A Machine Learning emulator of JULES soil moisture: Applications to African drought

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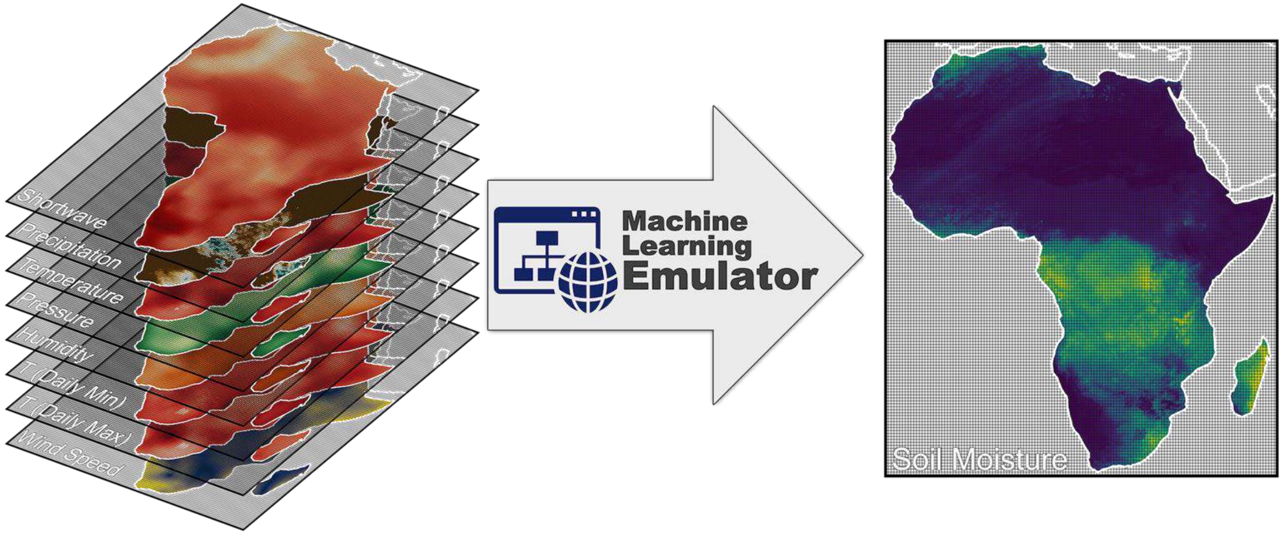
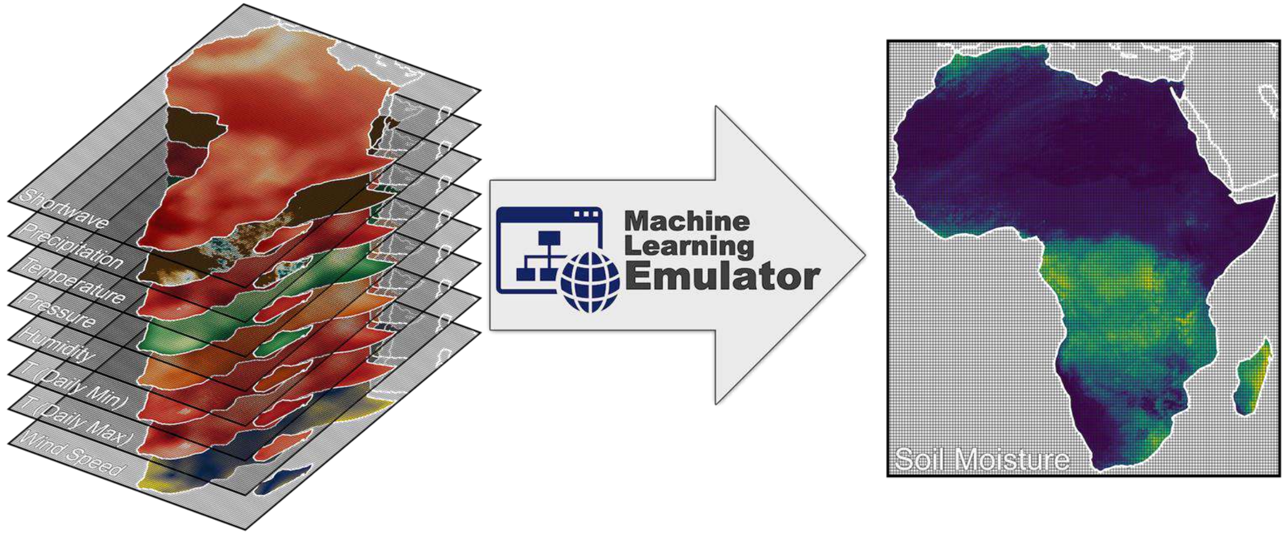
Machine Learning Emulation

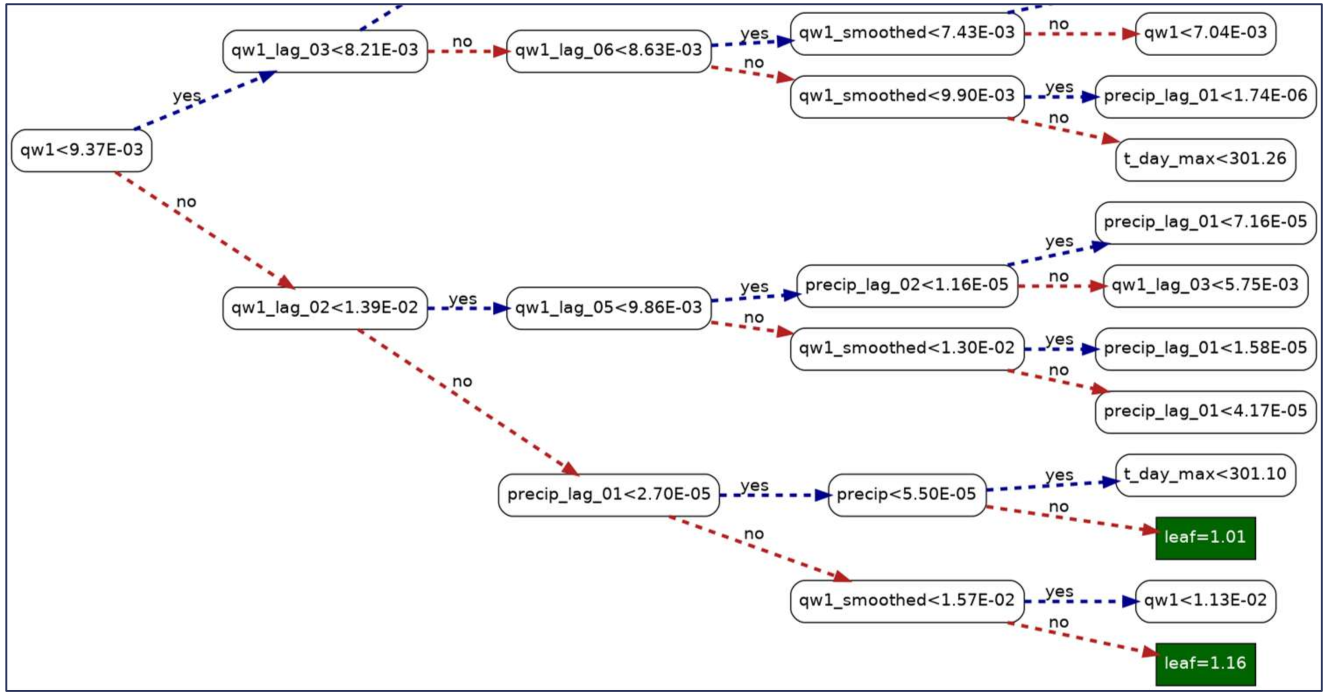
- **Key Question**: Can we emulate JULES soil moisture with a simple/fast machine-learning based algorithm?
- **Requirements and Objectives**:
  - Successfully develop emulator for African soil moisture
    - Needs to be fast and light-weight
    - Capable of running in a Jupyter Notebook and/or in the cloud
  - Assess emulator performance vs JULES simulations
  - Apply emulator to ISIMIP-driven climate scenarios to allow exploration of climate responses



Machine Learning Emulation

- We tested a **range** of machine learning methods:
  - Support Vector Machines, Penalised Regression, Decision Tree Methods
  - **All** worked (surprisingly) well but XGBoost has best performance
- The **Extreme Gradient Boosting** (XGBoost) algorithm
  - Output value of a single tree is determined through succession of **specific value tests** applied to input variables.
  - Gradient descent is used to determine which set of possible trees would **minimise the prediction error**
  - Nonlinear functions can be represented as a large **ensemble of trees** to cover a range of different scenarios.





Emulating JULES simulations driven by TAMSAT/CRU-NCEP data

Training data selection

- To train and test the emulator, JULES simulations of African soil moisture were made between **1999-2020** using **TAMSAT (precipitation)** and **CRU-NCEP (temperature)** as input data

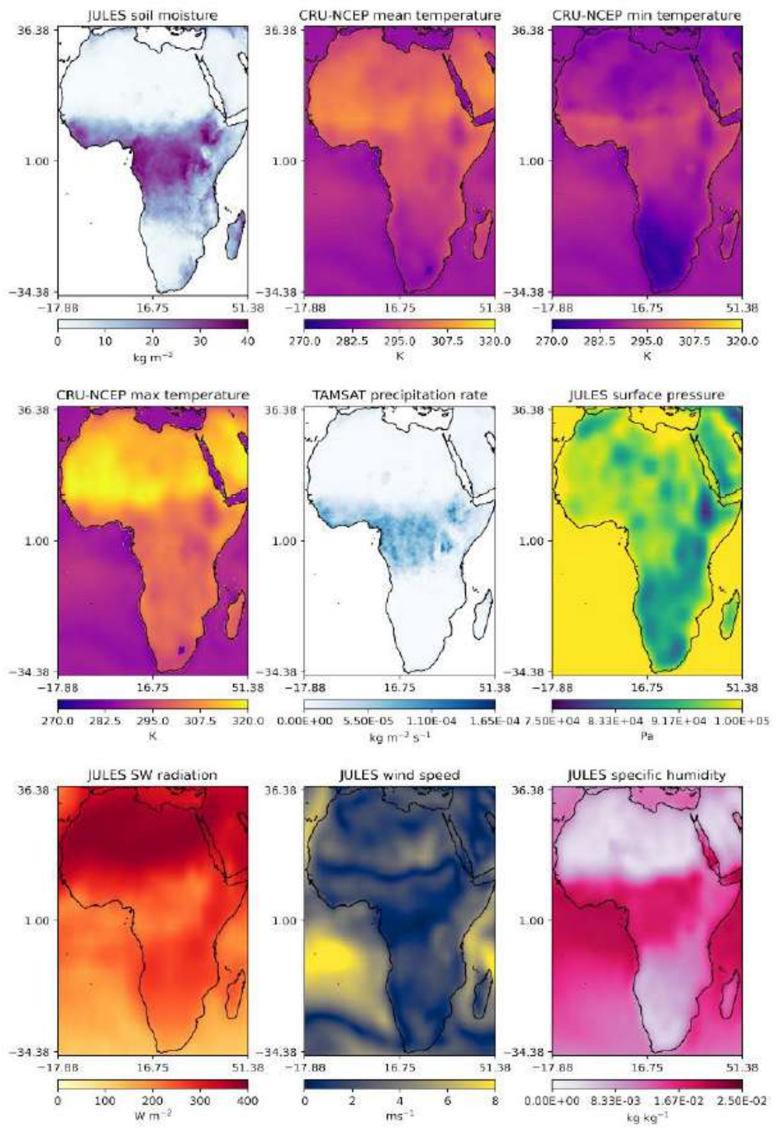
- **2000-2019** used as **training** data, while **2020** reserved for **validation** only

- Initially, **26 variables** were used as training data, taken from the following daily mean variables from the JULES output:

  - Temperature (also daily minimum & maximum)
  - Downward shortwave solar radiation
  - Precipitation
  - Specific humidity
  - Surface pressure
  - Wind speed

- To introduce memory of soil moisture dependence on seasonality and prior weather conditions, we also included:

  - 20-day smoothed temperature, specific humidity, and precipitation
  - 1-7 day lagged specific humidity and precipitation



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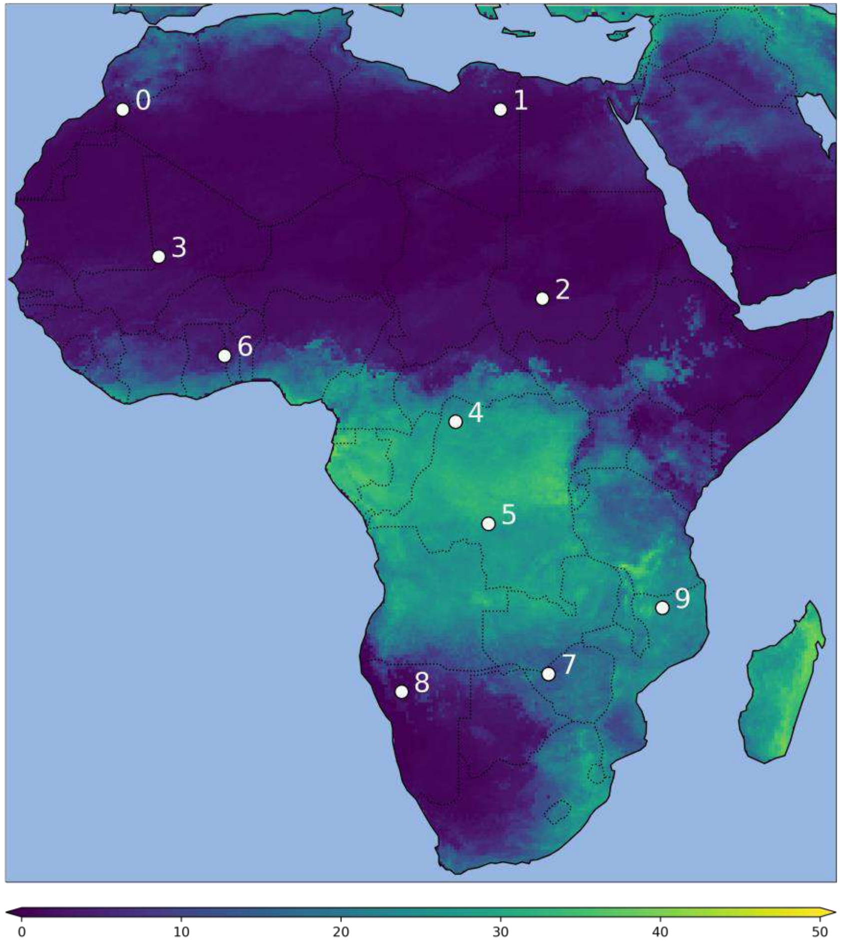
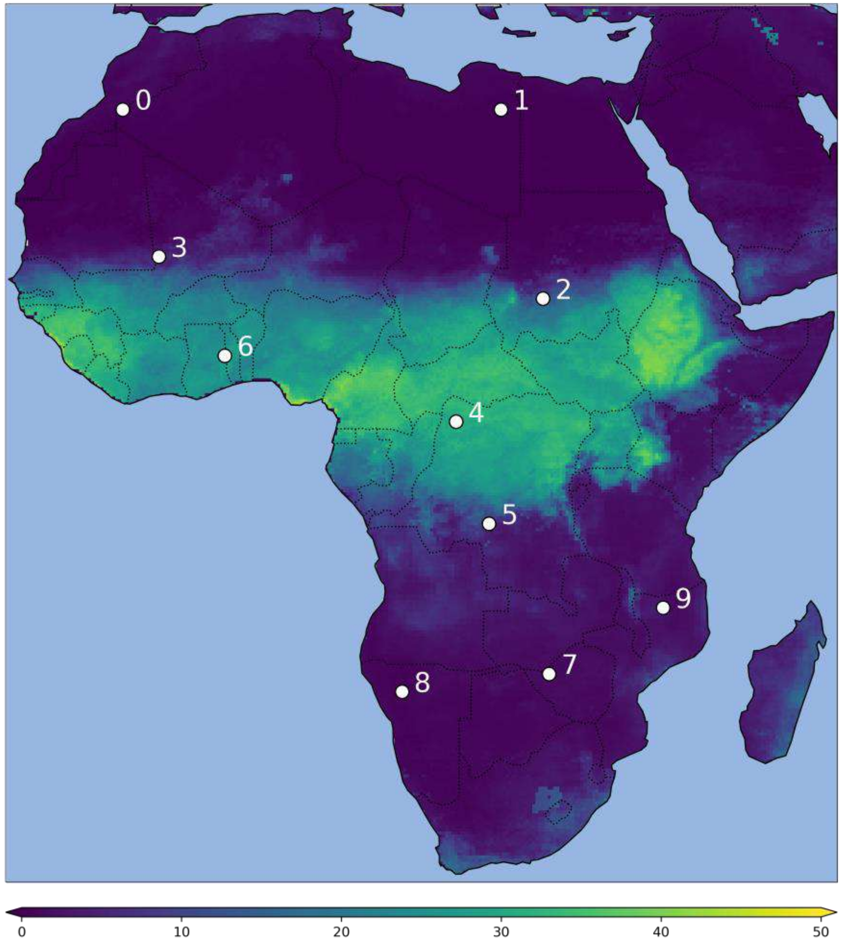
Training data needs to be representative of all possible African climates – sample data from 10 grid cells



JULES Soil Moisture [kg/m^2] for 2019-03-01



JULES Soil Moisture [kg/m^2] for 2019-08-01

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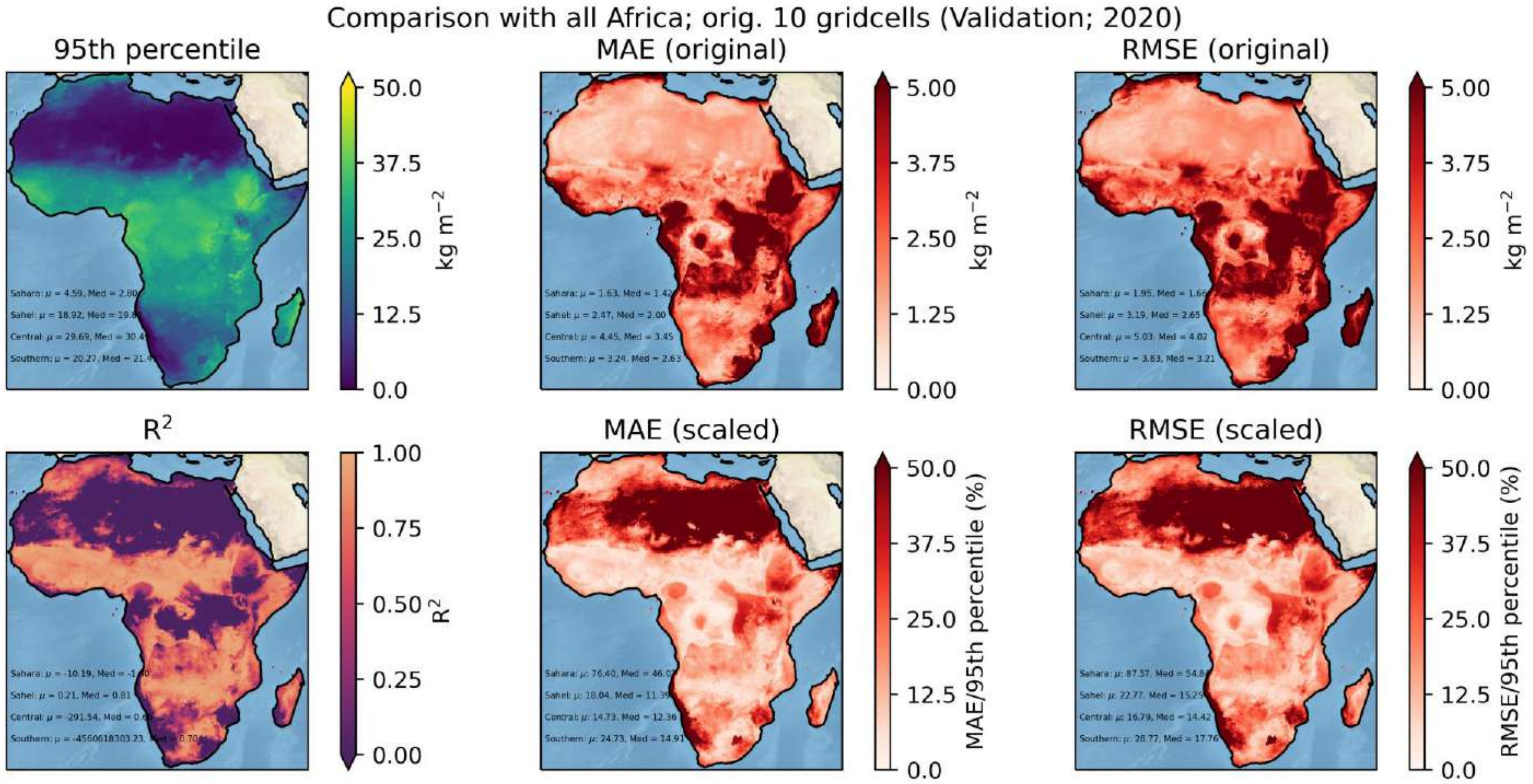
*Initial results trained with **only 10 grid points** demonstrated good overall agreement, but poor performance over the Sahara and Southern Africa*



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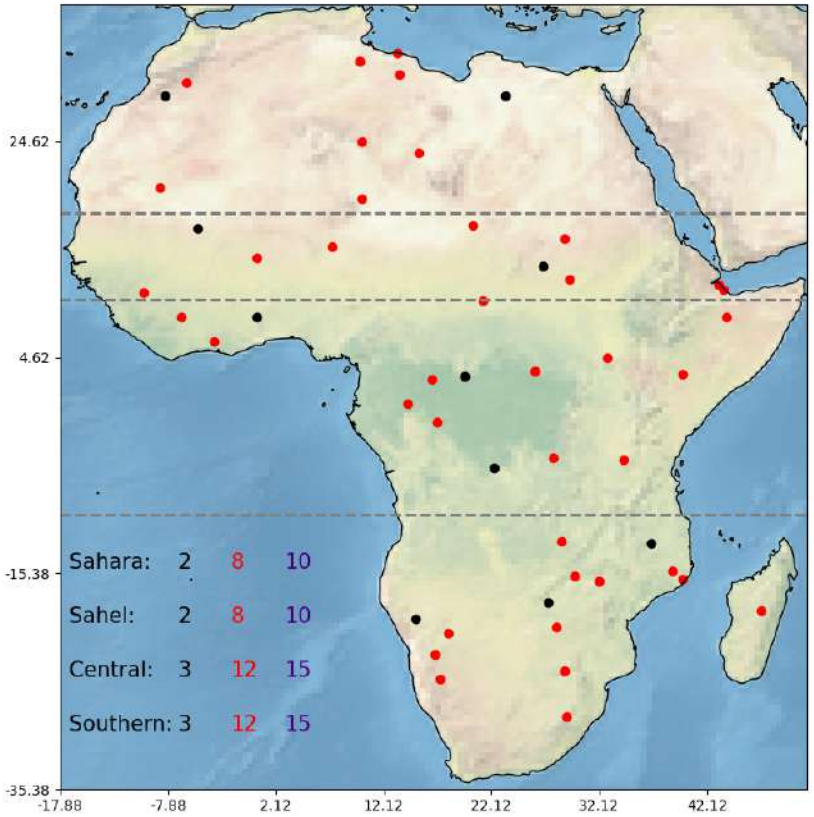
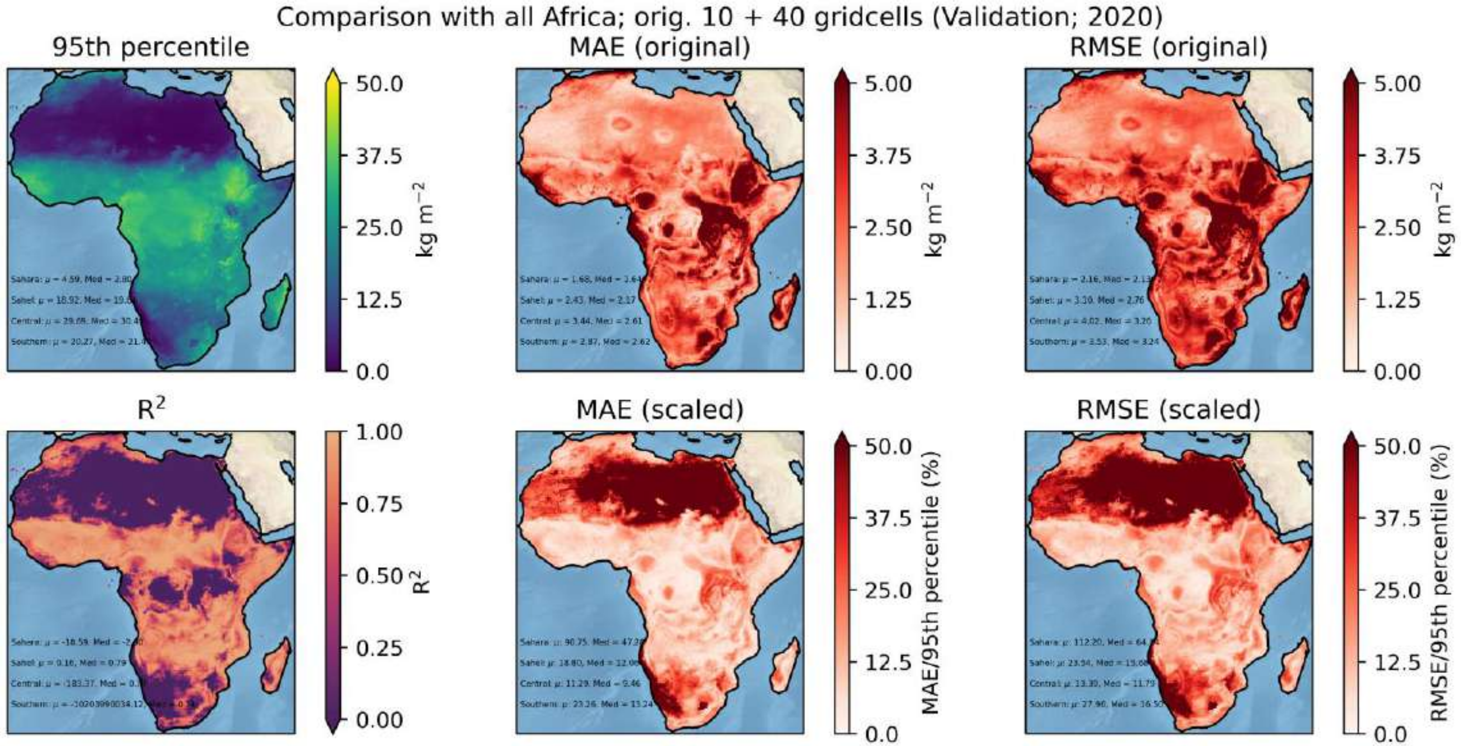
Emulating JULES simulations driven by TAMSAT/CRU-NCEP data

Adding more grid cells to training dataset helps to improve emulator performance…

Tested 10, 50, 200 and 1000 grid cells in training dataset





50 training grid cells

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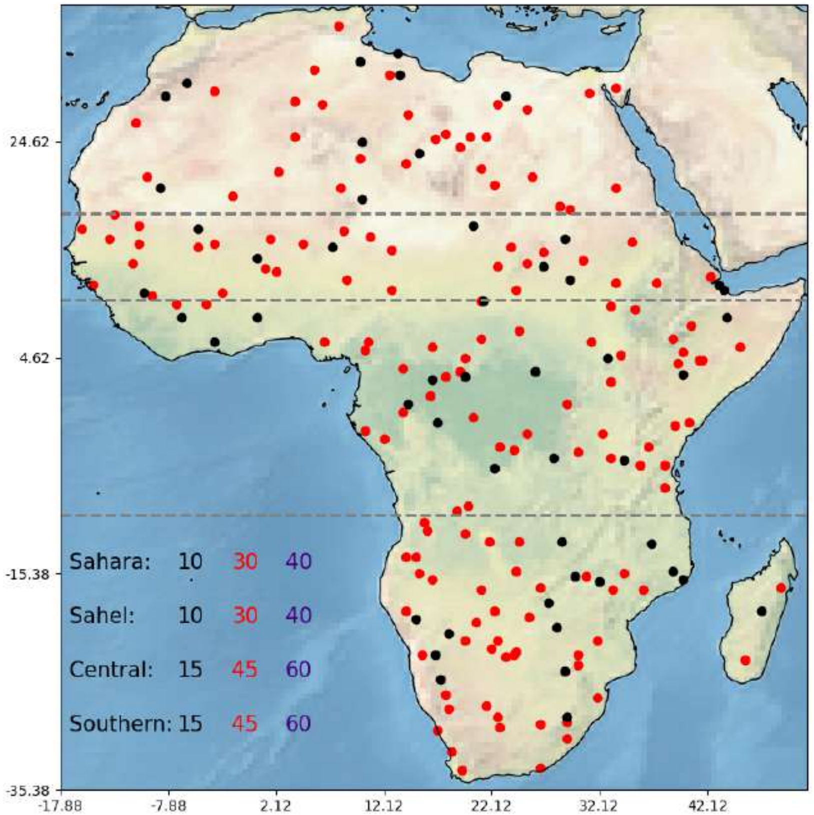
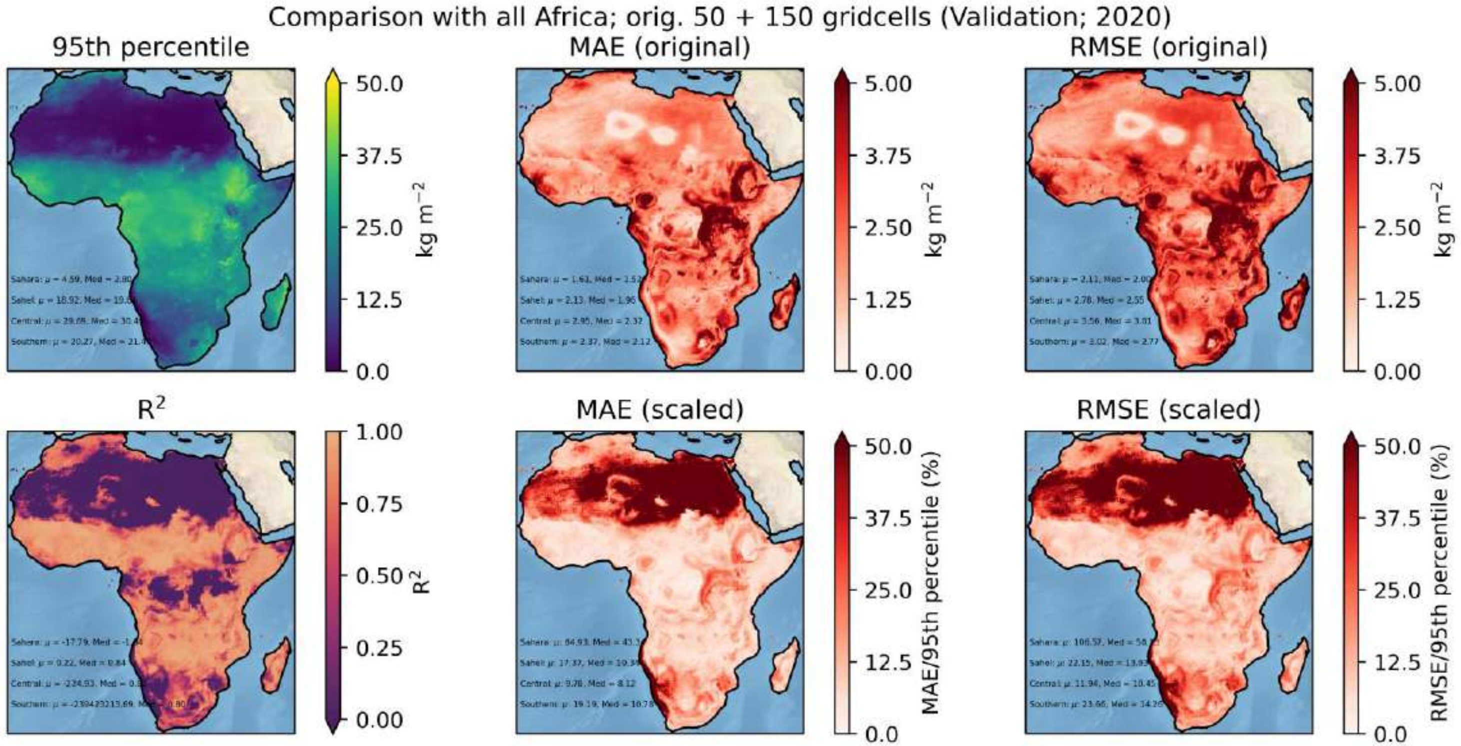
Adding more grid cells helps to improve emulator performance… to an extent





200 training grid cells

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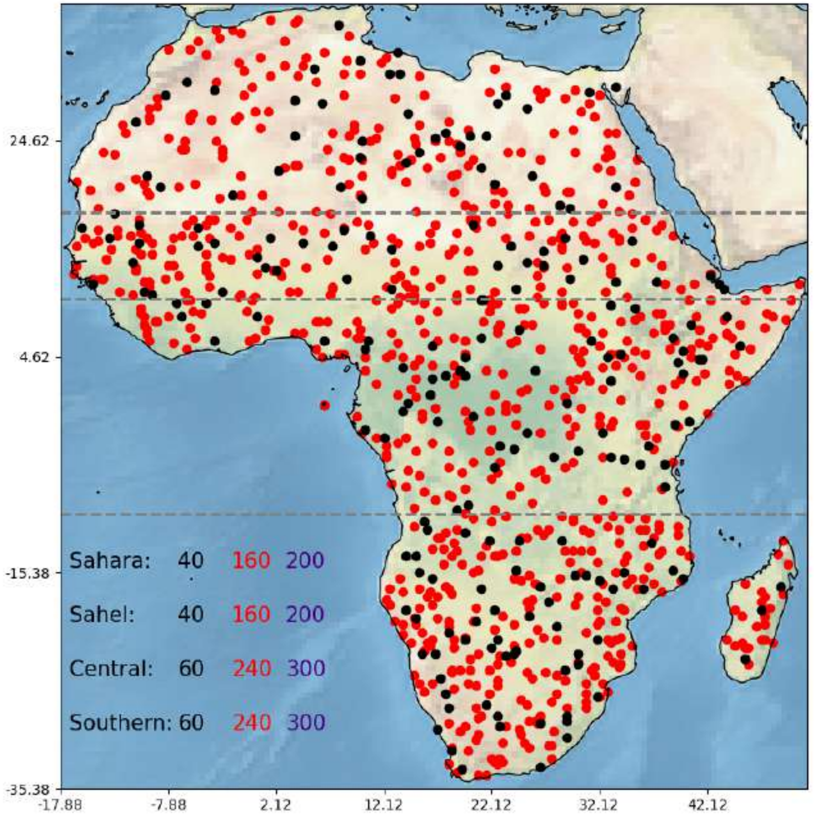
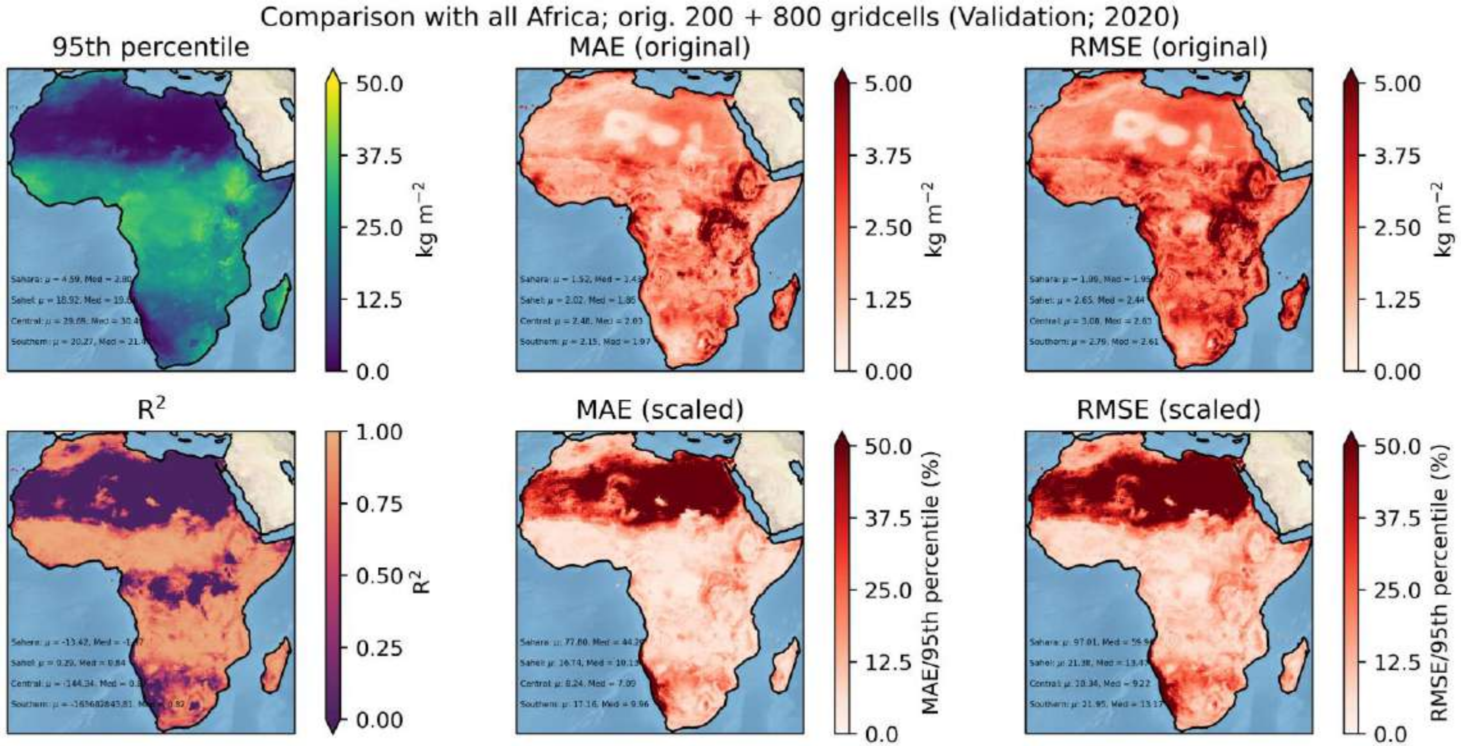
Adding more grid cells helps to improve model performance… to an extent





1000 training grid cells

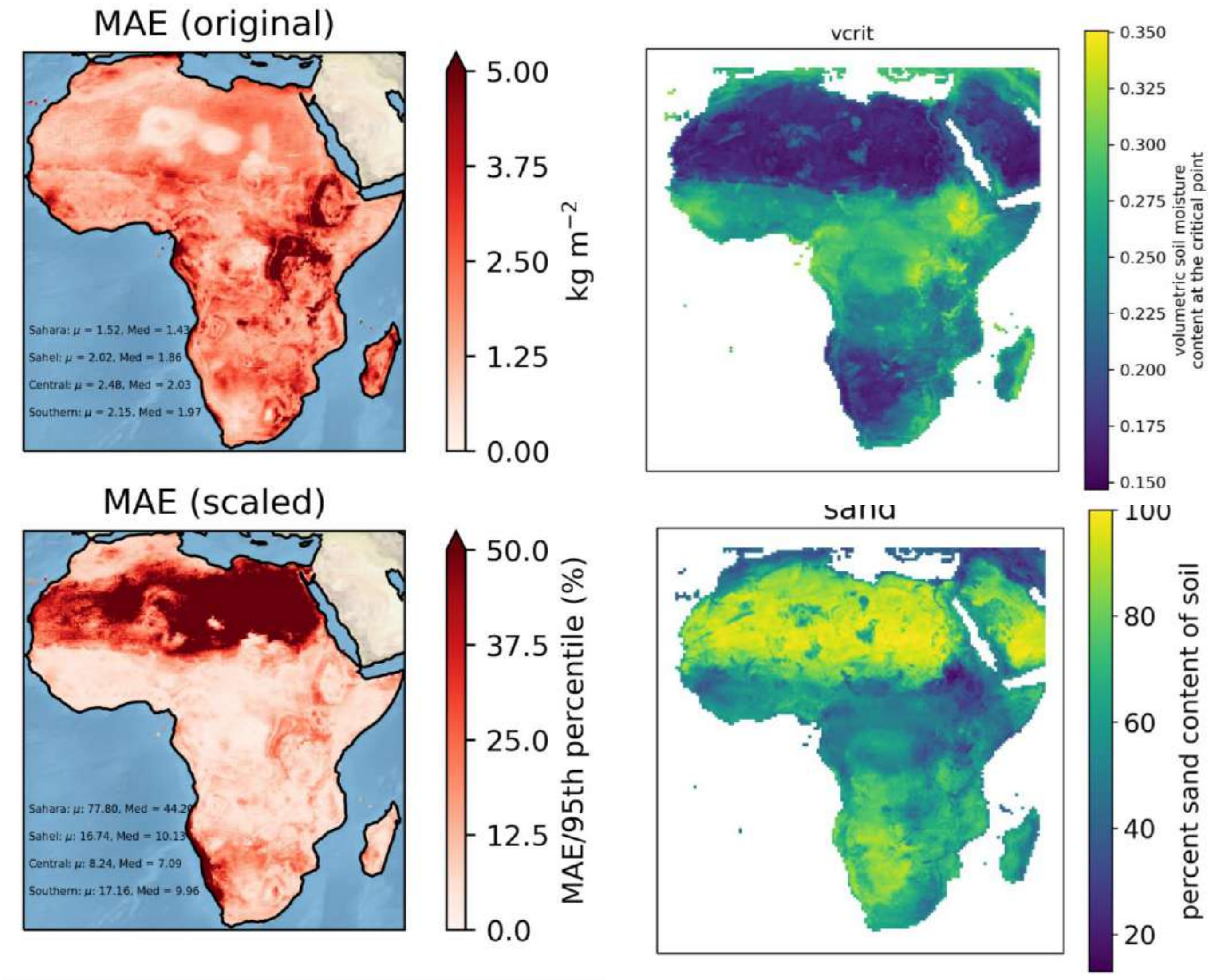
Emulating JULES simulations driven by TAMSAT/CRU-NCEP data

Update training dataset with ancillary information

- Despite improved accuracy, the overall model performance is still hampered by poor agreement over the Sahara and Namibian deserts, and savannah in Southern Africa – **Does the emulator need contextual information too?**

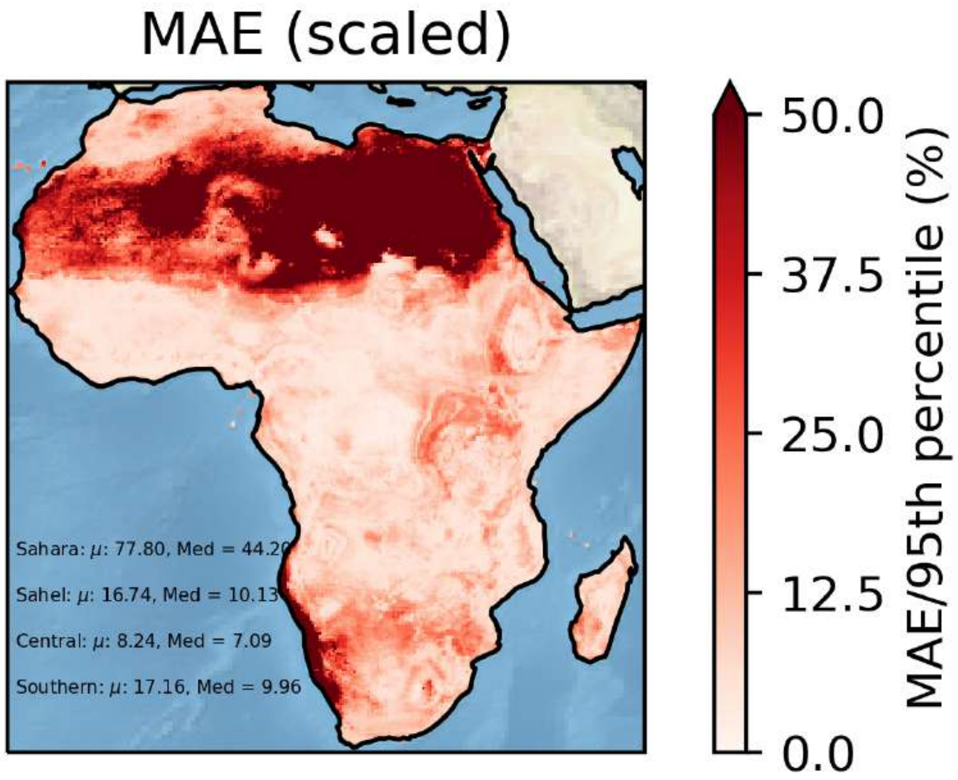
- Our biases have **similar patterns** to some of the ancillary data...

- Solution: Update training dataset with time-invariant JULES **ancillary variables** for each grid cell:
  - Soil type coverage
  - Soil bulk density
  - Vegetation type coverage
  - Soil carbon storage
  - Topography
  - Soil hydrological information

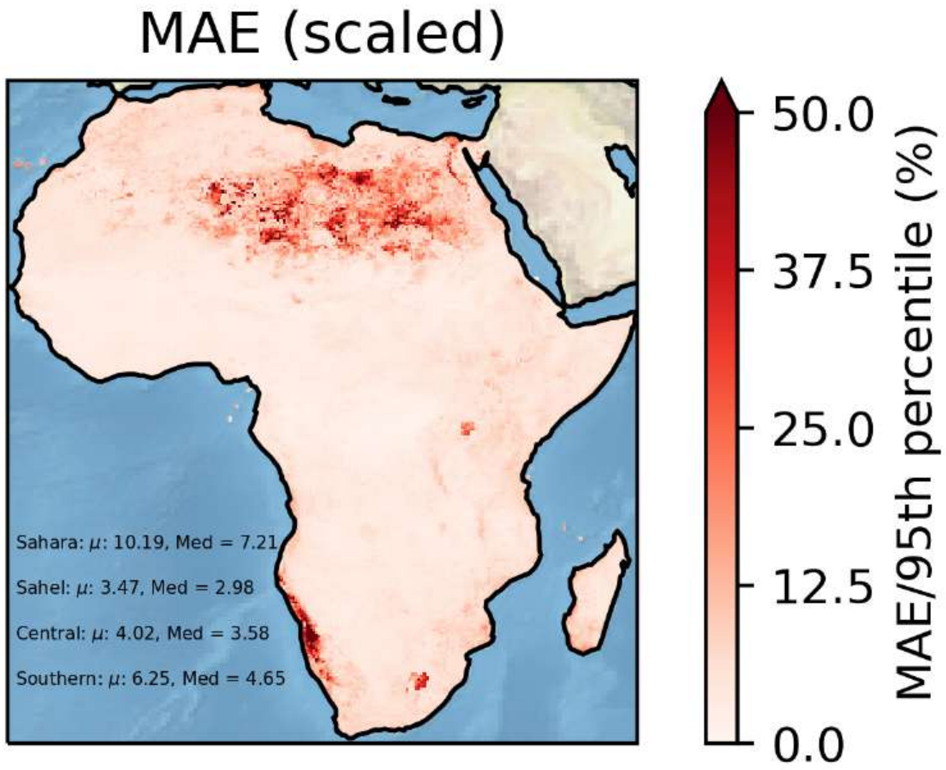


Emulating JULES simulations driven by TAMSAT/CRU-NCEP data

Adding ancillary information to training dataset greatly improves emulator performance



No ancillary data



With ancillary data

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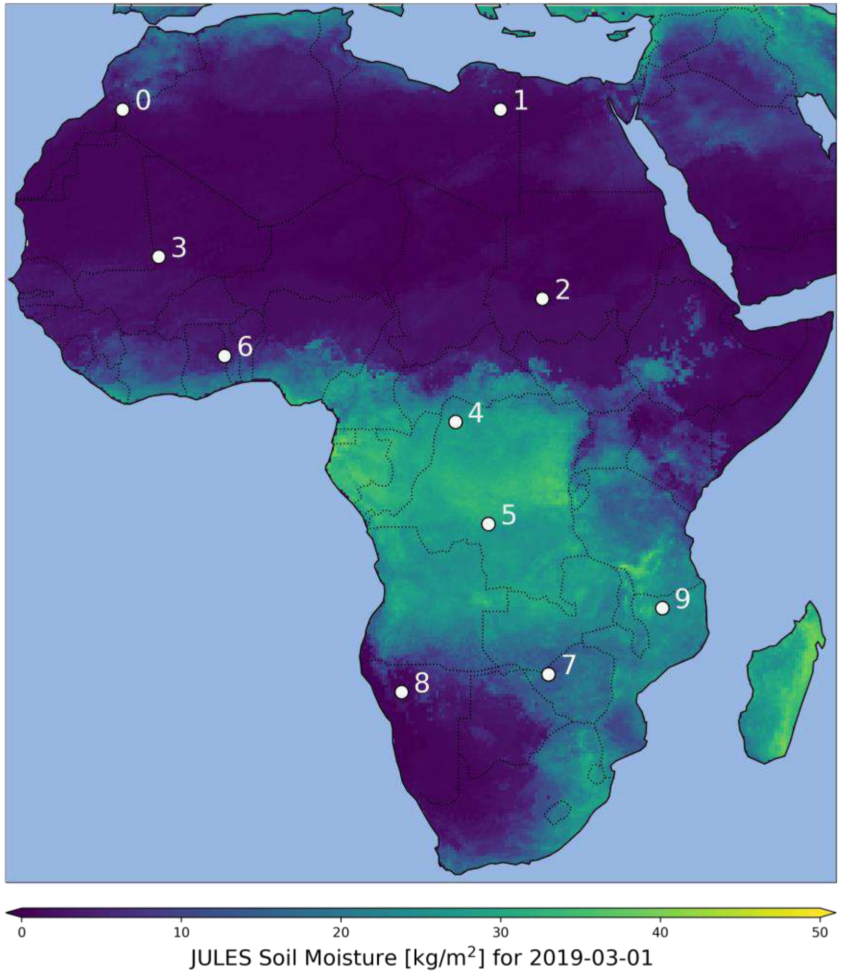
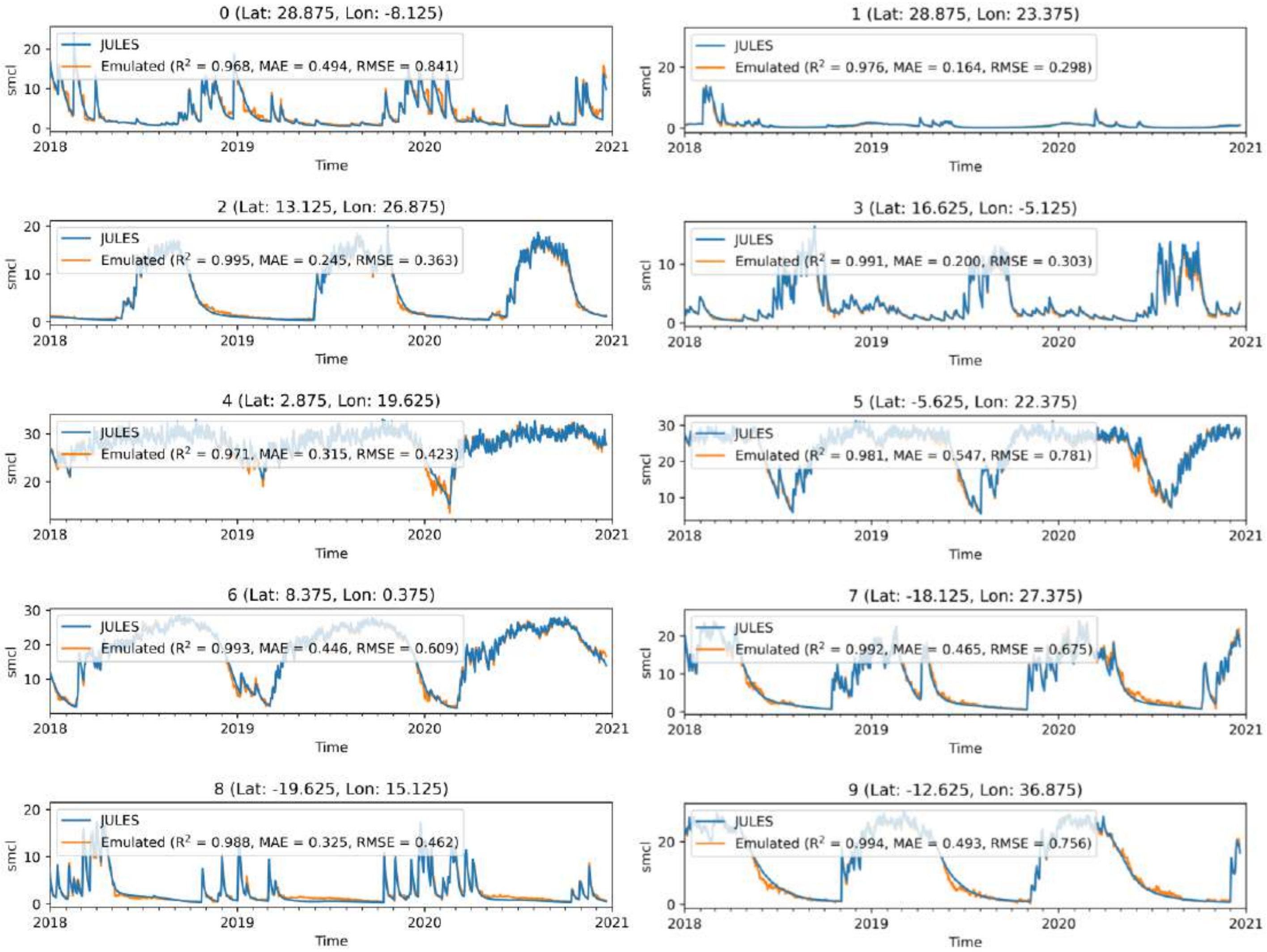
The emulator also shows excellent temporal agreement with the original JULES soil moisture

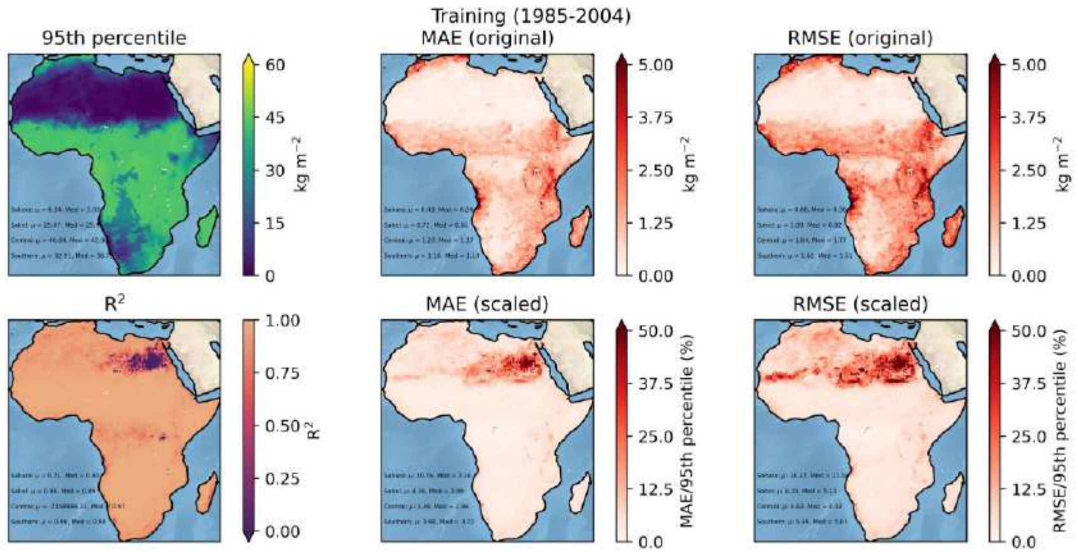




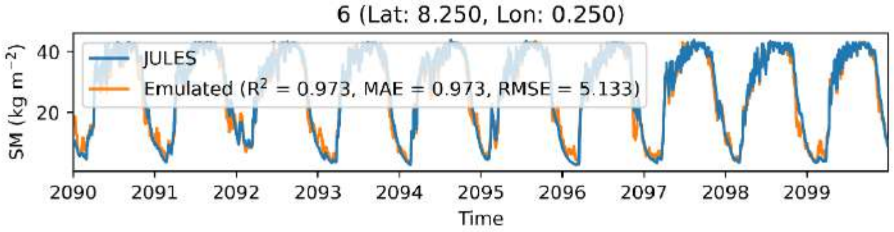
Emulating JULES forecasts using ISIMIP climate scenario data

Emulator retrained using ISIMIP historical data (1985-2005), then applied to predict RCP scenarios from 2006-2099

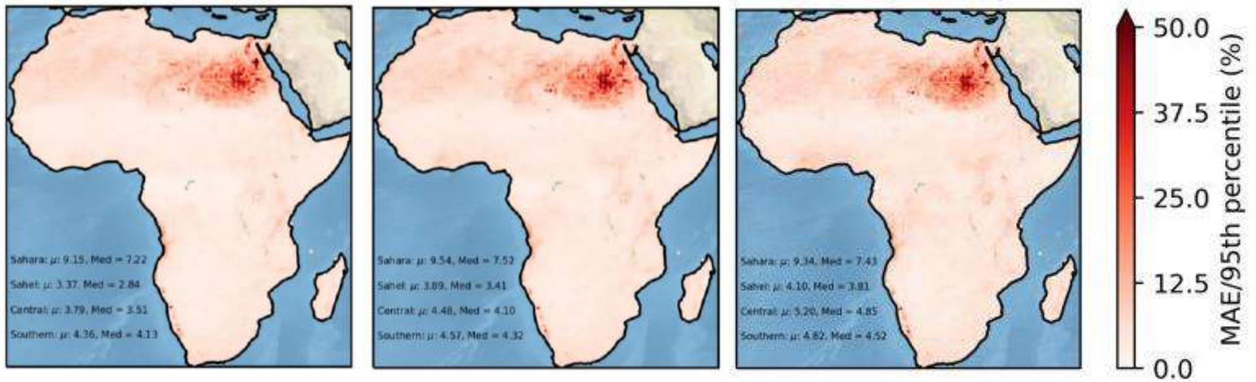
- ❑ JULES ISIMIP setup different than historical setup (resolution, ancils, etc) so model retrained, including [CO_2] as a feature
- ❑ Emulator used to predict soil moisture for ISIMIP-based RCP **climate scenarios**: RCP2.6 (< 2°C rise), RCP6.0 and RCP8.5 (BAU)
- ❑ For all of Africa, the **error is typically < a few %** after training on 1000 locations (~2% of total grid cells)
- ❑ Emulator reproduces 2006–2099 period simulated by JULES **very well**



HADGEM2-ES, RCP2.6, 2090-2099



MAE from emulating ISIMIP simulations



RCP 2.6 **RCP 6.0** **RCP 8.5**

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Summary and Conclusions

- **Successfully** developed machine-learning based emulator for JULES soil moisture
- Initial testing of various methods **all** gave good results but settled on XGBoost algorithm
- Emulator is **VERY** fast/light-weight (runs in a few ms per grid cell per year)
- Performance metrics (MAE and RMSE) used to assess performance over whole of Africa
- Emulator performance improved iteratively by:
  - Adding in more training **locations** (better sampling of feature-space)
  - Adding in more training **features** (e.g. soil ancil data)
- Final model performs **extremely well**
  - Error **typically < a few %** compared to original JULES simulation
- Model retrained on JULES ISIMIP historical simulations
  - Required as ISIMIP suite has different settings (different ancils, different resolution, etc)
  - Performance of ISIMIP simulations **very good** across multiple RCPs
  - Emulator can be used to **quickly explore** JULES response to different climate scenarios
- Lots of potential for expanding
  - Extend to other JULES processes
    - Rob/Tristan have proposal under consideration to do this for GPP
  - Extend to other land surface models and cross-compare
  - Do some interesting science with it!

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