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Estimation of aboveground terrestrial net primary productivity and analysis of its spatial and temporal trends in the conterminous United States from 1997 to 2007 using NASA-CASA model

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ESTIMATION OF ABOVEGROUND TERRESTRIAL NET PRIMARY PRODUCTIVITY AND ANALYSIS OF ITS SPATIAL AND TEMPORAL TRENDS IN THE CONTERMINOUS UNITED STATES FROM 1997 TO 2007 USING NASA – CASA MODEL

By

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ESTIMATION OF ABOVEGROUND TERRESTRIAL NET PRIMARY

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This study estimated monthly and annual Net Primary Productivity (NPP), an important indicator of carbon sequestration, in the Conterminous US from 1997 to 2007 using Carnegie-Ames-Stanford Approach. Vegetation condition, temperature, precipitation, photosynthetically active radiation and soil water holding capacity were used as model's inputs. NPP values were lower than mean annual values during the year 2000 to 2003 which was probably due to extreme drought conditions during these years. Higher NPP per square meter was generally found in Savannah and Subtropical eco-divisions whereas Tropical/Subtropical deserts had the lowest NPP. Southeastern states had the highest NPP per square meter thus, made the highest contribution to the terrestrial carbon sequestration in US. Since the vegetation is one of the main factors in NPP and thus carbon sequestration, the results of this study could help in various environmental policy decisions on forest and cropland management at the state, EPA and federal levels.

DEDICATION

I would like to dedicate this work to my family and friends who supported me till its accomplishment. I would especially like to thank my parents, Mrs. Rama Khanal and Mr. Ram Hari Khanal for all their encouragements, supports and love towards me.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

This chapter contains a brief introduction of the overall study. Section 1.1 contains a brief background on climate change issues and the importance of studies related to primary productivity using remote sensing techniques. Sections 1.2 and 1.3 present the problem statement and the objectives of this study. Section 1.4 contains the hypothesis and section 1.5 contains the overall organization of the thesis.

1.1 Background

This study examines the magnitudes and distributions of net primary productivity, as measured by remotely sensed data of the Conterminous United States on seasonal and decadal time scales. Global environmental changes are altering the structural and functional parameters of eco systems which can affect the flow of energy within eco systems (IPCC, 2008). There are considerable evidences that eco systems are already responding to the global climate changes, including an increase in mean annual air temperature, alterations in rainfall patterns, and changes in atmospheric chemistry (IPCC, 2008). Many studies (Ciais et al., 199; Keeling et al., 1996; Churkina et al.; 1998, CCSP, 2008; IPCC, 2008) have suggested that the climate change is associated with the dramatic increase in carbon dioxide (CO_2) and other greenhouse gases, such as water vapor, ozone, methane (CH_4) and nitrous oxide. These gases are released into the atmosphere primarily due to the anthropogenic activities, such as fossil fuel combustion, industrial processes and land use change due to deforestation (Keeling et al., 1976; Potter et al., 2003). Increase in atmospheric CO_2 has been measured continuously since 1958 at Mauna Loa, Hawaii and is known as the "Keeling Curve". This curve illustrates the impact of anthropogenic activities on the earth's atmosphere (Keeling et al., 1976; Running et al., 2004).

Continued monitoring of carbon fluxes and their response to global climate change is therefore essential for accurately developing alternative policies and practices to mitigate the continued buildup of atmospheric carbon and other greenhouse gases (Heinsch et al., 2006). In response to global concerns about global warming, the Kyoto Protocol was negotiated under United Nations Framework Conventions on Climate Change (UNFCC) in December 1997 with an objective of reducing CO_2 and other green house gases emissions to a level that would prevent climate from anthropogenic activities (UNFCC, 2008). As per the protocol, the developed countries must reduce their greenhouse gas emissions below the level specified for them in the treaty between 2008 and 2012. The United States, the world's largest CO_2 producer at that time, refused to support the protocol arguing that its economic interests would be threatened (UNEP, 2007). However, US believes that there is global warming and it needs to be addressed. The Kyoto Protocol increased the need for global climate change research and initiated the attempts to reduce atmospheric concentration of CO_2 (UNFCC, 2007). The options for reducing CO_2 include curbing of CO_2 producing anthropogenic activities, sequestrating CO_2 from the atmosphere into vegetation and soil and injecting CO_2

produced at power plants and industrial facilities into underground storage sites before it is emitted into the atmosphere (EPA, 2008).

Terrestrial eco-systems play a crucial role in the global carbon cycle, and thus, in global climate change. Depending upon the relative magnitudes of CO_2 uptake and release, a terrestrial region can act either as carbon "source," which adds carbon to the atmosphere or as carbon "sink", which removes carbon from the atmosphere (Matsushita et al., 2004) thus slowing down atmospheric CO_2 concentration. Terrestrial eco systems gain carbon through photosynthesis and lose it primarily as CO_2 through respiration in autotrophs (plants and photosynthetic bacteria) and heterotrophs (fungi, animals, bacteria, etc) (Reichstein and Martin, 2008).

Terrestrial net primary productivity (NPP), one of the fundamental ecological variables of terrestrial eco systems, is the net fixation of atmospheric CO_2. It helps to remove carbon from the atmosphere (Field et al., 1995) and it is directly related to carbon dynamics through the process of photosynthesis and photorespiration. It acts as the major driver of the seasonal fluctuations in atmospheric CO_2 concentration (Ciais et al., 1995, Churkina et al., 1998). Monitoring NPP and its seasonal fluctuations is vital for understanding both the functioning of living eco systems and their subsequent feedbacks to the environments.

CO_2 emissions in US has increased by 20 % from 1990 to 2004 while methane and nitrous oxide emissions have decreased by 10 % and 2 %, respectively (UNFCC, 2007, EPA, 2008). Consequently, there has been an increased emphasis on understanding the carbon dynamics and temporal changes in carbon sequestration in US (UNFCC, 2007). An accurate estimation of NPP is therefore critical to understanding of carbon dynamics within the atmosphere and vegetation. Understanding of atmospheric CO_2 could help in developing policies and practices to mitigate continued build of atmospheric CO_2.

Use of remote sensing techniques and eco-system process model calibrated with climatic and bio-physical parameters allow the estimation of NPP at regional or global levels. This study examined the magnitude, spatial pattern and variability of NPP in Conterminous US by a combination of National Aeronautics and Space Administration (NASA) developed CASA model and remote sensing.

1.2 Statement of the Problem

Estimation of NPP has various important theoretical and practical implications (Markon and Peterson, 2002; Potter et al., 2003; Running et al., 2004), such as estimation of crop productivity, wildlife habitat availability and determination of health and status of the vegetation communities. Several studies (Running et al., 2004; Potter et al., 1993; Kicklighter et al., 1999; Potter et al., 2003; Turner et al., 2006) have estimated NPP at global and different regional scales but were primarily targeted for certain time periods. Only few studies (Milesi et al., 2003; Turner et al., 2006) examined NPP in different biomes of US eco systems. Potter et al. (2006) estimated carbon budgets for US eco systems from 1982 to 1997 using Carnegie Ames Stanford Approach (CASA) Biosphere model. There are very few studies if any, that have investigated the nature of NPP in different eco-divisions (Bailey (1976) since 1997 in annual scale. Therefore, there is a big gap in understanding the amount and distribution of NPP and the impact of climatic factors in it within the different eco-divisions of the Conterminous US. Hence, the primary objective of this study was to estimate NPP in US from 1997 to 2007 and to examine its temporal and spatial patterns and determine its relationship with climatic factors. Understanding the nature of NPP in different eco-divisions has the potential to enhance knowledge in carbon dynamics and can provide input for climate mitigation plans.

1.3 Objectives of the Study

In order to accomplish the boarder objective of estimating and analyzing the distribution of NPP, following specific objectives were defined:

1. To estimate annual NPP in the Conterminous US from 1997 to 2007
2. To analyze the spatial and temporal trends in NPP in the Conterminous US from 1997 to 2007
3. To analyze the relation of NPP with climatic factors – temperature, precipitation, photosynthetically active radiation (PAR) and evapotranspiration and bio-physical parameters such as Normalized Difference Vegetation Indices (NDVI) that indicates the conditions of the vegetation.

By accomplishing the above mentioned objectives, this research could make two major contributions to the literature.

The first contribution is to the methodology. This study modified the method to derive certain model parameters such as Fraction of Photo synthetically Active Radiation (FPAR) used in the NASA - CASA model to estimate NPP. The model was also modified to use current and freely available data. This change in methodology can significantly contribute to the scientific estimation of carbon sequestration by adding alternative methods to calculate model parameters. Additionally, the use of remote sensing data and GIS techniques to estimate NPP also contribute towards the extension of GIS and remote sensing applications in environmental monitoring studies.

The second major contribution of this study is that it can fill the gap of annual NPP information for the Conterminous US after the year 1997. Estimation of annual NPP and its nature in different climate conditions in different parts of US might aid in the climate change research. Additionally, the analysis of spatial pattern of NPP in different Eco-Divisions and states as summary strata can help the policy makers in planning, implementing, and monitoring carbon management practices in US. This study can also aid in attaining one of the goals of the United States climate change research program by examining the magnitude and distribution of carbon sinks in US.

1.4 Hypotheses

Three null hypotheses were tested in this research.

1. Terrestrial NPP in U.S increased between the years 1997 and 2007.

This null hypothesis was developed based on the NPP trends observed in previous studies (Potter et al., 2006, and Hicke et al., 2002). Potter et al. (2006) used CASA model to estimate carbon budgets for the U.S eco-systems and he suggested that net terrestrial CO_2 sink in U.S eco-system exceeded by about 0.05 petagrams of carbon per year in positive direction in the 1980s and 1990s. Similarly, Hicke et al. (2002) found a small but significant increase in NPP i.e.0.03 Pg C yr^{-1} from 1982-1998 in North America using the CASA model.

2. Southeastern states contribute significantly to the higher NPP than other regions.

This null hypothesis is based on McNulty (2002) study which showed that southern forests contribute significantly to the carbon sink for the increasing atmospheric carbon dioxide associated with the anthropogenic activities in the United States.

3. Area with higher vegetation cover (which is measured by NDVI) will have higher NPP.

This null hypothesis is based on previous studies (Lim et al., 2004), which found the positive correlation between in the rate of change between carbon assimilation by plants and vegetation development.

1.5 Organization of the Thesis

This thesis is organized into five chapters. Chapter 1 introduced the research background, the problem statement, objectives, hypotheses and the overall organization of the thesis. Chapter 2 includes the literature review on different climatic and bio-physical factors and different previous models used for the estimation of NPP. Chapter 3 provides the methodologies used in this study that involves conceptual model, data preparation procedure and technical aspects of data processing. Chapter 4 introduces the methodology used in the research. Chapter 5 presents the relationship between NPP and different climatic variables and discusses about the different spatial and temporal trends of NPP. Chapter 6 provides a summary of the major findings of this research along with the agenda for future research.

CHAPTER II

LITERATURE REVIEW

Continuous rise in atmospheric CO_2 and the future change in global climate as its consequence have gained global attentions since mid 90's. Several studies (Maselli et al., 2006, Baez-Gonzalez et al., 2002, Running et al., 2000, Potter et al., 2006) have investigated the amount of carbon being sequestered by the vegetation in different parts of the world including Marine and terrestrial eco systems to understand the carbon dynamics. The methods used by these studies differed from each other in accordance with their simplicity, geographic scale, and computational capabilities. This chapter focuses on concepts, theories and applications of NPP and the different methodologies used in NPP estimation. Section 2.1 highlights the basic concepts of NPP, and the important factors that drive it. Sections 2.2 and 2.3 review the various NPP research specific to ecological modeling that integrate remote sensing techniques and climatic factors and the importance of remote sensing techniques in different environmental studies respectively.

2.1 Indicators of Carbon Fixation: NPP, GPP & NEP

Photosynthesis and primary production capture CO_2 (hence carbon) out of the atmosphere, while respiration releases it to the air. The three major indicators that are generally used to describe the process of carbon fixation by plants are NPP, Gross

Primary Productivity (GPP), and Net Eco-system Productivity (NEP) (University of Michigan, 2009).

GPP is the total amount of carbon assimilated by the plants during photosynthesis within a given area over a given timeframe. A fraction of GPP is used by the plant during metabolism, cellular respiration and maintenance of existing tissues. NPP is the net assimilation of atmospheric CO_2 after the costs of plant respiration is included (Roxburgh et al., 2005). NPP is often expressed mathematically as:

$$NPP = GPP - R \tag{2.1}$$

where, R = photorespiration

NPP is the fundamental ecological variable that indicates the condition of the land surface area and also represents the status of a wide range of ecological processes (Running et al., 2004, Field et al., 1995). NPP is normally expressed as grams carbon per unit area per unit time or grams biomass per unit area per unit time (both as g C m^{-2} yr^{-1}), or energy per unit area per unit time (cal m^{-2} yr^{-1} or watts m^{-2} yr^{-1}).

NEP is the net exchange of carbon between the eco-system and the atmosphere. It includes respiration cost by plant (R_p), heterotrophs (R_h) and decomposers (R_d) (Field et al., 1995). It is often expressed as:

$$NEP = GPP - (R_p + R_h + R_d) \tag{2.2}$$

Among these three indicators, NPP is the most commonly used indicator for the analysis of carbon dynamics in the atmosphere. It is driven by solar radiation and can be constrained by light, precipitation, temperature, soils, plant characteristics, distribution regime and a number of natural and anthropogenic factors (Leith, 1975, Field et al., 1995, Potter et al., 2006, 2003, Running et al., 2004). Anthropogenic activities alter resource, resource regulators, distribution regimes and plant characteristics (Field et al., 1995) and thus affect NPP.

2.2 Bio-physical and Climatic Factors Sensitive to NPP

Studies (Field et al., 1995; Potter et al., 1993, 2003; Seller et al., 1987; Running et al., 2004; Mu et al., 2008) have shown that bio-physical parameters such as vegetation condition, fractions of photo-synthetically active radiation (FPAR) and climatic factors such as photo-synthetically active radiation (PAR), evapotranspiration, temperature and precipitation are crucial with respect to the estimation of NPP. Details of these factors are discussed below:

2.2.1 Normalized Difference Vegetation Indices (NDVI)

NDVI is an indicator of relative abundance and condition of green vegetation (Jensen, 1996; Running et al., 2004). The relationship between NPP and NDVI is based on the concept that plant production of organic matter is related to both the absorbed radiation and reflected radiation by green vegetation (primarily leaves) (Sellers et al., 1987). Extensive experimentation (Sellers, 1987; Running et al., 1988; Prince, 1991; Running et al., 2004) has demonstrated a close relationship of NDVI with some important bio-physical parameters such as biomass, leaf area index (LAI), and FPAR. Thus, NDVI is widely used in vegetation studies and eco-system modeling. NDVI is calculated using red and near infrared (NIR) wavelengths of the electromagnetic spectrum using the following expression (2.3):

$$NDVI = (NIR - Red) / (NIR + Red) \tag{2.3}$$

NDVI ranges from -1 to 1. Densely vegetated areas yield NDVI value close to 1 because of high NIR reflectance and low red reflectance where as sparsely vegetated areas have low NIR reflectance and low red reflectance (Jensen, 1996) and have NDVI close to 0. NDVI from AVHRR satellite is a reliable index for describing the surface vegetation greenness as it reflects the condition of the biomass in a given area (Asrar & Myneni 1992; Prince, 1991).

2.2.2 Photo-synthetically Active Radiation (PAR)

PAR reaching the earth surface is one of the major driving variables that controls many bio-physical processes related to the vegetation (Rubioa et al., 2005). It is the portion of the sunlight spectrum from 400nm to 700nm required by plant during the photosynthesis process. Despite USefulness of incident PAR for the modeling of photosynthesis, there are very few stations that measure it. It is usually estimated from the solar radiation data. Field et al. (1995) computed PAR surface irradiance as the ½ of the total solar surface irradiance from the data of Bishop and Rossow (1991) while Alados et al. (2000) and Potter et al. (1993) estimated PAR from the measurements of global solar radiation.

2.2.3 Fraction of Photo-synthetically Active Radiation (FPAR)

FPAR, another key bio-physical variable related to NPP, is the measure of absorbed amount of incident visible light by plant during photosynthesis. Studies (Field et al., 1995; Running et al., 1988, 2004; Sellers et al., 1987) have found its close relationship with the NDVI and leaf area index. Sellers et al. (1987) derived FPAR from NDVI and Simple Ratio (SR) derived from NDVI based on the assumption of its linearity with NDVI while Running et al. (2004) derived FPAR using leaf area index. FPAR values ranges from 0 to 1.

2.2.4 Intercepted Photo-synthetically Active Radiation (IPAR) and Absorbed Photo-synthetically Active Radiation (APAR)

IPAR is the amount of PAR captured by various canopy layers as the PAR incident at the top travels down the through canopy layers to the ground. APAR is the amount of PAR actually consumed by green canopy during photosynthesis. The difference between IPAR and APAR depends upon the canopy closure, coverage over the background materials, canopy composition, density and reflectance (Myneni et al., 1992). For a canopy with dense coverage and green leaves, IPAR may be a good approximation of APAR as healthy green leaves do not reflect much PAR. The relation of APAR with FPAR and PAR has been extensively documented in several studies as the product of FPAR and PAR (Mu et al., 2008, Running et al., 2004, Hicke et al., 2002, Field et al., 1995, Potter et al., 1993) as shown in the expression (2.4):

$$APAR = FPAR * PAR \qquad (2.4)$$

2.2.5 Light Use Efficiency (ε)

Light use efficiency (ε) is the underlying variable for the estimation of carbon exchange in many eco-system models. It controls the efficiency with which vegetation harvest available light to fix carbon via photosynthesis. Variability of ε within the different vegetation is mainly because of the vegetation types and the climatic conditions. With any vegetation, some photosynthesis is immediately used for the maintenance respiration. For the perennial plants, the maintenance respiration cost is minimal; therefore perennial plants have higher ε than the woody stems (Running et al., 2004).

Vegetation attains maximum ε (ε_{max}) in an ideal climatic condition without any constraints. However, it is usually constrained by temperature and water (Field et al., 1995; Potter et al., 1993, 2003; Running et al., 2000). Studies have quantified it as the product of ε_{max} and the water (W) scalar and temperatures (T_1, T_2) scalar. Water scalar is a measure of soil moisture controlled primary through the precipitation and evapotranspiration while temperature scalar is a measure of effects of extreme temperature beyond the optimal temperature. ε for any location (x) and time (t) is represented as:

$$\varepsilon = \varepsilon_{max} * T_1 (x, t) * T_2(x, t) * W(x, t) \qquad (2.5)$$

There are lot of issues and concerns regarding the estimation of ε_{max} because of the complex physiological process within the different vegetation. Potter et al., (1993, 2003) and Field et al. (1995) ignored the variability of ε within the biomes and used single value for all biomes based on calibration of field based NPP and modeled NPP values. However, other studies (Running et al., 2004; Turner et al., 2006; Mu et al., 2008) used different ε_{max} for different biomes indicating that ε_{max} for each biome is not consistent and a comprehensive analysis for ε_{max} should be conducted imperatively with the site specific NPP.

Various measures of field NPP data and light use by plant suggested that the value of ε is about 0.3 to 3.7 g MJ^{-1} among a wide range of plant species, crop varieties and forest strands (Prince, 1991; Ruimy et al., 1994). Several studies have estimated NPP with the constant value of ε for different vegetation because of the unavailability of exact measured values (Goetz, 1997; Field et al., 1995; Potter et al., 1993). There are however large uncertainties in the estimates of NPP which are centered towards the acquisition of remote sensing data in different resolution and assumption of invariant value of ε.

2.2.6 Evapotranspiration (ET)

ET is the sum of evaporation from the soil surface and plant transpiration to atmosphere. It plays a significant role in regional and global climate through it portioning in hydrological cycles. It is important in assessing ground water recharge, predicting crop yields and planning land use (Penman, 1948). ET is usually expressed in millimeters per unit time (such as mm/month, mm /day) and is estimated through water balance model. Potential evapotranspiration (PET) and Actual evapotranspiration (AET) are frequently used terms in agronomy to assess crop water requirement. Figure 1 illustrates the various processes that underlie within the soil water balance.

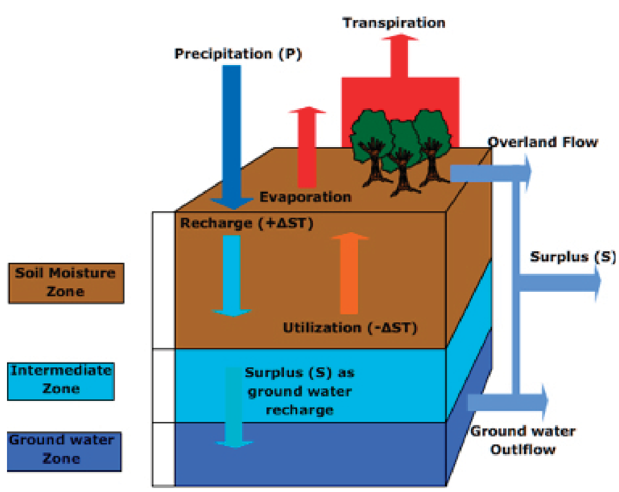


Figure 1 Soil Water Balance (After Strahler & Strahler, 2006)

(Source: http://www.uwsp.edu/geO/faculty/ritter/geog101/textbook/hydrosphere/water_balance_1.html)

Recharge period occurs when precipitation exceeds potential evapotranspiration but soil but has to reach its field capacity. Surplus period occurs when precipitation exceeds potential evapotranspiration and soil has reached its field capacity. Additional water applied to the soil results run off. Utilization period occurs when water is withdrawn from soil moisture storage. This occurs when PET exceeds precipitation but soil storage has yet to reach to 0. While deficit period occurs when PET exceeds precipitation and soil storage has reached 0 and soil has no water for plants.

2.2.6.1 Potential Evapotranspiration (PET)

PET is the amount of water that would be lost through the process of evaporation and transpiration from the surface under optimal supply of water. Many methods have been formulated for the estimation of PET which can be grouped into five categories: 1) Water Budget, 2) Mass transfer, 3) Combination (example. Penman, 1948), 4) Radiation (example Priestley and Taylor, 1972), 5) Temperature-based methods (example. Thornthwaite, 1948; Blaney and Criddle, 1950) (Xu and Singh, 2002). The need of wide range of data type and expertise to use various equations properly makes it difficult to select the most appropriate PET method for any study.

2.2.6.2 Actual Evapotranspiration (AET)

AET is the amount of water that is actually released to the air through the transpiration and evaporation process in the given environmental conditions of a place. It increases with the increase of temperature, so long as there is water to evaporate and water for plants to transpire (Ritter, 2006). Studies (Kolka and Wolf, 1998; Mehta, 2006) have estimated AET through the combination of PET, water holding capacity of soil and the precipitation.

2.2.7 Water Holding Capacity (WHC)

WHC is an estimate of the soil's ability to store water. Soil scientists have used parameters such as field capacity (FC) and wilting point (WP) to define available WHC (AWC) of soil under different conditions.

2.2.7.1 Field Capacity (FC)

FC is the maximum amount of water the soil can hold. The upper limit of soil moisture storage is FC and the lower limit is the 0 when the soil dries out (Ritter, 2006). It is dependent on soil structure and texture (Brady, N.C. et al., 1999). Fine grain soils have larger field capacities than coarse grain (sandy) soils.

2.2.7.2 Wilting Point (WP)

It is the state of soil at which plant can no longer extract health sustaining quantity of water from soil and begin to wilt as the consequences of deficiency of moisture in the soil.

Water holding capacity or water readily available to plants is the difference between water content at field capacity and the wilting point. . The Figure 2 shows the processes which result change in water holding capacity with the textural characteristic and the depth of soil. Relation (2.6) provides the expression for the estimation of AWC.

$$AWC = FC - WP \qquad (2.6)$$

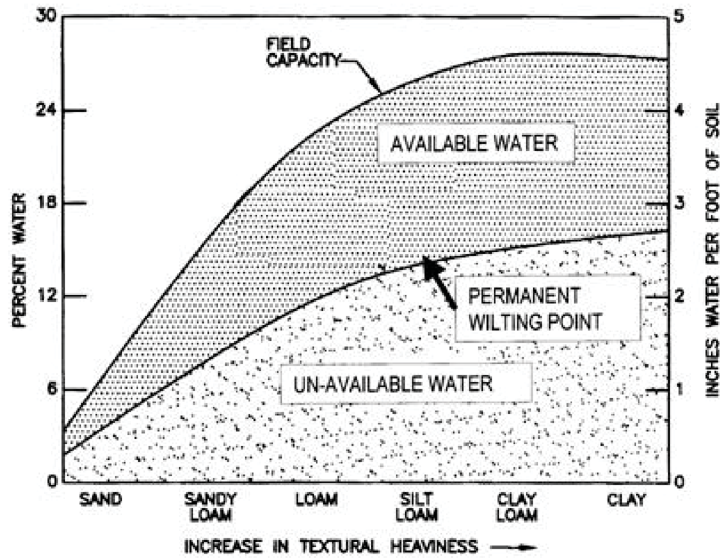


Figure 2 Relationship between Soil texture and Available Water

(Source: //www.ext.colostate.edu/mg/files/gardennotes/261-SoilWater.html)

2.3 Approaches to Net Primary Productivity Modeling

NPP is influenced by various Eco-physiological and bio-physical processes, some of which are very difficult to quantify, and are thus rarely measured (Clark et al. 2001a, b). The aboveground production is relatively easy to measure and comprises the majority of available NPP data. However, belowground production of woody roots and short-lived fine roots can form a significant proportion of total production (Clark et al. 2001a, b) but is extremely difficult to quantify. Thus, the most reliable component of NPP data is the aboveground component, and the belowground component is usually estimated with substantial uncertainty (Clark et al. 2001 a, b). So, the accuracy of the different vegetative models used in estimation of both above and belowground production is difficult to test precisely.

Aboveground terrestrial NPP is one of the most commonly modeled ecological parameters at both the regional and continental scales. NPP is controlled by climatic conditions and regulated by topography, soil and other environmental factors (Zheng, 1999). Studies have estimated NPP at global and regional scales using various models that ranged from simple correlation model (Leith, 1975) to complex Eco-physiological model (Potter et al., 1993, Running et al., 1988, 2000) that couples vegetation-atmosphere exchange of energy (Matsushita, 2004). NPP models reviewed in this section include statistical, climatical, Eco-physiological and process based models driven with remote sensing measurements.

Studies based on statistical models (Brown and Lugo, 1984; Leith 1975) estimated NPP as the function of mean annual temperature and precipitation through regression analysis. “Miami Model” (Leith, 1975) was the first global scale empirical model of terrestrial NPP. These models are strictly empirical in nature and offer little or no predictive or monitoring capability (Goetz, 1997). The approach was criticized because it failed to relate climate and vegetation photosynthetic activities properly because of its underlying assumption that the plant production has homogeneous responses to climate (Lieth, 1975; Emanuel et al., 1985; Goetz, 1997). However, it offers simplification of complex mechanistic models.

Soil-Vegetation-Atmosphere-Transfer (SVAT) models, which supplanted statistical models, included feedback mechanism between vegetation and the atmosphere by coupling plant physiological processes with climatic parameters (Goetz, 1997). SVAT improved the statistical models rather than monitoring terrestrial carbon dynamics.

Eco-physiological C-Flux models such as Terrestrial Eco-system Model (TEM: Raich et al., 1991) and Biogeochemical Model (BGC: Running and Hunt et al., 1993) were successful in stimulating short-term plant physiological responses to moisture, temperature and nutrient limitation and effect of these responses to carbon fluxes and energy fluxes (evapotranspiration and latent heat exchange).

TEM simulates carbon flux at the continental scale by calculating carbon during respiration in conjunction with photosynthesis, CO_2 concentrations, moisture extent, air temperature, nitrogen availability and seasonality of vegetation to some extent (Goetz, 1997). However, it requires calibration for each eco-system with the representative field data and the field data must be spatially calibrated like statistical models.

Biome-BGC was originally developed for conifer forests and is particularly sensitive to leaf area index (LAI) derived from satellite spectral measurements. Biome-BGC treats forest canopy as a homogenous three-dimensional leaf of depth proportional to LAI (Goetz, 1997). The results of Biome-BGC have been difficult to validate for large scale regions but have been validated at a local scale with field measurements. Running et al. (1988) noted that LAI estimated from satellite imagery at 1km spatial resolution may result in significant error with the model, particularly in heterogeneous landscapes. Biome-BGC is, however, useful and widely applied model to simulate NPP over large areas.

Kumar and Monteith (1982) introduced the concept of product efficiency model (PEM) by using annually integrated FPAR and incident PAR to measure annual NPP and crop productivity. Based on PEM, the product of FPAR derived from NDVI and PAR provides a measure of productivity as shown in expression (2.7).

$$NPP = \varepsilon^{N}{}_{t=1^*} * [FPAR * PAR] \rightarrow \quad \varepsilon^{N}{}_{t=1^*} * APAR \tag{2.7}$$

In the equation (2.7), 't' is the time interval over a growing season (of length N) and 'ε' is the light use efficiency. Applications of the simple production efficiency model with the constant value of ε, have provided moderate to strong correlation with surface measurement of NPP in crops (Asrar et al., 1993; Daughtry et al., 1992), semi-arid grasslands (Prince, 1991) and even at continental (Goward et al., 1985) and global scales (Potter et al., 1993; Ruimy et al., 1994). Spectral vegetation indices (SVI) were first used to estimate FPAR by Kumar and Monteith (1982) using Monsi and Saeki's (1953) function based on light incident in plant canopies as shown in expression (2.8).

$$FPAR = IPAR/PAR = 1\text{-}e^{-kl} \tag{2.8}$$

In the equation (2.8), 'k' is the coefficient that describes the average projection of leaves in any direction and is modified by a scattering coefficient based on canopy shape and 'l' is the projected LAI. Regardless of the radiative transfer modeling approaches, estimation of FPAR from SVIs is dependent on a number of factors including leaf display, leaf properties, solar geometry, presence of non-photosynthetic elements in the canopy, the quality of irradiance and background reflectance (Goetz, 1997). LAI driven models are likely to provide erroneous estimates of NPP unless some kind of distinction is made (Goetz, 1997).

Canopy radiative transfer simulation studies (Myneni et al., 1992) conducted with consideration of all these effects showed the non-linear relationship between SVIs and

FPAR and found it to be driven mostly by background properties such as surface. However, studies (Sellers et al., 1987; Zhu et al., 2005) have shown that relationship between FPAR and SVIs is the best for a continuous canopy. Non-linearity becomes problematic because the results of non-linear processes vary with the scale at which they are observed. However, accurate estimates of FPAR from SVIs may require frequent measurement during the day, depending upon the architecture and leaf display (Richardson et al., 1991).

2.3.1 CASA Model

Potter et al. (1993) used a process based model called Carnegie Ames Stanford Approach (CASA) which integrated bio-physical, such as NDVI, FPAR and climatic factors, such as temperature, precipitation and evapotranspiration acquired through remote sensing to estimate NPP. The model operates on a monthly interval to simulate seasonal patterns of carbon fixation by plants, biomass and nutrient allocation, litterfall, soil nitrogen mineralization and CO_2 production (Potter et al., 1993, 2006, Field et al., 2005). This model calculates monthly NPP as the product of APAR and LUE (ε). For each terrestrial grid cells, CASA model is used to calculate APAR as the product of PAR and FPAR derived from AVHRR NDVI (Field et al., 1995). The model calculates ε for each cell as the product of constant maximum LUE (ε_{max}) across all biomes and scalars representing the availability of water (W) and the suitability of temperature (T_1, T_2). NPP for a location (x) and time (t) is represented as in equation (2.9) or (2.10).

$$NPP(x, t) = APAR(x, t) * \varepsilon(x, t) \quad \text{OR} \tag{2.9}$$

$$NPP = PAR(x, t) * FPAR(x, t) * \varepsilon_{max} * T_1(x, t) * T_2(x, t) * W(x, t) \tag{2.10}$$

2.4 Use of Remote Sensing in Modeling of Primary Productivity

Satellite remote sensing has an advantage of providing nearly continuous observation over large areas thus has been used in several areas such as land use land cover change, climate change and water management to mention a few. Study related to NPP is essential to estimate the human impacts on biosphere-atmosphere functions (Cohen et al., 1999) and this requires a global terrestrial observing system that can integrate field based measurements, flux towers, remote sensing and eco-system modeling (Running et al., 2000; Potter et al., 2003; Turner et al., 2006). Several studies (Mu et al., 2008; Running et al., 2000; Field et al., 1995) have estimated global and regional NPP of terrestrial eco-system using remote sensing data. Satellite estimates, however, suffer due to the lack of large-scale field data required for validation of estimated NPP and also for the parameterization of LUEs (Lobell et al., 2002).

AVHRR and Moderate Resolution Imaging Spectro-radiometer (MODIS) are the most commonly used remote sensors that have been used to estimate historic NPP and seasonal exchange of CO_2 between the atmosphere and the terrestrial biosphere (Hicke et al., 2002, Rasmussen, 1998). MODIS was launched into Earth orbit by NASA in 1999 on board the Terra (EOS AM) satellite. This instrument captures data in 36 spectral bands ranging in wavelength from 0.4 µm to 14.4 µm and at varying spatial resolutions (2 bands at 250 m, 5 bands at 500 m and 29 bands at 1 km (NASA, 2009). Previous studies (Mu et al., 2008; Heinsch et al., 2006; Running et al., 2004) used MODIS datasets to estimate NPP across various regimes. AVHRR is a space-borne sensor on the board National Oceanic and Atmospheric Administration (NOAA) family of polar orbiting platforms. It measures the reflectance of the Earth in relatively wide spectral bands. In 1989, Earth Resource Observation and Science (EROS) started acquiring afternoon AVHRR 1-km resolution daily observations to produce weekly and biweekly maximum NDVI composites of the Conterminous United States and Alaska. AVHRR data are particularly relevant to vegetation activities, land surface properties, climate change and environmental degradation because of the comparatively long record of data (Nemani et al., 2003; Tucker et al., 2001; Goetz et al., 1999; Potter et al., 1993).

To provide validation to the global data products derived from MODIS and related sensors, NASA formed the EOS Validation Program. BigFoot is a network of validation sites, designed to provide the context using a combination of in situ ecological data, Landsat ETM+, and eco-system models (Cohen and Justice, 1999). Based on the comparison of BigFoot with the field data, accuracies of BigFoot maps can serve as validation media for global data products derived from MODIS and related sensors (Running et al., 2000; Cohen and Justice, 1999).

Although there are several studies (Potter et al., 2006; Hicke et al., 2002; Running et al., 2000) related to NPP across various biomes at global and regional scale, there are only few, if any, for the Conterminous US for recent years. Hicke et al. (2002) found small but significant increase in NPP by 8% or 0.03 Pg Cyr^{-1} over 17 years from 1982 – 1998 across North America driven mainly due to heterotrophic respiration . The largest increases occurred in the central and southeastern US, eastern Canada and northwestern North America. Potter et al. (2006) found inter annual variability of NPP across continuous US at the level of 3-3.5 petagrams of carbon per year from 1982 to 1997.

This study estimated NPP across different various eco-divisions and states of the Conterminous US from 1997 to 2007 using CASA model.

2.5 Role of Landscape Stratification

The decision to use Eco-Divisions and Environmental Protection Agency (EPA) regions as a stratum to analyze NPP spatially and temporally helps to analyze the effects due to the Modifiable United Area Problem (MAUP) (O'Sullivan and Unwin 2003). MAUP is an analytical artifact of choosing an area or strata that, if too large, results in loss of information specificity, and if too small, results in the loss of general pattern variation across the landscape. Eco-divisions were used to reduce the source of variance in analysis of NPP and its relationship with climatic factors due to landscape conditions that maintain homogeneity among various eco-regions in Conterminous US.

CHAPTER III

STUDY AREA: CONTERMINOUS UNITED STATES

As described in Chapter One, the Conterminous US is chosen as the study area for this research. Because U.S is the world's second largest contributor of CO_2, there is a need for studies on carbon sequestration. This study examines the carbon dynamics driven by photosynthesis in different eco-divisions, regions defined by environmental protection agency (EPA) and states within the continuous U.S from 1997 to 2007. This chapter briefly highlights on the different eco-divisions in the lower 48 states.

3.1 Eco-Divisions

The main purpose of using eco-divisions to analyze the temporal and spatial patterns in NPP was that they can help to analyze the relationship between NPP and a particular combination of temperature, precipitation and vegetation characteristics. Eco-regions defined by Bailey (1976) include domains, divisions, and provinces. It was developed through a regionalization or top-down process that focuses on differences in global, continental, and regional climatic regimes and gross physiography (Bailey, 1976, Bailey et al., 1994). There are 11 eco-divisions in the Conterminous US as defined by Bailey based on precipitation and temperature patterns.

3.1.1 Warm Continental Division:

The warm and humid continental division spans towards the south of the eastern area of the subarctic climate and between the continental interior and the east coast. Needle leaf and mixed needle leaf-deciduous forest exists throughout the colder northern parts of the humid continental climate zone, extending into the mountain regions of the Adirondacks and northern New England (Bailey et al., 1994).

3.1.2 Hot Continental Division:

South of the Warm Continental climate lies another division in the humid temperate domain – Hot Continental division. Hot summers and cool winters occur in this division. In the warmer sections of this division, the frost-free or growing season continues for 5 to 6 months whereas in the colder sections, it continues for only 3 to 5 months. Winter deciduous forest, dominated by tall broadleaf trees that provide a continuous dense canopy in summer, but shed their leaves completely in winter is the main vegetation of this region (Bailey et al., 1994).

3.1.3 Subtropical Division:

The humid Subtropical climate, marked by high humidity (especially in summer) and the absence of really cold winters, prevails in southern Atlantic and gulf coast states. Much of the sandy coastal region of the southeastern US is covered by second-growth forests of longleaf, loblolly, and slash pines. Inland areas have deciduous forest (Bailey et al., 1994).

3.1.4 Marine Division:

It is a zone that receives abundant rainfall from maritime polar air masses and has a rather narrow range of temperature as it borders on the ocean. Natural vegetation in the Marine division is needleleaf forest. In the coastal ranges of the Pacific Northwest douglas-fir, redcedar, and spruce grow to magnificent heights, forming some of the densest of all coniferous forests with some of the world's largest trees (Bailey et al., 1994).

3.1.5 Prairie Division:

The Prairie is typically associated with continental, mid-latitude climates that are designated as sub humid. Vegetation in this area is dominated by tall grasses associated with subdominant broad-leaved herbs. Trees and shrubs are almost totally absent, but a few may grow as woodland patches in valleys and other depressions (Bailey et al., 1994).

3.1.6 Mediterranean Division:

The Mediterranean is subject to alternate wet and dry seasons, the transition between the dry west coast desert and the wet west coast. The combination of wet winters with dry summers is unique among climate types and produces a distinctive natural vegetation of hard leaved evergreen trees and shrubs called sclerophyll forest (Bailey et al., 1994).

3.1.7 Tropical / Subtropical Steppe Division:

It borders the tropical deserts on both the north and south and also on the east as well. Locally because of altitude, plateaus and high plains within what would otherwise be desert have a semiarid steppe climate. Steppes typically are grasslands of short grasses and other herbs, and with locally developed shrub- and woodland (Bailey et al., 1994).

3.1.8 Tropical / Subtropical Desert Division:

It is characterized by extreme aridity and by extremely high air and soil temperatures. The region is characterized by dry-desert vegetation, a class of xerophytic plants that are widely dispersed and provide negligible ground cover. In dry periods, visible vegetation is limited to small hard-leaved or spiny shrubs, cacti, or hard grasses (Bailey et al., 1994).

3.1.9 Temperate Steppe Division:

Temperate Steppes are areas with a semiarid continental climatic regime in which, despite maximum summer rainfall, evaporation usually exceeds precipitation. The vegetation is typically steppe, sometimes called shortgrass Prairie, and semidesert. Typical steppe vegetation consists of numerous species of short grasses that usually grow in sparsely distributed bunches (Bailey et al., 1994).

3.1.10 Temperate Desert Division:

This region is characterized by low rainfall and strong temperature contrasts between summer and winter. The Temperate Desert has characteristics of a sagebrush (Artemisia) semidesert, with a very pronounced drought season and a short humid season. Temperate Desert climates support the sparse xerophytic shrub vegetation typical of semi desert (Bailey et al., 1994).

3.1.11 Savannah Division:

This region exists in southern Florida, where habitats and fauna are strongly influenced by fluctuating water level. The tropical wet-dry savanna climate has a wet season controlled by moist, warm maritime. Wet and dry seasons result in the growth of distinctive vegetation generally known as tropical savanna (Bailey et al., 1994).

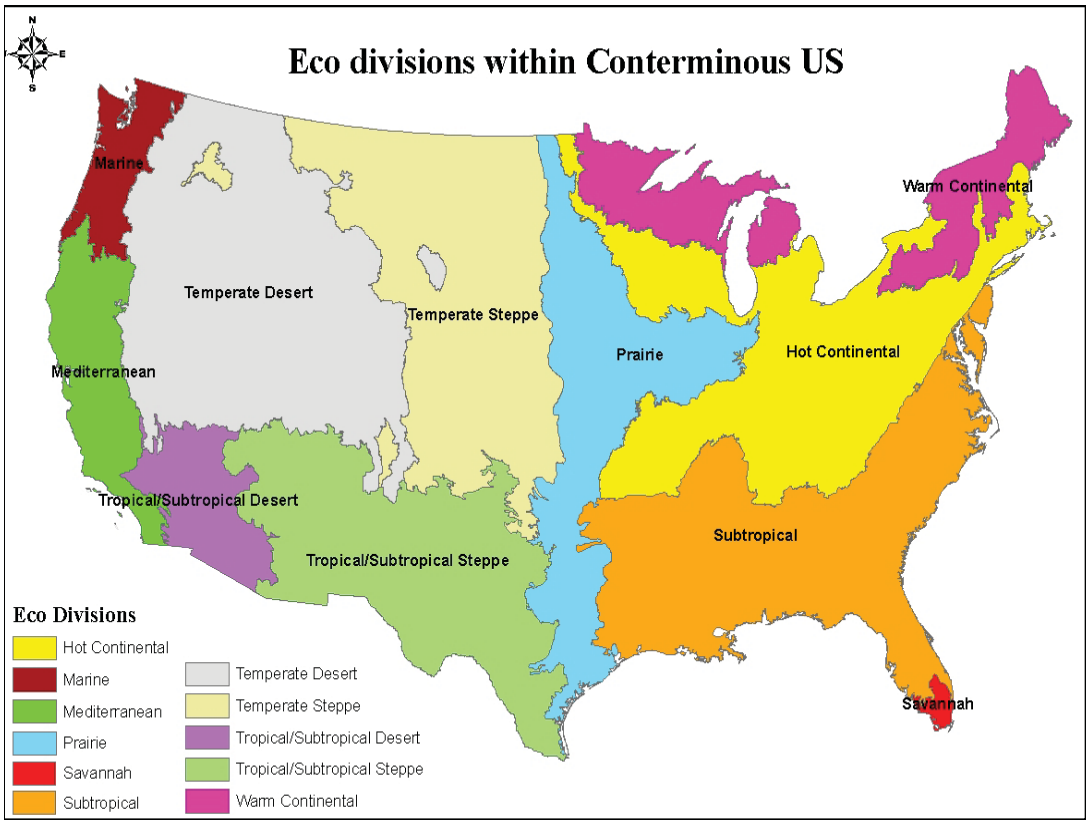


Figure 3 Eco-Divisions within the Conterminous US

3.2 Environmental Protection Agency (EPA) Regions

This study tried to examine the carbon dynamics driven by NPP within the 10 EPA regions of the Conterminous US. Each of these regions is responsible for the implementation of federal laws designed to protect the environment (EPA, 2008). So, analysis of NPP based on these regions helps to analyze the contribution of each region in carbon dynamics which could be useful in strengthening environmental protection programs and recommending policy changes in reducing CO_2 emissions. Each EPA regions includes different states as mentioned below (EPA, 2008):

Region 1 – It includes the states of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont.

Region 2 - It includes the states of New Jersey and New York.

Region 3 - It includes the states of Delaware, Maryland, Pennsylvania, Virginia, West Virginia, and the District of Columbia.

Region 4 - It includes the states of Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, and Tennessee.

Region 5 - It includes the states of Illinois, Indiana, Michigan, Minnesota, Ohio, and Wisconsin.

Region 6 - It includes the states of Arkansas, Louisiana, New Mexico, Oklahoma, and Texas.

Region 7 - It includes the states of Iowa, Kansas, Missouri, and Nebraska.

Region 8 - It includes the states of Colorado, Montana, North Dakota, South Dakota, Utah, and Wyoming.

Region 9 - It includes the states of Arizona, California, and Nevada.

Region 10 - It includes the states of Idaho, Oregon, and Washington.

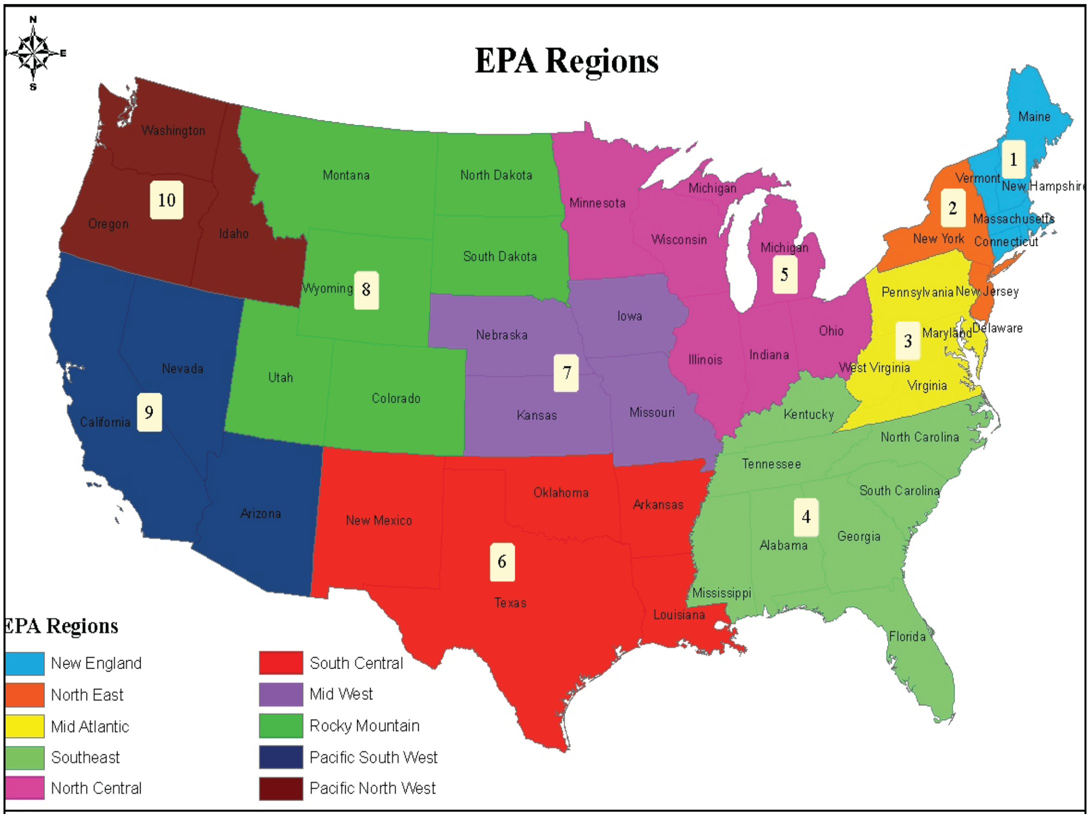


Figure 4 EPA Regions of the Conterminous US

3.3 Lower 48 States

All 48 states in the conterminous US were used in the analysis of spatial and temporal patterns of NPP. Estimation of NPP at the State level is imperative as the environmental policies are often made at the state level. Knowledge of NPP values and their trends in each state will help the state and the federal governments in making policy decisions regarding drought mitigation, forest management and other resource management issues.

CHAPTER IV

RESEARCH METHODOLOGY

To attain the objectives of this research, the theoretical framework of CASA model and the technical framework of GIS and remote sensing were adopted. Based on these two frameworks, the research methodology was designed to include five major parts: (1) conceptual model for the overall study, (2) data acquisition, (3) data preparation for CASA model, (4) NPP modeling, (5) validation of the results, (6) data extraction and analysis and (7) flow chart of the process, which are briefly explained in the sections 4.1, 4.2, 4.3, 4.4, 4.5, 4.6 and 4.7 of this chapter respectively.

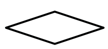
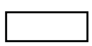
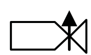
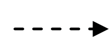
4.1 Conceptual Model

The overall process for the estimation of NPP was conceived as presented in the conceptual model to provide insight over the variables that are important for the CASA model. The interaction among various climatic and bio-physical variables during photosynthetic process has been represented through the figures 5, 6, 7 and 8.

4.1.1 Modeling Elements

The driving variables are the factors /stimuli that have direct impact on the system. Temperature (minimum temperature, maximum temperature, and average temperature), NDVI, precipitation, PAR and AWC were the basic driving variables for this study. The state variables are the variables that describe the condition/state of a system or components. Plant growth is the state variable for this study. Atmospheric CO_2 released after photosynthesis and consumed during photorespiration acts as both the source and sink. The auxiliary variables are the variables that have indirect impact in the system and are less important than the driving variables. Field based NPP are the auxiliary variables for this study which were required for the validation of modeled NPP. Parameters that were computed using the relationship between various driving variables were APAR, evapotranspiration (PET and AET), LUE, FPAR and thus NPP. Table 1 shows the symbols generally used in the conceptual model.

Table 1 Symbols Used in the Conceptual Model

Symbols	Stands for	Symbols	Stands for
	Driving Variables		Source/Sinks
	State Variables		Rate Equations
	Auxiliary Variables		Information Flow

The role of radiation (400nm-700nm) and healthiness of plants in determining the amount of radiation being absorbed by plants during photosynthesis process has been depicted in figure 5.

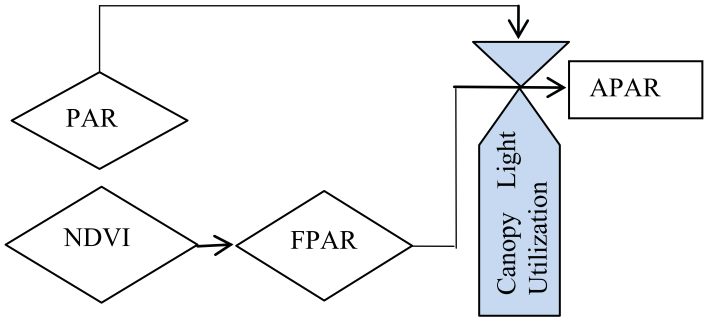


Figure 5 Conceptual Model for the Estimation of APAR

In Figure 6, the complicated concept of evapotranspiration has been simplified by considering the relation of temperature, precipitation and soil water holding capacity in evapotranspiration.

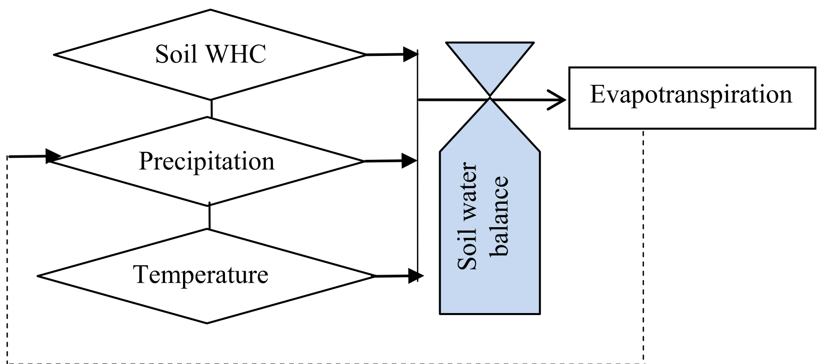


Figure 6 Conceptual Model for the Estimation of Evapotranspiration

Figure 7 shows the primary driving variables that help to determine the stress factors (such as water and temperature stress) upon the photosynthesis process.

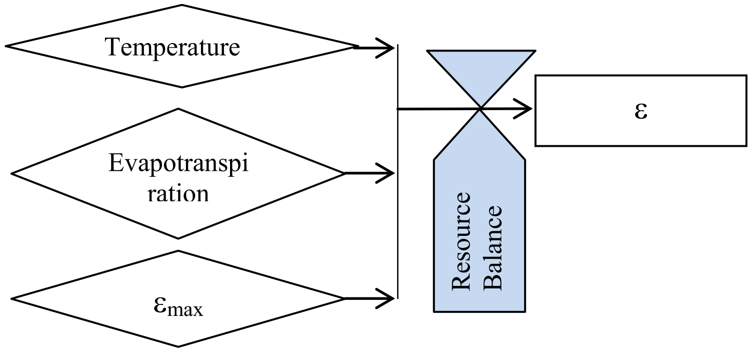


Figure 7 Conceptual Model for the Estimation of Light Use Efficiency

Figure 8 shows the overall variables that are considered for the computation and validation of the modeled NPP.

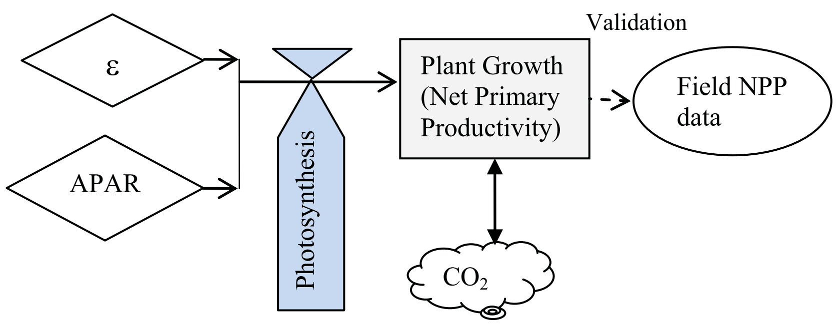


Figure 8 Generalized Conceptual Model for the Estimation of NPP and its Validation

4.2 Data Acquisition

Different data were downloaded from different sources in different format and resolution. Table2 shows the attributes of the different data used in this study.

4.2.1 NDVI

Fourteen day AVHRR composites from 1997 to 2007 with a 1-km spatial resolution available in the archive of United States Geological Survey (USGS[1]) Earth Explorer were used to extract NDVI dataset for this study. NDVI datasets were used with no image enhancement as the data are already preprocessed such as radio-metrically calibrated, geometrically registered, and atmospherically corrected (USGS, 2008).

4.2.2 Temperature and Precipitation

Four kilometer resolution spatial grids of monthly precipitation and monthly mean maximum and minimum temperature from Parameter – elevation Regressions on Independent Slopes Model (PRISM[2]) were used as the preliminary model input. These 4km climate data were prepared from US weather stations record and were interpolated first into 30 arc-seconds grid by PRISM. As the data were already in raster format, it became easier to work with than the data recorded by different national weather stations in some other formats such as excel. Monthly mean temperatures from 1997 to 2007 were computed by averaging monthly minimum and maximum temperature data.

4.2.3 Photo-synthetically Active Radiation (PAR)

Solar radiation impact to primary production was incorporated in the model by using PAR data provided by GEWEX Continental Scale International Project (GCIP) and

[1] http://edcsns17.cr.usgs.gov/EarthExplorer/
[2] http://prism.oregonstate.edu/

GEWEX Americas Prediction Project (GAPP)[3] surface radiation budget data. Monthly PAR datasets for the entire study period were available with the spatial resolution of ½ degree in the units of W/m^2 and in the format supported by the Fortan program. So, the data were first extracted into point format and then converted into arcGrid format by using Inverse Distance Weighted (IDW) interpolation method.

4.2.4 Soil Data

Amount of water available in soil has huge impact on plant productivity. Information regarding water holding capacity of the soil is very hard to achieve for the entire US. SURGO soil information available in USDA is based on soil series and it is available only for different sampling sites on county basis. It was very hard to put soil information based on different soil series together for entire US. For the purpose, information regarding AWC available in National Geophysical Data Center (NGDC-NOAA[4]) was used. This dataset was estimated for the Food and Agriculture Organization (FAO) digital Soil Map of the World (SMW) by employing continuous pedo-transfer functions (PTF) within global pedon databases (Reynolds et al., 1999). These datasets was computed based on the particle-size distribution; dominant soil texture; organic carbon content; coarse fragments; bulk density, and porosity for two-layers of depths (0-30 and 30-100 cm). AWC at 30-100 cm soil depth was used for this study.

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[3] http://www.atmos.umd.edu/~srb/gcip/
[4] http://www.ngdc.noaa.gov/ecosys/cdroms/reynolds/reynolds/reynolds.htm

4.2.5 Eco-Divisions Data

Eco-divisions data for the Conterminous United States, defined by Robert G. Bailey (Bailey et al., 1994), were used as summary strata for the examination of the temporal and spatial variation of NPP from 1997 to 2007. These data are available in eco-system management divisions of USDA[5].

4.2.6 BigFoot Sites NPP Data

BigFoot Sites NPP data available for different sites at different years were used to validate the estimated NPP data in this study. BigFoot NPP surfaces were developed initially to provide validation of MODLand (MODIS Land Science Team) science NPP products. These data are available in DAAC ORNL. BigFoot NPP surfaces data available in DAAC ORNL (http://daac.ornl.gov/data/BigFoot_val/) are 5km * 5km in size with the resolution of 25m in the ascii format.

There are very few BigFoot sites throughout the Conterminous US and only few of them have collected NPP data during 1997 to 2007. Apart from BigFoot sites, field specific NPP data can be obtained from Long Term Ecological Research Network (LTER[6]) sites but these data are available only from 1975 to 1998. Further, the NPP data available in LTER are based on plot level and they introduce additional difficulties related to scaling issues while comparing with estimated NPP as the estimated NPP were very coarse (1km resolution) compared to plot level data. So, this study validated modeled NPP with the BigFoot NPP surfaces data available for six different sites for

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[5] http://www.fs.fed.us/land/ecosysmgmt/colorimagemap/ecoreg1_divisions.html
[6] http://www.lternet.edu/sites/

different time period that varies widely in climate, land use and vegetation regimes (Figure9). There are no BigFoot sites with NPP data from 1997 to 2007 for the southeastern part of US.

Table 2 shows the details of the BigFoot Sites that includes the geographic location, types of biomes and the year for which field NPP data are available.

Table 2 BigFoot Sites used for the Validation of the Modeled NPP

Name	Location	Biome	Year
AGRO	Tolono, Il, USA	Crop (corn& soybean)	2000
KONZ	Manhattan, KS, USA (Konza LTER)	Tallgrass Prairie	2000
HARV	Petersham, MA, USA (Harvard Forest LTER)	Temperate Mixed Forest	2001, 2002, 2003
CHEQ	Park Falls, WI, USA (Tall Tower Site)	Temperate Mixed Forest	2000
METL	Sisters, OR, USA	Temperate Needle leaf Forest	2002

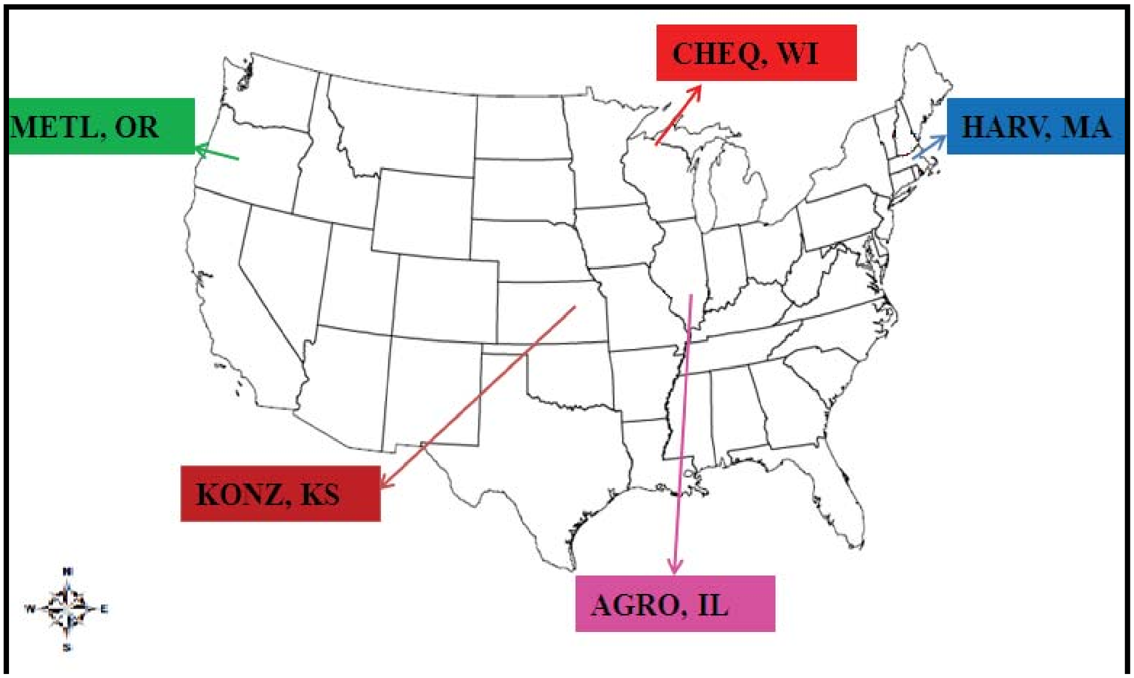


Figure 9 BigFoot Sites in the Conterminous US Used for the Validation

Table 3 Data Used in the Modeling of NPP

Data	Source	Format	Resolution
Monthly Minimum Temperature, Maximum Temperature, Monthly Precipitation	PRISM	ASCII	4Km
AVHRR 14 Days Composites	USGS science for a changing world	Raster	1Km
Monthly Photosynthetically Active Radiation (PAR)	GCIP SRB	Fortan	0.5 Degree ≈55Km
Maximum Soil Water Holding Capacity	NGDC NOAA	Raster	0.5 Degree ≈55Km
US Eco Divisions	US	Shape file	
BigFoot Sites NPP	DAAC	Raster	25 Meter

4.3 Data Preparation

The collected data were prepared so as to use them as the inputs for the modeling of NPP. AVHRR 14 days composites data were first geo-referenced to Lambert Azimuthal Equal Area Projection and then band 6 i.e. NDVI band amongst 14 bands of AVHRR was extracted. Monthly NDVI were computed from AVHRR composite data using raster calculator tool in ArcGIS software.

Monthly average PAR data downloaded from PRISM website were first extracted as point data using Fortran program. PAR data was in 0.5 degree resolution. The data were then interpolated using Inverse Distance Weighted (IDW) method based on Tobler law of geography which states that-*"Everything is related to everything else, but near things are more related than distant things''* (Tobler 1970). The extracted PAR data were in the unit of (W m^{-2} per hour per day) so those were converted to M J m^{-2} using relation (4.1).

$$M\ J\ m^{-2} = (W / m^{2}) \times 86400 \times 10^{-6} \times \text{total days of the month} \tag{4.1}$$

Total monthly precipitation, mean monthly minimum and maximum temperature datasets, available from PRISM, were first geo-referenced to geographic coordinate system and then re-projected to Lambert Azimuthal Equal Area Projection. These data were re-sampled to 1 km resolution similar to the resolution of NDVI data. Minimum and maximum monthly temperature data were then averaged to obtain the mean monthly temperature dataset. Similarly, soil AWC data was first projected to the geographic coordinate system and then re-projected and re-sampled for the model.

4.4 NPP Modeling

Many fundamental issues related to the global carbon cycle can be addressed using simulation models that operate by linking remote sensing, spatial databases of climate and soils and understanding of atmosphere-plant-soil biogeochemistry (Potter et al., 1993). In this study, fundamental concepts of CASA model were used for the estimation of monthly NPP.

4.4.1 CASA Model Parameters Estimation

4.4.1.1 APAR

Monthly APAR was calculated as the product of PAR surface irradiance and FPAR. FPAR was calculated as a linear function of the AVHRR simple ratio (SR), where

$$SR(x,t) = (1+NDVI(x,t))/(1-NDVI(x,t)) \qquad (4.2)$$

A linear relation between FPAR and SR is supported by theoretical results from Kumar and Monteith (1982), Sellers (1985, 1987). Based on Sellers et al. (1987), SR-FPAR relationship for different eco-system can be expressed as shown in expression (4.3).

$$FPAR\ (x,t) = \min\ (SR(x,t)/[SR_{max} - SR_{min}] - SR_{min}/[SR_{max} - SR_{min}],\ 0.95) \qquad (4.3)$$

In equation (4.3), 'SR_{min}' represents SR for unvegetated land areas and was set to 1.08 for the study site. SR_{max} is the maximum possible SR which differs by vegetation type based on rationale of Sellers et al. (1987). As the national land cover database (NLCD) for the study area was available only for the years between 1992 and 2001, the study modified the model and computed SR_{max} per pixel as the average value of maximum SR over the 11 years study period. However, previous studies (Field et al., 1995; Potter et al., 2006; 2003, Hicke et al., 2002) based on NASA-CASA model used NDVI and simple ratio (SR) in conjunction of land use land cover information to estimate FPAR. The basic assumption behind use of pixel information is that each NDVI pixel reflects the properties of different land cover. The value 0.95 was imposed on FPAR in the equation 4.3, reflects a finite upper limit to leaf area and the factor 0.05 accounts for the fact that approximately half of the incoming solar radiation is in the PAR waveband (0.4 – 0.7 μm) (Potter et al., 1993).

4.4.1.2 Water and Temperature Scalars

Inclusion of temperature and water scalars is a simple attempt to include as much as possible of the mechanistic basis of the effects of temperature and precipitation on productivity (Field et al., 1995). Temperature and precipitation data were used to determine T_1, T_2, and W. Monthly water scalar was calculated as a function of the ratio of actual evapotranspiration (AET) to potential evapotranspiration (PET) (Potter et al., 2006, 1993; Field et al., 1995):

$$W(x, t) = 0.5 + AET(x, t)/PET(x, t) \tag{4.4}$$

W takes into account of transitions between dry and wet seasons because the rate of evaporation is controlled by the soil moisture (Field et al., 1995). When AET equals PET, NPP is no longer restricted by soil moisture and W equals 1 (Zhu et al., 2004; Field et al., 1995).

The study used Thornthwaite (1948) method to estimate PET because of its simplicity with regard to data availability. This method requires only mean monthly temperature and day length as an input to estimate potential evapotranspiration from a reference grass surface. Willmott et al. (1985) summarized the Thornthwaite method to compute PET. PET in (mm/month) without adjustment for day length was computed with:

$PET_i = 0$ when $T<0^\circ$ C (4.5)

$PET_i = 1.6 * (10 * T_i/I)^a$ when $T>=0^\circ$C (4.6)

Where T is mean surface air temperature in month i ($^\circ$ C) and I is the heat index defined in Equation 4.7 below. The exponent 'a' in Equation 4.8 is the function of the heat index (I).

$$I = \sum_{i=1}^{N} (T_i / 5)^{1.514} \tag{4.7}$$

$$a = 6.7 \times 10^{-7} I^3 - 7.71 \times 10^{-5} I^2 + 1.79 \times 10^{-2} I + 0.49 \tag{4.8}$$

A monthly estimate of PET calculated with Equation 4.7 and 4.8 was adjusted for day length because 30 day months and 12 hour days were assumed when this relationship was developed. The PET was adjusted for month length and daylight duration with:

$$APE_i = PE_i[(d / 30)(h / 12)] \tag{4.9}$$

where APE is adjusted PET in mm/month, d is length of the month in days and h is the duration of daylight in hours on the fifteenth day of the month.

A commonly used water balance model was used to estimate the AET which recognizes the relationship between PET and AET (Kolka and Wolf 1998; Mehta, 2006). This model uses soil water storage in conjunction with PET and precipitation to estimate AET. Figure 10 represents the simple water balance model and Table 3 shows the details of the symbols used in the model.

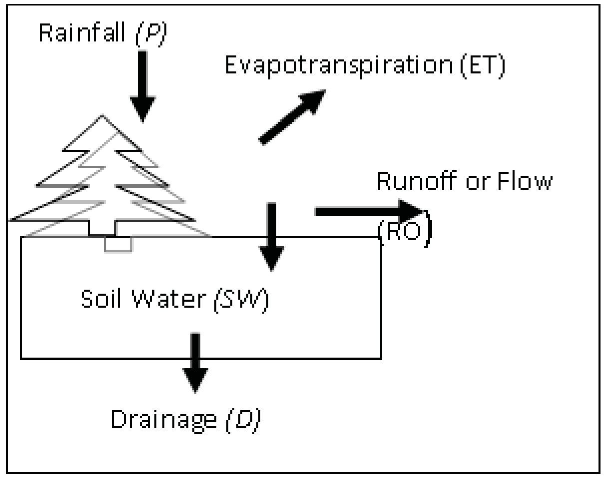


Figure 10 Conceptual Model for Water Balance (Mehta, 2006)

Monthly precipitation (P) and PET were used to calculate SW and APWL on monthly step. Excess water, i.e. net precipitation (ΔP) in excess of the soil's available water holding capacity (AWC) leaves the soil and is stored in the watershed and eventually released to the river. Table 4.below summarizes the calculations.

Table 4 Notation used for Water balance Model

AWC = Available Water Holding Capacity (i.e. field capacity-wilting point) X (soil depth)
SW = Available Soil Water (i.e. above wilting pt.)
APWL = Accumulated Potential Water Loss (negative)
ΔP = Net Precipitation; P – PET
P = Precipitation
PET = Potential Evapotranspiration
AET = Estimated Evapotranspiration

Table 5 Model Used for the Estimation of AET

Situation in the Watershed	*SW*	*APWL*	Excess
• Soil is drying $\Delta P < 0$	$= AWC \exp\left(\frac{APWL_t}{AWC}\right)$	$= APWL_{t-1} + \Delta P$	$= 0$
• Soil is wetting $\Delta P > 0$ but $SW_{t-1} + \Delta P \leq AWC$	$= SW_{t-1} + \Delta P$	$= AWC \ln\left(\frac{SW_t}{AWC}\right)$	$= 0$
• Soil is wetting above capacity $\Delta P > 0$ but $SW_{t-1} + \Delta P > AWC$	$= AWC$	$= 0$	$= SW_{t-1} + \Delta P - AWC$

* When P>PET, AET =PET and When P<PET, AET = dSW + P

This model was based on the assumption that soils are at field capacity in January Flow record shows that on average, months of January and February usually begins with no flow i.e. APWL = 0 (Mehta, 2006). Following this assumption, the study calibrated this model with APWL = 0 for January 1996. The reason behind computing AET for 1996 instead from 1996 is to minimize the possible limitation of considering no flow for the month of January 1997 directly.

The temperature scalars T_1 and T_2 in CASA attempt to capture two aspects of the regulation of vegetation growth by temperature. $T_1$is a stress term at very low or very high temperature where as T_2 is a stress term when temperature is below or above the optimum temperature (Zhu et al., 2004, Field et al., 1995). Despite the abundant evidence of temperature acclimation on photosynthesis, the hypotheses behind T_1 and T_2 in CASA have not been explicitly tested (Field et al., 1995). The value of T_1 and T_2 was calculated using equation. (4.10) and (4.11).

$$T_1 = 0.8 + 0.02\ T_{opt} - 0.0005\ T^2_{opt} \quad (4.10)$$

$$T_2 = 1.1814/ \{1+ \exp (0.2 (T_{opt} (x, t)-10- T(x, t))\}* 1/ \{1+\exp (0.3 (- T_{opt} (x, t)-10+ T(x, t))\} \quad (4.11)$$

Where T is the mean monthly temperature and T_{opt} is the mean temperature during the month of maximum NDVI. T_{opt} was computed on a pixel basis using mean temperature during the month of maximum NDVI in a year with USe of UPOS function available in ArcMap.

$$X = \text{UPos} (NDVI_1, NDVI_{2,\ldots\ldots}, NDVI_{12}) \quad (4.12)$$

Equation 4.12 helped to identify the month that has maximum NDVI value in a specified year for a pixel in the study area. The basic idea behind this computation is that different places experience maximum NDVI in different months during a year. After determining the month of the maximum NDVI values, conditional statement was used to assign the average temperature of a particular month identified through equation 4.13 for the pixels that has maximum NDVI values.

$$\text{Con} ([X] == 1, [Temp_1], \text{con} ([X] == 2, [Temp_2],\ldots, [Temp_{12}]))) \quad (4.13)$$

The scalars equal 1 when T equals T_{opt} and falls to 0.5 at approximately 10 ° c above and 13° c below T_{opt}. T_2 has a large impact on NPP in sites that experience seasonal variation in temperature. For the eco-system, where temperature varies little like low altitude deserts and tropical rainforests, T_2 has little effect (Zhu et al., 2004, Field et al., 1995).

4.4.1.3 Maximum Light Use Efficiency Parameter

Based on Potter et al. (1993, 2006) and Field et al. (1995), maximum light use efficiency parameter of constant value 0.389 g C MJ^{-1} PAR was applied over all vegetation types. This value was derived from previous field estimates (Potter et al., 1993, Field et al., 1995).

After the estimation of all these parameters, they were applied to the equation 4.3 which gave the final estimation of above ground NPP.

4.5 NPP Validation

Modeled NPP results were evaluated across various sites in different kinds of biomes to determine its accuracy. Because of limited field NPP datasets, BigFoot NPP surfaces were used to compare modeled NPP.

Bigfoot sites NPP data available in ASCII dataset were converted to grid using ASCII to Raster Conversion function available in ArcGIS. Before direct comparison could be made, the BigFoot products in Universal Transverse Mercator (UTM) coordinate system were re-projected to the Lambert Azimuthal Equal Area Projection of the modeled NPP products (Turner et al., 2005; Cohen et al., 2003b) to bring them both in same projection system. Use of same projection for two different layers allows to perform different kind of analysis between them.

To achieve spatial and temporal correspondence, modeled annual NPP of different years for which BigFoot NPP surfaces data exists were taken into consideration (Figure11). There were not any BigFoot sites for the southeast part of US. BigFoot NPP grids were rescaled to 1km to minimize the spatial resolution issues between two different datasets. Fifty random points were selected initially from both of the images to compare BigFoot NPP and modeled NPP values. The idea behind selection of 50 points is to include every pixel of rescaled BigFoot sites NPP surfaces. The points that fell into water bodies in BigFoot NPP surfaces were ignored during the comparison process.

4.6 Data Extraction and Analysis

4.6.1 Zonal Statistics to Extract NPP Values

Estimated monthly and annual NPP data were analyzed based on different eco-divisions, EPA regions and states. For this purpose, zonal statistics were computed in ArcGIS software where different eco-divisions, EPA regions and states were used as the zones. The idea behind using 48 states in analyzing annual NPP were to compare carbon fluxes driven by NPP in different states and identify the states that contribute highly per square meter. Mean monthly and annual NPP extracted by different eco-divisions using zonal statistics were used to analyze the annual and monthly trend of NPP within Conterminous US. Eleven years monthly NPP, NDVI, temperature, precipitation, PAR and EET were then averaged for the months of January through December to analyze the temporal relationship of NPP with these climatic and bio-physical factors.

4.6.2 Generation of Random Points

Five hundred random points of monthly NPP, NDVI, temperature, precipitation, PAR and AET within each eco-division were generated to compute Pearson's correlation coefficient. Yamane (1967) provided a simple formula ($n = N / (1+N*E^2)$) to calculate sample sizes. In the formula, n, N, and E represent the sample size, the number of population, and the sampling error, respectively. If the population is large enough, the minimum sample size goes to 400 with 5% sampling error (Israel, 2009). Therefore, this study used 500 samples that are larger than the minimum sample size 400 at 95% confidence level to include different geographic locations within the eco-divisions rather than just computing correlation coefficient based on 132 monthly mean data for each parameter.

4.6.3 Pearson Correlation Coefficients

Pearson Product Moment correlation (Pearson's correlation) coefficients for pairs of random points are generally used to investigate the relationship between two variables, including the magnitude and direction of relationship. The formula for this coefficient is:

$$r = \frac{\frac{\sum (X-\overline{X})(Y-\overline{Y})}{N}}{\sqrt{\frac{(X-\overline{X})^2}{N}}\sqrt{\frac{(Y-\overline{Y})^2}{N}}} \tag{4.14}$$

where r is the Pearson's correlation, $\overline{X}$ and $\overline{Y}$ represents the mean of X and Y respectively, N is the number of paired data. R ranges from -1.0 to 1.0; the signs indicates whether the relationship is direct (+) or inverse (-). T test was used to examine whether the relationship is significant. A relationship is considered significant if the probability of the observed test statistic ($\alpha = 0.01$ and $\alpha = 0.05$) is equal to or less than the test level. Smaller *p* values represent more consistent correlations (Wilks 2006).

Spatial variation of NPP at different geographic latitudes was examined by computing Pearson's correlation coefficient from extracted random points of mean annual NPP and their corresponding latitudes at the range of 0.5 degree.

4.6.4 Analysis of Variance

Analysis of variance (ANOVA) statistics were used to test whether the NPP vary significantly from one eco-divisions to other eco-divisions annually.

ANOVA: Single factor performs a simple analysis of variance on data for two or more samples. This analysis provides a test of the hypothesis that each sample is drawn from the same underlying probability distribution against the alternative hypothesis that underlying probability distributions are not the same for all samples. This technique is an extension of the two-sample t test. It test the difference between each pair of means and yield a matrix where asterisks indicate significantly different group means at an alpha level of 0.05 (Excel Help).

Table 6 Interpreting the Anova One Way Test Results

If	**Then**
test statistic > critical value (i.e. F> Fcrit)	Reject the null hypothesis
test statistic < critical value (i.e. F< Fcrit)	Accept the null hypothesis
p value < a	Reject the null hypothesis
p value > a	Accept the null hypothesis

4.6.5 Hot Spot Analysis and Getis-Ord Statistics

To understand the spatial pattern of NPP further, Hot Spot Analysis Tool in ArcMap software was used. This tool calculates the Getis-Ord Gi* statistics for each feature in a dataset. This test is also known as Hot Spot Analysis which is a measure of spatial autocorrelation. The result provides spatial autocorrelation of low values (cold spot) and high values (hot spots).

Hot Spot Analysis based on mean annual NPP of different states allows the test the second hypothesis of this study which is southeastern states contribute significantly to the higher NPP than other regions. The resultant Z score tells where the features with either high or low NPP values cluster spatially (ArcGIS Desktop 9.3 Help[7]). The Getis-Ord local statistic is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}} \tag{4.15}$$

Where G_i^* is a z-score, x_j is the attribute value (i.e. mean annual NPP per square meter in each states) for feature j (states), $w_{i,j}$ is the spatial weight between i and j, n is equal to the total number of features (states) and:

[7] http://webhelp.esri.com/arcgisdesktop/9.3/index.cfm?topicname=hot_spot_analysis_(getis-ord_gi*)_(spatial_statistics)

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{4.16}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\bar{X}\right)^2} \tag{4.17}$$

The critical Z score values with 95% confidence level are -1.96 and +1.96 standard deviations. The p-value associated with a 95% confidence level is 0.05. If the Z score is between -1.96 and +1.96, then p-value will be larger than 0.05 and null hypothesis cannot be rejected. Null hypothesis for pattern analysis tools is that there is no spatial pattern among the features.

4.7 Flow Chart

Flow chart in figure 10 summarizes entire processes that were done to estimate monthly and annual NPP. As the data downloaded were in different format, resolution and with different projections, it was necessary to bring them all in same resolution and projection systems to overlay on the top of each other and perform GIS and remote sensing operations. All the data were re-projected to Lambert Azimuthal Equal Area Projection and re-sampled to 1km as of NDVI data. PAR data were in point format at 0.5 degree interval so the PAR data were interpolated for Conterminous US. All the data were then fed into the CASA model framework to compute different parameters such as SR, FPAR, evapotranspiration, optimum temperature, temperature scalar, and soil moisture. After the estimation of monthly NPP, annual NPP was computed which were validated with five different BigFoot Sites NPP data. Then various spatial and statistical analyses were conducted as explained in previous sections.

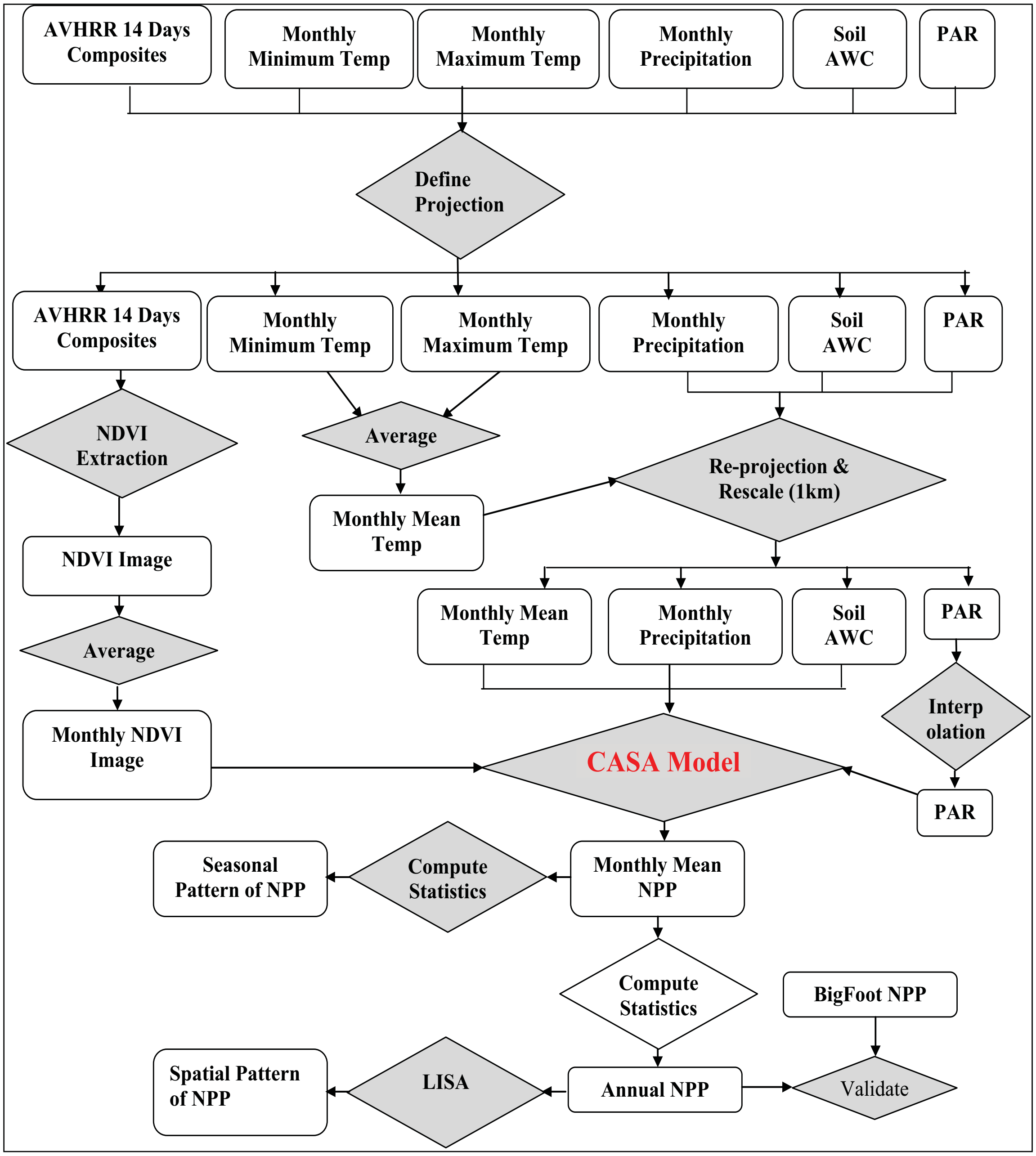


Figure 11 Flow Chart

The major software packages used in this study includes ERDAS Imagine, ArcGIS, SPSS and Geoda. The results and discussion of the study is provided in the next chapter.

CHAPTER V

RESULTS AND DISCUSSIONS

The sections 5.1, 5.2 and 5.3 of this chapter illustrate the main findings while fulfilling the objectives 1, 2 and 3 respectively, of this study. As described in Chapter One, the three objectives of this study were: (Objective 1) to estimate annual NPP in the Conterminous US from 1997 to 2007, (Objective 2) to examine the temporal and spatial trends in NPP in the Conterminous US and (Objective 3) to analyze the interaction of NPP with climatic and bio-physical factors.

5.1 Objective 1: Estimation of Annual NPP

5.1.1 Estimation of Annual NPP in the Conterminous US from 1997 to 2007

The NPP in the Conterminous US for the years 1997 to 2007 was found to be in the range 3472 T g C yr^{-1} (year 2002) to 4948 T g Cyr^{-1} (year 2005) (Figure 12) with mean annual NPP of 4234 T g C yr^{-1} . Figure 11 shows NPP anomalies with three different trends. Estimated total NPP were lower in the years 2000 to 2003 than the mean annual NPP during which the growing seasons were affected by extensive drought in most part of contiguous US. There was about 26 percent reduction in NPP in the year 2002 compared to 1997. An increasing trend was then observed for the years 2003 through 2005. NPP in the year 2005 was about 42 percent higher than in 2002. Years 2006 and 2007again showed a decreasing trend. In a nutshell, this trend suggested a very negligible change in NPP with the R^2 of 0.004 within the 11 years of study period. Thus, the first null hypothesis of the study that the NPP had an increasing trend from 1997 to 2007 was rejected.

NPP started decreasing since1999 and reached the lowest in 2002. There was about 18% of the nation's mean annual NPP during 2002 compared to previous year. During this period climatic conditions in most part of the US deviated hugely from their historical climatic records (NCDC-NOAA[8]). NPP started regaining slowly from 2003 and reached the maximum in 2005.

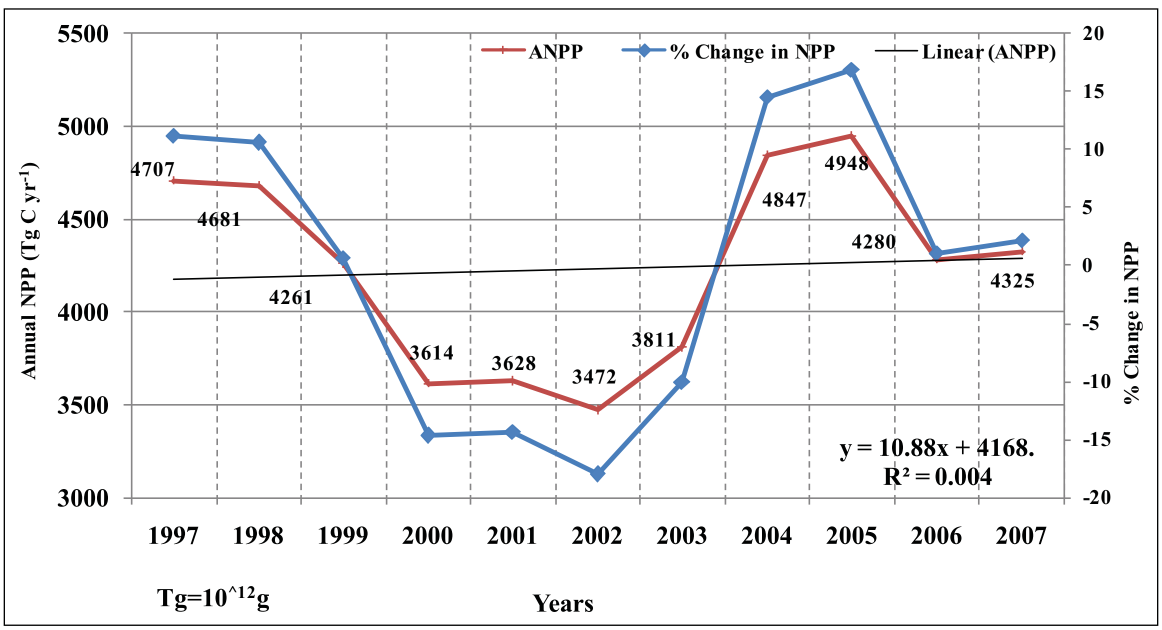


Figure 12 Annual Net Primary Productivity (T g C yr^{-1}) from 1997 to 2007

[8] http://www.ncdc.noaa.gov/oa/climate/research/2002/ann/us-summary.html

Upon examination of climatic and bio-physical factors during the 11 years study period, tremendous decrease in NDVI, precipitation and evapotranspiration were observed in 2000 to 2003 compared to other years which could be the most probable reason for lower NPP (Refer section 5.2.1 for details). During these years southeastern and western parts of US experienced dry conditions (NCDC-NOAA[9]). Extreme drought conditions and large acres of land burnt by wildfires as a result of extreme drought might have resulted loss of NPP during these years (NCDC-NOAA).

5.1.2 Estimation of Annual NPP across Different States of the Conterminous US

Estimation of mean annual NPP (g C m^{-2} yr^{-1}) across different states of the Conterminous US would help to identify the states that contribute to higher carbon sink. Southeastern states, such as Louisiana, Mississippi, Alabama, Georgia, South Carolina, North Carolina and Florida were found to have very high NPP per unit area (Table 7 and Figure 13). Among these states, Florida was the largest contributor. In contrary, the states of Nevada, Wyoming, Montana and North Dakota showed very low NPP per square meter (Figure 13). Large concentration of hardwood and deciduous forest in the southeastern states compared to other states could be one of the probable reasons for their higher NPP. However, the contribution of these states to the nation's total NPP was found to vary based on their total area. The total annual contributions of states (T g C yr^{-1}) to nation NPP during these 11 years periods are shown in Annex A. Mean annual NPP (g $Cm^{-2}yr^{-1}$) of different states for the year 1997 to 2007 are given in the Table 7.

[9] http://www.ncdc.noaa.gov/climate-monitoring/index.php

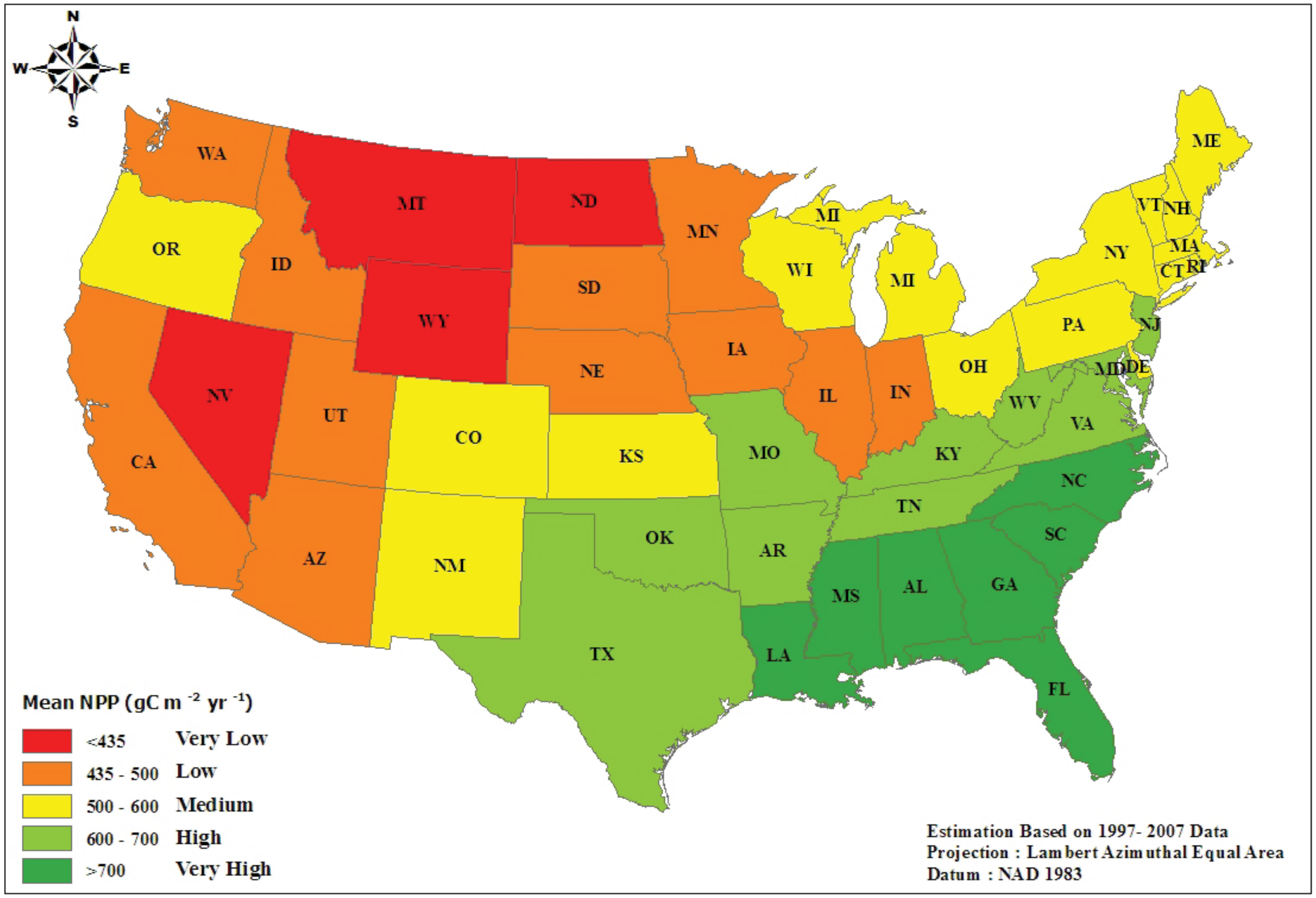


Figure 13 Mean Annual NPP (g C m^{-2} yr^{-1}) in the Lower 48 States of US

Table 7 Annual NPP (g C m^{-2} yr^{-1}) in Different States of the Conterminous US from 1997 to 2007

State	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean
Alabama	769	746	779	561	693	726	843	932	904	931	813	791
Arizona	570	761	545	447	404	211	345	444	639	422	398	471
Arkansas	689	630	611	506	583	542	637	737	685	783	604	637
California	515	566	481	487	392	363	432	512	649	468	454	484
Colorado	579	614	572	457	409	289	440	561	583	493	551	504
Connecticut	617	631	490	435	600	611	552	722	595	517	596	579
Delaware	626	583	513	508	595	541	541	711	567	567	466	565
District of Columbia	761	744	630	609	659	589	520	816	659	734	517	658
Florida	1043	950	920	796	783	868	916	1024	1050	1006	974	939
Georgia	827	759	769	636	685	722	833	912	902	899	828	797
Idaho	521	491	394	403	344	412	363	515	530	428	438	440
Illinois	460	492	414	423	452	399	469	582	477	478	488	467
Indiana	461	536	418	442	504	405	499	603	564	532	507	498
Iowa	445	481	375	376	378	472	410	568	511	436	482	449
Kansas	626	633	578	493	531	335	508	678	678	519	518	554
Kentucky	591	665	576	527	634	610	646	804	684	773	568	643
Louisiana	781	689	776	620	717	654	703	860	836	914	805	759
Maine	475	487	473	280	455	583	488	648	608	538	546	507
Maryland	639	656	565	525	628	583	549	775	621	634	541	610
Massachusetts	581	602	510	416	606	639	558	722	614	507	598	578
Michigan	518	566	479	428	462	565	509	606	592	556	542	529
Minnesota	466	497	382	381	381	544	416	513	509	432	437	451
Mississippi	751	693	749	551	692	693	768	873	862	871	781	753
Missouri	622	659	525	531	629	511	585	794	685	652	570	615
Montana	502	438	437	332	313	373	348	419	513	401	400	407
Nebraska	522	556	517	415	442	274	430	552	579	406	486	471
Nevada	566	671	503	480	230	219	251	395	579	435	358	426
New Hampshire	542	527	483	341	539	649	487	689	622	519	580	543
New Jersey	722	630	537	517	622	610	543	794	635	619	595	620
New Mexico	703	692	701	427	375	300	340	606	675	558	634	547
New York	559	613	468	399	549	633	552	680	623	525	555	560

Table 7 (Continued)

State	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean
North Carolina	770	776	674	589	671	674	728	870	790	879	746	**742**
North Dakota	372	384	393	384	375	338	336	382	458	304	380	373
Ohio	541	597	478	472	515	453	545	671	583	579	534	543
Oklahoma	703	584	637	549	541	500	594	737	706	567	633	614
Oregon	596	519	476	484	439	479	419	567	565	505	577	511
Pennsylvania	593	624	513	456	580	576	522	720	600	579	610	579
Rhode Island	586	599	497	432	606	601	543	702	580	495	563	564
South Carolina	882	828	777	635	664	717	798	909	862	919	824	**801**
South Dakota	546	520	539	434	404	248	363	486	515	327	418	436
Tennessee	662	706	662	534	632	638	704	824	725	806	624	683
Texas	725	590	627	466	496	448	570	768	695	565	734	608
Utah	584	605	511	428	320	269	312	446	608	460	469	456
Vermont	530	567	457	325	498	662	530	661	608	502	559	536
Virginia	691	693	615	537	663	640	662	821	698	770	638	675
Washington	524	477	375	417	404	469	416	503	525	487	496	463
West Virginia	619	644	582	439	618	629	549	718	615	684	575	606
Wisconsin	549	605	469	431	441	644	492	605	607	533	554	539
Wyoming	555	561	520	412	294	263	362	439	547	376	409	431

5.1.3 Validation of Modeled NPP

Estimated NPP was validated by comparing with the different BigFoot NPP sites data at different time period to determine the accuracy of the model in the estimation of NPP. Table 8 shows different BigFoot sites used for the validation of the estimated NPP, the sample sizes that were used for cross validation and their correlation.

Table 8 Correlation of Modeled NPP with BigFoot NPP Data

Year	Sites	Correlation (at 0.01 significance level)	Sample Size
2000	CHEQ	0.74	45
2000	KONZ	0.61	50
2000	AGRO	0.61	50
2001	HARV	0.80	45
2002	HARV	0.94	45
2002	METL	0.77	27
2003	HARV	0.66	45

Figure 14 shows the overall correlation and the trend line of BigFoot sites NPP data with the estimated NPP data based on 307 random points at different time period and locations. The R^2 was 0.88, which signified that the model is a good approximation for the NPP estimation.

Figure 15 shows the scatter plot of the modeled NPP versus BigFoot NPP data for the sites: HARV (2002, 2001, 2003), METL (2002), CHEQ (2000) and KONZ (2000). The estimated NPP were found to be highly correlated with NPP values estimated at each of the BigFoot sites for all time periods. Compared to other BigFoot sites, estimated NPP values for HARV sites had strong correlation with the site's NPP data. Quality of the driving variables in terms of resolution and the time when it was taken could be the potential reasons for these kind of over and under estimation (Turner et al., 2005, Running et al., 2000, Running et al., 2004). This cross validation across different sites signified that the values closely resembled with the field NPP data. This shows the accuracy of CASA- NASA model in estimating NPP fluxes with use of remote sensing data.

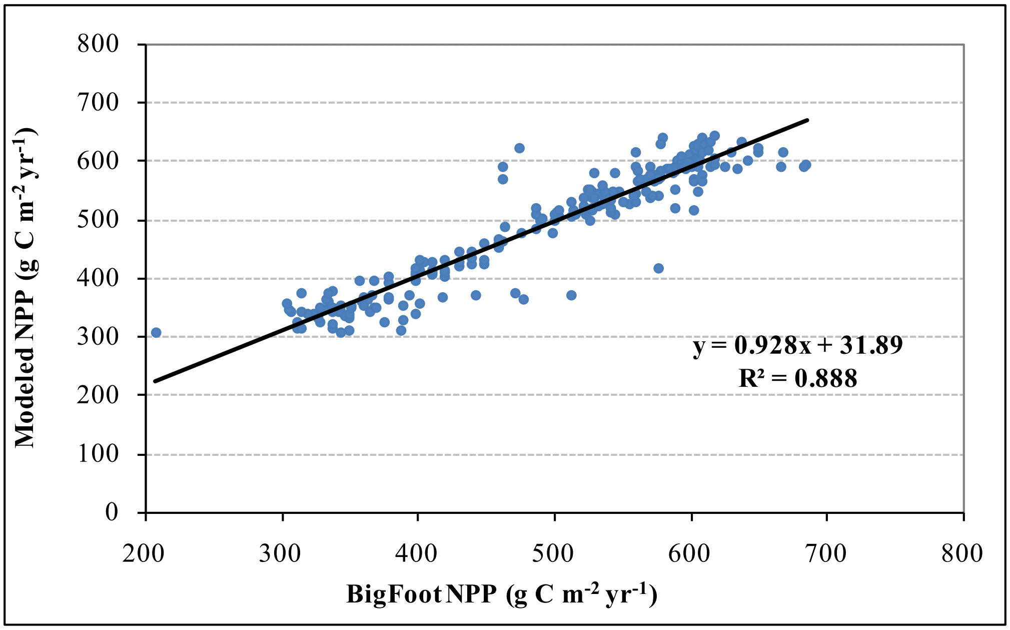


Figure 14 Overall Comparisons of Annual BigFoot Sites NPP with the Estimated NPP

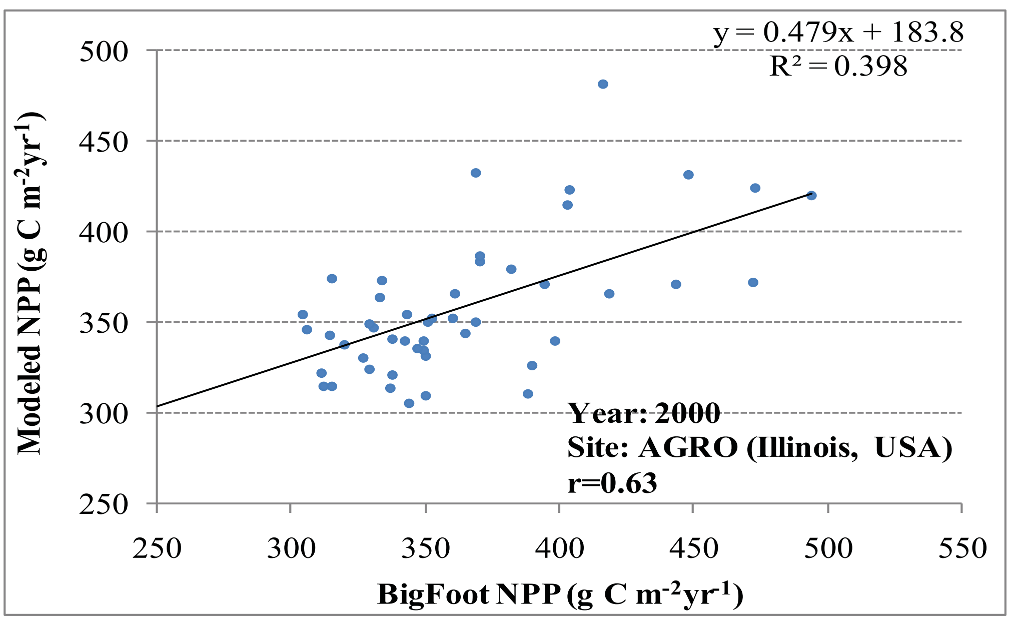


Figure 15 Comparisons of Annual BigFoot Sites NPP with the Estimated NPP

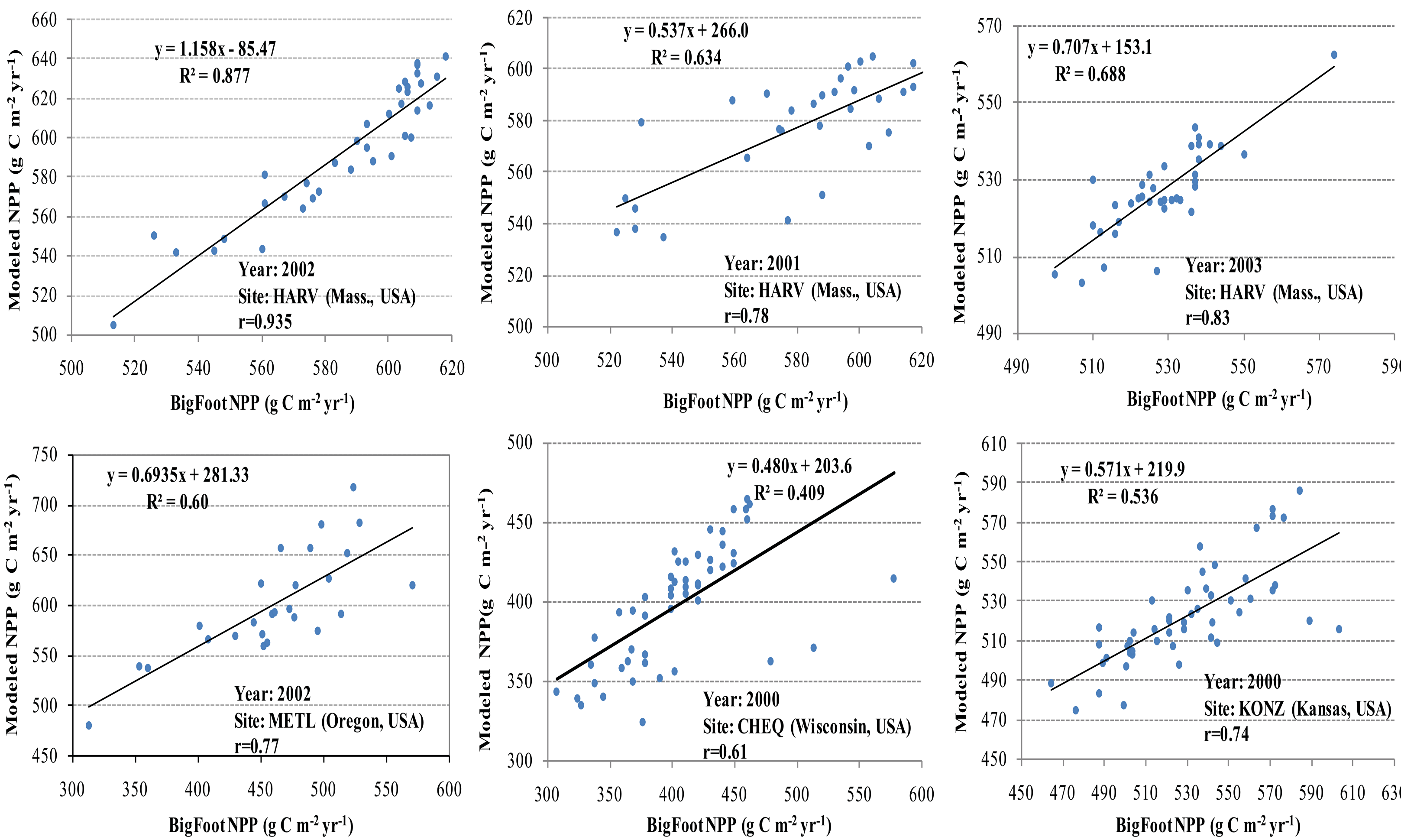


Figure 15 (Continued)

5.2 Objective 2: Spatial and Temporal Trends in NPP in the Conterminous US

5.2.1 Latitudinal Variation in NPP

Climate is directly related to the latitude. The global patterns of temperature and precipitation are well known to be the consequences of the angle of Earth's rotational axis. Evaporation of water vapor from warm water makes precipitation much higher near the equator than the poles. Various combinations of precipitation and temperature distributed at different location have a very predictable effect on vegetation type and structure (Michael and Steve, 2009).

NPP has been found to have negative relationship with latitude. In general, the values of NPP at lower latitudes are found to be higher compared to the higher latitudes. Figure 16 shows the profile of NPP at various latitudes in US. Similar trends were found by Kicklighter et al. (1999), where NPP values decreased from lower latitude to the higher latitude regions in the northern hemisphere. Altitudinal variation can also have impact on NPP as vegetation types and their characteristics differ with the altitude.

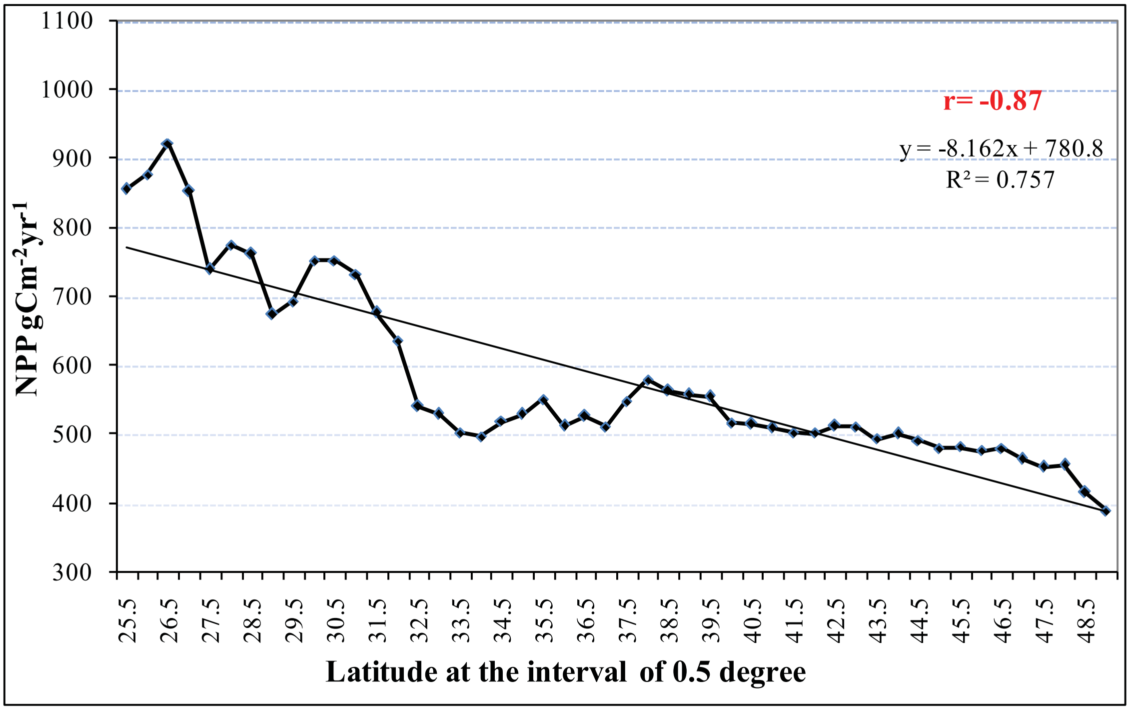
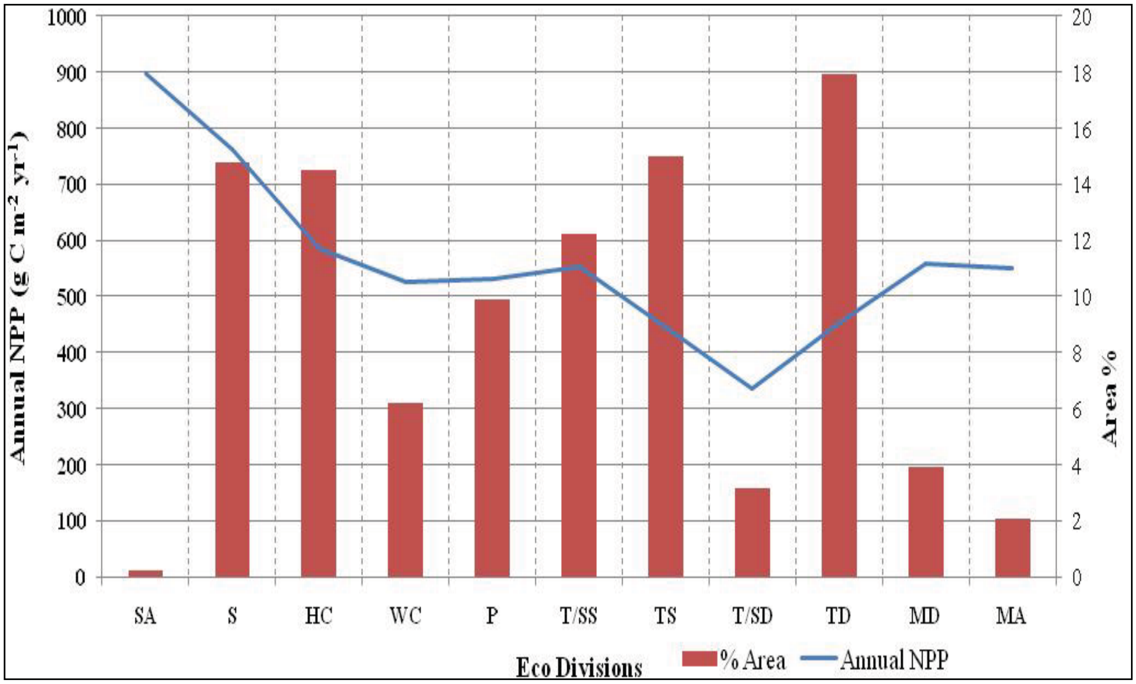


Figure 16 Latitudinal variations in NPP

5.2.2 Spatial Variation of NPP in Different Eco-Divisions

Spatial variation of NPP was further examined in different eco-divisional levels and it was found that NPP of one eco-division varied significantly from another. Figure 17 shows the variation of mean annual NPP and the area (in terms of percentage of the total area covered by Conterminous US) in each eco-division in the Conterminous US. It was found that the mean annual NPP (g C m^{-2} yr^{-1}) was the highest in Savannah eco-division followed by the Subtropical eco-division. However, in terms of areas, Savannah is the smallest eco-division in US.



SA = Savannah, S = Subtropical, HC= Hot Continental, WC = Warm Continental, P = Prairie, T/S S = Tropical Subtropical Steppe, TS = Temperate Steppe, T/S D = Tropical Subtropical Desert, TD = Temperate Desert, MD = Mediterranean, MA = Marine

Figure 17 Mean Annual NPP (g C m^{-2} yr^{-1}) and Total Area Covered by Each Eco -Division

Table 9 shows the total geographic coverage of each eco-division, annual mean NPP and their percentage contribution to the total terrestrial carbon sequestration due to NPP in the Conterminous US based on average of annual NPP during 11 years period. It was found that the Subtropical followed by Hot Continental and Temperate Desert contributed largely to the total carbon sink in the Conterminous US. Thought the mean annual NPP per square meter (g C $m^{-2}yr^{-1}$) for Savannah was found to be the highest, its contribution to total NPP was lower (0.4 %) than Tropical/Subtropical Desert which was found to have lowest NPP per square meter because of its reduced area compared to other eco-divisions.

Table 9 Mean NPP (g C m^{-2} yr^{-1}) in Different Eco-Divisions and Their Percentage Contribution

Eco Divisions	**Land Area (10^{3} Km^2)**	**Total NPP (T g C yr^{-1})**	**Contribution (%) to Total NPP of Conterminous US**
Hot Continental	1125.4	658.5	**15.5**
Marine	171.3	94.2	**2.2**
Mediterranean	318.5	177.6	**4.2**
Prairie	761.8	405.3	**9.6**
Savannah	20.7	18.5	**0.4**
Subtropical	1155.3	881.3	**20.8**
Temperate Desert	1380.1	626.8	**14.8**
Temperate Steppe	1156.2	513.1	**12.1**
Tropical/Subtropical Desert	241.8	81.4	**1.9**
Tropical/Subtropical Steppe	945.1	523.1	**12.3**
Warm Continental	488.7	256.8	**6.1**
Total	7764.84	4236.6	**100**

Table 10 and figure 18 both show that all the eco-divisions except Warm Continental and Marine lost significant NPP in the years 2000, 2001 and 2002. Mediterranean and Prairie experienced subtle change in NPP compared to other eco-divisions during these years. It was found that the most of these eco-divisions regained their productivity subsequently in the years 2003, 2004 and 2005.

Table 10 Mean Annual NPP (g C m^{-2} yr^{-1}) in Different Eco-Divisions from 1997 to 2007

Eco Divisions	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean
Hot Continental	583	625	527	480	559	562	562	713	627	632	567	585
Marine	603	484	412	467	552	593	508	637	605	569	624	550
Mediterranean	591	532	545	559	503	490	525	596	679	538	577	558
Prairie	560	542	490	468	503	479	498	669	585	513	544	532
Savannah	1035	1070	916	866	720	775	843	911	925	898	923	898
Subtropical	799	737	739	602	685	685	762	880	843	883	776	763
Temperate Desert	560	564	475	434	322	342	349	491	558	452	449	454
Temperate Steppe	523	519	531	408	382	266	386	494	547	378	447	444
Tropical/Subtropical Desert	386	683	342	340	223	77	228	362	578	297	188	337
Tropical/Subtropical Steppe	696	649	629	431	403	326	437	670	684	506	656	553
Warm Continental	521	563	459	374	475	616	509	611	596	524	531	525

Upon examination of national climatic condition during these years, it was found that 2000, 2001 and 2002 national drought had its origin in late 1999. Drought in year 2000 was found to affect about 36% of the contiguous US (NCDC, NOAA). The area most severely affected were deep south, the southern and central plains and much of the western US. There were hundreds of wildfires across several western states with the highest concentration in Idaho and western Montana. Record dryness occurred in the southern states of US as, Alabama, Florida, Georgia, Louisiana, Texas and Mississippi during 2000. The drought in 2001 affected about 20% of the contiguous US .The most severely affected areas included the parts of southern Great Plains and much of the western US. The three states Washington, Oregon, and Idaho declared drought emergencies. Record dry conditions from 2001 continued to early 2002 in the eastern US. The largest wildfires in state history occurred in Colorado, Arizona and Oregon in 2002.

During 2003, most of the parts of US were wet compared to earlier years. Precipitation in 2004 was characterized by persistent moderate dryness in the West and above average wetness in the South and East. This follows a record wet year in 2003 for some of the East coast (NCDC, NOAA). Due to these extremes conditions, there might have been significant impact on vegetation growth which might have resulted in the significant reduction of NPP during these years.

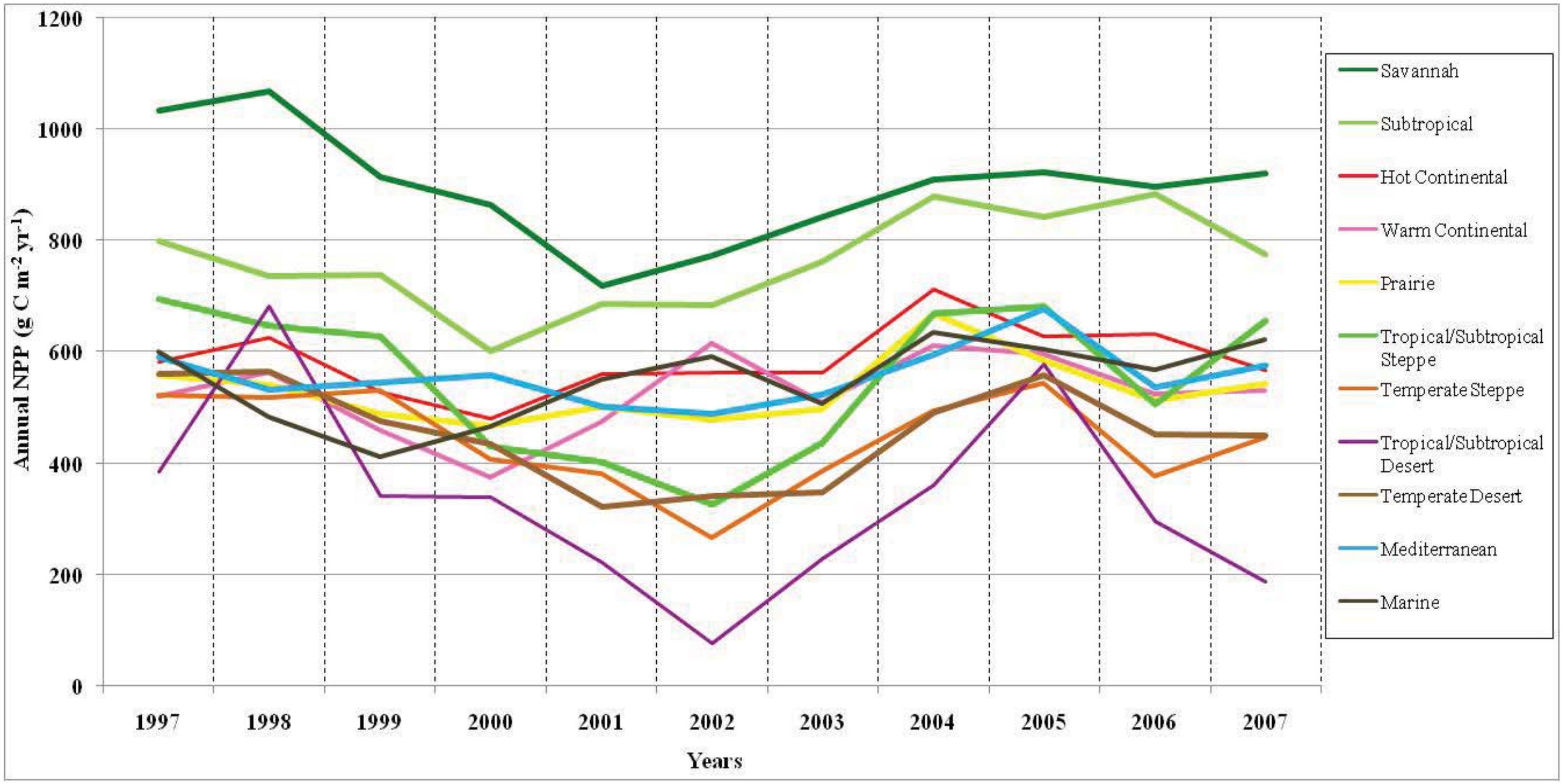


Figure 18 Mean Annual NPP (g C m^{-2} yr^{-1}) in Different Eco-Divisions from 1997 to 2007

Mean annual NPP per square meter in different eco-divisions computed using 11 years NPP data was visualized through figure 19 where the dark green color represents the highest NPP and red color represents the lowest NPP. It shows that Savannah and Subtropical have higher annual NPP per square meter and the Tropical/Subtropical Desert has very low annual NPP per square meter. The probable reasons for these differences in NPP could be different vegetation types and climatic conditions predominant in these regions.

Vegetation in Tropical /Subtropical Desert is very sparse and consists mainly of dwarf-shrub land. It has a climate of long, hot summers and mild winters with little precipitation and pronounced drought season. Vegetation in Subtropical and Savannah eco-divisions is dominated by conifers, with deciduous hardwoods along with floodplains and precipitation is abundant with rare period of summer drought (USDA, 2007). Forest provides typical vegetation throughout the Subtropical eco-divisions. Shrubs are more influential to drought seasons and extreme climatic conditions than hardwoods. This could be the reasons for the lower NPP in Tropical/Subtropical Desert than Subtropical and Savannah eco-divisions in general.

ANOVA – single factor analysis (Table 11) was used to analyze whether the NPP in different eco-divisions vary significantly with each other. The analysis showed the p value of 1E-25 which was less than 0.05 significance level. This helped to reject the null hypothesis that the mean annual NPP between different eco-divisions are same. F

(27.7619) was greater than *F critical* (1.91783), so again, it rejected the null hypothesis that the NPP variances among various eco-divisions are all equal.

Table 11 ANOVA: Single Factor Analysis Based on Mean Annual NPP of Different Eco-Divisions

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Hot Continental	11	6436.36	585.124	3843.72
Marine	11	6053.71	550.337	5298.11
Mediterranean	11	6134.78	557.707	2753.4
Prairie	11	5852.39	532.035	3371.33
Savannah	11	9882	898.364	10076.8
Subtropical	11	8391.07	762.825	7537.63
Temperate Desert	11	4995.77	454.161	7760.22
Temperate Steppe	11	4881.34	443.758	7716.87
Tropical/Subtropical Desert	11	3705.65	336.877	29723.9
Tropical/Subtropical Steppe	11	6088.12	553.465	18145.3
Warm Continental	11	5780.03	525.457	5206.6

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	2559997.52	10	256000	27.7619	1E-25	1.91783
Within Groups	1014339.01	110	9221.26			
Total	3574336.53	120				

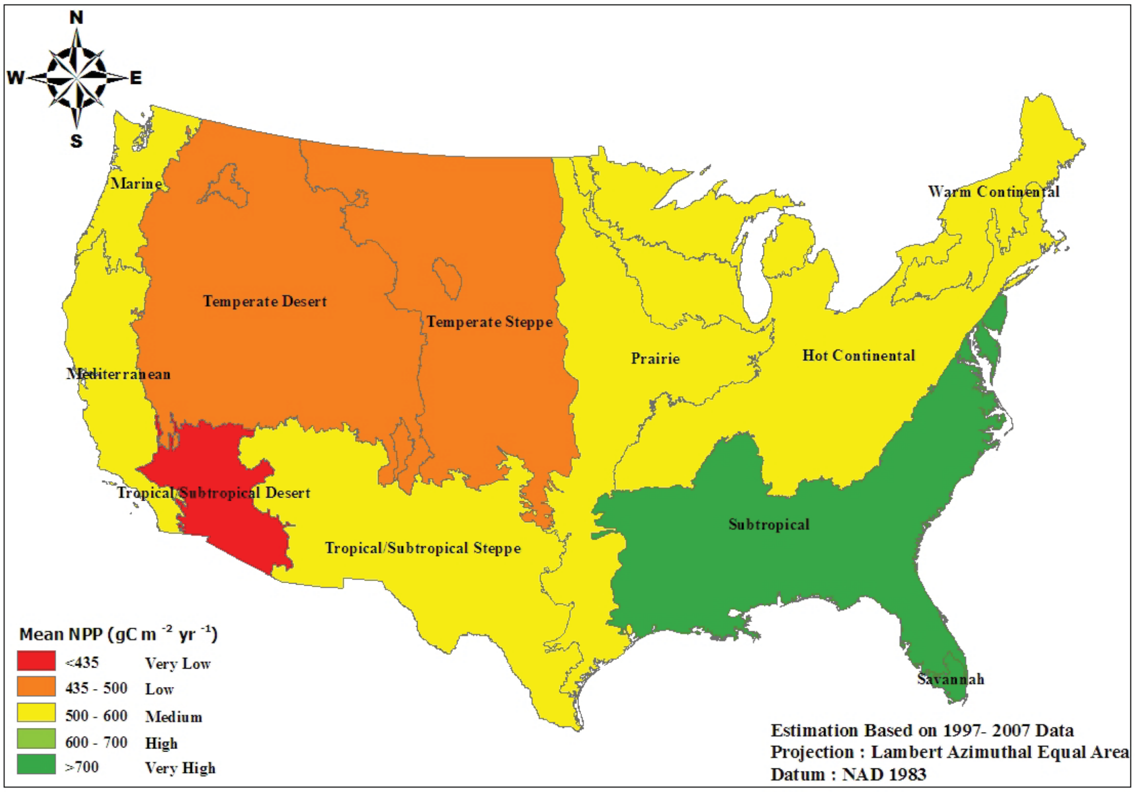


Figure 19 Mean Annual NPP (g C m^{-2} yr^{-1}) in Different Eco-Divisions

5.2.3 Spatial Variation of NPP in Different EPA Regions

Spatial variation of NPP was examined for different EPA regions of US (Figure 20). Southeast region was estimated to have the highest annual NPP on a unit area basis and Rocky Mountain the least. It was followed by Mid Atlantic and South Central. Pronounced drought and short humid season with sagebrush and shrub lands vegetation types could be the reasons for the lowest mean annual NPP per square meter in Rocky Mountain. However, based on the total area covered by different regions, South Central typically contributed about 21%, Southeast about 18% and Rocky Mountain 16% of the nation's total NPP. Table 12 shows the estimated annual mean NPP per unit area from

1997 to 2007 in EPA regions. Total annual NPP in EPA regions during 11 years period is tabulated in Annex C.

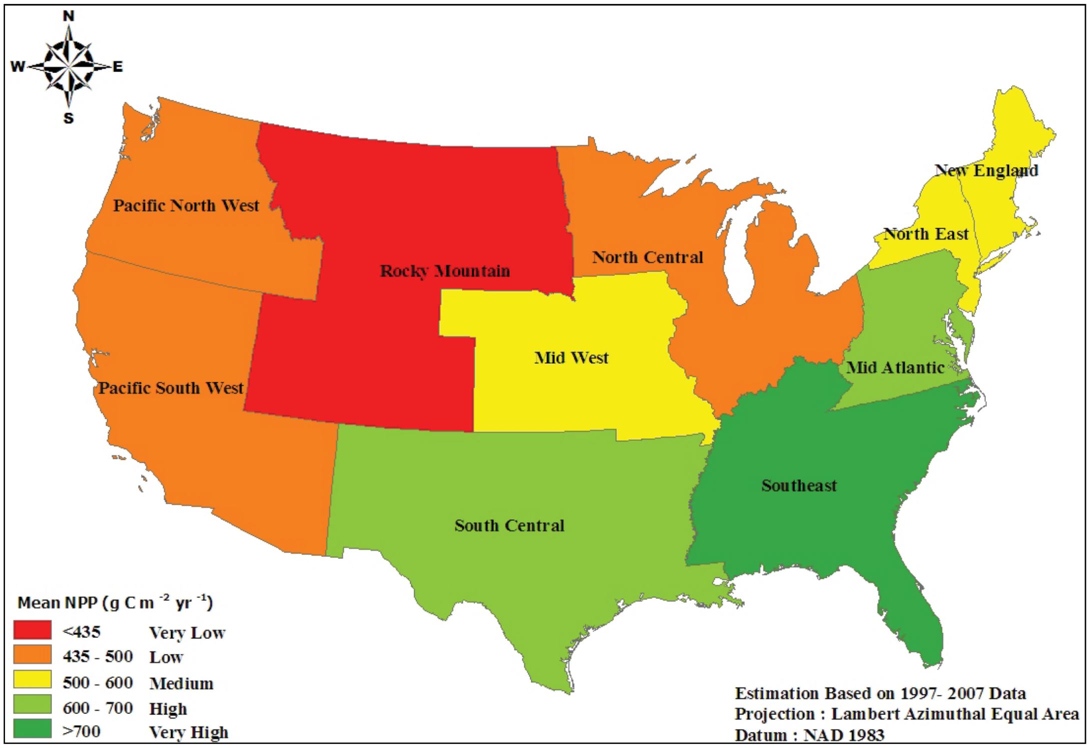


Figure 20 Mean Annual NPP (g C m^{-2} yr^{-1}) in Different EPA Regions

Table 12 Mean Annual NPP (g C m^{-2} yr^{-1}) in Different EPA Regions of the Conterminous US from 1997 to 2007

#	US Regions	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean
1	New England	519	533	478	327	506	615	509	672	609	523	564	532
2	North East	580	615	477	414	558	630	551	694	624	538	560	567
3	Mid Atlantic	634	652	564	485	619	608	575	757	636	667	604	**618**
4	Southeast	793	767	745	608	686	711	786	898	856	889	778	**774**
5	North Central	497	543	435	423	447	513	479	586	550	507	503	498
6	South Central	719	624	655	485	501	448	539	733	703	613	693	**610**
7	Mid West	561	589	509	458	501	388	486	651	620	505	515	526
8	Rocky Mountain	527	519	494	402	348	303	362	456	539	400	439	435
9	Pacific South West	547	656	507	473	348	275	353	457	626	444	409	463
10	Pacific North West	551	498	420	438	397	453	399	532	542	474	507	474

*U.S. Environmental Protection Agency regions: **1**, Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island,Vermont; **2**, New Jersey, New York; **3**, Delaware, Maryland, Pennsylvania,Virginia,West Virginia, District of Columbia; **4**,Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Tennessee;**5**, Illinois, Indiana, Michigan, Minnesota, Ohio,Wisconsin; **6**,Arkansas, Louisiana, New Mexico, Oklahoma,Texas; **7**, Iowa, Kansas, Missouri, Nebraska; **8**, Colorado, Montana, North Dakota, South Dakota, Utah,Wyoming; **9**,Arizona, California,Nevada; **10**, Idaho, Oregon,Washington.

5.2.4 Spatial Autocorrelation of NPP: The Hot Spot Analysis

Figure 21 shows the clusters of low and high NPP in different parts of US as the result of hot spot analysis based on Getis-Ord Gi* statistics based on mean annual NPP of 48 different states. Cluster of high NPP (NPP hotspots) was found in the southeastern part of USA which is shown in the red and orange color whereas cluster of low NPP (NPP cold spot) was found to exist in the western and northern parts of USA, as shown in the blue and light blue color. States with white color showed the insignificant spatial autocorrelation. States such as, Louisiana, Arkansas and Virginia have lower z scores as compared to Mississippi, Alabama, Tennessee, Florida, South Carolina, North Carolina and Georgia but are still the hot spots of higher NPP. Based on this analysis, the second null hypothesis that the southeastern states contribute significantly to the higher NPP than other regions was accepted.

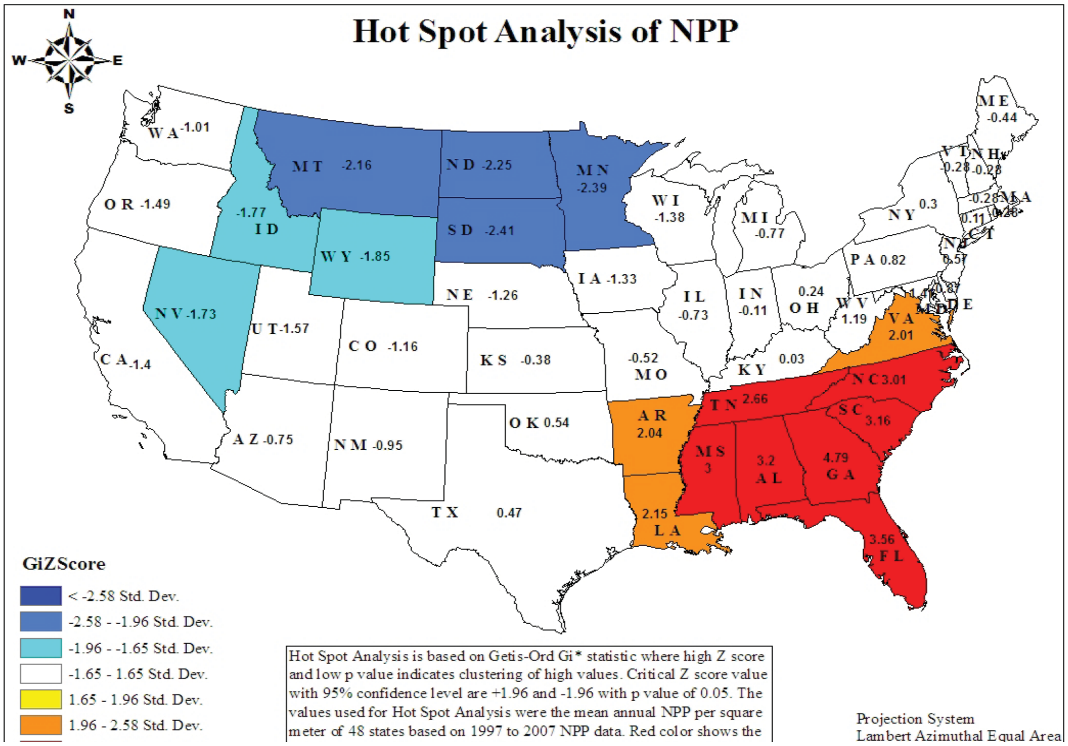


Figure 21 Hot Spot Analysis (Getis - Ord GI*) Based on Mean Annual NPP for 48 States of US

5.2.5 Seasonal Trends of NPP in the Conterminous US

The mean monthly variation in NPP in Conterminous US is represented through the box plot (also known as box and whisker diagram or plot) in the figure 22. This analysis was based on the average of 11 years monthly estimated NPP. Mean monthly NPP in the Conterminous US followed a bell shaped curve with lower NPP at the beginning and the end of the year and higher in the middle of the year (Figure 22). In general, it can be concluded that NPP starts increasing slowly from the month of January and reaches the maximum value in the month of June. Again it starts decreasing from the month of July till December. However, there could be variation in these seasonal trends depending upon the different parts of the contiguous US and their climatic, physiographic factors and vegetation types.

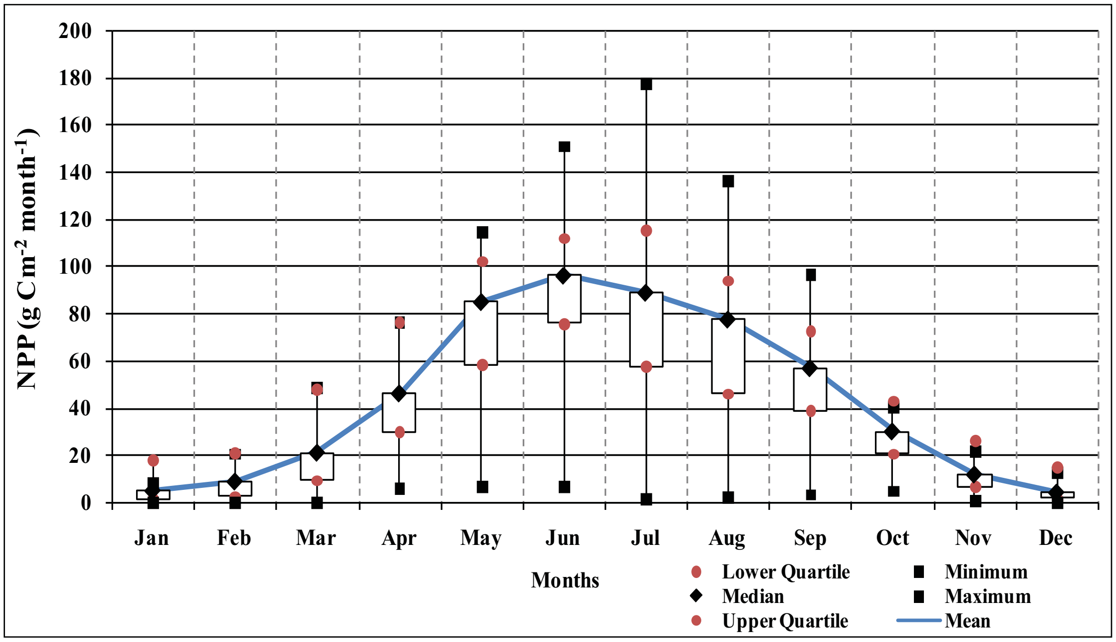


Figure 22 Seasonal Trend of NPP (g C m^{-2} $month^{-1}$) in the Conterminous US

Figure 23 shows the spatial and temporal variations of NPP in different parts of US. It shows that the most parts of the Conterminous US experience low NPP in the months of January, February and December (during winter). Southern parts of US start to gain NPP noticeably from March (beginning of spring). NPP reaches maximum in almost every location during the month of June and it again slows down from the month of July.

The southwestern part of US gain NPP slowly from the months of December and experience higher NPP in the months of April and May (Figure 23). This could be due to the lower temperature in these areas compared to other months. The other parts of US start gaining NPP slowly from March and attain the peak during the months of June.

Southeastern parts of US were observed to have longer growing seasons as compared to western and northern parts. Variation in climate especially temperature, precipitation and the drought could be the major driving variables for the variation in NPP. This study thus, has examined the relation of NPP with these different climatic factors in the later sections.

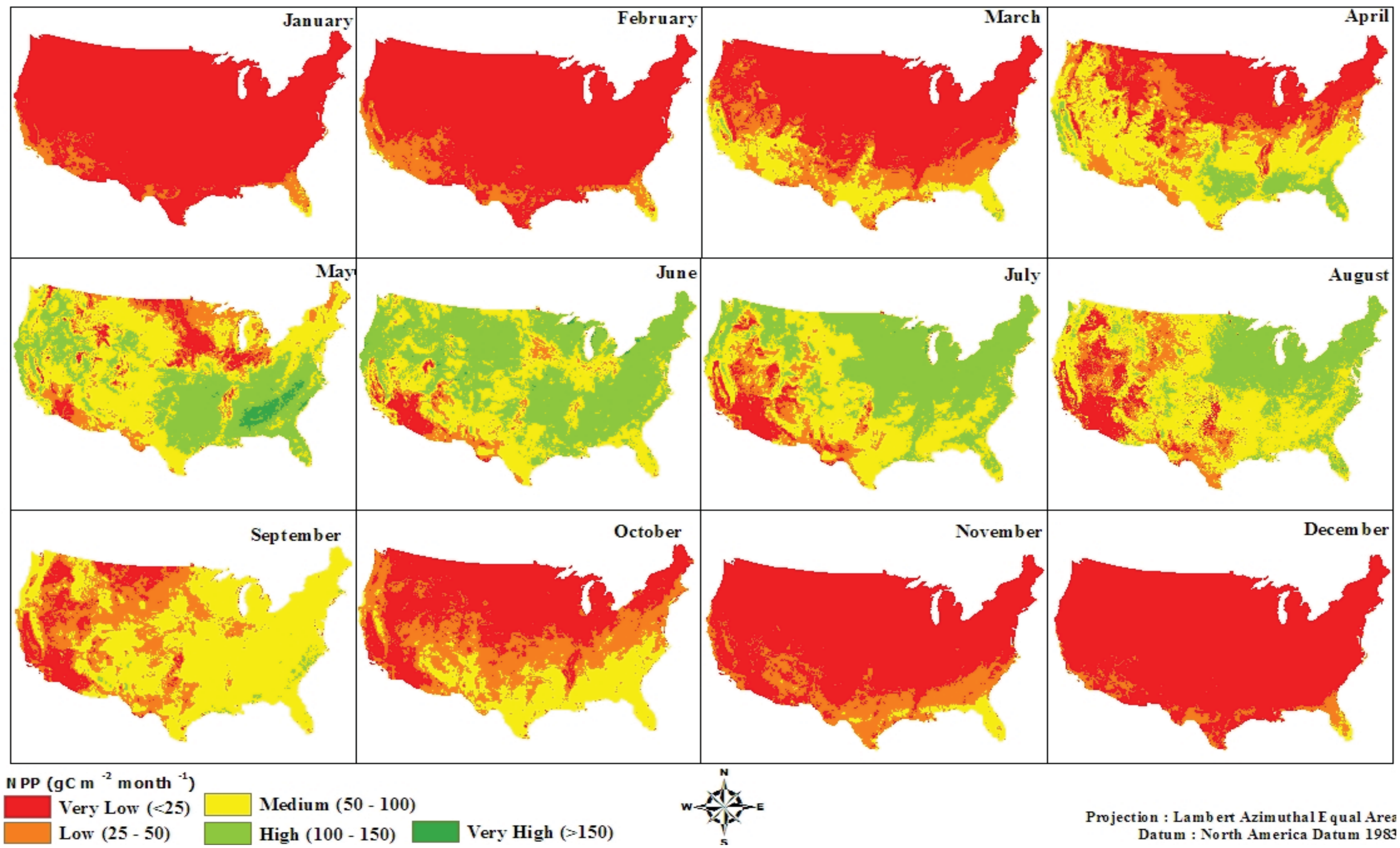


Figure 23 Temporal and Spatial Variation of Monthly NPP (g C m^{-2} $month^{-1}$) in the Conterminous US for the Period of 1997 to 2007

5.2.6 Seasonal Trend of NPP in Different Eco-Divisions

NPP was found to vary spatially and seasonally which can be visualized through figure 24. Figure 24 shows the variation in monthly NPP based on 11 years NPP data in 11 different eco-divisions. NPP in different eco-divisions were found to have trends different than the general trend (Figure 22). NPP in Savannah and Tropical /Subtropical desert shows bimodal nature with higher NPP in the months of May and July (Savannah) and April and November (Tropical/Subtropical Desert). NPP reaches maximum in the month of May in Subtropical and in Mediterranean, in July in Hot Continental, Warm Continental, Prairie and Marine, in June in Temperate Steppe and Temperate Desert and in April in Tropical/Subtropical Desert. Unlike other eco-divisions, Savannah faces less fluctuation in NPP throughout the year. It is also observed that Warm Continental experiences higher NPP for fewer months compared to other eco-divisions while tropical/Subtropical experiences lower NPP throughout the year.

Different climatic variables such as temperature, precipitation and photosynthetically active radiation, and drought could be the reasons for the variability of NPP in these eco-divisions.

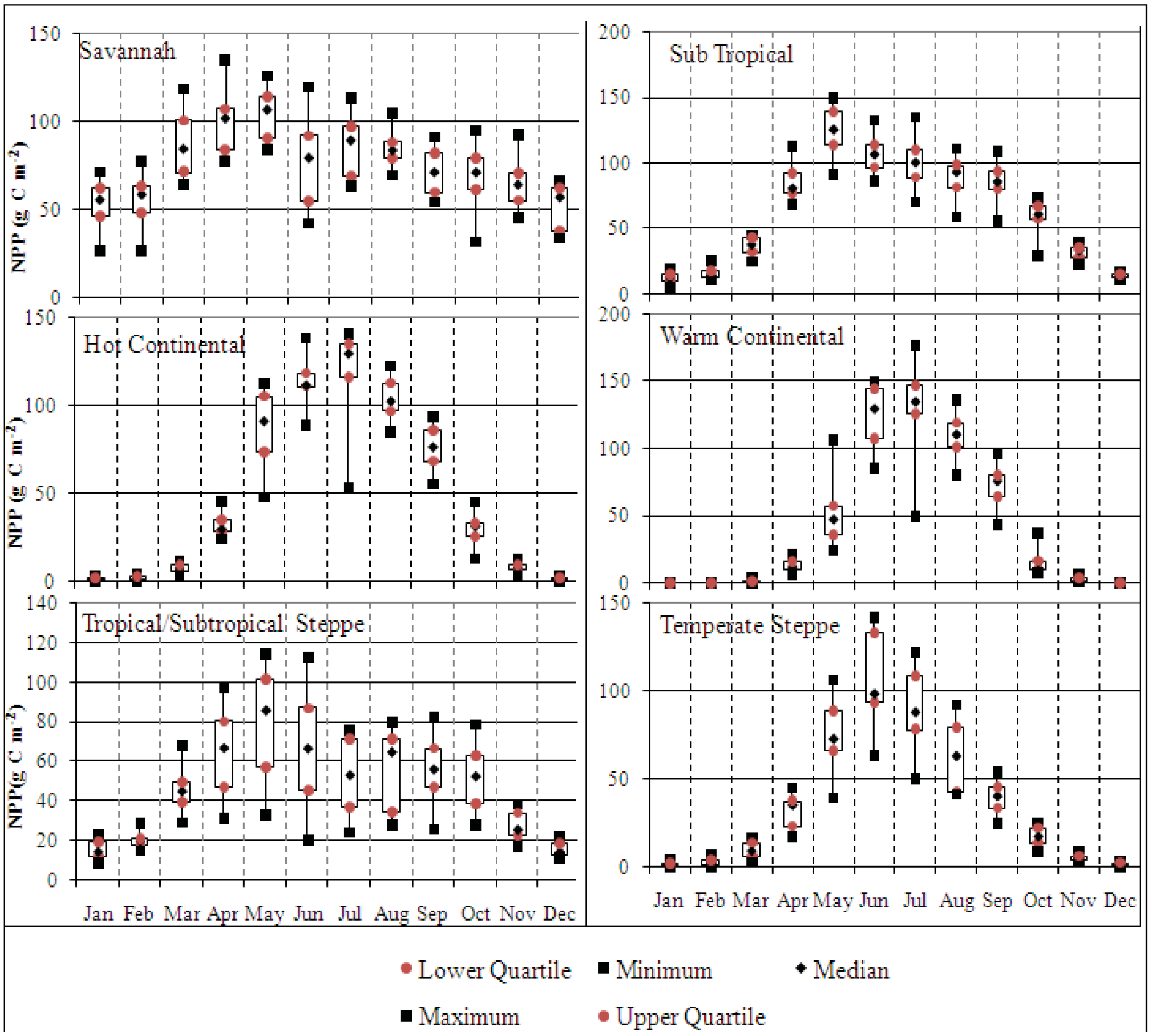


Figure 24 Seasonal Trend of NPP in Different Eco-Divisions

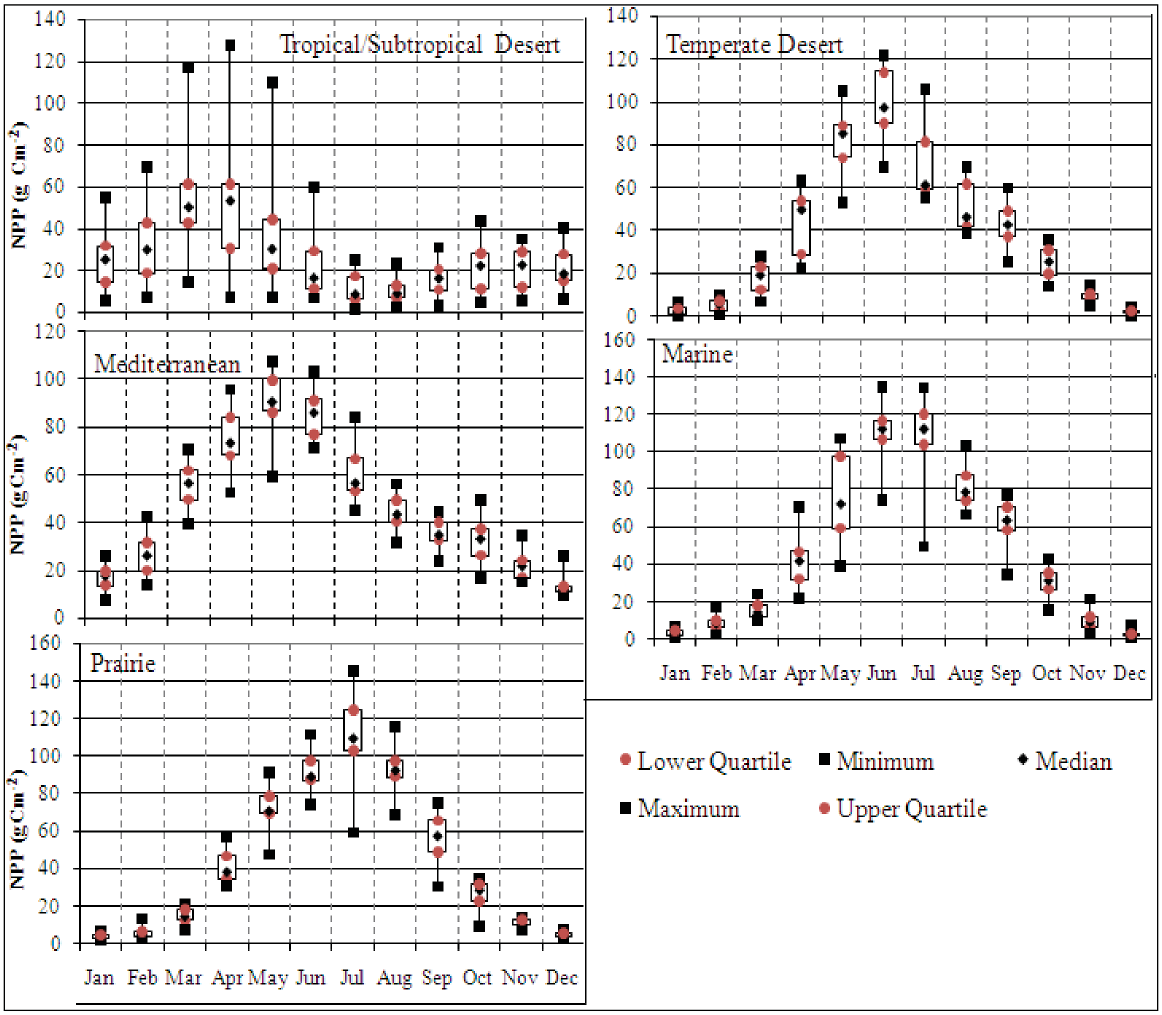


Figure 24 (Continued)

Figure 25 shows the temporal trend of NPP in different eco-divisions of US. All the eco-divisions were found to have the least NPP in the months of December and January. It is found to increase slowly from the month of February and reach maximum in the month of June and again starts declining from July. Tropical/Subtropical Desert experiences lower NPP fluxes throughout the year except the slight increase in the months of February, March and April whereas Savannah experiences higher NPP compared to other eco-divisions throughout the year.

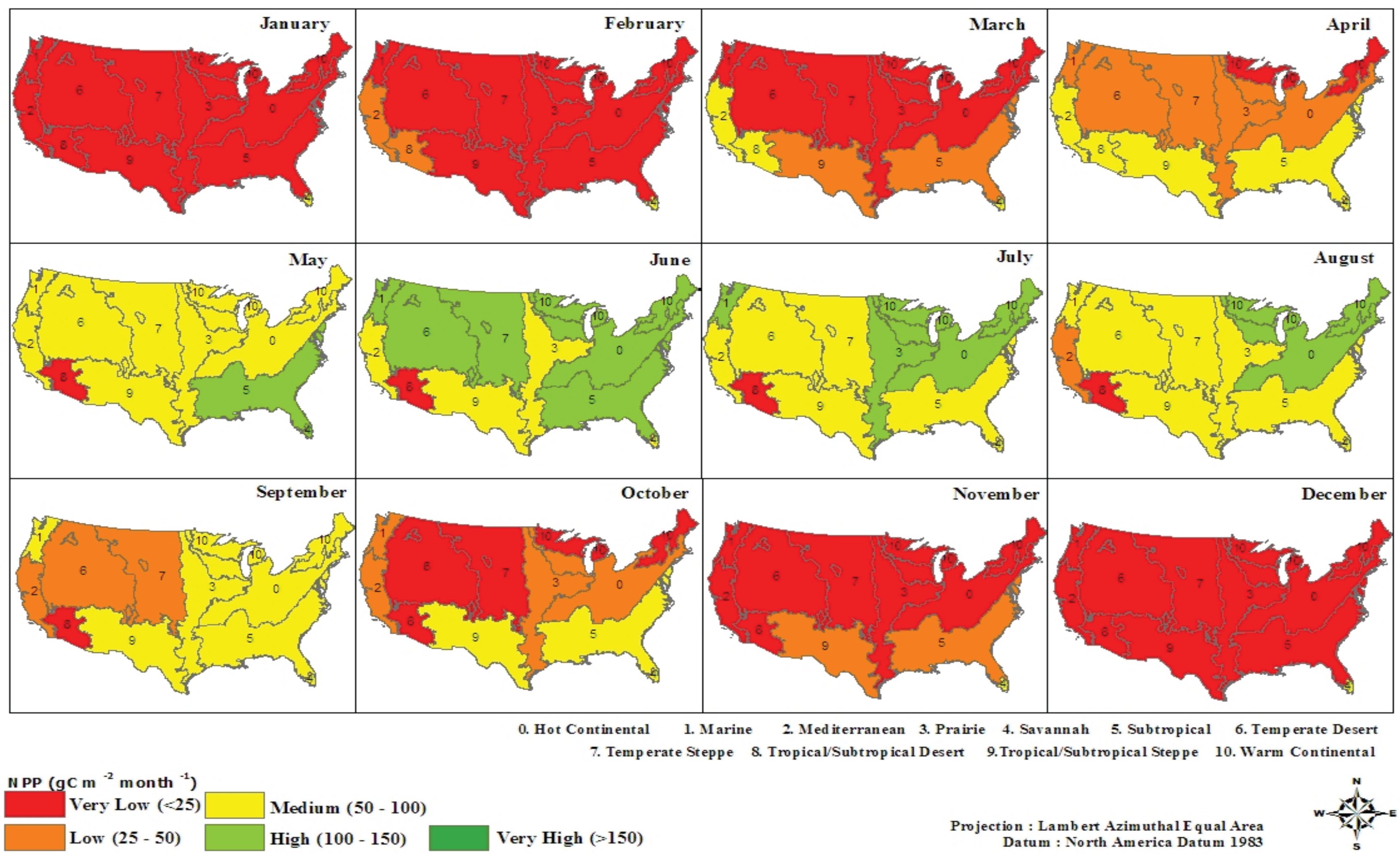


Figure 25 Temporal Trend of NPP in Different Eco-Divisions for the Period of 1997 to 2007

5.3 Objective 3: Analyze the relation of NPP with Climatic and Bio-physical Factors

Figure 26 depicts the general patterns of NDVI and climatic factors such as, precipitation, temperature, evapotranspiration and PAR nationally so as to see their relationship with NPP. NPP, NDVI and evapotranspiration were found to have very similar trends during these 11 years period. Upon examinations of climatic conditions in NCDC-NOAA, severe drought had been observed during those years. So, loss of NPP during 2000 to 2003 compared to mean annual NPP might be related to adverse climatic conditions such as drought and evapotranspiration during these years.

The result of this study supports the traditional knowledge on the relationship between the vegetation growth and CO_2 .As vegetation growth increases, more CO_2 will be assimilated from the atmosphere and the decrease in atmospheric CO_2 will be relatively larger (Keeling et al., 1996, Lim et al., 2004). NDVI, temperature, precipitation and photosynthetically active radiation were used linearly in CASA model to estimate NPP throughout the contiguous US. The equations used in the model are however not specific to particular locations and climatic conditions though the effects of climatic variables to NPP vary both linearly and non-linearly in different locations. So, the effects of these climatic variables in NPP in different spatial locations were analyzed using correlation coefficients.

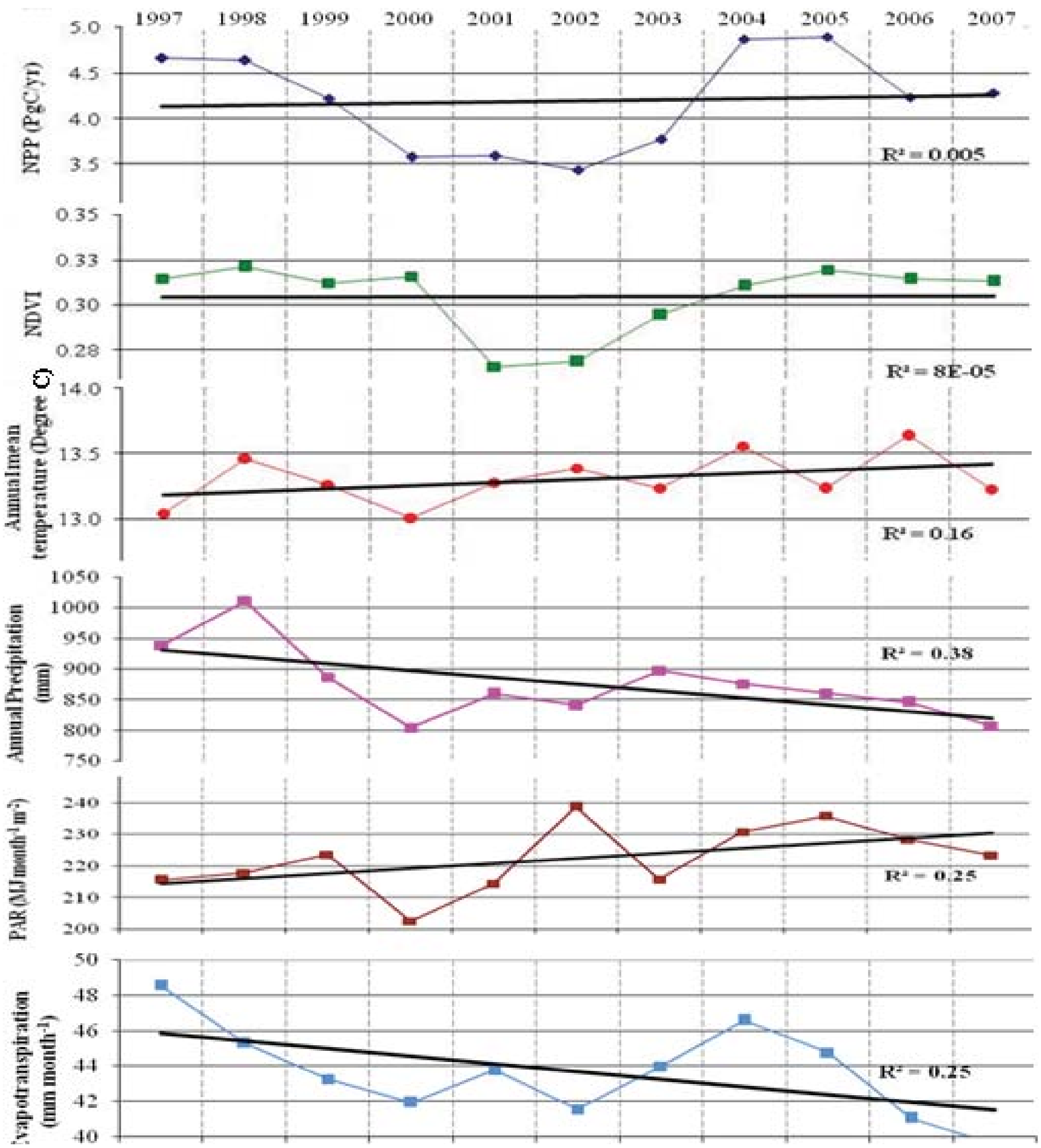


Figure 26 Annual Trends of NPP and Different Climatic Factors in the Conterminous US

Table 13 shows the correlation coefficients of NPP, temperature, precipitation, PAR and AET based on monthly mean data for the Conterminous US for the entire study period. It is found that in general, precipitation, PAR, NDVI and AET have positive correlation with the NPP without considering the temporal and spatial effects. Amongst all driving variables, NDVI and AET have higher correlation with the NPP. Rosenzweig (1968) found high correlation of NPP with evapotranspiration in different types of eco systems.

Table 13 Correlation of NPP with Climatic and Bio-physical Parameters

Driving Variables	**R Significant at P<0.005**
NDVI	0.87
Temperature	0.80
Precipitation	0.48
PAR	0.24
AET	0.93

Correlation coefficients were further examined within each eco-divisions of the Conterminous US (Table 14) based on the monthly mean for the entire study period. Significant correlation were found between NPP, NDVI, temperature, precipitation, PAR and AET. It has been noticed that in general, NDVI and PAR have significant positive impact on NPP in all eco-divisions. However, the correlation of temperature and precipitation with NPP in different eco-divisions was positive in some cases and negative in others. Except for Tropical/Subtropical Desert, NPP showed significant positive correlation with temperature in all eco-divisions. Marine and Mediterranean showed significant negative correlation of precipitation with the NPP while other eco-divisions showed positive correlation.

Table 14 Pearson's r Correlation Coefficients between NPP, NDVI, temperature, precipitation, PAR and AET by Eco-Divisions

Eco Divisions		**NDVI**	**TEMP**	**PPT**	**PAR**	**AET**
Hot Continental	***r***	0.916	0.909	0.468	0.880	0.954
	p	0.000	0.000	0.000	0.000	0.004
Marine	***r***	0.826	0.884	**-0.721**	0.913	0.877
	p	0.000	0.000	0.000	0.000	0.000
Mediterranean	***r***	0.666	0.480	**-0.478**	0.809	0.757
	p	0.000	0.000	0.007	0.000	0.000
Prairie	***r***	0.928	0.896	0.573	0.907	0.940
	p	0.000	0.000	0.000	0.000	0.000
Savannah	***r***	0.510	0.339	0.113	0.710	0.306
	p	0.000	0.000	0.000	0.000	0.000
Subtropical	***r***	0.847	0.850	0.078	0.923	**0.851**
	p	0.000	0.000	0.000	0.000	**0.116**
Temperate Desert	***r***	0.852	0.779	**-0.146**	0.859	0.938
	p	0.000	0.000	**0.373**	0.000	0.000
Temperate Steppe	***r***	0.906	0.808	**0.801**	0.844	**0.951**
	p	0.000	0.000	**0.247**	0.000	**0.082**
Tropical Subtropical Desert	***r***	0.783	**-0.301**	0.157	0.027	0.359
	p	0.000	0.001	0.000	0.000	0.000
Tropical Subtropical Steppe	***r***	0.728	0.598	0.439	0.707	0.723
	p	0.000	0.000	0.000	0.000	0.000
Warm Continental	***r***	0.904	0.863	0.509	0.760	**0.932**
	p	0.000	0.000	0.000	0.000	**0.493**

** Non significant correlations with p values >0.01 are bold faced with shaded gray.
Negative correlations are in red color and bold faced

The correlation between climatic variables and NPP were further examined considering temporal variations within each eco-divisions. Tables 15, 16, 17, 18 and 19 show the relationship of NPP with different driving variables in different eco divions for different months of a year based on the 500 random points generated from monthly data within the different eco-divisions.

Table 15 Correlation of NPP with NDVI in Various Eco-Divisions for Different Months of a Year

Eco divisions	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Hot Continental	0.56	0.84	0.76	0.64	0.74	0.88	0.98	0.68	0.88	0.85	0.47	0.40
Marine	0.91	0.90	0.78	0.90	0.95	0.79	0.82	0.65	0.79	0.83	0.47	0.95
Mediterranean	0.84	0.95	0.83	0.81	0.87	0.63	0.85	0.87	0.71	0.41	0.31	0.64
Prairie	0.56	0.73	0.90	0.75	0.67	0.71	0.94	0.70	0.93	0.91	0.28	0.43
Savannah	0.77	0.85	0.88	0.73	0.74	0.96	0.95	0.83	0.97	0.95	0.43	0.74
Subtropical	0.84	0.71	0.79	0.69	0.93	0.84	0.90	0.71	0.91	0.96	0.34	0.26
Temperate Desert	0.87	0.91	0.93	0.64	0.79	0.90	0.87	0.89	0.92	0.80	0.30	0.74
Temperate Steppe	0.54	0.82	0.87	0.64	0.60	0.94	0.88	0.95	0.90	0.90	0.38	0.51
Tropical /Subtropical Desert	0.91	0.97	0.93	0.82	0.94	0.94	0.90	0.92	0.94	0.85	0.74	0.53
Temperate /Subtropical Steppe	0.73	0.84	0.89	0.69	0.95	0.96	0.92	0.95	0.90	0.79	0.23	0.50
Warm Continental	0.48	0.74	0.81	0.85	0.75	0.64	0.89	0.75	0.92	0.73	0.83	0.67

Table 15 shows the close relationship of NPP with NDVI in all eco-divisions throughout the year. NPP closely follows the trend as the NDVI does (Figure 28). It thus reflects the significance of NDVI for carbon related studies. Based on this analysis, the third null hypothesis that the area with higher vegetation cover will have a higher NPP was accepted.

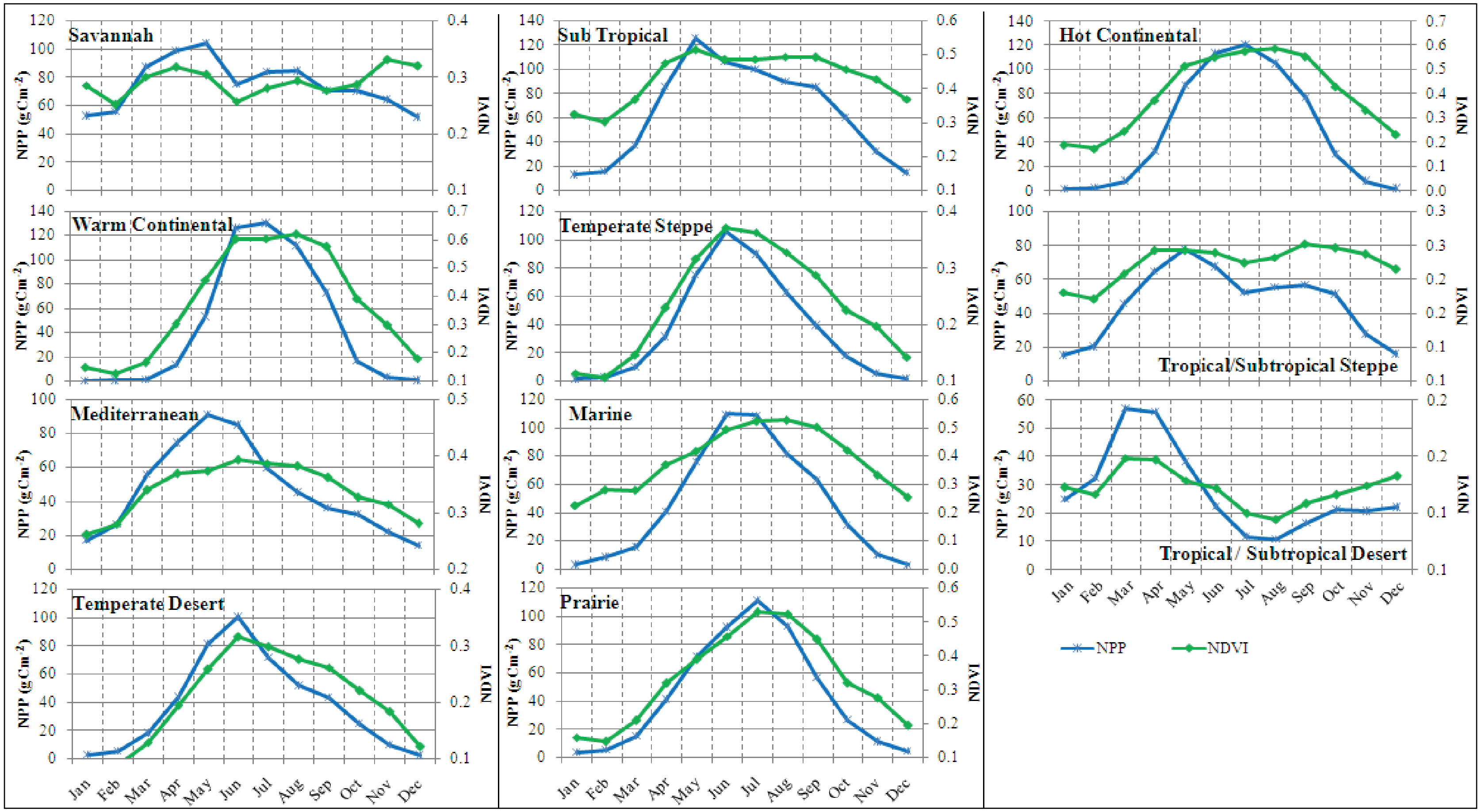


Figure 27 Mean Monthly NPP and NDVI in Various Eco-Divisions for Different Months of a Year

Table 16 verifies the fact that the temperature can have both the positive and negative relationship with the NPP. Increase of temperature during the months of December, January, February, March, April and November usually have positive impact on NPP i.e. higher the temperature higher the NPP in all eco-divisions except for Tropical/Subtropical Desert and Savannah. However, temperature in the months of June, July, August and September has negative correlation with NPP except in June for Marine and in August for Warm Continental. Tropical/Subtropical Desert was found to have negative correlation with temperature throughout the year.

Table 16 Correlation of NPP with Temperature in Various Eco-Divisions for Different Months of a Year

Eco divisions	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Hot Continental	0.58	0.53	0.65	0.65	0.45	0.07	**-0.36**	**-0.35**	0.03	0.49	0.56	0.54
Marine	0.50	0.55	0.50	0.51	0.53	0.38	-0.09	**-0.29**	-0.10	0.16	0.30	0.42
Mediterranean	0.50	0.57	0.61	0.42	-0.02	**-0.55**	**-0.50**	**-0.51**	**-0.54**	**-0.30**	0.13	0.48
Prairie	0.69	0.66	0.71	0.74	0.59	0.11	**-0.64**	**-0.67**	0.07	0.68	0.75	0.69
Savannah	0.28	-0.05	-0.21	-0.19	-0.08	0.23	-0.05	-0.14	-0.17	-0.06	0.34	-0.04
Subtropical	0.70	0.66	0.65	0.34	-0.17	-0.19	**-0.26**	**-0.36**	-0.17	0.32	0.68	0.67
Temperate Desert	0.42	0.50	0.51	0.50	0.27	**-0.38**	**-0.65**	**-0.66**	**-0.42**	0.05	0.40	0.36
Temperate Steppe	0.46	0.51	0.56	0.48	0.25	**-0.27**	**-0.36**	-0.11	0.21	0.43	0.55	0.48
Tropical /Subtropical Desert	0.02	0.03	**-0.18**	**-0.34**	**-0.57**	**-0.59**	**-0.48**	**-0.45**	**-0.45**	**-0.38**	**-0.35**	0.09
Temperate /Subtropical Steppe	0.29	0.21	0.14	0.05	-0.18	**-0.33**	**-0.32**	**-0.38**	**-0.34**	0.01	0.13	0.33
Warm Continental	0.38	0.43	0.64	0.35	0.54	0.18	**0.06**	**0.14**	0.51	0.70	0.60	0.00

Figure 29 shows the trends of mean NPP and mean temperature in different eco-divisions for different months. It shows the significant negative correlation of NPP with temperature in Tropical/Subtropical Desert for the months of June, July and August.

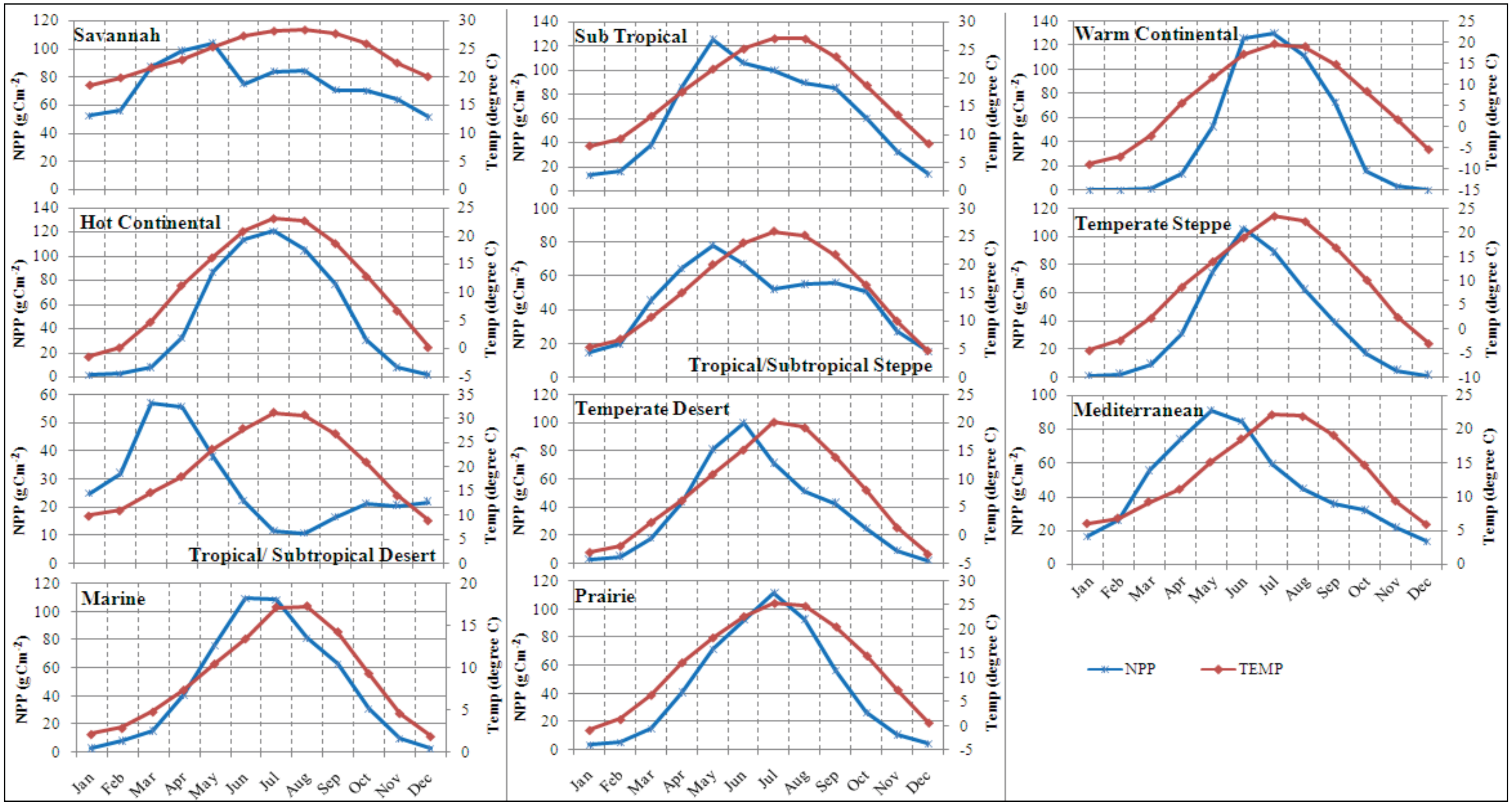


Figure 28 Mean Monthly NPP and Temperature in Various Eco-Divisions for Different Months in a Year

Table 17 Correlation of NPP with Precipitation in Various Eco-Divisions for Different Months of a Year

Eco divisions	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Hot Continental	0.34	0.16	0.27	0.18	0.05	-0.06	0.19	0.34	0.29	0.11	0.22	0.21
Marine	-0.07	**-0.23**	**-0.21**	**-0.20**	**-0.43**	**-0.20**	0.19	0.49	0.38	-0.15	**-0.33**	-0.04
Mediterranean	**-0.22**	**-0.29**	**-0.31**	**-0.27**	-0.05	0.42	0.31	0.41	0.55	**0.47**	-0.14	-0.10
Prairie	0.29	0.15	0.31	-0.12	0.09	0.19	0.41	0.46	0.37	0.35	0.37	0.23
Savannah	0.33	0.15	0.22	0.27	-0.11	**-0.27**	-0.10	-0.06	-0.10	**-0.24**	0.20	0.08
Subtropical	-0.14	-0.18	**-0.21**	-0.08	-0.07	-0.08	0.18	0.36	0.13	0.17	-0.06	-0.17
Temperate Desert	-0.13	-0.17	**-0.28**	**-0.33**	-0.16	0.24	0.48	0.59	0.59	0.11	**-0.27**	-0.17
Temperate Steppe	0.09	0.05	0.29	0.08	0.02	0.21	0.49	0.51	0.46	0.28	0.18	0.18
Tropical /Subtropical Desert	0.33	0.28	0.35	0.23	0.51	0.21	0.38	0.46	0.43	0.29	0.39	0.34
Temperate /Subtropical Steppe	-0.01	0.01	0.07	0.25	0.47	0.41	0.38	0.51	0.54	0.26	0.26	-0.02
Warm Continental	0.28	0.17	0.14	-0.06	0.05	-0.17	-0.19	0.28	0.23	0.02	0.17	0.07

Table 17 showed a positive correlation between NPP and precipitation in the months of July, August and September in almost all the eco-regions, except Savannah. Precipitation in Marine, Mediterranean, Subtropical and Temperate Desert was found to have negative impact on NPP in the months of January, February, March and April, Warm Continental in July andMarine in October. It is quite interesting to observe NPP in Tropical/Subtropical Desert having positive correlation with precipitation during all the months of a year while NPP in the Tropical/Subtropical Steppe also having positive correlation with precipitation throughout the year expect, for the months of January and December. Figure 30 showed the strong negative correlation of NPP with the precipitation for Marine and Mediterranean during the months of January, February, March, April, May, Novemeber and Decemeber.

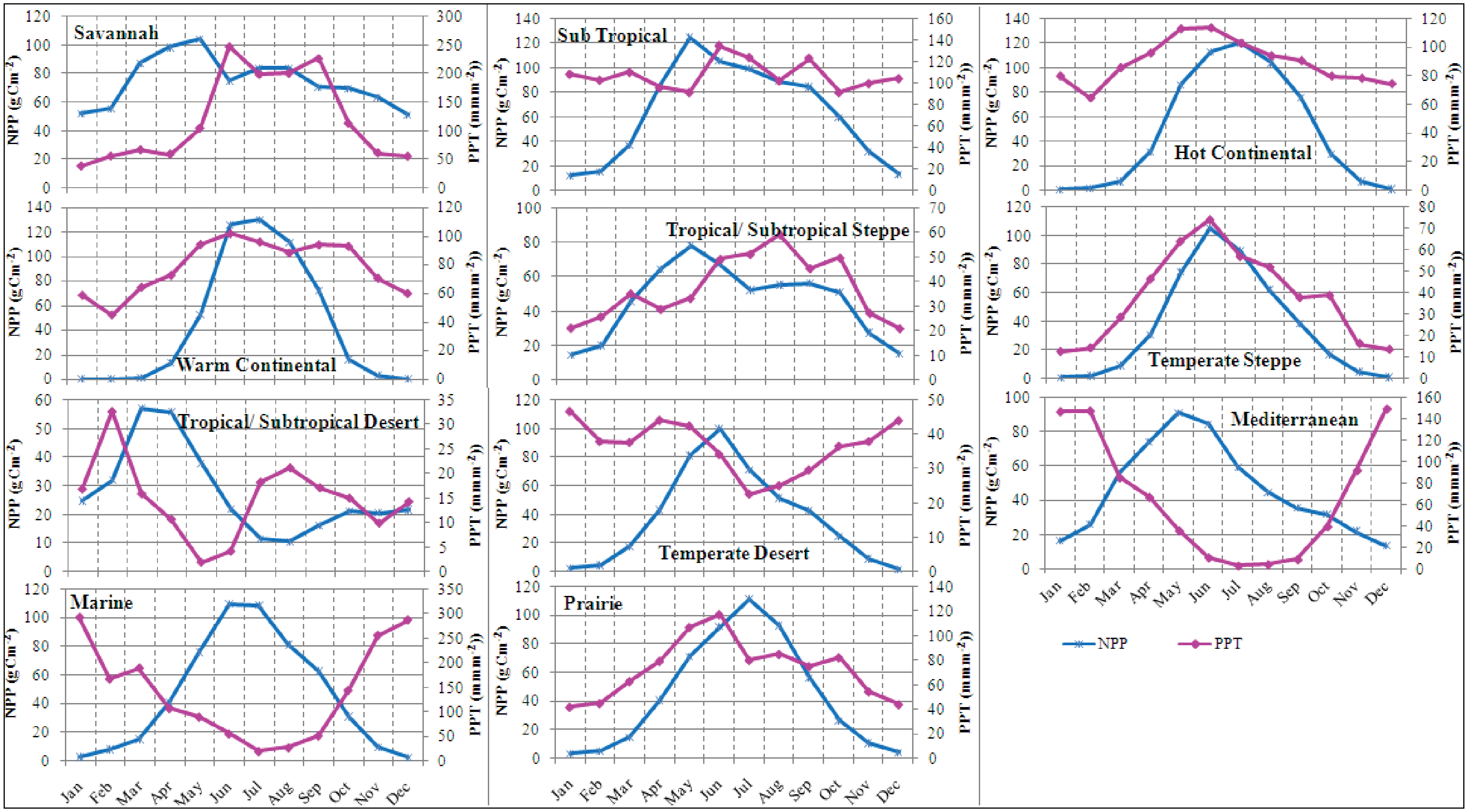


Figure 29 Mean Monthly NPP and Precipitation in Various Eco-Divisions for Different Months of a Year

Table 18 Correlation of NPP with PAR in Various Eco-Divisions for Different Months of a Year

Eco divisions	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Hot Continental	0.38	0.16	0.09	0.22	0.33	0.33	0.18	0.00	0.22	0.49	0.56	0.42
Marine	0.10	0.26	0.05	0.12	0.29	0.31	0.10	-0.10	0.09	0.53	0.56	0.19
Mediterranean	0.41	0.34	0.17	0.16	0.14	-0.24	0.03	-0.18	-0.26	-0.09	0.42	0.40
Prairie	0.53	0.34	0.28	0.39	0.32	0.13	-0.15	-0.34	0.17	0.72	0.68	0.66
Savannah	0.24	0.16	0.14	0.08	0.23	0.49	0.15	-0.02	0.04	0.30	0.38	0.30
Subtropical	0.66	0.52	0.61	0.43	0.30	0.26	0.01	-0.13	0.18	0.30	0.70	0.57
Temperate Desert	0.17	0.13	0.10	0.11	0.06	0.01	-0.04	-0.28	-0.03	0.43	0.25	0.22
Temperate Steppe	0.33	0.26	0.21	0.26	0.16	0.06	-0.12	0.08	0.36	0.56	0.41	0.38
Tropical /Subtropical Desert	0.04	-0.02	-0.06	0.14	-0.03	0.02	-0.11	-0.30	-0.24	0.15	-0.21	0.16
Temperate /Subtropical Steppe	0.23	0.10	0.07	-0.03	-0.17	-0.13	-0.10	-0.10	-0.25	0.25	0.10	0.31
Warm Continental	0.24	-0.01	-0.25	0.11	0.21	0.55	0.54	0.47	0.60	0.46	0.12	0.12

Table 18 shows that the NPP has a positive correlation with PAR in the months of January, February, October, November and December in almost all the eco-divisions, except for Tropical/Subtropical Desert (in February and November), Warm Continental (in February) and Mediterranean (in October). It is also quite interesting to see that NPP in Tropical/Subtropical Desert has negative correlation with PAR for the months of June, July, August and September. However, overall NPP is not highly correlated with PAR unlike NDVI, temperature and precipitation.

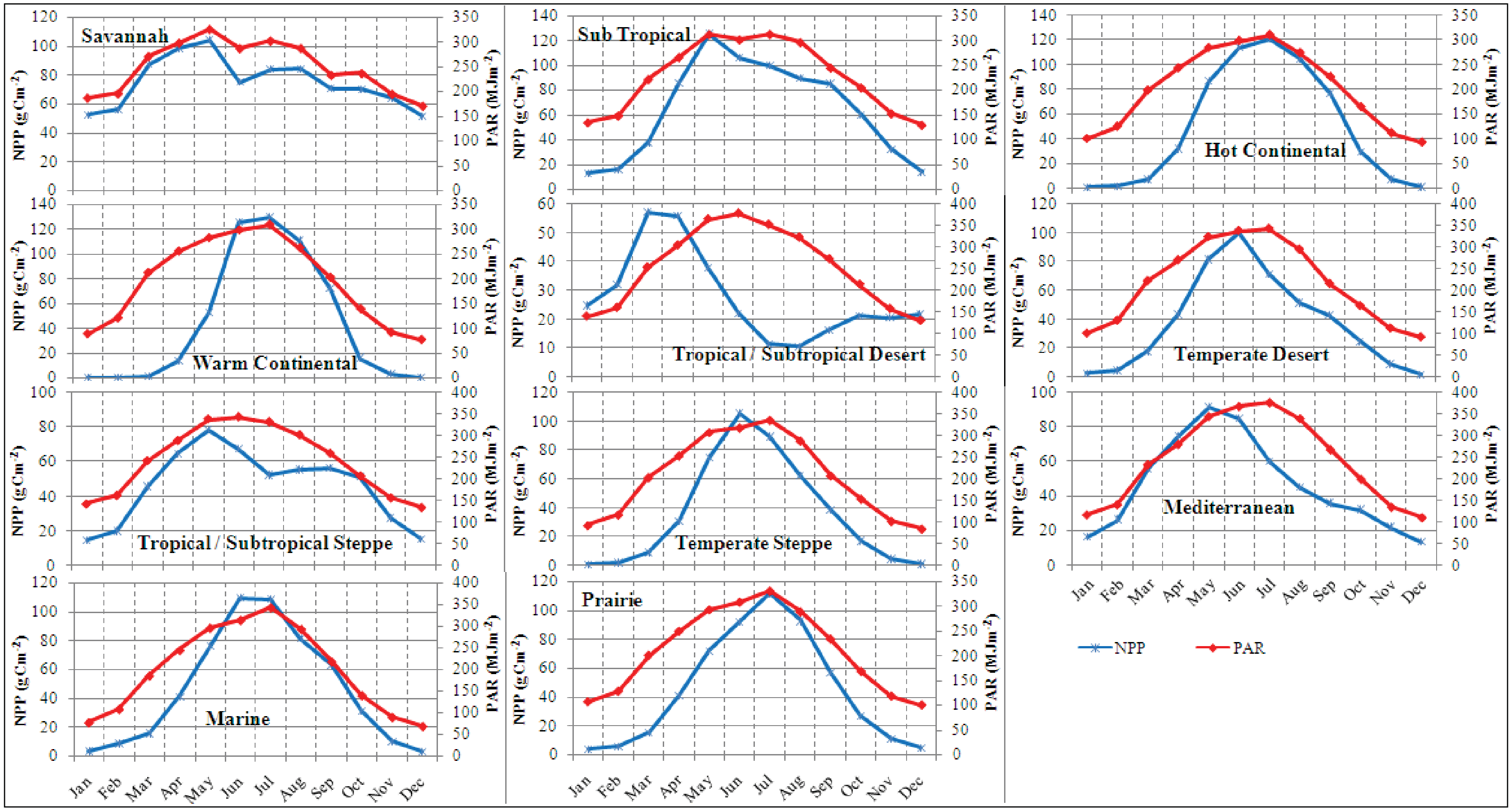


Figure 30 Mean Monthly NPP and PAR in Various Eco-Divisions for Different Months of a Year

Table 19 Correlation of NPP with AET in Various Eco-Divisions for Different Months of a Year

Eco divisions	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Hot Continental	0.71	0.58	0.66	0.59	0.39	0.07	0.27	0.44	0.39	0.43	0.53	0.55
Marine	0.50	0.52	0.52	0.45	0.13	0.13	0.42	0.60	0.58	0.23	0.36	0.37
Mediterranean	0.50	0.55	0.59	0.50	0.33	0.67	0.68	0.63	0.63	0.53	0.37	0.52
Prairie	0.78	0.77	0.70	0.61	0.42	0.33	0.54	0.56	0.54	0.58	0.72	0.75
Savannah	0.39	0.23	0.04	0.33	0.06	0.07	0.00	-0.02	-0.18	-0.05	0.39	0.04
Subtropical	0.73	0.65	0.57	0.20	0.00	0.04	0.34	0.44	0.28	0.43	0.65	0.63
Temperate Desert	0.39	0.52	0.49	0.46	0.29	0.62	0.76	0.74	0.67	0.37	0.37	0.27
Temperate Steppe	0.52	0.65	0.60	0.42	0.40	0.38	0.61	0.62	0.53	0.46	0.51	0.55
Tropical /Subtropical Desert	0.54	0.49	0.58	0.68	0.64	0.53	0.43	0.48	0.43	0.27	0.38	0.45
Temperate /Subtropical Steppe	0.39	0.29	0.28	0.55	0.53	0.55	0.59	0.58	0.58	0.45	0.46	0.39
Warm Continental	0.45	0.49	0.74	0.36	0.54	0.15	0.12	0.41	0.51	0.70	0.58	0.60

Table 19 shows positive correlation between NPP and AET in almost all the eco-divisions, except for Savannah (negative correlation was found in the months of September, October, November and December) and Subtropical (no correlation was found in the months of May and June). AET thus, is the important rate limitating resource in the photosynthesis (Rosenzweig, 1968). Figure 32 shows the relation of mean monthly NPP and AET for different eco-divisions.

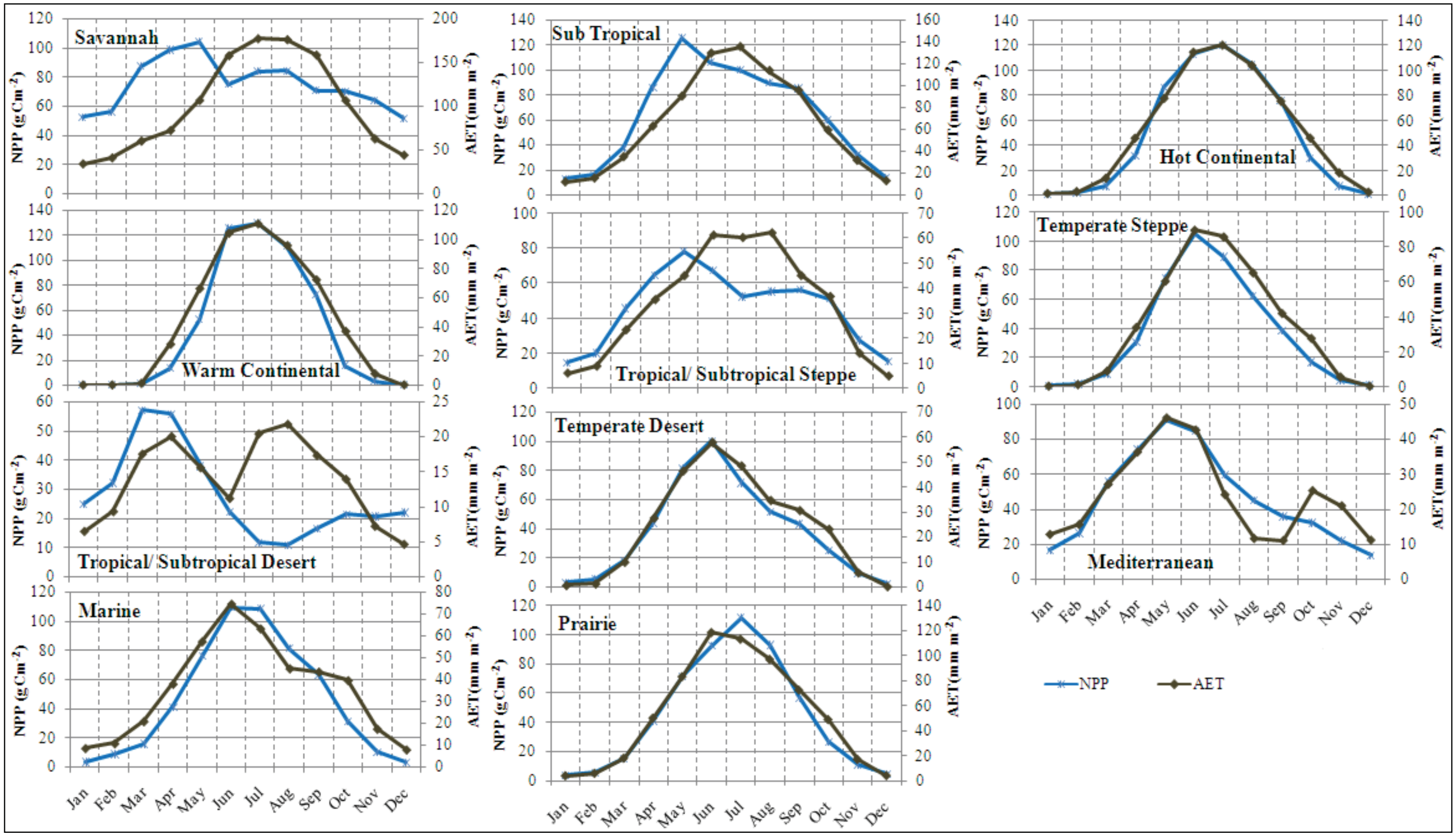


Figure 31 Mean Monthly NPP and Evapotranspiration in Various Eco-Divisions for Different Months of a Year

5.4 Mismatch of Estimated NPP with Previous Study

NPP is influenced by various eco-physiological and biophysical processes, some of which are very difficult to quantify, and are thus rarely measured (Clark et al. 2001a, b). Although the climatic variables are strong predictors of aboveground NPP patterns, the uncertainty remains usually high in large scale NPP prediction because of the lack of data that considers various biophysical and eco-physiological processes such as soil nutrient, soil respiration, biophysical parameters such as basal area, leaf area index etc. Similarly, the accuracy of the different vegetative models used in estimation of both above and belowground production is difficult to test precisely.

Though the estimated NPP was validated with BigFoot sites NPP data, the estimation is still uncertain. Use of land use land cover information, micro-climate, soil nutrient and biophysical parameters such as leaf area index may all add variability to the NPP estimation that is not represented by this model. This study computed FPAR using SR at pixel basis with an assumption that NDVI of each pixel reflects the characteristics of vegetation types unlike the previous model because of the lack of updated land use land cover information. This could add variability in the NPP estimation.

This study compared its estimated NPP for the year 1997 with the previous study conducted by Potter et al. 2006 which also used CASA model to estimated annual NPP fluxes for different EPA regions. Some differences were found between these studies though they used same model. Estimated NPP in this study closely matched with Potter et al (2006) estimation in most of the eco-divisions except for South Central, Rocky Mountain, Pacific Southeast and Pacific Northwest. The reasons for these anomalies are difficult to find out so, a comparison of the model parameter estimation procedures in each of these studies were revisited and explained below.

Table 20 Estimates from the NASA CASA Model for the NPP fluxes (1997) based on Potter et al. 2006

	U.S. Region[b]	*Land Area, 10^3 km^2*	*NPP (1997), Pg C yr^{-1}*
1	New England	193.9	0.12
2	Northeast	158.3	0.09
3	Mid-Atlantic	321.7	0.21
4	Southeast	1002.0	0.66
5	North central	885.6	0.47
6	South central	1487.9	0.61
7	Midwest	737.0	0.34
8	Rocky Mountain	1453.4	0.43
9	Pacific southwest	1009.6	0.21
10	Pacific Northwest	641.0	0.28
	Total	7890.5	3.42

Table 21 Estimates from the NASA – CASA model for NPP fluxes (1997) based on this study

	US Regions	**Land Area (10^3km^2)**	**NPP (1997) Pg C Yr^{-1}**
1	New England	168.9	0.09
2	North East	145.2	0.08
3	Mid Atlantic	314.1	0.20
4	Southeast	974.1	0.77
5	North Central	860.9	0.43
6	South Central	1437.3	1.03
7	Mid West	739.7	0.42
8	Rocky Mountain	1507.4	0.79
9	Pacific South West	989.8	0.54
10	Pacific North West	641.6	0.35
	Total	7779.1	4.71

For the estimation of FPAR, Potter et al. 2006 used MODIS one kilometer land cover map (Friedl et al., 2002) specified predominant land cover classes while this study used AVHRR monthly NDVI derived SR_{max} values on a pixel basis. The idea behind the use of AVHRR NDVI is the lack of updated land cover data type for the entire study period. Other major differences between these studies were the sources of the data used for different parameters estimation and their resolution. Potter et al. 2006 used monthly temperature, precipitation data from DAYMET and calibrated the CASA model at the resolution of 8-kilometer resolution while this study used monthly mean temperature and precipitation from PRISM group, NDVI data at 1-km resolution from AVHRR composites, PAR at 0.5 degree from GCIP/SRB project and maximum soil water holding capacity from NGDC – NOAA at 0.5 degree and calibrated the model at the resolution of 1-kilometer. However, both the studies validated their results with high correlation with the field NPP data. So, variability of the NPP fluxes between two studies might be due to quality of the data and their resolution used in the study. This study however, fails to compare its results with other studies because of the lack of estimated NPP fluxes for the contiguous US for the study period 1997 to 2007.

In a nutshell, the primary objective to estimate monthly and annual NPP from 1997 to 2007 in the Conterminous US was achieved. Analysis of annual trend showed decrease of NPP during 2000 to 2003 compared to mean annual NPP. Validation of estimated NPP was achieved using BigFoot sites NPP values. Then, the spatial pattern of NPP was observed in different parts of US using three broad classification systems: States, EPA regions and eco-divisions. Southeastern states, Subtropical eco-divisions and Southeast regions were found to have higher NPP per square meter when viewed from states, eco-divisions and regions perspective. Correlation coefficient analysis of NPP with climatic and biophysical variables showed the extent to which NPP is limited by these variables.

CHAPTER VI

CONCLUSIONS AND RECOMMENDATIONS

This final chapter summarizes the main findings and suggests the areas for future research.

6.1 Conclusions

NPP is an integral part of carbon dynamics (Running et al., 2004). Fundamental questions regarding environmental degradation, impact of pollution, fire and climate change are often addressed by evaluating changes in NPP. The capacity of terrestrial eco-system to sequester carbon from the increasing pool of atmospheric CO_2 is becoming integral research and policy issues for scientists and policy makers. Affordable and rapid methods to understand and quantify the productivity in different eco-regions are thus very crucial for the preservation of an eco-system.

Global climate change due to emission of green house gases is threatening the existence of mankind. Especially in the US, CO_2 emissions have increased by 20 percent from 1990 to 2004 (UNFCC, 2007, EPA, 2008). Biophysical, climatic and vegetation cover play a major role in carbon sequestration. An accurate estimation of NPP is therefore critical to understanding of carbon dynamics. Estimation of NPP in the US thus helps the policy makers and researchers to develop policies to increase carbon sequestration efforts in the US. With this broader goal, this study had the following three objectives.

1. To estimate annual NPP in the Conterminous US from 1997 to 2007
2. To analyze the spatial and temporal trends in NPP in the Conterminous US from 1997 to 2007
3. To analyze the relation of NPP with climatic factors – temperature, precipitation, photosynthetically active radiation (PAR) and evapotranspiration and bio-physical parameters such as Normalized Difference Vegetation Indices (NDVI) that indicates the conditions of the vegetation.

This study used a NASA developed model known as CASA model to estimate the NPP. Remote sensing data as primary input and GIS techniques as efficient method were used in the model. Specifically, bio-physical parameters such as NDVI and climatic factors such as temperature, precipitation, PAR and soil water holding capacity were the model parameters used in the estimatation monthly NPP fluxes over the Conterminous US from 1997 to 2007. AVHRR satellite derived NDVI values available at 1 km resolution was used as the minimum mapable area in the model. Therefore all other model inputs were also rescaled to 1 km resolution.

Predicted NPP fluxes from CASA model over the period from 1997 to 2007 showed an inter-annual variability nationwide that ranged from 3.42 – 4.95 petagrams of carbon per year (Figure12) with the mean annual NPP of 4.23 petagrams of carbon.

Validation of estimated NPP against BigFoot NPP sites at multiple locations in different years showed that model's estimation of NPP was reasonably accurate.

The annual NPP was found to be lower during the years 2000 to 2003, when the growing seasons were affected by the extensive droughts. The overall increase in NPP in the conterminous US during 11 years period was very negligible with R^2 of 0.004. Savannah and Subtropical eco-divisions were estimated to have higher NPP per unit area while Subtropical typically contributed more than 20 percentage of the nation's total annual NPP. Rocky Mountain regions (Figure 20) and Tropical/Subtropical Desert eco-divisions (Figure 19) had very low NPP per unit area. The southeast and south central regions of the country contributed more than 35percent of the nation's total annual NPP. Changes in seasonal NPP resulting from poor vegetation condition (measured by NDVI) due to periodic droughts and temperature variations are likely to be the main reasons for variation in NPP fluxes for any given year.

NPP was observed to have negative correlation with the latitude. NPP and NDVI exhibited significant positive correlation for all eco-divisions throughout the year. Tropical/Subtropical Desert was found to have higher NPP during the beginning of the year i.e. in March and April while other eco-divisions experienced higher in the months of May, June and July.

6.2 Recommendations

NASA-CASA model to estimate the NPP might perform better if the updated data especially land use land cover data with greater details are incorporated. Therefore, potential research can be focused towards obtaining high resolution datasets instead of the coarse resolution datasets as they might affect the accuracy of NPP estimation. High resolution datasets however are very difficult to obtain for the large study area like Conterminous US. Use of high resolution datasets could add challenges in terms of computational time and the computer resources.

Similarly, several other parameters such as, leaf area index, different maximum light use efficiency parameters and soil nutrient could be considered for the better approximation of NPP. These parameters are however very difficult to validate with field data. Another improvement could be done in the estimation of potential evapotranspiration by using models such as Penman–Monteith and Priestley–Taylor model. This study had to rely on Thornthwaite model instead of Penman–Monteith or Priestley–Taylor because of the lack of historical data such as humidity, solar radiation, wind speeds which are required by these models.

Improvements in NPP estimation can also be made through the validation of each parameter such as FPAR, evapotranspiration, soil moisture as errors during different parameters estimation could accumulate and propagate in the estimated final NPP.

Overall this study illustrated the spatial and temporal anomalies in NPP in the conterminous US. Since NPP is one of the important indicators of carbon cycle, this study provides some basic understandings of the situation of carbon sinks in the United States. Although NPP values are affected by the fluctuations in biophysical and climatic factors to certain extent, the vegetation condition (indicated by NDVI in this study) including species distribution and density can increase the carbon sinks. Thus the results of this study could be used in various environmental policy decisions especially in the policies on forest and cropland management at the state, EPA region and federal levels.

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APPENDIX A

TOTAL ANNUAL NPP (T G C YR^{-1}) FOR DIFFEENT STATES IN CONTERMINOUS US FROM 1997 TO 2007

State	Land Area ($10^3 km^2$)	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean Annual NPP
Alabama	133.9	103.0	99.9	104.4	75.2	92.8	97.2	112.9	124.9	121.2	124.7	108.9	105.9
Arizona	294.5	167.9	224.1	160.4	131.5	119.0	62.0	101.6	130.9	188.3	124.3	117.1	138.8
Arkansas	137	94.4	86.4	83.8	69.3	79.9	74.3	87.3	101.0	93.9	107.3	82.8	87.3
California	408.7	210.4	231.5	196.6	198.9	160.2	148.2	176.6	209.1	265.4	191.4	185.7	197.6
Colorado	269.6	156.0	165.7	154.1	123.2	110.4	78.0	118.6	151.3	157.1	132.9	148.5	136.0
Connecticut	12.9	8.0	8.1	6.3	5.6	7.7	7.9	7.1	9.3	7.7	6.7	7.7	7.5
Delaware	5.3	3.3	3.1	2.7	2.7	3.2	2.9	2.9	3.8	3.0	3.0	2.5	3.0
District of Columbia	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Florida	144.6	150.7	137.3	133.0	115.1	113.2	125.6	132.4	148.0	151.7	145.4	140.8	135.7
Georgia	151.9	125.6	115.3	116.8	96.5	104.1	109.6	126.5	138.5	137.0	136.5	125.7	121.1
Idaho	215.8	112.5	106.1	85.0	87.1	74.4	88.8	78.4	111.2	114.4	92.4	94.6	95.0
Illinois	145.8	67.1	71.7	60.3	61.7	65.9	58.2	68.4	84.9	69.6	69.7	71.1	68.0
Indiana	94.3	43.5	50.5	39.4	41.7	47.6	38.2	47.1	56.9	53.2	50.2	47.8	46.9
Iowa	145.7	64.9	70.1	54.7	54.8	55.1	68.7	59.8	82.8	74.4	63.5	70.3	65.4
Kansas	212.9	133.2	134.7	123.1	105.1	113.0	71.4	108.1	144.3	144.2	110.5	110.3	118.0
Kentucky	104.4	61.7	69.4	60.2	55.0	66.2	63.7	67.5	84.0	71.4	80.7	59.4	67.2

State	Land Area ($10^3 km^2$)	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean Annual NPP
Louisiana	118.7	92.7	81.8	92.1	73.6	85.1	77.7	83.4	102.1	99.2	108.5	95.6	90.2
Maine	83.3	39.5	40.6	39.4	23.3	37.9	48.6	40.7	54.0	50.6	44.8	45.5	42.3
Maryland	25.2	16.1	16.6	14.2	13.2	15.8	14.7	13.9	19.6	15.7	16.0	13.6	15.4
Massachusetts	21.2	12.3	12.8	10.8	8.8	12.8	13.5	11.8	15.3	13.0	10.7	12.7	12.2
Michigan	150	77.7	84.9	71.9	64.1	69.2	84.7	76.3	90.9	88.8	83.4	81.2	79.4
Minnesota	218.9	102.0	108.9	83.7	83.3	83.4	119.0	91.1	112.3	111.4	94.5	95.7	98.7
Mississippi	123.3	92.6	85.4	92.4	68.0	85.4	85.5	94.7	107.7	106.3	107.4	96.3	92.9
Missouri	180.9	112.5	119.2	94.9	96.1	113.7	92.4	105.7	143.6	124.0	118.0	103.2	111.2
Montana	381.4	191.3	166.9	166.7	126.7	119.4	142.2	132.6	159.8	195.8	153.0	152.6	155.2
Nebraska	200.3	104.6	111.3	103.5	83.1	88.6	54.8	86.1	110.5	116.0	81.4	97.3	94.3
Nevada	286.6	162.3	192.4	144.2	137.6	66.1	62.7	72.1	113.3	165.9	124.6	102.5	122.1
New Hampshire	24	13.0	12.6	11.6	8.2	12.9	15.6	11.7	16.5	14.9	12.5	13.9	13.0
New Jersey	19.4	14.0	12.3	10.4	10.1	12.1	11.9	10.6	15.4	12.3	12.0	11.6	12.1
New Mexico	315.3	221.8	218.1	220.9	134.7	118.3	94.7	107.1	191.2	212.9	176.0	200.1	172.3
New York	125.8	70.3	77.0	58.9	50.2	69.0	79.6	69.4	85.5	78.3	66.1	69.8	70.4
North Carolina	127	97.8	98.6	85.7	74.8	85.2	85.6	92.5	110.6	100.4	111.7	94.7	94.3
North Dakota	183.4	68.2	70.4	72.2	70.4	68.7	61.9	61.6	70.1	84.0	55.7	69.7	68.4
Ohio	106.7	57.7	63.7	51.0	50.4	54.9	48.4	58.2	71.6	62.3	61.7	57.0	57.9

State	Land Area ($10^3 km^2$)	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean Annual NPP
Oklahoma	181.3	127.5	105.9	115.5	99.6	98.1	90.7	107.7	133.6	128.1	102.7	114.8	111.3
Oregon	251.4	149.8	130.4	119.6	121.8	110.5	120.4	105.5	142.5	141.9	127.0	145.0	128.6
Pennsylvania	117.5	69.7	73.3	60.3	53.5	68.1	67.7	61.3	84.6	70.5	68.1	71.6	68.1
Rhode Island	2.7	1.6	1.6	1.4	1.2	1.6	1.6	1.5	1.9	1.6	1.3	1.5	1.5
South Carolina	79.9	70.5	66.2	62.1	50.8	53.1	57.3	63.8	72.7	68.9	73.5	65.9	64.1
South Dakota	199.9	109.2	104.0	107.8	86.8	80.7	49.6	72.6	97.1	102.9	65.5	83.5	87.2
Tennessee	109	72.1	76.9	72.2	58.2	68.9	69.6	76.7	89.8	79.0	87.8	68.0	74.5
Texas	684.9	496.9	404.1	429.5	319.5	339.6	306.7	390.1	525.9	476.1	386.8	502.8	416.2
Utah	219.8	128.4	132.9	112.3	94.0	70.3	59.2	68.7	98.1	133.7	101.1	103.0	100.2
Vermont	24.9	13.2	14.1	11.4	8.1	12.4	16.5	13.2	16.4	15.1	12.5	13.9	13.3
Virginia	103.1	71.2	71.4	63.4	55.4	68.4	66.0	68.3	84.7	72.0	79.4	65.8	69.6
Washington	174.3	91.3	83.1	65.4	72.6	70.4	81.7	72.6	87.7	91.4	84.9	86.5	80.7
West Virginia	62.8	38.8	40.4	36.5	27.5	38.8	39.5	34.5	45.1	38.6	42.9	36.1	38.1
Wisconsin	145.3	79.7	87.9	68.1	62.7	64.1	93.6	71.4	88.0	88.2	77.4	80.4	78.3
Wyoming	253.3	140.6	142.2	131.7	104.3	74.4	66.7	91.7	111.2	138.6	95.2	103.7	109.1

APPENDIX B

TOTAL ANNUAL NPP (T G C YR^{-1}) FOR DIFFEENT ECO-DIVISIONS IN CONTERMINOUS US FROM 1997 TO 2007

Eco-Divisions	Land Area 10^3 Km^2	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean Annual NPP	% Contribution to Total NPP
Hot Continental	1125.4	651.4	698.8	588.9	536.1	625.4	628.1	628.6	796.9	701.0	706.2	634.1	**654.1**	**15.6**
Marine	171.29	95.6	76.8	65.4	74.1	87.5	94.1	80.6	101.0	96.0	90.3	98.9	87.3	2.1
Mediterranean	318.49	179.7	161.9	165.9	170.2	152.8	148.9	159.7	181.3	206.5	163.7	175.4	169.6	4.0
Prairie	761.75	425.7	412.5	373.0	355.9	382.6	364.1	378.6	508.9	445.3	390.3	414.1	404.6	9.6
Savannah	20.65	19.8	20.5	17.5	16.6	13.8	14.8	16.1	17.4	17.7	17.2	17.7	17.2	0.4
Subtropical	1155.32	910.2	839.6	842.0	685.3	780.9	780.4	867.6	1002.2	960.3	1006.5	884.2	**869.0**	**20.7**
Temperate Desert	1380.13	773.0	778.4	655.8	598.7	443.9	472.0	481.0	676.9	769.7	623.9	619.9	**626.6**	**14.9**
Temperate Steppe	1156.18	604.4	600.2	613.8	472.0	441.3	307.5	446.6	571.6	630.2	436.4	516.9	**512.8**	**12.2**
Tropical/Subtropical Desert	241.78	93.3	165.0	82.7	82.3	54.0	18.6	55.2	87.4	139.7	71.7	45.4	81.4	1.9
Tropical/Subtropical Steppe	945.14	656.3	611.5	592.8	406.2	379.6	307.7	412.4	631.9	644.8	477.2	618.6	**521.7**	**12.4**
Warm Continental	488.71	248.5	268.7	219.2	178.6	226.6	294.0	242.8	291.5	284.6	250.0	253.5	250.7	6.0
Total Annual NPP ($T g C yr^{-1}$)	**7764.8**	**4657.9**	**4633.9**	**4217.0**	**3575.9**	**3588.5**	**3430.3**	**3769.1**	**4867.0**	**4895.7**	**4233.4**	**4278.7**	**4195.2**	**100.0**

APPENDIX C

TOTAL ANNUAL NPP (T G C YR^{-1}) FOR DIFFEENT EPA REGIONS IN

CONTERMINOUS US FROM 1997 TO 2007

#	US Regions	Area ($10^3 km^2$)	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean Annual NPP	% Contribution to Total NPP
1	New England	168.9	87.7	90.0	80.7	55.2	85.5	103.9	86.0	113.5	102.9	88.4	95.2	89.9	2.1
2	North East	145.2	84.2	89.3	69.3	60.2	81.1	91.5	80.0	100.8	90.7	78.1	81.3	82.4	1.9
3	Mid Atlantic	314.1	199.2	204.8	177.2	152.4	194.4	190.9	180.7	237.7	199.8	209.5	189.8	194.2	4.6
4	Southeast	974.1	772.1	747.5	725.5	592.1	668.2	692.9	766.0	875.0	834.2	866.5	757.8	**754.3**	**17.8**
5	North Central	860.9	427.5	467.4	374.2	363.8	385.1	442.1	412.5	504.3	473.2	436.7	433.2	429.1	10.1
6	South Central	1437.3	1033.1	896.3	941.6	696.4	720.5	643.6	775.0	1053.2	1009.9	880.7	995.5	**876.9**	**20.7**
7	Mid West	739.7	415.1	435.3	376.3	339.0	370.4	287.3	359.7	481.2	458.6	373.4	381.0	388.8	9.2
8	Rocky Mountain	1507.4	793.8	782.1	744.7	605.5	523.8	457.5	545.8	687.6	812.2	603.3	661.0	**656.1**	**15.5**
9	Pacific South West	989.8	541.0	649.2	501.5	467.8	344.6	271.7	349.1	452.4	619.1	439.9	404.6	458.3	10.8
10	Pacific North West	641.6	353.4	319.4	269.7	281.2	254.8	290.6	256.2	341.3	347.6	303.9	325.5	304.0	7.2
	Total	**7779.1**	**4707.2**	**4681.3**	**4260.8**	**3613.5**	**3628.3**	**3471.8**	**3810.9**	**4847.1**	**4948.3**	**4280.3**	**4325.0**	**4234.0**	**100.0**

*U.S. Environmental Protection Agency regions: **1**, Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island,Vermont; **2**, New Jersey, New York; **3**, Delaware, Maryland, Pennsylvania,Virginia,West Virginia, District of Columbia; **4**,Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Tennessee;**5**, Illinois, Indiana, Michigan, Minnesota, Ohio,Wisconsin; **6**,Arkansas, Louisiana, New Mexico, Oklahoma,Texas; **7**, Iowa, Kansas, Missouri, Nebraska; **8**, Colorado, Montana, North Dakota, South Dakota, Utah,Wyoming; **9**,Arizona, California,Nevada; **10**, Idaho, Oregon,Washington.