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REVIEW

Spatial Distribution of Grazing Sites and Dung of Beef Cows in a Sloping Pasture

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Abstract

Livestock select places in a pasture that offer high-quality and nutritious grass, and these selections cause spatial heterogeneity and reduced productivity. To maximize the efficiency of pasture systems, it is important to understand the spatiotemporal information regarding livestock grazing behavior. In this review, we describe studies conducted to develop a simple tool for determining cow foraging behavior, and to predict the spatial distribution of cow excrement (dung) in a steeply sloping pasture. An accelerometry-based activity monitor, the Kenz Lifecorder EX (hereafter, the LC), was used to differentiate between foraging and other activities of beef cows. A linear discriminant analysis yielded good discrimination accuracy of the minute-based data of the LC. The combination of the activity timeline and GPS tracking data successfully revealed the spatiotemporal distribution of cow foraging activity in a sloping pasture. Both foraging activity and excretion play important roles in the nutrient cycling in pasture ecosystems. We found that the spatial distribution of cow dung could be predicted using a Bayesian approach in conjunction with a generalized linear mixed model incorporating conditional autoregressive terms with two parameters (green herbage biomass and distance from a water trough). Dung deposits tended to be distributed in areas with higher green herbage biomass and in areas located closer to the water trough. We also describe a new pasture survey method of detecting cow dung and weed positions in a pasture by using unmanned aerial vehicle (UAV)-based imagery.

Discipline: Animal Science
Additional key words: accelerometer, cattle, dung, UAV

Introduction

Spatiotemporal information about livestock activities such as grazing and resting in a pasture provides insights into pasture and animal conditions, allowing for improved pasture management and animal care (Turner et al. 2000), and thus many studies have been conducted on livestock behavior. Global positioning systems (GPS) have been increasingly used to monitor the spatial distribution of livestock and their track routes (Ganskopp 2001, Barbari et al. 2006), and the use of GPS has often been combined with sensing devices to monitor livestock activities, especially grazing behavior. Information on grazing behavior can be acquired from these devices by measuring the electrical resistance of jaw opening (Rutter 2000); devices that record the sounds of bites and chewing in grazing (Ungar & Rutter 2006); and accelerometers fitted on the jaw or neck (Wark et al. 2007, Watanabe et al. 2008). However, farmers do not use most of these devices because the devices are only capable of taking measurements for a few days, entail high energy consumption and high cost, and require extensive experience in correctly attaching the devices to animals (Ungar & Rutter 2006).

The Kenz Lifecorder EX-4s or GS-4s (hereafter, the LC; Suzuken Co., Aichi, Japan) was developed as a commercially available tool for human health

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management and research at a relatively low price (approx. 37,000 JPY). Ueda et al. (2011) devised a simple method of identifying the foraging activity of dairy cows in a flatland pasture by using the LC and an identified threshold value. To further develop cow activity monitoring using the LC device, we tested the ability of the LC to monitor the activity of beef cattle in a steeply sloping pasture, as most of the grazed pasture in Japan is located in mountainous or hilly terrain.

Cattle select foraging locales in response to the forage quantity and quality attributes (Ganskopp & Bohnert 2009), and thus cattle play an important role in the nutrient cycling in pasture ecosystems (Hirata et al. 2011). Cattle extract nutrients from the plants and return those nutrients to the pasture through their urine and dung (Ledgard 2001). Cattle urine and dung in the ecosystems not only provide soil nutrients but are also a major source of greenhouse gas (GHG) emissions (Holter 1997, Sordi et al. 2014). With increasing pressure on farmers to minimize environmental pollution from farming operations, a better understanding of the spatial distribution of excreta from grazing cattle is required. Research concerning the excreta of livestock by observation is laborious. Urine sensors that detect and log each urination event of female sheep and cattle have been developed (Betteridge et al. 2010), but useful equipment to detect dung positions has yet to be developed. We have therefore attempted to predict the spatial distribution of cow dung in a sloping pasture by using data on manageable factors (i.e., green herbage biomass, distance from a water trough).

In this review, we describe the studies that have been conducted to develop a simple tool for determining cow grazing behavior in the pasture, and to predict the spatial distribution of cow excrement using the Bayesian approach. We also introduce a method of monitoring pasture information by using unmanned aerial vehicle (UAV) imagery.

Study site, animals, and equipment

The study was conducted in a mixed sown pasture (No. 37) at the Hokkaido Agricultural Research Center, National Agriculture and Food Research Organization (NARO), Japan (Fig. 1). Three paddocks were delimited using electric fences (paddocks I and II: 1.02 ha; paddock III: 0.85 ha) where 20 breeding Japanese Black cows and their five calves were moved every four days in the order of paddocks I, II and III (paddock I: May 17-21, 2010; paddock II: May 31-June 4, 2010; paddock III: June 14-18, 2010). Four cows (cow 1: 596 kg, 16 years old; cow 36: 516 kg, 6 years old; cow 50: 588 kg, 4 years old, and cow 63: 395 kg, 2 years old) were randomly selected from among the 20 cows, and each cow was fitted with a GPS collar (CM-10kx, Furuno Electric Co., Nishinomiya, Japan), with another collar being attached to a small fabric bag containing the LC.

Distinguishing the cows' foraging activities by using an accelerometry-based activity monitor (Yoshitoshi et al. 2013)

1. Data treatment and statistical analysis

This study was conducted in paddock III (Fig. 1). During the four-day grazing periods, the positions of the cows were recorded every min. by the GPS collars, and

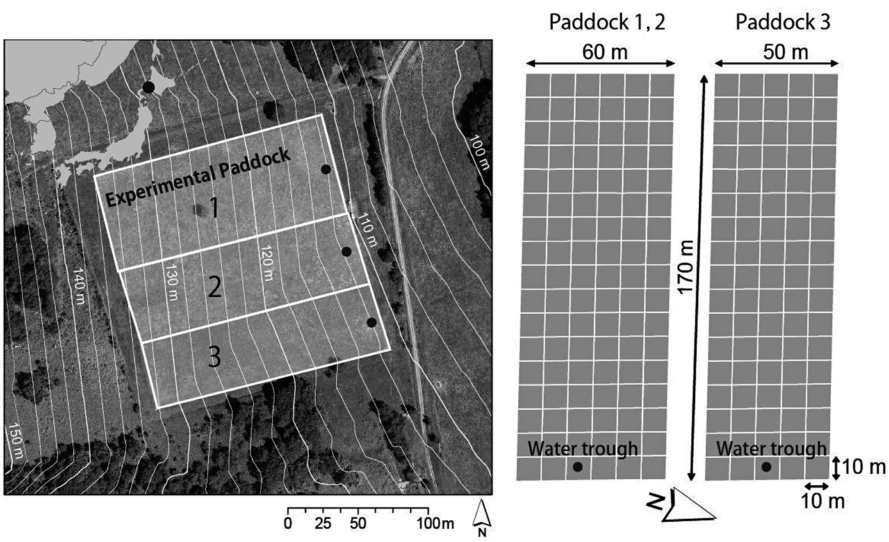

Fig. 1. Location of the three experimental paddocks, showing the 2-m contours and 10-m² grid cells in each paddock

the acceleration of the cows' neck movement was recorded at 4-sec. intervals by the LC. The LC records at 4-sec. intervals an intensity of movement at 11 scaled magnitudes: activity levels (AL) of 0 (none), 0.5 (subtle), and 1 to 9 (1, light; 9, vigorous). Three observers visually observed the cows' behavior, and the cows' posture (standing or lying down) and activities (i.e., foraging, ruminating, resting, walking, grooming, drinking) were recorded every min. by instantaneous scan sampling. A total of 15 hrs. of grazing behavior data per cow was obtained during the three-day field observation period.

The LC data were summed every min. to match the 1-min. interval used for the field observations. To distinguish between foraging and all other recorded activities, we subjected the 1-min interval data from the LC and observations to a logistic regression (LR) and linear discriminant analysis (LDA; Fisher 1936). To validate the accuracy of the LR and LDA functions, we applied a bootstrap procedure with 10,000 iterations based on an independent test data set. At each iteration, the data were randomly divided into a training subset for model development and a test subset for validation at a ratio of 2:1, respectively. Next, the training subset data were used to develop the LR and LDA functions. Finally, the classification accuracies of the foraging activities in the test subset were calculated using these functions.

Figure 2 shows histograms of the percentage of correct discrimination scores for foraging in the 10,000 bootstrap replicates using the LR and LDA functions. The threshold values (above which the activity is classified as foraging and below which is classified as other activities) for each cow based on the LR were larger (8.5 to 16.6 AL min^{-1}) than those based on the LDA (7.8 to 10.4 AL min^{-1}). For the pooled data set, the mean LR-based and LDA-based threshold values ($\pm$SD) were 10.8 ± 0.2 AL min^{-1} and 8.9 ± 0.1 AL min^{-1}, respectively. Overall, the LDA yielded higher correct discrimination for all cows (90.6%-94.6%) than the LR (80.8%-91.8%).

Similarly, correct discriminations for the LDA and LR for the pooled data set were 92.4% and 85.6%, respectively. The proportions of true nonforaging observations that were misclassified as foraging activity in analyzing the pooled data set using the LDA were 6.8% for resting and 0.8% for ruminating.

2. The spatiotemporal distribution of eating and other activities

By applying the LDA function, the hourly pattern of eating activity (eating time per hr.) was obtained for each cow. Figure 3 provides the spatial distributions of the four cows during their time spent on eating and other activities during the daytime (9:00 to 15:00) and nighttime (21:00 to 3:00). During the daytime (Fig. 3 a), the cows mostly grazed in the lower-altitude area of the paddock, covering

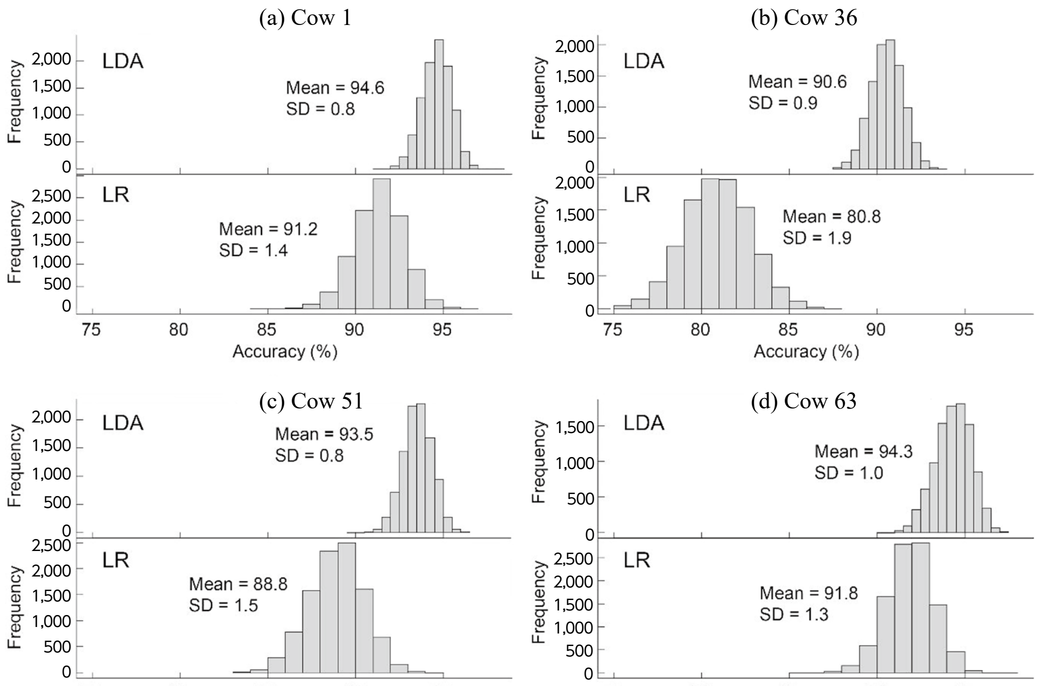

Fig. 2. Density distributions of the percentage of correct classification of foraging activity based on bootstrapping 10,000 times using logistic regression (LR) and linear discriminant analysis (LDA)

a wider area than at night. During the nighttime (Fig. 3 b), the cows spent most of their time in the higher-altitude area of the paddock, with less eating activity. The combination of the activity timeline and GPS tracking data was thus effective in determining the spatiotemporal distribution of cow foraging activity on pasture or rangeland.

Spatial modeling for predicting cows' dung positions (Yoshitoshi et al. 2015)

1. Dataset and modeling methodology

After four days of grazing in each of the three paddocks, each paddock was divided into 10 m×10 m grid cells (Fig. 1), and the number of dung deposits (N_d) in each cell was counted. The grid size was based on our previous study estimating the spatial distribution of green herbage biomass (GBM) and crude protein (CP) concentrations with the use of a hyperspectral radiometer over the same paddock (Lee et al. 2011). Considering the vegetation survey and labor required to count N_d, we used grid cells. Although topographical factors are related to cow dung positions, it is difficult to control the topography of a pasture (e.g., angle of inclination, slope shapes). As we would like to manage the distribution of excretion in the future, two controllable parameters—GBM and distance from a water trough (D_w)—were used in the present study as explanatory variables. GBM can be trimmed, the data can be obtained by remote sensing (Kawamura et al. 2010, Watanabe et al. 2014), and the land manager can control the location of the water troughs.

GBM was estimated using a rising plate meter (RPM) prior to the grazing trial in each of the three paddocks, and was defined as:

$$\text{GBM (g DM m}^{-2}) = 17.67x + 36.56 \quad (R^2 = 0.86)$$

in which x is the value of the RPM reading. D_w was computed using ArcGIS ver. 10 software (ESRI, Redlands, CA, USA). The mean values of the parameters for each cell were calculated based on the grid.

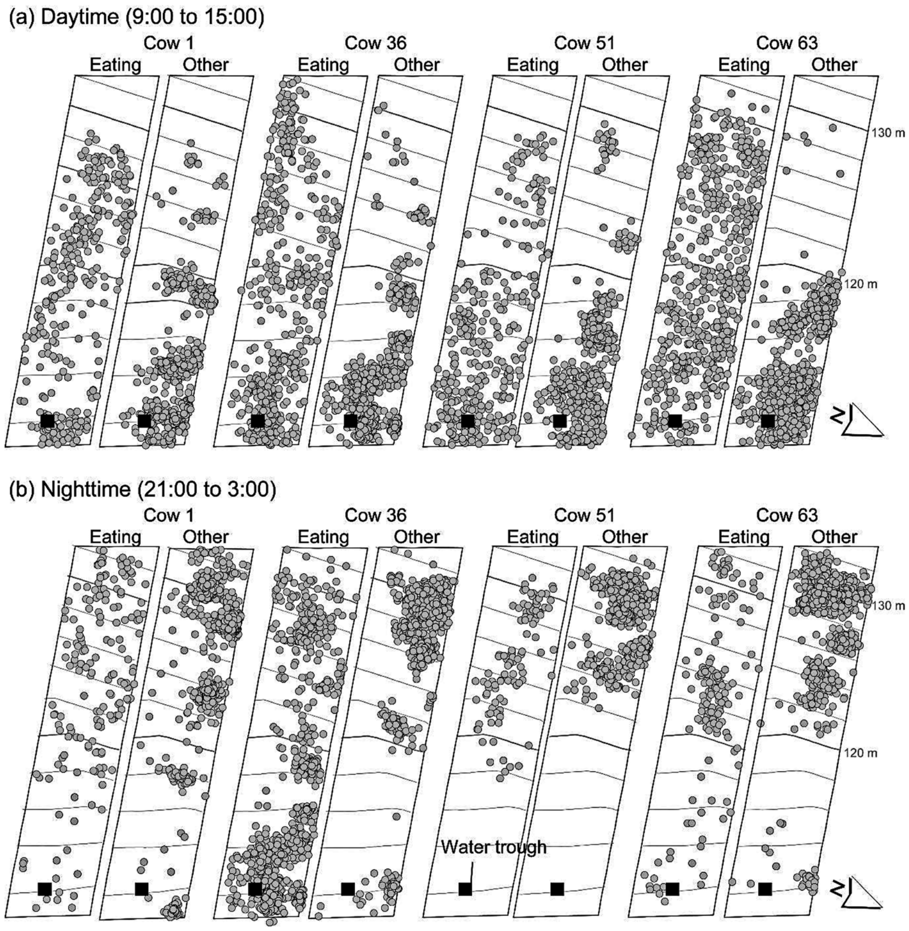

Fig. 3. Spatial distributions of the cows' time spent on eating and other activities during the (a) daytime (9:00 to 15:00) and (b) nighttime (21:00 to 3:00)

Because response variable N_d was a 'count' in nature, it was assumed to follow a Poisson distribution with the mean λ_i, which includes a spatial correlation random effect. The number of grid cells that contained zero values of N_d were three, one, and zero in the three paddocks, respectively. The corresponding variance values of N_d were 36.0, 76.1, and 64.6, respectively. This result indicated that these data cannot be explained well by a Poisson distribution. We thus used a generalized linear mixed model (GLMM) with a conditional autoregressive (CAR) term to incorporate the difference in location. The resulting Bayesian model was defined as:

$$N_d \sim \text{Poisson}\ (\lambda_i)$$
$$\log(\lambda_i) = b_1[j] + b_2[j]\log(GBM) + b_3[j]\log(D_w) + rho_i$$
$$b_1[j] \sim \text{Normal}\ (\mu_{b1}, \tau_{b1}),\ b_2[j] \sim \text{Normal}\ (\mu_{b2}, \tau_{b2}),$$
$$b_3[j] \sim \text{Normal}\ (\mu_{b3}, \tau_{b3}),$$
$$\mu_{b1} \sim \text{Uniform}\ (-10,10),\ \mu_{b2} \sim \text{Uniform}\ (-10,10),$$
$$\mu_{b3} \sim \text{Uniform}\ (-10,10),$$
$$\tau_{b1} = \frac{1}{\sigma_{b1} * \sigma_{b1}},\ \sigma_{b1} \sim \text{Uniform}\ (0,10),$$
$$\tau_{b2} = \frac{1}{\sigma_{b2} * \sigma_{b2}},\ \sigma_{b2} \sim \text{Uniform}\ (0,10),$$
$$\tau_{b3} = \frac{1}{\sigma_{b3} * \sigma_{b3}},\ \sigma_{b3} \sim \text{Uniform}\ (0,10)$$
$$rho_i \sim \text{CAR}\ (Adj_j[\,], Weight_j[\,], Num_j[\,], \tau),$$
$$\tau = \frac{1}{\sigma * \sigma},\ \sigma \sim \text{Uniform}\ (0,10)$$

where b_1 is the intercept, b_2 is the coefficient for GBM, b_3 is the coefficient for D_w, j is the paddock number, and *rho* represents the spatial random effects for each grid position. CAR terms were used to specify the intrinsic Gaussian CAR prior distribution (Thomas et al. 2004). *Adj*[] is a vector listing the ID numbers of the grid cells adjacent to each grid cell *i*; *Weight*[] is a vector the same length as *Adj*[] giving un-normalized weights associated with each pair of areas. Taking W*ij*=1 if areas *i* and *j* are adjacent gives a vector of 1's for *Weight*[] and implies a weight of 0 if areas *i* and *j* are not adjacent. *Num*[] is the number of sites adjacent to each grid cell, and τ is the precision or inverse variance parameter for the Gaussian CAR prior, where σ is assumed to follow a uniform (0, 10) distribution. All of the explanatory variables were standardized (mean=0, standard deviation=1) before use.

We performed Markov Chain Monte Carlo (MCMC) simulation to estimate the posterior distribution. The length of the MCMC chain for this model was 30,000 cycles after 10,000 burn-in cycles, with samples saved every 10 cycles. Three chains were used. All data handling and modeling analyses were performed using R statistical software ver. 2.15.2 (R Core Team 2012) and OpenBUGS ver. 3.2.2. (Lunn et al. 2009).

2. The MCMC results and spatial distribution of cow dung

Based on the results of the posterior distribution generated by the MCMC simulation, we observed similar estimates in all of the paddocks (i.e., positive values for GBM, negative values for D_w; Table 1, Fig. 4). This indicated that higher N_d tended to be associated with higher GBM and a location closer to the water trough. The 95% posterior probability interval (PPI) for μ_{b1} did not include zero. The means for μ_{b2} and μ_{b3} were 0.208 and 0.212, respectively, and the signs were as would be expected intuitively. The PPI values for both included 0, and the probability that they were above or below 0 was 87.2% and 91.7%, respectively. A small value of σ (with posterior mean of 0.631) was obtained, indicating weak spatial autocorrelation (Kubo 2009).

Table 1. Posterior means, standard deviations (SD), and quartiles (2.5%, 50.0% and 97.5%) obtained from the Markov Chain Monte Carlo (MCMC) simulation

Coefficient	Mean	SD	2.5%†	50.0%†	97.5%†
μ_{b1}	2.140	0.522	1.397	2.157	2.808
μ_{b2}	0.208	0.634	−0.753	0.209	1.129
μ_{b3}	−0.212	0.485	−0.855	−0.211	0.389
σ_{b1}	0.389	0.853	0.006	0.146	2.567
σ_{b2}	0.519	0.997	0.010	0.211	3.433
σ_{b3}	0.339	0.790	0.005	0.120	2.329
σ	0.631	0.048	0.541	0.630	0.730

† The values from 2.5% to 97.5% indicate the 95% posterior probability intervals (PPIs). μ is the hyper parameter of b_1, b_2, and b_3. b_1 is the intercept, b_2 is the coefficient of green herbage biomass, and b_3 is the coefficient of distance from the water trough. σ is the standard deviation.

Our present findings confirmed that the spatial distribution of cattle dung could be estimated using a Bayesian approach in conjunction with a GLMM model incorporating CAR terms with two parameters that the farmer can control (Fig. 5). We suspect that the bias on these plots was related to the cattle's activities. There were two major grazing periods during the day in this study: a long afternoon period and a shorter morning period, which are in accord with previous observations (Schlecht et al. 2004, Lin et al. 2011). It is likely that the grid cells that have large model residual values could be affected by these differences.

Detecting cow dung and weed positions using UAV-based imagery

UAVs have been applied to support precision agriculture. In the last decade, the use of UAVs has proliferated in applications of aerial photography and imaging over crop fields to assist with crop production management (Huang et al. 2013). UAVs have also been used for weed mapping (Tamouridou et al. 2017, Pflanz et al. 2018). We attempted to develop a method for detecting the positions of cow dung and reed canary grass (*Phalaris arundinacea*) by using high-resolution images from a UAV onboard camera. Reed canary grass is a perennial grass that spreads underground by its thick rhizomes. Due to its competitiveness and low palatability, reed canary grass is regarded as a major weed in Hokkaido, Japan.

We previously observed that the cows' fresh dung could be detected from its size and shape; old dried dung similar in color to soil was more difficult to detect (Yoshitoshi et al. 2015). The distribution of reed canary grass in orchard grass meadows could be detected using two digital surface models (DSM) before cutting and after harvest (Yoshitoshi et al. 2019). Although those results were obtained by traditional pixel-based image analysis based on the information in each pixel, this method has such disadvantages as the generation of noise and misclassification. As the information from surrounding pixels that may help in correctly identifying the target pixel's class is not used, each pixel is independently classified; thus, a class having high heterogeneity may have many misclassified pixels. Moreover, the application of high spatial resolution

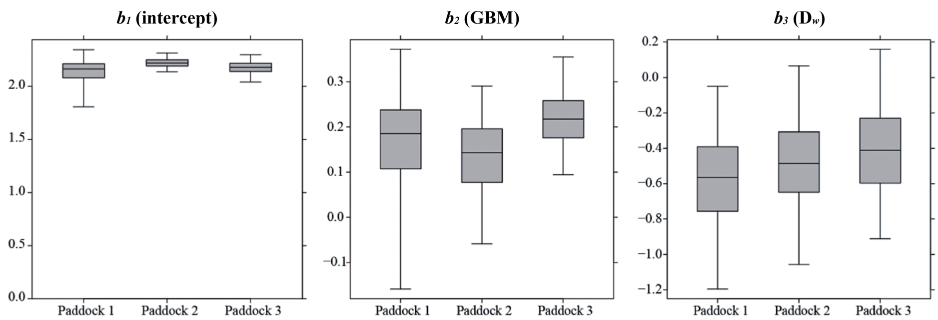

Fig. 4. Box plot of the 95% credible interval for each parameter
b_1 is the intercept; b_2 and b_3 are coefficients for log green herbage biomass (GBM) and log distance from the water trough (D_w), respectively.

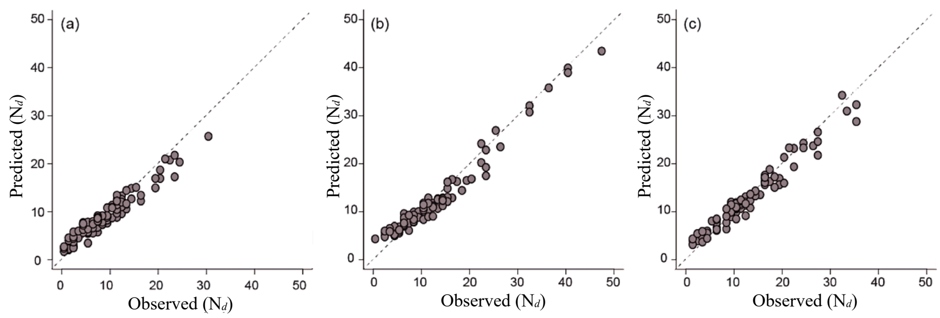

Fig. 5. Predicted and observed number of cattle dung deposits (*n*) in each 10-m² grid in paddocks I (a), II (b), and III (c) using a Bayesian model based on green herbage biomass (GBM) and distance from the water trough (D_w)
The predicted values were the medians from posterior distributions of the number of dung deposits (N_d) for each grid cell.

imagery to pixel-based image analysis leads to more errors due to the increased spectral heterogeneity (Myint et al. 2011, Whiteside et al. 2011). One of the approaches developed to overcome this problem is object-based image analysis (OBIA; Blaschke 2010). In OBIA, pixels are grouped together into objects or segments based on some criterion of homogeneity, and created objects (or segments) are far richer in information than that for individual pixels (Whiteside et al. 2011); therefore, the analysis results provide high classification accuracy and fast processing. Peña et al. (2013) suggested that the combination of ultra-high-spatial-resolution UAV remote images and OBIA permits the generation of weed maps in early maize crops. Pérez-Ortiz et al. (2016) confirmed the feasibility of UAV orthomosaic imagery and that of OBIA for both the early detection and mapping of weeds, and the saving of herbicides in sunflower and maize crops. The combination of UAV imagery and OBIA is expected to easily create highly accurate field maps.

Conclusion

In Japan, most grazing pastures are located in mountainous areas due to the limited land area available. A better understanding of livestock behaviors and their spatial distribution is important for increasing productivity and decreasing the environmental impact of grazing livestock. As described in this review, we used accelerometry-based activity monitor data with the LDA function to characterize the temporal organization of cows' eating activities in the pasture, and these data allowed the calculation of the hourly and daily time the cows spent on eating. We also attempted to predict the spatial distribution of cow dung in a slope pasture by using a Bayesian approach in conjunction with a GLMM model incorporating CAR terms with two controllable parameters (GBM and D_w). The dung deposits tended to be distributed in areas with higher green herbage biomass and those located closer to the water trough. As various methods are currently being developed, researchers will have to repeat the trial and error process to construct the most cost-effective procedure with better classification accuracy for creating maps of target sites.

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