Heat Adaptation in Distance Running

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Abstract

Does recent exposure to heat blunt the effects of future shocks? I examine how runners adapt to heat stress using data on 2.6 million distance race performances. This unique setting, where runners from different home climates compete in different locations with distinct weather conditions, allows me to distinguish the impact of recent variation in climate conditions from cross-sectional differences arising from population variation or climatic sorting. I find that race performances decline steeply in day-of wet bulb temperatures above 15 C and that heat effects are smallest among runners who experienced more hot days during the three months before their race, a differential that remains even after controlling for training climate. There are diminishing returns to heat exposure in the training period, and a monthly decomposition of the training window suggests the benefits may be concentrated in the most recent weeks. These findings suggest that short-run acclimatization plays a role in humans' capacity to adapt to heat.

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1 Introduction

Hot days are becoming more extreme, more frequent, and less predictable. As heat waves become increasingly common, understanding how adaptation can reduce their harmful effects could help people and governments design effective climate adaptation policies. For example: should governments deploy cooling centers or heat action plans more expansively for the first heat wave of the season at lower temperatures than they would for the fifth? Which demographic groups should be prioritized for proactive outreach checks during hot summer days? And how much should local heat adaptation strategies reflect differences from temperature normals in the area versus absolute temperature limits? Answering these questions requires a detailed understanding of how people adapt to heat exposure, and how that adaptation varies with recent exposure.

A large literature uses year-to-year variation in weather to estimate how temperature affects economic activity, health, and productivity.[1] These studies have found that temperature shocks reduce agricultural output (Schlenker and Roberts, 2009), lower labor productivity and work hours (Graff Zivin and Neidell, 2014), increase mortality (Carleton et al., 2022), and decrease GDP growth (Dell et al., 2012; Burke et al., 2015; Nath et al., 2024), with effects that tend to be negative in extreme temperatures, and present in both rich and poor countries. The extent to which people adapt away these impacts today, and how much they will be able to do so in the future, is important for projecting future damages and for the design of adaptation policy. Much of the existing evidence on adaptation relies on cross-sectional comparisons: people in hotter places appear to suffer less from heat. For example, Heutel et al. (2021) find that hot days are less deadly in warm regions of the U.S., and Carleton et al. (2022) document a similar pattern globally. Barreca et al. (2016) show that the relationship between temperature and mortality in the U.S. declined by 75% over the twentieth century, an effect they attribute almost entirely to the spread of air conditioning.

But these cross-sectional patterns bundle together different mechanisms: long-run investments like air conditioning, selection of heat-tolerant individuals into hotter places, and the body's own physiological ability to adjust to heat through repeated exposure. These mechanisms operate though different behavioral and physiological channels and impact climate damages on different time scales. Isolating the contribution of short-run physiological acclimatization helps predict the extent to which recent hot temperature exposure will mitigate the costs of exposures in the near future, if any. If acclimatization can help mitigate climate impacts, then understanding how and when it occurs can aid in designing adaptation policies.

In most empirical settings, separating the role of short-run acclimatization from other determinants of heat responsiveness is difficult for two reasons. First, the cross-sectional challenge described above: long-run average climate correlates with a wide range of observed and unobserved confounders including income, culture, infrastructure, and economic structure, all of which contribute to the responsiveness of economic outcomes to temperature. This is well documented in the climate econometrics literature (Dell et al., 2014; Hsiang, 2016). The second and more subtle problem is that even approaches that attempt to control for cross-sectional variation by interacting the effect of recent temperatures with the temperature today are limited by the variation available in the data. In most

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[1] See Dell et al. (2014) and Carleton and Hsiang (2016) for more comprehensive reviews.

empirical settings, recent heat exposure is hard to separate from contemporaneous heat: places that have experienced many hot days recently are likely to be hot tomorrow as well, and acclimatization is likely to occur over weeks or months (rather than years), so teasing out the adaptive contributions of recent temperatures from today's (highly correlated) temperature is empirically challenging.

To fill that gap, I estimate the role of short-run physiological heat acclimatization (the body's ability to become more heat-tolerant through recent exposure) by studying how weather during training affects the performance of long-distance runners on hot race days.

Long-distance running is uniquely well-suited for this question. It is an outdoor physical activity that is highly sensitive to heat, with performance declining sharply in hot conditions. But it is also a setting where participants are highly motivated to perform well, and where mitigating environmental conditions through training, equipment, and pacing strategies is both desirable and feasible. Finally, performance is precisely and individually measured, participants include a wide range of ages and abilities, and the races are held in a wide range of locations and weather conditions.

Most importantly, the nature of long-distance races creates a natural separation between training-period weather and race-day weather: runners travel from many different home locations, each experiencing distinct weather conditions during the months of training, and compete at many different race sites, each with their own distinct race-day conditions. The intuition of the analysis is that if recent heat exposure during training helps the body cope with heat, then it should reduce the sensitivity of race day performance to extreme temperatures experienced that day.

I assemble data on over 2.5 million race performances from distances as short as 5 km to as long as 100 miles and match it to high-resolution gridded and altitude-adjusted race-day weather. Using runner's reported home location, I also compute training-period weather for the three months leading up to the race. I find strong effects of wet bulb temperature (a measure of heat stress that reflects both temperature and humidity) on performance, with sharp increases in finish time above 15 C. These effects hold across a range of statistical approaches. I also find that heat effects are more pronounced for runners who are younger, slower, and male. Most notably, elite athletes are much better at maintaining race performance in hot weather.

Consistent with prior work, runners from hotter home climates are less sensitive to race-day heat. But when I isolate naturally occurring variation in training-period weather by comparing runners from similar locations who happened to experience different weather in the three months before their race, I find that recent heat exposure also reduces sensitivity to race-day heat. Runners who experience more than 30 hot training days during the three-month period show meaningfully smaller performance losses on hot race days, though the benefits level off beyond that threshold. A monthly decomposition suggests that heat exposure across the full training period contributes to this effect, though I cannot pin down the week-by-week timing precisely.

This work relates to research in exercise physiology, whose informative small-sample evidence provides context and helps inform the empirical specifications for the data-rich analysis in this paper. High body temperature impairs endurance by reducing blood flow to muscles, increasing perceived effort, and straining the cardiovascular system (Sawka et al., 2011). Performance declines progressively as wet bulb globe temperature (WBGT—a related measure that additionally accounts for solar radiation and wind) rises above 10 C (Ely et al., 2007; El Helou et al., 2012), with larger effects in longer events (Mantzios et al., 2022). Repeated heat exposure produces physiological adaptations (increased plasma volume, enhanced sweating, lower resting heart rate, and reduced core temperature) that develop within 5 to 14 days and are largely complete within two weeks (Périard et al., 2015; Racinais et al., 2015). Laboratory studies show that heat acclimation improves time-trial performance by about 6% (Lorenzo et al., 2010), and meta-analyses find consistent reductions in core temperature and heart rate from heat exposure in both laboratory and field settings (Tyler et al., 2016; Guy et al., 2015).

This paper contributes primarily to the literature on climate adaptation. Many papers in this field estimate the extent to which people living in different baseline climates are differentially affected by heat. Carleton et al. (2024) provide a more complete accounting of this literature, which, econometrically speaking, focuses on estimating heterogeneous treatment effects of weather across places with different average climates. For example, Dell et al. (2012) report that hot countries are more affected by heat shocks, though this relationship is primarily driven by differences in income rather than climate. In the U.S., Deschênes and Greenstone (2011) find that the relationship between temperature and mortality does not differ across regions with different climates, while Carleton et al. (2022) find that the relationship between temperature and mortality is less steep in hotter countries, even after controlling for income and other confounders. In agriculture, Hultgren et al. (2025) find that the relationship between temperature and crop yields is less steep in hotter countries. Broadly, most studies tend to find that people in hotter places are less affected by heat, though the extent to which this reflects physiological acclimatization versus selection and other factors is unclear.

A smaller number of papers attempt to leverage a combination of recent variation in weather and contemporaneous temperature to isolate the role of short-run acclimatization, primarily in the interest of identifying the impact of repeated hot days on mortality. Pearce et al. (2016) characterize "temperature trajectories" (the rate of temperature change over preceding days) and find that the mortality effect of daily temperature is modified by how temperatures evolved over the preceding 12 days. Callahan et al. (2026) report that allowing the effect of today's temperature to vary with the prior day's temperature improves the fit of mortality models to the data. However, these approaches are limited by the fact that recent and contemporaneous temperatures are highly correlated, and that acclimatization may occur over weeks or months rather than days, making it difficult to separate the effects of recent heat exposure from the direct effects of today's temperature.

The closest set of papers to this study come from a small but growing literature that uses athletic performance data to study heat effects. Burke et al. (2023) examine professional tennis players and find that players from warmer climates are better able to cope with hot temperatures. Aragon and Rezazadeh (2025) find that elite track runners from hotter countries are less affected by extreme temperatures, but their cross-country comparisons cannot separate physiological acclimatization from selection and other factors.

Aside from Sexton et al. (2022), I am not aware of any other papers that attempt to isolate the role of short-run acclimatization using variation in training weather. Sexton et al. (2022) study heat adaptation in collegiate track and field athletes, finding that athletes at schools in warmer climates are less affected by heat and that recent heat exposure also helps, though by a smaller amount. The current paper builds on this prior work in several ways. First, I study a different athletic population: marathon and ultramarathon runners across the ability spectrum rather than elite collegiates. Second, I look at running events that are much longer than track and field events. Long-distance running events invite both more opportunity for heat to impact performance (as the body heats up more over the course of a long event) and more opportunity for acclimatization to matter (as individuals can make more impactful investments in training and pacing strategies). By focusing on the full set of long-distance runners rather than elite student-athletes, I also capture a broader range of heat sensitivity across age, ability, and geographic location. Finally, the races I study are held in a wider range of locations and weather conditions, providing significantly more variation to identify the effects of heat and acclimatization.

2 Data

Distance running is a popular recreational fitness activity. Over 50 million people in the United States report running or jogging on annual surveys (Outdoor Industry Association, 2024), and around 12% of the population engages in running as a regular physical activity (Abildso et al., 2026). Trail running (i.e., running primarily on non-road surfaces) in particular has seen a surge in popularity, with around 16 million participating in 2024 compared to 6 million in 2012 (Abildso et al., 2026). Many of these runners participate in race events, where organizers set a course and time runners' performances. Around 400,000 people run a marathon each year, a number that has remained relatively stable over the past decade (Andersen, 2025). Meanwhile, ultramarathon participation has grown dramatically: participation in these events, which are defined as any races covering distances longer than a marathon, increased more than 16 times over between 1996 and 2018 (Ronto and Nikolova, 2020).

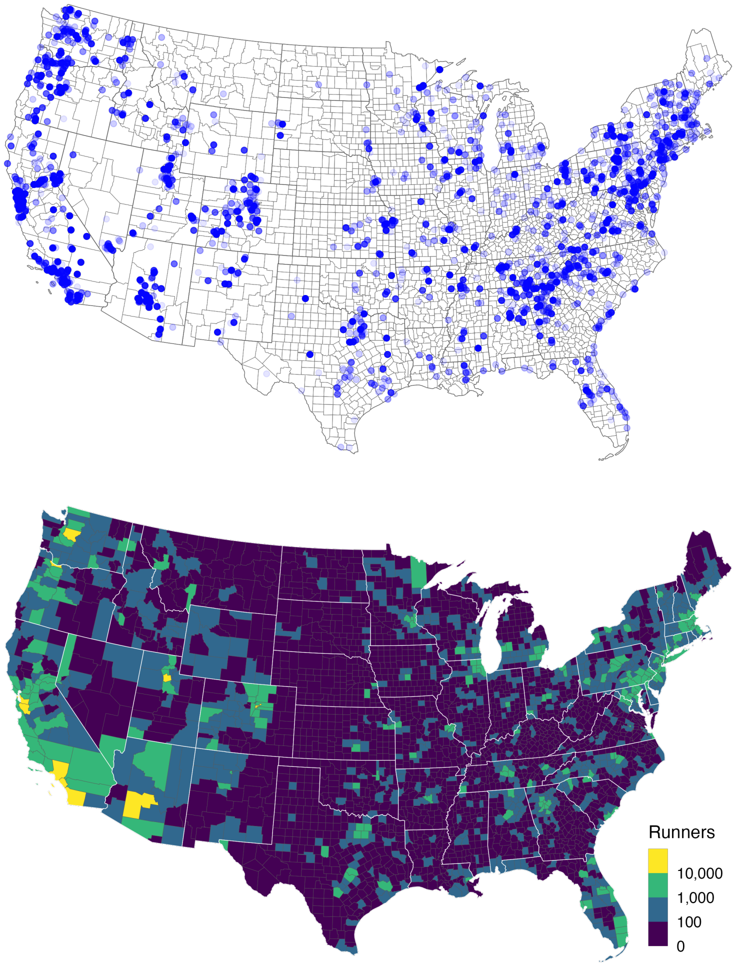
For this study, I combine data on running performances in races across the United States with detailed weather data for both the race and the athlete's training period leading up to it. The observational unit is a single athlete's performance in a given event. Each observation includes data on the athlete's race performance, the event's weather conditions, and variables that capture the athlete's training-period heat exposure based on their home location.

2.1 Race Performances

I compile race results from UltraSignup.com (approximately 1.9 million race results ranging from sub-marathon to ultramarathon distances, primarily on trail running courses, from 1978–2025) and MarathonGuide.com (approximately 627,000 marathon results from 2021–2024). These data include runner characteristics such as age, gender, and self-reported home location. After geocoding both race and runner locations, I match each race and runner to weather data from the PRISM 4km gridded dataset to obtain race-day weather conditions for each race and training-period weather for each runner for the three months before the race. I focus on races and runners across the continental United States. Figure 1 shows the geographic distribution of races and runners in the analysis sample.

Geocoding race and runner locations. To match weather data to each race and runner, I geocode

Figure 1: Race and runner locations across the United States



Notes: Top-left panel shows locations of races included in the analysis; top-right panel shows the distribution of runners' self-reported home locations. Both map panels are based on geocoded latitude and longitude data. Bottom panel shows the number of races per month over the sample period, split by sub-marathon, marathon, and ultra distance categories.

self-reported location strings using ArcGIS World Geocoding Service. I retain only geocoded locations with match scores exceeding 99.99%, ensuring high spatial accuracy. I manually remove obvious mismatches (e.g., distance labels like “5k” incorrectly geocoded as place names) and assign each location to a grid cell in the PRISM climate dataset for weather matching. This process successfully geocodes over 99% of race and runner locations.

Runner ability. To control for baseline runner ability in some empirical specifications, I construct a leave-one-out average finish quantile for each runner. First, for each race performance, I compute the runner’s finish quantile within that specific race using the empirical distribution of finish times. This quantile ranges from 0 (slowest finisher) to 1 (fastest finisher) and is comparable across races of different sizes and courses. Then, for each runner-race observation, I compute the average of the runner’s finish quantiles across all their *other* races, excluding the current race. This leave-one-out construction ensures that the ability measure is not mechanically correlated with the performance being analyzed. Including this control requires that runners appear in the dataset at least twice, which restricts the sample to more experienced participants but allows me to control for individual-level differences in running ability while still using within-runner variation across races held in different weather conditions.

2.2 Race Day Weather

I use weather data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group (PRISM Climate Group, 2024), which provides daily gridded climate data at 4km^2 resolution across the continental United States. PRISM incorporates digital elevation models to account for altitude differences that may affect weather, making it particularly well-suited for capturing microclimatic variation in mountainous areas where many trail races occur.

My primary measure of heat stress on race day is wet bulb temperature. The calculation I use combines air temperature and humidity into a single metric that reflects how effectively the body can cool itself through sweating.[2] Intuitively, wet bulb temperature is equal to temperature when relative humidity is at 100%. The lower the relative humidity, the lower wet bulb temperature is for the same air temperature. The difference between wet bulb and air temperature is more pronounced when air temperatures are highest, i.e., when low humidity offers the human body greater opportunity to cool itself off. Figure A2 illustrates how wet bulb temperature varies with air temperature and relative humidity for races in the dataset. The specific psychometric formula I use is drawn from Stull (2011) and takes as inputs PRISM daily maximum temperature T and relative humidity RH (rounded here to two significant digits for readability):

$$\begin{aligned}\text{WBT} = T \cdot \arctan\left(0.15\sqrt{RH + 8.3}\right) + \arctan(T + RH) \\ - \arctan(RH - 1.7) + 0.0039 \cdot RH^{3/2} \cdot \arctan(0.023 \cdot RH) - 4.7, \quad (1)\end{aligned}$$

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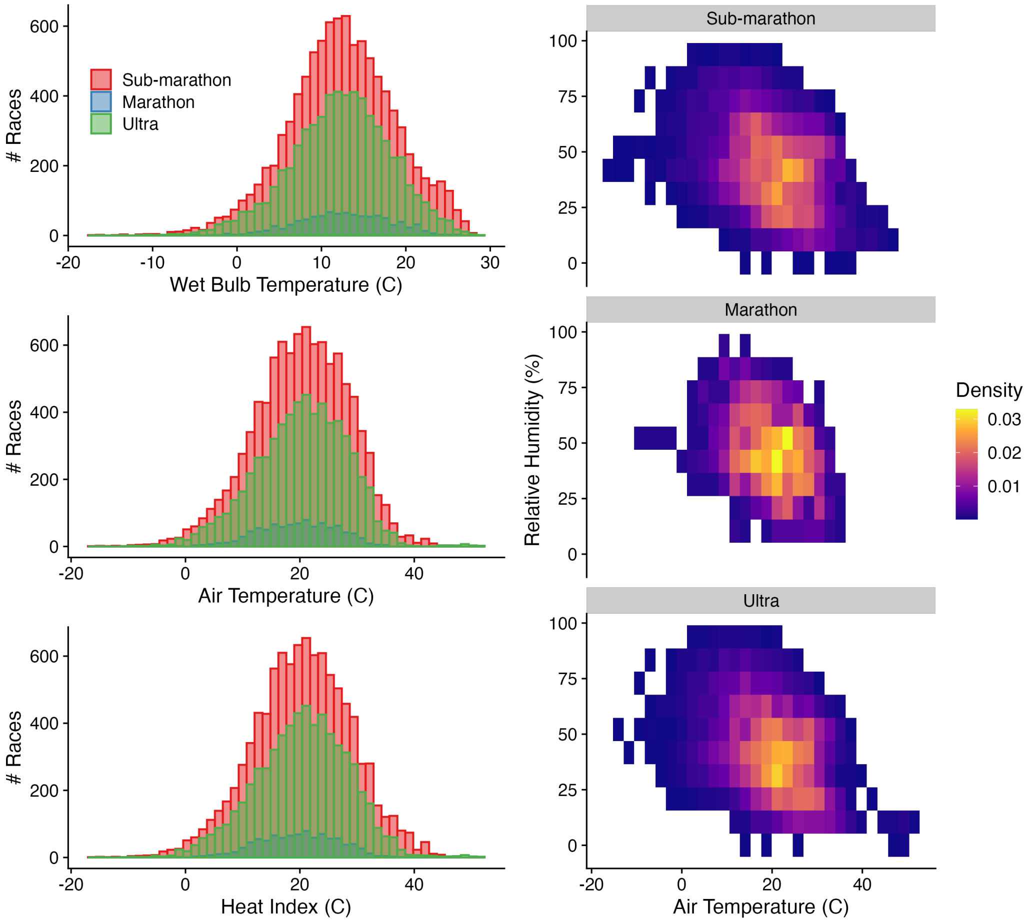
[2] The formal definition of wet bulb temperature also includes measures of solar exposure and wind, among others, which are not as readily available with the same geographic and temporal coverage as the PRISM data.

where T is the air temperature in degrees Celsius and RH is the relative humidity in percentage. Because PRISM provides daily maximum temperature as its primary temperature variable, this measure reflects the wet bulb temperature at peak daily heat; I refer to it throughout the paper as wet bulb temperature for brevity. Wet bulb temperature is more closely related to physiological heat stress than air temperature alone because high humidity impairs evaporative cooling. I also examine heat index as an alternative metric. Heat index is calculated using the formula from the National Weather Service (National Weather Service, 2024a), which combines air temperature and relative humidity to estimate the perceived temperature, or what it "feels like" to the human body. By contrast, wet bulb temperature is meant to capture the actual heat stress on the body, which should be more relevant for understanding performance effects (National Weather Service, 2024b).

Figure 2 shows the distribution of race-day weather conditions. The top panels show how wet bulb temperature and heat index vary across road marathons and trail events. The wider histogram for the trail races captures the value of including these events in the data: they are held in a wider range of locations and weather conditions, including many more hot days, than road marathons, which tend to be held in cooler locations and seasons. The right panels visualize how the races are distributed across air temperature and relative humidity, the core components of both wet bulb temperature and heat index. Again, the trail events cover a much wider range of conditions, with more races held in hot and humid conditions than road marathons. This variation is useful for identifying the effects of heat and acclimatization in the analysis that follows.

Figure 2: Distribution of race-day weather conditions

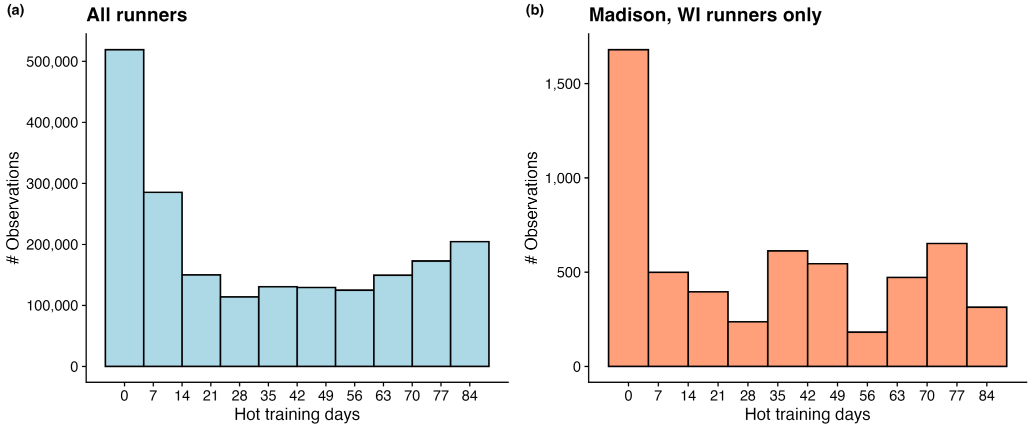


Notes: Figure shows the distribution of race-day weather conditions. Panels show the distribution of race-day wet bulb temperature and heat index across all race–year observations. Weather data are from PRISM (PRISM Climate Group, 2024).

2.3 Training Location Weather

To measure training heat exposure, I count the number of hot days (daily maximum wet bulb temperature above 15 C) at each runner's home location during the three months before their race. I choose three months to align with typical marathon and ultramarathon training periods, which generally span 12–20 weeks, and to capture the full window over which physiological heat adaptations can develop and be maintained (Périard et al., 2015).

Figure 3: Training Weather Exposure



Notes: Figure shows the distribution of training weather exposure. Left panel shows the raw distribution of hot training days (days with wet bulb temperature above 15 C) at each runner's home location in the three months before their race, across all runners. Right panel shows the same distribution restricted to runners from Madison, WI, illustrating the within-location variation in training weather exposure that identifies the training weather effects.

I choose 15 C wet bulb as a cutoff to reflect both the existing literature and estimates from the race data performances, approximately the lowest wet bulb temperature at which I observe statistically significant performance decrements (reported in Section 3.1). For context, occupational health guidelines set recommended wet bulb globe temperature (WBGT) exposure limits of 25–28 C for moderate-to-heavy work. I choose a lower cutoff since running generates substantially more metabolic heat than most occupational activities (National Institute for Occupational Safety and Health, 2016). Within distance running specifically, Ely et al. (2007) find that marathon finish times slow significantly once WBGT exceeds 10–15 C, which is consistent with the wet bulb temperatures I see.

2.4 Analysis Dataset and Descriptive Statistics

The observational unit for the analysis is a single athlete's performance in a given event. As an example of a single observation in this dataset, Courtney Dauwalter (the athlete) ran the 2023 Western States 100 (the event) in 15 hours, 29 minutes, and 33 seconds. To be in the dataset, I require that the athlete has a valid finish time, a self-reported home location that can be geolocated, and that the race has at least 50 finishers to ensure a minimum level of competitiveness and data quality. I also restrict the analysis to athletes training and races held in the contiguous United

States, where the race data are concentrated and where the PRISM weather data are available.

In total, after applying the data cleaning and sample restrictions above, the analysis dataset includes approximately 2.6 million race performances from 1978, though a large share of the data are from recent years (2021–2024) due to the growth in participation and improvements in data collection. Appendix Table A1 reports summary statistics for all variables used in the analysis.

Outcomes. The primary outcome variable in the study is the natural logarithm of finish time in seconds:

$$\text{log\_time}_{irt} = \ln(\text{time}_{irt}), \tag{2}$$

so that coefficients can be read as approximate percentage changes in finish time. As a secondary outcome, in some appendix materials I also examine normalized performance time, defined as the percentage difference from the course record:

$$\text{norm\_time}_{irt} = \frac{\text{time}_{irt} - \text{record\_time}_r}{\text{record\_time}_r} \times 100. \tag{3}$$

This benchmarks each performance against the fastest time ever recorded at that race (e.g., the fastest marathon ever recorded at the Eugene Marathon), allowing comparisons across different race distances and courses. The drawback of this metric is that for races with few editions, the course record itself may reflect heat effects, and slower runners will mechanically contribute more to estimates using this measure. Figure 4 shows the distribution of both outcome variables by race distance. The left panel shows that log finish time is roughly log-normally distributed, with longer races producing systematically longer finish times. The right panel shows normalized performance time: the distribution is right-skewed, with most runners finishing 20–100% above the course record, and the upper tail is longer for ultramarathon events where course conditions and race length add more variability.

3 Effects of Race-Day Heat on Performance

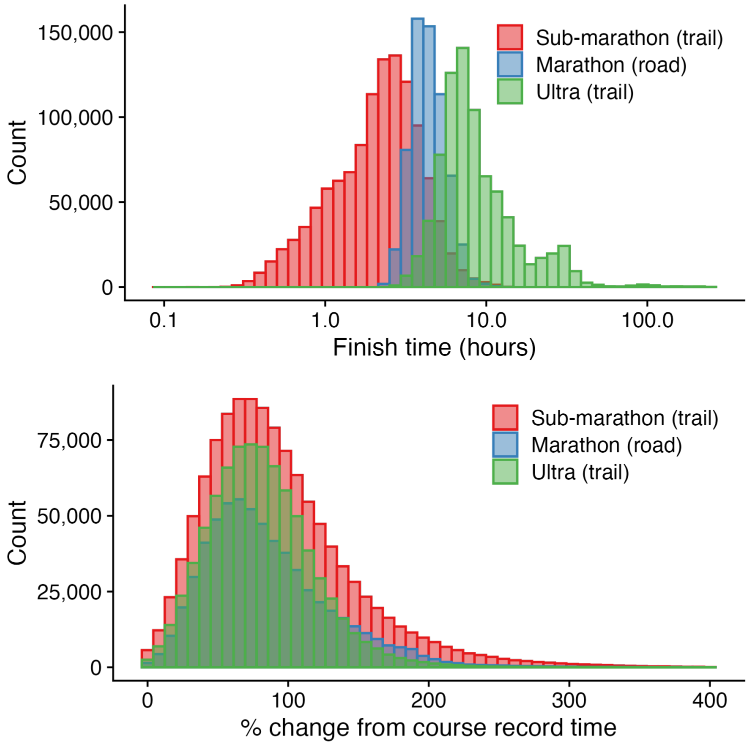
The empirical analysis proceeds in several parts. First, Section 3.1 estimates how race day temperature affects performance on average. Next, Section 3.2 examines heterogeneity by race distance, age, gender, and ability to see how different groups are affected by heat on the day of the event. Section 4 then turns to the sources of heat adaptation, combining cross-sectional evidence from home climate with short-run within-location evidence from training weather variation and examining how the timing of heat exposure within the training cycle shapes acclimatization.

3.1 Race-Day Effects of Heat

I begin by estimating the direct effect of race-day wet bulb temperature on performance. The general model is:

$$\text{log\_time}_{irt} = f(\text{WBT}_{rt}; \beta) + \theta + \varepsilon_{irt}, \tag{4}$$

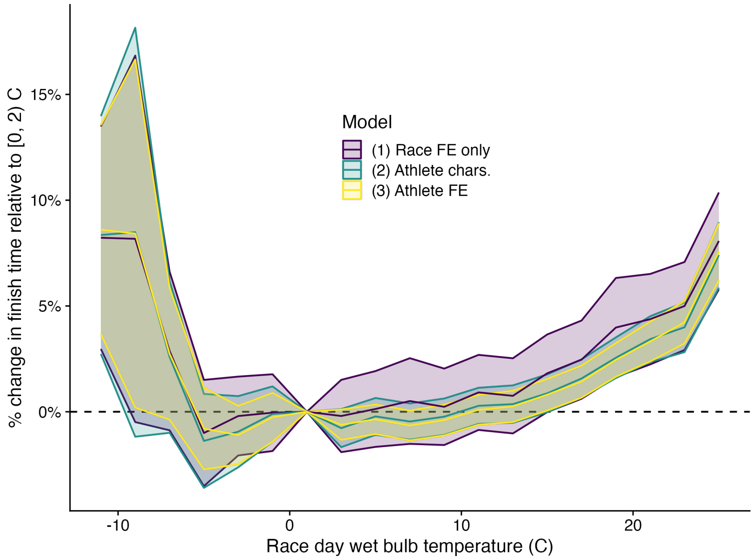
Figure 4: Distribution of finish time variables



Notes: Figure shows the distribution of the main outcome variables, split by race distance. Left panel shows the distribution of log finish time; right panel shows normalized performance time (percentage above course record).

where $f(\cdot)$ is a flexible function of wet bulb temperature (WBT), i indexes runners, r indexes races, t indexes years, and θ represents controls. To choose the right functional form, I begin with a flexible approach using two-degree temperature bins between -10 C and 26 C, roughly the range of the data. Figure 5 presents results from three versions: one controlling only for race fixed effects, a second adding runner characteristics (age group, gender, and performance in other races), and a third using runner fixed effects directly (comparing the same runner across different races).

Figure 5: Effect of wet bulb temperature on race time using temperature bins



Notes: Figure shows the effect of race-day wet bulb temperature on log finish time using 2 C temperature bins. Outcome variable is log finish time; each estimate is relative to the reference bin centered at 1 C. Three specifications are shown: (1) race fixed effects only, (2) race fixed effects with athlete controls (age group, gender, and leave-out finish quantile), and (3) race plus athlete fixed effects. Points show coefficient estimates; bars show 95% confidence intervals. Standard errors clustered by race location × date.

The relationship is consistent across all three approaches: finish times are roughly flat at moderate temperatures and decline steeply in conditions colder than -5 C and warmer than 10–15 C. Because the binned relationship is roughly piecewise linear with changes in slope around -5 C and 10 C, I parameterize race day weather using a piecewise linear specification with kinks at those temperatures for the rest of the paper. The benchmark piecewise specification is as follows:

$$\text{log\_time}_{irt} = \sum_{k=1}^{3} \beta_k p_k(\text{WBT}_{rt}) + \text{LOFP}_{i,-rt} + \phi_r + \phi_{\text{age}} + \varepsilon_{irt}, \tag{5}$$

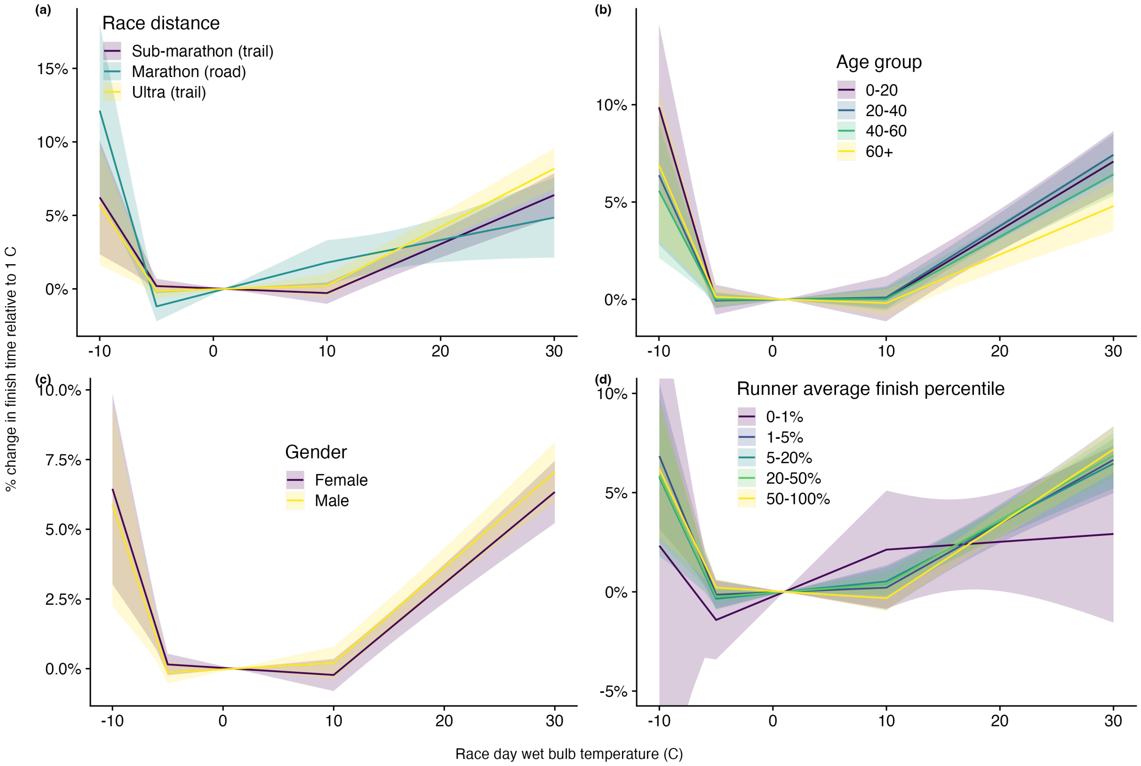
where $p_k(\text{WBT})$ are piecewise linear basis functions: $p_1(\text{WBT}) = \text{WBT}$, $p_2(\text{WBT}) = \max(\text{WBT} + 5, 0)$, and $p_3(\text{WBT}) = \max(\text{WBT} - 10, 0)$, with slope changes at -5 C and 10 C; ϕ_r are race fixed effects (which absorb all time-invariant differences across races), ϕ_{age} are age group fixed effects, and $\text{LOFP}_{i,-rt}$ is the runner's average finish quantile across their other races (a measure of baseline ability). Standard errors are clustered by race location × date.

The first panel in Appendix Figure B1 shows baseline effects with the piecewise linear model. The remaining panels show how the relationship varies using an alternative outcome variable (% difference in race time relative to the fastest time ever run on that course) and alternative race-day temperature variables (air temperature and heat index) in columns. The shape of the estimates is very similar across all alternative choices.

3.2 Who is Most Affected by Heat?

I next examine how the response to heat varies by race distance, age, gender, and ability. Figure 6 plots predicted effects normalized relative to each group's finish time at 1 C. I focus primarily on differences in the slope of the response curve above 10 C, where heat effects are most pronounced, but I also show the full curve to illustrate differences across the entire temperature range.

Figure 6: Heat effects on race time by runner/race characteristics



Notes: Figure shows the effect of race-day wet bulb temperature on log finish time, split by runner characteristics. Outcome variable is log finish time; all estimates are relative to the group-specific performance at 1 C. Panel (a) shows heterogeneity by race distance; panel (b) by age group; panel (c) by gender; panel (d) by average finish quantile in other races (a measure of ability). Estimates from the piecewise linear specification in Equation 5 with temperature terms interacted with the indicated group indicator. Controls include race, age group, and gender fixed effects and leave-out finish quantile. Shaded areas show 95% confidence intervals. Standard errors clustered by race location × date.

Panel (a) looks at differences by race distance and type, splitting the sample into sub-marathon (5 km to 42 km), marathon, and ultramarathon (any distance longer than a marathon) events.[3] This

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[3] I classify the (relatively few) trail marathons, i.e., marathons not run primarily on pavement or asphalt, as

complements the evidence in Sexton et al. (2022), who find that track and field athletes in longer events are more affected by heat. I find some similar evidence here, with ultramarathon runners more affected by heat than marathon or sub-marathon runners, though the differences are not large and the confidence intervals overlap.

Prior climate literature has documented that older individuals are far more sensitive to heat in other domains, such as mortality (Carleton et al., 2022). Panel (b) finds no such pattern here: the slope of the response curve above 10 C is similar across age groups, and in fact it is younger runners who experience larger performance losses in hot conditions, though these differences are slight.

Panel (c) shows gender differences; here the response curves are very nearly the same, with female runners slightly less affected by heat and slightly more affected by cold than male runners. These differences are small and not statistically significant, consistent with prior marathon evidence that warm-weather effects are less pronounced for female runners (Ely et al., 2007; El Helou et al., 2012), but in contrast to evidence from other domains that women bear larger heat burdens (Carleton et al., 2022).

Panel (d) shows differences by ability, measured by the runner's average finish quantile in other races. Work that examines elite tennis players has found that players from warmer home countries are better able to maintain performance in hot conditions (Burke et al., 2023). I see a similar pattern here: faster runners are far less affected by heat than slower runners, though the differences only emerge at the very top end of the field (i.e., the top 1% of finishers). This is consistent with the idea that faster runners are more likely to have access to resources that help them mitigate heat effects, such as better training, equipment, and pacing strategies, not to mention the professional incentive to take advantage of these resources.

4 Heat Adaptation and Acclimatization

To examine the sources of heat adaptation, I use two complementary approaches. The first (Section 4.1) compares runners grouped by their long-run home climate, dividing them into quartiles by the typical wet bulb temperature at their home location. I refer to this as the "training climate" approach. This approach is common in the prior adaptation literature and captures adaptation through any mechanism: selection, long-run infrastructure, long-run physiological changes, or short-run acclimatization. The second (Section 4.2) isolates within-location variation in training weather, comparing runners from the same place who happened to experience different numbers of hot days in the three months before their race. I call this the "training weather" approach. Because this comparison holds location fixed, it more specifically targets short-run acclimatization driven by recent heat exposure.

4.1 Training Climate Effects

As a first look at how long-run training climate shapes race-day heat sensitivity, Figure 7 plots response curves by training climate quartile, where quartiles are defined by the year-round average

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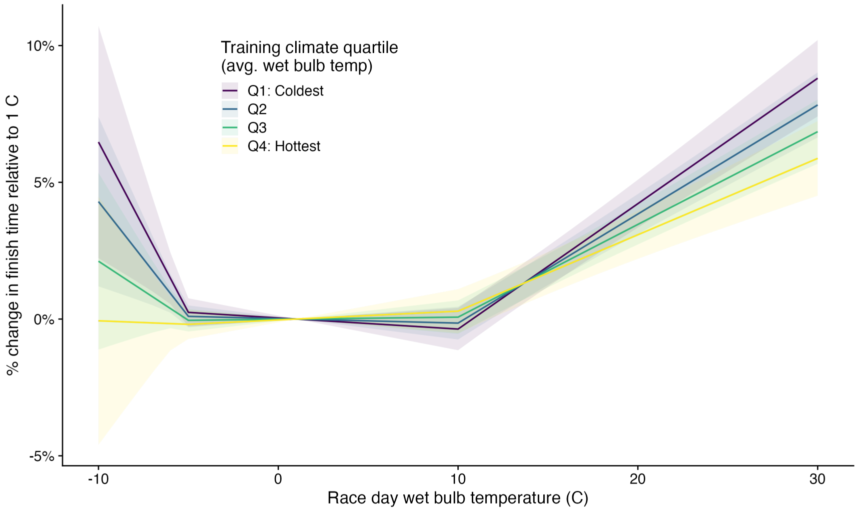
sub-marathons for this figure.

wet bulb temperature at the runner's home location. Runners from hotter training climates are less sensitive to race-day heat, with response curves shifting downward as climate quartile increases. This pattern is consistent with physiological acclimatization but could also reflect cross-sectional sorting, long-run infrastructure differences, or population composition. The within-location analysis in Section 4.2 addresses this confound.

Figure 7: Race-day heat sensitivity by training climate quartile



Notes: Figure shows the effect of race-day wet bulb temperature on log finish time, split by quartile of the average wet bulb temperature at the runner's home location (Q1 = coldest, Q4 = hottest). Outcome variable is log finish time; effects are normalized to zero at 1 C for Q1. Estimates from the piecewise linear specification in Equation 5 with temperature terms interacted with training climate quartile. Controls include race, age group, and gender fixed effects and leave-out finish quantile. Shaded areas show 95% confidence intervals. Standard errors clustered by race location × date.

These patterns are broadly consistent with findings from other papers that examine heat effects on athletic performance. Burke et al. (2023) show that professional tennis players from warmer home countries maintain better performance in hot conditions, and Aragon and Rezazadeh (2025) report a similar pattern for track and field athletes competing across countries with different average temperatures. Like the average training-period results presented above (Figure 7), these studies compare athletes from different home locations without leveraging variation in training-period weather, and therefore cannot distinguish short-run physiological acclimatization from selection into hotter places, long-run infrastructure differences, or other location-specific factors. The training weather analysis in Section 4.2 uses within-location variation to partially address this limitation.

4.2 Training Weather Effects

To isolate short-run acclimatization effects, I compare runners from the same location who experienced different training weather. The intuition here is to compare two runners who train in the same location, but have races in different parts of the year or different years, so that one runner experienced more hot days in the three months before their race. This comparison holds fixed the role of long-run factors that could yield adaptive (or apparently adaptive) effects, and focuses instead only on the role of recent heat exposure in shaping acclimatization.

For this analysis, I measure heat exposure as the number of hot days (daily maximum wet bulb temperature above 15 C) at the runner's home location in the three months before the race, grouped into bins: 0 hot days, 1–30, 31–60, and 60+. I interact these bins with race-day wet bulb temperature using a piecewise linear function that allows the temperature–performance relationship to change slope at −5 C and 10 C:

$$\begin{aligned}\text{log\_time}_{irt} = &\sum_{k=1}^{3} \beta_k p_k(\text{WBT}_{rt}) \\ &+ \sum_{q=2}^{4}\sum_{k=1}^{3} \gamma_q^k \left(p_k(\text{WBT}_{rt}) \times \text{HotDays}_{it}^{q}\right) \\ &+ \phi_{\text{climate}} + \phi_{\text{distance}} + \phi_{\text{age}} + \phi_{\text{gender}} + \varepsilon_{irt},\end{aligned} \tag{6}$$

where HotDays_{it}^{q} indicates whether runner i falls in hot-day bin q, ϕ_{climate} controls for the runner's home climate group, and ϕ_{distance} controls for race distance. I estimate three versions: Model 1 – Baseline (race distance, age, and gender fixed effects); Model 2 – Training Climate (adding home climate quartile fixed effects); and Model 3 – Training Location FE (adding training location fixed effects, comparing runners from the exact same location who experienced different weather during their training).

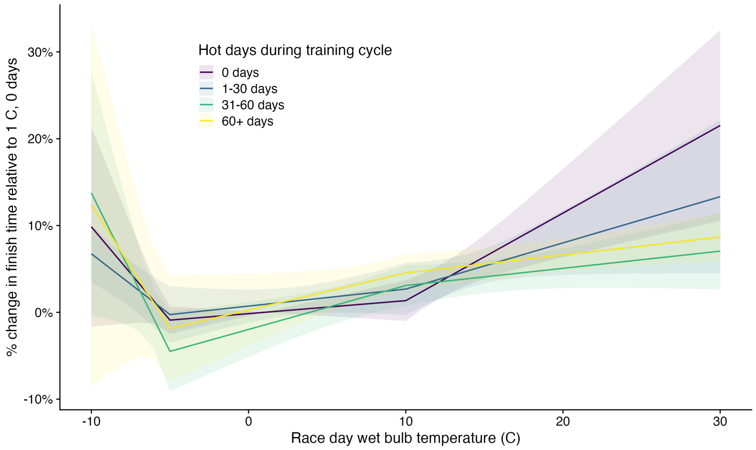
Figure 8 presents the results. Panel (a) shows the response curves by training weather group, and panel (b) summarizes the key result by plotting the estimated marginal effect of a 1 C increase in race-day wet bulb temperature, evaluated at 15 C (the steep part of the response curve where heat begins to bite) across training weather groups and model versions.

The sensitivity to race-day heat is highest for runners who experienced the fewest hot days during training, and lowest for those who experienced at least 31 hot days. Notably, there is no meaningful difference between runners with 31–60 hot days and those with 60+ hot days, suggesting that the benefits of heat exposure level off after approximately one month of hot days. The pattern is consistent across all three model specifications, including Model 3 with training location fixed effects, which provides the most direct test of short-run physiological acclimatization. This is consistent with the exercise physiology literature, which tends to find that physiological heat adaptations kick in within 5–14 days and reach full effect in about two weeks (Périard et al., 2015; Racinais et al., 2015).

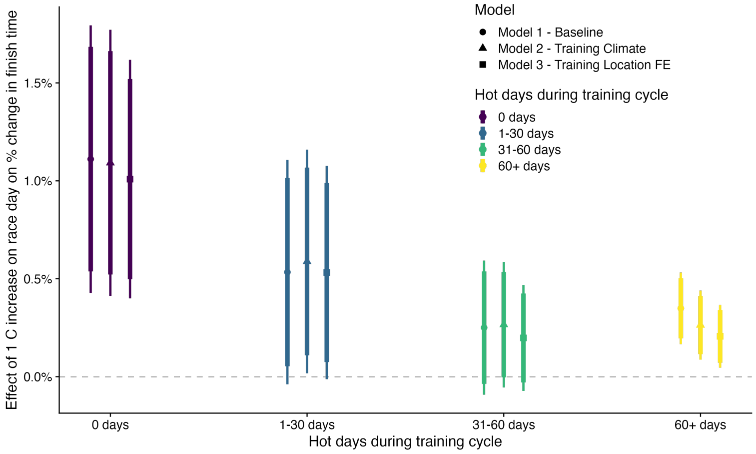
4.3 Timing of Training Heat Exposure

To examine whether the timing of heat exposure within the training cycle matters, I divide the 84-day training window into three monthly periods and estimate a separate effect for each. The three periods are: the most recent month (weeks 1–4 before race, days 1–28), the middle month (weeks 5–8, days 29–56), and the earliest month (weeks 9–12, days 57–84). For each period, I sum the number of hot days and interact it with the piecewise linear race-day temperature terms, controlling for training location fixed effects. This allows the per-hot-day effect to vary non-parametrically

Figure 8: Heat adaptation: training weather evidence



(a) By hot training days (response curves)

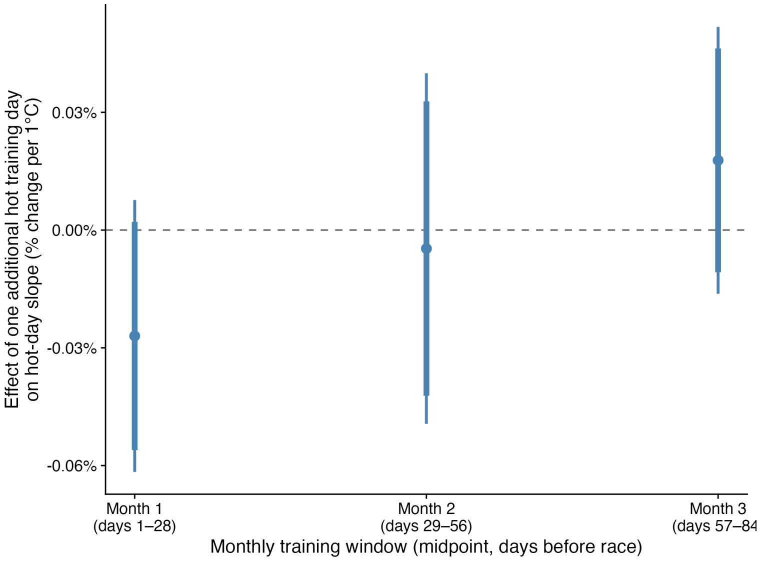


(b) Marginal effects by training weather group and model

Notes: Figure shows the sensitivity of log finish time to race-day wet bulb temperature, by training heat exposure group. Colors correspond to hot-day training bins in both panels. Outcome variable is log finish time. Panel (a): predicted log finish time against race-day wet bulb temperature for runners in each hot-day training bin (0, 1–30, 31–60, or 60+ days above 15 C wet bulb in the three months before the race); estimates from Equation 6 (Model 3); shaded areas show 95% confidence intervals. Panel (b): estimated marginal effect of a 1 C increase in race-day wet bulb temperature, evaluated at 15 C, by training weather group and model; point symbols indicate model (circle = Model 1 Baseline; triangle = Model 2 Training Climate; square = Model 3 Training Location FE). Thick bars show 90% confidence intervals; thin bars show 95% confidence intervals. Standard errors clustered by race location × date.

across the three segments of the training cycle.

Figure 9: Effect of a hot training day on race-day heat sensitivity, by days before race



Notes: Figure shows the effect of one additional hot training day on the high-temperature slope of the performance–weather relationship, by monthly training window. Outcome variable is the implied change in the marginal effect of race-day wet bulb temperature above 10 C per additional hot day. Three monthly periods are shown: Month 1 (days 1–28 before race), Month 2 (days 29–56), and Month 3 (days 57–84). Points show coefficient estimates; thick and thin bars show 90% and 95% confidence intervals, respectively. Controls include race distance, age group, and gender fixed effects and training location fixed effects. Standard errors clustered by race location × date.

Figure 9 shows the estimated per-hot-day effect on the high-temperature slope for each of the three monthly windows. None of the three estimates is statistically distinguishable from zero, so the monthly decomposition does not allow me to pin down the timing of acclimatization precisely. The point estimates are largest (most negative) for the most recent month (days 1–28 before the race) and smaller for the earlier two months. The evidence from this decomposition is suggestive that the benefits of training-period heat exposure are concentrated in the weeks immediately before the race and begin to fade after about a month, but the confidence intervals overlap substantially across all three periods. Still, this pattern is at least qualitatively consistent with the physiology literature's finding that adaptations begin to fade within a week or two after heat exposure ends (Périard et al., 2015).

5 Discussion and Conclusion

This paper makes three main contributions. First, I provide new estimates of the effect of heat on endurance running performance using a large dataset that includes both marathons and ultramarathons, with wet bulb temperature as the heat stress measure. Second, I document heterogeneity in heat sensitivity by race distance, age, gender, and ability; the most notable finding here is that higher ability runners are much less sensitive to heat than the general population, suggesting that training and experience can mitigate the effects of heat on performance. Third, and most importantly, I present evidence that short-run physiological acclimatization, driven by naturally occurring weather variation during training, meaningfully reduces sensitivity to race-day heat and that these effects cannot be explained by average training conditions.

There are several notable limitations to what I show here. First, runners, particularly those who run marathons and ultramarathons, are a highly selected and dedicated group with a strong incentive to adapt to heat. This means that the effects of heat on performance and the benefits of acclimatization measured here could well be a lower bound on what might be expected among the general population. Second, while the training weather analysis clarifies that short-run acclimatization is an important channel of adaptation, it does not rule out the possibility that other channels, such as selection into hotter places or long-run infrastructure differences, also contribute to the patterns observed in the training climate analysis. Finally, while the estimates suggest that training cycle exposure to heat reduces sensitivity through direct physiological acclimatization, I do not observe the specific training adaptations that athletes may undertake in the face of warmer than expected weather. This means that I cannot measure whether training-period heat exposure also induces behavioral changes that contribute to the observed effects, such as (for example) changes in the timing of training sessions or replacing outdoor activities with indoor alternatives.

This paper's focus is on running, but the findings are relevant for other domains as well. They suggest that the body's own ability to adjust to heat over weeks and months contributes to the adaptation patterns observed in cross-sectional studies of climate damages, and that this channel of adaptation may provide a meaningful but incomplete buffer against future heat shocks. Conversely, it highlights the hazard of heat waves that arrive after a long period of cooler temperatures, a finding that has broader importance for anticipating and mitigating the social and health impacts of an increasingly warm world.

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AI Disclosure

I used Anthropic's Claude for coding support and text editing in the preparation of this manuscript.

Appendix

A Data Construction

A.1 Descriptive Statistics

Table A1 reports summary statistics for all variables used in the analysis. The sample consists of approximately 2.6 million runner–race performance observations. Notable variation in sample size across variables reflects missingness: normalized performance time is only defined for races with an available course record, and the leave-out finish percentile is only defined for runners who appear at least twice in the data.

Table A1: Descriptive statistics

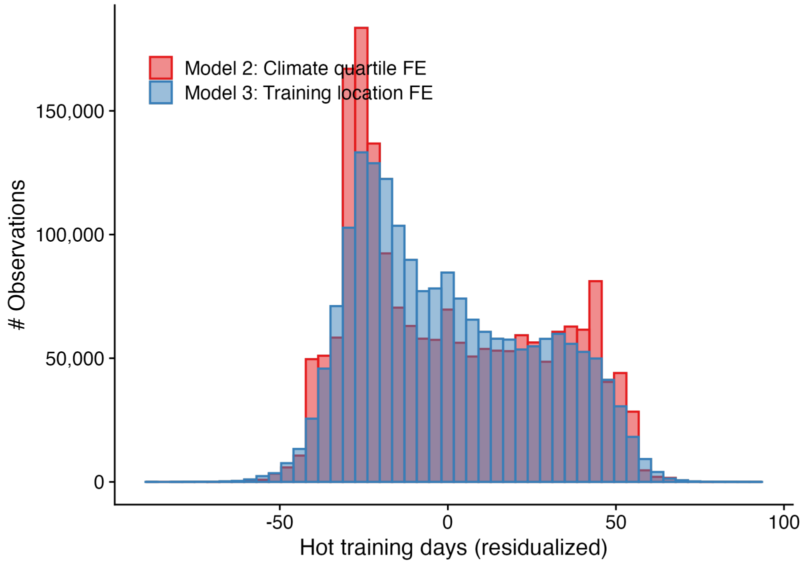
	N	Mean	SD	Min	Median	Max
Log finish time	2593311	9.53	0.83	5.81	9.58	13.70
Normalized finish time (pct)	2593311	87.20	47.12	0.00	79.77	399.91
Race WBT (C)	2352741	12.29	5.84	−17.19	12.36	28.86
Race air temperature (C)	2352741	19.89	7.66	−16.35	20.19	51.61
Race relative humidity (pct)	2352741	43.65	18.01	3.94	43.32	97.77
Race heat index (C)	2352741	20.01	7.86	−16.35	20.19	51.61
Hot training days	1979944	33.73	30.23	0.00	26.00	84.00
Normal WBT at home (C)	1979954	12.18	3.37	−3.86	11.86	22.91
Age (years)	2417835	40.39	11.67	10.00	40.00	100.00
Race distance (km)	2593311	39.62	32.82	1.00	42.20	564.88
Leave-out finish percentile	1685081	0.49	0.25	0.00	0.49	1.00
Male (0/1)	2593221	0.45	0.50	0.00	0.00	1.00

Unit of observation is a runner–race performance. Log finish time is log(finish time in seconds). Normalized finish time is the percentage difference from the all-time course record (missing when no course record is available). Race-day weather variables are measured at the race location on race day. Hot training days counts days with WBT above 15 C at the runner's home location in the 90 days before the race. Normal WBT at home is the long-run average wet bulb temperature at the runner's home location. Leave-out finish percentile is the runner's mean finish percentile across all other races in the sample (0 = slowest, 1 = fastest), and is missing for runners appearing fewer than twice in the data. Sample restricted to races with at least 50 finishers in the contiguous United States.

A.2 Residualized Training Weather

Figure A1 shows the distribution of the hot training days variable after removing variation accounted for by the fixed effects used in the training weather models. Model 2 residualizes by climate quartile, race distance, age group, and gender fixed effects; Model 3 additionally replaces climate quartile with training location (runner home grid cell) fixed effects. The residualized distributions illustrate the within-group variation used for identification in each specification.

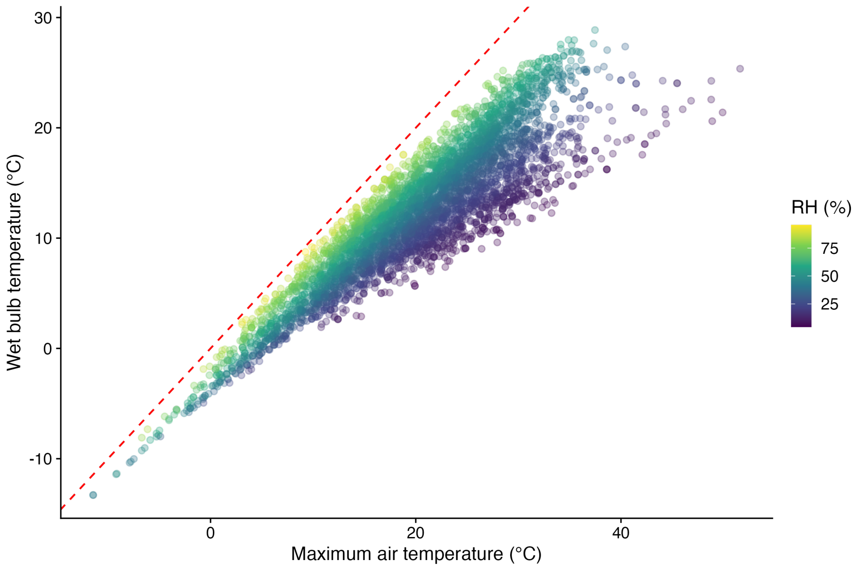
Figure A1: Residualized hot training days: within-group variation used for identification



Notes: Figure overlays the distribution of hot training days (days with wet bulb temperature above 15 C in the three months before the race) after residualizing by the fixed effects in each model. Model 2 residualizes by climate quartile, race distance, age group, and gender fixed effects. Model 3 residualizes by training location (runner home grid cell), race distance, age group, and gender fixed effects. Weather data from PRISM (PRISM Climate Group, 2024).

A.3 Wet Bulb Temperature vs. Maximum Air Temperature

Figure A2: Wet bulb temperature vs. maximum air temperature, by relative humidity



Notes: Scatter plot of race-day wet bulb temperature against maximum air temperature for a random 5,000 race-event sample, colored by relative humidity. Dashed line shows the 45-degree line (wet bulb = air temp, which occurs only at 100% humidity).

B Sensitivity

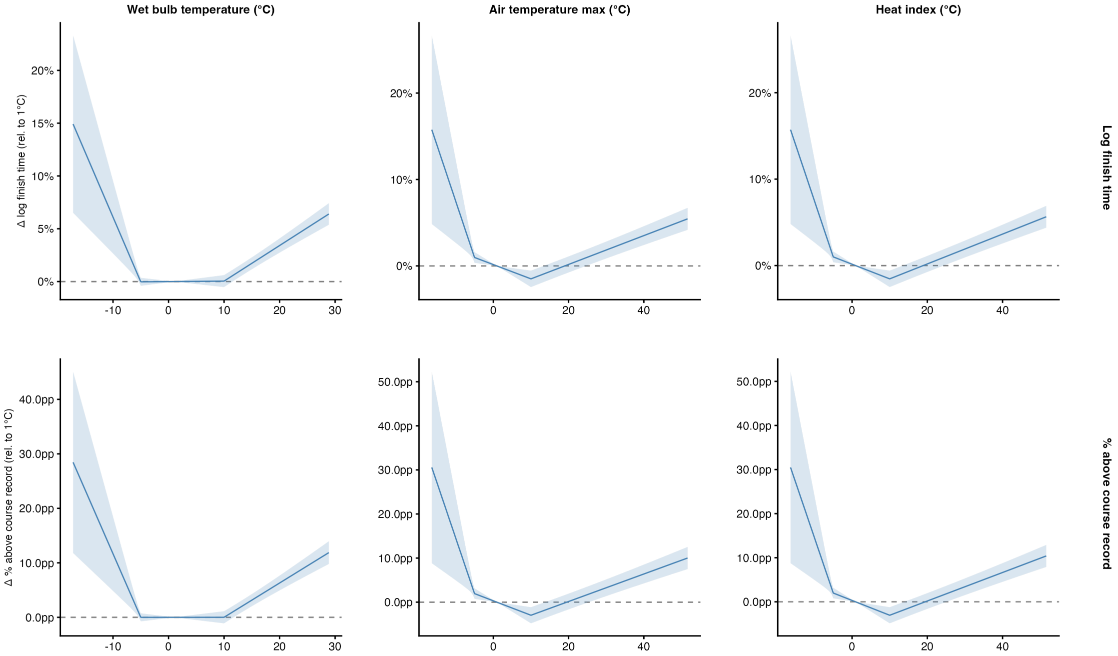
This section presents a series of sensitivity checks for the main results. Section B.1 shows that the dose-response shape is stable across alternative outcome variables and heat measures.

B.1 Outcomes and Heat Measures

Figure B1 presents a 2×3 set of piecewise-linear response curves varying both the outcome variable (rows) and the heat stress measure (columns). The two outcomes are log finish time (top row) and normalized performance time—the percentage difference from the course record (bottom row). The three heat measures are wet bulb temperature (left column), maximum air temperature (center column), and heat index (right column). All panels use the same piecewise-linear specification with race, age group, and gender fixed effects and a leave-out finish percentile control (Equation 5).

The results are qualitatively consistent across all six panels. The dose-response shape—roughly flat at low temperatures with a steep increase above 10–15 C—is robust to the choice of outcome and heat measure. The onset of heat penalties is somewhat sharper under wet bulb temperature and heat index than under maximum air temperature alone, consistent with the role of humidity in impairing evaporative cooling.

Figure B1: Piecewise-linear heat effects: robustness across outcomes and heat measures



Notes: Figure shows the effect of race-day heat on finish time across a 2×3 grid of outcome and heat measure combinations. All estimates are normalized relative to the predicted value at 1 C. Rows show the outcome: log finish time (top) and normalized performance time as percentage above course record (bottom). Columns show the heat stress measure: wet bulb temperature (left), maximum air temperature (center), and heat index (right). Estimates from the piecewise linear specification in Equation 5; controls include race, age group, and gender fixed effects and leave-out finish percentile. Shaded areas show 95% confidence intervals. Standard errors clustered by race location × date.