Engineering Applications
https://publish.mersin.edu.tr/index.php/enap
e-ISSN 2979-9201

Investigating lake drought prevention using a DRL-based method

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Cite this study: Ghatoomi, H., & Partohaghighi, M. (2023). Investigating lake drought prevention using a DRL-based method. Engineering Applications, 2 (1), 49-59

Keywords
Drought simulation
Mead Lake
Entity Component System
Deep reinforcement learning

Research Article
Received: 09.12.2022
Revised: 07.01.2023
Accepted: 18.01.2023
Published: 03.02.2023

Abstract

Drought and decrease in the level of lakes in recent years due to global warming and excessive use of water resources feeding lakes is of great importance and this research has provided a structure to investigate this issue. First, the information required for simulating lake drought is provided with strong references and necessary assumptions. Entity-Component-System (ECS) structure has been used for simulation which can consider assumptions flexibly in simulation. Three major users (i.e., Industry, agriculture, and Domestic users) consume water from ground water and surface water (i.e., streams, rivers and lakes). Lake Mead has been considered for simulation, and the information necessary to investigate its drought has also been provided. The results are presented in the form of scenario-based design and optimal strategy selection. For optimal strategy selection a deep reinforcement algorithm is developed to select the best set of strategies among all possible projects. These results can provide a better view of how to plan to prevent lake drought.

1. Introduction

A drought is a period during which a region or area receives less precipitation than usual. Lack of sufficient precipitation, whether rain or snow, can result in lessened stream flow, crop damage, decreased soil moisture, or groundwater, as well as a general water scarcity. After hurricanes, droughts are the weather phenomena that cost people the most.

Multiple elements (such as the amount of rainfall, the amount of use of the input resources of the lake, the pattern of cultivation, etc.) are involved in investigating the phenomenon of drought in lakes [1]. The spatio-temporal feature of these elements also adds to its complexity. Investigating this phenomenon has several dimensions and the environmental, social and governmental effects should also be investigated [2]. Numerical design and optimization are used in different fields like engineering design [3,4] and are accepted as a optimal design approach [5]. Researchers have tried to investigate this drought in different ways. Some have analyzed it qualitatively [6]. And from quantitative perspective, some modeled the drought mathematically [7-9]. Simulations using neural network are helpful for a wide range of engineering problems [10]. Another group of researchers have used simulation to analyze drought [11-13]. The simulation of this phenomenon is a suitable tool to investigate the complex and interdependent nature of this problem and is used in different other complex interdependent systems for example in resilience assessment [14], disaster management [15], resource management [16] and regional disaster planning [17].

Since entire information and internal decision processes cannot be attained, the creation of accurate and comprehensive simulation models is further complicated. Therefore, generic drought simulators that let users test and apply their own models might be useful. To the best of our knowledge, there is not so much comprehensive simulation tool capable of applying complex assumptions in drought of the lakes, considering the appropriate elements. This work is trying to provide a simulation tool by examining the elements of a real sample for Lake Mead, which involves the spatio-temporal characteristics of different elements and considers the assumptions that bring the modeling closer to reality. neural network

We utilize a model of Lake Mead to show the concepts of the simulator, and it can be assessed by the availability of more accurate data through simulation experiments to prove the idea. By employing random distributions for each uncertain variable, this model can mimic uncertainties; however, it can be improved following the release of more precise data. We chose Lake Mead since it is one of the most significant lakes in the USA that is now experiencing a drought. By including random variables and logics in the programming framework used to create the simulator, managers may use this simulator to incorporate any required legitimate assumption and uncertainty.

This work's major contribution is to provide the fundamental structure and ideas for a generic, modular lake drought simulator, which managers and researchers may use to develop, use, and evaluate their own models. Supplying scenario-specific data, such as geo-spatial data related to the lake, is a crucial part for the tool. The quality of the input data has a direct impact on the simulation's quality and the results it produces. The tool can therefore be referred to as data driven. In short, can provide the following features:

- Capability of simulating different basins, integrating inputs and consumers of each element as well as upstream basins feeding the reservoir.
- Geoplotlib-based visualization toolkit [18] that can visualize time series flows and consumptions (such as water flows, agricultural fields and their consumptions, etc.) and provides real information on entities and other resources for convenient visual study.
- The generation of time series outputs and event logs at each time step.
- Tools for analyzing output data, for example tools that compute several Key Performance Indicators (KPIs) including lake surface level, policy effectiveness, and others.
- scenario analysis based on the advice of the expert and feedback depending on the outcome to help the managers make a better decision and optimal strategy selection based on a dep reinforcement learning algorithm.

For the case study, Lake Mead drought is used to build an initial case study (Figure 1). Millions of people in seven states, tribal territories, and northern Mexico get water from the biggest reservoir in the United States named Lake Mead. Additionally, it currently serves as a striking example of climate change and what may be the greatest lake drought in the American West in the past 12 centuries. Water levels in Lake Mead are at their lowest point since April 1937, when the reservoir was still being filled for the first time, continuing a 22-year downward trend. Only 27% of Lake Mead's capacity was reached as of July 18, 2022 [19].

(a) (b)

Figure 1. Trend of drought and watersheds **a)** Lake Mead drought trend **b)** Upstream watersheds in Lake Mead

2. Material and Method

The key components of the simulation framework are covered in this section along with more information on outputs and a description of the Lake Mead model.

2.1. Simulation framework

The simulation framework uses the Entity-Component System (ECS) architectural pattern and its implementation [20]. An entity component system is a system made up of three main elements:

- Entities: labels for simulated entities without behavior
- Components: Substances that provide entities data (properties)
- Systems: pieces that offer mechanisms for component implementation (e.g., flow patterns, water input, and outputs to the resources, policy formulators)

An ECS for a lake drought simulator (DrSim) is shown in Figure 2. Entities in yellow stand in for the simulation's objects, such as lakes, basins, and farmlands. Green is used to indicate their components, which offer data associated with entities. Lastly, the systems that update the simulation by altering the data in an entity's component at each time step are blue. These components are all included in the simulation environment.

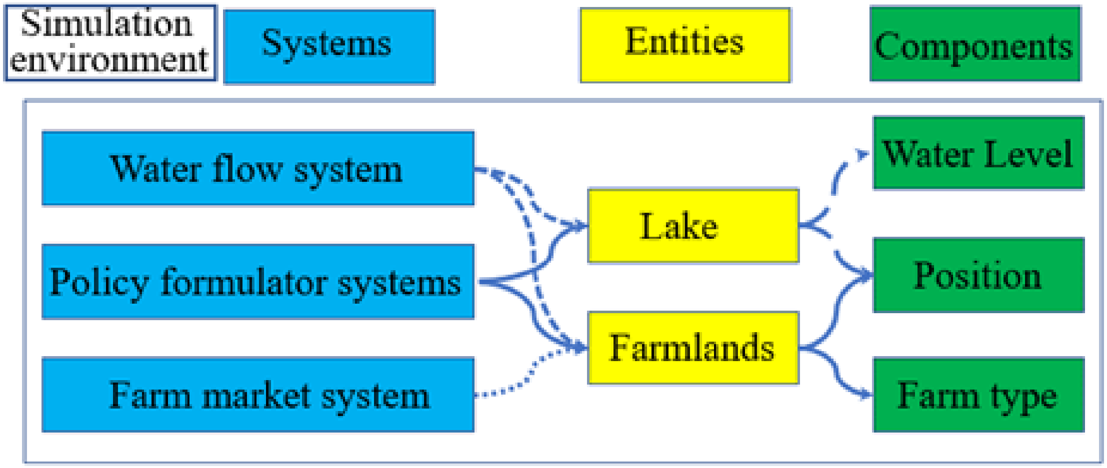

Figure 2. Simplified drought simulation environment

In this simulation with DrSim, dynamic decisions are made based on the analysis of defined logic and the conditions of other components and inputs, and it can evoke the principles of game theory that makes decisions based on players. DrSim can be considered as a central controller, which itself acts as a central decision maker for the rest of the system agents.

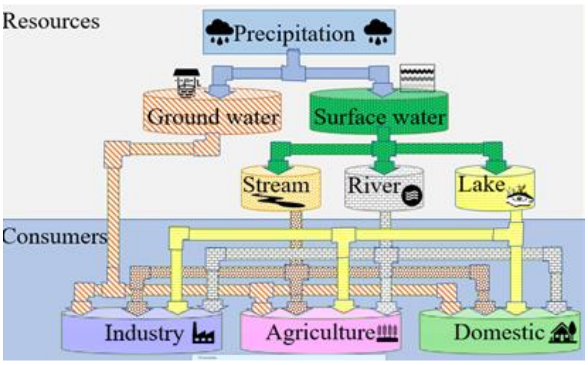

Figure 3. Water flow balance between resources and consumers

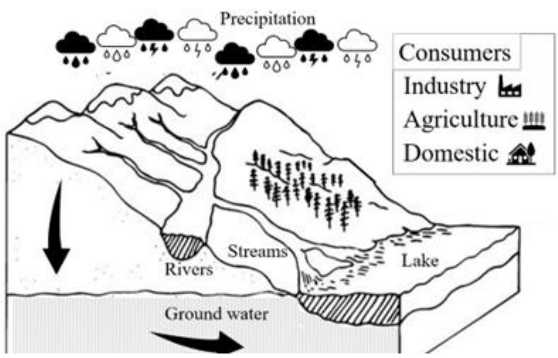

Figure 4. Watershed diagram in each catchment

Figure 3 and Figure 4 show the flow balance in each watershed. The inputs to the Lake are from the upstream catchments or precipitations and each watershed also can transfer water flow to other catchments. The water resources for each watershed are from precipitations which directs to ground water or surface water (including Streams, river waters and lakes). Consumers are industries, agricultures and domestic users which can supply water from different resources based on their logic dynamically. Geo-temporal characteristics of the inputs are considered in DrSim which is one of the important characteristics of the simulator that makes the results more realistic. This feature allows us to provide detailed analysis based on each specific element. For example, the fluctuation of the surface level of a specific lake can be monitored in a time series.

The systems in DrSim for making decisions about using water for each consumer are described in the following section. The required data are available in different formats like GeoJSON formats feeding DrSim.

Industry distributor system: Different types of industry consumers (e.g., thermoelectric power, mining etc.) can supply their resources based on the available resources nearby. This information is available in The United States Geological Survey (USGS) repository [21].

Agriculture distributor system: Each type of agriculture needs a certain amount of water in different periods which can be supplied from different water resources. This information is available in The United States Geological Survey (USGS) repository [21].

Domestic distributor system: Most of the domestic water are from Water treatments nearby the domestic area. They have their own logic and resources for distributing water. This information is available in The United States Geological Survey (USGS) repository [11] and National Water Dashboard website [22].

Visualization systems: Different visualization features can be used to visualize the inputs and outputs considering the great capability of python for mapping and providing interactive maps. The log files that track the geospatial outputs of DrSim are used to map the outcomes based on the requirements (Figure 5).

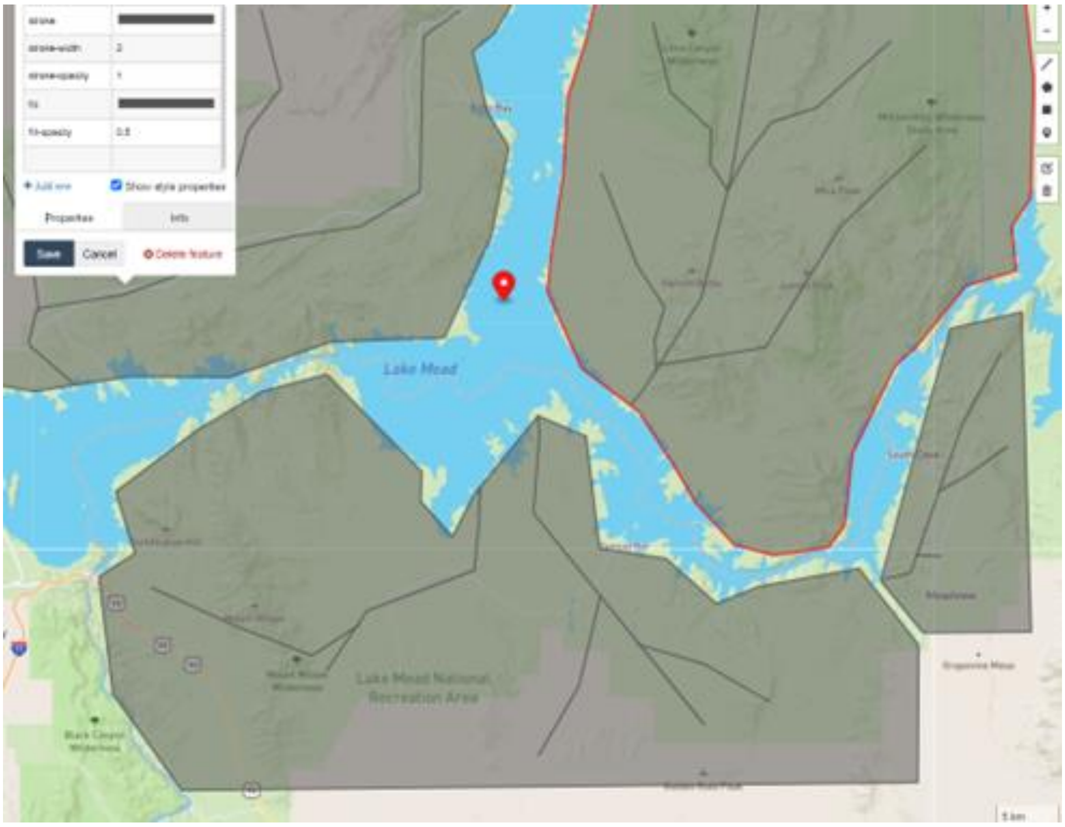

Figure 5. Interactive analysis for visualization of the outputs

Other optional systems can easily be embedded based on the availability of the data and the importance of the logic in the flow balance. For example, maybe the farm market can change the patterns of water consumption in agriculture in some places. A system for managing farm market can be added to DrSim by considering ECS concept and some extra coding.

Industry divided to resources (Ground water, Surface water, streams, lakes, and rivers) and consumers (industry, agriculture and domestic) based on Figure 3 described in the following section.

Ground water: Precipitation can feed ground water which are estimated based on the soil characteristics and other related parameters [23]. Groundwater resources can feed the consumers from wells and changes in the water level of groundwaters are tracked based on hydrodynamic models [24].

Surface water: Precipitation makes surface water based on intensity and other related characteristics which are estimated based on hydrodynamic models [25]. Surface waters are divided into three subcategories named streams, lakes, and rivers. Distribution of surface water in each catchment into these three resources are based on hydrodynamic estimation models and their characteristics.

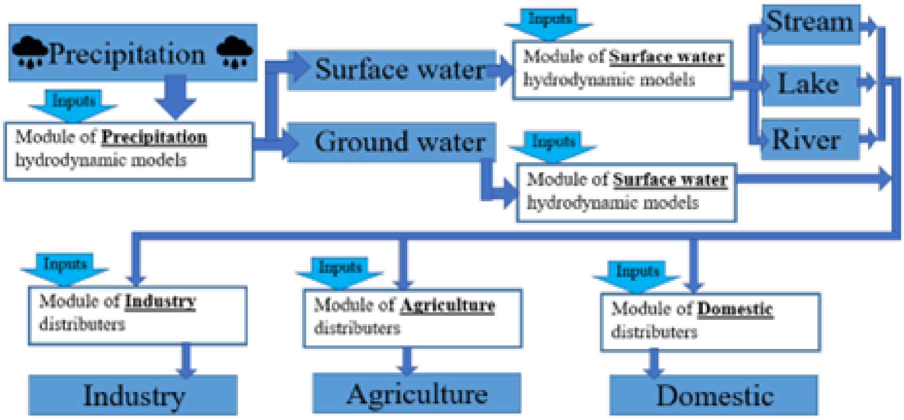

Figure 6. Diagram of modules for water distributions

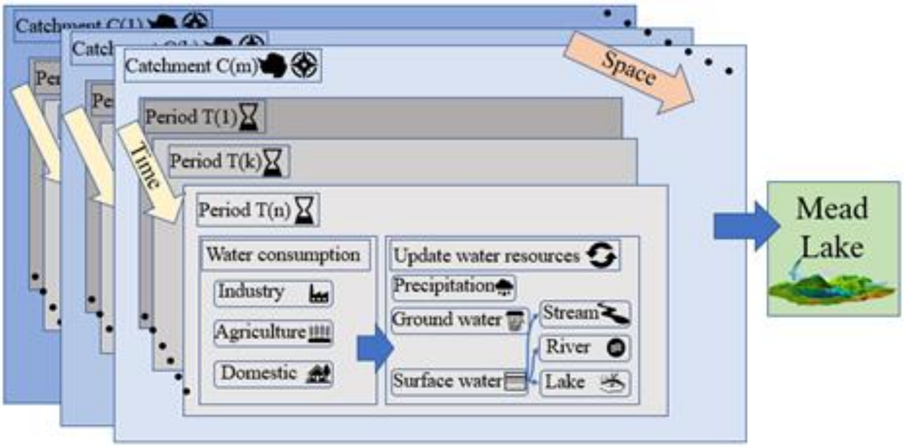

Figure 7. Framework and steps in DrSim

Figure 6 shows the required modules in DrSim for distributing water in each catchment. These modules are embedded in the model by defining logics based on the hydrodynamic models and logics for consumptions in industry, agriculture, and domestic entities.

Figure 7 shows the framework and steps in a round of simulation and how it can capture Geo-spatial characteristics of drought in Mead Lake. There are C(m) upstream catchments feeding Mead Lake. Each upstream catchment feeds nearby or downstream catchments to get to Mead Lake as shown in catchment map in Figure 1. Each catchment k is simulated in a time frame divided to T(n) period. in each T(k) period, water consumptions are calculated based on simulation modules of industry, agriculture and domestic. Then precipitations and water resources in that period are updated for ground water and surface water resources. These thread consequences in calculation of the final water feeding Mead Lake. A function for the level of water in Mead Lake is used to calculate the volume, height, and surface of water in Mead Lake.

There are some assumptions and logics for the simulation that are based on availability of data and the importance of considering those logics in the outcomes. DrSim provides the ability to test different assumptions easily by coding them in the body of simulation environment. For example, we can test to see which industry entities can change the water level the most and only consider those important ones in the final runs or how much detail is needed for simulating agriculture entities.

Some of the initial logic for simulating drought of Mead Lake are listed here. Note that these initial assumptions can be modified based on outputs and feedback.

2.2. Considering randomness and uncertainties in DrSim

One of the great features of DrSim is considering distributions for the parameters and inputs or other assumptions. Most of the parameters are not known clearly or are not available but there is an estimate or a distribution for them. For example, there is no exact data for consumption rate of water in a sensitive industry which consumes lot of water but there is an estimate from similar industries can be used for this industry. These estimates can be used as a distribution for that parameter and can be updated by availability of data in the future. These uncertainties are captured by assigning a distribution to each parameter (if required). Each run in the simulation uses a random value from that distribution assigned to that parameter and gives a distribution for the outputs rather than a specific value as a result. Uncertainties may also be for the logics forming a scenario. Anomalies also are the events with less probability but high impact in the system. For example, consider a situation where water consumption for a specific agriculture product has a distribution mean value of M. Due to the good market for this product, M can be doubled with probability of r. Therefore, in each run, if the random variable is less than r, then 2M is used for that specific run to consider this kind of uncertainty. This kind of simulation is used for precipitation systems where precipitations have a distribution, but they may have some decrease every K year named abnormal year based on the data from previous years. This is simulated with the same logic in the body of writing codes for each parameter. Figure 8 shows an algorithm for simulating these abnormal precipitations. These techniques can be used for other similar concepts based on expert's opinion.

Figure 8. Algorithm for simulating abnormal precipitations

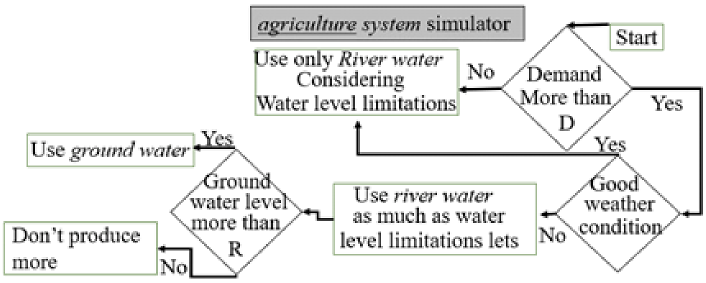

Figure 9. Diagram of resource constraint logics for agriculture system

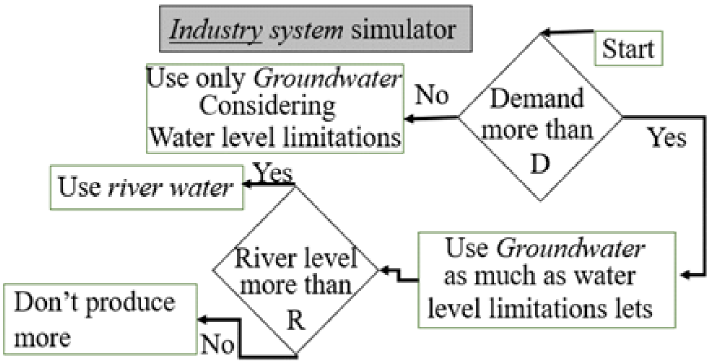

Figure 10. Algorithm for simulating abnormal precipitations

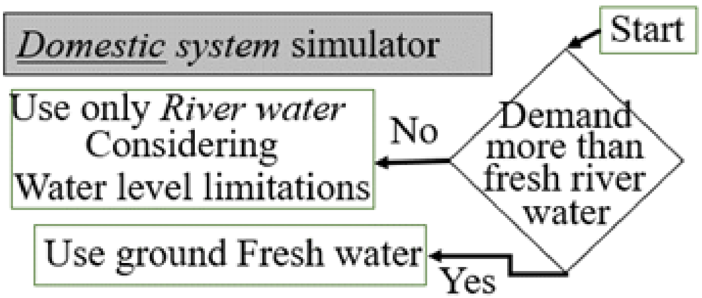

Figure 11. Diagram of resource constraint logics for Domestic system

2.3 Considering resource availability and resource-constrained logics:

System elements of ECS concept can treat as decision makers or in the other word, the elements of DrSim responsible for handling logics. Capability of simulating different assumptions within the body of each system provides the flexibility for logic and scenarios to be resource constrained. It means that each scenario may happen only if a certain amount of a specific resource is available. For example, a specific agricultural product is cultivated only if the water level of a nearby river is higher than a certain limit. Otherwise, they may decide to use groundwater resources or not to farm at all or any other reasonable assumption. Figure 9-11 show some of the resource constraint logics implemented in DrSim.

3. Scenario setup and Experiment

There are two types of design: Scenario based analysis and designing best strategies. In Scenario based analysis, a base case is provided with some basic assumption and the result of other scenarios are compared with the base case or other scenarios. Another approach is designing the best strategies with deep reinforcement design. For example, each project for reduction of water consumption needs some budget. The question is how we should assign this budget to different projects to get to the highest water level of the lake at the end of the design horizon. It is a more complicated problem that scenario-based analysis in which the simulation and design should be mixed to get the optimum design which is called simulation-optimization design. The optimization part can be based on metaheuristic optimizations like genetic algorithm, ant colony algorithm etc. For scenario design section of DrSim uses a deep reinforcement learning algorithm on top of the simulation to find the best allocation of budget between different strategies.

3.1 Scenario based analysis

Base scenario(B-Sc): In this base scenario, there is not any specific scenario and the base assumption for simulation is used based on the algorithm described in Figure *6*. This configuration serves as a baseline and the subsequent scenarios will be compared to this one.

Industry water reduction scenario (In-Sc): In this strategy, only Industry consumers reduce their consumption and the effect of these policies are tested and compared to the base case based on available resources [26]. Different combinations of industry consumers are tested in this scenario.

Agriculture water reduction scenario (Ag-Sc): Agriculture water consumers use a major water input and understanding how each type of product can change the water level of the lake is important. In this scenario, some types of agricultural products are not planted or are planted less so that the amount of lake level change in the design period can be checked [27].

Domestic water reduction scenario (Dom-Sc): The government can reduce the amount of Domestic water by developing public water conservation actions and encouraging plans to reduce urban water consumption or investing in the supply of fresh water from other sources [28]. Some of these strategies are selected and the changes in the lake water level are checked by applying these policies.

Combination reduction scenario (Com-Sc): Based on previous scenarios, a combination of some of the most significant scenarios are chosen and the outcomes are compared with the base case and other scenarios.

3.2 Optimal strategy selection:

In this section, we have a design problem in which a certain budget is assigned to a set of different industrial, agricultural, and domestic water conservation projects. The goal is to allocate this budget to the optimal set of projects to maximize the water level of the lake at the end of the design horizon. This is considered as a simulation-optimization problem in which DrSim simulates the nominated set of projects based on each allocated budget to different projects and a deep reinforcement learning algorithm on top of that finds the best budget allocation. Figure 12 shows the algorithm for this analysis based on deep reinforcement learning.

In a sequential decision-making process, reinforcement learning's objective is to maximize the expected cumulative rewards. Given a set of states $s(i)$ and actions $a(i)$, the agent performs action a after observing the current state s in each step, while follows to a set of policies π for water consumption reduction. Using the Bellmen equation [29], the anticipated return of each possible action an under state s is calculated.

$$\mathrm{Q}_{\pi}(s,a) = E\left(\sum_{i=1}^{\infty} \gamma^{i-1} R_i | S_0 = s, A_0 = a, \pi\right) \tag{1}$$

In Equation (1), discount factor γ is multiplied by reward R, to try to maximize the total future rewards in a sequential loop. This is implemented in simulation process in a sequential decision-making trend. States are the simulation frames of the environments and actions are all possible combinations that the parameters can be tuned. The policies are trained based on the actions that continuously provide better rewards. In Bellman Equation (1), it is hard to track all possible Q-values and optimize the best policy. Therefore, a Deep Q-Learning (DQN) algorithm is used to approximate Q-value based on a deep neural network. In each state s and the neural network weight of θ in DQN, the approximation of Q-values is provided from outputs of DQN for action $Q(s, a; \theta)$. Then a greedy action is selected based on $arg\ max_{a \in A} Q(s, a; \theta)$ which then tunes the parameters of the simulator. Figure 12 shows the DQN representation for DrSim. Some of the most important characteristics of the simulation environment indicate the current state. In an iterative manner, a gradient loss function is used, and weights of neural network are optimized. The details of the states, actions, rewards, and training are described as follows:

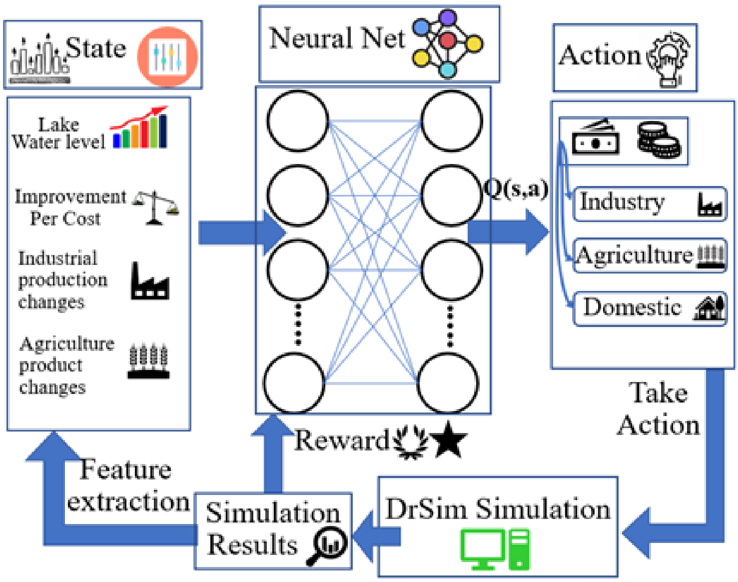

Figure 12. Interactive analysis for visualization of the outputs

States: we use some of the representatives of the lake environment based on the simulator. Sconce the lake water level and the ground water levels are important factors, they are saved. The industrial, domestic, and agricultural features representing the characteristics of consumers are also collected to provide information for the state of the simulation in each watershed.

Actions: The agent in each simulation step selects the action with the maximum expected cumulative reward (Q-value). The final changes in the water level in Mead Lake are based on the decisions that change the water consumption. Therefore, the actions are how much budget spend in each time step to each project. And the outcome of these decisions will change the water levels and water consumptions. These outputs can be used to feed reward sections and states of the DQN framework.

Rewards: in reinforcement learning, the agent decides based on positive or negative rewards. The agent uses Bellman equation to optimize parameters in neural network and find the optimal Q-value. The short-term reward can be calculated based on the number of changes in water levels after implementing that action in that watershed.

$$R = \sum_{m \in \omega} (\mu_m) \tag{2}$$

Where ω is the set of industrial, agricultural, and domestic water reduction projects in each watershed. The definition is that in each step we try to minimize the water consumption aiming to maximize the final water level in the lake. This is a complicated decision that depends on previous and future decisions and states but the capability of DQN for training the policies based on previous decisions will help to find proper actions.

Training: in the simulation, weights θ are updated by gradient descent function by minimizing the following loss function:

$$L(\theta) = E_{s,a}\left[\left(Q^* - Q(s, a; \theta)\right)^2\right] \tag{3}$$

Where $Q^* = R + \gamma\ max_{a'}\ Q(s', a'; \theta)$ tries to find optimal Q-value, which is the summation of short-term reward R and the optimal Q-value of the next step. The γ term is the penalty term for future rewards. In this algorithm a $\varepsilon - greedy$ strategy is used to consider the trade-off between exploration and exploitation. Therefore, with probability of ε, a random action is chosen instead of the optimal action for exploration and avoiding local optimum issues. After calculation of loss function, Weight θ are updated using gradient descent. The gradient of θ is given as follows:

$$\nabla_\theta L(\theta) = E_{s,a}[(Q^* - Q(s,a;\theta))\nabla_\theta Q(s,a;\theta)] \tag{4}$$

This algorithm is described in the following pseudo code:

Algorithm 1. Training of the Deep Reinforcement algorithm

Initialize parameters θ for the simulation
for each episode:
for each simulation set:
/ *Actions and simulating */
if $random() < \varepsilon$ **then:**
Select a random action a:
else:
Select $a = max\ Q(s,a;\theta)$:
end
Get short-term reward R and new state s' by simulating action a;
Save state transition data (s, a, s', R);
/* Updating Q-network parameters*/
Sample batch state transition $\{(s, a, s', R)\}$;
if simulator terminated **then**:
$Q^* = R$
else:
$Q^* = R + \gamma\, max_{a'}\, Q(s', a';\, \theta)$
End
Use equation 1 to perform using gradient descent on the loss $L\ (\theta)$ based on Q^*;
end
End

4. Simulation outputs

There are different outputs based on the framework for DrSim. First, the results for each individual decision-making procedure. Second, the result for different experiments and analysis for scenario-based analysis and the optimal strategy selection mentioned in section 3 (Scenario setup and Experiment).

The output data for each consequence of actions are logged for ground water, surface water, streams, lakes and rivers and consumers (industry, agriculture and domestic). Two kinds of output files are provided: one for events and one for the entity's metrics over time. Events are defined in DrSim as transitions in an entity's finite state and for each event the type, timestamp, water levels, output and input waters, and other entity info (e.g., consumptions, produced products etc.) are recorded. These geo-temporal data are collected in geo-temporal data frames which can be used for visualization and additional data analytic analysis. Writing the codes in python and using GIS based programing makes it simple to analyze outputs and inputs visually in interactive maps. Figure 5 shows an example of an interactive outcome for some polygons and streams nearby Mead Lake. This analysis can be shown over a period as well to show the trend of changes over time. It makes it easy to track anomalies in simulation and provides insight into different scenarios visually. The visualization also displays entity-specific metrics on mouse hover.

Other results are based on comparison of different kinds of scenario setup. These comparisons are based on scenario-based analysis where a base case is compared with other scenarios. For the Optimal strategy selection section, we provide a set of results related to the best strategies and budget allocation to projects. Also, the results for efficiency of DQN algorithm are provided.

5. Conclusion

The phenomenon of drought has become widespread. There is a need for a scientific structure to examine its various dimensions. This research first identifies the necessary and effective components and assumptions in the drought of the lake. Then it provides a measurable structure using the concept of ECS and explains its components. The elements and assumptions of DrSim simulator are explained. To analyze the water level of the lake under different conditions, two types of analysis are performed. First, the level of the lake has been examined in a scenario-based manner, in which a base case is compared with scenarios in which industry, agriculture, and urban users have each reduced water consumption. The next analysis is the optimal strategy selection, where a specific budget has been considered to reduce water consumption and should be optimally divided between various agricultural, industrial, and urban projects to finally achieve the maximum level of the lake water. In this case, a deep reinforced learning algorithm has been used to select the best set of projects. This article presents the basic structure and sources of information needed to investigate the drought phenomenon and how to analyze the lake level, but the providing simulation results with real data is considered for future work. The accuracy of the output results depends on the quality of the input data. Although it has been tried to use accurate and referenced data, one of the limitations of this work is the need for more accurate references for model inputs.

Funding

This research received no external funding.

Author contributions

Hadi Ghayoomi: Conceptualization, Methodology, Writing-Original draft preparation. **Mohammad Partohaghighi:** Data curation, Writing-Reviewing and Editing

Conflicts of interest

The authors declare no conflicts of interest.

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