Physics and Chemistry of the Earth xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Physics and Chemistry of the Earth

journal homepage: www.elsevier.com/locate/pce

Multilevel modeling of NPP change and impacts of water resources in the Lower Heihe River Basin

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ARTICLE INFO

Article history:
Received 28 August 2014
Received in revised form 24 October 2014
Accepted 11 December 2014
Available online xxxx

Keywords:
NPP
Ecosystem services
Heihe River Basin
Multilevel model
Decomposition analysis

ABSTRACT

Net primary productivity (NPP) lays the foundation for provision of various ecosystem services, and understanding the impacts of potential influencing factors on NPP is of great significance to formulating appropriate management measures to guarantee the sustainable provision of essential ecosystem services. This study analyzed the impacts of potential influencing factors on NPP in the lower Heihe River Basin, a typical arid and semi-arid region in China. First, NPP was estimated with the C-FIX model, and then the multilevel model was used to analyze the impacts of potential influencing factors on NPP during 2000–2008. Finally decomposition analysis was used to further analyze the contribution of influencing factors to NPP change during 2000–2008. The average NPP increased by approximately 9.07% during 2000–2008, and results of the multilevel model indicate that both the socioeconomic variables and demographic variables are useful in explaining NPP change. In particular, coefficients of rainfall and evapotranspiration which represent the water availability reached 0.0456 and 0.2956, respectively. Results of decomposition analysis suggested that the water availability played an important role in increasing NPP, with a contribution rate of 44.17%, and it is necessary to carry out some policies that can promote the water use efficiency to increase NPP under the background of climate change and intensified human activities. There are some uncertainties in the results of this study, but these results still can provide valuable reference information for the water resource management to increase the ecosystem service supply in the lower Heihe River Basin.

1. Introduction

Many of the benefits that humans gain from ecosystems are directly or indirectly related to freshwater, which are referred to as water related ecosystem services (Koschke et al., 2014), but little attention has been paid to the potential loss of ecosystem services (ES) due to water stress (Qin et al., 2014). Water is usually the single most important limiting factor for the growth and productivity of plants (Inman-Bamber et al., 2012; Nielsen, 2003), and many areas worldwide have been facing increasingly severe water scarcity (De Fraiture et al., 2008; Zhang and Xia, 2009), especially the arid and semi-arid regions that are very sensitive to climate change and human activities (Rockström and Gordon, 2001; Saue and Kadaja, 2014; Wang et al., 2012). In the arid and semi-arid regions, extracting water to meet human needs jeopardizes the health of vital ecosystems (Postel, 2000), and the ecological water demand of natural ecosystems have largely been neglected, leading to tragic ecological consequences and decreasing the provision of a wealth of ecosystem services (Richter et al., 2003). The rational water allocation has been considered as the fundamental method to solve problems resulting from water scarcity (Khare et al., 2007; Wang et al., 2012), and appropriation of water resources must be better managed if we hope to sustain these services related to water (Richter et al., 2003). The water resource management has undergone the succession from comprehensive management, to multi-purpose basin management and to the present push for ES-based governance, and the definition of ecosystem services might be used to strengthen sustainable water resource management (Cook and Spray, 2012). However, most of the current optimal water allocation methods are based on present water

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http://dx.doi.org/10.1016/j.pce.2014.12.001
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demand and supply and give less consideration to the water resource security and the ecological water demand which plays a key role in providing essential ecosystem services (Khare et al., 2007; Wang et al., 2012). In particular, it is of great significance to analyze the impacts of water resources on the net primary productivity (NPP), one of the most fundamental ecosystem services that underpin many other kinds of ecosystem services (Haines-Young and Potschin, 2010). New approaches of water resource utilization and management are needed in order to meet the increasing demand of a growing global population while protecting the ecological services provided by natural ecosystems (Postel, 2000), and the rational water allocation and decision analysis for sustainable development call for more in-depth research on the impacts of water resources on ecosystem service provision (Zhang and Xia, 2009).

Decline of NPP is one of the most serious ecological problems in the world, which is often triggered by human activities and climate change, especially in the arid and semi-arid regions, where the water availability is very sensitive to both the human activities and climate change (Deng et al., 2006; Potter, 2014; Wu et al., 2013). Besides, NPP is influenced by multiple drivers (Ahl et al., 2005; Wu et al., 2013; Zhan et al., 2012), and it is very necessary to analyze the relative roles of different drivers in influencing NPP, especially the water resources (Gao et al., 2004; Yang et al., 2014). There have been a number of studies that mapped the supply of ecosystem services and estimated their economic values, but the underlying role of the water resource in providing ecosystem services was seldom measured (Kremen, 2005). Knowledge on NPP change and its drivers can be effectively obtained with a combination of time series analysis of remote sensing data and regression analysis, and some studies have attempted to assess the relative contribution of climate change and human activities to the NPP change (Fabricante et al., 2009; Omuto et al., 2010; Wu et al., 2014; Xu et al., 2011).

The impacts of influencing factors on NPP change can be estimated with process-based terrestrial ecosystem models or statistical models, and most of the previous studies have used the following two approaches (Bai et al., 2014; Ciais et al., 2011). The first approach is to estimate the relative roles of different driving factors in influencing NPP by carrying out scenario simulation and comparing the simulated NPP under different scenarios (Evans and Geerken, 2004; Wu et al., 2014). However, it is difficult to simultaneously analyze the impacts of different driving factors on NPP through scenario simulation (Evans and Geerken, 2004). The other approach is to analyze the relationship between NPP and its driving factors with regression analysis models (Wu et al., 2014; Xin et al., 2008; Zhan et al., 2012). The regression analysis has solid statistical foundation (Seibel, 2003; Zhan et al., 2010, 2012), but it is difficult to involve all the potential driving factors of NPP in the regression analysis, and there may be some complex interaction among these driving factors, making it difficult to accurately estimate their relative roles in influencing NPP. More importantly, ecological processes including NPP change generally occur over a wide range of temporal and spatial scales and are driven by factors at multiple scales (Lambin et al., 2003; Starik and Rands, 1995), and it is necessary to analyze driving factors of NPP change at multiple scales (Sun et al., 2006), but previous studies using regression analysis generally focused on only a single scale (Verburg et al., 2003). The multilevel statistical modeling is a methodology designed for dealing with hierarchical data (Lehtonen, 2005). Driving variables at different scales can be simultaneously handled by organizing data in a nested hierarchical structures, with variables at lower levels partly explained by variation at the higher levels (Albright and Marinova, 2010; Jiang et al., 2012; Zhang et al., 2014). Multilevel statistical modeling has been recently introduced in ecology, but it has been rarely used to analyze the driving mechanism of change in ecosystem service provision (Chelgren et al., 2011; Zhang et al., 2014).

The arid and semi-arid regions are home to more than 38% of the global human population, where the ecosystems provide various important ecosystem services (Foley et al., 2005; MA, 2005a,b; Omuto et al., 2010), but the ecosystem service provision in these regions are very sensitive to disturbances due to the severe lack of water resources (Ye et al., 2010). This study aims to analyze the role of water resources in influencing the NPP change in the lower Heihe River Basin, a typical arid and semi-arid region in the northwest part of China, where there is serious water scarcity due to the strong impacts from human activities and global climate change in recent decades (Wang et al., 2009). The specific objectives of this study are to (1) estimate NPP in the Heihe River Basin in 2000, 2005 and 2008, (2) analyze the driving mechanism of NPP change with the multilevel model, and (3) further reveal the relative contribution of water resources to NPP change with decomposition analysis. The results of this study can provide some valuable reference information to enable better water resource management to guarantee sustainable provision of essential ecosystem services.

2. Methods and materials

2.1. Study area

The lower Heihe River Basin (between 97.13–103.12°E, 39.87–42.79°N) belongs to the second largest inland river basin in the arid area of China, and it is located in the middle part of the Hexi Corridor and western Inner Mongolia Plateau, covering Jinta County in Gansu Province and Ejina Banner in Alxa League of Inner Mongolia (Fig. 1). The lower Heihe River Basin is a typical arid and semi-arid region with the temperate continental climate, where the inter-annual average precipitation is only 50 mm while the inter-annual average evaporation reaches 3700 mm, making this region extremely dry and susceptible to climate change. The altitude ranges from 869 m to 1885 m in this region, and the plain accounts for approximately 60% of the total land area, most of which is covered by unused land such as barren land and sandy land. The local vegetation is mainly grassland, and the limited cropland mainly concentrates in the oases such as Yuanyang Oasis in Jinta County. However, there is the second largest populus euphratica forest of the world in Ejina Banner, which heavily depend on the runoff of Heihe River and serve as the first ecological barrier to intercept the sandstorms into China. However, the vegetation degraded very seriously due to the climate change and human disturbance, which greatly reduced the runoff of Heihe River into the lower reach during the past decades. The Chinese central government has started an ecological water diversion project in 2000 in order to restore the ecological environment and control the desertification in the lower Heihe River Basin. However, much still remains unknown about the contribution of water diversion to the change of ecosystem service provision in the lower Heihe River Basin, which can provide valuable information for improving the water management and ecological conservation.

2.2. Data and processing

A database for 2000–2008 was first built, including the data of NPP at the small watershed scale and potential drivers at three levels in 2000, 2005 and 2008. The data at the small watershed scale were aggregated by grids, while the data at the county level were extracted from statistical yearbooks. The 1 km resolution NPP data were calculated with the C-FIX model (Veroustraete et al., 2002) based on the meteorological data and Normalized Difference

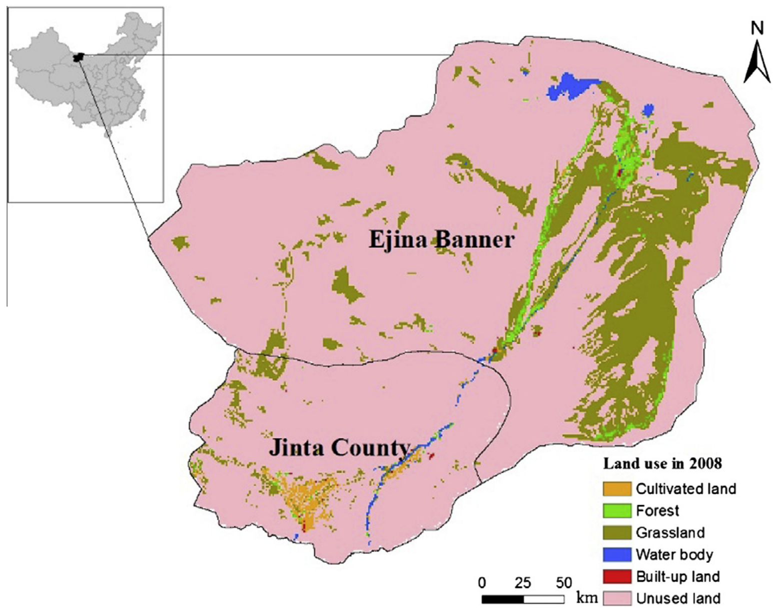

Fig. 1. Location of the lower Heihe River Basin and land use in 2008.

Vegetation Index (NDVI) data (Li and Jie, 2013). The driving factors of NPP change can be categorized into land use, geophysical (terrain and landform, soil), meteorological, location and socioeconomic variables, which are divided into three levels (Table 1). The time-variant socioeconomic variables at the county level (gdp, gdp1, pop, fertilizer) were used as the level 3 variables, the data of which were obtained from statistical yearbooks. The level 2 variables include the time-invariant terrain variables (altitude, slope), soil properties (soil_n) and location factors (d2road), which were obtained with the 90 m resolution digital elevation model (DEM) and 1 km resolution soil maps (Deng et al., 2008; Wei et al., 2011). The time-variant climate variables (ta, sun, rain, et, ur) and vegetation factors (contig, area, vcr) are used as the level 1 variables, which were obtained by interpolating the observation data from meteorological stations or calculated with the 1 km resolution land use data and NDVI data (Mardikis et al., 2005).

2.2.1. Estimation of NPP

Since it is difficult to directly measure NPP in a large area, this study has estimated NPP with the C-FIX model based on the 1 km resolution MODIS data in 2000, 2005 and 2008. The C-FIX model is a parametric model driven by temperature, radiation and fraction of Absorbed Photosynthetically Active Radiation (fAPAR), which has been successfully applied in estimating NPP over Europe and Africa (Lu et al., 2005; Veroustraete et al., 2002). In the C-FIX model, NPP was estimated as follows:

$$NPP_d = [p_{(T_{atm})} \times CO_2fert \times \varepsilon \times fAPAR \times c \times S_{g,d}] \times (1 - A_d) \quad (1)$$

where NPP_d is the daily NPP, $p_{(Tatm)}$ is the normalized temperature dependency factor which ranges between 0 and 1 (Wang, 1996), CO_2fert is the normalized CO_2 fertilization factor that is defined as the increase in carbon assimilation due to the CO_2 levels above the atmospheric background level (Veroustraete et al., 2002), ε is

Table 1
Variables for decomposing causality of NPP change in the lower Heiher River Basin.

Variable	Unit	Meanings	Mean	Std	Min	Max
Dependent variable						
npp	gC/(m^2 a)	Net primary productivity	55.69	68.36	0.00	799.83
Independent variables						
Small watershed level						
ta	°C	Temperature	8.84	0.81	5.71	10.09
sun	h	Sunshine hour	3431.09	70.69	3088.36	3587.86
rain	mm	Annual rainfall	43.02	12.89	22.56	100.16
et	mm	Evapotranspiration	81.52	56.55	0.00	1344.07
ur	%	Relative humidity	37.19	3.82	30.16	47.91
contig	–	Contiguity index	0.81	0.16	0.00	0.91
area	ha	Patch area	1376981	1397132	100.00	3072700
vcr	%	Vegetation coverage rate	22.41	6.73	0.00	86.08
altitude	m	Altitude	1155.38	203.99	888.00	1869.00
slope	°	Slope	0.46	0.48	0.01	7.26
soil_n	mg/kg	Nitrogen content in soil	0.03	0.02	0.01	0.11
d2road	m	Distance to the nearest road	10965.08	9028.04	1000.00	44181.45
County level						
gdp	10^4 yuan	Gross domestic product	3.15	44.40	1.00	6203.04
gdp1	10^4 yuan	GDP of the primary industry	1.95	19.38	1.00	2551.42
pop	person	Population	3.47	105.61	1.00	13978.99
fertilizer	t	Amount of used fertilizer	83.87	1054.41	1.00	14866

Please cite this article in press as: Yan, H., et al. Multilevel modeling of NPP change and impacts of water resources in the Lower Heihe River Basin. J. Phys. Chem. Earth (2015), http://dx.doi.org/10.1016/j.pce.2014.12.001

the radiation use efficiency that is equal to 1.1 (gC/MJ) (Wofsy et al., 1993), *fAPAR* is the fraction of absorbed Photosynthetically Active Radiation (PAR) absorbed by vegetation canopy, which is calculated as a linear function of the NDVI (*fAPAR* = 0.95 ∗ NDVI-0.04) according to the study of Fensholt et al. (Fensholt et al., 2004), *c* is the climatic efficiency giving the ratio of PAR to global radiation, which is 0.48 (Veroustraete et al., 2002); *Sg,d* is the daily incoming global solar radiation; *Ad* is defined as an autotrophic respiratory fraction of gross primary productivity, which is estimated with the parameterization method of Goward and Dye (Goward and Dye, 1987).

The data used to estimate the daily NPP include daily meteorological data and NDVI data. The daily temperature data were obtained from the daily meteorological observation data of meteorological stations covering the study area and were interpolated into grid data. The daily incoming global solar radiation data were calculated with the sunshine hour data and the solar radiation observation data of meteorological stations in the study area and neighborhood regions. The CO_2 concentration data were downloaded from http://www.esrl.noaa.gov/gmd/ccgg/trends/global.html. The NDVI data were extracted from the cloud-free NDVI data from 2001 to 2011 in the Heihe River Basin (Li and Jie, 2013).

2.2.2. Climate data and water availability data

The climate factors include the annual average temperature, annual sunshine hours, and relative humidity. All the climate data in 2000, 2005 and 2008 were derived from daily observation data of meteorological stations maintained by the China Meteorological Administration. The original meteorological observation data were saved in form of text and were interpolated into 1 km × 1 km grid data with the gradient plus inverse distance squares method (Mardikis et al., 2005; Zhan et al., 2010). In particular, the interpolated temperature data was adjusted with the DEM data since temperature declines linearly with the increasing altitude. The water availability data include the annual precipitation, evapotranspiration (ET), and distance to the nearest water body. The precipitation is a key limiting factor of terrestrial ecosystem production in arid and semi-arid regions (Nemani et al., 2003), and therefore the annual precipitation is chosen as a primary natural driver of NPP change. The annual precipitation data were obtained from the daily observation data of meteorological stations and were interpolated into 1 km × 1 km grid data with the gradient plus inverse distance squares method. The ET data for the study area were extracted from the monthly evapotranspiration datasets (2000–2012) with 1 km spatial resolution over the Heihe River Basin Version 1.0 (Wu et al., 2012). The distance to the nearest water body (d2water), which is used as the measure of accessibility to water resources, was measured on the basis of the water area maps.

2.2.3. Geophysical data

The geophysical factors include the terrain, location, and soil properties. The terrain data include the altitude and slope extracted from the 90 m resolution DEM data from http://srtm.csi.cgiar.org/, based on which the small watersheds were delimited for further analysis. Besides, the distance to the nearest road was measured on the basis of the road network map, which was derived from the topographic map of China at a scale of 1:250,000 (Deng et al., 2008). In addition, the soil properties include the soil nitrogen content, soil organic matter content and loam content, the data of which were derived from the HWSD soil texture dataset of the Heihe River Basin and the second national soil survey data (Nachtergaele et al., 2008; Wei et al., 2011).

2.2.4. Vegetation data and landscape indices

The vegetation factors include the NDVI, which was calculated with the cloud-free NDVI data from 2001 to 2011 in the Heihe River Basin (Li and Jie, 2013), and the vegetation coverage rate calculated with NDVI. Besides, this study also used the 1 km resolution land use/land cover data derived from Landsat TM/ETM images in 2000, 2005 and 2008, which were interpreted by Chinese Academy of Sciences (CAS) with the overall interpretation accuracy of 92.70% (Deng et al., 2008). The landscape indices, including the patch area and contiguity index, were calculated with Fragstat on the basis of the land use/land cover data.

2.2.5. Socioeconomic data

The socioeconomic data include the population, amount of used fertilizer which represents the agricultural input, Gross Domestic Product (gdp) and GDP of the primary industry (gdp1), which represent the overall economic development and the development of agriculture, respectively. The population data were provided by Heihe Plan Science Data Center (Wang et al., 2011), and the data of the amount of used fertilizer, gdp and gdp1 in 2000, 2005 and 2008 were derived from the census data of Gansu Province and Inner Mongolia Autonomous Region.

2.3. Multilevel modeling

Previous studies generally ranked the importance of explanatory variables according to their elasticities (i.e., regression coefficients) (Deng et al., 2008; Jiang et al., 2012). Elasticities are measurements of the marginal effects of the explanatory variables on the explained variable, which provide valuable information on the driving mechanism of the explained variable. But the elasticities cannot provide information on the overall contribution of each explanatory variable to the change of the explained variable (Jiang et al., 2012), and therefore the decomposition analysis was used to further explore the contribution of explanatory variables to NPP change in this study. A series of multilevel models were first constructed according to steps suggested in literatures to select the optimum one as the base model for including explanatory variables, and then the decomposition analysis was carried out. In this study, the NPP at the small watershed scale was used as the dependent variable and the potential driving factors of NPP change were used as in dependent variables. The multilevel statistical model includes time-variant dependent variables at small watershed levels and the independent variables at the county level and small watershed levels. For all multilevel models, we used the following notation: *t* indexes time, *i* indexes small watersheds, and *j* indexes counties.

Multilevel models were constructed for all small watersheds, and all the models were estimated using the restricted maximum likelihood (RML) method (Osgood and Smith, 1995). We used univariate tests of the individual variance components and multivariate tests of overall model fit to examine the random effects in order to select the optimum model. The unconditional growth model with only the random intercepts was first constructed to examine the relationship between NPP and the time at the small watershed level (assuming NPP varies randomly among small watersheds). In Eq. (2), only the Year is involved, and in Eq. (3) a squared term of Year is added, with other parts remaining the same as Eq. (2).

$$\ln(NPP_{it}) = \beta_0 + \beta_1 Year_{it} + \mu_{0i} + \varepsilon_{it} \quad (2)$$

$$\ln(NPP_{it}) = \beta_0 + \beta_1 Year_{it} + \beta_2 Year_{it}^2 + \mu_{0i} + \varepsilon_{it} \quad (3)$$

where μ_{0i} is the random intercept that varies randomly between counties and is assumed to be normally distributed with a zero mean and a variance of τ_0^2; ε_{it} is the error term which is normally distributed with a zero mean and a variance of σ^2; β_0 and β_1 are regression coefficients to be estimated. The estimation results of Eqs. (2) and (3) indicate that both linear and quadratic effects of time are significant (p-value < 0.001) (Table 2), and therefore both time effects should be incorporated when the multilevel models are established.

Next, the optimum number and form of random effects were determined through examining whether NPP varies randomly among counties and whether its relationship with the time varies among small watersheds. It is assumed that NPP randomly varies among small watersheds, but the relationship between NPP and the time may also vary among small watersheds, and NPP may vary randomly among counties. Eq. (4) was developed on the basis of Eq. (3), which allows the relationship between NPP and the time to vary randomly among small watersheds. Eq. (4) tests the slope variability of Year at the small watershed level, it involves two random terms, including the intercept variance term μ_{0ij} and the slope random term μ_{1ij}. Eq. (5) further tests both the slope variability of the time and the intercept variability at the county level. Eq. (5) has three random effects, including a small watershed level intercept random term μ_{0i}, a small watershed level slope random term μ_{1i} that interacted with the time, and a county level intercept random term v_{0j}, and it was assumed that μ_{0ij} and μ_{1ij} are multivariate normally distributed and v_{0j} is independently normally distributed (Table 2).

$$\ln(NPP_{ijt}) = \beta_0 + \beta_1 Year_{ijt} + \beta_2 Year_{ijt}^2 + \mu_{0ij} + \mu_{1ij} Year_{ijt} + \varepsilon_{ijt} \tag{4}$$

$$\ln(NPP_{ijt}) = \beta_0 + \beta_1 Year_{ijt} + \beta_2 Year_{ijt}^2 + \mu_{0ij} + \mu_{1ij} Year_{ijt} + \upsilon_{0j} + \varepsilon_{ijt} \tag{5}$$

The result of Eq. (4) shows that both the intercept random and the slope random are very significant ($p < 0.001$), indicating that it is necessary to include the slope random term of Year. Besides, the result of Eq. (5) shows that when the slope random term of Year is included, the intercept random at the county level is not significant, with the variance component of approximately zero, and the result of the likelihood ratio test does not show a significant improvement in overall fit, either. Since our data structure is characterized by the observations of 443 small watersheds nested within two counties, it is not surprising that the variance of NPP is not significant at the county level. The relative small sample size at the county level may hamper the estimation of intercept random, which is similar to the conditions in previous studies (Overmars and Verburg, 2006; Polsky and Easterling III, 2001). Overall, there is not significant county level intercept variation and there is not significant improvement in Eq. (5) compared to Eq. (4), and therefore Eq. (4) was selected as the base model (Model 1) for including explanatory variables at different administrative levels. Explanatory variables at different levels were step by step included in the base model to explore their impacts on NPP (Models 2–4), and the full model was established as follows, where explanatory variables above the 10% significance level were finally kept.

$$\ln(NPP_{ijt}) = \beta_0 + \beta_1 Year_{ijt} + \beta_2 Year_{ijt}^2 + \sum_{p=1}^{P} \alpha_p X_{pijt} + \sum_{q=1}^{Q} \lambda_q X_{qij} + \sum_{r=1}^{R} \gamma_r Z_{rj} + \mu_{0ij} + \mu_{1ij} Year_{ijt} + \varepsilon_{ijt} \tag{6}$$

where X_{ijt} consists of the time-variant variables at the small watershed level (climate factors, evapotranspiration, vegetation factors), X_{ij} refers to the time-invariant variables at the small watershed level (soil properties, terrain, location factors), which primarily serve as the control variables; Z_{ijt} includes the time-variant socioeconomic variables at the county level (GDP, population and so on).

2.4. Decomposition analysis

Since the results from the multilevel model only provide the information on marginal effects of influencing factors on NPP, the contribution of influencing factors to the overall change in NPP should be further analyzed with the decomposition analysis (Seibel, 2003; Zhan et al., 2012). Decomposition analysis is a mathematical instrument to determine the contribution of changes in single driving factors on changes in the dependent variable, it involves both the magnitude of change and coefficients of influencing factors (Nie and Kemp, 2014). In this study, the Fairlie method has been used for the decomposition analysis, which is tailored to nonlinear outcomes (Fairlie, 2005). The contribution of influencing factors to the NPP change was calculated with the regression coefficients for each influencing factor from the multilevel models (Nie and Kemp, 2014). The decomposition analysis was conducted as follows. The percentage change of each influencing factor was first calculated, which was then multiplied by the coefficients estimated with the fixed effects model or the random effects model to obtain the impacts of each influencing factor on the dependent variable, which was NPP in this study. Finally, impact of each influencing factor was divided by the percentage change of NPP to obtain contribution of each influencing factor.

3. Result and discussion

3.1. Variation of NPP

The results obtained with the C-FIX model indicate that NPP showed obvious spatial heterogeneity and no significant change in the spatial pattern during 2000–2008. The NPP is generally very low in most part of the lower Heihe River Basin but relatively high in the oasis regions (Fig. 2). NPP is generally below 50 gC/(m^2 a) or ranges between 50 and 100 gC/(m^2 a) in most part of the study area, where the major land use types include sandy land and Gobi. Besides, the regions with NPP of 100–200 gC/(m^2 a) are mainly distributed around the fringe of oases and Gurinai Lake and in a few part in the western and middle parts of the study area, where the major vegetation is grassland. In addition, the regions with NPP above 200 gC/(m^2 a) concentrate in the oases (e.g., Yuanyangchi irrigation district and Ejina Oasis,) and a few part around Gurinai Lake, where there is mainly cultivated land and forests. Overall, NPP in the lower Heihe River Basin ranged from 0 to 799.83 gC/(m^2 a) during the whole study period, with an average of 53.21 gC/(m^2 a), which is similar to that in previous studies (Lu et al., 2005; Zhou et al., 2013).

Table 2
Unconditional models for the model selection.

	Dependent variable: $\ln(NPP_{ijt})$			
	Eq. (2)	Eq. (3)	Eq. (4)	Eq. (5)
Intercept	3.8392 (0.0263)***	3.8392 (0.0263)***	3.8392 (0.0263)***	3.8239 (0.0282)***
Year	0.0114 (0.0007)***	0.0425 (0.0022)***	0.0425 (0.0022)***	0.0439 (0.0025)***
Year^2		−0.0040 (0.0003)***	−0.0040 (0.0003)***	−0.0041 (0.0003)***

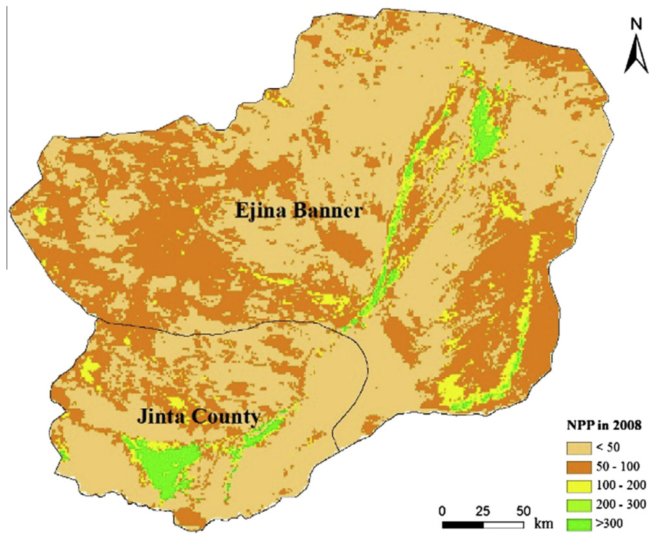

Fig. 2. Spatial variation of NPP in the lower Heihe River Basin in 2008.

There is obvious difference in the average NPP among land use types. For example, the average NPP of cultivated land is the highest, reaching 330.36 gC/(m^2 a), which is similar to the values estimated by Lu et al. and Zhou et al. (which is 210–350, and 364, respectively) (Lu et al., 2005; Zhou et al., 2013). In particular, the estimated average NPP of the forest is 242.06 gC/(m^2 a), which is close to that of Lu et al. (184–268 gC/(m^2 a)) but is lower than that of Zhou et al. (280–340 gC/(m^2 a)). NPP of forests is generally higher than that of the cultivated land, however, most of the forests in the lower Heihe River Basin have experienced long-term serious degradation, which leads to the relatively low productivity. In addition, the estimated average NPP of grassland is 79.82 gC/(m^2 a), which is lower the estimated average NPP of the whole basin in previous studies (Lu et al., 2005; Zhou et al., 2013). Most of the grassland in the lower Heihe River Basin is low-coverage grassland, the productivity of which is generally below the average level of the whole basin. In addition, the average NPP of the unused land is 42.07 gC/(m^2 a), which is very close to the estimated values of both previous studies (Lu et al., 2005; Zhou et al., 2013), reconfirming that the lower reach accounts for most part of the unused land with very low productivity in the whole basin. Overall, there is some difference between the estimated NPP in this study and previous studies, but the estimated average value and spatial pattern of NPP in this study are consistent with that of previous studies, indicating that it is reliable to estimate NPP with the C-FIX model in this study.

3.2. Random effects

The two-level nested mixed model specified in Eq. (6) was used to analyze the driving mechanism of NPP change in 443 small watersheds in two counties of the lower Heihe River Basin. Table 3 shows the estimation results of these multilevel models, where different explanatory variables were included step by step and explanatory variables with significant influence were finally kept. It is expected that a proportion of the variance associated with the base model will be captured by the newly explanatory variables, which may incorporate more information into the multilevel model. The results shows that the random effects within small watersheds and between small watersheds are both very significant in all these models. For example, in the unconditional growth model (Model 1), the variance of the within small watershed intercept and between small watershed intercept (σ_ε^2 and $\sigma_{\mu 0}^2$) in Model 1 are 0.01 and 0.30, respectively. Besides, there is also significant variance of the slope random of the year ($\sigma_{\mu 1}^2$) in Model 1. In addition, the intraclass correlation coefficients (ICC) at the two levels in Model 1 (ρ_ε and ρ_μ) are 0.02 and 0.98, respectively, indicating there is a high degree of clustering in terms of the NPP change at both levels, especially at the between small watershed level. What is more, there is generally decrease of the variance of the within small watershed intercept and between small watershed intercept from Model 1 to Model 4, which c data were extracted from the cloud-free data were extracted from the cloud-free an be attributed to the variance of the sequentially added explanatory variables as expected. In particular, variance of the between small watershed intercept declined obviously from 0.30 in Model 1 to 0.10 in Model 4, while the variance of the slope random of the year only changed slightly. The decrease of the variance of the within small watershed intercept indicates that there is less NPP variation that was not captured by the explanatory variables. Despite the differences in the variance component among the four models, there is strong evidence of clustering at the between small watershed level, indicating that the two-level model is required in order to adequately represent the nature of the nested underlying processes.

3.3. Fixed effects

The driving mechanism of NPP change was shown with the estimation results of four multilevel models, which involved different explanatory variables (Table 3). The unconditional growth model was firstly run, the result from which shows there is a significant negative coefficient of Year and a significant positive coefficient of Year^2, indicating that NPP will first increase and then decrease over the time. With more explanatory variables incrementally added into the models, it still suggests that NPP will still change nonlinearly as the time goes by. Besides, the regression coefficients of the subsequently added explanatory variables gradually changed, but their signs kept consistent and their impacts remained statistically significant (Models 2–4 in Table 3).

The results indicated that the climate factors played a fundamental role in influencing NPP, the importance of which was demonstrated by their significantly high coefficients when only the climate factors and water availability were included in the model (Model 2). For example, the coefficient of sunshine hour (lnsun) was 0.99 (Model 2 in Table 3), intuitively demonstrating that NPP will increase by 9.86% if the sunshine hour increases by 10%. There is generally high solar radiation in the arid and semi-arid areas, which can be beneficial to NPP (Houghton et al., 2001), and the increase of the sunshine hour indicates that there will be more solar energy that may be absorbed by vegetation. Besides, the temperature increase can accelerate biological processes, promote plant growth and may consequently increase NPP. The results show that the coefficient of the annual average temperature (lnta) is below zero (−2.47 in Model 4 in Table 3), indicating that the temperature rise has negative impacts on NPP. However, the coefficient of the cumulative temperature above 10 °C is above zero (2.78 in Model 4 in Table 3), indicating that higher cumulative temperature can increase NPP. The photosynthesis processes and respiratory processes are sensitive to temperature, and the temperature rise will lead to a decrease in the NPP when it is above the optimal temperature for photosynthesis (Betts et al., 2004; Fung et al., 2005). More importantly, the growing season is very short in the lower Heihe River Basin, during which the temperature rise may be beneficial to the primary production of vegetation. But the increase of the annual average temperature may be mainly caused by the temperature rise in the non-growing season such as the winter (Cao et al., 2003), which may decrease the overall NPP.

Table 3
Results of multilevel models for NPP change.

	Dependent variable: ln(NPP_{ijt})			
	Model 1	Model 2	Model 3	Model 4
Fixed effects				
Within and between small watershed				
Intercept	3.84 (0.03)***	−19.17 (2.45)***	−21.90 (2.77)***	−21.64 (2.81)***
Year	0.04 (0.00)***	−0.03 (0.01)***	−0.04 (0.01)***	−0.04 (0.01)***
Year^2	0.00 (0.00)***	0.00 (0.00)***	0.01 (0.00)***	0.01 (0.00)***
lnta		−1.58 (0.15)***	−2.34 (0.19)***	−2.47 (0.19)***
lnta10		2.10 (0.24)***	2.62 (0.29)***	2.78 (0.29)***
lnsun		0.99 (0.21)***	1.11 (0.21)***	1.05 (0.21)***
lnrain		0.06 (0.02)*	0.05 (0.02)*	0.05 (0.02)**
lnet		0.31 (0.03)***	0.24 (0.03)***	0.30 (0.04)***
contig		−1.72 (0.21)***	−0.98 (0.18)***	−0.90 (0.22)***
vcr		0.04 (0.00)***	0.04 (0.00)***	0.04 (0.00)***
percent_ld1			0.37 (0.13)**	0.29 (0.14)**
percent_ld2			2.40 (0.36)***	2.42 (0.37)***
percent_ld3			0.32 (0.08)***	0.36 (0.08)***
lnpop			0.18 (0.02)***	0.17 (0.02)***
lngdp1			0.40 (0.06)***	0.45 (0.06)***
lngdp			−0.48 (0.07)***	−0.56 (0.07)***
lnsoil_n				0.06 (0.03)*
lnsilt				−0.18 (0.04)***
Random effects				
Within small watershed				
σ_{ε}^2	0.01 (0.07)	0.00 (0.07)	0.00 (0.06)	0.00 (0.06)
ρ_{ε}	0.02	0.03	0.04	0.04
Between small watersheds				
$\sigma_{\mu 0}^2$	0.30 (0.55)***	0.14 (0.37)***	0.10 (0.32)***	0.10 (0.31)***
$\sigma_{\mu 1}^2$	0.00 (0.01)***	0.00 (0.01)***	0.00 (0.01)***	0.00 (0.01)***
ρ_{μ}	0.98	0.97	0.96	0.96

Note: *t* statistics in parentheses;
* Significant at 90%.
** Significant at 95%.
*** Significant at 99%.

The estimation results indicated that the water availability (lnrain and lnet) had significant impacts on NPP. The very significant coefficients of evapotranspiration (lnet) and annual rainfall (lnrain) (0.30 and 0.05 in Model 4) indicate the improvement of water availability will have positive impacts on NPP. The plant growth in arid and semi-arid regions is limited by water availability (Houghton et al., 2001), especially in the Lower Heihe River Basin where the annual rainfall is extremely low. The vegetation with high NPP is mainly distributed along the Heihe River, which heavily depends on the runoff of Heihe River and the underground water supplemented by the runoff. By comparison, in most part of the study area that is far from the main stream of Heihe River, the vegetation mainly depends on the rainfall and underground water, while both NPP are the rainfall are very low in these regions, therefore it is not surprising that both the coefficient and significance level of the evapotranspiration is higher than that of the rainfall.

The vegetation factors (vcr, contig) and soil properties (soil_n, silt) directly influence the vegetation growth and consequently have significant impacts on NPP. The results show that the coefficients of vcr and contig are 0.04 and −0.90, indicating the vegetation coverage rate had significant positive impacts on NPP, while the contiguity index (contig) had negative impacts on NPP. The increase of the vegetation coverage rate indicates there is more vegetation for photosynthesis, which is beneficial to NPP. By comparison, the large contiguity index indicate the existence of dominant landscape types, however, the dominant landscapes in the lower Heihe River Basin are the unused land such as sandy land and bare land, the average NPP of which is generally very low, and therefore it is not surprising that the increase of the contiguity index of these dominant landscapes will lead to decrease of NPP. Besides, the overall NPP is influenced by not only the vegetation coverage rate (vcr) but also the total area of vegetation, both of which are closely related with the water availability and human activities. What is more, the soil plays a fundamental role in influencing plant growth and distribution and also has some indirect impacts on NPP. The result shows that the nitrogen content in soil (soil_n) is positively related with NPP, with the coefficient of 0.06. The nitrogen content in soil is closely related to the soil fertility, and higher nitrogen content in soil is beneficial to promoting the vegetation growth, and consequently can have some impacts on NPP. By comparison, the silt content is negatively related with NPP, with the coefficient of −0.18, and this may be because the silt content is generally high in the widespread deserts and sandy land, where the habitat is generally unfavorable for the vegetation.

The human activities, including the land use and socioeconomic development both directly or indirectly influence the plant distribution, and consequently have some important influence on NPP. Land use is one of the major approach through which human beings influence the ecosystem (Foley et al., 2005), and the results indicated that the land use (percent_ld1, percent_ld2, percent_ld3) all had statistically significant impacts on NPP. The average NPP is generally high in cropland, forest and grassland, especially the forest, the productivity of which is generally the highest in the terrestrial ecosystem, and it is not surprising that the percentages of these three land use types all have significant positive impacts on NPP. The influence of the percentage of cropland (percent_ld1) is significant at the 90% level, while that of forest and grassland is significant at the 99% level, and the coefficient of percent_ld2 reaches 2.42, indicating that the forest played a more important role in influencing NPP. There is very limited cropland in the lower Heihe River Basin, but most of the cropland is in the oases or along the main stream of Heihe River, where the water resource is sufficient and the agricultural input is high; the high NPP of the cropland makes great contribution to meeting the food demand of local human beings. The forest, including the populus euphratica forest and some other shrub forest, NPP of which is very high, is a key component of local vegetation, and the change in the percentage of the forests (percent_ld2) can have great impacts on NPP as well as other ecosystem services. The average NPP of grasslands is relatively low, but the grasslands account for a large area of land and is the major component of vegetation in the lower Heihe River, and the change in the area percentage of grassland still can have very significant impacts on the overall NPP.

The human activities, including the population density and socioeconomic development, influence the vegetation distribution, water resource allocation and consequently may have significant impacts on NPP. The results show that the population density (pop) and gross domestic product of the primary sector (gdp1) have positive influence on NPP, with the coefficient of 0.17 and 0.45, respectively; while the overall gross domestic product (gdp) has negative influence on NPP, with the coefficient reaching −0.56. The local population density is very low in most part of the study area, with the major part of population concentrating in the oases, which provides labor input for the agricultural development can therefore increase the average NPP of cropland. The local agriculture mainly includes irrigation agriculture and animal husbandry, which depends on the primary production in irrigated cropland and grassland, and the positive coefficient of gdp1 shows that the agricultural development is beneficial to the increase of NPP. With the population growth and technical advance, more efficient management measures and increasing investment have promoted the productivity of both the cropland and grassland and led to the increase of NPP. By comparison, the negative coefficient of gdp (−0.56) shows that the economic development has negative overall impacts on NPP. This suggests that the development of the second industry and tertiary industry will lead to decrease of NPP. On the one hand, the second industry and tertiary industry has low dependency on the vegetation, while their development will generally occupy fertile land in the oases and consume more water resources, leading to the shrinkage of vegetation coverage and decrease of the overall NPP. On the other hand, the development of the second industry and tertiary industry can provide financial basis for increasing the agricultural investment such as the fertilizer. However, the results of this study show that currently the overall influence of development of the second industry and tertiary industry on NPP is still negative.

3.4. Result of decomposition analysis

The estimation results was further explored with decomposition analysis in order to derive more information on the ranking of the importance of explanatory variables in determining the NPP change, and special attention was paid to the role of the water availability. The average NPP increased from 51.57 gC/(m^2 a) in 2000 to 56.25 gC/(m^2 a) in 2008, with an overall increase percentage of 9.07%, indicating that the vegetation has recovered to some degree after the implementation of the water diversion program since 2000. NPP in the lower Heihe River Basin once declined seriously, and it started to increase after the implementation of the water diversion program in 2000, but it may reach a threshold due to various limiting factors except for the water resource. The decomposition analysis was carried out to further analyze effects of the influencing factors on NPP, and the results obtained with the full model (Column 4 in Table 3) were assumed to be accurate and realistic, and the contribution of these explanatory variables to the change in NPP was calculated with the percentage change in these explanatory variables and the estimated coefficients obtained with the multilevel model. The result from decomposition analysis shows the importance of the water availability to the NPP change (Table 4). In spite of the different signs associated with the marginal effects of the two explanatory variables, their total effects are both positive, which incorporate both the marginal effects and the changes in these variables. The evapotranspiration (et) is the most important factor and it explains 25.68% of the NPP change. The rainfall exerts less but still substantial influence, accounting for 18.50% of the NPP change. Overall, the water availability including jointly explains 44.17% of the NPP change, and therefore improving the water availability is of great significance to increase NPP as well as other ecosystem services.

The lower Heihe River Basin is in the arid and semi-arid area, where the water availability has great impacts on the vegetation growth and distribution and is the major limiting factor of NPP (Lu et al., 2005). It is not surprising the increase of NPP was mainly due to the improvement of water availability that can increase the vegetation coverage rate and improve the average primary productivity, which is consistent with the findings of previous research (Nemani et al., 2003). The water resource in the lower Heihe River Basin mainly originates from the runoff of Heihe River, which is greatly influenced by human factors. Besides, although the rainfall is very limited in the lower reach, it played a key role in influencing the vegetation growth in the widespread sandy land and bare land in a large area and exerted more widespread impacts on the overall NPP of the study area. However, since the rainfall varies greatly among years, it is more plausible to increase the water availability through improving the water diversion program to increase the total runoff into the Lower Heihe River Basin.

3.5. Uncertainties and management implication

Overall, the results suggest that both the demographic and socioeconomic variables are useful in exploring the driving mechanism of NPP change in the lower Heihe River Basin, but there are still some uncertainties and it is still necessary to implement more in-depth analysis. For example, some uncertainties exist due the data accuracy, which may subsequently bias the results of the multilevel model. For example, NPP is estimated to range from 0 to 799.83 gC/(m^2 a) during 2000–2008, with the average of 52.39 gC/(m^2 a) in 2000 in this study, which is close to the result of Lu et al. (Lu et al., 2005), i.e., 56.87 gC/(m^2 a). But the highest NPP differs significantly between this study that of Lu et al., which is 799.83 gC/(m^2 a) and 663.6 gC/(m^2 a), respectively. This may be due to the difference in the original NDVI data and climate data, et al. For example, MODIS NDVI data have been used this study, while SPOT/VEGETATION data have been used by Lu et al. (Lu et al., 2005), the difference between which may lead to the significant difference in the estimated NPP. It is necessary to estimate NPP with more accurate data and evaluate the ecosystem models against ground and satellite-based measurements and observations in order to improve the capacity of model simulation and prediction (Pan et al., 2014). The data accuracy of the explanatory variables may also influence the estimation results. For example, there are only a few meteorological stations within and around the study area, leading to low interpolation accuracy of the climate data which may bias the estimation results.

It is also necessary to improve the econometric model to analyze the driving mechanism of NPP with more robust models since there may be great difference in the results obtained with different estimation methods. First, it is difficult to take into account all the influencing factors in the estimation model since NPP change is a complex process. For example, although the policy factors were not explicitly considered in this study, it may be partly responsible for increase of NPP since the ecological water diversion project was implemented in 2000. Second, different division of levels of these explanatory variables may lead to different results from the multi-

Please cite this article in press as: Yan, H., et al. Multilevel modeling of NPP change and impacts of water resources in the Lower Heihe River Basin. J. Phys. Chem. Earth (2015), http://dx.doi.org/10.1016/j.pce.2014.12.001

Table 4
Results of decomposition analysis based on Column (4) in Table 3.

Variables	Estimated coefficients	Percentage changes in variables (%)	Impacts on NPP	Contribution rates (%)
rain	0.05	44.27	2.02	18.50
et	0.30	9.47	2.80	25.68
NPP		9.07		100.00

level models. The multilevel model was first applied in the social sciences, psychology, and education, and recently it has been introduced in ecology and land change science (Chelgren et al., 2011; Zhang et al., 2014). However, the levels of explanatory variables are not so clear in the ecology and land change science. For example, the influence extent of human activities may vary greatly, it is difficult to accurately determine the levels of time-varying explanatory variables related to human activities and socioeconomic development (Windzio, 2006). In this study, the socioeconomic variables (gdp, gdp1) were put into the within small watershed level, it may be more feasible to analyze their influence on NPP at the county level, but there are only two counties in the study area, between which the variance of NPP is negligible. Therefore it is necessary to further explore the influence of socioeconomic variables on NPP with more proper levels of the explanatory variables.

Although there are some uncertainties, the results of this study still can provide valuable reference information for improving the water management and guaranteeing the ecosystem service supply. There are numerous signs that human water use exceeds sustainable levels around the world (Postel, 2000), especially in the arid and semi-arid regions where the ecosystems provide various important ecosystem services and support a substantial portion of the human population (Foley et al., 2005; MA, 2005a). For example, natural vegetation has great ecological significance in inhibiting desertification and maintaining the stability of ecosystems in arid regions (Ye et al., 2010), but many changes increase vulnerability as a result of declining water availability (Schröter et al., 2005). New approaches of using and managing fresh water are required in order to meet the increased demands of a growing global population while protecting the services provided by natural ecosystems (Postel, 2000). In particular, since the rainfall is generally very limited in the arid and semi-arid regions, diversion of the surface water has been a key approach to meet the ecological water demand (Liu et al., 2013), Besides the water resources, other factors may also directly or indirectly influence the ecosystem service supply, and it is necessary to take these factors into account when formulating the water diversion plan. The ecologically sustainable water management is attainable in the vast majority of the world's river basins (Richter et al., 2003), but adequate knowledge is required to monitor mechanisms of change in ecosystem service supply and understand impacts of water resources on ecosystem service supply, eliminate its negative effects on environment and human society, and develop sustainable management strategies (Postel, 2000). The results of this study, including the driving mechanism of NPP change and contribution of the water availability to NPP change, can provide scientific foundation for formulating relevant policies to improve the water allocation to guarantee the provision of NPP and other ecosystem services. For example, it is necessary to carry out some policies that promote water efficiency and increase the ecosystem service supply with interdisciplinary knowledge on the influencing factors of NPP and other ecosystem services.

4. Conclusions

It is of great importance to understand the relationship between NPP and its influencing factors since NPP lays the foundation for provision of various ecosystem services. In this study, the C-FIX model was used to estimate NPP during 2000–2008 in the lower Heihe River Basin, a typical arid and semi-arid region in China, and the estimation result shows that the average NPP increased by approximately 9.07% during 2000–2008. Then the multilevel model was used to analyze the impacts of potential influencing factors on NPP, the results from which showed the marginal effects of explanatory variables on NPP. Finally the contribution of explanatory variables to the NPP change was further studied with the decomposition analysis, and special attention was paid to the role of the water availability.

Overall, results of the multilevel model showed that the signs and significance of all of these explanatory variables suggest that both the socioeconomic variables and demographic variables are useful in explaining NPP change in the lower Heihe River Basin. In particular, the coefficients of rainfall and evapotranspiration that represent the water availability reached 0.0456 and 0.2956, respectively, and the results of decomposition analysis suggested that the contribution rate of the water availability (rain, et) reached 44.17%, indicating the water availability played an important role in increasing NPP. It is not surprising the increase of NPP was mainly due to the improvement of water availability since the lower Heihe River Basin is in the arid and semi-arid area, where the water availability has great impacts on the vegetation growth and distribution. Since the water resource in the lower Heihe River Basin mainly originates from the runoff of Heihe River, which is greatly influenced by climate change and human factors, it is very necessary to carry out some policies to increase the water availability and improve the water efficiency in order to guarantee the sustainable supply of ecosystem services under the background of climate change and intensified human activities. There are some uncertainties in the results, and it is necessary to make further analysis by using more accurate data and more robust methods, but these results still can provide valuable reference information for formulating appropriate management measures to improve the water resource management and increase the ecosystem service supply in the lower Heihe River Basin.

Conflict of interest

The authors declare no conflict of interest.

Acknowledgements

This research was financially supported by the major research plan of the National Natural Science Foundation of China (Grant No. 91325302), and data support from Heihe Plan Science Data Center is also greatly appreciated.

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