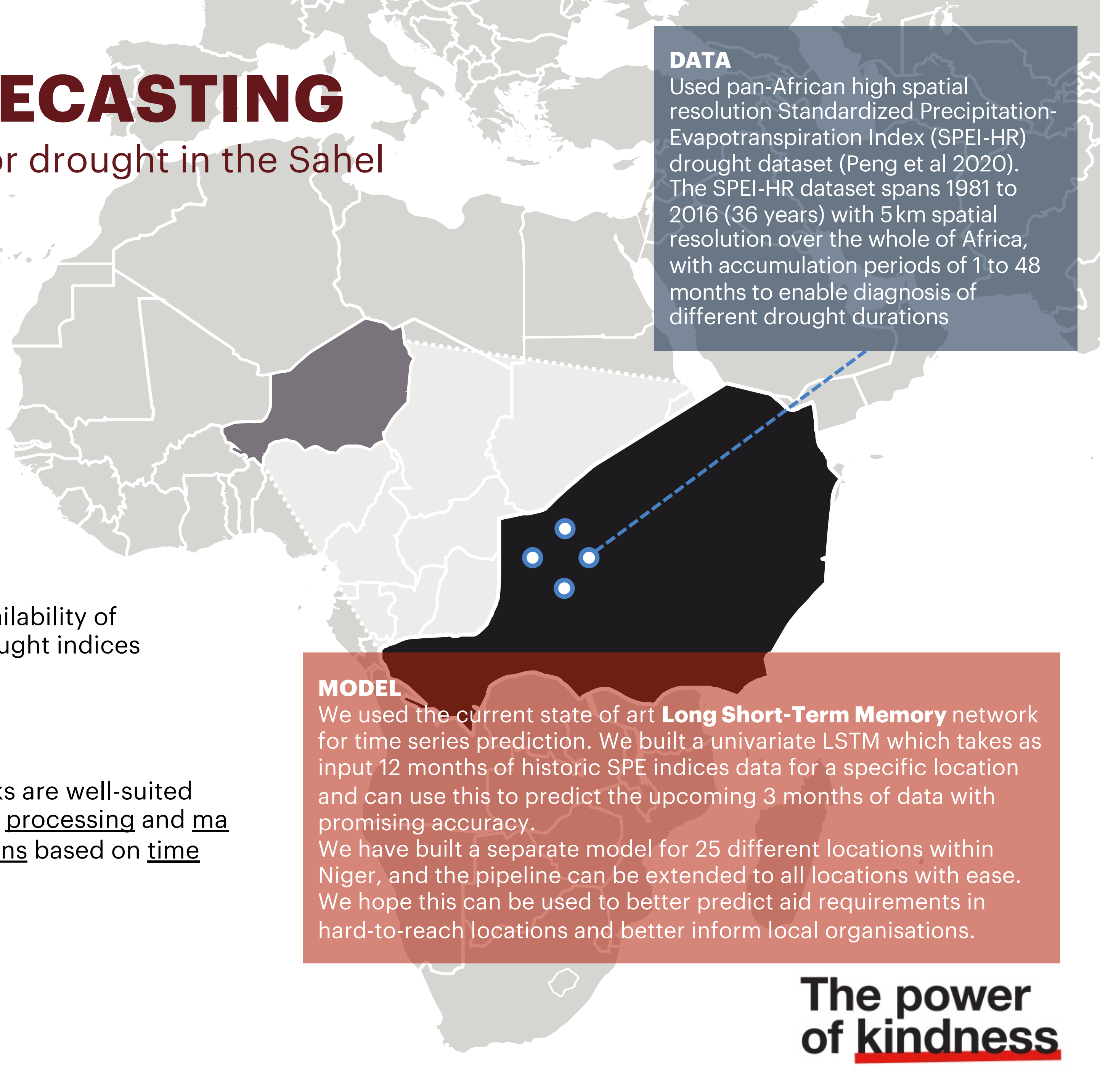
DROUGHT IMPACT FORECASTING

Green DataDen is an early warning system for drought in the Sahel

How can we support communities and organisations to know when to better prepare for emergencies by the prediction of a climate hazard?

Our solution focused on drought prediction in the Niger using temperature, precipitation, population, and socio-economic index data to support the delivery of aid approaches/ insight using insight data.



DATA
Used pan-African high spatial resolution Standardized Precipitation-Evapotranspiration Index (SPEI-HR) drought dataset (Peng et al 2020). The SPEI-HR dataset spans 1981 to 2016 (36 years) with 5 km spatial resolution over the whole of Africa, with accumulation periods of 1 to 48 months to enable diagnosis of different drought durations

- Drought is a complex phenomenon that is difficult to define and monitor.
- Droughts (meterological and other) operate on many different time scales

+ Increasing availability of long-term drought indices like SPEI
+ LSTM networks are well-suited to classifying, processing and making predictions based on time series data

MODEL
We used the current state of art **Long Short-Term Memory** network for time series prediction. We built a univariate LSTM which takes as input 12 months of historic SPE indices data for a specific location and can use this to predict the upcoming 3 months of data with promising accuracy.
We have built a separate model for 25 different locations within Niger, and the pipeline can be extended to all locations with ease.
We hope this can be used to better predict aid requirements in hard-to-reach locations and better inform local organisations.

BritishRedCross

Climate Centre

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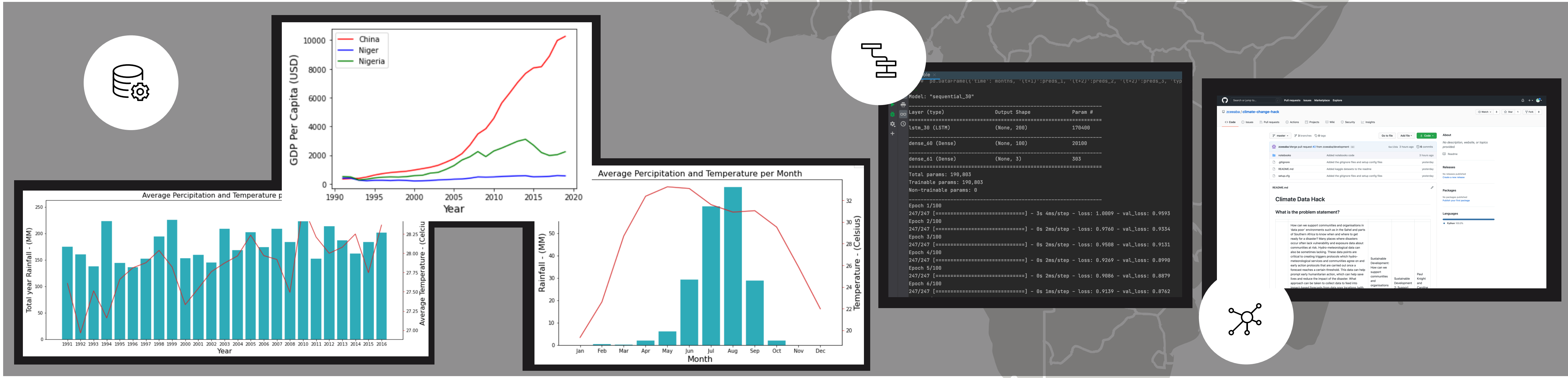
SOLUTION SUMMARY

Green DataDen is an early warning system for drought in the Sahel

25
DATASETS ANALYSED

25
MODELS BUILT

1
GIT REPO CREATED



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PROBLEM STATEMENT

The frequency, magnitude, and duration of extreme weather events like floods and drought are projected to increase in the Sahel, with significant implications on freshwater availability, food security, and socio-economic development. Different studies show how climate change will impact on all components of the hydrological system – with changes in temperature and precipitation impacting surface runoff, evapotranspiration, soil moisture, and groundwater recharge; all of which will pose serious challenges on food security, wellbeing and livelihood, and regional stability. Not all these changes will result from climate change, however – some changes will result from land use change and increased abstraction (amongst other things!).

Even without climate change, there exists substantial inter- and intra-annual variability in regional hydro-climatology which results in extreme weather events. Climate change will interact with these and other non-climatic drivers and stressors such as population and demographic changes; accelerating technological change and convergence; and shifting geopolitical and socio-economic patterns, to amplify existing vulnerabilities of water and agricultural systems; with increasing temperature and precipitation very likely to reduce cereal crop productivity, for example. There is already evidence from around the region of temperature rise adversely affecting high value perennial crops. These challenges are compounded by insufficient/ non-existing data for analysis and prediction, even in priority areas, and even with the new governance systems being developed as climate change adaptation response. Strengthening interlinkages between adaptation and development pathways with a focus on resilience can help counter current data and resilience deficits and reduce future risks.

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OUR SOLUTION

We propose that some of these risks can be reduced with systems that integrate climate action with hydromet, population and demographic, and socio-economic data within a framework of risk reduction. We have developed an early warning system in Niger using [X] to visualises [insert what] with the aim of forecasting drought events to help anticipate disaster and prepare communities.

We used the recently produced pan-African high spatial resolution Standardized Precipitation-Evapotranspiration Index (SPEI-HR) drought dataset (Peng et al., 2020). The SPEI-HR dataset spans 1981 to 2016 (36 years) with 5 km spatial resolution over the whole of Africa, with accumulation periods of 1 to 48 months to enable diagnosis of different drought durations. Normalized Difference Vegetation Index (NDVI) calculated from the Global Inventory Monitoring and Modeling System (GIMMS) project and root zone soil moisture modelled by GLEAM was found to be in agreement with SPEI-HR, with an average correlation coefficient (R) of 0.54 and 0.77, respectively (Ibid.).

The multiscalar drought index SPEI index was formulated by Vicente-Serrano et al (2010) to incorporate potential evapotranspiration (PET) in the then widely used precipitation only based index, the standardised precipitation index (SPI). Since 2010 the multiscalar drought index SPEI has been widely used (with over 4000 citations on Google Scholar). Recently, Ogunrinde et al (2020) evaluated the performance of three potential evapotranspiration models (Hargreaves, Penman-Monteith, and Thornwaite) as inputs to SPEI and assessed these against historic drought events (from the Emergency Events Database, EM-DAT) for five agroecological zones in Nigeria. All three indices identified earlier onset for both 3- and 12- month timesteps than that of EM-DAT.

THE MODELLING APROACH

Using a **Long Short Term Memory** model, which is a specific type of recurrent neural network, we have been able to successfully forecast the SPE index 3 months in advance.

The network we have built is a univariate model that uses the **1-month aggregations of the SPE index**, as input, as discussed in the following paper. These indices have been around since 2010 and are seen as the current best in class. We use 12 months of prior indices to predict the outcome of the upcoming 3 months. We chose these so as to be operationally sensible and allow time for action.

The data is calculated for 5km radius, across the continent of Africa and hence our initial model build narrowed this down to Niger, and then 25 specific locations within the country. The **pipeline** however can be used **across the whole continent** for every location point as required.

Coupling this data with our LSTM technique, we have seen significant improvements upon our baseline to successfully forecast the SPE index 3 months in advance. Using the Mean Absolute Error as our evaluation metric we can see:

BASELINE: *Using current months SPEI as a predictor of the next month – Location 1*

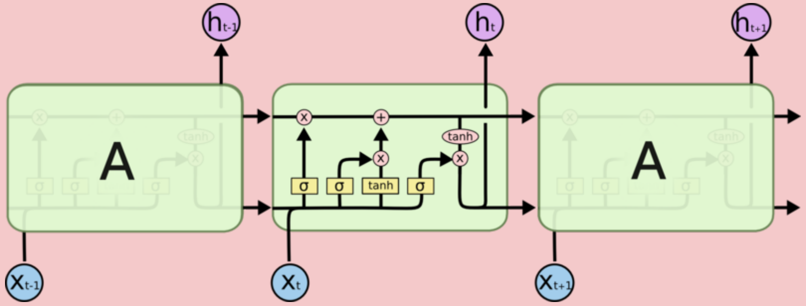
1-month in advance - 0.986

LSTM: *Using the LSTM network as a predictor of the next month – Location 1*

1-month in advance – 0.493

3-months in advance – Month 1: 0.529 Month 2: 0.542 Month 3: 0.537

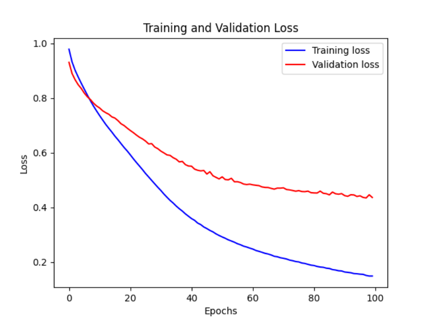
LSTM Network



Model Architecture

```
Model: "sequential_30"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_30 (LSTM)               (None, 200)               170400
_________________________________________________________________
dense_60 (Dense)             (None, 100)               20100
_________________________________________________________________
dense_61 (Dense)             (None, 3)                 303
=================================================================
Total params: 190,803
Trainable params: 190,803
Non-trainable params: 0
_________________________________________________________________
```

Location 1



We're confident we can improve on these results even further with targeted hyper parameter tuning and discovery.

NEXT STEPS AND EXTENSIONS

Due to the limited timeframe, we had available to us we wanted to highlight some of our proposed next steps to improve this initial solution:

- Experimentation with different accumulation periods, we used data accumulated from 1 month, but have also read in the literature that 4 months is often seen as suitable
- Adding multi-variate features into the LSTM to improve prediction accuracy, the data we have already defined includes the temperature and precipitation data at an overall Niger level
- Updating the pipeline so that we include a multi-input model and do not require individual training per 5km region, including the location as a one-hot encoded variable should enable this
- The data for the SPEI has been calculated for all African countries, the pipeline can easily be extended to other countries and analysis of performance across the continent would be very interesting.

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