Mitigation effectiveness on groundwater-dependent ecosystems revealed by counterfactual AI

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Abstract

Overexploitation of groundwater threatens groundwater-bound aquatic and terrestrial biodiversity and ecosystem stability, underscoring the need to devise appropriate mitigation strategies. Yet, substantial scientific evidence that mitigation measures effectively protect groundwater ecosystems is presently nonexistent. We provide unique and compelling evidence, using counterfactual artificial intelligence and ground truth data, that mitigation measures can successfully sustain ecologically sensitive spring flows and ensure the sustainability of groundwater-bound threatened and endangered endemic species and consumptive groundwater uses under a changing climate.

Main

Groundwater systems are essential for maintaining food and drinking water security as well as sustaining aquatic and terrestrial ecosystem functions[1–4]. However, groundwater depletion in numerous aquifers around the globe[5–10] due to continuous exploitation at a rate greater than replenishment[11–13] has been threatening groundwater-bound aquatic and terrestrial biodiversity and ecosystem stability[4]. This challenge calls for stringent mitigation plans to ensure the sustainability of groundwater-dependent species before they are extinct. Because implementation of even relatively simple mitigation strategies can be expensive, and even contentious, methods to evaluate their effectiveness should be included in the process[14]. We surveyed 710 aquifers globally that are home to 1,058 endangered and 651 threatened groundwater-bound species. Notably, 74% of the surveyed aquifers are home to endangered species while 41% are home to threatened species, and mitigation measures to protect their habitats are either proposed or established in 90% of studied aquifers (statistical summary and locations of these aquifers are provided in Supplementary Information-1). However, scientific evidence, besides anecdotal, in published forms on the effectiveness of existing mitigation strategies to ensure sustainable environmental flows to protect groundwater-dependent habitats is currently nonexistent.

In this study, we provide a unique and compelling data-driven assessment of the effectiveness of mitigation measures using ground truth data from the karstic Edwards Aquifer system in south-central Texas, USA (Supplementary Information-2). The ecologically delicate habitats sustained by the springs of the Edwards Aquifer system are home to endemic species that are found in no other locations on Earth[15]. Due to the potential for declines in spring flow by anthropogenic and natural causes, these species are continuously at risk and eight of them have already been listed as threatened or endangered under the federal endangered species act[15]. Through counterfactual AI analysis, also known as "what-if" analysis, we evaluate if the enforced mitigation measures have been effectively protecting the groundwater-bound habitat (i.e., lowering the intensity of hydrological droughts and maintaining higher spring flows) while simultaneously sustaining groundwater levels for human consumption and agricultural uses, especially during severe meteorological droughts. The counterfactual analysis also highlights the likely impacts on spring flows in the absence of mitigation measures that can help decision-makers better plan for the future and reinforce the case for implementing mitigation strategies.

The study area is ideal to quantitatively examine the effectiveness of mitigation measures for the sustainability of groundwater-reliant sensitive habitats due to: (i) the presence of federally listed threatened and endangered endemic groundwater-bound aquatic species; (ii) evidence from the regional hydroclimatic data indicating warming under a changing climate; (iii) enforcement of multifaceted habitat protection plans, consisting of both mandated strategies (e.g., critical period management program established in 2002 and enforced since 2006) and voluntary strategies (e.g., financial compensation-driven voluntary irrigation suspension program option established in 2010); (iv) availability of long-term (1946-present) highly granular hydroclimatic data, covering intense meteorological and groundwater drought periods, required for training accurate artificial intelligence (AI) models; and (v) a unique academic-industrial partnership that facilitates a seamless two-way transfer of data, knowledge, insights, and guidance.

This study hypothesizes that spring flows can be significantly improved and kept above the required minimum flow rates under climate change if appropriate mitigation measures are enforced (H_0). The mandated mitigation measures include curbing groundwater pumping under five critical groundwater levels and spring flow stages commensurate with the growing intensity of hydrological droughts (i.e., mandating up to 44% pumping cutback under critical stage 5). We have applied a dual counterfactual AI- and clustering-based data-driven approach to validate our hypothesis. Drawing lessons from our approach and analytical evidence documented in this study, new opportunities may arise to develop, implement, evaluate the efficacy of mitigation strategies, and identify the need for further improvements to achieve sustainable groundwater-dependent environmental flows for the well-being of society at large, with implications beyond the study area.

We utilized a tree-based ensemble AI-driven regression model[16,17], trained & validated on weekly resampled data for the years 1946 - 2005 (pre-mitigation period), to project the spring flows between 2006 and 2022 (post-mitigation period) that are juxtaposed with observed spring flows during the same period to visualize contrasting effects (Fig. 1). Since the model is trained on data acquired before 2006 - when the mitigation strategies were not enforced - the predicted outcomes (i.e., counterfactual spring flows) between 2006 and 2022 exclusively reflect natural variations (i.e., unregulated) under a changing climate. Conversely, the observed data (i.e., factual) between 2006 and 2022 reflect the natural variations and mitigation impacts.

We demonstrate that before the mitigation measures were enforced, i.e., prior to the year 2006, there were minor differences ($R^2 \sim 0.74$) in the predicted vs. observed levels of the spring flow (Fig. 1A). In contrast, we observe considerable differences ($R^2 \sim 0.33$) between the predicted vs. observed spring flow rates (Fig. 1B) since the mitigation strategies were enforced in 2006. The

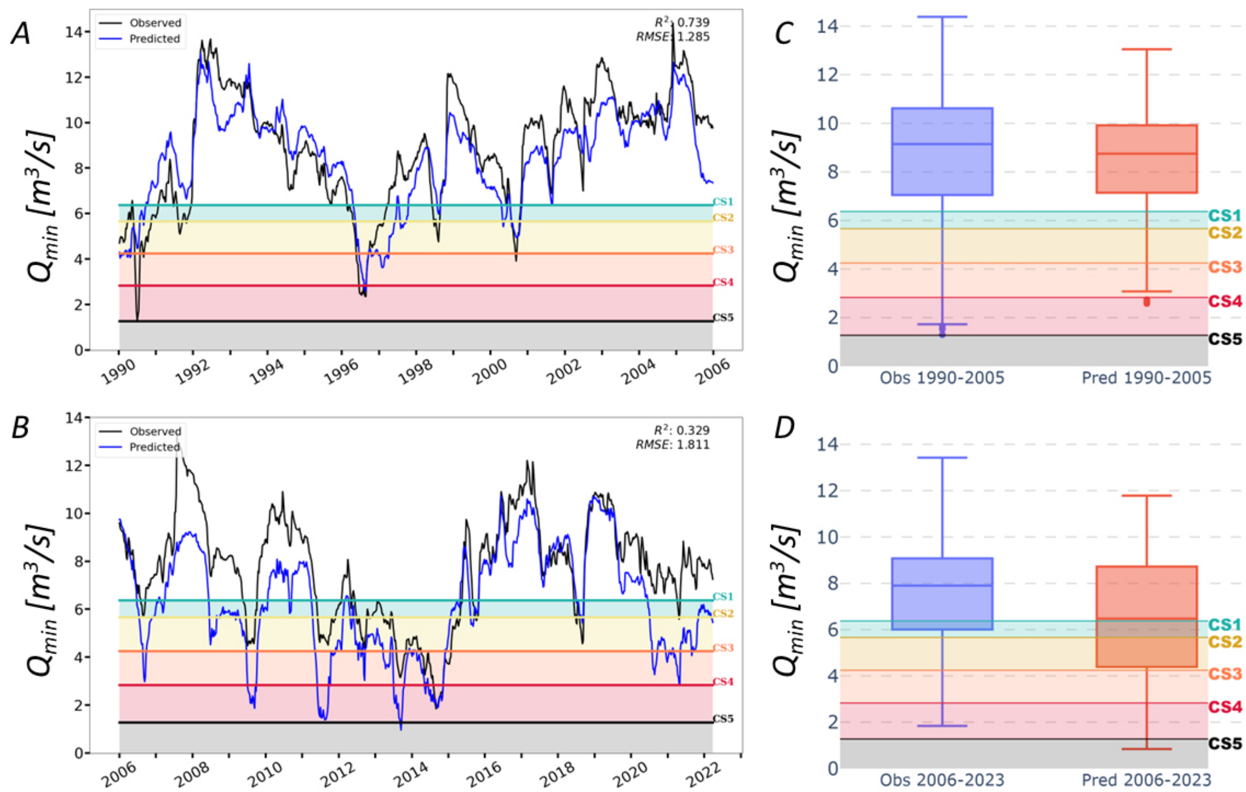

Figure 1 Counterfactual analysis to assess the effectiveness of mitigation measures for averting or minimizing climate change impacts on groundwater-dependent ecosystems. **A:** Predictive performance analysis of spring flow ($Q_{min}[m^3/s]$) model. **B:** Impacts of mitigation measures on $Q_{min}[m^3/s]$ untangled through hindsight analysis. **C & D:** Summarized annual observed vs. predicted $Q_{min}[m^3/s]$ before (**C**) and after (**D**) the mitigation measures were enforced in 2006. Predicted spring flows (i.e., counterfactual) are considerably lower than observed values (i.e., factual) during the post-mitigation period (**B & D**) in comparison to the pre-mitigation period (**A & C**). This supports our hypothesis that mitigation measures enforced since 2006 have effectively prevented spring flows from declining to critically low levels. In these plots, five critical stages (CS1-CS5) are designated based on flow rates in the springs to curb groundwater pumping (for human consumption and agricultural uses) depending on the intensity of the hydrological drought. Higher CS levels indicate larger depletion of the aquifer and declines in spring flows, and hence, mandate larger reductions in permitted groundwater withdrawals. The mitigation measures effectively kept spring flows above the CS2 or CS3 levels during intense hydrological droughts in 2006-2007, 2009-2010, 2011-2012, 2013-2014, and 2020-2022. Otherwise, the threatened and endangered aquatic endemic species would have experienced exacerbated stress if spring flows dropped below the CS4 and CS5 levels in the absence of mitigation measures, and the sustainability of consumptive groundwater uses would have been hampered due to greater mandated reductions in groundwater abstractions.

counterfactual explanation is that the spring flows would have been considerably lower between 2006 and 2022 if mitigation measures were not enforced in 2006 (evident from Fig. 1B & 1D), which would have: (i) imposed greater risk to the threatened and endangered species, and (ii) warranted mandated reductions in groundwater abstractions for human consumption and agricultural uses. However, due to the effectiveness of the mitigation measures, observed spring flows were significantly higher, thereby sustaining safe environmental flows for the threatened and endangered species while meeting the regional water demands with considerably fewer mandated groundwater pumping reductions over the years. These results provide compelling evidence that under changing climatic conditions and without any mitigation measures, it would be extremely challenging, if not impossible, to maintain desired flows in the springs and consequently ensure the sustainability of groundwater-dependent habitats of endangered and threatened species while simultaneously sustaining groundwater levels for human consumption and agricultural uses.

Furthermore, insights from our clustering[18] approach (summarized in Table 1) suggest that the spring flows were significantly lower during the pre-mitigation period for the years that were similar - based on clusters developed on the climatic factors (Supplementary Information-3), including temperature and precipitation - to the years during the post-mitigation period. For example, we observe that the year 2019 (recorded minimum spring flow = 8 m^3/s - Table 1) is similar to the years 1950, 1989, and 1995 (average of the recorded minimum spring flow = 4.9 m^3/s - Table 1) in terms of their proximity, which corroborates our assertion that the spring flows were significantly lower during the pre-mitigation period in comparison to the post-mitigation period. The summarized information provided in Table 1 reflects that the recorded spring flows were higher in 13-out-of-16 years during the post-mitigation period when compared to similar years during the pre-mitigation period. Thus, we can meaningfully quantify that the probability of our hypothesis (H_0) being true is: (P = 13/16 = 0.813).

Table 1 Summary of cluster information highlighting the differences between yearly minimum spring flows of post-mitigation and pre-mitigation years that are identified as similar based on the cluster analysis.

Year (Post mitigation)	$Q_{min}[m^3/s]$	**Similar to the year(s) (Pre mitigation)**	**Average** $Q_{min}[m^3/s]$
2006	5.7	1954	2.0
2007	7.1	1957, 1992	5.5
2008	7.4	1954	2.0
2009	4.5	1971	2.6
2010	8.6	1949, 1965, 1974, 1987	7.4
2011	4.5	1954	2.0
2012	4.4	1994, 1990	4.2
2013	3.1	1971	2.6
2014	1.8	1951,1964,1967, 1971	3.0
2015	3.7	1986, 1991, 1998	5.4
2016	7.9	1986, 1991, 1998	5.4
2017	7.4	1971, 1980	3.9
2018	4.6	1986, 1991, 1998	5.4
2019	8.0	1950, 1989, 1995	4.9
2020	6.7	1954	2.0
2021	5.6	1981, 1990, 2000	4.3

The findings of this study underscore the effectiveness of mitigation measures in maintaining and enhancing spring flow rates in aquifers, particularly during critical periods such as droughts. Post-mitigation period, the counterfactual AI model predictions consistently show lower flow rates compared to the observed data when the model was trained with data from the pre-mitigation period, highlighting the positive impact of mitigation strategies in protecting spring flow and alleviating stress on threatened and endangered species while simultaneously ensuring the sustainability of consumptive groundwater uses, which would have been otherwise hampered if spring flow levels fell below critical stage two or three. Thereby revealing a scientifically reasonable counterfactual insight that mitigation measures are essential to avert or minimize the consequences of climate change and allow sustained use of groundwater resources without depleting them or causing harm to the surrounding ecosystem. Furthermore, a cluster-based analysis of similar years, based on climatic factors, before & after the enforcement of mitigation measures suggests there is an 85% probability that the mitigation measures result in significantly increased spring flows. Evidence of the positive impacts of mitigation measures to avert or minimize the consequences of climate change on groundwater-dependent ecosystems can be adopted by other aquifer management programs globally to develop resilient groundwater operation plans by accommodating mitigation strategies to protect groundwater-dependent environmental flows and ecohydrology while overcoming challenges arising from social, economic, and political differences.

Collectively, our findings emphasize the need for: (i) implementation and enforcement of appropriate mitigation strategies to ensure the long-term sustainability of groundwater resources for consumptive water use and environmental flow demands, (ii) continuous data collection and analysis to quantify the impacts of mitigation strategies and identify scope for improvements, and (iii) establishing academic-industry partnerships, such as the one outlined in this paper, to carry out innovative and practical research in these areas. As climate change and other environmental challenges pose growing threats to groundwater resources worldwide, understanding and applying effective mitigation measures are crucial for safeguarding the health of aquifer systems and the species that depend on them. Implementation of mitigation measures could be achieved through the adoption or expansion of strategies in place at other aquifers. Mitigation strategies could be borrowed or adapted from the ones outlined in this study and other sustainability and source water protection approaches to guide new policies or management schemes[19]. Although our analyses revealed that the existing mitigation measures effectively safeguarded environmental flows for groundwater-fed habitats while ensuring the sustainability of consumptive groundwater uses during the 2010s and 2022 droughts in the Edwards Aquifer region, the efficacy of such mitigation measures should be periodically assessed to ensure that fragile groundwater-dependent ecosystems will remain protected in the future. Lessons from protecting ecologically important spring flows in the Edwards Aquifer system highlight opportunities to protect other prolific aquifers globally, supporting ecological functions in the face of hydrologic intensification under climate change.

Methods

Data

The daily climatic data for the primary study area, i.e., precipitation, maximum temperature, and minimum temperature for the year 1946-2023 were obtained from National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Database[20]. Daily observed spring flows for the year 1946-2023 were acquired from Edwards Aquifer Authority (EAA). Even though the relevant agencies tested the quality of the observed data, any missing data for a particular day was filled using linear interpolation. To facilitate the analysis of the data, the daily temperature records were resampled as weekly averages, and the weekly precipitation data was resampled as a sum of the daily values. The minimum spring flows for each week were resampled by finding the lowest spring flow value among the daily records each week.

Data-Driven Counterfactual AI and Clustering Approach

The tree-based ensemble AI model design, motivated from XGBoost[21] frameworks, can be represented by the equation: $\hat{Y} = f(X^1, X^2, \ldots, X^n)$; where $\hat{Y}$ represents the predicted outcomes, f is the functional representation of the relationship between X (i.e., the independent features – biomarkers) and Y (i.e., target – the true outcome). The function f is learnt by minimizing a regularized objective function that consists of two parts: the loss function ($L(y_i, \hat{y}_i)$) that measures the difference between the predicted outcome $\hat{y}_i$ using the weighted ensemble of regression trees and the true outcome y_i, and the regularization term ($\Omega(w)$) that penalizes complex models for a given set of w (vector of weights assigned to the individual regression trees). The regression trees are iteratively added to the ensemble by computing the negative gradient of the objective function with respect to the current ensemble predictions ($g_i^t = \partial L(y_i, \hat{y}_i^{t-1})/\partial \hat{y}_i^{t-1}$) where $\hat{y}_i^{t-1}$ is the predicted outcome of the ensemble in iteration $t-1$. The negative gradient represents the direction of steepest descent for the objective function, and it indicates how much the current ensemble output needs to be corrected to minimize the objective function. The model then fits a new tree $h_t(x)$ to the negative gradient values g_i^t, by minimizing an objective function ($Obj_t = \sum_i [g_i^t - h_t(x_i)]^2 + \Omega(h_t)$), where $h_t(x_i)$ is the predicted outcome of the t^{th} tree for the input x_i and $\Omega(h_t)$ is the regularization term that penalizes complex trees. The optimal weights for the new tree $h_t(x)$ are computed using $\gamma_t = argmin_\gamma \sum_i [g_i^t - \gamma h_t(x_i)]^2 + \Omega(\gamma)$; where γ_t is the optimal weight for the new tree $h_t(x)$ and $\Omega(\gamma)$ is the regularization term that penalizes large weights. The model then updates the predicted outcome by adding the new tree with weight γ_t ($\hat{y}_i^t = \hat{y}_i^{t-1} + \gamma_t h_t(x_i)$). This process is repeated until convergence of the objective function. The final predicted outcomes of the model are the weighted sum of the predicted outcomes from every tree in the ensemble.

The model was trained and tuned through a k-fold hyperparameter autotuning process using the weekly resampled climatic (independent variables) and spring flow (dependent variable) data from September 1946 to December 1989 and validated - i.e., estimated the predictive capability - with the data from January 1990 to December 2005 (used for the analysis in Fig. 1 A & C). The validation results suggested that the trained regression model was able to learn the nonlinear relationship in the hydroclimatic data with acceptable accuracy (R^2~0.74). After validation, the model (with hyperparameter obtained from the autotuning process) was retrained with the resampled hydroclimatic data from September 1946 to December 2005 and applied to project the spring flows for the post-mitigation period between January 2006 to March 2022 (i.e., expected outcome), which were compared to the recorded spring flows (i.e., actual outcome) (used for the analysis in Fig. 1B & D). The differences between the counterfactual (what-if outcome) and factual (actual outcome) during the critical stages (CS1 - CS5) provides hindsight evidence, through causal inference based on counterfactual, of how effectively mitigation measures protect groundwater-bound habitats. The expected outcome in the model portrays what would have happened if the mitigation measures were not enforced in 2006.

For the cluster approach we applied K-Means, which is an unsupervised machine learning algorithm that groups data into clusters. We have utilized centroid-based clustering methods, K-means, that rely on optimizing a central vector to find data clusters[18], Euclidean distance is used to measure the distance between the climatic data points for each individual year, and Elbow method is used to find the number of clusters. This clustering approach was applied to generate the results presented in Table 1.

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Competing Interests Statement The authors declare that there are no competing interests.

Author Contribution Conceived and designed the experiments: D.C. and H.B.; Performed the experiments: C.S.; Analyzed the data: All authors; Contributed materials/analysis tools: All authors; Wrote the paper: All authors.

Data Availability The datasets and code can be made available upon reasonable request.

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Supplementary Information-1

Information on groundwater-dependent species and mitigation measures for sustainability of their habitats was collected from710 aquifers globally (summarized in Table S1) by reviewing 2,224 published articles and reports. Among the 710 surveyed aquifers, 22.7% are in North America, 2.3% in South America, 10.6% in Asia, 42.2% in Europe, 13.2% in Australia, and 9% in Africa. Mitigation measures are either proposed or established in 90% of the surveyed aquifers. Notably, 74% of the surveyed aquifers are home to endangered species, while 41% are home to threatened species.

Table S2 Summary of the status of groundwater-reliant species and mitigation measures for protection of their aquatic habitats in aquifer systems surveyed across the globe.

COUNTRY	North America	South America	Asia	Europe	Australia	Africa	Total
Aquifers surveyed	161	16	75	300	94	64	710
Karst aquifers	40	0	46	272	24	47	429
Aquifers with mitigation measures	117	15	64	288	94	64	642

Endangered species in study aquifers	169	16	50	735	44	44	1,058
Threatened species in study aquifers	162	0	5	395	88	1	651
Aquifers home to endangered species	117	16	50	278	20	44	525
Aquifers home to threatened species	100	0	5	144	42	1	292

Supplementary Information-2

The Edwards Aquifer (map shown in Figure S1) is one of the most prolific karstic aquifer systems in the world and a source of environmental flow for several springs and rivers, including the two

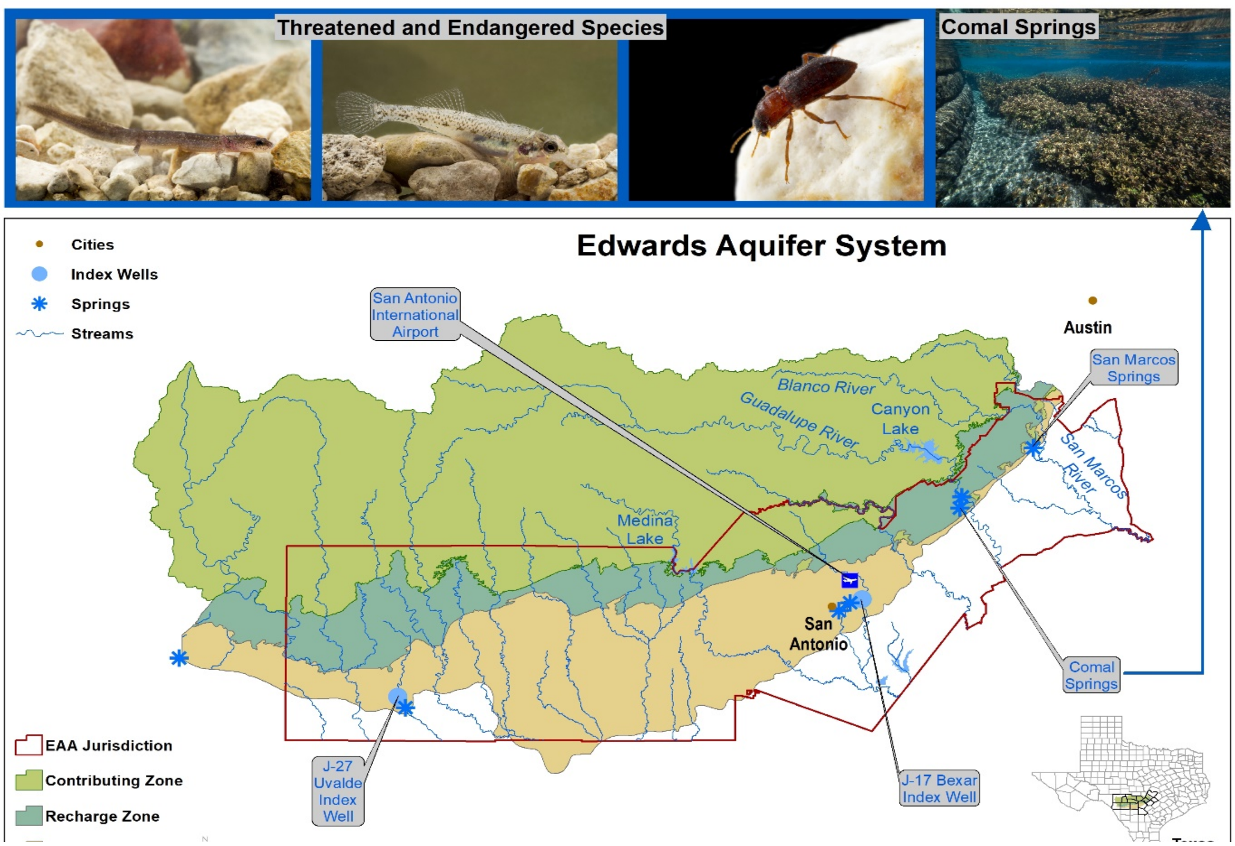

Figure S1 The map in the lower panel shows the Edwards Aquifer system under the jurisdiction of the Edwards Aquifer Authority. Groundwater levels at the J-17 Bexar Index well trigger mandated reductions in groundwater withdrawals during droughts in the eastern segment of the aquifer that extends from west of the city of San Antonio toward the Comal and San Marcos springs along the recharge and artesian zone (known as the San Antonio pool of the aquifer) under the Edwards Aquifer jurisdiction to offset the adverse impacts of droughts on groundwater levels and habitats of the endangered and threatened aquatic species in the Comal and San Marcos springs. The top panel shows a section from the Comal springs, which is home to threatened and endangered species, including the Comal springs salamander, the fountain darter, and the Comal springs riffle beetle (from left to right).

largest freshwater springs in Texas that form the San Marcos and Comal Rivers. The unique and ecologically delicate habitats sustained by these springs are home to endemic species that are found in no other locations on Earth.

Due to the potential for declines in spring flow by anthropogenic and natural causes, these species are continuously at risk and eight of them at the San Marcos and Comal springs have already been listed as threatened or endangered under the federal Endangered Species Act. The Edwards Aquifer Authority implemented the ``Edwards Aquifer Habitat Conservation Plan (EAHCP)" in 2002 to regulate the groundwater pumping at the permitted wells within its jurisdiction to protect the aquifer and groundwater-fed habitats of threatened and endangered species at the San Marcos and Comal springs under the influence of a growing population and warming climate in the region. Although threatened and endangered species have been identified in many regional aquifers across the globe, natural and anthropogenic pressure on the aquifers has been assessed, and a need for artificial regulation of aquifers to improve environmental flows to sustain ecosystems has been emphasized, 'mandated' mitigation measures have been implemented exclusively at the Edwards Aquifer system in south-central Texas, USA, till date to protect endemic threatened and endangered groundwater-bound species.

Supplementary Information-3

Table 1 in the main section of the paper is based on the clustering-driven proximity plot shown in Figure S2. The similar years before and after mitigation implementation are chosen based on the Euclidean distance (proximity) between datapoints.

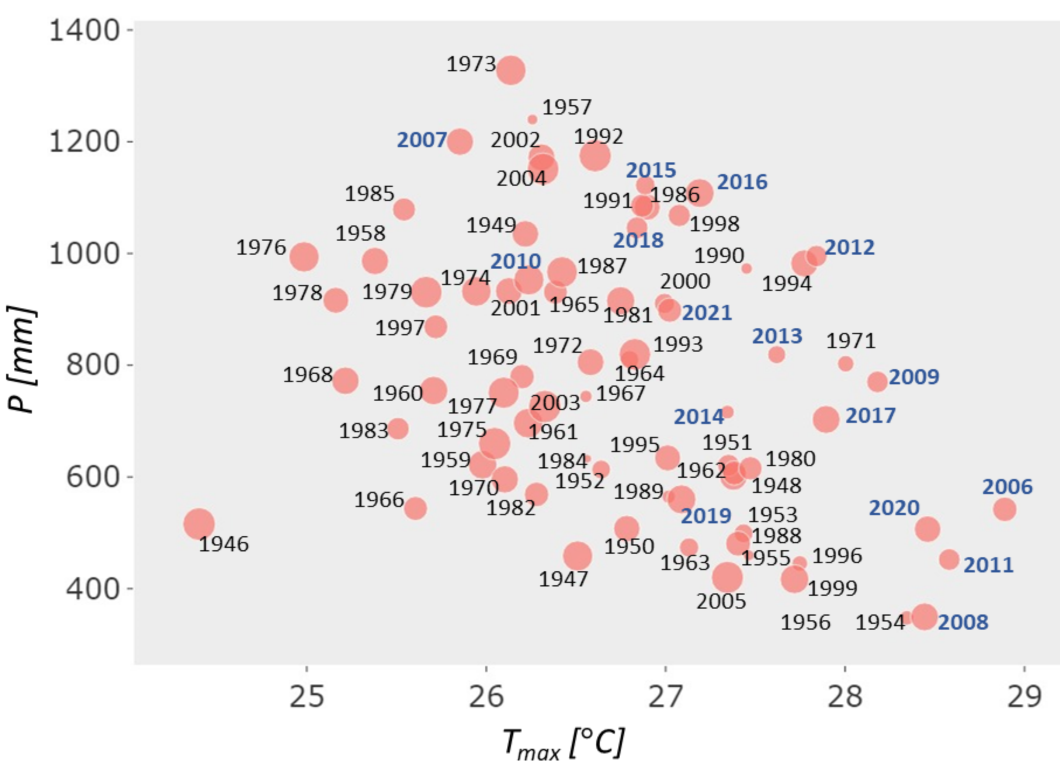

Figure S2 Proximity analysis of years based on climatic factors, which reveals similarity between years based on T_{max}[°C] (maximum air temperature) and *P[mm]* (precipitation). For example, 2019 is closest to 1989 in terms of proximity measured via Euclidean distance between the climatic data for the respective years. Post-mitigation period years (2006-2021) are in blue fonts. The size of the scatter points indicates the magnitude of minimum yearly spring flows - bigger circles represent higher flows and vice versa.