A METHODOLOGY FOR DETERMINING CATTLE'S DUNG POSITION IN GRAZED HILL PASTURE

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ABSTRACT: Livestock excrement is one of the major sources of greenhouse gas (GHG) emission in grazed pasture. This study compared several modeling approaches in estimating spatial distribution of cattle's dung from the animal activity and geographical data. Animal activities (grazing [active] or resting [inactive]) and their GPS locations were obtained in our previous results (Yoshitoshi et al. 2011, ACRS). The study was conducted in a mixed sown pasture plot (0.85 ha) located on a northeast slope ranging from 115 to 135 m above sea level. 20 cows were grazed there for four days (June 14 to June 18, 2010), and six cows in them were fitted with GPS-accelerometer (LCEX) collars. We observed the behaviors of the six cows for each 15 hours during the grazing period. After the four days grazing treatment, we set 10 m × 10 m grid cell in the plot and counted the number of dung in each cell. We also estimated the grazing time in each cell from the LCEX data. Of several modeling (Geographically Weighted Regression [GWR], k-Nearest Neighbour Regression [kNNR], Random Forest Regression [RFR] and the Generalized Additive Model [GAM]) approaches developed, the RFR model showed the best prediction (R^2 = 0.92) about the excrement distribution, using independent variables the animal activity, grass quantity and quality, slope, distance from water trough and fence, northings and eastings in 100 m^2 grid cells. This model will be revised as new data become available and by inclusion of farm features such as trees, shelter belts and gateways around which animals typically congregate.

1. INTRODUCTION

Global greenhouse gas (carbon dioxide [CO_2], methane [CH_4] and nitrous oxide [N_2O]) emissions due to human activities have grown since pre-industrial times, with an increase of 70% between 1970 and 2004. It is very likely that the observed increase in CH_4 concentration is predominantly due to agriculture and fossil fuel use. The increase in N_2O concentration is also primarily due to agriculture (IPCC, 2007). With increasing pressure coming on to farmers to minimize environmental pollution from their farming operations, mitigation strategies are required. Nitrogen (N), phosphorous (P) and faecal microbes are pollutants of major concern, where N can be leached as nitrate or emitted as ammonia or nitrous oxide, whereas organic N, inorganic P and faecal microbes move in water, predominantly in overland flow (McDowell et al. 2005; McDowell & Wilcock 2007; McDowell & Srinivasan 2009; McDowell 2012). A critical source area (CSA) is an area of land with a large source of nutrient or faecal contaminants that intersects with a transport mechanism – usually hydrological activity like surface runoff (McDowell & Srinivasan 2009). Where only urine is involved, each urine patch, but typically an aggregation of urine patches such as in a gateway or stock camp, is nutrient rich and can be a CSA of N (CSAN) with losses emitted as ammonia, nitrous oxide or as nitrate in leachate to groundwater. Toolboxes of potential mitigation strategies exist (Monaghan et al. 2007; Monaghan et al. 2008; Monaghan 2009), but unless these small CSA areas are targeted with the mitigation, the cost of mitigation may to be too high for whole-paddock treatment (McDowell & Srinivasan 2009; Betteridge et al. 2011). One tool recommended for reducing N leaching and CH_4 emission is the nitrification inhibitor dicyandiamide (DCD) (Di & Cameron 2007), but this is uneconomic on sheep and beef farms, especially on hill country. If we can know where livestock excrete, GHG palliative such as DCD is used economically and efficiently. To enable farmers to treat CSAs with a chosen mitigation strategy they will need to know where these are located. Also, a regulatory body may need independent verification that such areas have been correctly identified and treated. Because much anthropogenic

N_2O and CH_4 are produced by agricultural activities, it is important for farmers to understand the mechanisms of these gases production from agricultural fields and the factors that control these mechanisms.

To develop the GHG mitigation technologies from agriculture sector, intensive grazing team at NARO Hokkaido Agricultural Research Center in Japan has investigated, which has conducted joint research with us. The results indicated; (1) methane emission from cattle feces excreted in the bare area with high soil moisture is particularly high (Akiyama et al., 2010); (2) the distribution of dung is non-uniform and the number of dung increase around water trough when we set water trough on the lower slope (Watanabe et al., 2011); (3) the number of dung tends to increase at the place used for rest. This result is from multiple liner regression model about the excrement distribution, using independent variables the animal activity, grass quantity and quality, slope in 100m^2 grid cells. An underlying assumption of the MLR method is that the relationship under study is spatially constant and that the estimated parameters remain constant over space. In heterogeneous environments, such as grazed pastures, especially hill country pastures, variation of parameter values will often change in unison, i.e. they are auto-correlated. Thus, the basic premise of the parameters being stationary is violated and the MLR approach is invalid (Wang et al. 2005). Moreover, failure to account for auto-correlation prevents in-depth interpretation of almost all geographical analyses (Jetz et al. 2005) and can lead to incorrect conclusions. The aim of this study was to estimate distribution of livestock excrement in the pasture using the data obtained by LCEX and GPS collar placement and to evaluate several modeling approaches; Geographically Weighted Regression (GWR, Fotheringham et.al., 2002), k-Nearest Neighbour Regression (kNNR), Random Forest Regression (RFR) and the Generalised Additive Model (GAM, see Hastie et.al., 2009), which consider the spatial dependence. We have not linked urine distributions to these models although the distribution patterns of faeces are likely to be similar (White et al. 2001).

2. MATERIALS AND METHODS

2.1 Study site

The study was conducted in a mixed sown pasture (0.85 ha) located on a northeast slope (115-135 m above sea level) at the NARO Hokkaido Agricultural Research Center (42°59'N, 141°24'E) (Figure 1). The pasture was established in the 1960s by sowing orchardgrass (*Dactylis glomerata* L.), tall fescue (*Festuca arundinacea* Schreb.), meadow fescue (*Festuca pratensis* Huds.), Kentucky bluegrass (*Poa pratensis* L.), timothy (*Phleum pratense* L.), redtop (*Agrostis alba* L.) and white clover (*Trifolium repens* L.). This pasture has been used as grazing land for Japanese Black cattle without fertilizer application in last decade. In the paddock, twenty breeding Japanese Black cows and their five calves were stocked for four days during the period from 10:00 June 14 to 10:00 June 18, 2010. The mean air temperature was 18.1ºC, and the maximum and minimum temperatures were 24.5ºC and 15.2ºC, respectively. The sunrise, meridian passage, and sunset times (GMT+9) at the experimental paddock were 3:52, 11:35 and 19:18, respectively. We set water trough on the lower slope during this experiment.

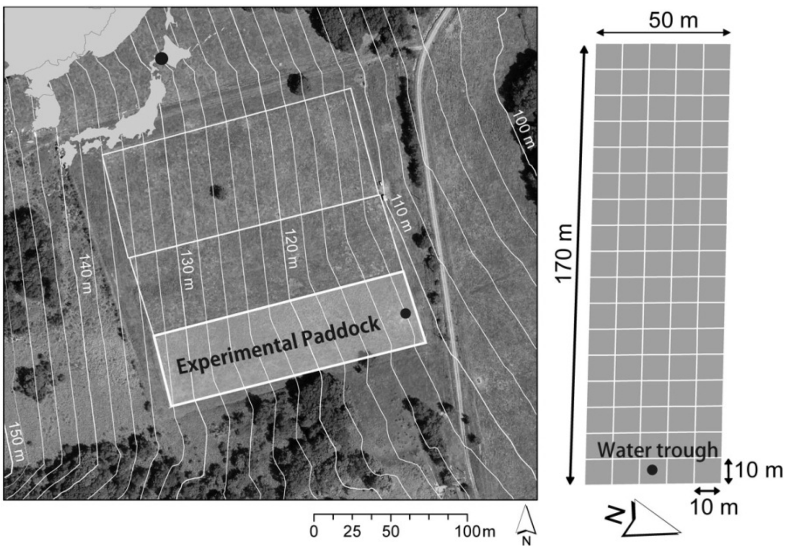

Figure 1: Location of the experimental paddock with 2-m contour and 10 m × 10 m grid cell in paddock.

2.2 Data set for modeling

We selected six cows (cow 1, 596 kg, 16 years old; cow 36, 516 kg, 6 years old; cow 50, 588 kg, 4 years old; cow 54, 458 kg, 3 years old; cow 62, 407 kg, 2 years old; and cow 63, 395 kg, 2 years old) from the 20 cows based on the balance for age and body weight. Each cow was fitted with a GPS collar (CM-10kx, Furuno Electric Co Ltd, Nishinomiya, Japan) and a collar attached to a small fabric bag containing an accelerometer, LCEX. The LCEX (Suzuken Co. Ltd., Nagoya, Japan. weight, 60 g; width, 72.5 mm; height, 41.5 mm; thickness, 27.5 mm) was wrapped in a vinyl bag for waterproofing and placed within the small fabric bag. During 4-day grazing periods, the positions of the cows were recorded every minute by the GPS collars. The LCEX is a single-axis accelerometer that records an intensity of physical activity at 11 scaled magnitudes, including 0 (no movement), 0.5 (subtle) and 1-9 (1, light; 9, vigorous) at 4-second intervals for 5 weeks. To match the interval of LCEX activity data with the GPS collar data-acquisition interval (1 min), the LCEX data was summed every minute after the experiment. We also recorded the behavior of four of six cows with attached LCEX and GPS monitors from June 16 to 18, 2010. In the 3-day field observation period, a total of 15 hours of grazing behavior data were obtained. Three observers monitored, and recorded cow's behavior (eating, ruminating or resting) every minute.

After the four days grazing treatment, we set 10 m × 10 m grid cell in the plot and counted the number of dung in each cell. The number of dung was used as dependent variable after log change. Using the 1-min interval data from the LCEX and field observations, we estimated animal activities (grazing [active] or resting [inactive]) during the experiment period (Yoshitoshi et al. 2011, ACRS). Animal activity, grass quantity and quality, slope, distance from water trough and fence, northings and eastings per $100m^2$ grid cell were calculated and used as independent variables.

2.3 Modeling methodology

All data handling and discriminant analyses were performed using R statistical software, version 2.15.0. R software was utilized to assess several potential models for predicting the distribution of dung. The main aim was to identify the best predictive regression model for determining the number of dung based on other measured variables. In the first instance, the MLR was used to quantify effects of measured variables. The Akaike Information Criterion (AIC) was used to determine those variables that would not be used as they contributed least towards the outcome of the final selected model (Akaike, 1973). The grid data were also used to generate a correlation matrix amongst all variables.

GWR, kNNR, RFR and GAM are methods that allow for variation in parameters in time and space, thereby overcoming the limitation of MLR analyses of spatially oriented data. Each modeling approach predicts the response value of a given cell by referencing values of surrounding cells in a certain way. kNNR uses the k number of surrounding cells, whereas GAM determines the smoothed response surface based on all surrounding cells. GWR explores spatial non-stationarity of a regression relationship for spatial data by locally fitting a spatially varying coefficient regression model. RFR, on the other hand, builds a large number of regression trees based on bootstrap samples together with a random subset of predictor variables. Tree models are grown without pruning and the final prediction is an ensemble of predictions from all trees.

These methods don't produce a model (that can be easily written up) but rather take an input training data set and predict dung distribution for the new paddock data. Input data must include the Northing and Easting values of each grid cell and all input data must be standardized so that the model built on the training data can be used to predict outcomes from the new data where the site will have local slopes, aspects, elevations and location co-ordinates (northing and easting).

Models were assessed using Mean-Squared-Error (MSE) and R-squared values in the usual manner (*i.e.* re-substitution approach) as well as via a leave-one-out cross-validation (CV) approach. Furthermore, graphics including grid-plots showing actual and fitted values were used for assessing the goodness-of-fit of the candidate models.

3. RESULTS AND DISCUSSION

3.1 MLR analyses

All LCEX and GPS collars successfully acquired scheduled records during the 4-day grazing periods. From the 15 hours of behavioral observation, 906 minutes of data were obtained for each cow, giving a total of 3,624 minutes of data (eating, ruminating, resting and others data were 1,123, 1,615, 757, 126 minutes, respectively).

Multiple linear regression analysis of trial data showed the number of dung was moderately related to resting time, less strongly related to grazing time and grass biomass and easting ($R^2 = 0.50$, $p < 0.01$).

3.2 A comparison of MLR, GWR, GAM, kNNR and RFR models

Based on the training mean square error (MSE = sum(y-f)^2/n, y – actual, f – fitted, n – sample size) values (Table 1), the lowest value was with the RFR model followed by kNNR, GAM and GWR, the highest being MLR. The CV MSE values also indicate that RFR followed by kNNR are the best models. The R^2 values (= 1 – {sum(y-f)^2/sum(y-x)^2}, x – average of y) indicate that RFR explains about 92% and 64% of the variation in the number of dung under re-substitution and CV model assessment scenarios respectively, followed closely by the kNNR and GAM models with values 86% and 54%, 79% and 44%, respectively.

Table 1: Mean-Squared-Error (MSE) and R-squared estimated values via re-substitution (Training) and cross validation (CV). "*" indicates unavailable in R software.

Model	Training Fitted R^2	Training Fitted MSE	Training Fitted AIC	CV Fitted R^2	CV Fitted MSE
MLR	0.54	0.30	161.22	0.42	0.38
kNNR	0.86	0.10	*	0.54	0.30
GAM	0.79	0.14	119.40	0.44	0.37
RFR	0.92	0.05	*	0.64	0.24
GWR	0.52	0.17	112.29	*	*

Using Moran's I test, we calculated spatial dependent for residual value of models. The residual values of MLR had spatial autocorrelation (Moran I = 0.30, p < 0.001), but other models resolved this problem (Table 2).

Table 2: Moran's I for residual values via re-substitution (Training).

Model	Moran's I
MLR	0.295 (p < 0.01)
kNNR	0.079 (p = 0.07)
GAM	-0.030 (p = 0.61)
RFR	0.054 (p = 0.07)
GWR	-0.001 (p = 0.43)

3.3 The spatial distributions of actual and predict values

Actual and predicted values clearly show that RFR and kNNR model are better models for estimating dung position compared to actual (Figure 2, 3). The estimation accuracy for the CV was much lower than training. Figure 4 is grid plots for distribution of dung showing actual and predicted values based on five models in the training data set. In MLR model, lower values could not be predicted well.

This conclusion is based purely on data collected from a single paddock. Ideally, the fitted model needs to be tested on independent paddocks with known values of predictor as well as response variables. The more we get data, the more estimation accuracy of RFR model is high. Thus, the low estimation accuracy for CV could be improved.

The models will be further developed using new paddocks for which we have contour, easting, northing, pasture and animal activity data. These paddocks will need to vary in size, elevation and slope ensuring that there are different ratios of hill and flat areas amongst the paddocks. This will ensure a more robust model of where cattle dung hotspots will likely be found in a randomly selected paddock for which the farm manager wishes to apply a N loss mitigation strategy.

A truly robust model will also needs to recognize physical features (trees, hedges and gateways) within a paddock that are likely to entice animals to excrete disproportionate amounts of feces within close proximity. Such features will need to be added manually into a GIS map layer using local knowledge or an aerial photograph. Furthermore, nutrient hotspots of organic N, inorganic P and faecal microbes will need to be linked to a hydrology model to determine transport.

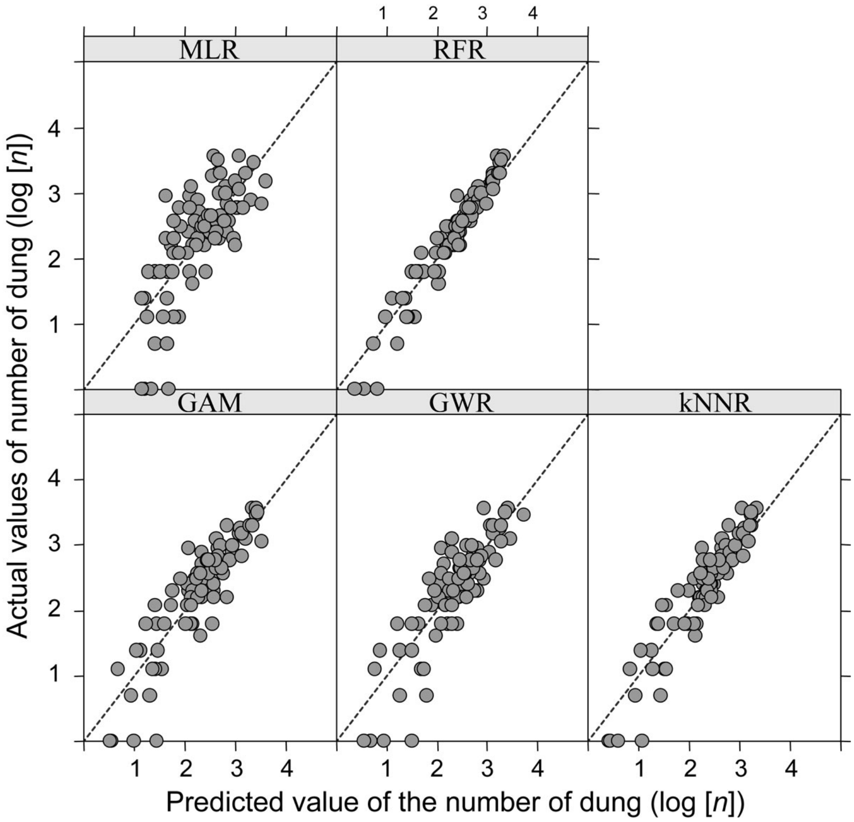

Figure 2: Actual and predicted values of the number of cattle's dung (log [n]) in each grid (10 m × 10 m) using training data set (N = 85) with MLR, GAM, RFR, GWR and kNNR

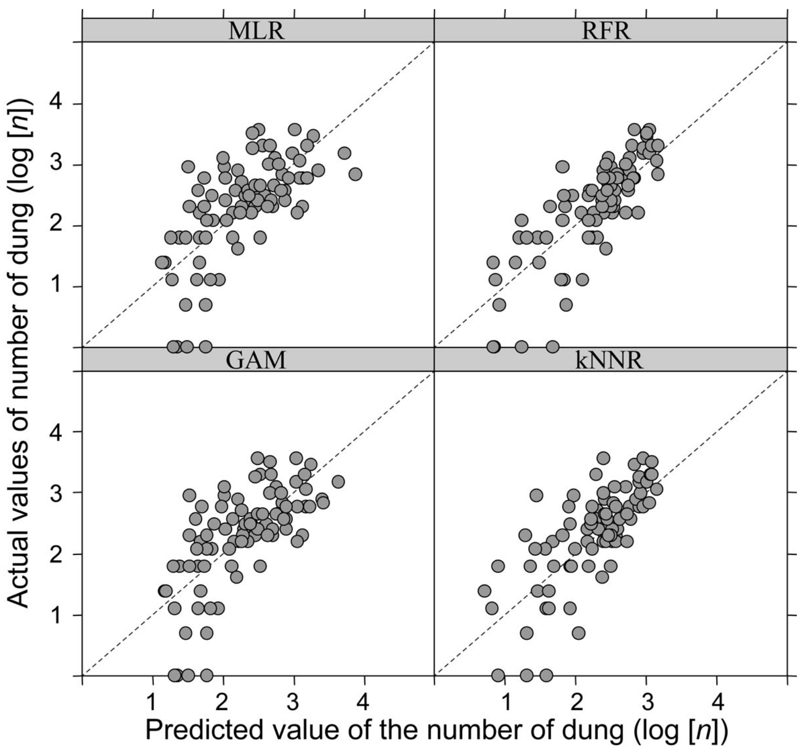

Figure 3: Actual and predicted values of the number of cattle's dung (log [n]) in each grid (10 m × 10 m) using test data set (N = 85) with MLR, GAM, RFR and kNNR.
*GWR was unable to predict dung position using GWR test data set because this model weighted location data.

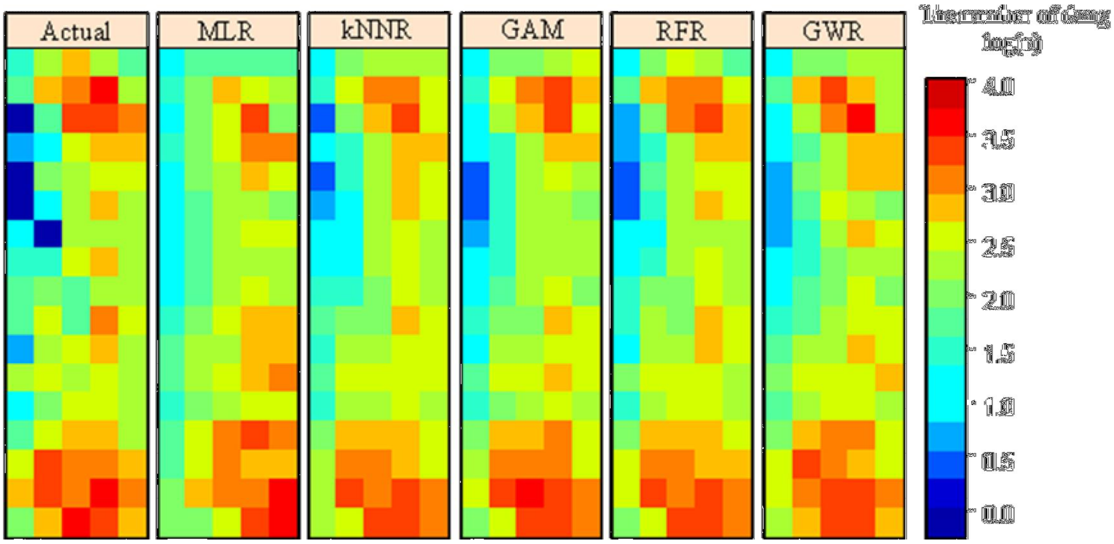

Figure 4: Grid plots for distribution of dung showing actual and fitted values based on five models for the training case.

4. CONCLUSIONS

Random Forest Regression model was the best model ($R^2 = 0.92$) to estimate dung distribution in a paddock, We recommended acquiring animal activity, grass quantity and quality, slope, distance from water trough and fence, northings and eastings for the paddock, based on a 10 m × 10 m grid. Used models will be improved when incorporating data from additional paddocks and features within paddock .

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