

The Influence of
Daily Weather
Variability on Tree
Growth

Richard H Manner
and Justin S Baker

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The Influence of Daily Weather Variability on Tree Growth

Forest and Agriculture Modeling Forum

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Motivation

The primary goal of this work was to predict tree growth in the Southeastern United States as influenced by weather.

More specifically, we wanted to predict tree growth using detailed information about:

- ▶ Site
- ▶ Competition
- ▶ Daily Weather

Fit in Literature

There are a number of process-based models that already incorporate sub-annual weather into their pipelines:

- ▶ Monthly: 3-PG Forest Growth Model (Landsberg et al. 1997)
- ▶ Daily: Vaganov-Shashkin Process-Model (Vaganov et al. 2006)

But there is a gap in the literature. To the best of our knowledge, there are no empirical models of tree growth that consider the daily variability of weather when predicting tree growth.

Some models consider:

- ▶ Counts of days meeting a criteria
- ▶ Monthly Averages
- ▶ etc...

Call to Action

It is becoming more and more apparent that we need to be able model growth responses due to climate change (Gilson et al. 2025).

- ▶ Though we are debating the merits of process-based vs empirical methods

We introduce a technique that pairs signal processing with artificial neural networks (ANNs) and a wide range of training data; proposing an alternative approach.

Merits of Artificial Neural Networks

ANNs are also called universal approximators due to their flexibility and ability to mimic underlying processes through training (Cybenko 1989; Hornik et al. 1989).

This makes them ideal for:

- ▶ Modeling complex processes
- ▶ Mixing linear and non-linear effects
- ▶ Cases where the exact functional form is unknown

Though there are a couple of drawbacks:

- ▶ Their flexibility comes with the risk of over-fitting the data.
- ▶ Predictions that are outside the scope of the training data are potentially spurious
- ▶ They are pretty “black-box”

Artificial Neural Networks in Forestry Applications

Some recent examples include:

- ▶ Capturing growth dynamics: Bolat et al. 2023; Kabildjanov et al. 2023; Salehnasab et al. 2022; Silva Tavares Júnior et al. 2020
- ▶ Predicting specific tree characteristics: Chiung et al. 2025; Abbas Sahin et al. 2023; Sahin 2024; İlker 2020; Shen et al. 2020
- ▶ Influence of weather on forests: Zhang et al. 2023; Habeeb et al. 2025; Hamidi et al. 2021.

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Tree Growth Data

We leverage tree level observations from the **USDA Forest Service's Forest Inventory and Analysis Data**.

Plot/Conditions:

- ▶ Site:
 - ▶ Slope, Aspect, Elevation, etc...
- ▶ Competition:
 - ▶ Basal area, invasive species
- ▶ Management:
 - ▶ Stand origin, interventions

Tree:

- ▶ DBH change
- ▶ Height
- ▶ Damage
- ▶ etc...

Keep in mind that this is not a “regular” panel dataset as the re-measurement period is not fixed (roughly 5 years).

Historical Weather Patterns

Between measurements we pull daily weather related variables in from **Oak Ridge National Laboratory's DAYMET** for each plot in our FIA dataset.

- ▶ Precipitation
- ▶ Minimum Temperature
- ▶ Maximum Temperature
- ▶ Diurnal Temperature Range (calculated)

Note, FIA plot locations are fuzzed. This includes swapping and moving (between 0.5 and 1 mile) plots (LaPoint 2005), exact locations are not known.

Extracting Weather Features

We apply three transformations to the weather related series to extract meaningful information.

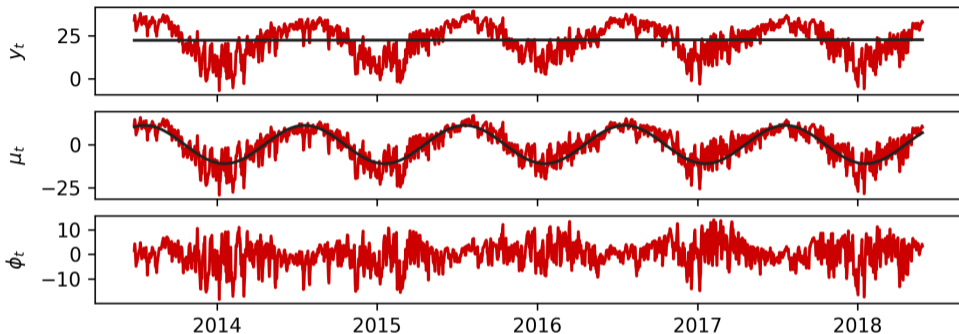
- ▶ Linear Trend Model
 - ▶ Intercept
 - ▶ Slope
- ▶ Sinusoidal Seasonal Model
 - ▶ Amplitude
 - ▶ Excludes precipitation
- ▶ Maximum Overlap Discrete Wavelet Transform
 - ▶ Variance using Haar Wavelets

$$y_t = \beta_0 + \beta_1 \times t + \mu_t$$

$$\mu_t = a \times \sin(p \times (t + o)) + \phi_t$$

$$\sigma_j^2 = \text{var} \left\{ \text{MODWT}_{j=2^1}^{2^8} \phi_t \right\}$$

Example Pipeline



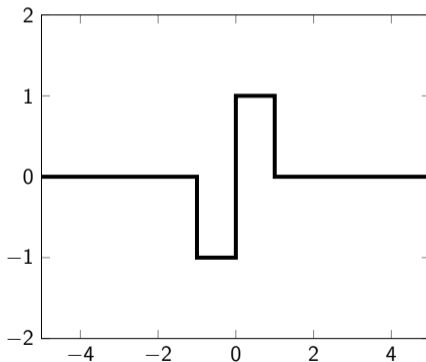
The linear and seasonal processes soak up a lot of the traditional measures of time series signal.

The remaining signal represents heat waves, cold snaps, droughts, etc...that would traditionally be thought of as noise.

Wavelet Basics

A Discrete Wavelet Transform involves sliding a wavelet function along a signal to capture how a signal changes through time.

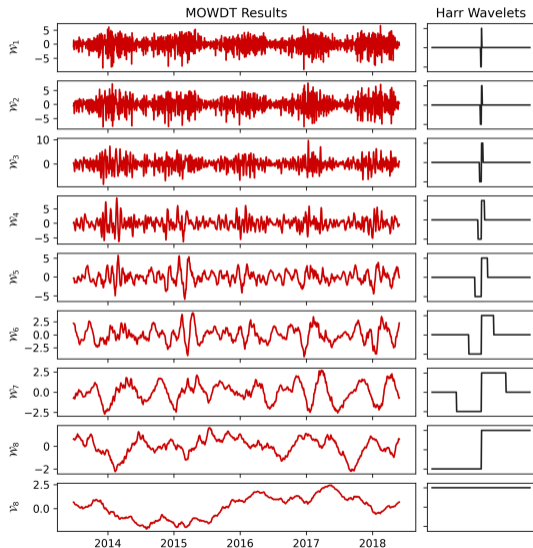
The simplest is the Haar wavelet, which is a square wave of period t .



Example Pipeline

- ▶ We employ Haar wavelets with width from 2^1 up to 2^8 days
- ▶ Shorter duration wavelets capture the signal's high frequency changes.
- ▶ The MODWT has a **cool** feature: the sum of the output variances is equal to the variance of the input signal (Percival et al. 2000)^a

^aUnder certain conditions, that are present here



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Artificial Neural Networks

Anatomy of an ANN

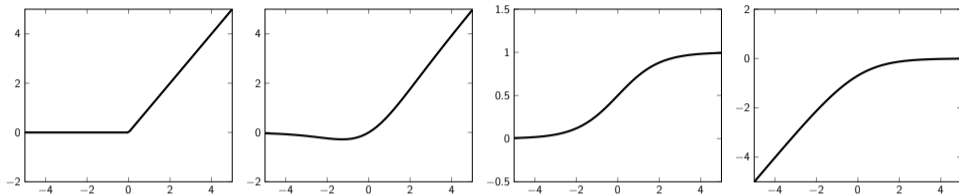
ANNs are composed of layers and nodes. We use Deep Neural Networks, which just means they are composed of multiple hidden layers.

During training, we test different depths (number of layers), widths (number of nodes per layer), and non-linear activation functions.

We also tested different model specifications:

Model Name	Description
Simple	Starting DBH, Starting Height, Number of Days Between Measurement
No Weather	Add in site characteristics, competition, and canopy description
Simple Weather	Add in the estimated linear and sine function weather parameters
Precip Weather	No Weather plus all of the variables associated with precipitation
Min Temp Weather	No Weather plus all of the variables associated with minimum temperature
Max Temp Weather	No Weather plus all of the variables associated with maximum temperature
Temp Difference Weather	No Weather plus all of the variables associated with temperature difference
Temp Weather	No Weather plus all of the variables associated with temperature
MODWT Weather	Simple Weather plus the variances from the MODWT

Activation Functions



Activation functions available in training (left to right).

- ▶ The **ReLU** is defined as $\max(0, x)$.
- ▶ The **SiLU** is defined as $x / (1 + \exp(-x))$.
- ▶ The **Sigmoid** is defined as $1 / (1 + \exp(-x))$.
- ▶ The **Log Sigmoid** is defined as $\ln(1 / (1 + \exp(-x)))$.

Training Process

Data was split into two groups, Train (70%) and Test (30%).

- ▶ Training data was used to fit model parameters.
- ▶ The test data was then used to determine the MSE of the model, inform the early stopping algorithm, and selected the best performing model

Models were allowed to train for up to 5,000 epochs.

We employed two kinds of regularization techniques to prevent overfitting

- ▶ Early Exit
- ▶ L2 Regularization (Ridge)

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Model Training Results

Species	Act. Func.	Layer Count	Expan. Factor	Learn Rate	Model Feats.	Test MSE	Train MSE	Best Epoch
Eastern Redcedar	Sigmoid	12	1	0.001	MODWT	0.18	0.17	491
Shortleaf Pine	Sigmoid	4	3	0.001	Temp	0.18	0.17	835
Slash Pine	Sigmoid	6	3	0.001	T-Max	0.36	0.34	907
Loblolly Pine	Sigmoid	4	1	0.001	MODWT	0.54	0.52	733
Virginia Pine	Sigmoid	6	3	0.001	Temp	0.17	0.17	581
Pondcypress	Sigmoid	6	1	0.001	Temp	0.21	0.18	328
Red Maple	Sigmoid	12	1	0.001	Temp	0.27	0.25	710
Sugar Maple	Sigmoid	6	2	0.001	T-Min	0.23	0.23	489
Black Hickory	Sigmoid	4	3	0.001	T-Max	0.07	0.06	382
Sweetgum	Sigmoid	4	2	0.001	Temp	0.31	0.30	501
Yellow Poplar	Sigmoid	4	3	0.001	Precip	0.51	0.48	744
Blackgum	Sigmoid	6	2	0.001	T-Diff	0.12	0.13	417
Swamp Tupelo	Sigmoid	6	2	0.001	Simple	0.15	0.25	399
Sourwood	Sigmoid	6	2	0.001	Temp	0.11	0.09	487
White Oak	Sigmoid	4	3	0.001	T-Diff	0.19	0.19	765
Scarlet Oak	Sigmoid	6	3	0.001	T-Diff	0.26	0.24	352
Laurel Oak	Sigmoid	4	1	0.001	MODWT	0.49	0.46	565
Water Oak	Sigmoid	12	2	0.001	Temp	0.51	0.45	409
Chestnut Oak	Sigmoid	6	3	0.001	T-Diff	0.15	0.14	444
Post Oak	Sigmoid	12	1	0.001	MODWT	0.15	0.24	338
Winged Elm	Sigmoid	12	1	0.001	T-Min	0.20	0.17	415

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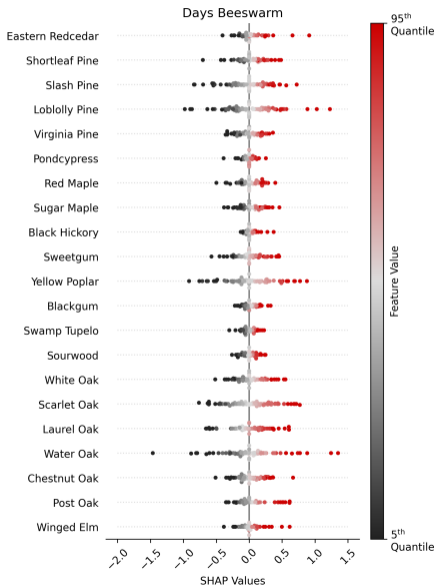
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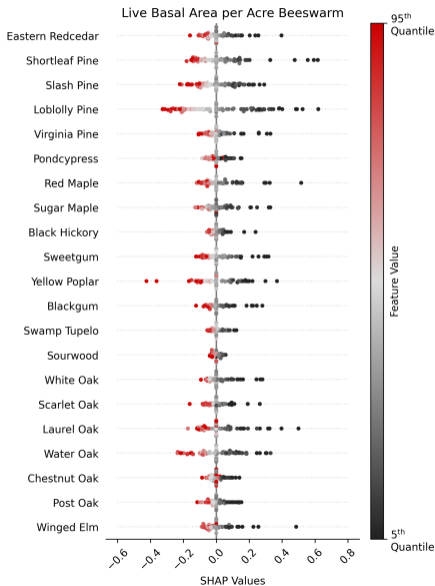
SHAP Analysis



Days Between Measurement

- ▶ The more time between tree-level observations, the more the tree grew
- ▶ This is, as expected, one of the more influential factors in predicting an individual tree's growth
- ▶ Nothing too exciting here, except that our ML model picks up on this

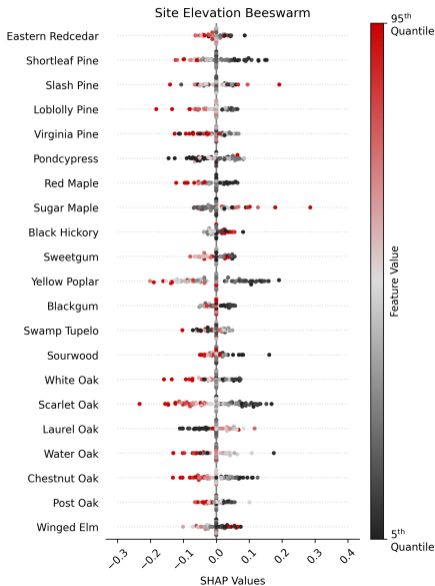
SHAP Analysis



Basal Area of Live Trees

- ▶ Higher basal areas tend to be associated with lower growth predictions
- ▶ Backs up extensive literature on competition measures and growth expectations (Opie 1968; Murphy et al. 1996; Hall 2004)
- ▶ Also a fairly influential variable in our predictions.

SHAP Analysis



Site Elevation

- ▶ For most species, growth rates are negatively correlated with elevation.
- ▶ The relationships here are a bit muddier, indicating potential interactions that are not captured by SHAP analysis
- ▶ A couple of species, like Sugar Maple and Laurel Oak, tend to prefer higher elevations

Influence of Weather

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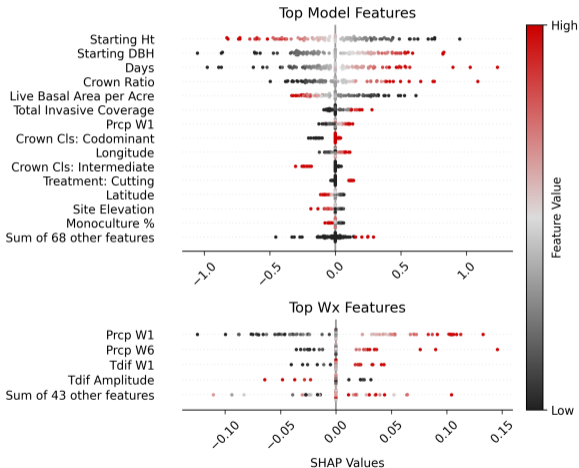
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Loblolly Pine Beeswarm Plot



Loblolly Pine

- ▶ The variability in precipitation at very short time scales tends to be the most influential weather related variable
- ▶ Other weather related variables do not crack the top 10
- ▶ Weather tends to play a secondary role in our model according to the SHAP Analysis.

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North Carolina Planted Loblolly Pine Case Study

Background

In the Southeastern US, private land-owners engage in monoculture planted forests for a variety of reasons (Messier et al. 2022).

These planted systems are often highly managed and produce timber as quickly as possible (Paquette et al. 2010).

Concerns over biodiversity loss in forest have prompted considerable research (i.e. (Feng et al. 2022; Liu et al. 2024; Tilman et al. 2014)) and some governments to explore strategies pursuant to its restoration (i.e. European Union Forest Strategy (European Union 2021) and Biodiversity Strategy (European Union 2020)).

Our concern comes from the correlative risks that fall out of diversified holdings and portfolio selection (Markowitz 1952).

Methods

We construct simulations of planted loblolly pine growth across 700+ FIA plots where it had been previously planted.

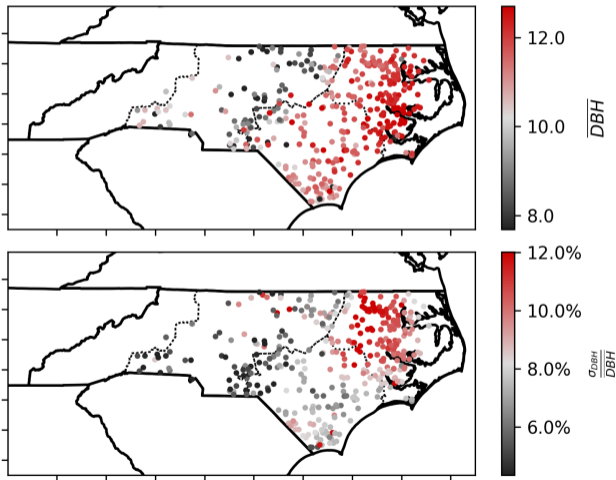
We use 88 different weather forecasts from the **NASA Earth Exchange Global Daily Down-scaled Projections (NEX-GDDP-CMIP6)** to produce a distribution of outcomes and explore the correlative risks.

Our simulations run 30 years out, through 2053. We calculate the expected value and variance at each plot.

The variance is driven by uncertainty in the weather forecasts

Results

NC Planted Loblolly Pine Simulated DBH in 2053
(30 years of growth)



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