Dynamics of Water Accounting Balance for Assessing Water Stress Vulnerability Considering Social Aspects

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Dynamics of Water accounting balance for assessing water stress vulnerability considering social aspects

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Abstract

To advance proper planning, water accounting (WA) could provide the possibility of linking physical and operational data to their interdisciplinary attributes. In its new form, WA, combined with a dynamic model considering socio-economic aspects, is a valuable tool for rectifying today's water issues. The social water-accounting-based system dynamics (SWA-SD) provides a feedback-based platform to better support flexible decision-making. Analyzing the indicators that correspond to water security in the context of DPSIR (driving force-pressure-state-impact-response) and SWA-SD combined with principal component analysis (PCA) for identifying data patterns is applied to a generic study area suffering from water stress to assess the environmental, economic, and social vulnerabilities. The water accounting has to be based on water balance data (called water accounting balance). As a practical solution to generate water balance data, a time series by the use of basic climatic and hydrologic data is synthesized. According to the results, the water stress and urbanization index were increased by a factor of 43% and 64% in 2020 during a 20-year time horizon, respectively, which is alarming for the region. Moreover, the economic and social water resources vulnerability shows an upward trend, and the environmental component shows many highs (as much as 2.24) and lows (as low as 0.73) due to different supply measures responded to the increasing demands. This study provides a basis that can be replicated for other developing regions to quantify this type of important planning information and for implementing different socially sensitive triggers and technically feasible to measure water vulnerabilities.

Keywords: Vulnerability, System Dynamics, Productivity, Water Stress, Principal Component Analysis.

1. Introduction

In order to quantify a water system's balance, a comprehensive understanding of variables affecting the state of water supply and demand, performance indicators, and their interdependencies is needed. Among the widely used performance criteria are resiliency, and vulnerability. Vulnerability is the extent at which the environment, the economy, or the social system (the responder) are prone to damage/degradation by a hazard or stressor (IPCC, 2014). The critical parameter of water resources vulnerability (WRV) is the water stress which is exposed to a system (Adger, 2006). In the traditional hazard-centric view of vulnerability, the focus was on hazard impacts assessment (Dwyer et al., 2004). However, vulnerability is not a product of a single factor and results from interactions of socio-economic attributes (Rajesh et al., 2018). The vulnerability components include environmental, economic, and social aspects of anthropogenic activities (Wei et al., 2020). Resiliency, as the system capacity to adapt to any stressed situation (Karamouz and Movahhed, 2021), is widely by quantifying the rapidity, robustness, resourcefulness, and redundancy (4 Rs) dimensions proposed by Bruneau et al. (2003). Water stress refers to having sufficient water for socio-economic development and addressing poor management's adverse effects. Based on the different related indicators, it is defined as when the annual water withdrawal divided by the annual water availability is higher than 0.4 (Kiguchi et al., 2015). Water security generally emphasizes risk management and vulnerability reduction in the water resources arena when encountering shocks from water-related disasters such as droughts (van Beek and Arriens, 2014) and water supply-demand management (Cook and Bakker, 2012). Due to increasing water use, water resources are progressively concerned with sustainable development. For describing water use, water accounting suggests a tool for economic analysis of water-related issues based on a systematic approach (Dutta, 2017). Water accounting is the process of communicating water-resources-related information and the services generated from consumptive use in a domain (Wateraccounting.org). IWMI (International Water Management Institute) (Molden, 1997), Water Footprint Accounting (Hoekstra and Chapagain, 2006), General Purpose Water Accounting (United Nations, 2009), and SEEA-W (System of Environmental and Economic

Accounts for Water) (UNSD, 2012) and Water Accounts Plus (WA+) (Karimi et al., 2013 a,b) are a few examples of water accounting frameworks. The WA+ includes explicit spatial information on water depletion and net withdrawal processes in complex river basins and is dependent on satellite data. Its application in the regions with qualified remote sensing data is stated, which is focused on hydrological aspects of water resources (Karimi et al., 2013 a). However, it does not consider any social variable compared to SEEA-W used in this study.

SEEA-W provides physical water data based on socio-economic aspects instead of focusing on water balance (Esen and Hein., 2020). It suggests the possibility of utilizing policies in an informed and integrated manner. This framework includes physical, hybrid (a combination of physical accounts and financial data), and asset accounts tables (UNSD, 2012). SEEA-W should be customized for applications based on the concerning attributes in each specific case and data availability.

DPSIR (Driver-Pressure-State-Impact-Response) provides the basic structure of conceptual modeling and helps capture the problem's primary components. Analytical frameworks could establish interdependencies among governing indicators to bring water's effect on environmental, economic, and social aspects into the light. The DPSIR, as an analytical framework, supports problem scoping and structuring in the system dynamics (SD) modeling process (Zare et al., 2019). The scope and uses of SD methodology have expanded in a variety of water and environmental problems. As the transparent interaction of the components on a system, the feedback loops are the main advantages of SD, among other simulation methods (Ekinici et al., 2020). SD is increasingly used to conceptualize and simulate complex water systems and offers new opportunities to develop dynamic alternatives to the decision support systems (Jin et al., 2009). A SD model can accurately describe system behavior under a given range of conditions and incorporate them to find acceptable solutions (Hjorth and Bagheri, 2006). Thus, coupling water accounting tables with simulation models results in describing the system and analyzing the effects of potential scenarios (Mahdavi et al., 2019). Hence, developing indicators and integrated sets of conceptual and analytical frameworks, as mentioned, would be worthwhile. Different studies have been carried out in the context of water accounting (WA)

applications. Contreras and Hunink (2015) proposed a SEEA-W framework for the Segura River Basin in Spain from 2000 to 2010. The indicators regarding the use and availability of water under normal and extreme climate conditions were analyzed. Borrego-Marín et al. (2016) utilized WA for the drought impact assessment on agricultural water productivity in the Guadalquivir River basin in Spain. In the context of investigating the indicators of water resources systems, Gasco et al. (2005) utilized an accounting physical input-output table (PIOT) to evaluate the water resources management in Spain. Karamouz et al. (2021) proposed a hybrid index named PI-Plus (P for Paydari as it is an indigenous term for sustainability). They also performed an uncertainty analysis to assess the random nature of variables in estimating water balance and quantifying water sustainability. This index consisted of available water, efficient water delivery, water supply reliability, aquifer storage, and river streamflow requirements. The Nash bargaining theory was utilized to capture the satisfaction of water users. Long and Ji (2019) assessed China's economic growth, environmental sustainability, and social welfare from 1997 to 2016. Among strategies aimed at agricultural water use management, reducing irrigated areas, and increasing irrigation efficiency have been investigated as among the most effective practices (Ebrahimi Sarindizaj and Zarghami 2019; Karamouz et al. 2021). Besides, deficit irrigation (DI) is widely used as a water-saving irrigation strategy in which irrigation water is applied at amounts less than full crop water requirements, thereby increases water use efficiency (Morison et al., 2008). Dealing with numerous indicators, principal component analysis (PCA) is used for exploratory data analysis. It is recently being used in water resources studies due to its ability to simplify correlated multivariate data into a few key dimensions.

Water accounting (WA) based on true and synthesized water balance data and causal modeling have not been widely used and coupled in previous studies. The WA so-called tables are often included five components with only some social attributes. A standalone table for social issues has not been developed. In addition, while previous studies have assessed the water resources vulnerabilities, less attention has been given to the estimation of the socio-economic and environmental aspects of the vulnerabilities. Water balance data (entails far more details of water supply and demand/allocation

than basic climatic and hydrologic data), which is the core of water accounting, is not widely available (is even scarce) in developing and even developed regions. See Karamouz et al. (2021) for more details.

In this study, these shortcomings have been realized. A separate table has been added to the WA structure. Vulnerabilities have been accounted for to see meaningful socio-economic indicators using a principal component analysis platform. This study investigates the application of social-based water accounting system dynamics (SWA-SD) for synthesizing system dynamics model outcomes in water resources vulnerability assessment. A combination of DPSIR and conceptual modeling techniques (cause and effect loops) is incorporated into a SWA-SD model to assess water resource vulnerabilities in the environmental, economic, and social sectors. Water resource vulnerabilities are estimated by employing a set of indicators that correspond to water stress. The dynamics of demographic changes, unemployment, and variation of income and water use in different sectors are addressed. Besides, the proposed algorithm considers the water, labor (employment) productivity of the agricultural, industrial, and urban/services sectors which are defined based on the income produced. A new water resources vulnerability index in three sub-indicators (water/environment, economic, social) are discussed based on the principal components. The needed water balance data are generated to offset the limited official data available by utilizing and extending the platform Karamouz et al. (2021) provided before. The case study is designed to be generic so that it can be applied to other geographic settings. However, the information for the components is based on the actual data of Tashk-Bakhtegan basin in the central part of Iran.

In the remainder of the paper, the methodology section consists of the DPSIR framework's details and derived indicators in environmental, economic, and social dimensions. The water resources system vulnerability is provided by water accounting tables followed by the system dynamics approach. The following section is the case study and the results and discussion. Finally, a summary and conclusion is given.

2. Materials and methods

A flowchart of the methodology for dynamic assessing a water system's vulnerability (SWA-SD) on a basin-scale is presented in Figure 1. Up to date water balance data is essential for the regions in which the official data is released after 5-10 years and is scarce in many developing and even developed regions. Therefore, assumptions and correlations are taken into account based on a platform developed by Karamouz et al. (2021) to synthesize a 20-year water balance data time series with the same attributes of official water balance data. Then, the DPSIR framework is utilized to configure the primary cause and effect relations in a water resource in line with vulnerability. Next, the SEEA-W is implemented to organize the hydrological-economic-social data. The SEEA-W framework is often included physical, hybrid (a combination of physical accounts and financial data), and assets categories with only some social attributes. This paper has developed a standalone table of social issues, and social water accounting is tabulated. Estimating water accounting tables with social inclusion can improve the combination of the economy and the environment. The social water accounting table focuses on population, employment, education, and social welfare.

The SWA-SD model simulates the feedback loops and stock-flow diagrams in the Vensim software (Ventana Systems, 2004). Different scenarios are assessed to simulate the system's behavior based on the SD model. In the next step, based on the water accounting tables' organized information, performance indicators are utilized to evaluate water security regarding water availability. The PCA method is used to reduce many variables into a smaller number of relevant principal components, making it possible to determine a more focused description of the data. Based on Fussel (2007), vulnerability assessment is performed by considering four components: system, threat, time reference, and the attribute of concern. The vulnerabilities are assessed in the water resources system. The threat is the water stress, and the time reference is annual. The attribute of concern is water security. Finally, environmental, economic, and social indices are assessed water resources vulnerability.

Figure 1. A framework of social water accounting based system dynamics model for assessing water resources vulnerabilities

2.1. DPSIR (driving force-pressure-state-impact-response) framework

Assessing the cause-and-effect relationships could offer a better insight into evaluating water resources sustainability and developing indicators. Unlike many previous studies on water resources causal analysis, a platform is developed to fine-tune governing elements and components assessment on a watershed scale (Figure 2). This analysis allows for refining supply-demand balance, better assessing socio-economic aspects, environmental issues, and system performance. Using this framework

resulted in clarification of human activities' impact (as 'driving forces'). These activities impose 'pressures' on the system, leading to changes in environmental conditions (the 'state'). Accordingly, society reacts to these changes and the corresponding 'impact' through environmental and economic policies responding to actions or feedbacks processes. Many pressure components make the system unsustainable; however, the system's 'response' is geared toward mitigating the pressures, providing necessary resistance against changes, and strengthening sustainability. DPSIR framework is utilized to system feedback identification and developing the feedback-based nonlinear relationship between the variables in the context of causal loop diagrams (CLDs) in the system dynamics methodology.

Figure 2. A flow work of the DPSIR framework for the development of causal loops

Generally, regional and national policies affect the population, demands, development plans, emerging technologies, and a system's topographic characteristics. Besides, temperature and precipitation variations and droughts are among the driving forces imposed by climate change as an external force. The pressure element includes the main categories of water demand, water and soil resources,

economic change, and environmental issues, which cause changes to the water system. Changes in the water usage and variations of available water should reflect the imposed pressure on resources and water supply and demand as the major components. Regarding the socio-economic part, costs and benefits related to human activities in different sectors (agriculture, industry, urban/services) are considered.

The state element refers to the water system's state under the pressure variables and describes the water system's physical characteristics. It consists of four main categories: surface water and groundwater resources, Labor productivity, and water productivity.

Impacts include water resources degradation, economic, and social challenges as follows:

- 1- Water resources degradation: Increasing water demand as the primary pressure component drives water users to exploit water resources further. Because of the water withdrawal increase, available water resources are affected. Water stress occurs when water demand exceeds the available amount, implying water resource scarcity due to the pressures and supply variability.
- 2- Economic challenges: Water-related activities are affected by water availability. As water withdrawals increase, the benefits resulting from these activities decrease due to the higher water supply costs. Besides, considering yield in the farmers' agriculture sector and profit, benefits can be investigated. The volatile price of agricultural products and the cost of consumed water impose pressure on farmers. They try to increase the actual yield and irrigation efficiency to maximize their profit.
- 3- Social challenges: Changes in water resources and food security affect the social state regarding unemployment and low labor productivity. The mentioned social challenges have associations with the environmental and economic aspects. Water stress results in low income, and low income as a significant economic problem leads to more severe environmental subsequences. Attempts to exploit more water increase conflicts.

Responses refer to measures adopted during the water resources development and utilization to guarantee higher efficiency and sustainability; however, this may lead to the rebound effect. These actions try to decrease the pressures and are principally composed of demand and supply-side management to have more available water and improve water productivity, including dam construction, deficit irrigation, modern irrigation technology expansion such as drip systems.

As shown in Figure 2, water quantity variations are attributed to water withdrawal increase and structural development (dam, irrigation network, etc.). Pressures such as sewage volume changes affect water quality. From an economic perspective, water productivity changes under pressure imposed by human activities, so-called driving forces. The tendency to gain higher productivity leads to more cultivation and technology usage, such as modern irrigation systems. Such systems can save water due to their higher efficiencies; however, this may lead to increased cultivated areas and the use of the saved water for irrigating newly added areas, known as the rebound effect. Furthermore, social welfare is affected by water availability. Mismanagement may result in challenges such as immigration and unemployment.

Among the major application of the DPSIR framework is facilitating the system identification and helping with recognizing or developing the most suitable indicators related to the effective variables of the system (Table 1). Besides, the relationship of the different variables and components in the DPSIR framework (which is often linear) helps identify the possible interdependencies. The basic information on the nonlinear relationship between the variables might be gained from the DPSIR; however, it can be considered the basis of analyzing the system's dynamics. DPSIR framework is utilized to identify and develop CLDs as the primary steps of system dynamics.

2.2. Water accounting framework

The SEEA-W framework is used to derive indicators for assessing the concerning attributes of the study area as a vulnerable system (Figure 3). Physical water supply and use, hybrid and economic, asset, and social accounts are the water accounts associated with SEEA-W. The social water accounting table is as essential as the physical, hybrid, and asset accounting tables, as shown in Figure

3. The physical supply and use tables show the water exchange between the environment and the economy. While the hybrid accounts indicate the costs and revenues of various water uses, the asset account elaborates the water storage variation. Due to the importance of social aspects in water resources planning and management, a separate table for social issues has been developed. It seems that the social water accounting table is the missing category of the SEEA-W. However, estimating water accounting tables with social inclusion can improve the efforts to integrate the economy and the environment. A social water account table is proposed to investigate the accounts based on population, employment, education, financial status, and social welfare.

Figure 3. The components of the modified SEEA-W framework for assessing the concerning attributes of a vulnerable system

The water accounts are usually compiled every five years and are estimated on a basin scale. Based on data availability, the past temporal reference on the study area's compiled water accounts is 2006 and 2011. Wheat, barley, rice, corn, apple, grape, and pomegranate are the selected crops.

2.3. Simulation model

As an efficient approach to conceptualizing the behavior of systems, SD deals with their internal feedback loops. Starting from the DPSIR framework, the feedback-based relationships of variables are investigated. A positive link indicates parallel behavior of variables: in the case of an increase (decrease) in the causative variable, the other variable also increases (decreases). In contrast, a negative link indicates an inverse linkage between the variables. A Causal Loop Diagram (CLD), as a

qualitative technique to investigate the problem's scope and structure, including variables' interrelationships, feedback loops, and delays (Mirchi et al., 2012). is proposed based on closed loops. Closed circles or loops may be either reinforcing (R) or balancing (B) loops. A reinforcing loop is a cycle in which the effect of any variable's variation propagates and reinforces the variable. In contrast, in a balancing loop, it is vice versa (Inam et al., 2015).

Based on CLDs and the SEEA-W framework, a SWA-SD model is built to study the system's behavior during a 20-year timeframe, from 2001 to 2020. In the proposed model, system components are regarded as stocks and flows. Vensim, as the SD tool platform, provided a flexible environment for conceptualization, simulation, and analysis of the dynamic system.

Taking agriculture as the primary sector of development in the study area, scenarios are defined based on water management in the agricultural sector as the primary water user (Iran ministry of energy, 2020). Then, the effectiveness of scenarios is tested by assessing the indicator's variation under different scenarios.

Selected indicators based on the water accounting tables, DPSIR, and SD model's associated variables to assess the system's water stress vulnerability from the environmental, economic, and social points of view are illustrated in Table 1. Among those are relative water stress (water withdrawals from the resources), water productivity (income of water use), agricultural water use efficiency (economic efficiency of delivered water), labor productivity (income of labor employment), and urbanization index. Most of the proposed indicators are simple. They are the primary governing factors in water resources planning and management literature. They have been chosen to provide a more perceptible understanding of the systems' vulnerabilities.

Table 1: Seventeen indicators derived from the WA and DPSIR frameworks

A: Water/Environmental resources dimension		
Indicator description	Equation	Variables
(1) Dependency on Groundwater**	$DG = \frac{WW_{Gw}}{TWW_{Gw+Sw}}$	WW _{Gw} : Water withdrawal from groundwater (MCM), TWW _{Gw+Sw} : Water withdrawal from groundwater and surface water (MCM).

(2)	Relative water stress	$RWSI = \frac{D + I + A}{I_{Ren}}$	D: Water withdrawal for urban/ services (MCM), I: Water withdrawal for industry (MCM), A: Water withdrawal for agriculture (MCM), I_{Ren} : Renewable water resources (runoff and infiltration) (MCM).
(3)	Water use index	$WC_I = \frac{WC_T}{I_{Ren}}$	WC_T : Water use in agriculture, industry, urban/services (MCM), I_{Ren} : Renewable water resources volume (runoff and infiltration) (MCM)
(4)	Agriculture impact on water balance (Mahdavi et al. 2019)	$RIB_A = \frac{WW_{w,A}}{I_{Ren}}$	$WW_{w,A}$: Water withdrawal in the agriculture (MCM), I_{Ren} : Renewable water resources (MCM)
B: Economic dimension			
(5)	Agricultural water productivity	$WEP_A = \frac{I_{w,A}}{WW_{w,A}}$	$I_{w,A}$: The income of the agriculture (USD), $WW_{w,A}$: Water withdrawal in the agriculture (MCM)
(6)	Industrial water productivity	$WEP_I = \frac{I_{w,I}}{WW_{w,I}}$	$I_{w,I}$: The income of the industry (USD), $WW_{w,I}$: Water withdrawal in the industry (MCM)
(7)	Urban/services water productivity	$WEP_U = \frac{I_{w,U}}{WW_{w,U}}$	$I_{w,U}$: The income of urban/ services (USD), $WW_{w,U}$: Water withdrawal in the urban/services (MCM)
	Total water productivity (Sum of indicators 5-7)	$WEP_T = WEP_A + WEP_I + WEP_U$	WEP_A : Agricultural water productivity (USD/MCM), WEP_I : Industrial water productivity (USD/MCM), WEP_U : Urban/services water productivity (USD/MCM)
(8)	Agriculture economic impact (Mahdavi et al. 2019)	$RIE_A = \frac{I_{w,A}}{I_w}$	$I_{w,Agr}$: The income of the agriculture (USD), I_w : The agriculture, industry, urban/ services income (USD)
(9)	Agricultural water use efficiency (Karamouz et al. 2021)	$WUE_A = \frac{A \times Y \times P_C}{WU \times IE \times P_w}$	A: Cultivated area (ha), Y: Yield (kg/ha), P_C : Crop price (USD/kg), P_w : Water price

			(USD/m ³), W_U : Water allocated to agriculture, IE : Irrigation efficiency.
C: Social dimension			
(10)	Agricultural labor productivity	$LP_A = \frac{I_{w,A}}{Emp_A}$	$I_{w,A}$: The income in agriculture (USD), Emp_A : The employee in agriculture (Person)
(11)	Industrial labor productivity	$LP_I = \frac{I_{w,I}}{Emp_I}$	$I_{w,Ind}$: The income in the industry (USD), Emp_I : The employee in the industry (Person)
(12)	Urban/services labor productivity	$LP_U = \frac{I_{w,U}}{Emp_U}$	$I_{w,U}$: The income in urban/ services (USD), Emp_A : The employee in urban/services (Person)
	Total labor productivity (Sum of indicators 10-12)	$LP_T = LP_A + LP_I + LP_U$	LP_A : Agricultural labor productivity (USD/Person), LP_I : Industrial labor productivity (USD/Person), LP_U : Urban/services labor productivity (USD/Person)
(13)	Agricultural employment productivity	$EP_A = \frac{Emp_A}{W_{w,A}}$	Emp_A : The employee in the agriculture (Person), $W_{w,A}$: The water uses in agriculture (m ³)
(14)	Industrial employment productivity	$EP_I = \frac{Emp_I}{W_{w,I}}$	Emp_I : The employee in the industry (Person), $W_{w,I}$: The water uses in the industry (m ³)
(15)	Urban/services employment productivity	$EP_U = \frac{Emp_U}{W_{w,U}}$	Emp_U : The employee in the urban/services (Person), $W_{w,U}$: The volume of water used in urban/ services (m ³)
	Total employment productivity (Sum of indicators 13-15)	$EP_T = EP_A + EP_I + EP_U$	LP_A : Agricultural employment productivity (Person/m ³), LP_I : Industrial employment productivity (Person/m ³), LP_U : Urban/services employment productivity (Person/ m ³)
(16)	Urbanization index (Li et al. 2019)	$UI = \frac{P_u}{P}$	P_u : Urban population (Person), P : total Population (Person)

(17)	Housing index (da Silva et al. 2020)	$HI = \frac{A_{Res}}{P}$	A_{Res} : Residential area (m ²), P : Population (Person)
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** From UNSD (2012) indicators unless otherwise stated

2.4. Water resources vulnerability index

As a performance metric, the water resources vulnerability index (WRV) is developed. Principal component analysis (PCA) is employed to evaluate the indicators listed in Table 1, in the practical aspects of the vulnerability assessment based on developing a set of uncorrelated principal components. PCA is a multivariate method and converts many potentially correlated variables (here indicators) into a set of uncorrelated components that capture the variabilities. PCA finds the accurate data representation to reduce the dimensionality of the dataset without significant loss of information (Haak and Pagilla, 2020).

As for the application of the principal components in this study, the values of the variables included in the indicators are derived by combining the SWA-SD model and the environment and human activities in the study area to characterize the region's ability to cope with water stress. After selecting the effective components, water resources vulnerabilities (WRV) are categorized in terms of environmental ($V_{Wat/Env}$), economic (V_{Eco}), and social (V_{Soc}) components. In the PCA procedure, first, assuming that matrix X presents the indicators, the original indicators of matrix X are standardized to produce matrix C through the standard score method (Cao et al., 2020). Based on the data's average and variance, this step ensures that differences in the scale are compatible by standardizing different indicators. Second, the correlation coefficient matrix (R) is calculated as below:

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1p} \\ \vdots & \ddots & \vdots \\ r_{p1} & \cdots & r_{pp} \end{bmatrix} \quad (1)$$

where r_{ii} represents the variance of C_i and r_{ij} represents the covariance of C_i and C_j . In this study, R is a 4×4 matrix for water/environment and 6×6 and 10×10 matrices for economic and social attributes. Then, the eigenvalues of the correlation matrix R (here, we have three matrices as mentioned in the previous sentence) are calculated to determine the principal component. The eigenvalues are ranked

as $\lambda_1 > \lambda_2 > \dots > \lambda_i > 0$, and the corresponding unit eigenvectors can be written as $\alpha_i = \alpha_{1i}, \alpha_{2i}, \dots, \alpha_{pi}$, in which $i = 1, 2, \dots, p$ (the number of indicators, here totally 20 indicators). The basis of selecting principal components is that the first principal component represents the most significant variance in the data (Zhou et al., 2017). Each principal component is summarized as a linear combination of the essential indicators, using the indicator scores for weighting (Eigen value-based weights). The principal component PC_i can be written as:

$$PC_i = \alpha_{1i}C_{1i} + \alpha_{2i}C_{2i} + \dots + \alpha_{pi}C_{pi} \quad (2)$$

where PC_i is the indicator's aggregate score for the i^{th} principal component and C_{pi} are the elements of matrix C (standardized indicators). For example, PC_1 represents the first principal component (a combination of indicators); PC_2 represents the second principal component. Therefore, we have a principal component for each of water/environment, economic and social attributes. In order to develop these principal components, in the next step, the cumulative contribution rate (E) is determined by Eq. 3 (Wei et al., 2020). The higher values of E show that the proposed principal component has a large cover of the initial inputs. If the E is acceptable, the remaining components can be ignored.

$$E = \lambda_i / \sum_{i=1}^p \lambda_i \quad (3)$$

Finally, based on the eigenvectors, the PC is calculated. Therefore, we have three principal components, namely ($V_{\text{Wat/Env}}$), economic (V_{Eco}), and social (V_{Soc}); considering these components, the vulnerability index is estimated as follows:

$$WRV_A = \frac{\sum_i \lambda_i PC_i}{\sum_i \lambda_i} \quad (4)$$

where A represents the attributes of environmental, economic, and social. PC_i is the indicator's aggregate score for the i^{th} principal component. The eigenvalues (λ_i) are the weights assigned to each component, as determined through PCA analysis. Finally, total water resources' vulnerability (WRV) is estimated based on the weighted average of three vulnerability components.

3. Study area

A generic watershed is assumed with some basic information from a real watershed, having most of the components of a catchment (Figure 4). Although the methodology is applied to a generic study area, the data of the Tashk-Bakhtegan basin (Figure 9, Appendix A), as the second-largest lake in Iran, located in the southwest of Fars province, is utilized in this study. The main water supplies of the basin area are Kor and Sivand rivers (River 1 and 2 in Figure 4, respectively), with 50-year average flow rates of about 21.3 and 3.7 m³/sec, and precipitation. The annual average rainfall is about 320 mm, and the average pan evaporation is 1763.1-2849.4 mm/yr (Iran ministry of energy, 2020). The basin includes large agricultural areas with intensive irrigation; about 60% of the irrigated area is dependent on groundwater resources (Delavar et al., 2020). This study area has dealt with water scarcity in the recent decade; several reservoirs have been built to alleviate water stress.

Figure 4. The developed generic schematic of the case study and the water resources sub-system for better adaptation to other regions

There are four hydrometric stations and three dams in the study area. The reservoir capacity of Dam 1 (Mollasadra dam) is 440 MCM, and for Dam 2 and Dam 3 (Sivand and Doroudzan dams) are 225 and 993 MCM, respectively. In addition to rivers, dams, rainfall, and hydrometric stations (Dehkadeh sefid, Tangbolaghi, Pole Khan, and Kharameh), there are different demand points for urban/service and industrial sectors. Furthermore, five irrigation networks as the agricultural demand points are demonstrated in Figure 4. The demands are supplied with surface and groundwater. With the

significant reduction in the surface water volume, a considerable part of the demand is supplied from the aquifers (Aspas, Namdan, Marvdasht, Arsanjan, Abadeh, and Neiriz).

3.1. Data Preparation

In order to implement the proposed algorithm, three data categories are used: hydrological, economic, and social data. The population is about 1.2 million in 2020 in Tashk-Bakhtegan. In the context of the land-use change, the agricultural area is approximately tripled from 1956 (223594 hectares) to 2020 (604700 hectares). Some other information, such as the water withdrawal from surface and groundwater resources, are shown in Table 2.

Table 2: Water resources usage and land-use changes in the study area (1956-2006)

	1956	2006
Surface water use (MCM)	1331	1487
Groundwater use (MCM)	259	3108

Among the variables of the water balance, the up to dated precipitation and evaporation have been reported in the synoptic stations, however, variables such as water withdrawals from groundwater and surface water and water demands in different sectors (agriculture, industry, and urban/services) have not been reported in any yearly official documents in most regions. The official reports are usually released every five years. Water balance data are not available on an annual basis in many developing, and even developed regions. The official data is published every five years or even longer, resulting in a drawback in watershed management. Therefore, the need for up-to-date water balance data should be responded to practically, satisfying the statistical acceptability measures. The data of Tashk-Bakhtegan basin is used as the basis of the data used for generating water balance data for the case study. This basin has only three formal reports of the water balance data for the years 2001, 2006, and 2011. Therefore, a model developed by Karamouz et al. (2021) is extended and applied to the basic data (precipitation, evaporation, etc.) of the case study to generate water balance data for the entire twenty years duration of the study (2001-2020). This is a practical exercise with the same reasonable assumptions and engineering judgments used by localities for preparing the official water balance (see

Karamouz et al., 2021). Certain details of synthesizing water balance data procedures are presented in Table B2 of Appendix B. The first part of this table is the equations of demands in agricultural, industrial, and urban/service sectors. Then the surface water and groundwater sections are presented. All these mentioned variables are vital in every research related to water resources water balance. The demands in each sector correspond to the water withdrawals, and the surface and groundwater resources volume represent water availability. Therefore, having these synthesized water balance data helps analyze and plan the water resources with up-to-date data. However, this approach is associated with some uncertainties due to the assumptions and estimations; it may significantly contribute to synthesizing water balance data, system's analysis, and planning and management.

4. Results and discussion

In this paper, water accounting tables are developed for 2006, 2011, and 2020. The proposed social table (Tables 3) expanded the social dimensions of the accounting framework. Table 3 shows demographic changes time series in the study area, and the values for 2006, 2011 official, and 2020 synthesized data are included. For the basin's organized data on physical supply and use, hybrid supply and use, and asset account tables using the SEEA-W framework, please refer to Tables A1-A3 in the Appendix, which corresponds to the mentioned data. As can be inferred from the tables in the Appendix, the abstraction for agricultural, industrial, and urban/services sectors are 3807, 49, and 112 MCM, respectively. Water consumption in agricultural, industrial, and urban/services sectors are 1728, 49, and 12.5 MCM, respectively, showing that the water consumption in the agricultural sector is much higher than in other sectors. In developing a social table, social and demographic changes in rural and urban sectors, are considered. Besides, the unemployment and employment divisions are included in the social table. The population classification follows the guidelines of the Iran Statistical Center (2020). The income in the different sectors and total water use/demand are included in Table 3 for the dynamic presentation of time series (2001- 2020) and values of the data in for 2006, 2011 and 2020 (based on synthesized data) are considered.

Table 3. The dynamics of social table time series in the study area (2001-2020).

Average	2001-2003	2004-2006	2007-2009	2010-2012	2013-2015	2016-2018	2019-2020
	Population (× 10 ³)						
Total	750.6	769.9	770.7	775.0	791.3	801.8	823.4

	Unemployment (%)						
Unemployment (%)	12.9	11.0	10.9	12.6	10.7	12.2	11.0
	Employment change (%)						
Agriculture	21.2	9.3	13.3	18.8	4.7	3.8	2.4
Industry	47.7	7.8	12.1	21.8	5.3	2.8	2.4
Urban/ Services	67.1	12.4	15.3	21.7	5.2	3.8	1.5

	Income (Million USD)						
Total	716.5	742.9	784.8	887.7	943.1	951.7	995.9
	Income change (%)						
Agriculture	8.1	8.6	-16.4	-9.2	1.7	3.1	5.6
Industry	2.0	7.0	6.2	5.1	4.8	3.8	8.0
Urban/ Services	20.1	4.3	26.5	10.7	0.4	5.1	2.5

	Total supply/demand of water (MCM)						
Demand	4128.4	4837.8	6828.6	8678.9	7908.1	6710.3	6133.9
Use	3229.3	3863.2	5522.0	7117.5	6227.1	5240.6	4406.4
	Water use change (%)						
Industry	34.6	47.4	37.6	28.2	32.8	38.7	43.5
Urban/ Services	99.4	109.5	102.6	103.1	105.1	102.0	99.3

As shown in Table 3, the total population has increased with a steady past during 2004-20012. In 2010 the urban population started exceeding the rural figures. The unemployment percentage reached 12% in 2010 that marked the maximum rate in the planning horizon. Although employment is increased in all sectors, the agricultural sector's employment was increased drastically until 2012 with as much as 21%; it has had a steady 2-4% increase in recent years. Comparing with the overall population increase, the tendency has been to get employed in other sectors. The income's trend has changed in 2011, showing a jump in the urban/services sector and a reduction in the agricultural sector due to industrial expansion and less labor dependence in the agricultural sector as it is modernized at a slow past. As for water use/demand, the values of 2011 reached a critical point but were lowered, maintaining a steady difference between water use and demand.

As mentioned in the methodology section, the feedback-based nonlinear relationship between the variables in Figure 2, DPSIR (mentioned as D, P, S, I, and R letters/labels in the following paragraph). This framework is utilized to identify system feedbacks and loops (mentioned as seven reinforcing loops R₁-R₇ and five balancing loops B₁-B₅ in Figure 5). The labels in the parenthesis in the following paragraph show the DPSIR classifications.

In developing CLDs, the pressure of the land-use change is regarded as the changes in the arable area and irrigated area, and the human activities are the activities in agricultural, industrial, and urban/services sectors and their demands. Resource availability, structural development (all labeled as P), and favorable policies that increased agricultural productivity (I), and income (I) as the impacts. However, water productivity state (S) is improved by using more water; all these affect surface water quantity (S) and groundwater level (S), and result in resource degradation (I) followed by water crisis

(water stress (I)). Labor productivity state (S) changes in the different sectors and non-uniform distribution of income and productivity may cause social challenges (I). Different supply and demand-side management measures are considered as responses for these conditions; among those are irrigation network expansions (R).

This results in the reduction of water resources availability and resource degradation, resulting in a water crisis. As shown in Figure 5, gaining more income motivated farmers to cultivate more (R4), improve water extraction potential (R6), and increase water withdrawals (R5). On the other hand, employment in labor productivity increased with more developed agriculture and higher production (R1 reinforcing loop). It should be noted that these loops and feedbacks might result in some social challenges, including unbalanced employment development and, in some cases, immigration (rural to urban); all these result in higher agricultural income. Expanded cultivated areas decreased available water. Thus, some measures are employed to exploit more water, causing an increase in the cultivated area and increased water demand (B3 balancing loop). Finally, agricultural development is prevented by limited available cultivation areas (B1 and B2). As agricultural water demand increases, developing irrigation technologies for increasing efficiency attracts more attention (R2), resulting in higher efficiency and decreased water use affecting water productivity. However, cultivating new areas may be inevitable due to the rebound effect (R3). By withdrawing more water, available water levels are reduced (B4) since the supply is developed regardless of water shortage (B5), which results in more water demand (R7). Different supply and demand-side management measures such as irrigation network expansions and increasing agricultural area to gain more benefit are the measures (temporary solutions) in recent years. For characterizing the behavior and processes of the system, the SFD (Stock Flow Diagram) is developed based on the CLDs (Figure 6).

Figure 5. Causal loop diagrams of Agro-economic attributes of a system

Figure 6. Stock-flow diagram (SD model) of socio-economic attributes of the water system in the study area

As shown in Figure 6, the model consists of two parts as follows:

1. Social-Economy: including population, urban and services, industries and mines, agriculture, and the employment (corresponded to the R1 loop in Figure 5) corresponding to each economic sector;
2. Water/Environment: including hydrological cycle's variables (precipitation, evaporation, etc.), water resource (inland water resource), water supply and demand, and return flows (corresponded to the B3, B4, B5 and R5, R6 loop in Figure 5).

The key variables to develop a SD model in the agricultural sector are water withdrawal (MCM), irrigation efficiency, water requirement (MCM), production (kg), and yield (kg/ha). The two stocks in this sector are agricultural area (hectare per month), arable area (hectare per month). Two income-based and water-based agricultural areas are modeled to estimate the desired agricultural area (Table 4). Considering these stocks and flows, in the context of the causal loop diagrams (CLDs), the agricultural systems' dynamics corresponded to the B1, B2, and R3, R4, and R5 loops in Figure 5. The arable area and agricultural area stocks are in a closed-loop by the variables of increasing and decreasing area. There is another loop between these two stocks with the difference between current and desired agricultural areas. More details on the equations of functional relationships considered in the SD model are shown in Table 4.

Table 4. Functional relationships of the SD model

Variable	Equation	Description
Agricultural water use (A_c)	$A_c = \text{If Then Else } (A_w > 0: \&: P > 0: \&: A_{wc} > 0, \text{ MIN } ((TA_w / T), A_{wc}), 0)$	A_w : Available Water (MCM), P : Population (Person), A_{wc} : Agricultural Water Allocation (MCM), TA_w : Total Agricultural Water Need (MCM), T : Time Step (Year)
Income-Based Agriculture Area ($A_{\text{Income-Based}}$)	$A_{\text{Income-Based}} = \text{Lookup Function } A_I \text{ and } A(A_I)$	A_I : Agricultural Income (IRR), A : Agricultural area (km^2)
Water-Based Agriculture Area ($A_{\text{Water-Based}}$)	$A_{\text{Water-Based}} = \text{If Then Else } (A_w > 0, (A_w \times T) / P_w, 0)$	A_w : Available Water (MCM), P_w : Product Water Need (cms / km^2), T : Time Step (Year)
Desired Agriculture Area (A_{AD})	$A_{AD} = \text{MIN } ("A_{\text{Income-Based}}", "A_{\text{Water-Based}}")$	$A_{\text{Income-Based}}$: Income-Based Agriculture Area (km^2), $A_{\text{Water-Based}}$: Water-Based Agriculture Area (km^2)

Difference Between Current & Desired agricultural Area (D _{AA})	$D_{AA} = (C_{AA} - A_{AD})$	C _{AA} : Current Agriculture Crop Area (km ²), A _{AD} : Desired Agriculture Area (km ²)
Increasing agricultural Area (I _A)	$I_A = \text{If Then Else } (D_{AA} / T \leq 0: \text{ or: } P \leq 0, \text{ MIN}(\text{ABS}(D_{AA}), A_A) / T, 0)$	D _{AA} : Difference Between Current and Desired Agriculture Area (ha), T: Time Step (Year), P: Population (Person)
Decreasing agricultural Area (D _A)	$D_A = \text{If Then Else } (D_{AA} > 0: \text{ or: } P \leq 0, (D_{AA}) / T, 0)$	D _{AA} : Difference Between Current and Desired Agriculture Area (km ²), P: Population (Person), T: Time Step (Year)
Arable Area (A _A)	$A_A = \sum (D_A - I_A)$	D _A : Decreasing Area (km ²), I _A : Increasing Area (km ²)
Production (Pr _A)	$Pr_A = A \times Y$	A: Agricultural area (ha) Y: Yield (kg/ha)
Yield (Y)	$Y = 5069.82 + 811.17(a \times h) - 0.092(a \times h)^2$	a: Irrigation efficiency (dimensionless), h: Applied agricultural water (m ³ /ha), Y: Yield (kg/ha)
Agricultural Income (A _I)	$A_I = 0.062 C_P - 0.53 A + 0.65 A_{wc} + 2079.1$	C _P : Crop price (IRR/kg), A: Agricultural area (km ²), A _{wc} : Applied Agricultural Water (MCM)

In this table, agricultural income as an important variable in estimating the irrigated area, which alters the variables mentioned above, is developed based on crop price, agricultural area, and agricultural water use. Agricultural crop production is assumed to have a quadratic relationship with water input (Caswell and Zilberman 1986). More effective water use leads to higher yields. However, after reaching the maximum yield, the crop yield decreases with additional effective water use (Karamouz et al., 2021). The indicators mentioned above (Table 1) are estimated based on the model's output values. The model is verified by the behavior reproduction tests based on the data of 2001- 2020.

Behavior-Reproduction Test is one of the critical tests that are conducted before using the model (Sterman, 2000). Comparing the model's output to historical data ensures that the model's structure

and behavior can be reproduced satisfactorily. Observed vs. estimated values for the variables are shown in Figure 7. As a statistical measure, the coefficient of determination (R^2) is used (Eq. 6).

$$R^2 = \left\{ \frac{\sum_{i=1}^n (Q_i - \bar{Q})(\ddot{Q}_t - \bar{\ddot{Q}})}{\sqrt{\sum_{i=1}^n (Q_i - \bar{Q})^2 \sum_{i=1}^n (\ddot{Q}_t - \bar{\ddot{Q}})^2}} \right\}^2 \quad (6)$$

where Q_i is the estimated value, $\bar{Q}$ is the average of estimated value, $\ddot{Q}_t$ is the observed value and $\bar{\ddot{Q}}$ is the average observed value. N is the period of the evaluation. The value of R^2 is obtained as 0.84 and 0.68 for agricultural income and area, respectively.

Figure 7. Observed and modeled variables in the SD model

After the model verification (acceptable R^2 's estimated by Eq. 6), indicators in environmental, economic, and social dimensions (derived from the SWA-SD model) are estimated. Table 5 shows the indicator values in 2001-2020, in three years intervals.

Table 5. Indicator values in 2001-2020 (derived from the SWA-SD model) with 3-year sequence

Indicator	2001	2004	2007	2010	2013	2016	2019	2020
DG	0.60	0.57	0.57	0.62	0.52	0.51	0.63	0.66
RWSI	0.44	0.33	0.51	0.64	0.46	0.58	0.53	0.63
WC	0.66	0.49	1.42	1.84	1.27	1.73	1.45	1.77
RIB _A	0.63	0.47	0.79	1.03	0.71	0.97	0.80	0.98
WEP _T	4.74	4.54	5.32	7.65	6.98	7.74	10.23	10.70
WEP _A	0.67	0.58	0.59	0.71	0.72	0.78	0.96	0.95

WEP_I	94.71	100.47	86.73	127.03	101.09	89.35	79.04	75.89
WEP_U	218.46	284.24	343.40	394.25	424.03	445.76	465.24	471.30
RIE_A	0.14	0.13	0.11	0.09	0.10	0.10	0.09	0.09
WUE_A	0.08	0.13	0.14	0.14	0.26	0.48	0.61	0.50
LP_T	0.18	0.22	0.27	0.29	0.27	0.25	0.24	0.23
LP_A	0.12	0.13	0.13	0.13	0.18	0.17	0.17	0.16
LP_I	0.60	0.55	0.36	0.39	0.24	0.19	0.16	0.15
LP_U	0.17	0.24	0.29	0.32	0.32	0.29	0.27	0.27
EP_T	26.63	20.45	20.03	26.56	25.88	30.69	43.00	45.94
EP_A	5.55	4.54	4.46	5.37	4.03	4.57	5.63	5.78
EP_I	156.93	184.06	242.80	327.99	423.34	462.32	496.81	506.92
Ep_U	1257.72	1202.91	1177.03	1216.76	1310.84	1520.67	1708.82	1767.28
UI	0.38	0.42	0.46	0.50	0.57	0.65	0.63	0.63
HI	19.50	23.54	27.63	32.43	36.22	38.55	46.43	47.20

*DG: Dependency on groundwater (MCM/MCM); RWSI: Relative water stress (MCM/MCM); WC: Consumption Index (MCM/MCM); RIB: Agriculture importance in local water balance (MCM/MCM); WEP: Water productivity (IRR/MCM); RIE: Agriculture economic importance (Dimensionless); WUE: Agricultural water use efficiency (Dimensionless); LP: Labor productivity (IRR/cap); EP: Employment productivity (cap/m³); UI: Urbanization index (cap/cap); HI: Housing index (m²/cap).

The values of the relative water stress index (RWSI) demonstrate that this basin faces water stress and the deficiency (RWSI>0.4) due to high water withdrawals. RWSI was 0.44 in 2001 and became 0.63 in 2020, indicating the worsening situation. Based on Table 5, the agricultural sector's impact on water balance grew significantly over time (from 0.63 to 0.98). Although the agricultural sector's water use results higher stress levels, it did not show remarkable water productivity. As for WEP (Water productivity), the value is increased from 94.71 (in 2000) to 127.03 (in 2010). It is decreased to 75.89 in 2020. The reason behind this reduction may be related to the fact that the significant proportion of the industrial sector in the case study are food industry and the variations in crop production results in variation in the industry sector. For agriculture economic importance (RIE), a reduction trend is shown, implying that the proportion of agricultural income to total gained

income, is reduced by the time. As for labor productivity, the values are increased for the urban/services sector, while a reduction is shown in industrial sector. As labor productivity is the value that each employed person creates per unit of his or her input, it implies a growth in income and output in the urban/services sector. Increases in labor productivity are driven by technological change, efficiency improvements, quality of labor, and capital deepening (when more capital is added to a given amount of labor). Therefore, the reduction in industrial labor productivity may be the result of poor labor education and investments.

PCA is utilized to recognize the most critical variables and evaluate the main components. According to Eq. 3, the number of components is evaluated based on the eigenvalues (Eq.7 and Eq. 8). In the water/environment attribute, the maximum Eigenvalue is 2.98 out of 4 and has a contribution of 74. The maximum Eigenvalue is 4.415 and 6.063 for the economic and social attributes, respectively. Total Eigenvalues are 6 and 10 for economic and social attributes, respectively. Based on the eigenvalues and the indicators standardized matrix, the eigenvectors are calculated. The eigenvectors show the coefficients of chosen indicators in principal components. The values of E (cumulative contribution rate) are estimated as 74, 74, and 61% for environmental, economic, and social aspects, respectively. Here, there is only one principal component in each attribute (three components in total).

$$WRV = w_1 V_{Env} + w_2 V_{Eco} + w_3 V_{Soc} \quad (7)$$

V_{Env} , V_{Eco} , and V_{Soc} show the vulnerability in environmental, economic, and social attributes based on the principal components in each group, respectively. The w_1 , w_2 , and w_3 are the weights of these components, respectively. Then, utilizing the SWA-SD and selected indicators, the environmental, economic, and social principal components are evaluated to estimate water resources vulnerabilities (WRV). The weights of these components are assumed to be equal. The values of the coefficients in Eq. 8 are estimated based on the eigenvalues and Eqs. 3, 4, and 5. These coefficients' signs may vary based on their nature and effect on the estimated principal component. Each component of WRV consists of certain indicators. The RWSI, WC, and RIB_A in

water/environmental attribute WEP_T , WEP_U , WUE_A , RIE_A , and WUE_A in economic attribute, and EP_I , UI , LP_I , EP_T , EP_U , and LP_A , in the social attribute are chosen based on principal component analysis. The WRV principal components are shown as follows:

$$\begin{cases} V_{Wat/Env} = 0.58RWSI + 0.57WC + 0.55RIB_A \\ V_{Eco} = 0.47WEP_T + 0.45WEP_U + 0.45WEP_A - 0.42RIE_A + 0.4WUE_A \\ V_{Soc} = 0.4EP_I + 0.39UI + 0.32LP_A + 0.36EP_T + 0.35EP_U + 0.33LP_A \end{cases} \quad (8)$$

The results of estimating different components of water resources vulnerability using Eq. 7 and Eq. 8 are shown in Figure 8.

Figure 8. Water resources vulnerability in environmental, economic, and social aspects in the study area (2001-2020)

Agricultural water concerns have also been accompanied by social concerns, including food security, migration from rural to urban areas, unemployment in rural areas, decreased social equality, etc. Applying some measures for improving employments in rural areas or increasing agricultural water productivity might reduce the social vulnerability.

However, the $V_{Wat/Env}$ decreased over some years, which could be attributed to the more water supply. It is demonstrated that increasing demands are responded to with different water-supply measures, which is why $V_{Wat/Env}$ has so many highs and lows. It lays in the range of 0.73-2.24. the maximum value corresponds to 2008. This water resource vulnerability component has increased in recent years, as the demands are not met. On the other hand, economic water resources vulnerability (V_{Eco}) with the range of 0.82-1.90 and social water resources vulnerability (V_{Soc})

with the range of 0.89-2.34 follow an upward trend. The maximum values for V_{Eco} and V_{Soc} correspond to 2019 and 2020, respectively. WRV is estimated based on the average values of the three vulnerability attributes and has a range of 0.89 - 2.04, implying the 20-year period vulnerability in the case study. Also, it can be stated that increasing trends may result in higher vulnerabilities if the limiting measures or policies are not considered in local and national policy and decision making. Considering the results of the vulnerability index, it may be implied that there was a period of using better technologies, enabling farmers to use water without the limitation concerns of the supply side. Water systems dynamic evolve hydrological and socio-economic processes. Therefore, for better system identification, the ability of socio-economic systems to withstand under certain conditions may be estimated in the context of resiliency.

In the context of better system identification, the scenario assessment is defined based on the practical measures in the agricultural drought management, including changing the irrigation efficiency, reducing cultivated area, and applying deficit irrigation (DI) (Table 6). However, increasing efficiency reduces the return flow and the GW resources in long-term periods; the rebound effect is another challenge in applying this scenario. Usually, DI decreases agricultural production based on the water use reduction in the production function mentioned in Table 4; however, applying DI can reduce water use.

Table 6. Different scenarios based on agricultural drought management

Policies	Description
Agricultural drought management	Scenario 1: Reducing cultivated area by 25%
	Scenario 2: Changing gravity irrigation to drip irrigation system (Increasing the irrigation efficiency by 40%)
	Scenario 3: Deficit irrigation by 50% for 50% of irrigated area.

Then the scenarios' effectiveness is evaluated based on the SD model during the study period. The values correspond to the different vulnerability indices are shown in Table 7.

Table 7. The scenarios' effectiveness on the system vulnerability in the year 2020 (percentage).

Vulnerability indices	Scenario 1	Scenario 2	Scenario 3
$V_{Wat/Env}$	28	45	48
V_{Eco}	21	34	41
V_{Soc}	13	22	30
WVR	21	34	40

As shown in Table 7, the third scenario is the most effective scenario. The effect of applying this scenario (deficit irrigation) is in line with the study by Goli et al. (2019). DI provides lower water use with acceptable yield (based on the production function); however, it results in some return flow reduction which is not significant. The second scenario is ranked second, implying that increasing irrigation efficiency is a good and practical measure in most cases if the rebound effect is neglected. Changing irrigation systems to drip systems (increasing irrigation efficiency by 40%) results in approximately zero return flow affecting the GW resources recharge. It may result in increasing the soil salt content.

5. Summary and conclusion

A framework for water resources systems assessment considering physical water resources and socio-economic aspects was presented. The methodology consisted of conceptual modeling methods (i.e., CLD, DPSIR), SEEA-W, and SFD to model the water system through the development of the SWA-SD (social water-accounting-based system dynamics). The analytical frameworks such as DPSIR and WA are utilized to evaluating the most effective variables in water resources performance. A water balance-based extension of the SEEA-W is developed considering the social accounts. The form of indicators representing the basin's characteristics is provided based on these frameworks. The feedback-based relationships are identified by causal loops, and the dynamic interaction of all variables is assessed in the system dynamics environment

(SWA-SD model). Without the SD framework, the interaction of the important variables in water balance and system's performance could not be evaluated.

The methodology is tested on a generic system that resembles Tashk-Bakhtegan basin in Iran and the real data of that basin was used. In addition, a practical approach is taken into account to estimate water balance components for 20 years based on the basic hydrological and water use data and limited available official water balance data.

As there is no social table in the list of tables of the SEEA-W framework, a dynamic social table based on the “heart bit” of time series of social data including the demographical changes, unemployment, migration (urban vs rural population changes), income, water use disparity compared with the water demand as an indicative of water system welfare.

Based on the relative water stress index values ($RWSI > 0.4$), the water stress and deficiency in the case study show the supply and demand management requirement of available water resources. Agriculture's impact on the water balance was increased from 0.47 to 1.28. It implied that water use in the agricultural sector led to higher water stress and did not produce remarkable water productivity. Urban/services water productivity was improved by the coefficient of 2.16, with 32% more water use in 20 years. It may be a result of local policies and measures in the case study. Principal components were evaluated to identify those with a more significant contribution to variabilities within that component. The principal component analysis (PCA) method was utilized to divide indicators into three environmental, economic, and social attributes. Then utilizing the results of the SWA-SD and selected indicators, the environmental ($V_{Wat/Env}$), economic (V_{Eco}), and social (V_{Soc}) components were evaluated to quantify water resources vulnerabilities (WRV). Based on the results, as increasing demands were supplied with different measures, $V_{Wate/Env}$ had many ups and downs. The economic and social water resources vulnerability (V_{Eco} and V_{Soc}) followed an increasing trend. The effect of applying this scenario (deficit irrigation) it is in line with previous similar studies (Goli et al., 2019). DI provides about 40% effect of the vulnerability indices. However, lower agricultural water use, with acceptable yield, results in return flow reduction.

Although changing irrigation system to drip systems (increasing irrigation efficiency) affects the GW resources recharge, it may be the most practical solution of effective water use.

Utilizing the analytical frameworks for evaluating the most effective variables, a water balance-based extension of the SEEA-W framework is developed considering the social dynamics accounts. Based on the identified feedback-based relationships, the dynamic interaction of the variables is assessed by a system dynamics approach. As for utilizing the PCA method, it helps to reduce some interdependent indicators into a manageable number of components to quantify water stress vulnerabilities. The result shows the significant value of utilizing water balance data in the development and practical application of seventeen indicators representing different water/environment, economic and social attributes of a water supply and demands system. The proposed methodology could be utilized as a tool for system analysts and decision-making in water systems with social and economic volatility in different developing geographic settings.

Declarations

Conflict of interest

The authors declare that there is no conflict of interest.

Ethical Approval

Not applicable.

Consent to Participate

Not applicable.

Consent to Publish

Not applicable.

Authors Contributions

E. Ebrahimi: Conceptualization; Data acquisition and preparation; Materials and Methods; Modeling setup; Analysis and presentation, Manuscript preparation.

M. Karamouz: Development of the original concepts and scope of the work; Materials and Methods; Validation; Manuscript preparation; Review and editing.

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Competing interests

The authors declare no competing interests.

Availability of data and materials

All input data used in this research can be found from the publicly available domains Ministry of Energy (<http://www.moe.gov.ir/>), Ministry of Agriculture (<https://www.maj.ir/>), Ministry of Industry, Mining, and Trade (<http://en.mimt.gov.ir/>), and Statistical Center (<https://www.amar.org.ir/>). Nevertheless, all data, models, or codes that support the findings of this study are available from the corresponding author upon request.

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Appendix A

The basin's data are organized using the SEEA-W framework water account tables (Tables A1, A2, and A3). In the agricultural sector, different crops are selected based on the cultivated areas of the five subareas of the Tashk-Bakhtegan basin (Figure 9) (UNSD, 2012).

Table A1. Water accounting table in the study area based on the 2006 data.

	Agriculture								Industry	Urban/ Services	Total
	Rice	Barely	Maize	Wheat	Apple	Grapes	Pomegranate	Total			
Total abstraction (MCM)	703.9	221.8	104.8	2281.9	249.7	90.9	153.7	3806.7	49.1	111.7	3967.5
Surface water (MCM)	166.5	43.3	24.8	471.2	58.8	64.7	2.9	832.2	4.9	27.9	865
Groundwater (MCM)	536.8	139.5	80	1519.4	190.9	6.1	0	2472.7	44.2	83.8	2600.7
Soil water (MCM)	0	38.8	0	274.2	1.1	6.1	2.9	323.1	0	0	323.1
Total returns (MCM)	385.8	121.7	57.4	1260	136.9	49.8	84.2	2095.8	0	29.7	2125.5
Total output (1000 USD)	216.7	11.9	4.8	1614.3	0.0	321.4	9.5	2178.6	51471.4	509047.6	562697.6
Total use (1000 USD)	62595.2	3695.2	1073.8	467797.6	23.8	92973.8	2481.0	630640.5	29173.8	386876.2	1046690.5
Evapotranspiration (MCM)											6204.4

As shown in Table A1, for the year 2006, about 96% of the total water use is corresponded to the agricultural sector. About 22% of the total abstraction is from surface water resources. As for the year 2011 (Table A2), the agricultural sector's proportion of total water abstraction is about 0.97%, with about 10% share of surface water. Showing the highest dependency on groundwater in 2011 due to the highest demand for water in that year.

Table A2. Water accounting table in the study area based on the 2011 data of the official record.

	Agriculture								Industry	Urban/ Services	Total
	Rice	Barely	Maize	Wheat	Apple	Grapes	Pomegranate	Total			
Total abstraction (MCM)	505.8	1992.2	575.1	3376	374.7	278.4	216.9	7319.1	27	108.3	7454.4
Surface water (MCM)	72.9	101	114.8	233.2	74.5	35.8	42.5	674.7	1.9	22.3	698.9
Groundwater (MCM)	404.2	291.7	459.3	932.7	298.2	143.2	170.2	2699.5	24.3	86	2809.8
Soil water (MCM)	0	1626.2	0	2199.2	1.6	99.3	4	3930.4	0	0	3930.4
Total returns (MCM)	278	102.2	315.8	1856.3	205.5	152.7	119	4019.5	18.6	21.7	4059.8
Total output (1000 USD)	178.6	52.4	38.1	876.2	0.0	9.5	9.5	1164.3	57111.9	713450.0	771726.2
Total use (1000 USD)	98433.3	28119.0	21364.3	479709.5	90.5	4819.0	5066.7	637604.8	39978.6	189778.6	867361.9
Evapotranspiration (MCM)											9691

As shown in Table A3, for the year 2020, the agricultural sector's proportion of total water use is about 0.98%, with about 14% share of surface water. Total economic output is increased by 11% from 2011 to 2020. Water abstraction for the industrial sector was increased after the lowest experienced in 2011.

Table A3. Water accounting table in the study area, synthesized for 2020 data, based on the framework proposed by Karamouz et al. (2021).

	Agriculture								Industry	Urban/ Services	Total
	Rice	Barely	Maize	Wheat	Apple	Grapes	Pomegranate	Total			
Total abstraction (MCM)	668.6	200.1	197.8	2400.3	412.6	205.1	242.5	4327	44.5	98.8	4470.3
Surface water (MCM)	77.3	96.9	83.5	208.6	81.3	33.6	50.3	631.5	9.9	24.2	665.6
Groundwater (MCM)	591.3	103.2	114.3	2191.7	331.3	171.5	192.2	3695.5	34.5	74.5	3804.5
Total returns (MCM)	308.1	131.5	98.8	1396.7	248.4	164.2	156.2	2503.9	26.7	69.2	2599.8
Total output (10 ³ USD)	223.8	45.2	40.5	1271.4	0.0	240.5	11.9	1833.3	63504.8	788104.8	853442.9
Total use (10 ³ USD)	148866.7	46404.8	26192.9	505842.9	121.4	6514.3	6045.2	739988.1	47559.5	314526.2	1102073.8
Evapotranspiration (MCM)

Figure 9. The location of the water resources sub-system based on the Tashk-Bakhtegan basin

Appendix B (Water Balance Estimation)

Table B1 shows the source of available data that are used for estimating water balance variables. The variables, relationships, assumptions, and the framework of technical information to generate water balance data are listed in Table B2.

Table B1. Time series of climatic and hydrologic data for generating water balance variables

Data	Source
Rainfall	Regional Water Authority (RWA)
Precipitation/Evaporation	RWA
Population	Iran statistical center
Irrigated area	Dept. of Agriculture

In Table B2, there are three parts. The first part is the equations of water demand in different sectors (agricultural, industrial, and urban/services). A regression equation is developed based on the income, irrigated area, population, and industrial units. The next parts correspond to the groundwater and surface water. Variables such as inflow, infiltration, and drainage are included in synthesizing groundwater resources balance data. The main components of surface water balance data that are not stated in official reports are the irrigation and non-irrigation backflows. The values of all these variables are synthesized based on official reports, time series of the basic hydrologic cycle variables (precipitation etc.), and judgment. See Karamouz et al. (2021) for more details.

Table B2. Water balance data technical framework - variables, relations, assumptions, (2001-2020)

Variable	Relationship	Assumptions	Note
Agricultural	$Demand_{agri} = 0.12 \times I + 1.35 \times A - 1340.9$	It is proportional to the cultivated area and income	$I = Income$ $A = Area\ of\ irrigation\ network$
Domestic	$Demand_{dom} = 0.05 \times P + 47.49$	It is proportional to the population	$P = Population$
Industrial	$Demand_{ind} = 0.02 \times n + 17.17$	It is proportional to the number of industrial units	$n = number\ of\ industrial\ units$
Groundwater variables			
Variable	Relationship	Assumptions	Note
Inflow to the aquifer	$Q_{in} = Inf + RF$		Inf= infiltration RF= Return flow
Infiltration from precipitation	Estimated according to the rate of infiltration from precipitation (reported in the formal reports)	16% of the precipitation	Time series for rainfall of available stations
Infiltration from surface water	Estimated according to the rate of infiltration from runoff (reported in the formal reports)	12% of the precipitation	Time series for rainfall of available stations
Infiltration from irrigation backflow	$Inf_{agri} = 0.12(0.12 \times I + 1.35 \times A - 1340.9)$	12% of the agricultural water demand	Estimated according to the official reports
Infiltration from non-irrigation backflow	$Inf_{ind} = 0.7[(0.05 \times P + 47.49) + (0.02 \times n + 17.17)]$	70% of the domestic water demand	Estimated according to the official reports
Drainage to surface water	$Max (0.01 \times GW\ storage\ and\ 370)$		Estimated according to the official reports
Surface water variables			
Variable	Relationship	Assumptions	Note
Inflow from out of the basin	0		According to the topography of the basin, there is no Inflow from the outside of the basin
Non-irrigation backflow	$backflow_{dom} = 0.3[(0.05 \times P + 47.49) + (0.02 \times n + 17.17)]$	30% of the domestic water demand	Estimated according to the official reports
Irrigation backflow	$backflow_{agri} = 0.3(0.12 \times I + 1.35 \times A - 1340.9)$	30% of the agricultural water demand	Estimated according to the official reports

Table B3 shows the values for available water (AW) in the last two years of official record (2006 and 2011) and the synthesized water balance data. The synthesized data closely follows the official record shown by the absolute error (%).

Table B3. Available water (AW) values from official and Synthesized data

Year	AW* (MCM)	AW ** (MCM)	Absolute Error (%)
2006	5292	5084	3.9
2011	4937	4912	0.5

*/**: based on official/synthesized water balance data