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

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NEURAL INFORMATION PROCESSING SYSTEMS

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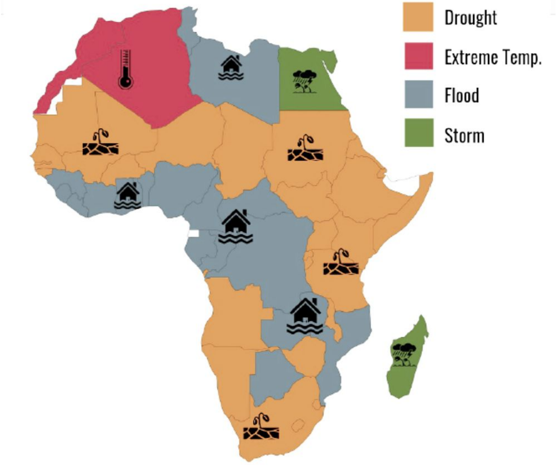
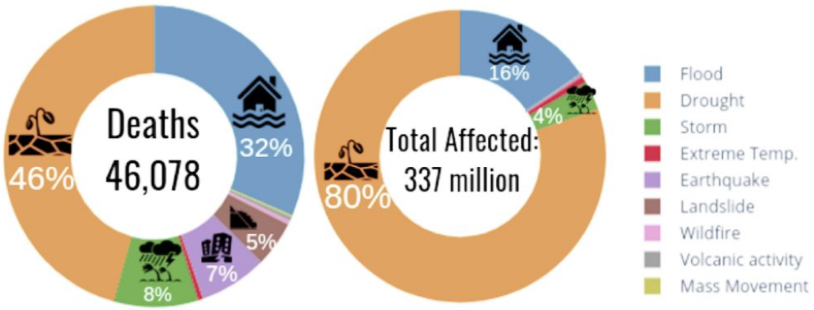
DEEP CUBE

# **Forecasting vegetation evolution** is one way to provide **early warning.**

**Disaster type affecting highest number of people**




**Share by disaster type**

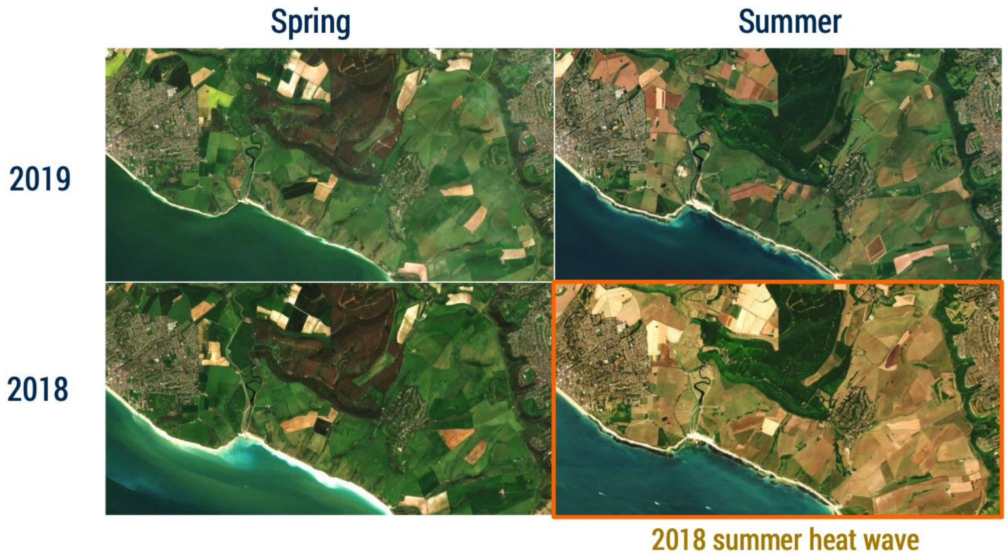



CRED crunch 56, 2019 (www.cred.be)

# Modeling challenge

Linking weather forecasts with their impacts on the surface at high resolution is a challenging task:

- **Spatio-temporal** dynamical system at **high-resolution** with **complex interactions** between drivers.
- Long and short term vegetation **memory effects** and **spatial context effects.**
- **Highly stochastic**, especially around human populated areas and in agriculture.

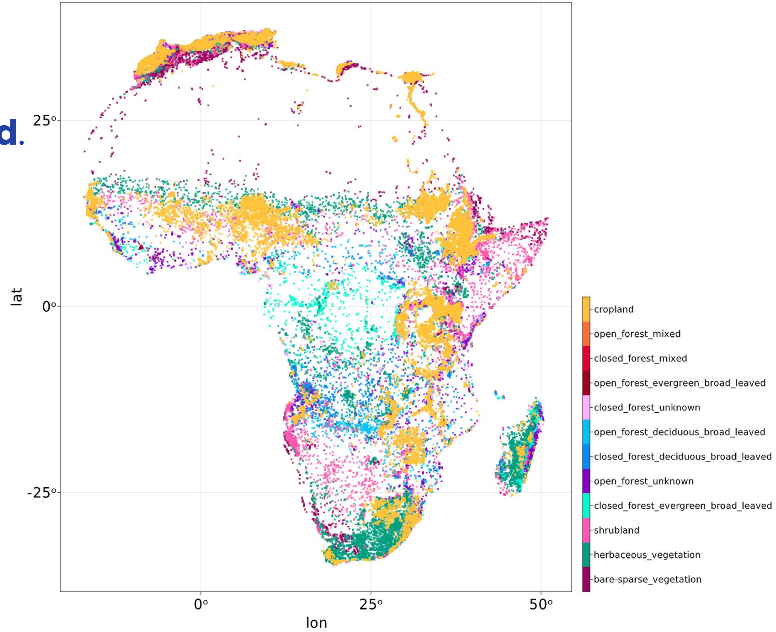


# **Land surface forecasting:**
## a strongly guided video prediction **task**[1]

- **Input variables**:
  - context period**:** 1 year of **NDVI**
  - **topography**
  - **meteorological variables** to guide the prediction during both, **context period and prediction period**.
- **Target**:
  - next 3 month (next 10 frames) **NDVI**

**Normalized Difference Vegetation Index**
Satellite proxy for vegetation state

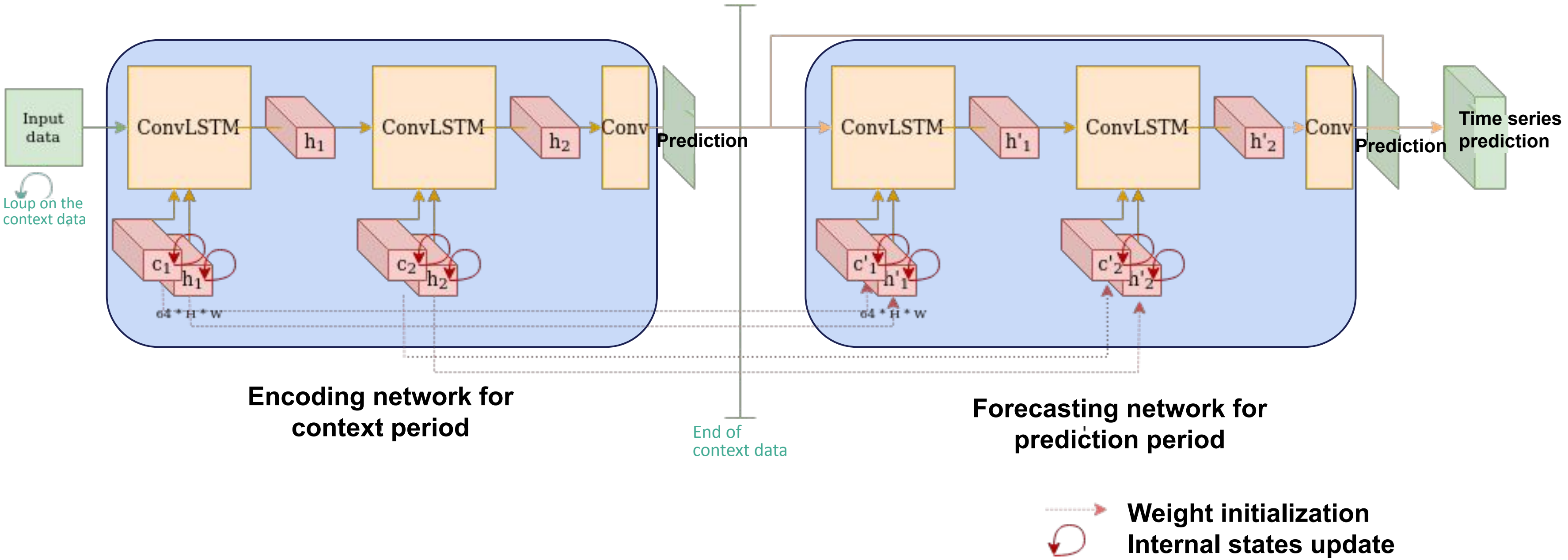
$$NDVI = \frac{NIR - RED}{NIR + RED}$$

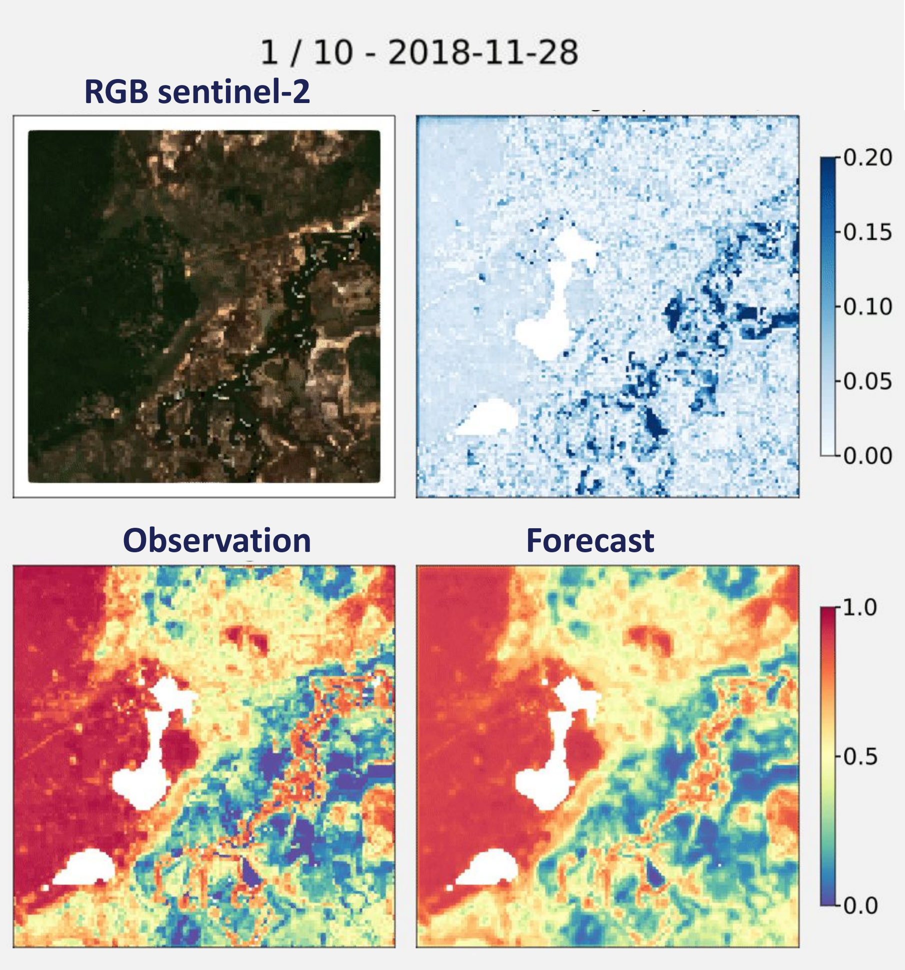


Location of samples in Africa

[1] *Earthnet2021: A large-scale dataset and challenge for earth surface forecasting as a guided video prediction task.* Requena-Mesa & al. (2021), CVPR2021.

# Encoding Forecasting architecture






# Single sample forecasts

- **Forecast close to the target**, especially in the **scrub area**
- Good prediction of **different landcover types** and dynamics.
- weaker prediction of the **specific evolution** of **shoreline** vegetation



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# Results

| Model | $RMSE \downarrow$ | $NSE \uparrow$ |
|---|---|---|
| Constant baseline | 0.3365 | -1.3922 |
| Previous season baseline | 0.2937 | -1.0561 |
| ConvLSTM without weather | 0.2331 | -0.3356 |
| ConvLSTM (ours) | **0.1882** | **0.0270** |

**Test set model performance (median values).**

# Results

| Model | $RMSE \downarrow$ | $NSE \uparrow$ | $\alpha$ | $\beta$ | $r$ |
|---|---|---|---|---|---|
| Constant baseline | 0.3365 | -1.3922 | 0.0 | 0.1559 | 0.0 |
| Previous season baseline | 0.2937 | -1.0561 | 1.0169 | -0.6084 | 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 |

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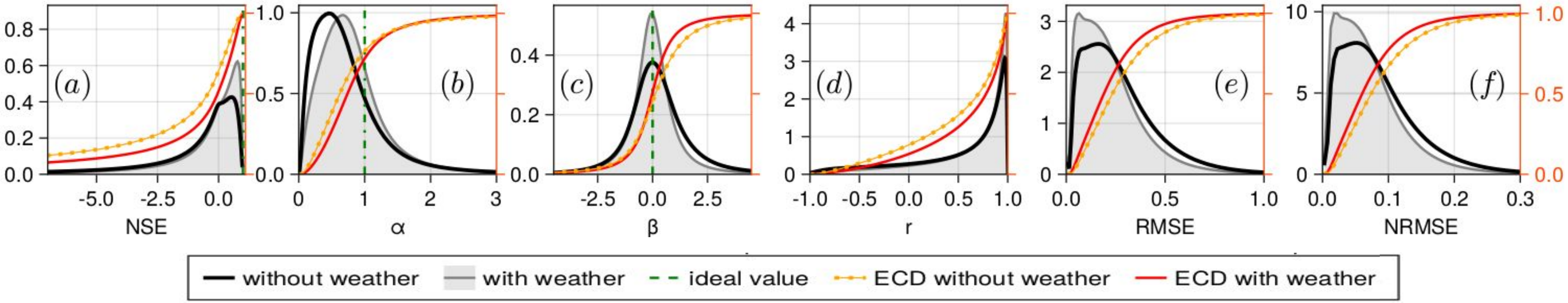


**Probability density plots of pixelwise test set performance.**

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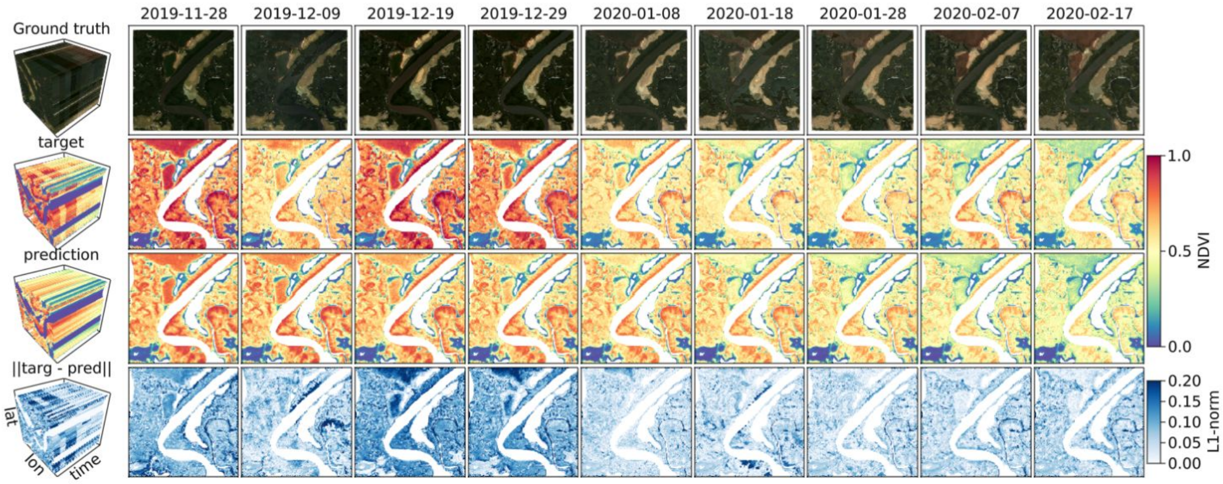
# Conclusion

- 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.**



# Thank you!

**Questions?**

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**Earthnet2021 Challenge:** www.earthnet.tech

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