* Does ML add value to a standard hydrological problem?
* Vegetation health prediction is relatively understudied compared with other hydrological variables of interest.
* What are the underlying assumptions made with a neural network compared with standard statistical tools?

ML = more variance, less bias

Stat = more bias, less variances

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## Introduction

Drought is estimated to be one of the world’s most costly hazards, accounting for 22% of damage from natural disasters (Wilhite et al 2007). Drought is expected to continue to be a damaging hazard in future decades. As the world warms longer periods of below average rainfall are expected to be interspersed with more extreme rainfall events (IPCC 2013). A general increase in extreme hydrological hazards requires accurate information to be delivered to policy makers, governments and NGOs in a timely manner to try and minimize the impact of these hazards.

Since 1980, East Africa has experienced a number of severe droughts. The 1984-1985 Ethiopian famine was in part caused by an anomalously low precipitation total for the Long Rains and the associated impact on agricultural productivity. This led to around 450,000 deaths in Sudan and Ethiopia (Guha-Sapir et al 2004, Vincente-Serrano et al 2012). More recently, the 2010-2011 Horn of Africa drought was caused by the consecutive failure of both the 2010 Short Rains (October-November) and the 2011 Long Rains (March-May) (Haile et al 2019). It is estimated that the drought and associated food crises affected around 12 million people (Aghakouchak 2015).

Kenya experienced severe droughts and associated increases in maize prices due to the 2008-2009 drought (Haile et al 2019). In response to this drought event, the National Drought Management Authority (NDMA) was set up in 2011. Since 2014 the NDMA has distributed Drought Contingency funds (DCF) to respond in a timely manner to drought threats (Klisch and Atzberger 2016). This fund is focused on the Arid and Semi-Arid Lands (ASAL), counties particularly prone to the impact of droughts.

There is evidence to suggest that droughts are becoming longer and more frequent in the region due to climate change (Nicholson 2017, IPCC 2013). An observed decrease in the total rainfall during the Long Rains season (March - May) since 1999 (Lyon 2014) is causing concern for regional policy makers and local NGOs. The possible increase in the frequency and magnitude of droughts in future decades makes mitigating their impacts through improved drought monitoring and prediction an important focus for research.

While there are a numerous drought definitions and drought indicators (Mishra and Singh 2010) this study focuses on the agricultural and vegetation based drought indicators. This is for two reasons. Firstly, it is comparatively understudied relative to other drought indicators, for notable exceptions see (Klisch and Atzberger 2016, ...). Precipitation based drought metrics tend to be used, particularly as they are recommended by the WMO as the de facto standard for drought monitoring (WMO 1996). Precipitation based indicators however, fail to capture the complex interaction of the precipitation with the land surface. In contrast, vegetation health based metrics integrate information from multiple meteorological conditions (precipitation, temperature) with land-surface variables (soil moisture). Furthermore, vegetation health indicators link closely to one of the key impacts of droughts, agricultural yields for both crops and livestock. This is a particularly important measure of drought in the region given the high reliance on subsistence agriculture (Rojas et al 2011, Agutu et al 2017).

An alternative metric would be streamflow. While this would be a valid choice because it integrates information from the atmosphere and land surface, we leave this drought indicator for a future study.

[WHY MACHINE LEARNING?]

The objectives of this study are:

1. To compare the accuracy of standard statistical approaches for vegetation health forecasting with a modern deep-learning algorithm to test whether there is value in such approaches.
2. Demonstrate how this model might be used in an operational context to improve response to drought conditions in particular events.
3. To show how the model can be used to derive insight into the processes that govern the interaction of hydro-meteorological variables with vegetation health.

To this end ...

The structure of the paper is as follows. Section 2 (Literature Review) outlines other approaches to drought monitoring and prediction. It also gives further detail on the operational context in Kenya. In Section 3 (Methods) we outline the EA-LSTM model, the data used and the experimental design. Here we will outline the assumptions of our approach. In Section 4 (Results) we first, outline how the EALSTM model performs against a standard statistical approach, demonstrating the potential value of machine learning based approaches. Secondly, we will consider the ways that we can interpret the model weights to better derive insight into the underlying hydrological processes. The aim of this subsection is to outline how machine learning based approaches might become more than just black-box prediction systems and actually be used to improve our physical understanding of the system we are hoping to predict. The final section, Section 5 (Discussion) will conclude with an overview of how our model performs and what implications this has for monitoring in the region. We will also outline how this model might be used and the steps required for the model to be used operationally by the NDMA.

## Literature Review

Drought monitoring and prediction

## Methods

### Datasets

#### ERA5 Reanalysis

ERA5 is ECMWFs most recent reanalysis product (CITE). Reanalysis data combine models and observations using data assimilation to provide the best estimate of hydro-meteorological variables over the earth. ERA5 has global spatial coverage for 1979-Present at 137 pressure levels (vertical resolution) on an hourly timestep. The spatial resolution is 0.31o (31km). There are [N] variables produced. For this study we use the spatial fields for 2m Air Temperature, Potential Evaporation, Evaporation and Soil Moistcure (Level 1 - 4).

These variables have not been validated over Kenya. However, ERA Interim, the precursor to ERA5 soil moisture has been shown to reproduce observed surface variability, however it overestimated soil moisture, especially in drylands (Albergel et al 2012). ERA Interim Soil Moisture has been used by other studies in the region (see, e.g. Agutu et al 2017, CITATIONS...). Tall et al (2019) validated precipitation and incoming short-wave radiation in Burkina Faso using in-situ measurements. They found that ERA5 was better able to reproduce observations of both precipitation and incoming short-wave radiation than ERA Interim. [**data validation over east africa**]

#### CHIRPS Precipitation

Climate (CHIRPS) is the precipitation product we decided to use as a predictor variable for our experiments (Funk et al 2015). CHIRPS is a quasi-global (50oS - 50oN) daily precipitation product produced at 0.05o spatial resolution. The data combines in-situ station observations and satellite precipitation estimates based on Cold Cloud Duration (CCD). The data has been validated against in-situ measurements (CITATION) and other gridded data products (GPCC - Funk et al 2015). Furthermore, it has been used extensively in drought-related studies in the region (Shukla et al 2014, Shukla et al , Funk et al 2018, Sjouke et al 2018).

#### MODIS NDVI

The NDVI data is derived from MOD13Q1 and MYD13Q1 NDVI collection 5 products and has been processed using the methods described by Klisch and Atzberger (2016).

“calculated from MOD13Q1 and MYD13Q1 NDVI collection 5 products of the MODIS Terra and Aqua satellites obtained through the online Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC) from 2000 onwards” ([Klitsh and Atzberger 2016](https://www.mdpi.com/2072-4292/8/4/267/htm#B1-remotesensing-08-00267))

All data has been regrid to the same spatial resolution as the ERA5 product using bilinear interpolation [JUSTIFY THIS].

**Table 1**: The input datasets

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | NDVI | Precip | Soil Moisture | 2m Air Temperature | Potential Evaporation | Altitude | Landcover |
| **Dataset** | Y, X | X | X | X | X | X (static) | X (static) |
| **Source** | NOAA AVHRR | CHIRPS  () | ERA5 (C3S 2017*)* | ERA5  (C3S 2017*)* | ERA5  (C3S 2017*)* | NASA SRTM | ESA  (C3S 2017*)* |

### Experimental Setup

The experimental setup is as follows. We are predicting a vegetation health indicator, NDVI. In order to predict this variable we use the prior 12 months of hydro-meteorological conditions. Most of these variables vary over each timestep. For example, precipitation (from CHIRPS), temperature, (all from ERA5). For more information on the input data please consult Table 1.

*Dataset citable as: Copernicus Climate Change Service (C3S) (2017): ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate . Copernicus Climate Change Service Climate Data Store (CDS), date of access. https://cds.climate.copernicus.eu/cdsapp#!/home*

*Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., … Michaelsen, J. (2015). The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes. Scientific Data. https://doi.org/10.1038/sdata.2015.66*

*Agutu, N. O., Awange, J. L., Zerihun, A., Ndehedehe, C. E., Kuhn, M., & Fukuda, Y. (2017). Assessing multi-satellite remote sensing, reanalysis, and land surface models’ products in characterizing agricultural drought in East Africa. Remote Sensing of Environment. https://doi.org/10.1016/j.rse.2017.03.041*

## Results

## Discussion and Conclusion