Improving the Scientific Understanding of the Paradox of Irrigation Efficiency: An Integrated Modeling Approach to Assessing Basin-Scale Irrigation Efficiency

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Abstract Irrigation is vital for the sustainability of water-limited agricultural areas. However, higher irrigation efficiency (IE) rarely reduces irrigation water consumption, a paradox well noted in the real world. Resolving this paradox requires rigorous assessment of basin-scale IE, which remains rare. This study holistically analyzed basin-scale IE using the Zhangye Basin (ZB), a typical agricultural area in arid northwestern China, as the testbed. A new basin-scale IE index was proposed that factors in irrigation return flow and groundwater’s direct contributions to crop evapotranspiration. A novel approach was also developed to calculate this new index based on integrated ecohydrological modeling. The major study findings for the ZB include the following. First, return flow accounts for approximately 13% of irrigation water, which creates a difference of 0.1 between the new basin-scale IE index and a traditional field-scale index. Second, although basin-scale IE has notable interannual fluctuation, its multiyear average shows stability, which may be dependent on the basin’s physical characteristics. Third, basin-scale IE reflects large spatial heterogeneity and is influenced by the intensity of surface water-groundwater interaction. Finally, under the projected future climate, return flow in the ZB will be enhanced by 3.2% per decade, and basin-scale IE shows an increasing trend. Overall, rigorous evaluation of basin-scale IE is critical to making heterogeneous policies and developing adaptive management strategies under the changing climate. The integrated modeling approach developed in this study provides a methodological foundation for overcoming misunderstandings about the IE paradox and benefits the reform of the current IE policy agenda.

1. Introduction

Global food demand is constantly increasing with population growth and is predicted to be nearly twice as high in 2050 as in 2005 (Tilman et al., 2011). Agriculture is the largest consumer of fresh water, accounting for approximately 75% of water use by humans (Wallace, 2000). However, approximately 4 billion people and 76% of global croplands are facing severe water scarcity at least 1 month of the year (Mekonnen & Hoekstra, 2016; Rosa et al., 2020). In vast inland arid regions, irrigated agricultural systems also compete intensely with vulnerable ecosystems for limited water resources (Sun et al., 2018). The regression of the Aral Sea, a well-known ecological tragedy, is largely attributed to the irrigation-intensive industries in the former Soviet Republics (Varis, 2014). Therefore, an irrigation system with high water-use efficiency is vital for the sustainability of such areas.

However, the paradox of irrigation efficiency (IE) has long been recognized; that is, higher efficiency rarely reduces irrigation water consumption (Burt et al., 1997; Scott et al., 2014). A recent perspective paper in Science (Grafton et al., 2018) revisited the paradox and summarized two major causes of this phenomenon. First, non-consumed water “losses” at the farm scale (e.g., the runoff return to rivers and groundwater recharge by irrigation water) are often recovered and reused at the basin scale. Second, advanced irrigation technologies subsidized by governments may encourage the expansion of irrigated areas. This previous paper further highlights the need to develop detailed water accounts from the farm scale to the basin scale to support decision-making in the public interest. While the paper conceptualizes the desired accounting for
water, it neither explicitly defines basin-scale IE nor provides quantitative approaches to water accounting and IE assessment, which motivated this study.

IE is an engineering term used to characterize irrigation system performance and the responses of crops to irrigation (Howell, 2003). Although IE has long been adopted in water resource management and strategies to conserve irrigation water (Batchelor et al., 1996; Deng et al., 2006; De Pascale et al., 2011), the definition of IE is not unanimous and is still developing due to the complicated water account in irrigated areas (Figure 1). Israelsen and Blaney (1946) first defined IE as the ratio of the amount of water used beneficially by the crop, that is, evapotranspiration (\(c\text{ET}\)), to the amount of water delivered to the cropped area, that is, irrigation water (IRR). Considering that a part of the water used for ET comes from precipitation but not IRR, Israelsen and Wiley (1950) further defined IE as the ratio of the IRR consumed by the crops, that is, ET, less effective precipitation (\(eP\)), to IRR. The classification of beneficial and nonbeneficial water consumption is one controversial point in defining IE (Molden, 1997). The major and most direct beneficial use of IRR is crop evapotranspiration (ET). Other beneficial uses include water for maintaining soil productivity, frost protection of plants, and germination of seeds. Jensen (1967) suggested that the quantity of water used to control salts should also be recognized as beneficial use by crops because sustained crop production requires a favorable salt concentration, and he further defined IE as the ratio of \((\text{ET}_c - P_r)\) plus the water regulating the salt concentration in the soil solution to IRR. However, researchers did not always consider the water for leaching, as many fields may have already obtained sufficient water for leaching (Jensen, 2007). Whether the water stored in the root zone should be considered to be beneficial is another controversial point. Burt et al. (1997) argued that it is inappropriate to regard this portion of water as beneficial before it is actually consumed by crops. However, in real-world agricultural water management practice, the water stored in the root zone is often counted regardless of whether it is actually consumed. For example, the guidelines for IE evaluation issued by the Ministry of Water Resources of China consider the total water storage in the root zone to be beneficial consumption.

In addition to all the controversies, a major limitation of the abovementioned indices is ignorance regarding the potential reuse of irrigation return flow (\(F_{\text{rf}}\)). \(F_{\text{rf}}\) consists of both surface and subsurface water originating from irrigation water that leaves irrigated fields and returns to river and groundwater systems (Keller, 1996) (the SW runoff and GW recharge originating from irrigation water in Figure 1). Reuse could occur in the original field (i.e., the \(F_{\text{rf}}\) is redelivered to the same field) during later irrigation events or in other fields (i.e., the \(F_{\text{rf}}\) is diverted to other fields, particularly those downstream of the original field).

**Figure 1.** A conceptual diagram of the detailed water account in an irrigated area. SW and GW represent surface water and groundwater, respectively. ET is the abbreviation for evapotranspiration, and \(\text{GW}_e\) denotes the direct groundwater extraction by crop. The portions of SW runoff and GW recharge that originate from irrigation comprise the irrigation return flow (\(F_{\text{rf}}\)) per this study’s definition.
Some refined indices reflect the impacts of $F_f$, but still do not explicitly account for $F_g$ (Burt et al., 1997; Keller & Keller, 1995). Another limitation of the existing definitions is the absence of direct groundwater extraction by the crop ($GW_f$), which is largely due to the difficulty in tracking the water movement in the subsurface. In fact, in regions where the water table is shallow, direct groundwater extraction can be an important source of crop ET. In addition, most existing definitions are designed for evaluating field-scale or district-scale irrigation performance without accounting for the complex water cycle at a basin scale. It has been reported that the IE of a given irrigation system may increase from the field scale to the basin scale (H. Chen et al., 2013; Droogers & Kite, 2001; Solomon & Davidoff, 1999) because the “water losses” per field-scale or district-scale definitions of IE may be recovered and reused at the basin scale (Bagley, 1965), a potential cause of the previously mentioned paradox. However, IE quantification at the basin scale remains a significant challenge. IE is usually evaluated based on field observations, satellite remote sensing, or modeling (Allen et al., 1998; Peter & Wim, 2002; Shah et al., 2011; Xu et al., 2010). The field observation approach becomes more labor intensive and time consuming when the definition becomes more complicated (Willardson & Allen, 1998). Although this problem can be alleviated with the improvement of technology, such as more sophisticated and accurate methods for estimating crop ET (Allen et al., 1998) and the availability of satellite remote sensing (Peter & Wim, 2002), water budget calculations based purely on data are still extremely difficult at a basin scale (Howell, 2003). Another limitation is that data-based evaluation can hardly be applied to future or hypothetical scenarios. For example, the impacts of climate change on agriculture have been a hot topic in research committees (Flörke et al., 2018; Wang et al., 2014; Wheeler et al., 2013), but few studies have addressed the responses of IE to climate change. Distributed hydrological models simulating complex watershed processes and capturing spatial variations have been attempted to assist in IE quantification at a basin scale (Gosain et al., 2005; Marek et al., 2017; Wu et al., 2019). For example, Wu et al. (2019) applied SWAT, a widely used distributed hydrological model, to evaluate the amount and reuse of $F_g$ in the Yangshudang watershed in China. However, due to the limitations of the hydrological models used, complex groundwater processes were largely ignored in previous modeling-based studies. This gap in groundwater processes makes the basin-scale quantification of IE inaccurate and leaves the scale effect of IE unaddressed. The inaccuracy due to the gap would be even more prominent in arid and semiarid areas where SW-GW exchanges are key hydrological processes (Newman et al., 2006).

This study performed a holistic analysis of basin-scale irrigation performance for different spatial units using an integrated SW-GW modeling approach. The Zhangye Basin (ZB) in Gansu Province, China, a typical semiarid to arid area with intensive agricultural irrigation, was chosen as the study area. ZB sits in the center of the Hexi Corridor, a vital passageway of the ancient Silk Road. From the 1970s to 2000, the rapidly expanding farmlands in the ZB deprived the middle Heihe River of a significant amount of flow and resulted in severe ecological issues in the Gobi Desert downstream of the ZB (Ji et al., 2006; Wen et al., 2005). This agriculture-ecosystem water conflict is a common challenge encountered in endorheic river basins globally. After the enforcement of diversion restrictions in the ZB in 2000, the ecosystems in the downstream area were considerably restored (Li et al., 2019; Zhou et al., 2018), but the agriculture-ecosystem water conflict was not fully resolved. Sun et al. (2018) conducted a system analysis on the water-ecosystem-agriculture nexus in the Heihe River Basin (HRB) and found that under rigid diversion restrictions, the only way to achieve the co-benefits of crop production, groundwater conservation and ecosystem recovery is to improve the water-use efficiency of irrigation. However, the IE in the ZB has not yet been systematically investigated. The study aims to answer the following key questions: (a) How can basin-scale IE be quantified and its spatiotemporal characteristics be revealed in areas with intensive SW-GW interactions? (b) How might the characteristics of basin-scale IE inform water resource management and policy making? (c) How might climate change impact irrigation performance at the basin scale? Overall, the new approach to IE quantification developed in this study is valuable for overcoming misunderstandings about the paradox of IE and provides strong support for water resource management in inland arid regions.

2. Data and Methods

2.1. Study Area

The Heihe River Basin (HRB) is the second largest endorheic basin in China, with a total area of approximately 14,000 km$^2$ (Li et al., 2018). The Heihe River originates from the Qilian Mountains at the
northeastern margin of the Qinghai-Tibetan Plateau, flows northward and ends at East Juyan Lake (Figure 2a). Yingluoxia is the divide between the upstream and midstream areas, while Zhengyixia is the divide between the midstream and downstream areas. The Heihe River flows through steep ecological gradients with decreasing elevation, changing from alpine biomes in upstream areas to farmlands, riparian forests, and grasslands in midstream areas and to deserts in downstream areas (Cheng et al., 2014). The middle HRB is an important food provision and storage base in Northwest China (Peng et al., 2007). Agricultural activities are practiced mainly in its core area, the Zhangye Basin (ZB) (Figure 2b), where maize is the main crop (Han et al., 2014). The ZB covers an area of approximately 9,670 km² and is divided into 20 irrigation districts (IRDs; Figure 2c). The elevation of the ZB changes from 1,200 m in the northwest to 3,880 m in the southeast, and the precipitation ranges from 50 to 400 mm. The groundwater depth in the study area ranges from approximately 3.3–125.5 m (Tian et al., 2018). The ZB is not a closed basin, as it has surface and subsurface boundary inflows and outflows. Therefore, the study area represents a general situation, and the methodology developed for it is applicable to all basins.

Irrigation activities in the ZB are comprehensively regulated by the Heihe River Bureau of the Yellow River Conservancy Commission. Local agriculture is decentralized, and the typical field size is approximately 0.3 ha. Flood irrigation is the major irrigation method, while water-saving technologies (e.g., drip irrigation under plastic film, spray irrigation, and low-pressure pipe irrigation) are only practiced at some pilot farms. The timing of irrigation is relatively fixed, which is typically 5 rounds within a year (March, April, June,
August, and December), and is scheduled based on the years of farmer experience in crop water demand. Many irrigation facilities have been built on the Heihe River and its tributaries, including water diversion hubs, main canals, branch canals, lateral canals, and sublateral canals.

It has been estimated that 1.6 billion m$^3$ of river flow and 0.26 billion m$^3$ of groundwater were extracted annually by farmers for agricultural irrigation in the ZB between 2000 and 2016 (Zheng et al., 2020). SW-GW exchanges in the study area are significant and closely connected with intensive irrigation. It was estimated that approximately 8.5% of total groundwater recharge (0.968 billion m$^3$/yr) occurs on irrigated farmlands, and the total groundwater discharge equals 0.889 billion m$^3$/yr (Tian et al., 2015). Thus, evaluating the IE in the ZB at the district and basin scales requires a detailed investigation of groundwater processes.

### 2.2. The HEIFLOW Model

The Hydrological-Ecological Integrated Watershed-Scale Flow (HEIFLOW) model (Han et al., 2021) is a physically based distributed ecohydrological model that was developed by improving an integrated hydrological model, namely, the Coupled Ground-Water and Surface-Water Flow (GSFLOW) model (Markstrom et al., 2008), and coupling it with new ecological modules. HEIFLOW is a general modeling tool, multiple versions of which have been applied in different geographic areas (Feng et al., 2018; Han et al., 2021; Joo & Tian, 2021; Wu et al., 2016). HEIFLOW has a general ecohydrological module (GEHM) that adopts heat unity theory to regulate the growth cycle of vegetation, and it can simulate the dynamics of basic ecological indicators, including the vegetation biomass, leaf area index (LAI), canopy height, and root depth (Sun et al., 2018). HEIFLOW also has an ecological model specifically designed for phreatophytes, which includes a coupled gas exchange submodel to simulate photosynthesis and transpiration rates based on stomatal activity (Li et al., 2017). GSFLOW itself couples a surface water model, the precipitation-runoff modeling system (PRMS; Leavesley, 1984), with a classic groundwater flow model, the modular groundwater flow (MODFLOW) model (Harbaugh, 2005). PRMS simulates surface water processes such as canopy interception, snowpack accumulation, runoff, infiltration, evapotranspiration (ET), and soil water flow, and MODFLOW simulates groundwater flow and the dynamics of surface water bodies. To determine the water exchange between the soil zone and groundwater zone, GSFLOW applies an iterative computing approach to solve the interdependent equations that govern surface water and groundwater flows. HEIFLOW calculates the direct groundwater use by vegetation (i.e., $GW_v$) when the groundwater becomes accessible to vegetation roots and when soil moisture is insufficient to meet the vegetation's transpiration demand (Han et al., 2021). More details regarding the calculation of $GW_v$ can be found in Text S1 of the Supporting Information S1.

This study used the most recent version of HEIFLOW (Zheng et al., 2020), which has added modules for representing water management policies (e.g., environmental flow regulation and groundwater pumping restriction) and internally simulating high-resolution irrigation activities. This version of HEIFLOW has two options for emulating irrigation activities, namely, scheduled and automatic irrigation methods, which differ in the calculation of irrigation water demand. The scheduled irrigation method requires predefined timing and quota levels (e.g., the desired depth of irrigation during a certain time period, which varies with the crop type, based on previous farming experience) to specify time-varying irrigation water demand. In the automatic irrigation method, irrigation is triggered when the deficit between the soil water content and field capacity exceeds a certain threshold, and irrigation water is therefore required to fill the deficit. In both methods, the extent to which the irrigation water demand at a certain time can be fulfilled depends on the water availability simulated by the model. In certain cases, such as insufficient river flow for diversion due to either dry conditions or environmental flow regulation or when further groundwater pumping is not allowed, the demand may be partially met. The automatic irrigation method is particularly suitable for modeling future climate scenarios in which historical farming experience may not be an adequate reference. More technical details about HEIFLOW can be found in the literature (Tian et al., 2018; Zheng et al., 2020).

A HEIFLOW model was built and well calibrated in previous studies (Tian et al., 2018; Zheng et al., 2020) for the entire middle and lower HRB, plus the western portion of the Badain Jaran Desert due to its hydraulic connection with the groundwater system in the lower HRB. This study used the recently updated version (Zheng et al., 2020). The entire modeling domain (Figure 2a) covers an area of 90,589 km$^2$, which consists of the Gobi Desert (63.7%), other deserts (18.4%), grasslands (5.9%), farmlands (5.6%), forests (1.1%), water
bodies (1%), and others (4.2%). Alluvial fans and floodplains are the major landforms in the middle HRB, while deserts dominate in the lower HRB and the western part of the Badain Jaran Desert. Both the surface and subsurface domains were delineated into 90,589 uniform 1 x 1 km grids horizontally. The subsurface domain was further divided into five layers, including one shallow unconfined aquifer, two confined aquifers and two aquitards. The boundary surface runoff brought to the middle HRB from the Qilian Mountains every year was estimated to be ~3.5 billion m$^3$, with 1.58 billion m$^3$ going through Yingluoxia in the main stream. Groundwater boundary inflow conditions were specified in the south, with an annual value of 0.4 billion m$^3$. The HEIFLOW model fuses multisource data and is able to offer detailed water balance information across different spatial and temporal scales (Li et al., 2018). Table 1 presents key water fluxes (average values over 2000–2016) of the 20 IRDs in the ZB derived from the model simulation. In this study, irrigation in the history modeling period (2000–2016) is scheduled based on annual irrigation statistical reports issued by the local government, and the automatic irrigation method is adopted for future simulation (2017–2060).

2.3. IE Indices Accounting for Groundwater and Return Flow

As we mentioned, a major limitation among almost all existing IE indices is the neglect of the direct contribution of groundwater to crop ET through a crop’s root system. Based on traditional definitions (Israelsen & Wiley, 1950; Keller & Keller, 1995; Molden, 1997), an IE index factoring in SW-GW interactions (denoted as $IE_1$) can be written as Equation 1, in which the beneficially consumed IRR is expressed as $ET_C - P_c - GW_{st}$. Note that $GW_{st}$ is not equal to $GW_{st}$ that originates from precipitation and irrigation water (IRR) during the evaluation period of IE such that double counting is avoided in the IE calculation. It is worth emphasizing that regardless of which spatial unit of IE is applied, this equation represents a field-scale IE index by nature because it does not account for $F_{ri}$. Thus, this study proposed a new basin-scale IE index (denoted as $IE_2$) to explicitly account for the role of $F_{ri}$ calculated with Equation 2.

\[
IE_1 = \frac{ET_C - P_c - GW_{st}}{IRR},
\]

\[
IE_2 = \frac{ET_C - P_c - GW_{st}}{IRR - F_{ri}},
\]

$IE_2$ is a real measurement of basin-scale irrigation efficiency, while $IE_1$ is not. In theory, both indices can apply to any spatial unit, from grid to basin, but the calculation of $IE_2$ is difficult because the term $F_{ri}$ is hard to quantify.

2.4. Integrated Modeling-Based IE Evaluation

The study developed an approach to evaluating the IE for different spatial units based on integrated eco-hydrological modeling and implemented the approach in the ZB. The HEIFLOW model for the HRB (see Section 2.2) was used as the modeling platform. $ET_C$ and IRR in Equations 1 and 2 can be directly extracted from the model outputs, but the derivation of $F_{ri}$, $P_c$, and $GW_{st}$ is not straightforward because typical hydrological models do not track the movement of a particular portion of input water. To address this difficulty, we first proposed a strategy to derive $F_{ri}$ via a comparison of two model simulations with and without irrigation. Taking the ZB case as an example, the HEIFLOW model was repeatedly run from 2000 to 2016 under

| IRD    | Area (km$^2$) | IRR  | DIV  | PUMP | $P_c$ | $ET_C$ | $F_{ri}$ |
|--------|---------------|------|------|------|-------|--------|---------|
| Liuba  | 18.02         | 0.99 | 0.93 | 0.25 | 0.33  | 1.16   | 0.16    |
| Pingchuan | 49.20      | 3.69 | 3.41 | 0.83 | 0.86  | 4.04   | 0.56    |
| Banqiao | 56.42         | 4.34 | 4.46 | 0.50 | 1.11  | 5.18   | 0.52    |
| Wujiang | 145.52        | 7.50 | 5.92 | 2.89 | 2.76  | 14.02  | 7.07    |
| Daman  | 258.75        | 19.31 | 17.22 | 4.59 | 7.07  | 26.06  | 9.77    |
| Yingke | 151.19        | 10.91 | 9.53 | 2.61 | 2.86  | 12.3   | 3.15    |
| Shangsan | 87.95      | 6.80 | 7.40 | 0.10 | 2.30  | 7.81   | 1.34    |
| Ganjun | 67.54         | 4.78 | 5.51 | 0.09 | 2.00  | 5.91   | 0.73    |
| Xigan  | 198.69        | 15.94 | 14.82 | 2.86 | 3.57  | 17.31  | 3.65    |
| Nijiaying | 20.32     | 1.24 | 1.24 | 0.25 | 0.60  | 1.55   | 1.06    |
| Xiaotun | 47.56         | 3.52 | 3.37 | 0.58 | 0.90  | 3.92   | 1.66    |
| Shahe  | 56.18         | 4.67 | 3.88 | 1.24 | 1.25  | 5.43   | 2.22    |
| Yanuan | 54.94         | 5.16 | 4.73 | 0.93 | 0.96  | 4.92   | 1.25    |
| Liaoquan | 57.96      | 5.39 | 5.29 | 0.67 | 1.02  | 5.54   | 1.69    |
| Xinhua | 107.38        | 9.00 | 8.69 | 1.29 | 2.29  | 9.88   | 1.23    |
| Luotuocheng | 89.24   | 5.64 | 4.43 | 2.11 | 1.92  | 6.48   | 0.93    |
| Dahuwan | 40.82         | 3.81 | 3.25 | 0.86 | 0.70  | 3.98   | 1.00    |
| Luocheng | 60.52        | 6.53 | 6.62 | 0.79 | 1.01  | 7.89   | 2.75    |
| Sanqing | 56.95         | 4.39 | 3.72 | 1.00 | 0.94  | 4.86   | 1.48    |
| Youlian | 108.31        | 9.33 | 8.22 | 2.01 | 1.49  | 9.70   | 2.49    |

Note. IRR, irrigation water arriving at the irrigated field; DIV, water diverted from the river for irrigation; PUMP, water pumped from groundwater; $P_c$, effective precipitation; $F_{ri}$, return flow.
the following 22 scenarios: Scenario 1: all IRDs are irrigated; Scenario 2: no IRD is irrigated; Scenario 3-i: all IRDs are irrigated except the \( i \)th IRD (\( i = 1, \ldots, 20 \)).

The 22 model runs only differed in the input files configuring irrigation behaviors. IRR applied on cropland has five main sinks: crop ET, bare land and/or weed ET (i.e., nonbeneficial consumption), stream flow, groundwater flow, and storage of both surface water and groundwater. The sum of the last three terms is often referred to as \( F_{ff} \) (Keller, 1996). With a comparison between Scenarios 1 and 2, we can calculate the basin-scale \( F_{ff} \) in any given evaluation period as follows:

\[
F_{ff} = DP - \left( \Delta S + \Delta SF + \Delta GWF + \Delta GW_{et}^* \right) - CS, \tag{3}
\]

where \( DP \) is the sum of the water diverted from the river and the water pumped from groundwater, \( S \) is the sum of soil moisture and groundwater storage, \( SF \) is the stream flow at Zhengyixia (i.e., leaving the ZB), \( GWF \) is the lateral groundwater flow that leaves the ZB, \( CS \) is the canal seepage to groundwater, and the symbol \( \Delta \) denotes the difference between two scenarios (Scenario 1 minus Scenario 2). Equation 3 is derived from the water balance equation, and the derivative process can be found in the Appendix. Note that \( IRR \) equals \( DP \) minus canal losses, which includes canal evaporation and canal seepage (CS).

In theory, the above difference-based approach to \( F_{ff} \) estimation could apply to any spatial unit. For example, Equation 3 can also be used to calculate the \( F_{ff} \) of individual IRDs by comparing Scenario 1 and Scenario 3-i (Scenario 1 minus Scenario 3-i), in which case all the terms are with regard to the particular IRD. However, the groundwater module in HEIFLOW is based on the finite difference method, and numerical error is inevitable. The calculation error may exceed the magnitude of \( F_{ff} \) when the spatial unit is too small.

In this study, we evaluated IE indices for both districts (between 18.02 and 258.75 km\(^2\)) and the ZB as a whole, with a tolerable numerical error in \( F_{ff} \).

There are many different ways to estimate \( EP \), such as empirical methods, soil water balance methods, and direct measurement techniques (Mohan et al., 1996; Patwardhan et al., 1990). In this study, we refer to the empirical equation adopted in China (Li, 2008):

\[
\alpha = \begin{cases} 1, & P < 50 \text{ mm} \\ 0.75 - 0.85, & 50 \text{ mm} < P < 150 \text{ mm}, \\ 0.70, & P > 150 \text{ mm} \end{cases} \tag{4}
\]

HEIFLOW calculates \( GW_{et}^* \), which does not exclude the portion (denoted as \( \beta \)) of groundwater that originates from precipitation and \( IRR \) during the evaluation period of IE. An estimation of \( \beta \) to derive \( GW_{et} \) based on \( GW_{et}^* \) is therefore needed. As IE is evaluated at an annual or longer time scale, it is appropriate to assume that the crop root system takes water proportionally from the newly recharged groundwater during the evaluation period and the historical groundwater storage. With this assumption, \( \beta \) can be approximated as \( 1/\tau \), where \( \tau \) denotes the groundwater residence time (or turnover time) in a year, which leads to

\[
GW_{et} = (1 - \beta)GW_{et}^* = \left(1 - \frac{1}{\tau}\right)GW_{et}^*, \tag{6}
\]

The groundwater residence time \( \tau \) can be estimated with different approaches (Cartwright et al., 2020; McCallum et al., 2014; Tosaki et al., 2011). In this study, \( \tau \) was set to 16 years for the study area based on Chen et al. (2006).

### 2.5. Climate Change Scenario

Few studies have investigated the response of IE to future climate change, largely due to the lack of adequate approaches to evaluating basin-scale IE. The new indices (Section 2.3) and the approach to index
evaluation (Section 2.4) make such an investigation feasible. We collected the climate change dataset (see Text S3 and Figure S2 in the Supporting Information) for the HRB, which was derived from the European community Earth (EC-EARTH) global climate model under the RCP4.5 scenario and downscaled via a high-resolution regional climate model with a horizontal resolution of 3 km from the National Tibetan Plateau Data Center (http://data.tpdc.ac.cn) (Xiong & Yan, 2013). The reason for using this dataset is two-fold. First, as many countries including China have made commitments and set timetables for peak carbon dioxide emissions to eventually achieve carbon neutrality, RCP4.5 appears to be a more reasonable scenario to evaluate the impact of climate change than RCP8.5. Second, this publicly accessible dataset has a fine resolution compatible with the HEIFLOW model used in this study and has been used in other studies (Zhao et al., 2019; Zou et al., 2016). The climate modeling period spanned from 2017 to 2060. Compared with historical data, future mean annual temperatures constantly increase by \( \sim 1.4\% \) per decade, while future mean annual precipitation has no obvious change, but the interannual variations become larger. Future boundary inflows of the HRB were generated by repeating the historical inflow data because our analysis indicated that boundary inflows and IE over the ZB have weak correlations \( (r = -0.22) \) as long as streamflow is sufficient for irrigation diversion, which is the current circumstance. Considering that there are no observations about future irrigation, we adopted the automatic irrigation method for future simulation. Additionally, to rule out the impact of change in irrigation behavior, the automatic irrigation method is also applied in the historical simulation. As shown in Figure S2 (which is found in the Supporting Information), there is no significant tendency in \( \text{IRK} \).
3. Results

3.1. Basin-Wide IE Over Time

Figure 3 presents the derived values of different IEs for the entire ZB from 2000 to 2016. Figure 3a shows that the overall IE in the ZB has significant interannual variations for both indices. IE$_1$ (i.e., the index per the traditional definition) varies between 0.62 and 0.84 for the individual years during the modeling period and has two peaks (2003–2004 and 2011–2013) and two troughs (2002 and 2007–2009). The temporal pattern of IE$_2$ (i.e., the real measurement of basin-scale IE that accounts for $F_{et}$) is very similar to that of IE$_1$ (Figure 3a), but IE$_2$ (which ranges from 0.70 to 0.96) is approximately 0.10 higher than IE$_1$ on average. The discrepancy between the two trajectories indicates that the ratio of $F_{et}$ to IRR at the basin scale is relatively constant (approximately 13%, 0.172 billion m$^3$/yr) over time.

The interannual variability in both IE$_1$ and IE$_2$ is largely due to the fluctuation of local precipitation (Figure 3a) because the annual amount of irrigation water that enters the system is relatively stable during the evaluation period. The correlations between annual IRR and IE are statistically insignificant ($r = -0.30$ for IE$_1$ with $p = 0.24$, and $r = -0.34$ for IE$_2$ with $p = 0.13$), which confirms the limited impact of the annual irrigation rate on IE under existing irrigation practice. High negative correlations ($r = -0.66$ for IE$_1$ and $r = -0.64$ for IE$_2$) are identified between IE and local precipitation, which means that IRR is used much less efficiently in wet years. Figure 3b demonstrates that from a long-term perspective, the basin-wide IE$_1$ and IE$_2$ exhibit much less interannual variability and stabilize at approximately 0.75 and 0.85, respectively, beyond 2013. Because the water inputs to the agricultural system, including precipitation, surface diversion (DIV) and groundwater pumping (PUMP), demonstrate no significant changing tendencies during the evaluation period (see Figure S1 in the Supporting Information S1), we speculate that the long-term stability in the cumulative irrigation efficiency largely reflects the basin’s physical characteristics (e.g., land use, cropping structure, soil properties, and hydrogeological conditions).

Figure 4 further explains the negative correlation between IE and local precipitation by illustrating the compositions of the water sources for crop ET in the wettest year (2002) and the driest year (2004) based on HEIFLOW. In 2002, with more local precipitation in the ZB, $P_e$ (the green bars in Figure 4) almost triples from that in 2004 (increasing from 2.10 to 7.15 × 10$^8$ m$^3$), but the percentage changes in IRR (blue bars), ET$_c$ (red bars) and $F_{et}$ (cyan bars) are much lower. Essentially, Figures 3a and 4 imply that current irrigation practices in the ZB result in overirrigation in wet years. If the future climate in the ZB becomes warmer and wetter per some projections (Zhang et al., 2016), then there will be a need to strategically adjust the annual irrigation in the ZB such that its basin-wide IE can be improved and more water can be conserved for vulnerable ecosystems in the lower HRB.

3.2. IE Across IRDs

To explore the spatial heterogeneity in IE, the long-term average values of IE$_1$ and IE$_2$ are considered in this section, excluding the impact of fluctuations in annual precipitation. As shown in Figure 5, both IE indices exhibit notable spatial heterogeneity across IRDs. In general, the IE$_1$ of those IRDs close to Yingluoxia, such as Daman, Shangsan, Ganjun, etc., is low, while IE$_2$ shows great uniformity in the downstream area of the ZB (Figure 5b). The groundwater table of Wujiang (ID = 4) has increased dramatically since 2007, which results in serious groundwater exposure (i.e., water-table outcrop) and poor crop production (Feng et al., 2008) due to a lack of appropriate drainage. Therefore, Wujiang was excluded from our further discussion. Deep groundwater depth appears to be a major cause of low IE$_1$. For example, Daman, Shangsan, Ganjun, Nijiaying, and Luotuocheng (IDs = 5, 7, 8, 10, and 16) have deep groundwater depths, with an average value of 86.6 m, while the remaining IRDs (excluding Wujiang where the water-table outcrop is significant)
have an average groundwater depth of only 11.4 m. After entering farmland, a fraction of IRR infiltrates and leaves the irrigated area. This part water cannot be directly used by local crops and becomes water loss based on the traditional evaluation approaches. Therefore, more IRR will be diverted to compensate for the loss, which leads to an increase in IRR and a decrease in IE1 (Equation 1). Field capacity may be another major factor impacting IE1. For example, the groundwater depth of Yingke is deeper than average (~26 m), but the IE1 of Yingke is much higher than that of the surrounding IRDs, which is attributed to its high water holding capacity. As one of the most ancient IRDs, Yingke has farmlands that have been cultivated for several hundred years, and the soil (the type is gray irrigated desert soil, based on the Soil Database of 1:1,000,000 Digital Soil Survey of China) can effectively prevent irrigation water from rapid leaching or substantial lateral flow and therefore retain abundant moisture for crop ET (Shi et al., 2004). With this exceptional capacity, the IRR per unit area required by Yingke is much lower than that of surrounding IRDs where a large proportion of farmland has been newly reclaimed with relatively low water holding capacity. IRDs with a higher water holding capacity require less IRR for producing the same amount of ETc and therefore have a higher IE1 according to Equation 1.

Figure 5. Irrigation efficiencies (IEs) across different irrigation districts (IRDs). (a) Annual average values of the two IE indices during 2000–2016; (b) map of IE1 distribution; (c) map of IE2 distribution.
The spatial pattern of \(IE_2\) is quite different from that of \(IE_1\) (Figure 5c). Overall, \(IE_2\) is high in IRDs along the river, but it is very low in IRDs far away from the river. Nijiaying, Daman, and Luotuocheng are three IRDs with the lowest values of \(IE_1\) (0.61, 0.61, and 0.63, respectively). While Luotuocheng has a low \(IE_2\) as well, Nijiaying and Daman have relatively higher values of \(IE_2\), particularly Nijiaying, whose \(IE_2\) reaches 0.94. The difference in \(IE_2\) can be explained by the ratio of \(rf/IRR\). \(rf/IRR\) only makes up 5% of the IRR in Luotuocheng, while the ratios are 19% and 33% in Daman and Nijiaying, respectively. A shallow groundwater depth and strong field capacity will lead to a high ratio of \(rf/IRR\), that is, a high \(IE_2\). In addition, the distance from an IRD to a river also influences \(IE_2\) significantly. When the distance is closer, a larger proportion of \(IRR\) becomes \(F_{rf}\) through lateral flow. In the ZB, intensive SW-GW interactions occur near the main river and tributaries where the groundwater depth is shallow (e.g., Xiaotun and Luocheng). In such areas, a significant portion of \(IRR\) can quickly return to the river system and be beneficially used elsewhere in the basin. In contrast, in Luotuocheng, with a deep groundwater depth (33.8 m on average), which is also far from a river, a substantial portion (approximately 32%) of the IRR input into crop fields either goes toward local nonbeneficial consumption or moves slowly in the soil, and the infiltrated IRR may take many years (beyond the modeling time period) to become \(F_{rf}\) again.

### 4. IE Under Climate Change

In this study, the future climate projection data used to drive the HEIFLOW model indicate a warmer but not significantly wetter climate (Figure S1 in the SI). Figure 6a shows the basin-wide \(IE_1\) and \(IE_2\) for individual years from 2000 to 2060, as simulated by the HEIFLOW model. Although statistically insignificant (according to the Mann-Kendall test at a 95% confidence level, with \(p = 0.88\) for \(IE_1\) and \(p = 0.67\) for \(IE_2\),
a decreasing trend in $\text{IE}_1$ ($\sim-0.002$ per decade) and an increasing trend in $\text{IE}_2$ ($\sim0.003$ per decade) are observed during the simulation period (2017–2060). The interannual variation is significant, and rapid drops in IE occur in very wet years (e.g., in 2024 and 2053, when $\text{IE}_1$ is lower than 0.65). The interannual variation in IE is largely dominated by precipitation (with correlation coefficients $r = -0.93$ for $\text{IE}_1$ and $r = -0.88$ for $\text{IE}_2$) rather than by temperature ($r = -0.08$ for $\text{IE}_1$ and $r = -0.19$ for $\text{IE}_2$), which is consistent with the findings in Section 3.1. Regarding the long-term average IE, the tendencies are similar, but the trajectories are much smoother (Figure 6b). Although Figure 6 demonstrates that the impact of climate change on IE in the study area may be mild, the discrepancy between the cumulative $\text{IE}_1$ and $\text{IE}_2$ will increase by 6%, from 0.090 in 2017 to 0.095 in 2060.

The different tendencies of projected $\text{IE}_1$ and $\text{IE}_2$ are due to the nonuniform responses (see Figure S2 in the Supporting Information S1) of the water flux terms in the IEs to the climate change predicted by HEI-FLOW. $\text{IE}_1$, IRR and $F_{\text{et}}$ increase by approximately 0.70%, 1.92% and 3.20% per decade from 2017 to 2060, respectively, while $P_d$ and GW$_{et}$ decrease by approximately $-2.12\%$ and $-1.24\%$ per decade from 2017 to 2060, respectively. As a result, the numerator (i.e., ET$_c - P_d - $GW$_{et}$) and denominator (i.e., IRR) of $\text{IE}_1$ increase by approximately 1.75% and 1.92% per decade from 2017 to 2060, respectively, which leads to a slight decreasing trend in $\text{IE}_2$. Similarly, the denominator of $\text{IE}_2$ (i.e., $F_{\text{et}}$) increases by approximately 1.57% per decade from 2017 to 2060, which is smaller than the 1.75% increase in the numerator, leading to a slight increasing trend in $\text{IE}_2$.

Overall, the above results highlight the importance of using the new $\text{IE}_2$ index instead of the traditional $\text{IE}_1$ index in managing water resources at a basin scale because the latter may lead to a significant underestimation of basin-scale IE in a fast-changing environment.

5. Discussion

It has been demonstrated that irrigated water in one district can be beneficial elsewhere within the basin through the mechanism of return flow. This positive externality has significant policy implications where irrigation water is a limited resource and is not freely obtained. In arid northwestern China, farmers pay water resource fees for both river water and groundwater, and there is an additional electricity cost for those who pump groundwater for irrigation. Taking the ZB as an example (Figure 5a), if the traditional field-scale index $\text{IE}_1$ is considered, then some districts (e.g., Nijiaaying) are highly water inefficient, which would discourage agricultural development. However, the new basin-scale index $\text{IE}_2$ suggests that these districts actually have a high water efficiency at the basin scale because the positive externality of the local irrigation is significant. From the perspective of water resource managers who aim to improve basin-scale water efficiency, irrigated agriculture should be encouraged in such districts. Thus, a differentiated price policy may be considered: for districts with low $\text{IE}_2$, but high $\text{IE}_1$, a discounted water resource fee can be applied. On the other hand, in districts where both $\text{IE}_1$ and $\text{IE}_2$ are lower (e.g., Luotucheng), appropriate policy measures should be taken to restrict the use of irrigation water, such as an increase in water resource fees, subsidies for spray irrigation, and compensation for leaving land fallow.

It is also worth emphasizing that lack of information on return flow in evaluating basin-scale IE may mislead policy making and management. Figure 5a implies that $\text{IE}_1$ and $\text{IE}_2$ lead to different rankings of the IRDs with regard to water efficiency. Thus, if water-saving practices, such as promoting water-saving irrigation technologies and ditch lining, were prioritized at IRDs with relatively low $\text{IE}_1$, but high $\text{IE}_2$, these practices may turn out to be ineffective at the basin scale because they may also significantly reduce the return flow (particularly the groundwater return flow as water infiltration declines) in such areas. In addition, as shown in Figure 6b, $\text{IE}_1$ and $\text{IE}_2$ exhibit opposite trends under future climate conditions. Based on $\text{IE}_2$, the basin-scale IE of the ZB will be high and even have a mild increase in the projected climate scenario, as discussed in Section 3.3. Therefore, future water management in the ZB should be focused on addressing the paradox of IE rather than on further improving field-scale IE. Appropriate policies (e.g., fees, taxes, and conservation requirements) are desired to avoid further farmland expansion in the ZB, and engineering measures (e.g., an improved drainage system) may be needed to enable the utilization of the enhanced return flow (which increased by 3.20% per decade from 2017 to 2060) to restore the degraded ecosystems (e.g., shrinking wetlands and salinized soils) in the ZB.
Although it is well known that IE should be higher at the basin scale due to the effect of return flow, which goes unaccounted for at the field scale, few studies have quantitatively addressed this scale-induced difference. The integrated modeling approach developed in this study enables this difference to be rigorously quantified, yielding the significant socioeconomic implications discussed above. Essentially, this approach provides a methodological foundation for quantitatively addressing region-dependent characteristics, mechanisms, and potential solutions of the IE paradox in a real-world setting. With this approach, misunderstandings about this paradox can be overcome, and the five-step reform of the current IE policy agenda proposed by Grafton et al. (2018) can be actualized. With a physically based integrated ecohydrological model such as HEIFLOW, physical water accounts (i.e., the first step) can be readily built (Li et al., 2018), and basin-scale IE can be quantified across a wide spectrum of spatial units. Uncertainty assessment (i.e., the third step) can be performed in a systematic way with novel algorithms (Wu et al., 2014), and tradeoffs among agriculture and ecosystems (i.e., the fourth step) can be evaluated through scenario analyses (Sun et al., 2018). Coupled with a decision model such as an agent-based model (Du et al., 2020), the integrated ecohydrological model can also be used to quantify the effects of policy actions on the behavior of irrigators (i.e., the fifth step), as well as the eventual impacts on basin-scale IE. In addition, the environmental flow regulation practiced in the Heihe River Basin (HRB) has demonstrated that a direct cap on water offtakes (i.e., the second step) can effectively save water for ecosystems (Zheng et al., 2020).

6. Conclusions

This study performed a holistic analysis of basin-scale irrigation efficiency (IE) using the Zhangye Basin, a typical semiarid to arid area with intensive agricultural irrigation in northwestern China, as the testbed. A new index of basin-scale IE, IEb, was proposed for areas with intensive SW-GW interactions that factors in the return flow of irrigation water and groundwater’s direct contribution to crop ET via a crop’s root system. A novel strategy was also developed to evaluate the basin-scale IE for different spatial units (e.g., IRDs and the whole basin). HEIFLOW was used as a representative ecohydrological model. The major study findings for the ZB include the following. First, Frc accounts for approximately 13% of irrigation water (IRR), which leads to an underestimation of 0.10 in basin-scale IE, as indicted by IEb, on average when the traditional index IEf (field-scale by nature) is used. Second, basin-scale IE in individual years fluctuates notably but exhibits stability in terms of the multiyear average, which is largely dependent on the basin’s physical characteristics. Third, basin-scale IE reflects notable spatial heterogeneity across IRDs and is largely influenced by the intensity of SW-GW interactions. Fourth, under the projected future climate scenario, the basin-scale index IEb exhibits an increasing tendency, but the field-scale index IEf shows the opposite trend, which further demonstrates the importance of including return flow in water accounting for agricultural water management in arid regions.

Overall, this study demonstrates that an appropriate evaluation of basin-scale IE is critical to making heterogeneous (in space) water policies and to developing adaptive water management strategies under a changing climate. The integrated modeling approach to IE evaluation by this study provides a methodological foundation for overcoming misunderstandings about the paradox of IE that has long been debated and paves the way for the five-step reform of the current IE policy agenda (Grafton et al., 2018). Developing more realistic models to simulate the behavior of irrigators and differentiating the hydrologic impacts of multiple irrigation techniques across a wide spectrum of spatial scales are two attractive research questions to resolve the paradox.

Appendix A: Derivation of $F_{rc}$

Upstream inflow is $S_{in}$, downstream outflow is $S_{out}$, river storage change is $\Delta S$, channel ET is $ET_{rc}$, channel precipitation is $P_{rc}$, net SW-GW exchange is $NEX$ in a river channel (a positive value indicates net SW loss to GW, and a negative value indicates net SW gain from GW), river diversion is $DIV$, and irrigation water returning to a river is $RFS$. In Scenario 1 (i.e., without irrigation) and Scenario 2 (i.e., with irrigation), the water balance of the river can be expressed with Equations a and b, respectively, where the superscripts indicate the scenarios.
The two external water input terms are unchanged from Scenario 1 to Scenario 2 (i.e., \(P_{\text{rc}}^1 = P_{\text{rc}}^2, SF_{\text{in}}^1 = SF_{\text{in}}^2\)). Subtracting Equation (A2) by Equation (A1) leads to

\[
RFS = \text{DIV} + \left( SF_{\text{out}}^2 - SF_{\text{out}}^1 \right) + \left( ET_{\text{rc}}^2 - ET_{\text{rc}}^1 \right) + \left( \Delta RS^2 - \Delta RS^1 \right) + \left( \text{NEX}^2 - \text{NEX}^1 \right).
\]  

(A3)

Because on an annual basis, \(ET_{\text{rc}}^E\) and \(\Delta RS^E\) are orders of magnitude less than other water balance items, \(\text{DIV}^1 = \text{DIV}^2\) and \(\text{NEX}^2 = \text{NEX}^1\) can be omitted, and Equation (A3) can be simplified as follows:

\[
RFS = \text{DIV} + \left( SF_{\text{out}}^2 - SF_{\text{out}}^1 \right) + \left( \text{NEX}^2 - \text{NEX}^1 \right).
\]  

(A4)

Lateral GW inflow is \(\text{GWF}_{\text{in}}\), lateral GW outflow is \(\text{GWF}_{\text{out}}\), original GW storage is \(S^E_{\text{GWF}}\), ending GW storage is \(E^E_{\text{GWF}}\), GW pumpage is \(\text{PUMP}\), irrigation water returning to the aquifer is \(\text{RFG}\), and non-irrigation water recharging the aquifer is \(\text{non irr RFG}\). The final expression of \(F_{\text{cf}}\) can be derived by adding Equations (A4) and (A7)

\[
F_{\text{cf}} = RFS + \text{RFG} \\
= \text{DIV} + \text{PUMP} + \left( SF_{\text{out}}^2 - SF_{\text{out}}^1 \right) + \left( GWF_{\text{out}}^2 - GWF_{\text{out}}^1 \right) + \left( S^2_{\text{GWF}} - S^1_{\text{GWF}} \right) - \left( RFG^2_{\text{non-irr}} - RFG^1_{\text{non-irr}} \right) - \left( \text{GW}^{r2}_{\text{et}} - \text{GW}^{r1}_{\text{et}} \right) - \Delta SF - \Delta GWF + \Delta S + \Delta GW_{\text{CS}}
\]  

(A8)

where \(\text{DP} = \text{DIV} + \text{PUMP}\), and \(\left( RFG^2_{\text{non-irr}} - RFG^1_{\text{non-irr}} \right)\) is approximated by \(CS\).

All the terms in the final expression of Equation (A8) can be derived from the integrated ecohydrological modeling by HEIFLOW or other models with a similar modeling capacity.

Table A1 is a list of the variables involved in the above derivation and in the calculation of IE indices.
Table A1
Notations of the Key Variables in This Study

| Variable notation | Description (unit*) |
|--------------------|----------------------|
| CS                 | Canal seepage to groundwater (L³) |
| ETi                | Crop evapotranspiration (L³) |
| ETc                | Channel evapotranspiration (L³) |
| PUMP               | Return flow (L³) |
| GWt                | Direct groundwater extraction by crop excluding the portion of groundwater recharged by precipitation and irrigation water (L³) |
| GWt*               | Direct groundwater extraction by crop calculated in HEIFLOW (L³) |
| GWFin              | Lateral groundwater inflow (L³/T) |
| GWFout             | Lateral groundwater outflow (L³/T) |
| IRR                | Water pumped from groundwater for irrigation (L³) |
| NEX                | Net surface water-groundwater exchange in a river channel (L³) |
| Pe                 | Effective rainfall (L³) |
| PrE                | Channel precipitation (L³) |
| PRG                | Groundwater recharge originating from precipitation (L³) |
| DIV                | Water diverted from a river for irrigation (L³) |
| PUMPE              | Water pumped from groundwater for irrigation (L³) |
| DP                 | DIV + PUMPE (L³) |
| ΔRS                | River storage change (L³) |
| RFG                | Irrigation water returning to the aquifer (L³) |
| RFG + non-irrig     | Non-irrigation water coming to the aquifer (L³) |
| RFS                | Irrigation water returning to a river (L³) |
| δe                 | Ending groundwater storage (L³) |
| δo                 | Original groundwater storage (L³) |

*In the units, L indicates length, and T indicates time.

Data Availability Statement
All the data used in this study can be accessed in the cited references and at the National Tibetan Plateau/Third Pole Environment Data Center (http://data.tpdc.ac.cn/en/).

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