High-Frequency Data Reveal Limits of Adaptation to Heat in Animal Agriculture

Claire Palandri[1*] Eyal G. Frank[*] Ayal Kimhi[†] Yaniv Lavon[‡] Ephraim Ezra[‡] Ram Fishman[§]

Abstract

While methodological advancements and greater data have improved the understanding of how climate affects economic production, the potential for adaptation and important sectors remain understudied, such as animal agriculture. We use daily data on the milk production of 130,000 cows over 12 years in Israel, and survey data on adaptation measures, to estimate the contemporaneous and delayed impacts of humid heat on milk yield. Heat exerts nonlinear negative effects reaching a 10% decrease in milk production on extreme days, and effects persist 10 days after direct exposure. Moreover, the adoption of cooling equipment, and changes in cow management practices are associated with only limited reductions in the impact of extreme heat. Given the technological advancement, long-standing exposure to heat, and climatic diversity of the Israeli dairy system, our results suggest that common adaptation strategies may hold limited potential to avert the impacts of climate change in this important sector.

[1]To whom correspondence should be addressed. E-mail: clairepalandri@uchicago.edu
[*]Harris School of Public Policy, University of Chicago, Chicago, IL 60637
[†]Department of Environmental Economics and Management, Hebrew University of Jerusalem, Rehovot 7610001, Israel
[‡]Israel Cattle Breeders Association, Caesaria Industrial Park, Caesarea 38900, Israel
[§]Department of Public Policy, Tel Aviv University, Tel Aviv-Yafo 6997801, Israel

Understanding the impacts of climatic variability on economic systems remains an active research agenda. As evidence about the severity of the potential damages of climate change accumulates [23], it has become increasingly important to extend the literature to under-studied economic sectors, and to improve our understanding of the degree to which adaptation can reduce those damages. But while methodological advances have enabled the precise estimation of response functions in multiple sectors of the economy, other important sectors remain insufficiently studied, such as animal agriculture, and crucial knowledge gaps persist about the extent to which the adoption of cost-effective technologies reduce the impacts of anomalous weather conditions.[1]

This study provides such novel evidence for the dairy sector, whose global production is projected to increase faster than most other main agricultural commodities [29]. Data of unusual scale and high spatio-temporal resolution, covering 12 years of the daily milk yield of each of 130,000 dairy cows in Israel, allow us to derive several novel insights which were difficult to obtain in previously studied contexts. The position of the Israeli dairy sector at the technological frontier of production and weather resilience further provides an opportunity to study the limits of existing cost-effective technologies for adaptation, while the country's wide climatological gradient supports the broad geographical relevance of the results.

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, 14, 30, 22].

Humid heat stress is considered to be one of the main limiting factors of milk production [37], and extreme humid heat events—which have more than doubled in frequency over the past four decades [32]—are predicted to occur over large regions for months at a time on a warmer planet, leading to the notion of a steambath world [10].[2] Yet existing estimates of the response of milk yield to weather remain limited in some respects, by 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.

We leverage exogenous high-frequency variation in weather realizations to estimate flexible models of the relationship between milk production and temperature and humidity. We 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 the adoption of these adaptation strategies.

Background

Cow response to humid heat

Cows, like all mammals, must maintain thermal homeostasis in order to function and grow. When the external temperature rises, a mammal's body adopts strategies to maximize heat loss, e.g., through evaporative cooling by perspiration and panting, or by resting to reduce its metabolic rate [13]. The amount of heat stress is thereby affected by not only dry-bulb temperature—which affects sensible heat loss—but also

[1] The Fifth Assessment Report of the Intergovernmental Panel on Climate Change notes that "In comparison to crop and fish production, considerably less work has been published on observed impacts for other food production systems, such as livestock or aquaculture [...] The relative lack of evidence reflects a lack of study in this topic, but not necessarily a lack of real-world impacts of observed climate trends" [31, p. 494]. Similar sentiments are expressed by other academic reviews, including McCarl and Hertel [28]: "Livestock will be affected by climate change, although studies are sparser on this topic, and widely available simulation models do not exist." Even the most comprehensive study of current and future climate change impacts on the U.S., across numerous social, agricultural, and economic sectors, does not include animal agriculture [23].

[2] In addition, over the next ten years, more than half of this growth in production is expected to occur in South Asia, where "heatwaves and humid heat stress will be more intense and frequent during the 21st century" [40].

ambient humidity—which hinders latent heat loss via evaporative cooling. Other environmental factors such as wind speed and incoming radiation also affect heat stress [5]. 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, morbidity and mortality rates, and on livestock, specifically cow milk yield and pig growth [18, 25, 33, 41].

The effect on lactating cows is known in principle to involve physiological and metabolic adjustments [4, 13]. Though many studies have investigated the impact on milk yield in the dairy science literature, 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), whose unitlessness and calibration to the contexts of original small-sample studies hinders the interpretability and generalizability [24, 1, 35, 37, 7, 9, 2, 8, 6, 26, 20, 21, 36].

In this paper, 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 very few assumptions as to the functional form. We subsequently use the wet-bulb temperature 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 gather a total standing population of about 133,000 cows, producing in 2020 over 1,521 million liters, the vast majority of which—72.7% over our whole sample—we observe at the individual cow-by-day level over 12 years. Such rich high-frequency outcome data allow us to leverage exogenous variation in weather and alleviate concerns of potential aggregation bias. Three features of the Israeli dairy sector further make it a particularly suited setting to produce estimates with both alleviated potential bias and global relevance. First, due to the land's topography, the dairy farms dispersed across its area experience a wide range of temperature and humidity values that are representative of large parts of the world. Such a narrow spatial scale combined with significant variation in climate strengthens identifying assumptions as potentially confounding variables should tend to be homogeneous [17]. Second, milk production is carried out under a quota system in which prices are centrally controlled, which reduces concerns of confounding from demand shocks. Finally, virtually all farms have adopted technologies to reduce heat stress,[3] and vary in the timing of their installation over our period of study, which we measure in a survey. We can therefore 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 size and management of the cows, show relatively low heterogeneity. Nearly all cows are Israeli-Holsteins, a breed obtained from several generations of cross-breeding to be specially 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 out of four are family farms in cooperative villages called moshavim; the rest are in kibbutzim, which are organized as collective economic units where means of production are communally owned. Lactating cows are milked on average three times a day, they do not graze, and are confined in permanent roofed enclosures exposed to outside air. They are fed a total mixed ration composed mostly of silages.

A cow's production of milk follows a lactation cycle that starts at the birth of her calf and lasts on average 14 months. Over the course of the cycle, the body and metabolism of the cow changes, and the expected milk output follows a distinctive shape where production increases rapidly until "peak milk"—expected

[3] 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 employed, such as ventilation, sprinklers or evaporative cooling systems, and installed in different areas of the farm.

at about two to three months—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 [4]. The dry period is relatively short as the typical cow has been inseminated again mid-cycle to produce a new calf, and thereby ensure the start of a new lactation cycle.

Results

Milk yield decreases at an increasing rate with elevated temperature and relative humidity, whose joint effect can be captured by the wet-bulb temperature

To extract the general shape of the milk yield response to weather, without making restricting assumptions on functional form, we first estimate semi-parametric models on continuous regressors. We specify a generalized additive model which expresses the relationship of the outcome with daily average T and RH as a bivariate smooth spline, to flexibly capture non-linear and interaction effects. We adjust for cow-level covariates including the stage of lactation, milking frequency, and lactation number, after demeaning the data by farm, year, and month (often referred to as including fixed effects in the applied microeconomics literature). Figure 1 shows the shape of the estimated response surface over the ranges of T and RH. It reveals a highly non-linear response, where the rate at which T and RH affect yield is itself increasing in these two variables.

This pattern is consistent with previous evidence of a non-linear combined effect of T and RH. 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 which are more tractable than a bivariate spline. The dairy science literature often uses variations of a "Temperature Humidity Index" (THI) for this purpose. One limit of these indices is that they are often calibrated empirically 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 unit-less, making results difficult to interpret and generalize [7, 16]. Here, we choose the wet-bulb temperature (Twb) as our preferred summary indicator of humid heat. The wet-bulb temperature is the lowest temperature to which an air parcel may cool by the adiabatic evaporation of water. As such, it reflects in part the cooling efficiency of sweat, and hence has a direct physiological relevance. We find that the Twb captures the response surface at least as well as THIs do, and also rivals them in predictive ability (SI Appendix, S2). The Twb is not calibrated to fit impacts, but relies on thermodynamic principles, ensuring its interpretability and validity across settings. It also provides a physiological limit—applicable to all placental mammals—of 35°C [34]. We therefore use Twb as our preferred index of humid heat in all subsequent analyses.

The highest 5% of the daily temperature distribution see reductions in milk output of over 5%—relative to a daily average within 10-12°C—precisely captured by the hourly exposure to wet-bulb temperatures

We estimate regressions of milk output on vectors of variables that capture the daily realization of wet-bulb temperature, adjusting for the stage of the lactation cycle, the cow's age proxied by her number of lactations, the number of milkings, and farm, year and month fixed effects. These fixed effects ensure that estimates are based on high-frequency variation in weather which lends itself to causal interpretability, rather than on differences between farms or across years and seasons, which are prone to potential bias.

We first consider a simple regression on a vector of binary indicators of whether the daily average wet-bulb temperature is in the given interval. The middle panel of Figure 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—nuancing the assumption of a sharp threshold made in a large part of the dairy literature.[4] Relative to a day with average wet-bulb temperatures in the 10-12°C range, a daily mean within 18-20°C reduces output by about 1.6%, one within 22-24°C by 3.7%, and one above 26°C by 9.6% (all values represent wet bulb temperatures).

The left panel of Figure 2 replaces the indicator bins with count bins of degree-hours, i.e., explanatory variables that count the number of hours that fall in specified temperature intervals. This specification captures the response of milk yield to the exposure to different levels of Twb within the course of the day. The reference category corresponds to the 10-12°C bin; each bin coefficient then represents the expected average difference in log of milk produced if one additional hour in the day had been exposed to the Twb of the given bin instead of the 10-12°C range. We find a similarly shaped response as in the previous specification. On average, one additional hour of Twb above 26°C relative to the 10-12°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 99.9% percentile at 26.19°C. For each percentile of the distribution of daily average Twb, the daily averages 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 various hourly temperature profiles, resulting in different predictions from the hourly model. For each top percentile, Figure 2C plots these predictions vis-a-vis the prediction of the daily average model. We find that the daily average model almost systematically underestimates the true effect—to which the hourly model gets closer—a discrepancy that reflects the concavity (increasing negative slope) of the hourly-response function. Other univariate models that use the daily minimum or maximum daily temperature perform similarly to the daily average model (see the SI Appendix, S4). Overall, the 95%-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 average wet-bulb temperature in the 10-12°C range.

Robustness of the shape and magnitude of the estimated response to the choice of heat index, size of degree intervals, and weather dataset, is documented in the SI Appendix, S4.

167 Heat still affects milk yield 10 days after exposure

Physiological considerations suggest that the impacts of humid heat on milk yield may not only be contemporaneous, but persist after direct exposure [4, 15]. To estimate the delayed effects of humid heat exposure, we add lagged daily wet-bulb temperatures as regressors to the model.

First, we examine how long effects persist, if at all, by including up to 21 daily lags of Twb as regressors. To keep the model tractable, we model each daily temperature realization as a single binary indicator of whether the daily average was above a given threshold. Results for the different thresholds of 22°C, 24°C and 26°C are presented in Figure 3A. We observe clear negative impacts of exposure to humid heat on milk production that persist over 10 days after exposure, with the highest negative effects on day-of-sample output caused by days -1 and -2.[5] Higher thresholds result in stronger negative impacts, but the dissipation of the delayed effects follows a similar pattern for the different thresholds. Including lags prior to day -10 does not affect the coefficients of the impacts of days -1 to -10 (effects have either almost entirely subsided beyond 10 days, or the last lagged regressor—day -10—captures most of the residual effects). We can therefore restrict our model to only include 10 lags without risk of misspecification.[6]

[4] Bryant et al. [9] is one exception which does estimate an inverted-U shaped relationship, by assuming a quadratic functional form.

[5] These results are consistent with West et al. [38], which found on a small sample that the THI of day -2 had the greatest effect on milk yield, and Bernabucci et al. [6], which estimated negative linear effects of THI from day -8 to 0 and the largest negative impact on day -4. Studies have also found evidence of delayed effects of heat stress on dairy cow fertility [15, 39].

[6] Specifications including less than 10 lags were also explored, and resulted in changes in the coefficients of the included lags, suggesting residual omitted variable bias.

To analyze *the full shape of* the response to past heat, we focus on these 10 lags, and now estimate a richer model that includes a vector of binary indicators for each Twb bin of each lagged day, extending our original specification. Results are presented in Figure 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 from days -1 and -2, and dissipate as we go further back in time).

Comparing the response to same-day exposure, when estimated in the baseline, contemporaneous model (Figure 2A) and in the model that includes lags (Figure 3B), shows the former estimate to be larger than the latter. Due to serial correlation in weather, coefficients estimated in the baseline specification capture both the contemporaneous effect of same-day heat exposure and the effects of the serially correlated previous days' exposure. In the subsequent heterogeneity analysis, we keep the no-lag specification for tractability, whose coefficients should hence be interpreted as embedding the delayed effect of previous days that are in relatively close ranges of temperature as the day of sample.[7]

The adoption of cooling technologies is associated with an attenuation of the direst effects of heat of less than half

We use data from a survey we administered in 2020-2021 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 areas of the cow sheds. Virtually all farm managers surveyed reported having some cooling system in place, but differed in the type of system, its location,[8] and the year of installation. Figure 4A shows the geographical variation in the year of adoption.

We estimate the differences in the response of milk production that are associated with the use of these technologies, by comparing estimates of the response function prior to and after adoption. We do so by adding interaction terms of the exposure to Twb values above 12°C with binary indicators of whether cooling equipment was installed in the farm by the year of observation. 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 10-12°C range). They further show that while cooling equipment is associated with an attenuation of the impact of heat, this attenuation capacity itself reduces 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 18-20°C days, the impact of heat reduces by only half, and on days above 24°C, by less than 40%. The decomposition of these observed differences by area of the barn where the equipment is installed reveals that they are predominantly driven by the holding yard, where cows are kept in higher densities before entering the milking parlor (SI Appendix, S5.A).

Our survey also elicited information about the adoption of two other potential forms of adaptation. First, cows go through different physiological processes throughout the stages of their lactation cycle, and may be more sensitive to heat depending on the timing of their calving.[9] This suggests that some shifting of the period of calving (mostly from summer to winter) may help reduce the impacts of heat. Second,

[7]We also endeavored to investigate the *accumulation or acclimation* effects of past heat, i.e., whether heat exposure affects the later *sensitivity* to heat. A net increase in sensitivity would suggest an accumulation effect; the reverse an acclimation effect. A model would capture this by allowing for interactions between temperatures across days. However, the interacted variables are so highly correlated in our data—given the values of the other covariates—that the attribution of the effect to either the main regressor or its interaction is not robust, and the analysis is inconclusive.

[8]The loose-housing system adopted in Israeli farms features three types of areas: the main area containing stalls, the feeding area with troughs, and the holding pen or pre-milk area where cows wait before entering the milking parlor.

[9]We also directly estimate the heterogeneity in heat sensitivity across the different stages of the lactation cycle. Using the same modeling approach of interacting the higher-degree bins with the categorical variable of interest—here, the lactation stage—we find indeed that cows are significantly more sensitive to heat in the first 100 days of the cycle, when the day-to-day increase in milk production is the steepest and body reserves are used for milk production (SI Appendix, S5.B).

the complex metabolic changes that support the condition of lactation, and their potential sensitivity to heat stress, suggest adjustments to feed patterns as another potential channel to reduce heat strain. We observe whether each surveyed farm adopted either of these approaches, but unlike in the case of the cooling technologies, we do not observe the year of adoption—nor the specific feed composition or schedule. To assess the association between the adoption of these adjustments and the impact of heat on milk production, we therefore restrict the sample to the most recent period in our data (2019-2020). By that time, all farms have installed cooling equipment. Within this sample, we estimate the differences in the sensitivity to high temperatures between those farms that adopted or did not adopt these two additional adjustments, by interacting the higher-degree temperature bins with categorical indicators of shifting birth periods only (86 farms), shifting feed timing only (10 farms), or implementing both (11 farms). Figure 4C displays the estimated response functions for each of these categories. We find suggestive evidence of additional abatement potential associated with these strategies, by up to 4 percentage points in the highest temperature bins, compared to farms which only implement cooling. A similar analysis of the heterogeneity of the response with the strategic changing of feed composition (implemented by 53 farms) does not yield any indication of a significant difference (SI Appendix, S5.B).

Discussion

Our results indicate that humid heat stress has highly non-linear and relatively 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 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 in cooled and un-cooled farms cannot be strictly causally attributed to the adoption of the cooling technology, as their adoption may be endogenous. However, we expect selection into adoption to be biased towards farms where it would be most beneficial, suggesting our estimates may even overstate the real average impacts of the cooling equipment.

In the context of a warmer planet where dairy farms experience elevated ranges of wet-bulb temperature, and given a limited abatement potential through common cooling technologies, 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 reduction 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 U.S. However, it may not be affordable in many parts of the world, and may replace one stressor—weather—with another—confinement. Evidence of the production and health benefits of letting cows having access to the outside suggests that reducing this access further may increase stress for cows and impact milk production [12].[10] In a world of increased exposure to heat stress, an alternative may be to alleviate other stressors, e.g., confinement or cow-calf separation [19], 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.

[10] There is even mixed evidence of the superiority of housing systems in altering heat stress effects on milk quantity and quality [27].

Methods

Data

Milk production data are obtained from the Israel Cattle Breeders Association and cover the majority of dairy farms in Israel from 2009 to 2020. The data are a panel of over 329 million observations at the cow-by-day level. They 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 8pm, the total daily amount of milk recorded in our data corresponds to that produced by the given cow from 8pm of the previous day to 8pm of the current day. In order 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 8pm cutoff.

We construct a panel dataset of hourly temperature and relative humidity 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 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 [32, 3]. 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, 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 the SI Appendix.

To explore the potential of adaptation to reduce heat impacts, we administered a survey in 2020-2021 to Israeli dairies. We collected information from 306 farm managers 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 semi-parametric models on continuous regressors. We consider the generalized additive model (GAM) (1), where the two-dimensional smooth function $f_2()$ is a tensor product spline that flexibly captures any joint nonlinear effects of daily average T and RH on log yield of cow i on day t. Controls 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 re-weighted least squares, and the optimal amount of smoothing is estimated using generalized cross validation.

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

In subsequent models, we use the wet-bulb temperature as preferred heat index to capture the effects of both temperature and relative humidity. 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 $f_1(\overline{\text{Twb}}_{it})$.

GAMs enable to extract 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 Equation (2), estimated using our entire panel dataset, where the function of interest $G()$ is approximated using the flexible specification of a piecewise-constant function.

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

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

$$G(\text{Twb}_{it}) = \sum_h \beta_h \times \mathbb{1}\left\{\overline{\text{Twb}}_{it} \in]h, h+k]\right\} \tag{3}$$

Alternatively, in order to take into account the entire distribution of weather during the day, we make the assumption that the effect of heat is additively substitutable *within-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 the SI Appendix. The resulting specification of the response function is the vector of degree-hour bins (4), where each bin $dh_{]h,h+k]}$ captures the number of hours of exposure to the heat interval $]h, h+k]$.

$$G(\text{Twb}_{it}) = \sum_h \beta_h \times dh_{]h,h+k]} \tag{4}$$

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 2009-2020 analysis), or adoption of sets of additional strategies (for the 2019-2020 analysis of birth and feed shifting).

Standard errors are clustered by farm in all specifications.

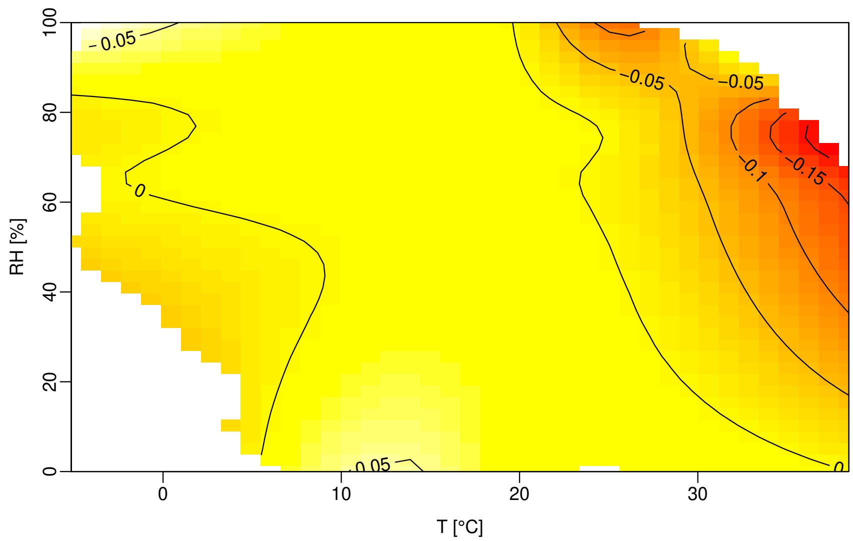

Figure 1: Contour plot with iso-value lines of the effect of the daily average dry-bulb temperature (T) and relative humidity (RH) on the logarithm of milk yield. Estimates are obtained from a bivariate smooth spline fitted on 0.5% of the sample (N = 1,645,477, adjusted $R^2 = 0.41478$.)

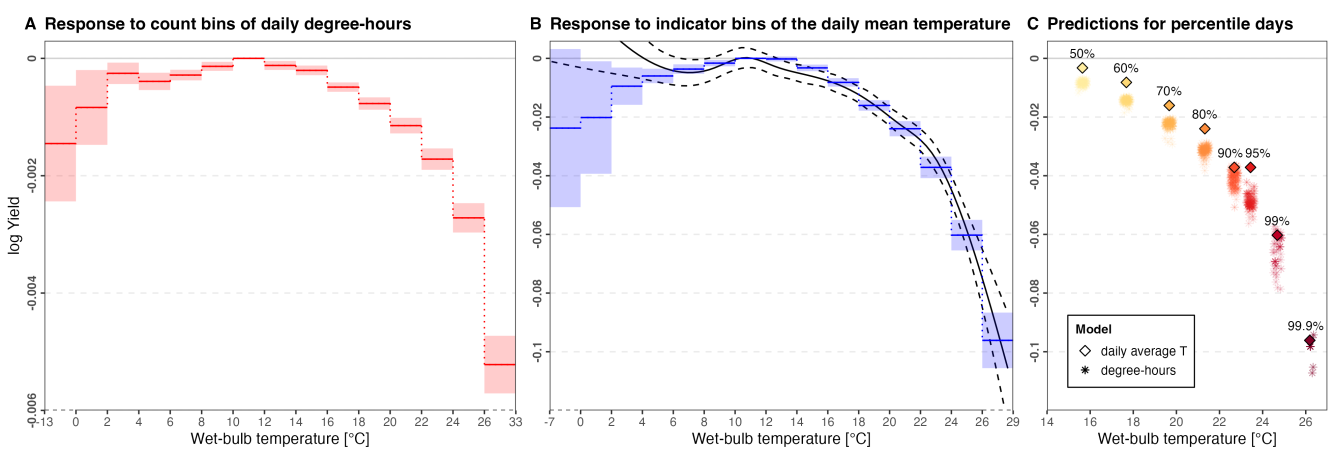

Figure 2: Daily milk yield response to wet-bulb temperature. (A) Response to the counts of hours in each temperature range. (B) Response to the range of the daily average temperature. (C) Corresponding predictions for the top percentile days of the temperature distribution, comparing the values obtained by using the estimates from models (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 correspond to their 95% confidence intervals, and the reference category is the interval [10-12°C]. Each bin coefficient represents the expected average difference in log of milk produced if, in (A) the daily average temperature, and in (B) one additional hour, had been in the given bin instead of in the 10-12°C range. The black solid and dotted curves in (A) correspond to the estimates and 95% confidence band of a spline specification, centered to match the reference bin of the binned regression. Bin estimates are based on the full sample of observations; spline estimates are based on a 0.5% sample of lactation times series, stratified by farm. The first and last bins are modeled with a larger width than the others in order to estimate them precisely—as the end parts of the distribution have smaller sample sizes—but are displayed similarly as the others for readability.

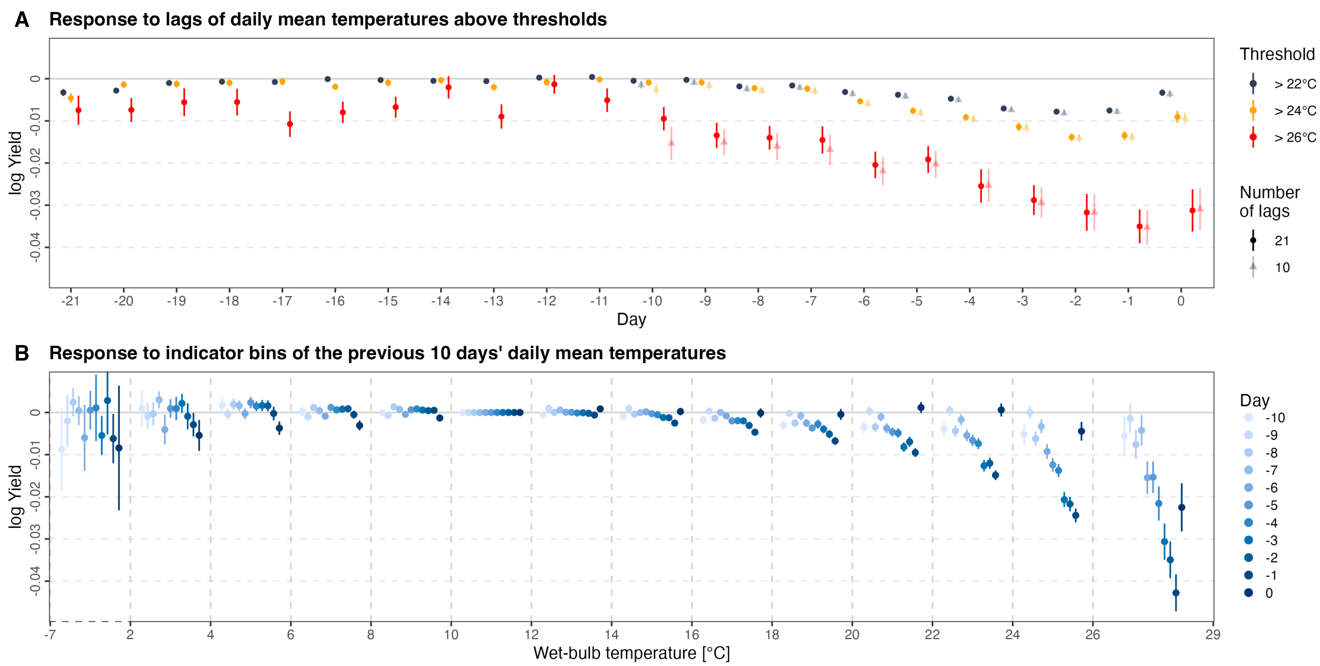

Figure 3: Delayed effects of past heat, measured by the wet-bulb temperature, on day-of-sample milk yield. (A) Effects of lagged daily average temperatures being over a given threshold; estimated from the full sample of observations. (B) Effects of lagged daily average temperatures being in a given range, relative to the 10-12°C range; estimated from a 10% sample of lactation times series, stratified by farm.

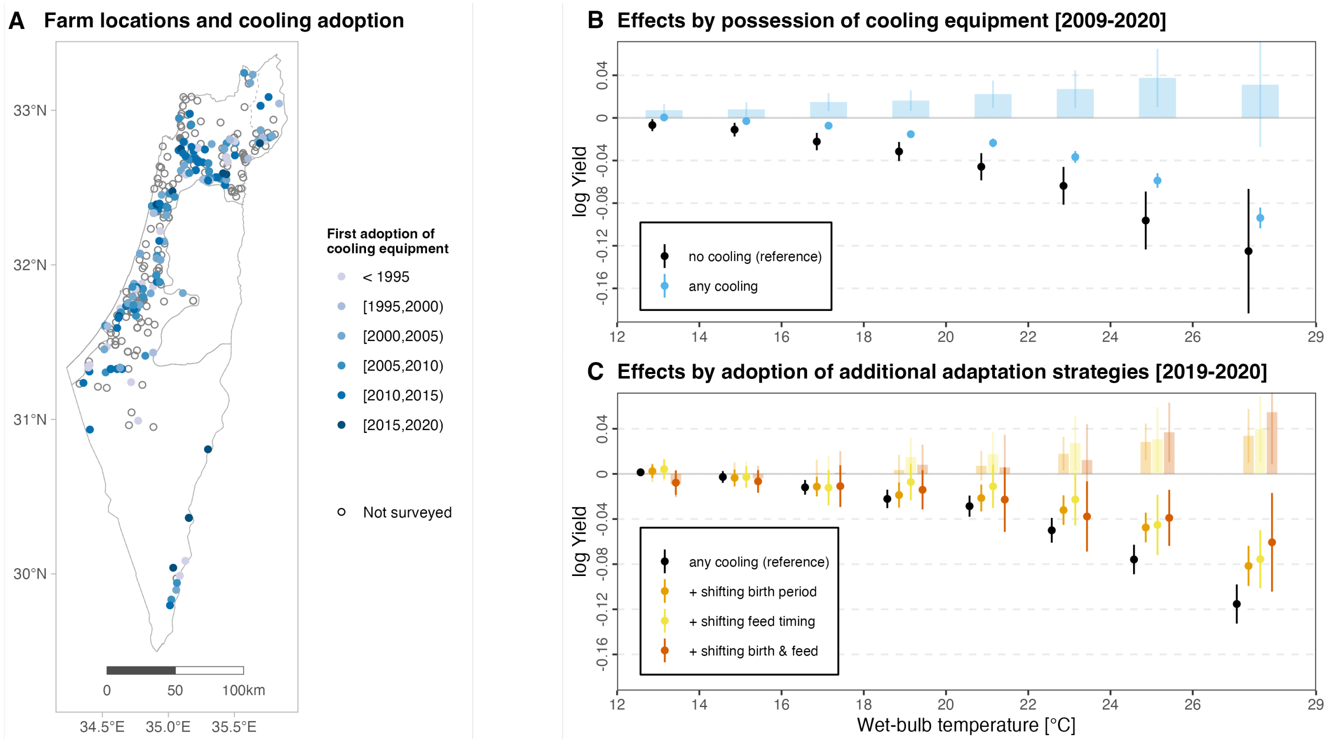

Figure 4: Farm adaptation strategies and associated heterogeneity of the effects of high-temperature bins. (A) Farm locations and years of their first installment of cooling equipment (grouped by 5-year period). (B,C) Heterogeneity of the effects of high-temperature bins by set of adopted strategies. Only the high-temperature bins are displayed. The reference range for the bins of wet-bulb temperature is the 10-12°C range, such that each bin coefficient represents the expected average difference in log of milk produced if the daily average wet-bulb temperature had been in the given bin instead of in the 10-12°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 farms by adoption of any cooling equipment, over the whole panel (N=143,367,607); (C) compares farms by adoption of additional adaptation strategies, in the last two years of our panel (N=29,415,613).

References

[1] Y. Aharoni, O. Ravagnolo, and I. Misztal. Comparison of lactational responses of dairy cows in Georgia and Israel to heat load and photoperiod. *Anim. Sci.*, 75:469–476, 2002. ISSN 1357-7298. doi: 10.1017/S1357729800053236.

[2] G. André, B. Engel, P. B. M. Berentsen, T. V. Vellinga, and 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(9):4502–4513, Sept. 2011. ISSN 0022-0302. doi: 10.3168/jds.2010-4139.

[3] M. Auffhammer, S. M. Hsiang, W. Schlenker, and A. Sobel. Using Weather Data and Climate Model Output in Economic Analyses of Climate Change. *Rev Environ Econ Policy*, 7(2):181–198, July 2013. ISSN 1750-6816. doi: 10.1093/reep/ret016.

[4] L. H. Baumgard and R. P. Rhoads, Jr. Effects of heat stress on postabsorptive metabolism and energetics. *Annual Review of Animal Biosciences*, 1:311–337, Jan. 2013. ISSN 2165-8110. doi: 10.1146/annurev-animal-031412-103644.

[5] A. Berman. Estimates of heat stress relief needs for Holstein dairy cows. *J. Anim. Sci.*, 83(6):1377–1384, June 2005. ISSN 0021-8812. doi: 10.2527/2005.8361377x.

[6] U. Bernabucci, S. Biffani, L. Buggiotti, A. Vitali, N. Lacetera, and A. Nardone. The effects of heat stress in Italian Holstein dairy cattle. *Journal of Dairy Science*, 97(1):471–486, 2014. ISSN 0022-0302, 1525-3198. doi: 10.3168/jds.2013-6611.

[7] J. Bohmanova, I. Misztal, and J. B. Cole. Temperature-humidity indices as indicators of milk production losses due to heat stress. *J. Dairy Sci.*, 90(4):1947–1956, Apr. 2007. ISSN 0022-0302, 1525-3198. doi: 10.3168/jds.2006-513.

[8] K. Brügemann, E. Gernand, U. König von Borstel, and S. König. Defining and evaluating heat stress thresholds in different dairy cow production systems. *Archives Animal Breeding*, 55(1):13–24, 2012.

[9] J. R. Bryant, N. López-Villalobos, J. E. Pryce, C. W. Holmes, and D. L. Johnson. Quantifying the effect of thermal environment on production traits in three breeds of dairy cattle in New Zealand. *New Zealand Journal of Agricultural Research*, 50(3):327–338, 2007. doi: 10.1080/00288230709510301.

[10] J. R. Buzan and M. Huber. Moist heat stress on a hotter earth. *Annu. Rev. Earth Planet. Sci.*, 48(1): 623–655, May 2020. ISSN 0084-6597. doi: 10.1146/annurev-earth-053018-060100.

[11] 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, and A. T. Zhang. Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics*, 137(4):2037–2105, 2022.

[12] G. L. Charlton and S. M. Rutter. The behaviour of housed dairy cattle with and without pasture access: A review. *Applied animal behaviour science*, 192:2–9, July 2017. ISSN 0168-1591. doi: 10.1016/j.applanim.2017.05.015.

[13] R. J. Collier and K. G. Gebremedhin. Thermal biology of domestic animals. *Annu Rev Anim Biosci*, 3:513–532, 2015. ISSN 2165-8110. doi: 10.1146/annurev-animal-022114-110659.

[14] J. Colmer. Temperature, labor reallocation, and industrial production: Evidence from india. *American Economic Journal: Applied Economics*, 13(4):101–124, Oct. 2021.

[15] F. De Rensis and R. J. Scaramuzzi. Heat stress and seasonal effects on reproduction in the dairy cow–a review. *Theriogenology*, 60(6):1139–1151, Oct. 2003.

[16] S. Dikmen and 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(1):109–116, Jan. 2009. ISSN 0022-0302, 1525-3198. doi: 10.3168/jds.2008-1370.

[17] C. Fezzi and I. Bateman. The Impact of Climate Change on Agriculture: Nonlinear Effects and Aggregation Bias in Ricardian Models of Farmland Values. *Journal of the Association of Environmental and Resource Economists*, 2(1):57–92, Mar. 2015. ISSN 2333-5955. doi: 10.1086/680257.

[18] A. D. Flouris, P. C. Dinas, L. G. Ioannou, L. Nybo, G. Havenith, G. P. Kenny, and T. Kjellstrom. Workers' health and productivity under occupational heat strain: a systematic review and meta-analysis. *The Lancet. Planetary health*, 2(12):e521–e531, Dec. 2018. ISSN 2542-5196. doi: 10.1016/S2542-5196(18)30237-7.

[19] F. C. Flower and D. M. Weary. The Effects of Early Separation on the Dairy Cow and Calf. *Animal welfare*, 12(3):339–348, Aug. 2003. ISSN 0962-7286. doi: 10.1017/S0962728600025847.

[20] E. Gernand, S. König, and C. Kipp. Influence of on-farm measurements for heat stress indicators on dairy cow productivity, female fertility, and health. *J. Dairy Sci.*, 102(7):6660–6671, July 2019. ISSN 0022-0302, 1525-3198. doi: 10.3168/jds.2018-16011.

[21] M. Gisbert-Queral, A. Henningsen, B. Markussen, M. T. Niles, E. Kebreab, A. J. Rigden, and N. D. Mueller. Climate impacts and adaptation in US dairy systems 1981–2018. *Nature Food*, 2(11):894–901, Oct. 2021. ISSN 2662-1355. doi: 10.1038/s43016-021-00372-z.

[22] J. S. Graff Zivin, Y. Song, Q. Tang, and P. Zhang. Temperature and High-Stakes cognitive performance: Evidence from the national college entrance examination in china. *Journal of Environmental Economics and Management, 104 (2020):*, 104(102365), 2020.

[23] S. Hsiang, R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. J. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, K. Larsen, and T. Houser. Estimating economic damage from climate change in the United States. *Science*, 356(6345):1362–1369, 2017. doi: 10.1126/science.aal4369.

[24] R. H. Ingraham, R. W. Stanley, and 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. *American journal of veterinary research*, 40(12):1792–1797, Dec. 1979. ISSN 0002-9645, 1943-5681.

[25] C. T. Kadzere, M. R. Murphy, N. Silanikove, and E. Maltz. Heat stress in lactating dairy cows: a review. *Livestock Production Science*, 77(1):59–91, 2002. doi: 10.1016/S0301-6226(01)00330-X.

[26] N. Key and S. Sneeringer. Potential Effects of Climate Change on the Productivity of U.S. Dairies. *Am. J. Agric. Econ.*, 96(4):1136–1156, July 2014. ISSN 0002-9092. doi: 10.1093/ajae/aau002.

[27] C. Lambertz, C. Sanker, and M. Gauly. Climatic effects on milk production traits and somatic cell score in lactating Holstein-Friesian cows in different housing systems. *Journal of dairy science*, 97(1): 319–329, 2014. ISSN 0022-0302, 1525-3198. doi: 10.3168/jds.2013-7217.

[28] B. A. McCarl and T. W. Hertel. Climate change as an agricultural economics research topic. *Applied Economic Perspectives and Policy*, 40(1):60–78, 2018. doi: 10.1093/aepp/ppx052.

[29] OECD and Food and Agriculture Organization of the United Nations. Chapter 7: Dairy and dairy products. In *OECD-FAO Agricultural Outlook 2023-2032*. OECD Publishing, Paris, 6 July 2023. doi: 10.1787/37c7b798-en.

[30] R. J. Park, J. Goodman, M. Hurwitz, and J. Smith. Heat and learning. *American Economic Journal: Economic Policy*, 12(2):306–339, May 2020.

[31] J. R. Porter, L. Xie, A. J. Challinor, K. Cochrane, S. M. Howden, M. M. Iqbal, D. B. Lobell, and M. I. Travasso. Chapter 7: Food Security and Food Production Systems. In 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, and L. L. White, editors, *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*, pages 485–533. Cambridge University Press, Cambridge, United Kingdom, 2014.

[32] C. Raymond, T. Matthews, and R. M. Horton. The emergence of heat and humidity too severe for human tolerance. *Science Advances*, 6(19):eaaw1838, 2020. ISSN 2375-2548. doi: 10.1126/sciadv.aaw1838.

[33] D. Renaudeau, J. L. Gourdine, and N. R. St-Pierre. A meta-analysis of the effects of high ambient temperature on growth performance of growing-finishing pigs. *Journal of animal science*, 89(7):2220–2230, July 2011. ISSN 0021-8812. doi: 10.2527/jas.2010-3329.

[34] S. C. Sherwood and M. Huber. An adaptability limit to climate change due to heat stress. *Proc. Natl. Acad. Sci. U. S. A.*, 107(21):9552–9555, May 2010. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.0913352107.

[35] N. R. St-Pierre, B. Cobanov, and G. Schnitkey. Economic Losses from Heat Stress by US Livestock Industries. *J. Dairy Sci.*, 86:E52–E77, June 2003. ISSN 0022-0302. doi: 10.3168/jds.S0022-0302(03)74040-5.

[36] W. Vroege, T. Dalhaus, E. Wauters, and R. Finger. Effects of extreme heat on milk quantity and quality. *Agricultural systems*, 210:103731, 1 Aug. 2023. ISSN 0308-521X. doi: 10.1016/j.agsy.2023.103731. URL `https://www.sciencedirect.com/science/article/pii/S0308521X23001361`.

[37] J. W. West. Effects of heat-stress on production in dairy cattle. *J. Dairy Sci.*, 86(6):2131–2144, June 2003. ISSN 0022-0302. doi: 10.3168/jds.S0022-0302(03)73803-X.

[38] J. W. West, B. G. Mullinix, and J. K. Bernard. Effects of hot, humid weather on milk temperature, dry matter intake, and milk yield of lactating dairy cows. *Journal of dairy science*, 86(1):232–242, Jan. 2003. ISSN 0022-0302. doi: 10.3168/jds.S0022-0302(03)73602-9.

[39] D. Wolfenson, Z. Roth, and R. Meidan. Impaired reproduction in heat-stressed cattle: basic and applied aspects. *Anim. Reprod. Sci.*, 60-61:535–547, July 2000.

[40] Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Regional Fact Sheet — Asia. IPCC, 2021.

[41] X. Ye, R. Wolff, W. Yu, P. Vaneckova, X. Pan, and S. Tong. Ambient temperature and morbidity: a review of epidemiological evidence. *Environmental health perspectives*, 120(1):19–28, Jan. 2012. ISSN 0091-6765. doi: 10.1289/ehp.1003198.