ECONOMICS

High-frequency data reveal limits of adaptation to heat in animal agriculture

Claire Palandri[1]*, Eyal G. Frank[1,2,3], Ayal Kimhi[4], Yaniv Lavon[5], Ephraim Ezra[5], Ram Fishman[6]

Understanding the impacts of climate change on food systems is a key research priority, but important sectors and the scope for adaptation remain underexplored. Here, we analyze more than 320 million daily observations of milk production across 12 years, paired with survey data, to provide estimates of the effect of humid heat and the scope for adaptation. Results indicate that extreme heat reduces milk yield by up to 10%, with effects that persist for more than 10 days. Effects are stronger when cows are at more productive stages, suggesting a productivity-resilience trade-off. Cooling infrastructure and management adjustments were widely adopted over the preceding two decades, but only partially mitigate these losses, reducing them by less than half. Given the technological advancement and the representation of the climate of key producing countries in our sample, these results suggest that adaptation strategies, even those at the technological frontier, may be insufficient to address climate change damages.

INTRODUCTION

Understanding the impacts of climatic variability on food systems remains an active research agenda. As evidence on the severity of potential damages from climate change accumulates (*1*), it has become increasingly important to extend the literature to understudied food sectors and to improve our understanding of the degree to which adaptation can reduce those damages. However, while methodological advances have enabled precise estimation of response functions in multiple sectors of the economy, other important sectors remain insufficiently studied, including animal agriculture. This gap is noted across multiple reviews (*2*, *3*), and even the most comprehensive national assessments of climate impacts often omit animal agriculture entirely (*1*). In addition, crucial knowledge gaps persist on the extent to which the adoption of cost-effective technologies can reduce the impacts of anomalous weather conditions.

This study provides evidence of the damages caused by humid heat and the potential for adaptation in animal agriculture. The dairy sector is deemed of enormous nutritional and economic importance, with an estimated 150 million households engaged in milk production globally (*4*). Global milk production is projected to increase faster than most other main agricultural commodities (*5*) to meet rising demand, but the extent to which climate change could slow growth is uncertain.

Humid heat stress is considered to be one of the main limiting factors of milk production (*6*), and extreme humid heat events—which have more than doubled in frequency over the past four decades (*7*)—are predicted to occur over large regions for months at a time on a warmer planet, leading to the notion of a steambath world (*8*). In addition, over the next 10 years, more than half of the growth in production is expected to occur in South Asia, where heat waves and humid heat stress are projected to be more intense and frequent (*9*). Yet, most existing estimates of the response of milk yield to weather remain limited in important respects by often making strong assumptions on functional form, relying on highly aggregated data or small sample sizes, and imperfectly accounting for the potential of adaptation to reduce impacts (*10*).

Data of unusual scale and high spatiotemporal resolution, covering 12 years of the daily milk yield of each of 130,000 dairy cows in Israel (300+ million observations), allow us to derive several insights into the impacts of humid heat. The position of the Israeli dairy sector on the technological frontier of production and weather resilience further provides an opportunity to study the limits of existing cost-effective technologies for adaptation, and the country's wide climatological gradient—which captures the high temperature ranges of the top milk-producing countries (text S1.3)—supports the broad geographical relevance of the results.

We leverage exogenous high-frequency variation in weather realizations to estimate flexible models of the relationship between temperature, humidity, and milk production. Our empirical approach adopts rigorous standards from the climate impacts literature and is designed to produce estimates that plausibly reflect causal effects while minimizing bias from potential confounders. The method and size of the sample also allow us to disentangle the contemporaneous and delayed effects of humid heat and estimate the rate of their dissipation. We further combine these data with farm-level survey responses on adaptation to analyze the heterogeneity of the relationship with respect to the adoption of common candidate adaptation measures, including cooling technologies (mostly ventilation and spraying systems), shifting of calving periods, and adjusting feeding practices. The analysis helps to assess how much of the adverse impacts of heat may be reduced by adopting these adaptation strategies.

In addition to its economic significance, the analysis of the dairy sector also sheds light on the physiological impacts of heat on the healthy functioning of mammals, joining studies that have found impacts on human physical and cognitive performance (*11*–*15*).

Background

Cow's response to humid heat

Cows, like all mammals, must maintain thermal homeostasis to function and grow. When external temperature increases, the body of a mammal adopts strategies to maximize heat loss, e.g., through evaporative cooling by perspiration and panting or by resting to reduce its metabolic rate (*16*). The amount of heat stress is thereby affected not

---

[1]Harris School of Public Policy, University of Chicago, Chicago, IL 60637, USA. [2]National Bureau of Economic Research, Cambridge, MA 02138, USA. [3]Center for Economic Policy Research, 75007 Paris, France. [4]Department of Environmental Economics, Hebrew University of Jerusalem, Rehovot 7610001, Israel. [5]Israel Cattle Breeders Association, Caesaria Industrial Park, Caesarea 38900, Israel. [6]Department of Public Policy, Tel Aviv University, Tel Aviv-Yafo 6997801, Israel.
*Corresponding author. Email: clairepalandri@uchicago.edu

only by dry-bulb temperature—which affects sensible heat loss—but also by ambient humidity—which hinders latent heat loss via evaporative cooling. Other environmental factors such as wind speed and incoming radiation also affect heat stress (*17*). As these determinants of heat stress increase, they make the dissipation of body heat more difficult, i.e., heat stress becomes heat strain. Multiple studies have documented deleterious effects on humans, in terms of productivity, behavior, and morbidity and mortality rates, and on livestock, specifically cow milk production and pig growth (*18*–*21*).

The effect on lactating cows is, in principle, known to involve physiological and metabolic adjustments (*16*, *22*). Although many studies have investigated the impact on milk production in the dairy science literature, most existing analyses present several limits. Most assume, rather than test, that the relationship follows a certain functional form, which is most often linear beyond a certain threshold; they tend to rely on small datasets, whether in experimental or observational settings, which raises the question of sensitivity to specification form; and they generally use as weather variables versions of a "Temperature Humidity Index" (THI), which lacks physical units and is calibrated to the contexts of original small-sample studies, limiting its interpretability and generalizability (*6*, *23*–*35*).

Here, we first estimate the shape of the daily milk yield response to dry-bulb temperature (T) and relative humidity (RH) using model specifications that make minimal assumptions about the functional form. We subsequently use the wet-bulb temperature (Twb) as our preferred summary index of heat stress in regression models, finding it to be at least as adequate as common THIs to account for the combined effects of T and RH but more easily interpretable and with greater external validity.

Israeli dairy farms and climate

The dairy farms in Israel produced more than 1521 million liters of milk in 2020 and gathered a total standing population of about 133,000 cows, the vast majority of which—an average of 72.7% across our entire sample—we observe at the individual cow-by-day level over 12 years. Such rich, high-frequency outcome data enable us to leverage exogenous variation in weather and alleviate concerns of potential aggregation bias. Three features of the Israeli dairy sector further make it an especially well-suited setting for generating estimates that both reduce potential bias and have global relevance. First, because of the topography of the land, the dairy farms scattered throughout the area experience a wide range of temperature and humidity values that are representative of many regions worldwide. This narrow spatial scale, combined with substantial climatic variation, strengthens identifying assumptions, as potentially confounding variables are likely homogeneous (*36*). Second, milk production operates under a quota system in which prices are centrally controlled, reducing concerns about confounding from demand shocks. Last, virtually all farms have adopted technologies to reduce heat stress and vary in the timing of their installation over our study period, which we measure in a survey. This allows us to leverage within-farm variation to estimate the range of effects that may be expected with or without the utilization of such adaptation potential.

Other characteristics of Israeli dairy farms, notably farm size and herd management, exhibit relatively low heterogeneity. Nearly all cows are Israeli Holsteins, a breed developed through several generations of crossbreeding to be specifically adapted to the local climate and which has the world's highest average milk yield per cow—around 12,020 kg/year. There are two main types of dairy farms: Three of four are family farms in cooperative villages called moshavim; the rest are located in kibbutzim, which are organized as collective economic units where the means of production are communally owned. Lactating cows are milked, on average, three times a day, do not graze, and are confined to permanent roofed enclosures that are exposed to outside air. They are fed a mixed total ration composed mostly of silages.

The milk production of a cow follows a lactation cycle that starts at the birth of her calf and lasts, on average, for 14 months. Over the course of the cycle, the body and metabolism of the cow change, and the expected milk output follows a distinctive pattern: Production increases rapidly until "peak milk"—expected at about 2 to 3 months—and then declines slowly. The cow goes through different physiological states throughout the lactation cycle, notably a highly negative energy balance at the beginning of the period accompanied by substantial weight loss (*22*). The dry period is relatively short as the typical cow is inseminated again midcycle to produce another calf, thereby initiating the next lactation cycle.

RESULTS

Milk yield decreases at an increasing rate with rising temperature and RH, whose combined effect is captured by the Twb

To extract the general shape of the milk yield response to weather without imposing restricting assumptions on functional form, we first estimate semiparametric models on continuous regressors. We specify a generalized additive model (GAM) that expresses the relationship of the outcome with daily average T and RH as a bivariate smooth spline to flexibly capture nonlinearities and interactions. We adjust for cow-level covariates, including stage of lactation, milking frequency, and lactation number, after demeaning the data by farm, year, and month—an approach commonly referred to as including fixed effects in the applied microeconomics literature. Figure 1A shows the estimated response surface over the ranges of T and RH. It reveals a highly nonlinear response, where the rate at which T and RH affect yield increases with the level of these variables.

This pattern is consistent with previous evidence of a nonlinear combined effect of T and RH on milk production. While this flexible specification captures the full shape of the response function, for the purpose of the subsequent analyses, it is useful to identify a single summary indicator of humidity and heat that allows for the estimation of response functions that are more tractable than a bivariate spline. The dairy science literature often uses variations of THIs for this purpose. One limitation of these indices is that they are often empirically calibrated from small historical samples of cows—whose average milk yield, and, hence, metabolic heat output, was much lower than it is today—and they are unitless, making results difficult to interpret and generalize (*34*, *37*). In this study, we select the Twb as our preferred summary indicator of humid heat. The Twb represents the lowest temperature to which an air parcel can be cooled through adiabatic evaporation of water. As such, it reflects, in part, the cooling efficiency of sweat and, hence, has a direct physiological relevance. A threshold near 35°C has been identified as a critical upper limit for thermoregulation in placental mammals, which share relatively high metabolic rates and rely on evaporative cooling to maintain stable core body temperatures (*38*). We find that the Twb captures the response surface well (Fig. 1B) and rivals THIs in predictive ability (text S4). Unlike THIs, Twb is not calibrated to fit impacts and relies on thermodynamic principles, ensuring both

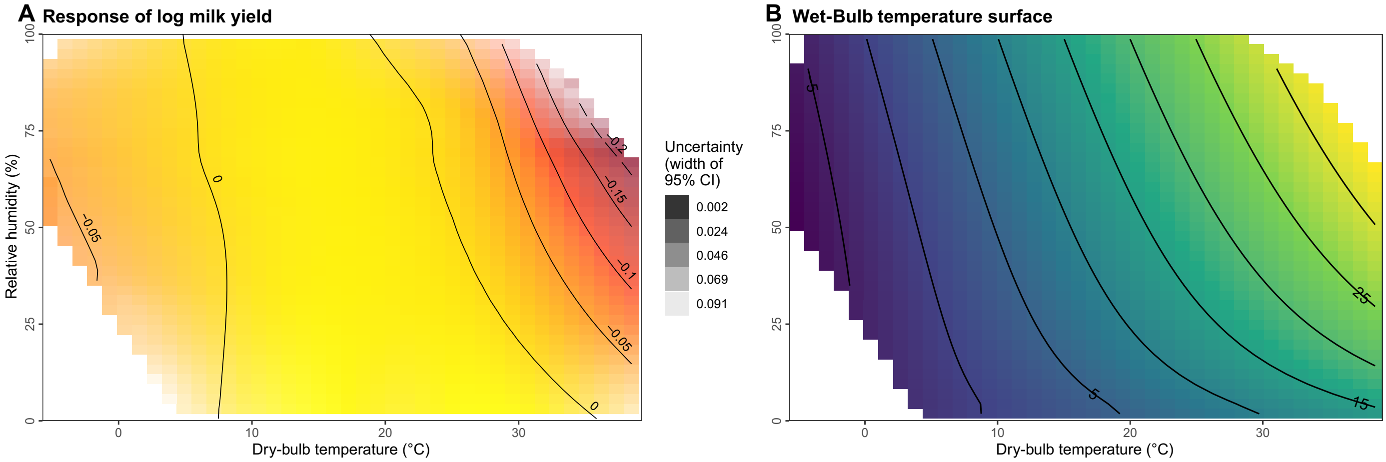


Fig. 1. Joint effects of dry-bulb temperature and RH on milk yield, alongside the corresponding Twb surface over the same range. (**A**) Contour plot showing isovalue lines of the estimated average effect of daily mean dry-bulb temperature (T) and RH on the logarithm of milk yield. Estimates are derived from 100 bivariate smooth splines fitted to random 1% subsamples of the full dataset ($n = 3{,}289{,}463$; adjusted $R^2 = 0.395$). Opacity indicates uncertainty on the basis of the width of the empirical 95% confidence interval (CI; 2.5th to 97.5th percentiles) across spline fits; wider intervals are more transparent. (**B**) Twb values across the same T and RH ranges as in (A).

interpretability and validity across different contexts. We therefore use the Twb as our preferred index of humid heat in all subsequent analyses. Comparisons to the THIs and other indices used in the literature are provided in the Supplementary Materials (text S6.4).

Larger yield declines on extreme days

We estimate regressions of milk output on vectors of variables that capture the daily realization of Twb, adjusting—similarly to the bivariate spline model—for the stage of the lactation cycle, the cow's age (proxied by her number of lactations), the number of daily milkings, and farm, year, and month fixed effects. These fixed effects ensure that estimates are based on high-frequency weather variation, which lends itself to causal interpretability rather than on differences across farms, years, or seasons that may introduce bias. Both the farm data and survey responses indicate that farmers do not adjust milking frequency in response to heat stress, which largely mitigates concerns about potential bias from including milking frequency as a control (text S5.1).

We first consider a simple regression on a vector of binary indicators of whether the daily average Twb is in the given interval. The middle panel of Fig. 2 shows the shape of the estimated step function overlaid with a univariate regression spline. We observe a somewhat inverted-U response, with a pronounced and gradually steeper decline above moderate temperatures—challenging the assumption of a sharp threshold made in a large part of the dairy literature. Relative to a day with average Twbs in the 10° to 12°C range, a daily mean within 18° to 20°C reduces output by about 1.6%, one within 22° to 24°C by 3.7%, and one above 26°C by 9.6%.

The left panel of Fig. 2 replaces the indicator bins with count bins of degree-hours, i.e., explanatory variables that count the number of hours that fall within specified temperature intervals. This specification captures the response of milk yield to exposure to different levels of Twb over the day. The reference category corresponds to the 10° to 12°C bin; each bin coefficient represents the expected average difference in the log of milk yield if one additional hour in the day had been exposed to the Twb of the given bin instead of the 10° to 12°C range. We find a similarly shaped response as in the previous model. On average, one additional hour of Twb above 26°C relative to the 10° to 12°C range reduces daily milk yield by 0.5%.

In the third panel, we evaluate how the estimates from the hourly and daily averages models compare and what they imply for certain percentiles of the daily temperature distribution: from the median at 15.64°C to the 99.9th percentile at 26.19°C. For each percentile of the distribution of daily average Twb, the daily model provides a unique prediction of the impact on milk production. However, the realizations of this daily value in the sample (i.e., specific date-farm observations) have varied hourly temperature profiles, resulting in different predictions from the hourly model. For each top percentile, Fig. 2C compares these predictions to those of the daily model. We find that the daily model almost systematically underestimates the true effect—an effect that the hourly model approximates more closely—a discrepancy that reflects the concavity (increasing negative slope) of the hourly response function. Other univariate models that use the daily minimum or maximum temperature perform similarly to the daily average temperature model (text S4). Overall, the 95th-percentile day, which corresponds to a daily average temperature of about 23.4°C, results in reductions in milk output of around 5% relative to a day with an average Twb in the 10° to 12°C range.

Those estimates are based on SEs clustered by farm in our preferred specification, but we also explore clustering by district-by-month-by-year to address spatial correlation; while SEs are slightly larger, all estimates remain significant. The robustness of the shape and magnitude of the estimated response to the choice of heat index, the size of degree intervals, and the weather dataset is documented in the Supplementary Materials (text S6).

Heat continues to affect milk yield more than 10 days after exposure

Physiological considerations suggest that the impacts of humid heat on milk yield may not only be contemporaneous but also persist after direct exposure (*22*, *39*). To estimate the delayed effects of humid heat exposure, we add lagged daily Twbs as regressors to the model.

First, we examine how long the effects persist, if at all, by including up to 21 daily lags of Twb as regressors. Initially, to keep the

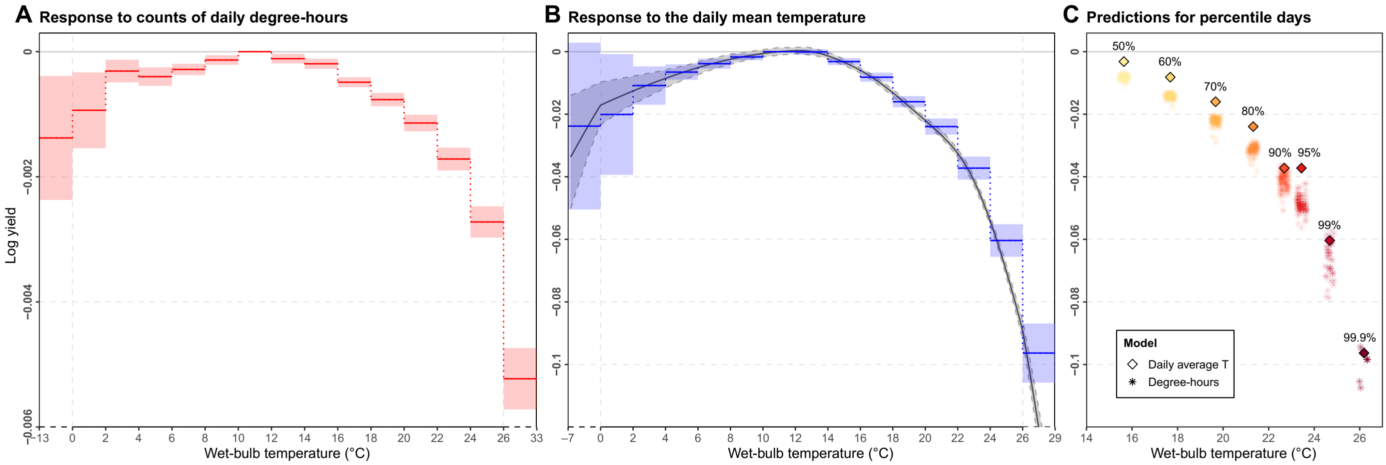


Fig. 2. Daily milk yield response to Twb. (**A**) Response to the number of hours in each temperature range. (**B**) Response to the daily average temperature. (**C**) Corresponding predictions for the top percentile days of the temperature distribution, comparing the values obtained by using the estimates from (A) and (B). The step response functions correspond to the specifications that fit a separate coefficient for each 2°C temperature interval; the shaded ribbons in (A) and (B) correspond to their 95% confidence intervals, and the reference category is the 10° to 12°C interval. Each bin coefficient represents the expected average difference in the log of milk produced if (A) one additional hour and (B) the daily average temperature had occurred in the given bin instead of in the 10° to 12°C range. The first and last bins are modeled with a larger width than the others to estimate them precisely but are shown with equal width for visual consistency. The dark gray solid line in (B) shows the mean of 100 spline fits on random 1% subsamples; the shaded ribbon is the empirical 95% interval (2.5th to 97.5th percentiles). The mean and ribbon are vertically centered to match the reference bin of the binned regression (n = 329,675,854 for binned regressions; ~3,289,510 on average per 1% subsample for the spline estimates).

model tractable, we model each daily temperature realization using a single binary indicator of whether the daily average exceeded a given threshold. The estimated impacts for the different thresholds of 22°, 24°, and 26°C are presented in Fig. 3A. We observe negative impacts of exposure to humid heat on milk production that persist for more than 10 days after exposure, with the highest negative effects on day-of-sample output caused by days −1 and −2. This pattern aligns with previous small-sample studies, which reported peak impacts occurring a few days before the day of observation, such as day −2 or −4 (*27*, *40*). However, the duration of the effects we observe is notably longer than that reported in previous work, which assumed or estimated shorter lag structures—typically under 1 week (*35*)—suggesting a more sustained impact of extreme heat than previously recognized. Higher thresholds result in stronger negative impacts, but the dissipation of the delayed effects follows a similar pattern across different thresholds.

These estimates allow us to calculate the cumulative impact of sustained exposure to humid heat. We find that 10 consecutive days with Twb above 22°, 24°, or 26°C reduce yields on day 11 by 4.7% (SE, 0.003), 8.3% (SE, 0.005), and 25.9% (SE, 0.019), respectively. Similarly, the impulse response sum, which captures the total yield reduction over the 10 days that follow a single hot day, shows comparable declines of 4.7% (SE, 0.003), 8.2% (SE, 0.005), and 25.6% (SE, 0.018) of a single day's baseline milk yield, respectively. In both simulations, losses only increase moderately when exposure rises from 22° to 24°C but increase sharply when exposure rises to 26°C, highlighting a nonlinear escalation in cumulative heat stress effects.

To analyze the full shape of the response to past heat, we focus on these 10 lags and estimate a richer model that includes a vector of binary indicators for each Twb bin on each lagged day, extending our original specification. Results are presented in Fig. 3B. Within each temperature bin, we observe a similar dissipation pattern of effects over the contemporaneous and 10 lagged days as found in the threshold model above (reading the graph from right to left within each bin: Negative effects are strongest on days −1 and −2 and dissipate as we go further back in time).

The impact of same-day exposure on milk yields is naturally lower when estimated in the contemporaneous baseline model without lags (Fig. 2A) than in the lagged model (Fig. 3B). Because of positive serial correlation in weather, the coefficients estimated in the baseline specification (without lags) capture both the contemporaneous effect of same-day heat exposure and the effects of serially correlated heat exposure from previous days. With this interpretation in mind, the subsequent heterogeneity analyses use the baseline no-lag regression specification for tractability. Lag models and cumulative effect computations are detailed in text S5.2.

Partial attenuation with cooling technologies

We use the data from a survey we administered in 2020 to 2021 to a representative sample of 306 dairy farm managers to explore their strategies to cope with heat stress. Our survey data provide information on the year of adoption of cooling technologies in various parts of the cow sheds. While shading is already the norm in virtually all farms, different systems capable of either cooling the cow directly or cooling the surrounding environment can be used, such as ventilation, sprinklers, or evaporative cooling systems, and can be installed in different parts of the farm. Figure 4A indicates that, while most farms in the sample have installed some cooling system, the year of installation shows substantial geographical variation. However, we do not find strong indications that the timing of adoption or the estimated response to heat is correlated with the size of the farm—contrary to results on US dairy farms (*35*)—or the severity of the local climate within Israel's climatological gradient, aside from a tendency for larger farms to adopt cooling technologies earlier (text S7.4).

We assess differences in the response of milk production to humid heat that are associated with the use of these technologies by

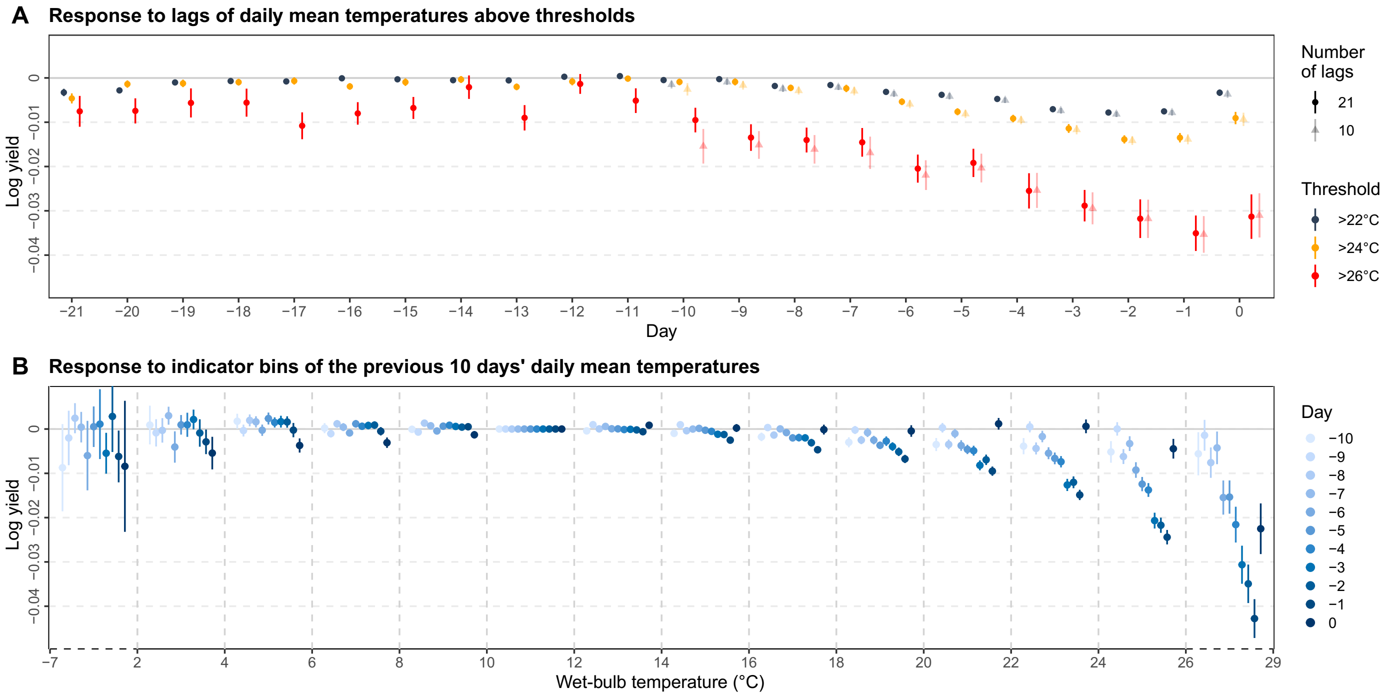


Fig. 3. Delayed effects of past heat, measured by the Twb, on day-of-sample milk yield. (**A**) Effects of lagged daily average temperatures being over a given threshold; estimated from the full sample of observations (*n* = 328,680,979). (**B**) Effects of lagged daily average temperatures being in each range, relative to the 10° to 12°C range; estimated from a 10% sample of lactation times series, stratified by farm (*n* = 32,903,809).

estimating a linear regression of log milk yield that also includes interactions between the highest bins of daily temperature and an indicator for whether cooling systems were already installed on the farm by the year of observation and used during the month of observation. As before, the model includes farm, year, and month fixed effects and is estimated over the whole period of 2009 to 2020. This approach leverages a combination of cross-sectional variation between farms with and without cooling in the same month and year, within-farm changes before and after installation, and seasonal variation within farms in the operation of these systems after installation. Figure 4B displays the estimated response functions with and without cooling technologies. They reveal a substantially steeper response curve in the absence of any cooling equipment, with impacts reaching a loss of 12% in milk production on days with average Twb exceeding 26°C (relative to the 10° to 12°C range). They further show that while cooling equipment is associated with an attenuation of the impact of heat, this attenuation capacity itself declines with higher temperatures. On moderately hot days with average Twb between 12° and 14°C, cooling seems to fully nullify the negative effects of heat. On 18° to 20°C days, the impact of heat is reduced by only half, and on days above 24°C, the impact of heat is reduced by less than 40%. Further decomposition of these observed differences by the part of the farm where the cooling system is installed—the free-stall area, the feeding area with troughs, or the holding pen where cows wait before entering the milking parlor—reveals that they are predominantly driven by the holding pen, which is where the cows are kept in higher densities (text S7.1).

We conduct a simple cost-benefit analysis to assess the economic returns of adopting cooling technologies for the typical dairy farm. Assuming a representative farm with 300 cows—of which 84% are lactating daily—we estimate the annual avoided loss in milk production associated with cooling by combining our temperature-specific effect estimates with the observed distribution of Twbs for each year in our sample. We monetize those estimates using yearly milk prices set by the Israel Dairy Council and find that the average annual gain in milk yield from 2009 to 2020 is equivalent to US$22,538 (2022 value). Compared with a one-time fixed cost of US$30,804 (2022 value) for cooling equipment—based on government data for farm upgrades—we find that the investment breaks even within 1.4 to 1.5 years at discount rates of 2 to 8%. This estimate excludes operational and maintenance costs, making it a lower bound; nevertheless, the analysis highlights the substantial and rapid economic returns from adopting cooling technologies. Full details of the calculations and assumptions are provided in text S8.

Our survey also elicited information about the adoption of two other potential forms of adaptation. First, cows go through different physiological processes across the stages of the lactation cycle and may be more sensitive to heat depending on the timing of calving. This suggests that some shifting of the calving period (primarily from summer to winter) may help reduce the impacts of heat. Second, the complex metabolic changes associated with lactation and their sensitivity to heat stress suggest that adjustments to feeding patterns could serve as another mitigation strategy. We observe whether each surveyed farm adopted either of these practices, although—unlike in the case of cooling technologies—we do not observe the timing of adoption or details regarding feed composition or scheduling. To assess the association between these practices and the sensitivity of milk production to heat, we restrict the sample to the most recent period

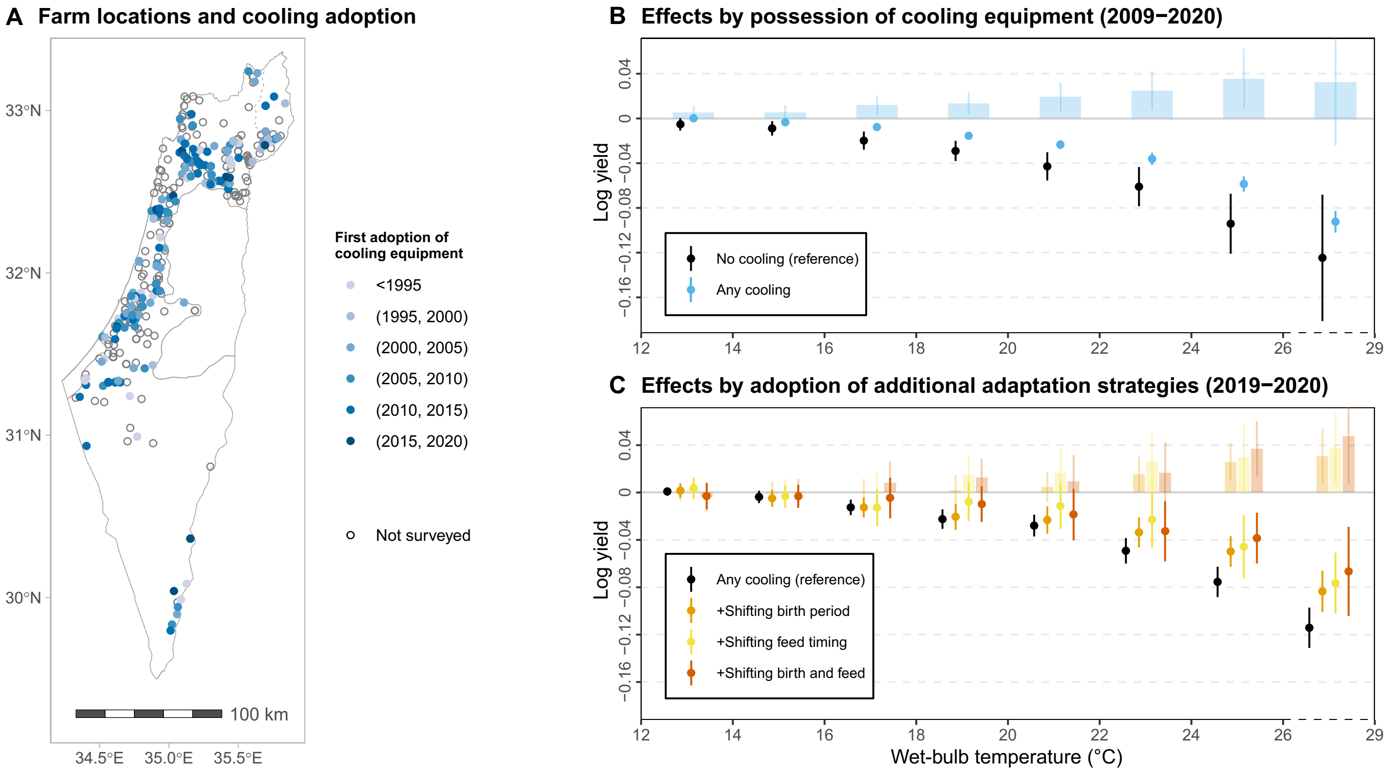
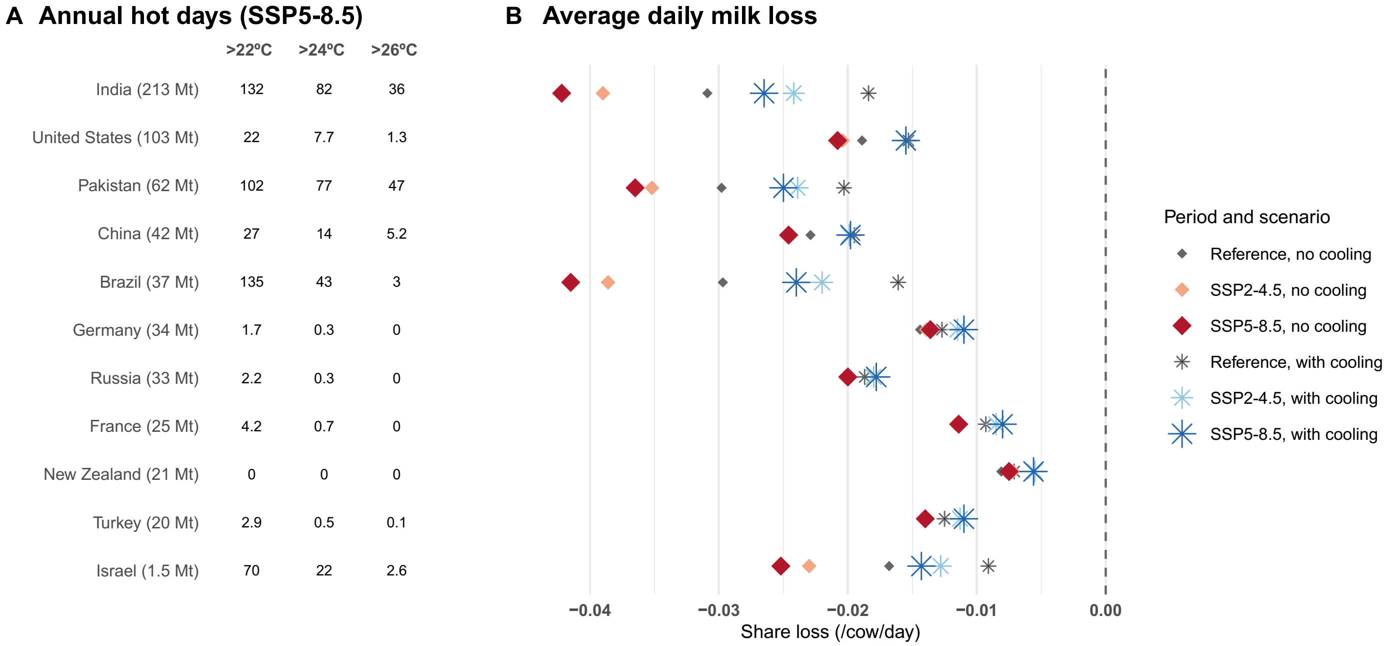


Fig. 4. Farm adaptation strategies and associated heterogeneity of the effects of high-temperature bins. (**A**) Farm locations and years of their first installment of cooling equipment (grouped by 5-year period). (**B** and **C**) Heterogeneity of the effects of high-temperature bins by a set of adopted strategies. Only the high-temperature bins are displayed. The reference range for the bins of Twb is the 10° to 12°C range, such that each bin coefficient represents the expected average difference in the log of milk produced if the daily average Twb had been in the given bin instead of in the 10° to 12°C range. The colors differentiate the categories of adaptation strategies; points represent the estimates for each category, and bars represent the difference of each category relative to the reference category. Vertical segments correspond to the 95% confidence intervals. (B) compares responses by adoption of any cooling equipment over the whole panel (n = 151,468,383); (C) compares responses by adoption of additional adaptation strategies in the past 2 years of our panel (n = 31,139,637).

in our data (2019 to 2020), when all surveyed farms had already adopted cooling equipment. Within this sample, we estimate the differences in temperature sensitivity between those farms that adopted and those that did not adopt these two additional strategies—shifting calving periods (adopted by 86 farms), shifting feed timing (10 farms), or both (11 farms)—by interacting the higher-degree temperature bins with categorical indicators for each adaptation group. Figure 4C displays the estimated response functions. We find suggestive evidence of additional mitigation potential associated with these strategies by up to four percentage points in the highest temperature bins compared to farms that only implement cooling. A similar analysis of the heterogeneity of the response associated with the strategic change in feed composition (adopted by 53 farms) does not yield any indication of a statistically significant difference (text S7.2). As in the case of cooling systems, these differences in the response to heat cannot be interpreted as necessarily being caused by these adaptation strategies, especially given the absence of observed temporal variation in their adoption. However, because economically viable adaptation has already occurred in most of the sampled farms by the time of the survey, the results do suggest that these adaptations have limited capacity to reduce the impact of humid heat. That said, the short time window limits generalizability, and further adjustments along these margins may emerge as temperatures continue to rise.

We use these estimates to project the midcentury impacts of temperature-related stress on dairy productivity under moderate and high greenhouse gas emissions scenarios. For the top 10 milk-producing countries, plus Israel, we use daily dry-bulb temperature and monthly RH projections from the high-resolution CNRM-CM6-1-HR climate model to estimate daily Twbs for the period 2045 to 2055. Baseline conditions are derived from the same model using the period 1995 to 2014. Temperature projections are aggregated to the country level by averaging grid cell values weighted by cattle density based on gridded livestock data. We then combine these projected temperatures with our estimated bin-level effects of heat stress on milk yield to calculate expected percent reductions in daily milk production per cow, both with and without cooling technologies. Because our empirical response function spans the full distribution of Twbs—including both hot and cold extremes—these projections capture not only the negative effects of heat stress but also the potential productivity gains from fewer cold days under future climate conditions. Figure 5A presents the projected number of hot days (with daily average Twbs above 22°, 24°, and 26°C) under the high-emission SSP5-8.5 scenario. Figure 5B displays the estimated average percent loss in daily milk production per cow due to weather under current, SSP2-4.5, and SSP5-8.5 conditions. Our findings suggest that, without adaptation, heat stress could reduce



A Annual hot days (SSP5-8.5)

	>22°C	>24°C	>26°C
India (213 Mt)	132	82	36
United States (103 Mt)	22	7.7	1.3
Pakistan (62 Mt)	102	77	47
China (42 Mt)	27	14	5.2
Brazil (37 Mt)	135	43	3
Germany (34 Mt)	1.7	0.3	0
Russia (33 Mt)	2.2	0.3	0
France (25 Mt)	4.2	0.7	0
New Zealand (21 Mt)	0	0	0
Turkey (20 Mt)	2.9	0.5	0.1
Israel (1.5 Mt)	70	22	2.6

Fig. 5. Projected heat exposure and impacts on milk production. (**A**) Projected number of hot days—defined as days with daily average Twb exceeding 22°, 24°, or 26°C—during the midcentury period (2045 to 2055) under the high-emission scenario SSP5-8.5. (**B**) Estimated average percent reduction in daily milk production per cow from exposure to the range of Twbs during the reference period (1995 to 2014) and under midcentury (2045 to 2055) climate projections for moderate-emission (SSP2-4.5) and high-emission (SSP5-8.5) scenarios, with and without cooling technologies. Results are shown for the top 10 milk-producing countries plus Israel; total national milk production in 2023 [in million tons (Mt)] is indicated in parentheses next to each country name. In both panels, distributions were calculated using cattle density–weighted grid cells.

the average daily milk yield—averaged over all days in a year—by 4% in some of the main dairy-producing countries by midcentury, with notable regional variation. Countries already experiencing high heat exposure also exhibit the most pronounced mitigation from cooling technologies—driven by the relative number of extreme hot days. These projected impacts are likely conservative, as they assume no effects of heat on herd fertility or mortality and no changes in the temporal correlation of hot days—a factor that, as shown in our earlier lagged model, can substantially amplify temperature-related stress. Full details of the calculations are provided in text S9.

Evidence of a productivity-resilience trade-off

Last, we explore heterogeneity in heat sensitivity across two characteristics of cows closely linked to productivity: lactation stage and parity (i.e., the number of calvings). Milk production follows a distinct curve along the lactation cycle—increasing sharply after calving, peaking around 2 to 3 months, and then gradually declining—such that some stages of the cycle are more productive than others. Similarly, cows in their first parity generally produce less milk over the lactation cycle than older, multiparous cows. Using the same interaction modeling approach used above to study heterogeneity in the response function—i.e., interacting Twb with categorical indicators of interest—we examine whether sensitivity to heat varies systematically along these two dimensions.

The results reveal that cows are substantially more sensitive to heat (in terms of the percentage reduction in their milk yield) when they are also more productive. This includes the first 100 days of lactation, when the day-to-day increase in milk production is steepest and body reserves are used for milk production (fig. S11A), and later parities, when milk production levels are typically higher (fig. S11B). The percentage declines in milk yield are more than twice as high for cows in their second or higher parity compared to those in their first, across all levels of heat exposure. This result is directionally consistent with, but more pronounced than findings in the existing literature (*35*). They point to a resilience-productivity trade-off, where cows that produce more milk—either due to lactation stage or parity—are also more vulnerable to heat stress. While we cannot identify the underlying physiological mechanisms directly, the patterns are consistent with greater metabolic demand and reduced thermoregulatory capacity in high-producing animals.

DISCUSSION

Our results indicate that humid heat stress has nonlinear and long-lasting impacts on milk production. Furthermore, the adoption of simple cooling technologies may be able to reduce less than half of the impacts of extreme exposure. Israel's diverse climate and the technological advancement of its dairy sector suggest that these indications may reflect an upper bound on the adaptation potential that can be achieved by economically viable technologies in broad world regions.

The differences we estimate between farms with and without cooling technologies cannot be strictly causally attributed to their adoption, as it is likely endogenous: Farms that invest in cooling may differ in unobserved ways, such as management practices or capital availability. However, we expect selection into adoption to be biased toward farms where it would be most beneficial. As such, the observed differences may overestimate the average effectiveness of cooling technologies across all farms. This reinforces that, even in settings where cooling technologies are most likely to be effective, such adaptation appears to offset, at best, only half of the productivity losses from hot days—underscoring both the value and the limitations of current adaptation measures as a resilience strategy.

Globally, the economic value of cattle production at risk due to increased heat stress may be substantial; it is projected to triple in size to exceed US $120 billion annually by 2100 under high-emission scenarios (*10*). Dairy systems—already contributing to most heat stress losses in the US livestock sector (*31*)—are expected to bear an important portion of future impacts. This underscores the urgency of identifying effective, scalable adaptation strategies, particularly in regions with growing heat exposure and expanding dairy sectors.

In the context of a warmer planet where dairy farms experience elevated ranges of Twb, given a limited abatement potential through common cooling technologies and a trade-off between productivity and resilience, how can the sector reduce the effects of heat to ensure a stable level of milk output? Can we alleviate either exposure or sensitivity? An approach focused on more capital-intensive reductions in exposure, such as completely enclosed indoor housing, which controls the cows' local environmental conditions and insulates them from weather variations, is already implemented in some large-scale operations in the United States. However, it may not only be unaffordable in many parts of the world but also actually replace one stressor—weather—with another—confinement. Evidence of the production and health benefits of allowing cows to have access to the outside suggests that reducing this access further may increase stress for cows and affect milk production (*41*). There is even mixed evidence of the superiority of housing systems in altering heat stress effects on milk quantity and quality (*42*). In a world of increased exposure to heat stress, an alternative may be to alleviate other stressors, e.g., confinement or cow-calf separation (*43*), to reduce the compound effect on cow sensitivity. More research is needed to quantify the actual performance and cost-effectiveness of a broader range of adaptation approaches.

MATERIALS AND METHODS

Data

Milk production data are obtained from the Israel Cattle Breeders Association and cover most dairy farms in Israel from 2009 to 2020. The data comprise a panel of more than 329 million observations at the cow-by-day level. Over the entire study period, 471,158 unique cows from 643 unique dairy farms are observed, each generally over several lactations. On any given day, the average number observed is 439 farms and 78,968 cows. The data include the total daily amount of milk produced, the start date of the cow's given lactation cycle, the number of calvings, which is a reliable proxy for the cow's age, and the number of milkings per day. As the last daily milking generally takes place around 8 p.m., the total daily amount of milk recorded in our data corresponds to that produced by the given cow from 8 p.m. of the previous day to 8 p.m. of the current day. To match the daily yields with the relevant period of weather exposure, we shift the definition of calendar days in our weather data to an 8 p.m. cutoff.

We construct a panel dataset of hourly temperature and RH at the farm level. To estimate the weather realized in the recent past, the existing climate-economy literature resorts to different types of sources. Two commonly used sources are (i) interpolations of direct observations from weather stations and (ii) climate reanalysis estimates produced by combining physics-based dynamic models with observations. Each method has advantages and limitations; station-based approaches are based on clear interpolation algorithms that enable the researcher to control the factors to account for (such as elevation and wind direction) but tend to be sensitive to observation error, while reanalysis products are constructed through some spatiotemporal averaging that may hinder capturing short, anomalous events but provide better estimates for data-sparse regions (*7*, *44*). With the quality and reliability of the weather data being particularly important in our study, we consider both approaches and construct separate weather datasets: one based on in situ observations from weather stations and the other based on climate reanalysis data, and we check the robustness of our results to that choice. The interpolation steps taken to construct farm-level hourly panels from *n*-hourly data and how we address potential concerns of bias from stations entering or exiting the record across the period are described in detail in text S1.

To explore the potential of adaptation to reduce heat impacts, we administered a survey in 2020 to 2021 to virtually all Israeli dairies. We collected information from 306 farm managers (representing 65% of the average number of farms observed in the 2020 panel data) about their operational characteristics and about the adaptation strategies they have adopted to address heat stress, notably cooling technologies and when these were installed.

Models

To extract the general shape of the milk yield relationship to weather with little assumptions on functional form, we first estimate semiparametric models on continuous regressors. We consider the GAM (Eq. 1), where the two-dimensional smooth function $f_2()$ is a tensor product spline that flexibly captures any joint nonlinear effects of daily average $\overline{T}$ and $\overline{RH}$ on the log yield of cow *i* on day *t*. Controls $\mathbf{X}_{it}$ include the cow's stage of lactation, daily number of milkings, and lactation number, and $\alpha_{f[i]}$, $\psi_{y[t]}$, and $\omega_{m[t]}$ are farm, year, and month fixed effects, respectively. Estimation is by penalized iteratively reweighted least squares, and the optimal amount of smoothing is estimated using generalized cross-validation

$$\log(\text{milk}_{it}) = f_2(\overline{T}_{it};\overline{RH}_{it}) + \mathbf{X}_{it}'\delta + \alpha_{f[i]} + \psi_{y[t]} + \omega_{m[t]} + \varepsilon_{it} \quad (1)$$

In subsequent models, we use the Twb as the preferred heat index to capture the effects of both T and RH. To estimate the shape of the relationship of milk yield with the daily average heat index, we replace the bivariate smooth function in model (1) with a univariate penalized cubic regression spline $f_1(\overline{Twb_{it}})$.

GAMs enable the extraction of high-level functional forms without making restrictive assumptions; however, their computation requirements imply using only a subset of the data. All subsequent analyses are based on simpler additive linear models of the general form presented in Eq. 2, which are estimated using our entire panel dataset, where the function of interest $G()$ is approximated using the flexible specification of a piecewise constant function

$$\log(\text{milk}_{it}) = G(Twb_{it}) + \mathbf{X}_{it}'\delta + \alpha_{f[i]} + \psi_{y[t]} + \omega_{m[t]} + \varepsilon_{it} \quad (2)$$

We consider two specifications of the step function to capture the distribution of heat *h* during the day. The first uses a simple summary statistic: The daily mean $\overline{Twb}_{it}$ defines each bin in $G()$ as a binary indicator of whether the statistic falls within the given k°C temperature interval $]h, h+k]$

$$G\left(Twb_{it}\right) = \sum_{h} \beta_h \times \mathbb{1}\left\{\overline{Twb_{it}} \in]h, h+k]\right\} \qquad (3)$$

Alternatively, to consider the entire distribution of weather during the day, we assume that the effect of heat is additively substitutable within the day, such that we can measure a cow's daily heat exposure through counts of "degree-hours." The derivation of the model from this assumption is detailed in Supplementary Text. The resulting specification of the response function is shown in Eq. 4, where each degree-hour bin $dh_{]h,h+k]}$ captures the number of hours of exposure to temperatures in the $]h, h+k]$ range

$$G\left(Twb_{it}\right) = \sum_{h} \beta_h \times dh_{]h,h+k]} \qquad (4)$$

Analyses of the abatement potential of adaptation strategies are conducted by interacting the high-degree bins in $G()$ with the relevant categorical variables: farm-level adoption of cooling technologies (for the 2009 to 2020 analysis) or adoption of sets of additional strategies (for the 2019 to 2020 analysis of birth and feed shifting). SEs are clustered by farm in all specifications.

Supplementary Materials

The PDF file includes:

Supplementary Text
Figs. S1 to S12
Tables S1 to S7
Legend for data S1
References

Other Supplementary Material for this manuscript includes the following:

Data S1

REFERENCES AND NOTES

1. S. Hsiang, R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. J. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, K. Larsen, T. Houser, Estimating economic damage from climate change in the United States. *Science* **356**, 1362–1369 (2017).
2. J. R. Porter, L. Xie, A. J. Challinor, K. Cochrane, S. M. Howden, M. M. Iqbal, D. B. Lobell, M. I. Travasso, "Chapter 7: Food security and food production systems," in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, P. R. Mastrandrea, L. L. White, Eds. (Cambridge Univ. Press, 2014), pp. 485–533.
3. B. A. McCarl, T. W. Hertel, Climate change as an agricultural economics research topic. *Appl. Econ. Perspect. Policy* **40**, 60–78 (2018).
4. Food and Agriculture Organization of the United Nations, "Milk production," 2025; www.fao.org/dairy-production-products/production/milk-production/.
5. OECD, FAO, *OECD-FAO Agricultural Outlook 2024–2033* (OECD Publishing, 2024).
6. J. W. West, Effects of heat-stress on production in dairy cattle. *J. Dairy Sci.* **86**, 2131–2144 (2003).
7. C. Raymond, T. Matthews, R. M. Horton, The emergence of heat and humidity too severe for human tolerance. *Sci. Adv.* **6**, eaaw1838 (2020).
8. J. R. Buzan, M. Huber, Moist heat stress on a hotter earth. *Annu. Rev. Earth Planet. Sci.* **48**, 623–655 (2020).
9. Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, *Regional Fact Sheet — Asia* (IPCC, 2021).
10. M. A. North, J. A. Franke, B. Ouweneel, C. H. Trisos, Global risk of heat stress to cattle from climate change. *Environ. Res. Lett.* **18**, 094027 (2023).
11. J. S. Graff Zivin, Y. Song, Q. Tang, P. Zhang, Temperature and high-stakes cognitive performance: Evidence from the national college entrance examination in China. *J. Environ. Econ. Manage.* **104**, 102365 (2020).
12. R. J. Park, J. Goodman, M. Hurwitz, J. Smith, Heat and learning. *Am. Econ. J. Econ. Policy* **12**, 306–339 (2020).
13. J. Colmer, Temperature, labor reallocation, and industrial production: Evidence from India. *Am. Econ. J. Appl. Econ.* **13**, 101–124 (2021).
14. T. A. Carleton, A. Jina, M. T. Delgado, M. Greenstone, T. Houser, S. M. Hsiang, A. Hultgren, R. E. Kopp, K. E. McCusker, I. B. Nath, J. Rising, A. Rode, H. K. Seo, A. Viaene, J. Yuan, A. T. Zhang, Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *Q. J. Econ.* **137**, 2037–2105 (2022).
15. A. J. Wilson, R. D. Bressler, C. Ivanovich, C. Tuholske, C. Raymond, R. M. Horton, A. Sobel, P. Kinney, T. Cavazos, J. G. Shrader, Heat disproportionately kills young people: Evidence from wet-bulb temperature in Mexico. *Sci. Adv.* **10**, eadq3367 (2024).
16. R. J. Collier, K. G. Gebremedhin, Thermal biology of domestic animals. *Annu. Rev. Anim. Biosci.* **3**, 513–532 (2015).
17. A. Berman, Estimates of heat stress relief needs for Holstein dairy cows. *J. Anim. Sci.* **83**, 1377–1384 (2005).
18. A. D. Flouris, P. C. Dinas, L. G. Ioannou, L. Nybo, G. Havenith, G. P. Kenny, T. Kjellstrom, Workers' health and productivity under occupational heat strain: A systematic review and meta-analysis. *Lancet Planet. Health* **2**, e521–e531 (2018).
19. C. T. Kadzere, M. R. Murphy, N. Silanikove, E. Maltz, Heat stress in lactating dairy cows: A review. *Livest. Prod. Sci.* **77**, 59–91 (2002).
20. D. Renaudeau, J. L. Gourdine, N. R. St-Pierre, A meta-analysis of the effects of high ambient temperature on growth performance of growing-finishing pigs. *J. Anim. Sci.* **89**, 2220–2230 (2011).
21. X. Ye, R. Wolff, W. Yu, P. Vaneckova, X. Pan, S. Tong, Ambient temperature and morbidity: A review of epidemiological evidence. *Environ. Health Perspect.* **120**, 19–28 (2012).
22. L. H. Baumgard, R. P. Rhoads Jr., Effects of heat stress on postabsorptive metabolism and energetics. *Annu. Rev. Anim. Biosci.* **1**, 311–337 (2013).
23. W. Vroege, T. Dalhaus, E. Wauters, R. Finger, Effects of extreme heat on milk quantity and quality. *Agr. Syst.* **210**, 103731 (2023).
24. N. Key, S. Sneeringer, Potential effects of climate change on the productivity of U.S. dairies. *Am. J. Agric. Econ.* **96**, 1136–1156 (2014).
25. E. Gernand, S. König, C. Kipp, Influence of on-farm measurements for heat stress indicators on dairy cow productivity, female fertility, and health. *J. Dairy Sci.* **102**, 6660–6671 (2019).
26. M. Gisbert-Queral, A. Henningsen, B. Markussen, M. T. Niles, E. Kebreab, A. J. Rigden, N. D. Mueller, Climate impacts and adaptation in US dairy systems 1981–2018. *Nat. Food* **2**, 894–901 (2021).
27. U. Bernabucci, S. Biffani, L. Buggiotti, A. Vitali, N. Lacetera, A. Nardone, The effects of heat stress in Italian Holstein dairy cattle. *J. Dairy Sci.* **97**, 471–486 (2014).
28. G. André, B. Engel, P. B. M. Berentsen, T. V. Vellinga, A. G. J. M. O. Lansink, Quantifying the effect of heat stress on daily milk yield and monitoring dynamic changes using an adaptive dynamic model. *J. Dairy Sci.* **94**, 4502–4513 (2011).
29. K. Brügemann, E. Gernand, U. König von Borstel, S. König, Defining and evaluating heat stress thresholds in different dairy cow production systems. *Arch. Anim. Breed.* **55**, 13–24 (2012).
30. J. R. Bryant, N. López-Villalobos, J. E. Pryce, C. W. Holmes, D. L. Johnson, Quantifying the effect of thermal environment on production traits in three breeds of dairy cattle in New Zealand. *New Zeal. J. Agr. Res.* **50**, 327–338 (2007).
31. N. R. St-Pierre, B. Cobanov, G. Schnitkey, Economic losses from heat stress by US livestock industries. *J. Dairy Sci.* **86**, E52–E77 (2003).
32. R. H. Ingraham, R. W. Stanley, W. C. Wagner, Seasonal effects of tropical climate on shaded and nonshaded cows as measured by rectal temperature, adrenal cortex hormones, thyroid hormone, and milk production. *Am. J. Vet. Res.* **40**, 1792–1797 (1979).
33. Y. Aharoni, O. Ravagnolo, I. Misztal, Comparison of lactational responses of dairy cows in Georgia and Israel to heat load and photoperiod. *Anim. Sci.* **75**, 469–476 (2002).
34. J. Bohmanova, I. Misztal, J. B. Cole, Temperature-humidity indices as indicators of milk production losses due to heat stress. *J. Dairy Sci.* **90**, 1947–1956 (2007).
35. J. Hutchins, M. Skidmore, D. Nolan, Vulnerability of US dairy farms to extreme heat. *Food Policy* **131**, 102821 (2025).
36. C. Fezzi, I. Bateman, The impact of climate change on agriculture: Nonlinear effects and aggregation bias in Ricardian models of farmland values. *J. Assoc. Environ. Resour. Econ.* **2**, 57–92 (2015).
37. S. Dikmen, P. J. Hansen, Is the temperature-humidity index the best indicator of heat stress in lactating dairy cows in a subtropical environment? *J. Dairy Sci.* **92**, 109–116 (2009).
38. S. C. Sherwood, M. Huber, An adaptability limit to climate change due to heat stress. *Proc. Natl. Acad. Sci. U.S.A.* **107**, 9552–9555 (2010).
39. F. De Rensis, R. J. Scaramuzzi, Heat stress and seasonal effects on reproduction in the dairy cow—A review. *Theriogenology* **60**, 1139–1151 (2003).
40. J. W. West, B. G. Mullinix, J. K. Bernard, Effects of hot, humid weather on milk temperature, dry matter intake, and milk yield of lactating dairy cows. *J. Dairy Sci.* **86**, 232–242 (2003).

41. G. L. Charlton, S. M. Rutter, The behaviour of housed dairy cattle with and without pasture access: A review. *Appl. Anim. Behav. Sci.* **192**, 2–9 (2017).
42. C. Lambertz, C. Sanker, M. Gauly, Climatic effects on milk production traits and somatic cell score in lactating Holstein-Friesian cows in different housing systems. *J. Dairy Sci.* **97**, 319–329 (2014).
43. F. C. Flower, D. M. Weary, The effects of early separation on the dairy cow and calf. *Anim. Welf.* **12**, 339–348 (2003).
44. M. Auffhammer, S. M. Hsiang, W. Schlenker, A. Sobel, Using weather data and climate model output in economic analyses of climate change. *Rev. Environ. Econ. Policy.* **7**, 181–198 (2013).
45. C. Daly, M. Halbleib, J. I. Smith, W. P. Gibson, M. K. Doggett, G. H. Taylor, J. Curtis, P. P. Pasteris, Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *Int. J. Climatol.* **28**, 2031–2064 (2008).
46. W. Schlenker, M. J. Roberts, Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proc. Natl. Acad. Sci. U.S.A.* **106**, 15594–15598 (2009).
47. R. Stull, Wet-bulb temperature from relative humidity and air temperature. *J. Appl. Meteorol. Climatol.* **50**, 2267–2269 (2011).
48. M. Gilbert, G. Cinardi, D. Da Re, W. G. R. Wint, D. Wisser, T. P. Robinson, Global cattle distribution in 2015 (5 minutes of arc). https://doi.org/10.7910/DVN/LHBICE (2022).
49. E. C. Thom, The discomfort index. *Weatherwise* **12**, 57–61 (1959).
50. C. Mora, B. Dousset, I. R. Caldwell, F. E. Powell, R. C. Geronimo, C. R. Bielecki, C. W. W. Counsell, B. S. Dietrich, E. T. Johnston, L. V. Louis, M. P. Lucas, M. M. McKenzie, A. G. Shea, H. Tseng, T. W. Giambelluca, L. R. Leon, E. Hawkins, C. Trauernicht, Global risk of deadly heat. *Nat. Clim. Chang.* **7**, 501–506 (2017).
51. Y. Epstein, D. S. Moran, Thermal comfort and the heat stress indices. *Ind. Health* **44**, 388–398 (2006).
52. R. E. Davis, P. C. Knappenberger, P. J. Michaels, W. M. Novicoff, Changing heat-related mortality in the United States. *Environ. Health Perspect.* **111**, 1712–1718 (2003).
53. O. Ravagnolo, I. Misztal, G. Hoogenboom, Genetic component of heat stress in dairy cattle, development of heat index function. *J. Dairy Sci.* **83**, 2120–2125 (2000).
54. J. S. Haldane, The influence of high air temperatures. *Epidemiol. Infect.* **5**, 494–513 (1905).
55. National Oceanic and Atmospheric Administration, “Livestock Hot Weather Stress” (Regional Operations Manual Letter C-31–76, 1976).
56. S. C. Sherwood, How important is humidity in heat stress? *J. Geophys. Res.* **123**, 11808–11810 (2018).
57. L. E. Maust, R. E. Mcdowell, N. W. Hooven, Effect of summer weather on performance of Holstein cows in three stages of lactation. *J. Dairy Sci.* **55**, 1133–1139 (1972).
58. H. Barash, N. Silanikove, A. Shamay, E. Ezra, Interrelationships among ambient temperature, day length, and milk yield in dairy cows under a Mediterranean climate. *J. Dairy Sci.* **84**, 2314–2320 (2001).
59. J. W. West, Interactions of energy and bovine somatotropin with heat stress. *J. Dairy Sci.* **77**, 2091–2102 (1994).
60. O. Ravagnolo, I. Misztal, Genetic component of heat stress in dairy cattle, parameter estimation. *J. Dairy Sci.* **83**, 2126–2130 (2000).
61. A. Berman, Y. Folman, M. Kaim, M. Mamen, Z. Herz, D. Wolfenson, A. Arieli, Y. Graber, Upper critical temperatures and forced ventilation effects for high-yielding dairy cows in a subtropical climate. *J. Dairy Sci.* **68**, 1488–1495 (1985).
62. Eurostat, “Milk and milk product statistics,” 2024; https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Milk_and_milk_product_statistics.
63. A. El Said, M. Glinton, S. Hopsch, L. Isaksson, R. Mladek, E. Olsson, A. Verrelle, Z. Q. Wang, S. Schimanke, M. Ridal, P. Le Moigne, L. Berggren, P. Undén, R. Randriamampianina, U. Andrea, E. Bazile, A. Bertelsen, P. Brousseau, P. Dahlgren, L. Edvinsson, “CERRA sub-daily regional reanalysis data for Europe on single levels from 1984 to present,” Copernicus Climate Change Service Climate Data Store, 2021; https://doi.org/10.24381/cds.622a565a.
64. W. Bianca, Relative importance of dry- and wet-bulb temperatures in causing heat stress in cattle. *Nature* **195**, 251–252 (1962).
65. National Research Council, Committee on Physiological Effects of Environmental Factors on Animals, *A Guide to Environmental Research on Animals* (National Academy of Sciences, 1971).
66. O. Ravagnolo, I. Misztal, Effect of heat stress on nonreturn rate in Holstein cows: Genetic analyses. *J. Dairy Sci.* **85**, 3092–3100 (2002).
67. O. Ravagnolo, I. Misztal, Studies on genetics of heat tolerance in dairy cattle with reduced weather information via cluster analysis. *J. Dairy Sci.* **85**, 1586–1589 (2002).
68. A. Vitali, M. Segnalini, L. Bertocchi, U. Bernabucci, A. Nardone, N. Lacetera, Seasonal pattern of mortality and relationships between mortality and temperature-humidity index in dairy cows. *J. Dairy Sci.* **92**, 3781–3790 (2009).
69. J. B. Holter, J. W. West, M. L. McGilliard, A. N. Pell, Predicting ad libitum dry matter intake and yields of Jersey cows. *J. Dairy Sci.* **79**, 912–921 (1996).
70. N. Key, S. Sneeringer, D. Marquardt, “Climate change, heat stress, and U.S. dairy production,” ERR 175, U.S. Department of Agriculture, Economic Research Service, 2014; https://doi.org/10.2139/ssrn.2506668.
71. P. L. Klinedinst, D. A. Wilhite, G. L. Hahn, K. G. Hubbard, The potential effects of climate change on summer season dairy cattle milk production and reproduction. *Clim. Change* **23**, 21–36 (1993).
72. G. L. Hahn, T. L. Mader, “Heat waves in relation to thermoregulation, feeding behavior and mortality of feedlot cattle,” in *Livestock Environment Proceedings of the 5th International Symposium, Bloomington, MN, USA, 29–31 May, 1997*, S. J. H. R. W. Bottcher, Ed. (American Society of Agricultural Engineers, 1997), vol. 1, pp. 563–571.
73. T. L. Mader, M. S. Davis, T. Brown-Brandl, Environmental factors influencing heat stress in feedlot cattle. *J. Anim. Sci.* **84**, 712–719 (2006).
74. M. Zähner, L. Schrader, R. Hauser, M. Keck, B. Wechsler, The influence of climatic conditions on physiological and behavioural parameters in dairy cows kept in open stables. *Anim. Sci.* **78**, 139–147 (2004).

Acknowledgments

Funding: This work was supported by US-Israel Binational Agricultural Research and Development Fund grant no. 5150-19 (E.G.F., A.K., and R.F.), Israel Dairy Board grant no. 118-0064-2022 (E.G.F., A.K., and R.F.), and Council for Higher Education of Israel’s PhD Sandwich Scholarship Program 2019 (C.P.). **Author contributions:** Conceptualization: C.P., E.G.F., A.K., Y.L., E.E., and R.F. Data curation: C.P., E.G.F., A.K., E.E., and R.F. Formal analysis: C.P., Y.L., and E.E. Funding acquisition: E.G.F., A.K., and R.F. Investigation: C.P., A.K., E.E., and R.F. Methodology: C.P., E.G.F., A.K., Y.L., E.E., and R.F. Project administration: C.P., E.G.F., and R.F. Resources: Y.L. and E.E. Software: C.P., E.G.F., and E.E. Supervision: E.G.F. and R.F. Validation: C.P. and E.E. Visualization: C.P. Writing—original draft: C.P., A.K., and R.F. Writing—review and editing: C.P., E.G.F., A.K., and R.F. **Competing interests:** The authors declare that they have no competing interests. **Data and materials availability:** All data needed to evaluate the conclusions in the paper are present in the paper and/or the Supplementary Materials. The milk production data used in this study are collected by the Israel Cattle Breeders Association (ICBA). Interested researchers may request access by contacting the ICBA at info@icba.org.il or yaniv@icba.org.il, by visiting www.icba.org.il, or by mail at North Industrial Park, P.O. Box 3015/20 Bareket, Caesarea 3088900, Israel.

Submitted 4 February 2025
Accepted 2 June 2025
Published 4 July 2025
10.1126/sciadv.adw4780