COMPARISON OF THREE REMOTE SENSING TECHNIQUES TO MEASURE BIOMASS ON CRP PASTURELAND

by

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APPROVAL

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This thesis has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citation, bibliographic style, and consistency and is ready for submission to The Graduate School.

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ABSTRACT

Biomass from land enrolled into CRP is being considered as a biofuel feedstock source. For sustainable production, harvesting, and soil protection, technology is needed that can quickly, accurately and non-destructively measure biomass. Remote sensing of vegetation spectral responses, which tend to be highly responsive to changes in biomass, may provide a means for inexpensive, frequent, and non-destructive measurements of biomass at management relevant scales. A valuable resource for land managers would be a biomass measurement model that could non-destructively measure biomass at different phenological growth stages across multiple growing seasons. The objective of this study was to compare remote sensing-based biomass measurement models using the normalized difference vegetation index (NDVI) and bandwise regression remote sensing techniques to determine which model best measures biomass at different phenological growth stages over multiple growing seasons on CRP pastureland in central Montana. Biomass and plant spectral response measurements were collected over the 2011 (n = 108) and 2012 (n = 108) growing seasons on an 8.1 ha CRP pasture. Measurements were stratified by phenological growth stage and growing season. Half of the data was used to build each measurement model and the other half was used to test the power of each model to measure biomass. Remote sensing-based biomass measurement models were constructed using NDVI measurements from an active ground-based sensor, NDVI measurements from Landsat images, and band combination measurements from Landsat images. All biomass measurement models showed no difference between actual and estimated biomass values (p-value > 0.05). The biomass measurement model using NDVI measurements from Landsat images had the smallest margin of difference between estimated biomass and actual biomass (22 kg/ha $\pm$ 96 kg/ha), followed by the combination of individual spectral bands from Landsat images (128 kg/ha $\pm$ 71 kg/ha), and NDVI measurements from a ground based sensor (182 kg/ha $\pm$ 94 kg/ha). Results indicate remote sensing-based biomass measurement models are accurate at measuring biomass at different phenological growth stages across multiple growing seasons. Land managers can implement remote sensing-based biomass measurement models into their land management strategies to quickly, accurately, and non-destructively measure biomass across a landscape.

INTRODUCTION

In 2003, the Biomass Research and Development Technical Advisory Committee to the Secretaries of Agriculture and Energy established a national goal that biomass will supply 5% of the nation's power, 20% of its transportation fuels, and 25% of its chemicals by 2030 (DOE 2003). Achieving these levels will require more than one billion dry tons of biomass feedstock annually, which is a fivefold increase over the current consumption (DOE 2003). Perlack et al. (2005) claims that agricultural land can provide nearly one billion dry tons of sustainably collectable biomass while continuing to meet food, feed and export demands.

To meet these goals, biomass from land enrolled in the United States Department of Agriculture's (USDA) Conservation Reserve Program is being considered as a biofuel feedstock source (DOE 2003; Perlack et al. 2005). Lands enrolled into CRP are fragile and contain a high degree of spatial variation in vegetative cover and soil types. For sustainable production, harvesting, and soil protection, it is critical to develop technology that is able to quickly and accurately measure biomass production in a non-destructive manner.

Several environmental factors influence plant phenology and plant morphology across a growing season which includes: photoperiod, temperature, and precipitation (Fahey et al. 1994; Taiz and Zeiger 2010). In return, these factors affect the spectral response of the plant canopy and biomass production at different phenological stages (Knipling 1970; Todd et al. 1998).

Direct harvesting is currently the most widely used method in determining biomass production (Harmoney et al. 1997; Flynn et al. 2006). This method, however, is costly, time consuming, and destructive and only allows individual samples to be measured accurately out of a potentially highly variable sward (Harmoney et al. 1997; Flynn et al. 2006). Therefore, a quick, accurate, and non-destructive method is needed to estimate the amount of biomass in a pasture or across a landscape (Harmoney et al. 1997).

Remote sensing of vegetation indices, such as the normalized difference vegetation index (NDVI) (Rouse et al. 1973), may provide a means for inexpensive, frequent, and non-destructive measurements of biomass at management relevant scales (Weiser et al. 1986).

There are several ways to obtain NDVI measurements. Two common approaches are to use satellite-based imagery or an active ground-based sensor such as Crop Circle (Holland Scientific 2013). Research has shown NDVI has a positive linear relationship with biomass (Paruelo et al. 1997; Todd et al. 1998; Stamatiadis et al. 2010). However, several factors have been reported to influence this relationship between biomass and NDVI including: (1) the existence of dead, dried, and dormant plant material (Todd et al. 1998; Todd and Hoffer 1998; Flynn 2006), (2) leaf area index >3.0 (Tucker 1977; Weiser et al. 1986; Turner et al. 1999; Serrano et al. 2000), and (3) varying soil conditions and soil types (Huete et al. 1985; Rondeaux et al. 1996; Todd et al. 1998; Todd and Hoffer 1998).

Another remote sensing technique that has been shown to have a positive linear relationship with biomass is bandwise regression (Lawrence and Ripple 1998; Maynard et al. 2006). Research indicates NDVI is a suboptimal way to relate biomass to spectral responses and using bandwise regression (i.e., multiple linear regression with individual spectral bands as potential explanatory variables) is a better method (Lawrence and Ripple 1998; Maynard et al. 2006).

The spectral responses of a plant canopy at different phenological stages pose unique challenges in being able to accurately measure biomass using remote sensing techniques. Creating a biomass measurement model that could measure biomass at any phenological growth stage across multiple growing seasons would be a valuable tool for land managers. The objective of this study was to compare remote sensing-based biomass measurement models using NDVI and bandwise regression remote sensing techniques at three different phenological growth stages across multiple growing seasons to determine which biomass measurement model best measures biomass on CRP pastureland in central Montana.

LITERATURE REVIEW

Introduction

Biomass from land enrolled in the United States Department of Agriculture's (USDA) Conservation Reserve Program (CRP) is being considered as a potential biofuel feedstock source (DOE 2003; Perlack et al. 2005). Land enrolled into CRP across the United States as of November 2012 was approximately 11 million ha, mostly dedicated to grasses (USDA 2013a). From these 11 million ha, an estimated 15.4 to 25.4 billion kgs of dry biomass could be available for bioenergy production (Perlack et al. 2005). In Montana, 664,000 ha of land are enrolled in the CRP (USDA 2013b). Land enrolled in the CRP in central Montana provides a landscape that has a high degree of variation in vegetative cover and soil types. This type of landscape allows the opportunity to examine the ability of different remote sensing techniques to measure biomass at different phenological stages.

The CRP is a voluntary program that provides rental payments and cost share assistance for agricultural landowners or operators (FSA, USDA 2013). The 1985 farm bill authorized the CRP in order to help agricultural producers safeguard environmentally sensitive lands by planting long-term, resource-conserving covers that would control soil erosion, improve water quality, and enhance wildlife habitat (FSA, USDA 2013).

Remote sensing of vegetation spectral responses collected from ground-based and satellite-based sensors may provide a means to measure CRP biomass at management relevant scales (Weiser et al. 1986). Normalized difference vegetation index (NDVI) measurements collected from ground-based and satellite-based remote sensing systems have been used to determine net primary production in both agricultural grain crop and grassland ecosystems (Paruelo et al. 1997; Wang et al. 2005; Teal et al. 2006). In addition to NDVI, bandwise regression has been shown to be a reliable remote sensing technique to measure biomass across landscapes that could be characterized as having high degrees of variation in vegetative cover and soil types (Lawrence and Ripple 1998; Maynard et al. 2006).

Normalized Difference Vegetation Index

NDVI was developed in order to take advantage of the reflectance properties of active photosynthetic plant tissue, or green biomass. The NDVI is the measurement of the ratio between red light and near infrared light along the electromagnetic spectrum represented in this formula (Rouse et al. 1973):

$$\text{NDVI} = \frac{\text{Near Infrared Light} - \text{Red Light}}{\text{Near Infrared Light} + \text{Red Light}}$$

There is a direct relationship between green biomass and the response in near infrared light energy (Knipling 1970). There is an inverse relationship between the response in red light energy and green biomass (Knipling 1970). Therefore, as green biomass increases, a greater amount of visible light energy will be absorbed, while more near infrared light energy will be reflected (Knipling 1970).

Measurements of NDVI collected from ground-based and satellite-based remote sensing systems have been used to assess biomass and grain yield for many agronomic crops. A positive linear relationship was found between NDVI and vine leaf production on merlot wine vines using a ground-based passive sensor (R^2 = 0.82) (Stamatiadis et al. 2010) when measured at veraison. Passive sensors rely on the sun to irradiate the terrain then record the amount of radiation that is reflected or emitted from the object on the Earth's surface (Shippert 2004). Corn (*Zea mays*) grain yields showed a positive linear relationship with NDVI (R^2 = 0.77) (Teal et al. 2006) when NDVI was measured at the V8 growth stage with a hand held active remote sensing unit. Winter wheat (*Triticum aestivum*) grain yields also showed a positive linear relationship with NDVI (R^2 = 0.83) (Raun et al. 2001) when measured with an active hand held remote sensing unit. Active sensors bathe the terrain in artificial light then record the amount of energy that is scattered back toward the sensor system (Jensen 2005).

NDVI has also been used to measure biomass in grassland and rangeland ecosystems. Positive linear relationships have been found between NDVI and biomass from perennial grasslands (R^2 = 0.89) (Paruelo et al. 1997) and shortgrass steppes (R^2 = 0.66) (Todd et al. 1998). More specifically, in a 2004 study, NDVI measurements were taken with a hand held active remote sensing unit in July and October on Kentucky pastureland (Flynn et al. 2008). A positive linear relationship was observed between biomass and NDVI when measured over a three week period in July (R^2 = 0.54) and when measured three separate times in the months of October and November (R^2 = 0.68) (Flynn et al. 2008). It is worth noting that 2004 was one of the wettest years in Kentucky. In 2004 the study area received 133 cm of rainfall (124 cm of rainfall is normal) (Flynn et al. 2008). This difference in amount of precipitation could have had an impact on plant growth and development, which resulted in larger quantities of green biomass on the landscape throughout the growing season in 2004. Therefore, with the increased levels of green biomass, NDVI was able to measure biomass with a greater degree of success than if senesced vegetation was intermixed in the plant canopy because of drought stress.

Active Ground-Based Sensors

Active ground-based sensors are getting attention because of their role in precision agriculture (Holland et al. 2006; Shaver et al. 2010). Active ground-based sensors can be mounted to any type of vehicle (tractor, truck, ATV, center pivot or wheel line irrigation system) and directly connected to a nutrient applicator (fertilizer spreader or irrigation pump for example). Most active ground-based sensors use some sort of vegetation or soil index to determine canopy cover or biomass production (Holland et al. 2006). The index measurements are calculated and recorded immediately by the sensor as it passes over the crop canopy. The sensor can be programmed to control the rate at which the nutrient is applied to the crop based on the recorded index value. For example, when an area of the crop has a large amount of biomass or canopy cover, the sensor can be programmed to apply smaller amounts of the nutrient to that specific area. By using active ground-based sensors, agriculture producers can apply nutrients only to the portion of the crop that is nutrient deficient. This saves resources and money by decreasing the amount of nutrients applied to a crop.

In addition to saving resources, active ground-based sensors are not affected by sources of error that hinder many passive sensors. Factors such as cloud cover, dust, atmospheric attenuation, temporal resolution, and spatial resolution have less impact on active sensors (Lamb et al. 2009; Holland et al. 2012). Most active ground-based sensors record spectral indices. One popular index recorded by almost all ground-based sensors is NDVI.

There are several factors that can impede the NDVI measurement. One factor is leaf area index (LAI). LAI is defined as the ratio of the total leaf area of the plant canopy to the ground area in the field of view (Tucker 1977). NDVI is correlated with biomass for LAI < 3.0 (Weiser et al. 1986; Serrano et al. 2000). NDVI increases curvilinear with increases in LAI and becomes saturated when LAI becomes greater than 3.0 ~ 5.0 (Turner et al. 1999; Serrano et al. 2000). This is due to asymptotic spectral reflectance. "Asymptotic spectral reflectance is the unchanging nature of spectral reflectance as vegetation density increases to the point where additional increases in LAI or biomass do not cause a change in the spectral reflectance" (Tucker 1977). Tucker (1977) further describes asymptotic reflectance by stating, "The asymptotic spectral reflectance in a grass canopy context is related to the incident light penetration within the canopy. When the reflectance at a given wavelength has become asymptotic, the addition of more vegetation per unit area effects no detectable change in canopy reflectance, because the incident light is incapable of additional canopy penetration."

Varying soil conditions and soil types also affect NDVI. The NDVI is extremely sensitive to soil optical properties, and is difficult to interpret with low vegetation cover (Rondeaux et al. 1996). Soil reflectance increases in a general linear trend with increasing wavelength from visible to near infrared to mid-infrared (Huete et al. 1985;

Rondeaux et al. 1996; Todd et al. 1998). Todd et al. (1998) stated that "reflectance properties of soil vary considerably with soil type, texture, moisture content, organic matter, color and the presence of iron oxides." Dark toned soils absorb more energy in the red and near infrared region of the electromagnetic spectrum than light toned soils (Huete et al. 1985; Todd et al. 1998). Therefore, NDVI values tend to decrease as soil brightness increases (Todd and Hoffer 1998). In our situation on CRP land in central Montana, this may be a problem because although biomass may be the same, the darker toned soils in one area of the field may return higher NDVI values than the lighter toned soils in another part of the field (Flynn 2006). Flynn (2006) concluded, "varying soil conditions and soil types across a large landscape make biomass more difficult to calculate from NDVI."

The existence of dead, dried, or dormant plant material can also affect NDVI. As plants senesce throughout the growing season, moisture content and pigmentation change (Todd and Hoffer 1998). As plants lose moisture and chlorophyll pigmentation because of maturation, drought stress, or the onset of dormancy, the reflection of red light and middle infrared light increases (Todd and Hoffer 1998). This causes NDVI to under-report biomass because the reflectance patterns of dry vegetation are more similar to that of soil than to healthy green vegetation (Todd et al. 1998; Flynn 2006). Todd et al. (1998) stated that "the visible and mid-infrared regions are highly reflecting for both dry vegetation and for most soils." Drought conditions often occur in Central Montana which leads to plants losing moisture content and chlorophyll pigmentation. In addition, the biofuel industry desires dormant vegetation because this is when plants contain the greatest amount of lignin, cellulose, and hemicellulose (Juneja et al. 2011). Therefore, the ability to measure dry and dead plant material at dormancy is essential.

Bandwise Regression

In addition to NDVI, multiple regression against raw, nonindexed spectral bands has shown to have a positive linear relationship with biomass (Lawrence and Ripple 1998; Maynard et al. 2006). Multiple regression against raw, nonindexed spectral bands is known as bandwise regression. Bandwise regression models the mean of a response variable as a function of several explanatory variables (Ramsey and Schafer 2002). Forward selection and backward elimination is one technique that can be used in bandwise regression to select explanatory variables for inclusion in the final inferential model (Ramsey and Schafer 2002).

Vegetative cover showed a positive linear relationship with bandwise regression (R^2 = 0.75) on a highly disturbed landscape measured 16 years after the 1980 Mount St. Helen's volcano eruption (Lawrence and Ripple 1998). Biomass on Montana rangelands also showed a positive linear relationship with bandwise regression (R^2 = 0.53) (Maynard et al. 2006). When ecological site descriptions were added as a categorical variable in this same study the variability explained in the measurement model between biomass and bandwise regression improved (R^2 = 0.66) (Maynard et al. 2006).

Bandwise regression has produced biomass estimate models that explained more variability than NDVI biomass estimate models on a highly disturbed landscape (NDVI R^2 = 0.65, Bandwise Regression R^2 = 0.75) (Lawrence and Ripple 1998) and rangelands

(NDVI R^2 = 0.41, Bandwise Regression R^2 = 0.66) (Maynard et al. 2006). When using any vegetation index the most likely way to determine forage production will be to use ordinary least squares regression analysis (Maynard et al. 2006). Using a regression analysis is a clear way to model the relationship between the response variable (an ecological variable of interest such as biomass) and the explanatory variable (NDVI) (Maynard et al. 2006). Using regression with biomass as the response variable and NDVI as the explanatory variable will result in inferior biomass estimates when compared to those using non-indexed spectral data (Lawrence and Ripple 1998). When using a vegetation index as an explanatory variable in a regression model will result in a single coefficient that is being applied to a combination of different bands in the spectrum (Maynard et al. 2006). Different biophysical mechanisms control different band responses. As a result, individual bands will not respond the same to ecological variables (Lawrence and Ripple 1998). Therefore, regression models have more explanatory power when each band can be modeled with its own coefficient (Maynard et al. 2006).

Plant Phenology

One biophysical mechanism that impacts the spectral response of plants on the Earth's surface is plant phenology. Plant phenology is defined as the "study of the onset and duration of the different phases of a plant's development during the year" (Taiz and Zeiger 2010). Three environmental factors that influence plant phenology are: temperature, moisture, and photoperiod (Taiz and Zeiger 2010). Cool-season (C_3) plants are unable to conduct photosynthesis and grow at ambient temperatures below 0° C

(Fahey et al. 1994). In C_3 plants, at temperatures between 5^{o} C and 7^{o} C photosynthesis and plant growth is able to occur but at a slow rate (Fahey et al. 1994). The optimum temperature for photosynthesis and plant growth is about 20^{o} C (Fahey et al. 1994). At temperatures above 25^{o} C photosynthetic activity and plant growth rate declines (Fahey 1994). Fahey et al. (1994) concluded that temperature affects photosynthetic rate by stating, "Temperature determines the kinetic energy of molecules, which in turn determines whether or not a reaction will occur."

Moisture also affects plant phenology. Water dissolves solvents, transports solutes, and removes heat from the plant through transpiration (Fahey et al. 1994; Jones and Vaughan 2010; Taiz and Zeiger 2010). For a plant to carry out photosynthesis, solar radiation and carbon dioxide (CO_2) are required (Fahey et al. 1994; Taiz and Zeiger 2010). A constant battle plants must overcome is to intake CO_2 through the stomatal pores, while retaining water during photosynthesis (Jones and Vaughan 2010). Fahey et al. 1994 stated, "The balance between CO_2 uptake and water loss or transpiration is difficult for a plant because these two systems share a common pathway." Therefore, large quantities of water are lost from the plant during photosynthetic periods (Fahey et al. 1994).

The third environmental factor that influences phenology is photoperiod. Photoperiod is defined as, "The amount of time per day that a plant is exposed to light or darkness" (Taiz and Zeiger 2010). C_3 plants are induced to flower as the amount of sunlight increases throughout the growing season (Fahey et al. 1994). Also, when plants are exposed to shorter days, lower temperatures, and lack of water, these environmental factors initiate the onset of dormancy (Fahey et al. 1994).

Plant Morphology

Plant phenology defines plant morphology. At different stages of phenological development plants contain different morphological features (i.e. different amounts of cellulose, hemicellulose, lignin and different stem:leaf ratios) (Fahey et al. 1994; Taiz and Zeiger 2010). This causes the plants to have different spectral responses at different phenological stages throughout the growing season (Todd and Hoffer 1998).

Three phenological stages that occur throughout the growing season are the boot stage, peak growth, and dormancy. The boot stage is the phenological growth stage "when a grass inflorescence is enclosed by the sheath of the uppermost leaf" (FIS 2013). Peak growth occurs immediately after plants flower, and dormancy occurs when plants have stopped conducting photosynthesis and have gone into a state of inactivity (Taiz and Zeiger 2010).

As plants mature lignin, cellulose, and hemicellulose content and the stem:leaf ratio increases (Morrison 1980; Nordkvist and Aman 1986; Fahey et al. 1994). Morrison (1980) showed that as timothy (*Phleum pratense*) matured over a growing season, lignin concentrations increased from 27 g/kg DM to 61 g/kg DM in the leaf portion of the plant and from 46 g/kg DM to 93 g/kg DM in the stem portion of the plant. In addition, Morrison (1980) showed that hemicellulose increased from 121 g/kg DM to 201 g/kg DM in the leaf portion of the plant and from 136 g/kg DM to 298 g/kg DM in the stem portion of the plant. Nordkvist and Aman (1986) found that the leaf composition of alfalfa (*Medicago sativa*) decreased from 72.9% to 18.4% of the total plant composition from May to August while the stem increased from 18.5% to 50.7% of the total plant composition. In our CRP pasture, the stem:leaf ratio may be important because as plants mature and the stem:leaf ratio increases, more bareground will be exposed which will influence the spectral response of the plant canopy.

The amount of chlorophyll present in the leaf tissue also changes throughout the growing season (Fahey et al. 1994). Chlorophyll breaks down with exposure to sunlight as the plant matures (Fahey et al. 1994). Chlorophyll are light-absorbing pigments located in plant cells that are mandatory for the plant to conduct photosynthesis (Jones and Vaughan 2010). Signals from the environment such as changing day length or temperature and different stresses such as water stress or temperature stress induce senescence (Taiz and Zeiger 2010). When plants senesce, chlorophyll pigments are broken down and the associated nutrients are redistributed throughout the plant (Taiz and Zeiger 2010). This will cause plants to reflect more red light while decreasing the amount of near-infrared light reflectance (Knipling 1970; Todd et al. 1998)

Study Objective

The spectral responses of a plant canopy at different phenological stages pose unique challenges in being able to accurately measure biomass using remote sensing techniques. Creating a biomass measurement model that could measure biomass at any phenological growth stage cross multiple growing seasons would be a valuable tool for land managers. The objective of this study was to compare remote sensing-based biomass measurement models using NDVI and bandwise regression remote sensing techniques at three different phenological growth stages across multiple growing seasons to determine which biomass measurement model best measures biomass on CRP pastureland in central Montana. NDVI measurements from a ground based sensor, NDVI measurements from satellite images, and a combination of individual spectral bands from Landsat images were compared.

COMPARISON OF THREE REMOTE SENSING TECHNIQUES TO MEASURE BIOMASS ON CRP PASTURELAND

Introduction

In 2003, the Biomass Research and Development Technical Advisory Committee to the Secretaries of Agriculture and Energy established a national goal that biomass will supply 5% of the nation's power, 20% of its transportation fuels, and 25% of its chemicals by 2030 (DOE 2003). To meet these goals, biomass from land enrolled in the United States Department of Agriculture's (USDA) Conservation Reserve Program (CRP) is being evaluated as a potential biofuel feedstock source (DOE 2003; Perlack et al. 2005).

The CRP is a voluntary program for agricultural landowners or operators that provides rental payments and cost share assistance to safeguard environmentally sensitive lands by planting long-term, resource conserving covers to control soil erosion, improve water quality, and enhance wildlife habitat (FSA, USDA 2013). Land enrolled in the CRP across the United States as of November 2012 was approximately 11 million ha, mostly dedicated to grasses (USDA 2013a). From these 11 million ha, an estimated 15.4 to 25.4 billion kgs of dry biomass could be available for bioenergy production (Perlack et al. 2005). In Montana, 664,000 ha of land are enrolled in the CRP (USDA 2013b).

Lands enrolled into the CRP are fragile and contain a high degree of spatial variation in vegetative cover and soil types. For sustainable production, harvesting, and soil protection, it is critical to develop technology that is able to accurately measure biomass production in a non-destructive manner across these landscapes.

Remote sensing of vegetation spectral responses collected from ground-based and satellite-based sensors may provide a means to measure biomass in a non-destructive manner at management relevant scales (Weiser et al. 1986). Plant spectral responses change as plants progress through different phenological stages (Knipling 1970; Todd et al. 1998). Environmental factors that influence plant phenology include: photoperiod, temperature, and precipitation (Taiz and Zeiger 2010). On CRP land in central Montana, plant phenology at different stages throughout the growing season pose unique challenges to be able to remotely sense the vegetation. Plants at different stages of phenology have different plant morphology (Morrison 1980). As plants mature the stem:leaf ratio and lignin, cellulose, and hemicellulose content increases while chlorophyll content decreases (Morrison 1980; Nordkvist and Aman 1986; Fahey et al. 1994). Land enrolled into CRP in central Montana allows the opportunity to examine the ability of different remote sensing techniques to measure biomass at different phenological stages across the growing season.

One common remote sensing technique that has been used for decades within the agricultural community is the Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1973). NDVI was developed to take advantage of the reflectance properties of active photosynthetic plant tissue, or green biomass. Active and passive ground-based sensors and satellite-based sensors have measured NDVI and shown positive linear relationships with many measures of vegetation amounts, for example, with corn (*Zea mays*) grain yields (R^2 = 0.77) (Teal et al. 2006), winter wheat (*Triticum aestivuum*) grain yields (R^2 = 0.83) (Raun et al. 2001), merlot wine vineyard biomass (R^2 = 0.82) (Stamatiadis et al. 2010), perennial grassland biomass (R^2 = 0.89) (Paruelo et al. 1997), pastureland biomass (R^2 = 0.68) (Flynn et al. 2008), and shortgrass steppe biomass (R^2 = 0.66) (Todd et al. 1998).

Several factors reduce the relationship between NDVI and biomass including: (1) the existence of dead, dried, and dormant plant material (Todd et al. 1998; Todd and Hoffer 1998; Flynn 2006), (2) leaf area index (LAI) > 3.0 (Tucker 1977; Weiser et al. 1986; Turner et al. 1999; Serrano et al. 2000), and (3) varying soil conditions and soil types (Huete et al. 1985; Rondeaux et al. 1996; Todd et al. 1998; Todd and Hoffer 1998).

Another remote sensing technique that has shown to be a reliable method to estimate biomass across a landscape that could be described as having a high degree of variability in vegetation cover and soil types is bandwise regression (i.e., multiple linear regression with individual spectral bands as potential explanatory variables) (Lawrence and Ripple 1998; Maynard et al. 2006). Bandwise regression has produced biomass measurement models that explained more variability than NDVI biomass measurement models on a highly disturbed landscape (NDVI R^2 = 0.65, Bandwise Regression R^2 = 0.75) (Lawrence and Ripple 1998) and rangelands (NDVI R^2 = 0.41, Bandwise Regression R^2 = 0.66) (Maynard et al. 2006).

A model that could quickly, accurately, and non-destructively measure biomass at any phenological growth stage across multiple growing seasons would be a valuable tool for land resource managers. The objective of this study was to compare different remote sensing-based biomass measurement models using NDVI and bandwise regression remote sensing techniques to determine which biomass measurement model best measures biomass at three different phenological growth stages across multiple growing seasons on CRP pastureland in central Montana.

Methods

Study Area

The study was conducted over two growing seasons in 2011 and 2012 on 8.1 ha of CRP pastureland located at Benchland, Montana, near the Montana State University Central Agricultural Research Station (CARC) (Judith Basin County, 47°05’21.37” N 110°00’44.47”W). The weather patterns across the 2011 and 2012 growing seasons in central Montana were quite different and set the stage for this study (Fig. 1). In 2011 the study area received 8 cm above average precipitation (average precipitation is 40 cm) (MSU, CARC 2013), while in 2012 the study area was in drought conditions, receiving only 28 cm of precipitation (MSU, CARC 2013). In addition to drought conditions in 2012, the study area received severe hail damage on June 5, 2012.

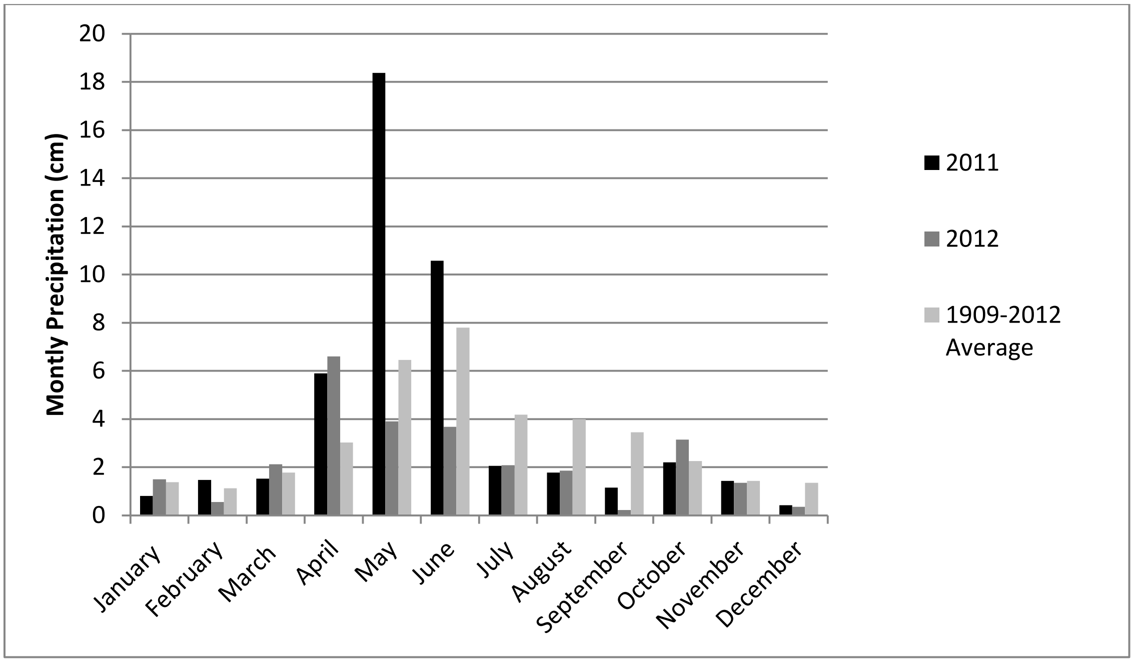

Figure 1. Monthly precipitation for 2011, 2012, and 103 year historical average (MSU, CARC 2013)

The soil on the study area is classified as fine-loamy, carbonatic Typic Calciborrolls (Judith clay loam series) (Chen et al. 2008). The dominant plant species on the study plots were intermediate wheatgrass (*Agropyron intermedium*), pubescent wheatgrass (*Thinopyrum trichophorum*), tall wheatgrass (*Thinopyrum ponticum*) and alfalfa (*Medicago sativa*).

Field Data Collection

The 8.1 ha CRP pasture was divided into nine 0.9 ha plots. Six 1-m^2 quadrats were randomly selected in each plot. When the plants reached the phenological growth stages of boot stage (May), peak growth (June/July), and dormancy (October), the 1-m^2 quadrats were scanned by the active ground-based remote sensing unit Crop Circle ACS-470 (Holland Scientific 2013) and the biomass was hand clipped to within 2.5 cm above the soil surface. This resulted in 108, biomass samples for each year from the 1-m^2 areas. All biomass samples were dried at 40.6° C for 72 hours. Total dry biomass production per 1-m^2 quadrat was then recorded.

<u>Spectral Data Collection</u>

The Crop Circle ACS 470 is a multi-channel remote sensing unit that has the ability to actively generate and record reflected radiation in the red (0.66 to 0.68 µm), red edge (0.72 to 0.74 µm), and near-infrared (NIR) (0.76 to 0.81 µm) wavelengths (Holland Scientific 2013). NDVI was calculated from the Crop Circle ACS 470 using the red and NIR wavelengths using the standard NDVI formula: NDVI = (NIR – Red)/(NIR + Red) (Rouse et al. 1973).

Landsat images of the study area were acquired using USGS Global Visualization Viewer (USGS 2013a). The acquired Landsat images were within 30 days of the corresponding field data collection date (Table 1).

Table 1. Harvest title, spacecraft and sensor ID, scene (path/row), scene dates, field biomass clipping dates, and days between image and clipping dates used in the study

Harvest Title	Spacecraft and Sensor ID	Scene (path/row)	Scene date	Field biomass clipping date	Days between image and clipping dates
2011 Boot Stage	Landsat 5 TM	38/27	6/4/2011	6/2-3/2011	1-2
2011 Peak Growth	Landsat 7 ETM+	38/27	6/28/2011	7/1/2011	3
2011 Dormancy	Landsat 5 TM	38/27	10/26/2011	10/27/2011	1
2012 Boot Stage	Landsat 7 ETM+	38/27	5/13/2012	5/7-8/2012	5-6
2012 Peak Growth	Landsat 7 ETM+	38/27	6/14/2012	6/27-28/2012	13-14
2012 Dormancy	Landsat 7 ETM+	38/27	9/18/2012	10/18/2012	30

When comparing multitemporal images, exogenous factors, such as differences in atmospheric conditions, solar zenith angles, and particulates in the air, can affect the amount of solar radiation reflected from objects on the Earth's surface on an image by image basis (Collins and Woodcock 1996). To account for this multitemporal variation, all images were radiometrically normalized to the June 4, 2011, image using the pseudo invariant target method described by Collins and Woodcock (1996). Pixels from 30 invariant features were located, 15 in each of two cover types, rock out crops and water (Lawrence and Ripple 1999). Of these 30 pixels, 18 (nine for each cover type) were randomly selected to compute regression equations for normalization, in each case predicting June 4, 2011, digital numbers for each spectral band in each image used in this study (Lawrence and Ripple 1999). The 12 pixels not used to compute the regression equations were used for independent verification of the equations (Lawrence and Ripple 1999). For each independent verification pixel, on an image by image, band by band basis, the squared error between the regression equation values and the actual June 4, 2011, values were compared to confirm that the regression equations improved the radiometric match with the June 4, 2011, image (Lawrence and Ripple 1999). Radiometric correction equations were only used when they improved the radiometric match based on the independent verification pixels (Lawrence and Ripple 1999). The Crop Circle ACS 470 generates its own, controlled, modulated energy and is not affected by ambient lighting conditions (Holland Scientific 2013). Therefore, radiometric normalization was not necessary for these spectral measurements.

Pixel values for bands 1 through 7 were extracted for all pixels that covered the study area from which a 1-m^2 quadrat had been clipped. Landsat pixels cover a 900-m^2 (30m X 30m) ground surface area (Landsat 2013). The dry biomass production measurements from the randomly selected 1-m^2 quadrats were used to represent the biomass that was produced in each pixel (Maynard et al. 2006). Therefore, the 1-m^2 quadrats that were used to represent the biomass produced in each pixel were substantially smaller than the land surface area covered by the pixel.

Pixel values extracted from the Landsat images were used to calculate explanatory variables used in the regression equations (Maynard et al. 2006). Satellite-based NDVI measurements were calculated from the red and near infrared band values from these pixels using the standard formula of: NDVI = (Band 4 – Band 3)/(Band 4 + Band 3) (Rouse et al. 1973).

Analysis

Multiple linear regression models were built to measure biomass. Each regression model was built by using biomass as the response variable and different remote sensing spectral values as the explanatory variables along with indicator variables that coded for each phenological growth stage (boot stage, peak growth, or dormancy). The first model used NDVI measurements collected by a ground-based sensor as one explanatory variable along with indicator variables coding for each phenological growth stage as additional explanatory variables (Table 2). The second model used NDVI measurements collected by the Landsat satellite-based sensors Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) as one explanatory variable along with indicator variables coding for each phenological growth stage as additional explanatory variables (Table 2). The third and final model used a combination of individual spectral bands from the Landsat satellite-based sensors TM and ETM+ determined by forward and backward stepwise regression as the explanatory variables along with indicator variables that coded for each phenological growth stage as additional explanatory variables. This multiple linear regression model was built by first conducting forward selection and backward elimination on the multiple linear regression model: Biomass = $\beta_o + \beta_1$ (Band 1) + β_2 (Band 3) + β_4 (Band 4) + β_5 (Band5) + β_6 (Band 6) + β_7 (Band 7). Once those explanatory variables deemed important were determined, indicator variables that coded for each phenological growth stage were then added as additional explanatory variables to this model. A potential biomass measurement model developed from bandwise regression with all explanatory variables included is described in Table 2.

Table 2. Biomass measurement models using biomass as the response variable and different remote sensing spectral values along with indicator variables that coded for each phenological growth stage as the explanatory variables

Remote Sensing Technique	Biomass Measurement Model
NDVI – Ground-Based Sensor	Biomass = β_0+(β_1*NDVI)+(β_2*ind.pg[a])+ (β_3 *ind.dh[b]) +(β_4*NDVI*ind.pg)+(β_5*NDVI*ind.dh)
NDVI – Landsat	Biomass = β_0+(β_1*NDVI)+(β_2*ind.pg)+ (β_3 *ind.dh) +(β_4*NDVI*ind.pg)+(β_5*NDVI*ind.dh)
Bandwise Regression	Biomass = β_0+(β_1*Band 1)+(β_2*Band 2)+(β_3*Band 3)+(β_4*Band 4) +(β_5*Band 5)+(β_6*Band 6)+(β_7*Band7)+(β_8*ind.pg)+(β_9*ind.dh) +(β_{10}*Band 1*ind.pg)+(β_{11}*Band 1*ind.dh) +(β_{12}*Band2*ind.pg) +(β_{13}*Band 2*ind.dh)+(β_{14}*Band 3*ind.pg) +(β_{15}*Band 3*ind.dh) +(β_{16}*Band4*ind.pg)+(β_{17}*Band 4*ind.dh)+(β_{18}*Band 5*ind.pg) +(β_{19}*Band 5*ind.dh)+(β_{19}*Band 6*ind.pg)+(β_{20}*Band 6*ind.dh) +(β_{21}*Band 7*ind.pg)+(β_{22}*Band 7*ind.dh)

[a]Indicator variable coding for the peak growth phenological stage.
[b]Indicator variable coding for the dormancy phenological growth stage. The boot stage was used as the base line for the regression models therefore no indicator variable was used to code for this stage. Peak growth was identified when the alfalfa within the sward had reached seven to eight percent bloom. Dormancy was identified when the study area had received at least one week of temperatures that fell below 0º C.

The 2011 and 2012 datasets were stratified by phenological growth stage and growing season to build and test each biomass measurement model. Half of the data points collected at each phenological growth stage were randomly selected and used to build each of the measurement models and the remaining half were then used to test the power of these models at measuring biomass actually occurring on the ground. Coefficients of determination (R^2) were used to evaluate the variability in biomass explained by each model (Lawrence and Ripple 1998; Maynard et al. 2006).

To test each model, estimated biomass values from each measurement model were compared with the actual biomass values that were hand clipped from the field. The data points used to test each model were not used to build any of the measurement models. The test dataset was only used to test the measuring power of each measurement model by comparing the actual biomass value that was hand clipped on the ground with the associated estimated biomass value determined by each measurement model. A paired *t*-test was used to determine whether there was a difference between actual and estimated biomass set at a p-value ≤ 0.05. The average actual biomass, average estimated biomass, and average differences between actual and estimated biomass were determined for each measurement model. Associated standard errors and confidence intervals were determined for each average calculation to establish which remote sensing technique measured biomass the best on the study area.

Results

Bandwise regression on all seven TM and ETM+ spectral bands against biomass in the dataset used to construct the biomass models determined bands two (green – 0.52 to 0.60 µm), three (red – 0.63 to 0.69 µm), four (NIR – 0.76 to 0.90), five (middle infrared – 1.55 to 1.75 µm), six (thermal infrared – 10.4 to 12.5 µm), and seven (short wave infared – 2.08 to 2.35 µm) to be significant (all p-values < 0.01) (Lawrence and Ripple 1998), and each band was used in the final linear regression model (Table 3). Bandwise regression accounted for the most variability in the dataset used to construct the models ($R^2 = 0.82$), followed by NDVI from the ground based sensor ($R^2 = 0.69$), and NDVI from Landsat sensors ($R^2 = 0.65$) (Table 3).

Table 3. Biomass measurement models constructed using half of the data from the 2011and 2012 growing seasons stratified by phenological growth stage and growing season

Remote Sensing Technique	Measurement Model	Adjusted R^2
NDVI – Ground-Based Sensor	Biomass = -444.8+(6918.6*NDVI)+(-125.8*ind.pg)+ (7462.4*ind.dh)+(6345.9*NDVI*ind.pg)+ (-80776.7*NDVI*ind.dh)	0.69
NDVI – Landsat	Biomass = 628.18+(1514.54*NDVI)+(799.3*ind.pg)+ (3804.64*ind.dh)+(3458.1*NDVI*ind.pg)+ (49391*NDVI*ind.dh)	0.65
Bandwise Regression	Biomass =174.404+(132.993*Band 2)+(-43.207*Band 3)+ (-3.155*Band 4)+(16.692*Band 5)+(-9.33*Band 6)+ (-49.824*Band7)+(-2820.025*ind.pg)+(6894.866*ind.dh)+ (-198.923*Band 2*ind.pg)+(-135.975*Band 2*ind.dh)+ (197.121*Band 3*ind.pg)+(212.829*Band 3*ind.dh)+ (104.64*Band4*ind.pg)+(44.345*Band 4*ind.dh)+ (-168.127*Band 5*ind.pg)+(-147.077*Band 5*ind.dh)+ (28.625*Band 6*ind.pg)+(-42.892*Band 6*ind.dh)+ (167.303*Band 7*ind.pg)+(191.788*Band 7*ind.dh)	0.82

Each remote sensing-based biomass measurement model performed very well at measuring actual biomass that occurred in the study area at each phenological growth stage across the 2011 and 2012 growing seasons. The *p*-values from the paired *t*-test indicated there was no difference ($p > 0.05$) between estimated biomass and actual biomass for all of the remote sensing-based biomass measurement models (Table 4).

Actual biomass produced on average across the entire 2011 and 2012 growing seasons was 2476 kg/ha $\pm$ 169 kg/ha. The NDVI biomass measurement model from Landsat images had the smallest margin of difference between estimated versus actual biomass (22 kg/ha $\pm$ 96 kg/ha), followed by the bandwise regression biomass measurement model (128 kg/ha $\pm$ 71 kg/ha), and the NDVI biomass measurement model from the ground based sensor (182 kg/ha $\pm$ 94 kg/ha) (Table 4).

Table 4. Associated *p*-value, mean actual biomass, mean estimated biomass, and mean differences between actual and estimated biomass for each remote sensing technique across the entire 2011 and 2012 growing seasons

Remote Sensing Technique	Mean Actual Biomass (kg/ha) ± SE	Mean Estimated Biomass (kg/ha) ± SE	Mean Difference (kg/ha) ± SE	95% Confidence Interval for Mean Difference	Sample Size	Degrees of Freedom	Paired *t*-test *p*-value
NDVI – Ground Based Sensor	2476 ± 169	2294 ± 131	182 ± 94	(-4,368)	96	90	$p = 0.06$
NDVI - Landsat	2476 ± 169	2454 ± 149	22 ± 96	(-169,213)	96	90	$p = 0.82$
Bandwise Regression	2476 ± 169	2348 ± 156	128 ± 71	(-14,269)	96	75	$p = 0.08$

Discussion

As plants mature and progress through different phenologic stages of development, plant morphological features change (Fahey et al. 1994; Taiz and Zeiger 2010). Because of these morphological changes, plant spectral responses change throughout their phenological development. At the boot stage during the 2011 and 2012 growing seasons, live, green, photosynthetically active plant material was intermixed with plant litter from the previous year. Young plants are known to have high chlorophyll content (Fahey et al. 1994; Taiz and Zeiger 2010), which allows them to absorb red light and readily reflect NIR (Knipling 1970).

As the growing season progressed and the plants matured into the peak growth stage over the 2011 and 2012 growing seasons, the plant communities were influenced by different environmental factors. For the month of May in 2011, the study area received over 18 cm of precipitation, which was more than 11 cm above the 102 year average (6.5 cm was the 102 year average) (MSU, CARC 2013). For the month of May in 2012, the study area received 4 cm of precipitation, which was 2.5 cm lower than the 103 year average (6.5 cm was the 103 year average) (MSU, CARC 2013). In addition, the study area received severe hail damage on June 5, 2012. Therefore, in 2011 at the peak growth pheonological growth stage, the study area had a dense stand of live, green, photosynthetically active plant tissue. In 2012, the study area contained live, green, photosynthetically active plant tissue, intermixed with bare soil and senesced vegetation that was suffering from drought stress. Mature plant vegetation at the peak growth stage has high chlorophyll content therefore readily absorbs red light while reflecting NIR (Knipling 1970). Plants suffering from drought stress tend to have higher stem:leaf ratios and mature earlier in the growing season to cope with the drought stress (Fahey et al. 1994). In addition, plants suffering from drought stress tend to have lower moisture content and lower LAI than healthy plants (Fahey et al. 1994). This causes more dry vegetation and bare soil to be exposed across the landscape. Reflectance for dry vegetation and bare soil increases in a general linear trend with increasing wavelength from the visible to NIR to middle infrared (Huete et al. 1985; Rodeaux et al. 1996; Todd et al. 1998).

At the dormancy stage, all the plant vegetation was dead or no longer actively conducting photosynthesis. All of the chlorophyll within the plant tissue had been broken down and the green pigmentation from the chlorophyll was no longer present. In 2011, the dormant vegetative stand was more dense than the 2012 vegetative stand. However, dry vegetation and bare soil have similar spectral responses and are highly reflective in the visible and middle infrared regions (Todd et al. 1998). Therefore, the density of the plant canopy had little impact on the spectral response.

Bandwise regression accounted for more variability (R^2 = 0.82) in the dataset used to construct the measurement models than the two NDVI models (R^2 = 0.65; R^2 = 0.69). The ability of bandwise regression to account for more variability in the construction dataset over the two NDVI linear regression models supports previous research (Lawrence and Ripple 1998; Maynard et al. 2006). Bandwise regression determined that the green, red, near infrared, middle infrared, thermal infrared, and short wave infrared bands were significant. The green, red, and near infrared portions of the spectrum are sensitive to green plant biomass and soil (Tucker et al. 1983; Todd et al. 1998; USGS 2013b). The middle infrared and short wave infrared portions of the spectrum are known to be sensitive to leaf moisture content, mineral soil content, and dry vegetation (Knipling 1970; Lawrence and Ripple 1998). In addition, the middle infrared band penetrates thin cloud cover (USGS 2013b).

Across the entire growing season bandwise regression was able to account for more variability in the construction dataset than the two NDVI models. The two NDVI models were restricted to the red and NIR bands, whereas bandwise regression had the potential to use all seven spectral bands from the Landsat images as explanatory variables. Therefore, bandwise regression was able to better capture the variation in ground features that occured across the Earth's surface than the two NDVI models.

When comparing the estimated versus actual biomass values determined by each remote sensing-based biomass measurement model using the test dataset across the 2011 and 2012 growing seasons, each model performed very well. The paired *t*-test *p*-values indicated there were no differences between estimated versus actual biomass ($p > 0.05$) for all the remote sensing-based biomass measurement models. However, the *p*-values for the bandwise regression biomass measurement model ($p = 0.08$) and NDVI biomass measurement model from Landsat images ($p = 0.06$) were close to the established significance level ($p \geq 0.05$). There was a 7% difference between estimated biomass and actual biomass using the NDVI biomass measurement model from Landsat images and a 5% difference between estimated biomass and actual biomass using the bandwise regression biomass measurement model. Based on the results of the paired *t*-tests and the margin of differences between estimated and actual biomass values, the NDVI biomass measurement model from the ground-based sensor and the bandwise regression biomass measurement model did not measure biomass as accurately as the NDVI biomass measurement model from the Landsat images.

A possible explanation for the NDVI biomass measurement model from the Landsat images having the smallest margin of difference between estimated biomass and actual biomass (22 kg/ha $\pm$ 96 kg/ha) may have been caused by the spatial resolution of the Landsat images. A Landsat image has a pixel size of 900-m^2. Because of this large pixel size, multiple biomass measurements were collected inside of the same pixel. Therefore, several biomass measurements had the same NDVI value because they were located within the same pixel. In return, this reduced the amount of variability that was introduced into the biomass measurement model.

This also might explain why the NDVI biomass measurement model from the ground based sensor had the largest margin of difference between estimated biomass and actual biomass (182 kg/ha ± 94 kg/ha). The ground based sensor has a spatial resolution of one meter. Each biomass measurement had its own NDVI measurement that was independent of any other sample collected. This increased the amount of variability that was introduced into the biomass measurement model.

In the bandwise regression model, 20 different explanatory variables were used to model the response variable. This model included a large number of explanatory variables, many of which may not have been necessary for explaining variation in the response variable. Including variables that did not help to explain important relationships with the response variable may have reduced the ability of this model to accurately measure biomass across the 2011 and 2012 growing seasons. Reducing this model to the fewest terms necessary to accurately model biomass may increase the power of this model to measure biomass.

Summary and Areas for Future Research

Remote sensing-based biomass measurement models using NDVI measurements from a ground-based sensor, NDVI measurements from Landsat images, and bandwise regression successfully measured biomass at three different phenological growth stages across the 2011 and 2012 growing seasons on a CRP pasture in central Montana (p-value > 0.05). The NDVI biomass measurement model from Landsat images had the smallest margin of difference between estimated and actual biomass (22 kg/ha ± 96 kg/ha), followed by the bandwise regression biomass measurement model (128 kg/ha $\pm$ 71 kg/ha), and the NDVI biomass measurement model from the ground based sensor (182 kg/ha $\pm$ 94 kg/ha).

Multiple biomass samples that were clipped on the land surface area that was covered by the same pixel may have been the reason why the NDVI biomass measurement model from Landsat images had the smallest margin of difference between estimated and actual biomass. To potentially reduce this margin of difference even more, increasing the biomass measurement size from a 1-m^2 quadrat to a larger land mass area (such as a 15m X 15m plot) may provide a better representation of the vegetation that is occurring inside the Landsat pixel.

A spatial resolution of 900-m^2 (30m X 30m) resulted in the most accurate biomass measurements. This suggests that higher spatial resolution imagery may not always increase the accuracy of a remote sensing-based biomass measurement model. The NDVI biomass measurement model from the ground base sensor, which had the finest spatial resolution (1-m^2) of all the sensors used in this study, had the largest margin of difference between estimated biomass and actual biomass.

This study indicated that a large number of explanatory variables used in a bandwise regression biomass measurement model may not be useful in accurately measuring biomass. Reducing the number of terms in a bandwise regression model to only those that are useful for explaining the most variation in biomass is an important consideration when building a bandwise regression model to measure biomass.

More research is needed to determine the spatial and temporal robustness of these models. The results of this study demonstrate that remote sensing-based biomass measurement models constructed from biomass and spectral response measurements collected over two consecutive growing seasons can produce biomass measurement models that can accurately measure biomass over those same growing seasons. However, this study does not provide evidence if these models could be used at another location that may contain different types of biomass or during a different growing season separate from those in which they were constructed.

Another area for further research is to investigate an alternative modeling approach in addition to linear regression. Another type of model that could be used to measure biomass is regression tree analysis. According to Lawrence and Ripple (2000), "Regression tree analysis is a computationally intensive approach that analyzes all explanatory variables and determines which binary division of a single explanatory variable best reduces deviance (defined as squared residuals) in the response variable." Lawrence and Ripple (2000) showed that models using regression tree analaysis explained substantially more variability in the response variable than did multiple linear regression models.

This study demonstrated that remote sensing-based biomass measurement models using NDVI measurements from Landsat images, NDVI measurements from a ground based sensor, and the best combination of individual spectral bands determined by bandwise regression are all methods that could be used to successfully measure biomass in a non-destructive manner, at different phenological stages across multiple growing seasons. According to the results of this study, remote sensing-based biomass measurement models are a useful tool for land resource management. Using the techniques described in this study, land managers can build remote sensing-based biomass measurement models for their specific area of interest and use those models to measure biomass to help make informed management decisions.

MANAGEMENT IMPLICATIONS

This study set out to develop a biomass measurement model that could be used to measure biomass in a non-destructive manner at any phenological stage across multiple growing seasons. The results from this study suggest that remote sensing-based biomass measurement models using NDVI measurements from ground-based sensors, NDVI measurements from Landsat images, and bandwise regression have the ability to measure biomass at three different phenological growth stages over two consecutive years. Land managers can use remote sensing-based biomass measurement models to quickly, accurately, and non-destructively measure biomass across multiple growing seasons.

The remote sensing-based biomass measurement models developed and used in this study have only been shown to accurately measure biomass on the 8.1 ha CRP field used in this study across the 2011 and 2012 growing seasons. The application of these biomass measurement models outside of these parameters may not accurately measure biomass on other areas of interest. However, the techniques that were used to construct these remote sensing-based biomass measurement models are sound and can be replicated to measure biomass anywhere. Land managers who incorporate remote sensing-based biomass measurement models into their land management strategies will be able to more effectively and efficiently manage biomass resources occurring across the landscape.

LITERATURE CITED

Chen, C., K. Neill, D. Wichman, and M. Westcott. 2008. Hard red spring wheat response to row spacing, seeding rate, and nitrogen. *Agronomy Journal* 100:1296-1302.

Collins, J.G. and C.E. Woodcock. 1996. An assessment of several linear change detection techniques for mapping forest mortality using multitemporal Landsat TM data. *Remote Sensing of Environment* 56:66-77.

DOE (U.S. Department of Energy). 2003. Roadmap for agriculture biomass feedstock supply in the United States. DOE/NE-ID-11129. U.S. Department of Energy, November 2003.

Fahey, G.C., M. Collins, D.R. Mertens, and L.E. Moser. 1994. Forage quality, evaluation, and utilization. American Society of Agronomy, Inc., Crop Science Society of America, Inc., Soil Science Society of America, Inc, 677 South Segoe Road, Madison, WI 53711 USA. 998 p.

FIS. 2013. Forage information system. Available at: http://forages.oregonstate.edu/glossary. Accessed March 28, 2013.

Flynn, S.E. 2006. Using NDVI as a pasture management tool. M.S. Thesis, University of Kentucky, Lexington, KY.

Flynn, S.E., C.T. Dougherty, and O. Wendroth. 2008. Assessment of pasture biomass with the normalized difference vegetation index from active ground-based sensors. *Agronomy Journal* 100: 114-121.

FSA, USDA. 2013. Conservation reserve program. Available at: http://www.fsa.usda.gov/FSA/webapp?area=home&subject=copr&topic=crp. Accessed January 23, 2013.

Harmoney, K.R., K.J. Moore, J.R. George, E.C. Brummer, and J.R. Russell. 1997. Determination of pasture biomass using four indirect methods. *Agronomy Journal* 89:665-672.

Holland Scientific. 2013. Holland Scientific©. Available at: http://hollandscientific.com/. Accessed 01 February 2013.

Holland, K.H., D.W. Lamb, and J.S. Schepers. 2012. Radiometry of proximal active optical sensors (AOS) for agricultural sensing. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 5(6):1793-1802.

Holland, K.H., J.S. Schepers, and J.F. Shanahan. 2006. Configurable multi-spectral active sensor for high-speed plant canopy assessment. In D.J. Mulla (Ed.), *Proceedings of the 8th International Conference on Precision Agriculture (CD).* Minneapolis, MN: University of Minnesota.

Huete, A.R., R.D. Jackson, and D.F. Post. 1985. Spectral response of a plant canopy with different soil backgrounds. *Remote Sensing of Environment* 17:37-53.

Jensen, J. R. 2005. Introductory digital image processing. Upper Saddle River, NJ, USA: Prentice Hall series in geographic information science. 526 p.

Jones, H.G. and R.A. Vaughan. 2010. Remote sensing of vegetation principles, techniques, and applications. Oxford University Press, Great Clarendon Street, Oxford ox2 6dp. 353 p.

Juneja, A., K. Deepak, J.D. Williams, D.J. Wysocki, and G.S. Murthy. 2011. Potential for ethanol production from conservation reserve program lands in Oregon. *Journal of Renewable and Sustainable Energy* 3(063102):1-8.

Knipling, E. B. 1970. Physical and physiological basis for the reflectance of visible and near-infrared radiation from vegetation. *Remote Sensing of Environment* 1:155-159.

Lamb, D.W., M.G. Trotter, and D.A. Schneider. 2009. Ultra low-level airborne (ULLA) sensing of crop canopy reflectance: a case study using a CropCircle™ sensor. *Computers and Electronics in Agriculture* 69:86-91.

Landsat. 2013. The enhanced thematic mapper plus. Available at: http://landsat.gsfc.nasa.gov/about/etm+.html. Accessed 31 March 2013.

Lawrence, R.L. and W.J. Ripple. 1998. Comparisons among vegetation indices and bandwise regression in a highly disturbed, heterogeneous landscape: Mount St. Helens, Washington. *Remote Sensing of Environment* 64:91-102.

Lawrence, R.L. and W.J. Ripple. 1999. Calculating change curves for multitemporal satellite imagery: Mount St. Helens. *Remote Sensing of Environment* 67:309-319.

Lawrence, R.L. and W.J. Ripple. 2000. Fifteen years of revegetation of Mount St Helens: a landscape-scale analysis. *Ecology* 81(10):2742-2752.

Maynard, C.L., R.L. Lawrence, G.A. Nielsen and G. Decker. 2006. Modeling vegetation amount using bandwise regression and ecological site descriptions as an alternative to vegetation indices. *GIScience & Remote Sensing* 43:1-14.

Morrison, I.M. 1980. Changes in the lignin and hemicellulose concentrations of ten varieties of temperate grasses with increasing maturity. *Grass Forage Science* 35:287-293.

MSU, CARC. 2013. The Montana State University Central Agriculture Research Center weather data. Available at: http://ag.montana.edu/carc/Weather.htm. Accessed 01 February 2013.

Nordkvist, E. and P. Aman. 1986. Changes during growth in anatomical and chemical composition and in vitro degradability of Lucerne. *Journal of Science Food and Agriculture* 37:1-7.

Paruelo, J.M., H.E. Epstein, W.K. Lauenroth, and I.C. Burke. 1997. ANPP estimates from NDVI for the central grassland region of the United States. *Ecology* 78:953-958.

Perlack, R.D., L.L. Wright, A.F. Turhollow, R.L. Graham, B.J. Stokes, and D.C. Erbach. 2005. Biomass as feedstocks for a bioenergy and bioproducts industry: the technical feasibility of a billion-ton annual supply. The United States Department of Agriculture (USDA) and the United States Department of Energy (DOE), DOE/GO-102005-2135, ORNL/TM-2005/66.

Ramsey, F.L. and D.W. Schafer. 2002. The Statistical Sleuth:A Course in Methods of Data Analysis, Second Edition. Belmont, CA, USA: Brooks/Cole Cengage Learning. 742 p.

Raun, W.R., J.B. Solie, G.V. Johnson, M.L. Stone, E.V. Lukina, W.E. Thomason, and J.S. Schepers. 2001. In-season prediction of potential grain yield in winter wheat using canopy reflectance. *Agronomy Journal* 93:131-138.

Rondeaux, G., M. Steven, and F. Baret. 1996. Optimization of soil adjusted vegetation indices. *Remote Sensing of Environment* 55:95-107.

Rouse, J.W., R.H. Haas, D.W. Deering, and J.A. Schell. 1973. Monitoring the Vernal Advancement and retrogradation (Green Wave Effect) of Natural Vegetation. NASA/GSFC Progress Report RSC 1978-2, Greenbelt, Maryland 20771.

Serrano, L., I. Filella, and J. Penelas. 2000. Remote sensing of biomass and yield of winter wheat under different nitrogen supplies. *Crop Science* 40:723-731.

Shaver, T., R. Ferguson, and J. Shanahan. 2010. Crop canopy sensors for in-season nitrogen management. *2010 Crop Production Clinics Proceedings* University of Nebraska-Lincoln Extension.

Shippert, P. 2004. Spotlight on Hyperspectral. Available at: www.geospatial_online.com/shippert. Accessed 10 April 2013.

Stamatiadis, S., D. Taskos, E. Tsadilla, C. Christofides, C. Tsadilas, and J.S. Schepers. 2010. Comparison of passive and active canopy sensors for the estimation of vine biomass production. *Precision Agriculture* 11:306-315.

Taiz, L. and E. Zeiger. 2010. Plant physiology. Sinauer Associates, Inc., 23 Plumtree Road, Sunderland, MA 01375 USA. 782 p.

Teal, R.K., B. Tubana, K. Girma, K.W. Freeman, D.B. Arnall, O. Walsh, and W.R. Raun. 2006. In-season prediction of corn grain yield potential using normalized difference vegetation index. *Agronomy Journal* 98:1488-1494.

Todd, S.W. and R.M. Hoffer. 1998. Responses of spectral indices to variations in vegetation cover and soil background. *American Society for Photogrammetry and Remote Sensing* 64(9):915-921.

Todd, S.W., R.M. Hoffer, and D.G. Michunas. 1998. Biomass estimation on grazed and ungrazed rangeland using spectral indices. *International Journal of Remote Sensing* 19:427-438.

Tucker, C.J. 1977. Asymptotic nature of grass canopy spectral reflectance. *Applied Optics* 16:1151-1156.

Tucker, C.J., C. Vanpraet, E. Boerwinkel, and A. Gaston. 1983. Satellite remote sensing of total dry matter production in the Senegalese Sahel. *Remote Sensing of Environment* 13:461-474.

Turner, D.P., W.B. Cohen, R.E. Kennedy, K.S. Fassnacht, and J.M. Briggs. 1999. Relationships between leaf area index and landsat TM spectral vegetation indices across three temperate zone sites. *Remote Sensing of Environment* 70:52-68.

USDA. 2013a. Summary of active and expiring CRP cropland acres by state – CRP – monthly contracts report. Montana FSA State Office, P.O. Box 670, Bozeman, MT 59771, (406) 587-6881.

USDA. 2013b. Summary of active and expiring CRP cropland acres by county – CRP – monthly contracts report. Montana FSA State Office, P.O. Box 670, Bozeman, MT 59771, (406) 587-6881.

USGS. 2013a. USGS global visualization viewer. Available at: http://glovis.usgs.gov/. Accessed 01 February 2013.

USGS. 2013b. Landsat missions. Available at: http://landsat.usgs.gov/best_spectral_bands_to_use.php. Accessed 01 February 2013.

Wang, J., P. M. Rich, K. P. Price, and W. D. Kettle. 2005. Relations between NDVI, grassland production, and crop yield in the central great plains. *Geocarto International* 20: 5-11.

Weiser, R.L., G. Asrar, G.P. Miller, and E.T. Kanemasu. 1986. Assessing grassland biophysical characteristics from spectral measurements. *Remote Sensing of Environment* 20:141-152.