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Spatio-temporal distribution of irrigation water productivity and its driving factors for cereal crops in Hexi Corridor, Northwest China

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ABSTRACT

The analysis of irrigation water productivity (IWP) can provide insights into taking measures to improve water-efficient irrigation. This study examines the temporal IWP trend of cereal crops over the Hexi Corridor in Northwest China by employing descriptive analysis, trend analysis, and change-point analysis. Spatial patterns of different typical years (dry, average and wet year) are analyzed by the spatial interpolation method and spatial autocorrelation method. The regional average IWP significantly increased from 0.51 kg/m^3 to 1.29 kg/m^3 during the period of 1981–2012 and no change point was detected. Spatial distribution of IWP reveals that IWP was higher in the plain oasis region, while lower in the mountainous and desert oasis region. The IWP ranged from 0.72 to 1.60 kg/m^3 for the dry year 2004, 0.77–1.66 kg/m^3 for the average year 2008, and 0.81–1.93 kg/m^3 for the wet year 2011, respectively. No significant spatial autocorrelation was observed. By 2012, there were still 3.9% of the area with IWP less than 1.0 kg/m^3, which implied an opportunity to increase IWP through better water management practices. The grey relational analysis of the influences of major driving factors (area supported by unit of irrigation water use, fertilization, agricultural film, agricultural pesticide, and annual mean temperature) on IWP showed that area supported by unit of irrigation water use, fertilization, and agricultural film had dominant impacts during the whole period.

1. Introduction

Water is a vital factor in agricultural production, and water shortage is seriously affecting China's agricultural production (Brown and Halweil, 1998; Oweis and Hachum, 2003; Kang et al., 2016). Under the pressure of water scarcity and the increasing population growth, agriculture is being challenged by producing more agricultural products with limited water resources (Zwart and Bastiaanssen, 2004). For irrigated agriculture in Northwest China, a step towards meeting this challenge is to improve irrigation water productivity (Molden, 1997; Molden et al., 2003).

Irrigation water productivity (IWP) is defined as the production per unit of irrigation water application (Molden, 1997; Playán and Mateos, 2006). It reflects the relationship between irrigation input and output, and represents not only water-use efficiency but also benefits of irrigation, which is a useful indicator for revealing the level of agricultural irrigation and crop management (Seckler et al., 2003; Abdullaev and Molden, 2004; Zoebl, 2006). Increased IWP is the result of comprehensive improvements in agricultural production and irrigation water-use efficiency (Ali and Talukder, 2008; Molden et al., 2010). Application of regional IWP assessment and analysis can provide insight for exploring macroscopically agricultural water-saving management practices (Ines et al., 2003). Increasing lower IWP values can greatly contribute to food production (Cai et al., 2009). Thus the analysis of IWP is attracting more attention. So far, two major procedures for assessing regional scale water productivity are widely applied. One is using statistical or model-simulated yield and water use data to assess water productivity (Droogers and Kite, 2001; Abdullaev and Molden, 2004; Garg et al., 2012), and the other is integrating RS/GIS technology with models to obtain spatio-temporal expression of yield and water use, and then assess water productivity (Ines et al., 2002; Bastiaanssen et al., 2003; Wesseling and Feddes, 2006; Zwart and Bastiaanssen, 2007; Immerzeel et al., 2008; Li et al., 2008; Zwart et al., 2010; Cai et al., 2012; Yan and Wu, 2014).

Many spatio-temporal studies on regional or basin-scale water productivity have been reported in literature, but they mainly focus on crop water productivity (CWP, ratio of yield to evapotranspiration). Abdullaev and Molden (2004) provided the analysis of CWP for different farm types and different basin segments in Syr Darya Basin of central Asia for three hydrological years. The ratio of the highest to lowest CWP was about 2. CWP in water-deficient years

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was higher than that in water-abundant years. Mainuddin and Kirby (2009) considered provincial administrative boundaries as the spatial units and analyzed spatial and temporal trends of CWP in Lower Mekong Basin comprising Laos, Thailand, Cambodia and Vietnam, and the results showed that CWP increased over time. There is a significant spatial variation among countries but not for provinces within a country. Lower CWP is attributed to the lower rainfall, longer drought period, poorer soil nutrition, and less fertilizer application. Cai et al. (2012) analyzed spatial and temporal variability of CWP in Limpopo River Basin of Southern Africa, and concluded that the basin CWP was very low with great variation, mainly due to the low yield, variable water availability, and variant water management levels. Yan and Wu (2014) analyzed CWP of winter wheat based on remote sensing data, and found a steady increase of CWP in recent years.

The spatial and temporal studies on regional IWP are relatively less reported. Droogers and Kite (2001) simulated IWP at basin scale for the Gediz River of Turkey with annual precipitation of 500–1000 mm in the basin, and found IWP in the dry years was much higher than that in the wet years. Irrigation water productivity of spring wheat in an irrigation district of Heihe River Basin, Gansu Province, China, was analyzed from 1995 to 2006, where the average IWP increased by 8.9% from the period of 1995–2000 to the period of 2001–2006 (Hu et al., 2010).

To improve IWP, it is essential to understand correlations between IWP and its driving factors. The factors influencing yield and irrigation water use certainly influence IWP (Zwart and Bastiaanssen, 2004; Ali and Talukder, 2008; Molden et al., 2010; Descheemaeker et al., 2011). The controllable and uncontrollable factors include: (1)climate factors, such as temperature, vapor pressure deficit, and precipitation (Zwart and Bastiaanssen, 2004), (2) agronomic management practices, such as irrigation management (Molden, 1997; Kang et al., 2000; Yazar et al., 2002; Oktem et al., 2003; Zwart and Bastiaanssen, 2004; Geerts and Raes, 2009), soil management (Hatfield et al., 2001; Molden et al., 2010), and crop management (Molden, 1997; Zwart and Bastiaanssen, 2004; Passioura, 2006) (3) crop species and varieties (Zwart and Bastiaanssen, 2004; Ali and Talukder, 2008), and (4) soil factors such as soil texture and organic matter(Hatfield et al., 2001; Ali and Talukder, 2008). Driving factors of IWP vary with regional differences and also depend on socioeconomic conditions. Thus, it is necessary to analyze the influences of driving factors for improving IWP.

The Hexi Corridor is located in the arid region of Northwest China, which is characterized as an irrigation district of "no irrigation, no agriculture". It is an important grain production base in Northwest China to fulfill crop demands in the region. In this region, water problems are being aggravated by the arid continental climate, water scarcity, competition among water-consuming sectors, and groundwater overexploitation (Bao and Fang, 2007; Su et al., 2007). Ensuring or increasing agricultural production with reduced or currently available irrigation water, in other words, improving irrigation water productivity, is increasingly important for the region. In order to improve IWP, the spatio-temporal analysis of IWP in Hexi Corridor and its major driving factors are necessary, and will provide insights for exploring measures to improve irrigation water-use efficiency and water saving management.

The previous studies on IWP and its driving factors in Hexi Corridor were limited to the field scale or a part of Hexi Corridor for a short time period, and to a single driving factor. None of them comprehensively analyzed IWP in the whole Hexi Corridor while considering long-term temporal trends, change points, spatial variations, and the influences of major driving factors on IWP. This study aims to examine spatio-temporal trends and the major driving factors of irrigation water productivity of cereal crops in Hexi Corridor for the period of 1981–2012. Therefore, the objectives of this study are to: (1) reveal the temporal trend of IWP over the past 32 years; (2) choose a relatively optimal method for interpolating IWP in terms of interpolation accuracy, by comparing the inverse distance weighed method, local polynomial interpolation method, and ordinary kriging method; (3) analyze spatial pattern and spatial autocorrelation of IWP in different typical years (i.e. dry (75% hydrologic frequency of annual precipitation), average (50%) and wet (25%) year); (4) evaluate major driving factors of IWP, analyze their influences on IWP in different periods, and provide valuable insights for improving IWP.

2. Materials and methods

2.1. Study area

Hexi Corridor lies in an arid region of Northwest China, between longitudes 92°12′E and 104°20′E and latitudes 37°17′N and 42°48′N, with a total area of 270,000 km^2. It is a long corridor and the distance from east to west is about 1000 km (Fig. 1). It can be approximately divided into three parts: the Qilian Mountain area, plain oasis, and mountainous region in the north, according to geomorphic features and ecological factors. There are three river systems, the Shiyang River, Hei River, and Shule River, from east to west (Bao and Fang, 2007).

In the Hexi Corridor, land, light and heat resources are abundant, but precipitation is limited and evaporation is high, with the annual mean precipitation of 50–150 mm, and the annual average evaporation of 1500–2500 mm. The crop water requirement is much greater than precipitation. Thus, agricultural production relies on irrigation. The main cereal crops are maize (*Zea mays* L.) and wheat especially spring wheat (*Triticum aestivum* L.), and high value crops are mainly oil crops, such as sunflower (*Helianthus annuus*), rapeseed (*Brassica napus*), and sesame (*Sesamum indicum*).

2.2. Data collection

The data, including cereal crops yield, the amount of irrigation, planting proportions of cereal crops, fertilization, agricultural film, agricultural pesticide, and disaster area, were obtained from field investigation and statistical data from the China Economic and Social Development Statistics Database (http://tongji.cnki.net/kns55/index.aspx), Gansu Water Statistical Yearbook, Gansu Development Yearbook and Gansu Rural Yearbook, collected by department of water management, agriculture. Data were available for the period of 1981–2012, and the county administrative boundaries were considered as the spatial unit basis. The data of fertilization, agricultural film and agricultural pesticide were collected in terms of the total use amount of each county. Irrigation water use for cereal crops were calculated by combing the synthetical irrigation quotas and the planting proportions of cereal crops. The disaster area means the area of yield reduction due to natural disaster. Daily climate data, including precipitation and mean temperature, were obtained from China Meteorological Data Sharing Service System (http://data.cma.cn). Descriptions about the indicators are listed in Table 1.

2.3. Methodology

2.3.1. Irrigation water productivity

Irrigation water productivity is defined as the yield per unit of irrigation water use, which can be expressed as:

$$IWP = Y/I \tag{1}$$

where *IWP* is irrigation water productivity, in kg/m^3, *Y* is yield, in kg/ha, *I* is irrigation water use, in m^3/ha.

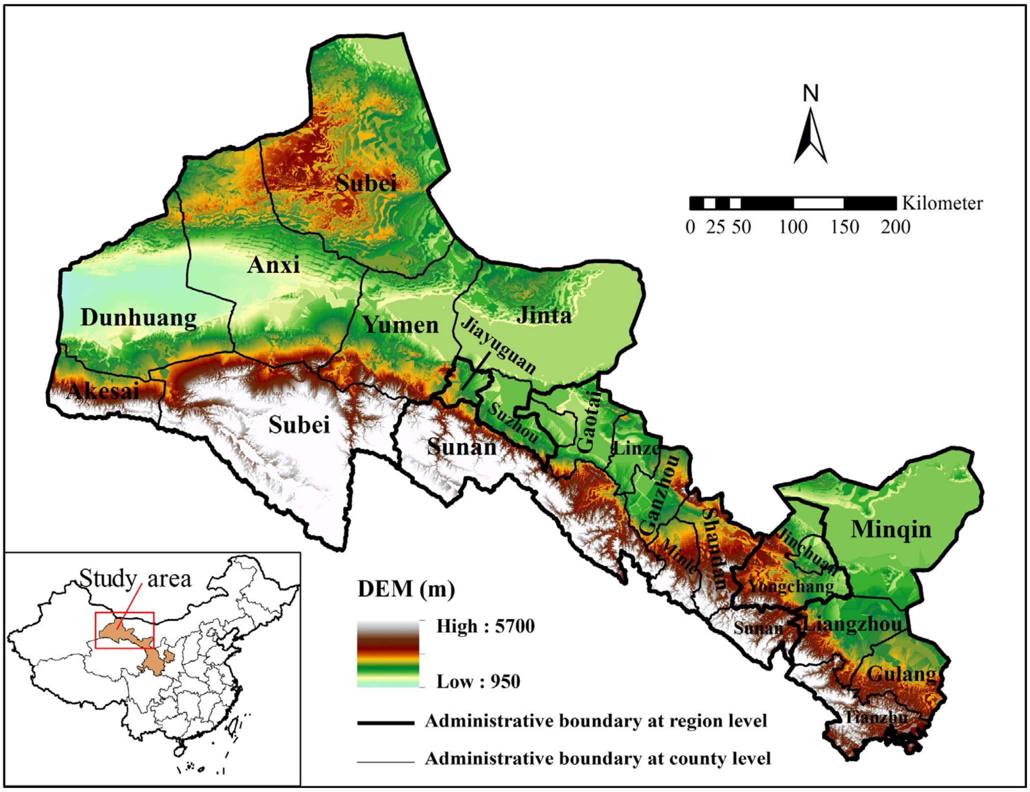

Fig. 1. Location and digital elevation model (DEM) of the Hexi Corridor.

Table 1
List of the selected indicators.

Indicator	Description
Yield	Total production of cereal crops per unit area (kg/ha)
Irrigation Water Use	Total irrigation amount applied to cereal crops per unit area (m^3/ha)
Area supported by unit of irrigation water use (AI)	Reciprocal of Irrigation Water Use (ha/m^3)
Fertilization (F)	Total amount of fertilizer usage per county (convert to element amount) (ton)
Agricultural Film (AF)	Total amount of agricultural film usage per county (ton)
Agricultural Pesticide (AP)	Total amount of pesticide usage per county (ton)
Annual Mean Temperature (T)	Average value of annual mean temperature (°C)
Precipitation (P)	Average value of annual precipitation (mm)
ET_0	Annual reference evapotranspiration calculated by Penman-Monteith equation recommended in FAO56 (Allen et al., 1998) (mm)
Disaster Area (DA)	Area of yield reduction affected by natural disaster (1000 ha)

2.3.2. Descriptive statistical analysis

Descriptive statistical characteristics including mean, maximum/minimum value, and standard deviation were calculated. The Kolmogorov-Smirnov (K-S) test was adopted to test whether the data set followed normal distribution. The original hypothesis of K-S test is that the tested data are not normally distributed. When calculated p value is greater than significance level α (0.05), the original hypothesis should be rejected and the data are normally distributed, and vice versa (Lilliefors, 1967). In this study, SPSS 21 version software (IBM SPSS Inc., USA) was used to compute descriptive statistical characteristics and test the distribution of IWP data.

2.3.3. Trend analysis

Kendall's rank test can quantitatively evaluate changing trends of time series, and it has been widely applied to assess the significance of trends in hydrometeorology (Kottegoda, 1980; Belle and Hughes, 1984). The calculating procedure is given by Kendall and Syuart (1964) and Mann (1945). For a data series $x_1, x_2, \ldots, x_n$, the number of all pairs of observations that $x_i < x_j$ ($j > i$), say p, should be determined. The ordered (i, j) subsets are ($i = 1$, $j = 2,3,\ldots,n$), ($i = 2$, $j = 3,4,\ldots,n$)... ($i = n-1$, $j = n$), and n is the length of data series.

The test is based on the statistic τ, where

$$\tau = \frac{4p}{n(n-1)} - 1 \quad (2)$$

For a random sequence

$$E(\tau) = 0 \quad (3)$$

$$Var(\tau) = \frac{2(2n+5)}{9n(n-1)} \quad (4)$$

The test statistic, U-statistic, is defined as

$$U = \frac{\tau}{[Var(\tau)]^{0.5}} \quad (5)$$

U converges rapidly to a standard normal distribution, at a given significance level (α). $N_{\alpha/2}$ is used as a threshold that can be obtained from Table of Standard Normal Distribution. If $|U| > N_{\alpha/2}$, a positive U indicates a significant increasing trend and a negative U indicates a significant decreasing trend. The linear trend analysis is also performed and compared for the purpose of trend analysis.

2.3.4. Change-point test

The Pettitt change-point test is a nonparametric method to test whether the mean of a variable significantly changes before or after a certain point of time (Pettitt, 1979). The test defines the basic statistic as

$$U_{i,n} = U_{i-1,n} + \sum_{j=1}^{n} sgn(x_i - x_j) i = 2, \cdots, n \tag{6}$$

The original hypothesis is that change-points do not exist, and test statistics are defined as

$$k\ i = Max_{1 \le i \le n}|U_{i,n}| \tag{7}$$

$$K_n = -\frac{(n^3 + n^2)Ln(\alpha/2)}{6} \tag{8}$$

where n is the length of the data series and α is a given significance level. If $k(i) > K_n$, the data series has a change-point at x_i.

2.3.5. Interpolation methods

To select a relatively optimal interpolation method to plot the spatial distribution of IWP, three interpolation methods, i.e. inverse distance weighed method, local polynomial interpolation method and ordinary kriging method, were applied and compared by using the Geostatistical Analyst Tools of ArcGIS 10.0 (ESRI, 2010). There are totally thirty-five data points over the studied area were used for the interpolation. The three interpolation methods are briefly introduced as below.

The inverse distance weighed (IDW) method has been used in meteorological and hydrographical studies in China (Zhao et al., 2005; Tang et al., 2011). It assumes values of predicted points are interrelated to those of sampling points nearby and predicts by weighted averaging of sampling points nearby. The weights are estimated as a function of distance between two points, which decreases with the increase of distance. The general formula is given as (Zhang, 2004):

$$Z(x_0) = \left[\sum_{i=1}^{m} \frac{1}{d_i^{\,q}} Z(x_i)\right] \bigg/ \left[\sum_{i=1}^{m} \frac{1}{d_i^{\,q}}\right] \tag{9}$$

where $Z(x_0)$ is the interpolated value of predicted point x_0, $Z(x_i)$ is the value of sampling point x_i ($i = 1,2,\ldots,m$), d_i is the distance between x_i and x_0, and q is the power parameter of the distance. In this study, q was set to 2.

The local polynomial interpolation (LPI) method is actually a local weighted least squares fitting method. It can reflect the changing trends of a curved surface well and joint data as smooth as possible. The distinguished feature of LPI is that relatively smooth transition surfaces can be obtained, especially when data are not abundant and scattered (Wang et al., 2014).

Ordinary kriging (OK) is a representative geostatistical interpolation method, which assumes the mean is an unknown constant. It focuses on spatial components and estimates predicted values by unbiased optimal estimation (Zhang, 2004). The general formula of OK method is given as

$$Z(x_0) = \sum_{i=1}^{m} \lambda_i Z(x_i) \tag{10}$$

where λ_i is the weight of $Z(x_i)$.

In order to assess which method gives the best interpolation, cross-validation was used to compare the performance of different methods, in terms of three assessment criteria, the mean absolute error (MAE), mean relative error (MRE) and root mean square error (RMSE). The three criteria are expressed as:

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|x_i - \hat{x}_i| \tag{11}$$

$$MRE = \frac{1}{m}\sum_{i=1}^{m}\frac{|x_i - \hat{x}_i|}{x_i} \tag{12}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(x_i - \hat{x}_i\right)^2} \tag{13}$$

where m represents the number of sampling points, x_i and $\hat{x}_i$represents the predicted and sampling values respectively.

2.3.6. Moran I

Global spatial autocorrelation is a general description of spatial characteristics of a certain property, and it is helpful to deeply understand spatial pattern and spatial differentiation. Moran I is one of the most frequently used statistics to measure global spatial autocorrelation, and is calculated as (Moran, 1950)

$$I = \frac{m\sum_{i=1}^{m}\sum_{j=1}^{m} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{m}(x_i - \bar{x})^2 \sum_{i=1}^{m}\sum_{j=1}^{m} W_{ij}} \tag{14}$$

where m is the total sample number, x_i is the sampling value of point i, $\bar{x}$ is average value, W_{ij} is the spatial weight values between sampling point i and j, W_{ij} was set to 1 if i and j are adjacent, otherwise 0.

The significance test statistic, normalized Z value, is defined as

$$Z = \frac{I - E(I)}{[Var(I)]^{0.5}} \tag{15}$$

I is generally in the range of (−1, 1), a significantly negative value shows negative spatial autocorrelation, i.e., the similar observation values (high or low) tend to be spatially scattered; significantly positive value shows positive spatial autocorrelation.

2.3.7. Grey relational analysis method

The grey relational analysis (GRA) method is developed based on the grey system theory, and grey system means a system contains both known and unknown information (Deng, 1989). GRA method can measure the degree of correlation between the research object and impact factors, which refers to irrigation water productivity and selected driving factors in this study. In the system impacting irrigation water productivity, relations between driving factors and irrigation water productivity are grey, i.e. the relations are uncertain. Hence it is difficult to distinguish which factors are dominant factors. Grey relational analysis provides an effective way to solve such problems (Deng, 2008). The computation procedures are as follows.

Grey relational coefficient is defined as

$$\xi_k(i) = \frac{\min_k \min_i \Delta_{0k}(i) + \rho \max_k \max_i \Delta_{0k}(i)}{\Delta_{0k}(i) + \rho \max_k \max_i \Delta_{0k}(i)} \tag{16}$$

where $k = 1,2,\ldots,l$ and $i = 1,2,\ldots,n$, $\Delta_{0k}(i) = |x_0(i) - x_k(i)|$, $x_k(i)$ is the kth specific comparative sequence, $x_0(i)$ is the reference sequence and ρ is distinguishing coefficient, $\rho \in [0,1]$ and was set to 0.5 in this study. The analysis is performed on the standardized data, which is obtained by the raw data minus the long-term mean and divided by its related standard deviation of the raw data over the same period.

Grey relational grade is a weighted average of grey relational coefficients. It is expressed as

$$r_k = \frac{1}{n}\sum_{i=1}^{n}\xi_k(i) \tag{17}$$

Table 2
Descriptive statistics and Kolmogorov-Smirnov (K-S) tests of irrigation water productivity (kg/m^3).

Year	Minimum	Maximum	Mean	Std. Deviation	K-S test p value
1981	0.26	0.77	0.51	0.136	0.825
1982	0.34	0.78	0.57	0.128	0.991
1983	0.33	0.82	0.61	0.135	0.827
1984	0.34	0.87	0.64	0.154	0.994
1985	0.39	0.90	0.68	0.156	0.939
1986	0.38	0.90	0.71	0.148	0.963
1987	0.35	1.01	0.72	0.163	0.958
1988	0.44	1.04	0.76	0.156	0.923
1989	0.44	1.06	0.78	0.163	0.992
1990	0.40	1.09	0.81	0.181	0.616
1991	0.41	1.03	0.79	0.180	0.977
1992	0.54	1.09	0.90	0.171	0.538
1993	0.45	1.13	0.91	0.188	0.648
1994	0.65	1.11	0.90	0.155	0.764
1995	0.66	1.14	0.95	0.128	0.896
1996	0.60	1.19	0.99	0.169	0.356
1997	0.63	1.23	1.01	0.169	0.729
1998	0.67	1.36	1.06	0.186	0.790
1999	0.72	1.35	1.09	0.185	0.455
2000	0.58	1.38	1.11	0.219	0.217
2001	0.59	1.56	1.09	0.266	0.919
2002	0.76	1.50	1.15	0.210	0.754
2003	0.76	1.52	1.15	0.195	0.902
2004	0.72	1.60	1.17	0.232	0.999
2005	0.74	1.55	1.17	0.231	0.980
2006	0.75	1.52	1.18	0.236	0.967
2007	0.77	1.56	1.21	0.243	0.896
2008	0.77	1.66	1.19	0.245	0.999
2009	0.72	1.79	1.20	0.292	0.999
2010	0.82	1.71	1.23	0.270	0.538
2011	0.81	1.93	1.25	0.292	0.617
2012	0.88	1.98	1.29	0.295	0.990

where r_k is the grey relational grade for the kth comparative factor.

The grey relational coefficient and grade represent the influence degrees of factors on the reference factor. A higher grade of correlation shows greater influences of the comparative sequence on the reference sequence, and vice versa.

3. Results and discussion

3.1. Temporal trend

3.1.1. Descriptive statistical analysis

Table 2 shows that the regional average value of IWP increased from 0.51 to 1.29 kg/m^3 during the period of 1981–2012, with the maximum and minimum values in the ranges of 0.77–1.98 kg/m^3 and 0.26–0.88 kg/m^3, respectively. This trend is the result of increasing yield and decreasing irrigation water use, resulting from breed improvement, improved cultivation technique, water-saving irrigation, and better agronomic management. The standard deviation values also increased slightly, indicating the increased spatial variation of IWP, which was mainly due to the varied adoption of the advanced agronomic and water-saving technologies among different counties. The p values of K-S test were all greater than 0.05, i.e., the IWP data studied were normally distributed.

3.1.2. Temporal variation of IWP

Table 3 shows the results of trend analysis and change-point test. A significant positive trend at significance level of 0.01 is detected by both Kendall and the linear regression test, which indicates that the regional average IWP has a significant increasing trend. No change-point is observed by performing the Pettitt change-point test. Therefore, the IWP in Hexi Corridor increased steadily without sudden change for the studied period.

Table 3
Results of trend analysis and change-point analysis of irrigation water productivity from 1981 to 2012.

Kendall test	Linear regression analysis			Pettitt test
U	Regression Equation	R^2	*Sig.*	
7.36	y = 0.0241x − 47.09	0.968	0	no change-point

U is test statistic of Kendall test, α = 0.01, $U\alpha_{/2}$ = 2.58, R^2 is coefficient of determination, *Sig.* is significance level.

Table 4
Assessment of three interpolation methods for IWP in three typical years.

Typical year	Methods	Parameter		
		MAE	MRE	RMSE
Dry (75%)	IDW	0.215	0.201	0.242
	LPI	0.244	0.227	0.279
	OK	0.215	0.202	0.253
Average (50%)	IDW	0.170	0.204	0.265
	LPI	0.178	0.212	0.279
	OK	0.171	0.207	0.269
Wet (25%)	IDW	0.220	0.190	0.238
	LPI	0.253	0.222	0.282
	OK	0.224	0.194	0.237

IDW is inverse distance weighted method, LPI is local polynomial interpolation, OK is ordinary kriging, MAE is mean absolute error (kg/m^3), MRE is mean relative error, RMSE is root mean square error (kg/m^3). Dry, average and wet year is 75%, 50% and 25% hydrologic frequency of annual precipitation, respectively.

Trends of regional average IWP, irrigation water use, and yield of cereal crops in the Hexi Corridor from 1981 to 2012 are shown in Fig. 2. The regional average IWP and yield increased over time, while irrigation water use decreased. IWP from 1981 to 2012 increased 0.78 kg/m^3 with an annual growth rate of 3.04%. These results are consistent with previous studies of IWP in Northwest China on a provincial basis. For example, in Gansu province, the average IWP is 1.36 kg/m^3 for the period of 1980–2010; increased IWP is observed with increased crop yield and decreased irrigation water use (Cao et al., 2014).

The annual growth rate of IWP was 5.45% for the period of 1981–1989, 3.35% for 1990–1999 and 1.26% for 2000–2012. The increase of IWP slowed down over the past three decades, as observed in Fig. 2. The reason is probably that with development of improved agronomic management and water-saving techniques, the opportunity for further improving yield level and irrigation water-use efficiency shrinks, and improvement in IWP are more difficult to achieve. For instance, the rate of lining of irrigation canals has gradually stabilized. In Zhangye Region (including counties of Ganzhou, Linze, Gaotai, Sunan, Shandan, Minle), intact rates of high standard lining for trunk and branch canals were 78% and 77% respectively in 1985, 87% and 83% in 2002, 90% and 88% in 2010. It should be noted that during the low-yield level period (e.g. 1981–1989), the grain production capacity was more influenced by production inputs such as improved variety, chemical fertilizers and pesticides (Duan and Wang, 2011). During this period, the efficiencies of production inputs increased significantly and corresponding yield and IWP also increased. However, the efficiencies of irrigation and production inputs reached a stable level, with the improvement of yield and water-saving level. Therefore the increase of IWP became smaller during the high-yield level period, e.g. the period of 2010–2012 (Molden et al., 2010).

3.2. Spatial variation

3.2.1. Interpolation method assessment

Table 4 shows the results of cross-validation of three interpolation methods (IDW, LPI, OK) for IWP in three typical years. Typical

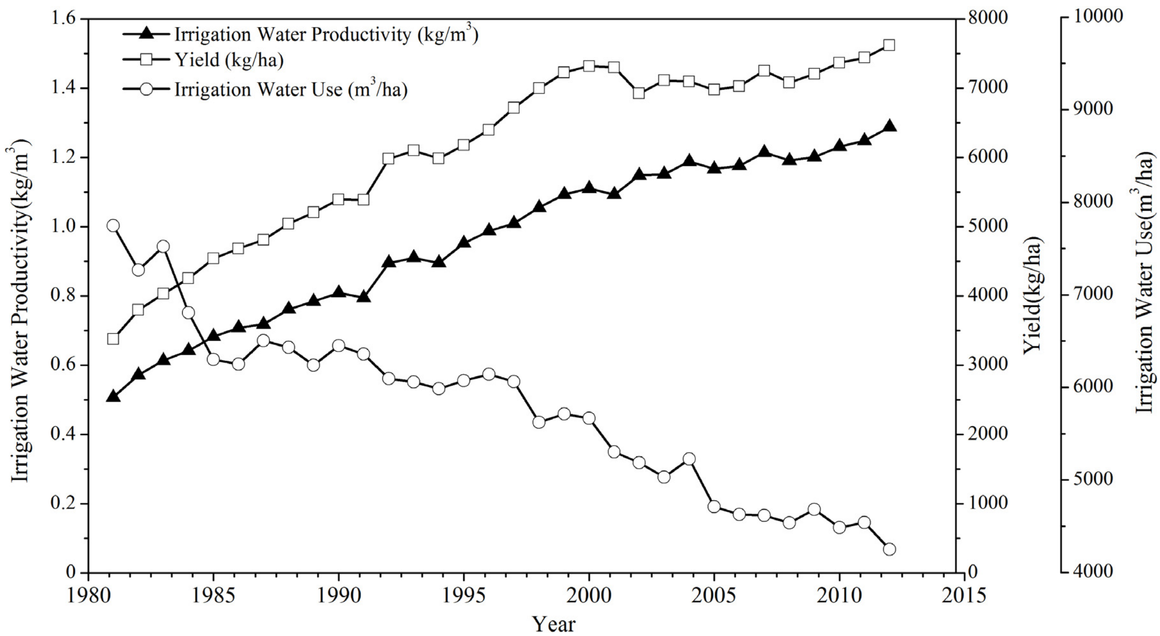

Fig. 2. Regional average yield, irrigation water use and irrigation water productivity of cereal crops in Hexi Corridor for the period of 1981–2012.

years are selected by hydrologic frequency of annual precipitation amount (i.e. dry (75% hydrologic frequency of annual precipitation), average (50%), and wet (25%)). Predicted values were calculated by the three methods. It is observed that MAE, MRE and RMSE of IDW were smaller than other the two methods, indicating that IDW is the relatively optimal method.

3.2.2. Spatial distribution of IWP

Fig. 3 shows spatial distribution of IWP for cereal crops in Hexi Corridor using the IDW method, for the dry year (2004), the average year (2008), the wet year (2011), and the mean for the whole study period (1981–2011), respectively. The spatial distribution of IWP was similar in the three typical years, as shown in Fig. 3a–c, which indicates that IWP was higher in the plain oasis region and lower in the mountainous and desert oasis (oasis near desert) region. The range of IWP was 0.72–1.60 kg/m^3 for the dry year, 0.77–1.66 kg/m^3 for the average year, and 0.81–1.93 kg/m^3 for the wet year. IWP was lower in the dry year, because yield was reduced due to lack of water and irrigation provided a larger portion of the crop water requirements due to low precipitation. This is opposite to the results reported by Droogers and Kite (2001), in which IWP was lower in the wet year due to the higher irrigation inputs despite higher yields.

Annual average IWP in the Hexi Corridor varied between 0.64 and 1.19 kg/m^3 across the region, as shown in Fig. 3d. The higher IWP values occurred in counties of Linze, Ganzhou, Gaotai, Jinchuan, and Liangzhou. The counties, Tianzhu, Minqin, Jiayuguan, Anxi, and Yumen, showed relatively lower IWP values. In general, higher values appeared in plain oasis, due to lower irrigation water use. Because in the plain oasis, agricultural management level is relatively high and soil is mainly loam with good water holding capacity. Lower IWP values in mountainous region are due to lower yield level, mainly caused by the higher elevation and lower temperatures. In the fringes of the desert areas, dry climate with high evaporation is a major constraint for agricultural production, and the permeable nature of the sandy soils is another constraint (Mainuddin and Kirby, 2009). In the desert fringes of Minqin county, sand content is over 50% and steady-state infiltration rate exceeds 0.15 cm/min (Jia et al., 2006), resulting in high infiltration and low irrigation water-use efficiency. Hence, IWP was lower as a result of higher application of irrigation water.

Table 5
Area proportions (%) under different irrigation water productivity (IWP) levels.

Year	IWP levels (kg/m^3)			
	<0.5	0.5–1.0	1.0–1.25	>1.25
1981	58.9	41.1	0	0
1991	0.9	97.9	1.3	0
2000	0	15.2	75.1	9.8
2004	0	6.2	68.0	25.8
2008	0	6.5	61.0	32.5
2011	0	7.4	33.9	58.7
2012	0	3.9	34.0	62.1

To further understand the spatial variation, the IWP values were divided into four levels, namely <0.5 kg/m^3, 0.5–1.0 kg/m^3, 1.0–1.25 kg/m^3, and >1.25 kg/m^3. The areas in different levels were calculated through the GIS software, based on the interpolation map plotted by the IDW method. The proportions of the area belonging to different IWP levels are listed in Table 5. The area with low IWP (<0.5 kg/m^3) decreased from 58.9% to 0 from 1981 to 2000, while area with high IWP (>1.0 kg/m^3) increased during the study period. By 2012, the proportion of area with IWP larger than 1.25 kg/m^3 reached 62%. IWP values increased cross the whole region. Fig. 4 shows the distribution of annual IWP growth rate from 1981 to 2012. The relatively fast increase occurred more in the east part of Hexi Corridor. For instance, Minqin county gradually became a relatively high IWP region, due to river improvement and management and the development of water-saving irrigation projects. There were still 3.9% of the area with IWP less than 1.0 kg/m^3 by 2012, as shown in Table 5, implying an opportunity to increase IWP through better management practices.

3.2.3. Spatial autocorrelation

Table 6 shows the Moran I test statistic values and corresponding *p* values. The results show approximately random distribution, as there is no significant spatial correlation for IWP in each typical year with $p > 0.05$, which demonstrates the complex effects on IWP, derived by spatial randomness of various factors, such as climate, soil texture, crop cultivation and agricultural management.

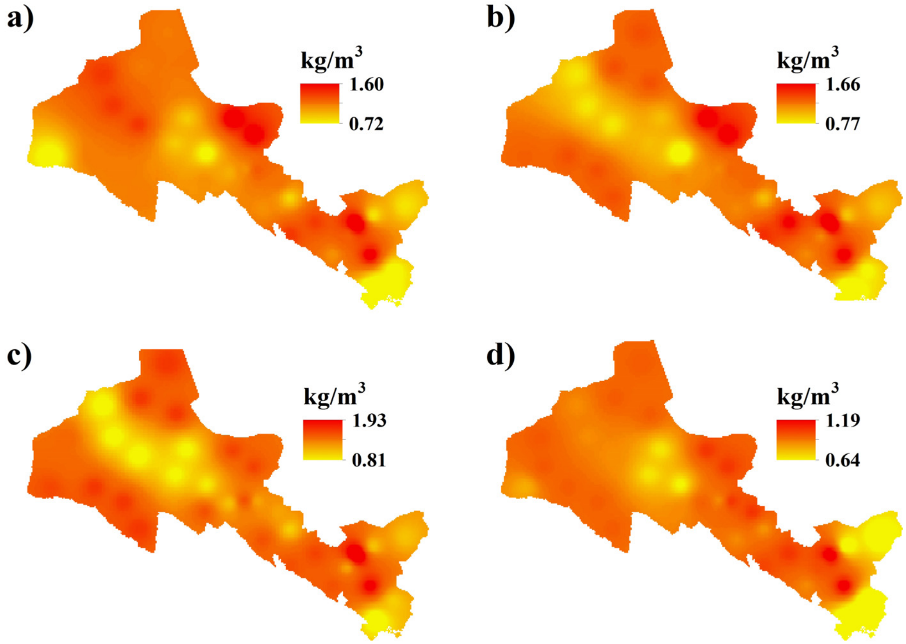

Fig. 3. Spatial distribution of IWP of cereal crops interpolated by IDW for (a) dry year 2004 (75% hydrologic frequency of annual precipitation), (b) average year 2008 (50%), (c) wet year 2011 (25%), and (d) annual average for the period of 1981–2012.

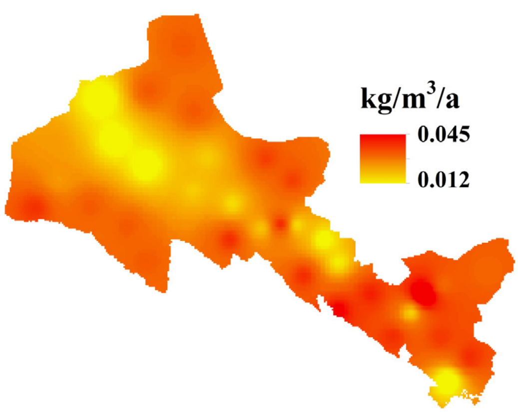

Fig. 4. Spatial distribution of average annual growth of IWP from 1981 to 2012.

Table 6
Moran I test statistic values and *p* values for irrigation water productivity in three typical years.

Parameter	2004	2008	2011
Moran I	0.0884	0.0868	0.1573
p value	0.4230	0.4317	0.2038

Table 7
Simple correlation coefficients (R) between IWP and driving factors.

Factor[a]	AI	F	AF	AP	T	P	ET_0	DA
R	0.926[b]	0.984[b]	0.926[b]	0.722[b]	0.750[b]	0.280	0.161	−0.083

[a] The full names and definitions of different factors are listed in Table 1.
[b] Denotes correlation is significant at 0.01 level.

3.3. Analysis of major driving factors

3.3.1. Identification of major driving factors

To analyze the major driving factors of IWP, a correlation analysis was first performed to identify the important factors. Table 7 shows correlation coefficients between IWP and the driving factors.

Table 8
The top-three ranked driving factors and grey relational correlations for sub-periods and the whole period of 1981–2012.

Rank	1981–1989		1990–1999		2000–2012		1981–2012	
	factor	r	factor	r	factor	r	factor	r
1	F	0.858	F	0.819	F	0.918	F	0.878
2	AI	0.728	AF	0.696	AF	0.809	AF	0.771
3	AF	0.720	AI	0.680	AI	0.763	AI	0.751

AI: area supported by unit of irrigation water use, F: fertilization, AF: agricultural film, r: grey relational grad.

It is found that the area supported by unit of irrigation water use (AI), fertilization (F), agricultural film (AF), agricultural pesticide (AP), and annual mean temperature (T) are positively correlated with IWP, at significance level of 0.01. The remaining factors (i.e. precipitation, ET_0, and disaster area) have no significant correlation with IWP. These results are basically consistent with the IWP studies for other regions. For example, IWP decreases with the increase of irrigation water applied (Ali and Talukder, 2008); thus IWP is positively correlated with reciprocal of irrigation water use, i.e. area supported by unit of irrigation water use. Fertilization, agricultural film and agricultural pesticide promote crop growth and yield (Molden, 1997; Ali and Talukder, 2008; Molden et al., 2010), and thus have positive correlations with IWP. In addition, suitable temperature facilitates crop growth and yield and influences IWP in northwest China (Hu et al., 2010). Based on the above analysis, the factors significantly correlated with IWP are selected as the major driving factors of IWP.

3.3.2. Grey relational analysis

Table 8 shows the top-three ranking driving factors and grey relational correlations for sub-periods and the whole period of 1981–2012. Area supported by unit of irrigation water use (AI), fertilization (F), and agricultural film (AF) were identified as the top-three ranking influence factors during each sub-period and the whole study period. These indicate that irrigation and other agronomic practice inputs, including F and AF, are main constraints to the improvement of IWP in the Hexi Corridor. In arid regions, water is a main factor that limits crop yield (Passioura, 2006), and irrigation has a strong influence on IWP. Mulching, one type of soil surface modification, helps to achieve greater water productivity through influencing the energy balance and water balance components of crop growth system, e.g. helping to increase crop yield through impacting the soil temperature (Hatfield et al., 2001). Soil nutrients status has shown to have a positive impact on water productivity. Improved crop growth and yield resulting from proper fertilizer additions could lead to increases in IWP (Hatfield et al., 2001; Zwart and Bastiaanssen, 2004). Therefore, to improve IWP, advanced water-saving irrigation and rational increase use-efficiencies of fertilization and agricultural film are essential and beneficial at the current stage.

4. Conclusions

The conclusions are drawn as follows:

(1) During the study period of 1981–2012, the regional average IWP of cereal crops significantly increased at significance level of 0.01, without any change-point detected. The rate of annual growth was slower in the last decade than the earlier two, which implies the difficulty to further improve IWP.
(2) Inverse distance weighed (IWD) method is considered as a preferred method, for spatial interpolation of IWP in Hexi Corridor, compared with two other interpolation methods.
(3) Spatial distributions of IWP in typical years were roughly similar, i.e. higher in the plain oasis region, lower in the mountainous and desert oasis regions. Annual average IWP varied regionally within the range of 0.64–1.19 kg/m^3. There were large differences in IWP values in different typical years. In the wet year, IWP was higher than that in the dry year, as the yield in the dry year was affected by the drought conditions. There was no significant spatial autocorrelation, due to the spatial randomness of various factors, such as climate, soil texture, crop cultivation, and agricultural management.
(4) The area with low IWP ($<$0.5 kg/m^3) decreased while the area with high IWP ($>$1.0 kg/m^3) increased from 1981 to 2012. However, there were still 3.9% of the area below 1.0 kg/m^3 by 2012, implying an opportunity to increase IWP through regional targeting of better management practices.
(5) Area supported by unit of irrigation water use, fertilization and agricultural film were ranked as the top-three highest influencing factors. Water and other agronomic practice inputs, such as fertilization and agricultural film, are key constraints to the improvement of IWP.

The analysis of IWP is essential for a better understanding of variations of irrigation water-use efficiency for Hexi Corridor, Northwest China. The identification of the major driving factors provides insights to explore strategies for improving IWP and regulating production inputs in this region. A quantification assessment of the influences of driving factors is needed for further study.

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