ASSESSING RESPONSES OF GRASSLANDS TO GRAZING MANAGEMENT USING REMOTE SENSING APPROACHES

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ABSTRACT

Grazing caused grassland degradation has occurred worldwide in recent decades. In spite of numerous efforts that have been invested to explore the mechanism of grassland responses to grazing management, the major challenge remains monitoring the responses over large areas. This research evaluates the synthetic use of remote sensing data and the Milchunas-Sala-Lauenroth (MSL) model for grazing impact assessment, aiming to explore the potential of remotely sensed data to investigate the responses of grasslands to various grazing intensities across different grassland types.

By combining field collected biophysical parameters, ground hyperspectral data and satellite imagery with different resolutions, this research concluded that 1) sampling scale played an important role in vegetation condition assessment. Adjusted transformed soil-adjusted vegetation index (ATSAVI) derived from remote sensing imagery with 10m or 20m spatial resolution was suitable for measuring leaf area index (LAI) changes in post-grazing treatment in the grazing experimental site; 2) canopy height and the ratio of photosynthetically to non-photosynthetically active vegetation cover were identified as the most sensitive biophysical parameters to reflect vegetation changes in mixed grasslands under light to moderate grazing intensities; 3) OSAVI (Optimised soil adjusted vegetation index) derived from Landsat Thematic Mapper (TM) image can be used for grassland production estimation under various grazing intensities in three types of grasslands in Inner Mongolia, China, with an accuracy of 76%; and 4) Grassland production predicted by NCI (Normalized canopy index) showed significant differences between grazed and ungrazed sites in years with above average and average growing season precipitation, but not in dry years, and 75% of the variation in production was explained by growing season precipitation (April-August) for both grazed and ungrazed sites.

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ANCOVA	Analysis of Covariance
ANOVA	Analysis of Variance
ARVI	Atmospherically Resistant Vegetation Index
ATSAVI	Adjusted Transformed Soil-Adjusted Vegetation index
AVHRR	Advanced Very High Resolution
BI	Brightness Vegetation Index
CI	Canopy Index
CRM	Coefficient of Residual
DEM	Digital Elevation Model
DVI	Difference Vegetation Index
EF	Modelling Efficiency
ETM+	Enhanced Thematic Mapper
EVI	Enhanced Vegetation Index
GLM	Generalized Linear Model
GNP	Grasslands National Park
GPS	Global Positioning System
GVI	Green Vegetation Index
LAI	Leaf Area Index
LUE	Light Use Efficiency
MCARI2	Modified Chlorophyll Absorption Ratio Index
MODIS	Moderate- resolution Imaging Spectroradiometer
MSAVI	Modified Soil-Adjusted Vegetation Index
MTVI1	Modified Triangular Vegetation Index1

NCI	Normalized Canopy Index
NDCI	Normalized Difference Canopy Index
NDVI	Normalized Vegetation Index
NPV	Non-photosynthetically Active Vegetation
NRMSE	Normalized Root Mean Squared Error
OSAVI	Optimised Soil Adjusted Vegetation Index
PD54	Perpendicular Difference Vegetation Index
PSRI	Plant Senescence Reflectance Index
PV	Photosynthetically Active Vegetation
PVI	Perpendicular Vegetation Index
RCI	Ratio Cover Index
RDVI	Renormalized Difference Vegetation Index
RMSE	Root Mean Squared Error
RVI	Ratio Vegetation Index
SAVI	Soil Adjusted Vegetation Index
SPOT	Satellite Pour I'Observation de la Terre
TSAVI	Transformed Vegetation Index
UTM	Universal Transverse Mercator
VI	Vegetation Index
WDVI	Weighted Difference Vegetation Index
WI	Wetness Index

CHAPTER1- INTRODUCTION

1.1 RESEARCH BACKGROUND

Grasslands are one of the most widespread vegetation types worldwide, accounting for nearly one fifth of the earth's land (Lieth, 1978; Scurlock and Hall, 1998). They represent the most important sources of livestock forage, biodiversity, and contribute to the aesthetics and diversity of rural landscapes (Bella et al., 2004). Furthermore, grasslands play a vital role in global carbon cycling and biodiversity conservation (Scurlock and Hall, 1998; Pärtel et al., 1999). However, in recent years, grassland degradation has become a serious issue on a global scale due to anthropogenic effects such as over-grazing and land use conversion, as well as climate change (UNCCD, 1994).

Livestock grazing is the most common form of land use in grasslands. More than 37.5 million km^2 (Dregene, 1983) or about 61% of the world's arid regions are used for livestock (UNEP, 1992). Well-managed grazing can be beneficial to grasslands in many aspects, such as enhancing grassland production and nutrient cycling, promoting biodiversity, and increasing C sequestration. However, in the face of the growing demand for animal products, most grasslands have been overgrazed. Overgrazing is when "forage species are not able to maintain themselves over time due to an excess of herbivory or related process" (Holechek et al., 1999) and is recognized as an important factor leading to degradation of grasslands. Globally, over 7% of grasslands have been overgrazed (Conant and Paustian, 2004). Management of grasslands for optimizing utilization of grassland resources without grassland degradation has been a challenge for grassland managers for several reasons (Marsett et al., 2006). First, obtaining spatial information on grassland production over vast areas in a timely manner is difficult; second, predicting vegetation production under variable annual climate is complex; third, investigating grassland condition and production with field methods is labour intensive, time consuming, and expensive, and finally, a thorough understanding of the effects of grazing and protection from grazing, on grasslands over large geographic areas is limited (Noy-Meir et al., 1989). Consequently, an effective, efficient, and economically sound method for monitoring grazing effects on grasslands is needed.

Remote sensing, with multi-spatial, multi-spectral, and multi-temporal resolutions, provides an ideal approach to use, develop, and manage grasslands, and has been used for assisting grassland resource development and management worldwide in the past several decades (Tueller, 1992). However, monitoring the effects of grazing using remote sensing has been understudied, in particular, the effects caused by grazing with light to moderate intensities, which are not readily detected. There is no direct comparative study to evaluate grazing effects under different intensities using applicable remote sensing technologies.

1.1.1 Effects of grazing on vegetation

The interaction between herbivory and vegetation is complex. McNaughton (1986) noted "a full understanding of vegetation responses to herbivory must encompass processes from individual plant to ecosystem level". At the individual plant level, the exact effects of grazing on plants are dependent on properties of the environment such as soils, rainfall, and season as well as properties of the affected plant such as morphological characteristics, growth form, reproductive strategies, and palatability (Owensby, 1993). Plant parts (leaves, stems, sap, inflorescences, or roots) are removed by herbivores, which reduces photosynthetic surfaces, nutrient and carbohydrate supplies, seed production, or surfaces for absorption of water and nutrients (Belsky, 1987). The direct result is a reduction in the ability of the individual plant to capture solar energy, which can lead to a decrease in competitive ability (Belsky, 1987). From this perspective, herbivory is harmful for individual plants. However, grazing can also benefit plants. Paige and Whitham (1987) found that the seed production of scarlet gilia was enhanced about two-fold in sites with grazing compared to those without grazing. Mechanisms contributing to such benefit attribute to the compensation or overcompensation capacity of plants for herbivory (McNaughton, 1986).

In addition to variation of individual plant properties, effects of grazing on community composition, structure (Sternberg et al., 2000; McIntyre et al., 2003), and productivity (Alejandro et al., 2006) were also investigated by many researchers. Grazing influences those biophysical characteristics in different ways, depending on the time and length of grazing, and the number and type of herbivores. Among those factors it is generally agreed that grazing intensity (stocking rate) has the greatest effect.

How grazing intensity affects vegetation is not fully understood. Some researchers report positive impacts of grazing, in particular light or moderate grazing. A study of grazing effects on vegetation reports relatively high species richness at intermediate levels of grazing compared with ungrazed and heavily grazed areas (Fensham, 1998). Other research (Noy-Meir et al., 1989) contends that light to moderate grazing is beneficial to annual species in grasslands that are dominated by tall perennials prior to grazing. A study in the Chihuahuan Desert rangeland indicates that light grazing intensity (forage utilization is 29%) did not increase perennial grass production compared to conservative grazing (forage utilization is 40%), but it could have a benefit in maintaining perennial grass cover during drought (Kbumalo et al., 2007). Grazing with light to moderate grazing intensity alters the competitive interaction between species by reducing the competitiveness of dominant species, which facilitates the increase of grazing-resistant species (Milchunas et al., 1988). Accordingly, the species richness increases. Furthermore, community composition and productivity were modified correspondingly. Heterogeneity, an effective factor to reflect the spatial variation and distribution pattern of vegetation, and also important to biodiversity and wildlife habitats conservation, can be enhanced by light grazing both in small scale and large scale. Bailey et al. (1998) found that small-scale heterogeneity, heavily grazed patches interspersed within ungrazed or light grazed patches, is induced by livestock selecting areas with less dead materials (litter and standing dead). Fuhlendorf and Engle (2001) reported that large-scale heterogeneity is affected by livestock concentrating on vegetation near water.

Other studies report negative impacts of grazing on grassland (Fleischner, 1994; Shaltout et al, 1996). The nature of the impacts ranged from a simple reduction of cover (Brady et al., 1989; Eccard et al., 2000) to variation in diversity (Ayyad and Elkadi, 1982; West, 1993) and productivity, and even worse, to shifts in community composition. In tallgrass prairie, standing crop of all major herbage components declined as grazing intensity increased (Gillen et al., 1998). Still in the tallgrass prairie, another two studies indicate that high stocking rates tend to increase midgrasses and shortgrasses at the expense of tallgrass (Briske, 1996; Gillen and Sims, 2006). Most negative effects are documented from high grazing intensity or over grazing. Heavy grazing often results in a dramatic decline of plant diversity, vegetation cover, and primary production. Plant community shifts under heavy grazing are reported from communities dominated by plants with perennial life histories, to plants with annual life histories (Steinschen et al., 1996; Todd and Hoffman, 1999) and less palatable species (James et al., 1999; Riginos and Hoffman, 2003; Anderson and Hoffman, 2007). If high grazing intensity is sustained, grassland condition will worsen due to a reduction of total plant cover, biomass, diversity, the introduction of weeds and exotic species (Risser et al., 1981; Sims, 1988), and fragmentation of vegetation patches (Bisigato and Bertiller, 1997). Eventually, grassland degradation and desertification will occur (Faraggitaki, 1985; Manzano and Navar, 2000; Zhao et al., 2005).

Herbivory does not occur in isolation but in a dynamic environment. Environmental factors such as soil nutrient and climate conditions modify effects of grazing on vegetation. Proulx and Mazumder (1998) reported variable responses of species diversity to grazing in nutrient-poor and rich ecosystems. They found that plant species richness decreases with high grazing intensity in nutrient-poor ecosystems but increases in nutrient–rich ecosystems. They attributed the decrease of species diversity to a limited available resource in nutrient-poor ecosystem, which prevents re-growth of species after grazing. Climate variation, particularly in precipitation, affects vegetation in grazed systems. However, it is difficult to define which is the dominant contributor to vegetation change when both grazing and climate factors are considered. Ellis and Swift (1988) reported that climate effects can completely override livestock impacts on yearly plant production in arid and semiarid rangelands. Holechek et al. (2006) found that climate had more impact on vegetation composition in grazed and ungrazed areas than livestock grazing in shortgrass prairie. Fuhlendorf et al. (2001) indicated that both grazing and climatic variability were important to vegetation change, however, grazing established the long-term direction of compositional and structural vegetation change, and climate influenced the short-term rate of this change. Olson et al (1985) concluded climate effects were dominant but climatic fluctuations could either strengthen existing trajectories or promote alternate trajectories. Robert and Sims (2006) found that stocking rate effects were most obvious under high precipitation, but the effects were absent during drought. They explained that limited soil water in years with low precipitation constrains the expression of stocking rate effects.

Grazing as a natural ecological process has significant impacts on grassland. However, how grazing affects the grassland and to what degree the effects are observable remain in question either at the individual plant or even ecosystem level. The degree of the effects is dependent both on grazing regime (such as increase or decrease in intensity, a change in type of herbivores or in temporal pattern of grazing), grassland variables (vegetation biophysical and chemical characteristics, plant composition and structure, soil nutrient and moisture, and so on), and also on the climate of study area. Nevertheless, the effects of grazing can be revealed through monitoring efforts, accounting for other effects.

1.1.2 Models concerning effects of grazing on vegetation

Considering the complicated interaction between grazing and vegetation, several models based on measuring different indicators were proposed to describe grassland responses to grazing. Widely accepted models include the range succession model, state-and-transition model, Milchunas-Sala-Lauenroth (MSL) model and grassland health assessment framework (Dyksterhuis, 1949, Milchunas et al., 1988; Westoby et al., 1989; NRC, 1994; USDA, 1997; Hunt et al., 2003; Briske et al., 2005). The first model aiming to explain the responses of vegetation to grazing was the range succession model, postulated by Dyksterhuis in 1949. This model assumes that a single equilibrium vegetation composition (climax vegetation) exists for each rangeland ecosystem in the absence of grazing. The climax vegetation is supposed to have the highest sustainable productivity and to be the most resistant to disturbance. Grazing can alter the direction of plant community succession. A shift in species composition away from climax vegetation is equated with a decline in range condition. Grassland responses to grazing can be identified by detecting the community composition change. This model has been widely accepted in rangeland management. However, this model has the limitation of describing the entire spectrum of vegetation dynamics that occur on grasslands (Laycock, 1989). For example, vegetation change can be trigged by changes in grazing intensity but also by changes in fire, extreme weather, or combinations of these events. To complement this limitation, the state-and-transition model was developed as an alternative framework (Westoby et al., 1989; Laycock, 1991). This model is based on succession theory also, with the difference that it has multiple end-state communities instead of a single climax community and transitions from one community state to another (Friedel, 1991; Laycock, 1991). Grassland responses to grazing can be detected by comparing the species present with the presumed succession end-state for a given ecological site (Briske et al., 2005). The state-and-transition model provides very useful reference frameworks both in scientific studies of vegetation responses to grazing and in management. However, one of its weaknesses is that it simplifies complicated ecological relations, making detail complex interactions difficult to understand (Hemstrom et al., 2007).

Grassland health is defined as the degree to which the integrity of the soil, vegetation, water, and air, in an ecosystem is balanced and sustained (Pyke et al., 2002). Compared with succession theory, grassland health assessment not only focuses on vegetation characteristics but also incorporates soil and hydrologic parameters. Seventeen indicators (rills, water flow patterns, pedestals and/or terracettes, bare ground, gullies, wind scoured, blowouts and/or deposition areas, litter movement, soil surface resistance to erosion, soil surface loss or degradation, plant community composition, compaction layer, functional group, plant mortality/decadence, litter amount, invasive plants, and reproductive capability of perennial plants) related to different grassland functions are applied to evaluate rangeland health, among which eight indicators reflect vegetation information (Pyke et al., 2002). Impacts of grazing on rangeland can be examined by investigating changes in these indicators.

Another model which is widely accepted and used as a reference framework in studies of vegetation responses to grazing is Milchunas-Sala-Lauenroth (MSL) model. This model developed from the intermediate disturbance model. The intermediate disturbance model predicts that diversity will be maximal at intermediate levels of disturbance, while diversity is low both at low and high levels of disturbance. The disturbance can be quantified using frequency of disturbance, extent of disturbance, intensity of disturbance, or duration of disturbance. According to the model, grassland respond to different kinds of disturbances and the appropriate magnitude of disturbances could be explored by detecting the diversity change. Milchunas et al (1988) modified the intermediate disturbance model by integrating grazing history of the site and climatic regime and came up with a generalized model, MSL model (Figure 1.1). Milchunas-Sala-Lauenroth model indicates that the relationship between diversity and grazing intensities is a function of grazing history of the site and climatic regimes: 1) in semiarid grassland with short history of grazing, grazing has a relatively small effect on diversity; 2) in climatically similar grassland with a shorter history of large mammal grazing low grazing intensity will lose diversity; 3) under wet conditions, low grazing usually enhances diversity regardless of differing grazing history (West, 1993). The model formulates the general prediction of vegetation diversity to grazing effects (Cingolani et al., 2005).

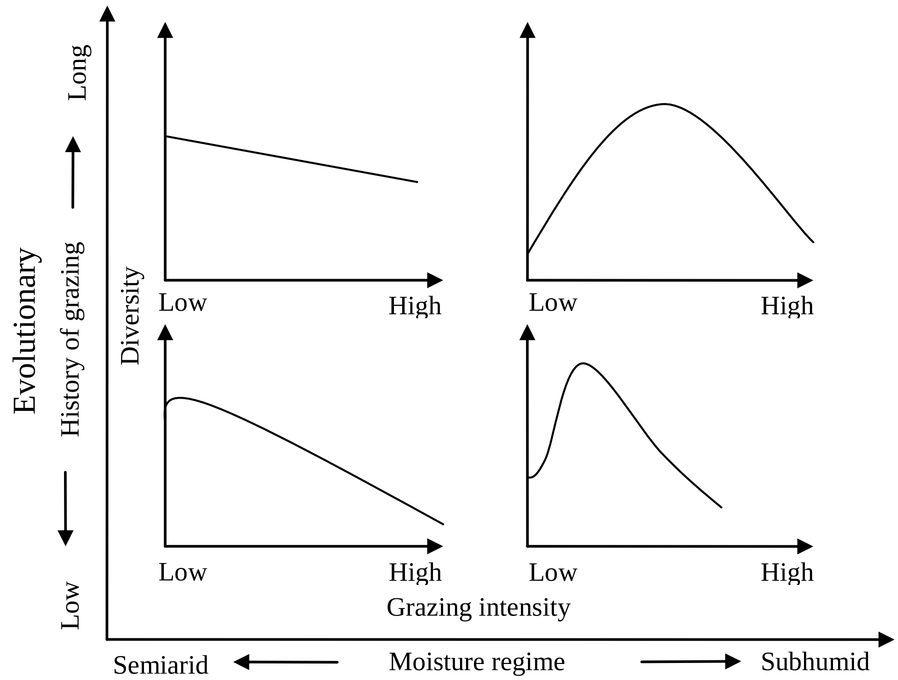

Figure 1.1 Milchunas-Sala-Lauenroth (MSL) model

1.1.3 Methods of investigating grazing effects on vegetation

Grassland monitoring is the ability to detect rangeland condition change with the objective of applying corrective action (Ludwig et al., 2005). However, grasslands are complex, dynamic and heterogeneous systems, which provide many characteristics to be monitored (West, 2003). Vegetation biophysical characteristics document the basis for evaluating rangelands under various grazing management regimes. Over the past decade, many researchers have been conducted to determine vegetation indicators and investigate corresponding methods for detecting grassland response to grazing management. The methods developed and applied in detecting grassland change can be grouped into two categories: ground-based methods and remote sensing-based methods.

1.1.2.1 Ground-based methods

Primary detection of grassland responses to grazing has relied heavily on building facilities and stations, and setting up diverse grazing experiments to measure vegetation biophysical variables that are sensitive to grazing (Alejandro et al., 2006). During the period of 1976 to 1995, major efforts by Chinese grassland scientists were directed at establishing field research facilities and stations for long-term grassland monitoring, and 36 national field monitoring and scientific research stations were built (Kang et al., 2007). However, most of the grazing experiment designs are based on an assumption that the grassland baseline is uniform before the grazing experiment is carried out, and the grazing induced changes are caused by grazing activities alone, which may not be true. At the same time, monitoring systems need to be cost effective, rapid, quantitative, repeatable, unbiased, and applicable at a variety of scales. Ground-based methods which are used for these grassland assessments provide limited temporal and spatial information, making their use difficult to detect spatio-temporal changes in grasslands if the extent of grassland is large. For example, in Australia, grassland grazing properties are typically 100-30000km^2 in size and contain from 5 to 40 individual fenced subdivisions or paddocks. Under these conditions, the entire landscape has to be assessed and collection of vegetation data by field methods is difficult because of the high spatial and temporal variability present (Ludwig et al., 2005). Furthermore, ground surveys are time consuming, costly, and cannot obtain data in inaccessible areas.

1.1.2.2 Remote sensing–based methods

Remote sensing provides a unique opportunity to monitor spatio-temporal changes of grasslands at different scales with rapid data acquisition and at lower cost and is accepted as a useful alternative for grassland assessment and management over a large geographic area. The major application of remote sensing for grassland assessment is providing estimation for many of the indicators proposed for grassland health assessment (Hunt et al., 2003). Previous studies (Boutton and Tieszen, 1983; Gamon et al., 1995; Liu et al., 2004; Marsett et al., 2006) indicate that remote sensing can be successfully used to estimate plant biomass, cover, leaf area index, height, productivity, diversity, and litter. Methods for estimating those indicators can be grouped into three categories: vegetation indices, spectral mixture modeling, and remote sensing-based process models.

1.1.2.2.1 Vegetation indices

Vegetation indices have typically been used to incorporate information from remote sensing platforms by combining two or more spectral bands (Qi et al., 1994). Many researchers find that vegetation indices have empirical relationships with a range of vegetation parameters, such as canopy cover (Purevdorj et al., 1998), leaf area index (He et al., 2006), biomass (Paruelo et al., 1997), production (Bella et al., 2004), and absorbed photo-synthetically active radiation (Moreau et al., 2003). Vegetation indices can be applied to predict or estimate vegetation parameters based on an empirical relationship, and thus can monitor grassland change directly. However, many factors, such as atmospheric condition, ground cover underneath vegetation canopy, illumination and observation geometry, and moisture condition in the soil, influence the reflected radiation in targets and, in turn, the accuracy in the vegetation prediction or estimation (Liu and Kafatos, 2005).

In recent decades, much effort has been made to explore diverse vegetation indices to estimate vegetation characteristics. These vegetation indices include ratio vegetation index (RVI)

(Jordan,1969), normalized difference vegetation index (NDVI) (Rouse et al., 1974), difference vegetation index (DVI) (Tucker, 1979), perpendicular vegetation index (PVI) (Richardon and Wiegand,1977), weighted difference vegetation index (WDVI) (Clevers, 1989), soil adjusted vegetation index (SAVI) (Huete,1988), transformed SAVI (TSAVI) (Baret and Guyot,1991), atmosphere soil-adjusted vegetation index (ATSAVI) (Baret and Guyot, 1991), modified soil adjusted vegetation index (MSAVI) (Qi et al.,1994), atmospherically resistant vegetation index (ARVI) (Kaufman and Tanre,1992), green vegetation index (GVI) (Dyer et al.,1991), brightness vegetation index (BI) (Lauver & Whistler,1993), wetness index (WI) (Todd et al.,1998), enhanced vegetation index (EVI) (Huete et al., 1999), and many more. Baugh and Groeneveld (2006) grouped these vegetation indices into two general categories: ratio based (ARVI, EVI, MSAVI, NDVI, RVI, SAVI, and TSAVI) and orthogonal/perpendicular based (DVI, PVI, and WDVI). Additional, they think that some of the indices can be categorized as soil resistant (MSAVI, SAVI, TSAVI), and atmospherically resistant (ARVI, EVI).

An important principle of employing vegetation indices to estimate or assess grassland characteristics is to find an optimal vegetation index that maximizes the sensitivity to parameters of interest while minimizing the sensitivity to other internal and external variables. Todd et al. (1998) analyzed the relationship between biomass and four different vegetation indices (GVI, BI, WI, and NDVI) under grazed and ungrazed management, and found that biomass from grazed sites was linearly related to four indices, and concluded that biomass on grazed sites can be estimated by these four spectral indices effectively. However, there was no relationship found for ungrazed sites because of high litter accumulation without grazing activity. In Liu et al.'s (2004) study, a strong relationship is documented between two degradation indicators (percent grass cover and proportion of unpalatable grass) and two vegetation indices (NDVI and SAVI), which were derived from Landsat Thematic Mapper (TM) image, and a degradation map near Qinghai Lake was created based on the two vegetation indices.

Even though many studies show satisfactory correlation between vegetation indices and vegetation characteristics, some problems are apparent, namely, the relationship between vegetation indices and vegetation characteristics are site or season specific. Relationships could be very diverse even at the same study site if using data from different years and no unique relationship can be generalized. Therefore, the vegetation indices which suit one study site probably are not good for other sites. The key of this method is to test if appropriate vegetation indices for a broad range of vegetation characteristics and study sites are available.

1.1.2.2.2 Spectral mixture modeling

Spectral mixture modeling assumes that spectral signals received by the remote sensor can be modeled as a linear or nonlinear combination of two or more "pure" spectral end members. There are two types of mixture modeling based on the combination of end members: linear or nonlinear. Compared with vegetation indices, a spectral mixture model can deal with sub pixel scales by deriving the fraction of background within a pixel that contributes to the observed reflectance at the pixel scale (Hall et al., 2003). So it can improve the estimation accuracy. Numata et al. (2007) studied grazing intensity using four vegetation indices and fractions derived from mixture spectral analysis. The results indicate that compared with a vegetation index (NDVI), spectral mixture analysis not only separates grazing treatments but also can identify related factors affected by the grazing treatment. The challenge in using this method for grassland assessment is to find the location of the pure end member for the green cover component, because the vegetation density in grassland is relatively low (Purevdorj et al., 1998).

1.1.2.2.3 Remote sensing-based processing model

Most remote sensing-based processing models focus on modeling biomass and productivity, resulting in indirect measures of grassland change. In past years, many ecosystem models were developed to estimate grassland productivity, such as BIOME-BGC (Running and Hunt, 1993), CENTURY4.0 (Parton et al., 1993), TEM4.0 (McGuire et al., 1995), Monteith's efficient (Monteith, 1972), and Light Use Efficiency (LUE) models (Seaquist et al., 2003). However, inadequate parameterization is still a challenge for model application. Combining remote sensing with an ecosystem model can provide an efficient way to parameterize ecosystem models. The logic of remote sensing-based processing models is that remote sensing data are used in a model as input variables directly or as surrogate measures of related vegetation parameters by building relationships with them. For example, in Monteith's efficient model (Monteith, 1972), vegetation index derived from a remotely sensed image was used as a surrogate of incident photosynthetically active radiation absorbed by canopy to compute photosynthetically active radiation. In the semi-arid grassland of the West African Sahel, to cope with sparse dataset available, Seaquist et al. (2003) used NDVI as an input of Light Use Efficiency model to simulate evaportranspiration and photosythetically active radiation. Mougin et al. (1995) developed a new model to simulate biomass by combining remote sensing spectral measurement with an ecosystem process model. Compared with vegetation index methods, remote sensing-based model incorporated data from more than one site would be able to reduce site specificity. On the other hand, model inputs involving disparate data are more efficient to understand variability in rangeland change. Besides vegetation properties, Bėniė et al. (2005) considered socioeconomic parameters as inputs to a model to predict biomass in Sahelian grazing system. However, the model application also faced some challenges in model parameterization, such as model transferability (Lu, 2006). Different models have their own algorithms and require different inputs. So, models developed in one site or specific time is seldom applicable to other areas without significant modifications.

1.2 SUMARRY OF RESEARCH GAPS

From the review of literature, it is evident that there have been no efforts to investigate grazing effects under different grazing intensities with remote sensing approaches since light to moderate grazing intensities induced changes are not apparent to be detected by remote sensing. Most grazing studies employed remote sensing approaches are limited to a focus on detecting grassland degradation caused by overgrazing or comparing grassland changes between grazed and ungrazed sites. However, it is critical to know how grassland responds to grazing with various intensities for understanding grassland changes comprehensively and making effective decisions for grassland management. Present studies employed field methods have limitation in investigating grassland changes under various grazing intensities in a timely and effective manner especially over large geographic areas.

Remote sensing is an ideal technology for studying effects of grazing on grasslands which can provide data with multiple temporal, spatial, and spectral resolutions for fixing with different requirements of grazing studies. Although many studies have documented that remote sensing could be successfully used to estimate grassland vegetation parameters, the feasibility of using remote sensing data to investigate grazing effects is not fully tested. An efficient method based on remote sensing data to model grassland changes under different grazing intensities over different grassland ecosystems is needed in current studies.

1.3 HYPOTHESES AND OBJECTIVES

My hypothesis is that remote sensing can be employed to identify the grazing effects on grassland not only under heavy grazing intensity, but also with light to moderate grazing activities through combination with the MSL model.

More specifically,

1) Vegetation biophysical parameters are effective indicators to reflect grazing effects and can be retrieved using spectral vegetation indices.
2) Satellite data driven generalized model can be used to simulate biophysical parameter responses to grazing. Some vegetation biophysical properties will be maximal at light to moderate intensities but not all in mixed grasslands.
3) The effects of grazing intensities on grassland are dependent on grazing history of the site and climatic regimes.

The proposed research will achieve the following objectives:

1) To assess the baseline of vegetation condition of grasslands prior to grazing effects and investigate the suitable spatial scale for detecting vegetation responses to grazing (Chapter 2).
2) To identify the suitable spectral vegetation indices to drive the generalized model for simulating vegetation responses to different grazing intensities in mixed grasslands (Chapter 3).
3) To investigate the influence of precipitation on detection of grazing induced vegetation change (Chapter 4).
4) To explore the variation in responses of vegetation to grazing intensity over different grassland types (Chapter 5).

1.4 THESIS STRUCTURE

The thesis uses a manuscript (i.e. paper) format and is composed of six chapters (Figure 1.2). Chapter one gives a general background of the research, summaries of pertinent literature, describes the current research gaps in grazing effects related studies and presents the research objectives. Chapter two is toward fulfillment of research objective one. Using remote sensing data with different spatial resolution coupled with field data, the feasibility of using remote sensing data for quantifying grassland vegetation baseline is tested. This manuscript demonstrated why it is critical for investigating the pre-condition of the vegetation before grazing is conducted. In addition, an appropriate spatial scale which is suitable for detecting grazing effects on vegetation in post-grazing is investigated.

Chapter three addresses the second objective. This chapter examines the responses of vegetation biophysical properties to grazing with light to moderate intensities and identifies the suitable parameters to reflect grazing effects on vegetation under light to moderate intensities. The empirical models based on remote sensing data are developed as surrogates of those biophysical parameters for detecting grazing effects.

Chapter four uses three Landsat images covering three types of grasslands and compares the responses of grassland production to grazing intensity between these grassland types. This chapter addresses the forth objective.

Chapter five employs two-years of field data, eleven-years of climate data and eleven Landsat images to investigate the relationship between grassland production and precipitation, and evaluates the influences of precipitation on detecting grazing-induced grassland production change. This chapter is toward fulfillment of third objective.

In chapter six, the main conclusion of this dissertation is summarized. The limitation of present research is discussed and outlook for future research is recommended.

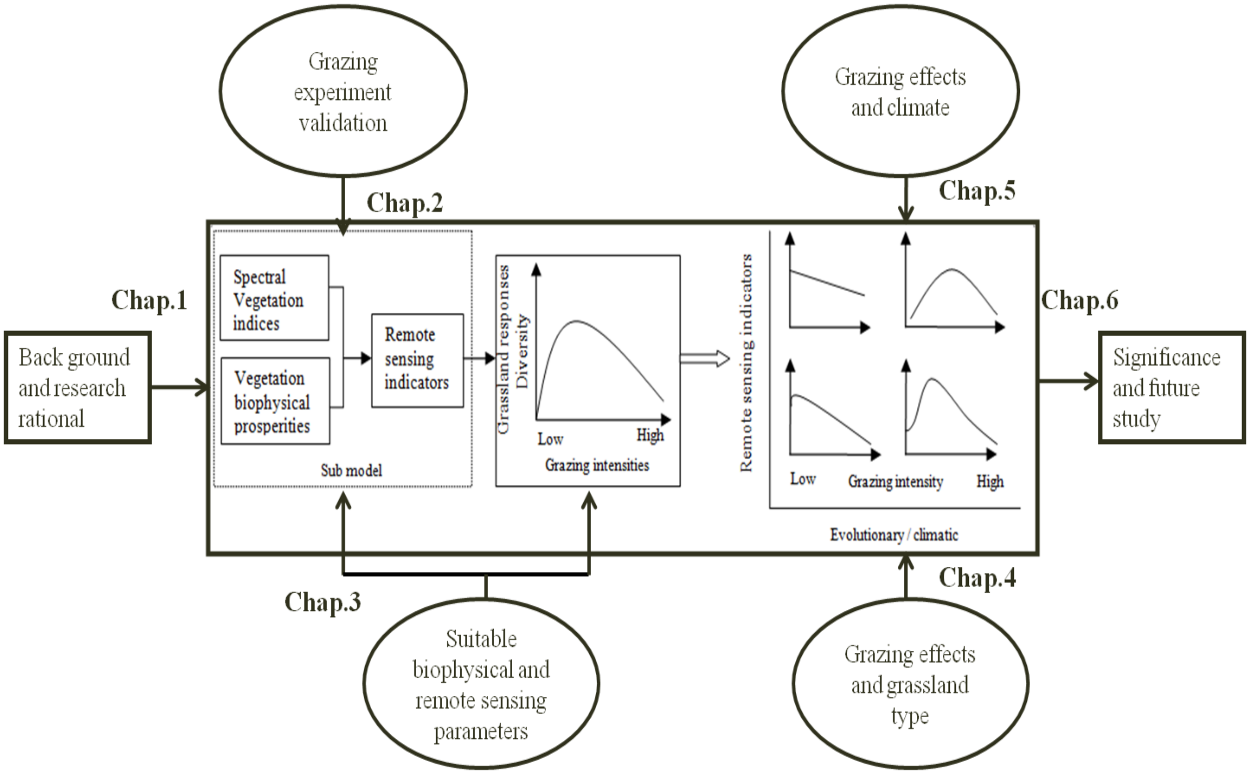

Figure 1.2 Methodology framework of the thesis

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CHAPTER 2−CAN SATELLITE IMAGERY EVALUATE THE PRE-CONDITION OF A GRAZING EXPERIMENT?

2.1 ABSTRACT

Most studies on grazing effects are based on the assumption that vegetation conditions at experimental sites that are subject to different grazing treatments are the same prior to grazing, which may not be true. The pre-existing differences in vegetation may be wrongly attributed to the influence of grazing if pre-validation of vegetation conditions at the site is not performed. In this paper, the assumption stated above was verified by comparing vegetation condition between nine experiment units (pastures) in a grazing experiment site set up by Grasslands National Park (GNP) before grazing started. The leaf area index (LAI) was applied to represent vegetation conditions within the grazing experiment site. The vegetation conditions between the nine pastures were compared at different scales and vegetation phenology. Results indicated that vegetation conditions measured with $1m^2$ sampling scale showed a significant difference among the nine pastures (p<0.1). No significant differences were observed when measurements were conducted with $100m^2$ and $400m^2$ sampling scales (p>0.1). Variation of vegetation conditions of the nine pastures in peak and late growing stages were very consistent. These results indicate that sampling scale plays an important role in vegetation condition assessment. Remote sensing offers data in multi-spatial resolution which provides an efficient way for investigating vegetation condition at different scales.

2.2 INTRODUCTION

Grasslands, covering nearly one fifth of the earth's land, are primarily used for livestock production. More than 37.5 million km^2 (Dregene, 1983) or about 61% of the arid regions of the world are used for ranching (UNEP, 1992). One of the primary challenges in rangeland studies has been to understand the effects of herbivore grazing on ecological processes and biophysical factors (Briske et al., 2003). Grazing effects are usually identified by comparing vegetation response variables (i.e. plant community composition, productivity, forage quality, and many others) in sites that are being grazed to those in areas without disturbances. However, grasslands are inherently spatially heterogeneous because of vegetation characteristics (i.e. productivity, diversity, and composition) that are highly variable across multiple scales (Ludwig and Tongway, 1995). This variation is related to different ecological processes such as topography, soil pattern, microclimate, and precipitation (Levin, 1978; Urban et al., 1987; Crawley, 1996; He et al., 2006). Small scale variation in vegetation is related to the heterogeneity of soil (Reynolds et al., 1997). At a large scale, variation in vegetation is controlled by topography or landforms (Sebastiá, 2004). These pre-existing variations in grazing response variables may confound interpretation of grazing effects. To reduce the influence of external factors other than grazing on vegetation, most studies on grazing effects attempt to select sites with similar initial vegetation conditions (Fisher et al., 2009).

However, from 1919 to present, none of the grazing trials that looked at variable rate grazing conducted in mixed and short grass prairie of North American had incorporated a before-treatment sampling period to test whether the vegetation conditions of these sites were the same before the experiment started (Koper et al., 2008). Since the effects of grazing on vegetation depend upon the interaction between the spatial pattern of grazing and pre-existing spatial pattern of vegetation (Adler, 2001), assessing before-treatment variation is important to separate them from background condition.

Recently, a large manipulative grazing experiment designed to study the ecological integrity of mixed grasslands was started in Grasslands National Park (GNP) of Canada. The mixed grasslands located in GNP had been protected from grazing and other anthropogenetic disturbances since the land was acquired in the mid 1990's (Henderson, 2005). The experiment was set up in 2007 and cattle were introduced to the experiment site in June 2008. This provides a unique pre-treatment period for examining the pre-existing environmental patterns across the study site and help further the understanding of grazing effects on this area in future studies.

The primary objective of this study is to verify the assumption proposed for most grazing studies that vegetation conditions are same among experiment units by examining the vegetation conditions across the experimental area in GNP prior to grazing. To achieve this goal, LAI is measured and used as an indicator of vegetation condition in the experiment site. LAI, defined as one-half of the total green leaf area per unit of ground surface area (Chen and Black, 1992), determines canopy water interception and carbon gas exchange between vegetation and the environment. Previous researchers have found that LAI correlates highly with many vegetation biophysical properties such as biomass, canopy height and ground cover (Guo et al., 2005; He et al., 2009) and is also an indicator of vegetation vertical structure. Thus, it has been broadly used to describe or quantify vegetation condition. On the other hand, considering the scale dependence of vegetation conditions, it is essential to examine vegetation condition at multiple scales. To quantify vegetation conditions at a smaller scale, field methods are feasible; however, it is commonly recognized as time-consuming and expensive when applied to measure vegetation conditions at a large scale. LAI can be easily derived from remote sensing providing an efficient way to quantify vegetation conditions at a large scale. In this study, conditions of vegetation between pastures are assessed by comparing LAI collected from different sampling scales. Small scale LAI is measured with field methods and large scale LAI is derived from remote sensing imagery. Vegetation conditions at different phenology are also investigated through comparing LAI collected in peak and late growing stages.

2.3 METHODS

2.3.1Experimental site description

The study was conducted in the East Block of GNP in Saskatchewan, Canada (Lat 49°01′00″N, Long 107°49′00″W), which is located in southern Saskatchewan along the Canada-United States border (Figure 2.1). This area falls within the Great Plains and is characterized by a semiarid climate with approximately 350mm of annual precipitation and 347mm of annual evapotranspiration (Coupland, 1992; Kottek et al., 2006). The experimental area is 26.5km^2 in size, comprising nine experimental units (pastures) which were constructed specifically for the experiment. Each pasture occupies nearly 300ha and incorporates similar landscapes, vegetation communities, and natural water source locations. (Henderson, 2005). Four major vegetation types are found at the experiment site: upland, slope, and valley grasslands along with riparian shrub communities. Experimental pastures are dominated by upland and valley grasslands with some riparian shrub and slope grasslands also present (Michalsky and Ellis, 1994). Upland grasslands are composed primarily of grasses or sedges and low percentage of shrub. The dominant native grass species in the uplands are needle-and-thread (*Stipa comata Trin. & Rupr)*, blue grama grass (*Bouteloua gracilis (HBK) Lang. ex Steud)*, and western wheatgrass (*Pascopyrum smithii Rydb)* (Fargey et al., 2000). Valley grasslands are characterized by a high abundance of shrubs such as silver sagebrush (*Artemisia cana*) and snowberry (*Symphoricarpos albus*) as well as grasses including wheatgrass (*Pascopyrum spp.)* and bluegrass *(Poa spp.)*. The major soil type in the experiment site is Chernozemic soil (Zhang and Guo, 2007). The surface horizon of grassland soil is dark and fertile due to accumulations of organic matter over time from grasses and herb roots (Westworth and Associated Ltd, 1994). In June 2008, cows were introduced to six of the pastures which resulted in 20%, 33%, 45%, 57%, 70%, and 70% annual forage utilization respectively, the remaining three pastures were used as ungrazed control sites (Koper et al., 2008).

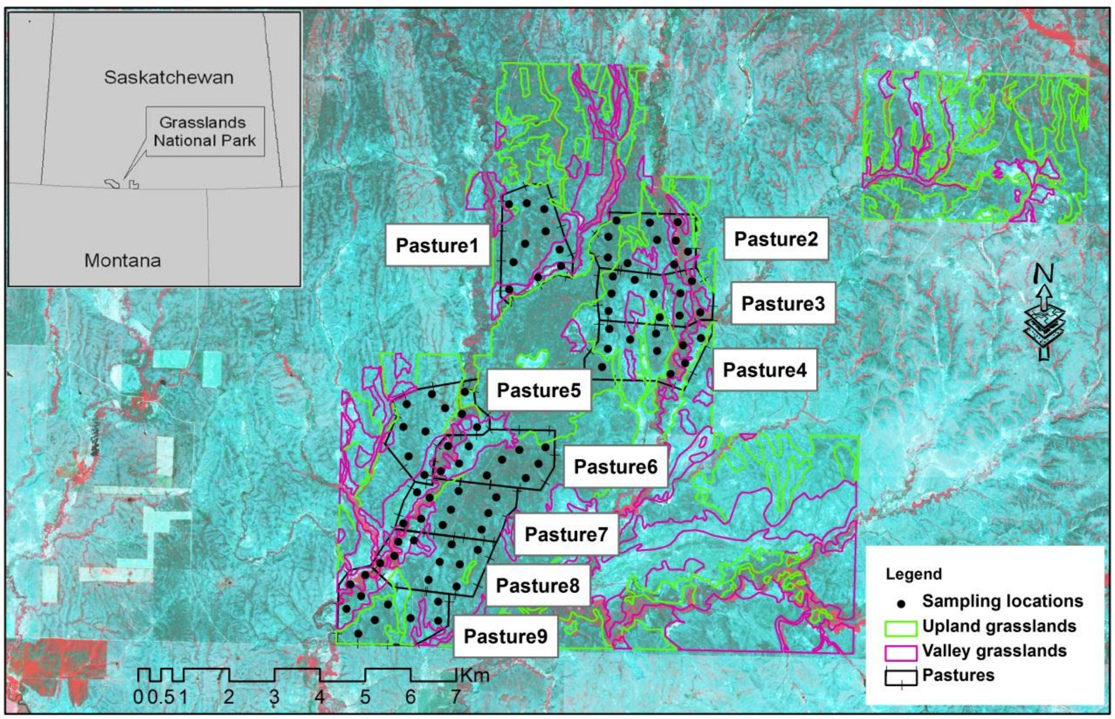

Figure 2.1 Location of study area and grazing experiment sites

2.3.2 Data Collection and Pre-processing

Field work was conducted at the peak of the growing season, June 2007, in nine designated pastures inside of the grazing experimental site. Ten sampling plots were set up in each pasture, with six located in upland communities and four in valley communities. LAI measurements were collected using LiCOR-LAI-2000 Plant Canopy Analyser at each sampling plot using 1×1m quadrats. In each quadrat, one above canopy reading and six below canopy readings were recorded. The value of LAI for each sampling site was the average of these six values. Three SPOT multispectral images were acquired for the years of 2005 (June 22nd, SPOT4 with 20m spatial resolution), 2006 (July 22nd, SPOT5 with 10m spatial resolution) and 2007 (June 20th, SPOT5 with 10m spatial resolution). Geometric and radiometric corrections, including atmospheric corrections were applied to all images. The images were geometrically corrected by a geo-coded image which was further corrected using ground training sites, with accuracy better than 0.3 root mean square error (RMSE), representing approximately three meters error in ground for SPOT5 image and six meters for SPOT4 image. Distortion caused by topography was corrected using a digital elevation model (DEM), found in the GNP GIS database. Radiometric and atmospheric corrections were done with the ATCOR2 module from the PCI Geomatics software package.

Vegetation indices computed with reflectance from two or more bands can overcome most atmospheric and background influence, and enhance the ability to measure ground information. For this study area, previous information indicated that atmosphere transformed soil adjusted vegetation index (ATSAVI) showed better results compared to other indices (normalized difference vegetation index, perpendicular vegetation index, soil-adjusted vegetation index, etc.) when used to predict ground LAI (He et al., 2006). Therefore, ATSAVI was computed to use as a proxy of LAI collected with large sampling scale. ATSAVI was calculated with the equation below:

$$ATSAVI = \frac{a \times (NIR - a \times RED - b)}{a \times NIR + RED - a \times b + X(1 + a^2)} \quad (1)$$

where NIR is the reflectance in near infrared band, RED is the reflectance in the red band and X is the soil line adjustment factor with a default value 0.08. “a” and “b” are the slope and intercept of the “soil line” with corresponding values, of 1.22 and 0.03 respectively (Zhang, 2006).

2.3.3 Data analysis

We overlaid the pasture polygons on top of a SPOT 5 image acquired in 2007 . Spectral data was extracted from a 3×3 pixel area (30m×30m on the ground) centered on each field location where LAI was measured. The median of these nine pixel values was used to eliminate extreme values. To examine vegetation condition among pastures in different scales, LAI collected with different sampling scales, namely $1m^2$, $100m^2$, and $400m^2$, were applied. LAI with $1m^2$ sampling scale was measured in the field. ATSAVI values derived from satellite images were used as surrogates for LAI collected with $100m^2$ or $400m^2$ sampling scales. LAI and ATSAVI data were tested for normality before any further statistical analysis was performed, to ensure that the data were normally distributed. The capability of ATSAVI to characterize vegetation conditions instead of LAI at a large scale, was verified by investigating the relationship between ATSAVI and LAI. A linear regression analysis was applied to describe the relationship between LAI and ATSAVI (He et al., 2006). To test the vegetation condition at different times, vegetation conditions measured in 2006 and 2007 which represent the peak and late vegetation growing stages, were examined. The analyses were based on data from six pastures, because three pastures are covered by haze in the 2006 image (the peak of vegetation growing stage). Given that upland and valley grasslands are dominated by different plant communities, comparison of vegetation conditions between pastures was conducted for upland and valley grasslands separately. Analysis of variance (ANOVA) was performed to analyze the differences among pastures in the grazing experiment site using SPSS (version 16.0). Differences in ATSAVI or LAI between nine pastures were considered statistically significant when $p<0.1$ because of the small dataset.

2.4 RESULTS

2.4.1 Relationship between LAI and ATSAVI

Leaf area index shows a significant positive correlation with ATSAVI with 41% of its variation explained by ATSAVI (Figure 2.2). The result indicates the applicability of ATSAVI as a proxy of LAI for quantifying vegetation conditions at a large scale.

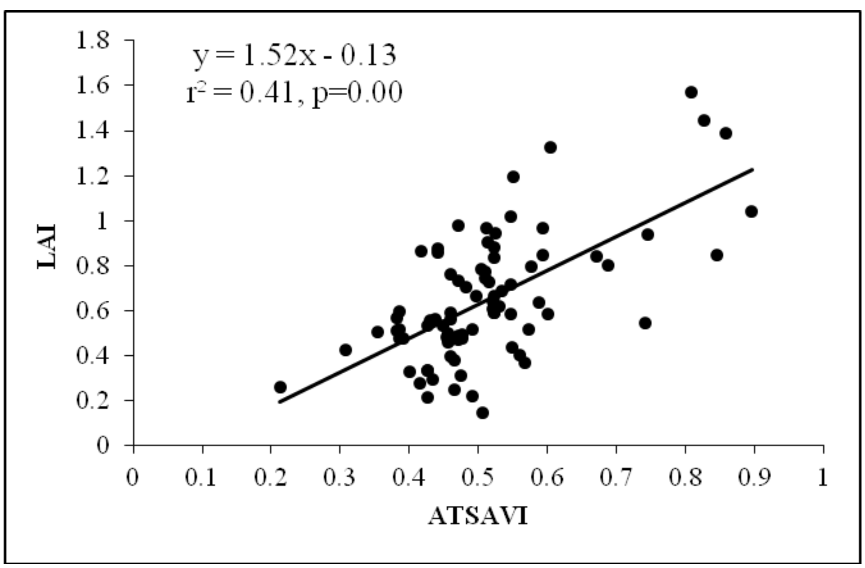

Figure 2.2 Relationship between LAI and ATSAVI: y=1.52x-0.13(r^2=0.41). ATSAVI was derived from SPOT 5 image acquired in 2007. It is the median value of 3×3 pixels.

2.4.2 Vegetation conditions and sampling scale

Significant differences were found in both upland and valley vegetation, as measured by LAI collected with a $1m^2$ sampling frame, between pastures (Table 2.1). In upland communities, LAI is shown as the highest in pasture 1 and a significant difference is found between pasture 1 and six other pastures (p<0.1), pastures 6 and 7 showed no significant difference. For valley grasslands, differences occur between pastures 1 and 3, 4, and 5 (p<0.1). The results vary when the observation scale increases from $1m^2$ to 100 m^2 or 400 m^2. No significant difference in vegetation condition is detected among pastures either in upland, or valley grasslands with a 100 m^2 sampling unit. Similar results are obtained when using a 400 m^2 sampling unit.

Table 2.1 Comparison of vegetation conditions between pastures with different sampling scales. Values within the same column followed by different letters are significant at p<0.1.

Pastures	Sampling scales					
	1m×1m (LAI)		10m×10m (ATSAVI)		20m×20m (ATSAVI)	
	Upland	Valley	Upland	Valley	Upland	Valley
1	0.98±0.30a	0.75±0.08a	0.52±0.09a	0.34±0.19a	0.51±0.04a	0.42±0.07a
2	0.67±0.14abcd	0.79±0.40ab	0.57±0.10a	0.59±0.16a	0.54±0.11a	0.58±0.16a
3	0.50±0.13bcd	0.42±0.12b	0.49±0.05a	0.48±0.06a	0.48±0.07a	0.50±0.15a
4	0.42±0.19bc	0.86±0.56ab	0.49±0.08a	0.62±0.25a	0.48±0.07a	0.59±0.15a
5	0.36±0.12b	0.49±0.11b	0.47±0.04a	0.47±0.15a	0.47±0.04a	0.47±0.13a
6	0.82±0.19ad	0.80±0.47ab	0.51±0.05a	0.58±0.23a	0.48±0.04a	0.53±0.12a
7	0.74±0.17ac	0.80±0.32ab	0.51±0.02a	0.44±0.11a	0.49±0.03a	0.44±0.12a
8	0.63±0.20bcd	0.58±0.34ab	0.52±0.07a	0.49±0.22a	0.48±0.07a	0.47±0.19a
9	0.57±0.23bcd	0.87±0.48ab	0.50±0.05a	0.45±0.07a	0.45±0.05a	0.47±0.06a

2.4.3 Vegetation conditions and vegetation growing stages

Vegetation conditions of the peak and late growing seasons in six pastures, represented by ATSAVI, are shown in Figure 2.3. The highest ATSAVI in peak growing season for upland grasslands is in pasture 2. Pasture 3 has the lowest value. This variation pattern of ATSAVI does not change with vegetation phenology, indicated by consistent ATSAVI patterns among all six pastures between peak and late growing seasons. Variation pattern of ATSAVI in valley grasslands in two growing stages are also consistent with the highest ATSAVI in pasture 2 and the lowest in pasture 9.

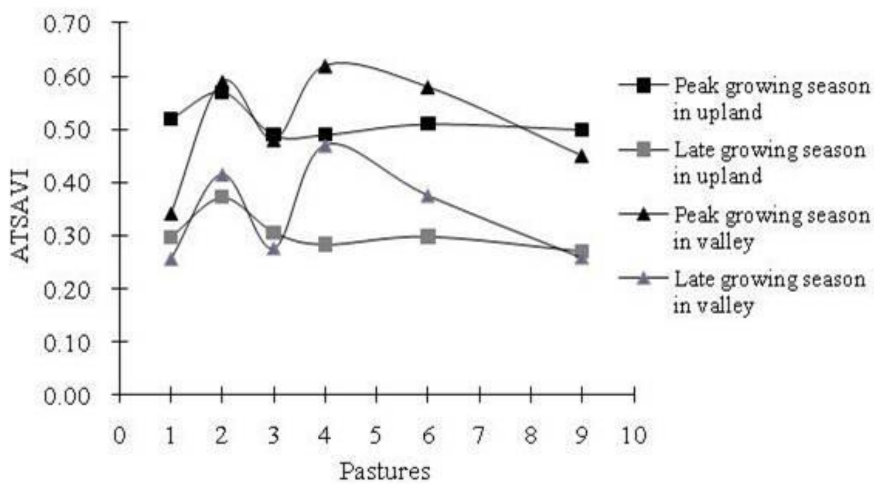

Figure 2.3 Vegetation conditions in different vegetation phenological growth stages. Lines with triangle markers represent valley vegetation conditions in peak and late growing seasons. Lines with square markers represent upland vegetation condition in peak and growing seasons.

2.5 DISCUSSIONS

Our work demonstrates several important principles in the design of experiments in which time and space contribute significantly to treatments. First, it is correct to assume that experimental units will differ from each other even prior to the application of treatments (Koper et al., 2008). Substantial variation was found in LAI measurement at a smaller scale, however, the differences diminished as sampling scale increased. This is no surprise given the inherent scale-dependent characteristic of vegetation conditions. Variations in vegetation conditions measured at the small sampling scale, among pastures are due to inherent within site/pasture heterogeneity in soil properties, for example, soil moisture and nutrient elements (Reed et al., 1993; He et al., 2007). Therefore, if this sampling scale is applied for comparison of vegetation condition among pastures in post-grazing experiments, the pre-existing differences needed to be taken into consideration for accurate interpretation of grazing effects. With a large sampling scale, a portion of site variation could be contained within a sample. Inter-sample variations are decreased and the possibility of detecting differences between pastures is increased (Wiens, 1989). Sampling at a large scale ($100m^2$ and $400m^2$), No differences in vegetation conditions among pastures were found prior to grazing treatment, implying that effects of grazing on vegetation condition could be isolated accurately if the same sampling scales are employed in post grazing treatment.

Second, incorporating multi-scale observation methods into experimental design is essential for acquiring comprehensive information on vegetation condition within the study site. We only investigated vegetation condition based on three sampling scales. Using a gradient sampling frame allows for identifying the suitable sampling scale for measuring vegetation conditions. In this research, both field and remote sensing methods were applied for quantifying vegetation conditions at different scales. Vegetation conditions at a small scale could be easily quantified using field methods, but field methods are limited in obtaining representative data for revealing variation at a larger scale. Remote sensing is a valuable data source for characterizing vegetation condition at multiple scales as it is available from a range of satellite sensors and covers a broad geographic extent. Our approach to use archived, remotely sensed images to quantify vegetation condition is one that we feel could prove valuable in a number of field settings.

Third, remote sensing may not be the ideal tool to completely replace ground measures of vegetation conditions, due to its failure to capture all the information or achieve the desired level of accuracy. However, remote sensing can provide researchers with baseline information, particularly for experiments with large-scale extents where a full suite of variables is impractical to measure prior to treatment applications. The biophysical changes that are readily detected by light reflectance provide a relatively quick overview of potential compositional and structural variation of a grass sward (Guo et al., 2004). Thus, this relatively inexpensive method could be used to focus pre-sampling efforts appropriately. As well, they can provide an accurate, quantitative assessment of treatment induced change if they are measured both prior to and following treatment application in an a priori design.

2.6 MANAGEMENT IMPLICATIONS

Comparing sites spatially has been considered as a means to study the grazing effects for a long time. Understanding the vegetation condition among sites prior to experiment design is essential for researchers or land managers to interpret vegetation change post treatment. In light of the scale dependence of vegetation condition found in our study, the influence of post grazing treatment may be expressed at different levels of organizations (landscape, community, population, and individual) (Fuhlendorf and Smeins, 1997, 1998). We do suggest that multi-scale observations should be applied both before and after treatment to better understand the grazing effects. Given consideration of expenses, time, and accuracy, remote sensing methods appear to be a better choice for detecting multi-scale vegetation change especially in sites with a broad geographic extent.

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CHAPTER3−INVESTIGATING VEGETATION BIOPHYSICAL AND SPECTRAL PARAMETERS FOR DETECTING LIGHT TO MODERATE GRAZING EFFECTS: A CASE STUDY IN MIXED GRASSLAND PRAIRIE

3.1 ABSTRACT

Identifying effective vegetation biophysical and spectral parameters for investigating light to moderate grazing effects on grasslands improves monitoring and management practices on grasslands. Using mixed grasslands as a case study, this paper compared responses of vegetation biophysical properties and spectral parameters derived from satellite images to grazing, and identified the suitable biophysical and spectral parameters to detect grazing effects in these areas. Biophysical properties including, cover, canopy height and leaf area index (LAI) were measured in three grazed sites with different grazing managements and one benchmark site in 2008 and 2009 in Grasslands National Park and surrounding provincial pastures, Saskatchewan, Canada. Thirteen vegetation spectral indices derived from remote sensing images were evaluated. The results indicated that canopy height and ratio of photosynthetically active vegetation cover to non-photosynthetically active vegetation cover (PV/NPV) showed significant differences between ungrazed and grazed sites. All spectral vegetation indices except Canopy Index (CI) showed a significant difference between grazing treatments. Red-NIR based vegetation indices, such as Modified Triangular Vegetation Index 1 (MTVI1), Soil-adjusted Vegetation Index (SAVI) and so on, were significantly correlated to PV/NPV. Green/Mid-infrared (Green/MID) related vegetation indices, i.e. Plant Senescence Reflectance Index (PRSI) and Normalized Canopy Index (NCI), showed significant correlation with canopy height. Models based on linear combination of MTVI1 and SAVI were developed for PV/NPV and PRSI and NCI for canopy

height. Model simulated PV/NPV and canopy height showed significant correlation with grazing intensity, suggesting the feasibility of remote sensing to quantify light to moderate grazing effects in mixed grasslands.

3.2 Introduction

Grazing is the most common form of land use in grasslands, and more than 37.5 million km^2 of the world's arid regions are used for ranching (Dregene, 1983). Managing grasslands either for conservation or animal production thus requires a thorough understanding of grazing impacts on grasslands (Noy-Meir et al., 1989). Grazing effects could be quantified by observing changes in vegetation properties such as vegetation cover, cover fractions, plant species diversity, and production (Harris and Asner, 2003; Liu et al., 2004; Kawamura et al., 2005; Jacobo et al., 2006; Blanco et al., 2009).

The magnitude of grazing effects vary with grazing intensity, the length of grazing, and the type of grazing regimes applied (Volesky et al., 2004; Vermeire et al., 2008). Among these factors, grazing intensity (stocking rate) has been documented as having the most direct impact on grasslands in the short term (Mwendera et al., 1997). Some studies have shown overgrazing to be harmful for grasslands as it can cause excess defoliation, nutrient loss, and pasture degradation (Boddey et al., 2004). Light to moderate grazing are suggested to benefit grasslands as indicated by the grazing optimization hypothesis (McNaughton, 1979). However, no consistent results have been reported in existing research regarding light to moderate grazing effects on grasslands. Patton et al. (2007) indicated that moderate grazing in a Kentucky bluegrass-dominated grassland can maintain a higher level of herbage production as compared to complete rest or overgrazing, while Belsky (1986) and Painter and Belsky (1993) reported no evidence that herbivory benefited grazed plants. Milchunas et al. (1994) found that production was highest in ungrazed treatments, and decreased as grazing intensity increased in short-grass prairie.

The dichotomy is primarily explained by the differences in environment moisture or the evolutionary history of grazing (Milchunas, 1994). Furthermore, it may also be partly attributed to the fact that limited vegetation information was acquired for the study area. The selective behaviour of herbivores results in vegetation patterns with grazed and ungrazed patches. Commonly used field method has limitation in obtaining enough measurements to represent vegetation condition in large areas, which affects the grazing impact investigation.

Remote sensing-based techniques have been widely used in grazing studies to solve the inherent limitation of ground methods due to their advantage in high temporal frequency and complete spatial coverage (Pickup, 1994). Spectral data are efficiently correlated with many vegetation biophysical and biochemical properties (e.g. biomass leaf area index, canopy cover, chlorophyll and nitrogen content) (Todd et al., 1998; Asner et al., 2004; Mutanaga and Skidmore, 2004; He et al., 2006; Gianelle and Vescovo, 2007; Dabishzadeh et al., 2008; Fava et al., 2009), and therefore have been used as proxies for many vegetation properties. In previous research, remote sensing data solely or combined with ground measurements have been used to investigate grazing impact. In some studies, grazing effects have been explored by analyzing changes of vegetation biophysical properties or spectral indices as a function of distance from a watering point (Harris and Asner, 2003; Pickup et al., 1994). Others focused on detecting overgrazing-induced grassland degradation or comparing grassland changes between heavily grazed and ungrazed areas (Liu et al., 2004). Few studies have looked at how remote sensing may be utilized to develop complimentary indicators for studying effects of grazing with light to moderate intensities. Compared to overgrazing or grazing with high intensity, the impacts caused by light to moderate grazing are less obvious. Thus, the documented vegetation spectral indicators for revealing grassland changes under heavy grazing intensities may not be effective enough for detecting light to moderate grazing intensity induced changes, while its assessment is important for the recognition of the impacts and protect from grassland degradation.

The objective of this study was to investigate the potential biophysical and spectral parameters to detect light to moderate grazing impacts. Specifically, 1) responses of both ground measured vegetation properties and spectral data to grazing were compared; 2) relationships between grazing-sensitive ground variables and remotely sensed spectral indices were analyzed to test the feasibility of spectral indices as surrogates of ground indicators to detect grazing effects; and 3) ground measured grazing intensity data were further applied to assess performances of identified spectral alternatives for studying light to moderate grazing effects on grasslands. Grazing activities in mixed grasslands of GNP and surrounding pastures were examined and used as a case study to achieve the above objectives. These areas are excellent sites to investigate light to moderate grazing effects. First, grazing intensities in these areas are light to moderate and considered lower than recommended for the purpose of maintaining the ecological integrity and maximizing long-term profits (Wallace, 2002). Second, a portion of the area in GNP where no anthropogenic disturbances have occurred for approximately 23 years is a perfect benchmark site for investigating grazing effects. It is hard to find intact reference sites for grazing studies as most grasslands experience disturbances. Finally, although primary knowledge of light to moderate grazing impact on mixed grasslands in many other regions are known (Biondini et al., 1998; Gillen et al., 2003; Gillen et al., 2004), the impacts of grazing in this area have not been quantitatively measured and our knowledge about the characteristics of grasslands in this area are very limited.

3.3 MATERIALS AND METHODS

3.3.1 Study area description

The research was carried out in the Grasslands National Park (GNP) (49°N, 107°W) and surrounding community pastures, Val Marie, Saskatchewan, Canada (Figure 3.1). This area is located along the border with the United States and represents the northern extent of mixed grasslands. The park is approximately 906 km^2 in area and incorporates two discontinuous blocks, West and East blocks. Land was first acquired by the park in 1984, and some areas of the park have been under protection from grazing for over 20 years (Zhang, 2005).

This region is marked by a continental semi-arid climate with dry, cold winters and a warm summer. Average temperature in July is 18.3^0C and -12.4^0C in January. Mean annual precipitation is approximately 325mm (Environment Canada, 2003). Half of the annual precipitation occurs in June, July, and August. Three broad vegetation-landscape units occur in this area: riparian shrubland, upland grasslands, and valley grasslands (Michalsky and Ellis, 1994). Upland grasslands cover approximately two-thirds of the park area. The dominant plant community of uplands contain needle and thread (*Stipa comata Trin.& Rupr)*, blue grama grass (*Bouteloua gracilis (HBK) Lang. ex Steud*), and western wheatgrass (*Agropyron smithii Rydb*). Valley grasslands are dominated by western wheatgrass and northern wheatgrass (*Agropyron dasystachym*) along with higher densities of shrubs and occasional trees. Common soil types in the park area are Chernozemic and Solonetzic soils (Fargey et al., 2000). In grassland communities, Chernozemic soil, characterized by a dark color and high amounts of organic matter, is most common (Zhang, 2005; Zhang and Guo, 2008).

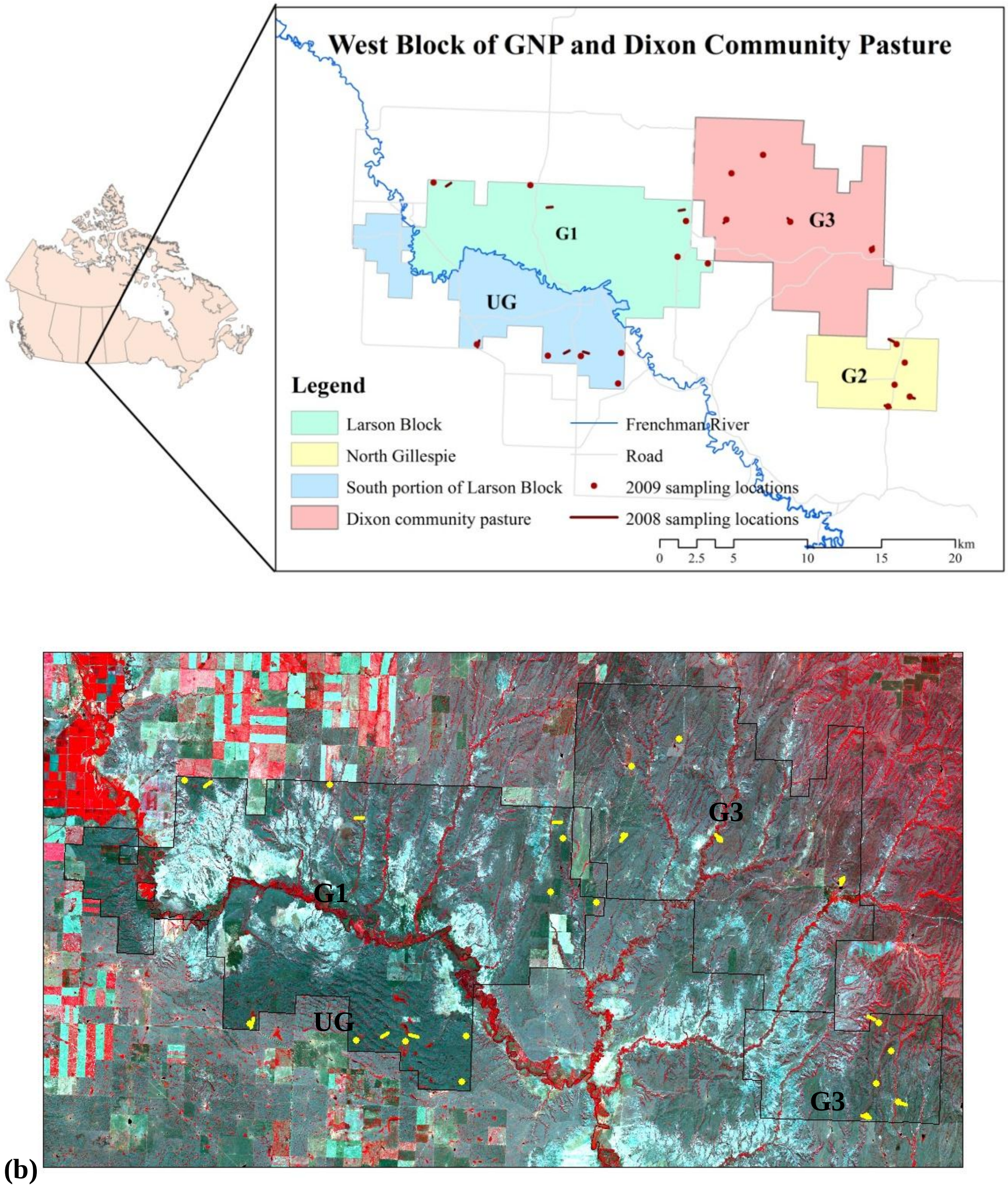


Figure 3.1 Study area, west block of GNP and Dixon community pasture (a), and a false-colour composite of SPOT5 image (©SPOT image copyright CNES) taken on 28 June 2009 (b).

3.3.2 Grazing regimes

In order to fully understand light to moderate grazing effects, four sites: the North portion of Larson block, South portion of Larson block, North Gillespie, and Dixon Community Pasture (hereafter referred to G1, UG, G2 and G3 respectively) were selected in study area (Figure 3.1). Three of them (G1, G2, and UG) are within GNP, and one (G3) is outside of the Park. The details of grazing activities in the four sites were indicated in Table 3.1. Number of droppings per unit area was collected and applied to indicate grazing intensity (3.3.4). Even though the grazing intensities in the three grazed sites (2.0, 5.0, and 12.0 droppings/100m^2) are slightly different, they are all belong to light to moderate grazing, in that the grazing intensities are lower than the recommended level for these area. The grazing history is different in three grazed sites. Compared to G1 and G2, the grazing history of G3 is longer. So, it is expected that the magnitude of grazing disturbance is largest in G3.

Fire is another major factor affecting vegetation structure in grasslands. Uncontrolled wildfire is suppressed in the park area as it poses a threat to human life, property, livestock, and natural resources. Prescribed burns are lit in some places for management purposes. None of the four sites has been known to have experienced fire over the past several decades, making grazing the only known disturbance to these sites.

Table 3.1 Grazing regimes of study sites

Study site	Grazing intensity (Droppings/100m^2)	Grazing history	Herbivore
G1	2.0	Year-long grazing since 2006	Bison
G2	5.0	Fall grazing since 2007	Cattle
G3	12.0	Rotational grazing for at least 20 years	Cattle
UG	0	Protection from grazing for more than 20 years	None

3.3.3 Vegetation measurements

Field work was conducted between the end of May and early June of 2008 and 2009 in upland grasslands in each of study sites (Figure 3.1). Different sampling methods were applied in 2008 and 2009. In 2008, three long transects were set up in upland grasslands in each site as three replications. Each transect was formed by 128, 50cm× 50cm quadrats at a 3-meter fixed interval. Within each quadrat, vegetation cover measures including percent cover of green grasses, forbs, shrub, standing dead litter, moss, lichen, and bare ground were estimated visually. Plant cover was estimated to the nearest 5% for cover values from 10% to 90% and to the nearest 1% for the cover less than 10% and greater than 90% (Daubenmire, 1959). Leaf area index was measured using a LiCor-LAI-2000 Plant Canopy Analyzer.

In 2009, a stratified random sampling method was used. In each study site, five sampling locations were selected as five replications. Two, 100m transects were set up in each sampling location perpendicularly at North-South and East-West directions. Six, 50cm×50cm quadrats were set up along each of the four arms. In total, 24 quadrats were set up for each sampling location. Distances between the quadrats and the cross of transects were 2.5m, 5m, 10m, 20m, 30m, and 50m, respectively. Percentage vegetation cover and LAI were measured for all quadrats using the same methods as 2008.

3.3.4 Dropping counts

In 2008, three transects were set up close to transects that used for measuring vegetation biophysical properties in each sampling location. One hundred twenty eight, 10m×2m quadrats were placed at 2m intervals along each transect. Number of pats within each quadrat was recorded. Since bison or cattle droppings are relatively durable and easily identifiable, they have been used as an indicator of grazing intensity in many studies (WallisDeVires, 2001; Vulliamy et al., 2006). The average of 128 quadrats was used to indicate the grazing intensity for each sampling location. The grazing intensity is expressed as dropping per 100 square meters

3.3.5 Image data and processing

SPOT5 multispectral images (© SPOT image copyright CNES) for the study area were acquired on June 1st, 2008 and June 28, 2009 with the overpass time as close to the field measurements as possible. Images were geometrically and radiometrically corrected using PCI Geomatics software (10.0). Radiometric and atmospheric corrections were done with the ATCOR2 module from PCI Geomatics software package. Twenty-eight ground training points collected using GPS were applied to do the geometric correction. The accuracy was 0.35 pixels for the 2008 image and 0.45 pixels for the 2009 image, which represents 3.5 meters and 4.5 meters of error on the earth’s surface respectively. Distortions caused by topography were corrected using a digital elevation model (DEM) with 20m spatial resolution, which was provided by the park.

3.3.6 Calculation of spectral vegetation indices

To fully consider grassland characteristics (sparse vegetation and accumulated dead materials) in our study area, thirteen commonly used broad band vegetation indices (NDVI, SAVI, ATSAVI, RDVI, PVI, MTVI1, MCARI2, CI, NCI, RCI, NDCI, PD54, and PSRI) were computed. Formulas and notable references for these indices are presented in table 3.2. The selected spectral vegetation indices can be roughly grouped into two categories according to their applications from literature. One group is mainly based on red and near infrared bands (hereafter named Red-NIR based vegetation index). Vegetation indices in this group include NDVI, SAVI, ATSAVI, RDVI, PVI, MTVI1, and MCARI2. The other group incorporates green or mid-infrared bands in to its calculation instead of red and near infrared bands. We classified vegetation indices in this group as Green/MIR bands related vegetation index. CI, NCI, RCI, NDCI, PD54, and PSRI were assigned to this group. Theoretically, live green plants have a strong absorption in the red wavelength region and reflectance in the near infrared region; therefore, vegetation indices based on red and near infrared wavelengths are primarily well-correlated with green vegetation properties (e.g. cover, leaf area index, and total biomass) (Marsett et al., 2006). Green and mid-infrared wavelengths relate to water content or senescence (Hardisky et al., 1983; Hunt and Rock, 1989); these wavelengths have been used to quantify biophysical characteristics of both green and dead vegetation.

3.3.7 Statistical analysis

The study was unreplicated like some grazing studies, but our sampling locations were all located in upland grasslands where topographic are very similar. In addition, within each study site, grazing is the primary factor dictating the effects on vegetation. Under this circumstance, Li et al. (2009) indicated that it is reasonable to assume that experimental error could be represented by sampling errors. Here, I made the same assumption for this study. Measurements from two years (2008 and 2009) were treated as replications to account for potential correlations and increase the power of statistics. All variables were tested for normality before further analysis was conducted. A T-test was used for all mean comparisons, which were considered as significant only at $p<0.1$. Pearson correlation coefficients were calculated to characterize the relationship between spectral indices and biophysical variables. Multiple linear regression analysis, which incorporates more independent variables into the function and improves model prediction capability, was further applied to model these relationships. The forward multiple regression analysis was applied and an alpha value of 0.05 was used to determine variable inclusion or removal. Jack-knife cross validation was applied to validate the developed models which has been shown to be better than split-sample validation, particularly for studies with smaller sample sizes (Goutte, 1997). This approach was implemented by withholding one sample and building the regression model using the data from the remaining samples. The process of removing one sample from the dataset was repeated until all samples had been withheld. Considering magnitude differences may occur in spectral or biophysical variables, Normalized Root Mean Squared Error (NRMSE) was calculated to indicate the prediction precision of the models for estimating vegetation biophysical variables. NRMSE is computed by the following equation.

$$\text{NRMSE}=\sqrt{1/n\sum_{i=1}^{n}(x_i-\hat{x}_i)^2}\Big/(x_{\max}-x_{\min})$$

Where n is the site number, i is each site sequence, x_i is the measured value and $\hat{x}_i$ is the simulated value calculated from the regression model.

3.4 RESULTS

3.4.1 Responses of vegetation biophysical characteristics

Vegetation biophysical parameters showed differences between sites with different levels of grazing (Table 3.3). Green grasses were higher in grazed sites compared to ungrazed sites. The highest canopy height and dead materials were found in the UG site. When comparing biophysical variables of each grazed site with those in ungrazed site with T-tests, green grass cover was significantly higher in the G2 and G3 sites than in the UG site ($p<0.1$). Standing dead cover in the UG was significantly higher than in the G1 and G3 sites. No significant differences were found in forb cover and LAI between grazed sites and the ungrazed site. Canopy height and PV/NPV in the UG site were significantly different from those in three grazed sites respectively.

Table 3.2 Computation of various spectral vegetation indices

	Index Acronym	Equation	Description and use	Reference
Red-NIR based vegetation indices	NDVI: Normalized vegetation index	$(\rho nir - \rho red)/(\rho nir + \rho red)$	One of most used indexes for green biomass estimation.	Rouse et al., 1973
	SAVI: Soil-adjusted vegetation index	$(1+L)(\rho nir - \rho red)/(\rho nir + \rho red + L)$ L=0.5	Minimizes soil brightness-induced variation based on a soil adjusted factor, L.	Huete, 1988
	ATSAVI (atmospheric adjusted soil adjusted vegetation index)	$\alpha(\rho nir - \alpha\rho red - b)/\left(\alpha\rho nir + \rho red - ab + X\left(1+a^2\right)\right)$ X=0.08	Minimizes soil brightness-induced variation. The soil adjusted factors (a and b) are needed to be investigated for specific area	Baret and Guyot, 1991
	RDVI: Renormalized difference vegetation index	$(\rho nir - \rho red)/\sqrt{\rho nir + \rho red}$	Suitable for low and high leaf area index values	Reujean and Breon, 1995; Haboudane et al., 2004
	PVI: Perpendicular vegetation index	$(\rho nir - \rho red - b)/\sqrt{1+a^2}$	Minimizes the soil background influence based on the Euclidean distance to the soil line	Richardson and Wiegand, 1977
	MTVI1: Modified Triangular vegetation index 1	$1.2[1.2(\rho nir - \rho green) - 2.5(\rho red - \rho green)]$	Sensitive to leaf and canopy structure change and insensitive to pigment level change	Haboudane et al., 2004
	MCARI2: Modified chlorophyll absorption ratio index 2	$1.5[2.5(\rho nir - \rho red) - 1.3(\rho nir - \rho green)]/\sqrt{(2\rho nir+1)^2 - (6\rho nir - 5\sqrt{670}) - 0.5}$	More resistance to chlorophyll influence and sensitive to leaf area index	Haboudane et al., 2004
Green/MIR related vegetation indices	CI: Canopy index	$\rho mir - \rho green$	Linearize relationships with vegetation biophysical parameters using the MIR and the green bands	Vescovo and Gianelle, 2008
	NCI: Normalized canopy index	$(\rho mir - \rho green)/(\rho mir + \rho green)$	Linearize relationships with vegetation biophysical parameters using the MIR and the green bands	Vescovo and Gianelle, 2008
	RCI: Ratio cover index	$\rho mir/\rho red$	Able to detect canopy moisture condition	Zhang and Guo, 2008
	NDCI: Normalized difference cover index	$(\rho mid - \rho red)/(\rho mir - \rho red)$	Response to canopy moisture condition	Zhang and Guo, 2008
	PD54: Perpendicular difference vegetation index	$(\rho red - \rho green - b)/\sqrt{1+a^2}$	Robust measure of the total amount vegetation cover which includes both green and dry materials	Pickup et al., 1993
	PSRI: Plant senescence reflectance index	$(\rho red - \rho green)/\rho nir$	Sensitive to Car/Chl ratio, and used to estimate leaf senescence	Merzlyak et al., 1999

Table 3.3 Comparison of vegetation characteristics between grazed and ungrazed sites

Measured variables	Mean				p-value		
	G1	G2	G3	UG	G1-UG	G2-UG	G3-UG
Green grass cover %	11.55±5.18	14.80±4.79	11.66±2.18	9.23±2.04	0.27	**0.02***	**0.04***
Standing dead cover %	32.12±7.19	41.80±15.37	24.43±12.37	49.56±12.73	**0.00***	0.29	**0.00***
Forb cover%	3.20±2.07	3.49±0.80	4.51±2.13	3.16±1.37	0.96	0.56	0.15
LAI	0.46±0.31	0.58±0.37	0.39±0.29	0.74±0.26	0.21	0.52	0.17
Canopy height	10.32±1.03	10.67±3.10	9.02±1.57	12.96±1.66	**0.00***	**0.09***	**0.00***
PV/NPV	0.35±0.14	0.37±0.10	0.60±0.36	0.19±0.06	**0.01***	**0.00***	**0.02***

*p<0.1

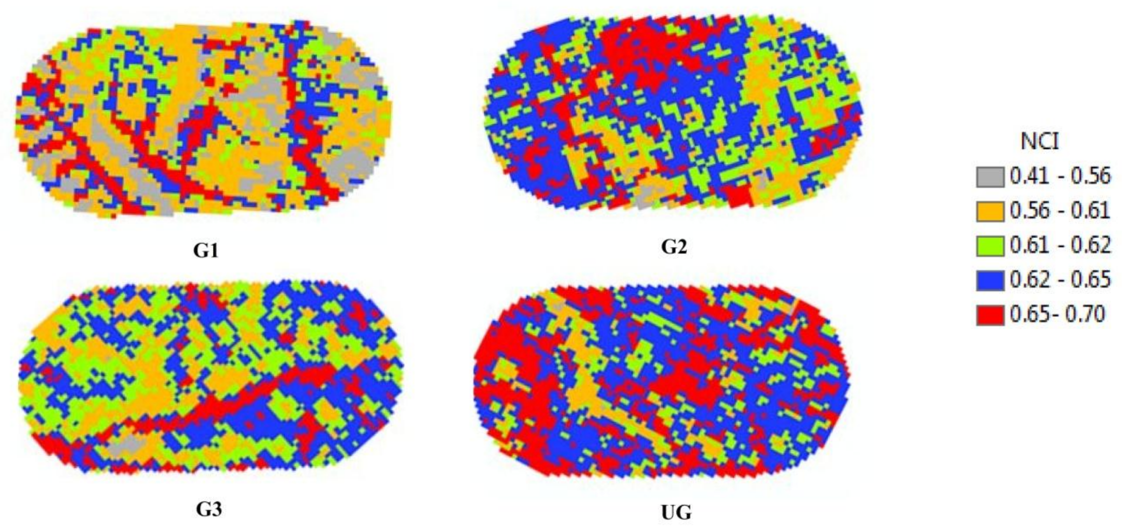
3.4.2 Responses of spectral vegetation indices

Vegetation indices showed variation among the four sites (Figure 3.2). Greenness sensitive indices, Red-NIR based vegetation indices, showed significant differences between UG and G2 as well as G3 ($p<0.1$) (Table 3.4). Most Green/MIR related vegetation indices in G1 and G3 are significantly lower than these in UG. PSRI only showed a significant difference between UG and G3.

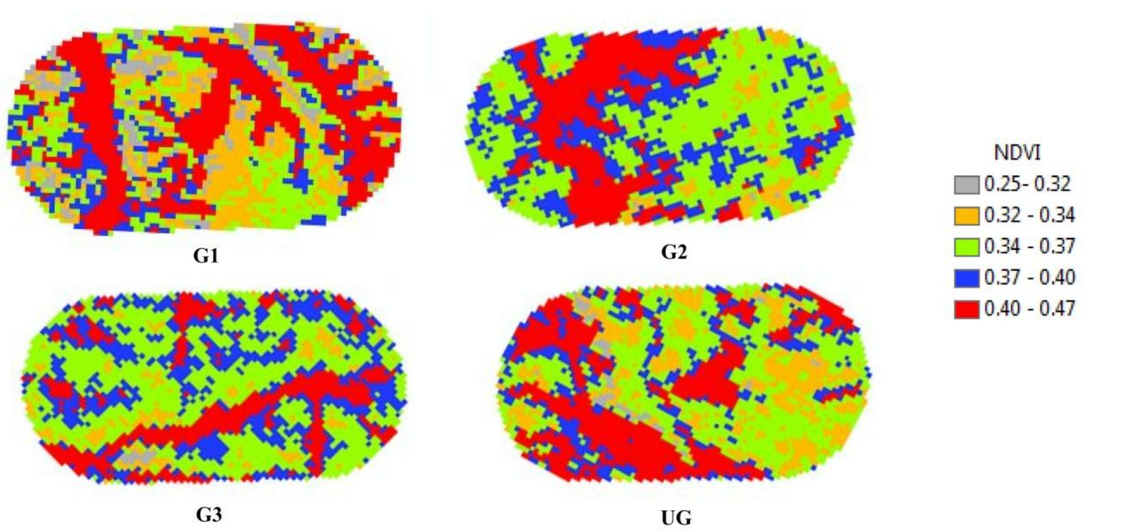
Table 3.4 Comparison of the spectral vegetation indices between grazed and ungrazed sites

Spectral indices		Mean				p-value		
		G1	G2	G3	UG	G1-UG	G2-UG	G3-UG
Red-NIR based vegetation indices	NDVI	0.33±0.04	0.38±0.02	0.37±0.03	0.33±0.04	0.89	**0.01***	**0.04***
	SAVI	0.19±0.04	0.22±0.02	0.22±0.03	0.18±0.04	0.54	**0.02***	**0.03***
	ATSAVI	0.12±0.04	0.15±0.02	0.15±0.03	0.10±0.05	0.62	**0.02***	**0.03***
	RDVI	0.19±0.03	0.21±0.02	0.21±0.03	0.18±0.03	0.58	**0.02***	**0.03***
	PVI	0.048±0.01	0.057±0.01	0.059±0.01	0.042±0.01	0.43	**0.04***	**0.03***
	MTVI1	0.11±0.03	0.13±0.02	0.14±0.03	0.10±0.03	0.49	**0.04***	**0.03***
	MCARI2	0.10±0.03	0.12±0.01	0.13±0.03	0.09±0.03	0.55	**0.03***	**0.03***
Green/MIR related vegetation indices	CI	0.26±0.03	0.25±0.03	0.26±0.02	0.26±0.02	0.95	0.73	0.93
	NCI	0.61±0.01	0.63±0.01	0.61±0.01	0.63±0.01	**0.00***	0.94	**0.00***
	RCI	3.15±0.15	3.32±0.08	3.25±0.09	3.36±0.12	**0.01***	0.48	**0.07***
	NDCI	0.52±0.02	0.54±0.01	0.53±0.01	0.54±0.01	**0.01***	0.50	**0.07***
	PD54	-0.035±0.0008	0.035±0.003	-0.033±0.001	0.034±0.0006	**0.10***	0.58	**0.01***
	PSRI	0.12±0.02	0.12±0.01	0.10±0.01	0.13±0.02	0.53	0.18	**0.02***

*p<0.1



(a)



(b)

Figure 3.2 Variation of vegetation indices in four sites. (a) An example of NCI. (b) An example of NDVI. NCI and NDVI are derived from the 2009 SPOT5 image

3.4.3 Relationships of spectral indices with canopy height and PV/NPV

Pearson correlation coefficients were computed between spectral vegetation indices and canopy height, and PV/NPV (Table 3.5). Not all vegetation indices were significantly correlated with these two biophysical properties. Compared to Green/MIR-related vegetation indices, Red-NIR based vegetation indices showed weaker negative correlations with canopy height with r values around 0.30 ($p<0.1$, $n=32$). Among all Green/MIR related vegetation indices, PRSI had the highest correlation with canopy height. On the other hand, for PV/NPV, Red-NIR based vegetation indices were more highly correlated than Green/MIR related vegetation indices. MTVI1, MCARI2, and PRSI showed highest correlations with PV/NPV with r values around 0.60.

Table 3.5 Correlation between grazing-sensitive biophysical variables and spectral indices

Vegetation indices		Canopy height		Photosynthetically active vegetation cover to non-photosynthetically active vegetation cover	
		r	p	r	p
Red-NIR based vegetation indices	NDVI	-0.31	**0.09***	0.48	**0.00***
	SAVI	-0.30	**0.10***	0.55	**0.00***
	ATSAVI	-0.31	**0.09***	0.54	**0.00***
	RDVI	-0.30	**0.10***	0.55	**0.00***
	PVI	-0.28	0.11	0.57	**0.00***
	MTVI1	-0.34	**0.06***	0.60	**0.00***
	MCARI2	-0.34	**0.06***	0.60	**0.00***
Green/MIR related vegetation indices	NCI	0.41	**0.02***	-0.27	0.14
	RCI	0.14	0.46	0.03	0.87
	NDCI	0.13	0.48	0.04	0.81
	PD54	-0.37	**0.04***	0.19	0.31
	PSRI	0.52	**0.00***	-0.60	**0.00***

*p<0.1

3.4.4 Models of canopy height and PV/NPV

Since both Red-NIR based and Green/MIR related vegetation indices showed significantly high correlation with canopy height and ratio of green grass cover to standing dead cover, multiple regression analysis that can incorporate more than one independent variable into its analysis, was applied to improve the model prediction using grazing sensitive biophysical variables as dependent variables and spectral indices as independent variables. Significant linear relationships were found between spectral indices with canopy height and PV/NPV ($p<0.1$, $n=32$) (Table 3.6). The model developed for PV/NPV is better than that for canopy height as it has relatively higher r^2 (0.5) and lower NRMSE (0.16) (Table 3.6). Jack-knife cross-validation was further applied to test the accuracy of the developed model. Model simulated values versus measured values are depicted in Figure 3.3.

Table 3.6 Modeling relationships between grazing-sensitive variables and spectral vegetation indices

Biophysical indicators	Models	r square	Adjusted r square	NRMSE
Canopy height	-25.44+58.71×PRSI+47.19×NCI	0.37	0.33	0.18
PV/NPV	1.5+27.6×MTVI1-22.11×SAVI	0.50	0.46	0.16

*p<0.1

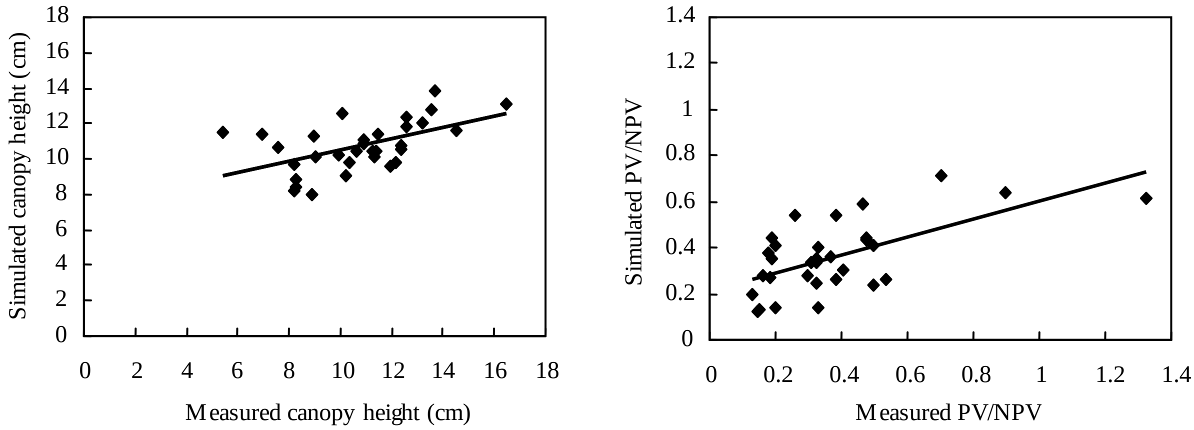


Figure 3.3 Agreement between model simulated values and measured values

3.4.5 Spectral vegetation indicators and grazing intensities

The relationships of grazing intensities with model simulated canopy height and PV/NPV are depicted in Figure 3.4. Grazing intensities showed a significant positive relationship with PV/NPV (p=0.00, n=12) and a negative relationship with canopy height (p=0.05, n=12).

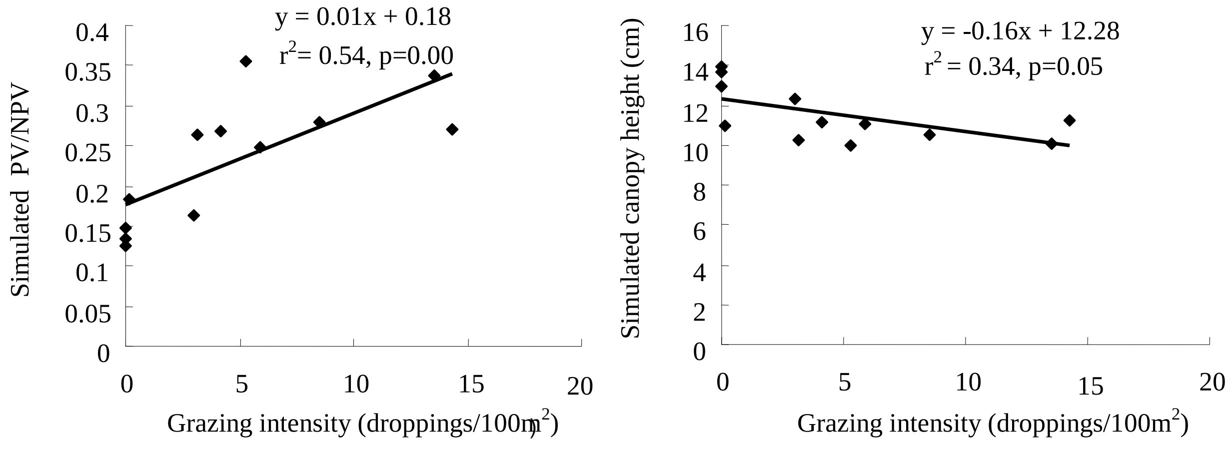


Figure 3.4 Relationship between grazing intensity and spectral vegetation indices

3.5 DISCUSSION

3.5.1 Vegetation biophysical parameters for detecting light to moderate grazing effects

Grazing intensity is commonly considered a primary, if not the most important, factor influencing grasslands (Vermeire et al., 2008). Unlike heavy grazing or overgrazing, where dramatic changes in vegetation (such as a decline in vegetation cover and biomass, or increase in bare ground) can be easily observed, this study did not find obvious changes in LAI under light to moderate grazing intensities. Instead, we found that the percentage of vegetation component was modified by light to moderate grazing in that grazing significantly reduced the standing dead cover but increased green grass cover and PV/NPV. Reduction of dead materials (standing dead grass and fallen litter) in grazed grasslands has been reported in previous studies (Coupland, 1979; Naeth et al., 1991), where grazing reduced dead materials through defoliation, tramping, or treading them into small particles, accelerating their decomposition. Dead materials are the major component of vegetation in this area, accounting for about 67.6% of total biomass in the early growing season (May) and 47.0% in the peak growing season (June to July) respectively (Guo, 2005). Dead materials intercept heat and water flow at the soil surface (Facelli and Pickett, 1991; Willms et al., 1993). Removal of dead materials by grazing modifies the micro-environment of plant and soil, consequently affecting the plant community. More green grass cover, as a result of grazing, may be the consequence of reduced dead materials. First, reduction in dead material increases light intensity at grass crown and simulates development of new tillers (Willms et al., 1986; Willms et al., 1993). Second, less dead materials may increase the soil temperature, which promotes earlier grass green-up (Lecain et al., 2003). Shorter canopy height in grazed sites is partially attributed to defoliation itself. An alternative explanation may be the consequence of reduced water available for plant growth due to the reduction of dead materials (Willms et al., 1993).

Even though we found that green grass cover, standing dead cover, canopy height, and PV/NPV are more sensitive to grazing than other vegetation biophysical variables tested, only PV/NPV and canopy height showed significant differences among all grazing treatments. The absence of significant differences in green grass cover between UG and G1, and standing dead cover between UG and G2 indicated that despite the importance of grazing intensity in determining the magnitude of grazing impacts, grazing history may also contribute to the effects of grazing on vegetation. Masbiri et al. (2008) indicated that two criteria must be met for grazing effects to be detected: the effects must be larger than the variability in the system and they must reach this size during the period of observation. Compared to G3, the length of grazing treatment in sites G1 and G2 are relatively short. It is possible that changes in green grass cover in G1 and standing dead cover in G2 have not accumulated to a level to be able to indicate grazing effects if not, the grazing treatment itself does not produce effects. From this aspect, we identified PV/NPV and canopy height as the best suitable vegetation biophysical parameters for detecting light to moderate grazing effects in these areas. Although we used two years of data to increase the power of our analysis, the samples size may still be a potential factor influencing the detection of grazing effects especially for studies based on ground sampled vegetation variables. Fortunately, this limitation could be overcome by using contemporary remote sensing indicators. That is why we think it is important to investigate the correspondent spectral parameters for detecting grazing effects in our study area.

3.5.2 Remote sensing of light to moderate grazing effects

To explore the suitable spectral indices for investigating light to moderate grazing effects, two factors needed to be taken into account: the sensitivity of the spectral parameter itself to grazing treatment and performance of identified spectral indices as a proxy of vegetation biophysical indicator for detecting grazing effects. Previous studies have successfully identified grazing impacts using vegetation biophysical variables retrieved from remote sensing data as indicators. In these studies, NDVI and other chlorophyll based indices have been used to characterize vegetation biophysical indicators such as grass biomass, canopy height, and vegetation cover (Todd et al., 1998; Numata et al., 2007). Numata et al. (2007) pointed out that the success of using remote sensing to detect grazing effects depended upon grassland phenology and background substrates. They explained that if the studies were conducted at a stage when greenness is the dominant vegetation component, grazing effects were better represented by greenness variation and chlorophyll sensitive vegetation indices, such as NDVI, were more appropriate for vegetation estimation or grazing detection. For a site dominated by dry, cured grass (senescent grass) grazing effects were more represented by attributes of senescent grass (quantities, brightness and water content) rather than greenness variation. Numata et al. (2007) found that the Normalized Difference Infrared Vegetation Index (NDII5 and NDII7) was suitable for monitoring grazing effects on grasslands in the dry season, as they showed a higher correlation with ground biomass than NDVI and SAVI.

In the case of this study, senescent grass was the dominant vegetation component and grazing effects were expressed by variation in green grass and senescent grass, so both greenness and senescence related vegetation indices were applied and tested. Results indicated that most vegetation indices are sensitive to grazing. Regarding their performances for predicting biophysical variables (canopy height and PV/NPV), the negative relationships between Red-NIR based indices and canopy height were reasonable because canopy height is determined by the height of standing dead in the study area. As much as 49% variation in canopy height is attributed to standing dead cover (data not shown). Standing dead grass has a masking effect on green grass and, therefore, weakens the contrast between red and near infrared bands. It is expected that the more standing dead grass there is, the smaller the Red-NIR vegetation indices values (Zhang and Guo, 2008). Most Green/MIR related vegetation indices showed significant correlation with canopy height, and only PSRI was significantly correlated to the PV/NPV. The lower significant correlation of Green/MIR related vegetation indices with PV/NPV may due to their sensitivities to the effects from background substrate. Effects of background substrate on performance of vegetation indices have been documented in many studies (Huete, 1988; Van Leeuwen et al., 1996; Vulliamy et al., 2006). Depending upon whether the background is litter or soil, the spectral signature for the vegetation canopy will change and the performance of vegetation indices intended to characterize grass will be affected. For vegetation condition such as mixed grasslands, litter and microphytic communities (lichen and moss) are the permanent background substrate. In the same study area, Zhang's study (2008) indicated that the relationships between vegetation indices (such as NDVI or soil reflectance corrected vegetation indices) and vegetation biophysical variables were hampered by accumulated litter and biophysical soil crust.

Models developed for canopy height and PV/NPV solve the difficulty for detecting, mapping or monitoring grazing effects due to insufficient sampling coverage especially for studies with large spatial extent. Variations explained by the models were substantial, 37% for canopy height and 50% for PV/NPV; a little bit lower than the values reported in other studies. Numata et al. (2007) found that Normalized Difference Index (NDII5) derived from Landsat Thematic Mapper 5 (TM5) can explain 42% variation in grassland canopy height. In addition to grassland phenology and background substrate, there are other unexplained variations that may prevent higher r^2 values in this study. One possible factor is a one month lag existed between field work and a satellite image acquisition in 2009. Vegetation phenology changes in the one month were not account for. Even though the models showed moderate goodness of fit they are significant. Developed models were further applied to quantify the grazing intensity. As expected, simulated canopy height decreased with grazing intensity increase due to defoliation or tramping disturbances by herbivore. Ratio of photosynthetically active vegetation cover to non-photosynthetically active vegetation cover is an indirect measure of vegetation composition as it reflects the amount of contrast between green and dead vegetation. Grazing at moderate intensity benefits grasslands because of increased plant structure and composition heterogeneity indicated by pervious research (). The increased PV/NPV along grazing intensity in this study supported results reported by previous research. The good relationships between grazing intensity and simulated canopy height and PV/NPV implied the feasibility of remote sensing indicators to reflect light to moderate grazing effects.

For further analysis in future studies, there are some issues to be considered. First, there still is room to improve the model predictability for canopy height and PV/NPV. In this study, we tested spectral indices based on the electromagnetic spectrum in visible and infrared portions. Remote sensors operating in other regions of the electromagnetic spectrum (i.e. microwave (Kellndorfer et al., 2004)) or finer spectral resolutions (e.g. hyperspectral remote sensing (Nagler et al., 2003)) have been shown to be good for this particular application. Second is the model application. Since models were developed using data collected from the early growing season they may not be extended to detect grazing effects in other growing seasons without validation. Finally, grazing intensity was characterized by herbivore droppings. It is assumed that a 1:1 ratio exists between bison droppings and cattle droppings which needs further analysis to validate. In addition, animals may not defecate where they feed. Instead, they may defecate in bedding or resting areas. To reflect the grazing intensity in those areas accurately in future studies, stocking rate needs to be measured.

3.6 CONCLUSIONS

In this study, ground biophysical variables and spectral indices of an ungrazed site and three grazed sites under light to moderate intensities were compared to investigate the potential for these parameters to characterize light to moderate grazing effects on mixed grasslands. Ground biophysical variables, canopy height, and PV/NPV were more sensitive to light to moderate grazing with various grazing periods compared to rest of biophysical variables. Models developed for these two grazing-sensitive biophysical indicators were based on a linear combination of different spectral variables (PSRI and NCI; MTVI1 and SAVI) and their abilities to quantify grazing intensity demonstrates the feasibility of remote sensing driven model to detect grazing effects under light to moderate intensities in mixed grasslands.

For improving the capability of developed models for quantifying light to moderate grazing effects, RADAR, LiDAR, or high spectral resolution remote sensing data are needed. In addition, since we use a single date satellite image and field data, the consistency of these results should be tested at a different time to investigate whether remote sensing driven models provide the best estimate for assessing light to moderate grazing effects over longer time periods. Temporal analysis using high temporal resolution sensors such as MODIS or AVHRR should be able to address this question.

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CHAPTER 4- APPLICATION OF REMOTE SENSING INFORMATION TO ASSESS GRASSLAND PRIMARY PRODUCTION UNDER DIFFERENT GRAZING INTENSITIES IN INNER MONGOLIA, CHINA

4.1 ABSTRACT

In this study, variations in grassland biomass in different grazing intensities were analyzed using field data and remote sensing images in three types of grasslands: desert grassland, typical grassland, and meadow grassland in Inner Mongolia, China. A set of spectral vegetation indices derived from remote sensing have been tested and compared for biomass estimation. Cross validation showed that a linear regressive model based on Optimized Soil Adjusted Vegetation Index (OSAVI) was the most predictive. Grazing intensities influenced the relationship between OSAVI and biomass. The correlation was higher in lightly and heavily grazed sites than in non-grazed sites. However, analysis of covariance revealed that no improvement in the linear regressive model was found when data was used separately. Those results indicated that the satellite derived information can provide a valuable tool for the assessment of grassland primary production under various grazing intensities in three types of grasslands of Inner Mongolia.

4.2 INTRODUCTION

Grassland in Inner Mongolia accounts for more than 70% of native grasslands in China and is one of the largest remaining grassland ecosystems in the world (Kawamura et al., 2005; Han et al., 2008). It has a significant role in serving the environment and economy of the region as it provides a food source for humans, homes to the majority of ethnic people, and habitat for more than 2000 plant species and over 600 animal species (Zhao et al., 2005; Kang et al., 2007). However, over the past several decades, this region has been subjected to serious degradation due to the increasing demand for natural resources and animal products. Currently, 39% of total useable grasslands (25 million ha) in Inner Mongolia has been degraded (Zhao et al., 2005).

One of the main factors causing grassland degradation in this region was firmly recognized to be overgrazing (Kawamura et al., 2005). The mean available land area allocated to one sheep in the grazing season (May to September) in this region decreased from 6.8 ha in the 1950s to 1.6 ha by the 1980s (Yiruhan et al., 2001), and the trend had continued. Establishing an appropriate stocking rate helps prevent grasslands degradation. Stocking rate is primarily determined by grassland primary production (Paruelo et al., 2000). Therefore, quantifying grassland net primary production accurately is an essential step in establishing appropriate stocking rates, and maintaining a sustainable grassland ecosystem in Inner Mongolia.

Different approaches based on field measurements and remote sensing data have been applied for net primary production estimation (Lu, 2006). The traditional method (based on biomass harvest) is the most accurate for quantifying production; however, it is only practical for relatively small field plot experiments (Lu, 2006; Boschetti et al., 2008). Satellite-based remote sensing data has been documented as an efficient data source for production quantification. It has the capability for collecting data in a quick and efficient way, capturing spatial variability of land surfaces with large extents, and observing changes at different spatial scales (Eisfelder et al., 2010). The use of spectral data to assess production is primarily based on the differential reflectance of photosynthetic tissue in the red and near-infrared portion of the electromagnetic spectrum (Guyot, 1990). Spectral indices, such as the Normalized Difference Vegetation Index (NDVI), have been widely used to estimate grassland production at local, regional, or global scales (Todd et al., 1998; Paruelo et al., 2000; Huete et al., 2002; Mutanga and Skidmore, 2004a, b; Edirisinghe et al., 2011). However, the performance of NDVI for estimating production was limited under certain situations. For example, previous studies found that in densely vegetated areas, NDVI did not respond to variations in biomass after a certain biomass density (Curran, 1983; Huete et al., 1985; Carloson and Ripley, 1997; Diaz and Blackburn, 2003). Therefore, NDVI yields poor estimates in those areas. Moreover, in semiarid environments with sparse vegetation, the capability of NDVI to describe vegetation biophysical parameters (fractional vegetation cover, leaf area index, and biomass) was weakened due to the significant contribution of bare soil and dry vegetation materials reflectance (Graetz and Gentle, 1982; Huete, 1988; Asrar et al., 1992). Therefore, vegetation indices aimed at compensating for the relative effects of soil and dead materials were developed. Boschetti et al. (2007) compared several soil-adjusted vegetation indices with two commonly used vegetation indices (SR and NDVI) for production estimation in an Alpine pasture and found that MSAVI gave the best estimation of production among all vegetation indices tested. Yang et al. (2012) reported that compared to NDVI, NCI computed using data from the green and mid-infrared wavelength region showed better performance in quantifying grassland production in mixed grasslands.

Although various vegetation indices have been used for production estimation, the problem is that an optimal vegetation index identified at one site or time period may not apply to other sites or the same site at other times due to the variation in environment (i.e. soil, precipitation, and temperature), vegetation characteristics (i.e. phenology, canopy composition, structure) and the remote sensing sensor applied in the study (spectral and spatial resolution) (Davidson and Csillag, 2001; Foody et al., 2003; Schino et al., 2003; Flynn et al., 2008; Li and Guo, 2011). Responses of grassland production to grazing vary from one grassland ecosystem to another. It is a widely accepted notion that grassland production decreases as grazing intensities increase, although some researchers have reported that production can be maintained or stimulated by grazing (McNaughton, 1983; Hik and Jefferies, 1990; Biondini et al., 1998). As more vegetation is removed by herbivores, vegetation canopy structure or plant community composition have been modified in that there is more bare ground exposed and less dead plant materials left (Willms et al., 1986). The spectral characteristic of vegetation canopy was changed accordingly, which consequently may affect the relationship between the vegetation index and the vegetation biophysical properties. Studies conducted in Western Australia have shown that the power of the relationship between NDVI and biomass declined as the vegetation growing season progressed due to the part presence of senescent vegetation (Edirisinghe et al., 2011). Fan et al. (2009) investigated the relationships between NDVI and LAI in three sites that were non-grazed, lightly grazed, and heavily grazed and found that the correlation coefficients between them were 0.99, 0.77, and 0 respectively. Since most grassland in Inner Mongolia has been subjected to grazing and few studies have focused on the effects of grazing intensity on production estimation using remote sensing data (Edirisinghe et al., 2011), the main objective of this study is to test the feasibility of remote sensing derived vegetation indices on estimation of production under various grazing intensities. More specifically: 1) to analyze the responses of above ground biomass to different grazing intensities; 2) to test the possibility of using remote sensing information to quantify grassland production; and 3) to assess the influence of grassland types and grazing intensity on grassland production estimates.

4.3 METHODS AND MATERIALS

4.3.1 Study area

The study area is located in the Inner Mongolia Autonomous region, China (Figure 4.1). Within the region, three representative study sites with different vegetation characteristics and productivity were selected as experimental sites:

1) Desert grassland is located in Siziwang banner (Lat 41°46′ -41°50′ N, Long: 111°50′ -112°01′ E, altitude around 1450m). This region is dry and hot in summer and cold in winter with a long-term annual precipitation of 280mm (Han et al., 2008). Mean annual temperature is 1.6℃. The soil is brown Chermozem (Canadian Soil Classification) with a loamy sand texture (Li et al., 2008). Dominant species occurring in this type of grassland includes: *Stipa breviflora* Griseb., *Artemisia frigida* Willd., and *Cleistogenes songorica* (Roshev.) Other species are found in the site including *Convolvulus ammannii* Desr., *Heteropappus altaicus* (Willd.) Novopokr., *Neopallasia petinata* (Pall.) Pojak., *Kochia prostrata* (L.) Schrad., *Caragana stenophylla* Pojark., and *Leymus chinensis* (Trin.) Tzvel (Li et al., 2008)

2) Typical grassland is located in Keshiketeng banner (Lat: 43°27′ -43°33′ N, Long: 116°33′ -116°40′ E, altitude around 1280m). Typical steppes are developed under semi-arid climates, occurring in areas with annual precipitation around 350mm (Sun, 2005). Mean annual temperature is 1-2℃. The soil is brown Chernozem (Canadian Soil Classification) with loamy and clay texture (Liang et al., 2008). Major plant species found in this area are *Leymus chinensis* (Trin.) Tzvel., *Stipa grandis* P. Smirn, *Cleistogenes squarrrosa* (Trin.)

keng, *Artemisia frigida* (Willd.), *Potentilla acaulia* L., and *Carex duriuscula* C.A. Mey. A. (Liang et al., 2008).

3) Meadow grassland is located in Xuwuzhumuqi banner (Lat: 44°28′ -44°29′ N, Long: 117°59′ -118°01′ E, altitude around 760m). Meadow steppe occurs on the most moist and fertile sites among the three grassland types. Annual precipitation is around 450mm. Mean annual temperature is 1℃. The soil is a dark brown Chernozem (Canadian soil classification) with a clay texture (Han et al., 2008). The dominant species are *Leymus chinensis* (Trin.) Tzvel. and Stipa baicalensis Roshev. Associated species mainly include *Filifolium sibiricum* (L.) Kitam., *Cleistogenes squarrrosa* (Trin.) keng, *Carex duriuscula* C.A. Mey. A. *Sanguisorba officinalis* L., *Adenophora stenathina* (Led eb.) Kitagawa. and *Dianthus chinensis.*

Grazing is the primary disturbance occurring in our study sites. Fire was suppressed for many years and no other disturbances have occurred over past years as we know. As a result, grazing was the major anthropogenic disturbance causing biomass changes in our study sites.

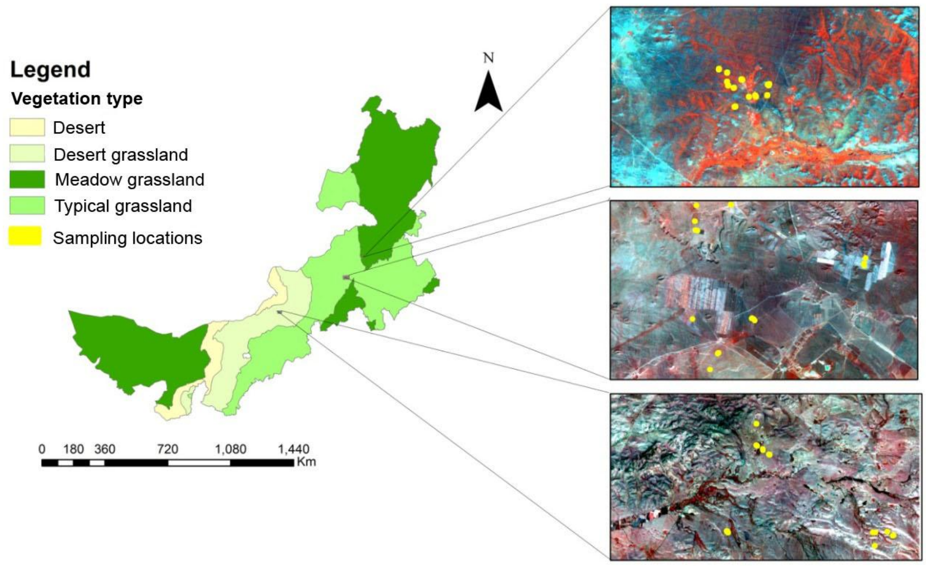

Figure 4.1 Locations of study sites and sampling locations in each site. Yellow dots denote the sampling locations in each type of grassland.

4.3.2 Sampling design and biomass data collection

Field work was conducted at the time of peak biomass, usually mid-August to early Sepetember, in 2006 in the three types of grasslands. In each type of grassland, nine sites with different grazing treatments (none, light to moderate and heavy grazing) were identified. Three sites were chosen for each grazing treatment. For meadow steppe, only two sites were identified with heavy grazing intensity. In each site of desert and meadow grasslands, three, 50-meter-long transects were set up. A handheld global positioning system (GPS) was used to record the coordinates of each transect. Above ground biomass including live biomass and dead biomass were harvested along each transect at 5m intervals, using a 1m×1m quadrat. Biomass samples were brought back to the laboratory, oven-dried at 60℃ for 48 hours, and weighed. Averaged dry biomass data for each transect were used in the following analysis. In typical grasslands, stratified random sampling was applied to collect biomass samples. In each site, three random locations were selected. Coordinates of each location were recorded using GPS. In each location, five biomass samples were randomly collected within 50m×50m areas, using a 1m×1m quadrat. The average value of the five dry biomass data was used to represent the biomass for each location. Because decompositions of dominant vegetation communities in the three grasslands are relatively low (Liu et al., 2009), we assumed that the total biomass at the time of peak growing season approximated primary production for that year. Therefore, total biomass was used as a measure of primary production in this study.

4.3.3 Remotely sensed imagery and pre-processing

Three Landsat TM images covering the study sites in desert, typical, and meadow grasslands respectively, were acquired in 2006 with the time matching the field campaign as close as possible. Images for desert and typical grasslands were obtained in August and fairly close to the date of the field work. The image for meadow grassland was obtained in

September because no high quality images were available in August. The time lag between satellite overpass and the time of field work is likely to introduce error in the analysis. However, this is unavoidable given the Landsat TM revisiting period (16 days) and the problem of accessing data with a minimal cloudiness (Edirisinghe et al., 2011). Considering that changes in biomass are minor in meadow grasslands during the maximum growing stage, it is unlikely that time lag significantly affects the data quality. The Landsat images obtained were standard level 1T products, which were systematically geometrically corrected. The positional accuracy that was documented is quite accurate, and the error is within a half pixel (15m) (Yang et al., 2011). Thus, no further geometrical correction was applied on those images. The geocorrected images were reprojected to a UTM WGS 49 map projection for desert steppe, and a UTM WGS 50 map projection for meadow steppe and typical steppe. Radiometric correction, including atmospheric correction, was applied to reduce radiometric errors introduced by the remote sensor system and atmosphere. Considering the decaying detector sensitivity of Landsat TM, a time-dependent function was applied to calculate the gain and offset factors for image calibration (Chandler et al., 2009). An improved dark-object subtraction method (Chavez, 1988) was used to eliminate the effects of atmosphere. More detailed information on how to calculate the gain and offset as well as the advantages of the improved dark-object subtraction method can be found in Yang et al. (2011).

After correction, the sampling locations recorded by GPS were overlaid on top of the images. Spectral data were extracted from 2×2 pixels (representing a 60m×60m area on the ground) centred on each GPS point to match the ground measurements. Finally, vegetation indices were calculated using the extracted spectral data.

4.3.4 Data analysis

Two-way Analysis of Variance (ANOVA) was applied to examine the variation in biomass for different grazing treatments, grasslands and their interaction. The Pearson correlation coefficient was calculated between the biomass and vegetation indices to examine the performance of the vegetation index on biomass estimation. Regression analysis was then conducted to study the relationship between the biomass and vegetation indices presenting the highest correlations with biomass. The results allowed the development of an empirical model for biomass prediction. Vegetation indices used in this study are presented in Table 4.1.

Table 4.1 List of vegetation indices used in this study

Name	Acronym	Formula	Reference
Normalized difference vegetation index	NDVI	$\frac{\rho_{NIR}-\rho_{red}}{\rho_{NIR}+\rho_{red}}$	Rouse et al., 1974
Soil adjusted vegetation index	SAVI	$1.5\frac{\rho_{NIR}-\rho_{red}}{\rho_{NIR}+\rho_{red}+0.5}$	Huete, 1988
Modified soil adjusted vegetation index	MSAVI	$\frac{1}{2}\left[(2\rho_{NIR}+1)-\sqrt{(2\rho_{NIR}+1)^2-8(\rho_{NIR}-\rho_{red})}\right]$	Qi et al.,1994
Optimised soil adjusted vegetation index	OSAVI	$1.16\frac{\rho_{NIR}-\rho_{red}}{\rho_{NIR}+\rho_{red}+0.16}$	Rondeaux et al., 1996
Normalized difference cover index	NDCI	$\frac{\rho_{MIR}-\rho_{red}}{\rho_{MIR}+\rho_{red}}$	Zhang and Guo, 2008
Normalized Canopy index	NCI	$\frac{\rho_{MIR}-\rho_{green}}{\rho_{MIR}+\rho_{green}}$	Vescovo and Gianelle, 2008

In the formulas, ρ_{red} refers to the reflectance measured in red band (nm), ρ_{green} in green band (nm), ρ_{NIR} in near infrared band (nm) and ρ_{MIR} in mid-infrared band (nm).

To validate the performance of the developed empirical models on biomass prediction Jack-knife cross validation was applied. Several difference based statistics were calculated to quantify the agreement between model outputs and field measurements, including root mean square error (RMSE), relative RMSE, modelling efficiency (EF), and coefficient of residual mass (CRM) (Loauge and Green, 1991). Modelling efficiency quantifies the capability of the model to reproduce the trend of the observed values (Boschetti et al., 2007). The optimum value for EF index is 1. The closer the calculated EF index to 1 the better the model. CRM indicates whether the model overestimates (CRM<0) or underestimates (CRM>0) (Boschetti et al., 2007). The equations for calculating EF and CRM are as follows:

$$EF=\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2-\sum_{i=1}^{n}(\hat{x}_i-x_i)^2}{\sum_{i=1}^{n}(x_i-\bar{x})^2}$$

$$CRM=\frac{\sum_{i=1}^{n}x_i-\sum_{i=1}^{n}\hat{x}}{\sum_{i=1}^{n}x_i}$$

Where x_i are the observed values; $\hat{x}_i$ are the predicted values; n is the number of samples; and $\bar{x}$ is the mean of the observed data.

Furthermore, analysis of covariance (ANCOVA) was conducted to study the influence of grassland type and grazing treatment on biomass-vegetation index relationship. Analysis of covariance is a type of generalized linear model (GLM), which allows the introduction of categorical variables, such as grassland type and grazing intensities, as further explanatory variables of a linear regression model.

4.4 RESULTS AND DISCUSSION

4.4.1 Biomass among different grazing treatments and grassland types

Descriptive statistics of the biomass measurements are reported in Table 4.2. Biomass shows a high variation among all sites with CV ranges from 11.9% to 58.7%. As expected, among the three grassland types, meadow grassland is the most productive pastures in Inner Mongolia, having the highest biomass with an average value of 361 grams per square meter (Table 4.2). The lowest productive pasture is desert grassland, where the climate is dry and is associated with sparse and short grasses (Li et al., 2008). The differences in biomass between three grasslands were significant (d.f.=2/87, $F=165.04$, $P<0.001$) as indicated by the ANOVA analysis.

Grazing intensity is also a source of variation in biomass. While the responses of biomass to grazing intensity varied among the three grasslands, in typical grassland, grazing significantly reduces biomass compared to non-grazed sites ($p<0.05$) (Table 4.2). The results coincided with those presented in previous research which was conducted in typical grasslands (Liang et al., 2009). Biomass is slightly increased but not significant ($p>0.05$) in lightly grazed sites compared to non-grazed or heavily grazed sites in meadow grassland (Table 4.2).Wang et al. (2010) indicated similar findings in this area; net primary productivity was at a maximum in moderately grazed sites. This was attributed to the plant compensatory growth and the higher precipitation in the year the study was conducted. It is reasonable that the highest biomass was found in heavily grazed sites in desert grassland. Successional retrogression of grasslands in these sites had occurred due to over grazing. The dominant species such as *Stipa breviflora* and *Cleistogenes squarrosa* in the community had been replaced by pasture sage (*Artemisia frigida*) which is a shrub in terms of plant form, and the weight is heavier than original dominant species which are grasses (Zhanbula et al., 1999).

The interactive effects of grassland type and grazing intensity on biomass were also determined by ANOVA analysis. Results indicated that the interaction was significant but only in typical grassland (d.f.=4/87, F=3.69, P<0.001).

Table 4.2 Descriptive statistics of biomass measurements in different grazing intensities relative to the three types of grasslands

Grassland type	**Test sites**(1)	**Forage utilization (%)** (2)	**Dry biomass (g/m^2)**				
			Mean	Mean	n	SD	CV%
Desert steppe	UG	0	49.1	44.0a	9	5.2	11.9
	LG	18±7.8		45.3a	9	19.3	42.5
	HG	49±12.7		58.1a	9	21.3	42.2
Typical steppe	UG	0	123.7	203.8a	15	84.5	41.5
	LG	15±1.2		96.3b	15	56.5	58.7
	HG	62±2.6		71.0b	15	29.3	41.3
Meadow steppe	UG	0	361.2	350.0a	9	82.0	23.4
	LG	31±18.3		401.7a	9	94.4	23.5
	HG	68±18.1		331.8a	6	109.8	33.1

(1) UG represents non grazed sites; LG: lightly grazed sites; and HG: heavily grazed sites

(2) Forage utilization of Desert steppe and Typical steppe were adapted from Li et al. (2008) and Liang et al. (2008) respectively

4.4.2 Relationships between biomass and vegetation indices

The relationship between biomass and vegetation indices was compared using Pearson correlation coefficients (r) (Figure 4.2). Significant relationships (p<0.01) were found between biomass and all tested vegetation indices except NCI which showed poor correlation with biomass (p>0.05). All tested vegetation indices, soil-adjusted vegetation indices, SAVI, MSAVI, and OSAVI, show higher correlations (SAVI r=0.88, MSAVI r=0.88 and OSAVI r=0.89) with respect to NDVI and NCI. A higher correlation was also found between NDCI and biomass (r=0.88).

Previous studies have demonstrated that the strengths of the correlations between biomass and vegetation indices were strongly influenced by the presence and abundance of grass species as well as the presence and absence of bare ground and dead materials and other spectral distraction features (Numata et al., 2008; Mašková et al., 2008; Chen et al., 2011; Yang et al., 2011). In our study, dead vegetation materials and bare ground are two major factors likely affecting the relationships between vegetation indices and biomass. In ungrazed sites, more dead materials were accumulated as a result of no grazing disturbance. In grazed sites, as vegetation was depleted by herbivores, bare ground was exposed, and this trend is enhanced as grazing intensity increased. Taking the study site in typical steppe as an example, the average percentage of bare ground and dead material accounting for the total vegetation cover is 39% in non-grazed sites, and increases to 55% in heavily grazed sites. Soil adjusted vegetation indices have the capability to minimize the influences of bare ground and dead materials (Huete, 1988; Qi et al., 1994; He et al., 2006). Thus, it is expected that they showed higher correlation with biomass. NDVI is primary related to chlorophyll absorption and expressed high correlation with biomass when the proportion of green vegetation is high (Numata et al., 2008). Kawamura et al. (2003) reported a correlation coefficient of 0.66 between the NOAA/NDVI and biomass in Inner Mongolia. Even though the correlation coefficient between NDVI and biomass found in this study was higher than that in Kawamura et al.'s study, NDVI was found to not be a reliable index for estimation of biomass in our study because of the bare ground and dead materials found in our study sites, which has also demonstrated by other studies (Chen et al., 2011). Numata et al. (2008) suggested that the use of vegetation indices based on water absorption spectra may improve the accuracy of biomass estimation in semi-arid grasslands. Chen et al. (2011) supported Numata's suggestion finding significantly high correlations between biomass, water content, and water-sensitive indices (i.e. NDWI, RDWI). Our results also support their findings in that a strong correlation was found between NDCI and biomass.

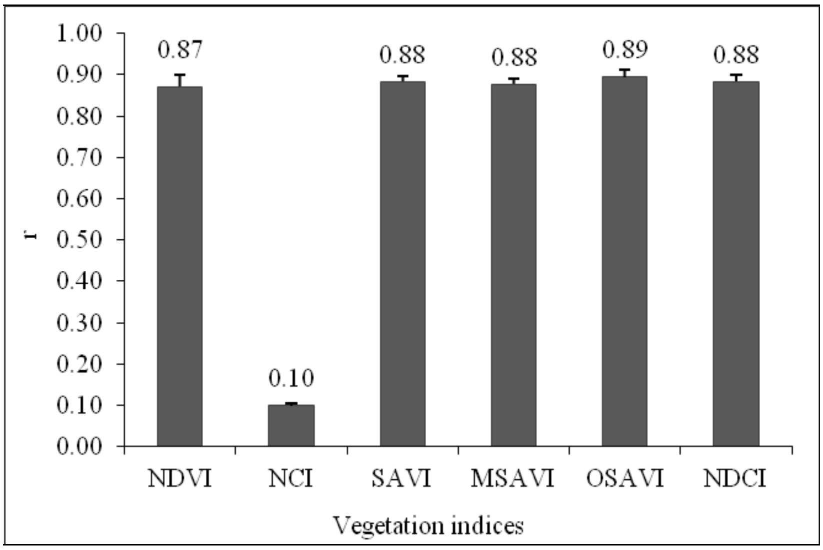

Figure 4.2 The r values with error bar between biomass and VIs. All r values are significant at $p<0.05$ except NCI (n=26).

Considering that both soil-adjusted vegetation indices and NDCI gave comparable capability in biomass estimation in terms of r values, regression analysis with a series of statistics was further applied with the purposes of developing an empirical model based on a vegetation index which shows the best performance in biomass prediction. The model developed based on OSAVI, is presented in figure 4.3 as an example. From the analysis of table 4.3, the OSAVI based model gave the highest Jack-knife r^2, the lowest RMSE value and an EF index closest to 1. Scatter plots between the observed and OSAVI based model predicted biomass values showed a good level of agreement with an r^2 of 0.76 (Figure 4.4). The statistical results illustrated that among these fitting models, OSAVI based model is the most predictable for biomass estimation in our study area.

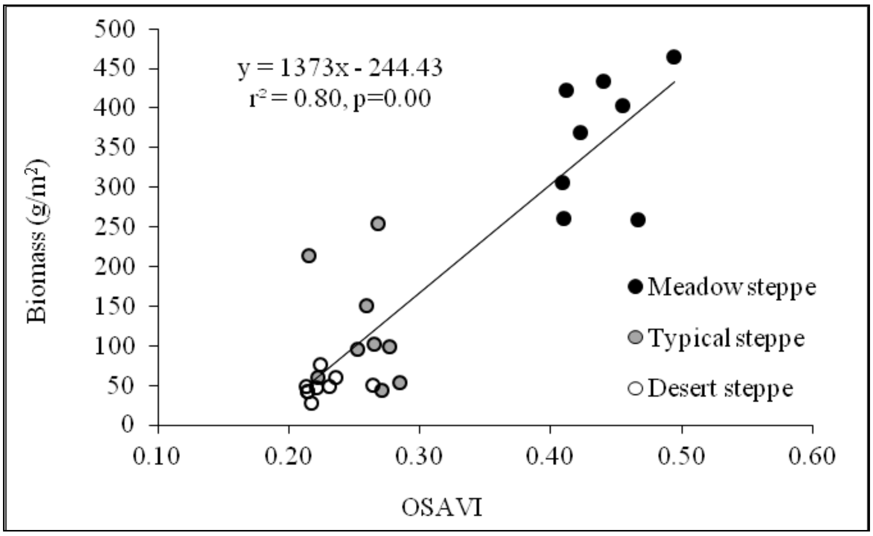

Figure 4.3 The relationship between OSAVI and biomass (n=26). Dots filled with dark, grey, and white color indicate samples collected from Meadow, Typical and Desert grasslands respectively.

Table 4.3 Indices of agreement between measured and model simulated biomass value of 26 randomly selected independent samples for the three soil-adjusted VIs

	Jack-knife r^2	slope	intercept	RMSE	EF	CRM
Range	[0,1]	[-∞,+∞]	[-∞,+∞]	[0,+∞]	[-∞,1]	[-∞,+∞]
optimum	1	1	0	0	1	0
SAVI	0.74	0.76	40.52	74.67	0.74	0.001
OSAVI	**0.76**	**0.78**	**36.84**	**70.84**	**0.76**	0.001
MSAVI	0.73	0.75	41.93	76.15	0.72	0.001

Bold values represent the best result for each index of fitting

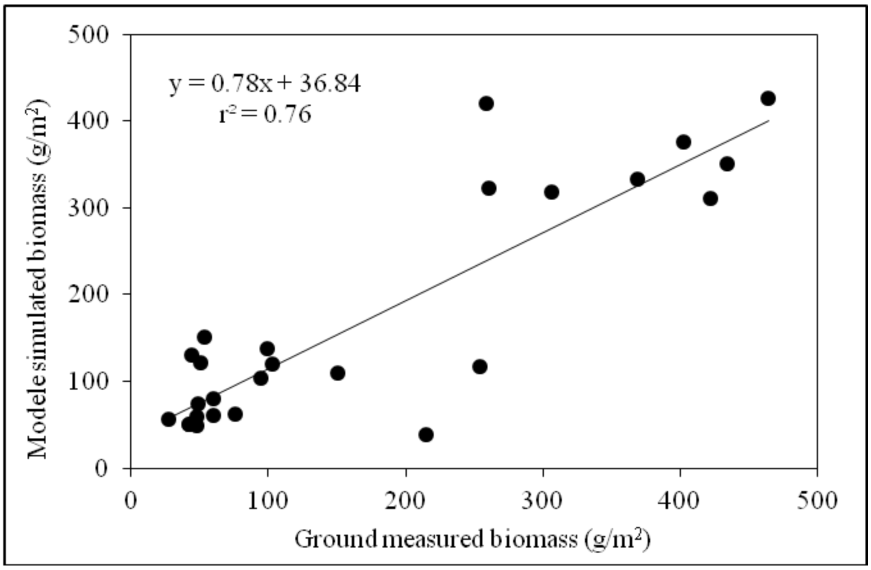

Figure 4.4 Model simulated biomass and ground measured biomass (n=26).

4.4.3 Influence of grazing intensity and grassland type on biomass prediction

The OSAVI based model was further investigated by dividing the full data set into single grassland types and single grazing intensities. Results of the analysis indicated that no significant correlation was found between OSAVI and biomass when regression was calculated separating different grassland types ($p>0.05$). When analysis was conducted for grazing intensities separately, OSAVI was more correlated with biomass in lightly and heavily grazed sites than non-grazed sites (Figure 4.5). However, Analysis of covariance (ANCOVA) revealed that incorporating “grazing intensity” into the developed model as an additional explanatory variable did not increase the model predictability significantly (d.f.=2/20, F=0.99, P=0.39). This suggests that it is not necessary to build models separately for different grazing intensities. One OSAVI based empirical model, developed using the whole dataset, could be used to estimate biomass in all three grasslands and varied grazing intensities in Inner Mongolia.

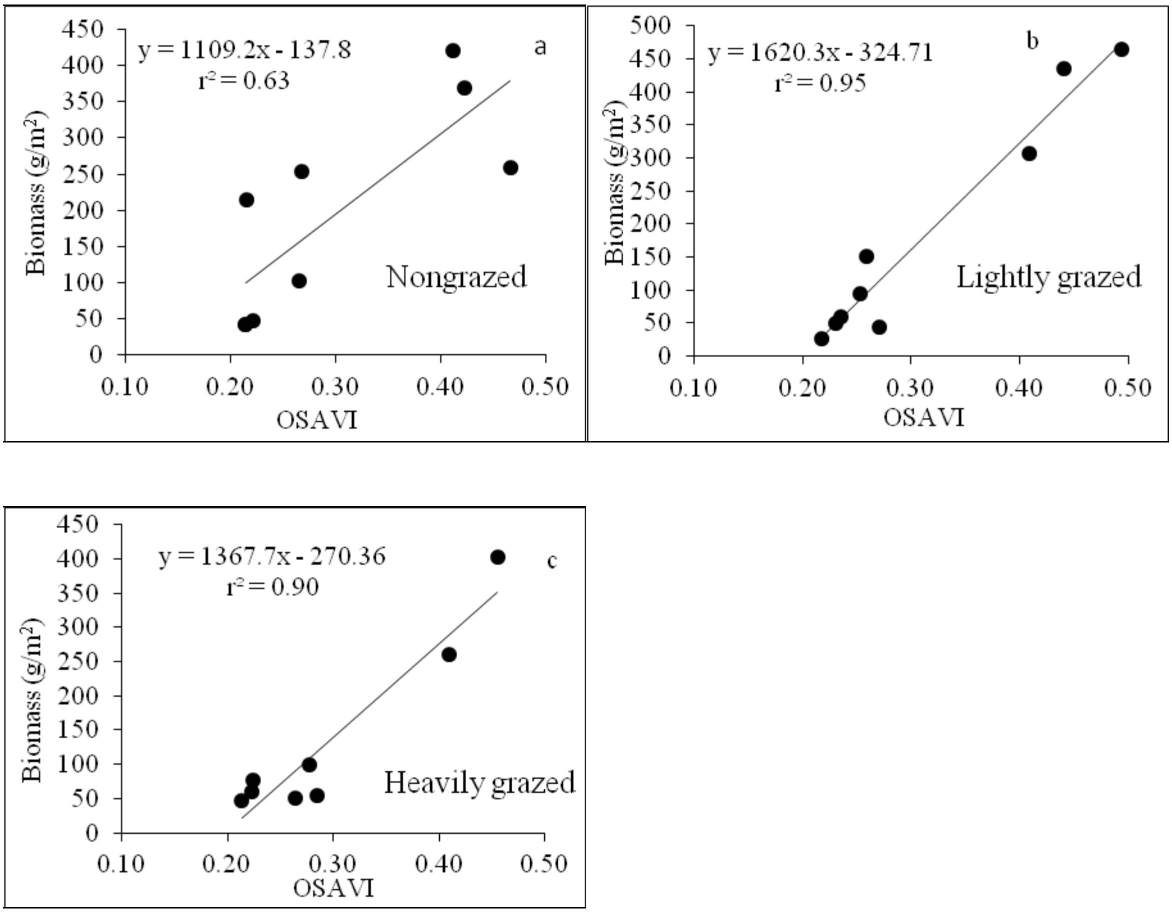

Figure 4.5(a-c). Relationships between OSAVI and biomass for each grazing intensity.

4.5 CONCLUSIONS

This study focused on biomass estimation in three grasslands under different grazing intensities in Inner Mongolia. A suite of vegetation indices were derived from remotely sensed images and compared for correlation with biomass. It was noted that bare ground and dead vegetation material influenced the strength of relationships between biomass and vegetation indices. Soil-adjusted vegetation indices (SAVI, OSAVI, and MASVI) and NDCI showed better correlation compared to the commonly used vegetation index, NDVI. Based on the correction results, an empirical model based on OSAVI for estimation of biomass has been developed and validated. The model estimated biomass explained 76% of the observed biomass. The model is robust for grazing intensity and grassland type; however, factors reported in other studies which likely influence the accuracy of biomass estimates derived from remote sensing data such as vegetation typology, vegetation phenology, and temporal dynamics of vegetation production can be addressed in future work to help improve the accuracy of biomass estimation in grasslands of Inner Mongolia.

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CHAPTER 5- ASSESSING LIGHT TO MODERATE GRAZING EFFECTS ON GRASSLANDS PRIMARY PRODUCTION USING REMOTE SATELLITE IMAGERY

5.1 ABSTRACT

Understanding the influences of grazing intensity on grassland production is essential for grassland conservation and management. Grazing at light to moderate intensity can theoretically enhance grassland production, thus benefiting grassland ecosystems. However, inconsistent results of the beneficial effects of light to moderate grazing on grassland production have been reported due to the lack of accurate and repeatable techniques for discriminating grazing effects from other abiotic factors. Advanced remote-sensing techniques provide a promising tool for filling this gap in grazing effects research due to their high spatial and temporal resolution. In this article, the influence of light to moderate grazing on grassland production in mixed grasslands were investigated for the period 1986 to 2005, using spectral data derived from satellite images. The effects of precipitation on the detection of grazing-induced production change were also analyzed. The results revealed that the Normalized Canopy Index (NCI) showed superior performance in quantifying grassland production in mixed grasslands. Significant differences in grassland production between grazed and ungrazed treatments occurred in the three years with above average and average growing-season precipitation (April-August), but not in the dry years. Most of the variation in production (75%) was explained by growing-season precipitation for both grazed and ungrazed sites. Our results demonstrate the feasibility of using remote-sensing data to monitor long-term light to moderate grazing effects and the important role of precipitation, especially growing-season precipitation, in modulating production in mixed grassland ecosystems.

5.2 INTRODUCTION

Mixed grasslands cover approximately 270,000km^2 of the land surface, and play important roles in providing habitat, water, and food for an array of mammals, birds, insects, and reptiles, as well as humans (World Wildlife Fund and McGinley 2008). Worldwide, over the past few decades, grasslands have experienced degradation due to overgrazing, land-use conversion, climate change, mining, urbanization, or the combined influence from these factors. Records in 2003 indicated that only 25%-30% of Canadian mixed grass prairies remained in a native state (Gauthier and Wiken, 2003). Grasslands National Park, created in the 1980s, represents one of the most intact mixed grasslands in Canada. After the park was established, no livestock grazing occurred until 2005. In 2002, a report indicated that the loss of habitat for rare grassland species was the result of grazing elimination. In 2006, grazing was reintroduced in the park as a management tool to restore and preserve wildlife habitats, as well as to maintain ecological integrity.

Various grazing management strategies have been developed in an effort to meet different grassland management goals. Grazing at light to moderate intensity has been adopted by both park managers and ranchers as a low-cost management initiative for sustaining biological and economical productivity. The grazing optimization hypothesis states that productivity should be maximized at a light to moderate level of grazing, which can increase photosynthetic rates, allocation of substrates from roots to shoots, tillering, and thus productivity (McNaughton, 1979; Detling et al., 1981; Richards, 1984; Belsky, 1986). Later, Painter and Belsky (1993) reviewed the relevant research and indicated that whole-plant compensation or overcompensation rarely occurs based on the available evidence. Currently, the debate is ongoing as to how light to moderate grazing affects grassland productivity.

In arid or semiarid rangelands, another factor confounding the detection of grazing effects is the climate, particularly precipitation fluctuation (DeAngelis and Waterhouse, 1987; Fuhlendorf and Smeins, 1997). Biondini and Manske (1996) indicated that climate variations were the major controlling factors in trends of production and plant species in northern mixed-grass prairie, while grazing played a secondary role. Gillen and Sims (2004) reported similar results for sand sagebrush grasslands in the Southern Great Plains. Ellis and Swift (1988) noted that climate effects could completely override livestock impacts on annual plant production in arid and semiarid rangelands. Fuhlendorf et al. (2001) considered the influence of spatial and temporal dimensions when explaining grazing effects and stated that grazing established the long-term direction of structural and compositional change in vegetation, and climate mediated the short-term rate of these changes. Derner and Hart (2007) emphasized the importance of temporal dimensions in examining grazing-induced modification of peak standing crop and the influence of precipitation in detecting these modifications in the northern mixed prairie.

Since the length of the observation time is an essential element for recognizing production changes caused by different processes (i.e. grazing and precipitation), measuring vegetation production at a few points in time is insufficient for differentiating grazing – induced changes from those caused by other factors. With its ability to acquire data in multiple temporal resolutions remote sensing is a promising alternative for characterizing vegetation responses to grazing effects at different timescales. Many researchers have demonstrated its ability for monitoring vegetation dynamics in grassland ecosystems (Pickup et al., 1996; Pelkey et al., 2000; Thoma et al., 2002; Reeves et al., 2006; Rőder et al., 2008). Among these studies, the quantification of vegetation from remote sensing has mainly been based on vegetation indices. Normalized Difference Vegetation Index (NDVI) is one of the most extensively used indices as it can be directly derived from many if not all sensors such as Advanced Very High Resolution Radiometer (AVHRR) data, Moderate-resolution Imaging Spectroradiometer (MODIS) data, Satellite Pour I'Observation de la Terre (SPOT) sensors. These high temporal resolution NDVI image products are commonly used for regional to global vegetation studies as the spatial resolution is usually on the order of 1000m, which is too coarse to be used for local-scale or individual site vegetation monitoring.

The Landsat series of satellites with more than 30 years of images offer the longest running time series of systematically collected remote-sensing data. Acquiring most of the spectral measurements at 30m spatial resolution provides Landsat TM and Enhanced Thematic Mapper (ETM+) with significant advantages in monitoring land cover and land use changes at the local scale. Röder et al. (2008) used vegetation cover derived from a time series of Landsat TM and ETM+ images as an indicator while investigating grazing-induced vegetation dynamics in Mediterranean rangelands and concluded that remote-sensing data served as an essential component in landscape-level monitoring. Furthermore, Landsat TM and ETM+ provide spectral information in major portions of the solar electromagnetic spectrum (visible, near-infrared, shortwave-infrared), which enables the use of vegetation indices based on spectral regions other than the red and near-infrared regions. This is important for enhancing the capability of remote sensing in quantifying vegetation properties, especially in arid or semiarid areas where NDVI shows weak performance for vegetation quantification (Pickup and Chewings, 1994).

The goal of this study is to assess how mixed grassland production responds to long-term (1986-2005) grazing of light to moderate intensity using the spectral data derived from Landsat images. This is to be assessed by answering the following three questions: 1) Is it possible to use a vegetation index derived from remote sensing as an indicator of vegetation production for studying grazing effects in mixed grassland? 2) To what extent does long-term light to moderate grazing affect vegetation production as represented by the vegetation index?, and finally, 3) How does precipitation alter the detection of light to moderate grazing?

5.3 STUDY AREA

The study area was the west block of Grasslands National Park (GNP) of Canada (49º12′ N, 107º 24′ W) and surrounding areas (Figure 5.1). The park represents one of the most intact areas of mixed grasslands; it was excluded from grazing since it was identified as a national park in 1986. In 2006, grazing was first introduced to the park for restoring ecological integrity. During this time, the surrounding areas continued to be used for cattle grazing. The grazing history in the surrounding areas goes back at least 100 years, and grazing intensity is lower than the recommended stocking rate for this type of region; therefore, the grazing intensity is categorized as light to moderate. As grazing in the park began in 2006, we will confine our focus to the pre-grazing period of 1986-2005.

The climate in this area is a semiarid continental climate, with hot summers and cold winters. Annual precipitation is approximately 340mm, and mainly occurs in June to August. Annual mean temperature is 3.6°C, ranging from -12.4°C in January to 18.3°C in July. Three vegetation communities occur in this area: upland grasslands, valley grasslands, and riparian shrubland (Michalsky and Ellis, 1994). Upland grasslands occupy approximately two-thirds of the park and are the major vegetation community in the study area. The dominant plant species in the Upland grasslands are needle and thread (*Stipa comata Trin.& Rupr*), blue grama grass (*Bouteloua gracilis (HBK) Lang. ex Steud*), and western wheatgrass (*Agropyron smithii Rydb*). Valley grasslands are dominated by western wheatgrass and northern wheatgrass (*Agropyron dasystachym*) along with higher densities of shrubs and occasional trees. Common soil types in the park are Chernozemic and Solonetzic soils (Fargey et al., 2000).

5.4 METHODOLOGIES

5.4.1 Monitoring sites

Vegetation production differs with variation in soil, topography, and vegetation types. In order to isolate the impacts of grazing from that of spatial variation in soil, topography, and vegetation composition, five paired grazed and ungrazed sites (UG0-G0, UG1-G1, UG2-G2, UG3-G3, UG4-G4, UG5-G5) were selected as monitoring sites for the analysis (Figure 5.1). Each pair was located in upland grasslands of the park and surrounding pastures. The distance between each pair of sites ranged from 1km to 8km. The sites were selected to ensure that vegetation, soil, and topography were as similar as possible between each pair of sites. These sites had been used by park managers as indicator sites for monitoring vegetation change within the park relative to areas outside the park. The analysis of grazing effects on vegetation production is based on the assumption that vegetation is sufficiently similar between paired sites, so that the variations in vegetation production can be attributed to grazing effects rather than natural landscape and soil variation.

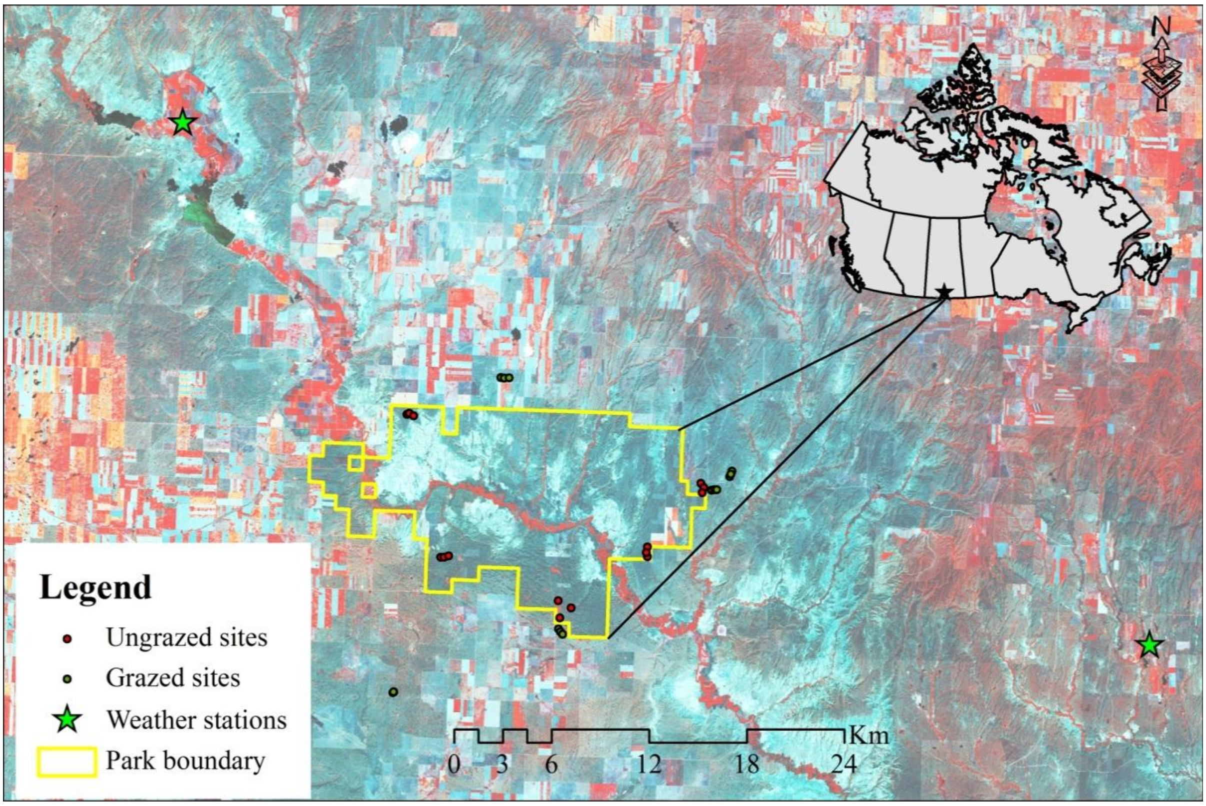

Figure 5.1 Study site map

5.4.2 Satellite images and pre-processing

Plants in our study site belong to two types: C3 and C4 species. To reduce the effects from phenological changes on vegetation production, in this study we focus on changes of vegetation production in maximum growing season for C3 species, as the majority of the plants in our study area are C3 species. According to Zhang's study (2006), the peak growing season for C3 species in the study site is in early summer (June to July) and for the C4 species it is late summer (August). Thus, the ideal time for image acquisition is between June 15 and the end of July. Since the revisit time period of the Landsat satellite series is 16 days, the maximum number of the images that can be acquired within the ideal window is one to three for every year. However, the presence of haze or cloud on these days would prevent any useful data from being collected for that year. We reviewed the Landsat TM and ETM+

images in the United States Geological Survey (USGS) archives for the time period 1986-2005. In total, twelve cloud-free (0% cloud cover) images were acquired. The one acquired in 1989 is from the Landsat 4 satellite, two obtained in 1999 and 2000 are from Landsat ETM+, and the rest are from Landsat TM5. The characteristics of these images are given in Table 5.1. As fieldwork was conducted in 2003 and 2005 the only high-quality image with an acquisition time close to our field date was acquired on 10 August, 2003. Considering that this acquisition date is out of our ideal time window, it was only used for testing the feasibility of remote-sensing data as a surrogate of ground-measured production data.

The Landsat images acquired were standard level 1T products which were systematically geometrically corrected. The geocorrected images were reprojected to the Universal Transverse Mercator Coordinate system (UTM zone 13). The geometric accuracy was validated by the perfect match (within half of a pixel) of roads in the images with those from previously geometrically corrected images. Atmospheric correction, including radiometric correction, was applied to reduce the radiometric errors caused by the remote sensor system. Atmospheric correction of the images involves two steps. The first step is to convert the raw digital numbers (DN_{raw}) of the images to at-satellite radiance values (L_λ), which requires the application of re-scaling factors. Considering the decaying detector sensitivity of Landsat TM, a time-dependent function (equation (1)-(3)), published by Chander et al. (2009), was applied for calculating the gain and offset factors for the Landsat TM image calibration. The same function was applied for Landsat ETM+ image calibration.

$$L_\lambda = G_{rescale} \times Q_{cal} + B_{rescale} \quad (1)$$

Where:

$$G_{rescale} = \frac{LMAX_\lambda - LMIN_\lambda}{Q_{cal\max} - Q_{cal\min}} \quad (2)$$

$$B_{rescale} = LMIN_{\lambda} - \left(\frac{LMAX_{\lambda} - LMIN_{\lambda}}{Q_{cal\max} - Q_{cal\min}} \right) Q_{cal\min} \quad (3)$$

Where L_{λ} is at-satellite radiance [W (m^{2}sr μm)$^{-1}$]; Q_{cal} is the quantized calibrated pixel value (DN); Q_{calmax} is the maximum quantized calibrated pixel value corresponding to $LMAX_{\lambda}$; Q_{calmin} is the maximum quantized calibrated pixel value corresponding to $LMIN_{\lambda}$; $LMIN_{\lambda}$ is the spectral radiance that is scaled to Q_{calmin} [W (m^{2}sr μm)$^{-1}$]; $LMAX_{\lambda}$ is the spectral radiance that is scaled to Q_{calmax} [W (m^{2}sr μm)$^{-1}$]; $G_{rescale}$ is the band-specific rescaling gain factor [(W (m^2 sr μm)$^{-1}$) DN^{-1}]; $B_{rescale}$ is the band-specific rescaling bias factor [W (m^{2}sr μm)$^{-1}$].

The next step is to covert at-satellite radiance to at-surface reflectance (ρ) to eliminate the atmospheric effects of scattering, absorption and scattering on the images. The most dominant atmospheric effect is scattering, also called haze (Siegel et al., 1980; Slater et al., 1983). Various methods were developed to correct or remove atmospheric effects, and Song et al. (2001) reported that simple dark-object subtraction can produce better results than more complex models, such as the path radiance approach and the ridge method. An improved dark-object subtraction method (Chavez, 1988) was applied to calculate at-surface reflectance. The advantage to current dark object subtraction is that haze values can be determined solely based on the DN from the image and no other extrinsic information is required. This is particularly useful because in our study site it is hard to find dark objects from which to obtain a haze value. In addition, the haze value derived from this method is spectral band dependent allowing better results to be generated.

Table 5.1 Scenes characteristic of the images

Acquisition Date	Sensor	Acquisition time (GMT)	Sun elevation (°)	Sun azimuth (°)
24 June 1986	Land sat 5/TM	17:23:04	56.65	129.93
11 June 1987	5/TM	17:24:07	56.97	131.85
15 July 1988	5/TM	17:30:20	55.47	133.26
26 July 1989	4/TM	17:33:07	53.93	135.86
26 July 1992	5/TM	17:22:29	52.59	132.22
30 June 1994	5/TM	17:18:11	55.67	128.13
17 June 1995	5/TM	17:05:43	54.59	124.72
24 July 1997	5/TM	17:30:25	54.06	134.71
27 July 1998	5/TM	17:37:57	54.34	137.78
8 July 2000	7/ETM+	17:51:10	58.74	140.43
10August 2003	5/TM	17:36:48	46.76	144.87
14 July 2005	5/TM	17:47:23	57.57	139.44

5.4.3 Normalized canopy vegetation index and vegetation production measurement

In long-term vegetation monitoring studies, NDVI is one of the most widely used indices. Strong relationships have been reported between NDVI and vegetation production by many researchers (Gerberman et al., 1984; Baret et al., 1989). Nevertheless, NDVI is not always sensitive to changes in production especially in arid or semiarid grassland ecosystems where variation in soil and dead vegetation can affect the relationship between NDVI and production (Pickup and Chewings, 1994). Furthermore, while NDVI is a good indicator of green vegetation, it is of limited application for quantifying standing dead grass, and consequently the production of grassland with mixed green and dead vegetation. For this study area, Zhang et al. (2008) found that reflectance in the mid-infrared region showed better correlation with total biomass compared to other wavelength regions (red, green and near-infrared), and indicated that reflectance in the mid-infrared region can be used to indirectly capture variation in biomass. The mid-infrared region of the spectrum is sensitive to water content (Hunt et al., 1989) as the reflectance in the mid-infrared region increases with decreasing leaf water content (Ripple, 1986). In previous studies, the reflectance in the mid-infrared region had been reported to provide accurate assessments of Leaf Area Index and biomass (Everitt et al., 1989; Ustin et al., 2004). Vescovo and Gianelle (2008) concluded that the accuracy of current methods, based on greenness or chlorophyll information for estimating vegetation parameters can be improved by incorporating water content, as it can provide additional information on vegetation. They developed the Normalized Canopy Index (NCI) (Equation (4)) which makes use of the mid-infrared band together with a greenness reflectance band (green band) to quantify grassland production. A strong correlation (R^2=0.92) was found between NCI and Phytomass even in the dry season when grasslands are dominated by both green grass and dead grass (Vescovo and Gianelle, 2008). Based on previous studies and the vegetation characteristics of our study sites, NCI was used for estimating grassland production.

To validate the performance of NCI in quantifying vegetation production, field work was conducted in June and July of 2003 and June of 2005. At each paired sites, three 100m×100m plots were randomly selected and set up. Within each plot, two 100m perpendicular transects intersecting in the centre in the north-south and west-east directions were set up. The coordinate of the centre point for each plot was recorded using a handheld global positioning system (GPS) with 6m accuracy. The GPS points were overlaid on top of Landsat images. Spectral data were extracted from 3×3 pixels (representing a sample area of 90m×90m on the ground) centered on each GPS point to match the ground measurements. Then the NCI was calculated using the extracted spectral data. To balance the workload and get enough representative samples, along each 100 m transect, biomass was clipped at 20m intervals within a 20cm × 50cm daubenmire quadrat (six locations per transect). In all, a total of 12 samples were measured within each plot. Clipped fresh biomass were sorted in to four groups (green grass, dead grass, forbs, and shrubs) then dried in an oven for 48 hours at 60℃ and weighed. Biomass from the four groups in each quadrat was summed, which yielded the total biomass of that quadrat. The total biomass within each plot was averaged then the biomass of the three plots per site was also averaged to represent the total production of each site. Ground vegetation reflectance was also measured within each daubenmire quadrat using an ASD FR Pro spectroradiometer (produced by ASD Inc. Colorado, United States) within 2 h of solar noon on clear days. Averaged reflectance values from three plots were used to characterize vegetation reflectance for that site. The equation used for calculating NCI is:

$$NCI = \frac{R_{Mid\text{-}infrared} - R_{Green}}{R_{Mid\text{-}infrared} + R_{Green}} \qquad (4)$$

Where $R_{Mid\text{-}infrared}$ represents spectral reflectance in the spectral range of mid-infrared is 1.55-1.75˘μm; and R_{Green} represents spectral reflectance in the spectral range of 0.52-0.60μm.

5.4.4 Precipitation data

Precipitation data for the time period 1986-2005 were obtained from the Val Marie and Mankota weather stations, which are about 20km and 30km away from the study area, respectively (Figure 1). Daily precipitation for each year was downloaded from the Environment Canada website for these two weather stations (Environment Canada, 2003). In order to increase the accuracy and utility of those data, average precipitation from these two stations were used to indicate precipitation of the study area. Based on the daily data, growing-season precipitation (April-August) and the annual total precipitation were calculated.

5.4.5 Statistical analysis

Pearson's correlation coefficients were calculated between the total biomass and ground-measured spectral reflectance to examine the performance of individual spectral bands in total biomass estimation. Regression analysis was applied between total biomass and Landsat image derived NCI, acquired in 2003, in order to explore the feasibility of using NCI as a surrogate of total biomass for detecting the long-term grazing effects. The relationship was further validated using data collected in 2005. Due to biomass data missed in one ungrazed site, the relationship was re-examined based on data collected in nine sites. Two-way Analysis of Variance (ANOVA) uses a regression approach to analyze variations that allows the researcher to test the significance of the effects of two or more independent variables on the dependent variable. The test was conducted in SPSS v. 18.0 (Provided by Dr. Xulin Guo) and investigated the impacts of grazing treatments and precipitation on production as well as the interaction of these two factors. If the ANOVA test returned a significant F-value, then a Tukey-Kramer (Tukey's HSD) post-hoc analysis was applied because it is more powerful than the Bonferrroni test, the Dunnett test, and so on when a large number of pairs are tested.

Annual relative difference in production between grazed and ungrazed sites was examined by Relative Difference Index (RDI). RDI provides a measure of the grazing impact relative to the expected ungrazed mean value which is calculated as the difference between ungrazed mean NCI and grazed mean NCI and expressed as a percentage of the ungrazed mean NCI value for the growing season (equation (5)).

$$RDI = \frac{NCI_{grazed} - NCI_{ungrazed}}{NCI_{ungrazed}} \times 100 \qquad (5)$$

This index uses the variable ungrazed as a baseline for the entire time period and effectively accounts for interannual variability in growing season experienced by both grazed and ungrazed areas (Geerken and Haiwi, 2004; Blanco et al., 2009). Regression analysis was applied between precipitation with production and RDI to examine the contribution of precipitation to the changes of these variables.

5.5 RESULTS

5.5.1 Vegetation characteristics in mixed grasslands

The five paired grassland sites that were investigated displayed a large range in vegetation production (155.5g m^{-2}-285.17g m^{-2}) (Table 5.2). Also the role that each functional group played in the total production varied considerably. Grass (green grass and dead grass) was the major component contributing to the total vegetation biomass, while forbs accounted for a small amount. Shrubs were seldom found in the investigated site, only appearing in one of three plots in the G1 site, and were therefore ignored for the analysis. In the five ungrazed sites, more than 50% of the total vegetation biomass consisted of dead biomass. Compared to ungrazed sites, there was less dead biomass in the grazed sites.

Table 5.2 Vegetation composition characteristics measured during the field campaigns in 2003

Sampling sites*	Biomass (g/m^2)			
	Green grass	Forb	Dead materials	Total biomass
G0	91.42	20.21	90.31	201.93
G1	77.97	12.97	64.56	155.50
G2	84.75	29.38	72.17	186.29
G3	63.50	24.75	88.79	177.04
G4	76.25	6.13	78.25	160.63
UG0	95.75	26.94	115.83	238.53
UG1	95.92	31.42	138.75	266.00
UG2	106.38	19.83	158.96	285.17
UG3	93.00	10.98	97.17	201.00
UG4	71.06	26.47	89.28	186.81

5.5.2 Application of NCI

To understand how the biophysical parameters affect the signal measured at the satellite level, and which wavelengths can be used for vegetation parameter retrieval, Pearson's correlation coefficients (r) between total biomass and reflectance at all wavelength regions were calculated. These coefficients are shown in Figure 5.2. Negative relationships were found between vegetation production and reflectance throughout the entire wavelength region. In the comparison of the relationship between vegetation production and reflectance in each wavelength region, reflectance in the green region showed the highest correlation with vegetation production with the absolute value of r ranging from 0.84 to 0.88, followed by reflectance in mid-infrared region (0.79 to 0.80). A higher correlation was also found in the blue region with r values of 0.83- 0.85. In contrast, reflectance in the near-infrared region showed weak correlation with vegetation production with a maximum absolute value of r only 0.50.

The relationship between vegetation production and NCI, which is the arithmetic combination of spectral reflectance in mid-infrared and green bands, was investigated using regression analysis. Results indicated that there was a significant positive linear relationship existing between NCI and vegetation production (Figure 5.3), with 60% of the variation in production explained by NCI in 2003. The relationship was re-examined in 2005. The linear relationship was significant but had a lower value of R^2 (0.45) value compared to that in 2003 (Figure 5.4).

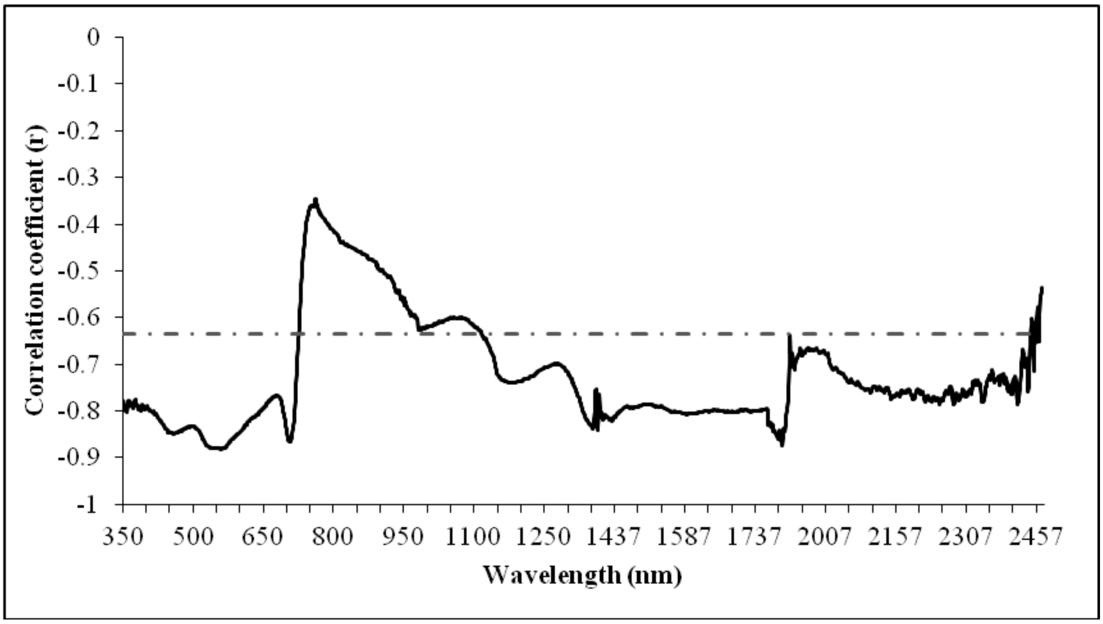

Figure 5.2 Correlation coefficient between total biomass and ground reflectance. Noise regions caused by sensor connection are omitted (1361-1397nm, 1811-1930nm and 2470-2500nm). R-values below -0.635 (indicated by the horizontal dash line) are significant at $p<0.05$

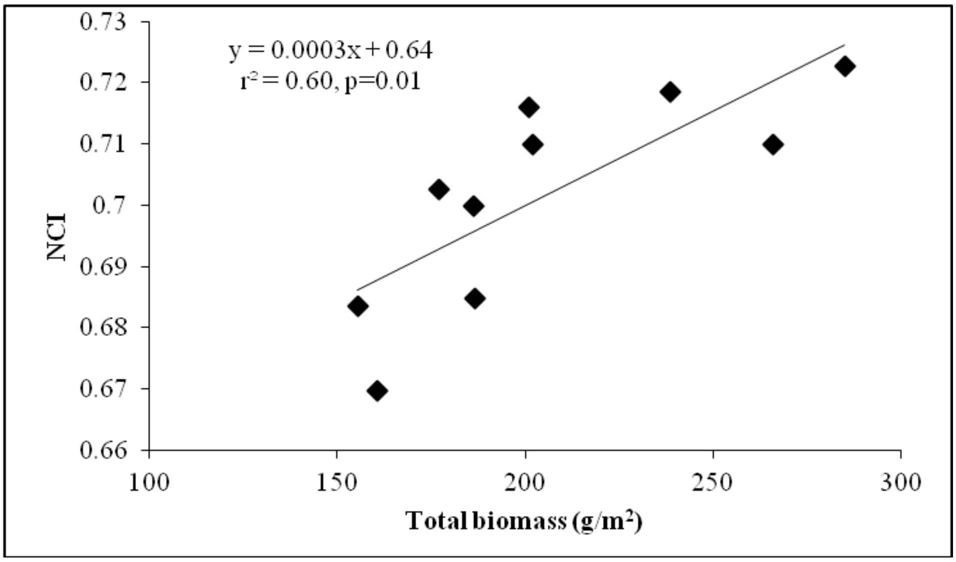

Figure 5.3 Relationship between total biomass and NCI in 2003

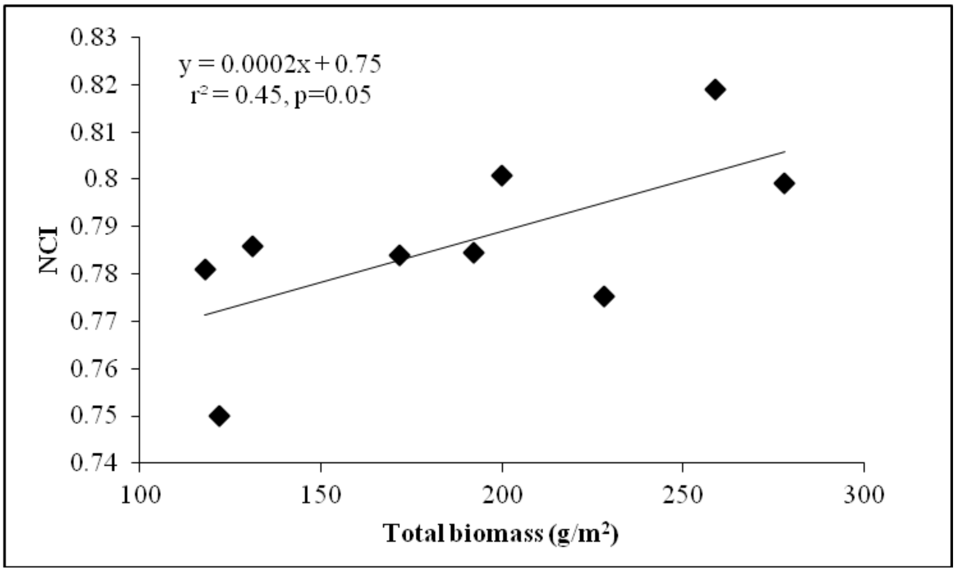

Figure 5.4 Relationship between total biomass and NCI in 2005

5.5.3 NCI in grazed and ungrazed sites

A two-way ANOVA test was used to investigate the effects of grazing, year, and their interaction on production in terms of NCI across the study period (1986-2005). Results indicated that all factors including grazing, year, and their interaction had significant impacts on NCI (Table 5.3). Detailed information on the impacts of these factors from Tukey's HSD post-hoc analysis indicated that there were no significant differences in NCI between eight pair of years (1988 and 1986; 1994 and 1987; 1987 and 1997; 1992 and 1995; 1994 and 1997; 1994 and 1998; 1998 and 1995; and 1997 and 1998), the remaining time period did show significant difference in NCI from each other (Figure 5.5). Grazing effects on NCI varied among years (Figure 5.6). Grazing-induced NCI variations were significant only in 1989, 1995 and 2005. No significant differences were found for the rest of the time periods.

Table 5.3 Two-way ANOVA results for analyzing the effects of grazing and year on NCI

Sources	Degree of freedom	F-value	P-value
GLM model	21	204.93	0.00**
Intercept	1	493021.7	0.00**
Grazing	1	5.36	0.02**
Year	10	426.13	0.00**
Grazing and Year	10	3.69	0.00**

** denotes significance at 0.05 level

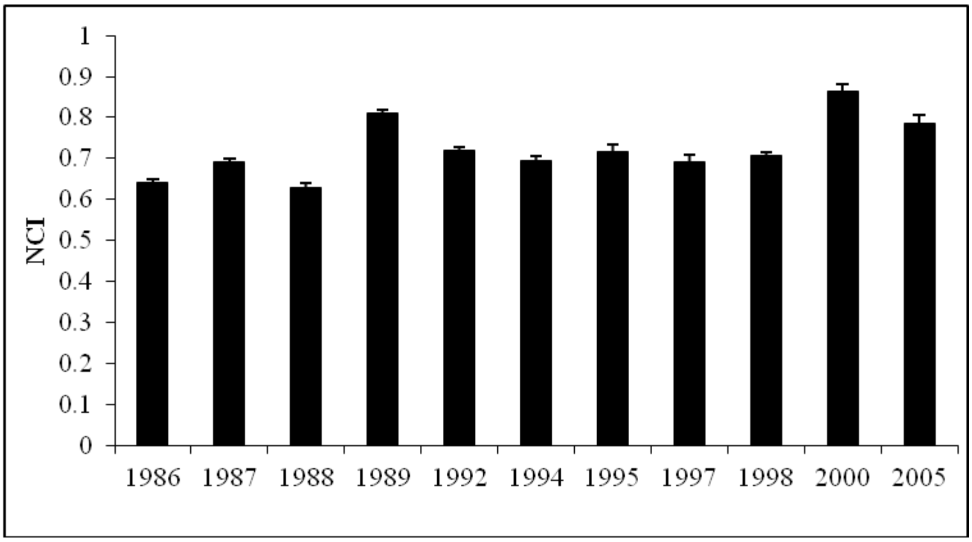

Figure 5.5 Variation in NCI during time period of 1986-2005 in mixed grasslands of Grasslands National Park and surrounding areas

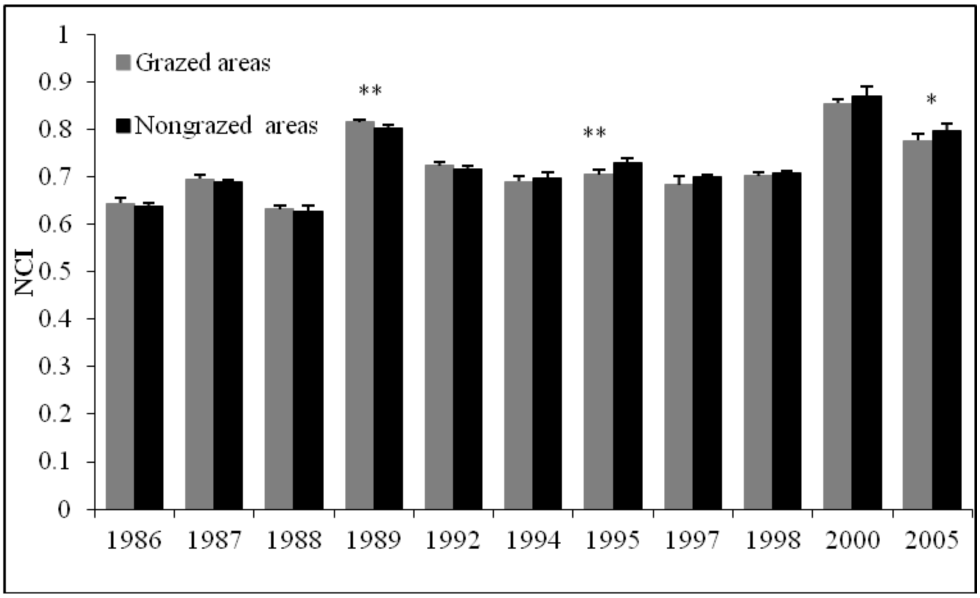

Figure 5.6 NCI in grazed and ungrazed areas from 1986 through 2005 at the mixed grasslands of Grasslands National Park and surrounding areas. * denotes the difference in NCI between grazed and ungrazed areas is significant at 0.1 significant level. ** denotes the difference in NCI between grazed and ungrazed areas is significant at 0.05 significance level.

5.5.4 Responses of NCI to precipitation

Growing-season precipitation was variable from 1986 to 2005. Precipitation exhibited a twofold difference from the lowest (156.25mm in 1988) to the highest (334.45mm in 2000) value (Table 5.4). Compared to the 30 year mean value (223mm), growing-season precipitation in most years was above and close to the average value. Growing-season precipitation in 1988 and 1998 were relatively low, caused by the strong El Niño conditions in these two years (Stormax Inc., 2010). El Niño events were found to be correlated with warmer and drier weather at our study sites (Garnet et al., 1998, Bonsal and Lawford, 1999). Annual precipitation also varied considerably with an almost twofold difference between the driest (231.4mm in 1988) and wettest (435.5mm in 1986) periods.

The dynamic of NCI was consistent with the change of growing-season precipitation both in grazed and ungrazed sites (Figure 5.7). Growing-season precipitation explains 76% and

75% of the variations in NCI of grazed and ungrazed site respectively. When correlating relative differences in NCI between grazed and ungrazed sites with growing-season precipitation, a weak correlation was found, indicating that precipitation was only one of many factors contributing to the magnitude of grazing effects (Figure 5.8).

Table 5.4 Growing-season (April-August) precipitation and annual precipitation (mm) at the study sites (1986-2005)

Year	April	May	June	July	August	Growing season	Annual
1986	21.40	94.45	54.65	18.50	3.70	192.70	435.40
1987	12.50	47.40	35.50	115.85	14.40	225.65	284.70
1988	1.80	26.95	62.50	59.95	5.05	156.25	231.35
1989	19.75	70.85	78.35	52.35	48.90	270.20	395.60
1992	5.00	14.00	98.7	61.35	40.20	219.25	293.95
1994	12.20	35.90	99.00	30.65	21.70	199.45	291.45
1995	34.40	22.05	82.45	70.10	35.10	244.10	372.60
1997	43.30	39.05	69.40	25.40	36.45	213.60	307.05
1998	7.00	6.50	89.00	26.70	46.65	175.85	354.65
2000	30.10	101.05	67.10	106.30	29.90	334.45	420.85
2003	43.45	69.85	68.35	13.90	15.20	210.75	398.40
2005	17.65	23.95	115.70	13.10	48.55	218.95	286.15
1971-2000 mean						223.05	340.40

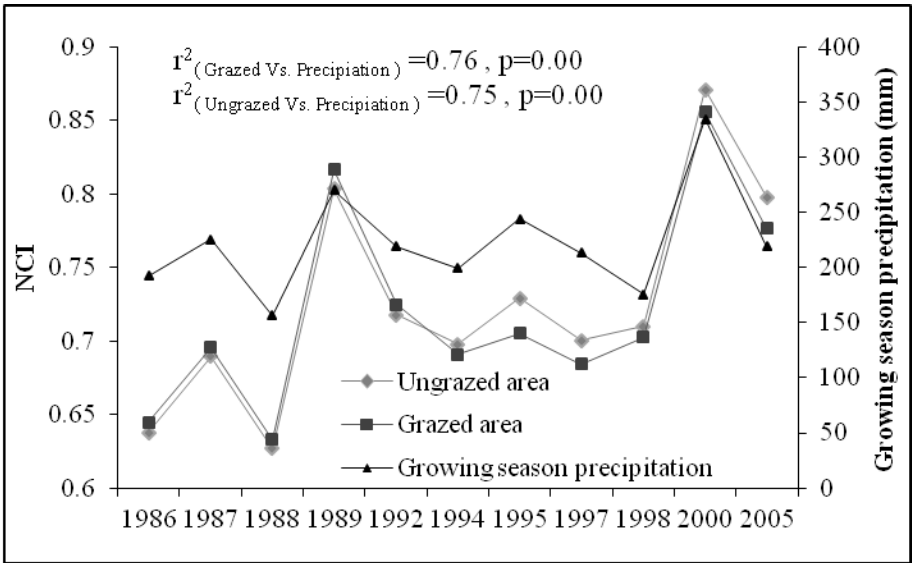

Figure 5.7 Relationship of NCI with growing-season precipitation in grazed and ungrazed areas during the time period of 1986-2005

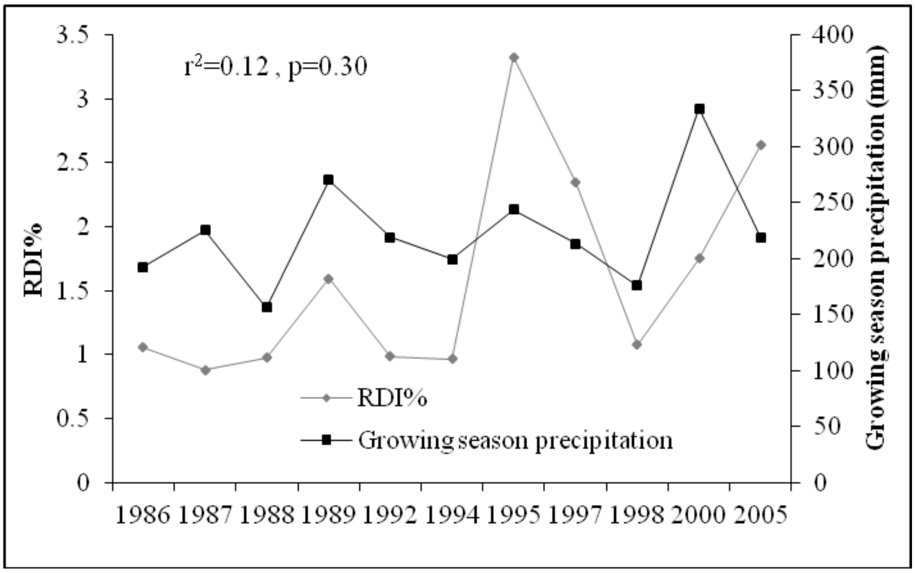

Figure 5.8 Relationship between RDI% and growing-season precipitation in 1986-2005

5.6 DISCUSSIONS

5.6.1 Application of NCI on grassland production estimate in mixed grasslands

Mixed green and dead vegetation is one of the typical characteristics of mixed grasslands. We found that even in the peak growing season, dead vegetation accounted for almost 50% of the total vegetation; thus to quantify grassland production, dead vegetation cannot be ignored. The quantification of grassland production by means of current advanced remote-sensing techniques is usually accomplished through an empirical relationship between grassland production and the value of its corresponding pixels on a satellite image (Friedl et al., 1994). Prior to the quantification, the satellite image is transformed to various indices, such as NDVI, soil-adjusted vegetation index (SAVI), and so on. It is well documented that these vegetation indices are not only well correlated with vegetation biophysical properties, but also sensitive to external factors, such as solar and viewing geometry, background information, and atmospheric effects (Rondeaux et al., 1996), which could confound their performance for estimating vegetation. Research in dead materials dominated systems indicated that traditionally used vegetation indices (i.e. NDVI, SAVI) may not be as efficient for quantifying production in this system as they are for other ecosystems since standing dead materials tended to decrease the contrast in the red and near infrared wavelength region between vegetation and background, thus influencing the performance of correspondent vegetation index on vegetation quantification (Zhang et al., 2006). Our results are consistent with their findings in that moderate correlations were found between spectral information in the red and near-infrared bands and production. Instead, reflectance in the green and mid-infrared regions showed the highest correlation with production in our study sites compared to other wavelength regions. Reflectance in the mid-infrared region is sensitive to leaf water content. Vegetation canopies with high biomass tend to have high canopy moisture and large amounts of dead materials. Sites with a lot of dead materials have high soil moisture due to the role of litter retaining soil moisture. Therefore, it is expected that the variation of total biomass could be accurately monitored via reflectance in the mid-infrared region. The negative relationships between total biomass and spectral reflectance in all wavelength regions can be explained by the high percentage of standing dead grass, litter and moss in the study area (Guo, 2005).

Despite the higher correlation of total biomass with these two spectral indices (mid-infrared and green), we used NCI as an estimator of total biomass in our study instead of each individual band. This is because this vegetation index is less affected by changes in sun angle, atmosphere, canopy background, topography, and soil variation compared to single spectral bands (Jensen, 2007). A significant correlation between NCI and total biomass was found in 2003 and 2005. The correlation coefficient value in 2003 was slightly higher than that in 2005 which may be because of the climatic conditions during these two years. However, in general, the correlation coefficients in this study are higher than those found in the other study conducted in the same region, approximately r^2=0.43 (Zhang et al., 2006). The significant relationship between NCI and total biomass indicates the feasibility of NCI as an indicator to monitor production change in a dead material-dominant grassland ecosystem. Reflectance in the blue region showed significant relationship with total biomass as well. Blue band-based vegetation indices were not used because a limited number of remote sensors are designed with a blue band, which prevents the utility of blue band-based vegetation indices for cross-sensor translation (Jiang et al., 2008). However, it is still worthwhile to try out vegetation indices which use a blue band for estimating biomass in a dead vegetation material dominant grassland in future studies.

5.6.2 Grazing effects on production in mixed grasslands

Production differences between grazed and ungrazed sites have only shown significant differences in some years (1989, 1995, and 2005). Derner and Hart (2007) reported that apparent differences in peak standing crop among different stocking rates in northern mixed grasslands occurred in years with above average and average precipitation but were absent in dry years. They explained that constraints of soil water limited the expression of productive potential in dry years. Illius and O' Conner (1999) implied that vegetation response would be more tightly coupled to grazing intensity during periods of higher precipitation. Our results partially support Derner and Hart's findings as growing-season precipitation in the three years (1989, 1995 and 2005) are above and close to the average. A lack of obvious differences in production between grazed and ungrazed sites for the remaining years with relatively high growing-season precipitation (1986, 1987, and 1992) illustrated that precipitation is only one of many factors influencing the detection of grazing effects. Our results found that precipitation can explain 12% of the variation in relative production difference between grazed and ungrazed sites. Other factors, such as air temperature, vapor pressure deficit, and soil temperature, may also contribute to the magnitude of difference in production between different grazing treatments (Lauenroth and Whitman, 1977). Future studies need to be conducted to explore this further.

Compared to grazing-introduced modifications in production, the magnitude of annual variation in production was more apparent. Growing-season precipitation was found to be the major factor influencing production. This finding was congruent with most studies in that production in semiarid rangelands is influenced largely by precipitation (Lauenroth, 1979; Sala et al., 1988; Lauenroth and Sala, 1992; Smart et al., 2007). Derner and Hart (2007) found that spring (April-June) precipitation explained at least 54% of the variation in peak standing crop in northern mixed grassland. They attributed the strong effects of spring precipitation on production to the fact that perennial cool-season grasses are the dominant species in this grassland ecosystem. Milchunas et al. (1994) emphasized the important contribution of other factors to variation of production, finding that cool-season precipitation, warm-season precipitation, grazing intensity, year of treatment, and relative pasture productivity together explained 61% of variance in forage production of shortgrass steppe. We considered both spring and summer precipitation, with the result that the variation of production explained by precipitation increased by 75% compared to Derner and Hart's result.

5.7 CONCLUSIONS

Our study has overcome some of the limitations in traditional field-based methods in detecting grazing effects on vegetation dynamics, particularly those for long-term monitoring purposes. NCI derived from a series of remote-sensing images allows the estimation of grassland production and the investigation of changes between different grazing treatments. Livestock grazing, precipitation in the growing season, and their interaction influenced grassland production over the study time period (1986-2005) in mixed grasslands. Grazing-induced modification to production was more obvious in 3 of the 11 years (1989, 1995, and 2005). However, the significant interannual variation in production suggests that in northern mixed grasslands, growing-season precipitation is more important than grazing with light to moderate intensity in the control of grassland production.

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CHAPTER 6 SUMMARY

An understanding of the effects of grazing on grassland is crucial for the long-term sustainability of grassland management worldwide. Investigating or monitoring variations in grassland vegetation properties under grazing is an effective way for exploring grazing effects. Although numerous methods were applied for studying the grassland vegetation responses to grazing in previous studies, an effective, efficient, and reliable method which can be used to model grassland changes under various grazing intensities over different grassland ecosystems is still a challenge in present grazing studies. In light of the shortfall, the overall objective of this research is to test the feasibility of combining remote sensing data and the generalized model to assess vegetation changes under various grazing intensities in different grassland types. The hypotheses of this study are that: 1) vegetation biophysical parameters are an effective indicator of grazing effects and can be retrieved using vegetation indices; 2) satellite data driven MSL model can be used to simulate biophysical parameter responses to grazing. Some vegetation biophysical properties will be maximal at light to moderate intensities but not all, in mixed grasslands; 3) the effects of grazing intensities on grassland depend on the grazing history of the site and climatic regimes. Remote sensing imagery with different spatial resolutions (SPOT 4 &5, Landsat TM, and ETM^+), ground hyperspectral data, and field biophysical data were applied to test the hypotheses and all hypotheses are validated.

6.1 CONCLUSIONS

6.1.1 Pre-condition vegetation assessment for detection of grazing effects

Using ATSAVI derived from remote sensing imagery with different spatial resolutions and ground-based leaf area index, this study assessed vegetation conditions in nine pastures before grazing treatment was conducted. Results revealed that sampling scale plays an important role in vegetation condition assessment. Significant differences in vegetation conditions among nine pastures were found when comparisons were based on leaf area index collected at a $1m^2$ sampling scale. In contrast, when using the ATSAVI as a surrogate of the leaf area index for representing vegetation conditions and upscaling the sampling scale to $100m^2$ and $400m^2$ there were no significant differences in vegetation conditions between pastures. Therefore, we recommend ATSAVI derived from images with 10m or 20m resolution to be used to investigate vegetation changes in post grazing treatment.

6.1.2 Suitable vegetation biophysical properties and spectral vegetation indices were identified for modeling grazing effects on grasslands

Vegetation biophysical properties and spectral vegetation indices were compared for detecting grazing effects under light to moderate grazing intensities in mixed grasslands. The results indicated that canopy height and the ratio of photosynthetically active vegetation cover to non-photosynthetically active vegetation cover (PV/NPV) were more sensitive to grazing than other vegetation biophysical parameters tested. All spectral vegetation indices except CI (canopy index) showed sensitivity to grazing. The feasibility of using spectral vegetation indices for modeling grazing-sensitive biophysical variables was also analyzed. Red-NIR based vegetation indices, Modified Triangular Vegetation Index 1 (MTVI1) and Soil-adjusted Vegetation Index (SAVI) showed significant correlation with PV/NPV, and a model based on linaer combination of these two spectral vegetation indices was developed for PV/NPV prediction. Green/MIR related vegetation indices, the Plant Senescence Reflectance Index (PRSI) and the Normalized Canopy Index (NCI), showed significant correlation with canopy height and a model based on a linear combination of these two spectral vegetation indices developed for canopy height prediction. Model simulated PV/NPV and canopy height showed significant correlation with grazing intensities, suggesting the feasibility of remote sensing to quantify light to moderate grazing effects in mixed grasslands.

6.1.3 Comparison of vegetation responses to grazing effects over different grassland types in Inner Mongolia, China

Vegetation responses to grazing were compared between different grassland types in terms of biomass in Inner Mongolia, China. In typical grassland, biomass was reduced significantly in heavily grazed sites because successional retrogression occurred in heavily grazed sites. The dominant position of grass species has been replaced by pasture sage, therefore, a higher but not significant biomass was found in the heavily grazed site. A set of spectral vegetation indices derived from remote sensing have been tested and compared for biomass estimation. Results indicated that soil adjusted vegetation indices (SAVI, MSAVI, and OSAVI) showed a better correlation with biomass than NDVI and NCI. OSAVI was the most predictive among three soil vegetation indices. The correlation between OSAVI was higher in lightly and heavily grazed sites than in non-grazed site when data was used separately. However, analysis of covariance revealed that the model could not be significantly improved by incorporating the grazing intensity as an explanatory variable. Those results suggested that satellite derived information can provide a valuable support for estimating grassland production under various grazing intensities irrespective of grassland types in Inner Mongolia, China

6.1.4 Influences of precipitation on detection of grazing impacts on grassland production in mixed grasslands

Responses of grassland production to light to moderate grazing in mixed grassland were investigated for the period of 1986 to 2005, using spectral data derived from satellite images. Unlike production quantification for grasslands in Inner Mongolia, Normalized Canopy Index

(NCI) showed superior performance in quantifying grassland production in mixed grasslands. Relationships between precipitation and grassland production were analyzed also. The majority of the variation in production (75%) was explained by growing-season precipitation for both grazed and ungrazed sites. Precipitation influences the detection of grazing-induced production change. Significant differences in grassland production between grazed and ungrazed treatments occurred in the three years with above average and average growing-season precipitations (April-August), but not in the dry years. These results demonstrate the feasibility of using remote sensing data to monitor long-term light to moderate grazing effects and the important role of precipitation, especially growing-season precipitation, in modulating production in mixed grassland ecosystems.

6.2 RESEARCH SIGNIFICANCE

There are a number of potential applications of this research from a theoretical and practical perspective. Theoretically, knowledge of responses of vegetation biophysical properties and spectral vegetation indices to grazing management provides crucial information to help further our understanding of the relationship between grazing management and grassland condition. In addition, grassland production is important for scientific studies of grassland productivity, energy, and nutrient flows, and for assessing the contribution of changes to the global carbon cycle. Accurate estimation of grassland production under various grazing intensities from remote sensing data could be used as a model input for simulating those ecosystem processes. Practically, remote sensing-based models were developed for grazing-sensitive biophysical parameters in mixed grasslands and three types of grasslands in Inner Mongolia. Retrieving grazing-sensitive biophysical parameters from satellite images using developed models is more time efficient compared to ground measurements, which can facilitate grassland managements for stakeholders, park management, or ranchers.

6.3 LIMITATIONS

This research assessed responses of grassland vegetation to grazing management using a remote sensing approach, and improved the understanding and the ability to quantify and monitor grassland changes under various grazing management. Nevertheless, there are still some shortfalls that need to be addressed in future studies.

1) Pre-condition of a grazing experiment assessment

   The assessment of vegetation condition before a grazing experiment is conducted is essential for discriminating grazing effects from pre-existing differences. Considering limited biophysical variables were measured to represent vegetation condition and the temporal periods studied were short, we recommend that more biophysical variables (such as biomass, canopy height, and species composition) with longer time periods should be compared among pastures to completely reveal the vegetation condition within the study sites. Multispectral or hyperspectral images could be used for species composition investigation. In addition we only investigated vegetation condition based on three sampling scales. Using a gradient sampling frame allows for identifying the suitable sampling scale for measuring vegetation condition.

2) Grazing-sensitive biophysical indicators

   Current acquired imagery and field data are working well for estimating grazing effects on vegetation characteristics (i.e. LAI, total biomass, cover, and so on.) and monitoring temporal and spatial vegetation dynamics in grazed areas, but it cannot provide information on grazing introduced heterogeneity, such as grazed and ungrazed patches, due to the low spatial resolution of the imagery. Since managing grazing introduced heterogeneity is crucial for habitat conservation, satellite imagery with high spatial resolution or aerial photography is recommended for future studies as it can provide information on grazing-introduced heterogeneity in a relatively large area.

3) Model improvement and application

Models developed for predicting ground grazing-sensitive biophysical parameters were validated using data from the same area and same time as the models were developed. Therefore, the model may not be extended to other areas and times. Field data collected from different times or areas could be used to test the robustness of these models. The accuracy of the model developed for canopy height is low. To improve the capability of modeling canopy height, remote sensors operating in other regions of electromagnetic spectrum (i.e. LiDAR) could be tested.

APPENDICES

FIELD DATA COLLECTION FORM (PLOT)

Study site:			**Date:**			**Time:**			**Recorder:**			**Plot:**	
Dominant species:					**Weather:**					**Elevation:**			
Quad.	**Easting:**			**Northing :**			**Easting:**			**Northing:**			
	Series (m)	2.5N	5N	**10N**	20N	30N	**50N**	2.5E	**5E**	10E	**20E**	30E	50E
Cover of top layer	Grass												
	Forbs												
	Shrub												
	Standing dead												
Cover of low layer	Litter												
	Moss												
	Lichen												
	Rock												
	Bare ground												
Biomass													
Canopy height													
Central point the Plot					**Easting :**					**Northing:**			
Quad.	**Easting:**			**Northing :**			**Easting:**			**Northing:**			
	Series	2.5S	5S	**10S**	20S	30S	**50S**	2.5W	**5W**	10W	**20W**	30W	50W
Cover of top layer	Grass												
	Forbs												
	Shrub												
	Standing dead												
Cover of low layer	Litter												
	Moss												
	Lichen												
	Rock												
	Bare ground												
Biomass													
Canopy height													

FIELD DATA COLLECTION FORM (TRANSECT)

Study site:		Data:		Time :		Recorder:		Transect:	
	Series	**1**	**2**	**3**	**4**	**5**	**6**	**...**	**128**
Quadrat	Latitude								
	Longitude								
	Elevation								
	Aspect								
	Slope								
Cover of top layer	Grass								
	Forbs								
	Shrub								
	Standing dead								
Cover of low layer	Litter								
	Moss								
	Lichen								
	Rock								
	Bare ground								
Canopy height									
Utilization	percentage removal of weight/height								
Tracks density	Number								