Interpolated climate grids developed with deep neural networks for Africa

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Introduction

Researchers, resource managers and decision makers need access to high-quality climate data to represent historical trends, current conditions and future projections. **Access of such data in Africa is limited** to global products that have methodological and data limitations.

In this study, I am compiling an extensive weather station data base for Africa, and creating interpolated climate grids **with deep neural networks**.

The grids will then form the basis of a software package **ClimateAF** (programmed by collaborators at UBC as in Wang et al, 2016 to provide easy access to 48 monthly climate variables (Tmin, Tmax, Tave, Prec), and 36 bioclimatic variables (such as dryness indices) from 1901 to present and for CMIP6 future projections.

Materials & Methods

- **Weather station data** (**Fig 1**) was compiled from Climate Research Unit (CRU), FAO World Climate Data, World Meteorological Organization (WMO), Global Historical Climatology Network (GHCN), European Climate Assessment (ECA), National Oceanic & Atmospheric Administration (NOAA) and the global precipitation database by Castellanos-Acuna & Hamann, 2020. Following duplicate removal, quality control, and missing value estimation 4530 weather stations were available.

Materials & Methods

- **Covariates** are key for machine learning applications, and were generated with in ArcGIS from topographic information (e.g. tpi, cti, exposure indices), remote sensing (e.g. land cover), and ocean-atmospheric general circulation models (e.g. wind direction and strength). Some covariate examples are shown in **Fig 1**.

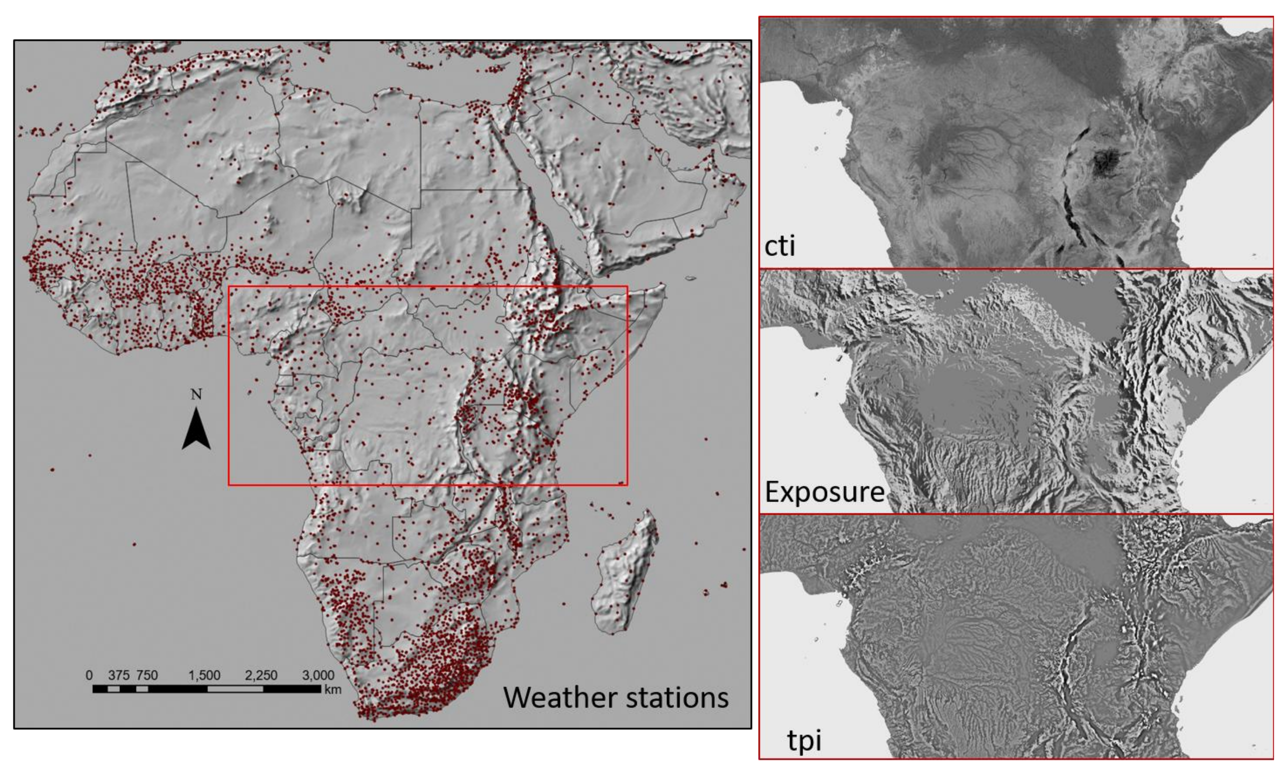

Fig 1. Weather stations and examples for covariates

- **Deep Neural Networks** were then applied to fine-tune a basic thin-plate spline interpolation using covariates, according to the schematic shown in **Fig 2**.

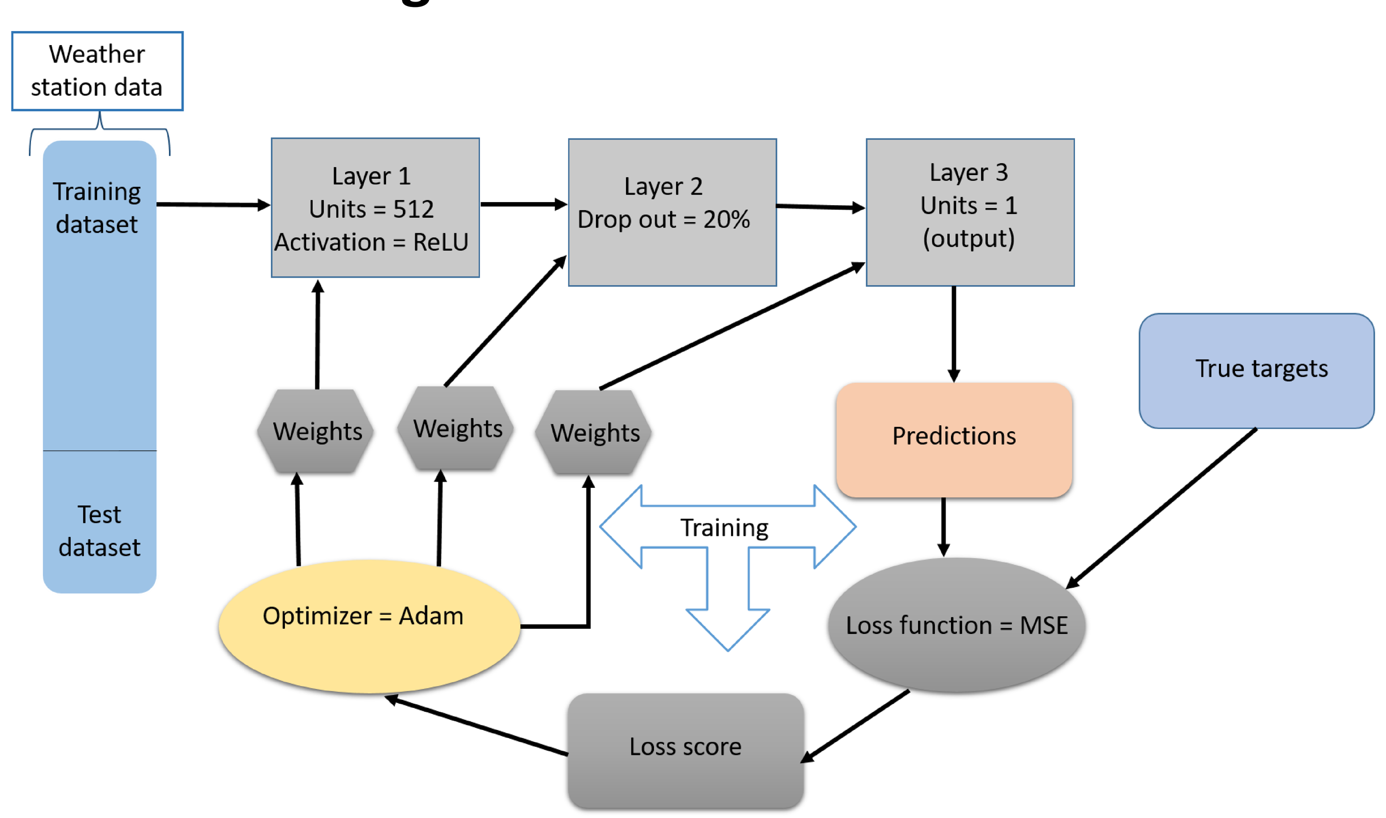

Fig 2: Conceptual model of DNN

Results & Discussion

Usage of covariates in generating gridded climate data allows modeling of **local climate effects** that are not included in global interpolation products that only use latitude, longitude, and elevation for interpolation.

For example, **rain shadows** and precipitation due to **orographic lift** on the leeward side of mountains are generated by the machine learning model, as can be seen in **Fig 3**. In this example, monsoons come from the south-east for the month of January, leading to precipitation being heaviest on the leeward facing slops, just below the top of mountains. Such effects are typically only modeled by sophisticated expert systems, such as PRISM from Oregon State University, developed for the United States (Daly et al 2008).

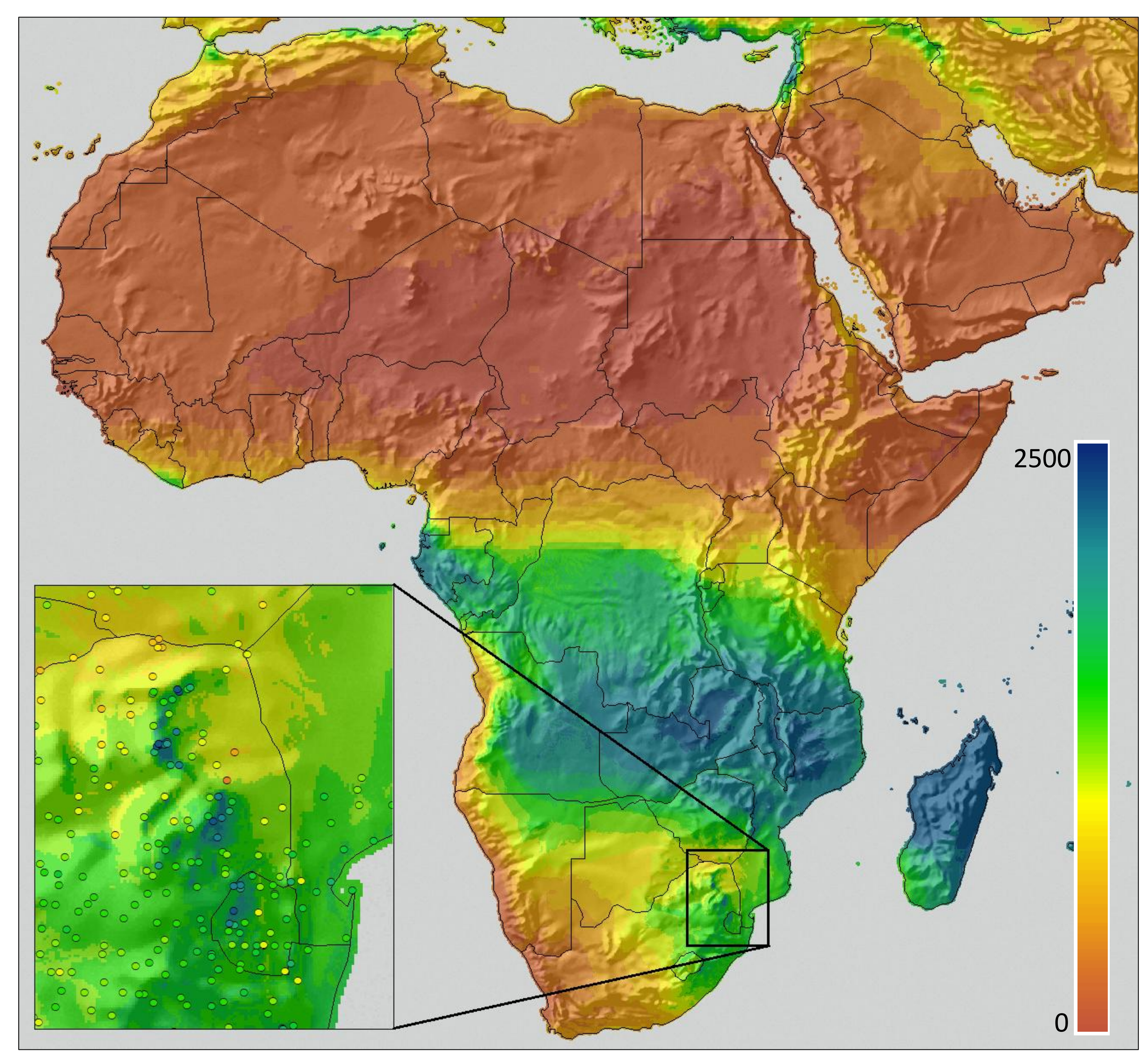

Fig 3: Interpolation of Prec01 (mm)

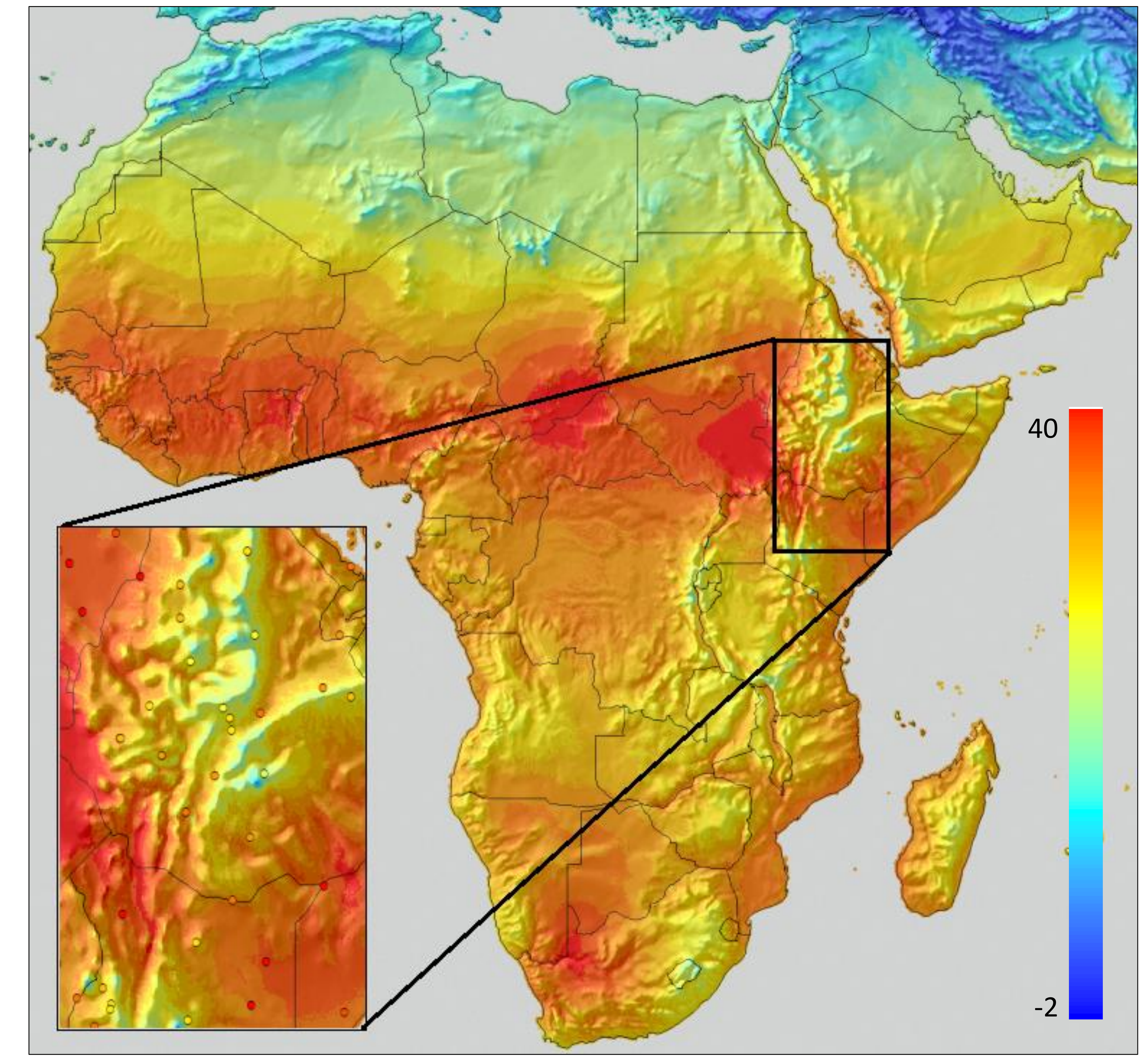

Fig 4: Interpolation of Tmax01 (°C)

In **Fig 4**, the DNN is able to capture the variation in maximum temperature (January) influenced by elevation, slope exposure and local lake effects for example in the Ethiopian highlands. High temperatures in this region (horn of Africa) are also influenced by the dry Harmattan and monsoon winds from the Arabic Peninsula.

References

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