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Vulnerability of US dairy farms to extreme heat[☆]

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ABSTRACT

Livestock agriculture, and dairy more specifically, is threatened by climate change as extreme weather conditions become more frequent. When temperature and humidity increase above critical levels, dairy cows become heat-stressed and experience a drop in milk production. We quantify the impact of heat stress on the dairy industry throughout the Midwestern and Eastern United States in the years 2012–2016 using animal-level production data. We estimate that 1% of total annual yield is lost to heat stress, and losses are predicted to increase about 30% by 2050 on average under various climate scenarios. We provide three new insights compared to previous estimates with aggregated data. (1) Heat stress disproportionately affects milk quality, having larger impacts on farm income and nutritional value than previously estimated. (2) Small farms experience the largest losses to heat stress, suggesting they face barriers to adaptation. (3) Cows in the highest-yield production stage are the most vulnerable to heat stress in both relative and absolute terms. Our results have global implications given the prevalence of dairy as a source of income and nutrition in high- and low-income contexts. We outline ways that funds for climate-smart agriculture could be used to increase climate resilience in the dairy industry.

1. Introduction

Global food production faces an impending challenge: increasingly frequent extreme heat events due to climate change (IPCC, 2022). The future food supply depends on whether and how the industry builds resilience to such extreme events. Dairy production is especially vulnerable to heat since cattle experience “heat stress” at high levels of temperature and humidity. Heat-stressed cattle eat less, which causes their milk productivity to drop (Key et al., 2014; St-Pierre et al., 2003; West et al., 2003). Heat stress also impacts cattle health and reproductive performance, which can cause additional productivity losses (Rhoads et al., 2009).

Damages to livestock agriculture will have repercussions throughout the world, as livestock agriculture contributes 40% of agricultural production in high-income countries and 20% in low-income countries (Food and Agriculture Organization of the United Nations, 2021). As a low-cost protein source for smallholder farmers and low-income populations worldwide, dairy is also a source of key nutrients (e.g., calcium, vitamins B12 and B5, and magnesium) for vulnerable groups like pregnant women and children (Givens, 2020) and are associated with improved anthropometric outcomes (Miller et al., 2020; Mehrab Bakhtiar and Hoddinott, 2023; Ramahaimandimby et al., 2023; Tricarico et al., 2020).

The impact of heat stress on dairy production has been quantified using state-level data aggregated to the monthly or annual level (Gisbert-Queral et al., 2021; St-Pierre et al., 2003). These data and methodology leave three gaps in the understanding of heat stress impacts.[1] First, without a daily measure of milk production, it is difficult to understand the precise timing and impacts of heat waves on milk production. Second, aggregated data typically only report milk yield in fluid measures (e.g., gallons), which misses the significant

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[1] While studies with farm-level data from a limited number of herds (Bohmanova et al., 2007; Key et al., 2014; Lopez et al., 2022) offer insight into the biological impacts of heat stress, they do not offer estimates of losses or adaptation at a larger scale.

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variation in milk quality that may occur in response to heat stress. Finally, aggregated data are measured at such a level that they mask heterogeneity across and within farms. Farm scale is correlated with differences in capital and production practices that may affect resilience to heat shocks. Additionally, where a cow is in her lactation cycle impacts her vulnerability to heat stress. Without these dimensions, studies with aggregate data may misunderstand key risks and opportunities for the sector.

Our research fills these gaps by using a novel data source to study the short-run impacts of heat stress. We pair panel data on cow-level milk production collected every month for 18,000 dairy farms throughout the Midwestern and Eastern United States with gridded daily temperature and humidity data. We estimate that 1% of annual milk yield is lost to heat stress. The quality adjustment to milk output is crucial, as not adjusting milk production for its fat and protein content in our sample led to a significant underestimate of the impacts of heat stress.

Our data allows us to demonstrate the changing impact of heat stress over a cow's year-long production cycle. We find that heat stress vulnerability coincides with the most productive phases in a cow's lactation cycle: cows that have recently given birth and have given birth more than once. These cows account for 31% of the total yield and 33% of the total losses in our sample. This result highlights that farm decisions around the timing of cattle production cycles is an important determinant of the effects of heat stress.

We also find significant heterogeneity across farm size. Farms with less than one hundred cows are far more vulnerable to heat stress than larger dairy farm with more than 500 cows. Dairy farms with more than 500 cows saw only a modest losses (1% of single-day yield) in the week following a day of low levels of heat stress, but small dairies experienced more than double the yield losses (2.5–3.9% of single-day yield) compared to these farms. Farms under one hundred head, which account for 61% of herds in our sample, produce less than 20% of the total output in our sample but constitute 27% of the yield losses from heat stress. While smaller farms remain vulnerable to heat stress, this suggests that the current production systems on large farms can mitigate losses under low and even moderate levels of heat stress.

Our results have significant implications for understanding the impact of heat stress and adaption on the dairy sector in the US and worldwide. While large farmers have adapted to mitigate low-stress events, adaptation does not yet protect from extreme conditions. Under several climate projections for the year 2050, the number of days with extreme heat stress will almost double and the damages from extreme heat stress to dairy farming will significantly increase. Nevertheless, the timing of cattle production cycles is a significant determinant of heat stress impact as is the size of the dairy farm. Future damages from climate change will be greatly impacted by management decisions around calving, which determines the time of year cattle hit peak production, as well as the already ongoing pattern of farm consolidation.

We discuss some options for research and policy to invest in climate-smart dairy. Over the past few decades, the US dairy industry has been rapidly consolidating as small farms exit and large farms increase their herd size. While small farms produce less than 20% of total production in our sample, they make up more than 60% of the total operations and remain a crucial component of the local farm economy in the Midwest and Northeast. We highlight that climate change will not only harm the productive capacity of the dairy sector but also exacerbate the ongoing loss of smallholder dairy farms without intentional funding and technical assistance to help them adapt to extreme heat.

2. Background

2.1. Cattle and heat stress

Heat stress impacts both the production ability and health of dairy cattle. At high levels of temperature and humidity, cattle experience an increase in their body temperature that causes them to eat less (West et al., 2003). The milk production ability of dairy cattle begins to decrease when the Temperature Humidity Index (THI) goes above 72 (Bohmanova et al., 2007; West, 2003). Ravagnolo et al. (2000) find that, for each unit increase above 72, milk production drops about 1%. Heat stress also makes it more difficult for cows to become pregnant (Jordan, 2003). Each additional day a cow is not able to become pregnant costs the dairy operation $2.50 per cow due to lost production in the next production cycle (St-Pierre et al., 2003). Finally, heat stress weakens a dairy cow's immune system and makes them more vulnerable to disease and early mortality (Bagath et al., 2019; Bishop-Williams et al., 2015).

Dairy producers have options to mitigate heat stress by changing day-to-day production practices, investing in cooling systems, and changing the timing of breeding decisions. Within a cow's production cycle, farms can change the timing of feeding and rest to avoid additional movement or metabolic processing at the warmest parts of the day. Farms can also make capital investments into shade, fans, and sprinklers that cool cattle down during heat waves (Key et al., 2014; Armstrong, 1994). These capital investments vary in their cost-effectiveness. Using a simulation model, St-Pierre et al. (2003) calculate that optimum heat abatement could reduce heat stress costs from all livestock industries by about $700 million. However, Gunn et al. (2019) find that heat abatement is only cost-effective in the most intense heat waves. An arguably less-costly heat abatement strategy for some producers is to change the timing of their management decisions. Skidmore (2022) finds that Brazilian cattle ranchers sell cattle early to avoid having to raise cattle during the dry season. Even more relevant to the dairy industry is work by Ferreira et al. (2016), which uses a simulation model to show that cows about to give birth are the most vulnerable to heat stress. This suggests that changing the timing of when cows give birth is another way for dairy farms to mitigate heat stress.

A number of studies have attempted to quantify the impacts of heat stress on the dairy industry using milk production data aggregated to the farm level or the state level. Mukherjee et al. (2013), Qi et al. (2015), and Key et al. (2014) use data at the farm level and stochastic frontier analysis to examine the impact of THI on the efficiency frontier of dairy farms throughout the country. In 100 farms in Florida and Georgia, higher THI was associated with less efficiency and investments in cooling systems were associated with higher efficiency (Mukherjee et al., 2013). The most expansive study, by Key et al. (2014), uses data from the Agricultural Resource Management Survey (ARMS) from 2005 and 2010, and finds a similar, negative relationship between THI and dairy farm efficiency. Njuki et al. (2020) use a sample of Wisconsin dairy farms and calculates that the cost of heat abatement depresses productivity growth in dairy by about 0.3%.

In terms of adaptation, Gisbert-Queral et al. (2021) use state-level data in the US from 1981 to 2018 and finds that sensitivity to extreme THI was lower in 2018 than in 1981, supporting the idea that the dairy industry has adapted to extreme climate shocks over the past few decades. Gisbert-Queral et al. (2021) also find that losses at the state level are even higher when THI dips below 45, that is, exposure to cold. While cattle are usually resilient to temperatures as low as 0 degrees Celsius (Young, 1981; Lopez et al., 2022; Qi et al., 2015), extreme cold can impact calf mortality and may cause dairies to divert resources away from milk production into protecting calves (Roland et al., 2016).[2]

[2] We return to the question of the impact of low temperatures on milk yield in Appendix E.4.

2.2. Consolidation in the dairy industry

Consolidation is another feature of the US dairy industry that is relevant to the impacts of heat stress. Over the past fifty years, small dairy farms have exited at an increasing pace as large dairy farms have grown even larger. This is especially apparent in areas of the country where herd sizes are usually smaller than 500 cows. In the Midwest and Northeast, where the average herd size was usually below 300 cows in 2020, herd size increased 275% in just twenty years (2002 to 2022). These states have seen higher rates of herd size increase than states in the West, where herd sizes are already above 500 cows on average (Hutchins and Janzen, 2023).

Dairy farming has significant economies of scale: the cost per unit of milk produced tends to drop significantly as herd size increases (Tauer and Mishra, 2006; Mosheim and Lovell, 2009; MacDonald et al., 2016). Studies find that a driving force behind this consolidation is improvements in productivity and economies of scale. There is a robust relationship between firm exit and efficiency and/or productivity: dairy farms that have lower total factor productivity (Hutchins et al., 2024) or technical efficiency (Dong et al., 2016; Tauer and Mishra, 2006) tend to exit at higher rates.

The current economies of scale in the US dairy industry and consolidation pattern suggest that an increasing frequency of heat stress could exacerbate consolidation. Many investments for heat stress mitigation, like sprinklers and better ventilation, have high fixed costs. These sorts of investments may become more profitable as farms increase their scale. If heat stress significantly lowers dairy farming productivity, small farms could decide to expand their herd to counter this productivity loss or exit the sector altogether.

2.3. Data

Our dairy production data comes from Dairy Records Management Systems (DRMS), a cooperative that tracks dairy production on herds that are members of a Dairy Herd Improvement Association (DHIA). Farms that are members of DHIAs have each cow's yield measured once a month by a trained milk tester. All measurements within a herd are collected at the same time, and yields are then corrected for time of day in which the milking occurs. The milk is then tested in a laboratory for butterfat content, protein content, and somatic cell count (an indicator of bacteria and poor health). The DHIA tests all of the cows that are currently milking in the herd and also keeps records on their calving dates, their birth dates, and the number of production cycles they have completed. The cow-level records are used to produce benchmarking reports for each member farm and by the USDA to estimate the genetic contribution of dairy bulls on the market. One advantage of this data is that milk can be adjusted for protein and fat so that cow milk yield is adjusted for quality. Unless otherwise stated, we use energy-corrected milk when measuring milk yield. Energy correction standardizes the raw pounds of fluid milk to the pounds of milk with 3.5 percent butterfat and 3.2 percent protein.[3]

We use over 56 million dairy cow production records sourced from over 18 thousand dairy farms from the years 2012 to 2016. Cows are sampled once per month in each month that they are producing (i.e., roughly ten observations per cow per year). All producing cows on a farm are sampled on the same day in a given month. The data are an unbalanced panel that provide twelve observations per farm per year of single-day cow-level production for each farm that is a DHIA member. Our sample for this analysis covers the states shown in Fig. 1.[4] About 44% of dairy farms nationwide are members of DHIAs and in our chosen states DHIA participation is about 50% (Council on Dairy Cattle Breeding, 2023). The states in this region have similar-sized dairy farms and similar climates, allowing for a more comparable production system across states.

Daily weather data comes from gridMET, which measures temperature and humidity at the 1/24th degree (4-km grid) level (Abatzoglou, 2013). We process these to daily, county-level maximum and minimum temperature humidity index (THI) measurements. THI is the best measure of the stress a cow experiences, as the combination of heat and humidity limits the cow's ability to cool through sweating or other forms of evaporative cooling (Armstrong, 1994; Bohmanova et al., 2007). We use the formula for THI: $THI = .8T + RH \times (T - 14.3) + 46.4$, where T is air temperature in degrees Celsius and RH is relative humidity between 0 and 1.

Cattle are even more negatively impacted when THI remains above their critical threshold during the day, not allowing them to recover. To incorporate this, we use not just the THI max but the amount of time spent above a cow's critical THI threshold (72) to calculate THI heat load (St-Pierre et al., 2003; Key et al., 2014). Heat load is calculated using the daily minimum and maximum of THI and modeling changes in THI throughout the day with a sine curve (see Appendix Figure B1, which comes from Key et al. (2014), for a visual depiction). THI heat load measures the area under the sine curve but above the THI threshold, which increases when both THI minimum and maximum increase. This measure is often used in the literature to account for days where there is a lower maximum THI but still prolonged exposure to heat because of a high minimum THI. We estimate heat load with a critical THI threshold of 72 (St-Pierre et al., 2003) and include more details on our calculation of heat load in Appendix B.

We discretize heat load into quartiles of days with a non-zero heat load: (0 - 35], (35 - 70], (70 - 140] and 140 or above. These quartiles roughly map to the categories of heat stress based on maximum daily THI developed by Armstrong (1994). Non-zero heat loads below 70 are equivalent to low-stress days (THI max 72–80), days with a heat load between 70 and 140 are equivalent to moderate-stress days (THI max 80–90), and days with heat load above 140 are equivalent to extreme stress days (THI max > 90).[5]

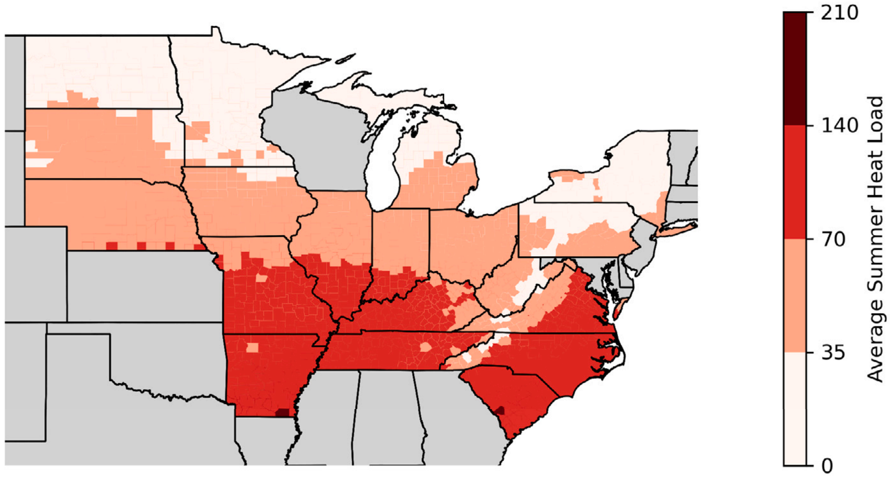
Fig. 1 panel a shows the stress quartile of each county's average summer (April through August) heat load during our sample time frame. Southern states and parts of the Midwest (e.g. Illinois, Missouri, Indiana) on average see a heat load above 70 in the summer, whereas states further to the North on average see a heat load under 70. The incidence of extreme days with heat load above 140 is also higher farther South. Panel b of Fig. 1 shows the annual average number of days of extreme (> 140) heat load a county experiences across the five summer months. Northern states experience on average fewer than one month of extreme heat load, while states like Missouri and South Carolina may experience nearly three months of extreme heat load.[6]

[3] The energy correction formula for milk yield used by the DHIA system is Energy-Corrected Milk = .327×Milk lbs+12.95×Fat lbs+7.65×Protein lbs (Dairy Records Management Systems, 2014)

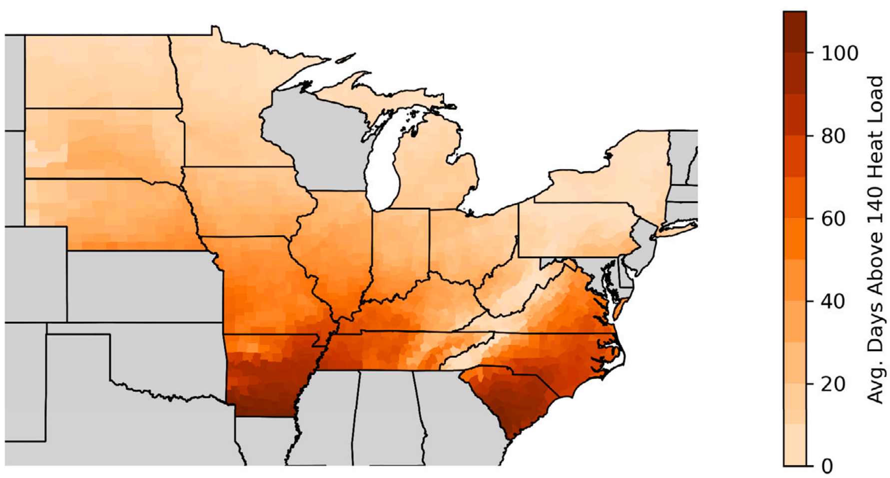
[4] The coverage of states depends on the Dairy Records Processing Center being accessed. In this study, we partner with a Dairy Records Processing Center which covers most of the Northeast and Midwest. Wisconsin, however, is served by a separate Dairy Records Processing Center and cannot be included in our analysis.

[5] For more information on the heat load calculation as well as precise formulas, Appendix B contains more information about the calculation of THI heat load and the relationship between heat load and daily THI min and max.

[6] We map the total extreme heat days in a county in each year in Figure B4.



(a) Average summer heat load



(b) Number of days above 140 heat load in the summer

Fig. 1. Heat load patterns across sample states.
Note: Daily county-level heat load is estimated by fitting a sine curve between the minimum and maximum THI and calculating the area above a critical threshold of 70 THI. Weather data are from gridMET.

2.4. Empirical strategy

We estimate a cow's daily production as a function of her physical environment and where she is in her production cycle. On average, cow production cycles are 10 months long and births are spaced one year apart to allow two months of rest before a cow begins another cycle by giving birth again. The relationship of daily milk production to the days since the cow gave birth ("days in milk" or DIM) is called the lactation curve (Fig. 2). The lactation curve is modeled mathematically in the Wood Model as a half-gamma curve which quickly peaks in the first four months before gradually tapering Daily production reaches its peak in the first 120 days of a lactation cycle and is higher most point in the cycle for cows that have given birth multiple times (i.e., "multiparous" rather than "primiparous").

Following Hutchins and Hueth (2021), we adapt the Wood model to incorporate heat stress and estimate how heat stress explains deviations of milk production from the biological lactation curve:

$$ln(y_{ihctym}) = f(d_{ihctym}, l_{ihctym}) + \sum_{p\in\mathbf{P}} \sum_{k=0}^{K} \beta_{pk}\, \mathbb{1}\{z_{c,t-k} \in P\} + \alpha_h + \gamma_y + \delta_m + \epsilon_{ihctym}. \tag{1}$$

Our outcome, $ln(y_{ihctym})$ measures the log milk production for cow i in herd h and county c at time (measured daily) t in year y that calved in month m. Based on the Wood model, we include $f(d_{ihctym}, l_{ihctym}) = a(l_{ihctym} > 1) + bln(d_{ihctym}) + cd_{ihctym} + b'ln(d_{ihctym}) \times \mathbb{1}(l_{ihctym} > 1) + c'd_{ihctym} \times \mathbb{1}(l_{ihctym} > 1)$ where l_{ihctym} is a positive number that indicates the number of production cycles the cow has experienced (i.e., 1 indicates that the cow is in their first production cycle) and d_{ihctym} is days in milk. The indicator variable $\mathbb{1}(l_{ihctym} > 1)$ is interacted with the other variables to allow cows which have given birth more than once a different parameter for the lactation curve. We test alternative specifications of the lactation curve in Appendix E.3.

Our treatment is a series of dummy variables, $z_{c,t-k}$, representing the set P of categories of THI heat load: (0–35), [35–70), [70–140) and 140 or more. We omit the base category of days with no heat load. One day of extreme heat load can have impacts on not just that day's milk production but potentially up to a week after. To test this, we include six lags of each heat load category and report our results as the sum of the coefficients of the lags.

We control for time-invariant herd characteristics (α_h), as we anticipate that average milk yield varies at the herd level with management practices. We also include year (γ_y) and calving month (δ_m) fixed effects

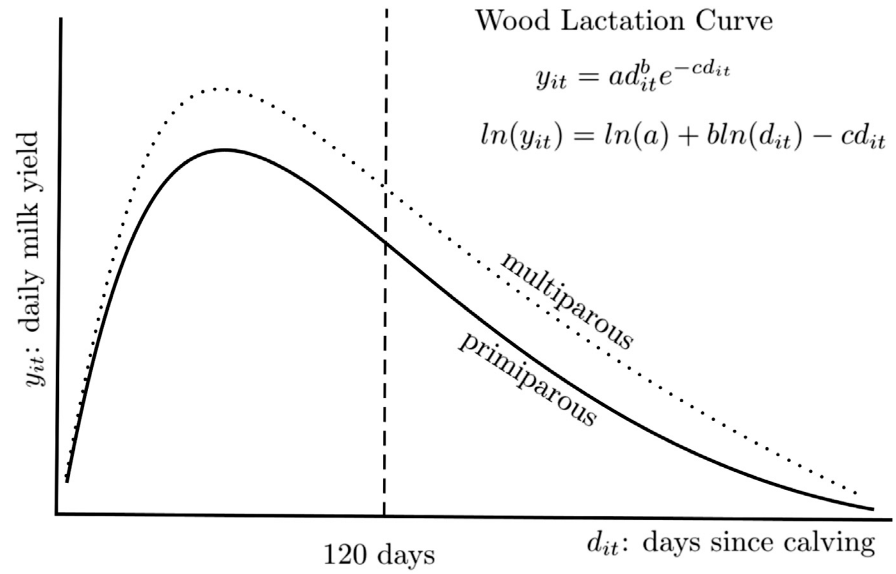


Fig. 2. Lactation curve and the Wood model.

and estimate standard errors that are robust to clustering at the county level. We test the model with alternative fixed effects (cow and herd-by-year) and standard error specifications (robust to spatial correlation and clustering at the county and county-by-year level) in Appendix E.2.

We also consider the heterogeneous impacts of heat stress based on the cow's lactation cycle and herd size. We estimate the model separately for each heterogeneity cohort. This estimates cohort-specific responses to heat stress while also allowing for cohort-specific coefficients on all other variables (e.g., fixed effects) (Feigenberg et al., 2023).

In periods of high milk production, dairy cattle put more energy into milk production, which may leave them more vulnerable to heat events. To reflect this, we separate cows into lactation-cycle cohorts based on two dimensions: how many times she has given birth and long it has been since she gave birth. We separate cows into primiparous (no previous birth) and multiparous (at least one previous birth) and early days in milk (less than 120 days postpartum at time t) and late days in milk (120 or more days postpartum).

Management practices and technology may vary with herd size in a way that makes a farm more or less vulnerable to heat stress. To test this, we estimate the model separately for four categories of herd size: less than 100 cows, 100–250 cows, 250–500 cows, and more than 500 cows. We also estimate herd-level coefficients using a random effects model in Appendix E.1.

To measure the total impact of a single day of heat stress, we sum the day-of and six lagged coefficients. We report losses as a percent of a single day's milk production, although these losses occur over a week. The standard error of the sum of the coefficients is calculated using the variance–covariance matrix estimated from the model since the coefficients are all estimated in the same linear model and as a linear function.

Using these impacts, we conclude our estimation by calculating a "back-of-the-envelope" estimate of revenue loss for our sample using the incidence of heat stress days and number of cows in each county. To project losses forward to 2050, we use the distribution of dairy cattle in 2017 from the USDA Agricultural Census and the average predictions of 22 different climate models.

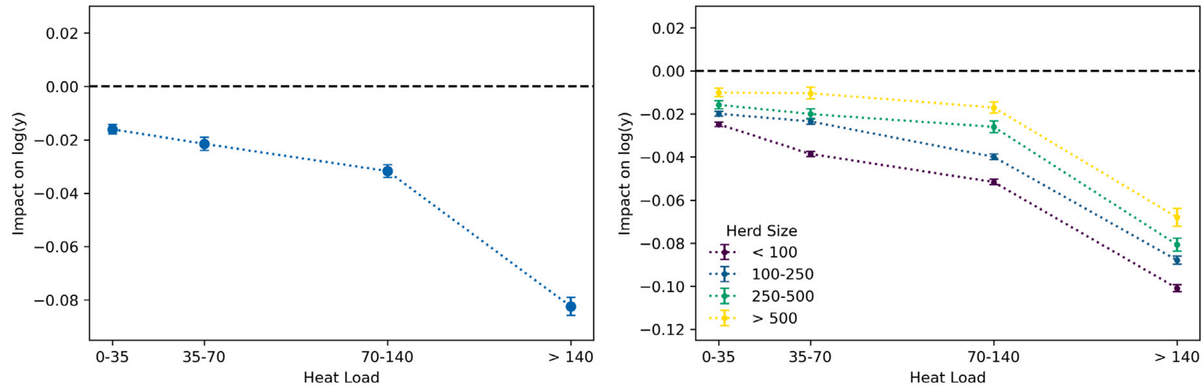
3. Results

3.1. Average impacts of heat stress on the US dairy herd

Using our model with six lags, we find that the impact of a single day of heat stress persists up to a week after the event. We calculate the cumulative impact of a heat stress event over the following week by summing the coefficients of the lags and calculating the standard error of their sum using the variance–covariance matrix of the model. One day of heat load exposure over 140 reduces milk production by 8.2% of a day's yield, spread over the course of a week (Fig. 3 panel a). Low-stress days reduce yield by 1.6–2.2% over the week, while moderate stress days reduce yield by 3.2%. In Appendix C, we show the full lagged effects as well as test the impact of leads to see whether farmers anticipate heat events or not. While we find large lagged effects, we find that leads have no significant impact.

Yield losses grow with cumulative days of exposure. We examine the impact of cumulative exposure to heat stress by estimating the impact of multiple days of heat stress within a seven-day period. Fig. 4 shows the coefficient from a model where one-day yield is based on the count of days in the past week the cow experienced heat load above three heat-load thresholds: above 0, above 70, and above 140. These categories do not have upper limits. If a cow experienced only one day above 0 heat load in the last week, her yield on the seventh day is 0.3% lower than a cow with no days of heat load in the previous week. If a cow instead experienced four days of heat load in the last week, she produces 1.2% less. A cow that has experienced a heat load above zero every day for a week produces 3.5% less on the seventh day. Taken to its extreme, a cow that has experienced a full week of heat load above 140 loses about 8% of their milk yield on the seventh day alone.

In Appendix D, we map the effect of heat stress across states. As in our sample-wide estimates, we see increasing losses at higher levels of heat load. More states experience significant losses during moderate- and extreme-stress days, and states' losses increase in magnitude as heat load increases. Some southern states such as South Carolina, Arkansas, Missouri, and Kentucky experience the highest losses from heat stress. North Dakota stands out as a state that has less heat stress during the summer but experiences a large loss from the heat stress that it does experience. Since those estimates do not incorporate the stress



(a) Heat Effects Across All Herds (b) Heat Effects Across Herd Size

Fig. 3. Impact of heat stress on same-day milk yield by heat load categories.
Note: Observations are an unbalanced panel at the cow-by-day level. Outcome is (log) total daily energy-adjusted milk yield. Daily county-level heat load is estimated by fitting a sine curve between the minimum and maximum THI and calculating the area above a critical threshold of 70 THI, which we divide into four bins. All models include the Wood lactation curve and year, herd, and calving month fixed effects as described in Eq. (1). We graph the linear combination of the same-day and six lagged coefficients and 95% confidence intervals using standard errors that are robust to clustering at the county level.

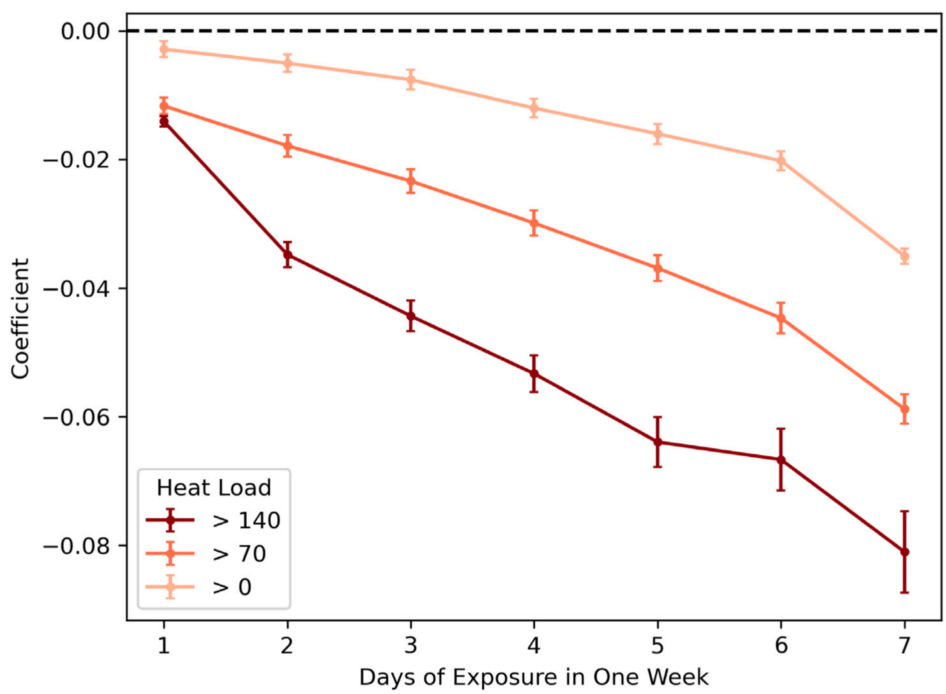


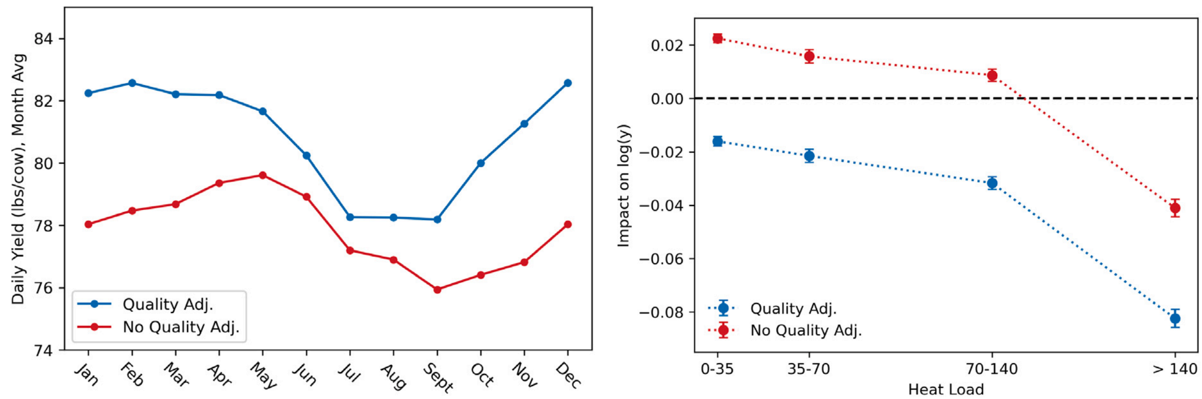
Fig. 4. Impact of heat stress in previous week by count of days with heat load above varying thresholds.
Note: Observations are an unbalanced panel at the cow-by-day level. Outcome is (log) total daily energy-adjusted milk yield. Daily county-level heat load is estimated by fitting a sine curve between the minimum and maximum THI and calculating the area above a critical threshold of 70 THI. We then count the number of days in the past week where daily heat load exceeded 0, 70, or 140 and include these as dummy variables (excluded category: no days). All models include the Wood lactation curve and year, herd, and calving month fixed effects as described in Eq. (1). We graph coefficients and 95% confidence intervals using standard errors that are robust to clustering at the county level.

in preceding days, the results may in part reflect higher frequency of consecutive heat days in these states.

3.2. Impact of heat stress with and without quality adjustment

Our data allows us to adjust for quality (i.e., fat and protein content). This is an advantage over aggregated data that reports milk yield in fluid measures (e.g., gallons or liters) without considering the quality of the components. These components are vital to fully understanding the impact of heat stress on milk production for two reasons. First, farmers are paid for milk based on components rather than solely on gallons of output (Nepveux, 2019). Thus, quality-adjusted milk better reflects the revenue that farmers receive. Second, most of milk's nutritional content is in its components, so quality-adjusted output better reflects the nutritional value of milk.

Fig. 5 panel (a) shows that there is seasonal variation in both quality-adjusted and non-quality-adjusted milk yield. While the warm months still show the lowest yield, the key difference is that yield without considering quality is significantly lower in the winter months than in the late spring. In contrast, quality-adjusted yield peaks in the winter months but declines significantly into a trough from July to September. Without adjusting for quality, milk production would appear to dip in the winter, which may underestimate the impacts of heat stress.



(a) Average Daily Yield Across Months (b) Heat Effects and Quality Adjustment

Fig. 5. Impact of heat stress on same-day milk yield with and without quality adjustment.
Note: Panel a estimates monthly averages across all milk readings in the sample using quality adjusted milk (i.e., adjusting for fat and protein content) and without quality adjustment (i.e., fluid volume only). Panel b observations are an unbalanced panel at the cow-by-day level. Outcome is (log) total daily energy-adjusted milk yield. Daily county-level heat load is estimated by fitting a sine curve between the minimum and maximum THI and calculating the area above a critical threshold of 70 THI, which we divide into four bins. All models include the Wood lactation curve and year, herd, and calving month fixed effects as described in Eq. (1). We graph the linear combination of the same-day and six lagged coefficients and 95% confidence intervals using standard errors that are robust to clustering at the county level.

In Fig. 5 panel b, we re-estimate the average impact of heat load over the following week without adjusting for milk quality. We now find significantly lower impacts of heat stress, and indeed find small positive impacts of low or even moderate heat stress. The positive impacts of moderate heat stress are modest (2% or less of a single day's yield), though they are statistically different from zero due to our large sample size. In this case, positive impacts are very likely due to the fact that they are relative to days with no heat load. Without adjusting quality, winter days would appear to be damaging to milk yield and so days with a moderate amount of heat load would appear to be good for milk yield by comparison. This confirms the intuition from Fig. 5 panel a, which is that using milk production data that are not quality-adjusted may lead to an underestimate of the true heat stress impact on dairy cow yield.

These results highlight the value of data that allows quality adjustment, as we use here. Omitting this information can lead to incorrect conclusions about the impact of extreme weather on dairy production. Our work suggests that previous work using milk yield that is not quality-adjusted may have underestimated the losses from heat stress both in terms of economic impact on farmers and the net nutrient availability. In Appendix E.4, we look more specifically at the effects of low THI on dairy production, broadly finding that there are no yield losses from cold stress in our sample, in contrast to what Gisbert-Queral et al. (2021) finds with state-level data. Though we cannot rule out losses from cold stress outside of our sample, particularly in regions with other breeds of cattle or different housing conditions, our results suggest that cold stress is not a major concern for our sample of dairy farms.

3.3. Heterogeneous impacts by herd size

Our results are not purely biological effects. Instead, they are the impacts of heat stress mitigated by management and capital investment made by farms to lessen heat stress. Fig. 3 panel (b) shows how the impact of heat load differs across herd sizes. We expect that larger dairy farms may have more resources to invest in machinery such as fans and sprinklers and should be the least impacted by heat stress.

Small farms are a critical part of the US dairy herd and are well represented in our sample. Fig. 6 charts the share of herds and production in our sample that fall in each size category. The majority of herds in our sample (61%) are under 100 head. An additional 26% are from 100–250 head. Fig. 7 maps the locations of these smallest herds (under 100 cows). Two things stand out. First, in absolute terms, more small herds are located in cooler regions like the Northeast and Minnesota.[7] Second, in terms of the share of total herds in a community, small herds are relevant across our sample area. Every state in our sample has at least one county where small herds make up more than 50% of all herds.

We also see considerable consolidation in our period. Herds under 100 head produced 19% of total production in 2012 but only 16% in 2016. Similarly, the share of production from herds from 100–250 head fell from 27% to 23%. Herds over 500 head increased their share of production from 38% to 46%.

Our estimates confirm that the effects of heat load are decreasing in herd size. In the week following a single day of heat stress, the smallest herds (0–100 cows) lose from 2.5%–3.9% of a single day's yield from a low-stress day and 5.1% from a moderate-stress day. In contrast, dairy farms with more than 250 cows experience no more than a 2% loss from low-stress days, and the largest herds in our sample, more than 500 cows, lose only 1% from a low-stress day.

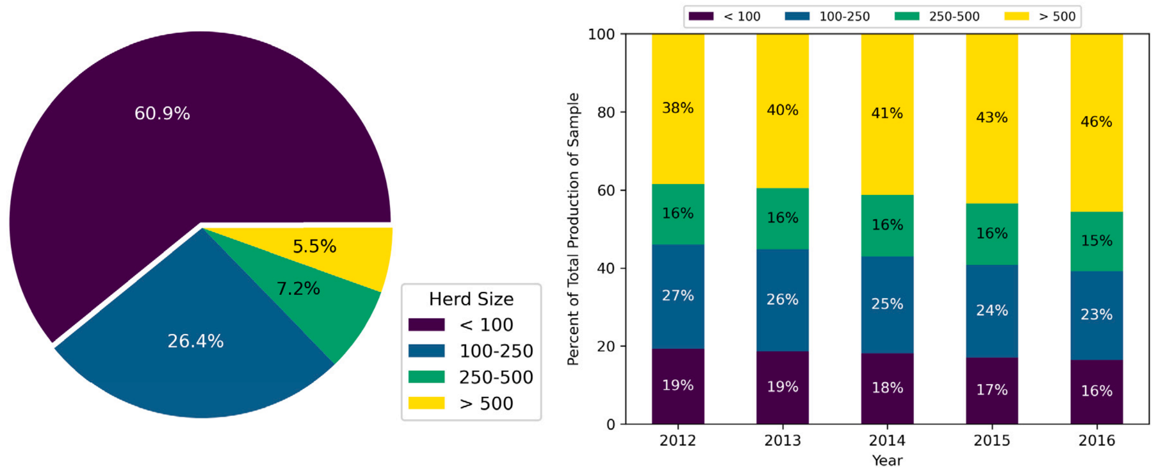
All herds experience larger drops in milk yield under extreme stress, though the differences across herd size persist. Herds under 100 cows lose 10% of a day's yield in the week following a day with extreme stress, while herds over 500 cows see a 6.8% drop in milk yield.

These findings emphasize the continued role of smallholder dairy farms in the US food system and the significance of their vulnerability to heat stress. Herds with less than 100 cows are still more than half of dairy operations in our sample, and their lack of resilience to heat stress suggests that more extreme heat events may accelerate the exit of small farms and thus contribute to farm consolidation.

3.4. Heterogeneous impacts by production stage

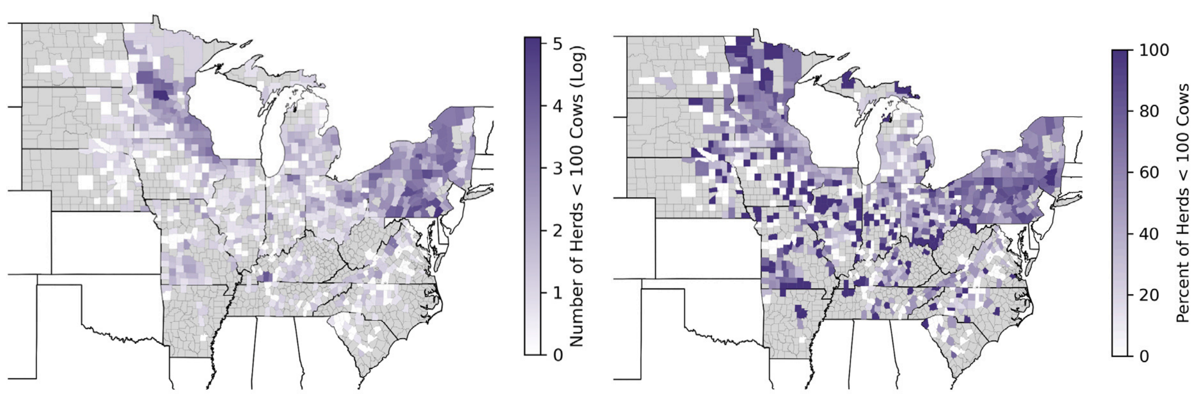
Next, we examine the impacts of heat stress on different cohorts of dairy cattle. After a cow gives birth, daily milk yield increases to its peak in the first four months before slowly declining over the last six months (making a typical production cycle ten months). Daily milk yield also increases with subsequent births, so a cow giving birth for the second time will have higher daily milk yield in most of its cycle than it did its first time. However, cows in these higher-yielding periods

[7] Though it is outside our sample region, Wisconsin's dairy industry is also characterized by a high number of small farms (Skidmore et al., 2023)



(a) Percent of Herds in Herd Size Category (b) Proportion of Production by Herd Size

Fig. 6. Herd Size Distribution in the Sample.
Note: Herd size is estimated across all herds participating in the Dairy Herd Improvement Association from 2012–2016. This sample has a larger average herd size than the US Agricultural Census and is more representative of professional milk producers.



(a) Number of Herds Under 100 Cows (b) Percent of Herds Under 100 Cows

Fig. 7. Distribution of Small Herds (Less than 100 Cows).
Note: Sample includes all herds participating in the Dairy Herd Improvement Association from 2012–2016. This sample has a larger average herd size than the US Agricultural Census and is more representative of professional milk producers.

are also more vulnerable to heat stress since a greater portion of their energy is being devoted to milk production.

Fig. 8 shows the cohort-specific cumulative losses in the week following a single day of heat stress. The cows in the highest-yield production stage, those with multiple births (“Multi”) and that are less than 120 days post-birth (“Early”), experience the highest losses due to heat stress. These cows lose 3.4–3.9% of a single day’s yield even under low-stress conditions and up to 11% of a day’s yield in the week following a day with extreme stress. Later in their cycle, cows with multiple births see at most a 1% loss from low- or medium-stress and 7% following a day of extreme heat.

In comparison, cows giving birth for the first time lose up to 3% from a day of low- or medium-stress and 7.7% in the week following a day of extreme stress. These results indicate that the average effects of heat stress are largely driven by cows in the most productive phase of the lactation cycle and by when in the year dairy farmers decide to breed cattle. They also indicate that calving patterns are an important determinant of the effects of heat stress on the dairy industry, as changing the time of year that cattle yield the highest may change how vulnerable farms are to heat stress.

3.5. *Current and projected losses from heat stress*

We find that an average of 1% of annual yield is lost to heat stress in our five-year period (Table 1). For our sample, which includes around 40% of herds from nineteen states, this amounts to a loss of 1.4 billion pounds of energy-adjusted milk over a five-year period.[8] At $20 per hundredweight, the average milk price in 2014, this is equivalent to $253 million in lost revenue over five years or $50.6 million in lost revenue per year on average. One-third (33%) of the total yield lost in our sample was due to cows that have given birth multiple times and are early in their cycle. These cows lose an average of 3.8% of annual yield to heat stress due to their higher relative and absolute losses.

We also find that the smallest herds in our sample shouldered a disproportionate amount of the losses. Herds with less than one hundred cows lost an average of 1.6% of annual yield. While these

[8] Our sample captures commercial milk producers with higher average herd size than the full set of dairies in the US Agricultural Census. In the 2017 Census, the average herd size in our sample states was 101 head. In our sample in 2016, the average herd size was 182 head.

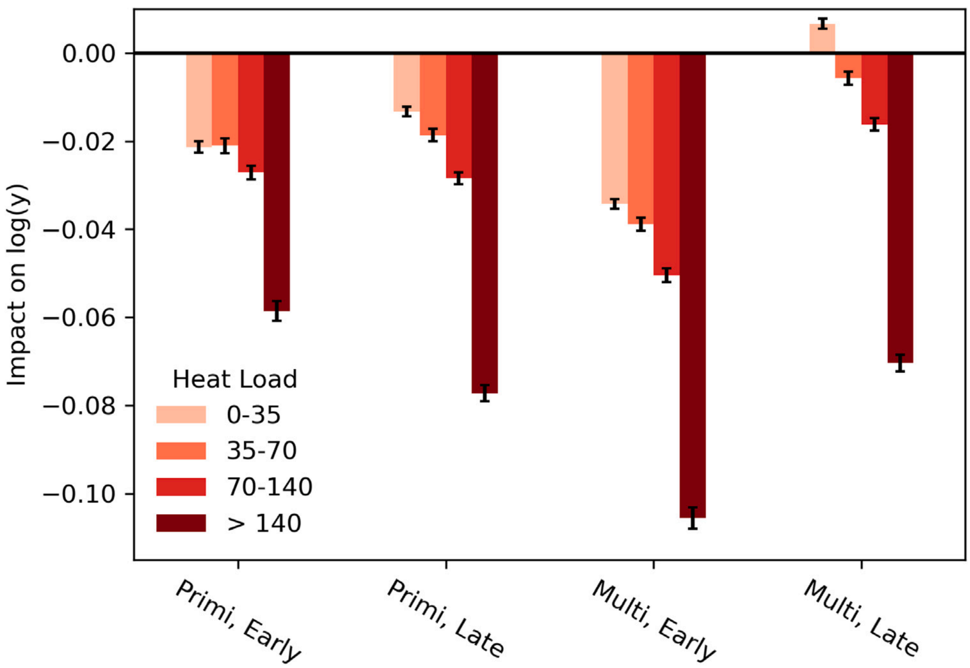


Fig. 8. Heterogeneous impact of same-day heat load on milk yield by lactation cycle and phase.
Note: Observations are an unbalanced panel at the cow-by-day level. Outcome is (log) total daily energy-adjusted milk yield. Daily county-level heat load is estimated by fitting a sine curve between the minimum and maximum THI and calculating the area above a critical threshold of 70 THI, which we divide into four bins. Cows are divided based on where they are in their lactation cycle (less than 120 post-birth, i.e., "Early", or more than 120 days post-birth, i.e., "Late") and whether it is their first lactation cycle ("Primi") or all subsequent cycles ("Multi"). All models include the Wood lactation curve and year, herd, and calving month fixed effects as described in Eq. (1). We graph the linear combination of the same-day and six lagged coefficients and 95% confidence intervals using standard errors that are robust to clustering at the county level.

Table 1
Estimated Total Damages from 2012 to 2016.

Heat Load	0–35	35–70	70–140	> 140	Total
All Cows					
% Reduction from 1 Day Exposure	1.61	2.20	3.17	8.24	
% Annual Yield Lost	0.21	0.18	0.30	0.32	1.01
Total Yield Loss, millions lbs	291.76	240.93	409.35	430.40	1,372.43
Revenue Loss ($20/cwt), million USD	52.10	43.02	73.10	76.86	245.08
Cows in the Most Productive Phase					
% Reduction from 1 Day Exposure	3.42	3.89	5.04	10.56	
% Annual Yield Lost	0.89	0.77	1.22	0.99	3.82
Total Yield Loss, millions lbs	107.63	93.25	148.01	120.66	469.54
Revenue Loss ($20/cwt), million USD	19.22	16.65	26.43	21.55	83.84
Smallest Herds (< 100)					
% Reduction from 1 Day Exposure	2.68	3.98	5.33	10.40	
% Annual Yield Lost	0.35	0.33	0.53	0.41	1.61
Total Yield Loss, millions lbs	79.91	77.21	123.16	95.54	375.83
Revenue Loss ($20/cwt), million USD	14.27	13.79	21.99	17.06	67.11

Note: Percent Reduction from 1 Day Exposure is the total losses over the following week, which we calculate as the sum of the day-of and lagged coefficients from Eq. (1) with six lags. Percent Annual Yield Lost is calculated as the sum of (Percent Loss × Number of Stress Days in Month × Number of Cows in County-Month/Total Cow-By-Day Observations) over all counties and months. Yield Loss is calculated as: the sum of (Percent Loss × Number of Stress Days in Month × Number of Cows in County-Month × 81.8) over all counties and months. Yield for the high-producing cows is assumed to be 97 lbs/cow, which is the sample average for multiparous cows early in their cycle. All values are estimated for our sample only, which represents around 50% of herds in nineteen states from 2012–2016.

farms only supply 16%–19% of the total output in the sample, they represent 27% of total damages. In contrast, the largest dairy farms produce 38%–46% of the total output but only represent 28% of the damages.[9] To put it in further perspective, one hundred cows in our sample are expected to lose nearly twice as much milk (50,449 lbs) per year on average if they are in a herd with less than one hundred cows compared to if they are in a herd of more than 500 (27,834 lbs). The higher vulnerability of small dairy farms in our sample thus explains a significant portion of the damages from heat stress.

Under current climate conditions, most of the losses are due to low- and moderate-stress days. Low-stress days (0–70 heat load) accounted for 38% of estimated losses, 30% of estimated losses were due to moderate-stress days (70–140 heat load), and 32% were due to extreme-stress days (> 140 heat load). This is due to the relative frequency of low- and moderate-stress events; the average county in our sample experienced 78 low-, 41, moderate- and 25 extreme-stress days per year. However, the yield loss per cow due to an extreme-stress day is more than double that of a moderate-stress day.

[9] This is despite the fact that smaller dairy farms have on average lower yield compared to larger dairies (69 lbs/cow on the smallest dairies versus 87 lbs/cow on the largest dairies). The full calculations for each size of herd can be found in the supplementary Table A1.

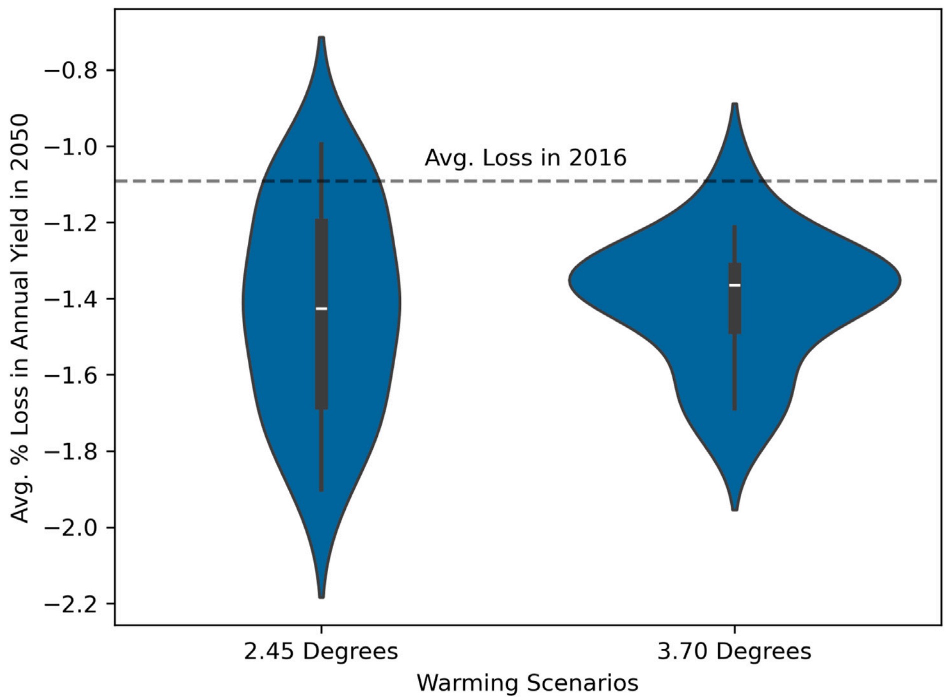


Fig. 9. Projected yield impacts in 2050 as a percent of annual yield.
Note: Predicted losses are based on our estimates of daily milk yield loss in response to current heat load as reported in Fig. 3 panel a, the total herd from the 2017 USDA Agricultural Census in our sample states, and potential heat load scenarios in 2050. Violin graphs represent the distribution of predicted losses based on twenty-two climate models under 2.45 and 3.7 degree warming scenarios.

Under most climate scenarios, days with extreme heat load will be much more frequent. Using twenty-two different climate models, we project yield losses in 2050 under 2.45 and 3.7 degree warming scenarios. For these projections, we calculate the average maximum and minimum THI for each county in our study states using average humidity, maximum temperature, and minimum temperature downscaled to a quarter-degree resolution.[10] We use the day-level projections to calculate the number of days in each heat stress category and multiply this by the current average yield, our calculated heat stress impacts from Fig. 3 Panel a, and the number of dairy cows in each county as reported in the 2017 Agricultural Census. Climate model projections are made available through the NASA Earth Exchange Global Daily Downscaled Projections dataset as part of the Coupled Model Intercomparison Project Phase 6 (NEX-GDDP-CMIP6) (Thrasher et al., 2022).

Fig. 9 shows violin plots of the projected yield impacts across all twenty-two climate models. We also include the average percent yield loss in 2016 using the 2017 USDA Census numbers which is around 1.1%. Both scenarios predict higher average yield losses in 2050 than in 2016. In the 2.45 degree scenario, the variance is much higher. Scenarios predict from less than 0.8% loss of annual yield to nearly 2.2% of annual yield. In the 3.7-degree scenario, the lowest predicted yield losses in 2050 are nearly that of the current yield loss in 2016.[11]

Table 2 shows the yield losses from each heat stress category in 2016 and the projected impact for 2050. The projected higher losses are primarily driven by more days with above 140 heat load. The damages from these days are projected to double relative to 2016.

Using the 2017 Agricultural Census numbers to project heat impacts assumes that our sample reflects the types of dairy farms in these counties. However, it is very likely that our sample over-represents larger farms. Since larger farms are less affected by heat stress, our projected impacts are likely lower than they would be in reality. Nevertheless, a variety of factors could lead to lower impacts in 2050 than what we calculate. Increasing consolidation in the dairy sector would lead to more farms being bigger, which would lead to lower heat stress impacts than we project here. If dairy farms made changes to calving patterns, we may also see less exposure to summer months in the most vulnerable period of dairy cow production.

4. Discussion and policy implications

Heat stress is a significant cost for dairy production in the United States, and the challenge is likely to increase as extreme heat becomes more frequent. Our results show that farms are not uniformly prepared for these events. In the United States, one of the most technically advanced dairy industries in the world, smaller herds are still vulnerable to extreme heat.

Our results likely underestimate the impact of heat stress on dairy producers worldwide. Dairy consumption already lags in low- and middle-income countries relative to high-income countries, and a warmer climate has been proposed as one of the drivers of this existing gap (Headey et al., 2024). Moreover, our results indicate the potential impact of dairy losses due to climate change on global nutrition could be significant. We find that the nutritional value of dairy (i.e., fat and protein content) suffers disproportionately to overall milk production (i.e., gallons of fluid milk) during heat events. These nutrients from dairy are vital to children and other physically vulnerable groups (Tricarico et al., 2020), and dairy consumption is shown to improve anthropometric outcomes for children (Mehrab Bakhtiar and Hoddinott, 2023; Ramahaimandimby et al., 2023). Heat stress may reduce the availability of dairy-provided nutrients in these regions even further than previous work suggests.

[10] Unlike our GRIDMET data, maximum and minimum relative humidity were not available for the CMIP-6 climate projections. For a complete list of our climate models, see Table F8 in Appendix F

[11] For a more detailed discussion of the differences in these scenarios, see Appendix F.

Table 2
Projected yield losses in 2050 and 2016.

Heat Load	0–35	35–70	70–140	> 140	Total
2016 Yield Loss (millions lbs)	178.41	171.31	366.82	295.19	1011.74
2050 Yield Loss (millions lbs)					
2.45 Scenario	182.26	146.26	337.35	627.82	1293.69
3.70 Scenario	178.63	150.99	359.06	603.96	1292.64
Avg Percent Additional Loss from 2016 to 2050	1.14	−13.24	−5.07	108.64	27.82

Note: The yield loss is calculated as: Percent Loss × Number of Stress Days in Month × Number of Cows in County-Month × average yield. Percent loss is based on the average loss also reported in Table 1 and Fig. 3 Panel A. Number of dairy cows in each county is based on the 2017 Agricultural Census, and average yield is estimated at 81.8 lbs/cow. Losses in 2050 are an average across 22 climate models for each scenario.

We find strong evidence that some farmers have adapted to low-stress since our average impacts are smaller than previous studies. The estimates from Ravagnolo et al. (2000) imply that a 10 unit increase in the THI index, equivalent to about a 70 point increase in heat load, should reduce the test-day milk yield by 7%. Accounting for a full week of lagged effects, we find that a 70-point heat load increase reduces milk yield of the average cow by 3% of a day's milk yield compared to no heat load and by 8% when increasing from moderate to extreme heat load. This could be attributed to investment in infrastructure such as sprinklers and fans as well as management practices such as timing of calving and timing of feeding during a heat event. Further research could clarify which of these practices provide the most resilience to heat stress and provide cost–benefit analysis for each practice under different climate scenarios.

This is in line with the work of Gisbert-Queral et al. (2021), who find evidence of adaptation in US dairy from 1981–1999 to 2000–2018. Gisbert-Queral et al. (2021) use 40 years of monthly state-level yield data and find that losses associated with moving from a no-stress THI bin (64.5–69.4) to the next two five-unit bins fell over the period. However, they found no reduction in losses associated with moving to the highest THI bin (over 80 THI), which reduced milk yield by an average of 3.7% in both 1981 and 2018.

Despite the potential for adaptation, there is no silver bullet to fully protect the dairy sector from heat stress. We find that, under extreme stress conditions, even cows on the largest farms suffer significant losses, showing that current management practices and technology cannot fully protect herds from heat stress. Indeed, the adaptive strategies available today each face significant constraints. We highlight the constraints of two adaptive strategies here. First, infrastructure investments like sprinklers prevent losses under low- and moderate-stress conditions and may explain some of the differences in losses between large and small farms in our data. However, sprinklers cannot prevent losses when relative humidity is sufficiently high, as evaporative cooling is no longer effective (Bohmanova et al., 2007). Second, our results show that multiparous cows lose the most yield to heat stress in both relative and absolute terms soon after they give birth. This suggests that the timing of calving to avoid the spring or summer months could reduce total losses from heat stress. However, this strategy may be impeded by labor constraints (e.g., not enough veterinarians to assist the entire herd delivering in a relatively short period) or infrastructure constraints (e.g., not enough calf housing on an individual farm to house the year's calves all in one period). While milking cows are relatively resilient to cold stress, calves are vulnerable to cold, so timing their birth after the summer may incur additional costs up to an increased risk of calf fatalities in cooler states (Hulbert and Moisá, 2016; Litherland et al., 2014).

How farmers are adapting to heat stress remains a key question to understanding the full impact of heat stress. First, an estimate of the impact of heat stress on profit requires understanding of the cost of adaptation. This includes, but is not limited to, investment, maintenance, and energy costs for cooling technology as well as potential changes in feed costs. Such an estimate is beyond the scope of this paper. As such, our results are limited to the impact of heat stress on revenue. Second, our projections of heat stress in 2050 are a worst-case scenario assuming no adaptation. Better adaptation measures that we cannot currently foresee will likely be developed in the future. Additionally, we assume that herd size remains fixed at 2017 levels. In reality, herd size has increased rapidly over the recent decades and is likely to continue on this trajectory. As we find that larger farms are less vulnerable to heat stress, our results would overestimate damages if more cows were in larger and more resilient herds by 2050.

Though beyond the scope of this paper, the relationship between dairy and climate change is complex due to the greenhouse gas emissions from the industry. Previous work on climate-smart dairy production has focused on how to measure and reduce the industry's contribution to greenhouse gas emissions (Gerber et al., 2011; Owen and Silver, 2015; Rotz, 2018; Crosson et al., 2011). Our work sheds light on climate-smart dairy through another lens: how the industry will be affected by climate change. The United States government, and many governments worldwide, are making investments to improve the resilience of the nation's food production to climate change. Should dairy be considered a policy priority, our results highlight two ways these resources could improve the resilience of dairy production. First, climate-smart dairy will require additional research to develop new adaptation methods. Second, technical and financial support to farmers will likely increase the adoption of new technology or practices. Our work also shows that small dairy farms currently lag in terms of resilience to extreme heat. If policymakers prioritize the continued existence of smallholder farms, these farms will require even greater targeted support to remain competitive in the face of climate change.

CRediT authorship contribution statement

Jared Hutchins: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Marin Skidmore:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Derek Nolan:** Resources, Methodology, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Appendix material, including additional results and robustness check, are available at https://doi.org/10.1016/j.foodpol.2025.102821.

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