Satellite NDVI Forecasting with Growth Curve Regression

Project Status Presentation

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Project Overview

Objective

- Forecast vegetation dynamics over 100-day horizon
- Multi-spectral Sentinel-2 imagery prediction
- Incorporate weather and land cover information

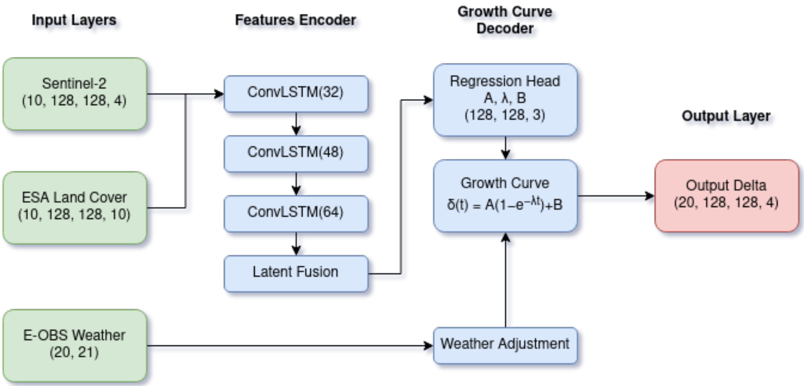
Inspiration

- Based on "Explainable Earth Surface Forecasting Under Extreme Events"
- Pellicer-Valero et al., 2024
- DOI: 10.1029/2024EF005446

Key Features

- Historical Sentinel-2 observations (10 frames, 50 days)
- E-OBS climate variables (7 weather features)
- ESA WorldCover land classification
- Growth curve parametric decoder

Model Architecture (Simplified)



Growth Curve Formula

$\delta(t) = A \cdot (1 - e^{-\lambda \cdot T \cdot t \cdot \mathrm{adj}(t)}) + B$ where $t \in [0, 1]$, $\quad T = 20 \quad$ and $\mathrm{adj}(t) \in [0.5, 1.5]$

Loss Function: Improved kNDVI Loss

Components (normalized to similar scales)

1. **Regression Loss** (Huber $\delta = 0.1$)

$$\mathcal{L}_{\text{reg}} = \text{Huber}(\delta_{\text{true}}, \delta_{\text{pred}}) \times (1 - m_{\text{cloud}})$$

2. **Variance Penalty**

$$\mathcal{L}_{\text{var}} = |\text{Var}_{\text{spatial}}(\delta_{\text{true}}) - \text{Var}_{\text{spatial}}(\delta_{\text{pred}})|$$

3. **kNDVI Loss** (RBF kernel $\sigma = 0.5$)

$$\text{kNDVI} = \frac{1 - k(n,r)}{1 + k(n,r)}, \quad k(n,r) = e^{-\frac{(n-r)^2}{2\sigma^2}}$$

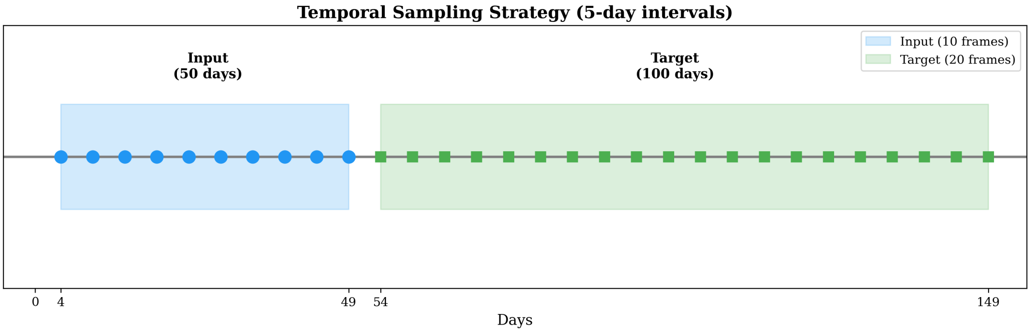
Combined Loss

$$\mathcal{L} = w_{\text{reg}} \cdot \mathcal{L}_{\text{reg}} + w_{\text{var}} \cdot \mathcal{L}_{\text{var}} + w_{\text{kndvi}} \cdot \mathcal{L}_{\text{kndvi}}$$

Component	Weight
Regression	10.0
Variance	1.0
kNDVI	$0.0 \rightarrow 1.0$

kNDVI enabled after epoch 20 via callback

Temporal Sampling Strategy



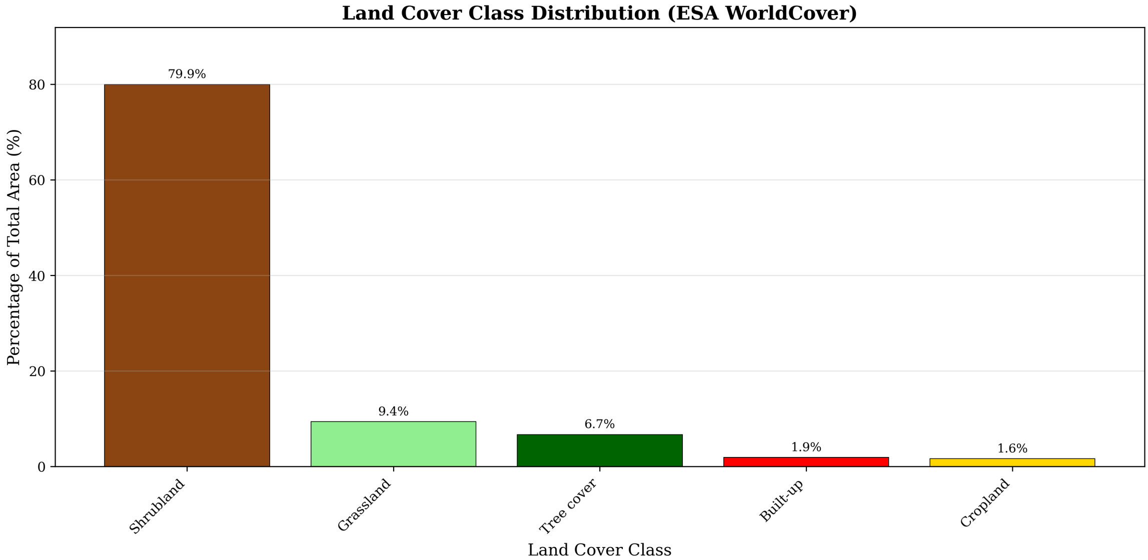
Input Period

- Days 4–49 (50 days)
- 10 frames at 5-day intervals

Target Period

- Days 54–149 (100 days)
- 20 frames at 5-day intervals

Land Cover Distribution (ESA WorldCover)



Results: Error Metrics

Band	MAE	RMSE
B02 (Blue)	0.029	0.057
B03 (Green)	0.032	0.058
B04 (Red)	0.041	0.066
B8A (NIR)	0.053	0.077
Overall	**0.039**	**0.064**

Table: Per-band error metrics

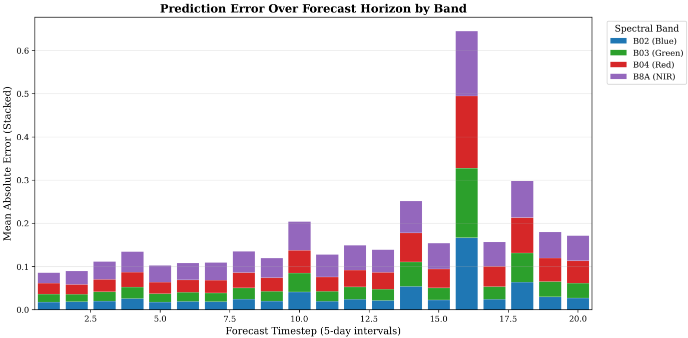
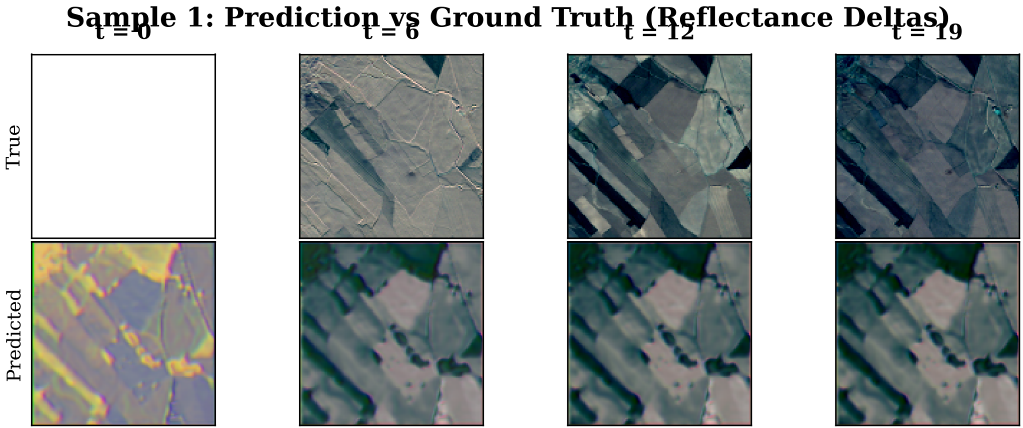


Figure: Prediction error over forecast horizon by spectral band

Observations

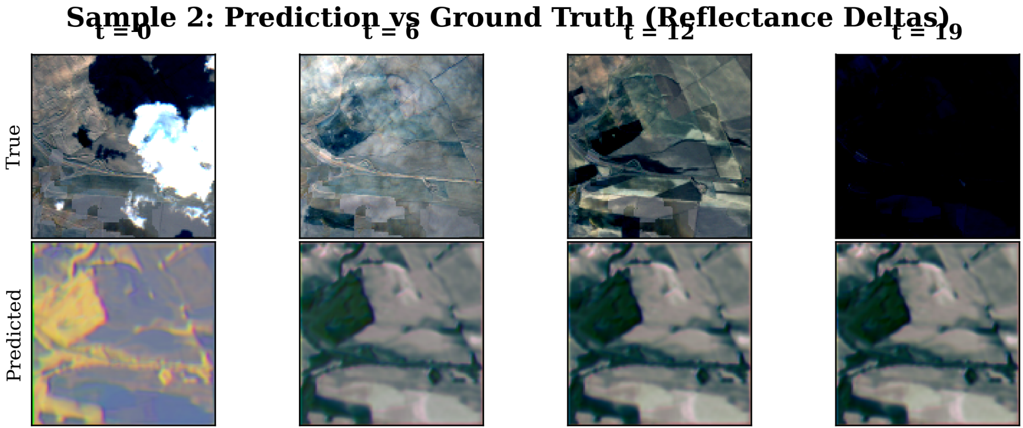
- NIR band has highest error
- Blue band has lowest error
- Errors in reasonable range for delta prediction

Results: Prediction Comparison (Sample 1)



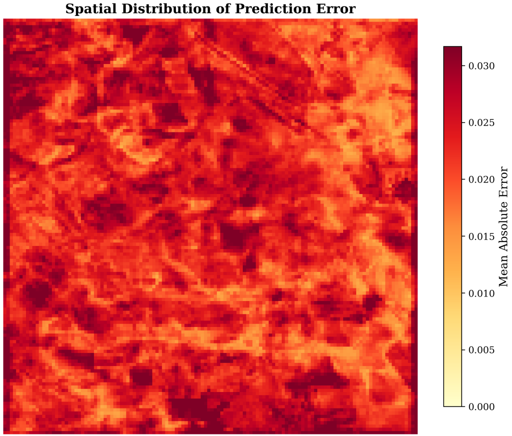
Ground truth vs. predicted reflectance deltas across forecast timesteps

Results: Prediction Comparison (Sample 2)



Ground truth vs. predicted reflectance deltas across forecast timesteps

Results: Spatial Error Distribution



Spatial Error Analysis

- Error distribution across image
- Identifies challenging regions
- Useful for model improvement

Key Insights

- Edges may have higher error
- Heterogeneous areas more challenging
- Cloud boundaries affect accuracy

Validation Strategy (GreenEarthNet)

Dataset Splits

- **Train**: 23,816 minicubes (85 tiles)
- **val_chopped**: IID validation set
- **ood-t**: Out-of-distribution temporal
- **ood-s**: Out-of-distribution spatial
- **ood-st**: Out-of-distribution spatio-temporal

Evaluation Protocol

- 50 days context $\rightarrow$ 100 days target (IID/OOD)
- Primary validation on `val_chopped`
- Generalization testing on OOD splits

Vegetation Score (NSE-based)

$$\text{NSE} = 1 - \frac{\sum(y - \hat{y})^2}{\sum(y - \bar{y})^2}$$

- Computed on cloud-free vegetation pixels
- Normalized: $\text{nNSE} = \frac{1}{2-\text{NSE}}$
- Averaged over Trees, Scrub, Grassland
- Score: $1 =$ perfect, $0 =$ climatology

Model Comparison (GreenEarthNet Benchmark)

Model	Parameters	Type	Veg. Score↑
ConvLSTM	$\sim$2M	RNN-based	0.21
SGED-ConvLSTM	$\sim$3M	RNN-based	0.24
PredRNN	$\sim$24M	Video Pred.	0.19
SimVP	$\sim$22M	Video Pred.	0.22
Earthformer	$\sim$12M	Transformer	0.28
Contextformer	**6M**	**Transformer**	**0.31**
Ours (Growth Curve Reg.)	**$\leq$1M**	**RNN-Based**	**TBD**

Table: Model comparison on GreenEarthNet IID validation. Scores from Benson et al., CVPR 2024.

Key Differentiators of Our Approach:

- Parametric growth curve decoder for interpretable predictions
- Significantly fewer parameters ($\sim 6\times$ smaller than Contextformer)
- Explicit modeling of vegetation phenology dynamics

Next Steps

1. Full Dataset Training

- Currently: 200 training samples
- Target: Full GreenEarthNet (23,816 samples)
- Estimated training time: $\sim$48h on GPU

2. Benchmark Evaluation

- Compute Vegetation Score on val_chopped
- Evaluate on OOD test sets
- Compare with Contextformer baselines

3. Model Improvements

- Hyperparameter tuning
- Loss weights optimization
- Architecture refinements

4. Analysis

- Per-landcover performance breakdown
- Extreme event case studies
- Growth curve interpretability analysis

References

1. **Benson, V., Robin, C., Requena-Mesa, C., Alonso, L., Carvalhais, N., Cortés, J., Gao, Z., Linscheid, N., Weynants, M., & Reichstein, M.** (2024).
   Multi-modal learning for geospatial vegetation forecasting.
   Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).
   https://arxiv.org/abs/2303.16198

2. **Pellicer-Valero, O. J., Robin, C., & Reichstein, M.** (2024).
   Explainable Earth Surface Forecasting Under Extreme Events.
   Earth's Future, 12, e2024EF005446.
   https://doi.org/10.1029/2024EF005446

Thank You!

Questions?