Improved Drought Forecasting Using Surrogate Quantile And Shape (SQUASH) Loss

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Abstract

Droughts are amongst the most damaging natural hazard with cascading impacts across multiple sectors of the economy and society. Improved forecasting of drought conditions ahead of time can significantly improve strategic planning to mitigate the impacts and enhance resilience. Though significant progress in forecasting approaches has been made, the current approaches focus on the overall improvement of the forecast, with less attention on the extremeness of drought events. In this paper, we focus on improving the accuracy of forecasting extreme and severe drought events by introducing a novel loss function Surrogate Quantile and Shape loss (SQUASH) that combines weighted quantile loss and dynamic time-warping-based shape loss. We show the effectiveness of the proposed loss functions for imbalanced time-series drought forecasting tasks on two regions in India and the USA.

1 Introduction

Droughts are amongst the most damaging natural hazard with cascading impacts across multiple economic sectors, the environment, and society. For instance, droughts can lead to agriculture production losses, intense wildfires, waterways disruptions, water supply shortages, and many others. Improved drought forecasts followed by proper strategic planning can help to deal with these severe impacts of drought. However, despite several decades of progress, accurate forecasting of drought is still a challenge that is further compounded by climate change.

Drought indices are commonly used to monitor and quantify droughts. Several drought indices have been proposed with different degrees of complexity, data requirements, physical processes, and purpose. Standardized Precipitation Index (SPI) [1] and Standardized Precipitation Evapo-Transpiration (SPEI) [2] are two powerful and commonly used drought indices. For the purpose of this study, we focus on the SPEI as it takes the atmospheric water balance into account and is a more suited drought indicator in the context of climate change.

Several approaches based on stochastic, probabilistic, and machine learning techniques have been proposed in the literature to forecast the SPEI and other indices at multiple time scales. The models like Artificial Neural Network(ANN) [3], Long Short-Term Memory (LSTM) [4], Convolutional LSTM [5], Wavelet ANN [6], integrated ANN [7] have been demonstrated. In [7], a hybrid neural network is proposed that combines multiple models trained using different losses to improve the accuracy of drought forecasting. However, this approach does not explicitly capture the temporal dimension while predicting extreme drought conditions. Despite significant progress, a key challenge

Tackling Climate Change with Machine Learning: workshop at NeurIPS 2021.

in forecasting drought indices, including SPEI, remains. The existing work on drought forecasting does not emphasize both evaluation and analysis of the extreme and severe drought as well as wet events. Specifically, current approaches do not adequately address the imbalance in time-series forecasting aspects. The imbalance is due to the fact that the extremely dry and wet events are few as compared to normal events and therefore are difficult to forecast.

In this paper, we attempt to address the above-mentioned challenge by developing a novel loss function (SQUASH) that is differentiable, captures the shape error of the time-series aspect of the problem, handles imbalanced data, and is computationally efficient. We validate our approach for multi-step forecasting of SPEI drought index over two regions in the USA and India. A detailed ablation study with different surrogate loss functions is present in this article.

2 Methodology

We pose the problem of forecasting SPEI drought index at a regional level as a multi-horizon forecasting task. Let $\mathbf{L}$ be a set of locations in the chosen region and let $\mathbf{T}$ be a set of timestamps. Each entity of the SPEI time-series is defined as $\mathrm{y_{l,t}}$, where $l \in \mathbf{L}$ and $\mathrm{t} \in \mathbf{T}$, q is the quantile, $\mathrm{l_{id}}$ is the location ID of a particular region, mathematically it can be written as:

$$\hat{\mathrm{y}}_{\mathrm{t}+\tau,\mathrm{l},\mathrm{q}} = \mathbf{f}_{\mathrm{drought}}(\mathrm{q}, \mathbf{U}_{\mathrm{l},[\mathrm{t-k:t}]}, \mathbf{K}_{\mathrm{l},[\mathrm{t-k:t}+\tau]}, \mathbf{St}_{\mathrm{l}}) \tag{1}$$

where $\mathbf{U}_{\mathrm{l},[\mathrm{t-k:t}]}$ is a set of unknown future inputs (e.g., historical observation of drought indices), $\mathbf{K}_{\mathrm{l},[\mathrm{t-k:t}+\tau]}$ is a set of known future inputs (e.g., forecasted attributes from climate models), $\mathbf{St}_{\mathrm{l}}$ is a set of static covariates (e.g., location) and $\hat{\mathrm{y}}_{\mathrm{t}+\tau,\mathrm{l},\mathrm{q}}$ is the prediction of drought indices τ step ahead.

The goal of training a drought forecasting model is to improve the overall forecasting accuracy as well as that of rare events such as severe and extremely dry conditions. The standard quantile losses do not address the problem of highly imbalanced time-series data. We introduce a SQUASH loss that combines weighted quantile loss and shape loss to improve the accuracy of extreme event forecasting. We used this loss functions to train a Temporal Fusion Transformer (TFT) [8] model. We used TFT as it is a state-of-the-art model for multi-horizon forecasting and can model different types of inputs. TFT uses LSTM-based encoder-decoder architecture for encoding historical observation and future known inputs. It also uses a variable selection network and attention mechanism to identifying the importance of the features.

2.1 Surrogate Quantile and Shape (SQUASH) Loss

For reliable drought forecasting, one has to consider two main aspects of modeling the transition of drought conditions over time and explicit attention on rarely occurring events. To address this, we propose a SQUASH loss that takes care of these two aspects by two loss components: weighted quantile loss and shape loss. The shape loss helps in minimizing the shape distortion errors in the temporal dimensions that arise from a transition of drought conditions. The weighted quantile loss helps to model complex drought indices data distribution. This is defined as:

$$\mathbf{SQUASH}_{\mathrm{loss}}(\mathrm{q}, \mathrm{y}_{\mathrm{t:t}+\tau}, \hat{\mathrm{y}}_{\mathrm{t:t}+\tau}) = \alpha \times \mathbf{Q}^{\mathrm{weight}}_{\mathrm{loss}}(\mathrm{q}, \mathrm{y}_{\mathrm{t:t}+\tau}, \hat{\mathrm{y}}_{\mathrm{t:t}+\tau}) + (1-\alpha) \times \mathbf{S}^{\mathrm{shape}}_{\mathrm{loss}}(\mathrm{y}_{\mathrm{t:t}+\tau}, \hat{\mathrm{y}}_{\mathrm{t:t}+\tau}) \tag{2}$$

where α is the weight parameter, $\mathbf{Q}^{\mathrm{weight}}_{\mathrm{loss}}$ is the surrogate quantile loss that captures the weight of the extreme classes, $\mathbf{S}^{\mathrm{shape}}_{\mathrm{loss}}$ is the shape loss that acts as a penalty term while estimating quantile predictions.

2.1.1 Weighted Quantile Loss

The weighted quantile loss gives the flexibility to model the imbalanced data distribution by including a weight term (w) in the standard vanilla quantile loss function used in TFT to provide forecasts for different specified quantiles which is defined as:

$$\mathbf{Q}^{\mathrm{weight}}_{\mathrm{loss}}(\mathrm{q}, \mathrm{y}, \hat{\mathrm{y}}) = \sum_{\mathrm{i}=1}^{\mathrm{n}} \Big((\mathrm{q}) \times max(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i}, 0) + (1-\mathrm{q}) \times max(\hat{\mathrm{y}}_\mathrm{i} - \mathrm{y_i}, 0) \Big) \times w_i \tag{3}$$

where, $\mathrm{y_i}$ is the true SPEI value, $\hat{\mathrm{y}}_\mathrm{i}$ is the predicted SPEI value, q is the quantile value and n is the total number of samples. The standard quantile loss performs best with uniform or near-uniform data distribution. To address imbalanced data distribution which represents rare events such as extreme drought, extreme wet, severe drought, and severe wet, we introduce three different definitions of weighted quantile loss functions to estimate w_i.

Discrete Weighted Quantile (DWQ) loss: For each category of drought, a weight value is fixed according to the domain knowledge. The weight ($\mathrm{w_i}$) is estimated based on a set of predefined rules or categories over historical observation of drought indices. We assign higher weights to rare events. **Continous Weighted Quantile (CWQ) loss**: We propose a continous weighted loss, where continous weights are assigned across the target variables. We assigned weights proportional to the $|\mathrm{y}|^{\mathrm{a}}$, where y is the target variable. We experimented with different values of a and found best results with $a = 3$. It is mathematically defined as, $\mathrm{w_i} = (|y_i|)^a, \mathrm{for}|\mathrm{y_i}| >= 1$.

Inverse frequency weighted Quantile (IFWQ) loss: In imbalanced classification weights are generally assigned proportional to the inverse frequency of a class. We tried to use a similar approach in time-series forecasting task. The target values Y are divided into $\mathbf{b}$ bins with equal intervals i.e. $(\mathrm{y_0}, \mathrm{y_1}), (\mathrm{y_1}, \mathrm{y_2}), ..., (\mathrm{y_{b-1}}, \mathrm{y_b})$. In practice, the defined bins reflect a minimum resolution we care for grouping data in the forecasting task. For each bin, inverse frequency is computed and weights are assigned proportional to the inverse frequency. It is defined as, $\mathrm{w_i} \propto \frac{1}{\mathrm{frequency(y_i)}}$.

2.1.2 Shape Loss

Shape loss captures the distortion between the two time-series sequences. The SPEI time series have a frequent and large number of peaks and dips. The higher value of the shape loss indicates that the drought forecasting model does not accurately model the sudden changes in the drought indices. We perform shape matching in the temporal dimension using dynamic time warping (DTW) to accurately estimate the error between two shapes (temporal sequences) by learning the optimal path and update the forecasting model parameters using the shape loss. We use work by [9] for formulated a smoothed and differentiable version of DTW, called soft-DTW, for computing shape loss.

3 Experiments and Results

To evaluate the effectiveness of our proposed weighted dilated loss function for drought forecasting, we perform experiments on two different geographies (Texas and Maharashtra) for 3 months ahead of a period using TFT [8].

3.1 Dataset Description

We used Precipitation and Potential Evapotranspiration from ERA5 Land Reanalysis data [10] to calculate the SPEI. We used 3 months moving average of SPEI, called SPEI-3. The ERA5 data is available at a spatial resolution of 0.1° and temporal resolution of 1 month from 1981 to 2021. This accounts for 483 timestamps (one for each month). We used data from years 1981 to 2000 as the training set, years 2001 to 2010 as the validation set, and years 2011 to 2020 as the test set for both regions (Maharashtra and Texas) with 2615 and 280 locations respectively.

SPEI	**CLASS**	**FREQUENCY**	
		Texas	Maharashtra
$y >= 2$	EW	1.37%	1.91%
$1.5 < y <= 2$	SW	4.99%	5.49%
$1 < y <= 1.5$	MW	9.76%	9.17%
$-1 < y <= 1$	N	64.09%	66.65%
$-1.5 < y <= -1$	MD	12.58%	10.02%
$-2 < y <= -1.5$	SD	5.23%	5.32%
$y <= -2$	ED	1.95%	1.19%

Table 1: Class distribution of SPEI where EW, SW, MW, N, MD, SD and ED are Extreme Wet, Mild Wet, Normal, Mild Drought, Severe Drought and Extreme Drought respectively.

Implementation Details: For our experiments, we used a look-back period (k) of 18 months (selected by empirical experiments) and a forecast period of 3 months (1<= τ <=3). We set $\alpha = 0.5$. We used the following input variables in the TFT model: SPEI-3 ∈ U, Month ∈ K, Year ∈ K and Location ID ∈ St. For the Surrogate Quantile Loss, we chose CWQ as its overall performance is better as compared to other Surrogate Loss Functions (see Ablation study).

Table 2: Results of the proposed approach on Texas region in USA.

Error Metrics	1^{st} **Month**		2^{nd} **Month**		3^{rd} **Month**	
	Quantile	**SQUASH**	**Quantile**	**SQUASH**	**Quantile**	**SQUASH**
RMSE	1.0275	**0.7386**	1.1137	**0.9558**	1.0983	**1.0777**
Accuracy	38.94%	**53.83%**	40.56%	**48.09%**	44.85%	**47.2%**
W-F1	0.4093	**0.5301**	0.4203	**0.4694**	0.4391	**0.4490**
M-F1	0.1429	**0.2158**	0.1036	**0.1304**	0.1004	**0.1150**

Table 3: Results of the proposed approach on Maharastra region in India.

Error Metrics	1^{st} Month		2^{nd} Month		3^{rd} Month	
	Quantile	**SQUASH**	**Quantile**	**SQUASH**	**Quantile**	**SQUASH**
RMSE	**0.6595**	0.7859	**0.9853**	1.037	**1.1671**	1.1705
Accuracy	**57.34%**	57.16%	54.78%	**54.64%**	**54.15%**	**54.15%**
W-F1	0.4642	**0.5271**	0.3925	**0.4452**	0.3805	**0.4260**
M-F1	0.1429	**0.2158**	0.1036	**0.1304**	0.1004	**0.1150**

3.2 Results

To evaluate the results we report Macro-F1 and Weighted-F1 along with RMSE and accuracy using two different losses such as quantile and SQUASH for a three months ahead period in Texas, USA and Maharshtra, India. Macro-F1 and Weighted-F1 scores are helpful to analyze the performance for extreme and severe drought categories. Table 2 shows the best RMSE, Accuracy, Weighted-F1 and Macro-F1 for 1^{st}, 2^{nd} and 3^{rd} month forecast using the proposed combined surrogate loss (SQUASH) as compared to quantile loss on the Texas region. Table 3 compares the performance of our approach with quantile loss on the Maharastra region in India. It shows the best Weighted-F1 and Macro-F1 using SQUASH loss for the task of extreme event forecasting.

3.3 Ablation study

We compare 4 models corresponding to different variants of quantile loss (standard quantile, DWQ, CWQ, and IFWQ) in the Maharashtra region in Table 4. The model trained with CWQ loss provided the best Weighted-F1 and Macro-F1 scores. We also visually compare these 4 models across the distribution of target values in Fig. 1. The quantile loss (represented in orange) curve shows the best RMSE over normal and near-normal regions whereas its performance is unsatisfactory in the extreme and severe regions. The IFWQ loss (represented in blue) does the opposite. The CWQ loss performs consistently over the complete range.

Table 4: Results on Maharashtra region for 1 month ahead forecast.

Loss	RMSE	Accuracy	Weighted-F1	Macro-F1
Quantile	**0.6686**	**60.47%**	**0.5491**	0.1558
DWQ	0.7811	51.08%	0.5314	0.3101
CWQ	0.7153	56.82%	0.5663	**0.3265**
IFQ	0.7881	51.08%	0.5314	0.3101

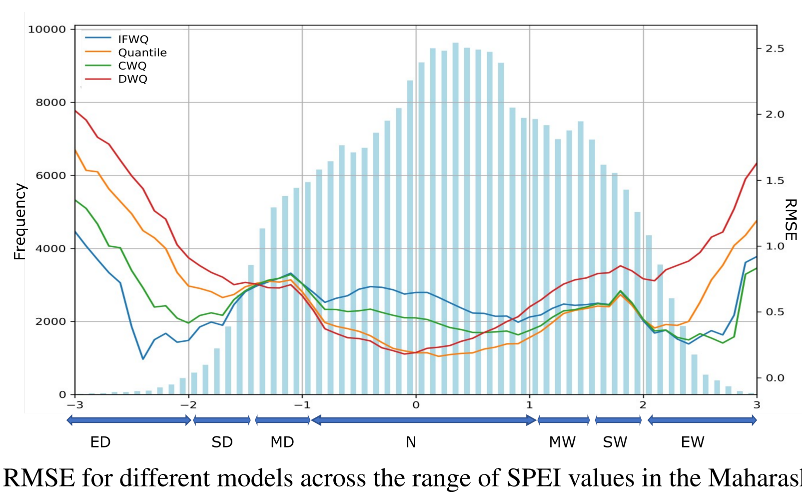

Figure 1: RMSE for different models across the range of SPEI values in the Maharashtra region.

4 Conclusion and Future Work

Seasonal drought forecasting for early warning systems is very important for mitigating damages and reducing vulnerabilities. We have introduced a novel loss function combining weighted quantile and shape losses for multi-horizon drought forecasting and validated on the two geographies. We observed 14.4% and 12.1% improvement with respect to the standard quantile loss in Weighted-F1 in Texas and Maharashtra regions, respectively. In the future, drought forecasting can be improved by including forecasts from climate models and climatic and oceanic signals such as El-Nino, Southern Oscillations, etc.

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