Potential Usage of Artificial Intelligence and Machine Learning for the enhancement of weather and climate related services

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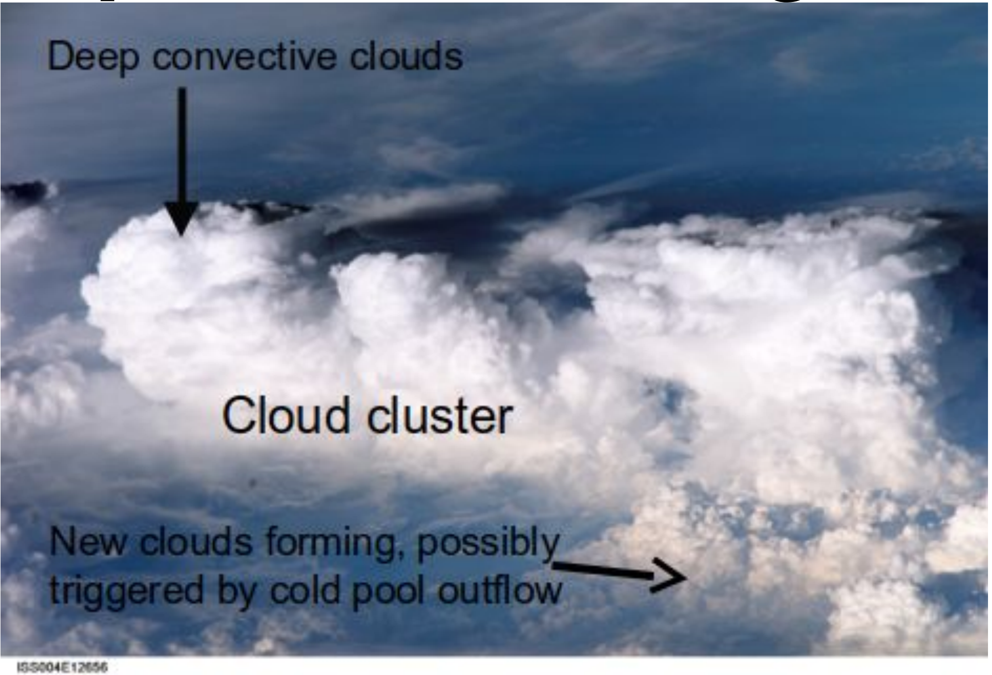
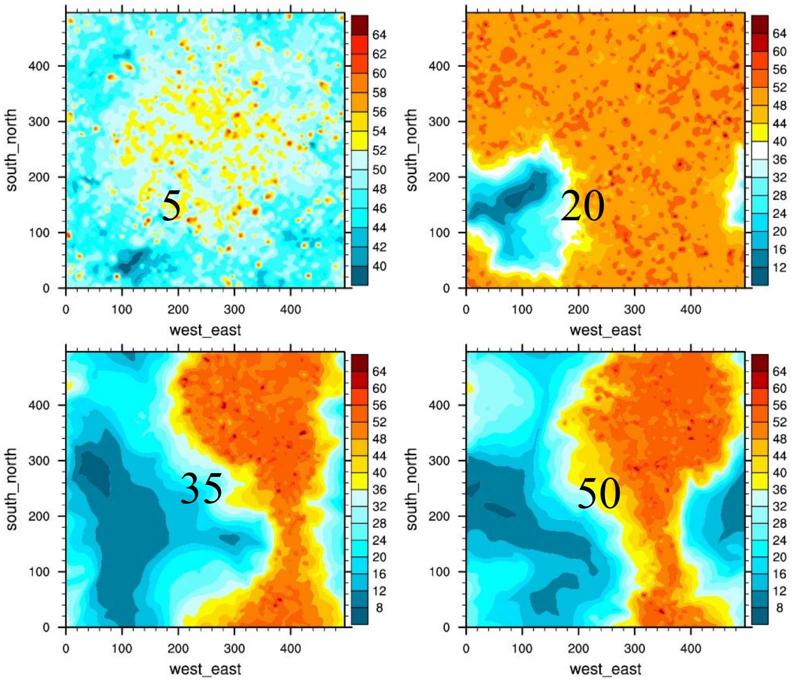
SEEK WISDOM, ELEVATE YOUR INTELLECT AND SERVE HUMANITY !

Little about me

- Computational Data Science Faculty – AAU
- Regular Associate at ICTP
- Post-doc research fellowship - CNRS, Paris
- PhD in Environmental and Industrial Fluid Mechanics from University of Trieste,Italy
- ICTP TRIL fellowship - Trieste, Italy
- MSc degree in Computational Science with specialization of Computational Mechanics and Dynamics from AAU
- Participate in the installation and configuration of HPC cluster (AAU, ICTP and University of Douala)
- Research interest - Weather, Climate Science and Energy

Spontaneous organization of convection





- Understanding the organization of tropical convection is important for understanding both tropical and global climate variability
    - The process of organization has also been recently suggested as a potential regulator of climate

- Idealized modeling of organized convection in RCE using a cloud resolution model (CRM) -WRF
- Organization metrics - I_{org} (*Tompkins and Semie, 2017*)

JAMES | Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE
10.1029/2020MS002186

Special Section:
Using radiative-convective equilibrium to understand convective organization, clouds, and tropical climate

Impact of a Mixed Ocean Layer and the Diurnal Cycle on Convective Aggregation

Adrian M. Tompkins[1] and **Addisu G. Semie**[2,3]

[1]Earth System Physics, Abdus Salam International Centre for Theoretical Physics (ICTP), Trieste, Italy, [2]Laboratoire de Meteorologie Dynamique (LMD/IPSL), Sorbonne University, CNRS, Paris, France, [3]Computational Data Science Program, Addis Ababa University, Addis Ababa, Ethiopia

AGU PUBLICATIONS

Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE
10.1002/2016MS000802

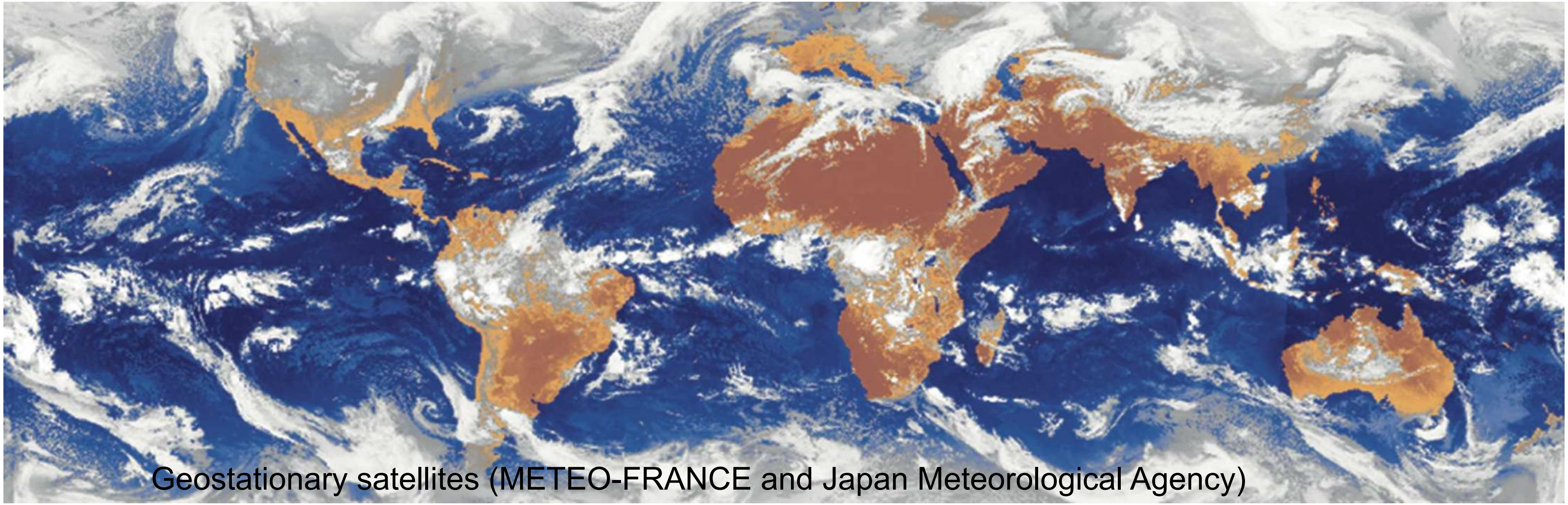
Organization of tropical convection in low vertical wind shears: Role of updraft entrainment

Adrian M. Tompkins[1] and **Addisu G. Semie**[1,2]

[1]Earth System Physics, Abdus Salam International Centre for Theoretical Physics, Trieste, Italy, [2]Now at: Laboratoire de Météorologie Dynamique, Paris, France

Key Points:
- Updraft entrainment a critical process for spontaneous organization of deep convection
- With O(km) horizontal grid sizes, updraft entrainment represented by

Influence of the organization of deep convection



- Observations suggest a strong link between the intensity of extreme rainfall at the local scale and the organization of deep convection, especially over land. *Semie and Bony, 2020*
- Organization of convection and atmospheric stability complement each other to modulate significant fraction of monthly interannual variance of the net tropical radiation budget. *Bony et. al 2020*

Geophysical Research Letters

RESEARCH LETTER
10.1029/2019GL086927

Key Points:
- The link between tropical precipitation extremes and the mesoscale organization of deep convection is investigated using satellite data
- The strength of local precipitation

Relationship Between Precipitation Extremes and Convective Organization Inferred From Satellite Observations

Addisu Gezahegn Semie[1,2] and **Sandrine Bony**[1]

[1]Laboratoire de Meteorologie Dynamique (LMD/IPSL), Sorbonne University, CNRS, Paris, France, [2]Computational Data Science Program, Addis Ababa University, Addis Ababa, Ethiopia

AGU Advances

RESEARCH ARTICLE
10.1029/2019AV000155

Key Points:
- The monthly variability of deep convective organization in the tropics is investigated using satellite observations
- An enhanced organization of deep convection is associated with a drier troposphere, fewer high clouds, and a radiative cooling of the tropics
- Observations suggest equal and complementary modulations of the

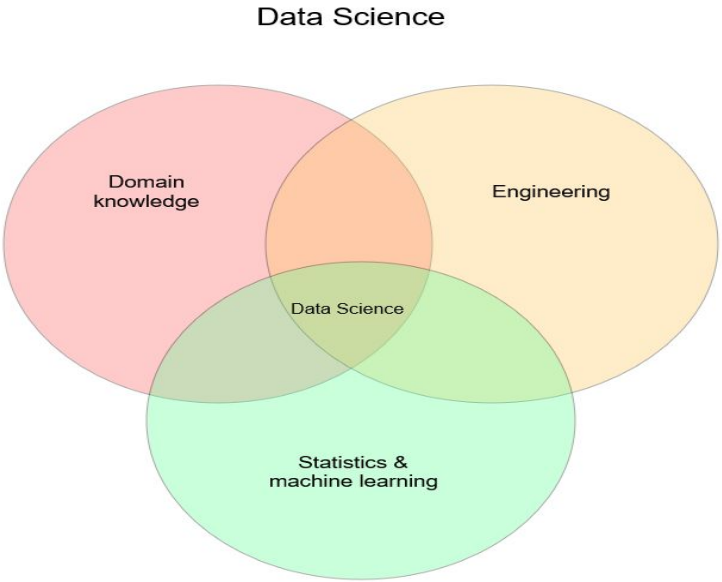
Observed Modulation of the Tropical Radiation Budget by Deep Convective Organization and Lower-Tropospheric Stability

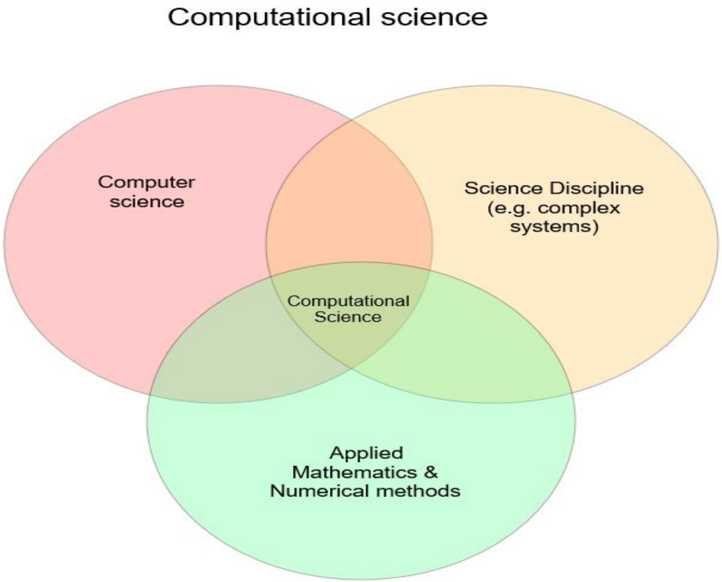
S. Bony[1], **A. Semie**[1,2], **R. J. Kramer**[3,4], **B. Soden**[5], **A. M. Tompkins**[6], **and K. A. Emanuel**[7]

[1]LMD/IPSL, Sorbonne University, CNRS, Paris, France, [2]Computational Data Science Program, Addis Ababa University, Addis Ababa, Ethiopia, [3]Climate and Radiation Laboratory, NASA Goddard Space Flight Center, Greenbelt, MD, USA, [4]Universities Space Research Association, Columbia, MD, USA, [5]RSMAS, University of Miami, Miami, FL, USA, [6]ICTP, Trieste, Italy, [7]Department of Earth, Atmospheric and Planetary Science, Massachusetts Institute of Technology, Cambridge, MA, USA

AAU, Computational Data Science Program

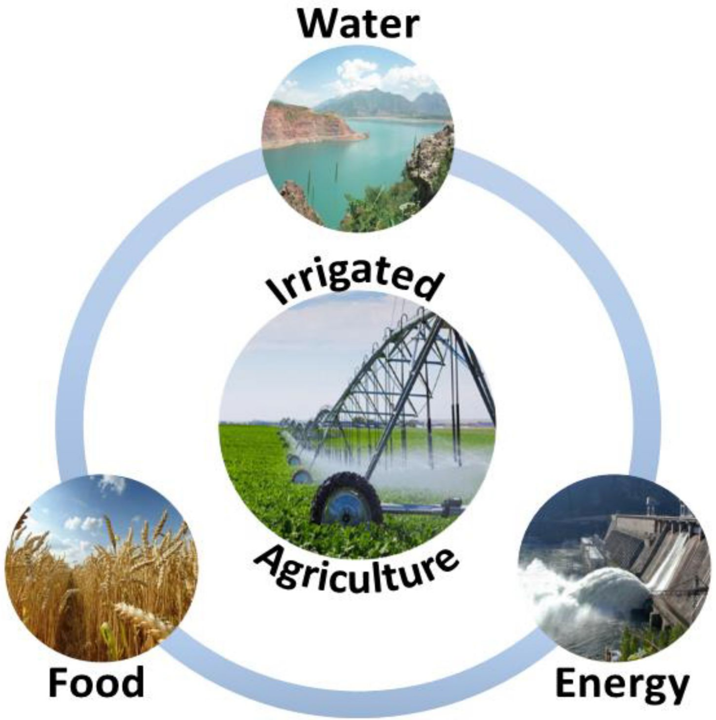
- The curriculum is revised in 2019 and it now called Computational Data Science Program
- We used Computational Data Science tools to solve real-world problems.





Weather Forecasting

- Accurate weather and climate forecasts are essential for informing decision-making across sectors like agriculture, water management and energy.



Weather forecasting

Currently, numerical weather prediction (NWP) models are the most accurate forecasting systems, employing discretized grids and solving complex partial differential equations to describe atmospheric states.

Difficulties in predicting weather and climate

- The Earth's immense size poses limitations on resolution, making it challenging to accurately represent all crucial processes in model simulations.

- The Earth System shows “chaotic” dynamics which makes it difficult to predict the future based on equations

- Some of the processes involved are not well understood

- The simulations are computationally expensive

- How to solve these difficulties?

Artificial intelligence and machine learning (AI/ML)

- Huge number of observations and Earth system data creates conducive environment for the application of AI/ML for weather forecasting

- AI/ML present new opportunities to improve weather and climate services by supplementing physical models across various time scales.

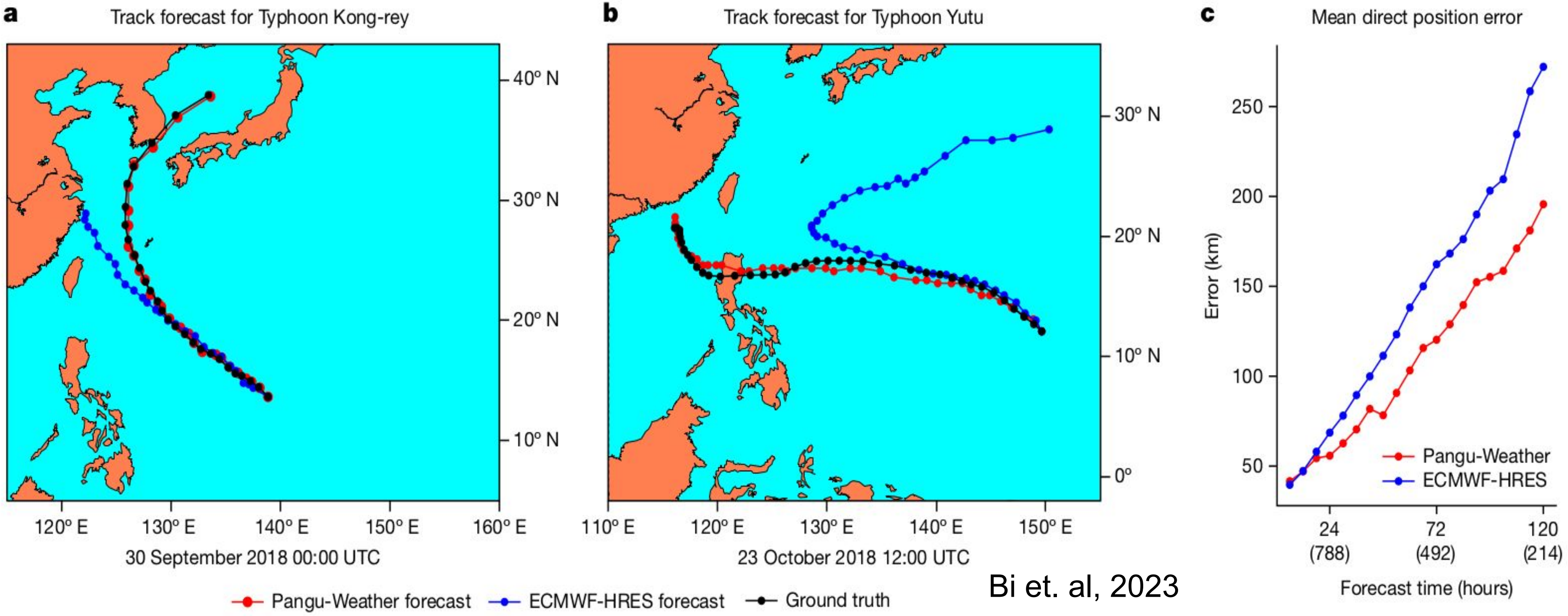
Satellites, airplanes, ships, buoys, radars, balloons, dropsonds

Artificial Intelligence and Machine Learning (AI/ML)

- AI/ML can help address issues like computational constraints, model uncertainty, coarse resolutions, and inadequate representation of small-scale phenomena like atmospheric convection.

Tracking tropical cyclones

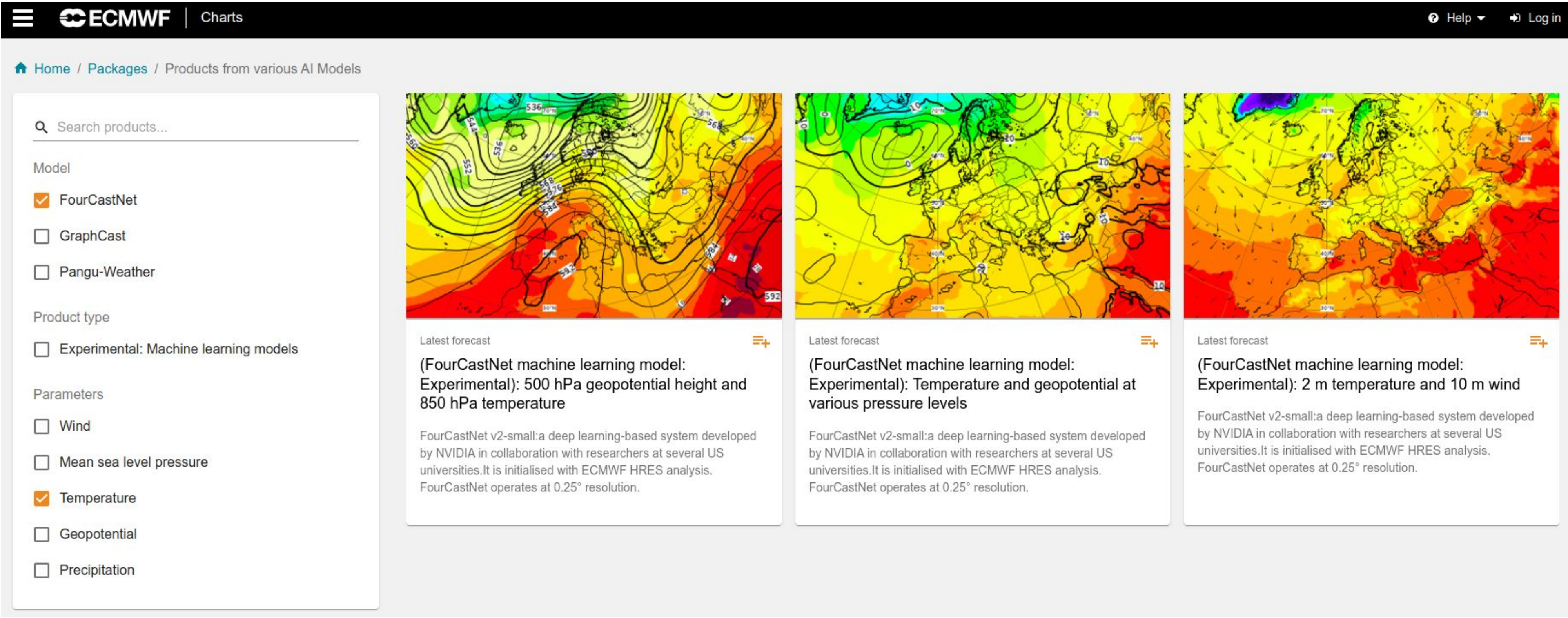
Pangu-Weather is AI-based weather forecasting system



Bi et. al, 2023

Products from various AI models

https://charts.ecmwf.int/catalogue/packages/ai_models/?facets=%7B%22Parameters%22%3A%5B%5D%2C%22Model%22%3A%5B%5D%7D

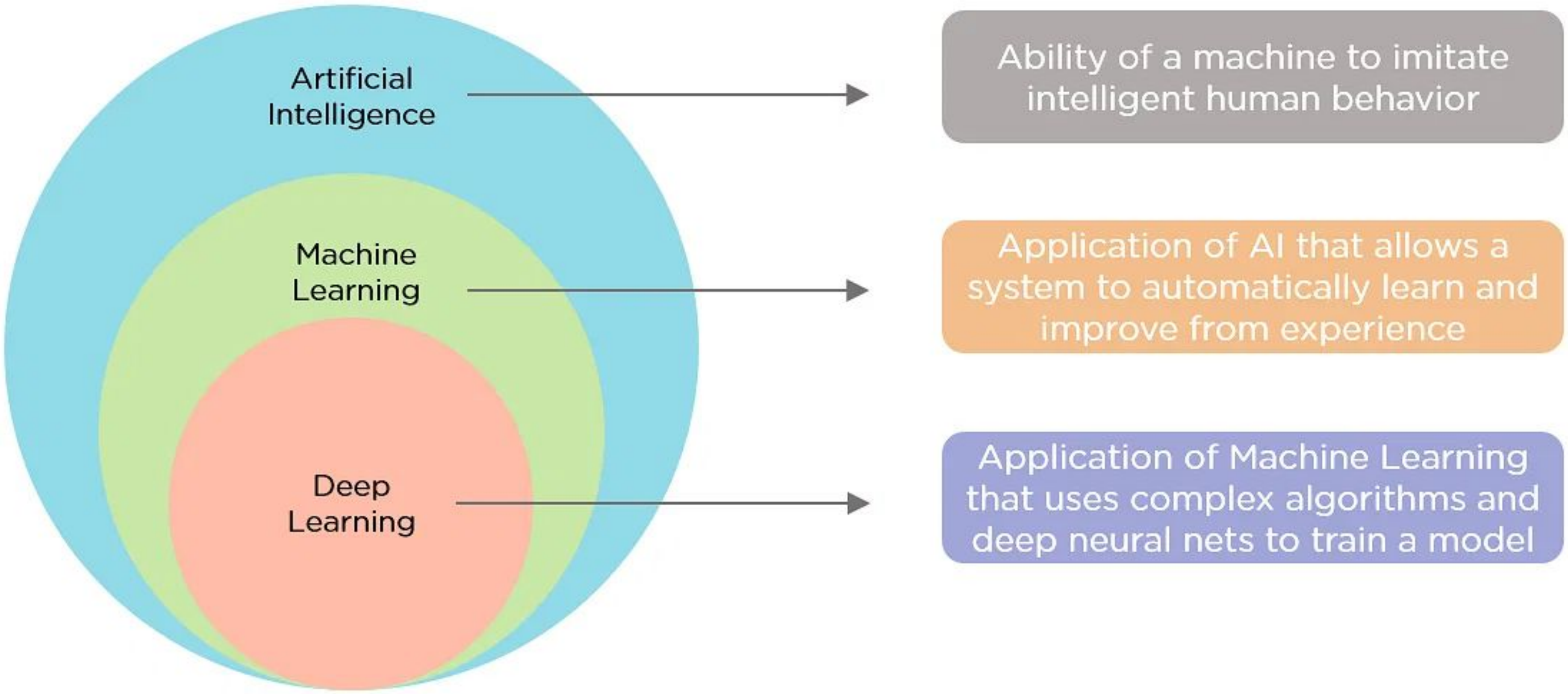


Usage of AI/ML for the enhancement of weather and climate related services

The following list indicates some of initiatives that are being taken by our research team:

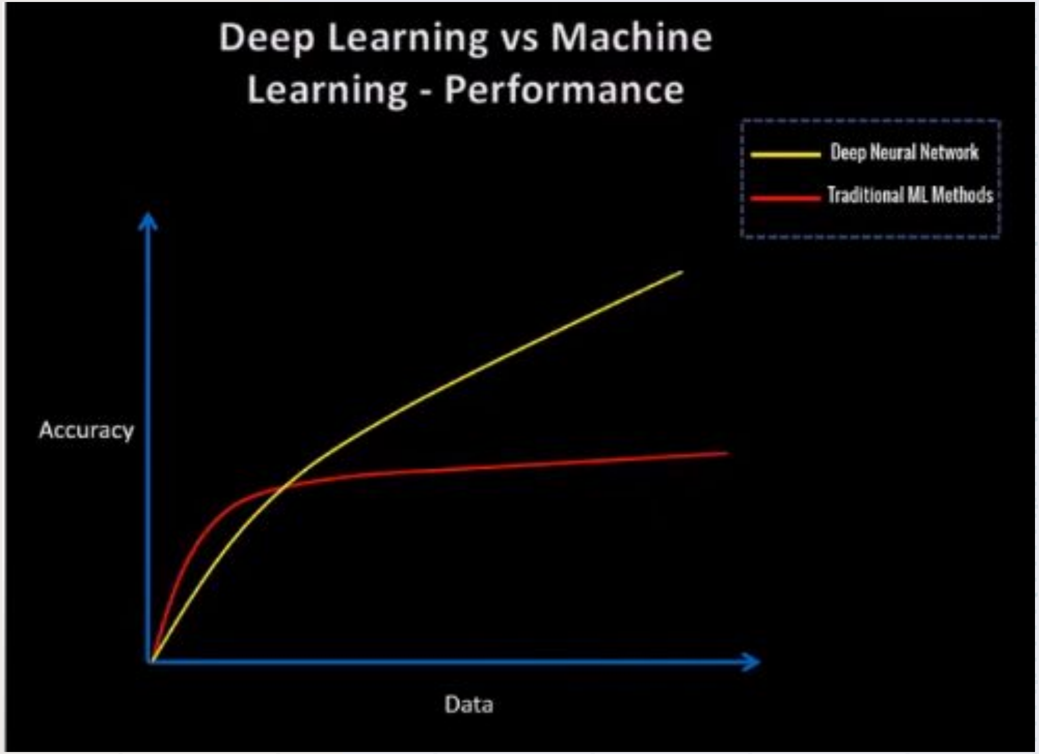
- Prediction of high-impact events like droughts.
- Improving sub-seasonal to seasonal forecasts.
- Forecasting renewable energy (solar, wind)

Deep Learning (DL)

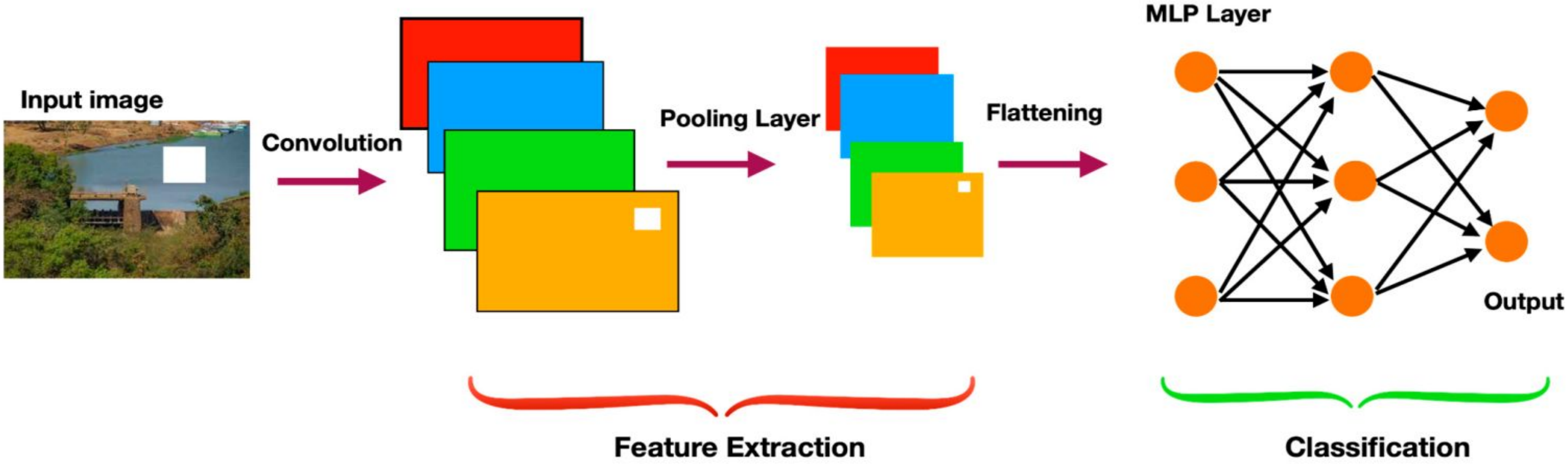


Why Deep Learning Model?

- Ability to capture complex relationships.
- Automatic feature extraction.
- Handling large-scale datasets.
- Transfer learning and pre-trained models.
- Adaptability to changing conditions.



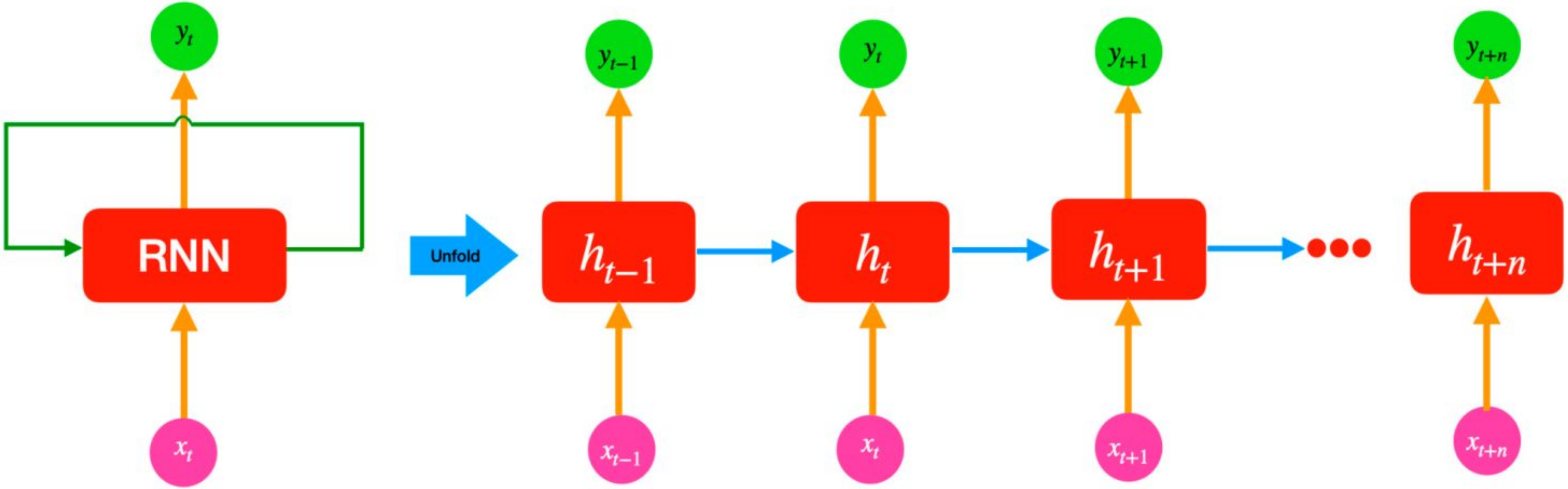
DL - Convolutional Neural Networks (CNNs)



CNNs

- Are efficient in processing spatial data, such as images or data with grid-like structures.
- Can extract features from spatial images or grids, helping identify patterns, structures, or anomalies.

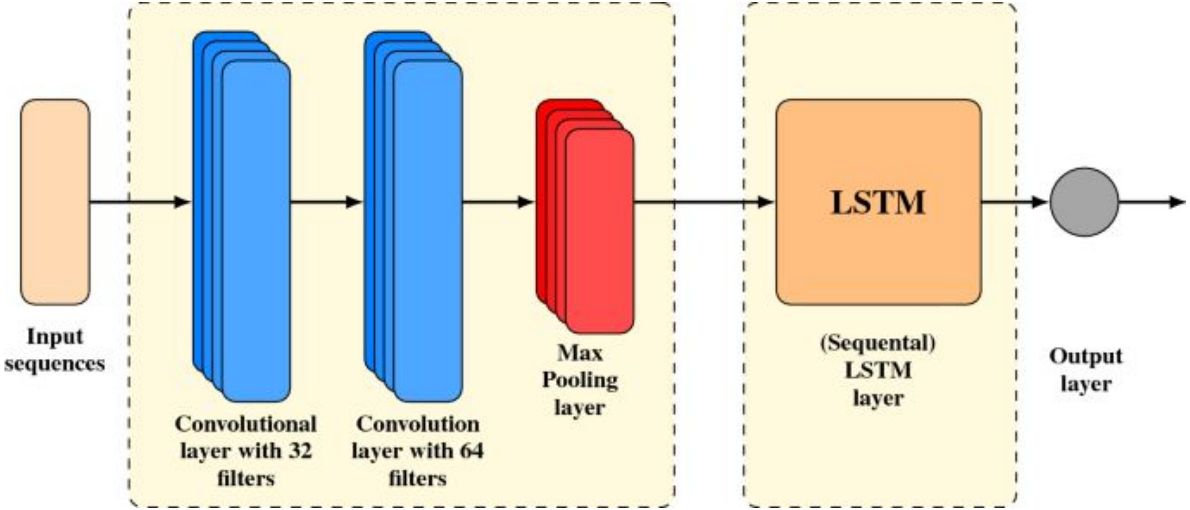
DL - Recurrent Neural Network (RNNs)



RNNs

- Are well-suited for processing sequential or time-dependent data.
- Can capture temporal dependencies and long-term relationships within time series data.

Hybrid CNN-RNN Architecture



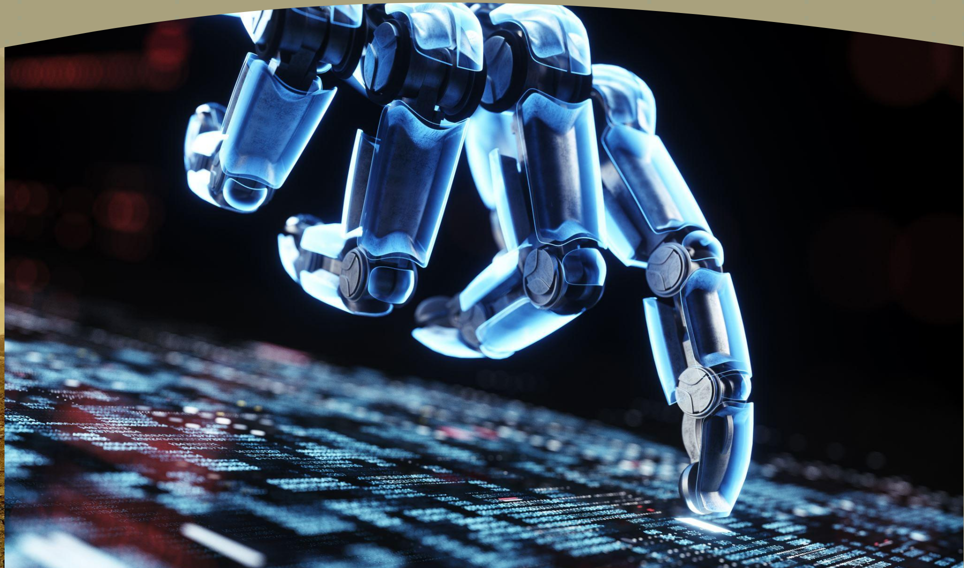
Input Layer

Convolution Layer

RNN Layer

- Integrating Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) in a hybrid model allows for the simultaneous analysis of spatial and temporal patterns.

Development of Drought Early Warning System Using Deep Learning Models



Introduction

Drought is a significant natural disaster that impacts agriculture, water resources, ecosystems, and socio-economic activities.

Early warning systems play a crucial role in mitigating the impacts of drought by providing timely information to decision-makers.

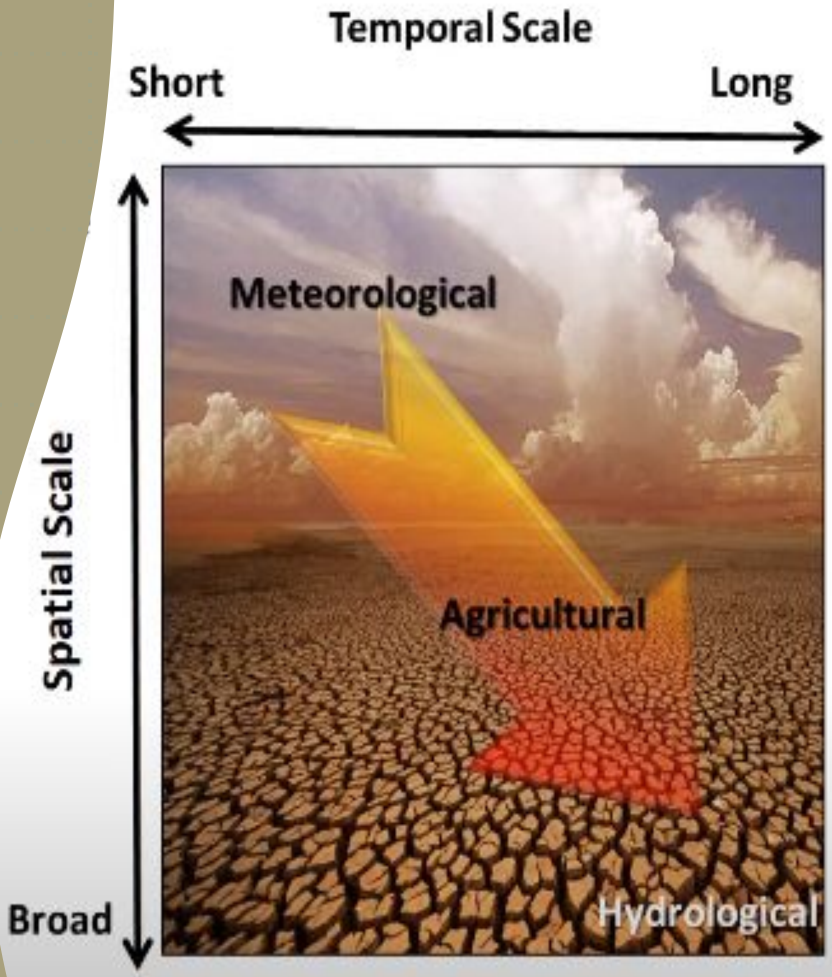
AI/ML techniques have the potential to revolutionize drought forecasting by improving accuracy and lead time.

What is Drought?

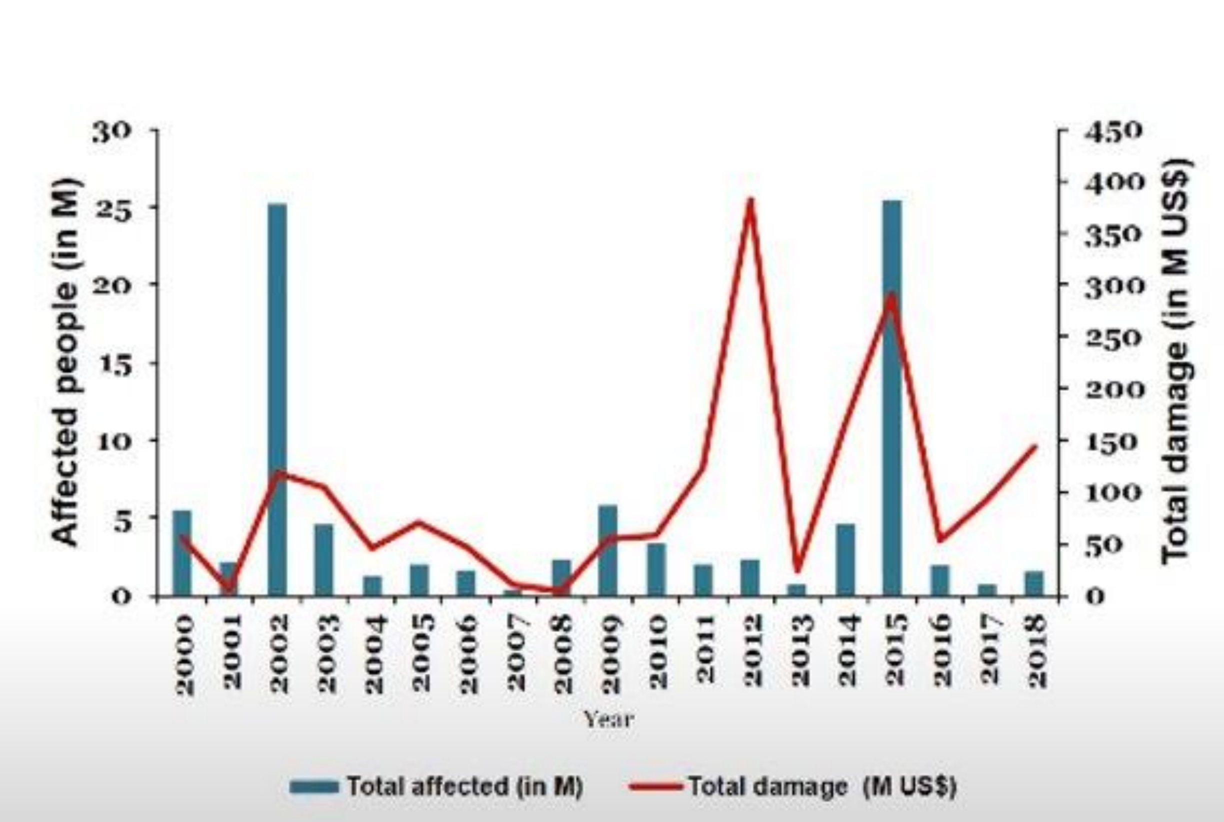
1) *Drought* is a prolonged period of abnormally low precipitation that leads to water scarcity and affects various sectors.

2) There are different types of drought, including *meteorological* drought (a deficit in precipitation), *agricultural* drought (insufficient soil moisture for crops), and *hydrological* drought (reduced water availability in rivers, reservoirs, and groundwater).

3) Droughts can occur at *local*, *regional*, or even *global* scales, and their impacts can be severe, leading to water shortages, crop failures, and environmental degradation.

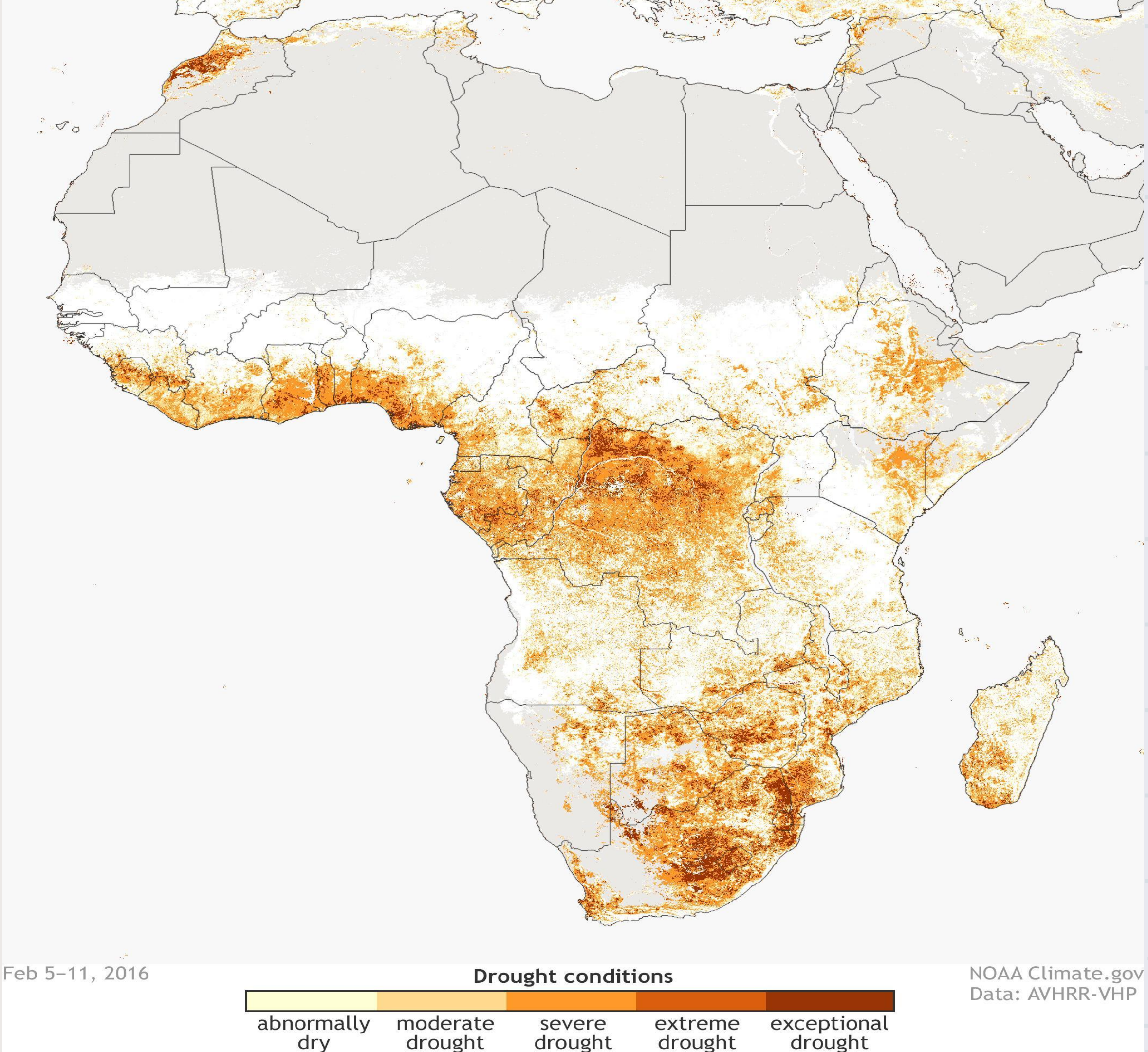


Drought Damage



1. Source: Emergency Events Database (EM-DAT), Centre for Research on the Epidemiology of Disasters (CRED): https://www.emdat.be/

Drought Spatial Distribution in Africa



Source: NOAA, Climate, Feb 5 – 11, 2016

Drought Indices

Drought indices are tools used to quantitatively assess and monitor drought conditions.

They provide valuable information about the severity and extent of droughts based on various environmental parameters.

- Standardized Precipitation Index (SPI)
- Palmer Drought Severity Index (PDSI)
- Standardized Soil Moisture Index (SSI)
- Crop Moisture Index (CMI)
- Vegetation Condition Index (VCI)
- Evaporative Stress Index (ESI)

Role of Early Warning Systems

- Drought are not preventable, but they are predictable.
- Developing early warning systems are essential for proactive drought management.
- They provide decision-makers with timely information on drought conditions, allowing for effective planning and response.
- Early warnings enable to minimize cost of drought and mitigation measures in agriculture and other socioeconomic sectors.

Challenges of Drought Early Warning Systems

Drought is a complex phenomenon that poses challenges for traditional prediction methods.

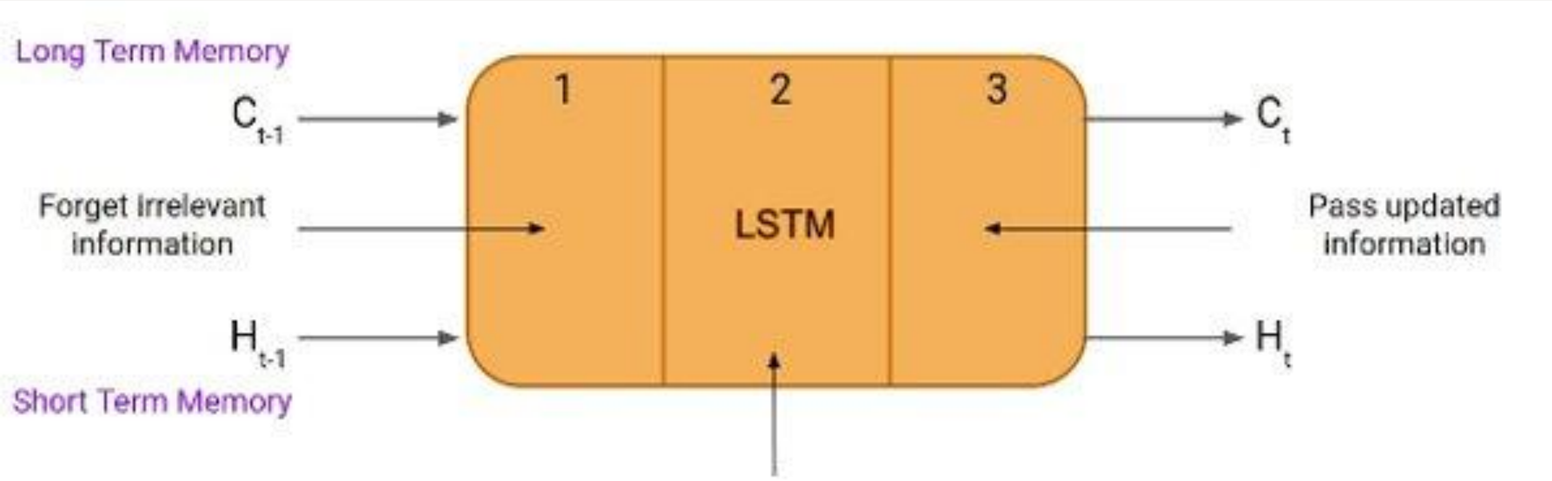
Accurate prediction of drought is hindered by:

- Multiple predictors
- Non-linear relationships, and feedback

The forecast lead time provided by traditional methods is insufficient for effective planning, response, and mitigation measures.

Long Short-Term Memory Algorithm

- LSTM model is a special kind of RNN, capable of learning long-term dependencies in processing sequential data (Hochreiter & Schmidhuber,1997).
- LSTM cells consists of ***three gates*** and ***memory cell*** (cell state).
- The first gate is called ***Forget gate***, the second gate is known as the ***Input gate***, and the last one is the ***Output gate***.



Objective

To design and deploy an AI/ML-based drought early warning application that improves the accuracy of drought prediction, enhances the lead time for decision-making, and enables targeted interventions to mitigate the impacts of drought on agriculture, water resources, ecosystems, and society.

Specific Objectives

Develop

Develop a robust AI/ML model for drought prediction.

Improve

Improve the lead time and accuracy of drought early warning system.

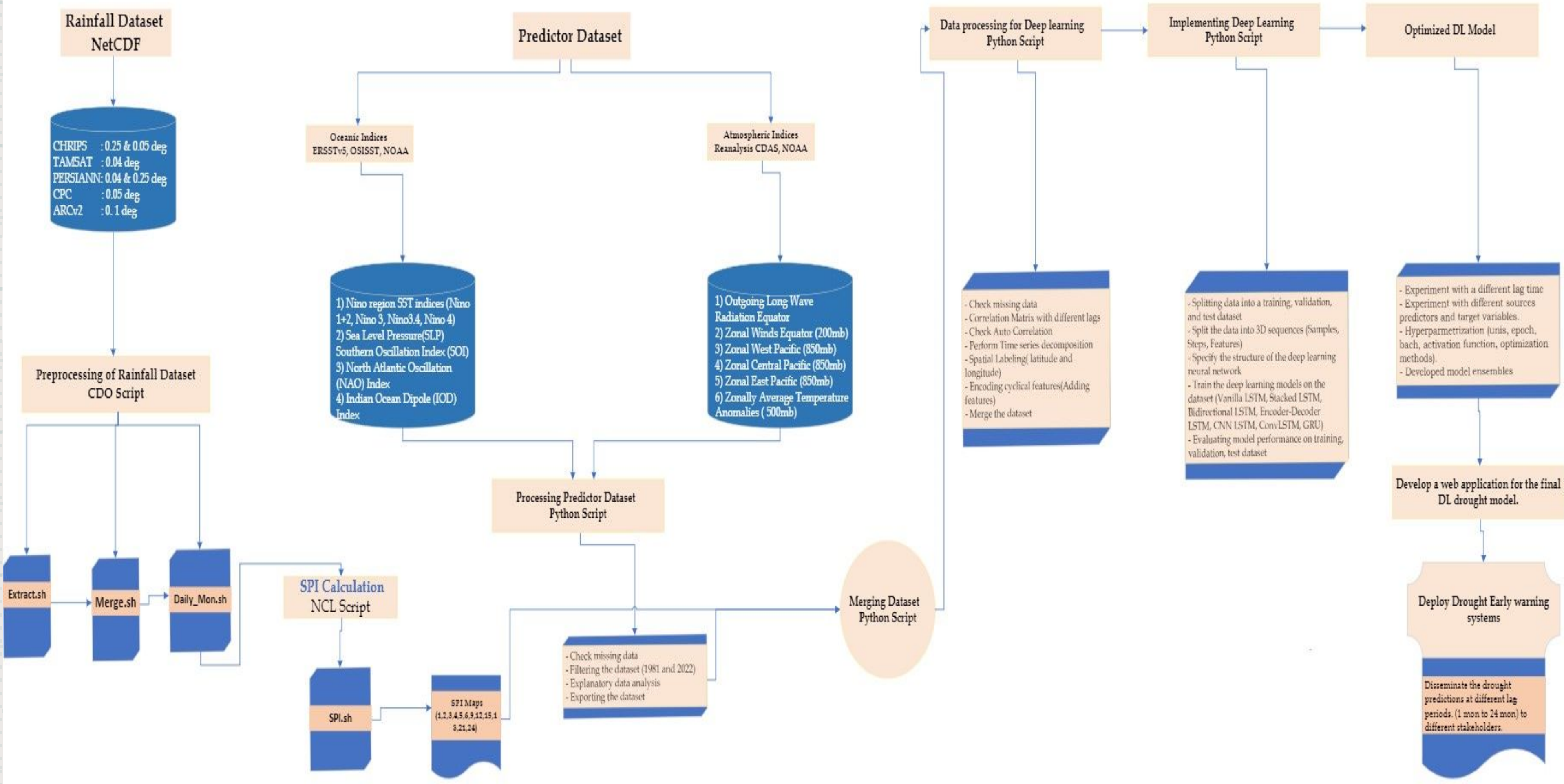
Deploy

Deploy the drought forecasting AI model into a usable application.

Establish

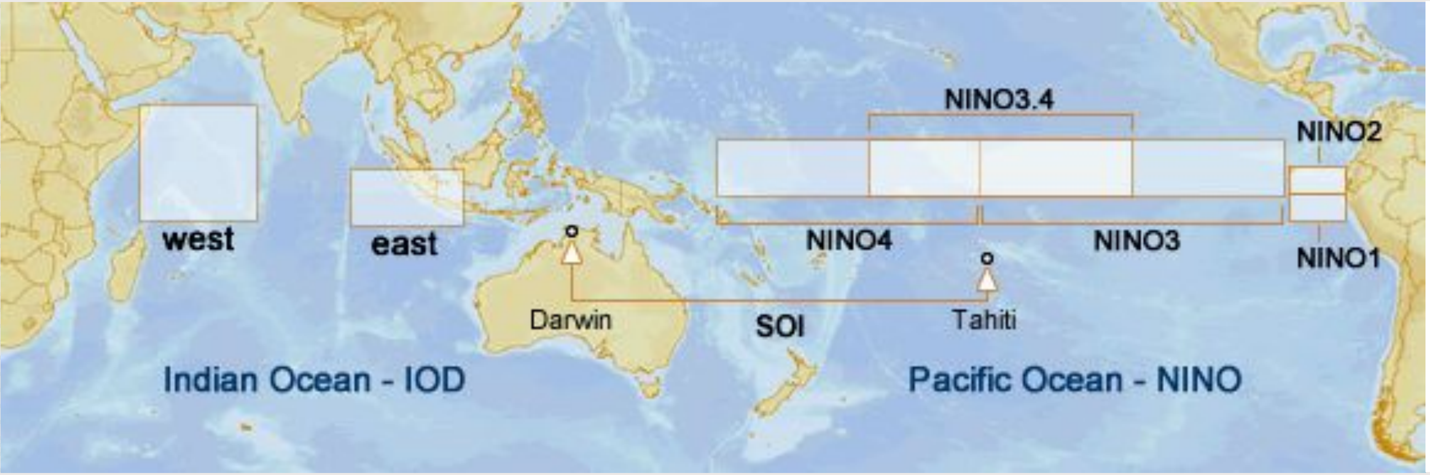
Establish a collaborative framework for sharing data, knowledge, and best practices among relevant stakeholders in drought management.

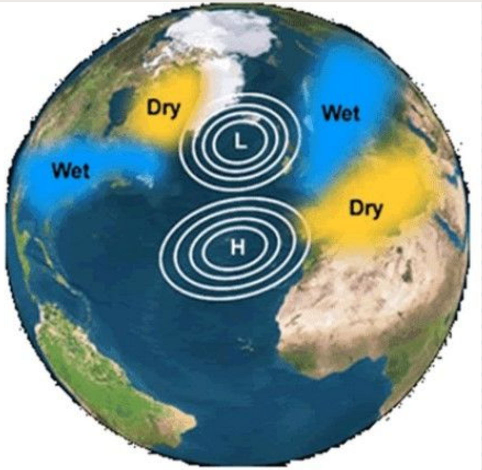
Method



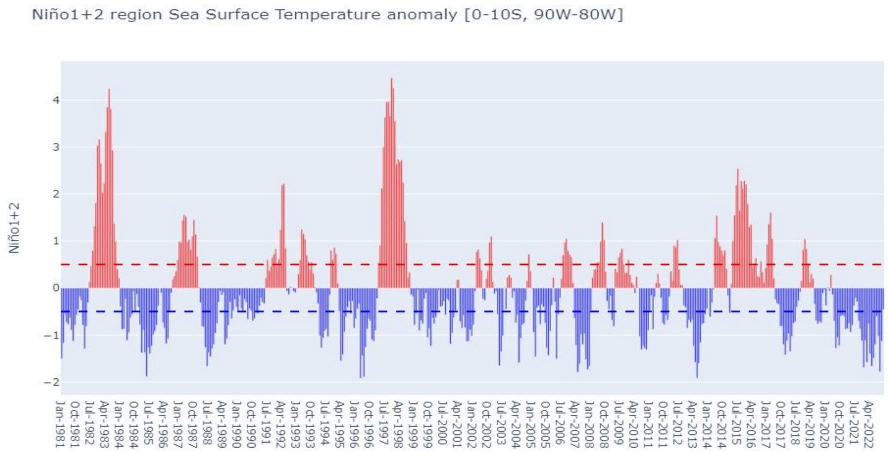
Rainfall Dataset
NetCDF
CHRIPS : 0.25 & 0.05 deg
TAMSAT : 0.04 deg
PERSIANN: 0.04 & 0.25 deg
CPC : 0.05 deg
ARCv2 : 0. 1 deg
Preprocessing of Rainfall Dataset
CDO Script
Extract.sh
Merge.sh
Daily_Mon.sh
SPI Calculation
NCL Script
SPI.sh
SPI Maps (1,2,3,4,5,6,9,12,15,18,21,24)
Predictor Dataset
Oceanic Indices
ERSSTv5, OSISST, NOAA
Atmospheric Indices
Reanalysis CDAS, NOAA
1) Nino region SST indices (Nino 1+2, Nino 3, Nino3.4, Nino 4)
2) Sea Level Pressure(SLP) Southern Oscillation Index (SOI)
3) North Atlantic Oscillation (NAO) Index
4) Indian Ocean Dipole (IOD) Index
1) Outgoing Long Wave Radiation Equator
2) Zonal Winds Equator (200mb)
3) Zonal West Pacific (850mb)
4) Zonal Central Pacific (850mb)
5) Zonal East Pacific (850mb)
6) Zonally Average Temperature Anomalies (500mb)
Processing Predictor Dataset
Python Script
- Check missing data
- Filtering the dataset (1981 and 2022)
- Explanatory data analysis
- Exporting the dataset
Merging Dataset
Python Script
Data processing for Deep learning
Python Script
- Check missing data
- Correlation Matrix with different lags
- Check Auto Correlation
- Perform Time series decomposition
- Spatial Labeling(latitude and longitude)
- Encoding cyclical features(Adding features)
- Merge the dataset
Implementing Deep Learning
Python Script
- Splitting data into a training, validation, and test dataset
- Split the data into 3D sequences (Samples, Steps, Features)
- Specify the structure of the deep learning neural network
- Train the deep learning models on the dataset (Vanilla LSTM, Stacked LSTM, Bidirectional LSTM, Encoder-Decoder LSTM, CNN LSTM, ConvLSTM, GRU)
- Evaluating model performance on training, validation, test dataset
Optimized DL Model
- Experiment with a different lag time
- Experiment with different sources predictors and target variables.
- Hyperparametrization (unis, epoch, bach, activation function, optimization methods).
- Developed model ensembles
Develop a web application for the final DL drought model.
Deploy Drought Early warning systems
Disseminate the drought predictions at different lag periods. (1 mon to 24 mon) to different stakeholders.

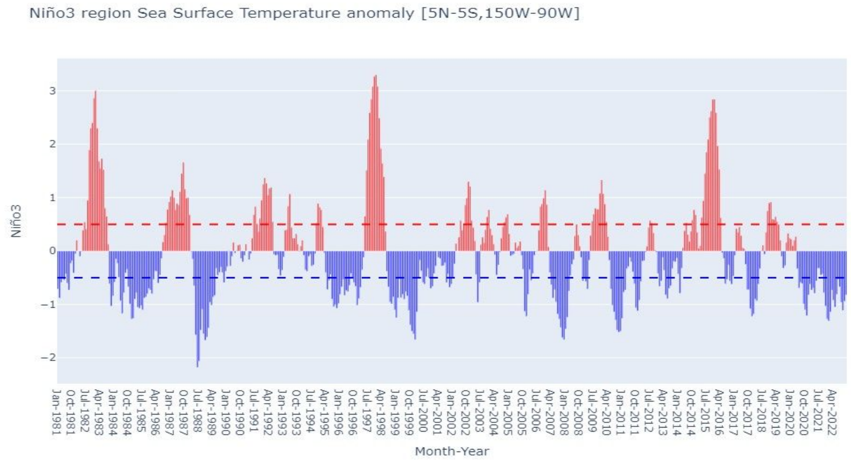
Predictor Domains

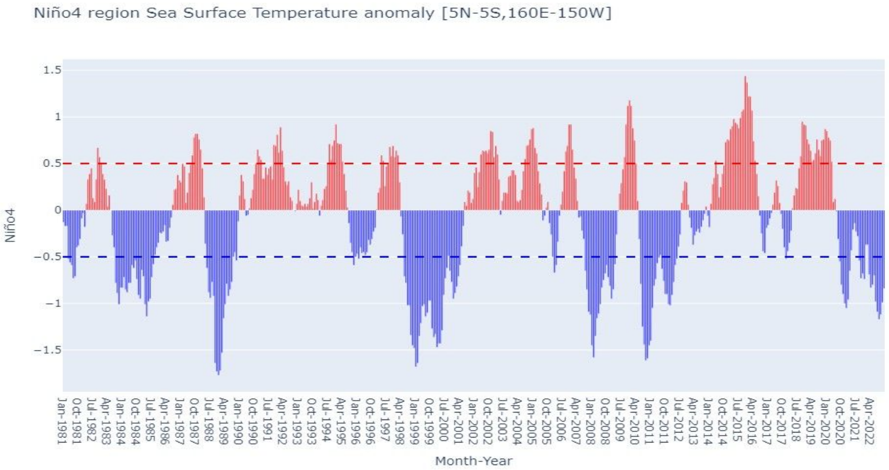


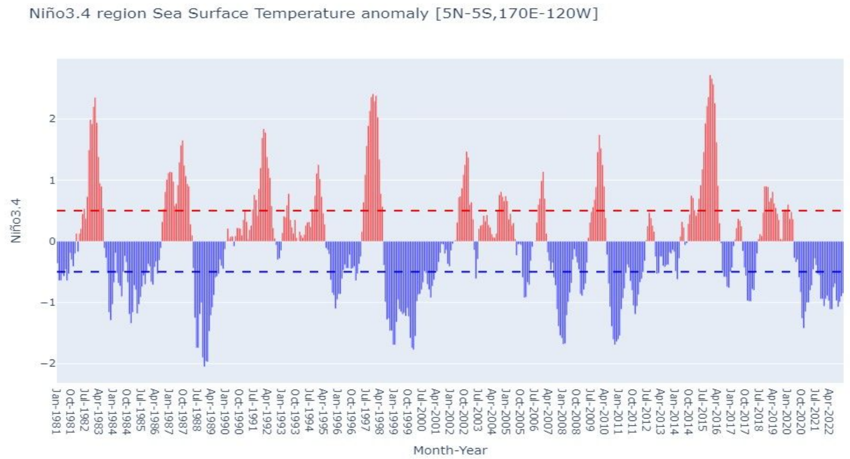


SST Anomaly


Niño1+2 region Sea Surface Temperature anomaly [0-10S, 90W-80W]
Niño1+2

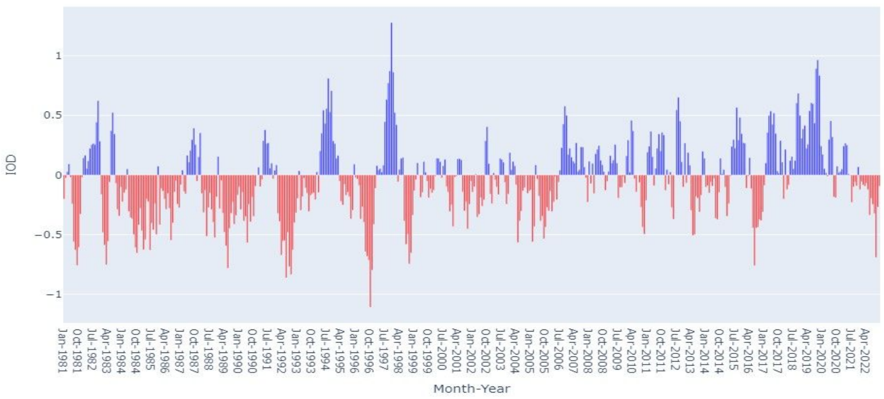

Niño3 region Sea Surface Temperature anomaly [5N-5S,150W-90W]
Niño3
Month-Year


Niño4 region Sea Surface Temperature anomaly [5N-5S,160E-150W]
Niño4
Month-Year

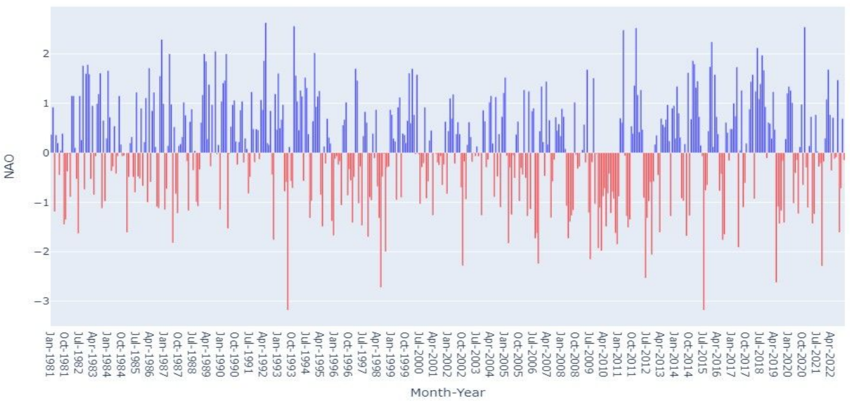

Niño3.4 region Sea Surface Temperature anomaly [5N-5S,170E-120W]
Niño3.4
Month-Year

IOD, NAO, SOI, OLR Anomaly

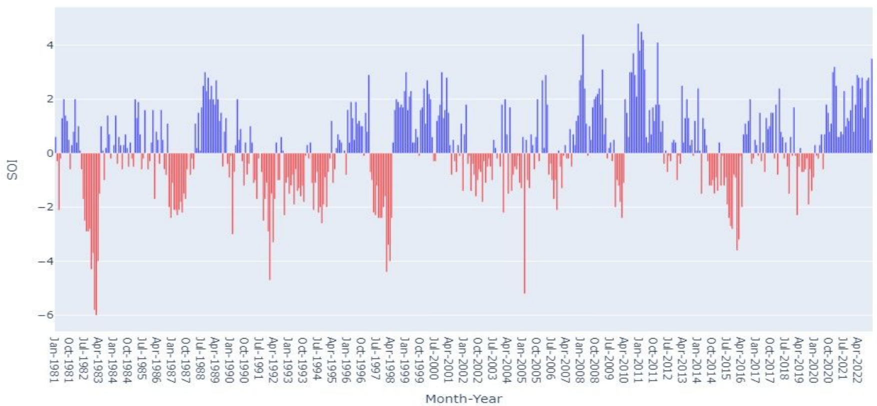
Indian Ocean Dipole Index (IOD)



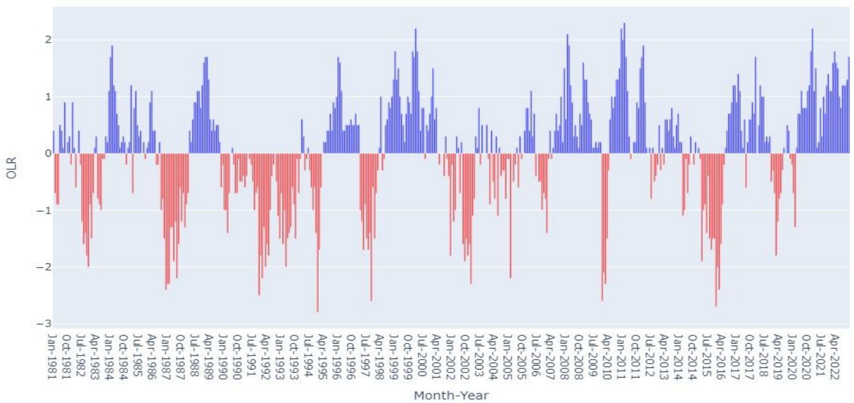
North Atlantic Oscillation (NAO)



Southern Oscillation Index (SOI)

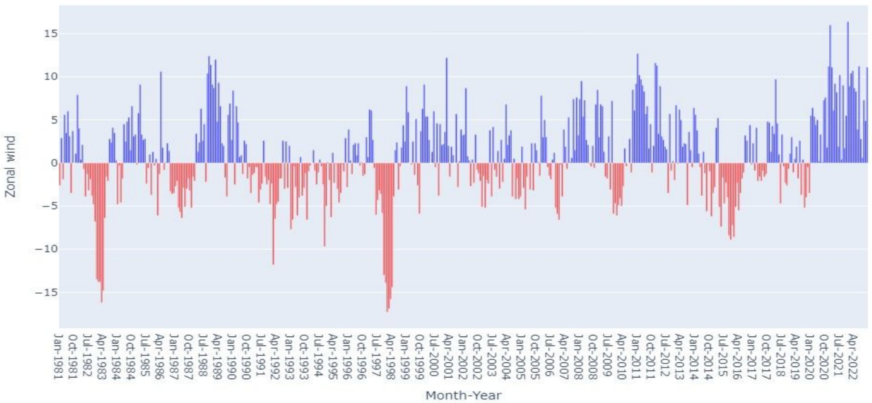


Outgoing Long Wave Radiation (OLR) at 160E-160W and 5S-5N

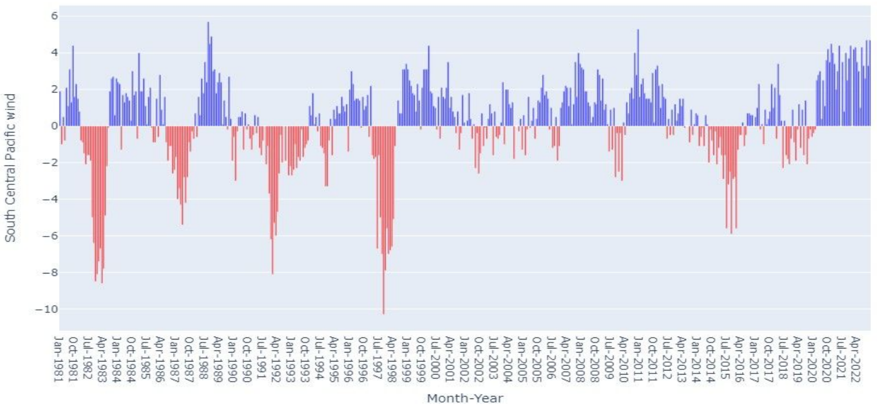


Zonal Wind Anomalies

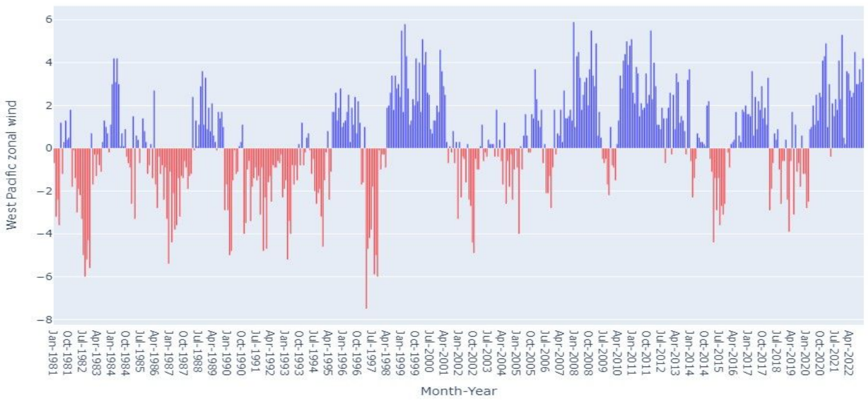
Zonal Wind anomalies at Equator at 200-mb 5N-5S, 165W-110W



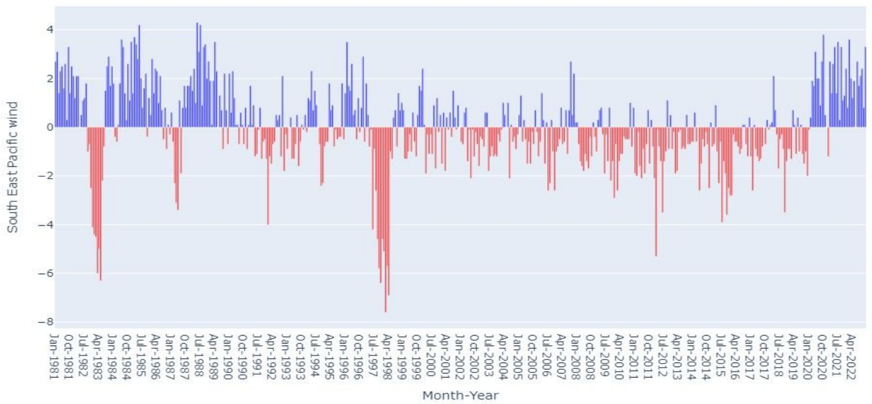
South Central Pacific zonal wind anomalies at 850-mb, 175W-140W, 5N-5S



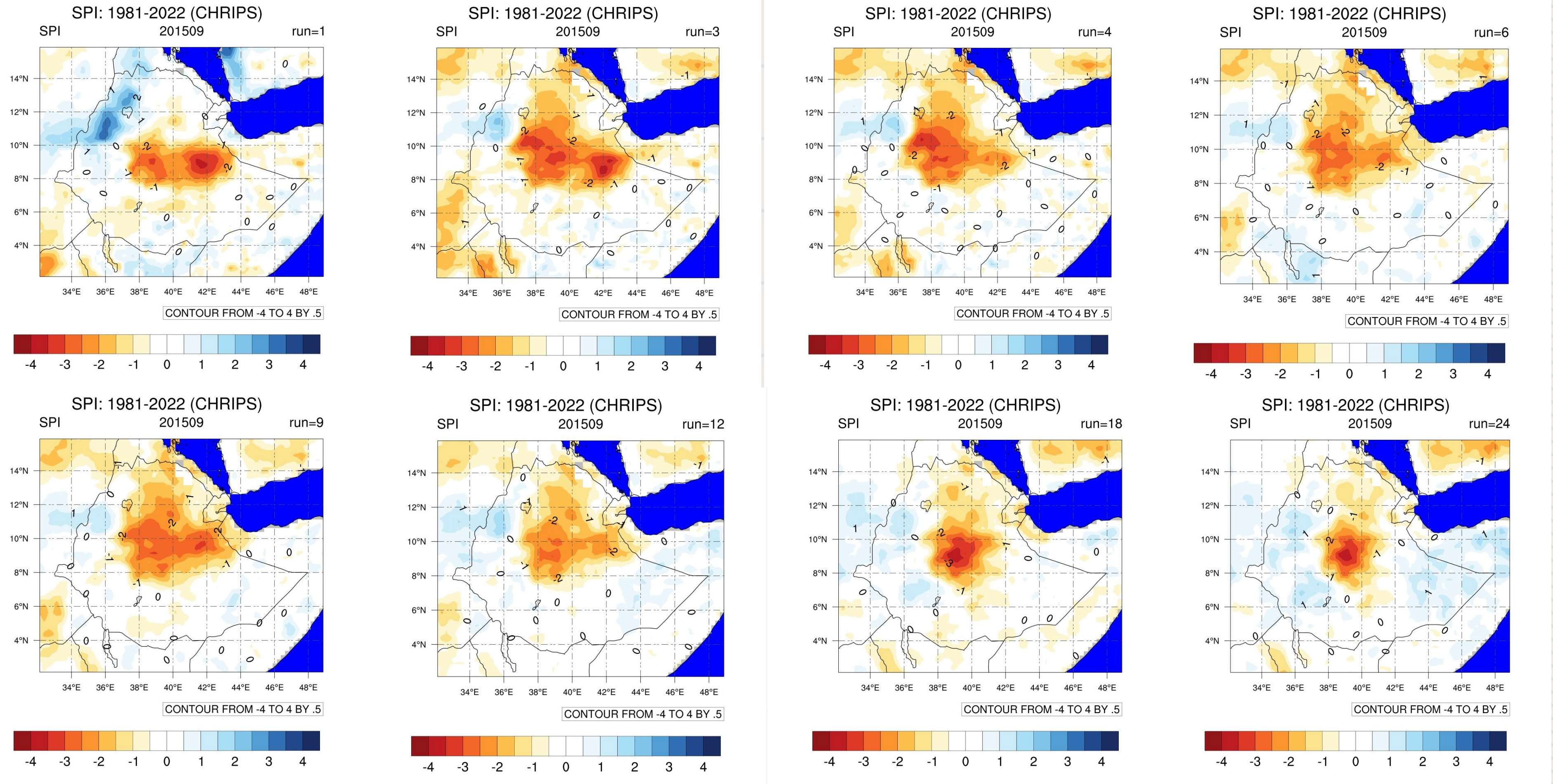
West Pacific zonal wind anomalies at 850-mb 135E-180W, 5N-5S



South East Pacific zonal wind anomalies at 850-mb, 135W-120W, 5N-5S

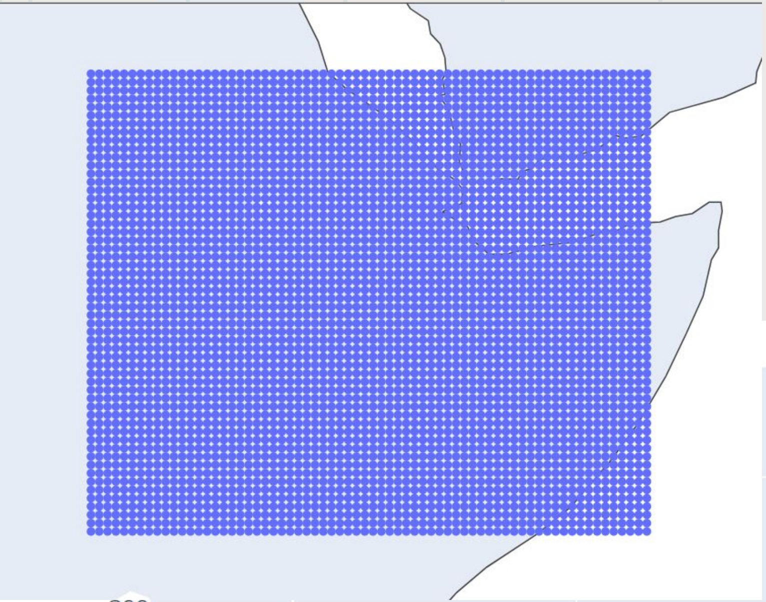


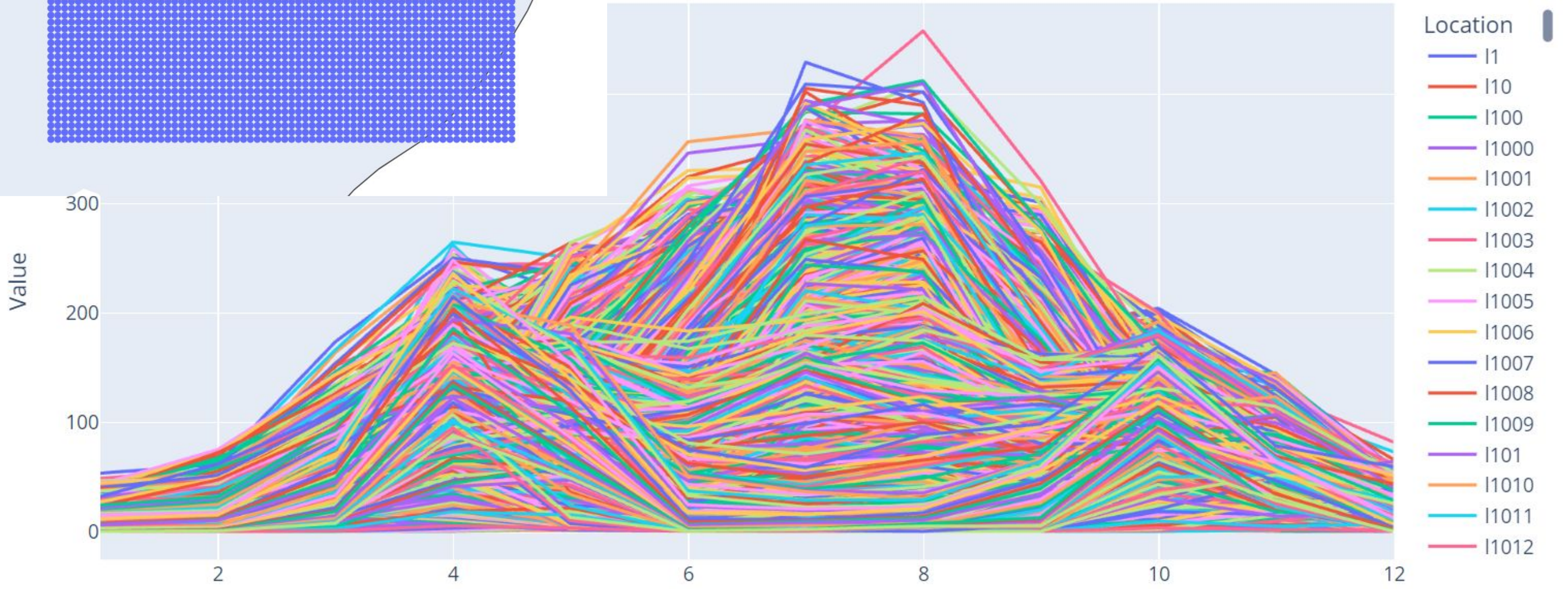
Calculated SPI at d/f lag Periods



Labeled locations & monthly mean rainfall

- 3,428 labeled locations (longitude: 68 & latitude: 56)





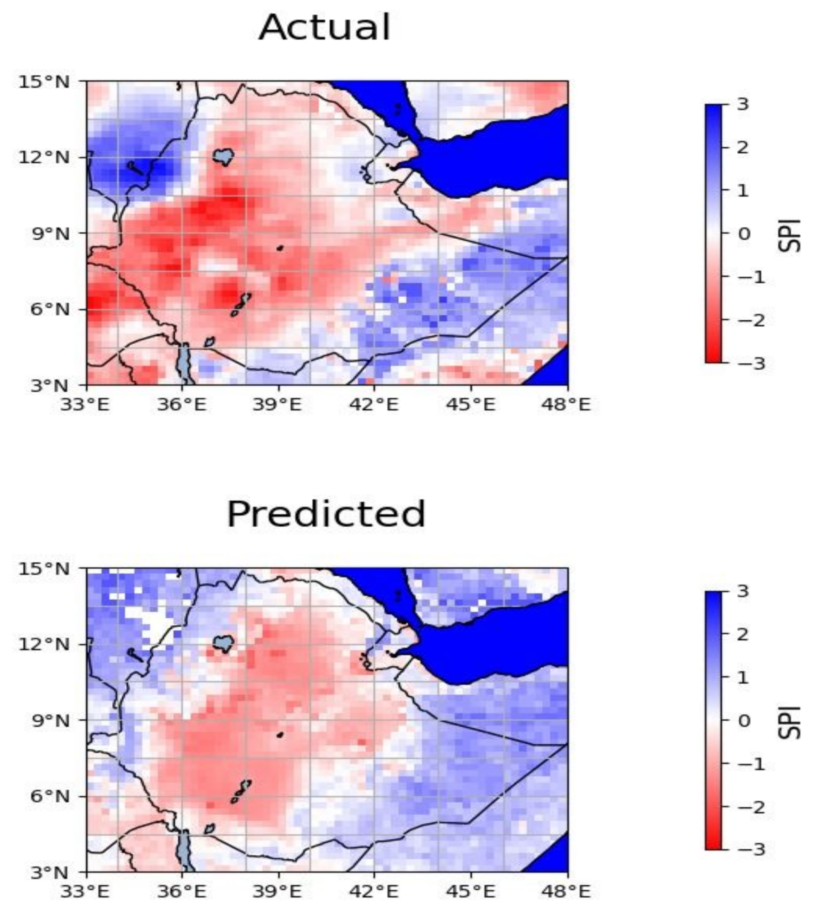
Merged Dataset

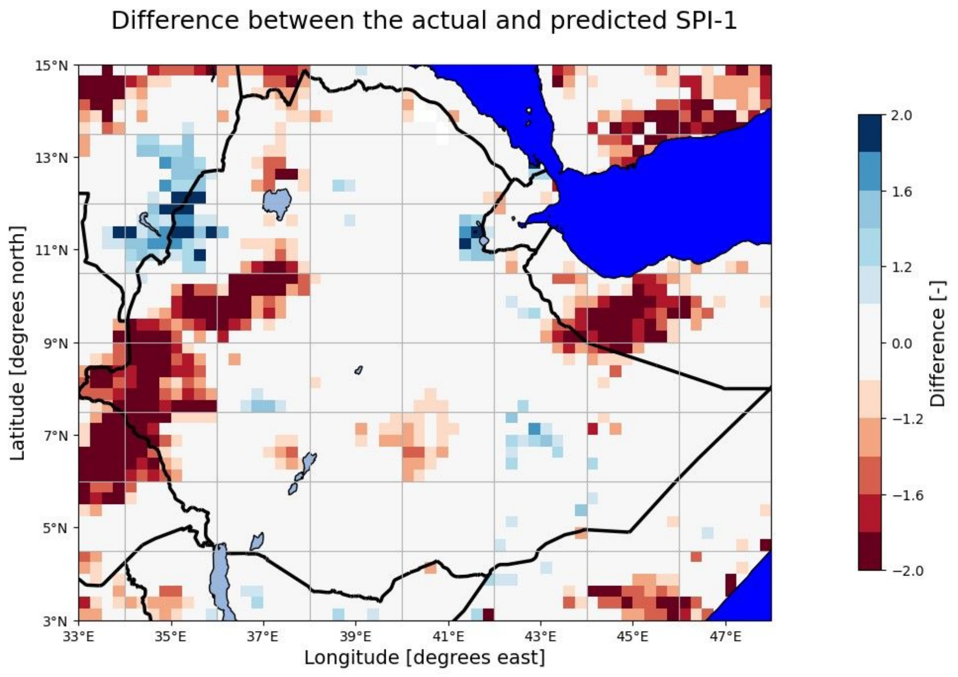
	Year-Month	ANOM_NINO1+2	ANOM_NINO3	ANOM_NINO4	ANOM_NINO3.4	SOI	...	I994	I995	I996	I997	I998	I999
0	1981-01	-1.50	-0.71	-0.13	-0.36	0.6	...	0.637156	0.712172	1.067593	1.067593	1.309366	1.309366
1	1981-02	-1.17	-0.88	-0.17	-0.64	-0.3	...	0.382652	0.876008	0.565574	0.430292	0.496789	0.526824
2	1981-03	-0.55	-0.59	-0.17	-0.64	-2.1	...	2.659780	2.824804	2.544740	2.293281	2.232384	2.349052
3	1981-04	-0.73	-0.52	-0.52	-0.53	-0.2	...	0.993349	1.090022	1.149011	1.121511	1.061071	1.103248
4	1981-05	-0.77	-0.54	-0.56	-0.57	1.3	...	0.715724	0.594208	0.399251	0.249374	[illegible]	0.006612
...	...	...	...	...	...	...	...	...	...	...	...	...	...
499	2022-08	-0.60	-0.67	-1.09	-0.97	1.7	...	-0.322593	-0.890070	-1.116787	-1.666193	-1.119901	-1.692297
500	2022-09	-1.02	-0.96	-1.17	-1.07	2.7	...	-0.824753	-1.326393	-0.813159	-0.055246	-0.218348	-0.581796
501	2022-10	-1.78	-1.11	-1.12	-0.99	2.8	...	0.107265	-0.031670	0.098833	0.136501	0.043186	-0.065646
502	2022-11	-1.13	-0.94	-0.99	-0.90	0.5	...	-0.675650	-0.399150	-0.066127	-0.130335	0.031247	0.153081
503	2022-12	-0.46	-0.82	-0.84	-0.85	3.5	...	0.430292	0.637156	0.712172	0.967363	0.967363	0.876008

504 rows × 3442 columns

Actual Vs Predicted SPI Values

1-month SPI of August, 2015





Expected Outcomes

Improved accuracy: enhanced prediction models and techniques leading to more accurate and reliable drought forecasts.

Timely warnings: early detection and timely communication of drought onset, duration, and severity, enabling proactive measures and preparedness.

Future drought risk: enhanced understanding of future drought risk areas and vulnerability under different emission scenarios, facilitating long-term planning and climate resilience.

Policy support: Informing the development of robust drought management policies and guidelines based on scientific evidence and reliable forecasts.

Capacity building: strengthened technical capacities and expertise in drought forecasting, monitoring, and response at various levels.

Improving sub-seasonal to seasonal forecasts

Motivation of the Research

Importance

- Seasonal forecasting (rainfall) is the most important variable

Existing Potential

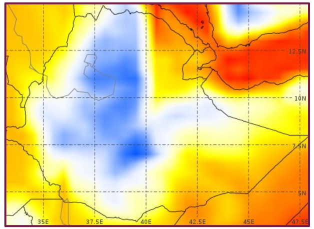
- Recent improvements to the LSTM and Transformer architecture provides an objective approach and believed to provide a better prediction

Existing Limitations

- The seasonal forecast in Ethiopia utilizes analog method which makes it subjective and has some limitation in terms of accurate seasonal prediction.

Bridging the Gap

- To adopt and implement the official Temporal Fusion Transformers (TFT) to enhance spatio-temporal awareness for seasonal and sub-seasonal prediction



Objective

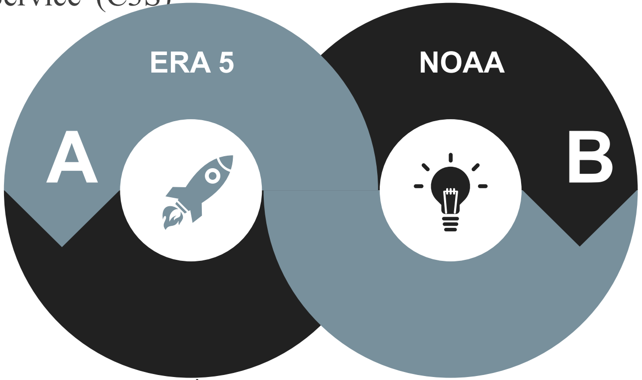
To provide a better seasonal and sub-seasonal prediction and interpretation for the region of Ethiopia

Regional/Oceanic Data Collection

Copernicus Climate Change Service (C3S)

ERA5 geo-gridded regional data was downloaded from Copernicus Climate Change Service (C3S) - Climate Data Store (CDS)

- All weather data 1960 - 2022
- 0.5 Spatial Resolution
- Daily Temporal Resolution



- All SSTs from 1960 - 2023
- Specific Spatial Resolution
- Monthly Temporal Resolution

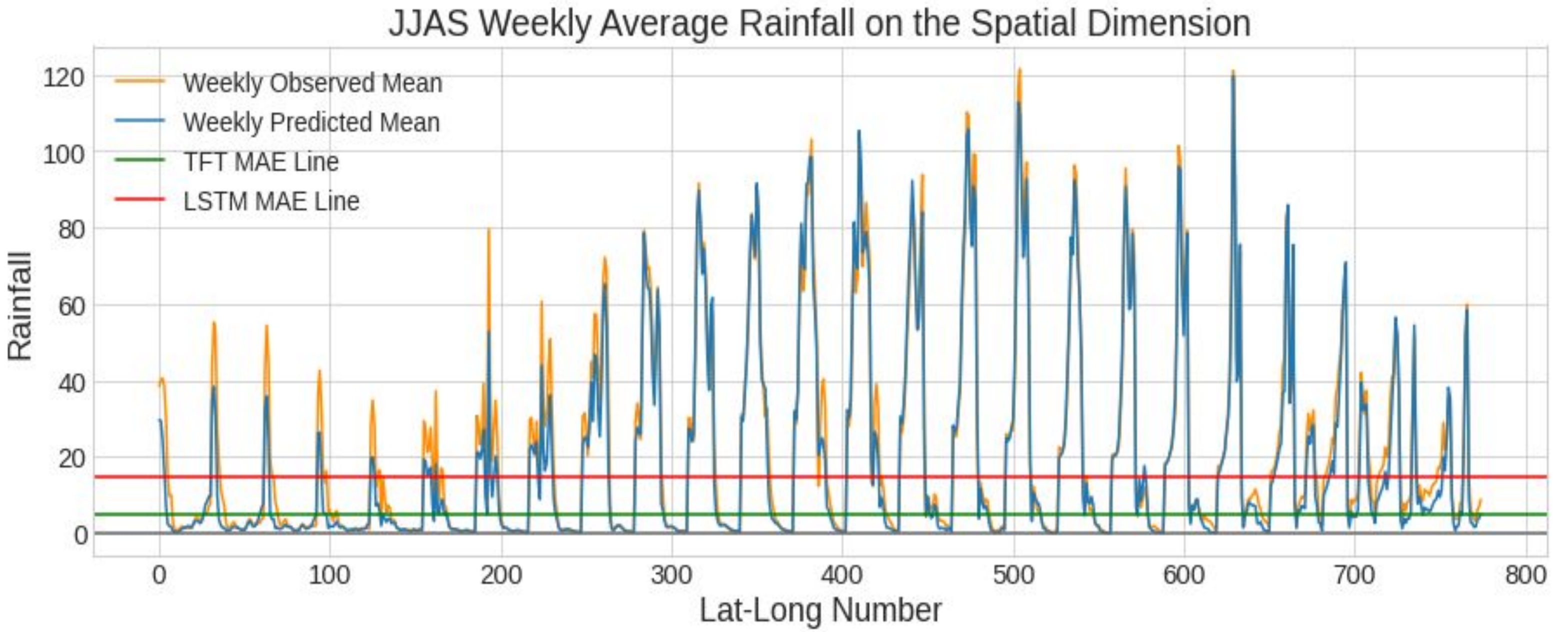
The National Oceanic and Atmospheric Administration

Merged Dataset

	year	months	nino34	nina4	nina1	npi	dmi	nao	gmsst
0	1950	1	0.232365	0.167102	0.396702	0.750713	0.487607	0.560166	0.133929
1	1951	1	0.215768	0.237598	0.503395	0.483910	0.603796	0.603043	0.035714
2	1952	1	0.531120	0.516971	0.527643	0.567821	0.477924	0.683264	0.263393
3	1953	1	0.524896	0.436031	0.505335	0.248065	0.622386	0.568465	0.254464
4	1954	1	0.531120	0.537859	0.362755	0.586558	0.373354	0.549101	0.111607
...	...	...	...	...	...	...	...	...	...
873	2018	12	0.653527	0.822454	0.479146	0.456619	0.624322	0.587828	0.799107
874	2019	12	0.558091	0.812010	0.373424	0.462729	0.598761	0.629322	0.888393
875	2020	12	0.248963	0.323760	0.319108	0.284725	0.516266	0.449516	0.767857
876	2021	12	0.230290	0.391645	0.213385	0.812627	0.458172	0.495159	0.803571
877	2022	12	0.273859	0.365535	0.332687	0.459470	0.469016	0.145228	0.714286

Performance Metric

TFT		LSTM		Pers.
92%	R2	83%	R2	67%
5.108	MAE	14.826	MAE	14.826
9.381	RMSE	19.647	RMSE	31.590



Forecasting renewable energy (solar, wind)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Forecasting Renewable Energy Generation with Machine Learning and Deep Learning: Current Advances and Future Prospects

by Natei Ermias Benti *, Mesfin Diro Chaka and Addisu Gezahegn Semie *

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- This article reviews advances in renewable energy generation forecasting using ML and DL techniques.
- Accurate forecasting is crucial with the growing use of renewable energy sources in the grid.
- ML and DL are preferred due to their ability to handle complex data and provide accurate predictions.
- The review covers various approaches and models for renewable energy forecasting, discussing their strengths and limitations.
- Challenges like handling uncertainty, data availability, and model interpretability are highlighted.
- The paper emphasizes the need for robust forecasting models to support the integration of renewable energy into the grid for a sustainable energy future.

Woldegiyorgis et al., *Cogent Engineering* (2023), 10: 2220489
https://doi.org/10.1080/23311916.2023.2220489

cogent engineering

CrossMark

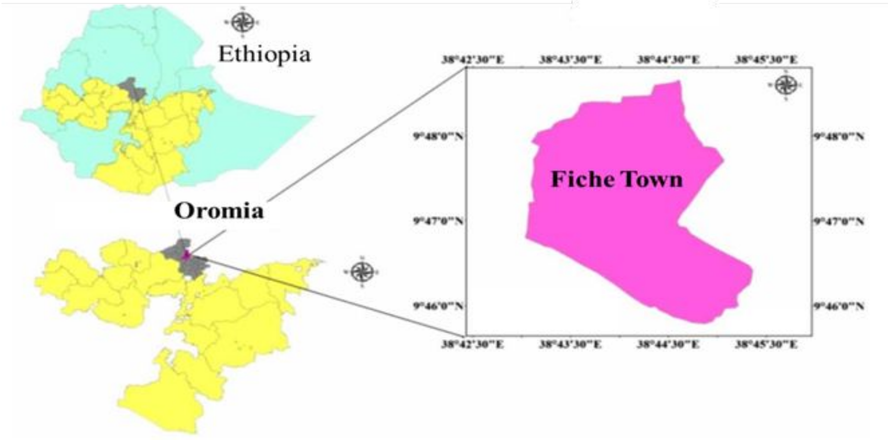
ENVIRONMENTAL ENGINEERING | RESEARCH ARTICLE

Estimating solar radiation using artificial neural networks: a case study of Fiche, Oromia, Ethiopia

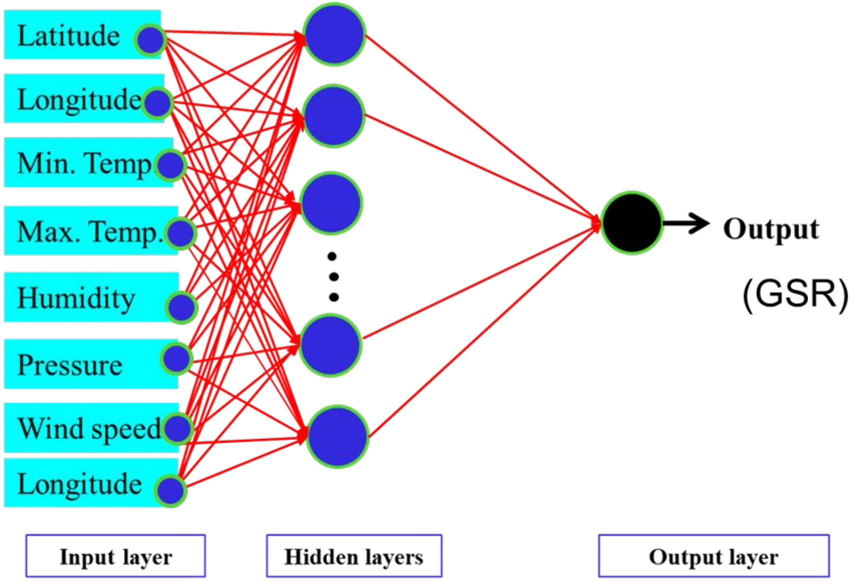
Tegenu Argaw Woldegiyorgis[1*], Natei Ermias Benti[2*], Mesfin Diro Chaka[2] Addisu Gezahegn Semie[2] and Ashenafi Admasu Jemberie[1]

- Accurate assessment of global solar radiation (GSR) is crucial for effective solar energy system design.
- In developing countries like Ethiopia, the cost and maintenance of measuring devices for GSR are insufficient.
- Researchers have investigated alternate techniques, such as empirical models, which have lower accuracy in estimating GSR in such regions.
- In this article we try to use different artificial neural networks (ANN) types (CFBP, FFBP, LR, EBP)) to predict daily and monthly averaged horizontal GSR around Fiche town in Ethiopia.

Map of the study site

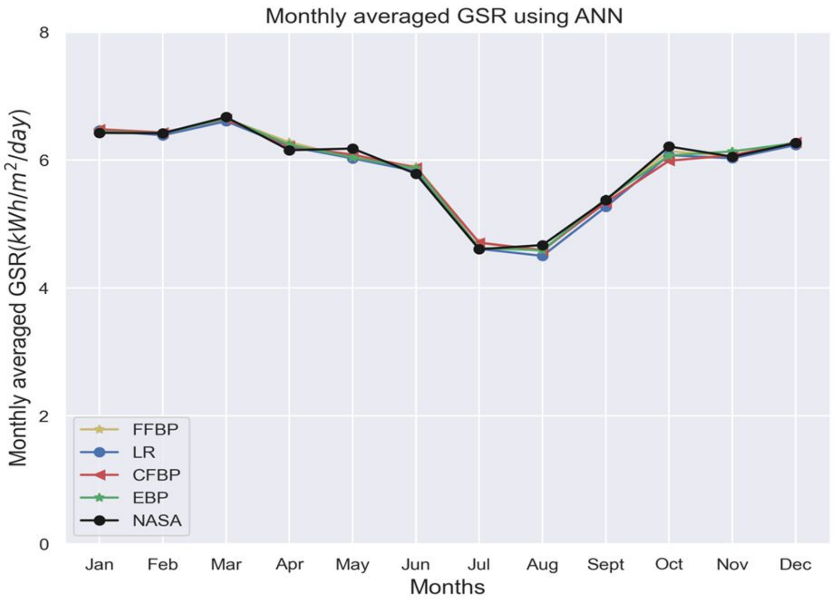


Structure of ANN to predict GSR



Prediction of monthly averaged GSR

ANN network types	MSE	RMSE	MAPE
FFBP	0.0063	0.0795	1.0989
LR	0.0079	0.0893	1.2525
CFBP	0.0079	0.0889	1.2075
EBP	0.0057	0.0757	0.0966



- All ANN network types accurately predicted mean daily and monthly HGSR.
- Predicted daily GSR: 3.28 kWh/m^2/day to 6.97 kWh/m^2 /day.

Unleashing the Power of Artificial Neural Networks: Accurate Estimation of Monthly Averaged Daily Wind Power at Adama Wind Farm I, Ethiopia

Tegenu Argaw[*1], Natei Ermias Benti[*2], Mesfin Diro Chaka[2], Addisu Gezahegn Semie[2], Birhanu Asmerom Habtemicheal[1], Ashenafi Admasu Jembrie[1]

Aim:

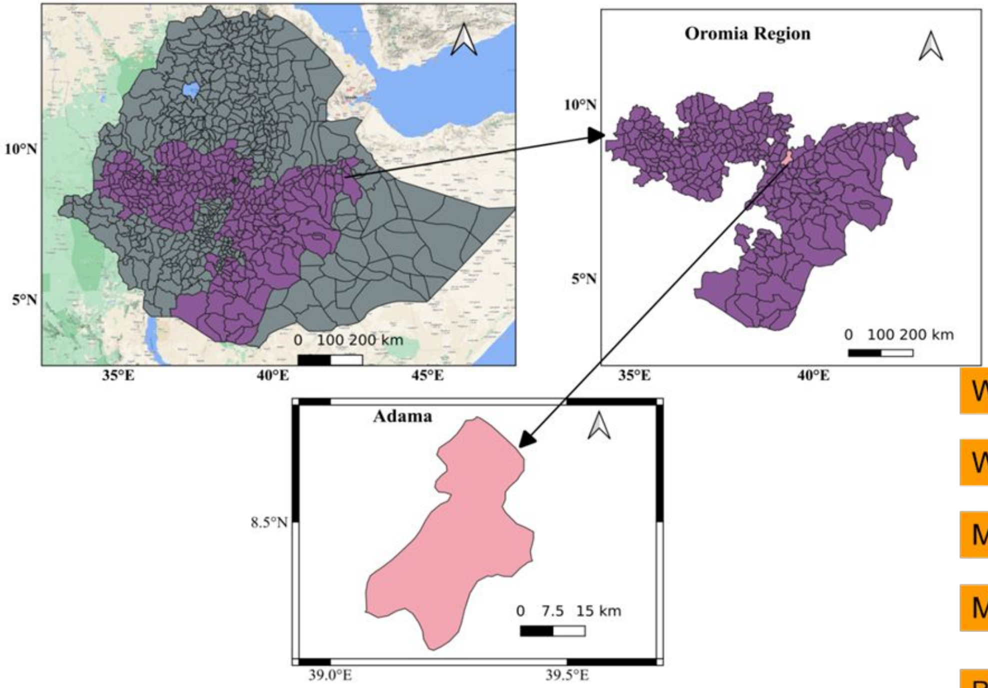
- Evaluate the effectiveness of various ANN network types in estimating monthly average daily wind power at Adama Wind Farm I.

Motivation:

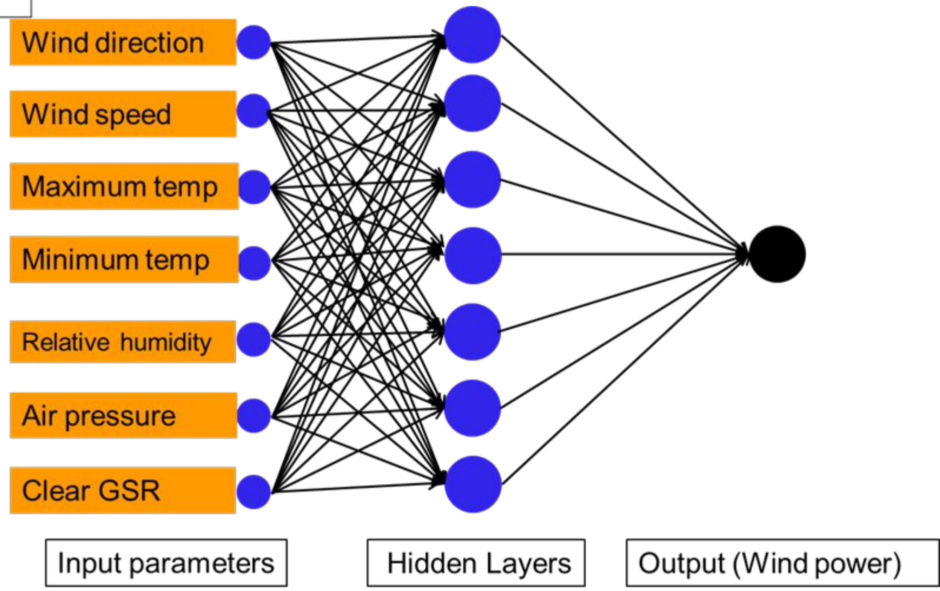
- Wind power is vital for Ethiopian electricity generation, complementing hydropower during dry seasons.
- Accurate wind energy prediction is challenging due to randomness and variability.
- ANN models show promise for improved accuracy in wind energy estimation.

Methods:

- Four ANN network types (FFBP, CFBP, EBP, LR) with seven input parameters.
- Evaluation based on MAPE and R2 metrics.
- EBP network type excelled in wind power estimation for all turbines.



Study site (Adama)



Structure of ANN to predict wind power

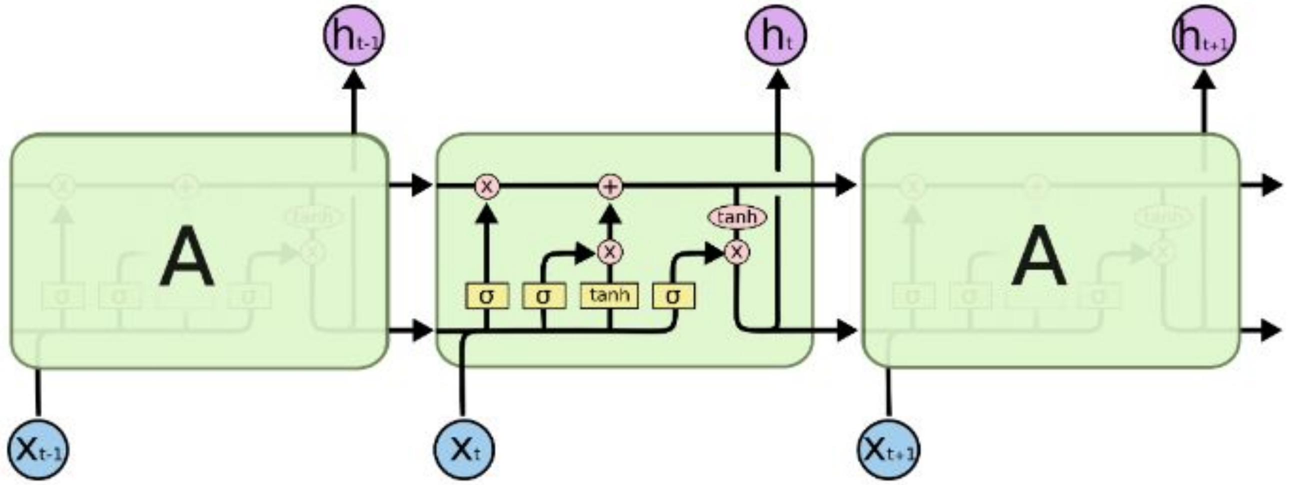
Conclusions

- Improved forecasts can guide better decision-making and planning in weather-sensitive sectors.
- There is a growing potential for AI/ML to complement physics-based NWP models and enhance weather and climate prediction capabilities across timescales.
- We underscore the need for continued research and collaboration between weather/climate experts and AI/ML technologists to fully realize the benefits.

Way forward & Comments...

Thank you !

LSTM Architecture



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right)$$

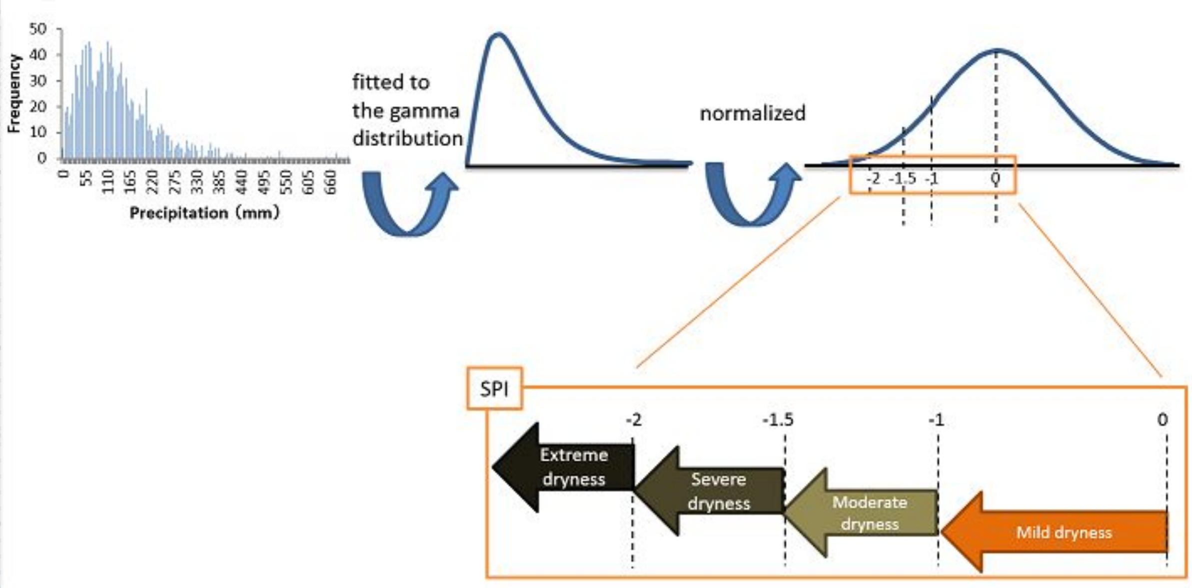
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

$$o_t = \sigma\left(W_o \; [h_{t-1}, x_t] + b_o\right)$$

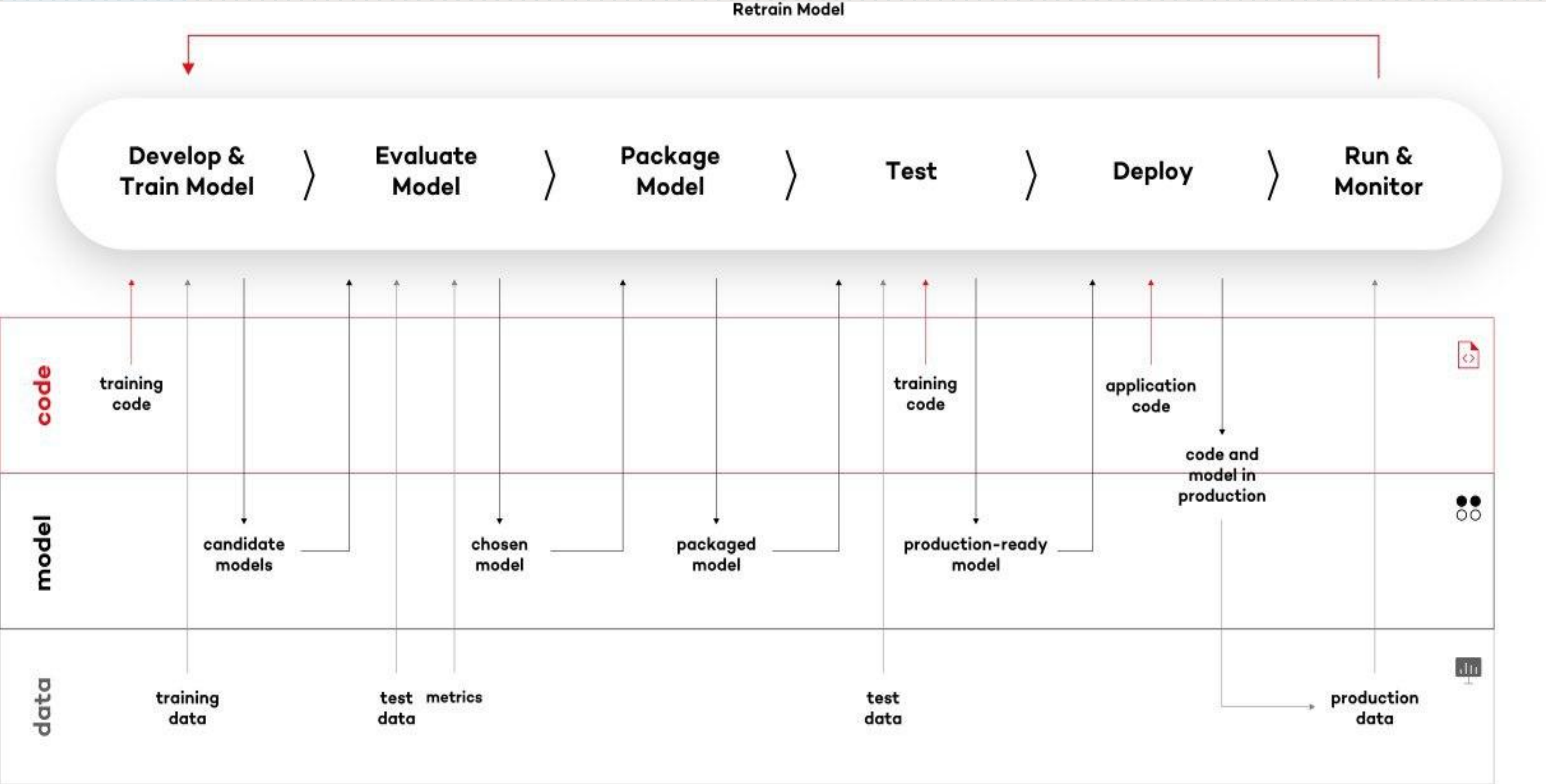
$$h_t = o_t * \tanh\left(C_t\right)$$

Standardized Precipitation Index (SPI)



SPI	*Classification*
2.00 >	Extremely wet
1.50 to 1.99	Very wet
1.00 to 1.49	Moderately wet
0 to 0.99	Near Normal
0 to -0.99	Mild drought
-1 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought

Workflow


Retrain Model
Develop & Train Model
Evaluate Model
Package Model
Test
Deploy
Run & Monitor
code
model
data
training code
candidate models
chosen model
packaged model
training code
production-ready model
application code
code and model in production
training data
test data
metrics
test data
production data

Encode cyclical features for use in DL

- Many features commonly found in climate datasets are cyclical in nature.

- The problem is letting the deep learning algorithm know that features occur in cycles.

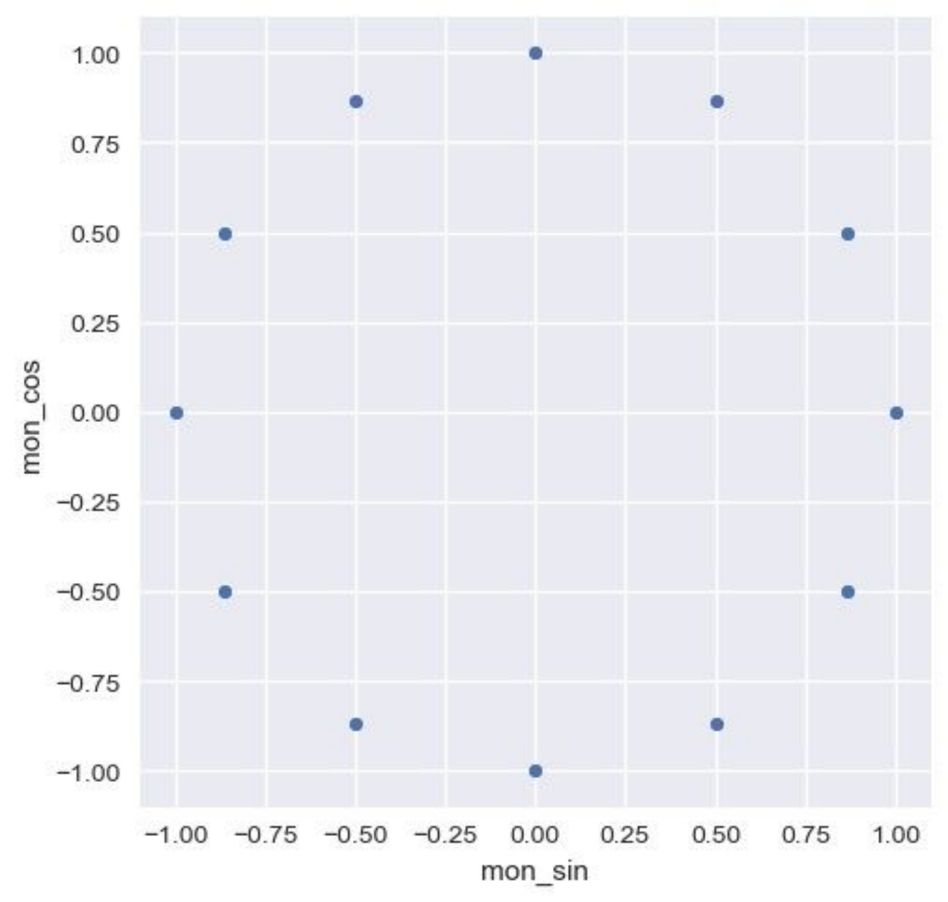
- Also ensures Equidistant timestamps (constant time intervals).

Transformation Function

$$x_{sin} = \sin\left(\frac{2 * \pi * x}{\max(x)}\right)$$

$$x_{cos} = \cos\left(\frac{2 * \pi * x}{\max(x)}\right)$$

```
data1['mon_sin'] = np.sin(2 * np.pi * data1['month']/12.0)
data1['mon_cos'] = np.cos(2 * np.pi * data1['month']/12.0)
```



Compile & Evaluation of Encoder-Decoder LSTM to model

```python
# define model
model = Sequential()
model.add(LSTM(200, activation='relu', input_shape=(n_steps_in, n_features)))
model.add(RepeatVector(n_steps_out))
model.add(LSTM(200, activation='relu', return_sequences=True))
model.add(TimeDistributed(Dense(n_features)))
```

```python
# Compile model
model.compile(loss='mse', optimizer=Adam(learning_rate=0.0001), metrics=['mae', 'mse'])
```

```python
# Fit the model
history = model4.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=100, batch_size=1, callbacks=[cp4], verbose=1)
```

Evaluation

```
==============Evaluation============
Final loss : 0.02841190993785858
Final mae : 0.12637433409690857
Final mse : 0.02841190993785858
Final val_loss : 0.05382310599088669
Final val_mae : 0.18171735107898712
Final val_mse : 0.05382310599088669
```