# UbuntuNet-Connect2025

## Artificial Intelligence and Data-Driven Innovation

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# Tropical Cyclone Trajectory Forecasting in Southwest Idian Based on Deep Learning

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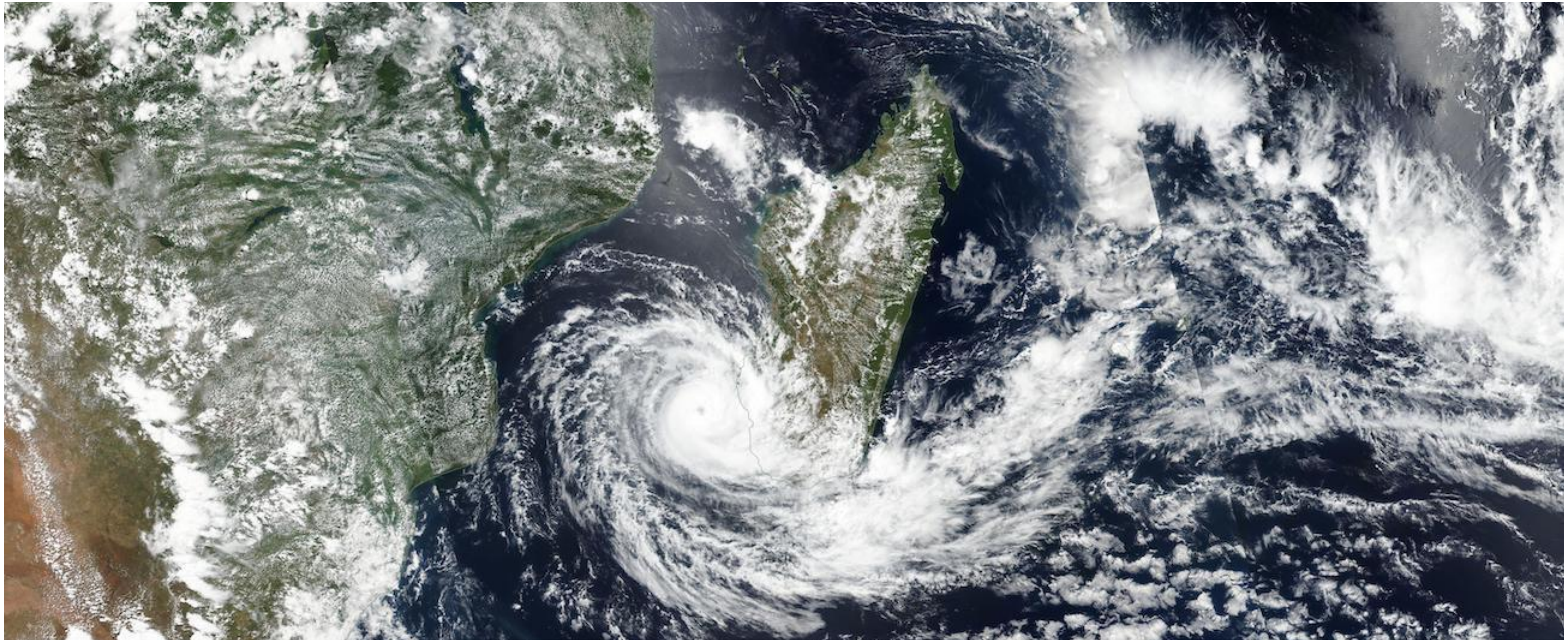
# 0. Presentation Structure

1. Introduction
2. Literature Review
3. Materials and Methods
4. Results and Discussion
5. Conclusion
6. References

# 1. Introductio n

- Tropical cyclones are intense, rotating low-pressure systems that develop over warm tropical oceans, evolving from tropical depressions into tropical storms and eventually mature cyclones (called hurricanes, typhoons, or cyclones depending on the region) once sustained winds exceed 119 km/h (74 mph); in extreme cases, winds can surpass 240 km/h (150 mph) and gusts may exceed 320 km/h (200 mph).



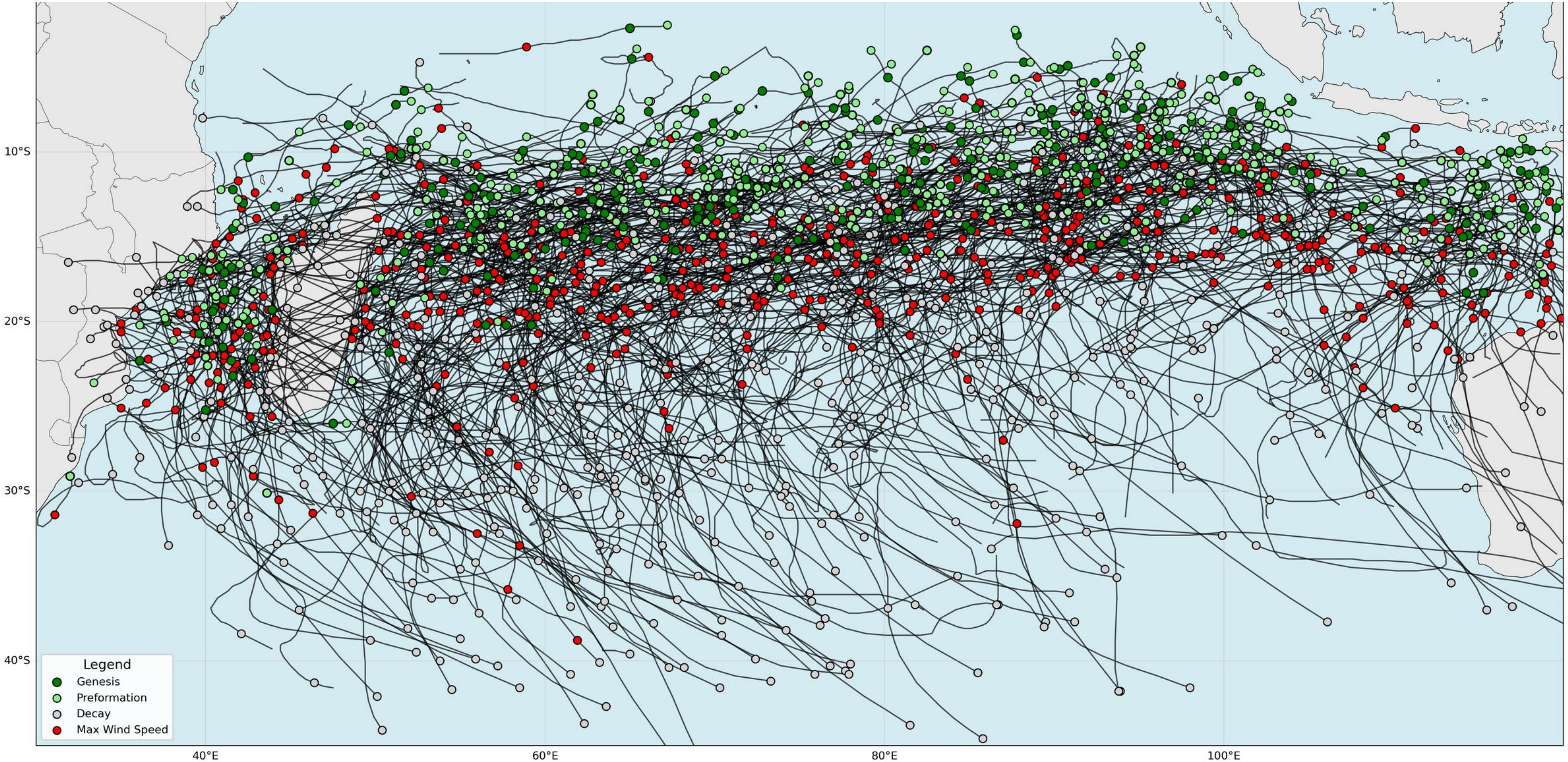
Tropical Cyclone Freddy (March 2023)Over Mozambique Channel

# 1. Introductio
n

Tropical cyclones (TCs) are among the most devasting natural events, causing severe socioeconomic damage to coastal areas worldwide. TCs are characterized by strong winds, heavy rains, lightning, floods, and storm surges, and cause widespread damage and fatalities upon landfall

# 1. Introduction

Annually, about 30% of global TCs form in the Southern Hemisphere , spanning a large area from the western Indian Oceanto thecentral Pacific and covering three TC basins: the southwest Indian Ocean (West of 90E), the Australian Region (90E–160E) and the South Pacific Ocean (East of 160E)




TCs Trcaks over southwest Indian Ocean from 1993-2023

# 1. Introduction

We need to accurately forecasting TC tracks

→ Supports early warning, evacuation planning, and disaster risk reduction.

## Traditional Methods

→ Dynamical models (numerical simulations)

→ Statistical models (empirical relationships)

## Modern Approaches

→ Machine Learning (ML): learns patterns from data

→ Deep Learning (DL): delivers faster, more accurate, and efficient forecasts

→ Few studies exist for the Southwest Indian Ocean (SWIO) – this study fills that gap

## 1. 1. General Objective

- To develop deep learning-based models for forecasting tropical cyclone (TC) trajectories over the Southwest Indian Ocean (SWIO) with a 6–72-hour prediction horizon.

# 2. Literature Review

**Weather Prediction Methods**

Traditional Methods

→ Dynamical models (NWP)

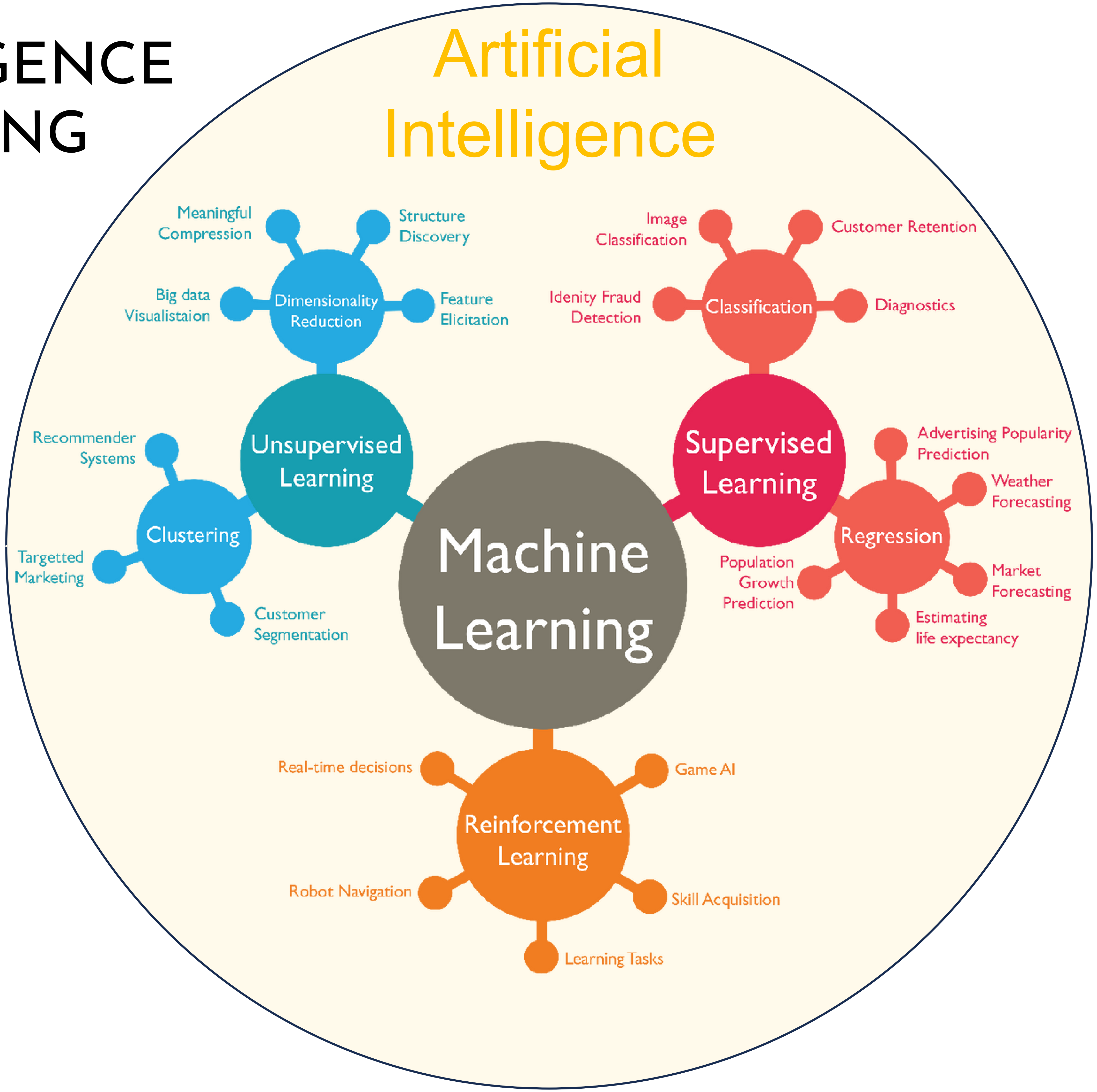
→ Statistical models

Modern Approaches-AI-Based:

→ Machine Learning (ML)

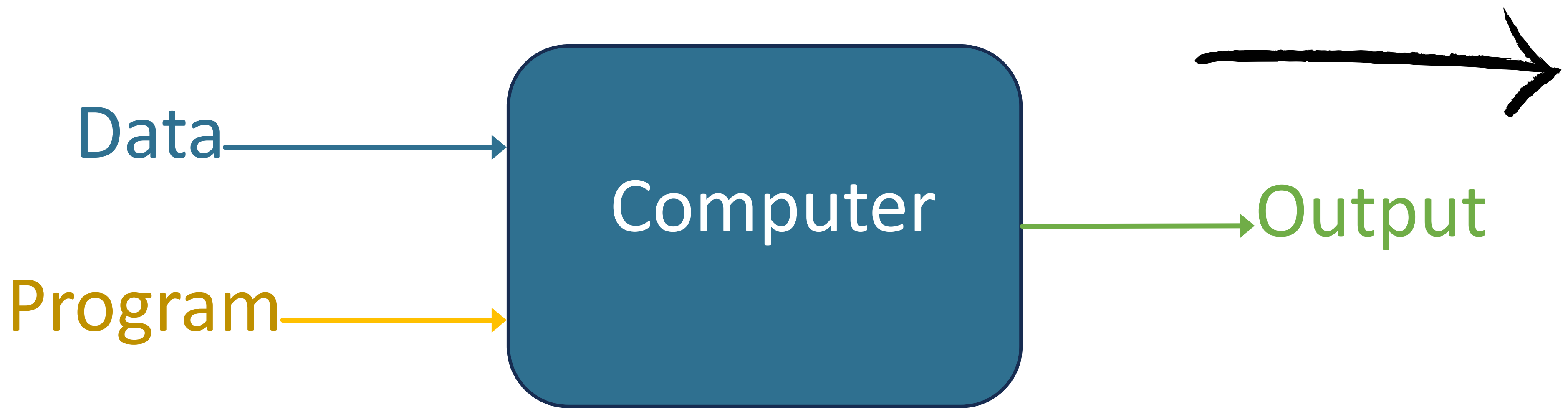
→ Deep Learning (DL)

# ARTIFICIAL INTELLIGENCE or MACHINE LEARNING or DEEP LEARNING?

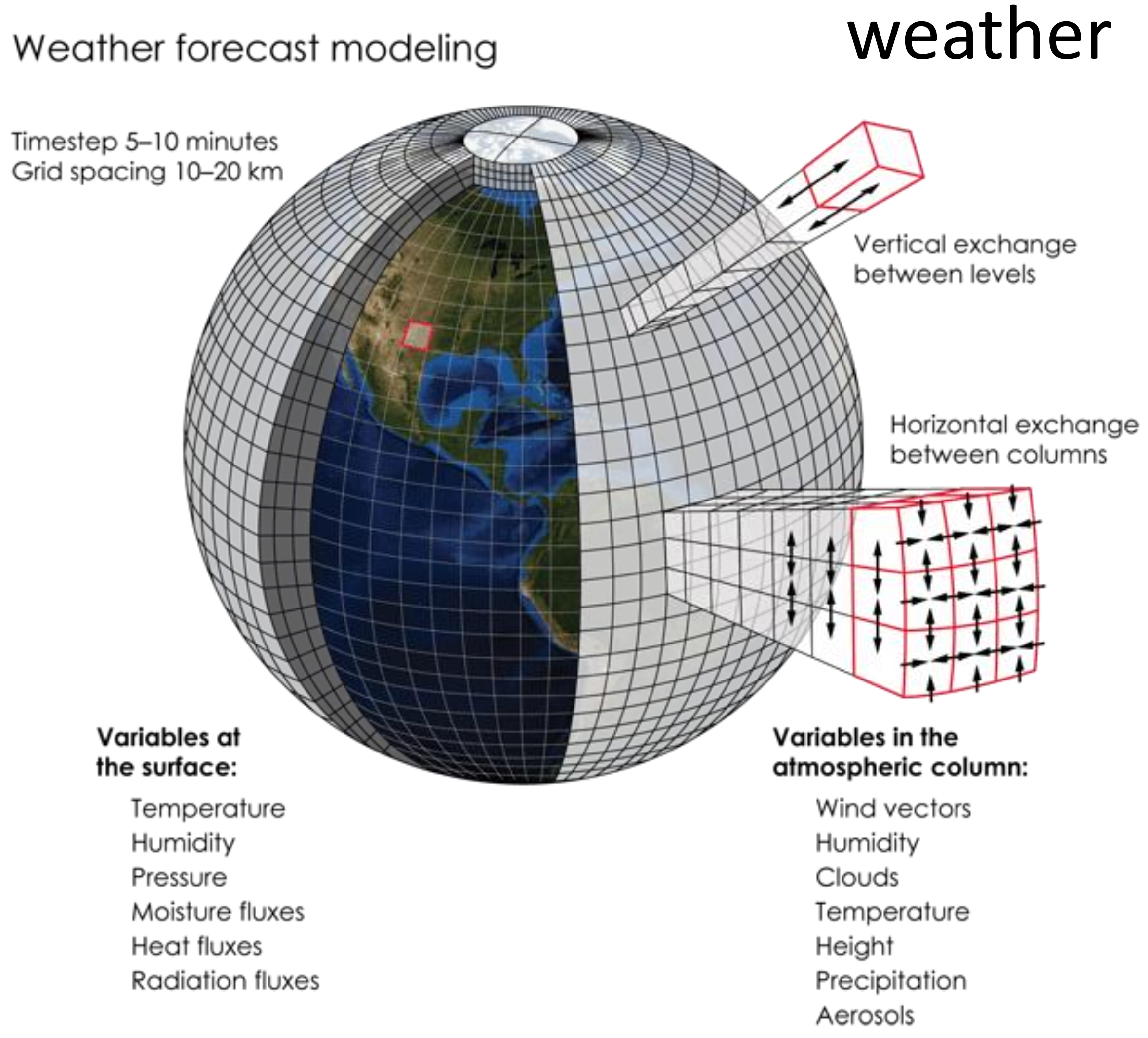


# TRADITIONAL PROGRAMMING vs MACHINE LEARNING

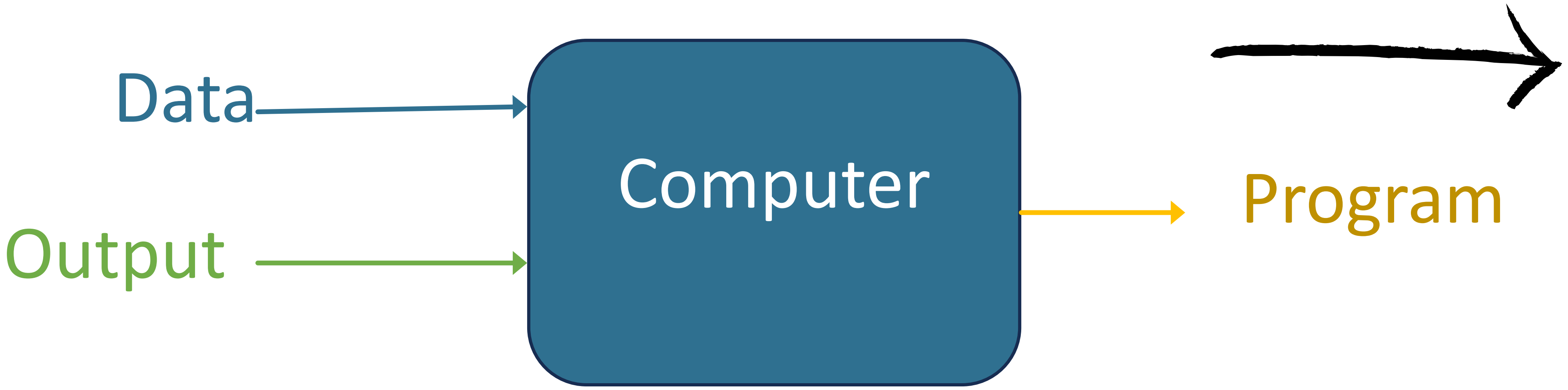
## Traditional Programming



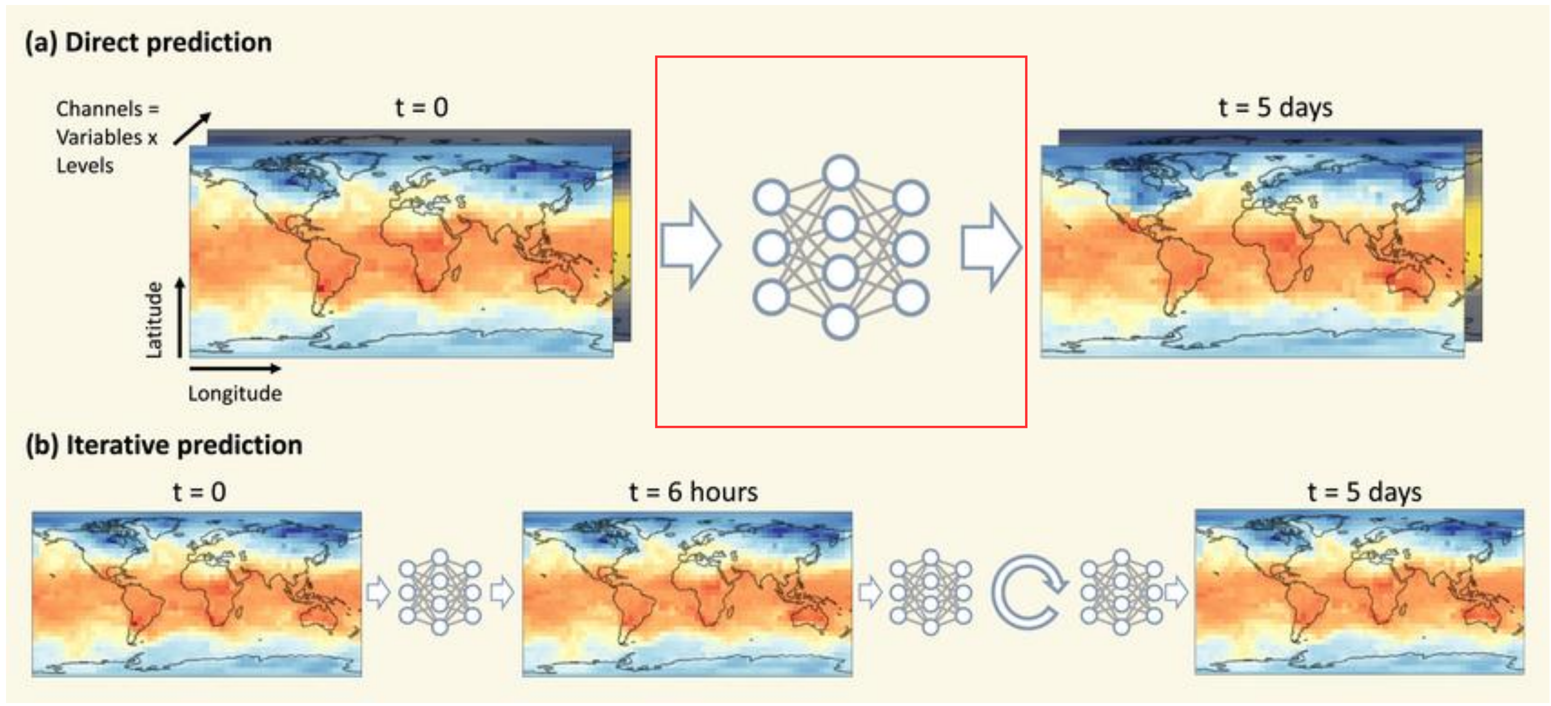

Computer program for weather




## Machine Learning

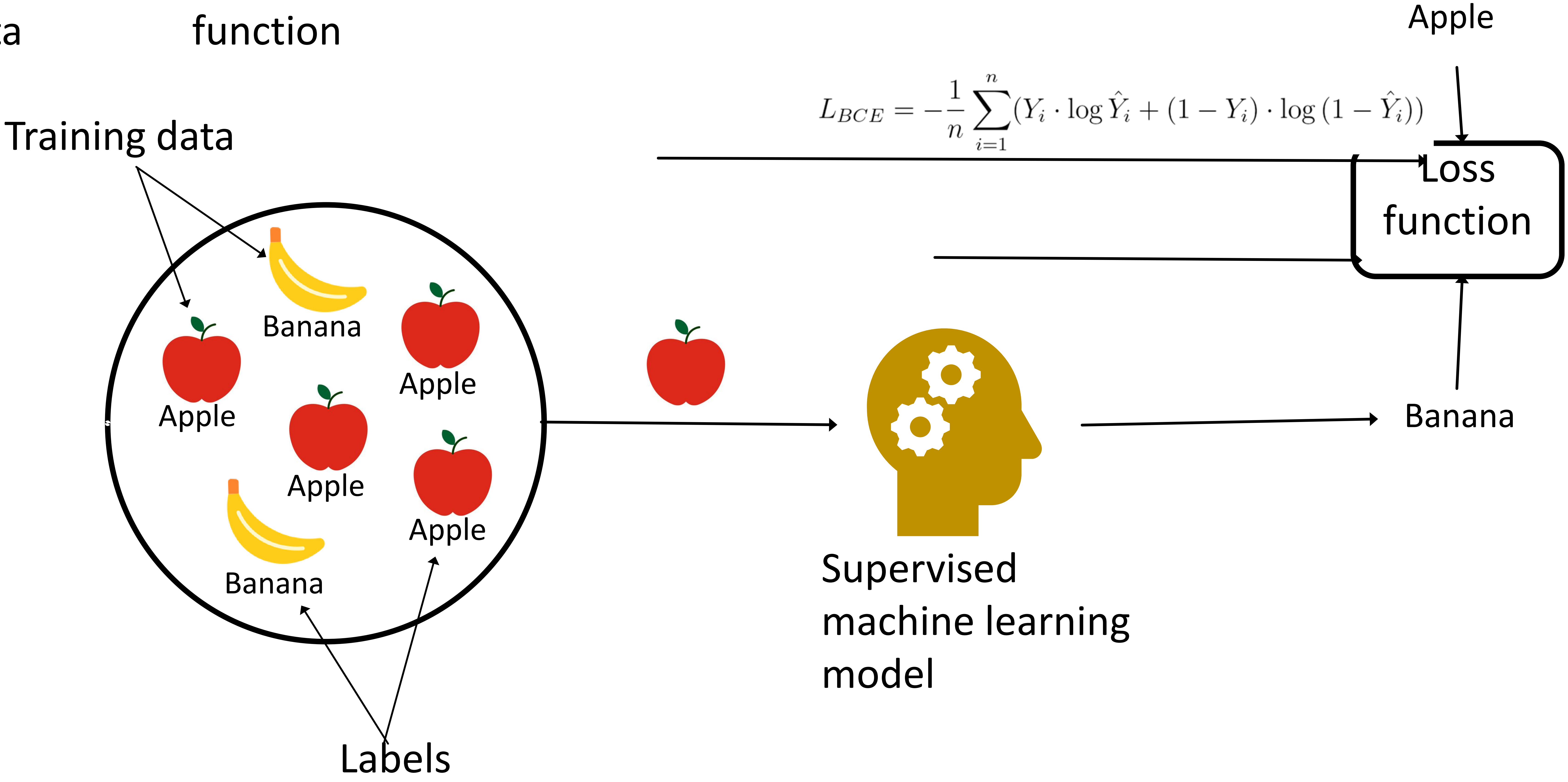



Supervised ML

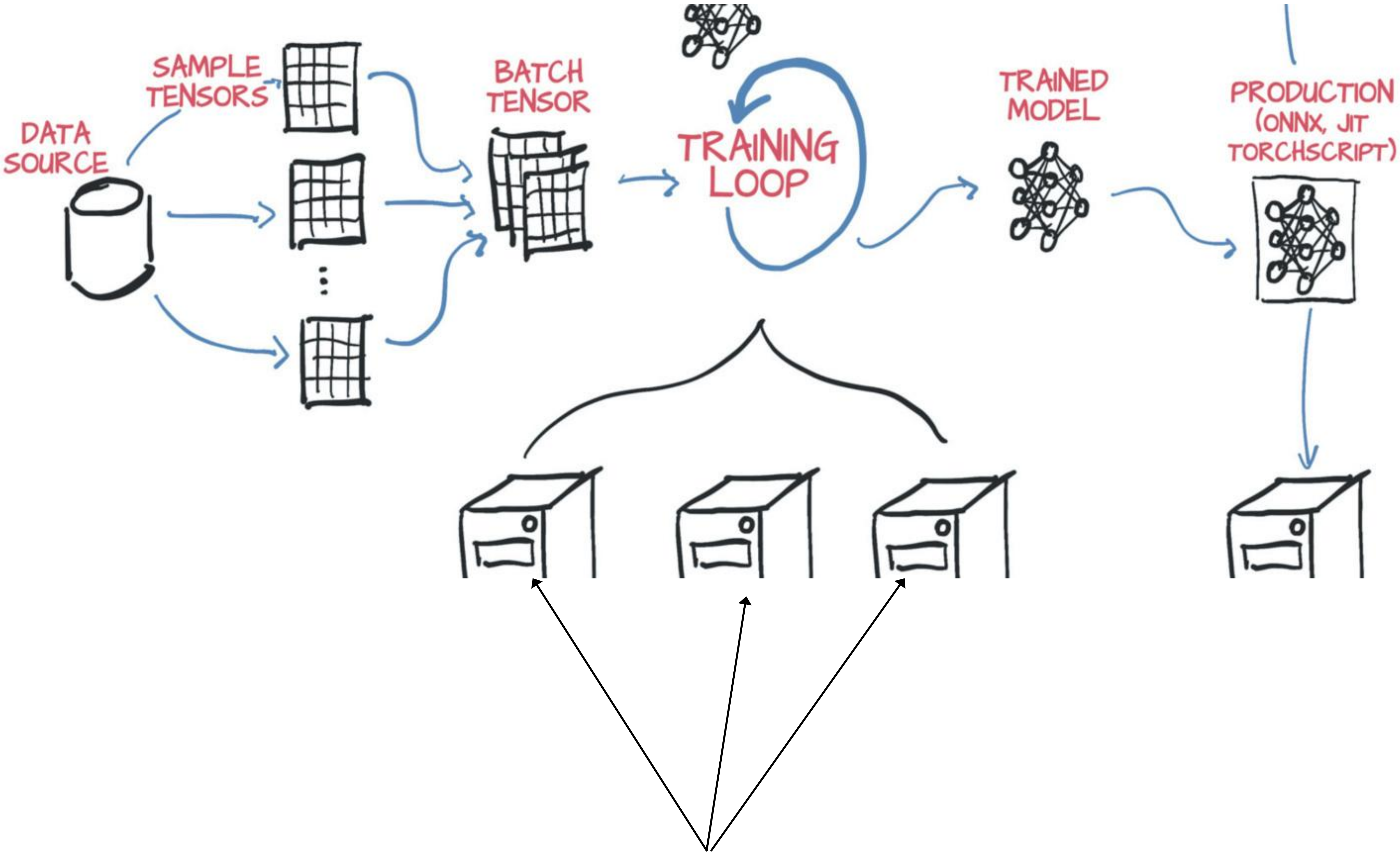


# KEY INGREDIENTS FOR SUPERVISED LEARNING

- Labelled data
- Loss function
- Optimizer
- Model

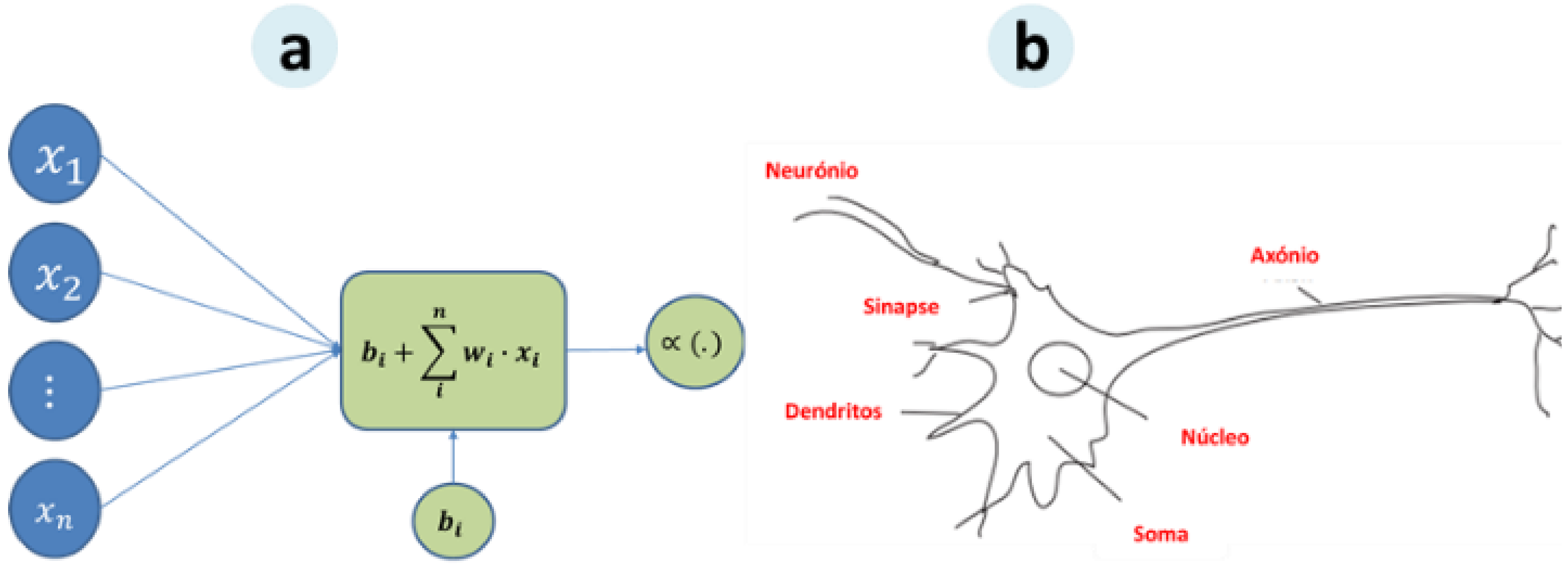


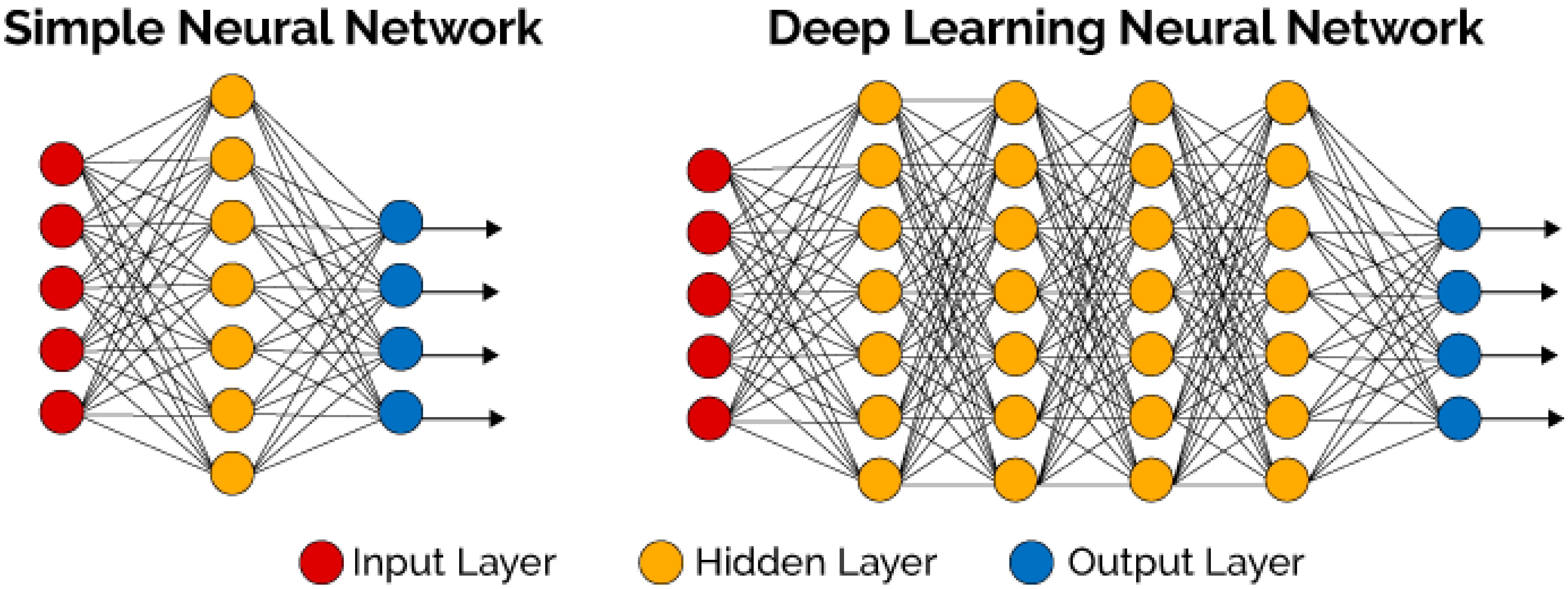
# HPC PLATFOMS IN THE TRAINING LOOPS OF ML MODELS



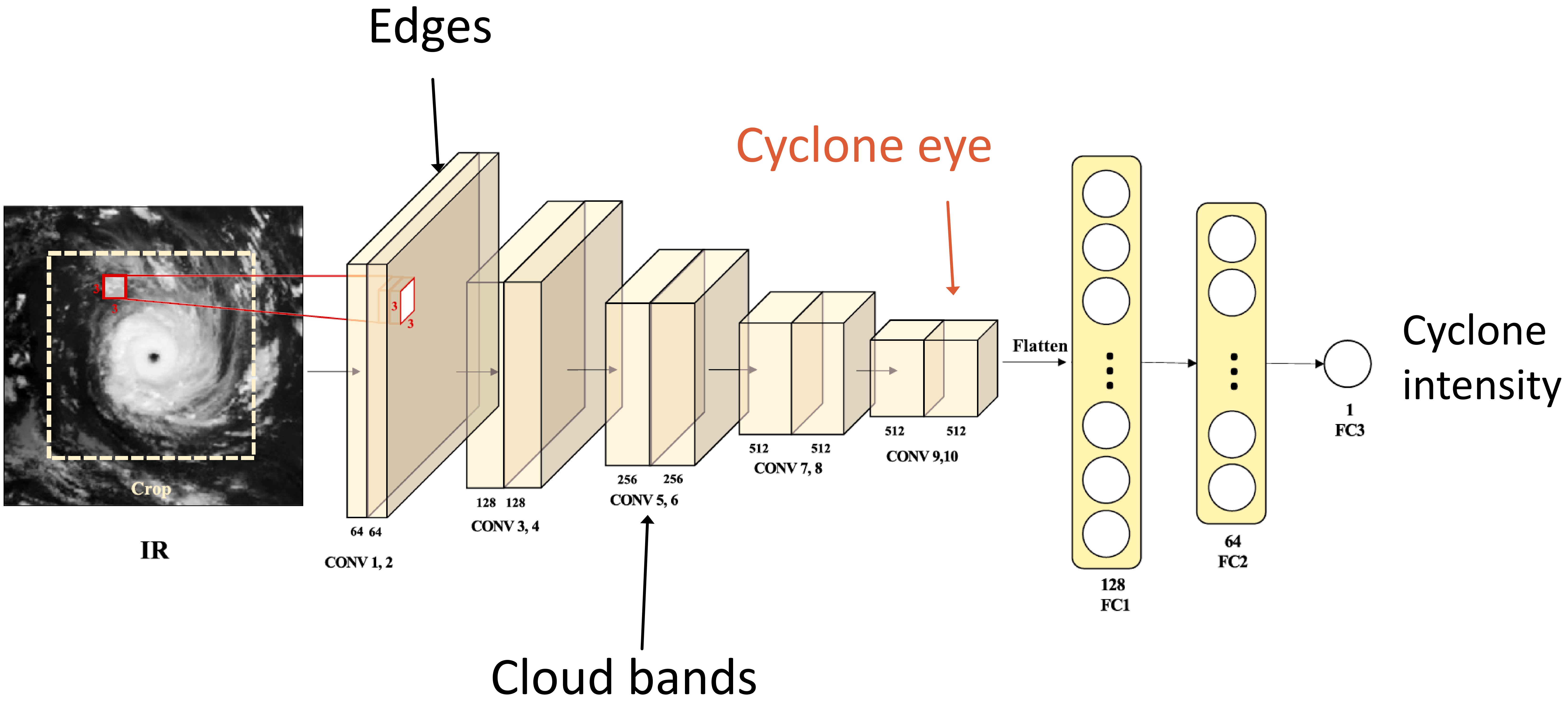

MORENET HPC CLUSTER

# DEEP LEARNING?

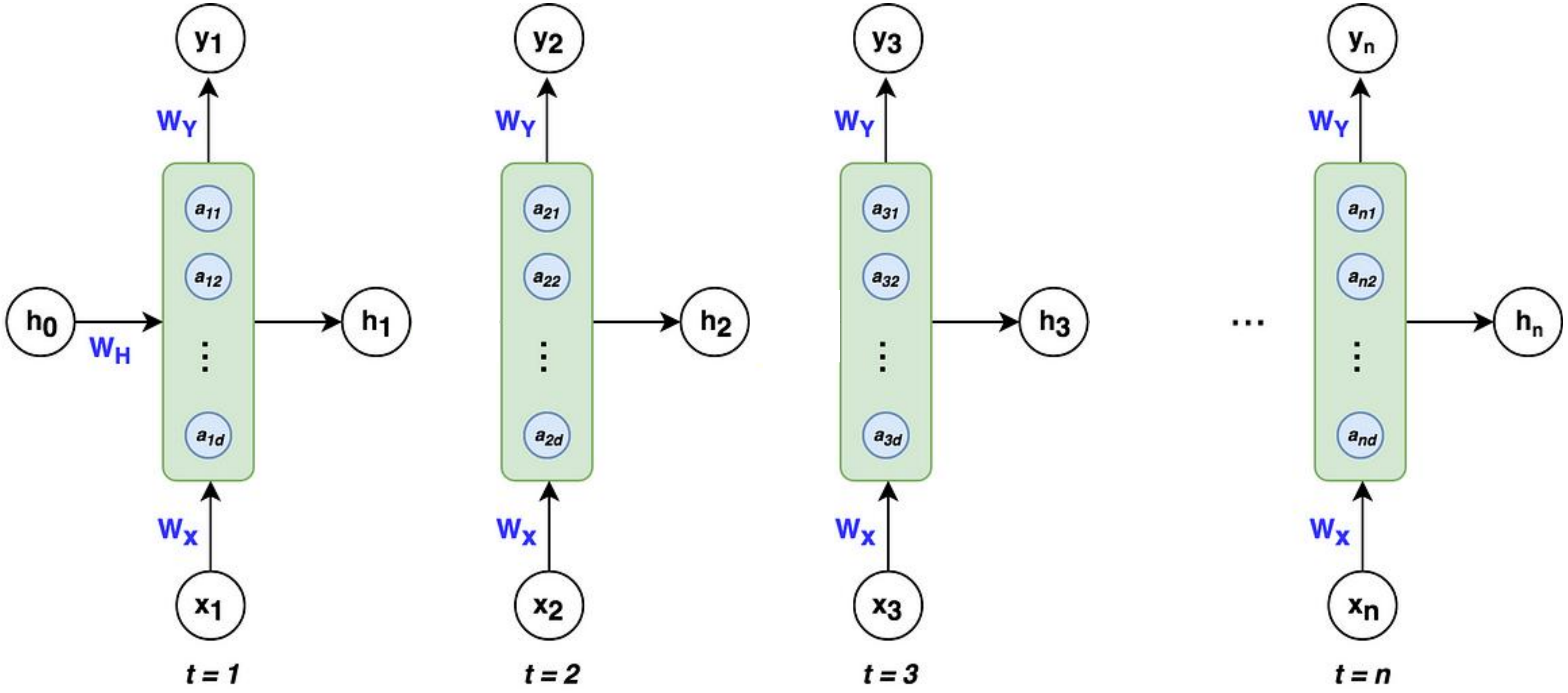


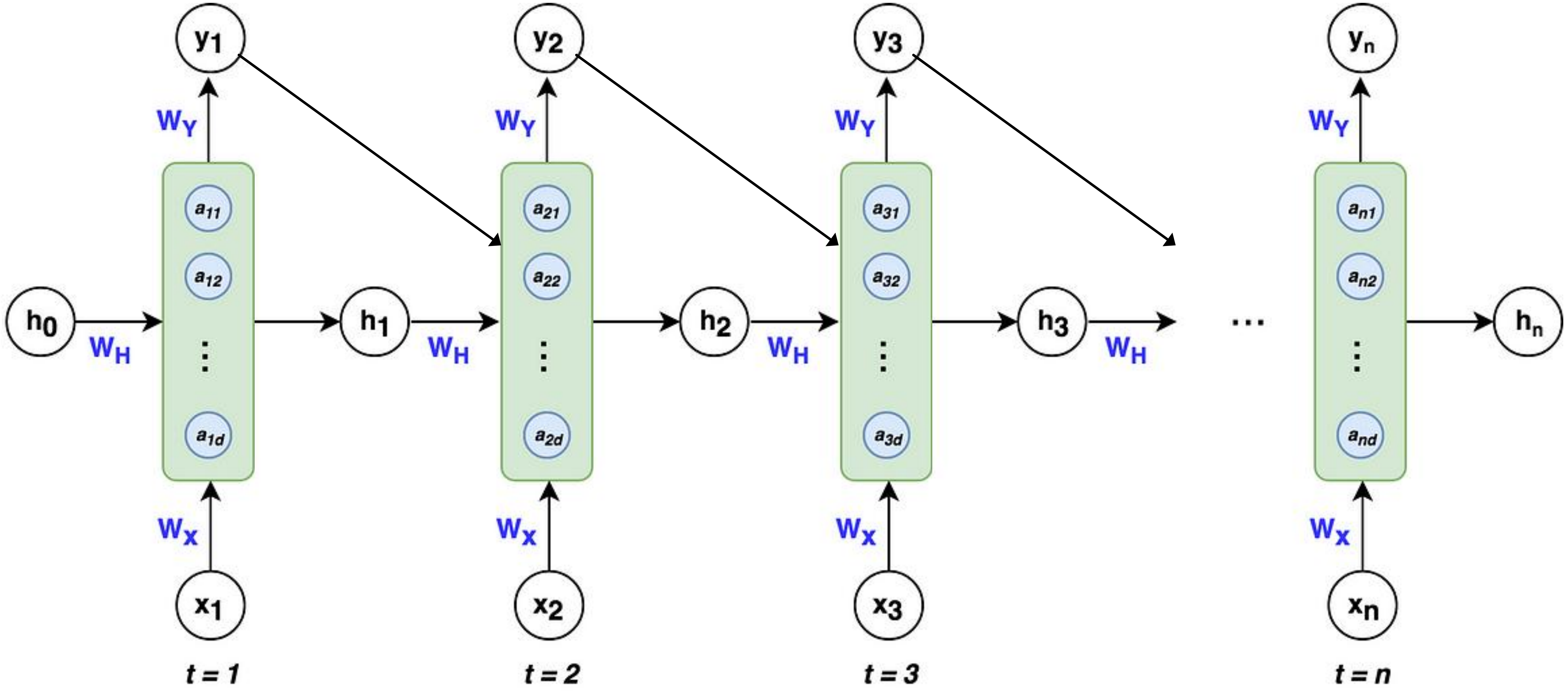
# CONVOLUTIONAL NEURAL NETWORKS (CNNs)



# RECURRENT NEURAL NETWORKS (RNNs)



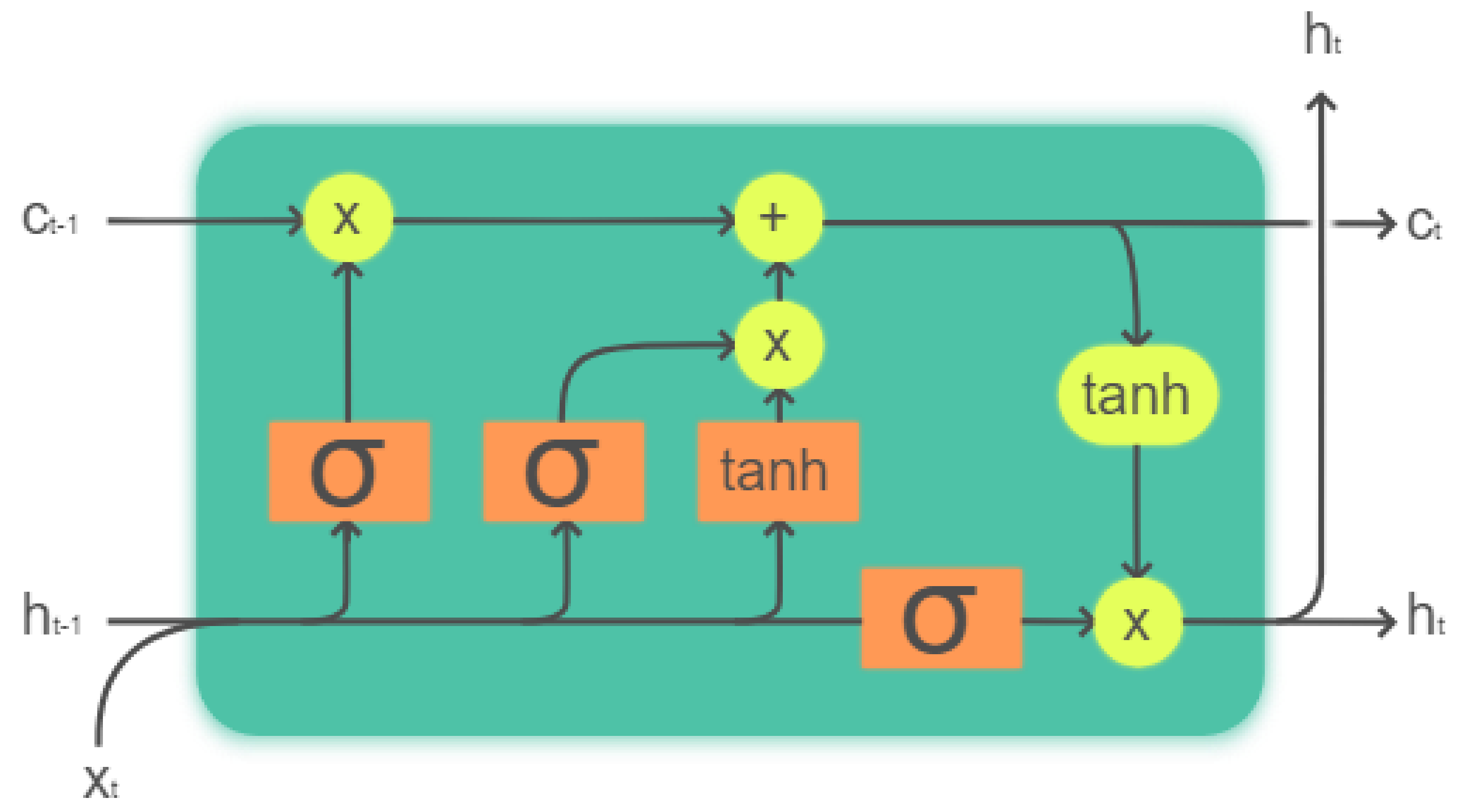
# RECURRENT NEURAL NETWORKS (RNNs)

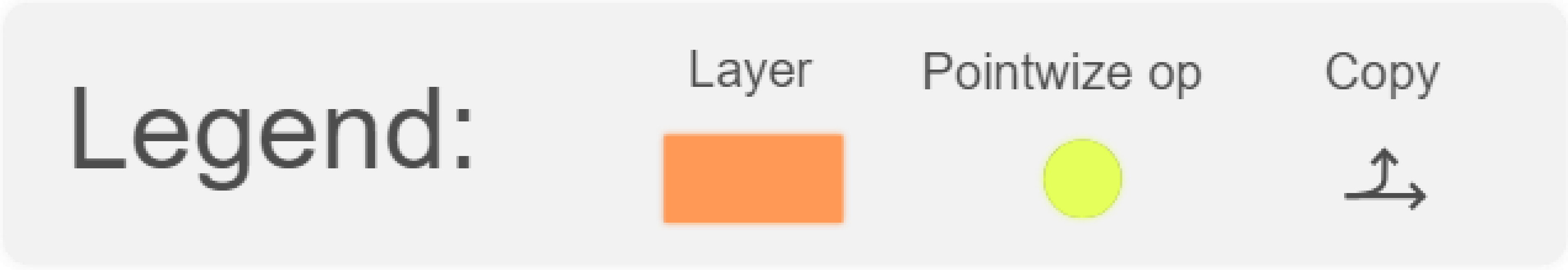



CLINT
CLIMATE INTELLIGENCE

# LONG SHORT-TERM MEMORY NETWORKS (LSTMs)

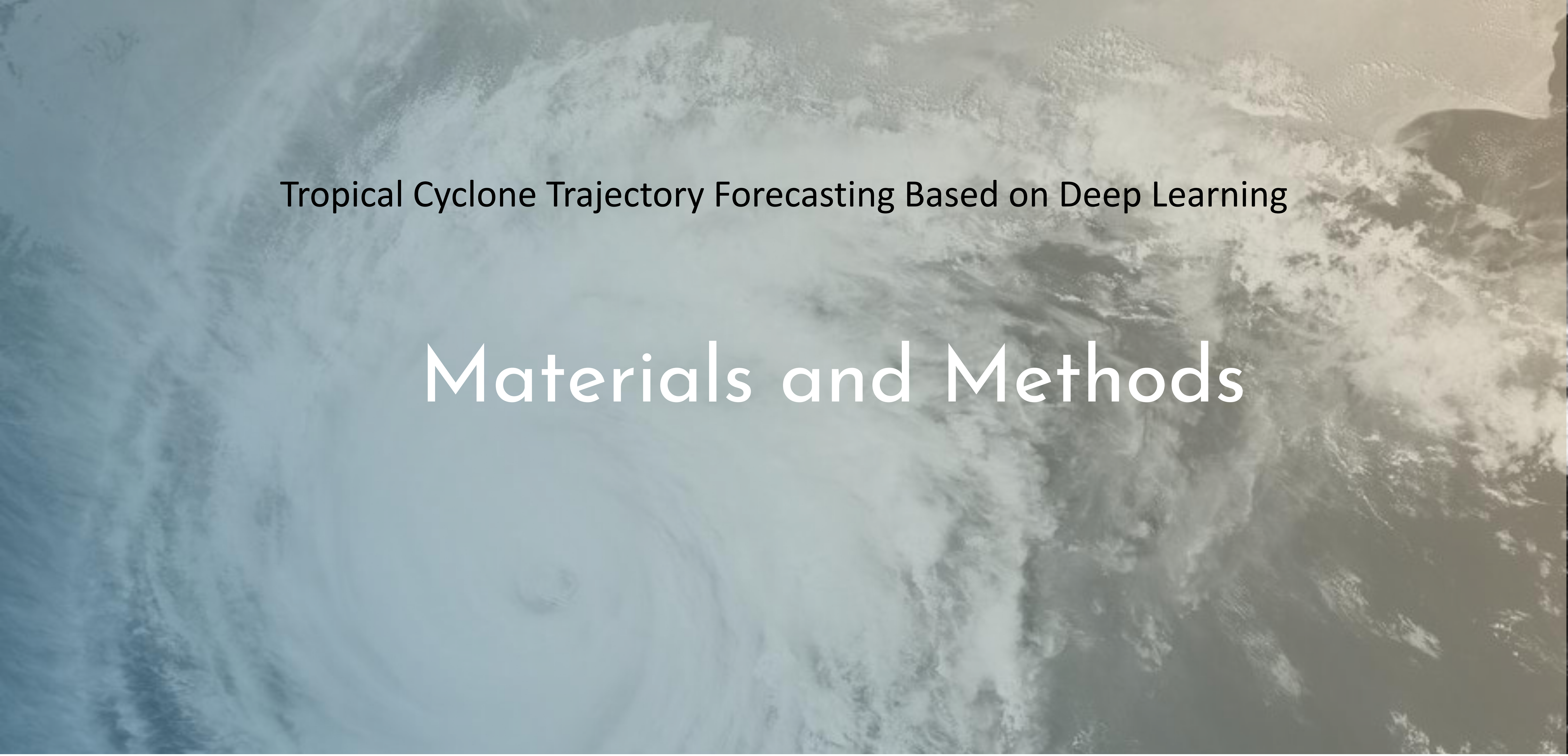
## A special kind of recurrent neural network



Tropical Cyclone Trajectory Forecasting Based on Deep Learning

# Materials and Methods

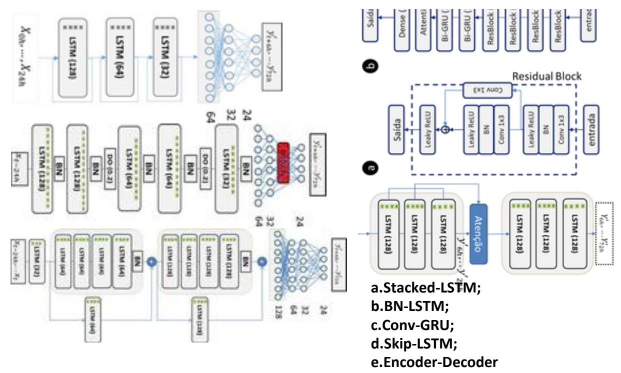


# 1. Architecture and experiment pipeline of TC Tracks Time Series.

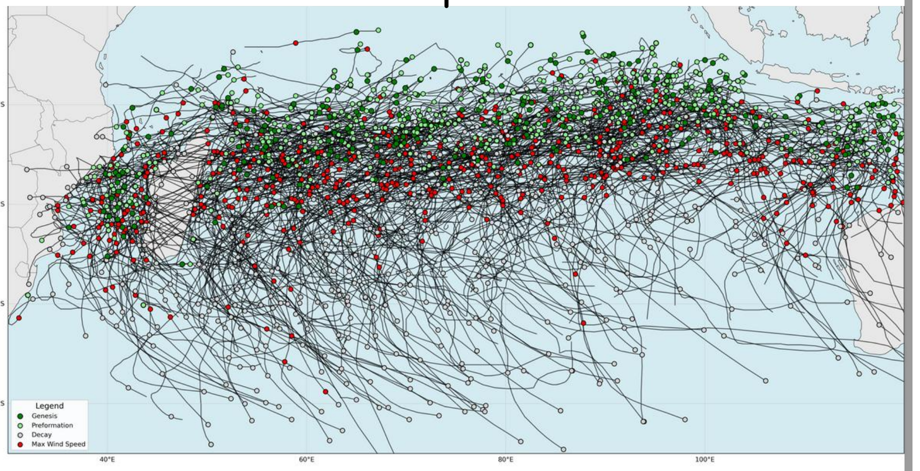
Left: Unified training and evaluation process. Right: Overall Architecture.

Performance Evaluation

MODEL TRAINING AND ANALYSIS




DATA PROCESSING



TRAINING PIPELINE

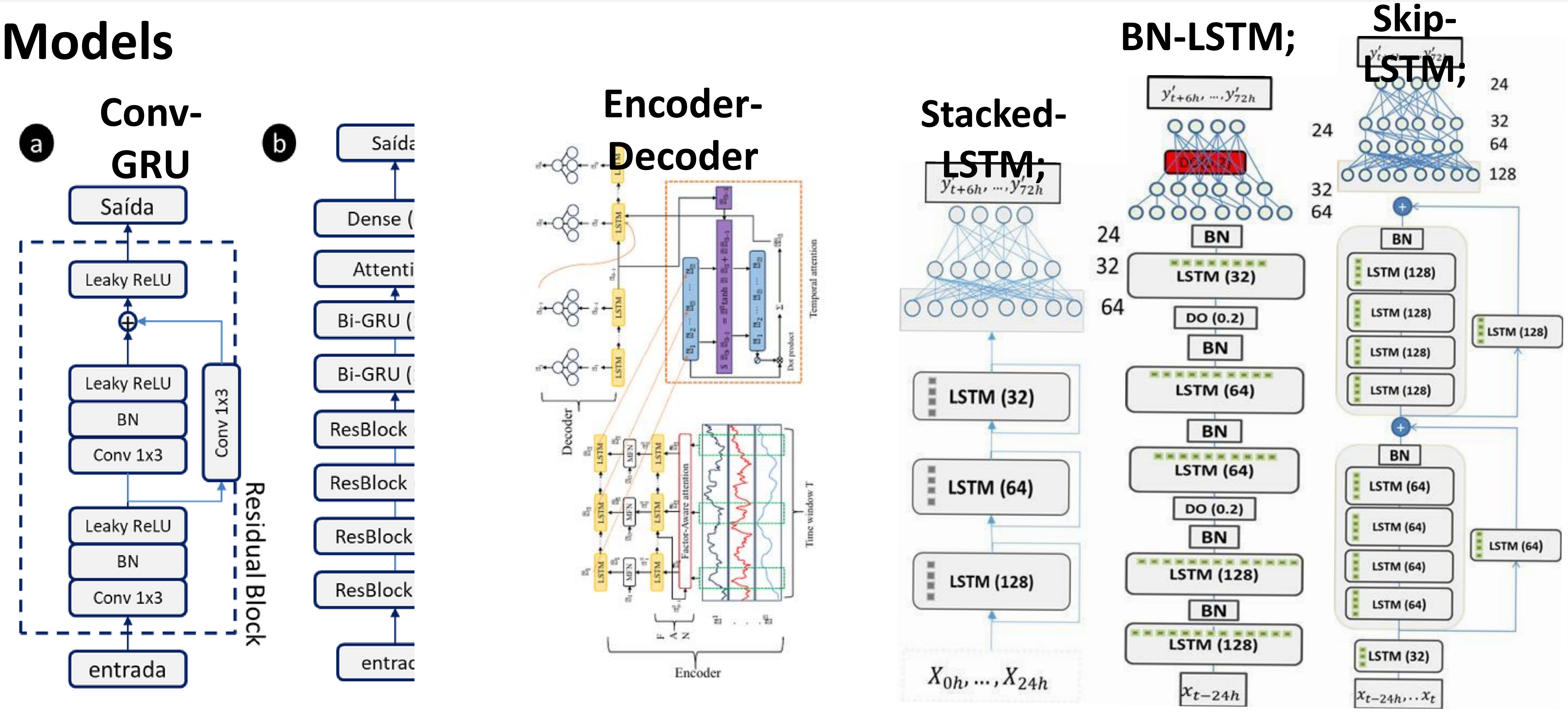
### 3.1. Pre-Processing

- **Data Collection**: IBTrACS dataset
- **Definition of X and Y (Sliding Window)**: Inputs (X): 24-hour segments of TC track
- **Outputs/Targets (Y)**: 72-hour TC trajectory
- **Feature Selection**: Using Decision Trees

### 3.2. Training

- **Model**: TC trajectory prediction using RNN-based models
- **Performance Metrics**: MAE, RMSE, Euclidean Distance (ED)

## Models



Tropical Cyclone Trajectory Forecasting Based on Deep Learning

# Results and discussion

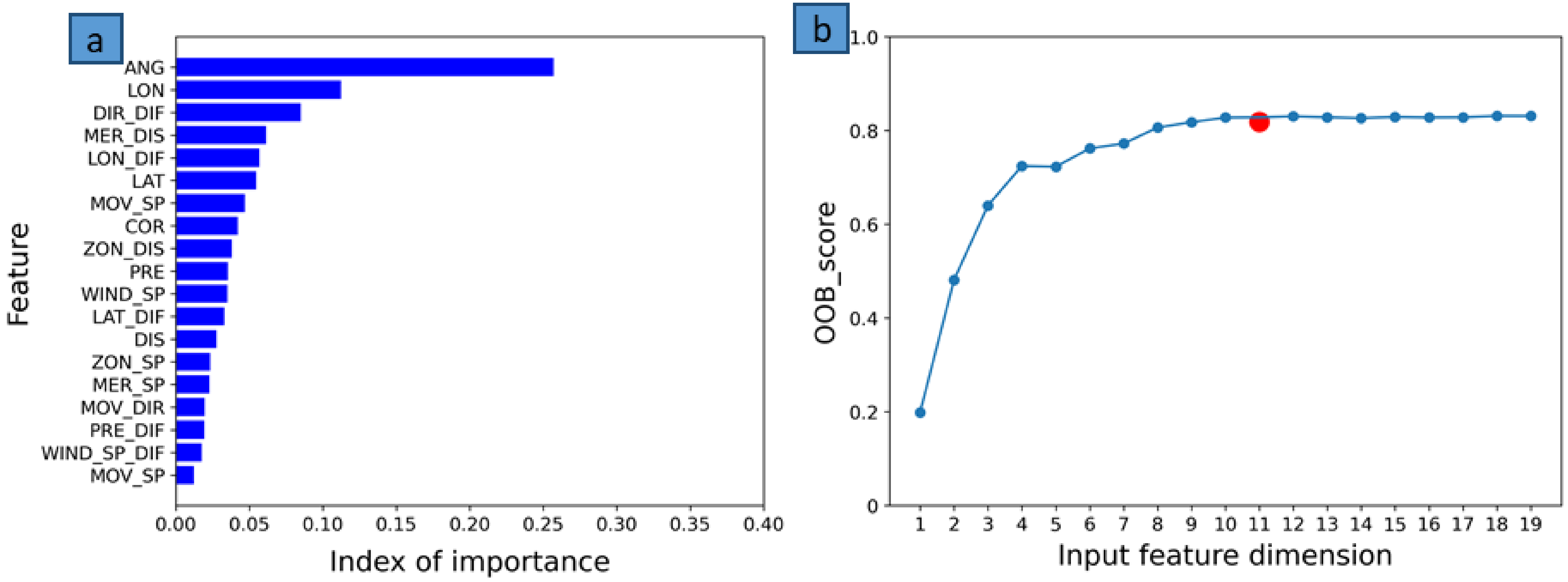
# 4. Results and discussions

## 4.1. Variables Selection

| # | Full Name (Description) | Abbreviation |
|---|---|---|
| | | |
| 1 | Angle formed between past and current moments | ANG |
| 2 | Longitude of past moments | LON |
| 3 | Difference in direction between past and current moments | DIR_DIF |
| 4 | Meridional distance between past and current moments | MER_DIS |
| 5 | Difference in longitude between past and current moments | LON_DIF |
| 6 | Latitude of past moments | LAT |
| 7 | Difference in movement speed between past and current moments | MOV_SP |
| 8 | Coriolis parameters of past moments | COR |
| 9 | Zonal distance between past and current moments | ZON_DIS |
| 10 | Central atmospheric pressure of past moments | PRE |
| 11 | Maximum wind speed of past moments | WIND_SP |
| 12 | Difference in latitude between past and current moments | LAT_DIF |
| 13 | Displacement distance between past and current moments | DIS |
| 14 | Zonal movement speed of the past moment | ZON_SP |
| 15 | Meridional movement speed of the past moment | MER_SP |
| 16 | Movement direction of past moments | MOV_DIR |
| 17 | Difference in atmospheric pressure between past and current moments | PRE_DIF |
| 18 | Difference in maximum wind speed between past and current moments | WIND_SP_DIF |
| 19 | Movement speed of past moments | MOV_SP |

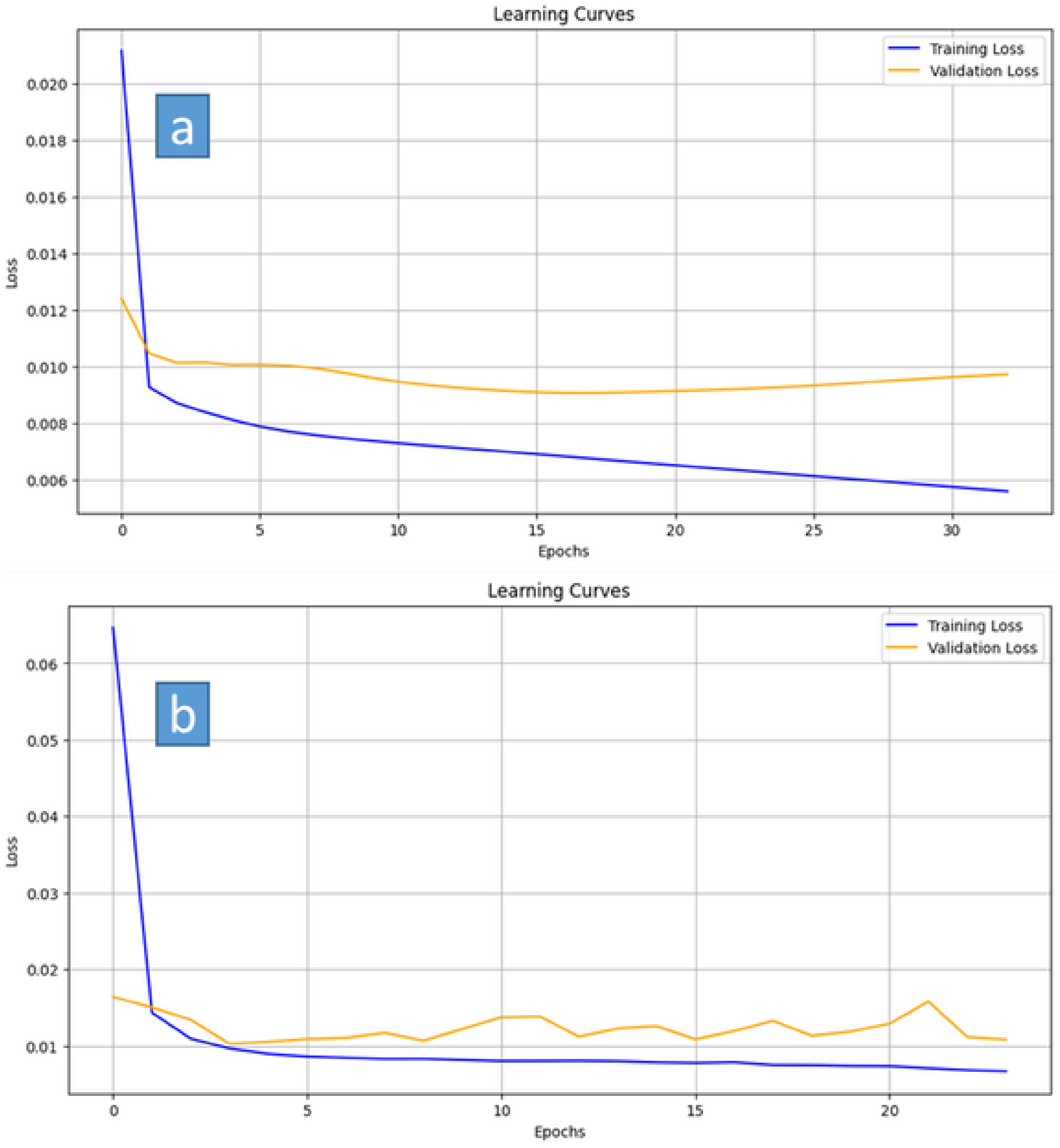
# 4. Results and discussions

## 4.1. Variables Selection

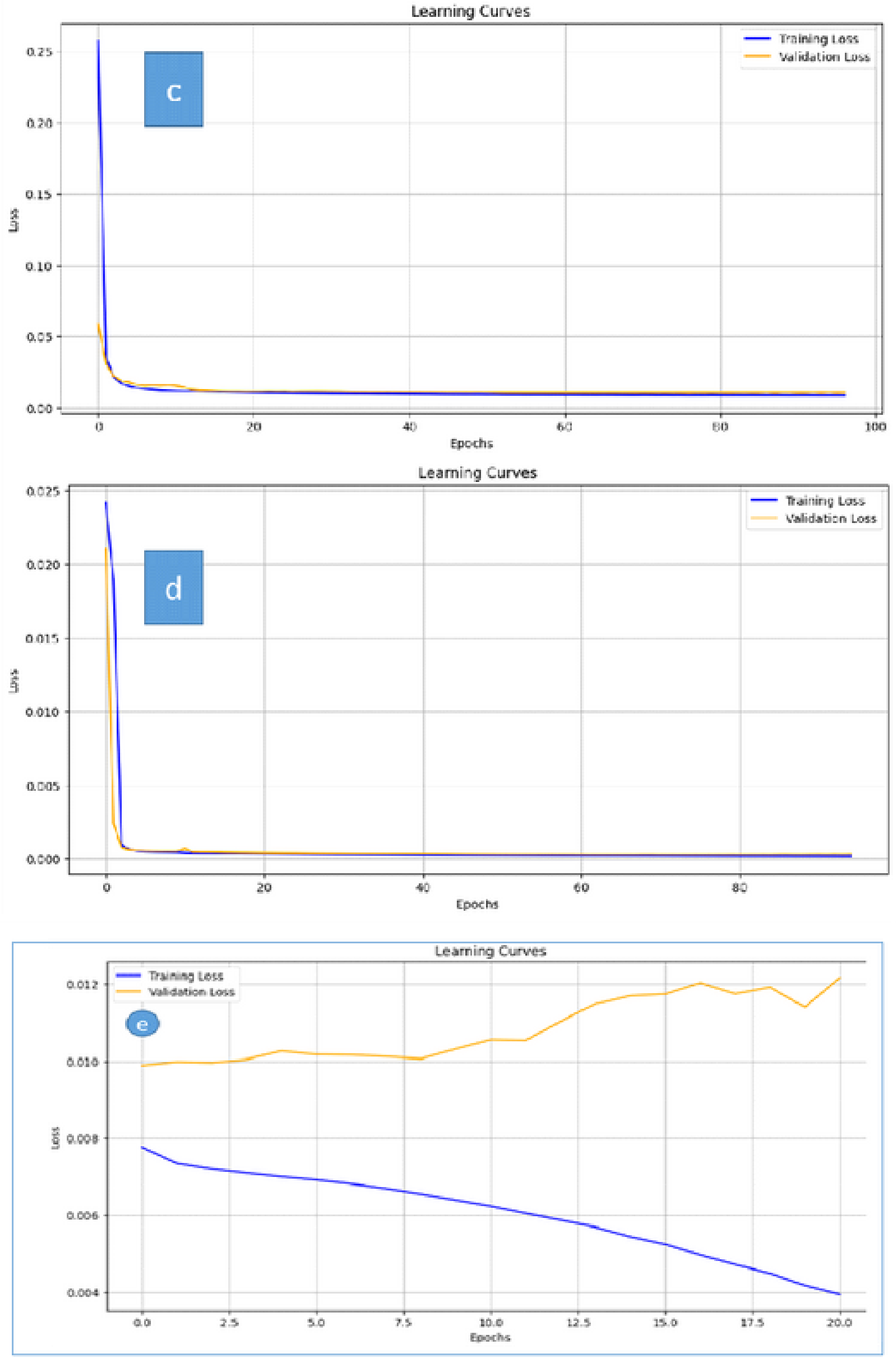


# 4. Results and discussions

## 4.2. Models Training Analysis

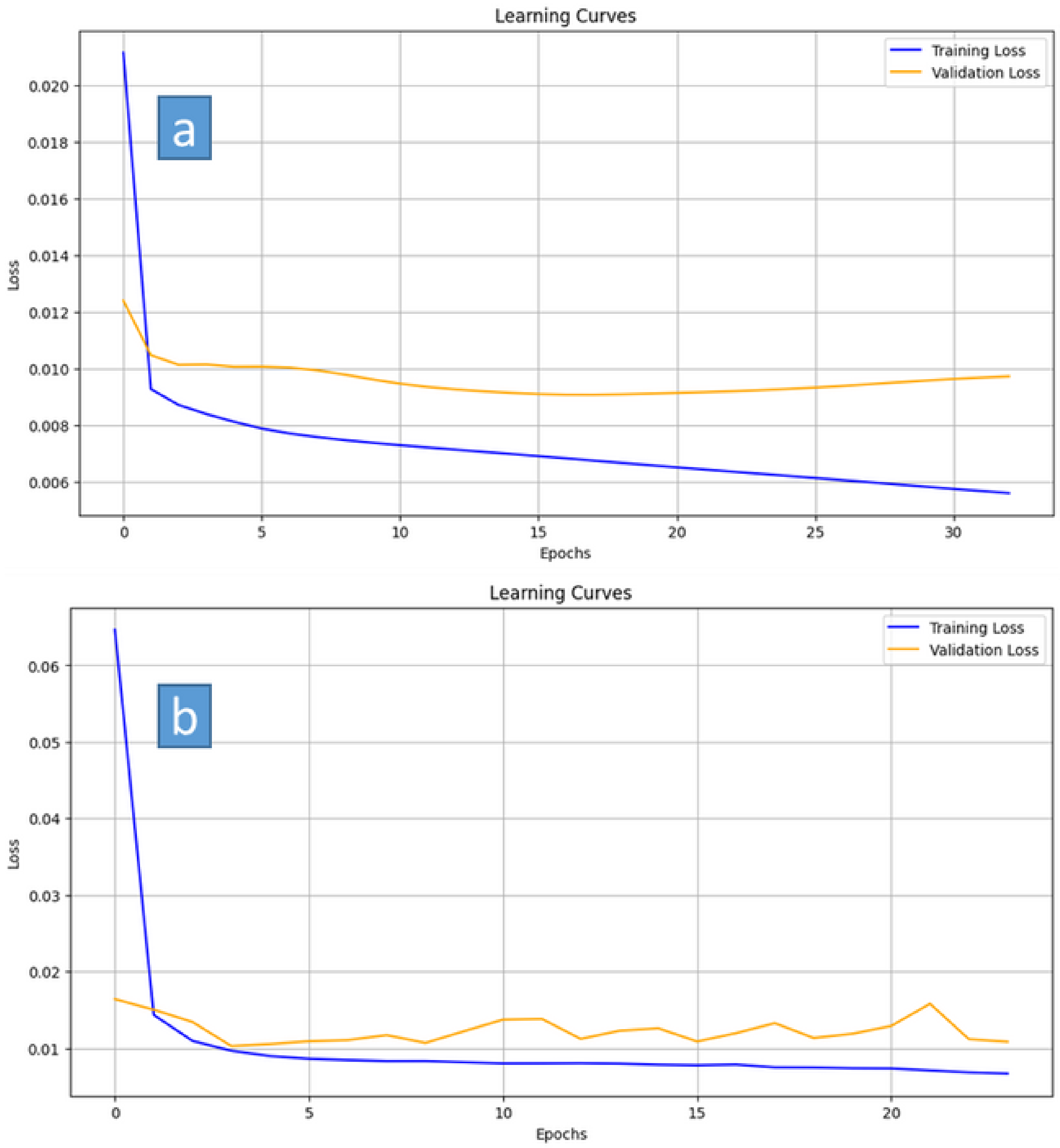



Learning Curves: a- Stacked-LSTM, b- BN-LSTM



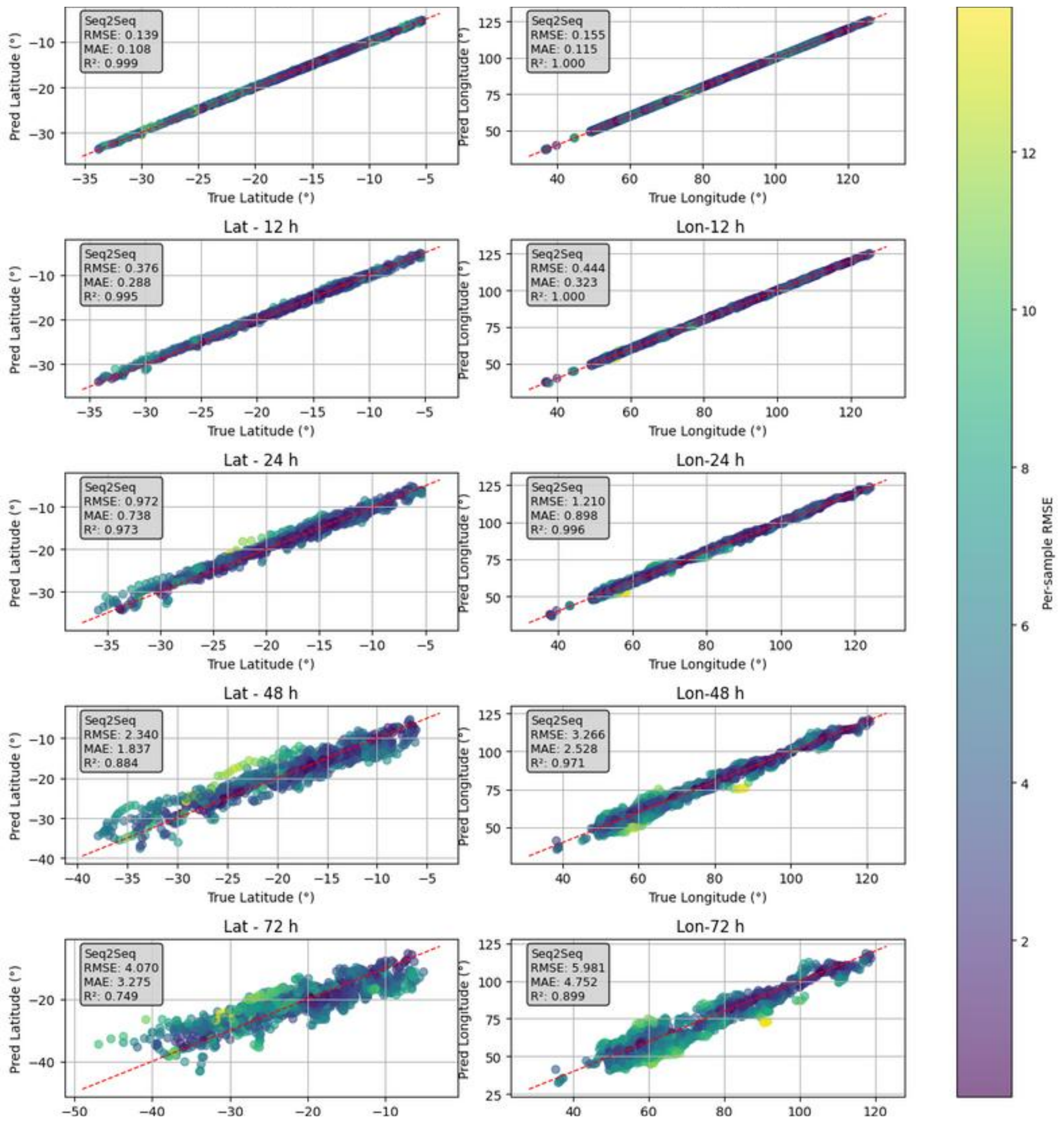

Learning curves: c- Conv-GRU, d- ENCODER-DECOR, e- SKIP-LSTM

# 4.2. Análise dos treinamentos




**a - Stacked-LSTM,**
**b - BN-LSTM**

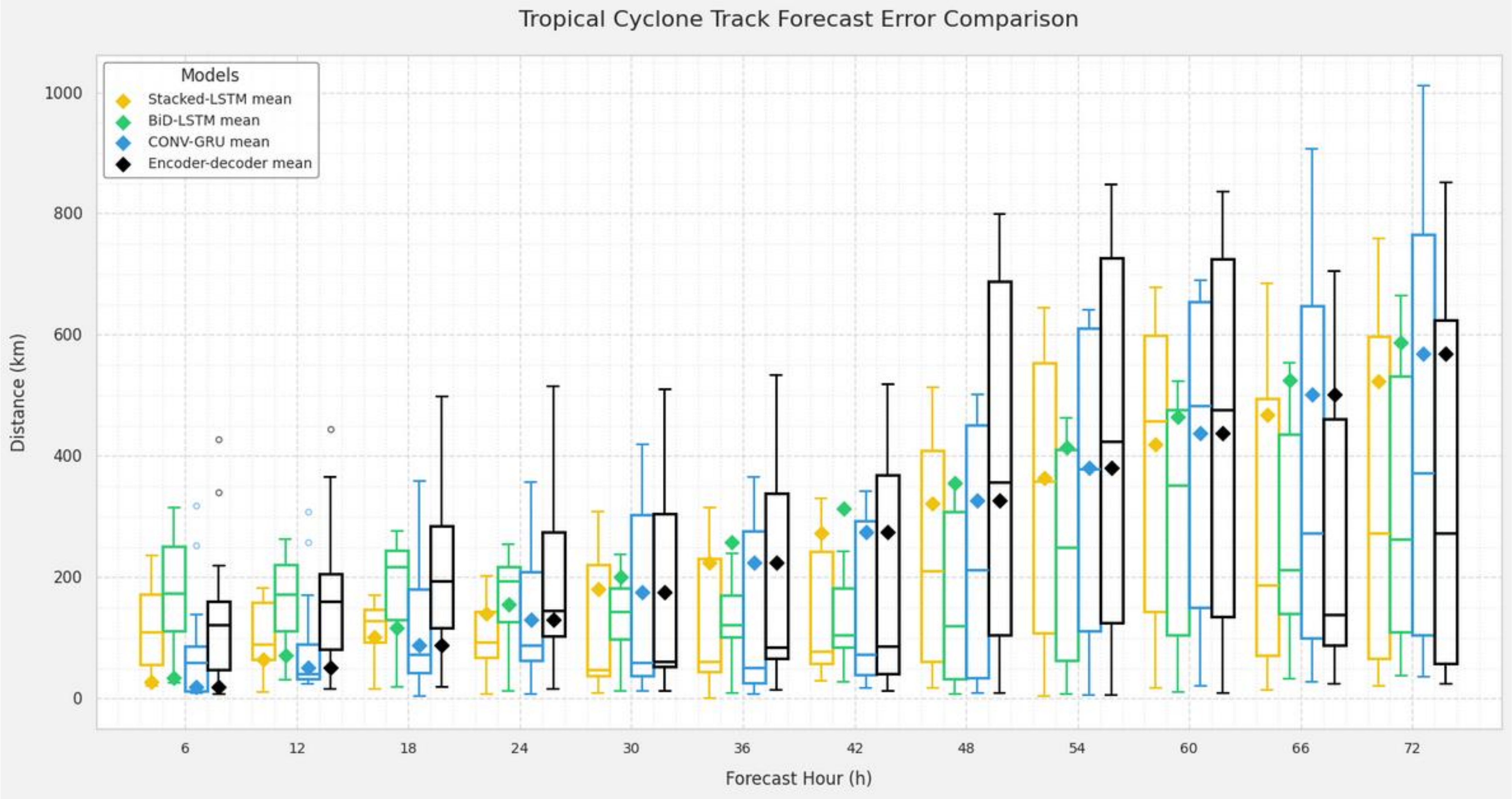
# 4. Results and discussions
## 4.3. Models Testining Analysis




**Scatter plot distributions of latitude and longitudes predictions for the Encoder-Decoder model. The color bar represents the RMSE, including the longitude and latitude forecasts at 6, 12, 24, 48, and 72 h**

# 4. Results and discussions

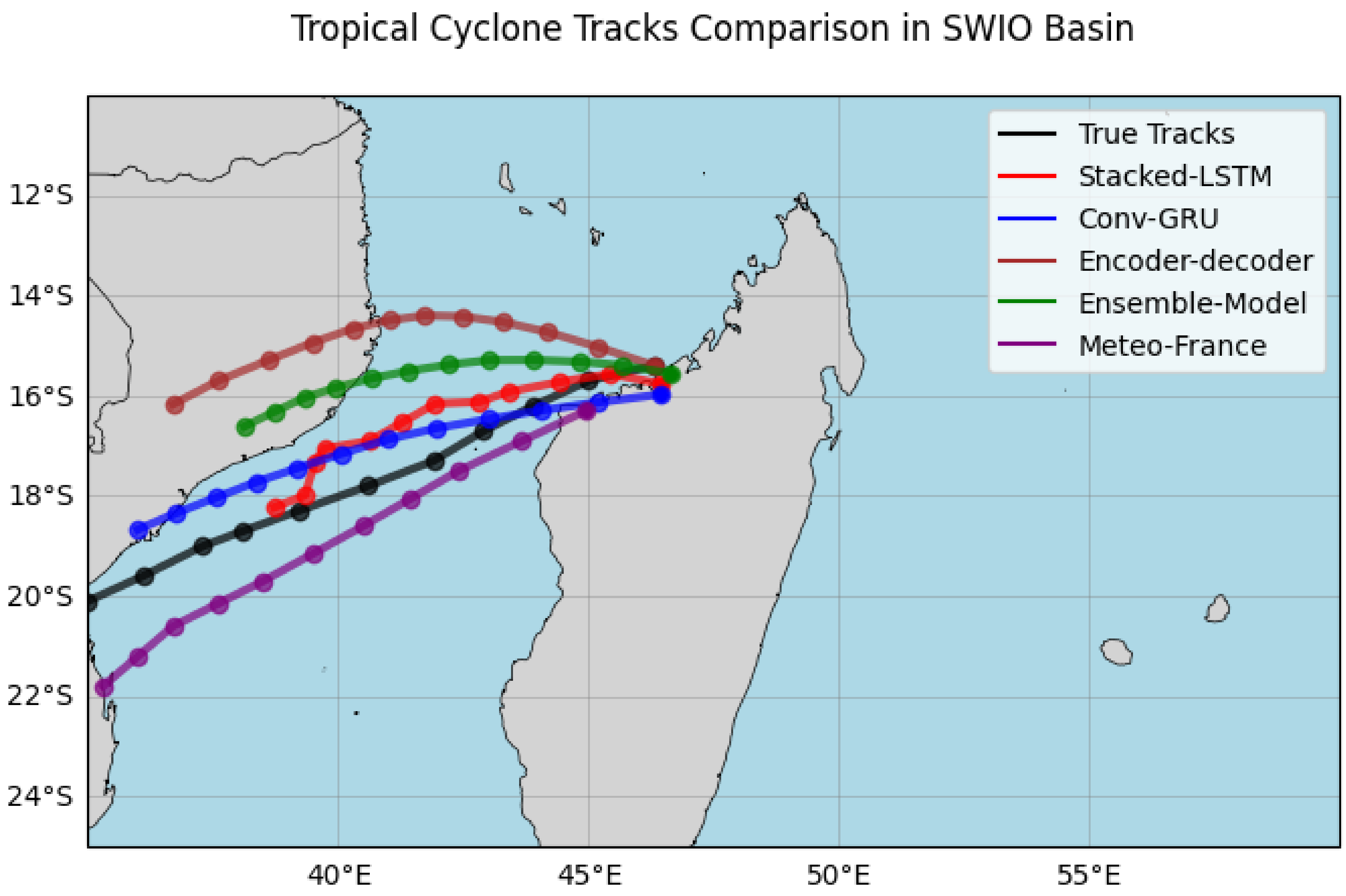
## 4.4. Models Testining Analysis




The boxplot of the Encoder-Decoder (black), Stacked-LSTM (yellow), and Conv-GRU (blue) model that creates 6–72 h forecasts (intervals of 6 h)

# 4. Results and discussions

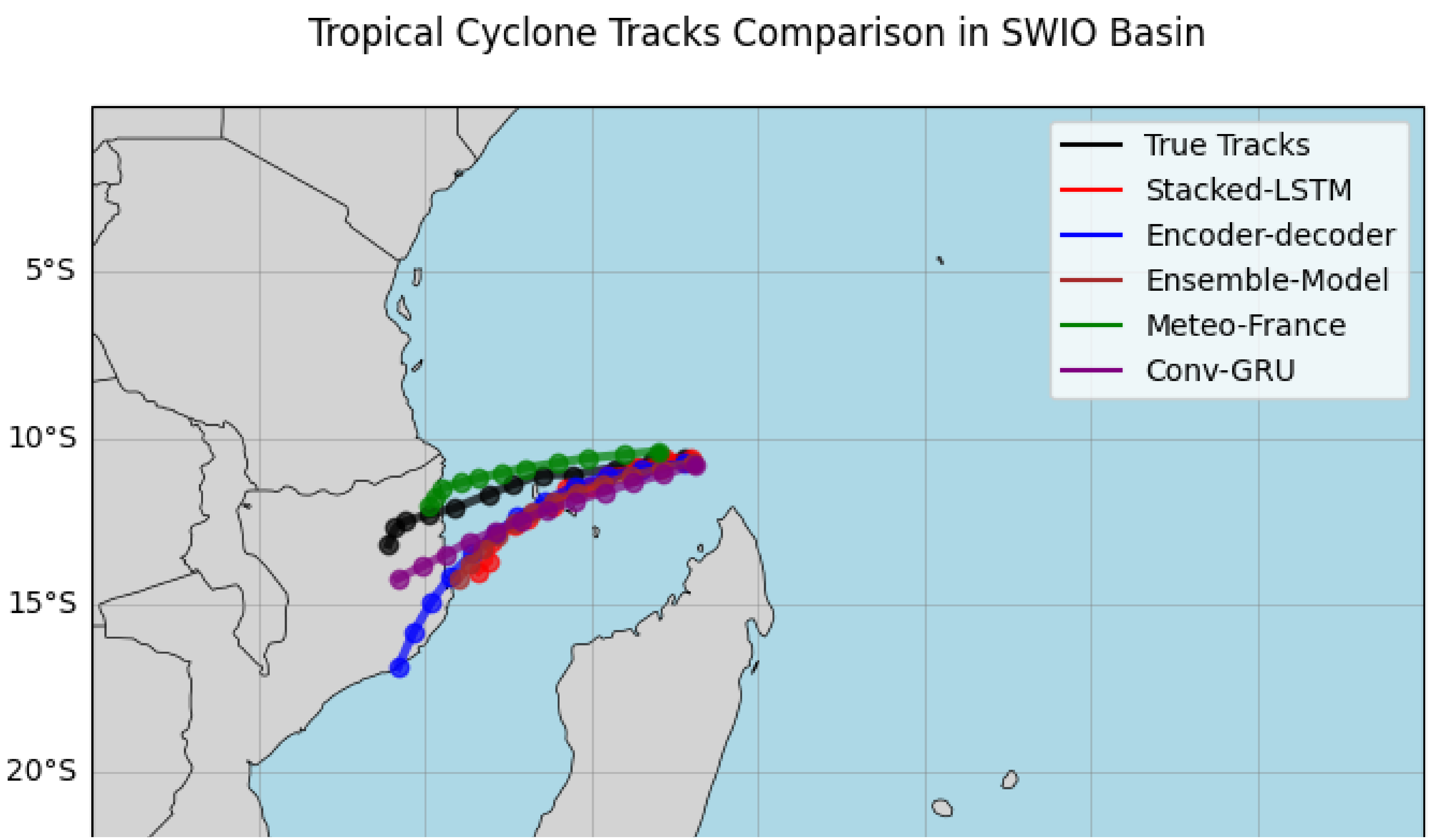
## 4.5. Forecasting Tracks




72h Forecast tracks of tropical cyclone Eloise (2021-202 season). The lines represent the predicted tracks: True (Black), Stacked-LSTM (Red), Conv-GRU (Blue), Encoder-Decoder (Brown), Ensemble (Green), Météo-France Model (Purple)

# 4. Results and discussions

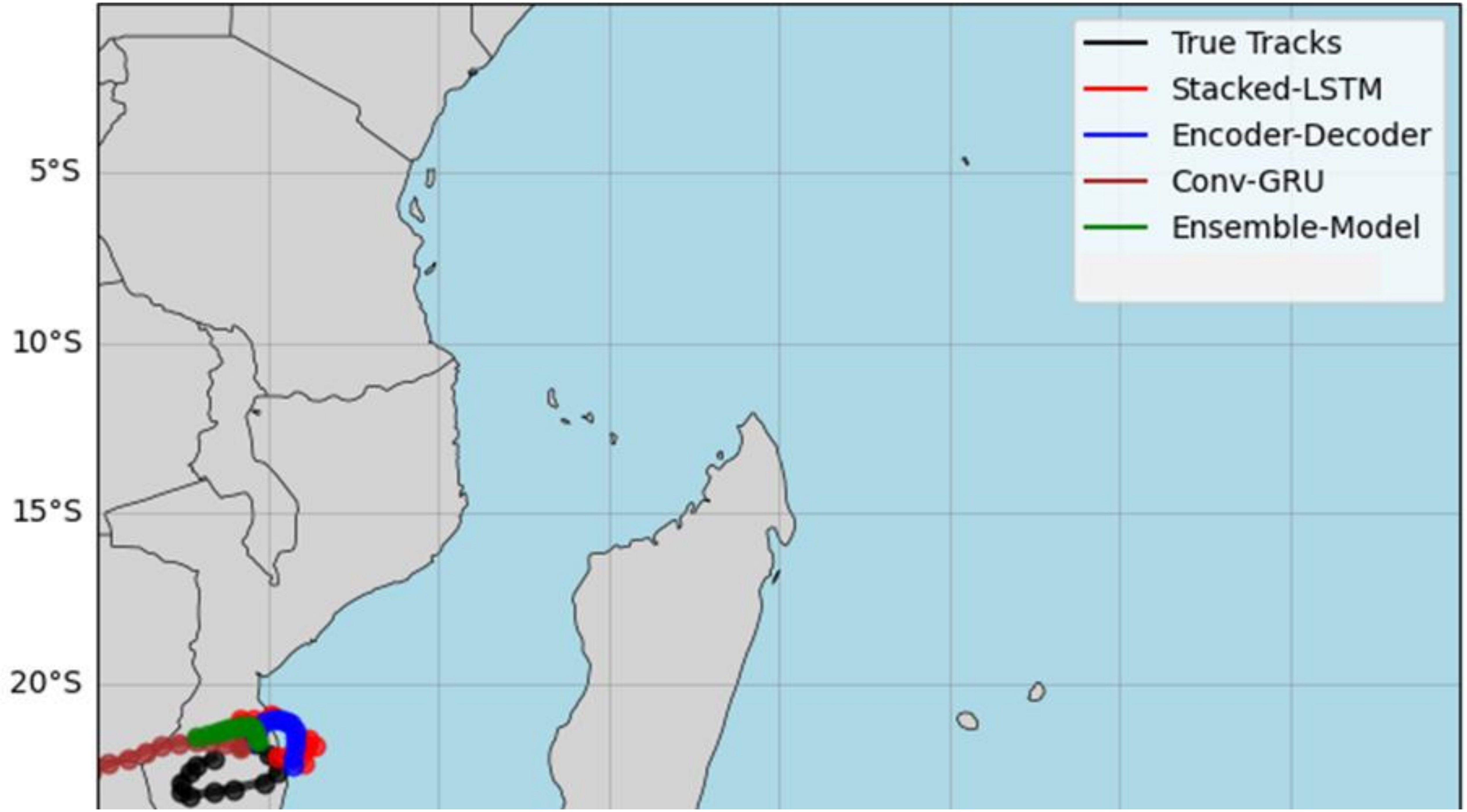
## 4.5. Forecasting Tracks




72h Forecast tracks of tropical cyclone Kenneth (2019-2020 season). The lines represent the predicted tracks: True (Black), Stacked-LSTM (Red), Conv-GRU (purple), Encoder-Decoder (Blue), Ensemble (Brown), Météo-France Model (green).

# 4. Results and discussions

## 4.5. Forecasting Tracks



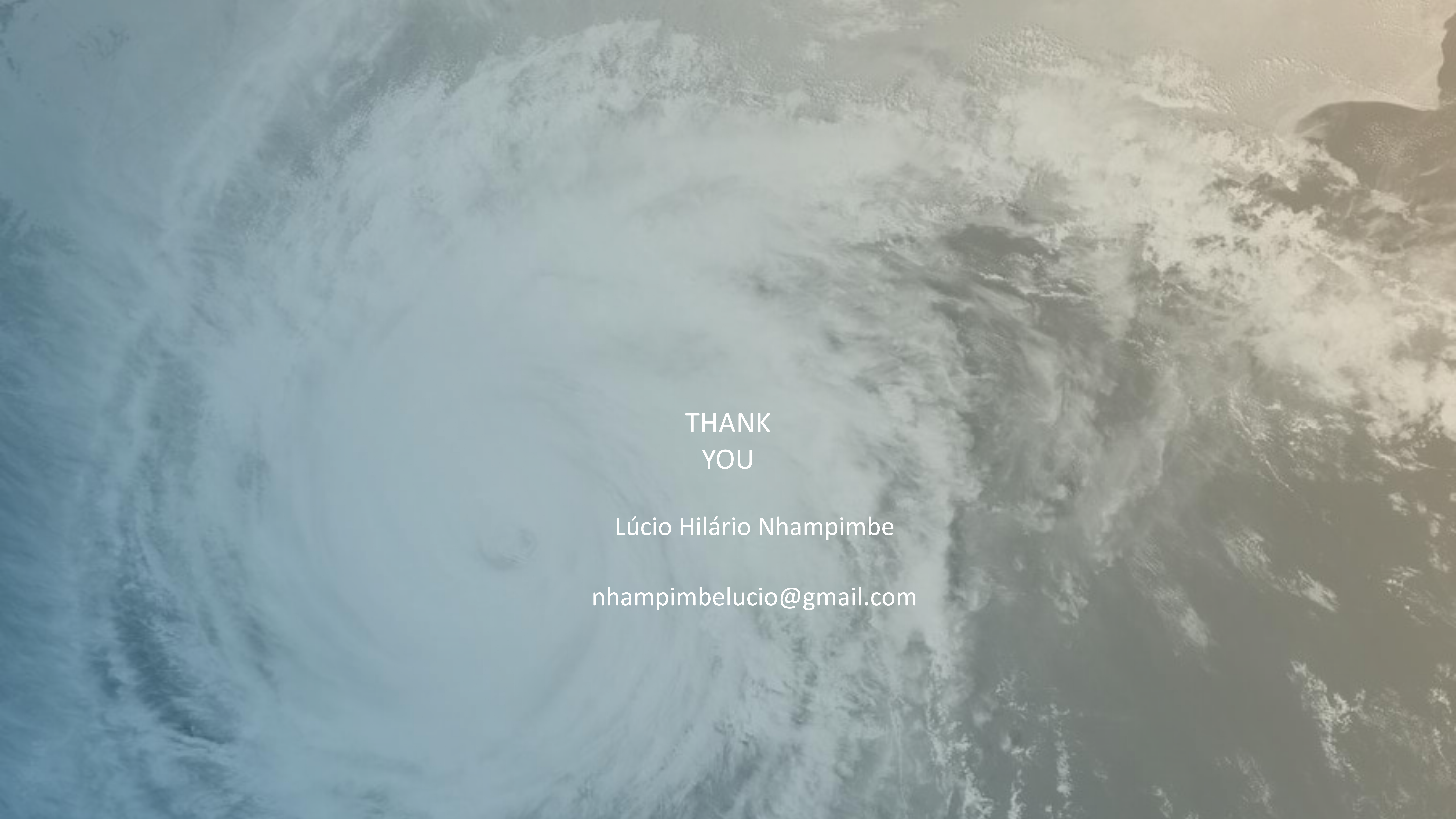

72h Forecast tracks of tropical cyclone Guambe (2022-2023 season). The lines represent the predicted tracks: True (Black), Stacked-LSTM (Red), Encoder-Decoder (Blue), Conv-GRU (Brown), Ensemble (Green).

Tropical Cyclone Trajectory Forecasting Based on Deep Learning

# Conclusion

# 5. Conclusion

- **Models & inputs**: Developed five RNN-based models (Stacked-LSTM, BN-LSTM, Skip-LSTM, Conv-GRU, Encoder-Decoder) trained on the past 24 h of meteorological and track data; a Random Forest selector identified 11 key variables driving next-6–72 h δlat/δlon.
- **Top performers & horizon skill**: Conv-GRU, Stacked-LSTM, and Encoder-Decoder performed best—Encoder-Decoder excelled at short lead times (≤42 h), Stacked-LSTM at medium ranges (42–72 h), and Conv-GRU provided the most stable performance across all horizons.
- **Error characteristics**: Prediction errors grow with lead time; models systematically underestimate latitude and longitude for southwestward/recurving cyclones (more pronounced at 48–72 h and at higher southern latitudes), though high $R^2$ indicates strong overall correlation between predicted and observed tracks.
- **Operational recommendation**: Favor Encoder-Decoder, Stacked-LSTM, and Conv-GRU for operational use and consider an ensemble (to exploit complementary strengths); models are relatively lightweight and computationally efficient—suitable for near-real-time deployment in the SWIO.
- **Next steps**: Improve accuracy by incorporating additional environmental predictors and implementing ensemble/uncertainty quantification methods to reduce bias and increase robustness.



THANK
YOU

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