SPATIALLY FAR, ECOLOGICALLY CLOSE: EVALUATING EXTRAPOLATION ON VEGETATION FORECASTING MODELS

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INTRODUCTION

CONTEXT

We aim to predict **local vegetation responses** to **extreme events** like droughts or heatwaves **using satellite data and machine learning**.

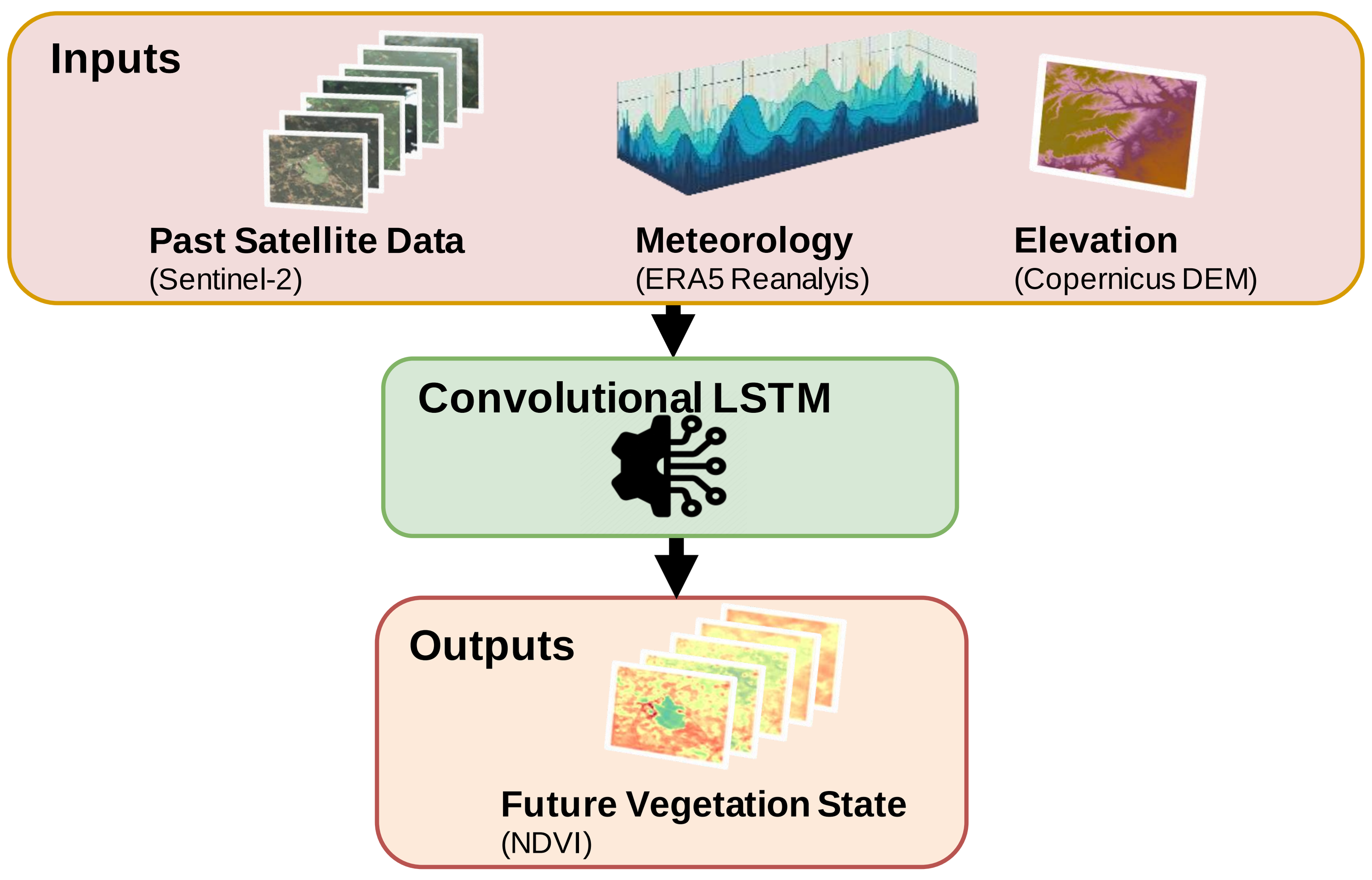

Figure 1. Vegetation Forecasting Task. Future vegetation status is predicted with deep learning models from past satellite imagery, past and future weather and elevation [1, 2].

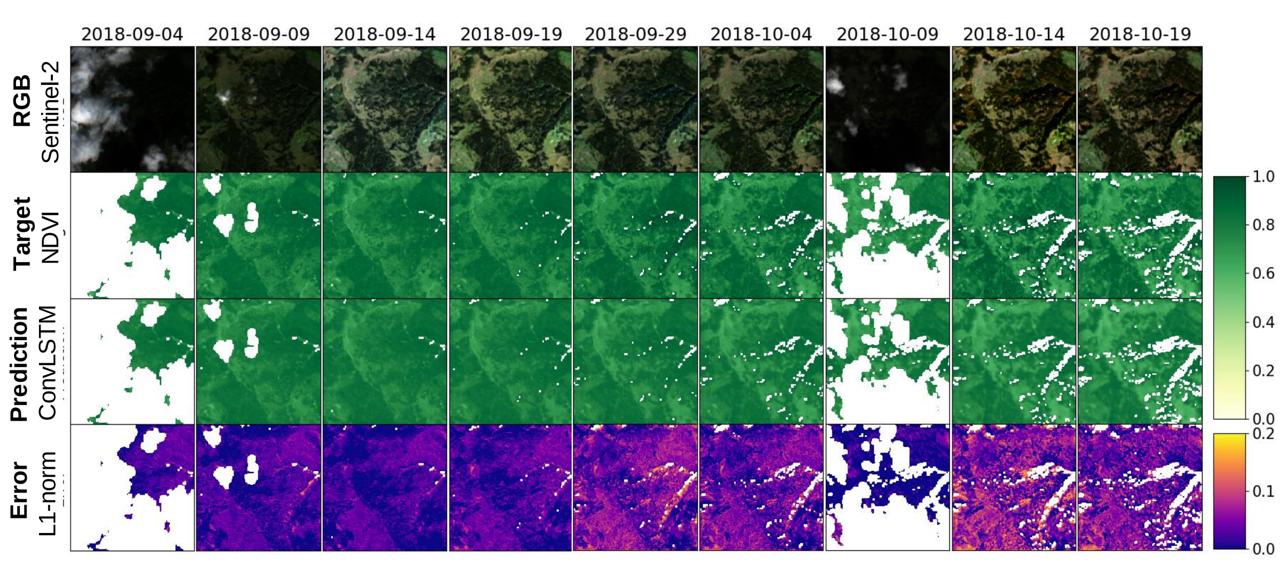

Figure 2. Prediction of a sample. Location: 47°05'24.0"N 8°52'48.0"E, Switzerland.

RESEARCH OBJECTIVE

SPATIAL EXTRAPOLATION

OBJECTIVE

Assess the robustness of spatial extrapolation of a vegetation forecasting model.

PROBLEM

- Model performance may drop in unseen areas due to **distribution shifts** [3, 4].
- It can occur **temporally from climate change** and **spatially from spatial auto-correlation**.
- Evaluation in time is limited by data scarcity, but possible in space.

HYPOTHESIS

Distant areas might be close in the feature space due to **evolutionary convergence,** which can help for generalization in geographical space**.** We group them by **biomes**.

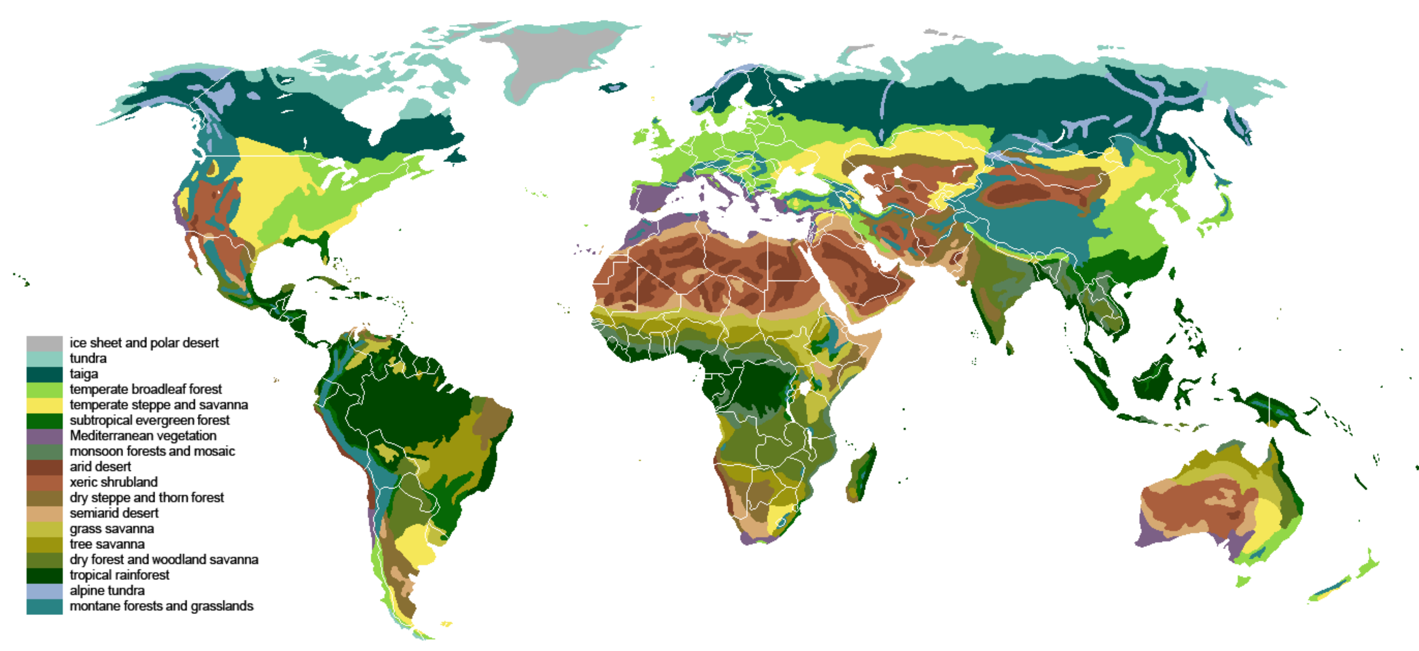

Figure 4. Global biomes map [3]

METHOD

ROBUSTESS IN SPACE

- **GOAL:** We want to evaluate **accuracy on samples spatially far** from the training samples.
- **TWO DATASET SPLITS:** ***"With Africa"*** includes all regions while ***"Without Africa"*** excludes African samples.
- **MODEL:** We trained a **Convolutional LSTM** to predict **NDVI on each data splitting method.** We reproduce each experiment 5 times with different folds.
- **EVALUATION:** We evaluate the **difference of performance** between the 2 splits per biome.

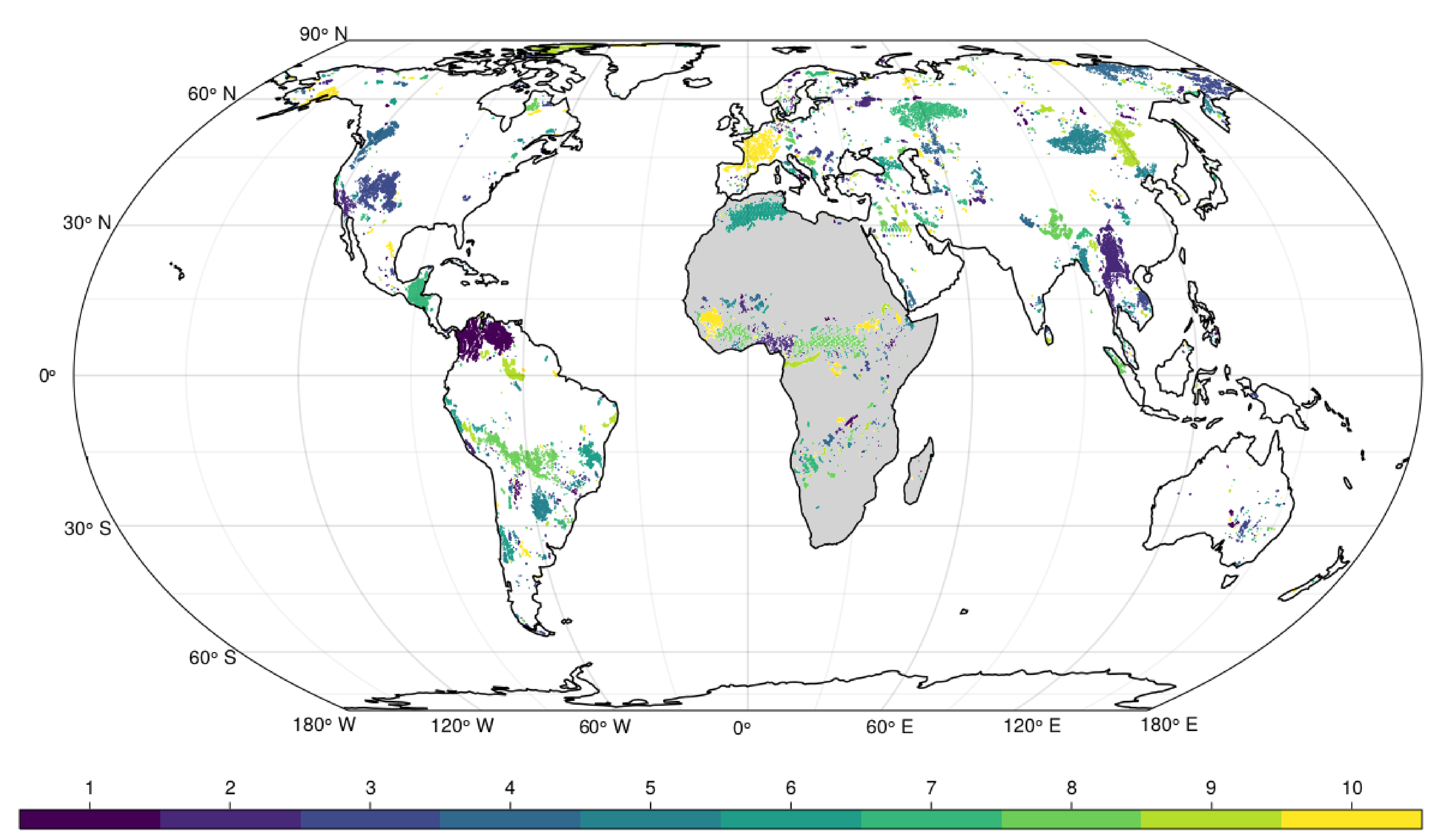

Figure 3. Map of the samples' location [4], with colors corresponding to the 10-fold split utilized to mitigate spatial auto-correlation. In gray, the African continent is used as the OOD in our experiment.

RESULTS

Biome	*'With Africa'*			*Relative Performance (%)*		
	$RMSE\downarrow$	$r^2\uparrow$	$NNSE\uparrow$	$RMSE\downarrow$	$r^2\uparrow$	$NNSE\uparrow$
Tropical and Subtropical Grasslands, Savannas and Shrublands	0.05	0.69	0.46	7.90	-1.80	-4.36
Flooded Grasslands and Savannas	0.05	0.61	0.37	4.77	-3.03	-2.39
Deserts and Xeric Shrublands	0.02	0.41	0.35	4.68	-1.35	-2.42
Tropical and Subtropical Dry Broadleaf Forests	0.02	0.51	0.56	4.32	1.84	-2.91
Tropical and Subtropical Moist Broadleaf Forests	0.05	0.62	0.37	3.79	0.49	-2.23
Montane Grasslands and Shrublands	0.06	0.56	0.32	-0.60	2.83	2.07
Mediterranean Forests, Woodlands and Scrub	0.03	0.38	0.37	-1.45	-2.23	-2.91
all biomes	0.046	0.67	0.44	6.84	-1.43	-3.75

Figure 5: Performance Comparison with and without African Sample in Training. Red indicates biomes that are widely distributed in Africa.

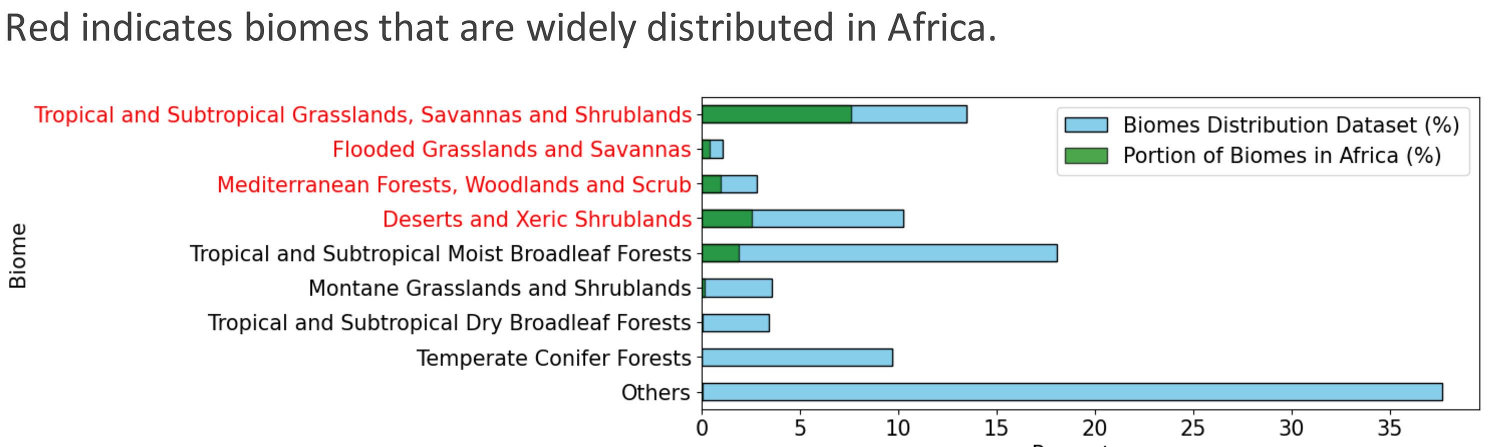

Figure 4. Biome distribution of the dataset, and portion located in Africa. Red indicates biomes that are widely distributed in Africa.

ANALYSIS

SMALL PERFORMANCE DECLINE: All biomes show a **performance decrease of less than 8%** across all metrics.

AFRICAN BIOME: Strongest performance decrease are in **biomes predominantly distributed in Africa**.

CONCLUSION: Support the hypothesis that samples from the same biome are close in the feature space and help for generalization in geographical space.

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Citations

[1] Christian Requena-Mesa, Vitus Benson, Markus Reichstein, Jakob Runge, and Joachim Denzler. Earthnet2021: A large-scale dataset and challenge for earth surface forecasting as a guided video prediction task. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 1132–1142, 2021.
[2] Claire Robin, Christian Requena-Mesa, Vitus Benson, Lazaro Alonso, Jeran Poehls, Nuno Carvalhais, and Markus Reichstein. Learning to forecast vegetation greenness at fine resolution over africa with convlstms. arXiv preprint arXiv:2210.13648, 2022.
[3] Hanna Meyer and Edzer Pebesma. Predicting into unknown space? estimating the area of applicability of spatial prediction models. Methods in Ecology and Evolution, 12(9):1620–1633, 2021.
[4] Esther Rolf. Evaluation challenges for geospatial ml. arXiv preprint arXiv:2303.18087, 2023.
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NEXT

METHOD IMPROVEMENT:

- Disentangle different types of distribution shifts.

VALIDATION IMPROVEMENT:

- Across all continents.
- Explore biome-based data splitting.