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Quantitative analysis of the human intervention impacts on hydrological drought in the Zayande-Rud River Basin, Iran

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ABSTRACT

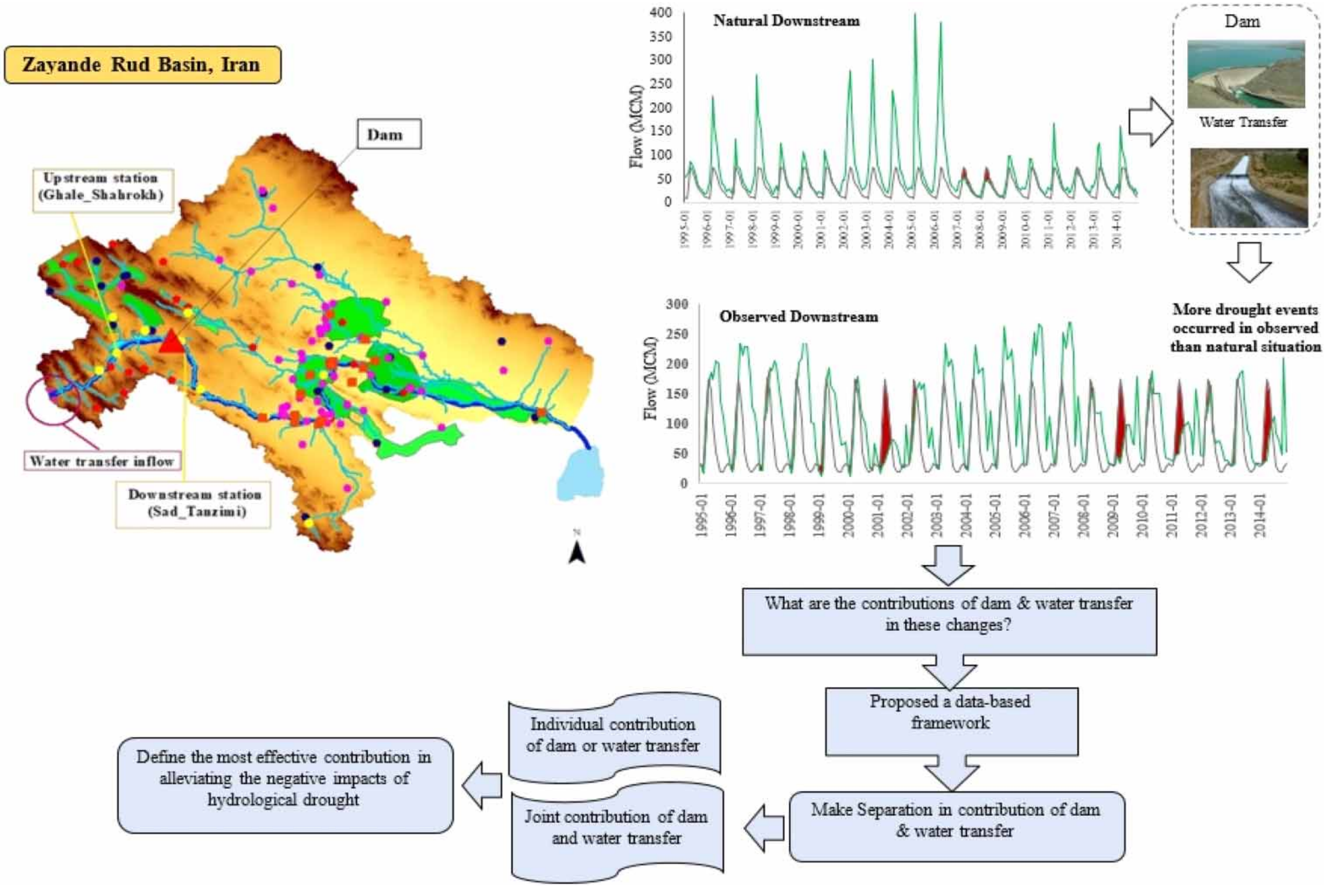
In a human-dominated world, access to sustainable water resources has led to complex management policies that affect hydrological droughts. Applying the best approach to assess the contribution of these human-made changes to hydrological droughts is still underexplored. In this study, the individual and joint impacts of dam and inter-basin water transfer projects are quantified for the characteristic changes of hydrological drought using a developed data-based framework and were tested in a semi-arid, data-scarce basin in central Iran. The proposed data-based framework combines the upstream–downstream comparison method and the individual–station–drought analysis. This framework could properly assess the individual and joint contributions of dam and water transfer projections to making aggravations or alleviations in hydrological drought. It identified the dam and joint impacts of the dam with water transfer by 66 and 55%, respectively, as the most effective human intervention to alleviate the duration of hydrological drought. The proposed framework gives the flexibility to form different comparative analyses by using different types of flow data to assess the impacts of human interventions. This framework is also applicable in other regions to quantify the contributions of point-based human interventions to hydrological droughts. The comprehensive knowledge of solutions to alleviate the adverse impacts of droughts can reduce the damage in water-stressed regions.

Key words: human impacts, hydrological drought, reservoir, semi-arid regions, SWAT, water transfer

HIGHLIGHTS

- This study proposed a new framework to separate human impacts on hydrological droughts.
- This study assessed the most effective contribution of human impacts to drought alleviation.
- The results showed both aggravation and alleviation contributions of human impacts.
- This study is an effective framework to apply in data-scarce and semi-arid regions.
- The framework can separate combined or individual impacts of any point-based interventions.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Drought definitions vary and can be grouped into different categories depending on the variables used to describe the drought (Mishra & Singh 2016). Meteorological drought is defined as a natural phenomenon caused by a lack of precipitation compared to normal conditions over a long period (Tallaksen & Van Lanen 2004; Sheffield & Wood 2011; Mishra & Singh 2016; Van Loon *et al.* 2016b). Prolonged precipitation deficits (meteorological drought) can gradually spread into the drainage systems and lead to a lack of soil moisture (agricultural drought) and even more to hydrological droughts. Hydrological drought is associated with the departure of surface water (streamflow, lakes, reservoir levels, and snowpack) or sub-surface water (groundwater levels) from some average conditions at different points in time (Wilhite & Pulwarty 2017). The classical definition of drought considers climatic factors as the sole driving force leading to the formation and development of drought. In other means, in this extremely changing human world, from a unilateral point of view, drought is only considered concerning climatic factors.

There are significant gaps regarding the impacts of human activities on hydrological droughts (Van Loon *et al.* 2016b). However, quantifying the impacts of human activities on hydrological drought provides a complete understanding of successful drought preparation (Rangecroft *et al.* 2019). Therefore, there has been a call to consider human activities and interventions as one of the most important drivers and modifications in the process, propagation, and changes of characteristics of droughts (McMillan *et al.* 2016; Van Loon *et al.* 2016a, 2016b; Firoz *et al.* 2018; Wang *et al.* 2021). Various human activities and interventions (e.g., exploitation of groundwater and surface water storages, land-use changes, deforestation, construction of reservoirs, and inter–intra water transfer projects) directly and indirectly alter the hydrological processes (e.g., evapotranspiration, infiltration, and runoff) (Wagener *et al.* 2010) whose changes in hydrological cycles can affect the development of droughts as a specific hydrological process (Van Loon *et al.* 2016b) and some of these changes may affect the hydrological drought characteristics such as deficit or severity. Therefore, quantifying the alleviation or aggravation impacts of human activities and interventions on hydrological drought is vital to find out the contribution of their effects on historical events or future drought events to successfully mitigate the drought severity and reduce the negative impacts of drought (Van Loon *et al.* 2016b).

To address the impacts of human activities and interventions on hydrological droughts, comparing drought events in a natural situation with a human-influenced situation is a dominant approach that has been implemented in various studies (Van Loon & Van Lanen 2013, 2015; Wada *et al.* 2013; Wanders & Wada 2015; Liu *et al.* 2016; Rangecroft *et al.* 2016; He *et al.* 2017; Zou *et al.* 2018; Kakaei *et al.* 2019; Rangecroft *et al.* 2019; Van Loon *et al.* 2019; Jiao *et al.* 2020; Qi *et al.* 2020; Yang *et al.* 2020; Cheng *et al.* 2021). Several approaches have also been developed to assess these impacts. Based on Rangecroft *et al.* (2019), these approaches mostly include the so-called pre- and post-disturbance, observation-modelling framework, upstream–downstream comparison method, and the so-called paired-catchments.

One approach is the so-called pre-and post-disturbance period that has quantified various human activities in basin scales such as in the Laohahe catchment, Northern China (Liu *et al.* 2016). The main limitation of this approach is that it only compares different drought events from different periods with different meteorological forcing (Peñas *et al.* 2016). Another well-known approach is the observation-modelling framework (Van Loon & Van Lanen 2013, 2015; Kakaei *et al.* 2019), which is based on a comparison between the simulated natural situation and the disturbed human situation. This framework is practical enough to identify the various effects of human activities such as land-use change, over-exploitation of surface and subsurface water, high pressure of population growth, and increasing agricultural and residential areas on hydrological droughts (Kakaei *et al.* 2019). It has also been applied to configure the mitigating effects of inter-basin water transfer on the negative impacts of hydrological droughts (Van Loon & Van Lanen 2015).

To apply the observation-modelling framework, the adequacy of pre-disturbed data (meteorological and hydrological) is required for an acceptable calibration of the developed hydrological model to simulate the natural flow (Van Loon *et al.* 2019) by considering the model uncertainty. However, some case studies suffer from pre-disturbed data access.

Another method of quantifying human-induced impacts on hydrological droughts is the upstream–downstream comparison method (Rangecroft *et al.* 2016, 2019), which compares upstream drought events (representing the natural situation) with downstream drought events (disturbing the situation by a human). The upstream–downstream comparison method was used to quantify the impact of the reservoir on the hydrological drought characteristic changes in a basin in northern Chile, once applying model-based data as a human-disturbed situation (Rangecroft *et al.* 2016) and the other one by applying observation-based data (Rangecroft *et al.* 2019). The results indicated that the reservoir in this case study alleviated short-term and minor hydrological drought impacts by reducing the negative effects of drought characteristics such as deficit and duration. This method does not tolerate comparing different periods with different meteorological forcing (e.g., the so-called pre- and post-disturbed approach). Another advantage of this method is the ability to use observational data easily and understandably (Rangecroft *et al.* 2019), so the uncertainty associated with the modelling process is no more a limitation in the observation-based analysis of the upstream–downstream comparison method (Rangecroft *et al.* 2019). Besides the strength of the upstream–downstream comparison method, the potential uncertainty between upstream and downstream due to their non-linear relationship should not be disregarded (Van Loon *et al.* 2019).

Another method is the so-called paired catchment method, one of the classical hydrological approaches in which a human-influenced catchment is compared with a benchmark catchment where the human activities of interest are not introduced. Although finding two catchments with similar physical characteristics is challenging, many studies have tested the approach to quantify different human activities on hydrology (Brooks *et al.* 2003; Brown *et al.* 2005; Zégre *et al.* 2010; Folton *et al.* 2015; Putro *et al.* 2016). Van Loon *et al.* (2019) used this approach to quantify the impacts of human activities on hydrological drought and concluded that this approach could be the first estimate of human-induced impacts on hydrological droughts.

A critical open question of the choice of an appropriate approach for determining human-induced impacts is significantly related to the characteristics, limitations of the study area, and objectives of the study. To determine the human intervention impacts on hydrological droughts, limitations such as the ability to access pre-disturbed time series (as in the so-called pre–post-disturbed approach) (Liu *et al.* 2016), a sufficiently long natural-simulated time series (as for observation-modelling framework) (Van Loon & Van Lanen 2013, 2015; Kakaei *et al.* 2019), and an upstream station as a natural proxy (as in the upstream–downstream comparison method) (Rangecroft *et al.* 2016, 2019) should be taken into account. However, it is difficult to quantify the impact of human interventions on the hydrological drought for data-scarce watersheds. Watersheds, where data are scarce, may not have enough access to pre-disturbed data or enough high-resolution data to establish qualified modelling. In addition, in some cases, the upstream flow regime is altered by the human intervention as if this modification (besides the human intervention between the two stations) affects downstream hydrological droughts. Moreover, considering the objectives of this scope of inquiry, adopting appropriate approaches to separate distinct impacts of various human interventions would become even more challenging. In other words, although studies have been conducted by many authors, this problem is still insufficiently explored. The previous studies have investigated the impacts of either one or a joint human intervention impacts on hydrological droughts. However, studying the degree of individual impacts of human interventions on the hydrological drought is of paramount importance and enhances the management of water resources, drought adaptation, and mitigation strategies. To the best of the researchers' knowledge, few studies have separated the individual impacts of different human interventions on hydrological droughts (Jiao *et al.* 2020; Yang *et al.* 2020; Cheng *et al.* 2021). The aforementioned studies assessed the individual impacts of different human interventions by comparing natural- and human-induced scenarios through hydrological modelling. The implemented hydrological models in these studies were mostly large scale and were capable of effectively differentiating the impacts of different types of human interventions. In the former studies, the coarse resolution of large-scale models can be considered as a limitation in separating the impacts of human interventions which are often not regionally validated or calibrated (Van Loon *et al.* 2019). In addition, the need for highly qualified human water resource management data collection to have an acceptable simulation of human-induced scenarios has been one of the tough challenges in this domain.

Therefore, based on the prior research on the approaches, their characteristics, strengths, and limitations, additional studies to understand more completely the key tenets of human impacts on hydrological drought are required. Due to the objectives of the current study and the features of the study area, a comprehensive data-based drought analysis framework was proposed to investigate the degree of the contribution of human interventions to hydrological drought. This framework was a combination of the so-called individual–station–drought analysis and a previously established method, i.e., the upstream–downstream comparison. As mentioned before, the most frequent and dominant approach to quantifying the impacts of human-disturbed changes on hydrological drought is comparing a natural situation with a human-disturbed situation. Meanwhile, for applying the upstream–downstream comparison method, the upstream station may not be considered a natural proxy in comparison to the downstream station. In other words, the impacts of human intervention on the upstream station that affects the changes in hydrological drought, besides the human intervention between the stations at the downstream station, cannot be ignored. Additionally, it is significant to find out the individual and joint impacts of the impressive human interventions on the hydrological drought downstream. In addition to the mentioned challenges, access to highly qualified data of human-disturbed changes in highly disturbed situations seems impossible, which affects the accuracy of modelling the human-disturbed situation. Due to these challenges, this data-based framework allows for applying the upstream–downstream comparison method where the upstream station cannot be considered as a natural proxy and is affected by the human intervention. In addition, the comparative nature of this framework makes it possible to separate the contribution of human intervention impacts to hydrological drought. Furthermore, our proposed framework obviates the need for using hydrological models, in which all aspects of human water resource management are applied to the rainfall–runoff process models to systematically consider the impacts of human interventions. This study evaluates the effectiveness of our proposed data-based drought analysis in separating the impacts of point-based human interventions and classifying the most effective contribution of human intervention aiming at mitigating the negative impacts of hydrological drought in a data-scarce basin. However, due to the objectives of the present study, the proposed framework can adopt a hydrological model to simulate the natural situation of the study area. The core of this framework is based on the variation of flow data types. Generally, previous studies have almost focused on applying the types of flow data such as simulated natural flow, modelled human-induced flow, or observed flow to identify and analyse the hydrological drought of surface flow. This study aimed to facilitate the quantification of the impacts of human intervention on hydrological drought in complex managed, high water-stressed, and data-scarce basins where highly qualified modelling considering all aspects of human interventions seems impossible.

2. METHODOLOGY

In this study, a data-based drought analysis framework is evaluated in a semi-arid region. This new framework is developed by combining the upstream–downstream comparison method and individual–station–drought analysis (Figure 1). The framework emphasizes the importance of selection for the types of flow data to be applied. The selection of different flow data types within the proposed framework makes it possible to quantify the contribution of different human intervention impacts

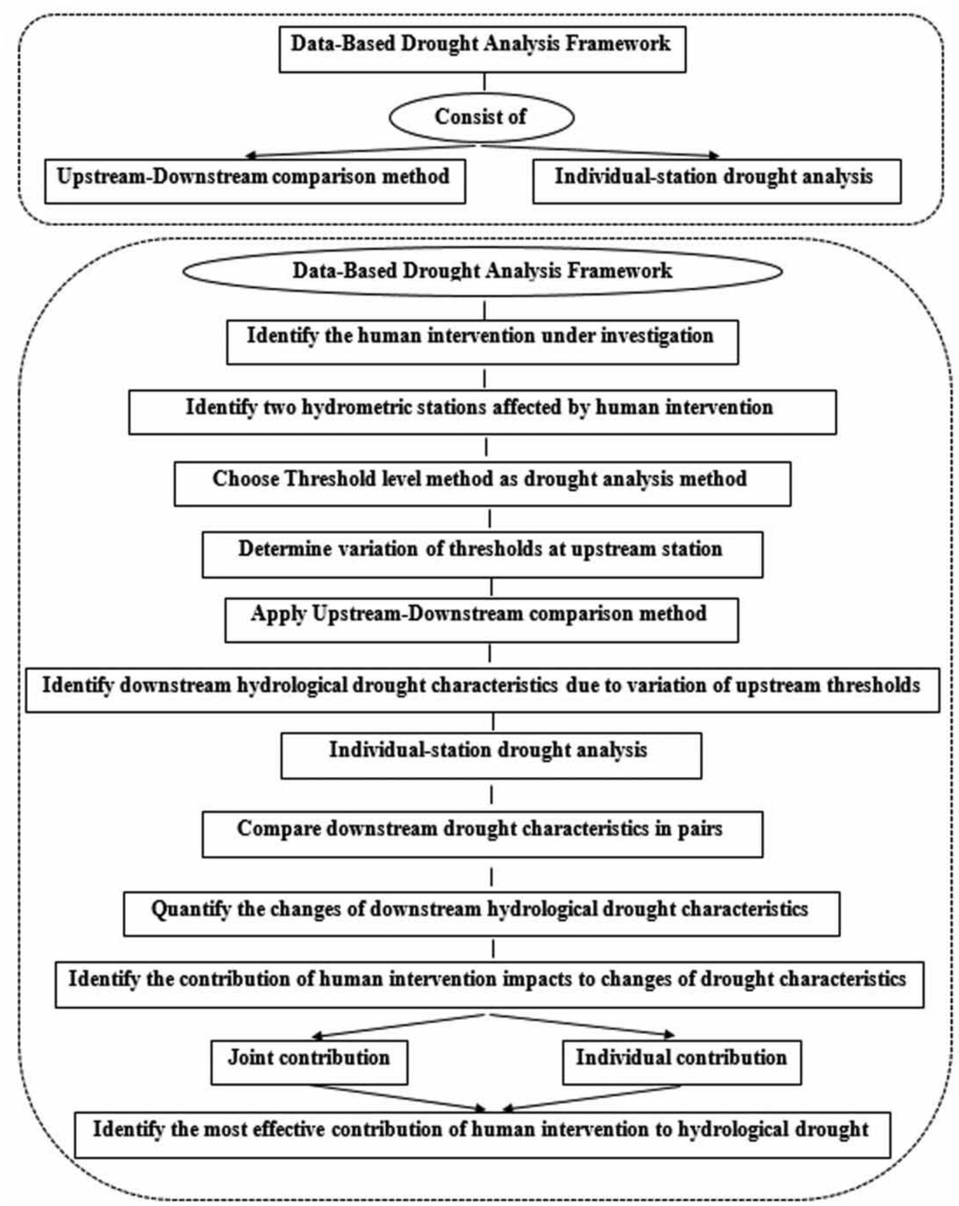


Figure 1 | The flow diagram of the data-based drought analysis framework.

on hydrological drought. The flow data in this work consist of three different types of flow: Type A as observed flow, Type B as reduced flow, and Type C as simulated natural flow. The observed flow includes the real natural condition plus the human-induced changes which are observed and reported at the stations during a specified period. The reduced flow is the flow data type where the enhanced impact of the water transfer regime is excluded from the observed flow regime. In addition, to simulate natural flow as one of the flow data types, the hydrological behaviour of the basin was simulated using the Soil and Water Assessment Tool (SWAT) model. Drought events and drought characteristics were determined by applying the threshold-level method (TLM) as the drought analysis method.

2.1. Study area

The Zayande-Rud River Basin (ZRRB) with an area of approximately 28,193 km^2 lies between 31° and 34° north latitude and 49° and 53° east longitude (Figure 2). The Zayande-Rud River originates in the Zagros Mountains, west of the city of Isfahan,

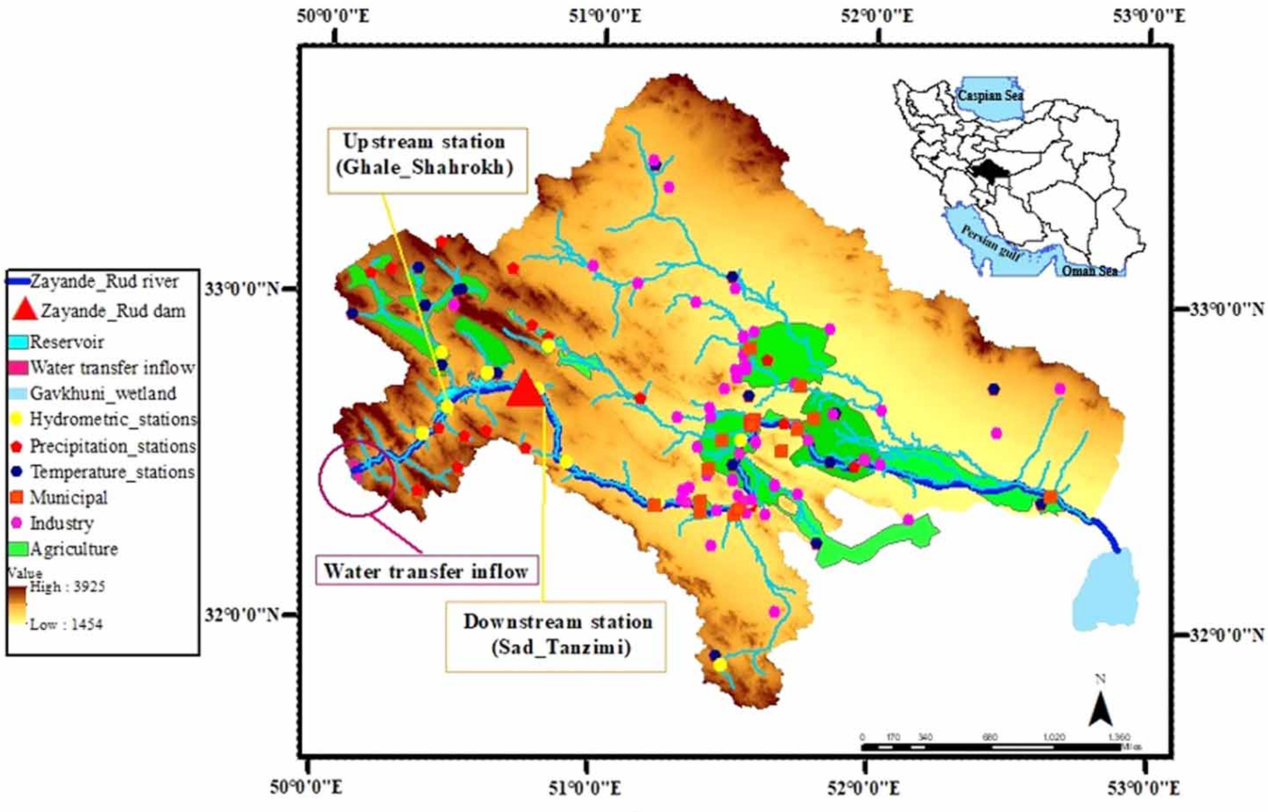


Figure 2 | Location, river systems, stations, dam reservoir, and water user locations in the Zayande-Rud river basin.

and flows 350 km to the east before terminating in the Gavkhouni swamp, a seasonal salt lake, in the southeast, from the city of Isfahan (central Iran). The Zayande-Rud River relies highly on annual snowfall from the Zagros Mountains. The elevation varies from 1,454 to 3,925 m, which has a pronounced influence on the diversity of the climate. The climate is semi-arid in the highlands (west) and arid in the lowlands (east). The precipitation exhibits large spatial and temporal variability. The average annual precipitation is 211 mm. The northern areas and high-latitude areas in the west receive about 300–1,345 mm yr^{-1}, while the central and eastern parts of the basin receive only 75–230 mm yr^{-1}.

Due to water availability stress in the basin, the inter-basin water transfer projects supply some basin water shortages. In 1954, the Kouhrang-First tunnel and, 32 years later, the Kouhrang-Second tunnel were built and put into operation. These two tunnels transfer water into the Zayande-Rud River in the upper reaches of the basin. This water transfer has affected the streamflow regime by increasing it upstream of the basin (Gohari *et al.* 2013; Samadi-Boroujeni & Saeedinia 2013; Ziaei 2020).

The multipurpose Zayande-Rud dam with a reservoir volume of 1,500 million cubic metres (MCM) and an annual average outflow of 47.5 $m^3 s^{-1}$ (cubic metre per second) has been in operation since 1972. The hydrometric stations, Ghale_Shahrokh called the 'upstream station' and Sad_Tanzimi called the 'downstream station' as the closest station to the reservoir, are demonstrated (Figure 2). The Zayande-Rud dam controls spring flooding and regulates water due to high downstream demand during summer. This kind of operation policy develops summer cultivations, produces 55.2 MW of electricity, and allocates water to downstream water users (Besalatpour *et al.* 2020). Recently, due to the high amount of water demand, reduction in rainfall amounts, and recent droughts, it has become vital to consider and study the impact of different human interventions on the hydrological behaviour of the basin.

2.2. Hydrological modelling

A variety of model types can be selected as a hydrological model in the framework as long as it can accurately reproduce the natural situation, particularly during low flow and drought, including distributed or lumped models, physically based models, conceptual models, and even stochastic models (Beven 2000; Wagener *et al.* 2004). To simulate the hydrological behaviour of the basin and simulate accurately the spatial variations of natural flows according to the natural processes of the basin without being affected by any significant human activities and interventions, we used the SWAT model. The SWAT is a physical, semi-distributed, continuous model that can manage large watersheds in a data-efficient manner (Arnold *et al.* 1998). The model is process-based, computationally efficient, and capable of continuous simulation over long periods (Arnold *et al.* 2012). The SWAT is efficient in simulating surface and deep recharges under land management practices (Tripathi *et al.* 2005; Rostamian *et al.* 2008; Zhu *et al.* 2018; Zhe Yuan *et al.* 2019), climate change, and land-use changes on a daily time scale and in different geographical scales, which has obtained acceptable results. The spatial parameterization of the SWAT model is implemented by distributing topographic, land-use, soil, and climate data as inputs and simulating water quality and quantity, sediment, soil nutrients, pesticide ingredients, and bacteria as outputs (Neitsch *et al.* 2011). The model delineates the watershed by the digital elevation module (DEM) and then subdivides the sub-watersheds due to homogenous units called hydrological response units (HRUs) with identical soil, slope, and land-use classes. The specific subdivision of the watershed by the SWAT allows for more detailed and accurate simulation. Additionally, the SWAT applies the Hargreaves relationship in addition to the Penman–Montier relationship to calculate potential evaporation and transpiration. The information needed to calculate the potential transpiration–evaporation with the Hargreaves relationship is more limited than the Penman–Montier relationship, and by considering the surface temperature in this relationship and the direct effect of temperature on the rate of potential transpiration evaporation, the ability of the SWAT model to model the real conditions of the basin increases (Faramarzi *et al.* 2013).

The model has been efficient in large-scale applications and also on basin scales in the country of Iran. One of the best applications of the SWAT on a large scale is the work accomplished by Faramarzi *et al.* (2009) to simulate spatial and temporal changes in the availability of water resources in Iran in which the model has shown good performance. Additionally, the SWAT hydrological model has been chosen as an efficient model to achieve the objectives of many studies in basin scales, as well as in the ZRRB. It has been used in various fields such as simulating the qualitative and quantitative water status in the basin (Ababaei & Sohrabi 2009), simulating flow (Nikoudel *et al.* 2011), the hydrological impacts on the water resources of the basin (Nikoudel *et al.* 2011), water balance (Amini *et al.* 2019), the inflow to the Zayande-Rud dam under climate change impacts (Khalilian *et al.* 2021), and environmental side effects of water pollution generated by agricultural activities, on the qualitative and quantitative management at the basin (Kavand *et al.* 2021). The SWAT was applied to consider land management practices on water resources in complex and highly managed basins, and therefore, in the ZRRB, the model is fed up with comprehensive management data of the basin such as water allocations to different users (agricultural, industrial, and municipal) (Figure 2) and water transfer projects. The simulation was considered from 1992 to 2014. Modelling by the SWAT model, the warm-up period, allows the model to consider the state of the basin before the simulation and applies its effects in the desired period of simulation; so, in this study, 3 years was considered as the warm-up period and it was calibrated in 1995–2009 and validated in 2010–2014 for the entire ZRRB with the highest resolution data recorded for this watershed.

2.2.1. Input data

The primary input data into the SWAT model are land use, DEM, and soil maps as well as climatic data (precipitation, temperature, and snowfall), hydrometric data (streamflow – daily/monthly), reservoir operation information, water management data, and point sources, which can be found in detail in Table 1. The land-use/land cover map of 2005 on a scale of 1:250,000 was obtained from the Iranian Forest Rangeland and Watershed Management Organization (IFRWMO). DEM map with 90 m of accuracy was used for stream network and sub-basin delineation. The 353 soil profile information was acquired from the Isfahan Agricultural Research Institute (IARI) to create the soil map of the study area. Climate data from 58 stations of the rain gauge, evaporation gauge, climatology, and synoptic and also 23 stations of evaporation gauge, climatology, and synoptic, including daily total precipitation (mm), maximum and minimum temperature, wind speed, and solar radiation, were obtained from the Iran Meteorological Organization, Regional Water Company of Esfahan, and verified by the Iranian Ministry of Energy. The availability of climate data was the main criterion to decide the simulation period from 1992 to 2014.

2.2.2. Sensitivity analysis, calibration, validation, and uncertainty analysis

SWAT-Calibration Uncertainty Program (SWAT-CUP) is an interface that was developed for the SWAT. Using this generic interface, any calibration/uncertainty or sensitivity programme can easily be linked to the SWAT. Generalized likelihood uncertainty estimation (Glue), parameter solution (Parasol), particle swarm optimization (PSO), sequential uncertainty fitting

Table 1 | Description of the SWAT input data (Faramarzi & Besalatpour 2015)

Input	Required information
DEM map	Resolution of 90 × 90 m
Land-use map	Land-use map must be accompanied by a database that describes the map units, 2005, 1:2,500,000
Soil map	An accompanying soil database is needed with the following parameters: the number of soil layers up to 10 may be specified, soil hydrologic group (A, B, C, or D), maximum rooting depth (mm), textural class of first soil layer, depth from the soil surface to the bottom of each layer (mm), moist bulk density (g/cm^3), available water capacity (mmH_2O/mm soil), saturated hydraulic conductivity (mm/h), organic carbon content (%soil weight), clay content (%soil weight), silt content (%soil weight), sand content (% soil weight), rock fragment content (%total weight), moist soil albedo, soil erodibility factor, K, in USLE equation
Stream network map	River names are also required
Climate station data	Daily precipitation (mm), daily maximum temperature (°C), daily minimum temperature (°C), wind speed (m/s) (if available), relative humidity (if available), solar radiation (MJ/m^2/day) (if available) For stations need to know latitude, longitude, and elevation
Reservoir operation information	Detailed information about the year of reservoir started to be operational, surface area and needed water volume to the emergency spillway, surface area and needed water volume to the principal spillway, initial reservoir volume and initial sediment concentration, hydraulic conductivity of the other reservoir bottom, and daily reservoir outflow
Inlet	• Latitude and longitude for any inlet to the watershed are required (i.e., springs and water transfer) • Daily or monthly discharge data for any inlet
Water management	• Water transfer information • Water use from the river
River discharge data	• Daily river discharge (m^3/s), latitude and longitude of the stations, the river names where the stations are located, tributary area
Point sources	• Input from water treatment plants (quantity and quality of water, and latitude-long location) • Springs (quantity and quality, and latitude-long location)

version 2 (SUFI-2), and Mark Chain Monte Carlo (MCMC) have been interfaced with the SWAT in a single package called SWAT-CUP (Abbaspour 2011). Sensitivity analysis, calibration, validation, and uncertainty analysis were performed by the SWAT-CUP interface using monthly river discharge data for the surface water. The SUFI-2 algorithm (Abbaspour 2011) was applied, and the model was calibrated and validated using the observed monthly river discharge for the years 1995–2009 and 2010–2014, respectively.

As the SWAT model involves a large number of parameters, a sensitivity analysis was essential to identify the key parameters across different regions of the study area. As different calibration procedures produce different parameter sets, we used two different approaches here for a comparison of observed and simulated discharge data to provide more confidence in the results. These include (i) the 'global approach', where all discharge gauges from all river basins were calibrated within a single calibration framework and (ii) the 'regional approach' (Besalatpour *et al.* 2020), where discharge gauges were separately calibrated for different water regions. Based on hydro-climatologically different conditions in upstream and downstream Zayandeh-Rud dam, and tributary rivers which are ungauged but highly managed for different purposes, we considered seven major water regions for the regional calibration.

SUFI-2 starts by assuming a large parameter uncertainty. The parameter uncertainties resulting in model output uncertainties are calculated as 95 Percent Prediction Uncertainty or 95PPU at the 2.5 and 97.5% levels of the cumulative distribution of output variables. The measured data initially fall within the 95PPU, then decrease this uncertainty in steps until two rules, the *P*-factor and *R*-factor, are satisfied (Abbaspour *et al.* 2004, 2007). The *P*-factor varies from 0 to 1, where 1 indicates 100% enveloping of the measured data within the model prediction uncertainty (i.e., a perfect model simulation considering the uncertainty). The *R*-factor, on the other hand, is the thickness of the 95PPU band and the standard deviation of the measured variable. A value of *R*-factor <1.5, depending on the situation, would be desirable for this index (Abbaspour *et al.* 2004, 2007, 2015). SUFI-2 tries to get a reasonable value of these two factors, which means enveloping most of the measured data in 95PPU and at the same time making the thickness of 95PPU smaller. While the accepted values of the *P*-factor and *R*-factor are assessed, the parameter uncertainty is the desired range for the parameters. In SUFI-2, simulations with a *P*-factor of 1 and *R*-factor of 0 closely match the observed data. The degree of deviation from these values can be used to estimate the accuracy of the calibration.

The SWAT model efficiency was also quantified by the coefficient of determination, R-Square (R^2), Nash–Sutcliffe efficiency (NSE) coefficient (Nash & Sutcliffe 1970), percentage of bias (PBIAS), and root mean square error (RMSE)-observations standard deviation ratio (RSR). The coefficient of determination, R^2, is used to analyse the percentage of variation between observed and simulated data and ranges from 0 to 100%. The higher the R^2, the less error variance, and generally R^2 values greater than 0.5 are considered acceptable. The NSE can range from $-\infty$ to 1, and the efficiency of 1 corresponds to a perfect match of the modelled discharge to the observed data. The optimal value of PBIAS is 0.0. Generally, the lower the values of PBIAS, the more accurate the simulation. Positive values indicate underestimation bias, while negative values indicate model overestimation bias (Gupta *et al.* 1999). The RSR uses the observed standard deviation to normalize the RMSE and incorporates the benefits of error index statistics, and also includes scaling/normalization coefficients, so that the reported values and statistics can be applied to different components (Moriasi *et al.* 2007). The model evaluation criteria were selected based on robustness and are commonly being used (Moriasi *et al.* 2007).

2.3. Drought analysis method

Drought events and their related characteristics can be assessed by applying the common TLM or through drought indices like standardized indices (SI) (Tallaksen & Van Lanen 2004; Vicente-Serrano *et al.* 2004; Van Loon 2015). Due to Rangecroft *et al.* (2016), the best approach in this domain is to apply the TLM, considering the strength of the method to exclude the human-disturbed period from the threshold. The TLM is one of the most frequently applied methods to identify droughts and drought characteristics (Tallaksen & Van Lanen 2004; Vicente-Serrano *et al.* 2004; Van Loon 2015; Van Loon & Van Lanen 2015; Rangecroft *et al.* 2016, 2019; Gurrapu *et al.* 2022; Shupeng *et al.* 2022; Yang *et al.* 2022) also known as the 'deficit index' (Van Loon 2015) since it measures deficit as one of the most critical drought characteristics by a defined threshold. The deficit determination by the TLM is one of the strong points, which is very effective in decision-making on water resource management (Van Loon 2015).

The TLM defines droughts as periods in which specific variables (precipitation, streamflow, groundwater, and reservoir level) are below a defined threshold (Yevjevich 1967; Hisdal & Tallaksen 2000; Fleig *et al.* 2006). The threshold is defined based on annual, monthly, or daily flow duration curves, where between the 70th and 90th percentiles is the recommended threshold for the determination of hydrological drought (Fleig *et al.* 2006; Van Loon 2015).

A fixed or variable threshold can be applied to study drought events by the TLM (Tallaksen *et al.* 1997; Hisdal & Tallaksen 2000; Fleig *et al.* 2006). Observing seasonality in the flow regime, the variable threshold should be recommended since the variable threshold considers the seasonality more appropriately than the fixed threshold. In this study, the variable TLM using 80th percentile (Q_{80}) values was performed to study hydrological drought events (Hisdal & Tallaksen 2000; Tallaksen & Van Lanen 2004; Fleig *et al.* 2006; Heudorfer & Stahl 2016). The threshold according to Q_{80} is derived from the flow duration curve and is the streamflow value that equalled or exceeded 80% of the time. In other words, months by flow values under the Q_{80} value are considered drought events. By defining hydrological drought events, drought characteristics, such as duration (maximum and mean) in a monthly timescale, deficit (maximum and mean) in a million cubic metres (MCM), and the number of identified events, were quantified. Duration refers to the number of months where the flow value is below the identified threshold (Wang *et al.* 2021). The deficit (the most important drought characteristic) is the accumulated monthly deficit during each drought period. Finally, the number of events is the number of times drought events have occurred during the studied period. An advantage of TLM analysis on monthly data is that it requires no pooling on daily scales as only drought events greater than 1 month were identified (Rangecroft *et al.* 2016). Minor drought events, which are events of short duration and/or small deficit volume, can be excluded from the analysis for a defined minimum duration

(Rangecroft *et al.* 2016). Therefore, in this study, drought events with less than 1 month under the threshold level were excluded. In addition to this type of exclusion, drought events less than 2 months with small amounts of deficit due to study area specifications were also excluded, since these types of drought events with small deficits in our study area had the chance to recover from their deficit.

2.4. Upstream–downstream comparison method

The upstream–downstream comparison method compares hydrological drought events and characteristics between an upstream and the nearest downstream stations of human intervention (Rangecroft *et al.* 2016, 2019). This direct comparison allows for identifying the human intervention impact between the two stations on downstream hydrological droughts. While studying the impacts of human interventions between two stations, the upstream station is, generally, a natural proxy compared to the downstream station.

The application of the TLM (Tallaksen & Van Lanen 2004) as a drought analysis method in the upstream–downstream comparison method makes it possible to select different upstream thresholds. The variation of upstream thresholds identifies the variation of downstream hydrological drought characteristics by applying the upstream–downstream comparison method. Noticeably, different thresholds may influence the results and their interpretations (Tallaksen *et al.* 1997). In this study, three different types of flow data (Types A, B, and C) were applied in the upstream–downstream comparison method to account for the variation of the thresholds (see Table 2).

The variable thresholds for the three types of flow on a monthly scale from 1995 to 2014 are shown (see Table 3).

The main goal of this section is to use the concept of the upstream–downstream comparison method to quantify three different hydrological drought characteristics downstream under three different upstream thresholds. The detailed methodology for three variations of thresholds and the upstream–downstream comparison method is described as follows:

- Type A: observed flow

In this section, the variable Q_{80} is calculated using the monthly observed upstream flow from 1995 to 2014. Due to the effectiveness of the upstream–downstream method in quantifying human intervention impacts on hydrological droughts (López-Moreno *et al.* 2009; Wu *et al.* 2009; Rangecroft *et al.* 2016, 2019), the observed variable Q_{80} was applied to the observed upstream and downstream flow. Afterwards, drought events and subsequent drought characteristics (duration, deficit, and number of events) were determined.

For quantifying the changes in hydrological drought characteristics caused by human interventions from upstream to the downstream station, Equation (1) was used (Rangecroft *et al.* 2016, 2019).

$$\mathrm{IHI} = \left[\frac{(C_{\mathrm{down}} - C_{\mathrm{up}})}{C_{\mathrm{up}}}\right] \times 100 \tag{1}$$

where IHI refers to impacts of human intervention and represents the percentage change of drought characteristics due to specific human intervention, and C_{down} and C_{up} refer to drought characteristics at the downstream and upstream stations identified under the upstream observed variable Q_{80}, respectively.

- Type B: reduced flow

Table 2 | Description of flow data types applied in the upstream–downstream comparison method

Station	Type	Flow	Threshold	Drought characteristic quantification
Upstream station	A	Observed	Upstream observed variable Q_{80}	Observed drought characteristics
Downstream station		Observed		Observed drought characteristics
Upstream station	B	Reduced	Upstream reduced variable Q_{80}	Reduced drought characteristics
Downstream station		Undefined		Expected drought characteristic
Upstream station	C	Natural simulated	Upstream natural variable Q_{80}	Natural drought characteristics
Downstream station		Natural simulated		Natural drought characteristics

Table 3 | Monthly upstream variable threshold Q_{80} (MCM) for three types of flow data type

	Variable threshold Q_{80}		
Months	**Type A**	**Type B**	**Type C**
1	29	9	10
2	33	21	8
3	100	57	38
4	174	72	72
5	155	40	70
6	103	28	52
7	54	10	41
8	30	10	31
9	21	6	25
10	20	7	19
11	28	14	13
12	34	15	11

Water transfer projects affected the downstream flow regime by increasing the flow regime at the upstream station. A long-term monthly average of the water transfer discharge into the basin can be found in Table 4.

To exclude these impacts of water transfer on the upstream river, the total discharge of the water transfer was subtracted from the monthly observed discharge at the upstream station. The remaining discharge is called reduced flow. The variable Q_{80} was then determined based on the reduced flow data. The reduced variable Q_{80} was applied to the reduced flow regime, and the hydrological drought events and their related characteristics have been identified at the upstream station. The calculated IHI% of the observed situation (Section 2.4, observed flow) is based on the transition of drought characteristic changes from upstream to downstream and was used to identify the expected downstream hydrological drought characteristics in the absence of water transfer project impacts.

Therefore, the expected hydrological drought characteristic at the downstream station can be quantified by the following equation:

$$\mathrm{IHI} = \left[\frac{(C_{\exp} - C_{\mathrm{up}})}{C_{\mathrm{up}}}\right] \times 100 \tag{2}$$

Table 4 | Long-term monthly average discharge of the water transfer project (MCM)

Months	**Discharge**
Jan	16.85
Feb	16.62
Mar	43.25
Apr	98.22
May	128.26
Jun	101.95
Jul	62.82
Aug	29.98
Sep	18.68
Oct	15.62
Nov	15.84
Dec	17.95

where IHI refers to the changes in hydrological drought characteristics caused by the human intervention and is evaluated from the observed situation, and C_{exp}, as an unknown variable, is the expected drought characteristics at the downstream related to the reduced variable Q_{80}. Finally, the C_{up} is the drought characteristics of the reduced upstream flow data identified by the reduced variable Q_{80}.

- Type C: natural-simulated flow (SWAT-based)

The observed flow and reduced flow data are affected by human interventions. Another type of flow regime needs to be considered for upstream and downstream stations to examine our proposed framework. This type of flow regime is a natural flow, which is simulated by the SWAT.

The simulated upstream natural flow data identified the natural variable Q_{80}. The natural variable Q_{80} determined the hydrological drought characteristics of the simulated natural flow for upstream and downstream stations. Here, the changes in hydrological drought characteristics between upstream and downstream can be considered a natural transition of drought characteristics from upstream to downstream.

2.5. Individual–station–drought analysis

The individual–station–drought analysis is often applied to assess drought quantifications and interpretations at an individual station. In this study, the individual–station–drought analysis was applied at the downstream station. This analysis allows for separating and specifying the contribution of human intervention impacts to downstream hydrological drought characteristic changes. We compared the characteristics of the downstream hydrological drought in pairs that have been quantified in Section 2.4 (Table 2, highlighted in grey). For maximum consistency, it is necessary to compare the events from the same period with the same threshold-level methods. Figure 3 shows the process of combining the upstream–downstream results in the

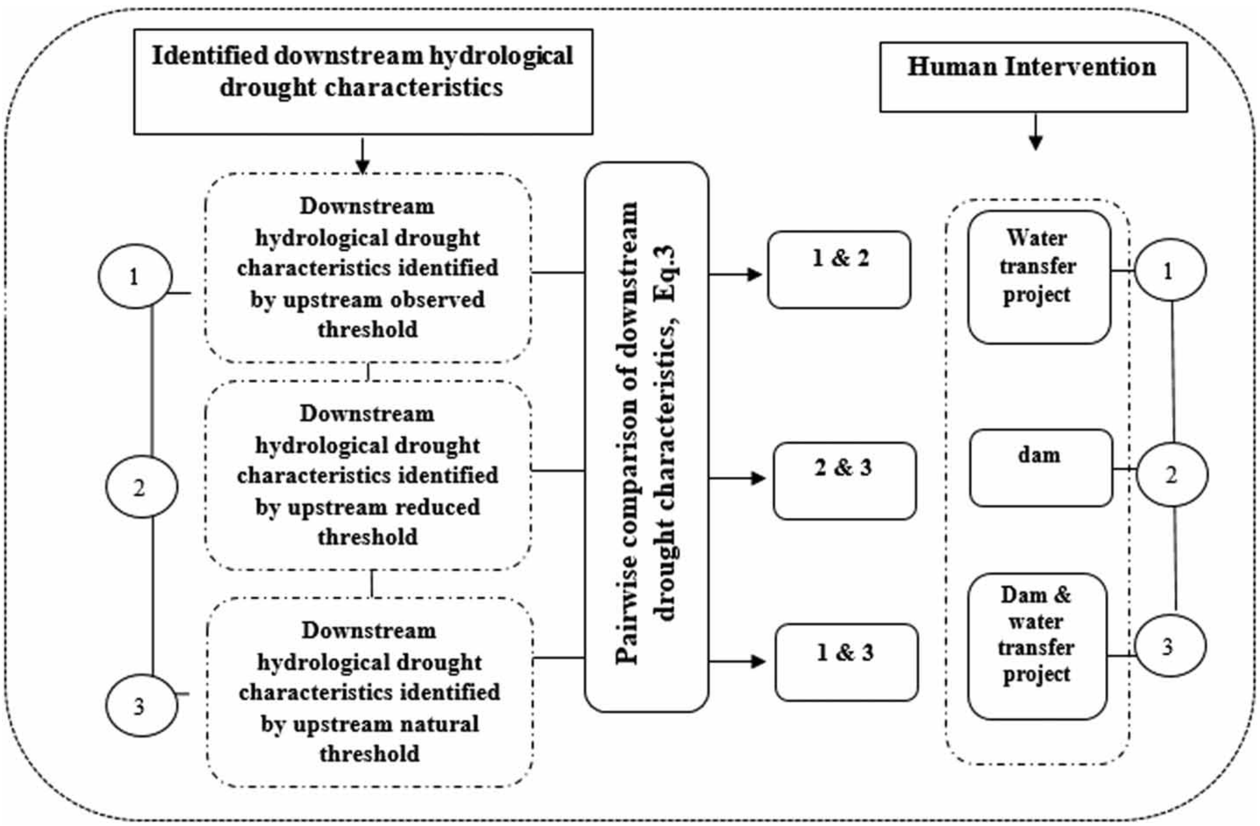


Figure 3 | The flow diagram of the individual–station–drought analysis.

individual–station–drought analysis.

$$\%\text{CHANGES} = \left[\frac{C_2 - C_1}{C_1}\right] \times 100 \tag{3}$$

The assessment of %CHANGES (Equation (3)) in water transfer project (1), dam (2), and dam and water transfer project (3) represents the characteristic changes of the downstream hydrological drought under the individual impacts of the water transfer project (1) or the dam (2) and the joint impacts of dam and water transfer project (3). In the water transfer project (1), C_2 refers to the downstream drought characteristics identified by the upstream observed Q_{80}, and C_1 refers to the downstream drought characteristics identified by the upstream reduced Q_{80}. In dam (2), C_2 refers to the downstream drought characteristics defined by the upstream reduced Q_{80} and C_1 represents the downstream drought characteristics defined by the upstream natural Q_{80}. Finally, in the dam and water transfer project (3), C_2 and C_1 are associated with the downstream drought characteristics defined by the upstream observed Q_{80} and the upstream natural Q_{80}, respectively.

2.6. Identifying the most effective contribution

Once the changes in the characteristics of downstream hydrological droughts under individual and joint human intervention impacts are identified (see Section 2.5), the key contribution of human intervention to mitigate the adverse effects of drought can be assessed. The most negative values of changes in drought characteristics under individual impacts of the water transfer project, individual impacts of dam, and joint impacts of the dam and water transfer project were selected as the most effective contribution of human intervention and considered as the degree of effective contribution in this study. Identifying the degree of effective contribution of human intervention is the beginning of the way to refining the management plans of the study area.

3. RESULTS AND DISCUSSION

3.1. SWAT model sensitivity analysis, calibration, validation, and uncertainty analysis

As the SWAT model involves a large number of parameters, a sensitivity analysis was essential to identify the key parameters across different regions of the study area. For the sensitivity analysis, both 'Global sensitivity' and 'One-at-a-time' methods were examined, and the most sensitive parameters integrally related to the streamflow were selected. Considering the sensitive parameters, the evaluation criteria such as Nash–Sutcliff, R^2, PBIAS, and RSR resulted in acceptable values in the calibration process from 1995 to 2009 as well as the validation process in 2010–2014 (see Table 5). The obtained Nash–Sutcliffe coefficients for the calibration and validation periods were higher than the acceptable value (by 0.5) for the selected upstream and downstream stations. The PBIAS and RSR showed very good performance for the model simulation (Moriasi *et al.* 2007). The SWAT model considers many different parameters, which can take various values in different sub-basins of the study area. Therefore, the results of the simulation are subject to uncertainty. However, in the modelling procedure, an attempt to reduce the range of parameter changes by calibration and uncertainty analysis was done. Applying the SUFI-2 algorithm to do the uncertainty analysis, the uncertainty of the parameters in different sub-basins was reduced to the least amount. Noteworthy that the results of the *R*-factor and *P*-factor that are used to judge the strength of the calibration and validation (Abbaspour *et al.* 2015) showed an acceptable and little uncertainty to simulate discharge (see Table 5). The values of the *R*-factor and *P*-factor, less than 1.5 and >0.7, respectively, can be considered adequate (Abbaspour *et al.* 2015).

Table 5 | SWAT model efficiency coefficients for the calibration and validation periods

Station	Period	NSE[a]	R^{2a}	RSR[a]	PBIAS (%)	*P*-factor	*R*-factor
Upstream	Calibration (1995–2009)	0.67	0.71	0.37	−4.64	0.65	0.76
Downstream		0.59	0.67	0.37	−7.27	0.98	0.53
Upstream	Validation (2010–2014)	0.63	0.76	0.34	7.26	0.55	0.59
Downstream		0.71	0.83	0.02	−1.22	0.93	0.66

[a]The efficiency coefficients are calculated using monthly simulated and observed data.
NSE, Nash–Sutcliff efficiency; R^2, coefficient of determination; RSR, RMSE-observations standard deviation ratio; PBIAS, percentage of bias.

Based on the graphical interpretation, a reasonable agreement between observed and modelled streamflow can be detected during calibration and validation periods at upstream and downstream stations (Figure 4).

3.2. Upstream–downstream comparison

This section presents the results of determining the hydrological drought events and characteristics for the three different thresholds, including observed, reduced, and natural variable Q_{80}, using the upstream–downstream comparison method for the period of 1995–2014.

Figure 5 shows a long-term monthly comparison among three types of flow data at upstream and downstream stations. As can be seen, the highest values of flow are related to the observed flow at the upstream station, which is completely affected by the water transfer project. A time shift can be detected in the observed flow downstream which is due to the presence of the dam. The natural flow upstream and downstream relatively follows the same trend as well as the reduced flow upstream. This fact implies that the water transfer has a significant impact on the upstream flow so that without considering it, the natural upstream flow and reduced flow would follow similar trends.

The changes induced by human interventions in hydrological drought characteristics between upstream and downstream are expressed as IHI% (see Table 6). A negative amount of IHI% indicates an alleviation of the drought's negative impacts at the downstream station, while positive changes mean an exacerbation of the negative impacts of drought.

Comparison of the maximum and the average characteristics implies the alleviation of downstream drought duration concerning observed, reduced, and natural situations. Simultaneously, an aggravation was detected for the maximum deficit in the reduced situation as well as for the observed situation, but an alleviation was quantified for the natural

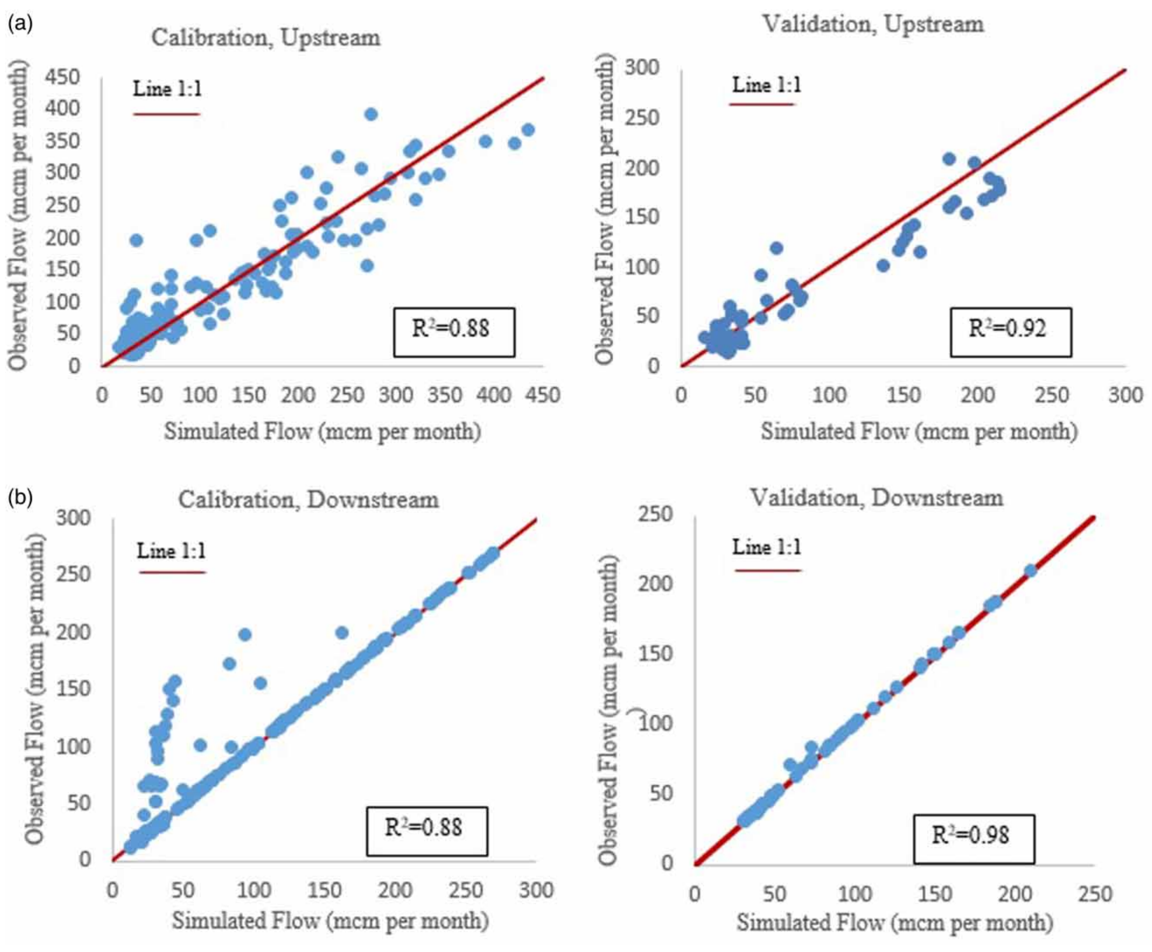


Figure 4 | A comparison of simulated and observed flow at (a) upstream and (b) downstream stations during the calibration and validation periods.

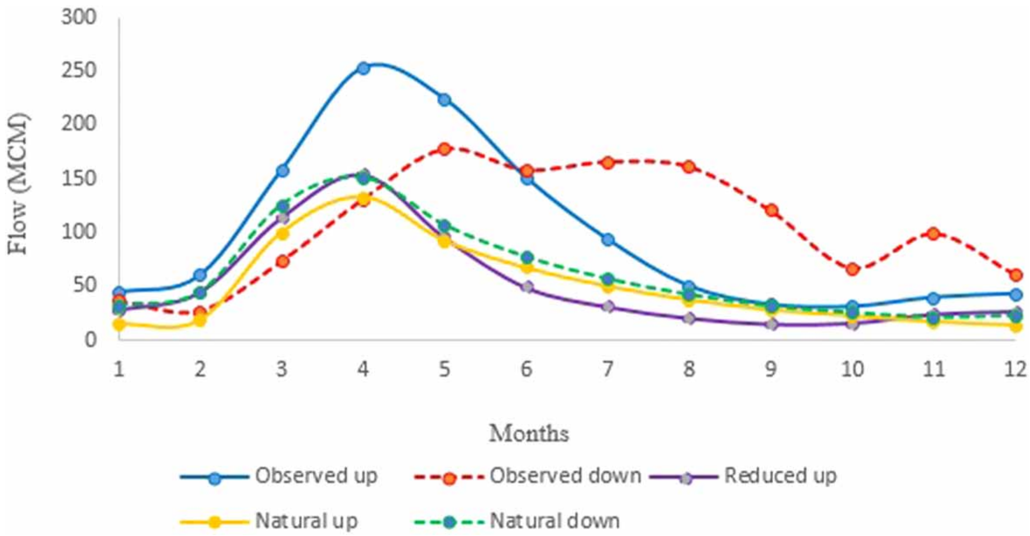


Figure 5 | A comparison of three types of flow for the upstream and downstream stations.

Table 6 | Hydrological drought characteristics and quantified IHI% identified by the observed, reduced, and natural Q_{80}

Station	Maximum duration (months)	Mean duration (months)	Maximum deficit (MCM)	Mean deficit (MCM)	No. of events[a]
Observed situation					
Upstream	13.0	4.6	139.0	36.0	9.0
Downstream	5.0	3.6	373.0	121.3	17.0
IHI	– 62	– 22	168	237	89
Reduced situation					
Upstream	7.0	4.8	86.7	33.2	6
Expected downstream	2.7	3.8	232.7	111.9	11
IHI[b]	– 62	– 22	168	237	89
Natural situation					
Upstream	24	16	290.3	155.7	2
Downstream	8	8	83.2	80.7	2
IHI	– 67	– 50	– 71	– 48	0

[a]Number of events.
[b]Quantified in the observed situation.

situation. It appears that in the observed situation, the human interventions were not effective in alleviating the negative impacts of major drought events for the deficit characteristic from upstream to downstream. For instance, a drought occurred in the upstream station in 2008–2009 and lasted for 13 months with a deficit volume of about 139 MCM. This drought event transformed into a drought event with a duration reduced to 5 months at the downstream station but with a larger deficit volume of approximately 318 MCM. Furthermore, it can be seen that aggravating effects are identified for the mean deficit and the number of events in the observed and reduced situations. The aggravation of the mean deficit is linked to the operation policies that store water during the wet season to release water in dry seasons and lead to more frequent droughts in the first 4 months of each year, and this conclusion is consistent with previous studies (Wang *et al.* 2022), which inferred that reservoirs regulate the downstream flow regime (Petts & Gurnell 2005; Assani *et al.* 2013). This fact is more vital in arid and semi-arid regions which are sensitive to droughts (Dehghan *et al.* 2020) and small changes in water availability (Rangecroft *et al.* 2016, 2019).

As a consequence of the hydrological droughts (Table 6, natural situation, IHI%), an alleviation for the duration (maximum, mean) and deficit (maximum, mean) were observed at the downstream station in a natural situation. In other words, the negative effects of hydrological droughts could be mitigated from upstream to downstream in a natural situation, but human interventions made the situation more complex. Additionally, an equal number of drought events can be detected upstream and downstream in the absence of any human interventions. In other means, without human interventions, the negative impacts of drought are alleviated downstream, while in the human-induced situation, the negative impacts of drought are exacerbated.

A visual comparison of hydrological drought events is shown in Figure 6 for observed and natural situations.

Additionally, a comparison has been made in Table 7 with the similarities and differences among studies and their approaches. Rangecroft *et al.* (2016, 2019) investigated the impact of dam on hydrological drought downstream. Both aggravations and alleviations were seen for the impacts of the dam on hydrological drought. One reason could be the choice of thresholds and approaches. For instance, due to two different thresholds, fixed and variable, both aggravations and alleviations were observed in the results (Rangecroft *et al.* 2016). There were also disagreements between the results of the two methods, the upstream–downstream comparison method and the observation-modelling method, which can be related to the accuracy of modelling the human activities to simulate the human-induced situation (Rangecroft *et al.* 2016). Another reason can be related to the purpose of the dam construction (water supply, hydropower, and water security for downstream users or upstream users) that has been seen in another study's results too (López-Moreno *et al.* 2009; He *et al.* 2017). In the present study, providing water security for downstream users (agricultural, industrial, and domestic) has the highest priority. This type of operation policy lowers peak flows, regulates the flow regime downstream, and has impacts on drought characteristics such as duration, number of events, and also deficit. In this study, the number of events was aggravated due to the application of a variable threshold that identifies drought events both in low- and high-flow periods while the duration was alleviated. Additionally, the deficit showed diverse responses to the impacts of the dam. Not only the purpose of operation policy but also the storage capacity of the reservoirs has an impact on the deficit (Rangecroft *et al.* 2019), and this may be more reasonable in our study to aggravate the deficit downstream.

In previous studies (VanLoon & Van Lanen 2015; Rangecroft *et al.* 2016, 2019), individual impacts of dam or water transfer were investigated. Applying the upstream–downstream comparison method, the upstream station was considered a natural proxy compared to the downstream. In the present study area, the upstream flow regime is influenced by the water transfer project, and besides the dam, it affects the downstream flow regime and consequently drought characteristics. It was expected that water transfer alleviated the negative impacts of drought as in a previous study (Van Loon & Van Lanen 2015) because water transfer enhances the flow regime upstream. Therefore, there was a need to show the contribution of these two human interventions to the changes in drought characteristics, which was impossible by applying the upstream–downstream method without the proposed data-based framework.

3.3. Individual–station–drought analysis

The downstream hydrological drought characteristics given in Table 8 (highlighted in grey) must be compared pair-wise to assess the %CHANGES (Equation (3)) of drought characteristics under individual or joint impacts of the water transfer project and dam. The quantitative changes in the downstream hydrological drought characteristics are shown in Table 8.

The quantified %CHANGES values under the water transfer project (1) are a response of downstream drought characteristics to the inter-basin water transfer project or the individual impact of the water transfer project. Quantitative values of % CHANGES under the dam (2) indicate the individual dam and its operation policy impacts. Furthermore, in the dam and water transfer project (3), the joint impact of the dam and water transfer project was assessed.

The magnitude of alleviation for the drought characteristics and their negative impacts are as follows: mean duration by 4% with the water transfer project (1), maximum and mean duration by 66 and 53%, respectively, with the dam (2), and maximum and mean duration by 38 and 55%, respectively, with the joint impacts of water transfer project and dam (3) (see Table 8).

The presence of the dam and the water transfer project is thought to improve the system resilience by changing the flow regime downstream. However, the joint impacts of the two human interventions were only effective in duration (see Table 8 (3)). By comparing the mean duration under the water transfer project (1), dam (2) and dam and water transfer project (3), the higher alleviation of mean duration under the joint impacts of dam and water transfer project (3) can be inferred from higher alleviation in individual impacts of water transfer project (1) and dam (2). In other words, the alleviation for the mean

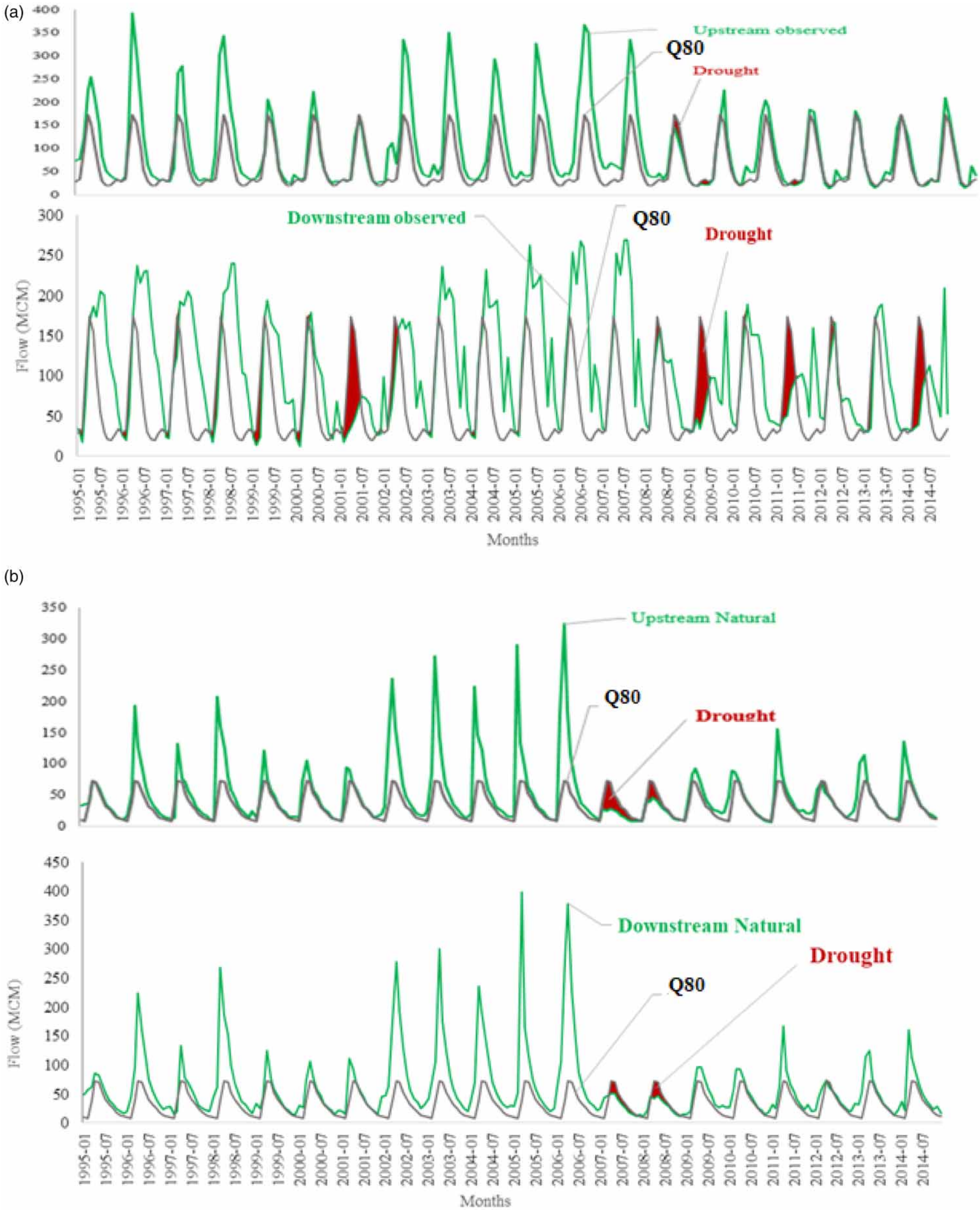


Figure 6 | The drought events quantified by (a) observed Q_{80} in the upstream and downstream observed flow and (b) natural Q_{80} in the upstream and downstream simulated natural flow.

Table 7 | The comparison among the previous study methods and results with the present study

Studies	Human activity under investigation	Flow Data Type	Approach	Drought Analysis Method	Threshold-based flow	Results
Rangecroft *et al*. 2016	Dam	Observed	Upstream-Downstream Comparison Method	TLM (Fixed Threshold)	Upstream pre-dam Flow	1. All drought characteristics are alleviated due to the presence of the dam (% human influence)
		Modeled (Natural & Human-Disturbed)	Observation-Modeling		Naturalized Flow	1. Showed less reduction on maximum characteristics results compared to average characteristics 2. Aggravation of number of drought events
Rangecroft *et al*. 2019	Dam	Observed	Upstream-Downstream Comparison Method	TLM (Variable Threshold)	Upstream Observed Flow	1. Aggravation was observed for all characteristics due to variable threshold
Van Loon & Van Lanen 2015	Water Transfer	Modeled (Natural) & Observed	Observation-Modeling	TLM (Fixed Threshold)	Naturalized Flow	1. Reduction of the number of drought events in presence of water transfer 2. Reduction of deficit especially for maximum events
Present Study	Dam & Water Transfer	Observed Reduced Modeled (Natural)	Upstream-Downstream Comparison Method & Individual-Station-Drought Analysis	TLM (Variable Threshold)	Upstream Observed Flow Upstream Reduced Flow Upstream Natural Flow	1. Aggravations were observed of deficit and number of events except for duration in both observed and reduced situation 2. Generally, the characteristics were alleviated in the natural situation 3. Individual contribution of dam was the most effective in alleviating the maximum duration 4. Joint contribution of dam and water transfer was effective to alleviate mean duration 5. Dam and water transfer were not effective in the alleviation of deficit (maximum & mean)

duration by the individual impacts of the dam (2) was improved by the individual impacts of the water transfer project (1) since the water transfer project was effective only for the mean duration. The changes observed of alleviation in mean duration from the impact of water transfer project (1), −4%, and impact of dam (2), −53%, to impact of dam and water transfer project (3), −55%, indicate the consistency of the approach. Additionally, this consistency can be observed as well as for the other characteristics in Table 8.

3.4. Identifying the most effective contribution

Finding the most effective contribution of human interventions to alleviate the negative impacts of hydrological drought is vital. Highlighting and clarifying the degree of contribution of human intervention impacts to each drought characteristic can make advancements in targeted water management programmes. Among the three different impacts (Table 8), the most negative value of the drought characteristic indicates the most effective human intervention that needs to be addressed to make refinements of ZRBB water resource management. As shown in Table 8 (highlighted in grey), the individual impact

Table 8 | Quantified %CHANGES values of data-based drought analysis framework

	Impacts		
Downstream drought characteristics	**Water transfer project (1)**	**Dam (2)**	**Dam and water transfer project (3)**
Maximum duration changes	86*	−66*	−38
Mean duration changes	−4	−53	−55
Maximum deficit changes	60	180	348
Mean deficit changes	8	39	50
No. of event changes	50	467	750

*Negative values of %CHANGES show alleviation in drought characteristics and positive values of %CHANGES indicate aggravation in drought characteristics.

of the dam (2) effectively alleviated the maximum duration, whereas the mean duration is improved by the joint impacts of the dam and water transfer project (3).

In addition, we suggest looking at the impacts relative to the least positive values of characteristic changes as a reasonable priority for an indication of progress in mitigating the negative effects of hydrologic drought characteristics. Therefore, the individual impact of the water transfer project (2) can be considered the effective priority of human interventions in alleviating the maximum deficit of extreme drought events and building resilience to major drought events because the water transfer project is operational to meet downstream demands. It can also help decrease the number of drought events that have occurred. As the most critical characteristic, the amount of alleviation for the mean deficit was unsatisfactory under human interventions. However, the least positive amount for mean deficit (8%, see Table 8) has been identified by water transfer project impacts (1). Due to the consistency of the proposed framework, it can be concluded that imposing the new policies can diminish the negative impacts of the mean deficit under the water transfer project impact (1) and may improve the outcomes of the mean deficit changes under joint impacts of water transfer project and dam (3). The more negative the changes of the mean deficit under the water transfer project impact (1), the more alleviation can be expected for the positive values of dam impact (2). Therefore, the combination of the individual impacts of the water transfer project and the dam allows for making alleviation for the joint impacts of the water transfer project and dam.

4. CONCLUSIONS

The proposed data-based drought analysis framework in this study provides the possibility of separating the degree of contribution of the dam and the water transfer project to the changes in hydrological drought characteristics as two important human interventions in the study area.

The proposed data-based drought analysis framework uncovered the importance of using appropriate flow data in the process of impact analysis of the dam and water transfer project by combining the efficient method upstream–downstream comparison method and the individual–station–drought analysis. This method assessed well the individual impact contributions of the dam and water transfer project and provides the ability to detect even the most effective contribution to changing the characteristics of hydrological drought.

The proposed framework needs to assess the variation of flow data types to distinguish the impacts of human interventions. Therefore, the TLM as a commonly used drought analysis method that allows for assessing the variation of flow data types is used. This study shows the importance of differentiating the impacts of human interventions on changing hydrological drought characteristics in the current world to reduce the adverse impacts of hydrological drought and improve the purposeful management of water resources to take fruitful steps. It is important to note that the data-based framework can be adapted to different basins with the same human interventions or different point-based human interventions (Rangecroft *et al.* 2019) to discover the individual contribution of human intervention impacts. Additionally, there is no limitation considering upstream stations that are influenced by point-based human interventions, as long as it is possible to eliminate the influence of the human intervention on the flow at the upstream station. This method in addition to arid and semi-arid regions that are very sensitive to water availability changes can be tested in any type of climatic region with complex management conditions and is highly subject to human-made changes. However, due to the water stress issue in arid and semi-arid regions, many water policies and water resource mismanagements can occur which might affect the hydrological processes, so as hydrological droughts. So regarding the new call for considering human changes as the cause of droughts, modifications, or intensifiers, it is vital to clarify the impacts of these policies and mismanagements on the hydrological droughts while this type of climatic region experiences droughts continuously. Further research on the efficiency of the framework will be done to consider climate change impacts in addition to point-based human interventions and also the framework will be tested with more recent data to examine and improve its consistency related to the recent situation of the basin.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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