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A WEB-BASED APPLICATION TO ASSIST SELECTION FOR HEAT TOLERANCE IN COMBINATION WITH THE BALANCED PERFORMANCE INDEX IN AUSTRALIAN DAIRY CATTLE

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SUMMARY

The aim of this study was to develop a future-scenarios selection tool to assist farmers in making selection decisions, that combine the current national dairy selection index, known as the Balanced Performance Index (BPI) with a proposed heat tolerance (HT) genomic estimated breeding value (GEBV). Heat tolerance GEBV was estimated for 12,062 genotyped cows and 10,981 bulls, using an established genomic-prediction equation. Publicly available future daily average temperature and humidity data were used to calculate mean daily temperature–humidity index for each dairy herd. One way to ascertain heat tolerance is the rate of decline in milk production traits to rising heat loads, this definition was the basis of the heat tolerance breeding values (BV_HT). An economic estimate of an individual cow's BV_HT was calculated by multiplying HT GEBVs for milk, fat and protein yields by their respective economic values that are used in the BPI. This was scaled for each region by multiplying BV_HT by the heat load, which is the temperature–humidity index (THI) units exceeding the threshold per year at a particular location. BV_HT were incorporated into the BPI as: BPI_HT = BPI + BV_HT; where BPI_HT is the 'augmented BPI' breeding value including HT. A web-based application was developed enabling farmers to predict the future heat load of a herd and take steps to aim at genetic improvement in future generations by selecting bulls and cows that rank high for the 'augmented BPI'.

INTRODUCTION

It is widely recognised that heat stress has significant impacts on the performance of dairy cows. When heat stressed, animals consume less feed, followed by a decline in milk yield (St-Pierre et al., 2003). In Australia, it is projected that major dairying regions will experience an increase in daily average temperatures as well as more frequent heat waves (CSIRO and BoM, 2015). Therefore, there is a need for the industry to develop strategies to mitigate the impacts of a warming climate on animal performance.

Apart from providing cooling devices and managing diets for cows on hot days, selection for more heat tolerant animals is an approach worthy of investigation. In this regard, Nguyen *et al.* (2016) developed genomic estimated breeding values (GEBVs) for heat tolerance (HT) for Australian Holsteins and Jerseys, which is the rate of decline in milk production traits to rising heat loads. The study found that using high-density single-nucleotide polymorphism (SNP) genotypes, HT GEBV can be predicted with an accuracy ranging between 0.42–0.61. The HT GEBV has unfavourable correlations with production traits, but a favourable correlation with fertility. In addition, the HT GEBVs were validated through an experiment where genomically predicted heat-susceptible and predicted heat-tolerant animals show a significant difference in milk yield losses, and rectal and intra-vaginal temperatures when experiencing a mild simulated heat wave (Garner *et al*., 2016). A breeding value for HT is planned to be released to the dairy industry in the near future.

Given the complexity in the relationships between HT and other traits in the current selection indices, one relevant question is how farmers can balance the selection for HT with their existing priorities. Farmers in regions where heat stress is more of an issue may prioritise selection for HT to a greater extent than those in cooler climates. In the present study, we developed a future-scenarios selection tool that enables farmers to make informed decisions so as to balance the selection of current economic drivers traits in the BPI with HT simultaneously by varying the weight applied to HT_BV for individual farms by heat load.

MATERIALS AND METHODS

Projected future climate data. The Commonwealth Scientific and Industrial Research Organisation (CSIRO) and the Bureau of Meteorology (BoM) have provided details of projected future climate-change scenarios in Australia over the 21st century (CSIRO and BoM, 2015). Appropriate climate projection models used in the present study were selected following the advice of CSIRO climate scientists. We chose medium and high emission scenarios (RCP4.5 and RCP8.5 (carbon dioxide level of 540 x10^{-6} µmol/mol by 2100) and RCP8.5 (carbon dioxide concentration of 940 x 10^{-6} µmol/mol by 2100) as examples.

On the basis of the selected models, projected average daily temperature and humidity for weather stations (namely weather station data) were downloaded from the 'Climate Change in Australia' website (http://www.climatechangeinaustralia.gov.au/, 01 March 2016). In addition, gridded average daily temperature and humidity data (namely gridded data) were also obtained directly from the Climate Research and Services, CSIRO Oceans and Atmosphere (Aspendale, Victoria). We used data from the nearest grid (≤1 km distance to weather station) to patch missing weather-station data. Weather data were matched to the nearest postcode provided the distance between the weather station and centroid of the postcode was no more than 60 km.

Daily average THI was calculated for each day from 2020 to 2035, as per Nguyen *et al*. (2016). According to Hayes *et al*. (2003), averaged THI of the test day and 1, 2, 3 and 4 days before the test day of exceeding 60 could result in a decline in milk yield. Therefore, we defined heat load of a given year as the total of five-consecutive-day-average THI units exceeding 60 in that year, which is referred to as THI hereafter.

HT and BPI breeding values. In order to calculate the future profitability of a herd with and without selection for HT, and under different climate-change scenarios, the current genetic merit of a herd is required, as well as the genetic merit of the bulls on offer. So as to have a reasonably large group of cows and bulls that would span many herds and many bull-selection possibilities, HT GEBVs of genotyped cows and bulls were predicted using the equation developed by Nguyen *et al*. (2016) for all genotyped cows and bulls. BPIs for both cows and bulls of the February 2016 release were obtained from DataGene (formally Australian Dairy Herd Improvement Scheme).

The heat-tolerance breeding value (BV_HT) in dollars (so it can be readily combined with the BPI) was expressed as:

$$\mathrm{BV\_HT} = (\mathrm{EW_m EBVht}_{\ m} + \mathrm{EW_f EBVht}_{\ f} + \mathrm{EW_p EBVht}_{\ p})\,\mathrm{HL},$$

where BV_HT is the breeding value of heat tolerance in monetary term; $\mathrm{EW_m} = -0.10$, $\mathrm{EW_f} = 1.79$, $\mathrm{EW_p} = 6.92$ are economic weight of milk, fat and protein respectively, which are currently used in the BPI (Byrne *et al*., 2016); $\mathrm{EBVht}_{\ m}$, $\mathrm{EBVht}_{\ f}$ and $\mathrm{EBVh\ t_p}$ are genomic breeding values of heat tolerance in relation to milk, fat and protein respectively; HL is the total number of THI units exceeding 60 in a year.

We combined BPI and BV_HT for each animal as follows:

$$\text{BPI\_HT} = \text{BPI} + \text{BV\_HT},$$

where BPI_HT is the 'augmented BPI' breeding value with heat tolerance included; and BV_HT is breeding value of heat tolerance.

Data visualisation. The application HOTdAIRy v.01 developed in R (R Core Team 2015), using the 'shiny' package (Chang *et al*., 2016) in RStudio (RStudio Team, 2015). We obtained the postal area shape file from the Australian Bureau of Statistics for postcode boundaries (http://www.abs.gov.au/, 01 March 2016).

RESULTS AND DISCUSSION

We successfully obtained daily average temperature and humidity for 58 weather stations in Australia. Of these, we were able to match 57 stations with 1861 postcodes covering 3836 herds (85.4% of the total number of Australian dairy herds). The average number of days per year with THI exceeding the threshold of 60 were 313, 235, 242, 176, 164, 120, 121 in Queensland, New South Wales, Western Australia, South Australia, Northern Victoria, Gippsland and Western Victoria, respectively. The average number of THI units exceeding the threshold (THI > = 60) per year ranged from 2,587 (Gippsland) to 2,676 (Western Victoria), 3,240 (Northern Victoria), 3,445 (South Australia), 4,338 (Western Australia) and 6,019 (Queensland), indicating that all major dairying regions will be affected by excessive heat load, but at different levels.

For demonstration purposes, we have included only information from genotyped cows that currently belong to the Genomic Information Nucleus (Ginfo) herds, and genomic bulls, in our tool. We successfully estimated HT GEBV for 12,062 genotyped cows (10,680 Holsteins and 1,382 Jerseys from 80 Ginfo herds), and 10,981 genomic bulls (9,306 Holsteins and 1,675 Jerseys). The BV_HT significantly varied according to the level of heat load. For example, if the heat load of year 2025 was applied, BV_HT among the 10,981 bulls analysed ranged between AU$–29 to A$21 per cow (mean set at zero) under the conditions in Johanna, Victoria, but the range of BV_HT changes to AU$–174 to AU$126 per cow at the conditions in Rockhampton, Queensland. The correlation between BPI and BPI_HT for bulls was, therefore, higher (0.99) if the heat load in Johanna was applied, than it was under Rockhampton (0.95) conditions. Figure 1 shows an example scatter plot of BPI vs BPI_HT for the bulls under the conditions in Rockhamton.

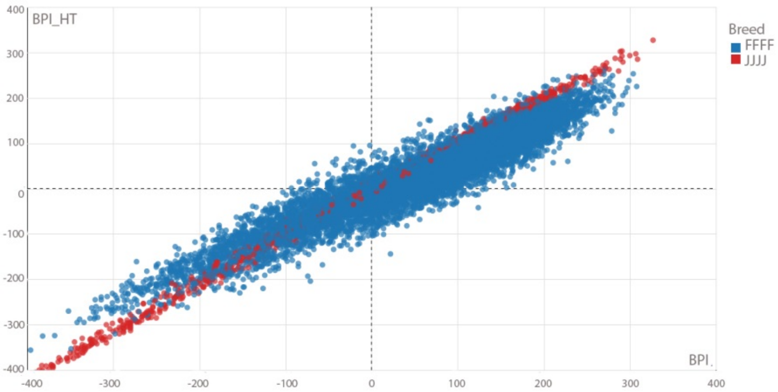

Figure 1. An example scatter plot between BPI_HT and BPI for 10,981 bulls (FFFF = Holsteins and JJJJ = Jerseys) under the conditions in Rockhamton

A typical workflow in the web-based application HOTdAIRy v.01 (https://tnshinyr.shinyapps.io/app12) begins with providing inputs, including a herd postcode, a herd ID, a future year (2020, 2025, 2030 or 2035) and a greenhouse gas-emission scenario. The outputs include the amount of heat load calculated based on the inputs, scatter plots between BPI_HT and BPI for cows and bulls, and relevant tables which can be sorted and downloaded. The ranked cow and heifer list can then be used to make selection decisions on which animal to keep in the herd, and which to cull, on the basis of predicted performance with the projected future heat load. The highest-ranked bulls maximising the profit under the given projected future climate conditions on the farm.

One special characteristic of HT is that its breeding value depends on the amount of heat load animals are expected to experience. Heat load varies between regions and our approach was to use heat load as a weight for the trait, i.e. in regions with high heat load, emphasis on selection for HT is higher and *vice versa*. That means BV_HT for an animal depends on the herd locality. In the study, we were able to use projected climate data from CSIRO and BoM (2015) to determine levels of heat load for most dairying regions in Australia, which also serves as a weight for HT in the 'augmented BPI' index. This method of inclusion of a new trait opens opportunities for the inclusion of other traits of this nature in the index.

Our demo version of future-scenarios selection tool is currently a standalone web-based application. However, it is also flexible in terms of incorporation into other existing tools that farmers are currently using. Once possible option is to integrate it into the Good Bulls app (http://www.datagene.com.au/); thereby, BPI_HT breeding values and ranking can be viewed along with BPI, HWI and TWI.

In summary, we have created a practical future-scenarios selection tool that can be used by dairy farmers and breeders to make informed decisions in selecting for HT and BPI, that is customised to their dairy region and includes options for various future climate-change scenarios. The tool will become particularly relevant given the continuing increase in average temperature and frequency of heat-wave events. Our study is the first attempt to incorporate HT into selection indices for dairy cattle. It is important because profitability and animal welfare can be improved simultaneously through identifying animals that are able to cope with current and future climate change in a way that is consistent with the impact of HT on local farm profitability.

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