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99. Resilience indicators based on daily milk yield data for genetic selection in dairy cattle

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Abstract
Dairy cows face many kinds of environmental challenges throughout their life, such as pathogens, sudden changes in feed quality, or heat waves. Resilient cows are cows that can cope well with such challenges – they are minimally affected and recover quickly. Having resilient cows is beneficial for both the cows themselves and farmers. We investigated if newly developed traits, based on daily milk yield can be used to genetically select for improved resilience. Cows change their milk yield in response to challenges. The hypothesis was, therefore, that daily patterns in milk yield can indicate resilience. Breeding for low variability in milk yield and for low autocorrelation, i.e. dependency between day-to-day deviations in milk yield, can help to improve resilience. Genetic improvement of resilience will likely improve welfare and profitability of cows, and improve job satisfaction of farmers.

Introduction
Resilience is the ability of animals to be minimally affected by, and to quickly recover from environmental disturbances, such as pathogens, extreme weather, or changes in feed quality (Colditz and Hine, 2016; Berghof *et al.*, 2019). Resilience is important for the welfare of animals and work pleasure of farmers, especially given the expected increase of disturbances in the future (Boichard and Brochard, 2012; Elgersma *et al.*, 2018).

There are several ways to improve resilience of animals, and one of them is through genetic selection (Colditz and Hine, 2016; Berghof *et al.*, 2019). However, as resilience is a broad concept, it is difficult to quantify and thus difficult to identify which animals are genetically most resilient. Therefore, indicator traits are needed to improve resilience.

Nowadays, many sensor and other automated data are available on animals (Rutten *et al.*, 2013), and these data may contain information about resilience. Many traits recorded by sensors and automated systems are sensitive to disturbances. Hence, the fluctuation patterns in such longitudinal traits are expected to contain information about resilience (Scheffer *et al.*, 2018; Berghof *et al.*, 2019). Two traits based on longitudinal data have been proposed as indicators of resilience: the variance and lag-1 autocorrelation (Scheffer *et al.*, 2018). Variance indicates the variability of a trait, and thus the sensitivity of the animal to disturbances. Autocorrelation indicates the dependency of subsequent records on each other, and thus at what rate the animal recovers from disturbances.

In this paper we summarize results on the resilience indicators variance and autocorrelation of daily milk yield. We focus on the heritability and genetic correlations with other resilience-related traits, the associations with economic performance and we discuss its usefulness for selection.

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Materials & methods

Data. The original data set contained 1,782,373,113 milk yield records on 1,120,550 cows, obtained during single milk visits to automatic milking systems (AMS) and conventional milking systems. Only records from AMS were selected and single milk visit records were converted to daily records. Only cows were selected that were registered in the herd-book and that were more than 87.5% Holstein Friesian. The milk yield data were corrected for lactation curve shape by fitting a polynomial quantile regression curve for each cow. The residuals from the fitted curves contained information about short-term fluctuations that are informative about resilience. These residuals were used to calculate the resilience indicators for each cow in lactation 1: variance (LnVar; 198,725 cows) and autocorrelation (r_{auto}, 198,580 cows).

Analyses. We estimated genetic parameters for the resilience indicators using mixed animal models in ASReml (Gilmour *et al.*, 2015). We estimated genetic correlations with traits that are currently in routine genetic evaluation using the multiple across country evaluation (MACE) procedure (Schaeffer, 1994; Klei and Weigel, 1998; Interbull, 2017). We estimated genetic correlations with several traits describing milk yield response to real-life disturbances at herd level using sire-maternal grandsire models in ASReml (Gilmour *et al.*, 2015). Real-life disturbances at herd level were selected based on days where mean milk yield of all cows in a herd suddenly declined, probably due to a disturbance. The traits describing response to the disturbances at herd level were the total yield loss during the temporary decline in milk yield (kg) and the time that the temporary decline lasted (days).

In addition to genetic analyses, we analysed the phenotypic association between the resilience indicators and lifetime gross margin. We performed an analysis of covariance based on records of 1,337 cows from 21 herds, with mean milk yield in lactation 1 as a covariate. Lifetime gross margin of each cow was calculated as the difference between all lifetime revenues (milk, calves, slaughter) and lifetime costs (feed, calving, rearing, insemination, treatment, destruction).

Results

All results are presented in Table 1. Both LnVar and r_{auto} were heritable, with LnVar having a higher heritability (0.21) than r_{auto} (0.09). Both had a positive genetic correlation with mean milk yield and negative genetic correlations with udder health, ketosis, and longevity, with the strongest correlation always for LnVar. These correlations indicate that cows with low LnVar or r_{auto} (good resilience) had low milk yield, good udder health and few ketosis cases, and high longevity, genetically. LnVar had a strong genetic correlation with total yield loss upon real-life herd disturbances (0.90), which means that cows with low LnVar had only a small decline in milk yield upon disturbances. The r_{auto} had no genetic correlation with yield loss upon herd disturbances, but was strongly genetically correlated with the time until milk yield recovered again. This means that cows with low r_{auto} had quick recovery upon real-life disturbances at herd level. The r_{auto} did not have a significant association with lifetime gross margin. However, LnVar did have a significant association with lifetime gross margin, which means that cows with low LnVar in first lactation had generated more profit at the end of life than cows with the same milk yield but with high LnVar.

Discussion

Low LnVar and r_{auto} were expected to be indicators of good resilience based on the assumption that resilient cows have milk yield that does not fluctuate much around its expected value, and if it deviates, recovers quickly (Scheffer *et al.*, 2018; Berghof *et al.*, 2019). Both resilience indicators were heritable, which means that they can be changed using genetic selection. The favourable genetic correlations with health traits, longevity (Poppe *et al.*, 2020; 2021a), and response in milk yield to real-life disturbances at herd level (Poppe *et al.*, 2021b) confirm that selection for these traits will result in improved resilience.

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Table 1. Genetic variance (VarA) and heritability (h^2) of resilience indicators, genetic correlations (r_g) with other traits (SE between brackets), and regression coefficients explaining relation with lifetime gross margin.

		Resilience indicator[1]	
		LnVar	$\mathbf{r_{auto}}$
Genetic parameters	VarA	0.056 (0.002)	0.003 (0.000)
	h^2	0.21 (0.01)	0.09 (0.01)
r_g with other traits[2]	AMY (kg)	0.79 (0.02)	0.16 (0.04)
	UH[3]	-0.32	-0.21
	KET[3]	-0.48	-0.15
	LON[3]	-0.16	-0.02
	Yield loss (kg)	0.90 (0.05)	-0.01 (0.13)
	Yield loss length (d)	-0.00 (0.29)	0.97 (0.35)
Association with lifetime gross margin	Regression coefficient	-427.98	404.77
	P-value	0.01	0.41

[1] LnVar = natural log-transformed variance of deviations from expected milk yield; r_{auto} = lag-1 autocorrelation of deviations from expected milk yield.
[2] AMY = average daily milk yield; UH = udder health; KET = ketosis; LON = longevity; yield loss = total yield loss upon real-life disturbances at herd level; yield loss length = time until yield is recovered upon real-life disturbances at herd level.
[3] Genetic correlations are estimated with Multiple Across Country Evaluation procedure, which does not give standard errors.

The strong genetic correlations with traits quantifying response to real-life disturbances at herd level confirm that the resilience indicators contain information about the severity of response to disturbances and recovery rate. The current breeding goal does not include response and recovery to disturbances yet, but only incidence of disease for example (CRV, 2020). Therefore, the resilience indicators contain new and relevant information, and resilience could be considered as an additional trait in the breeding goal.

The favourable association between LnVar and lifetime gross margin also suggests that LnVar has economic importance. However, some of the traits used to calculate lifetime gross margin are also included in the current breeding goal, such as milk yield, longevity, and fertility. To avoid double counting in the breeding goal, the marginal economic value, or effect of LnVar partial on these traits should be established first. Moreover, resilience is expected to have an additional non-economic value through its association with animal welfare. Hence, alternative methods are needed to determine the weight in the breeding goal, such as desired gains (Nielsen *et al.*, 2005), choice experiments with farmers (Nielsen *et al.*, 2011), or more research into associations with labour costs (Berghof *et al.*, 2019). Once the weight of resilience in the breeding goal is determined, an index of LnVar and r_{auto} can be used to genetically improve resilience.

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