## A machine learning approach targeting parameter estimation for PFT coexistence modeling using ELM-FATES

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## **CESM Workshop 2023**

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## **Challenge in modeling PFTs coexistence in FATES**

• FATES is a "cohort-based" VDM model

represent competition/coexistence between different plant functional types (PFTs)

• The challenge is to reasonably simulate the coexistence of PFTs





## **Coexistence theory and modeling**

Niche-based coexistence theory

Filtering

**Environmental** convergence in strategy to adapt to the surrounding environment

Niche partitioning divergence in strategy to ensure differentiation in resource requirements





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## **Research goal and testbed**

### **Research goal**

Utilize machine learning (ML) to

- alleviate the challenge of modeling PFTs coexistence
- reduce model errors against observations



XGBoost

SHAP

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#### **Testbed**

• a tropical forest site: Manaus





## **Model configuration**

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#### **Two PFTs represented in FATES**

Low

- Early vs. late successional broadleaf evergreen tropical tree
- 11 parameters, trait ranges based on tropical tree measurements

High



Parameter name	Early PFT Late PFT	Г Range
Maximum carboxylation rate of Rub. at 25 °C, canopy top	$V_{cmax,early} > V_{cmax,late}$	40–105
Specific leaf area, canopy top	$SLA_{early} > SLA_{late}$	0.005–0.04
Background mortality rate	$M_{bk,early} > M_{bk,late}$	0.005-0.05
Wood density	$WD_{early} < WD_{late}$	0.2–1.0
Leaf longevity	$L_{leaf,early} < L_{leaf,late}$	0.2–3.0
Maximum size of storage C pool, relative to the maximum size of leaf C pool	same	0.8–1.5



## **Overall flowchart and research questions**

#### P1. Parameter sampling

Latin hypercube sampling, and tradeoffs  $V_{cmax,early} > V_{cmax,late}$ ,  $SLA_{early} > SLA_{late}$   $M_{bk,early} > M_{bk,late}$ ,  $WD_{early} < WD_{late}$  $L_{leaf,early} < L_{leaf,late}$ 

#### P2. Initial FATES experiments

Exp-OBS, consideration of observed trait \_ relationships

Exp-CTR

### P3. Build ML models and sensitivity analysis

ML models train and test SHAP importance analysis

#### P4. Parameter selection and validation

Exp-ML, ELM-FATES simulation using ML selected parameters

### **Specific research questions**

- Q1: Whether observed trait relationships can improve PFTs coexistence?
- Q2: Can simple parameter correlations be constructed to improve PFTs coexistence?
- Q3: Can ML selected parameter values improve PFTs coexistence?



## Q1 $\rightarrow$ Observed trait relationships cannot improve PFTs coexistence modeling

Two experiment ensembles

- Exp-CTR, traits tradeoffs
- Exp-OBS, traits tradeoffs + observed trait relationships

#### $\rightarrow$ degraded the PFT coexistence simulations



Koven et al. (2020) and Longo et al. (2020)							
$M_{bk} = 0.0082 \times e^{(0.0153 \times V_{cmax})}$	(1)						
$L_{leaf} = 0.0001 \times SLA^{(-2.32)}$	(2)						
$WD = -0.583 \times \ln(SLA) - 1.675$	4 (3)						

PFT coexistence : Biomass ratio between early PFT and total biomass

 $\begin{array}{l} BR_{e2t} \in (0.9, 1.0], \, \text{``early''} \\ BR_{e2t} \in [0.1, 0.9], \, \text{``coexistence''} \\ BR_{e2t} \in [0.0, 0.1), \, \text{``late''} \end{array}$ 



### Q2 $\rightarrow$ Simple constructed correlations are also insufficient

### Based on Exp-CTR, build empirical simple parameter correlations



- $SLA_{late} > 0.35 \times SLA_{early} + 0.003$
- $V_{cmax,diff} < -4800 \times SLA_{diff} + 100$
- $WD_{diff} > 55 \times SLA_{diff} 1.3$

Within these constrained parameter spaces,

- Coexisting cases increases from 20.6% to 32.6%
- 67.4% is still either early or late
- Optical cases account only about 2.3%





Northwest

## **Build ML surrogate models**

### In Exp-CTR, 1500 samples of

- Xn, parameters and their difference e.g., V<sub>cmax,early</sub>, SLA<sub>diff</sub>,
- Yi, ELM-FATES outputs e.g., ET, SH, GPP, AGB, BW

Build emulators  $Y_i = \mathbf{f}_i (X_1, X_2, X_3, ...)$ 

> Machine learning algorithm e.g., XGBoost (Chen et al., 2016)

> > SHAP (SHapley Additive exPlanations, Lundberg et al., 2017)

Parameters selection







## ML surrogate models have good performance

- 6 XGBoost surrogate models: ET, SH, BW, GPP, AGB, and  $BR_{e2t}$
- Overall good performance in training and testing samples
  - AGB and  $BR_{e2t}$  are relatively difficult to emulate





## Which parameters are important

• Only 3 features dominate the prediction of ET, SH, BW, and GPP





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## Which parameters are important

- More than 6 features are most important for predicting AGB and  $BR_{e2t}$
- Trait parameter differences between early and late PFT are very important
  - e.g, *SLA<sub>diff</sub>*, *Vcmax<sub>diff</sub>*



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## **Parameter selection using ML surrogate models**







### **ML** selected parameter values largely improve FATES simulation

- ML selected parameters  $\rightarrow$  better capture observations
- ML selected parameters  $\rightarrow$  more well-coexistent runs





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### Compared with **Exp-CTR** and **Exp-ML** have

- 3.6 times more coexistence cases,  $20\% \rightarrow 73\%$
- 23.6 times more optimal cases,  $1.4\% \rightarrow 33\%$ , with higher model accuracy

Category	$BR_{e2t}  AGB_b  \in [0.1, 0.9] < 15\%$	AGB_bias	s   GPP_bias  < 15%	ET_bias  <15%	SH_bias  < 15%	BW_bias  < 15%	Exp-CTR		Exp-ML		Patio
		<15%					count	percent	count	percent	Katto
Late							130	8.7%	174	11.6%	1.3
Coexistence							309	<mark>20.6%</mark>	1097	<mark>73.1%</mark>	<mark>3.6</mark>
Early							1059	70.6%	229	15.3%	0.2
All dead							2	0.1%	0	0.0%	
Total							1500		1500		
Add observation constraints	+						309	20.6%	1097	73.1%	3.6
	+	+					98	6.5%	620	41.3%	6.3
	+	+	+				85	5.7%	618	41.2%	7.3
	+	+	+	+			23	1.5%	572	38.1%	24.9
	+	+	+	+	+		23	1.5%	502	33.5%	21.8
	+	+	+	+	+	+	21	<mark>1.4%</mark>	495	<mark>33.0%</mark>	<mark>23.6</mark>



Northwest

## Parameter tradeoffs align with niche-based coexistence theory





Niche

partitioning

divergence in strategy

### Relative difference should not be considerable

• Large difference in SLA more likely favors the early PFT

#### Some degree of differences should exist

- Small difference in SLA more likely favors the late PFT
- For Exp-CTR, coexistence have intermediate differences in SLA,  $V_{cmax}$ , WD,  $M_{bk}$  and  $L_{leaf}$
- For Exp-ML, coexistence have intermediate differences in SLA,  $V_{cmax}$ , and  $L_{leaf}$

M\_bk and WD show large difference but they show tradeoff to make coexistence

### Niche-based coexistence theory



Parameter relative difference (%) between early PFT and late PFT



Northwest

## Parameter tradeoffs align with niche-based coexistence theory



 Environmental Filtering
convergence in strategy
Niche partitioning
divergence in strategy

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M\_bk and WD show large difference but they show tradeoff to make coexistence

### Niche-based coexistence theory



Parameter relative difference (%) between early PFT and late PFT



Pacific Northwest

## Parameter tradeoffs align with niche-based coexistence theory

### Difference should not be considerable

Large difference in SLA more likely favors the early PFT

#### Some degree of differences should exist or balance

- Small difference in SLA more likely favors the late PFT
- For Exp-CTR, coexistence have intermediate differences in SLA, V<sub>cmax</sub>, WD, M<sub>bk</sub> and L<sub>leaf</sub>
- For Exp-ML, coexistence have intermediate differences in SLA, V<sub>cmax</sub>, and L<sub>leaf</sub>

 $M_bk$  and WD show large difference but they show tradeoff to make coexistence

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Environmental

Filtering

Niche

partitioning

divergence in strategy

convergence in strategy



Parameter relative difference (%) between early PFT and late PFT



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