Learning to forecast vegetation greenness at fine resolution over Africa with ConvLSTMs

C. Robin[1], C. Requena-Mesa[1], V. Benson[1], L. Alonso[1], N. Carvalhais[1,2], and M. Reichstein[1,2]

MAX PLANCK INSTITUTE FOR BIOGEOCHEMISTRY

Introduction

Application context

Drought is the **main disaster** type affecting **African population**, and causing the most deaths. **Early warning system** is an effective way, encouraged by IPCC, for **disaster risk reduction**. One way to provide early warning is to **examine the effects of drought on vegetation**.

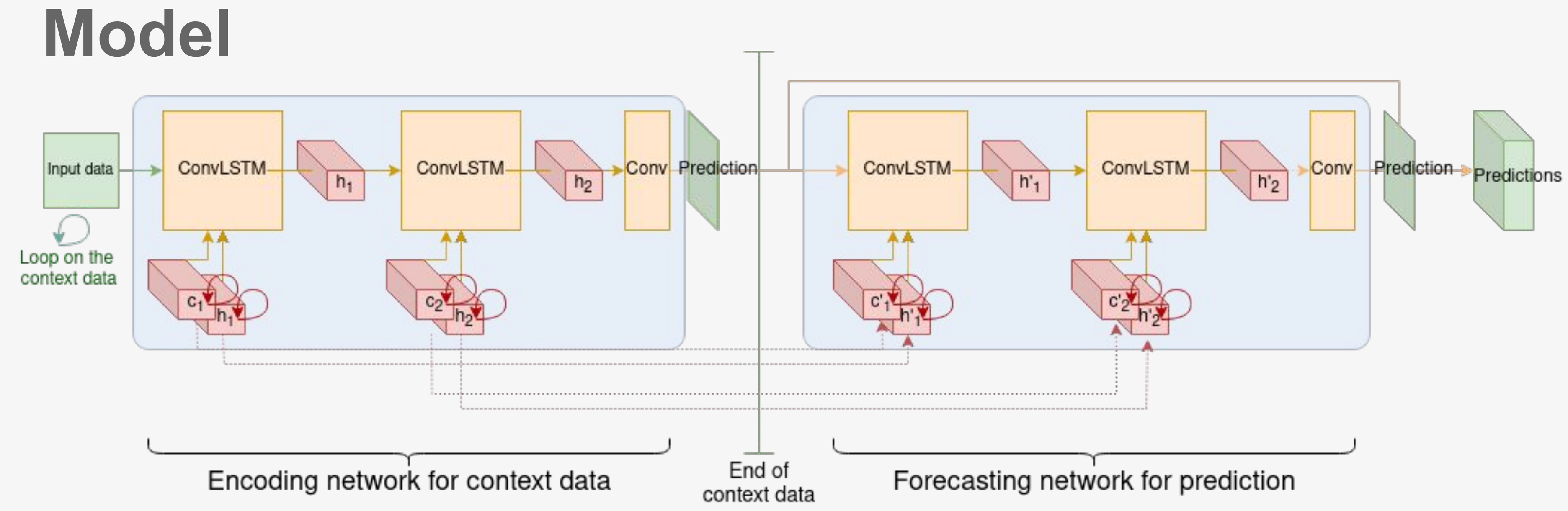
Objective

The **land surface forecasting task** as a strongly guided video prediction task where the objective is to **forecast** the **vegetation evolution** at very **fine resolution** using **topography and weather variables to guide the prediction**.

Modelling challenge

- **State of the vegetation** depends on **weather** and **environmental conditions**.
- **Past states of the vegetation matters**
  - Ecological processes take place on multiple time scales, with instantaneous and time-lagged effects.
- **Spatial context matters**
  - The spatial characteristics and environmental factors in the surrounding area, (*e.g.* a river) have a significant influence on the state of the vegetation.

Model



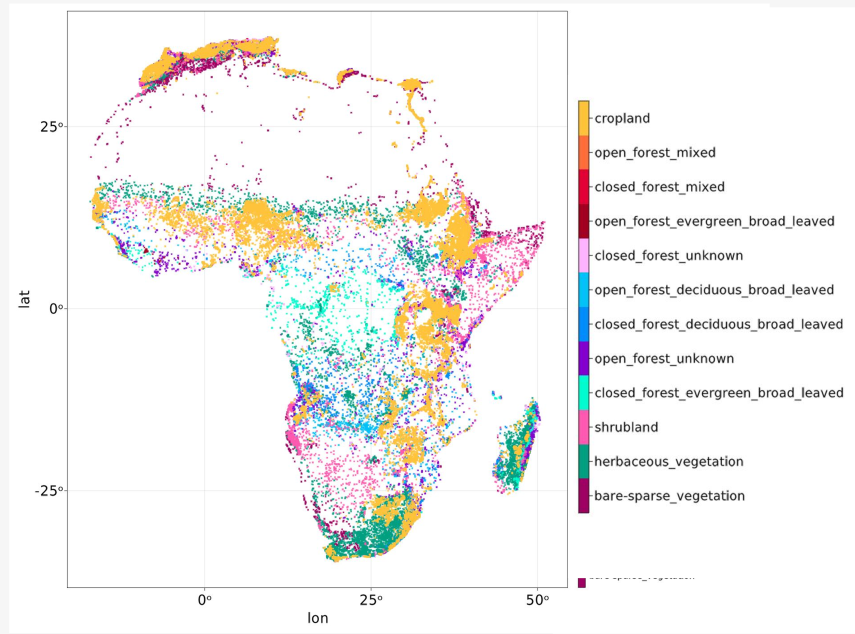
ConvLSTM encoding forecasting architecture

weight initialization
hidden states update

Task

- Forecast:
  - **next 3 month NDVI** (next 10 frames)
- Input variables:
  - **1 year of NDVI** for the context period
  - **topography**
  - **meteorological variables**
    - Guide during the context period but also during the prediction period.

Normalized Difference Vegetation Index (NDVI): *Satellite proxy for vegetation state based on red and infrared bands.*

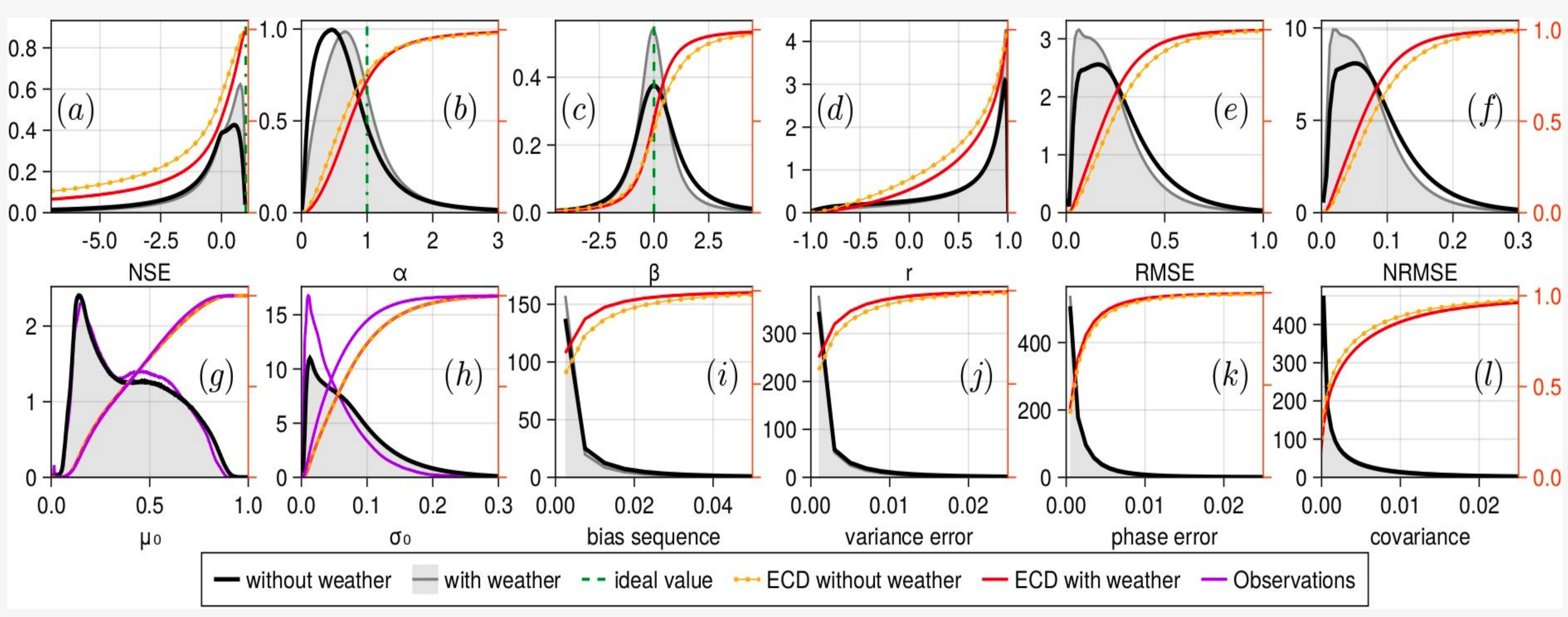


Location of samples in Africa

Results

Baselines and ablation

- **Constant baseline:** predict the last NDVI seen during the context period.
- **Previous season baseline:** predicting the NDVI during the same season, one year ago.
- **ConvLSTM w/o weather:** ablation model without weather information to see how much the model learns from only the seasonal cycle.



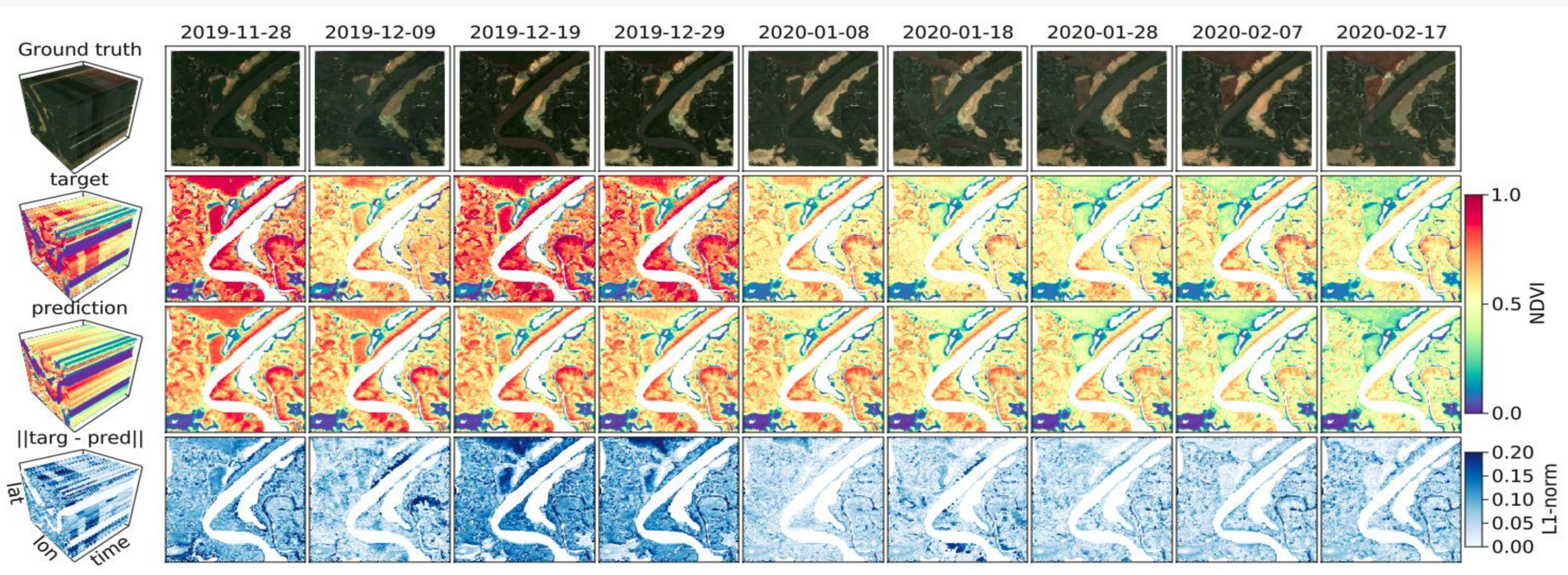
Probability density plots of pixelwise test set performance. *ECD is the empirical cumulative distribution function. 50% of the pixels in our model reach NSE greater than 0, while this is only 35% in the ablation without weather.*

Model	$RMSE\downarrow$	$NSE\uparrow$	α	β	r
Constant baseline	0.3365	-1.3922	0.0	0.1559	0.0
Previous season baseline	0.2937	-1.0561	1.0169	-0.0084	0.5504
ConvLSTM without weather	0.2331	-0.3356	0.6512	0.1699	0.7348
ConvLSTM (ours)	**0.1882**	**0.0270**	0.7570	0.0628	0.8024

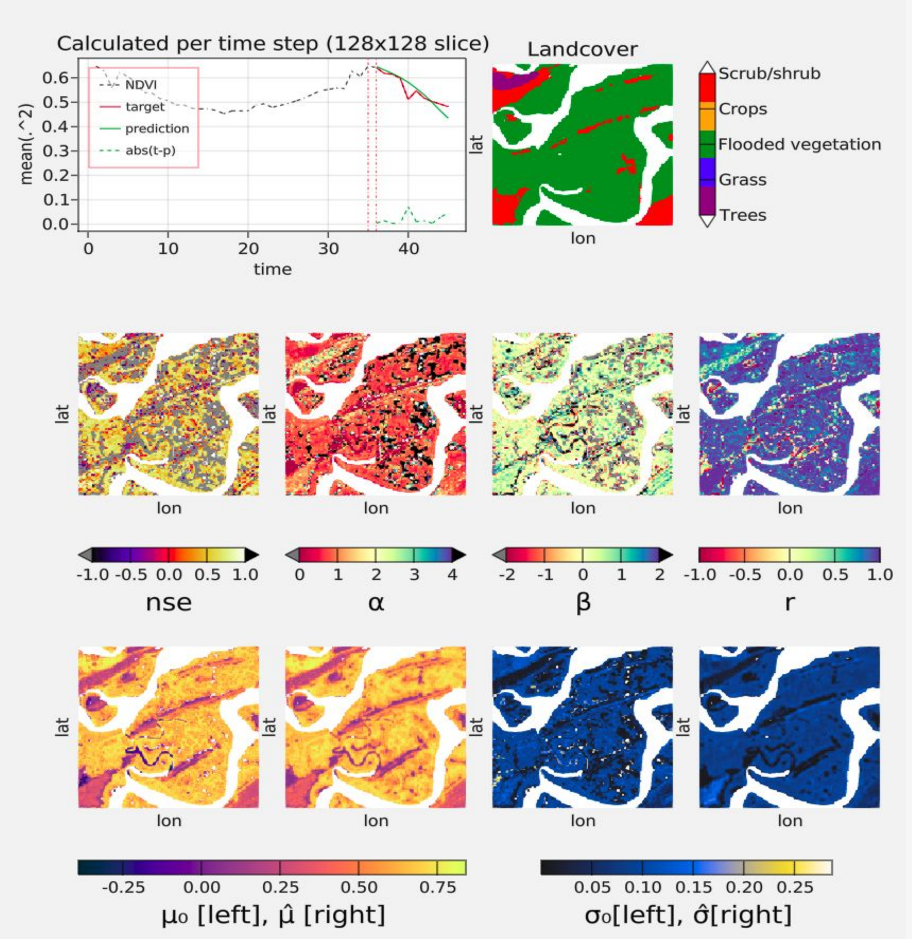
Test set model performance (median values).

- Our ConvLSTM model **beats the baselines** by a large margin in **both RMSE and NSE.**
- Our model makes use of the **topology and weather variables in order to achieve its effectiveness** (not only past observations).
- An ablation of it not using weather covariates performs worse than our model using them. This supports the intuition that **weather should be driving vegetation dynamics.**

Single sample forecasts



Top. Model prediction every 10 days.
For each frame, RGB satellite imagery, NDVI target, NDVI predicted by the model and L1-norm between the target and the prediction.



Left. NSE decomposition.
The NSE is close to its ideal value for the scrubs area. For the tree area, the NSE and the correlation is lower (probably due to cloud). The NSE is low in the flooded region, the model underestimate the impact of the river on shoreline vegetation.

α is a measure of relative variability
β is the bias normalized by the standard deviation
r is the correlation coefficient
Ideal values:
NSE = 1, α = 1, β = 0, r = 1.

$$NSE = 1 - \frac{MSE}{\sigma_0^2},$$

$$NSE = 2\alpha r - \alpha^2 - \beta^2,$$

$$\alpha = \frac{\hat{\sigma}}{\sigma_0} \qquad \beta = \frac{\hat{\mu} - \mu_0}{\sigma_0}.$$

Conclusions

- We proposed a **ConvLSTM deep learning model to predict vegetation greenness in Africa at high spatial resolution from coarse-scale weather.**
- Our model is a **proof-of-concept of high resolution vegetation modeling in Africa.**
- In an ablation study we confirm **our model is able to extract information from meteorology, spatial and temporal context.**

Email: crobin@bgc-jena.mpg.de
Earthnet Challenge: www.earthnet.tech
Affiliations:
[1] Biogeochemical Integration, Max-Planck-Institute for Biogeochemistry, Jena, Germany
[2] ELLIS Unit Jena, Michael-Stifel-Center Jena for Data-driven and Simulation Science, Jena, Germany

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