From Oasis to Opportunity. Replenish the Future.

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March 3, 2024

Contents

1 Executive Summary

"Hoover Dam power production down 33%, official says"—read the headline of a 2022 media publication [31]. This is one of the many publications that are alarming residents in the American Southwest (Arizona, Nevada, California) as Hoover Dam loses hydroelectric power due to an unprecedented decline in the dam's reservoir, Lake Mead, water levels. With water levels reaching historic lows, the lowest since its construction completion in 1937 [9], it is becoming an increasingly urgent issue that needs to be confronted. Because Hoover Dam hydroelectric power generation solely depends on the amount of water rushing through its generators, our modeling focuses on how to slow down the decline of amount of water passes through hoover dam. Through our model, we aim to understand and forecast declining water volume in order to estimate hydroelectric power decline. We also layout recommendations to curb its decline or potentially increase water levels.

To begin, we gathered data for the volume of water (dependent variable), water consumption, and several environmental variables—all of which were reported by articles and scientific publications to be crucial factors. Before modeling, we cleaned our data and removed correlated variables to avoid multicollinearity to ensure a robust model. Using data for these parameters, we used symbolic regression techniques to derive a mathematical relationship between our explanatory variables and the volume of water.

After obtaining the aforementioned relationship, we applied Facebook Prophet—a powerful seasonality forecasting algorithm—to predict the future values of each parameter until 2030. Combining our symbolic regression equation with forecaster parameters, our model predicts from 2022 (the latest data) to 2030 there will be a 29.2% drop in volume of water. Finally, to obtain our ultimate risk of loss of hydroelectric power, we perform a regression between average water volume and total hydroelectric power generation on the annual scale.

With a model in place, we heavily utilize our model's forecast to 2030 to quantify the risks. First, we performed a sensitivity analysis on our model to establish which variables the model was sensitive or resilient to. We found that our model was most sensitive to consumption use; this fact enabled us to recommend and advocate strongly for a reduction in water consumption. Second, to put severity into context, we determined that it costs $440 million to cover the losses of hydroelectric power through 2030 using unit costs of alternative energy sources like coal.

Aside from the cost, we discussed the environmental ramifications of losing a key source of renewable energy. Third, when comparing average monthly distributions of water volume and hydroelectric production, the summer months were most vulnerable. A key fact our recommendations base on. Lastly, we revisited our Prophet model and examined trends of three of our predictive variables, and found that while water consumption is improving, soil moisture and snow water equivalent are drastically declining. If those trends continue without intervention, our model estimates that in the early 2030s, Hoover Dam will reach minimum power generation, where hydroelectric power generation is no longer possible.

Based on our risk analysis and interpretation of related literature, we outline four interstate risk mitigation strategies that will require Arizona, Nevada, California, and other stakeholders to partake in. These diverse strategies try to lessen the dramatic losses in hydroelectric power demonstrated by our model. As aforementioned, our sensitivity analysis showed us that changes in water consumption have an immense influence on the water volume. With that in mind, we recommend that the three states ratify legislation or encourage their respective agriculture industries—that consume the most water—to reduce water consumption, especially those that grow alfalfa, an outrageously thirsty crop. Another way to mitigate water consumption in the agriculture industry is for policy makers to consider further tax, subsidiaries, or tax breaks.

We recommend municipalities implement policies to reduce urban water consumption, upgrade to water-efficient appliances, avoid over-watering, and promote water reuse. Additionally, cities can adopt electricity reduction measures and invest in alternative renewable energy sources like solar panels and wind energy, given their positive cost-benefit. Finally, we suggest exploring cloud seeding technology, which has shown promise in increasing precipitation and could contribute to the future sustainability of Lake Mead and Hoover Dam's hydroelectric power.

2 Background

Standing tall against the backdrop of the majestic Colorado River, Hoover Dam stands as an enduring symbol of American ingenuity, resilience, and unity. Built during the challenging times of the Great Depression, this engineering marvel represents the triumph of the human spirit over adversity and was referred to as one of the 7 wonders of the industrial world[65]. As a vital source of hydroelectric power, Hoover Dam not only provides electricity to 1.3 million people[35] but also fuels the prosperity of the American West, like Las Vegas.

Las Vegas, the shimmering jewel of the desert, beckons with its vibrant energy and endless possibilities. Hosting an impressive 38.8 million visitors per year[44], it's a playground for those seeking excitement, luxury, and unforgettable experiences. From dazzling casinos to world-class entertainment, Las Vegas captivates the imagination and embodies the spirit of indulgence and adventure. But it relies heavily on Hoover Dam's hydroelectric power.

That is all under threat.

What people don't know is that the city's main water and power source may soon be crippled. Amidst the arid landscape of the American Southwest, Hoover Dam's reservoir, Lake Mead, is experiencing a crisis. The water volume of this reservoir—the driver of hydroelectric source for three states, dozens of cities, and millions of people—have plummeted to historic lows. This water decline poses a significant threat to hydroelectric power security and has many ramifications, both on a demand basis and an environmental basis. In the Colorado River is the Hover Dam, which generates a lot of electricity per day. The decrease in water will bring less hydroelectric power to the states as shown in figure 1.

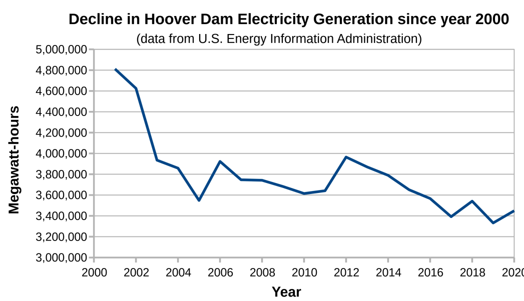

Figure 1

To understand the threat to Hover Dam, we must first understand how it works. The dam works with an elevation difference. On the top of the dam, the water enters through the intake. From there, it travels downstream through turbines and generators, which rotates to obtain mechanical energy and later electricity. This form of energy creation is the cheapest and most reliable to use. Since there is a continuous flow of water, it always spins at a steady rate, generating a continuous flow of energy. If the water volume is lower, less water passes through the generator, producing less electricity. Will its turbine stop spinning?

Its an increasingly probably reality. With its water volume being the lowest since its inception in 1937[9]. at around 27% of capacity. This results in a reduction of over 2.8 megawatt hours in power generation, which create a major clean energy crisis for the reliant states. This dire situation stems from a combination of factors. The region is currently facing a mega-drought, exacerbating water scarcity issues. Additionally, decreased snow-pack, reduced precipitation, and increased temperatures have led to diminished water inflows into Lake Mead. Moreover, high consumption rates and outdated interstate agreements regarding water allocation and usage have further complicated the management of this precious resource. On top of that, electricity demand and increasing. As demands on the Colorado River continue to grow, finding sustainable solutions to address these challenges becomes increasingly urgent.

It goes without saying that cities and people won't lose electric power to power their every day lives. That is because any hydro-power deficit from hoover dam will be made up in other forms of energy, often non-renewable energy like coal and natural gas. While this is a financially viable alternative, it veers away from the federal government's agenda to transform to greener energy, an important risk. Given this, maintaining hydroelectric power generation from Hoover Dam is not just uphold electricity demand, but also to support the Southwest's commitment to green energy.

Our model and risk analysis will delve into the numbers of this issue, creating forecasts that could be beneficial for public policy makers to take into consideration. Furthermore, we are able to quantify environmental costs (like CO2 added) into this. But, most importantly, this information will support how we can address declining hydroelectric power.

To address the imminent threat posed by the dwindling water levels at Lake Mead, several potential risk mitigation strategies are being or considered to be pursued. These include reducing overall water consumption through conservation efforts, diversifying energy sources with a focus on renewable, enhancing infrastructure efficiency, and exploring cloud seeding as one of the solutions. Implementing these measures mitigates the impact of Hoover Dam's potential decline and ensures the resilience of our water and energy systems in the face of adversity, as well as protecting clean hydroelectric power for the millions of residents.

However, solutions to this multifaceted issue is tough. This is not just a technical issue, but an issue regarding ties to legal, cultural, and historical situations. For example, if state actors were to implement water cuts in order to increase water flow through the dam, they would have to consider water rights of important groups like the Navajo Nation, the largest indigenous group. Passing interstate legislation that ensures equity and fulfillment of ALL groups' water rights is extremely challenging.

2.1 Problem Statement

As Lake Mead's water levels decrease, a plethora of risks follow. Our project focuses on the risk associated with the loss of hydroelectric power generation from Hoover Dam and its impact on Arizona, Nevada, and Southern California. Producing over 4 billion megawatts-hours per year [42], Hoover Dam is the primary renewable energy source to many adjacent municipalities. Losing this vital energy source would necessitate turning to non-renewable, an additional environmental risk. These are the two risks this paper centralizes on.

2.2 Definitions

- Water Volume: the amount of water stored in a reservoir, in acre-feet.
- Water Level: the height reached by the water in a reservoir, in this case Lake Mead. This is in feet. Water level is different from water volume although both tell a similar story.
- Evapotranspiration: The process of transferring moisture from the earth to the atmosphere by evaporation of water and transpiration from plants. [20]
- Upper Colorado River Basin: The river network above Lee's Ferry in northern Arizona. The lower portion is called the Lower Colorado River Basin. [2]
- Snow Water equivalent: Determines how much water the snow-pack contains, helping water and resource managers plan for water use.

3 Data Methodology

Our project relies on four essential data sources: the U.S. Bureau of Reclamation (USBR) for historical water trends in the Colorado River, the Global Land Data Assimilation System (GLDAS) for past and projected water availability trends, the NOAA Physical Sciences Laboratory for climate and weather patterns' impact on water resources, and the U.S. Energy Information Administration (EIA) to assess the severity and risk related to hydroelectric power at Hoover Dam. Each data source is crucial in understanding historical trends, projecting future scenarios, and assessing the impact of climate change on water resources and energy generation. We analyze the significance, parameters, data cleaning processes, credibility, and purpose of each data set.

We also made assumptions due to missing data; for instance, we couldn't find information on water contributions to Lake Mead from other tributaries (Assumption 3). Similarly, the absence of data on dates and magnitudes of water regulatory activities led to Assumption 2, affecting our ability to analyze specific changes in water levels.

Note: our project does not include a "frequency" aspect, since we are not analyzing risks of instances but rather a trend over a sustained period of time.

3.1 U.S. Energy Information Administration[73]

Incentive of Data
Since our project focuses on the loss of hydroelectric power produced by Hoover Dam, we derive hydroelectric generation from the dam from the U.S. Energy Information Agency (EIA).

Parameters and Scope
The combined hydroelectric production of Arizona and Nevada side of the Hoover Dam from 2001 - 2022 by month, in megawatt-hours.

Data Manipulation and Cleaning
The data (illustrated in figure 2) exhibits seasonality, but also a clear downward trend. According to basic outlier analysis, there are no significant outliers, so no data cleaning or adjusting is required for this data set.

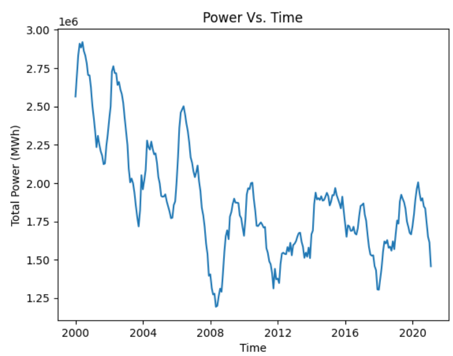

Figure 2

Credibility
The EIA is a highly scrutinized governmental organization given the increasing desire for energy production and consumption information.

Purpose
This EIA data will be used to measure the magnitude of hydroelectric power generation and how that will compare and correlate with Lake Mead water volume. In other words, it could be thought of as a severity component of Lake Mead's declining water volume, which is also the focus of our project.

3.2 U.S. Bureau of Reclamation[7]

Incentive
Because this paper focuses on declining hydroelectric power of hoover dam, we look for water-related measurements to quantify the declining water volume in Lake Mead, the key causation of hoover dam's loss of hydroelectric power. We derive two water-related measurements (Water Volume and Water Consumption, both in acre-feet) from the US Bureau of Reclamation, the official governing body of US water management projects.

- Volume of Water in Lake Mead

- Water Consumptive Use (total between Arizona, Nevada, Southern California, and Mexico[1])

Parameters and Scope
This data set provides the two aforementioned variables for average monthly data from January 1964 to December 2022.

Data Manipulation and Cleaning
Upon exploratory data analysis, there are no missing values, corrupted formats, however there is an "outlier" period that cannot be explained by regular water consumption or the selected environmental variables. This period is marked by an unusual large growth, illustrated in figure 3. We discovered that this unusual jump was caused by the artificial release of reservoir water from Lake Powell (the dam upstream of Lake Mead) to Lake Mead [1]. More specifically, the U.S. Department of the Interior ordered the Bureau of Reclamation to release of 11.56 million acre-feet of water from Lake Powell to Lake Mead in accordance to their water management strategies.

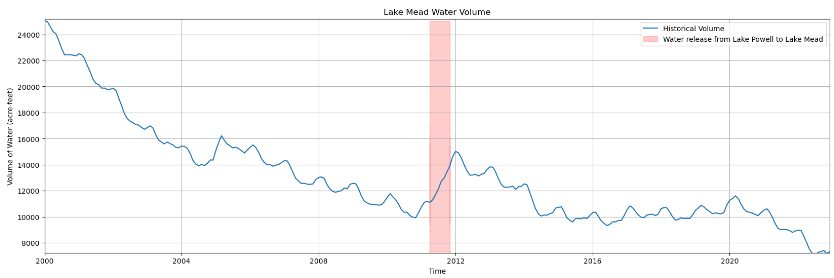

Figure 3: Lake Mead Water Volume Outlier Period

This outlier period was considered in our modeling process and will be discussed further in section 4.

Credibility
Since this is a government-issued report and is rigorously reviewed, the data is expected to be correct. However, to ensure fullest accuracy, we conducted comparisons between this government's source and other 3rd party sources [76] [41], and found no significant deviations.

Purpose
The Volume of Water in Lake Mead data from 2000 to 2022 by month helps us define historical trends and projecting future trends both annually and seasonally. Furthermore, it can also separate outcomes based on seasons and months, a key way we produce more specific risk characterization and recommendations.

3.3 NASA Global Land Data Assimilation System (GLDAS) [27]

Incentive
To quantify the natural influence on the decline of water volume and thus decline of hydroelectric power, we gather five pertinent environmental variables provided by NASA's GLDAS data source. Note this data source is a product of data assimilation[2].

Parameters and Scope
GLDAS not only provides time series data for each variable from 2000 to 2023 but also provides geospatial data at a resolution of 0.25 x 0.25 degrees. There are over two dozen environmental variables available in GLDAS's data set, however, we selected the following variables that are known to impact Lake Mead's water volume, and by extension, Hoover Dam's hydroelectric power generation.

- Evapotranspiration
- Air Temperature
- Rainfall

[1] Mexico water consumptive use is considered since the river runs through northern Mexico. Specifically, the Mexican Water Treaty of 1944, allotted to Mexico a guaranteed annual quantity of 1.5 million acre-feet of water from the Colorado River, plus additional or fewer deliveries in specific circumstances.

[2] Data assimilation (DA) is a technique by which numerical model data and observations are combined to obtain an analysis that best represents the state of the atmospheric phenomena of interest. (NOAA: [17])

- Soil Moisture (40cm - 100cm depth)
- Snow Water Equivalent

Data Manipulation and Cleaning

To avoid creating an overly complex spatiotemporal model by considering each 0.25 x 0.25 degree geographic pixel, we chose two main geographic regions and took the average values of all geographic pixel within those regions. We considered the two regions: (1) Adjacent to Lake Mead and (2) the Upper Colorado River Basin (UCRB). Considering Lake Mead region will capture direct water contributions to and withdrawal from the reservoir, while considering the Upper Colorado River Basin will capture the indirect contributions to and withdrawal from the Colorado River, Lake Mead's main source of water supply.

An example of this process is shown in figure 4, showing the Snow Water Equivalent variable in the Upper Colorado River Basin. For each month in the years 2000 to 2023, all geospatial grids in the region are being averaged to create a monthly time series average. That process is repeated for both locations and each variable.

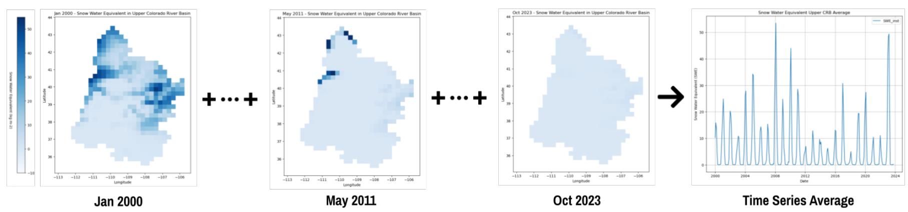

Figure 4: GLDAS Geospatial data gathering and transformation to average time series

The time series averages for all the variables are shown below. Note, the data for soil moisture and snow water equivalent does not apply in the Lake Mead region, only in the UCRB region. There is huge seasonality involved.

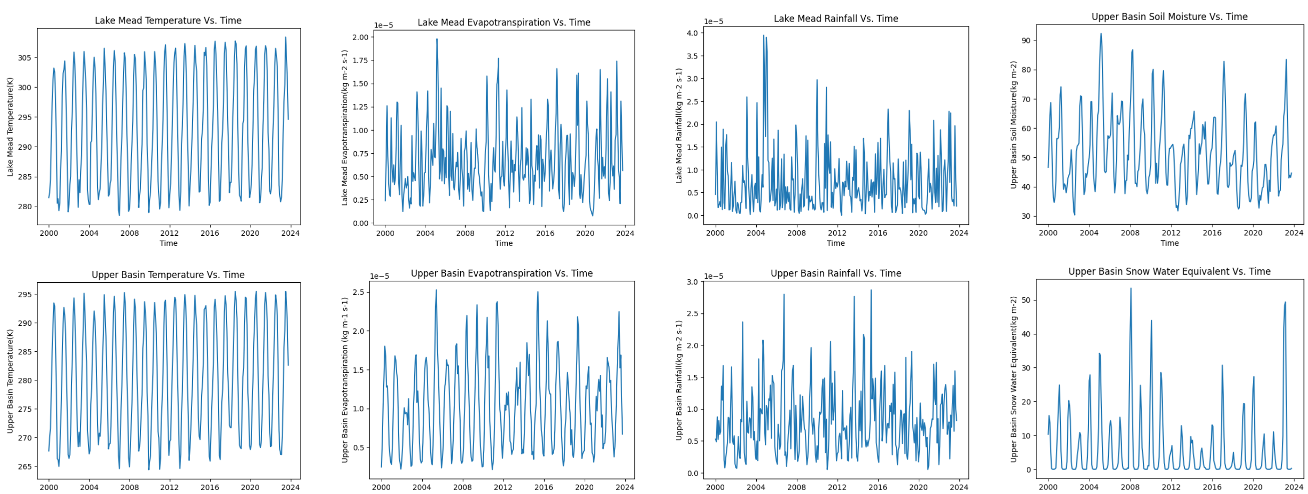

Figure 5: Data extracted for the 8 variables from GLDAS

Credibility

Given the institutional credibility of NASA and the countless scientific citations to this data, we can assume this data set to be truthful to the greatest extent possible.

Purpose

The time series of each variable helps us define historical trends and project future trends of the Volume of Water in Lake Mead, which influences hydroelectric power generation. There may be a potential correlation or causation between the Volume of Water and those environmental variables, which we can extract by analyzing its historical trends and afterward use to project future trends.

3.4 NOAA Physical Sciences Laboratory[77]

Incentive

The over two decade long mega drought of the American Southwest, which may be the worst the US west has faced in 12 centuries[9], has stagnated water levels of the entire Colorado River Basin system including Lake Mead. Given that drought severity is a significant factor, we consider it in our model using the Palmer Drought Severity Index (PDSI), a quantitative measure.

Scope of Data

Monthly data from January 1900 to January 2024 in the Southwest Region.

Data Manipulation and Cleaning

In in the plot below, we notice that there are months that have abnormally high or abnormally low PDSI values. However, these are both not considered outliers based on a IQR outlier analysis, plus abnormal values of PDSI often correlate with abnormal values of volume of water. Therefore, no data cleaning is required.

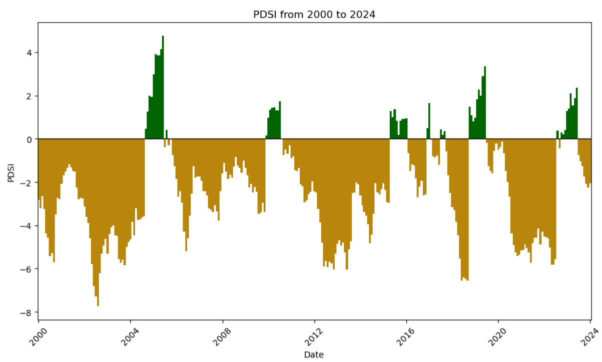

Figure 6

Credibility

The Palmer Drought Severity Index is a widely used index by government agencies and non-government groups.

Purpose

As another independent variable, this helps us understand the historical patterns of drought and help us determine what future drought severity might look like. Additionally, we are able to separate outcomes by analyzing our risk changes in magnitude based on different categories of PDSI.

4 Mathematics Methodology

In our model, we aim to forecast the future quantities of hydroelectric power produced by Hoover dam. To ensure a robust model, first, we eliminated unnecessary variables by addressing multicollinearity among variables. Second, we utilized a Symbolic Regression Model to establish a mathematical relationship between the selected predictive variables with volume of water in Lake Mead. Third, we leveraged Facebook Prophet forecasting Algorithm to project future values for each explanatory variable and integrated them into our model to forecast Lake Mead's water volume until 2030. Finally, drawing upon the proportional relationship between water volume and hydroelectric power production, we estimated the latter for 2030.

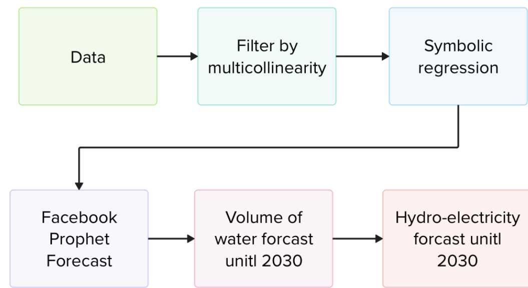

Figure 7

4.1 Assumptions

1. **The observed patterns and relationships in the data over the past 22 years are not purely random but exhibit continuity and predictability.** Climate dynamics, while complex, demonstrate periods of stability and change. By assuming continuity in these patterns, we can leverage historical trends to inform our forecasts. This allows us to capture underlying dynamics and improve the accuracy of our predictions by incorporating past behavior into our models.

2. **The influence of abnormal dam operations and water regulatory activities on the volume of water in the Colorado River and Lake Mead is considered negligible.** Although numerous dams exist along the Colorado River, the complexities of water management and human decision making makes it challenging to incorporate these operations into our analysis. Therefore, we exclude those effects from our model to focus solely on the intrinsic dynamics affecting water volume, and thus hydroelectric power generation.

3. **The contribution of water from the Virgin, Muddy, and Las Vegas Wash tributaries to Lake Mead is considered negligible in our model.** As reported by the National Park Service (NPS[43]), approximately 97% of Lake Mead's water originates from the Colorado River, with only a minor portion sourced from these tributaries[43]. By focusing on the primary water source, the Colorado River, we aim to streamline our model while still capturing the predominant factors influencing water volume dynamics.

4. **Drought severity, as measured by the Palmer Drought Severity Index (PDSI), is assumed to follow a probabilistic distribution.** Analysis of PDSI data from 2000 to 2024 reveals no discernible trend or seasonality, suggesting the inherent complexity and unpredictability of drought patterns. By treating drought severity as probabilistic, we acknowledge the challenges in forecasting future drought conditions while leveraging historical trends to estimate likelihoods for future scenarios. While not a perfect predictor, this assumption provides a practical framework for incorporating drought variability into our modeling efforts.

5. **Direct water consumption does not exhibit a simple 1:1 relationship with the observed volume of water changes.** While direct consumption activities theoretically withdraw a certain volume (acre-feet) of water from Lake Mead, the actual impact on water levels is influenced by various factors, percolation, leakage, and inefficiencies in water distribution systems. These additional losses, which are correlated with water consumption, contribute to a more nuanced understanding of the relationship between human water use and changes in reservoir volume.

4.2 Variables

We selected the variables listed in Table 1 based on a thorough review of various sources. These variables represent the common factors consistently identified across multiple sources as influencing water volume, as also explained in 3.3 Motivations for selecting these variables are explained in Data Methodology.Furthermore, notice that the two locations we are focusing on are directly around Lake Mead and the Upper Colorado River Basin. We do not consider other tributaries or other flows of water into Lake Mead because of assumption 3. There are also no "human intervention" variables per assumption 2.

Table 1: Variables

Variables	Descriptions	Units
ΔV	Each of the difference of Lake Mead water volume from previous year	Thousand acre-feet
S_c	Sum of the water consumptions of Arizona, California, Nevada, and Mexico	Acre-feet
$PDSI$	Palmer drought severity index	no units
$mead_{tair}$	Air temperature at Lake Mead	K
$mead_{evap}$	Evaporation from Lake Mead	kg/m^2s
$mead_{rainf}$	Rainfall at Lake Mead	kg/m^2s
$UCRB_{tair}$	Air temperature at upper Colorado River Basin	K
$UCRB_{evap}$	Evaporation from upper Colorado River Basin	kg/m^2s
$UCRB_{rainf}$	Rainfall at upper Colorado River Basin	kg/m^2s
$UCRB_{soilmoi}$	Soil moisture at upper Colorado River Basin	kg/m^2
$UCRB_{swe}$	Snow water equivalent at upper Colorado River Basin	kg/m^2

4.3 Symbolic Regression

4.3.1 Overview

Symbolic Regression (SR), a data-driven modeling method, constructs mathematical functions by combining various mathematical operations, constants, and explanatory variables to generate a function that is able to estimate a chosen target variable with a given table of data. To leverage SR, we make use of Heuristic Lab which, in addition to SR outputs, has a comprehensive graphical user interface that enables for efficient and wide range diagnosis. Its diagnosis allows us to unveil the optimal mathematical function to calculate the amount of water in Lake Mead, our target variable.

We chose to use Symbolic Regression because of its outstanding in its ability to uncover complex relationships between multiple variables and create a mathematical expression [29]. In order to calculate the volume of water in Lake Mead, the complex water circulation system in the Colorado River needs to be considered in our model. It can sufficiently take into consideration its complexity using symbol regression, by revealing the relationship between the independent variables and the volume of water. This includes the severity of impact and the trend each variable has.

We feed in a large tabular data of the independent variables and volume of water from the years 2000 - 2022 to capture how historically those explanatory variables influence the volume of water. It is acknowledged that historical patterns does not guarantee to reflect in the future, therefore, we establish a firm reliance on assumption 1.

4.3.2 Model and Data Preparation

To generate a function for the volume of water in Lake Mead, we opted to use the difference in Lake Mead volume as the target variable instead of the absolute water volume. This issue was made to address the issue of seasonality, which can significantly impact the observed changes in water volume. By considering the difference in volume, the seasonal variations become more apparent, as the change in volume is more directly, meaning the change in value will be significantly dependent on each season. This modification is easier to predict, since all of the other independent variables are heavily affected by seasons.

Moreover, our decision to take the difference in Lake Mead volume was reinforced by the observation of stationary in the other explanatory variables. Stationary implies that the variables exhibit consistent statistical properties over time, facilitating similar analyses and interpretations across different time periods. By applying a difference, we successfully transform the volume of water data to be stationary, as proven by outputs of an Augmented-Dickey

Fuller test. Both stationary and seasonality motivations to apply a difference helps ensure robustness in our SR and eventual forecast model.

Another issue was the large number of input variables, which causes multicollinearity issues for SR models [69] and general confusion and unreliability in the model. To address this, we decided to remove variables that exhibit significant correlations between another (R^2 value above 0.7), a commonly practiced modeling procedure [70]. We made a multicollinearity chart (figure 8) to visually illustrate potential correlations between each of the possible variables.

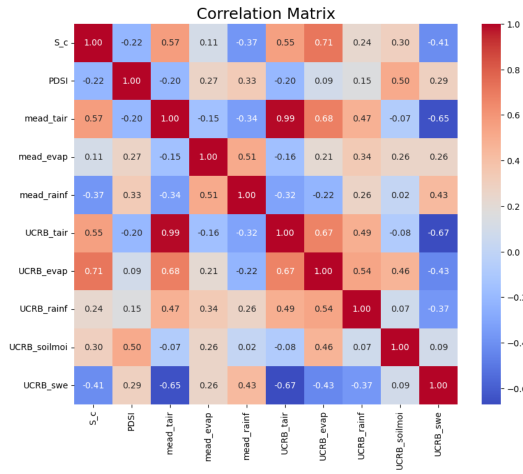

Figure 8

If two variables were correlated to each other, one of the two variables should be dropped from the input of the model. According to figure 8, the correlations that are above 0.7 R^2 value are the following: S_c and $UCRB_{evap}$, and $mead_{tair}$ and $UCRB_{tair}$. Then we tested all of the combinations for dropping the variables to avoid the multicollinearity between any two variables. The actual variables after dropping one of the correlated variables in each pair and used in the model: S_c, $PDSI$, $mead_{evap}$, $mead_{rainf}$, $UCRB_{rainf}$, $UCRB_{soilmoi}$, $UCRB_{swe}$

4.3.3 Model Parameters

In the process of running symbolic regression with Heuristic Lab, there were several user-side parameters to modify in order to obtain better results. The available parameters are listed listed below.

- Ratio of training and testing data
- Model depth, Model length
- Number of generation
- Relative number of evaluated samples
- Tree grammar

First, we aim to determine the optimal size of training proportion ($p_{training} = 1 - p_{testing}$). Finding this is a known challenge in machine learning models because there isn't an across-the-board correct answer. So, to determine the best training proportion for SR regression for our data, we conducted many trials. We rigorously tested our model by running it hundreds of times with different training proportions. Each run was carefully recorded to identify the range of $R2̂$ values that consistently delivered optimal results (highest R^2). Below, you'll find a summary of our testing process and its outcomes, where the x-axis shows the range of training proportion and the y-axis shows the accuracy of the model in each proportion, measured in R^2.

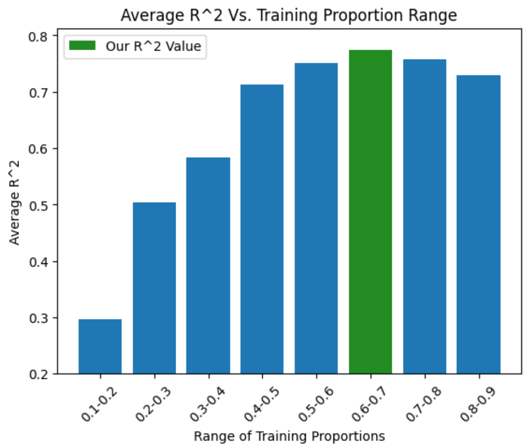

Figure 9

From this analysis, we found that the best training proportion falls in the range of 0.6 to 0.7. After narrowing down, we tested more refined training proportions between the 0.6 to 0.7 range to find the most suitable ratio for our model. Consequently, we arrived at the training data ratio of 0.66.

For the next two parameters, model depth and model length, we used 15 and 55 respectively. This was the standard ration for SR, as prompted by Heuristic Lab. These numbers were the optimal values because there was a significant decrease in the model accuracy when changing those predetermined values.

Third, the number of generations we used is 50, which is also the default value in Heuristic Lab. The model should be more accurate if we increase the number of generations, since generating more always enhance the chance of getting better results. However, upon increasing number of generations to test the influence, results didn't change. We infer this is because 50 generations was already large enough to produce good equations and increasing the size would increase it by insignificant amounts.

Fourth, the relative number of evaluated samples were set to 100%, to ensure that all of our data is accounted for in the modeling process to create as accurate of model as possible.

Lastly, we test the tree grammar parameter. Tree grammar is a parameter in Heuristic Lab that dictates which math operations and functions are considered in the equation generation process for the symbolic regression. We tested all of the combinations of math function usage and figured out which to use in the model. We found that adding very complex functions (e.g. gamma function) was more harmful to our R^2 than sticking with simple functions. The math operations and functions we chose to use are listed below.

- Arithmetic Functions
  - Addition
  - Subtraction
  - Multiplication
  - Division
- Exponential and Logarithmic Functions
  - Exponential
  - Logarithmic
- Terminals

- Constant
- Variables

4.3.4 Results

Using the variables selected in 4.3.2 and parameters selected in 4.3.3, we ran the symbolic regression. Below is the decision tree that blueprints how the SR model obtained its final equation:

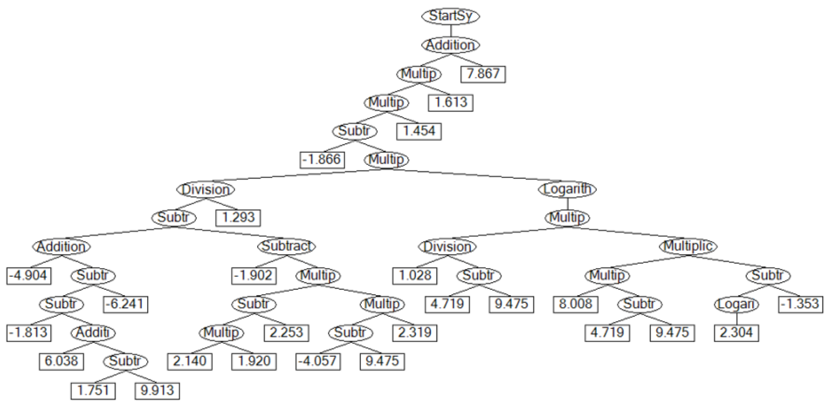

Figure 10

The mathematical equation from this (which is too long to print) is used to calculate our target variable, in our case ΔV. The equation contains independent variables with the basic four arithmetic operations, logarithm, and constants. Note: the model did not consider $mead_{evap}$, $mead_{rainf}$, and $UCRB_{rainf}$ in the equation, meaning that those variables had little to no influence on ΔV because its explanatory influence was already explained by other variables (not by correlation). Using the four remaining variables (S_c, $PDSI$, $UCRB_{soilmoi}$,$UCRB_{swe}$) produce the fit shown in figure 11.

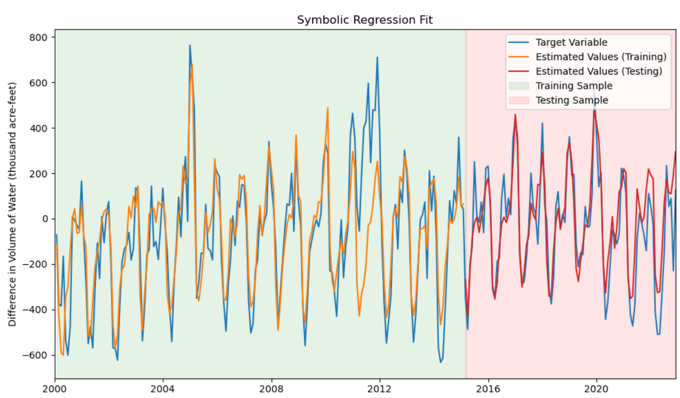

Figure 11

Ultimately, for cross-validation our model calculated a Pearson's R^2 value of 0.761 for the testing data; this value is high enough to justify the accuracy of the model, seeing that the value passes the 0.7 threshold, which is widely considered as a strong correlation [30].

We extend this cross-validation analysis by examining the model residual distribution (figure 12). Upon examination, the residual distribution is approximately normal with several outliers. This indicates that our model captures most of the variance, with a few struggling to capture it.

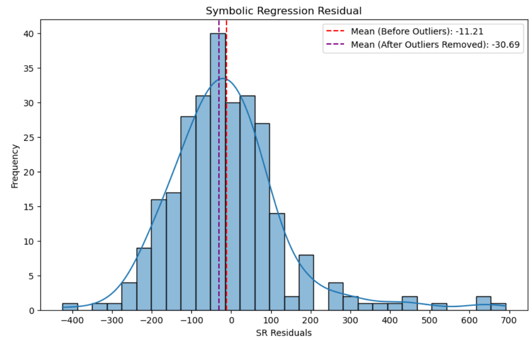

Figure 12

Going back to figure 11, we notice the model fails to capture the 6 month period around 2011. This is an expected outlier as we discussed in the data section (refer to 3.2), where there was an artificial water release of 11.56 maf into Lake Mead. To determine whether this impacted SR's model development, we tested the algorithm with and without those outliers data points—the model's accuracy did not change. We infer that the model algorithm already detects that period as outliers so the equation development doesn't affect the process of generating the equation and a strong R^2. Therefore we decided to keep the data as it is.

4.4 Fitting and Forecasting

Unlike other "risks" in the real world (e.g. natural disasters, homicides), the risk of Lake Mead is highly trend oriented. This means that to understand the severity of the issue, we must look at the rates of water declining, rather than at a single instance time.

Rather than applying a trend on the uni variate version of Volume of Water to obtain that trend, we utilize our Heuristic Lab equation that was built in section Symbolic Regression 4.3 and rely on the forecasted inputs of the four variables to produce a Volume of Water forecast. This choice is driven by the desire for a more specific and interdependent model.

To achieve this objective, we used methods to predict how each variable is expected to change from December 2022 (the end of our sufficient data) through 2030. The three variables—sum consumptive use, SWE, and Soil Moisture—are all variables that exhibit a trend over the 22 years of provided data. However, for the PDSI, given the chaotic nature of weather and climate situations, it does not exhibit a clear trend.

4.4.1 Facebook Prophet Model

For the three trend-exhibiting variables, we employ Facebook Prophet[3]. It's a robust Generalized Additive Model (GAM) that is capable of forecasting uni variate time series data that works best with data manifesting strong seasonality[51]. This works perfectly with our purpose given that those three variables emit strong yearly seasonality.

To optimally make use of Prophet's strong and flexible algorithms, we tinker and deduce optimal strength of regularization, the primary user-side parameter. With a stronger regularization, the model will perform worse (on a residual basis) but avoid over fitting. On the other hand, weakening the regularization will fit the training data more closely (lower residuals) but may be subject to more over fitting.

We tailored the strength of regularization differently for each of the three trend-exhibiting variables in our modeling process. For sum consumptive use, we opted for weaker regularization to reduce the magnitude of residuals, especially given its strong significance as observed in 2. This adjustment enabled Prophet to capture more abrupt changes in its predictions, which are often linked to human-produced legislation or significant behavior shifts. Conversely,

[3]A powerful open source time series forecasting algorithm created by Facebook's Core Data Science Team

for variables like SWE and Soil Moisture, we applied stronger regularization to uncover overarching trends while minimizing the impact of data noise. This approach allowed us to better identify long-term patterns and significant shifts in these environmental indicators, essential for understanding broader climatic and environmental dynamics.

Applying individualized parameters to the three variables, we produce individual fits and forecasts for each variable shown in figure 13:

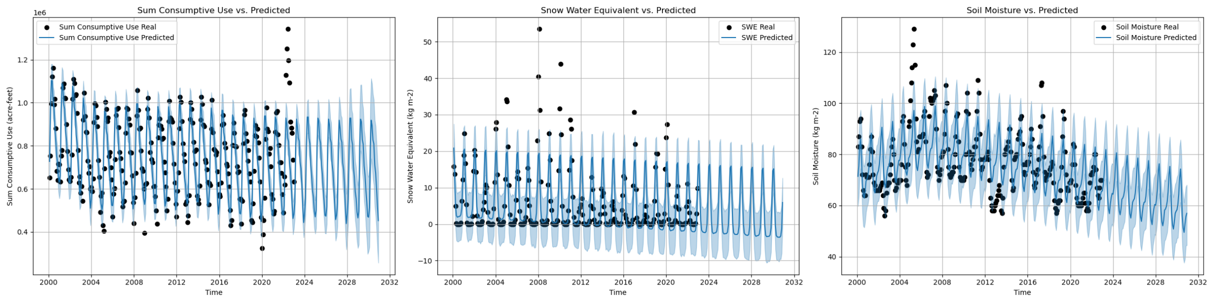

Figure 13

4.4.2 PDSI Expected Value

Drought severity (PDSI) is unpredictable. Its dependence on the chaotic nature of humid and sub humid climates and other atmospheric conditions makes drought incredibly difficult to prepare for [71]. Additionally, observing PDSI values from 2000 through 2024, there is no visible trend or seasonality. In light of this, Prophet is not a suitable forecasting option.

To accurately generate a PDSI forecast, we rely on the assumption that PDSI is probabilistic (ref assumption 4) to calculate an "expected value" or "expected severity" to utilize for each month until and including December 2030, our forecast range. We took into consideration using a simulation based approach to tackle the non-uniformity nature of PDSI. However, given that the expected value is a long term average of a variable based on its probability distribution [48], we deduced that an expected value sufficed for our purpose.

To calculate the expected value of PDSI, we use PDSI monthly data from 2000 from 2022 distribution to account for the full duration and some argue the aftermath of the Southwestern North American Mega drought [52]. With that distribution (shown in 14), we use the relative frequency by integer intervals and their corresponding PDSI severity values to calculate the expected value of PDSI

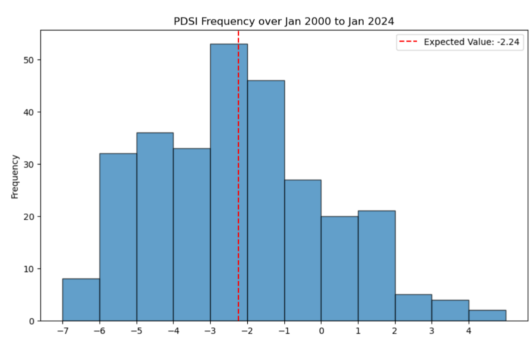

Figure 14

4.4.3 Results

Evaluating equation (from section 4.3.4) with the forecasted values from section 4.4.1 and 4.4.2, we produce the Difference in Volume of Water forecast; then, applying a cumulative sum to transform the Difference in Volume of Water (ΔV), we generate the Volume of Water forecast. Note, any forecast that requires returning from the difference will use a cumulative sum. We find that from 2022 (the latest data) to 2030, there is an approximate 29.2% drop in water volume.

4.5 Conversion to Hydroelectric Power

Recall, our project focuses on the decline of hydroelectric power, which is chiefly motivated by Lake Mead's water volume. To convert our water volume forecasts to hydroelectric power, we run a linear regression between annual average Volume of Water and total Hydroelectric Power Generation, with sufficient explanatory power given its R^2 of 0.79. The choice to work with annual instead of monthly was to reduce the seasonal offsets between the variables, because a regression run on a monthly basis obtained an R^2 less than 0.2.

The process to obtain yearly forecasts through 2030 of hydroelectric power generation is depicted in figure 15.

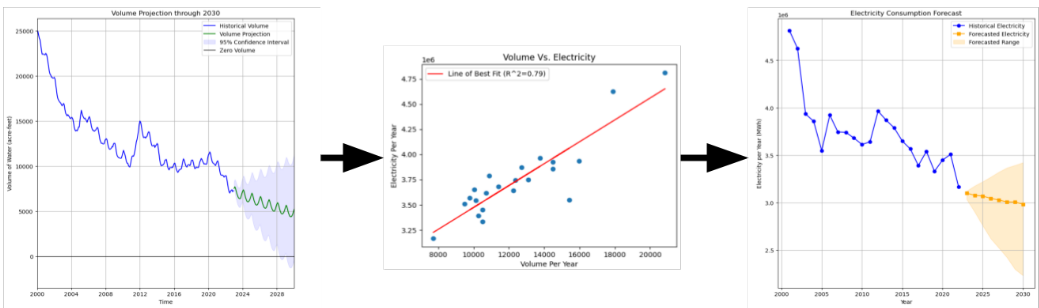

Figure 15: Water Volume to Hydroelectric Power Forecast

4.6 Strengths and Weaknesses

4.6.1 Strengths

Modeling Hydrological Systems are greatly hampered by uncertainties and heterogeneity [63], making it difficult to capture relationships. Therefore, an apparent strength of our model is its ability to capture that complex relationship between four environmental and consumptive use variables with the Volume of Water.

The model's R^2 of 0.76 exceeds the widely accepted threshold of a "strong correlation" of 0.7 [5], meaning that 70% of the variability is explained by equation from section 4.3.4.

Furthermore, what we've noticed is that our model is almost perfectly capturing the seasonality of the difference in Volume of Water, however, it does not fully capture the magnitude of the abnormal peaks and troughs—or in other words, underfitting. However, for our purpose, because we are interested in the long term trend, we deem this to be not too underfit nor too overfit.

A last strength of the model is its ability to not be negatively affected by outliers and keep a robust seasonality pattern and trend for forecasting purposes. Prophet is a strong algorithm that uses fourier sums and partial fourier sums to work with seasonality [3]; given that fourier series are incredibly powerful methods, Prophet works well with seasonality, a feature extremely prevalent in our data.

4.6.2 Weaknesses

In our modeling for Lake Mead's water volume, we assumed stationary by taking differences in data to stabilize mean and variance. While this helped address some variability, it may limit capturing system dynamics. Environmental systems, like Lake Mead and its adjacent watersheds, are complex and influenced by climate change, policies, and natural factors. Assuming stationary may overlook key trends, impacting long-term forecast accuracy. Given this, our forecasts to 2030 will likely decline in accuracy the further into the future we predict.

Another limitation of our model is our "expected value" approach to forecast PDSI, which may not fully capture the chaotic and interconnected nature of drought events. Furthermore, our expected value is based on data from 2000 to 2022, meaning that forecasted PDSI are a reflection of past values. However, future drought values may be totally independent of preceding years, so the model may overlook potential shifts in drought patterns or extremes in the future. This may lead to an underestimation or overestimation of water volume forecasts.

5 Risk Analysis

5.1 Preface

In this section, we aim to uncover the risk of Hoover Dam's hydroelectric power generation loss due to rampantly declining Lake Mead. Hoover Dam not only provides immense quantities of hydroelectric power to adjacent communities but also serves as an American industrial icon. If water levels of Lake Mead continue to plunge, so will hydroelectric production, and so will America's industrial symbol. To better understand the dynamics of this risk, we first address the severity tied to our four predictive variables. Or, in question form: if a predictive variable were to increase or decrease, what would be the severity of the aftermath on Volume of Water and hydroelectric generation? To tackle this question, we perform a sensitivity analysis.

Adding to this severity analysis, we conduct a cost analysis, combining forecasts from our Prophet model with electricity production costs of hydroelectric generation alternatives to determine loss of opportunity cost. For baseline comparison, we choose electricity generation by coal, where we discuss both monetary and environmental losses.Then, we will address the distribution of risks, including months of least hydroelectric power generation and which states are expected to be most impacted by loss of hydroelectric power. Lastly, we observe expected trends, including reaching the point of no return: dead pool.

To keep values consistent with our model and projections, we use water volume in this section. We are aware that water level is more commonly used when identifying risks. Therefore, any values that rely on water level are automatically converted into volume with this regression between volume and level (figure 16).

$$log(y) = 3.09 \cdot 10^{-3}x + .658 \tag{1}$$

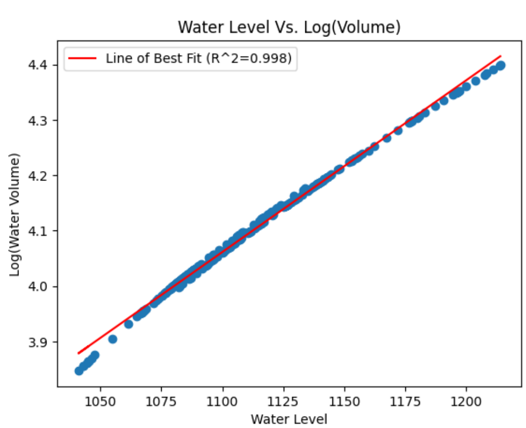

Figure 16

In this section, we don't address frequency because our project does not revolve around discrete events with defined occurrences. Unlike risks associated with specific events, such as car crashes or lost phones, our analysis focuses on trend-based risks. Specifically, we are concerned with the gradual decline in water levels over time rather than isolated incidents.

5.2 Sensitivity Analysis

To check the severity of impact of each variable has on the model, we perform a sensitivity analysis for the four variables from our Symbolic Regression (S_c, $UCRB_{soimoi}$, $UCRB_{swe}$, and PDSI). We varied each variable by ±10% for each month entry from 2000 - 2022 and recorded the percent change.

We utilized Facebook Prophet values for each variable due to their lower occurrence of outliers compared to the original dataset. However, some outliers remained, potentially affecting our analysis. To address this, we applied the interquartile range method to identify and remove these outliers. Then, we analyzed the distributions of percent change, and reported the average percent change of each variable in table 2.

Table 2: Variable Impact

Variables	+10%	−10%
S_c	−63.06%	+63.06%
$UCRB_{soimoi}$	+0.35%	−0.35%
$UCRB_{swe}$	+1.05%	−1.11%
$PDSI$	+0.39%	−0.39%

The signs of each variation indicate their respective impacts. For instance, an increase of 10% in S_c results in a negative impact of -63.06% on the volume of water difference (ΔV). This aligns with expectations; as water consumption rises, the volume of water decreases. Similarly, the signs of percent impacts for other variables also validate their effects on the volume of water.

S_c exerts the most significant impact, with a percent impact of ±63.06%. Conversely, $UCRB_{soimoi}$, $UCRB_{swe}$, and $PDSI$ have small impacts, approximately ±1% or less. Therefore, the model is more resilient to shifts in those variables compared to water consumption.

Furthermore, we infer that the severity of impact on the volume of water mirrors its impact on hydroelectric production, as the volume of water linearly correlates with electricity generation.

5.3 Cost Analysis

Hydroelectric power is one of the cheapest forms of electricity averaging at .85 cents per kWh [61]. If water levels continue to drop, electricity generation will follow. To make up for this deficit in power, other means of energy are needed, such as coal power. However, a much larger price of 10 cents per kWh [4] is associated with electricity generated from coal. This price includes not only the cost of production, but costs from health and climate damages associated with the carbon emissions. To put this cost deficit in perspective, we estimate how much more it costs to have coal alternatives fill the loss of hydroelectric power from 2022 to 2030.

The Cost of Hydroelectric Power if the water level remains at year 2022 levels:
By using the average water level and energy production from our last year of data, 2022, we project the total energy generated from 2022 to 2030 will be 28.5 billion kWh and cost $242 million if water levels stay the same.

Cost of Electricity if we have to make up for loss with coal
However, using our models for volume and energy, we project energy from 2022 to 2030 to be (table 3):

Table 3: Predicted Energy Generated From 2023 to 2030

Year	Predicted Volume	Billion kWh generated(using linreg)
2023	6,949.41	3.15
2024	6,580.98	3.11
2025	6,216.10	3.07
2026	5,870.12	3.03
2027	5,542.71	2.99
2028	5,214.72	2.96
2029	4,907.75	2.92
2030	4,608.45	2.89
Total	101,834.24	24.12

The difference between energy generated if the water level stays the same and if the water level decreases according to our model is 4.4 billion kWh. Covering this loss of hydroelectric power with coal energy will is estimated to cost $48.8 million per year and $440 million over 9 years.

5.4 Environmental

Furthermore, reliance on coal energy (or other non-renewable energy sources) as an alternative energy sources poses a significant threat to our environment and contradicts the climate goals set by the government. To combat climate change, countries worldwide have proposed transitioning from fossil fuels to clean, renewable energy sources. Hydroelectric power, provided by dams like the Hoover Dam, stands out as a cost-effective and eco-friendly energy option. However, without the billions of kWh of energy generated by the dam, the United States will struggle to achieve its target of 100% carbon-free energy by 2030[53]. According to our projections on water levels and hydroelectric generation (refer to Section 5.3), a loss of 4.4 billion kWh of energy is anticipated. Considering that coal energy emits approximately 1.04 million metric tons of carbon per kWh[23], compensating for the loss of hydroelectric power with coal energy would result in an additional 4.6 million metric tons of carbon pollution[23]. To put this into perspective, the carbon emissions from this scenario would be equivalent to those produced by approximately 1 billion passenger vehicles[28].

5.5 Distributions

5.5.1 Monthly Analysis of Risk

As of now, our risk analysis on hydroelectric power have been on the annual scale. In this section we will uncover the monthly trends and comparison of monthly water volume and monthly hydroelectric power generation. Using monthly averages from 2000 to 2022 for each variable, we produce the following two charts (figure 17) as a visual for comparison.

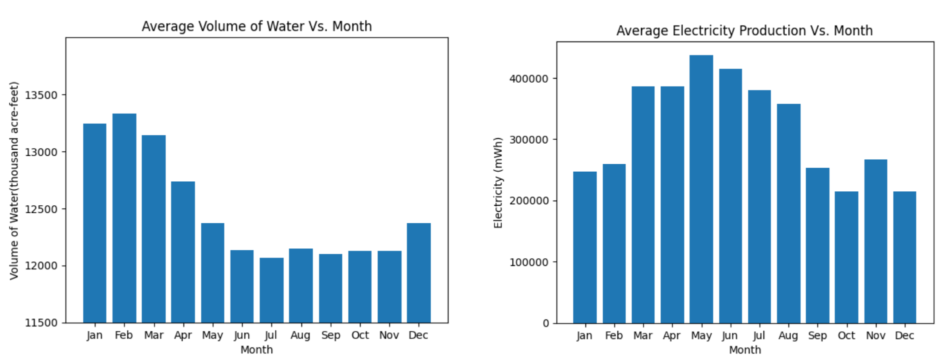

Figure 17: Monthly Distribution of Water Volume and Hydroelectric Production

Upon observation, we observe distinct patterns in the rise and fall of water volume throughout the months. Notably, the water volume tends to rise during winter months, peaking in February, and subsequently decreasing from March through June. This fluctuation suggests a correlation between water levels and temperature, as colder temperatures typically coincide with increased snowfall and subsequent melting during the spring months.

Similarly analyzing electricity production, we see a different pattern. It is during the spring and summer months where hydroelectric production is greatest, with a peak during May. This is reasonable given that in the arid American Southwest, during the summer months demand for electricity is the greatest. Note, for most electricity production, production largely correlates with demand because generators provide straight to the user over electricity storage.

It is worth discussing the implications behind the greater value months don't coincide between water volume and hydroelectric production. There are many possible interpretations behind these differences. Our best interpretation is that during the summer months, hydroelectric power is most at risk. This is because there is less water volume to flow through the generators on top of a higher demand. Therefore, our recommendations will be highly recommended to be followed during the summer months.

5.5.2 States of Highest Risk

The electricity from the Hoover Dam gets distributed to the surrounding states. 19% of the electricity from the Hoover Dam goes to Arizona, 23% to Nevada, and 58% to California. This information identifies California as being at the most risk of loss of energy. 15% of the dam's electricity goes to Los Angeles alone[36]. If the hydroelectric power from the Hoover Dam continues to decrease, California will be the most affected. Due to the reduced amount of energy from the dam, California will have to use alternative sources of energy (possibly non-renewable) that will end up costing more money to the citizens and municipalities. Following California will be the other states, which will all have to decrease their hydropower use and find alternative, non-renewable sources to quench the needs of the population.

5.6 Trends

We refer back to our Prophet Model to determine how each of the four risk factors develop over time. Another productive feature of the Prophet model is its ability to look long-term trends; in other words, it looks beyond the seasonality component and deduces how the variable magnitude changes throughout the years. Using the same regularization parameters as mentioned in section 4.4.1, the trends for Consumptive Use, Soil Moisture, and SWE are represented in figure 18. Note: the forecast years have been included and are delineated by the red vertical divider.

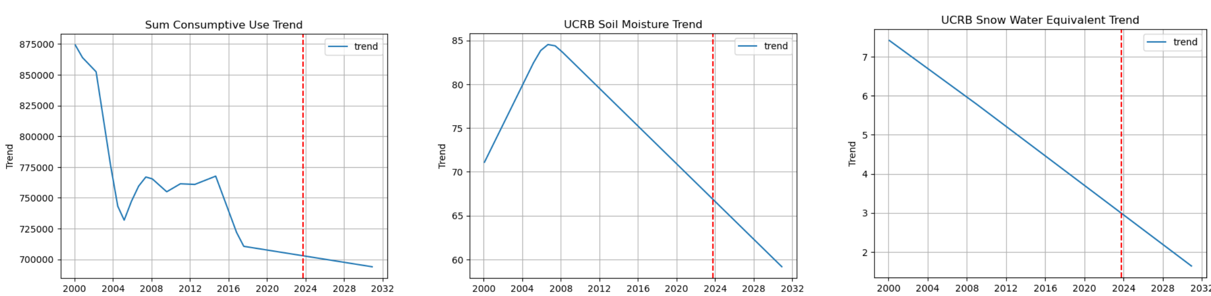

Figure 18: Trends

First, it is observant to point out that the trend of Sum Consumptive Use has more abrupt shifts than UCRB Soil Moisture and UCRB SWE. This is a result of weaker regularization (closer fits), which is able to capture a more detailed picture of trend changes, some as a result of proactive water management strategies by municipalities. For example, around the early 2000s, consumptive use greatly decreased, coinciding with Las Vegas's water conservation acts which included replacing thirsty lawns with desert plants[39]. Furthermore, it is evident that consumption rates have been improving since the year 2000, drastically. Municipalities like Los Angeles, which gets 58% of its from Lake Mead , have managed to plateau or decrease water consumption[57]. With that said, we suggest municipalities can go further, given that even slight cuts improve water volume remarkably as shown in our model's sensitivity analysis (section 2). This will be further discussed in our recommendations.

Next, our model predicts that Soil Moisture will plummet, even after peaking for an unusually moist set of years. Interestingly, the PDSI index reflects this unusual moist period of time, with PDSI values reaching moderately high moisture levels. Regardless, our model projects an unrelenting exacerbation of arid soil moisture in the Upper Colorado River Basin—Lake Mead's majority water supplier.

Likewise, the Snow Water Equivalent in the Southern Rocky Mountains—which supplies the hundreds of tributaries ultimately leading into Lake Mead—is declining, a lot. Further reports support these arguments, citing alarmingly low levels of snow [47] [56]. Contrary to several media publications, we are cautious to place full blame on climate change, given the extremely chaotic nature of the southwestern climate and the dwindling effects of Southwestern North American megadrought.

5.6.1 Minimum Power Generation

With drastic declines in Lake Mead's water level, stakeholders and researchers are concerned about the possibility of "inactive pool," where the minimum water elevation for power generation (950 feet) is met [38].
. In other words, if the water elevation of Lake Mead is less than 950 feet, the electric generators does not have enough pressure or force to produce electricity. So, while the water is running through the intake gate, no electricity will be produce.

To understand the urgency of this issue, we use our model to estimate at what year "inactive pool" will be met. As stated throughout the paper, the model in section 4 uses the Volume of Water in the model as opposed to the water level. We use the regression defined in section 5.1 to determine that 950 feet is approximately 3910 acre-feet of water. With this, we visually conclude from the figure below (figure 19) that if not improved, the dam will reach "inactive pool" in less than a decade!! However, it is important to note the uncertainty that comes with forecasting, which is illustrated through the 95% confidence interval bounds.

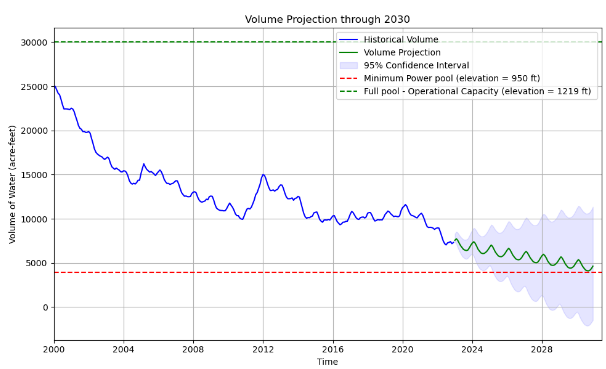

Figure 19

We understand that many news sources state that Hoover Dam will reach inactive pool as early as 2025 [38], based on "recent trends." Our model estimates that Hoover Dam will reach inactive pool around the early 2030s. Our model does not match the media's narrative primarily because our model is based on a 22 year analysis as opposed to a "recent trend" which media publications allude to. An extension of this model could look at different ranges of years of analysis, whether looking at the very recent years or looking at a 22 year analysis. However, for the purpose of this project we are only considering a 22 year analysis.

6 Recommendations

We now propose recommendations for action that can be taken by Arizona, Nevada, California, and other stakeholders to help improve water levels of Lake Mead. These recommendations will use information from our model and our risk analysis. In the distribution section of our risk analysis (section 5.5.1), we deduced that the summer months are at the greatest risk for loss of hydroelectric power.

Therefore, for each of our risk mitigation strategies, we recommend the actors are extra responsible during those months. While our recommendations are hard to choose a "best" on a cost-benefit basis, we most strongly suggest that the most powerful method for improving water volume and hydroelectric production is reducing water consumption.

Furthermore, we recognize that our three environmental variables (soil moisture, snow water equivalent, and PDSI) are present. However, from our sensitivity analysis (refer to table 2) we found that they have little impact, and mitigating these environmental variables is neither feasible nor economical.Also, we have carefully examined insurance benefits for our project. However, given the nature of our project, we determined there were not suitable insurance recommendations.

6.1 Reduced Consumptive Use in the Agriculture space

Our first recommendation focuses on how to mitigate risk in the root cause of hydroelectric power reduction: the reduction of water use in agriculture. In our model's sensitivity analysis, it was proven that reductions in water consumption can increase water volume of Lake Mead significantly, leading to huge improvements of hydroelectric power generation. Furthermore, increasing water volume of Lake Mead comes with a plethora of other benefits, making this our top recommendation.

Over 54% of the southwest's water consumption is used for agriculture [66]; this heavy reliance on water for agriculture has become a critical driver for the loss of water in Lake Mead and loss of hydroelectric power generation [40]. Reduced water consumption in the agriculture space is a viable behavior change risk mitigation strategy. Here's why we are strong advocates for this. According to our model and sensitivity analysis, a 10% reduction in water consumption can increase Lake Mead's water volume by 60%!! While a 10% reduction is incredibly difficult given that every drop of water counts in the American Southwest, nonetheless, it proves that even minute cuts can have huge implications.

So, what are ways to achieve this?

1. We recommend farmers to switch from alfalfa—extremely thirsty crops—to its alternative Sorghum. In a Pacific study (Cohen et al., 2013), they estimated that switching 74,000 acres from alfalfa to sorghum would save around 140,000 acre-feet of water consumption per year [15]. The change in net returns shows base costs of $13.5 million or $96 per acre-feet. With 2.7 million acres of alfalfa covering the entire Colorado River Basin in 2022, with sufficient base costs, this could save significant amounts of water [22]. This can also be financially beneficial to farmers in the long run. Stephen Hawk, a fourth-generation farmer, reported in a Guardian article that adopting other sustainable crops has not only enabled him to conserve water but also to diversify revenue streams [24]. A diversification of revenue makes farming businesses more resilient to fluctuations in revenue, a huge plus to crop switching.
2. Furthermore, for a more government involved approach, the government could promote the use of less-thirsty crops, drought-resistant crops, adoption of efficient irrigation techniques through subsidies or tax breaks. Currently, in some places there are subsidies to improve production. However, those programs, while increased produced, have increased water usage [49]. We recommend that governments should switch the focus on their subsidies to not just provide for production, but provide for adoption of new and more water-efficient adaptions or technologies.
3. Another avenue is implementing higher water taxes to incentives more efficient farming practices. A 20% tax is estimated to reduce consumption by 20% [45], which is significant considering that, according to our model's sensitivity analysis, it could raise water volume by over 10%! If agreed upon between politicians and farmers, This could have huge implications and benefits.

It goes without saying the massive legal, cultural, historical problem this poses to those involved with this issue.

Water rights, for example, is an ongoing issue. This is because there are many actors involve that need this water, including the Navajo Nation, the largest group of indigenous people. Another example, is the culture around Alfalfa may be hard to dissolve given that its one of the American Southwest's most prominent crops and has been around with the farmers for an extended duration of time. To conclude, while we strongly recommend water consumption reduction, getting there is not so simply as signing a bill. It demands careful navigation, research, collaboration between all groups to find viable solutions that addresses not just technical aspects but also the rooted societal norms and practices.

Moreover, we suggest implementing higher water taxes to incentives more efficient farming practices. We recommend a 10% in taxes, as it is estimated to reduce water consumption by 2%. While 2% may not seem like a lot, when you account for all the 1.89 million farms in the U.S., it ends up saving a lot of water. This approach would reduce overall water consumption, thereby preserving more water in the Colorado River. By enforcing these measures, the rate of water overflow from the dam would decrease significantly. While this is a massive ongoing issue, it proves as an easy problem to solve.

6.2 Alternative Renewable Energy Sources

Next, we propose a modifying outcome risk mitigation strategy of adopting alternative renewable energy sources. The amount of clean generated electricity shrinking rapidly, with our model projecting 4.4 billion kWh loss over the span of 9 years in section 5.3. This loss will likely force states to resort to using non-renewable energy sources, such as gas or coal, due to their availability. While these may be easily accessible options, non-renewable energy sources are extremely bad for the environment. In 5.4, we predicted around 4.6 million metric tons of carbon will be emitted over a span of 9 years if coal energy is used to make up the hydroelectric power generation deficit.

To be in accordance with the federal government's environmental agenda, it is vital that California, Arizona, Nevada (states that rely on renewable energy from hoover dam) to adopt other more environmentally friendly energy sources. The first option is solar energy. The Colorado River basin receives abundant sunlight, making solar power an excellent choice. Solar panels installed on rooftops, open land, or even floating solar arrays on reservoirs can provide clean energy. Producing 4.4 billion kWh of solar energy will have net-zero emissions compared to the 4.6 million metric tons of carbon emissions from coal (ref section 5.4).

If 6% of Lake Mead's water/land were devoted to solar power, it could yield at least 3,400 megawatts of electric-generating capacity — more than the Hoover Dam's capacity of 2,074 megawatts [75]! This 6% is just 247 square miles (640 km^2) of space. We would install floatovoltaics, which are solar panels that float in the water. Therefore, based on various calculations on solar panels, we will need about 24 million solar panels to produce the same amount of electricity that is lost by the Colorado River. In Colorado, the price price of installing a solar panel is $2 per watt [37]. Therefore, it will cost just $0.75 billion dollars for 9 years to install the solar panels. Compared to other methods like desalination (which can cost between $400 to $1,000 per acre-foot), cloud seeding is considered cost-effective. [60] In this single purchase, we will put an end to the entire electricity depletion problem. Utilizing solar energy instead of coal energy to compensate for energy lost will be much better for the environment, and for the residents and citizens, who get to enjoy more clean water to use.

Another renewable energy source is wind power. In the Colorado River Basin, wind speeds average around 8.3 miles per hour [33]. However, from March to August wind speeds average about 9.6 miles per hour [33]. The ideal speed for wind turbines is about 9 miles per hour making these months suitable for wind power generation [78]. Those summer months were also shown to produce low levels of hydroelectric power (figure 5.5.1). It will take about 402 wind turbines to match the amount of electricity lost from the mega drought. Installing these turbines will cost about 220 million dollars per year for 9 years (based on calculations in [59]. Our recommendation is to harness the wind during these months to replace the loss of hydroelectric power, especially since our risk analysis determined that those months are at highest risk (section 5.5.1). Like solar energy, wind power will eliminate the environmental damages caused by using coal.

There are many other renewable energy options that can be considered, such as geothermal energy and biomass energy. However, solar and wind energy is already present in the Colorado River Basin and can easily be expanded [16]. In conclusion, there are many ways to make up for lost energy from lower water levels without sacrificing the environment.

6.3 Changing water and electricity practices in Urban settings

Our model shows that consumption use is the number one thing that is driving the decrease in water levels in the Colorado River. When states agreed to use less water in 2012, the water level rose dramatically. Therefore, the main recommendation sticks with reducing water use. Therefore, to reduce the amount of water consumed, we should look to the residents, and see what residents and governments should do to help prevent the loss of water in the Colorado River. Our recommendations are aimed for Urban/city settings, since they use 31% of water after agriculture [66]. Again, referring to our sensitivity analysis, even small reductions in consumption can hugely influence water volume and thus power. There is no "one adoption" that can sufficiently cut urban water use, since its ways of usage is incredibly diverse. Listed below are a couple proposed urban water reduction strategies that, together, can make a difference.

1. **Repairing water leaks from pipes.** Water leaks leak a significant amount of water, which then cause the residents to request more water.
2. **Installing water-efficient appliances**. Using high-efficiency items, such as aerators on bathroom faucets, toilets, and water-efficient shower heads will reduce the amount of water used. It will also use less electricity, which all aids in stopping the drying of the Colorado River.
3. **Implementing Xeriscaping Practices.** Xeriscaping involves designing landscapes with drought-resistant plants that require minimal water. This reduces the need for irrigation, conserves water, and promotes sustainable landscaping practices in urban areas. Additionally, using mulch and incorporating rainwater harvesting systems can further enhance water conservation efforts in xeriscaped areas. This is already being done in Arizona! [80]

The other side of this behavior change in urban settings is to reduce electricity consumption, which, like water consumption, also works best with multiple initiatives.

1. **Tracking electricity and water usage.** By measuring and looking into what products are using electricity and water, we can see what appliances are using the most of them, and eliminate them, especially those on a wide scale.
2. **Implementing Smart Street Lighting Systems.** Utilize smart technologies such as sensors and automated controls in street lighting systems. These systems can adjust light levels based on real-time data, reducing energy consumption during periods of low activity or daylight. Additionally, using energy-efficient LED bulbs in streetlights further enhances energy savings.
3. **Promoting Passive Cooling Techniques in Buildings.** The American Southwest is incredibly hot, which is a reason why monthly distribution of electricity consumption is high in the summer (refer to 5.5.1. We recommend involved actors to design buildings with passive cooling features such as natural ventilation, shading elements, and thermal insulation. These techniques minimize the need for air conditioning, reducing electricity usage and improving energy efficiency in urban structures.

6.4 Cloud seeding

For our last recommendation, we look into Cloud Seeding. Cloud seeding presents a promising solution to combat the chronic aridification of the Colorado River and the consequential challenges of water scarcity and reduced hydroelectric power generation at Hoover Dam. This innovative technique involves the introduction of substances like silver iodide and dry ice into clouds to enhance precipitation. Cloud seeding works best when cloud temperatures range from -20°C to 7°C [11] [10], the temperature of the Colorado River Basin during the winter. Therefore, we recommend that cloud seeding activities predominantly take place during the winter. By encouraging rainwater formation, cloud seeding can significantly increase water flow in the Colorado River, helping to prevent its drying and ensuring sustained hydroelectric power generation.

Studies have shown that cloud seeding can lead to a notable increase in snowfall, up to 15%, and associated stream flows, up to 5%. This translates to adding approximately 80,000 acre-feet of water annually, enough to serve around 160,000 households. Despite concerns about cost, cloud seeding can be relatively affordable, with estimates suggesting an annual expenditure of about $30,000 per targeted area [11].

Water providers and governments are already investing substantial resources in cloud seeding efforts. For example, water providers in the Lower Colorado River Basin contribute approximately $1.5 million annually to cloud seeding initiatives in the Upper Basin[14]. Additionally, the federal government has allocated $2.4 million to support cloud seeding activities[55]. In this theoretical scenario where the Hoover Dam operates at total capacity, it would generate 2,080 megawatt-hours (MWh) of electricity[36]. This impressive output would power homes, businesses, and industries across the region, contributing significantly to the energy needs of the southwestern United States.

Cloud seeding has proven successful in other regions such as Dubai and China, where it has led to increased rainfall, reduced air pollution, protection of crops, and enhanced water security. Implementing cloud seeding on a wider scale along the Colorado River holds significant promise in restoring water levels and ensuring a stable source of hydroelectric power for the region.

7 Conclusion

In conclusion, our model has provided valuable insights into the future volume of water in the Colorado River, allowing us to identify key factors contributing to its drying. Through our analysis, we have determined that unsustainable water usage and environmental degradation are among the primary causes of this concerning trend.

Several proactive measures are recommended to address these challenges and ensure the continued stability of hydroelectric production. First and foremost, diversifying our energy sources by integrating other clean and renewable sources, such as solar and wind power, will bolster our resilience to fluctuations in water availability while promoting sustainability. Additionally, prioritizing infrastructure maintenance and improvements to Hoover Dam is essential to optimize hydroelectric power generation efficiency. Furthermore, replenishing water levels in the Colorado River through water conservation efforts, water management strategies, and potential augmentation projects can help mitigate the impacts of water scarcity.

Recognizing that these actions come with associated costs and trade-offs is crucial. Implementing these measures may lead to increased electricity production and stability in the long term, but electricity prices will likely rise in response to declining water volumes. As such, policymakers and stakeholders must carefully balance the economic implications with the imperative to safeguard the river's health and ecosystem integrity.

In summary, by leveraging our model's forecasts and proactive implementation of our recommendations, we can address the challenges facing the Colorado River and safeguard our renewable energy future. Ultimately, if states and stakeholders collaborate, we can make a more resilient and environmentally responsible energy system for generations to come. Let's transform our symbol of Oasis of challenges into an opportunity-filled horizon and replenish the future.

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Acknowledgements

We would like to sincerely thank our coach Mrs. MacDonald for unconditional support through tough and humorous times.

We would also like to thank Mrs. Witcraft for her help in providing us insight.

We would also like to thank the Actuarial Foundation for creating and organizing this incredible program, and providing us the opportunity to explore into mathematical modeling and actuarial science.