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School of Biological Sciences
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Multi-scale fundamental phenology mechanism in response to global climate change

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1. Introduction

Plant phenology is the study of **recurring life history events of plants** and how these are influenced by seasonal and interannual variations in environmental conditions. Therefore, understanding **spring phenology mechanism** is essential and a prerequisite for predicting deciduous forest responses to inter-annual and long-term climate variation and change.

Here we want to address two key questions:

(1) How can the spring phenology mechanism model monitor ecosystem-scale pheno-metric?
(2) What are the mechanistic controls of deciduous forests spring phenology across different ecosystems?

2. Process of Spring phenology

A typical spring phenology model is composed by:
(1) The effects of environmental cues on annual growth cycle in trees
(2) A trait-based spring phenology model which combines frost damage and photosynthesis gain mechanism

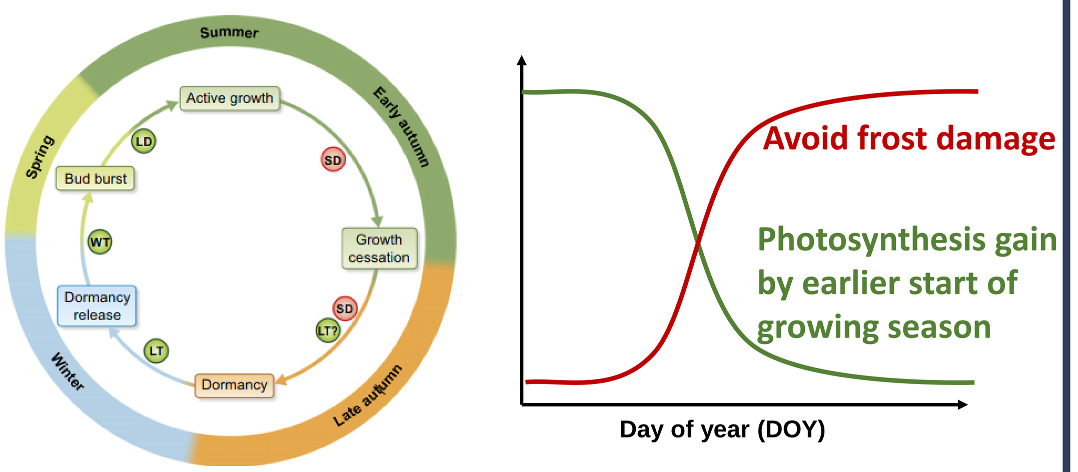

Fig.1. (a) A schematic figure of tree phenology: LD: Long Days, SD: Short Days, LT: Low temps, Warm Temps (source: Singh et al 2017, New Phytologist); (b) A trait-based model we proposed.

3. Methodology

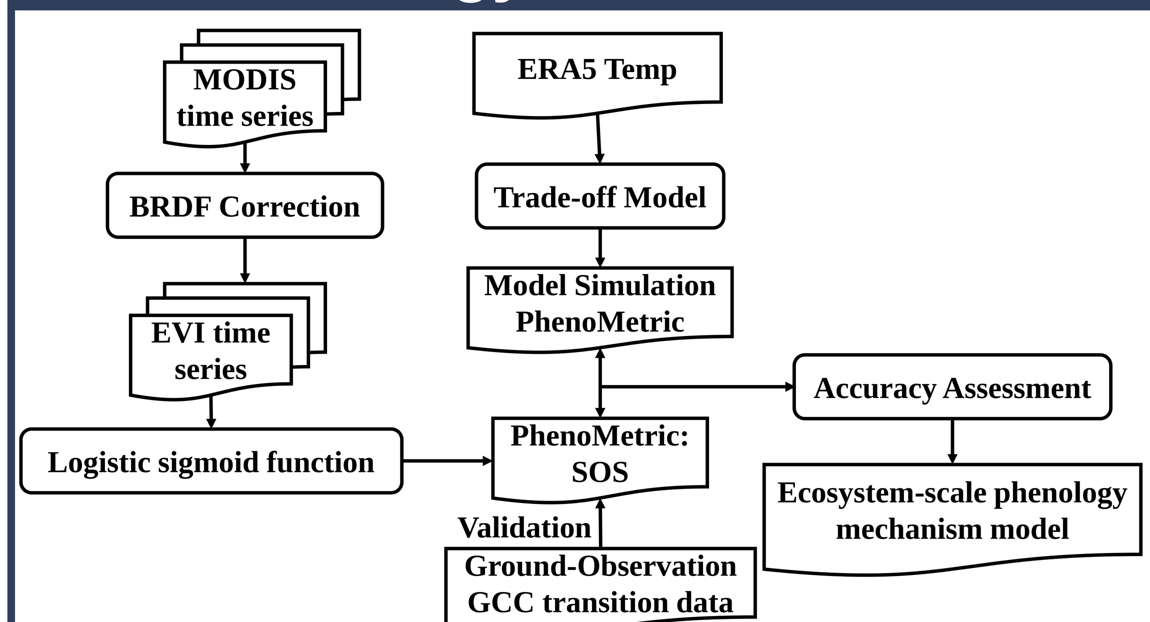

Fig.2. Flowchart of the three key steps of deriving ecosystem-scale phenology mechanism model. Step 1: we conducted BRDF correction for each MODIS image and then extracted the start of season (SOS) from the extracted EVI time series; Step 2: we used the reanalysis ERA5 temperature data to simulate the plants trade-off process; Step 3: we used the ground observation data to validate the model results and applied this model to ecosystem scale in North American.

4. Sites and Materials

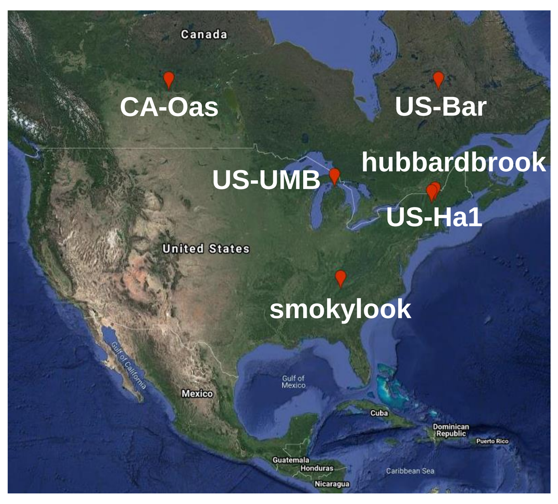

Fig.3. Test sites' location in MODIS data. The sites we select have a great latitude and longitude range, so that we can differ different driven factors which influence the phenology more clearly. Also, these sites have Phenocam data which can be used as ground observation benchmark to validate our results.

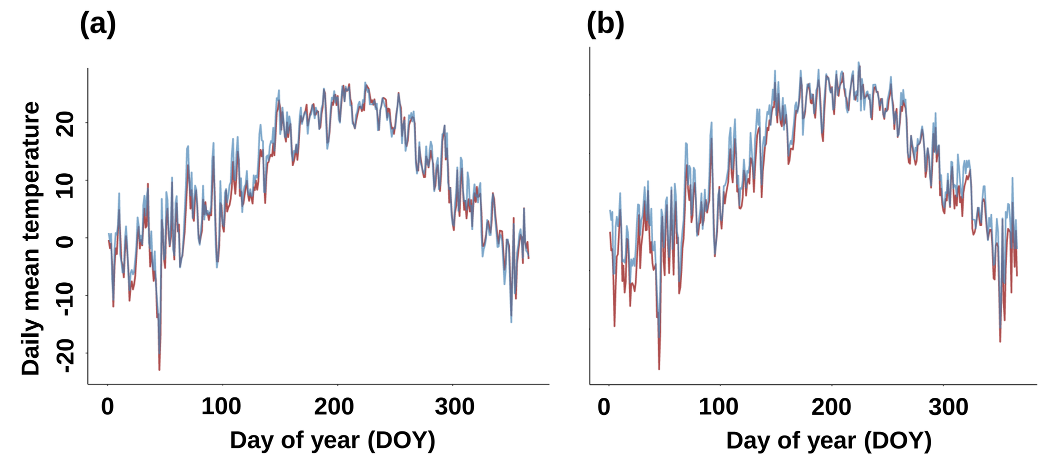

Fig.4. Two representative sites daily mean temperature. The red line denotes the ERA5 reanalysis data while the blue line denotes the AmeriFlux ground observation data: (a) US-Ha1; (b) US-Bar.

5. Satellite data phenometric extraction

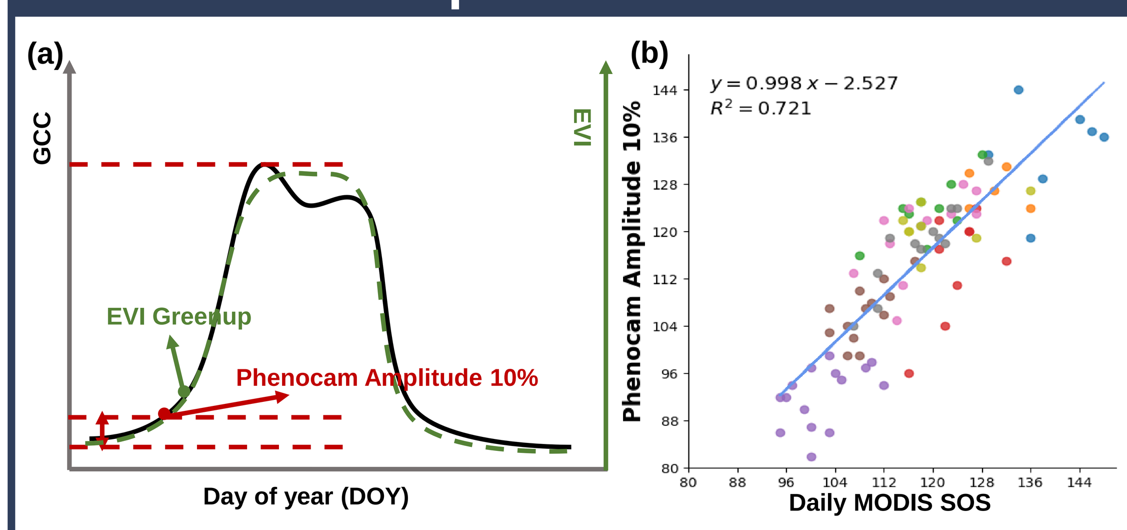

Fig.5. (a) We used logistic sigmoid function to simulate the EVI time-series and extracted the green up point from the curve. To validate the results, we used the ground observation data PhenoCam Green Chromatic Coordinate (GCC) and set the amplitude threshold 10% to validate the result. (b) Ground observation data v.s. MODIS extracted green up point (Start of Season, SOS)

6. Trade-off model

$$R_f(t) = \begin{cases} \dfrac{28.4}{1+\exp(3.4-0.185 * x(t))}, & x(t) > T_{base} \\ 0, & x(t) \le T_{base} \end{cases}$$

$$S_f(t) = \sum_{t_0} R_f(x(t)) \times R_p$$

$$R_c(t) = \begin{cases} 0, & x(t) > 10.4 \ or \ x(t) \le -3.4 \\ \dfrac{x(t)+3.4}{T_{opt}+3.4}, & -3.4 < x(t) \le T_{opt} \\ \dfrac{x(t)+3.4}{T_{opt}-10.4} & T_{opt} < x(t) < 10.4 \end{cases}$$

$$S_c(t) = \sum_{t_0} R_c(x(t))$$

$$R_p(t) = \frac{PPFD(t)}{12} \times e^{c \times S_c(t)}$$

As shown in Fig.1.(b), spring leaf-out is predicted to occur when $S_f(t) \ge a * \exp(b * S_{cmax}(t))$, where $b < 0$. t is the day of year, $x(t)$ is daily temperature, $PPFD(t)$ is daily photosynthetic photon flux density, T_{opt} is the optimum temperature for chilling accumulation, $S_f(t)$ and $S_c(t)$ are the states of forcing and chilling respectively. $R_f(t)$, $R_c(t)$, and $R_p(t)$ are the rates of forcing, chilling, photosynthesis gain respectively. a, b, c, and T_{opt} are parameters to be calibrated.

7. Both factors affect phenology

7.1 Model Validation:

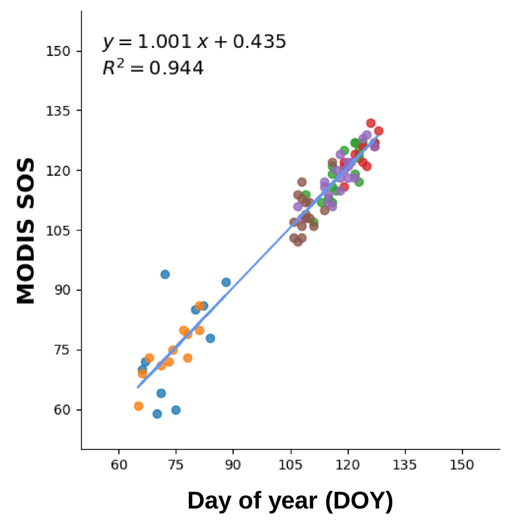

Fig.6. The proposed trade-off model across sites. Compared with results before (not shown here), if we use phenology mechanism free model across the test sites. From figure shown on the left, we can conclude that that our model is feasible across sites in a larger pattern.

7.2 Model across site application

Table.1. Climate-driven phenology models as evaluated against other representative models (Better accuracy is marked in bold).

			Trade-Off Model			Thermal Model			Sequential Model		
Site	Latitude	Longitude	RMSE	R^2	p	RMSE	R^2	p	RMSE	R^2	p
smokylook	35.6325	-83.9431	0.3059	**0.3058**	0.0213	4.6209	0.1536	0.1197	12.5467	0.2053	0.0779
US-Ha1	44.0646	-72.1715	2.9114	0.7331	0.0000	2.4103	**0.8323**	0.0000	3.8210	0.5666	0.0001
hubbardbrook	44.3167	-71.701	2.8762	**0.5869**	0.0060	3.3710	0.4238	0.0301	3.1766	0.4762	0.0188
US-Bar	53.6289	-71.2881	3.5285	**0.6408**	0.0000	4.0927	0.5253	0.0003	4.5073	0.4819	0.0010
umichbiological	45.5598	-84.7138	3.2051	**0.7385**	0.0007	4.6807	0.4733	0.0193	4.1670	0.5722	0.0071
CA-Oas	53.6289	-106.1978	4.0788	**0.8782**	0.0000	5.7997	0.7475	0.0006	10.0648	0.3473	0.0730

8. Future work

(1) Spatial pattern: What's the model application scenarios? Such as elevation, spring snow, precipitation, and soil type.

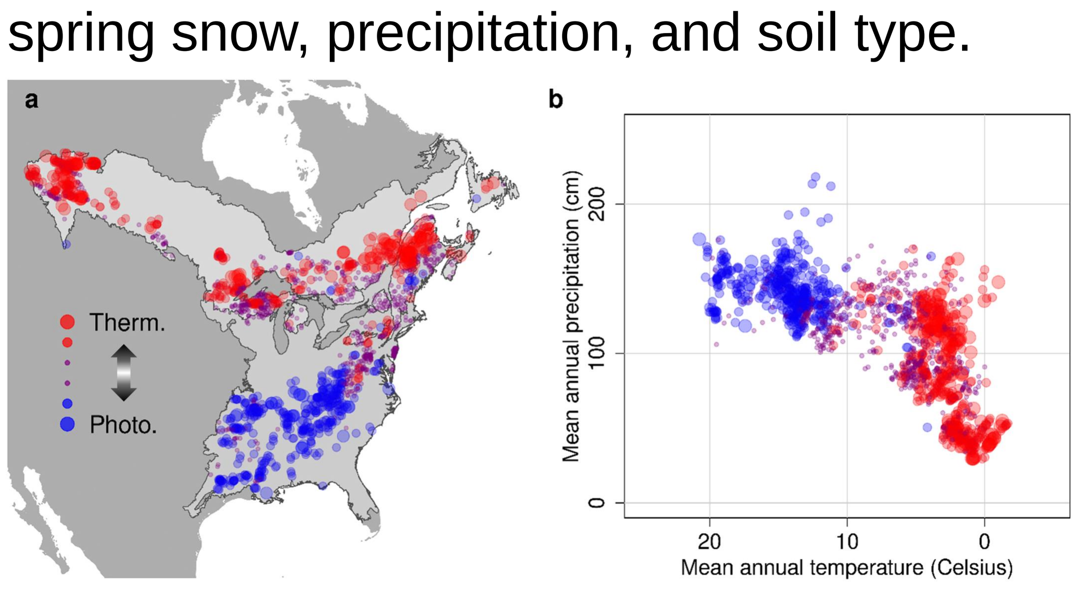

Fig.7. Expected results of our future work: (a) Different application scenarios of different driven factors; (b) Other variables we can consider to apply to our map and their correlation (image source: Minkyu Moon et al 2021, Remote Sensing of Environment).

(2) Domain drivers under different scenarios:

- Mechanism-free model
- Linear regression model
- Spatial and temporal model

9. Summary

We demonstrate that:

(1) Phenology metrics extracted from **daily MODIS** data is **more sensitive** to 16-day interval dataset MCD12Q2.
(2) When confronted with frost damage, the plants may have a '**chilling memory**', which can help plants better suffer from frost.
(3) The spring phenology model across sites has a **spatial and temporal mechanism pattern**.

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