Preventive Veterinary Medicine 147 (2017) 158–162

Contents lists available at ScienceDirect

Preventive Veterinary Medicine

journal homepage: www.elsevier.com/locate/prevetmed

Estimating the true prevalence of bovine digital dermatitis in taranaki, New Zealand using a bayesian latent class model

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ARTICLE INFO

Keywords:
Digital dermatitis
Dairy cattle
True prevalence
Latent class
Bayesian

ABSTRACT

A Bayesian latent class model was developed to estimate the true prevalence of bovine digital dermatitis (BDD) in Taranaki, New Zealand. This model allowed farms to have zero prevalence as well as also accounting for between farm heterogeneity that was conditional on whether a farm was positive for bovine digital dermatitis. The estimated true farm level prevalence was 68.9% (95% credible interval [CrI]: 50.0%-85.7%), while on infected farms the overall cow level prevalence (number of infected cows/total number of cows on infected farms) was 2.9% (95%CrI: 2.1%–4.3%). The sensitivity analyses suggested that the prevalence estimates were reasonably robust when the variation of the priors fell within the biologically plausible range. These results indicated that visual inspection of standing animals during milking was sufficiently accurate to identify infected farms. However, for every 100 animals identified through visual inspection, 84 animals with lesions were missed. In the other words, 46% (calculated as 84/184) of true positives at the animal level could be missed by visual inspection. The high and robust specificity (99.9%, 95%CrI: 99.8%–99.9%) suggested that lesions reported as BDD were very unlikely to be false positives.

1. Introduction

Worldwide, bovine digital dermatitis (BDD) has been found in all production systems (Laven and Logue, 2007; Capion et al., 2009; Holzhauer et al., 2012; Chapinal et al., 2013) including the pasture-based systems which predominate in New Zealand (NZ). A recent study in Taranaki on the North Island of New Zealand suggested that > 60% of farms had the disease although most infected farms had < 3% of cows with lesions that were detectable using visual inspection during milking (Yang et al., 2017). This low within-farm prevalence means that on NZ farms, early identification and treatment of lesions should be able to significantly reduce the spread of BDD within a farm and perhaps even eliminate the disease from a farm.

Early identification of BDD requires all cows to be regularly examined for BDD as examining lame cows only will miss a significant proportion of cases as not all cows with BDD are lame (Laven and Proven, 2000). Lifting and examining the feet of all cows in a foot crush or chute is likely to be the most effective way of identifying lesions but it is extremely time consuming and unlikely to be feasible on many dairy farms in NZ as facilities such as foot crushes are absent on many farms. Probably the best alternative to lifting feet is visual inspection during milking (Rodriguez-Lainz et al., 1998), as this means all cows in the milking herd can be examined without significant disruption to cow management, and this is what we used in our survey of BDD in Taranaki (Yang et al., 2017). However visual observation during milking is an imperfect process which would have resulted in misclassification errors. For example, Rodriguez-Lainz et al. (1998) reported an apparent prevalence of 20.5% when individual cows were visually inspected for approximately 2 min during milking whereas the prevalence when cows were inspected in the chute was 27%. Compared to examination in the chute, visual inspection during milking had a sensitivity and specificity of 72% (95% confidence interval (CI): 53%–86%) and 99% (95% CI: 93%–99%), respectively (Rodriguez-Lainz et al., 1998). However the chute examinations were made 1–4 weeks after the milking parlour examination, which may have influenced the specificity and sensitivity as BDD is a dynamic disease (Holzhauer et al., 2008; Berry et al., 2012; Döpfer et al., 2012).

The accuracy of visual inspection is likely to be influenced by a range of factors; in particular, the time available for inspection and the size of the lesions. Thomsen et al. (2008) reported, for an examination that lasted 15 s/cow, the sensitivity and specificity for small lesions (diameter ≤ 2 cm), were 57% (95%CI: 45%–69%) and 84% (95%CI:

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http://dx.doi.org/10.1016/j.prevetmed.2017.09.008
Received 24 April 2017; Received in revised form 11 August 2017; Accepted 18 September 2017

81%–87%), respectively, whereas for larger lesions (> 2 cm) the equivalent figures were 69% (95%CI: 62%–76%) and 84% (95%CI: 81%-87%). Most of the lesions reported in Taranaki were small (Yang et al., 2017) which means the sensitivity of our visual observation was likely to be low, which could have a significant impact on the accuracy of our estimate of BDD prevalence.

Thus to properly assess the status of BDD in Taranaki, we needed to estimate its true prevalence. However, two issues prevented a simple calculation of true prevalence from this dataset. Firstly, the results from the visual inspection were the only measure of BDD prevalence that we had, and, secondly, there is no true gold standard method of BDD diagnosis (Vink et al., 2009) to compare with.

To estimate the true prevalence of BDD at both farm and cow level after correcting misclassification errors, a Bayesian latent class approach was therefore chosen, based on the approach used by (Branscum et al., 2004) which allows the accuracy of a single test to be estimated based on data from multiple herds, some of which may have zero disease prevalence.

2. Materials and methods

The data used in this analysis came from 224 dairy farms in Taranaki on the North Island of NZ (Yang et al., 2017). These 224 farms were a subset of the source population (equivalent to target population in this study) which were the clients of Energy Vet Taranaki (314 farms). At the start of the study 310 out of 314 farm owners agreed to participate in the study, but after 224 farms were inspected, the herd screening was decided to stop as it was clear that the proportion of infected herds was much higher than expected.

A technician visited each farm during milking (two farms per day, six days a week) and examined the rear feet of all the cattle for lesions of BDD during milking. If necessary, the cows' feet were cleaned using a low pressure hose and visualisation of lesions was aided by the use of head torch. The time spent inspecting cows was minimised to avoid disrupting the normal milking routine.

As all the animals in a herd were inspected, the number of positive animals within a farm followed a binomial distribution (McAloon et al., 2016). This meant that the number of BDD cows detected by visual inspection on the i^{th} farm (x_i) was linked to the apparent BDD prevalence within the i^{th} farm (p_i) and the number of cows on the i^{th} farm (M_i) by the relation:

$$x_i \sim \text{Binomial}(p_i, M_i) \quad (1)$$

It meant that the relationship between p_i, true prevalence π_i, sensitivity η, and specificity θ of visual inspection could be summarised using the following equation:

$$p_i = \pi_i * \eta + (1 - \pi_i) * (1 - \theta) \quad (2)$$

The true prevalence for a random farm i will be zero if the farm is free of BDD. Therefore, the model allowed for farms with zero prevalence as follows:

$$\pi_i = z_i * \varphi_i \quad (3)$$

Here the true within-farm prevalence π_i was divided into farms with zero prevalence (for all $z_i = 0$) and farms with prevalence φ_i if $z_i = 1$; z_i follows a Bernoulli distribution of farms level prevalence γ.

$$z_i \sim \text{Bernoulli}(\gamma) \quad (4)$$

For farms with lesions, the within farm prevalence φ_i was modelled by an intercept-only random effect logistic regression (Stringer et al., 2013):

$$\text{logit}(\varphi_i) = \beta + \mu_i \quad (5)$$

where β was the intercept, i.e. overall logit-mean within-farm prevalence and μ_i was the random effect in a random infected farm which followed a normal distribution at the logit-level:

Table 1
Estimates of sensitivity, specificity with 95% confidence intervals (CI) of visual inspecting bovine digital dermatitis lesions in milking parlour.

Source	Sensitivity	95%CI	Specificity	95%CI
Rodriguez-Lainz et al. (1998)	72%	53%–86%	99%	93%–99%
Jacobs et al. (2015)	73.6%		96.7%	
Thomsen et al. (2008)[1]	65%	59%–72%	84%	81%–87%
Thomsen et al. (2008)[2]	57%	45%–69%	84%	81%–87%

[1] Overall sensitivity and specificity when both large and small lesions inspected.
[2] Sensitivity and specificity for small lesions only.

$$\mu_i \sim \text{Normal}(0, \tau) \quad (6)$$

where the software models τ as precision of the random effect (= 1/variance).

To allow comparison with the overall cow level prevalence on infected farms (number of infected cows/total cows inspected on farms where infection was detected) reported by Yang et al. (2017), β was converted to a population average parameter β_{PA} (Dohoo et al., 2009).

$$\beta_{PA} = \beta / \sqrt{1 + 0.346 * \tau^{-1}} \quad (7)$$

Priors on sensitivity and specificity were available from overseas studies (Table 1). However, there were no reliable NZ data on BDD prevalence and test accuracy. Furthermore, we considered that the ease of visualising lesions during milking might be different in NZ compared to overseas as all the cows would be based at pasture rather than confined in housing. An opinion from a NZ-based expert was therefore sought. Prior to any analysis of data from the prevalence study, R. N. Chesterton, who had been investigating BDD in NZ for two years prior to the start of the study, and who was familiar with the technique used to identify the lesions, was asked to provide his opinion on likely sensitivity, specificity and prevalence. His estimated sensitivity and specificity were 0.65 and 0.9; he was 95% sure that the sensitivity was greater than 0.5 and specificity was greater than 0.7. The median within-farm prevalence was assumed to be 7% and he was 95% sure that it was over 1%. The precision τ followed a gamma (1, 1) distribution. A diffuse prior such as beta (1, 1) was defined for farm level prevalence to express our uncertainty due to this being the first study of BDD prevalence in NZ. The priors and their corresponding distribution parameters are summarised in Table 2.

Sensitivity analyses were conducted to assess to what extent posterior distributions depended on priors or data. Optimistic and pessimistic priors were used for the sensitivity (increasing and decreasing by 10%), a pessimistic prior for specificity (15% less) and a wider prior for the within farm prevalence (median = 15%, 95% sure > 1%).

The model was developed in OpenBUGS (Spiegelhalter et al., 2007). The three chains were each thinned by five to reduce autocorrelation and run for 30,000 iterations, after discarding a burn-in period of 8000. Model convergence was assessed by BGR-diagnostics plot; the auto-correlation was assessed by auto-correlation plots.

Table 2
Prior information on prevalence, visual inspection sensitivity and specificity for Bayesian latent class model.

Prior	Estimate	5th/95th Percentiles	Distribution
Farm level prevalence			Beta (1, 1)
Within-farm prevalence	7%	> 1%	Logit-normal (−2.5867, 0.67084)
Sensitivity	65%	> 50%	Beta (20.9967, 11.7675)
Specificity	90%	> 70%	Beta (15.0342, 2.5594)