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Multi-Temporal Analysis of Crop Biomass Using Selected Environmental Variables and Remote Sensing Derived Indices

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by

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MULTI-TEMPORAL ANALYSIS OF CROP BIOMASS USING SELECTED ENVIRONMENTAL VARIABLES AND REMOTE SENSING DERIVED INDICES

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Measuring biomass in crops is important for yield prediction, nutrient management and analysis of carbon sequestration. Studying crop phenology via biomass can also provide insight into not only the state of the ecosystem but also environmental factors which may affect crop growth. Remote sensing techniques, as an alternative to traditional *in-situ* sampling methods for biomass assessment, provide potentially more efficient data acquisition and cost-effective procedures. Numerous vegetation indices (VI) have been developed which use spectral reflectance data to measure plant biophysical characteristics. The first objective of this research was to examine the correlation between crop biomass and selected environmental variables at multiple lag periods of 14, 28, 56, and 84 days prior to biomass measurement. Environmental variables studied were daily soil moisture (SM), growing degree days (GDD) and precipitation, and were correlated to field-measured biomass from 2002 – 2011. The second aim of this research was to compare three VIs for predicting the biomass of corn and soybeans in a rain-fed field. The VIs used were Normalized Difference Vegetation Index (NDVI), Red-Edge Chlorophyll Index ($CI_{Red\text{-}Edge}$) and Wide Dynamic Range Vegetation Index

(WDRVI).Canopy-level spectral reflectances acquired by a field spectroradiometer and digital aerial images acquired by the AISA-Eagle airborne hyperspectral sensor, during the 2002 – 2008 growing seasons, were analyzed in order to address this objective. Results from biomass correlation with environmental variables were more distinct in corn than soybean and showed that as lag periods increased, there was both increase and decrease in correlations with SM and GDD respectively. Prediction of biomass via VIs showed R^2 values which ranged from 0.72 – 0.99, with NDVI having the highest overall.

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1 INTRODUCTION

1.1 Importance of Biomass

Green biomass is a measure of the overall productivity of terrestrial vegetation, and studying this biophysical parameter is important for several reasons. For example, green biomass measurements aid in examining the state of the ecosystem by providing inputs for biome and climate models (Watson *et al*., 2001). Furthermore, green biomass has also been shown to be associated with carbon sequestration by plants which results in the replacement of carbon dioxide (CO_2) with oxygen in the environment (http://www.epa.gov/sequestration/faq.html), and thus can be studied for environmental assessment. A significant portion of terrestrial vegetation, the biomass of which is studied for assessing the environment, are cultivated systems and agricultural/crop lands which cover at least 24% of the earth's total land area (Reid *et al*., 2005; DeFries, 2008). Monitoring and measuring biomass of agricultural crops is important because agricultural crops play a significant and unique role in the environment as a result of the management practices employed for agriculture. The management practices, such as irrigation and fertilizer applications, are aimed at minimizing costs and maximizing yields, and they have significant environmental and economic impacts which differ from other forms of terrestrial vegetation.

1.2 Impact of Environmental Variables on Crop Growth

The growth and accumulation of biomass in agricultural crops follows a seasonal pattern which is closely related to characteristics of the lower atmosphere (Reed *et al*., 2004). Atmospheric characteristics such as air temperature, CO_2, and environmental variables such as precipitation and soil moisture affect the rate and amount of biomass accumulated in crops seasonally (Eastin and Sullivan, 1984; Moss, 1984; Russelle *et al*., 1984; Hodges, 1991). Numerous studies have investigated the effects some of these environmental variables have on the growth of crops, and many of them have been done over large spatial extents using remotely sensed data (Denmead and Shaw, 1960; Di *et al*., 1994; Yang *et al*., 1994; Rundquist *et al*., 2000; Li *et al*., 2002; Ji and Peters, 2005). A drawback to analyzing remotely sensed data with broad spatial coverage is the general non-availability of ground reference measurements for assessing and improving the accuracy of the remote estimates. Thus, vegetation indices (VIs), many of which are documented indicators of the relative abundance of numerous biophysical characteristics of vegetation, including biomass, are based on the spectral reflectance of healthy green vegetation are used as proxies for biomass (Yang *et al*., 1994; Rundquist *et al*., 2000; Ji and Peters, 2005).

Using biomass proxies of varying accuracies for studying the effects environmental factors have on crop growth may introduce unseen variables which can affect observed relationships between biomass and environmental factors. Thus, it seems logical to avoid the use of biomass proxies for studying crop seasonal growth if at all possible, and ground measured biomass is far more desirable. However, a limited amount of research exists that examines the relationships between crops and environmental factors by means of field measured crop biomass due, very likely, to the difficulties associated with the required destructive sampling.

This research makes use of crop biomass destructively measured from a rain-fed field at intervals throughout multiple growing seasons in order to examine the relationships between crop growth and environmental variables. The field measurements were used as ground-reference data. The research also examines the relationships among three VIs derived from canopy level as well as airborne altitudes in terms of environmental factors. Examining these relationships over a long period of time should shed more light on the interactions of crops with long-term changes which may be observed in the ecosystem such as climate change.

1.3 Remote Estimation of Crop Biomass

Traditionally crop biomass measurements have been done via *in situ* destructive sampling. Although biomass measurements obtained by this method may be of higher quality than alternative means such as remote data acquisition, the data collection process is time- and labor-intensive, and is not feasible over large spatial extents. Conversely, estimating biomass using data which are acquired from remote sensors such as field spectroradiometers and aerial or satellite borne sensors offers numerous advantages including the non-destructive and non-obtrusive nature of the data collection methods; as well as the large spatial coverage of a given sensor system (Hatfield and Prueger, 2010). The challenge for scientists is to validate the feasibility and accuracy of the remote measurements.

Biomass estimation from remotely sensed data is accomplished by applying a number of VIs which are indicative of vegetation biophysical characteristics (Viña, 2004; Jensen, 2005). Applying VIs for estimating crop biomass has been predominantly done using data acquired by low- to mid-resolution spatial and/or spectral sensors such as Landsat, SPOT, and AVHRR. This is because these data are relatively inexpensive and cover large spatial extents. Limited research has been done on estimating crop biomass using data of high spatial and spectral resolutions acquired via canopy level or airborne sensors because data acquisition by means of these sensors can be labor intensive and fairly expensive . Data from both sensor types have the advantage (for studying crop biomass), over satellite borne sensors, of being acquired on demand, thus enabling spectral reflectance and/or imagery to be collected at specific stages of the phenological cycle of crops.

This research applies VIs to aerial imagery acquired from a high spatial (2-m) and spectral (62 narrow bands in the visible to near infra-red spectrum) resolution sensor at multiple times during each of six growing seasons. The research also uses spectral reflectances acquired at canopy level by means of a hyperspectral field radiometer with a spectral resolution of 2024 individual channels with bandwidths of approximately 1.5nm in the visible to near infra-red spectrum and mounted on an all-terrain platform, to predict biomass across seven growing seasons. These studies may enable us identify small differences in the capabilities of each VI for estimating green biomass at different growth stages of crops, as well as at different proximities from the targets.

1.4 Research Objectives

The objectives of the research are to:

Objective 1:

I. study temporal changes in green biomass of rain-fed corn and soybeans across ten growing seasons (2002 – 2011) at the field level.

II. correlate the biomass changes of these crops during each growing season with growing degree days (GDD), precipitation and soil moisture.

Objective 2:

I. estimate green biomass of rain-fed corn and soybeans across seven growing seasons (2002 – 2008) using three selected VIs derived from canopy level spectral reflectance measurements acquired in close proximity to the canopy.

II. compare the accuracy of these VIs for predicting green biomass of both crop types.

III. correlate seasonal crop biomass measurements and VI-estimated biomass with GDD and soil moisture.

Objective 3:

I. estimate green biomass of rain-fed corn and soybeans across six growing seasons (2002 – 2007) using three selected VIs derived from aerial hyperspectral imagery.

II. compare the accuracy of these VIs for predicting green biomass of both crop types.

III. correlate seasonal biomass measurements and VI-estimated biomass with GDD and soil moisture.

1.5 Thesis Structure

This thesis consists of five chapters. Chapter One comprises the introduction and identifies the objectives of this research. Chapters Two, Three and Four are presented in manuscript style, with each addressing individual objectives.

Chapter Two is focused on examining the inter- and intra-annual changes in destructively sampled biomass of rain-fed corn and soybeans. Biomass measurements were also correlated with environmental variables i.e., growing degree days (GDD), precipitation and soil moisture in order to analyze the relationships between and among the environmental variables and crop growth throughout a growing season.

In Chapter Three, there is an analysis of three VIs derived from canopy level spectral measurements which are used to estimate green biomass in the rain-fed corn and soybean field. These VIs include the NDVI, Red-Edge Chlorophyll Index ($CI_{RedEdge}$) and Wide Dynamic Range Vegetation Index (WDRVI). Field measured biomass and VIs were also correlated with GDD and soil moisture to analyze the relationships between and among the selected environmental variables and crop growth during each growing season.

Chapter Four constitutes an examination of three VIs used to estimate green biomass in the rain-fed corn and soybean field. These VIs derived from 2-meter resolution airborne hyperspectral imagery include the NDVI, $CI_{RedEdge}$ and WDRVI. Biomass and VIs were also correlated with GDD and soil moisture at multiple temporal lag periods in order to analyze the relationships between the selected environmental variables and field measured as well as estimated crop growth during each growing season.

A summary of the research is presented Chapter Five. The chapter examines the potential contributions of the findings to the professional literature on the topics of this research. Results from the research are compared with findings and conclusions of previously published related studies.

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2 ANALYSIS OF GREEN BIOMASS AND ENVIRONMENTAL VARIABLES IN A RAIN-FED FIELD ACROSS MULTIPLE GROWING SEASONS

2.1 Introduction

2.1.1 Plant Growth

Plant growth is the accumulation of biomass as a whole or in certain organs within the plant (Hodges, 1991), and can be described at a basic level as the irreversible increase in plant size as a result of increase in cell numbers (by division) and cell size. Plant growth may be expressed as increase in height or dry weight/biomass, or the advancement from one developmental stage to another (Brown, 1984).

2.1.1.1 Phenology

The advancement of a plant through developmental stages is referred to as phenology, which Hodges (1991) defined as the development, differentiation, and initiation of plant organs. The temporal progression of a plant through developmental stages from emergence to physiological maturity and finally senescence is remarkably constant (Hodges, 1991). This temporal consistency of events results in the seasonality of plants and the very close relationship of phenological events to seasonal dynamics.

Studying the phenology of agricultural crops improves our understanding of crop development and growth processes (Viña, 2004). Accurately predicting crop growth patterns, from studying their phenology, enables farmers to plant crops so the most critical growth stages occur during favorable weather conditions (Hodges, 1991).

Acquiring information about the phenology of crops would be essential for evaluating crop productivity and management (Sakamoto *et al.*, 2005), and assessing crop growth under various weather conditions (Zhongxin *et al*., 2008). It can then be said that studying crop phenology may help in optimizing crop management techniques in efforts to maximize yield.

Studying the phenology of plants allows for monitoring the state of the ecosystem. The seasonal characteristics of plants are closely related to seasonal characteristics of the lower atmosphere such as annual weather patterns, temperature and humidity (Reed et al., 1994). In the same light, Delbart et al., (2005) have shown that climatic changes disturb the phenology of many organism types in terrestrial ecosystems. Because of this strong association between terrestrial plants and their environments, the timing of plant growth stages may provide information about the condition of plants and the variables of their environment, such as soil moisture and temperature, illumination and air temperature (Reed et al., 1994).

2.1.1.2 NPP

Net Primary Productivity (NPP), the total amount of new organic matter produced in an ecosystem during a time interval, can also be represented as the difference between total photosynthesis and total respiration in an ecosystem (Clark *et al*., 2001). NPP is a fundamental ecological variable because it measures the energy put into the atmosphere, carbon dioxide assimilation in terrestrial environments, as well as indicating the condition of the land and its ecological processes (http://daac.ornl.gov/NPP/html_docs/

npp_est.html). Kimball *et al*., (2004) have shown that regional patterns of NPP are closely related to the timing of spring thaw and length of growing season in coniferous forests. Therefore studying the phenology of terrestrial plants can be useful in estimating NPP and the state of the terrestrial ecosystem.

2.1.1.3 Photosynthesis and Plant Growth

Photosynthesis is the physico-chemical process by which plants, algae and photosynthetic bacteria use light energy to drive the integration of organic compounds (Whitmarsh and Govindjee, 1999). The process results in the removal of carbon dioxide from the atmosphere that is used to synthesize carbohydrates, and the release of oxygen. By the mid-19th century, the key components of photosynthesis had been identified and the chemical process is represented as follows:

$$6CO_2 + 12H_2O + Light\ Energy = C_6H_{12}O_6 + 6O_2 + 6H_2O$$

Where: CO_2 = carbon dioxide
H_2O = water
$C_6H_{12}O_6$ = carbohydrate
O_2 = oxygen

Photosynthesis provides the organic matter and energy required for the maintenance of higher plants; thus it is an important yield determining process (Gaastra, 1959). Photosynthesis is important to crop production because many of the factors that limit plant growth and yield (e.g. nutrients and moisture) do so by suppressing photosynthesis. Despite the obvious importance of photosynthesis to crop production, the relationship is not a direct one. For example, a crop with inadequate photosynthesis cannot produce high yields while a crop with leaves that have optimum photosynthetic rates may not necessarily lead to a high economic yield (Moss, 1984). Thus much of crop management is, in reality, management of photosynthetic rates because cropping practices like early planting, multiple cropping and/or use of locally adapted cultivars are designed to make the best use of a crop's "photosynthetic factory".

2.1.2 Phenology of Corn and Soybean

2.1.2.1 Corn

Corn (*Zea mays L.*), like most principal food crops of the world, is an annual plant, completing its life cycle in one year and perpetuating itself by seed. It is a short day plant, which means that the photoperiod (or day length) necessary for initiating the reproductive cycle is less than 14 hours. It also is a warm season crop as it requires temperatures between 68 and 73^{o}F for optimum growth and production (Burger, 1988).

Corn phenology is generally described in terms of vegetative and reproductive stages (Viña, 2004). An example of the temporal change in biomass through phenological stages of corn is shown in Figure 2.1. The vegetative stage is designated from the emergence of the seedling (VE) to tasseling (VT), when the last tassel branch is visible and silks have not emerged. Stages between VE and VT are numerically designated as V1, V2, and so on, through Vn based on the number of fully expanded leaves. Rapid growth of the plant begins at stages V7 – V8, and the total number of leaves that the plant will develop is determined at these stages. Also, senescence may occur in lower leaves if the plant is stressed at this stage. Right before reproduction, at VT, the plant attains its full height and is most vulnerable to moisture stress and leaf loss. Corn plants typically develop 20 – 21 leaves in total, and silk and mature about 65 days and 125 days respectively after VE.

The reproductive stages of the corn plant are designated from R1 to R6, beginning with the first appearance of silk through physiological maturity. At R1/Silking, the silks are exposed outside the husk, and pollen grains which fall on the silk can result in fertilization. R2/Blister occurs about two weeks after silking, and the kernels are white in a “blister” shape. At this stage, nutrients are being directed to the kernels from the vegetative parts of the plant. About a week after Blister, the kernels appear yellow on the outside with a milky white inner fluid, and this stage is called R3/Milk, at which time the kernels are experiencing a rapid rate of dry matter accumulation. During R4/Dough (about 24 - 28 days after silking), starch continues to accumulate and thicken in consistency. At R5/Dent, which happens about 35 – 42 days from R1, most of the kernels have “dents” or are denting. Physiological maturity/R6 occurs about two months after silking with the kernels having achieved maximum dry weight and a brown or black layer forming immediately above the kernel tip of the kernel (http://www.clemson.edu/extension/rowcrops/corn/guide/growth_stages.html, http://weedsoft.unl.edu/documents/GrowthStagesModule/Corn/Corn.htm#).

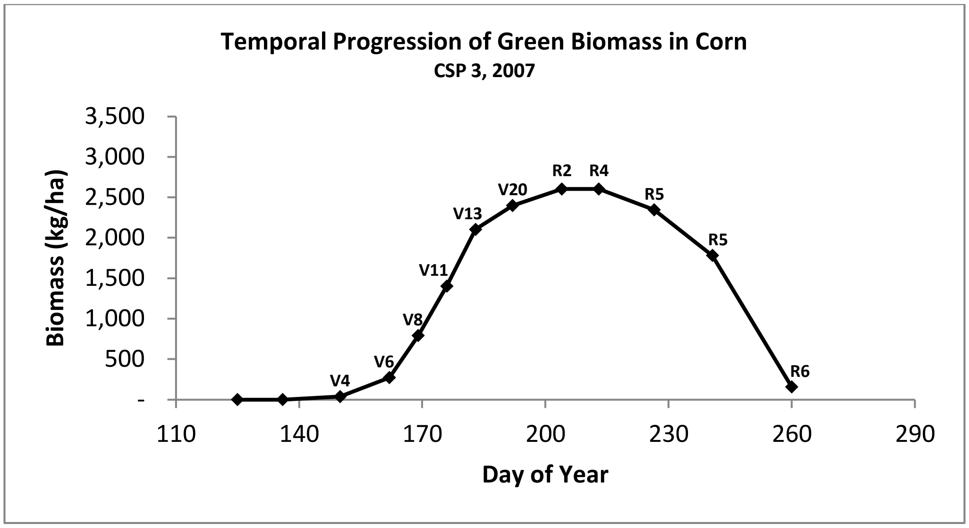


Figure 2.1: Chart showing the temporal progression of the green biomass of corn through vegetative and reproductive stages. Biomass data were acquired from CSP 3 during the 2007 growing season.

2.1.2.2 Soybeans

Soybeans (*Glycine max Merrill*) is also an annual crop like most principal food crops, completes its life cycle in one year and perpetuates itself by seed. It is a day-neutral/short day plant, which means that it can reach reproductive development under either long or short photoperiods, and the main branch continues to develop leaves throughout the flowering period (Padersen *et al*., 2008). It also is a warm season crop as it requires temperatures between 68 and 86^{o}F for optimum growth and production. (Burger, 1988).

Like corn, soybean phenology is generally divided into vegetative and reproductive stages. Plant emergence (VE) occurs about one to two weeks after planting, depending on temperature and available moisture. VC occurs when the cotyledons have fully expanded and the unifoliate leaves have unfolded. Numbered V stages (i.e. V1, V2…Vn) are based on the number of unrolled leaves present.

The reproductive stage starts at R1/Beginning Bloom when one flower is open on the main stem of the plant. Typically plants at R1 are at the V7/V8 stage of development and are between 15 – 18 inches in height. At R2/Full Bloom plants are typically in the V8 – V12 stages of growth, during which the plant is rapidly accumulating dry matter and nutrients in its vegetative tissues. At this stage, the plant is about 17 – 22 inches tall, approximately half of its maximum height. At Beginning Pod/R3, pods are about 3/16 inch long on the uppermost stem nodes, and plants are typically about 23 – 32 inches tall. R4/Full Pod sees the uppermost pods elongating to about 3/4 inch, with the plant at about 28 – 39 inches tall. During the Beginning Seed/R5 stage, pods continue elongating and the plant reaches 30 – 43 inches in height. At this stage, seeds start to rapidly accumulate dry matter, so nutrients are redistributed from the vegetative tissue of the plant to the developing seeds. R6/Full Seed occurs when the plants are in the V16 – V25 stages, with the growth rate beginning to decline. Leaf senescence begins in the older (lower) nodes, and Maturity/R7 occurs when dry weight accumulation has stopped, and both the seed and the pod turn yellow. Full Maturity/R8 occurs when 95% of the pods have reached maturity (http://weedsoft.unl.edu/documents/ GrowthStagesModule/Soybean/Soy.htm#, http://www.clemson.edu/extension/rowcrops/ soybeans/guide/growth_stages.html). Figure 2.2 provides an example of the phenological stages of soybeans with regard to temporal changes in corresponding green biomass.

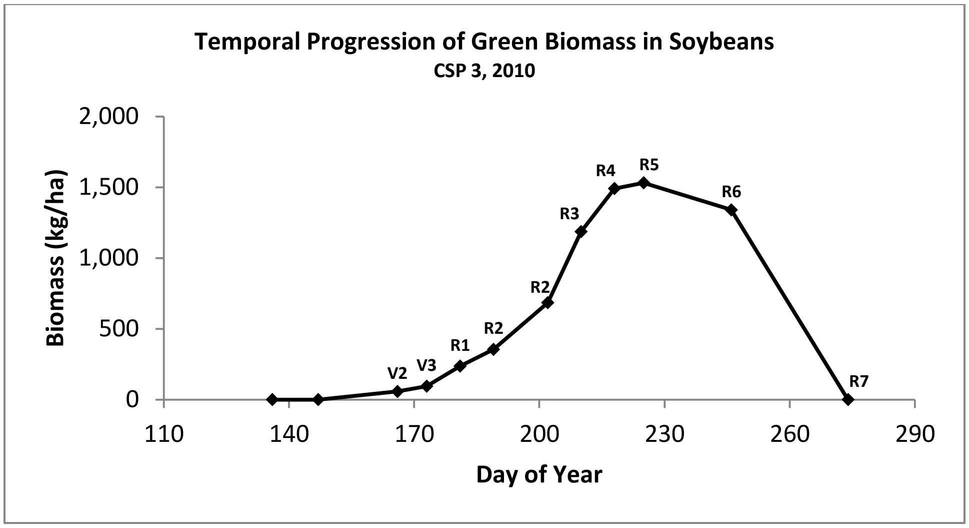


Figure 2.2: Chart showing the temporal progression of green biomass through vegetative and reproductive stages in soybeans. Biomass data were acquired from CSP 3 during the 2010 growing season.

2.1.3 Environmental Variables Affecting Plant Growth

The rate of photosynthesis occurring in crop leaves and canopies is strongly dependent on the status and condition of the crop itself, as well as certain environmental factors. These factors include light intensity (or amount of incoming photosynthetically active radiation) and duration, CO_2 concentration, mineral nutrients/soil fertility, air temperature and available water (Eastin and Sullivan, 1984; Moss, 1984; Russelle *et al*., 1984; Hodges, 1991).

The effects of plant stresses due to environmental variables are difficult to identify and analyze individually because one seldom occurs without another (Eastin and Sullivan, 1984). For example, water stress rarely occurs in nature without the influence of temperature and vice versa (i.e., during a field drought, high temperatures generally accompany lack of moisture). The role of temperature-moisture interactions in natural production ecosystems (e.g. crop growth in rain-fed fields) is critical, and there is a clear need to measure and monitor these two variables (Eastin and Sullivan, 1984).

Water stress on plants results primarily in cell dehydration. Depending on the severity of the dehydration, stress can cause multiple reversible or irreversible effects, such as reduced photosynthetic rates and/or the accumulation of metabolic (intermediate or waste) products to the extent of toxicity (Eastin and Sullivan, 1984). The effects of soil moisture stress on corn growth and development reduces stalk height, cob length, leaf area, assimilation and grain yield, with the greatest effects of stress observed in the yield (Denmead and Shaw, 1960).

The effects of extreme air temperatures on a plant are largely brought about by their impact on internal chemical reactions. Cell growth, especially elongation, is a chemical phenomenon which can be affected by temperature extremes (Went, 1953). High temperatures may reach a point when trapped PAR does not exceed plant respiration, resulting in growth cessation. On the other hand, chilling temperatures affect the permeability of cell membranes; this can result in problems of growth, development and storage of agricultural crops (Eastin and Sullivan, 1984).

2.1.4 Previous Work done on Monitoring Plant Phenology

Villegas *et al*., (2001) studied the pattern of biomass accumulation in irrigated and non-irrigated durum wheat. The study showed that drought reduced the final biomass of the crops by about 40%; while maximum crop dry weight was significantly lower in the rain-fed site (1076g/m^2) than the irrigated (1729g/m^2). Phenological development of corn was studied by Viña *et al*., (2004) using canopy level spectral measurements. The authors showed that the Visible Atmospherically Resistant Index (VARI) allows for detecting the onset of grain fill period and senescence 110 growing degree days (GDD) earlier than Normalized Difference Vegetation Index (NDVI).

Reed *et al*., (1994) applied metrics to biweekly composited Advanced Very High Resolution Radiometer (AVHRR) NDVI images to describe phenological phenomena of various land cover types in the conterminous United States. Their analysis of agricultural crops (including corn and soybeans) over a period of two years showed consistency in the metrics, because of the reliable moisture regime of the agricultural environments studied. AVHRR NDVI-based metrics were also employed by Hill and Donald (2003) to explore spatial and temporal variability in agricultural landscapes of Western Australia. This study showed that time-integrated NDVI, which is indicative of the 'magnitude' of the season, proved to be the most sensitive metric (of those studied) to crop production in cases where rainfall and crop production are highly correlated as well as areas with rainfall values of approximately 600mm.

Yang *et al*., (1994) looked at the correlation of biweekly AVHRR NDVI composited images with eco-climatological parameters in the central Great Plains, such as accumulated growing degree days (AGDD), soil temperature, potential evapotranspiration and precipitation. The research showed that on the average, correlation of NDVI with AGDD, precipitation with a 5 to 7 week lag, and precipitation with no lag had coefficients of above 0.8, 0.55 to 0.7 and 0.2 respectively. Monthly AVHRR NDVI images were correlated to GDD and precipitation data by Li *et al*., (2002). This study, carried out in China, showed NDVI and rainfall correlations reaching a peak (0.86) in areas with annual rainfall of 500 – 700mm. In addition, NDVI/GDD correlations were consistently higher than NDVI/precipitation in all vegetation types studied.

Using Landsat-MSS NDVI images, Di *et al*., (1994) examined vegetation responses (via NDVI) to precipitation events in the Sandhills region of Nebraska. The study created a model which showed that NDVI response time varied during the course of a growing season, ranging from 14, 25 and 12 days at the beginning, middle and end of the growing season respectively. Ji and Peters (2005) also looked at the correlation between NDVI and precipitation using biweekly composites of AVHRR images. Their study showed a close relationship between NDVI and precipitation, as well as a variation in NDVI lag time response to precipitation with shorter lags (4 – 8 weeks) in the early season and longer lags (12 – 14 weeks) in the mid to late season.

Rundquist *et al*., (2000) looked at statistical relationships between monthly precipitation, temperature and AVHRR NDVI data at a mesoscale in nine climatic divisions of Kansas, US. The results showed lower correlations than from other studies (NDVI/Precipitation r = 0.42 and NDVI/Temperature r = 0.32) because of mixed land cover classes; while NDVI values were generally higher in the ‘wet’ year and lower in ‘dry’ years.

Abundant research has been directed at the phenological cycle of plants as well as the response of these cycles to environmental factors. A very large portion of the research has been done using remotely sensed data acquired at different spatial scales, ranging from local to regional. Because data required for studying crop growth need to be collected frequently and systematically throughout a growing season, data from sensors which have low to mid spatial resolutions such as AVHRR and Landsat have been used widely for regional-scale research. Satellite images are transformed to vegetation indices (VI), most commonly NDVI, which are good indicators of vegetation presence and vigor, and are used in lieu of ground measurements of the object(s) being studied.

There is a lack of research focused on crop phenological changes and their responses to environmental variables at the field level using ground measured data over a period of at least a decade. The purpose of this research was to study the temporal changes in green biomass of rain-fed corn and soybeans across ten growing seasons (2002 – 2011) at the field level, and to correlate the biomass changes in these crops during each growing season as compared to precipitation, GDD and measured soil moisture.

2.2 Materials and Methods

2.2.1 Study Area

The study site is a 65.4 ha rain-fed field located at 41.18^{o}N; 96.44^{o}W near Mead Nebraska (Figure 2.3). This field (CSP 3) has been maintained by the University of Nebraska-Lincoln (UNL) Agricultural Research and Development Center (ARDC) since 2001 as a part of the UNL Carbon Sequestration Program (CSP).

The soil textures within CSP 3 are deep silty clay loams that consist of Filbert (fine, smectitic, mesic Vertic Argialbolls), Filmore (fine, smectitic, mesic Vertic

Argialbolls), Tomek (fine, smectitic, mesic Pachic Argialbolls) and Yutan (fine-silty, mixed, superactive, mesic Mollic Hapludalfs) soil series (http://ameriflux.ornl.gov/). This mix of well-drained and poorly-drained mollisols promotes soil moisture retention and plant growth.

The climate of the study area is a temperate semi-arid one, with a mean annual precipitation of 887mm (based on annual average values from 1961 to 1990), with a range from 544mm to 892mm (based on data from 2002 to 2005 summarized at http://ameriflux.ornl.gov/). Because of Nebraska's variable precipitation regime, droughts occur frequently in this region.

The management practices of CSP 3 include non-irrigation; the field receives moisture only from precipitation. A single nitrogen fertilizer application, which is adjusted for residual nitrate measured from soil samples, is made to CSP 3 before planting each spring. The double-crop rotation system, with corn and soybean planted in

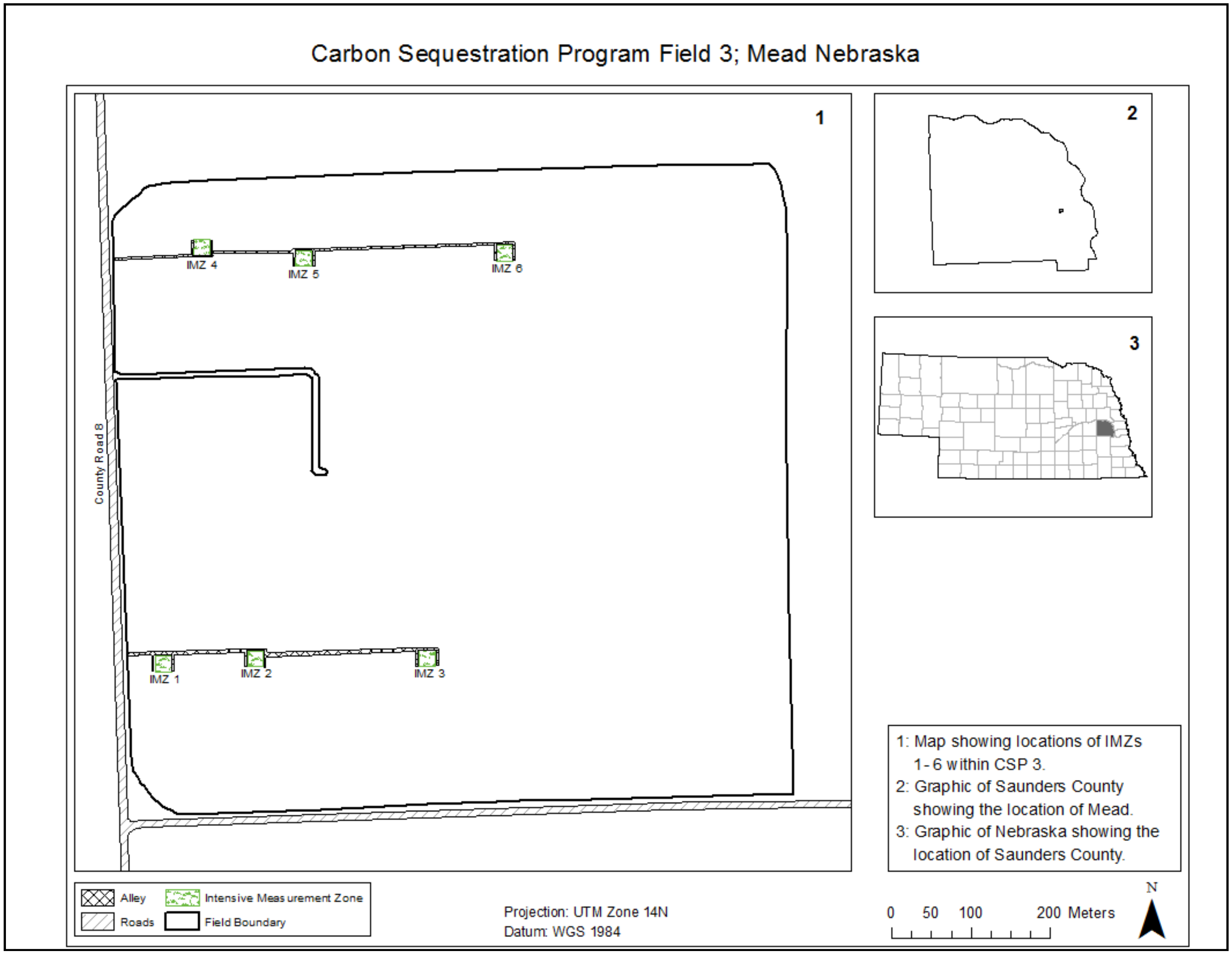


Figure 2.3: CSP 3 and the distribution of IMZs within the field, the location of Mead in Saunders County, and the location of Sunders County in Nebraska.

alternate years, is practiced on this field. The corn cultivar grown in this field is the Pioneer 33B51 while the soybean cultivar is Asgrow 2703 (http://www.epa.gov /sequestration/faq.html).

2.2.2 Data Processing and Analysis

2.2.2.1 Biomass Data

Biomass data used in this study were destructively sampled from intensive measurement zones (IMZ) located within CSP 3. Each IMZ is a 20m x 20m area from which biophysical measurements of the crops are taken. There are six IMZs in CSP 3 which are spatially distributed to represent all soil type occurrences within the field (Figure 2.3). The spatial distribution of the IMZs allows for accurate extrapolation of the measurements taken from these zones to the entire field.

Dry matter samples were collected from sampling plots which are 1-meter long in the six center rows of planter pass two of the IMZ (Figure 2.4). These sampling plots are located so that each is 3-meters away from the next plot on the same row and 1-meter away from a plot on the adjacent row. Samples were collected from one plot every 7 – 10 days, starting from the plots closest to the ‘alley’ and worked systematically to the center of the IMZ. Dry matter samples were collected every 7 – 10 days, resulting in 10 – 12 samplings being carried out each growing season; this leaves a few extra sampling plots available in case of poor stands or any other plant measurement problems.

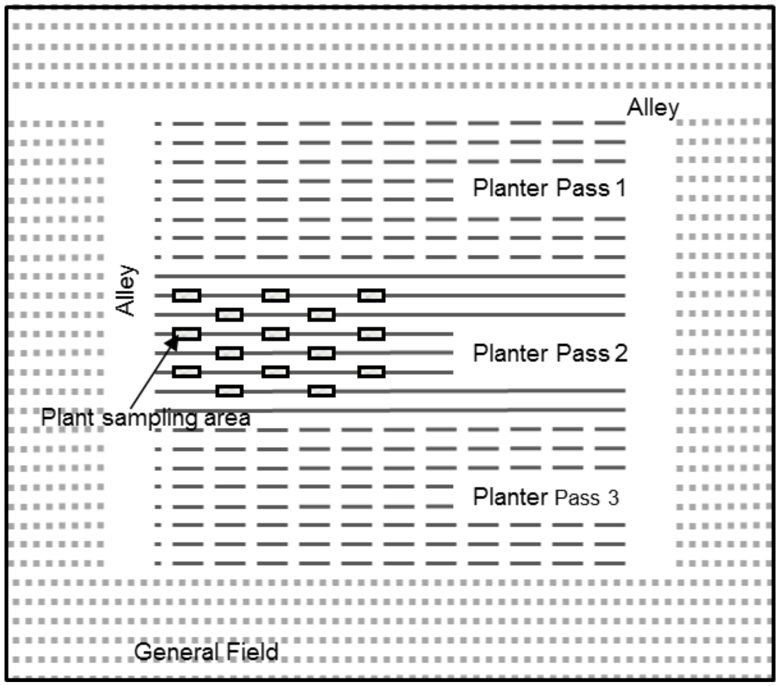


Figure 2.4: An intensive measurement zone within CSP3 showing plant rows, alleys and biomass sampling locations.

During each field-measurement campaign, the height of every plant within the sampled plot was measured, and then cut as close to the ground level as possible with no brace root materials included. After processing in the lab to separate the plant into green leaves, dead leaves, stalk (corn)/stem (soybeans), and reproductive parts, these plant parts were dried at 105°C to allow for dry weight measurement in kg/ha. In this study, biomass measured from the green leaves of the crops after processing was used to represent green biomass.

2.2.2.2 Environmental Variables (Temperature, Precipitation, Soil Moisture)

Daily temperature and precipitation data were collected from the University of Nebraska Lincoln High Plains Regional Climate Center (HPRCC) weather station located at Mead NE. This station (Mead 4 SSE 255362) is approximately 16km south-east of

CSP 3. For this research, temperature and precipitation data were analyzed beginning with the first day of April and ending with the last day on which biomass measurements were taken (generally sometime in September).

Daily soil moisture measurements were acquired from the CSP 3 field. Soil moisture sensors were placed in four locations within the rain-fed field, at depths of 10cm, 25cm, 50cm and 100cm in each location. Hourly readings were taken from each sensor and the average from a 24-hour period represented daily soil moisture from a sensor. For this research, soil moisture data were also analyzed beginning with the first day of April and ending with the last day on which biomass measurements were taken (generally in September).

2.2.2.3 Correlation of Biomass with Growing Degree Days (GDD)

Rates of plant growth responds to air temperature, which, in turn, affects many processes associated with plant growth and phenology (Russelle *et al*., 1984). GDD was derived using the equation:

$$\mathrm{GDD} = \left[\frac{(T_{max} + T_{min})}{2}\right] - \mathrm{B}$$

Where: T_{max} = daily maximum temperature

T_{min} = daily minimum temperature

B = base temperature of 10^{o}C

In the GDD calculations, the following adjustments were made based on the work done by Russelle *et al*., (1984) and Viña *et al*., (2004):

i. Minimum temperatures below 10^oC were set at 10^oC

ii. Maximum temperatures above 30^oC were set at 30^oC.

Based on the methods used by Rundquist *et al*., (2000) and Li *et al*., (2002), daily GDD data were summed up in 14, 28, 56 and 84 day intervals preceding each date on which biomass measurements were collected. Statistical analyses were carried out using simple linear correlations of biomass values from each date in the growing season with its' respective accumulated GDD. The procedure was repeated for each GDD aggregation (i.e. 14, 28, 56, and 84 days) and each of the ten growing seasons.

2.2.2.4 Correlation of Biomass with Precipitation

Daily precipitation data were summed up in 14, 28, 56 and 84 day intervals prior to each date on which biomass measurements were available. Statistical analyses were conducted using simple linear correlations of biomass values for each date of the growing season with its' respective accumulated precipitation data. This procedure was repeated for each precipitation aggregation (i.e. 14, 28, 56, and 84 days) and for each of the ten growing seasons

2.2.2.5 Correlation of Biomass with Soil Moisture

The soil moisture values used in this research were the average of measurements from the sensors located in CSP3at depths of 10cm, 25cm, and 50cm. It was observed that fluctuations in soil moisture readings due to precipitation events reduced steadily with increasing depth, showing minimal changes at 100cm. Because this research looked at the effect of variations in environmental factors, readings from the sensors at 10cm, 25cm and 50cm were used, while data from the sensor at 100cm was excluded.

Daily soil moisture data were also summed up in 14, 28, 56 and 84 day intervals preceeding each date on which biomass measurements were available. Statistical analyses were conducted using simple linear correlations of biomass values for each date of the growing season with the respective accumulated soil moisture data, and the process was repeated for each soil moisture aggregation (i.e. 14, 28, 56, and 84 days) and for each of the ten growing seasons

2.2.2.6 Correlation of Biomass with GDD and Soil Moisture

Statistical analyses were also conducted using simple linear correlations of biomass values for each day in the growing season with the respective accumulated daily GDD and soil moisture data. This procedure was carried out for each GDD and soil moisture lag time (i.e. 14, 28, 56, and 84 days), and each of the ten growing seasons

2.3 Results

This research analyzed the changes in field sampled green biomass of corn and soybeans from ten growing seasons (five for each crop). The seasonal changes in biomass of these crops were also correlated with daily measurements of GDD, precipitation and soil moisture which had been summed up in 14, 28, 56, and 84 day intervals prior to each date on which biomass measurements were taken.

2.3.1 Yearly biomass variations for each crop

The evaluation of corn and soybean growth during each growing season was done by plotting the field measurements of green biomass against the dates on which they were destructively sampled. Figures 2.5(A – E) and 2.6(A – E) show the line charts which illustrate the temporal changes in green biomass of corn and soybeans respectively from 2002 – 2011.

Green biomass growth of corn in the 2003 growing season is represented in Figure 2.5A. Corn seeds were planted on Julian day 132, and noticeable increase in biomass accumulation rate is observed about 39 days afterwards. This chart shows a uni-modal curve with peak biomass of 2,633kg/ha being measured on day 204.

Temporal increase in green biomass of corn during the 2005 growing season is illustrated in Figure 2.5B. Seeds were planted on Julian day 117, and noticeable increase in the rate of biomass accumulation is observed about 43 days later. Of note in this chart is a bi-modal curve with two peaks; the maximum biomass of 2,665kg/ha is observed in the second peak on day 229.

Green biomass growth of corn in the 2007 growing season is shown in Figure 2.5C. Corn seeds were planted on Julian day 125, and noticeable increase in biomass accumulation rate is observed about 38 days afterwards. This chart shows a distinct bell-shaped curve with peak biomass of 2,603kg/ha on day 213.

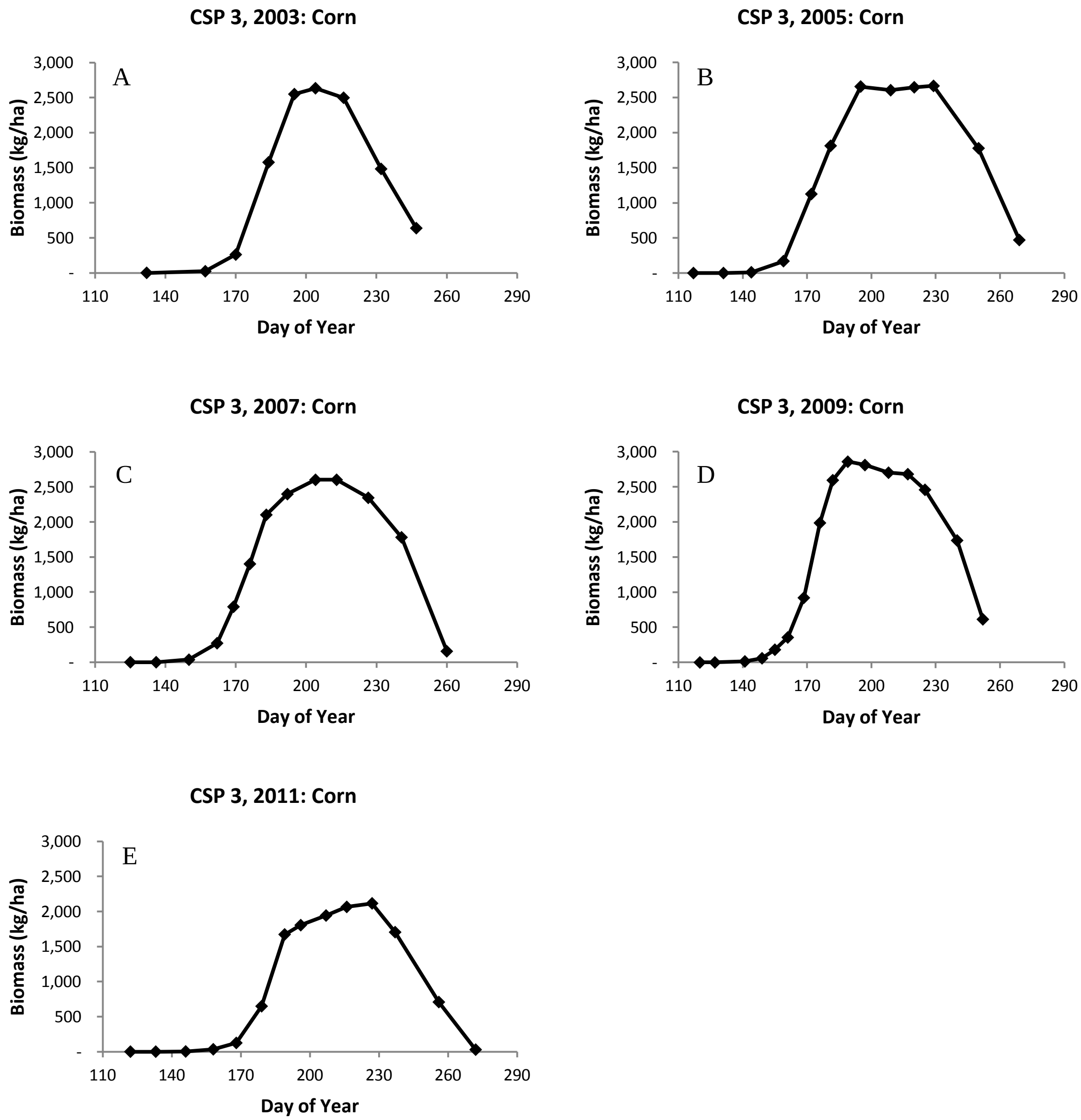


Figure 2.5: Charts showing temporal change in green biomass of corn in CSP 3 during each of the five growing seasons studied (2003, 2005, 2007, 2009 and 2011).

Temporal increase in green biomass of corn during the 2009 growing season is shown in Figure 2.5D. Seeds were planted on Julian day 120, and noticeable increase in the rate of biomass accumulation is observed about 42 days later. This chart has a uni-modal curve with the maximum biomass of 2,665kg/ha measured on day 189.

Temporal increase in green biomass of corn during the 2011 growing season is displayed in Figure 2.5E. Seeds were planted on Julian day 122, and noticeable increase in the rate of biomass accumulation is observed about 47 days later. This chart also has a uni-modal curve with the maximum biomass of 2,116kg/ha measured on day 227.

Green biomass growth of soybeans during the 2002 growing season is represented in Figure 2.6A. Soybean seeds were planted on Julian day 141, and noticeable increase in biomass accumulation rate is observed about 36 days afterwards. This chart shows a right-skewed uni-modal curve with peak biomass of 1,445kg/ha being measured on day 221.

Temporal increase in green biomass of soybeans during the 2004 growing season is shown in Figure 2.6B. Seeds were planted on Julian day 155, and noticeable increase in the rate of biomass accumulation is observed about 26 days afterward. This chart also has a uni-modal curve skewed to the right with the maximum biomass of 1,702kg/ha measured on day 232. Of note is the rapid drop in green biomass during the last ten days of the growing season.

Temporal increase in green biomass of soybeans during the 2006 growing season is displayed in Figure 2.6C. Soybean seeds were planted on Julian day 131, and noticeable increase in the rate of biomass accumulation is observed about 42 days later. This chart also has a right-skewed uni-modal curve with the maximum biomass of 1,889kg/ha measured on day 222.

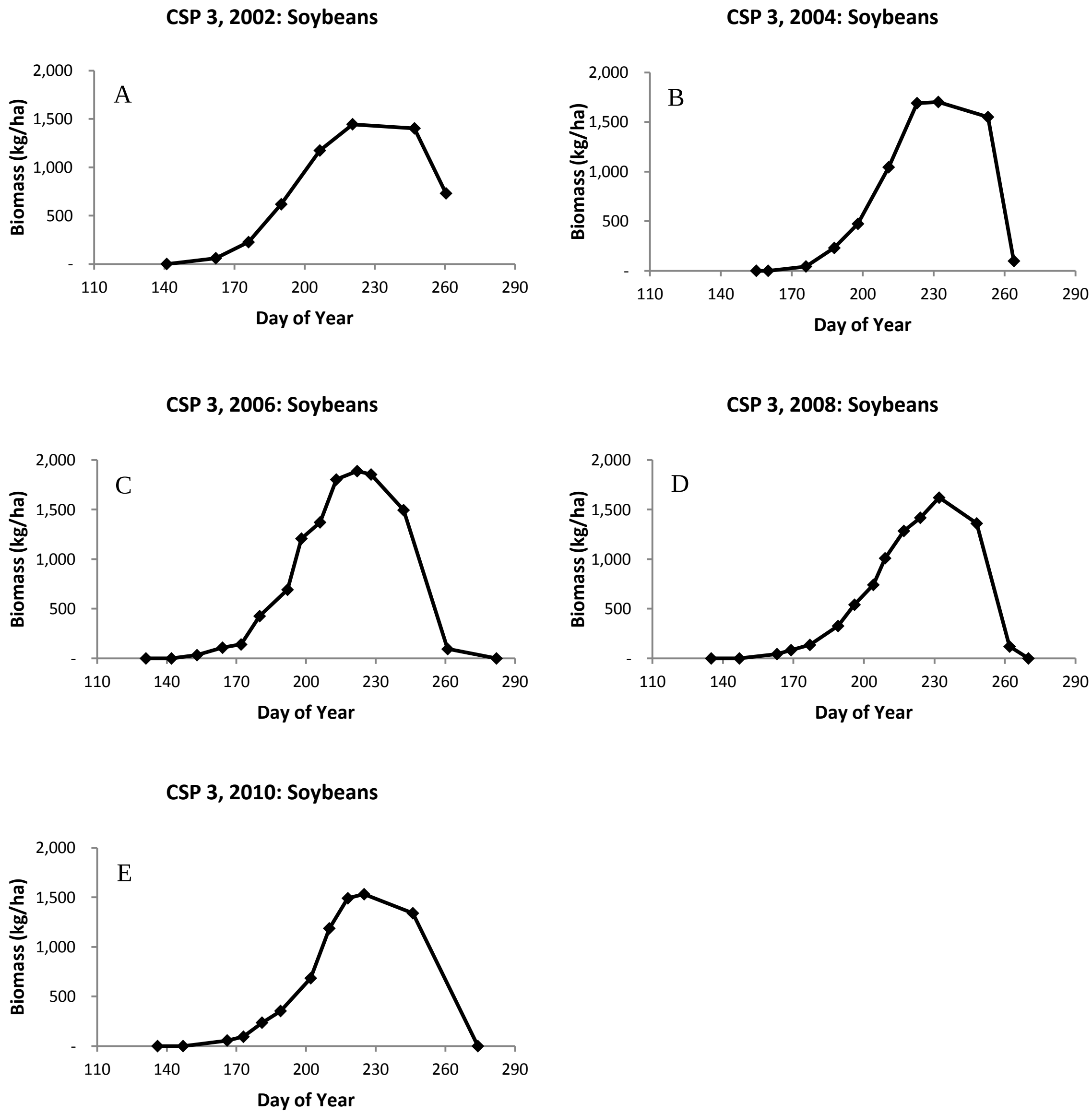


Figure 2.6: Charts showing temporal change in green biomass of soybeans in CSP 3 during each of the five growing seasons studied (2002, 2004, 2006, 2008 and 2010).

Green biomass growth of soybeans during the 2008 growing season is represented in Figure 2.6D. Soybean seeds were planted on Julian day 131, and noticeable increase in biomass accumulation rate is observed about 42 days afterwards. This chart shows a right-skewed uni-modal curve with peak biomass of 1,889kg/ha measured on day 232.

Green biomass growth of soybeans during the 2010 growing season is displayed in Figure 2.6E. Seeds were planted on Julian day 136, and noticeable increase in biomass accumulation rate is observed about 38 days later. This chart also shows a right-skewed uni-modal curve with peak biomass of 1,531kg/ha which was measured on day 225.

Growing season green biomass values of corn and soybeans obtained from the decade of study showed variations in the accumulation of biomass for each year. The growing season biomass values for all five years of study for corn are shown in Figure 2.7 while soybeans biomass for the remaining five years are represented in Figure 2.8. During the study period, noticeable differences in the peak biomass of both crops can be seen. The average peak biomass of corn for the study years was 2,575kg/ha while that of soybeans was 1,637kg/ha.

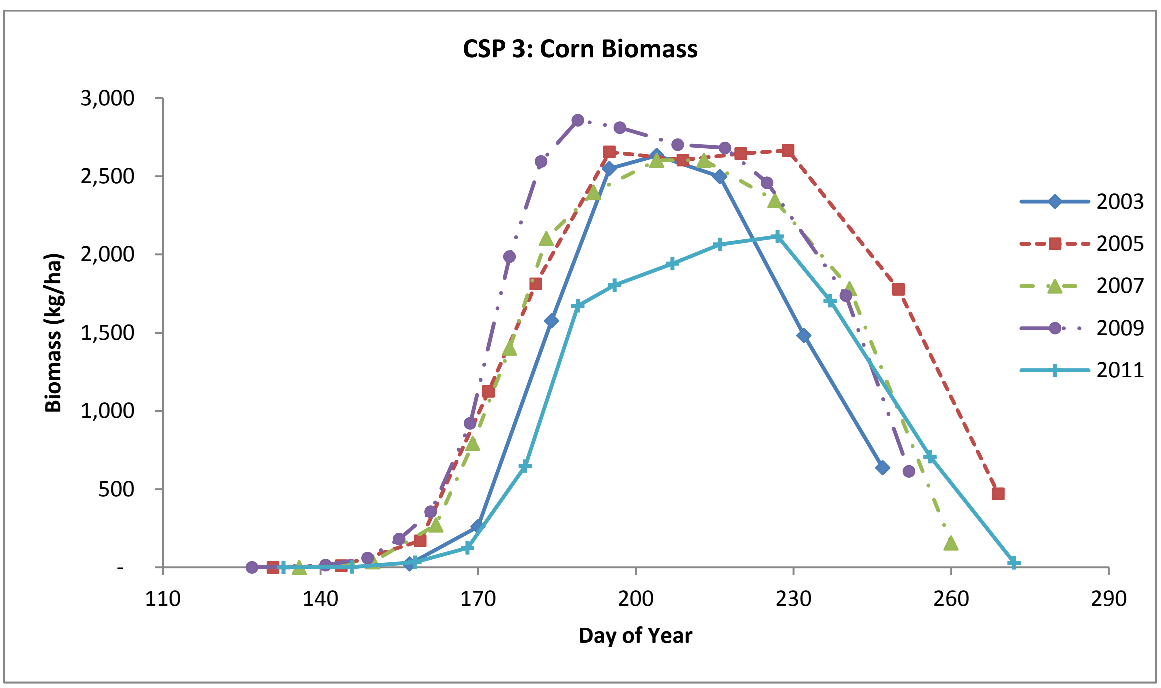


Figure 2.7: Green biomass values of corn from all five growing seasons studied.

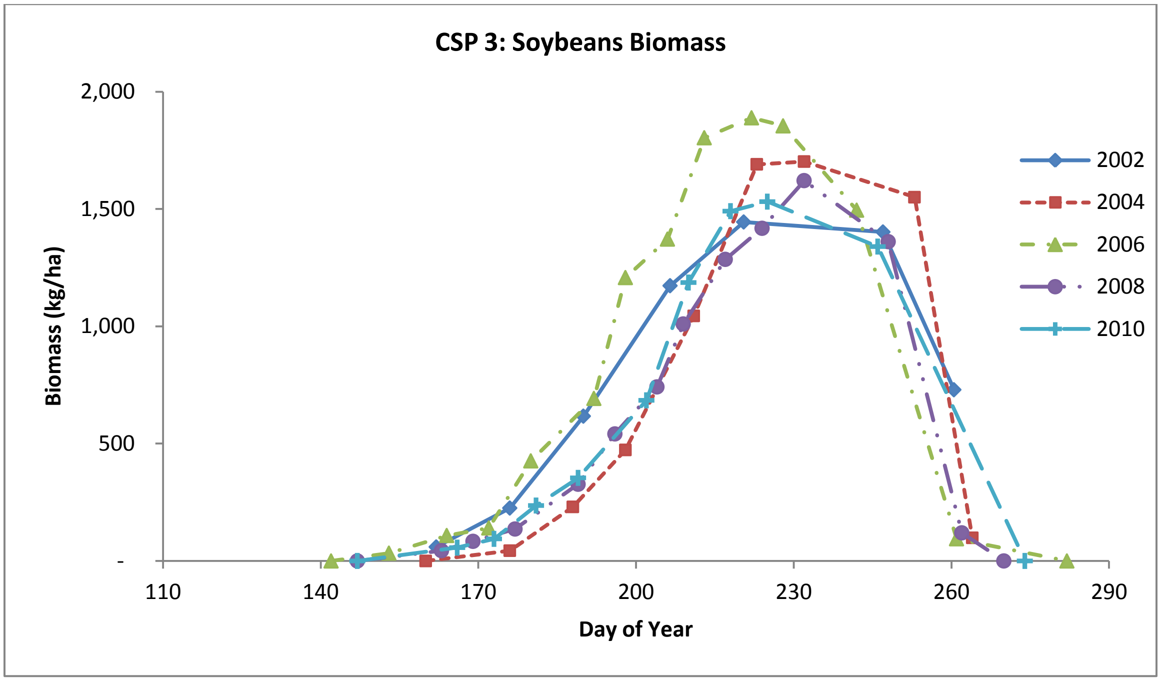


Figure 2.8: Green biomass values of soybeans from all five growing seasons studied.

2.3.2 Yearly variations of Environmental Variables

Charts showing daily GDD values for each of the ten growing seasons are represented in Figure 2.9 (A – J). From the charts, the growing season (i.e., the period from April to September) with the highest total GDD occurred in 2002 with a total of 2368°C while the lowest total GDD was in 2009 with 2036.28°C.

Charts showing daily precipitation and soil moisture values for each of the ten growing seasons are represented in Figure 2.10 (A – J). From the charts, the 'driest' growing season (i.e., the period from April to September) occurred in 2005 with a total of 15.55" while the 'wettest' was 2010 with 32.08". As can be seen in the charts, there is a direct relationship between precipitation and soil moisture in this rain-fed field. Occurrence of precipitation events results in a clearly visible peak in soil moisture content. This peak in soil moisture starts to decline with time, and with a longer interval between precipitation events the reduction in soil moisture content becomes pronounced.

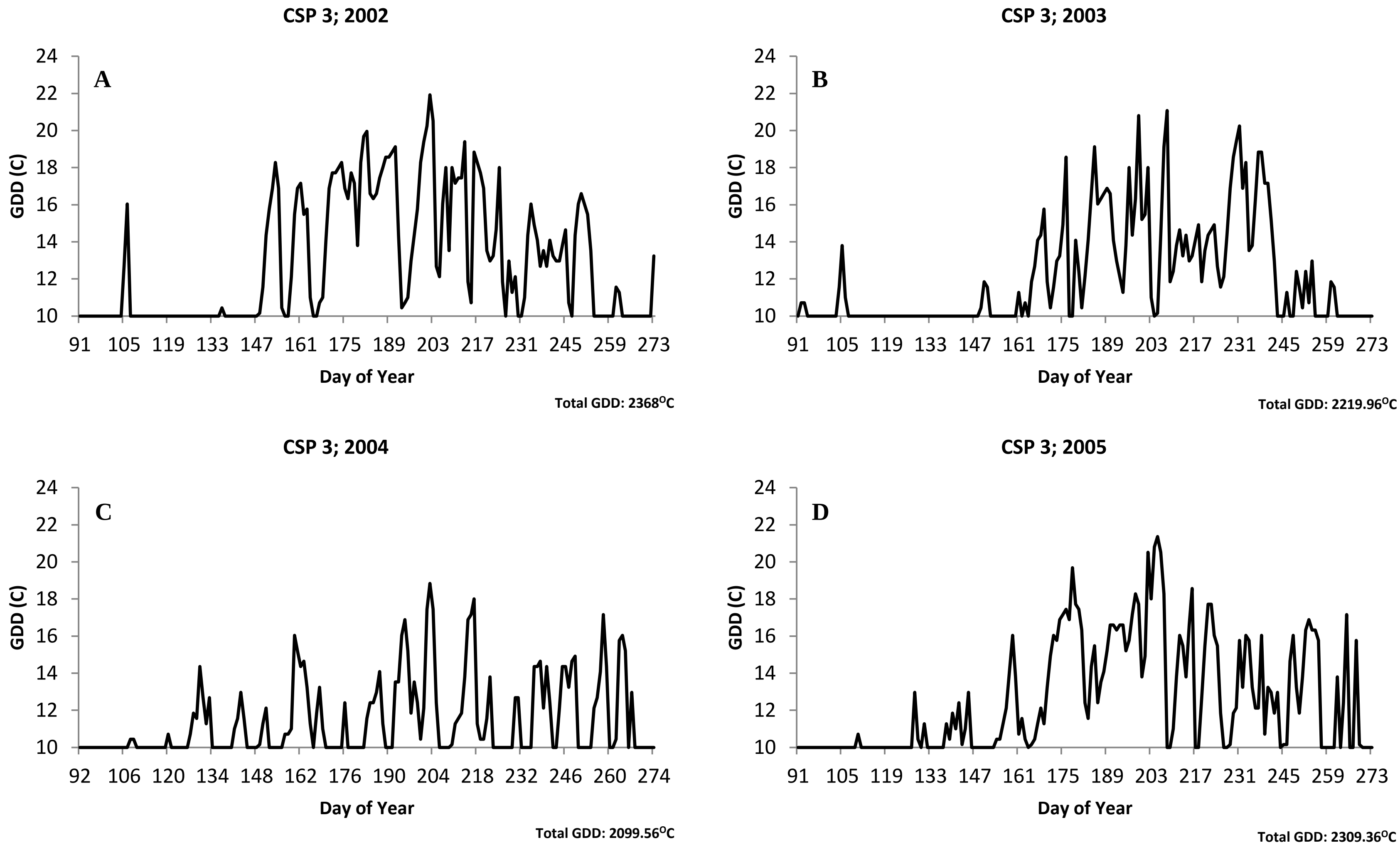


Figure 2.9 (A – D): Charts showing the growing degree days calculated for the 2002 to 2004 growing seasons from April 1st to September 30th. GDD was derived using equation 1.

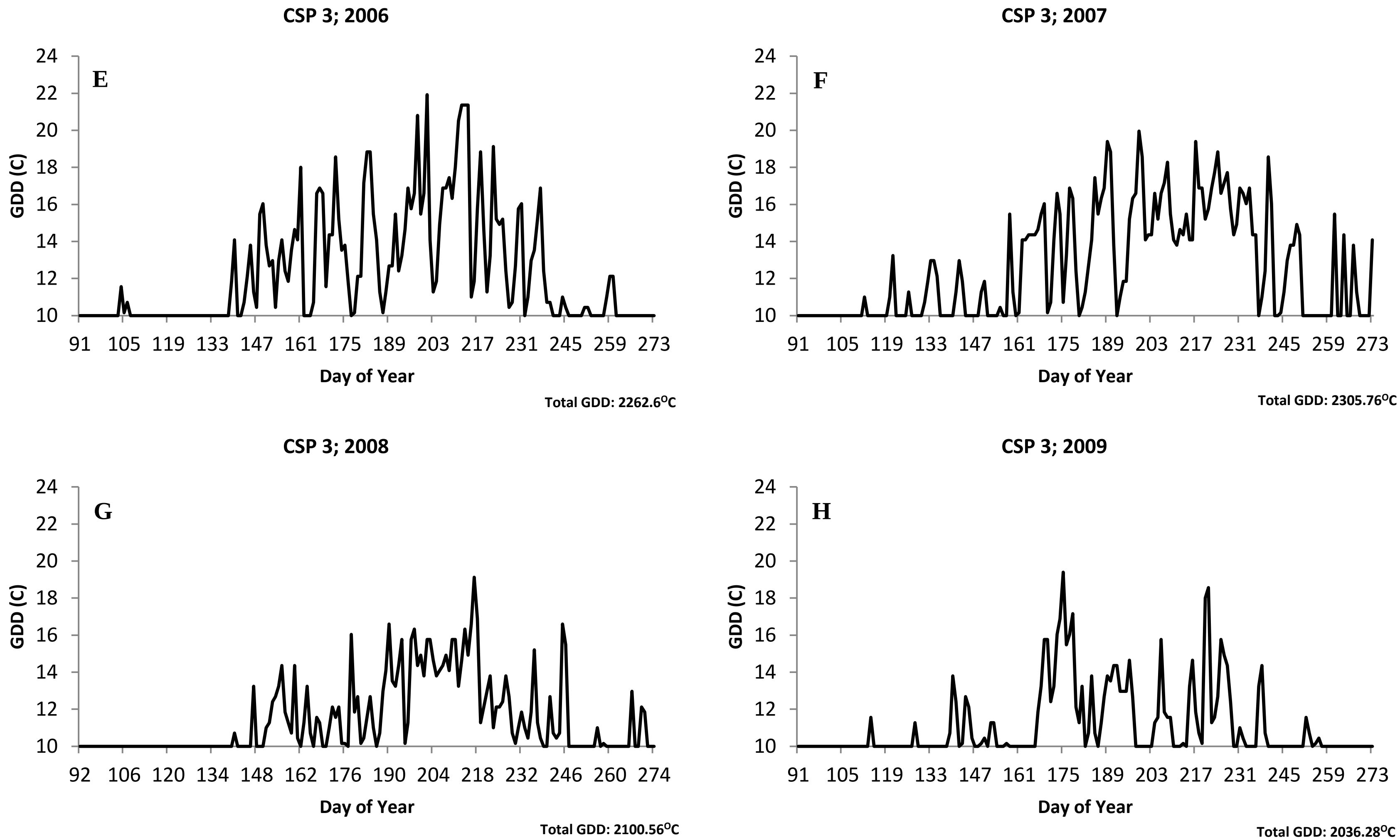
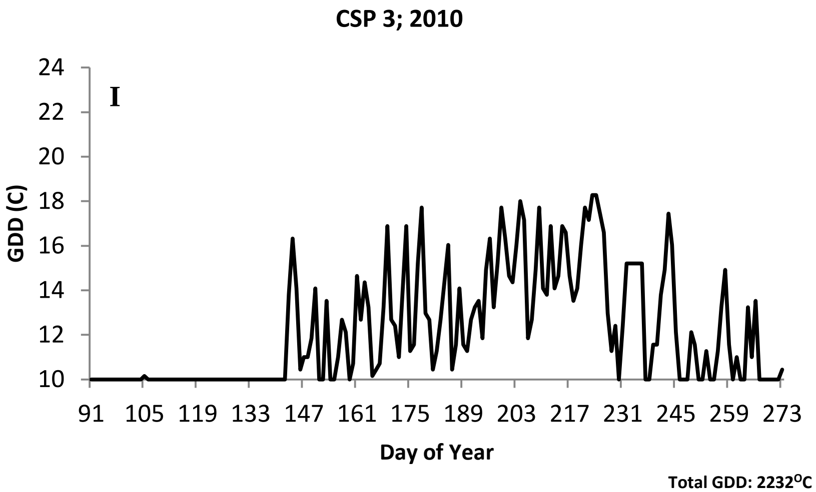


Figure 2-9 (E – H): Charts showing the growing degree days calculated for the 2005 to 2008 growing seasons from April 1st to September 30th. GDD was derived using equation 1.



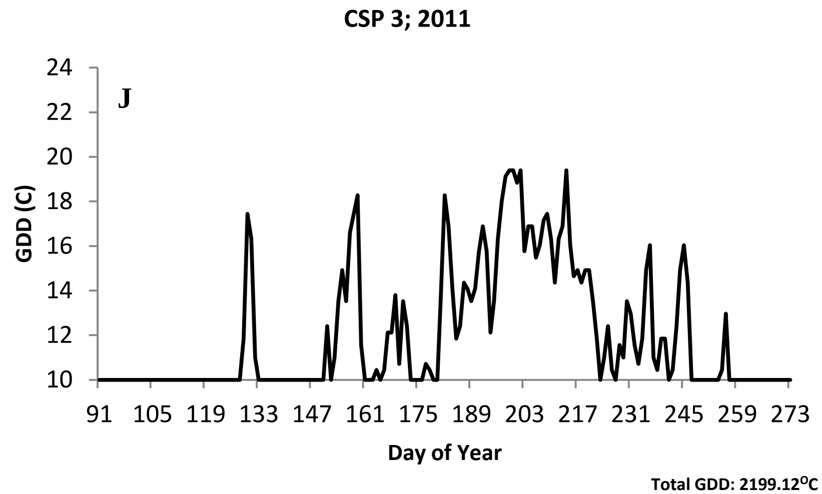


Figure 2-9 (I – J): Charts showing the growing degree days calculated for the 2009 and 2010 growing seasons from April 1st to September 30th. GDD was derived using equation 1.

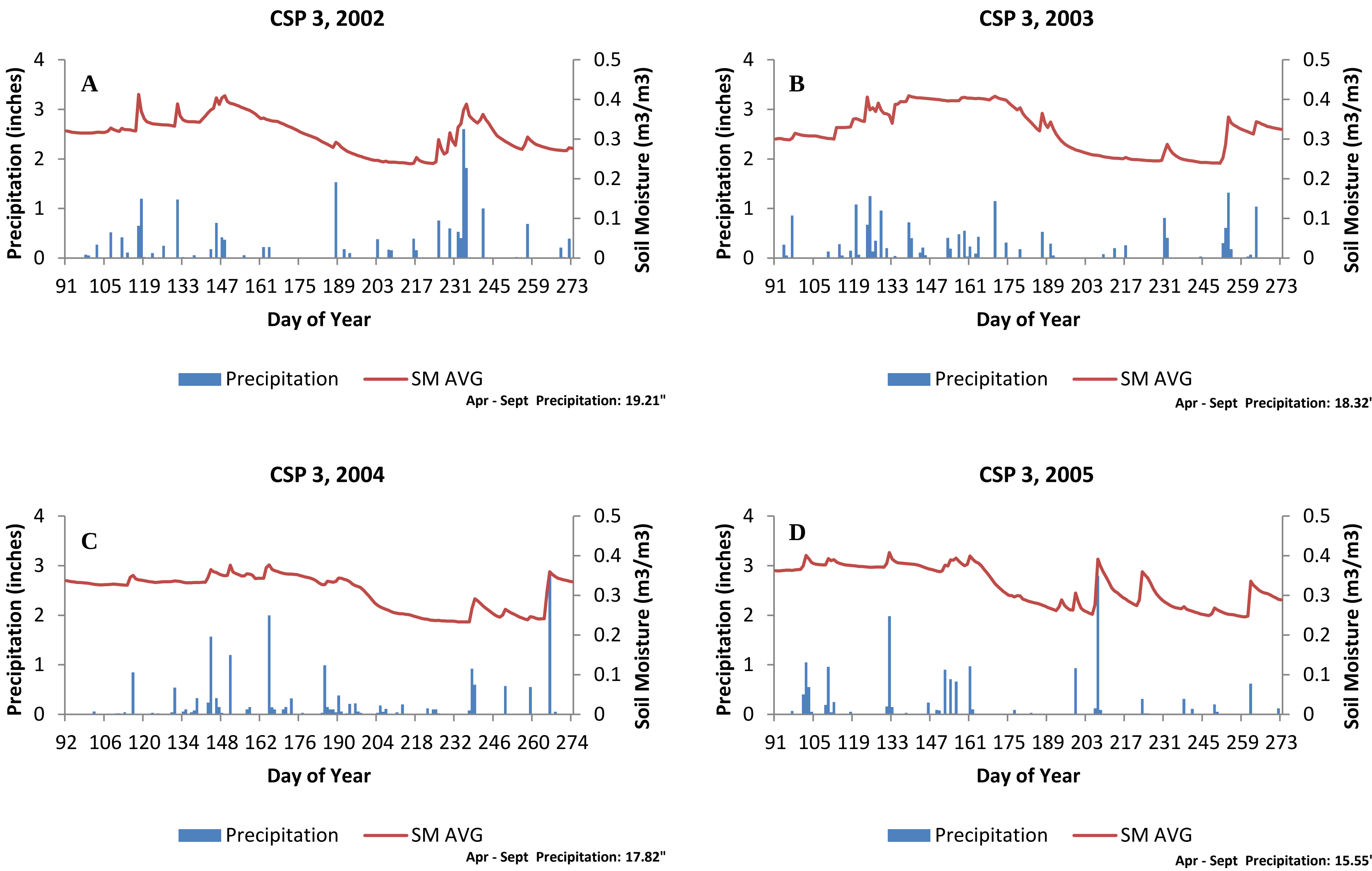


Figure 2.10 (A – D): Charts showing the precipitation and soil moisture values for the 2002 to 2004 growing seasons from April 1st to September 30th.

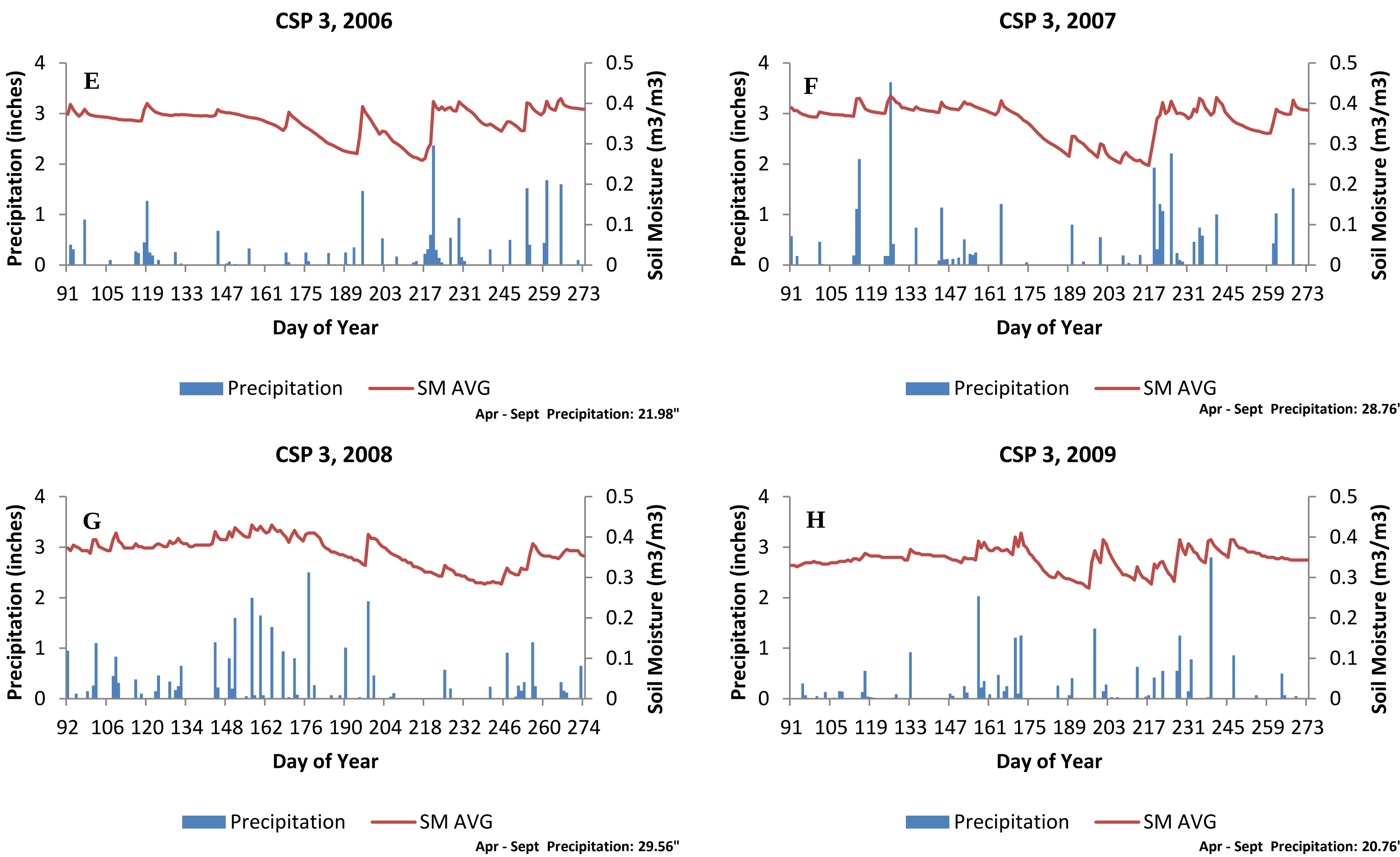
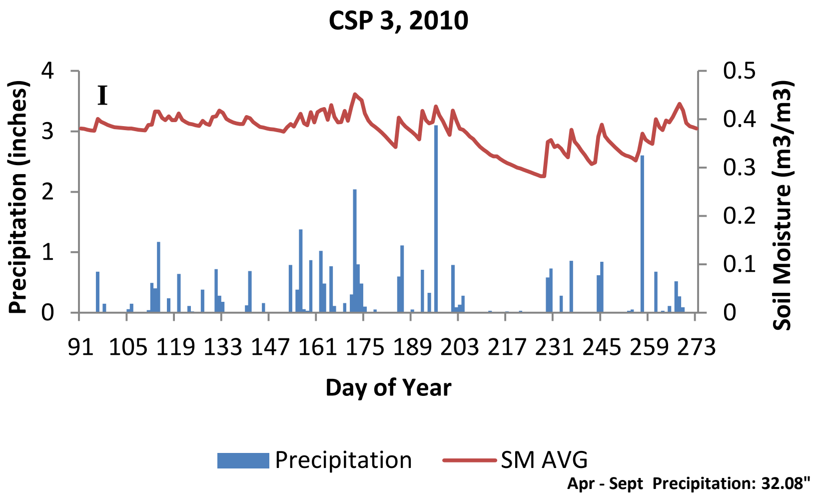


Figure 2-10 (E – H): Charts showing the precipitation and soil moisture values for the 2005 to 2008 growing seasons from April 1st to September 30th.



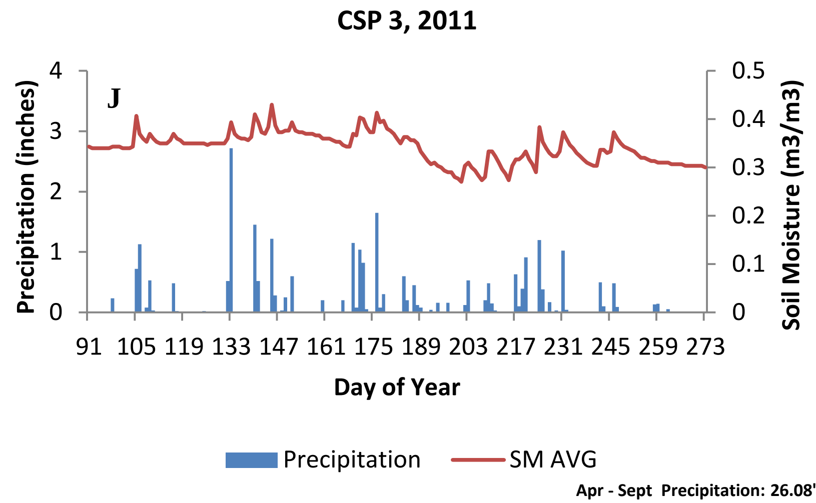


Figure 2-10 (I – J): Charts showing the precipitation and soil moisture values for the 2009 and 2010 growing seasons from April 1st to September 30th.

2.3.3 Correlation of Biomass with Individual Environmental Variables

The investigation into the relationships between green biomass and the environmental variables of interest (i.e. GDD, precipitation and soil moisture) was done by determining the Pearson's correlation coefficient (r) from simple linear and multiple regressions. Using r-value to identify the correlation between biomass and environmental factors would showcase the relationships as either positive or negative. Only correlations which were significant at $\rho = 0.05$ were analyzed in this research.

The correlation coefficients for the growing season biomass of corn with GDD for each of the study years are represented in Figure 2.11. Of note are the generally good r values for lag times of 14, 28 and 56 days; these range from 0.42 – 0.91 (Table 2.1). The correlation of biomass with 84-day GDD lag has negative and very low positive values.

A graph which shows r values of soybeans biomass and GDD for the five study years is displayed in Figure 2.11. All of the correlations are positive ranging from 0.15 to 0.96 (Table 2.2), with the lowest r values observed in 14-day lags of the 2002 and 2004 growing seasons.

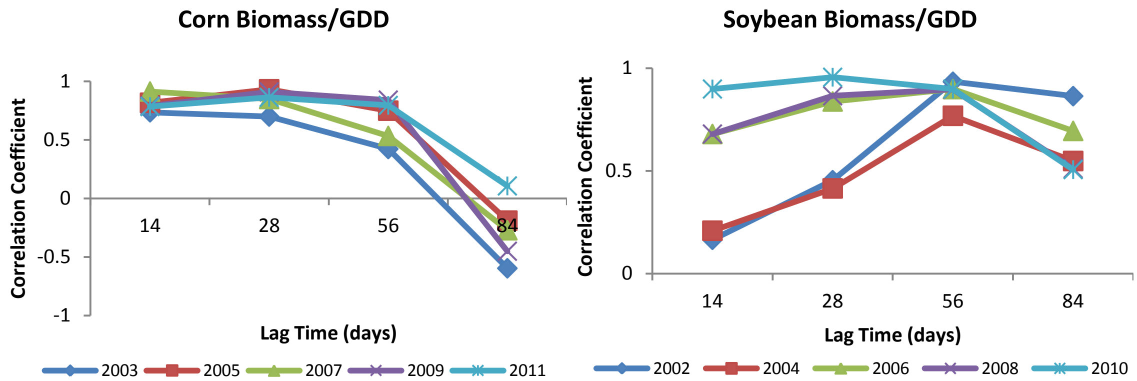


Figure 2.11: Pearson's correlation coefficient (r) values for the relationships of growing season green biomass of corn and soybeans with accumulated GDD. GDD was lagged in periods of 14, 28, 56 and 84 days prior to each biomass measurement.

Table 2.1: Pearson's correlation coefficient (r) values of corn biomass versus accumulated growing degree days from the five years of study i.e. 2003, 2005, 2007, 2009 and 2011.

Lag Time (days)	Corn Biomass/Accumulated GDD				
	2003	**2005**	**2007**	**2009**	**2011**
14	0.74	0.82	0.91	0.79	0.78
28	0.70	0.93	0.85	0.91	0.86
56	0.42	0.75	0.53	0.84	0.79
84	-0.60	-0.20	-0.27	-0.45	0.11

Table 2.2: Pearson's correlation coefficient (r) values of soybean biomass versus accumulated growing degree days from the five years of study i.e. 2002, 2004, 2006, 2008 and 2010.

Lag Time (days)	Soybean Biomass/GDD				
	2002	**2004**	**2006**	**2008**	**2010**
14	0.16	0.21	0.68	0.68	0.90
28	0.45	0.41	0.84	0.87	0.96
56	0.93	0.77	0.90	0.90	0.90
84	0.86	0.55	0.70	0.51	0.51

2.3.3.1 Correlation of biomass and precipitation

The correlation coefficients for the growing season biomass of corn with precipitation for each of the study years are represented in Figure 2.12. The r values for all lag times do not show any increasing or decreasing trend; they range from -0.81 to 0.65 (Table 2.3) with high and low positive and negative values distributed among the years and lag times in a seemingly random manner.

A graph which shows r values of soybeans biomass and precipitation for the five study years is displayed in Figure 2.12. The correlations are both positive and negative ranging from -0.87 to 0.65 (Table 2.4). These positive and negative r values do not exhibit any general positive or negative trend in either the lag days or growing seasons.

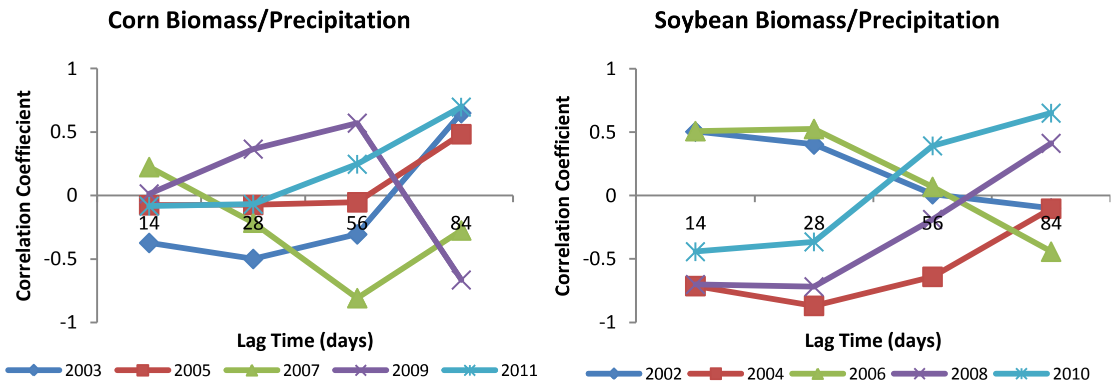


Figure 2.12: Pearson's correlation coefficient (r) values for the relationships of growing season green biomass of corn and soybeans with accumulated daily precipitation. Precipitation was lagged in periods of 14, 28, 56 and 84 days prior to each biomass measurement.

Table 2.3: Pearson's correlation coefficient (r) values of corn biomass versus accumulated precipitation from the five years of study i.e. 2003, 2005, 2007, 2009 and 2011.

Lag Time (days)	**Corn Biomass/Precipitation**				
	2003	**2005**	**2007**	**2009**	**2011**
14	-0.37	-0.08	0.22	0.01	-0.08
28	-0.50	-0.07	-0.21	0.37	-0.07
56	-0.30	-0.05	-0.81	0.57	0.25
84	0.65	0.48	-0.27	-0.66	0.70

Table 2.4: Pearson's correlation coefficient (r) values of soybean biomass versus accumulated precipitation from the five years of study i.e. 2002, 2004, 2006, 2008 and 2010.

Lag Time (days)	**Soybean Biomass/Precipitation**				
	2002	**2004**	**2006**	**2008**	**2010**
14	0.51	-0.70	0.51	-0.70	-0.44
28	0.40	-0.87	0.53	-0.72	-0.36
56	0.01	-0.64	0.07	-0.19	0.39
84	-0.10	-0.10	-0.44	0.41	0.65

2.3.3.2 Correlation of biomass with soil moisture

The correlation coefficients for the growing season biomass of corn with soil moisture for the five study years are represented in Figure 2.13. The r values for all lag times show a general increasing trend as the lag days increase; the r values range from -0.8 – 0.82 (Table 2.5).

A graph which shows r values of soybeans biomass and soil moisture for each of the study years is displayed in Figure 2.13. The correlations also show a general increasing trend for lag times, with values ranging from -0.90 to 0.20 (Table 2.6).

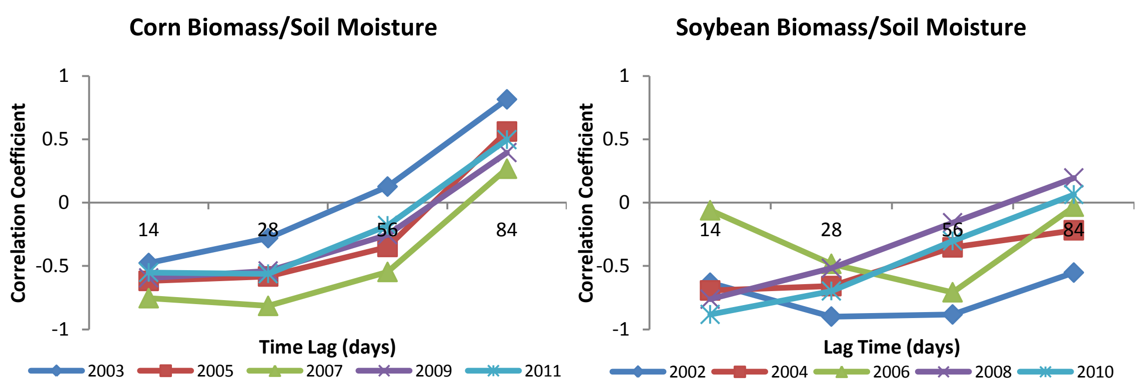


Figure 2.13: Pearson's correlation coefficient (r) values for the relationships of growing season green biomass of corn and soybeans with accumulated soil moisture. Soil moisture was lagged in periods of 14, 28, 56 and 84 days prior to each biomass measurement.

Table 2.5: Pearson's correlation coefficient (r) values of corn biomass versus accumulated soil moisture from the five years of study i.e. 2003, 2005, 2007, 2009 and 2011.

Lag Time (days)	**Corn Biomass/Soil Moisture**				
	2003	**2005**	**2007**	**2009**	**2011**
14	-0.48	-0.62	-0.75	-0.59	-0.55
28	-0.28	-0.58	-0.82	-0.54	-0.56
56	0.13	-0.35	-0.55	-0.26	-0.18
84	0.82	0.56	0.27	0.40	0.50

Table 2.6: Pearson's correlation coefficient (r) values of soybean biomass versus accumulated soil moisture from the five years of study i.e. 2002, 2004, 2006, 2008 and 2010.

Lag Time (days)	**Soybean Biomass/Soil Moisture**				
	2002	**2004**	**2006**	**2008**	**2010**
14	-0.63	-0.69	-0.06	-0.76	-0.88
28	-0.90	-0.66	-0.48	-0.52	-0.70
56	-0.88	-0.35	-0.71	-0.16	-0.30
84	-0.55	-0.22	-0.03	0.20	0.06

2.3.3.3 Correlation of biomass with GDD and soil moisture

To examine any relationships between the combined effect of multiple environmental variables on green biomass, GDD and soil moisture were regressed against biomass. These two variables were used because each showed general decreasing and increasing correlation trends respectively with increasing lag times for both crop types.

The multiple correlation coefficients of green biomass of corn regressed against GDD and soil moisture has very high values ranging from 0.83 to 0.99 (Table 2.7). The chart of these multiple r against lag times for all of the five years shows a clear increase in correlations as lag times get longer (Figure 2.14).

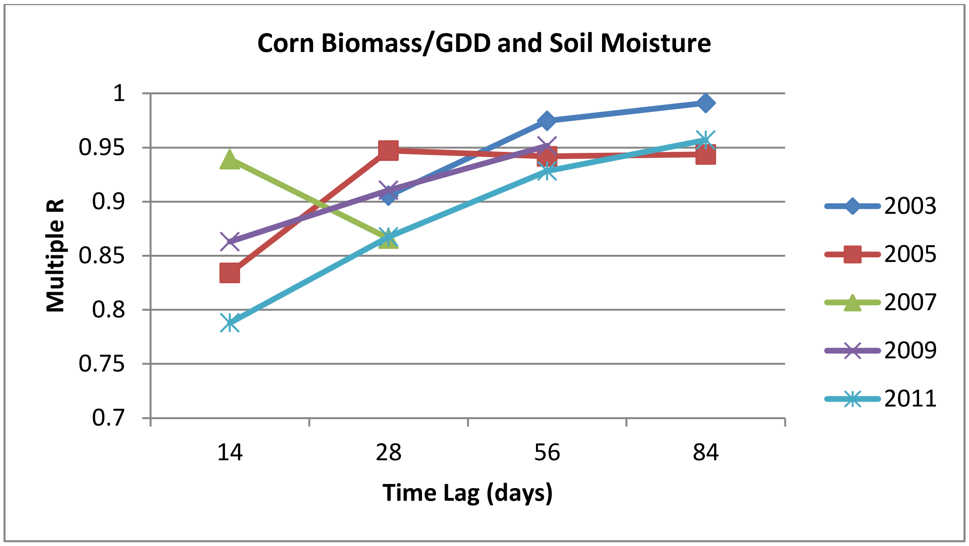


Figure 2.14: Multiple correlation coefficient (multiple r) values for the relationships of growing season green biomass of corn and soybeans with accumulated GDD and soil moisture. GDD and soil moisture values were lagged in periods of 14, 28, 56 and 84 days prior to each biomass measurement.

Table 2.7: Multiple correlation coefficient (multiple r) values of corn biomass versus both accumulated growing degree days and soil moisture from the five years of study i.e. 2003, 2005, 2007, 2009 and 2011. Values which are not significant at ρ = 0.05 are indicated by *.

Lag Time (days)	Corn/GDD and Soil Moisture				
	2003	**2005**	**2007**	**2009**	**2011**
14	0.79*	0.83	0.94	0.86	0.79
28	0.91	0.95	0.87	0.91	0.87
56	0.97	0.94	0.55*	0.95	0.93
84	0.99	0.94	0.27*	0.48*	0.96

The multiple correlation coefficients of soybeans green biomass regressed against GDD and soil moisture has very high values ranging from 0.74 to 1.0 (Table 2.8). The chart of these multiple r against lag times for all five years shows increase in correlations as lag times get longer for three years (2002, 2004 and 2006) while the latter two years have peak correlations at either 28 or 56 day lags (Figure 2.15). Equations of best fit for the relationships between both crops and both environmental variables are represented in Appendix 1.

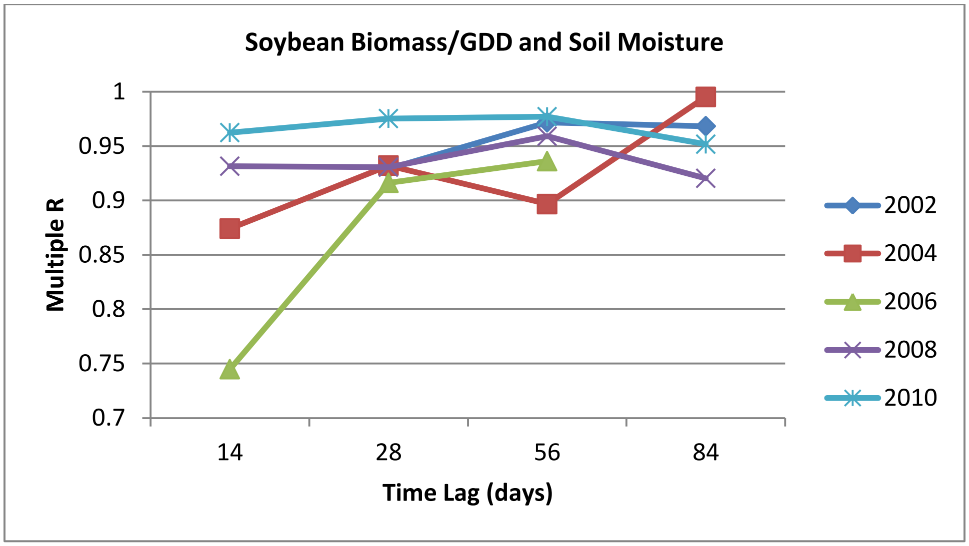


Figure 2.15: Multiple correlation coefficient (multiple r) values for the relationships of growing season green biomass of corn and soybeans with accumulated GDD and soil moisture. GDD and soil moisture values were lagged in periods of 14, 28, 56 and 84 days prior to each biomass measurement.

Table 2.8: Multiple correlation coefficient (multiple r) values of soybean biomass versus both accumulated growing degree days and soil moisture from the five years of study i.e. 2002, 2004, 2006, 2008 and 2010. Values which are not significant at ρ = 0.05 are indicated by *.

Time Lag (days)	Soybeans/GDD and Soil Moisture				
	2002	**2004**	**2006**	**2008**	**2010**
14	0.64*	0.87	0.74	0.93	0.96
28	0.93	0.93	0.92	0.93	0.98
56	0.97	0.90	0.94	0.96	0.98
84	0.97	1.00	0.74*	0.92	0.95

2.4 Discussion

Temporal biomass curves for each crop show slight variations in each growing season. These variations may be attributed to changes in environmental factors such as temperature, precipitation, and soil moisture which also showed variation from year to year.

The results obtained from the correlation of green biomass and accumulated GDD were good overall. The r values varied from -0.60 in the 84-day lag period to 0.91 in the

14-day lag. From each growing season, r values were highest for corn during the 28-day lag period while for soybeans this occurred during the 56-day lag. This can be attributed to differences in phenology of both crops; corn plants displayed a bell shaped curve with gradual increase and decrease in green biomass while soybeans reached peak biomass later in the season (average of two weeks) with rapid decline during senescence. The earlier occurrence of senescence in corn caused reduction in correlation with ever-increasing accumulated GDD at longer lag times to start at 56-days while in soybeans the later occurrence of senescence caused the reduction in r to occur at 84-day lag periods.

With regard to the correlation of green biomass with accumulated precipitation for the study period, r values showed no observable pattern. R values varied from -0.70 to 0.87, but the negative and positive correlations were mixed randomly across the increasing lag times as a result of the erratic nature of precipitation events. Periods of consistent rainfall during the biomass accumulation period in the growing season would result in positive correlations while dry spells would result in negative correlations. However, during senescence this relationship would be reversed. These results differ from those achieved by previous research into the relationships between NDVI and precipitation. These differences could have stemmed from the higher spatial and temporal scale at which this research was carried out compared to previous studies. The field-scale biomass and daily precipitation values revealed a lot more variation in data which might have caused the random distribution of r values across changing lag periods.

Correlation of green biomass and accumulated soil moisture were also good overall. This environmental variable, when regressed against biomass, showed increasing r values as the lag time increased. The r values varied from -0.90 to 0.82 with the lowest correlations occurring at lag times of 14 days and highest correlations at 84 day lags. The temporal soil moisture charts show general decrease in soil moisture content as rapid biomass accumulation starts to occur and an increase as senescence sets in. This may be as a result of increase in leaf area of the plants which causes increased transpiration and contributes to soil moisture loss via evaporation and transpiration (Morrison and Gifford, 1984).

Of note is the biomass accumulation of corn during the 2005 growing season. The temporal curve is bimodal which, in comparison with all other curves acquired during this study, is abnormal. The decrease in biomass during the peak of the growing season may be related to the reduction in soil moisture due to a dry spell which lasted for 39 days (Figure 2.10). With minimal rainfall, soil moisture levels dropped substantially during the period of rapid biomass accumulation causing a delay in growth. With the soil moisture replenishment from two major precipitation events, biomass growth resumed till peak biomass was achieved. This occurrence echoes the findings of Denmead (1960) in which soil moisture stress delayed enlargement of plant parts in corn but recommenced when the plants were supplied ample water.

The correlation of green biomass with the combination of accumulated GDD and soil moisture showed positive multiple r values for all lag periods. These multiple r values varied from 0.74 to 1.0. In majority of the cases, the multiple r values were higher than the individual r values obtained for each environmental variable. These results show that the combined effects of temperature and moisture have a very strong influence on the growth rate of the crops studied. The results also agree with the statements by Eastin and Sullivan (1984) that the effects of environmental variables on plant growth are difficult to separate, and phenomena like temperature and water stress go hand in hand.

2.5 Conclusion

Numerous authors have focused on analyzing plant growth and the impact which environmental variables have on the seasonal patterns and variations in dry matter accumulation, but minimal research has been carried out at field scale using measured biomass values over a long period of time. This research focused on studying changes in green biomass of corn and soybeans measured destructively from a rain-fed field across ten growing seasons (2002 – 2011). Also, the growth and senescence of yearly measured biomass were correlated with accumulated GDD, precipitation and soil moistures using lag times of 14, 28, 56 and 84 days.

Analysis of the growing season biomass of both crops showed slight variations from year to year which indicate the effect of environmental variables on the growth of the crops. Also, there was a noticeable difference in the peak biomass of both crops, with corn having higher values than soybean. Temporal growth curves showed corn having a bell-shape with peak occurring typically at the middle of its growth cycle. Soybean on the other hand had a right-skewed curve in each year studied, with a green-up rate which is much slower than the senescence rate.

The relationship of biomass with individual environmental factors including GDD, precipitation and soil moisture was done using accumulated lag times of 14, 28, 56 and 84 days. Biomass showed decreasing correlation values as lag times increased in GDD, while the relationship was reversed in the case of soil moisture. Biomass versus precipitation, on the other hand, had correlations which showed no trends.

Examination of the relationship between biomass and the variables which showed specific trends i.e. GDD and soil moisture was done by determining the multiple correlation coefficients of accumulated data in lag periods of 14, 28, 56 and 84 days as well. The output correlation values from the combined environmental variables were noticeably higher than those observed in the individual regressions.

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Appendix 1: Equations of Best Fit for Multiple Regressions of Corn and Soybean Biomass against Accumulated Growing Degree Days and Soil Moisture

2002	
14	Biomass = 3779 - 3.14GDD - 541.31SM
28	Biomass = 6664.82 - 3.57GDD - 504.56SM
56	Biomass = 3.40GDD - 114.94SM + 191.10
84	Biomass = 6.88GDD + 202.38SM - 12420.4

2003	
14	Biomass = 51.72GDD + 642.11SM - 11159.2
28	Biomass = 31.71GDD + 630.61SM - 16122.5
56	Biomass = 18.46GDD + 625.14SM - 23538.5
84	Biomass = 13.0GDD + 788.21SM - 34750.6

2004	
14	Biomass = 0.16GDD - 40.19SM + 354.61
28	Biomass = 0.02GDD - 22.06SM + 396.29
56	Biomass = 0.36GDD - 7.45SM + 23.34
84	Biomass = 0.35GDD - 6.67SM + 56.18

2005	
14	Biomass = 25.11GDD - 370.55SM - 1470.05
28	Biomass = 20.94GDD + 228.37SM - 8303.65
56	Biomass = 16.36GDD + 513.55SM - 19766.2
84	Biomass = 15.04GDD + 714.89SM - 34321.8

2006	
14	Biomass = 20.05GDD - 204.94SM -2016.24
28	Biomass = 11.78GDD - 242.66SM - 1302.48
56	Biomass = 14941.01 - 0.63GDD - 701.42SM
84	Biomass = 18.02GDD + 1389.22SM - 59086.9

2007	
14	Biomass = 26.13GDD - 493.41SM -1088.73
28	Biomass = 10.41GDD - 297.57SM + 504.50
56	Biomass + 10.41GDD - 297.57SM + 504.50
84	Biomass = 1.67SM - 1.86GDD + 3895.93

2008	
14	Biomass = 12.63GDD - 736.27SM + 2212.97
28	Biomass = 1086GDD - 234.95SM - 655.91
56	Biomass = 11.1GDD + 135.64SM - 9610.48
84	Biomass = 10.22GDD + 301.73SM - 18870.4

2009	
14	Biomass = 38.26GDD + 343.73SM + 1771.26
28	Biomass = 32.26GDD - 432.16SM - 4718.06
56	Biomass = 28.66GDD + 1094.29SM - 37774.5
84	Biomass = 43732.22 - 17.87GDD - 832.95SM

2010	
14	Biomass = 13.52GDD - 693.88SM + 1809.7
28	Biomass = 13.90GDD - 114.06SM - 8498.26
56	Biomass = 8.89GDD + 136.83SM - 8498.26
84	Biomass = 8.54GDD + 341.73SM - 19054.5

2011	
14	Biomass = 19.67GDD - 202.50SM - 1488.79
28	Biomass = 15.0GDD + 148.42SM - 5736.02
56	Biomass = 12.07GDD + 509.27SM - 17230.1
84	Biomass = 10.85GDD + 817.15SM - 33939.1

3 ANALYSIS OF CANOPY LEVEL BIOMASS ESTIMATION AND CORRELATION WITH ENVIRONMENTAL VARIABLES IN A RAIN-FED FIELD

3.1 Introduction

The term "biomass" can be related to a variety of phenomena: agriculture (e.g., crops), forestry (e.g., slash, pre-commercial thinnings), and waste (e.g., food, yard) (Bracmort and Gorte, 2012). In disciplines such as forestry and crop production in agriculture, biomass is generally defined as the oven-dry mass of the above ground portion of a group of plants (Vazirabad and Karslioglu, 2011). Throughout history, plant biomass has served many purposes for humans such as providing food, fuel and construction material (Rosillo-Calle, 2008; Matovic, 2011), as well as being indicative of the condition of the environment in which the plants are found (Reed *et al*., 1994); thus vegetative biomass is an important biophysical parameter.

Monitoring biomass over time is important because it is an indicator of plant growth status (Bao *et al.*, 2009). Plant growth is affected by environmental factors such as temperature and soil moisture, so looking at seasonal biomass not only allows us to monitor growth (Bao *et al.*, 2009), but also to track, detect and quantify the environmental stresses which affect plant growth (Royo and Villegas, 2011). Thus, by studying seasonal crop biomass, we are afforded the opportunity to study the ecosystem because efficient and accurate detection of the temporal and spatial variations of plant biomass aid in the monitoring of key properties and processes in a variety of ecosystems (Wang *et al.*, 2011).

Biomass is an integral part of the carbon cycle, which refers to carbon fluxes as relates to four main reservoirs on the planet: fossil carbon, the atmosphere, the oceans, and the terrestrial biosphere (Schimel, 1995). Carbon sequestration, the process by which plants absorb carbon dioxide from the atmosphere and store it as organic material, is an important process in the carbon cycle which can be monitored when plant biomass is considered a surrogate. Also, biomass measurements are incorporated into climate and biome models, and are used for ecosystem modeling (Watson *et al.*, 2001). As crops and cultivated systems make up 25% of the terrestrial land cover (DeFries, 2008), studying the biomass of crops is beneficial and necessary for monitoring the ecosystem.

Monitoring crop development patterns is important for farm management because yield maximization requires that crops optimize their consumption of nutrients and grow under favorable conditions (Hodges, 1991; Haboudane *et al*., 2008). In recent times, interest in precision agriculture, which is based on time- and site-specific intra-field assessments via remote sensing and field-scale proximal GIS technologies for crop management, has been on the rise (Haboudane *et al*., 2002). This trend is due to the potential for precision crop management to save money and reduce environmental pollution while maximizing yield and profit (Haboudane *et al.*, 2002; Price, 2011). Precision farmers and agricultural managers are interested in measuring and assessing the status of their crops at critical times in their phenology, and this can be done non-destructively with the use of remote sensing technologies such as *in situ* vegetation spectra measurement which are capable of providing time- and location-specific crop biophysical information (Haboudane *et al*., 2002).

In situ measurement of vegetation spectra for monitoring biomass is advantageous for reasons such as providing a fast non-destructive and relatively cheap method of studying crop status, flexibility in collecting spectra at specific stages in the phenological cycle of the crop, as well as looking at the status of crops in different locations within a field which is necessary for precision agriculture. Data collected from field measurements also have the capability and advantage of being extended to regional levels for analysis at multiple spatial scales.

3.1.1 Interaction of Light with Terrestrial Vegetation

Electromagnetic radiation in the visible spectrum (wavelength = 400 to 700nm) is absorbed by plant pigments in typical green vegetation (Figure 3.1). Radiation in parts of the blue (400 to 500nm) and red (600 to 700nm) portions of the spectrum are efficiently absorbed for photosynthetic use by the chlorophyll *a*, chlorophyll *b* and β-carotene pigments present in the plant. Relatively less absorption occurs in the green band (500 to 600nm), which creates a “reflectance peak” in this region resulting in the green coloration of plants as perceived by the human eye. The spongy mesophyll cells are associated with pronounced scattering of near-infrared (NIR) radiation, causing a typical high spectral reflectance in the 700 to 1200nm region of the spectrum (Di *et al*., 1994; Jensen, 2000). The spectral reflectance in the red region for healthy, actively growing vegetation typically diminishes as plants develop (because of increasing photosynthetic activity and thus greater absorption at that wavelength), while the NIR reflectance increases steadily with increasing amounts of canopy. Increases in leaf thickness, may also be correlated with increases in NIR reflectance (Gitelson *et al*., 2003).

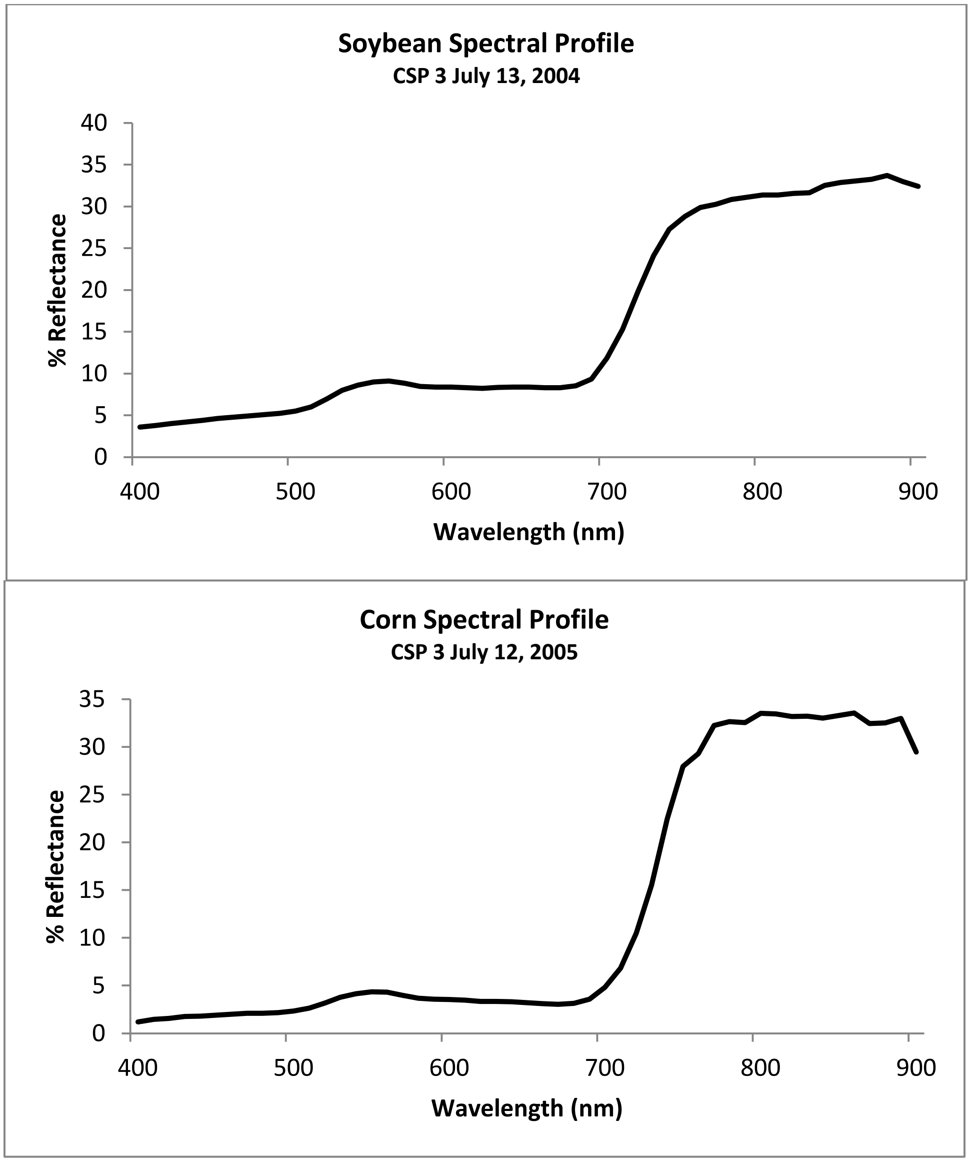


Figure 3.1: Spectral reflectance of soybeans and corn in the visible to NIR regions of the spectrum. The spectra shown were acquired by the canopy level Ocean Optics USB2000 radiometers on the dates noted in subsequent text. Characteristic of healthy green vegetation is the dominant absorption in the blue and red regions, and less absorption in the green. Pronounced reflectance in the NIR portion of the spectrum is also typical.

3.1.2 Vegetation Indices

Because of the characteristic reflectance responses of vegetation within the red and NIR portions of the spectrum (as related to the chlorophyll content and canopy architecture of a plant, respectively), data acquired from these two regions have been widely used to create spectral transformations generally referred to as "vegetation indices" (VIs), and a large number of such indices have been developed. VIs are dimensionless, radiometric measures that function as indicators of relative abundance and activity in green vegetation, and have been shown to correlate to varying degrees of accuracy with biophysical variables such as leaf area index (LAI), chlorophyll content, and biomass, all of which vary with the phenology of the plant (Di *et al*., 1994; Jensen, 2000; Gitelson *et al*., 2003).

Another advantage of VIs is that they reduce the dimensionality of datasets. For any dataset there is a maximum size or amount of spectral information present above which classification or feature extraction becomes inefficient. Using a mathematical ratio of bands may be useful in extracting a maximum amount of variation in the inherent spectral information. Measured spectral reflectance data from various bands are thus compressed into VIs through mathematical manipulation (Myneni *et al*., 1995). Such a spectral transformation can, in fact, result in improved information content requiring less digital storage space than was needed for the original raw data. Also, VIs correct for certain troublesome effects associated with varying conditions related to data acquisition at multiple times. Atmospheric condition, solar angle, soil background, canopy architecture, sensor calibration and view angle are some of the external factors which vary when spectral data are acquired on more than one date (Jackson and Huete, 1991). Normalization of the effects of these variations in studying multiple co-registered datasets is one of the benefits of linear or ratio manipulation of spectral bands into VIs (Jensen, 2005).

3.1.3 Previous work done on use of field measurement of crop reflectance spectra for biomass estimation and correlation with environmental variables

A large number of studies have been carried out using reflectance measured at canopy-level to estimate chlorophyll content of leaves and biomass of crops. For example, hyperspectral field data, Landsat TM and MODIS images were used by Bao *et al* (2009) to estimate winter wheat biomass in China during the growing seasons of 2004 and 2005. The biomass estimation was done via seven Normalized Difference Spectral Indices (NDSIs). During the growing seasons, the highest correlation of correlation coefficient (r) of = 0.89 was obtained before wheat flowering based on the NDSIs derived from the field measured spectra, while data from both satellite-borne sensors showed similar but slightly lower maximum r of 0.84 each.

Gitelson *et al*., (2003) used hyperspectral field measured spectra acquired by a dual fiber system (i.e., two instruments simultaneously collecting downwelling irradiance and upwelling radiance) to predict leaf area index (LAI) and green leaf biomass in irrigated rain-fed corn fields. Using reflectances in the green, red-edge and near-infra red portions of the spectrum, two new indices CI_{Green} and $CI_{RedEdge}$ were proposed to study and improve LAI and green biomass prediction accuracy over the benchmark Normalized Difference Vegetation Index (NDVI). Results showed NDVI was sensitive to biophysical variables at the beginning of the growing season but remained virtually invariant after that. CI_{Green} and $CI_{RedEdge}$ on the other hand temporally followed LAI and biomass throughout the growing season. Also, the newly proposed indices showed close linear relation with both biophysical variables ($R^2 > 0.95$) before silking.

An active (produces its own light source) canopy level sensor was used by Solari *et al*., (2008) to collect spectral reflections at $\rho590$ and $\rho880$ for use in applying the NDVI and Red Chlorophyll Index (CI_{Red}) for monitoring corn vegetative growth and assessing nitrogen (N) status as well as yield in relation to chlorophyll content at canopy level. Results showed that chlorophyll levels and sensor readings were affected by N treatments, corn hybrid, corn growth stage and the interaction of N with growth stages. Also the active sensor showed reductions in correlations after tasselling, just as had been observed in studies using passive sensors. Finally CI_{Red} was determined to be more sensitive than NDVI ($R^2 = 0.74$ and 0.54 respectively) for detecting spatial variations in canopy greenness and crop N status during vegetative growth.

Viña *et al*., (2004) used NDVI and Visible Atmospherically Resistant Indices (VARI) derived from canopy level spectral measurements to study the phenological development of irrigated and dry land corn. The authors showed that VARI was able to detect the onset of grain fill period and senescence 110 growing degree days (GDD) earlier than Normalized Difference Vegetation Index (NDVI). Also it was suggested that VARI may be useful for detecting early stages of stress in crops because of the sensitivity it exhibited to both green vegetation fraction and leaf chlorophyll content.

Using Landsat-MSS NDVI images, Di *et al*., (1994) examined vegetation responses (via NDVI) to precipitation events in the Sandhills region of Nebraska. The study created a model which showed that NDVI response time varied during the course of a growing season, ranging from 14, 25 and 12 days at the beginning, middle and end of the growing season respectively. Ji and Peters (2005) also looked at the correlation between NDVI and precipitation using biweekly composites of AVHRR images. Their study showed a close relationship between NDVI and precipitation, as well as a variation in NDVI lag time response to precipitation with shorter lags (4 – 8 weeks) in the early season and longer lags (12 – 14 weeks) in the mid to late season.

Rundquist *et al*., (2000) looked at statistical relationships between monthly precipitation, temperature and AVHRR NDVI data at a mesoscale in nine climatic divisions of Kansas, US. The results showed lower correlations than from other studies (NDVI/Precipitation $r = 0.42$ and NDVI/Temperature $r = 0.32$) because of mixed land cover classes; while NDVI values were generally higher in the 'wet' year and lower in 'dry' years.

It can be seen that ample research has been directed at using canopy level spectral measurements to estimate crop biophysical variables such as biomass. Also, a large amount of research have been directed at using vegetation indices derived from satellite imagery to study the phenological cycle of plants as well as the response of these cycles to environmental factors. This leaves a gap in research focusing on crop phenological changes and their responses to environmental variables using data measured at field scale over an extended number of consecutive growing seasons. Therefore, the objectives of this research were to:

1. Estimate the green biomass in rain-fed corn and soybeans across seven growing seasons (2002 – 2008) using hyperspectral canopy reflectance data transformed to three selected vegetation indices.
2. Correlate changes in biomass and vegetation indices derived from canopy level reflectances during each growing season with GDD and soil moisture accumulated at multiple lag times.

3.2 Materials and Methods

3.2.1 Study Area

The study site is a 65.4 ha non-irrigated field located at the University of Nebraska-Lincoln (UNL) Agricultural Research and Development Center (ARDC) near Mead, NE. The location of this site, areas of canopy spectral measurement and the Intensive Measurement Zones (IMZs) delineated within it, are represented in Figure 3.2. It is one of three fields which have been maintained since 2001 by the ARDC in support of the UNL Carbon Sequestration Program (CSP). This field, hereafter referred to as CSP 3, is located at 41.18^{o}N; 96.44^{o}W and receives moisture only from precipitation. A single nitrogen fertilizer application, which is adjusted for residual nitrate measured from soil samples, is made to CSP3 each spring before planting. The double-crop rotation system, with corn and soybean planted in alternate years, is practiced on this field.

The climate of the study area is a temperate semi-arid one, with a mean annual precipitation of 887mm (based on annual average values from 1961 to 1990), with a range from 544mm to 892mm (based on data from 2002 to 2005 summarized at http://ameriflux.ornl.gov/). Because of Nebraska's variable precipitation regime, droughts occur frequently in this region.

The soil types of study area are deep silty clay loams consisting of Filbert (fine, smectitic, mesic Vertic Argialbolls), Filmore (fine, smectitic, mesic Vertic Argialbolls), Tomek (fine, smectitic, mesic Pachic Argialbolls) and Yutan (fine-silty, mixed, superactive, mesic Mollic Hapludalfs) soil series (http://ameriflux.ornl.gov/). This mix of well-drained and poorly-drained mollisols facilitates soil moisture retention and plant growth.

3.2.2 Data

3.2.2.1 Canopy Level Spectral Reflectance Measurements

Spectral measurements were made using a dual-fiber system, with two inter-calibrated Ocean Optics USB2000 radiometers mounted on an all-terrain sensor platform named "Goliath" (Rundquist *et al*., 2004). Measurements were taken in the range of 400 – 900nm and with a spectral resolution of about 1.5 nm. Radiometer 1 was equipped with a 25^{o} field of view optical fiber and pointed down to measure upwelling radiance from the crops. The position of the radiometer above the canopy was kept constant at approximately 5.4m, resulting in an instantaneous field of view of about 2.4m. Radiometer 2 which was pointed up simultaneously to measure downwelling irradiance was equipped with an optical fiber and cosine diffuser (yielding a hemispherical field of view).

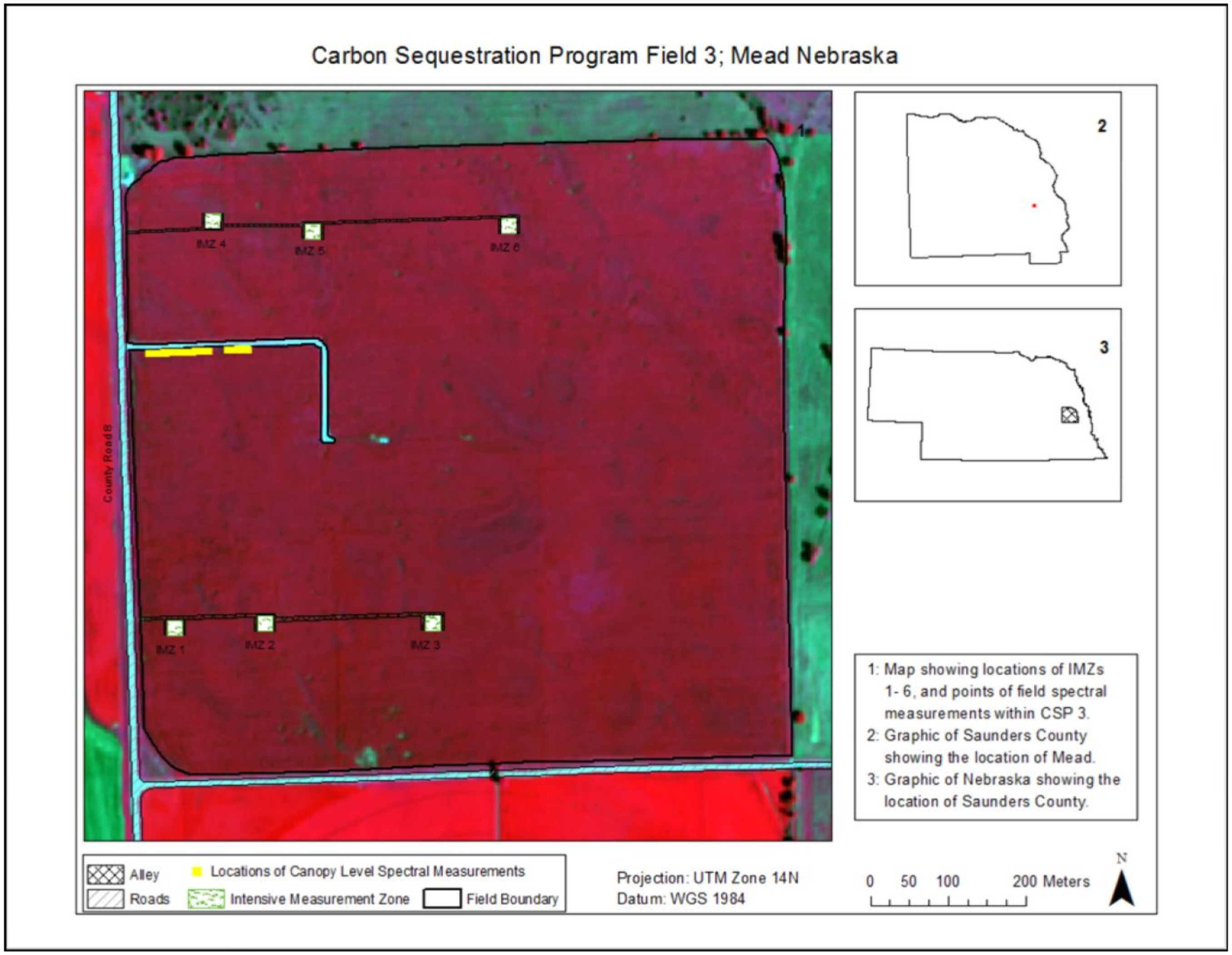


Figure 3.2: Color infra-red map of CSP 3 showing the locations at which canopy reflectance spectra were collected as well as locations of IMZs from which biomass was destructively sampled.

Canopy spectral measurements were taken multiple times (7 – 10 day intervals) during each growing season starting from late May/early June through mid/late September. Locations at which spectral measurements were collected are shown in Figure 3.2. The spectral measurements were representative of the entire field based on the work done by Gitelson *et al*., (2003), which showed that there is no statistical difference between and among the locations where destructive biomass sampling and spectral measurements took place. The dates on which spectral and biomass measurements were taken did not all coincide, but the latter was generally less in number than the former for each year. For this research, all of the spectral measurement were used (Table 3.1), and applied to predicting biomass sampled on or within two days of each spectral measurement date.

3.2.2.2 Field Reference Data

3.2.2.2.1 Biomass

CSP 3 contains six IMZs from which measurements corresponding to various plant biophysical parameters were taken. Each IMZ is a plot 20m x 20m in size, and the six IMZs represent all major occurrences of the various soil types and crop production zones within the field (Figure 3.2). Such a spatial framework allows accurate up-scaling of ground measurements to the level of the whole field.

A graphic describing an IMZ within CSP 3 is provided as Figure 3.3, where corn rows are represented by the dotted light gray lines, while rows within the IMZs are shown by the dark gray lines. The spacing of each row on the ground is 0.76m. The IMZ is separated from the larger field on three sides by non-vegetated areas called “alleys” (white space between the different row types in Figure 3.3). These alleys provide access to the IMZ for the members of a field-research team. For measurements which require destructive sampling, plant sampling plots (indicated by black rectangles) are pre-marked on the six center rows of planter pass two within each IMZ. Each sampling plot is 1m in length and positioned based on two criteria:

1) A distance of a least 3m between sampling plots in the same row; and

2) A distance of at least 1m between sampling plots in adjacent rows.

Various types of samples were taken from each plot every seven to ten days, starting from the alley and progressing (by the end of the growing season) to the center of the IMZ. Typically 10 to 12 samplings were carried out during each growing season, leaving 3 to 5 extra sample areas available in case of problems that may arise with the samples taken in the "established plots."

Table 3.1: Dates of canopy level reflectance spectra collection.

Year (Crop Type)	**Date of Spectra Collection**												
	May	June			July				August			September	
2002 (Soybean)	-	06/13	06/24	-	07/08	07/25	-	-	08/09	-	-	09/13	09/17
2003 (Corn)	-	06/5	06/19	-	07/03	07/14	07/24	-	08/01	08/20	-	09/02	-
2004 (Soybean)	-	06/25	-	-	07/08	07/16	07/30	-	08/13	08/20	-	09/10	09/20
2005 (Corn)	05/23	06/06	06/22	06/30	07/15	07/29	-	-	08/09	08/17	-	09/06	09/29
2006 (Soybean)	-	06/14	06/22	06/28	07/14	07/19	07/25	-	08/03	08/10	08/23	09/01	-
2007 (Corn)	-	06/21	06/26	-	07/03	07/11	07/25	-	08/15	08/24	-	09/12	-
2008 (Soybean)	-	06/12	06/20	06/30	07/10	07/17	07/25	07/31	08/07	08/15	-	-	-

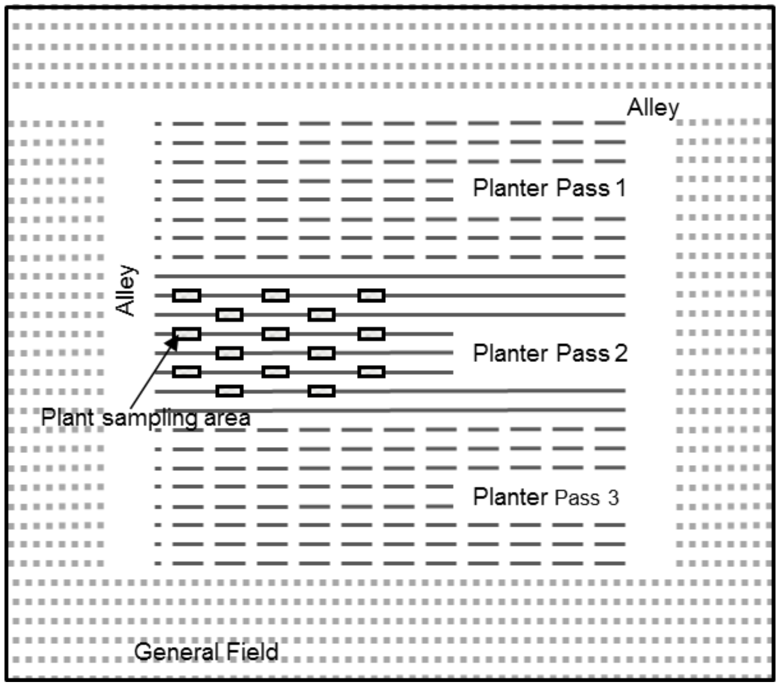


Figure 3.3: An intensive measurement zone within CSP3 showing plant rows, alleys and biomass sampling locations.

3.2.2.2.2 Temperature and Precipitation

Daily temperature and precipitation data were collected from the University of Nebraska Lincoln High Plains Regional Climate Center (HPRCC) weather station located at Mead NE. This station (Mead 4 SSE 255362) is approximately 16km south-east of CSP 3. For this research, temperature and precipitation data were analyzed beginning with the first day of April and ending with the last day on which biomass measurements were taken in September.

3.2.2.2.3 Soil Moisture

Daily soil moisture measurements were acquired from the CSP 3 field. Soil moisture sensors were placed in four locations within the rain-fed field, at depths of 10cm, 25cm, 50cm and 100cm in each location. Hourly readings were taken from each sensor and the average from a 24-hour period represented daily soil moisture from a sensor. For this research, soil moisture data were also analyzed beginning with the first day of April and ending with the last day on which biomass measurements were taken in September.

3.2.3 Prediction of Green Biomass via Vegetation Indices

The biomass measurements for each growing season were estimated using three vegetation indices of interest which are the Normalized Difference Vegetation Index (NDVI), Red Edge Chlorophyll Index ($CI_{RedEdge}$) and Wide Dynamic Range Vegetation Index (WDRVI) derived from canopy spectral data. Biomass measurements were regressed against each VI to calculate the coefficient of determination (r^2) using best fit functions for NDVI and $CI_{RedEdge}$, while linear regressions were used for WDRVI. The regression analysis was done on individual crops for each of the seven growing seasons studied i.e., 2002 - 2008; and also on all the data collected from each crop type (three years for corn and four years for soybean). Further statistical analysis was done on the crop specific data to determine the root mean square error (RMSE) and coefficient of variation (CV) from biomass estimation.

3.2.3.1 Normalized Difference Vegetation Index (NDVI)

The widely known NDVI, developed by Rouse *et al*., (1974), is a good indicator of the ability of vegetation to absorb photosynthetically active radiation. It has been employed by researchers to estimate several plant biophysical characteristics as well as general productivity patterns (Wang *et al*., 2003). Undoubtedly, NDVI is the most widely used VI for various types of regional and global vegetation studies (e.g., Huete *et al*., 1997; Viña, 2004). The index is expressed as:

$$NDVI = \frac{\rho\text{NIR} - \rho\text{Red}}{\rho NIR + \rho Red}$$

Where: ρNIR is the average of 770nm and 780nm bands

ρRed is the average of 660 and 670nm bands.

The wavelength ranges were chosen with regard to both the characteristics of the sensor system of choice (described above) and the professional literature.

3.2.3.2 Red Edge Chlorophyll Index ($CI_{RedEdge}$)

The Red Edge Chlorophyll Index was developed based on the relationship between total canopy chlorophyll content and the reciprocal of reflectance at wavelengths in the green and red-edge regions of the spectrum (520 to 585nm and 695 to 740nm) (Gitelson *et al*., 2003). Chlorophyll content in plants, like other leaf pigments, may provide information about the physiological state of the plant and its leaves (Sims and Gamon, 2002); thus the index was used to estimate the biomass biophysical parameter of crops in this research. It is expressed as:

$$CI\ RedEdge = \left(\frac{\rho\text{NIR}}{\rho\text{Red Edge}}\right) - 1$$

Where: ρNIR is the average of 770nm and 780nm bands

ρRed Edge is the average of 710 and 720nm bands

3.2.3.3 Wide Dynamic Range Vegetation Index (WDRVI)

In response to the problem of NDVI saturation at high canopy densities, this Wide Dynamic Range Vegetation Index (WDRVI) was developed to linearize NDVI. It is expressed as:

$$WDRVI = \frac{\alpha * \rho\text{NIR} - \rho\text{Red}}{\alpha * \rho NIR + \rho Red}$$

Where: ρNIR is the average of 770nm and 780nm bands

ρRed is the average of 660 and 670nm bands

α is a value <1

As shown by Gitelson (2004), NDVI sensitivity depends on the ratio of ρNIR to ρRed. The highest correlation between NDVI and certain biophysical variables (i.e., Leaf Area Index and Vegetation Fraction) occurred at lower ratios of ρNIR /ρRed when the vegetation canopy was sparse and there were ρRed reflectance values of 10 to 20% (because of low absorption in this region). To increase the range of sensitivity of NDVI to high density vegetation canopies, a weighting coefficient with a value of <1 was applied to the NIR reflectance, which reduces the ρNIR value, thereby decreasing the ρNIR/ρRed ratio. In the current research, α was given a value of 0.2 because in Gitelson (2004), of the three α's of 0.05, 0.1 and 0.2 which were used to predict vegetation fraction in corn and soybeans, 0.2 had the highest correlations (R^2 values of 0.94 to 0.98).

3.2.4 Correlation of Biomass and Vegetation Indices with Soil Moisture

The soil moisture values used in this research were the average of measurements from the sensors located in CSP 3 at depths of 10cm, 25cm, and 50cm. It was observed that fluctuations in soil moisture readings due to precipitation events reduced steadily with increasing depth, showing minimal changes at 100cm. Because this research looked at the effect of variations in environmental factors, readings from the sensors at 10cm, 25cm and 50cm were used, while data from the sensor at 100cm was excluded.

Daily soil moisture data were also summed up in 14, 28, 56 and 84 day intervals prior to each date on which biomass measurements were available. Statistical analyses were conducted using simple linear correlations of biomass values for each date of the growing season with the respective accumulated soil moisture data, and the process was repeated for each soil moisture aggregation (i.e. 14, 28, 56, and 84 days) and for each of the seven growing seasons

3.2.5 Correlation of Biomass and Vegetation Indices with Growing Degree Days

Rates of plant growth responds to air temperature, which, in turn, affects many processes associated with plant growth and phenology (Russelle *et al*., 1984). GDD was derived using the equation:

$$\mathrm{GDD} = \left[\frac{(T_{max} + T_{min})}{2}\right] - \mathrm{B}$$

Where: T_{max} = daily maximum temperature
T_{min} = daily minimum temperature
B = base temperature of 10^{o}C

In the GDD calculations, the following adjustments were made based on the work done by Russelle *et al* (1984) and Viña *et al* (2004):

iii. Minimum temperatures below 10^{o}C were set at 10^{o}C

iv. Maximum temperatures above 30^{o}C were set at 30^{o}C.

Based on the methods used by Rundquist (2000) and Li *et al*., (2002), daily GDD data were summed up in 14, 28, 56 and 84 day intervals preceding each date on which biomass measurements were collected. Statistical analyses were carried out using simple linear correlations of biomass values from each date in the growing season with its' respective accumulated GDD. The procedure was repeated for each GDD aggregation (i.e. 14, 28, 56, and 84 days) and each of the seven growing seasons.

3.3 Results

3.3.1 Relationships between Biomass and Vegetation Indices

This research examined the relationships between destructively sampled biomass of corn and soybean with vegetation indices derived from reflectance spectra collected at canopy level.

3.3.1.1 Annual Biomass vs. Field Measured Vegetation Indices

Scatter plots which show the relationships between VIs derived from field-measured spectra and crop biomass are represented in Figures 3.4 through 3.10, and Table 3.2 provides a summary of all R^2 values from the relationships. Figure 3.4 documents the relationships for the 2002 growing season between NDVI, $CI_{RedEdge}$, and WDRVI, respectively, with measured soybean biomass. There are good correlations overall, ranging from 0.83 to 0.98, with NDVI yielding the highest R^2 and $CI_{RedEdge}$ yielding the lowest. The best fit functions for NDVI and $CI_{RedEdge}$ were curvilinear, while that for WDRVI was linear. The best fit for WDRVI will always be linear because the concept for this VI is based upon the need to linearize NDVI.

For the growing season of 2003, the correlations between the biomass for soybeans and NDVI, $CI_{RedEdge}$ and WDRVI, respectively were also very high, with R^2

values ranging from 0.89 to 0.94 (Figure 3.5). NDVI had the highest R^2 of 0.94, while $CI_{RedEdge}$ and WDRVI both had R^2 values of 0.89 and 0.90 respectively. The best fit functions for NDVI and $CI_{RedEdge}$ were also curvilinear.

Relationships for the 2004 growing season between NDVI, $CI_{RedEdge}$, and WDRVI, respectively, with measured soybean biomass are documented in Figure 3.6. Very good correlations are observed overall, ranging from 0.85 to 0.98, with both NDVI and $CI_{RedEdge}$ yielding the highest R^2. In this instance, the best fit function for NDVI was curvilinear, but that for $CI_{RedEdge}$ appeared linear.

Figure 3.7 depicts the scatter-plots and R^2 values from the correlation of the three VIs with corn biomass for 2005. These were high values, ranging from 0.87 to 0.91. The lower R^2 of 0.87 was for both $CI_{RedEdge}$ and WDRVI, while NDVI had a value of 0.91. Once again, the best fit function for NDVI and $CI_{RedEdge}$ were both curvilinear.

In the growing season of 2006, the correlations between the biomass for soybeans and NDVI, $CI_{RedEdge}$ and WDRVI, respectively were also very high, with R^2 values ranging from 0.88 to 0.98 (Figure 3.8). $CI_{RedEdge}$ had the highest R^2 of 0.98, while NDVI and WDRVI both had R^2 values of 0.95 and 0.88 respectively. The best fit function for NDVI was curvilinear, but that for $CI_{RedEdge}$ appeared linear.

Figure 3.9 shows relationships for the 2007 growing season between NDVI, $CI_{RedEdge}$, and WDRVI, respectively, with measured corn biomass. Correlations were

0.72, 0.93 and 0.94; with NDVI yielding the highest R^2 and WDRVI yielding the lowest. The best fit functions for NDVI was curvilinear while $CI_{RedEdge}$ was linear.

Relationships for the 2008 growing season between NDVI, $CI_{RedEdge}$, and WDRVI, respectively, with measured soybean biomass are documented in Figure 3.10. The best overall correlations are observed, ranging from 0.95 to 0.99, with both NDVI and $CI_{RedEdge}$ yielding the highest R^2. In this instance, the best fit function for NDVI was curvilinear, but that for $CI_{RedEdge}$ appeared linear.

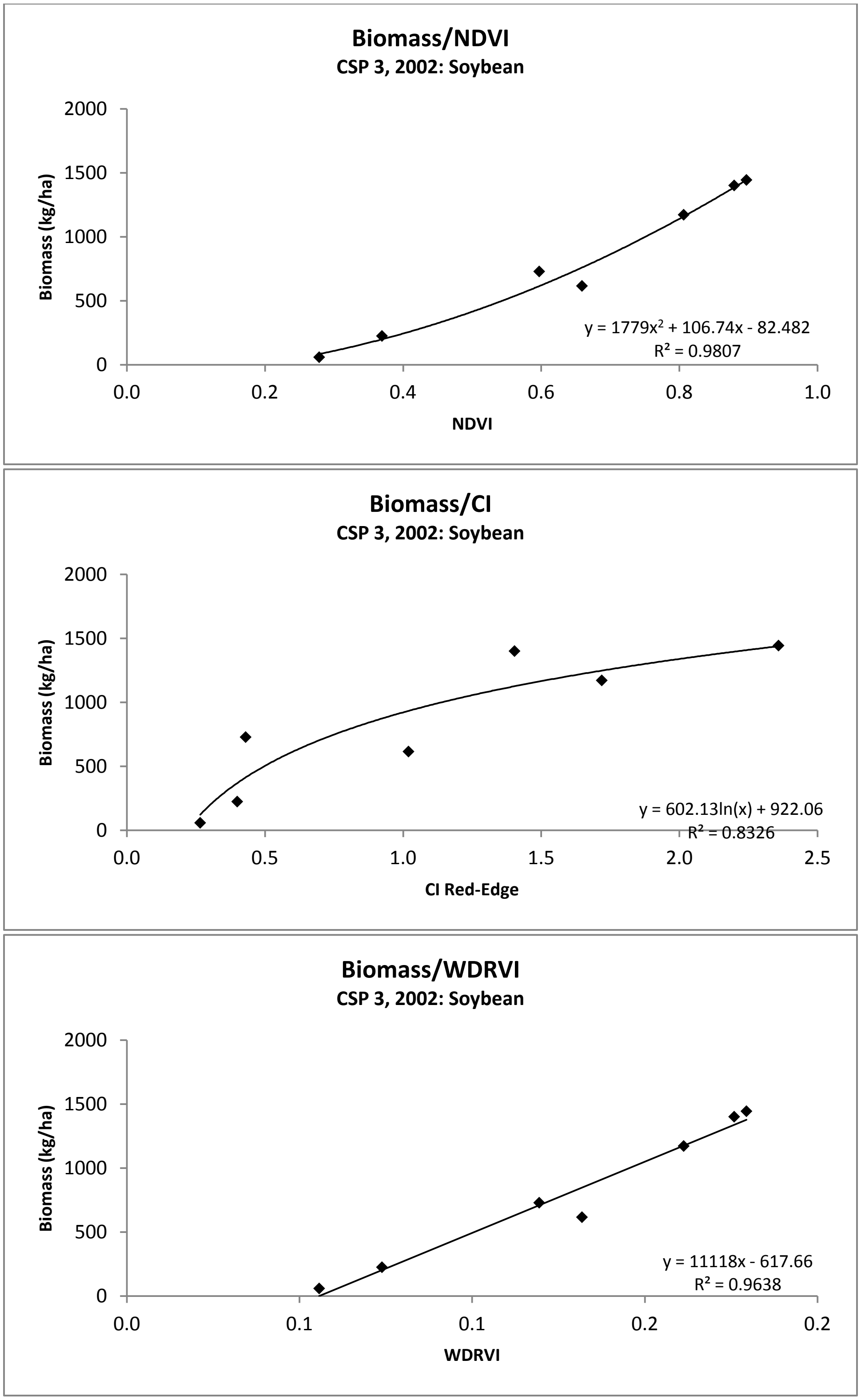


Figure 3.4: Correlation between vegetation indices and soybean biomass from year 2002.

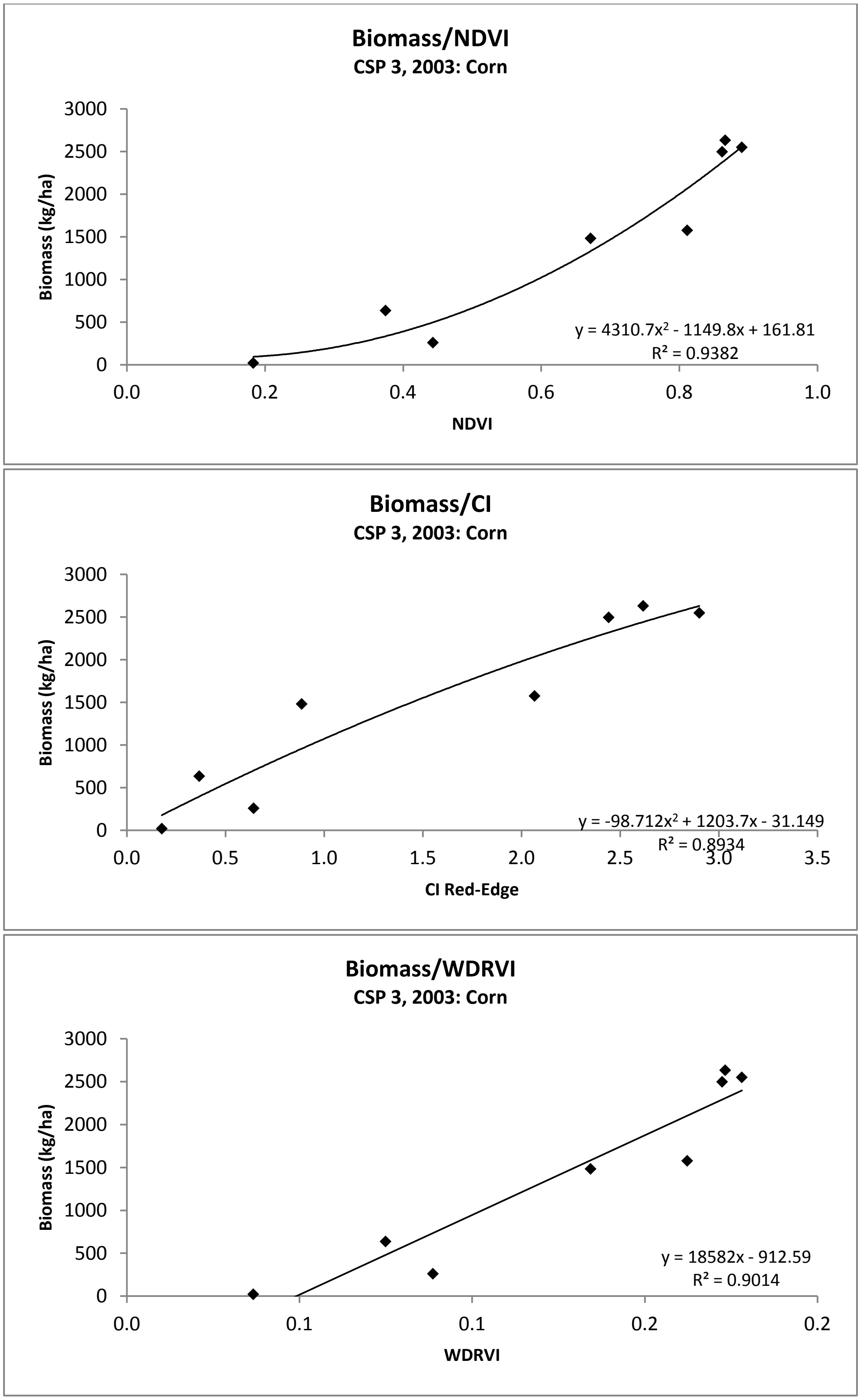


Figure 3.5: Correlation between vegetation indices and corn biomass from year 2003.

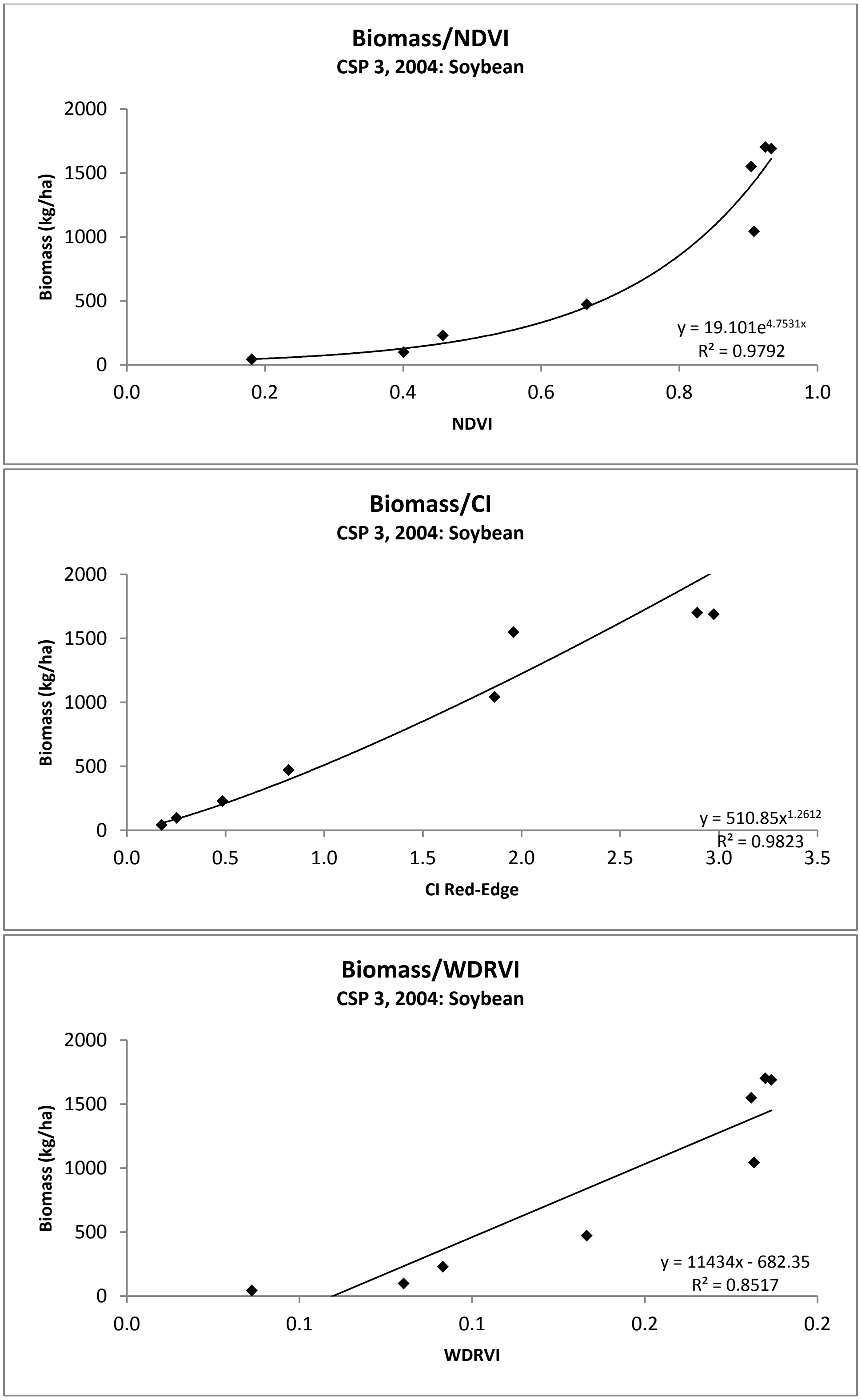
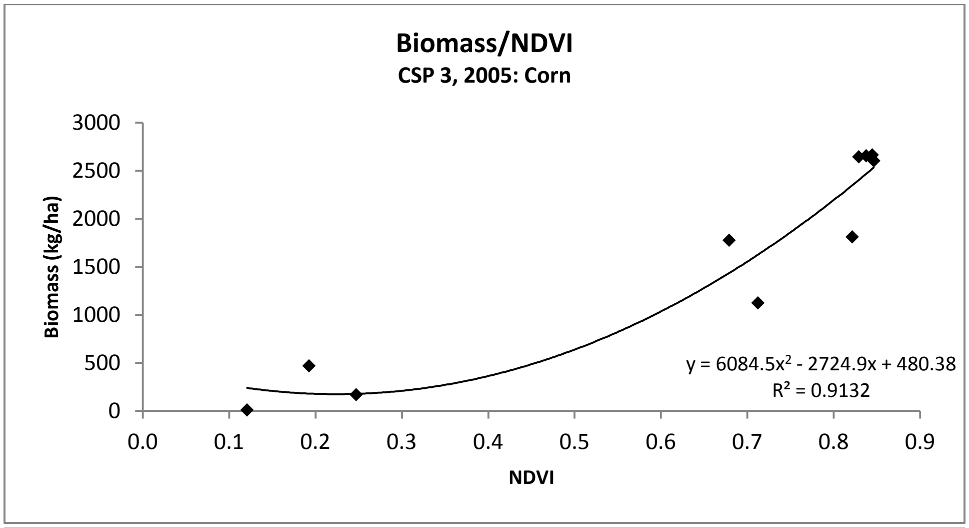
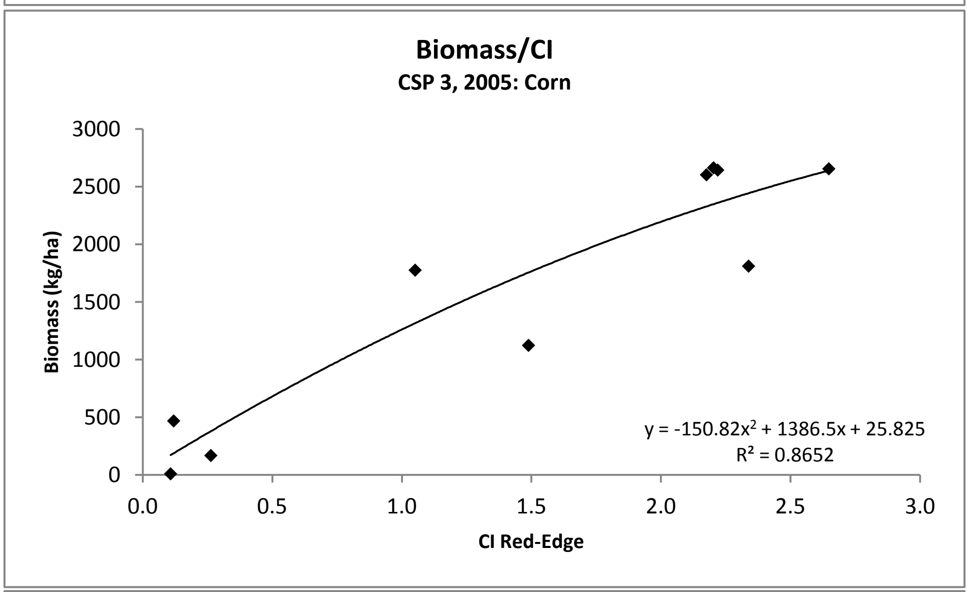


Figure 3.6: Correlation between vegetation indices and soybean biomass from year 2004.


Biomass/NDVI
CSP 3, 2005: Corn
Biomass (kg/ha)
NDVI
y = 6084.5x² - 2724.9x + 480.38
R² = 0.9132


Biomass/CI
CSP 3, 2005: Corn
Biomass (kg/ha)
CI Red-Edge
y = -150.82x² + 1386.5x + 25.825
R² = 0.8652

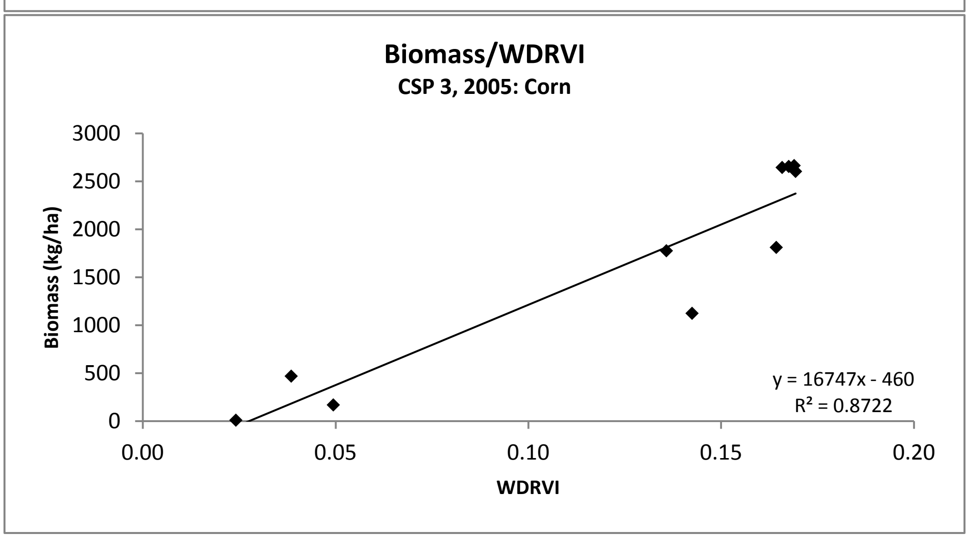

Biomass/WDRVI
CSP 3, 2005: Corn
Biomass (kg/ha)
WDRVI
y = 16747x - 460
R² = 0.8722

Figure 3.7: Correlation between vegetation indices and corn biomass from year 2005.

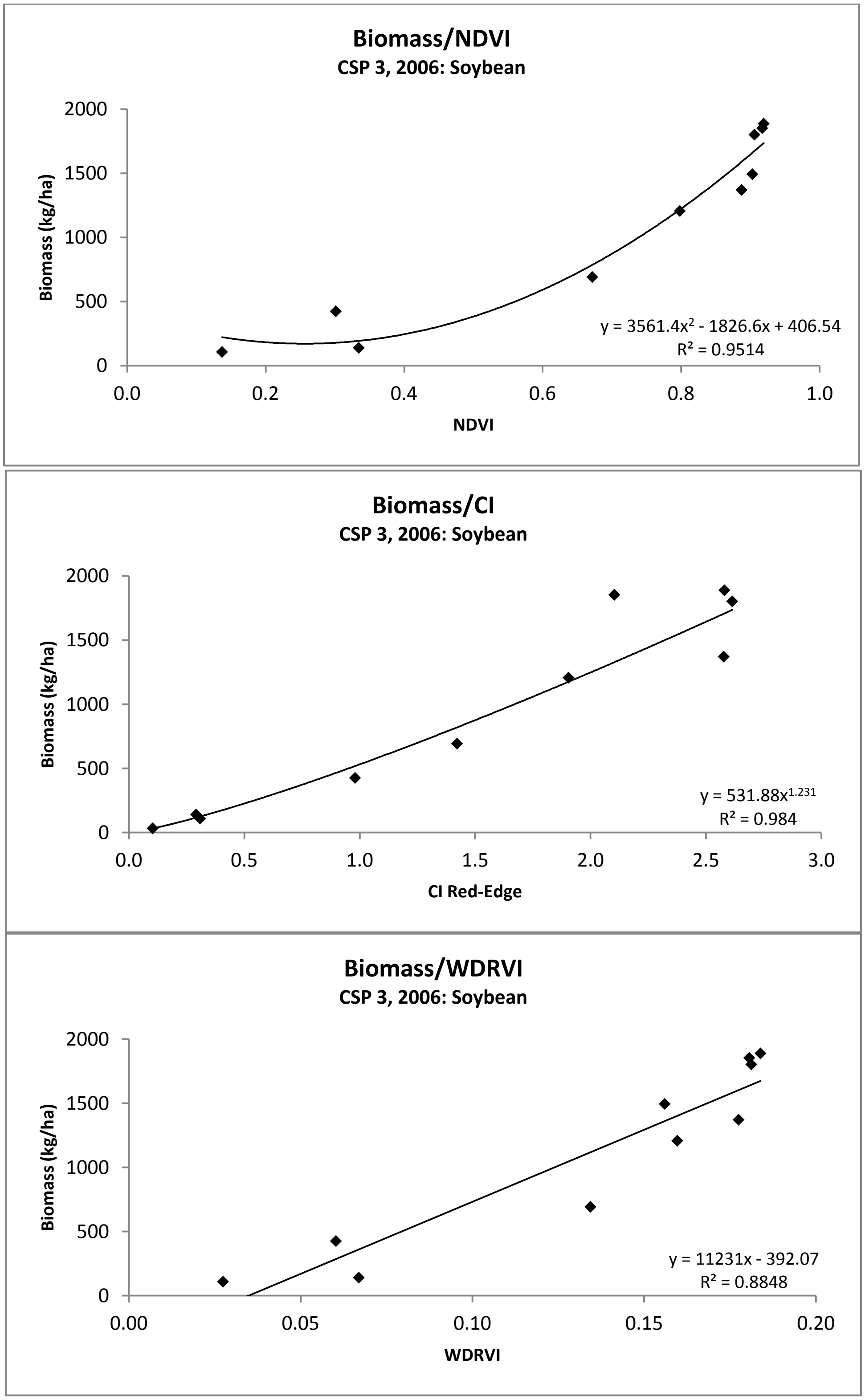
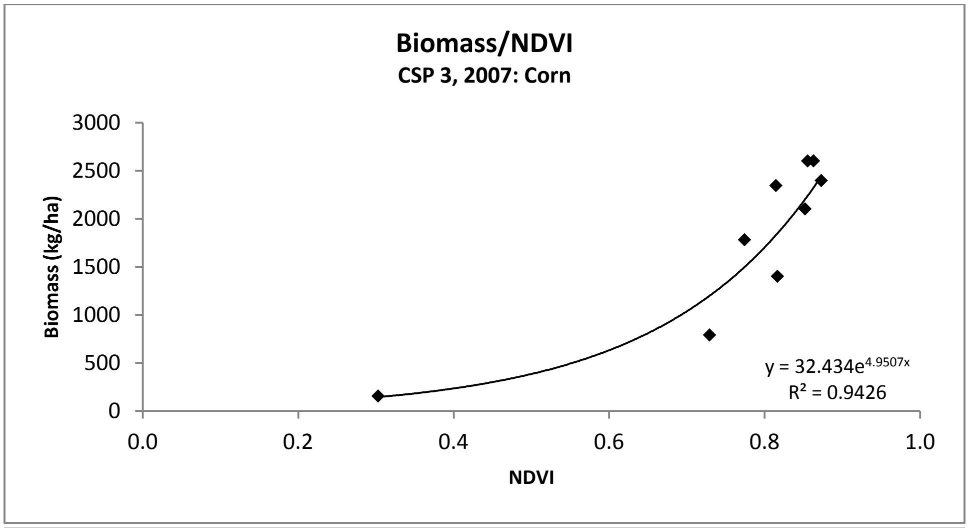
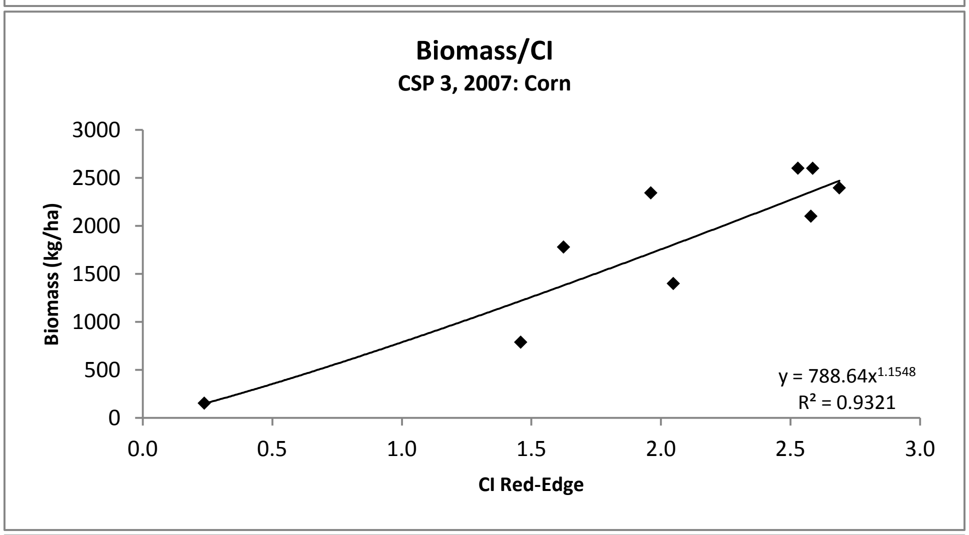


Figure 3.8: Correlation between vegetation indices and soybean biomass from year 2006.





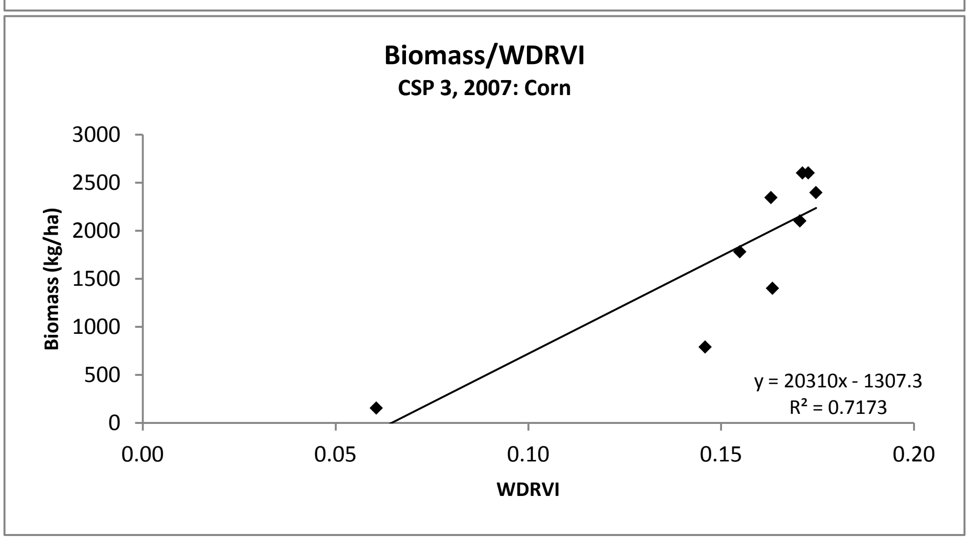


Figure 3.9: Correlation between vegetation indices and corn biomass from year 2007.

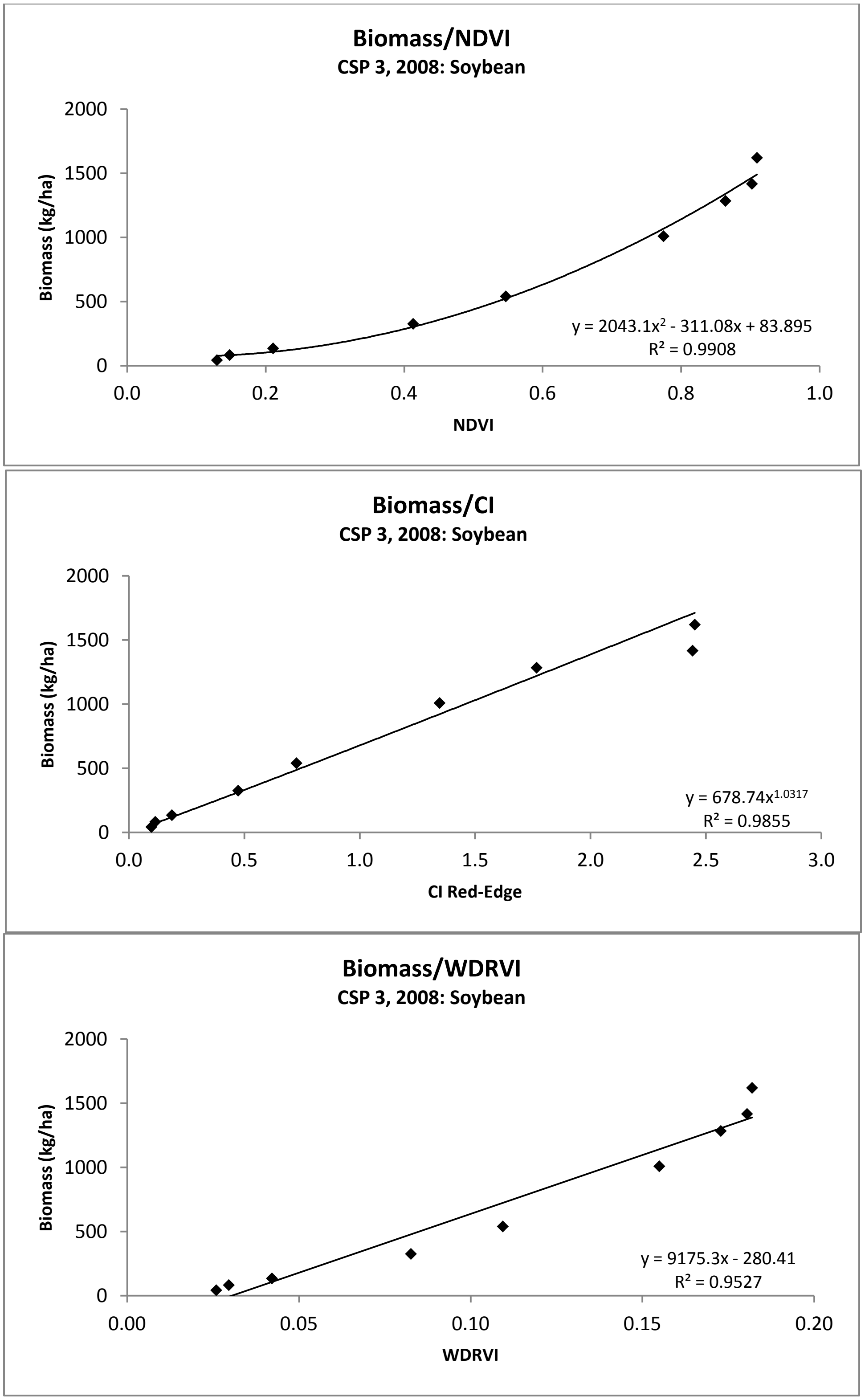


Figure 3.10: Correlation between vegetation indices and soybean biomass from year 2008.

Table 3.2: Results of the coefficient of determination (R^2) derived from best-fit functions for the green biomass/VI correlations across seven growing seasons.

Year	Crop Type	R^2		
		NDVI	$CI_{RedEdge}$	WDRVI
2002	Soybean	0.98	0.83	0.96
2003	Corn	0.94	0.89	0.90
2004	Soybean	0.98	0.98	0.85
2005	Corn	0.91	0.87	0.87
2006	Soybean	0.95	0.98	0.88
2007	Corn	0.94	0.93	0.92
2008	Soybean	0.99	0.99	0.95

3.3.1.2 Crop Specific VI-Biomass Relationships

Further investigation into applying VIs derived from field measured reflectance spectra for estimating crop biomass was done using the combined biomass data collected for the individual crops across multiple growing seasons. This was done in order to compare differences, if any, between the observed biomass of corn and soybean as well as the capabilities for estimating their biomass using the three VIs of interest. There was a considerable difference in the peak biomass of both crops with corn having 2,665kg/ha and soybeans with 1,889kg/ha. Figures 3.11 to 3.13 represent the scatter plots and best fit functions between VIs and biomass of both crops.

Figure 3.11 contains all the data for corn and soybean biomass (three and four study years each, respectively) versus NDVI. The correlation between NDVI and corn biomass has a best fit function which is a polynomial curve with an R^2 value of 0.88. The RMSE was 334.65kg/ha and the CV was 20.64%. The correlation between soybean biomass and NDVI has a best fit function which is a polynomial curve with an R^2 value of 0.94. The RMSE was 151.54kg/ha and the CV was 16.85%. These statistical parameters from the correlation of NDVI with all biomass data are summarized in Table 3.3.

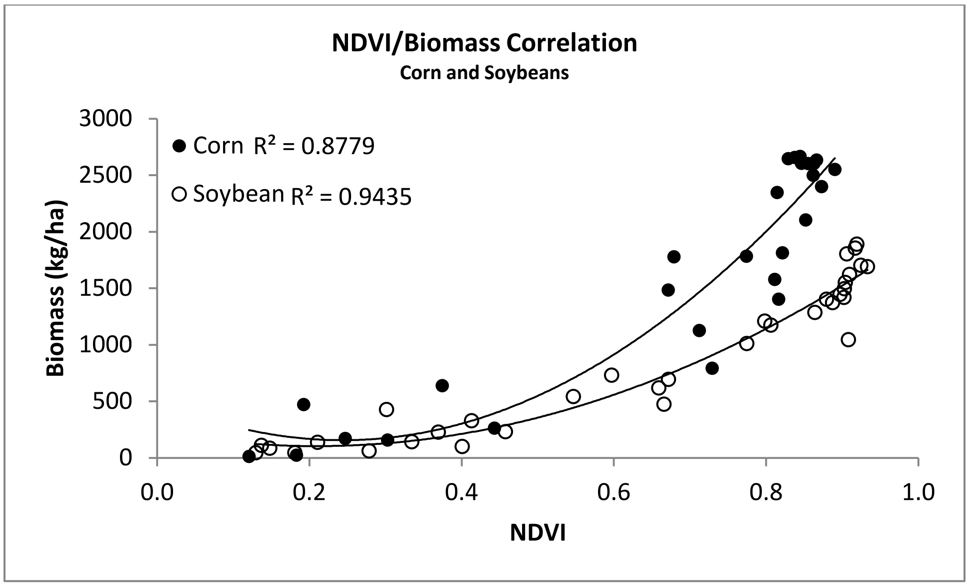


Figure 3.11: Correlation between NDVI and combined biomass of corn (2003, 2005 and 2007) and soybeans (2002, 2004, 2006 and 2008).

Figure 3.12 provides a summary of all corn and soybean biomass versus $CI_{RedEdge}$. The best fit function between corn biomass from three study years combined and $CI_{RedEdge}$ is almost linear with an R^2 of 0.85. The RMSE was 375.16kg/ha and the CV was 23.14%. The best fit function between soybean biomass from the four study years combined and $CI_{RedEdge}$ is also almost linear with an R^2 of 0.93. The RMSE was 208.53kg/ha and the CV was 24.67%. These statistical parameters from the correlation of $CI_{RedEdge}$ with all corn and soybeans biomass data are summarized in Table 3.3.

A summary of all corn and soybean biomass (three and four study years each, respectively) versus WDRVI is provided in Figure 3.13. The linear regression between WDRVI and corn biomass has an R^2 value of 0.82. The RMSE was 405.20kg/ha and the

CV was 24.99%.The best fit linear function between soybean biomass and WDRVI led to an R^2 of 0.87. The RMSE and CV values are 227.99kg/ha and 25.34% respectively. These statistical parameters from the correlation of WDRVI with all biomass data from corn and soybeans are also summarized in Table 3.3.

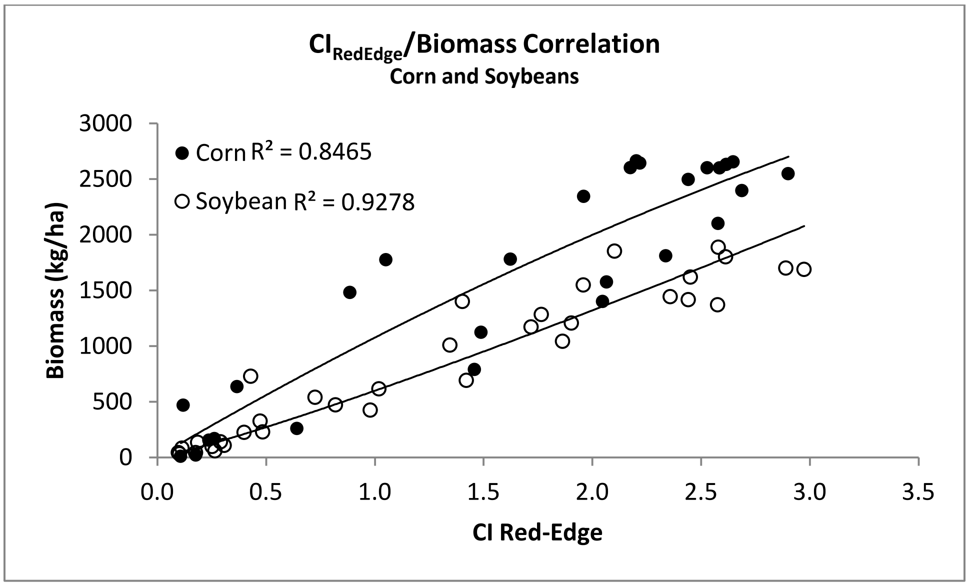


Figure 3.12: Correlation between $CI_{RedEdge}$ and combined biomass of corn (2003, 2005 and 2007) and soybeans (2002, 2004, 2006 and 2008).

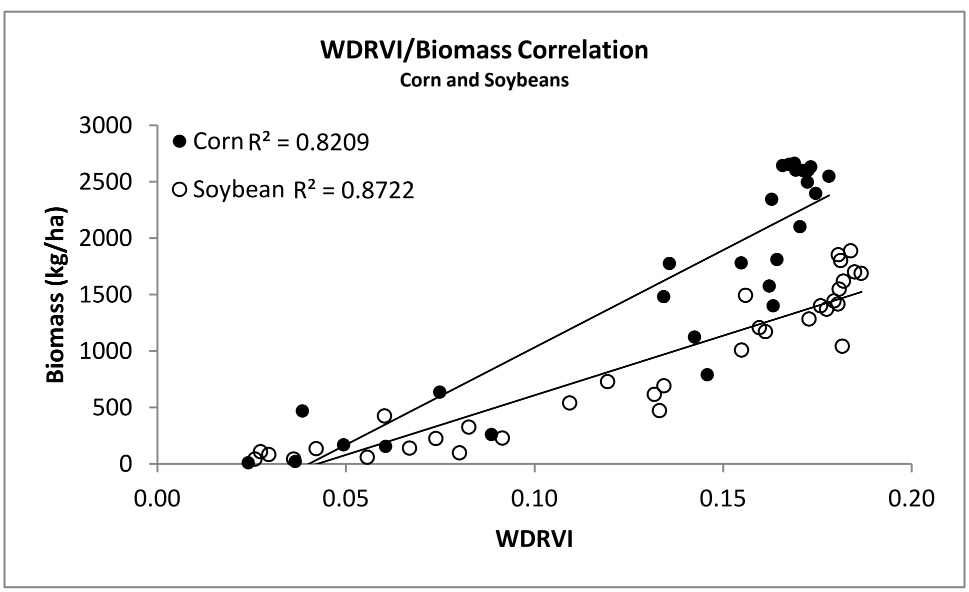


Figure 3.13: Correlation between WDRVI and combined biomass of corn (2003, 2005 and 2007) and soybeans (2002, 2004, 2006 and 2008).

Table 3.3: Results of parameters used in the statistical analyses of the best-fit functions for the green biomass/VI correlations of each crop type using all of the data acquired for each crop during the study period (i.e. three growing seasons for corn and four growing seasons for soybean). The parameters are the square of the coefficient of correlation (R^2), root mean square error (RMSE) and coefficient of variation (CV).

Crop (Sample size)	**Vegetation Index**	**R^2**	**RMSE (kg/ha)**	**CV (%)**
Corn (n = 27)	NDVI	0.88	334.65	20.64
	$CI_{RedEdge}$	0.85	375.16	23.14
	WDRVI	0.82	405.20	24.99
Soybeans (n = 34)	NDVI	0.94	151.54	16.85
	$CI_{RedEdge}$	0.93	208.53	24.67
	WDRVI	0.87	227.99	25.34

In general, observed R^2 values for corn ranged from 0.82 to 0.88 with NDVI having the highest and WDRVI with the lowest. Corn RMSE ranged from 334.65kg/ha observed in NDVI to 405.2kg/ha which was observed in WDRVI. CV for corn ranged from 20.64% to 24.99% with NDVI having the lowest value and WDRVI having the highest. Overall NDVI had the highest correlation and lowest errors and variations for corn, while WDRVI had the lowest correlation and highest variations and errors. Statistical parameters observed for $CI_{RedEdge}$ had values which were between the observations for both of the other VIs.

R^2 values observed for soybean ranged from 0.87 to 0.94 with NDVI having the highest and WDRVI with the lowest. RMSE ranged from 151.54kg/ha observed in NDVI to 227.99kg/ha which was observed in WDRVI. CV for soybean ranged from 16.85% to 25.34% with NDVI having the lowest value and WDRVI having the highest. Overall NDVI had the highest correlations and lowest errors and variations for soybean, while WDRVI had the lowest correlations and highest variations and errors. Statistical parameters observed for soybean/$CI_{RedEdge}$ had values which were between the observations for both of the other VIs.

3.3.2 Correlation of Biomass and VIs with Environmental Variables

Investigations were carried out to discover if there are any relationships between the seasonal increase in green biomass of both crops and environmental variables including soil moisture and GDD. Similar research on correlations with environmental variables was done using the VIs derived from the field measured crop spectra. The investigations into the relationships between green biomass, VIs and the environmental variables of interest were done by determining the Pearson's correlation coefficient (r) from simple linear regressions. Using r values to identify the correlation between biomass, VIs and environmental factors would reveal the relationships as either positive or negative.

The correlations between biomass, NDVI, $CI_{RedEdge}$, WDRVI and accumulated soil moisture and GDD for each study year are represented in charts shown in Figures 3.14 to 3.20 (A – D). In general, similar r values were observed in all instances of correlation for each year, therefore similar charts representing these correlations were produced each year.

Correlations of soybean biomass and all VIs with accumulations of soil moisture and GDD during the 2002 growing season are represented in Figure 3.14 (A – D). The observed trend line for soil moisture showed a steady increase as lag time increased, while a steady increase then slight decrease in correlation with lag time is observed for

GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.94 and -0.1 which occurred with the 28- and 84-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are 0.08 and 0.97 which occurred during the 14- and 56-day lag periods respectively.

Correlations of corn biomass and all VIs with accumulations of soil moisture and GDD during the 2003 growing season are represented in Figure 3.15 (A – D). The observed trend line for soil moisture showed a steady increase as lag time increased, while a slight increase then steady decrease in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.50 and 0.93 which occurred at the 14 and 84-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are -0.83 and 0.67 which occurred during the 84- and 28-day lag periods respectively. An intersection between the soil moisture and GDD trend lines occurred at about the 56-day lag time.

Correlations of soybean biomass and all VIs with accumulations of soil moisture and GDD during the 2004 growing season are represented in Figure 3.16 (A – D). The observed trend line for soil moisture showed a small decrease and then steady increase as lag time increases, while a steady increase then slight decrease in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.71 and -0.16 which occurred at the 14- and 84-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are 0.14 and 0.76 which occurred during the 14- and 56-day lag periods respectively. No intersections were observed in these trend lines.

Correlations of corn biomass and all VIs with accumulations of soil moisture and GDD during the 2005 growing season are represented in Figure 3.17 (A – D). The observed trend line for soil moisture showed a steady increase as lag time increased, while a slight increase then steady decrease in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.65 and 0.86 which occurred at the 14- and 84-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are -0.56 and 0.95 which occurred during the 84- and 28-day lag periods respectively. An intersection between the soil moisture and GDD trend lines occurred at about the 84-day lag time.

Correlations of soybean biomass and all VIs with accumulations of soil moisture and GDD during the 2006 growing season are represented in Figure 3.18 (A – D). The observed trend line for soil moisture showed a steady decrease then a slight increase as lag time increased, while a steady increase then slight decrease in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.97 and -0.2 which occurred with the 56- and 14-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are 0.47 and 0.98 which occurred during the 14- and 56-day lag periods respectively.

Correlations of corn biomass and all VIs with accumulations of soil moisture and GDD during the 2007 growing season are represented in Figure 3.19 (A – D). The observed trend line for soil moisture showed a steady increase as lag time increased, while a steady decrease in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.80 and 0.60 which occurred at the 14- and 84-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are -0.77 and 0.68 which occurred during the 84- and 14-day lag periods respectively. An intersection between the soil moisture and GDD trend lines occurred around the 56-day lag time.

Correlations of soybean biomass and all VIs with accumulations of soil moisture and GDD during the 2008 growing season are represented in Figure 3.20 (A – D). The observed trend line for soil moisture showed alternating decrease and increase in correlation with lag time, while very high values which were almost even for all lag periods is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.98 and -0.76 which occurred during the 28- and 56-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are 0.90 and 1.0 which occurred during the 14- and 56/84-day lag periods respectively.

A summary of correlations from all study years for corn biomass and VIs with soil moisture and GDD are represented in Figures 3.21 to 3.22 (A – D). Correlation values vary from negative to positive for both accumulated soil moisture and GDD. General trends observed for correlations with GDD show that correlation decreased as lag times increased, with peak values observed at either 14 or 28-day lag periods. For soil moisture correlations, there was general increase as lag times increased; highest correlations were observed at the 84-day lag period. Intersections were also observed between the correlations of both environmental variables because of the nature of their trend lines. The points of intersection for each studied year occurred at longer lag times i.e., approximately 56 and 84-day lag periods.

Charts representing correlations derived from soybean biomass and VIs with soil moisture and GDD are represented in Figures 3.23 to 3.24 (A – D). The correlations with GDD were observed to be positive in all instances and had an increasing trend as lag time increased, with highest correlation observed at the 56-day lag period on majority of the years studied. On the other hand, all correlations with soil moisture resulted in negative values with a trend that had lowest values in the 28-day lag and then increased to peak at 84-day lag.

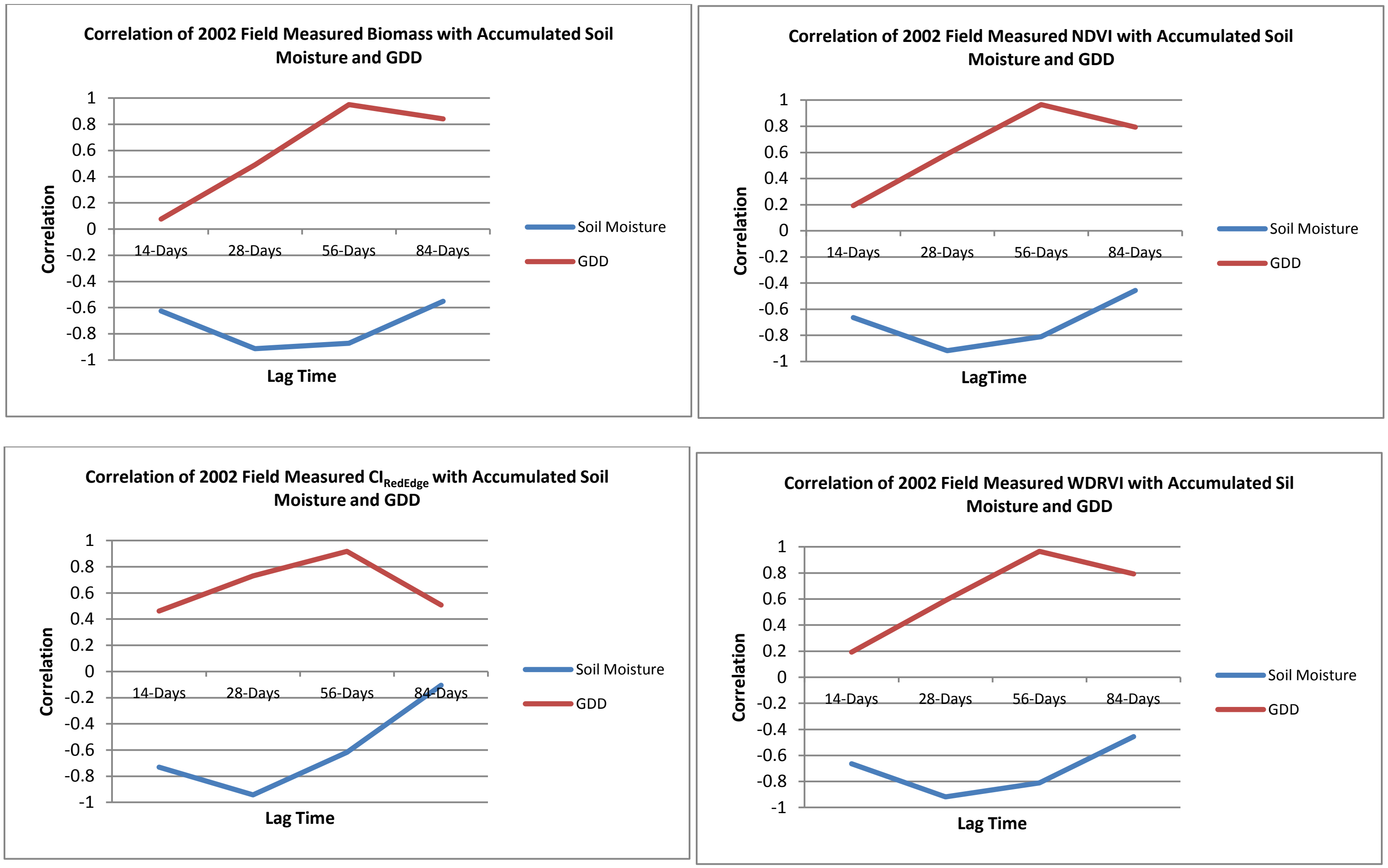


Figure 3.14: Pearson's correlation coefficient (r) values for the relationships of 2002 growing season green biomass of soybeans and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

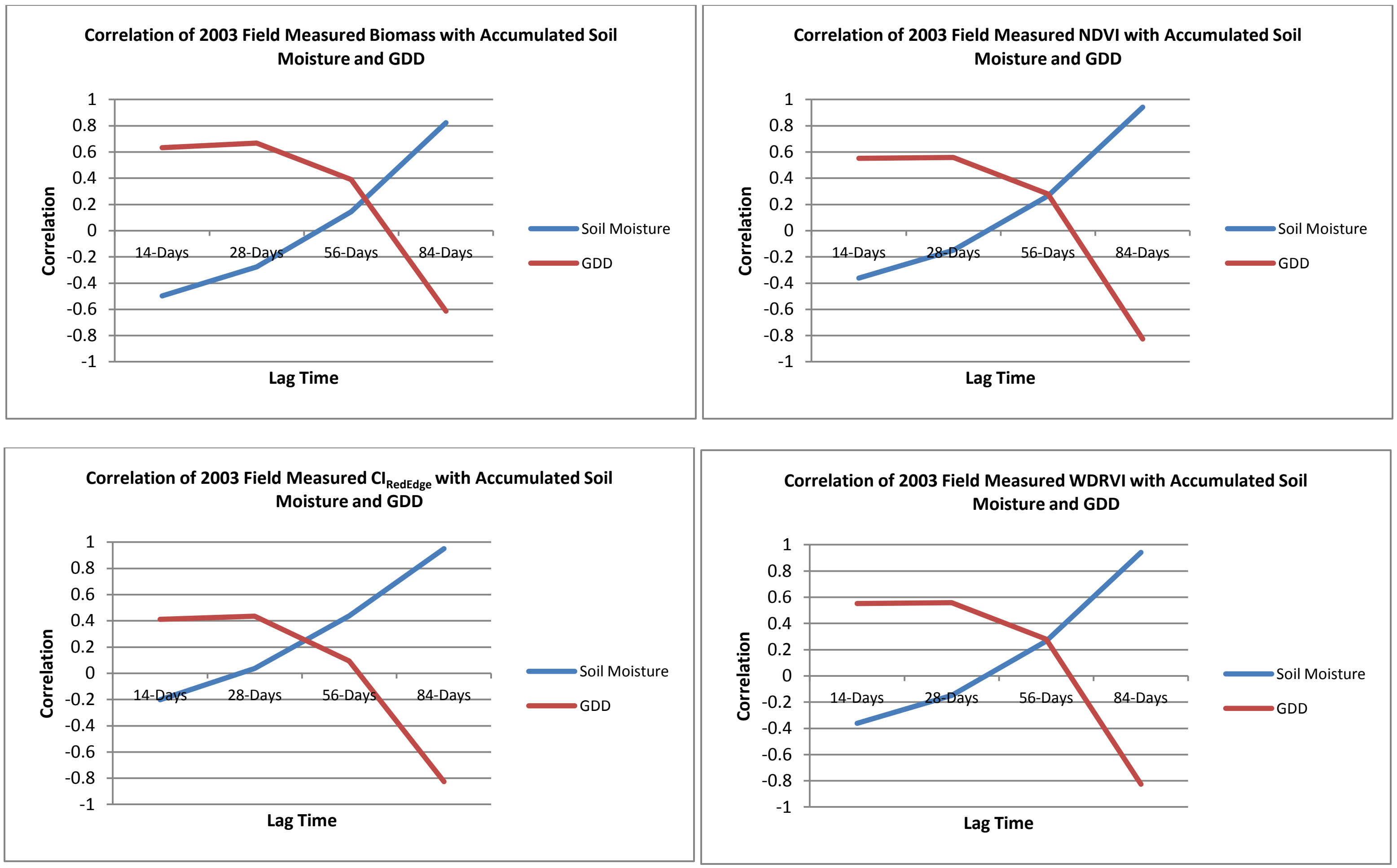


Figure 3.15: Pearson's correlation coefficient (r) values for the relationships of 2003 growing season green biomass of corn and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

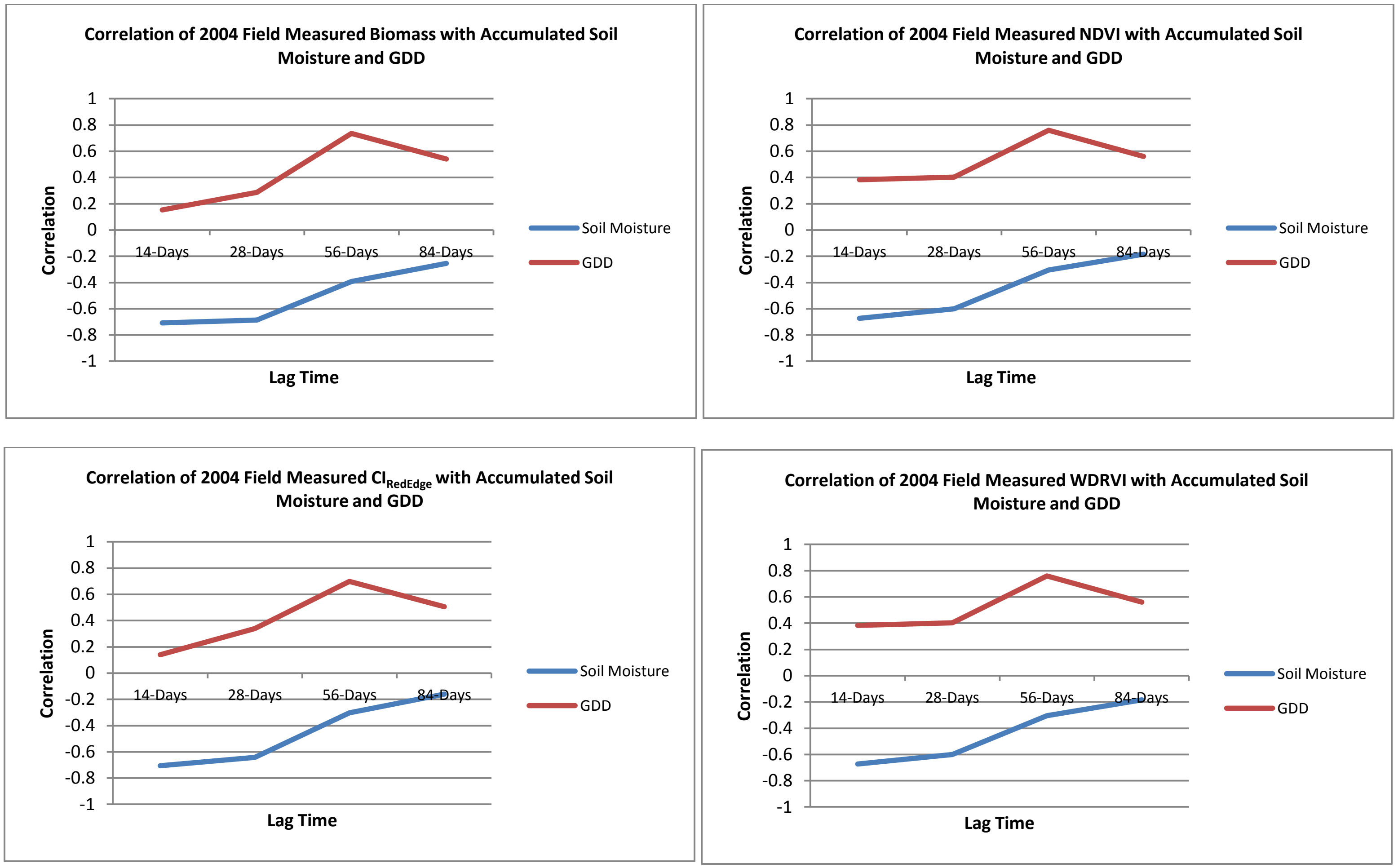


Figure 3.16: Pearson's correlation coefficient (r) values for the relationships of 2004 growing season green biomass of soybeans and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

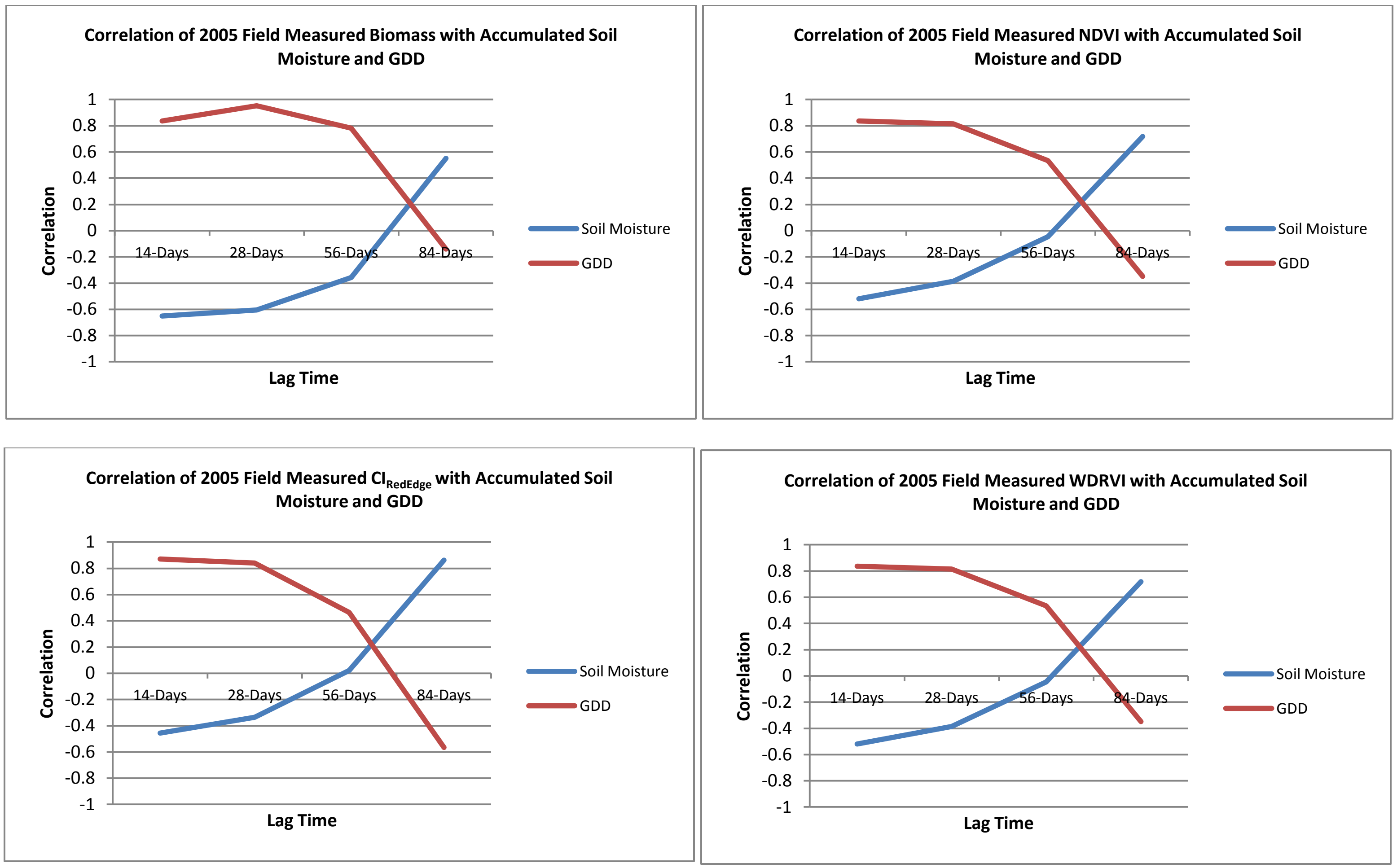


Figure 3.17: Pearson's correlation coefficient (r) values for the relationships of 2005 growing season green biomass of corn and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

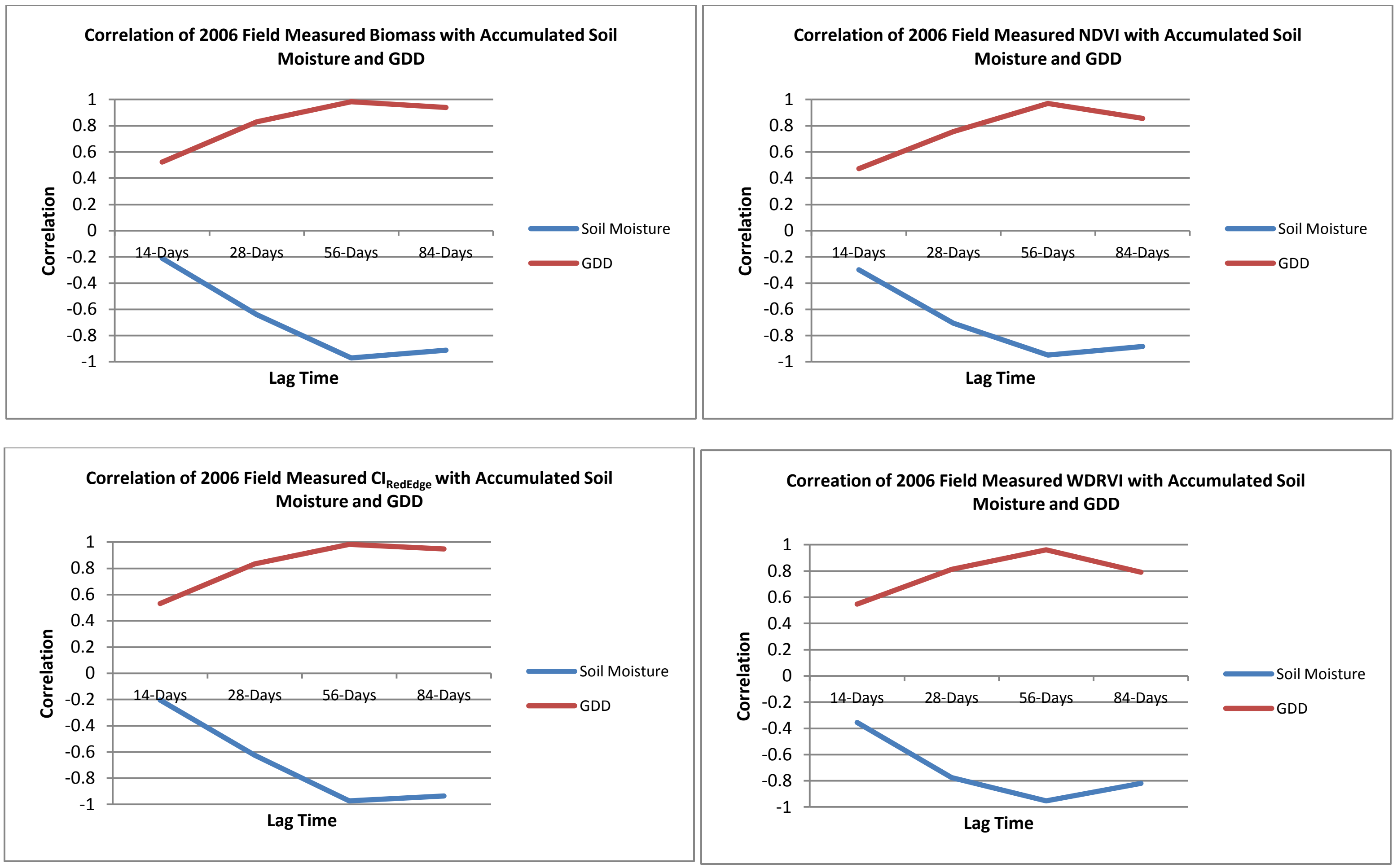


Figure 3.18: Pearson's correlation coefficient (r) values for the relationships of 2006 growing season green biomass of soybeans and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

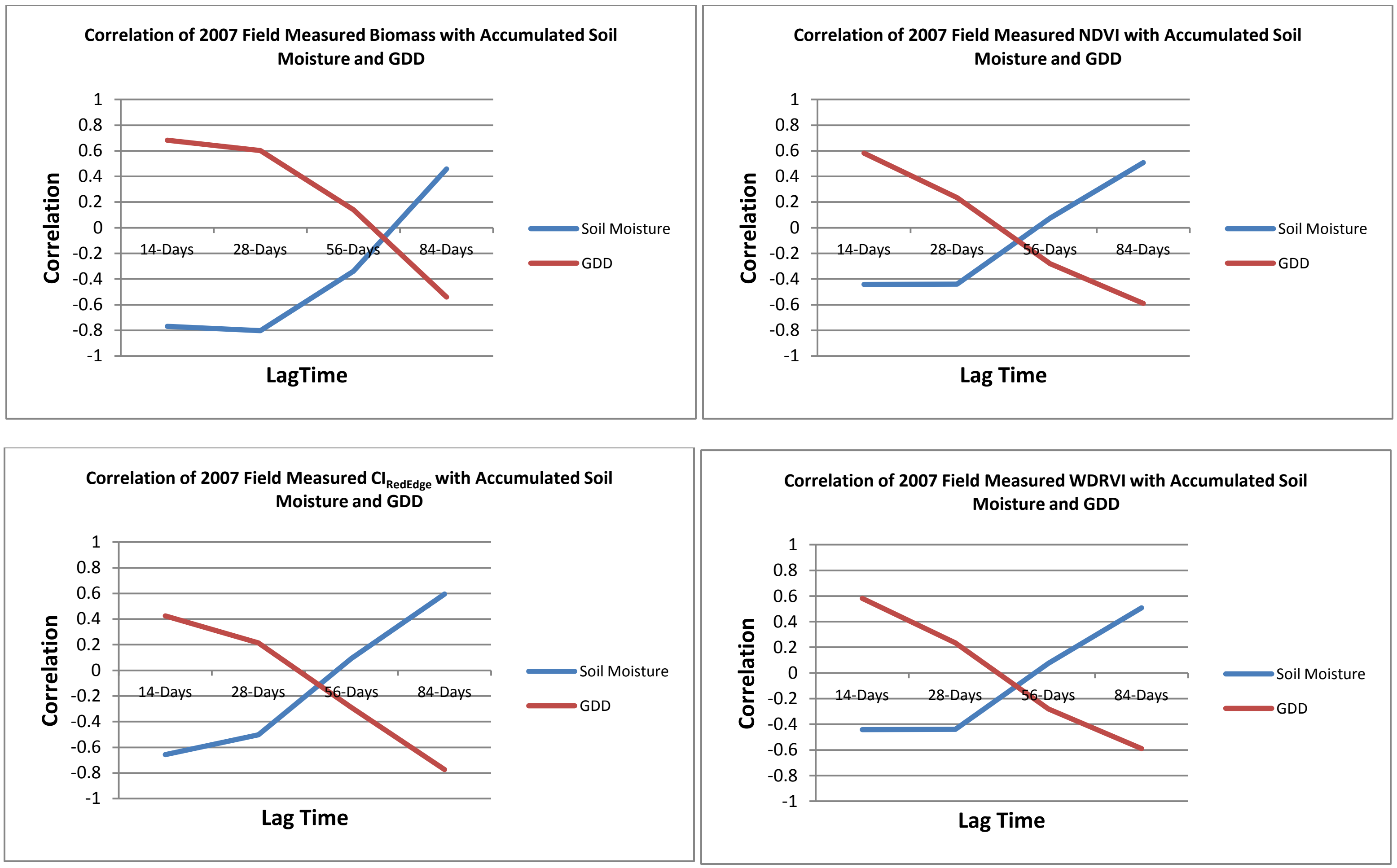


Figure 3.19: Pearson's correlation coefficient (r) values for the relationships of 2007 growing season green biomass of corn and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

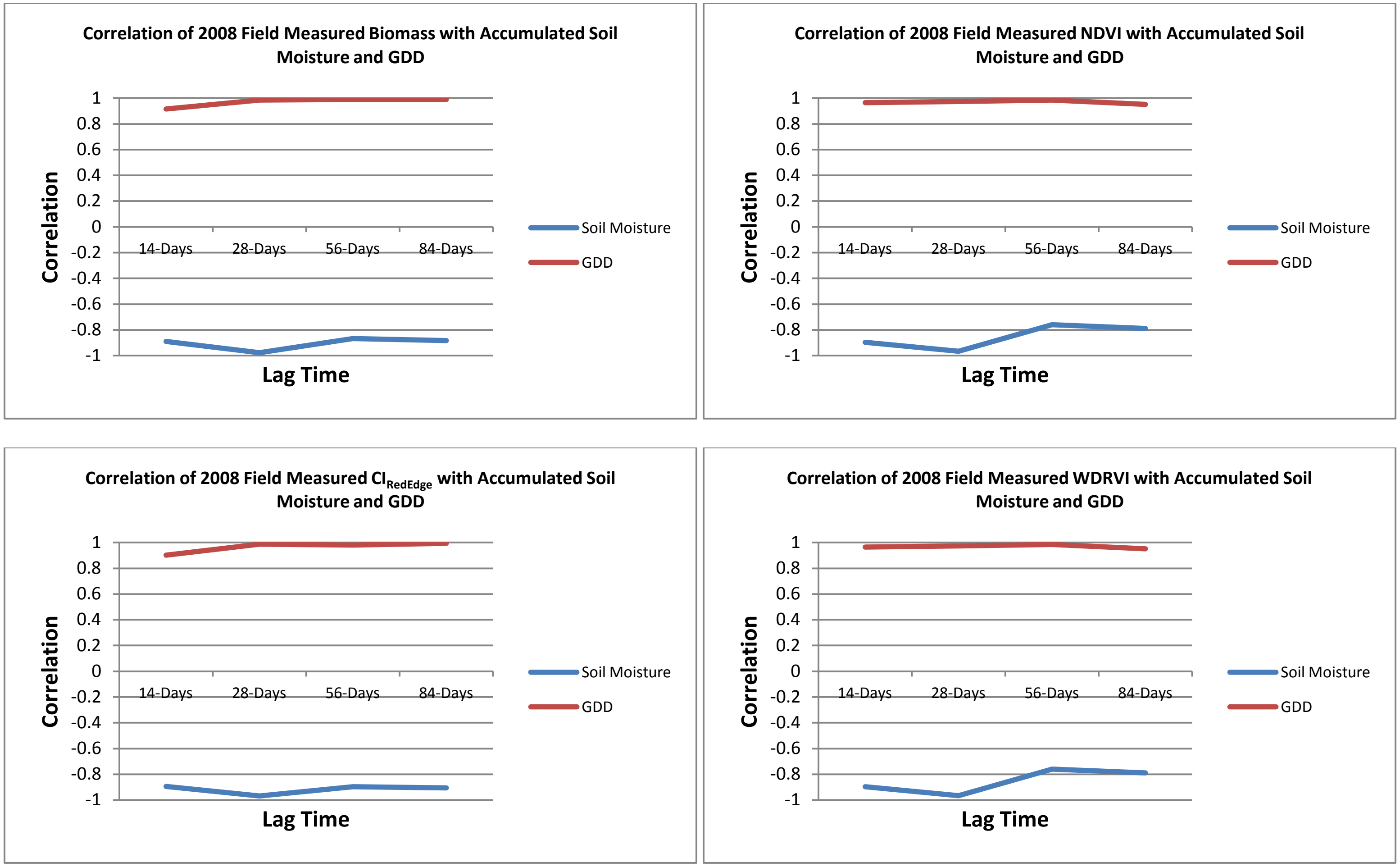


Figure 3.20: Pearson's correlation coefficient (r) values for the relationships of 2008 growing season green biomass of soybeans and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

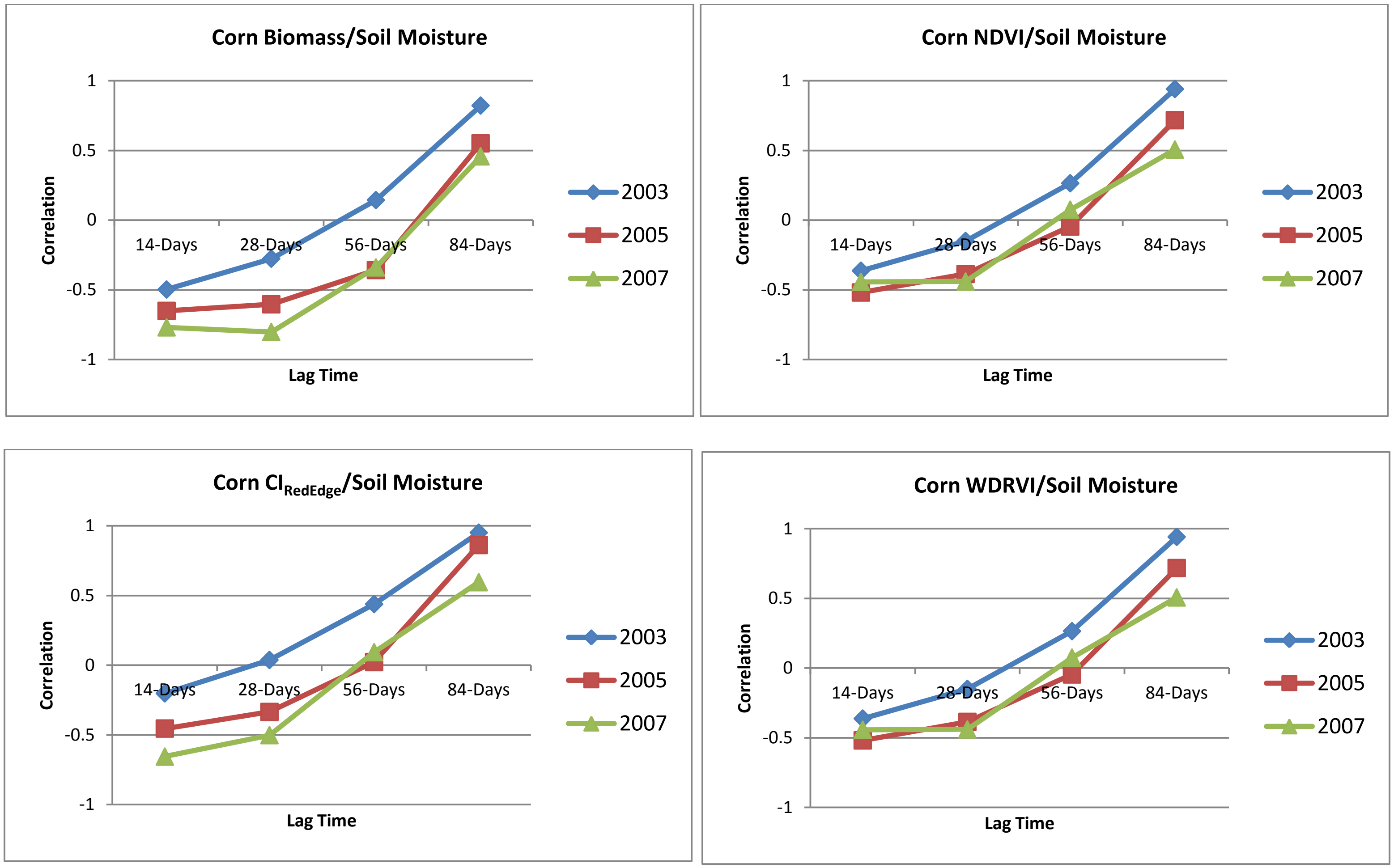


Figure 3.21: Summary of Pearson's correlation coefficient (r) values for the relationships of corn growing season green biomass and selected vegetation indices with accumulated soil moisture during each study year (2003, 2005 and 2007).

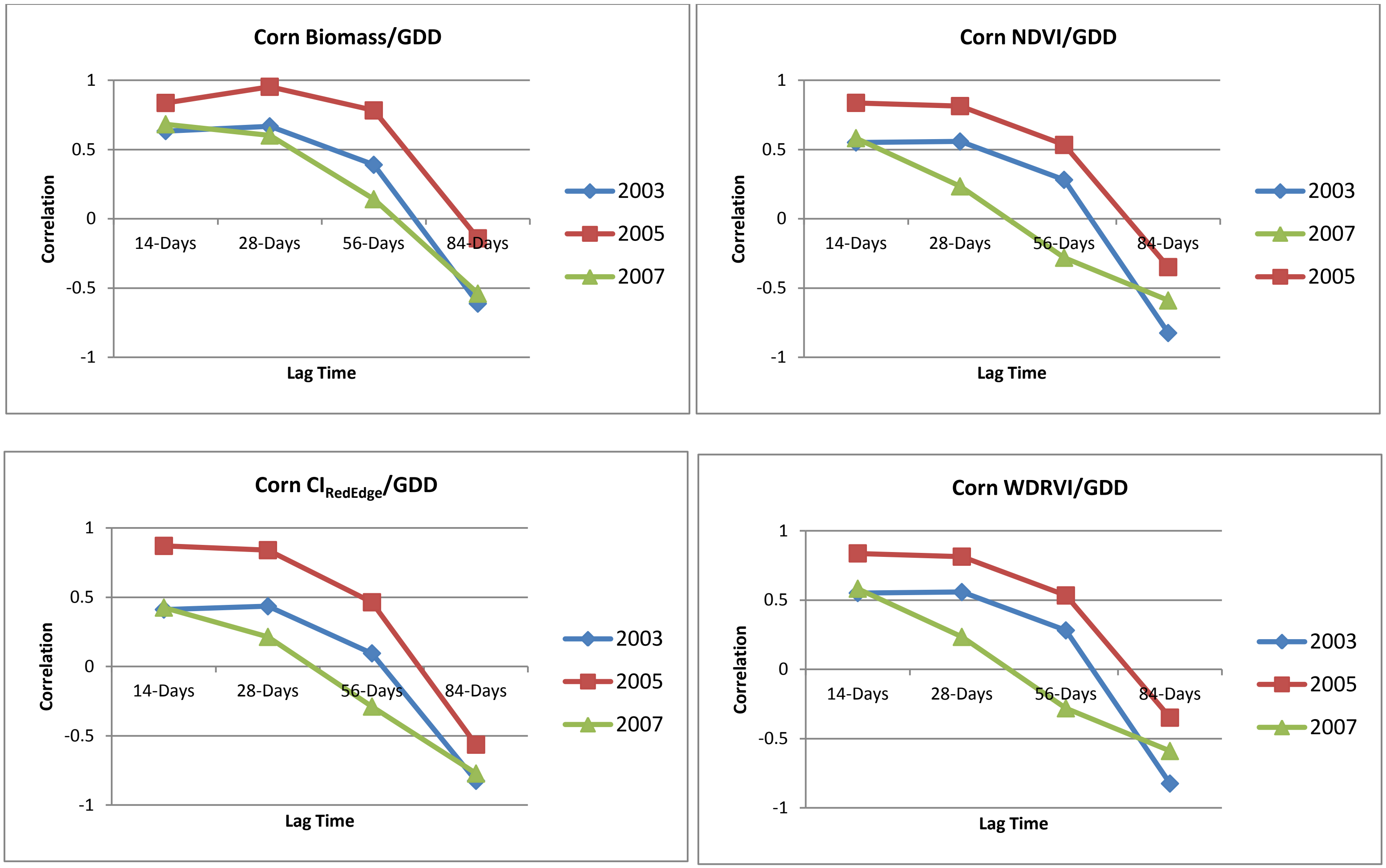


Figure 3.22: Summary of Pearson's correlation coefficient (r) values for the relationships of corn growing season green biomass and selected vegetation indices with accumulated growing degree days (GDD) during each study year (2003, 2005 and 2007).

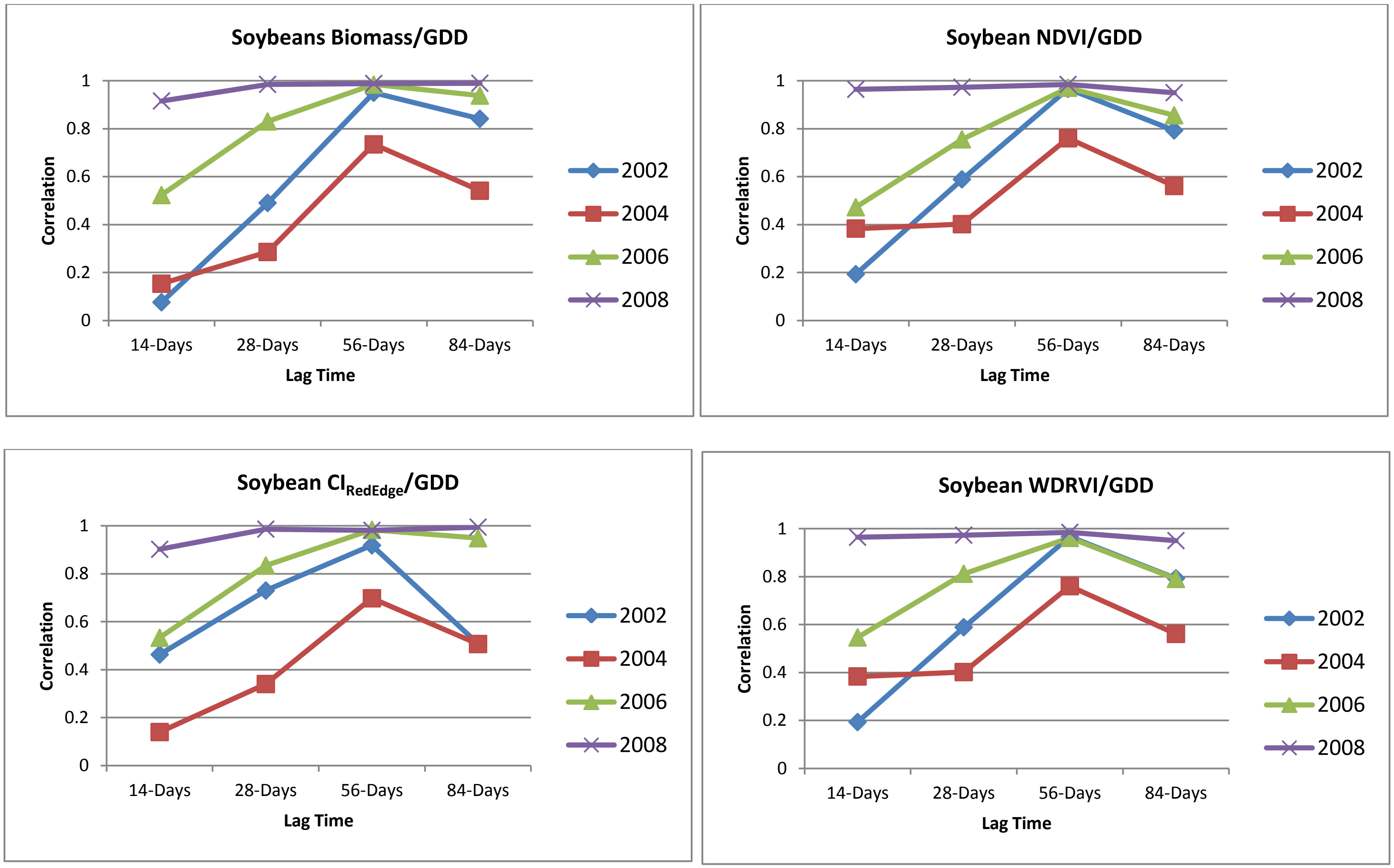


Figure 3.23: Summary of Pearson's correlation coefficient (r) values for the relationships of soybean growing season green biomass and selected vegetation indices with accumulated growing degree days (GDD) during each study year (2002, 2004, 2006 and 2008).

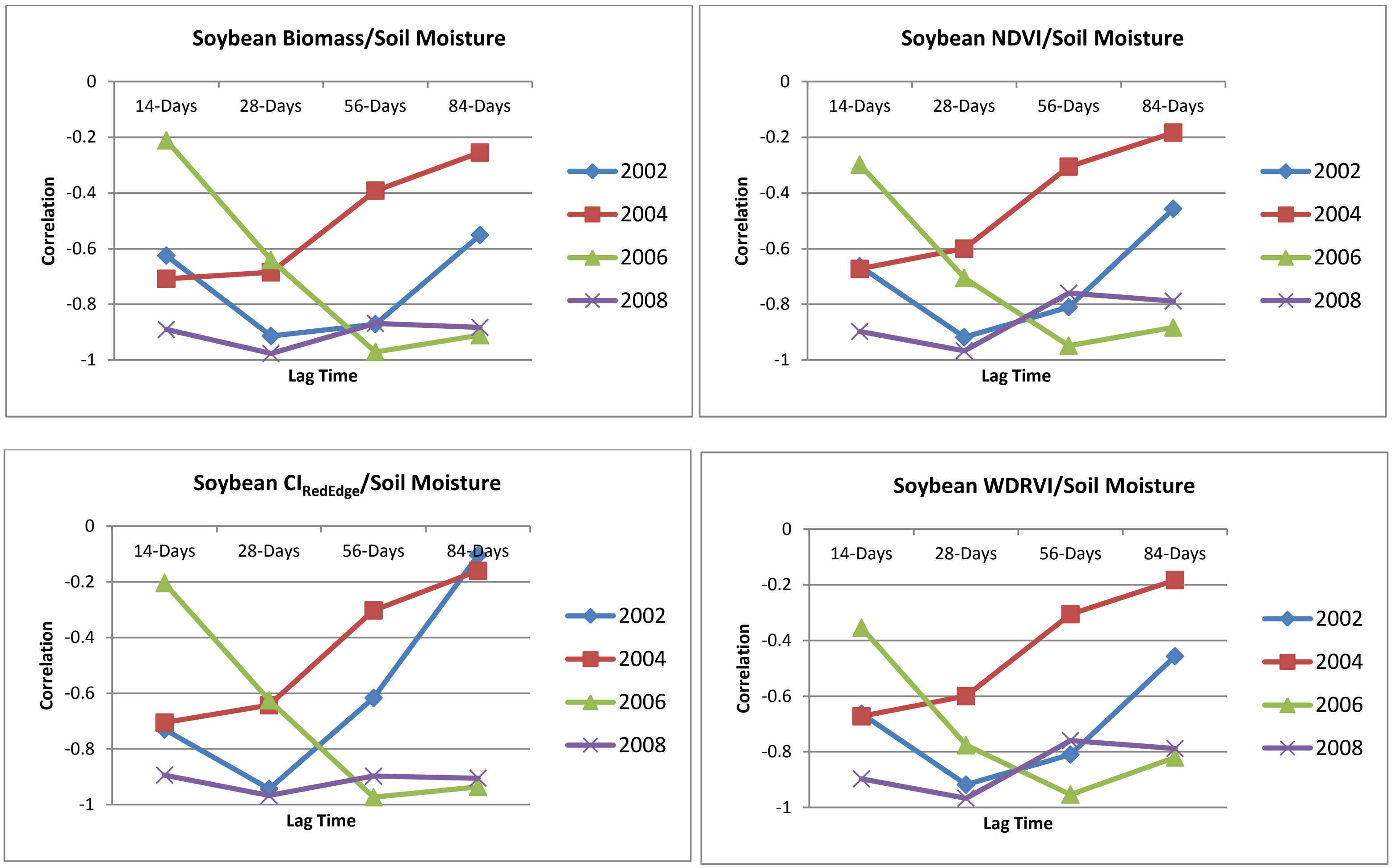


Figure 3.24: Summary of Pearson's correlation coefficient (r) values for the relationships of soybean growing season green biomass and selected vegetation indices with accumulated soil moisture during each study year (2002, 2004, 2006 and 2008).

3.4 Discussion

Results obtained from the examination of relationships between crop biomass and spectral indices were very good overall. All of the R^2 values ranged from 0.72 to 0.99 with reasonably low RMSE's below 405.2kg/ha and CV's below 25.34% for the crop specific relationships. However, some variation occurred with regard to the statistical parameters. Slight variability was observed among the yearly biomass estimation results from each crop as well as in the results obtained for both crops.

Annual variations in biomass of the crops may be affected by environmental factors. Plant growth is affected by numerous factors including temperature, precipitation, soil moisture, intensity and duration of insolation (Eastin & Sullivan, 1984), and variability in any of these may reflect in the VIs. Annual variation of these environmental factors would contribute to the variations in biomass of corn and soybeans being studied yearly. Differences in the accuracies associated with yearly biomass predictions of the specific crops could be as a result of the inter-annual variations of biomass. It is expected that issues of variations in plant growth and condition will occur from one growing season to the next.

Correlation of green biomass and accumulated GDD showed good results overall. This environmental variable, when regressed against biomass and the VIs, showed generally reversed behaviors for each crop type. In the case of corn, there were decreasing r values as the lag time increased with the highest correlations occurring at lag times of 14 days and lowest correlations at 84 day lags. Soybean on the other hand, had increase in correlation of accumulated GDD with biomass and VIs as lag time increased, with lowest r values at the 14 day lags and highest at 84 day lag periods.

The difference in correlations of both crops with accumulated GDD can be attributed to differences in phenology of both crops. Corn plants typically display a bell shaped curve with gradual increase and decrease in green biomass (http://weedsoft.unl.edu/documents/GrowthStagesModule/Corn/Corn.htm#), while soybeans attain peak biomass later in the season with rapid decline during senescence (http://weedsoft.unl.edu/documents/ GrowthStagesModule/Soybean/Soy.htm#). The later occurrence of soybean senescence caused reduction in r to occur at a later lag time of 56-days.

The correlation results of corn biomass and VIs with accumulated soil moisture show that lag time of 14 – 28 days have negative values, but after approximately 56 days there is a positive correlation. This implies that accumulated soil moisture from longer times have a stronger influence on vegetation growth than the current/more recent soil moisture. Soybean on the other hand, had occurrences of either annual increase or decrease in correlation of soil moisture with biomass and VIs as lag time increased, but all correlation values were negative.

3.5 Conclusion

Numerous studies have been directed at using field measured spectral data to estimate plant biophysical variables. Large amounts of research have also focused on correlating environmental variables with VIs derived from satellite imagery. Minimal research has been carried out focusing on crop biomass estimation and looking at how the phenology of the crops correlates with environmental variables. This research used canopy level spectral measurements acquired from rain-fed corn and soybean fields across seven growing seasons to compare the green biomass estimation capabilities of selected VIs. It also looked at how the growing season biomass and derived VIs correlated with daily measurements of environmental variables accumulated in lag-times of 14, 28, 56 and 84 days.

Analysis of the relationships between corn and soybean with NDVI, $CI_{RedEdge}$ and WDRVI showed very high correlations in all of the seven study years (R^2 = 0.83 to 0.99). NDVI consistently showed the highest correlations in all of the study years.

Crop specific analysis also resulted in good correlations with high R^2 and low RMSE and CV values overall. NDVI was also the best VI for biomass estimation for each crop with the highest R^2 and lowest RMSE and CV in all cases for both crops. Biomass estimation by all three VIs showed better results in soybean than corn for all three statistical parameters applied for analyses.

Research into the correlation of accumulated soil moisture with field measured biomass and derived VIs showed very similar trends for all study years. Correlation trends observed for corn were very clear and involved increase in correlations as lag times increased. Soybean/soil moisture trends were not quite as clear, but also showed a general decrease in negative correlation as lag time increased.

For the correlation of accumulated GDD with field measured biomass and VIs, the trends were also very similar for each growing season. Corn correlation with GDD showed very clear decrease as lag times increased. Soybean/GDD correlations were also evident in general, and showed increase in correlation with increase in lag time.

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4 REMOTE ESTIMATION OF CROP BIOMASS IN A RAIN-FED FIELD AND CORRELATION WITH ENVIRONMENTAL VARIABLES

4.1 Introduction

4.1.1 Rationale for Measuring and Monitoring Green Biomass

The biophysical parameter referred to as "green biomass" is a measure of the overall productivity of terrestrial vegetation; i.e., it is the amount of photosynthetically active vegetation existing in an area of interest. Being able to measure such a biophysical parameter is important for a variety of reasons. For example, green biomass can be linked to the amounts of CO_2 consumption and O_2 production due to the carbon sequestration capabilities of vegetation.

Carbon sequestration is the process by which atmospheric CO_2 is absorbed by photosynthesizing plants and stored within their biomass as carbon. This is important because both natural and managed vegetation canopies absorb atmospheric CO_2, which is the most important gas emitted by the activities of humans (Carbon Sequestration in Agriculture and Forestry, 2010). The sequestration process as applied to agricultural crops should provide a means for reducing the amount of fossil fuel CO_2 emissions into the atmosphere, thereby not only reducing atmospheric heating but also restoring air quality (Hutchinson *et al*., 2007). Measuring the amount of carbon present in plant biomass is one way of assessing environmental changes caused by shifts in the rate of carbon exchange between the atmosphere and biosphere induced by land use transitions. As an example, for both irrigated and rain-fed corn at physiological maturity, the cumulative carbon gain by the plant is within 2-21% of its biomass (Suyker *et al*., 2004).

Biomass measurements are also included in climate and biome models, and are used for ecosystem modeling (Watson *et al*., 2001). Kardol *et al*., (2010) showed that the effects of climate change on plants are clearly reflected in their biomass amounts.

Being able to measure the biomass of agricultural crops is also important with regard to nutrient management. The amounts of nitrogen present in the above ground biomass of crops (especially non-leguminous crops such as corn) play a role in the vegetative loss of this nutrient. Accurately accounting for these losses in nitrogen balance calculations is important for developing cropping systems that improve efficient use of nitrogen fertilizers and reduce adverse environmental impacts (Francis *et al*., 1993). Corn and soybeans accounted for over 14 million agricultural acres and were valued at over $10 billion in Nebraska in 2010, and an estimated $1.18billion were spent on fertilizer for enhancing crop production (USDA, 2011). Thus, monitoring the biomass of corn and soybeans throughout the growing season should be beneficial.

4.1.2 Remote Sensing: A Potential Useful Tool for Assessing Green Biomass

One potential method of measuring and monitoring green biomass in crops is to make use of remote sensing. Advantages of collecting biomass data by means of sensors operating at aircraft or satellite altitudes include the non-destructive nature of the technology (Hatfield and Prueger, 2010). Remote assessment should also be important because of the synoptic view provided by airborne or orbital sensors, the capability for acquiring data in both visible and non-visible portions of the electromagnetic spectrum, the capability for digital processing of the retrieved information, and the cost-effectiveness of the technology.

4.1.3 Light and Terrestrial Vegetation

Electromagnetic radiation in the visible spectrum (wavelength = 400 to 700nm) is absorbed by plant pigments in typical green vegetation (Figure 4.1). Radiation in parts of

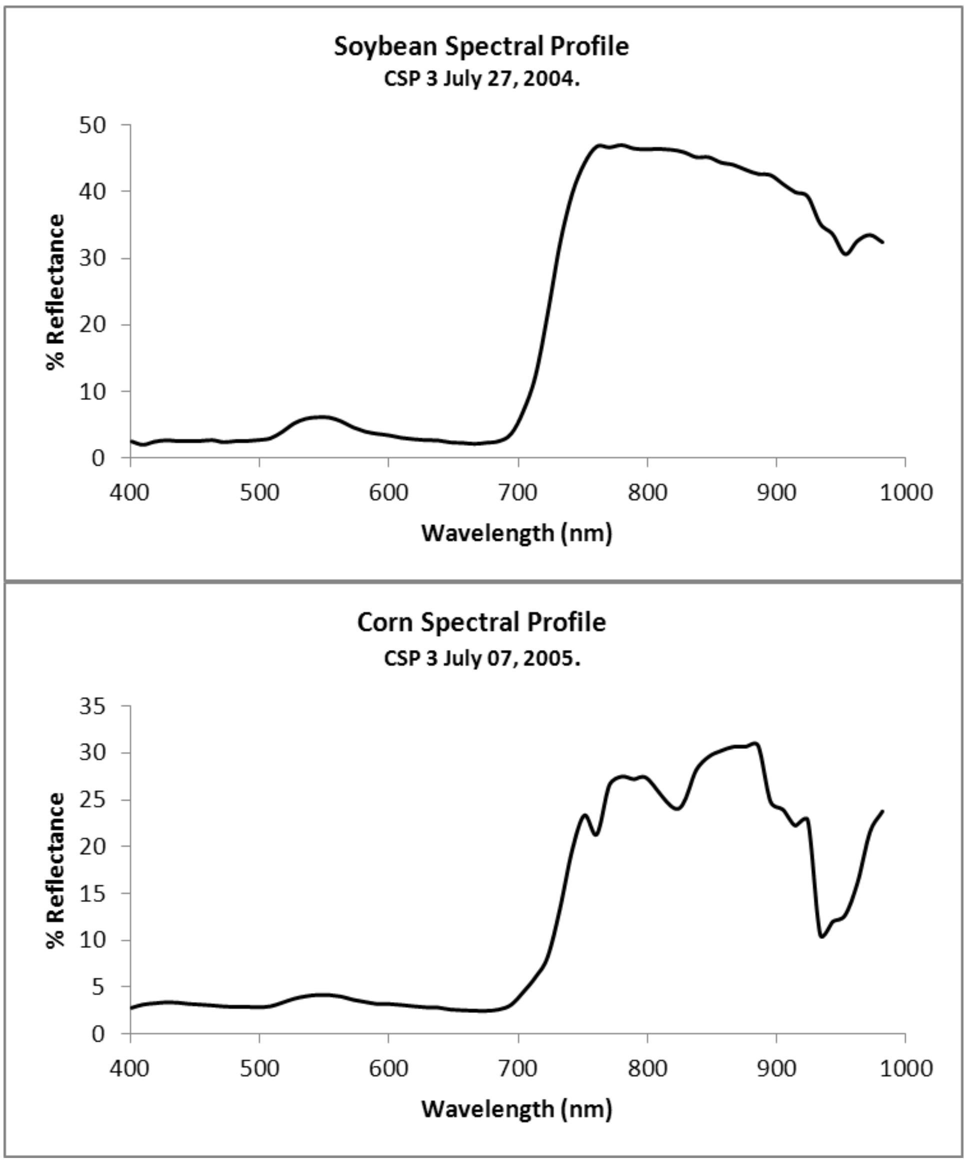

Figure 4.1: Spectral reflectance of soybeans and corn in the visible to NIR regions of the spectrum. The spectra shown were acquired by the AISA Eagle airborne hyperspectral radiometer on the dates noted in subsequent text. Characteristic of healthy green vegetation is the dominant absorption in the blue and red regions, and less absorption in the green. Pronounced reflectance in the NIR portion of the spectrum is also typical.

the blue (400 to 500nm) and red (600 to 700nm) portions of the spectrum are efficiently absorbed for photosynthetic use by the chlorophyll *a*, chlorophyll *b* and β-carotene pigments present in the plant. Relatively less absorption occurs in the green band (500 to 600nm), which creates a "reflectance peak" in this region resulting in the green coloration of plants as perceived by the human eye. The spongy mesophyll cells are associated with pronounced scattering of near-infrared (NIR) radiation, causing a typical high spectral reflectance in the 700 to 1200nm region of the spectrum (Di *et al*., 1994; Jensen, 2000). The spectral reflectance in the red region for healthy, actively growing vegetation typically diminishes as plants develop (because of increasing photosynthetic activity and thus greater absorption at that wavelength), while the NIR reflectance increases steadily with increasing amounts of canopy. Increases in leaf thickness, may also be correlated with increases in NIR reflectance (Gitelson *et al*., 2003).

4.1.4 Vegetation Indices

Because of the characteristic reflectance responses of vegetation within the red and NIR portions of the spectrum (as related to the chlorophyll content and canopy architecture of a plant, respectively), data acquired from these two regions have been widely used to create spectral transformations generally referred to as "vegetation indices" (VIs), and a large number of such indices have been developed. VIs are dimensionless, radiometric measures that function as indicators of relative abundance and activity in green vegetation, and have been shown to correlate to varying degrees of accuracy with biophysical variables such as leaf area index (LAI), chlorophyll content, and biomass, all of which vary with the phenology of the plant (Di *et al*., 1994; Jensen, 2000; Gitelson *et al*., 2003).

Another advantage of VIs is that they reduce the dimensionality of datasets. For any dataset there is a maximum size or amount of spectral information present above which classification or feature extraction becomes inefficient. Using a mathematical ratio of bands may be useful in extracting a maximum amount of variation in the inherent spectral information. Measured spectral reflectance data from various bands are thus compressed into VIs through mathematical manipulation (Myneni *et al*., 1995). Such a spectral transformation can, in fact, result in improved information content requiring less digital storage space than was needed for the original raw data. Also, VIs correct for certain troublesome effects associated with varying conditions related to data acquisition at multiple times. Atmospheric condition, solar angle, soil background, canopy architecture, sensor calibration and view angle are some of the external factors which vary when spectral data are acquired on more than one date (Jackson and Huete, 1991). Normalization of the effects of these variations in studying multiple co-registered datasets is one of the benefits of linear or ratio manipulation of spectral bands into VIs (Jensen, 2005).

4.1.5 Previous Work on Use of Aerial Imagery for Biomass Estimation and Correlation with Environmental Variables

A number of researchers have studied vegetation other than agricultural crops from satellite platforms at regional or global scales (e.g., Hayes and Decker, 1996; Huete *et al*., 1997; Wardlow, 2007) as compared to investigations using aircraft data, probably due to the greater availability of data for the former as compared to the latter. A wide range of studies (summarized by Lu, 2006) have been carried out on remote estimation of above ground biomass in forest canopies in order to monitor changes over time and their effects on carbon sequestration. Nichol and Sarker (2011) estimated forest biomass using spectral bands from two 10-m multi-spectral sensors, and achieved a moderate accuracy of about 60% using simple band ratios, while combined processing of texture analysis and ratios yielded R^2 values of about 0.94. Zheng *et al*., (2004) used medium resolution Landsat 7 ETM+ data to predict above ground biomass in a managed forest landscape using models derived from individual bands in the blue to middle infra-red parts of the spectrum, as well as five vegetation indices including the Normalized Difference Vegetation Index (NDVI), Simple Ratio (SR), Modified Soil Adjusted Vegetation Index (MSAVI), Corrected NDVI ($NDVI_C$), and the ratio of Blue/Red). The author developed three models to predict biomass of the vegetation in three groups: coniferous trees, hardwood trees, and both tree types combined. The biomass models yielded R^2 values of, 0.86, 0.95 and 0.82 respectively.

Some research has been done using remote sensing as a means of estimating biomass in crops. For example, Aparicio *et al*., (2000) used VIs (including SR, NDVI and the Photochemical Reflectance Index [PRI]), derived from data acquired using portable field spectroradiometers, along with other integrative physiological traits, to determine productivity in durum wheat. That author determined, for rain-fed environments, that all three indices correlated with yield at accuracies ranging from 37 to 59%, while the accuracies for irrigated fields were within the range of 26 to 39%. The same type of research was also undertaken by Shanahan *et al*., (2001) using NDVI, Green NDVI (GNDVI) and the Transformed Soil Adjusted Vegetation Index (TSAVI), all calculated from high resolution airborne multi-spectral data. The objective was to predict yield in corn. Shanahan *et al*., (2001) found that GNDVI had the best correlations with values of 0.70 and 0.92 calculated for the two study years. Vina (2004) , using data from an airborne sensor of high spatial as well as high spectral resolution, estimated green leaf biomass in corn and soybean at field level using a model designed to estimate crop canopy chlorophyll content per unit ground area. Their model predicted biomass of both crops with a 0.97 R^2 value and root mean square error of 241.7kg/ha.

Monthly AVHRR NDVI images were correlated to GDD and precipitation data by Li et al (2002). This study, carried out in China, showed NDVI and rainfall correlations reaching a peak (0.86) in areas with annual rainfall of 500 – 700mm. In addition, NDVI/GDD correlations were consistently higher than NDVI/precipitation in all vegetation types studied.Yang *et al*., (1994) looked at the correlation of biweekly AVHRR NDVI composited images with eco-climatological parameters in the central Great Plains, such as accumulated growing degree days (AGDD), soil temperature, potential evapotranspiration and precipitation. The research showed that on the average, correlation of NDVI with AGDD, precipitation with a 5 – 7 week lag, and precipitation with no lag had coefficients of above 0.8, 0.55 – 0.7 and 0.2 respectively.

Using Landsat-MSS NDVI images, Di *et al*., (1994) examined vegetation responses (via NDVI) to precipitation events in the Sandhills region of Nebraska. The study created a model which showed that NDVI response time varied during the course of a growing season, ranging from 14, 25 and 12 days at the beginning, middle and end of the growing season respectively. Ji and Peters (2005) also looked at the correlation between NDVI and precipitation using biweekly composites of AVHRR images. Their study showed a close relationship between NDVI and precipitation, as well as a variation in NDVI lag time response to precipitation with shorter lags (4 – 8 weeks) in the early season and longer lags (12 – 14 weeks) in the mid to late season.

It can be seen, then, that several authors have addressed the issue of remote sensing of vegetative biomass, but a scant amount of research has been carried out in crops using sensors with both high spatial and spectral resolutions for the purpose of estimating biomass over extended periods of time. Furthermore, minimal research has been done using aerial imagery to correlate the effects of environmental varibles on crop phenology. Therefore, the first objective of this research was to estimate the green biomass in rain-fed corn and soybeans across six growing seasons (2002 – 2007) using hyperspectral remotely sensed aerial images transformed to three selected vegetation indices.   The resulting estimations were compared to field-measured, destructively sampled crop biomass. The second objective focused on correlating changes in biomass and said vegetation indices, during each growing season, with GDD and soil moisture accumulated at multiple lag times.

4.2 Methods and Procedures

4.2.1 Study Area

The study site is a 65.4 ha non-irrigated field located at the University of Nebraska-Lincoln (UNL) Agricultural Research and Development Center (ARDC) near Mead, NE. The location of this site, and the Intensive Measurement Zones (IMZs) delineated within it, are represented in Figure 3.2. It is one of three fields which have been maintained since 2001 by the ARDC in support of the UNL Carbon Sequestration Program (CSP). This field, hereafter referred to as CSP3, is located at 41.18^{o}N; 96.44^{o}W. It receives moisture only from precipitation, unlike the other two fields which are irrigated. A single nitrogen fertilizer application, which is adjusted for residual nitrate measured from soil samples, is made to CSP3 each spring before planting. The double-crop rotation system, with corn and soybean planted in alternate years, is practiced on this field.

The climate of the study area is a temperate semi-arid one, with a mean annual precipitation of 887mm (based on annual average values from 1961 to 1990), with a range from 544mm to 892mm (based on data from 2002 to 2005 summarized at http://ameriflux.ornl.gov/). Because of Nebraska's variable precipitation regime, droughts occur frequently in this region.

The soil types present in the study area are deep silty clay loams consisting of Filbert (fine, smectitic, mesic Vertic Argialbolls), Filmore (fine, smectitic, mesic Vertic Argialbolls), Tomek (fine, smectitic, mesic Pachic Argialbolls) and Yutan (fine-silty, mixed, superactive, mesic Mollic Hapludalfs) soil series (http://ameriflux.ornl.gov/). This mix of well-drained and poorly-drained mollisols facilitates soil moisture retention and plant growth.

4.2.2 Data

4.2.2.1 Airborne Hyperspectral Data

Aerial digital images were obtained using the AISA-Eagle remote hyperspectral sensor, operated by the Center for Advanced Land Management Information Technologies (CALMIT), University of Nebraska-Lincoln. The spectral range of the sensor includes the visible and near infra-red region from 400 to 970nm. Data were collected in 62 discrete wavelengths at a spatial resolution of 2.0m. The 12-bit

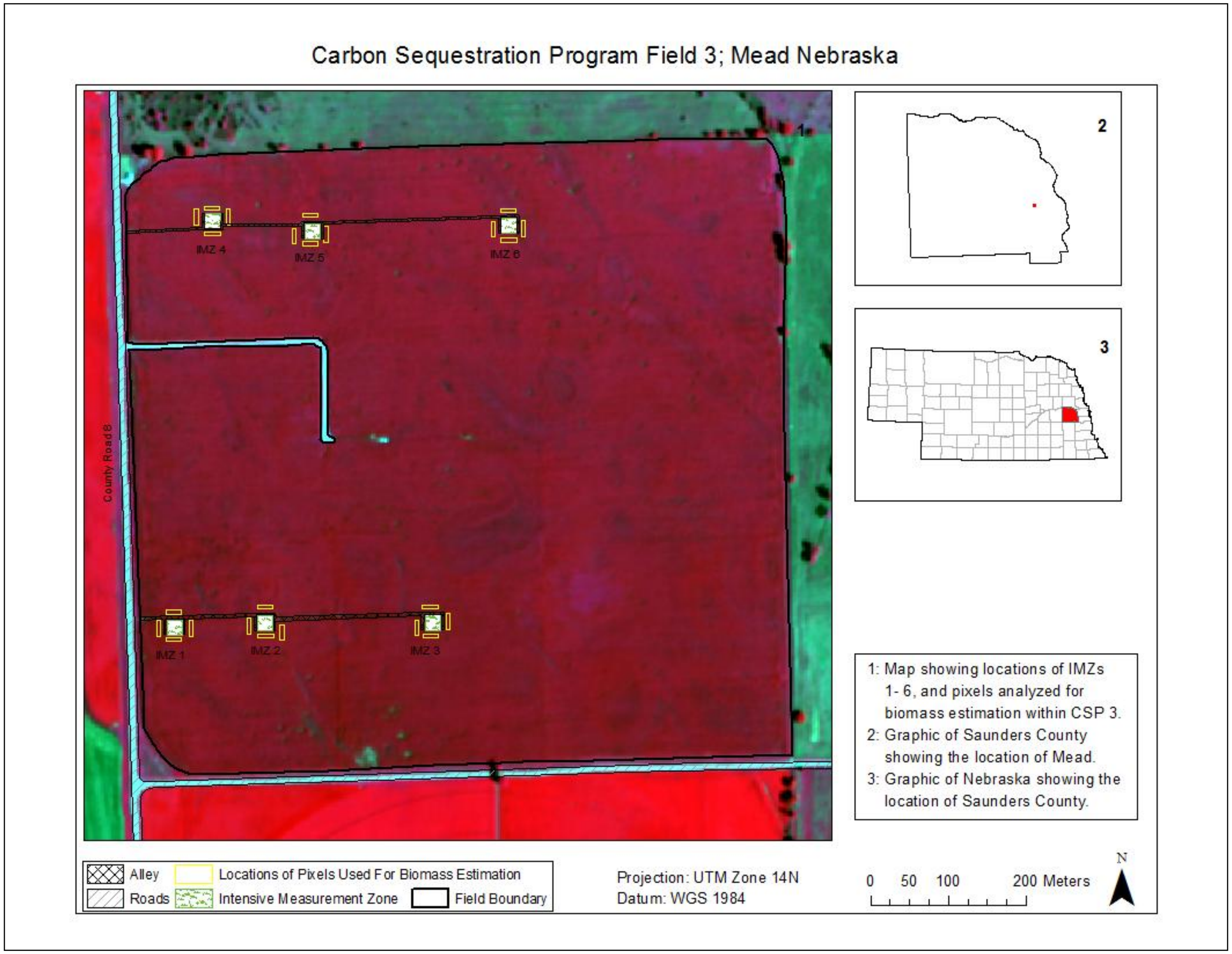

Figure 4.2: CSP 3 and the distribution of IMZs within the field, the location of Mead in Saunders County, and the location of Sunders County in Nebraska.

radiometric resolution of the images allows image brightness to be quantified to 65,536 shades of gray. The high radiometric range enhances the detection of slight differences in the upwelling signals from terrain objects; e.g. subtle changes in the greenness of vegetation across the field. The AISA sensor was flown over the study site numerous times during each growing season from 2002 through 2007 (Table 4.1). Images were acquired from 10,048ft above ground level (AGL).

The atmospheric conditions for every airborne mission were 100% free of cloud cover. In spite of this, radiometric error can be introduced into the image data by atmospheric attenuation of the electromagnetic waves caused by both absorption and scattering in the atmosphere (Jensen, 2000). Therefore, it was deemed essential to atmospherically correct (using the "QUAC" algorithm) the remotely sensed data so subtle differences in the reflectance associated with the various dates of vegetation analysis was not lost. QUAC (with the acronym representing the Quick Atmospheric Correction software module), is based on mathematically modeling the physical behavior of radiation as it moves through the various levels of the atmosphere (i.e., radiative transfer), can be applied to spectral data ranging from the visible through shortwave infra-red regions of the spectrum. The model determines the parameters for atmospheric compensation from the information contained in a series of scene pixels, with no need for ancillary information such as geographic location of the image, date and time of year the image was acquired, altitude of data acquisition, or local atmospheric visibility at time of acquisition etc. QUAC is based on the assumption that the average reflectances of a collection of diverse spectra are scene-independent. It results in the rapid computational

Table 4.1: Dates of AISA Eagle image acquisition.

Year (Crop Type)	**Date of Image Acquisition**									
	May	June		July			August		September	
2002 (Soybean)	-	06/21	06/27	07/12	07/15	-	-	-	09/07	09/17
2003 (Corn)	-	06/19	-	07/02	07/10	07/21	08/25	-	-	-
2004 (Soybean)	-	06/25	-	07/19	07/27	-	08/09	08/22	09/02	09/10
2005 (Corn)	05/19	06/06	-	07/07	-	-	08/05	08/30	09/09	09/27
2006 (Soybean)	-	-	-	07/26	-	-	08/15	08/23	-	-
2007 (Corn)	-	06/21	-	07/05	-	-	-	-	09/04	09/14

speed of this atmospheric correction method, which is much faster when compared with physics-based first-principle methods.

As the aerial platform proceeds along a flight line, there are three types of movements occurring which can cause distortion and displacement of objects within the image – roll, pitch and yaw. Roll occurs when the wings of the plane rotate about the axis of the fuselage. Pitch occurs when the nose and tail oscillate up and down relative to an axis along the wings. Yaw happens when the flight path is altered because of cross-winds. In order to remain on a prescribed linear path, the aircraft ‘crabs’ into the wind, which then distorts the acquired image (Jensen, 2005). To correct geometric errors introduced into the image from these movements of the aircraft, the aerial images were rectified to Nebraska Farm Service Agency (FSA) aerial images of the study area. Data of high spatial resolution lead to improved rectifications results, so the 2006 FSA image, with 1-meter resolution, was most helpful. Ground control points were easily identifiable on both the distorted and corrected (base) images. The reprojection led to a root mean square error (RMSE) of less than 0.5 pixel. The rectification process was applied to every AISA image acquired over the study area.

4.2.2.2 Field-Reference Data

4.2.2.2.1 Biomass

CSP 3 contains six IMZs from which measurements corresponding to various plant biophysical parameters were taken. Each IMZ is a plot 20m x 20m in size, and the six IMZs represent all major occurrences of the various soil types and crop production zones within the field (Figure 4.3). Such a spatial framework allows accurate up-scaling of ground measurements to the level of the whole field.

A graphic describing CSP 3 is provided as Figure 4.3, where corn rows are represented by the dotted light gray lines, while rows within the IMZs are shown by the dark gray lines. The spacing of each row on the ground is 0.76m. The IMZ is separated from the larger field on three sides by non-vegetated areas called "alleys" (white space between the different row types in Figure 4.3). These alleys provide access to the IMZ for the members of a field-research team. For measurements which require destructive sampling, plant sampling plots (indicated by black rectangles) are pre-marked on the six center rows of planter pass two within each IMZ. Each sampling plot is 1m in length and positioned based on two criteria:

1) A distance of a least 3m between sampling plots in the same row; and
2) A distance of at least 1m between sampling plots in adjacent rows.

Various types of samples were taken from each plot every seven to ten days, starting from the alley and progressing (by the end of the growing season) to the center of the IMZ. Typically 10 to 12 samplings were carried out during each growing season, leaving 3 to 5 extra sample areas available in case of problems that may arise with the samples taken in the "established plots."

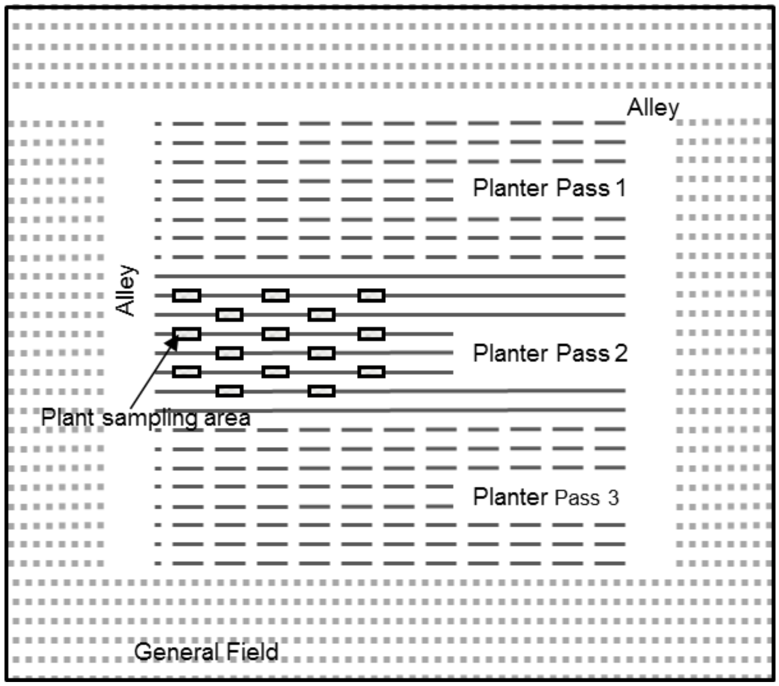

Figure 4.3: An intensive measurement zone within CSP3 showing plant rows, alleys and biomass sampling locations.

4.2.2.2.2 Temperature and Precipitation

Daily temperature and precipitation data were collected from the University of Nebraska Lincoln High Plains Regional Climate Center (HPRCC) weather station located at Mead NE. This station (Mead 4 SSE 255362) is approximately 16km south-east of CSP 3. For this research, temperature and precipitation data were analyzed beginning with the first day of April and ending with the last day on which biomass measurements were taken (generally sometime in September).

4.2.2.2.3 Soil Moisture

Daily soil moisture measurements were acquired from the CSP 3 field. Soil moisture sensors were placed in four locations within the rain-fed field, at depths of 10cm, 25cm, 50cm and 100cm in each location. Hourly readings were taken from each sensor and the average from a 24-hour period represented daily soil moisture from a sensor. For this research, soil moisture data were also analyzed beginning with the first day of April and ending with the last day on which biomass measurements were taken (generally in September when?).

4.2.2.3 Vegetation Indices

Three vegetation indices were tested as part of the research: NDVI, Red-Edge Chlorophyll Index ($CI_{Red\text{-}Edge}$), and Wide Dynamic Range Vegetation Index (WDRVI).

4.2.2.3.1 Vegetation Index #1: Normalized Difference Vegetation Index (NDVI)

The widely known NDVI, developed by Rouse *et al*., (1974), is a good indicator of the ability of vegetation to absorb photosynthetically active radiation. It has been employed by researchers to estimate several plant biophysical characteristics as well as general productivity patterns (Wang *et al*., 2003). Without doubt, NDVI is the most widely used VI for various types of regional and global vegetation studies (e.g., Huete *et al*., 1997; Vina, 2004). The index is expressed as:

$$NDVI = \frac{\rho \mathrm{NIR} - \rho \mathrm{Red}}{\rho NIR + \rho Red}$$

Where: ρNIR is a single band in the range 773 to780nm

ρRed is a single band in the range 665 to 670nm.

The wavelength ranges were chosen by the author with regard to both the characteristics of the sensor system of choice (described above) and the professional literature.

4.2.2.3.2 Vegetation Index #2: Red-Edge Chlorophyll Index ($CI_{RedEdge}$)

The Red Edge Index was developed based on the relationship between total canopy chlorophyll content and the reciprocal of reflectance at wavelengths in the green and red-edge regions of the spectrum (520 to 585nm and 695 to 740nm) (Gitelson *et al*., 2003[a]). Chlorophyll content in plants, like other leaf pigments, may provide information about the physiological state of the plant and its leaves (Sims and Gamon, 2002); thus the index was used to estimate the biomass biophysical parameter of crops in this research. It is expressed as:

$$CIRedEdge = \left(\frac{\rho\text{NIR}}{\rho\text{Red Edge}}\right) - 1$$

Where: ρNIR is a single band in the range 773 to 780nm

ρRed Edge is a single band in the range 710 to 720nm

4.2.2.3.3 Vegetation Index #3: Wide Dynamic Range Vegetation Index (WDRVI)

In response to the problem of NDVI saturation at high canopy densities, this index was developed to linearize NDVI. It is expressed as:

$$WDRVI = \frac{\alpha * \rho\text{NIR} - \rho\text{Red}}{\alpha * \rho NIR + \rho Red}$$

Where: ρNIR is a single band in the range 773 to 780nm

ρRed is a single band in the range 665 to 670nm

α is a value <1

As shown by Gitelson (2004), NDVI sensitivity depends on the ratio of ρNIR to ρRed. The highest correlation between NDVI and certain biophysical variables (i.e., Leaf

Area Index and Vegetation Fraction) occurred at lower ratios of ρNIR /ρRed when the vegetation canopy was sparse and there were ρRed reflectance values of 10 to 20% (because of low absorption in this region). This effect is shown in Figure 4.4. In dense vegetation, reflectances in the red region were generally low, ranging from 2 to 6% (because of great absorption) resulting in high ρNIR /ρRed ratios and decreased sensitivity in NDVI (Figure 4.4).

To increase the range of sensitivity of NDVI to high density vegetation canopies, a weighting coefficient with a value of <1 was applied to the NIR reflectance, which reduces the ρNIR value, thereby decreasing the ρNIR/ρRed ratio. In the current research, α was given a value of 0.2 because in Gitelson (2004), of the three α's of 0.05, 0.1 and 0.2 which were used to predict vegetation fraction in corn and soybeans, 0.2 had the highest correlations (R^2 values of 0.94 to 0.98). To avoid working with negative values, a constant of one was added to all the outputs from this index (thus, WDRVI + 1).

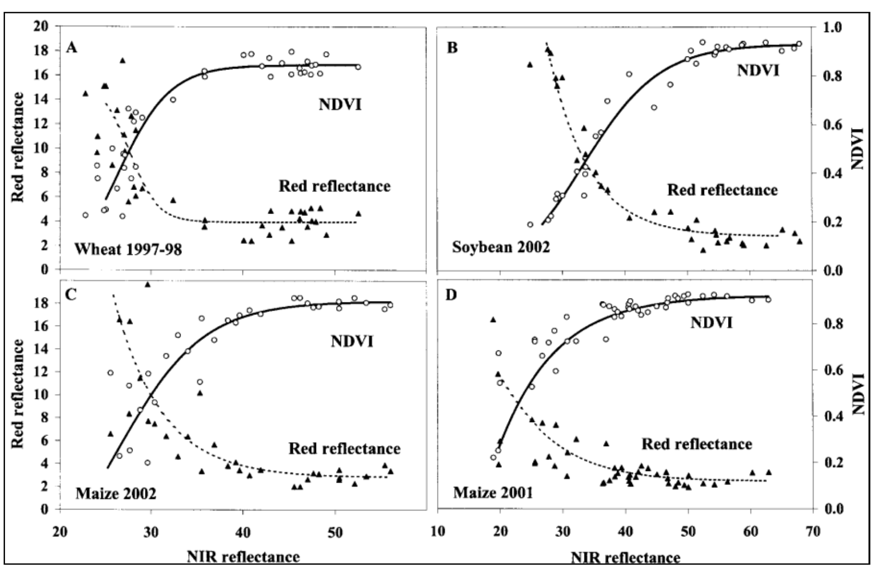

Figure 4.4: Curves showing the variations in NDVI and Red reflectance at varying NIR reflectance values for wheat, corn and soybeans from the work of Gitelson, 2004. NDVI saturation is visible at NIR reflectance values above 30% and sensitivity drops with Red reflectance values below 7%.

4.2.3 Correlation of Biomass and Vegetation Indices with Soil Moisture

The soil moisture values used in this research were the average of measurements from the sensors located in CSP 3 at depths of 10cm, 25cm, and 50cm. It was observed that fluctuations in soil moisture readings due to precipitation events reduced steadily with increasing depth, showing minimal changes at 100cm. Because this research looked at the effect of variations in environmental factors, readings from the sensors at 10cm, 25cm and 50cm were used, while data from the sensor at 100cm was excluded.

Daily soil moisture data were also summed up in 14, 28, 56 and 84 day intervals preceding each date on which biomass measurements were available. Statistical analyses were conducted using simple linear correlations of biomass values for each date of the growing season with the respective accumulated soil moisture data, and the process was repeated for each soil moisture aggregation (i.e. 14, 28, 56, and 84 days) and for each of the seven growing seasons

4.2.4 Correlation of Biomass and Vegetation Indices with Growing Degree Days

Rates of plant growth responds to air temperature, which, in turn, affects many processes associated with plant growth and phenology (Russelle *et al*., 1984). GDD was derived using the equation:

$$\mathrm{GDD} = \left[\frac{(T_{max} + T_{min})}{2}\right] - \mathrm{B}$$

Where: T_{max} = daily maximum temperature

T_{min} = daily minimum temperature

B = base temperature of 10^{o}C

In the GDD calculations, the following adjustments were made based on the work done by Russelle *et al*., (1984) and Viña *et al*., (2004):

i. Minimum temperatures below $10^{o}C$ were set at $10^{o}C$

ii. Maximum temperatures above $30^{o}C$ were set at $30^{o}C$.

Based on the methods used by Rundquist (2000) and Li *et al*., (2002), daily GDD data were summed up in 14, 28, 56 and 84 day intervals preceding each date on which biomass measurements were collected. Statistical analyses were carried out using simple linear correlations of biomass values from each date in the growing season with its' respective accumulated GDD. The procedure was repeated for each GDD aggregation (i.e. 14, 28, 56, and 84 days) and each of the seven growing seasons.

4.3 Results

A central element of the current research was to examine the correlations between field-derived (destructively sampled) crop biomass and the estimates generated using VIs calculated from digital AISA-Eagle hyperspectral data. The examination was based upon both individual crops (corn and soybean) for each year of the six years comprising the investigation and also all corn and soybeans combined over the six year period of study (thus, three years of data for each crop).

4.3.1 Image VIs vs. Biomass Relationships

The comparative investigation involving image-based VIs and field-based biomass was undertaken by means of producing scatterplots and best fit functions (e.g., exponential, linear, logarithmic, polynomial, or power) to summarize (i.e., quantify) relationships. The scatterplots illustrating relationships are shown as Figures 4.5 through 4.10. Figure 4.5 documents the relationships for the 2002 growing season between NDVI, $CI_{RedEdge}$, and WDRVI, respectively, with measured soybean biomass. Of note are the generally good correlations, ranging from 0.72 to 0.89, with NDVI yielding the highest R^2 and $CI_{RedEdge}$ yielding the lowest. The best fit functions for NDVI and $CI_{RedEdge}$ were curvilinear, while that for WDRVI was linear. Note that the latter will always be the case because the WDRVI concept is based upon the need to linearize NDVI.

The relationships of the 2003 growing season biomass of corn and the three VIs of interest are represented in Figure 4.6. The correlations are consistently high with R^2 of 0.95 from each VI. In this case, the best fit function for NDVI was curvilinear, but $CI_{RedEdge}$ was linear.

For the growing season of 2004, the correlations between the biomass for soybean and NDVI, $CI_{RedEdge}$ and WDRVI, respectively were also very high, with R^2 values ranging from 0.91 to 0.99 (Figure 4.7). NDVI had the highest R^2 (of the entire study period) with 0.99, while $CI_{RedEdge}$ and WDRVI both had R^2 values of 0.91. Once again, the best fit function for NDVI was curvilinear, but $CI_{RedEdge}$ was linear.

Figure 4.8 depicts the scatter-plots and R^2 values from the correlation of the three VIs with corn biomass for 2005. These were also very high, ranging from 0.92 to 0.95. The lowest R^2 of 0.92 was for NDVI while $CI_{RedEdge}$ and WDRVI both had a 0.95 R^2

value. In this instance, the best fit function for NDVI was linear, but that for $CI_{RedEdge}$ was curvilinear.

The correlation of soybean biomass from the 2006 growing season and all three VIs of study are represented in Figure 4.9. The number of samples (17) is the lowest of all the six years of study and also has the narrowest temporal spread (from July to late August). The correlations represented in Figure 9 were significantly lower than all other study years. The range of R^2 values was from 0.48 to 0.60, with the lowest and highest being obtained from $CI_{RedEdge}$ and NDVI, respectively. The best fit function for NDVI was again curvilinear while that for $CI_{RedEdge}$ was linear.

The correlations for the 2007 growing season between corn biomass and NVDI, $CI_{RedEdge}$ and WDRVI, respectively, are represented as Figure 4.10. Overall, the R^2 values ranged from 0.89 to 0.93. The R^2 value of 0.89 was obtained from $CI_{RedEdge,}$ while 0.93 was obtained for NDVI versus biomass. The best fit functions were linear in all cases.

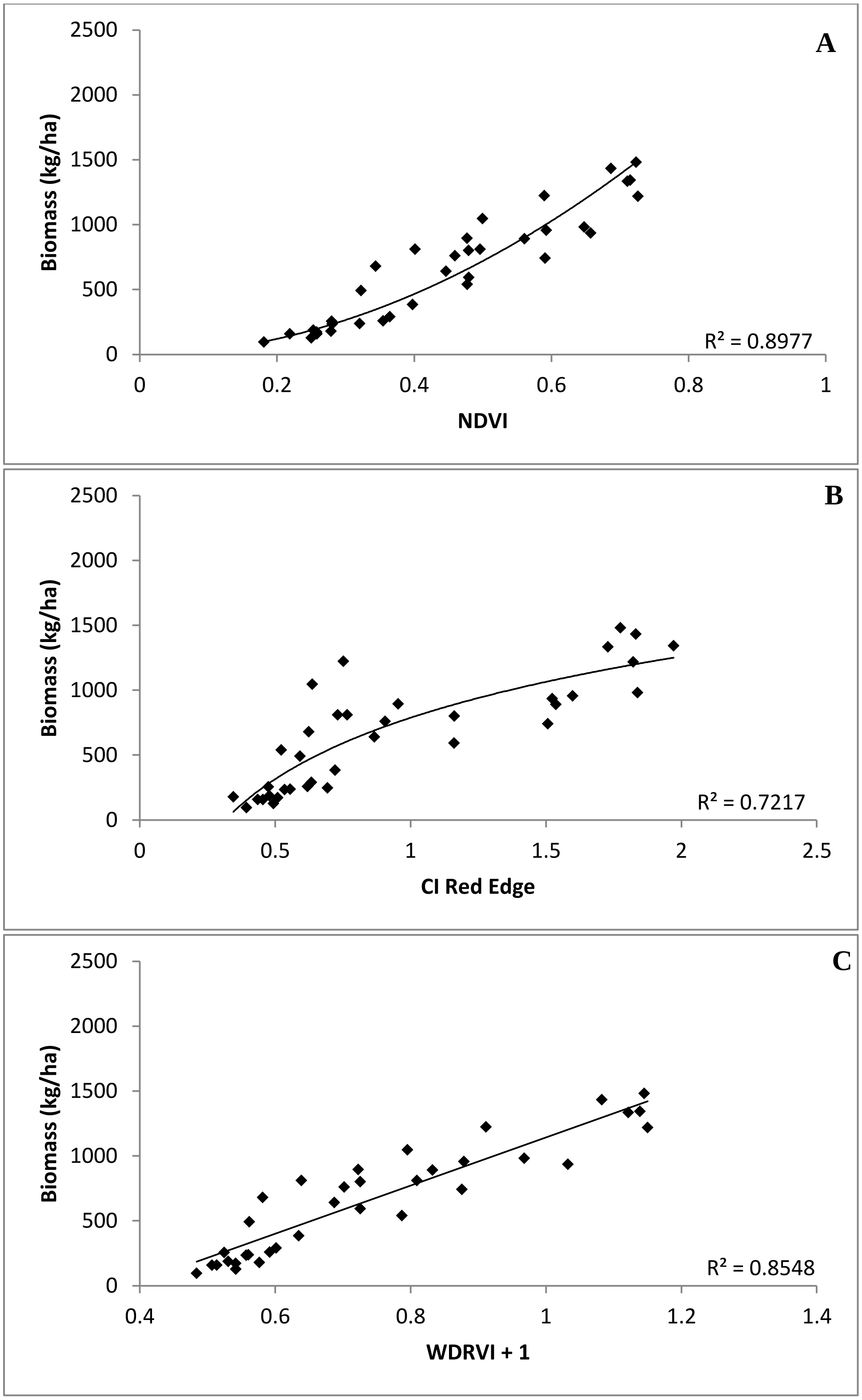

Figure 4.5: Correlation between vegetation indices and soybean biomass from year 2002. N = 35.

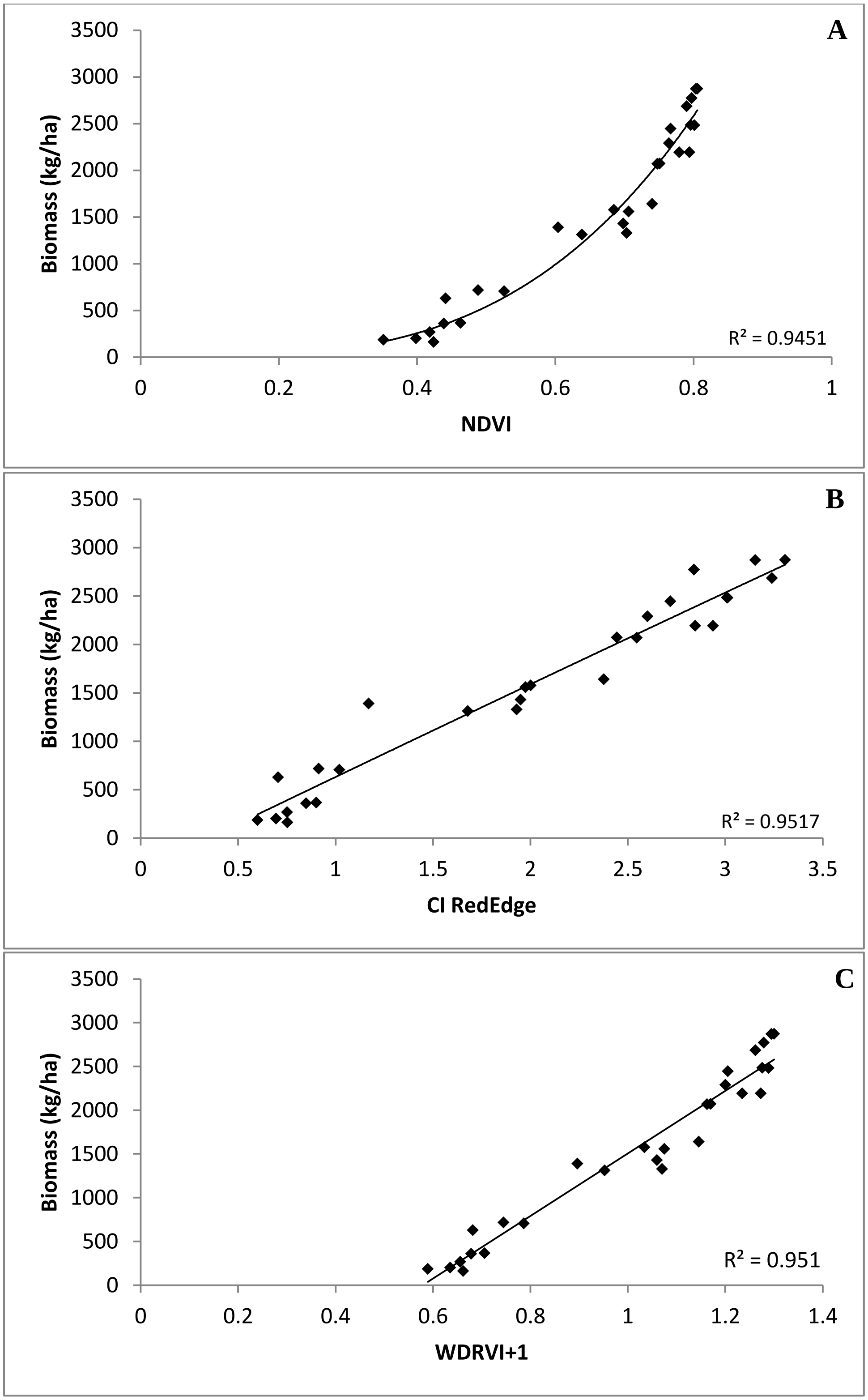

Figure 4.6: Correlation between vegetation indices and corn biomass from year 2003. N = 28.

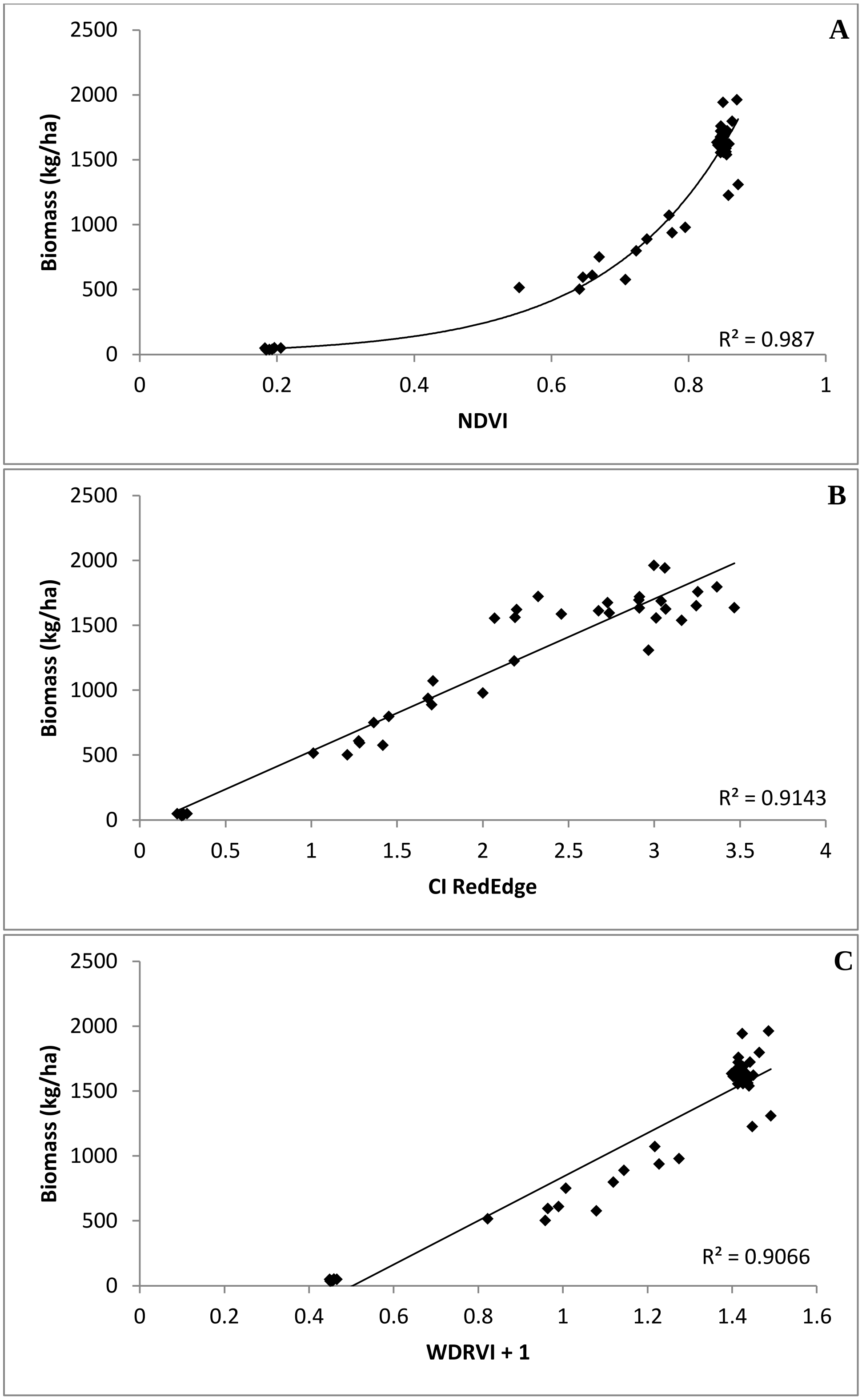

Figure 4.7: Correlation between vegetation indices and soybean biomass from year 2004. N = 40.

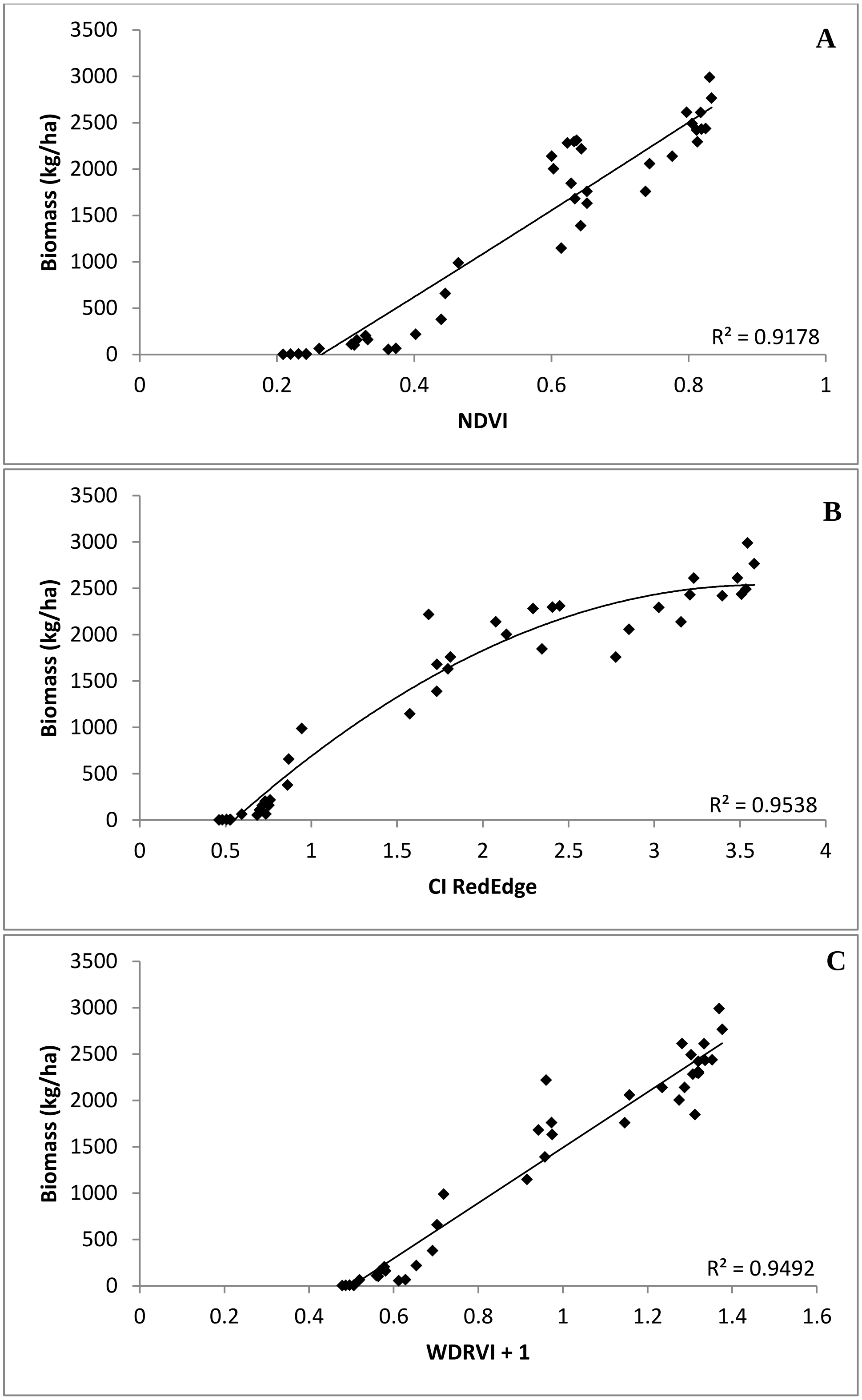

Figure 4.8: Correlation between vegetation indices and corn biomass from year 2005. N = 42.

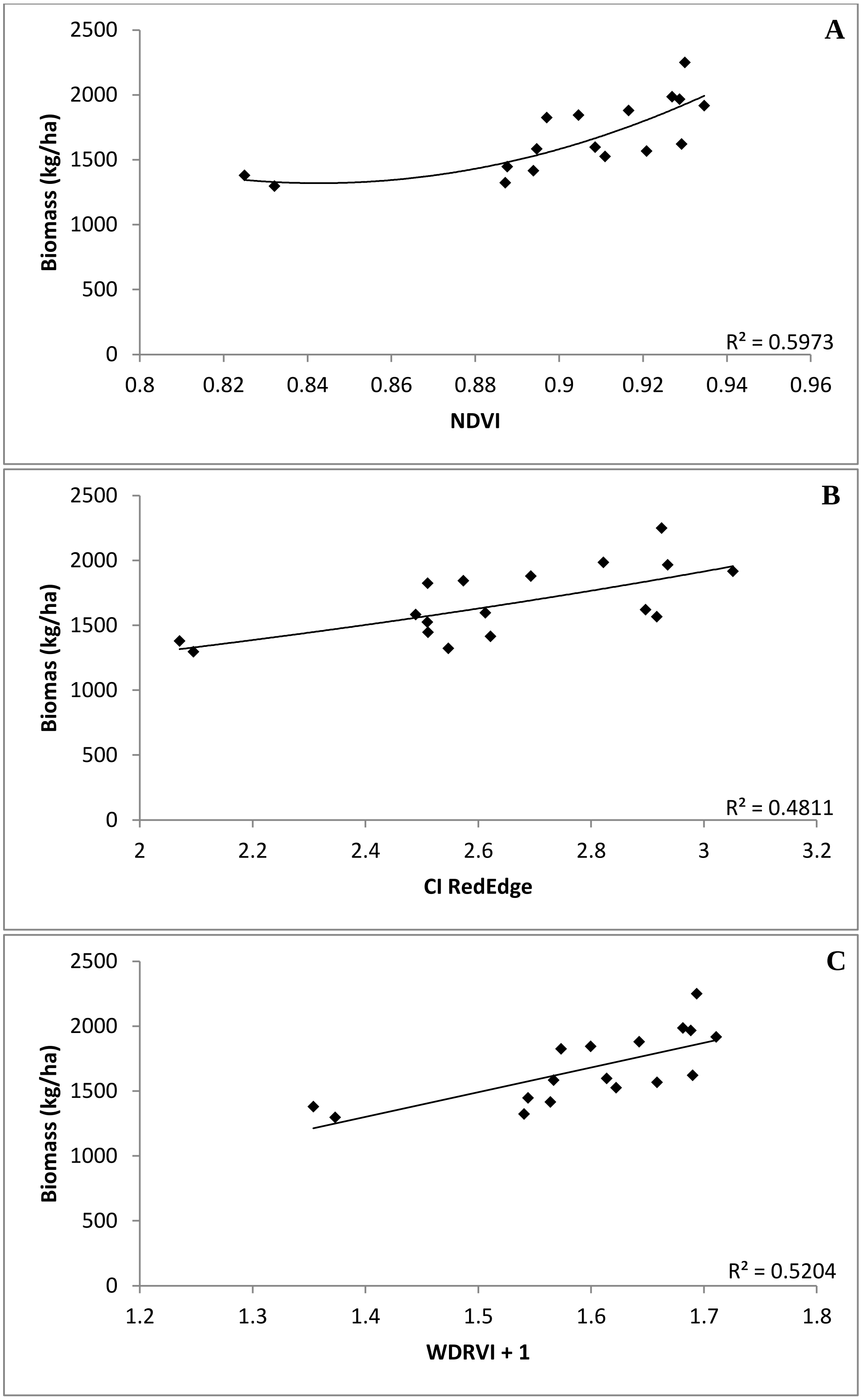

Figure 4.9: Correlation between vegetation indices and soybean biomass from year 2006. N = 17.

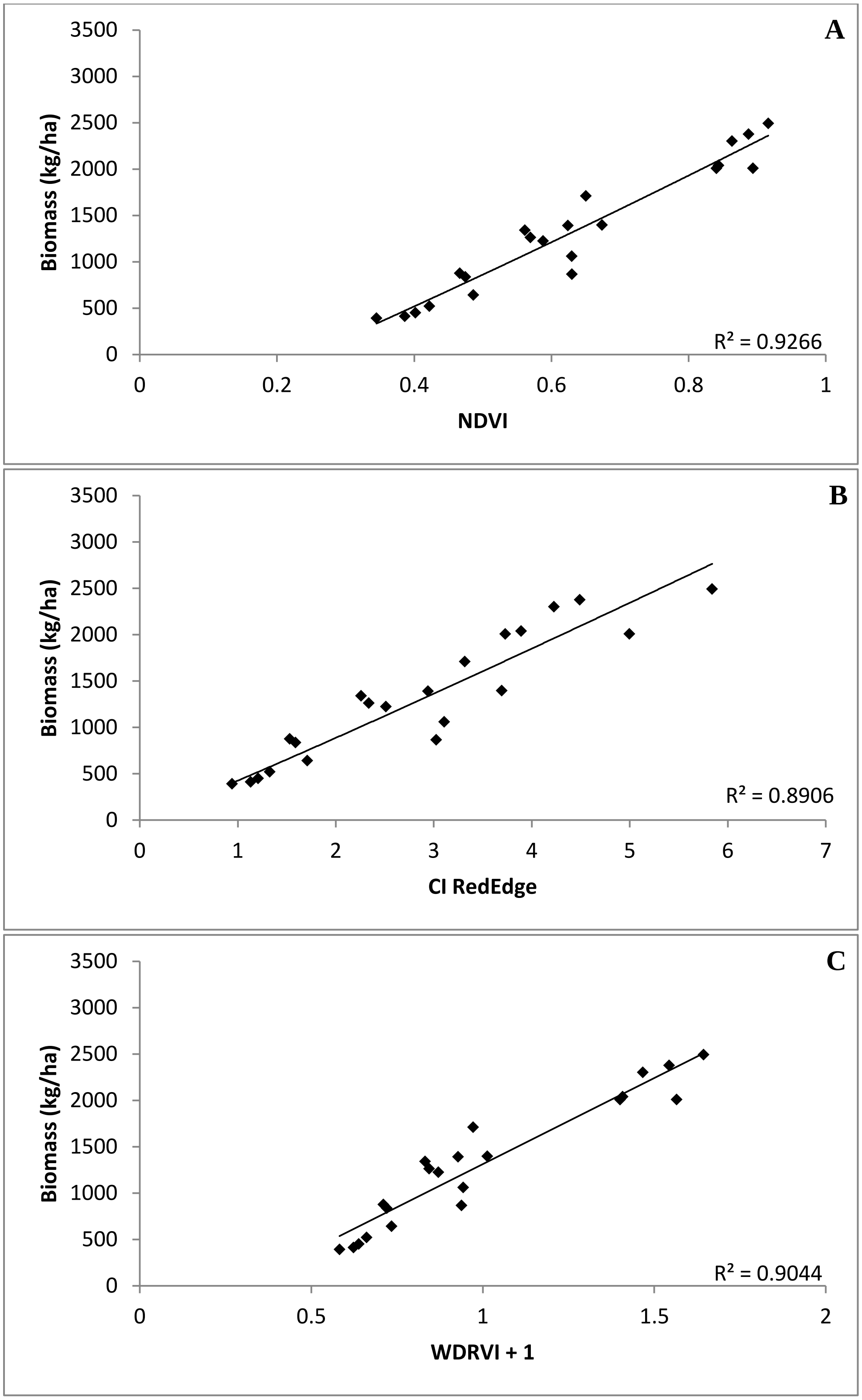

Figure 4.10: Correlation between vegetation indices and corn biomass from year 2007. N = 22.

As was shown by Figures 5 through 10, all the VIs tested were strongly correlated to the above ground green biomass for both corn and soybeans for all years of study. Table 4.2 provides a summary of the R^2 values as well as Root Mean Square Errors (RMSE) and Coefficients of Variation (CV). The R^2 values were discussed above in association with each of the figures. The general high correlations (R^2 > 0.72; with the exception of the anomalous results from 2006) between VIs and biomass measurements, which were taken at different times during the growth cycle of the crops under varying field and environmental conditions, indicate that the changes in VIs were influenced very strongly by biomass.

The RMSE values for soybean biomass and NDVI ranged from 149.38 (in 2004) to 167.72kg/ha (in 2006), while the range for $CI_{RedEdge}$ was 193.79 (in 2006) to 259.62 kg/ha (in 2004), and for WDRVI it was 159.96 (in 2002) to 190.72 kg/ha (in 2004). For corn biomass, the RMSE values for NDVI ranged between 180.89 (in 2007) and 299.50 kg/ha (in 2005), while for $CI_{RedEdge}$ the range was between 200.02 (in 2003) and 248.69 kg/ha (in 2007), and for WDRVI the range was between 201.51 (in 2003) and 235.46 kg/ha (in 2005).

The CV values for soybean biomass and NDVI ranged from 10.03% (in 2006) to 23.98% (in 2002), while the range for $CI_{RedEdge}$ was 11.59% (in 2006) to 33.74% (in 2002), and for WDRVI it was 10.95% (in 2006) to 23.95% (in 2002). For corn biomass, the CV values for NDVI ranged from12.40% (in 2003) to 22.91% (in 2005), while the range for $CI_{RedEdge}$ was 12.93% (in 2003) to 18.91% (in 2007), and for WDRVI it was 13.03% (in 2003) to 18.01% (in 2005).

Table 4.2: Results of parameters used in the statistical analyses of the best-fit functions for the green biomass/VI correlations across six growing seasons. The parameters are the square of the coefficient of correlation (R^2), root mean square error (RMSE) and the coefficient of variation (CV).
Mean Biomass[1] was derived by dividing the sum of weights from each sample by sample size. The dates of biomass samples used in this analysis are the same as the dates on which AISA Eagle images were acquired, and these are listed in Table 4.1.

Year	Sample Size	Mean Biomass[1] (kg/ha)	R^2			RMSE (kg/ha)			CV (%)		
			NDVI	$CI_{RedEdge}$	WDRVI	NDVI	$CI_{RedEdge}$	WDRVI	NDVI	$CI_{RedEdge}$	WDRVI
Corn											
2003	28	1546.34	0.95	0.95	0.95	191.79	200.02	201.51	12.40	12.93	13.03
2005	42	1307.09	0.92	0.95	0.95	299.50	224.48	235.46	22.91	17.17	18.01
2007	21	1314.99	0.93	0.89	0.90	180.69	248.69	206.21	13.74	18.91	15.68
Mean			0.93	0.93	0.93	223.99	224.40	214.39	16.35	16.34	15.57
Soybeans											
2002	35	667.90	0.90	0.72	0.85	160.16	221.42	159.96	23.98	33.74	23.95
2004	40	1154.41	0.99	0.91	0.91	149.38	259.62	190.72	12.94	22.49	16.52
2006	17	1672.16	0.60	0.48	0.52	167.72	193.79	183.04	10.03	11.59	10.95
Mean			0.83	0.70	0.76	159.09	224.94	177.91	15.65	22.61	17.14

4.3.2 Crop Specific VI-Biomass Relationships

The investigation into using VIs to remotely estimate crop biomass extended to a combining of the biomass data collected for the individual crops across multiple growing seasons. This was done in order to compare differences, if any, between corn and soybean biomass and their estimation using the three VIs of interest. Peak biomass values of both crops were considerably different with maximum values of 2989.7kg/ha for corn and 2249.8kg/ha for soybeans for all of the study years combined. Figures 4.11 through 4.13 represent the scatter plots and best fit functions between VIs and biomass of both crops.

Figure 4.11 contains all the data for corn and soybean biomass (three study years each) versus NDVI. The correlation between NDVI and corn biomass has a best fit function which is nearly linear with an R^2 value of 0.88. The RMSE was 327.61kg/ha and the CV was 23.70%. The best fit function between soybeans biomass from three study years combined and NDVI is curvilinear with an R^2 of 0.90. The RMSE was 226.58kg/ha and the CV was 21.28%. These statistical parameters from the correlation of NDVI with all biomass data from corn and soybeans are summarized in Table 4.3.

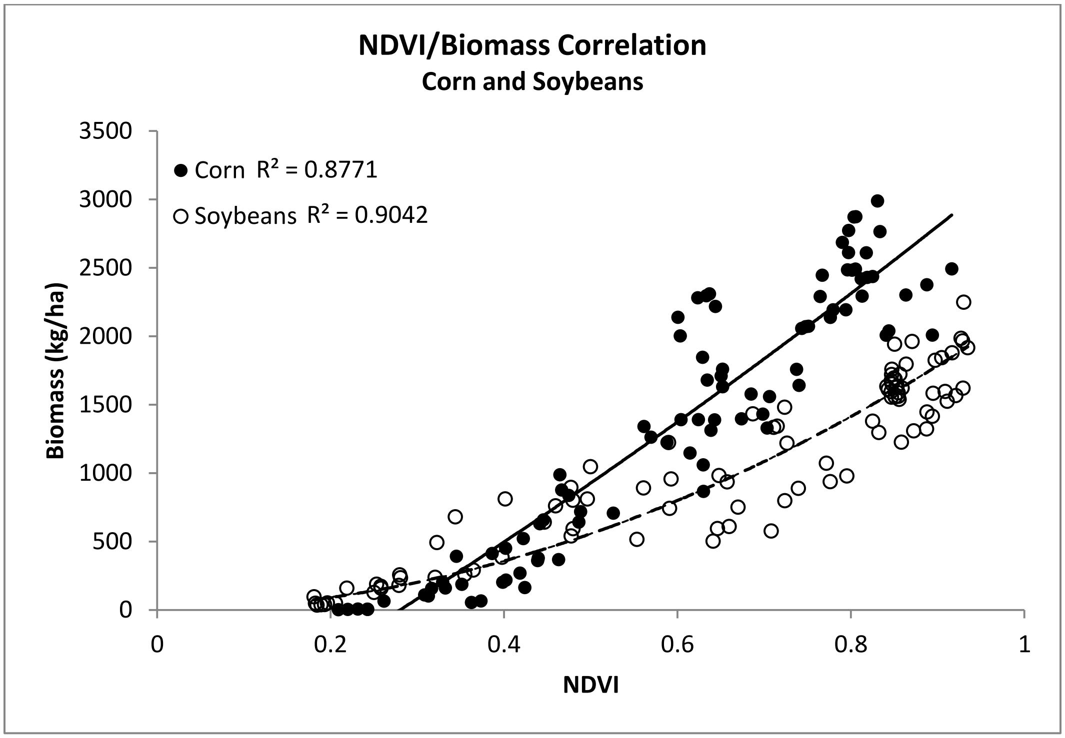

Figure 4.11: Correlation between NDVI and combined biomass of corn (2003, 2005 and 2007) and soybeans (2002, 2004 and 2006).

Figure 4.12 depicts the relationships between all corn and all soybean biomass (three study years for each) versus $CI_{RedEdge}$. The best fit function involving the corn biomass was curvilinear with an R^2 value of 0.81. The RMSE was 405.04kg/ha and the CV was 29.30%. The best fit function between soybean biomass and $CI_{RedEdge}$ was also curvilinear with an R^2 of 0.88. The RMSE's and CV's were 212.07kg/ha and 20.08%, respectively. These statistical parameters from the correlation of $CI_{RedEdge}$ with all of the biomass data from corn and soybeans are summarized in Table 4.3.

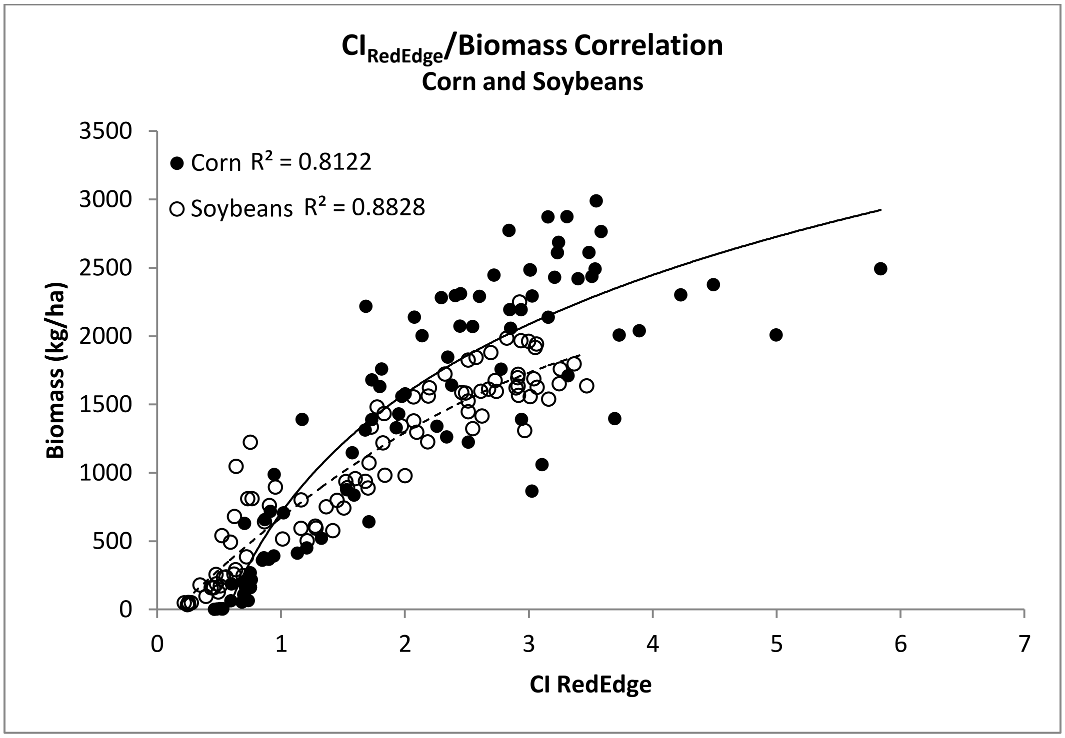

Figure 4.12: Correlation between $CI_{RedEdge}$ and combined biomass of corn (2003, 2005 and 2007) and soybeans (2002, 2004 and 2006).

Figure 4.13 provides a summary of all corn and all soybean biomass (three study years each) versus WDRVI, using a linear regression. The R^2 value between corn biomass and the spectral index was 0.90. The RMSE was 302.03kg/ha and the CV was 21.85%. The best fit function between soybean biomass and WDRVI led to an R^2 of 0.88. The RMSE and CV values are 214.09kg/ha and 20.10% respectively. The best fit function can be seen to be significantly steeper in corn (solid line) than in soybeans (dashed line). These statistical parameters from the correlation of WDRVI with all biomass data from corn and soybeans are summarized in Table 4.3.

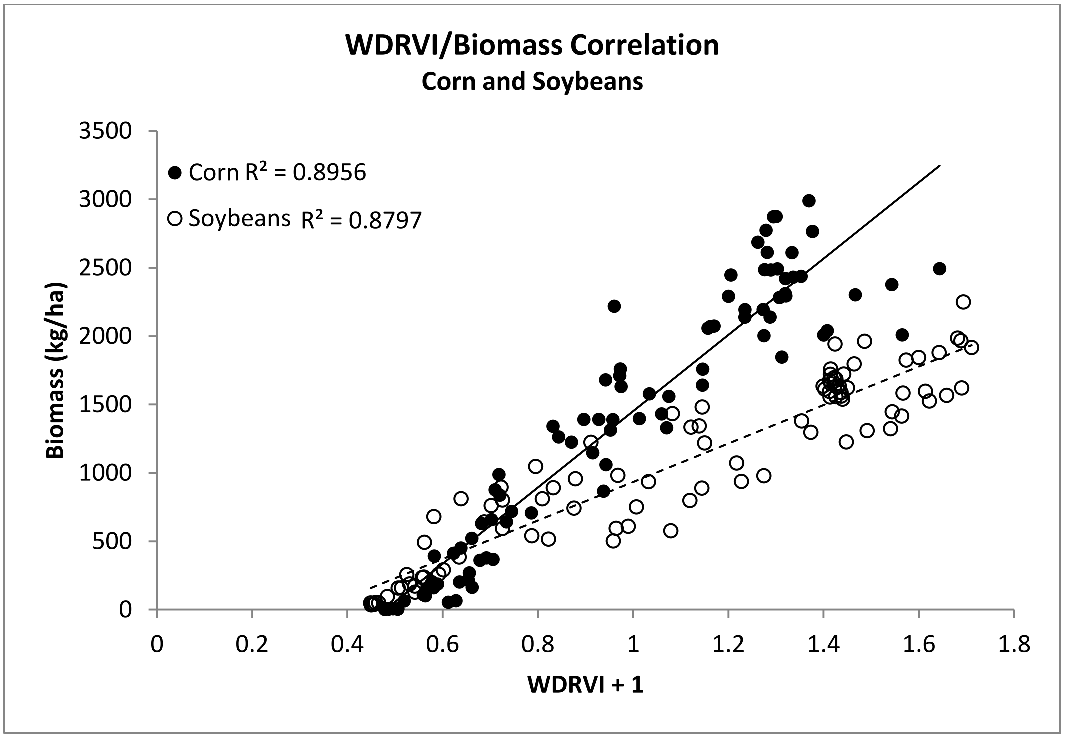

Figure 4.13: Correlation between WDRVI+1 and combined biomass of corn (2003, 2005 and 2007) and soybeans (2002, 2004 and 2006).

Table 4.3: Results of parameters used in the statistical analyses of the best-fit functions for the green biomass/VI correlations of each crop type using all of the data acquired for each crop during the study period (i.e. three growing seasons per crop). The parameters are the square of the coefficient of correlation (R^2), root mean square error (RMSE) and coefficient of variation (CV).

Crop (Sample size)	**Vegetation Index**	**R^2**	**RMSE (kg/ha)**	**CV (%)**
Corn (n = 91)	NDVI	0.88	327.61	23.70
	$CI_{RedEdge}$	0.81	405.04	29.30
	WDRVI	0.90	302.03	21.85
Soybeans (n = 92)	NDVI	0.90	226.58	21.28
	$CI_{RedEdge}$	0.88	212.07	20.08
	WDRVI	0.88	214.09	20.10

4.3.3 Correlation of Biomass and AISA Derived VIs with Environmental Variables

Investigations were carried out to discover if there are any relationships between the seasonal increase in green biomass of both crops and environmental variables including soil moisture and GDD. Similar research on correlations with environmental variables was done using the VIs derived from the field measured crop spectra. The investigations into the relationships between green biomass, VIs and the environmental variables of interest were done by determining the Pearson's correlation coefficient (r) from simple linear regressions. Using r values to identify the correlation between biomass, VIs and environmental factors would reveal the relationships as either positive or negative.

The correlations between biomass, NDVI, $CI_{RedEdge}$, WDRVI and accumulated soil moisture and GDD for each study year are represented in charts shown in Figures 4.13 to 4.18 (A – D). In general, similar r values were observed in all instances of correlation for each year, therefore similar charts representing these correlations were produced each year.

Correlations of soybean biomass and all VIs with accumulations of soil moisture and GDD during the 2002 growing season are represented in Figure 4.13 (A – D). The observed trend line for soil moisture showed decrease followed by slight increase as lag time increased, while a steady increase then slight decrease in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.84 and -0.18 which occurred at the 56- and 14-day lag periods respectively. The minimum and maximum r values observed for the correlations with

GDD are -0.29 and 0.89 which occurred during the 14- and 56-day lag periods respectively.

Correlations of corn biomass and all VIs with accumulations of soil moisture and GDD during the 2003 growing season are represented in Figure 4.14 (A – D). The observed trend line for soil moisture showed a steady increase as lag time increased, while a slight increase then steady decrease in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.4 and 0.9 which occurred at the 14 and 84-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are -0.68 and 0.73 which occurred during the 84- and 28-day lag periods respectively. An intersection between the soil moisture and GDD trend lines occurred at about the 56-day lag time.

Correlations of soybean biomass and all VIs with accumulations of soil moisture and GDD during the 2004 growing season are represented in Figure 4.15 (A – D). The observed trend line for soil moisture showed a steady increase as lag time increased, while a steady increase then leveling off in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.99 and -0.63 which occurred at the 14- and 84-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are -0.22 and 0.98 which occurred during the 14- and 84-day lag periods respectively. No intersections were observed in these trend lines.

Correlations of corn biomass and all VIs with accumulations of soil moisture and GDD during the 2005 growing season are represented in Figure 4.16 (A – D). The observed trend line for soil moisture showed a steady increase as lag time increased, while a steady decrease in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.74 and 0.86 which occurred at the 14- and 84-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are -0.53 and 0.98 which occurred during the 84- and 14-day lag periods respectively. An intersection between the soil moisture and GDD trend lines occurred at about the 84-day lag time.

Correlations of soybean biomass and all VIs with accumulations of soil moisture and GDD during the 2006 growing season are represented in Figure 4.17 (A – D). The observed trend line for soil moisture showed an increase, decrease and increase as lag time increased, while an increase then slight decrease in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -1.0 and 0.64 which occurred with the 56- and 28-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are -0.58 and 1.0 which occurred during the 14- and 84-day lag periods respectively.

Correlations of corn biomass and all VIs with accumulations of soil moisture and GDD during the 2007 growing season are represented in Figure 4.18 (A – D). The observed trend line for soil moisture showed a slight decrease then steady increase as lag time increased, while a steady decrease in correlation with lag time is observed for GDD. The minimum and maximum r values observed for the correlations with soil moisture are -0.77 and 1.0 which occurred at the 28- and 84-day lag periods respectively. The minimum and maximum r values observed for the correlations with GDD are -0.98 and 0.92 which occurred during the 84- and 14-day lag periods respectively. An intersection between the soil moisture and GDD trend lines occurred at between the 28- and 56-day lag times.

A summary of correlations from all three study years from corn biomass and VIs with soil moisture and GDD are represented in Figures 4.19 to 4.20 (A – D). Correlation values varied from negative to positive for both accumulated GDD and soil moisture. General trends observed for correlations with GDD show that correlation decreased as lag times increased, with peak values observed at the 14-day lag period. For corn/soil moisture correlations, there was general increase as lag times increased; highest correlations were observed at the 84-day lag period. Intersections were also observed between the correlations of both environmental variables because of the nature of their trend lines. The points of intersection for each studied year occurred at longer lag times i.e., approximately 56 and 84-day lag periods.

Charts representing correlations derived from soybean biomass and VIs with soil moisture and GDD are represented in Figures 4.21 to 4.22 (A – D). The correlations with GDD were observed to be positive in majority of the instances and had an increasing trend as lag time increased, with highest correlation observed at the 56-day lag period in majority of the years studied. On the other hand, correlations with soil moisture resulted in negative values in most instances with different trends for each VI and biomass.

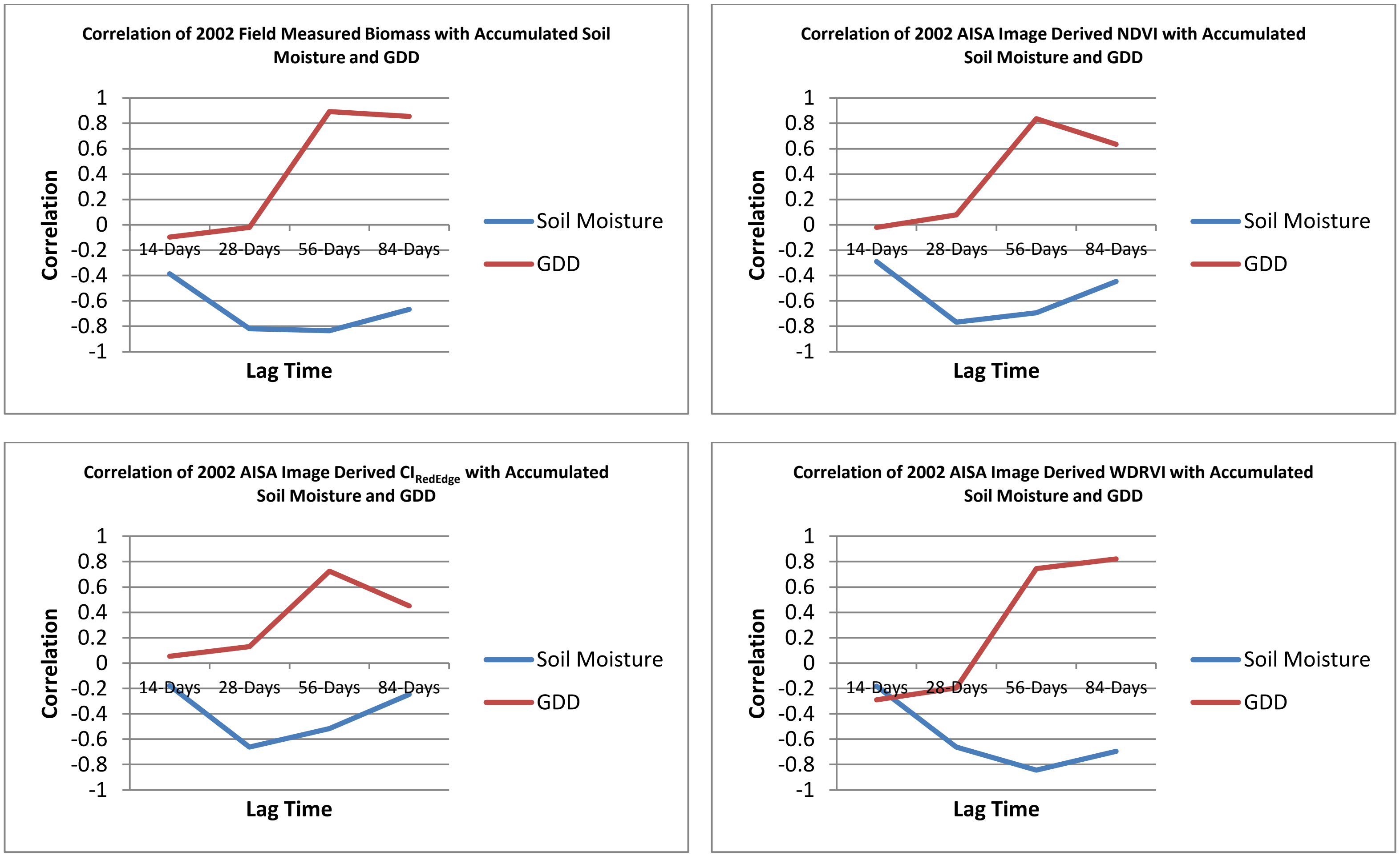

Figure 4.14: Pearson's correlation coefficient (r) values for the relationships of 2002 growing season green biomass of soybean and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

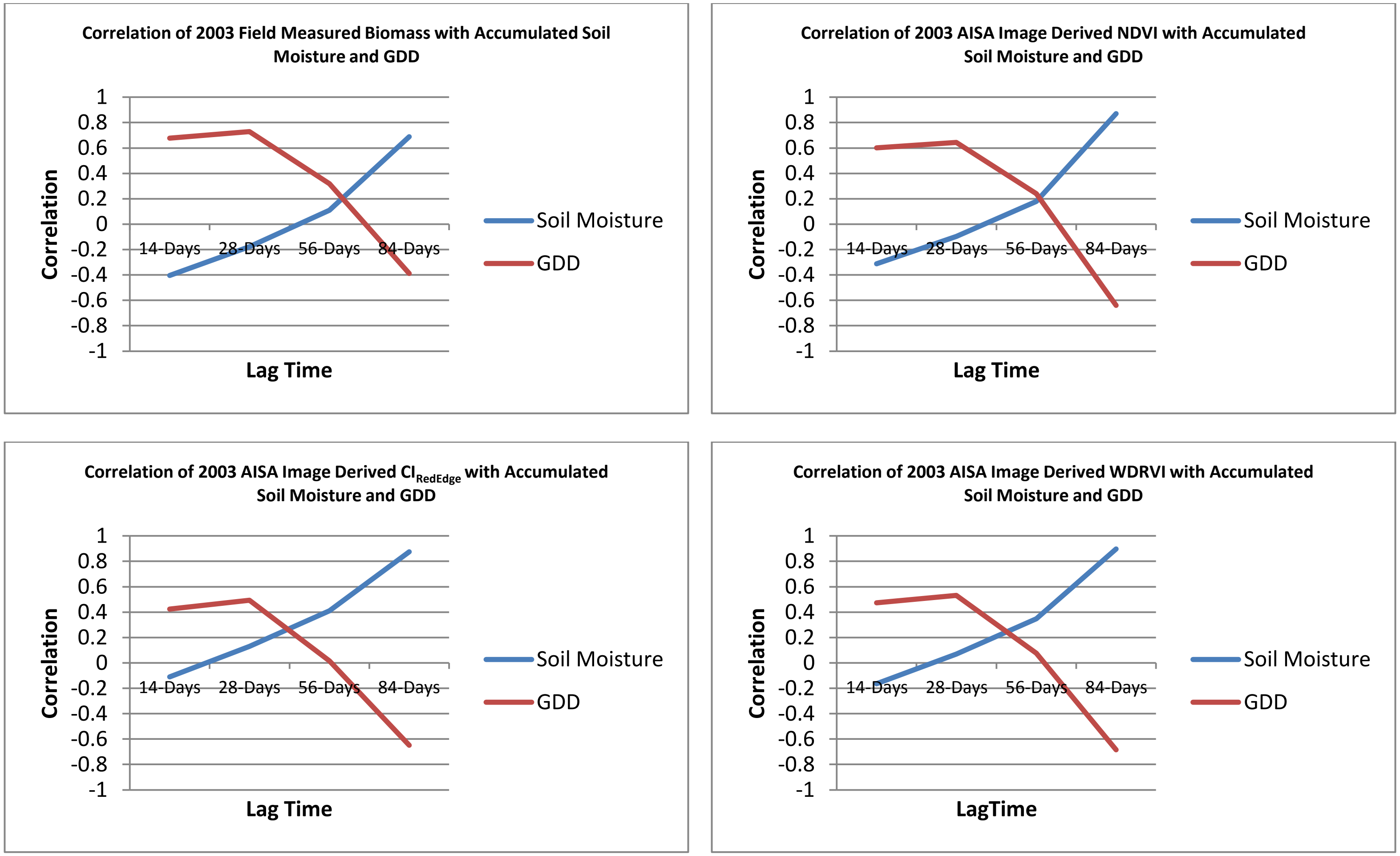

Figure 4.15: Pearson's correlation coefficient (r) values for the relationships of 2002 growing season green biomass of corn and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

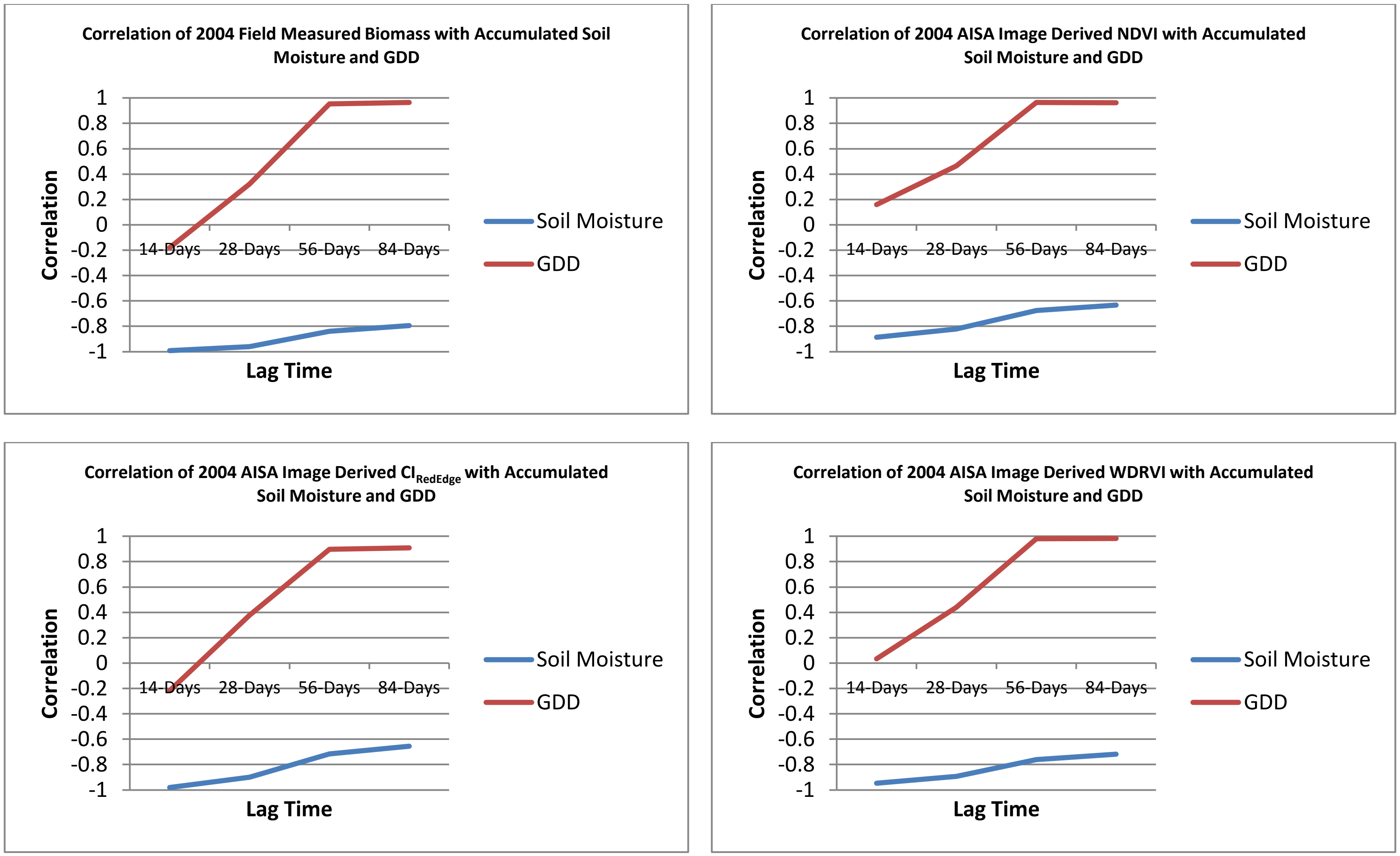

Figure 4.16: Pearson's correlation coefficient (r) values for the relationships of 2004 growing season green biomass of soybean and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

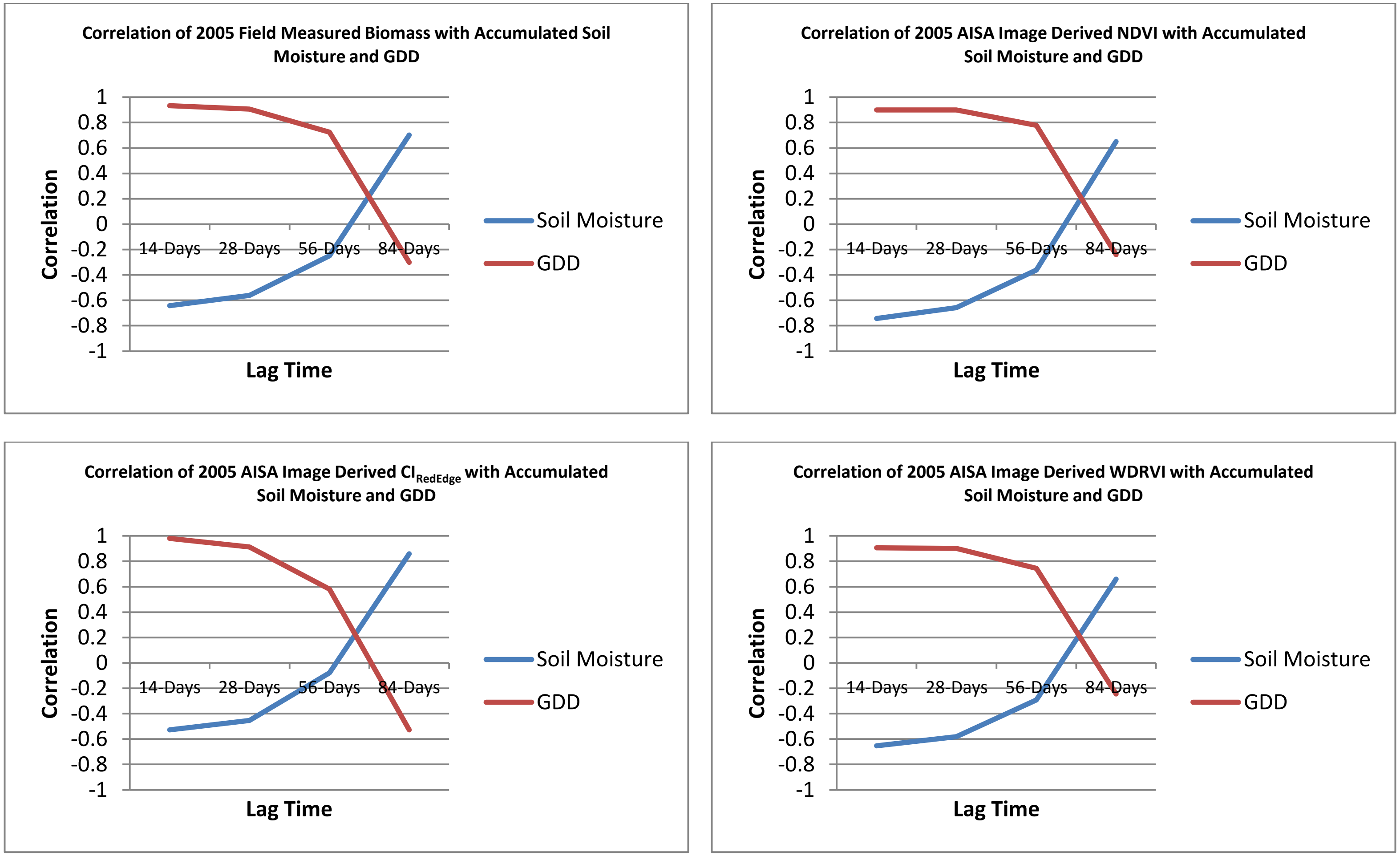

Figure 4.17: Pearson's correlation coefficient (r) values for the relationships of 2005 growing season green biomass of corn and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

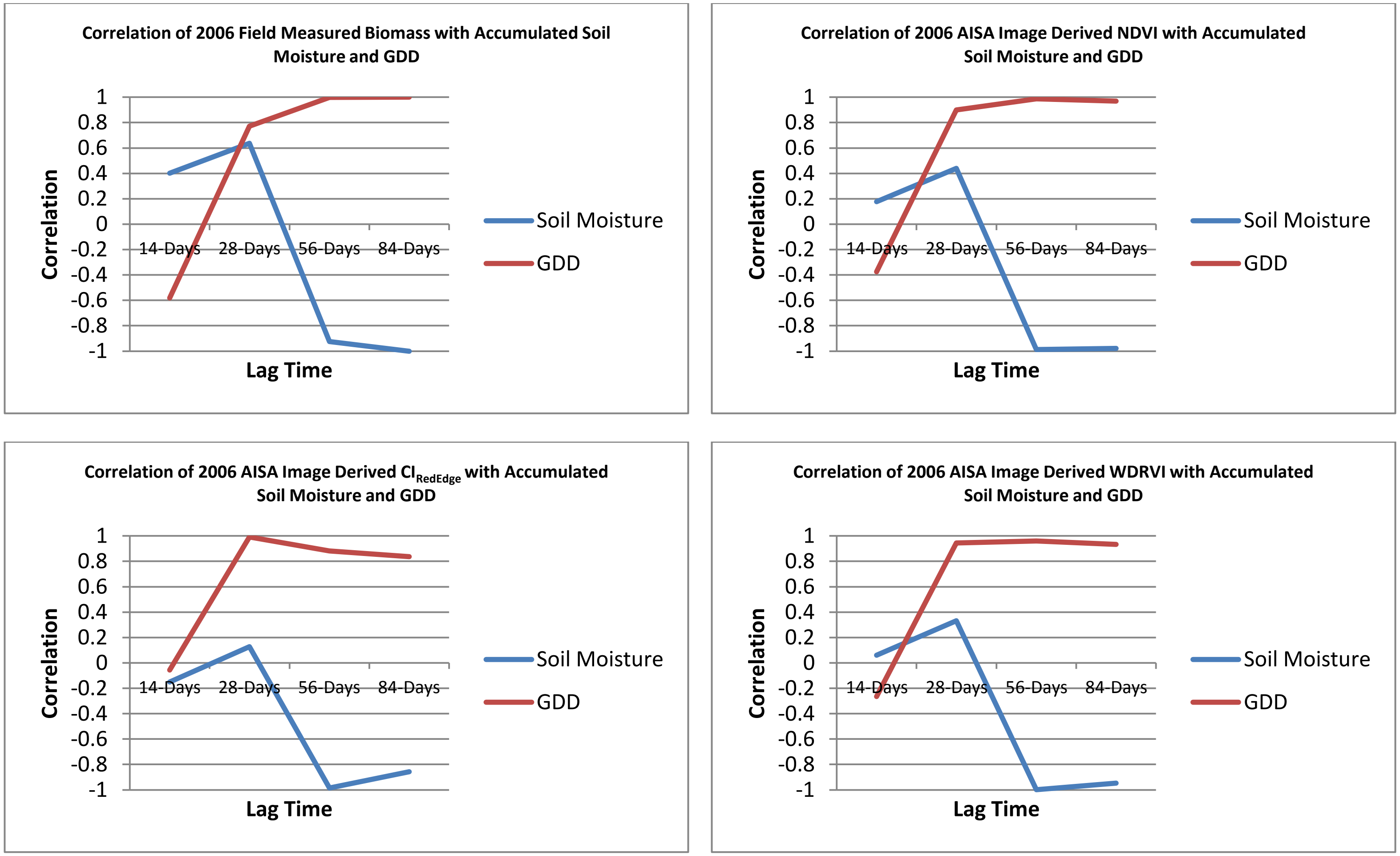

Figure 4.18: Pearson's correlation coefficient (r) values for the relationships of 2006 growing season green biomass of soybean and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

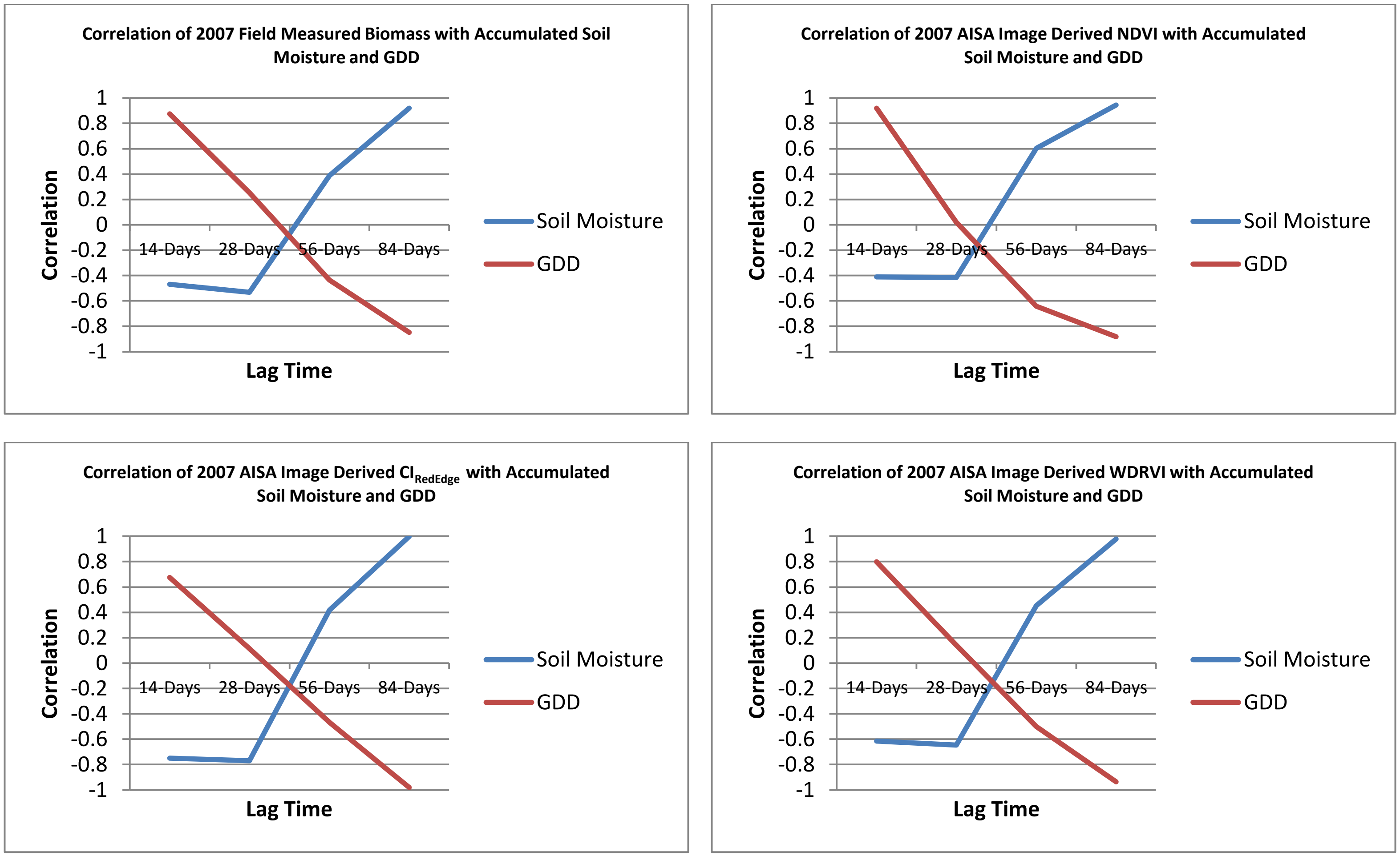

Figure 4.19: Pearson's correlation coefficient (r) values for the relationships of 2007 growing season green biomass of corn and selected vegetation indices with accumulated daily soil moisture and growing degree days (GDD). Soil moisture and GDD were lagged in periods of 14, 28, 56 and 84 days prior to each biomass and VI measurement.

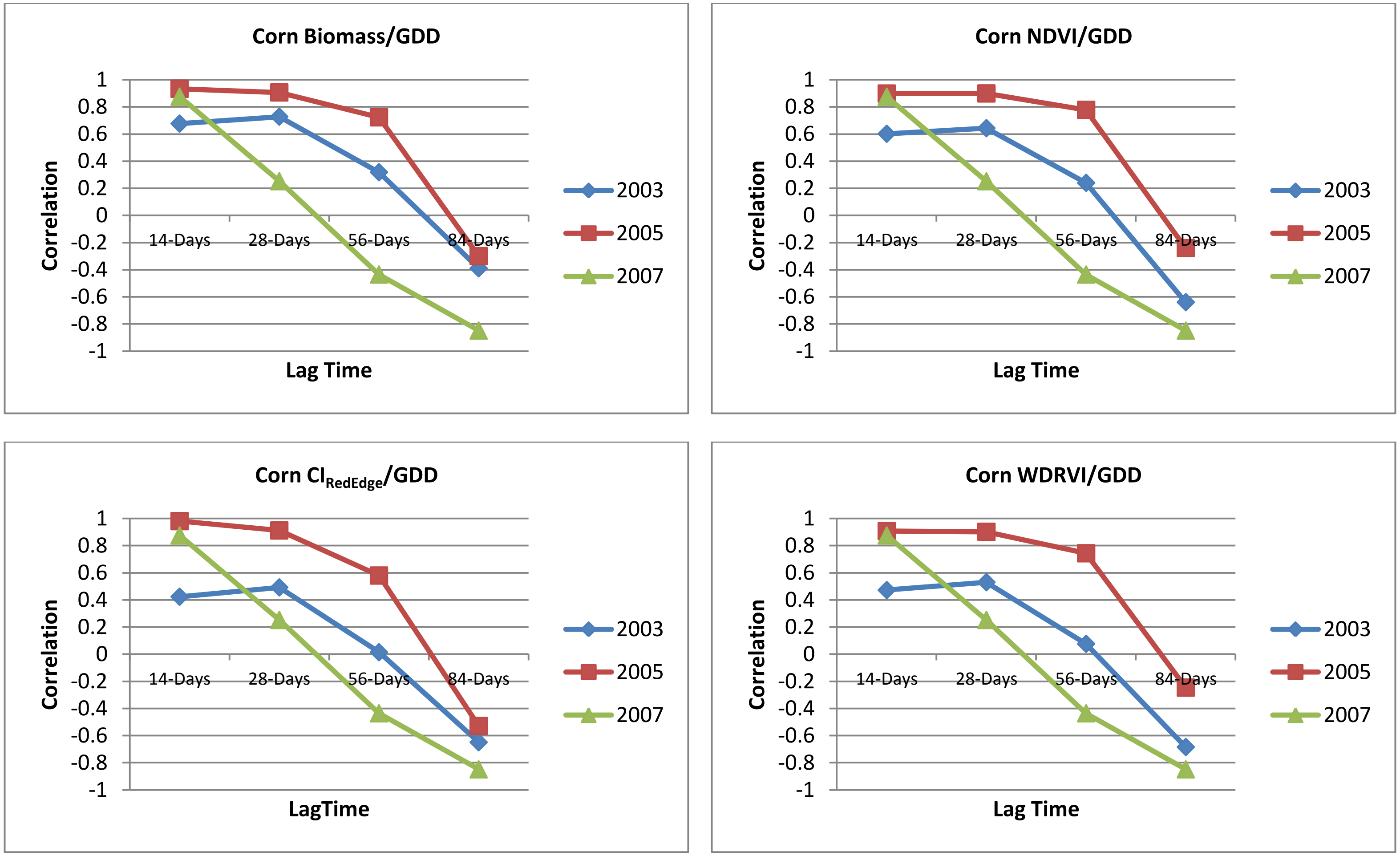

Figure 4.20: Summary of Pearson's correlation coefficient (r) values for the relationships of corn growing season green biomass and selected vegetation indices with accumulated growing degree days (GDD) during each study year (2003, 2005 and 2007).

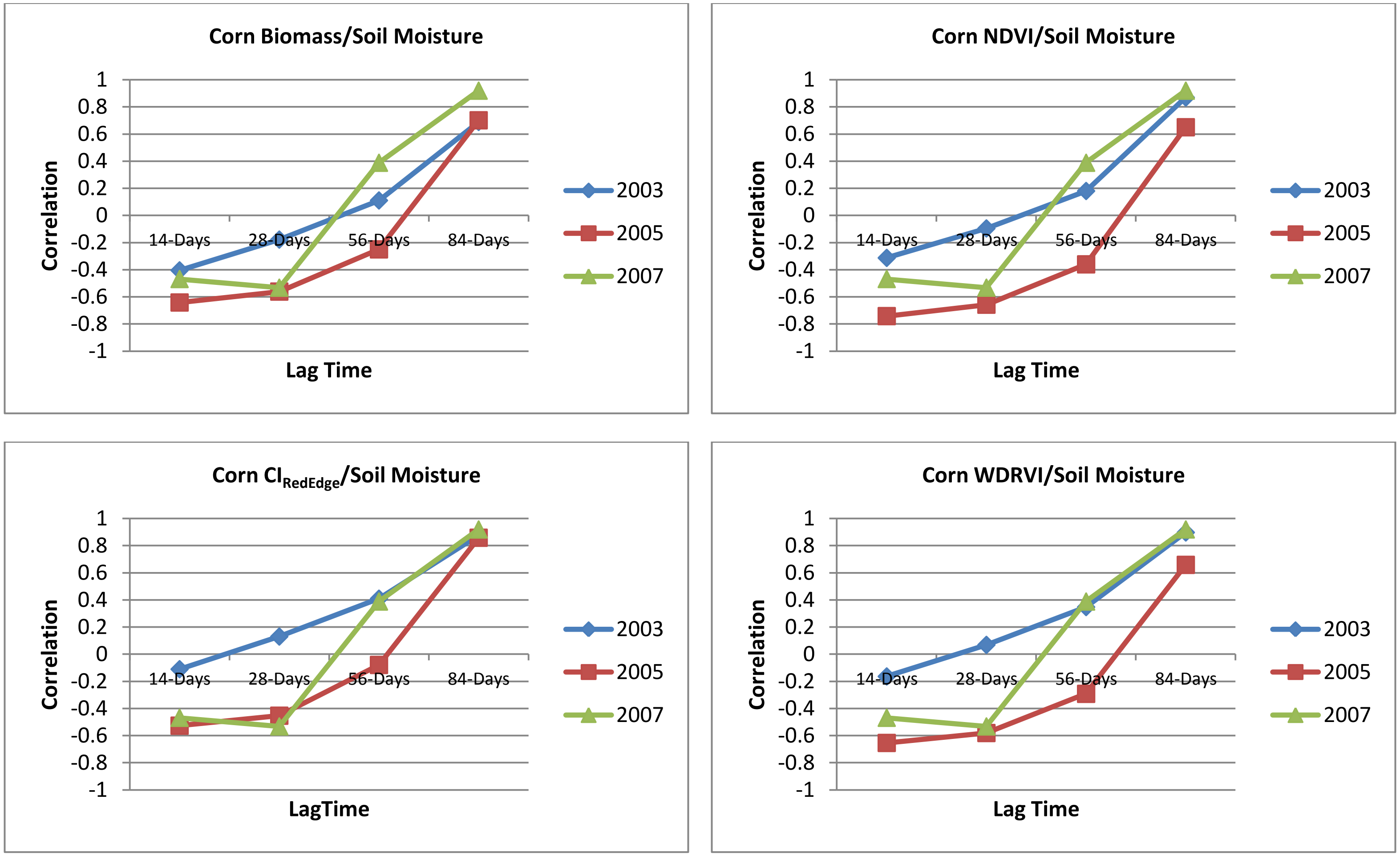

Figure 4.21: Summary of Pearson's correlation coefficient (r) values for the relationships of corn growing season green biomass and selected vegetation indices with accumulated soil moisture during each study year (2003, 2005 and 2007).

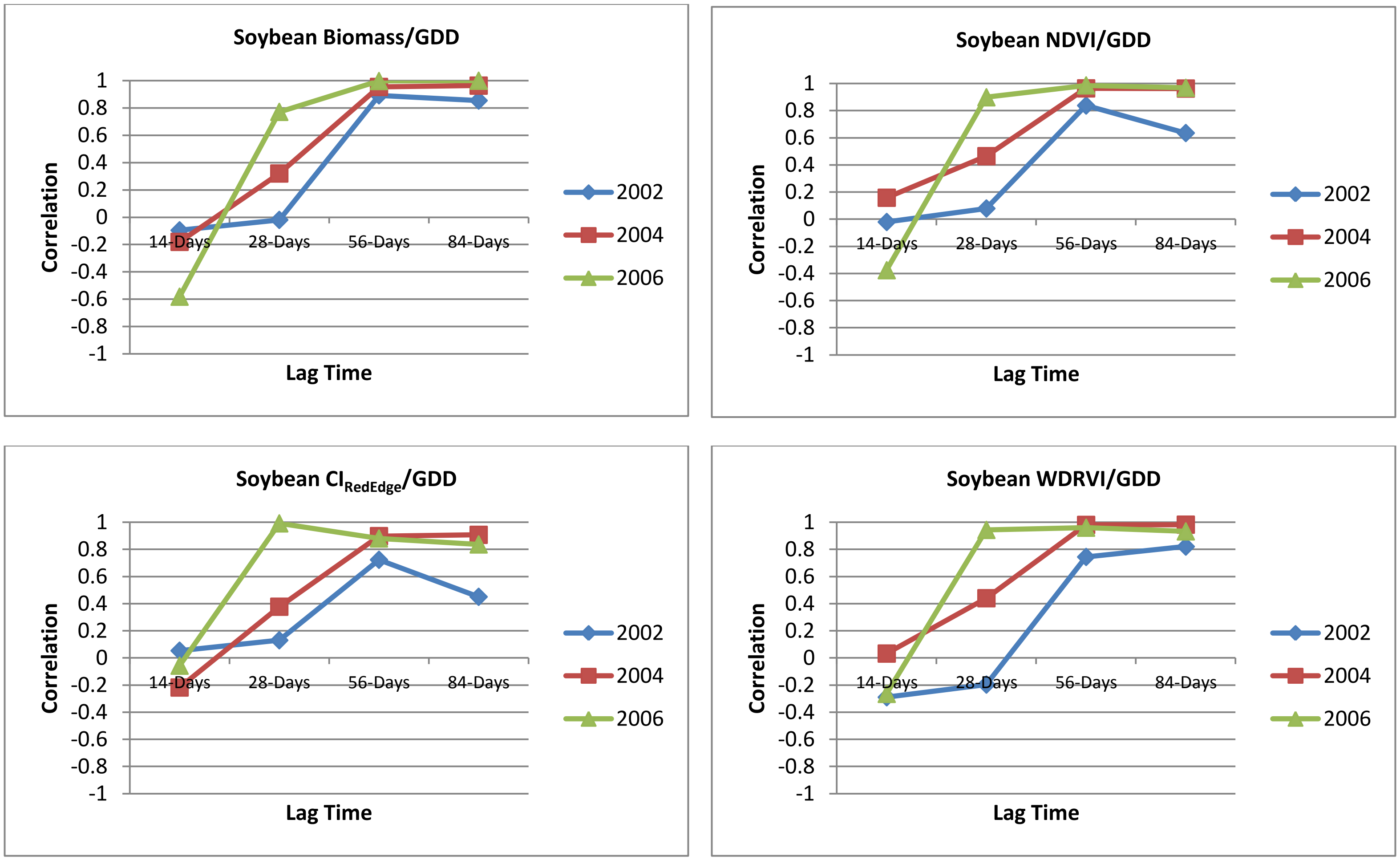

Figure 4.22: Summary of Pearson's correlation coefficient (r) values for the relationships of soybean growing season green biomass and selected vegetation indices with accumulated soil moisture during each study year (2002, 2004 and 2006).

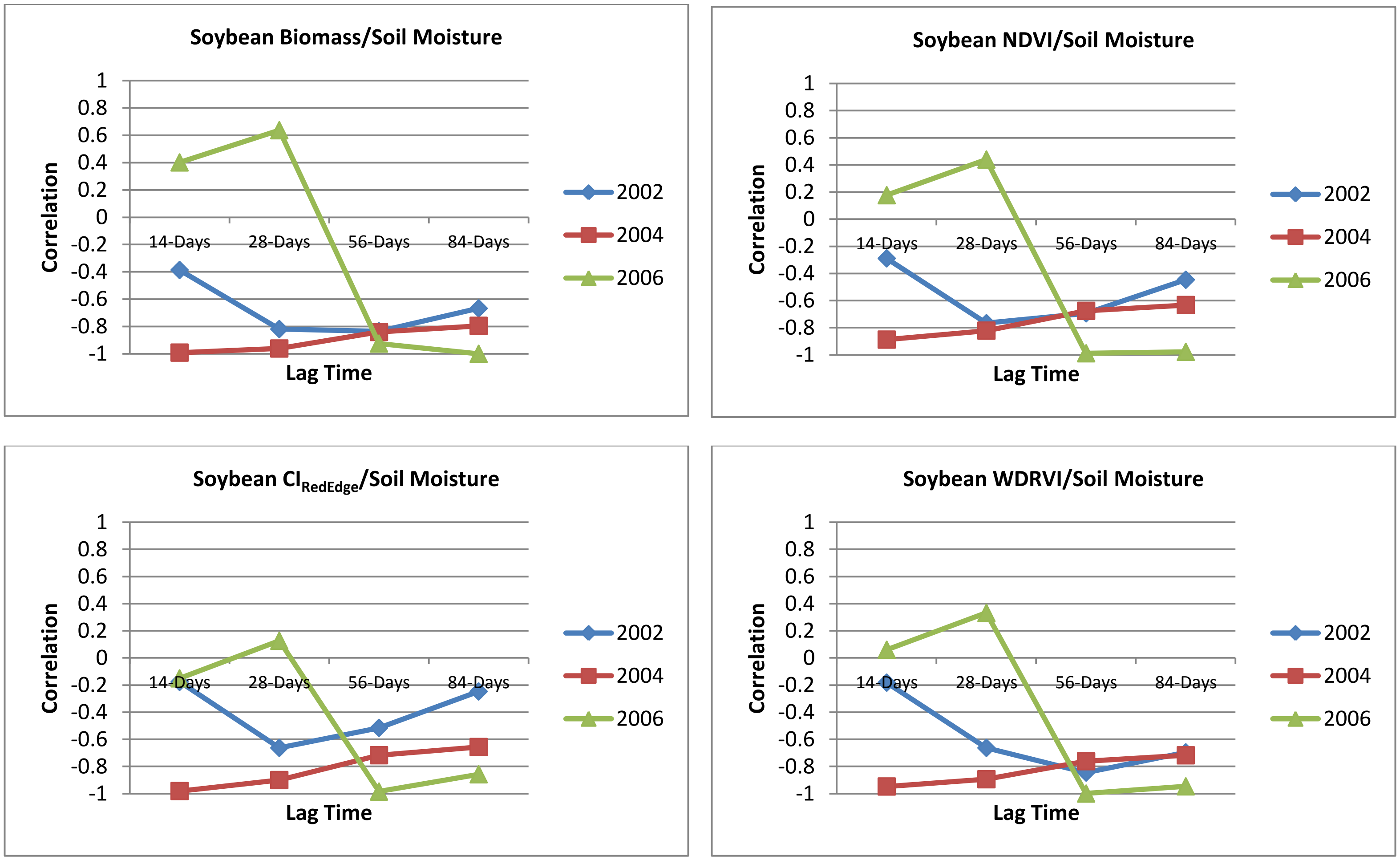

Figure 4.23: Summary of Pearson's correlation coefficient (r) values for the relationships of soybean growing season green biomass and selected vegetation indices with accumulated growing degree days (GDD) during each study year (2002, 2004 and 2006).

4.4 Discussion

In general, the results were quite good with reference to the examination of relationships between above ground green biomass and spectral indices. All of the R^2 values were above 0.48 with reasonable and acceptable RMSE's below 405.04kg/ha and CV's below 33.74%. However, some variation occurred with regard to the statistical parameters (Tables 4.2 and 4.3). Slight variability occurs among the yearly biomass estimation results from each crop as well as between the results obtained for both crops and these are visible in the range of results listed in tables 4.2 and 4.3.

With regard to annual variations in biomass of the crops, one factor is certainly related to environmental perturbations. For example, temperature, precipitation, soil moisture, intensity and duration of insolation may affect plant growth (Eastin & Sullivan, 1984), and this type of variability may manifest itself in the VIs. Annual variation of these environmental factors would contribute to the variations in biomass of corn and soybeans being studied from year to year. Inter-annual variations of biomass in the specific crops could also lead to differences in the accuracies associated with yearly biomass predictions. It is expected that issues of variations in plant growth and condition will occur from one growing season to the next.

Spectral data acquired by the airborne AISA sensor may also be influenced by environmental factors, which may contribute to variations in accuracy of biomass prediction. For example, soil moisture may differ from one image acquisition date to the next, which in turn could cause an effect (of lightening or darkening) on the soil background component of the signal upwelling from the crop Of course, the soil background effect is greater when the plant canopy is sparse than when it is full. Finally, as noted above, the remote estimation of biomass was compared to the destructive samples done in the field, and the correlations were, for the most part, very good. It is possible, however, that errors may be introduced into those data through human error.

Accuracies obtained from the 2006 growing season are of particular interest because for all VIs the R^2 values are considerably lower than the values obtained from all other study years. This may be attributed to the three dates of data acquisition (07/26, 08/15, 08/23) which are all within a 1-month period in the mid to late growing season. To effectively monitor vegetation phenology via remote sensing, images should be temporally distributed to capture the key phenological phases in the plants growth cycle: green-up, maturity, senescence and dormancy (Zhang, *et al*., 2003). The low correlations are probably due to the fact that the images acquired from 2006 are clustered in the mature phase of the crop's growth and thus are not a proper representation of soybean phenology during a growing season.

The 2006 study year also had a small sample size which is made up of biomass values that are generally high for soybeans, as compared with the other two growing seasons during which the soybean crop was studied (Figure 4.9). High biophysical measurements in crops have been shown to result in saturation and reduced sensitivity in VIs (Hatfield and Prueger, 2010), and this is reflected in the low biomass/VI correlations in 2006 (Table 4.1). The problem of non-linear scaling (i.e. uneven sensitivities at varying biophysical levels) that is common in VIs also affects the CV which is the lowest in all of the study years, despite high RMSE results, because the average biomass in 2006 is notably higher than from the other “soybean years.”

Results obtained from the correlation of green biomass and accumulated GDD were good overall. GDD, when regressed against biomass and the VIs, showed generally reversed behaviors for each crop type. In the case of corn, there were decreasing r values as the lag time increased with the highest correlations occurring at lag times of 14 days and lowest correlations at 84 day lags. Conversely, soybean showed increase in correlation of accumulated GDD with biomass and VIs as lag time increased, with lowest r values at the 14 day lags and highest at 84 day lag periods.

The difference in correlations of both crops with accumulated GDD can be attributed to differences in phenology of both crops. Corn plants typically display a bell shaped curve with gradual increase and decrease in green biomass (http://weedsoft.unl.edu/documents/GrowthStagesModule/Corn/Corn.htm#), while soybeans attain peak biomass later in the season with rapid decline during senescence (http://weedsoft.unl.edu/documents/ GrowthStagesModule/Soybean/Soy.htm#). The later occurrence of soybean senescence caused reduction in r to occur at a later lag time of 56-days.

The correlation results of corn biomass and VIs with accumulated soil moisture show steady increase with as lag time increased with lag time of 14 – 28 days having negative values, but after approximately 56 days the correlations were positive. This implies that accumulated soil moisture from longer times have a stronger influence on vegetation growth than the current/more recent soil moisture. Soybean on the other hand, had occurrences of either annual increase or decrease in correlation of soil moisture with biomass and VIs as lag time increased, but with no general trends observed for all VIs and biomass.

4.5 Conclusion

As noted previously, several authors have addressed the issue of remote sensing of vegetative biomass, but a scant amount of research has been carried out in crops using sensors with both high spatial and spectral resolutions for the purpose of estimating biomass over extended periods of time. Neither has any research been applied using data from such sensors and field measurements been applied towards the effects of environmental variables on the phenology of crops across multiple growing seasons.

Therefore, this research estimated the green biomass in rain-fed corn and soybeans across six growing seasons (2002 – 2007) using hyperspectral remotely sensed aerial images transformed to three selected vegetation indices (VI). Although there is a large number of VIs that have been shown to correlate well with various vegetation biophysical characteristics, this research was focused on three specific VIs (NDVI, $CI_{RedEdge}$, and WDRVI). The research also examined how growing season biomass and VIs correlated with daily measurements of environmental variables accumulated in lag-times of 14, 28, 56 and 84 days.

Analysis of the relationships between VIs and both crops annually showed very high correlations in five of the six study years, with reasonable margins of prediction error. There were only slight variations in the correlations between VIs and both crops, which may have been introduced by environmental factors as well as the data collection and analysis processes.

The examination of crop specific relationships between VIs and biomass was done by collectively looking at all of the biomass and remotely sensed data acquired from three growing seasons each for both crops. This also showed very high correlations as well as acceptable prediction errors, which were slightly higher for corn than for soybeans.

Analysis of correlations between accumulated soil moisture and field measured biomass with derived VIs showed trends which were very similar for all study years. Correlation trends observed for corn were very distinct and involved increase in correlations as lag times increased. Soybean/soil moisture trends were not quite as clear, but also showed a general decrease in negative correlation as lag time increased.

Correlation of accumulated GDD with field measured biomass and VIs, also showed trends which were very similar for each growing season. Corn correlation with GDD showed very distinct decrease as lag times increased. Soybean/GDD correlations were also evident in general, and showed increase in correlation with increase in lag time.

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5 CONCLUSION

5.1 Summary and Conclusion

A wide variety of research has been carried out on biomass estimation using remotely sensed data. Of this, only a limited amount has focused on remote estimation of crops. In this research, two crops – corn and soybean – were selected in a non-irrigated landscape. This study contributes findings on the estimation of green biomass in rain-fed corn and soybeans during multiple growing seasons to the existing literature on remote sensing of crop biomass. Biomass estimation was done using canopy level spectral reflectance data as well as high resolution spatial and spectral aerial imagery acquired at multiple times during each growing season. Because of the field scale at which this study was carried out, destructively sampled biomass measurements from the study site were used in assessing the accuracy of results derived from three vegetation indices (VI) applied for biomass estimation. The VIs applied were Normalized Difference Vegetation Index (NDVI), Red-Edge Chlorophyll Index ($CI_{RedEdge}$) and Wide Dynamic Range Vegetation Index (WDRVI).

The biomass measurements were also used in correlating growing season crop phenology with daily growing degree day (GDD), precipitation and soil moisture measurements. The environmental variables were summed up in two-week, four-week, eight-week and twelve-week lags prior to each day of biomass measurement over several growing seasons. This study is important and unique in the body of work done on analyzing the effects environmental variables have on crop growth because of the field scale at which it was carried out, the use of field measured biomass, as well as use of VIs derived from sensors at canopy and aerial levels for analysis.

The first aspect of this study analyzed temporal changes in green biomass of rain-fed corn and soybean across ten growing seasons (2002 – 2011), and this was correlated with growing degree days (GDD), precipitation and soil moisture. General trends observed showed decrease in biomass/accumulated GDD correlation as the lag time increased for corn and soybean respectively. Correlation of biomass with precipitation showed no distinct increasing or decreasing patterns. Also, biomass correlation with soil moisture showed increasing r values as lag time increased. Multiple regression of biomass with GDD and soil moisture resulted in overall positive correlations with higher r values than were observed from the correlation of biomass with the variables individually.

The second section of this study focused on the use of three VIs i.e., NDVI, $CI_{RedEdge}$ and WDRVI derived from spectral reflectances acquired at canopy level for estimating green biomass of corn and soybean in a rain-fed field as well as comparing the accuracy of each VI for biomass estimation. In this part of the study, analysis of the relationships between crop biomass and VIs with accumulated soil moisture and GDD was also carried out.

Overall, each VI derived from canopy level reflectance spectra estimated each crop type with high accuracies. From all seven study years, R^2 ranged from 0.83 to 0.99, with higher R^2 observed in soybean than in corn. In general, NDVI was observed to be the best biomass predictor for both crops in this study. Observations from crop specific analysis showed very high R^2, low errors and low variations in biomass prediction for both crops, with better accuracies also observed in soybean than in corn.

Observing the relationships of environmental variables with crop biomass and VIs showed r values which were similar across the board. These similar values showed very clear trends in corn and some mixed correlations for soybean with each environmental variable. Soil moisture correlations with corn increased as lag time increased, while for soybean there were no distinct relationships visible at different lag periods. Correlations of GDD with corn biomass and VIs showed decrease as lag times increased while there was increase in correlation as lag times increased for soybean.

The third part of this study was aimed at estimating green biomass of corn and soybean in a rain-fed field by means of NDVI, $CI_{RedEdge}$ and WDRVI derived from images of high spatial and spectral resolution; as well as the analysis of correlations between crop biomass and VIs with accumulated soil moisture and GDD.

In general, each VI derived from aerial imagery had good estimating powers for each crop type. From all six study years, R^2 as high as 0.95 and 0.99 were observed in corn and soybean respectively. Prediction errors were as low as 180.69kg/ha in corn and 149.38kg/ha for soybean. Coefficient of variation values were also low, 12.4% in corn and 10.03% in soybean. Overall, NDVI was observed to be the best biomass predictor for both crops in this study. Observations from crop specific analysis were better R^2 and lower errors and variations in biomass prediction of corn than soybean.

Correlation of environmental variables with crop biomass as well as the three VIs showed r values which were similar across the board. These similar values showed very clear trends in corn and soybean with each environmental variable. Soil moisture correlations with corn increased as lag time increased, while for soybean there were decreasing correlations with longer lag periods. Correlations of GDD with corn biomass and VIs showed decrease as lag times increased while there was increase in correlation as lag times increased for soybean.

Results of this research on the correlations between environmental factors and crop growth show clearly that the relationships are dynamic and vary throughout a growing season. This is similar to previous studies carried out over larger spatial extents which show that NDVI response to precipitation events are shorter early in the growing season and longer as time progresses (Di et al., 1994; Ji and Peters, 2005). In addition, the increased correlation from the combined effects of GDD and soil moisture supports statements from Eastin and Sullivan (1984) that temperature and moisture effects on vegetation growth are closely associated.

The results obtained from the estimation of biomass via VIs derived from canopy level spectra and aerial imagery are similar to those obtained by Viña (2004) in which models designed for predicting crop canopy chlorophyll content were used to estimate biomass in corn and soybeans using high spatial and spectral resolution aerial images. Similar high resolution data using different VIs, including NDVI, were also applied by

Shanahan et al., (2001) for predicting corn yield in two growing seasons, resulting R^2 values were slightly lower than those obtained in this study.

5.2 Future Research

The success of this research into the relationships between crop growth and environmental variables is beneficial for assessing and improving management practices in agriculture. Because of the close relationship between crop growth and atmospheric characteristics (Reed *et al*., 2004), agricultural practices such as timing of planting, use of locally adapted cultivars and fertilizer applications are implemented to maximize the growth and yield of crops based on their interactions with environmental variables. The strong correlations observed in the results of temperature- and moisture- based environmental variables with seasonal crop growth are important for improving agricultural practices.

The estimation of crop biomass using data from multiple platforms across multiple growing seasons with very high accuracies observed in this research is important for remote assessment of crops and their biophysical variables. Remote estimation is especially beneficial because it provides a medium for crop studies without the need for on-site destructive sampling; circumventing the destruction of the target allows for long-term studies of a single target. Using canopy level sensors will be most useful in precision agriculture while an aerial based sensor can be used for larger study areas.

One of the main factors which affected this research, and consequently the results, is the variable data collection frequency for each source. Destructive biomass samples and canopy spectral reflectances were collected every 7 – 14 days, while AISA imagery were collected anywhere from three times a growing season to thrice a month. As a result of this, during biomass prediction, there were (in several cases) intervals of several days between predicted biomass and ground truth data; with discrepancies in biomass measured by the sensors and the biomass value against which it is regressed. Concurrently collecting all data used for biomass estimation i.e., biomass measurements, canopy spectra and AISA images would result in less discrepancies between what is 'seen' by the sensors and what is actually measured by destructive sampling. Also there will be uniformity in the amount of data and collection dates during each growing season studied, enabling a more even comparison of results from the two sensors studied.

In the correlation of soil moisture and GDD at multiple lag times with biomass, observed r values were noticeably strong (i.e., ±0.9 and above) in majority of the instances, while there were no discernible trends observed for precipitation. Previous research by Ji and Peters (2005) in studying the lag effect of precipitation on crop growth using lagged time intervals showed effects of precipitation on crops which varied depending on the crops' growth stage. Applying this technique of using specific time interval lags to the three environmental variables and biomass researched in this paper would be possible if the biomass and spectral measurements were taken simultaneously at specific intervals, and may show more variations in the correlations of crop growth with the environmental variables.

Applying this research and the suggested improvements would be useful in monitoring the effects of warmer climate trends on crop growth. The US Environmental Protection Agency (EPA) has shown that plant hardiness zones within the contiguous United States have shifted northward between 1990 and 2006 as a result of warmer temperatures, with most places experiencing a shift by one to two zones (http://epa.gov/ climatechange/science/indicators/ index.html). This has also had an effect on the length of growing seasons, with an average increase of two weeks for crops in the U.S. from the turn of the 20th century (http://epa.gov/climatechange/science/indicators/index.html). The success of this research in monitoring crop growth and correlations with environmental variables across multiple growing seasons can lead to its replication in the same study area to study expected changes in the plant hardiness zone of south-eastern Nebraska over time. The historical dataset which will be necessary for conducting this type of change analysis may require at least ten more years to build for any significant changes to be visible. With the development of a historical dataset of environmental factors and the growth patterns of crops, there is the potential for examining other environmental factors which affect crop growth such as soil types, mineral and non-mineral nutrients as well as radiant energy.

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