Drought Risk Assessment for Surface Water Distribution Systems in Irrigation Districts

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Abstract

This study puts forward a practical risk assessment framework for agricultural Surface Water Distribution Systems (SWDS) operation under drought conditions. It accounts for situations when the diverted flow from the diversion dam fails to cover the total water rights within the districts. The risk probability is based on drought analysis and the Stream Drought Index (SDI) classification using the DrinC calculator. The risk consequence is determined based on SWDS operational performance appraisal, which includes hydraulic simulation by HEC-RAS, temporal analysis of adequacy, efficiency, and equity indices, spatial assessment in GIS, and combining performance evaluation indices using the Simple Weighted Sum (SAW) method. SWDS risk assessment is conducted considering the probability and consequences of drought hazard on the monthly and annual time scales. The obtained results show the monthly and yearly risks vary between (73.7, 76.1) % and (46.3, 63.9) % under the extreme-critical condition; (46.0, 53.2) % and (38.1, 51.1) % under the critical condition; (24.4, 35.1) % and (18.7, 27.5) % under the semi-critical condition; and (16.6, 25.5) % and (10.7, 16.6) % under the normal condition. The outcomes of the present study can empower dam owners, utility companies, and irrigation district managers to have realistic water planning, emergence action,

and recovery plans for optimum surface water distribution between the hydraulic off-take structures.

Keywords: Agricultural Water Management; Drought; Risk Assessment; Modernization; Hydraulic simulation

List of abbreviation

cms: cubic meters per second

DrinC: Drought Indices Calculator

ED: Extreme Drought

HEC-RAS: Hydrologic Engineering Center- River Analysis System

HPO: Historical Probability of Occurrence

IUs: Irrigated Units

MAE: Mean Absolute Error

MCDM: Multi-Criteria Decision-Making

MCM: Million Cubic Meters

O_Sc: Operational Scenarios

RMSE: Root Mean Square Error

SAW: Simple Weighted Sum

SDI: Stream Drought Index

SWDS: Surface Water Distribution Systems

USBR: US Bureau of Reclamation

WSC: Weighting Scenarios

1. Introduction

The unreliable performance of traditional off-farm agricultural water operating systems (i.e., surface water conveyance & distribution structures operated by the dam owners) during water shortage periods is causing dissatisfaction among farmers and additional expenses for tube-well drilling licenses and pump station operation and maintenance in the irrigation districts.

Studies reveal that water supply in Iranian irrigation districts exceeds agricultural demand by 67% to 200%. Also, the number of issued drilling licenses to farmers has risen by 45% to 213% (Avargani et al., 2022). Therefore, it is crucial to modernize hydraulic infrastructures and identify factors that impact modernize these hydraulic infrastructures, including recognizing water sources, assessing performance during shortages, and estimating hazards (Tsihrintzis, 2017). Accordingly, two approaches for studying SWDS performances: pro-active orientation (risk assessment/management) (Bozorgi et al., 2021) and sustainability appraisal orientation (environment-food-energy-water nexus) (Bayat et al., 2022). This study offers a risk assessment framework for SWDS failure during droughts.

SWDS's global projects face issues with unreliable operations, causing social conflicts and environmental degradation due to water right violations and groundwater overexploitation. For instance, Over 50% of irrigation water was lost in a Mediterranean community due to improper operation. (Serra et al., 2016); Poor performance and damaged structures caused unfair water distribution in Ethiopia (Dejen et al., 2015); and an appraisal project carried out by USBR the showed that the average amount of water losses within AWDS were about 35% (Barkhordari et al., 2020). SWDS water losses are significant, and diverted water often fails to reach intended agricultural land. Water scarcity is a natural risk that reduces SWDS efficiency and requires investigation using risk assessment methods (Zhong et al., 2020).

Bozorgi et al. (2021) developed a new risk assessment model to identify and evaluate threats to agricultural water supply systems using a hybrid Bayesian network. This approach has been commonly used in managing water resources for irrigation and agriculture water supply systems. Babaei et al. (2018) used the fuzzy fault tree analysis technique for risk assessment of undesirability of agricultural water supply & delivery in an irrigation district. Likewise, a risk management framework for SWDSs in irrigation districts was developed using a fuzzy hierarchical method to investigate failure and prioritize modernization alternatives based on

SDGs criteria (Orojloo et al., 2018). However, there is a need for more comprehensive evaluations of water systems during shortages. Specifically, there is a lack of research on drought risk analysis and the impact of drought-induced scenarios on SWDS performance. This paper proposes a framework to measure the consequences of drought on SWDS performance. In terms of practicality, the paper provides guidance for irrigation districts on how to manage operations during water scarcity.

The purpose of this study is to propose a practical approach for assessing the risks associated with SWDS operations in different drought inflow scenarios. To accomplish this, there are four subsidiary objectives: i) develop a hydraulic simulation model for SWDS to allocate surface water fairly among; ii) analyze drought risk probability using SDI index and DrinC calculator by Tigkas et al. (2015). Irrigation districts rely on surface water from dams and are affected by stream flow droughts. The SDI is a commonly used drought index for studying rivers. Hydrological droughts can threaten crops in these districts, which the SDI can help detect (David and Davidová, 2017); iii) spatiotemporal assessment of surface water distribution; iv) analyzing discrepancies between historical water-rights and the supplied water. The proposed practical approach can be applied by agro-tech enterprises, dam owners, insurance companies, and utilities to improve the off-farm surface water planning. It is worth noting that the proposed approach was performed and investigated in Roodasht Irrigation District located in Zayandeh-Rud River Basin, Iran.

2. Materials and methods

2.1. Research methodology

The research methodology, **Fig. (1).**, included different steps conducted in SWDS operation's risk assessment under drought conditions on an annual and monthly basis, as explained below:

Step 1: A field survey was conducted to collect data, measure, observe, interview, and brainstorm. The objectives were to obtain flow rate measurements, gather hydraulic information, and acquire operational data. Field observation verified the data, and the hydraulic simulation model was calibrated.

Step 2: Drought analysis and SDI classification using DrinC software. To calculate monthly and yearly SDI, the DrinC software created by Tigkas et al. (2015) was utilized. DrinC calculates SDI using the Hargreaves equation and weather data. The index ranges from -4 to 4, reflecting drought to wet conditions.

Step 3: Drought probability determination based on the calculated SDI classification.

Step 4: Simulate water flow in open canals to determine discharge at off-take structures for different operational scenarios.

Step 5: Evaluated water distribution and performance monthly and annually. Used the results to create an integrated consequence index and presented it to stakeholders for feedback. Helped understand the current operational performance.

Step 6: Drought consequences determination by combining performance evaluation indices using SAW method.

Step 7: SWDS risk assessment considering the probability and consequences of drought hazard in monthly and annual time-scale.

<Fig. 1. >

2.2. Draught Risk Probability

The probability of drought in the study area was calculated using the SDI method. This method analyzes river flow and drought extent to predict onset and duration. Historical flow data from 1990 to 2021 at the Chom-Bridge station were evaluated using DrinC software and the Gamma distribution was determined as the best fit. The calculation method of the flow drought index is summarized in equations (1) to (3), and a description of SDI scores and detailed of the drought classification are well explained in .

$$V_{i,k} = \sum_{j=1}^{k} Q_{i,j} \quad i = 1,2,3, \ldots \;\; j = 1,2,3, \ldots, 12 \;\; k = 1,2,3, \ldots \tag{1}$$

$$y_{i,k} = \ln(V_{i,k}) \;\; i = 1,2,3, \ldots \;\; k = 1,2,3, \ldots \tag{2}$$

$$SDI_{i,k} = \frac{y_{i,k} - \bar{y}_k}{s_{y,k}} \; i = 1,2,3, \ldots \;\; k = 1,2,3, \ldots \tag{3}$$

Where $Q_{i,j}$ and $V_{i,k}$represents the measured discharge and accumulative discharge, and i, j, k are months, water-year, and the number of months, respectively. Also, $\bar{y}_k$ and $s_{y,k}$ are the average and standard deviation, respectively.

The probability of the drought occurrence (P) was calculated based on equation (4), in which the SDI score's upper (max) and lower limit (min) vary in the range of (-4,4).

$$P = 1 - \frac{SDI - min}{max - min} \tag{4}$$

2.3. Draught Risk Consequence

2.3.1 Determination of the SWDS's operational performance assessment

To investigate drought risks in an irrigation district, performance evaluation indices were used to measure water distribution efficiency (called "O_Sc" in this article). These indices were calculated at different time scales and operating conditions using a hydraulic simulation model. The variables of these indices (Equations 5-7) were specified using the hydraulic simulation model which are the delivery discharge hydrograph to each individual off-take. The surface water adequacy index (Eq. (5)) shows the ability of the SWDS to meet the water-rights at the off-takes, the efficiency index (Eq. (6)) represents the system's ability to prevent any extra-water delivery at each off-take, and the equity index (Eq. (7)) evaluates the system capability in equitable water distribution through the entire off-takes located at each individual open canal.

$$Adequacy = \frac{1}{T}\sum_{T}\left[\frac{1}{R}\sum_{R}(P_A)\right] \qquad P_A = \frac{Q_D}{Q_R} \quad if \quad Q_D \le Q_R \quad otherwise \quad P_A = 1 \tag{5}$$

$$Efficieny = \frac{1}{T}\sum_{T}\left[\frac{1}{R}\sum_{R}(P_B)\right] \qquad P_B = \frac{Q_R}{Q_D} \quad if \quad Q_R \leq Q_D \quad otherwise \quad P_B = 1 \tag{6}$$

$$Equity = \frac{1}{T}\sum_{T} CV_R\left(\frac{Q_D}{Q_R}\right) \tag{7}$$

where Q_R indicate the off-take's water-right, and Q_D is representative of the off-take's delivered discharge, $\frac{1}{T}\sum$ & $\frac{1}{R}\sum$ are the period and number of off-takes in each open canal, and CV_R is the coefficient of variation.

2.3.2. The Simple Additive Weighting (SAW):

SAW method (Eq. (8)) is a popular technique used in multi-criteria decision-making for to combine different criteria and create a single overall measure for evaluating and ranking alternatives. This method is particularly useful when you have multiple criteria that need to be considered simultaneously in a decision-making process (Orojloo et al., 2018).

$$I_i = \sum_{j=1}^{n} W_j \, \mathrm{r}_{ij} \tag{8}$$

Where I_i is the risk's consequences, W_j is assigned weights, and r_{ij} normalized criteria using the min-max technique. In this study, two indices of adequacy and efficiency got a negative score, and the equity index got a positive score based on the intrinsic concepts of these indicators. Eq.s (9)&(10) define the positive and negative scores, respectively, as below:

$$r_{ij} = \frac{X_{ij}}{Max\ X_{ij}} \tag{9}$$

$$r_{ij} = \frac{Min\ X_{ij}}{X_{ij}} \tag{10}$$

Where r_{ij} is the normalized criterion, X_{ij} is the indices values, $Max\ X_{ij}$ & $Min\ X_{ij}$ represent the max & min indices.

2.3.3. HEC-RAS hydraulic simulation model

HEC-RAS performs one-dimensional hydraulic simulations along rivers and irrigation canal systems. The water surface profiles are achieved by solving the energy equation (Eq. 11) from one section to the next using an iterative algorithm according to the standard step method (Barkhordari et al., 2020):

$$z_1 + y_1 + \frac{\alpha_1 v_1^2}{2g} = z_2 + y_2 + \frac{\alpha_2 v_2^2}{2g} + h_e \tag{11}$$

where z_1 and z_2 are the levels of the main canal bed, y_1 and y_2 are the water depth in cross-sections, v_1 and v_2 are the mean velocity, α_1, and α_2 are the velocity coefficients, g is the gravity acceleration, and h_e is the energy loss. Energy loss (Eq. (12)) can be obtained by the summation of losses due to friction and the loss caused by opening and narrowing:

$$h_e = L\overline{S}_f + C\left|\frac{\alpha_2 v_2^2}{2g} - \frac{\alpha_1 v_1^2}{2g}\right| \tag{12}$$

where $\overline{S}_f$ is the slope of the energy line between two successive sections (Eq. (13)), C is the drop coefficient for opening and narrowing, and L is the weighted mean of the length of canal reach. The slope of the energy line at each point is obtained using the Manning formula:

$$s_f = \left(\frac{Q}{k}\right)^2 \tag{13}$$

where k is the section's transmission coefficient (Eq. (14)) calculated using:

$$k = \frac{1.486}{n} AR^{\frac{2}{3}} \tag{14}$$

where n is Manning's roughness coefficient, A is the section area, and R is the hydraulic radius. The HEC-RAS model inputs for this study included plan and profiles of the SWDS canal networks, structural data for conveyance, water-level control, and off-take structures, Manning coefficients, hydraulic coefficients, and boundary specifications for unsteady-state hydraulic simulation. This included inflow and structural boundaries and additional boundary conditions for time-varying flow simulation. The Root Mean Square Error (RMSE) (Eq. (15)) and Mean Absolute Error (MAE) (Eq. (16)) were used to compare the simulated and measured values in the n calibration and validation stage:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{n}} \tag{15}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - X_i\right| \tag{16}$$

where Yi and Xi are simulated and observed values, respectively, the water distribution and delivery (at the location of each off-take structure) were evaluated using the water delivery index's adequacy. Finally, the risk is calculated by multiplying the probability (*P*) and consequences (*C*) as shown in the (Eq. (17)):

$$Risk = P \times C \tag{17}$$

2.4. Roodasht Irrigation District

Roodasht Irrigation District is in the southeast part of Esfahan in Iran. It covers 31,000 ha, has an elevation of 1,510 m, an annual precipitation of 120 mm, and evapotranspiration of 1600 mm. Primary water supply comes from surface water and groundwater. Table (1) provides details on the main canal, and Fig. (2) shows the district's location.

The main irrigation canal in the area is 42.17 km long and supplied by the Zayandeh-Rud River, with a maximum capacity of 9 cms. It distributes surface water to 13 main Irrigated Units (IUs) through 14 duckbill weirs and 26 Nyrpic Module off-takes. This study found that 80MCM of groundwater was used in the 2020-2021 operating year, compared to lower amounts in previous years. Groundwater use has caused a drop in the aquifer's water level and an aquifer storage deficit. Aerial photos show no change in green areas during cultivation season. Insufficient surface water resources may be causing farmers to turn to groundwater exploitation. This district in central Iran is vulnerable due to frequent water shortages causing inflow fluctuations, conflicts over water rights violations, and groundwater deterioration from overexploitation.

<Fig. 2. >

<Table 1.>

The O_Scs considered as initial conditions for hydraulic simulation are as follows. It should be noted that, in addition to the normal scenario, the other scenarios presented are dominant patterns extracted from historical data of the district's operation between 1990-2021, where the canal inflow (at the diversion dam) occurred under unusual and unforeseen conditions.

Normal O_Sc: The flow deviation at the deviation dam covers the entire agricultural water-rights (historical probability of occurrence (HPO): 8.91%).

Mild fluctuation O_Sc: The inflow hydrograph at the head-source is oscillatory and variable compared to the total demand; discharge variation was (-20,0)% of the total inflow (HPO: 12.18%).

Moderate fluctuation O_Sc: The inflow hydrograph is oscillatory and variable compared to the total demand; discharge variation was (-40,-20)% of the total inflow (HPO: 17.51%).

Severe fluctuation O_Sc: The inflow hydrograph is oscillatory and variable compared to the total demand; discharge variation was in a range of (-60,-40)% of the total inflow (HPO: 15.61%)

3. Results and Discussion

In this section, the results of the drought analysis will be shared, including the probability of risk. Additionally, the hydraulic flow simulation results will be presented, which evaluate the SWDS's performance through indicators such as adequacy, efficiency, and equity. These results will form the foundation for determining the consequences of the risk analysis. Lastly, monthly and annual risk analyses will be provided.

3.1. Drought hazard risk probability

Based on historical base flow data at the hydrometry station, the probability of drought occurrence was determined through calculation using SDI index values. This process was explained in section 2.2. In Figure (3) and Table (2), the findings of the drought analysis are displayed. The SDI index was calculated on a monthly and annual basis and classified into seven categories according to the classification suggested by Hong et al. (2015). Based on the SDI index, June 2008-2009 had the lowest value with a magnitude of -2.42, classified as "Extreme Drought (ED)." On the other hand, February 2000-2001 had the highest SDI value of 2.74, classified as "Extremely Wet." The probability of drought classes varies from 0.63 to 0.80 on a monthly scale, corresponding to an average inflow variation of 0.87 to 1.73 cms at the diversion dam. In yearly intervals, the probability varies from 0.64 to 0.82 for drought classes, corresponding to an average inflow variation of 1.09 to 1.48 cms.To sum up this section, investigated the probability of drought hazards using SDI classification and determined the average range of inflow variations for each class as given in Table (2). The classification of inflow was used to select the appropriate inflow hydrograph for the unsteady-state hydraulic simulation. Seven drought classes were obtained, but they were reorganized into four categories to comply with operational regulations in the study area.

The drought analysis results were used practically to classify inflow in this irrigation district. This classification helps interpret the severity of drought for the operation and maintenance craw, which then reschedules water delivery planning and adjusts hydraulic structures manually based on the level of drought hazard.

<Fig (3). >

<Table (2)>

3.2. Drought hazard risk consequence

Section 3.2.1 presents the results of the hydraulic simulation and evaluates the performance of the surface water distribution over time and space. In addition, Subsection 3.2.2 explains the implications of the drought results.

3.2.1. Hydraulic simulation and SWDS operational spatio-temporal assessment

The MAE and RMSE indices were employed for the calibration/validation of the developed HEC-RAS hydraulic simulation model. These indicators values for calibration and validation were respectively obtained as 0.0091 and 0.0122 (m^3/s) for MAE and 0.0086 and 0.0072 (m^3/s) for RMSE for the steady-state model. Similarly, for the unstead-state model the indices values for calibration and validation were respectively obtained as 0.0110 and 0.0207 (m^3/s) for MAE and 0.0113 and 0.0129 (m^3/s) for RMSE. After comparing the calibration and validation results with other studies, it has been confirmed that they are reasonable. The RMSE and MAE indicators calculated in (Dejen et al., 2015; Kaghazchi et al., 2022) varied in the range of (0.035-0.037) and (0.020-0.022) (m3/s), respectively.

After calibration and validation of the hydraulic model, different O_Sc was assigned as the initial conditions for unsteady flow simulation. These operational scenarios, explained earlier in subsection 2.4, included Normal O_Sc (HPO: 8.91%), Mild fluctuation O_Sc (HPO: 12.18%), Moderate fluctuation O_Sc (HPO: 17.51%), and Severe fluctuation O_Sc (HPO:15.61%). The inflow range, diverted from the diversion dam, varied from a minimum of 0.5 to a maximum of 4.5 cms, as explained earlier and given in **Table (2)**.

Calculating the average discharge delivered to the 26 off-takes in SWDS was performed on an hourly, daily, and weekly time scales during simulation periods (142 to 184 days) ranging from 1990 to 2021, depending on the cultivating season. Based on the simulation results, it was found that there were more under-deliveries in off-takes that had higher capacity. Specifically, off-takes #4 and #5 in the 2nd and 3rd reaches, off-takes #8 and #9 in the 4th and 5th reaches, off-take #12 in the 6th reach, off-takes #19 and #20 in the 10th reach, and off-take #21 in the

11th reach experienced the most under-deliveries. Manual-based operating systems have led to over-delivery in upstream canal reaches and under-delivery in downstream off-takes. The simulated hydrographs show poor performance by SWDS, with significant discrepancies between delivered off-take discharge and water rights. Unsteady flow modeling provides clear insight, while systematic evaluation is done with indices (Eq. (5) to (7)). The SWDS performance evaluation analyzed operational performance (**Fig. 4 (a)-4(b))** and spatial distribution using GIS, in **Fig. 5 (a)-5(c)**. Efficiency was measured through water loss due to over-delivery, with monthly and yearly indices ranging from 0.962 to 1.00. Overall, SWDS's efficiency is considered "good," delivering less than 10% excess water to stakeholders.

The SWDS's ability to distribute water among stakeholders is measured by the adequacy index, which was found to be in the "average and poor" performance category with a monthly range of 0.060-0.886. This index has been consistently poor annually, falling within the range of 0.192-0.599. This leads to unreliable water supply and farmers resorting to digging tube wells. The number of deep and semi-deep wells has increased from 2014 to 2022 in the irrigation district.

The equity index measures how fairly water distibutes within an irrigation canal upstream to downstream. This index falls within the range of 0.227 to 0.724 for monthly intervals, and 0.353 to 0.627 for annual intervals. The water distribution system is performing poorly, resulting in unequal distribution of water to farmers. A spatial analysis was conducted, and the results are shown in Figures 5(a) to 5(c). This study has identified helpful spatial maps for managers to compare surface water distribution with groundwater extraction from scattered wells in the district. This information can assist managers in controlling groundwater extraction and mapping drought risks.

<Fig 4. >

<**Fig 5.** >

3.2.2. Drought risk consequence's on SWDS operation

The SAW method calculated the drought risk's consequence index. It was weighted based on a variety of perspectives from professors, researchers, activists, legal reps, and operation crews. Assuming that the adequacy index represents the technical criteria (W_{P_a}), equity index represents the social criteria (W_{P_e}), and the efficiency index represents the environmental criteria ($W_{P_{ef}}$), the interviews conducted with all of these target groups, and a summary of the practical interpretation of the conducted weighting scenarios (WSC) are explained below:

- ✓ **Farmers Representative (WSC#1):** They believed all three criteria are equally important in SWDS operational evaluation and then have a common weight of $W_{P_a} = W_{P_e} = W_{P_{ef}} = 0.33$.
- ✓ **Operational Craws (WSC#2):** They believed the technical criterion holds the primary ranking with $W_{P_a} = 0.50$, followed by the social and environmental criteria with $W_{P_e} = 0.33$ and $W_{P_{ef}} = 0.17$. Technical criteria affects water sales and revenue, while improving social index reduces complaints and costs for the operations team.
- ✓ **Regional Water Board (WSC#3):** It is worth noting that the weighting approach of regional/provincial managers concluded that the social ($W_{P_e} = 0.50$), environmental ($W_{P_{ef}} = 0.33$), and technical ($W_{P_a} = 0.17$) criteria have been placed in the first to last positions.
- ✓ **Environmental activists (WSC#4):** Naturally, as expected from environmental activist's standpoints, the environmental criteria hold the highest importance ($W_{P_{ef}} = 0.61;\ W_{P_a} = 11; W_{P_e} = 0.28$), representing the surplus water delivered at the off-take structures. Over-delivery has caused waterlogged areas, drainage and soil salinity issues, and violation of environmental water rights.
- ✓ **Researchers (WSC#5):** They believed the technical criterion holds the primary ranking with $W_{P_a} = 61;\ W_{P_{ef}} = 0.11; W_{P_e} = 0.28$.

Fig. 6. clearly illustrates the range of variations (max, min & standard deviation) of the integrated consequence index, categorized by different weighting scenarios in monthly time

intervals. Drought poses the greatest environmental damage (Fig.6(e)), followed by social perspective (Fig.6(c)) in second, economic and farmer's point of view (Fig.6(a)) in third, technical priorities (Fig.6(b)) in fourth, and a purely theoretical and design-oriented single-objective water distribution approach (Fig.6(d)), which typically dominates academic environments, in the fifth position.

<Fig 6.>

3.3. Risk Assessment Results

Fig.s (7)-(8) provide the drought hazard risk assessment results. A summary of the obtained results is listed below:

Fig. (7(a)-7(e)) shows the variation of the monthly risk for WSC #1- WSC #5, where the calculated risk variation range is (0.083, 0.764), (0.053, 0.769), (0.088, 0.765), (0.0415 to 0.773), and (0.116 to 0.750). Using WSCs classification is crucial for high-level officials in government to interpret results. The study shows that current surface water distribution systems are exhibiting unsustainable behavior, with performance levels nearing failure even in moderate drought conditions. This is justified by the SWDS operational appraisal benchmark.

<Fig 7.>

Figs (8(A)-(B)) show monthly and yearly risk assessment results in four inflow variation ranges of <1.5, (1.5,2.5), (2.5, 3.5), (3.5-4.5) cms representative of the four operational conditions of extreme-critical, critical, semi-critical, and normal following the irrigation districts' standard operating procedure. Middle managers and frontline supervisors should use the system's inflow classification to interpret results for optimal hydraulic adjustments and effective water supply planning.

The results show in Fig 8 show that the monthly and yearly risks vary in (73.7,76.1)% & (46.3,63.9)% under the extreme-critical condition; (46.0,53.2)% & (38.1,51.1)% under the critical condition; (24.4,35.1)% & (18.7,27.5)% under the semi-critical condition; and (16.6,25.5)% & (10.7,16.6)% under the normal condition. The SWDS needs to be maintained for optimal performance in wet conditions, but it is at risk of failure in drought scenarios.

<Fig 8. >

This study used a sustainable livelihoods framework to evaluate the impact of drought on irrigated apple production in South Africa's Western Cape. It compared its methodology and results to similar studies, including one by Theron et al. (2023). SDI and SWDS indexes were used to assess natural and physical capital, respectively. The approach was approved and based on Theron et al. (2023) methodology. Tsai et al. (2023) created a risk-based irrigation decision-making system to address prolonged drought impacts on the Shihmen Reservoir Irrigation District in Taiwan. By predicting water shortages based on demand and proposing recovery plans, the study highlights the importance of prompt action during drought periods. This approach could be integrated with similar systems for a comprehensive risk assessment.

Studies have assessed risks of poor irrigation water distribution caused by inadequate operation and maintenance. A few studies have been conducted to assess the risks associated with poor irrigation water distribution caused by inadequate operation and maintenance activities by utilizing fuzzy fault tree analysis (Babaei et al., 2018), fuzzy hierarchical framework (Orojloo et al., 2018), and multi-hazard risk assessment model based on hybrid Bayesian network Bozorgi et al. (2021). These study aims to clarify the risks associated with these systems when multiple hazards threaten various components simultaneously. The present study aims to build on previous research that emphasizes the importance of employing a proactive management approach to agricultural water management. However, this study proposes a practical risk assessment that specifically focuses on the hazards of drought and SWDS.

4. Conclusions

A new risk assessment approach has been introduced for evaluating irrigation districts' manual operating systems in surface water distribution. It helps identify the most suitable mitigation measures, ensuring safe, efficient, and sustainable water distribution activities. The investigation's findings can help dam owners and water supervisors with water management, emergency response, and recovery plans for optimal allocation. The results can determine if the system can meet water demands with surface and groundwater resources. The methodology provides reliable information for decision-makers on improving agricultural water infrastructure.

The proposed methodology improves routine inspections for groundwater withdrawal by analyzing the effects of the Surface Water Distribution System. The present study's assessment confirmed the unreliable performance of the investigated surface water distribution system and validated farmers' preference for using groundwater to meet their irrigation water demands. This study suggests an approach to investigate potential failure modes in hydraulic systems, which can aid in identifying vulnerable sections that may need replacing or decommissioning during long-term planning.

Based on research, it is highly recommended to upgrade the underperforming and ineffective manual operating systems in the agriculture sector with modern automatic control systems to address the urgent need for change. Failure to do so may result in uncontrolled groundwater overexploitation and environmental water-rights violations in developing countries. However, considering various aspects of the SDGs criteria when making decisions regarding SWDS modernization and revitalization is crucial. This may include incorporating environmental, technical, social, and economic criteria, or a combination of them. Therefore, it is essential to prioritize the modernization and revitalization of SWDS to ensure sustainable and responsible water management practices.

Declaration

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish Not applicable.

Authors Contributions

JP: Investigation, Methodology, Software, Modeling & Simulation, Formal analysis, Writing—original draft. - **SMHS:** Conceptualization, Supervision, Validation, Writing—Review & Editing. - **AR:** Conceptualization, Supervision, Validation, Writing—Review & Editing.

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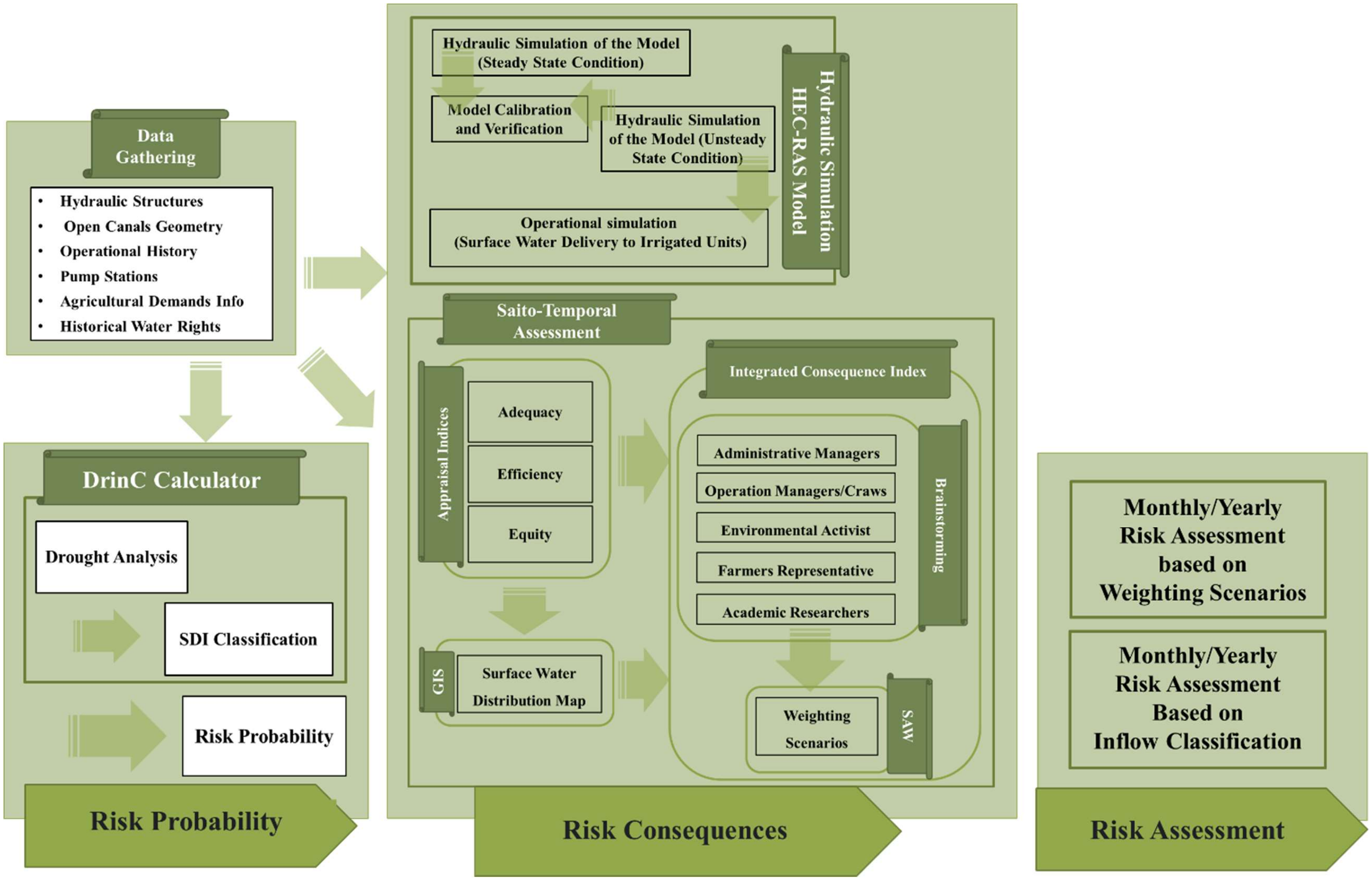


Data Gathering
Hydraulic Structures
Open Canals Geometry
Operational History
Pump Stations
Agricultural Demands Info
Historical Water Rights
DrinC Calculator
Drought Analysis
SDI Classification
Risk Probability
Risk Probability
Hydraulic Simulation of the Model (Steady State Condition)
Model Calibration and Verification
Hydraulic Simulation of the Model (Unsteady State Condition)
Operational simulation (Surface Water Delivery to Irrigated Units)
Hydraulic Simulation HEC-RAS Model
Saito-Temporal Assessment
Appraisal Indices
Adequacy
Efficiency
Equity
GIS
Surface Water Distribution Map
Integrated Consequence Index
Administrative Managers
Operation Managers/Craws
Environmental Activist
Farmers Representative
Academic Researchers
Brainstorming
Weighting Scenarios
SAW
Risk Consequences
Monthly/Yearly Risk Assessment based on Weighting Scenarios
Monthly/Yearly Risk Assessment Based on Inflow Classification
Risk Assessment

Fig. 1. Schematic view of the steps conducted in methodology of this study

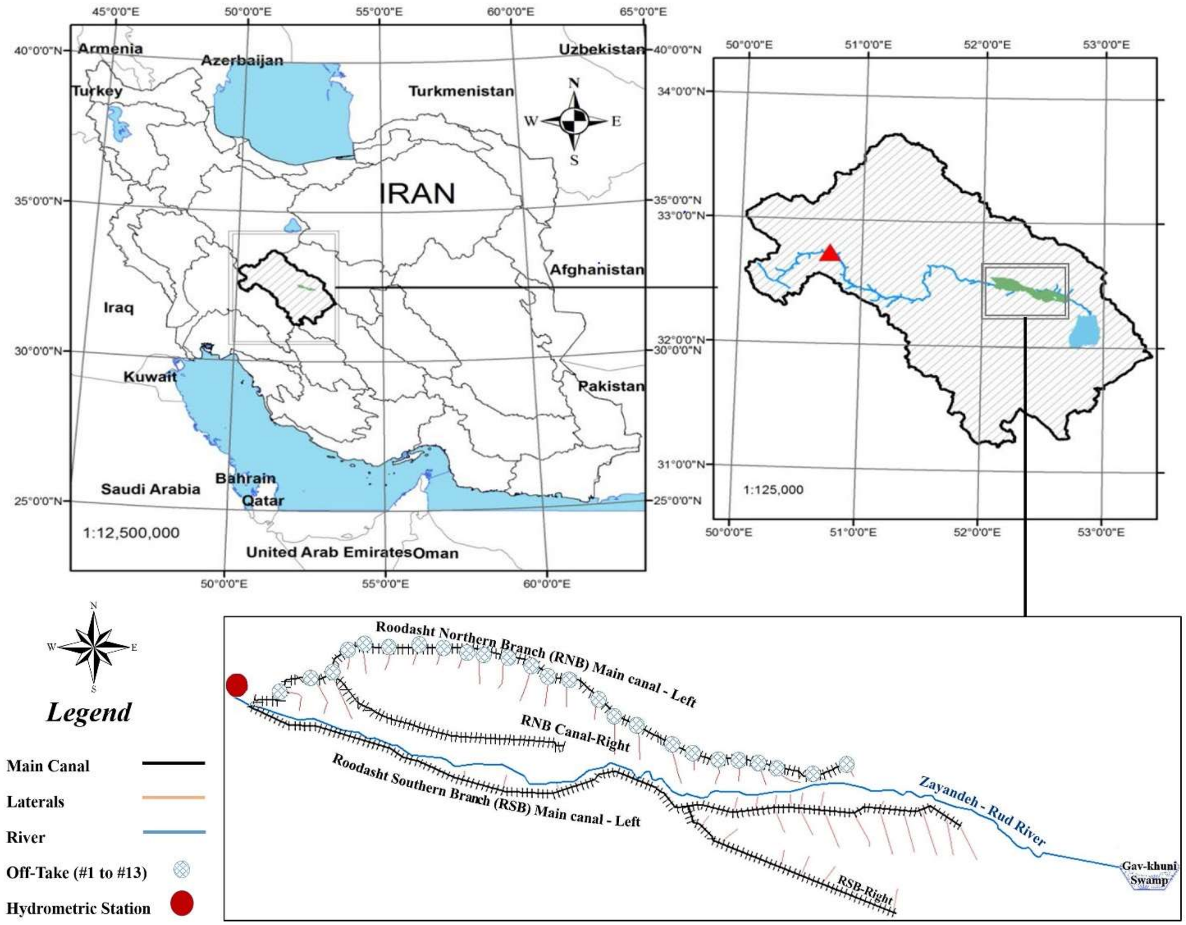


Fig. 2. Schematic view of the open canal networks responsible for surface water conveyance and distribution in the Roodasht Irrigation District, Esfahan, Iran

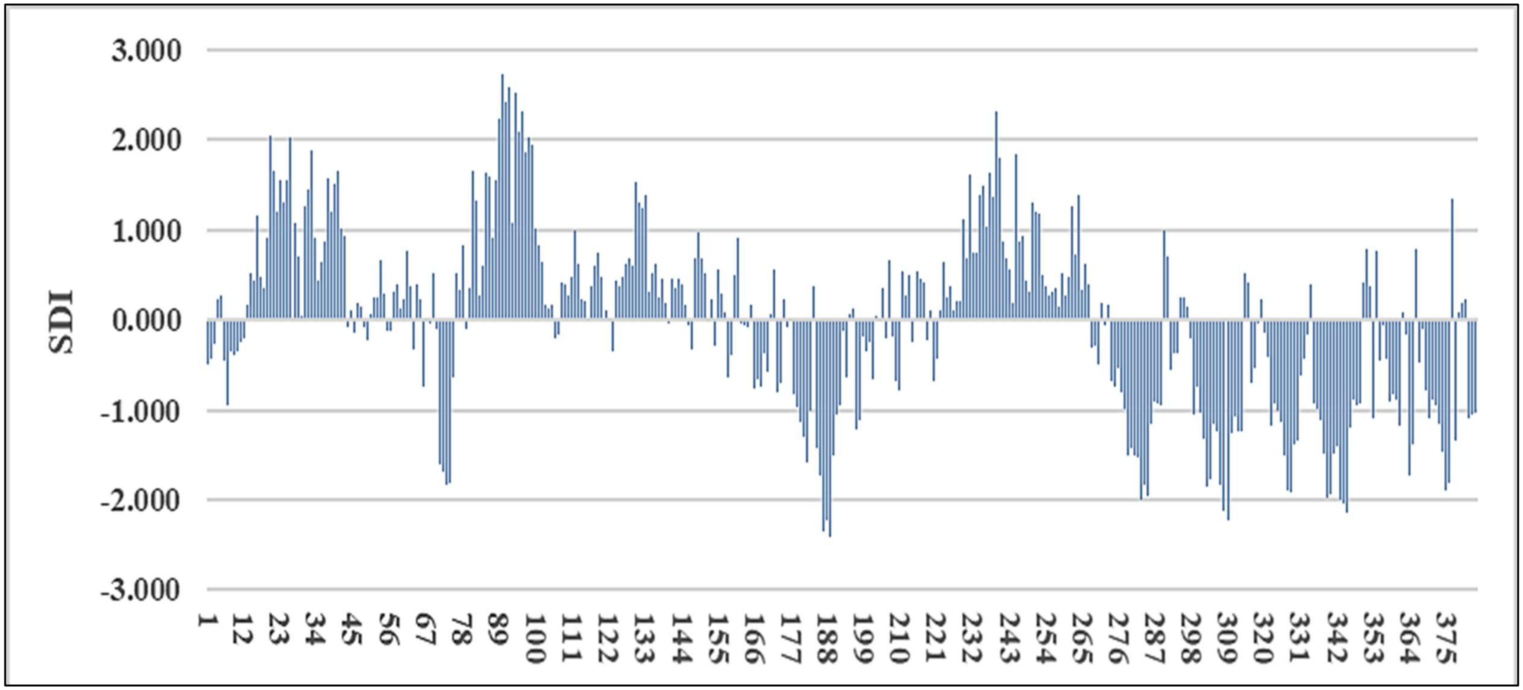


Fig (3). Calculated SDI index in monthly time intervals (1990-2021)

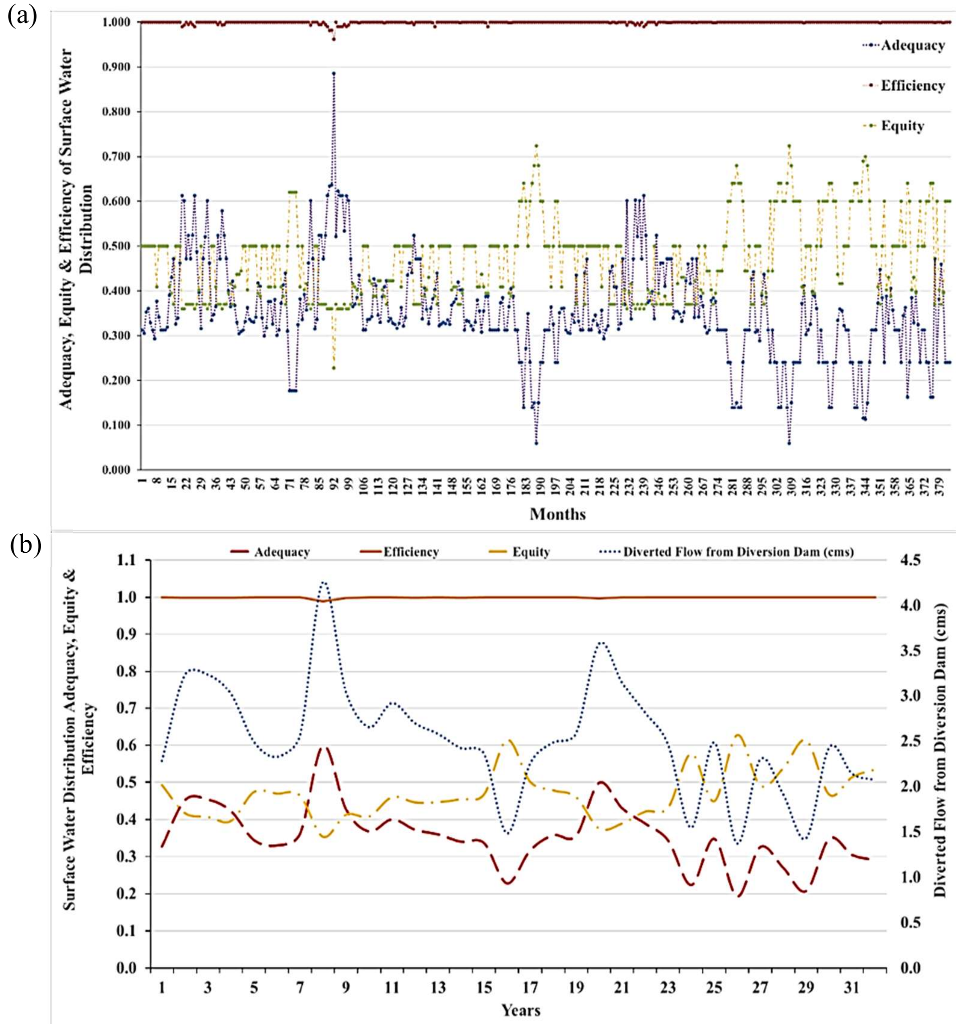

(a)
Adequacy, Equity & Efficiency of Surface Water Distribution
Adequacy
Efficiency
Equity
Months
(b)
Adequacy
Efficiency
Equity
Diverted Flow from Diversion Dam (cms)
Surface Water Distribution Adequacy, Equity & Efficiency
Diverted Flow from Diversion Dam (cms)
Years

Fig 4. SWDS operational performance evaluation based on the average values of the adequacy, efficiency, and equity (a) for monthly time intervals, and (b) for the yearly time interval from 1990 to 2021

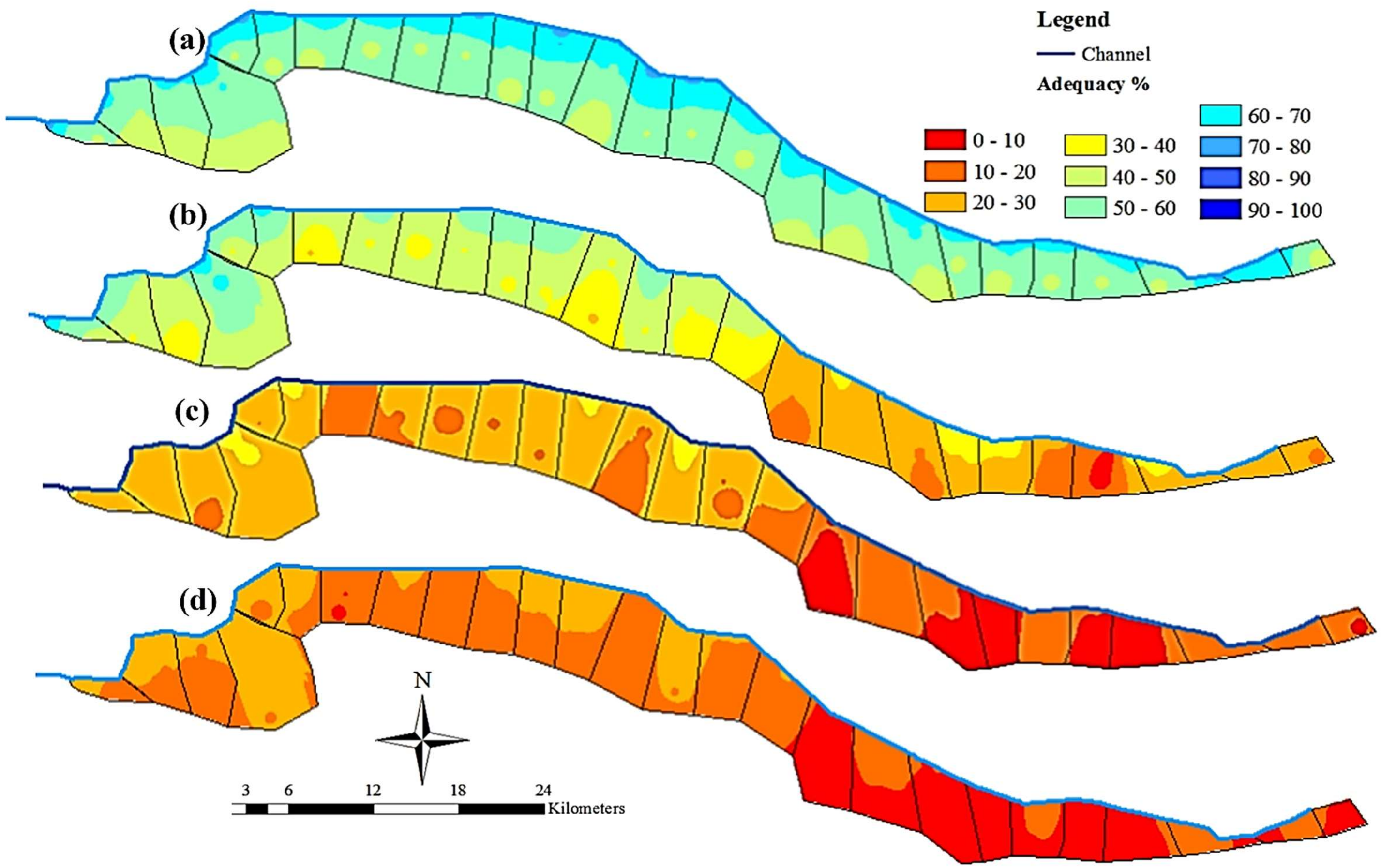
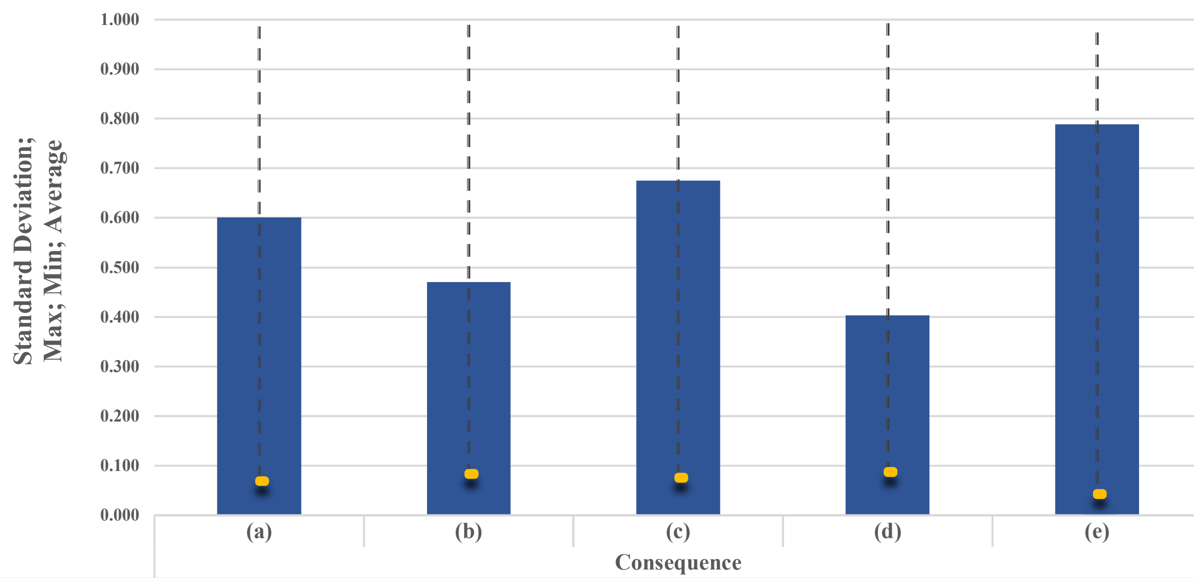


Fig 5. Spatial distribution of the average surface water distribution adequacy under operational scenarios of (a) normal operation in wet (inflow variation (4.62 to 3.90 cms), (b) normal operation in mild wet (inflow variation (2.05 to 3.90 cms), (c) mild-moderate drought conditions (inflow variation (1.1 to 2.05 cms), (d) severe drought conditions (inflow < 1.0 cms)



	(a)	(b)	(c)	(d)	(e)
Average	0.601	0.470	0.675	0.403	0.788
Max	0.986	0.990	0.987	0.993	0.974
Min	0.460	0.304	0.499	0.238	0.704
Standard Deviation	0.068	0.083	0.075	0.087	0.042

Fig 6. Calculated risk consequences of the weighting scenarios

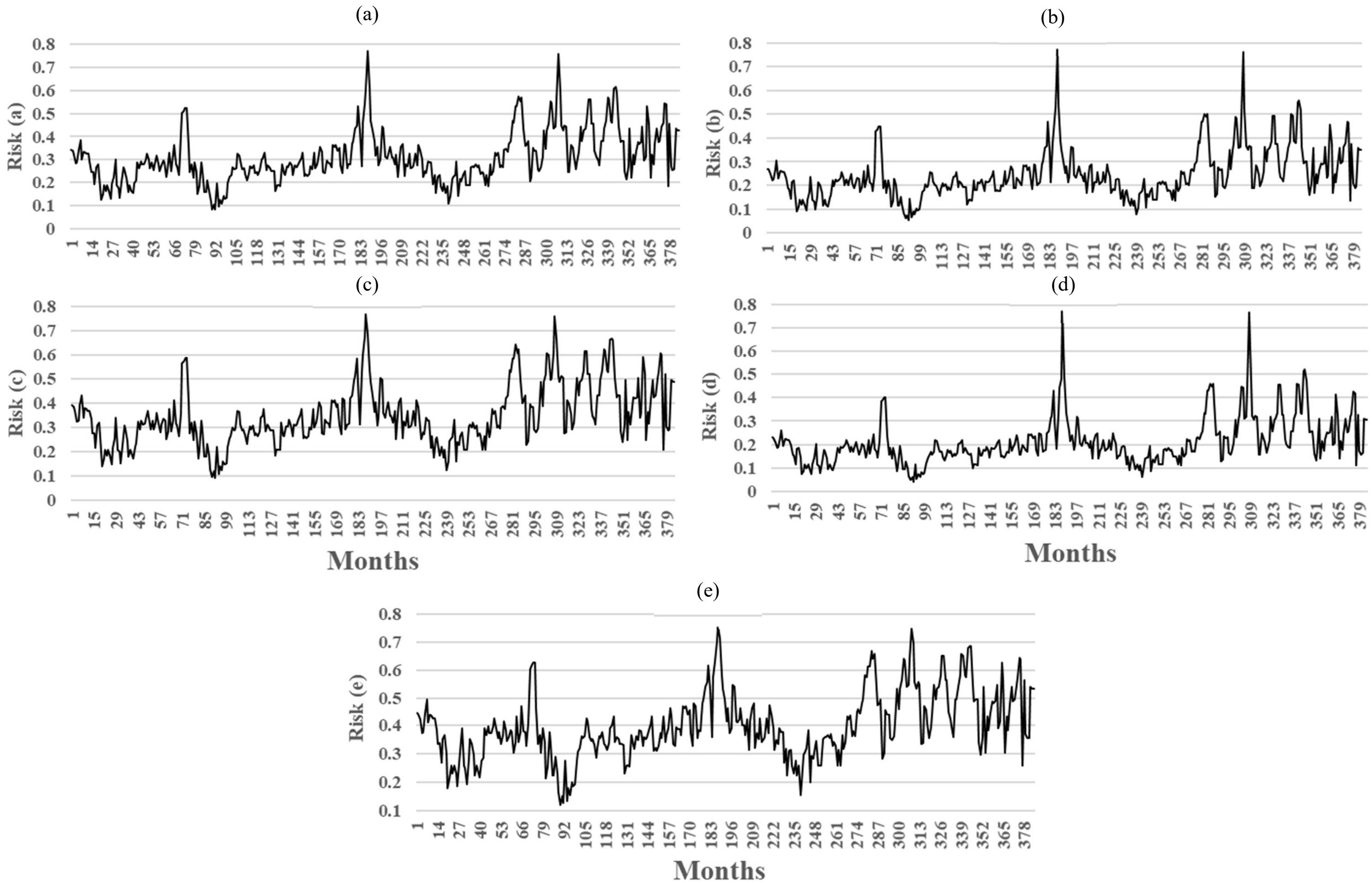


Fig 7. The results of the monthly risk assessment of drought are categorized by different weighting scenarios (a) to (e).

(A) (B)

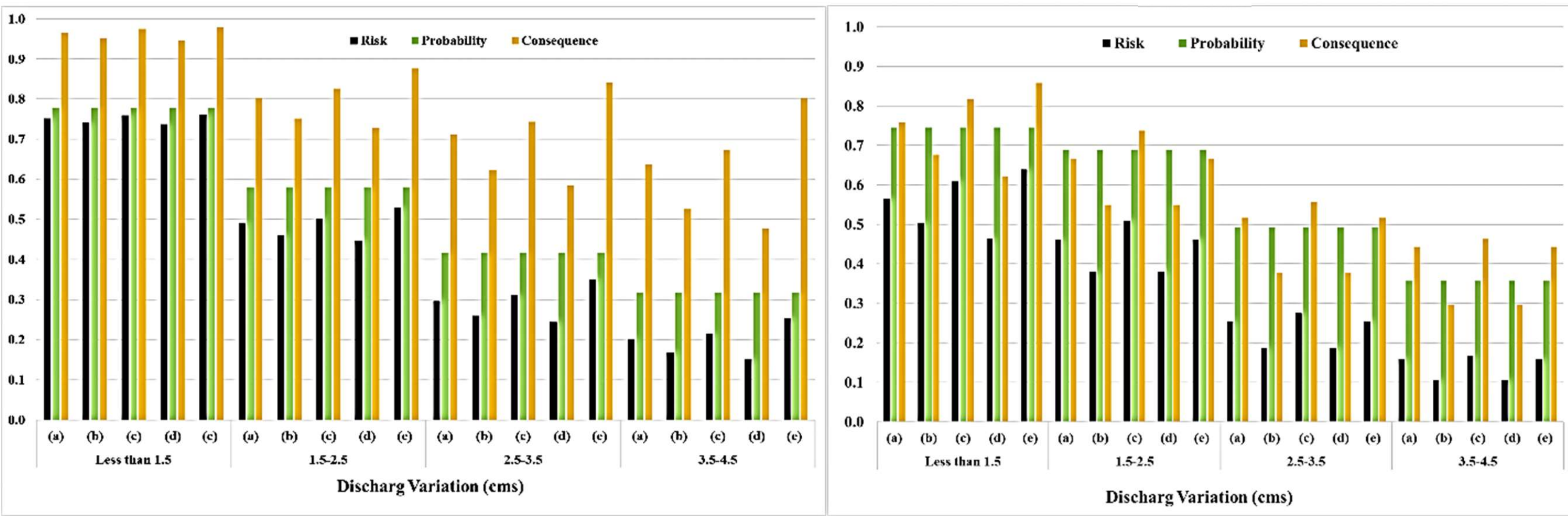


Fig 8. Summary of the risk assessment results included average risk, consequence & probability in (A) monthly & (B) yearly time intervals in four SWDS inflow categories and for individual weighting scenarios (a) to (e).

Table 1. Average monthly climatic information during the study and Roodasht main canal reaches physical properties.

Parameter	1990 - 2021									
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
Max. temp. (°C)	13.4	13.6	19.2	26.8	32.2	37.7	37.9	36.1	33.3	28.1
Min. temp. (°C)	-3.6	-2.0	5.2	10.6	15.2	19.2	22.1	18.6	15.0	8.0
RH (%)	39.4	38.8	35.1	26.6	24.3	9.4	10.3	12.5	12.8	16.5
Rainfall (mm)	0.1	0.5	0.3	0.3	0.4	0	0	0	0	0
Wind (m s^{-1})	0.8	1.3	1.4	1.8	1.6	1.6	2.2	1.8	1.2	0.9

Canal Reach	b (m)	y (m)	Length (m)	Canal Reach	b (m)	y (m)	Length (m)
1	4.2	2.5	5522	8	3.0	1.8	3062
2	4.2	2.5	4027	9	3.0	1.8	2451
3	4.2	2.5	2907	10	3.0	1.8	3322
4	3.8	2.0	3880	11	2.0	1.5	3261
5	3.8	2.0	2450	12	2.0	1.5	4104
6	3.8	2.0	2065	13	2.0	1.5	3061
7	3.0	1.8	2057	-	-	-	-

RH= Relative Humidity, temp=Temperature, b = canal width, y = canal height

Table (2). Summary of the drought hazard risk probability analysis

	Extremely Wet	Severely Wet	Moderately Wet	Mildly Wet	Mild Drought	Moderate Drought	Severe Drought	Extreme Drought
SDI range (Hong et al., 2015)	> 2.00	1.5 – 2.0	1.0 – 1.5	0.0 – 1.0	0.0 – (-1)	(-1.0) – (-1.5)	(-1.5) – (-2.0)	< -2
SDI Frequency (monthly interval)	10	11	19	24	160	101	49	9
SDI Frequency (yearly interval)	0	1	2	13	10	1	2	3
Drought's Probability (monthly) %	0.16 - 0.25	0.26 – 0.31	0.32 - 0.37	0.38 - 0.62		0.63 - 0.69	0.69 - 0.75	0.75 - 0.80
Drought's Probability (yearly) %	0.17 - 0.29	0.29 – 0.34	0.34 - 0.36	0.40 - 0.61		0.64 - 0.71	0.70 - 0.73	0.74 - 0.82
Average Inflow Variation	3.5 – 4.5 cms			2.5 – 3.5 cms		1.5 – 2.5 cms	< 1.5 cms	