COMBINING FIELD EXPERIMENTS, MODELING, AND ANALYTICS FOR INTEGRATED CROP-LIVESTOCK SYSTEM MANAGEMENT

BY

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DISSERTATION

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ABSTRACT

Integrated crop-livestock systems have been suggested as a promising means for diversifying agricultural production as an alternative to specialized cropping systems in modern agriculture. In the U.S. Corn Belt, tremendous amounts of corn residues left on the land after harvest represent a vast potential nutrition source for beef cattle producers, particularly when farms are specialized in continuous corn operations. Allowing cattle to graze corn residues after harvest has been suggested as a simple and economical approach to integrating cattle and corn operations. While residue grazing can significantly reduce winter feed cost, its effects on croplands remain unclear. For example, spatially uneven grazing may potentially lead to heterogeneous impacts on cropland, possibly resulting in adverse impacts on subsequent crop development. Furthermore, the integration usually increases system complexity, and consequently requires more complicated management. This dissertation seeks to provide insights into the development of decision support for managing integrated corn-cattle systems, through combining field experiments, data analytics, and model simulations.

A three-year residue grazing trial was conducted on an integrated corn-cattle farm in central Illinois. Two grazing management practices (continuous grazing and strip grazing) were both investigated during the trial. A custom GPS tracking system was successfully developed, tested, and then implemented to monitor beef cattle movements during the residue grazing. Results of GPS accuracy evaluation showed that the mean horizontal error of the tracking system was less than 4 meters and was not significantly affected by its position on a cow's neck. The long-term performance and reliability of the system were evaluated based on the maintenance records and the success of data collection across multiple years' tests and applications. Results showed that intermittent data loss was typical during the studies. An initial adaptation period was

recommended for effectively reducing shaking and rubbing that may lead to damage to the GPS equipment or problems for the animals.

Data collected during the grazing studies were investigated via a set of analytical tools to identify the spatiotemporal characteristics of cattle movements during residue grazing. Results of the movement characterization showed that individual cow movements were highly synchronized within the group. Cattle under the strip grazing treatment had averagely greater daily travel distances than those under the continuous grazing treatment. Results of the spatial analysis show that cattle had spatially heterogeneous visitations to the residue fields. The distributions of cattle locations were affected by management factors such as the locations of supplement feeders and the cross-fence settings in the strip grazing treatment. Results of the periodic pattern analysis suggested that cattle had periodic movements associated with their bedding areas likely due to the circadian rhythmicity of their behaviors. Besides mining GPS data for movement patterns, a computational approach was developed to evaluate errors in subsequent GPS data analysis caused by monitoring subset groups of cattle instead of the entire herd. Results suggested that monitoring an appropriate subset group can be sufficient to preserve information with acceptable errors for subsequent analysis.

Results of grazing impact analysis showed that the mean subsequent corn yields were not affected by residue grazing under the two management treatments (i.e. continuous grazing and strip grazing) as compared with the ungrazed control at the study site. However, areas around the supplemental feeders have shown a significant decline in yield after the grazing, which was likely caused by the trampling effects of heavy cattle traffic. While experimental validation is needed in the future, it is expected that management strategies such as moving supplemental feeder during residue grazing may alleviate such negative impacts.

With the field data collected during the grazing experiments, a spatially explicit agent-based model has been developed to simulate cattle movements during corn residue grazing. The model was calibrated and validated for two management scenarios (continuous grazing and strip grazing) using the experimental data. Results showed that the simulated spatial distributions of cattle during grazing were consistent with observation data. It is anticipated that, with further model refinement, this model can serve as a research tool to aid future development of decision support tools for managing integrated corn-cattle systems.

To my family,
for their constant support and unconditional love.
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CHAPTER 1
INTRODUCTION

1.1 Problem Statement

Among the Earth's natural systems, the agroecosystem is perhaps the one that interacts with human beings more tightly than any other systems. Humans can directly manage agroecosystems to provide society with ecosystem goods (such as food, fiber, fuel, and energy) and services (such as air quality maintenance and water purification), which sustain and fulfill human life. The structure of agriculture, in the form of farms, farm households, and the rural communities, has evolved and been accompanied by the growth of human population over different historical periods. For instance, agricultural systems that combined crop production and animal husbandry have been employed globally for millennia. In the 20th century, however, agriculture in the U.S. has become more highly specialized since the end of the Second World War, resulting in the decoupling of crop and livestock production. Small and diversified farms have been replaced by large-scale, concentrated and specialized farms, with an accompanying decrease in the average number of commodities produced per farm (Dimitri, Effland, & Conklin, 2005). This change has been very apparent in the Midwestern U.S. Corn Belt, where cattle production has declined and moved to the western U.S., as more lands became dominated by highly specialized systems growing corn and soybeans (Sulc & Tracy, 2007). According to National Agricultural Statistics Service (2006), 85% of the planted acreage is currently occupied by corn and soybean, while only 8.6% is occupied by hay in six Midwestern states (Ohio, Indiana, Illinois, Iowa, Wisconsin and Minnesota). This transformation to more specialized crop farming in Midwestern U.S. Corn Belts has isolated crop and livestock production, both functionally and operationally.

Although the current highly specialized agricultural system has been economically successful with dramatic growth in farm output, it has also led to some deleterious consequences, especially with regards to environmental costs, including impairments of water quality (Ritter, 1990); depletion of soil fertility (Horrigan, Lawrence, & Walker, 2002) and increased soil erosion (Pimentel et al., 1995); increased eutrophication of surface and marine water (Boesch, Brinsfield, & Magnien, 2001; McIsaac, David, Gertner, & Goolsby, 2001); increased greenhouse gas emissions (Lal, Kimble, Follett, & and Cole, 1999); and unbalanced nutrient cycling (Chang & Entz, 1996). Many scientists and innovative producers have been exploring new strategies to deliver the products of agroecosystems. One alternative to specialization is diversified agricultural production, for instance, reintegrating crop and livestock farming. Studies and reviews have shown that integrated crop-livestock systems may create synergies among system components that could improve resilience and sustainability of agroecosystems while providing multiple ecosystem services (Acosta-Martínez, Zobeck, & Allen, 2004; Allen et al., 2005; Sanderson et al., 2013; Sulc & Tracy, 2007). As greater food demand has placed increasing pressure on agricultural systems, integrated crop-livestock systems are suggested as a key solution for new conservation agriculture, in which production goals are matched with the resource base to achieve both profitability and environmental benefits (Russelle, Entz, & Franzluebbers, 2007).

Crop and livestock production can be integrated in many ways. In the U.S. Corn Belt, tremendous amounts of corn residues can accumulate on the land after harvest, particularly when farms are specializing in continuous corn operations. Allowing livestock (mostly cattle) to graze corn residues after grain harvest is one of the simplest and most economical methods to integrate livestock and corn operations (Sulc & Franzluebbers, 2014; Sulc & Tracy, 2007). Take Illinois for example, 18 million Mg corn residues are estimated to be available after harvest, assuming that approximately a quarter of total residues can be removed via grazing. Putting aside logistical challenges of delivering cattle and feed, the corn residues in Illinois alone might be sufficient to feed 80% of gestating cows (6.1 million) and calf crop (34 million) currently accounted for in the US Agricultural Census for a 45-60 day period each fall after harvest. The alternative to directly grazing would be purchasing or producing winter feeds, which has been shown to be the most expensive element of producing cattle (Reid & Klopfenstein, 1983). Grazing crop residue has been widely adopted in the western U.S. Corn Belt but is less seen in the eastern U.S. Corn Belt (Sulc & Tracy, 2007).

The overall effects of crop residue grazing on croplands, however, are unclear and worthy of scientific exploration. It is suggested that manure produced by cattle can likely enhance the carbon sequestration processes in soils (Smith, Powlson, & Schlesinger, 2000) and increase soil organic matter (Allen, Baker, Segarra, & Brown, 2007). Conversely, grazing may cause negative impacts on soils, such as increasing soil compaction (Tracy & Zhang, 2008), which may affect crop productivity. Previous studies have also shown that cropland covered by corn residues were not evenly visited by beef cattle during residue grazing after fall harvest (Liu et al., 2012). This spatial diversity of grazing distributions could potentially lead to spatially heterogeneous impacts on cropland, which represents missed opportunities that may be captured by developing innovative management practices to improve system performance. Besides the uncertainty of grazing effects, integration of crop and livestock operations usually increases system complexity and requires a high degree of management skills. However, the current generation of farmers in the Midwestern U.S Corn Belt, especially young farmers, may lack knowledge of integrated farming systems. In summary, the underlying questions, remaining to be solved, are whether the overall benefits of integrating cattle with corn operations can be justified, and how farmers can adopt it in the Midwestern Corn Belt.

Much research is needed to provide a system level understanding of integrated crop-livestock systems for farmers in the Midwestern U.S. Corn Belt, considering economic, environmental and social outcomes. Combining experimental farm data with scientific models could be an appropriate approach to address the complexity of integrated crop-livestock systems, and provide knowledge and guidance to the decision-making processes used by crop and livestock farmers. However, many challenges remain in the development of modeling and decision support capabilities for integrated systems. Although there is a wide variety of separate crop and livestock models, the complex nature of interactions between crop and livestock, as well as lack of reliable data for calibration and validation, makes the integration of models difficult (Thornton & Herrero, 2001). Further, decision support for agricultural systems is generally targeted for use in crop production systems, supported by several leading crop models, such as the decision support system for agrotechnology transfer (DSSAT) and the Agricultural Production System Simulator (APSIM). Currently, there are no existing decision support tools that integrate both crop and livestock production systems. Therefore, developing models and decision support tools that integrate both crop and livestock production remains challenging work, as is obtaining reliable data for model calibration and validation. It is anticipated that, with adequate data and models, management practices can be developed to improve the profitability and stability of integrated crop-livestock systems, while minimizing environmental impacts.

1.2 Objectives

This dissertation seeks to provide a better understanding of how to develop management strategies for integrated crop-livestock systems in the Midwestern U.S. Corn Belt region. Since much cropland in this region is strongly dominated by highly specialized systems of growing corn, this study will focus on investigating agricultural systems that integrate corn and beef cattle operations through crop residue grazing. Acquiring field experimental data and using model simulations were the major approaches used in this dissertation to develop decision support capabilities for managing integrated systems. The objectives of studies in the dissertation were to:

1. Apply and validate a specialized GPS tracking system for monitoring beef cattle movements during fall corn residue grazing experiments on an integrated corn-cattle farm in central Illinois.

2. Characterize cattle movements based on GPS data and investigate spatial and temporal patterns of cattle locations during residue grazing. Evaluate the effects of number of cattle monitored on subsequent GPS data analysis.

3. Assess grazing impacts that were associated with different management practices on subsequent crop yield.

4. Develop a computational model to simulate beef cattle movements during corn residue grazing and provide management strategies through scenarios assessments.

1.3 Dissertation organization

The remainder of the dissertation is organized as follows: Chapter 2 gives an overview introduction of integrated crop-livestock systems and discusses related data, models, and decision support based on literature review. Chapter 3 describes the experimental designs for collecting field data during corn residue grazing experiments after harvest each fall. A previously developed GPS tracking system was applied and validated during the experiments to collect location data of multiple groups of cows under different grazing management practices. The long-term reliability of the GPS system was evaluated based on the data collected across multiple years of grazing experiments. Chapter 4 focuses on GPS-based characterization of beef cattle movements during residue grazing, and data mining to identify spatial and temporal patterns of cattle behaviors and associated factors, which were later utilized in model development. In addition, the effects of number of cattle monitored on subsequent GPS data analysis were evaluated. The impacts of crop residue grazing on the performance of integrated systems are presented in Chapter 5. Chapter 6 describes a cattle movement model that was developed based on data collected in the grazing experiments. Various scenarios were simulated to identify strategies for managing crop residue grazing. Finally, an overall summary of the main findings and conclusions is presented in Chapter 7.

CHAPTER 2
LITERATURE REVIEW

Crop and livestock production are often considered as complementary systems, as resources including both products and wastes generated from one can be beneficial and utilized for the other. Integrated crop-livestock systems provide a greater variety of commodities than do either enterprise alone, while offering a means of utilizing and cycling wastes or underutilized resources to benefit both crop and livestock production. Humans have a long history of integrating crop and livestock operations. Mixed crop-livestock systems provide over half of the world's meat and over 90% of its milk (Thornton & Herrero, 2001). While agricultural systems have become more specialized in many developed countries (e.g. in the U.S.) during the past century, mixed crop-livestock systems are still the most common form of livestock operation in developing countries (Thornton & Herrero, 2001). In the U.S., highly specialized agricultural systems, with decoupled crop and livestock production, have greatly improved agronomic productivity and been economically successful. However, these positive outcomes do not necessarily come without the risk of some unintended negative environmental impacts associated with the current agricultural systems. Reintegrating crop and livestock systems has been purported to alleviate many of the environmental impacts and improve system resilience and sustainability (Sanderson et al., 2013), yet integration has also increased system complexity for management. Combining experimental data and models has been suggested as an appropriate approach for addressing the complexity of integrated crop-livestock systems (Sulc & Tracy, 2007; Thornton & Herrero, 2001).

Based on published research, this chapter starts with an overview of integrated crop-livestock systems discussing the scales, methods, benefits and challenges of integration, particularly focusing on a specific type of integration through crop residue grazing. This is followed by a review of some research efforts that are related to the data and models for integrated crop-livestock systems, as well as the development of decision support for managing integrated systems.

2.1 Overview of integrated crop-livestock systems

In agricultural systems, crop and livestock operations can be integrated not only via numerous methods but also at different spatial scales. Ruminants (mostly cattle) are described as the highest species in most studies of integrated agriculture (Hilimire, 2011). While the benefits of integration have been shown in many studies, concerns have also been raised with regards to the impacts of integration, such as increased soil compaction caused by residue grazing in integrated systems. Furthermore, there are various existing challenges that obstruct the adoption of integrated system by farmers.

2.1.1 Scales and methods of integration

From a practical perspective, crop and livestock farming can be integrated at two scales in the U.S.: (i) among-farm integration; and (ii) within-farm integration (Russelle et al., 2007; Sulc & Tracy, 2007).

Russelle et al. (2007) describe the differences, advantages and challenges of these two scales. For among-farm integration or regional integration, spatially separated crop and livestock farms work together via contracts or partnerships to create system synergies between crop and livestock systems, for example, exchanging crop residue and manure for use. This integration is commonly seen where government regulations for nutrient management require the distribution of manure from concentrated animal feeding sites to cropland or pasture (Schmitt, Russelle, Randall, & Lory, 1999). There is much less integration on each farm than on a regional level, and the biological and economic diversities are improved on a regional scale rather than on a farm level (Sulc & Tracy, 2007). There are several challenges associated with among-farm integration, especially when integration is based on handshakes rather than a formal contract that describes an explicit economic value for exchanging goods and services between partners. For instance, Files and Smith (2001) identified several key issues that constrained the development of regional integration of potato-dairy farm operations in Maine, such as distance between individual farms, basic trust between individuals, and a willingness to begin slowly with modest exchanges. Questions also remain as to whether partners can achieve the same range of synergies through collaborations.

Within-farm integration is defined as spatial and temporal integration of crop and livestock operations that occur on the same land base via rotations, intercropping, and relay cropping of grain crops and forages (Sulc & Tracy, 2007). Based on the temporal and spatial combination of livestock and crop, Hilimire (2011) further delineates three types of within-farm integration: (i) spatially separated (animals and crops are maintained in separated parts of a farm), (ii) rotational (animals and crops occupy the same land but at different times), and (iii) fully combined (animals graze underneath or in between crops). On one hand, physical and financial stability of integrated farms could be improved as compared with specialized enterprises because of complementary interactions between crops and animals (Ewing & Flugge, 2004); on the other hand, complex interactions at the soil-plant-animal interface also bring management challenges, especially when livestock directly graze forages on croplands (Sulc & Tracy, 2007). Farmers need to be more cognizant of the nutrient flows on integrated farms, where the complexity and rapidity of N cycling are increased (Russelle, 1992), and nutrient distribution may be heterogeneous due to animal behavior (White, Sheffield, Washburn, King, & Green J.T., 2001).

There are many ways that crop and livestock production can be integrated. Sulc and Franzluebbers (2014) outlines six most commonly studied and practiced integration methods in the U.S.: (i) sod-based crop rotations, (ii) livestock grazing of cover crops within cash-crop rotations, (iii) grazing of crop residues, (iv) sod intercropping, (v) dual-purpose cereal crops, and (vi) agroforestry and/or silvopasture. The remainder of this dissertation has been chosen to focus on within-farm integration of crop residue grazing, which is considered as one of the most economical and simplest integration methods in the U.S. (Russelle et al., 2007; Sulc & Franzluebbers, 2014; Sulc & Tracy, 2007). Crop residues represent a vast feed source available to livestock producers, especially in the Midwestern Corn Belt where an enormous amount of corn residue are underutilized after harvest. In this type of integration, ruminant livestock (mostly cattle) are allowed to graze crop residues remaining after grain harvest. The practice has been adopted in the western Midwest and east-central Great Plains region (Sulc & Franzluebbers, 2014), while there is a need to address the complexity of those systems and provide insights into the design and management of integrated crop-livestock systems for the U.S. Corn Belt. It is believed that those systems represent the potential for providing additional ecosystem services by capturing positive ecological interactions and avoiding negative environmental impacts, while maintaining or improving profitability.

2.1.2 Benefits of integration

There has been ample published research that suggests well-managed integrated crop-livestock systems can be economically competitive while being environmentally beneficial. The following discussion is mainly focused on the benefits of integration that adds livestock into cropping systems through crop residue grazing. For information about the advantages of all kinds of integrated crop-livestock systems, see these review papers (Hilimire, 2011; Sulc & Franzluebbers, 2014).

Profit is of primary importance for farmers to adopt any farming practice that either reduces production costs or improves farm productivity. Crop residues represent a large underutilized feed source for ruminant livestock producers and can significantly lower winter feed costs. For example, wintering dry-pregnant beef cows on swathed forages and crop residues provide a potential daily savings of $0.24 per cow when compared to bale feeding in a drylot (Karn et al., 2005). Additionally, integrating livestock and crop production can increase land-use efficiency beyond that of crop-only farms, which can subsequently yield greater profitability (Hilimire, 2011). Other studies on cost efficiency analysis of agriculture have shown that crop and livestock could be produced at much lower cost at integrated farms as compared to specialized enterprises in Wisconsin (Chavas & Aliber, 1993) and Missouri (Wu & Prato, 2006). Though there has been limited work published on the impacts of crop residue grazing on subsequent crop yield, a three-year trial suggests that corn yield was higher in an integrated system (11.6 Mg ha^{-1}) compared with a continuous corn system (10.6 Mg ha^{-1}) (Tracy & Zhang, 2008). Risk management can be another factor that affects farmers' decisions regarding farming practices. Integration of crop and livestock farming, as a means of diversifying agricultural systems, may provide risk reduction by including income from a range of enterprises that are influenced differently by varying weather and market conditions. The overall variation in income can be reduced in this way because incomes from these enterprises are usually not perfectly correlated (Sanderson et al., 2013).

Besides economic returns, previous studies have suggested multiple ecosystem benefits of integrated crop-livestock systems, including reduced water requirement for crop production (Allen et al., 2007), lower fertilizers inputs (Allen et al., 2007; Liebig, Tanaka, Kronberg, Scholljegerdes, & Karn, 2012), reduced soil erosion (Allen et al., 2007), and enhancement of soil organic carbon storage (Allen et al., 2007; Drinkwater, Wagoner, & Sarrantonio, 1998; Fultz, Moore-Kucera, Zobeck, Acosta-Martfnez, & Allen, 2013; Liebig et al., 2012). It should be noticed that several studies reviewed here, especially those studying aggregated changes in soil nitrogen or carbon, are long term in nature (Drinkwater et al.(1998): 15 years; Allen et al.(2007): 7 year; Liebig et al.(2012): 9 years; Fultz et al.(2013): 13 years). This indicates that long periods may be required to appropriately evaluate the aggregated effects of integrating crop and livestock operations on agroecosystems.

2.1.3 Concerns and challenges

Several concerns have been raised regarding potential detrimental impacts of integrating crop and livestock farming. One major concern of crop residue grazing is soil compaction if not managed properly. Compaction and the resulting increased bulk density of the soil can cause poor aeration (Lal, 1996), restricted water infiltration (Willatt & Pullar, 1984), delayed plant emergence (Flowers & Lal, 1998), impaired root growth (Voorhees, 1992) and reduced transport of oxygen and nutrients (Scholefield, Patto, & Hall, 1985). However, there is some evidence that effects of soil compaction can be avoided or minimized in colder regions or under appropriate management (Liebig et al., 2012; Sulc & Franzluebbers, 2014). For example, restricting grazing to periods when soils are dry or frozen, which may be practical in northern regions of the Corn Belt, or tilling soils before planting a cash crop has been suggested as useful means to minimize soil compaction caused by animal grazing (Sanderson et al., 2013).

Methane production from cattle is another concern for agricultural systems that include cattle and other ruminant livestock. Methane emissions from enteric fermentation have increased by 2.3% from 1990 to 2012; annual methane emissions were estimated to be 100.6 Tg CO_2 Eq from beef cattle and 35.0 Tg CO_2 Eq. from dairy cattle (USEPA, 2014). Modifying cattle diets has been considered as a strategy to reduce methane generation. For example, lactating beef cattle foraging on mixed alfalfa and grass pastures were shown to eructate less methane than those grazing grass only, as a percentage of gross energy intake; however, dry matter intake was greater for cows grazing mixed alfalfa and grass pastures resulting in more methane generation than those grazing grass-only pastures, possibly due to higher digestibility (McCaughey, Wittenberg, & Corrigan, 1999; Minson & Wilson, 1994). Supplementation is one of the most effective and commonly practiced ways to provide livestock with additional nutrients during grazing crop residues that have low quality and decline at an accelerated rate. Supplementation of diets using lipids has been suggested as a means of reducing methane production (Busquet, Calsamiglia, Ferret, Cardozo, & Kamel, 2005; Czerkawski, Blaxter, & Wainman, 1966). Supplementation with distiller's dried grains (McGinn, Chung, Beauchemin, Iwaasa, & Grainger, 2009) or whole cottonseed (Grainger, Williams, Clarke, Wright, & Eckard, 2010) has shown persistent reductions in methane emissions.

Various existing challenges constrain farmers from integrating livestock into crop systems, such as lack of technology and knowledge, attractive government policies and regulations, and supporting infrastructures (Hilimire, 2011). Sulc and Tracy (2007) emphasize several key issues that should be considered for adopting integrated crop-livestock systems in the U.S. Corn Belt region: "(i) the tradition of single enterprise farming has become the norm for the current generation of farmers; (ii) government support programs favor large-scale grain cropping systems over more complex, diversified production systems; (iii) the complexity of integrated systems requires higher management skills; (iv) many farmers lack a comprehensive understanding of system-level performance; (v) incentives are limited for greater diversity and environmental conservation in production systems."

Much research is needed to address those concerns and provide a comprehensive understanding of how to develop and manage integrated crop-livestock systems in the Midwestern Corn Belt considering economic, environmental and social benefits. I agree with Sulc and Tracy (2007) that combining modeling and field validation experiments seems to be especially appropriate for studying the complex interactions among integrated crop-livestock systems. However, developing models and decision support tools that integrate both crop and livestock production remains as a challenging work as well as obtaining adequate data for model calibration and validation.

2.2 Data, models, and decision support for integrated corn-livestock systems

Livestock grazing is an essential process in integrated crop-livestock systems that should be included in model development. Several grazing models can be found in the literature with varying degrees of complexity (Blackburn & Kothmann, 1989; Brereton, Holden, McGilloway, & Carton, 2005; Fernandez-Rivera, Lewis, Klopfenstein, & Thompson, 1989; Loewer Jr., 1998; Rook & Yarrow, 2002). Most of those models are deterministic, and very few of them simulate the spatial dynamics of livestock during grazing. Grazing, in fact, is a fundamental yet complex spatiotemporal phenomenon that is tightly associated with animal movements that are driven by numerous biotic and abiotic factors such as animal internal needs, forage availability and quality, weather, predator, and topography, some of which might be heterogeneous and stochastic in nature. Until the recent development and application of technology in both tracking and observing animal movements, there have been very few publications that describe models of spatiotemporal processes during grazing in heterogeneous environments, mostly due to lack of data for validation. The recent integration of Global Positioning System (GPS) and Geographic Information System (GIS) has provided a robust set of tools for researchers to track a wide range of animals, including mammals (Mech & Cluff, 2011; Pépin, Adrados, Mann, & Janeau, 2004; Rodgers, Rempel, & Abraham, 1996), reptiles (Yasuda & Arai, 2005), fish (Gudbjornsson, Godø, & Palsson, 2004), and birds (Dell'Ariccia, Dell'Omo, Wolfer, & Lipp, 2008; Fritz, Said, & Weimerskirch, 2003; Vyssotski et al., 2006). The rapid development of advanced computing technology also enables researchers to perform large-scale, long-term and spatially explicit simulation of animal movements (Bennett & Tang, 2006). However, because of the extremely complex interactions between animals and the environment in which they are embedded, there are still many challenges in modeling animal movements, such as developing methodologies to explore mass movement data in order to link movement processes to patterns, and ultimately identifying and modeling the underlying mechanisms that drive and affect animal movements.

2.2.1 Tracking and analyzing animal movements

2.2.1.1 Tracking data

A variety of methods have been developed and implemented for animal movement tracking including observation (Kareiva & Shigesada, 1983; Šárová, Špinka, Panamá, & Šimeček, 2010), mark and capture (Ovaskainen, Rekola, Meyke, & Arias, 2008; Ovaskainen, 2004), Radio Frequency Identification tags (Catarinucci et al., 2013; Voulodimos, Patrikakis, Sideridis, Ntafis, & Xylouri, 2010), digital videos (Delcourt, Denoël, Ylieff, & Poncin, 2013; Roy, Bryant, Cao, & Heck, 2011), GPS satellite tags (Davis, Darr, Xin, Harmon, & Russell, 2011; Moen, Pastor, Cohen, & Schwartz, 1996), and accelerometers (Guo et al., 2009; Moreau, Siebert, Buerkert, & Schlecht, 2009) for a wide range of organisms. The preceding list shows just a small portion of the explosion of animal movement data in recent years; however, it gives the idea of the diversity of the types of rapidly developing technologies that were applied in animal movement tracking.

2.2.1.2 Analytical methods

Despite the continuously growing body of movement data, movement ecology has not yet established a set of standard analytical methods. However, there has been a wide range of approaches for quantification of movement data that were collected via different methods. Patterson et al. (2008) break these methods down into three stages: error-correction; calculation of movement metrics; and either pattern identification or statistical analysis for biological inference.

Observation errors are unavoidable in animal movement tracking due to many reasons ranging from instrumental limitations to operation errors. Austin et al. (2003) developed a three-stage algorithm for filtering erroneous Argos satellite locations, and suggested that analysis of animal home range may be meaningful only if the same filtering algorithm has been used. Christopher and Visscher (2005) investigated the influence of measurement error on the parameters used to create movement models. They used Monte Carlo simulation to quantify the measurement error for estimates of turning angel and step length as a function of the distance between consecutive locations. The results show that estimates of turning angle and step length are accurate only when the measurement error is relative smaller to the distance between two locations. A typical pitfall in error-correction methods is that they usually contain implicit assumptions about how animals move (Patterson et al., 2008). These assumptions might contaminate the error-corrected data and affect the results of statistical analysis.

The complexity of movement data has often led researchers to focus more on descriptive statistics that quantify the movement characteristics of animals instead of embracing its complexity. Despite the difficulties in identifying movement patterns, modeling and predicting individual movement, it is relatively easier to characterize animal movement from data in terms of movement metrics. Patterson et al. (2008) delineate movement metrics as quantities that might be calculated directly from raw, uncorrected and unprocessed movement data. Examples of movement metrics include step length, speed, heading, turning angles between subsequent locations, daily cumulative travel distance and so on. Another descriptive analysis method is named fractal analysis, which is used to characterize animal movement paths. Movement paths can be treated as geographical curves that are often statistically "self-similar" (Mandelbrot, 1967). This means that each portion can be considered as a reduced-scale image of the whole. In that case, a quantity D is used to describe the degree of complication. The fractal dimension D of an object measures its ability to fill Euclidian space. The fractal analysis has been applied to several organisms' paths including copepods, spider mites, grasshoppers, clownfish, albatrosses, sheep, martens, wolves, polar bears and narwhals (Gurarie, 2008). The estimated fractal dimension D is usually compared with some environmental or internal state factor to provide a straightforward and indirect index of animal behaviors. One potential pitfall of fractal analysis is that it treats movement paths as purely spatial objects, which in fact are objects in space and time, thus losing some information such as various velocities. However, it can be a robust tool for movement path analysis in some cases, like characterizing movements in a controlled behavioral experiment (Gurarie, 2008).

The third stage of movement data analysis is focused on pattern identification for further revealing underlying ecological mechanisms. A research arena that represents emerging growth points for the theory of movement is called home-range analysis. Home-range is often represented as a utilization distribution, which is a two-dimensional relative frequency distribution of animal locations, and may change through time (Smouse et al., 2010). Worton (1989) used kernel methods for the nonparametric estimation of the utilization distribution from a random sample of locational observations made on an animal in its home range. The results show that kernel methods will usually suffice for estimating the utilization distribution density unless there is a clearly appropriate parametric model. Usually, the location and sizes of home ranges are be correlated with the needs of the individual animal and the distribution of resources across the landscape (D. P. Anderson et al., 2005; Mitchell & Powell, 2004). Besides the analysis of utilization distribution patterns, some advanced computational techniques and data mining algorithms have been developed to extract information from movement data for identifying spatiotemporal patterns, like repetitive patterns and periodic patterns. Bar- David et al. (2009) applied two new techniques of analysis (recursion analysis and circle analysis) on data generated by a simple large-herbivore movement model, as well as two sets of empirical data on movements of African buffalo, to identify the patterns associated with animals' repeated visits to particular sites or patches ("recursions"). The results show that with available ecological data, using recursion analysis can contribute to the understanding of various factors influencing movement, such as resources, topographical and landscape factors. Animals usually have periodic movement behaviors, such as daily foraging behaviors, acquiring water, or yearly migration behaviors. Li et al. (2012) developed a two-stage data mining algorithm, Periodica, to address the problem of mining periodic behaviors for moving objects. The main assumption is that the observed movement is generated from multiple interleaved periodic behaviors associated with certain reference locations. At the first stage, multiple periods associated with corresponding reference locations are detected from movement data using a method that combines Discrete Fourier Transform and Circular Autocorrelation. At the second stage, a probabilistic model is proposed to characterize and statistically generate periodic behaviors from partial movement sequences through hierarchical clustering. The algorithm was applied on both synthetic and real movement data sets. The results show that Periodica can deal with both noisy and complicated cases, and may also help interpolate missing data. These advanced pattern-based or hypothesis- testing approaches for movement data analysis reveal some hidden patterns of animal movement. However, the ability to directly incorporate underlying ecological mechanisms is still limited.

2.2.2 Modeling animal movements

Investigating why, when, where, and how animals move provides insights to solving issues associated with animal movement in many disciplines (Tang & Bennett, 2010). Developing scientific models to simulate and predict animal movement represents a powerful approach to study animal movement. Models, not only can simulate movement processes based on understandings of animal movement data, but could also provide researchers the capability to predict animal movement under various conditions that may not be obtained through experiments and observations, which appears to be very helpful to meet potential challenging issues in animal movement ecology in the future. This section will introduce the two classic modeling approaches for animal movement and several general animal movement modeling approaches, including stochastic models (e.g. random walk, and state-space models), and agent-based or individual based models.

2.2.2.1 Two classic modeling approaches

Based on different sorts of questions that are asked, there are two classic modeling approaches of animal movement: Lagrangian and Eulerian. In fluid mechanics, Lagrangian models focus on changes that occur to a moving particle, while Eulerian models consider the changes that occur at given points in space (Gurarie, 2008). Similarly, in animal movement modeling, Lagrangian models predict detailed movement of single individuals across a landscape and their behavioral responses to environmental variables; while Eulerian models generally focus on larger scale questions about the spatial patterns of an individual animal or population, such as habitat usage of animals. In fact, there is much overlap between these two approaches as there is a long tradition of deriving Eulerian models from Lagrangian descriptions (Gurarie, 2008; Smouse et al., 2010).

For individual movement data that are collected at discrete time intervals such as GPS tag data, Lagrangian approaches are particularly well suited since it involves discrete steps and time segments (Smouse et al., 2010). State-space models (SSM) (See section 2.2.2.2) seem to be one of the most promising Lagrangian approaches because it can handle both measurement errors and process stochasticity (Patterson et al., 2008). Lagrangian approaches are also the usual choice for spatially explicit individual/agent-base models (IBM or ABM) (See section 2.3.2.3), in which individual animal movement and environmental factors are explicitly modeled (Grimm, 1999).

Compared to the Lagrangian approaches that focus on individual-based stochastic processes, the Eulerian approaches can address questions regarding the spatial patterns such space usage as they focus on the dynamic changes in the probability of individual's occurrence in space. The models thus become "place-based" (Smouse et al., 2010). A typical example using

Eulerian approaches is home-range analysis, as its primary concerns are the characteristics and the geographical landscapes used by an animal. Early study on home-range analysis attempted to determine the home-range area using minimum convex polygons (Odum & Kuenzler, 1955); current research tends to treat home-range as a utilization distribution (Getz & Wilmers, 2004; K. A. Keating & Cherry, 2009), which describes the probability of observing an animal at any given location and time.

2.2.2.2 Stochastic models

"Most willful movement processes are very complicated deterministic processes with multiple unknown factors, some of which might be stochastic in nature." - Gurarie (2008).

Similar to other processes in nature, animal movement is a complex phenomenon that could involve many stochastic processes. An important aspect of movement analysis and modeling is to compare field data with predictive theories and expected mechanisms, which usually involves modern statistical analysis and modeling. Besides that animal movement could involve many stochastic processes, the fact that much movement data is error-ridden is another challenge in modeling animal movement. Recently, several more statistically sophisticated approaches have emerged. State-space model (SSM) approach is a powerful and promising tool to handle such data for statistical modeling, which has been applied in several animal movement studies (Buckland, Newman, Thomas, & Koesters, 2004; Dowd & Joy, 2011; Jonsen, Flemming, & Myers, 2005; Jonsen, Myers, & Flemming, 2003; Ovaskainen et al., 2008; Royer, Fromentin, & Gaspar, 2005). It is a stochastic time-series model in which an observation model mathematically describes the future states of a system based on predictions generated via a process model that predicts the future state of a system from its previous states probabilistically – an assumption known in mathematics as the Markov condition (Patterson et al., 2008). A process model could be a correlated random walk that predicts the future state of an animal, which may include several variables like animal's spatial location, or possibly behavioral mode, while the observation model might be a standard Gaussian error. Maximum-likelihood or Bayesian approaches are usually used for the parameterization of a model (Gurarie, 2008). A hypothetical and useful approach in SSM is to partition animal movement paths into different movement phases or behavioral modes, such as foraging, migrating, or resting, each characterized by a particular combination of parameters describing the probability distributions of step sizes and turning angles (Smouse et al., 2010). Switching between sequential behavior modes can be modeled as transition probabilities as functions of current habitat type or distance to a particular habitat type (Morales, Fortin, Frair, & Merrill, 2005). Guo et al. (2009) developed a cattle movement model using a Hidden Markov model (HMM) and a long-term prediction algorithm. In this model, cattle movement was partitioned into three hidden behavior states such as relocating, foraging and bedding based on the animal's directional speed and turning angles calculated from GPS data. The state transition behaviors associated with several "stay" areas where cows remained for long periods were predicted via the long-term prediction model. The major advantage of SSM approach is that it integrates the three analysis phases – error correction, calculation of metrics and statistical analysis (Patterson et al., 2008), though the approach is usually computationally demanding and few applications of the model have been truly validated (Tremblay, Robinson, & Costa, 2009). Another limitation of the SSM approach is that it is ultimately only as good as the underlying movement model and the behavioral hypotheses associated with it. And for movement data like GPS, acoustic and video-tracking data, there is little direct need to apply the SSM approach because the errors are essentially negligible (Gurarie, 2008).

2.2.2.3 Individual-based / agent-based simulation models

The proceeding list of modeling approaches describes animal movements as stochastic processes, and animals' behavioral changes are usually modeled as basic responses to coarse environmental variables. Few studies attempted to model explicit behavioral rules because they are difficult to model. In fact, animal movement is a composite outcome of behavioral responses to individual's internal states, interactions among individuals, and interactions between individuals and their environment (Bailey et al., 1996; Nathan et al., 2008). With rising research interest on individual –level movement behavioral rules and advanced computing technology, individual-based or agent-based models (IBMs/ABMs), a bottom-up problem-solving approach, have been increasingly applied to study animal movement (Abbott, Berry, Comiskey, Gross, & Luh, 1997; Beecham & Farnsworth, 1998; Bennett & Tang, 2006; Carter & Finn, 1999; Dumont & Hill, 2001; Linard, Ponçon, Fontenille, & Lambin, 2009; Mitchell & Powell, 2004; M. G. Turner, Yegang, Wallace, Romme, & Brenkert, 1994), as it captures the three main components described above and allows for explicit representation of the underlying individual behavioral rules. There have been historical differences between IBMs and ABMs: IBM focused on individual variability and local interactions, whereas ABMs focused on decision-making and adaptive behavior. However, these differences are fading away, and they can be used interchangeably in most cases now (Railsback & Grimm, 2012).

The agent-based approach is a bottom-up approach, which models the "parts" (e.g. individuals) of a system and then studies how the system's properties emerge from the interaction among these parts (Grimm, 1999). Agents, environments, and events are the three fundamental components of ABMs. Real-world entities are represented as agents and environments in ABMs. An agent (e.g. individual animals) is characterized by a set of properties (including attributes and state variables) and behaviors, and the environment is often represented as a one, two, or three (mostly two) dimensional space consisting of continuous (object-based) or discrete (grid-based) patches (Tang & Bennett, 2010) with attributes (e.g. spatial coordinates, elevations). Agents make decisions to solve problems based on their internals states and stimulus that they received from other agents and the environment where they are embedded in. A set of events is modeled in ABMs to update the states of agents and environments and simulate the dynamic changes in real-world systems.

Nathan et al. (2008) proposed a new movement ecology framework that integrates conceptual, theoretical, methodological, and empirical frameworks for studying the spatial dynamics of organisms. This framework is based on four basic mechanistic components of animal movement: the internal state, motion capacities, navigation capacities of individuals, and the externals factors affecting movement. These four components build on a suite of existing theories that suggest that animal movement can be described by biomechanical, cognitive, random, and optimization processes.

The internal states of animals include both physiological states (e.g. body mass/weight, bioenergy flux) and psychological states (e.g. perception, memory, learning and decision-making (Shettleworth, 2001). Animal movement can be driven by a set of internal state variables and goals, like energetic need. The optimal foraging theory assumes that animals maximize their net energetic intake rate, which guides animal's movement decisions. Turner et al.(1994) simulated the winter foraging behaviors of large ungulates, whose movement is driven by daily intake requirements and intake rates and constrained by the maximum daily travel distance. The daily energy balances were computed by subtracting energy cost from energy gain. ABMs are also well suited to represent the psychological states of animals and associated cognitive processes.

Animal's spatial memory can be represented as a two-part code, reference and working memory (Bailey et al., 1996). Reference memory is the map-like representation of the foraging environment, while working memory is used to remember the recently visited areas thus avoid revisiting where food had already been consumed. Dumont and Hill (2001) modeled the spatial memory of sheep on foraging behaviors and found that the advantages of a good spatial memory vary according to the size of the environment to be explored. Bennett and Tang (2006) simulated both short and long term memory in elk's migration. In their model, immediate environmental stimuli are stored as short-term memory, and successful movement decisions receive positive reinforcement, captured as long-term memory in the form of a cognitive map.

The external environment plays a significant role in animal movements as it affects animal behaviors through complex interactions with the animal. In ABMs, the environment is characterized as a combination of abiotic (e.g. elevation, slope, distance to water) and biotic factors (forage quality, plant productivity, species composition). Large herbivore grazing distribution patterns show that abiotic effects are usually consistent and can be predicted more reliably than biotic factors (Bailey et al., 1996). Abiotic factors such as slope, distance to water, and microsite characteristics (e.g. wind and shade) can affect grazing distribution patterns (Cook, 1966; Senft, Rittenhouse, & Woodmansee, 1985; Senft et al., 1987). The environmental factors can be categorized into two general classes: resources (e.g. food, water) and risks (climate change and predation), which can be modeled as attractive or repulsive forces that guide animal movement in ABMs (Bennett & Tang, 2006). Animal movement, in turn, can modify the spatial distribution of resources and risks. ABMs are well suited for representing spatially explicit environments as it can incorporate empirical data obtained from remote sensing, GPS, and sensor networks (Tang & Bennett, 2010).

Animal can change their space-time locations using different movement modes (e.g. foraging mode and relocating mode), which are changed in response to their internal states and external conditions. In ABMs, different movement modes can be modeled as different types of random walk that are driven by stochastic processes that are constrained by internal and external factors (Turchin, 1998). Bennett and Tang (2006) studied elk migration by designing two movement modes for elk: local movement constrained by resource patterns and inter-patch movement directed by snow distributions. Through a set of stimulus-response processes, animal can learn how to effectively switch movement modes to achieve their goals. ABMs are also capable of modeling the learning processes and adaptive behaviors (Bennett & Tang, 2006; Morales et al., 2005).

Animals can use both external and environmental cues and their cognitive capabilities to navigate across landscapes (Tang & Bennett, 2010). Various approaches have been used to model how animal movements are navigated. For instance, for destinations within the perceptual range of animals, direct targeting can be used to guide animal movement (Trullier, Wiener, Berthoz, & Meyer, 1997). For destinations outside of the perceptual range of animals, Trullier et al. (1997) present navigation strategies within a four-level hierarchical framework: landmarks learning and guidance, place recognition-triggered response, topological navigation, and metric navigation. In ABMs, spatial learning algorithms, machines learning algorithms and neural networks can be applied to simulate how animal movements are navigated (Bennett & Tang, 2006).

Several software packages have been developed for agent-based modeling. Tang and Bennett (2010) provide a list of software packages: Swarm (http://www.swarm.org/), NetLogo (https://ccl.northwestern.edu/netlogo/), RePast (http://repast.sourceforge.net/), and MASON (http://www.cs.gmu.edu/~eclab/projects/mason/). These software packages use object-oriented programming languages (e.g. Java, C++), and some provide user-friendly GUI (graphic user interface). They are often integrated with other domain-specific functionality such as GIS, spatial statistics, and machine learning algorithms (Tang & Bennett, 2010). A drawback of ABMs is that it is hard to test how realistic a model might be since the structure of the model itself is based largely affected by the modeler's assumptions (Gurarie, 2008). However, accurate and useful predictions are a satisfactory objective for engineering-oriented purposes of the model.

2.2.3 Integrated models and decision support

Although there is a wide variety of separate crop and livestock models, the complex nature of interactions between crop and livestock, as well as lack of reliable data for calibration and validation, makes the model integration difficult. Thornton and Herrero (2001) present a conceptual modeling framework for the integration of detailed biophysical crop and livestock simulation models varying in level of aggregation and data requirements. They outline a set of goals that integrated crop-livestock models should be able to do: "(1) describe and quantify interactions within the system, (2) represent the farmer's management practices, (3) determine management impacts, (4) quantify nutrient balance at the whole-system level, (5) quantify weather variability on system performance, (6) provide insight into trade-offs (economic, environmental and social), (7) allow studying both medium- and long-term effects of strategies, (8) translate model outcomes to operational support for management, (9) use minimum data sets for parameterization, validation and general use, and (10) integrate data from different levels of aggregation." Characterizing crop-livestock production system and modeling the key components and processes are suggested as two primary steps required for achieving those goals.

Currently, decision support for agricultural systems is generally targeted for use in crop production systems, supported by several leading crop models. For instance, the decision support system for agrotechnology transfer (DSSAT) has been used since 1998, including models and software for 16 different crops (Jones et al., 2003). Similar tools include the Agricultural Production System Simulator (APSIM) (B. A. Keating et al., 2003) and Precision Agricultural-Landscape Modeling System (PALMS) (Norman & Molling, 2006). Both tools have an increased focus on the soil, soil water, and soil and plant interactions. Much research and work is needed to develop decision support tools that integrate both crop and livestock production systems, which not only can model system performance at different levels of complexity but also can translate model outcomes into operational support for farm management.

2.3 Conclusions

Integrated crop-livestock systems represent a promising alternative for the current specialized agricultural systems in the U.S. Corn Belt region. This literature review demonstrates that integrated livestock-crop systems (e.g. integrated corn and cattle operations through crop residue grazing) have potentials to improve farmer’s income while alleviating many environmental impacts, if concerns and constraints associated with integration can be properly addressed. Combining field experiments and modeling was suggested as an appropriate studying approach for providing farmers with insights into management strategies. However, the complex nature of interactions among integrated systems, as well as lack of reliable data, makes the integration of crop and livestock models difficult. There have been various livestock grazing models in the past, while many old models are deterministic or empirical models, and few of them address the spatial dynamics of animals that are tightly associated with grazing behavior. The recent development and application of animal tracking technology have led to an explosion of animal movement data. Integrating GPS, GIS, and advanced computing technology has provided a robust toolset for researchers to analyze and model the movements of grazing animals. Among various modeling approaches, Agent-based models are suggested to be a well-suited approach for simulating animal movements, when tracking data such as GPS data is available. Challenges still exist with regards to how crop and livestock models and decision support tools can be integrated to provide insights into managing strategies for integrated systems. Some studies have outlined some conceptual frameworks for modeling, while there is still much research needed to provide decision support for managing integrated crop-livestock systems.

CHAPTER 3

APPLICATION AND VALIDATION OF A SPECIALIZED GPS TRACKING SYSTEM FOR GRAZING CATTLE

Global Navigation Satellite System (GNSS) and Global Positioning System (GPS) have been increasingly applied to track livestock movements in the past two decades (Capece & Mozaffari, 1997; Liu et al., 2012; Sigua, Williams, & Coleman, 2007). For example, location data of cattle have been utilized to understand behavioral activities (Agouridis et al., 2004; Davis et al., 2011; L. W. Turner, Udal, Larson, & Shearer, 2000) and estimate grazing preferences (Agouridis et al., 2004; Dean M Anderson, Anderson, Estell, & Cibils, 2013; Swain, Friend, Bishop-Hurley, Handcock, & Wark, 2011). GPS data acquired from livestock and wildlife have been accomplished with commercial and custom-constructed GPS tracking units (Agouridis et al., 2004; Dean M Anderson et al., 2013; Cargnelutti et al., 2007; P. E. Clark et al., 2006; Davis et al., 2011; Swain et al., 2011). Several commercial manufacturers offer collar-mounted GPS units (Advanced Telemetry Systems, Isanti, MN, USA; Lotek, Newmarket, Ontario, Canada; Telonics, Mesa, AZ, USA; Blue Sky Telemetry, Aberfeldy, Scotland) for wild and domesticated animal monitoring. The major limitation is the cost of these collars, which range from several hundred to several thousand dollars per unit, not including the cost of software or additional features. Custom-built GPS units by Davis et al. (2011) and Clark et al. (2006) have shown advantages in research applications because they feature economic designs, construction, and customization for specific research purposes. With limited information available regarding the number of cattle required to represent a group or herd, instrumenting the entire group is often desirable (Dean M Anderson et al., 2013; Swain et al., 2011) but often limited by the cost of commercial GPS units and required customization for research application.

GPS performance has been extensively studied to evaluate accuracy and precision of location data for different environments and animal activities (Hansen & Riggs, 2008). Static and dynamic tests were conducted to evaluate GPS accuracy while stationary and moving, respectively (Agouridis et al., 2004; Perotto-Baldivieso et al., 2012; Recio, Mathieu, Denys, Sirguey, & Seddon, 2011). In addition, GPS accuracy under different vegetative covers (Belant, 2009; Obbard, Pond, & Perera, 1998; Recio et al., 2011) and topography was used to quantify location biases to simulate animals in thick canopy covers on mountainous terrains (Jiang et al., 2008). Several studies determined GPS accuracy and location fix rates were affected by GPS receiver orientation (compass directions) and position around the neck (Belant, 2009; D'Eon & Delparte, 2005; Moen et al., 1996). Animal activity affects the GPS receiver position because the collar is able to rotate about the animal's neck and the animal's head is at different angles during different activities. GPS accuracy may be impacted by the physical composition of the animal (Dean M Anderson et al., 2013). While these effects haven been studied for some commercial units (less accurate than some custom GPS receivers), similar tests are needed for custom-built GPS units. Besides GPS accuracy, several studies have reported the successes and failures of using commercial GPS collars by means of classifying costs, lost units, achieved fixes, repairs, and unit failures (C. J. Johnson, Heard, & Parker, 2002; Matthews et al., 2013; Schleppe, Lachapelle, Booker, & Pittman, 2010), so future studies can be better designed and implemented. Similarly, there is also a need to document the long-term performance and reliability of custom-built GPS collars under field conditions to continue developing and improving the application of GPS technology in cattle behavioral studies.

The objective of this chapter is to introduce an updated design of GPS HAWK (Davis et al., 2011) and its implementation in tracking beef cattle locations during crop residue grazing experiments. Based on field data from several cattle monitoring studies, the long-term performance and reliability of this tracking system are evaluated and documented using a summary of project logistics including strengths and weaknesses of GPS units based upon the success of data collection, reliability, failure rates, and maintenance records.

3.1 Materials and Methods

3.1.1 An updated design of the GPS-HAWK

The initial GPS-Herd Activity and Well-being Kit (GPS-HAWK) was developed for cattle behavior monitoring to provide an alternative to the high cost of commercial GPS units and the need for a user-selected sampling interval (Davis et al., 2011). The design features a GPS receiver with a Wide Area Augmentation System (WAAS) accuracy of less than 3 m (9.8 ft), placed on top of an aluminum housing secured on a should-mounted harness to maintain the GPS receiver facing skyward. The housing contained a microcontroller, compact flash storage, and circuit board controlled sampling while being powered by a lead-acid battery. The GPS-HAWK was able to achieve approximately 4 d of sampling, record location fixes as frequent as one per 15 s, and cost significantly less than a commercial unit. This design offered customization needed to further develop a unit expandable for applications on a large number of cattle. The major limitations of the GPS-HAWK units included the mounting method and low monitoring duration. Instrumentation of a whole group required inexpensive design, long logging duration and easy to install GPS unit.

The updated design used a nylon neck collar (C14597N, Nasco Inc., Fort Atkinson, WI, USA) (Figure 3.1) to replace the shoulder-mounted harness. Hardware and a custom battery were secured in a smaller weatherproof polycarbonate housing (1553K2GY, Hammond Manufacturing Company Limited, Guelph, Ontario, Canada) (Figure 3.2). The mounting was bolted to the nylon collar such that it would rest below the neck of the animal, directly opposite the GPS receiver on the top of the neck. The collar design intended that the weight of the housing would reduce rotation of the collar, which would keep the GPS receiver facing skyward and reduce potential location bias.

Figure 3.1 A Garmin GPS18X LVC with a data logger unit has been outfit onto a collar suitable for cattle use. Cattle were trained to wear the GPS collars 24 hours-a-day during monitoring.

Hardware components and design followed the reported design of the GPS-HAWK platform (Davis et al., 2011). The GPS receiver was updated to a 12-channel Garmin GPS 18x LVC disk-shape receiver with an accuracy of < 15m (49.2ft) non-WAAS corrected and <3 m (9.84 ft) with WAAS correction at 95% typical (Garmin International, Inc., Olathe, KS, USA). The circuit board was custom designed in Eagle PC Design Software (Cad Soft Inc., Pleishkerschen, Germany), fabricated by BatchPCB (Sparkfun Electronics, Boulder, CO, USA), and mounted on a custom cut 3 mm (0.12 in.) thick sheet metal divider secured in slots within the housing. A micro compact flash card (1GB micro SD, TS1GUSD, Transcend Information Inc., Taipei, Taiwan) stored data via a Serial Datalogger (Logomatic v2, SparkFun Electronics, Boulder, CO, USA). A custom battery (6V, 10Ah Nih-MH Powerizer, AA portable Power Corp., Richmond, CA, USA) power the unit fit snugly in the housing, and foam was added as needed so that it did not shift as the box was tilted.

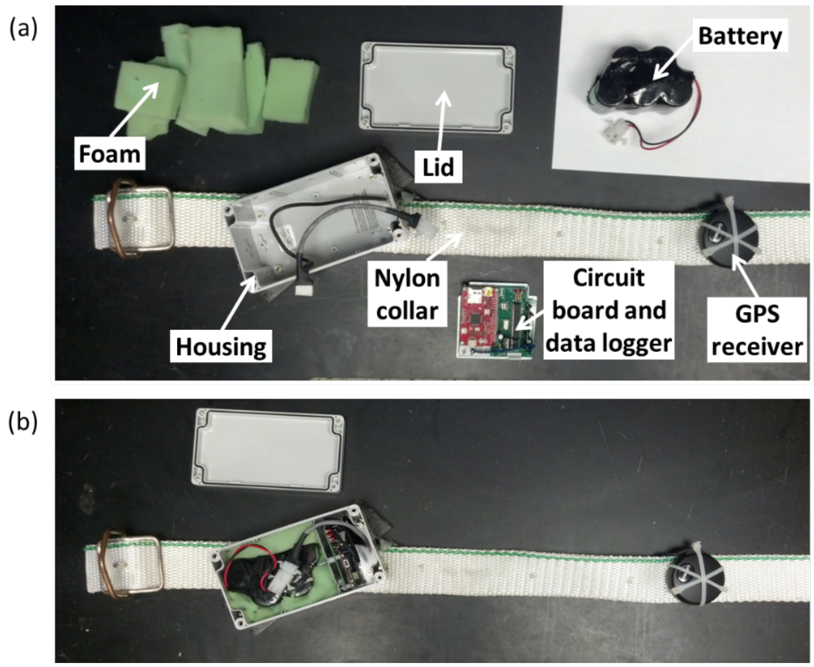


Figure 3.2 (a) Hardware included GPS receiver, circuit board (mounted on sheet metal), datalogger and battery. Custom connector supplies power to the circuit board and connects GPS receiver. (b) Hardware was assembled inside the collar with foam padding around the battery and the lid firmly secured to ensure the unit is weatherproof. Silicone was used to seal the GPS wire entering the housing.

A microcontroller (32 kb flash, 1536 RAM, 256 EEPROM, 25 I/O, SPDIP-28, Microchip Technology, Inc., Noblesville, IN, USA) was programmed to allow the GPS unit to record location fixes at a predetermined interval, and limit power consumed by the hardware. A sample of 4 min was implemented based on previous work by Davis et al. (2011). On connection to the power source, the microcontroller was initialized, and the GPS receiver was given approximately 60 s to search for satellite almanac information and acquire a GPS signal. A location fix was returned as a National Marine Electronics Association (NMEA) 0183 v. 2.0 (2002) string, stored on the Electrically Erasable Programmable Read-Only Memory (EEPROM), and then the GPS receiver was powered off for 3 min with no other external hardware powered on, to conserve power. Collection repeated until 15 location fixes were stored to the EEPROM; then 160 the datalogger was powered on and the 15 location fixes were transferred via serial connection to the datalogger to create a text file on a compact flash card.

3.1.2 Grazing experiments and data collection

The updated GPS tracking system has been applied in several cattle studies across multiple years (Table 3.1). It was firstly tested and applied in grazing studies at the University of Illinois Beef and Sheep Field Research Laboratory (lat 40° 04.7' N, long 88° 13.8' W; elevation 215m), a research farm (owned and managed by University of Illinois) contiguous to the Urbana-Champaign campus, in fall 2010 and summer 2011, while procedures for data collection and GPS unit maintenance were continuously developed and improved during those trials. An 80-hectare pasture of the farm was dedicated to rotational grazing of beef cattle, with approximately 1.53 to 1.83 hectares for each paddock. A mixed group of 24 beef cows and heifers were monitored on fenced fescue pastures by GPS collars for seven consecutive weeks during the summer grazing season of 2011. Two sets of 24 GPS units were exchanged such that the group of cattle was constantly monitored, over eight monitoring periods, for a total of 40 days of monitoring. Two sets were used such that the batteries could be charged, units repaired, and validated for one set while the other set was on cattle. After each set was removed, the condition of the units, completed repairs, and replaced hardware were recorded. For any unit that was beyond repair, it was replaced, such that there were always 24 GPS units deployed at a given time.

Table 3.1 Summary of data collection using a specialized GPS system for tracking grazing cattle locations

Study	Location	Number of units deployed	Monitoring periods
Fall 2010	UIUC Beef Research Farm (Urbana, IL)	8	3×5 days
Summer 2011	UIUC Beef Research Farm (Urbana, IL)	24	8×5 days
Fall 2011	Dudley Smith Farm (Pana, IL)	48	3×5 days
Fall 2012	Dudley Smith Farm (Pana, IL)	36	4×5 days
Fall 2013	Dudley Smith Farm (Pana, IL)	36	4×5 days
Fall 2014	Dudley Smith Farm (Pana, IL)	36	4×5 days

Crop residue grazing studies were implemented at the southern croplands of the Dudley Smith Initiative (DSI) Farm (lat 39° 26.4' N, long 89° 07.1' W; elevation 202m), 6 km northwest of Pana, Illinois, in fall 2011. The Dudley Smith Farm is owned by the University of Illinois, and jointly managed by the Office of Research, within the College of Agriculture Consumer and Environmental Sciences, and the Dudley Smith Initiative. In 2011, the southern croplands of the DSI Farm were divided into six strips used for two grazing management practices (continuous grazing and strip grazing). For each strip, a group of eight heifers was allowed to graze corn residues for 42 days after harvest. The difference between continuous grazing management and strip grazing management is that cattle under continuous grazing management practices had access to all fields within the continuous grazing paddock during the entire grazing period, while a strip grazing paddock was divided into three sections using electric fences and cattle were allowed access to the next section every 14 days. The hypothesis is that strip grazing management may alleviate some adverse effects such as forage quality decrease due to trampling, thus may preserve forage quality as compared to continuous grazing management. Since fall 2012, the residue grazing experiments have been moved to the northern croplands of the DSI Farm. Similarly, the two grazing management strategies (continuous and strip grazing) were compared to ungrazed areas in a randomized complete block design with three replications (Figure 3.3). For both studies in fall 2012 and fall 2013, cows in each group (36 cows, 6 groups) were all instrumented with GPS collars during grazing corn residues. For fall 2014, 6 of 7 cows in a group (42 cows, 6 groups) were instrumented, which was considered a proper subset group size for instrumenting to preserve information with acceptable data loss (see discussions in Chapter 4.2.4).

During the fall grazing studies, cattle were fitted with GPS collars to track their locations during the experiments. Prior to equipping cattle with GPS units, an initial adaptation period was implemented to allow cattle to adjust to wearing weighted collars. Approximately one week before GPS data were collected, cattle were sequentially fitted with a collar and empty equipment box for 1 to 2 days; then a collar and weighted equipment box (similar weight to the GPS collar) for 2 to 4 days; then with functioning GPS for data collection. Collars were secured such that they did not hang loosely or swing from below the neck, but still allowed at least one hand easily placed between the collar strap and the side of the neck. With each subsequent collar placement, fit was adjusted (if needed) to minimize slack in the strap, while avoiding any buildup of fluid beneath the neck.

GPS data were collected at a specified sampling interval of four minutes. To reduce the risk of data loss, data were collected and stored as space delimited text (.txt) files every hour. Each GPS location fix (date, time, latitude, longitude, number of satellites in view, and differential correction status) was held in temporary memory and written to removable compact flash storage after 15 consecutive GPS location fixes were collected; a new file was created for every save event. Spatial coordinates were calculated using the World Geodetic System 1984 earth datum, and the receiver output the date and time in Coordinated Universal Time. GPS accuracy was tested and validated before each deployment. Damaged or inaccurate GPS units were replaced and removed from use.

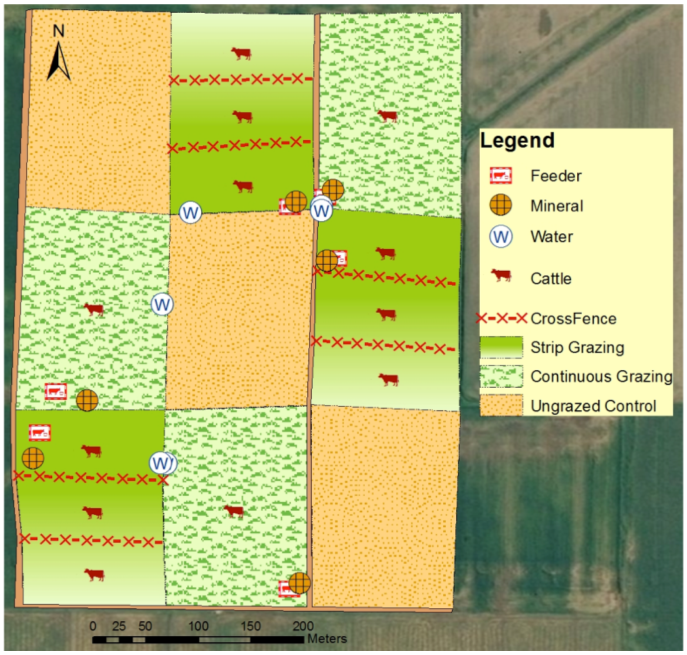


Figure 3.3 Fall corn residue grazing experiments have been implemented at the Dudley Smith Initiative Farm, where the lands were divided into strip grazing, continuous grazing, and ungrazed control paddocks, each of which has three replicates.

3.1.3 Evaluation of GPS accuracy

Data were collected to assess GPS receiver location bias under two scenarios: (i) with receiver vertical (perpendicular from the ground), and (ii) with receiver rotated with respect to vertical and oriented in the four cardinal directions. First, static tests were conducted at the UIUC Agricultural Engineering South Farm (N 40° 4' 14.9", W -88° 12' 41.9", elevation 215m) for 24 h duration under no canopy to evaluate the accuracy of the GPS units (Figure 3.4). Accuracy was assessed by horizontal errors and mean (average centroid) errors based on the 95% confidence interval as described in the Institute of Navigation (ION) Standard 101 Recommended Test Procedures for GPS Receivers (ION, 1997). Data were post-processed in ArcGIS 10 (ArcMap, ESRI, Redlands, California, USA) and the Geospatial Modeling Environment (GME) (Beyer,

2012) to calculate the distance between GPS locations and benchmarks. The center of each GPS receiver was placed directly above a plastic benchmark established by a Real Time Kinematic (RTK) GNSS (R6, Trimble Engineering & Construction Group, Dayton, OH, USA) with a static GNSS surveying horizontal accuracy of 3 mm (0.12 in.). Stated accuracy of the Garmin GPS is 4 m (13.12 ft). Prior to beginning the rotational and orientation study, twelve GPS units were verified for similarity by a means comparison using the average horizontal location errors and were not found to be different.

Each GPS receiver was rotated around a model neck (Figure 3.5), which was constructed of a five-gallon plastic bucket half filled with 5.86 mL of agar-agar to water ratio (to simulate animal body composition) suspended 0.91 m (3 ft) away from the end of a wood sawhorse and placed 0.50 m (1.64 ft) above the benchmark. The bucket was secured to the end of the sawhorse such that the filled end of the bucket was over the benchmarks, and the GPS receiver was rotated about the filled section (Figure 3.5). GPS collars were randomly assigned to benchmark locations and test apparatus (Figure 3.4). The same GPS unit and test apparatus was always tested in the same location, and each apparatus was always oriented the same direction. Half of the units were oriented North/South, and half were oriented East/West, evenly distributed across the physical space in blocks of two units (Figure 3.5).

Data were collected for 24 h for each rotational position: 0° (vertical; GPS receiver directly facing the sky), 45° (angle each side of vertical), 90° (angle each side of vertical), and 180° (GPS receiver directly facing the ground; Figure 3.5). Every GPS collar was rotated in each of the six positions in a Latin square arrangement, such that every position was represented simultaneously. Two Latin squares were completed simultaneously such that all twelve GPS units collected data simultaneously for a consecutive 6 d period under no canopy interference and centered over the previously detailed benchmarks.

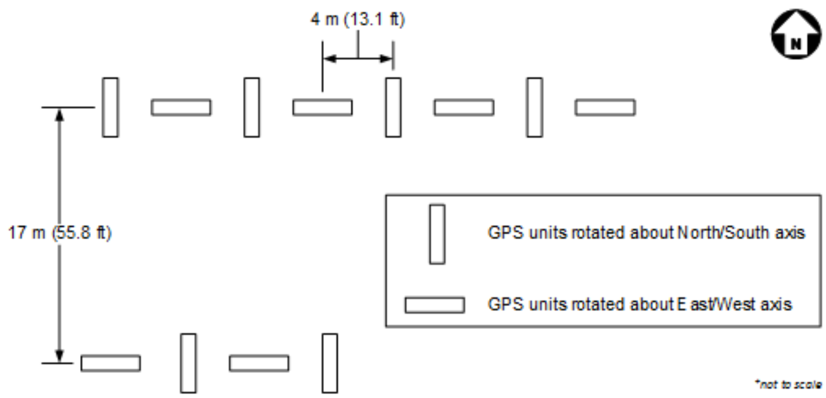


Figure 3.4 Schematic representing physical arrangements of benchmarks and test apparatus to which GPS rotational experiment was applied. Data for each position were recorded for 24 h under no canopy interference.

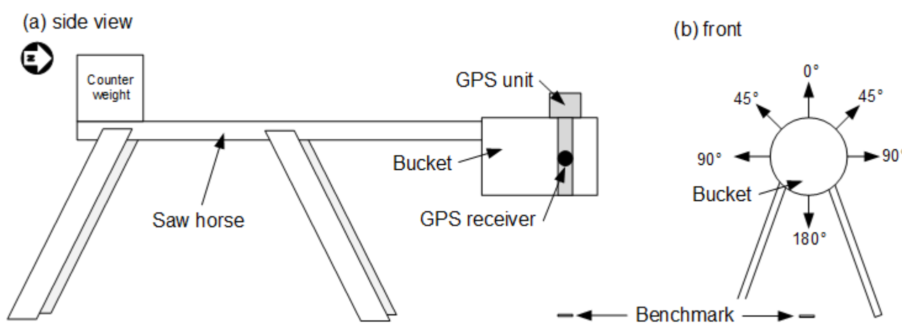


Figure 3.5 (a) Apparatus for GPS rotational experiment (orientated about North/South axis as shown) constructed with a wood sawhorse and five-gallon bucket half filled with an agar-agar mixture to simulate the animal's mass suspended over the benchmark. (b) GPS receivers were placed at 0° (vertical), 180° (bottom), and at 45° and 90° (angle from vertical) facing East and 45°, and 90° facing West.

Position data collected from GPS collars were used to calculate horizontal location errors based on the distance from GPS coordinate to benchmark. An ANOVA was completed including the effects of position, orientation, block, day, and interaction of position and orientation using SAS PROC GLM (SAS Institute Inc., Cary, NC, USA). GPS location error was treated as a repeated measure for the multiple measurements from the GPS receiver over each 24 h period. Treatment effects were considered significant at $\alpha \leq 0.05$.

3.1.4 Assessment of long-term reliability

A protocol for deployment of the GPS units on cattle was developed to minimize the amount of damage to units, or injury to handler and cattle. Reliability of the data was determined by comparing collected location fixes to the expected location fixes per monitoring period. For each monitoring period (4 to 5 days' interval when the GPS units were on the animals), the expected number of location fixes was calculated based on the programmed sampling frequency (1 location per 4 min). Successes and failures of each set of deployed GPS units were evaluated by comparing the collected number of fixes to the expected number of fixes for that monitoring period and expressed as the percentage of GPS units with greater than 90% and less than 10% of the expected location fixes. Further, information regarding GPS units that required repair or replacement after each deployment was also documented for analysis.

3.2 Results and Discussions

3.2.1 GPS accuracy

There was no significant effect of rotation, orientation, block, day, or rotation-orientation interaction (Table 3.2). For orientation, location error (mean ± SE) for GPS receivers was 3.67 ± 0.98 m (North), 3.22 ± 0.48 m (South), 3.07 ± 0.49 m (East), and 3.03 ± 0.28 m (West). For rotation, location errors were 2.76 ± 0.50 m (0°), followed by 3.11 ± 0.59 m (45°), 3.39 ± 0.24 m (180°), and 3.39 ± 0.57 m (90°). The accuracy of the GPS receiver used in this study was much greater than those used in similar studies using wildlife tracking collars; thus, location errors may be less sensitive to different orientation and rotation. With this specific GPS receiver, different animal behaviors (e.g. foraging when the head is lowered, and the GPS receiver would be potentially facing between 0° to 180°) will have a negligible impact on location data. Potential locations could be reduced by maintaining the GPS receiver should be maintained facing skyward (0° to 90°) (D'Eon & Delparte, 2005), but due to the high accuracy of this receiver no adjustments to maintain a skyward-facing receiver are not necessary for data quality assurance during a study using these GPS units.

Table 3.2 Summary of location errors (m; mean ± SE) for effects of position (angle from vertical), orientation (cardinal direction), block, and day.

Position (P = 0.16)	0°	45°	90°	180°		
	2.76 ± 0.50	3.11 ± 0.59	3.39 ± 0.57	3.39 ± 0.24		
Orientation (P = 0.12)	North	South	East	West		
	3.67 ± 0.98	3.22 ± 0.48	3.07 ± 0.49	3.03 ± 0.28		
Block[1]	1	2	3	4	5	6
	3.27 ± 0.55	3.35 ± 0.57	3.15 ± 0.53	3.11 ± 0.49	2.85 ± 0.32	3.41 ± 0.84
Day[2]	1	2	3	4	5	6
	3.17 ± 0.31	3.26 ± 0.62	3.58 ± 0.72	3.14 ± 0.75	3.12 ± 0.63	2.87 ± 0.19

[1] P = 0.43
[2] P = 0.27

3.2.2 Long-term reliability

Over the course of all the grazing studies (expect fall 2010), GPS units were deployed 762 times (during 23 monitoring periods) and collected GPS location data on average (± standard deviation) for 3.63 d (±1.25) d for each monitoring period (Table 3.3). The average duration of data collection was 81.7% of the expected monitoring duration (mostly 4- or 5-day).

All GPS units exhibited some intermittent failure at some point during the monitoring period. Approximately 68% of all GPS units had greater than 90% of the expected and roughly 6% of all units less than 10% of expected data (Table 3.3). Results indicated that as the number of monitoring periods in the study increased, the number of units collecting greater than 90% of the expected data also increased. This may be attributed to the cattle becoming accustomed to the GPS unit and our ability to repair/construct higher quality new GPS units. Although greater than 90% of the expected data was collected, it is still possible that the data will not be continuous (i.e. intermittent gaps), which has an impact on the intended data analysis. Eight of the 23 monitoring periods had no units with less than 10% of the expected data. Suggested reasons for early GPS failure included possible high impact collision with other animals, fences, shelter, and water, causing the connections to break or wear rapidly. Some GPS units returned from the field with GPS receiver wires severed, housing loosened from the nylon collar, or SD card loosened from the slot. Other possibilities include poor battery quality or an error in the electronics, such as a damaged or defective component.

Table 3.3 Long-term reliability assessment (mean ± standard deviation) with the whole group instrumented showed intermittent failure. Knowledge of the data quality should be considered for potential biases in analysis and representation of individual animals

Study	Location	Monitoring period	Number of units deployed	Duration of monitoring period (d)	Mean no. of operating	% units with > 90% data	% units with < 10% data	% of expected total fixes collected	% units requiring some repair after deployment
Summer 2011 (06/03-07/11)	UIUC Beef Research Farm (Urbana, IL)	1	24	4.73	3.65±1.50	67	8	77.2%	79
		2	24	4.72	2.62±1.96	42	25	55.5%	54
		3	24	4.00	2.83±1.83	46	0	70.8%	58
		4	24	4.73	3.84±1.30	67	4	81.2%	71
		5	24	4.76	3.85±1.38	71	4	80.9%	58
		6	24	3.87	3.62±0.46	88	0	93.5%	46
		7	24	4.67	4.39±0.49	83	0	94.0%	46
		8	24	4.86	4.50±0.70	88	0	92.6%	42
Fall 2011 (10/14-11/11)	Dudley Smith Farm (Pana, IL)	1	48	4.35	3.25±1.54	58	15	74.7%	19
		2	48	5.00	4.08±1.49	63	4	81.6%	25
		3	48	5.00	3.95±1.70	65	6	79.0%	23
Fall 2012 (09/13-10/30)	Dudley Smith Farm (Pana, IL)	1	36	4.93	3.74±1.48	55	3	75.9%	21
		2	36	4.93	4.37±1.20	81	3	88.6%	[1]
		3	36	4.93	4.43±1.24	78	0	89.9%	[1]
		4	36	4.93	4.16±1.33	66	6	84.4%	[1]
Fall 2013 (11/02 - 12/15)	Dudley Smith Farm (Pana, IL)	1	36	5.00	3.91±1.72	69	11	78.2%	[1]
		2	36	5.00	4.38±1.12	67	6	87.6%	[1]
		3	36	4.92	3.63±2.01	67	19	73.8%	[1]
		4	36	2.15	1.81±0.66	69	8	84.2%	[1]
Fall 2014 (10/03 - 11/15)	Dudley Smith Farm (Pana, IL)	1	36	3.92	3.16±1.03	61	0	80.6%	39
		2	36	4.88	4.25±1.14	75	0	87.1%	17
		3	35	4.88	4.28±1.07	74	0	87.7%	6
		4	31	1.00	0.81±0.34	74	13	81.0%	[1]

[1] no repair data recorded for these periods

There were always some repairs required after each monitoring period, and typical repairs were cosmetic, including broken zip ties securing the GPS wire to nylon collar, tightening of loose bolts, and silicone replacement (hole for GPS wire to inside box). There were scratches and dents on the polycarbonate housing, and occasionally the circuit board and data logger became dislodged from the metal mount. Failed GPS units not caused by a poor battery occurred randomly throughout the studies. This may have been attributed to the poor or inconsistent construction of some units, which is a viable consideration because several different people contributed to the effort of building units. Although all units were validated prior to implementation, durability would not be predictable in validations. Custom GPS units are significantly less expensive to produce, but may not be as uniform or as a robust in assembly as a commercial product.

A common challenge encountered for wearing a collar-mounted GPS unit is the accumulation of fluid beneath the neck, which requires that the collar is not cinched too tightly around the animal's neck, while still preventing a loosely hanging collar. The rule of the thumb employed in this work for cattle was to secure collar such that they did not hang loosely or swing from below the neck, but still allowed at least one hand easily placed between the collar strap and the side of the neck. With each subsequent collar placement, fit was adjusted (if needed) to minimize slack in the strap, while avoiding any buildup of fluid beneath the neck. An initial adaptation period should be considered before starting a monitoring experiment. Allowing the animal to adapt to adjust to wearing a weighted collar around its neck prior to placing instruments on the animal can help to reduce damage to units. It is recommended to first use a collar without any housing or GPS to acclimate the animal to having something around their neck, followed by a collar with a weighted housing to simulate the actual GPS unit. In the course of these grazing studies, this adaptation period and the fit were shown to be effective to reduce shaking and rubbing that resulted in damage to GPS equipment or problems for the animals.

3.3 Summary and Conclusions

The application of GPS technology has provided researchers with a robust tool to track animal locations for better understanding their spatial dynamics and activities. An updated design of the GPS-HAWK (Davis et al., 2011) was successfully developed and implemented to track beef cattle locations at a 4 min frequency for several grazing studies across multiple years. Results of GPS accuracy evaluation showed that the mean location error of the GPS tracking system was less than 4 meters and was not significantly impacted by position; thus, adjustment of these GPS receivers due to collar rotation during a study is not necessary. Experience and time with multiple field applications of the custom GPS units helped develop cattle acclimation protocols and provide insights to the quality of collected data. Results showed that data loss was common during those studies. Even with entire groups of cattle instrumented, intermittent data loss occurred. Average operating time was 81.7% of the expected duration for all those studies. Approximately 68% of all GPS units had greater than 90% of expected data collected, and approximately 6% of all units had less than 10% of expected data. Long-term reliability assessment showed that data collection was improved during these studies, which may be attributed to the cattle becoming accustomed to the GPS unit and our ability to repair/construct higher quality new GPS units. An initial adaptation period was suggested that can be effective to reduce shaking and rubbing that resulted in damage to GPS equipment or problems for the animals.

CHAPTER 4

MINING GPS DATA FOR PATTERN IDENTIFICATION OF CATTLE MOVEMENT AND EFFECTS OF NUMBER OF ANIMALS MONITORED ON SUBSEQUENT ANALYSIS

The Global Positioning System (GPS) has become an important tool to study animal movements and behaviors. It provides researchers the capability of recording spatial and temporal information for a variety of animals. In agricultural studies, GPS technology has been utilized to study livestock behaviors and activities (Davis et al., 2011; Šárová et al., 2010; L. W. Turner et al., 2000; Ungar et al., 2005). Compared to previous methods of tracking animal locations by visual observation, GPS units worn by animals enable researchers to track animal locations at a user-specified frequency and duration while saving labor costs, achieving higher accuracy, and yielding more complete results. With sufficient animal movement data captured by GPS, the spatiotemporal patterns of animal movements can be better explored. Scientific models can then be developed as a computational approach to simulate animal movement and their interactions with the environment in complex systems (Guo et al., 2009; Tremblay et al., 2009).

While there has been a wide range of approaches for analyzing animal movement data recorded by GPS units, this chapter will focus on three analytical approaches, which are beneficial for understanding the spatiotemporal characteristics of cattle movement during crop residue grazing. These approaches include GPS-based characterization of cattle movement, spatial occupancy analysis of land by cattle, and periodic pattern identification. Movement characterization quantifies cattle movement and provides information for parameterization in model development. Analysis of spatial occupancy converts GPS data into a density map that illustrates the spatial patterns in grazing and facilitates the correlation between cattle locations and their impacts on agricultural lands. It is common that movements of animals may follow some repetitive patterns such as relocating between their bedding areas and foraging areas. If periodic patterns can be detected from raw movement data, it would provide insights into interactions between cattle behaviors and the environment, which may give farm producers additional information for grazing management.

Besides selecting appropriate approaches to analyze cattle movement data collected by GPS units, special caution is also needed for the design of data collection to ensure that data collected via experiments can truly represent the objective of study while introducing as few errors as possible. A reported and persisting challenge regarding tracking animals is labor and cost for monitoring all animals in a group (Swain et al., 2011). There has not been sufficient research regarding the minimum number of animals required to be instrumented within a group in order to accurately preserve information representative enough for describing group behaviors (Anderson et al., 2013; Swain et al., 2011). Further, when monitoring a subset group of animals, the extent of the information loss and its impact on subsequent analysis is unknown. Therefore, this chapter will also evaluate the effects of subset group size on subsequent analysis in tracking cattle movements with GPS collars.

4.1 Materials and Methods

4.1.1 GPS-based characterization of cattle movement

4.1.1.1 Data preprocessing

GPS data of cattle locations were collected using the specialized GPS tracking system for several grazing studies as described in 3.1. All data were downloaded from GPS collars after each collection period. A C++ program was used to merge all the text files into one comma-separated-value (.csv) file while preserving GPS information for each animal. In addition, the program removed corrupted text and converted date and time from Coordinated Universal Time to Central Standard Time, the time zone of the grazing studies. The csv files were then imported to ArcGIS (ESRI, Redlands, CA) and stored as shapefiles for visualization and analysis. Location data were converted from latitude and longitude to the Universal Transverse Mercator (NAD UTM 1983 zone 16N) format to enable calculations of algebraic derivation of distance between locations. Location data with UTM coordinates were then exported as csv files for further computation of movement characteristics.

4.1.1.2 Calculating movement metrics

Based on previously published papers related to characterization or modeling of ungulate movements (Anderson et al., 2012; Davis et al., 2011; Mech & Cluff, 2011; Morales et al., 2005; Moritz, Galehouse, Hao, & Garabed, 2012; Šárová et al., 2010; Shiyomi & Tsuiki, 1999), a set of individual and group movement metrics were defined to characterize cattle movement based on GPS data as described below, including individual travel speed $V_{n,i}$ (m/min), individual distance to herd centroid $D_{n,i}$(m), individual cumulative travel distance $L_{n,i}$ (m), herd centroid coordinates (X_n^c, Y_n^c), herd travel speed V_n^c(m/min), herd radius R_n^c(m), and herd cumulative travel distance L_n^c (m), where *n* denotes the n^{th} time stamp, *i* denotes the cow ID, and *c* denotes the herd centroid. Although GPS data were recorded at a fixed interval (approximately 4 min) on all receivers, data on different receivers were not recorded at exactly the same timestamps throughout the experiments. In order to calculate group movement parameters, a linear interpolation algorithm was used to align the data to the same timeline using the sampling interval. To manage data loss during the experiments, if a GPS receiver failed to receive location data for more than twenty minutes (five consecutive potential records), that portion of the dataset was not interpolated and the animal with that GPS receiver was removed from calculations of group movement parameters for that period of time.

Individual travel speed $V_{n,i}$ was defined as the Euclidean distance between two consecutive GPS locations of an animal divided by the GPS sampling interval Δt (Eq. 4-1). It does not represent the actual animal movement speed, but quantifies the measured displacement of animal locations over time.

$$V_{n,i} = \frac{\sqrt{(X_{n,i} - X_{n-1,i})^2 + (Y_{n,i} - Y_{n-1,i})^2}}{\Delta t} \tag{4-1}$$

$X_{n,i}$, $Y_{n,i}$ – UTM coordinates of cow i at the nth time stamp.

Individual cumulative travel distance $L_{n,i}$ was defined as the cumulative distance traveled by individual cow i at the nth time stamp (Eq. 4-2).

$$L_{n,i} = \sum_{t=2}^{t=n} \sqrt{(X_{t,i} - X_{t-1,i})^2 + (Y_{t,i} - Y_{t-1,i})^2} \tag{4-2}$$

Herd centroid coordinate (X_n^c, Y_n^c) was defined as the geometric center of the herd, and was calculated by averaging the coordinates of all animals with GPS records at the nth time stamp (Eq. 4-3).

$$X_n^c = \frac{\sum_i X_{n,i}}{I_n}, Y_n^c = \frac{\sum_i Y_{n,i}}{I_n} \tag{4-3}$$

I_n - Number of animals with GPS records at the nth time stamp.

Individual distance to herd centroid $D_{n,i}$ was defined as the Euclidean distance between cow i and the herd centroid at the nth time stamp (Eq. 4-4).

$$D_{n,i} = \sqrt{(X_{n,i} - X_n^c)^2 + (Y_{n,i} - Y_n^c)^2} \tag{4-4}$$

Similar to individual travel speed, herd travel speed V_n^c was defined as the Euclidean distance between two consecutive locations of the herd centroid divided by the sampling interval Δt (Eq. 4-5).

$$V_n^c = \frac{\sqrt{(X_n^c - X_{n-1}^c)^2 + (Y_n^c - Y_{n-1}^c)^2}}{\Delta t} \tag{4-5}$$

Further, herd radius R_n^c was defined as the average distance to herd centroid for all cattle in the group at the n[th] time stamp (Eq. 4-6).

$$R_n^c = \frac{\sum_i D_{n.i}}{I_n} \tag{4-6}$$

Herd cumulative travel distance L_n^c was defined as the cumulative distance traveled by the herd centroid at the n[th] time stamp (Eq. 4-7).

$$L_n^c = \sum_{t=2}^{t=n} \sqrt{(X_t^c - X_{t-1}^c)^2 + (Y_t^c - Y_{t-1}^c)^2} \tag{4-7}$$

To analyze cattle movements throughout 24 hours and identify potential periodic patterns in individual travel speed, individual travel speed was resampled every two hours using the mean values of speed calculated via Eq. 4-1. Multiple days' results were then combined to calculate the means and standard deviations of individual travel speed for every two-hour interval (e.g. 00:00 a.m. to 02:00 a.m.).

During GPS data collection as described in 3.1.2, some GPS units may have undergone intermittent failure due to many reasons. Errors due to incomplete collection of GPS could be introduced into subsequent analyses. To reduce the impacts of data loss, GPS datasets that have high completeness are desired. Therefore, based on data completeness, GPS datasets of one group of cattle were selected for calculating movement metrics, for each grazing treatment and for each year, from 2012 to 2014 as shown in Table 4.1.

Table 4.1 Selected GPS datasets for calculating cattle movement metrics

No	Year	Group name	Number of cows monitored	Selected period of data
1	2012	CG3	6	2012-09-29 to 2012-10-02
2		SG2	6	2012-10-13 to 2012-10-16 2012-10-27 to 2012-10-30
3	2013	CG3	6	2013-11-03 to 2013-11-07
4		SG1	6	2013-11-16 to 2013-11-20 2013-11-30 to 2013-12-04
5	2014	CG2	6	2014-10-04 to 2014-10-07
6		SG1	6	2014-10-17 to 2014-10-21 2014-10-31 to 2014-11-04

Note: CG – Continuous grazing; SG – Strip grazing

4.1.2 Analysis of spatial occupancy of land by cattle

ArcGIS 10.1 (ESRI, Redlands, CA) spatial analysis tools were used to quantify the spatial occupancy of land by cattle. Two density analysis tools were considered: point density and kernel density. Both methods implement raster-based density calculation to represent discrete points (GPS fixes) as a field of values. The point density tool calculates the density of point features around each output raster cell. A neighborhood is defined around each raster cell center, and the number of points that fall within the neighborhood is totaled and divided by the area of the neighborhood. Several options for neighborhood shape can be specified, including annulus, circle, rectangle and wedge (ArcGIS Help 10.1). The kernel density tool also calculates the density of point features around each output raster cell. However, a smoothly curved surface is fitted over each point. The surface value is highest at the location of the point and diminished with increasing distance from the point, reaching zero at the search radius distance from the point. Only a circular neighborhood can be used. The volume under the surface equals to the population field value for the point. The density at each output raster cell is calculated by adding the values of all the kernel surfaces where they overlay the raster cell center. The kernel density tool in ArcGIS 10.1 uses the quadratic kernel function described in Silverman (1986, p.76, equation 4.5) (ArcGIS Help 10.1).

Selecting the appropriate density analysis tool may depend on study objective, spatial resolution of data, and the size of output raster cells. In this study, GPS location fixes were treated as point data to generate density maps, and the accuracy of the GPS receiver was approximately 4 meters at 95% confidence. Kernel density that uses a circular neighborhood with the search radius of 4 m is a feasible approach for quantifying the spatial density of cattle locations, if the cell size of the output raster cell is compatible with the search radius (e.g. cell size = 2 m and search radius = 4 m). However, if the output cell size is relatively too large as compared to the search radius (e.g. cell size = 20 m and search radius = 4 m), GPS fixes outside the search neighborhood but still within the output raster cells may not be counted for determining the density values of the output cells when implementing kernel density estimation. In this study, the spatial occupancy of land by cattle will later be correlated with other datasets (e.g. crop yield data) to evaluate grazing impacts. Thus, a common spatial resolution is desired for correlation analysis. Considering this need, the cell size of output raster for density analysis of cattle locations was set to 10 meters, same as the spatial resolution of crop yield data. Therefore, instead of using kernel density (output cell size (10m) is not compatible with the search radius (4m)), point density tool was implemented for analyzing all the GPS data collected at the DSI Farm during 2012 to 2014. The search neighborhood was set to a square (10m * 10m), and the size of the output raster cell is 10 m * 10 m too.

4.1.3 Pattern identification for cattle movement

To identify potential periodic behaviors in cattle movements, a data mining algorithm (Periodica, Li et al, 2012) for periodic behavior identification of moving object data was considered for this analysis. This approach includes two stages: 1) detecting periods that are associated with specific spots, and 2) statistically modeling the periodic behaviors using a generative model. As this study focused on whether cattle have periodic activities that are associated with specified areas in the field such as shelters, bedding areas and water sources, only the first stage of the algorithm was adapted for analysis.

The first step of the approach is to identify the areas of interest, namely reference spots, assuming cattle have periodic movements associated with these spots. The reference spots are usually dense areas that are frequently visited by cattle, such as bedding areas, or areas that have specific functioning facilities for cattle, such as shelters, water tanks, feed bunks and so on. These areas can be identified using a density-based method or can be specified if the locations of facilities are known previously. For example, using point density analysis for GPS data, areas with the highest densities can be detected as the potential bedding areas for cattle. Note that bedding areas are obtained via density analysis for each animal individually. Areas with cattle facilities can also be specified based on satellite images or through a field survey using a handheld GPS.

Let $D = \{(x_1, y_1, t_1), (x_2, y_2, t_2), ...\}$ be the raw GPS locational data for an individual cow, which may not have been collected at a constant time interval in the experiment due to various reasons such as GPS intermediate failures. (x, y) are the coordinates of a location fix under the NAD_1983_UTM coordinate system. The raw data were linearly interpolated with a constant time gap (236 seconds), which was the mean customized sampling interval for GPS units used in the experiments. The interpolated location sequence is denoted as $L = (loc_0, loc_1, loc_2, ..., loc_{N-1})$. Viewed from a reference spot, the location sequence was then converted into a binary sequence $B = (b_0, b_1, b_2, ..., b_{N-1})$, where $b_i = 1$ when the animal is within the reference spot at timestamp i

and 0 otherwise. This transform filters out the spatial noise and turns the problem from a 2-dimensional space (i.e. spatial) to a 1-dimensional space (i.e. binary) (Periodica, Li et al, 2011). As long as the animal has periodic patterns visiting the reference spot, the periodicity can then be detected from the binary sequence associated with the reference spot.

To detect periodicity in the binary sequence, a two-tier approach named AUTOPERIOD (Vlachos, Yu, & Castelli, 2005) was adapted in Periodica, combining periodogram and circular autocorrelation. The periodogram was used for extracting period candidates from the signal (binary sequence), namely "hints"; circular autocorrelation was then used to validate the period hints and refine it if the periodicity hint refers to a broad range of period. The detailed steps of AUTOPERIOD are described as follows.

Given a binary sequence $B = (b_0, b_1, b_2, ..., b_{N-1})$ for analysis, the normalized Discrete Fourier Transform (DFT) of B is a sequence of complex numbers $X(f)$:

$$X(f_{k/N}) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} b(n) e^{-\frac{j2\pi kn}{N}}, k = 0, 1, ..., N-1 \tag{4-8}$$

Where k / N denotes the frequency that each coefficient $X(f)$ captures.

The periodogram is defined as the squared length of each Fourier coefficient:

$$P(f_{k/N}) = \left\| X(f_{k/N}) \right\|^2, k = 0, 1, ..., \left\lceil \tfrac{N-1}{2} \right\rceil \tag{4-9}$$

Each element of the periodogram provides the power at frequency k / N. Since period is the inverse of frequency, by identifying the frequencies that carry most of the energy, the most dominant periods can be discovered. In order to find which frequencies are important from the periodogram, we need to determine an appropriate threshold that can distinguish the energy carried by the dominant frequencies of energy that has been attributed to a random process.

The threshold was determined using the following method. Let sequence B' be the outcome of a random permutation on the elements of the sequence B. Since the new sequence B' should not exhibit any periodicities, even the maximum power in the periodogram does not indicate periodicities in B'. Thus, we recorded the maximum power ($p_{\max}$), and only the frequencies in B that have higher power than $p_{\max}$ could be considered as candidates for periodicity. To provide a 99% confidence interval on what frequencies are important, the above random permutation experiment was repeated 100 times and the maximum power of each permutated sequence was recorded as well. The 99th largest value of these 100 experiments should provide a sufficient estimator of the power threshold.

Given $P(f_{k/N})$ is greater than the power threshold, we still need to determine the exact period, because the coefficient $X(f_{k/N})$ corresponds to a range of periods $[\frac{N}{k}, \frac{N}{k-1})$. To do this, the Circular Autocorrelation Function (ACF) was used, which examines how similar a sequence is to its previous values for different τ lags:

$$ACF(\tau) = \frac{1}{N}\sum_{n=0}^{N-1} B(n) \cdot B(n+\tau) \qquad (4\text{-}10)$$

The significance of a candidate period can be determined by examining the curvature of the ACF around the candidate period. For each period range $[\frac{N}{k}, \frac{N}{k-1})$ given by the periodogram, we test whether there is a peak in $\{ACF(\frac{N}{k}), ACF(\frac{N}{k}+1), ..., ACF(\frac{N}{k-1}-1)\}$ by fitting the data with a quadratic function. If the resulting function is concave downward in the period range, which indicates the existence of a peak, we return the closest peak

$T = \arg\max_{\frac{N}{k} \le t < \frac{N}{k-1}} ACF(t)$ as a detected period. Similarly, a 99% confidence level was implemented to eliminate false positive caused by noise.

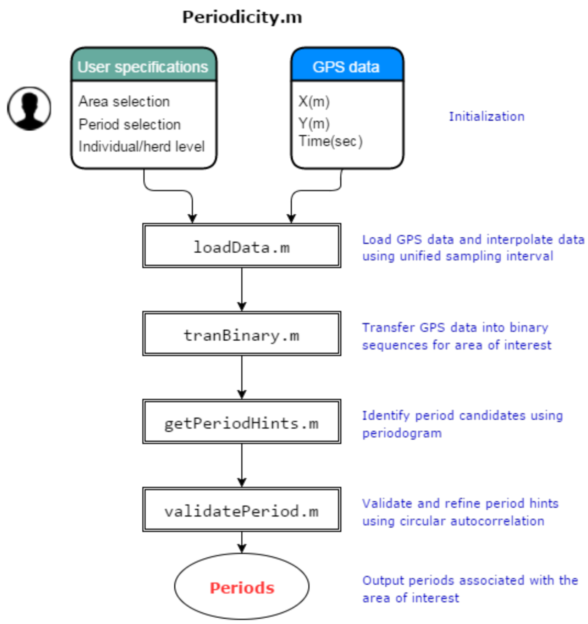


Figure 4.1 Diagram of MATLAB programs for identifying periodic movements of cattle. Input datasets include animal location data recorded by GPS, and user specifications that include the area of interest, the length of data and options to study at individual or herd level.

The algorithm was implemented in MATLAB (R2012b, The MathWorks, Natick, MA) (Figure 4.1). GPS data collected during summer (2011) and fall (2012) grazing experiments as described in 3.1.2 were investigated for identification of cattle periodic behaviors. Three types of reference spots that might be associated with cattle periodic behaviors were considered, including bedding areas of cattle, surrounding areas of water tanks, and surrounding areas of feed bunks. The bedding areas were identified using the point density analysis tool in ArcGIS (ESRI, Redlands,CA) that outputs the density values of cattle visitation for each cell (10 m×10 m). Areas with the top 10% density values among all the density values of all cells were determined as the bedding areas. Surrounding areas of water tanks or feed bunks were determined as a 10 m×10 m square area where the water tank or feed bunk was located. GPS data of beef cattle collected at the University of Illinois Beef and Sheep Field Research Laboratory (lat 40° 04.7' N, long 88° 13.8' W; elevation 215m) during 2011 summer grazing and at the DSI Farm (lat 39° 26.4' N, long 89° 07.1' W; elevation 202m) during 2012 fall grazing were both mined for potential periodic patterns.

4.1.4 Effects of number of animals monitored on subsequent analysis

In order to investigate the effects of number of animals monitored on subsequent analysis, two analytical approaches for GPS data were considered: cattle movement characterization and analysis of spatial occupancy by cattle. The hypothesis is that there exists a subset group size that is representative of the entire herd with acceptable errors for characterization of cattle movement and cattle spatial occupancy analysis. As herd size may have influences on group movement characteristics that may yield different outcomes, this analysis has included two groups of cattle with different herd sizes from two different study sites for investigation. Results of movement data analysis were compared across subset groups and the entire herd, followed by a comparative statistical analysis to evaluate the impacts of monitoring a subset group of cattle on subsequent GPS data analysis.

The first study site was located at the University of Illinois Beef and Sheep Field Research Laboratory (lat 40° 04.7' N, long 88° 13.8' W; elevation 215m). A mixed group of 24 beef cows and heifers (group A, mean body weight 452.2 24.9(SD) kg) were monitored on fenced fescue pastures by GPS collars for seven consecutive weeks during the summer grazing season of 2011. The second study site was located at the DSI Farm (lat 39° 26.4' N, long 89° 07.1' W; elevation 202m), 6 km northwest of Pana, Illinois. The second group (group B, mean body weight 526.4 6.7(SD) kg) including 8 Angus heifers was monitored on the corn residue fields for six consecutive weeks during the fall grazing season of 2011. Based on the data availability and quality, two sets of GPS data were selected from the two groups respectively: GPS records beginning at 00:00 June 2, 2011 and ending at 00:00 June 10, 2011 (eight consecutive days) were selected for analysis of group A; GPS records beginning from 10:00 October 24, 2011 and ending at 00:00 October 28, 2011 (approximately three and a half consecutive days) were selected for analysis of group B. For both selected periods, cattle were grazing within the same paddocks at their respective farm locations. Approximately 1.83 hectares of pasture (a 96 m × 378 m × 390 m right triangular paddock) was available to group A, and approximately 1.75 hectares' corn residue land (a 68 m × 257 m rectangular paddock) was available to group B during their respective periods. Both studies were conducted on flat areas under no canopy (variations of elevation < 3 m). During the course of the studies, GPS units were never dislodged by the animals. GPS accuracy was tested and validated before each deployment. Damaged or inaccurate GPS units were replaced and removed from use.

4.1.4.1 Cattle movement characterization

Data synchronization

To calculate group movement metrics, GPS data from different individuals were firstly synchronized using the method described in 4.1.1.2. For group A, the average number of location fixes collected per day per animal was 318 (about 87.0% of expected location fixes). Group B acquired almost all data of expected fixes (only 9 fixes were lost for the entire group during the whole study period), as each animal had about 363 fixes per day.

Generating subset groups

Subset groups were generated by randomly using different combinations of animals. For group A, subset group sizes were generated ranging from 4 to 20 animals with an increment of one. Given a subset group size k, the subset group should contain k distinct cows from group A, and the number of k-combinations is equal to the binomial coefficient C(24,k). Since group A had 24 animals in total, even the smallest number of k-combinations (C(24,4) or C(24,20)) is 10,626, while the largest number (C(24,12)) is 2,704,156. Therefore, instead of considering all possible combinations, 1000 unique random subset groups, a number large enough to represent the characteristics of the population, were generated for each subset group size of group A. Similarly, for group B, subset group sizes were generated ranging from 1 to 7 with the increment of one. All possible subset groups for each subset group size were considered (largest number of k-combinations is 70).

Calculating movement metrics

Movement parameters were defined and calculated using Eq. 4-1 ~ 4-7 as described in 4.1.1.2. All the parameters were stored as time series that were calculated at every time stamp. In order to compare results between subset groups and the entire herd, mean values over the whole period were calculated including average herd travel speed $\bar{V}^c$ (m/min), average herd radius $\bar{R}^c$ (m), and average herd daily travel distance $\bar{L}^c$ (m/day) for comparison between subset groups and the entire group. Additionally, average centroid location deviation $\bar{C}_{dev}$ (m) and average herd radius deviation $\bar{R}_{dev}$ (m) were calculated to quantify the average errors caused by subsampling.

Average herd travel speed $\bar{V}^c$ was defined as the mean value of centroid speed over the whole period (Eq.4-11).

$$\bar{V}^c = \frac{\sum_{n=1}^{n=N} V_n^c}{N} \qquad (4\text{-}11)$$

N - Total number of time stamps

Average herd daily travel distance $\bar{L}^c$ was defined as the mean daily distance traveled by the centroid of herd over the whole period (Eq.4-12).

$$\bar{L}^{c} = \frac{L_{N}^{c}}{T_{N}} \quad (4\text{-}12)$$

T_N - Total period length (day)

Average herd radius $\bar{R}^{c}$ was defined as the mean herd radius of the group over the whole period (Eq.4-13).

$$\bar{R}^{c} = \frac{\sum_{n=1}^{n=N} R_{n}^{c}}{N} \quad (4\text{-}13)$$

Average centroid location deviation $\bar{C}_{dev}$ was defined as the mean distance between the centroids of subset group and the entire herd over the whole period (Eq.4-14).

$$\bar{C}_{dev} = \frac{\sum_{n=1}^{n=N} \sqrt{(X_{n}^{c'} - X_{n}^{c})^{2} + (Y_{n}^{c'} - Y_{n}^{c})^{2}}}{N} \quad (4\text{-}14)$$

($X_{n}^{c'}, Y_{n}^{c'}$) – Centroid coordinates of the subset group at the n^{th} time stamp

Average herd radius deviation $\bar{R}_{dev}$ was defined as the mean deviation between subset group and herd radii over the whole period (Eq.4-15).

$$\bar{R}_{dev} = \frac{\sum_{n=1}^{n=N} \sqrt{(R_{n}^{c'} - R_{n}^{c})^{2}}}{N} \quad (4\text{-}15)$$

$R_{n}^{c'}$ - Herd radius of the subset group at the n^{th} time stamp.

4.1.4.2 Spatial occupancy analysis

Generating subset groups

Because group A had a larger herd size than group B, group A was considered a better demonstration of the results for a wider range of subset group size (similar results have been observed for group B). As described in 4.1.4.1, the number of possible combinations of subgroups of group A is enormous. Due to limitations (e.g. data storages and processing time), a selection of possible combinations was included in this analysis, consisting of subset group sizes ranging from 4 to 20 with an increment of 2. For each subset group size, five different random subset groups were selected for analysis.

Kernel density estimation

A kernel density estimation (KDE) was performed to convert GPS point data to a raster map that quantifies cattle visitation rates at specific locations throughout the fields. This allows us to consider herd impacts upon field characteristics. The GPS R95 accuracy (4 m) was used as the search radius, with output raster map cell size of 2 m by 2 m.

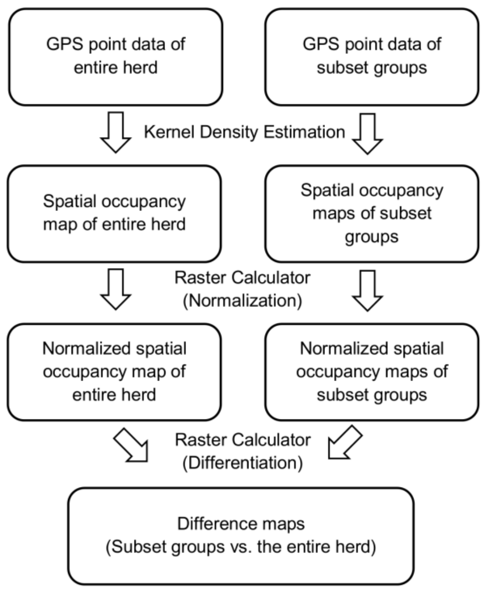


Figure 4.2 Geoprocessing workflow for comparing KDE maps of subset groups with the entire herd.

ArcGIS ModelBuilder (ESRI, Redlands, CA) was used to facilitate the spatial comparison of density maps of grazing distributions between subset groups and the entire herd via GPS point data.

The geoprocessing workflow in ArcGIS includes generation and comparison of normalized density maps between subset groups and the entire herd (Figure 4.2). Kernel density estimation was performed for subset groups and the entire herd. Then, the density maps were clipped to ensure that all maps had the same domain. Since the range of output raster cell values was different for different subset groups, for each density map, all cell values were normalized linearly to a common range (0 to 1) for comparison. Finally, these normalized density maps were compared between subset groups and the entire herd based on their spatial locations, and new raster maps were created that denoted the differences. The cell values in the new maps were equal to the differences between subset groups and the entire herd.

4.1.4.3 Comparative statistical analysis

For each subset group size, there were many different combinations of animals to form the subset group; thus, an error tolerance was introduced to evaluate the effects of subset group size on the results of movement characterization and spatial occupancy analysis statistically based on whether the subset group's results lie within the error tolerance.

For average herd travel speed, average herd daily travel distance, and average herd radius, the entire herd's results were assigned as the "true" value, and the error tolerance was defined as an interval with a ±5% bandwidth of the true value. For average centroid location deviation and average herd radius deviation, the GPS R95 accuracy (4.0 m) was used as the error tolerance. Any results that were below R95 were considered acceptable because the source of this error cannot be distinguished between the limitation of GPS accuracy or by using the subset group instead of the entire herd. For each subset group size, the percentages (S) of results calculated by subset groups that were within the error tolerance were calculated (Eq.4-16 and Eq.4-17).

$$S = \frac{N_{|errors \leq 5\%|}}{N_{total}} \times 100\% \tag{4-16}$$

$$S = \frac{N_{errors \leq R95}}{N_{total}} \times 100\% \tag{4-17}$$

In spatial occupancy analysis, a normalized KDE map illustrated the field visitations by cattle. Further, a difference map was created to denote the differences between subset group and the entire herd. The cell values of this map were close to zero if KDE maps of subset groups and the entire herd were similar. Likewise, an error tolerance of ±0.05 was introduced, and the percentage (S) of cells in the difference map whose value is less than or equal to 0.05 was calculated (Eq. 4-18).

$$S = \frac{N_{|errors| \leq 0.05}}{N_{total}} \times 100\% \tag{4-18}$$

S - The percentage of instances (subset groups in movement characterization) or cells (KDE maps in spatial occupancy analysis) within the error tolerance.

N_{total} - Total number of instances (subset groups in movement characterization) or cells (KDE maps in spatial occupancy analysis).

$N_{|errors| \leq 5\%}$ - Number of instances within the error tolerance that is an interval with a ±5% bandwidth off the true value.

$N_{errors \leq R95}$ - Number of instances within the error tolerance that is below the GPS R95 accuracy

$N_{|errors| \leq 0.05}$ - Number of cells within the error tolerance in the KDE map.

4.2 Results and Discussions

4.2.1 Cattle movement characterization

Beef cattle are usually considered as group-living ungulates, as they prefer to stay together in groups, and members are often highly interactive with each other. They often synchronize their behaviors to a large extent (e.g. resting and grazing) (Šárová, Špinka, &

Panamá, 2007); and their movements are often coordinated in time (synchronization) and in space (cohesion of the herd) (Šárová et al., 2010). According to the GPS data collected during the fall grazing experiments at the DSI farm from 2012 to 2014, the results of movement characterization show that individual travel speeds of cattle were highly synchronized within each group but not necessarily across different groups (Figure 4.3 ~ 4.5). Individual cows under strip grazing or continuous grazing management both have shown similar patterns for individual travel speed with regards to synchronization within a group. However, the maximum individual speeds derived from GPS data have shown differences with regards to grazing periods when comparing the two grazing management practices; the maximum individual speed was presumably constrained by the accessible size of land for grazing, given a 4-minute sampling interval for GPS data collection. In a strip grazing paddock, the field was divided into three equal strips by using electrified fences, and a group of beef cattle were allowed access to the first strip for the first 14 days, and then the next strip every 14 days. As cattle had increasing area of land for access during strip grazing, the maximum individual travel speed in a group derived from GPS data also increased as grazing area was expanded. For example, the maximum individual speeds of cattle from SG1 in year 2013 were 22.5 m/min, 31.5 m/min, and 45.0 m/min for the first, second, and third data collection period of strip grazing, respectively. Cattle under continuous grazing management had fixed areas for grazing during the entire grazing experiment; therefore, the maximum individual speed for each grazing period did not increase in strip grazing. For example, the maximum individual speeds of cattle from CG3 in year 2013 were 48.1 m/min, 47.9 m/min, and 38.7 m/min for the same three data collection periods as strip grazing. For both strip and continuous grazing, the values of maximum individual speeds were close to the values of longest Euclidian distances within accessible areas divided by the GPS sampling interval (4 minutes). This indicates that the actual maximum moving speed of a cow may be higher than the values derived from GPS data, as the speed variable only quantifies the straight displacement of animal locations over time as defined above. Therefore, to capture the real travel speed of a cow, higher GPS sampling frequency is required.

To further investigate the synchronization of travel speeds within a group, the mean individual travel speed of all animals in the group was calculated at every time stamp and then compared with herd travel speed that quantifies how fast the centroid of the entire herd moves. Results show that the dynamics of mean individual travel speed were highly coordinated with centroid travel speed in time (Figure 4.6). A strong positive linear relationship was found between the two variables (Figure 4.7a). In fact, herd travel speed is always no greater than mean individual travel speed, theoretically. The only circumstance under which the two variables are equal requires all animals in the group to move towards exactly the same direction. Since types of cattle behaviors are often associated with individual travel speed (Guo et al., 2009; Moritz et al., 2012; Šárová et al., 2010), the strong linear correlation between mean individual speed and centroid travel speed implies that cattle behavior may be identified not only at the individual but also at the herd level. However, as centroid speed increases, the variability of individual cow speed has also increased (Figure 4.7b). This variation of individual speed indicates the differences among individuals during movements, which may be associated with the social hierarchy in the herd, with the top dominant individuals leading most of the herd's activities and low-ranking individuals following the leaders.

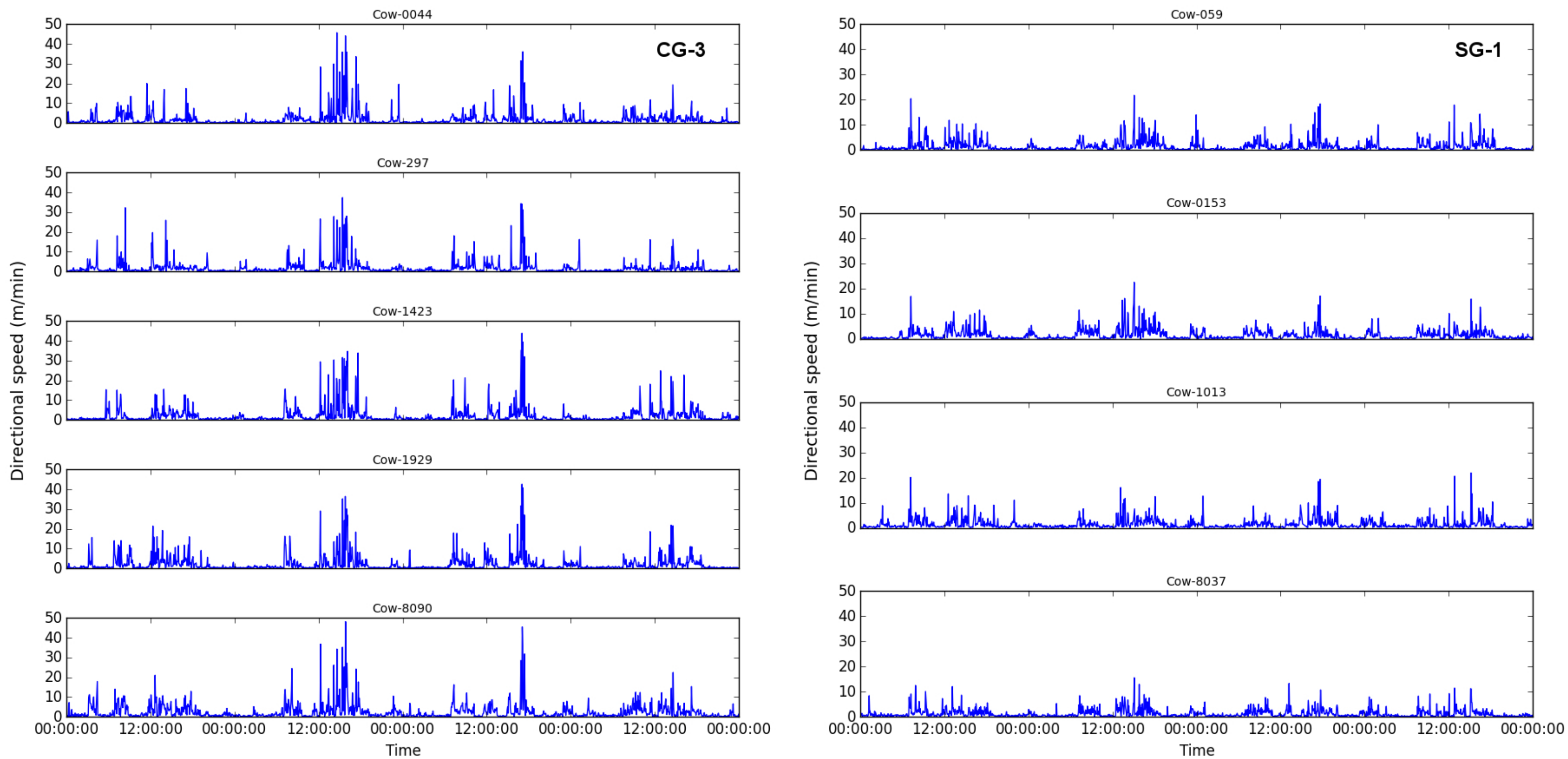


Figure 4.3 Individual cow travel speeds of two groups (CG3 and SG1) during the first grazing period in 2013 (00:00:00 a.m. November 3rd, 2013 ~ 00:00:00 a.m. November 7th, 2013)

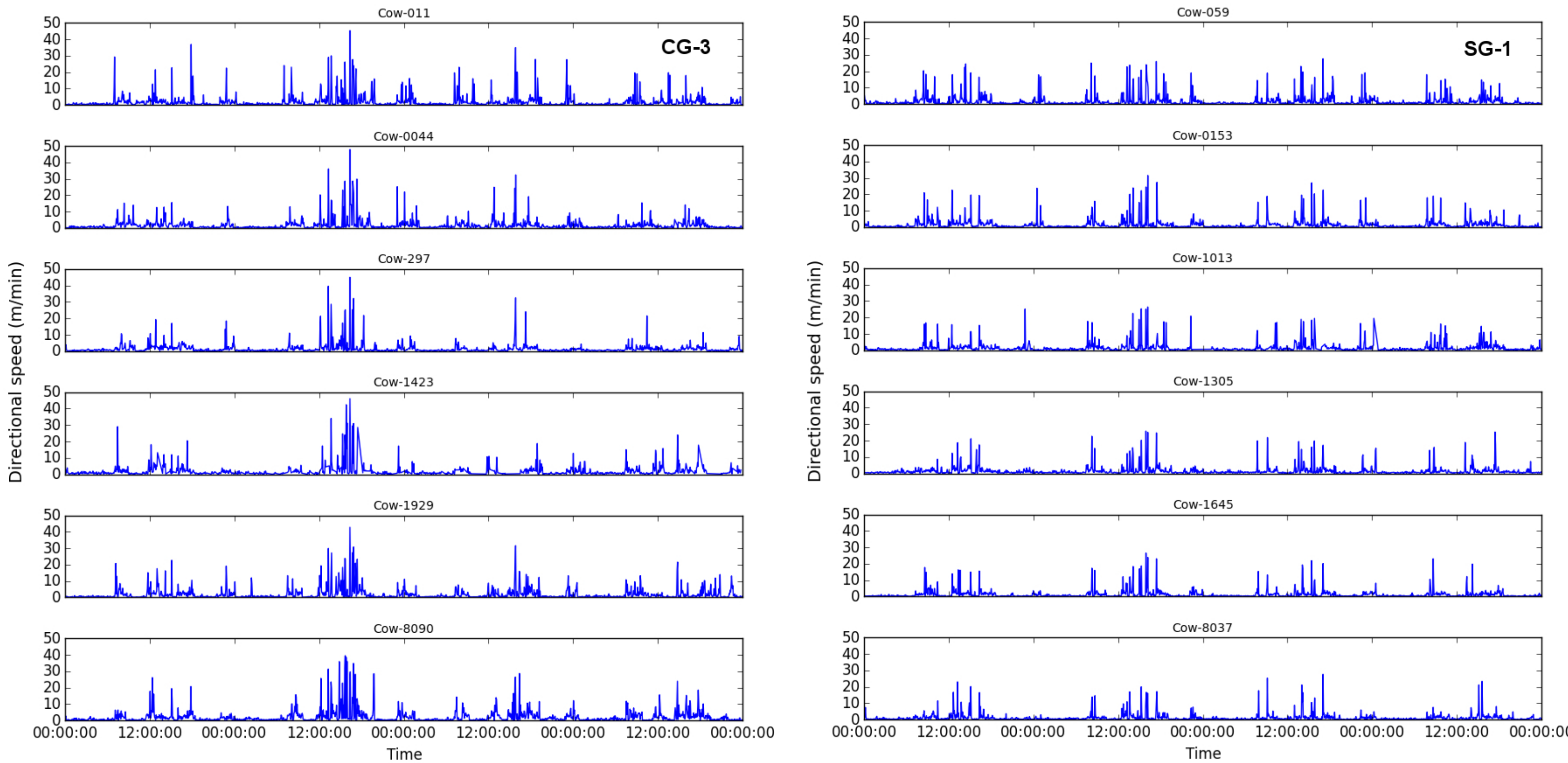


Figure 4.4 Individual cow travel speeds of two groups (CG3 and SG1) during the second grazing period in 2013 (00:00:00 a.m. November 16th, 2013 ~ 00:00:00 a.m. November 20th, 2013)

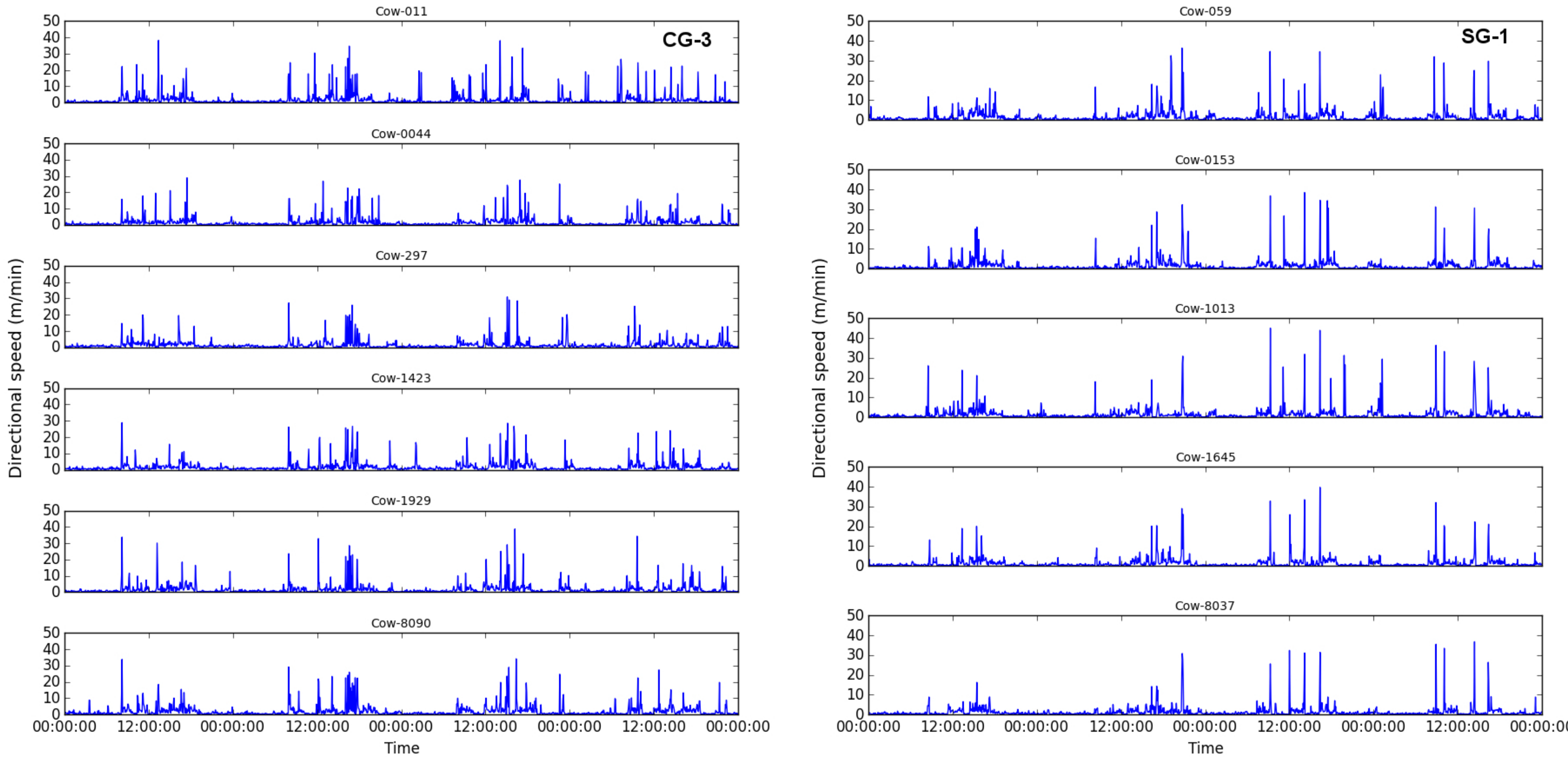


Figure 4.5 Individual cow travel speeds from two groups (CG3 and SG1) during the third grazing period in 2013 (00:00:00 a.m. November 30th, 2013 ~ 00:00:00 a.m. December 4th, 2013)

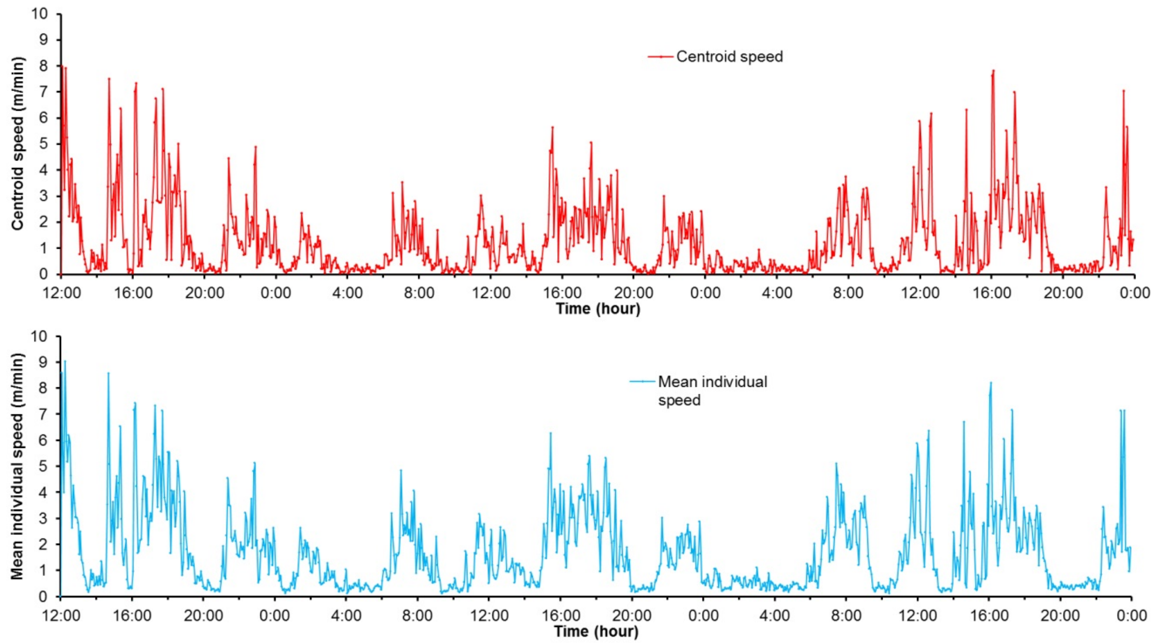
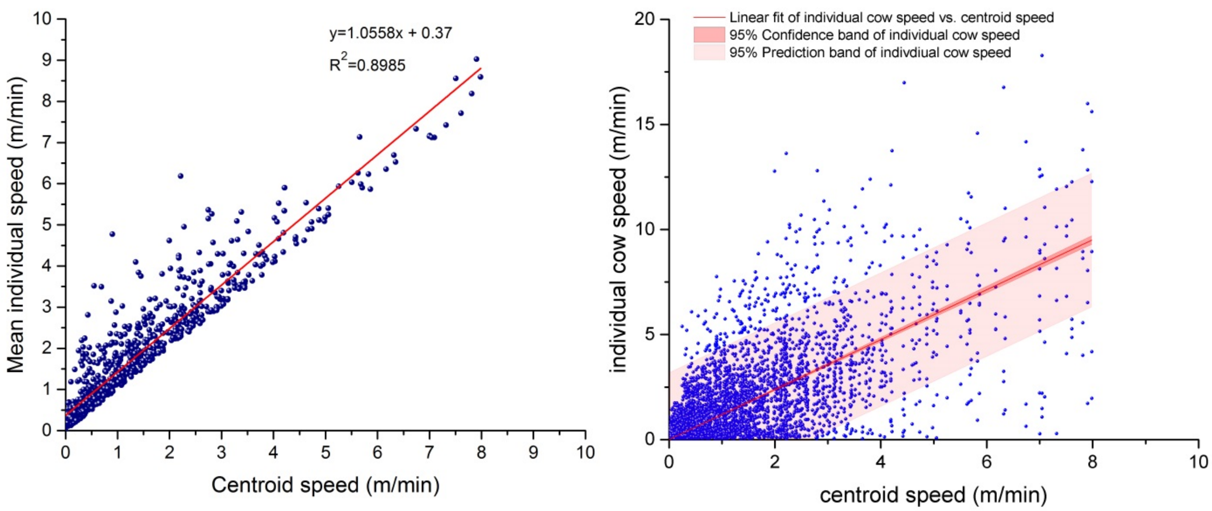


Figure 4.6 Mean individual speed vs. centroid speed of cattle from SG2 during the first grazing period (12:00:00 p.m. September 29th, 2012 to 00:00:00 October 2nd, 2012)



(a) (b)

Figure 4.7 Correlation between mean individual speed and centroid speed of cattle from SG2 during the first grazing period (12:00:00 p.m. September 29th, 2012 to 00:00:00 October 2nd, 2012)

As results show that individual travel speeds were highly coordinated in time, relative distances of individual animals from the centroid of the herd were also investigated for considering the cohesion of the herd (in space). Movement metrics were filtered using a threshold value (1 m/min) of the mean individual speed for a distinction between behavioral states of the herd, given that the accuracy of the GPS receiver was approximately 4 meters at

95% confidence and location fixes were collected at a 4-min interval. Using the speed threshold, herd activities were coarsely classified as active (mean individual speed > 1 m/min) or inactive (mean individual speed ≤ 1m/min). Results show that the herd radius was greater when the herd behavioral state was active, and also had a greater variability than that when the herd was inactive (Figure 4.8). For instance, the herd radii of SG2 during the three monitoring periods in 2012 were 20.8(mean) ± 9.1(SD) m, 22.8 ± 8.8 m, and 26.4 ± 15.3 m when the herd was active, and were 16.0 ± 7.1 m, 14.0 ± 6.7 m, and 11.5 ± 7.5 m when the herd was inactive. This indicates that cattle intended to stay closer to each other when the herd was inactive (usually during resting). Such information extracted via calculating movement metrics could be used in parameterization and calibration for modeling animal movements. However, while animal movements are usually linked to specific behaviors that can be characterized by models, using GPS data alone to distinguish and determine cattle behavioral states remains difficult, especially when predicting resting and grazing activities (Ungar et al., 2005) or the transition between behavioral states (Swain et al., 2011). In addition to GPS data, additional behavioral data are often collected to improve the predictive ability for cattle behavioral activities (Guo et al., 2009; Schwager, Anderson, Butler, & Rus, 2007; L. W. Turner et al., 2000; Ungar et al., 2005).

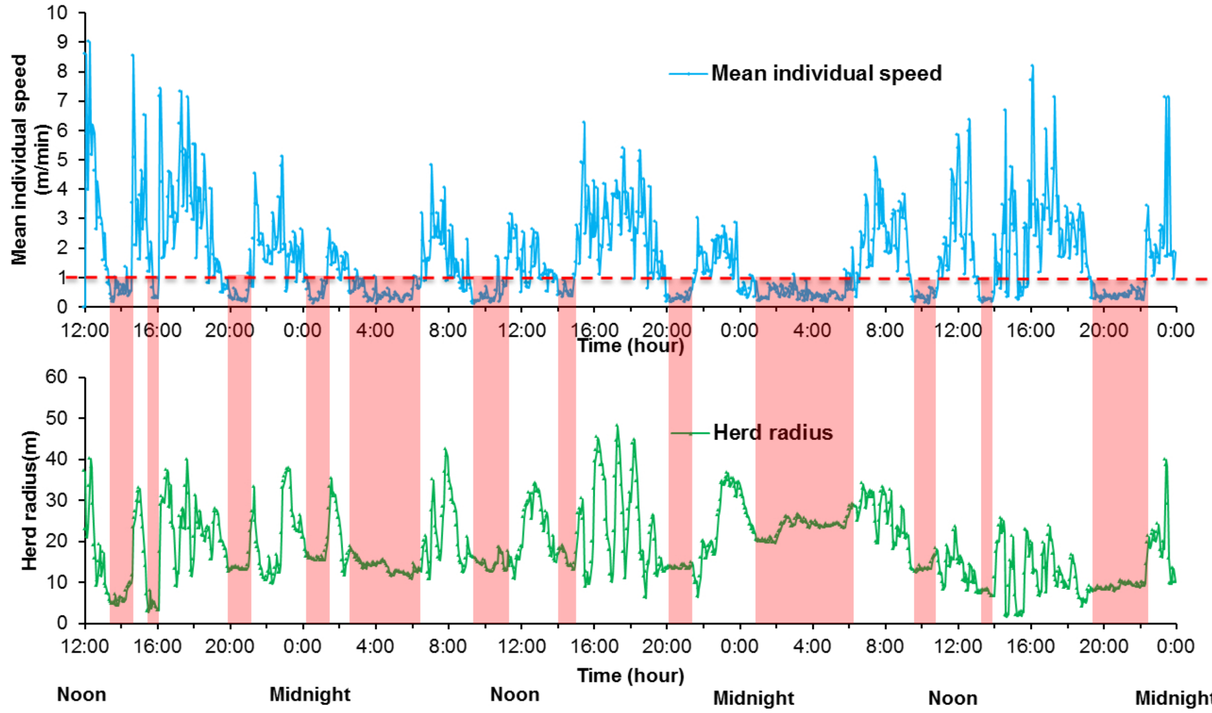


Figure 4.8 Individual speed vs. herd radius of cattle from SG2 during the first grazing period (12:00:00 p.m. September 29th, 2012 to 00:00:00 October 2nd, 2012)

Resampling and averaging the individual travel speed for every two hours give an overview of cattle movements during a day (Figure 4.9 ~ 4.11). Results show that most of the cattle movements occurred during the daytime (i.e. between 6 a.m. and 6 p.m.), and the cows had some minor movements before midnight (i.e. between 8 p.m. and the midnight). The peak of individual bi-hourly mean speed occurred between 2 p.m. and 4 p.m. for most of the cows monitored, but it also had relatively greater day-to-day variability for that period. During the night (i.e. between the midnight and 4 a.m.), the cows had much fewer movements as compared to that in daytime, and the day-to-day variabilities were also smaller, presumably due to the fact that cattle were resting at night.

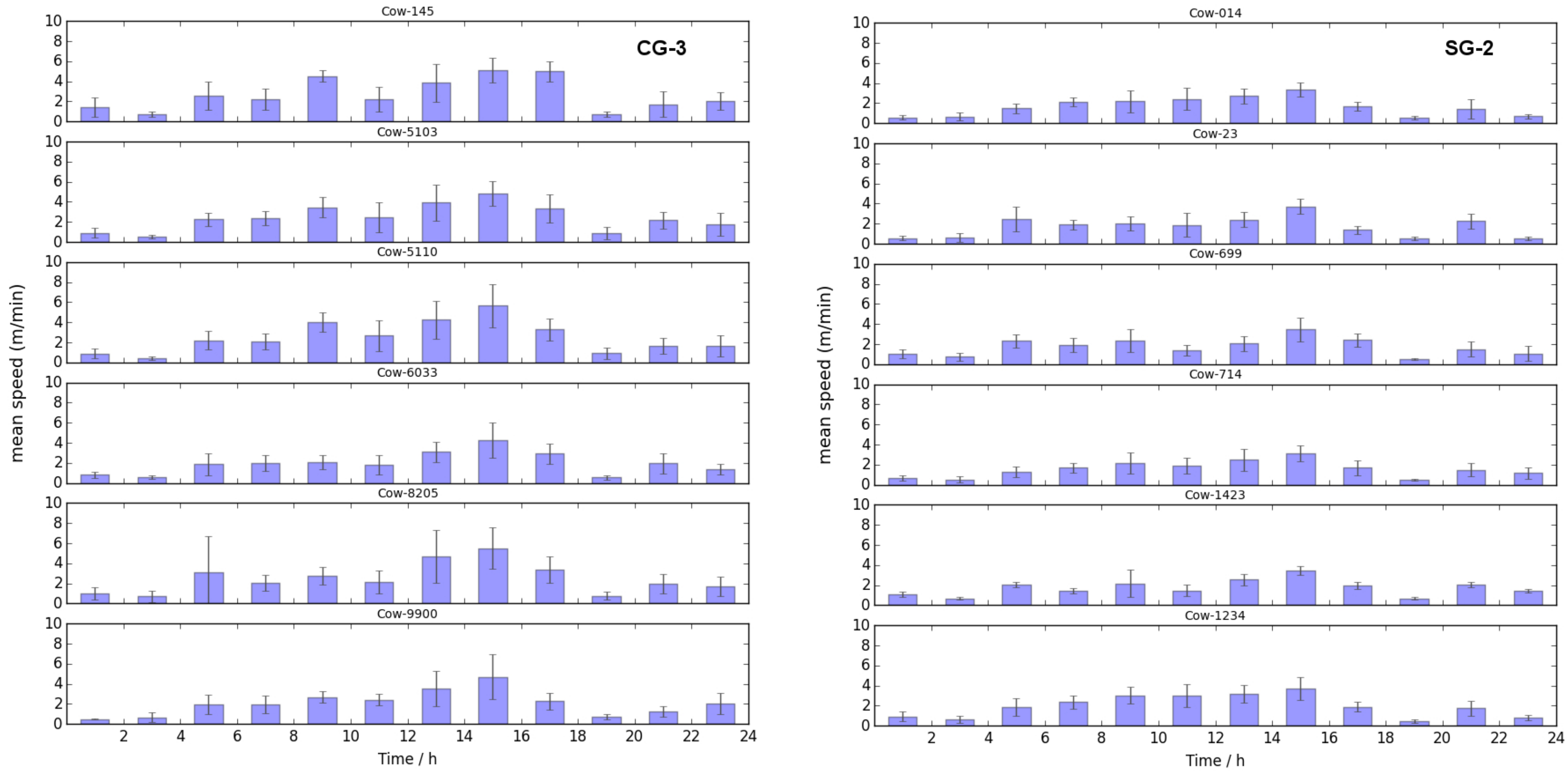


Figure 4.9 Mean bi-hourly individual speeds from two groups of cattle (CG3 and SG2) during fall grazing in 2012. Error bars exhibit day-to-day variations.

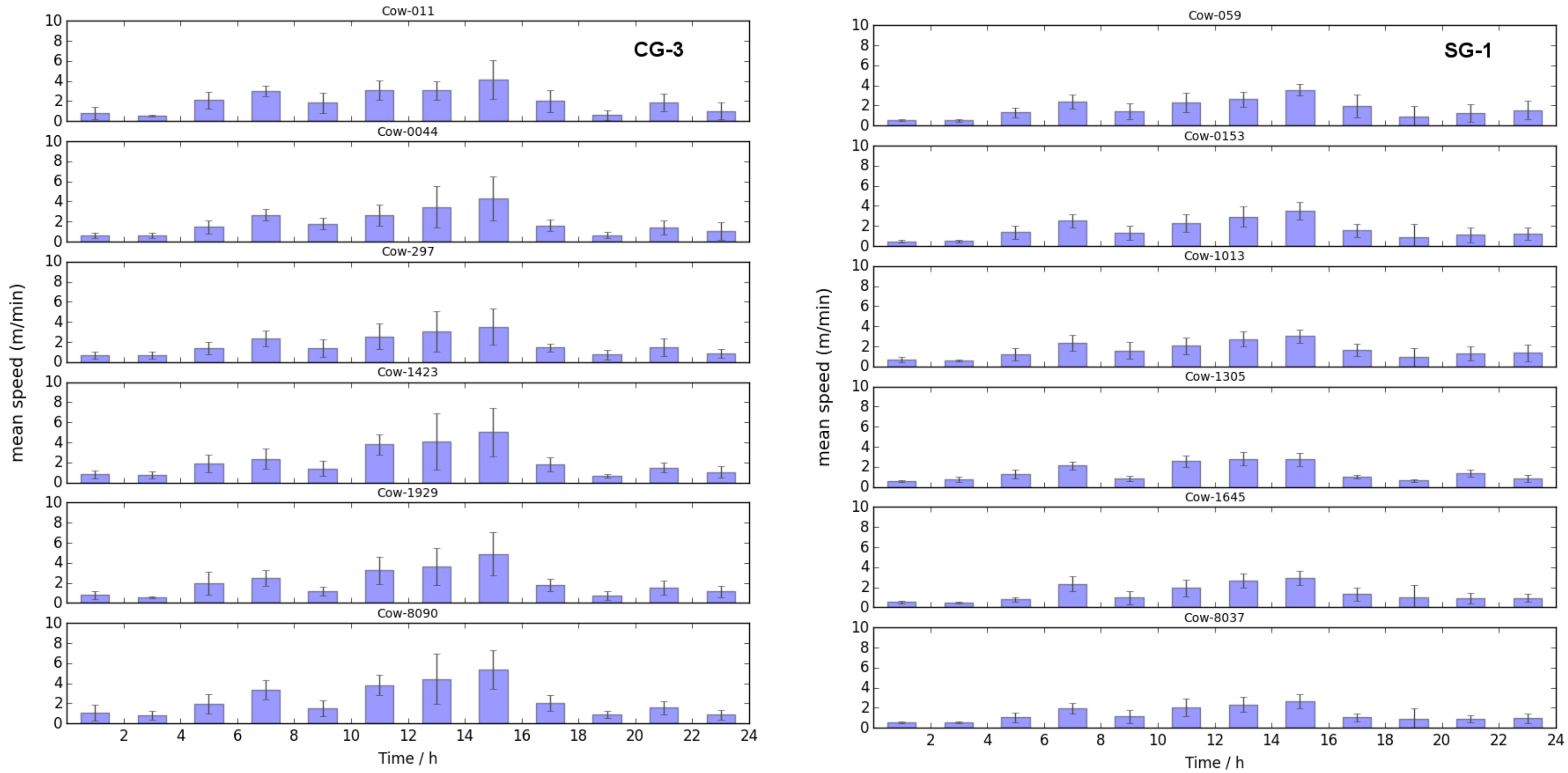


Figure 4.10 Mean bi-hourly individual speeds from two groups of cattle (CG3 and SG1) during fall grazing in 2013. Error bars exhibit day-to-day variations.

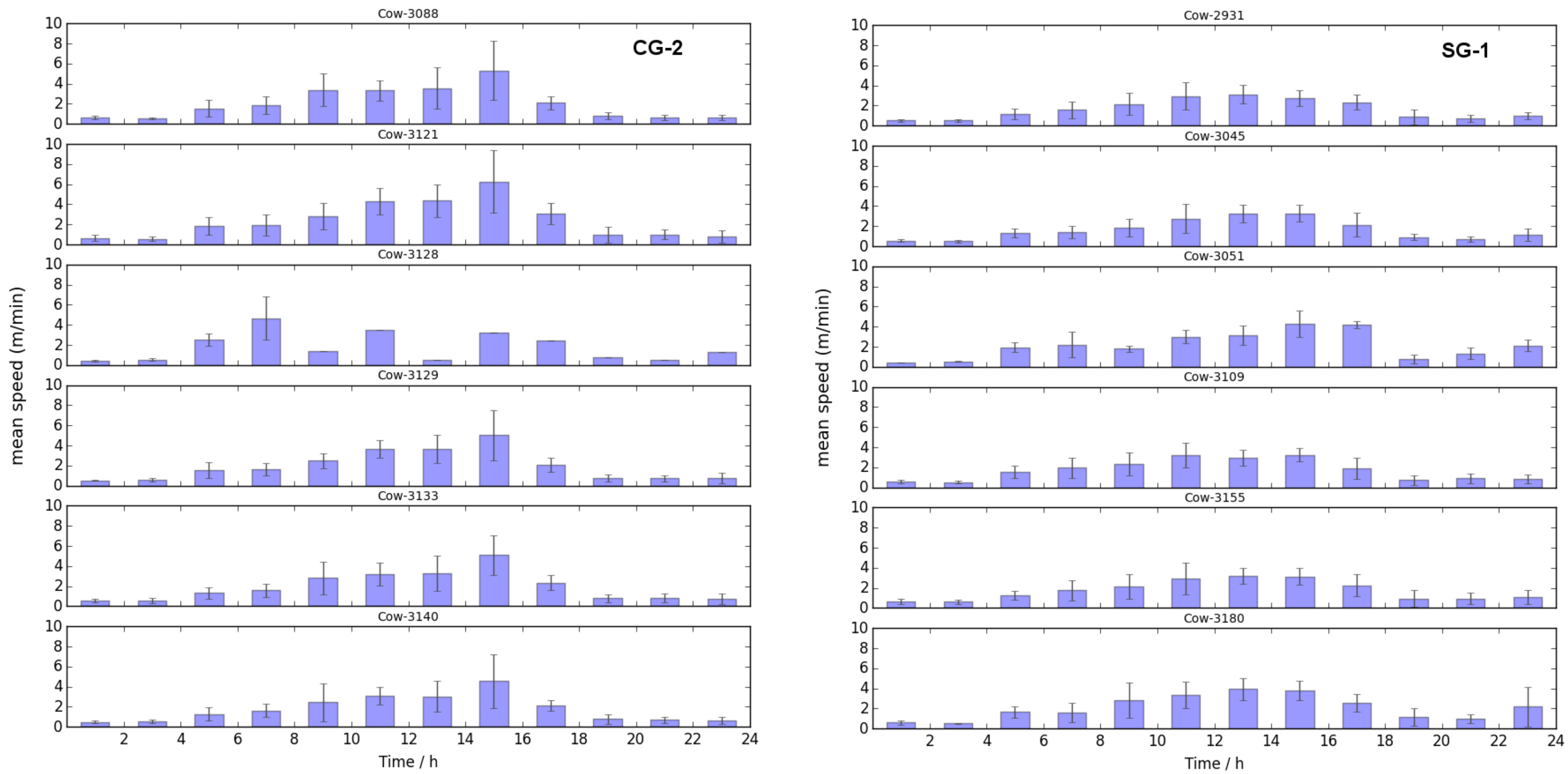


Figure 4.11 Mean bi-hourly individual speeds from two groups of cattle (CG2 and SG1) during fall grazing in 2014. Error bars exhibit day-to-day variations.

ANOVA results show that grazing treatment had significant impacts on the daily travel distance by cattle ($P<0.01$), based on the three years' (2012 ~ 2014) results derived from GPS data (Figure 4.12). Cattle under continuous grazing management had longer daily travel distance during the monitoring periods as compared to those under strip grazing management, likely due to the difference in the size of accessible land for cattle controlled by grazing management practices. For example, during the first grazing monitoring, the daily travel distances of cattle under continuous grazing management were 4143.4 ± 480.6 m (2012), 3111.8 ± 385.8 m (2013), and 2871.5 ± 409.5 m (2014), while the daily travel distances of cattle under strip grazing management were 2376.8 ± 100.3 m (2012), 2175.4 ± 185.7 m (2013), and 2715.9 ± 330 m (2014). The smaller accessible area of land early in the strip grazing experiments presumably had decreased the daily distance traveled by cows, which might result in fewer energy expenditures and more energy savings toward body weight gains, as cows in the strip grazing treatment showed more body weight gains than those in the continuous grazing treatment after grazing.

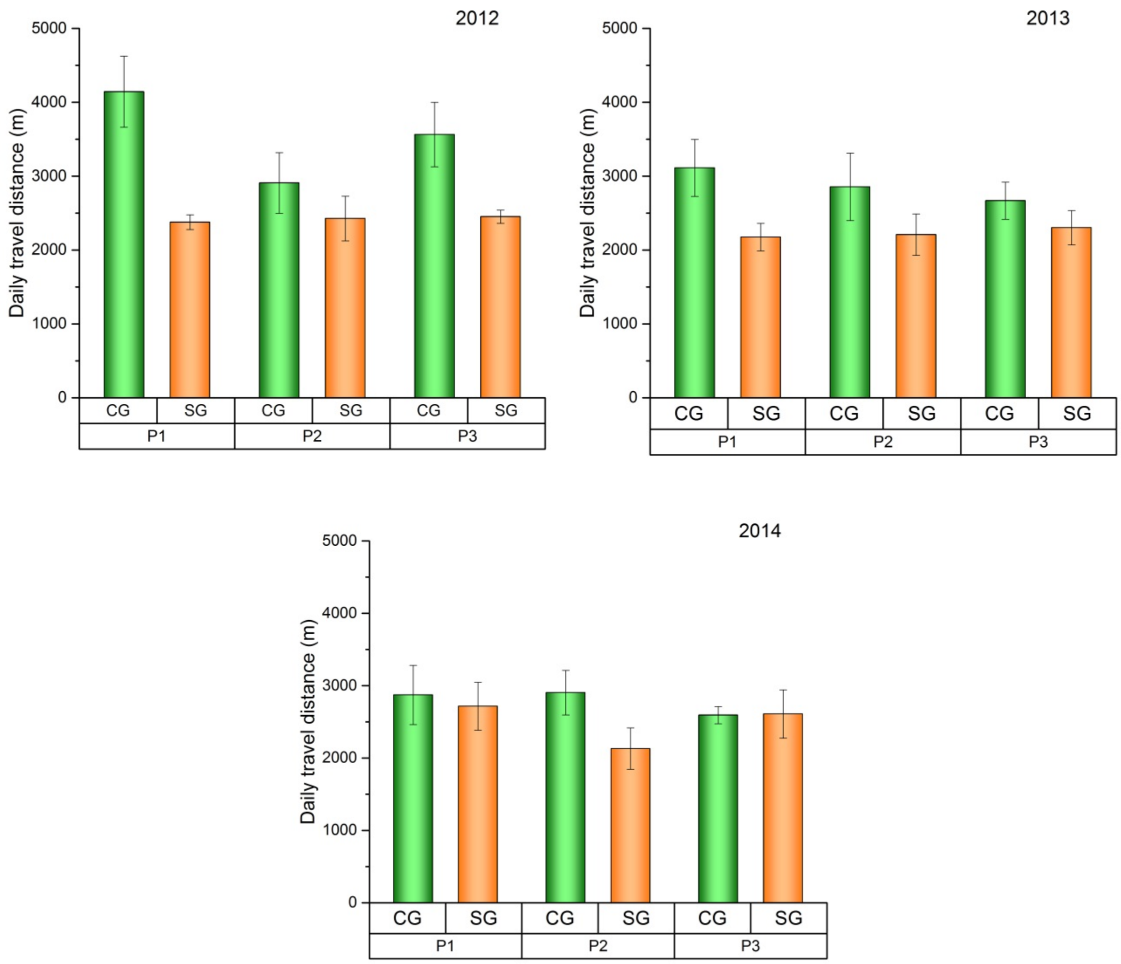


Figure 4.12 Mean individual daily travel distances under two grazing treatments (CG and SG) during three grazing periods (P1, P2, and P3) of fall 2012, 2013, and 2014.

4.2.2 Understanding spatial heterogeneity of grazing and management practices

As social animals, cattle not only synchronize their behaviors, but also have the same favored areas for various activities such as resting, grazing, and drinking (Guo et al., 2009; D. D. Johnson & Ganskopp, 2008). Based on the GPS tracking data collected during the fall residue grazing experiments from 2012 to 2014, results of spatial occupancy analysis show that the cattle locations recorded by the GPS units were unevenly distributed during the treatments (Figure 4.13). The most heavily trafficked areas were identified as bedding areas for cattle. As discussed in 4.2.1, GPS data have shown that individual cows in a group tended to stay closer to the herd when they were inactive (e.g. during resting). Cattle may spend a significant amount of time (e.g. up to half) for resting during a day (Ungar et al., 2005), thus huge amounts of GPS location fixes could accumulate on those favored bedding areas, which became heavily trafficked spots as shown in the density maps (Figure 4.13). Individual cows often had similar bedding areas potentially due to high interactions within the same group; interactions among different groups of cattle might also affect the locations of bedding areas. For example, bedding areas of the cows from CG1 and SG1 were close to each other and were located near the shared fences of those two paddocks, so were bedding areas of the cows from CG3 and SG3 (Figure 4.13).

For both continuous and strip grazing paddocks, the areas around the stationary feed bunks were also identified as heavily trafficked spots (Figure 4.13). Since corn residue is usually considered as a low-quality feedstuff for livestock due to its physiological maturity, cattle were supplemented three times weekly in stationary feed bunks with mixed pelleted corn gluten feed (50%) and soybean hull (50%). During the grazing treatments, it was often observed that cows were loitering near the feed bunks and expecting supplementation. Once supplemental feeds were provided, cattle would quickly move towards the feed bunks and start to consume the feeds. As the areas around the feed bunks were associated with heavy cattle visitation shown by the GPS data, it is expected that changing supplementation strategies (e.g. amount of feeds, supplementation frequency and locations of feed bunks) may be used as a means of grazing management strategies to manipulate cattle movements and alter the spatial patterns of cattle distributions during crop residue grazing.

Comparing with continuous grazing, strip grazing management had shown more significant impacts on cattle movements across time. The cattle were found to be very sensitive to the locations of the electrified cross fences, which were temporarily used to divide the strip grazing paddock into three equal fields for grazing. Point density analysis based on multiple years' data show that cattle relocated most of their movements to the new strip that was available to them after the next cross fence was removed for each strip grazing period, and seldom went back to the previous strips except a few visits to the water tanks and feed bunks (Figure 4.14). These results may indicate that cattle would use external and environmental cues (i.e. removal of cross fences) and their cognitive capabilities to navigate across the field and choose grazing sites based on the amount of available food left on the ground. While cattle under continuous grazing management were having access to all the residues left in the corn field from the first day of grazing, it is anticipated that strip grazing can be used to manipulate the spatial patterns of the herd across time and temporally allocate forages for grazing. The quality of forages in the following strips thus may be preserved for later use in such way to improve cattle performance, as trampling from cattle can reduce forage quality.

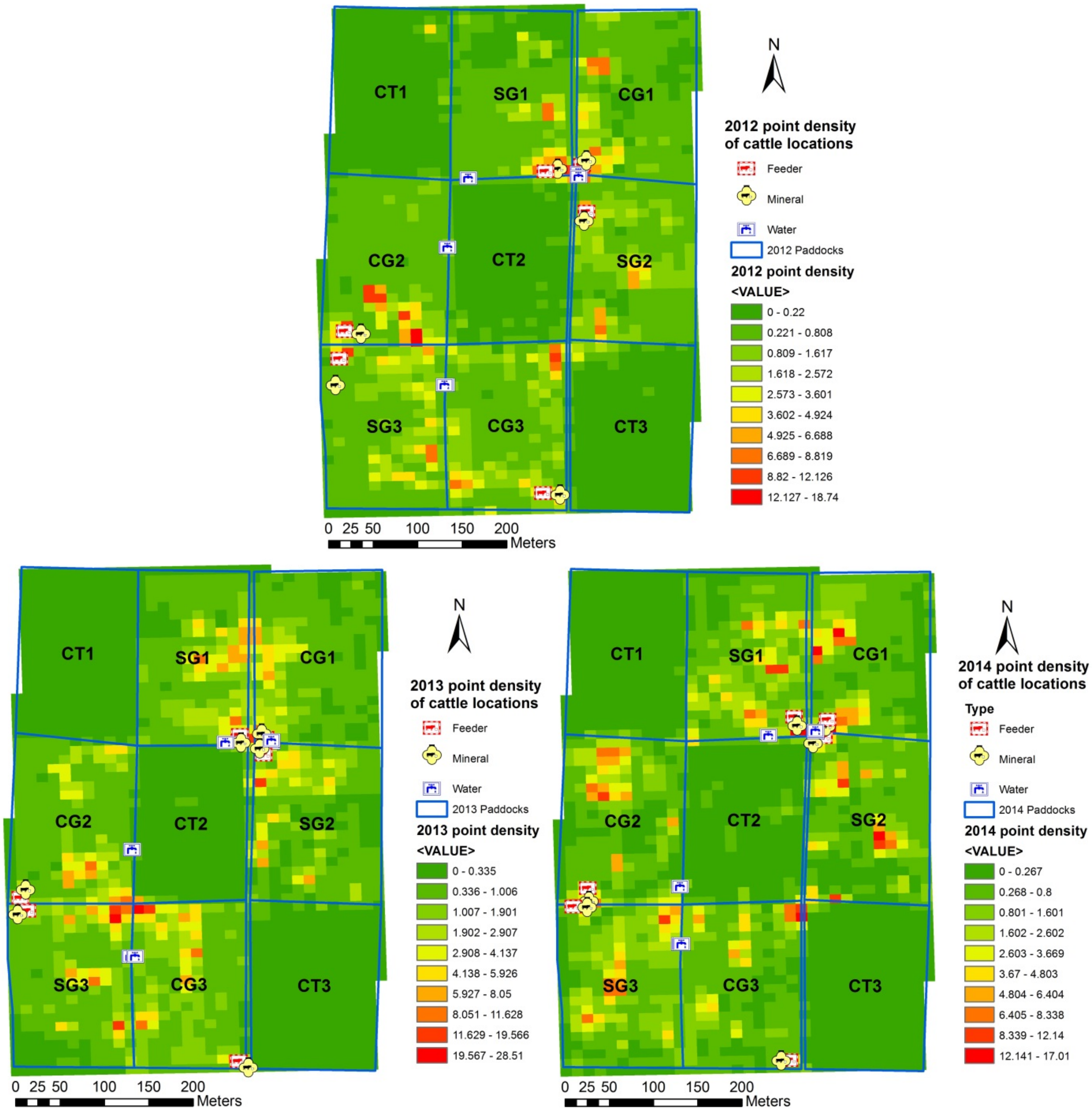


Figure 4.13 Point density maps of field visitation by cattle illustrate uneven distributions of cattle locations on continuously grazed and strip grazed corn residues at the Dudley Smith Initiative Farm in fall grazing studies of 2012, 2013 and 2014.

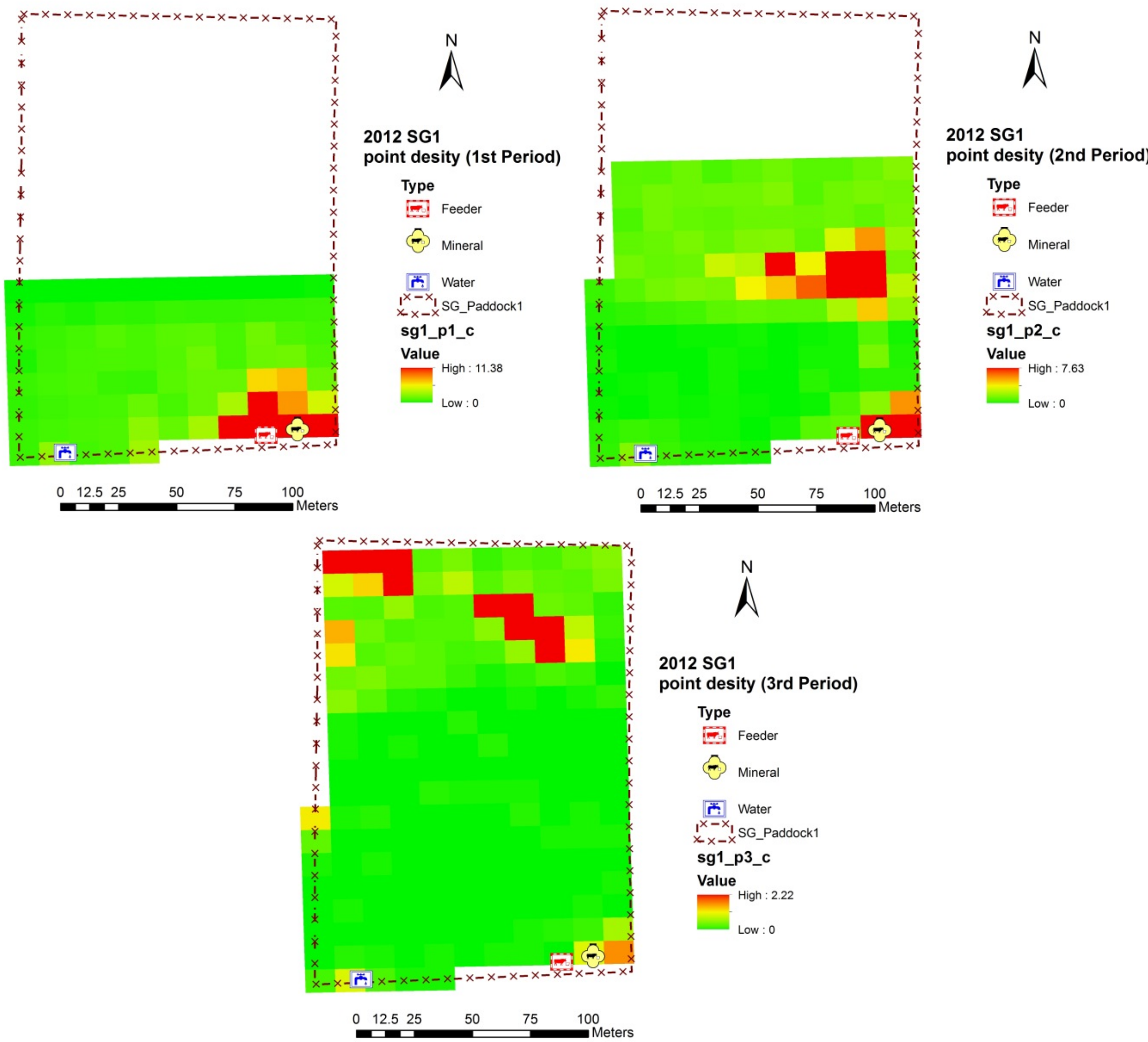
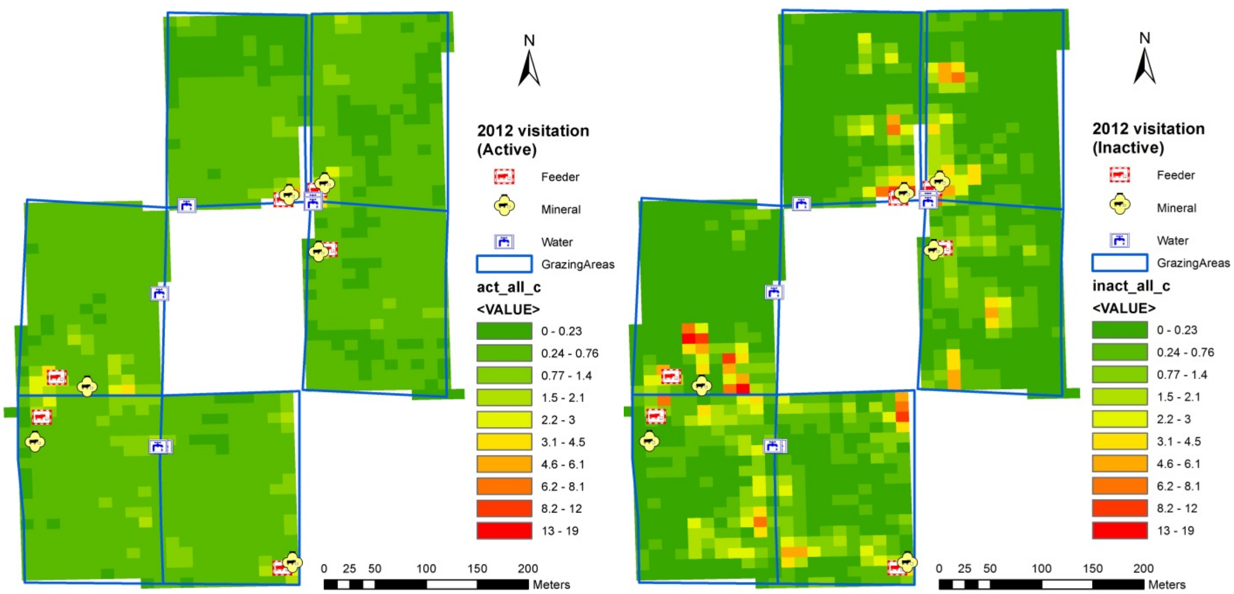


Figure 4.14 Point density maps of field visitations by cattle of SG1 during three grazing periods of fall 2012

Results of point density analysis also suggest that the spatial distributions of cattle locations were comparatively different with regards to two behavioral states distinguished via a coarser classification method. Similar to the method in 4.2.1, this method used a threshold value (1 m/min) of individual travel speed to classify cattle activities as two states: active (speed > 1 m/min) and inactive (speed ≤ 1 m/min), given that the accuracy of GPS receiver was approximately 4 meters at 95% confidence and location fixes were collected at a 4-min interval. GPS location fixes were then analyzed separately for the two states using the point density method. Results show that the locations of cattle were more evenly distributed throughout the field when they were active (Figure 4.15a), and were heavily concentrated to some specific areas when they were inactive (Figure 4.15b). The highest point density value for the active state is 4.76 (points / m^2), which is much lower than the highest point density value, 19.46 (points / m^2), for the inactive state. The high-density spots for the active state were mostly identified as surrounding areas of the feed bunks where supplemental feeds were provided (Figure 4.15a). The high-density spots for the inactive state were presumably bedding areas for cattle, as the individual travel speeds were smaller than 1 m/min (Figure 4.15 b).



(a) (b)

Figure 4.15 Point density maps of field visitation by cattle under active (speed > 1 m/min) and inactive states (speed ≤ 1 m/min) during fall grazing in 2012.

The histograms and box plots of the two density maps further illustrate the difference between the two behavioral states (Figure 4.16). The histogram for the active state appears to be more symmetric with the highest data value of 4.76, comparing to the histogram for the inactive state which is strongly right-skewed with the highest data value of 19.46. More than half of the density values lied within the range from 0.2 to 0.6 for the active state, while more than half of the density values were lying within the range from 0 to 0.2 for the inactive state. The box plots show that there was a much larger gap between the mean and the median of the inactive state comparing to the active state, because the distribution of the inactive state had some extreme values and was strongly skewed to the right. These results indicate that cattle tended to stay at some specific areas during the inactive state, and the rest of the field was seldom visited by the herd. As the herd usually remained stationary at rest, those areas with the highest density values can be identified as bedding areas for the herd, which later may be integrated into modeling cattle movements.

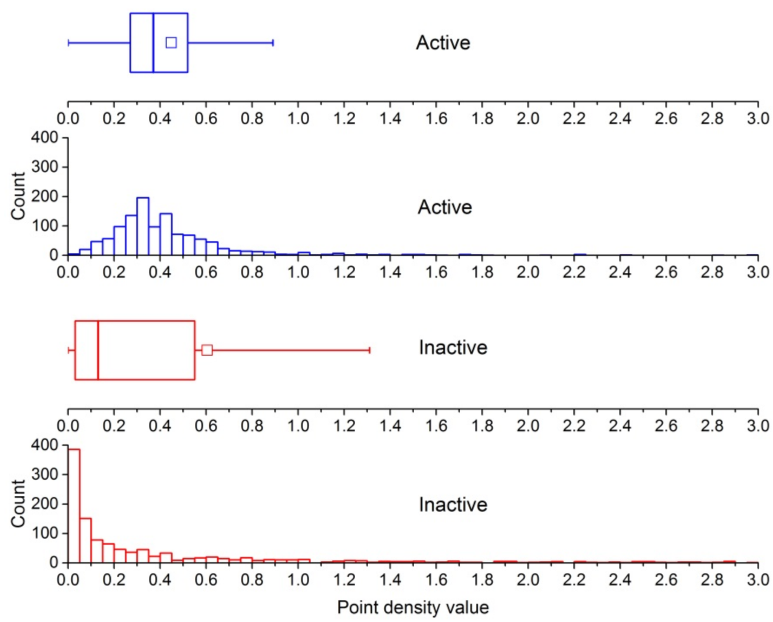


Figure 4.16 Box plots and histograms of density maps of field visitation by cattle under active (speed > 1 m/min) and inactive states (speed ≤ 1 m/min) during fall grazing in 2012.

4.2.3 Periodic behaviors and Trajectory analysis

Results of periodic pattern mining for cattle movement data suggest that a group of beef cattle had daily repetitive visitations to the shelter areas at the South Farm of the University of Illinois Beef and Sheep Field Research Laboratory during the summer grazing season of 2011 (Figure 4.17 and 4.18). The studied group was made up of 24 mixed beef cows and heifers, and each animal was equipped with a GPS collar. The shelter areas were determined as the areas where the farm facilities such as cattle shelters, water tanks, and feed bunks were located (marked as a red rectangle in Figure 4.17). GPS data of four consecutive days (from 00:00:00 a.m. July 2nd, 2011 to 00:00:00 a.m. July 6th, 2011) were selected for analysis.

Results of individual-level movement analysis show that cattle appeared to have similar periodic patterns associated with the shelter areas (Figure 4.18). The mean detected period for individual animals was approximately 23.9 hours. Each individual cow was staying in the shelter areas for about 7 hours daily, mostly between mid-morning and late afternoon (i.e. between 10 a.m. and 5 p.m.). As heat continued building up in the afternoon during the summer grazing season in 2011, the peak of temperature usually occurred around 3 p.m., according to the weather observations for Champaign-Urbana (Illinois State Water Survey, Prairie Research Institute, University of Illinois, 2011). It is expected that cattle would reduce their activities and prefer to stay in the shade and near the water to avoid the heat. Cattle then left the shelter area and went to the fescue pastures in the late afternoon. After sunset, almost all cattle's activities were within the pastures and they seldom went back to the shelter areas during night rest until the next morning. The herd-level movement analysis shows that the centroid of the herd had exhibited similar periodicity visiting the shelter areas as individual animals, with a period of approximate 23.8 hours (Figure 4.19). This indicates that the movements of individual cows and heifers in the same group were coordinated in both time and space, as viewed from the shelter areas.

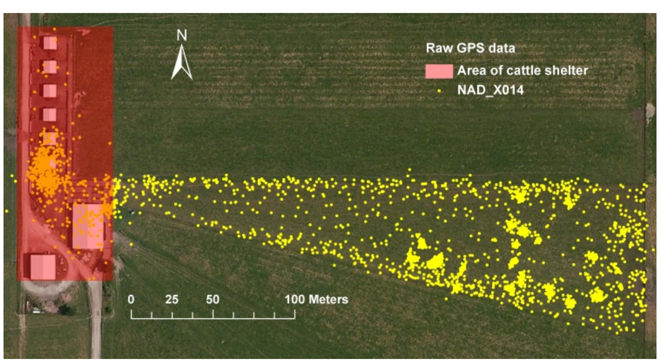


Figure 4.17 Identifying cattle periodic movements associated with shelter areas during summer grazing season in 2011. Shelter areas are marked with red rectangle. Yellow dots denote the raw GPS data of an individual cow (X014).

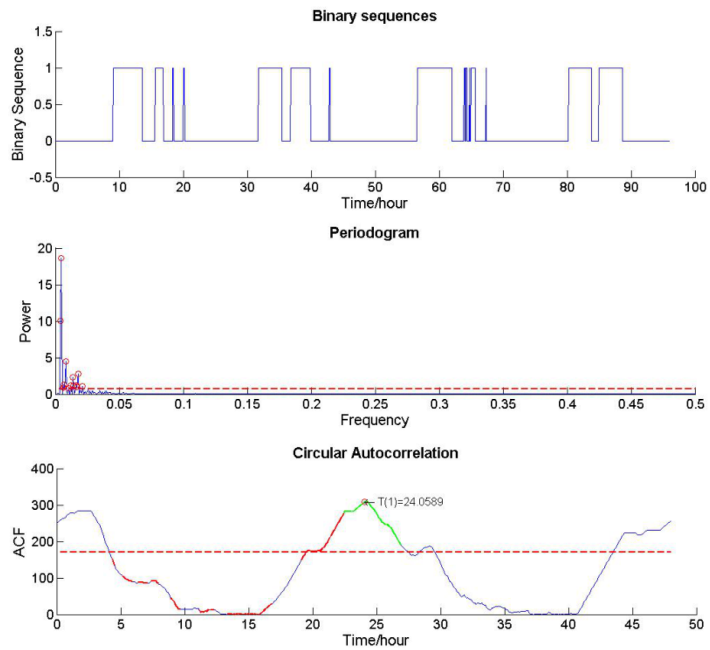


Figure 4.18 Periodic movements (T≈ 24.1h) associated with shelter areas were detected for an individual cow X014 during the summer grazing season in 2011. Viewed from the area of interest, GPS locations of the individual were converted into a binary sequence. Periodogram and circular autocorrelation were used to identify periodicities. Red dashed lines denote threshold values for the two analysis.

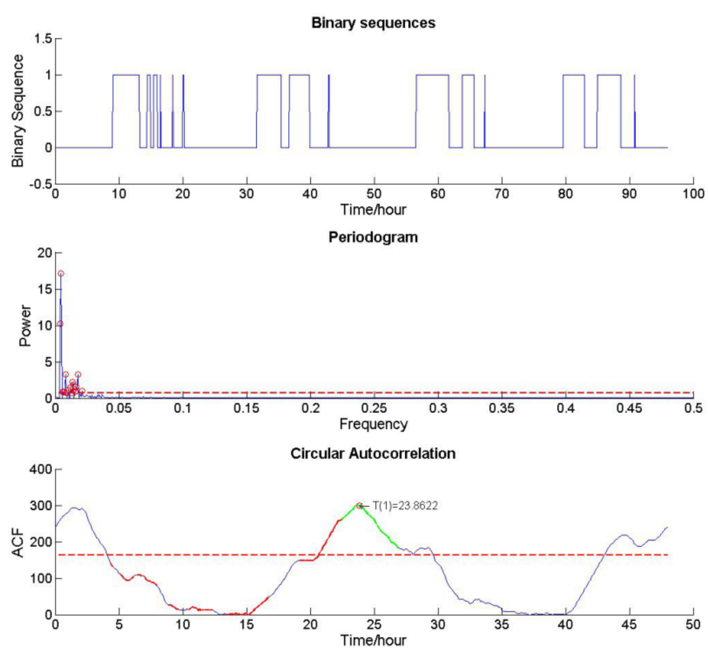


Figure 4.19 Periodic movements (T≈ 23.9h) associated with shelter areas were detected for the centroid of a herd that was made up of 24 mix cows and heifers during the summer grazing season in 2011.

Periodic behaviors have also been detected in the movements of grazing beef cattle on corn stover at the DSI farm. Based on the completeness and quality of data, GPS data from two different groups of cows were selected for mining periodic behaviors: GPS data of group SG2 (strip grazing) collected from 12:00:00 p.m. October 26th, 2012 to 12:00:00 p.m. October 29th, 2012, and GPS data of group CG3 (continuous grazing) collected from 12:00:00 p.m. October 25th, 2012 to 12:00:00 p.m. October 29th, 2012. Cows from the two groups have both shown periodic movements associated with their bedding areas, which were determined as areas with the top-10% density values in the point density maps (Figure 4.20). The identified periods for individuals in both groups were approximately 25 hours (Figure 4.21 and 4.22), which were also close to the period of circadian rhythms. The average time that cattle spent in the bedding areas was about 11 hours, and was mostly during darkness (e.g. between 7 p.m. and 6 a.m.). These periodic movements viewed from the bedding areas were possibly associated with cattle behaviors such as resting and ruminating. For example, rumen fermentation and post-rumen nutrient assimilation have evolved to exhibit circadian rhythmicity (Nikkhah, 2011). Rumination is psychologically linked to resting and occurs when the ruminant is relaxed (Nikkhah, 2013). Cattle usually spend seven to eight hours per day ruminating (Gordon, 1958). Rumination takes place mainly overnight, between 8 p.m. and 8 a.m. (Hancock, 1954). Therefore, these detected periodic patterns imply that rumination would have mostly occurred in those bedding areas too.

Besides bedding areas, surrounding areas of water tanks or feed bunks were also investigated for potential cattle periodic behaviors. However, no significant periodicity in GPS data was detected for any of these areas. Cattle movements associated with the feed bunks could be greatly influenced by supplementation schedules, as cows usually would visit the feeders when supplements became available and then left after the feeds were consumed. During the experiments, cattle might not have been supplemented at a strictly constant frequency. Therefore, inconsistence of supplementing time gaps may have resulted in no periodicity in cattle movements to the feeders. Comparing to those areas used for bedding and supplementation, areas around the water tanks had relatively lower densities of cattle visitations. This indicates that cattle had spent less time around the water than the bedding areas and the areas around the feed bunks. They might leave the water shortly after they obtained enough water. Thus, the GPS sampling interval (4 minutes) may not be short enough to capture cattle's every visit to the water. In addition, the linear interpolation of GPS for a constant time gap in the beginning required by the periodic mining algorithm could also reduce the number of sampled locations near the water. Therefore, challenges remain for identifying periodic patterns for those spots that are less dense areas, utilizing the current GPS sampling frequency and the algorithm above.

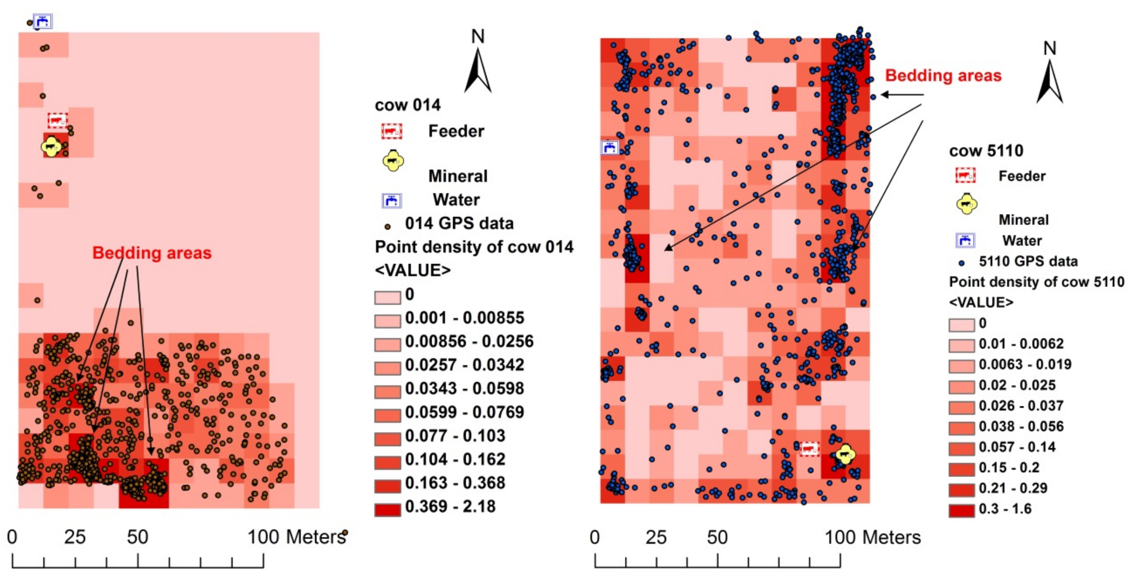


Figure 4.20 Identifying of bedding areas for individual cows (e.g. cow 014 under SG management and cow 5110 under CG management). Areas with the top-10% density values in the point density maps of individual GPS data were determined as the bedding areas for each individual.

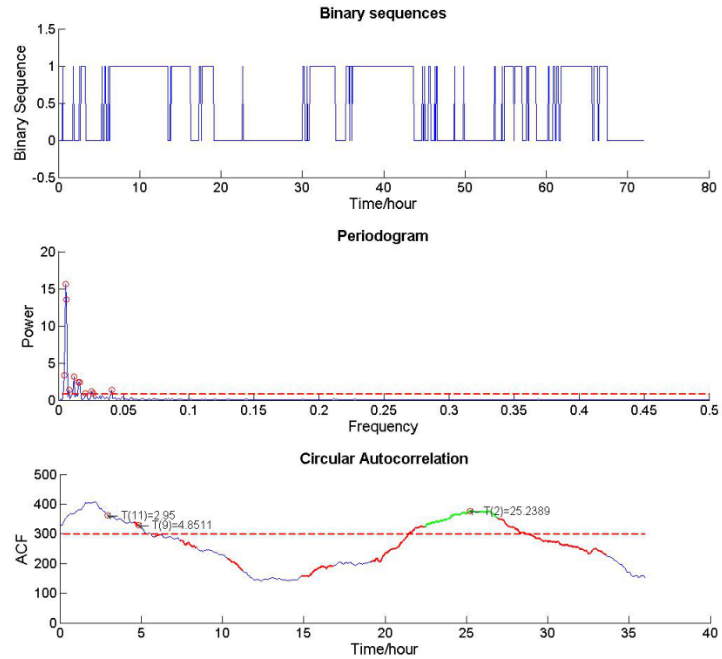


Figure 4.21 Periodic movements (e.g.T≈ 25.2h) associated with the bedding areas were detected for individual cows (e.g. 014) under strip grazing management (SG2) during the fall grazing season in 2011.

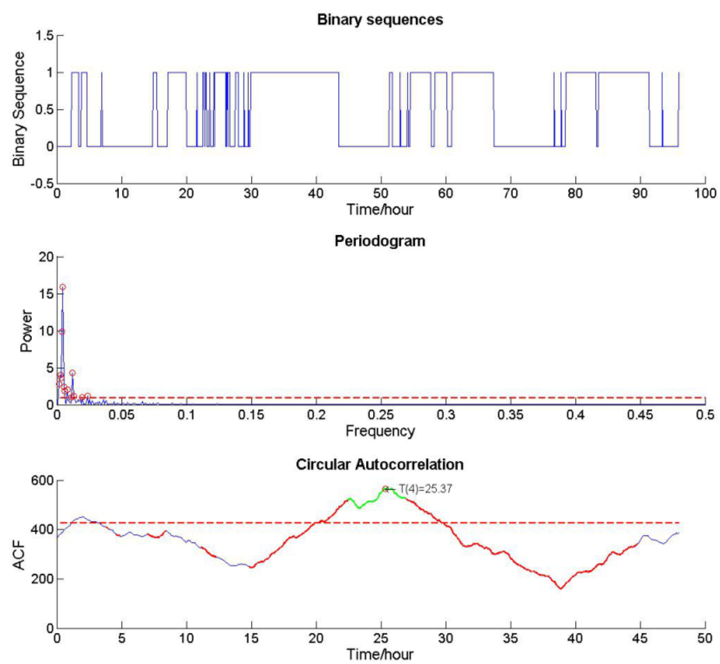


Figure 4.22 Periodic movements (e.g.T≈ 25.4h) associated with the bedding areas were detected for individual cows (e.g. cow 5110) under continuous grazing management (CG3) during the fall grazing season in 2012.

4.2.4 Effects of number of animal monitored on subsequent analysis

4.2.4.1 Movement characterization

Average herd travel speed

Cattle movement can be classified into three movement modes: resting, traveling, and foraging, which results in different patterns in group movement and individual movement. During resting, both individual animal speeds and herd centroid speed are close to zero; when the herd is traveling from one location to another location (e.g. a water station), animals move approximately at the same speed, therefore the herd speed is close to individual speeds; while animals are foraging, herd travel speed may be quite different from, usually lower than, individual animals' speeds. As subset group size decreases, herd centroid movement tends toward individual animal movements and selection of different subset groups generates a wider range of variability within results due to variations of animals within the herd (Figure 4.23A and B). As the subset group sizes decreases, for both group A and B, the mean values of average herd centroid travel speed increase, as well as the standard deviations.

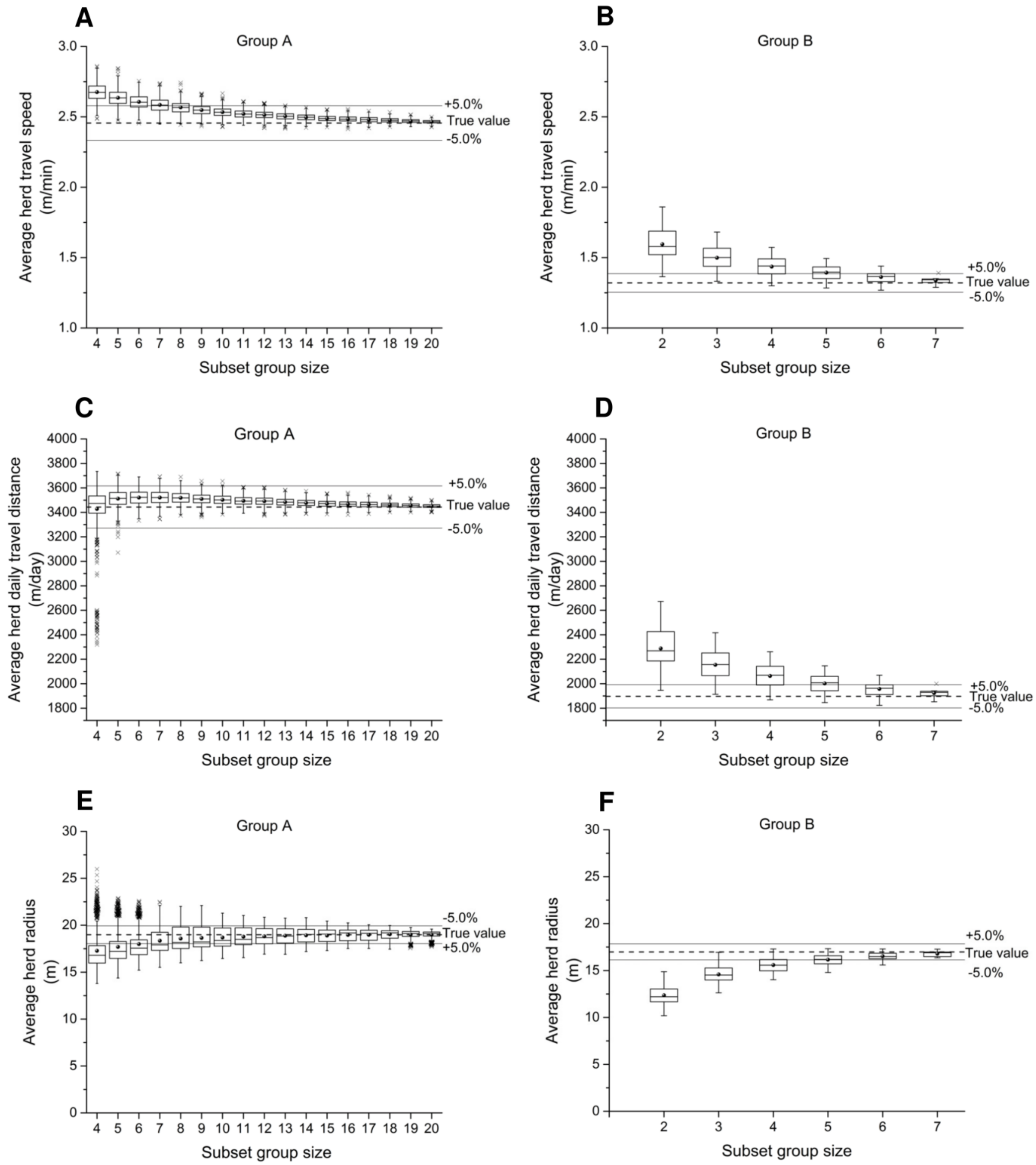


Figure 4.23 Effects of subset group size on measurement of group movement parameters. Average herd travel speed (A and B), daily travel distance (C and D) and herd radius (E and F) of subset groups are compared with the entire herd (denoted as "true value" in the figures). First, second and third quartiles are displayed by boxes, the range by whiskers, mean values by solid dots, and outlying values by crosses. A bandwidth of ±5% of the true value is used as the error tolerance.

Average herd daily travel distance

Travel distances are associated with travel speeds; hence, similar to average herd travel speed, means and standard deviations of herd daily travel distance also increase as the subset group size decreases. A notable difference between group A and B is that group A has an increasing number of outliers (denoted as crosses) when subset group size decreases as compared to group B (Figure 4.23 C and D). The magnitude of most outliers were smaller than the “true” value of average herd daily travel distance, calculated using the entire herd, which is in conflict with the trend shown in Figure 4.23C and D that decreasing subset group size leads to potential overestimation of average herd daily travel distance. This was caused by GPS data loss during monitoring. It is very common in animal monitoring studies with GPS collars that GPS units undergo intermittent failure due to many reasons such as bad weather, poor satellite signal, damage caused by animals, and so on. As group A suffered more GPS data loss during data collection than group B (about 87% of expected fixes were collected for group A while nearly all expected fixes were collected for group B), the data loss becomes increasingly impactful in estimation of travel distance when subset group size is small. Impacts of GPS data loss during collection can be considered similar to increasing data sampling frequency for that period of loss, as fewer or no location fixes are recorded. Several studies had shown that animal daily travel distance estimated from GPS data can significantly decrease when GPS sampling frequency was decreased. This helps explain why loss of GPS data leads to the underestimation of average herd daily travel distances. Therefore, monitoring a small subset group of animals has a greater probability to cause significant inaccuracy in estimation of herd daily travel distances, which is further increased if data loss occurs during collection.

Average herd radius

As the subset group size decreases, the mean of average herd radius over time is less than the true value while the standard deviation increases (Figure 4.23 E and F). Herd radius is calculated by averaging individual distance to the herd centroid (an alternative movement parameter is the average distance between individual animals). Thus, it can be considered as a magnitude that denotes the range of the herd, which is often associated with the areas visited by cattle. In addition, herd radius may vary for different cattle activities. For instance, cattle usually have a larger radius when cows are spread out over pastures for grazing or during traveling as compared to resting. Therefore, average herd radius can be used as a factor for distinguishing different cattle behaviors based on GPS data. In modeling, herd radius can also be used as a parameter that specifies the range of the herd during different activities to simulate synchronized group behaviors (e.g. traveling, foraging and resting). The results suggest that using a subset group for monitoring could potentially underestimate herd radius, thus this may introduce errors when classifying cattle behaviors.

Average centroid location deviation and average herd radius deviation

Both average centroid location deviation and average herd radius deviation quantify the differences between subset groups and the entire herd at every time step. Average centroid location deviation gives the distances between the two centroids of subset groups and the whole herd. Average herd radius deviations denote the differences of herd radius between a subset herd and the entire herd.

Both groups' mean deviation linearly increases ($r_A^2 = 0.973$ and $r_B^2 = 0.973$) as subset group size decreases. As subset size decreases, the individual variability has more impacts on subsampling, which leads to an increase of standard deviation. Using GPS R95 as the error tolerance (horizontal lines in Fig 4.24) requires a subset group containing at least 16 animals to have all the deviations within R95 for group A (Figure 4.24A). Similarly, at least 6 animals are required for a group of eight animals, as in group B (Figure 4.24B). Average herd radius deviation and its standard deviation also increase linearly ($r_A^2 = 0.950$ and $r_B^2 = 0.953$) as subset group size decreases. Using GPS R95 accuracy as the error tolerance shows that subset groups including at least 19 cows from group A and 6 cows from group B have nearly all errors within R95 (Figure 4.24C and D).

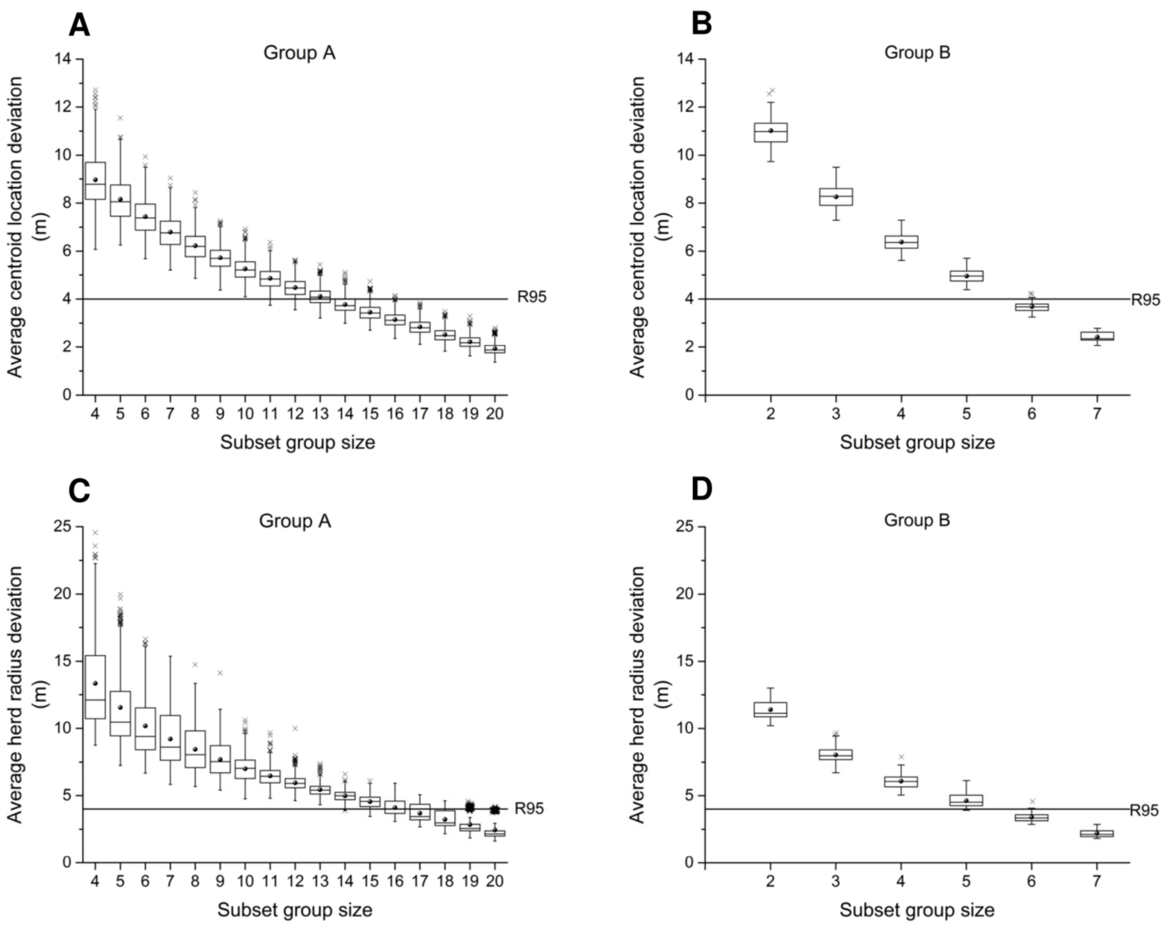


Figure 4.24 Effects of subset group size on deviation of herd centroid location and herd radius. Average centroid location deviations (A and B) and herd radius deviations (C and D) are compared with GPS accuracy (R95). First, second and third quartiles are displayed by boxes, the range by whiskers, mean values by solid dots, and outlying values by crosses. GPS R95 accuracy is used as the error tolerance.

Comparative statistics

For both group A and B, S increases as subset group size increases, approaching 100% as subset size gets close to the herd size (Figure 4.25). Different patterns of average herd travel speed and daily travel distance were found between group A and B (Figure 4.25A and B). For group A, which had a relatively large herd size, and worse GPS data quality compared to group B, the increase of S can be distinguished into two phases as subset group size increases. When group size is small, S increases rapidly during the first phase, and then slightly increases during the second phase. For a subset group size that is greater than 12, about 95% of subset groups' average herd travel speed and daily travel distance are within the error tolerance range as compared to the entire herd. When considering average herd radius and a small subset group size, a lower percentage of subset groups within error tolerance were reported for group A (Figure 4.25A). To achieve a greater percentage of instances within the error tolerance (i.e. 95%), monitoring 18 cows from group A is required. For group B, which had a nearly complete dataset of location fixes, S values for the average herd travel speed and daily travel distance were linearly correlated (crosses and diamonds in Figure 4.25B), because travel distance can be calculated using travel speed and time interval if no data loss occurs. Unlike group A, S values for the three movement parameters of group B increase steadily as subset group size increases (Fig. 4B). These different patterns between group A and B (Figure 4.25A and B) may result from several factors including treatment differences that could affect animal movement (e.g. different forage types, grazing seasons, water demand, weather and shape of paddocks), different herd sizes, and varying levels of completeness of GPS data collected. However, results of group A and B both indicate that selecting 75% animals of the entire herd will maintain errors within tolerance for all three movement parameters with 80% probability.

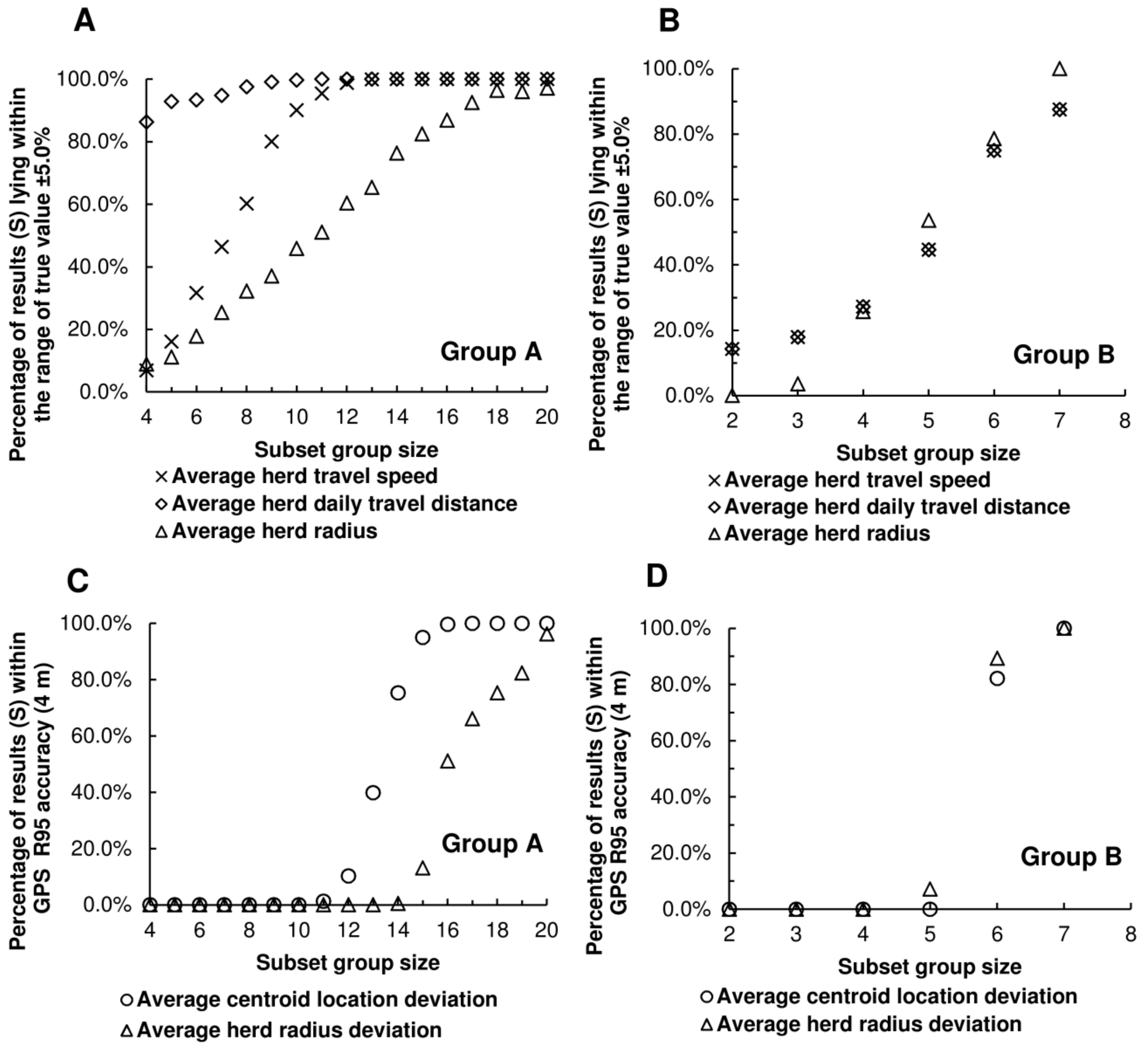


Figure 4.25 Comparative statistics for error evaluation of movement characterization. The results illustrate the percentage of subset groups that are within the error tolerances: percentage of results within the range of the true value ±5% for average herd travel speed, average herd daily travel distance, and average herd radius (A and B); percentage of results within R95 for average centroid location deviation and average herd radius deviation (C and D).

Similar patterns of S were found for average centroid location deviation and average herd radius deviation (Figure 4.25C and D). One difference between group A and B is that, for group A, the increase of S for average centroid location deviation decreases after the subset group size is large enough (e.g. 16) and S is greater than 90%. This is similar to the patterns observed with average herd travel speed and average herd daily travel distance (Figure 4.25A), which indicate that increasing subset group size, when subset group size is large enough (e.g. at least 16 cows), will not make significant improvement in the results as errors become very small.

Appropriate animal subset group size to monitor for modeling purposes depends on many factors, such as the movement characteristics one would like to obtain, as well as tolerance for error. In summary, results of two groups suggest that there is a greater inaccuracy in movement characterizations for monitoring a subset group, when the entire herd size is small. For instance, monitoring 7 animals out of 8 has about 15% chance to cause a relative error of more than 5% of the true value for herd travel speed and daily travel distance. However, for cattle groups with greater sizes, there may be a proper subset group size that can generate results close to the true values. For instance, monitoring 20 out of 24 cows has about 95% chances to maintain the errors of movement parameters within 5% of the true values.

4.2.4.2 Spatial occupancy analysis

Cattle are usually regarded as social animals as they prefer to live together in groups, and members can be highly interactive with each other. Their behaviors are often coordinated in time (synchronization) and in space (cohesion of the herd), and this leads to the phenomenon that they usually have the same favored resting areas, feeding sites and water locations. In the spatial occupancy analysis, results show that instead of randomly visiting areas within the pasture, animals repeatedly visited certain areas, which leads to a spatially uneven location visitation by cattle (Figure 4.26). Previous studies have shown that grazing animals living in social groups often have synchronized activities and behaviors, which can lead to similar distributions of spatial occupancy of land among individuals. The KDE results of the spatial occupancy analysis show that individual animals, subset groups, and the entire herd have similar spatial patterns

(Figure 4.26). The highly visited areas (intense white area in Figure 4.26) identified from the KDE maps can be classified as either bedding areas, feeders, water stations or foraging areas.

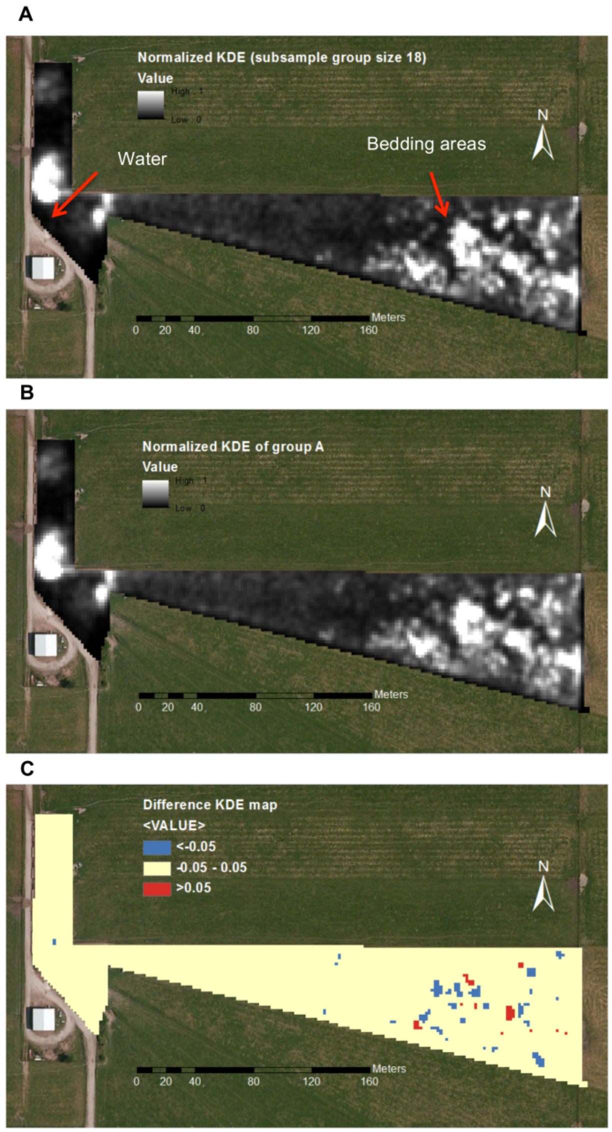


Figure 4.26 Comparison of KDE maps between subset groups and the entire herd. GPS location data of a subset group of size 18 (group A) were converted to a rasterized map, which quantifies the pasture visitation rates by cattle using KDE analysis. White and black areas denote the grazing areas for the herd. Intense white areas are indicative of high cattle visitation rates. The map was further normalized (A) in order to compare with a similar map (B) of the entire herd. A difference map (C) was created to denote the differences between the two maps (pixels with values larger than 0.05 are shown in red, smaller than -0.05 in blue, and others in beige). The same highly visited areas can be identified based on (A) or (B) since they are very similar spatially, as white intense areas on both maps are located around watering and bedding areas.

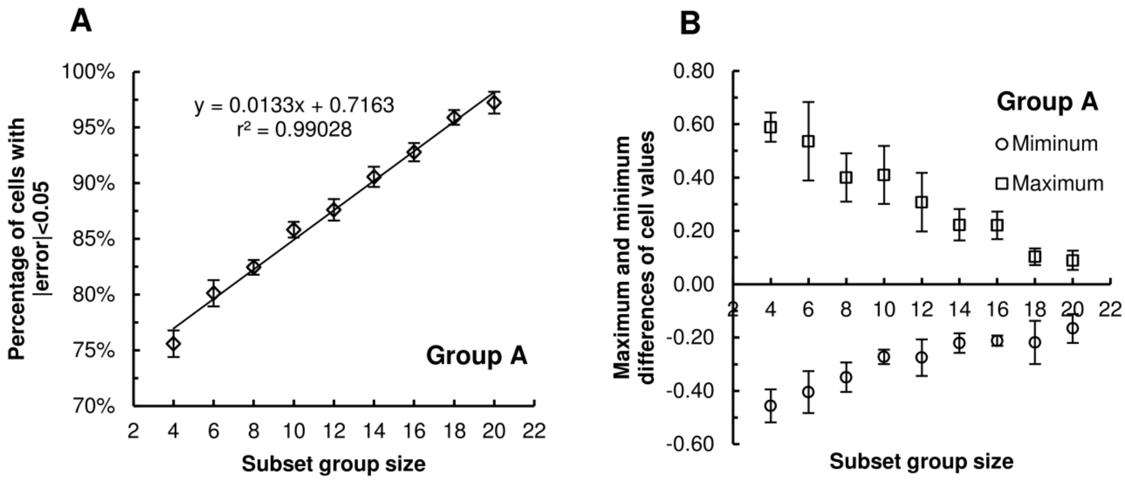


Figure 4.27 Comparative statistics for error evaluation of spatial occupancy analysis. The average percentage of cells within difference maps within the error tolerance (|errors|<0.05) increases linearly (r2 = 0.99028) as subset group size increases (A). The average maximum and minimum difference values decrease as subset group size increases (B). Error bars denote ± SE.

As described in section 2.5, the accuracy of cattle spatial occupancy analysis was evaluated using a subset group by creating a difference map to denote the differences between the subset group's field visitation map and the entire herd. The similarity of two KDE maps was investigated by counting the percentage (denoted as S in Eq. 14) of cells with values that are within the error tolerance (0.05) in the difference map. This analysis suggests that S linearly increases as the subset group size increases (Figure 4.27A). For instance, S reaches 95% when the subset group size is 18; thus, the spatial occupancy map of a subset group of size 18 is about 95% similar to that of the entire herd of size 24 given an error tolerance of 5%. Further, the absolute values of both maximum and minimum cell values in the difference maps decrease as the subset group size increases (Figure 4.27B). Results of spatial occupancy rates also show that using a relatively small subset group size, for instance 4 out of 24 animals, a KDE map can still be generated that is about 75% similar to that of the entire group, which may be useful in some cases. In fact, if the only parameter of interest is the identification of heavily visited areas, it may be possible to use as few as four animals. If the goal of a study is to quantify cattle spatial occupancy and later correlate it with other data that have similar spatial resolutions as cattle movement data, such as soil characteristics and crop yields, it is recommended to use a larger subset group (e.g. 18 cows out of 24 cows) for monitoring in order to improve accuracy.

4.3 Summary and Conclusions

Animal movement is a complex phenomenon that can be driven or affected by many factors such as animal internal states (e.g. body weight, perception, and memory) and external environment (e.g. availability of forage and water, weather, predators and topography), which may be stochastic in nature. Exploration of animal movement data recorded via GPS trackers would help researchers better understand the spatiotemporal patterns in animal movements and facilitate model development.

Based on GPS data, movement characterization uses a set of movement metrics to describe cattle movement quantitatively at both individual and herd level. The results suggest that although individual cows exhibited variability in movement speeds, the dynamics of mean individual travel speed was highly coordinated with the speed of the herd centroid in time. Mean individual distance to the herd centroid was greater and had greater variability when the herd behavioral state was active (mean individual speed > 1m/min). The peak of individual movements usually occurred between 2 p.m. and 4 p.m. for most cows monitored during the fall residue grazing experiments at the DSI farm. Cattle had much fewer movements during darkness as compared to daytime, presumably due to resting. Grazing treatment had significant impacts on cattle daily travel distance. Cattle under strip grazing management practices traveled significantly less per day than those under continuous grazing management, which might have resulted in fewer energy expenditures and more energy saving toward body weight gain.

Cattle locations were unevenly distributed during the fall residue grazing experiments, based on the results of spatial occupancy analysis of GPS data. The most heavily trafficked areas were identified as bedding areas and areas around stationary feed bunks. Individual cows often favored same bedding areas within the group due to high interactions; interactions among different groups might also have affected the locations of bedding areas. Strip grazing had greatly altered the spatial patterns of cattle locations across time, as cattle movements would relocate most of their activities to a new strip available to them after the removal of cross fences. This indicates that strip grazing management strategies can be utilized to manipulate the spatial patterns of cattle and temporally allocate resources for grazing. In addition, the distributions of cattle locations were more even throughout the field when they were active (mean individual speed > 1m/min), and were heavily concentrated in some specific areas, perhaps bedding areas, when they were inactive.

Results of periodic pattern mining suggest that cattle movements exhibited a 24-hour pattern associated with the shelter areas at the South Farm of the University of Illinois Beef and Sheep Field Research Laboratory during summer 2011. The majority of time that cattle were in shelter areas was mostly between mid-morning and late afternoon, presumably linked with the changes of temperature in summer. Fall grazing cattle on corn residues had shown periodic behaviors associated with bedding areas, with an approximately 25 hours' period. The periodic movements were possibly linked with cattle behaviors such as resting and ruminating, which usually exhibit circadian rhythmicity.

Previous studies may not have instrumented enough animals to provide accurate information of herd activities due to the cost of technology or other technical constraints. Appropriate subset group size for animal movement monitoring with GPS is dependent on specific research objectives. The development of a computational approach for analyzing cattle movement data statistically evaluated the errors in subsequent location data analysis caused by monitoring subset groups of animals instead of the entire herd. Results showed that monitoring an appropriate subset group of cattle could preserve most information with acceptable errors for subsequent analysis. On the one hand, it may be interesting to note that some parameters (i.e. average herd travel speed and daily travel distance) quantifying cattle movement were generally over-predicted when subsampling from the herd, while the other parameter (i.e. average herd radius) was under-predicted. On the other hand, heavily visited areas can be identified with very few data, while correlation to other environmental factors may require more data. Analogous results were expected for similar experimental environments and herd sizes. Further, the computational approach we developed here can be applied to other systems (e.g. other livestock or wildlife) that utilize GPS units for animal movement monitoring, providing insights into future experimental designs when considering tradeoffs between data quality and costs. A limitation of this analysis results from the time consuming and great computing requirements in order to consider all possible combinations of subset groups regarding the group sizes. Based on this, a lesser number of randomly chosen instances were included in the analysis. Considering sufficient number of combinations of subset group sizes for this analysis remains a challenge for future work.

CHAPTER 5
ASSESSMENT OF GRAZING IMPACTS ON SUBSEQUENT CROP YIELD IN AN INTEGRATED CORN-CATTLE SYSTEM

Crop residue grazing can significantly lower the feed costs for wintering cows with little additional input costs (Sanderson et al., 2013); however, the potential effects of cattle presence on subsequent crop yield are unclear and may be influenced by various environmental and anthropogenic factors such as weather, location, and farm management. Some studies have shown that presence of cattle on cropland can increase soil compaction and potentially reduce crop yield (Krenzer Jr., Chee, & Stone, 1989; Mullins & Burmester, 1997); yet no detrimental effects on subsequent crop yields were found in other studies (J. T. Clark et al., 2004; Tracy & Zhang, 2008). One major potential concern of residue grazing is soil compaction near soil surface caused by animal traffic; however, some studies have shown that the effects of soil compaction can be avoided or minimized in colder regions or under appropriate management such as restricting grazing to periods when soils are dry or frozen (J. T. Clark et al., 2004; Liebig et al., 2012). Another potential drawback crop residue grazing may be poor distribution of nutrients from manure and urine (Sanderson et al., 2013), which may lead to uneven crop development.

The application of modern combine harvester has enabled us to use data collected during harvest for mapping grain yield at a fine spatial resolution. Given the locations of grazing cattle during crop residue grazing, there is an opportunity to assess the heterogeneity of grazing impacts on subsequent crop development by investigating the spatial relationships between cattle locations and crop yield data. As results of spatial occupancy analysis of cattle location data have illustrated the spatial heterogeneity of cattle locations during grazing crop residues, this could potentially lead to spatial variability of grazing impacts on agricultural land and affect subsequent crop growth. Therefore, this chapter seeks to investigate the potential impacts of grazing on subsequent crop yield by integrating cattle location and corn yield data for analysis, and also evaluate the impacts of grazing management practices.

5.1 Materials and Methods

5.1.1 Experiment design and data collection

A three-year experiment was implemented to study the effects of beef cattle grazing of corn residues on cattle performance, residue quality and utilization, and subsequent corn yield at the Dudley Smith Initiative (DSI) Farm (lat 39° 26.4' N, long 89° 07.1' W; elevation 202m), 6 km northwest of Pana, Illinois since 2012. Experimental plots were on Virden silty clay loam (fine, smectitic, mesic Vertic Argiaquolls). The Virden series consists of very deep, poorly drained, moderately slowly permeable soils formed in loess on nearly level summits on till plains. Slope ranges from 0 to 2 percent. Mean annual temperature is 12.2 to 13.9 °C, and mean annual precipitation is 939.8 mm to1371.6 mm (National Cooperative Soil Survey, Version 8, Sep 13, 2014). Electrified wires were used to divide the corn field into 9 equal fields (Figure 1) for different grazing management practices: strip grazing (SG), continuous grazing (CG) and ungrazed control (CT), each of which had three replicates (Figure 5.1). A randomized block design was applied such that each row and column consisted of all three treatments. Three fields were left as CT while three fields were used for CG and the other three for SG. The area of each paddock was 1.97 ± 0.03 ha, and the same design was utilized during each fall grazing for three consecutive years of study duration. The coordinates of paddock dimensions were marked with a handheld GPS (Garmin International Ltd., Olathe, Kansas, USA), so that the same treatment was applied to the same field each year.

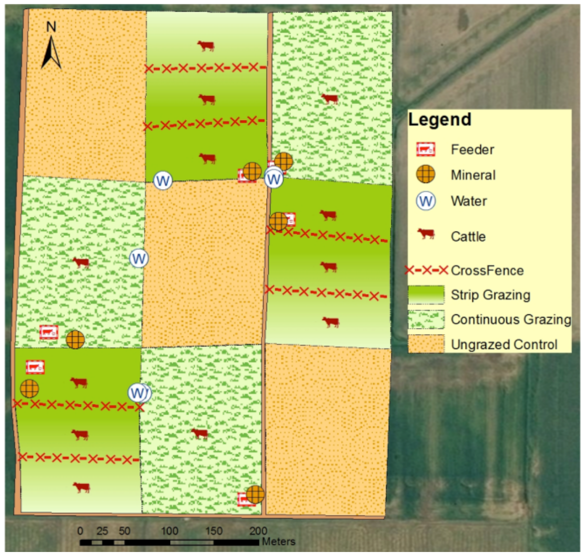


Figure 5.1 Field layout of crop residue grazing experimental design. Fall corn residue grazing experiments have been implemented at the Dudley Smith Initiative Farm, where the lands were divided into strip grazing, continuous grazing, and ungrazed control paddocks, each of which has three replicates.

36 spring-calving, multiparous, Angus cows were utilized in 2012 (BW (body weight) = 648 ± 41 kg) and 2013 (BW = 710 ± 71 kg) at a stocking density of 3.0 cow·ha^{-1}, and 42 winter-calving Angus heifers (BW = 566 ± 39 kg) were utilized in 2014 at a stocking density of 3.6 heifers·ha^{-1}. Following crop harvest, a group of cattle (six in 2012 and 2013, seven in 2014) were randomly allotted to a CG or SG paddock for six weeks (42 days). Cattle under the CG treatments were allowed access to the full paddock throughout the entire duration of grazing. In the SG treatments, each paddock was divided into three equal strips using one strand of temporary electrified wires. Cattle were allowed access to a new strip every 14 days. More specifically, cattle were allowed to graze the first strip for the first 14 days, then the first and second strip for the next 14 days, and the entire paddock for the last 14 days. The hypothesis is that SG management may alleviate some negative effects such as forage quality decrease due to cattle trampling, thus, may preserve forage quality as compared to CG management. During the

experiments, each paddock included a water tank and a mineral feeder (Figure 5.1). Cattle were supplemented in stationary feed bunks three times per week to receive 1.8 kg· hd^{-1}· d^{-1} of a 50% pelleted corn gluten and 50% soybean hull mix. In 2013, supplement feeding was increased to 4.5 kg· hd^{-1}· d^{-1} during the last 14 days of the experiment due to low temperatures.

During the experiments, cattle were fitted with GPS collars to track their location with a specified sampling interval of four minutes (see methods in 3.1.2). For experiments in 2012 and 2013, cattle in each group (36 cows, 6 groups) were all instrumented with GPS collars during grazing corn residues. In 2014, 6 of 7 cows in each group (42 cows, 6 groups) were fitted with GPS collars, which was considered a proper subset group size for instrumenting to preserve information with acceptable data loss (Liu, Green, Rodríguez, Ramirez, & Shike, 2015). The dates for deploying GPS collars (Table 5.1) were determined according to the schedule of the SG treatments such that GPS data of cattle locations were obtained before and after the removal of temporary electrified wires in SG.

Table 5.1 Summary of GPS data collection during fall grazing experiments

Year	Number of cows	Number of cows monitored	Data collection dates
2012	36 (6 groups)	36	2012-09-27 to 2012-10-02; 2012-10-11 to 2012-10-16; 2012-10-25 to 2012-10-30.
2013	36 (6 groups)	36	2013-11-02 to 2013-11-07; 2013-11-15 to 2013-11-20; 2013-11-29 to 2013-12-04.
2014	42 (6 groups)	36	2014-10-03 to 2014-10-07; 2014-10-16 to 2014-10-21; 2014-10-30 to 2014-11-04.

Corn was harvested on 28th Aug. 2012, 21st Oct. 2013, 19th Sept. 2014, and 16th Sept. 2015 with a John Deere S680 combine (Deere & Company, Moline, IL, USA) equipped with a 16-row head. Yield data was collected during harvest and later managed using the APEX Farm Management Software (Deere & Company, Moline, IL, USA). Residue grazing began on 29th

Sept. 2012, 2nd Nov. 2013 and 4th Oct. 2014. Spring tillage was applied to the entire field before planting each year. A 550 Case IH Quadtrac tractor (Fargo, ND, USA) and Case IH 330 Turbo Vertical Tillage implement (CNH Industrial, Lebanon, IN, USA) was used for tillage, to a depth of approximately 5 cm. Corn was planted in 76 cm rows with a 16-row John Deere 8230 (Deere & Company, Moline, IL, USA). Stone 6148 (Stone Seed Group, Monsanto, Geneseo, IL, USA) seed corn was planted to a density of 93,860 plants· ha^{-1} on 20th May 2013 and 24th April 2014.

5.1.2 Data analysis

Corn yield was calculated by yield monitor at discrete locations during harvest, and the yield data were further imported as point shapefiles into ArcGIS for analysis. The Inverse Distance Weighted (IDW) interpolation tool in ArcGIS was used to convert point-based yield data into a gridded map with a uniform cell size of 10 m by 10 m. The raster cell values were determined using a linearly weighted combination of a set of nearby sample points. Based on the spatial resolution of yield data, a circle with the radius of 20 meters was used as the search radius to determine the sampled points used in interpolation for estimating yield at prediction locations. Mean corn yield were calculated for each subplot and the main plot. The MIXED procedure of SAS was used to investigate the effects of grazing treatment (CG, SG and CT) on subsequent corn yield. Grazing treatment was included as a fixed effect and year was treated as a random effect. There were three replications per treatment per year.

Cattle location data were downloaded from GPS collars after each collection period. A C++ program was used to merge all raw GPS files into one comma-separated-value (.csv) file for each animal. The program also removed corrupted texts, and converted date and time from Coordinated Universal Time to Central Standard Time, the time zone of the study site. The csv files were then imported to ArcGIS (ESRI, Redlands, CA) and stored as shapefiles for visualization and analysis. The point density tool in ArcGIS 10.1 (ESRI, Redlands, CA) was used to quantify the spatial occupancy of land by cattle. The point density tool calculates the density of point features around each output raster cell. A neighborhood is defined around each raster cell center, and the number of points that fall within the neighborhood is totaled and divided by the area of the neighborhood. Both the search neighborhood and the output raster cell were set to a square (10 m * 10 m) with the same center. Each cell in the crop yield maps and each cell in the spatial occupancy maps of cattle had a common geographic reference point so these two datasets could be spatially jointed as one dataset for correlation analysis.

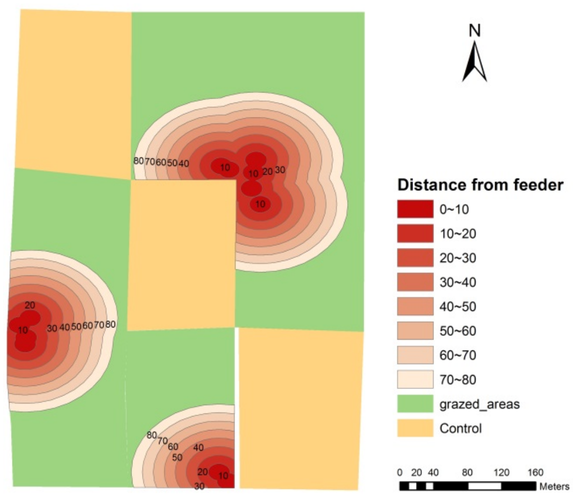


Figure 5.2 A contour map for grazed areas with regards to distance from supplemental feeders. Areas around the feeders were delineated by contour lines that join points of equal distance from the feeders with an interval of 10 m.

During the three-year study, feed bunks used for supplementing cattle were permanently placed at approximately the same locations across multiple grazing seasons (Figure 5.1). The effects of cattle trampling due to heavy traffic on those areas near feeders could potentially accumulate over years because of the same grazing design. To assess these impacts associated with feeders during crop residue grazing, a contour map using an interval of 10 m that indicated the distance from the feeders was created (Figure 5.2). The mean corn yields and the mean density of cattle visitations were calculated for areas with a variety of distances from the feeders.

5.2 Results and Discussions

5.2.1 Effects of grazing treatments on subsequent crop yield

Corn yield had shown great spatial variability at the DSI farm both before (2012) and after (2013, 2014, and 2015) the grazing trials were implemented in 2012 (Figure 5.3). Yields mapped at a spatial resolution of 10 m by 10 m squares ranged from 30.3 bushels/acre to 241.5 bushels/acre in 2012, from 58.0 bushels/acre to 456.2 bushels/acre in 2013, from 27.5 bushels/acre to 298.0 bushels/acre in 2014, and from 19.3 bushels/arc to 262.6 bushels/arc in 2015. The mean yields over the entire study site were 151.4 (28.8 SD) bushels/acre in 2012, 197.2 (24.8 SD) bushels/acre in 2013, 183.9 (31.8 SD) bushels/acre in 2014, and 136.3 (34.0 SD) bushels/acre in 2015. Although corn yields have exhibited across-year variability during the studies, no significant differences were detected across the treatments (CG, SG, and CT) for either mean corn yield in 2012 before the grazing experiments (P= 0.89), or for mean subsequent corn yields in 2013, 2014, and 2015 after grazing (P=0.15) (Table 5.2). These results suggest that the mean yield in grazed croplands did not decrease as compared with that in ungrazed areas, nor had it exhibited any difference between continuous grazing and strip grazing management.

Table 5.2 Mean and standard deviation of corn yield by plot under three treatments

Treatment	2012		2013		2014		2015	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
CT	149.3	7.5	196.2	3.5	189.1	11.5	146.6	21.2
CG	151.3	25.1	195.8	7.0	173.9	14.1	125.3	8.3
SG	154.1	15.2	198.4	6.8	186.9	6.9	136.4	9.8

Note: Yield unit is bushels/acre.

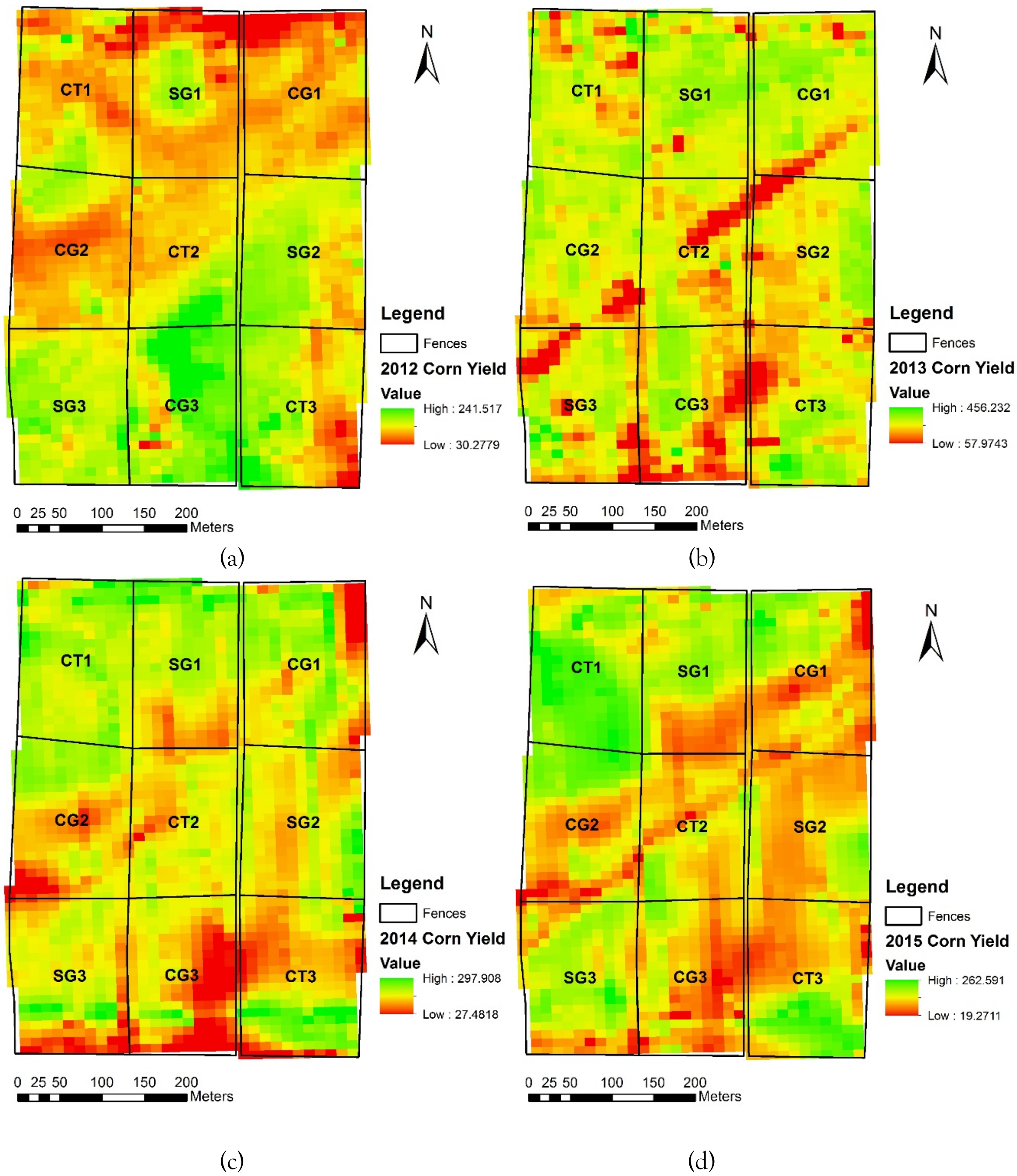
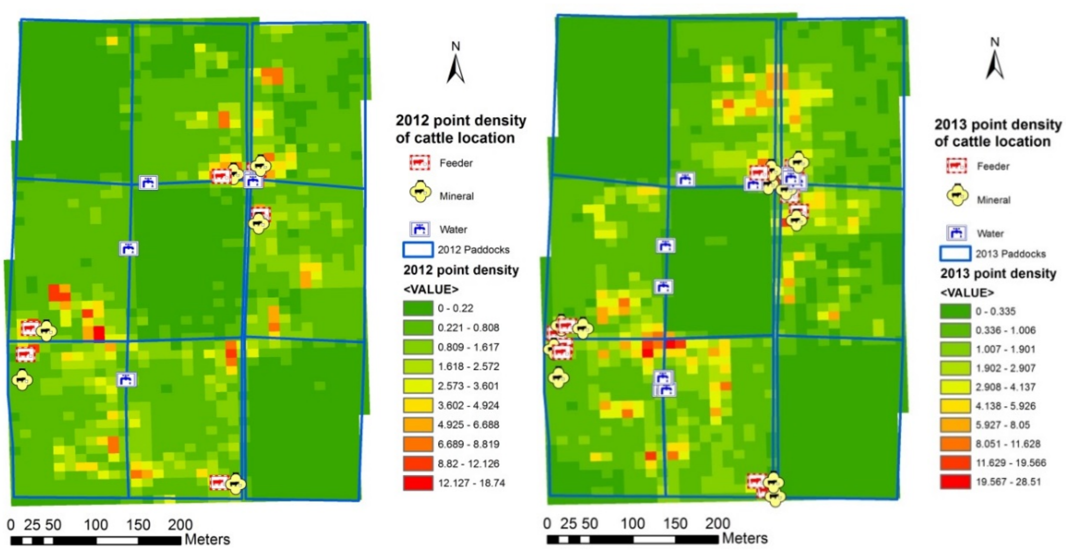


Figure 5.3 Corn yield maps of 2012(a), 2013(b), 2014(c), and 2015(d) at the DSI Farm. Yield exhibited spatial and across-year variabilities on experimental sites.

5.2.2 Spatial heterogeneity of cattle locations

Results of point density analysis show that cattle locations recorded by GPS collars during the fall grazing studies from 2012 to 2014 exhibited spatially uneven distributions on croplands (Figure 5.4). Areas with the highest visitations were identified as bedding areas for cattle. As social animals, the movements of cattle were usually highly synchronized among groups shown by previous studies (Guo et al., 2009; D. D. Johnson & Ganskopp, 2008; Liu et al., 2015). Individual cows in a group tended to stay closer to the herd when they were inactive. Cattle can spend a significant amount of time (e.g. up to half) for resting during a day (Ungar et al., 2005). For example, the results of GPS data analysis in our study suggest that the average time that cattle spent in bedding areas (areas with the top-10% density values) was approximately 11 hours, and was mostly during darkness (e.g. between 7 p.m. and 6 a.m.). Therefore, huge amounts of GPS location fixes could accumulate on these favored bedding areas.



(a) (b)

Figure 5.4 Point density maps of cattle locations recorded via GPS collars during corn residue grazing at the DSI Farm in fall 2012 (a) and fall 2013(b). Bedding areas and areas surrounding supplemental feeders were identified as areas with high density of cattle visitations.

For both continuous and strip grazing paddocks, areas around stationary feed bunks were also identified as heavily trafficked areas (Figure 5.4). Cattle were continuously observed loitering near the feeders and expecting supplementation. Once supplemental feeds were provided, cattle would quickly move towards the feed bunks and start to consume the feeds. It is anticipated that the reoccurrence of cattle to these feeding areas might be strongly influenced by supplementation strategies (e.g. feed amount and frequency of supplementation) and therefore could be changed by management to manipulate the spatial patterns of cattle locations during residue grazing.

Heavy cattle trampling can result in severe soil compaction (Betteridge et al., 1999; Usman, 1994; Willatt & Pullar, 1984), potentially decreasing subsequent crop yield. These effects due to cattle treading might be spatially linked to the amount of time that cattle spent in the areas, which was indicated by the density of cattle visitations derived from GPS data. In our studies, no significant location-based correlation was detected between the density of cattle visitations and subsequent crop yield during the studies at DSI farm from 2012 to 2015. Areas with the highest densities of visitations by cattle had not necessarily led to decreased subsequent corn yield. For example, the mean corn yield in 2013 of areas with the top-10% densities of cattle visitations in 2012 was 194.5 (18.4 SD) bushels/acre, which was not considered significantly lower than the mean yield (196.3 (24.7 SD) bushels/acre) in 2013 of ungrazed areas. It is possible that the spatial patterns of grazing effects on subsequent crop yield were masked by the effects of other environmental (e.g. elevation, pest, and so on) and management factors (tillage, fertilizer and so on), hence, could not be discerned from the data. The results can also imply that the effects of cattle presence on croplands may not only be associated with the time they spent in the areas (e.g. indicated by the density of visitation derived from GPS data), but could also be influenced by cattle behaviors and activities in the areas. For instance, although GPS data have indicated that cattle had spent a significant amount of time (about 11 hours) in those bedding areas, most of the time was during darkness and the GPS locations of cattle were concentrated in those spots. This implied that cattle had very few movements; hence trampling effects caused by cattle traffic were possibly light for those areas.

Since animal behavioral data were not collected during our studies, a coarser classification approach was used to distinguish two behavioral states of cattle based on individual speed derived from GPS data. Individual travel speed was defined as the Euclidean distance between two consecutive GPS locations of an animal divided by the time interval. A threshold value (1m/min) of individual travel speed was then applied to classify cattle behaviors into two states: active (speed >1 m/min) and inactive (speed ≤ 1 m/min), given that the accuracy of GPS receiver was approximately 4 meters at 95% confidence and location fixes were collected at a 4-min interval. Results of point density analysis show that the areas with the highest density values for the active state were mostly identified as areas surrounding the feed bunks (Figure 5.5). This may indicate that the areas near the feed bunks had received the heaviest cattle traffic throughout the experimental field, which could potentially lead to negative effects on soils and subsequent crop yield due to trampling. Since the feed bunks were placed at approximately the same locations across the three-year experiments, the impacts of cattle trampling on those areas around feeders could potentially accumulate over years of grazing. Therefore, special attentions are needed for these areas, as addressed in the next section.

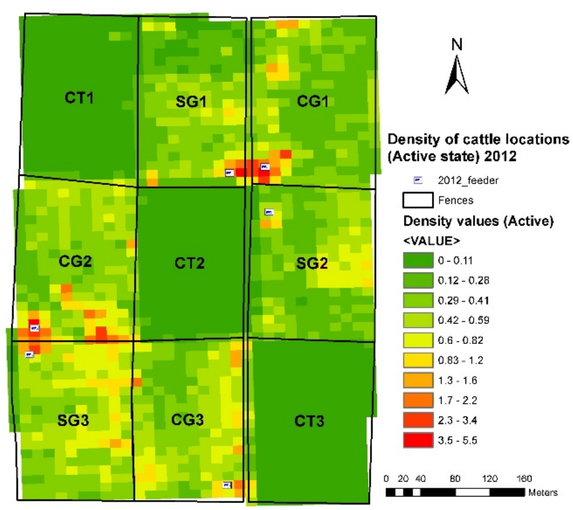


Figure 5.5 Point density map of field visitation by cattle at “active state” (speed > 1 m/min) during fall grazing in 2012. High dense areas were mostly areas near feeders, which indicate heavy cattle traffic in these areas.

5.2.3 Grazing effects near feeders

Given the contour map (Figure 5.2) that delineates areas with different distances from feeders, results show that mean corn yield in 2012 did not vary with respect to the distance from feeders ($P > 0.05$) (Figure 5.6a). The results suggest that no significant yield difference between areas around the feeders and other areas was detected before the grazing trials in 2012. After residue grazing in 2012, 2013, and 2014, a trend for significant yield decline was observed for areas near the feeders (Figure 5.6b, 5.6c, and 5.6d). Results of Fisher's Least Square Distance tests indicate that the mean subsequent corn yields of the areas within 30 m (i.e. 0~10 m, 10~20 m, and 20~30m) from the feeders were significantly lower than those with longer distances (i.e. 30~40m, 40~50m, 50~60m, 60~70m, and 70~80m), for both 2013 (Figure 5.6b) and 2014 (Figure 5.6c). No significant difference was observed among the mean yields of areas with the distances of 30~40m, 40~50m, 50~60m, 60~70m and 70~80m from the feeders in 2013 and 2014. In 2015, the decline in yield was observed in areas with greater distances from the feeders. For example, significant declines in yields were found in areas within 40 m (i.e. 0~10 m, 10~20 m, 20~30m, and 30~40m) from the feeders in 2015. However, whether this decline in yield would further expand is not clear, which requires the continuance of the residue grazing trial and data collection in the future.

Results of point density analysis suggest that the density of cattle visitations was higher as it got closer to the feeders during the three years' grazing (Figure 5.7). Since the feeders were placed at approximately the same locations across the three-year studies, these results indicate that effects of the increased trafficking density near the feeders may accumulate over years and result in growing decline of subsequent crop yield. Therefore, special cautions are needed for managing the feeder locations during residue grazing in order to avoid or alleviate the negative trampling effects due to continued high cattle trafficking on these areas. For example, changing feeder locations during residue grazing may be considered as a management strategy to reduce the density of cattle traffic in a specific area. Removing feeders and supplementing cattle outside the croplands may be another approach, although it may require additional labor and time.

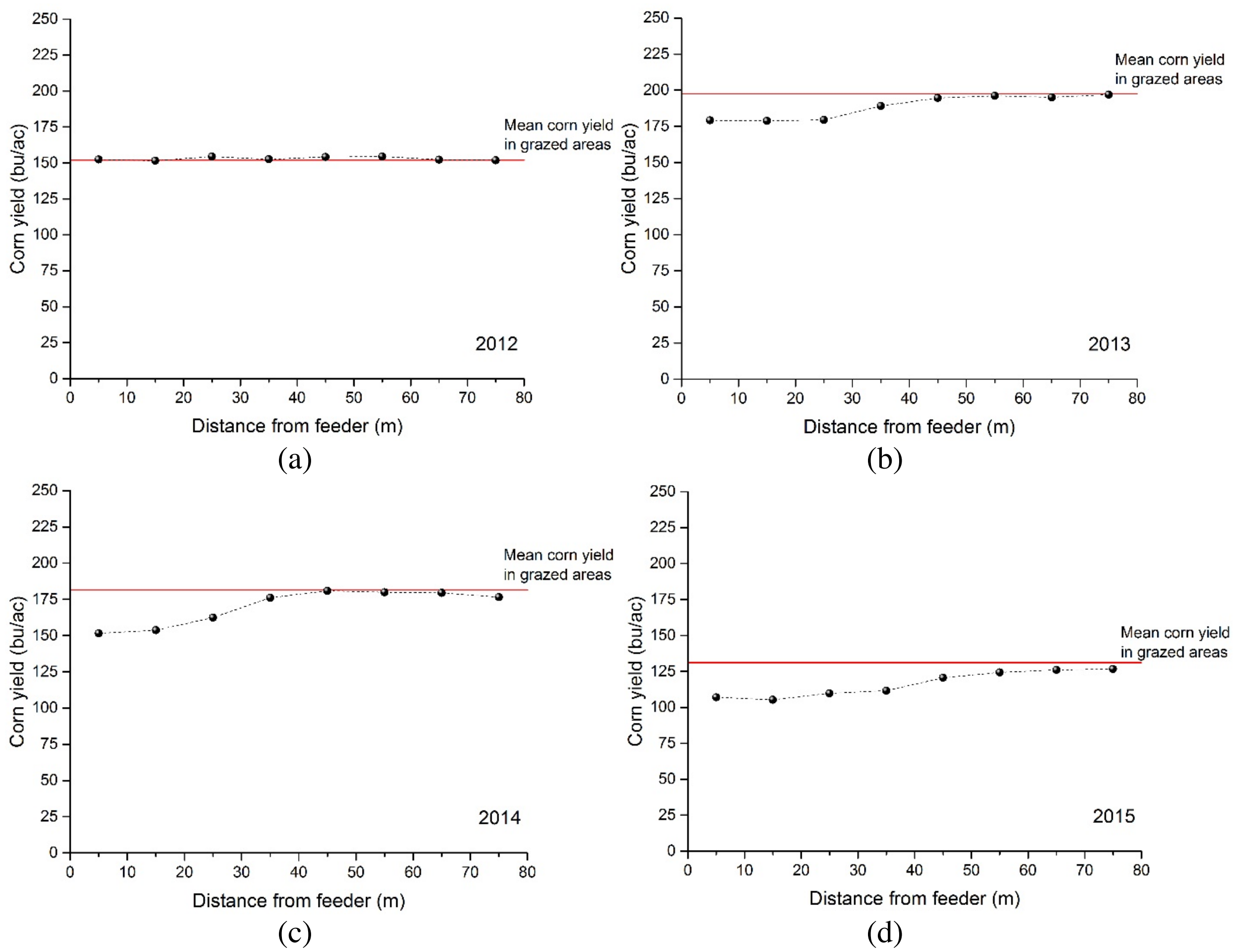


Figure 5.6 Mean corn yields of 2012(a), 2013(b), 2014(c), and 2015(d) in areas with different distance from the feeders. Corn yield in areas surrounding the feeders with a radius of 30 m significantly decreased every year since 2012.

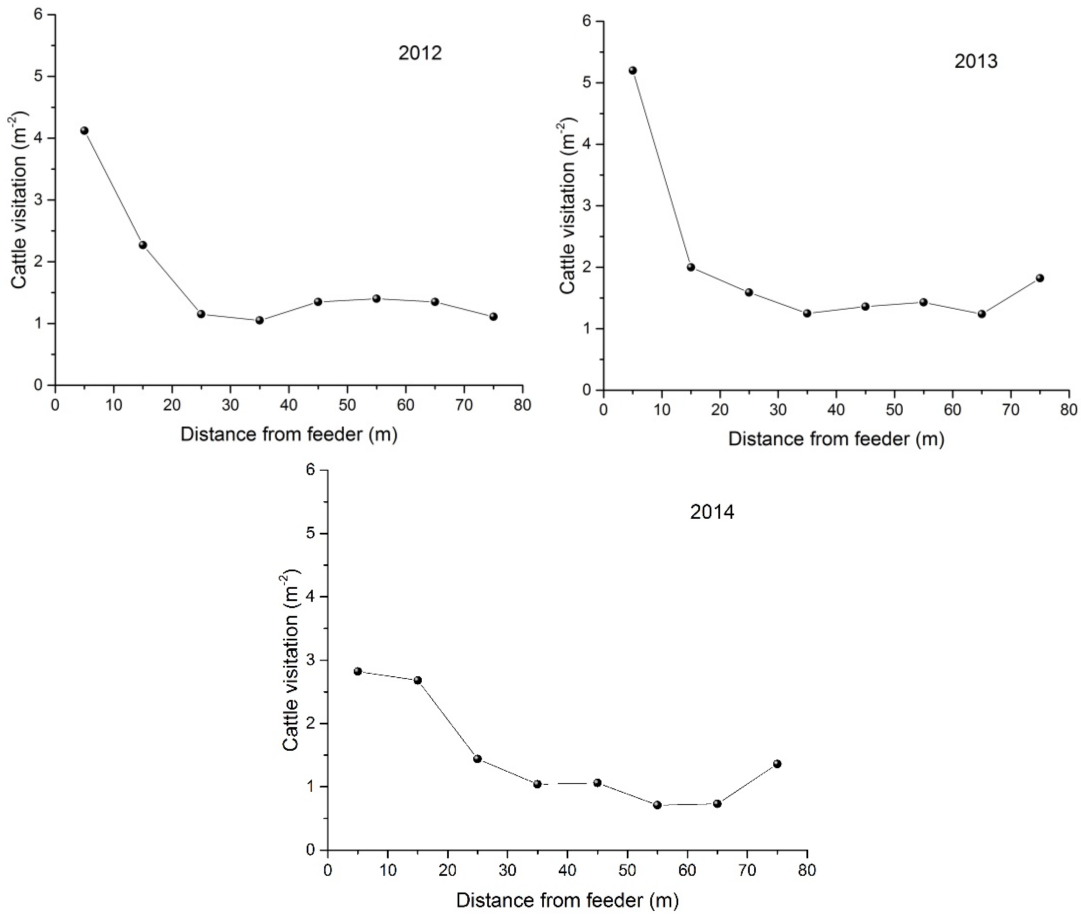


Figure 5.7 Mean point density of Cattle visitation in areas with different distance from the feeders. Density value increases as it gets close to the feeders.

5.3 Summary and Conclusions

Crop residue grazing is considered one of simplest and most economical way to integrate grain and livestock production; yet the complex interactions among these integrated systems were unclear, such as potential grazing effects on subsequent crop yield. This study seeks to leverage geospatial data collected during corn residue grazing to advance our understanding of the spatial patterns of cattle locations and impacts on subsequent crop yield, which would facilitate developing management strategies to improve system performance. The results of this study suggest that although the mean subsequent crop yields were not affected by corn residues grazing under two management practices (i.e. continuous and strip grazing), yield tended to decline in areas near supplemental feeders, potentially due to accumulated trampling effects of higher cattle trafficking. While experimental validation is needed in the future, management strategies such as changing feeder locations during residue grazing were suggested in order to alleviate these negative effects.

CHAPTER 6
DEVELOPMENT OF A SPATIALLY EXPLICIT, AGENT-BASED MODEL FOR SIMULATING MOVEMENTS OF CATTLE GRAZING CORN RESIDUES

Corn residues represent a vast source of feedstuffs available for ruminant livestock producers in the U.S. Corn Belt (Russelle et al., 2007; Sulc & Tracy, 2007). Allowing livestock (mostly cattle) to graze corn residues left on the ground after grain harvest is one of the simplest and most economical methods to integrate livestock and corn operations (Sulc & Franzluebbers, 2014). The alternative to directly grazing would be purchasing or producing winter feeds, which has been shown to be the most expensive element of producing cattle (Reid & Klopfenstein, 1983). While residue grazing can significantly lower feed cost for wintering cows, the presence of cattle on cropland may have negative impacts on soils and subsequent crop development, such as increased soil compaction (Tracy & Zhang, 2008) and poor distribution of nutrients from manure and urine (Sanderson et al., 2013). Previous studies have also shown that cropland covered by corn residues were not evenly visited by beef cattle during residue grazing after fall harvest (Liu et al., 2012). This spatial diversity of grazing distributions could potentially lead to heterogeneous impacts on cropland. Developing management strategies to control such impacts requires understanding the spatiotemporal characteristics of animal grazing on cropland. Quantitatively describing these biological processes presents a challenge because of the extremely complex interactions between animals and the environment in which they are embedded. Combining models and field experiments is suggested as an appropriate approach to address the complexity of integrated crop-livestock systems (Sulc & Tracy, 2007).

Several grazing models can be found in the literature with varying degrees of complexity (Blackburn & Kothmann, 1989; Brereton et al., 2005; Fernandez-Rivera et al., 1989; Loewer Jr., 1998; Rook & Yarrow, 2002). Most of these models are deterministic and focus on the growth and development of animals and forage; thus grazing is often simulated on a daily basis. Further, few of these models have considered the spatial dynamics of animals during grazing. Grazing, in fact, is a complex spatiotemporal phenomenon, which is tightly bonded with animal movements that are driven or affected by numerous biotic and abiotic factors such as animal internal needs, cognitive ability, forage availability and palatability, weather, predator, and topography, some of which may vary dynamically and stochastically in time and space (Bailey et al., 1996; Dumont & Hill, 2001; Nathan et al., 2008). Thus, the inherent complexity of animal movements may require finer spatial or temporal scales for modeling. Until the development and application of technology in tracking animal movements in the late 1990s, there have been few models that simulate the spatiotemporal processes of animal grazing, mostly due to lack of data for validation. The integration of Global Positioning System (GPS) and Geographic Information System (GIS) has provided a robust set of tools for researchers to collect movement data for a wide range of animals (Mech & Cluff, 2011; Rodgers et al., 1996; Vyssotski et al., 2006; Yasuda & Arai, 2005), thus has facilitated model development. With the rising interest in individual-level movement processes and advanced computing technology, agent-based model (ABM), a bottom-up problem solving approach, have been increasingly applied to study animal movement (Abbott et al., 1997; Beecham & Farnsworth, 1998; Bennett & Tang, 2006; Carter & Finn, 1999; Dumont & Hill, 2001; Linard et al., 2009; Mitchell & Powell, 2004; M. G. Turner et al., 1994).

The ABM approach models the “parts” (e.g. individuals) of a system and then studies how the system’s global properties emerge from the fine scale interactions among these parts (Grimm, 1999).

In this paper, we present a spatially explicit agent-based model that simulates small scale movement and foraging decisions made by beef cattle during crop residue grazing on small-middle size integrated farms. Two grazing management scenarios, continuous grazing (CG) and strip grazing (SG), were implemented in the model. Cattle under the CG management are allowed access to the full residue field throughout the entire grazing period, while cattle under the SG management are allowed access to a new portion of the residue field by period. The goal of this model is to investigate how spatial characteristics of aggregated cattle movements emerged from fine-scale movement decisions that can potentially be influenced by grazing management, rather on predicting the locations or trajectories of cattle at specified timestamps. Notably, one main difference between our model and other ABMs is that we were able to use real data collected from grazing experiments for model calibration and validation.

6.1 Data collection

Field data were collected in grazing studies conducted at the Dudley Smith Initiative (DSI) Farm during fall grazing seasons from 2012 to 2014. Thirty-six spring-calving, multiparous, Angus cows were used in 2012 (bodyweight = 648 ± 41 kg) and 2013 (bodyweight = 710 ± 71 kg) at a stocking density of 3.0 $cow \cdot ha^{-1}$, and forty-two winter-calving Angus heifers (bodyweight = 566 ± 39 kg) were used in 2014 at a stocking density of 3.6 $heifers \cdot ha^{-1}$. The 2012 and 2013 scenarios were chosen for model calibration and validation in our study, since the cows used in 2012 and 2013 scenarios were more similar with regards to age and physiological state as compared with the heifers used in 2014. For each year, cattle were divided into six equal groups and were allowed to graze corn residues under two management practices (CG and SG) after harvest. Cattle under the CG management were allowed access to the full field for 42 days. The corn field under the SG management was divided into three equal strips, and cattle were allowed access to a new strip every 14 days. CG usually allows cattle to gain weight during the early phase of grazing, and maintain weight later in the grazing season (Rasby, Drewnoski, & Stalker, 2014). SG allows cattle to graze a corn field in stages by fencing off portions of the field with electric fences. Thus it may provide a more uniform nutrient intake.

During residue grazing, each cow was fitted with a GPS collar to track its locations at a specified sampling interval of four minutes. For each year, cattle were tracked by GPS collars over three monitoring periods, each of which last for 5 days with approximately 8 days' time lapses between monitoring periods. Each GPS location fix includes date, time, latitude, longitude, number of satellites in view, and differential correction status. Spatial coordinates were calculated using the World Geodetic System 1984 earth datum; date and time were recorded in Coordinated Universal Time.

Corn was harvested on 28th August 2012 and 21st October 2013 with a John Deere S680 combine Software (Deere & Company, Moline, IL, USA) equipped with a 16-row head. Yield data were collected during the harvest and later managed using the APEX Farm Management Software (Deere & Company, Moline, IL, USA). Corn residue samples were collected on 23 Oct 2013 (10 days before the start of grazing). Three samples were collected per paddock. For each sample, a 1.8 m^2 sampling square was randomly tossed three times within each third of each paddock. Residue within the sampling square was collected except for the bottom portion of the corn stalks that were still attached to the soil surface. Residue samples were sorted by plant component, and the percentage of each component (leaf, husk, stalk and cob) was estimated.

6.2 Model framework

6.2.1 Basic model concepts

The fundamental concepts of this model were based a new movement ecology framework proposed by Nathan et al. (2008) for modeling the spatial dynamics of individuals. The framework emphasizes four components that are inherently linked to the fundamental processes of animal movement: internal state, external factors, motion capacities, and navigation capacities. The internal states of animals include both physiological states (e.g. body weight, bioenergy flux) and psychological states (e.g. perception, memory and decision-making (Shettleworth, 2001) of animals. The external factors, consisting of abiotic (e.g. elevation, weather, solar radiation) and biotic (e.g. biomass distribution and quality, plant productivities, and species composition) factors, can affect animal behaviors through complex interactions with them. Animals can change their locations via different movement modes (e.g. foraging, exploring, and traveling), which may vary dynamically as responses to their internal states and external conditions. Animals can also utilize external cues and their cognitive capabilities to navigate across landscapes (Tang & Bennett, 2010).

In this model, the spatial dynamics of cattle movements were explicitly simulated as the results of behavioral decisions made by cattle, based on their internal biological motivators (i.e. hunger and hydration) and external conditions (i.e. forages such as corn residues left on the ground and supplemental feeds provided by farmers, water, day-night cycles, and space constraints created via grazing management) (Figure 6.1). The model includes three major components: cattle, forages, and grazing management. Each animal was modeled as an agent who makes decision independently. The internal states of the agent and external stimuli (environment and management) jointly affect the behavioral decision-making process, and were modeled using a decision tree that leads to three types of goal-driven behaviors: foraging (to improve fitness), obtaining water (to maintain body water balance), and resting (to avoid risks during darkness).

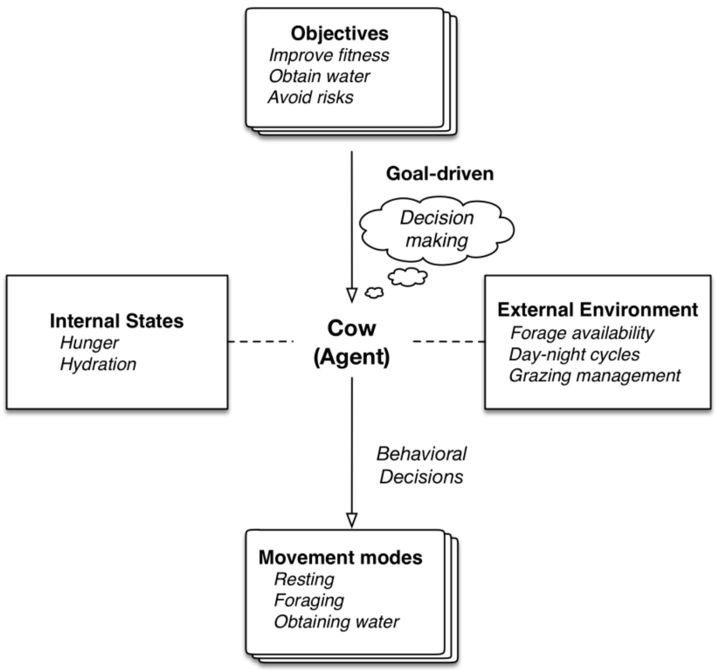


Figure 6.1 Schematic representations of the model concepts. Each cow is simulated as an individual agent whose movement decisions were jointly affected by its internal biological motivators and interactions with the environment, which result in three goal-driven behaviors: resting, foraging, and obtaining water.

This model has been implemented using the agent-based programming language under NetLogo (Wilensky, 1999). Simulations were run for a user-specified grazing length with a 1-min time step. In the following sections, we present the model representations of real world entities (i.e. cattle and forages) and how interactions between these entities were modeled.

6.2.2 Model entities

6.2.2.2 Beef cattle

Each animal is represented as an agent and is characterized using three basic state variables that include body weight, location coordinates, and behavioral modes (i.e. foraging, resting, and obtaining water). Other agent variables are defined and derived from these state variables such as distance to other animals, body energy content, body water content, and decision-making indices based on internal biological motivators and external conditions. The model also keeps track of travel distance, forage and water intakes for each agent at every simulation step. Detailed definitions and uses of these agent variables are described later in the following sections.

Agents are assumed to have a visual perception of surrounding environment and other agents. Specifically, each animal has the ability to sense darkness and daylight hours, distances from other agents, locations of supplement feeder, water tank and fences, forage type and amount within a certain visual range, and availability of supplements in the feeder.

6.2.2.2 Forage distributions and characteristics

Corn yield is used to estimate the amount of corn residues available for grazing after harvest. The cropland is represented using a discrete two-dimensional grid under the Moore neighborhood adjacency rule. Base on the resolution of yield data, we use a 10 m × 10 m grid cell to represent patch structure. The amount of residues is calculated for each cell according to the yield data. We assume that the amount of residues is positively correlated with corn yield, and approximately 50 lbs. of residues are left in the field per bushel of corn harvested (Lardy, 2011).

Cattle can selectively graze forages, and they usually choose the most palatable and nutritious plant part first (Lardy, 2011). According to published nutritional data of corn residues (Rasby et al., 2014), the grain is highest in nutrient quality. The corn leaf and husk are intermediate in nutrient quality but high in palatability. The corn cob and stalk are lowest in protein and palatability. Several studies have suggested that, when grazing residues, cattle will consume grain first, followed by the husk and leaf and finally the cob and stalk (Fernandez-

Rivera et al., 1989; Lamm & Ward, 1981; Lardy, 2011; Rasby et al., 2014). In this model, we assume there is little grain left in the field after harvest; thus residues available for grazing consist of corn leaf, husk, cob, and stalk. Similar to a residue grazing model developed by Fernandez-Rivera (1989), we assume that cattle consume leaf and husk first, and consume cob and stalk only when the availability of leaf plus husk is insufficient to allow a maximal leaf plus husk intake. Therefore, we classify residues into two categories: 1) leaf and husk; 2) cob and stalk. According to corn residue data collected at the DSI Farm, the mass percent of leaf and husk, cob and stalk are estimated as 36% and 64% of total corn residues. The digestibility of leaf and husk is calculated using an empirical equation derived by Fernandez-Rivera et al (1998):

$$D_{lh} = \left\{(73.1 - 0.071 \times t_0) - \left[(0.766 - 0.000448 \times IALA) \times t_g\right]\right\} / 100 \qquad (6\text{-}1)$$

where t_0 is the number of days between harvest and date to start grazing, t_g is days of grazing and IALA is the initial amount of leaf and husk available per animal (kg). The first term estimates the husk digestibility at the date grazing started (McDonnell, 1982). The second term estimates the daily rate of decline and includes both animal selection and environmental losses, which was derived from data presented by Fernandez-Rivera and Klopfenstein (1989). Similar to Fernandez-Rivera's model, we assume that the digestibility of cob and stalk is 35% for the entire simulated period.

The environmental loss of leaf and husk per unit area at any simulation step (1 min) is calculated as 0.00005 of the biomass available, according to data presented by Lamm and Ward (1981) for leaf disappearance in ungrazed fields. This change can be attributed to wind loss and plant deterioration during grazing.

6.2.2.3 Grazing management

Two grazing management strategies (CG and SG) are both considered in this model. Each paddock includes a water tank and a supplement feeder. SG paddocks are divided into three strips, and cattle are allowed access to a new strip every 14 days (Figure 6.2). Cattle are supplemented three times weekly to receive 1.8 $kg \cdot hd^{-1} \cdot d^{-1}$ of a mixed pelleted corn gluten feed (50%) and soybean hull (50%) during residue grazing. For instance, the amount of supplement for a group of six cows is 25 kg per time if receiving three times a week. Both water and feeder are located in the first strip of strip grazing paddock, so cattle always have access to them. The locations of the water tank and feeder are stationary during grazing. According to the site coordinates collected during grazing experiments using a handheld GPS device, water tank and feeder are placed in the corresponding locations in the model environment. Cattle are assumed to have access to water or supplements if they are on the same patch where the water or feeder is located.

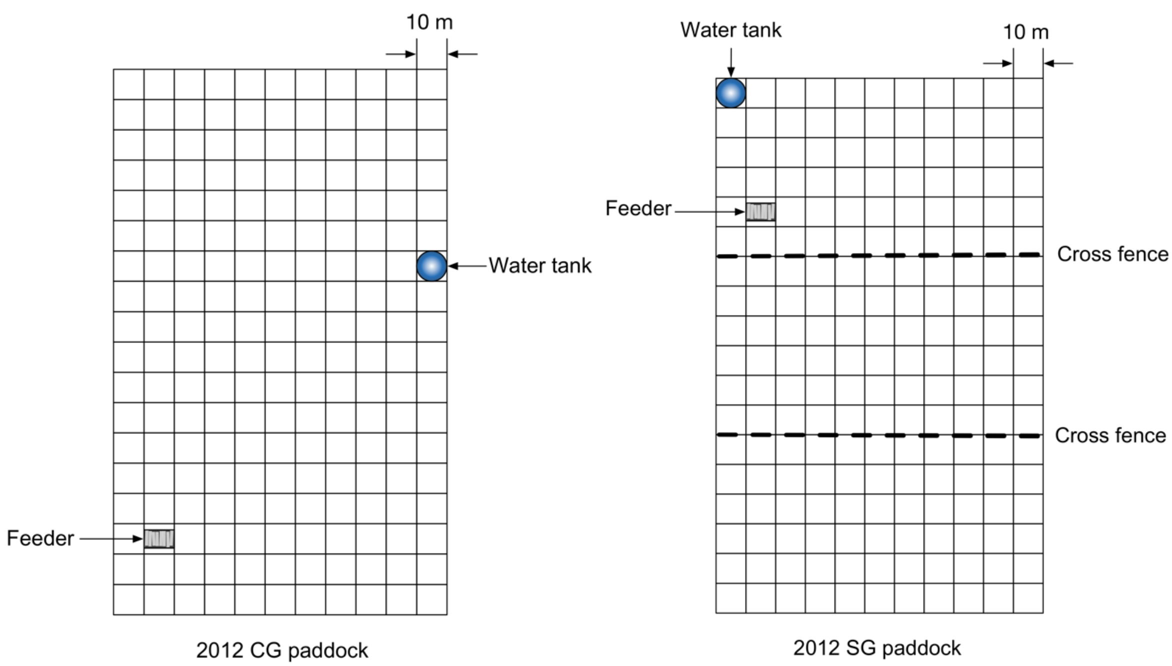


Figure 6.2 Model representation of the grazing environment in 2012. A two-dimensional grid is used to represent the cropland with a cell size of 10m by 10m. The cropland is divided into three strips using electrical fences for the SG management. A water tank and a feeder are located in the first strip.

6.2.3 Behavioral decisions

In this model, agents try to consume enough forage to meet their energetic demands and potential growth. Meanwhile, agents also try to obtain enough water to maintain their body water balance. During night, agents prefer resting than other activities; thus, they have very few movements after sunset. Therefore, simulated cattle have three basic movement behaviors: 1) resting, 2) foraging, and 3) obtaining water. For one simulation step, each agent can only adopt one behavior. Behavioral decisions made by each agent are determined via a decision tree (Figure 6.3) that uses three behavioral indices ($B_{rest}, B_{forage}, B_{drink} \in [0,1]$) to indicate the likelihood of choosing a corresponding behavior, assuming that behavioral decisions made by an agent are driven by its internal biological motivators (i.e. hunger and hydration) and external conditions (i.e. day-night cycles, forages, supplement feeds, water, and grazing management). Generally, the greater the value of B is, it is more likely that agent will choose the corresponding behavior. When a tie between B_{forage} and B_{drink} occurs, agents will prefer foraging behavior to drinking behavior.

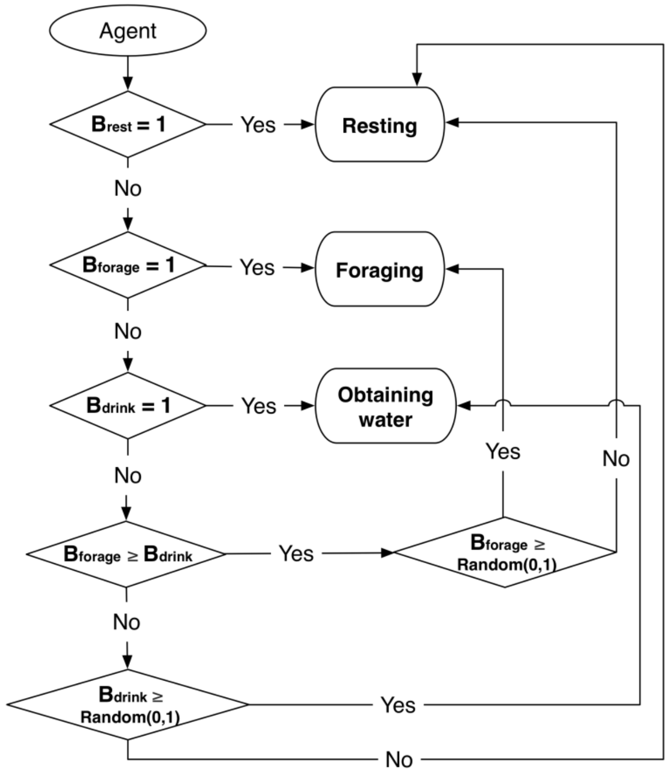


Figure 6.3 Behavioral decision tree for an agent. Behavioral indices are determined based on agent's internal state and external environment. For one simulation step, an agent can only adopt one behavior according to the outcome of the decision tree.

The behavioral index for resting (B_{rest}) is calculated as:

$$B_{rest} = \begin{cases} 0, & \text{in the daytime} \\ 1, & \text{in the night} \end{cases} \tag{6-2}$$

This assumes that agents will choose to rest during the night instead of having any other activities. Note that the outputs of the decision tree indicate that agent may also choose to rest during the daytime under certain circumstances.

For calculating the foraging index (B_{forage}), we assume that the amount of forage an agent can consume per day is limited by a maximum daily forage intake cap. Agents will not choose foraging once they have achieved the intake cap during a simulated day. The cap for leaf plus husk intake under unlimited supply is calculated using a modified equation (Fernandez-Rivera et al., 1989) from Konandreas and Anderson (1982) as:

$$I_{\max - lh} = \frac{0.0365 BW^{0.75} - 0.2 I_s}{1 - D_{lh}} \quad (6\text{-}3)$$

where BW is the weight (kg) of an agent at the beginning of a simulated day, I_s is the supplement (kg/d) and D_{lh} is leaf plus husk digestibility. The term $0.0365BW^{0.75}$ is total fecal output estimated from data obtained by Roth (1987). The digestibility of supplement is assumed to be 80%. Since D_{lh} is calculated at every day step in model simulations, the cap for leaf plus husk intake is also calculated at every day step and BW is set to the weight of an agent at the beginning of a simulated day. Thus the value of $I_{\max - lh}$ remains constant within a day but varies across days. The cap for cob plus stalk intake under unlimited supply is calculated similarly.

The behavioral index for foraging is calculated as:

$$B_{forage} = \begin{cases} 0, & bw \geq BW \cdot b \text{ or when reaching daily forage intake cap} \\ 1 - (bw - BW \cdot a) / (BW \cdot b - BW \cdot a), & BW \cdot a \leq bw \leq BW \cdot b \\ 1, & bw \leq BW \cdot a \text{ or when supplement is available at feeder} \end{cases}$$

(6-4)

where bw is the body weight (kg) of an agent at a simulation step, BW is the body weight (kg) of an agent at the beginning of a simulated day, a and b ($a < 1 < b$) are two parameters that are used to estimate the likelihood of foraging behavior. The values of the two parameters may vary for different physiological states of cattle (e.g. gestation, lactation, and calving); thus, they are calibrated for specific scenarios (e.g. $a = 0.975$ and $b = 1.025$ for gestating cows with mean body weight of 646 kg monitored at the DSI farm in 2012). The model assumes that agents will stop foraging once they have achieved the daily forage intake cap or their body weights are greater than or equal to $BW \cdot b$. The model also assumes that cattle will immediately consume supplement feed once the feed becomes available, based on observations during the grazing trials at the DSI farm.

Similarly, the behavioral index for obtaining water is calculated as:

$$B_{drink} = \begin{cases} 0, & wc \geq WC \cdot d \\ 1-(wc - WC \cdot c)/(WC \cdot d - WC \cdot c), & WC \cdot c \leq wc \leq WC \cdot d \\ 1, & wc \leq WC \cdot c \end{cases} \quad (6\text{-}5)$$

Where wc is the body water content (L) of an agent at a simulation step, WC is the body water content (L) of an agent at the beginning of a simulated day, c and d ($c < 1 < d$) are two parameters that used to estimate the likelihood of drinking behavior (e.g. $c = 0.95$ and $d = 1.05$). The body water content of a cow ranged from 615 to 809 ml/kg (Springell, 1968). In this model, we assume that the body water content is 700 ml/kg; thus wc and WC are calculated based on bw and BW , correspondingly.

In each simulation step, agents can adopt only one behavior based on the output of the behavioral decision tree (Figure 6.3). The resulted behaviors are presented as three submodels below.

6.2.3.1 Resting

In this model, we assume that agents have very few movements during resting. The displacement of an agent during resting is set to a random floating-point number between 0 and 1 (m) per simulation step. Agents are assumed to rest during the night time, but they may also rest during the daytime. Compared with daytime resting, some restrictions are applied to agents during nighttime resting. Agents would prefer to stay in specific areas, namely “bedding” areas, during nighttime. The “bedding” areas were identified using point density analysis of cattle location data based on their activeness. Areas with the highest density values (e.g. top-5%) for inactive status were determined as the bedding areas.

6.2.3.1 Foraging

For the foraging behavior, we adopted an ungulate grazing model presented by Turner et al. (1993) with some modifications. We assume that agents would first consume supplement feeds if the feeds are available at the feeders; otherwise, agents would graze corn residues left on the ground.

During foraging, the forage intake, FI (kg), at every simulation step, is calculated using a modified equation presented by Turner et al. (1993) as:

$$FI = MFIR \times f(\mathrm{F}) \times \Delta t \tag{6-6}$$

where $MFIR$ is the maximum forage intake rate (kg/min), $f(\mathrm{F})$ is a negative feedback related to forage amount, and Δt is the time length of one simulation step (1 min). $MFIR$ is assumed to be a function of the maximum daily forage intake cap $I_{\max}$ (kg) and foraging time length $T_{foraging}$ (hour) of a day:

$$MFIR = I_{\max} / T_{foraging} \tag{6-7}$$

$I_{\max}$ varies across forage types (e.g. leaf/husk, and cob/stalk) due to different digestibility (eq 6-3), thus $MFIR$ is calculated for each forage type accordingly. Foraging time length $T_{foraging}$ is estimated to be 56% of daylight hours suggested by the data presented by Hart et al. 1993. The daylight length is determined based on daylight duration data from US Astronomical application department.

The negative feedback term $f(\mathrm{F})$ in eq. 6-6 is calculated as:

$$f(\mathrm{F}) = \left\{ \begin{array}{cc} 1, & F \geq \alpha \\ 1-[(\alpha - F)/(\alpha - r), & r < F < \alpha \\ 0, & F \leq r \end{array} \right\} \tag{6-8}$$

It assumes that agent can achieve its maximum foraging rate if the amount of corn residues in the current cell (F) is at or above a threshold α . Forage intake rate will decline linearly as the residue amount falls below α , and reaches zero when available residues fall below some refuge level r , which means they are no longer available to the agent (M. G. Turner, Wu, Romme, & Wallace, 1993). For supplement feed, we assume that agent can always achieve maximum forage intake rate, thus $f(\mathrm{F})$ is set to 1 for supplement feed.

During foraging, when forage amount in the current cell declines, agents are assumed to have an increased likelihood of searching for a new cell for grazing instead of grazing in the current cell. The probability of moving to a new cell, P_{search}, is calculated as:

$$P_{search} = \begin{Bmatrix} 0, & E_{\max} \le E_0 \\ (E_{\max} - E_0)/R, & 0 < E_{\max} - E_0 < \Delta E \\ 1, & E_{\max} - E_0 \ge \Delta E \end{Bmatrix} \quad (6\text{-}9)$$

where E_0 (kcal) is the metabolizable energy value of residues left in the current cell, $E_{\max}$ (kcal) is the highest metabolizable energy value of forages in a neighbor cell within a certain foraging search radius (R_{search}) from the current cell. We assume that agent would graze in the current cell if E_0 is higher than $E_{\max}$. As energy value of forages declines, the probability of choosing a new cell for grazing linearly increases, and reaches 1 when the difference between $E_{\max}$ and E_0 exceeds a threshold ΔE or when available forages in the current cell fall below the refuge level r . P_{search} is then compared with a random floating-point number between 0 and 1 to determine whether agent would graze on the current cell or move to a new cell. If a moving decision is made, agent will move to the cell that has the highest energy value of forages within the search radius. Detailed calculations of the metabolizable energy value from forages are presented in 6.2.4.

6.2.3.1 Obtaining water

Cattle water requirement and consumption are dependent on various factors such as air temperature, humidity level, animal physiological states, diet type and physical activities (Parish & Rhinehart, 2008). Water intake usually consists of free drinking water and water from feedstuff. Cattle lose water from the body through urine, feces, sweat and by water vapor from skin and lungs (NCR, 1996). For practical purpose, we ignore water from feedstuff and assume that water is only provided from drinking at the stationary water tank. Because increased physical activity increases water loss through evaporation and sweating (NCR 1996), we assume that water expenditure rate at resting is half of that of other activities. Water expenditure rates are then estimated to be 0.0185 L/min for resting, 0.037 L/min for foraging and drinking, assuming that daily water loss is approximated equivalent to the water requirements of cattle (NCR 1996).

A stationary water tank is placed at a user-specified location. For drinking behavior, an agent will move towards the water tank if it is not in the cell where the water is located. If the agent is currently in the water cell, agents are assumed to have the access to water, and water intake rate is set to be 10 L/min.

6.2.4 Cattle energetics

Since the main goal of this model is to simulate the spatial dynamics of cattle during crop residue grazing, we avoided incorporating too many realistic details. Therefore, we adopted a simple ungulate energetic model (Turner et al., 1993) with some modifications specifically made for beef cattle to simulate energy balance and weight gain, rather than implementing a detailed physical model for cow body growth. We assume a general relationship between cow body weight and energy content: 1 kg animal body mass ~ 2000 kcal energy content. Energy balance and body weight change are then calculated at every simulation step for each agent as the difference between metabolizable energy gained from forage and total energy costs.

The metabolizable energy available from forages are estimated based on the total digestible nutrients for each forage types (Rasby et al., 2014, NRC 1996). Energy available in leaf/husk, cob/stalk, and mixed corn gluten/pelleted soyhulls supplement feed is estimated as 1950 kcal/kg, 1330 kcal/kg and 2890 kcal/kg, respectively.

The total energy cost (EC, kcal) is assumed to be a basal metabolic cost plus a travel movement cost. The basal metabolism cost rate at resting is estimated based on the relationship given by Crampton and Harris (1969):

$$BMC_{resting} = 70 \times ACTWT^{0.75} \tag{6-10}$$

where $BMC_{resting}$ (kcal/day) is the minimum heat production associated with basal metabolism, and $ACTWT$ (kg) is the empty body weight of animals.

If the cow is active, the total heat production would include some allowance for the work associated. Thus, the basal metabolism cost rate at foraging and drinking is estimated using the relationship given by Lofgreen and Garret (1968):

$$BMC_{active} = 77 \times ACTWT^{0.75} \tag{6-11}$$

where BMC_{active} (kcal/day) is the heat production associated with basal metabolism and moderate activity. For each agent, the body weight at the beginning of each simulated day is used for $ACTWT$. BMC is calculated on a daily basis using eq. 6-10 and 6-11, and then is rescaled for the time resolution (1 min) of the model.

We assume that energy cost for travel movement is dependent on animal body weight and travel distance. To estimate travel energy cost, we assume that the maximum energy expenditure allowed for travel in a day is approximately half of the basal metabolism energy cost (Morehouse

& Miller, 1976; Turner et al., 1993). Assuming that an agent spends 12 h resting and 12 h for moderate activities, energy expenditure allowed for travel is $0.5\left(BMC_{resting}+BMC_{active}\right)$. Energy cost rate for travel movement (TMC, kcal*min^{-1}*kg^{-1}) is then calculated as:

$$TMC=\frac{0.5\times(BMC_{resting}+BMC_{active})}{BW\times L} \tag{6-12}$$

where BW is the body weight of an agent, and L is daily travel distance (estimated as 2500m based on GPS data). For practical purpose, TMC is estimated at the beginning of the simulation and remains as a constant during simulation.

Therefore, total energy cost at each simulation step is calculated as:

$$EC=\frac{BMC}{24\text{h}\times 60\,\text{min}}\times\Delta t+TMC\times bw\times l \tag{6-13}$$

where BMC (kcal/day) is the daily basal metabolism energy cost ($BMC_{resting}$ for resting and BMC_{active} for moderate activities), TMC (kcal*min^{-1}*kg^{-1}) is the energy cost rate for travel, bw is the body weight of an agent, l is the distance travelled during the simulation step, and Δt (1 min) is the time length of one simulation step.

6.2.5 Input data, simulation, and outputs

User inputs (shown in Figure 6.4) include composition of corn residues, corn yield map, harvest date, number of animals, initial body weight of animals, date and time to start grazing, length of grazing, sunset/sunrise time, animal bedding areas, grazing management (fence settings), and supplementation (amount, feed type, and schedule). The outputs (shown as Figure 6.4) include animal weight gain after grazing, daily forage and water intake, daily travel distance, percentiles of different animal behaviors (i.e. grazing, resting and drinking), and density maps that illustrate the spatial distribution of cattle locations.

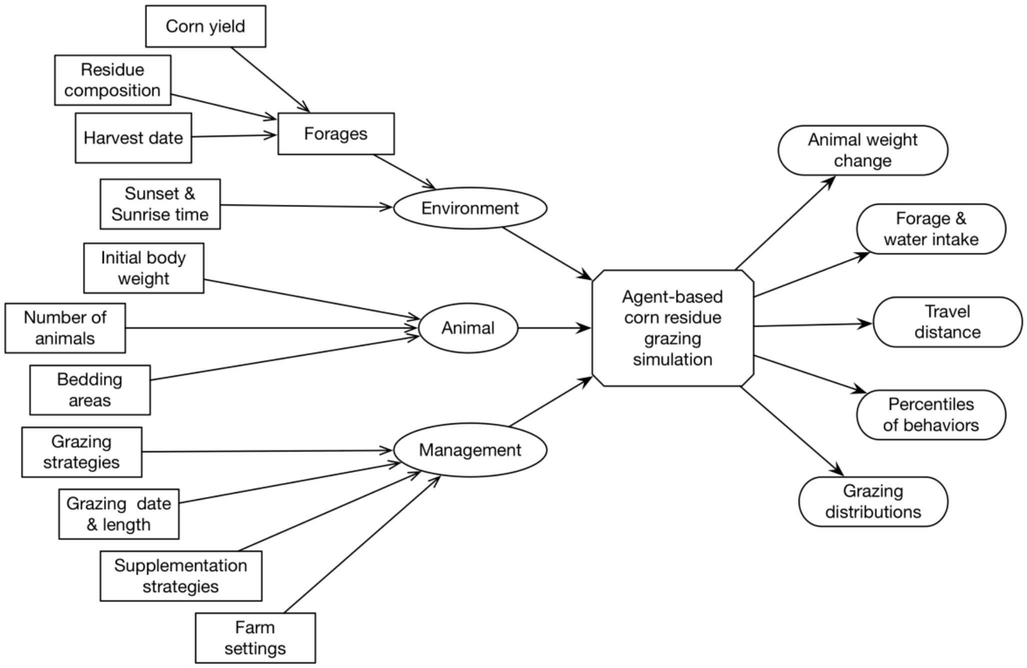


Figure 6.4 Model inputs and outputs. The model is initialized via user inputting animal, environment, and management information. After simulation, results are summarized and exported into tables.

A full model run includes three steps: initialization, simulation, and outputting results (Figure 6.5). Inputs, as shown in Figure 6.4, are specified by the user (i.e. residue composition, harvest date, number of animals, initial body weights, grazing date & length, and farm settings) or loaded from files (corn yield, sunset & sunrise time, supplementation strategies, and bedding areas) to initialize the model. During simulation, the model keeps tracking the state of each agent and patch variables at every simulation step. Summarized agent variables (e.g. mean body weight, cumulative travel distance, forage and water intake, and mean distance to herd centroid) can be dynamically plotted and viewed from the NetLogo user interface. After simulation ends, the model writes result as tables that record the final states of model entities (agents and environment) and can optionally output these variables as time series. To quantify the spatial distribution of cattle locations during grazing, the model performs a point density calculation and outputs the density of agent visitations. The density calculation uses the same patch structure as used in forage distributions. The number of agent visits for each 10m × 10m cell is totaled and divided by the area of the cell.

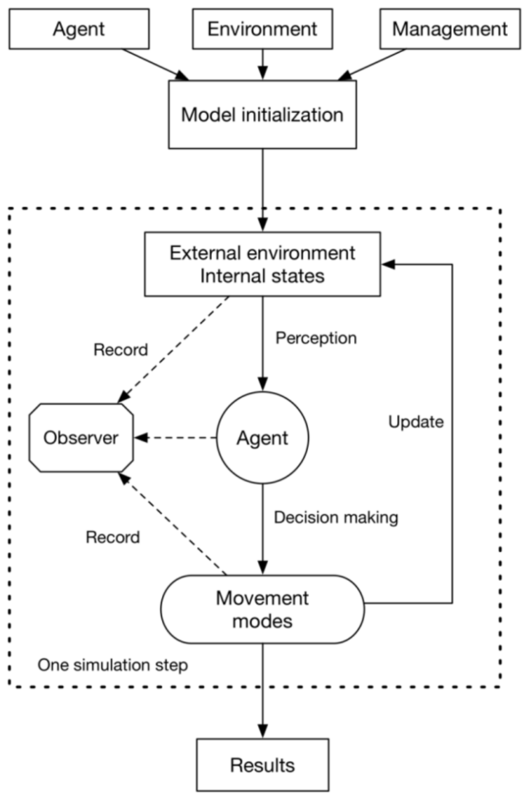


Figure 6.5 Model process overview and scheduling. A full run includes model initialization, simulation, and results summarization.

6.2.6 Calibration and validation

A common challenge for agent-based models is that very few of them are truly validated due to the lack of data (Dumont & Hill, 2001). In this study, we were able to use real field data from grazing experiments to calibrate and verify our model. Specifically, we calibrated the model using data from 2012 grazing experiments, and then used data from 2013 for model validation. The calibration procedure for this model followed the ABM parameterization and calibration guidelines presented by Railsback and Grimm (2012). A sensitivity analysis was conducted to identify a set of parameters that are both uncertain and important to evaluate via calibration. The calibration range and increment of model parameters were determined based on literature or user specifications (See appendix A for a full list of model parameters). To quantitatively compare model predictions with experiment observations, several calibration criteria that summarize the key patterns in the system were considered, including the spatial distribution of cattle locations during residue grazing, mean final cow body weight after grazing (FBW), mean percentiles of activities, and mean daily travel distance (DTD). For spatial distribution of cattle locations, point density of cattle visitations was compared between normalized density maps (value ranges from 0 to 1) generated from model simulation and GPS data. A pixel-wise comparison was used to evaluate the similarity of the two maps. The root mean square deviation for comparison was calculated as:

$$rmsd = \sqrt{\frac{\sum_{i=1}^{n}(d_i^m - d_i^g)^2}{n}} \tag{6-14}$$

where d_i^m is the point density value for cell i given by the model, d_i^g is the point density value for cell i given by the GPS data, and n is the total number of cells.

Determining the types of cattle behavior only based on GPS data without behavioral data remains a challenge in our studies. Therefore, the percentiles of cow behaviors predicted by the model were compared with data collected in another study presented by Ungar et al. (2005). In this study, 12 to 13 hours of visual observations were conducted at 20-min sampling interval during the daylight time to determine cattle behaviors.

Since DTD derived from GPS data could be affected by the sampling interval (Davis et al., 2011). In our experiments, GPS fixes were collected at a 4-min interval. Thus, DTD calculated based GPS data were then adjusted (i.e. multiplied by 1.136) according to data presented by Davis et al. (2011) to match the time resolution used in model simulation (1 min).

For each combination of parameter values, the model was run for five times and the mean values of outputs were used for evaluation. A threshold (0.1) was used for *rmsd*, and the 90% confidence interval of experiment data was used for other calibration criteria.

6.3 Results and discussions

6.3.1 Model calibration and validation

Calibrated spatial distributions of cattle during the entire residue grazing period (quantified as a 10m × 10m normalized point density map of field visits) were compared with values derived from cattle locational data collected via GPS collars at the DSI farm during fall 2012 (Figure 6.6). The values of *rmsd* for the pixel-wise comparison between the predicted and observed density maps were 0.055 ± 0.002SD for CG and 0.083 ± 0.002SD for SG for 10 replicated runs. Results of pixel-wise linear regression analysis suggest that predicted cattle spatial distributions were in good agreement with observed GPS data of cattle under CG ($r^2 = 0.82$) as well as SG($r^2 = 0.71$) management in 2012. Areas with relatively high-density values (e.g. ≥ 0.2) of visitation were the bedding areas and areas where the stationary feeder and water tank were placed, suggested by both model predictions and observation data (Figure 6.6). These areas only represented a small portion (about 5%~10%) of the entire paddock, while other areas (about 90%~95%) in the paddock had relatively low cattle visit density (e.g. < 0.2). This was presumably due to the management settings that supplements and water could only be accessed via permanently placed feeders and water tanks. In addition, individual cows usually have similar bedding areas and may spend a significant amount of time (e.g. up to 50%) for resting during a day (Ungar et al., 2005). Therefore, a small portion of the paddock that had special functionality for cattle behaviors (i.e. consuming supplements, obtaining water and resting) resulted in having high densities of cattle visitation, while other areas that constituted a considerable proportion of the paddock, possibly being associated with only the foraging behavior, had relatively low densities.

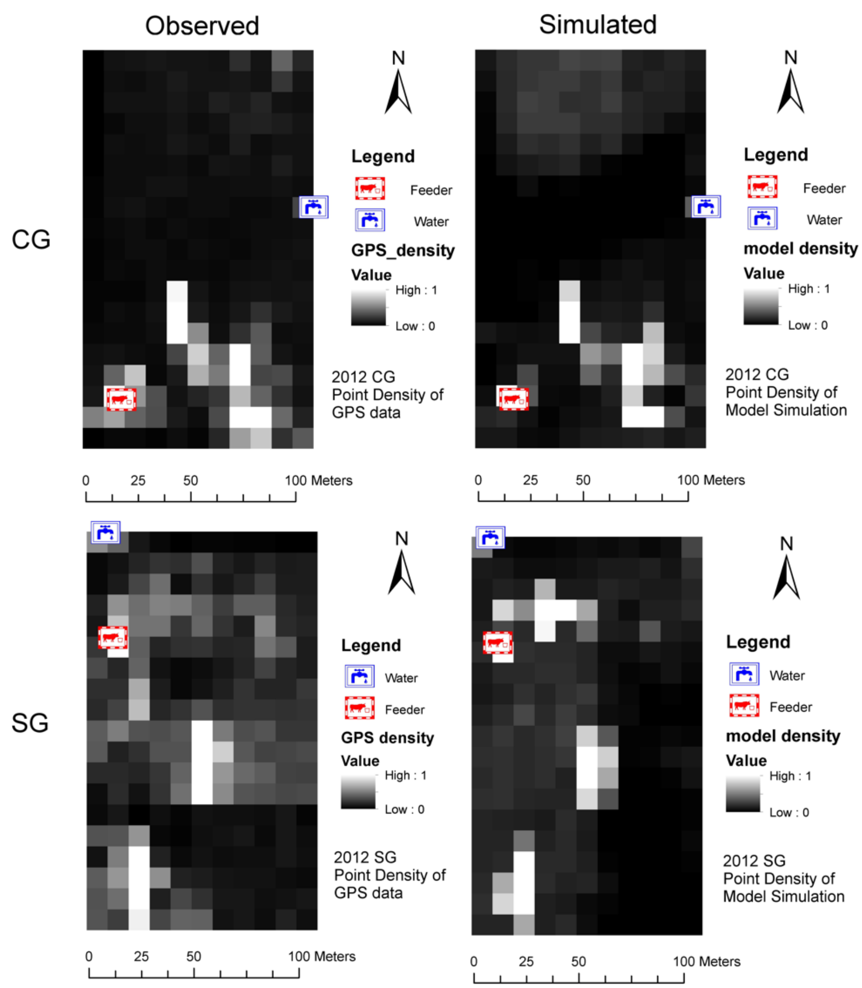


Figure 6.6 Model calibrations results. Simulated grazing distributions were compared against results derived from GPS data of cattle under the CG and SG management at the DSI farm in fall 2012.

Calibrated model predictions of FBW and DTD were compared with experimental data (Table 6-1 and 6-2). Both simulation results and observed data suggest that cattle under SG outperformed those under CG. Average daily weight gain was about 0.48 kg for cows under CG and 1.10 kg for cows under SG. The calibrated model performed well in predicting the final body weight after grazing with errors smaller than 5 kg. Values of mean DTD derived from experimental data suggest that cattle under CG management had greater DTD than those under SG management. The calibrated model underestimated DTD for CG cows, while overestimating

DTD for SG cows. However, these errors were within acceptable ranges (<10% of observation values).

The simulated percentages of cattle behaviors during daylight time show good agreement with the observation data presented by Ungar et al. (2005) (Table 6-1 and 6-2). Simulation results show that grazing accounted for about half of the daylight time under both CG and SG scenarios. Resting accounted for about 46% and 47% of the daylight time under CG and SG, respectively. Simulated percentages of drinking behaviors were slightly higher as compared to data presented by Ungar et al. (2005), in which drinking accounted for less than 1% of the observation time. These minor differences compared against Ungar's data may be interpreted as the results of different classification methods for cattle behaviors. For instance, traveling was treated as a stand-alone cow behavior in Ungar's experiments, which accounted for 6% of the observations. In our model, traveling was driven by other behaviors such as foraging and obtaining water; thus, it was then incorporated into other behaviors instead of being viewed separately.

Table 6-1. Comparison of calibration results against experimental data at the DSI farm (2012 CG) and data from other literature

Values calculated based on experimental data or other literature						
	FBW (kg)	Weight change (kg)	DTD(m)	Percentage of behaviors during daylight time		
				grazing	resting	drinking
	665.4	20.3	4396.7	45%	50%	<1%
Simulation results: average over 10 runs (60480 steps for each run)						
	FBW (kg)	Weight change (kg)	DTD(m)	Percentage of behaviors during daylight time		
				foraging	resting	obtaining water
Mean	660.9	15.8	4118.2	52.19%	45.58%	2.22%
Std.	0.75	0.75	17.19			
Relative error	-0.68%		-6.33%			

Table 6-2. Comparison of calibration results against experimental data at the DSI farm (2012 SG) and data from other literature

Values calculated based on experimental data or other literature

	FBW (kg)	Weight change (kg)	DTD(m)	Percentage of behaviors during daylight time		
				grazing	resting	drinking
	692	46	2841	45%	50%	<1%

Simulation results: average over 10 runs (60480 steps for each run)

	FBW (kg)	Weight change (kg)	DTD(m)	Percentage of behaviors during daylight time		
				foraging	resting	obtaining water
Mean	694.2	48.2	3110.8	49.56%	46.69%	3.77%
Std.	1.19	1.19	10.86			
Relative error	0.32%		9.50%			

A full list of calibrated model parameters and input data is presented in Appendix A. Notably, some parameters may vary according to grazing management (CG or SG). For example, cattle under CG management had averagely higher travel speed over the entire grazing period than those under SG management, and they tended to be more active in searching for new foraging patches. This has resulted in greater DTD of cow under CG management as shown by both model simulation and experimental data. The impact of cross fence used in SG paddocks may be accounted for these differences in cattle behaviors, because it constrained the areas that cattle had access to and therefore might have impacts on cattle behavior.

Calibrated model parameters were applied to simulate grazing scenarios at the DSI farm in 2013 for model validation. Similar to 2012 scenarios, the predicted spatial distributions of cattle were in good agreement with observed GPS data (Figure 6.7). The values of *rmsd* for the pixel-wise comparison between the predicted and observed density maps were 0.088 ± 0.005SD for CG and 0.111 ± 0.003SD for SG for 10 replicated runs. According to the results of pixel-wise linear regression analysis, the model performed better on predicting the grazing distribution of cattle under CG ($r^2 = 0.64$) than the SG scenario ($r^2 = 0.48$). Similar to 2012 scenarios, bedding areas and areas around stationary feeders and water tanks had the highest density values of visitation in both CG and SG scenarios, suggested by the simulation results and experimental data (Figure 6.7). These areas (i.e. with density value ≥ 0.2) only account for about 7% ~ 14% of the entire paddock. Compared with the CG scenario, the SG scenario was more complicated for modeling because it included additional fence operations that could have significant impacts on grazing behaviors. Generally, the model has better predictions of grazing distributions for CG scenarios.

The model overestimated FWB and DTD for both CG and SG scenarios in 2013 (Table 6-3 and 6-4). Simulated FWBs after grazing were 5.2% and 6.0% greater than the observed values in CG and SG scenarios, respectively. Predicted DTDs were about 20% greater than DTDs derived from GPS data for both CG and SG scenarios. Similar to 2012 scenarios, percentages of cattle behaviors during daylight time predicted by the model were close to the observation data presented by Ungar et al. (2005) (Table 6-3 and 6-4).

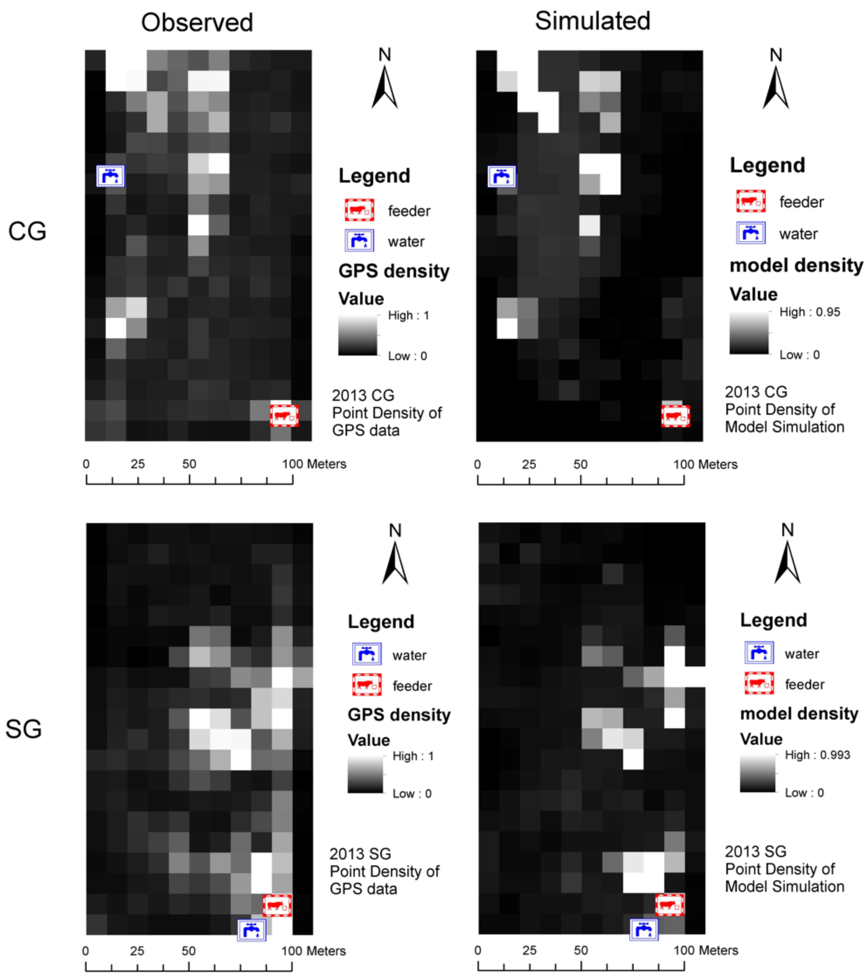


Figure 6.7 Model validation results. Simulated grazing distributions were compared against results derived from GPS data of cattle under the CG and SG management at the DSI farm in fall 2013.

In our model, weather impacts on the grazing system were not included, which could affect both forage and cattle. However, information on that is very limited. For example, snow cover reduces residue availability to cattle, but the effect is unclear and is hard to study. In addition, the energy requirement for maintenance is usually dependent on environmental temperature. Under cold stress, cattle may increase metabolic rate for additional heat production used for warmth. Our simulated cattle gained considerably more weight after grazing, which might be due in part to an overestimation of residue availability and an underestimation of energy consumption under extreme temperature conditions. These effects of weather on forage and cattle were ignored in our model because of lack of information. Fernadez-Rivera et al.

(1989) simulated these effects in their residue grazing model based on several assumptions, which may be adopted to improve our model performance. However, these assumptions were not verified and thus remain a challenge for study.

Table 6-3. Verification of simulation results against experimental data at the DSI farm (2013 CG) and data from other literature.

Values calculated based on experimental data or other literature						
	FBW (kg)	Weight change (kg)	DTD(m)	Percentage of behaviors during daylight time		
				grazing	resting	drinking
	698.5	-10.1	3271.6	45%	50%	<1%
Simulation results: average over 10 runs (60480 steps for each run)						
	FBW (kg)	Weight change (kg)	DTD(m)	Percentage of behaviors during daylight time		
				foraging	resting	obtaining water
Mean	734.4	25.8	3927.0	48.74%	49.38%	1.88%
Std.	1.32	1.32	24.73			
Relative error	5.15%		20.03%			

Table 6-4. Verification of simulation results against experimental data at the DSI farm (2013 SG) and data from other literature.

Values calculated based on experimental data or other literature						
	FBW (kg)	Weight change (kg)	DTD (m)	Percentage of behaviors during daylight time		
				grazing	resting	drinking
	710	721.6	2531.8	45%	50%	<1%
Simulation results: average over 10 runs (60480 steps for each run)						
	FBW (kg)	Weight change (kg)	DTD (m)	Percentage of behaviors during daylight time		
				foraging	resting	obtaining water
Mean	752.6	42.6	3045.2	46.82%	49.80%	3.37%
Std.	0.76	0.76	12.86			
Relative error	6.00%		20.28%			

Modeling animal movement is indeed complex because animal movement can be driven or affected by numerous abiotic and biotic factors, which may be stochastic in nature. Quantitatively describing the interactions between animal and the environment presents an even greater challenge. Capturing all factors in a residue grazing system is impossible because of the complex nature of the system and also the lack of data. While the results suggest that the model performed well in predicting the spatial distributions of cattle during grazing, a limitation of the model is that the bedding areas of the cows were specified as a model input based on the GPS data. The impact of this input on model predictions, however, is only limited to the determination of animals' locations during resting at night. Predicting animals' bedding areas remains difficult and requires a comprehensive understanding of animals' resting behaviors. In case there is no data available for determining bedding areas, users may specify the bedding areas as a model input based on observation or personal experience with the specific group of cattle used in the study. Meanwhile, several factors that may affect behavioral decisions are not included in our model, such as spatial memory, and social interactions between individuals. Furthermore, the effect of cattle tramping on residue quality is ignored in our model because of the difficulties in determining such effect without any data collected. Future development of the model requires considering weather and animal trampling effects, and possibly adopting a more detailed physical model for animal body growth. Notably, perfect model verification will not be possible until the theoretical concepts in the model are truly validated by experiments. Our model is valid for a particular set of experiment conditions.

6.3.2 Effects of grazing management

Management has noticeable influences on cattle grazing crop residue. Locations of stationary feeders and water tanks may partially determine the distribution of cattle since they were frequently visited by the animals as shown by the results above. In addition, grazing strategies can also affect the spatiotemporal patterns of cattle movements during residue grazing. For instance, both simulation and experiment results show that the distributions of cattle visitation under SG management varied evidently across the three SG periods (Figure 6.8). Cattle were found to be sensitive to the cross fences, which were temporarily used to divide the SG paddocks into three strips for grazing. Results show that cattle relocated most of their activities to a new strip once it became available after the removal of the cross fence. They spent the most time in the new strip resting and foraging, and seldom went back to previous strips except visiting the water and feed bunks (Figure 6.9). If cattle trampling was found to reduce residue quality during grazing, it is anticipated that grazing strategies such as SG management can be used to manipulate the spatial distribution of cattle across time, potentially preserving the quality of forages for later use to improve animal performance.

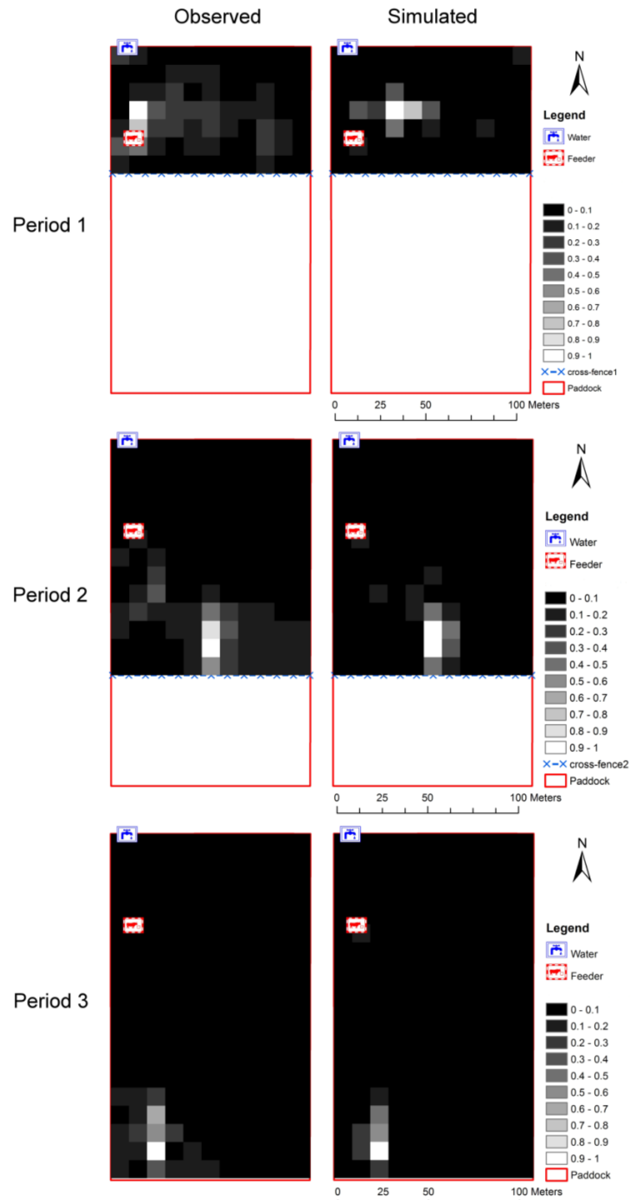


Figure 6.8 Observed vs. simulated distributions of cattle visitation for different strip grazing periods at the DSI farm in 2012. Observation and model simulation results suggested similar patterns in the change of cattle locations with regards to cross-fence removal under the SG management.

Information on how much corn residue cattle consume is very limited. Simulation results show that predicted daily total forage intake (including both residue and supplement intake) decreased with time of grazing in both CG and SG scenarios. Forage intake for an individual cow was about 9~10 kg/d in the first few days of grazing, and then gradually decreased to 5~7 kg/d at the end of the 42d grazing period. Several reasons can be accounted for this decline in forage intake, such as decreasing residue digestibility, decreasing availability of residue due to animal grazing and environmental loss, and daytime allowed for grazing getting shorter. Snow cover and trampling effect could also reduce availability and quality of residue, but was not considered in this model. Increasing the amount of supplements near the end of grazing may be considered in order to alleviate such decline of daily forage intake by cattle, especially when snow occurs.

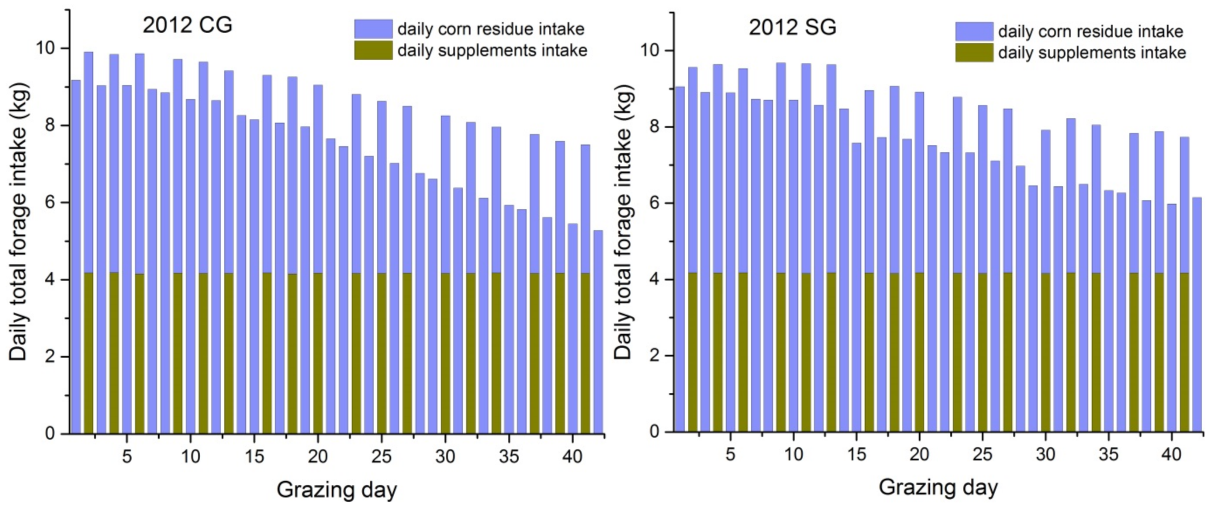


Figure 6.9 Simulated daily forage intake of cattle under the CG and SG management at the DSI farm in fall 2012. Predicted daily total forage intake declined with time of grazing in both CG and SG scenarios.

Simulation results suggest that daily total forage intake was affected by the supplementation. In both CG and SG scenarios, supplements were provided three times per week. Cattle generally had higher forage intake on days when supplements were provided than days with no supplements (Figure 6.9). This difference gradually grew with the length of grazing, from 0.7 kg/d (CG) and 0.5 (SG) at the beginning of grazing to 2.2 kg/d (CG) and 1.6 kg/d (SG) at the end of the 42d period. During the grazing trials, we observed that cattle preferred to consume supplements than to graze corn residue when supplemental feeds were provided at stationary feed bunks. Compared with corn residue that was heterogeneously distributed in the field, cattle could consume supplements more directly without traveling and searching for residues. According to simulation results, cattle generally had longer DTD on days when they could only graze corn residue with no supplements provided (Figure 6.10). Furthermore, the digestibility of leaf and husk declined during grazing, while the digestibility of supplements is greater and remains the same. These facts explained the results that cattle had higher forage intake when they were supplemented, and that this difference increased with time of grazing.

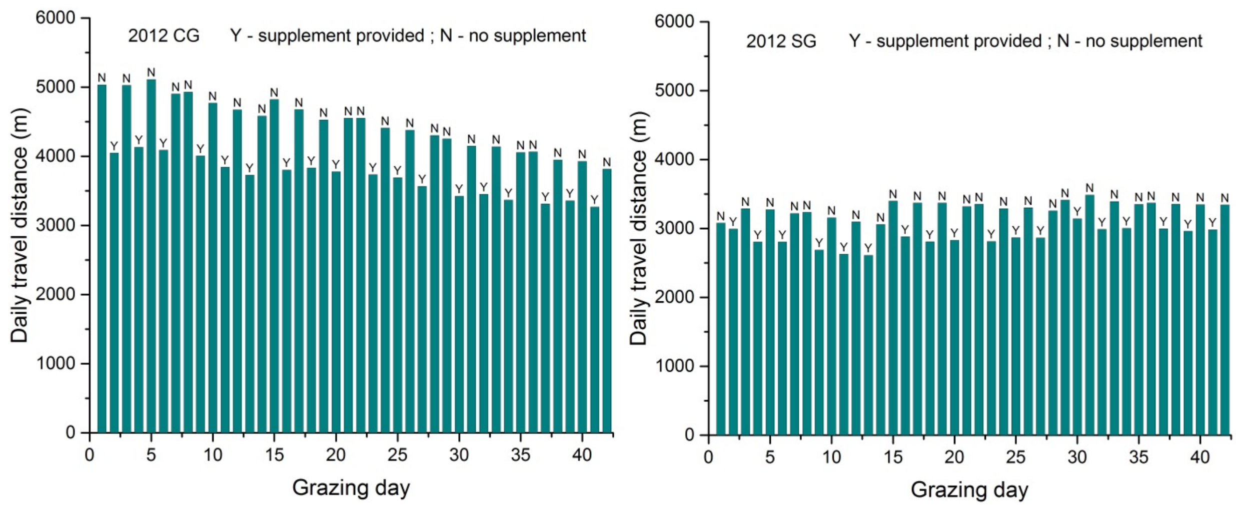


Figure 6.10 Simulated daily travel distance by cattle under the CG and SG management at the DSI farm in fall 2012. Simulated cattle under the CG management had greater daily travel distance than those under the SG management.

Besides effects of supplements, results also indicate that grazing strategies had significant impacts on DTD by cattle. Simulated cattle under the CG management had greater mean DTD over the entire grazing period than those under the SG management (Figure 6.10), likely due to the different size of land accessible to cattle controlled by the management. For example, simulated average DTDs by cattle over the 42d grazing period by were 4118.2 m (CG 2012) and 3110.8 m (SG 2012), respectively. This was in good agreement with observed data (Table 6-1 and 6-2). In addition, both observations and simulation results show that DTD by cattle under CG management tended to decline with time of grazing, while DTD by cattle under SG management stayed at about the same level. Different space allocation strategies for cattle controlled by the management may be accounted for these differences in animal behaviors. For instance, most of the cow activities occurred within a new strip under SG management for the corresponding stage (Figure 6.8) because there were more residues available in the new strip; therefore, their DTDs were not likely to change over time because each strip had about the same size of areas. In CG scenario, cattle were allowed full access to the field throughout the entire grazing period. Thus, they had more areas accessible than those under SG management at the beginning. As the spatial diversity of residue distribution declined over time in the CG scenario due to animal consumption and environmental loss, cattle tended to search less frequently for forage, which led to a decrease in travel distance.

For both CG and SG scenarios, model results show that daily weight gained by cattle gradually decreased with time of grazing (Figure 6.11a), presumably due to decreased forage intake over time. Cattle generally had more weight gains on days when supplements were provided (Figure 6.11b), because of more forage intake (Figure 6.9) and less travel distance (Figure 6.10). The results also show that cattle under SG management had more weight gains than those under CG treatment at the end of grazing (Figure 6.11a), which was consistent with measurements (Table 6-1~ 6-4). Results suggest that this difference in cattle performance was due to different grazing strategies. For instance, cattle under SG treatment had shorter daily travel distance, which has resulted in fewer energy expenditures and more energy savings toward body weight gain. Other factors, such as impacts of more animal trampling occurred in CG treatment, may also affect forage quality and animal performance. However, the trampling effect was not modeled in our study due to the lack of data for validation. Our study suggests that strip grazing resulted in better cattle performance than continuous grazing. These results are valid for our experimental conditions. In practice, decisions on grazing strategies should be made according to actual conditions. For instance, if extended periods of deep snow and icy conditions occur, CG may be considered as a better choice than SG because some of the best feed may be left ungrazed under SG management (Rasby et al., 2014). Determining appropriate grazing strategies remains a ‘topic’ where future research is needed.

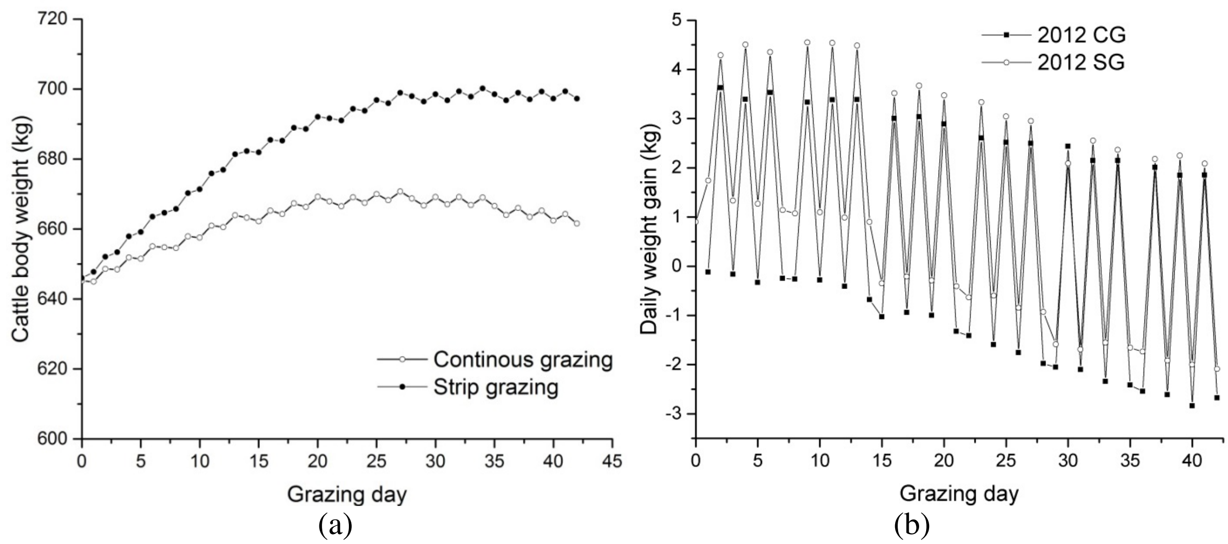


Figure 6.11 Simulated cattle weight changes under continuous grazing and strip grazing management at the DSI farm in fall 2012. Cattle under the SG management had greater weight gain than those under the CG management at the end of grazing. Daily weight gain declined with the time of grazing in both scenarios.

6.4 Conclusions

Residue grazing has been considered as a simple and economical means to integrate corn and cattle operations, while the complexity of the integrated systems remains a challenge for management and study. Previous cattle grazing models were often focused on the growth and development of animals and forage with little attention on the spatial dynamics of the animal during grazing. With the advent of animal tracking and advanced computing technology, spatially explicit agent or individual based models have been increasingly utilized to study animal behaviors in grazing systems. In this paper, we presented a spatially explicit agent-based model to help understand the spatiotemporal characteristics of cattle during grazing residue. The model was calibrated and validated for two management scenarios (continuous grazing and strip grazing) based on real field data collected during grazing experiments. It has been shown that spatial distributions of cattle during grazing predicted by our model are consistent with observation data. With much work remains to be done for future research and model refinement, results suggest that this model, built on an effort to understand the fundamental processes of cattle movements during grazing residue, can be used as a research tool in decision making for managing residue grazing in the future.

CHAPTER 7
CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

Great food demand has placed increasing pressure on agriculture. Integrated crop-livestock system has been suggested as a promising approach to improve the long-term sustainability and resilience of agricultural systems. In the U.S. Corn Belt, integrating cattle and corn production through directly grazing residues after harvest can help reduce winter feed costs. However, the effects of residue grazing on croplands are unclear. Furthermore, integration usually increases system complexity and requires more complicated management. This dissertation focuses on investigating integrated corn-cattle systems through combining field experiment, data analytics, and model simulation. Data, analytical tools, and models presented in this dissertation can serve as a solid foundation for providing insights into decision support for sustainable management of integrated crop-livestock systems.

A three-year fall residue grazing experiment was conducted on an integrated corn-cattle farm in central Illinois. A custom GPS tracking system was successfully developed and implemented to monitor beef cattle movements during residue grazing across multiple years. The long-term performance and reliability of this system were evaluated via analyzing data quality and maintenance records. Results show that mean location error of the GPS tracking system was less than 4 m and was not significantly impacted by its position on animal's neck. GPS application protocols developed in this study recommends that an initial animal acclimation period can effectively reduce shaking and rubbing that results in damage to GPS unit or problems for the animals.

GPS data collected during the experiments were analyzed to identify the spatiotemporal characteristics of cattle movements during residue grazing. Results of movement characterization suggest that the mean travel speed of individual cows was highly coordinated with the speed of the centroid of herd in time. Grazing strategies had notable impacts on cow daily travel distance. Cattle under strip grazing treatment traveled significantly less per day than those under continuous grazing treatment, which might result in more energy saving toward body growth. Results of spatial analysis show that cattle locations were unevenly distributed during residue grazing. Bedding areas and areas around stationary feed bunks were identified as the most heavily visited areas. The spatial distribution of cattle under strip grazing management was significantly affected by the cross-fence settings. This indicates that management strategies can effectively manipulate the distributions of cattle and allocate residues for grazing. Periodic pattern mining suggests that cattle had periodic behaviors associated with their bedding areas, which was possibly linked with resting and ruminating behaviors that have circadian rhythmicity. In addition to mining GPS data for movement patterns, a computational approach has been developed to evaluate errors in subsequent GPS data analysis caused by monitoring subset groups of cattle instead of the entire herd. Results show that monitoring an appropriate subset group of cattle could preserve most information with acceptable errors for analysis. Analogous results are expected when applying this approach to systems that have similar experimental designs.

Impacts of grazing on subsequent crop yield were analyzed for the three-year residue grazing study. Results show that mean subsequent crop yields were not affected by residue grazing under two management practices (i.e. continuous grazing and strip grazing) as compared with the ungrazed control. However, yields in areas near the supplemental feeders decreased after grazing, likely due to accumulated trampling effects of heavier cattle traffics in these areas. Thus, management strategies, such as replacing stationary feeders with mobile feeders, were suggested in order to alleviate such negative impacts.

Based on a comprehensive understanding of the data collected during the grazing experiments, a spatially explicit agent-based model has been developed to simulate cattle movements during corn residue grazing. The model was calibrated and validated using field data for two management scenarios (continuous grazing and strip grazing). Results predicted by the model showed good agreement with observation data. It is anticipated that, with further model refinement, this model can be utilized as a research tool to aid future development of decision support for sustainable management of integrated corn-cattle systems.

7.2 Future work

The long-term goal of the work presented in this dissertation is to provide decision support capabilities for agricultural producers and policy makers to develop innovative management practices that increase the productivity while simultaneously improving the sustainability of agroecosystems. This requires a comprehensive understanding of the interrelationships among components of integrated crop-livestock systems, as well as necessary information needed such as the spatial and temporal scales of integration, for expansion to other locations. A decision support platform (Figure 7.1) that integrates data analysis, model simulation, and decision support tools will meet the need, using the DSI study presented in this dissertation as a case study to create a workflow, which provides the capability to expand this effort to other regions under various conditions. This platform will also include tools for quantifying and evaluating trade-offs between economic returns and ecosystem services, facilitating management decision-making based on predictions of the overall outcomes of integrated crop-livestock systems.

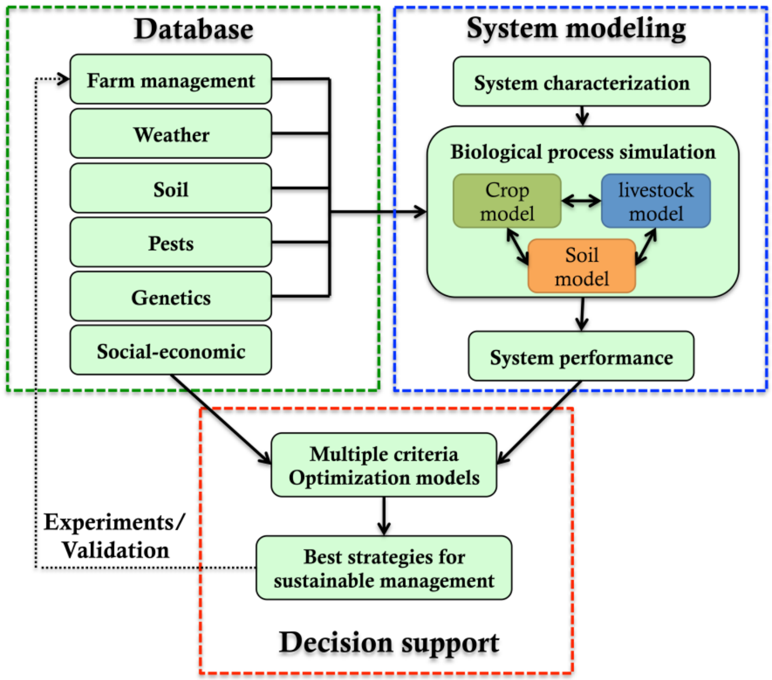


Figure 7.1 Schematic of a decision support system for integrated crop-livestock systems.

Data and modeling analysis in the decision support platform will focus on identifying, characterizing and quantitatively describing key system components and interactions that ought to be included in integrated crop-livestock models (Figure 7.2). Besides livestock and crop data, soil data should also be collected and included in analysis to assess grazing impacts on soil fertility in both short and long-term. This can be potentially integrated into crop models to provide higher resolution (e.g. field-scale) of crop yield prediction considering the impacts of grazing. The agent-based model developed in this dissertation will be continuously refined to include more realistic details in simulation, such as weather data and detailed physical model of livestock development and growth. Management strategies suggested by modeling analysis will be verified via field experiments.

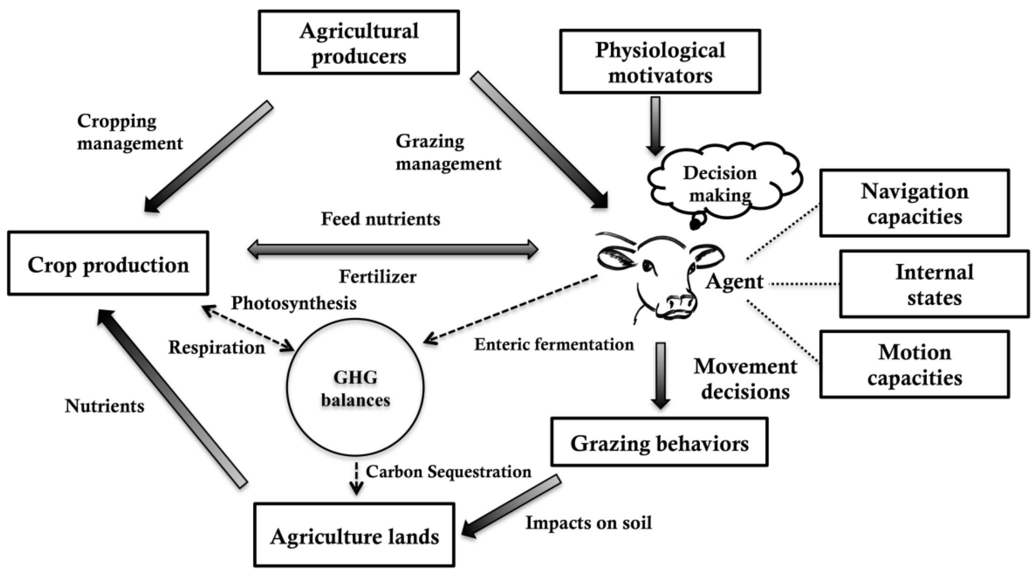


Figure 7.2 Schematic of components and interactions of integrated crop-livestock systems. Identification, quantification and modeling of key system components and interactions will provide agricultural producers with insights into management strategies for enhancing the overall system performance.

Many questions need to be answered regarding how to utilize the data, models and decision support tools generated here to guide or improve the design of integrated systems in other appropriate regions. Thus, a feasibility analysis will be carried out to utilize the integrated corn-cattle system described in this dissertation as a system-level case study for identifying potential economical and agroecosystem benefits that allow expansion to other regions in the Corn Belt. The feasibility study will be divided into two phases. The first phase will focus on utilizing resources generated under previous projects, peer-review literature, and public databases to identify regions with similar geospatial and agronomic features as the Dudley Smith Initiative Farm in the Corn Belt. Whether there exist opportunities for integrating corn and cattle farming in these regions will be investigated by considering various factors including the current farming systems, climates, topography, soil types, transportation, and markets. The second phase of the feasibility analysis will focus on utilizing the assimilated data and models to study the uncertainty and sensitivity of input variables that are correlated with the performance of integrated systems such as crop yield, nutrient cycling, soil fertility, and other potential ecosystem services. This will help identify other regions where potentially promising combinations of input variables are viable for integrating corn and cattle farming to increase both economic and ecosystem outcomes.

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APPENDIX A: LIST OF ABM PARAMETERS

Name	Value	Description
initial body weight	Experimental data. E.g. 645.1 kg, 2012 CG scenario	Initial body weight of an agent
herd size	Experimental data. E.g. 6, 2012 CG scenario	Number of agents
(herd_x, herd_y)	Experimental data. E.g. (0, 1), 2012 CG scenario	Model coordinates of initial herd centroid location
maximum move speed	Calibrated. 5 model cells/min (CG) and 3 model cells/min (SG)	The maximum move speed of an agent
foraging search radius	Calibrated. 5 model cells	Agent sensing radius used in searching for a new foraging cell
graze_lower_thres	Calibrated. 1.025	Parameter used for calculating index for foraging (Eq. 6-4)
graze_upper_thres	Calibrated. 0.975	Parameter used for calculating index for foraging (Eq. 6-4)
water_lower_thres	Calibrated. 0.95	Parameter used for calculating index for obtaining water (Eq. 6-5)
water_upper_thres	Calibrated. 1.05	Parameter used for calculating index for obtaining water (Eq. 6-5)
TMC	Calibrated 0.003 kcal/(kg*m)	Travel movement energy cost
WCR-active	Estimated based on model assumption. 0.037 L/min	Water consumption rate during activities
WCR-resting	Estimated based on model assumption. 0.0185 L/min	Water consumption rate during resting
WIR	User specified. 10L/min	Water ingestion rate
t0	Experimental data. E.g. 32 d, 2012CG scenario	Time between harvest date and residue grazing date
grazing length	Experimental data. E.g. 42 d, 2012CG scenario	Total length (days) of grazing
first-period-length	Experimental data. E.g. 14 d, 2012CG scenario	Length(days) of the first period under strip grazing
second-period-length	Experimental data. E.g. 14 d, 2012CG scenario	Length(days) of the second period under strip grazing
third-period-length	Experimental data. E.g. 14 d, 2012CG scenario	Length(days) of the third period under strip grazing
starting-time	Experimental data. E.g. 11 a.m., 2012CG scenario	The time in a day when residue grazing begins
(feeder-x, feeder-y)	Experimental data. E.g. (1.35, 1.84), 2012 CG scenario	Model coordinated of feeder location
(water-x, water-y)	Experimental data. E.g. (10,11), 2012 CG scenario	Model coordinated of water location
sup-amount	Experimental data. E.g. 25 kg, 2012 CG scenario	The amount of supplements per time
e-f1	Experimental data. 1950 kcal/kg, 2012 CG scenario	Energy content of residue type 1 (leaf/husk)
e-f2	Experimental data. 1330 kcal/kg, 2012 CG scenario	Energy content of residue type 2 (cob/stalk)
e-sf	Experimental data. 2890 kcal/kg, 2012 CG scenario	Energy content of supplement (50% pelleted corn gluten and 50% soybean hull)
forage-loss-rate	Estimated from data presented by (Lamm and Ward 1981). 0.00005	The environmental loss rate of leaf/husk at every simulation step
energy-diff	Calibrated. 600 (CG), 1000 (SG)	Threshold of metabolizable energy from residues used in foraging model (Eq. 6-9)
forage-upper-thres	Calibrated. 70 kg	Parameter used for calculating negative feedback in foraging model (Eq. 6-8)
refuge-level	Calibrated. 30 kg	Parameter used for calculating negative feedback in foraging model (Eq. 6-8)
cell-size	User specified. 10 m	Size of square cell used in model.