Monitoring beef cattle resilience through a measure of growth variability

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Abstract

Australian beef cattle are located across a diverse landscape, and our new, increasingly extreme climate is impacting the sustainability of this typically extensive production system. Resilient cattle and complementary management approaches are required for this new environment. Previous work has used milk yield variability as an indicator of dairy cattle resilience linking low variability in production with greater resilience; however, there is a paucity of work using the same method for beef cattle. Here we determine growth variability within a herd using 37,621 live weight observations from 3,813 cattle over two years. Liveweight (LW) was measured using the Optiweigh system, where LW was obtained opportunistically in-paddock as cattle access a molasses-based lick block. Firstly, data were pre-processed in three steps, and growth curves for each animal were created using a linear mixed model. Each animal's residual standard deviation (SD) of LW (SD of the residuals about the fitted model) was calculated as a measure of resilience. The lowest, mean, and highest residual SD were 4.41 kg, 10.24 kg, and 21.67 kg, respectively. Cattle with the lowest residual SDs were less variable around their LW growth trajectory, indicating they could cope with extreme climatic events. In conclusion, the residual SD is a promising resilience indicator, with the reasons for the diversity in this indicator forming the basis for further work.

Keywords: Climate extremes, live weight profiles, resilience, beef cattle

Introduction

The Australian cattle industry is one of the significant contributors to the Australian economy, where beef production represents about one-fifth of Australia's total agriculture production value (Meat and Livestock Australia, 2020). Beef production systems in Australia have diversified (Bell et al., 2011) and are typically extensive. The productivity of these extensive cattle systems is affected by extreme climate or weather events (Ali et al., 2020), with the incidence and severity of these events likely to increase (IPCC, 2007). Despite this, there is significant variability in how cattle cope with the same environment determined by on-animal sensors monitoring animal behavior (Islam et al., 2021). An animal is considered resilient if it is minimally affected by the environmental impact or soon regains its average level of productivity (Berghof et al., 2019). Determining such diversity in resilience and the capacity to cope with environmental stresses will be critical for future genetic selection of beef cattle for our increasingly extreme environment to maintain the industry as a significant contributor to the Australian economy. However, such herd-level data for extensive systems are lacking due to issues with connectivity and cost (Burrow, 2012). By incorporating new knowledge fields like phenomics and 'big data,' management programs that maximize productivity and animal welfare while minimizing the environmental impact can be created (Vélez-Terranova, 2019). The creation of automated cattle phenomics will be made possible by big data, supporting innovations in genetic improvement and precision pasture, lifecycle, and supply chain management. Poppe et al. (2020) used a data-driven approach to explore variability in daily milk levels around a lactation curve as indicators for breeding resilient cows.

These approaches were predicated on cows continually being exposed to unidentified disruptions, which led to variations in routinely measured features. Compared to cows with higher variation, those with fewer fluctuations were less susceptible to perturbations. As a result, the fluctuation pattern was anticipated to reveal information concerning resilience. However, no thorough research has been done on applying such data-driven methodologies employing substantial data on beef cattle production to understand how extreme climate events affect a large-scale beef production system. This study aimed to collate and create individual cattle liveweight (LW) change profiles from sporadic, field-based LW data to explore the variability in the response of cattle LW change profiles to climate extremes.

Figure 1: Optiweigh used at Nowley Farm, NSW, measuring cattle liveweight

There are numerous ways to measure and record animal liveweight. Static weigh (SW) systems capture the LW of animals in most scenarios but require animals to be moved to weighing scales within a fixed set of yards, which is laborious and time-consuming (Alawneh et al., 2011). In contrast to the SW or other systems, the Optiweigh (OW) is a mobile system that can be towed and set up with each paddock rotation without additional fencing or infrastructure (Figure 1). Optiweigh scales facilitate the remote collection of LW data individually, voluntarily, but sporadically. The system determines front-end weight, which estimates the overall LW (Strohbehn, 2008). While remotely recorded cattle LW data can assist in on-farm decision-making (Mardhati et al., 2021), novel phenotypes based on these data offer an excellent possibility for selective breeding for greater cattle resilience. The longitudinal phenotypic and environmental profiles enable the development of markers to enhance animal resilience (Mulder, 2017). By analyzing the opportunistically collected LW data from the OW system, growth curves can be fitted, and from these, resilience estimated.

Materials and methods

Data collection

Liveweight data were collected using the Optiweigh (Platinum Agribusiness, NSW, Australia) system from various locations in Australia from 28 March 2021 to 12 January 2022. However, only the data from a single client with a maximum number of cattle were utilized for the current analysis.

Data pre-processing

Descriptive statistics were calculated for raw data before and after pre-processing. The total number of LW records across the experimental period was 37,621 from 3,813 cattle. The data pre-processing steps were as follows:

1. One record per day: if there were multiple LW records for a given animal on a given day, the mean LW value was used, resulting in one record for the animal on that day.
2. Monitored for greater than 28 days: the monitored animal had to have more than 28 days from its first to last weight recording.
3. Removed cattle with less than ten records: minimum dates per animal were ten.

The number of observations and cattle at each step is shown in Table 1.

Table 1: Data pre-processing steps, number of observations, and cattle present after each pre-processing step

Pre-processing step	Number of observations	Number of cattle
Original data set (one herd)	37,621	3,813
One record per day	19,149	3,813
Monitored for greater than 28 days	14,297	1,669
Removed cattle with less than ten records	8,731	553

Statistical Model

A two-stage approach was used to evaluate the individual cattle LW variability and the pattern of variability in the LW data. First, individual animal growth curves were produced using a linear mixed model with splines, also known as a generalized additive mixed model (GAMM). The model fitted to the LW data was:

$$\text{Weight}_{it} = \beta_0 + (\beta_1 + b_{1i})\, t + \text{Animal}_i + s(t) + s_i(t) + \varepsilon_{it}$$

where Weight_{it} is the liveweight (kg) of animal *i* recorded on day *t*, with fixed effect parameters β_0 (intercept) and β_1 (overall linear growth rate); Animal_i is the random intercept effect for animal *i*; b_{1i} is a random effect for the deviation of the linear trend of the animal *i*, $s(t)$ is an overall smoothing spline function of time *t*; $s_i(t)$ is the smoothing spline deviation for animal *i*, and ε_{it} is a random error.

The model was fitted using ASReml-R via the asreml package (Butler et al., 2017) in the R environment (R Core Team, 2020). Note that for ASReml-R, all spline terms are fitted as random effects in the model. For both splines, five knots were used as an appropriate amount of smoothing. Residual diagnostic plots were obtained, and records with a standardized residual over 4 in absolute value were removed from the data set and the model re-fitted. For the second stage, residuals were obtained from the fitted model, and the SD of these was calculated for each animal (Residual SDs).

Results and discussion

Our study determined cattle variability in the fluctuation of liveweight yield as an indicator of resilience. Liveweight data from the OW system before and after pre-processing is shown in Figure 2, and the model-based growth curves for each animal derived from these data are shown in Figure 3.

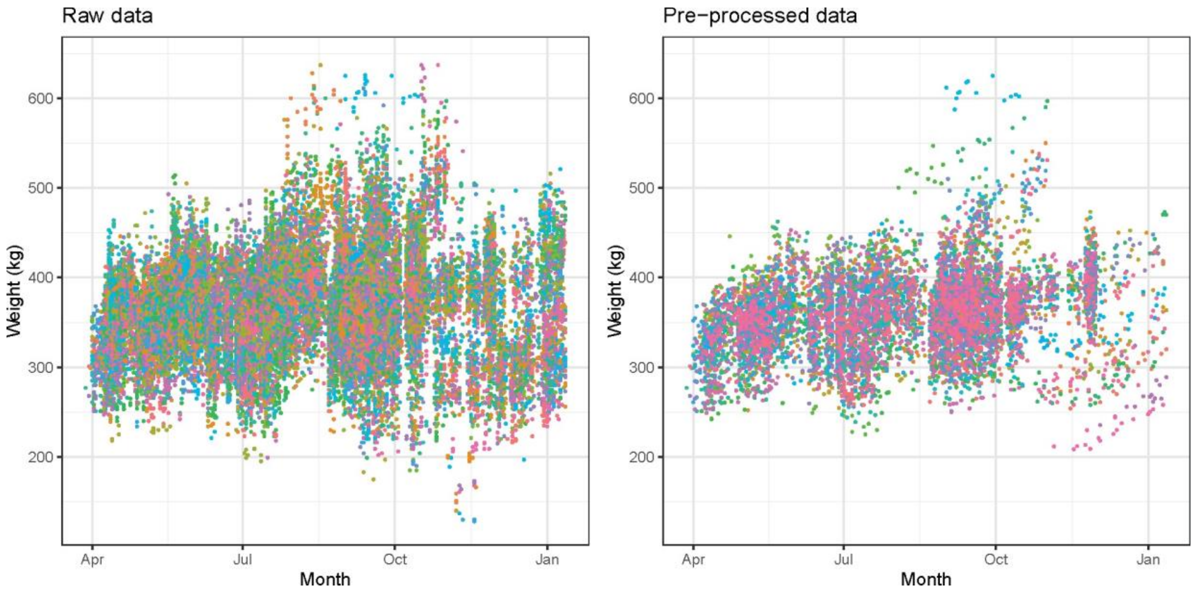

Figure 2: Optiweigh liveweight data for a herd before (on the left) and after pre-processing (on the right); different colors are used for each animal.

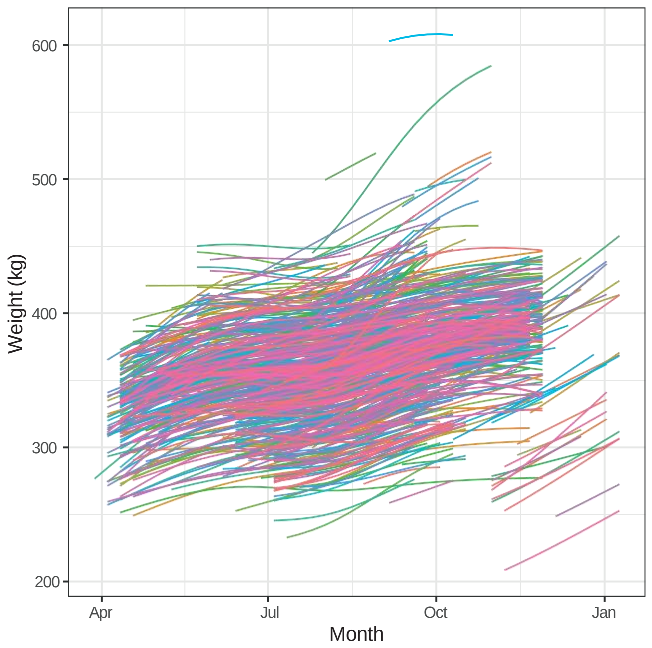

Figure 3: Model-based each cattle smoothed growth curve over the data collection period.

After extracting the residuals from the fitted models, a histogram of the residual SDs for each animal around the model-based growth curve is shown in Figure 4.

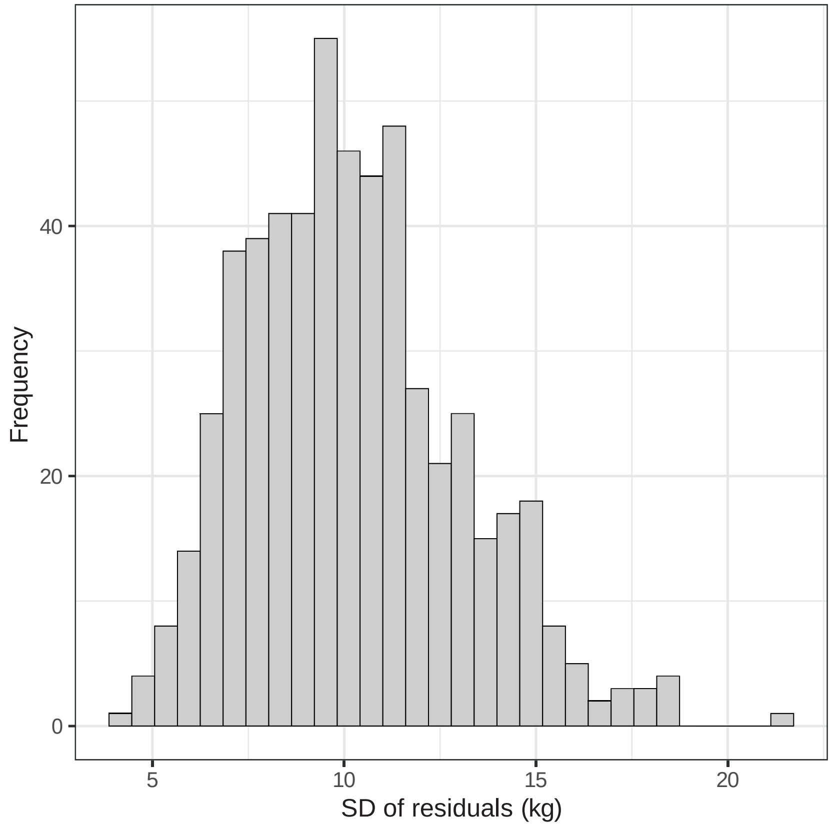

Figure 4: Histogram of each cattle standard deviation of the residuals as a resilience indicator.

The lower the residual SD, the less variable the LW of individual cattle around their growth trajectory. Further, some cattle were more variable than others, where the lowest and highest residual SDs 4.41 kg and 21.67 kg, respectively, as shown in Figure 5. Cattle with the lowest and highest residual SDs were extracted, and LW was plotted around their growth curves. In Figure 5, animals A and B had residuals of SD 4.41 and 4.49 kg, with low variation around their growth curves, and therefore were assumed to be more resilient. In contrast, animals C and D had residuals of SD 18.02 and 21.67 kg, indicating less resilience. Ehsaninia et al. (2019) and Elgersma et al. (2018) suggested that the variance of milk yield is a resilience indicator. Our findings are directly in line with this hypothesis.

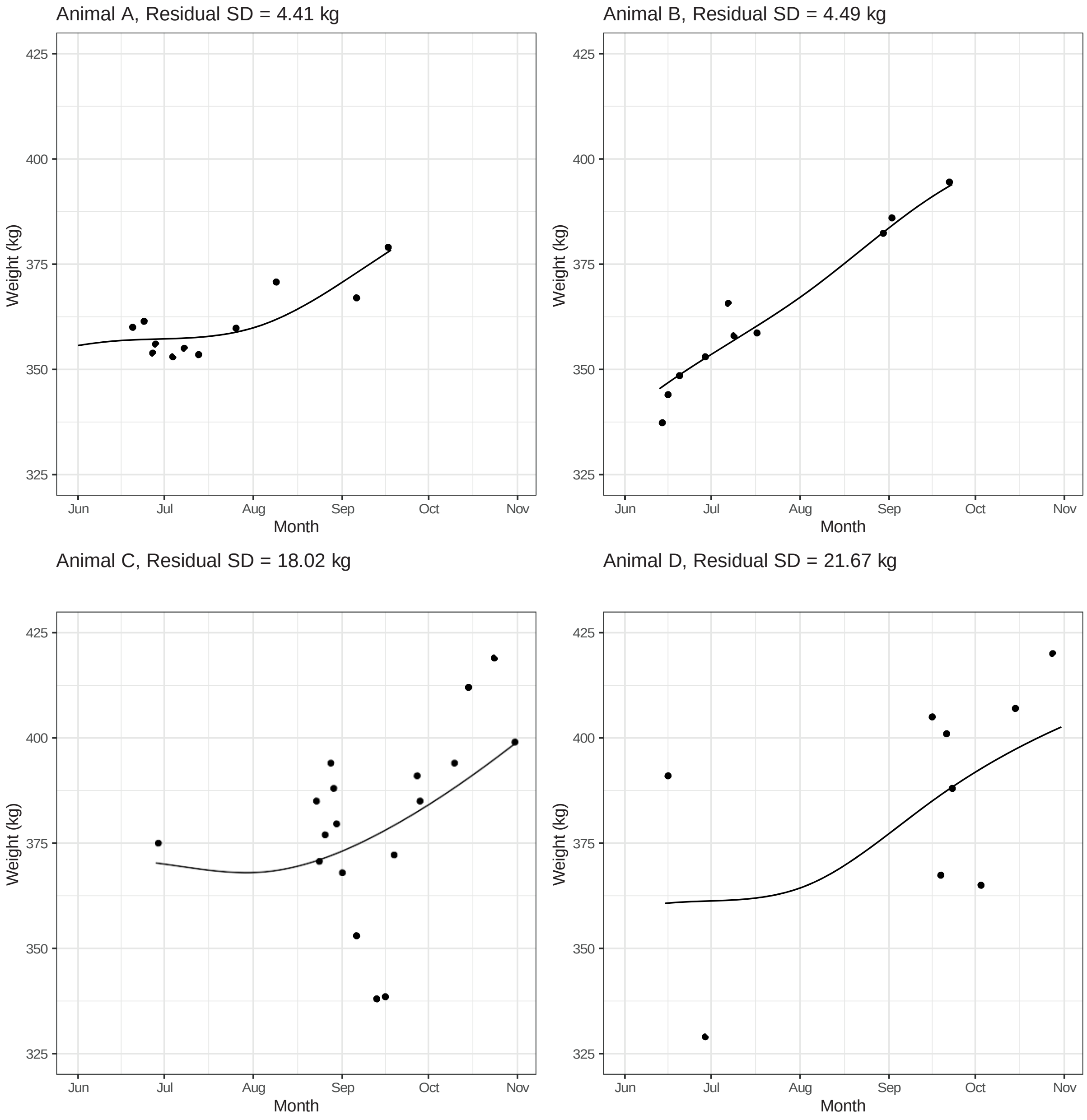

Figure 5: Identified cattle having the lowest (A, B) and highest (C, D) residual SD as an indicator of resilience in the extensive production system.

Although there is a dearth of studies to which our findings can be compared, Poppe et al. (2020) also explored milk yield fluctuation as an indicator for breeding resilient dairy cattle, with less fluctuation in dairy milk yield indicating greater resilience. The causes of LW variability could be biological variability or other extraneous events. Therefore, there is a need to identify the causes of variability between animals or locations for identifying new phenotypes for genetic selection.

Conclusions

Our work shows substantial variability between cattle in their LW fluctuation, as measured by each animal's residual standard deviation. This resilience indicator has promise for identifying cattle better at coping in the extensive production system. Future work aims to determine the association between these findings and weather variables, expanding this work to include more cattle from more herds. This research serves as a crucial first step in exploring the interaction between the environment and animals in extensive environments.

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