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Evaluation of spatial interpolation methods for groundwater level in an arid inland oasis, northwest China

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Abstract The Wuwei oasis, situated in the upper reaches of the Shiyang River basin in the arid inland of northwest China, is intensively cultivated using both groundwater and irrigation water originating from the Qilian Mountains. Groundwater levels are declining due to overuse of irrigation water. To estimate the decline over the entire Wuwei oasis, eight different interpolation methods were used for interpolating groundwater levels over 3 years, i.e. starting in 1983, followed by 1988 and ending with 1992. Cross-validation and orthogonal-validation were applied to evaluate the accuracy of the different methods. Root mean squared error and the correlation coefficient (R^2) were calculated for each of the interpolation methods and years. Three kriging methods (simply, ordinary, and universal) gave the best fit. Modified ordinary kriging was found better than simple and universal kriging methods with a smaller number of points having large differences (>50 m) between estimated and predicted values. Based on the groundwater surfaces determined by the ordinary kriging as modified by Yamamoto, the groundwater decline was found from 1983 to 1992 to be a modest 2.1 m in average.

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Introduction

Scarcity of water in many parts of the world has become a common problem (Oki and Kanae 2006). Over 2 billion people live in water stressed river basins with less than 1,700 m³/year of available water per person constraining economic development, particularly agriculture (Johnson et al. 2001). Groundwater is often overexploited to relieve water stress (Yang and Zehnder 2002), and in several regions, such as in the North China Plain, it represents the only source for irrigated agriculture. To estimate the degree of overexploitation of water in these basins the groundwater surface should be known and can be determined from the available well data integrated in various interpolating techniques. However, there are questions concerning the best interpolating method for estimating groundwater surfaces. The objective of the present manuscript is to test different interpolating techniques to find the best method by which

estimating the temporal and spatial variations of the groundwater level. The Wuwei oasis in northwest China was chosen as a test case because groundwater level data was publicly available (Tang 2009). In addition, in the oasis irrigation takes place from both groundwater and surface water sources that originate from the mountainous area. However, the depletion of the groundwater source is not known in the mountainous area to the south, and for the domain to the east of the oasis which is located in an arid area (i.e. desert, please see Fig. 1) the amount of overuse of groundwater is still unknown.

Various interpolation methods have been developed to date, consisting of global and local interpolators, and geostatistical methods (see Meijering 2002 for a historical overview). Global interpolation methods consist of trend surfaces (Whitten and Koelling 1973) and regression models (Gllbert et al. 2005). Local interpolation methods comprise Thiessen polygons (Goovaerts 2000), inverse distance weighting (IDW) (Bartier and Keller 1996), and splines (Unser 1999; including thin-plate smoothing

splines, shorten as ANUSPLIN; Hutchinson 1995a). Geostatistical methods include kriging methods and a statistical method termed 'gradient plus inverse-distance-squared' (GIDS, Price et al. 2000). Interpolation methods have long been used in cartography (Keys 1981; Grevera and Udupa 1996, 1998; Frakes et al. 2008). Kriging methods consisting of simple, ordinary, and universal kriging (UK) were originally developed for the mine industry but are now used for interpolation of scalar values in such applications as three-dimensional medical image surface rendering, wind speed spatial estimation, regional analysis of irrigation water requirements, forest inventory, finding the spatial variability of soil properties, etc. Stytz and Parrott (1993) found that kriging is an accurate interpolation technique for 3D medical imaging. A fourth-order nonlinear interpolation procedure based on the essentially nonoscillatory (ENO) methodology has been presented and evaluated by Hermosilla et al. (2008), with the purpose of increasing the geometric accuracy of edge detection in digital images. They found that the proposed methodology
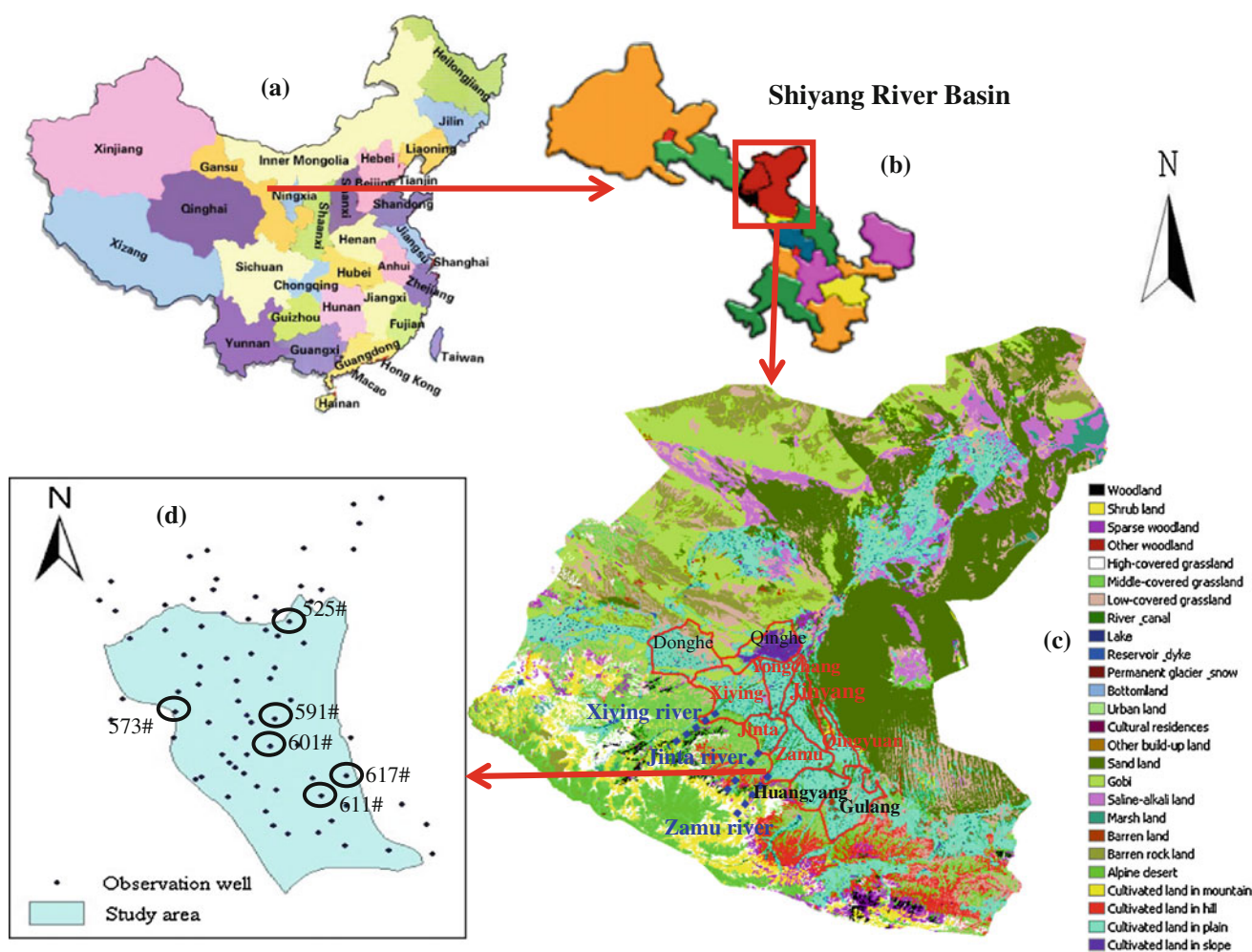

Fig. 1 Location of Wuwei oasis and observation wells (**d**) in the Shiyang River basin

based on ENO interpolation improves the detection of edges in images. In addition, many interpolation methods have been applied on climatic variables. As an example, Hutchinson (1995b) interpolated mean rainfall using ANUSPLIN. Martinez-Cob (1996) interpolated long-term mean total annual reference evapotranspiration and long-term mean total annual precipitation using three geostatistical interpolation methods [ordinary kriging (OK), co-kriging and modified residual kriging] in a mountainous region. Nalder and Wein (1998) estimated 30-year averages of monthly temperature and precipitation at a specific site in western Canada using four forms of kriging (detrended kriging, co-kriging, UK, OK) and three simple alternatives (GIDS, nearest neighbour, inverse distance squared). Goovaerts (2000) used simple kriging (SK) with varying local means, kriging with an external drift and collocated cokriging for incorporating a digital elevation model into a spatial prediction of rainfall. Price et al. (2000) interpolated 30-year monthly mean minimum and maximum temperature and precipitation data from regions in western and eastern Canada using ANUSPLIN and GIDS. Dalezios et al. (2002) investigated the spatial variability of reference evapotranspiration in Greece using geostatistic methods. Mardikis et al. (2005) predicted the spatial variability of long-term mean daily reference evapotranspiration for each month in Greece using OK, inverse distance squared, residual kriging and GIDS. Boer et al. (2001) predicted monthly maximum temperature and monthly mean precipitation in Jalisco State of Mexico using four forms of kriging and three forms of thin plate splines. Swan and Sandilands (1995) applied the spatial interpolation method for geological data analysis.

There is not a general agreement on what constitutes the best interpolation method (Goodin et al. 1979; Caruso and Quarta 1998; Weng 2006; Sun et al. 2009; Yang et al. 2011). Indeed, each interpolation method comes with some drawbacks, and the reliability of the results from the interpolation strongly depends on external factors as the amount of available input data, their spatial and temporal coverage, their characteristics, the kind of spatial model desired and the like. Hutchinson (1995b) concluded that the final reliability of the interpolation depends on the temporal and spatial coverage of the data when using thin plate smoothing splines for interpolating mean rainfall. Tabios and Salas (1985) found out that for estimating annual precipitation in North Central US, the kriging technique performed best. In contrast, Nalder and Wein (1998) found that for estimating 30-year averages of monthly temperature and precipitation in western Canada, the GIDS was the most accurate interpolation method because it was simple to apply and avoided the subjectivity involved in defining variogram models and neighbourhoods. However, Price et al. (2000) found that thin-plate smoothing splines

(ANUSPLIN) performed better than GIDS. Mardikis et al. (2005) compared kriging and other interpolation methods for daily evapotranspiration on a monthly basis and found that the optimal method was not unique but depends on the specific month. In addition, Martinez-Cob (1996) found that the differences among the studied spatial interpolation methods could be determined by the data's spatial configuration and the assumptions drawn, rather than the spatial interpolation method itself. For the Wuwei oasis, understanding temporal and spatial variations of groundwater level is a prerequisite to achieving sustainable water use in the oasis. However, groundwater level in the whole area is rather difficult or costly to be measured directly. Moreover, because of the excessive exploitation and disorderly management of groundwater resources, the groundwater level presents significant spatial variability. Therefore, it is very difficult to gain the real groundwater spatial distributions according to limited observation wells. Interpolation is one advisable method to achieve this goal based on some measurements of groundwater levels. Determining an optimal interpolation method which is suitable for this region is the key point of the present study.

With the introduction of geographic information systems (GIS), interpolation of groundwater level data has become feasible (Burrough 1986; Flowerdew and Green 1994). Sun et al. (2009) found that in northwest China, SK performed best for groundwater table interpolations. GIS has been an important tool in analysing the character of groundwater. Wei et al. (2003) discussed GIS and its application to groundwater from five aspects: groundwater simulation and evaluation, evaluation of groundwater environment, well-field protection, conjunctive groundwater and surface water management in a watershed, decision support systems and expert systems. Finally, they prospected the development tendencies of the applications of GIS to groundwater research.

Kriging methods are one of the exact and powerful interpolation schemes based on geostatistics (Davis 1973; Journel and Huijbregts 1978; Deutsch and Journel 1993; Kitanidis 1997; Chiles and Delfiner 1999). Nowadays, kriging methods are widely used for studying the spatial distribution of groundwater (Volpi and Gambolati 1978; Domenico and Schwartz 1990; Knotters and Bierkens 2001) in America (Dunlap and Spinazola 1984), India (Sharda et al. 2006), Iran (Ahmadi and Sedghamiz 2007) and China (Sun et al. 2009).

However, a common drawback of all kriging methods is related to the so-called "smoothing effect" in which small values are usually overestimated and large values underestimated (Yamamoto 2005). Moreover, Isaaks and Srivastava (1990) found that using more sample values will increase the smoothness of the estimates. In order to correct for the smoothing effect, some solutions based on

postprocessing of the resulting image have been proposed by Guertin (1984), Olea and Pawlowsky (1996) and Journel et al. (2000). These studies found that global accuracy and local accuracy are conflicting objectives because they corrected the smoothing effect at a loss of local accuracy. For example, based on Yao's spectral postprocessing algorithm which has been proven to be efficient in reproducing the semivariogram model, Journel et al. (2000) have proposed a solution, and concluded that this semivariogram reproduction is achieved at a loss of local accuracy. Yamamoto (2000, 2005, 2007) developed a post-processing approach to correct the smoothing effect of OK estimates. Subsequently, Rocha et al. (2007) and Yang et al. (2011) has successfully applied such approach and presented the real spatial distributions of regionalized variables without losing local accuracy.

Therefore, to select an optimal interpolation method given a study area, eight interpolation methods including IDW, polynomial interpolation, radial basis function and different kriging methods were evaluated. Furthermore, Yamamoto's post-processing method was used for correcting the smoothing effect for the OK method for groundwater levels interpolation. At the last, the temporal and spatial variations of groundwater level in the study area were analysed based on the corrected interpolation method.

Materials and methods

Study area and data

The Wuwei oasis, situated in the upper reaches of the Shiyang River basin in the arid inland of northwest China, includes ten irrigation districts (Fig. 1c). In this study, the Xiying, Jinta, Zamu, Yongchang, Jinyang and Qinghe irrigation districts in Wuwei oasis were selected as the study area. The study area occupies an area of 2,524.56 km^2 and has a typical arid climate with annual precipitation of 164 mm and annual pan evaporation of 2,000 mm. Average annual temperature is 7.7 °C. The main surface water sources are the Xiying, Jinta and Zamu rivers. Surface runoff has significantly decreased in the last 40 years (from 8.42×10^8 m^3 in 1956 to 6.56×10^8 m^3 in 1995). Groundwater plays an important role for agriculture, social economy development and maintaining ecological environment in this area. As a result of a recent increase in population (from 0.51 million in 1979 to 0.74 million in 2000), in irrigated land (from 7.2×10^8 m^2 in 1979 to 10.04×10^8 m^2 in 2000) and further economic development, groundwater levels have been declining over the last 40–50 years (Kang et al. 2004).

Eight interpolation methods for groundwater level were evaluated and optimized for asserting groundwater level variations during 3 years, namely 1983, 1988 and 1992. Groundwater level records for 75 observation wells (the locations are shown in Fig. 1d) in the Wuwei oasis were available for 1983 and 1992, and 92 observation wells were available for 1988. The groundwater data were provided by the Water Resources Department of Wuwei. Based on the monthly average groundwater level, a dataset of average annual groundwater level was established for each observation well and its geodetic coordinates. All observed data in the Wuwei oasis were used for interpolating, i.e. for 1983 and 1992, groundwater level records for 75 observation wells were used for interpolating, and for 1988, groundwater level records for 92 observation wells were used for interpolating, based on the interpolated results (used all wells), the interpolated results of the study area were plotted.

To understand the character of the groundwater levels dataset, observed values for 75 observation wells (Sample size is 75 which can be found in Table 4) for 1983 have been statistically analysed (Fig. 2a). It was found that the groundwater level ranges from 1,691.4 to 1,415.06 m with a mean value of 1,501.2 m. The standard deviation of the data is 45.93 m; the kurtosis is 1.561; and the skewness is 0.732. Therefore, the kriging interpolation could be applied due to the fact that the dataset follows a normal distribution. Groundwater level records for 75 observation wells were used for interpolating, the groundwater level records for 50 observation wells (random selection) of these 75 observed data were used to model the space structure and to create the interpolated surface, while the remaining groundwater level records for 25 observation wells were used for validation and prediction. The parameters were adjusted to minimize the error generated in the process of model operation and the final parameters are summarized in Table 1.

Interpolation methods for groundwater level

Altogether eight interpolation methods—the IDW, the global polynomial interpolation (GPI), the local polynomial interpolation (LPI), the regularized spline (Rspline), the tension spline (Tspline), the OK, the SK, the UK—were evaluated to spatial interpolation of regional groundwater levels.

The GPI method referred to as trend surface analysis has been originally introduced into the earth sciences by Miller (1956), Krumbein (1959) and Whitten (1970). They used the method for analysing environments of sedimentation, contour-type map and elevation. In trend surface analysis, the distribution of observational data is described by means of a two-dimensional polynomial equation of the first, second or a higher degree.

The LPI method introduce the concept of distance weight, it combined the advantage of GPI method
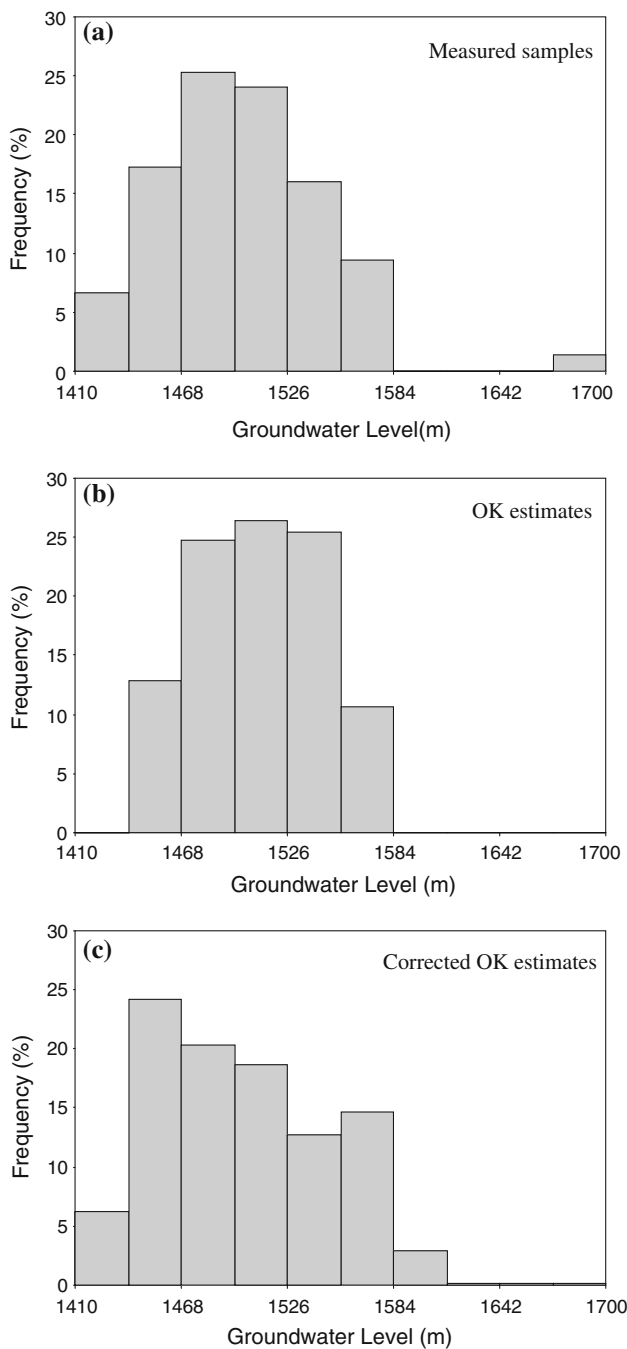
Fig. 2 Groundwater level frequency distribution histograms in 1983

reflecting tendency variation and the advantage of IDW method reflecting local characters. In general, LPI fits different polynomials, each within a specified overlapping surface into which the study area has been subdivided. It fits the specified order of the polynomial only within the defined region. Since the regions overlap, the value used for each prediction is the value of the fitted polynomial at the centre of the region. The way LPI method works can be

shortly described as follows. At first a complex plane is divided into small (sub) planes, then by predicting the other values in the study area using the central value in every small plane; one accurate and real surface thus can be presented by fitting. The curved surface created in this way is more depended on the variation of local data.

Journel and Huijbregts (1978) and Sun et al. (2009) gave detailed descriptions about theory and application for kriging, IDW and RBF.

Cross-validation and orthogonal-validation

The cross-validation and orthogonal-validation are used to assess which method gives the best interpolation effect (Zhang 2005; Sun et al. 2009). Root mean squared error (RMSE) was selected as a main criterion for cross-validation and orthogonal-validation. It considers stationary points and extrema, and can be calculated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - Q_i)^2}, \tag{1}$$

where P_i is the estimated value; Q_i is the measured value at sampling point i ($i = 1, \ldots, n$); and n is the number of values used for the estimation.

Another criterion to assess the interpolation method is the correlation coefficient (R^2) which is a measure of the correlation between the observed and estimated values (Sun et al. 2009). It can be calculated as follows:

$$R^2 = \frac{\left[\sum_{i=1}^{n} (P_i - P_{\text{ave}})(Q_i - Q_{\text{ave}})\right]^2}{\sum_{i=1}^{n} (P_i - P_{\text{ave}})^2 \sum_{i=1}^{n} (Q_i - Q_{\text{ave}})^2},$$

where P_{ave} is the averaged estimated value; Q_{ave} is the averaged measured value; and n is the number of values used for the estimation.

Yamamoto's method

Correcting the smoothing effect of OK estimates by Yamamoto's (2005) method was based on a reliable measurement of the uncertainty associated with them. The kriging variance is not available for uncertainty assessment because only a configuration index of data points was used to make the OK estimate and the kriging variance does not measure the local data dispersion (Yamamoto 2005). Therefore, the kriging variance was replaced by the interpolation variance in Yamamoto's method. The local data dispersion is measured by the interpolation variance, because the interpolation variance depends on data-value and semivariogram function through the OK weights (Yamamoto 2005). More detailed description of Yamamoto's method has been given in Yamamoto (2005).

Table 1 Parameters using in the interpolation model for 1983

Interpolation methods	Data conversion	P parameter or smooth parameter[a]	The maximum predicted points used in search radius	The minimum predicted points used in search radius	Direction search angle (°)
IDW	None	2	5	3	0
GPI	None	4	–	–	–
LPI	None	2	10	6	0
Rspline	None	1.8×10^{-4}	5	3	0
Tspline	None	1.5×10^{-8}	5	2	0
SK	None	1	10	5	45
UK	Logarithm	2	5	3	45
OK	Logarithm	1	10	5	45

[a] The exponential value in the formula of calculating weight, or the times of fitting surface polynomial

Results and discussion

Cross-validation and orthogonal-validation

Table 2 shows the cross-validation and orthogonal-validation results of groundwater level for 1983. The orthogonal-validation results in the table (Table 2) show that the RMSE sorting is IDW > Rspline > UK > SK > OK > LPI > Tspline > GPI, with their values being 28.10, 25.20, 24.64, 24.31, 24.22, 23.45, 22.09, 21.41, respectively. However, the cross-validation results in the table shows that the RMSE sorting is Rspline > IDW > Tspline > LPI > OK > UK > SK > GPI, with their values be 31.65, 27.27, 24.63, 23.37, 22.25, 22.22, 20.90, 20.08, respectively. By combining the results from both validation methods, it was found that GPI and kriging methods share the smallest RMSE value. Moreover, both the cross-validation R^2 results and the orthogonal-validation R^2 results corroborate this conclusion. The cross-validation R^2 sorting is Rspline < IDW < LPI < Tspline < OK = UK < SK < GPI, with their values be 0.57, 0.65, 0.70, 0.71, 0.76, 0.76, 0.77, 0.78, respectively. The orthogonal-validation R^2 is sorting IDW < Rspline < LPI < Tspline < UK = OK < SK < GPI, with their values be 0.71, 0.72, 0.75, 0.77, 0.78, 0.78, 0.79, 0.86, respectively. Similar conclusions can be derived by comparing simulated and measured groundwater levels for IDW, GPI, LPI, Rspline, Tspline, OK, SK and UK (Fig. 3). As for GPI and kriging (including OK, SK and UK) interpolation, the fitting effect is relatively better. Performance of GPI is the best ($R^2 = 0.777$), followed by SK ($R^2 = 0.765$), then UK ($R^2 = 0.755$) and OK ($R^2 = 0.754$). But there are more data with absolute error greater than 20 m for GPI than for the three kriging methods (as shown in Table 3). This last aspect can be attributed to GPI requirements of lots of input data and of having an interpolated surface which should change smoothly. It can be concluded that the calculated surfaces using GPI method are highly susceptible to outliers (e.g. extremely high and low values), especially at the edges; thus, GPI is inexact (Johnston et al. 2001). For the kriging

Table 2 The statistic of the errors in the process of groundwater interpolation for 1983

Interpolation methods	Cross-validation		Orthogonal-validation	
	RSME (m)	R^2	RSME (m)	R^2
IDW	27.274	0.651	28.100	0.714
GPI	20.076	0.778	21.410	0.856
LPI	23.373	0.702	23.452	0.748
Rspline	31.651	0.565	25.202	0.718
Tspline	24.630	0.712	22.090	0.771
SK	20.899	0.77	24.311	0.789
OK	22.253	0.758	24.221	0.784
UK	22.216	0.759	24.644	0.777

methods, SK regards the mean value of variable as constant which leads to an over/under-estimate of the values of extreme points. However, as shown in Table 3, OK and UK are more flexible to deal with extreme points comparing with SK. Moreover, OK is more flexible to deal with extreme points comparing with UK. Therefore, OK method is the optimal method for interpolating groundwater level in the study area.

Spatial variation of groundwater level interpolated with different methods

Figure 4 shows the interpolation effect of groundwater level in the Wuwei oasis from the eight interpolation models for the 1983 dataset. There is evidence of a so-called "buphthalmos" phenomenon (look rough, it means the interpolation effect is not so good) in the map generated based on IDW method. The "buphthalmos" (Yang et al. 2011) phenomenon is caused by those overestimated or underestimated values in the process of interpolation. This is because the distribution of observation wells is nonuniform, i.e. anisotropy in IDW method. There are "buphthalmos" phenomenon in the map of IDW method, which are caused due to extreme data, which resulted in those

**Fig. 3** Comparison of simulated and measured groundwater levels
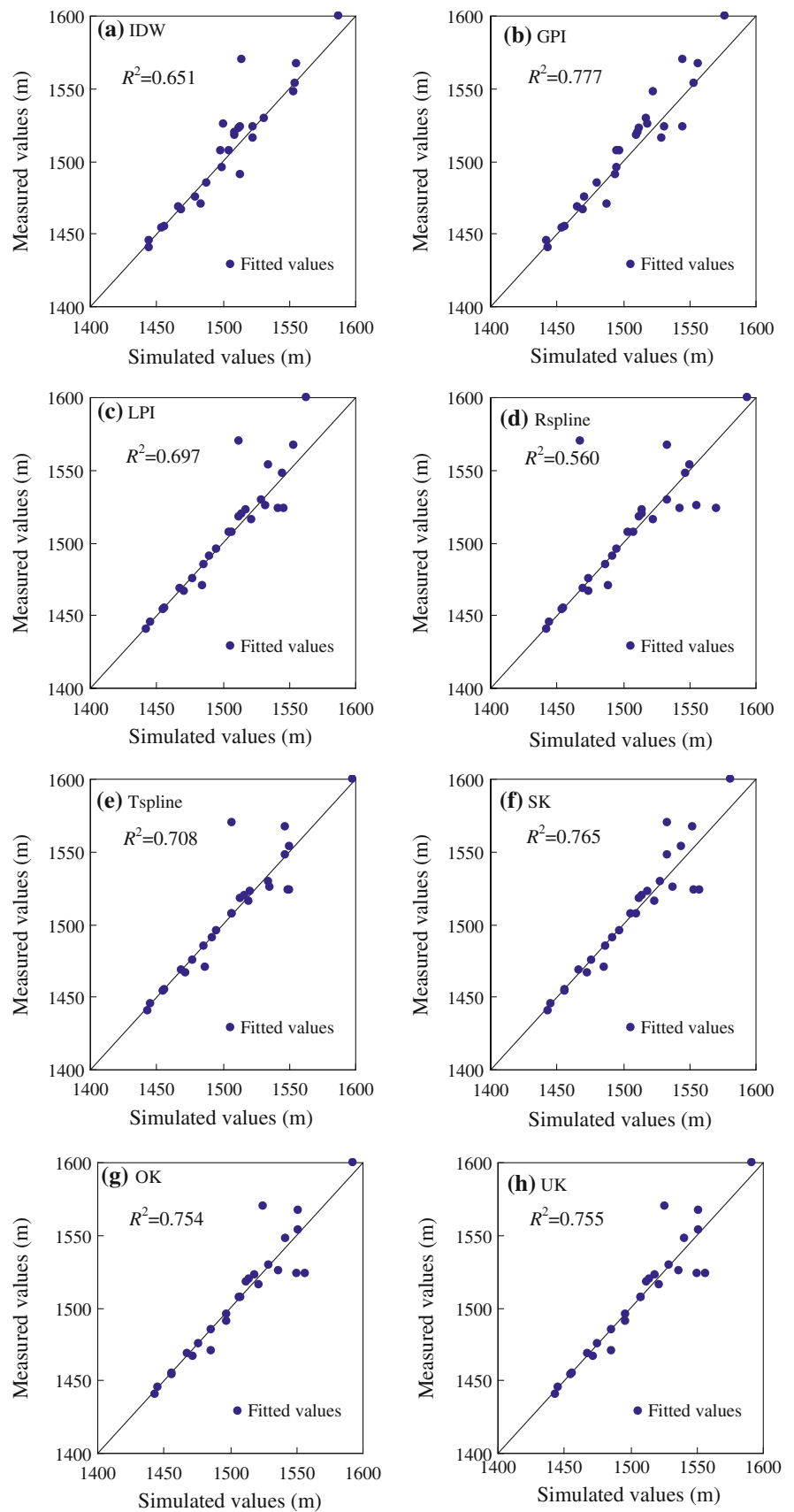
overestimated or underestimated values in the final interpolation. For GPI, the interpolation effect is very smooth as its treatment of the globality of data. However, GPI neglected local variations, a fact that makes this method not conforming to practical situations. The interpolated surface using GPI method changes gradually and captures coarse-scale pattern in the data, it can use low-order polynomials that possibly describe some physical process to create a slowly varying surface. However, the more

complex the polynomial, the more difficult it is to ascribe physical meaning to it (Apaydin et al. 2004). Tspline considered local variations and the interpolated trend surface is also smooth, but the fitting effect is relatively bad (Fig. 3), i.e. there are more data with absolute error larger than 20 m than obtained by all kriging methods (Table 3). For LPI and Rspline, the created trend surface is not smooth, there are "buphthalmos" phenomena in the maps, which may be due to extreme data or due to few input data available in these areas and to a nonuniform distribution of groundwater observation wells in the study area. Kriging combines the influence of distance and direction and it assumes the properties which may show a continuous or an irregular change in space, and that cannot therefore be simulated by any mathematical function, but can be simulated by stochastic models. Therefore, kriging interpolation is theoretically better than other interpolation methods. As shown in Fig. 4, the kriging interpolation results are more approximate to the real situation and the interpolated

Table 3 The statistic of cross-validation absolute errors

Absolute error (m)	IDW	GPI	LPI	Rspline	Tspline	OK	SK	UK
>50	2	1	2	2	2	0	1	1
20–50	2	4	2	3	3	3	3	2
10–20	5	4	3	2	2	2	5	3
<10	18	18	20	20	20	22	18	21

Fig. 4 Interpolation effect of groundwater level in Wuwei oasis through the eight interpolation models in 1983
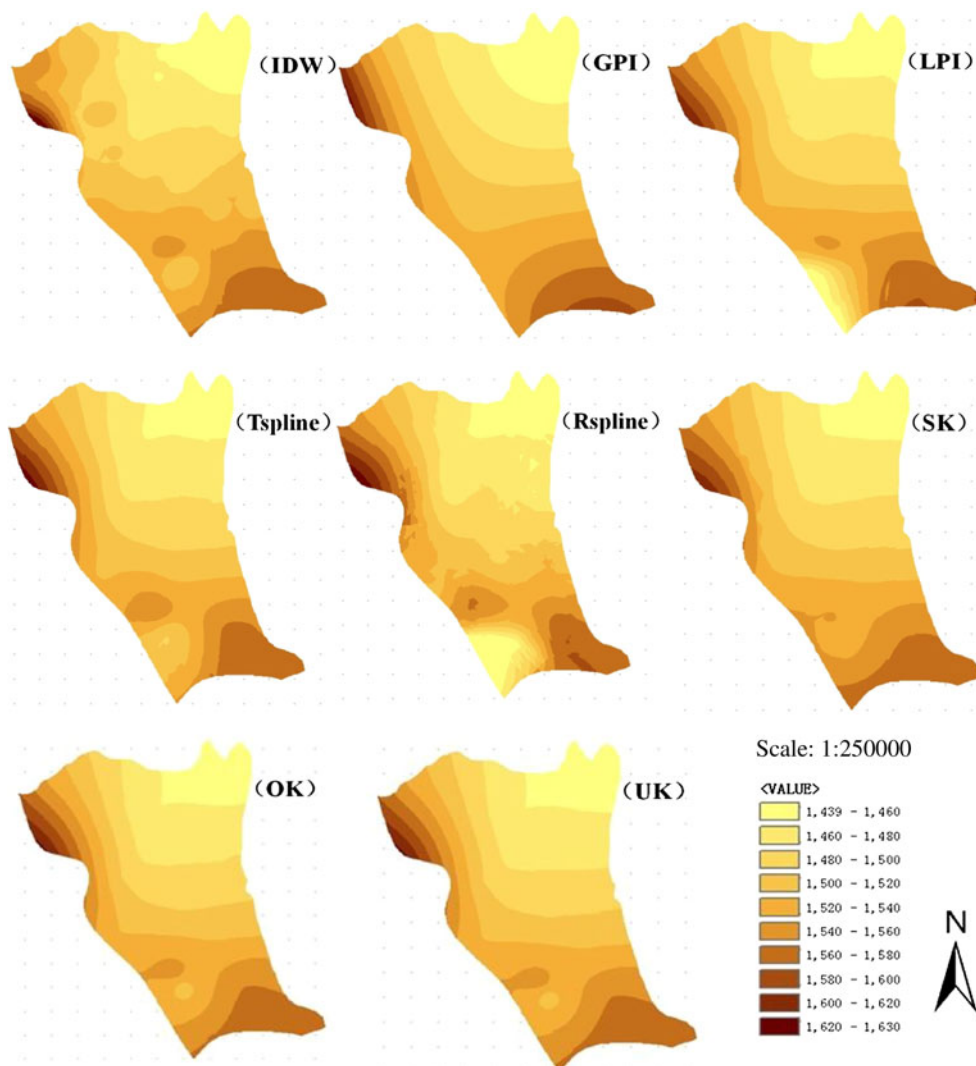
groundwater surface looks smooth (it means the interpolation effect is good). Therefore, combined with the analysis in the above paragraph, OK is to be considered as the optimal method for interpolating groundwater level in this region. As shown in Fig. 4, groundwater level as obtained by OK is high in northwest and southeast, and low in northeast. In addition, the terrain of the Wuwei oasis slopes downwards from southwest to northeast. The OK interpolation result is approximate to the real situation. Moreover, the interpolated groundwater surface used the OK method looks smooth; it means the interpolation effect is good.

The correction of smoothing effect with Yamamoto's method

Although OK was found to be the optimal method for interpolating groundwater level in the study area, it also presents a serious inherent drawback known as the smoothing effect, i.e. decreased variation of estimates. In this study, Yamamoto's (2005) method is used to correct the smoothing effect of OK estimates in observed groundwater level interpolation, aim to gain the real groundwater surface.

OK was used to interpolate the groundwater levels for 75 observation wells in the Wuwei oasis (Fig. 5a). As shown in Table 4, the mean of measured groundwater levels is very close to estimated values with OK. This indicates that the OK estimates can be met without any bias. However, the standard deviation of measured sampling points is far greater than OK estimates. This means that the smoothing effect has occurred in the process of OK interpolation. The sharp decrease of range also shows the smoothing effect in OK estimates. In detail, the coefficient of variation of groundwater levels in the study area decreased from 0.031 for measured samples to 0.022 for OK estimated samples.

Figure 5b shows the image of groundwater level estimated with smoothing corrected OK in 1983. As shown in Table 4, the mean groundwater level estimated with smoothing corrected OK is about equal to the mean measured value. This indicates that Yamamoto's (2005) method keeps the un-biasedness of OK estimates. Secondly, the standard deviation of groundwater levels estimated with smoothing corrected OK estimates almost equals to that of groundwater levels measured and has been greatly improved compared with that calculated from OK estimates. The range of smoothing of corrected OK estimates also has been greatly improved compared with OK estimates and the variation tendency of the range is the same as the standard deviation. Thirdly, the coefficient of variation of groundwater levels estimated with smoothing corrected OK equals to that of measured groundwater levels. Therefore, it can be concluded that Yamamoto's

(2005) method effectively corrects the smoothing effect of OK estimates. The groundwater surface should look smooth in the actual situation, because the groundwater level is a gradual change (except fault). Therefore, the interpolated surface using corrected OK is able to effectively reflect the real spatial distribution of groundwater level by comparing Fig. 5a and b. It also concluded that OK method with Yamamoto's (2005) method can be successfully applied in interpolating groundwater level in the arid area where the groundwater level presents significant spatial variability because of the excessive exploitation and disorderly management of groundwater resources.

To further illustrate how groundwater levels corrected by the Yamamoto's (2005) method present a spatial distribution closer to the real one than OK estimates, the groundwater level frequency distribution histograms of sampling points (Observed values for 75 observation wells, Fig. 2a), OK estimates (Fig. 2b, sample size is 1,248 which can be found in Table 4) and corrected OK estimates (Fig. 2c, sample size is 1,248 which can be found in Table 4) were plotted. As shown in Fig. 2 the estimated values with OK is distributed into few classes around their
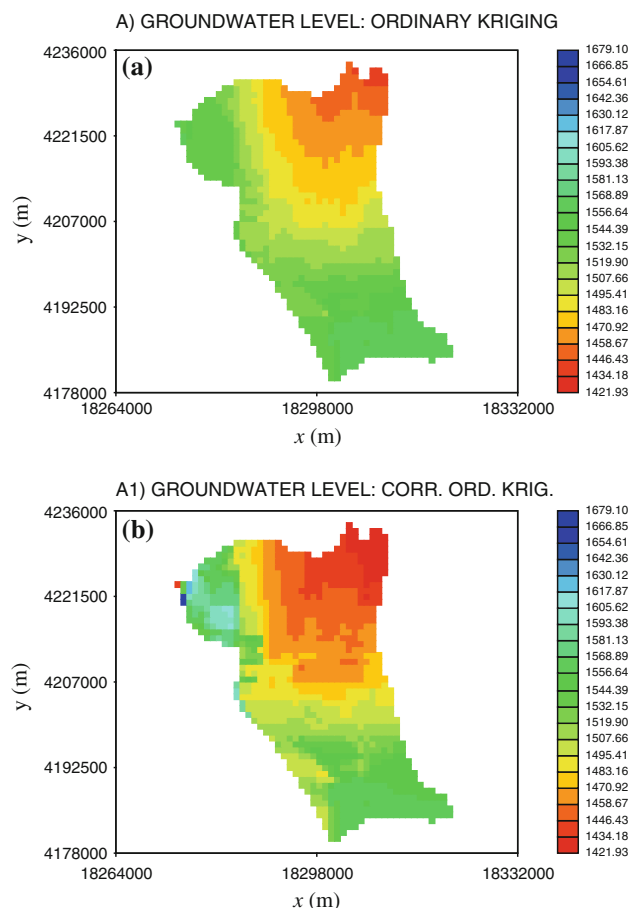

Fig. 5 Images of groundwater level estimated with OK estimates and smoothing corrected OK in 1983

Table 4 Statistical summaries for distribution of sampling points, OK estimates and corrected OK estimates of groundwater level in 1983 and 1988

| Samples	Sample size	Mean	Standard deviation	Median	Coefficient of variation	Range	Maximum	Minimum
1983								
Measured samples	75	1,501.20	45.93	1,498.00	0.031	276.34	1,691.40	1,415.06
OK estimates	1,248	1,509.86	32.87	1,511.18	0.022	124.58	1,567.68	1,443.10
Corrected OK	1,248	1,501.20	45.85	1,496.54	0.031	257.16	1,679.10	1,421.94
1988								
Measured samples	92	1,510.42	70.25	1,502.96	0.047	390.08	1,792.28	1,402.20
OK estimates	1,248	1,514.74	38.60	1,510.49	0.025	157.76	1,602.41	1,444.65
Corrected OK	1,248	1,510.42	70.21	1,491.66	0.046	382.95	1,785.15	1,402.20
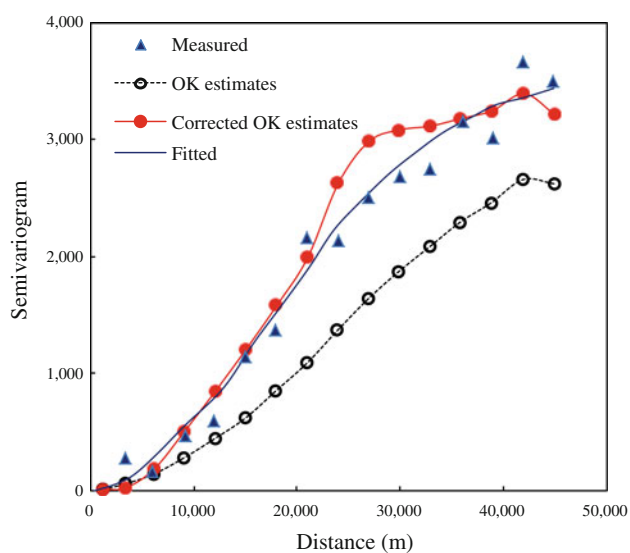
Fig. 6 Semivariograms for the sampling groundwater level, OK and corrected OK estimates in 1983

mean values. It is very different from the measured samples histogram. However, the histogram of corrected OK estimates is very similar to the measured samples histogram. At the same time, corrected OK estimates represent the real spatial distribution of groundwater. It follows that the experimental semivariogram of corrected groundwater levels is relatively consistent with that of measured samples; even so, there is still a discrepancy, which may be attributed to the fact that there are no or very few measured points in some interpolation areas. However, the lack of consistency between the semivariogram estimated from OK and measured samples (as shown in Fig. 6), reflects that OK presents a serious inherent drawback known as the smoothing effect.

Groundwater levels in 1988 were spatially interpolated, respectively, with OK and corrected OK and statistical results were compared (Table 4). Groundwater level frequency distribution histograms (Fig. 7) and semivariograms

(Fig. 8) for the sampling groundwater levels for OK and corrected OK estimates respectively are presented. As shown in Fig. 8, there are some errors between the interpolated results and measured values. This may be due to the distribution of measured points which is non-uniform (i.e. there are no or very few measured points in some interpolation areas) thus resulting in the bad interpolation effect in these areas. Comparing with Figs. 6 and 8 shows that the consistency between the semivariograms estimated from corrected OK and measured samples is not so good, although more measured points were used for interpolating groundwater level in 1988 (Fig. 8). This may be due to the same reason mentioned above; the amount of measured points is important, but more measured points are not always mean that the distribution is more uniform. The uniform distribution of measured samples is the key point for the interpolation in such a large area. For some measured samples (nonuniform distribution), it is not easy to eliminate the smoothing effect that occurred during the interpolation used kriging method. However, as a whole, Figs. 7 and 8 almost show the same tendency with that in 1983. The interpolated groundwater surface used corrected OK method looks smoother than the used OK method. Therefore, it can be concluded that the Yamamoto's (2005) method can effectively correct the smoothing effect.

Analysis of temporal and spatial variations of groundwater level

Knowledge of the real groundwater distribution is important for the planning of a quantitative water management, especially in the Wuwei oasis of the arid inland of northwest China, in which the groundwater level presents a significant spatial variability because of the excessive exploitation and disorderly management of groundwater resources. Therefore, groundwater levels in 1983 and 1992 were spatially interpolated with corrected OK method to investigate temporal and spatial variations of groundwater level in the study area. Fig. 9 shows the groundwater level
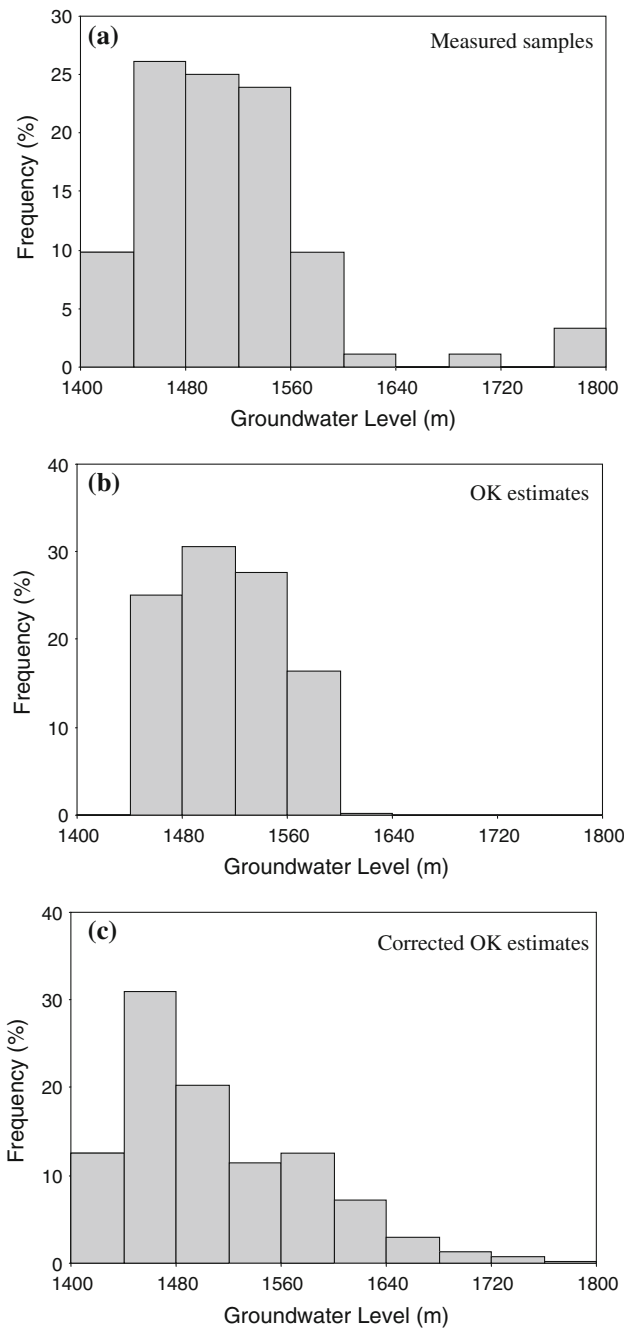
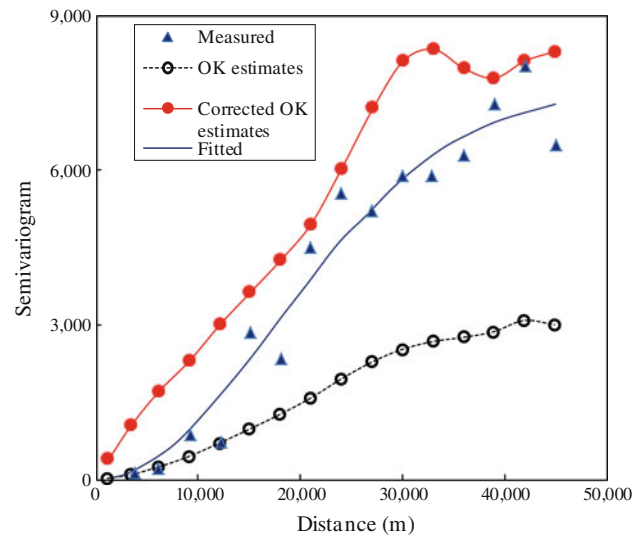Fig. 7 Groundwater level frequency distribution histograms in 1988

Fig. 8 Semivariograms for the sampling groundwater level, OK and corrected OK estimates in 1988

Fig. 9 Images of groundwater level estimated with smoothing corrected OK in 1992

map as estimated with smoothing corrected OK for the 1992 dataset. As a whole, the groundwater level in 1992 is generally lower than in 1983 (as shown in Fig. 5b); the groundwater decline was 2.1 m in average from 1983 to 1992. Averaged annual decline rate of groundwater level (take average for all measured values for each year, then getting the difference between the years, i.e. averaged annual decline) is 0.44 m in the 1990s and greatly larger than 0.17 m in the 1980s (Table 5). Excessive groundwater extraction is the main cause of the severe decline in the

water table due to an increase in population. Moreover, the main surface water sources have reduced every year over the past 40 years, which has led to lower groundwater recharge (Ma et al. 2005). In addition, improved irrigation channel efficiency also leads to lower groundwater recharge.

To study further the variation trend of groundwater level, temporal variation of groundwater levels from six observation wells were analyzed. These wells represent different land use, including irrigation area (611#), cities and towns (591# and 601#), grassland (573#), edge of the desert (617#), and upper reaches of river in the study area (525#). Table 5 shows that the average annual decline rate of groundwater level is different for the same land use in the 1980s and 1990s. In the 1980s, the average annual decline rate of groundwater level is relatively high with

Table 5 The average annual decline rate of groundwater level for observation wells

Period	Averaged annual decline rate	Well number					
		611#	591#	601#	573#	617#	525#
1983–1989	0.17	0.13	0.12	0.13	0.07	0.07	0.02
1990–1999	0.44	0.19	0.19	0.19	1.01	0.26	0.04

rates of 0.13, 0.12 and 0.13 m per year for irrigation area and cities and towns; however, it is relatively low for grassland, edge of the desert, and upper reaches of river. This can be attributed to overexploitation of groundwater resources in irrigation areas, cities and towns, while the influence of human activities is relatively minor in grassland and edge of the desert. Moreover, the average annual decline rate of the groundwater level for the upper reaches of the river reaches its minimum in the selected six observation wells. This fact may be due to higher amount of infiltration of surface water into soil and higher amount of recharge groundwater due to abundance of surface water in the upper reaches of river. Table 5 also shows that the average annual decline rate of groundwater level in the 1990s is significantly greater than in the 1980s for the same land use, especially for grassland and edge of the desert. This is consistent with the results of the above paragraphs. The observed trend may be due to the increase in population and overexploitation of groundwater in the whole Wuwei oasis. Due to the lack of surface water, groundwater has become a major resource of irrigation water especially in the lower reaches of the Shiyang River basin, i.e. Minqin oasis. The climate in Minqin oasis is characterized by about 110 mm of rainfall and 2,650 mm of potential evaporation (Sun et al. 2009). Groundwater resources have been excessively exploited, and this overexploitation resulted in the degradation of the environment; thus, leading many people to move from the Minqin oasis to the Wuwei oasis. Therefore, groundwater level has been decreasing in the Wuwei oasis with the increase of population and overexploitation of groundwater.

A continuous decline of groundwater level will lead to a series of environment problems, e.g. oasis atrophy and die out, sand storm, the psammophytic vegetations withered and die, well dried, and so on. Consequently, in order to slow down the decrease of groundwater level, the exploitation of different groundwater wells should be further optimally configured. Given the additional fact that the irrigated area was reduced by the government, some groundwater wells thus should be closed with the reduction of irrigated area. Therefore, two exploitation strategies should be carried out: (1) reducing the number of groundwater wells, and (2) reducing the exploitation of

groundwater by replacing the groundwater with surface water to irrigate.

As is known, groundwater level is a very important index for evaluating the groundwater environment, especially for the arid regions where water resources is very deficient; groundwater resources are very important for promoting economic prosperity in these regions. This study can provide a theory basis for studying the spatial and temporal distribution of groundwater, and provide a quantification of processes affecting the groundwater systems in the arid region.

Conclusions

Eight spatial interpolation methods to simulate spatial distribution of groundwater level based on GIS were analyzed and evaluated in the Wuwei oasis. It is concluded that OK is the optimal method for interpolating groundwater level in this region. However, just like other interpolation methods, OK estimates also present a serious inherent drawback well known as the smoothing effect with decreased variation of estimates. Yamamoto's method is used to correct the smoothing effect of OK estimates. The results showed that Yamamoto's method effectively corrected the smoothing effect, and the real spatial distribution of groundwater level thus was presented without losing local accuracy.

The corrected OK by Yamamoto's method was used for studying and analysing the temporal and spatial variations of groundwater level in the Wuwei oasis. The results showed that the groundwater level in 1992 is generally lower than in 1983. Excessive groundwater extraction is the main cause of the severe decline in the water table with the increase in population. Therefore, this study can provide one effective interpolation method (corrected OK method) for studying the temporal and spatial variations of groundwater level in arid regions, and provide guidance for groundwater resources extraction and management. It will be good for optimizing configuration of the exploitation of different groundwater wells and slowing down the decrease of groundwater level. Consequently, it will restore good ecologic environment.

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