Selection Criteria for Heat Tolerance in Dairy Cattle Production.

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ABSTRACT: Test day milk, fat and protein yields from first lactations of 29,914 cows in 139 herds were used together with average daily temperature to study alternative selection criteria for heat tolerance. A random regression model fitting a cubic Legendre polynomial to the additive genetic effect was used. Eigenfunctions of the estimated additive genetic covariance matrices showed a dominant component associated to the level of production and a second component showing constant values in the mid range of temperatures and increasing or decreasing values outside that range, which could be used as a selection criteria for heat tolerance. This component explained 4, 15 and 11 % of the total variation for milk, fat and protein yield, respectively. The results suggest that the antagonistic relationship found between level and slope in previous studies might be avoided using the eigendecomposition of the additive genetic covariance matrix of the random regression coefficients.

Keywords: dairy cattle; heat tolerance; selection criteria

Introduction

A significant part of dairy cattle production is located in regions under hot conditions during several months of the year. Moreover, predictions under climate change scenarios forecast temperature increases in the next decades that may compromise the sustainability of production in some regions. Selection for heat tolerance has therefore received increasing attention in the last decade. Misztal (1999) proposed the use of a model fitting a comfort zone, with no effect of temperature on production, followed by a linear decay in production, providing two parameters, the thermotolerance threshold and the subsequent slope of decay for each animal in the most complex model of Sánchez et al. (2009). This type of model is attractive because of the direct biological interpretation of the genetic parameters obtained for each animal. However, it relies on strong assumptions such as that production decays abruptly after the threshold, that the decay is then linear, and, in the simplest versions, that there is a common known or unknown comfort threshold for all animals. In the more parameterized models, where individual threshold and slopes are fitted, slow mixing and convergence rates have been observed (Sánchez et al. (2009)). Moreover, the parameters representing the overall level of production (intercept) and the tolerance to heat stress (slope) are genetically antagonistic (Ravagnolo et al. (2000); Sánchez et al. (2009); Bernabucci et al. (2013)). Alternatively, Brügeman et al. (2011) have used random regressions to fit both the effects of days in milk and THI on production traits. Random regression parameters lack biological interpretation but these models are attractive because of the large flexibility to fit smoother patterns of decay and the possibility of using the eigendecomposition of the additive genetic covariance matrix to find selection criteria (as in Kirkpatric et al. (1990)) that are not correlated among them and could help in the improvement of tolerance to heat stress with no impact on production level.

The objective of this study was to investigate the possibility of using the canonical variables obtained through the eigendecomposition of the additive genetic covariance matrix obtained from random regression models to select for heat tolerance in a highly selected dairy cattle population under heat stress conditions.

Materials and Methods

Data. The production database consisted of test-day records from the first five lactations of Spanish Holstein cows calving between 2002 and 2012 in two regions with hot and dry summers. Meteorological records from 718 stations in both regions were used. Because not all weather stations had humidity records and because of the low humidity condition of the days with high temperatures, average daily temperature alone was the variable used to define the heat load.

The data set used contained 280,958 milk, fat and protein yield test-day records from first lactations of 29,914 cows in 139 herds in the same period of time as for the whole data set. The genealogical file contained 64,922 animals.

Statistical analyses. The general model equation was:

$$y_{ijk\_T} = HYS_i + ADIM_j + \sum_{q=0}^{3} b_q Z_q(T) + \sum_{r=0}^{3} a_{rk} Z_r(T) + \sum_{r=0}^{3} p_{rk} Z_r(T) + e_{ijk\_T}$$

where, y_{ijk_T} is the test day fat or protein yield at temperature T; HYS_i is the herd-year-season of test day (i=1,… 3,898); $ADIM_j$ is the age-days in milk effect (130 levels); b_q (q=0,…,3) are regression coefficients for temperature, $Z_q(T)$ are the covariates of the Legendre polynomial of order q evaluated at daily average temperature T; a_{rk} and p_{rk} (r=0,…,3) are the additive genetic and permanent environmental random regression coefficients on T for animal k, respectively; $Z_r(T)$ are the covariates of the Legendre polynomial, and, e_{ijk_T} is the residual effect, with e_{ijk_T} i.i.d. $N(0, \sigma_e^2)$. The (co)variance structure for regression coefficients for individual animals was assumed to be:

$$var(a) = \mathbf{G} = \mathbf{G}_o \otimes \mathbf{A} \; ; \; var(p) = \mathbf{P} = \mathbf{P}_o \otimes \mathbf{I}$$

where, **a** and **p** are vectors of additive genetic and permanent environmental coefficients for all animals, respectively, and, $\mathbf{G}_o$ and $\mathbf{P}_o$ are the additive genetic and permanent environmental (co)variances for all the regression coefficients, respectively.

Eigenvalues, eigenvectors and eigenfunctions of the estimated $\mathbf{G}_o$ were obtained to explore the possibility of alternative selection criteria for heat tolerance. In addition, the linear additive genetic regression coefficient (linear), the slope (derivative) of the additive genetic curve for each individual at a heat stress temperature of 30ºC (slope30) and the estimated genetic value at 30ºC (EBV30) were also considered as possible selection criteria.

A Bayesian approach via Gibbs sampling was used to obtain samples from marginal posterior distributions of the parameters of interest with software written in fortran90 language (López-Romero et al. (2003)).

Results and Discussion

The observed means for the analyzed traits were 28.4, 0.99 and 0.92 kg for milk, fat and protein, respectively, corresponding to a selected dairy population. Maximum of monthly averages along the studied period was 26.5 ºC and 34.5ºC, attained in the month of July for average and maximum temperatures, respectively.

Table 1. Eigenvectors obtained from the estimated (co)variance matrices for the additive genetic random regressions.

	Eigenvectors			
	1	2	3	4
MILK				
	1.00	-0.03	-0.06	0.03
	-0.07	-0.17	-0.90	0.40
	-0.01	-0.49	0.43	0.76
	0.02	0.85	0.07	0.51
FAT				
	1.00	-0.31	-0.04	-0.21
	-0.31	1.00	-0.54	0.43
	-0.04	-0.54	1.00	-0.30
	-0.21	0.43	-0.30	1.00
PROT				
	1.00	-0.20	0.03	-0.05
	-0.20	1.00	-0.21	0.17
	0.03	-0.21	1.00	-0.17
	-0.05	0.17	-0.17	1.00

Table 1 and Figure 1 present the eigenvectors and associated eigenfunctions together with the percentage of variation explained by each eigencomponent. For all traits, the first eigenfunction was associated to a nearly constant level of production across the range of temperatures, corresponding to a large weight on the intercept coefficient (Table 2). For milk yield, this variable accounted for 91% of the variability, leaving little room for improvement of the pattern of response to temperature through the other components. On the other hand, the percentage of variability associated to the first new variable was much lower, 76% and 79% for fat and protein yields, respectively. This would indicate that selection to modify the pattern of response for other components, particularly the second variable, might be efficient. For milk, fat and protein, the second eigenfunction explained 4%, 15%, 11%, respectively, and showed a flat line between 9 and 25ºC for daily average temperature and decreasing or increasing values outside those temperatures.

Table 2 presents EBV correlations among production level and heat tolerance criteria. The intercept coefficient and the first eigenvariable showed a unity correlation, indicating that both measure the level of production. From the alternative heat tolerance criteria, the second eigenvalue showed the lowest correlation with the level of production, as expected, while the linear coefficient showed intermediate correlations and EBV30 the largest. To verify the behaviour of the alternative criteria, EBVs at different temperatures of the best and worst animals according to eigen2 or the linear criteria are presented in Figure 2. As expected from the observed correlations, the top tolerant animals according to the linear coefficient showed lower production levels and vice versa while top tolerant animals according to the second eigenvector did not show a clear association with production. The association was clearer for milk than for fat and protein yield.

Table 2. Product moment correlations between EBVs for level indicators (inter and Eig1) and heat tolerance criteria (Eig2, linear, deriv30, EBV30)

	Eig1	Eig2	linear	deriv30	EBV30
MILK					
Interc.	1.00	0.03	-0.73	0.13	1.00
Eig1		0.03	-0.73	0.14	1.00
Eig2			0.49	-0.25	0.10
linear				-0.37	-0.68
deriv30					0.12
FAT					
Interc.	1.00	0.14	-0.60	-0.56	1.00
Eig1		0.12	-0.61	-0.57	0.99
Eig2			0.56	0.25	0.20
linear				0.40	-0.52
deriv30					-0.55
PROT					
Interc.	1.00	0.15	-0.41	-0.08	0.99
Eig1		0.14	-0.42	-0.08	0.99
Eig2			0.75	0.14	0.25
linear				0.09	-0.30
deriv30					-0.05

Conclusions

Results suggest that the antagonistic relationship found between level and slope in previous heat stress studies might be avoided using the new variables arising from the eigendecomposition of the additive genetic covariance matrix of the random regression coefficients. However, most of the observed variability is associated to production level and only a little fraction is associated to heat stress response independent of level of production and, therefore, efficiency of selection might be low.

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Figure 1: Eigenfunctions obtained from the estimated (co)variance matrices for the additive genetic random regressions, and , percentage of variation associated to each of them (in parenthesis). TAVE: Average daily temperature.

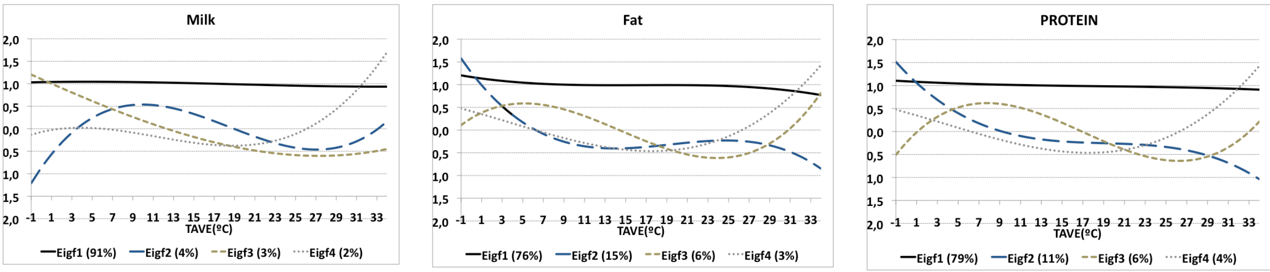

Figure 2. Estimated breeding values along daily average temperatures for animals with the highest (black circles) and lowest (red triangles) EBVs for the second eigenvariable and the linear regression coefficient