Forecasting Global Drought Severity and Duration Using Deep Learning

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Abstract

Drought detection and prediction are challenging due to the slow onset of the event and varying degrees of dependence on numerous physical and socio-economic factors that differentiate droughts from other natural disasters. In this work, we propose DeepXD (Deep learning for Droughts), a deep learning model with 26 physics-informed input features for SPI (Standardised Precipitation Index) forecasting to identify and classify droughts using monthly oceanic indices, global meteorological and vegetation data, location (latitude, longitude) and land cover for the years 1982 to 2018. In our work, we propose extracting features by considering the atmosphere and land moisture and energy budgets and forecasting global droughts on a seasonal and an annual scale at 1, 3, 6, 9, 12 and 24 months lead times. SPI helps us to identify the severity and the duration of the drought to classify them as meteorological, agricultural and hydrological.

1 Introduction

Climate change will increase the likelihood of extreme climatic events such as heatwaves, drought, excessive rainfall, wildfires, and floods, with severe negative impacts on food security, supply chains, and the world economy [1]. Droughts are a major risk to food security [2]. 700 million people suffer from malnutrition and hunger [3], leading to lower immunity, delayed development [4] and an increased risk of chronic diseases [5]. Heatwaves and droughts together are often a pre-condition to wildfires [6]. The economic cost of a single drought is estimated to be up to 9.6 billion US dollars [7]. However, predicting droughts to mitigate their impacts is challenging due to the slow onset of the event and varying degrees of dependence on numerous physical and socio-economic factors that differentiate droughts from other natural disasters [1]. Recently developed machine learning methods, computational resources and earth observation datasets can aid global drought forecasting [8].

Water in the Earth system is cycled between its gaseous, liquid and solid forms and remains effectively constant on timescales relevant to drought prediction (months-years) [9]. When there is water deficit over a prolonged period of time at the land (agricultural), in the atmosphere (meteorological) or underground (hydrological) level, the region is said to be experiencing a drought [1] (Figure 1). In this work, we propose extracting features by considering the relevant atmosphere and land moisture and energy budgets [9] and predicting global droughts by modelling SPI (Standardised Precipitation Index) on a seasonal and an annual scale and predicting precipitation at 1, 3, 6, 9, 12 and 24 months lead times using our deep learning model. SPI helps us to identify the severity and the duration of the drought to classify them as meteorological, agricultural and hydrological [10].

2 Related Work

Standardized Precipitation Index (SPI) is a drought index and is used to measure droughts [11]. The World Meteorological Organization (WMO) recommends all countries to use SPI for monitoring and

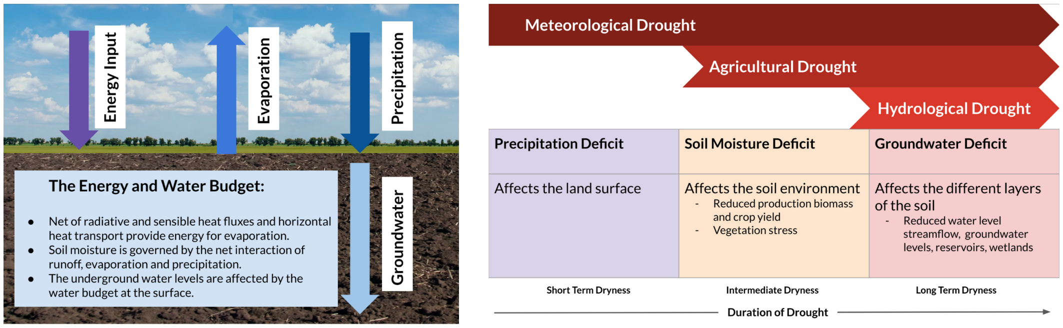

Figure 1: Physical constraints on droughts and drought subtypes [26, 28, 29].

reporting purposes [12]. Several algorithms based on stochastic, probabilistic, and machine learning techniques have been proposed in the literature to forecast SPI at multiple regional and temporal scales. Machine learning models such as Artificial Neural Network (ANN) [13], Wavelet ANN [14, 15], Long Short-Term Memory (LSTM) [16], Convolutional LSTM [17], integrated ANN [18], and Transformers [10, 19, 20] have been successful for precipitation and drought forecasting individually [15, 21, 22, 23].

The majority of existing machine-learning drought prediction techniques train separate models for each region [24, 25, 26, 27, 19]. Models confined to a small region are not able to learn patterns that are consistent over different types of heterogeneous regions, are more likely to overfit to regional observational data in earth observation (EO) datasets and less likely to be used by environmental stakeholders [19]. However, recent work suggests that a location agnostic, as opposed to location specific approach, may be preferable for drought forecasting, [19], indicating that global drought forecasting is a promising direction.

3 Dataset

The dataset for DeepXD is curated to predict SPI and is characterised by a temporal coverage from 1982 to 2018 at a monthly resolution (444 timesteps), and spatial coverage across the globe at a resolution of 0.5 x 0.5 degree. The input variables are processed and re-sampled to the specified resolution after being collected from the global dataset ERA5 (atmospheric winds and humidity at 850, 500 and 250 hPa, near-surface (2m) temperature, surface pressure, soil moisture (at 4 levels), soil temperature (at 4 levels), surface and subsurface runoff, shortwave and longwave radiative heat fluxes, sensible heat fluxes, evaporation, precipitation, land-sea mask, leaf area index for low and high vegetation) [30], the oceanic indices are collected from NOAA [31] and the target variable is SPI, computed from precipitation from the global land dataset WFDE5 [32].

Improving climatic features can enhance the performance of attention-based models [19]. Recent machine learning literature [10] has flagged the inclusion of Pacific variability as a means of improving drought forecasts. More generally, we can consider temperature variability in the Pacific, Indian and Atlantic ocean, reflected respectively by the Niño3.4 Index, Dipole Mode Index, and Tropical Northern Atlantic Index, which have been linked to drought [33, 34, 35, 21]. In pre-processing, we will remove the linear trend to better focus on anomalies and reduce the potential impact of non-stationarities [21].

Our choice of features is motivated by underlying physical considerations, as follows [9, 36]:
(i) Vertically-integrated atmospheric moisture budget: In steady state, $P - E = \frac{-1}{g\rho_w}\nabla \cdot \int_0^{p_s} \vec{u}q dp$ where P represents precipitation, E represents evapotranspiration, g is gravitational acceleration, ρ_w is the density of water, p and p_s are pressure and surface pressure, $\vec{u}$ comprises of zonal and meridional winds and q is specific humidity.
(ii) Land moisture budget, $g_w = P - E - \delta f$, where g_w represents groundwater storage and δf represents runoff, assuming long-term averages and negligible surface condensation.
(iii) Land energy balance: As energy storage is small on monthly timescales, the balance is between surface radiative fluxes (R_s), energy leaving through evaporation (LE), sensible heat

Creation of a Global Dataset	Informed by Physics Considerations	Data Processing and Temporal Splits:	DeepXD Model: Forecasting SPI	Model Evaluation: Regression Task	Identify Severity, Type of Drought
Input Features: 26 Meteorological and Land from ERA5, Location, Time, Oceanic Indices from NOAA **Target Feature:** SPI Computed from Precipitation from WFDE5 **Temporal:** 1982 to 2018, monthly **Spatial:** Global, 0.5 x 0.5 degree	**Consideration 1:** Vertically integrated atmospheric moisture budget **Consideration 2:** Land moisture budget **Consideration 3:** Land energy balance	**Calculation:** Standardised Precipitation Index (SPI) **Severity of drought** SPI range [-2, +2] where [-1.5, -1] = moderate [-2, -1.5] = severe **Data Split:** 1982-2010: Train 2010-2014: Validation 2014-2018: Test	**Model:** Temporal Fusion Transformer to forecast SPI **Lead time:** 1, 3, 6, 9, 12 and 24 months **Baseline:** Random Forest **Proposed Comparison:** Wavelet-ANN, LSTM, Conv LSTM	**Evaluation:** Between observed and predicted SPI **Metrics:** MSE: Mean Squared Error MAE: Mean Absolute Error NSE: Nash–Sutcliffe coefficient of efficiency **Diagrams:** Scatterplot: Correlations between them **XAI:** Shapley value	**Total duration of drought** The number of months SPI is in the range [-1,-2] **Classify drought** Based on duration: 1-3 months : Meteorological Drought 3-6 months: Agricultural Drought 9-24 months: Hydrological Drought

Figure 2: DeepXD uses physics-informed feature selection and deep learning for drought prediction.

(SH) and horizontal transport (ΔF) : $R_s = LE + SH + \Delta F$ [9]. ΔF will be calculated as a residual.

4 Model

The data will be split temporally into training (1982-2010), validation (2010-2014), and test (2014-2018) datasets. Our model (Figure 2) will predict SPI as a continuous and supervised forecasting task at recommended lead times of 1, 3, 6, 9, 12 and 24 months to identify the three types of droughts at seasonal and annual scales [15, 24]. The meteorological, oceanic, vegetation, and land cover vectors are merged and sequentially fed to the DeepXD, which is a Temporal Fusion Transformer [37, 38]. The encoded inputs are then passed to a fully connected neural network along with the spatial information to predict precipitation at different lead times.

The total duration of the drought is calculated as a temporal period of continuously low SPI values, usually in the range of [-1,-2]. SPI's sub-ranges can help us classify if the drought is mild or extreme [39] and the duration of the drought allows us to classify them as meteorological, agricultural and hydrological [24]. The forecasts from DeepXD can be useful for farmers to select drought resistant crops, water resource managers for reservoir management, food manufacturers and distributors to prepare for delays, government officials for subsidising and optimising resources, policymakers to provide data-driven suggestions and social workers to feed the most vulnerable groups [40, 41].

5 Conclusion

We propose DeepXD, a deep learning framework for forecasting global drought using SPI (Standardised Precipitation Index) to mitigate meteorological, agricultural and hydrological drought impacts using 26 meteorological variables from 1982 to 2018. We demonstrate a physics-informed feature selection strategy using water and energy budget equations as a guide. Our deep learning pipeline integrates earth observation data and predicts the occurrence, severity, duration, and type of droughts as forecasting tasks at sub-seasonal, seasonal and annual scales to minimise their catastrophic effects on the climate.

Acknowledgments and Disclosure of Funding

Our work has been spun off from the Climate Change and AI Summer School in 2022, and we would like to thank our group members Flora Desmet and Patrick Farnole for sharing their knowledge and participating in engaging discussions that contributed to the proposal's development. We would also like to thank the mentors and lecturers in the program, especially Dr Andrew Ross, who guided us towards the right direction.

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