Climate Predictions using Machine Learning Approaches

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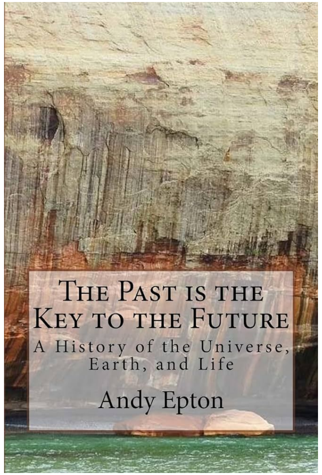

Motivation

Problem:

- The Horn of Africa has experienced severe and recurring droughts over the past few decades, making the quality of long-term weather prediction fundamentally important.
- Modern climate models suggest that the precipitation will increase as temperatures rise.

Goal:

- Using multiple past climate proxy records to build a machine learning model to determine whether we can predict the future climate of the Horn of Africa.

Deep Learning for Climate Predictions

CLIMATE CHANGE

New Machine Learning-Based Model Boosting Africa's Preparedness and Response to Climate Change

By Aimable Twahirwa

Reprint | | Print |

Scientists have recently unveiled a first-ever weather forecasting model using artificial intelligence (AI) aimed at creating resilience in Africa. Credit: Kureng Dapel/World Meteorological Organization

Postprocessing East African rainfall forecasts using a generative machine learning model

ATMOSPHERIC SCIENCES | EAST AFRICA | FORECASTING | MACHINE LEARNING | POSTPROCESSING | PRECIPITATION | TROPICAL

Bobby Antonio, Andrew T T McRae, David MacLeod, Fenwick C Cooper, John Marsham, Laurence Aitchison, Tim N Palmer, Peter A G Watson

nature > npj climate and atmospheric science > articles > article

Article | Open access | Published: 03 August 2023

Predicting extreme floods and droughts in East Africa using a deep learning approach

Kalpesh Ravindra Patil, Takeshi Doi & Swadhin K. Behera

npj Climate and Atmospheric Science **6**, Article number: 108 (2023) | Cite this article

Dataset Description

Article

Reversed Holocene temperature–moisture relationship in the Horn of Africa

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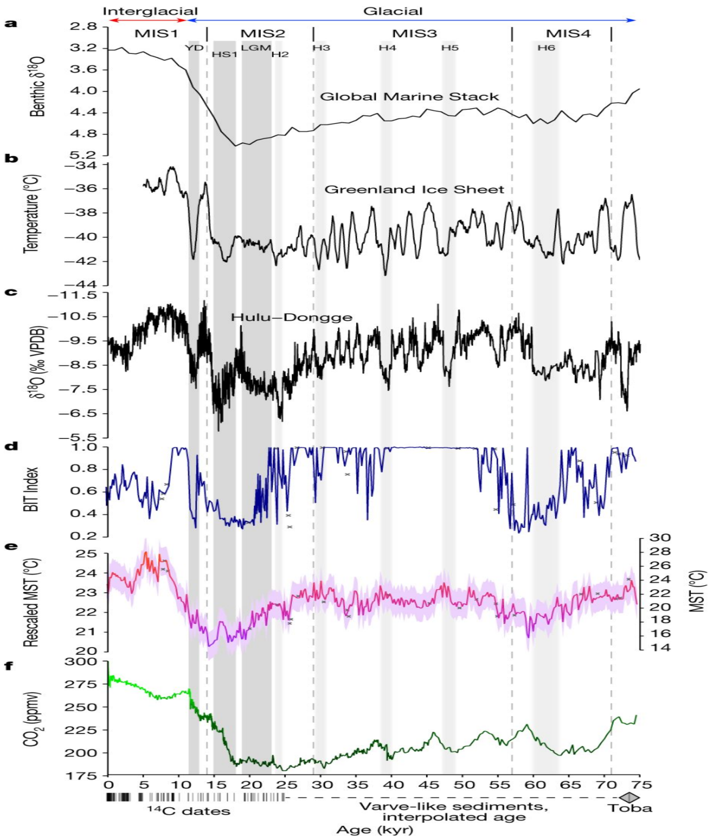
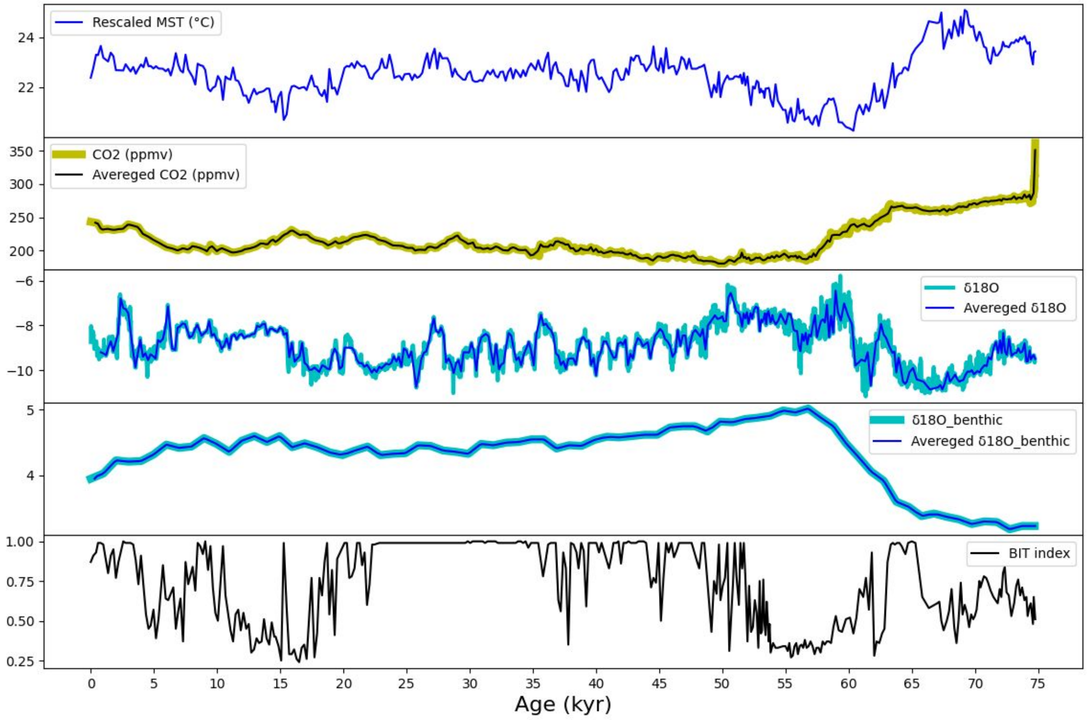
A. J. Baxter[1,10] ✉, D. Verschuren[2,10], F. Peterse[1], D. G. Miralles[3], C. M. Martin-Jones[4], A. Maitituerdi[5], T. Van der Meeren[2], M. Van Daele[6], C. S. Lane[4], G. H. Haug[7], D. O. Olago[8] & J. S. Sinninghe Damsté[1,9]



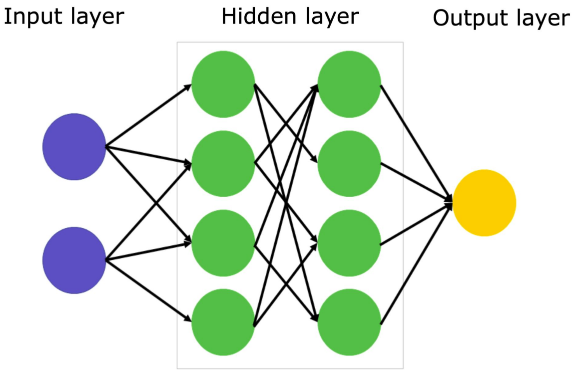
- ➔ **Benthic δ18O:** Global ice volume
- ➔ **δ18O:** East Asian summer monsoon intensity
- ➔ **BIT index:** Lake water-balance variation
- ➔ **MST:** Mean summer temperature
- ➔ **Atmospheric CO2 concentration**

Data Preparation



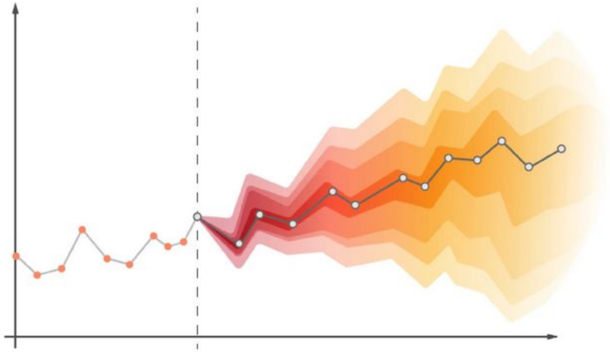
Methods

Neural Network

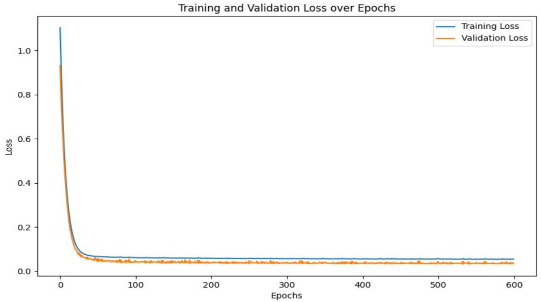


Artificial neural networks

Time series forecasting



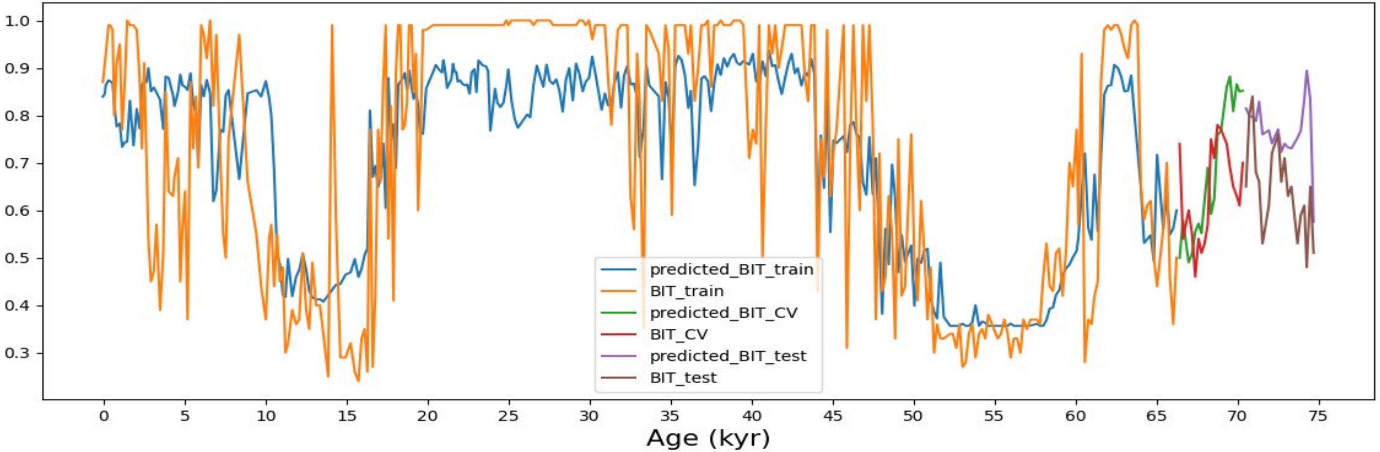
Neural Network




```python
reg = 0.0034
model_2 = Sequential(
    [
        tf.keras.Input(shape=(4,)),    #specify input size
        Dense(15, activation = "relu",kernel_regularizer=keras.regularizers.l2(reg)),
        Dense(50, activation = "relu",kernel_regularizer=keras.regularizers.l2(reg)),
        Dense(50, activation = "relu",kernel_regularizer=keras.regularizers.l2(reg)),
        Dense(50, activation = "relu",kernel_regularizer=keras.regularizers.l2(reg)),
        Dense(50, activation = "relu",kernel_regularizer=keras.regularizers.l2(reg)),
        Dense(50, activation = "relu",kernel_regularizer=keras.regularizers.l2(reg)),
        Dense(50, activation = "relu",kernel_regularizer=keras.regularizers.l2(reg)),
        Dense(15, activation = "relu",kernel_regularizer=keras.regularizers.l2(reg)),
        Dense(1, use_bias = True, activation = "sigmoid")

  ], name = "my_model"
)
```

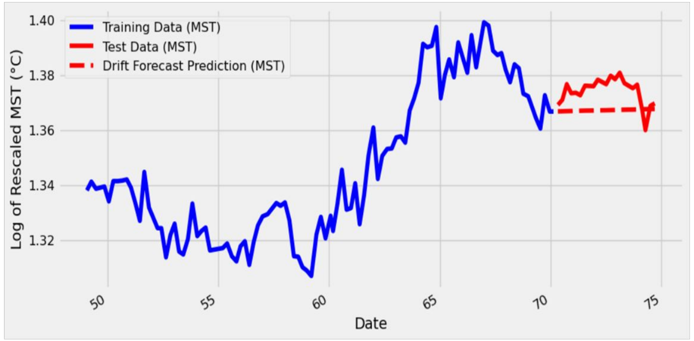
```python
model_2.compile(loss = tf.keras.losses.MeanSquaredError, optimizer=tf.keras.optimizers.Adam(0.001))
```

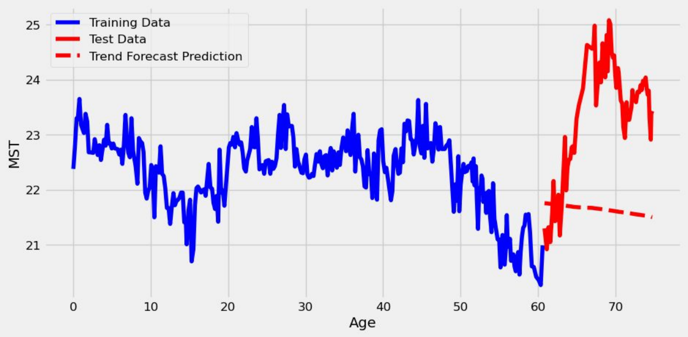


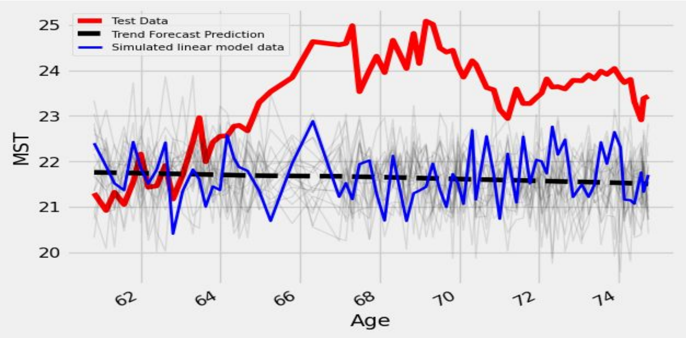
Time series forecasting

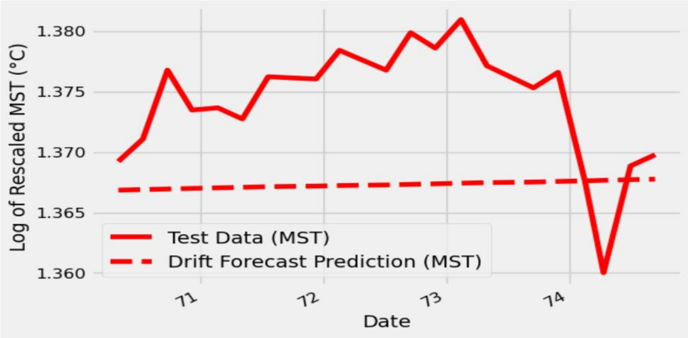
Linear trend model

Random walk with drift model









Time series forecasting

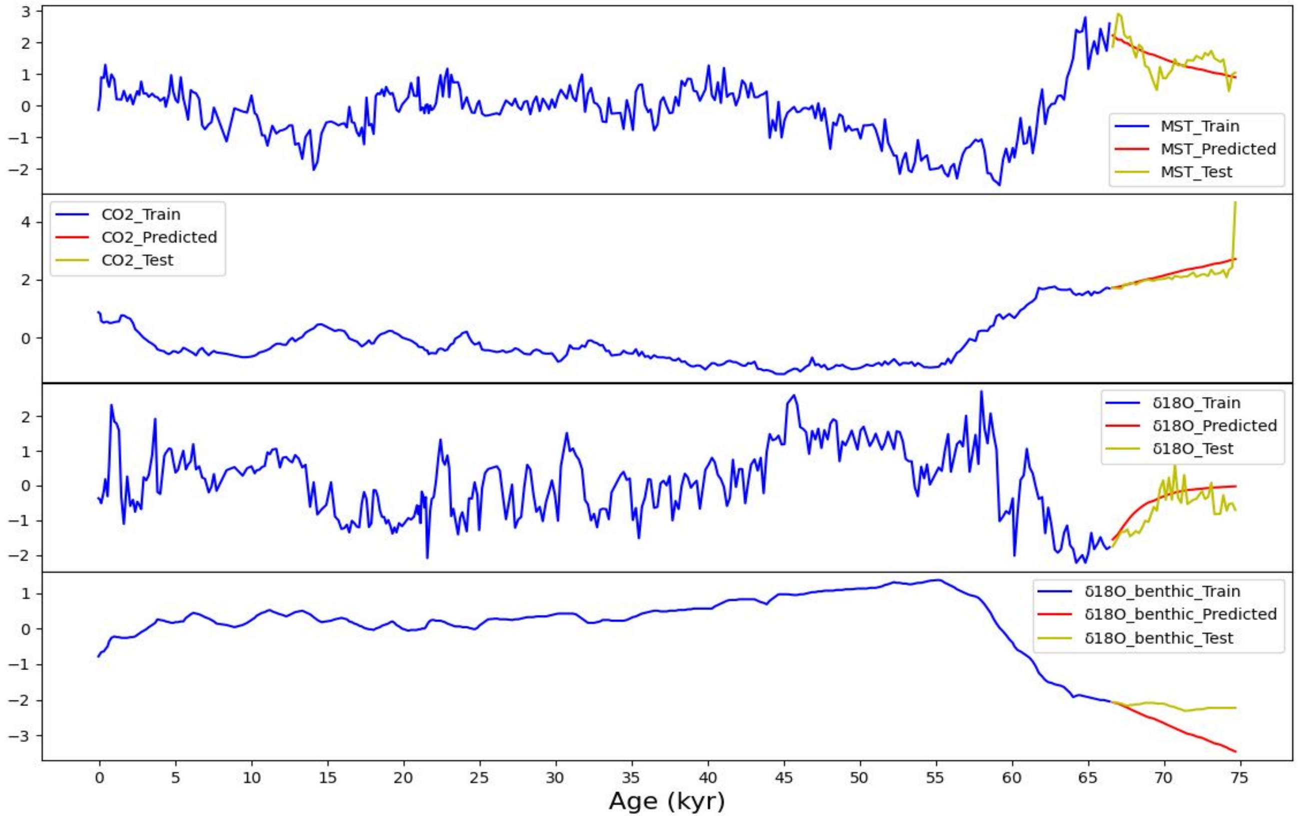
ARIMA theoretical background

Autoregressive (AR) and Moving Average (MA) models

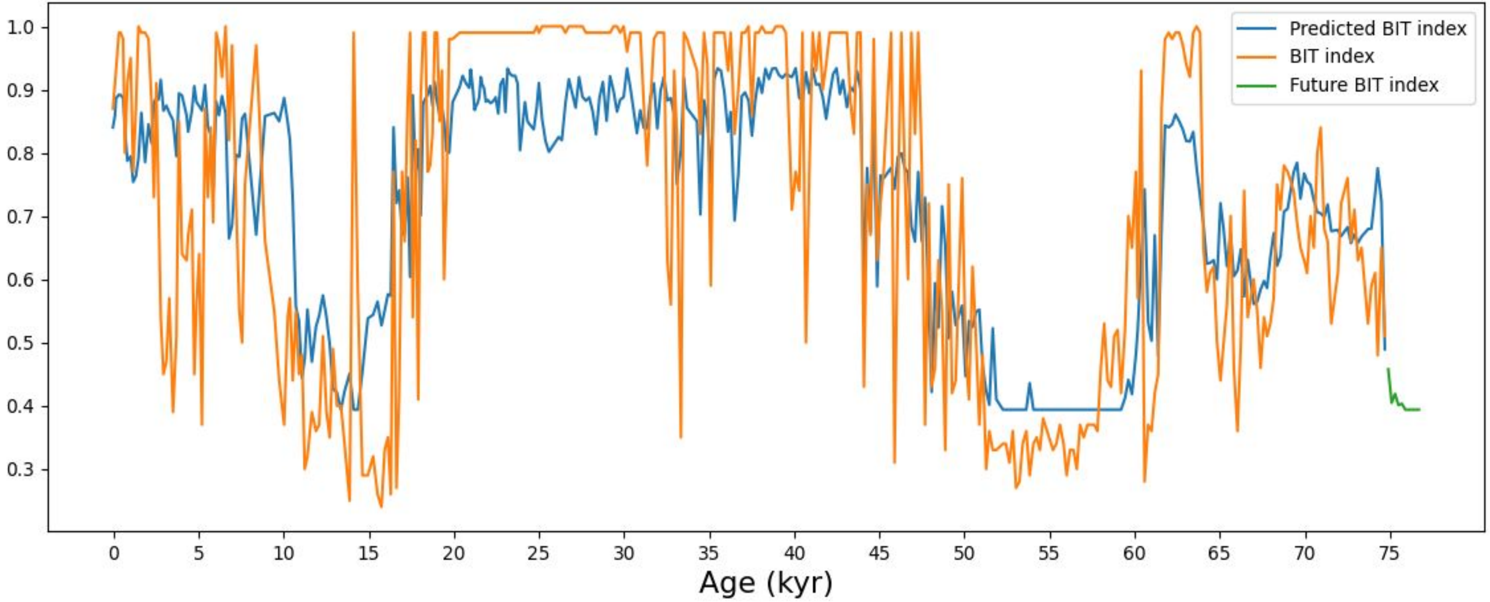
- **AR(p):** $Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} \,..+ \beta_p Y_{t-p} + \varepsilon_{\mathbf{t}}$
- **MA(q):** $Y_t = \alpha + \varepsilon_t + \phi_1 Y_{t-1} + Y_{t-2} \,..+ \phi_q Y_{t-q}$

ARIMA(p,d,q)

- ARIMA models combine both AR and MA components along with differencing (d) to handle non-stationary data.
- **Predicted** $\mathrm{Y}_t' = \mu + \sum_{i=1}^{p} \beta_{\mathrm{i}} \mathrm{Y}_{t-i}' + \sum_{i=1}^{q} \phi_{\mathrm{i}} Y_{t-i}$


MST_Train
MST_Predicted
MST_Test
CO2_Train
CO2_Predicted
CO2_Test
δ18O_Train
δ18O_Predicted
δ18O_Test
δ18O_benthic_Train
δ18O_benthic_Predicted
δ18O_benthic_Test
Age (kyr)

Results



Predicted BIT index
BIT index
Future BIT index
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
5
10
15
20
25
30
35
40
45
50
55
60
65
70
75
Age (kyr)

Conclusion and future work

- Our prediction aligns with recent scientific findings indicating that the Horn of Africa is likely to undergo further drying.
- Seeking professional advice on feature selection will improve our neural network performance
- Modern-day climate data from instrumental records will help to build a better model, enabling more promising predictions.
- More sophisticated neural network models such as Recurrent Neural Networks (RNNs) or LSTMs, optimized for time series data, are recommended.

Thank You !