Bayesian modeling for estimating cattle's dung position in pasture

Rena Yoshitoshi [A], Nariyasu Watanabe [B], Kensuke Kawamura [A], Seiichi Sakanoue [B], Jihyun Lim [A] and Taisuke Yasuda [C]

[A] Hiroshima University, Japan, http://www.hiroshima-u.ac.jp/idec
[B] National Agriculture and Food Research Organization (NARO) Hokkaido Agricultural Research Center, Japan http://www.naro.affrc.go.jp/harc
[C] Yamanashi Institute of Environmental Sciences, Japan, http://www.yies.pref.yamanashi.jp
Contact email: rena.yoshi1210@gmail.com

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Introduction

Livestock excrement is one of the major sources of greenhouse gas (GHG) emission in pasture. As a first step in evaluating its contribution to overall GHG emissions, an understanding of excretion distribution patterns in pastures is required. Betteridge *et al.* (2010) describe a urine sensor that detects and logs each urination event of female sheep and cattle. The urine sensor records time and ambient temperature at one-second intervals however, patters of dung distribution are not specified. The objective of this study was to predict spatial distribution of cattle dung. The knowledge of livestock excrement position may be useful for farmers to minimize overall GHG emissions.

Methods

Both animal activity data and pasture data were collected in this study. Animal activities (grazing [active] or resting [inactive]) were estimated using an accelerometry-based activity monitor, the Kenz Lifecorder (LCEX; Suzuken Co Ltd, Nagoya, Japan), combined with a global positioning system (GPS) (Yoshitoshi *et al.* 2013). The study was conducted on a mixed sown pasture (0.85 ha) located on a north-east slope ranging from 115 to 135 m above sea level at the National Agriculture and Food Research Organization (NARO) Hokkaido Agricultural Research Centre, Japan (42°59'N, 141°24'E). We selected four cows from a herd of 20 based on the common age and body weight. Each cow was fitted with a LCEX-GPS collar and monitored for four days from June 14 to 18 (2010). The activity and location of each cow was recorded for a total of 15 hours. After four days a 10 m×10 m grid (total 85 cells) in the pasture and the number of dung in each cell counted. We also estimated the grazing time in each cell from the LCEX data. Using these data sets, several modelling approaches (generalized linear model [GLM], generalized linear mixed model [GLMM] and Bayesian model) were evaluated. The green biomass (GBM) and the distance from water trough were used as independent variables. Thus, this data was assumed Poisson distribution. The model has the form:

$y_i \sim$ Poisson (λ_i)
log ($y_{i)}$ = b_1 + b_2 GBM + b_3 distance from water trough + r_i (grid number)$b_1 \sim$ Uniform (-10,10), $b_2 \sim$ Uniform (-10,10), $b_3 \sim$ Uniform (-10,10), $r_i \sim$ Normal (0,tau)
tau = 1/σ* σ, σ ~ Uniform (0,1000)

where: b_1 is intercept, b_2 and b_3 are coefficient, respectively. The r is individual difference (grid number). Number of chains was three. The length of the MCMC chain for this model was 100,000 cycles after 30,000 burn-in cycles, with samples being saved every 100 cycles. All data handling and modeling analyses were performed using R statistical software, version 2.12.1 (R Core Team 2010).

Results and discussions

Figure 1 shows actual and predicted values using GLM, GLMM and Bayesian model. Predicted accuracy has improved when Bayesian model was used. Bayesian model had a posterior mean b_1 of 2.365, with 95% PPI of

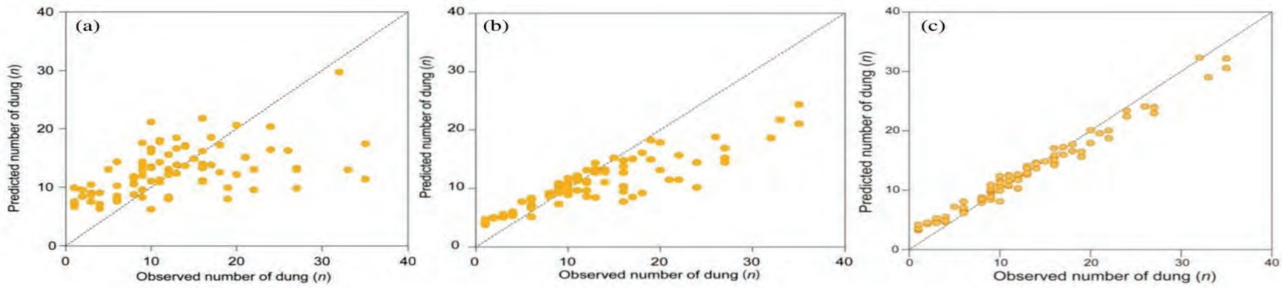

Figure 1. Actual and predicted values of the number of cattle's dung (log [n]) in each grid (10 m × 10 m) using GLM (a), GLMM (b) and Bayesian model (c)

Table 1. Posterior means (PMEAN), posterior standard deviations (PSD), 95% posterior probability intervals (PPI), R hat and effective sample size (ESS) for coefficient, obtained by MCMC

Coefficient	PMEAN	PSD	PPI	R hat	ESS
b_1	2.365	0.066	2.233 to 2.492	1	210000
b_2	0.363	0.070	0.227 to 0.504	1	210000
b_3	-0.062	0.068	-0.195 to 0.072	1	210000

2.233 to 2.492, a posterior mean b_2 of 0.363, with 95% PPI of 0.227 to 0.504 and a posterior mean b_3 of -0.062, with 95% PPI of -0.195 to 0.072 (Table 1). b_1 and b_2 did not have 0 with 95% PPI. Probability of $b_3 < 0$ was 82%.

To implement these models practically, the information of GBM can be gained from remote sensing. Furthermore, It is important to control the location of water trough to avoid the concentration of faeces because methane emission from cattle faeces excreted on bare area that are high in soil moisture is particularly high (Akiyama *et al.* 2010). For estimating dung position, data was insufficient and there is need for improvement and adaptation of the model. In this study, we didn't identify the amount of actual GHG emissions resulting from livestock excrement in the pasture. Then, the actual GHG emissions from grazing pasture should be measured to establish precise GHG mitigation techniques.

Conclusions

In this study, applying the classifying animal activity method, distribution of cattle dung was estimated in pasture and several modelling approaches were evaluated. The Bayesian model was best (R^2 = 0.96), but conclusion is based purely on data collected from a single paddock. Ideally, the fitted model needs to be tested in a number of contrasting paddocks.

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