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Uneven warming, uneven responses: Within-season trends in thermal accumulation in the northeastern U.S.

Theresa Crimmins

theresa@usanpn.org

University of Arizona https://orcid.org/0000-0001-9592-625X

Kerissa Fuccillo Battle
Eric Scott
Erin Zylstra
Nathan Siegert
R. Talbot Trotter
Aaron Weed
Kristina Riemer
John Daigle
Anthony D'Amato

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Abstract

For many arthropod and plant species in temperate regions, seasonal events such as emergence or flowering are largely driven by accumulated warmth. We examined the dates growing degree day (GDD) accumulations have been reached in recent decades to better understand how species activity may be affected by changing temperature conditions. We analyzed six GDD thresholds (50, 350, 650, 1250, 1950, 2500 GDD) across the northeastern quadrant of the US over the period 1981-2023. For each threshold, we evaluated temporal trends in the date each threshold was reached, then assessed compression or lengthening of periods between thresholds.

Most locations exhibited advancements in threshold dates, though rates of change varied across the region. Consequently, the duration between when threshold pairs were reached varied regionally. Southern and eastern areas showed lengthening between the first two thresholds (50-350 GDD), while mid-season periods were generally compressed. Late-season patterns were most pronounced; northeastern states experienced strong compression, while northwestern portions of the study region showed the opposite pattern with substantial lengthening. At a local scale, the rate of change among various thresholds resulted in unique patterns of compression and lengthening within the season. Such changes have strong implications for plants and animals dependent on warmth to cue transitions among developmental stages, with consequences for the timing and pace of species development and temporal overlap between interacting species. These findings reveal spatially heterogeneous responses to observed temperature accumulation trends from 1981 to 2023 that could significantly impact ecosystem functioning and species interactions across the northeastern US.

Introduction

Globally, temperatures have increased by nearly 2.0°F (1.08°C) since 1850 (NOAA National Centers for Environmental Information, 2025), with substantial impacts to species and ecosystem functioning (IPCC, 2023). The rate of warming has not been consistent around the globe; since 1970, the continental U.S. has warmed more than 50% faster than the planet as a whole (Marvel et al., 2023). The northeast region of the United States, in particular, is warming more rapidly than other parts of the continental U.S. (Hansen et al., 2010; Rohde and Hausfather 2020; Karmalkar and Horton, 2021; Young and Young, 2021), and within this region, changes in temperatures have not been uniform. In particular, coastal, mountain, and higher latitude areas show substantially greater increases in air temperatures than other regions (Karmalkar and Horton 2021; Marvel et al. 2023, Young and Young 2025).

Recent, rapid increases in temperature are directly impacting the timing of seasonal activity in plants and ectotherms. In temperate and boreal ecosystems, temperature is the primary driver of phenology, or seasonal activity in plants and animals. The substantial increase in winter and spring temperatures over the last century has had well-documented effects on plant and arthropod phenology, largely resulting in earlier activity than in previous decades (Parmesan and Yohe 2003; Cohen et al. 2018; Park et al. 2019; Cordes et al. 2020; Fuccillo Battle et al. 2022). Direct observations of plants and animals, including insects, in the northeastern U.S. reveal clear shifts in the timing of spring leaf-out, flowering, egg hatch, and emergence from hibernation in response to this warmth, although the magnitude of response is not consistent among species, and interacting factors (e.g., photoperiod) can lead to complex, species-specific responses (Cook et al. 2008; Tobin et al. 2008; Panchen et al. 2014; Wolkovich et al. 2014; White et al. 2014; Fuccillo Battle et al. 2022). Such changes have both ecological and economic implications. In Vermont, sugar maple trees have leafed out weeks ahead of schedule in many recent years, with implications both for syrup production and leaf-peeping (Vermont Agency of Natural Resources 2025).

Many studies that document shifts in the timing of seasonal activity attribute these to changes in coarse measurements of temperature such as monthly or seasonal averages. However, the amount of warmth an organism must receive to initiate spring-season activity is species specific (Hunter and Lechowicz 1992; Basler 2016). Predicting seasonal activity based on temperature accumulations (e.g., thermal energy), rather than monthly or seasonal averages, more accurately captures and reflects the specific warmth individual species require to meet distinct developmental thresholds. In many species, the amount of accumulated warmth required to trigger a transition such as leaf-out or egg hatch has been quantified in the form of growing degree day (GDD) sums (e.g., Herms 2004; Murray 2008). Used to predict the timing of activity in plants and animals for nearly a century (Arnold 1959; Wang 1960; Campbell et al. 1974), growing degree days are frequently implemented in agriculture, horticulture, and turfgrass and pest management fields to optimize timing of planting, harvest, mowing, and pest survey and treatment application because of their specificity and ease of implementation (Frank and Hofmann 1989; Siegert et al. 2006; Crimmins et al. 2020).

Because each species responds to unique warmth requirements, plant and arthropod species initiate their activity at distinct moments over the course of the season, rather than all at once (Panchen et al. 2014; Park 2016; Wang et al. 2016). Species active early in the season initiate activity once low thermal sums have been reached; later-active species require exposure to greater amounts of warmth. Because increases in temperature are not uniform across space or throughout the season, individual species are uniquely affected by long-term changes in temperature, with individuals in some locations exhibiting much larger advancements in the timing of their activity than others. However, understanding how the recent, spatially and temporally uneven changes in temperature in the northeastern U.S. are affecting plants and animals remains largely unexplored, especially at regional to local scales (Tourville et al. 2024).

Understanding how temperatures—and more specifically, biologically meaningful temperature accumulations—are changing can offer insight into how phenology has changed as well as how species might be affected by future changes in thermal accumulations. Uneven changes in phenology could have profound ecosystem impacts due to cascading effects on overall ecosystem structure and functioning and species interactions (Rafferty et al. 2015; Samplonius et al. 2016; Thackeray et al. 2016; Renner and Zohner 2018). Differential rates of advancement or delay in when GDD thresholds are met could result in some interacting species becoming disconnected in space (particularly for migratory species) and time while others may experience increased temporal overlap. As well, changes in when thresholds are reached can open up temporal niches, allowing for invasion by novel species (Wolkovich and Cleland 2011). A more detailed understanding of changes in when GDD thresholds are being met across the region can help unpack impacts to community and ecosystem structure and functioning. This temporally granular approach can also help optimize scheduling of management activities such as pest and pathogen detection or harvesting of native seeds for restoration purposes (Buisson et al. 2010; Enquist et al. 2014).

In this study, we evaluated trends and patterns in six GDD thresholds that encompass the growing season in the northeastern quadrant of the United States (50, 350, 650, 1250, 1950, 2500 GDD, calculated using temperature measured using the Fahrenheit scale) at a fine spatial grain. The six thresholds represent several points of thermal accumulation throughout the growing season, from the beginning of thermal accumulation in the spring to the conclusion or near conclusion of the growing season in this region. Our aim was to better understand changes in thermal conditions across the region from a biologically relevant perspective. This entailed evaluating recent change at a finer spatial and temporal resolution than is typically undertaken. Relatedly, we were interested in understanding whether the temporal duration between when pairs of thresholds were met was being compressed

or lengthened across the region as a consequence of differential shifts in when thresholds were met. We focus on the northeastern U.S. for this analysis, where warming is occurring more rapidly than in other regions, and where seasonal activity in plants and insects is heavily influenced by spring-season warmth (Miller-Rushing and Primack 2008; Panchen et al. 2014; Fuccillo Battle et al. 2022).

Materials and methods

To capture changes in biological activity occurring over the breadth of the growing season, we evaluated six GDD thresholds (50, 350, 650, 1250, 1950, and 2500 GDD) that largely encompass the period of biological activity in the northeastern U.S. To do this, we downloaded 4km resolution rasters of daily minimum and maximum temperatures for the entire period available from PRISM, 1981–2023 (PRISM Climate Group, Oregon State University 2025). Rasters were cropped to 22 northeastern states (Connecticut, Delaware, Illinois, Indiana, Iowa, Kentucky, Maine, Maryland, Massachusetts, Michigan, Minnesota, Missouri, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhode Island, Vermont, Virginia, West Virginia, and Wisconsin). Using these rasters, we calculated the number of accumulated GDD in degrees Fahrenheit on each day of each year using the Baskerville-Emin method, or single sine method (Baskerville and Emin, 1969) with a base temperature of 50ºF and a start date of January 1 and then determined the day of the year (DOY) each threshold was met. No upper thermal limit was imposed. When a threshold was not met within the calendar year (365 days; 366 days in a leap year) for a particular pixel, we set the DOY as missing (rather than continuing to accumulate GDD into the next calendar year) and did not use this value in further analyses or calculations. We implemented a 50ºF base temperature as this is a commonly used value for predicting seasonal plant and insect activity, particularly in agricultural systems. Using the yearly DOY layers, we calculated the mean DOY each GDD threshold was met over the study period (1981–2023) as well as the standard deviation in the DOY each threshold was met.

To approximate temporal trends in the DOY each threshold was reached, we calculated a linear slope for each pixel that reached a given threshold at least 10 times over the 42-year period (0.007%, 3.38%, and 9.27% of pixels excluded from thresholds 1250, 1950, and 2500, respectively). Linear slopes for each pixel were obtained using the lm() function in R (R Core Team 2024):

$$DOY_i \sim \beta_0 + \beta_1 \times (year_i - 1981) + \epsilon_i$$

where DOY_i is the day of year a threshold was reached in that pixel in year *i*, the intercept, β_0, is the predicted day of year a threshold was reached in 1981, β_1 is the predicted slope, and ϵ_i is a random year effect drawn from a normal distribution with mean zero and estimated standard deviation, σ.

The distribution of the resulting slopes was highly leptokurtic with most data points concentrated near the median and few extreme slopes. Therefore, for visualization purposes, we used scale limits for the slope equal to the 0.005 and 0.995 quantiles in order to restrict the color range to values including the middle 99% of the data. To assess lengthening or compression of different portions of the growing season, we calculated the difference between slopes at successive GDD thresholds. A positive value of this metric would indicate a lengthening in the time between the two thresholds being met; a negative value would indicate compression of the duration between the two thresholds being met. There are several pathways to achieving a lengthening or compression in the period of time between two thresholds (Fig. 1).

All calculations and analyses were conducted in R version 4.4.2 (R Core Team 2024). Data were downloaded using the httr2 package (Wickham 2025), spatial data calculations were handled with the terra package (Hijmans 2025),

plots were generated using ggplot2 (Wickham 2016) and tidyterra (Hernangómez 2023), and the workflow was managed using the targets (Landau 2021) and geotargets (Tierney et al. 2024) packages. The entire workflow was run on a Jetstream2 cloud instance (Boerner et al. 2023; Hancock et al. 2021).

Results

The average DOY that the six thresholds were met show patterns that clearly follow latitude and elevation, with lowest latitudes and elevations reaching each threshold earliest (Fig. 2). As expected, the average DOY a given threshold was reached varied considerably across the study area (Fig. 1, Table S1). The earliest DOY that thresholds were met across the study area were consistently in Kentucky, while the latest DOY that thresholds were met were consistently in Maine. The six GDD thresholds evaluated in the study encompass the majority of the biological activity in the study region; the latest thresholds, 1950 and 2500 GDD, were not reliably reached in the northernmost areas of the study region.

Variability in when the different thresholds were met was more irregular across the region, reflecting underlying patterns in seasonal warmth and weather (Fig. 3). Comparatively large variability occurred in the early-season threshold, 50 GDD, with SD values ranging from 6.7 to 21.6 days and the greatest variation in the southern reaches of the region. Mid-season thresholds (350, 650 and 1250 GDD) showed less variation across the region. The two late-season thresholds (1950 and 2500 GDD) showed substantial variation in the northern portions of the region, with SD values ranging from 0 to 63.6 days. At the state-level, the range of days to meet the 50, 350, 650, 1250, 1950, and 2500 GDD thresholds across the 22-state study area were 72, 54, 52, 59, 77, and 82 days, respectively (Table S1). Furthermore, minimum and maximum average DOY that thresholds were met in each state from 1981–2023 varied by 55 ± 2 days for 50 GDD, 32 ± 2 days for 350 GDD, 27 ± 1 days for 650 GDD, 29 ± 1 days for 1250 GDD, 41 ± 3 days for 1950 GDD, and 50 ± 3 days for 2500 GDD (Table S1). Similarly, the range of average DOY that thresholds were met in each state from 1981–2023 varied by latitude with greater variation occurring in southern states for the early-season GDD thresholds and in the northern states for the late-season thresholds.

Trend maps reveal that, for the most part, dates that thresholds are reached between 1981–2023 have shifted earlier in the year (Fig. 4). The strongest shifts toward earlier timing occurred in the northeastern states in the late-season thresholds (1950–2500 GDD). There was also clear advancement in the early-season threshold (50 GDD) in the southeastern portion of the region. In contrast, there was a trend toward later timing in both early and late-season thresholds in the northwestern portion of the region, primarily in Minnesota, Wisconsin and parts of Michigan. In the late-season thresholds (1950–2500) this later timing could be in part driven by regions that in some years did not reach these thresholds within a calendar year—these values would be dropped when calculating a slope which may have caused the slopes to be less negative since those missing values happened more often in earlier years.

The pattern of compression and lengthening between thresholds being met was variable across the study region (Fig. 5). Across the southern and eastern portions of the region, the period between the first two thresholds (50 and 350 GDD) became longer as a consequence of the 50 GDD threshold being met earlier in the year (i.e., accumulating thermal warmth earlier in the spring), although this pattern was not apparent across the entire region. By late spring to mid-summer, the duration between thresholds being met largely became more compressed (i.e., more rapid accumulation of thermal warmth during those periods of the growing season), with the strongest patterns occurring in Minnesota between 350 and 650 GDD and in Maine between 650 and 1250 GDD. Patterns were strongest in the latest portion of the growing season. The periods between 1250 and 1950

GDD and 1950 and 2500 GDD were both compressed to a strong degree, by several days per decade (i.e., more rapid thermal accumulations), particularly in the northern Lower Peninsula of Michigan and areas from northwestern Pennsylvania to Maine.

In the northwestern reaches of the region (Minnesota, Upper Peninsula of Michigan, Wisconsin), the opposite pattern was apparent; the periods between 1250 and 1950 GDD and 1950 and 2500 GDD lengthened to a strong degree, by several days per decade in these locations as a consequence of thermal accumulation later into the year. This lengthening was also the result of overall warming during the study period. In the earlier part of the period of record, 2500 GDD was not reached at the highest latitudes of the study region within the calendar year. Because these values were dropped when calculating slopes, the trends in DOY to reach this threshold are less negative than they might be otherwise. When these values are then compared with the DOY that the previous threshold is met (1950 GDD), it suggests a strong lengthening of the season, which may not accurately represent reality.

Over the entire duration of the season (between 50 and 2500 GDD), the time to reach 2500 GDD has shortened, from a day per decade to more than a week per decade in numerous states, including Pennsylvania, New York, Massachusetts, Connecticut, and southern New Hampshire as well as in southern Michigan.

Patterns of compression and lengthening between the various thresholds being met vary substantially by geography (Fig. 6). In large swaths of the region, all thresholds have advanced to earlier dates (i.e., accumulating thermal warmth earlier in the year) (Fig. 4). However, because of different rates of change among the thresholds at discrete locations (Fig. 5), many different combinations of compression and lengthening of the periods between the thresholds may occur. For example, in Georgetown, DE (Fig. 6a), all six GDD thresholds have advanced to earlier dates. However, because the strongest advancements occurred in the earliest and latest thresholds, the time between thresholds in the earliest part of the season lengthened (pathway depicted in Fig. 1a) while the time between thresholds in the latest part of the season compressed (pathway depicted in Fig. 1f). In contrast, in Kansas City, MO (Fig. 6d), compression between the first and second thresholds resulted in a greater rate of advancement in the second threshold (pathway depicted in Fig. 1f). Harvard Forest, in Petersham, MA (Fig. 6c) has also experienced advancement in all six thresholds, with the strongest advancements occurring at the end of the season. Consequently, substantial compression has occurred in the latter portion of the season (Fig. 1f pathway), but the period between the first two thresholds has lengthened, similar to Georgetown, DE (Fig. 1a pathway). Finally, while the direction in trend is inconsistent among thresholds in Grand Rapids, MI (Fig. 6b) -- the first threshold became delayed over the study period -- the outcome is similar to that occurring in Kansas City, MO, where the periods between all thresholds became compressed (Fig. 6b).

Discussion

While recent increases in temperature and consequent shifts in seasonal plant and animal activity are well documented, the majority of studies investigating these phenomena are at large spatial and temporal scales. Understanding how temperature is changing within the season and at regional to local scales can greatly enhance our understanding of recent change, inform short-term decision making, and aid in future planning and adaptation, especially related to management directed toward particular species. In this study, we evaluated how the timing of six heat accumulation thresholds, which encompass the growing season in the northeastern U.S., have changed over the past four decades at a fine spatial grain.

The patterns of heat accumulation in the northeastern U.S. that we observed confirm previously documented patterns in spring temperature across a latitude gradient. First, as expected, our results revealed a clear gradient, or progression, in when individual thresholds are reached, progressing from south to north and upslope in elevation. These findings are consistent with other studies evaluating when conditions associated with biological activity are reached across a large region (Ault et al. 2015; Mehdipoor et al. 2018; Izquierdo-Verdiguier et al. 2018; Mehdipoor et al. 2020). In the Northern Hemisphere, warmth accumulates first in the southern latitudes and progresses northward. The variation we observed in the day of year that early-season thresholds are reached—with the greatest variation occurring in the southernmost reaches of the study area—also generally aligns with patterns reported by others (Ault et al. 2015; Crimmins and Crimmins 2019a). In general, weather patterns exhibit greater variability in the early months of the year, stabilizing as spring and summer progress due to shifts in atmospheric circulation (Stine and Huybers 2012; James and Arguez 2015; McKinnon et al. 2016). Consequently, the greatest variability in when GDD thresholds are reached is usually seen early in the season. A similar pattern of high variability in the northernmost portions of the study range appears at the end of the season. This reflects the higher variability in temperature conditions experienced at these northern latitudes at the end of the growing season.

Thresholds are generally being reached earlier, with spatial and temporal nuance

In our analyses, we documented an overall pattern of advancement in the timing of temperature accumulation thresholds being met, although the strength of the advancement varied over the season. In addition, not all locations exhibited advancements; delays in several thresholds were apparent in the northwestern portion of the study region. Several recent studies have evaluated trends in when the Spring Indices are reached across the U.S. (Ault et al. 2015; Mehdipoor et al. 2018; Izquierdo-Verdiguier et al. 2018; Mehdipoor et al. 2020). The Spring Indices, synthetic models reflecting conditions associated with leaf-out and flowering activity in several early-season plants, consist of two distinct indices, the Leaf Index and the Bloom Index; inputs for these models are primarily accumulated warmth, with emphasis on multi-day synoptic weather events (Schwartz et al., 2006; Ault et al., 2015). Because the inputs to the Spring Indices are slightly different from those for GDD thresholds, it is difficult to make direct comparisons. However, we estimate that the Leaf Index, an index intended to capture the onset of biological activity in the spring season, occurs between 50 and 350 GDD and the Bloom Index, which reflects biological activity a bit later in the spring season, falls between the 650 and 1250 GDD thresholds.

The spatial patterns in trends documented in evaluations of the Spring Indices are somewhat different than those documented in GDD thresholds in the present study. Specifically, Ault et al. (2015) reported a strong advancement of the Leaf Index in Michigan and Wisconsin; this pattern does not surface in our results. However, Ault et al. (2015) evaluated trends over 1981–2010, whereas our results extend through 2023. In a similar effort evaluating the period 1980–2014, Mehdipoor et al. (2020) explored trends in both the Leaf Index and a thermal time (temperature accumulation) model. Both maps of trend over this period reveal a delay in onset for most of the northeastern U.S., also in opposition to our findings. However, in maps of trend in the Leaf and Bloom Indices calculated using various gridded temperature products over the period 1980–2016, Mehdipoor et al. (2018) show advancements in when the two indices are met across the northeastern U.S., with spatial patterns that more closely match those documented in our study. Finally, Izquierdo-Verdiguier et al. (2018) reported very little trend in when the Leaf and Bloom Indices were met across the northeastern U.S. in a study evaluating 1980–2015. Linear trends can be strongly affected by the years evaluated; the stark differences in findings between these previously

published studies and our own results suggest shifts in the spatial and within-season patterns in the accumulation of warmth in this region in the most recent ten to fifteen years. The warmest years on record occurred during the most recent ten years of our study (NOAA National Centers for Environmental Information, 2025). The differences in findings between the present study and similar recent analyses underscore the importance of maintaining current estimates of change for use in decision making.

To our knowledge, few other studies have examined within-season patterns in heat accumulation with the intent of understanding the consequences of such non-linear changes to organisms. Crimmins and Crimmins (2019b) undertook a similar analysis though at a coarser spatial scale and using different thresholds. These authors reported similar patterns of lengthening among the earliest thresholds, driven by a more rapid advancement in the earliest threshold due to rapid warming early in the season. As well, these authors reported a compression among early-season thresholds in New England states. A comparison of mid-season thresholds included in Crimmins and Crimmins (2019b) approximately equates to the mid-season comparisons made in the present study (1250 – 650 GDD and 650 – 350 GDD). Crimmins and Crimmins (2019b) report very slight compressions between mid-season thresholds, which generally aligns with the patterns observed in the present study. However, the patterns reported in the present study reveal a great deal more spatial variability than reported in Crimmins and Crimmins (2019b) -- valuable insight for supporting local-scale adaptive decisions and planning.

Mehdipoor et al. (2018) similarly evaluated the consequences of differing rates of change in two seasonal thresholds, the Spring Leaf and Bloom Indices, which approximately align with 350 and 1250 GDD. These authors report a lengthening of the period between the two indices, in alignment with our findings. Although we do not make a direct comparison between 350 and 1250 GDD in this study, we can infer a lengthening between the two thresholds from a more rapid advancement in 350 than 1250 GDD in much of the study area (Fig. 4). However, importantly, in this study we also evaluate 650 GDD, a threshold situated between 350 and 1250 GDD. The comparisons between 350 and 650 GDD and between 650 and 1250 GDD reveal nuance in when and where periods between thresholds are shortening and lengthening (Fig. 5b,c). In particular, south-central Virginia reveals spatial anomalies in this measurement that are lost when comparisons are made at a coarser spatial scale (as in Crimmins and Crimmins, 2019b) or at a coarser temporal resolution (as in Mehdipoor et al. 2018).

Many management decisions such as when to treat pest insects or invasive plant species, when to collect seeds, or when to mow or burn are done so at a local scale (Pike et al. 2020). Accordingly, local-scale information regarding when conditions are optimal for implementing these activities can be of great value to land managers. Growing degree thresholds, which reflect conditions specific to life-cycle events in individual species, offer the temporal granularity most relevant to species-specific decisions. Estimates of when GDD thresholds are met on a fine spatial scale are further relevant for supporting management decisions, providing information regarding variability across a region.

The span of time between thresholds is changing, but not consistently across space or time

In this study, we evaluated the implications of differential rates of change in the time at which various seasonal thermal accumulations were reached across the northeastern U.S. Different directions and/or rates of change in thresholds result in either compression or lengthening of time between the thresholds being met. Our analyses revealed substantial nuance across space and between thresholds regarding both the direction and magnitude of

change, and consequently, notable nuance in how the duration of time lapsed between thresholds is changing across the region.

This nuanced understanding of how the duration of time between thresholds being met is changing both throughout the season and across the region has important implications for managing under dynamic conditions. For example, an extended period between when the first two thresholds are reached, as seen in locations such as Georgetown, DE and Harvard Forest, MA, translates into a longer period of time for species that become active early in the year, such as emerald ash borer (*Agrilus planipennis*) and spongy moth (*Lymantria dispar*), to initiate development. The longer span between the earliest thresholds means that ectothermic organisms may remain in an early life stage for a longer duration before transitioning to the next developmental stage than in previous decades. At locations where this early-season period is being compressed, such as Grand Rapids, MI and Kansas City, MO, opportunities for these species to initiate development are being abbreviated.

The duration of time between mid- and late-season thresholds is largely being compressed, with the strongest compression occurring in the New England states and between the latest thresholds. The consequence of compression between when GDD thresholds are reached is that species are pushed through sequential life cycle stages more rapidly, increasing the probability of temporal overlap among species that historically underwent activities at distinct times.

Because sensitivity to temperature varies by trophic level, implications for interacting species are species- and location-specific. Temperature-dependent development in many insects is non-linear (Huey and Stevenson 1979; Gillooly et al. 2002). And so, earlier or more rapidly accumulated thermal energy acts to decrease developmental times, potentially leading to increases in the number of generations per year for multi-voltine species (Kingsolver et al. 2011). As well, insects tend to be more sensitive to temperature than plants, leading to variable rates of development among interacting species (Thackeray et al. 2016), although the exact mechanisms resulting in increased temporal mismatches between plants and interacting species are complex (Kudo et al. 2025). Such mismatches are likely to have negative consequences for specialist beneficial insects such as pollinators or parasitoids whose success is tightly linked to the timing of their ephemeral resources (Kudo and Ida 2013). Consequently, outcomes could be negative, neutral, or positive depending on the species interactions involved.

Limitations and opportunities

A strength of the approaches implemented in this study is in the spatial and temporal granularity of the patterns, revealing nuance that has previously not been considered. However, the temperature data evaluated are interpolated from weather stations and thus, imperfect. As such, the changes shown here may not accurately reflect changes in temperature accumulations across the study region (Pielke et al. 2002; Daly 2006).

The base temperature and accumulation start date used in this study is commonly used in agriculture, integrated pest management, and turf management applications (e.g., Alessi and Power 1971; Herms 2004; Cardina et al. 2011). In reality, individual species respond to a wide range of base temperatures and heat sums. Further, species in more northerly latitudes do not respond similarly to exposure to warmth very early in the year as to warmth occurring several months into the year. Alternative start dates for accumulation may yield different results. As well, many phenological events are shaped by additional variables such as daylength or winter chill (Hunter and Lechowicz 1992; Basler 2016; Panchen 2016). The trends documented here may not reflect changes in the phenology of species cued by multiple environmental variables.

Finally, trends in changes over the period evaluated may not be linear. Conditions such as El Niño or other oscillations may have exerted influence over temperatures within the time period evaluated; these events are not accounted for in our analyses. Future work could explore the impact of these large-scale phenomena in concert with underlying increases in temperature and how they affect the timing of seasonal transitions in plants and animals.

Next steps

Because many plant and insect species in temperate regions are strongly cued by temperature, GDD thresholds such as those depicted in this study are a strong proxy for when species undergo life cycle transitions. To support their adoption in real-world planning and decision-making applications, the USA National Phenology Network has developed a set of real-time, publicly available maps indicating the day of year that a suite of GDD thresholds are reached across the northeastern U.S. Companion maps indicate when these thresholds are typically met and whether the timing in the current year is earlier or later than usual (using a climatological 30-year average). These maps and the work in this study collectively establish a baseline for assessing future change at fine spatial and temporal scales.

Abbreviations

DOY
day of year
GDD
growing degree days
IPCC
Intergovernmental Panel on Climate Change
NOAA
National Oceanic and Atmospheric Administration
USA
NPN–USA National Phenology Network

Declarations

Ethics approval

not applicable

Consent for participation and publication

not applicable

Availability of data and materials

Data and code used for this analysis is available https://doi.org/10.5281/zenodo.17087407 (Scott et al. 2025).

Competing interests

First author, Theresa Crimmins, is a member of the Editorial Advisory Board for the *International Journal of Biometeorology.*

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Authors' contributions

TMC, KFB, KR, ERS, NWS, and ERZ conceptualized the project and analysis. TMC, JD, AWD, NWS, RTT, and AW acquired project funding. ERS and ERZ performed the analyses and data visualization. TMC, KFB, and NWS wrote the original draft and all authors reviewed and approved the final draft.

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Clinical Trial Registration

not applicable

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Figures

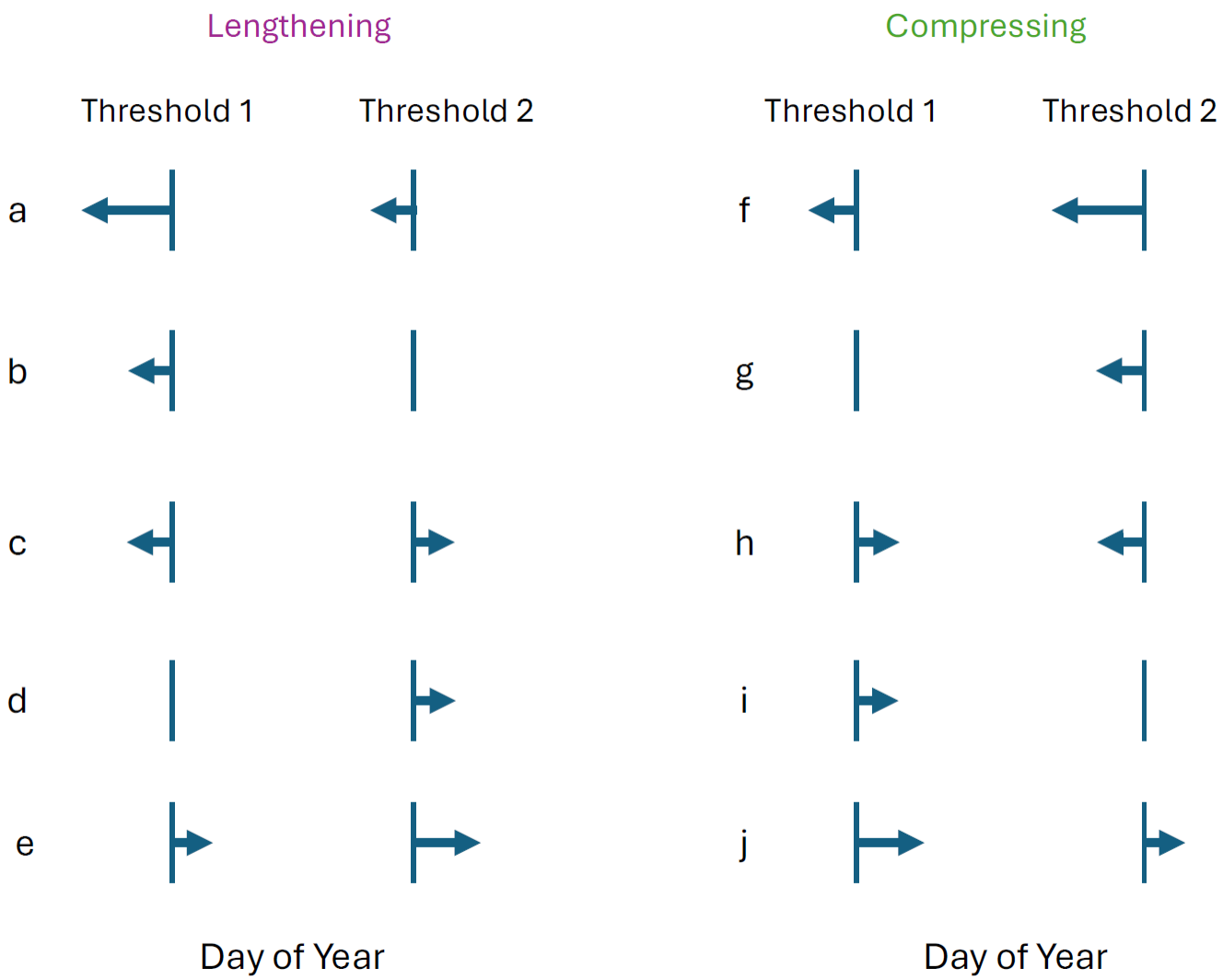


Figure 1

Various pathways to lengthening or compression in the span of time between when two growing degree day thresholds are met. The duration between thresholds lengthen when a) the first threshold advances to a greater degree than the second; b) the first threshold advances and the second does not; c) the first threshold advances and the second delays; d) the first threshold does not change and the second delays; or e) the second threshold delays to a greater degree than the first. The duration between the thresholds compress when f) the second threshold advances to a greater degree than the first; g) the second threshold advances and the first does not; h) the first threshold delays and the second threshold advances; i) the first threshold delays and the second does not change; or j) the first threshold delays to a greater degree than the second.

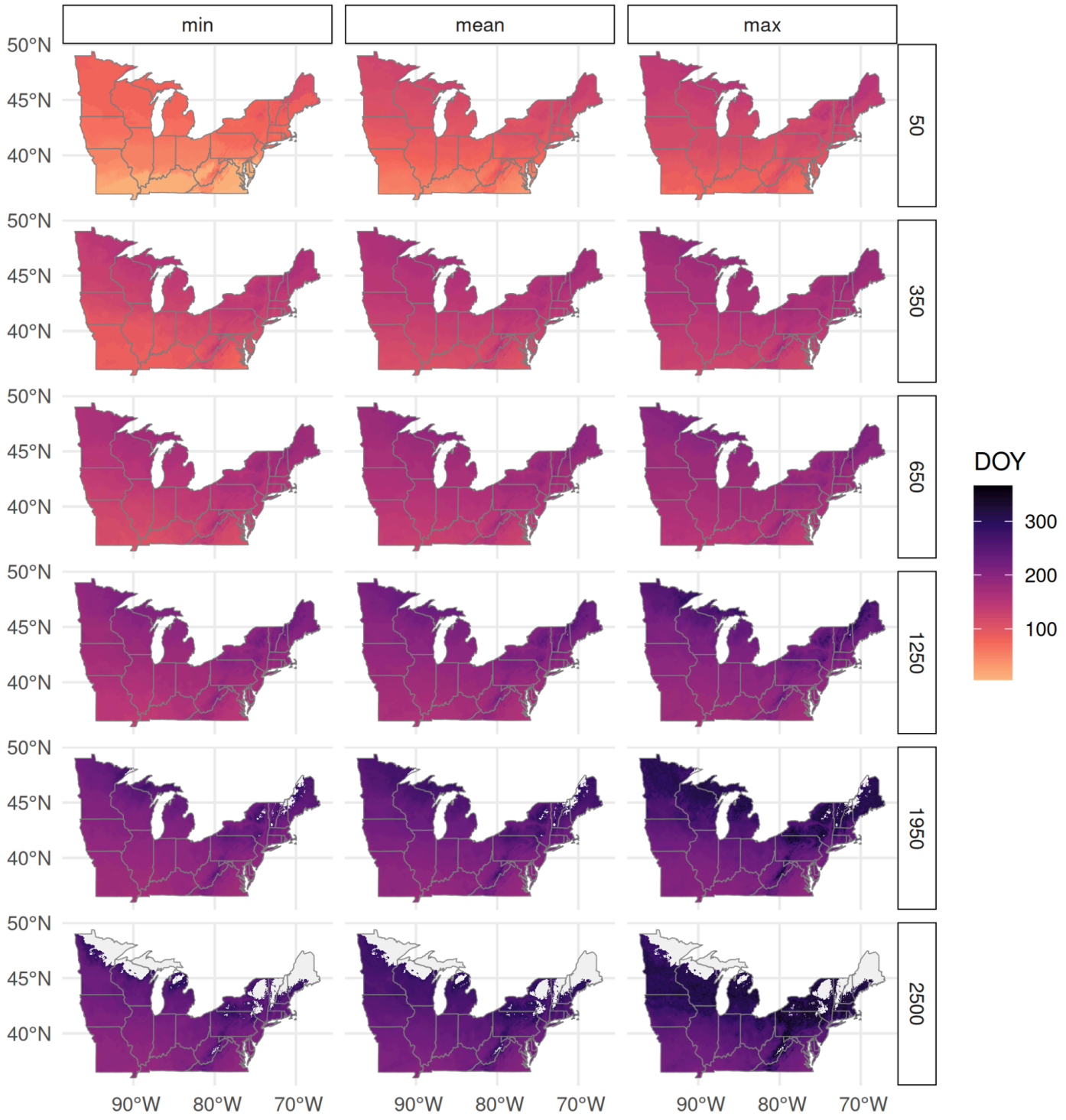


Figure 2

Earliest (min), latest (max), and average (mean) day of year (DOY) that six GDD thresholds were met across the northeastern U.S., 1981-2023.

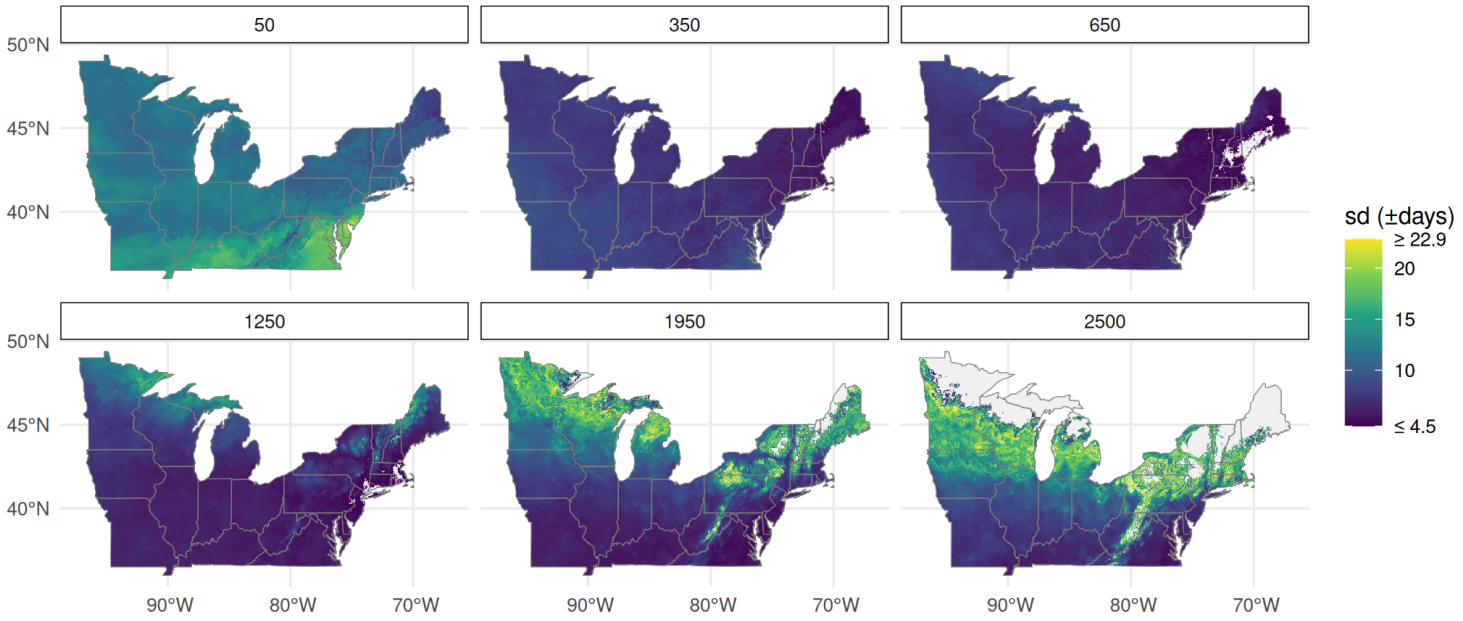


Figure 3

Variability in the day of year (represented as standard deviation) when six GDD thresholds are met across the northeastern U.S., 1981-2023. The range of the color scale includes 99% of the observed standard deviations (full range is [0.00, 63.6]) with more extreme values sharing the color with the nearest scale limit in order to make it easier to visualize spatial differences in trends. Areas in gray reached the threshold in fewer than two years.

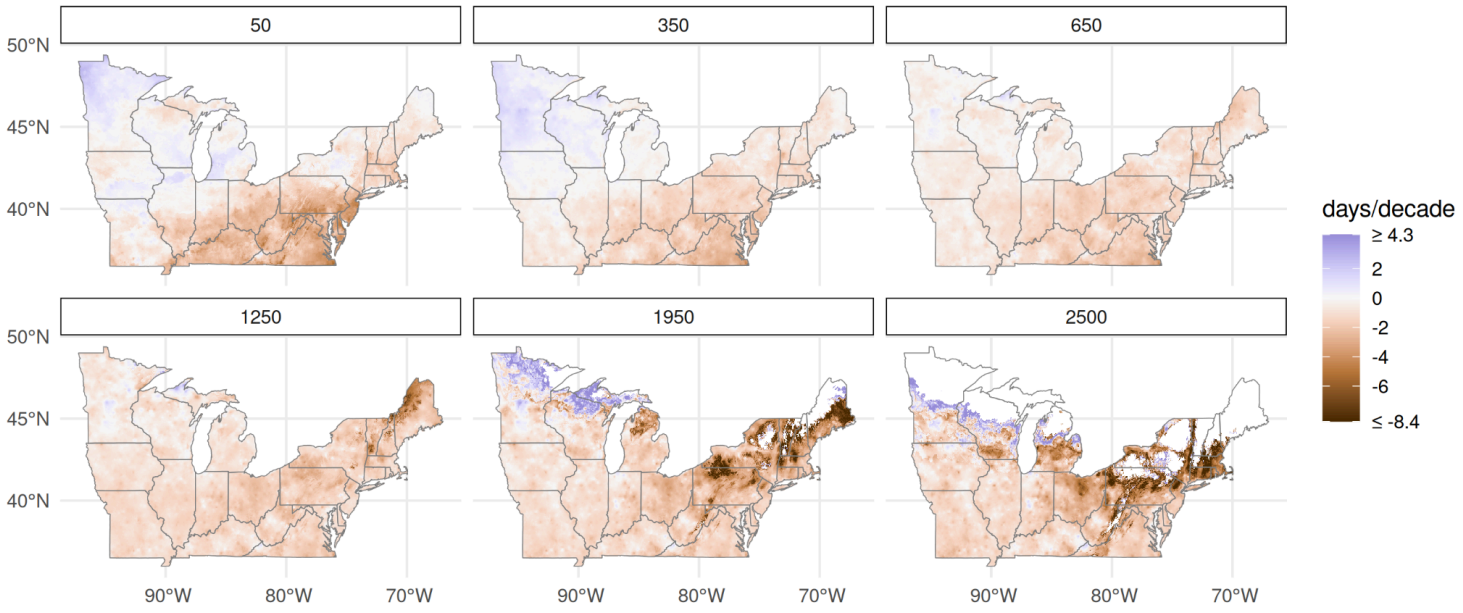


Figure 4

Trends in the day of year that six GDD thresholds are met (1981-2023) for all locations that reached a given threshold in 10 or more years. Color represents the slope from a best-fit line for each pixel as days/decade, with blue indicating where thresholds have shifted to being met later and orange indicating locations where thresholds have shifted to being met earlier. The range of the color scale includes 99% of the observed slopes (full range is [-27.9, 26.7]) with more extreme values sharing the color with the nearest scale limit in order to make it easier to visualize spatial differences in trends.

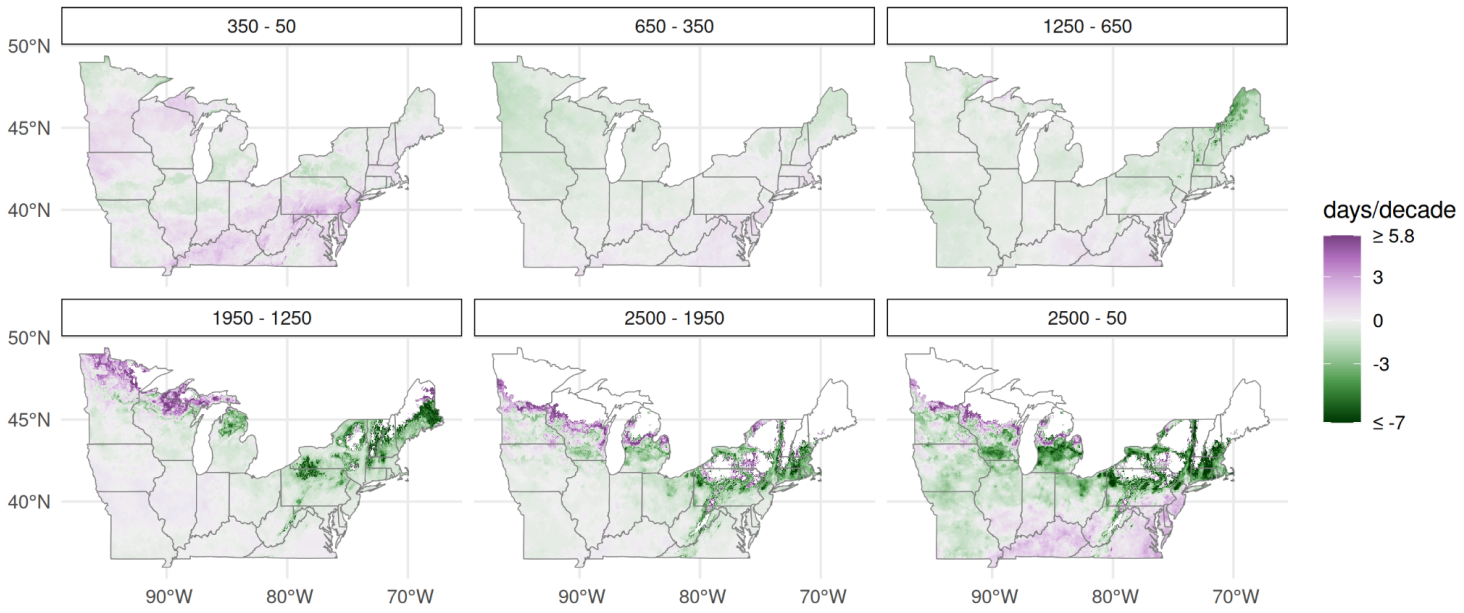


Figure 5

Changes in the duration between dates when different GDD thresholds were reached in the northeastern U.S. (1981-2023), measured in days per decade. Positive values (purple) indicate a lengthening interval, and negative values (green) indicate compression in the period between when the two thresholds are met (see Fig. 1). The bottom right panel reflects changes in the duration between the earliest (50 GDD) and latest (2500 GDD) thresholds evaluated. The range of the color scale is set to include 99% of the observed values (full range is [-25.6, 30.5]) with more extreme values sharing the color with the nearest scale limit in order to make it easier to visualize spatial patterns. White pixels reflect locations where thresholds were not met in at least one year of the study period.

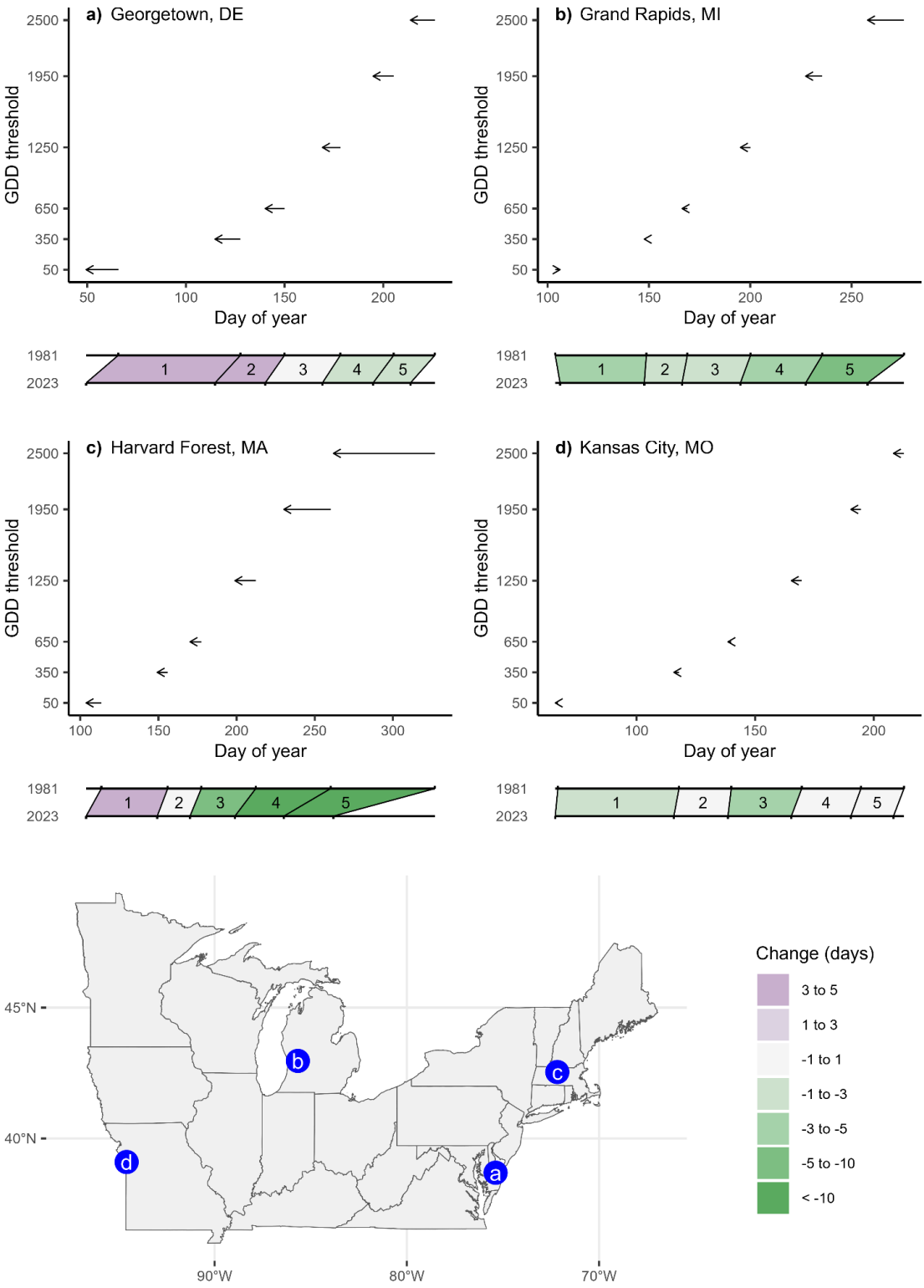


Figure 6

Changes in the time at which different GDD thresholds were met in a) Georgetown, DE, b) Grand Rapids, MI, c) Harvard Forest, Petersham, MA, and d) Kansas City, MO. In each of the top four panels, the start of each arrow represents the predicted day a threshold was reached in 1981 and the arrow tip represents the predicted day a threshold was reached in 2023. The shaded polygons below depict changes that occurred between 1981 and 2023 in the length of time between when consecutive thresholds were reached, with 1 = period between thresholds 50 and 350 GDD; 2 = 350 to 650; 3 = 650 to 1250; 4 = 1250 to 1950; and 5 = 1950 to 2500. Polygon

shading indicates whether the duration of each period lengthened (purples; positive values) or was compressed (greens; negative values).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- TableS2.pdf
- thresholdstatesummarystatsTableS1.pdf