Doctoral Dissertation

Agro-Environmental Study on Grazing System: Sensing Grazing Behavior and Spatial Modeling

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Abbreviations

CAR	Conditional autoregressive
CH_4	Methane
CO_2	Carbon dioxide
CP	Crude protein
CSA	Critical source area (CSAN, CSA of N)
DIC	Deviance information criterion
D_w	Distance from a water trough
GBM	Herbage green biomass
GHG	Greenhouse gas
GIS	Geographical information system
GLM	Generalized linear model
GLMM	Generalized linear mixed model
GPS	Global positioning system
IT	Information technology
LCEX	Kenz Lifecorder EX (Suzuken Co Ltd, Nagoya, Japan)
LR	Logistic regression
LDA	Linear discriminant analysis
MCMC	Markov Chain Monte Carlo
MLR	Multiple linear regression
N	Nitrogen
N_2O	Nitrous oxide
NARO	National Agriculture and Food Research Organization
N_d	Number of dung deposits
NIR	Near-infrared
P	Phosphorus
PA	Precision agriculture
PPIs	Posterior probability intervals
QGIS	Quantum GIS [software]
RFR	Random forest regression
RPM	Rising plate meter
ROI	Region of interest
SD	Standard deviation
TIFF	Tagged Image File Format
UAV	Unmanned aerial vehicle
UTM	Universal Transverse Mercator coordinate system

Abstract

Agro-Environmental Study on Grazing System: Sensing Grazing Behavior and Spatial Modeling

Spatio-temporal information on the grazing behavior of animals provides insights into pasture and animal conditions, allowing for improved pasture management and animal care. Various sensors and analytic tools have been developed to assist with the collection and analysis of data regarding the activities of animals at pasture. However, most of these devices cannot be used by farmers because they are only capable of taking measurements for a few days, due to their high energy consumption, or because they are expensive and require extensive experience to correctly attach them to animals. Moreover, the data obtained by such sensing devices are complex, and the grazing behaviors are strongly influenced by surrounding environments.

The objectives of this study were (1) to develop a simple tool for determining cattle grazing behavior in the pasture (chapters 2 and 3), and (2) to predict spatial distribution of cattle excrement, one of the main sources of greenhouse gas (GHG) emission from pasture, using Bayesian approach (chapters 4 and 5) and unmanned aerial vehicle (UAV) on-boarded camera images (chapter 6).

The global positioning system (GPS) data sometimes contains many missing values. In chapter 2, thus, the author tried to determine the minimum requirement of GPS recording rate (100% = 1,440 GPS points per day) that is sufficient to know the spatial distribution of livestock (especially, distance traveled). Using 1,000 simulations of random sampling method between 75 (1,080 GPS points per day) to 100% recording rate, daily distance (m) traveled by

cow was calculated. The results indicated that there is no significant difference between 91−100% GPS recording rate on the distance (t-test, $p > 0.05$). The 1,459 days from five-year data set were greater than 91% of the GPS recording rate in one day and used for appropriate in determining the spatial distribution of cattle. The distance traveled tended to have similar trends that younger cows walked longer distance. During the daytime, the cows mostly stayed in the lower-altitude area of the paddock, while during the nighttime, the cows spent most of their time in the higher-altitude area of the paddock.

In chapter 3, the author evaluated the feasibility of an accelerometry-based activity monitor, the Kenz Lifecorder Ex (LCEX; Suzuken Co. Ltd., Nagoya, Japan), combined with a GPS, in order to differentiate between foraging and other activities of beef cows in a steeply sloping pasture. The grazing trial was conducted in a mixed sown pasture (0.85 ha) and four cows from the 20 cows were fitted LCEX-GPS collars in four days (June 14–18, 2010). During the period, three researchers recorded the animal activities (eating, resting and ruminating) and postures in every minute for 15 hours. Logistic regression (LR) and linear discriminant analysis (LDA) – two of the most widely used techniques for distinguishing animal activities based on sensing device information – were applied to the dataset (LCEX and observation data) to distinguish eating and other activities (resting, ruminating, etc.). The LDA results showed a higher correct discrimination percentage for all cows (90.6–94.6%) than that of the LR results (80.8–91.8%). Applying the LDA function over the whole period of LCEX data, the time spent eating averaged 443–475 min day^{-1} (30.7–33.0%). Combining with the GPS locations, the spatial distribution patterns of eating and other activities of cattle were compared between daytime and nighttime. During the daytime, the cows mostly grazed in the lower-altitude area of the sloped paddock, covering a wider area than that at nighttime.

Meanwhile, at the nighttime, the cows spent most of their time in the higher-altitude area of the paddock, without eating activity. These results are in agreement with the results of chapter 2 and other previous researches.

In chapters 4 and 5, the spatial distribution of cattle dung was estimated based on Bayesian approach using generalized linear mixed models (GLMM) with an added intrinsic conditional autoregressive (CAR) term. The predicted herbage green biomass (GBM) with rising plate meter (RPM) and distance from a water trough (D_w), which can be controlled by farmers, were considered as predictors in the models. The field experiments was conducted in three mixed sown pastures (I and II, 1.02 ha; III, 0.85 ha) in Hokkaido, Japan. After a four-day grazing trial using 20 Japanese Black cows (*Bos taurus* L.), the paddocks were divided into 10 m × 10 m grid cells (I and II, 102 cells; III, 85 cells) and for each grid cell the number of dung deposits (N_d) was counted and the mean values of the GBM and D_w were computed using geographical information system (GIS). First, the spatial distribution of cattle dung was estimated using single paddock data (chapter 4). Then, the model was improved to be more general and used three paddocks data (chapter 5). The results of a Markov Chain Monte Carlo (MCMC) simulations indicated that a higher N_d tend to be associated with a higher GBM and locations closer to the water trough. The N_d showed spatial autocorrelation and it is likely that the grid cells that have large residual values could be affected by the difference between cattle activities in the daytime and nighttime. These results suggested that the spatial distribution of cow dung can be predicted from two controllable factors in short term grazing trials. Ideally, farmer use this knowledge to control the excrement position by managing grass condition and changing a water trough location.

In chapter 6, the author tried to detect the position of cattle dung in pasture using a very high resolution image acquired by a UAV on-boarded camera. In a grazed paddock (1.0 ha), two control plots A and B (20 m × 20 m, protected from cow by electronic fence) were installed, and UAV images were acquired on June 20, 2014. The spatial resolutions on ground level in plot A and B images were 1.4 cm (1891 × 1929 pixels) and 2.2 cm (1222 × 1228 pixels), respectively. After the UAV flight, the position of cattle dung were recorded using differential GPS (DGPS) and ground survey. Image processing was done using random forest regression (RFR) analysis to determine cattle dung from RGB image values. The results indicated that the fresh dung could be detected with high accuracy from the image using RGB values with their size and shape information. Meanwhile, old dried dung is difficult to distinguish from soil due to similarity of RGB values. The subject of a future study could be look for a characteristic wavelength to distinguish between old dung and soil. It is necessary to consider the short-wavelength (ultra violet) and near-infrared (NIR) not just the visible region (RGB colors) and investigate whether it is possible to distinguish how many days after excretion the fresh dung looks like old dung. The author also detect the dung position with other photographic images provided by the UAV at different altitudes and verified the size estimate precision.

Limitation of this study is that the actual amount of GHG emissions resulting from livestock excrement in the pasture were not quantified. Future study requires to examine the actual GHG emissions from a grazing pasture in order to establish precise GHG mitigation techniques. Nevertheless, the knowledge of livestock excrement position could be useful for farmers to minimize environmental pollution. The result of this thesis could contribute to do precision agriculture that can minimize environmental effects and enhance productivity.

－Chapter 1－

General introduction

“Learn from yesterday, live for today, hope for tomorrow.
The important thing is not to stop questioning”

Albert Einstein (1879–1955)

Chapter 1: General introduction

1.1. Background

1.1.1. Utilization of grazing systems

Livestock grazing systems are techniques that have been used at various times and places. Those benefits includes: saving livestock food, litter cost and human power because feeding and excreta removal work is unnecessary, improvement of reproductive performance and group feeding is possible, having a great impact on the vegetation (Perevolotsky and Etienne, 1999). Further, these have pleiotropic effects such as farmland restoration, environmental protection, species and community diversity (Collins et al., 1998; Sternberg et al., 2000), landscape (Hartnett et al., 1996; Adler et al., 2001), regional activation and effective utilization of abandoned farmland. Grazing is an important technology in narrow land such as Japan where workers have been reduced. Disadvantages in grazing systems were; increasing nutrient concentrations (Day and Detling, 1990; Rietkerk et al., 2000; Augustine and Frank, 2001); difficulties of health and nutritional management of individual because of excreta and concentration of utilization rate in pasture; and increasing risks of erosion due to the amount of bare ground, and soil compaction

1.1.2. Precision agriculture

In grazing pasture, the dispersion of productivity is caused by the presence of grass, livestock and excrement. Therefore, in order to produce a high-quality grass it is necessary that management and analysis of spatial information about the growth, soil and the livestock used by the geographical information system (GPS), global positioning system (GIS) and remote sensing (RS). Recently, as the alternatives of conventional agriculture, there is significant change to shift toward precision management. It is generally called precision agriculture (PA) or precision farming (PF). The principal concept of PA was initiated in the middle of 1980s, using newly available technologies, to improve the application efficiencies of fertilizers by varying rates and blends as needed within fields (Robert, 2002). PA is defined as the agricultural method using advanced technologies such as GPS, GIS and RS (McBratney et al., 2005). Using the RS and GPS, the present status of target, such as position of livestock, crop growth and soil fertilities were sensed with spatial information. The data are evaluated, analysed and mapped by GIS. Based on the evaluation map, optimized management strategies are planned and applicated such as pesticide spraying or fertilization (Gebbers and Adamchuk, 2010). Here, the RS is the acquisition of *in situ* information about an object or phenomenon without making physical contact with the object, which is a key technology of timely assessment on present target status. Also, these site specific optimization technologies can be expected to minimize environmental impacts and enhance productivity. Nowadays, the RS technology is being used for environmental monitoring in various field; forest, water, bare soil and urban area. Unmanned aerial vehicles (UAV) are the one of the RS technologies and using of UAV is growing rapidly (Blyenburgh, 1999). UAV have advantages; executing dangerous or difficult tasks safely and efficiently, saving time, saving money and lives. In recently, private use of UAV has been increased because of developing of high-performance camera and software, weight lighted and miniaturization.

1.1.3. Animal behavior in grazing pasture

Spatio-temporal information on animal 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). Therefore, various studies on animal behavior have long been conducted. Earlier studies indicate that cattle select patches with higher levels of crude protein (CP) concentration (Hirata et al., 2006). Gillen et al. (1984) found that slope steepness was the only physical factor consistently associated with cattle grazing distribution on mountain rangeland and cattle preference shifted to the lower distance classes during late grazing. Okamoto et al. (1994) investigated utilization of a pasture consisting of an improved area (high herbage allowance) and a native area (low herbage allowance) by Japanese Brown cows. They found that the cows find the advantage on the herbage of the improved area as the acceptable canopy structure of the community for grazing, the high dry matter digestibility etc. under the severe quantitative condition of herbage. Cattle rested at night on the upper half of the slope in extensive settings, regardless of the season (Ohno and Tanaka, 1966). Arnold et al. (1978) reported that cattle rested on the higher ground in the nighttime. Moreover, Yause et al. (1997) found that cattle shifted the resting site to the lower elevation zones in daytime and in the higher elevation zone in the nighttime, and during nighttime resting, cattle preferred to rest on relatively gentle slopes (0–15°) and avoided resting on steep slopes (>25°). When temperatures were over 21°C cattle rested most of the time in places where wind was relatively strong, and when temperatures were below 20°C, cattle rested most of the time in places where wind was relatively weak through a grazing season (Kurosaki et al., 1956). Many environmental and management variables affect the distribution of grazing cattle on pasture. Several animal attributes affect distribution including: species or breed (Bailey et al., 2001), prior experience with a landscape (Bailey et al., 1996), age (Wells, 2004), and reproductive status (Bailey et al., 2001). Environmental characteristics affecting distribution include: proximity and/or relative elevation of drinking water (Roath et al., 1982); degree of slope (Ganskopp et al., 1987); density of woody vegetation (Holechek et al., 1998); presence of trails (Ganskopp et al., 2000); location of mineral (Kruelen, 1985) or protein supplements (Bailey et al., 1999); grazing history of the landscape and its attending effects on herbage (Ganskopp et al., 2006); fertilizer and fire effects (Hooper et al., 1969; Bondini et al., 1999); plant community composition and its associated effects on forage quantity (Smith et al., 1992) and quality (Pinchak et al., 1991); diurnal temperature dynamics of the landscape (George et al., 2007).

Livestock select the place where indicates high quality and nutritious grass, which cause the deviation of grazed pasture and the productivity decline. To maximize efficiency of pasture systems, it is important to understand the spatial distribution of livestock and impact of management variables on cattle behavior and subsequent performance.

1.1.4. Livestock grazing systems and environmental issues

Livestock excrement is not only a source of soil nutrients but are also a major source of global greenhouse gas (GHG) emission in grazed pasture. GHG such as 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). Thus, with increasing pressure coming on to farmers to minimize environmental pollution from their farming operations, mitigation strategies are required.

Many researches on GHG emission from grazing systems have widely been conducted. 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, 2007, 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 et al., 2009). Defecation and urination by grazers have direct effects on the spatial distribution of soil nutrients (Day and Detling, 1990; Rietkerk et al., 2000; Augustine and Frank, 2001; Orwin et al., 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, 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 et al., 2009; Betteridge et al., 2011). Farmers 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.

1.2. Objectives

Better understanding of spatial information in grazing pasture is crucial to maximize efficiency of pasture systems and to minimize environmental pollution. In this thesis, the author focused on animal activities based on PA to improve productivity of forages and animals, and reduce environmental impact from grazed systems. The author aims for developing monitoring technology of grazed cattle using IT technologies. This study consists of two main objectives; (1) to develop a simple, cost-effective method for monitoring spatio-temporal changes in the eating activities of grazing cows in conjunction with GPS collar placement (chapters 2 and 3), and (2) to estimate spatial distribution of livestock excrement in the grazing systems with a Bayesian approaches (chapters 4 and 5) and UAV images (chapter 6).

1.3. Overview of the study site

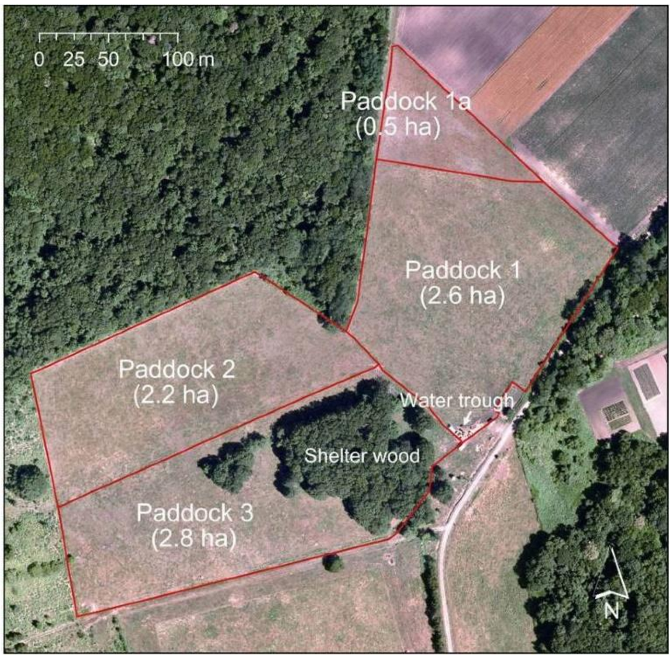
This study conducted in two experimental sites; the National Agriculture and Food Research Organization (NARO) Hokkaido Agricultural Research Center, Japan (chapters 2–5) and the Setouchi Field Science Center (Saijo Station), Hiroshima University, Japan (chapter 6).

In the NARO Hokkaido Agricultural Research Center, two experimental paddocks (No. 35 in chapter 2 and No. 37 in chapters 3–5) were used in this study. The paddock No. 35 (7.6 ha), established in 1967 with five temperate species (Figure 1.1a) consisted of three paddocks (almost identical sizes) differing in terrain, vegetation and renovation history: paddock I, a relatively flat section renovated by over-sowing in 2002; paddock II, a sloped section (no renovation); and paddock III, a sloping section partially covered with trees (no renovation). All of the paddocks were established by sowing orchardgrass (*Dactylis glomerata* L.), Kentucky bluegrass (*Poa pratensis* L.), meadow fescue (*Festuca pratensis* Huds.), perennial ryegrass (*Lolium perenne* L.) and white clover (*Trifoliumrepens* L.) in 1967. Ten Japanese Black breeding cows (*Bos taurus* L.) and their calves have been stocked during the period from early May to late October for the past 10 years in this pasture and they were able to move freely among the three paddocks.

Paddock No. 37 locates on a northeast slope (115–135 m above sea level, 7.95° average slope degree) (Figure 1.1b). The pasture was established in the 1960s by sowing orchardgrass (*Dactylis glomerata* L.), tall fescue (*Festuca arundinacea* Schreb.), meadow fescue (*F. pratensis* Huds.), Kentucky bluegrass (*Poa pratensis* L.), timothy (*Phleum pratense* L.), redtop (*Agrostis alba* L.) and white clover (*Trifolium repens* L.). The pastures have long been used as grazing land for Japanese Black cattle (*Bos taurus* L.) without fertilizer application for the last decade. Three paddocks were delimited using electric fences (I and II, 1.02 ha [60 m × 170 m]; III, 0.85 ha [50 m × 170 m]) and a water trough was located. Twenty breeding Japanese Black cows and their five calves were stocked.

In chapter 6, the study conducted at the Setouchi Field Science Center Saijo Station, Hiroshima University, in a grazing paddock No.4 (Figure 1.2). This pasture was dominated by bahiagrass (*Paspalum notatum*), white clover (*Trifolium repens* L.), Kentucky bluegrass (*Poa pratensis* L.) and dallisgrass (*Paspalum dilatatum*).The annual precipitation is 1,503 mm, annual temperature is 13.2°C, annual minimum temperature is 8.3°C and annual maximum temperature is 18.6°C.

(a)



(b)

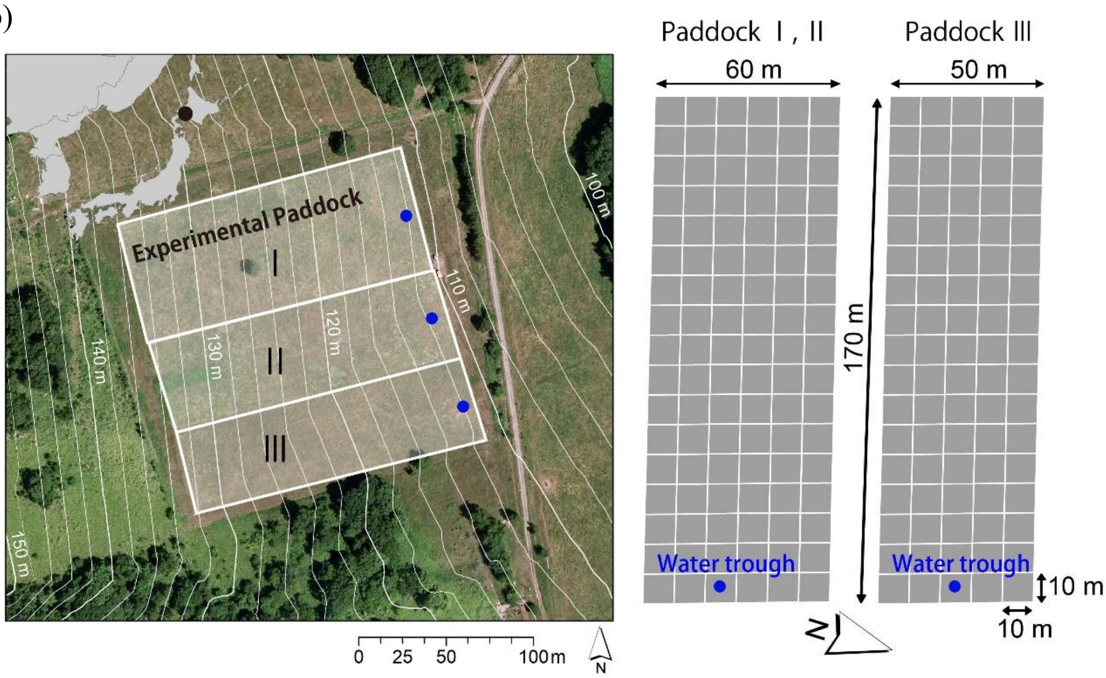


Figure 1.1 Locations of the experimental paddocks at the NARO Hokkaido Agricultural Research Center, Japan: (a) stationary pasture (No.35), (b) mixed sown pasture (No.37).

Figure 1.2 Location of the experimental paddock No. 4 in the Setouchi Field Research Center, Hiroshima University, Japan.

1.4. The structure of the thesis

The thesis is composed of seven chapters, as shown in Figure 1.3. Chapter 1 clarifies the background and the objectives of the present study, as mentioned above. In chapter 2, affecting of GPS recording rate on the grazing behavior and spatial distribution of cattle was mentioned. In chapter 3, a statistical method for classifying the eating activity from other activities using an accelerometry-based activity monitor and GPS was developed. In chapter 4, the spatial distribution of cattle's dung was estimated using single paddock data. In chapter 5, the model used in chapter 4 was improved to be more general and used three paddock data. In chapter 6, the author tried to detect the position of cattle dung using UAV image. In chapter 7, general discussions were described.

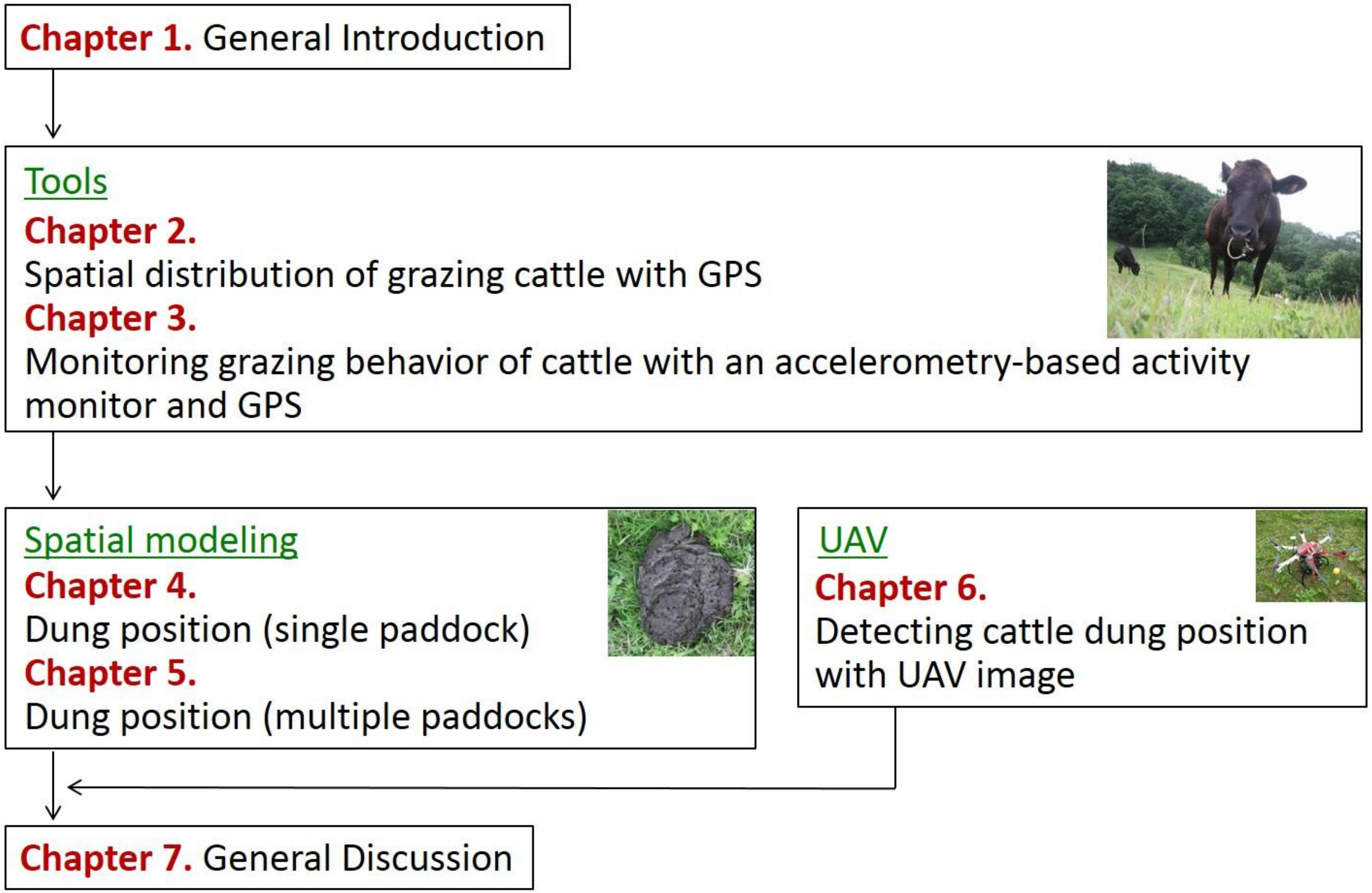


Figure 1.3 Flow and contents of this study.

－Chapter 2－

GPS recording rate effect on cattle grazing behavior and their spatial distribution on grazed hill pasture

"No man becomes rich unless he enriches others."

Andrew Carnegie (1835–1919)

Chapter 2: GPS recording rate effect on cattle grazing behavior and their spatial distribution on grazed hill pasture

2.1. Introduction

Spatio-temporal information on animal activities in a pasture, provides insights into pasture and animal conditions, allowing for improved pasture management and animal management (Turner et al., 2000). Previous research focused on tracking animals using data gathered by observation. Observation of animal activities is ideal to be conducted 24 hours continuously which is time consuming and difficult with human eyes at nighttime or foggy condition. Even though in daytime, observers requires patience and great difficulty. When there are plural observers, the possibility that a personal subjective element is included. By using remote observation equipment, we could record the grazing activities automatically and grasp the details of the action that it was hard to understand with visual method (Langbein et al., 1996; Scheibe et al., 1998). GPS have increasingly been used to monitor spatial distribution and track routes (Ganskopp et al., 2000; Ganskopp, 2001; Barbari et al., 2006) and are often combined with sensing devices to monitor animal activities, especially grazing behavior.

Although GPS collars are useful tool for tracking animal movements, they often loss the satellite signals and the data sometimes contains many missing values. To draw the daily movement, the distance of each successive point straight line has been used (Heezen and Tester, 1967; Harris et al., 1990; Reynolds and Laundre, 1990; Breitenmoser et al., 1992; Musiani et al., 1998; Johnson et al., 2002). However, if the GPS data cannot be recorded time interval, the calculation of distance traveled by the cattle is reduced. What GPS recording rate is sufficient when the time interval is set? In this chapter, the author tried to determine the minimum rate using simulation. Although, there is a report about GPS location accuracy (Pépin et al., 2004), the analysis using the GPS data for the long term like this study (five-year) has not been performed. In addition, the study site consists of relatively new paddock and sloping old paddock and the utilization rate of old paddock from cattle does not be known. It is need for performing pasture management effectively to indicate the availability of new paddock and old paddock. The objective of this chapter is to clarify the seasonal change of the spatial distribution pattern of cattle using GPS data.

2.2. Material and methods

2.2.1. Study site

The study was conducted in a mixed sown pasture (No.35, 7.6 ha) at the NARO Hokkaido Agricultural Research Center, as mentioned in section 1.3 (Figure 1.1a). The pasture consisted of three three paddocks differing in terrain, vegetation and renovation history: paddock I, a relatively flat section renovated by over-sowing in 2002; paddock II, a sloped section (no renovation); and paddock III, a sloping section partially covered with trees, in which *Betula platyphylla* var. *japonica* and *Quercus* spp. were dominant at the canopy height of 20–30 m (no renovation).

2.2.2. Methods

Ten breeding Japanese Black cows and their calves have been stocked during the period from early May to late October for the past 10 years in this pasture and they were able to move freely among the three subunits. The grazing trial was conducted from May 15 to November 2 in 2006 (172 days), from May 10 to November 5 in 2007 (180 days), from May 2 to October 31 in 2008 (183 days), from April 28 to July 29 in 2009 (93 days) and from May 5 to October 27 in 2010 (176 days). Each year between 3 and 6 cattle were fitted with GPS units (Figure 2.1) and the data was collected five minute interval. The cattle fitted GPS units information was mentioned on Table 2.1.

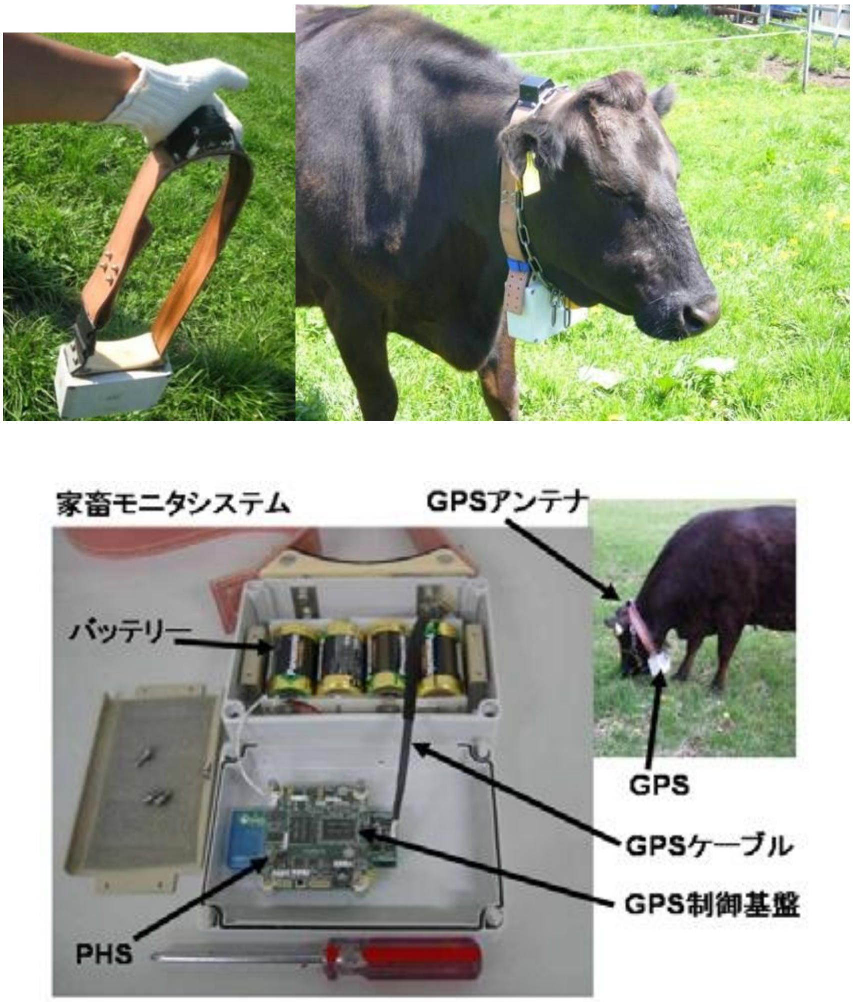


Figure 2.1 Photographs showing a cattle fitted GPS collar (above) and inner structure of the GPS collar (below).
(Photographs are provided by Dr. Nariyasu Watanabe of the NARO Hokkaido Agricultural Research Center, Japan)

Table 2.1 Age and body weight information of cattle attached GPS collar.

Cattle No.	Year	Age (Year)	Weight (kg)
1	2006	12	560
2		9	524
15		4	554
22		3	504
40		1	408
1	2007	13	556
2		10	606
42		2	433
46		2	443
1	2008	14	638
2		11	622
23		5	672
24		5	652
49		2	522
52		2	467
24	2009	6	646
49		3	576
52		3	504
24	2010	7	614
44		4	514
49		4	610
52		4	526

2.2.3. Preprocessing and random sampling

At first, the GPS data from fewer than five satellites (2D precision) were removed and the GPS recording rate per one day were calculated. Over the five year period, 256 days had 100% data (Table 2.2). Let compute the number of samples in a 100% day, it has 288 data points per day ([60 min / 5 min] × 24 hour = 288). In case of the recording rate was 95%, the number of data points per day was computed as 288 × 0.95 = 274 points per day. Similarly, 1,000 simulations of random sampling between 75 to 100% recording rate were performed. Based on the simulations, the walking distances of cow (m) were calculated, and *t*-test was performed to compare the walking distance in case of 100% recording rate against 75–99% recording rate (Figure 2.2). All data handling was performed using R statistical software ver. 2.15.2 (R Core Team, 2012). The distance traveled in one day were calculated based on R software using functions of "spDistsN1" version 0.4–19 in "SpatialKernel" package and determined as the integrated value of the distance between two points obtained in five minute intervals. Individual differences in distance traveled in one day were performed multiple comparison with Tukey-Kramer test after one-way ANOVA based on R software using functions of "TukeyHSD" and "anove".

Table 2.2 Cattle number (No.) and number of days that recorded 100% GPS recording rate per day in 2006–2010.

Year	Cattle No.	100**%** (the number of date)
2006	1	30
	15	22
	22	17
	40	6
2007	1	24
	2	13
	42	10
	46	16
2008	1	8
	24	8
	49	10
	52	13
2009	24	7
	49	11
	52	14
2010	24	6
	44	19
	49	19
	52	3
Sum		256

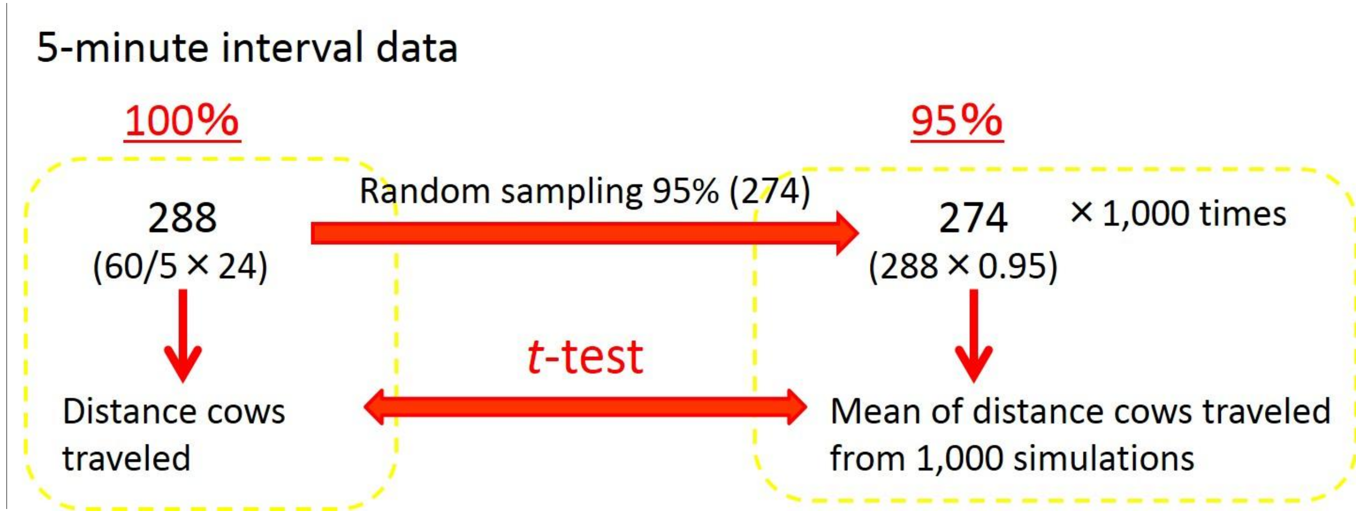


Figure 2.2 Schematic chart of the 1,000 simulations for *t*-test with random sampling (*e.g.* GPS recording rate is 95%).

2.3. Results

2.3.1. *t*-tests

Figure 2.3 shows the relationship between GPS recording rate and the distance traveled after 1,000 simulations of random sampling. The higher GPS recording rate, the fewer the difference traveled with 100% data. If the recording rate is fewer, the distance traveled in the day is calculated to be less than actually traveled. The result from the *t*-tests is shown in Figure 2.4. As data recording rate is fewer, a *p*-level goes down and the GPS recording rate that was greater than 91%, *p*-value was higher than 0.05. Data of 1,459 days indicated greater than 91% of the GPS recording rate, and can be used for further analysis in this chapter (Table 2.3).

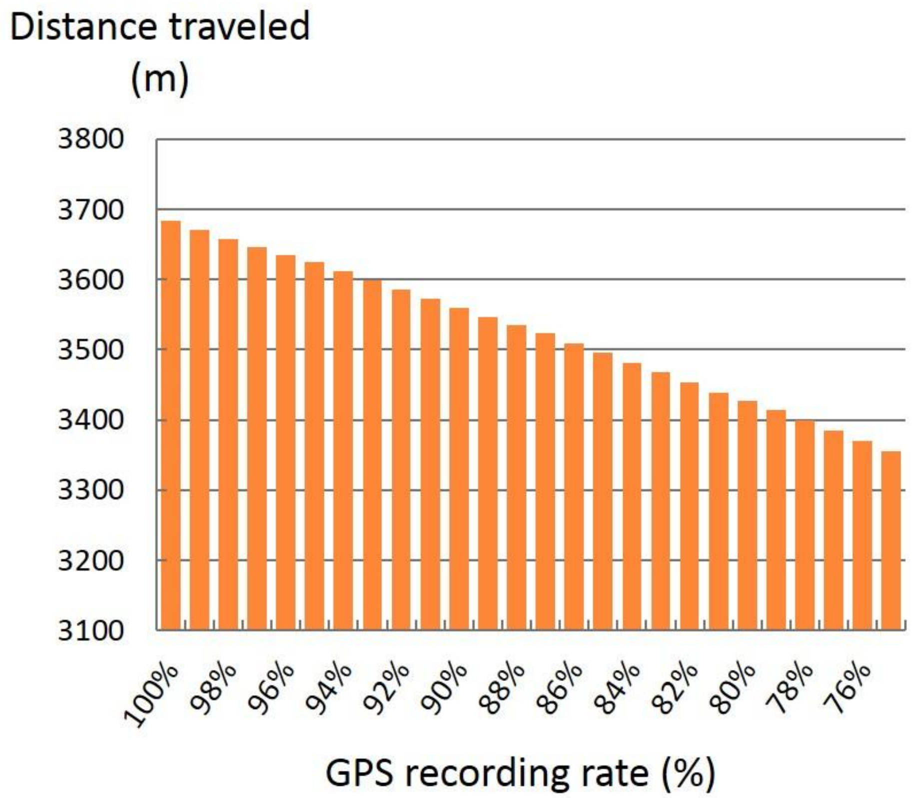


Figure 2.3 GPS recording rate in 100–75% and their distance traveled by cattle.

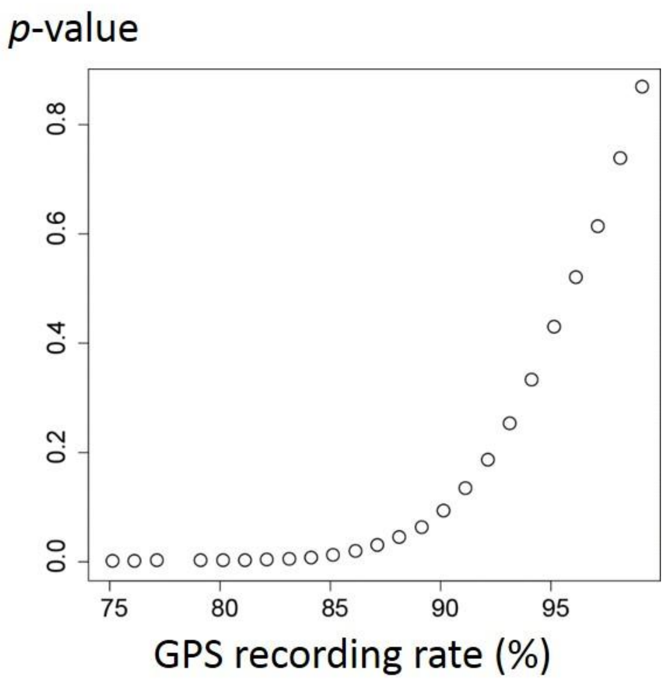


Figure 2.4 Significance (*p*-value) in GPS recording rate between 75% and 99% (*t*-test for 100%).

Table 2.3 Number of days in total and greater than 91% of GPS recording rate.

Year	Cattle No.	All data	>91%	deleted
2006	1	76	76	0
	2	49	25	24
	15	77	71	6
	22	32	32	0
	40	31	30	1
2007	1	95	88	7
	2	139	136	3
	42	138	86	52
	46	77	62	15
2008	1	146	144	2
	2	6	6	0
	23	15	14	1
	24	121	108	13
	49	95	92	3
	52	88	68	20
2009	24	90	84	6
	49	47	27	20
	52	56	49	7
2010	24	106	86	20
	44	76	53	23
	49	109	75	34
	52	69	47	22
Sum		1738	1459	279

2.3.2. Distance traveled

Figure 2.5 shows the distance traveled by cattle per one day over five years, giving similar change patterns of distance traveled for each cattle. In 2006, the distance travelled by cattle tended to increase from summer season. In 2007 and 2008, however, the distance decreased from summer season.

Table 2.4 shows the mean values of distance traveled of each cattle. Younger cows (cow No. 40, 42, 44, 49, 52) walked longer than older cows (cow No. 1, 2, 15) in the most years. The distance traveled by cows tended to show similar behavior among cows in same age. It is fact that cattle moved in a group, and thus, the older cattle followed younger cattle. Otherwise, older cattle might graze at same areas after leading the way.

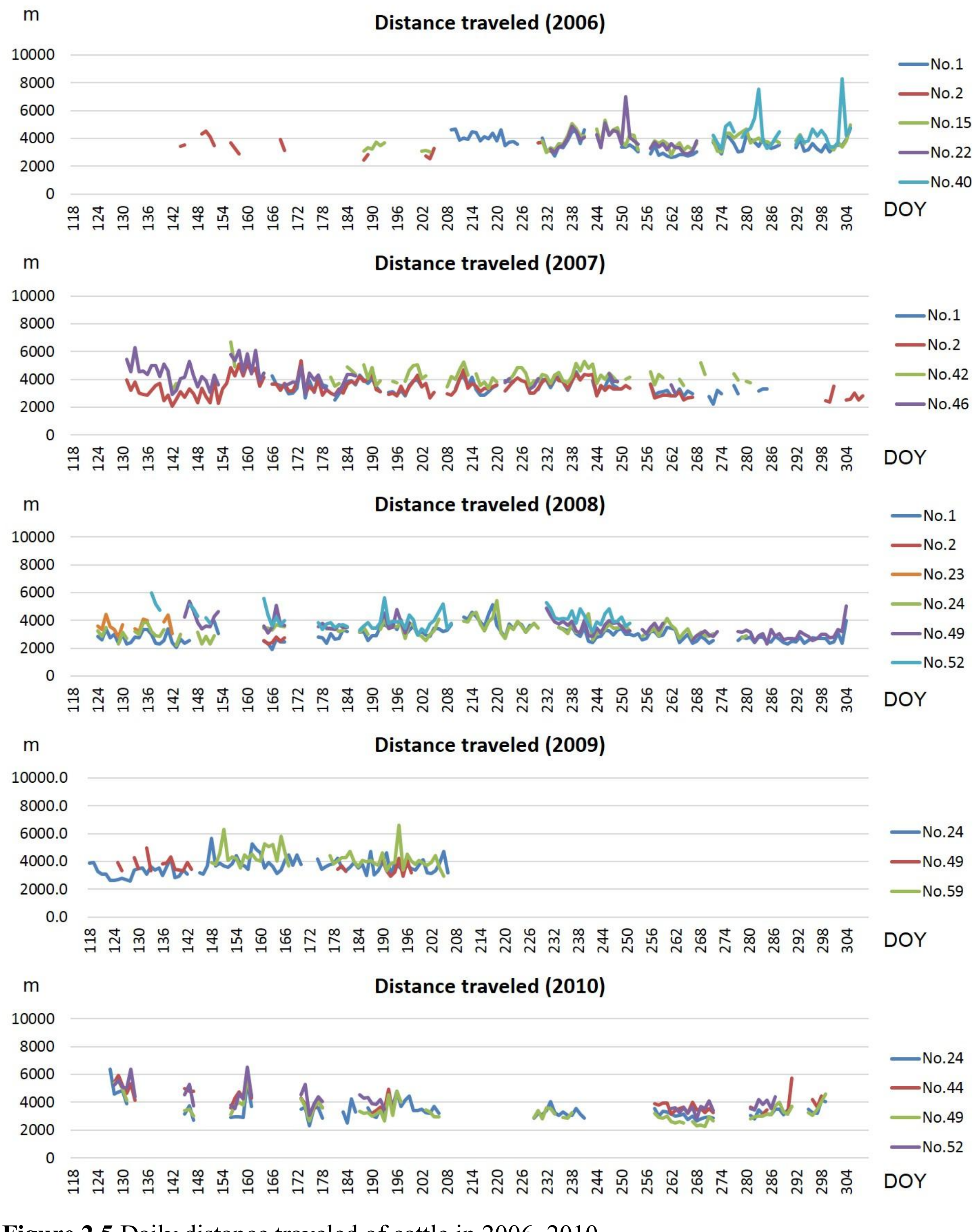


Figure 2.5 Daily distance traveled of cattle in 2006–2010.
DOY: day of year.

Table 2.4 Mean and standard deviation (SD) values of distance traveled for each cattle.

Cattle No.	Year	The number of date	Distance traveled (m) Mean ± SD†
1	2006	76	3569.0 ± 553.5^{abc}
2		25	3409.2 ± 579.1^{ade}
15		71	3766.2 ± 562.2^{bdf}
22		32	3844.2 ± 806.8^{cefg}
40		30	4387.0 ± 1114.4^{g}
1	2007	88	3464.0 ± 509.0^{h}
2		136	3418.1 ± 509.0^{h}
42		86	4238.5 ± 556.6^{i}
46		62	4224.4 ± 820.6^{i}
1	2008	144	2998.7 ± 542.7^{jk}
2		6	2541.5 ± 190.9^{ji}
23		14	3629.2 ± 485.0^{mno}
24		108	3331.1 ± 617.9^{klmp}
49		92	3454.1 ± 617.9^{np}
52		68	4084.6 ± 643.6^{o}
24	2009	84	3610.1 ± 589.4^{q}
49		27	3661.3 ± 498.9^{q}
52		49	4219.1 ± 694.7^{r}
24	2010	86	3430.6 ± 650.4^{s}
44		53	3995.0 ± 769.4^{t}
49		75	3397.0 ± 730.8^{s}
52		47	4156.0 ± 797.8^{t}

†SD, standard deviation. Values with different letters show significant differences among different cattle in the year (Tukey-Kramer tests).

2.3.3. Monthly changes in utilization rate of the paddocks

Figure 2.6 shows the monthly changes in utilization rate of the three paddocks. Paddock I, where locates flat area including a small renovated area, was mainly used by cattle for their grazing over the five years grazing trial. The utilization in paddock I tended to decrease after August, while the utilization of paddock II and II were increased. It is considered that cattle moved to the west wide paddocks (II and III), which is a relatively fast location of sunlight strikes because the temperature was lower after August. Particularly, in August, the utilization of paddock III (a sloping section partially covered with trees) was increased.

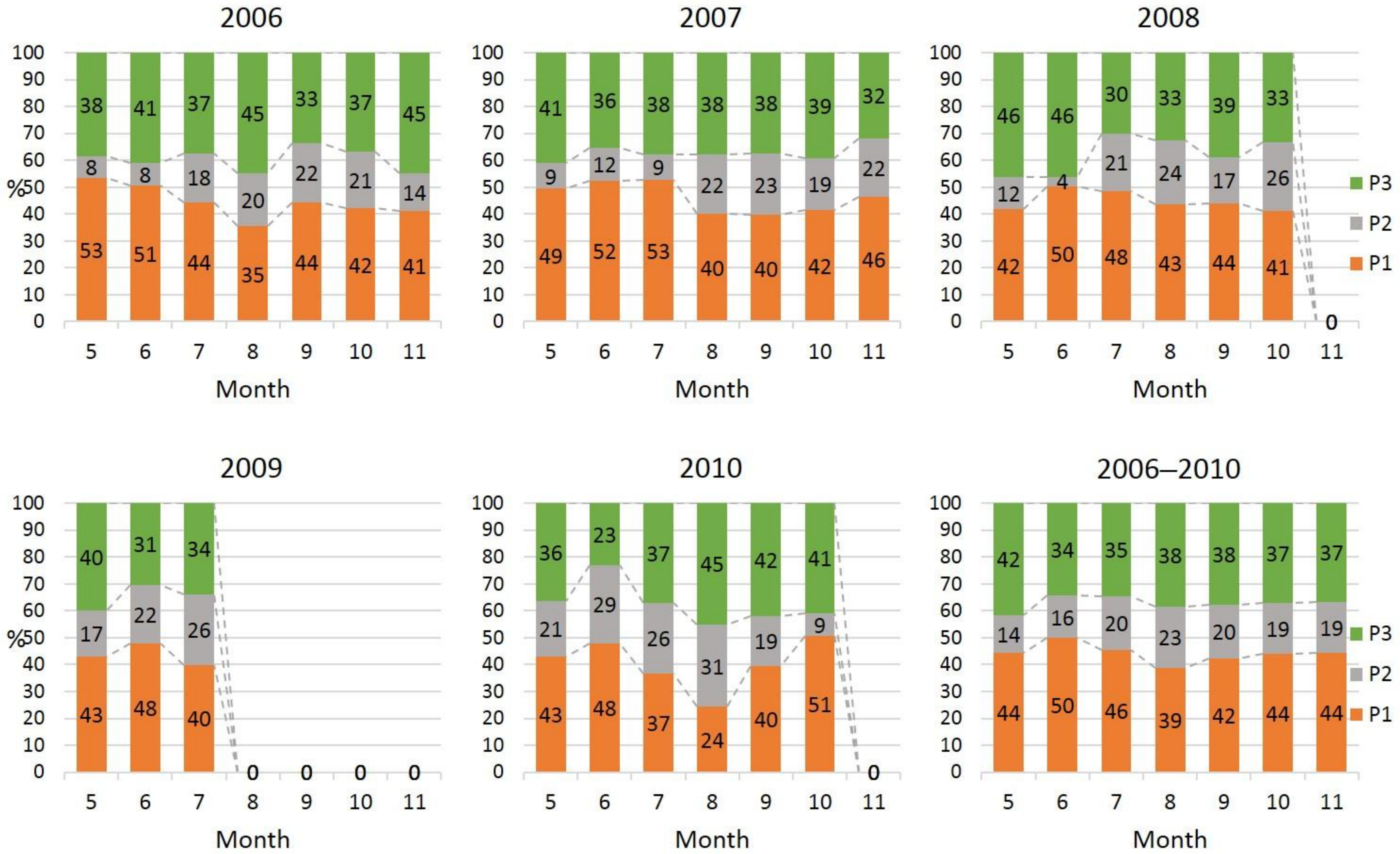


Figure 2.6 Monthly changes of utilization rate for three paddocks by cattle in 2006–2010.

2.3.4. Changes in utilization rate with the time of day

To compare the utilization rate with the time of day, the author divided the daily GPS data into four periods of each six hour period as 3:00–9:00, 9:00–15:00, 15:00–21:00 and 21:00–3:00, and computed their monthly changes. The results showed; (i) In the early morning (3:00–9:00), the cattle uqually used for all of the paddocks (Figure 2.7a); (ii) In the daytime (9:00–15:00), the cattle spent the majority of their time in paddock I (Figure 2.7b); (iii) In the late afternoon and evening (15:00–21:00), the utilization rate of paddocks II and III were increased (Figure 2.7c); and (iv) At nighttime (21:00–3:00), it seems that cattle rested in paddocks II and III (Figure 2.7d). Overall, these results suggested that the cows mostly stayed in the lower-altitude area of the paddock during the daytime, while the cows spent most of their time in the higher-altitude area of the paddock during the nighttime.

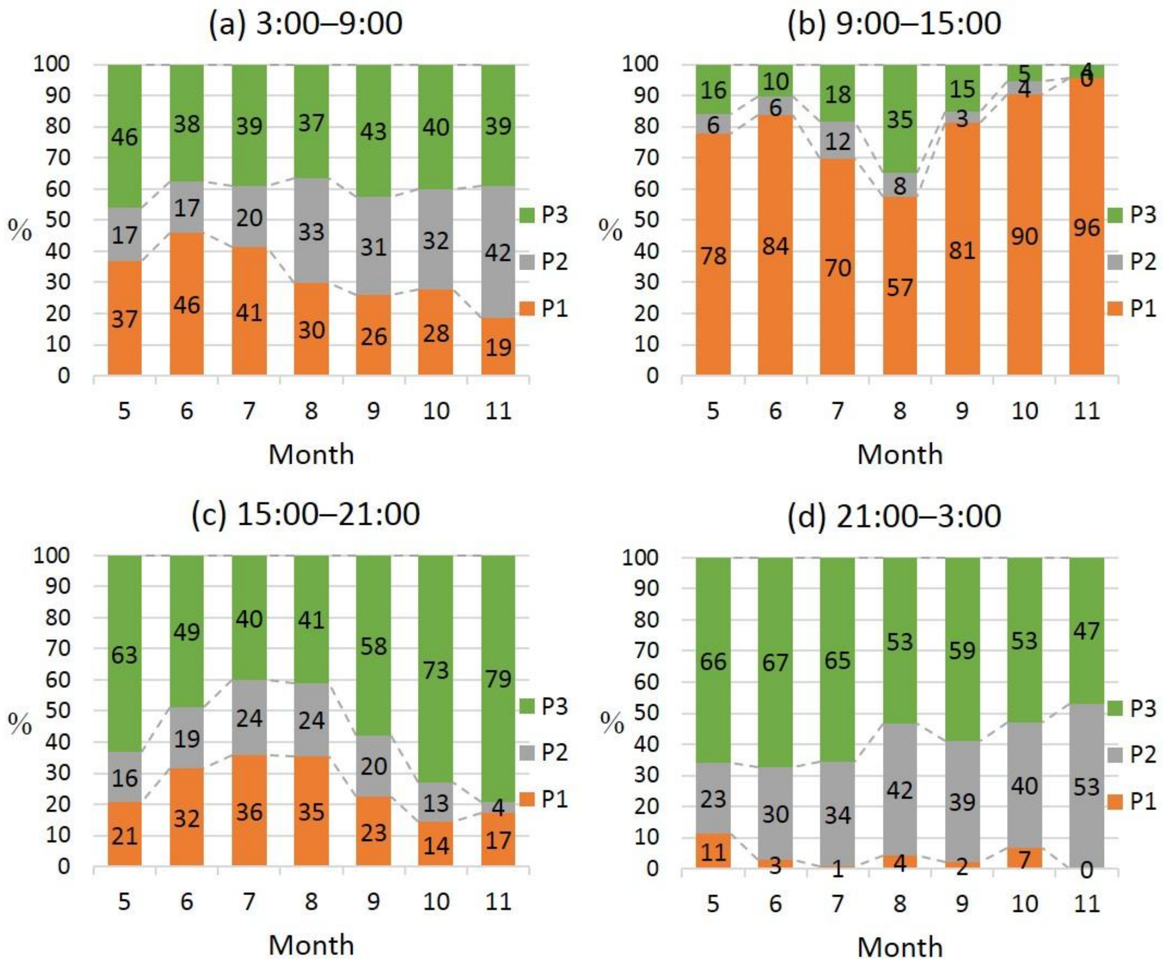


Figure 2.7 Utilization rate of three paddocks in four equal size periods based on the time of day (2006–2010).

2.4. Discussion

The results of this chapter indicated that the paddock I, a relatively flat section renovated, was mainly used by cattle for their grazing over the five years grazing trial, especially in daytime. Moreover, the utilization of paddocks II and III were decreased in hot summer season (August). In the summer season, cattle often prefer to spend riparian areas, and spend a disproportionate amount of time in these areas as compared to uplands (Smith et al., 1992). In this experiment, the water trough was located in paddock I. Cattle selected patches with higher levels of CP concentration and sward bulk density (Hirata et al., 2006). Moreover, Okamoto et al. (1994) investigated utilization of a pasture consisting of an improved area (having high herbage allowance) and a native area (having low herbage allowance). The paddock I had more CP content than paddocks II and III (Watanabe et al., 2010). It is likely that cattle concentrated in paddock I that had high quality grass and the amount of grasses were increased there, and cattle began to disperse from summer. It could be related to the change of distance traveled from summer. However, there were not the significant differences in herbage mass between paddocks. The sloping level was related to increase the utilization of paddocks II and III. Slope steepness was the only physical factor influencing cattle distribution on mountain rangeland (Gillen et al., 1984).

The sloping areas, paddocks II and III in this study were mainly used at nighttime. The result confirmed previous finding that cattle rested at nighttime on the upper half of the slope in extensive settings, regardless of the season (Ohno and Tanaka, 1966). Arnold and Dudzinski (1978) also reported that cattle rested on the higher area in the nighttime. Moreover, Yause et al. (1997) found that cattle shifted the resting site to the lower elevation zones in daytime and in the higher elevation zone in the nighttime. Similar to previous studies, cattle tended to move to sloping area (paddocks II and III) in this study. In the early morning, the sloping area was mostly used by cattle. It was related that the increasing utilization rate in the paddocks II and III in the nighttime. During nighttime resting, cattle preferred to rest on relatively gentle slopes (0–15°) and avoided resting on steep slopes (>25°) (Yasue et al., 1997). In the present study, the sloping degree in paddock II and III were 9.0° and 8.2°, respectively. Although, several areas in the paddocks showed steep land surface (>15°), it is easily for cattle to move to another place. It is believed that cattle move to higher position at nighttime in order to ensure a wider field of view, which becomes easy to find the enemy for cattle.

Based on the results, it is necessary to increase the utilization of paddock II to prevent premature degradation of the paddocks I and III. Grassland renovation is one of the solutions, but it is hard to use machines in paddock II due to the slope. Thus, it is need to consider the other solutions, such as an installation of supplements and water tank. In previous study, water developments, salting, and fencing have been used successfully to improve livestock grazing distribution on both private and public lands (Bailey et al., 2001). Moreover, earlier studies suggested that the location of cattle was related to a particular area and their activities in that area, which can be affected by grazing management and pasture topography (Yamada et al., 2011), concentrations and sward bulk densities (Senft et al., 1985; Ganskopp and Bohnert, 2009), and distance from water (Roath and Krueger, 1982; Ganskopp, 2001).

－Chapter 3－

Monitoring grazing behavior of cattle with an accelerometry-based activity monitor and GPS

"Everything should be made as simple as possible, but not simpler."

Albert Einstein (1879–1955)

Chapter 3: Monitoring grazing behavior of cattle with an accelerometry-based activity monitor and GPS

3.1. Introduction

Spatio-temporal information on the grazing behavior of animals can help farmers do the efficient management of the pasture and animals. Thus, the development of simple, cost-effective tools for timely monitoring of grazing cows would benefit herders and researchers.

An increasing number of analysis tools have been developed to aid the collection of data on spatio-temporal changes in grazing behaviors. GPS which record animal locations with high temporal frequency, have increasingly been used to monitor spatial distribution and track routes (Ganskopp et al., 2000; Ganskopp, 2001; Barbari et al., 2006) and are often combined with sensing devices for monitoring animal activities, especially grazing behavior. Information on grazing behavior can be acquired from these devices by measuring the electrical resistance of jaw opening (Penning, 1983; Matsui et al., 1991; Rutter, 2000) or by pendulum pedometers fitted around the neck (Phillips and Denne, 1988; Umemura et al., 2009), tilt sensors attached to a commercial GPS collar (Ganskopp, 2001), devices that record the sounds of bites and chews in grazing (Ungar and Rutter, 2006) and accelerometers fitted on the jaw or neck (Wark et al., 2007; Watanabe et al., 2008; Moreau et al., 2009). However, most of these devices cannot be used by farmers because they are capable taking measurements for only a few days due to their high energy consumption or because they are expensive and require extensive experience to attach them to animals (Ungar and Rutter, 2006). Moreover, the data obtained by such sensing devices are complicated, and the classification of grazing behavior requires specific analysis software, such as the “Graze” program (Rutter, 2000).

Recently, simple accelerometry-based activity monitors have been developed for studies of human health (Kumahara et al., 2004; McClain et al., 2007). Although these devices convert raw accelerometer data into an activity level and output by the criteria considered in each proprietary subtly different human activity, they can be used for animal behavior studies that include data processing and analysis. Ueda et al. (2011) developed a simple method for identifying the eating activity of dairy cows in flatland pasture using the Kenz Lifecorder EX (LCEX; Suzuken Co. Ltd., Nagoya, Japan), which has recently been developed into a commercially available tool for management of and research on human health at a relatively low price (approximately 430 US dollars per unit). Ueda et al. (2011) processed the data obtained from the device with linear discriminant analysis (LDA) and succeeded in identifying the eating activity of cows in pasture with a correct discrimination score of 94.5%. The results suggest that an accelerometry-based activity monitor is a useful tool for identifying the activities of cows in pasture and that the LCEX system allows for the easy measurement of eating time and facilitates determining the pattern of eating activity of cows grazing on pasture. However, for the further development of cow activity monitoring using the device, we needed to test the LCEX system and LDA in a pasture with a heterogeneous environment, especially slope pasture, because most grazed pasture in Japan is located on mountainous or hilly land. Moreover, in conjunction with GPS location information, it is expected that spatial information on cow grazing behavior can be obtained easily and cost-effectively.

The aim of this study was to develop a statistical method for classifying the eating activity from other activities using the data obtained by LCEX and to monitor spatio-temporal changes in the eating activities of grazing cows in conjunction with GPS collar placement. In the present study, logistic regression (LR) and an LDA function analysis (Fisher, 1936) were attempted for the classification, which have been frequently used for animal activity pattern classification (Schleisner et al., 1999; Ungar et al., 2010). And using the estimated eating activity data and the GPS location data, the spatial pattern map of eating or other in the paddock was created.

3.2. Material and methods

3.2.1. Study site

The study was conducted in a mixed sown pasture (No.37, paddock III, 0.85 ha) at the NARO Hokkaido Agricultural Research Center, as mentioned in section 1.3 (Figure 1.1b). In this paddock, 20 Japanese Black breeding cows and their five calves were stocked for four days during the period from 10:00 June 14 to 10:00 June 18, 2010.

3.2.2. Kenz lifecorder EX (LCEX)

The LCEX (weight, 60 g; width, 72.5 mm; height, 41.5 mm; thickness, 27.5 mm) is a single-axis accelerometer that measures acceleration at a rate of 32 samples per second and records a step count for humans and an intensity of physical activity at 11 scaled magnitudes, including 0 (no movement), 0.5 (subtle) and 1–9 (1: light; 9: vigorous) at four-second intervals for five weeks (Figure 3.1). According to Kumahara et al. (2004) and McClain et al. (2007), an activity level of 0 (AL_0) indicates that the acceleration values are always less than 0.06 G during the four-second sampling interval. However, AL_0.5 indicates that, although acceleration values above the minimum threshold (0.06 G) exist, these values were found for fewer than three pulses during the four-second sampling interval. When the sensor detects three or more acceleration pulses in the four-second interval, the activity is categorized from AL_1 (0.06 G) to AL_9 (1.94 G). The collected data can be easily downloaded to a computer for analysis using Kenz Physical Activity Analysis software ver. 1.0 (Suzuken Co. Ltd., Nagoya, Japan).

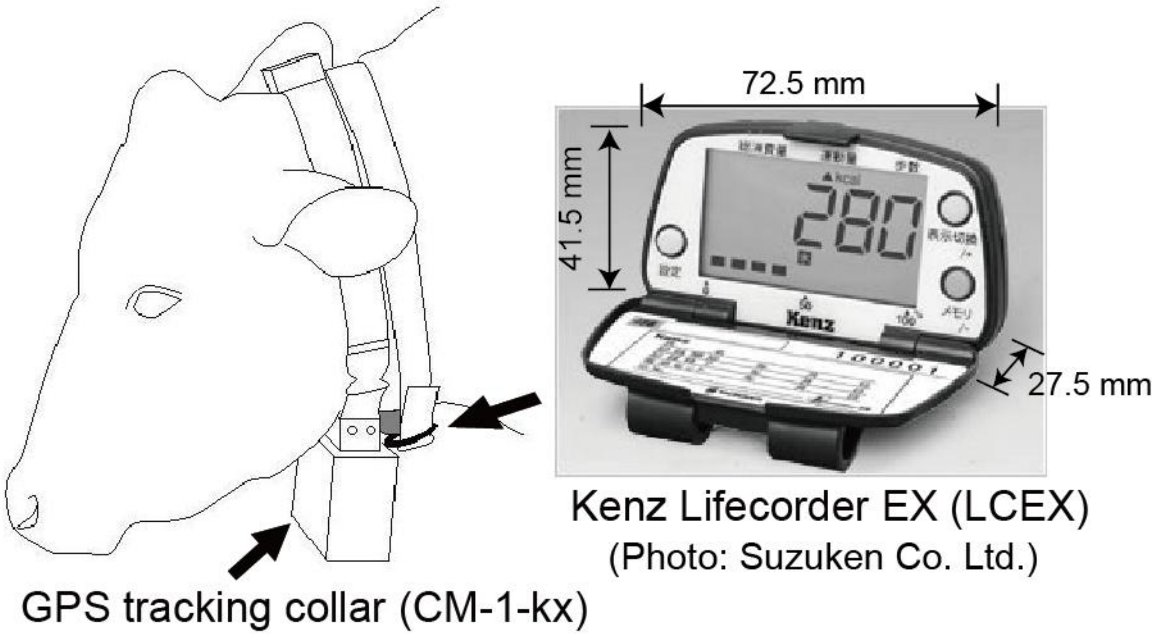


Figure 3.1 Diagrammatic representation of location of GPS tracking collar and LCEX accelerometer on the neck of grazing cattle evaluating the utility of accelerometers for quantifying the foraging times of cattle.

3.2.3. Fitting GPS and LCEX to cattle

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 selected 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) that had a 12-channel GPS receiver that allowed the simultaneous use of signals from up to 12 satellites and a collar attached to a small fabric bag containing an LCEX. The LCEX was wrapped in a vinyl bag for waterproofing and placed within the small fabric bag (Figure 3.1). During four-day grazing periods, the positions of the cows were recorded every minute by the GPS collars.

3.2.4. Field observation of cattle's grazing behavior

The author recorded the behavior of four cows with attached LCEX and GPS monitors from June 16 to 18, 2010. In the three-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. The weather during this experiment was clear except for day three; it rained a total of 26.5 mm between 14:00 June 16 and 4:00 June 17. 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 at the experimental paddock were 3:52, 11:35 and 19:18, respectively.

3.3. Discriminant analysis for estimating animal activity

In this study, logistic regression (LR) and linear discriminant analysis (LDA) were used to estimate animal activities. All data handling and discriminant analyses were performed using R statistical software, version 2.12.1 (R Development Core Team, 2010).

3.3.1 Logistic regression (LR)

LR model arises from the desire to model the posterior probabilities of the *K* classes via linear functions in *x*, while at the same time ensuring that they sum to one and remain in [0,1]. According to Hastie et al (2008), the model has the form

$$log \frac{P_r(G = 1|X = x)}{P_r(G = K|X = x)} = \beta_{10} + \beta_1^T x \qquad [3.1]$$

$$log \frac{P_r(G = 2|X = x)}{P_r(G = K|X = x)} = \beta_{20} + \beta_2^T x \qquad [3.2]$$

$$\vdots$$

$$log \frac{P_r(G = K-1|X = x)}{P_r(G = K|X = x)} = \beta_{(k-1)0} + \beta_{k-1}^T x \qquad [3.3]$$

The model is specified in terms of K−1 log-odds or logit transformations (reflecting the constraint that the probabilities sum to one). Although the model uses the last class as the denominator in the odds-ratios, the choice of denominator is arbitrary in that the estimates are equivariant under this choice. A simple calculation shows that

$$P_r(G = k|X = x) = \frac{exp(\beta_{k0} + \beta_k^T x)}{1 + \sum_{l=1}^{K-1} exp(\beta_{l0} + \beta_l^T x)}, k = 1, \dots, K-1 \qquad [3.4]$$

$$P_r(G = K|X = x) = \frac{1}{1 + \sum_{l=1}^{K-1} exp(\beta_{l0} + \beta_l^T x)} \quad [3.5]$$

and they clearly sum to one. To emphasize the dependence on the entire parameter set $\theta = \{\beta_{10}, \beta_1^T, \dots, \beta_{(K-1)}, \beta_{K-1}^T\}$, we denote the probabilities $P_r(G = k|X = x) = p_k(x; \theta)$.

When K = 2, this model is especially simple, since there is only a single linear function. It is widely used in bio-statistical applications where binary responses (two classes) occur quite frequently. For example, patients survive or die, have heart disease or not, or a condition is present or absent.

3.3.2. Linear discriminant analysis (LDA)

Discriminant analysis, which is developed by R.A. Fisher in 1936 (Fisher, 1936), is a classic method of classification. This analysis is used to determine variables discriminate between two or more naturally occurring groups. The model has form

$$discriminant\ function = \alpha_0 + \alpha_1 x_1 + \cdots + \alpha_n x_n \quad [3.6]$$

Coefficient α_i is obtained by maximizing the ratio of the variance for between-groups and within-groups under the assumption of equal variances for the group.

$$coefficient\ vector\ (A^t) = [\alpha_1, \alpha_2 \dots, \alpha_n] \quad [3.7]$$

$$the\ variance\ of\ between - groups = between\ groups\ sum\ of\ squares\ (BS)$$

$$= \frac{1}{g-1} \sum_{i=1}^{g} m_i\, (\bar{X}_\iota - X)(\bar{X}_\iota - X)^t, \quad [3.8]$$

$$the\ variance\ of\ within-groups = within\ groups\ sum\ of\ squares\ (WS)$$

$$= \frac{1}{m-g}\sum_{i=1}^{g}\sum_{j=1}^{m_i}(X_{ij}-\bar{X_i})(X_{ij}-\bar{X_i})^t, m = \sum_{i=1}^{g} m_i \qquad [3.9]$$

3.3.3. Data treatment and comparison of LR and LDA

The LCEX data were summed every minute to match the 1-min interval used for field observations. To distinguish between foraging and all other recorded activities, the 1-min interval data from LCEX and the observations were subjected to LR and LDA.

To validate the accuracy of the LR and LDA functions, a bootstrap procedure with 10,000 iterations was applied, based on an independent test data set, as in Watanabe et al. (2008). For each iteration process, the data were randomly divided into training and test subsets in a proportion of two to one, respectively. Then, the training subset data were used to develop the LR and LDA functions. Finally, using the functions, classification accuracies of eating activities in the test subset data were calculated based on R software using functions of "glm" version 1.0 and "lda" version 1.3.2.

3.4. Results

3.4.1. Eating activity

All LCEX and GPS collars successfully acquired scheduled records during the four-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 and 126 minutes, respectively). The overall mean activity level (AL min^{-1}) values and standard deviations (SD) were 15.1 ± 7.2 for foraging and 2.7 ± 5.9 for other activities (Figure 3.2 and Table 3.1). For each cow, the mean activity level for foraging and for other activities ranged from 13.9 to 16.4 AL min^{-1} and 1.4 to 4.5 AL min^{-1}, respectively.

Figure 3.3 shows the histograms of the percent correct discrimination scores for eating in 10,000 bootstrap replicates using the LR and LDA functions. The threshold values in the LR results for each cow were larger (8.5–16.6 AL min^{-1}) than the LDA threshold values (7.8–10.4 AL min^{-1}) (Table 3.1). For the pooled data set, the mean LR and LDA values (± SD) were 10.8 ± 0.2 and 8.9 ± 0.1, respectively. Overall, the LDA results showed a higher correct discrimination percentage for all cows (90.6 to 94.6%) than did the LR results (80.8 to 91.8%). Similarly, the correct discrimination percentages for LDA and LR on the whole data sets were 92.4% and 85.6%, respectively. The proportion of true non-foraging observations using LDA in pooled data set was resting (6.8%) and ruminant activities (0.8%) that were misclassified as foraging activity.

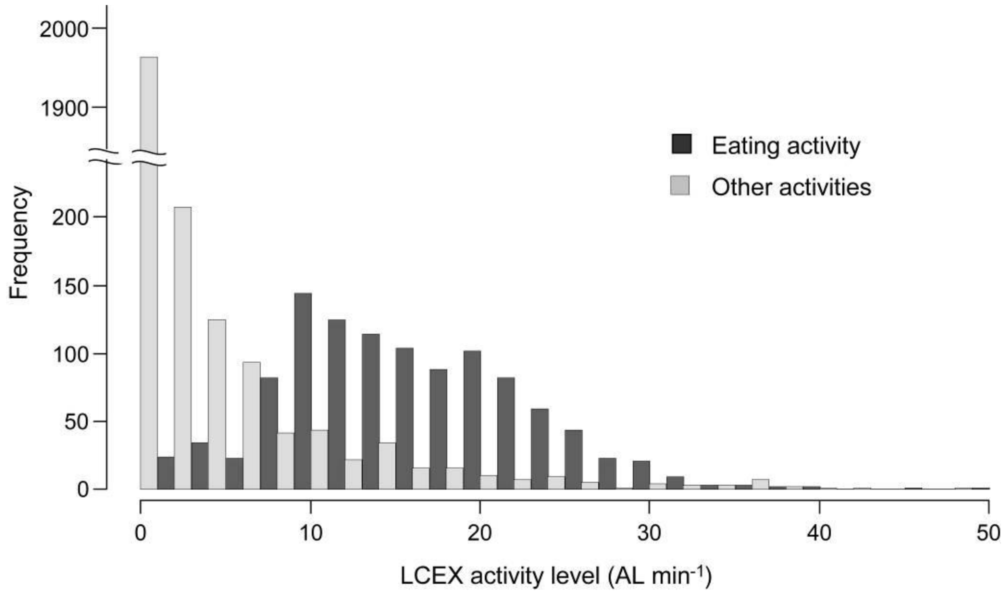


Figure 3.2 Distributions of the LCEX activity levels (AL min^{-1}) for eating activity and other activities in total of four cows during 15 hours behavioral observation.

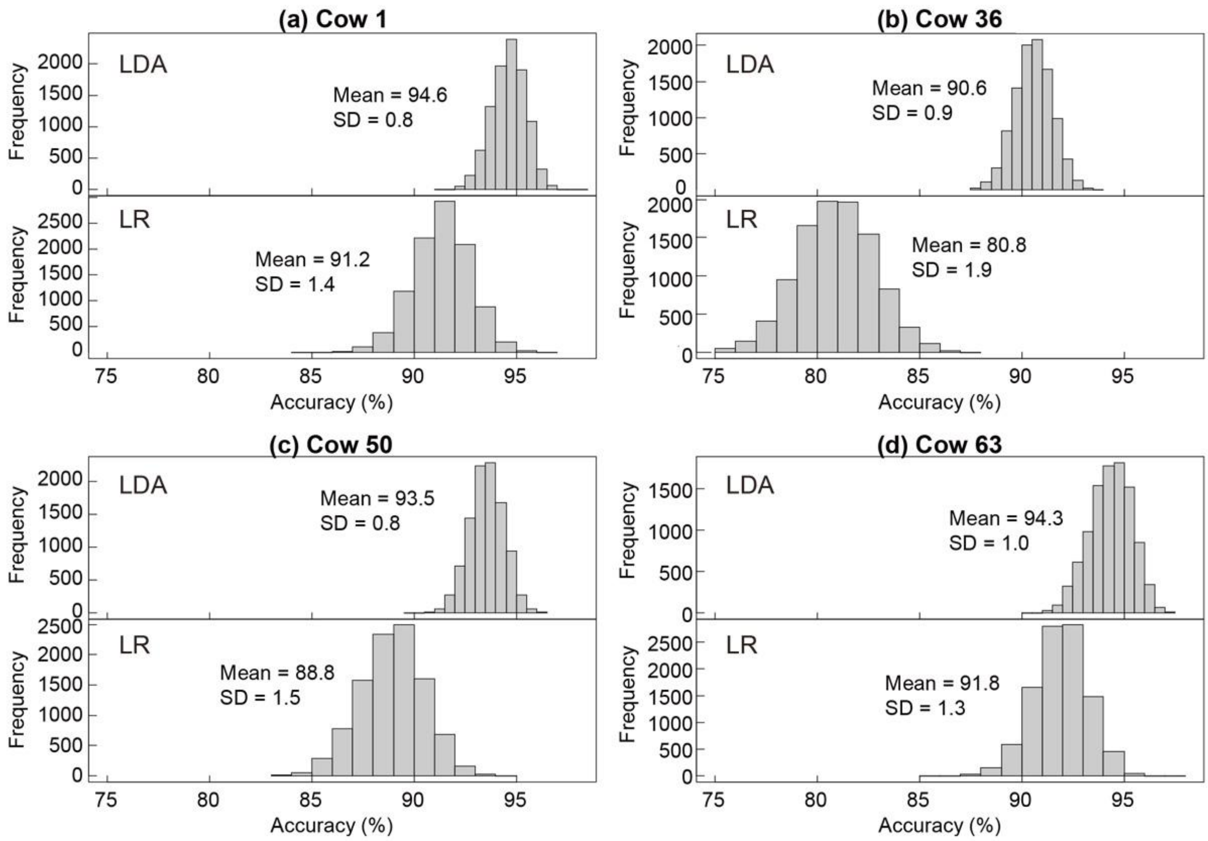


Figure 3.3 Histogram showing the percentage of correct answers obtained in the feeding activity of bootstrapping 10,000 times using logistic regression (LR) and linear discriminant analysis (LDA).

Table 3.1 Activity level (AL min-1) in eating activity and other activities, threshold value and percent correct discrimination using logistic regression (LR) and linear discriminant analysis (LDA).

	Activity level (AL min^{-1})†		Logistic regression (LR)‡		Linear discriminant analysis (LDA)	
Data set	Eating activity	Other activities	Threshold value	Percent correct discrimination (%)	Threshold value	Percent correct discrimination (%)
Cow 1	14.1 ± 7.1	1.4 ± 4.0	8.5 ± 0.4	91.2 ± 1.4	7.8 ± 0.2	94.6 ± 0.8
Cow 36	16.4 ± 8.8	4.5 ± 7.8	16.6 ± 0.7	80.8 ± 1.9	10.4 ± 0.2	90.6 ± 1.9
Cow 50	16.2 ± 7.3	2.3 ± 5.0	10.1 ± 0.4	88.8 ± 1.5	9.3 ± 0.2	93.5 ± 0.8
Cow 63	13.9 ± 5.1	2.6 ± 5.3	8.5 ± 0.3	91.8 ± 1.3	8.2 ± 0.1	94.3 ± 1.0
Total	15.1 ± 7.2	2.7 ± 5.9	10.8 ± 0.2	85.6 ± 0.9	8.9 ± 0.1	92.4 ± 0.4

† Activity levels are means ± standard deviation for each cow (n = 906) or for total cow (n = 2436) in eating activity and other activities.

‡ Threshold values (median efficient level) of activity level and percent correct discrimination values (%) in LR and LDA are means ± standard deviation (n = 10,000).

3.4.2. Eating time

Applying the LDA function, the hourly pattern of eating activity (eating time per hour) was obtained for each cow (Figure 3.4), and Table 3.2 summarizes the cow eating time per day (min day^{-1}) and the percentage of time spent eating. Each cow primarily grazed during the daylight period, which started at sunrise and ended at sunset. The main periods of time that the cows spent on eating activity were after sunrise (4:00 to 5:00), before noon (10:00 to 12:00), and before sunset (16:00 to 20:00). Over the course of a day, the cows spent on average 443 to 475 minutes (30.7 to 33.0% per day) eating (Table 3.2).

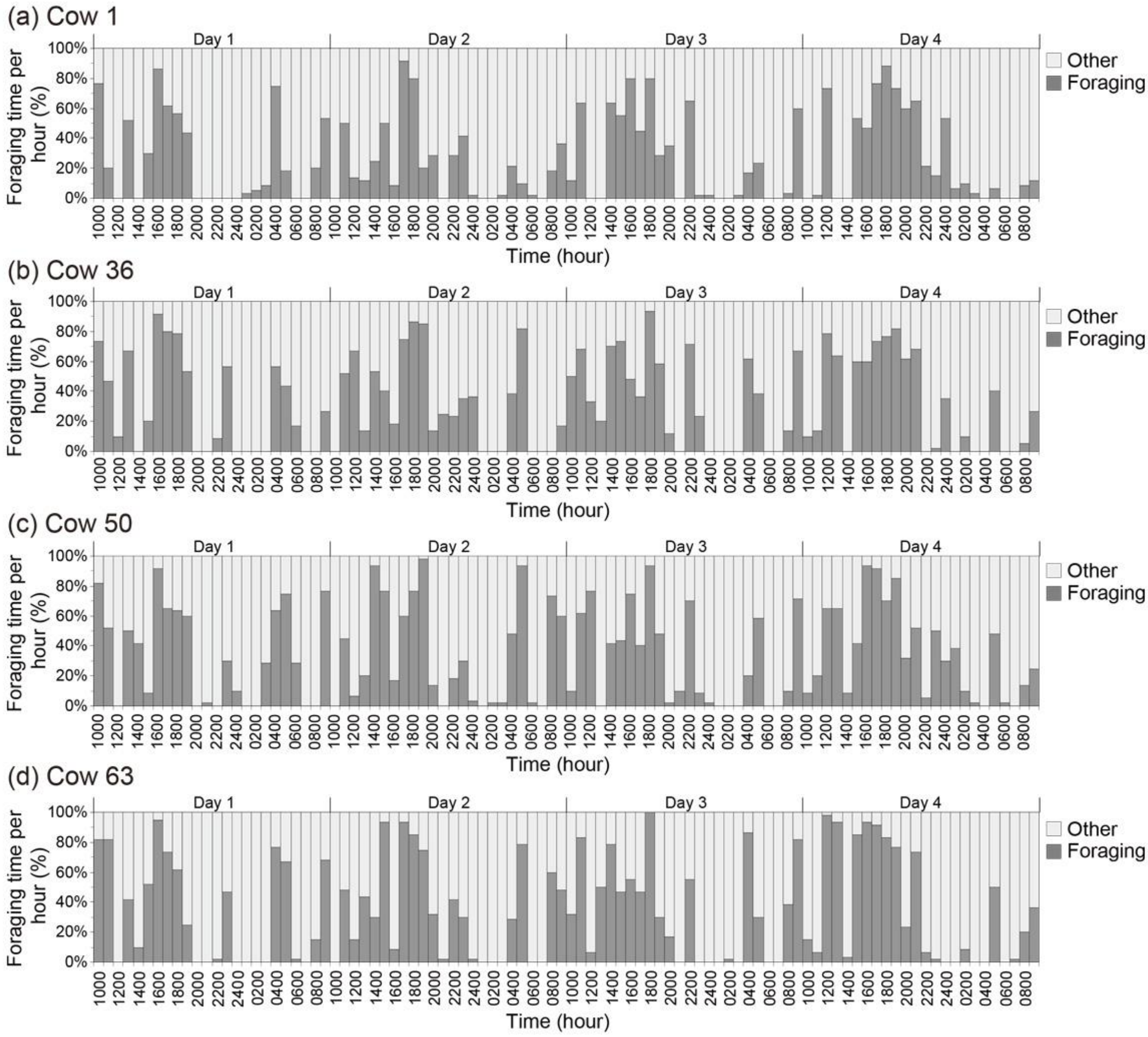


Figure 3.4 Hourly distributions of cow eating activity obtained from LCEX during a four-day grazing experiment.

Table 3.2 The daily eating time for the results of LDA and the percentage per one day for each cow.

	Eating time by LCEX (min d^{-1}) and the percent per day (%)[1]			
Cow no.	Day 1	Day 2	Day 3	Day 4
1	366 (25.4%)	324 (22.5%)	381 (26.5%)	405 (28.1%)
36	437 (30.3%)	456 (31.7%)	503 (34.9%)	459 (31.9%)
50	496 (34.4%)	503 (34.9%)	445 (30.9%)	513 (35.6%)
63	479 (33.3%)	488 (33.9%)	503 (34.9%)	521 (36.2%)
Mean	445 (30.9%)	443 (30.7%)	458 (31.8%)	475 (33.0%)

[1] Eating time was predicted by using LDA functions.

3.4.3. Spatial distribution of eating time and other activities during the daytime and nighttime

Figure 3.5 shows the spatial distributions of the four cows during their time spent eating and in other activities during the daytime (9:00 to 15:00) and nighttime (21:00 to 3:00). During the daytime (Figure 3.5a), the cows mostly grazed in the lower-altitude area of the paddock, covering a wider area than at night. During the nighttime (Figure 3.5b), the cows spent most of their time in the higher-altitude area of the paddock, with less eating activity.

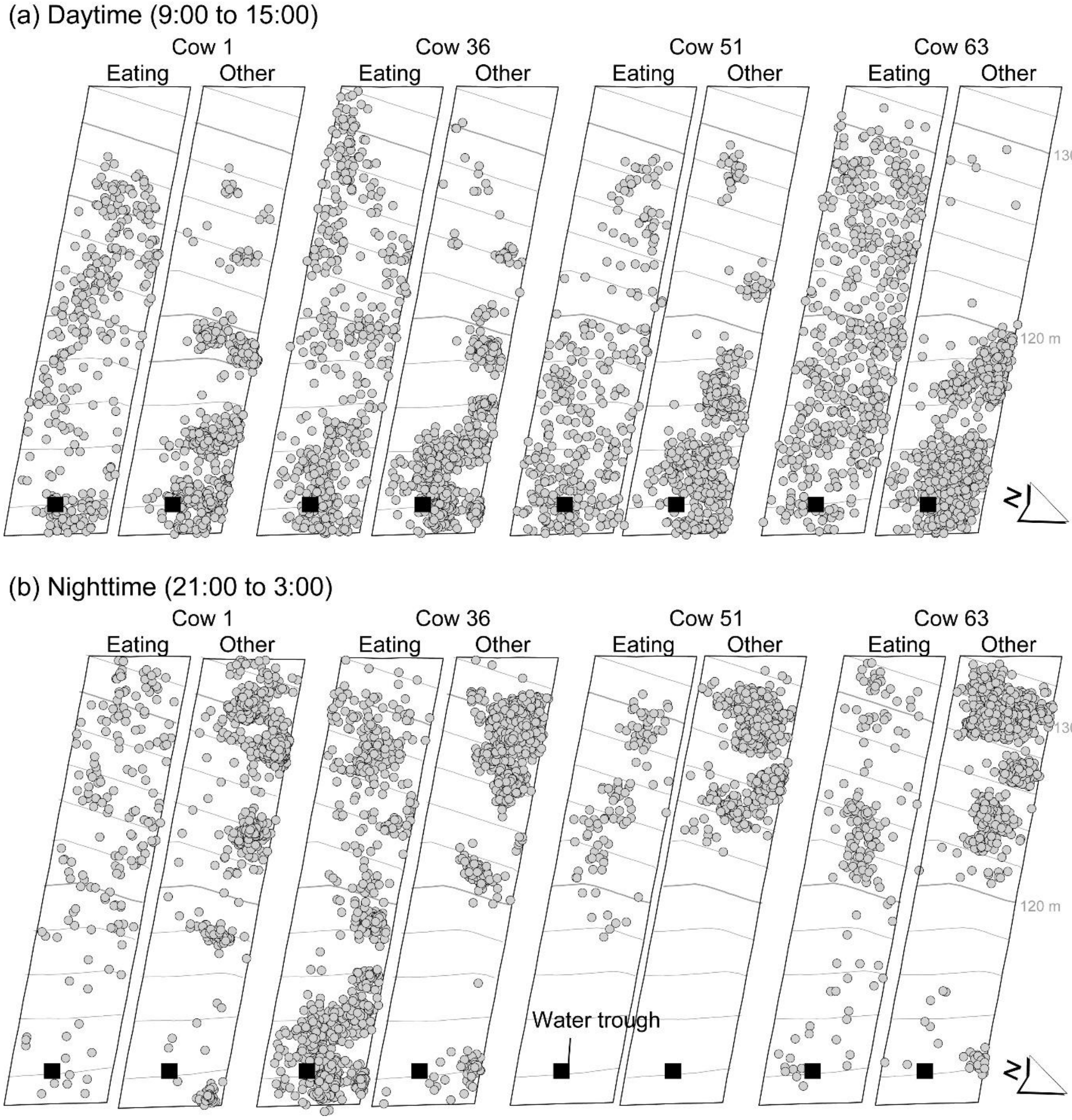


Figure 3.5 Spatial distributions of the cows' time spent eating and other activities during the (a) daytime (9:00 to 15:00) and (b) nighttime (21:00 to 3:00).

3.5. Discussion

This study demonstrates that LCEX can be used to determine eating activity in grazing beef cows. The LCEX device was originally developed for research on human health and human health management (Kumahara et al., 2004; McClain et al., 2007) and was recently used by Ueda et al. (2011) for monitoring the eating activity of dairy cows. Ueda et al. (2011) showed that eating activity can be identified with less than 5.5% misclassification using AL_1 as a threshold value based on the four-second data set, which corresponds to an activity level of 15 when simply calculated on a per-minute basis. Compared to this finding, our results based on the accumulated values of one-minute intervals indicated that results using the threshold values of 10.8 min^{-1} for LR and 8.9 min^{-1} for LDA obtained similar misclassification rates. Some previous studies have indicated that discriminant analysis is a useful method for identifying accelerometer variables that classify series of successive cow jaw movements into rumination and eating behaviors (Schleisner et al., 1999; Watanabe et al., 2008). In the present study, the author found that LDA results showed a higher correct discrimination percentage for all cows (90.6 to 94.6%) than did the LR results (80.8 to 91.8%) (Figure 3.3).

The accelerometry-based activity monitor data using the LDA function was used to characterize the temporal organization of the cows' eating activities in the pasture and allowed calculation of the hourly and daily time the cows spent eating (Table 3.2 and Figure 3.5). The diurnal pattern of the cows observed in the present study confirmed previous reports that cows graze more during daylight hours than at night (Ueda et al., 2011). There were two major grazing periods during the day: a long afternoon period and a shorter morning period, which were in accordance with the results of Schlecht et al. (2004) and Lin et al. (2011). By combining the cow GPS locations and the spatial distributions of eating and other activities during the daytime and nighttime, the author can conclude that the cows preferred to graze on the lower-altitude areas of the paddock during the day and, in contrast, spent most of in the night in the higher-altitude area with little eating activity (Figure 3.5). These results are in agreement with a previous study of bovine spatial distribution during grazing and resting in a hilly paddock (Yasue et al., 1997; Watanabe et al., 2010).

—Chapter 4—

A methodology for determining cattle dung position

"Without ambition one starts nothing. Without work one finishes nothing.

The prize will not be sent to you. You have to win it."

Ralph Waldo Emerson (1803–1882)

Chapter 4: A methodology for determining cattle dung position

4.1. Introduction

Cattle plays an important role in the nutrient cycling in pasture ecosystems (Hirata et al., 2011). They remove nutrients from the plants and return the nutrients to the pasture through their urine and dung (Betteridge et al., 2010). However, cattle urine and dung (feces) in the ecosystems provide not only a source of soil nutrients but are also a major source of greenhouse gas (GHG) emissions (Holter, 1997; Sordi et al., 2014). With the increasing pressure on farmers to minimize environmental pollution from farming operations, better understanding of the spatial distribution of excreta from grazing cattle is required.

Knowledge of the sites where livestock excrete will contribute to ensuring that GHG palliatives such as dicyandiamide and 3,4-dimethylpyrazole phosphate are used economically and efficiently. However, the excreta research of domestic animals by observation is laborious. Consequently, urine sensors that detect and log each urination event of female sheep and cattle have been developed. In addition, in combination with a global positioning system (GPS), these devices can detect livestock urinary event frequency and location (Betteridge et al., 2010). Using the device, the distribution of cattle and sheep urinary events in target fields is predictable (Betteridge et al., 2008), whereas useful equipment to detect dung position has not yet been developed. Previous research has suggested that the position of dung is related to grazing management and pasture topography. Excretal clumps are influenced by the effects of grazing equipment, such as drinking stations and salt racks (Hakamata and Hirashima, 1978). The proportion of an area occupied by fresh dung pats was considerably greater in a gently sloping site used for resting and decreased with an increase in the slope angle of inclination (Ide et al., 1998). Furthermore, earlier studies suggested that the location of cattle dung was related to the time spent by cattle in a particular area and their activities in that area, which can be affected by grazing management and pasture topography (Yamada et al., 2011), including crude protein (CP) concentrations and sward bulk densities (Senft et al., 1985; Ganskopp and Bohnert, 2009), plant species composition and forage quantity (Smith et al., 1992), geographical factors (*e.g.* slope, aspect) (Yasue et al., 1997), and distance from water (Roath and Krueger, 1982; Ganskopp, 2001). Excretion frequency is influenced by the quantity and quality of forage, outside temperature, humidity, milk yield and individual differences between cattle (Hafetz, 1975).

To improve upon previous knowledge obtained in field studies, considerable effort has been made to predict and understand the spatial distribution of cattle dung in grazing systems using a multiple linear regression (MLR) approach (Yamada et al., 2011). However, Wang et al. (2005) noted that the basic premise that the residual variance of response variable is constant (homoscedasticity) is violated, and the MLR approach is deemed inappropriate. 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. A generalized linear model (GLM) is a framework for statistical models that includes linear and logistic regression as special cases (Gelman and Hill, 2006) and allows for response variables that have error distribution other than a normal distribution. However, a GLM cannot express an individual difference that a researcher cannot measure and did not observe. Variability of the data obtained in the investigation cannot be explained well by a simple Poisson or binomial distribution.

In heterogeneous environments, such as grazed pastures and especially hill country pastures, the variation of parameter values will often occur in unison and therefore show auto-correlation (Fukasawa et al., 2009). We usually anticipate that adjacent locations are more similar than those further apart (Besag et al., 1991). An extension to GLM, GLMM, can account for non-normal data when random effects are present (Bolker et al., 2009). A CAR term is added to the GLMM to account for spatial heterogeneity in the data that the simpler GLM does not account for. The CAR term allows us to express the spatial non-independency between adjacent locations by introducing a spatial effect to model some of the random variation. In this way it is possible to infer the unknown factors affecting the subject by estimating the pattern of spatial random effects (Fukasawa et al., 2009).

Moreover, the application of a Bayesian approach provides a more flexible strategy that expresses parameters as a probability distribution (Kubo, 2009). One advantage of Bayesian estimation is the ease of including the CAR term in the analysis. Therefore, the use of Bayesian approaches to modeling spatial data is becoming increasingly popular (Clark, 2005).

In this study, the GLMM and the addition is the CAR term model on a Bayesian approach were employed to predict the spatial distribution of cattle dung in a slope pasture. As a first step, herbage green biomass (GBM) and the distance from a water trough (D_w) were used as explanatory variables. Based on a simple model involving only two parameters, we discuss the influence of these parameters and the spatial autocorrelation of the cattle dung distribution. The author has not linked urine distributions to these models although the distribution patterns of faeces are likely to be similar (White et al., 2001).

4.2. Material and methods

4.2.1 Dataset for modeling

The study site was same in chapter 3. After the four-day grazing experiment, the experimental paddock was divided into 10 m × 10 m grid cells (5 × 17 = 85 cells), and the number of dung deposits (N_d) in each cell was counted (Figure 1.1b, paddock III). The 10 m × 10 m grid size was based on our previous study estimating the spatial distribution of GBM and CP concentration using a hyperspectral radiometer over the same paddock (Lee et al., 2011), and this study suggested that the appropriate sampling grid size for GBM and CP concentration in the pasture should be <15 m × 15 m. Moreover, considering the vegetation survey and labor required to count N_d, the grid cells (10 m × 10 m) were used. Two parameters, GBM and D_w, were used in the current study as explanatory variables. GBM was estimated using a rising plate meter (RPM) prior to the grazing trial and was defined as:

$$\text{GBM}\ \ (\text{g DM m}^{-2}) = 17.67x + 36.56 \qquad (R^2 = 0.86) \qquad [4.\ 1]$$

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

4.2.2. Generalized liner model (GLM), generalized linear mixed model (GLMM) and Bayesian model

Figure 4.1 shows the method to extend the model from linear model to hierarchical Bayesian model. GLMs are flexible generalization of ordinary linear regression and allow for response variables that have error distribution models not only a normal distribution but also Poisson, binomial, categorical, etc. By allowing the linear model to be related to the response variable via a link function and by allowing the variance of each measurement to be a function of its predicted value, linear model is generalized to GLM. R function name is "glm" version 1.0.

GLMMs are an extension to the generalized linear models to allow in which the linear predictor contains random effects in addition to the usual fixed effects. These random effects are usually assumed to have a normal (or Gaussian) distribution. R function name is "glmmML" version 0.82-1.

The basis for Bayesian inference is Bayes' rule, also called Bayes' theorem, which is a simple result of conditional probability. Bayes' rule describes the relationship between the two conditional probabilities $p\ (A|B)$ and $p\ (B|A)$:

$$p\ (A|B) = \frac{p\ (B|A)\ p\ (A)}{p\ (B)}. \qquad [4.2]$$

$p\ (A|B)$ is the conditional probability of A given B and $p\ (B|A)$ is the conditional probability of B given A. The equation [4.2] is an undisputed fact and can be proven from simple axioms of probability. However, what used to be more controversial, and partly still is (*e.g.* Dennis, 1996; de Valpine, 2009; Lele and Dennis, 2009; Ponciano et al., 2009), is how Bayes used Bayes' rule. He used it to derive the probability of the parameters θ, given the data x, this is the posterior distribution $p(\theta|x)$:

$$p\ (\theta|x) = \frac{p\ (x|\theta)\ p\ (\theta)}{p\ (x)}. \qquad [4.3]$$

$p\ (\theta)$ is the prior distribution for θ. $p\ (\theta|x)$ is the posterior distribution for θ. The conditional distribution $p\ (x|\theta)$ is likelihood and describes how the data depend on the parameter values. To make this product a genuine probability distribution function, with an integral equal to 1, a normalizing constant $p\ (x)$ is needed as a denominator; this is the probability of observing one's particular data set x. To ignore the denominator, Bayes' theorem essentially states that

$$\text{Posterior distribution} \propto \text{Likelihood} \times \text{Prior distribution},$$

where ∝ reads as “is proportional to”. Thus, Bayesian inference works by using the lows of probability to combine the information about parameter θ contained in the observed data x, as quantified in the likelihood function $p(x|\theta)$, with what is known or assumed about the parameter before the data are collected or analyzed.

A Markov Chain Monte Carlo (MCMC) is a general method based on drawing from the posterior distribution p $(\theta|x)$ given a model, a likelihood p $(\theta|x)$, and data x, using dependent sequences of random variables. That is, MCMC yields a sample from the posterior distribution of a parameter. One of the most widely used MCMC techniques is Gibbs sampling (Geman and Geman, 1984). The author expended GLMM to Bayesian model using R and OpenBUGS, a software package for performing Bayesian inference using Gibbs sampling. R function name is “R2OpenBUGS” version 3.2–2.1.

Reference: Kéry, 2010

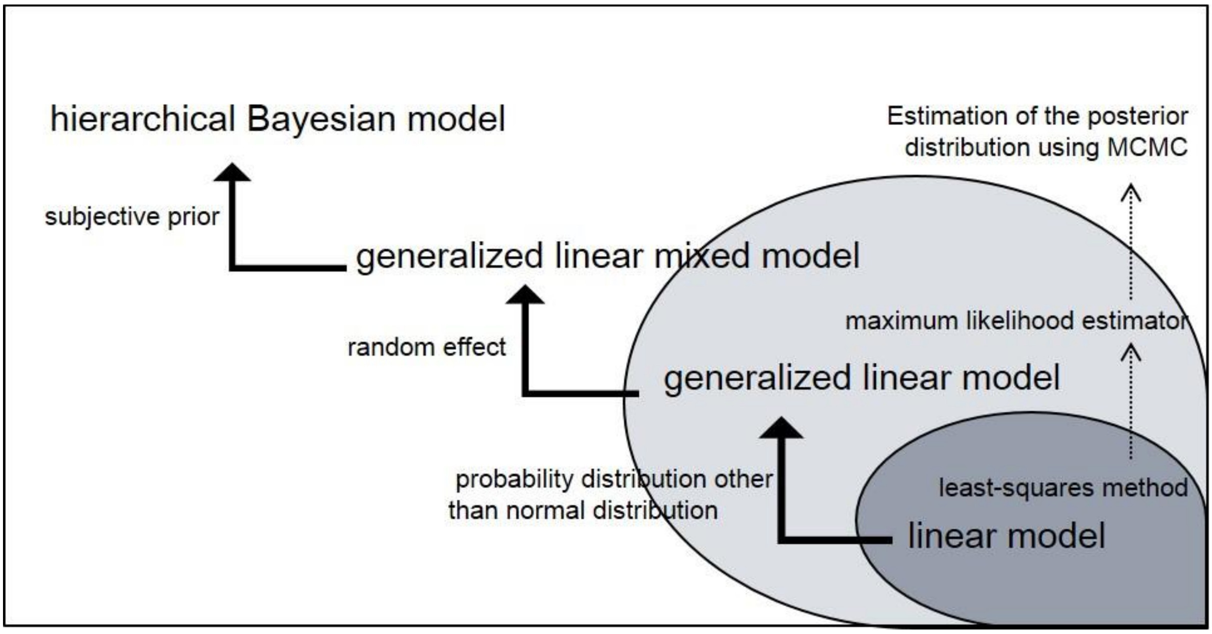


Figure 4.1 Schematic chart of the method to extend the model from linear model to hierarchical Bayesian model (Kubo online: IwanamiBook.html).

4.2.3. Modeling methodology

Hirata et al. (1990) reported that the dispersion pattern of dung pats within rectangular areas within a pasture is generally well described by a Poisson distribution. Because the response variable N_d was count data, it was assumed to follow a Poisson distribution with mean λ_i where λ_i includes random effects with spatial correlation. The author assumed a Poisson GLMM defined as:

$$\mathrm{N}_d \sim Poisson(\lambda_i) \tag{4. 4}$$

$$\log(\lambda_i) = b_1 + b_2\mathrm{GBM} + b_3\log\,(\mathrm{D}_w) + r_i \tag{4. 5}$$

$$b_1 \sim Uniform(-10{,}10), b_2 \sim Uniform(-10{,}10), b_3 \sim Uniform(-10{,}10)$$

$$r_i \sim Normal(0, \tau_1), \tau_1 = \frac{1}{\sigma_1 * \sigma_1}, \sigma_1 \sim Uniform(0{,}10)$$

where b_1 is the intercept; b_2 and b_3 are coefficients; and r_i represents random effects for grid number i = 1, 2, …, 85 with mean of zero and variance of τ_1. Similarly, the author assumed GLMM with the CAR term defined by

$$\log(\lambda_j) = b_1 + b_2\mathrm{GBM} + b_3\log\,(\mathrm{D}_w) + rho_j \tag{4. 6}$$

$$b_1 \sim Uniform(-10{,}10), b_2 \sim Uniform(-10{,}10), b_3 \sim Uniform(-10{,}10)$$

$$rho_j \sim \ \mathrm{AR}(\,d\ \ ,\ \ eight\ \ , Num\ \ , \tau_2),$$

$$\tau_2 = \frac{1}{\sigma_2 * \sigma_2}, \sigma_2 \sim Uniform(0{,}10)$$

where *rho* represents the spatial random effects for each grid position. The CAR term was used to specify the intrinsic Gaussian CAR prior distribution (Thomas et al., 2004), *Adj*[] is a vector listing the ID numbers of the adjacent areas for each grid cell; *Weight*[] is a vector the same length as *Adj*[] giving unnormalised weights associated with each pair of areas. Taking W_{ij} = 1 if areas i and j are neighbors 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_2 is the precision or inverse variance parameter for the Gaussian AR 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.

MCMC simulation is used for estimation and inference (Zhao et al., 2006). The length of the MCMC chain for this model was 100,000 cycles after 30,000 burn-in cycles, with samples saved every 100 cycles. The number of chains was three. 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).

4.3. Results

The mean, maximum and minimum values of N_d were 12.7, 35.0 and 1.0, respectively. The posterior means, standard deviation (SD) and 95% posterior probability intervals (PPIs) obtained through MCMC simulation are presented in Table 4.1. The R-hat values, which are an indicator of the convergence assessment (data are not shown), for all parameters achieved 1.0, and the effective sample size was sufficient for MCMC sampling. In the GLMM, the posterior means for b_1, b_2 and b_3 were 2.365 (95% PPI = 2.232–2.492), 0.363 (0.227–0.504) and −0.061 (−0.194–0.072), respectively. In the CAR model, the posterior means for b_1, b_2 and b_3 were 2.361 (95% PPI = 2.283–2.438), 0.219 (0.085–0.351) and −0.367 (−1.018–0.270), respectively. Deviance information criterion (DIC) in the GLMM and added CAR term were 502.6 and 291.5, respectively.

The predictive accuracies of the GLMM and added CAR term model between the observed and predicted values of N_d were evaluated using a validation plot (Figure 4.2) and a spatial distribution map (Figure 4.3). The predicted values of N_d were the median of the posterior distribution. Increased N_d values were primarily identified in two areas (the upper area and the lower area near the water trough), whereas larger random effects were obtained exclusively in the upper area.

Table 4.1 Posterior means (Mean) and standard deviations (SD) and quartiles (2.5, 50.0 and 97.5%) obtained in the generalized linear mixed model (GLMM) and added the intrinsic conditional autoregressive (CAR) term through Markov Chain Monte Carlo (MCMC) simulation. b_1 is the intercept, b_2 is the coefficient of herbage green biomass and b_3 is the coefficient of the distance from a water trough. σ are the standard deviations.

Model	Coefficient	Mean	SD	2.5%†	50.0%†	97.5%†
GLMM	b_1	2.365	0.066	2.232	2.367	2.492
	b_2	0.363	0.070	0.227	0.362	0.504
	b_3	–0.061	0.068	–0.194	–0.062	0.072
	σ_1	0.497	0.057	0.393	0.494	0.619
GLMM +	b_1	2.361	0.039	2.283	2.367	2.438
CAR term	b_2	0.219	0.067	0.085	0.234	0.351
	b_3	–0.367	0.327	–1.018	–0.365	0.270
	σ_2	0.597	0.079	0.455	0.592	0.764

† The values from 2.5% to 97.5% indicate the 95% posterior probability intervals.

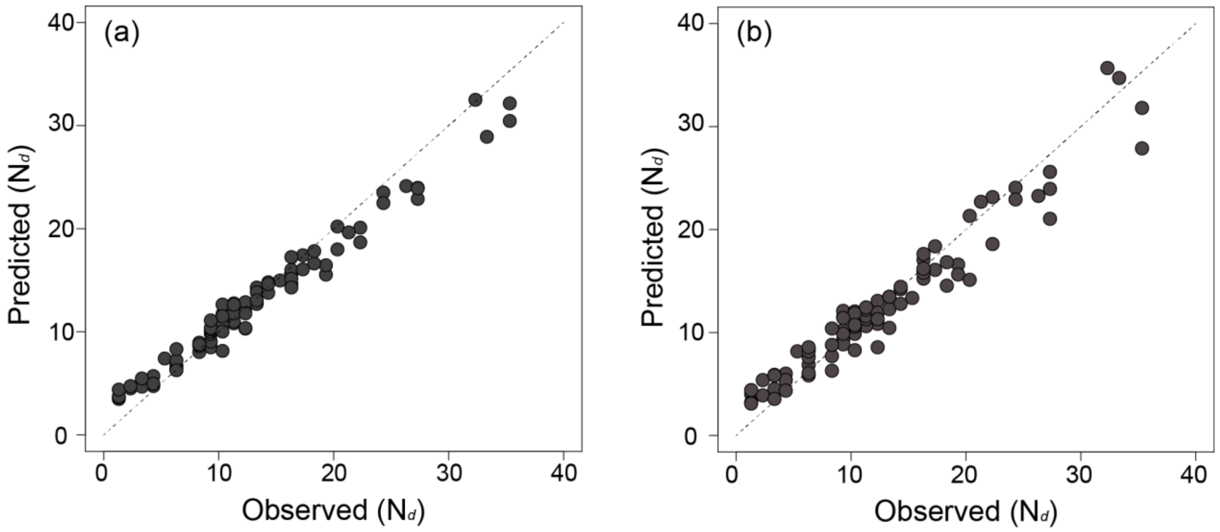


Figure 4.2 Predicted and observed number of cattle dung deposits (n) in each grid (10 × 10 m) from the generalized linear mixed model (GLMM) (a) and added the intrinsic conditional autoregressive (CAR) term (b) based on the herbage green biomass (GBM) and distance from the water trough (D_w).

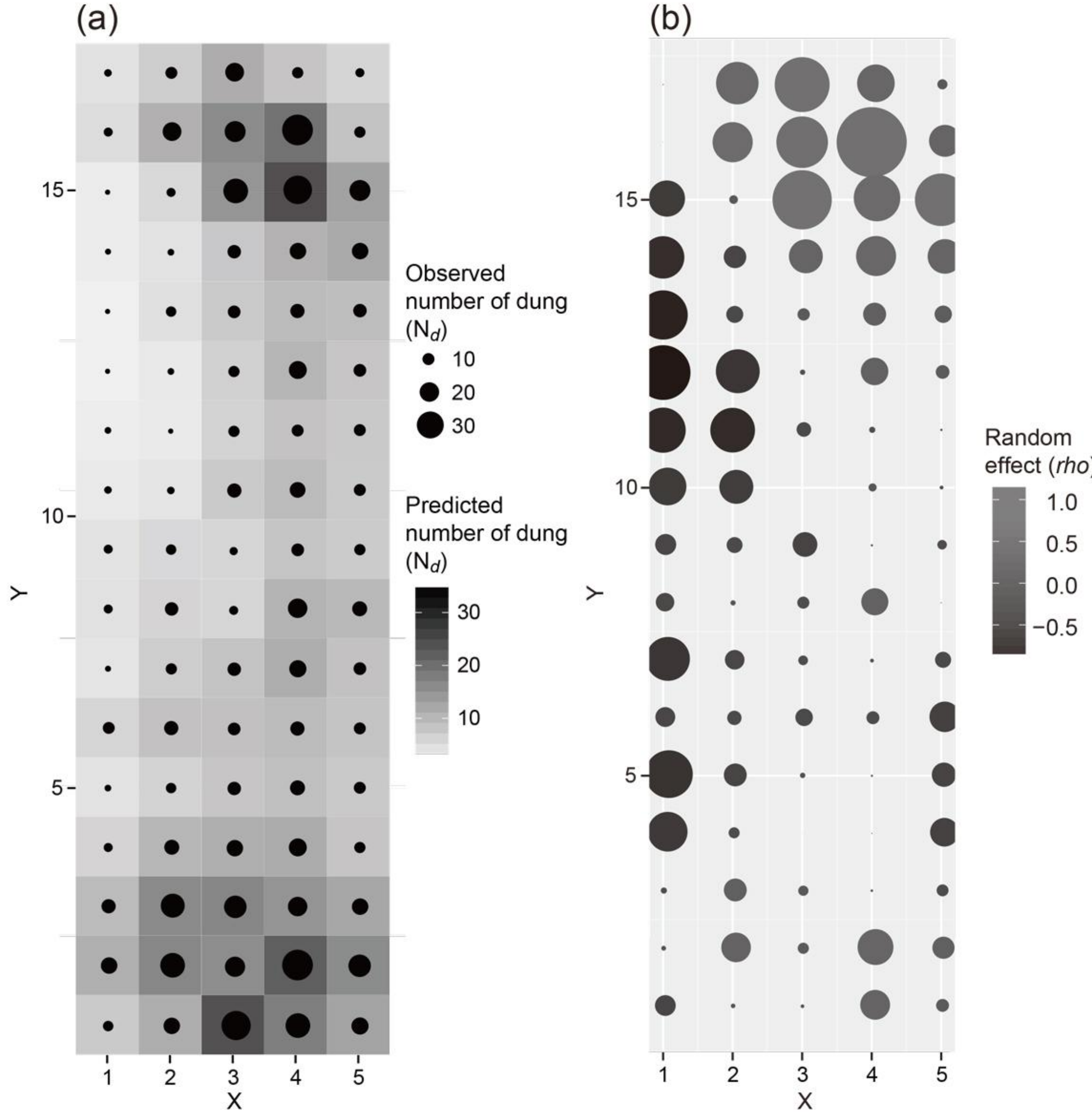


Figure 4.3 The 10 m × 10 m grid cells in the paddock and spatial distributions of the observed and predicted number of dung deposits per cattle (a) and the predicted random effects (b) in each cell (10 m grid) based on added the intrinsic conditional autoregressive (CAR) term for the experimental paddock.

4.4. Discussion

Our results indicated that the distribution of cattle dung can be estimated using GLMM and added CAR term model that consider random effects. DIC in the GLMM and added CAR term model were 502.6 and 291.5, respectively. Adding a CAR term, that has advantages in cases where there are missing values coverage because it restricts the variance of prediction values and can predict missing values. In this study, the small σ_2 value obtained indicated that spatial autocorrelation was not strongly influenced (Kubo, 2009); hence, GLMM was also applicable for this dataset.

The GBM and D_w were selected as explanatory variables to predict N_d because several studies show the relationship between cattle use of pasture, the distance from water (Martin and Ward, 1973; Beck, 1978) and the location of watering points was the major factor influencing forage utilization by cattle (Hodder and Low, 1976). Moreover, livestock prefer to graze in areas with higher forage quality and quantity (Senft et al., 1985; Bailey et al., 2001). Ganskopp and Bohnert (2009) indicated that cattle could simultaneously be responding to nutritional characteristic (CP, neutral detergent fiber, forage digestibility and standing crop) as they select areas to graze. Furthermore, the GBM and water troughs can be easily managed. The 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. The posterior distribution between the GLMM and added CAR term model showed similar estimates generated through MCMC simulation (Table 4.1), with positive values observed for GBM and negative values for D_w. These values suggested that increased N_d

values were spatially distributed in areas with a higher GBM and those situated closer to the water trough (Figure 4.3a). In previous studies, the relationship between the position of a drinking station and excretion was described (Roath and Krueger, 1982; Ganskopp, 2001). Excretal clumps are influenced by the effects of grazing equipment, such as drinking stations and salt racks (Hakamata and Hirashima, 1978). Although there is none of study in terms of the relationship between GBM and excretion, it might be explained indirectly from cattle grazing behavior. Feces tend to increase in places where the time spent is longer, and the time spent correlated with GBM. Cattle simultaneously respond to more than one nutritional attribute as they select foraging locales (Ganskopp and Bohnert, 2009). As can be seen from Table 4.1, no zero values were included within the 95% PPI for GBM and the mean value was positive. These mean that N_d values were spatially distributed in areas with a higher GBM. However, cattle tend to avoid grazing in the vicinity of dung pats (Edwards and Hollis, 1982). In this study, we used GBM before grazing and took no account of relationship of dung position and GBM after grazing. Thus, to further verify the results, future work should take into consideration about these relationships.

In the upper area of the paddock, however, the distribution of feces could not be explained using these parameters (Figure 4.3b), and it could be related to the time spent by the cows in the pasture. Hirata et al. (1990) reported that the resting sites of animals are related to dung pat deposits. These authors also found that the percentage of dung pats per rectangle was explained by the distance from the resting area and the fence on the opposite side of the resting area. Furthermore, the increase observed in the upper area could be related to time spent there at night, as cattle generally rest on the higher grounds at nighttime (Arnold and

Dudzinski, 1978). The percentage of the area occupied by fresh dung pats was shown to be much greater within a gentle sloping site used for resting and to decrease with an increase in the slope angle of inclination (Ide et al., 1998). Thus, the selection of parameters (*e.g.* the distance from fences, relative elevation, angle of inclination and shape of the slope) that affect resting activity in particular will be necessary to evaluate more robust model.

Because the models evaluated in this study were constructed using data from a single paddock, it is necessary to validate other paddocks in different seasons. A truly robust model must recognize physical features within a paddock that are likely to entice animals to excrete disproportionate amounts of feces within a close proximity. In chapter 5, the model was improved to be more general.

―Chapter 5―

Spatial modeling for estimating cattle dung position (multiple paddocks)

“ s I grow older, I pay less attention to what men say.
I ust watch what they do”

Andrew Carnegie (1835–1919)

Chapter 5: Spatial modeling for estimating cattle dung position (multiple paddocks)

5.1. Introduction

Patches of cattle dung (feces) in grazing systems are not only a source of soil nutrients but also a major source of GHG emissions (Sordi et al., 2014). GHG emissions are different varies according to the difference of the place, such as soil condition and vegetation state. Knowledge of the sites where livestock excrete will contribute to ensuring that GHG palliatives such as dicyandiamide and 3,4-dimethylpyrazole phosphate are used economically and efficiently.

To predict the spatial distribution of cattle dung, in chapter 4, the author used GLMM and the addition is the CAR term on a Bayesian approach using herbage green biomass (GBM) and the distance from a water trough (D_w) as explanatory variables (chapter 4). The results of chapter 4 suggested that the distribution of cattle dung was related to GBM and the position of the water trough. However, because the models evaluated in the previous study were constructed using data from a single paddock in one season, it is necessary to validate the models using other paddocks during different seasons. Furthermore, the results suggested that GLMM model including a CAR term is more flexible than the ordinary GLMM because of advantages when the data includes missing values. A lower deviance information criterion (DIC) value was obtained for the model with the added CAR term (DIC = 291.5) compared to that for the ordinary GLMM (DIC = 502.6), so the author concluded that the GLMM with the CAR term was better.

In this chapter, therefore, was to predict the position of cow dung using manageable factors, and to generalize the modeling framework using data from three paddocks. Although topographical factors are related to cow dung position, it is difficult to control the topography of a pasture (e.g. angle of inclination and slope shapes). Thus, the author examined parameters that can be easily managed by farmers, and below the influence of these parameters and the differences between the paddocks were discussed.

5.2. Material and methods

5.2.1. Dataset for modeling

The study was conducted in a mixed sown pasture (No.37) at the NARO Hokkaido Agricultural Research Center, as mentioned in chapter 1.3 (Figure 1.1b). Three paddocks were delimited using electric fences (I and II, 1.02 ha [60 m × 170 m]; III, 0.85 ha [50 m × 170 m]) and twenty breeding Japanese Black cows and their five calves were stocked for four days (paddock I, from 10 am May 17 to 10 am May 21, 2010; paddock II, from 10 am May 31 to 10 am June 4, 2010; paddock III, from 10 am June 14 to 10 am June 18, 2010). Six cows were selected (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 a balance between age and body weight. Each cow was fitted with a GPS collar (CM-10kx, Furuno Electric Co. Ltd., Nishinomiya, Japan). For paddocks I, II and III, the mean air temperatures were 14.0°C, 11.9°C and 17.6°C; the minimum air temperatures were 6.4°C, 2.6°C and 14.8°C; and the maximum air temperatures were 22.9°C, 21.0°C and 24.5°C, respectively. After each paddock was grazed for four days, it was divided into 10 m × 10 m grid cells (I and II, 6 × 17 = 102 cells; III, 5 × 17 = 85 cells). In Chapter 4, the dataset of paddock III was only used. In this chapter, three paddocks dataset were used to estimate the position of cattle dung. The methodology of getting dataset was mentioned in chapter 4.2.1.

5.2.2. Modeling methodology

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

$$\mathrm{N}_d \sim \mathrm{Poisson}(\lambda_i) \qquad [5.\ 1]$$

$$\log(\lambda_i) = b_1[j] + b_2[j]\log(\mathrm{GBM}) + b_3[j]\log(\mathrm{D}_w) + rho_i \qquad [5.\ 2]$$

$$b_1[j] \sim \mathrm{Normal}(\mu_{b1}, \tau_{b1}), b_2[j] \sim \mathrm{Normal}(\mu_{b2}, \tau_{b2}), b_3[j] \sim \mathrm{Normal}(\mu_{b3}, \tau_{b3}),$$

$$\mu_{b1} \sim \mathrm{Uniform}(-10, 10), \mu_{b2} \sim \mathrm{Uniform}(-10, 10), \mu_{b3} \sim \mathrm{Uniform}(-10, 10),$$

$$\tau_{b1} = \frac{1}{\sigma_{b1} * \sigma_{b1}}, \sigma_{b1} \sim \mathrm{Uniform}(0,10), \tau_{b2} = \frac{1}{\sigma_{b2} * \sigma_{b2}}, \sigma_{b2} \sim \mathrm{Uniform}(0,10),$$

$$\tau_{b3} = \frac{1}{\sigma_{b3} * \sigma_{b3}}, \sigma_{b3} \sim Uniform(0,10)$$

$$rho_i \sim \ \mathrm{AR}\left(Adj_j\ , Weight_j\ , Num_j\ , \tau\right), \tau = \frac{1}{\sigma * \sigma}, \sigma \sim \mathrm{Uniform}(0,10)$$

where b_1 is the intercept, b_2 and b_3 are coefficients, j is the paddock number, *rho* represents the spatial random effects for each grid position. The CAR term was used to specify the intrinsic Gaussian CAR prior distribution (Thomas et al., 2004), *Adj*[] is a vector listing the ID numbers of the adjacent areas for each grid cell; *Weight*[] is a vector the same length as *Adj*[] giving unnormalised weights associated with each pair of areas. Taking $W_{ij} = 1$ if areas i and j are neighbors 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 AR 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.

MCMC simulation was performed 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. The number of chains was three. All of the 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).

5.3. Results and discussion

5.3.1. MCMC results

SD and 95% PPIs obtained with MCMC simulation are presented in Table 5.1, and Figure 5.1 depicts box plots of the 95% PPIs for each parameter. The R-hat values, which are indicators of the convergence assessment, achieved 1.0 for all of the parameters, and the effective sample size was sufficient for MCMC sampling. Based on the results of the posterior distribution generated by MCMC, we found similar estimates in all of the paddocks, *i.e.*, positive values for GBM and negative values for D_w (Table 5.1, Figure 5.1). This indicated that a higher N_d tended to be associated with a higher GBM and a location closer to the water trough. The 95% 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 are as would be expected intuitively. The PPIs for both included 0 and the probability that they were above or below 0 respectively were 87.2% and 91.7%. A small value of σ (the posterior mean was 0.631) was obtained, which indicated that there was the weak spatial autocorrelation (Kubo, 2009).

Although no studies have been conducted on the relationship between GBM and excretion, this relationship might be indirectly explained based on cattle grazing behavior. The dung count tended to be higher in places where more time was spent, and the time spent by the cattle correlated with GBM. Previous studies have shown that grazing cattle move to areas with high forage quantity and quality attributes (Okamoto et al., 1994; Ganskopp and Bohnert, 2009). In this study, the author used the GBM measured prior to grazing to predict the location of dung deposits. Previous research revealed that cattle tend to avoid grazing in the vicinity of dung pats (Edwards and Hollis, 1982). Weeda (1967) found that herbage close to dung pats was usually between three and five cm higher than the herbage of the surrounding pasture. The author did not identify a relationship between dung position and GBM after grazing.

The relationship between N_d and D_w found here, is in agreement with previous studies (Nakamura and Fukuoka, 1974; Yoshitoshi et al., 2015). Hirata et al. (1990) reported that the animal resting sites are related to dung pat deposits. In addition, these authors observed that the percentage of dung pats per grid cell could be explained by the distance from the resting area and the distance from the fence on the opposite side of the resting area. Dung events frequently occurred immediately before and after moving and just after resting (Sugimoto et al., 1987). Yamada et al. (2011) suggested that dung was frequently found in the vicinity of fences because cattle tracks tend to develop near fences (Oikawa et al., 1981), which results from the cattle spending longer periods in these locations. However, the current grazing experiment was conducted for only four days in each paddock, indicating that it is likely that these factors had little effect on the time spent by the cattle in a particular location. Because a water trough was located on the lower slope near the fence in all of the paddocks, the influence of water trough position should to be examined in more detail. Furthermore, N_d could be affected by geographical features since the water trough was located at the bottom of the slope.

Table 5.1 Posterior means (Mean), standard deviations (SD) and quartiles (2.5, 50.0 and 97.5%) obtained from the Markov Chain Monte Carlo (MCMC) simulation. μ is the hyper parameter of b_1, b_2 and b_3. b_1 is the intercept, b_2 is the coefficient of herbage green biomass and b_3 is the coefficient of the distance from a water trough. σ are the standard deviations.

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.

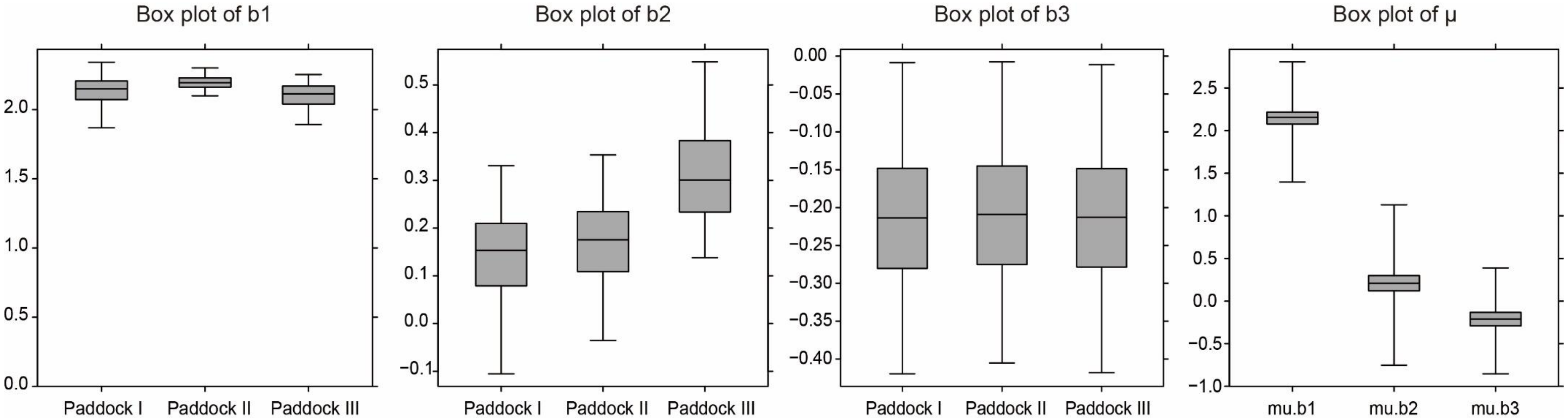


Figure 5.1 Box plot of the 95% credible interval for each parameter. b_1 is the intercept, b_2 and b_3 are coefficients for log green biomass (GBM) and log distance from water trough (D_w).

5.3.2. Spatial distribution of cow dung

The GPS collars recorded cow velocity data during the four-day grazing periods in each paddock, and this was used to determine the time spent by six cows in each grid. The GPS data was recorded in 'one-minute' intervals during the four-day grazing period. The number of intervals spent by the six cows in each grid cell was summed for the four-day grazing period, and the descriptive statistics and spatial distributions of N_d, GBM and the time spent in each grid are shown in Table 5.2 and Figure 5.2. The location of cattle dung was related to the time spent by the cattle in a particular location similar to previous studies (Yamada et al., 2011).

Figure 5.3 shows the predicted versus observed values of N_d. The predicted values were the medians from the posterior distributions of N_d for each grid cell. It is believed that the bias on these plots was related to cattle activities. Furthermore, we could not separate out cattle activities between daytime and nighttime. Previous studies indicated that cattle prefer to graze on the lower-altitude areas of the paddock during the day and, in contrast, spend most of the night time in higher-altitude areas with little eating activity (Yasue et al., 1997; Watanabe et al., 2010). There were two major grazing periods during the day, in the current study: a long afternoon period and a shorter morning period, which were in accordance 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.

A previous study collected data from a single paddock (Yoshitoshi et al., 2015, chapter 4); therefore, the author generalized the modeling framework using data from three paddocks in this study. Present results 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 (Figure 5.3). Furthermore, the main finding is that dung deposits tended to be distributed in areas with higher herbage green biomass and those located closer to the water trough.

Table 5.2 The descriptive statistics of the number of dung deposits (N_d), herbage green biomass (GBM) and the time spent in each grid.

	Paddock No.	Mean	SD	Minimum	Maximum
N_d	I	8.7	6.0	0	30
	II	11.6	8.7	0	47
	III	12.7	8.0	1	35
GBM (g DM m^{-2})	I	198.3	36.6	141.3	309.0
	II	323.7	61.0	204.9	455.6
	III	373.0	82.8	220.9	658.0
Time spent (minute)	I	174.8	163.1	0	787
	II	197.4	226.7	12	1389
	III	224.1	187.4	26	715

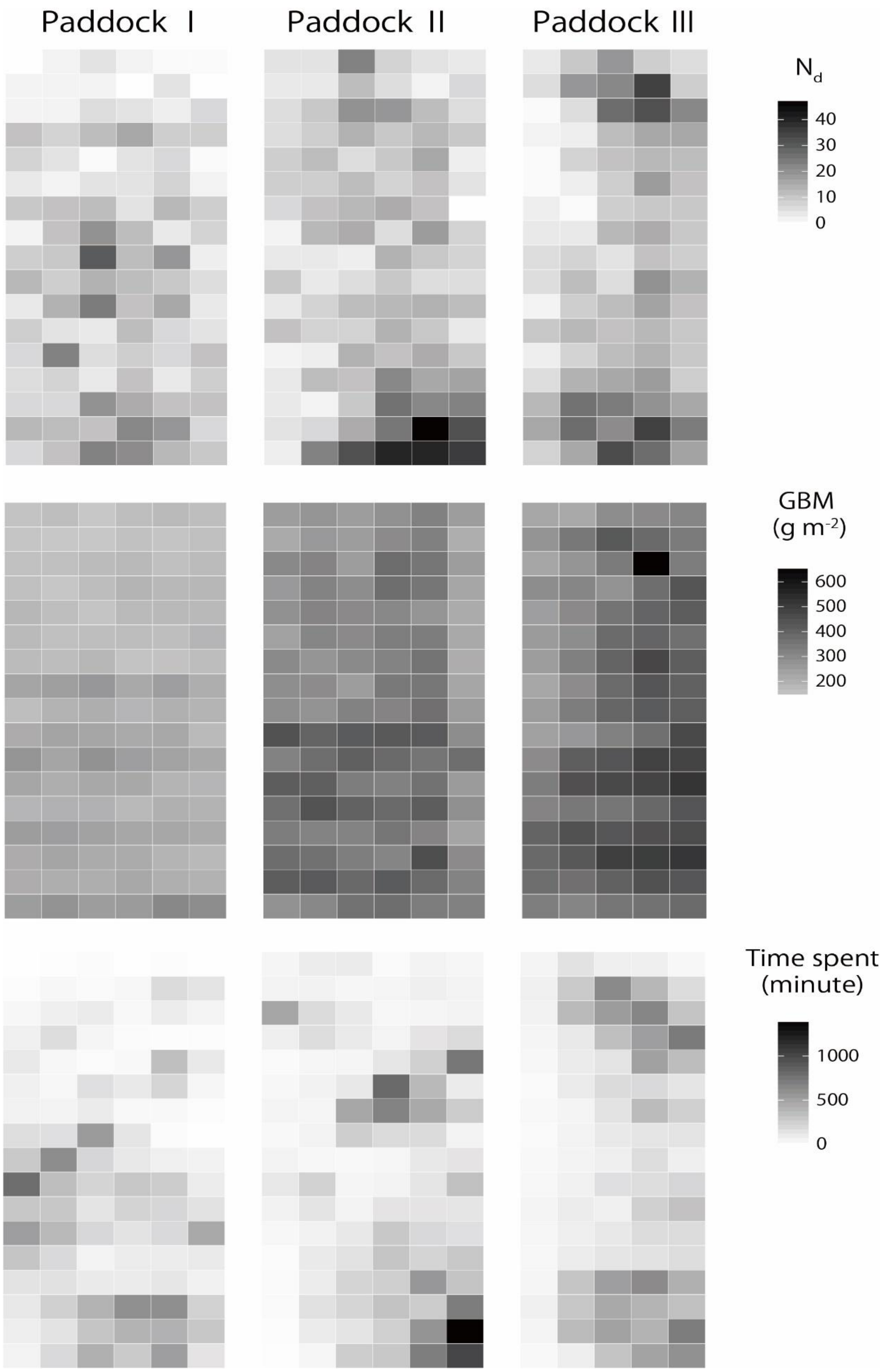


Figure 5.2 The distributions of the number of dung deposits (N$_d$), herbage green biomass (GBM) and the time spent by cattle in each grid.

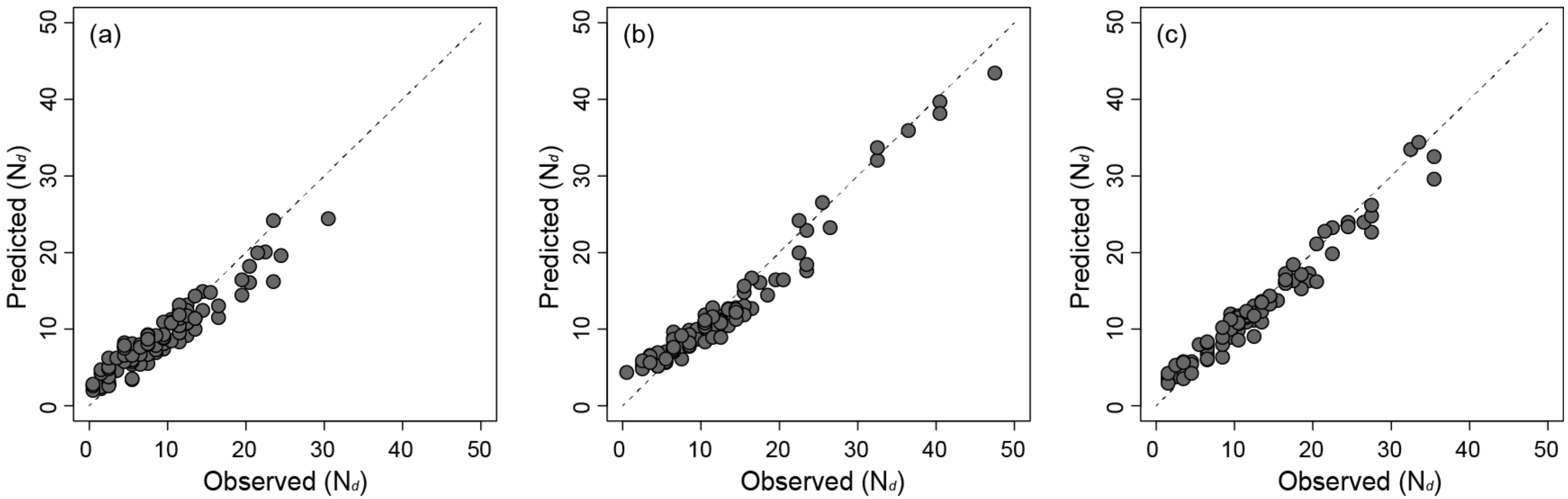


Figure 5.3 Predicted and observed number of cattle dung deposits (*n*) in each grid (10 × 10 m) in paddocks I (a), II (b) and III (c) using Bayesian model based on the herbage green biomass (GBM) and distance from the water trough (D_w).

－Chapter 6－

Detecting cattle dung position with UAV image

"The more I learn the more I realize I don't know.
The more I realize I don't know the more I want to learn"

Albert Einstein (1879–1955)

Chapter 6: Detecting cattle dung position with UAV image

6.1. Introduction

In RS technologies, UAVs are understood as uninhabited and reusable motorised aerial vehicles, which are remotely controlled, semi-autonomous, autonomous, or have a combination of these capabilities. The UAVs can catty various types of pay loads, making them capable of performing specific tasks within the earth's atmosphere, or beyond, for a duration, which is related to their missions (Blyenburgh, 1999). Although the UAVs were used by the military in early stages, use of other purposes is increasing rapidly (Blyenburgh, 1999). For example; natural disaster response (Zhou and Wu, 2006), mapping grass species (Hardin and Jackson, 2005) and forest fires (Hinkleya and Zajkowski, 2011), traffic surveillance and management (Mirchandani et al., 2003) and scientific research in archaeological prospecting (Eisenbeiss, 2004). In agriculture, UAV have been used for field trails and research, determination of the biomass, crop growth and food quality (Herwitz et al., 2004). Moreover, UAVs have been developed and applied to support precision agriculture (Huang et al., 2013); for monitoring crop biomass (Hunt, 2005; Swain et al., 2010), for examining the results of various nitrogen treatments on crops (Hunt 2005; Swain et al., 2007).

The aim of this study was to develop a methodology to detect the cattle dung position using high-resolution image from UAV on-boarded camera. To densify the evaluation of GHG emissions from the pasture, the model to predict the spatial distribution of dung in chapters 4 and 5, and in this chapter, the dung position has been detected directory.

6.2. Material and methods

6.2.1. Study site

This study was conducted in grazing paddock No. 4 at the Setouchi Field Research Center, Hiroshima University, Japan, as mentioned in section 1.3 (Figure 1.2). From four to six Japanese Black breeding cattle have been grazed between June and October. In order to protect by the cattle during field/UAV observation, three plots (20 m × 20 m) were installed inside the paddock. The plots were protected by cattle using electric fence. UAV images were taken and dung position were recorded using GPS (Geo7X, Trimble) in these plots one time per every month. Raw image was taken by UAV (four multirotor, motor axis distance was 45 cm, 1 kg) attached with camera (DSC-RX100, SONY, 20.2 million pixel, 240 g) using interval function (every 5 sec) (Figure 6.1). Flight altitude was about 50 m, and a flight time was approximately five minute.

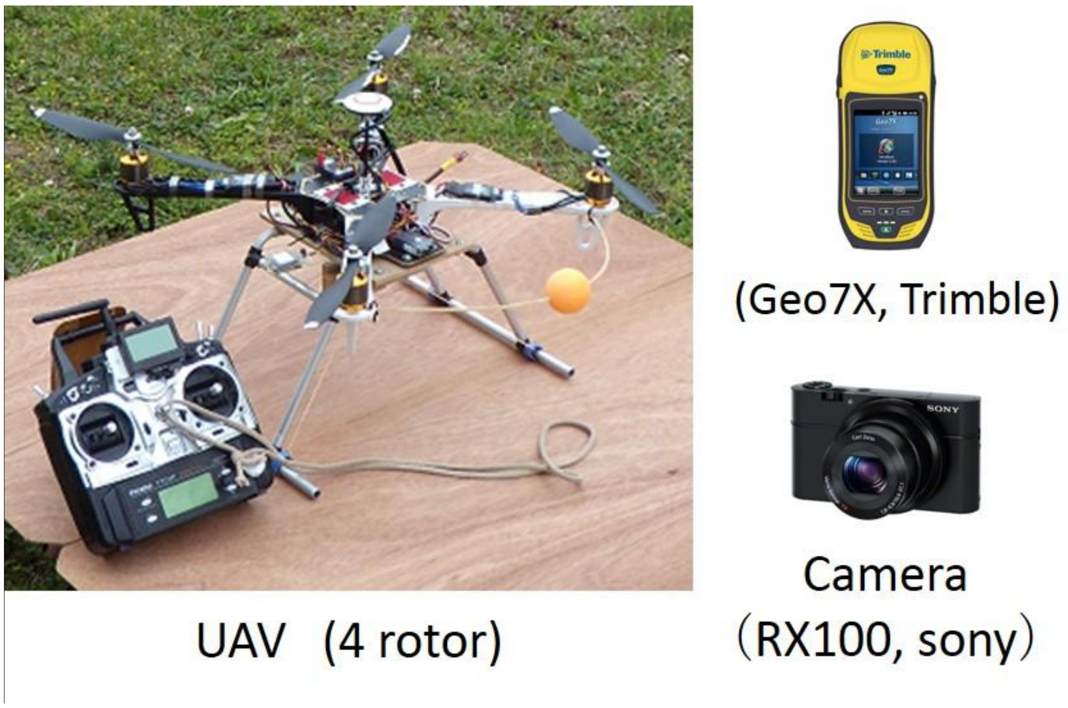


Figure 6.1 Photographs for unmanned aerial vehicle (UAV), differential GPS (DGPS) and camera.

6.2.2. Image processing

First, the raw image was converted to Tagged Image File Format (TIFF) data using Dcraw ver 9.26 (Coffin, 2015), an open-source computer program which is able to read numerous raw image formats, typically produced by high-end digital cameras. Second, because the TIFF image did not have location information, geometric correction (UTM zone 53N, JGD2000) was performed using QGIS (Quantum GIS software ver. 2.6.1). In the geometric correction process, from four to six ground control points (GCPs) were used by georeferencer tool (change type = thin-plate spline; resampling method = cubic spline) in QGIS. Figure 6.2 shows the original TIFF image (prior geometric correction) and the GeoTIFF image (post geometric correction). Third, RGB image and training image were created using region of interest (ROI) tool of ENVI software ver. 5.1 (Exelis VIS, USA). Using DGPS locations and RGB color information, the dung pixels on image were manually selected as a training data (pixel value: 1 = dung, 0 = others, and 2 = outside of the target plot area) (Figure 6.3).

In this study, images taken by two plots (A and B) on June 20, 2014 were used in the analysis due to low quality of image in one of three plots. Spatial resolutions at ground level in Plot A (1,891 × 1,929 pixels) and Plot B (1,222 × 1,228 pixels) were 1.4 cm and 2.2 cm, respectively. The number of dung deposits in plot A and B were 45 and 56, respectively.

Random forest regression (RFR) (Breiman, 2001) was used for detecting dung pixel using the training image data and RGB color information including normalized red, green and blue values as explanatory variables. The RFR was performed using functions of “randomForest” version 4.6–7 on R software. To equalize the number of pixel in dung and others, selected 3,970 pixels (dung: 1985 pixels, other: 1985 pixels) in plot A and 5,300 pixels (dung: 2,630, other: 2,630 pixels) in plot B were used.

Figure 6.2 Original TIFF image (prior geometric correction) and the GeoTIFF image (post geometric correction).

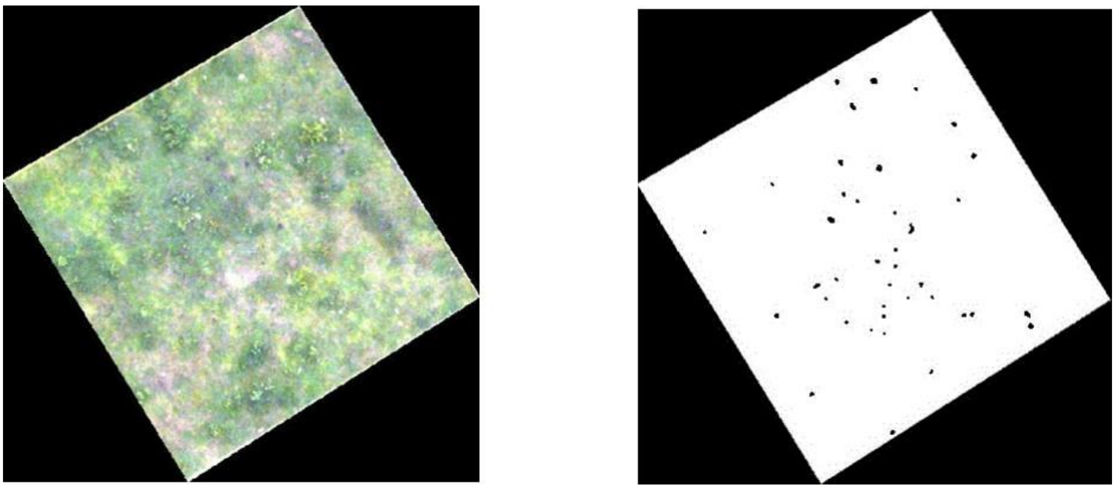


Figure 6.3 RGB image (a) and training image (b).

6.2.3. Random forest regression (RFR)

RFR 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. Details of making regression trees are listed below (Hastie et al., 2008).

1. For $b = 1$ to B:

(a) Draw a bootstrap sample Z^* of size N from the training data.

(b) Grow a random-forest tree T_b to the bootstrapped data, by re-cursively repeating the following steps for each terminal node of the tree, until the minimum node size n_{min} is reached.

i. Select m variables at random from the p variables.

ii. Pick the best variable/split-point among the m.

iii. Split the node into two daughter nodes.

2. Output the ensemble of trees $\{T_b\}_1^B$.

To make a prediction at a new point x:

Regression: $\hat{f}_{rf}^B(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$

Classification: Let $\hat{C}_b(x)$ be the class prediction of the bth random-foresttree.

Then $\hat{C}_{rf}^B(x) = magority\ vote\{\hat{C}_b(x)\}_1^B$

6.3. Results

6.3.1 The correct discrimination percentages from the RFR analysis

Table 6.1–4 shows the cross tabulation of predicted values and observed values from the RFR analysis. The vertical axis shows the number of predicted values (no dung 0 or dung 0) and the horizontal axis shows the number of observed values (no dung 0 or dung 0). The red numbers show the number of correctly predicted pixels. The correct discrimination percentages for plot A on the same data was 88.9% (= (1,752 + 1,779) / 3,970 × 100) (Table 6.1). The correct discrimination percentages for plot B on the same data was 85.1% (= (2,244 + 2,267) / 5,300 × 100) (Table 6.2). The results of validation using these data also had similar percentages (Tables 6.3 and 6.4). Figure 6.4 shows the predicted the location of dung in whole paddock using plot A model. White colors represented the predicted dung position, and the number of predicted dung pixel was 21,460. These results indicated that it is difficult to distinguish dung from only RGB color information, especially between dung and soil.

Table 6.1 The cross tabulation of predicted values and observed values from the random forest regression analysis for plot A data on the same data.

	no dung (0)	dung (1)
no dung (0)	1752	233
dung (1)	206	1779

Table 6.2 The cross tabulation of predicted values and observed values from the random forest regression analysis for plot B on the same data.

	no dung (0)	dung (1)
no dung (0)	2244	406
dung (1)	383	2267

Table 6.3 The cross tabulation of predicted values and observed values from the random forest regression analysis for plot B on the plot A data.

	no dung (0)	dung (1)
no dung (0)	1692	293
dung (1)	173	1812

Table 6.4 The cross tabulation of predicted values and observed values from the random forest regression analysis for plot A on the plot B data.

	no dung (0)	dung (1)
no dung (0)	2368	282
dung (1)	519	2059

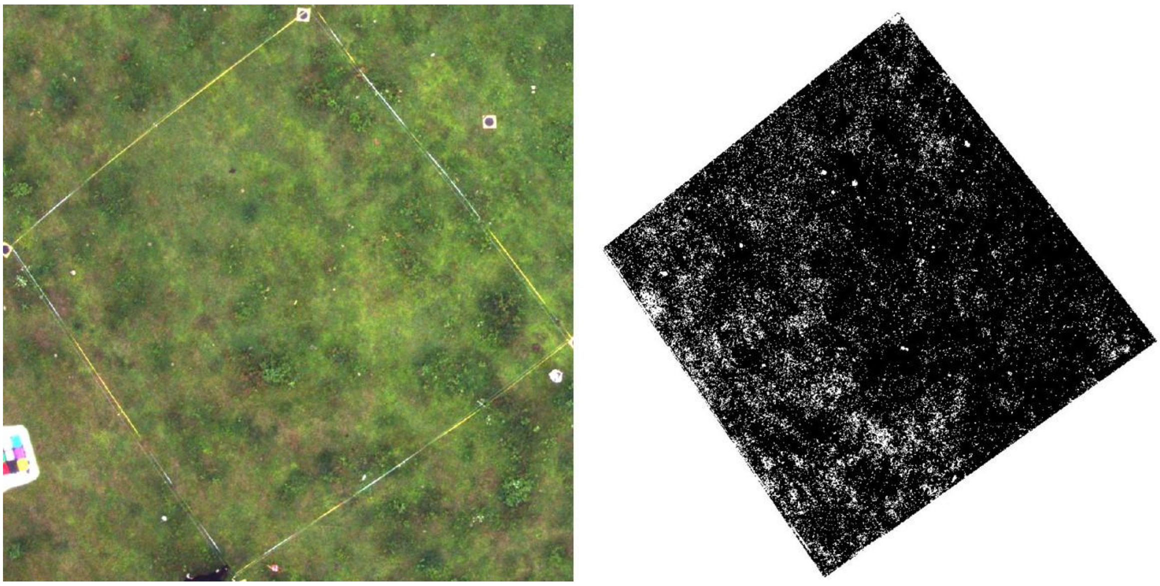


Figure 6.4 RGB image (left) and predicted dung positions (right) in the target paddock (plot A).

6.3.2 Threshold processing

The predicted image (Figure 6.4) had a lot of independent pixel (*e.g.* one-pixel). The author tried to detect the dung position using threshold with Matlab ver. 2014b (MathWorks Inc., Sherborn, MA, USA). The predicted dung pixels were done binarization processing and clusters of pixels which were too small and too large were removed ($100 \leq \text{Area} \leq 330$). After this processing, the relatively round clusters were selected ($\text{MajorAxisLength} \leq 35$ and $\text{Perimeter} \leq 130$). Figure 6.5 shows the step of threshold processing of predicted image from plot A data and red points shows the results. The number of clusters was 89 after these processing. It seems that the position of most of the dung could be detected from its size and shape.

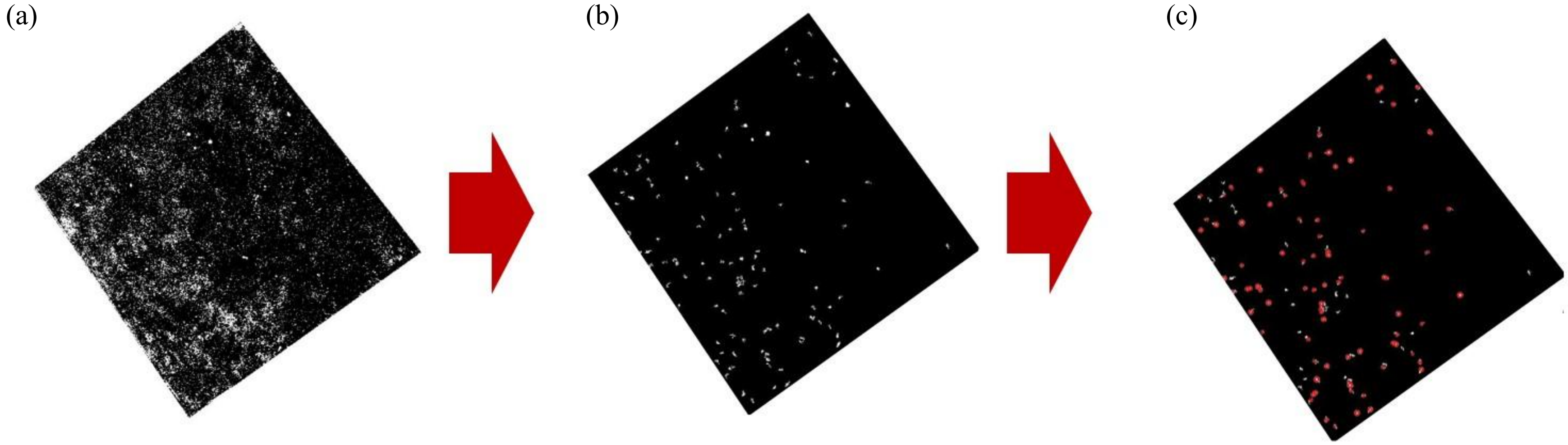


Figure 6.5 The step of threshold processing of predicted image; (a) the predicted dung position in whole paddock using plot A model; (b) After removing clusters of pixels which were too small or too large; (c) After selecting the relatively round objects.

6.4. Discussion

In this chapter, the author tried to detect the cattle dung position in pasture using a very high resolution image taken by a camera attached to a UAV. The result indicated that the fresh dung could be detected from its size and shape. However it is difficult to distinguish between old dried dung and soil. Figure 6.6 shows the spectrum of fresh, middle and old dung. The fresh dung had characteristic spectrum (green was low and blue was high), but when the dung became dry, the spectrum was similar to soil. The distinguishing of old dung and soil is difficult only using RGB information. Figure 6.7 shows the light reflectance of fresh dung (passed three days), dry soil and wet soil measured by FieldSpec (ASD Inc., Boulder, CO, USA). The author considered the ultra violet and near-infrared wavelengths not just the visible region. It is necessary to consider the short-wavelength (ultra violet) and near-infrared (NIR) not just the visible region (RGB).

The subject of a future study could be to look for a characteristic wavelength to distinguish between old dung and soil. The author would also like to investigate whether it is possible to distinguish how many days after excretion the fresh dung looks like old dung. The author have also detected the dung position with other photographic images provided by the UAV at different altitudes and verified the size estimate precision.

UAV technologies are relatively new and there are limitations of current agricultural UAVs. Although the costs of the aircraft and the camera could be minimized, the assembly and integration require significant labor and time even for highly skilled technicians and engineers (Huang et al., 2013).

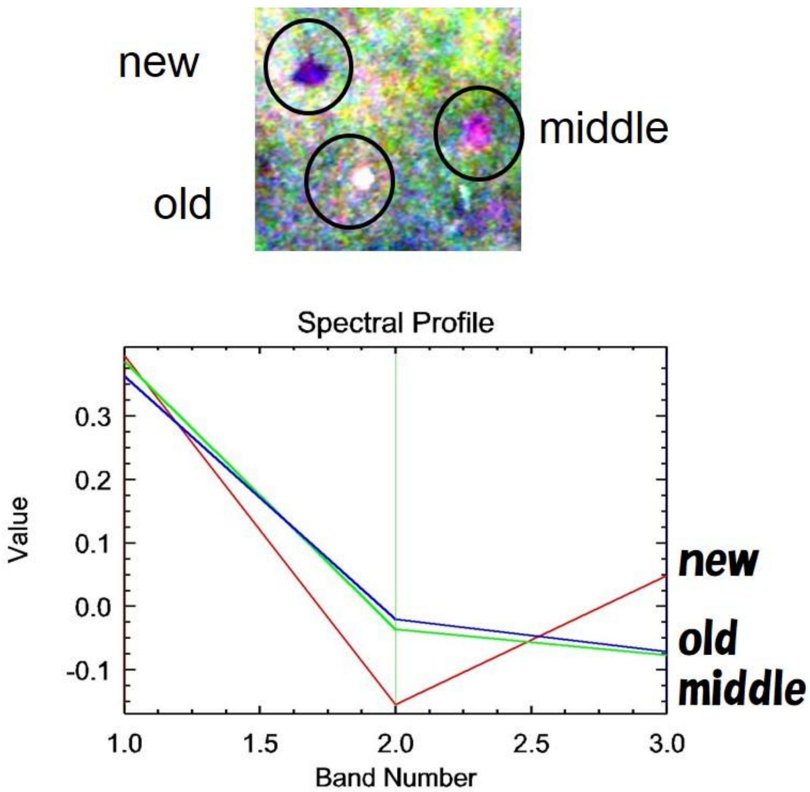


Figure 6.6 The RGB image of new, moderate and old dung (above), and their spectrum (bottom).

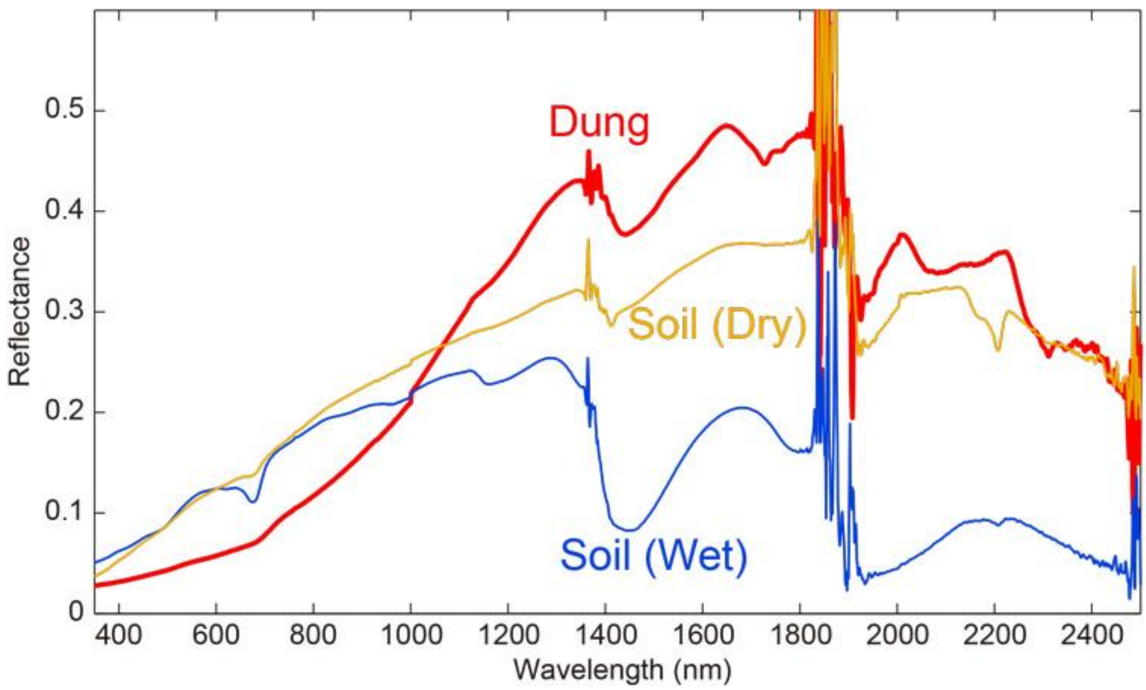


Figure 6.7 Spectral characteristics in relative reflectance for fresh dung (passed three days), dry soil and wet soil.

－Chapter 7－

General discussion

"People do not lack strength, they lack will."

Victor Hugo (1802–1885)

Chapter 7: General discussion

Spatio-temporal information on the grazing behavior of animals provides insights into pasture and animal conditions, allowing for improved pasture management and animal care. To date, various sensors and analytic tools have been developed to assist the data collection and analysis regarding the animal activities in pasture. However, most of these devices cannot be used by farmers because they are only capable of taking measurements for a few days, due to their high energy consumption, or because they are expensive and require extensive experience to correctly attach them to animals. Moreover, the data obtained by such sensing devices are complex, and the grazing behaviors are strongly influenced by surrounding environments. In this study, therefore, the objectives of this study were (1) to develop a simple tool for determining cattle grazing behavior in the pasture (chapters 2 and 3), and (2) to predict spatial distribution of cattle excrement using Bayesian approaches (chapters 4 and 5) and UAV images (chapter 6)

In chapter 2, the results of this study indicated that during the daytime, the cows mostly stayed in the lower-altitude area of the paddock (Figure 2.7b). During the nighttime, the cows spent most of their time in the higher-altitude (Figure 2.7d). Earlier studies suggested that the weight of the device attached to the animal affects the activity pattern (Rutter et al., 1997). The device to attach to the animal should be less than 5% of body weight of the animal (Cuthill, 1991). For example, grazing activity of red deer (*Cervus elaphus*) attached a device of the weight of 3.5% decreased remarkably (Blanc and Brelurut, 1996), and 16 Scottish Blackface ewes did not have influence as weight of 2.2% (Hulbert et al., 1998). As upon previous knowledge, it is clear that attached device was preferred smaller and lighter. The GPS collar used in this study were 0.5% of the weight (the mean of 22 cattle weight was 556.9 kg, GPS collar was 2.8 kg). Thus, it is considered that there is not the influence of the any behaviors of cattle by the GPS collar in this study.

Recent advances in both sensor and hardware (downsizing, power saving, etc.) are able to observe the grazing behavior of cattle more simply and longer period. GPS also have been continuously improved, and GPS guidance systems are the most commonly adopted PA technique.

In chapter 3, a statistical method for classifying the eating activity from other activities using simple equipment was developed. LR and LDA were applied to distinguish eating and other activities (resting and ruminating). The results confirmed that the LCEX accelerometry-based activity monitor can be used to distinguish between foraging and other activities of grazing beef cows on a hilly pasture. Some previous studies have indicated that discriminant analysis is a useful method for identifying accelerometer variables that classify series of successive cow jaw movements into rumination and eating behaviors (Schleisner et al., 1999; Watanabe et al., 2008). While in this study, the results indicate that linear discriminant (90.6 to 94.6%) analysis yields better discrimination accuracy than logistic regression (80.8 to 91.8%) when using minute-based data, which is a time interval suitable for integrated use with GPS location information. The combination of the activity timeline and GPS tracking data can determine the spatio-temporal distribution of cow foraging activity on pasture or rangeland. In the future, it is expected that we get a lot of knowledge about livestock behaviour in pasture because of improvement of the identification method and increasing the recording capacity of the accelerometer. In addition, LCEX is a simple, low-cost device. Thus, general dissemination to farmers is expected and LCEX could cooperates with the RS technology. By combining the cattle GPS locations and the spatial distributions of livestock, it may give important information to management of grass and livestock. LCEX can be used to distinguish between foraging and other activities, but this could not be used to determine cattle ruminating activity, important information to manage health of grazing cattle because this is a single-axis accelerometer. Using a three-axis microelectromechanical systems accelerometer, eating, ruminating and resting activities of cattle could be classified (Watanabe et al., 2008), though this equipment is expensive. In the future, it is needed to develop a simple tool for determining cattle grazing as well as ruminating activity toward the establishment of precise grazing management techniques.

In chapters 4 and 5, distribution of cattle dung in pasture was estimated using a Bayesian approach. It is important for farmers to understand the mechanisms of these gases production from agricultural fields and the factors that control these mechanisms because much anthropogenic N_2O and CH_4 are produced by agricultural activities. Betteridge et al. (2010) developed urine sensor that detects and logs each urination event of female sheep and cattle. In contrast, the place of dung has not been specified. Then, 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) the distribution of dung indicates non-uniform pattern, and the number of dung are increased around water trough when they set a water trough on the lower slope (Watanebe et al., 2011); (2) the number of dung tends to increase at the place used for rest (Watanebe et al., 2011). These result are analysed using multiple liner regression model. 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. Thus, it is needed to consider the spatial dependence because the number of dung per adjacent grid has spatial information. In order to estimate spatial patterns of cattle dung position, the present study used a Bayesian model based on GLMM and added CAR term using GBM and D_w as explanatory variables in 100 m^2 grid cells. For estimating dung position, data is insufficient and it is needed for improvement and adaptation of the model. In chapter 4, the spatial distribution of cattle dung was estimated using single paddock data. In chapter 5, the model used in chapter 4 was improved to be more general and used three paddock data. The results of MCMC simulations indicated that a higher N_d tended to be associated with a higher GBM and locations closer to the water trough. N_d had spatial autocorrelation and it was likely that the grid cells that have large residual values could be affected by the difference between cattle activities in the daytime and nighttime. Based on our results, it is suggested that the spatial distribution of cow dung can be predicted from two controllable factors in short term grazing trials.

In chapter 6, the author tried to detect the dung position using a very high resolution image taken by a camera attached to a UAV. The results indicated that the fresh dung could be detected with high accuracy using RGC color values combined with their size and shape in image. However, there are a lot of subjects; looking for the characteristic wavelength to distinguish between old dried dung and soil; detecting the dung position with other photographic images provided by the UAV at different altitudes and verifying the size estimate precision.

Although many studies have been made on spatial distribution of feces from the viewpoint of nitrogen cycle, it is relatively new in Japan, from the viewpoint of GHG discharge source. There is a few, limited number of studies conducted for GHG emissions from pasture in Tochigi prefecture and Hokkaido, Japan. Particularly, in western Japan, there is none of report have been found sort of the research.

In future study, the actual GHG emissions from grazing pasture should be measured to establish precise GHG mitigation techniques. Actually, the trial measured GHG emission from cattle dung was conducted twice from June 23 to July 10, 2014 and from September 13 to 29, 2014 in two grazed pastures at Hiroshima University using closed chamber method (Akiyama et al. 2010). Collected 1,000 g of fresh dung by cattle in the field was separated into 0 (control), 200, 350 and 500 g and put to each frame (50 cm × 50 cm) on the pastures (Figure 7.1). Then, filed observations were carried out in day 1–6, 9, 12, 15 and 18. The airs were gotten in three times (1, 11 and 21 min after closed the chamber) (Figure 7.2). Temperature and soil water contents were also recorded at the same time. Concentrations of CH_4 and N_2O were determined at NARO Hokkaido Agricultural Research Center. Figures 7.3 and 7.4 show CH_4 and N_2O emissions from dung, respectively. However, this trial had two problems. First, the measurers have not done these experiments. Second, there were many insects in the experiment paddocks. It is expected to be possible to reduce effectively GHG emissions by GHG palliatives such as dicyandiamide and thiourea are used economically and efficiently. In the future, the amount of GHG emissions from whole pasture could be estimated by measuring the occurrence of GHG emission from one dung and it could be possible to simulate the effect of inhibitors by varying the parameters.

In Japan, the food self-sufficiency ratio is about 40% (food self-sufficiency ratio based on the total calorific value supplied), and about 60% of food supplies in Japan depends on supplies from abroad on a caloric-value-supplied basis (Ministry of agriculture, forestry and fisheries in Japan, 2015). It is important for both sides of the food security and environmental protection to ensure the highest possible the food self-sufficiency rate. Furthermore, the feed self-sufficiency ratio is about 27%, 88% of the concentrated feed and 24% of the roughage depends on import from abroad. It is important for safe and secure food supply, healthy rural society and good land conservation to produce livestock products stably. In this thesis, the author have developed monitoring technology of grazed cattle using IT technologies. Determining changes in spatial distribution and feeding behavior of grazing animals provides knowledge that can support to understand the relationship between their internal state (i.e., nutrition, health, etc.) and their environment (i.e., sward state, climate, etc.) (Penning, 1983). This knowledge would provide optimum resource management and forecasting to support decision making. The results of this study are converted to the general technique and modified and improved by practicing the test operation, and are expected to develop into PA which enables the simultaneous achievement of improvement productivity and reducing environmental impact. Improvements in production efficiency, saving of input resources and practicing the reduction of pollution through precise control could contribute greatly to both sustainable food production and environmental conservation.

Required for future Japanese agricultural technology is considered to be a production system that could do best use of spatial information and robotic automation technology by RS, GIS and GPS. Along with these research and development, it is thought to be necessary that trains farmers to increase productivity by actively introducing a new technology.

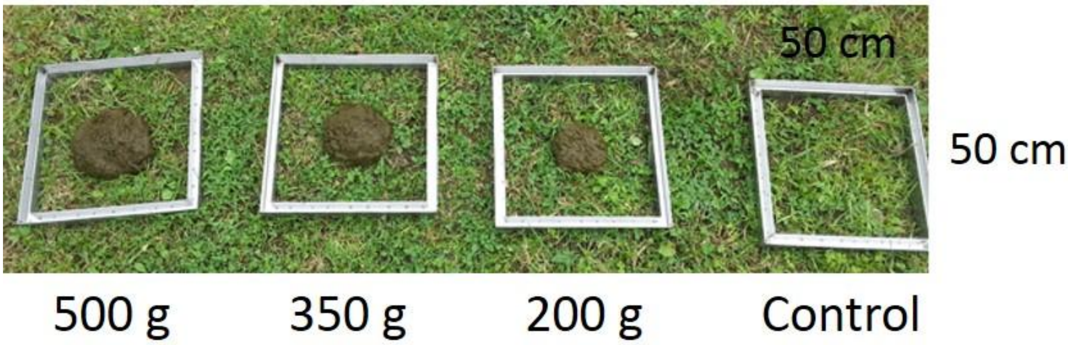


Figure 7.1 Photograph showing set up for fresh dung with 500, 350, 200 and 0 g.

Figure 7.2 The equipment to measure greenhouse gas emissions.

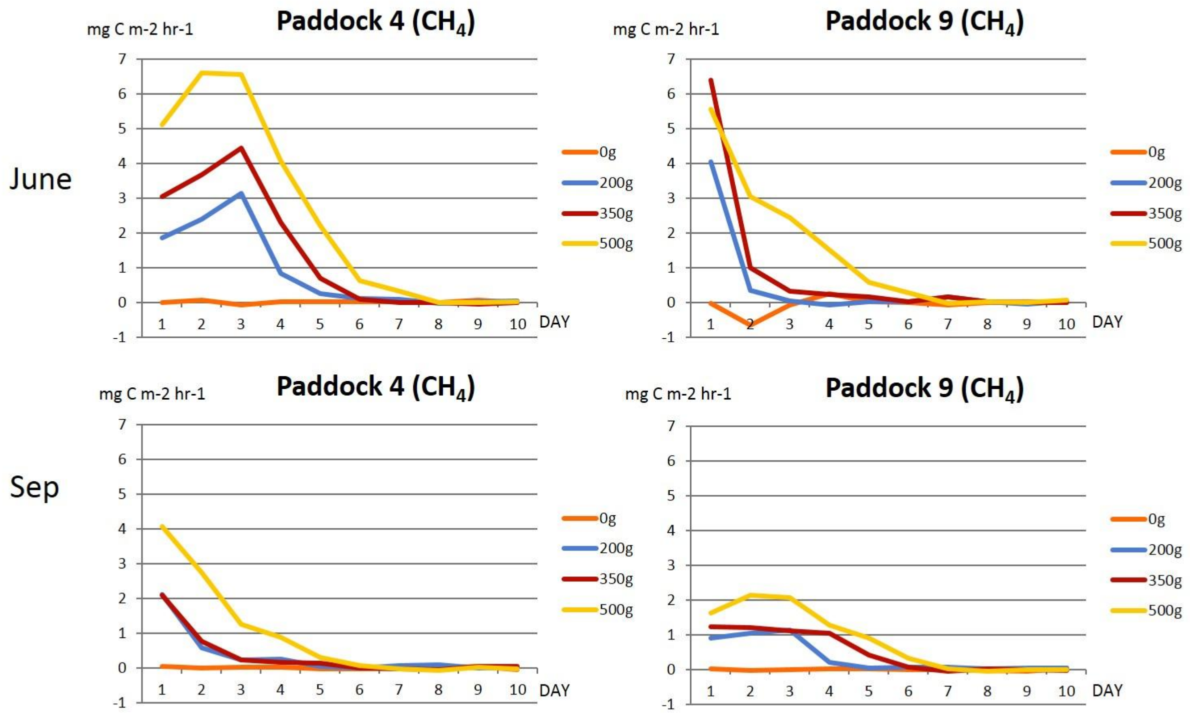


Figure 7.3 Methan (CH_4) emission from dung in two paddocks (4 and 9) in 2014.

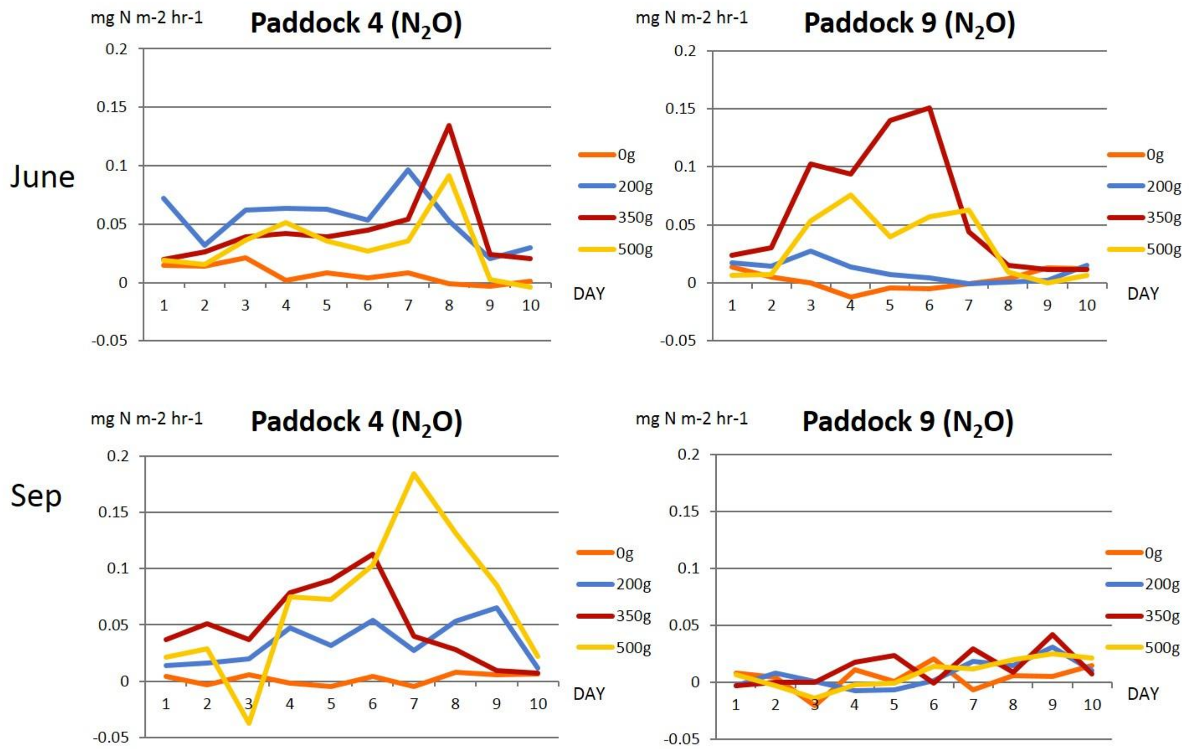


Figure 7.4 Nitrous oxide (N_2O) emission from dung in two paddocks (4 and 9) in 2014.

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Lastly, I wish to dedicate this effort to my colleagues, especially my family.

Publications

Chapter 2 was published as

Book:

Kawamura, K., Watanabe, N., **Yoshitoshi, R**., (2014) Utilization of remote sensing and IT equipment for the precise grassland management. In: *Remote Sensing Handbook on Agriculture*, enlarged edition, Akiyama et al. (Eds), Sato Print Co. Ltd., Mito, Japan. (In Japanese.)

Chapter 3 was published as

Journal Article (Peer-reviewed):

Yoshitoshi, R., Watanabe, N., Kawamura, K., Sakanoue, S., Mizoguchi, R., Lee, H., Kurokawa, Y. (2013) Distinguishing cattle foraging activities using an accelerometry-baced activity monitor. *Rangeland Ecology & Management*, 66, 382–386.

Chapter 4 was published as

Journal Article (Peer-reviewed):

Yoshitoshi, R., Watanabe, N., Yasuda, T., Kawamura, K. , Sakanoue, S., Lim, J. and Lee H-J (2015) Preliminary study to predict the spatial distribution of dung from beef cattle in a slope-grazed pasture. *Grassland Science*, 61, 50–55.

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References

Adler, P., Raff, D. and Lauenroth, W. (2001). The effect of grazing on the spatial heterogeneity of vegetation. *Oecologia* 128: 465– 479.

An Assessment of the Intergovernmental Panel on Climate Change (IPCC) (2007). Climate Change 2007: Synthesis Report. [http://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr_spm.pdf].

Akiyama, F., Yagi, T., Sudo, K., Syoji, A., Watanabe, N., Sakanoue, S., Matsumura, T. and Nagata, O. (2010). Estimation of greenhouse gas emissions from grazed pasture.- Emissions of CH_4 and N_2O from pasture poured cattle urine in Hokkaido -. *Grassland Science* 56: 173.

Arnold, G. W. and Dudzinski, M. L. (1978). *Ethology of free-ranging domestic animals.* Elsevier, Amsterdam, pp. 1–198.

Augustine, D. J. and Frank, D. A. (2001). Effect of migratory grazers on spatial heterogeneity of soil nitrogen properties in a grassland ecosystem. *Ecology* 82: 3149–3162.

Bailey, D. W., Gross, J. E., Laca, E. A., Rittenhouse, L. R., Coughenour, M. B., Swift, D. M. and Sims, P. L. (1996). Mechanisms that result in large herbivore grazing distribution patterns. *Journal of Range Management* 49: 386–400.

Bailey, D. W., Kress, D. D., Anderson, D. C., Boss, D. L. and Miller, E. T. (2001). Relationship between terrain use and performance of beef cows grazing foothill rangeland. *Journal of Animal Science* 79: 1883–1891.

Bailey, D. W. and Welling, G. R. (1999). Modification of cattle grazing distribution with dehydrated molasses supplement. *Journal of Range Management* 52: 575–582.

Barbari, M., Conti, L., Koostra, B. K., Masi, G., Guerri, F. S. and Workman, S. R. (2006). The use of global positioning and geographical information systems in the management of extensive cattle grazing. *Biosystems Engineering* 95: 271–280.

Beck, R. (1978). *A grazing system for semiarid lands.* International Rangeland Congress 1: 569–572.

Besag, J., York, J. and Mollié, A. (1991). Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics* 43: 1–59.

Betteridge, K., Costall, D., Roberts, A., Catto, W., Richardson, A. and Gates, J. (2011). Targeting DCD at critical source areas as a nitrogen mitigation strategy for hill country farmers. Adding to the knowledge base for the nutrient manager. Currie, L. D. and Christensen, C. L. eds. Massey University, Palmerston North, Fertilizer and Lime Research Centre.

Betteridge, K., Hoogendoorn, C., Costall, D., Carter, M. and Griffiths, W. (2010). Sensors for detecting and logging spatial distribution of urine patches of grazing female sheep and cattle. *Computers and Electronics in Agriculture* 73: 66–73.

Betteridge, K., Kawamura, K., Costall, D., Carter, M., Hoogendoorn, C., Griffiths, W. and Inoue, Y. (2008). Tools to determine impact of animal behaviour on nitrogen leaching and nitrous oxide emissions. Carbon and Nutrient Management in Agriculture. Massey University, Palmerston North, New Zealand, Fertilizer and Lime Research Centre, pp. 286–298.

Blanc, F. and Brelurut, A. (1996). Short-term behavioral effects of equipping red deer hinds with a tracking collar. *Zeitschrift für Saugetierkunde-International Journal of Mammalian Biology* 62: 18–26.

Blyenburgh, P. V. (1999). UAVs: An overview. *Air and Space Europe* 1: 43–47.

Bolker, B. M., Brooks, M. E., Clark, C. J., Geange, S. W., Poulsen, J. R., Stevens, M. H. H. and White, J. S. (2009). Generalized linear mixed models: a practical guide for ecology and evolution. *Trends in Ecology & Evolution* 24: 127–135.

Bondini, M. E. and Steuter, A. A. and Hamilton, B. G. (1999). Bison use of fire-managed remnant prairies. *Journal of Range Management* 52: 454–461.

Breiman, L. (2001). Random forests. *Machine Learning* 45: 5–32.

Breitenmoser, U., Breitenmoser-Würsten, Ch., Zuleta, G.A., Bernhart, F. and O'Donoghue, M. (1992). *A method to estimate travel distances of fast moving animals*. Biotelemetry XII, Ancona, Italy, pp. 318–326.

Clark, J. S. (2005). Why environmental scientists are becoming Bayesians. *Ecology Letters* 8: 2–14.

Coffin, D. (2015). [Web site] Decoding raw digital photos in Linux. [http://www.cybercom.net/~dcoffin/dcraw/]

Collins, S., Knapp, A., Briggs, J. and Blair, J. (1998). Modulation of diversity by grazing and mowing in native tallgrass prairie. *Science* 280: 745–747.

Cuthill, I. (1991). Field experiments in animal behaviour: methods and ethics. *Animal Behaviour* 42: 1007–1014.

Day, T. A. and Detling, J. K. (1990). Grassland patch dynamics and herbivore grazing preference following urine deposition. *Ecology* 71: 180–188.

de Valpine, P. (2009). Shared challenges and common ground for Bayesian and classical analysis of hierarchical statistical models. *Ecological Applications* 19: 584–588.

Dennis, B. (1996). Discussion: should ecologists become Bayesians?. *Ecological Applications* 6: 1095–1103.

Eisenbeiss, H. (2004). A mini unmanned aerial vehicle (UAV): system overview and image acquisition. *Proceedings of International Workshop on Processing and Visualization using High-Resolution Imagery*, Pitsanulok, Thailand, pp. 1–7.

Edwards, P. J. and Hollis, S. (1982). The distribution of excreta on New Forest grassland used by cattle, ponies and deer. *Journal of Applied Ecology* 19: 953–964.

Fisher, R. A. (1936). The use of multiple measurements in taxonomic problems. *Annals of Eugenics* 7: 179–188.

Fukasawa, K., Ishihama, F., Oguma, H., Takeda, T., Tanaka, N., Takenaka, A. (2009). Analyses for distributions of organisms considering spatial autocorrelation using the conditional autoregressive models. *Japanese Journal of Ecology* 59: 171–186. (In Japanese).

Ganskopp, D. (2001). Manipulating cattle distribution with salt and water in large arid-land pastures: a GPS/GIS assessment. *Applied Animal Behaviour Science* 73: 251–262.

Ganskopp, D. and Bohnert, D. (2006). Do pasture-scale nutritional patterns affect cattle distribution on rangelands? *Rangeland Ecology & Management* 59: 189–196.

Ganskopp, D. and Bohnert, D. (2009). Landscape nutritional patterns and cattle distribution in rangeland pastures. *Applied Animal Behaviour Science* 116: 110–119.

Ganskopp, D., Cruz, R. and Johnson, D. E. (2000). Least-effort pathways: a GIS analysis of livestock trails in rugged terrain. *Applied Animal Behaviour Science* 68: 179–190.

Ganskopp, D. and Vavra, M. (1987). Slope use by cattle, feral horses, deer, and bighorn sheep. *Northwest Science* 61: 74–81.

Gebbers, R. and Adamchuk, V. I. (2010). Precision agriculture and food security. *Science* 327: 828–831.

Gelman, A. and Hill, J. (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models*, Cambridge University press.

Geman, S. and Geman, D. (1984). Stochastic relaxation, gibbs distributions, and the Bayesian restoration of images. *Pattern Analysis and Machine Intelligence, IEEE Transactions on* PAMI-6: 721–741.

George, M., Bailey, D., Borman, M., Ganskopp, D. and Surber, G., Harris, N. (2007). Factors and Practices that Influence Livestock Distribution, *University of California Agriculture and Natural Resources Communication Services*, ANR Publication 8217, Oakland, CA 20.

Gillen, R. L., Krueger, W. C. and Miller, R. F. (1984). Cattle distribution on mountain rangeland in Northeastern Oregon. *Journal of Range Management* 37: 549–553.

Hafetz, E. S. E. (1975). *The Behavior of domestic animals*, Bailliere Tindall, London, pp. 234–235.

Hakamata, T. and Hirashima, T. (1978). Evaluation of cattle excreta on pasture fertility: I. The excretal dispersion models and their applicable conditions. *Journal of Japanese Society of Grassland Science* 24: 162–171.

Hardin, P. and Jackson, M. (2005). An unmanned aerial vehicle for rangeland photography.

Rangeland Ecology & Management 58: 439–442.

Hartnett, D., Hickman, K. and Fisher, L. (1996). Effects of bison grazing, fire, and topography on floristic diversity in tallgrass prairie. *Journal of Range Management* 49: 413–420.

Harris, S., Cresswell, W. J., Forde, P. G., Trewhella, W. J., Woollard, T. and Wray, S. (1990). Home-range analysis using radio-tracking data - A review of problems and techniques particularly as applied to the study of mammals. *Mammal Review* 20: 97–123.

Hastie, T., Tibshirani, R. and Friedman, J. (2008). *The elements of statistical learning: data mining, inference, and prediction*, second edition. Springer, New York, pp. 1–745.

Heezen, K. L. and Tester, J. R. (1967). Evaluation of radio-tracking by triangulation with special reference to deer movements. *Journal of Wildlife Management* 31: 124–141.

Herwitz, S., Johnson, L., Dunagan, S. E., Higgins, R., Sullivan, D., Zheng, J., Lobitz, B. M., Leung, J., Gallmeyer, B., Aoyagi, M., Slye, R. and Brass, J. A. (2004). Demonstration of UAV-based imaging for agricultural surveillance and decision support. *Computers and Electonics in Agriculture* 44: 49–61.

Hinkleya, E. A. and Zajkowski, T. (2011). USDA forest service-NASA: Unmanned aerial systems demonstrations-pushing the leading edge in fire mapping. *Geocarto International* 26: 103–111.

Hirata, M., Sugimoto, Y. and Ueno, M. (1990). Return of dung to bahiagrass (*Paspalum notatum* Flügge) pasture by dairy cattle. *Journal of Japanese Society of Grassland Science* 35: 350–357.

Hirata, M., Higashiyama, M. and Hasegawa, N. (2011). Diurnal pattern of excretion in grazing cattle. *Livestock Science.* 142: 23–32.

Hirata, M., Kanemaru, E. and Tobisa, M. (2006). Patch choice by cattle grazing tropical grass swards: A preliminary study. *Applied Animal Behaviour Science* 97: 134–144.

Holechek, J. L., Piper, R. D., Herbel Deceased, C. H. (1998). *Range Management: Principles and Practices*, Prentice Hall, Upper Saddle River, New Jersey, pp. 542.

Holter, P. (1997). Methane emissions from danish cattle dung pats in the field. *Soil Biology & Biochemistry* 29: 31–37.

Hodder, R. M. and Low, W. A. (1976). Grazing distribution of free-ranging cattle at three sites in the Alice Soring District, Central Australia. *Australian Rangeland Journal* 1: 95–105.

Hooper, J. F., Workman, J. P., Gumbles, J. B. and Cook, C. W. (1969). Improved livestock distribution with fertilizer - a preliminary economic evaluation. *Journal of Range Management* 22: 108.

Huang, Y. B., Thomson, S. J., Hoffmann, W. C., Lan, Y. B. and Fritz, B. K. (2013). Development and prospect of unmanned aerial vehicle technologies for agricultural production management. *International Journal of Agricultural and Biological Engineering* 6: 1–10.

Hulbert, I. A. R., Wyllie, J. T. B., Waterhouse, A., French, J. and McNulty, D. (1998). A note on the circadian rhythm and feeding behaviour of sheep fitted with a lightweight GPS collar. *Applied Animal Behaviour Science* 60: 359–364.

Hunt, E. R., Cavigelli, M., Daughtry, C. S. T., McMurtrey, J. E. and Walthall, C. L. (2005). Evaluation of digital photography from model aircraft for remote sensing of crop biomass and nitrogen status. *Precision Agriculture* 6: 359–378.

Ide, Y., Kojima, M. and Hayashi, H. (1998). Topography and pasture management in the mountainous slopeland: 1. The distribution of bare area and cattle dung. *Journal of Japanese Society of Grassland Science* 44: 208–214. (In Japanese with English abstract).

Jetz, W., Rahbek, C. and Lichstein, J. W. (2005). Local and global approaches to spatial data analysis in ecology. *Global Ecology and Biogeography* 14: 97–98.

Johnson, C. J., Parker, K. L., Heard, D. C. and Gillingham, M. P. (2002). Movement parameters of ungulates and scale-specific responses to the environment. *Journal of Animal Ecology* 71: 225–235.

Kawamura, K., Watanabe, N., Sakanoue, S., Lee, H-J., Inoue, Y. and Odagawa, S. (2010). Testing genetic algorithm as a tool to select relevant wavebands from field hyperspectral data for estimating pasture mass and quality in a mixed sown pasture using partial least squares regression. *Grassland Science* 56: 205–216.

Kéry, M. (2010). *Introduction to WinBUGS for Ecologists Bayesian approach to regression, ANOVA, mixed models and related analyses*, first edition. Academic Press, pp. 1–302.

Kruelen, D. A. (1985). Lick use by large herbivores: a review of benefits and banes of soil consumption. *Mammal Review* 15: 107–123.

Kubo, T. (2009). An introduction to spatial statistical modeling for ecologists. *Japanese Journal of Ecology* 59: 187–196. (In Japanese).

Kubo, T. (2012). [http://hosho.ees.hokudai.ac.jp/~kubo/ce/IwanamiBook.html]

Kumahara, H., Schutz, Y., Ayabe, M., Yoshioka, M., Yoshitake, Y., Shindo, M., Ishii, K. and Tanaka, H. (2004). The use of uniaxial accelerometry for the assessment of physical-activity-related energy expenditure: a validation study against whole-body indirect calorimetry. *British Journal of Nutrition* 91: 235–243.

Kurosaki, J., Iizumi, S. and Sugawara, K. (1956). On the relationships between grazing habits and vegetation of grassland. II. Behaviour forms and environments. *Reports of the Institute for Agricultural Research Tohoku University, D,* 8.

Langbein, J., Scheibe, K. M., Eichhorn, K., Lindner, U., and Streich, W. J. (1996). An activity-data-logger for monitoring free-ranging animals. *Applied Animal Behaviour Science* 48: 115–124.

Lee, H-J., Kawamura, K., Watanabe, N., Sakanoue, S., Sakuno, Y., Itano, S. and Nakagoshi, N. (2011). Estimating the spatial distribution of green herbage biomass and quality by geostatistical analysis with field hyperspectral measurements. *Grassland Science* 57: 142–149.

Lele, S. R. and Dennis, B. (2009). Bayesian methods for hierarchical models: Are ecologists making a Faustian bargain. *Ecological Applications* 19: 581–584.

Lin, L., Dickhoefer, U., Mùler, K., Wurina and Susenbeth, A. (2011). Grazing behavior of sheep at different stocking rates in the Inner Mongolian steppe, China. *Applied Animal Behaviour Science* 129: 36–42.

Lunn, D., Spiegelhalter, D., Thomas, A. and Best, N. (2009). The BUGS project: Evolution, critique and future directions. *Statistics in Medicine* 28: 3049–3067.

Martin, S. and Ward, D. (1973). Salt and meal-salt help distribute cattle use on semidesert range. *Journal of Range Management* 26: 94–97.

Matsui, K. and Okubo, T. (1991). A method for quantification of jaw movements suitable for use on free-ranging cattle. *Applied Animal Behaviour Science* 32: 107–116.

McBratney, A., Whelan, B., Ancev, T. and Bouma, J. (2005). Future directions of precision agriculture. *Precision Agriculture* 6: 7–23.

McClain, J. J., Craig, C. L., Sisson, S. B. and Tudor-Locke, C. (2007). Comparison of Lifecorder EX and ActiGraph accelerometers under free-living conditions. *Applied Physiology, Nutrition & Metabolism* 32: 753–761.

McDowell, R. W. (2012). *Challenges and opportunities to decrease phosphorus losses.* in: Advanced Nutrient Management: Gains from the Past - Goals for the Future. Currie, L. D. and Christensen, C. L. eds. Massey University, Palmerston North, New Zealand, Fertilizer and Lime Research Centre.

McDowell, R. W., Monaghan, R. M. and Wheeler, D. (2005). Modelling phosphorus losses from pastoral farming systems in New Zealand. *New Zealand Journal of Agricultural Research* 48: 131–141.

McDowell, R. W. and Srinivasan, M. S. (2009). Identifying critical source areas for water quality: 2. Validating the approach for phosphorus and sediment losses in grazed headwater catchments. *Journal of Hydrology* 379: 68–80.

McDowell, R. W. and Wilcock, R. J. (2007). Sources of sediment and phosphorus in stream flow of a highly productive dairy farmed catchment. *Journal of Environmental Quality* 36: 540–548.

Ministry of agriculture, forestry and fisheries in Japan. (2015). Annual report on food, agriculture and rural areas in Japan FY 2014. [http://www.maff.go.jp/e/pdf/fy2014.pdf].

Mirchandani, P., Hickman, M., Angel, A. and Chandnani, D. (2003). *Application of aerial video for traffic flow monitoring and management*. The European Ostracod Meeting, 12: 10–17.

Monaghan, R. M. (2009). The BMP Toolbox - selecting the right Best Management Practice for mitigating farming impacts on water quality. *Proceedings of the Fertiliser and Lime Research Centre*, Currie, L. D. and Lindsay, C. L. eds. Massey University, Palmerston North, New Zealand., Fertiliser and Lime Research Centre.

Monaghan, R. M., Hedley, M. J., Di, H. J., McDowell, R. W., Cameron, K. C. and Ledgard, S. F. (2007). Nutrient management in New Zealand pastures - recent developments and future issues. *New Zealand Journal of Agricultural Research* 50: 181–201.

Monaghan, R. M., de Klein, C. A., Muirhead, R. W. (2008). Prioritisation of farm scale remediation efforts for reducing losses of nutrients and faecal indicator organisms to waterways: A case study of New Zealand dairy farming. *Journal of Environmental Management* 87: 609–622.

Moreau, M., Siebert, S., Buerkert, A. and Schlecht, E. (2009). Use of a tri-axial accelerometer for automated recording and classification of goats' grazing behaviour. *Applied Animal Behaviour Science* 119: 158–170.

Musiani, M., Okarma, H. and Jedrzejewski, W. (1998). Speed and actual distance traveled by radiocollared wolves in Bialowieza Primeval Forest (Poland). *Acta Theriologica* 43: 409–416.

Nakamura, Y. and Fukukawa, T. (1974). Decomposition of organic materials and soil fauna in pasture. I. Distribution of cow dung pats. *Bulletin of the National Grassland Research*

Institute 5: 14–19.

Ohno, W. and Tanaka, A. (1966). Studies on action of dairy heifer during pasturing. II. On relationship of herd's action and topography and climate. *Journal of Japanese Society of Grassland Science* 11: 138–143. (In Japanese with English abstract).

Oikawa, M., Simamura, M., Ushiyama, M. and Fukuyama, M. (1981). Cattle behaviour and pasture management in the slope land: II. Wedth, depth, number, length and distribution of cattle tracks. *Bulletin of the National Grassland Research Institute* 20: 190–215. (In Japanese).

Okamoto, C., Kabata, K. and Kikuchi, M. (1994). Productivity of grazing pasture comprising both native and improved areas in Aso area of Kyushu district, Japan, 2: Grazing behavior of cows among both areas. *Journal of Japanese Society of Grassland Science* 40: 53–60. (In Japanese with English abstract).

Orwin, K. H., Bertram, J. E., Clough, T. J., Condron, L. M., Sherlock, R. R. and O' allaghan M. (2009). Short-term consequences of spatial heterogeneity in soil nitrogen concentrations caused by urine patches of different sizes. *Applied Soil Ecology* 42: 271–278.

Pépin, D., Adrados, C., Mann, C., Janeau, G. and Rickart, E. A. (2004). Assessing real daily distance traveled by ungulates using differential GPS locations. *Journal of Mammalogy* 85: 774–780.

Penning, P. D. (1983). A technique to record automatically some aspects of grazing and ruminating behaviour in sheep. *Grass and Forage Science* 38: 89–96.

Phillips, C. J. C. and Denne, S. K. P. J. (1988). Variation in the grazing behaviour of dairy cows measured by a vibrarecorder and bite count monitor. *Applied Animal Behaviour Science* 21: 329–335.

Pinchak, W. E., Smith, M. A., Hart, R. H. and Waggoner, J. W. (1991). Beef cattle distribution patterns on foothill range. *Journal of Range Management* 44: 267–275.

Ponciano, J. M., Taper, M. L., Dennis, B. and Lele, S. R. (2009). Hierarchical models in ecology: confidence intervals, hypothesis testing, and model selection using data cloning. *Ecology* 90: 356–362.

Perevolotsky, A. and Etienne, M. (1999). La gestion raisonne´e des parcours du Bassin Me´diterrane´en: Un de´fi pour le XXI8 sie`cle. Opt. Me´d. 39, 129–136.

R Development Core Team (2010). R: A language and environment for statistical computing. Vienna, Austria, R Foundation for Statistical Computing, Vienna, Austria. [http://www.R-project.org/].

R Core Team (2012). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. [http://www.R-project.org/].

Reynolds, T. D. and Laundre, J. W. (1990). Time intervals for estimating pronghorn and coyote home ranges and daily movements. *Journal of Wildlife Management* 54: 316–322.

Rietkerk, M., Ketner, P., Burger, J., Hoorens, B. and Olff, H. (2000). Multiscale soil and vegetation patchiness along a gradient of herbivore impact in a semi-arid grazing system in West Africa. *Plant Ecology* 148: 207–224.

Roath, L. R. and Krueger, W. C. (1982). Cattle grazing and behavior on a forested range. *Journal of Range Management* 35: 332–338.

Robert, P. C. (2002). Precision agriculture: a challenge for crop nutrition management. *Plant and Soil* 247: 143–149.

Rutter, M. S. (2000). Graze: Aprogram to analyze recordings of the jaw movements of ruminants. *Bahavior Research Method, Instruments & Computers* 32: 86–92.

Rutter, S. M., Beresford, N. A. and Roberts, G. (1997). Use of GPS to identify the grazing areas of hill sheep. *Computers and Electronics in Agriculture* 17: 177–188.

Scheibe, K. M., Schleusner, T., Berger, A., Eichhorn, K., Langbein, J., Dal Zotto, L. and Streich, W. J. (1998). ETHOSYS(R) - new system for recording and analysis of behaviour of free-ranging domestic animals and wildlife. *Applied Animal Behaviour Science* 55: 195–211.

Schlecht, E., Hüsebusch, C., Mahler, F. and Becker, K. (2004). The use of differentially corrected global positioning system to monitor activities of cattle at pasture. *Applied Animal Behaviour Science* 85: 185–202.

Schleisner, C., Norgaard, P. and Hansen, H. H. (1999). Discriminant analysis of patterns of jaw movement during rumination and eating in a sow. *Acta Agriculturae Scandinavica: Section A, Animal Science* 49: 251.

Senft, R. L., Rittenhouse, L. R. and Woodmansee, R. G. (1985). Factors influencing patterns of cattle grazing behavior on shortgrass steppe. *Journal of Range Management* 38: 82–87.

Smith, M. A., Rodgers, J. D., Dodd, J. L. and Skinner, Q. D. (1992). Declining forage availability effects on utilization and community selection by cattle. *Journal of Range Management* 45: 391–395.

Sordi, A., Dieckow, J., Bayer, C., Alburquerque, M. A., Piva, J. T., Zanatta, J. A., Tomazi, M., da Rosa, C. M. and de Moraes, A. (2014). Nitrous oxide emission factors for urine and dung patches in a subtropical Brazilian pastureland. *Agriculture, Ecosystems & Environment* 190; 94–103.

Sternberg, M., Gutman, M., Perevolotsky, A., Ungar, E. D. and Kigel, J. (2000). Vegetation response to grazing management in a Mediterranean herbaceous community: a functional group approach. *Journal of Applied Ecology* 37: 224–237.

Sugimoto, Y., Hirata, M. and Ueno, M. (1987). Energy and matter flows in Bahiagrass pasture: V. Excreting behavior of Holstein heifers. *Journal of Japanese Society of Grassland Science.* 33: 8–14. (In Japanese).

Swain, K. C., Jayasuriya, H. P. W. and Salokhe, V. M. (2007). Suitability of low-altitude remote sensing images for estimating nitrogen treatment variations in rice cropping for precision agriculture adoption. *Journal of Applied Remote Sensing* 1: 013547.

Swain, K. C., Thomson, S. J. and Jayasuriya, H. P. W. (2010). Adoption of an unmanned helicopter for lowaltitude remote sensing to estimate yield and total biomass of a rice crop. *Transactions of the ASABE* 53: 21–27.

Thomas, A., Best, N., Lunn, D., Arnold, R. and Spiegelfalter, D. (2004). GeoBUGS User Manual Version 1.2.

Turner, L. W., Udal, M. C., Larson, B. T. and Shearer, S. A. (2000). Monitoring cattle behaviour and pasture use with GPS and GIS. *Canadian Journal of Animal Science* 80: 405–413.

Ueda, Y., Akiyama, F., Asakuma, S. and Watanabe, N. (2011). The use of a physical activity monitor to estimate the eating time of cows in pasture. *Journal of Dairy Science* 94: 3498–3503.

Umemura, K., Wanaka, T. and Ueno, T. (2009). Technical note: Estimation of feed intake while grazing using a wireless system requiring no halter. *Journal of Dairy Science* 92: 996–1000.

Ungar, E. D. and Rutter, S. M. (2006). Classifying cattle jaw movements: comparing IGER behaviour recorder and acoustic techniques. *Applied Animal Behaviour Science* 98: 11–27.

Ungar, E. D., Schoenbaum, I., Henkin, Z., Dolev, A., Yehuda, Y. and Brosh, A. (2010). Inference of the activity timeline of cattle foraging on a mediterranean woodland using GPS and pedometry. *Sensors* 11: 362–383.

Wang, Q., Li, Y. and Klassen, W. (2005). Influence of summer cover crops on conservation of soil water and nutrients in a subtropical area. *Journal of Soil and Water Conservation* 60: 58–63.

Wark, T., Corke, P., Sikka, P., Klingbeil, L., Guo, Y., Crossman, C., Valencia, P., Swain, D. and Bishop-Hurley, G. (2007). Transforming agriculture through pervasive wireless sensor networks. *IEEE Pervasive Computing* 6: 50–57.

Watanabe, N., Sakanoue, S., Kawamura, K. and Kozakai, T. (2008). Development of an automatic classification system for eating, ruminating and resting behavior of cattle using an accelerometer. *Grassland Science* 54: 231–237.

Watanabe, N., Umemura, K., Sakanoue, S., Kozakai, T. and Kawamura, K. (2010). Utilization by cattle of a pasture including aged hilly sections. *Grassland Science* 56: 160–167.

Watanabe, N., Sakanoue, S. and Kawamura, K. (2011). Provision of grazing method for reduction of greenhouse gas emissions. - The effects of watering place on slope on dung distribution by cow in hilly pasture -. *Grassland Science* 57(Ext.): 59.

Watanabe, N., Sakanoue, S., Lee, H. J., Lim, J., Yoshitoshi, R. and Kawamura, K. (2014). Use of a hand-held crop growth measuring device to estimate forage crude protein mass of pasture. *Grassland Science* 60: 214–224.

Weeda, W. C. (1967). The effect of cattle dung patches on pasture growth, botanical composition, and pasture utilisation. *New Zealand Journal of Agricultural Research* 10: 150–159.

Wells, M. (2004). Influence of cow age/experience and landscape thermal regimes on distribution and grazing patterns of cattle in northeastern Oregon mixed conifer forested rangelands. Thesis (M.S.), Oregon State University, Corvallis, Oregon 97733.

White, S. L., Sheffield, R. E., Washburn, S. P., King, L. D. and Green, J. T. Jr. (2001). Spatial and time distribution of dairy cattle excreta in an intensive pasture system. *Journal of Environmental Quality* 30: 2180–2187.

Yamada, D., Higashiyama, M., Yamaguchi, M., Shibuya, T., Shindo, K. and Tejima, S. (2011). Spatial distribution of cattle dung excretion and dung nutrients on a sloping pasture. *Journal of Japanese Society of Grassland Science.* 57: 129–135. (In Japanese with English abstract).

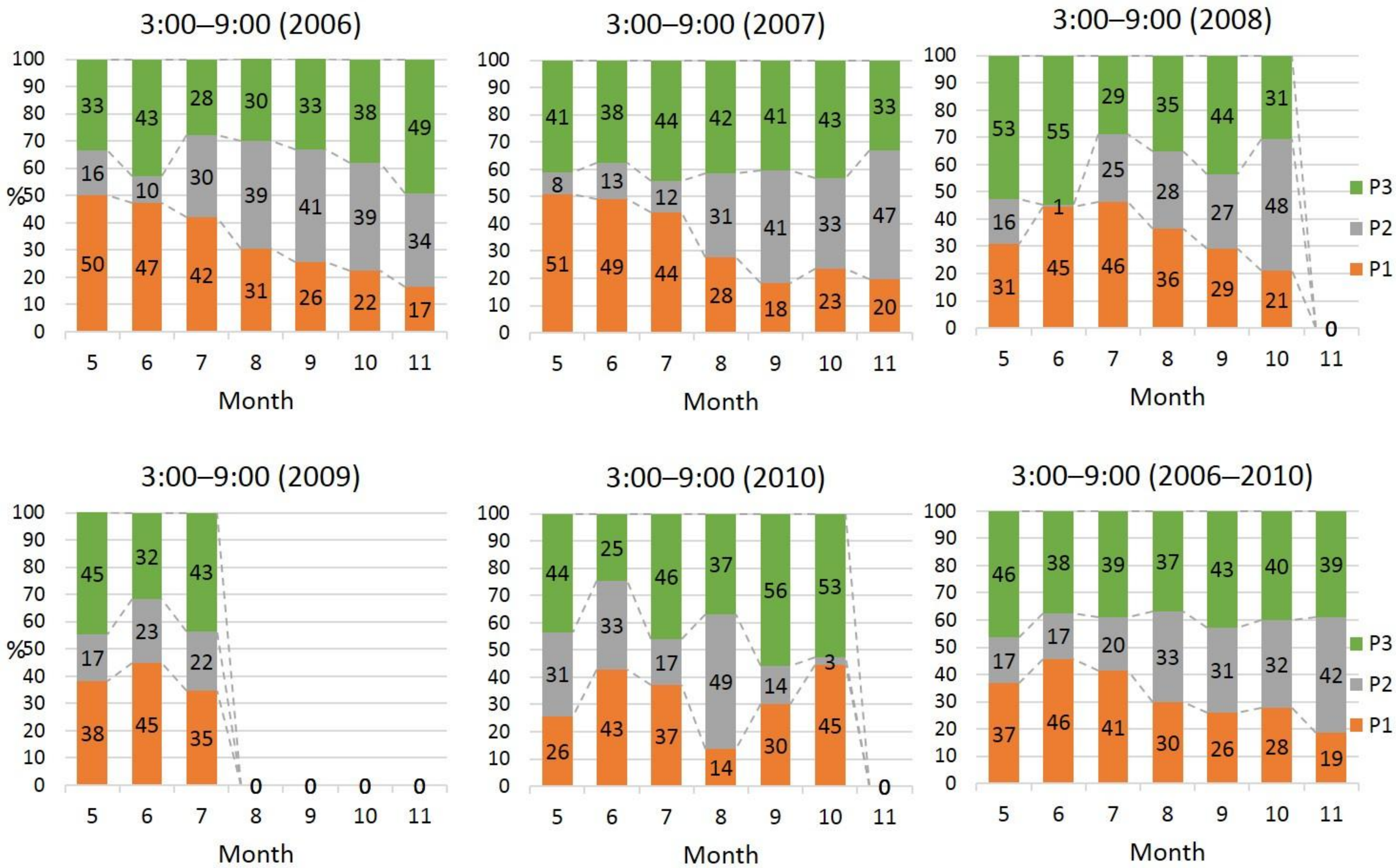
Yasue, T., Kondo, S., Okubo, M. and Asahida, Y. (1997). The effect of paddock topography on resting-site preference of grazing cattle in a hilly pasture during summer season. *Grassland Science* 43: 196–201.

Yoshitoshi, R., Watanabe, N., Yasuda, T., Kawamura, K., Sakanoue, S., Lim, J. and Lee, H-J. (2015). Preliminary study to predict the spatial distribution of dung from beef cattle in a slope-grazed pasture. *Grassland Science* 61: 50–55.

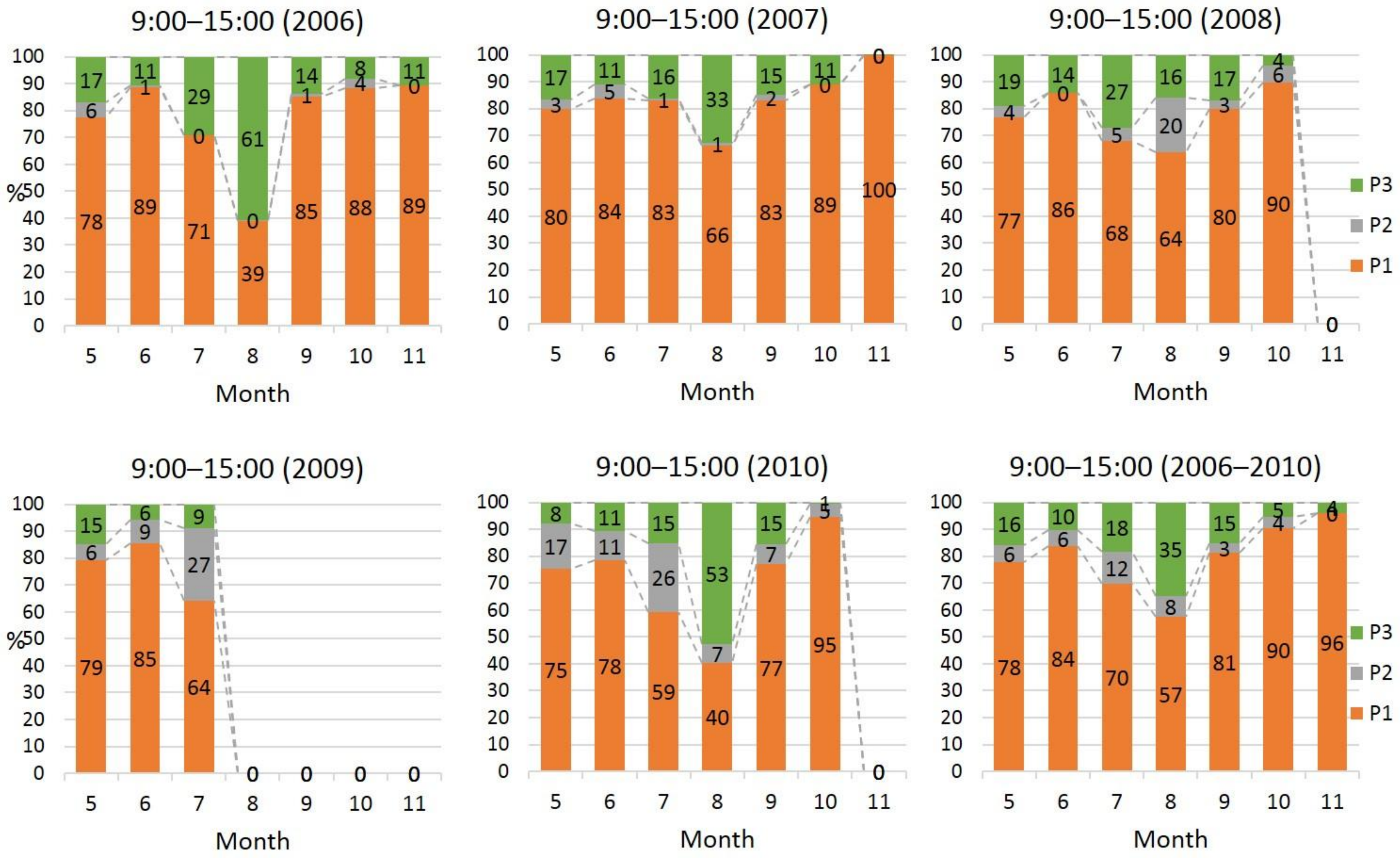
Zhao, Y., Staudenmayer, J., Coull, B. A. and Wand, M. P. (2006). General design Bayesian generalized linear mixed models. *Statistical Science* 21: 35–51.

Zhou, G. and Wu, J. (2006) UAV data flow processing for natural disaster response. Proceedings of ASPRS Annual Conference, Reno, Nevada, USA, pp. 1–8.

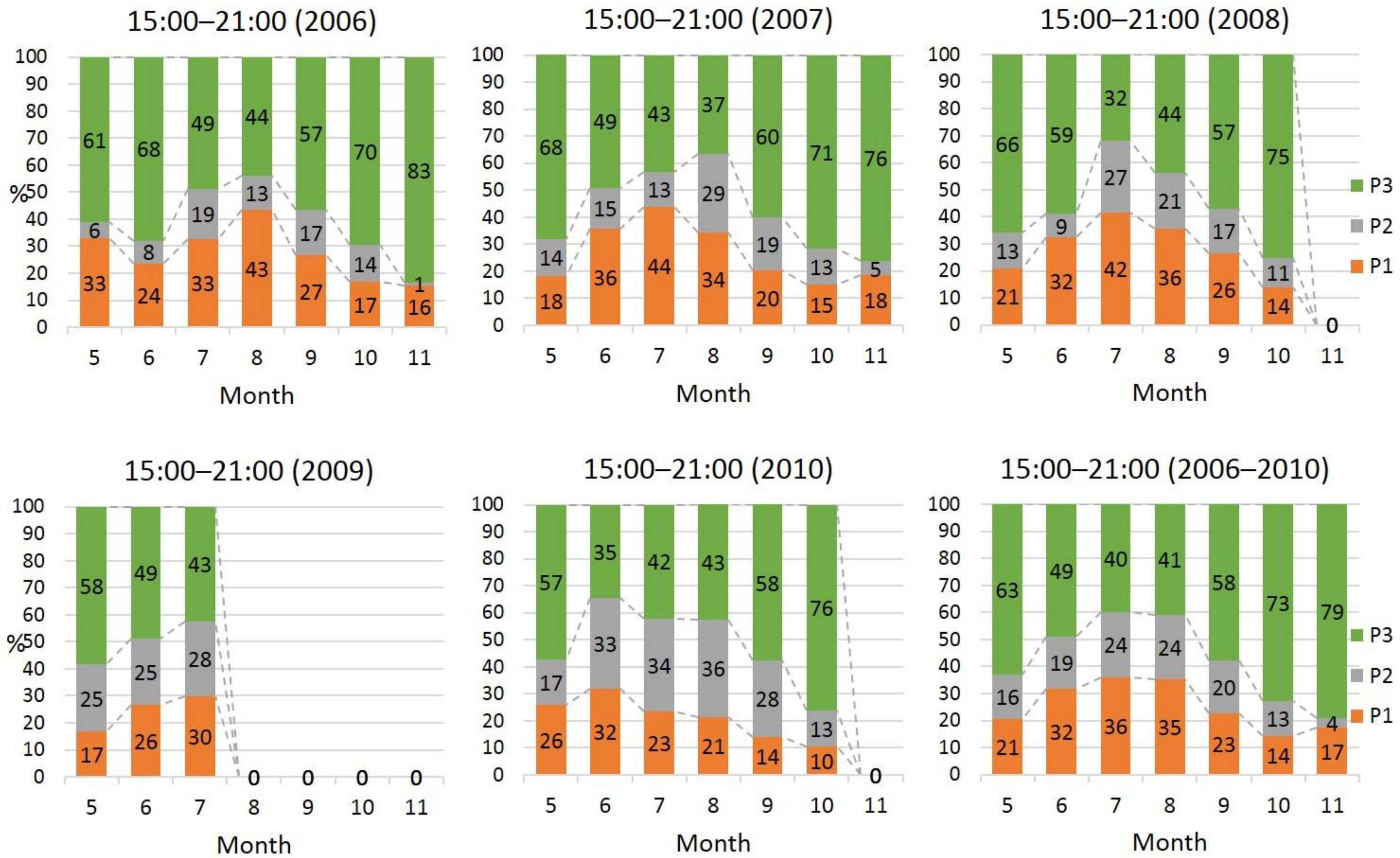
Appendix A: The utilization rate of cattle in three paddocks between 3:00–9:00 (chapter 2).



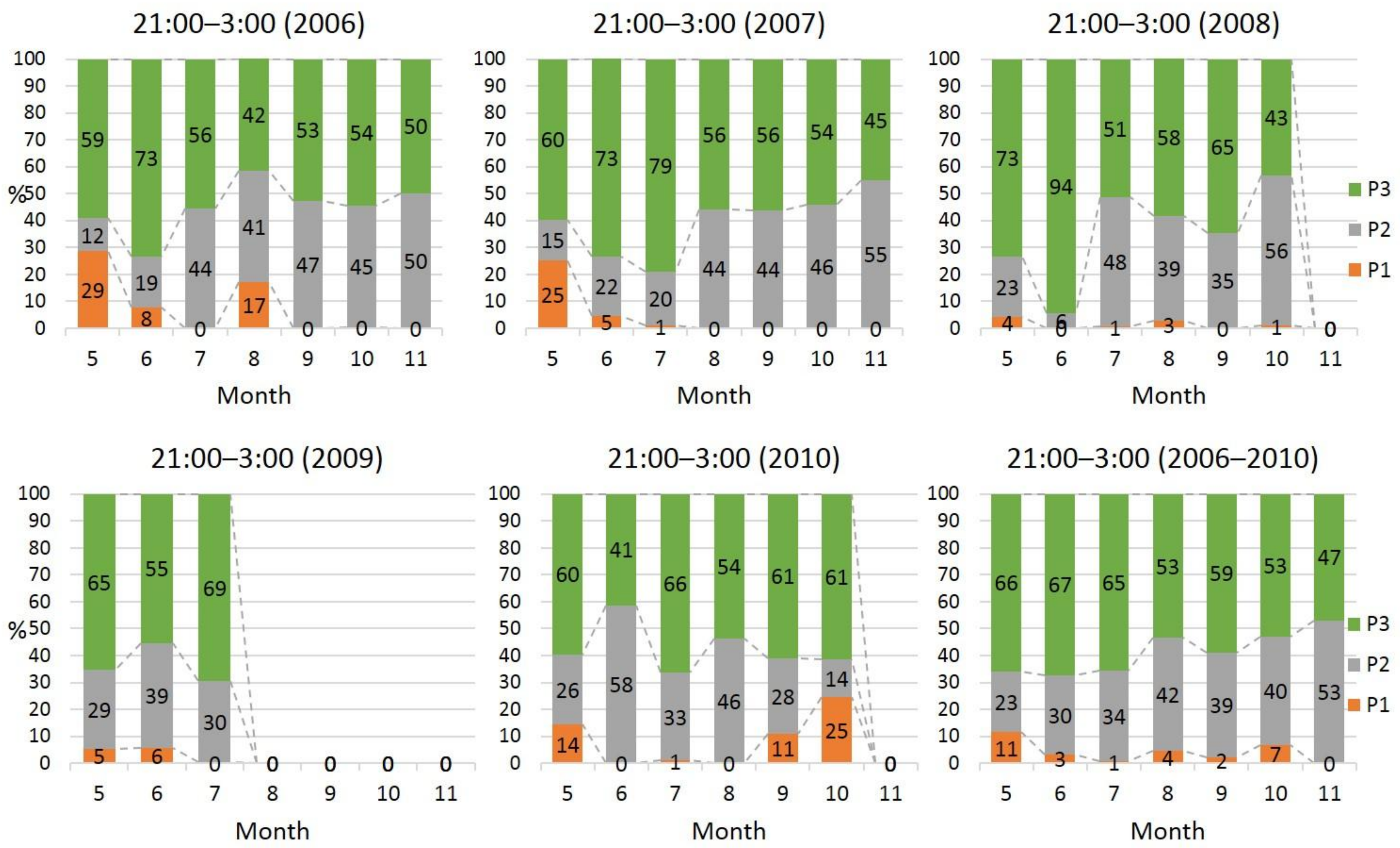
Appendix B: The utilization rate of cattle in three paddocks between 9:00–15:00 (chapter 2).



Appendix C: The utilization rate of cattle in three paddocks between 15:00–21:00 (chapter 2).



Appendix D: The utilization rate of cattle in three paddocks between 21:00–3:00 (chapter 2).



Appendix E: R code on MCMC for analyzing Bayesian model (chapter 5).

```
model{
#Priors
for (k in 1:3){
b1 [k] ~ dnorm (mu.b1,tau.b1)
b2 [k] ~ dnorm (mu.b2,tau.b2)
b3 [k] ~ dnorm (mu.b3,tau.b3)
}
mu.b1 ~ dunif (-10,10) #Hyperprior for b1
mu.b2 ~ dunif (-10,10) #Hyperprior for b2
mu.b3 ~ dunif (-10,10) #Hyperprior for b3
tau.b1 <- 1 / (sig.b1*sig.b1)
tau.b2 <- 1 / (sig.b2*sig.b2)
tau.b3 <- 1 / (sig.b3*sig.b3)
sig.b1 ~ dunif (0,10)
sig.b2 ~ dunif (0,10)
sig.b3 ~ dunif (0,10)

#CAR prior distribution for spatial random effects
rho [1, 1:102] ~ car.normal (Adj1[], Weights1[], Num1[], tau1) #Paddock I
rho [2, 1:102] ~ car.normal (Adj2[], Weights2[], Num2[], tau2) #Paddock II
rho [3, 1:85] ~ car.normal (Adj3[], Weights3[], Num3[], tau3) #Paddock III
tau1 <- 1 / (sig.r1*sig.r1)
tau2 <- 1 / (sig.r2*sig.r2)
tau3 <- 1 / (sig.r3*sig.r3)
sig.r1 ~ dunif (0,10)
sig.r2 ~ dunif (0,10)
sig.r3 ~ dunif (0,10)

#Likelihood
for (i in 1:289){
Nd [i] ~ dpois (lam [i])
log (lam [i]) <- mu [i] + rho [PaddockNo. [i], GridNo. [i]]
mu [i] <- b1 [PaddockNo. [i]] + b2 [PaddockNo. [i]]*log(GBM [i]) + b3 [PaddockNo. [i]]*log(Dw[i])
}
}
```

All of the 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).