Monitoring Shifts in Flowering Phenology Using Satellite Imagery and Deep Learning

Joséphine Gantois[1] and Mathias Lecuyer[2]

[1]Columbia University of New York
[2]Microsoft Research

November 22, 2022

Abstract

The onset of plant flowering is one of many factors affected by climate change. This has important consequences for ecosystems, where plants and pollinators are at risk of a temporal mismatch. This also has implications for crops. The timing of their highest-sensitivity window is affected, despite some control exerted by agricultural management. Current efforts to monitor the onset of flowering rest on numerous but sparse ground observations, or on proxies like temperature models or vegetation indices. In crop studies, a time-invariant harvesting calendar is most widely used to infer the flowering period for crops. We use spectral data from satellite imagery, combined with convolutional neural networks, to create a large-scale, high-resolution proxy for the timing of flowering. We exploit a transfer learning method to overcome the sparsity of ground truth data on plant phenology. We first train a temporal convolutional neural network to predict a temperature-based proxy for flowering (the First Bloom Index from the National Phenology Network), using as input the 8-day composite from MODIS at a 500m resolution. This model learns relevant temporal patterns on both short and long time scales within a year, thanks to a dilated convolution structure. We then fine-tune the parameters from the last fully connected layer using ground observations from the National Phenology Network as training data. The root mean squared error of our model is about 8.6 days, though this average hides much spatial heterogeneity: in many places, the model performs well-enough to capture year-to-year variations, with a prediction within a couple days of the target, while it performs extremely poorly in a few places. Our model outperforms the temperature-based proxy since the latter has a root mean squared error of about 9.3 days on the same testing data. More importantly, our model extrapolates much better over space: it has a root mean squared error of about 12 days when predicting outside of our study region, compared to a 35-day error for the temperature-based model. This is a key feature, since our goal is to fill in the spatial gaps left by the sparse ground truth observations. These large-scale predictions of annual flowering times could offer insights into plant-pollinator desynchronization and crop calendar variation under climate change, and could be used for further applications like studying the health impacts of shifts in spring flowering times.

Monitoring Shifts in Flowering Phenology Using Satellite Imagery and Deep Learning

Joséphine Gantois[1] and Mathias Lécuyer[2] [1] Columbia University, [2] Microsoft Research jg3479@columbia.edu

Research Questions

- How can satellite imagery be synthesized into a large-scale, high-resolution proxy for the timing of flowering?
- Is this proxy able to capture year-to-year variations in the onset of flowering? How well does it extrapolate across space?

Motivation

The onset of plant flowering captures the start of a critical period. Plants and pollinators engage in their mutualistic interaction, crops become particularly sensitive to environmental factors, and many allergies soar. The timing of this event varies from year to year, especially in the context of climate change [1], which has implications for the synchronization of plants and pollinators [7], and for the sensitivity of crop yield to climate [2].
Current efforts to monitor the onset of flowering rest on numerous but sparse ground observations, or on proxies like temperature models or vegetation indices. In crop studies, a time-invariant harvesting calendar is most widely used to infer the flowering period for crops [5]. Our goal is to construct a proxy for the onset of flowering that captures annual variations locally, and across phenological patterns.

Data

Input features: MODIS Terra Surface Reflectance 8-Day Global 500m

- 7 reflectance bands, quality layer, 4 observation bands, day of year
- 2000-2018

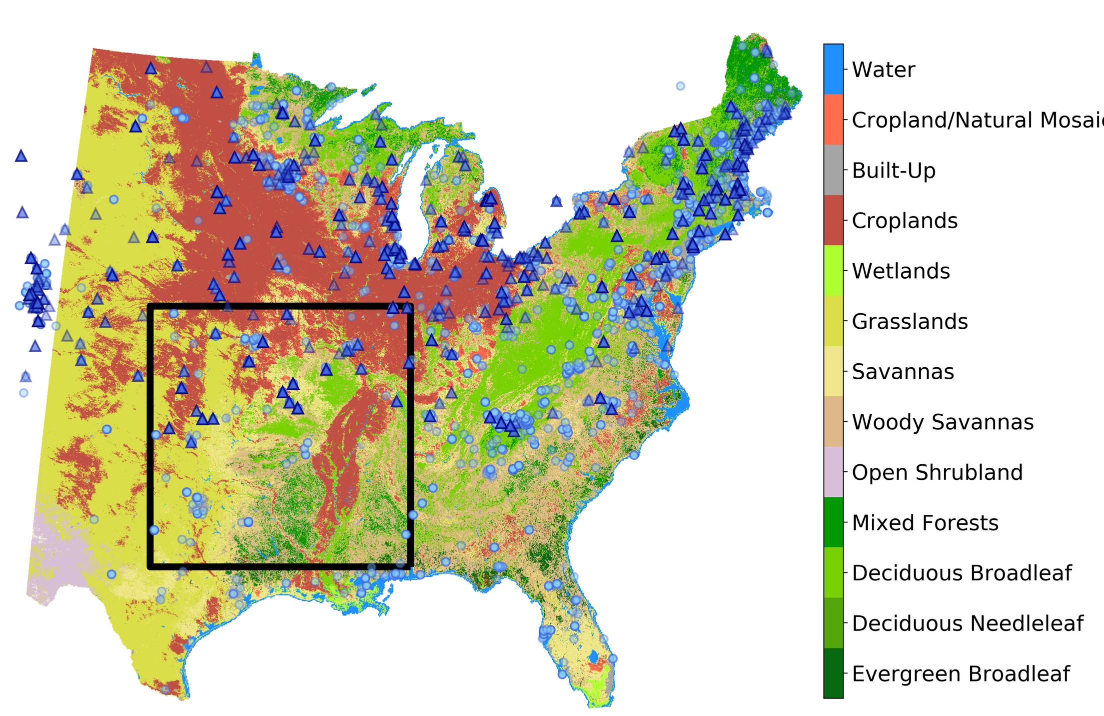

Figure 1: MODIS-based Land Cover Type 1 classification. Study region outlined in black. [Dark blue triangles] lilac/honeysuckle ground-truth locations. [Light-blue circles] National Phenology Network ground-truth locations.

Intermediate label: First Bloom Index from the National Phenology Network

- temperature model that uses PRISM temperature data [6]
- trained using lilac and honeysuckle first bloom date observations
- 2001-2018

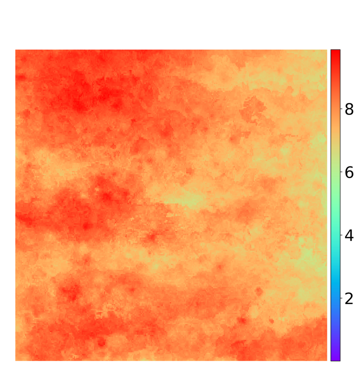

Figure 2: Standard Deviation of the First Bloom Index over 2001-2018, in days.

Ground truth data:

- lilac and honeysuckle first bloom and full bloom dates, 2001-2014 [4]
- USA National Phenology Network observational data: first bloom and full bloom dates, 2003-2019

Model Architecture

Task. For a given pixel, the model takes a sequence of MODIS observations between September 1st of year `t-1`, and August 30th of year `t`, in order to predict the first flowering date at that pixel in year `t`.

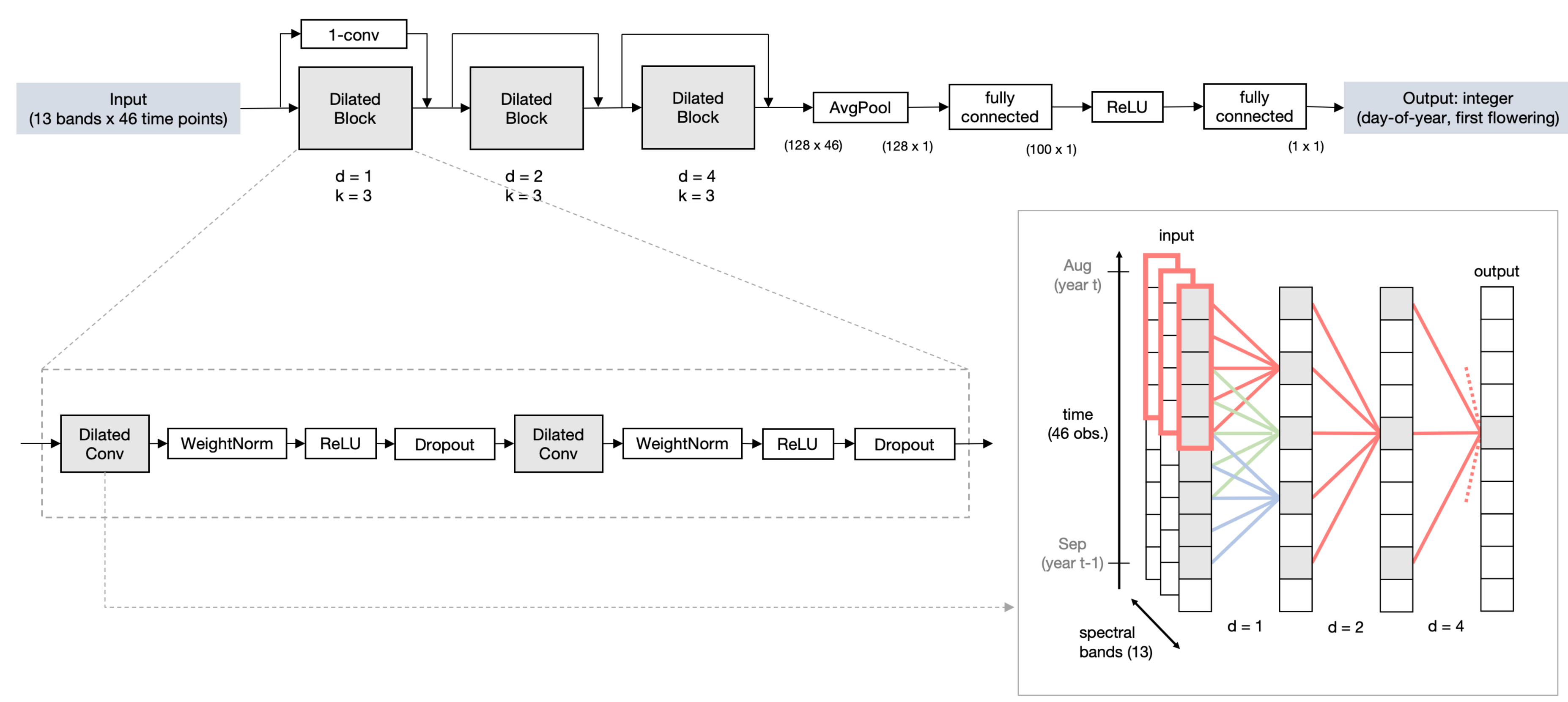

Figure 3: Temporal convolutional network architecture, adapted from [3]. [Top] Overall architecture. [Bottom left] A dilated block. A 1-convolution is included when input and output have different dimensions. The model includes 3 such dilated blocks. [Bottom right] Illustration of a dilated convolution with dilation factors d = 1, 2, 4 and filter size k = 3.

Key feature. The model looks for temporal patterns, both local in time (3 consecutive snapshots of the MODIS 8-Day product), and more spread out over a year (regularly spaced but non-consecutive snapshots).

Transfer Learning: Intermediate Performance

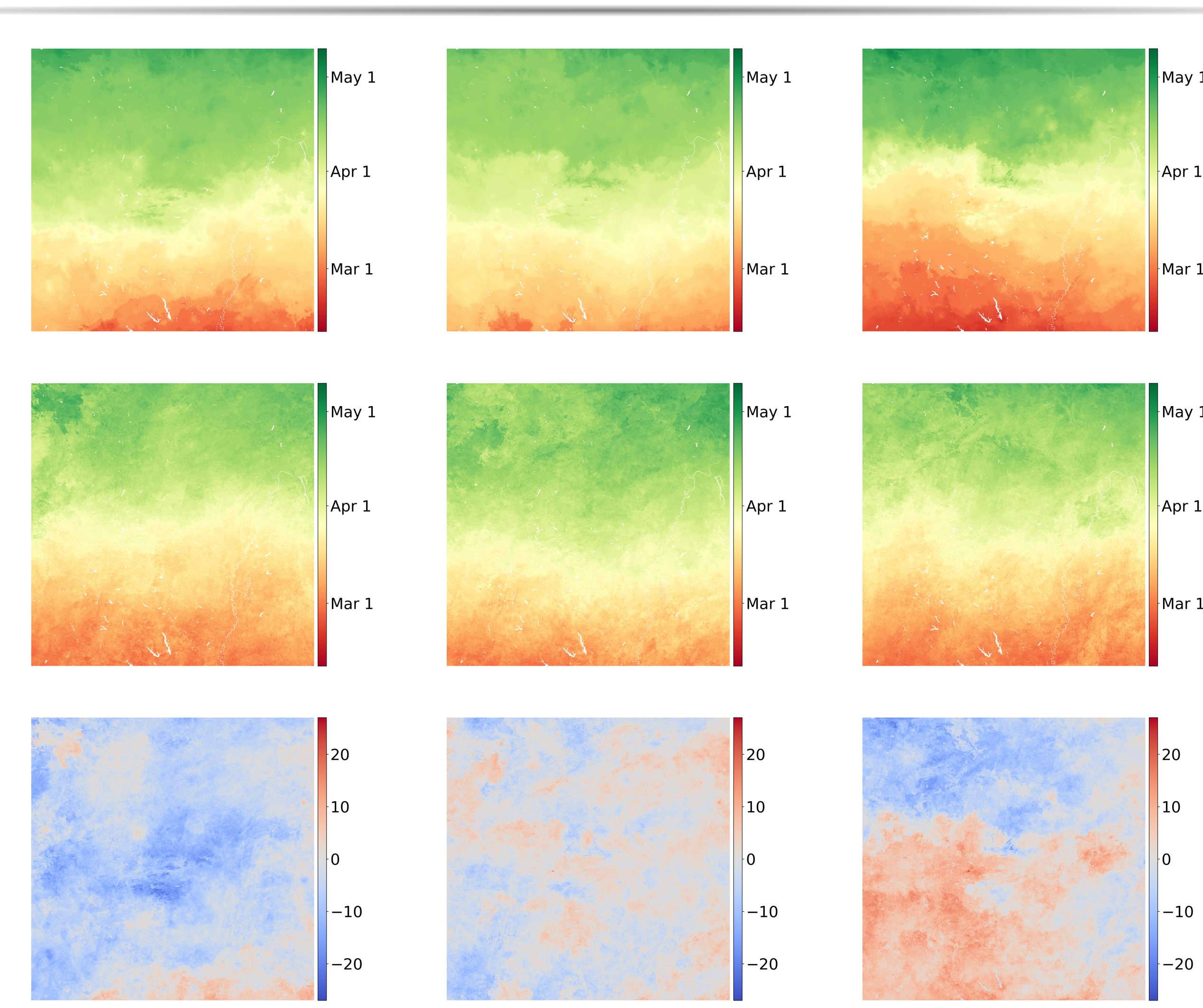

Figure 4: [Top panel] Label value (first bloom index). [Middle panel] Prediction value. [Bottom panel] Prediction error (prediction minus label). Each column corresponds to a different testing year: (from left to right) 2002, 2003, and 2009.

	Null model (average across train years)	Our model (intermediate stage)		
		2002	2003	2009
`Root Mean Squared Error (days)`	7.76	6.65	3.57	6.95

Fine-Tuning: Results

Model update: The last fully connected layer is re-trained, using lilac/honeysuckle ground-truth labels.

`Root Mean Squared Error, days (averaged over 5 random train/test splits)`	
	Study region
Temperature model	9.33
Our model (intermediate)	9.83
Our model (final stage)	8.58
	Eastern US
Temperature model	35.17
Our model (intermediate)	35.58
Our model (final stage)	12.04

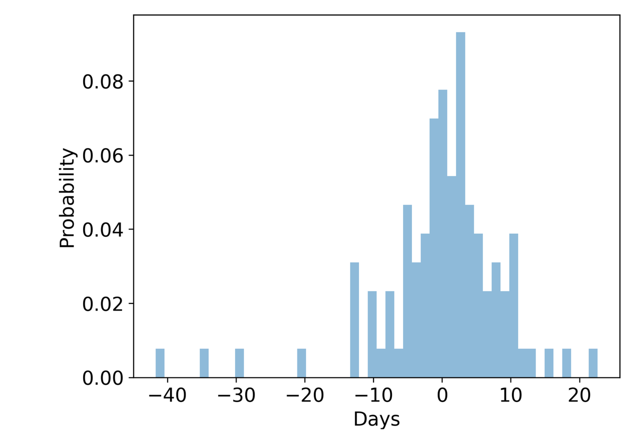

Figure 5: Probability histogram of prediction error, relative to the ground-truth labels.

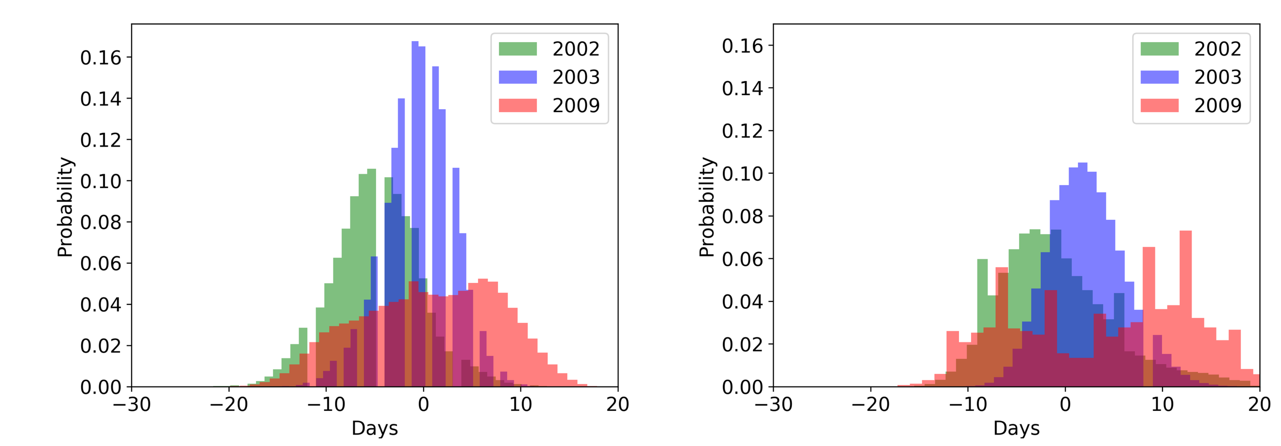

Figure 6: Departure from the temperature model: probability histogram of prediction error, relative to the intermediate label (first bloom index). [Left] Intermediate-stage model. [Right] Final-stage model.

Next Steps

Model:

1. examine model features and importance of the different spectral bands
2. compare performance against the predictive power of the best leaf-out model
3. multi-task learning: train the model to predict a more detailed sequence of events

Ground-truth:

1. exploit historical records from herbarium specimens
2. use crop flowering records

Application:

1. evaluate the model separately by land-use type
2. target well-defined applications: year-to-year variation in crop calendars, wild fields, urban phenology, cherry blossoms, etc.

References

[1] J. T. Anderson, D. W. Inouye, A. M. McKinney, R. I. Colautti, and T. Mitchell-Olds. Phenotypic plasticity and adaptive evolution contribute to advancing flowering phenology in response to climate change. *Proceedings of the Royal Society B: Biological Sciences*, 279(1743):3843–3852, 2012.

[2] W. Anderson, R. Seager, W. Baethgen, and M. Cane. Crop production variability in north and south america forced by life-cycles of the el niño southern oscillation. *Agricultural and forest meteorology*, 239:151–165, 2017.

[3] S. Bai, J. Z. Kolter, and V. Koltun. An empirical evaluation of generic convolutional and recurrent networks for sequence modeling. *arXiv preprint arXiv:1803.01271*, 2018.

[4] A. H. Rosemartin, E. G. Denny, J. F. Weltzin, R. L. Marsh, B. E. Wilson, H. Mehdipoor, R. Zurita-Milla, and M. D. Schwartz. Lilac and honeysuckle phenology data 1956–2014. *Scientific data*, 2:150038, 2015.

[5] W. J. Sacks, D. Deryng, J. A. Foley, and N. Ramankutty. Crop planting dates: an analysis of global patterns. *Global Ecology and Biogeography*, 19(5):607–620, 2010.

[6] M. D. Schwartz, R. Ahas, and A. Aasa. Onset of spring starting earlier across the northern hemisphere. *Global change biology*, 12(2):343–351, 2006.

[7] M. J. Solga, J. P. Harmon, and A. C. Ganguli. Timing is everything: an overview of phenological changes to plants and their pollinators. *Natural areas journal*, 34(2):227–235, 2014.