Satellite NDVI Forecasting with Growth Curve Regression

Partial Results & Model Diagnosis

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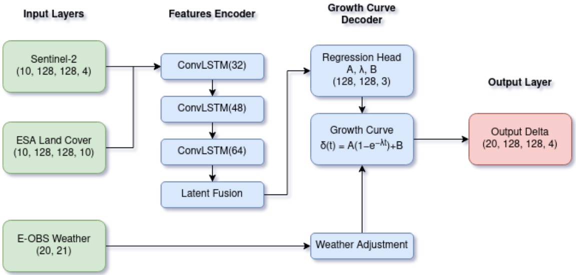
Outline

Project Recap

Objective

- Forecast vegetation dynamics over 100-day horizon
- Input: 10 Sentinel-2 frames (50 days)
- Output: 20 predicted delta frames (100 days)
- Parametric growth curve decoder for interpretability



Data

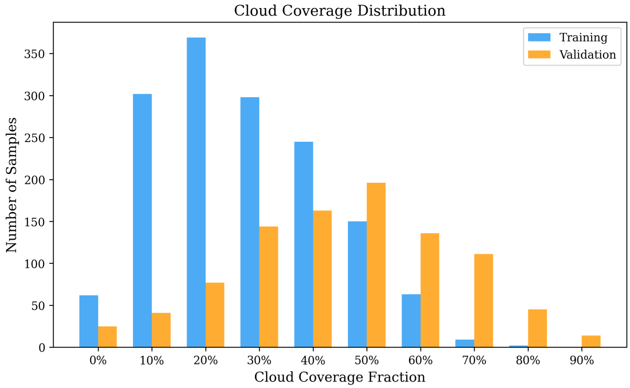
- GreenEarthNet dataset (Sentinel-2 + E-OBS)
- 4 spectral bands: B02, B03, B04, B8A
- ESA WorldCover land classification

Growth Curve Formula

$$\delta(t) = A \cdot (1 - e^{-\lambda \cdot T \cdot t \cdot \mathrm{adj}(t)}) + B$$

Dataset Statistics

Metric	Train	Val
Samples	14213	952
Input Frames	10	10
Output Frames	20	20
Image Size	128×128	128×128
Spectral Bands	4	4
Cloud Cover	**31.8%**	**50.5%**



Cloud Coverage Disparity

Validation set has ∼**1.6**× **more cloud coverage** than training — fewer valid pixels for evaluation.

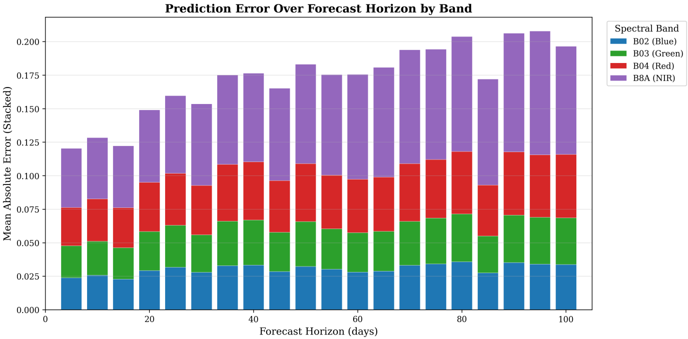
Per-Band Error Metrics

Band	MAE	RMSE
B02 (Blue)	0.031	0.048
B03 (Green)	0.031	0.048
B04 (Red)	0.039	0.058
B8A (NIR)	0.071	0.093
Overall	**0.043**	**0.062**

Table: Delta prediction errors

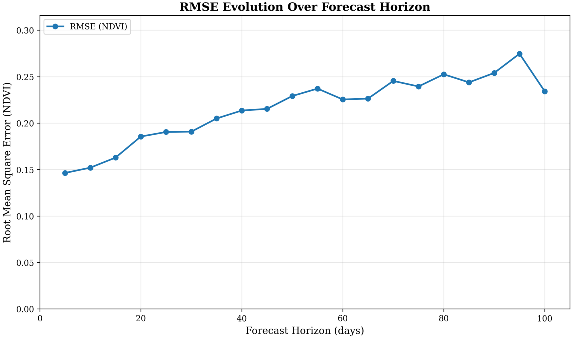
Observations

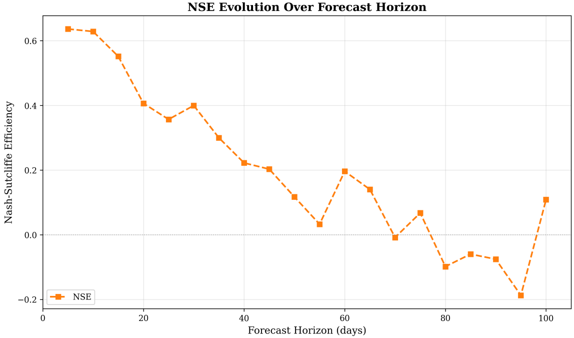
- NIR has **2**× the error of visible bands
- NIR is the most dynamic vegetation band
- Critical for NDVI computation



Error increases monotonically with forecast horizon, dominated by NIR band error.

Temporal Error: NDVI Metrics

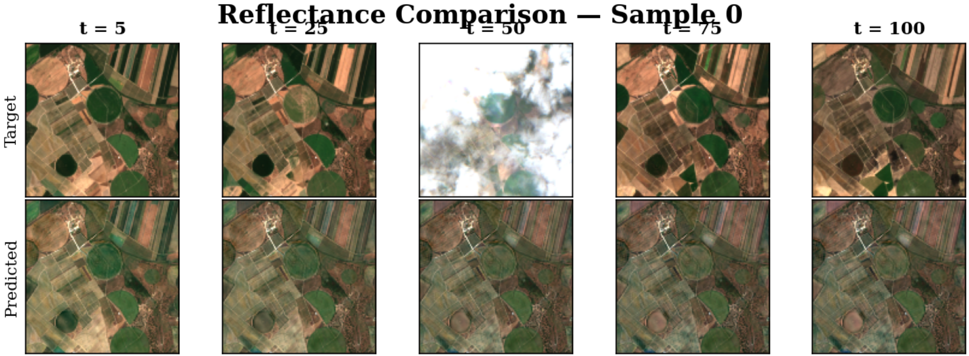




- RMSE grows from 0.146 to 0.229
- Steepest degradation in first 30 days

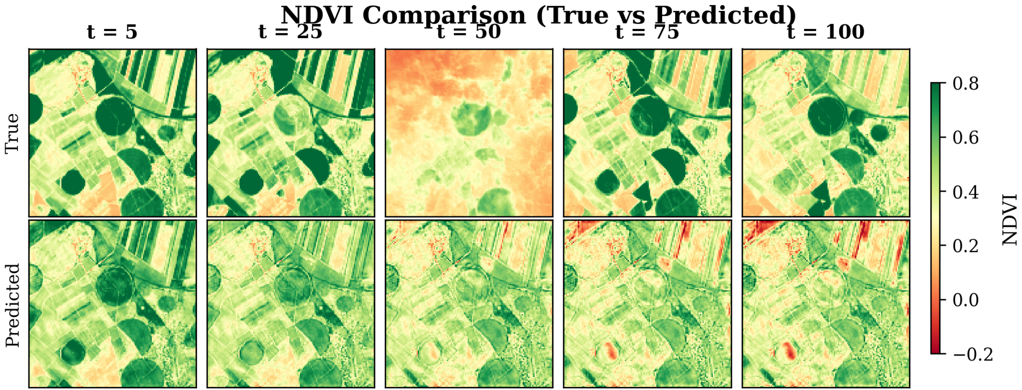
- NSE starts at **0.636** (day 1) but drops to **0.117** (day 50)
- Model tracks short-range dynamics reasonably well

Prediction Comparison: Reflectance



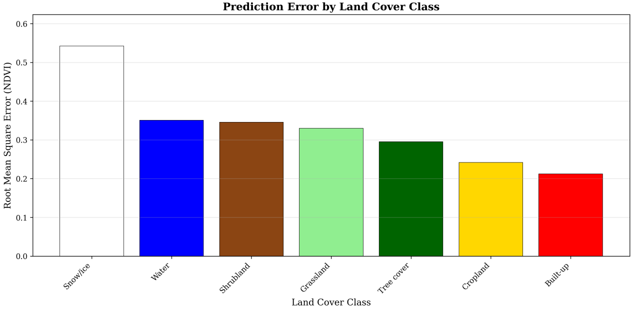
Top rows: ground truth reflectance. Bottom rows: predicted reflectance. Model captures broad spatial patterns but produces monotonic changes over time.

NDVI Comparison: True vs. Predicted



NDVI tracks well at early steps (t=5, t=25) but diverges at later steps (t=75, t=100).

Error by Land Cover Class



Key Findings

- **Snow/ice** has the highest NDVI RMSE (∼0.55) — extreme reflectance values poorly handled
- **Water** and **Shrubland** follow at ∼0.35
- **Cropland** and **Built-up** have the lowest error (∼0.22–0.25) — more spectrally stable
- Vegetation classes (**Tree cover**, **Grassland**, **Shrubland**) cluster around 0.30–0.35

Implication

Errors are distributed across all classes, not restricted to dynamic vegetation.

Vegetation Score: Benchmark Comparison

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$600K	RNN-Based	**Negative values**

Table: GreenEarthNet IID validation. Literature scores from Benson et al., CVPR 2024.

Current Gap

- Current: far below the 0.0 threshold
- Target: ≥ 0.31 (match Contextformer)

Current result

- Per-step NSE is positive (0.636 at step 1)
- Model *does learn signal*, but it degrades fast

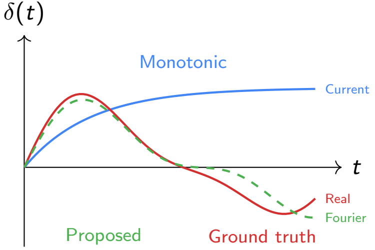
Root Cause #1: Monotonic Growth Curve

The Problem

The growth curve formula is a **saturating exponential**:

$$\delta(t) = A \cdot \underbrace{(1 - e^{-\lambda \cdot T \cdot t \cdot \mathrm{adj}(t)})}_{\text{monotonic saturation}} + B$$

- Can only model **monotonic** increase or decrease toward a plateau
- **Cannot capture**: seasonal cycles, growth followed by senescence, fluctuations
- Over a 100-day horizon, vegetation NDVI may rise *then* fall — impossible with this curve



Primary Limitation

This is the **most critical** architectural issue. NSE drops from 0.636→0.117 as the model cannot track non-monotonic dynamics.

Root Cause #2: Weather Adjustment Flaws

Three Issues with Weather and Time Adjustment

1. **Temporal collapse**: per-step weather features $(B, T, 21)$ are averaged $\to (B, 32)$, losing when specific events (drought, frost) occur
2. **Spatially uniform**: output is (B, T) — a single scalar per timestep, broadcast to all (H, W) pixels identically
3. **Disconnected from curve**: adjustment only scales effective time $t \cdot \mathrm{adj}(t)$, it cannot change the *shape* of the growth curve

Current Pipeline

$$\underbrace{w(t)}_{\text{weather}} \xrightarrow{\text{mean}} \underbrace{\mathrm{adj}(t)}_{\mathbb{R}^{(B,T)}} \xrightarrow{\times t} \delta(t)$$

Consequence

A rainy week vs. a dry week in August produces nearly the same curve shape – only stretched or compressed in time.

Proposed: Fourier Harmonics Decoder

Replace the monotonic growth curve with a sum of harmonics — a natural fit for vegetation phenology.

Proposed Formula

$$\delta(t) = \sum_{k=1}^{K} [a_k \cos(k\omega t) + b_k \sin(k\omega t)]$$

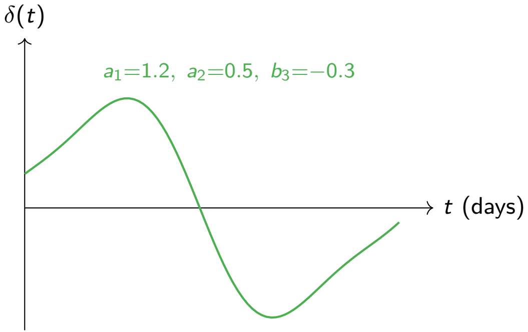
- a_k, b_k: amplitude coefficients predicted per pixel per band by the encoder
- $\omega = 2\pi/P$: base angular frequency (linked to the forecast period)
- K: number of harmonics (controls expressiveness)

Why harmonics fit phenology:

- Vegetation **naturally oscillates**: growth $\rightarrow$ senescence $\rightarrow$ dormancy
- $K{=}1$: captures the dominant seasonal trend
- $K{=}2{-}3$: adds sub-seasonal detail (rapid greening, drought dips)
- Fourier basis is **orthogonal —** each harmonic captures independent variation

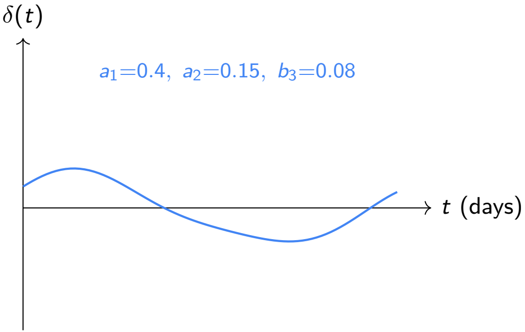
Fourier Harmonics: Fitting Different Vegetation Dynamics

Grassland: rapid growth-senescence



High-amplitude harmonics → strong oscillation → fast green-up followed by senescence over the 100-day horizon.

Forest canopy: slow, stable trend



Small coefficients → gentle oscillation → stable canopy with minimal change, different phase from grassland.

The encoder learns different (a_k, b_k) per pixel — the harmonics naturally adapt to each land cover type.

Proposed: Weather & DOY Conditioning MLP

Goal: scale and shift the base Fourier coefficients according to weather conditions and time of year.

Step 1: Per-step weather encoding

Process each forecast timestep independently (no temporal averaging):

$$h_w(t) = \mathrm{MLP}\big(w(t)\big) \in \mathbb{R}^{(B,T,d)}$$

Step 2: Inject DOY context

$$h(t) = \big[h_w(t) \,\|\, \cos(\omega_{\mathrm{doy}} \cdot t) \,\|\, \sin(\omega_{\mathrm{doy}} \cdot t)\big]$$

Step 3: Predict scale & shift per harmonic

For each harmonic k, output a scaling factor γ_k and a shift β_k:

$$\gamma_k(t),\ \beta_k(t) = \mathrm{Linear}\big(h(t)\big)$$

Step 4: Modulate Fourier coefficients

$$\tilde{a}_k(t) = \gamma_k^a(t) \cdot a_k + \beta_k^a(t)$$
$$\tilde{b}_k(t) = \gamma_k^b(t) \cdot b_k + \beta_k^b(t)$$

vs. Current Design

Current MLP averages all weather into a single scalar that only stretches time.
New MLP preserves per-step weather and directly modulates each harmonic's amplitude and phase.

Timeline: Next Month

Week 1–2: Architecture Improvements

1. Replace monotonic growth curve with **Weather-Conditioned Fourier** decoder
2. Per-step FiLM conditioning from weather MLP (no temporal collapse)
3. $K=3$ harmonics (6 base params/pixel/band)

Week 3: Retraining & Validation

4. Retrain on full GreenEarthNet dataset (23,816 cubes, $\sim$48h)
5. Evaluate on `val_chopped` and OOD splits
6. Benchmark against Contextformer

Week 4: Writing Preparation

7. Generate final figures for results chapter
8. Interpretability: visualize learned harmonics and FiLM weights
9. Begin writing `full_article` results and discussion chapter

References

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Thank You!

Questions?