ESTIMATING ANNUAL NET PRIMARY PRODUCTIVITY OF THE TALLGRASS PRAIRIE ECOSYSTEM OF THE CENTRAL GREAT PLAINS USING AVHRR NDVI

BY

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Submitted to the graduate degree program in Department of Geography and the Faculty of the Graduate School of the University of Kansas in partial fulfillment of the requirements for the degree of Master of Arts.

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Date defended: January 26, 2009

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ABSTRACT

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Aboveground Net Primary Productivity (ANPP) is indicative of an ecosystem's ability to capture solar energy and store it in the form of carbon (or biomass). Annual and interannual ecosystem variation in ANPP is often linked to climatic dynamics and anthropogenic influences. The Great Plains grasslands occupy over 1.5 million km^2 and are a primary resource for livestock production in North America. The tallgrass prairies are the most productive of the grasslands of the region and the Flint Hills of North America represent the largest contiguous area of unplowed tallgrass prairie (1.6 million ha) (Knapp and Seastead, 1998). Measurements of ANPP are of critical importance to the proper management and understanding of climatic and anthropogenic influences on tallgrass prairie, yet accurate, detailed, and systematic measurements of ANPP over large geographic regions of this system do not exist. For these reasons, this study was conducted to investigate the use of the Normalized Difference Vegetation Index (NDVI) to model ANPP for the tallgrass prairie. Many studies have established a positive relationship between the NDVI and ANPP, but the strength of this relationship is influenced by vegetation types and can significantly vary from year-to-year depending on land use and climatic conditions. The goal of this study is to develop a robust model using the

Advanced Very High Resolution Radiometer (AVHRR) biweekly NDVI values to predict tallgrass ANPP. This study was conducted using the Konza Prairie Biological Station as the primary study area with data also from the Rannells Flint Hills Prairie Preserve and other sites near Manhattan, Kansas. The dominant study period was 1989 to 2005. The optimal period for estimating ANPP using AVHRR NDVI composite datasets is prairie 30 (late July). The *Tallgrass ANPP Model* (TAM) explained 53% ($r^2 = 0.53$, $r = 0.73$) of the year-to-year variation. Efforts to validate the TAM results were frustrated by considerable variations among existing remote sensing based ANPP model estimates and *in situ* clipplot measurements of peak season tallgrass production. These findings support the conclusion that ecosystem specific ANPP models are needed to improve global scale ANPP estimates.

The creation of 1 km x 1 km resolution ANPP maps for a four county (~7,000 ha) for years 1989 – 2007 showed considerable variation in annual and interannual ANPP spatial patterns suggesting complex interactions among factors influencing ANPP spatially and temporally. The observed patterns on these maps would be lost using the much coarser resolution ground weather recording stations.

For my dear parents and my love Ran Zhao

ACKNOWLEDGEMENTS

I would like to express my great gratitude and appreciation to my parents for their great support. Although they are back in China, they always encourage me to overcome the difficulties. They always believe in my and my ability, and afforded my more opportunities in life than they realized. And they knew how to teach me to strive toward my goal and achieve it.

I need to thank my love, Ran Zhao. She always uses the most beautiful words to praise what I achieve. She never wavered in her support of my efforts because she understands my love for my research. Because of her warm-hearted and encouraging words in those mid-night, I can overcome all of the difficulties.

My advisor, Dr. Kevin Price, is the most important one I want to express my great appreciation. He has been extremely generous with encouragement, ideas, resources and opportunities throughout my time as his graduate student. He used lots of time to help me to edit papers with patience and teach me how to write a good English paper. I will never forget he always tell me "…this is not the end of world…" Because of these words, I can achieve my goal today. He is a great mentor and roommate.

I want to thank my committee members: Dr. Stephen Egbert and Dr. Christopher Brown for their patience and help for my thesis writing. I also thank Jude Kastens, Jonathan Thayn and Matthew Dunbar for their help. They are great colleagues and friends when I worked at KARS. Additionally, I thank Dr. John Blair (professor of Division of Biology in Kansas State University), Dr. Clenton Owensby and Dr. Walter Fick (professor of Department of Agronomy in Kansas State University), and Mary Knapp (State Climatologist for Kansas) for their great suggestion and valuable field data.

This research was supported by NSF EPS-0552722 titled “Phase V: Building research Infrastructure to Address Grand Challenge Problems in Ecological Forecasting” with state matching funds provided by Kansas Technology Enterprise Corporation. The PI on the grant is Kristin Bowman-James at the University of Kansas. Direct support for the project came from the University of Kansas (first half) and Kansas State University (second half).

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Chapter 1

INTRODUCTION

There is increasing research documenting the impacts of climatic variation on anthropogenic and “natural” ecosystems (Lauenroth et al.1999). These climatic variations influence ecosystem biogeochemical cycles through modification of energy and nutrient flow as modified by changing temperature and precipitation patterns (Breshear *et al*. 2005, Pielke *et al.* 1998, Woodward 1987). Highly dynamic climatic conditions have been shown to impact ecosystem equilibrium, and if system perturbations are frequent enough, they may preclude the development of closely coupled cybernetic interactions among plant and animal organisms resulting in alteration of ecosystem processes that influence system climatically-determined equilibrium (Ellis and Smith, 1988).

One of the best indicators of ecosystem response to climate change is variation in plant and animal development states (phenology - the timing of seasonal activities of animals and plants) (Parmesan, 2006). Changes in phenological patterns may be among the easiest ways of tracking species response to changing ecosystem conditions (Walther *et al.* 2002). Phenology is usually measured in Julian dates or days since December 31 (Ahas *et al.* 2002).

Temperature is the main driver of phenology that influences biophysical processes (*i.e*., phenophases) such as seasonal spring events like plant emergence, growth rate, blooming period, *etc*. (Price *et al.* 2004; Yu *et al.* 2004). Spring temperatures have been found to be the most important factor influencing phenophases at all other times of the growing season (Walther *et al.* 2002). For example, changes in spring temperature influence the onset date of vegetation that can alter plant productivity. Price *et al.* (2004) showed that vegetation phenological patterns could be influenced by water budgets that are significantly altered by climatic variations in temperature and precipitation. For this reason, changes in vegetation phenological patterns can be utilized as an index of varying climatic conditions.

An ecosystem of particular interest in terms of climatic influences on processes is grasslands. The tallgrass ecosystem of the Great Plains is among the most species diverse and productive warm-season (C_4 Carbon fixing) grassland ecosystems in North America (Knapp *et al.* 1998). These tallgrass prairies store vast amount of above and belowground biomass (carbon (C)) and therefore variations in climatic factors such as precipitation and temperature can significantly alter ecosystem processes affecting the carbon pool associated with this system (Knapp *et al.* 2002). Due to its diversity of species, the tallgrass prairie ecosystem is one of the most responsive terrestrial ecosystems to interannual or annual variability in precipitation and temperature (Knapp *et al.* 2002). Consequently, the tallgrass prairie is an ideal ecosystem for monitoring and identifying ecosystem response to varying climatic conditions such as those predicted by the Global Climate Models (GCMs) (Running *et al.* 2004).

In North America, the distribution and composition of tallgrass prairie are primarily determined not only by regional climatic factors, but by edaphic characteristics, and land use and land management practices such as burning grazing and haying (Fay *et al.* 2003, Sala *et al.* 1988, Epstein *et al.* 1997). For example, the use of fire is one of the most important and widely implemented treatments for managing grasslands worldwide, and it is an important ecological factor in maintaining the compositional integrity of tallgrass prairies (Knapp *et al.* 1998). Historically, humans have used fire as a means of limiting the growth of woody plants and promoting greater grass productivity (both net and gross) (Collins and Wallace 1990). Many studies have also documented that nitrogen (N) availability and cycling of N is highly related to fire frequency (Blair 1997). Thus, different tallgrass prairie management practices (*i.e.*, fire, haying, grazing), together with variation in the dominant climatic factors, influence tallgrass ecosystem dynamics and their associated biogeochemical cycles.

Net Primary Productivity (NPP) is defined as "the rate at which all the plants in an ecosystem produce net useful chemical energy, which is equal to the difference between the rate at which the plants in an ecosystem produce useful chemical energy and the rate at which they are used for cellular respiration" (http://en.wikipedia.org/wiki/Primary_production#cite_ref-0). NPP is an important component of the carbon cycle and a useful indicator of ecosystem performance (Seaquist *et al.* 2003, Lobell *et al.* 2002) that can be used to quantify biogeochemical cycles and available energy and nutrient resources within the system. The term, “primary production”, on the other hand is defined as the synthesis of organic compounds from carbon dioxide, so it can be thought of as a measure of a plant’s ability to transform visible energy into chemical compounds. Aboveground Net Primary Production (ANPP) is the accumulated NPP above the ground that marks the first visible step of carbon accumulation that quantifies the conversion of atmospheric carbon dioxide into biomass (Running *et al.* 2004). Without a correct understanding of ANPP, the processes through which ecosystems respond to environmental fluctuations, one cannot completely understand how photosynthetically produced chemical energy can be made available and transferred within an ecosystem. Therefore, the quantification of annual ANPP over large geographic regions is critical to understanding ecosystem energy balances and how these balances influence biological and ecological processes throughout a region.

In the past, biologists, ecologists and biogeographers have estimated ANPP for large geographic regions using atmospheric models (Running *et al.* 2004), which is a time-consuming and expensive process. Running *et al.* (2004) describe the early efforts by Lieth and Whittaker (1975) to estimate global NPP, which involved the use of temperature in a regression model to calculate annual actual evapotranspiration (AET) and from this estimate they produced a global estimate of NPP using the following equation:

$$NPP = 3000\{1 - \exp[-0.0009695(AET - 20)]\}.$$

While the work of Lieth and Whittaker (1975) proved to be a major step forward in improving our understanding of ecosystem dynamics, the method was limited by the sparsely distributed weather stations throughout most of the world. Even today, in the US, weather stations can be located hundreds of kilometers apart, which means AET estimates for locations between stations must be interpolated, and such interpolations can be very inaccurate especially in areas of complex terrain variation. In addition, the methods for collecting climatic measurements vary considerably around the world, and maintenance of the weather stations is a significant problem in many places. For these reasons, more reliable and higher spatial resolution data are needed for modeling ecosystem NPP. Since the launch of the early satellite earth observation systems starting in the 1970s, scientists have been working on methods for using remotely sensed spectral data for characterizing earth system processes and land use and land cover types.

In 1973, Rouse *et al.* (1974) introduced the Normalized Difference Vegetation Index (NDVI), generated using the ratio of the difference between the near-infrared band (NIR) and the red band (R) and the sum of these two bands (Eidenshink and Faundeen 1994). The equation for the NDVI is

$$NDVI = \frac{NIR - R}{NIR + R}$$

where NIR is the near-infrared portion of the electromagnetic spectrum that has a nominal wavelength range from 0.75 to 1.10 μm and R is the red spectrum that has a wavelength range from 0.58 to 0.68 μm (Eidenshink and Faundeen 1994). Chlorophyll in plant tissue absorbs visible energy for photosynthesis primarily in the blue and red regions of the electromagnetic spectrum. Plants either reflect or transmit all near-infrared (NIR) energy away from or through their plant tissue where it is either reflected back into space or absorbed by other forms of matter such as soils or water. Therefore, as plant productivity increases, the NDVI values for each image picture element (pixel) will also increase.

Before the 1980s, ecological studies were mostly confined to research questions limited to small field plots, and the ability to conduct regional-to-global scale ecosystem studies was limited (Running *et al.* 2004). Since then, the availability of satellite remotely sensed data and development of ecosystem models that employ these data have enabled geographers and ecologists to better analyze the interaction between climatic variation and vegetation response to this variation – this is especially important to an improved understanding of how ecosystem carbon budgets are influenced by varying climatic conditions.

During the last decade, scientists have begun to develop ecosystem-specific models that use remotely sensed data as input to estimate ANPP. For example, Paruelo *et al.* (1997) developed an NDVI-based ecosystem model for the grasslands of the Central Great Plains. Recent studies have focused on the use of NDVI to model global scale ANPP (Running *et al*. 2004; Zhao *et al.* 2005). While work has focused on global scale modeling of ANPP, much less work has focused on more specific regional scale ecosystem or specific species modeling. This study therefore will present a discussion and propose methods for modeling ANPP for the tallgrass prairie ecosystem of the Central Great Plains by using NDVI derived from remotely sensed data.

Research Background

There are generally three approaches for studying ANPP dynamics. These approached include, 1) directly measuring plant biomass accumulated over the growing season, 2) use of physical process models to estimate ANPP and 3) use of remotely sensed measurements to empirically model ANPP.

Examples of studies that used direct biomass measurements to study climatic influences on ANPP include Briggs *et al.* (2005) and Reed *et al.* (2005) who focus on the regional-scale ANPP measurement. Some of the previous studies, such as Amthor *et al.* (1998) focus on the global-scale ANPP measurement. And some research focus on the ANPP measurement based on varying ecosystems level: Briggs *et al.* 1991; Bragg and Hulbert (1976); Briggs and Knapp (1995). The problem with this measurement method is that is is practical at the watershed scale, but becomes very impractical in terms of time and money costs as the work is moved up to the regional and global scales.

Many physical-based model studies have examined the influences of climatic variation on ANPP (Churkina and Running 1998; Pielke *et al.* 1998; Landsberg and Gower 1997; Melillo *et al*. 1993; Walther *et al.* 2002; Pearson and Dawson 2003). Models have also been developed to estimate ANPP at the ecosystem to global scales. Some of the earliest work in modeling ANPP was at the global scale. For example, Leith (1975) developed global scale ANPP models using climatic factors as input.

Many ecosystem-process models were developed that were based on climate, soil properties, and biome specific characteristics to responses in biochemical processes of vegetation (Haxeltine and Prentice, 1996; Parton *et al*. 1987). Consequently, ANPP models range from fairly simple regressions between main climatic variables to quasi-mechanistic models that attempt to simulate the ecosystem processes at the plant level (Churkina and Running 1998). The results of these studies strongly suggested that vegetation ANPP is a result of the interaction of several climatic factors, but these studies also presented the direct measures of ANPP at large scales were still problematic, and model-based estimates were at global scales. But the weakness of these studies is lack of climate data at high spatial scales, and missing vital climate measurements in many parts of the world.

In recent years, an increasing number of studies on the influences of climate on ANPP have focused on the use of remotely sensed data for modeling ANPP. A few models for estimating NPP have been developed to calculate global scale NPP (Churkina and Running 1998; Running *et al.* 2004) directly from remotely sensed data. Zhao *et al.* (2005) indicated that for monitoring vegetation, the Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI datasets is critical to global scale plant dynamics studies. Running *et al.* 2004 states that the globally annual NPP can be calculated by using the equation:

$$NPP = \sum(\varepsilon \times NDVI \times PAR - R_{lr}) - R_g - R_m,$$

where ε is the conversion efficiency; R_{lr} is 24-hour maintenance respiration of leaves and fine roots; R_g is annual growth respiration required to construct leaves, fine roots, new woody tissues; R_m is the maintenance respiration of live cells in woody tissues. By validating annual NPP across a full range of biome types and climates, Running and colleagues found that their MODIS data-derived estimates of NPP for ecosystems around the world fell within the ranges of values published in research findings of other scientists.

Paruelo *et al.* (1997) presented methods for estimating ANPP for the central grassland region by using NDVI data derived from the Advanced Very High Resolution Radiometer/National Oceanic and Atmospheric Agency (AVHRR/NOAA).

Huete (1989) and Paruelo *et al.* (1997) found that considerable soil background in arid and semi-arid regions can significantly alter ANPP estimate accuracy. Price *et al.* (2002) also found that semiarid sites with less that 30% ground cover could not be distinguished from bare soil and that the strength of the relationship between tallgrass biophysical factors and spectral properties can significantly over the growing season and from year to year (Price *et al*. 2002).

Paruelo *et al.* (1997) found the relationship between ANPP and NDVI varied and was not always linear over the growing season. Paruelo and colleagues used the average annual NDVI (NDVI-I for integral NDVI) to estimate grassland ANPP. ANPP data from KPBS was among many datasets in grassland areas that were used to develop the NDVI-I ANPP model. The NDVI-I model was found to explain 89% of the variation in ANPP for 19 sites within the Central Grassland Region (Paruelo *et al.* 1997).

During a search of the literature, no ANPP models specific to the tallgrass prairie type were identified. Therefore, a question that needs to be addressed is whether an remote sensing based ANPP model designed specifically for tallgrass prairie types in the Central Great Plains might provide more accurate estimates of ANPP than existing global or large regional scale models such as the GNPP or the NDVI-I models referenced above.

STATEMENT OF GOAL

In this study I seek to develop an ANPP model designed specifically for tallgrass prairies of the Central Great Plains and compare productivity estimates against ANPP ground reference measurements and existing remotely sensed based ANPP model estimations. To achieve this goal, I propose to:

Goal 1 *– Determine the optimal period during the growing season for using AVHRR NDVI biweekly composites to model ANPP of Tallgrass prairie ecosystems representative of the Central Great Plains.*

Goal 2 *– Develop an ANPP model and validate its accuracy for all years that ANPP in situ data and AVHRR composite images are available (1989 to 2005 or 17 years).*

Goal 3 *– Analyze the variation in ANPP among the 19 years (1989 - 2007) of the study period to determine how ANPP varies geographically and temporally among years.*

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Chapter 2

Estimating Annual Net Primary Productivity of the Tallgrass Prairie Ecosystem of the Central Great Plains using AVHRR NDVI

ABSTRACT

Aboveground Net Primary Productivity (ANPP) is indicative of an ecosystem's ability to capture solar energy and store it in the form of carbon (or biomass). Annual and interannual ecosystem variation in ANPP is often linked to climatic dynamics and anthropogenic influences. The Great Plains grasslands occupy over 1.5 million km^2 and are a primary resource for livestock production in North America. The tallgrass prairies are the most productive of the grasslands of the region and the Flint Hills of North America represent the largest contiguous area of unplowed tallgrass prairie (1.6 million ha) (Knapp and Seastead, 1998). Measurements of ANPP are of critical importance to the proper management and understanding of climatic and anthropogenic influences on tallgrass prairie, yet accurate, detailed, and systematic measurements of ANPP over large geographic regions of this system do not exist. For these reasons, this study was conducted to investigate the use of the Normalized Difference Vegetation Index (NDVI) to model ANPP for the tallgrass prairie. Many studies have established a positive relationship between the NDVI and ANPP, but the strength of this relationship is influenced by vegetation types and can significantly vary from year to year depending on land use and climatic conditions. The goal of this study is to develop a robust model using the

Advanced Very High Resolution Radiometer (AVHRR) biweekly NDVI values to predict tallgrass ANPP. This study was conducted using the Konza Prairie Biological Station as the primary study area with data also from the Rannells Flint Hills Prairie Preserve and other sites near Manhattan, Kansas. The dominant study period was 1989 to 2005. The optimal period for estimating ANPP using AVHRR NDVI composite datasets is period 30 (late July). The *Tallgrass ANPP Model* (TAM) explained 53% (r^2 = 0.53, r = 0.73) of the year to year variation. Efforts to validate the TAM results were frustrated by considerable variations among existing remote sensing based ANPP model estimates and *in situ* clipplot measurements of peak season tallgrass production. These findings support the conclusion that ecosystem specific ANPP models are needed to improve global scale ANPP estimates.

The creation of 1 km x 1 km resolution ANPP maps for a four county (~7,000 ha) area for years 1989 – 2007 showed considerable variation in annual and interannual ANPP spatial patterns suggesting complex interactions among factors influencing ANPP spatially and temporally. The observed patterns on these maps would be lost using the much coarser resolution ground weather recording stations.

INTRODUCTION

The tallgrass ecosystem of the Great Plains is among the most species diverse and productive warm-season (C_4 carbon fixing) grassland ecosystems in North America (Knapp *et al.* 1998). These tallgrass prairies store vast amount of above and belowground biomass (carbon (C)) and therefore variations in climatic factors such as precipitation and temperature can significantly alter ecosystem processes affecting the carbon pool associated with this system (Knapp *et al.* 2002). Due to its diversity of species, the tallgrass prairie ecosystem is one of the most responsive terrestrial ecosystems to interannual or annual variability in precipitation and temperature (Knapp *et al.* 2002). Consequently, the tallgrass prairie is an ideal ecosystem for monitoring and identifying ecosystem response to varying climatic conditions.

Aboveground Net Primary Productivity (ANPP) is an important component of the carbon cycle and a useful indicator of ecosystem performance (Seaquist *et al.* 2003) that can be used to quantify biogeochemical cycles and available energy and nutrient resources within the system. In the past, biologists, ecologists and biogeographers have estimated ANPP for large geographic regions using atmospheric data (Running *et al.* 2004), which is expensive and time consuming to collect and process.

Nippert *et al.* (2006) found a strong linear relationship ($r = 0.79$) between growing-season (May to September, 1984 to 1999) precipitation and total tallgrass ANPP at the Konza Prairie Biological Station (KPBS). In contrast, Towne and Owensby (1984) examined the relationship between tallgrass ANPP from different burned sites and precipitation from 1928 to 1982 and found correlation values to be very low (the strongest relationship they found yielded an r value of 0.37). They examined five possible precipitation summary combinations (yearly total, previous year's total, January to April, May to June, and May to September) and still found no strong correlation between these factors. These findings suggest that depending on the scale of the study, model estimate accuracy of ANPP for tallgrass using precipitation data may produce questionable results.

Remotely sensed data have been investigated for years as a possible parameter for estimating ANPP. The most popular remotely sensed vegetation index in use today is the Normalized Difference Vegetation Index that was introduced by Rouse *et al.* in 1973.The index is derived by computing the difference between the near-infrared (NIR) energy that is reflected by plant tissue and the red energy that is absorbed by plant tissue for photosynthesis. The difference between NIR and red energy is than normalized by dividing the difference by the sum of the NIR and red energy. While considerable research has been conducted to examine the relationship between NDVI and biomass/ANPP, selected examples of such work include: Gausman (1974), Rosental *et al*. (1985), Sellers (1985, 1987), Tucker and Sellers (1986), Goward and Dye (1987), Prince (1991), Sellers *et al*. (1992), Hayes and Decker (1996), Paruelo et *al*. (1997), Tieszen *et al*. (1997), Guo *et al*. (2002a and 2002b), Running *et al.* (2004)

Many previous studies (Cao *et al.* 2004, Churkina and Running 1998, Goetz *et al.* 1999, Running *et al.* 2004, Zhao *et al.* 2005; Zhao *et al.* 2006) have focused on using remotely sensed NDVI to build global scale models for estimating primary productivity. Zhao *et al.* (2005) state that the Moderate Resolution Imaging

Spectroradiometer (MODIS) NDVI data are among of the primary global remotely sensed datasets in the NASA Earth Observing System (EOS) database for monitoring vegetation. Goetz *et al.* (1999) developed a modified production efficiency model (PEM) that estimated the conversion efficiency of absorbed photosynthetically active radiation (APAR) and turned it into estimates of net and gross primary production. Cao *et al.* (2004) built a model by using a similar theory called the GLObal Production Efficiency Model (GLO-PEM) used to quantify global NPP at the 8 km and 10-day resolution from 1981 to 2000. Running *et al.* 2004 stated that global annual NPP (hereafter GNPP) could be modeled by calculating the fraction of photosynthetically active radiation (FPAR) that is highly correlated with NDVI. Running *et al*. found that the gross net primary production (GNPP) estimates were within minimum and maximum ANPP measurements for various ecosystems as published in the literature. For example minimum and maximum ANPP *in situ* values for global grasslands varied from 70 to 410 g carbon per m^2 and their model estimates fell within these limits (Running *et al*. 2004). The GNPP model uses remotely sensed measurements from the MODIS satellite based sensor. A limiting factor in using MODIS data as input to ANPP estimates is that the TERRA and AQUA satellites on which the MODIS imaging systems reside were launched in 2000 and 2002, respectively, and so the GNPP estimates only go back to the years since TERRA and AQUA were launched.

Paruelo *et al.* (1997) and Wang *et al.* (2001) presented methods for estimating ANPP for the central grassland region by using NDVI derived from the Advanced

Very High Resolution Radiometer/National Oceanic and Atmospheric Agency (AVHRR/NOAA) data. The spatial resolution of AVHRR NDVI data is 1 km, which is very high when compared to the weather measurements from stations in the study area, which are often as much as 40 km apart.

Huete (1989) and Paruelo *et al.* (1997) found that considerable soil background in arid and semi-arid regions can significantly alter ANPP estimate accuracy. Price *et al.* 1992 also found that semiarid sites with less that 30% ground cover could not be distinguished from bare soil. Paruelo *et al.* (1997) found the relationship between ANPP and NDVI varied significantly over the growing season. Paruelo and colleagues used the average annual NDVI (NDVI-I for integral NDVI) to estimate grassland ANPP. ANPP data from KPBS was among many datasets in grassland areas that were used to develop the NDVI-I ANPP model. The NDVI-I model was found to explain 89% of the variation in ANPP for 19 sites within the Central Grassland Region (Paruelo *et al.* 1997).

During a search of the literature, no ANPP models specific to the tallgrass prairie type were identified. Therefore, a question that needs to be addressed is whether an ANPP model designed specifically for tallgrass prairie types in the Central Great Plains might provide more accurate estimates of ANPP than more global or large regional scale models such as the GNPP or the NDVI-I models referenced above.

Statement of Goal

For this study I seek to develop an ANPP model designed specifically for tallgrass prairies of the Central Great Plains and compare productivity estimates against ANPP ground reference measurements and existing remotely sensed based ANPP model estimations. To achieve this goal, I propose to:

Goal 1 – *Determine the optimal period during the growing season for using AVHRR NDVI biweekly composites to model ANPP of tallgrass prairie ecosystems representative of the Central Great Plains.*

Goal 2 – *Develop an ANPP model and validate its accuracy for all years that ANPP in situ data and AVHRR composite images are available (1989 to 2005 or 17 years).*

Goal 3 – *Analyze the variation in ANPP among the 19 years (1989 - 2007) of the study period to determine how ANPP varies geographically and temporally among years.*

METHODS

Study Area

The primary study areas for this research are Konza Prairie Biological Station (KPBS) (39°05' N, 96°35' W), the Rannells Flint Hills Prairie Preserve (39°08' N, 96°32' W) and the Washington Marlatt Memorial Park (WMMP) (39°13' N, 96°37' W) all near Manhattan, Kansas (Figure 1). These sites are dominated by native tallgrass prairie of the Flint Hills, which is the largest continuous tallgrass prairie in North America (Knapp *et al.* 1998). The interannual and annual climatic characteristics of the area are highly variable with respect to precipitation and temperature. The 30-year average for annual precipitation is from 835 to 859 mm (depending on the field site), and growing season precipitation is about 622 mm/y. Seventy five percent of the precipitation comes as rainfall between April and October (Hayden 1998). Mean monthly air temperature varies from -3°C in January to 27°C in July, and mean monthly soil temperature at a 5 cm depth ranges from 1.6°C in January to 29.3°C in July (Blair 1997).

The plant community is dominated by native warm-season (C_4) grasses that can provide > 80% of the ANPP for annually burned prairie sites (Knapp *et al*. 1998, Freeman 1998). The KPBS and Rannells sites are located within the Benfield-Florence soil complex with a range site soil of loamy upland. These soils reside on slopes ranging from 5 to 20% range in depth from 0 (surface to 1 m). The WMMP site resides within the Dwight-Irwin soil complex and the range site is characterized as a clay upland with slopes ranging from 1 – 4%. All three sites reside within an elevational range from 340 to 420 m above mean sea level (USDA SCS Soil Survey, 1975).

The plant species composition within the three sites is relatively diverse. The vegetation is dominated by native warm-season grasses including big bluestem (*Andropogon gerardii Vitman*), little bluestem (*Schizachyrium scoparium Michx*.

(Nash)), Indiangrass (*Sorghastrum nutans* (L.)), and switchgrass (*Panicum cirgatum* (L.)). The vegetation in the lowlands is also interspersed with a variety of forbs and less common grass species (Freeman 1998).

Field Data

Estimates of ANPP that were used for this study were collected at three locations that used varying data collection methods. The three sites are: 1) KPBS, 2) Rannells and the 3) WMMP.

1) ANPP for the KPBS site was collected across watershed 001D that has been burned annually in the spring since 1980 and has not been grazed by domestic livestock or bison since it was purchased by the Nature Conservancy in 1971 (Knapp *et al*. 1998). Clipplot samples for watershed 001D were taken from 20 plots (with 6 quadrats per plot sampled) for each topographic position for a total of 40 plots per watershed and 240 quadrats sampled per watershed per year. The mean ANPP was determined by computing the average ANPP for all 240 samples collected for each watershed annually. It is possible that this mean would be different if a weighted mean by area of the three topographic positions were used, but such weightings are seldom used because of the difficulty of computing such a weighting factor for such a geographically diverse site.

Clipplot measurements from watershed 001D that were used in this study spanned from 1989 (earliest year AVHRR NDVI data were available) to 2005 (latest year clipplot data were available). Clipplot samples are normally collected between late August and early September, which is near the time of the peak aboveground biomass accumulation. Plots were located on soils of the same or very similar types (Blair 1997).

The ANPP clipplot samples were sorted into grasses and forbs and dried in an oven at 60°C for at least 24 hours and then allowed to cool before weighing to estimate dry weight ANPP (Briggs and Knapp 1991). Fay *et al.* 2003 states that "since the plots were burned each spring and are ungrazed, all above ground biomass represented the current year's production." ANPP was calculated using the following equation:

$$ANPP/m^2 = \text{sum of aboveground biomass} \times 10.$$

2) ANPP estimates for the Rannells site were taken near the peak plant production period (~ mid August) from a 30.5 ha pasture that has been ungrazed by livestock since 1996. Samples have been taken annually from this pasture since 1998. Estimates of ANPP were derived by clipping all the vegetation within four $0.25 m^2$ quadrats and sorting by life-forms. The quadrats were located in random fashion near the center of the pasture in close proximity to a carbon flux tower. Plant samples were dried for 72 h at 55°C and weighted after the samples cooled to room temperature (Owensby *et al*. 2006).

3) The final ANPP datasets used for comparison purposes were gathered by Kansas State University students enrolled in the Agronomy Range Research Techniques (RRT) class. The ANPP data used for this study are collected in September every other year starting in 1990 (no data were collected in 1994). Clipplot samples are taken using six randomly located 0.25 m^2 quadrats in which all the vegetation is clipped at ground level and sorted by major live-forms (grass and forbs). The plants are dried at 60°C for a minimum of 48 hours and weighted after they have cooled to room temperature.

For all three field sites, total (grasses and forbs combined) ANPP measurements were used for the correlation analysis between NDVI and ANPP.

Spectral Data

The spectral dataset in this study was extracted from the biweekly time-series composites of the AVHRR NDVI dataset for the United States that extend from 1989 to the present. These data were obtained from the U.S. Geological Survey Earth Resources Observation Systems (EROS) Data Center (EDC) (Kastens *et al.* 2005). These data were selected over other similar datasets such as the Moderate Resolution Imaging Spectrometer (MODIS) data because the AVHRR dataset extends back to 1989, thus providing more years of NDVI data that could be correlated with the ANPP data. The ANPP data on the KPBS extends back to 1982.

The format of the NDVI is unsigned 8-bit integer, which is linearly rescaled to the integer range of 0 – 200 from the original NDVI range which was -1.0 to 1.0.

Values less than 100 typically represent snow, ice, water, and other non-vegetated soil background, while values between100 to 200 typically indicate a biomass feature (Jakubauskas *et al.* 2002). Because of the limitation of precision of original 8-bit format (precision is 0.01), the numerical error is 0.005 in the pixel-level NDVI values. The spatial resolution of AVHRR NDVI imagery is 1 km × 1km or 100 ha/pixel (Kastens *et al.* 2005), and the projection is Lambert Azimuthal Equal-area. AVHRR NDVI data are composited using the highest NDVI value over the two-week composite period to reduce the effects of cloud cover and aerosol contamination. The composite periods for sequential NDVI images overlap by one week, so there are 52 images spanning the entire calendar year. This is relatively high temporal resolution compared to other remotely sensed datasets. The time periods of growing season for this study will be from AVHRR NDVI composite period 16 (mid April) to period 44 (the end of October).

Data Analysis

Goal 1: *Determine which NDVI AVHRR composite period is optimal for estimating ANPP of the tallgrass ecosystems of the Central Great Plains.*

There are 29 NDVI near cloud-free weekly composite periods from mid-April to the end of October that normally span the growing season of the Central Great Plains. One challenge of this study is to determine the optimal period over the growing season for estimating ANPP of the tallgrass prairies of the Central Great Plains. This segment of the study is designed to identify the NDVI composite period that most strongly correlates year after year with ANPP clipplot data for the period for which NDVI and ANPP data are both available, which is from 1989 to 2005. The NDVI composite period that is identified as the best overall predictor of ANPP will then be used to develop the mathematical transformation equation for estimating ANPP for all years in which NDVI composite data are available which was from 1989 to 2007 at the time the image analysis research was being completed.

Given the 1 x 1 km spatial resolution of the AVHRR pixels, the watershed boundaries often intersect more than one pixel as demonstrated in Figure 2, where parts of four pixels are found within watershed 001D. For this reason the NDVI value for the watersheds was determined by using a weighted NDVI value according to area within the watershed occupied by each pixel. The weighted value was calculated using the Area Calculation Tool I developed in ArcGIS 9.2. The optimal correlation period between the ANPP clipplot measurements and the weighted NDVI values was determined by computing the correlation coefficients (r-values) between the ANPP clipplot measurements and each of the 29 growing season periods for each year. The optimal NDVI composite period was then determined by identifying the period with the highest correlation value among the 29 composite periods of the growing season. Period 30 (most closely coinciding with the third week in July) was found to be the optimal ANPP prediction period with an r value of 0.73.

Goal 2: *Model ANPP for all years that AVHRR composites and ANPP data are available, which for the study was from 1989 to 2005 (17 years).*

The accuracy of the linear regression model used for predicting ANPP was tested using a Jackknife Cross-Validation (JCV) approach as described in (Price *et al.* 2002). This approach was implemented by withholding the NDVI and ANPP values for one year and using the remaining 16 years to build the regression models. This process was repeated 16 more times to generate an estimate of *out-of-sample* model accuracy (Price *et al.* 2002). The results of this process allowed for a comparison of year-by-year *out-of-sample* and *in-sample* model estimates.

Goal 3: *Analyze the variation in ANPP among the 19 years (1989 - 2007) of the study period to determine how ANPP varies geographically and temporally among years.*

Once the ANPP model was developed, the AVHRR optimal period 30 (late July) NDVI values were submitted to the linear regression equation to estimate ANPP for a four county (Geary, Pottawatomie, Riley and Wabaunsee) area (~ 7,000 ha) surrounding the study area. This resulted in the production of ANPP maps for the four-county area for each year from 1989 to 2007 (19 years). Matlab software was then used to extract statistical information from the map time-series sequence including ANPP means and standard deviation values on a pixel-by-pixel basis. Such information was used to compare the predicted ANPP value in each year with map values for the other 18 years. From these values, ANPP deviations from the mean “normal” could be maps to create anomaly maps that were used to identify areas of change in ANPP within each map and over the study period.

RESULTS AND DISCUSSION

1. Correlation between ANPP and precipitation

Given the conflicting results concerning the relationships between tallgrass ANPP and precipitation as discussed in the introduction section of this paper, it was decided to also examine the relationship between these factors. Using the same time interval as Nippert *et al*. (2006), but for years 1989 to 2005, correlation analysis that was able to explain 28% ($r = 0.53$) of the variation in ANPP using seasonal precipitation (Figure 3). These findings suggest using precipitation data to model ANPP can produce varying results, and there is a significant amount of variation in tallgrass ANPP that is not explained by precipitation data. From these findings, models that rely on precipitation measurements to estimate ANPP for tallgrass ecosystems in the central Great Plains as a parameter input for modeling such factors as CO_2 flux could be affected by the weak correlations reported in our study and Towne and Owensby (1984).

2. Determining the optimal AVHRR NDVI composite period

Since NDVI composite data are produced on a weekly basis using a biweekly sample period, there are normally four composites produced per month. Given multiple composite periods to select from over a growing season, I needed to determine the optimal period for estimating ANPP over the 17 year study period. This was accomplished by computing the correlation between NDVI and ANPP for each composite periods starting with period 21 (early April) and ending with period 40 (late October). The results of these computations indicate that period 30 (late July) had the highest correlation explaining 53% ($r = 0.73$) of the variation in ANPP (figure 4). The correlation coefficient (r) values increase as AVHRR NDVI values increase starting in late April when the tallgrass plant species begin to emerge from winter dormancy (green-up) and begins to decline after reaching peak plant foliage production and continues to decline as plants progress towards full senesces.

As shown in Figure 4, the highest AVHRR NDVI value showed up in period 27 (late June), but the highest correlation values were found in late July, which is closer to the time that the ANPP samples were taken in the field. Note that the stronger correlation results were two composite periods after peak NDVI. Also note the drop in correlation between period 27 and 28. After plotting the points on a scatter plot for period 28, it was note that 1989 (drought year) and 1993 (extremely wet year) showed up as outliers more so in this period than other periods. Why this might be the case is unknown at this time.

The robustness of the correlation analysis results was examined by computing and plotting correlation results for another KPBS watershed (watershed 002D). The available data for watershed 002D allows such an examination using years 1989 to

2000. Here too, period 30 (late July) was shown to be the optimal period for predicting ANPP using the AVHRR NDVI composite data (r = 0.86). These corroborating result show AVHRR NDVI composite period 30 was consistently identifies as the best period for estimating ANPP for the study area. Therefore this period was used to develop the prediction equation discussed in the following section.

3. Development of the Tallgrass ANPP model

A positive and statistically significant relationship between AVHRR NDVI and ANPP has been identified as described in the in the previous section. Using the optimal modeling period of late July, the Tallgrass ANPP estimation equation was derived.

$$\text{Tallgrass ANPP} = 11.874 \times \text{NDVI} - 1503.324$$

The linear regression results used to produce this equation are shown in scatter diagram form in figure 5. The correlation coefficient for the AVHRR and NDVI show a strong relationship between these two factors ($r = 0.73$; $r^2 = 0.53$).   An ANPP *out-of-sample* dataset for testing the accuracy of the model could not be found in the region, so the robustness of the model was evaluated using a Jackknife Cross-Validation (JCV) method described in Price *et al*. (2002).   Figure 6 shows a year to year comparison of the *in-sample* and *out-of-sample* prediction results. As shown in this figure, the years that exhibited the greatest difference between *in-* and *out-of-sample* estimates were1989 (drought year), 1993 (extreme wet year), 2002 (drought year) and 2004 (normal year following two-years of below normal precipitation).

The JCV results show the prediction model to be relatively robust with little variation between the *in* and *out-of-sample* predictions for ANPP (Figure 6). All-in-all, the *out-of-sample* model approach produced similar results to the *in-sample* dataset with the greatest differences between estimates manifest in extreme dry and wet years.

A comparison among varying independent ANPP model predictions can provide in-sights into how similar or dissimilar predictions among various models might be. A review of the literature revealed two NDVI-parameterized models used to predict ANPP for grasslands in the study region. These models were the GNPP (Running *et al.* 2004) and the NDVI-I (Paruelo *et al.* 1997). Figure 7 shows a comparison between GNPP, NDVI-I and the new Tallgrass ANPP model, as well as ANPP estimates from the three independent clipplot datasets (Konza, Rannells and Kansas State University (KSU)) Range Research Techniques (RRT) class field data measurements to validate the Tallgrass ANPP model accuracy.

In the Figure 7, ANPP clipplot measurements from the KPBS watershed 001D are represented by the bold red line, the Rannells by the green line, and the more intermittent RRT datasets by orange dots. The GNPP MODIS model estimates are plotted on the graph using a light blue line, the NDVI-I estimates using a light purple line and the Tallgrass ANPP model estimates using a black line. In general, this graph shows considerable variation in ANPP model and clipplot measurements, with the NDVI-I model estimating higher values than the other models and clipplot data, and the MODIS derived GNPP estimates being lower than most of the other ANPP estimates. There are significant differences within years between the Konza and Rannells clipplot estimates even though the sites were only about 7.5 km apart and both reside a loamy upland range sites. The year to year clipplot data for the RRT estimates are also mostly different from the Konza and Rannells estimates, but this site is 18 and 13 km from the Konza and Rannells sites, respectively and on a different range site as described in the study area section above.

Figure 7 show the Tallgrass ANPP model estimates to be closer to the KPBS clipplot ANPP estimates than those produced by the GNPP and the NDVI-I models. Table 1 provides a year to year comparison of the ANPP estimates from the three remote sensing based ANPP models relative to the KPBS clipplot ANPP estimates. From this table we see that estimates from the GNPP model averaged 84.5 g/m^2 below the KPBS estimates, with all estimates falling below the KPBS estimates. The NDVI-I year to year estimates averaged 189.4 g/m^2 above the KPBS estimates with all but one year being above the KPBS estimates. The out-of-sample Tallgrass ANPP year to year model estimates averaged 66.7 g/m^2 above the KPBS estimates, with 9 estimate years above and 8 years below the KPBS ANPP estimates.

4. Construct the ANPP Greenness Maps and Variation Maps among 19 years

Once the Tallgrass ANPP model was developed and its prediction accuracy validated, maps of ANPP were generated for four Kansas counties that surrounded the study area. These counties included: Geary, Pottawatomie, Riley and Wabaunsee, which occupy an area of approximately about 7,000 ha. These maps were made to examine the temporal and spatial dynamics of ANPP over a 19 year period (1989 – 2007). Figure 8 shows ANPP maps for eight selected years. The selected maps represent extreme wet and dry years and near "normal" years.

According to the Manhattan precipitation data, 1989 and 2002 were drought year and the effects of the drought are manifest in the lower ANPP estimates for these years (Figure 8). The rainfall data also show 1993, 2004 and 2007 to be wet years, with 1993 qualifying as extremely wet. In these three years, estimates of ANPP were much higher than in the dry years

By using a Change Detection method, a series of anomaly maps were produced and the same selected years as shown in Figure 8 are also displayed in Figure 9. These anomaly maps show deviations from normal on a pixel-by-pixel basis, where the average (based on ANPP from 1989 – 2007) ANPP value for a pixel is compared to the pixel's ANPP value for a given year. Each pixel was then classified into a "deviation from normal" category (see Figure 9).

These anomaly maps showed considerable spatial and temporal variation in ANPP, which is indicative of the annual and interannual climatic variation common to the region. The observed patterns are too complex to verbally describe, but these maps do show just how dynamic ANPP can be within a year and among years in the region. Since ANPP is only collected at select locations, maps showing variation in ANPP over large geography regions do not exist. By storing such maps in a GIS database, trend analysis can be performed to identify areas where ANPP is increasing or decreasing or remaining more or less constant. Since ANPP is an important indicator of energy flow within an ecosystem and considered a measure of ecosystem health, such maps could be used to monitor ecosystem changes that are indicative of the systems response to natural and anthropogenic factors that place stressing the system. Future work could focus on the development of ecosystem health indicators and methods for assessing an ecosystem's potential of undergoing environmental retrogression. The advantage here is that such maps can be produced for larger geographic regions that allow the systems within a region to be monitored in ways not feasible using conventional ground sampling approaches.

Unfortunately, because measurements of ANPP are not collected in a systematic manner over much of the region, validation of the map accuracy outside of the study area is not possible. One might use ANPP estimates from other models such as the GNPP or the NDVI-I, but as shown in this study, there is some question as to how accurate such models are for the tallgrass ecosystem and even the clipplot data showed considerable variation in ANPP for very similar range sited residing within a relatively close distances of each other.

CONCLUSION

The results of this study show that the optimal period for using NDVI to estimate ANPP in the study area is around the end of July. The results also show that estimates of ANPP using remotely sensed data and ground level ANPP clipplot measurements are highly variable. Unfortunately, at this time it is unknown which estimate or measurement of ANPP is most accurate. If one were to assume that the site where the greatest number of ANPP samples were collected would have the most accurate estimate of ANPP, then the KPBS dataset would be considered the most accurate, which is why the KPBS estimates were used as the benchmark against which all other estimates were compared. Use of a simple linear regression model produced estimates of ANPP that fell within acceptable limits and were most closely aligned with the KPBS clipplot measurements. Given the considerable variation in estimates of ANPP among the various sites and models, it is difficult to assess the absolute accuracy of the Tallgrass ANPP model at this time. The findings in this study, do however suggest that development of ecosystem specific models of ANPP might be needed to more accurately estimate this biophysical factor.

It is believed that scaling up directly from the submeter level ANPP clipplot measurements to the 1 km spatial resolution of the AVHRR NDVI data might have weakened the relationship between the NDVI and ANPP clipplot data. For this reason, future research will investigate the linkage between fine resolution (~ 1.0 m pixels) multispectral imagery acquired using an airborne remote sensing system and the clipplot ANPP measurements. If strong linkages are found to exist, then ANPP estimated could be made at the 1.0 m resolution over areas larger than the MODIS or AVHRR pixel resolutions and the finer resolution ANPP estimates could be aggregated to the coarser pixel resolutions. These aggregated values could then be used in regression analysis to see if a stronger relationship between ANPP and coarser resolution remotely sensed data can be established.

Finally, once accurate estimates of ANPP can be developed, the development of regional scale ANPP maps should be tested. If ANPP models are robust enough to accurately predict this biophysical factor over a region, then the next logical step would be to develop methods for accessing ecosystem health and susceptibility to natural and anthropogenic disturbance.

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Table 1. Difference among the MODIS Global, NDVI-I and Tallgrass ANPP models for estimating ANPP compared to KPBS clipplot samples from watershed 001D. For example, in 1998, the NDVI-I model estimate of ANPP was 316.8 g/m^2 higher than the KPBS estimate based on clipplot samples for that year. The results in this table show that the average difference in model estimates relative to the KPBS values was 84.5 g/m^2 for the MODIS Global model, 189.g/m^2 for the NDVI-I model and 66.7 g/m^2 for the Tallgrass ANPP model. These results show that on average the Tallgrass ANPP model produced estimates of ANPP that were closer to the clipplot data for the KPBS clipplot measurements.

Year	MODIS Global ANPP (2000-2005)	NDVI-I Model (1989-2005)	Out-of-Sample (Tallgrass ANPP Model) (1989-2005)
1989		316.8	111.6
1990		115.3	-56.3
1991		161.6	0.1
1992		66.9	-61.7
1993		-57.1	-126.7
1994		224.9	77.7
1995		10.4	-74.6
1996		134.7	5.7
1997		341.3	94.5
1998		186.4	-38.6
1999		201.6	10.7
2000	-174.1	190.7	-36.4
2001	-66.8	196.6	-41.8
2002	-45.4	198.7	-130.4
2003	-51.0	280.4	102.2
2004	-126.7	206.3	65.9
2005	-43.1	330.2	99.5
$\frac{\Sigma\sqrt{x^2}}{n}$	84.5	189.4	66.7

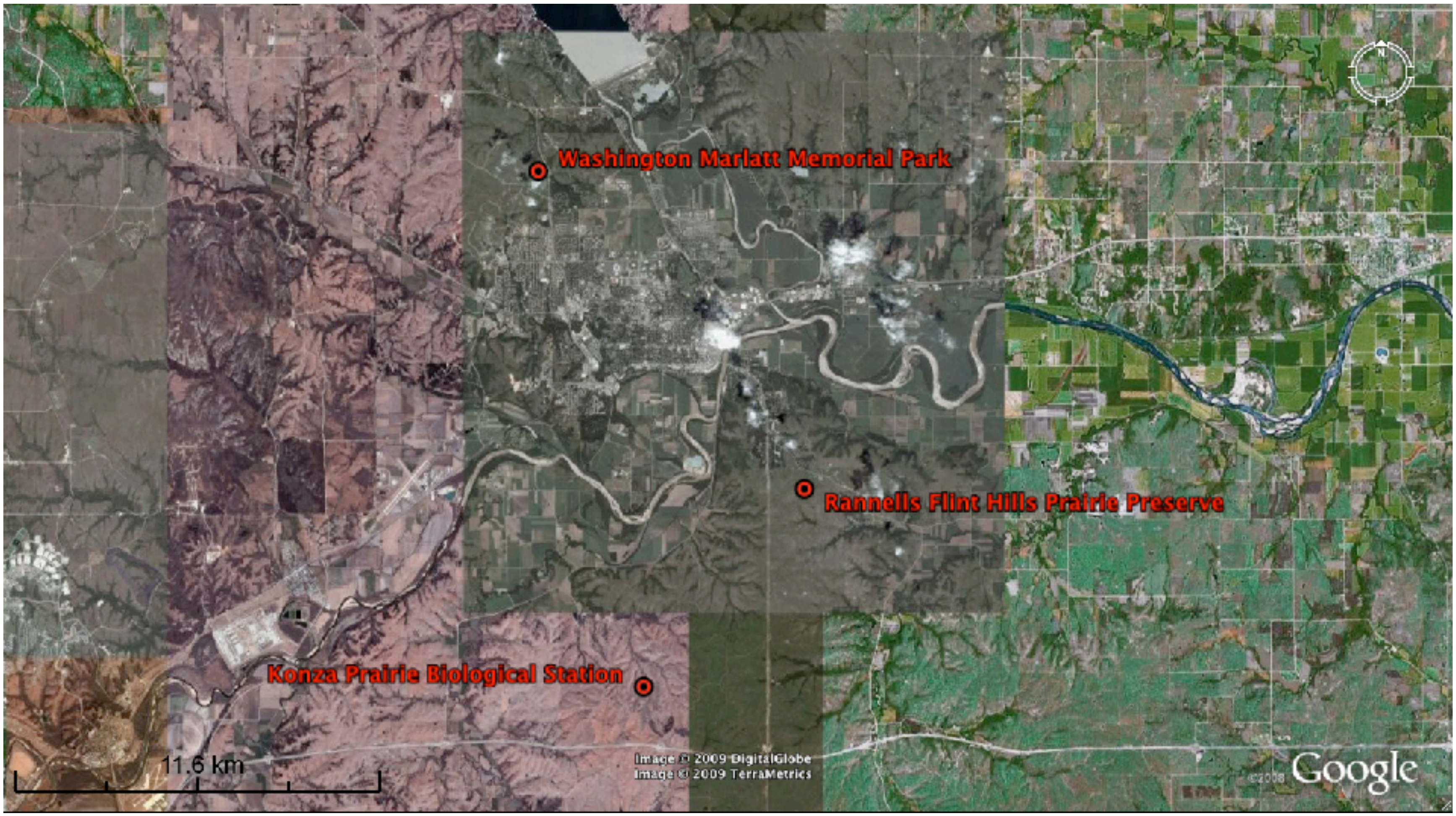

Figure 1. Location of the study sites within the study area which are near Manhattan, Kansas.

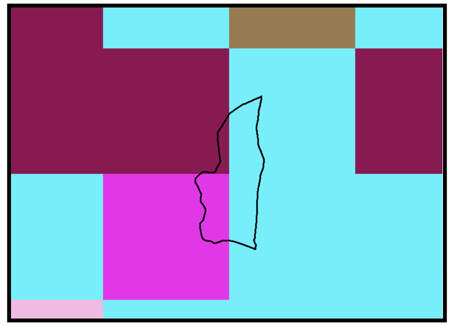

Figure 2. AVHRR pixels with watershed 001D boundaries superimposed onto the pixels.

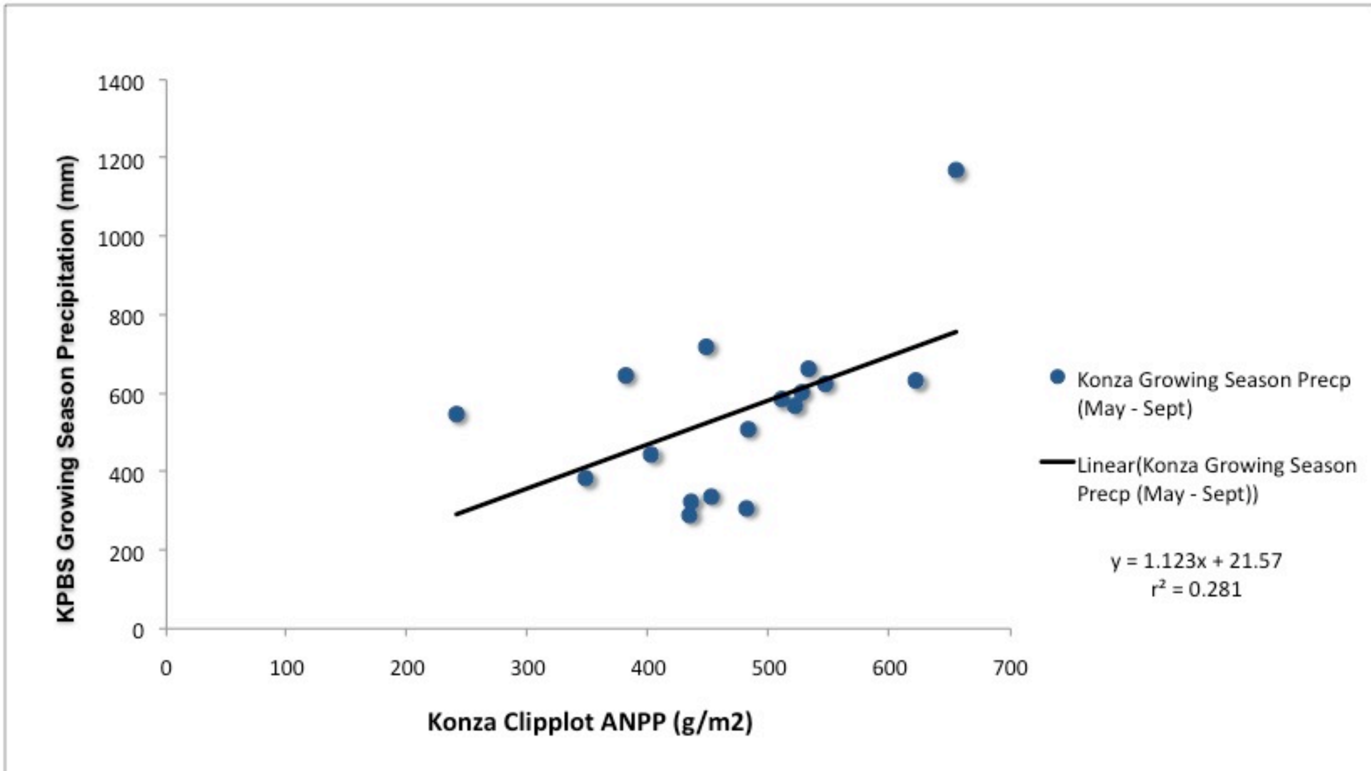

Figure 3. Relationship between growing season precipitation (from May to September) and aboveground net primary productivity for clipplot data collected at watershed 001D at the KPBS. This regression model shows that precipitation explained only 28% of the variation in tallgrass ANPP during our study period from 1989 to 2005.

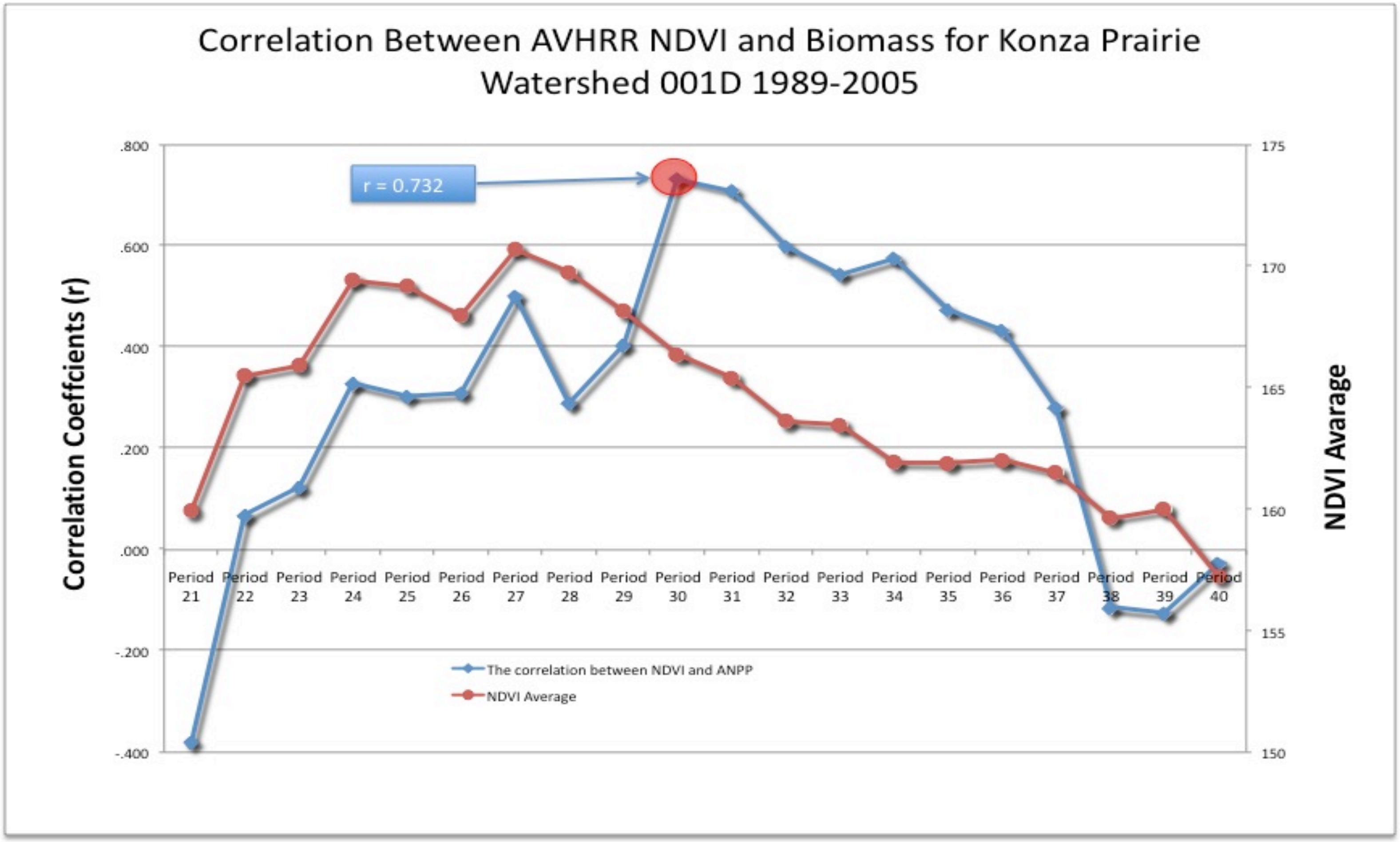

Figure 4. Correlation between AVHRR NDVI and ANPP for Konza Prairie Watershed 001D from 1989 to 2005. These data show that NDVI reached its peak in period 27 (mid June), but the strongest correlation between NDVI and ANPP is in period 30 (late July).

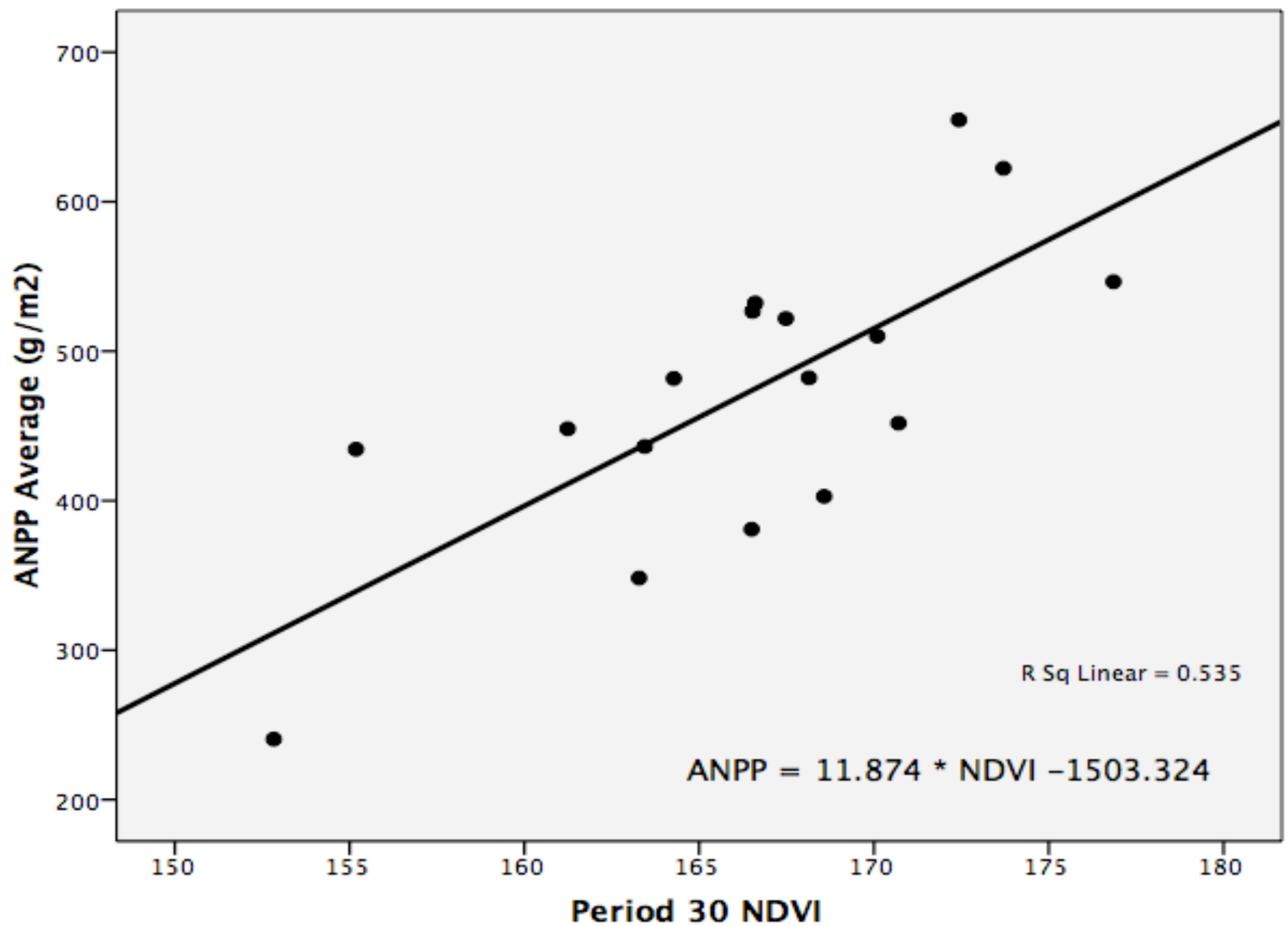

Figure 5. The Tallgrass ANPP model derived from clipplot data collected at watershed 001D within the KPBS and AVHRR NDVI values from period 30 (late July) for years from 1989 to 2005.

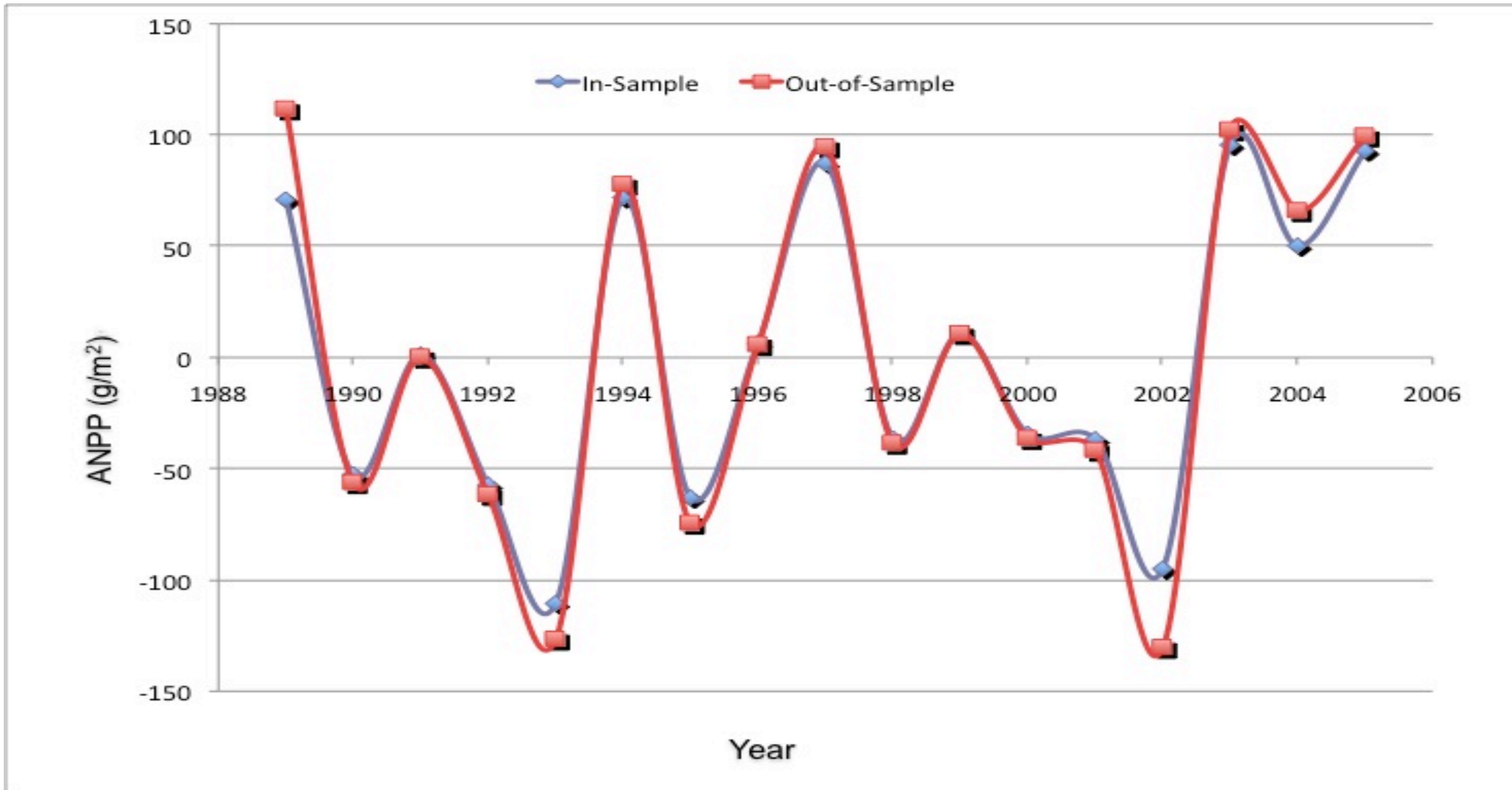

Figure 6. This graph shows the difference between the *In-sample* prediction model results verses the ANPP clipplot data, and difference between the *out-of-sample* (Jack-knife approach) prediction model verses the ANPP clipplot data. Years 1989, 1993, 2002 and 2004 produced results in which the *in-* and *out-of-sample* estimates were least like each other. These years experienced significantly drier and wetter than normal years.

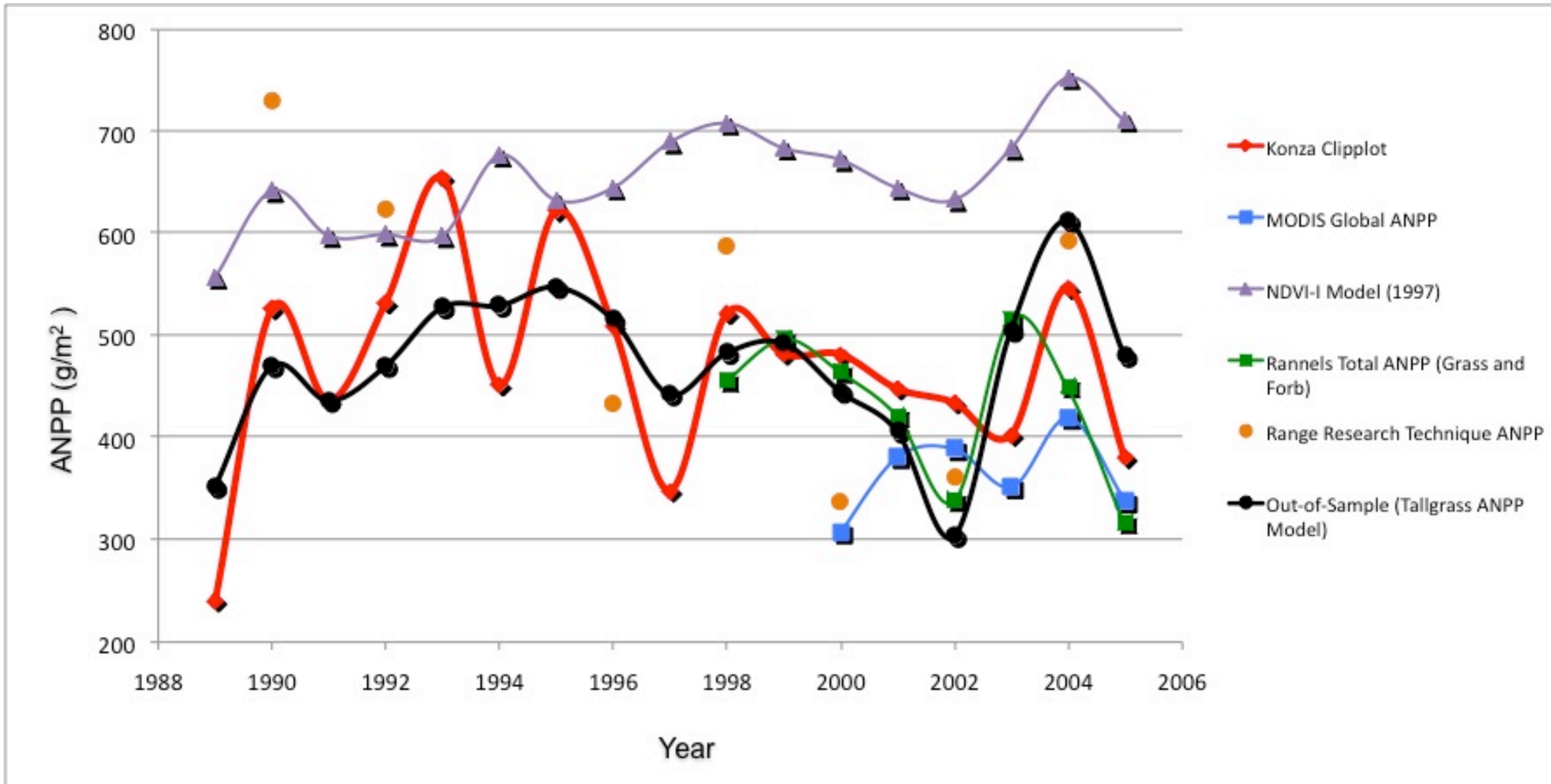

Figure 7. This graph shows a comparison between ANPP clipplot data and model estimates that use remotely sensed measures to estimate ANPP. The red line represents the clipplot derived estimates of ANPP for the KPBS. The Tallgrass ANPP model results are shown in black.

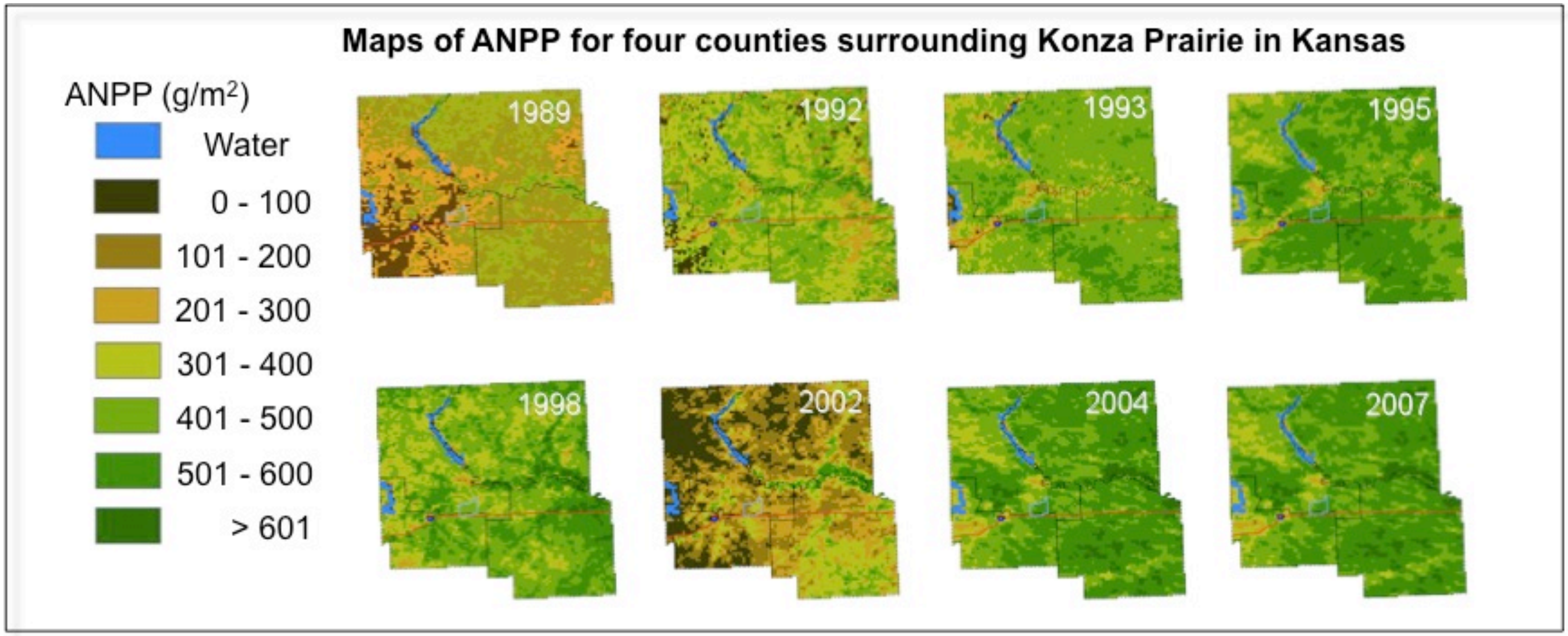

Figure 8. ANPP maps for four Kansas counties surrounding the KPBS. These counties are Geary, Pottawatomie, Riley and Wabaunsee and their combined area is approximately 7,000 ha. These maps show the significant spatial and temporal variation in ANPP within the four county area and among years from 1989 – 2007. The effects of strong drought years are seen in 1989 and 2002.

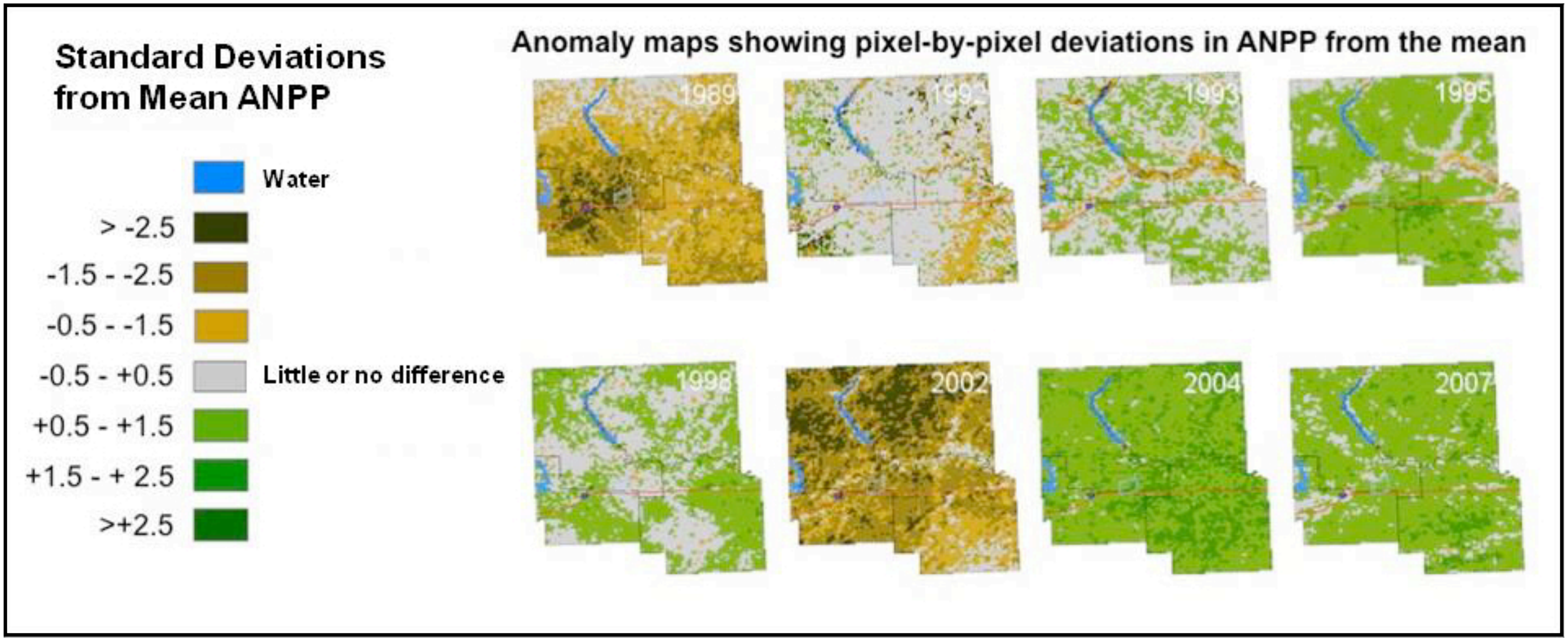

Figure 9. ANPP anomaly maps for four Kansas counties surrounding the KPBS. These counties are Geary, Pottawatomie, Riley and Wabaunsee and their combined area is approximately 7,000 ha. These maps show the significant spatial and temporal variation in ANPP deviations from normal (gray tone) within the four county area and among years from 1989 – 2007. The effects of strong drought years are seen in 1989 and 2002.