Modeling landscape-scale vegetation response to climate: Synthesis of the EarthNet challenge

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Sharing is encouraged

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ellis unit JENA

Q: Is Deep Learning useful for predicting NDVI conditioned on weather at Sentinel 2 resolution?

Starting Point: EarthNet challenge → Predict Satellite imagery from weather
Idea: Synthesize the results: Are Models useful for Vegetation Modeling?
Impact: If so, useful for Farming, Anticipatory Action, Forest Monitoring, …
Our **Contributions**:

- New SOTA models
- These are robust across Europe, but best for Croplands
- First time competitive baseline: Climatology for Sentinel 2
- EN21 models have reduced skill for vegetation modeling

Outlook:

- Use these models to predict downstream GPP (we show pilot study)
- We model only 150 days → Longer timeseries may help (but a lot of data!)
- Also, larger datasets / foundational models might help

EarthNet2021 leaderboard

Rank	Model Name	Group Name	MAD
1	Earthformer	Earthformer-Team	0.2749
2	Diaconu ConvLSTM	TUM	0.2638
3	SGConvLSTM	ETH Zurich	0.2589
4	SGEDConvLSTM	ETH Zurich	0.2580
5	Channel-U-Net Baseline	EN-Team	0.2482
6	Arcon Baseline	EN-Team	0.2414
7	Persistence Baseline	EN-Team	0.2315

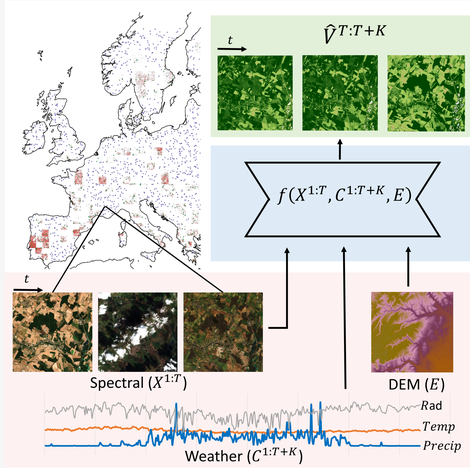
Improved Dataset

EarthNet2021x

✓ New Cloud Mask
✓ Vegetation-centric Evaluation
✓ Geocoding

Algorithm	Works on EN21	Prec	Rec	F1
Sen2Cor	Yes	0.83	0.60	0.70
FMask	No	0.85	0.85	0.85
KappaMask	No	0.74	0.88	0.81
UNet RGBNir	Yes	0.91	0.90	0.90
/w SCL	Yes	0.83	**0.93**	0.88
UNet 13Bands	No	**0.94**	0.92	**0.93**

Task: Vegetation forecast

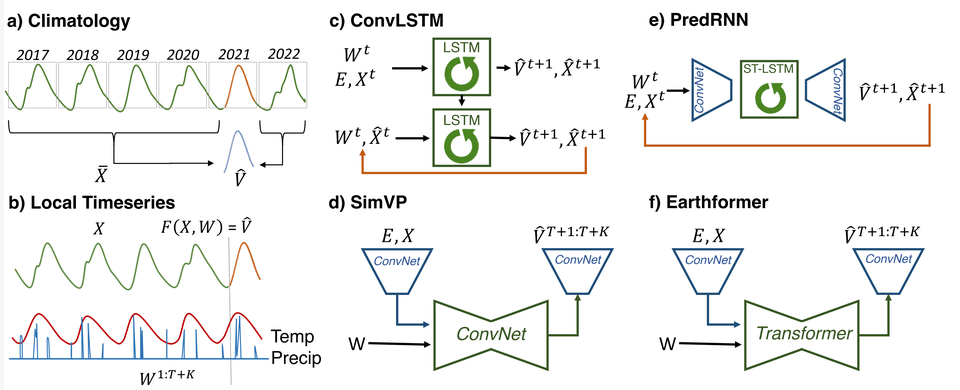


Poster Contest

This presentation participates in OSPP
EGU
Outstanding Student & PhD candidate Presentation contest

Preprint

Models



Main Results

	Model	R^2 ↑	RMSE ↓	NSE ↑	|bias| ↓	Outperform ↑ Climatology	RMSE ↓ 25 days	#Params
NON-ML	Persistence	0.00	0.23	-1.28	0.17	21.8%	**0.09**	0
	Previous year	0.56	0.20	-0.40	0.14	19.3%	0.18	0
	Climatology	0.58	0.18	-0.34	0.13	0.0%	0.16	0
LOCAL TS	Kalman filter	0.41	0.19	-0.57	0.13	27.0%	0.16	$\mathcal{O}(10)$
	LightGBM	0.51	0.17	-0.22	0.12	42.2%	0.11	n.a.
	Prophet	0.57	0.16	-0.05	0.11	60.6%	0.13	$\mathcal{O}(10)$
EN21	ConvLSTM [10]	0.51	0.18	-0.37	0.12	43.9%	0.12	0.2M
	SG-ConvLSTM [23]	0.53	0.19	-0.33	0.14	45.8%	0.11	0.7M
	Earthformer [16]	0.49	0.17	-0.27	0.12	47.2%	0.11	60.6M
THIS STUDY	ConvLSTM-meteo	**0.62** ±0.01	**0.14** ±0.00	**0.11** ±0.03	0.10 ±0.00	**68.2%** ±1.8%	0.10 ±0.00	1.0M
	PredRNN-meteo	**0.62** ±0.00	0.15 ±0.00	0.03 ±0.00	0.10 ±0.00	64.7% ±1.2%	0.10 ±0.00	1.4M
	SimVP-meteo	0.60 ±0.00	0.15 ±0.00	0.03 ±0.01	**0.09** ±0.00	64.1% ±1.0%	0.10 ±0.00	6.6M
	Earthformer-meteo	0.52	0.16	-0.13	0.10	56.5%	**0.09**	60.6M

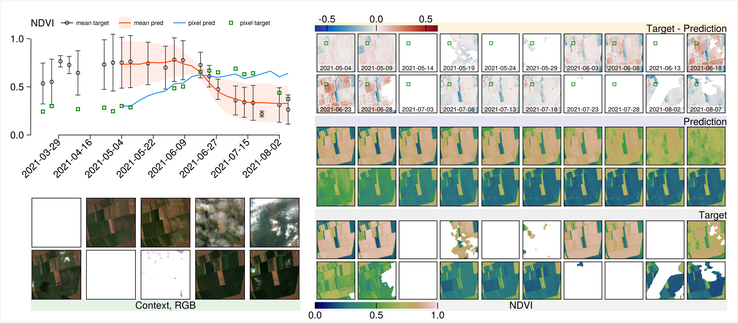
Extrapolation

Model	OOD-s R^2 ↑	OOD-s RMSE ↓	OOD-st R^2 ↑	OOD-st RMSE ↓
Climatology	0.50	0.15	0.56	0.19
ConvLSTM	**0.55**	**0.14**	**0.58**	**0.15**
PredRNN	0.54	0.15	**0.58**	**0.15**
SimVP	0.50	0.15	0.54	**0.15**
Earthformer	0.47	0.15	0.47	0.16

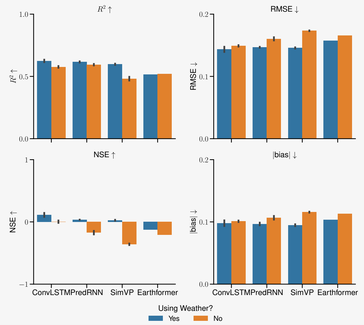
Spatial Features

Model	R^2 ↑	Diff ↑	RMSE ↓	Diff ↓
Climatology	0.58		0.18	
1x1 LSTM	0.57		0.17	
spatial shuffle	0.57	0.00	0.17	0.00
Next-frame UNet	0.51		0.19	
spatial shuffle	0.48	-0.03	0.21	+0.02
Next-cuboid UNet	0.56		0.16	
spatial shuffle	0.43	-0.13	0.21	+0.05
ConvLSTM	0.62		0.14	
spatial shuffle	0.60	-0.02	0.16	+0.02
PredRNN	0.62		0.15	
spatial shuffle	0.45	-0.17	0.22	+0.07
SimVP	0.60		0.15	
spatial shuffle	0.49	-0.11	0.22	+0.07

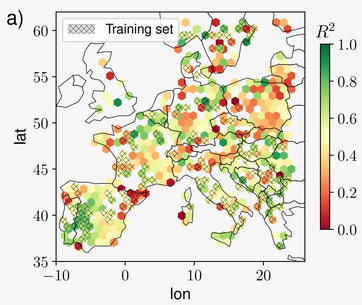
Example Prediction

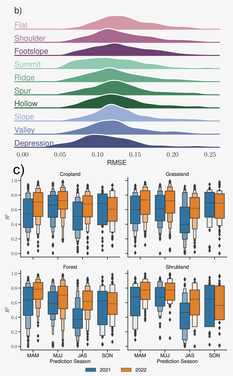


Weather Matters

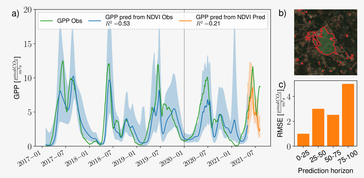


Model Skill can differ





GPP: Pilot Study



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