ML & Climate | Final Paper

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1 Introduction

Historically, California has long faced recurrent and prolonged droughts, a pattern only expected to intensify with ongoing climate change and its associated rise in global temperatures (PPIC Water Policy Center, 2021). These droughts have profound agricultural, social, and economic consequences, particularly in central and southern California where water demand is high and agricultural dependence is intense (Mehran et al., 2020). This study seeks to better understand and predict drought events by examining both historical and projected climate data, with the goal of identifying changes in the severity, frequency, and underlying drivers of drought across the state, particularly in San Bernardino County.

Drought, at its core, is a prolonged absence or imbalance of water, best conceptualized as a ratio problem, where demand (e.g., through evapotranspiration) exceeds the natural supply (precipitation). This distinction sets drought apart from permanent arid conditions and allows for classification into several types. Our focus is on meteorological drought, which stems from a persistent lack of precipitation, and hydrological drought, which manifests through reduced water levels in rivers, lakes, and aquifers (Khanna et al., 2024). The former often precedes the latter, making both critical indicators of worsening drought conditions.

To monitor and classify drought severity, the U.S. Drought Monitor (USDM) uses a scale ranging from D0 to D4, where D0 signifies abnormally dry conditions without drought, D1 is moderate drought, D2 represents severe drought, and D3 and D4 represent extreme and exceptional drought conditions, respectively. San Bernardino County, a major agricultural region, has recently experienced all five categories across its territory, making it an ideal case study to understand how drought severity manifests and evolves under varying conditions (National Integrated Drought Information System (NIDIS), 2024).

This study aims to predict drought severity levels through integrating multiple climate indicators, from precipitation and temperature to soil moisture to determine how these elements interact over time to produce periods of drought or recovery. Using Random Forest and TreeFFuser autoregressive models, we use historical observed data and drought labels to train and predict future D0-D4 cumulative percent areas drought severity levels affecting San Bernardino County, CA based on different climates and emissions levels. With projections for 2025-2099, we hope to explore the hypothesis that California's climate alternates between extended dry spells and relatively wet periods. Historical drought "blocks," such as those in 2007–2009, 2012–2017, and 2021–2023, suggest these events may occur in multi-year phases, punctuated by brief periods of relief. Understanding whether these wet-dry cycles are random, climate-driven, or increasingly influenced by anthropogenic warming is critical for future resource planning.

2 Related Works

Historical drought analyses have proven to be an essential tool for understanding California's drought patterns and their impacts on agricultural communities and resources and the general population. Recent studies have developed diverse approaches to understand drought dynamics and patterns, particularly in regions with high variability like California or Australia.

Williams et. al integrated a combination of hydrological models (the Noah Land-Surface model, VIC (Variable Infiltration Capacity) model, CMIP5 Climate models, Palmer Drought Severity Index) and tree-ring reconstructions to predict drought severity to depict the role of anthropogenic warming on drought levels (Williams et al., 2020). To do so, the models calculated soil moisture using observed climate data, validated results using the tree-ring reconstructions, and captured the effects of warming-driven reductions in snowpack and increased evapotranspiration, evaluating the contribution of anthropogenic climate trends to the severity of the 2000-2018 drought (Williams et al., 2020).

Other approaches included combining linear stochastic components with artificial neural networks (ANN), which improved the accuracy of the prediction of the standardized precipitation index (SPI) by comparing other trained neural networks and regression models Belayneh et al. [2014], or using integrated soil moisture indicators with climate variables within a random forest framework to provide drought forecasts up to 6 months in advance (Hameed et al., 2024).

Most relevant to our research and methods is (Brust et al., 2021) , which developed "DroughtCast," an RNN to predict the United States Drought Monitor classification up to 12 weeks in advance using satellite-observed soil moisture data from NASA's Soil Moisture Active Passive (SMAP) mission and some meteorological variables. However, like the relevant works mentioned previously, (Brust et al., 2021) focuses on short-term drought predictions.

Longer-term drought predictions extending to decadal projections have relied mostly on downscaled climate models rather than machine learning models. (Swain et al., 2018) used high-resolution climate model ensembles to project changes in California's precipitation patterns through the mid-century, identifying a "precipitation whiplash" event – an intensification of wet and dry extreme events. However, these approaches usually have difficulty in taking into account temporal resolution and lack drought-specific projections, creating a developmental and methodological divide between short-term forecasting and long-term projection.

Our research attempts to address this critical gap by developing a hybrid framework that integrates pattern recognition and drought-specific domain knowledge to predict drought cycles through the end of the century.

3 Data

3.1 Data Collection and Preprocessing

To collect data to train our model to attempt to predict drought severity values, which are cumulative percent areas of San Bernardino County, CA, we first collected PRISM data that spanned the entirety of the conterminous United States. However, because it only had a subset of variables we wished to examine, we collected Livneh-VIC and LOCA-VIC data.

Meteorological	Hydrological
Air Temperature (°C)	Baseflow (mm/day)
Rainfall (mm/day)	Runoff (mm/day)
Snowfall (mm/day)	Evapotranspiration (mm/day)
Snow Water Equivalent (mm/day)	Soil Moisture (mm/day)

Figure 1: Livneh-VIC and LOCA-VIC variables (Livneh et al., (2015), (California Energy Commission, 2018))

3.1.1 USDM Drought Label Data

Drought labels were obtained from the U.S. Drought Monitor (U.S. Drought Monitor, 2024), which reports drought severity as the percentage of land area affected at each of five drought levels (D0-D4) from 2000 and onwards. In addition to observational records with drought severity levels, this source also provides historical dryness and wetness conditions from 1895 to the present, based on the Standardized Precipitation Index (SPI) (National Integrated Drought Information System (NIDIS), 2024). This SPI-based dataset also reports the total percentage of land in each dryness (D0-D4) and wetness (W0-W4) category, using the same categorical thresholds as the USDM drought labels.

While USDM drought labels from 2000 are derived from multiple indicators, including SPI, soil moisture, streamflow, and satellite observations, the historical data from 1895 onwards are based solely on SPI. However, despite this difference, we collected and used the SPI-derived data as a proxy for USDM drought severity levels during the 1950-1999 period, which is an approach supported by the fact that SPI thresholds align closely with the D0-D4 classification framework.

We subset the SPI-based dataset to be from 1950 to 1999 and only used the standardized 'date' and D0-D4 variables, cutting the wet condition variables. Then, we combined this data with the USDM drought label data. For consistency, we ensured temporal consistency across the datasets by aggregating the weekly dryness/drought data were to monthly resolution, aligning with the native resolution of future climate projections.

These percent-area labels in these datasets served two purposes in our study: as regression targets for our drought prediction models and inputs to a binary D4 indicator to detect and highlight extreme drought periods across time.

3.1.2 PRISM Data

The PRISM (Parameter-elevation Relationships on Independent Slopes Model) dataset is a high-resolution gridded climate dataset developed by the PRISM Group at Oregon State University using spatial interpolation that generates spatially continuous meteorological variables across complex terrain in the United States.

For our initial data collection, we extracted daily meteorological time series data from 1981 to 2024 via the PRISM API. This compiled dataset provided 800m and 4km spatial resolution grids and temporal granularity for variables, including daily and monthly total precipitation (ppt), maximum temperature (tmax), minimum temperature (tmin), mean temperature (tmean), mean dew point temperature (tdmean), and both minimum and maximum vapor pressure deficit (vpdmin, vpdmax). These variables offered valuable historical context, providing strong training data for understanding climatic patterns that may affect drought within San Bernardino County.

However, this dataset lacks hydrological variables, which are arguably more important for predicting drought severity. We believed that building a comprehensive understanding of drought dynamics would require additional data and variables that captured water storage, movement, and soil-vegetation interactions. Thus, we moved onto Livneh-VIC historical analysis and LOCA-VIC climate projections from the Cal-Adapt platform.

3.1.3 Livneh-VIC data

The Livneh-VIC dataset provides a comprehensive, observationally-based foundation for our drought prediction model. It was developed through an extensive process of quality-controlling and processing meteorological station observations across contiguous North America, ultimately offering gridded daily observed meteorological and limited hydrological data over the contiguous United States. What distinguishes the Livneh-VIC dataset is its integration with the VIC hydrological model to allow for more accurate representation of evapotranspiration processes, runoff generation mechanisms, snow accumulation physics, and soil moisture dynamics at different depths (Livneh et al., 2015).

To match our later datasets, we've set the temporal resolution to monthly values. As for spatial consistency, we addressed the discrepancy between the original high-resolution 1/16° gridded datasets and the county-level aggregated data available through Cal-Adapt by standardizing all analyses at the county level. This county-level approach not only accommodated the constraints of publicly available data but also aligned our predictions with the administrative units where drought management decisions are implemented.

Additionally, our Livneh-VIC dataset was missing data from 2014 to 2024. To remedy this lack of observed data, we took the predicted data from the LOCA-VIC climate models. Specifically, we chose to use the feature data from the HadGEM2-ES model, which represents a warm and dry climate like San Bernardino County, with RCP 8.5. We subset this projected data from 2014 to 2024 and combined this data with our observed Livneh-VIC data. Then, to complete our training dataset, we concatenated this dataset from 1950 to 2024 with the drought label data we retrieved and created from the U.S. Drought Monitor.

3.1.4 LOCA-VIC data

For projected climate data, we used LOCA-VIC downscaled simulations, which provided us monthly projections of all eight input variables spanning 2006-2099 (California Energy Commission, 2018). These GCM simulations use the LOCA (Localized Constructed Analogues) downscaling method used to generate these projections, which was specifically designed to better represent daily extreme weather conditions compared to previous methods by preserving the coherence of the input fields while avoiding spurious changes to the original GCM-predicted climate change signal. As with the Livneh set, we've kept the data at a county-level spatial resolution given the data format availability.

However, the combined LOCA and VIC processes allowed for our selected models represent a wide range of future climate possibilities for California: HadGEM2-ES assumes a warmer/drier future climate, CNRM-CM5 a cooler/wetter one, and CanESM2 the average of the former two. Each model was run under two emissions scenarios: RCP 4.5, representing an emissions peak in 2040 and a total of 2-4°C increase by end of century, and RCP 8.5, representing a high emissions trajectory with a 4-7°C increase by end of century. These six scenarios combined offer a robust framework for exploring climate uncertainty through the end of the century.

For all of our datasets, we converted all 'date' columns to have standardized timestamps, added cyclical and seasonal encodings through sine and cosine transformations of individual months ('month_sin', 'month_cos') and one-hot encoding for calendar quarters to help capture seasonal effects that could affect drought dynamics. Additionally, we calculated monthly climatological means and standard deviations to help with anomaly detection, normalization, and imputation of lagged values. These steps were taken after attempting to predict drought severity values with the original eight features with D0-D4 drought severity values as our target variables and receiving poor predictions and performance metrics, where all four categories were determined to have negative R^2 values.

4 Methods

4.1 Feature Engineering

From our data collection and preprocessing, we understood that our data would present us with a unique set of challenges, including its temporal dependencies and seasonal memory. These characteristics likely would affect drought prediction, and to counter these effects we saw in our initial model fitting, we engineered a few time-series features to add to our integrated datasets before training our model(s):

1. Lag features were created for all drought severity levels (D0-D4) with lags at the 1, 2, 3, 6, 12, 24, and 36 months to capture short and long-term drought persistence.
2. Seasonal lags were computed using same month lags from the prior 1-3 years to help capture interannual recurrence patterns.
3. Rollings means for our hydrological and meteorological features at 3, 6, and 12 months to smooth short-term noise that may be present and affect the prediction values.
4. Interaction terms between key hydrological and meteorological features to account for nonlinear effects and domain knowledge.

We also defined a binary classification target (D4_binary) where a value of 1 indicates the presence of extreme drought conditions (D4 > 0), allowing for just detection of this drought event. This was in response to continuous subpar performance for predicting D4 drought level values.

4.2 Initial Modeling Attempts

Our initial approach explored more traditional model fitting and machine learning models, including Random Forest, XGBoost, and LSTM. We chose these particular models because tree based models effectively capture nonlinear relationships between our climate variables and drought conditions without explicit specification of interaction terms as well as handle sequential data. These models also provide feature importance analysis, allowing us to understand which variables most significantly impact drought severity and development and were also used in (Hameed et al., 2024) and (Brust et al., 2021) successfully for more short-term drought prediction.

The models were first trained using direct autoregressive approaches across all target variables simultaneously with time series cross-validation to account for temporal dependencies, rolled mean and standard deviation calculated with a window of 7 months, and added lag features (1, 2, and 3 month histories) for our target variables (D0-D4 drought values). These models provided good predictions and performance metrics (highest R^2 = 0.89) during cross-validation.

We faced difficulties in predicting drought levels on future data because they lacked D0-D4 values we used for the lag and rolled features. To accommodate, we decided to do recursive predictions, where we calculated the lag values and rolled features for each time step in our future data. While this was successful, we faced scaling issues when inputting the features into the model for predictions and noticed that our features were highly correlated, posing a problem in predicting drought severity level values as our models could likely predict the same value as previous time-steps.

4.3 Final Modeling Framework

Per suggestion and after evaluating multiple approaches, we used TreeFFuser as our autoregressive model for drought severity level prediction to better capture larger scale climate phenomena. TreeFFuser is a probabilistic diffusion-based tree ensemble model that takes advantage of the interpretability and feature selection abilities of tree-based models with the uncertainty quantification advantages of diffusion models. Additionally, this model produces full predictive distributions rather than point estimates, and handles rare extreme events through the diffusion-based approach.

With this model, we also assured that in computational environments where TreeFFuser was unavailable, we would utilize the RandomForestREgressor as an alternative due to its good performance but also its robustness, availability, and proven effectiveness with environmental modeling applications.

This integrated TreeFFuser AutoRegressor model used separate TreeFFuser models for D0-D4 regression with 5-fold time-series cross validation using expanding windows to simulate forecasting and ensure proper evaluation of temporal generalization. Moreover, for extreme drought detection (D4_binary), we trained a RandomForestClassifier on the binary target with class weights to account for the extreme imbalance between drought and non-drought periods.

Using this framework, we implemented a recursive monthly forecasting approach for years 2025-2099. We included domain-specific constraints, where we enforced a drought hierarchy constraint (D0 $\rightarrow$ D1 $\rightarrow$ D2 $\rightarrow$ D3 $\rightarrow$ D4) to maintain the progression of drought severity and forecast volatility. At each timestep, the model generated predictions using the hydrometeorological feature inputs from the LOCA-VIC projections and lagged drought values from previous predictions. Each timestep produced prediction intervals through a bootstrap-based approach where we construct prediction distributions by sampling from a normal distribution centered on the predicted value with month-specific variance calculated from error patterns from historical data. Then, using these prediction distributions, we calculated 90% confidence intervals with each point forecast for each drought level.

Our final model outputs included forecasted drought indices (D0-D4) and binary predictions for D4 values (extreme drought), time series visualizations and classification performance metrics, confidence intervals for each forecast at each timestep, and performance metrics.

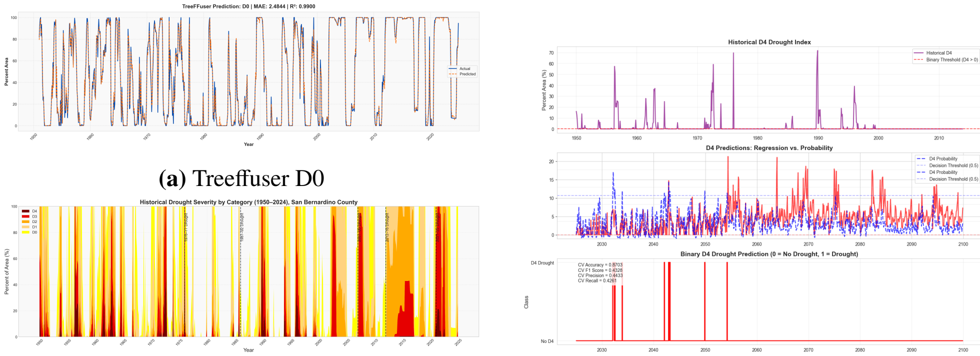
5 Results

5.1 Predictive Model

Our TreeFFuser model successfully captured the historical drought patterns from 1950 to 2024 in San Bernardino County. The model demonstrated robust performance across all drought categories with R^2 values ranging from 0.97 to 0.99 and mean absolute errors (MAE) between 0.31 and 2.5 percentage points. Notable historical drought events were accurately identified, including the major California droughts of 1976-77, 1987-92, 2007-09, 2012-16, and 2021-22. These historical patterns provided a solid foundation for validating our model before applying it to future climate scenarios.

5.2 Future Predictions

Looking at all six of our future predictions, we have found three key findings. Firstly, we've found that the drought severity will increase regardless of emission scenario: both RCP 4.5 and RCP 8.5 scenarios project significant increases in drought frequency and severity compared to historical patterns. The drought cycles identified in the projections show more rapid transitions between drought categories, a higher percentage of land in drought, and less time in low D0 or



(a) Treeffuser D0

(b) Treeffuser Historical Prediction

(c) D4 Binary Prediction

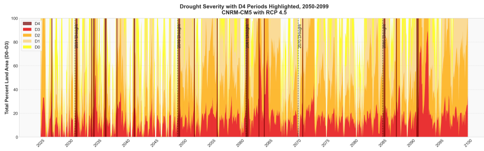
Figure 2: Treeffuser Model Performance on the historical dataset (D0 and complete stacked graph), and D4 binary prediction performance.

D1 states in between major periods of droughts. And though the increased severity and duration of these droughts varies depending on the scenario, this agreement across all models suggests that some degree of climate adaptation will be necessary, regardless of mitigation efforts, as San Bernardino moves into the mid and end-of-century. That being said, the drought patterns differ between emission scenarios: our second finding shows that all three models pointed to higher percentages of land in severed drought (D3) in the RCP 8.5 scenario, with only 0.5 percentage points difference for the wet/cool climate, but up to a 15.77 percentage point difference as we move up to the average and warm/dry climate. They also tend to rise further into the century, starting around 2060 and occasionally peaking around the 2080s. This is in contrast to the RCP 4.5 scenarios, which were found to project more frequent exceptional drought (D4) episodes concentrated towards the earlier half of the century (from 2025 to 2065), rather than prolonged severe drought towards the end. HADGEM2-ES has 17 total months of D4 drought in RCP 8.5 compared to the 12 months in RCP 4.5, CanESM2 predicts 23 months of D4 instead of 16, and CNRM-CM5 predicts 33 months of D4 under RCP 8.5 as opposed to 24 months under RCP 4.5. This was a slightly counterintuitive finding, given that we expected higher emission scenario to unanimously worsen in all drought categories relative to the lower emission scenario, and we were not expecting that the wet/cool climate would be the one with the most total D4 months regardless of emissions. This highlights the complex relationship between emissions trajectories and drought manifestations, which may necessitate different adaptation strategies depending on both the emissions pathway and the given climate.

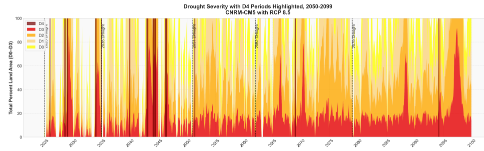
6 Conclusion

Our findings reveal that drought patterns are likely to intensify significantly compared to historical baselines, though the specific characteristics of these droughts vary between emission scenarios. These results highlight the urgent need for both climate mitigation and adaptation strategies to address the challenges posed by increasing drought severity. This will have profound implications for agriculture and society in San Bernardino County. More frequent and severe droughts will reduce crop yields, increase irrigation demands, and potentially render certain agricultural practices unsustainable without significant adaptation Medellín-Azuara et al. [2024].

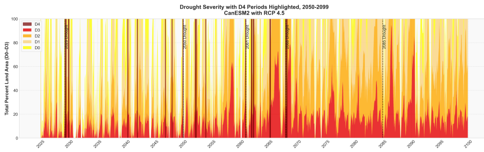
Water scarcity during extended drought periods will likely intensify competition between agricultural, municipal, and ecological water uses. Communities dependent on agriculture for their livelihoods may face economic hardship, potentially leading to demographic shifts as agricultural viability declines in certain areas. The socioeconomic impacts extend beyond agriculture. More frequent water restrictions will affect residential water use, potentially reducing quality of life and increasing water costs Hanak et al. [2024]. California has already implemented stringent water conservation policies during past drought emergencies, such as the 2015 mandate requiring a 25% reduction in urban water use statewide, and a 2018 mandate establishing long-term efficiency standards that include indoor residential water targets of 55 gallons per person per day until 2025, decreasing to 50 gallons by 2030 California Department of Water Resources



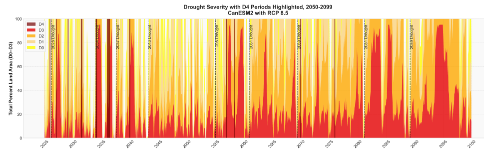
(**a**) CNRM-CM5 with RCP 4.5



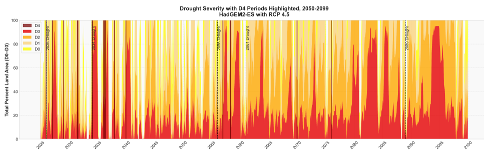
(**b**) CNRM-CM5 with RCP 8.5



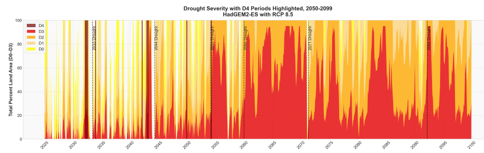
(**c**) CanESM2 with RCP 4.5



(**d**) CanESM2 with RCP 8.5



(**e**) HADGEM2-ES with RCP 4.5



(**f**) HADGEM2-ES with RCP 8.5

Figure 3: Projected drought severity in San Bernardino County under all 6 scenarios, with D4 conditions indicated as a shaded binary. Potential future drought onsets marked with a dashed vertical line. As you can see on the right column of RCP 8.5 scenarios, the percentage of land in D3 has notably increased, especially towards the end of the century. Spaces between droughts are hardly noticeable, and the frequency of droughts decreases towards the end of century as the duration goes into multi-year long droughts.

[2018]. As droughts intensify under climate change, such policies may become more restrictive, creating financial strain particularly for lower-income households and those with larger families Hanak et al. [2024]. Such policy-based strategies are inevitable if San Bernardino County is to successfully navigate the future climate, which will have to include water efficiency targets as a part of long-term water resource management, if multi-year droughts are to occur again. We hope that the predictions of drought indices serves as an early warning system and motivation to begin building resilient infrastructure so that residential communities and agricultural industries can begin adapting to water restrictions.

While our results show that drought conditions will intensify under both emission scenarios, they also demonstrate that lowering emissions remains absolutely worthwhile. The magnitude of drought severity, particularly in terms of persistent D3 conditions, is substantially higher under RCP 8.5 scenarios. By pursuing ambitious emissions reductions consistent with RCP 4.5 or lower scenarios, the extent and persistence of severe drought conditions could be meaningfully reduced. From a water management perspective, occasional extreme droughts interspersed with periods of recovery may be preferable to persistent moderate-to-severe drought conditions that offer little reprieve for water systems and ecosystems to recover Song et al. [2023].

Therefore, our findings strongly support continued and enhanced efforts to reduce greenhouse gas emissions. Even though some degree of drought intensification appears unavoidable, the worst outcomes can still be prevented through decisive climate action. The difference between RCP 4.5 and RCP 8.5 scenarios represents not just statistical variations but tangible differences in human quality of life, economic losses, and ecological damage.

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