Dominant role of climate in determining spatio-temporal distribution of potential groundwater recharge at a regional scale

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Knowledge of spatio-temporal groundwater recharge (GR) is crucial for optimizing regional water management practices. Daily potential GR at 58 sites over the Chinese Loess Plateau (CLP) during 1981–2009 was simulated using the HYDRUS-1D and robust model inputs. The objective was to explore the impacts of soil, vegetation, and climate on potential GR at a regional scale. The median potential GR over the CLP during 1981–2010 was 1.8 cm, accounting for 4.1% of the annual precipitation (P). As dominated by P, the annual potential GR decreased from 18.8 cm (28% of P) at the southeast to 0.0 cm at the northwest. Temporally, consistent low-intensity of GR interspersed with extreme rainfall-induced high GR, being episodic or seasonal depending on sites and years. The lag (average of 5 months) between deep drainage at 3 m depth and rainfall was controlled by climate (i.e., P). From 1981 to 2010, annual potential GR significantly decreased as a result of increased ET\textsubscript{p} and leaf area index (LAI) over time. A warmer and wetter CLP at the end of this century as predicted by the HadCM3 model may decrease the potential GR because of the increased ET\textsubscript{p}. This study highlights the dominance of water input factors (P) on the spatial GR and water output factors (ET\textsubscript{p} and LAI) on the temporal GR. Measures such as water-saving practices and land use optimization should be taken to mitigate climate change effect on groundwater recharge.

1. Introduction

A thorough assessment of the dynamics and controls of groundwater recharge (GR) is of great interest for water resources management, especially in water-limited environment (Crosbie et al., 2013a; Ng et al., 2010). The Chinese Loess Plateau (CLP) has been suffering from both surface water and groundwater stress (Wang et al., 2011b). The “Grain for Green” project has successfully reduced sediment transport into the Yellow River, but it also contributed to over 20% of the decrease of water yield (Wang et al., 2016). Over intensive planting and unsuitable land use patterns usually cause soil desiccation and in some cases termination of GR via deep drainage (Chen et al., 2008; Huang and Pang, 2013; Jian et al., 2015; Li et al., 2018, 2019). To determine sustainable groundwater use requires accurate estimates of GR rates in a spatio-temporal domain and thorough understanding of spatio-temporal controls upon GR (Jasechko et al., 2014).

The GR can be influenced by many factors. Previous studies have focused mainly on the individual influence of soil, vegetation/land use, and climate on GR (Asseng et al., 2001; Gates et al., 2011; Jankovic and Andricic, 1996; Nolan et al., 2003; Wang et al., 2012a). On the CLP, land use was recognized as a critical factor for GR variability at a small watershed scale where the same climates operate (Huang and Pang, 2011; Huang et al., 2013). Over the CLP, all these factors are considerably variable in space (see Section 2.3). During the last six decades, vegetation coverage and the potential evapotranspiration (ET\textsubscript{p}) significantly increased and P slightly decreased (Li et al., 2012; Wang et al., 2016). It is unclear on how these factors interactively affect spatial and temporal change in GR at the regional scale. Such knowledge is helpful not only for sustainable management of groundwater resources, but also for spatial parameterization in GR modeling at a regional scale.

Previous studies on GR usually focused on limited points in space because of difficulties in measuring GR (Huang et al., 2013). Ignoring
the spatial variability of GR may invalidate model predictions for regional water budget calculations and water resource management studies (Dripps and Bradbury, 2010). On the CLP, GR was estimated mainly with environmental tracer methods such as chloride mass balance which has large uncertainties (Gates et al., 2011; Huang and Pang, 2011; Huang et al., 2013; Lin and Wei, 2006), although water-table-fluctuation, saturated zone Darcian method, and water-budget methods were also used (Yin et al., 2011). Time series of GR are difficult to obtain with these methods, which prevents the understanding of temporal changes in GR. While different methods can be used to determine the range of potential GR for a given location, the methodological differences make the results uncomparable (Grismer et al., 2000; Yin et al., 2011). To this end, numerical modeling can be an alternative to characterize the spatio-temporal variability of GR (Asseng et al., 2001; Crosbie et al., 2013b). Soil, vegetation, and climate have been intensively measured in situ or remotely on the CLP. However, those data have not been integrated in GR modeling except in a very recent study (Turkeltaub et al., 2018) where the shape parameters (α and n) of soil water retention curve and residual water content were obtained not directly from measurements but from the Rosetta pedotransfer function.

Daily extreme precipitation increased in the world’s dry and wet regions over the past six decades, and will continue with global warming (Donat et al., 2016; Ingram, 2016). While classical theory asserts that GR was dominated by low-intensity precipitation over long time periods (Freeze and Cherry, 1979), extreme precipitation was found to play a significant role in determining GR over the Northern High Plains in the USA (Zhang et al., 2016). On the CLP, the regionally averaged daily rainfall intensity and extreme precipitation decreased, whereas consecutive dry days increased over the past six decades (Sun et al., 2016; Wan et al., 2014). It is unclear how these temporal changes in rainfall pattern affected the GR dynamics (Shao et al., 2019). Seasonality of precipitation was also reported to significantly affect GR (Lee et al., 2006). Based on the 2H and 18O stable isotopic compositions of ground water from six semiarid sites, Huang et al. (2013) suggested that precipitation from summer mainly contributed to GR on the CLP. However, residence time of GR may vary with soil and rainfall characteristics (Maxwell et al., 2016). This implies that the seasonality of GR via deep drainage may not be universal across the CLP, which needs to be confirmed.

The impact of future climate change on GR has been widely assessed (Crosbie et al., 2010; Crosbie et al., 2013a; Ng et al., 2010; Peng et al., 2013). For example, Crosbie et al. (2013b) reported that the GR in the Northern High plains of USA would increase by 8% and that in the Southern High plains would decrease by 10% under a 2050 climate relative to a 1990 climate. However, previous studies may not be generalized to other areas because of different interactions of soil, vegetation, and climate. In addition, continuous time series of GR is usually not predicted, which may disenable the quantitative assessment of GR dynamics. Different future climate variants including 16 Global Climate Models (GCMs) and three global warming scenarios were usually evaluated for the uncertainty of climate change on GR. Previous studies have shown that the HadCM3 (Hadley Centre Coupled Model, version 3) generated the past climate for China better than the other GCMs (Cao and Zhang, 2009). Based on the HadCM3, Li et al. (2012) observed that both P and ETp on the CLP would increase in the future as compared with that in 1961–1999 and P increased more than ETp, resulting in a wetter and warmer CLP in the future. The possible impacts of future climate change on GR of the whole CLP, however, are not evaluated.

The objectives of this study were (1) to characterize the spatio-temporal variations of annual GR on the CLP during 1981 to 2010, (2) to assess the controls of spatial-temporal distribution of annual GR at the regional scale; and (3) to evaluate the future change of the annual GR under the scenario of wetter and warmer climate in the future. Based on spatial datasets of soil, vegetation, and climate, daily GR at multiple sites (SB) during 1981–2099 on the CLP were simulated by the HYDRUS-1D.
2. Materials and method

2.1. Study area

This study was conducted over the CLP (34°43′–41°16′N, 100°54′–114°33′E) (Fig. 1), covering an area of about 624,000 km². As influenced by the continental monsoon, 60–70% of the rainfall is received from July to September (Liu et al., 2016). Annual precipitation and temperature decrease from 800 mm to 150 mm and from 14.3 °C to 3.6 °C, respectively, from the southeast to the northwest (He et al., 2003), forming climatic groups of subhumid, semiarid, and arid, respectively (Li et al., 2012). Along the climatic gradient, vegetation zones are distributed in a sequence of forest, forest-steppe, typical-steppe, desert-steppe, and steppe-desert (Wang et al., 2013). The soils are developed from eolian deposit with dominant texture of silt loam (Staff, 2010). The main landforms of the CLP consist of plateau, ridges, hillslopes, and gullies.

2.2. Flow model

Water flow was simulated with the Richard’s equation-based HYDRUS-1D code (see supporting information Text S1) (Simunek et al., 2005). Lateral subsurface flow was not considered because coarse-textured soils dominated and impermeable or semipermeable layers were not commonly observed on the CLP. A standard atmospheric upper boundary condition and a free drainage lower boundary condition were used. Root water uptake was simulated by potential transpiration (\( T_p \)), root density distribution function \( (b(x)) \), and root water uptake stress response function (Feddes, 1982). Among which, \( T_p \) were obtained from the \( E_T \) by the Beer’s law (Ritchie, 1972). The \( b(x) \) was derived with an empirical distribution function (Jackson et al., 1996), which defines the cumulative root fraction \( (Y(x)) \) (between 0 and 1) from the soil surface to depth \( x \) as:

\[
Y(x) = 1 - \beta^x
\]

(1)

Therefore, \( b(x) \) is the difference between \( Y \) values at consecutive depths (i.e., \( x \) depth and immediately above that). We found that the empirical distribution function described the root distribution of CLP well, and the \( \beta \) varied from 0.900 to 0.996 (Cheng et al., 2007, 2008; Han et al., 2009; Li et al., 2005, 2011; Ma et al., 2012; Wang and Zhang, 2010; Wei and Shangguan, 2006; Zhou and Shangguan, 2007) (Fig. 2). The average \( \beta \) from 35 profiles over the CLP was 0.965, which is very close to the global mean (i.e., 0.966) (Jackson et al., 1996). For simplicity, spatial variability of root distribution was ignored and \( \beta \) of 0.965 was assumed. In this respect, almost all (99.997%) root was located above 300 cm. Therefore, the depth of simulation profile was set as 300 cm and the water uptake below 300 cm was ignored. In contrast to actual groundwater recharge, the water percolating into the unsaturated zone below root zone (user-specified) is referred as potential recharge since it is unlikely to be removed upward to the surface (Rushton, 2017). In this study, possible focused recharge and the time lag between deep drainage below 300 cm and recharge at the water table was not considered. Potential recharge (or deep drainage) below the lower boundary (300 cm depth) is labelled as GR for brevity.

Water flow simulations were implemented daily from 1961 to 2099 at 58 sites over the CLP. The whole simulation profile was discretized in 1 cm increments with 301 nodal points. The initial profile distribution of pressure heads was set to decrease linearly from the bottom (−300 cm) to the top (−600 cm) with a unit gradient. Simulations with different initial conditions indicated that deeper soils were influenced more by the initial values, and maximum of 18 years is required to obtain soil water content at 300 cm depth with relative error of < 1%. To minimize the effect of initial conditions, simulation results from 1961 to 1980 were removed for data analysis. The simulated volumetric soil water data from selected sites and dates were compared with the corresponding observations made by Wang et al. (2012b) and She et al. (2015) to examine the model performance. Gravimetrical soil water content of Wang et al. (2012b) was converted to volumetric water content by multiplying with the bulk density of surface layer.

2.3. Datasets for modeling

A total of 58 sites (Fig. 1) were selected for soil water flow simulations. Datasets for modeling at each site comprised soil, vegetation, and historical and future climate data. They are briefly introduced here. Please refer to the supporting information (see Text S2, Fig. S1–S6, and Table S1) for the detailed description.

The measured hydraulic properties (i.e., \( \theta_s \), \( \theta_r \), \( q \), \( n \), and \( K_s \)) from surface layer (Wang et al., 2013, 2015) were used to represent those of 0–300 cm for simulating water flow (Fig. S1a–e). In general, significantly \( (p < 0.05) \) lower values of all hydraulic properties were observed in arid region than in semiarid and subhumid environments (Table S1). The daily \( LAI \) during 1981–2010 at each site was linearly interpolated from the GLOBMAP \( LAI \) product at a 8 km resolution (Liu et al., 2012a). The temporal patterns of \( LAI \) depended on the land use (Fig. S2a). Over the CLP, the mean \( LAI \) showed a significant \( (p < 0.01) \) increase with time from 1981 (0.24) to 2010 (0.33) (Fig. S3a). The temporal mean of \( LAI \) decreased from 0.65 in the southeast to 0.09 in

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**Fig. 2.** Cumulative root fraction (biomass or root density) versus soil depth over the Chinese Loess Plateau. The \( \beta \) parameter in the empirical distribution function (Eq. (1)) (Jackson et al., 1996) and references are shown.
the northwest (Fig. S1f). The LAI during the spinning up periods (1961–1980) was assumed to equal that in 1981, and the LAI during 2011–2099 was assumed to equal that of 2010. Daily series of $P$ (cm day$^{-1}$) and $ET_p$ (cm day$^{-1}$) were obtained from China Meteorological Administration for the period 1981–2010. From the southeast to the northwest, the annual $P$ decreased, and the $ET_p$ and aridity index (AI) (ratio of annual $ET_p$ to annual $P$) increased (Fig. S1g–i). From 1981 to 2010, a slight decreasing trend was observed for the annual $P$, while a significant ($p < 0.05$) increase was found for $ET_p$ (Fig. S3). The conditional $P$ and non-conditional $ET_p$ ensemble for 2011–2099 were projected with SDSM (Statistical DownScaling Model) version 4.2 (Li et al., 2012; Wilby et al., 2002). Only data from HadCM3 under A2 (Medium–high) and B2 (Medium–low) emission scenarios were used because the HadCM3 generated the past climate for China better than the other general circulation models (GCMs) (Cao and Zhang, 2009). Compared with 1981–2010, the projected annual $P$ will increase by 11%, 22%, and 29% for scenario A2 and by 16%, 24%, and 24% for scenario B2 in 2011–2040 (2020s), 2041–2070 (2050s), and 2071–2099 (2080s), respectively (Fig. S4). The projected annual $ET_p$ will increase by 3%, 6%, and 13% for scenario A2 and increase by 1%, 3%, and 7% for scenario B2 in 2020s, 2050s, and 2080s, respectively (Fig. S5). Because of the greater increase of $P$ than $ET_p$, AI will decrease by 13% for scenario A2 and 16% for scenario B2 in 2080s (Fig. S6), indicating that the CLP will be wetter and warmer in the end of this century (Li et al., 2012).

2.4. Statistical analyses

Spearman’s rank correlation coefficients ($R_s$) were calculated to investigate the impacts of environmental factors on spatial and temporal distribution of annual $GR$ because the Shapiro-Wilk test indicated that the spatial $GR$ data was not normally distributed. The response of $GR$ to $P$, $ET_p$, and LAI was explored by the cross correlation analyses. The lag time was identified as that corresponding to the maximum absolute value of cross correlation coefficients. The spatial distribution of each hydrological variable was interpolated using the inverse distance weighted (IDW) method because it is suitable to the hydrological variable that usually does not follow a normal distribution (Chen and Liu, 2012).

Measurement errors may be one source of uncertainties in simulated $GR$. To this end, each of soil hydraulic properties (i.e., $\theta_{r}$, $\theta_{s}$, $a$, $n$, and $K_s$) at each site was changed by ±10% and $GR$ was estimated for the period of 1981–2010 to explore its absolute ($AC$, cm) and relative changes ($RC$, %) by

$$AC = A - A_i \quad (2)$$

$$RC = \frac{A - A_i}{A_i} \times 100% \quad (3)$$

where $A_i$ and $A$ represent the annual $GR$ simulated with the original and adjusted soil properties, respectively.

Based on the interpolated maps, $GR$ and $GR/P$ were averaged for three consecutive 30 years, i.e. 2011–2040 (2020s), 2041–2070 (2050s), and 2071–2099 (2080s). Their temporal changes relative to the past (1981–2010) were characterized. These analyses were made for each climatic group and the whole CLP. For this purpose, the $RC$ in percentage was calculated with Eq. (3), where $A$ and $A_i$ represent the projected (2020s, 2050s, and 2080s) and the past $GR$s (1981–2010), respectively.

3. Results and discussion

3.1. Model performance examination

Fig. 3a shows the simulated and observed soil water profiles at a specific day for various representative land uses and climatic conditions. In the arid environment, our simulation usually underestimated soil water content by up to 0.20 cm$^3$ cm$^{-3}$. This is because all soil water contents in the arid environment were measured in croplands with irrigation (Wang et al., 2012b) which was ignored in our model. On the other hand, soil water contents especially at deeper layers were usually overestimated by 0.10–0.15 cm$^3$ cm$^{-3}$ at the forests in both semiarid and humid environment. For cropland and grassland under the semiarid and humid environment, the simulated soil water profile matched well with the observed. The vegetation data (LAI) come from a large pixel scale (i.e., 8 km × 8 km). However, the soil water contents were only available from a local scale under a given land use (Wang et al., 2012b). The local cropland and grassland in the semiarid and subhumid environment may be representative of the average vegetation at a large scale, resulting in good match between simulations and observations. The large deviations between simulated and observed soil water content for other cases indicate that it is risky to extrapolate our simulated $GR$ values to a specific land use in a given area. We expect that mean soil water content of different land uses should be closer to our simulations for a given site. A good example is the soil water storage data from site 24 (Yulin) (She et al., 2015, Fig. 3b). While soil water storage of 0–300 cm in the grassland (*N. geana*) was close to the simulation during 2007–2008, both underestimation and overestimation of soil water storage were observed for other land uses. As expected, mean soil water storage of 20 sampling points from multiple land uses in an area of 2 km$^2$ mimicked the simulation (Fig. 3b). Therefore, our model seems to be reasonable from the aspect of soil water simulation.

Local scale $GR$ has been estimated at various sites over the CLP by various methods (Table 1). In general, our simulated $GR$ was comparable to the previous estimates. For example, annual $GR$ at Guyuan (site 39) and Xifeng (site 47) in the winter wheat farmland was estimated to be 5.5 and 3.3 cm (Huang and Pang, 2011), which was close to our simulated results (i.e., 3.3 and 4.1 cm) for 1981–2010. It is worth noting that different degrees of deviation existed between our simulations and previous estimates (Table 1).

First, spatial scale mismatching may be the main reason for the deviation. The vegetation (LAI) data were representative of a large pixel scale, so the simulated $GR$ should be interpreted in the context of a large scale although our simulation is point-based. The previous $GR$ estimates were usually based on tracers and point modeling which is susceptible to vegetation and land use changes at the local scale. At the Guyuan site, for example, the Chloride mass balance method indicated that conversion from natural spare grass to winter wheat could reduce the annual $GR$ from 10.0 cm to 5.5 cm (Huang and Pang, 2011).

Second, underestimation of $GR$ compared with others may be related to the inconsistency of time scales. The $GR$ decreased in recent years because of the increased vegetation coverage and $ET_p$ (Li et al., 2012; Wang et al., 2011a) (see Section 3.3). According to the observations from Xifeng (site 47), the water table dropped annually at an average rate of 1–2 m since 1995 (Huang and Pang, 2013). The $GR$ previously estimated by environmental tracers usually represented longer time scale (e.g., several decades or centuries) and was too high to represent the $GR$ of recent decades.

Third, management practices (e.g., irrigation) and soil variability would also affect the results. Compared with rainfed cropland, irrigated cropland usually have more water input and produce more $GR$ (Turkeltaub et al., 2018). However, if the irrigation water originally come from the rainfall of the same area, which is probably usually the case at a regional scale, the irrigation impact on the $GR$ is less significant at a regional scale. The simulated $GR$ in this study was almost half of that in non-irrigated areas of CLP (Turkeltaub et al., 2018) (Table 1). Our sensitivity analysis indicated that our model was most sensitive to $n$ and $\theta_r$ and not sensitive to the changes in $\theta_s$, $a$, and $K_s$ (Table 2). Increase of $n$ and $\theta_r$ by 10% resulted in increase and decrease of annual $GR$ by about 20%, respectively. While direct measurements of shape parameter $n$ was used in this study (Wang et al., 2015), Rosetta
The pedotransfer function was used to derive shape parameter $n$ in Turkeltaub et al. (2018). The measured $n$, with mean value of 1.37 (Wang et al., 2015), differed with those (1.47) derived by the Rosetta pedotransfer function (Turkeltaub et al., 2018). The mean $\theta_s$ of this study was 0.48 cm$^3$ cm$^{-3}$, much > 0.39 cm$^3$ cm$^{-3}$ used in Turkeltaub et al. (2018). Therefore, the lower $n$ and higher $\theta_s$ values in this study compared with Turkeltaub et al. (2018) could result in significant lower GR values.

Last, estimation method may also affect the results. None of methods can be termed the “best” for estimating GR (Grismer et al., 2000; Yin et al., 2011). Interestingly, on the Ordos Plateau (130,000 km$^2$) located in the northern part of CLP, different methods have been compared to estimate GR (Wu et al., 2019; Yin et al., 2011), and annual GR ranged from 2.5 cm for the Chloride mass balance to 6.1 cm for water budget method. Our simulated value (3.6 cm) was similar to the average of these two methods and exactly the same to the empirical and saturated-zone Darcian methods. It was also similar to a similar study (4.8 cm) from the Gravity Recovery and Climate Experiment (GRACE) and Global Land Data Assimilation System (GLDAS) data (Wu et al., 2019). Anyway, previously reported annual GR ranged from 0.1 to 11.0 cm (with GR/P ratio between 2 and 23%) on the CLP (Table 1), being comparable to the simulated range (i.e., 0.0–18.8 cm, the GR/P ratio between 0 and 28%) during 1981–2010. This further increases the reliability of our model. Also note that the main parameters including soil hydraulic properties ($\theta_s$, $\theta_r$, $\alpha$, $n$, and $K_s$), climate, and LAI data were measured either in situ or with remote sensors. The root distribution function was validated against different types of vegetation (Fig. 2). Therefore, our simulations are expected to represent well the spatio-temporal patterns of GR at a regional scale.

### 3.2. Spatial pattern of GR and controls

Simulated annual GR varied spatially, and it generally decreased from the southeast to the northwest (Fig. 4). Temporal average of annual GR ranged from 0.0 to 18.8 cm, corresponding to GR/P ratio of 0–28%. The median of annual GR was 1.8 cm, accounting for 4.1% of the annual $P$. Annual GR changed significantly ($p < 0.05$) with climate zone, with median of annual GR values (GR/P) being 3.8 cm (6.5%), 1.6 cm (4.1%), and 0.01 cm (0.04%) in the subhumid, semiarid, and arid environments, respectively (Table 3).

Fig. 5a presents the $R_s$ values between 30-year average of annual GR and environmental factors. Precipitation was significantly correlated with annual GR ($R_s = 0.74$, $p < 0.01$), indicating that $P$ dominated GR distribution over the CLP. The warm and humid air currents (monsoon) from the southeast and east are the dominant airflows that control the precipitation on the CLP (Mu and Chen, 1993). This results in precipitation and GR patterns that are highly related with geographic location and elevation. The degree of impacts of $P$ on GR varied with years, and greater degree of impacts usually occurred in wetter years when $P$ variation was greater (Fig. 5b). This implies that precipitation will have more controls on the spatial distribution of potential groundwater recharge in the future if it became wetter as predicted (Li et al., 2012).

On average, the $E_T$ had little impacts on the spatial distribution in GR (Fig. 5a). However, $R_s$ of GR and $E_T$ was usually more negative in years with lower $E_T$ ($R_s = 0.53$, $p < 0.01$) (Fig. 5c). This indicates that $E_T$ was more likely to affect GR in years with lower $E_T$. For example, during years of 1981–1984 and 1989–1993 when the mean $E_T$ was below the temporal average of 1981–2010, significant rank correlation ($p < 0.05$) between $ET_A$ and $ET_p$ was observed. This may be because in wetter, cooler climate, actual ET ($ET_p$) is controlled more by energy: higher $ET_p$, the higher $ET_A$, and consequently lower GR. However, in drier, hotter years, $ET_p$ is controlled more by water availability or soil water content, thus higher $ET_p$ does not necessarily lead to higher $ET_A$ and lower GR (Jia et al., 2015). Similarly, the GR was negatively correlated ($p < 0.05$) to the AI, indicating that the drier area would have less GR, particularly in drier years ($p < 0.01$).

Soil properties were slightly correlated to the GR, and their impacts on GR were much smaller than the impact from $P$. Among all soil properties, $\theta_s$, $K_s$, and $\alpha$ had slightly positive correlations with GR, with $R_s$ of 0.35 ($p < 0.01$), 0.32 ($p < 0.01$), and 0.32 ($p < 0.05$), respectively (Fig. 5a). This was because coarser textured soils with higher $K_s$ and $\alpha$ values would facilitate rainfall infiltration and drainage below the root zone. Under the same climate, soils with smaller $\theta_s$ would usually conserve less water and have greater GR. The significant positive relationship between $\theta_s$ and $E_T$ in this study was because the areas with greater $\theta_s$ values are located at subhumid or semiarid zones where GR was greater than the arid zone (Table S1).

The absence of significant correlation between GR and the two soil parameters $n$ and $\theta_s$ may be related to their smaller variations compared with other parameters. The maximum values of $n$ and $\theta_s$ were 1.7 and 1.9 times higher than their minimum values, whereas the ratio of maximum to minimum for $\theta_s$, $K_s$, and $\alpha$ were 149, 183, and 47, respectively. Although the spatial patterns of annual GR were not affected by $n$ and $\theta_s$, the simulated GR was sensitive to $n$ and $\theta_s$ (Table 2). The soil texture is relatively coarse (dominated by silt loam) on the CLP, but...
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<td>Environmental isotope</td>
<td>Carrrell et al. (2010)</td>
<td>0.1–1.0</td>
<td>1.8</td>
<td>50#</td>
</tr>
<tr>
<td>9</td>
<td>Ordos plateau</td>
<td>Water budget</td>
<td>Yin et al. (2011)</td>
<td>6.1 (2.1–10.9)</td>
<td>3.6 (2.0–7.3)</td>
<td>17#, 18#, 19#, 23#, 24#, 29#, 30#, 31#</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Empirical</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Unsaturated-zone Darcian</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Saturated-zone Darcian</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Water table fluctuation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gravity Recovery and Climate Experiment (GRACE) and Global Land Data Assimilation System (GLDAS)</td>
<td>Wu et al. (2019)</td>
<td>3.6 (1.7–6.0)</td>
<td>4.8 (3.1–4.7)</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Part of the CLP</td>
<td>HYDRUS-1D modeling</td>
<td>Turkeltaub et al. (2018)</td>
<td>6.4 ± 2.2</td>
<td>3.3 (0.0–7.5 cm)</td>
<td>All sites covered by Turkeltaub et al. (2018)</td>
</tr>
</tbody>
</table>

\(^a\) Ranges in the bracket.
the n value was relatively low (mean of 1.37) because of the poor soil structure as a result of low soil organic carbon (mean of 1.0% for 0–20 cm) (Liu et al., 2012b). Increasing the n value would significantly increase the water movement and deep drainage. The θi largely determines the water storage capacity especially under the large rainfall events when great drainage usually happens. The absence of sensitivity of GR to θi, Ks, and a was partly attributed to the fact that there were consistently low (i.e., θi) or high (i.e., Ks and a) which did not limit soil water movement on the CLP. The paradox results indicate that attention should be paid to the spatial variability of θi, Ks, and a for regional GR modeling purpose, while accurate measurement of n and θi become more important at a point scale.

Surprisingly, LAI was not significantly correlated to the GR in a spatial domain. The lack of LAI influence on GR was consistent with Gates et al. (2008) who observed a weak relationship between vegetation density and GR in the Badain Jaran Desert located on the north of CLP. However, the effect of vegetation on GR was usually observed in small watershed scales where the climatic condition was relatively uniform (Dripps and Bradbury, 2010; Gates et al., 2011; Kim and Jackson, 2012). Therefore, the impacts of LAI on GR were masked by the climatic forcing (e.g., P) at the regional scale.

As discussed before, the relative significance of P with respect to GR variability depends primarily on the P variability across the area of interest (Dripps and Bradbury, 2010). Therefore, the factors affecting GR distribution should be scale-specific. While the GR was dominated by the P over the CLP at regional scales, other factors may be more important at smaller watershed scales. Among these, land use change usually affect GR significantly (Allison et al., 1990; Walker et al., 1991). For example, the mean GR in plots after cutting down orchard (0.9 cm year\(^{-1}\)) during the recovery period was half of that for land that always grows winter wheat at Changhaiyu site (site 48) (Huang and Gallichand, 2006). At Guyuan site, the conversion from native grassland to winter wheat has reduced GR by 42–50%, and the conversion from winter wheat to alfalfa terminated deep drainage (Huang et al., 2013). Although the conversion from wheat-corn rotation system to a forest caused faster reduction of GR than the conversion from wheat-corn rotation system to an alfalfa yield, Turkeltaub et al. (2018) observed that the land use changes at the regional scale only slightly reduced GR by 6.1% from 1975 to 2008. Furthermore, topography (Hayashi et al., 1998; Si and de Jong, 2007; Woods et al., 2006), mulching (Zhang et al., 2007), deep tillage (Scanlon et al., 2008), and micro-topography reconstruction (Yang et al., 2012) could also affect GR. However, their effects on GR are likely to be masked by the large variation of climatic forcing at the regional scale. Therefore, understanding the scale-specific controls of GR on the CLP should be a focus in future studies.

Water input was limited to precipitation only and irrigation was not considered in this study. Excess deep percolation from the surface irrigation could result in a substantial increase in GR (Grimes et al., 2000; Turkeltaub et al., 2018). In the Hetao Irrigation District (5.74 × 10\(^6\) km\(^2\)) located at the northern CLP, about 70–87 cm water from Yellow River was irrigated annually. This would result in greater GR than that simulated and change the spatial distribution of GR. Therefore, the controls of spatial GR can also be location-specific and possibly influenced by human practices, which should be considered when interpreting the results. However, at the regional scale especially when most of the irrigated water (surface or ground water) comes originally from the precipitation received from the same region, the irrigation may have limited influence on the GR.

### 3.3. Temporal pattern of GR and controls

The annual GR presented different magnitudes of temporal variability (Fig. 6). While some sites especially in arid environment (e.g., sites 2, 16, and 17) had constantly negligible GR, some sites presented great temporal variability of annual GR. For example, the GR at site 21 in 1998 was 3.2 cm because of the low rainfall in 1997 (32 cm) and 1998 (50 cm). However, the GR at site 21 in 1988 was high up to 63.2 cm (GR/P of 60 %) because of the extremely high rainfall in 1988 (106 cm) and well drained soil (Ks of 23 cm day\(^{-1}\)). The importance of rainfall to GR was also noted by Shao et al. (2018) who found that wet years with P > 65 cm were the main source of groundwater recharge.

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**Table 2**

Sensitivity of simulated annual GR to the changes in soil hydraulic properties by ±10%.

<table>
<thead>
<tr>
<th>Soil properties</th>
<th>θi</th>
<th>θs</th>
<th>α</th>
<th>n</th>
<th>Ks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute change in median annual GR (cm)</td>
<td>0.02</td>
<td>−0.40</td>
<td>0.15</td>
<td>0.34</td>
<td>−0.00</td>
</tr>
<tr>
<td>Relative change in median annual GR (%)</td>
<td>1.1</td>
<td>−18.5</td>
<td>6.4</td>
<td>19.7</td>
<td>−0.3</td>
</tr>
</tbody>
</table>

**Table 3**

Classical statistics of simulated annual GR and GR/P in different climatic zones and over the CLP.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Climatic zone</th>
<th>Median(^a)</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>GR (cm)</td>
<td>Subhumid</td>
<td>3.8A</td>
<td>0.0</td>
<td>18.8</td>
</tr>
<tr>
<td></td>
<td>Semiarid</td>
<td>1.68</td>
<td>0.0</td>
<td>4.6</td>
</tr>
<tr>
<td></td>
<td>Arid</td>
<td>0.007C</td>
<td>0.002</td>
<td>0.012</td>
</tr>
<tr>
<td>GR/P (%)</td>
<td></td>
<td>Total</td>
<td>1.8</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>Subhumid</td>
<td>6.5A</td>
<td>0.0</td>
<td>28.0</td>
</tr>
<tr>
<td></td>
<td>Semiarid</td>
<td>4.1B</td>
<td>0.0</td>
<td>10.0</td>
</tr>
<tr>
<td></td>
<td>Arid</td>
<td>0.04C</td>
<td>0.01</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>4.1</td>
<td>0.0</td>
<td>28.0</td>
</tr>
</tbody>
</table>


\(^b\) The statistical test was done based on the log10-transformed values. Values with same letters are not significantly different at p < 0.05.

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**Fig. 4.** Temporal mean of (a) annual potential groundwater recharge (GR) during 1981–2010 on the CLP and (b) its standard deviation over time.
mean and standard deviation of \( P \) from 1981–2010, the median of annual \( GR \) to the deep soil (e.g., >75 m) in the Changwu site (site 48). During (dashed line) are also shown, (b) relationship between \( R_s \) (GR and \( P \)) and spatial mean and standard deviation of \( P \), (c) relationship between \( R_s \) (GR and \( ET_p \)) and spatial mean and standard deviation of \( ET_p \). For better readability, standard deviation of \( P \) and \( ET_p \) are multiplied with 3 and 6, respectively.

to the deep soil (e.g., >75 m) in the Changwu site (site 48). During 1981–2010, the median of annual \( GR \) presented a significant \((p < 0.01)\) decrease over time (Fig. 6). However, only slight and insignificant decrease of total rainfall and frequency of large rainfall events \((> 3 \text{ cm day}^{-1})\) were observed. Therefore, the decrease of annual \( GR \) is probably because of the significant increase of both \( ET_p \) and LAI over time (Fig. S3). The increased LAI was partly a result of planting trees and grasses, which resulted in widespread soil desiccation (Chen et al., 2008; Wang et al., 2011b) and degraded vegetation on the CLP (Fig. S7).

Temporal patterns of \( GR \) for some selected sites are shown in Fig. 7 for further elucidation of the controls on temporal dynamics in \( GR \). Subhumid sites generally had more \( GR \) than semiarid sites because of more rainfall input. For example, the average annual \( GR \) for the selected three sites were 3.3 (site 24), 3.3 (site 39), 1.8 cm (site 50) at semiarid sites and 4.1 (site 47), 4.9 (site 54), and 16.1 cm (site 56) at subhumid sites. In general, two \( GR \) temporal patterns operating at different scales were superimposed. At the short time scales \((~\text{days})\), there was a consistent low intensity of \( GR \) with no obvious seasonality (e.g., 0.005–0.04 cm day\(^{-1}\)) for the sites shown in Fig. 7 which largely determines the mean annual flux in a long term. At the larger time scales \((~\text{years})\), however, relatively high \( GR \) driven by extreme rainfall events was observed. Depending on sites and years, the high \( GR \) flux can be either episodic or seasonal. For example, at sites 50 and 56, the high rainfall intensity (with maximum intensity of 3–12 cm day\(^{-1}\)) in the summer of 1981–1985 triggered periodically high \( GR \), with strong seasonality. However, extremely large rainfall event did not always mean high \( GR \). For instance, the high rainfall intensity in July 2007 at site 50 did not produce high \( GR \), and actually no seasonally high flux was observed after 1986 at site 50. The reason was probably related to the low initial soil water content prior to the extreme rainfall. At site 56, however, seasonally high flux was observed consistently because of relatively high precipitation (77.6 cm). Similar results were observed across the whole CLP. In 2003, although \( P \) was relatively high and \( ET_p \) was relatively low, significant high \( GR \) was not observed (Fig. 6). However, as the high \( P \) and low \( ET_p \) contributed to the high initial soil water content, increased \( GR \) was observed in the following two years (2004 and 2005) although lower rainfall was received. There was a trend that \( ET_p \) and LAI increased significantly over time (Fig. S3). This usually decreased the initial water content and hence the likelihood occurrence of high \( GR \) even at a high rainfall intensity. Because of the increased \( ET_p \) and LAI over time, a unit change in precipitation will result in a smaller change to the \( GR \). Therefore, the long time scale changes in \( ET_p \) and LAI most likely drive the temporal changes in \( GR \) and seasonality of high flux on the CLP.

The medium lag time of \( GR \) relative to precipitation was 150 days (i.e., 5 months). This indicates that on average the peak flux below 300 cm soil depth occurs in winter (December) by considering that the rainfall usually peaks in July. The \( GR \) response from rainfall differed with site, ranging from 9 to 361 days. For example, the \( GR \) response from rainfall was slower in the three semiarid sites (146–198 days) than the three subhumid sites (29–78 days) shown in Fig. 8. Spearman’s correlation analysis indicated that the lag time was negatively related to the rainfall \((R_s = -0.60, p < 0.01)\) (Fig. 9). This indicates that rainfall is a dominating factor driving the residence time of ground-water (Maxwell et al., 2016). At higher rainfall intensity, larger pores become more important in conducting water, which will speed up the response of \( GR \). This is in agreement with Jasechko et al. (2014) who
found that tropical climates had a maximum GR during the wet season, and arid and temperate climates had higher winter time GR ratios. However, soil properties including Ks did not affect the residence time as Maxwell et al. (2016) found. This was mainly related to the relatively uniform coarse soils on the CLP. On the other hand, the delayed response of GR from P was linked to the time required for rainfall water infiltrating below the root zone. Therefore, the depth of root zone or unsaturated zone can largely determine residence time and the degree of influences from soils. According to Huang et al. (2013), it usually takes decades to hundreds of years for annual precipitation to reach water table on the CLP. In the case of deeper unsaturated zone, therefore, soil properties (e.g., Ks) may become more important in controlling the response time of GR from rainfall.

Water loss by evapotranspiration decreases the water drainage below the root zone, and this also resulted in delayed GR response from ET_p and LAI (Fig. 8). For example, the GR response from ET_p was determined to be 48 (site 24), 48 (site 39), and 34 days (site 50) in the semiarid sites, being longer than 26 (site 47), 6 (site 54), and 0 days (site 56) in the subhumid sites. Spearman’s correlation analysis showed that the GR response from ET_p was also negatively related to the rainfall

![Fig. 7. Time series of potential groundwater recharge (GR) at selected sites in the semiarid (a) and subhumid environment (b). Precipitation (P) and potential evapotranspiration (ET_p) (tripled for better readability) are also shown.](image)

![Fig. 8. (a) Cross correlation coefficients (CC) between future potential groundwater recharge (GR) and past precipitation (P), potential evapotranspiration (ET_p) and leaf area index (LAI) for selected sites in the semiarid (a) and subhumid environment (b).](image)
(Rs = −0.52, p < 0.01) (Fig. 9). Similarly, the GR response from LAI was longer in the semiarid sites (e.g., 28, 11, and 92 days for site 24, 39 and 50) than subhumid sites (e.g., 0 days at sites 47, 54, and 56). This implies that potential drainage in the wetter environments was less sensitive to the evapotranspiration loss. Therefore, optimizing land use layout by avoiding high water demanding species on the CLP especially in the arid and semiarid environments is crucial to sustainable groundwater replenishment.

3.4. GR under wetter and warmer future

The spatial patterns of GR will change in the future under the HadCM3 scenario (Fig. 10). The GR generally decreased from the northeast to the southwest, with the minimum values in the southern and western CLP. Compared with the past (1981–2010), the GR will

![Fig. 9. Relationship between precipitation (P) and residence time of GR relative to P and ET.](image)

![Fig. 10. Projected spatial distribution of (a) annual potential groundwater recharge (GR) and (b) its relative change during 2020s, 2050s, and 2080s compared with 1981–2010.](image)
decrease in the southern CLP and part of the western CLP, while increased GR is likely to occur in the northern CLP (Fig. 10). The decreased GR in the south may be mainly related to the decreased P and increased AI (Fig. S4, Fig. S6). In the north, although both P and ET_p will likely increase, the climate will be wetter because of the decreased AI (Fig. S4–S6). This would contribute to the increased GR in the north.

The GR over the whole CLP will decrease with time, and the decrease rate will be relatively stable (Fig. 11). Of particular note is that the change rates for GR and GR/P were very similar (Fig. S8). At the end of the 21st century, the GR will decrease by 80% under scenario A2 and by 75% under scenario B2. This indicates an amplification of change in potential groundwater recharge compared with changes in P and ET_p as Crosbie et al. (2013b) also observed. However, high emission scenario (i.e., A2) will only slightly amplify the climate change impacts in groundwater system compared with the low emission scenario (i.e., B2). This implies that GR in the water stressed region with high ET_p may be less sensitive to greenhouse gas emissions than humid regions. The degree of GR change is much higher than that in the High Plains Aquifer, USA (Crosbie et al., 2013b), partly attributed to the much lower GR on the CLP. The temporal change in GR will differ with climatic zones. The GR in the subhumid and arid zones will become smaller in the future, and eventually disappear by the end of this century. This may imply that more concerns should be given to these areas for sustainable use of groundwater. Comparatively, smaller temporal changes in GR will likely occur in the semiarid zone. In the future, the annual GR will be temporally episodic (Fig. 12), and the patterns of temporal change are similar at different periods under both emission scenarios (data not shown). The greatest temporal change of GR will occur in the northeastern CLP under both scenarios, and the temporal changes of GR is mainly associated with that of P (Fig. S9).

It is easy to understand that the decrease of GR is attributed to the decrease of P (Ng et al., 2010). As discussed before, extremely large rainfall event is the main contributor to the high peak flux. We found that GR in the future will significantly increase at sites where more frequent large rainfall (> 3 cm day\(^{-1}\)) events occurs such as site 39. Future GR decrease at sites where less frequent large rainfall event happens such as at site 56. By contrast, higher frequency of large rainfall events can also produce decreased GR in the future (e.g., sites 35, 36, 42, and 51) and vice versa. This indicates that the impact of frequency of large rainfall events on GR will be site specific, and this will be associated with the ET_p. Across the whole CLP, even the total P may increase and frequency of large rainfall events on GR will be site specific, and this will be associated with the ET_p. This reason may be related to that evapotranspiration on the CLP is more water content limited than energy input limited (Jia et al., 2015). Accompanying P increase, there is a greater increase in ET_p and ET_a, resulting smaller P-ET_a. By 2080s, most areas with decreased P will be located in the southern subhumid area. Although the average P in the subhumid region will increase slightly, the drier climate (greater AI) in this region would contribute to higher ET_a/P and hence decreased GR in the subhumid area (Fig. 11). The decrease of GR with the increase of ET_a is consistent with the results obtained from Jinghe River watershed (Peng et al., 2013). Therefore, measures should be taken to increase the GR for sustainable water use in this area. Although this study did not consider the uncertainty of future change in GR by considering different GCMs, our simulation clearly showed the decrease of GR as a result of the global warming even accompanied by an increased precipitation and frequency of large rainfall event. Most models project future increase of ET_p on the CLP. The problem of groundwater recharge would be more serious if precipitation over the CLP decreased in the future. In addition, the possible future change in vegetation was not considered in this study. However, if enrichment of CO_2 facilitate the vegetation growth (Taub, 2010), more water will be lost via evapotranspiration, which will exacerbate the problem of groundwater recharge.

![Fig. 11. Relative change of (a) precipitation (P), (b) potential evapotranspiration (ET_p), (c) aridity index (AI), and (d) annual potential groundwater recharge (GR) during 2020s, 2050s, and 2080s compared with 1981–2010 for different climatic zones.](image)

![Fig. 12. Standard deviation of annual potential groundwater recharge (GR) during 2020s, 2050s, and 2080s for scenarios (a) A2 and (b) B2.](image)
4. Conclusions

Based on the intensively robust data of soil, climate and vegetation, HYDRUS-1D was used to simulate the daily dynamics of GR at 58 sites over the CLP. The impacts of soil, climate, and vegetation on annual GR were explored.

(1) The simulated GR was sensitive to van Genuchten n and α parameters. A decrease of n and α by 10% resulted in a decrease and increase of GR by about 20%, respectively.

(2) The simulated annual GR decreased from the southeast (18.8 cm, 26% of P) to the northwest (0.0 cm), with median of 1.8 cm over the CLP, accounting for 4.1% of the annual P. The spatial distribution of GR was dominated by P, and its impact was greater in wetter and cooler climates. Soil properties (i.e., Ks and α) also affected spatial GR, whereas LAI did not affect spatial pattern of GR at a regional scale.

(3) In a temporal domain, the GR showed a decreasing trend from 1981 to 2010 as a result of increased ETp and LAI. Temporally, consistent low-intensity of GR interspersed with extreme rainfall-triggered high GR, being episodic or seasonal depending on sites and years.

(4) The dominant control of P on spatial GR and its residence time and dominant control of ETp on temporal GR highlights the strong dependence of potential groundwater recharge on climate at a regional scale.

(5) Global warming with increased rainfall will result in a decrease of 75–80% for GR over the CLP in the 2080s relative to 2010, which could accelerate depletion of the soil reservoir and aquifer on the CLP. This may threaten the ecological and social stability in this region. This study presented a regional distribution of GR, whereas LAI did not affect spatial pattern of GR at a regional scale.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2019.124042.

References


