Global Vegetation Modeling with Pre-Trained Weather Transformers

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Summary

We adapt the publicly available pre-trained weather model FourCastNet to model vegetation activity while accounting for short-term weather dynamics. We investigate how the learned global representation of the atmosphere's state can be transferred to model the normalized difference vegetation index (NDVI), a proxy for vegetation health. Our model globally estimates vegetation activity at a resolution of 0.25° while relying only on meteorological data. We demonstrate that leveraging pre-trained weather models improves the NDVI estimation compared to learning an NDVI model from scratch.

Motivation

- Vegetation models provide insights into the interplay of vegetation state and environmental conditions
- Short-term and small-scale weather phenomena affect vegetation state
- Modeling the interplay between vegetation and meteorological variables is currently handled at coarse spatial or temporal resolution or locally only
- Deep learning weather forecasting models learn atmospheric representation during pre-training at high spatial and temporal resolution
- Those representations are usable for novel finetuning tasks

Method

- Global modeling of daily vegetation activity from daily weather data by fine-tuning a pre-trained weather model
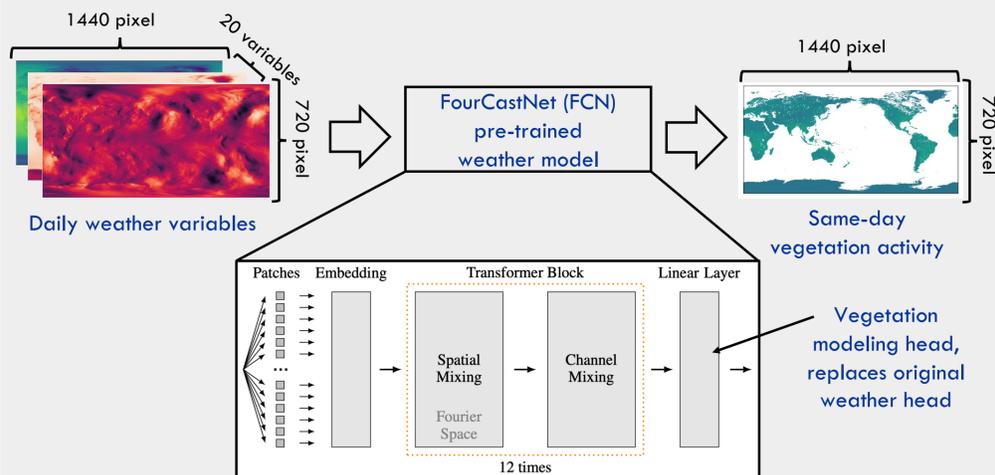
- We load FCN's [1] pre-trained weights and replace its weather head
- We finetune FCN on global vegetation activity at daily temporal resolution

NDVI

- Normalized difference vegetation index (NDVI) [3] measures "greenness"
- -1 (water) to 1 (dense vegetation); around 0 means bare land
- Derived from remote sensing data
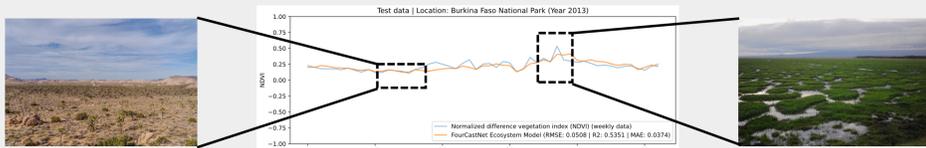
Dataset

	Meteorological Variable	Level / Altitude
Input	Temperature	2m, 1000 hPa, 850 hPa
	Geopotential	1000, 850, 500, 50 hPa
	Zonal and meridional winds	10m, 1000 hPa, 850 hPa, 500 hPa
	Relative humidity	1000 hPa, 850 hPa
	Surface pressure	Surface
	Mean sea level pressure	Surface
	Total column water vapour	Integrated
Target	NDVI	Surface

- 20 daily weather variables from ERA5 [2] at 0.25° (720x1440 pixel) as input
- Same-day gridded daily NDVI values at 0.25° as target

Baselines and Evaluation

We compare us to **a CNN** and **from-scratch FCN** baselines and **LSTM and State Space Modeling results from literature** and evaluate modeling performance locally and globally, adopting the respective evaluation schemes from literature

Local baseline
- Literature results: State Space Models (SSM) [4]
  - Models plant growth from meteorological and soil variables
  - Plant growth guided by equations
  - Separate model for 100 selected locations
  - Works on individual pixel time-series at weekly temporal resolution

Local evaluation
Following [4], we aggregate FCN output and target values at the same 100 locations to weekly resolution

Global baselines
- Hyperparameter-optimized CNN
- FourCastNet trained from scratch
- Literature results: LSTM [5]
  - Utilizes global pixel-wise weight sharing at 0.5° spatial resolution
  - Models vegetation from current and past meteorological data
  - 15-daily temporal resolution

Global evaluation
Following [5], we globally aggregate output and target values to 15-daily resolution while excluding pixels with >50% missing NDVI values, which mainly removes high-latitude areas

Results and Discussion

Our model reaches a globally averaged R^2 of _0.6331_ which indicates that a weather model finetuned for modeling the NDVI from high resolution meteorological data can capture substantial amounts of the NDVI's variability.

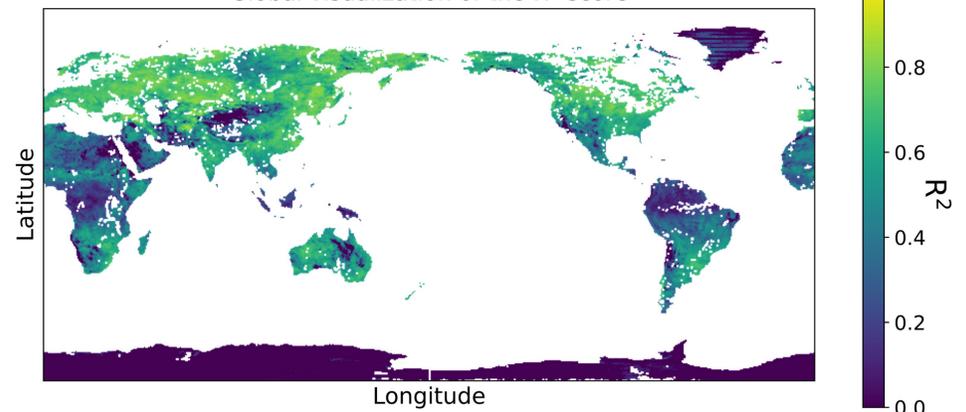| Model	FCN finetune	SSM	FCN finetune	FCN scratch	CNN	LSTM
Evaluation	local, 7-daily		global, 15-daily			
RMSE	**0.0547**	0.0548	_0.0403_	0.0512	0.0431	**0.017**
R^2	**0.5151**	0.4038	_0.6331_	0.4977	0.6061	**0.904**

Local evaluation
- **Single global FourCastNet outperforms location-specific models**
  → Global ecosystem model can capture location-specific patterns

Global evaluation
- **Finetuning (*FCN finetune*) outperforms training from scratch (*FCN scratch*)**
  → Finetuning performance indicates that weather pre-training leads to structural knowledge about the atmosphere useful for vegetation modeling
  → Training FCN from scratch might not yield the same structural knowledge
- **Finetuning outperforms a hyperparameter-optimized CNN but is inferior to a global, history-incorporating pixelwise LSTM**
  → Incorporating past states into a global model might improve performance

Global visualization of the R^2 scores (clipped to 0) of the finetuned FCN on the test set. In high latitude regions, remote sensing data availability is limited.

References

[1] Pathak, Jaideep, et al. "Fourcastnet: A global data-driven high-resolution weather model using adaptive fourier neural operators." *arXiv preprint arXiv:2202.11214* (2022).
[2] Hersbach, Hans, et al. "The ERA5 global reanalysis." *Quarterly Journal of the Royal Meteorological Society* 146.730 (2020): 1999-2049.
[3] Tucker, Compton J., and P. J. Sellers. "Satellite remote sensing of primary production." *International journal of remote sensing* 7.11 (1986).
[4] Higgins, Steven I., Timo Conradi, and Edward Muhoko. "Shifts in vegetation activity of terrestrial ecosystems attributable to climate trends." *Nature Geoscience* 16.2 (2023).
[5] Kraft, Basil, et al. "Identifying dynamic memory effects on vegetation state using recurrent neural networks." *Frontiers in Big Data* 2 (2019).