

# Species-Specific Responses of Urban Tree Phenology to Climate Drivers in Denver, Colorado

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## Abstract

### 1. Introduction

Urban trees are among the most effective natural mitigators of the urban heat island (UHI) effect—a phenomenon in which urban regions consistently exhibit higher average temperatures than nearby rural areas. The UHI arises primarily from the prevalence of impervious surfaces, such as asphalt, concrete, and rooftops, which absorb and retain solar radiation and reduce nighttime cooling (Oke, 1982; EPA, 2023). These elevated temperatures exacerbate energy demand, degrade air quality, and increase heat-related health risks for urban residents (Stone, 2012). As global temperatures continue to rise and urbanization expands, the effects of UHIs are expected to intensify in the coming decades (Stone, 2012). By providing shade and facilitating evapotranspiration, trees can reduce surface and ambient air temperatures by several degrees. Studies have demonstrated that neighborhoods with mature tree canopy cover experience measurably cooler microclimates compared to areas with limited vegetation (Ziter et al., 2019; Alonzo et al., 2021). Given the increasingly critical role of urban forests in climate resilience strategies, it is essential to understand the drivers of urban tree phenology—the seasonal patterns of leaf emergence, growth, and senescence—and how these patterns may shift as environmental conditions change.

The timing and duration of these seasonal patterns are strongly influenced by climate, particularly temperature and precipitation. Elevated temperatures caused by anthropogenic climate change can lengthen the growing season of urban trees (Zhang et al., 2022; Yang et al., 2020). Higher spring temperatures typically accelerate leaf emergence, while warmer fall temperatures may delay leaf senescence, extending the period of active growth and canopy cover (Zhang et al., 2022; Zhou et al., 2020). This extended canopy period can enhance the cooling benefits of urban trees by increasing shade and evapotranspiration, helping to mitigate the urban heat island effect. However, these benefits are not guaranteed: warmer winters followed by late

spring freezes can delay leaf-out, disrupt flowering, and reduce the expected benefits of extended growing seasons, particularly in species that leaf out early in spring (Chamberlain et al., 2021; Fu et al., 2024).

Precipitation patterns add another layer of complexity. Spring drought can delay leaf-out and flowering, while wet conditions may accelerate growth but increase vulnerability to disease and root stress. In the fall, low precipitation or drought stress can trigger earlier leaf senescence, shortening the period of active growth and reducing canopy cover (Cleland et al., 2007; Peñuelas et al., 2004; Li et al., 2019). Critically, the interaction of temperature and precipitation determines ultimate outcomes, as insufficient soil moisture can counteract the effects of warmer temperatures, underscoring the complex challenges that climate change poses for urban tree health and their role in mitigating urban heat.

Monitoring and predicting these phenological responses require appropriate observational tools. The body of research on urban phenology has evolved along multiple scales of observation. Coarse-scale studies often rely on remote sensing platforms such as MODIS, which provide high temporal but low spatial resolution data to monitor citywide phenological trends and seasonal canopy dynamics (Zhang et al., 2004; Melaas et al., 2016). At the opposite end of the spectrum, fine-scale studies use in-situ observations or near-surface imaging networks like PhenoCam to capture species-level variation and microclimate effects that are often obscured at broader scales (Richardson et al., 2018; Klosterman et al., 2018). More recently, high-resolution satellite constellations such as PlanetScope have emerged as a valuable intermediate approach, combining the spatial precision needed to monitor the location of individually identified trees with the temporal frequency required to monitor phenological changes at an almost daily bases (Bolton et al., 2020; Alonzo et al., 2020). Researchers can now study urban vegetation across large urban areas on an unprecedented detail and scale. This new approach also allows researchers to simulate and predict how different urban tree species may respond to future climate conditions, supporting proactive planning for urban resilience and heat mitigation.

## 1.1 Study Context

These new methodological advances are particularly valuable for cities facing significant projected climate changes. Denver, Colorado provides a compelling case study, as the city confronts both substantial warming and precipitation uncertainty that will directly affect urban tree phenology and the cooling services trees provide. Understanding these dynamics is critical not only for Denver but also for similarly positioned mid-latitude cities experiencing rapid warming and uncertain precipitation futures. According to Colorado State University’s Colorado Climate Center’s most recent Climate Change in Colorado report, by mid-century, Denver is projected to see temperatures rise between 1.4°C and 3.1°C compared to the 1971–2000 baseline. The city has already warmed by approximately 1.1°C over the past 30 years, with the most pronounced increases occurring during summer and fall. Under moderate emissions

scenarios, Denver’s climate will resemble that of Pueblo, Colorado today, whereas higher emissions scenarios could make it feel more like Albuquerque, New Mexico. Summer and fall are expected to warm slightly more than winter and spring, with summer temperatures increasing by 2.2–3.3°C and winter by 1.7–2.2°C. This warming is projected to drive dramatic increases in extreme heat events: by mid-century, Denver could experience an average of 7 days per year exceeding 37.8°C (100°F) and roughly 35 days above 35°C (95°F), compared to very few such days historically. In essence, the typical year in 2050 may be as warm as the hottest years on record today.

Future precipitation patterns for Denver remain highly uncertain, compounding the challenge for urban forest managers. Climate models (CMIP5 and CMIP6 under RCP 4.5 scenarios) disagree on whether precipitation will increase or decrease, with projections ranging from -7% to +7% by 2050. While northern Front Range projections, including Denver, are generally shifted toward wetter outcomes compared to southern Colorado, the consensus is weak outside of winter, when most models project an increase in precipitation. Overall, the share of precipitation falling during heavy downpours is expected to rise from about 46% to 50% by mid-century. Despite these potential increases, warmer temperatures may offset benefits by pulling more moisture from snowpacks, soils, and plants, compounding the risk of drought and reducing water availability. This risk is not hypothetical: Denver has already experienced persistent dry conditions in the 21st century, with four of the five driest years in the 128-year record occurring since 2000.

## 1.2 Objectives

Using near-daily PlanetScope NDVI observations and daily climate data from 2018 to 2024, this study models individual tree phenological metrics against climate variables and land cover in an attempt to control for localized microclimates. We address three key research questions:

1. How do phenological metrics vary among tree species in Denver’s semi-arid urban environment?
2. Which climate variables best predict phenological timing for each species?
3. Do species show differential sensitivities to temperature versus precipitation drivers?

The study period captures years with temperatures and precipitation both above and below the 1971-2000 baseline. Notably, 2024 was Denver’s third warmest year on record, with temperatures 1.8°C above baseline—approximating mid-century projections—while 2019 and 2020 were notably drier than average. This climate variability enables us to model how Denver’s urban trees respond to conditions projected for 2050.

By examining species-level variation in phenological responses, we identify which tree species may be more vulnerable or resilient to future climate conditions. These findings will inform species selection and management strategies for Denver and comparable semi-arid cities.

## 2. Methods & Materials

### 2.1 Denver Tree Set

Overview of the data set

- sources
- number of trees ~300k across denver county
- variables included species size of the tree, diameter
- also GPS location (enable to remotely sense the identified trees location)

To narrow the sample down to a useable sample the trees were sampled based:

- diameter 24"
- Evenly distributed throughout the county
- Among the most popular trees in the county
- Considerations was given for different types of trees (conifers vs. deciduous) and inter-genus (cottonwood) (native/invasive)
- Finally Average crown size for mature species was also considered (usda)
- A shiny application was developed to added in identifying of appropriate sample.
- Results 23,779 Individual trees from 16 different species (**chart** Species | Genus | n | Native/Invasives)

### 2.2 Remotely Sensed NDVI

- What is NDVI
- Used to identify the greenness of the environment and has been used since to study the health and growing cycle of plants.
- 1. NDVI Raw Extracts, 2. Season Breakdown)
- sensors on the planet scope satellites
- Near daily NDVI images were stitched together.
- normalization of the images was conducted with planet scope
- NDVI was then extracted based on location of the id. over the 7 years of images.

## 2.3 Extracted Phenological Metrics

- Metrics extracted using the Pheno-fit package to fit phenological curves to the raw NDVI values
- First NDVI values were despiked using 5 sd away from the mean
- Then a multi-season curve was fitted to the data to derive the multi-year phenological cycle.
- For the most part these the calendar year, however for some years id. growing seasons from phenoy fit leak in to the beginning of the next calendar year.
- To improve the accuracy of the multi-year cycle, the raw NDVI data was de-trended using a lm to account for the season over season increase of some / growing trees in the study.
- Once individual growing season were derived, yearly phenological curves are fitted.
- The fit of each curve was assessed using Adjusted r<sup>2</sup>. If any tree had an r<sup>2</sup> of less than .9 or a growing season detected in 6 years or less, the tree was removed from the sample and phenological metrics were not calculated.
- Based on the criteria outlined above tuning function was used to find the method for fitting a phenological curve to each tree and deriving the phenological season. 3 season and 4 curve
- Elmore Curve with wWHIT season we used as the produced the most used able annual curves.
- BASED ON the curve the metrics were calculated using the (derivative, inflection, ...). Inflection point was used because ....
- All metrics were calculated and saved in the final output. Along with the metadata for season and annual curves for each observation in the data set.
- Custom function was created to easily graph the annual curves and extracted metrics based on the metadata. Github
- in total after processing, the 3450 trees remained out of the initial sample. (chart) (plot of curve and metrics, )

## 2.5 Climate Data

- Source NOAA daily from Denver Central Park (Old denver airport)
- chosen because of its central location
- TMAX, TMIN, PRCP AND SNOW,
- daily tmean was calculated  $(tmax + tmin/2)$
- These based observation were then used to calculate seasonal averages, totals and cumulative totals
- **chart** breaking down the metrics the months they correspond to.

- consitance was strived for

## 2.4 Landcover Data

- Denver LCD souce
- 1 meter reselutions
- it breaks the region down in to 9 different land categories (chart)
- A 90m and 250m buffered was created around the location of each tree in the sample.
- Each individual pixel of the raster was counted to derive for a given category. This data was then turned into %
- For our analysis we used methodology similar to (crawford ), consolidated the 9 categories into 5 different catergories.