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The effect of climate on water resources in Iraq using AI

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Abstract

Climate change is increasingly affecting global water resources, considering their availability, quality, and distribution. The temperature rise, altered rainfall pattern, and extreme weather incidents further water challenges brought gains in vulnerable but dry areas. In this regard, the study adopted the utilization of AI, in particular, machine learning approaches for climate adaptation sciences concerning water resources. The models of decision tree, Naive Bayes, and linear regression evaluate relationships between temperature, humidity, wind speed, evaporation, and subsequent water balance using climatic data from 1991 to 2021 for three Iraqi governorates: Diwaniya, Najaf, and Karbala. The discovered trend indicates that rising temperature causes an increase in evapotranspiration brought about by water deficiency that persists. The application of AI in the research reflected that while the models can capture long-term phenomena at a gross scale, they are limited in making precise predictions, thereby making it imperative to develop solutions with ensemble learning and deep neural networks. Another thing gleaned from the study is the importance of AI as a complementary tool for water resource management based on data in the face of climate change. Another factor worthy of attention would be how to address the limits of the present when it comes to using data, model interpretability, and interdisciplinary integration so that we can define and implement sustainable climate adaptation options for tomorrow's water security. This study fills the gap in knowledge as it adopted a novel model using AI to predict the effect of climate change on water resources in Iraq. This study also opened a wide gate for future research in this domain.

Keywords: Artificial intelligence, Hydrological modeling, Rainfall prediction, Streamflow forecasting, Groundwater management, Water quality monitoring

1. Introduction

Currently, humanoid requirements are boundless [1], [2]. Increase in demand for various resources is highly related to the rise of population [3], [4], [5]. Nevertheless, these events harmfully influence the environment [6], [7]. Thus, discovering new methods to control those problems is highly required [8], [9]. Clearly, climate change, influence on resources of water resources has become more undeniable [10], [11], warranting a substantive evaluation of current trends in the subject matter [12], [13]. With sea levels expected to increase by the year 2080 due to climate change, freshwater supplies will be reduced by 10% to 30% in most tropical and arid regions [14]. Amoo and Fagbenle [15] state that developing countries are the most susceptible to climate change. Other climate risk factors in developing nations in Asia and the Pacific include the presence of Asian river deltas, exposure to coral reef damage [16], cyclone activity [17], and high risks to economic growth [18]. Water resources are essential for the maintenance of biodiversity and the delivery of social and economic benefits for people [19], [20], [21]. With rising temperatures, water resources are already heavily impacted [22], which is expected to worsen the symptoms of environmental change and future repercussions [23]. Such changes are due to a shift in economic activities, increased industrial activities, a rise in pollution, and demand for energy and water [19]. Srivastav et al. [24] provided extensive literature on different strategies for dealing with water supply problems created by climate change. According to the IPCC AR5 assessment [14], a global warming of 4°C by 2100 will have drastic consequences on water resource supply and demand across the globe. It is also predicted that the net effect of water supply and demand could widen the supply-demand gap and aggravate the existing water management problems [23]. Climate change can directly influence groundwater supplies as a result of predicted alterations of rainfalls, evapotranspiration, as well as spatiotemporal distributions of these essential water balance jets [25]. An increase in rainfall may result in greater runoff values, flooding probabilities, and lower groundwater recharge [26]. If temperatures rise, then the respiration and evapotranspiration induced by this higher temperature will result in increasing irrigation demand [27]. Climate change effects on water levels should, therefore, be assessed at regional and down to basin levels for water management to prepare for future issues. This problem has gathered more research focus over the last few decades [24].

Thus, more recently, some studies [28], [29] have combined machine learning with climate projections from the future to examine climate change influences on groundwater [30], [31]. The Danish case study has been presented in [32] for predicting groundwater level variations in a changing climate. While Chen et al. [33] estimated shallow groundwater levels within the Wuqiao area of the North China Plain, human activity, and climate change impacts comprising about 20 models were analyzed. Afterward, a training process for back-propagation ANN was implemented using collected data, including weather conditions and pumping rate, to regenerate ground water level values. Future climates would then be projected, and the trained network would be assigned to simulate groundwater levels regarding changes in climatic variables by taking into account the ensemble mean of the climate models. Chang et al. [34] developed two artificial neural networks (ANNs) to appraise, model, and forecast suprapermafrost groundwater levels. Having been trained on simple temperature and precipitation data or historical records of antecedent groundwater levels, temperature, and precipitation in past years, scientists examined by scientists on different precipitation and temperature scenarios to see how this change would affect groundwater levels. Recently, ANN as an application of artificial intelligence techniques [35], [36] can be considered as one of the most efficient tools in problem solving [37]. Therefore, adopting such a tool can be very beneficial in this domain. Idrizovic et al. [29] considered climate change influences on the Toplica River basin in Serbia. Afterward, the study implemented a model for simulating runoff based on registered data, including precipitation, temperature, and potential evapotranspiration. Ghazi et al. [31] carried out comparisons for groundwater level variation that had been observed for the desert plateau in Iran. The study covered modelled climate change circumstances between three methods of machine learning: ANN, AVM, and NARX. The outcome indicated that NARX is the most effective method in predicting groundwater level variations.

While the above-described machine learning techniques are helpful in several domains [38], [39], especially in predicting groundwater levels, their supervised nature limits their capability to infer information outside of the training dataset. Input data for the machine learning models may deviate from the range defined by the learning dataset due to anticipated rises in global warming and severe weather conditions, i.e., temperature and precipitation, which becomes a reason for inaccurate results [40]. To address the extrapolation problem, new deep learning techniques were proposed. Few studies adopted the design and construction of specialized models in the domain of groundwater level prediction based on deep learning. Nourani et al. [41] implemented a comparison among these methods; LSTM neural networks for the groundwater level time series prediction over history with conventional feed-forward neural networks, an auto-regressive integrated moving average model, and exogenous input data. The results indicated LSTM to be the best performing compared to the other two methods. Wunsch et al. [42] adopted a deep learning approach with the assistance of CNN to examine climate change effects on groundwater supplies for 118 widely dispersed locations in Germany. The networks were trained by the authors to reproduce piezometric values using historical meteorological data. Then, using temperature and precipitation forecasts from various climate models based on various RCP scenarios (RCP2.6, RCP4.5, and RCP8.5), they employed the trained CNN models to study future groundwater levels. In addition to these studies previously abstracted, a number of reviews in this domain were covered [43], [44]. The review exposes that no such study was implemented to adopt artificial intelligence as a recent effective technique to cover the effect of climate on water resources in Iraq. Therefore, this study aims to fill this gap in knowledge using AI models in evaluating how climate change affects the levels of water resources [45], [46]. Three artificial intelligence (AI)-based approaches are contrasted: Naive Bayes, decision trees, and linear regression. The three machine learning models were developed using the MATLAB computer environment.

2. Methodology

An organized research process is necessary in order to harness AI regarding how climate change affects water supplies. Decision tree and Naive Bayes algorithms are reliable and explicable techniques to simulate a complicated environmental interaction for evaluating the climate change influences on water supplies using artificial intelligence. Especially suitable in this context, decision trees can simultaneously handle continuous and categorical variables, thus ideally combining hydrological results such as river discharge, reservoir levels, or groundwater fluctuations with a variety of climate indicators like temperature, precipitation, humidity, and wind speed. By creating a tree-like structure of decisions on the input variables, the model reveals trends and important thresholds that govern water availability variability. This ultimately enables scientists and decision-makers to understand not only what is happening, but also how particular transformations within a climatic situation might lead to particular hydrological outcomes. The Naive Bayes classifier, which is rooted in Bayesian probability theory, becomes relevant for a given set of observable climatic variables in estimating the likelihood of water resource situations (such as drought or flood conditions). While it oversimplifies situations, Naive Bayes can work very well even under extremely high-dimensional datasets, as would usually be the case when handling huge amounts of climate and environmental data, making it very computationally economical. When used in tandem, both models can be complementary, with Naive Bayes providing probabilistic classification for anticipating future scenarios and decision trees providing interpretability and rule-based insights. When used in tandem, they may strengthen early warning systems, advance techniques for managing water resources, and facilitate flexible policymaking to eliminate the influences of a changing climate.

A straightforward and practical probabilistic classifier that relies on adopting Bayes' theorem is the Naive Bayes classifier. Every attribute's element is treated as an independent variable by Naive Bayes. In addition to being highly effective at supervised learning, this classifier may be used to address challenging real-world scenarios. The training examples' attributes were all thought to be independent of one another. Every pattern (X) is represented by the Naive Bayes classifier as a vector with n dimensions for attribute values denoted by [a1, a2, a3,......an] and class numbers [c1, c2, c3....cn]. X is allocated to a class according to Equation 1 [47] where,

$$(Ci \mid X) > (CJ \mid X) \quad (1)$$

For $1 <= j < i$ and $j \neq i$ using Equation 1, getting Equation 3 [47]:

$$(Ci \mid X) = (X \mid)(Ci)\ P(X) \quad (2)$$

The classifier makes the naive assumption that the features (which is indicated by n for its total number) are conditionally independent of one another to reduce the calculated expenses to estimate the continuous probability of the data set. Equation 2 [48] can be used:

$$(X|Ci) = \prod (xj\ |Ci)\ n\ j{=}1 \tag{3}$$

When P(X)=constant for each class and $P(CJ) = |Ci \mid N$, the Naive Bayesian classifier must raise $P(X|Ci)$ just because it computes class distribution alone, which lowers computation costs. Because the Bayesian classifier only has to scan data once, it is relatively easy to use and offers excellent accuracy [48].

C4.5 is a decision tree algorithm that builds a decision tree from training data by operating on theoretically quantified information, considering gain and gain ratio. For each specific training set, each sample owns the same structure. Two groups into which the food product training set (TS) is usually separated: acceptable level (AL) and unacceptable level (UL). Next, the data (I) needed to identify a TS element's class is supplied by Equations 4 and 5 [49].

$$\mathrm{I(TS)} = \frac{|\mathrm{AL}|}{|\mathrm{TS}|}\ \log 2\ |\frac{|\mathrm{AL}|}{|\mathrm{TS}|} - \frac{|\mathrm{UL}|}{|\mathrm{TS}|}\log 2\ \frac{|\mathrm{UL}|}{|\mathrm{TS}|} \tag{4}$$

$$\mathrm{Entropy} = -\sum(\mathrm{p(i)} * \log 2(\mathrm{p(i)})) \tag{5}$$

where p(i) is the proportion of data points in the set that belong to class i.

The data obtained on a single feature distinguishes between information required for identifying a TS element and the information required to recognize a TS element once the function's meaning has already been determined. As a result, the understanding gained regarding xk can be attained using Equation 6 [49].

$$\mathrm{gain}_{(\mathrm{xk,\ TS})} = \mathrm{I(TS)} - \mathrm{I(xk,.\ TS)} \tag{6}$$

The decision tree's root is the attribute that has increased the most. Finding the feature that offers the most advantage among the attributes that haven't been considered yet for each node along the path from the root is the process of rebuilding the decision tree. Measuring the gain is harmful when features have several values. To solve this issue, the gain ratio is used rather than the gain. For instance, the gain ratio of xk is defined as in Equation 7 [49, 50].

$$\mathrm{Gain\ ratio.}_{(\mathrm{xk,\ TS})} = \frac{\mathrm{gain(xk,TS)}}{\mathrm{split(xk,TS)}} \tag{7}$$

where split(xk, TS) is the data that comes from TS's split based on the value of feature xk. As previously mentioned, recursively splitting a training set can sometimes produce a very complex decision tree with long, unequal paths. To fix this issue, the decision tree is pruned using an error-based technique that just swaps out a whole subtree for a node that has leaves [49].

The data was collected from different governorates in Iraq, like Najaf, Diwaniya, and Karbala. The data was gathered from 1991 to 2021 regarding temperature, humidity, evaporation, rainfall, solar radiation, and others in order to see the effect of these factors on water resources.

3. Results and discussion

Table 1, Table 2, Table 3, and Table 4 show data collected within the period (1991-2021) related to temperature, humidity, wind speed, and evaporation, respectively.

Temperature is one of the most prevailing climatic elements that influences the hydrological cycle and water availability. Rising temperatures have a direct influence on accelerating the process of evaporation from the surface water bodies, including rivers, lakes, and reservoirs. Additionally, elevated temperatures increase plant transpiration, leading to a combined rise in evapotranspiration. This cumulative water loss results in the depletion of soil moisture and surface water storage, which are extremely important for irrigation of agriculture, drinking water supply, and ecosystem stability. At longer time scales, high temperatures also lower the groundwater recharge rates due to less water percolation into the ground as a consequence of high surface evaporation. In the semi-arid and arid regions of Diwaniya, Najaf, and Karbala, where water is already scarce, ongoing temperature rises place additional stress on limited water resources, raising the risk of drought and water insecurity. Moreover, temperature variability influences the timing of snowmelt (where applicable), altering the pattern of seasonal water availability and disrupting traditional agricultural cycles. Temperature records show a consistent rise in all three locations over the 30-year period. For example, Diwaniya's mean yearly temperature increased from 24.3 °C in 1991 to 26.7 °C in 2021, approximately a 2.4 °C rise. The same trends are observed in Karbala, with an increase from 30.1 °C to 33.7 °C, and in Najaf from 23.6 °C to 24.4 °C (with peaks over 26 °C during the 2010s). These temperature increases directly lead to greater surface water body evaporation and greater transpiration from vegetation. Based on empirical observations, a 1 °C rise in temperature can translate to a 5–15% rise in evapotranspiration, depending on local humidity and wind conditions. The 2–3 °C rise thus implies a 10–30% rise in water loss from natural and agricultural systems. This raises the requirement for irrigation and lowers the availability of surface water, undermining both agricultural productivity and drinking water availability.

Table 1. Temperature data within the years 1991-2021

Year	D	N	K
1991	24.3	23.6	30.1
1992	22.9	22.6	29.0
1993	24.0	23.8	30.5
1994	24.7	24.4	31.0
1995	24.8	24.6	30.8
1996	24.9	24.9	31.4
1997	24.0	23.7	30.1
1998	25.2	25.3	31.9
1999	25.4	25.3	32.1
2000	24.9	24.7	31.6
2001	25.4	25.2	32.0
2002	26.2	24.7	32.0
2003	26.5	26.4	33.2
2004	24.8	24.1	31.6
2005	25.1	24.6	31.4
2006	24.8	25.2	31.3
2007	25.1	25.4	31.4
2008	25.6	29.2	31.4
2009	25.1	25.4	31.7
2010	25.6	26.9	33.8
2011	24.7	24.7	31.1
2012	24.6	25.7	32.0
2013	25.1	25.0	30.9
2014	25.5	25.8	32.0
2015	25.9	26.2	32.5
2016	25.7	26.1	32.5
2017	25.9	26.3	32.9
2018	26.2	23.6	32.5
2019	25.8	22.6	32.2
2020	26.1	23.8	32.9
2021	26.7	24.4	33.7

Humidity, particularly relative humidity, regulates the water-holding capacity of air and is the primary determinant of evapotranspiration rates. Low humidity provides the air with a larger capacity to absorb water vapor, leading to increased evaporation from water bodies and soil. Low humidity also triggers increased transpiration in vegetation, making the available soil water become depleted faster, and irrigation demands need to be raised. This is especially problematic when it is hot, since the tandem efforts of dryness and heat can potentially create a situation of dramatic water loss. Greater humidity, conversely, decelerates the evaporative process by the saturation of the air, which has the practical effect of holding moisture within the soil and relieving pressure on water reserves. In regions of typically low humidity, such as central Iraq, even small reductions in relative humidity can greatly exacerbate water stress, particularly during the summer. This makes humidity an important, yet often overlooked, element of water resource planning and drought prediction. Relative humidity measurements over the 1991-2021 period exhibit significant inter-annual fluctuations. In Diwaniya, for instance, humidity ranged from 37.8% in 2009 to 52.7% in 2015. Najaf showed an even larger variation, from 35% in 2001 and 2017 to 51% in 1991. Karbala's rates also show the same trend, with a high of 56.8% in 2000 and a low of as much as 39.0% in both 2016 and 2017. Low-humidity years coincide with years of higher water stress, since drier air allows for more evaporation and drying of the soil. For example, in 2001, when Najaf's humidity was at a low of 35% and the temperature was above 25 °C, the conditions would have increased evapotranspiration significantly, accelerating water depletion. Conversely, years with higher humidity, such as 2015 and 2000, would have partially mitigated the impacts of evaporation even under high temperatures.

Table 2. Humidity data within the years 1991-2021

Year	Diwaniya	Najaf	Karbala
1991	40.7	51	48.3
1992	45.3	48	46.6
1993	43.9	41	46.9
1994	48.3	46	47.4
1995	46.3	42	48.8
1996	46.3	38	50.2
1997	46.9	49	50.3
1998	49.8	40	49.3
1999	50.2	43	49.8
2000	49.4	43	56.8
2001	48.3	35	48.3
2002	44.3	36	49.0
2003	43.5	40	50.9
2004	40.3	42	45.8
2005	43.1	43	48.2
2006	41.1	46	46.7
2007	42.8	42	46.7
2008	40.0	48	42.9
2009	37.8	46	46.2
2010	40.3	36	44.3
2011	40.1	40	43.9
2012	41.3	44	44.1
2013	43.9	46	47.0
2014	51.7	45	46.9
2015	52.7	47	43.1
2016	51.8	39	39.0

Year	Diwaniya	Najaf	Karbala
2017	47.2	35	39.0
2018	40.9	50	44.2
2019	44.1	42	43.3
2020	43.5	44	43.5
2021	45.5	40	39.4

Wind speed influences water resources primarily by altering evaporation and transpiration. Wind favors evaporation by removing the thin layer of saturated air that forms just above moist surfaces, clearing the way for drier air and allowing prolonged loss of moisture. The process enhances both open-water evaporation and soil drying, especially in agricultural areas. Wind also facilitates plant transpiration by increasing the vapor pressure gradient between leaf surfaces and the air. Higher wind speeds, therefore, lead to rapid soil moisture decreases and higher irrigation demands. Extremely low wind speeds, on the other hand, will reduce atmospheric mixing, leading to localized heat trapping and stagnant conditions with similar thermal as well as water stress intensification. Trends in the long-term series of Diwaniya and Karbala show a linear decrease in mean wind speed that can influence evaporation dynamics within the localities. On the other hand, wind speed values in Najaf appear exceptionally high during recent decades and would have to be verified. In either case, wind speed is a significant climatic variable in climate modeling and water budgeting because it controls the rate of water loss to the atmosphere under different environmental conditions. Wind speed is another essential atmospheric water loss factor. Diwaniya sees an overall decrease in wind speed, from 2.8 m/s in 1991 to 0.9 m/s in 2021.

Table 3. Wind speed data within the years 1991-2021

Year	Diwaniya	Najaf	Karbala
1991	2.8	3.1	6.5
1992	2.7	2.6	2.8
1993	2.2	2.2	2.5
1994	2.5	2.1	2.7
1995	2.2	1.6	2.4
1996	2.3	1.4	2.6
1997	1.8	1.4	2.5
1998	2.3	1.3	2.4
1999	2.8	1.3	2.8
2000	2.7	1.1	3.0
2001	2.5	1.3	2.9
2002	2.4	1.6	3.5
2003	2.5	1.7	3.0
2004	2.1	1.8	2.5
2005	2.2	1.4	2.6
2006	2.2	1.8	2.8
2007	1.9	1.8	2.6
2008	1.8	1.9	3.0
2009	1.6	1.7	2.4
2010	1.7	1.7	2.5
2011	1.5	1.8	3.0
2012	1.5	1.8	2.4
2013	2.5	2.2	2.9
2014	2.1	25.8	2.8
2015	2.2	26.2	2.6

Year	Diwaniya	Najaf	Karbala
2016	2.1	26.1	2.3
2017	2.0	26.3	2.1
2018	2.0	23.6	2.2
2019	1.7	22.6	2.1
2020	0.8	23.8	1.9
2021	0.9	24.4	1.9

Karbala's wind speed also decreased from 6.5 m/s in 1991 to 1.9 m/s in 2021. These decreases may decrease wind-evaporation, but they can lead to stagnant air conditions, which increase heat holding. Najaf, though, presents anomalous data in the following years (e.g., over 23 m/s for 2014–2021), which significantly varies from previous years (~1.4 to 2.2 m/s). The anomalies may likely be attributed to sensor or entry mistakes and need verification. Ignoring the anomalies, wind speeds of 2–3 m/s are typically good for moderate evaporation. But the unexpected drop in Diwaniya's wind speed might have partially offset evaporation losses even as temperatures rose.

Table 4. Evaporation data within the years 1991-2021

Year	Diwaniya	Najaf	Karbala
1991	187.3	166.8	189.1
1992	170.8	156.8	162.1
1993	152.0	147.1	157.2
1994	150.7	156.4	166.9
1995	154.1	154.8	158.5
1996	143.3	152.2	158.7
1997	136.6	140.6	164.8
1998	135.7	158.2	154.7
1999	139.1	174.0	171.9
2000	139.0	165.4	165.8
2001	127.7	172.2	163.7
2002	134.5	157.0	170.3
2003	142.3	164.2	165.1
2004	146.3	155.2	165.7
2005	155.3	156.8	157.0
2006	138.5	153.9	168.7
2007	154.6	148.2	159.4
2008	151.3	143.0	169.9
2009	147.9	161.4	155.6
2010	139.2	143.7	159.7
2011	144.9	153.3	174.8
2012	139.9	143.8	164.3
2013	143.0	150.0	163.4
2014	152.0	161.0	164.3
2015	152.2	162.7	167.3
2016	136.9	162.4	160.8
2017	142.9	167.4	157.5
2018	124.4	152.6	157.7
2019	125.7	146.8	150.4
2020	113.3	118.0	144.8
2021	120.3	149.4	151.0

Temperature is the primary driver of evaporation. In Diwaniya, the average temperature increased from 24.3 °C in 1991 to 26.7 °C in 2021, while evaporation decreased from 187.3 mm to 120.3 mm. At first glance, this is paradoxical—rising temperatures should increase evaporation. However, this reverse trend may be caused by two reasons. First, wind speed reduction: Wind in Diwaniya has reduced from 2.8 m/s in 1991 to 0.9 m/s in 2021, reducing the energy available for evaporation of moisture from surfaces. Second, cloud cover and humidity change: higher humidity or greater cloud cover in some years may reduce solar radiation and net evaporation even with higher temperatures.

However, in years of high temperature and moderate wind, evaporation is maximized. For instance, in 1991, Diwaniya recorded 24.3 °C, 2.8 m/s wind, and 40.7% humidity, with the maximum evaporation of 187.3 mm, which reveals the combined impact of moderate humidity and high winds on evaporation. The attained data was utilized to predict water balance as shown in Table 5.

Table 5. Water balance data within the years 1991-2021

Year	Diwaniya	Najaf	Karbala
1991	-160.3	-167.0	-183.2
1992	-150.0	-145.1	-156.4
1993	-134.7	-139.5	-150.4
1994	-147.7	-145.2	-161.3
1995	-147.9	-139.1	-152.9
1996	-144.8	-130.9	-151.4
1997	-133.8	-126.9	-156.9
1998	-151.5	-133.9	-151.1
1999	-168.0	-136.1	-169.6
2000	-152.1	-124.5	-163.4
2001	-166.2	-129.7	-158.8
2002	-144.5	-138.1	-164.9
2003	-156.9	-141.9	-160.4
2004	-151.7	-152.1	-162.1
2005	-150.7	-134.0	-153.1
2006	-147.3	-142.7	-163.3
2007	-145.5	-149.1	-157.2
2008	-140.3	-143.4	-165.5
2009	-158.5	-135.0	-153.8
2010	-140.5	-141.6	-154.6
2011	-148.1	-135.4	-169.2
2012	-138.0	-140.1	-159.9
2013	-142.4	-142.6	-152.8
2014	-154.5	-146.0	-158.1
2015	-154.3	-128.3	-160.4
2016	-158.1	-137.0	-150.2
2017	-165.4	-122.0	-154.6
2018	-140.4	-115.6	-147.0
2019	-140.5	-106.9	-145.1
2020	-107.7	-112.3	-140.9
2021	-147.4	-121.6	-148.8

Temperature plays a strong role in evaporation and, by consequence, in water balance. As an example, in 2000, Karbala registered its highest mean temperature (31.6 °C), in association with increased evaporation (165.8 mm) and extreme water deficit (-163.4 mm). Similarly, Diwaniya in 2001 measured a temperature of 25.2 °C, with evaporation of 127.7 mm, resulting in a critical deficit of -166.2 mm. The expected link can be that higher temperatures accelerate water loss, further exacerbating the deficit, especially when rainfall is low. Wind increases evaporation by replacing saturated air with drier air. This can be observed in earlier years when wind speeds were higher. Karbala, in 1991, observed the highest wind speed (6.5 m/s), temperature was 48.3 °C, and maximum evaporation at 189.1 mm, giving rise to the highest water deficit of -183.2 mm, which was the worst across all years and cities. Diwaniya in 1991, with wind at 2.8 m/s and evaporation at 187.3 mm, had a deficit of -160.3 mm. When wind speed declined, e.g., in 2020, to only 0.8 m/s, evaporation dropped to 113.3 mm, and the water balance improved substantially to -107.7 mm, the highest positive value during the past 31 years—lower wind speeds affirm that they minimize water losses.

Humidity also acts to protect by capping evaporation, especially under high temperatures. For instance, in Najaf (1996), with a low humidity of 38 °C, the relatively higher humidity level (38%) and moderate evaporation (152.2 mm) resulted in a water deficit of -130.9 mm, which was improved compared to during hotter, drier years. Conversely, years of low humidity, such as Diwaniya in 2001 (35% humidity), combined with high temperatures and moderate wind, yielded high evaporation and huge deficits (-166.2 mm). Thus, the relationship between humidity and evaporation is clear: low humidity leads to increased evaporation, worsening water deficits.

Water balance results for all cities were negative, reflecting persistent hydrological stress long-term trends. However, the results show consistent improvement in some locations. In Najaf, the values were shifted from 167mm in 1991 to -106.9mm in 2019. This is an indication of a slight reduction in evaporation and possibly enhanced rainfall or lower solar radiation. In Karbala, whereas continuing to face shortages, the values improved from -183.2mm in 1991 to -140.9mm in 2020. The outcomes of the decision tree are shown in Figure 1.

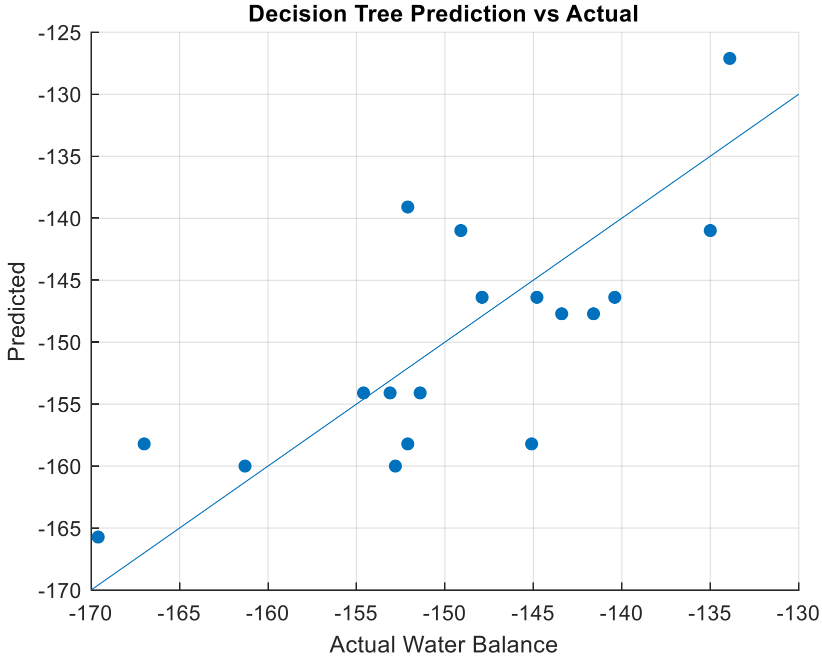

Figure 1. Decision tree prediction vs actual

The scatter plot in Figure 1 visually indicates the output of a decision tree regression model used to predict water balance in terms of environmental features like temperature, humidity, wind, and evaporation. Every blue dot in the scatter plot indicates a single test sample with its x-coordinate marking the true water balance (ground truth) and the y-coordinate marking the predicted value in the model. The diagonal line of reference (y = x) displays the perfect prediction—any point that falls precisely on this line is an indication that the value predicted is equal to the actual value with no error. However, in this case, points are distributed around the line, with most of the predictions falling below or above the true values, indicating prediction error. Some points fall way above or below the line, and this indicates cases where the model's prediction was relatively accurate. The spread indicates that although the model is picking up broad trends in the data, it is not accurate in most individual instances, perhaps because of overfitting, underfitting, or unmolded complexity in the data. The bunching of points and deviation from the line indicate the poor generalization ability of a single decision tree, particularly in regression problems where variables' relationships might be noisy and non-linear. To introduce accuracy and robustness, even more sophisticated methods such as ensemble methods (i.e., Random Forests or Gradient Boosting) or hyper-parameter optimization may be necessary. Practically, this plot is employed as a diagnostic measure to monitor visually the reliability of the predictions and emphasizes the importance of model choice and testing within predictive modeling efforts.

Figure 2 represents another graphical evaluation of how well the model predicts water balance, likely based on a different model or process than the previous decision tree. The x-axis here is the actual values of water balance, and the y-axis is the predicted values from the model. Each blue point is a prediction for a single test instance. Ideally, all points should be on the red dashed diagonal line (y = x), i.e., actual and predicted values will perfectly match. But in this plot, we can observe that there is a very large deviation between most predictions and actual values. Most points lie near a smaller range of predictions, near -140 and -160 in most instances, indicating that the model tends to regress towards the mean.

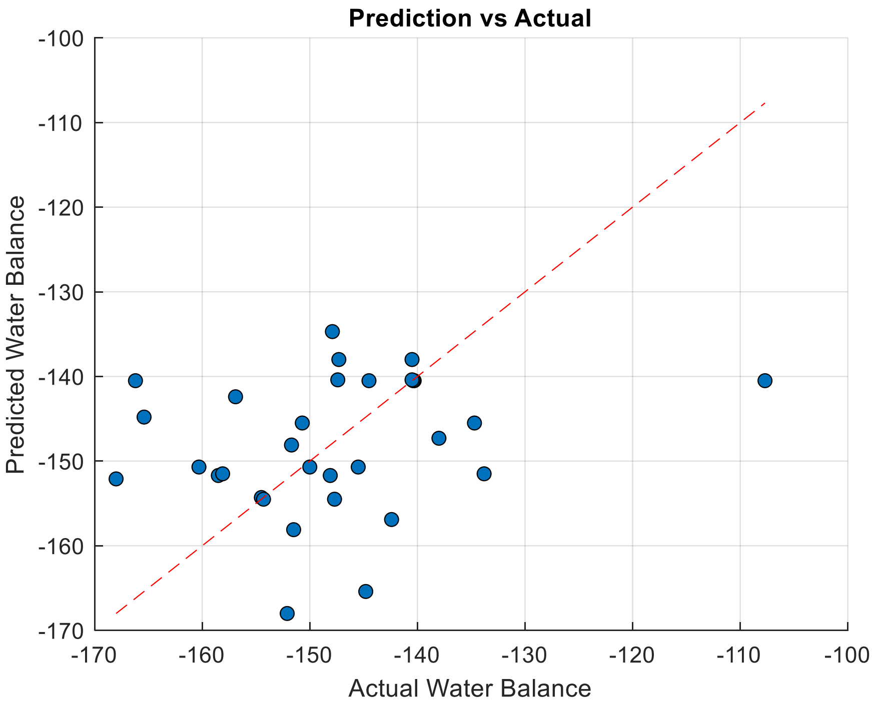

Figure 2. Naive Bayes prediction vs Actual

4. Conclusions

Climate change is increasingly producing complex and severe impacts on the planet and regional water resources. Considering a 31-year-long period (1991–2021), the study in Diwaniya, Najaf, and Karbala governorates uncovered critical climate-induced changes in the key meteorological parameters—temperature, humidity, wind speed, and evaporation—that control water availability and water balance. The findings showed that with continuous temperature rise, evapotranspiration and water losses have been increasing; surface and groundwater availabilities have been diminishing.

1. Humidity irregularities, especially at low humidity and high evaporation, lead to the drying up of soil moisture and enhance the demand for irrigation.

2. Wind speed, being a major mechanism in evaporation, has declined in certain portions, thereby somewhat reducing water loss; however, air stagnation worsens heat retention.
3. Accepting that some areas have witnessed water balance improvement, all values remain in the negative region, indicating chronic water stress enhanced by climate conditions.

Using artificial intelligence (AI), particularly machine learning methods such as decision trees and Naive Bayes, the water balance was modeled and predicted using climatic variables. These models can recognize trends but are deficient in accuracy and generality, with the highly variable nature of the data and the limited complexity of the models possibly being to blame. To obtain higher rates of prediction and applicability to reality, advanced AI approaches such as ensemble methods (Random Forests, Gradient Boosting) or deep learning architectures (LSTM, GRU) need to be considered. Yet, the effective use of AI can only happen if problems concerning data scarcity, model interpretability, and the integration of hydrological domain knowledge are resolved.

In conclusion, AI will not really be an end-all, but rather a powerful complementary tool for climate-resilient and data-driven water resource management. To confront the interconnected challenges of water scarcity and climate change, inter-disciplinarity will have to be stimulated, AI will have to fortify the policy platforms, and continued investments will have to be made in environmental monitoring systems. Only through these converging efforts will sustainable water management driven by climate change acceleration be possible.

Finally, this study provides a novel model to predict the effect of climate change on water resources in Iraq using artificial intelligence as a recent effective technique. In addition, this study opened a wide gate for future studies in this domain in Iraq.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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