was of greater importance than precipitation.

In this study, the VIP values of climate factors, including precipitation, GDD, and Rs, indicated that these factors played an important role in the yield of variety Q_4, with the absolute weight of 0.235. This may be due to the short planting period and therefore the lack of time for significant changes to have occurred in soil nutrients. Additionally, the fallow precipitation (P_7 and P_8) and the winter precipitation (P_{12} and P_1) were found to play important roles in determining the wheat yield for C_1. Payne et al. (2000) reported that wheat yield is more influenced by winter than spring precipitation in the wetter zones of the inland Pacific Northwest. Dang and Gao (2003) using double-screening stepwise regression also found that winter-period precipitation has an important impact on wheat yield. It may be that winter precipitation is particularly important in crown root initiation (Jha and Tripathi, 2011). The Rs was also found to play an important role in the yield of variety C_1. The Rs is a major source of energy for plants and it drives several essential plant processes such as photosynthesis and transpiration (Christopher, 2006). Additionally, pre-heading radiation was found to be a strong predictor of wheat yield (Ortiz-Monasterio et al., 1994).

Nitrogen fertilizer was found to be most important factor for the wheat yield in all four groups tested in this study, with large weight (>0.3, Fig. 1) in the second component, large VIP (1.266–2.100, Fig. 2), and positive RCs (Fig. 3). This indicates that N is the main factor controlling the wheat yield and that the yield increases with more N fertilizer in the study area. The importance of N may be attributable to the low baseline soil N content on the Loess Plateau, China. Nitrogen is an important constituent of proteins and determines photosynthetic capacity, and is therefore an essential macronutrient for plant growth and development (Lu et al., 2015; Qiu et al., 2014; Zhao et al., 2014). Holford and Doyle (1992) also found a positive and significant response of the wheat yield to N in southern New South Wales, a region frequently subject to drought conditions. When growing conditions are favorable, there is evidence for a stronger response of the yield to N (Carew et al., 2009). Direct N input is one way to improve soil N nutrients and potentially increase the yield.

The weights of TN and SOM in the first or second component were larger than 0.3 for variety C_1, C_4, and across varieties in the 31-yr planting. The VIPs for TN and SOM were also larger than 1 for the above three groups. As Q_4 was only planted for 2 yr, there might be insufficient time for the addition of fertilizer to significantly change the TN and SOM. Thereafter, with the addition of different fertilizers, the TN and SOM changed differently, which could impact the wheat yield. During long-term fertilization, SOM and TN have been found to gradually accumulate at different rates, and the resulting availability of C and N show significant effects on the wheat yield (Aula et al., 2016; Fan et al., 2005).

Soil AK and P fertilizer were found to play important roles in the yield of variety C_4 (VIP > 0.1). Wheat yield and AK had negative RCs as large as −0.186. The AK in the no-fertilizer treatment was higher than in the other treatment because long-term addition of N and P produces higher biomass and grain yield, depleting the K compared to the control treatment (Qiu et al., 2014). The average AP reached 13.43 mg kg^{-1} for the variety C_4, with a moderate CV of 57.36%. This is similar with previous results that a steady increase in AP occurred over 24-yr planting in the topsoil where there was a P surplus in P-treated plots (Shen et al., 2007).

Furthermore, variety (C_4, C_1, and Q_4) was found to play an important role in determining the wheat yield when planted and locally managed over 31 yr. The weight of Q_4, C_1, and C_4 reached 0.369, 0.126, and -0.308. The VIPs, with $C_4 > C_1 > Q_4$ in the PLSR, showed that the model could reflect the planting sequence and support the agronomy breeding results. This is in contrast to a multiple-regression analysis performed by Hu et al. (2016) who found that variety was not important to the wheat yield in the same study area. Taken together, these results indicate that PLSR is superior to multiple-regression in reflecting the importance of crop variety to the wheat yield under long-term locally managed planting. This approach may be applicable for evaluating the importance of variety in the yield of other crops, and we also recommend using PLSR to evaluate the effects of control factors on crop yield in other areas or on a large scale.

CONCLUSIONS

This study identified the relative importance of various factors on winter wheat yield in the semiarid Loess Plateau region, China. The results of the correlation analysis and multi-collinearity diagnosis showed that many of the factors were co-linear. Using PLSR, which is relatively insensitive to co-dependencies among the predictor variables, we found that N was the most important control factor for wheat yield in all four groups. The second most important factors were climate factors for Q_4, P_2, AnP, and FSP for C_1, and TN, SOM, and AK for C_4, and TN and SOM for 31-yr planting across the three varieties. This study suggests that the wheat yield can be improved by properly changing the variety, optimizing the amount of N fertilizer, and using protective measures during the FSP. The PLSR methodology is beneficial in that it helps eliminate co-dependency among the variables and allows a less-biased view of the contributions of factors to the winter wheat yield. We have used PLSR in one long-term site, but it could also be used in a large region, or even on a global scale.

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REFERENCES

Abdi, H. 2010. Partial least squares regression and projection on latent structure regression (PLS Regression). WIREs Computational Statistics 2:97–106. doi:10.1002/wics.51

Akinwande, M.O., H.G. Dikko, and A. Samson. 2015. Variance inflation factor: As a condition for the inclusion of suppressor variable(s) in regression analysis. Open J. Stat. 05:754–767. doi:10.4236/ojs.2015.57075

Angstrom, A. 1924. Solar and terrestrial radiation. Report to the international commission for solar research on actinometric investigations of solar and atmospheric radiation. Q. J. R. Meteorol. Soc. 50:121–126. doi:10.1002/qj.49705021008

Aula, L., N. Macnack, P. Omara, J. Mullock, and W. Raun. 2016. Effect of fertilizer nitrogen (N) on soil organic carbon, total N, and soil pH in long-term continuous winter wheat (*Triticum aestivum* L.). Commun. Soil Sci. Plant Anal. 47:863–874. doi:10.1080/00103624.2016.1147047

Awan, S.I., S.D. Ahmad, M.A. Ali, M.S. Ahmed, and A. Rao. 2015. Use of multivariate analysis in determining characteristics for grain yield selection in wheat. Sarhad J. of Agric. 31:139–150. doi:10.17582/journal.sja/2015/31.2.139.150

Bao, S.D. 2000. Soil and agricultural chemical analysis. 3rd ed. (In Chinese.) Agriculture Press, Beijing, China.

Basso, B., D. Cammarano, A. Troccoli, D. Chen, and J.T. Ritchie. 2010. Long-term wheat response to nitrogen in a rainfed Mediterranean environment: Field data and simulation analysis. Eur. J. Agron. 33:132–138. doi:10.1016/j.eja.2010.04.004

Basso, B., C. Fiorentino, D. Cammarano, G. Cafiero, and J. Dardanelli. 2012. Analysis of rainfall distribution on spatial and temporal patterns of wheat yield in Mediterranean environment. Eur. J. Agron. 41:52–65. doi:10.1016/j.eja.2012.03.007

Carew, R., E.G. Smith, and C. Grant. 2009. Factors influencing wheat yield and variability: Evidence from Manitoba, Canada. J. Agric. Appl. Econ. 41:625–639. doi:10.1017/S1074070800003114

Carrascal, L.M., I. Galván, and O. Gordo. 2009. Partial least squares regression as an alternative to current regression methods used in ecology. Oikos 118:681–690. doi:10.1111/j.1600-0706.2008.16881.x

Chen, H.X., Y. Zhao, H. Feng, H.J. Li, and B.H. Sun. 2015. Assessment of climate change impacts on soil organic carbon and crop yield based on long-term fertilization applications in Loess Plateau, China. Plant Soil 390(1-2):401–417. doi:10.1007/s11104-014-2332-1

Chloupek, O., P. Hrstkova, and P. Schweigert. 2004. Yield and its stability, crop diversity, adaptability and response to climate change, weather and fertilisation over 75 years in the Czech Republic in comparison to some European countries. Field Crops Res. 85:167–190. doi:10.1016/S0378-4290(03)00162-X

Christopher, T.B.S. 2006. Introduction to mathematical modeling of crop growth: How the equations are derived and assembled into a computer model. Brown Walker Press, Boca Raton, FL.

Dai, J., Z.H. Wang, M.H. Li, G. He, Q. Li, H.B. Cao, S. Wang, Y.J. Gao, and X.L. Hui. 2016. Winter wheat grain yield and summer nitrate leaching: Long-term effects of nitrogen and phosphorus rates on the Loess Plateau of China. Field Crop Res. 196:180–190. doi:10.1016/j.fcr.2016.06.020

Dang, T.H., and C.Q. Gao. 2003. Study on key water factors of affecting wheat yield in weibei dry highland. Res. Soil Water Consev. 10: 9–11, 36.

Diacono, M., A. Castrignanò, A. Troccoli, D. De Benedetto, B. Basso, and P. Rubino. 2012. Spatial and temporal variability of wheat grain yield and quality in a Mediterranean environment: A multivariate geostatistical approach. Field Crops Res. 131:49–62. doi:10.1016/j.fcr.2012.03.004

Fan, T.L., B.A. Stewart, Y. Wang, J.J. Luo, and G.Y. Zhou. 2005. Long-term fertilization effects on grain yield, water-use efficiency and soil fertility in the dryland of Loess Plateau in China. Agric. Ecosyst. Environ. 106:313–329. doi:10.1016/j.agee.2004.09.003

Fan, Y.H., M.Y. Tian, Q. Jing, Z.W. Tian, H.M. Han, D. Jiang, W.X. Gao, and T.B. Dai. 2015. Winter night warming improves preanthesis crop growth and postanthesis photosynthesis involved in grain yield of winter wheat (*Triticum aestivum* L.). Field Crops Res. 178:100–108. doi:10.1016/j.fcr.2015.04.001

Fang, N.F., Z.H. Shi, F.X. Chen, and Y.X. Wang. 2015. Partial least squares regression for determining the control factors for runoff and suspended sediment yield during rainfall events. Water 7:3925–3942. doi:10.3390/w7073925

Guo, S.L., H.H Zhu, T.H Dang, J.S Wu, W.Z Liu, M.D Hao et al. 2012. Winter wheat grain yield associated with precipitation distribution under long-term nitrogen fertilization in the semiarid Loess Plateau in China. Geoderma 189-190:442–450. doi:10.1016/j.geoderma.2012.06.012

He, G., Z.H. Wang, F.C. Li, J. Dai, Q. Li, C. Xue, H.B. Cao, S. Wang, and S.S. Malhi. 2016. Soil water storage and winter wheat productivity affected by soil surface management and precipitation in dryland of the Loess Plateau, China. Agric. Water Manage. 171:1–9. doi:10.1016/j.agwat.2016.03.005

Holford, I.C.R., and A.D. Doyle. 1992. Yield responses and nitrogen fertilizer requirements of wheat in relation to soil nitrate levels at various depths. Soil Res. 30:683–694. doi:10.1071/SR9920683

Hu, Y.T., M.D. Hao, X.R. Wei, X. Chen, and J. Zhao. 2016. Contribution of fertilisation, precipitation, and variety to grain yield in winter wheat on the semiarid Loess Plateau of China. Acta. Agric. Scand B-S P. 66:406–416. doi:10.1080/09064710.2016.1149215

Huang, M.B., T.H. Dang, J. Gallichand, and M. Goulet. 2003. Effect of increased fertilizer applications to wheat crop on soil-water depletion in the Loess Plateau, China. Agric. Water Manage. 58:267–278. doi:10.1016/S0378-3774(02)00086-0

Huang, M.B., J. Gallichand, and L.P. Zhong. 2004. Water-yield relationships and optimal water management for winter wheat in the Loess Plateau of China. Irrig. Sci. 23:47–54. doi:10.1007/s00271-004-0092-z

Jha, B., and A. Tripathi. 2011. Isn't climate change affecting wheat productivity in India? Ind. Jn. of Agri. Econ. 66:353–364.

Karam, F., R. Kabalan, J. Breidi, Y. Rouphael, and T. Oweis. 2009. Yield and water-production functions of two durum wheat cultivars grown under different irrigation and nitrogen regimes. Agric. Water Manage. 96:603–615. doi:10.1016/j.agwat.2008.09.018

Kraaijvanger, R., and A. Veldkamp. 2015. The importance of local factors and management in determining wheat yield variability in on-farm experimentation in Tigray, northern Ethiopia. Agric. Ecosyst. Environ. 214:1–9. doi:10.1016/j.agee.2015.08.003

Li, X.C., Y.J. Zhang, J.H. Luo, X.L. Jin, Y. Xu, and W.Z. Yang. 2016. Quantification winter wheat LAI with HJ-1CCD image features over multiple growing seasons. Int. J. Appl. Earth Obs. Geoinf. 44:104–112. doi:10.1016/j.jag.2015.08.004

Li, Y.S., and M.B. Huang. 2008. Pasture yield and soil water depletion of continuous growing alfalfa in the Loess Plateau of China. Agric. Ecosyst. Environ. 124:24–32. doi:10.1016/j.agee.2007.08.007

Liu, Y., M.S. Gao, W. Wu, S.K. Tanveer, X.X. Wen, and Y.C. Liao. 2013. The effects of conservation tillage practices on the soil water-holding capacity of a non-irrigated apple orchard in the Loess Plateau, China. Soil Tillage Res. 130:7–12. doi:10.1016/j.still.2013.01.012

Lu, C.H., and L. Fan. 2013. Winter wheat yield potentials and yield gaps in the North China Plain. Field Crops Res. 143:98–105. doi:10.1016/j.fcr.2012.09.015

Lu, D.J., F.F. Lu, J.X. Pan, Z.L. Cui, C.Q. Zou, X.P. Chen et al. 2015. The effects of cultivar and nitrogen management on wheat yield and nitrogen use efficiency in the North China Plain. Field Crops Res. 171:157–164. doi:10.1016/j.fcr.2014.10.012

Mehmood, T., K.H. Liland, L. Snipen, and S. Sæbø. 2012. A review of variable selection methods in Partial Least Squares Regression. Chemom. Intell. Lab. Syst. 118:62–69. doi:10.1016/j.chemolab.2012.07.010

Nuttall, J.G., R.D. Armstrong, and D.J. Connor. 2003. Evaluating physicochemical constraints of Calcarosols on wheat yield in the Victorian southern Mallee. Crop Pasture Sci. 54:487–497. doi:10.1071/AR02168

Onderka, M., S. Wrede, M. Rodný, L. Pfister, L. Hoffmann, and A. Krein. 2012. Hydrogeologic and landscape controls of dissolved inorganic nitrogen (DIN) and dissolved silica (DSi) fluxes in heterogeneous catchments. J. Hydrol. 450-451:36–47. doi:10.1016/j.jhydrol.2012.05.035

Ortiz-Monasterio, I., S.S. Dhillon, and R.A. Fischer. 1994. Date of sowing effects on grain yield and yield components of irrigated spring wheat cultivars and relationships with radiation and temperature in Ludhiana, India. Field Crops Res. 37:169–184. doi:10.1016/0378-4290(94)90096-5

Payne, W.A., P.E. Rasmussen, C. Chen, R. Goller, and R.E. Ramig. 2000. Precipitation, temperature and tillage effects upon productivity of a winter-dry pea rotation. Agron. J. 92:933–937. doi:10.2134/agronj2000.925933x

Pradhan, P., G. Fischer, H. van Velthuizen, D.E. Reusser, and J.P. Kropp. 2015. Closing yield gaps: How sustainable can we be? PLoS One 10:e0129487. doi:10.1371/journal.pone.0129487

Qian, B., R. De Jong, and S. Gameda. 2009. Multivariate analysis of water-related agroclimatic factors limiting spring wheat yields on the Canadian prairies. Eur. J. Agron. 30:140–150. doi:10.1016/j.eja.2008.09.003

Qiu, S.J., J.G. Xie, S.C. Zhao, X.P. Xu, Y.P. Hou, X.F. Wang et al. 2014. Long-term effects of potassium fertilization on yield, efficiency, and soil fertility status in a rain-fed maize system in northeast China. Field Crops Res. 163:1–9. doi:10.1016/j.fcr.2014.04.016

Sadras, V.O., C. Lawson, P. Hooper, and G.K. McDonald. 2012. Contribution of summer rainfall and nitrogen to the yield and water use efficiency of wheat in Mediterranean-type environments of South Australia. Eur. J. Agron. 36:41–54. doi:10.1016/j.eja.2011.09.001

Salazar-Gutierrez, M.R., J. Johnson, B. Chaves-Cordoba, and G. Hoogenbooma. 2013. Relationship of base temperature to development of winter wheat. Int. J. Plant Prod. 7:741–762.

Shan, X.L., Z.S. Su, Z. Zhang, S.Z. Li and N. Wang. 2012. Impact of spring precipitation on the growing period and production of winter wheat in Ningxia Southern Mountain Regin. J. of Arid Meteorol. 30:426–430. doi:1006-7639.

Sharabian, V.R., N. Noguchi, and K. Ishi. 2014. Significant wavelengths for prediction of winter wheat growth status and grain yield using multivariate analysis. Engineering in Agriculture. Environ. Folio 7:14–21. doi:10.1016/j.eaef.2013.12.003

Shen, M.X., L.Z. Yang, Y.M. Yao, D.D. Wu, J.G. Wang, R.L. Guo, and S.X. Yin. 2007. Long-term effects of fertilizer managements on crop yields and organic carbon storage of a typical rice–wheat agroecosystem of China. Biol. Fertil. Soils 44:187–200. doi:10.1007/s00374-007-0194-x

Shi, Z.H., L. Ai, X. Li, X.D. Huang, G.L. Wu, and W. Liao. 2013. Partial least-squares regression for linking land-cover patterns to soil erosion and sediment yield in watersheds. J. Hydrol. 498:165–176. doi:10.1016/j.jhydrol.2013.06.031

Tilman, D., C. Balzer, J. Hill, and B.L. Befort. 2011. Global food demand and the sustainable intensification of agriculture. Proc. Natl. Acad. Sci. USA 108:20260–20264. doi:10.1073/pnas.1116437108

Wang, S.Y., L. Wang, J. Zhang, and L.S. Zhang. 2016. Comparison of soil hydrological characteristics for main cropland and orchard in dry highland of the Loess Tableland. Sci. of Soil and Water Conserv. 14:10–18. doi:10.16843/j.sswc.2016.03.002

Wei, X.R., M.D. Hao, M.A. Shao, and W.J. Gale. 2006. Changes in soil properties and the availability of soil micronutrients after 18 years of cropping and fertilization. Soil Tillage Res. 91:120–130. doi:10.1016/j.still.2005.11.009

Yang, X.Y., P.R. Li, S.L. Zhang, B.H. Sun, and X.P. Chen. 2011. Long-term-fertilization effects on soil organic carbon, physical properties, and wheat yield of a loess soil. J. Plant Nutr. Soil Sci. 174:775–784. doi:10.1002/jpln.201000134

Zhang, H.Y., Z.H. Shi, N.F. Fang, and M.H. Guo. 2015. Linking watershed geomorphic characteristics to sediment yield: Evidence from the Loess Plateau of China. Geomorphology 234:19–27. doi:10.1016/j.geomorph.2015.01.014

Zhao, S.C., S.J. Qiu, C.Y. Cao, C.L. Zheng, W. Zhou, and P. He. 2014. Responses of soil properties, microbial community and crop yields to various rates of nitrogen fertilization in a wheat–maize cropping system in north-central China. Agric. Ecosyst. Environ. 194:29–37. doi:10.1016/j.agee.2014.05.006