IMPROVED DROUGHT FORECASTING USING SURROGATE QUANTILE AND SHAPE (SQUASH) LOSS

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DROUGHT AND ITS IMPACTS

- A drought is an **event of shortages in the water supply**, whether atmospheric, surface water or ground water.
- Most damaging natural hazard with cascading impacts across multiple economic sectors, the environment, and society.



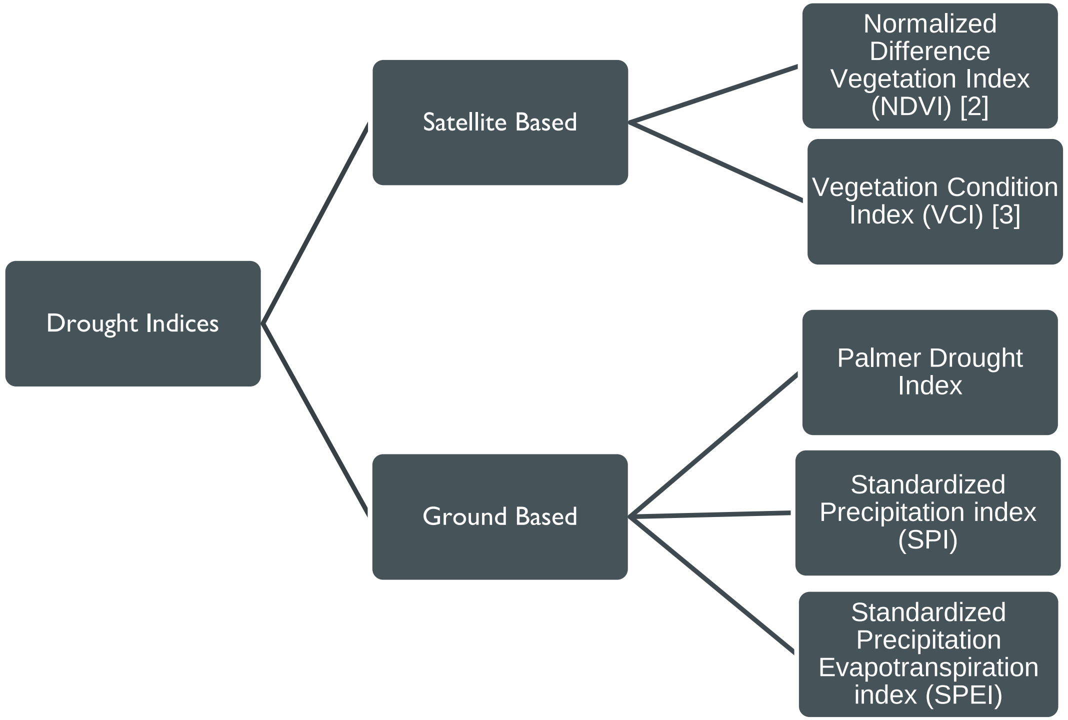
Drought Impacts

- **Food security-** In half of the years of the twenty-first century, drought was the main cause of shortage in world grain production[1]
- **Wild-fires**- Drought like condition ignited The Camp Fire - California- destroying nearly 14,000 buildings, causing billions of dollars in damage and killing 88 people[2]
- **Supply chains logistics-** Rhine and Danube-transport 27% and 10% lower-10% drop in Germany’s production of chemicals and pharmaceuticals - $220million in additional logistics costs[3]

[1] Kogan, Felix, Wei Guo, and Wenze Yang. "Drought and food security prediction from NOAA new generation of operational satellites." *Geomatics, Natural Hazards and Risk* 10.1 (2019): 651-666.
[2] https://wildfiretoday.com/tag/atlas-fire/
[3] A report by McKinsey Global Institute, Could climate become the weak link in your supply chain?

DROUGHT INDICES

- Used to monitor and quantify droughts.
- Several drought indices have been proposed with different degrees of complexity, data requirements, physical processes, and purpose [1]



Standardized Precipitation Evapotranspiration index (SPEI) =
Precipitation – Potential Evapotranspiration

[1] https://www.droughtmanagement.info/literature/GWP_Handbook_of_Drought_Indicators_and_Indices_2016.pdf
[2] Carlson, Toby N., and David A. Ripley. "On the relation between NDVI, fractional vegetation cover, and leaf area index." *Remote sensing of Environment* 62.3 (1997): 241-252.
[3] Liu, W. T., and F. N. Kogan. "Monitoring regional drought using the vegetation condition index." *International Journal of Remote Sensing* 17.14 (1996)

RELATED WORK & CONTRIBUTIONS

Related Work

- The models like Artificial Neural Network(ANN) [1], Long Short-Term Memory (LSTM) [2], Convolutional LSTM [3], Wavelet ANN [4], integrated ANN [5] have been used.
- The existing **does not emphasize both evaluation and analysis of the extreme and severe drought** as well as wet events.

Contributions

- We attempt to address the above-mentioned challenge by developing **a novel loss function (SQUASH)**
- We validate our approach for multi-step forecasting of SPEI drought index over two regions in the USA and India.

[3] Akinwale T Ogunrinde, Phillip G Oguntunde, Johnson T Fasinmirin, and Akinola S Akinwu-miju. Application of artificial neural network for forecasting standardized precipitation and evapotranspiration index: A case study of nigeria.Engineering Reports, 2(7):e12194, 2020.
[4] Abhirup Dikshit, Biswajeet Pradhan, and Alfredo Huete. An improved spei drought forecasting approach using the long short-term memory neural network.Journal of environmental management,:111979, 2021.
[5] SHI Xingjian, Zhourong Chen, Hao Wang, Dit-Yan Yeung, Wai-Kin Wong, and Wang-chun Woo. Convolutional lstm network: A machine learning approach for precipitation nowcasting.In Advances in neural information processing systems, pages 802–810, 2015.
[6] Anshuka Anshuka, Floris F van Ogtrop, and R Willem Vervoort. Drought forecasting through statistical models using standardised precipitation index: a systematic review and meta-regression analysis.Natural Hazards, 97(2):955–977, 2019.
[7] Petr Maca and Pavel Pech. Forecasting spei and spi drought indices using the integrated artificial154neural networks.Computational intelligence and neuroscience, 2016, 2016

METHODOLOGY

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

- We pose the problem of forecasting SPEI drought index at a regional level as a **multi-horizon forecasting task.**
- 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.

- Each entity of the SPEI time-series is defined as $y_{l,t}$
- q is the quantile
- L_{id} is the location ID of a particular region
- $U_{l,[t-k:t]}$ is a set of unknown future inputs (e.g., historical observation of drought indices)
- $K_{l,[t-k:t+\tau s]}$ is a set of known future inputs (e.g., forecasted attributes from climate models),
- St_l is a set of static covariates (e.g., location)
- $y_{t+\tau,l,q}$ is the prediction of drought indices τ step ahead

[1] Lim, Bryan, et al. "Temporal fusion transformers for interpretable multi-horizon time series forecasting." *International Journal of Forecasting* (2021).

SQUASH LOSS

- Two main aspects:
  1. Modeling the transition of drought conditions over time
  2. Explicit attention on rarely occurring events

- SQUASH loss that takes care of these two aspects by two loss components:
  1. **Weighted quantile loss** - The weighted quantile loss helps to model complex drought indices data distribution
  2. **Shape loss** - The shape loss helps in minimizing the shape distortion errors in the temporal dimensions that arise from a transition of drought conditions

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

WEIGHTED QUANTILE LOSS

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

Loss	Definition	Pros	Cons
Quantile Loss	Standard Quantile loss	Minimize overall error Best suited for uniform dist.	No Emphasis on extreme classes (tails of distribution)
Discrete Weighted Quantile Loss	weights ratio: W_e:W_s:W_m:W_n=10:5:2:1	Easy to codify Emphasis on extreme classes	Discrete weights Will not work with complex dist. Weights - no info about dist.
Inverse Frequency Weighted Quantile Loss	W_i=c / freq(y_i)	Can work with complex dist.	Poor performance - normal classes Discrete weights
Continuous Weighted Quantile Loss	W_i= |y_i|^3 (if |y_i|>1)	Considers continuous weights	Same weights for extreme drought and extreme wet

DATA

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, Severe Wet, Mild Wet, Normal, Mild Drought, Severe Drought and Extreme Drought respectively.

DATASET

- **ERA5 land reanalysis data** [2] - Precipitation, Evapotranspiration - outperforms other reanalysis products [3]
  - Forecasts are calibrated and bias corrected w.r.t. ERA5 data
  - Spatial resolution - 0.1 º
  - Temporal resolution - 1 month
  - Training set - 1981 to 2000
  - Validation set - 2001 to 2010
  - Test set - 2011 to 2020

[1] https://spei.csic.es/spei_database/

RESULTS

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.

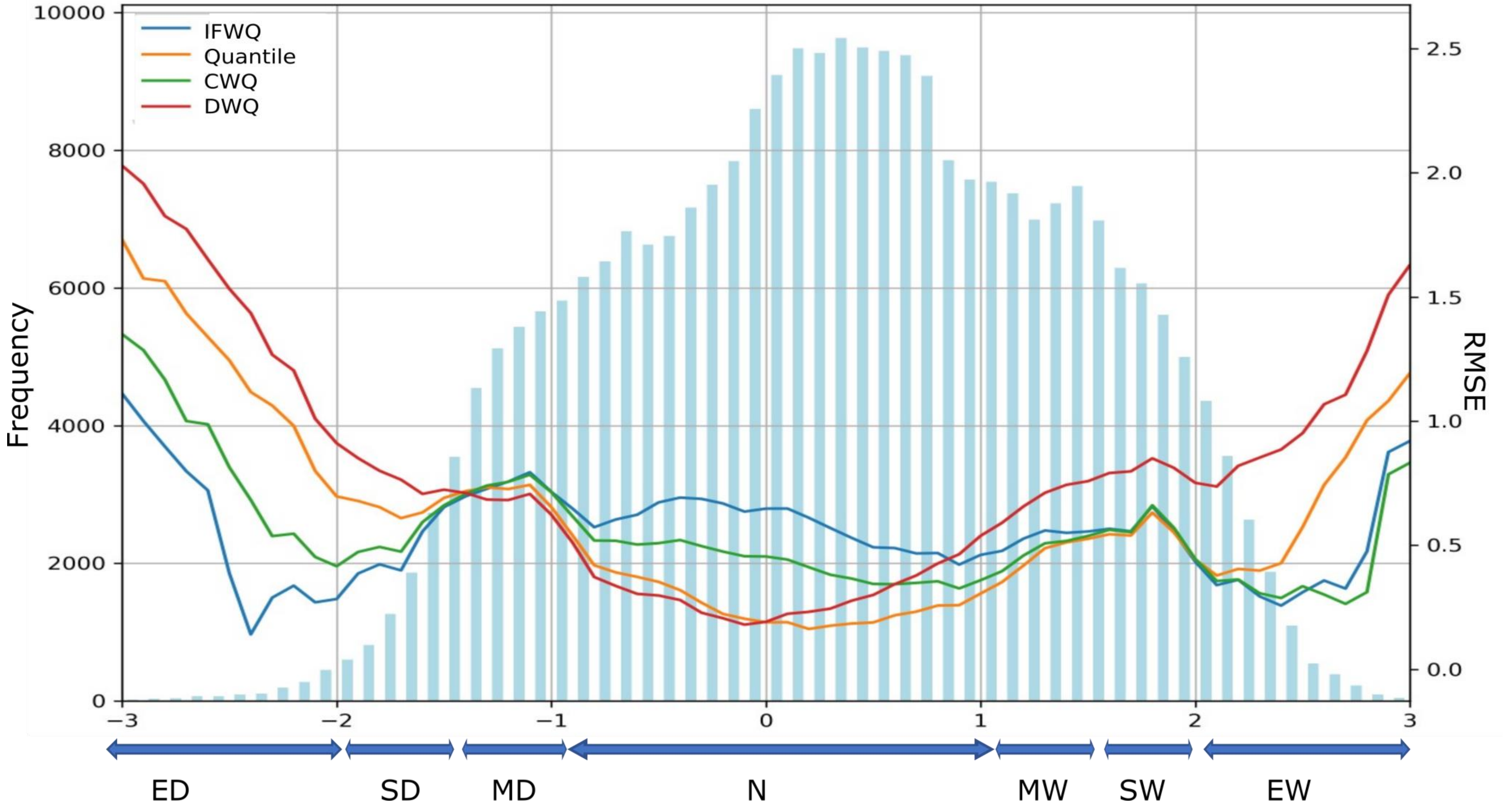
Error Metrics	1^{st} Month		2^{nd} Month		3^{rd} Month	
	Quantile	SQUASH	Quantile	SQUASH	Quantile	SQUASH
RMSE	**0.6595**	0.7859	**0.9853**	1.037	**1.1671**	1.1705
Accuracy	**57.34%**	57.16%	54.78%	**54.64%**	**54.15%**	**54.15%**
W-F1	0.4642	**0.5271**	0.3925	**0.4452**	0.3805	**0.4260**
M-F1	0.1429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

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

- Macro-F1 and Weighted-F1 scores are helpful to analyze the performance for extreme and severe drought categories
- **Texas** - Best RMSE, Accuracy, Weighted-F1 and Macro-F1 for 1^{st} ,2^{nd} and 3^{rd} month forecast using the proposed SQUASH as compared to quantile loss
- **Maharashtra** – Best Weighted-F1 and Macro-F1 using SQUASH loss for the task of extreme event forecasting

ABLATION STUDIES



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 **(SQUASH loss)** 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.