Analyzing green-up phenology of North American forest ecosystems with PhenoCam and AmeriFlux data

[ Short Title ]

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**Abstract**

Terrestrial forest ecosystems play a major role in sequestering atmospheric carbon dioxide, which can offset the detrimental effects of anthropogenic carbon emissions. However, climate change has and will continue to affect the timing of forest ecosystems’ carbon uptake, changing the “green-up” date at which forests transition from a net carbon source to a net carbon sink. Prior studies have investigated the relationship between the green-up date and temperature data, hypothesizing that a site’s green-up date correlates to the date when soil temperature crosses over the mean annual air temperature. In this study, we analyze 50 site years of recent climate and green-up data to clarify our understanding of the correlation between these variables. Results show that, while the hypothesis holds very strongly in deciduous broadleaf forests in the midwestern United States and others, it breaks in northern United States forests, likely due to the colder winters of this “boreal-adjacent” zone interfering with the warming of soil temperatures in the spring. Therefore, this phenological rule is rendered inapplicable in these regions.

**Introduction**

Atmospheric carbon dioxide (CO2) is a crucial factor influencing modern climate change, accounting for 60% of anthropogenic warming (IPCC 2019). Forest ecosystems act as the largest land-based carbon sink, as they intake and sequester a significant portion of anthropogenic CO2 during photosynthesis. However, the land sink is the least understood portion of the global carbon cycle, and the variable seasonal flux of photosynthesis contributes to this knowledge gap. The phenology, or recurring timing, of forest photosynthesis activity is an especially critical factor now, as climate change has started to alter and warp its timing. Phenological shifts can have drastic effects on the trophic web and ecosystem health — changes in forest phenology can alter species’ migration patterns, breeding patterns, and interspecies competition (Mayor et al. 2017; Wilsey et al. 2011). As trees “green-up,” or put out leaves in the spring, earlier due to changing climate (Keenan et al. 2014), many species will inevitably struggle to keep up, which could lead to asynchronous predator-prey occurrence and other cases of trophic collapse. Along with these ecological impacts, changing forest phenology also has major implications for surface energy and water fluxes (Arora 2002). Forest green-up impacts albedo, evapotranspiration, trace gas exchange, and cloud formation via effects on the planetary boundary layer (Santanello et al. 2007).

In addition to providing information about a forest’s carbon sequestration potential, the green-up date has been used in recent decades as a proxy for global climate change itself. The green-up date is one of the best metrics to examine how climate impacts an ecosystem’s biology and metabolism, factors that then control the ecosystem’s productivity. Numerous studies have shown that green-up has shifted progressively earlier as climate warms (Keenan et al., 2014; Jeong et al. 2011; Zhang et al. 2004). However, these dynamics vary over latitudes and ecosystem types, and require closer study to examine and predict how green-up is changing. Perhaps most importantly, the green-up date has direct implications for a forest’s photosynthetic productivity and carbon sequestration potential. The start date of the growing season plays a large role in determining its length, which then determines the amount of carbon uptake throughout the duration of the growing season (White et al., 1999; Keenan et al. 2014; Tao et al. 2020). Additionally, recent studies have examined the impacts of climate change on the timing of autumn senescence, finding that leaf-fall is delayed in many cases by climate change (Ibáñez et al. 2010; Gonsamo et al. 2017). Together, the earlier green-up and delayed autumn senescence could lead to an overall increase in carbon uptake, therefore mitigating some increases in anthropogenic emission of carbon dioxide.

Experimental studies have also investigated the impacts of anthropogenic carbon emissions on forest photosynthetic productivity, investigating the potential “boost” that CO2 emissions could provide for forest photosynthesis. Free Air Carbon Enrichment (FACE) uses vent pipes to release CO2-enriched air at the periphery of forest plots, which is then dispersed across the area via wind and diffusion. These FACE experiments have found that carbon enrichment at levels within 475-600 ppm leads to increased light carbon uptake and increased forest productivity (Ainsworth et al. 2004). Additionally, stomatal conductance decreased as a result of heightened carbon levels, which could reduce plant water stress, an important factor considering growing drought concerns (Bernacchi et al. 2003).

A longer and more productive growing season bodes well for mitigating climate change. However, these altered dynamics could also lead to the earlier depletion of plant-available water, therefore decreasing overall growth and productivity (Buermann et al. 2018; Gonsamo et al. 2019). Additionally, autumn warming could lead to net losses of CO2 from the longer growing season (Piao et al. 2008).

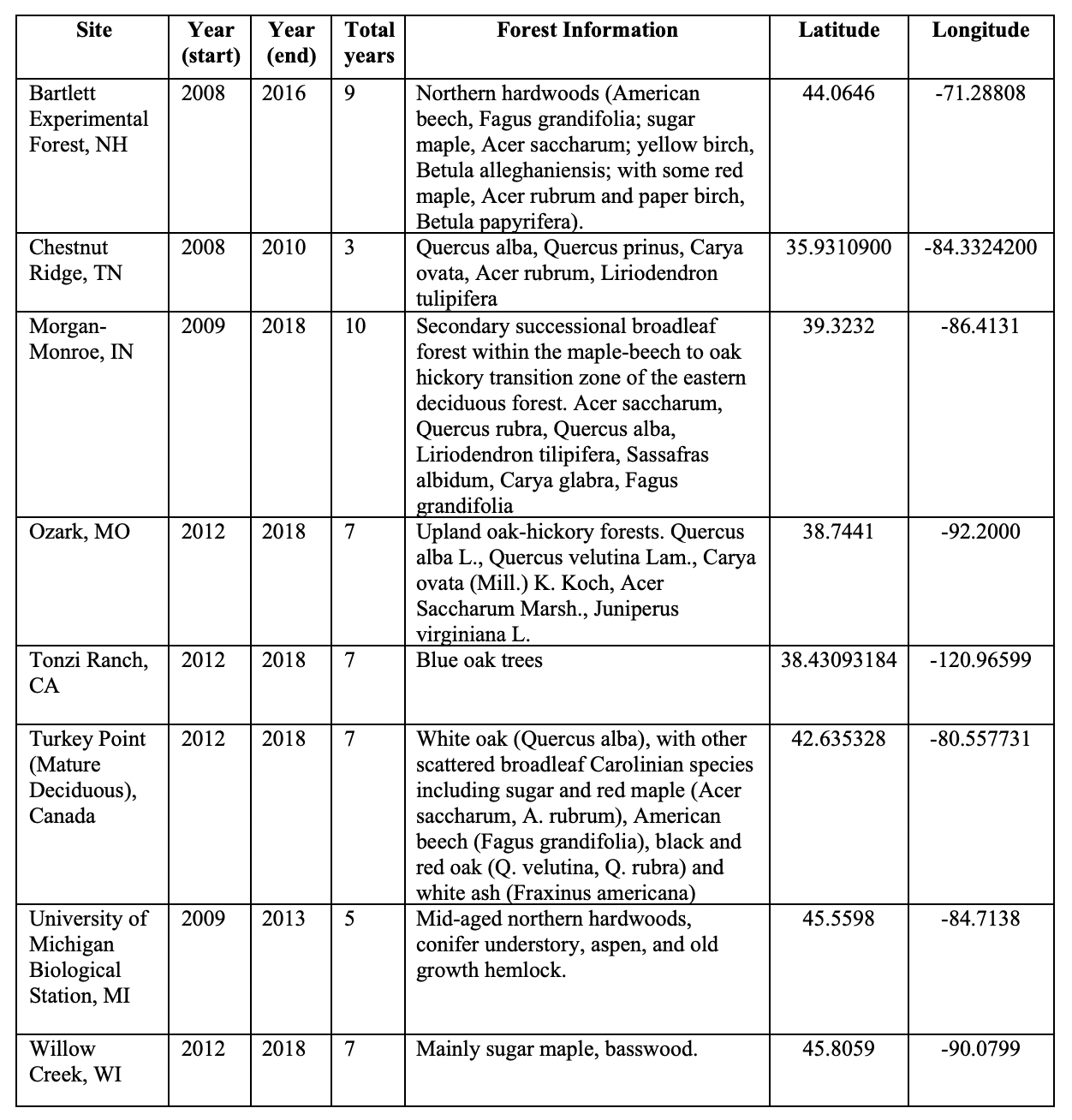
The start of the growing season plays a crucial role in this complex, multifaceted issue of carbon uptake in a changing climate — therefore, being able to understand and predict forests’ green-up dates is increasingly important. Green-up is also often a crucial parameter in biogeochemical, agricultural, and other ecosystem models (Zhang et al. 2018; Bonan 2019; Field et al. 2018; Zhao et al. 2012). Not only does the length of the growing season play a large role in determining crop yield (and therefore fuel yield, in the case of cellulosic biofuels, for example), but the presence or absence of a forest canopy also controls latent and sensible heat flux (Schwartz 1992). Being able to understand the drivers of forest green-up across latitudes and ecosystem types would improve the accuracy and implementation of these models.

Baldocchi et al. tested the phenological hypothesis that the onset date for net carbon uptake by forests (the leaf-out or green-up date) corresponded to the date when the mean soil temperature at the site equals its mean annual air temperature (2005). Originally observed anecdotally in Oak Ridge, Tennessee, this hypothesis was tested across sites in North America and Europe, and was found to explain 61% of variance. Mechanistically, this hypothesis can be justified by the relationship between soil temperature and accumulated heat and chill units. To balance the potential benefits of bud burst with the dangers of frost damage, plants have evolved to use temperature cues to time their leaf-out — as modelled by plant phenologists, the plant must accumulate a certain number of “chilling units” during their winter endodormancy, and a certain number of heat units, or heat forcings, in the spring that trigger bud swelling and burst (Samish 1954; Saure 1985; Tanja et al. 2003; Basler et al. 2012; Campoy et al. 2011). Essentially, trees have evolved to sense how long winter was, and how long the start of spring has been, to determine the time of least risk to put out leaves for the spring. Soil temperature can be used as a proxy for these heat and chill units due to its thermal inertia — its tendency and ability to hold heat (Baldocchi et al. 2005). This explains why such a strong correlation has been found between the annual trajectory of soil temperature, mean annual air temperature, and forest green-up.

In this study, we retest the hypothesis of Baldocchi et al. (2005) with over 50 site-years of new data across the United States, sourced from AmeriFlux, a network of PI-managed meteorological sites, and PhenoCam, an ecosystem phenology camera network using digital cameras at over 500 study sites to continually monitor and record vegetation and ecosystem data.

**Methods**

The joint AmeriFlux and PhenoCam sites used in this study include a wide range of latitudes across the US. Sites originally studied by Baldocchi et al. (2005) were included, as well as new sites to examine particular regions of interest. All sites included primarily deciduous broadleaf species, with some conifers and grasslands. A site table listing locations, years, forest genera and species, and latitude and longitude is shown below (Table 1). Air temperature (TA), measured half-hourly above the canopy, and soil temperature (TS) data for each site were acquired from open-access AmeriFlux datasets. While available recorded depths varied for soil temperature data across sites, the median depth available at each site was selected. Soil temperature was often gap-filled by the site team. To examine the green-up dates at each site, publicly available data via the PhenoCam site was used.

**Table 1:** Includes all study sites, with start and end years, forest genera and species, latitude, and longitude. (Ouimette et al. 2018; Meyers 2016; Novick and Phillips 2020; Wood and Lianhong 2019; Ma et al. 2016; Arain 2018; Gough et al. 2021; Desai 2021)

PhenoCam provides near-real time RGB imagery at each of its sites, as well as various vegetation index data such as NDVI. For sites with a single yearly cycle of vegetation activity, PhenoCam provides date estimates for the ecosystem’s spring “green-up” and autumn “green-down” phases (Richardson et al. 2018). We used PhenoCam’s transition estimates derived from 3-day-aggregated vegetation data, selecting the dates that corresponded to 50% of the GCC amplitude for the green-up stage (Seyednasrollah et al. 2019). Since a range of green-up dates were provided in the confidence interval, there may be some uncertainty in the data as to the precise date most accurately reflecting the forests’ green-up. To refine these dates for use in future studies, one could integrate by-eye validation of PhenoCam imagery to detect the dates where the forest begins to put out leaves, or combine the PhenoCam-provided transition dates with observations of daily integrated net CO2 exchange (NEE) or the onset of canopy photosynthesis.

Half-hourly soil temperature (TS) data was resampled to find daily means, and the half-hourly air temperature (TA) data over the entire study period was resampled to find the mean annual air temperature at each site. The date at which TS crossed over the mean annual air temperature was plotted against the PhenoCam-sourced green-up date to investigate the correlative strength of our hypothesis.

*Statistical Methods*

Software

Statistical tools and packages used for this analysis included Pandas and Scipy. To output our visualizations, we used Mathplotlib and Seaborn packages.

Data Processing, Outliers, and Missing Values

For the Ameriflux data, the independent variable was the timestamp at which the soil and air temperatures (our dependent variables) were collected. We observed no outliers for our temperature data, except for temperatures recorded as -9999. We determined that this meant the data for this entry was missing, and therefore we omitted rows with this value in our analysis. Our purpose for omitting missing data entirely as opposed to interpolating the data was that whenever there was missing data in the “middle” of the dataset, it would often span several rows. For this reason, it is likely that interpolating would fail to capture the cyclical pattern of temperature, but rather falsely represent a stable temperature over a large period of time. In addition, we often found the missing data to be in the beginning and the end extremes of the datasets. It therefore made more sense to focus on a subset of entries across which we had more consistently available data.

Technical Procedure

Half-hourly soil temperature (TS) data was resampled to find daily means, and the half-hourly air temperature (TA) data over the entire study period was resampled to find the mean annual air temperature at each site. The date at which TS crossed over the mean annual air temperature was plotted against the PhenoCam-sourced green-up date to investigate the correlative strength of our hypothesis. We wished to perform a linear regression between the temperature records, but first we had to check for assumptions of a linear regression, namely linearity, homoscedasticity, co-linearity, and normality of the distribution. To check linearity (i.e. the assumption that there is a linear relationship between our independent and response variables), we will simply observe a scatterplot of our variables, as seen below.

Chart, scatter chart

Description automatically generated

As one can see, there appears to be some form of a linear relationship, albeit a rather weak one. We can verify this assumption by looking at the residual plot of fitted values from our model. This plot shows the how much the green-up dates for each site predicted by our model differ from the actual green-up dates observed from the PhenoCam data.

Chart, scatter chart

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Here we notice that the residuals appear to be evenly distributed across the residual line with roughly constant variance. This observation satisfies the assumption of linearity.

We can also use this same plot to check our homoscedasticity assumption, which is the assumption the variance of the residuals is roughly constant across the data. As stated before, this is the case for our analysis, and therefore we have satisfied this assumption as well.

Co-linearity is the dependence of the independent variables on each other. The co-linearity assumption states that all independent variables must be independent from one another. Fortunately, we do not need to check co-linearity in our analysis, as there is only one independent variable.

Chart, scatter chart

Description automatically generatedFinally, we will check our residuals follow the normal distribution. We will do this using a histogram and a Q-Q plot of the residuals.

Chart, histogram

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From the histogram, we see that the relative frequency of the residuals roughly follows the normal distribution, as depicted by the solid black line in the plot on the left. On the right we see a QQ plot of the residuals. As one can see, the data points fall closely to the diagonal reference line, suggesting that these residuals do in fact follow a normal distribution. Therefore, this final assumption is satisfied.

A linear regression was generated between these temperature recordings, giving us the slope, intercept, R2, and p-value of our regression. For this analysis, we used a p-value threshold of 0.05 to determine statistical significance.

The analysis was then repeated for a subsection of the sites located in lower-altitude regions that we postulated would better fit our hypothesis. We checked the assumptions of the linear model for this subset as well, which can be seen as follows:

Chart, scatter chart

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From the scatterplot on the left, we see the data appears to follow a strong linear pattern. From the residual plot on the right, we see that the residuals appear to be evenly distributed across the residual line with roughly constant variance. Therefore, we have satisfied the assumptions of linearity and homoscedasticity.

Chart, line chart, scatter chart

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Description automatically generatedAgain, co-linearity does not need to be checked, as there is still only one independent variable. For normality:

From the histogram on the left, we observe that the residuals roughly follow the normal distribution. From the QQ plot on the right, we observe that the data points appear to be fall close to the diagonal reference line. Therefore, we have satisfied the assumption of normality as well.

**Results and Discussion**

Across our selection of study sites, we were able to find examples of site-years where our hypothesis was strongly supported, and sites where it seemed to break. One example of the latter was the Willow Creek, WI site, at which the soil temperature crossed over the mean annual air temperature consistently early compared to the green-up date (Fig. 1).

Chart, line chart

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**Figure 1**: Consistent early cross date between soil temperature and mean annual air temperature in comparison to the PhenoCam green-up estimate for Willow Creek, WI (2012-2016).

One potential explanation for the results at this site could be high latitude and colder winter climate. Out of the entire site group, Willow Creek had the lowest mean annual air temperature (5.4° C) over the study duration, followed by the University of Michigan Biological Station (6.9° C). As can be seen in Fig. 2, this site also fared quite poorly.

Chart, line chart

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**Figure 2**: Graphs exhibiting the annual course of soil temperature, the mean annual air temperature, and the green-up date. Similar weak correlation at the University of Michigan Biological Station (2009-2013).

Though not truly in the North American boreal zone, these forests could represent a boreal-adjacent zone, where colder winter temperatures and lingering snow cover impact the timing of crossing between soil and air temperature (Brandt 2009; Griffis et al. 2003). While Baldocchi et al. (2005) stated that their phenological rule does not hold for deciduous forests in the boreal zone, we would extend this statement to the “boreal-adjacent” latitudes in the northern United States as well.

However, sites in the lower latitudes exhibited much stronger correlations. This hypothesis was originally posited through observation in Oak Ridge, Tennessee, and, indeed, deciduous forests in the midwest and southern states fared best. One of the strongest examples of our hypothesis occurred at Ozark, MO (Fig. 3).

Chart, line chart

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**Figure 3**: Graphs exhibiting the annual course of soil temperature, the mean annual air temperature, and the green-up date. These graphs show a strong correlation between the date when Ts = Ta and the green-up date at Ozark, MO (2012-2017).

This strong support of our hypothesis was echoed across other sites in similar latitudes, suggesting that climate and latitude plays a large role in determining whether this hypothesis works, or breaks.

While the site-wide correlation of this phenological rule was weaker than originally exhibited by Baldocchi 2005 (Fig. 4), the correlation strength vastly increased within a grouping of lower latitude sites (Fig. 5). When considering all sites, we found that linear regression explained only 11% of the variance between the day when the soil temperature crossed the mean annual air temperature, and the green-up date. However, removing three of the highest-latitude sites, along with the Tonzi Ranch, California, site, allowed the r-squared value to increase to .76 (76%).

**Chart, scatter chart

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**Figure 4:** Graphing the day when Ts > Ta, and the green-up day across all site-years, exhibiting the relatively low strength of the hypothesis (r-squared = .119; p-value = .011) when tested across all site-years.

Chart, scatter chart

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**Figure 5:** Graphing the day when Ts > Ta, and the green-up day across all site-years, exhibiting the strength of the hypothesis (r-squared = .759; p-value = 0) when tested across lower latitude sites.

In particular, a surprising development was the relative weakness of our hypothesis at Tonzi Ranch, CA, in recent years. While Baldocchi et al. found the relationship to hold very well at Tonzi Ranch, new data showed the date when soil temperature crossed air temperature to skew very late compared to the green-up date. Similar to the newer breaking of the hypothesis at higher latitude sites with colder winters, this change could be due to the increased intensity of drought and milder winters in California. More investigation at these sites with wider climate fluctuation could aid in understanding the new changes.

Two potential sources of error — the depth variation of soil temperature recording, and the use of PhenoCam’s green-up estimates — could potentially exist here. Due to certain soil temperature depth measurements being unavailable at some sites, the closest depth had to be substituted into an otherwise standardized dataset. Additionally, PhenoCam’s green-up estimates only serve as a proxy for the actual, quantifiable green-up date — the date when the forest transitions from a net carbon source to a net carbon sink. While the PhenoCam’s estimates vastly increase efficiency and accessibility for testing this hypothesis, their use does sacrifice some of the precision gained by using measurements of daily net ecosystem carbon exchange.

Overall, our findings suggest that this phenological rule can be applied to a vast number of sites, especially with the implementation of field validation to improve green-up day estimates and soil temperature measurements. Especially for lower latitude eastern deciduous broadleaf sites, this method could be extremely helpful in generating wide green-up estimates which can then be used to refine biogeochemical models requiring phenological input. With further refinement, this method can be quickly and easily implemented to not only estimate but also predict forest phenology and carbon cycling.

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