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From satellites to the milking parlor: National Aeronautics and Space Administration prediction of worldwide energy resources as an information source for the national genetic evaluation of heat stress tolerance in Holstein and Gir cattle

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ABSTRACT

Heat stress is a major constraint to dairy productivity in tropical regions, where environmental conditions frequently exceed thermoneutral thresholds. The primary objective of this study was to quantify heat-related milk yield losses and estimate genetic parameters for thermotolerance in Brazilian Holstein and Gir cattle. In addition, because routine national genetic evaluations require complete and consistent environmental coverage, we evaluated the agreement between temperature-humidity index (THI) values derived from the National Aeronautics and Space Administration (NASA) prediction of worldwide energy resources (POWER) and those obtained from ground-based weather stations to determine whether satellite-based data can serve as a reliable alternative environmental input. The phenotypic dataset included 2,161,001 first-lactation test-day milk yield (MY) records from 253,972 Holstein cows across 1,013 herds and 155,816 first-lactation records from 20,388 Gir cows across 316 herds. Three datasets were created by linking MY records to THI values derived from public weather stations (WS), NASA POWER (NASA), or both (NASAWS), allowing direct comparisons of phenotypic and genetic inferences across data sources. Random regression models incorporating DIM and THI were used to estimate genetic parameters and breeding values for heat tolerance. Divergent estimates of MY decline were observed between ground- and satellite-based data, with maximum average losses ranging from −0.440 to −0.367 kg/d per THI unit in Gir and −1.562 to −0.522 kg/d in Holstein. For Holstein, a consistent heat stress threshold was detected at 67 THI units, while thresholds in Gir varied from 70 to 75.853 depending on the data source. In contrast, estimates of additive genetic variance, heritability, and genetic correlations were nearly identical across meteorological sources, and sire ranking showed high consistency. Posterior heritability means (95% high posterior density intervals) in Holstein were 0.230 (0.217–0.243) for WS and 0.231 (0.218–0.244) for NASAWS; in Gir, values were 0.231 (0.195–0.269) for WS and 0.229 (0.194–0.267) for NASAWS. The genetic correlation between intercept and slope was consistently negative in both breeds (ranging from −0.428 to −0.397 in Holstein and from −0.282 to −0.275), confirming the antagonism between general production level and thermotolerance. The use of NASA POWER enabled broader spatial and temporal coverage, improved genetic prediction accuracy, and facilitated the identification of heat stress thresholds and associated losses. These results support the adoption of NASA POWER as a reliable and scalable alternative for genetic evaluations of heat tolerance, especially in regions with limited ground-based meteorological infrastructure.

Key words: genotype by environment interaction, Gyr, random regression, temperature-humidity index, tropical environment

INTRODUCTION

Climate change continues to impose significant obstacles to the dairy industry worldwide (Cartwright et al., 2023; Giannone et al., 2023). Selection for improved heat stress tolerance in dairy cattle has been under development for more than 2 decades (Ravagnolo and Misztal, 2000; Misztal et al., 2025) and requires access to me-

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The list of standard abbreviations for JDS is available at adsa.org/jds-abbreviations-26. Nonstandard abbreviations are available in the Notes.

teorological information, particularly ambient temperature and relative humidity. These data can be collected directly on farms or obtained from nearby weather stations (Freitas et al., 2006) and are especially valuable for calculating the temperature-humidity index (**THI**). Linking test-day records to their corresponding THI values enables the identification of heat stress effects on animal performance at both the phenotypic and genetic levels (Misztal et al., 2025).

In 2018, the prediction of worldwide energy resource (**POWER**) team at the National Aeronautics and Space Administration (**NASA**)'s Langley Research Center (Hampton, VA) released the first version of its modernized geophysical data platform, which integrates Esri geographic information system tools. This web-based application offers access to both time-series and climatological datasets, covering periods from just a few days before real time back to the early 1980s, with high spatial resolution. These features represent a clear advantage over ground-based weather stations, which often suffer from data gaps and are limited to a few specific locations. In addition, NASA POWER data can be programmatically accessed through an application programming interface (**API**; Stackhouse, 2018). As a result, the use of NASA POWER data has gained prominence across various scientific disciplines, including dairy cattle genetic evaluations (Nguyen et al., 2017; Mbuthia et al., 2021; Rockett et al., 2023a).

Understanding the reliability and suitability of alternative meteorological data sources is essential for implementing breeding programs targeting improved heat stress tolerance. Thus, the primary objective of this study was to quantify heat-related milk yield losses and estimate genetic parameters for thermotolerance in Brazilian Holstein and Gir cattle. Because routine genetic evaluations depend on complete and consistent environmental coverage, we also examined the agreement between THI values derived from NASA POWER and those obtained from ground-based weather stations to verify the feasibility of using satellite-based information as an alternative environmental input in national evaluations.

MATERIALS AND METHODS

Holstein and Gir Data

The Holstein (*Bos taurus*) dataset was provided by the Brazilian Association of Holstein Cattle Breeders (Associação Brasileira de Criadores de Bovinos da Raça Holandesa, ABCBRH, Castrolanda, Paraná, Brazil). It comprised test-day milk yield records (**MY**, in kg) from first lactations of Holstein cows calving between 1993 and 2021, belonging to 1,013 herds located in 383 municipalities across 10 Brazilian states: Paraná (74.51% of total MY records), Minas Gerais (11.53%), São Paulo (7.23%), Rio Grande do Sul (3.55%), Goiás (1.94%), Santa Catarina (0.53%), Espírito Santo (0.39%), Pernambuco (0.18%), Rio de Janeiro (0.11%), and Sergipe (0.03%). These dairy herds represent the most intensive dairy production areas in Brazil. The southern region, characterized by a subtropical climate, accounted for 78.59% of all MY records. The southeastern states, with tropical highland or humid tropical climates, contributed 19.26%. The central-western region, predominantly characterized by a semihumid tropical climate, accounted for 1.94% of records. The northeastern region, mainly tropical Atlantic and semiarid, accounted for only 0.21%.

Herd management systems of Holstein farms were predominantly based on freestall housing with the use of concentrate feed, corn silage, and sugarcane supplemented with urea. In some areas (e.g., Minas Gerais and São Paulo states), rotational grazing systems were also adopted in combination with concentrate feeding. Most farms used mechanical ventilation systems, and the more technologically advanced operations additionally employed sprinkler systems. These environmental interventions are expected to mitigate, at least partially, the effects of heat stress on the animals evaluated.

The Gir (*Bos indicus*, called zebu) data used in the present study were provided by the Brazilian Zebu Breeders Association (Associação Brasileira dos Criadores de Zebu, ABCZ, Uberaba, Minas Gerais, Brazil). The dataset included MY records from the first lactations of purebred cows calving between 1990 and 2021. These animals belonged to 316 herds located in 205 municipalities across 16 Brazilian states. Of the total records analyzed, 62.66% originated from Minas Gerais, 14.74% from Goiás, and 13.62% from São Paulo. Thus, more than 90% of the Gir records came from regions with predominantly tropical highland, humid tropical, or semihumid tropical climates. In general, Gir herds are managed on *Brachiaria* spp. or *Panicum* spp. pastures, with seasonal or year-round supplementation. The level of technological adoption varies considerably by farm size and region. In semi-intensive or intensive systems, strategic supplementation includes high-energy concentrates, mineral mixes, silage (typically corn or sorghum), and sugarcane supplemented with urea. As the Gir breed is known for its high adaptability to tropical conditions, animals are typically only provided with shade as a means of alleviating heat stress. The geographic distribution of Holstein and Gir herds across Brazil is shown in Figure 1.

Quality Control of Phenotypic Data

Test-day records obtained between 5 and 305 DIM were used. Only cows with at least 3 individual MY records per lactation were included in the analyses, with

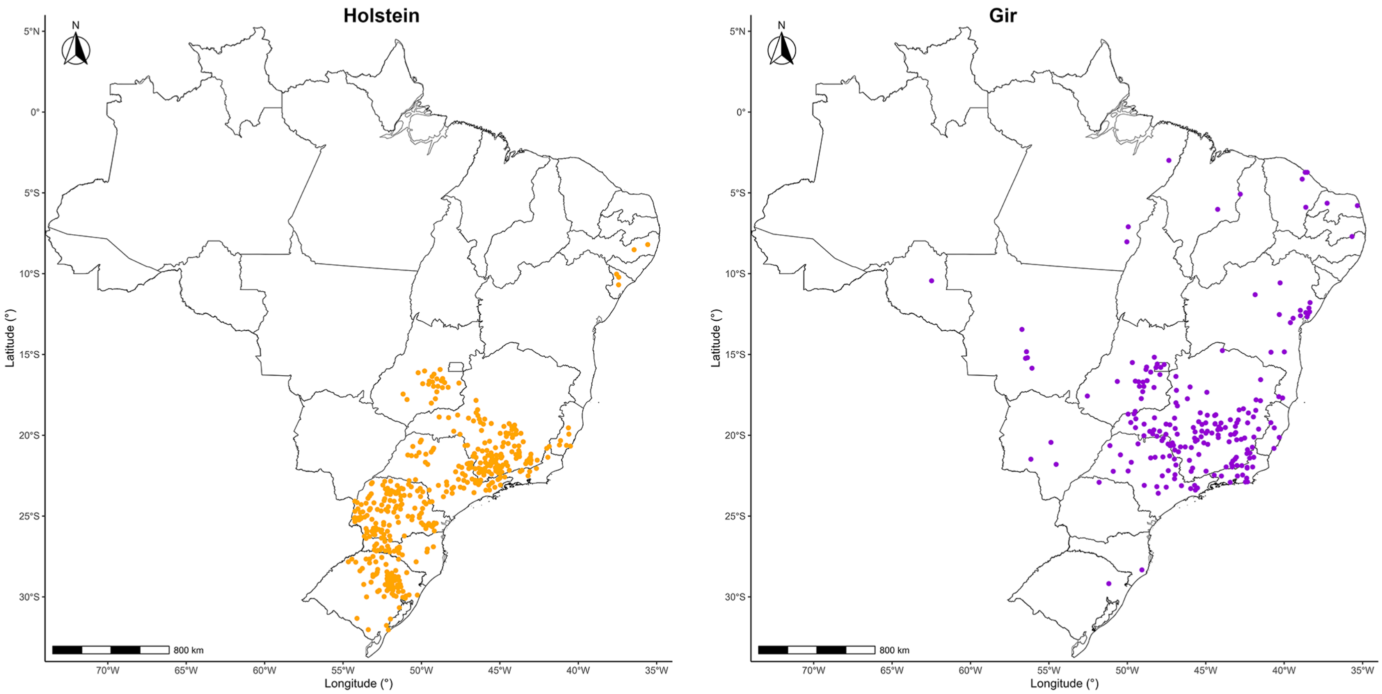

Figure 1. Spatial distribution of dairy herds from Holstein and Gir breeds across Brazil used in the genetic evaluation of heat stress tolerance.

the first milk test occurring within 45 d postpartum. Contemporary groups were defined as herd-test-date, with the restriction that each group must contain at least 3 animals. Test-day records deviating by more than ±3.5 SD from the mean of their respective contemporary group were excluded. For Holstein cows, age at first calving ranged from 18 to 48 mo, whereas for Gir cows, it ranged from 22 to 60 mo. All data quality steps were performed in R version 4.3.3 (R Core Team, 2025) using functions from the dplyr and tidyr packages within the tidyverse ecosystem. A detailed description of the datasets after quality control is provided in Table 1.

Meteorological Data

The environmental variables considered in this study were daily dry-bulb temperature (**T**, °C) and relative humidity (**RH**, %), obtained from 2 distinct data sources. The first source consisted of observed data from ground-based public weather stations operated by the Brazilian National Institute of Meteorology (Instituto Nacional de Meteorologia, INMET, Brasília, Distrito Federal, Brazil), made available through the Meteorological Database for Teaching and Research (Banco de Dados Meteorológicos para Ensino e Pesquisa – **BDMEP**; https://bdmep.inmet.gov.br/). The weather stations were located within a maximum distance of 150 km from the municipalities in which the herds were situated (Table 1). Temperature and RH were recorded hourly.

The second source comprised gridded meteorological data retrieved from the NASA POWER platform (https://power.larc.nasa.gov/), based on the geographic coordinates of each municipality where herds were located. Unlike the BDMEP dataset, which provides direct observational data from ground-based weather stations, NASA POWER data are generated through satellite remote sensing and assimilated reanalysis models. These estimates integrate satellite observations and outputs from numerical weather prediction systems, offering spatially continuous coverage, including areas with limited or no ground-based climatic monitoring. The NASA POWER data, specifically daily averages of T and RH, were programmatically accessed using the "nasapower" R package version 4.2.1 (Sparks, 2018), which interfaces with the platform's API to allow automated and reproducible data retrieval within the R programming environment (R Core Team, 2025).

In both meteorological datasets, average daily T and RH values were used to calculate the THI using the equation proposed by the NRC (1971): $THI = (1.8 \times T + 32) - [0.55 - (0.0055 \times RH)] \times (1.8 \times T - 26)$. This formula was selected due to its compatibility with the type of data typically recorded by Brazilian weather stations and its widespread use in studies addressing heat stress in livestock species.

For each MY, THI was calculated for the day of the test as well as for the 2 preceding days to account for the delayed physiological effects of heat stress. This approach

Table 1. Summary of data structure for test-day milk yield (MY) of Brazilian Holstein and Gir cattle[1]

	Holstein		Gir	
Item	WS and NASAWS	NASA	WS and NASAWS	NASA
Animals in the pedigree file (n)	313,601	372,300	34,515	36,680
Sires with progeny records (n)	5,189	6,765	1,020	1,083
Dams with progeny records (n)	130,991	172,325	8,183	8,802
Cows with phenotypic records (n)	190,158	253,972	18,380	20,388
Herds (n)	799	1,013	301	316
Contemporary groups (n)	52,974	87,383	12,374	13,729
MY (n)	1,564,612	2,161,001	137,981	155,816
Mean of MY (kg)	29.19	28.03	15.46	15.42
SD of MY (kg)	7.00	7.05	6.76	6.73
Minimum MY (kg)	3.06	3.00	0.50	0.50
Maximum MY (kg)	62.05	62.05	42.18	42.18
Municipalities of herds (n)	351	383	200	205
Municipalities of weather stations (n)	105	—	103	—
Average distance[2] (km)	40.45	—	58.11	—
SD of distance[2] (km)	23.64	—	39.02	—
Maximum distance[2] (km)	117.00	—	149.98	—
Mean of THI[2] (units)	64.66	65.72	71.79	70.43
SD of THI[2] (units)	5.82	5.91	3.96	3.92

[1]WS = THI derived from weather stations; NASAWS = subset comprising municipalities located near a weather station, but with meteorological data sourced from NASA POWER; NASA = full dataset comprising municipalities with meteorological data entirely sourced from NASA POWER; THI = temperature-humidity index.

[2]Values refer to THI obtained from the weather stations closest to the municipalities where the herds were located.

was based on previous studies that evaluated the impact of thermal stress on dairy cattle performance (Ravagnolo and Misztal, 2000). A preliminary comparison conducted in the Holstein dataset indicated that using the mean THI across the test day and the 2 previous days provided the best model fit, outperforming models based solely on the test day or on mean THI from 1, 3, or 4 d before the test, as assessed by the deviance information criterion (**DIC**; Spiegelhalter et al., 2002). Although this procedure was performed explicitly in the Holstein data, the same 3-d window was adopted for the Gir population based on biological plausibility and prior evidence for this breed, including the delayed heat stress responses reported for the same Gir population by Santana et al. (2015). The model applied in this stage of the study is detailed below (Equation 1). The distribution of MY records according to THI values is shown in Figure 2.

Comparison of Meteorological Data from Ground Stations and NASA POWER

For each dairy cattle dataset, 3 data subsets were created to compare ground-based and NASA POWER meteorological data for THI calculation, assess milk production losses due to heat stress, and evaluate genetic tolerance to heat stress in both populations. The first subset (THI derived from weather stations), hereafter referred to as **WS**, included all MY records that could be matched to THI values calculated using data from the nearest ground-based weather stations. In this case, due to the limited number of available weather stations, a portion of the phenotypic records was excluded due to missing meteorological information.

For the same subset of animals and MY records included in the WS dataset, corresponding THI values were also calculated using data retrieved from NASA POWER, resulting in a second dataset referred to as **NASAWS**. Thus, WS and NASAWS comprised identical phenotypic and animal records, differing only in the source of meteorological data used for THI calculation.

Finally, the third dataset, referred to as **NASA**, included all available MY records and their respective THI values calculated exclusively from NASA POWER data. In this case, no animal or phenotypic record was excluded, as the NASA POWER platform provided complete spatial and temporal coverage of the meteorological variables required for each herd municipality. Pearson correlations, mean bias error (**MBE**), root mean square error (**RMSE**), and herd-station distances were evaluated between THI values derived from WS and NASAWS data to assess the agreement between the 2 meteorological sources.

Milk Yield Losses Due to Heat Stress

Milk production losses attributable to heat stress were estimated for Holstein and Gir cows by fitting a random regression animal model to each population and weather dataset (WS, NASAWS, and NASA). We employed cubic Legendre orthogonal polynomials to model the additive genetic variance, permanent environmental variance, and

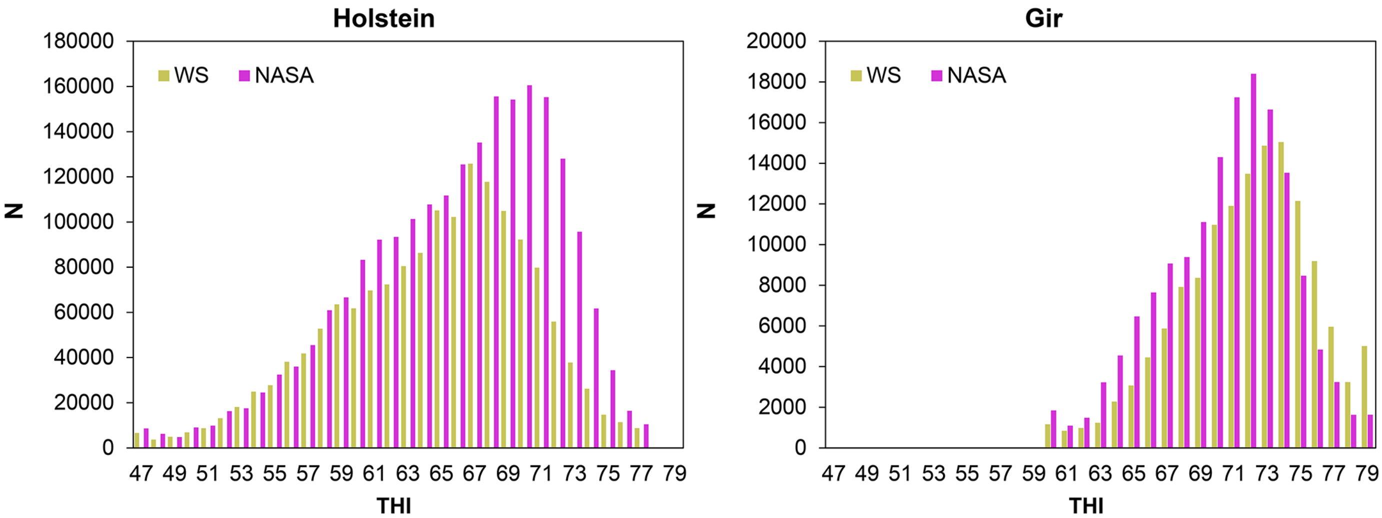

Figure 2. Distribution of test-day milk yield records (N) according to temperature-humidity index (THI) values based on ground weather stations (WS) and NASA POWER data.

the average population trajectory as functions of DIM. The programs GIBBSF90+ and BLUPF90+ (Misztal et al., 2014) were used to estimate (co)variance components and to obtain least squares estimates (**LSE**) of milk yield as a function of THI. The numerator relationship matrix (**A**) was constructed based on the pedigree information available for each dataset (Table 1). The model adopted can be described as follows:

$$MY_{ijqo(d)} = HTD_i + AD_{jo} + THI_q + \sum_{m=0}^{3} \beta_m \varphi_m(d) + \sum_{m=0}^{3} \alpha_{cm} \varphi_m(d) + \sum_{m=0}^{3} p_{cm} \varphi_m(d) + e_{ijqo(d)}, \quad [1]$$

where $MY_{ijqo(d)}$ is the test-day milk yield record; HTD_i is the effect of the ith subclass of herd-test-date; AD_{jo} is the systematic effect of the jth subclass of age of calving nested within class o of DIM (Holstein: 18–20, 21–23, 24–26, 27–29, 30–32, 33–36, 37–39, 40–45, 46–48 mo; Gir: 20–26, 27–32, 33–36, 37–39, 40–42, 43–51 mo); THI_q is the effect of the qth unit of THI (47 to 77 for Holstein and 60 to 79 for Gir); β_m is the mth "fixed" regression coefficient on DIM; α_{cm} and p_{cm} are the mth regression coefficients for random additive genetic and permanent environmental effects of cow c, respectively; $\varphi_m(d)$ is the mth Legendre orthogonal polynomial corresponding to day d of lactation; and $e_{ijqo(d)}$ is the residual effect associated with the record. The residual variance was assumed to be homogeneous. We acknowledge that residual heteroskedasticity across DIM or THI may occur under heterogeneous production environments, and evaluating models that accommodate such variation would be a valuable direction for future research.

Subsequently, a segmented linear regression model was applied to identify threshold points (breakpoints [**BP**]) in the relationship between MY and increasing levels of THI. Least squares estimates of MY for each THI class were used as the response variable. The "segmented" R package version 2.1.3 (Muggeo, 2003) was used to fit linear models with slope discontinuities at statistically identified BP. A single-breakpoint segmented structure was fitted consistently across WS, NASAWS, and NASA datasets within each breed. The segmented linear regression model can be described as follows:

$$y_q = a + b_1 X_q + e_q, \text{ when } X_q \leq \text{BP, and}$$

$$y_q = a + b_1 X_q + b_2(X_q - \text{BP}) + e_q, \text{ when } X_q > \text{BP},$$

where y_q is the LSE of the MY corresponding to the qth THI value; X_q is the qth THI value; a is the intercept; b_1 and b_2 are the regression coefficients (slopes) of the response variable on THI before and after the BP (heat stress threshold), respectively; and e_q is the residual term.

Estimation of Genetic Parameters

(Co)variance components and genetic parameters were estimated using a random regression animal model similar to that described in the "Milk Yield Losses Due to Heat Stress" section. However, in this case, the additive genetic effect, the permanent environmental effect, and the mean trajectory of the population were additionally modeled as functions of THI. As in the previous analysis, the residual variance was assumed to be homogeneous. Accordingly, EBV were expressed as a function of both

DIM and THI, as previously implemented in studies by Brügemann et al. (2011), Bohlouli et al. (2013), and Santana et al. (2017). The adopted model is specified as follows:

$$MY_{ijo(d,q)} = HTD_i + AD_{jo} + \sum_{m=0}^{3}\beta_m \varphi_m(d) + \sum_{m=0}^{3}\alpha_{cm}\varphi_m(d) + \alpha_{c4}\psi_1(q) + \sum_{m=0}^{3}p_{cm}\varphi_m(d) + p_{c4}\psi_1(q) + e_{ijo(d,q)}, \quad [2]$$

where α_{c4} is the random regression coefficient for the additive genetic effect of cow c; $\psi_1(q)$ is the Legendre orthogonal polynomial corresponding to the q value of THI; and p_{c4} is the random regression coefficient for the permanent environment effect of cow c. All other terms are defined as previously described.

The vector of additive genetic random regression coefficients is

$$\boldsymbol{\alpha}_c = [\alpha_{c0}\ \ \alpha_{c1}\ \ \alpha_{c2}\ \ \alpha_{c3}\ \ \alpha_{c4}]',$$

representing the intercept, first-, second-, and third-order Legendre terms for DIM and the first-order Legendre term for THI, respectively. Its (co)variance structure is $Var[\alpha_c] = \mathbf{G}$, where $\mathbf{G}$ is a 5 × 5 symmetric matrix:

$$\mathbf{G} = \begin{bmatrix} \sigma^2_{\alpha 0} & \sigma_{\alpha 0\alpha 1} & \sigma_{\alpha 0\alpha 2} & \sigma_{\alpha 0\alpha 3} & \sigma_{\alpha 0\alpha 4} \\ \sigma_{\alpha 0\alpha 1} & \sigma^2_{\alpha 1} & \sigma_{\alpha 1\alpha 2} & \sigma_{\alpha 1\alpha 3} & \sigma_{\alpha 1\alpha 4} \\ \sigma_{\alpha 0\alpha 2} & \sigma_{\alpha 1\alpha 2} & \sigma^2_{\alpha 2} & \sigma_{\alpha 2\alpha 3} & \sigma_{\alpha 2\alpha 4} \\ \sigma_{\alpha 0\alpha 3} & \sigma_{\alpha 1\alpha 3} & \sigma_{\alpha 2\alpha 3} & \sigma^2_{\alpha 3} & \sigma_{\alpha 3\alpha 4} \\ \sigma_{\alpha 0\alpha 4} & \sigma_{\alpha 1\alpha 4} & \sigma_{\alpha 2\alpha 4} & \sigma_{\alpha 3\alpha 4} & \sigma^2_{\alpha 4} \end{bmatrix}.$$

The permanent environment coefficients were modeled with the same 5 × 5 structure. After estimating the additive genetic and permanent environment (co)variance matrices, point heritability was computed for every desired combination of DIM and THI. Let $\mathbf{z}(d,q)$ be the vector that collects the orthogonal basis functions evaluated at a given combination of DIM and THI: $\mathbf{z}(d,q) = [0.7071\ \varphi_1(d)\ \varphi_2(d)\ \varphi_3(d)\ \psi_1(q)]'$, the additive genetic and permanent environment variances at (d,q) were computed as $\sigma^2_A(d,q) = \mathbf{z}'(d,q)\,\mathbf{G}\,\mathbf{z}(d,q)$ and $\sigma^2_P(d,q) = \mathbf{z}'(d,q)\,\mathbf{P}\,\mathbf{z}(d,q)$.

The point heritability was calculated as

$$h^2(d,q) = \frac{\sigma^2_A(d,q)}{\sigma^2_A(d,q) + \sigma^2_P(d,q) + \sigma^2_e}.$$

The genetic correlation between MY at DIM = d_1, THI = q_1 and MY at DIM = d_2, THI = q_2 was computed as

$$r_g\left[(d_1,q_1),(d_2,q_2)\right] = \frac{\mathbf{z}'(d_1,q_1)\,\mathbf{G}\,\mathbf{z}(d_2,q_2)}{\sqrt{\left[\mathbf{z}'(d_1,q_1)\,\mathbf{G}\,\mathbf{z}(d_1,q_1)\right]\ \left[\mathbf{z}'(d_2,q_2)\,\mathbf{G}\,\mathbf{z}(d_2,q_2)\right]}}.$$

The analyses were performed under a Bayesian framework. All priors followed the default specifications of the GIBBSF90+ program (Misztal et al., 2014), including inverse-Wishart priors for the (co)variance matrices. Each chain consisted of 350,000 samples, with a burn-in period of 50,000 samples and a thinning interval of 50. Convergence was assessed visually using trace plots to evaluate chain mixing. Posterior means and 95% highest posterior density intervals were computed from the remaining 6,000 posterior samples.

Implications of Different Meteorological Data Sources for Sire Selection

To assess potential differences in sire selection between Holstein and Gir cattle using alternative sources of meteorological data, we adopted the following procedures with the WS and NASAWS datasets. Holstein and Gir sires with at least 50 and 15 daughters with phenotypic records, respectively, were included in this analysis. The Spearman rank correlation was calculated for this sample of sires. Sires were ranked in descending order according to their solutions for the genetic linear heat stress coefficient, which were obtained using WS and NASAWS data. For this same sample of sires, the top 10% and 20% within each dataset were selected, corresponding to 79 and 175 Holstein sires and 10 and 17 Gir sires, respectively. The number of sires selected in common across WS- and NASAWS-based evaluations was then assessed for each breed separately.

To further evaluate the impact of including all available records in the genetic evaluation, the average number of daughters with MY records per sire and the change in mean accuracy of sires for the linear heat stress coefficient were examined for each population using WS- and NASA-based evaluations.

Genetic Trends

We calculated the genetic trends for Holstein and Gir cattle to examine whether ongoing selection for higher MY may have affected heat stress tolerance in both populations. To this end, we plotted the EBV for the intercept (general level of production) and the linear heat stress slope of the random regression model by year of birth. The analyses were carried out separately for each breed and for both meteorological datasets (WS and NASAWS).

RESULTS

Data Distribution

Holstein herds were predominantly concentrated in Brazilian states with milder climates, particularly in the southern and southeastern regions of the country (Figure 1). Approximately 86% of the MY records originated from the state of Paraná and the southern region of Minas Gerais. In contrast, Gir herds were more broadly distributed across regions characterized by predominantly hotter climates, including the Southeast, Midwest, Northeast, and Northern Brazil.

Milk Yield Losses Due to Heat Stress

Using the Holstein breed as a reference to determine the most appropriate time window to capture the delayed physiological effects of heat stress on MY, we observed that higher THI values on the test day (0 d) and on all preceding days evaluated (−1, −2, −3, −4, and −5) were associated with reductions in milk performance (Figure 3). However, the model that incorporated the average THI calculated over the test day and the 2 preceding days (i.e., a 3-d average) provided the best fit to the data. Consequently, this period was adopted for THI calculation in all subsequent analyses in this study. The DIC values for each period, expressed as deviation from the best model, were 0.0 (−2 d), 35.3 (0 d), 35.6 (−1 d), 73.7 (−4 d), and 104.9 (−3 d). The overall Pearson correlation between THI values calculated from WS and NASAWS sources was 0.920 for Holstein and 0.827 for Gir. State-level correlations, along with MBE, RMSE, and herd-station distances, are presented in Table 2. For Holstein, correlations ranged from 0.589 to 0.962 across states; for Gir, values ranged from 0.646 to 0.980. The MBE and RMSE also varied geographically, reflecting regional climatic and topographic differences. The inclusion of the average distance between each herd and its nearest weather station helps contextualize this variation in agreement metrics. Agreement between THI values derived from NASA POWER and those obtained from weather stations was further visualized using hexbin plots for Holstein and Gir (Figure 4). In both breeds, paired observations were predominantly concentrated along the 1:1 line, indicating close numerical correspondence across the observed THI range. Holstein records exhibited a narrow diagonal distribution with limited dispersion, whereas Gir records displayed a slightly broader pattern while maintaining the same overall alignment. These density patterns show that THI estimates from both meteorological sources followed similar numerical gradients for most test-day records.

A segmented regression model was fitted to the LSE of MY for Holstein and Gir cattle using each weather data source, as illustrated in Figure 5 and detailed in Table 3. In all scenarios, MY declined with increasing THI. For Holstein cattle, a clear heat stress threshold (BP) was successfully identified near 67 THI units across all weather data sources. In contrast, for Gir cattle, the identification of a breakpoint varied depending on the weather data used. When using WS data, no BP was detected, and a simple linear regression was fitted instead, implying that the entire observed THI range was within the critical zone of MY decline. However, BP were successfully detected when using NASAWS or NASA data, ranging from 70 to 75.853 THI units. Based on the critical THI range, from the identified BP to the maximum observed THI value (77 for Holstein and 79 for Gir), the estimated maximum average MY losses for Gir were −0.367, −0.482, and −0.440 kg/d using WS, NASAWS, and NASA, respectively. For Holstein, the corresponding maximum average losses were −1.562, −0.794, and −0.522 kg/d for WS, NASAWS, and NASA, respectively.

Genetic Parameters

The 95% high posterior density intervals for all (co)variance components largely overlapped across the different weather data sources within each breed (Figure 6). The genetic correlation between the intercept (representing the general production level of the animals) and the slope (specific response to heat stress) was consistently negative in both Holstein and Gir cattle. The posterior means of these correlations were −0.428, −0.397, and −0.413 for Holstein when using WS, NASAWS, and NASA data, respectively. For Gir, the corresponding posterior means were −0.282, −0.276, and −0.275 for WS, NASAWS, and NASA, respectively. Additionally, the average genetic slope-to-intercept ratio was greater in Gir (0.018) compared with Holstein (0.008).

The posterior means of additive genetic variance and heritability estimates for MY in Holstein and Gir cattle showed consistent patterns across DIM and THI levels. In general, the posterior means of additive genetic variance tended to decrease as THI increased in both populations (Figure 7). The estimates showed highly similar posterior means and 95% high posterior density intervals across the different meteorological data sources (WS, NASAWS, and NASA). For Gir, the 95% high posterior density intervals were consistently wider compared with those for Holstein. As observed for additive genetic variance, heritability estimates also showed a slight down-

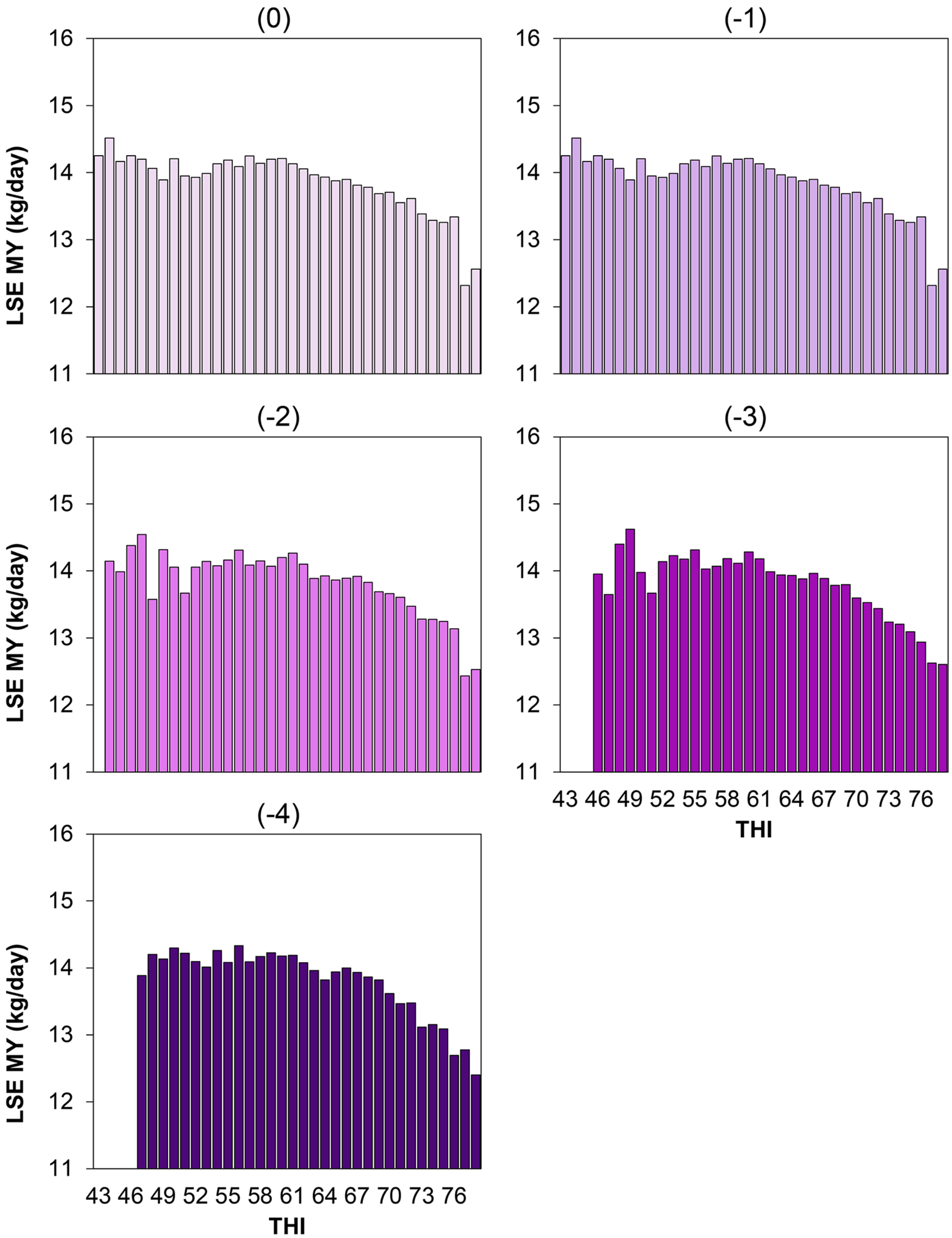

Figure 3. Least squares estimates (LSE) of milk yield (MY) for Holstein cows in relation to temperature-humidity index (THI) values recorded on the test day (0) and preceding days (−1, −2, −3, and −4).

ward trend with increasing THI across all weather data sources (Figure 8). Heritability estimates based on WS and NASA data were in near-perfect agreement, with simple correlations of 0.99 for the posterior means of additive genetic variance and heritability across DIM–THI combinations. Posterior means and 95% high posterior density intervals for heritability in Holstein were 0.230 (0.217 to 0.243) for WS, 0.231 (0.218 to 0.244) for NASAWS, and 0.244 (0.234 to 0.255) for NASA. In Gir, the corresponding values were 0.231 (0.195 to 0.269) for WS, 0.229 (0.194 to 0.267) for NASAWS, and 0.224 (0.193 to 0.257) for NASA.

Table 2. State-level Pearson correlations, mean bias error (MBE), root mean square error (RMSE), and average herd-station distance (km) between temperature-humidity index values derived from ground-based weather stations and NASA POWER

	Holstein				Gir			
State	Correlation	MBE	RMSE	Average distance	Correlation	MBE	RMSE	Average distance
Bahia	—	—	—	—	0.814	−0.705	2.493	66.7
Ceará	—	—	—	—	0.646	−0.599	0.809	10.2
Distrito Federal	—	—	—	—	0.826	0.154	1.476	8.1
Espírito Santo	0.664	3.168	5.262	15.9	0.796	−0.233	2.369	78.3
Goiás	0.815	1.675	2.605	8.5	0.787	−3.148	3.633	50.4
Minas Gerais	0.850	0.040	2.237	49.2	0.831	−1.177	2.487	61.3
Mato Grosso do Sul	—	—	—	—	0.956	0.050	1.569	9.4
Mato Grosso	—	—	—	—	0.843	−0.896	1.768	37.6
Pará	—	—	—	—	0.814	−2.090	2.630	111.2
Pernambuco	0.906	−2.310	2.561	67.6	—	—	—	—
Paraíba	—	—	—	—	0.922	−0.415	0.930	18.1
Piauí	—	—	—	—	0.848	−0.893	1.452	6.0
Paraná	0.945	1.707	2.577	28.7	0.778	−1.147	2.696	58.2
Rio de Janeiro	0.738	6.446	7.839	28.3	0.748	1.068	4.045	30.3
Rio Grande do Norte	—	—	—	—	0.750	−1.356	1.865	25.1
Rio Grande do Sul	0.962	−0.067	1.998	33.2	0.980	−0.676	1.200	5.0
Santa Catarina	0.958	0.313	2.035	37.3	—	—	—	—
Sergipe	0.589	−0.109	2.170	27.6	—	—	—	—
São Paulo	0.894	0.933	2.513	49.4	0.904	−0.755	2.072	66.3

The estimates of genetic correlations for MY across the 2 meteorological data sources, WS and NASAWS, showed clear and consistent patterns in both Holstein (Figure 9) and Gir (Figure 10) populations. The Pearson correlation between the genetic correlation estimates obtained using WS and NASAWS data was 0.99. Within each breed and data source, genetic correlations were higher for comparisons involving combinations with similar DIM and THI, decreasing progressively as differences in DIM or THI increased. For Holstein, genetic

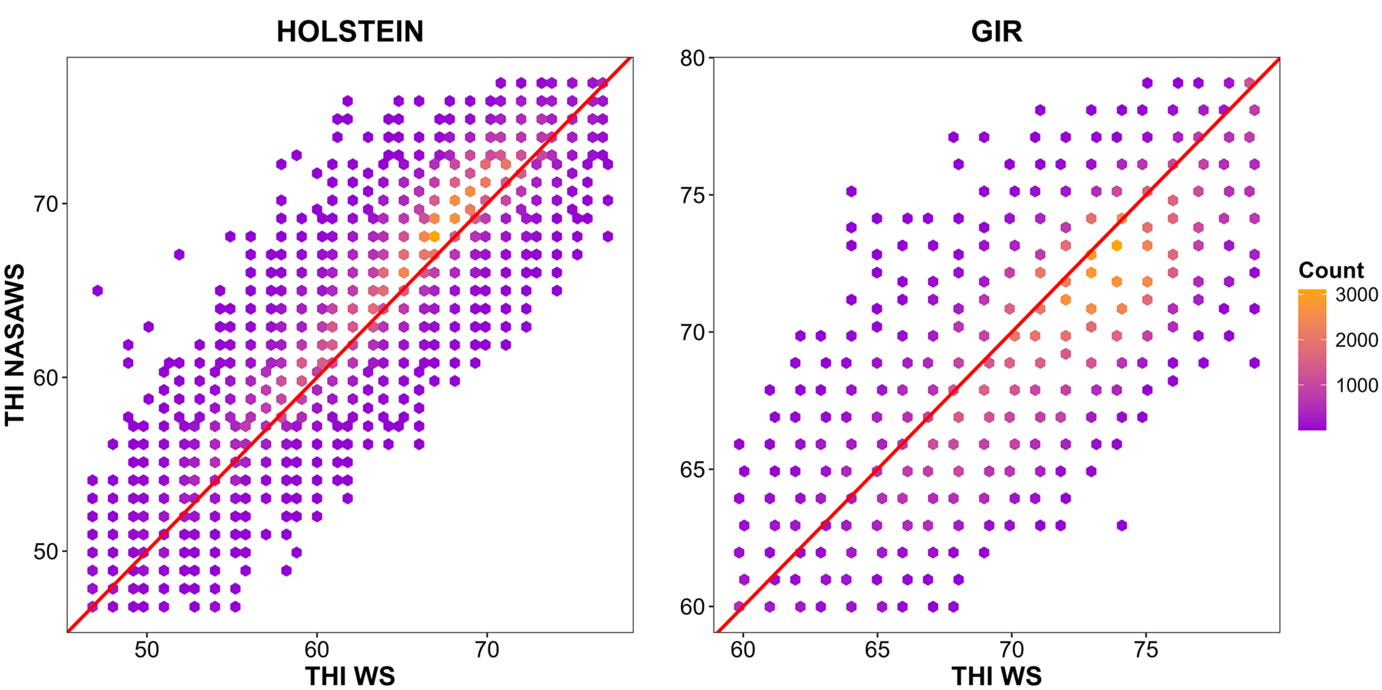

Figure 4. Hexbin plots illustrating the agreement between temperature-humidity index (THI) values derived from ground-based weather stations (WS) and NASA POWER data restricted to the spatial domain of weather stations (NASAWS) for Holstein and Gir cattle.

Table 3. Estimates (SE) of the intercept (a) and regression coefficients (b_1 and b_2) describing the relationship between least squares milk yield means and temperature-humidity index, obtained from segmented and simple linear models for Holstein and Gir cattle[1]

Breed	Data	Breakpoint	a	b_1	b_2	P-value	R^2
Holstein	WS	67.493 (0.674)	15.120 (0.297)	−0.007 (0.005)	−0.164 (0.017)	0.000	0.939
	NASAWS	67.500 (1.100)	15.299 (0.025)	−0.011 (0.004)	−0.084 (0.014)	0.000	0.891
	NASA	66.798 (2.077)	14.430 (0.316)	−0.008 (0.006)	−0.051 (0.015)	0.007	0.727
Gir	WS	NA	7.416 (0.162)	−0.019 (0.002)	NA	0.000	0.794
	NASAWS	70.000 (2.149)	6.094 (0.908)	0.001 (0.014)	−0.054 (0.020)	0.020	0.656
	NASA	75.853 (0.827)	6.625 (0.412)	−0.008 (0.006)	−0.140 (0.051)	0.012	0.689

[1]a = intercept; b_1 and b_2 = linear coefficients for each segment; NA = not applicable, because only a simple linear model was fitted.

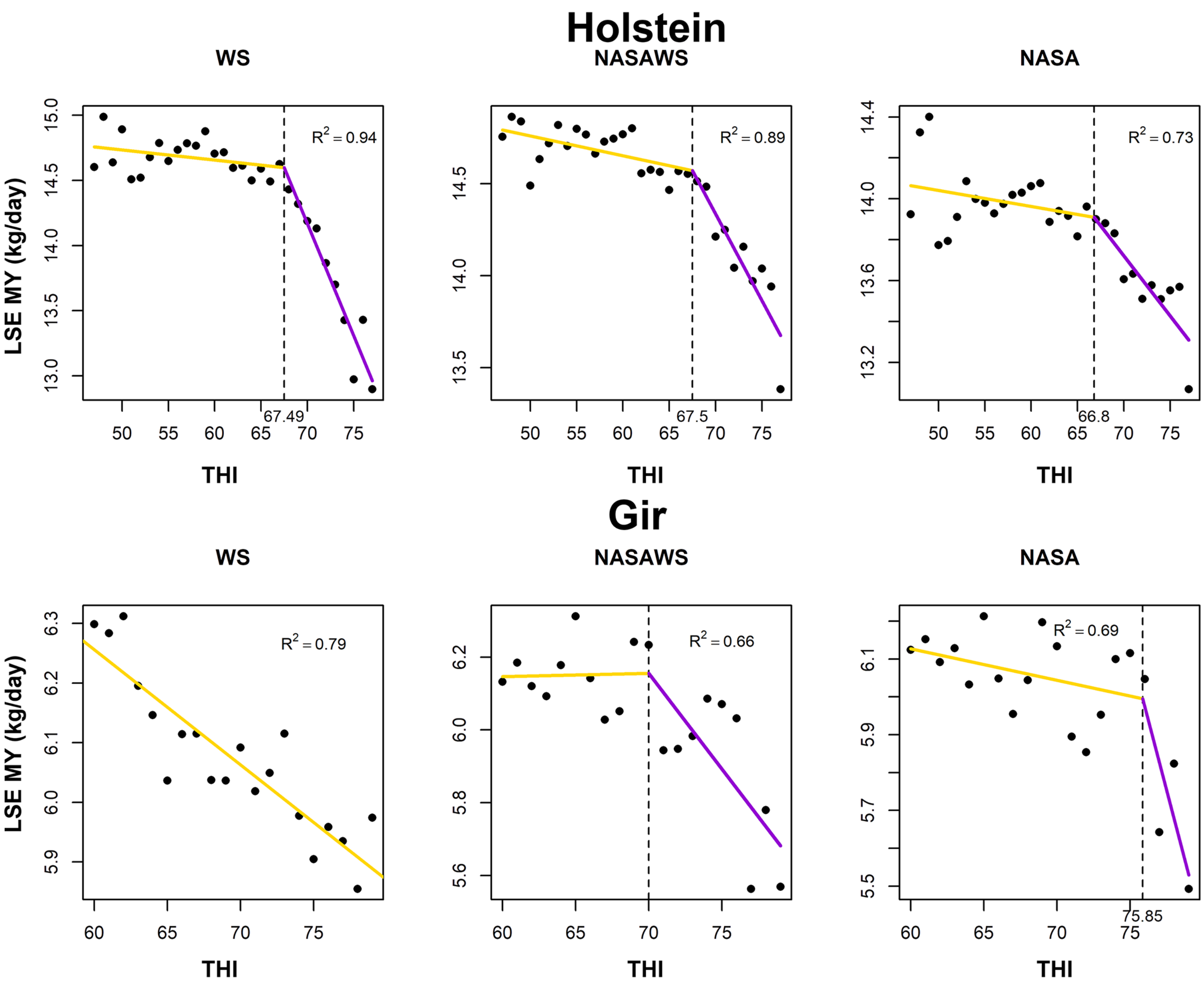

Figure 5. Segmented or simple linear regression models fitted to least squares estimates (LSE) of milk yield (MY) across temperature-humidity index (THI) values for Holstein and Gir cattle using meteorological data from ground-based weather stations (WS), NASA POWER restricted to the WS spatial domain (NASAWS), and full-coverage NASA POWER (NASA).

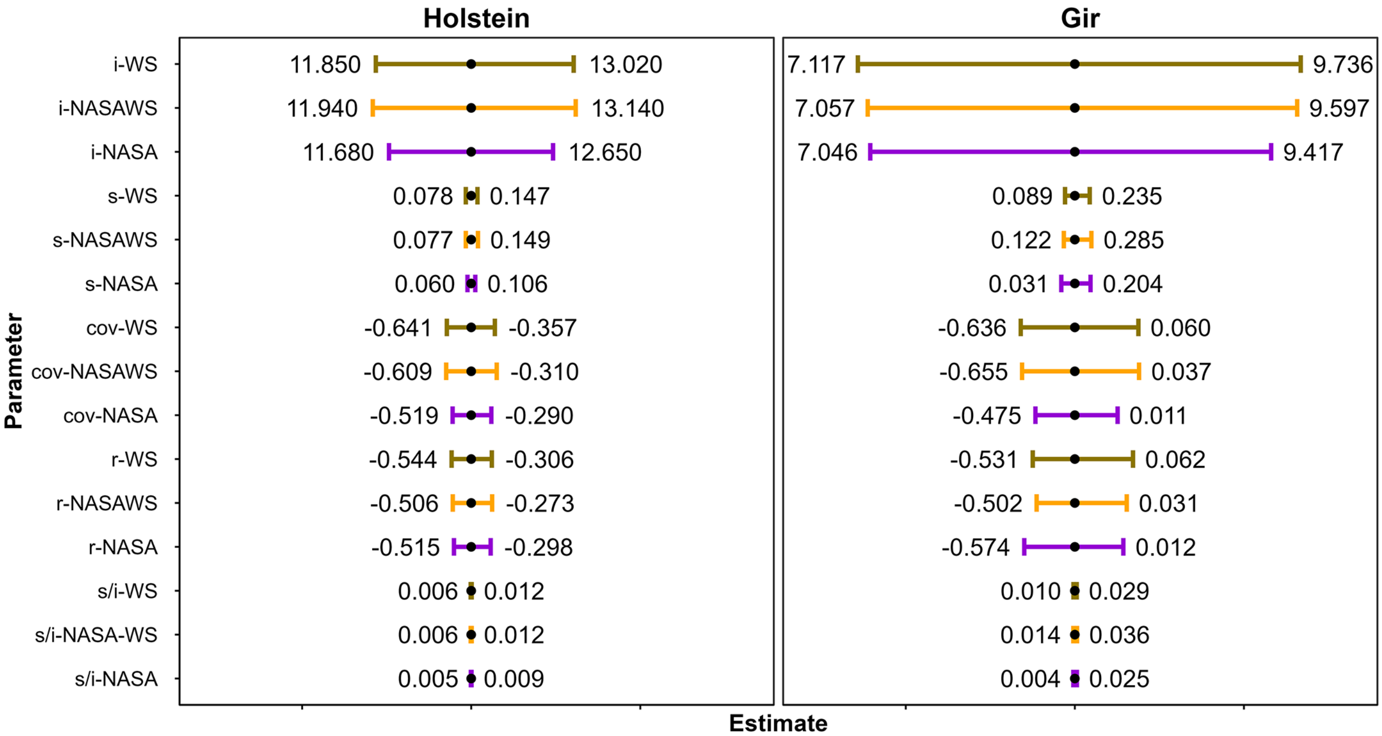

Figure 6. Posterior means (dots) and 95% high posterior density intervals (horizontal lines) for (co)variance components estimated using random regression models incorporating both DIM and temperature-humidity index as covariates for Holstein and Gir data. Results are presented for 3 meteorological data sources: ground-based weather stations (WS), NASA POWER restricted to the spatial domain of WS (NASAWS), and full-coverage NASA POWER (NASA). i = intercept; s = slope; cov = genetic covariance between intercept and slope; r = genetic correlation between intercept and slope; s/i = slope-to-intercept ratio.

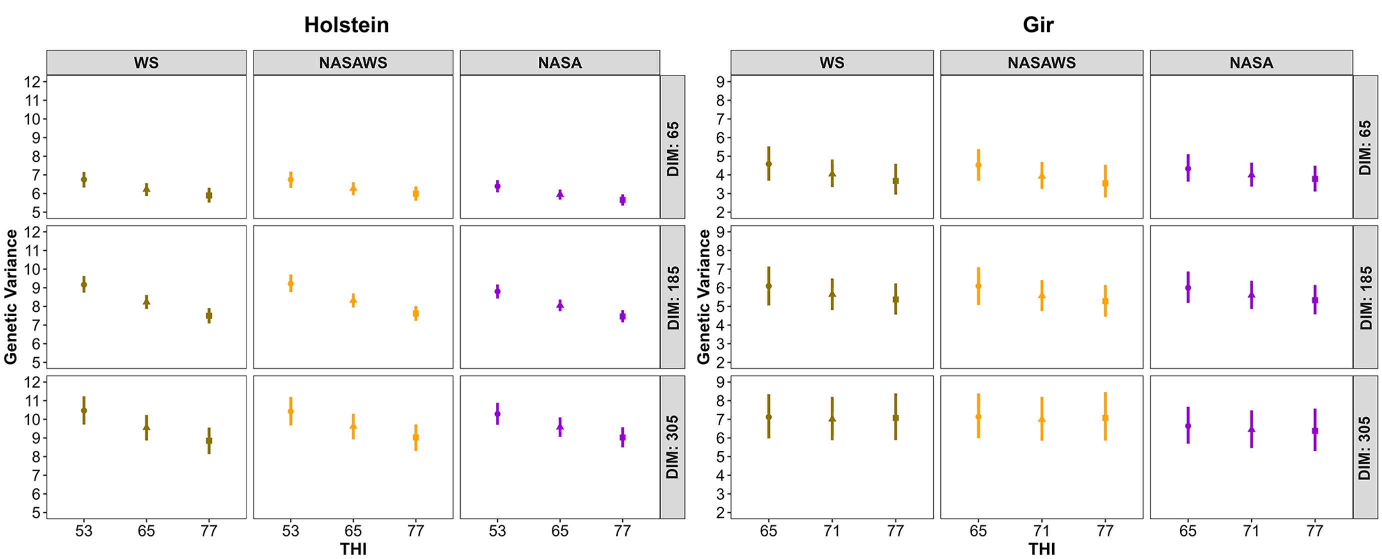

Figure 7. Posterior means (symbols) and 95% high posterior density intervals (vertical lines) of additive genetic variance estimates for test-day milk yield across selected combinations of DIM and temperature-humidity index (THI) in Holstein and Gir cattle. Results are presented for 3 meteorological data sources: ground-based weather stations (WS), NASA POWER restricted to the spatial domain of WS (NASAWS), and full-coverage NASA POWER (NASA).

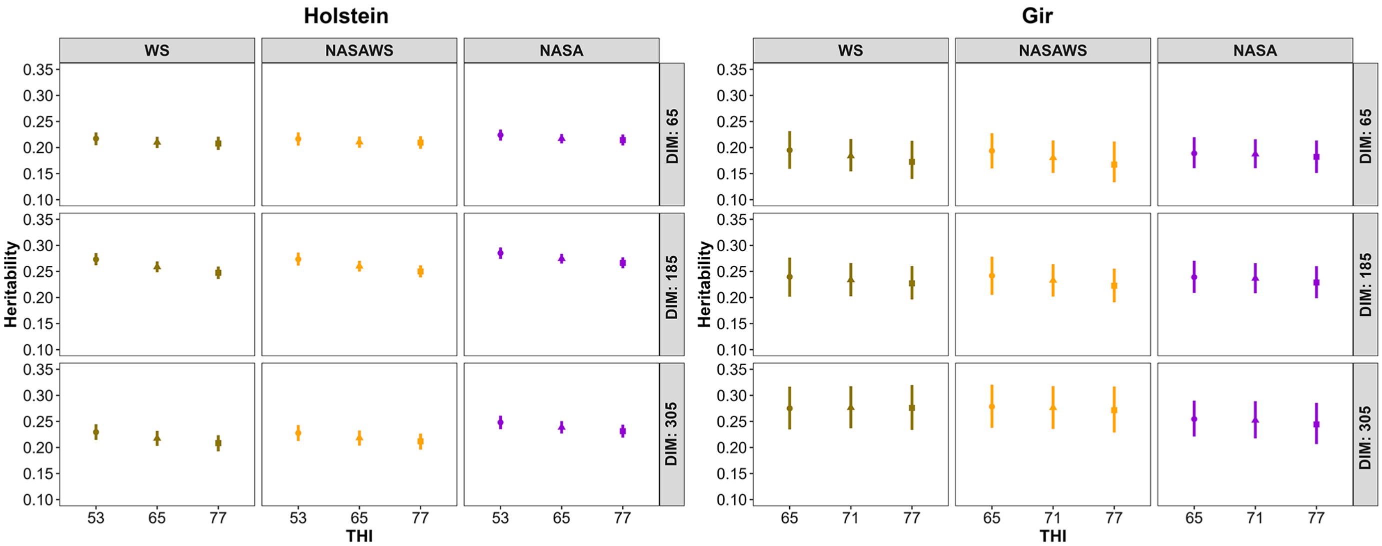

Figure 8. Posterior means (symbols) and 95% high posterior density intervals (vertical lines) of heritability estimates for test-day milk yield across selected combinations of DIM and temperature-humidity index (THI) in Holstein and Gir cattle. Results are presented for 3 meteorological data sources: ground-based weather stations (WS), NASA POWER restricted to the spatial domain of WS (NASAWS), and full-coverage NASA POWER (NASA).

correlations calculated using WS data were close to unity when DIM and THI combinations were identical or very similar. For example, correlations between DIM 65 and THI 53 with DIM 65 and THI 59 were 0.998 (WS). As differences increased, either in DIM or THI, correlation estimates decreased notably. For instance, correlations between DIM 65 and THI 47 with DIM 305 and THI 77 dropped markedly, reaching 0.639 (WS). A similar pattern was observed using NASA-derived (NASAWS) data, where the correlation between DIM 65 and THI 53 with DIM 305 and THI 77 was 0.633, closely matching the WS estimates. For Gir cattle, the same general trends were observed. Within WS data, correlations at identical DIM and THI were again very high; for example, DIM 65 and THI 71 with DIM 65 and THI 74 had a genetic correlation of 0.998. Conversely, correlations significantly

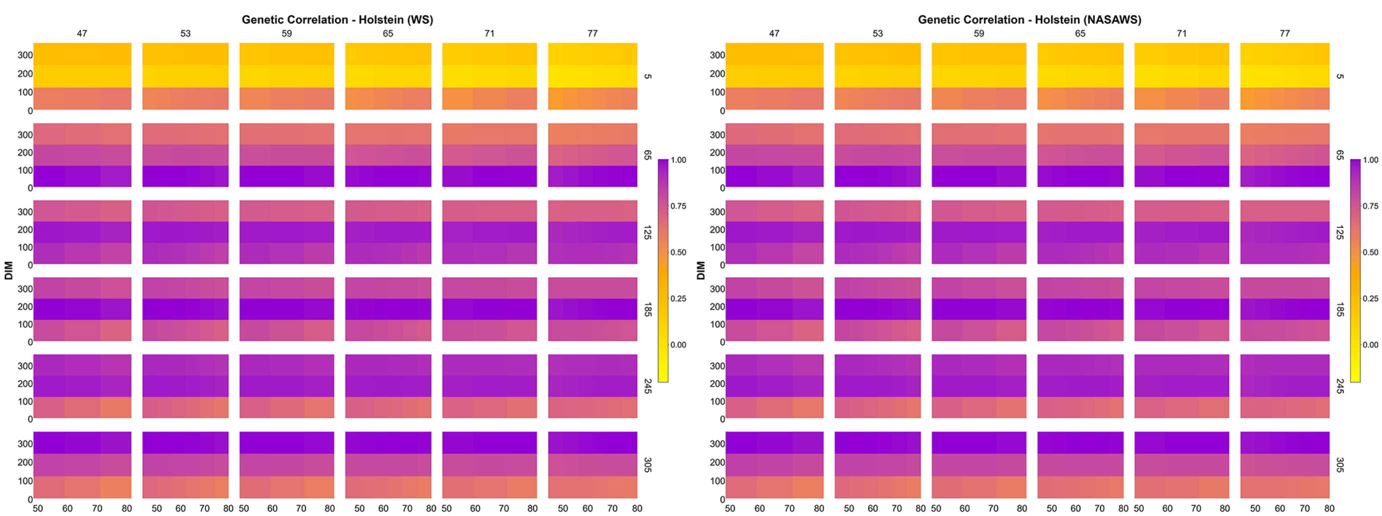

Figure 9. Posterior means of the genetic correlation estimates for milk yield across selected combinations of DIM and temperature-humidity index (THI) in Holstein cattle, estimated using data from ground-based weather stations (WS) and NASA POWER restricted to the spatial domain of WS (NASAWS).

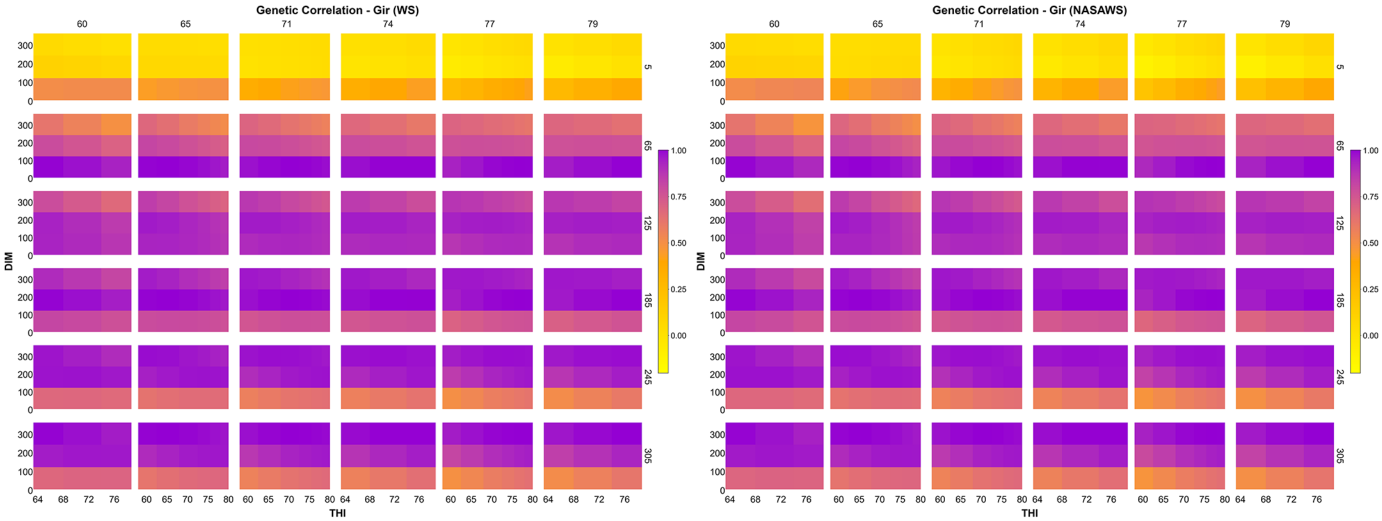

Figure 10. Posterior means of the genetic correlation estimates for milk yield across selected combinations of DIM and temperature-humidity index (THI) in Gir cattle, estimated using data from ground-based weather stations (WS) and NASA POWER restricted to the spatial domain of WS (NASAWS).

decreased when DIM and THI differences increased. For instance, correlations between DIM 65 and THI 60 with DIM 305 and THI 77 reduced to 0.494 (WS). This pronounced reduction in Gir correlations under greater DIM and THI differences was also mirrored in NASAWS data, which exhibited even lower estimates, such as 0.479 between DIM 65 and THI 60 compared with DIM 305 and THI 77. Overall, the pattern of decreasing genetic correlations with increasing differences in DIM or THI, or both, was consistent between breeds, yet the magnitude of decrease was more pronounced in Gir than in Holstein cattle, particularly at combinations involving advanced lactation stages and more stressful thermal conditions (higher THI).

As observed for genetic correlations, the posterior estimates of permanent environmental correlations between MY records across various combinations of DIM and THI exhibited clear and consistent patterns for both Holstein (Supplemental Figure S1, see Notes) and Gir (Supplemental Figure S2, see Notes) cattle. Estimates obtained using WS and NASAWS data sources were similar within each breed (Pearson correlation of 0.99). In general, the highest correlations, frequently exceeding 0.95, were observed between records with comparable DIM and THI conditions. Conversely, as the temporal and climatic distance between records increased, the correlations progressively declined, often falling below 0.50 when contrasting early-lactation, low-THI records with late-lactation, and high-THI records. Holstein cattle tended to present slightly higher average estimates and a more gradual decay in correlation across DIM–THI combinations compared with Gir.

Implications of Different Meteorological Data Sources for Sire Selection

Selection of the top 10% and 20% of sires based on the linear heat stress coefficient resulted in 81% and 77% of the same Holstein bulls being selected across both the WS- and NASAWS-based evaluations, respectively. For the Gir population, the corresponding proportions of common sires selected were 100% and 85%, respectively. The Spearman rank correlation for the sire rankings between WS and NASAWS was 0.97 for Holstein and 0.96 for Gir.

The average number of daughters with MY records per sire increased from 36.59 to 46.70 when comparing WS- and NASA-based evaluations in Holstein, resulting in an average gain of 34.65% in sire accuracy for the linear heat stress coefficient. In Gir cattle, the average number of daughters per sire increased from 18.01 to 19.82, corresponding to a 9.47% increase, which led to a 24.22% improvement in the accuracy of the linear heat stress coefficient for Gir sires.

Genetic Trends

Genetic trends derived from WS- and NASA-based evaluations were nearly identical for both the intercept and the slope in the Holstein population (Figure 11). In contrast, the Gir population showed slight discrepancies in the genetic trend for the linear heat stress coefficient in more recent years, whereas the trends for the intercept remained nearly identical, as observed in Holstein. In both populations, the slope estimates associated with

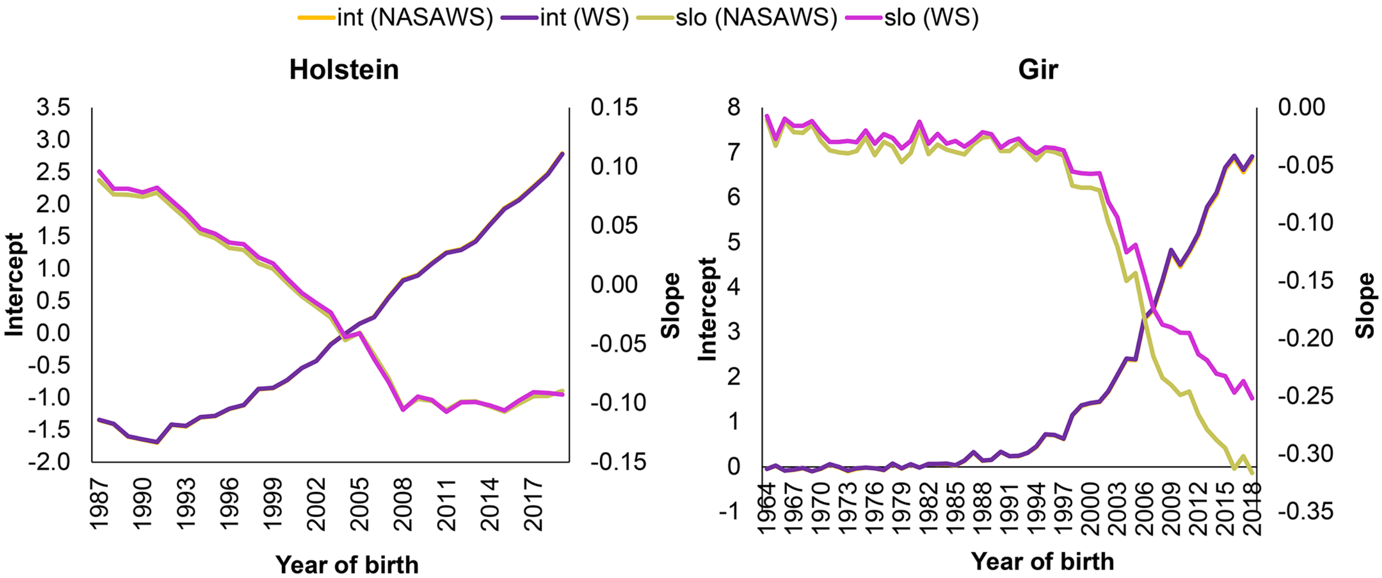

Figure 11. Genetic trends for heat stress tolerance (linear heat stress slope; slo) and general milk production level (intercept; int) in Holstein and Gir cattle, based on data from ground-based weather stations (WS) and NASA POWER restricted to the spatial domain of WS (NASAWS).

heat stress showed a declining trend over time. This reduction was more evident in Holstein until around 2008, whereas in Gir, the decline became apparent beginning in the early 1990s. For the intercept, Holsteins exhibited a nearly linear increase across birth years, while in Gir cattle, the most noticeable improvement in intercept estimates occurred from the 1990s onward.

DISCUSSION

Mitigating the economic losses caused by heat stress on dairy cattle performance has become an increasingly important concern among stakeholders. In this context, genetic selection for improved heat tolerance is widely recognized as a valuable strategy to address this challenge (Ravagnolo and Misztal, 2000; Carabaño et al., 2019; Misztal et al., 2025). The need for a genetic evaluation system capable of identifying the thermotolerance potential of dairy cattle in tropical regions was the primary motivation for the present study.

We analyzed all official MY records available for Holstein and Gir dairy cattle in Brazil, representing 2 genotypes with contrasting thermotolerance profiles. This contrast was clearly reflected in the geographic distribution of herds: Holstein herds were concentrated in the milder southern regions of the country, whereas Gir herds were more broadly distributed across hotter regions. Despite the recognized adaptation of zebu cattle to tropical conditions (Cardoso et al., 2015), adverse effects of heat stress on MY were observed in both breeds regardless of the meteorological data source used. Srikandakumar and Johnson (2004) reported significant reductions in milk yield in Holstein, Jersey, and Australian Milking zebu cows exposed to heat stress, along with physiological changes such as increased rectal temperature, respiratory rate, and altered blood parameters. However, Australian Milking zebu exhibited a smaller magnitude of loss compared with Holstein and Jersey, underscoring its greater heat tolerance. Gayari et al. (2024) applied segmented regression to crossbred zebu × Jersey cows and identified a decline in MY of −0.04 kg/d per THI unit beginning at a threshold of 77. In a previous study using the same Gir population evaluated here, Santana et al. (2015) found milk losses ranging from −0.039 to −0.099 kg/d per THI unit during the high-production period (DIM 31 to 270), aligning with the present findings of −0.054 to −0.140 kg/d using NASAWS and NASA data.

As expected, Holstein cows exhibited steeper MY decline rates than Gir. These losses were consistent with those reported by Carabaño et al. (2016), who found average losses of −0.010 to −0.100 kg/d per THI unit across European dairy cattle populations, with values reaching −0.100 kg/d under THI 73 in Belgium and Spain. Notably, individual cows, especially high-producing ones, showed milk losses as high as −0.800 kg/d per THI unit. Similarly, McWhorter et al. (2023) reported average losses of −0.168 and −0.135 kg/d per THI unit above the threshold in Holstein and Jersey cows, respectively. Using a threshold of 67 THI units, Rockett et al. (2023b) observed MY reductions in Canadian Holsteins ranging from −0.03 to −0.05 kg/d. Likewise, Mendonca et al. (2025) demonstrated that Girolando (3/4 Holstein × 1/4

Gir) cows were susceptible to heat stress, showing increased vaginal temperature and cortisol levels, reduced DMI, lower rumination frequency and MY, and altered expression of genes involved in milk synthesis in mammary epithelial cells.

We were unable to identify a heat stress threshold for Gir cows using WS data. However, when NASAWS and NASA meteorological datasets were employed, a heat stress breakpoint was detected of 70 and 75.853 THI units. The absence of a clearly defined heat stress threshold in zebu cattle has also been reported in previous studies using the same Gir population analyzed here, as well as in Guzerat cattle (Santana et al., 2020). Santana et al. (2015) only identified a heat stress threshold for MY in Gir cows when restricting the analysis to the high-production phase of lactation. For Guzerat cattle, no threshold was detected, and milk losses were observed only during the initial and intermediate stages of lactation (Santana et al., 2020). In contrast, a consistent threshold of approximately 67 THI units was identified for Holstein cows across all meteorological datasets in the present study. Bernabucci et al. (2014) reported heat stress thresholds for MY in Italian Holsteins ranging from 70 to 78 THI units, depending on the period (up to 8 d) before test day. Similarly, thresholds ranging from 69 to 73 THI units were reported for Holstein cows in Belgium, Luxembourg, Slovenia, and Spain (Carabaño et al., 2016). Rockett et al. (2023b) identified 3 distinct breakpoints in Canadian Holsteins: 47 to 50, 61 to 69, and 72 to 76 THI units. Farm-level mitigation strategies such as sprinklers and fans may partly explain some of these differences. Additionally, variations in the observed range of THI values across dairy cattle populations in different countries likely contributed to discrepancies in threshold detection. In our study, ~51% and 64% of MY records were obtained above the heat stress threshold for Holstein and Gir cattle, respectively. In comparison, Carabaño et al. (2016) reported that only 10% to 30% of MY records for Holsteins in 4 European countries occurred under heat stress conditions. McWhorter et al. (2023) similarly indicated that 14.6% and 9.9% of test-day records for Holstein and Jersey cows, respectively, exceeded the heat stress threshold in the United States. From this comparative perspective, it becomes evident that heat stress is a critical challenge for multiple countries, particularly those with predominantly tropical climates.

Our results also confirmed the delayed effect of heat stress on milk yield, with the period spanning the test day and the 2 preceding days providing the best model fit. This finding aligns with that of Bohmanova et al. (2008), who reported that weather data from 3 d before the test date explained more variability in MY than weather data from 1 or 2 d before or from the test day itself in American Holsteins. Similarly, Bernabucci et al. (2014) found that THI exerted a persistent effect on all milk production and milk quality traits in Italian Holsteins from 8 to 12 d before the test date, with the most significant effects occurring 3 to 4 d prior.

In countries with large territorial dimensions, particularly in the Southern hemisphere, the lack of reliable meteorological data remains one of the major limitations to implementing genetic evaluations for heat stress tolerance. As highlighted by Rockett et al. (2023b) and Carrara et al. (2023), ground-based weather stations often present limitations due to data gaps, unavailability, and significant distances from farm locations. Therefore, validating the use of NASA POWER data represents an important step forward in advancing genetic selection for heat tolerance in tropical dairy systems. We acknowledge that relying on weather stations located far from herd locations may introduce environmental exposure misclassification; however, this constraint reflects the sparse and uneven distribution of meteorological stations in Brazil rather than a limitation of the analytical framework. Imposing restrictive distance thresholds (e.g., ≤20 km) would eliminate more than half of all test-day records and compromise the national representativeness required for genetic evaluations. For this reason, all stations providing consistent temporal information were retained.

At the phenotypic level, we observed considerable divergence in MY decline rates beyond the heat stress threshold when comparing WS and NASAWS data, despite representing the same phenotypic records. This discrepancy was particularly evident in Holstein cattle, for which the same segmented regression model could be applied successfully across datasets, yielding consistent threshold estimates. Although THI values derived from ground stations and NASA POWER data were highly correlated, both in the present study and in others (Monteiro et al., 2018; Carrara et al., 2023), biases may still be present. In particular, Carrara et al. (2023) evaluated NASA POWER under Brazilian conditions and reported strong overall correspondence with WS observations, characterized by high correlations and favorable regression metrics, while also noting that the level of agreement varied across regions with different climatic zones and elevations. These nuances are consistent with our findings, as the correlation between WS- and NASAWS-derived THI values varied appreciably across Brazilian states. Nevertheless, although the magnitude of concordance differed across regions, the overall patterns of correlation, bias, and error were sufficiently consistent to support the use of satellite-derived THI as a practical environmental input for national genetic evaluations. Rockett et al. (2023b) reported that NASA POWER values for wind speed and RH were poorly correlated with ground-station observations. Monteiro et al. (2018) recommended regional bias correction for minimum temperature, especially in high-latitude or high-altitude regions, to better capture extreme values. Similarly, Aboelkhair et al. (2019) concluded that although NASA POWER can be a suitable option in the absence of weather observations, further improvements are needed to account for regional specificities, particularly in RH estimates. These findings are consistent with our observations, as the correlation between WS- and NASAWS-derived THI values varied substantially across Brazilian states.

Understanding the dynamic pattern of genetic and environmental variances across lactation and environmental stressors is essential for improving selection accuracy and robustness in dairy cattle. In the present study, substantial heterogeneity in both additive genetic and permanent environmental variances was observed across different combinations of DIM and THI in Holstein and Gir cattle. In a comprehensive analysis by Brügemann et al. (2011), protein yield records from first-lactation Holstein cows were evaluated using a random regression model that incorporated DIM- and THI-dependent covariates. Additive genetic variances were lowest at the onset of lactation and under conditions of severe heat stress, increasing progressively toward later stages of lactation and under thermoneutral conditions. Similarly, Bohlouli et al. (2013) found that genetic variance for milk yield increased with advancing DIM but decreased at elevated THI values, highlighting a differential expression of genetic potential under thermal stress. In line with these patterns, heritability estimates obtained here also varied along the DIM–THI trajectory. Brügemann et al. (2011), Bohlouli et al. (2013), and Negri et al. (2021) reported higher heritability values in later lactation and under milder environmental conditions, which favor the phenotypic expression of genetic potential and enhance differentiation among individuals. Conversely, under elevated THI and early lactation, when physiological demands are highest (Kadzere et al., 2002), heritability estimates declined, mainly due to reductions in additive genetic variance while residual variance remained relatively stable.

Interestingly, the genetic slope-to-intercept ratio was substantially higher in Gir compared with Holstein cattle. This finding suggests that genotype × thermal environment interactions may be more pronounced in the Gir population. We hypothesize that this pattern may reflect the greater heterogeneity of production environments typically encountered by Gir herds across Brazil, as opposed to the relatively more homogeneous conditions under which Holsteins are raised. Additionally, the shorter history of intensive selection for milk yield in Gir may have preserved greater genetic variability for heat stress response in this population, thereby allowing for a more detectable expression of thermotolerance under varying climatic conditions.

Across different meteorological data sources, high concordance was observed in all genetic parameter estimates when the same MY records were used, specifically in comparisons between WS and NASAWS datasets. Posterior means of additive genetic variances, heritability, and genetic correlation estimates for various combinations of DIM and THI were virtually identical between the 2 sources. Moreover, the 95% high posterior density intervals for all (co)variance components showed substantial overlap, indicating that the use of meteorological information from NASA POWER does not compromise the consistency of genetic estimates when compared with conventional ground-based weather stations. These results were further supported by the ranking of top sires for heat stress tolerance, with a high proportion of bulls being selected in common across WS- and NASAWS-based evaluations. Notably, when using the full NASA dataset, which provided complete meteorological spatial and temporal coverage, a substantial increase in sire prediction accuracy was observed due to the inclusion of all available MY records. This is because NASA POWER allowed for comprehensive recovery of environmental information for all farm locations, thus maximizing data utilization. Together, these findings indicate that NASA POWER is a reliable alternative for genetic evaluations, a particularly relevant outcome for countries such as Brazil, where ground-station coverage is sparse. To our knowledge, this is the first study to directly compare genetic parameter estimates and selection results for dairy cattle heat tolerance using both ground-based and NASA POWER meteorological data sources.

In general, genetic trends estimated using WS and NASAWS datasets were consistent. The results showed that both Holstein and Gir populations have steadily increased their overall milk production levels, albeit at the cost of reduced genetic tolerance to heat stress. These patterns agree with previous findings (Santana et al., 2015, 2017), which reported similar trends in subsets of the same populations evaluated herein. Comparable results have also been described for other zebu (Santana et al., 2020) and Holstein (Aguilar et al., 2010; Carabaño et al., 2019) populations. In Australia, Nguyen et al. (2017) observed a slight decline in genetic merit for heat tolerance over time in both Holstein and Jersey cattle. Based on these findings, the authors suggested the inclusion of heat stress resilience in multitrait selection indices to mitigate further deterioration in thermotolerance. The antagonistic relationship between general production level and heat stress response was further supported by the negative genetic correlation observed between the intercept and the linear heat stress coefficient. The estimates obtained in the present study were consistent with those previously reported in various dairy cattle populations (McWhorter et al., 2023; Rockett et al., 2023a;

Carabaño et al., 2025). This antagonism reflects the metabolic trade-off wherein selection for enhanced milk production inadvertently compromises thermotolerance, given that higher-producing animals generate more metabolic heat and are therefore more susceptible to thermal stress (Kadzere et al., 2002). Accordingly, dairy breeds, especially those subjected to intensive genetic improvement programs, tend to exhibit heightened sensitivity to heat stress. In the Gir population, for instance, Santana et al. (2015) documented a substantial increase in milk production levels following the official implementation of the national genetic improvement program, which was paralleled by a decline in genetic tolerance to heat stress.

CONCLUSIONS

This study demonstrated that NASA POWER is a reliable alternative to ground-based weather stations for estimating THI and conducting national genetic evaluations for heat stress tolerance in Holstein and Gir cattle. Across all analyses, THI values derived from NASA data produced nearly identical genetic parameter estimates and sire rankings compared with conventional station-based sources, while enabling broader spatial coverage and improved prediction accuracy due to complete data availability. From a phenotypic standpoint, however, the estimates of milk yield losses due to heat stress were not fully consistent between ground-based and NASA-derived data. Nevertheless, both meteorological sources consistently indicated significant heat-induced reductions in milk yield for both breeds, with Holsteins exhibiting greater sensitivity and more clearly defined heat stress thresholds. Together, these findings support the integration of NASA POWER data into routine national genetic evaluations for heat tolerance in tropical dairy systems. The results provide a robust framework for selection under heat stress and underscore the feasibility of extending genetic evaluation programs to regions where ground-based meteorological information is limited or unavailable.

NOTES

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Nonstandard abbreviations used: API = application programming interface; BDMEP = Banco de Dados Meteorológicos para Ensino e Pesquisa; BP = breakpoints; DIC = deviance information criterion; int = intercept; LSE = least squares estimates; MBE = mean bias error; MY = milk yield; NASA = National Aeronautics and Space Administration; NASA dataset = THI derived from NASA POWER; NASAWS = THI derived from NASA POWER restricted to WS locations; POWER = prediction of worldwide energy resources; RH = relative humidity; RMSE = root mean square error; slo = linear heat stress slope; T = temperature; THI = temperature-humidity index; WS = THI derived from weather stations.

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