Forecasting Global Drought Severity & Duration Using Deep Learning

Akanksha Ahuja, Xin Rong Chua

Motivation

- **What is a drought?**
  Water deficit over a prolonged period of time.

- **How do we measure droughts?** Drought index such as the Standardized Precipitation Index (SPI) is commonly used and recommended by the World Meteorological Organization (WMO).

Threatens food security

Threatens water supply

Linked to biodiversity loss, wildfires

Types of Droughts and Their Impacts

Meteorological Drought

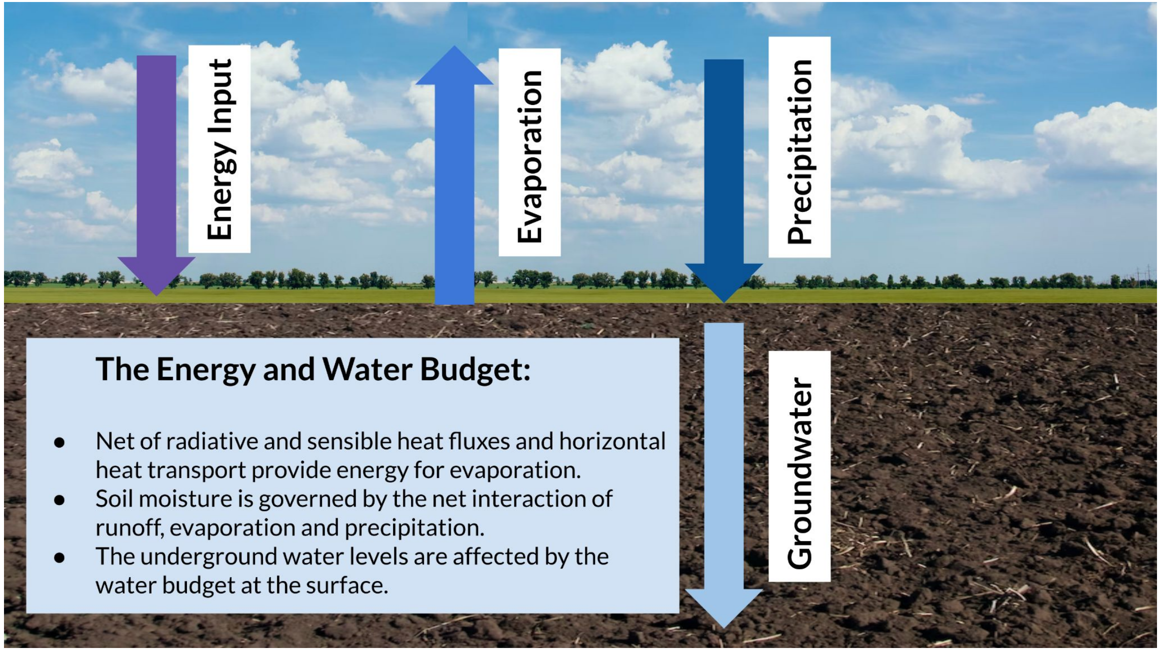
Agricultural Drought

Hydrological Drought

Precipitation Deficit	Soil Moisture Deficit	Ground-Water Deficit
Affects the land surface	Affects the soil environment - Reduced production biomass and crop yield - Vegetation Stress	Affects the different layers of the soil - Reduced water level streamflow, ground water levels, reservoirs, wetlands
Short Term Dryness	**Intermediate-Dryness**	**Long Term Dryness**

Duration of Drought →

Physical Drivers of Drought



The Energy and Water Budget:

- Net of radiative and sensible heat fluxes and horizontal heat transport provide energy for evaporation.
- Soil moisture is governed by the net interaction of runoff, evaporation and precipitation.
- The underground water levels are affected by the water budget at the surface.

Soil moisture is strongly constrained by the **land energy balance and land moisture budget.**

Precipitation is in turn linked to the vertically integrated **atmospheric moisture budget** in steady state.

Relevant variables implied:
Consideration 1 - Atmospheric Moisture Budget: Winds, moisture, precipitation, evapotranspiration, surface pressure

Consideration 2 - Land Energy Balance: Groundwater storage, runoff, precipitation, evapotranspiration

Consideration 3 - Land Moisture Budget: Precipitation, evaporation, groundwater storage, runoff

Pipeline for Drought Forecasting

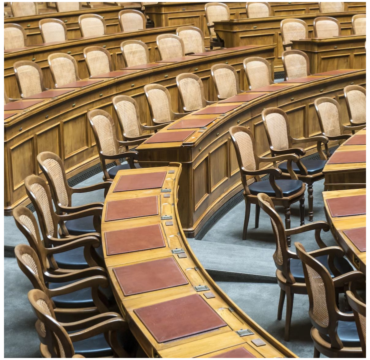
Creation of a Global Dataset	Informed by Physics Considerations	Data Processing and Temporal Splits:	DeepXD Model: Forecasting SPI	Model Evaluation: Regression Task	Identify Severity, Type of Drought
Input Features: 26 Meteorological and Land from ERA5, Location, Time, Oceanic Indices from NOAA **Target 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

Pathway to Socio-Economic Impact

Stakeholders:
Farmers, Supply chain industry, Politicians, Supermarkets, Water Resource Managers, Consumers

Reducing the Drought Impact on the Economy- 9 Billion USD per drought (US NOAA/NIDIS)

Reducing the Drought Impact on People:
13 million estimated affected by a drought in Feb 2022 (UN/UFP)]



Adaptive Resource Allocation and Policymaking: Identify the short term and long term risks of the compound droughts

Thank you CCAI

Akanksha Ahuja
Machine Learning
Author

Dr Xin Rong Chua
Climate Science
Author

Dr Andrew Ross
Machine Learning
Mentor

Acknowledgements: CCAI Summer School, Flora Desmet, Patrick Farnole

Thank you for your time
Join us if you are interested

References - Part 1

[1] Hao, Z., Singh, V. P., & Xia, Y. (2018). *Seasonal drought prediction: advances, challenges, and future prospects. Reviews of Geophysics, 56*(1), 108-141
.

[2] Felsche, E., & Ludwig, R. (2021). *Applying machine learning for drought prediction using data from a large ensemble of climate simulations*. Nat. Hazards Earth Syst. Sci. Discuss, 1-20.

[3] Gottfriedsen, J., Berrendorf, M., Gentine, P., Reichstein, M., Weigel, K., Hassler, B., & Eyring, V. (2021). *On the Generalization of Agricultural Drought Classification from Climate Data*. arXiv preprint arXiv:2111.15452.

[4] Lambhate, D., Marvaniya, S., Singh, J., & Gold, D. (2021, December). *Improved Drought Forecasting Using Surrogate Quantile And Shape (SQUASH) Loss.* In Annual Conference on Neural Information Processing Systems.

[5] Minixhofer, C., Swan, M., McMeekin, C., & Andreadis, P. (2021, July). D*roughtED: A dataset and methodology for drought forecasting spanning multiple climate zones*. In Tackling Climate Change with Machine Learning: Workshop at ICML 2021.

[6] Mittermeier, M., Weigert, M., & Rügamer, D. (2021). *Identifying the atmospheric drivers of drought and heat using a smoothed deep learning approach.* arXiv preprint arXiv:2111.05303.

References - Part 2

[7] Civitarese, D. S., Szwarcman, D., Zadrozny, B., & Watson, C. (2021). *Extreme Precipitation Seasonal Forecast Using a Transformer Neural Network*. arXiv preprint arXiv:2107.06846.

[8] Ebert-Uphoff, I., Lagerquist, R., Hilburn, K., Lee, Y., Haynes, K., Stock, J., ... & Stewart, J. Q. (2021). *CIRA Guide to Custom Loss Functions for Neural Networks in Environmental Sciences--Version 1*. arXiv preprint arXiv:2106.09757.

[9] NIDIS, NOAA (2020). T*he High Cost of Drought*. Drought.Gov. https://www.drought.gov/news/high-cost-drought
[10] Code Carbon. (2022). *CodeCarbon.io*. Https://Codecarbon.Io/. https://codecarbon.io/

[11] Bravar, L., & Kavvas, M. L. (1991). *On the physics of droughts. I. A conceptual framework*. Journal of Hydrology, 129(1-4), 281-297.

[12] Holt, K. (2022, February 11). *Severe drought threatens 13 million with hunger in Horn of Africa*. UN News. https://news.un.org/en/story/2022/02/1111472

[13] Thompson, E. (2021, April 27). *A better way to understand drought*. Https://Phys.Org/News/2021-04-Drought.Html. https://phys.org/news/2021-04-drought.html

[14] Bravar, L., & Kavvas, M. L. (1991). *On the physics of droughts. II. Analysis and simulation of the interaction of atmospheric and hydrologic processes during droughts.* Journal of Hydrology, 129(1-4), 299-330.

References - Part 3

[15] Sazib, N., Mladenova, L. E., & Bolten, J. D. (2020). *Assessing the impact of ENSO on agriculture over Africa using earth observation data.* Frontiers in Sustainable Food Systems, 4, 509914.

[16] Naylor, R. L., Battisti, D. S., Vimont, D. J., Falcon, W. P., & Burke, M. B. (2007). *Assessing risks of climate variability and climate change for Indonesian rice agriculture.* Proceedings of the National Academy of Sciences, 104(19), 7752-7757.

[17] Cirino, P. H., Féres, J. G., Braga, M. J., & Reis, E. (2015). *Assessing the impacts of ENSO-related weather effects on the Brazilian agriculture.* Procedia Economics and Finance, 24, 146-155.

[18] Prodhan, F. A., Zhang, J., Hasan, S. S., Sharma, T. P. P., & Mohana, H. P. (2022). *A review of machine learning methods for drought hazard monitoring and forecasting: Current research trends, challenges, and future research directions.* Environmental Modelling & Software, 105327.

[19] Kashinath, K., Mustafa, M., Albert, A., Wu, J. L., Jiang, C., Esmaeilzadeh, S., ... & Prabhat. (2021). *Physics-informed machine learning: case studies for weather and climate modelling.* Philosophical Transactions of the Royal Society A, 379(2194), 20200093.

[20] Welcome to the SHAP documentation — SHAP latest documentation. (2022). SHAP. https://shap.readthedocs.io/en/latest/index.html

[21] Mouatadid, S., Orenstein, P., Flaspohler, G., Oprescu, M., Cohen, J., Wang, F., ... & Mackey, L. (2021). Learned benchmarks for subseasonal forecasting. arXiv preprint arXiv:2109.10399.

References - Part 4

[22] Bryan Lim et al. *Temporal Fusion Transformers For Interpretable Multi-horizon Time Series Forecasting*. In: International Journal of Forecasting 37.4 (2021), pp. 1748–1764.

[23] Marco Cucchi et al. *WFDE5: Bias-adjusted ERA5 Reanalysis Data For Impact Studies*. In: Earth System Science Data 12.3 (2020), pp. 2097–2120

[24] P.W. Team. *Climate Indices: Monthly Atmospheric And Ocean Time Series: NOAA Physical Sciences Laboratory*. URL: https://psl.noaa.gov/data/climateindices/list/ (visited on 07/17/2022).

[25] Hans Hersbach et al. *The ERA5 Global Reanalysis*. In: Quarterly Journal of the Royal Meteorological Society 146.730 (2020), pp. 1999–2049.

[26] Zaher Mundher Yaseen et al. *Forecasting Standardized Precipitation Index Using Data Intelligence Models: Regional Investigation Of Bangladesh*. In: Scientific Reports 11.1 (2021), pp. 1–25