ESTIMATING NET PRIMARY PRODUCTIVITY OF FOREST ECOSYSTEMS OVER TURKEY USING REMOTE SENSING APPROACH

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ABSTRACT

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Understanding the fluctuations in carbon balance and global warming with respect to the global climate change and creating solutions, has become one of the most important topics in ecological studies especially during last decades. These changes, in particular for the terrestrial ecosystems, can be monitored using gross primary productivity (GPP), its derivative net primary productivity (NPP) (the subtraction of autotrophic respiration from GPP) and net ecosystem productivity (NEP) (subtraction of both plant respiration and autotrophic use from GPP) as key components, which are directly affected from climate change. Despite their importance for the ecological researches, the difficulties in field measurements forced the scientists to find new methods such as statistical methods and process based modelling techniques to estimate these quantities. The aims of this study are (i) to evaluate a widely used global model's outputs for Turkey's forest ecosystems using field measurements, (ii) to improve the accuracy of a global model using local datasets and (iii) to create a new modelling approach to increase the accuracy of NPP estimation over forest ecosystems. Results show that the global model has a significant correlation with field data of Turkey (R^2 = 0.34). However, it still lacks reflecting actual conditions over the area. The usage of local data slightly improves the accuracy of the model (R^2 = 0.35). In this study, a new modelling approach for the optimum temperature was also implemented. The results show that, the distribution of the optimum temperature values is more meaningful (the value of each pixel with respect to its neighbours). Moreover, the model accuracy was increased from 35% to 43% and from 39% to 43% for two different APAR (Absorbed Photosynthetically Active Radiation) estimation methods which are discussed in the thesis. The analysis showed that only 51% accuracy can be achieved using the field data. The potential reasons are discussed in the study.

Keywords: Net Primary Productivity, Remote Sensing, Modelling

ÖZ

TÜRKİYE ÜZERİNDEKİ ORMAN EKOSİSTEMLERİNİN NET BİRİNCİL VERİMLİLİĞİNİN UZAKTAN ALGILAMA YAKLAŞIMI İLE BELİRLENMESİ

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Küresel iklim değişikliği çerçevesinde, küresel ısınma ve karbon dengesindeki değişimlerini anlamak ve çözüm üretmek, özellikle son yıllarda ekoloji çalışan bilim insanları için en önemli başlıklardan birisi olmuştur. Bu değişimler, özellikle karasal ekosistemlerin anahtar bileşenleri olan ve iklim değişikliğinden doğrudan etkilenen Bürüt Birincil Verimlilik (BBV), bunun türevi olan Net Birincil Verimlilik (NBV), BBV'den bitki solunumu çıkarıldıktan sonra kalan kısım, ve Net Ekosistem Verimliliği (NEV), BBV'den bitki solunumu ve ototrofik solonum çıkarıldıktan sonra kalan kısım, kullanılarak gözlenebilmektedir. Bu değişkenlerin ekolojik araştırmalardaki önemlerine karşın, arazi ölçümleri ile ilgili zorluklar bilim insanlarını istatistiksel ve süreç temelli modeller gibi yeni yaklaşımlar geliştirmeye zorlamıştır. Bu çalışmanın amacı (i) yaygın bir şekilde kullanılan bir küresel modelin çıktılarını Türkiye ormanlarından alınan arazi ölçümleri ile doğrulanması, (ii) küresel bir modelin yerel verilerle geliştirilmesi, ve (iii) modellerin doğruluğunun arttırılması için yeni bir modelleme yaklaşımının oluşturulmasıdır. Bulgular, kullanılan küresel modelin Türkiye

ormanları ile kayda değer bir ilişkisi olduğunu (R^2 = 0.34) göstermiştir. Ancak, bu durum hala çalışma alanı üzerindeki gerçek durumu yansıtmamaktadır. Yerel verilerin kullanılmasının ise modelin başarısını bir miktar arttırdığı (R^2 = 0.35) gözlenmiştir. Bu çalışmada, optimum sıcaklık değerlerinin hesaplanması için yeni bir yaklaşım uygulanmıştır. Sonuçlar, optimum sıcaklık değerlerinin dağılımlarının daha anlamlı (herhangi bir pikselin, komşu piksel değerleri ile ilişkisi) olduğunu göstermiştir. Bununla beraber, modellerin açıklayıcılığı ileriki bölümlerde tartışılan iki farklı APAR (Absorbed Photosynthetically Active Radiation, fotosentetik olarak aktif radyasyonun soğuran kısmı) hesabına göre %35'ten %43'e ve %39'ten %43'e yükselmiştir. Ayrıca analizler, kullanılan arazi verisi ile yapılan çalışmaların açıklayıcığılının en fazla %51'e ulaşabileceğini göstermiştir. Bununla ilgili potansiyel nedenler çalışma içerisinde tartışılmıştır.

Anahtar Kelimeler: Net Birincil Verimlilik, Uzaktan Algılama, Modelleme *to my family old*

and

to my family new

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A_{BL}	Aboveground Biomass for Broad Leaf Trees
A_{NL}	Aboveground Biomass for Needle Leaf Trees
AEG-MED	Aegean and Mediterranean Region
AEI	Annual Expected Increment
AF	Adjustment Factor
AGB	Above Ground Biomass
AGC	Above Ground Carbon
APAR	Absorbed Photosynthetically Active Radiation
AVHRR	Advance Very High Resolution Radiometer
BIOME-BGC	Biome Biogeochemical Cycles Model
BPLUT	Biome Parameters Look-Up table
C	Carbon
CANA	Central and Eastern Anatolia Region
CARAIB 2.1	Carbon Assimilation in the Biosphere Model
CASA	Carnegie-Ames-Stanford Approach
CD	Climatic Districts
CORINE	Coordination of Information on the Environment
CPM	Canopy Photosynthesis Models
DAO	Data Assimilation Office
DBH	Diameter at Breast Height
DM	Number of Days in a Month
EEA	European Environment Agency
EET	Estimated Evapotranspiration
EODIS	The Earth Observing System Data and Information System

FBM	Frankfurt Biosphere Model
FPAR	Fraction of Photosynthetically Active Radiation
GLO-PEM	Global Production Efficiency Model
GPP	Gross Primary Production
GWR	Geographically-Weighted Regression
HDF	Hierarchical Data Format
HRBM 3.0	High Resolution Biosphere Model
I	Thermal Heat Index
ICP Forest	International Co-operative Program on Assessment and Monitoring of Air Pollution Effects on Forests
IDW	Inverse Distance Weighted
JC	Jenkins Coefficients
KGBM	Kergoat Global Biosphere Model
Landsat	Land Remote Sensing Satellite
LC	Land Cover
LUE	Light Use Efficiency
MAT	Mean Annual Temperature
MAP	Mean Annual Precipitation
MC	Ministry Coefficients
MFWA	The Ministry of the Forest and Water Affairs
MID-EBS	Middle and Eastern Black Sea Region
MODIS	Modarate Resolution Imaging Spectroradiometer
MRT	MODIS Reprojection Tool
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NEP	Net Ecosystem Productivity
NOAA	The National Oceanic and Atmospheric Administration

NPP	Net Primary Production
PAR	Photosynthetically Active Radiation
PEM	Production Efficiency Models
PET	Potential Evapotranspiration
PLAI 0.2	Postdam Land Atmosphere Interaction Model
PP	Primary Productivity
PPT	Precipitation
RMSE	Root Mean Square Error
SDBM	Simple Diagnostic Biosphere Model
SH	Sunshine Hour
SIB2	Simple Interactive Biosphere Model
SILVAN 2.2	Simulating Land Vegetation and NPP Model
SLR	Simple Linear Regression
SOL	Solar Radiation
SPOT	Satellite Pour l'Observation de la Terre
SR	Simple Ratio
T	Temperature
TAGB	Total Above Ground Biomass
TAGC	Total Above Ground Carbon
TEM 4.0	Terrestrial Ecosystem Model
TURC	Terrestrial Uptake and Release of Carbon
TSMS	Turkish State Meteorological Service
USA	United States of America
VI	Vegetation Index
VPD	Vapor Pressure Deficit
WBS-MAR	West Black Sea and Marmara Region

CHAPTER 1

INTRODUCTION

Primary productivity of the natural ecosystems, specifically the forest ecosystems, has had great importance during last decades due to their roles in carbon cycle and their response to climate change. GPP, the total amount of carbon fixed during photosynthesis, NPP, the amount of stored carbon after plant respiration and NEP, the amount of carbon in a certain terrestrial ecosystem after plants respiration and other heterotrophic usages, can be thought of three basic types of primary productivity (Rast, 2004 [56]; Hilker,2008 [25]). Among these three quantities, NPP is the most basic parameter due to its response to the environmental variations such as change in climate, water and nutrient constraint in soil due to natural changes or human impacts (Field et al., 1995 [12]). To understand the effects of environmental change on NPP many global models were created (Ruimy et al., 1999 [58]). However, despite their success on global scale, these models lack reflecting country scale conditions and changes. Turkey has extreme topographical, and climatic variations and many different ecosystems. Due to these properties, it is not easy to explain the natural conditions over Turkey using global models. Modelling net primary productivity for Turkey's forest ecosystem may help the scientists to understand and create solutions to these environmental variations. Ruimy et al. (1994) [59] and Yu et al. (2009) [77] stated that field measurement (direct measurement of NPP), statistical approaches and the models based on the photosynthetic process are the three methods used to estimate/calculate NPP.

1.1 Methods Used to Estimate/Calculate NPP

1.1.1 Field Measurements

The basic idea of the field measurement is to learn the weight of all plants in the predetermined area. This was firstly done by cutting all the plant and weigh them after drying process. Despite the fact that, this is the most certain method, it makes a great damage on the ecosystems. Nowadays, because of this damage, species-based coefficients are used to calculate NPP which is mostly calculated using the amount of carbon stored by the plant. Each country (climate zone/ecosystem) has its own calculation coefficients depending on the ecosystem types. The Ministry of the Forest and Water Affairs (MFWA) calculates these coefficients for the forest ecosystems over Turkey depending on the land cover classification created by the ministry (Figure 1.1).

McCallum et al. (2009) [37] stated the difficulties of the field measurements of NPP as follows;

a. Spatio-temporal dynamics of environmental differences over large areas.

b. Limits on accuracy of the measured and calculated quantities with respect to the real size and/or weight of the plants.

1.1.2 Statistical Models

Statistical estimation (or calculation) of NPP is a curve fitting issue by means of regression models. The collected field data are tried to explain using the explanatory (independent) variables (Equation 1.1). Environmental variable such as precipitation, temperature, water vapour pressure deficit (VPD) and remotely sensed data (such as satellite/airborne images of the study area) can be used as explanatory variables.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon \tag{1.1}$$

where y is the response (dependent) variable, x_i is the explanatory variables, β are the coefficients and ε is the error.

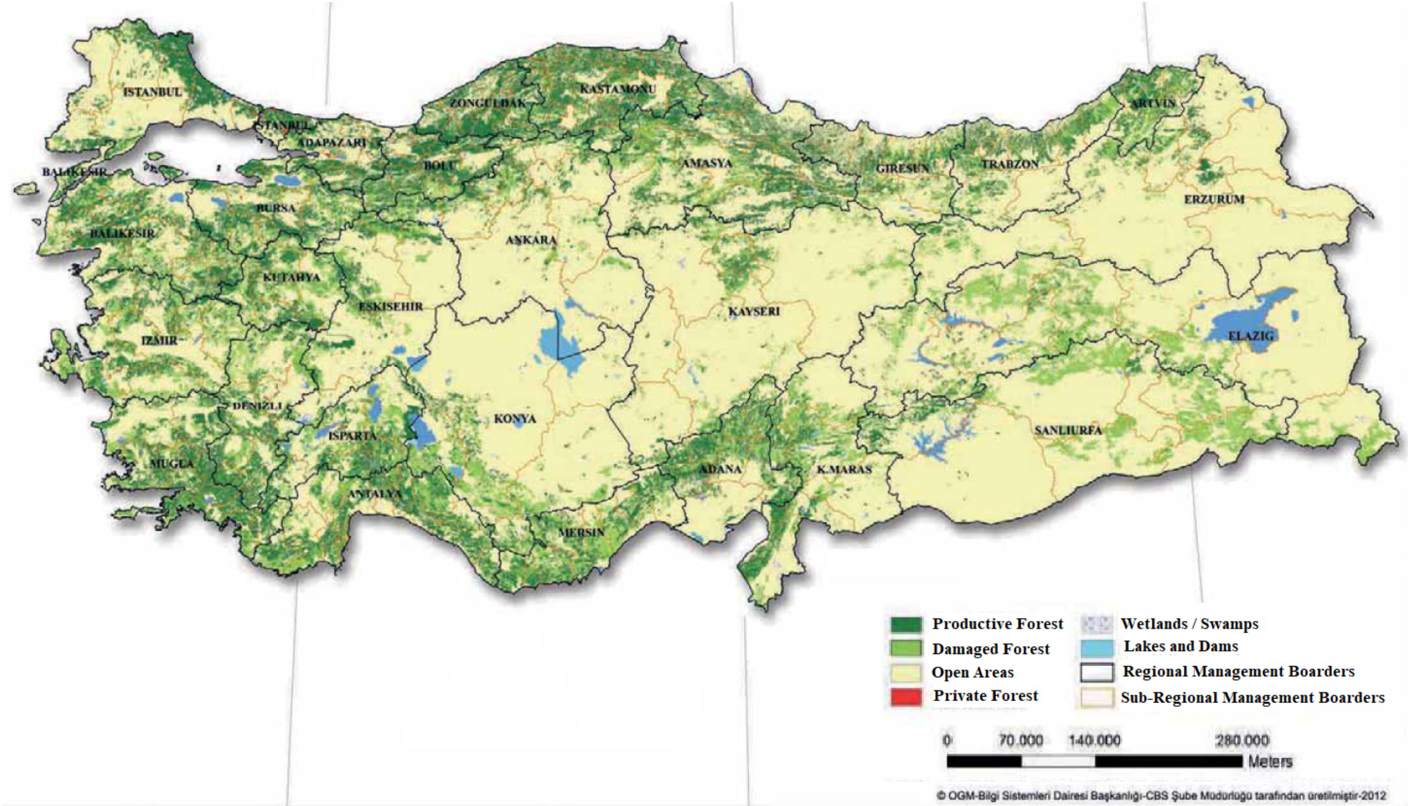


Figure 1.1: MFWA forest classification types for Turkey (Created by MFWA, 2012 [44]).

Wang et al. (2005) [73], studied Geographically-Weighted Regression (GWR) method to estimate NPP for 17 forest types over China using data from 1248 sites from 29 regions. Their results show that GWR technique can be used to estimate NPP, better than Ordinary Least Square, if there are enough data distributed across the study area. The basic problem faced with the statistical methods is that they are being data driven methods and due to this reason the models are time and space dependent. These factors limit the models feasibility to be applied to another time/spaces to predict new conditions. Another issue for the statistical models is the selection of the explanatory variables, since the model tries to fit a curve to every parameters determined before.

1.1.3 Process-Based Models

This approach is in the basis of modelling the whole process that resulted with the final product i.e. photosynthesis in this case. It works, when there is a state variable to be calculated, and the driving variables affecting this stock directly or indirectly. For instance, the photosynthesis process is directly related to the sunlight (explanatory variables) in terms of wavelength (relation). Temperature, on the other hand, affects this process as a stress factor. Although it is not related to the process directly, as a stress factor it slows the process down or stops. Since it is known that photosynthesis is a process of turning the inorganic material into organic material using the sunlight, it is a concern of determining the basic variable ruling the process. In remote sensing, for example, light use efficiency, (LUE) and photosynthetically active radiation (PAR) and its derivatives such as fraction of photosynthetically active radiation (FPAR) or absorbed photosynthetically active radiation (APAR) (Figure 1.2) can be the basic input parameters (Equation 1.2).

$$NPP = APAR \times LUE \tag{1.2}$$

where NPP is the Net Primary Productivity, APAR and LUE are absorbed photosynthetically active radiation and light use efficiency, respectively.

LUE is defined as the ratio of the NPP to APAR, so it becomes a constant within the ecosystem despite it changes with respect to the environmental conditions (Haxeltine and Prentice, 1996 [20]; Landsberg et al, 1997 [33]). Moreover, not only the environmental conditions but also the canopy structure and the angle of the leaves affect LUE.

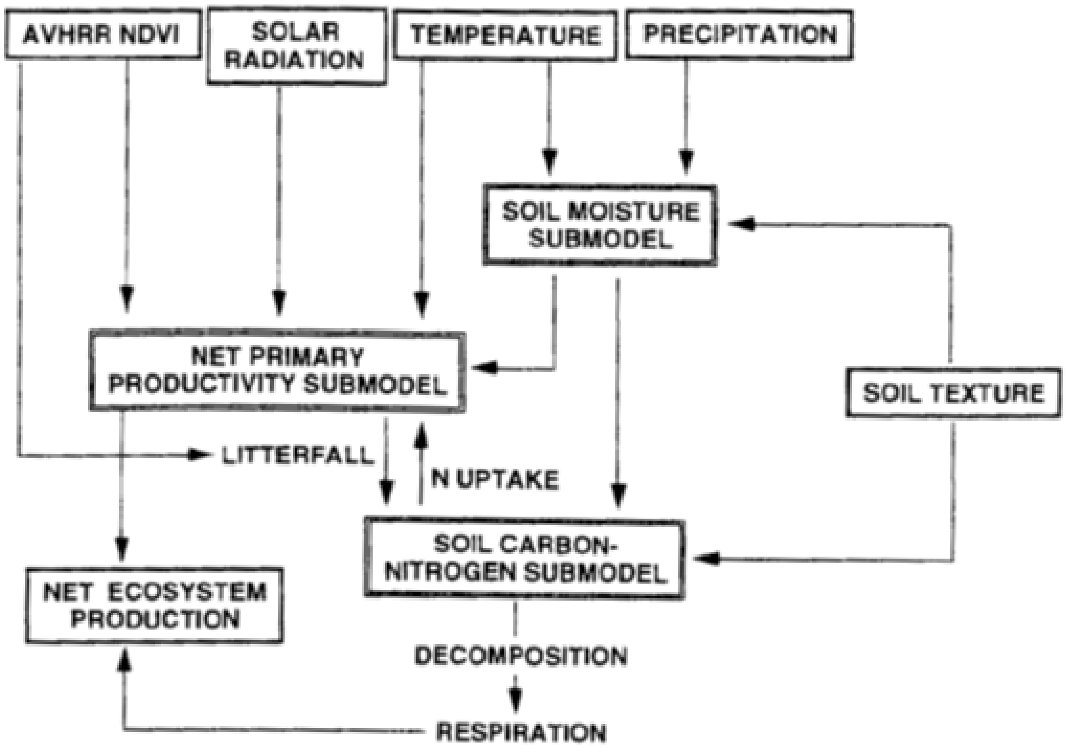


Figure 1.2: Basic modelling chart for CASA NPP model (Potter et al., 1993 [51]).

1.2 Previous Related Studies

Due to its importance, many studies have been conducted to model not only NPP but also its component such as light use efficiency (LUE), land cover and photosynthetically active radiation (PAR). Global NPP models were divided into three categories, models that are using remotely sensed data; biogeochemical fluxes-based models; and models including functional and structural components of the canopy (Cramer et al., 1999 [7]). However, according to Ruimy et al (1999) [58], these models can be classified into two categories: production efficiency models (PEM) including remote sensing approach and canopy photosynthesis models (CPM) including other two approaches (Table 1.1). Production efficiency models are based on light absorbed by the vegetation. First, fraction of photosynthetic radiation is calculated using remote sensing data (i.e. NDVI). Using a conversion constant, total amount of absorbed radiation is converted into dry matter. CPM on the other hand, is the first leaf level GPP calculated using mechanistic models (e.g. CO_2 exchange). Cramer et al. (1999) [7] compared seventeen NPP models (CASA, GLO-PEM, SDBM, SIB2, TURC, BIOMEBGC, CARAIB 2.1, CENTURY 4.0, FBM 2.2, HRBM 3.0, KGBM, PLAI 0.2, SILVAN 2,2., TEM 4.0, BIOME3, DOLY and HYBRID 3.0) and Ruimy et al. (1999) [58] compared twelve NPP models (CASA, GLO-PEM, SDBM, SIB2, TURC, CARAIB, FBM, KGBM, PLAI, SILVAN, BIOME3, and HYBRID) NPP models. Since most of the fluxes occur on leaf level, small homogeneous ecosystems are the keys to the wider and more complex ecosystems and scaling from regional to global level is key to understanding the interrelations of the global ecosystems, these two topics are claimed to have important implications for water and carbon fluxes (Cramer et al., 1999 [7]). Potter et al. (1993) [51] developed a process based model named as The Carnegie-Ames-Stanford approach (CASA), using Advance Very High Resolution Radiometer (AVHRR) sensor on board of The National Oceanic and Atmospheric Administration (NOAA) satellite. The remotely sensed data were used to model APAR and LUE. It was claimed that model estimated the global NPP as 48 PgC$year^{-1}$ with maximum LUE of 0.39 g C MJ^{-1} PAR. Yu et al. (2009) [77] improved CASA model and applied it to eastern region of Asia. Original CASA model calculates water stress value using complex calculation with detailed soil data. However, this improved model uses Thornthwaite (1948) [68] evapotranspiration modelling approach to estimate water stress.

Ogutu and Dash (2013) [46] compared three production efficiency models (CASA model (Potter et al., 1993 [51]), C-Fix model (Veroustraete et al, 2002 [71]; Verstraeten et al., 2006 [72]), MOD17 (Running et al., 2000 [63]) model and their capacity. They claimed that all three models failed to estimate (underestimate) crop sites (agricultural areas), which was explained as the change of the crop types. However, for the natural areas (especially for the broadleaf) models work well. Apart from the models described above, GLO-PEM (Prince 1991 [52]; Prince and Goward, 1995 [53]), SDPM (Knorr and Heimann, 1995 [30]); SIB2 (Sellers et al., 1996a [65]; Sellers et al., 1996b [66]; Randall et al., 1996 [55]), and TURC (Ruimy et al., 1996 [57]) are the remote sensing based models to estimate the NPP. Cramer et al., 1999 [7], stated that satellite based models estimate the NPP higher like GLO-PEM or TURC or lower like CASA and SIB2. However, they all estimate the APAR lower than actual. Since LUE and PAR are the basic components to model NPP, many studies were conducted on these two variables. Ahl et al. (2004) [3] studied the change (heterogenic structure) of LUE from the land cover types and considering the temporal changes with respect to the climate variables such as temperature. Nowadays, using eddy covariance towers is another common method for measuring LUE (and PAR). This method uses optical measurement techniques during day and night continuously, and it measure both down-welling and up-taking fluxes.

1.3 Objectives

During last decades scientist have created many global models including the land-cover and NPP models. Despite their success in global scale, the models are not reflecting the reality in regional scale due to the lack of data or averaging the existing data by means of scale. Moreover, up-scaling and/or downscaling of the created models (maps) is another problem to understand the relation between country scale and the global scale conditions. Overcoming this problem may help scientist to understand the nature of the climate change and its effects, not only on the certain ecosystems but also globally. Therefore, the objectives of this study are,

i. To understand how well a global model can reflect reality over a regional (country) scale (Chapter 2) (Figure 1.3).

ii. To create a new approach to improve the accuracy of a NPP model (Chapter 3) (Figure 1.4).

iii. To understand the spatio-temporal changes in net primary productivity over Turkey between 2000 and 2015 (Chapter 4).

The description of the study area and the used data sets are summarized in the following sections. Detailed informations are given in the related chapters.

Table 1.1: NPP models depend on their major inputs and modelling strategies. According to Cramer et al. (1999) [7](first three rows) and Ruimy et al. (1999) [58](last two rows).

Characteristics	**Models**
Models Use satellite data as major input	CASA, GLO-PEM, SDBM, SIB2, TURC
Models simulate carbon fluxes using a prescribed vegetation structure	BIOME-BGC, CARAIB 2.1, CENTURY 4.0, FBM 2.2, HRBM 3.0, KGBM, PLAI 0.2, SILVAN 2,2., TEM 4.0
Models simulate both carbon fluxes and vegetation structure	BIOME3, DOLY and HYBRID 3.0
Production Efficiency Models (PEMs)	CASA, GLO-PEM, SDBM, TURC
Canopy Photosynthesis Models (CPMs)	CARAIB, FBM, KGBM, PLAI, SILVAN, BIOME3, HYBRID, SIB2

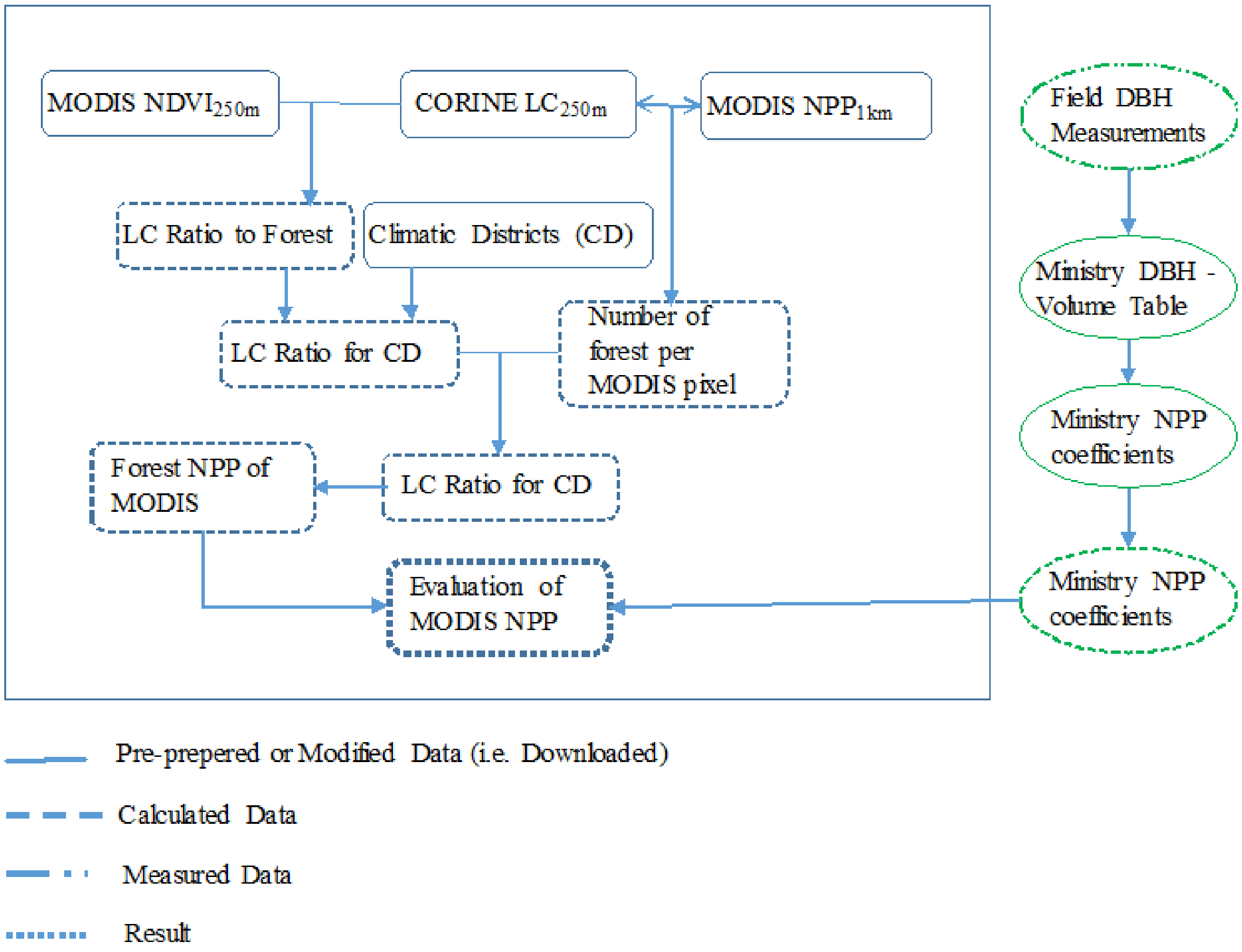


Figure 1.3: Flow chart for the study presented in Chapter 2.

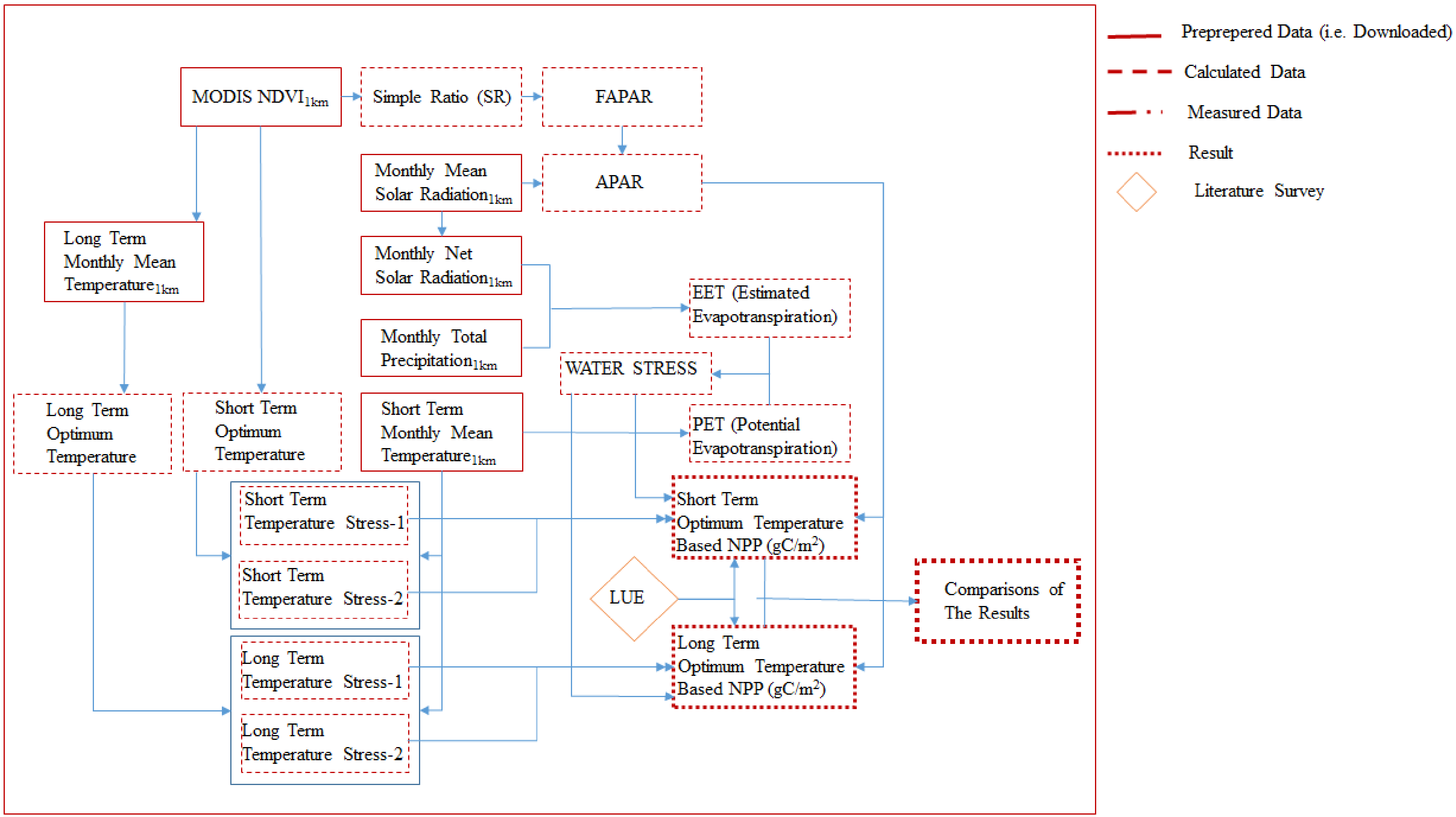


Figure 1.4: Flow chart for the study presented in Chapter 3.

1.4 Description of The Study Area

The study area covers all natural forest ecosystems in Turkey. The area lays between 36 and 42 North latitudes and 27 and 45 East longitudes. Turkey's basic forest types include mixed, broadleaf and needleleaf forest in the north and needleleaf forest in the west and south (Evrendilek and Gulbeyaz, 2011 [10]). According to CORINE (Coordination of Information on the Environment) land cover classification, total forest cover of Turkey is approximately 16% of its total area (approximately 780 000 km^2). 31 percent of total forest cover is deciduous broadleaf, 37 percent is needleleaf and 32 percent is mixed forest. Dominant tree species are eastern beech (*Fagus orientalis*), chestnut (*Castanea sative*), Cappadocia maple (*Acer cappadocicum*), eastern hornbeam (*Carpinus orientalis*), Turkish Sweetgum (*Liquidambar orientalis*), olive tree (*Olea europea*), oriental plane(*Platanus orientalis*) for deciduous forest, Turkish fir (*Abies bornmuelleriana - endemic*), Caucasian fir (*Abies nordmanniana - endemic*), Taurus fir (*Abies cilicica*), Lebanon cedar (*Cedrus libani*), common juniper (*Juniperus communis*) oriental spruce (*Picea orientalis*), Turkish pine (*Pinus brutia*) for needleleaf forest. Moreover, mostly fir, hornbeam, spruce and beech are dominant in mixed forest especially in Black Sea region of Turkey. It should be noted here that according to MFWA, the total coverage of Turkey's forests is 28.6% (22342.935 ha) of total area (MFWA, 2015 [45]). However, this value includes not only forest areas, but also areas without forest cover under jurisdiction of MFWA.

1.5 Field Data

All field data were obtained from MFWA. The data consist of two basic tables: (i) an "installation" table, which contains data about each plot and (ii) "measurements" tables. Originally installation tables have 1511 selected plot areas. However, due to security issues 613 and 470 plot measurements were obtained for 2008 and 2013 respectively. Moreover, after the combination of 2008 and 2013 measurements, total number of the plots decreases to 461 (Table 1.2.). These data are not publicly available, but can be obtained from the Ministry for scientific research purposes. MFWA plot determination protocol is based on the International Co-operative Program on

Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forest) Level 1 protocol (ICP, 2016 [27] (ICP Forest Manual)). To determine the plots, first a grid with 16 km $\times$ 16 km spacing was created over all forest ecosystems of Turkey. The intersection points of the grids were selected as the centre points of the 50 m $\times$ 50 m plots. Four different points were determined having 25 m from each other, following cardinal compass directions, (i.e. north, south, east and west). At each of these 4 points, MFWA field crews measured the diameter of six representative or dominant trees in 2008 and 2013. The Ministry of Forest and Water Affairs measurements cover only dominant trees in each plot area. Unfortunately, forestry is mostly related to dominant trees in Turkey, not to the understorey. This leads underestimation of the primary production of other plant species in the area. Calculation protocol of NPP in a plot area includes, aboveground tree carbon, belowground tree carbon, litter fall, dead woods and soil carbon. Since there was not any information about understorey vegetation, it was not possible to include them to the calculations. It is also important to note that in some cases, it was not possible to record the same trees due to tree mortality in five-year period between two measurements.

1.6 Climate Data

All meteorological measurements are obtained from Turkish State Meteorological Service (TSMS). Data cover daily and monthly measurements between the years 2000 and 2015. The TSMS has over 1100 measurement points over Turkey (Figure 1.5). However, not all climate variables are measured at all stations. Moreover, there are missing data among measurements. The climate variables were used to create stress coefficients, as a mitigation factor for the LUE of each ecosystem. Three variables were used for the study, monthly mean temperature, monthly total solar radiation and monthly total precipitation. Surface maps of all three variables are created for each month between 2008 and 2013 using "IDW" (Inverse Distance Weighting) interpolation techniques in ArcGIS. IDW is used to acknowledge the importance of the original measured values at the meteorological stations.

Table 1.2: Basic information about measurements in 2008 and 2013, and the set of their intersection according to the same plot, the same tree and the same tree number criteria.

Measurement Year	**Number of Plots**	**Total Number of Trees**	**Number of Trees Per Plot**
2008	613	14904	24.31
2009	470	9486	20.18
2008 and 2009 merged	461	9038	19.6

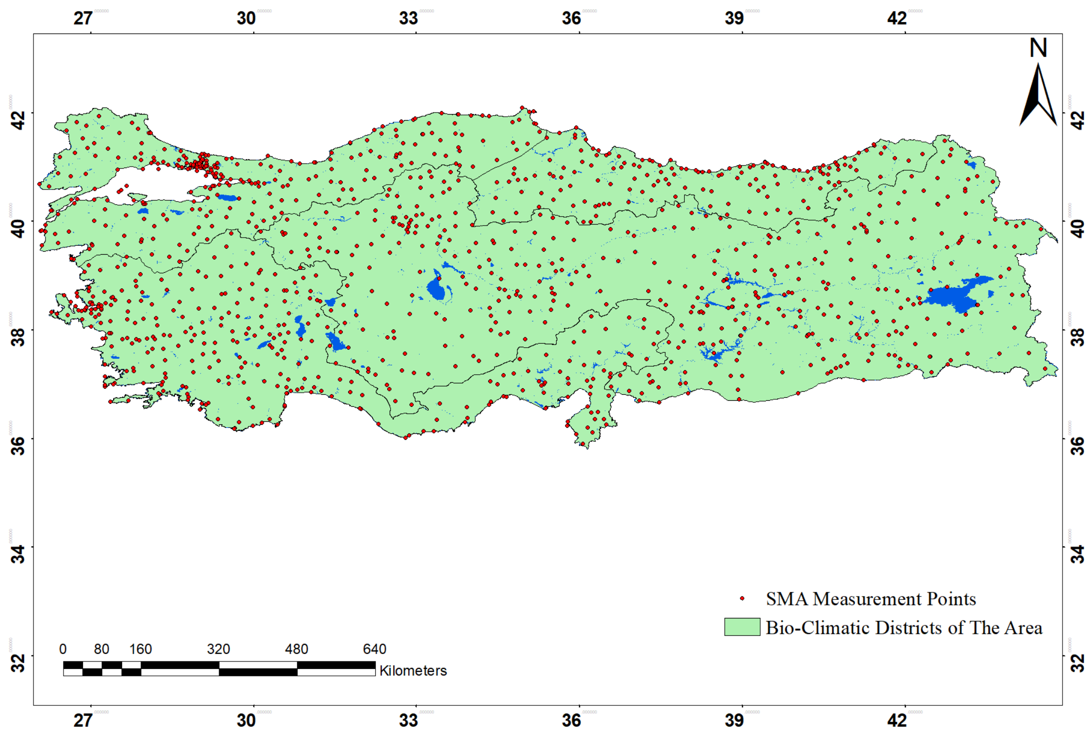


Figure 1.5: Climate variables measurement stations over Turkey (TSMS, 2016 [2], https://www.mgm.gov.tr/).

1.7 Satellite Data

In this study three different MODIS data sets with 1km spatial resolution were used as remote sensing data. MODIS MOD17A3 NPP product was used to evaluate the success of a global model with respect to field measurements and MOD13Q1 16 days vegetation indices product was used to create NDVI ratios between land cover types. Finally, MOD13A3 (Figure 1.6) product NDVI (Normalized Difference Vegetation Index) was used as an input to CASA model. MODIS NDVI data is provided as integers which ranges between -3000 to +10000. This data is multiplied by 0.0001 to scale the data between -3 to +1.

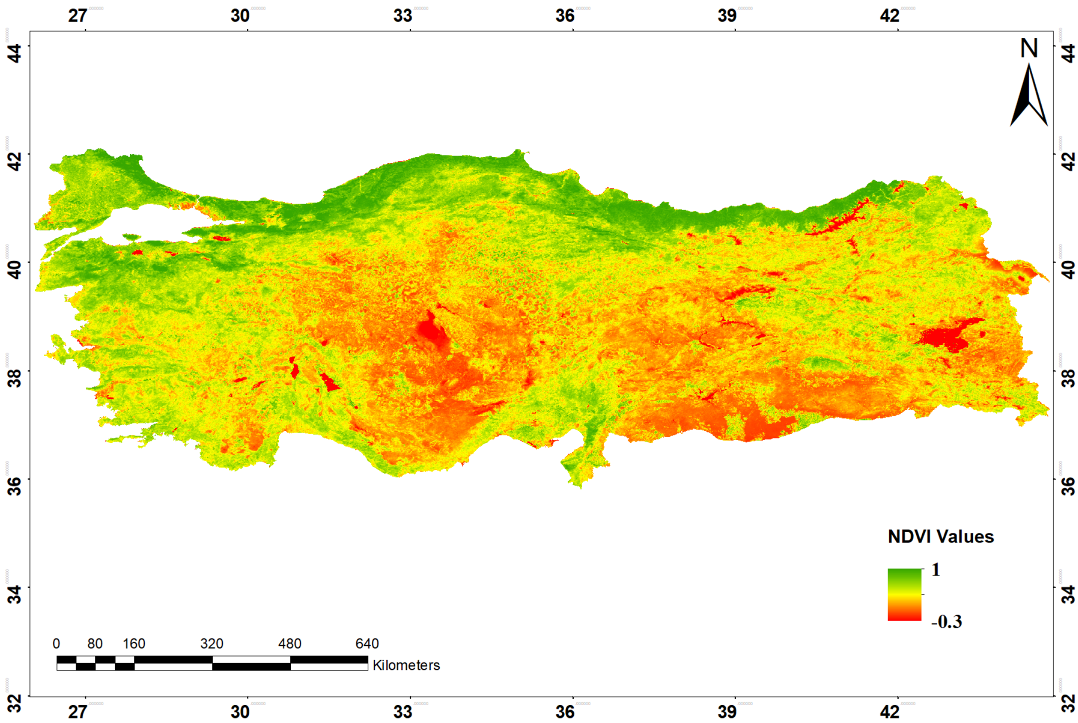


Figure 1.6: MODIS MOD13A3 Vegetation indices product (2008 May NDVI map).

1.8 Land Cover Data

The European Union's European Environment Agency (EEA) land cover (LC) data CORINE (Coordination of Information on the Environment) with a resolution of 250 m × 250 m is used for this study (Figure 1.7). The CORINE data represents the Earth surface using five different land cover classes, (i) artificial areas, (ii) agricultural areas, (iii) forest and semi-natural areas, (iv) wetlands, (v) water bodies. However, since the field data only covers forest ecosystems and the aim of the study is to calculate the NPP of forest ecosystems only, CORINE class of "forest and semi-natural areas" was divided into forest areas and semi natural areas. As a result, all calculations were done based on 6 (six) different land cover types.

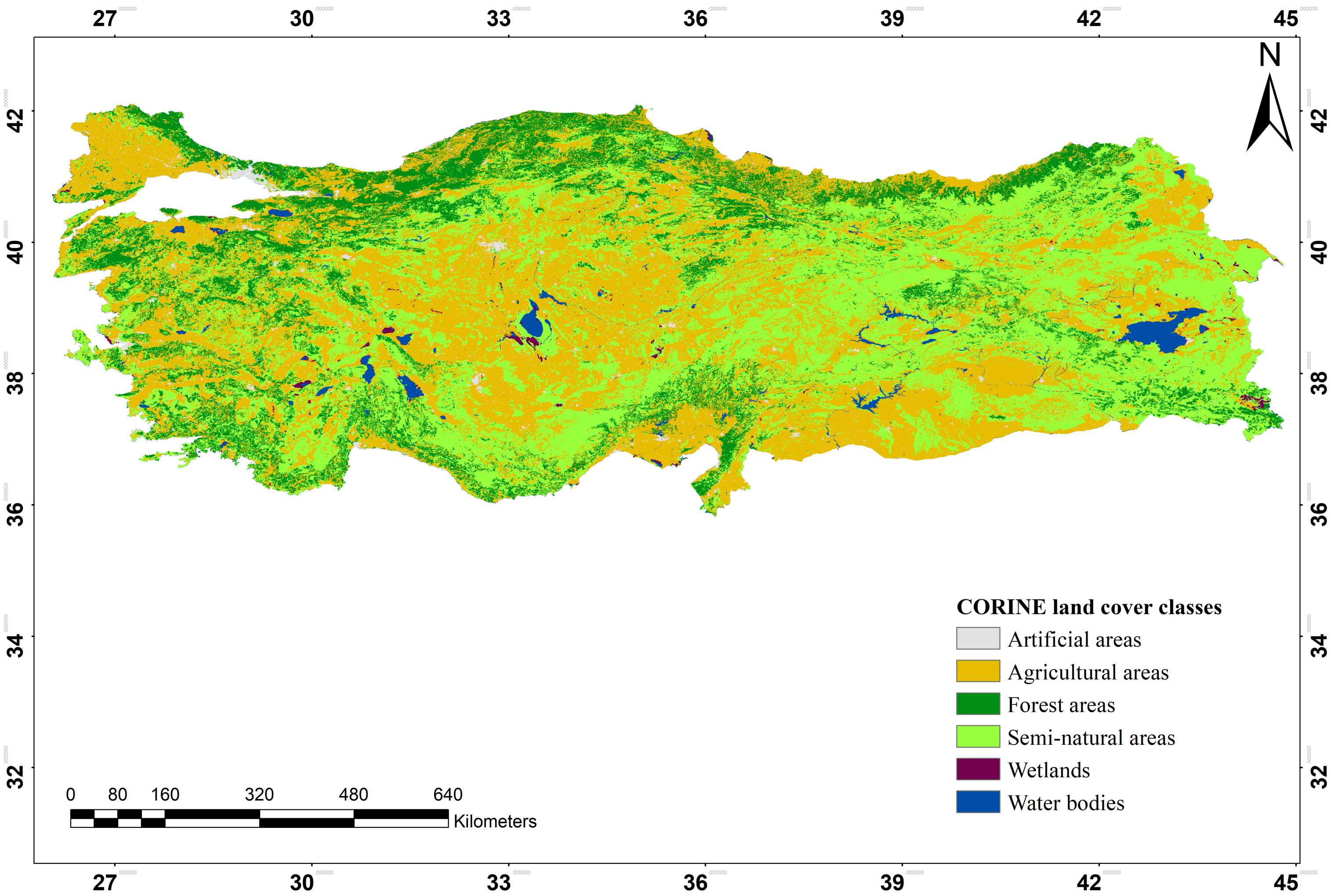


Figure 1.7: The CORINE Land Cover Map for Turkey (The European Union's European Environment Agency (EEA), 2006 [1], http://www.eea.europa.eu/data-and-maps).

CHAPTER 2

EVALUATION OF A GLOBAL NPP MODEL RESULTS: A CASE STUDY OF MODIS MOD17A3 NPP PRODUCT OVER TURKEY'S FOREST ECOSYSTEMS USING FIELD DATA

2.1 Introduction

Remotely sensed imagery can be used to model current and future conditions of natural (i.e. forest) and man-made (i.e. agricultural lands) vegetated areas, using products such as vegetation index (VI) and fraction of photosynthetically active radiation (FPAR), thereby enabling estimations of net primary productivity (NPP) (Zeng et al., 2007 [80]; Goetz et al., 1999 [15]; Potter et al., 1993 [51]). Although MODIS (MODerate resolution Imaging Spectroradiometer) sensors have coarser spatial resolution compared to other sensors (e.g. Landsat (Land Remote Sensing Satellite), SPOT (Satellite Pour l'Observation de la Terre – Satellite for Observation of Earth), etc.), it has high temporal (daily, 8-days, 16-days, monthly and yearly products) and spectral resolutions (2 bands for 250 m, 5 bands for 500 m and 29 bands for 1 km). These properties of MODIS allow scientists to create finer scale products such as NPP products with 500 m resolution. (https://modis.gsfc.nasa.gov). In this aspect, MODIS provides many data and modelling opportunities for the analysis of natural ecosystems (Zeng et al., 2007 [80]; Running et al., 1999b [62]; Prince and Goward,1995 [53]) including marine ecosystems. Currently, the near real time MODIS GPP/NPP (gross/net primary productivity) is one of the most used products for global and regional studies (Pachavo and Murwira, 2014 [47]; Heinsch et al., 2006 [24]; Zhao et al., 2005 [78]). Its algorithm relies on basic light use efficiency (LUE) models (Ahl et al., 2004 [3]; Heinsch et al., 2003 [23]; Gower et al., 1999 [17]; Monteith and Moss,1977 [40]; Monteith, 1972 [39]), which state under optimum conditions the productivity of a plant is proportional to the quantity of absorbed light. The algorithm is known to under-estimate NPP in areas with high productivity, and over-estimate NPP in areas with low productivity (Turner et al., 2006 [70]). MODIS NPP uses globally modelled climate data from NASA (National Aeronautics and Space Administration) (Zhao et al., 2005 [78]; Heinsch et al., 2003 [23]). The resolution of the climate data is $1.00^o \times 1.25^o$. It may be used with acceptable results at the global scale, but it can show poor results with local data (Zhao et al., 2005 [78]). Although this can be mitigated with spatially enhanced coarse resolution climate data o work with 1 km $\times$ 1 km MODIS images, the results can be misleading for predicting country and local scale temporal and spatial differences (Neumann et al., 2016 [42]; Zhao et al., 2005 [78]). To quantify and decrease these errors, evaluation of the product is required for multiple biome and climate types (Turner et al., 2006 [70]; Ahl et al., 2004 [3]). This is a challenging issue due to uncertainties in scaling plot level data to 1 km $\times$ 1 km MODIS pixel as well as the heterogeneity of land cover types within a pixel (Heinsch et al., 2006 [24]; Turner et al., 2006 [70]; Turner et al., 2004 [69]; Zhao et al., 2005 [78]). Turner et al. (2006) [70] performed the most comprehensive evaluation for the MODIS GPP/NPP product mostly in North America. They used tower measurements to model flux tower measurements of GPP and NPP, which were then scaled to 5 km $\times$ 5 km area using Landsat images to match better with the MODIS footprint. Turner et al. (2006) [70] found that, the MODIS NPP estimate was related to FPAR estimate, and suggested that the largest errors were due to estimated error in plant respiration. Evaluation of coarse resolution NPP product is generally done using one of the following methods. The first one is creating a new NPP model (based on flux tower data, long term inventory data, etc.) for the study area using finer resolution images to decrease uncertainties between coarse resolution pixels and field data (Potter et al., 2012 [50]; Gebremichael and Barros, 2006 [14]; Turner et al., 2006 [70]; Turner et al., 2004 [69]; Kimbell et al., 2000 [29]; Running and Hunt 1993 [61]). The new model is then compared with global models such as the MODIS NPP product. The second method aims to improve the global model (i.e. MODIS NPP product) by using local data sets such as climate and land cover data (Yu et al., 2009 [77]) and then the improved model is compared with the global model. In both cases, the models must reflect the study area with a high accuracy and its accuracy can be measured using field data sets. The process is complicated by the fact that NPP cannot be measured directly in the field, as it is the difference between two large carbon fluxes of GPP and autotrophic respiration (Clark et al., 2001 [6]). Instead biomass is measured at two points in time, combined with species-and-area specific allometric coefficients (Jenkins et al., 2003 [28]) to estimate NPP. For this reason, creating a reliable forest database, using tree and plot level measurements help in improving estimates of forest NPP (Clark et al., 2001 [6]); in turn improving the evaluation of remote sensing based NPP products. The main goal of this chapter is to upscale forest measurement data obtained from the Ministry of Forest and Water Affair (MFWA) of Turkey, and to evaluate the MODIS NPP product for the forest ecosystems in Turkey. In this study, a new approach was used to find the contribution of each land cover type to respective MODIS pixels for evaluation of the NPP product. Turner et al.(2004) [69] applied a similar approach to extrapolate plot measurements to a larger scale but their extrapolation was done within homogeneous area. Here, the most challenging part of the evaluation process is to determine the NPP contribution of the forest areas to each MODIS pixel, which is the result of different land cover (LC) types. This is the first effort to evaluate the MODIS NPP for Turkey. This is important as the flux towers and filed biomass data used for model evaluation are typically either located in developed countries (e.g. Western Europe or USA (The United States of America)) or in particular ecosystem of interest (e.g. tropical forests), potentially introducing a bias into the NPP estimates for other regions.

2.2 Materials and Methods

2.2.1 Field Data

All field data were obtained from MFWA (Ministry of Forest and Water Affairs). MFWA plot determination protocol is based on the International Co-operative Program on Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forest) Level 1 protocol (ICP, 2016 [27] (ICP Forest Manual)). Each sampling point covers 50 m by 50 m area having 16 km between each others. Four different points were determined at a distance of 25 m from the centre point following cardinal compass directions (i.e. north, south, east and west) (Figure 2.1).

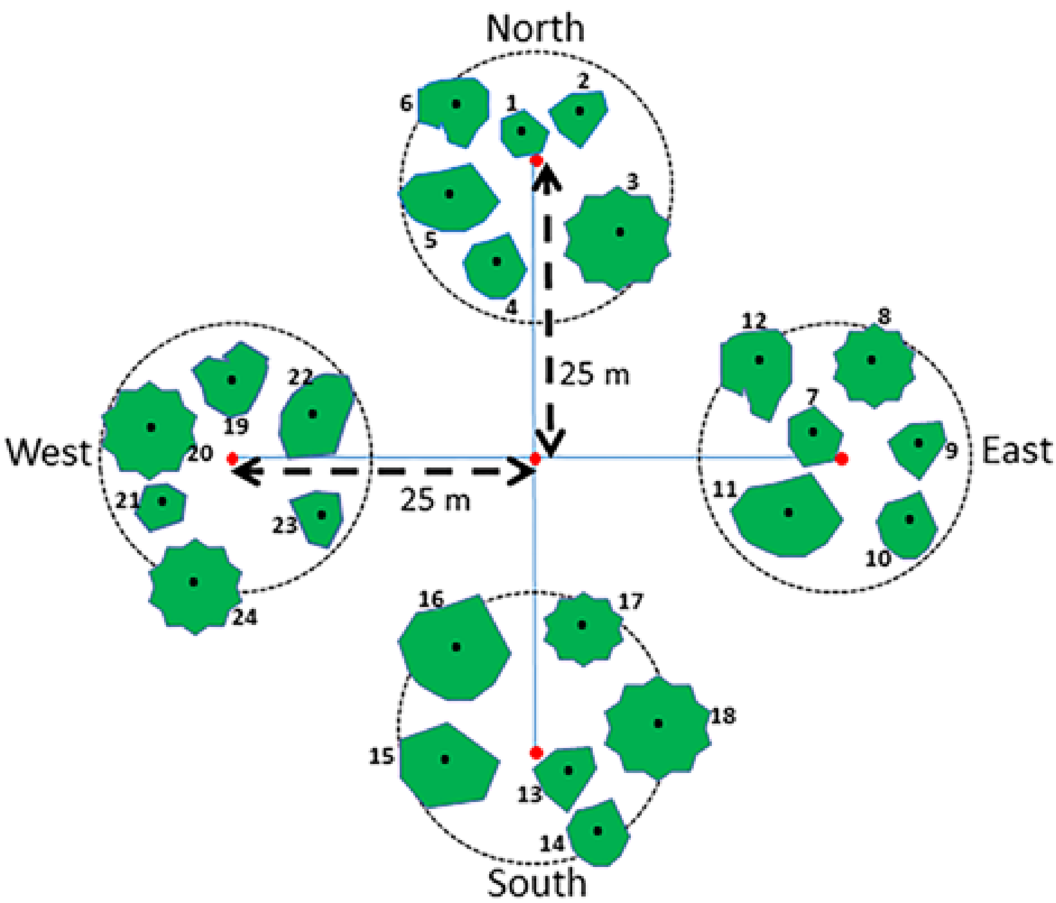


Figure 2.1: Schematic diagram of the field plot sampling design (MFWA, 2013).

In this study three different methods were used to calculate aboveground NPP from the raw field measurements: (i) ministry (MFWA) provided coefficients (MC) from Asan (1995) [4], (ii) published allometric coefficients from Jenkins et al. (2003) [28] (JC), a widely cited compendium of North American tree growth equations, and (iii) annual expected increment (AEI). The first two methods (MC and JC) derive NPP using two different years' measurements (2008 and 2013) whereas the AEI method uses the MFWA-provided "expected increment" under optimum conditions by diameter class. In our analysis, for the MC and JC methods, the same trees within the same plot were always selected, i.e. trees those died between 2008 and 2013 inventories were excluded from the calculations. Firstly, total amount of NPP was calculated for the years 2008 and 2013 for the same trees in the same plot. Secondly, total NPP of each plot area was calculated for 2008 and 2013 by using number of trees per ha for each plot. Finally, NPP values of 2013 and 2008 were subtracted to get total NPP produced during that 5 years.

i. Ministry Coefficients (MC) NPP Calculation

After the selection of the same trees, all DBH (Diameter at Breast Height) values were converted into above ground bole volume (V) using a DBH-volume table (Table 2.1). This table was generated by MFWA by considering species, age, location and closeness of the forest. This table shows the corresponding volume of each tree species with respect to their DBH values. It also gives the growth expectance of each tree species under optimum conditions according to the given DBH values. In this table "Tree species" is the species codes used by the MFWA. Average DBH is the mid-point of the minimum and maximum DBH. V is aboveground bole volume. In DBH-volume table Annual Expected Increment (AEI) shows the increment to be expected for each tree species according to its DBH range under optimum conditions. It was driven from ministry DBH-volume table (Table 2.1). These bole volume values were then used to estimate total above ground biomass using equation (2.1) and (2.2) (Asan, 1995 [4]). The DBH-volume relation was also modelled using a linear regression method to avoid stair-step effect. However, this model did not change the results significantly.

$$A_{BL} = V(m^3) \times 0.541 \times 1.310 \times 1000 \tag{2.1}$$

$$A_{NL} = V(m^3) \times 0.446 \times 1.212 \times 1000 \tag{2.2}$$

where A_{BL} and A_{NL} are total aboveground biomass (kg) for broadleaf and needleleaf trees respectively; V (m^3) is above-ground bole volume calculated for each tree using DBH-volume table; 0.541 and 0.446 are conversion coefficients from above-ground bole volume to aboveground bole biomass and 1.310 and 1.212 are coefficients to expand the aboveground bole biomass into total aboveground biomass (ton (t)) including branches for broadleaf and needleleaf trees respectively. The multiplier ‘1000’ is used for conversion to kg. These coefficients were calculated by the MFWA (Asan, 1995 [4]), considering the basic structures and conditions of the forest types and tree species of Turkey's forest ecosystems.

ii. Jenkins Coefficients (JC) NPP Calculation

Jenkins et al. (2003) [28] derived allometric equations, the relation between growth in biomass and body parts (root, bole) of an individual plant (Niklas, 2004 [43]), for hardwood and softwood tree species in the United States. Each major group was also divided into sub-groups according to tree structures. Coefficients for allometric equations were created for each sub-group. Since tree species in Turkey differ from those in USA, coefficients from the same tree genera were instead used. Aboveground biomass was then computed based on these genus-specific coefficients.

iii. Annual Expected Increment (AEI) Approach

Coarse resolution climate data may reflect the climate averages of a study area but do less well at capturing local seasonal extremes. This may cause the model to predict close to the expected production under optimum conditions, but not seasonal extreme conditions. For this reason, annual expected increment for each tree species for a given area was also calculated using field data (Table 2.1). AEI shows the expected increment of each tree under optimum climate condition for a year, based on its current DBH. These values were calculated by the MFWA, considering the geographical location, closeness of the forest areas, climate conditions of the area and basic properties of the tree species (i.e. age, structure). Table 2.1 is an example for ministry DBH-volume tables, where DBH is Diameter at Breast Height, V is the Above Ground Bole Volume and AEI is Annual Expected Volume Increment for the given tree species.

Table 2.1: An example for ministry DBH-volume tables. Where DBH is Diameter at Breast Height, V is the Above Ground Bole Volume and AEI is Annual Expected Volume Increment for the given tree species.

Tree Species	**Minimum DBH (cm)**	**Maximum DBH (cm)**	**Average DBH (cm)**	V**(m^3)**	**AEI year (m^3)**
1 (field maple)	8	11.9	10	0.032	0.0025
1 (field maple)	12	15.9	14	0.081	0.0042
1 (field maple)	16	19.9	18	0.151	0.0062
1 (field maple)	20	23.9	22	0.243	0.0080
19 (oriental beech)	8	11.9	10	0.041	0.0032
19 (oriental beech)	12	15.9	14	0.087	0.0055
19 (oriental beech)	16	19.9	18	0.159	0.0072
19 (oriental beech)	20	23.9	22	0.263	0.0090
110 (Mediterranean cypress)	8	11.9	10	0.029	0.0020
110 (Mediterranean cypress)	12	15.9	14	0.062	0.0043
110 (Mediterranean cypress)	16	19.9	18	0.110	0.0066
110 (Mediterranean cypress)	20	23.9	22	0.175	0.0100

2.2.2 Calculation of Total Above Ground Carbon and Mean Plot Carbon

Calculated TAGB (kg), using all three methods, was converted to above ground carbon (AGC) (kgC). Although, a universal coefficient can be applied for most plant types (FAO, 2015 [11]; Ahl et al., 2004 [3]; Gower etal., 1997 [16]; Landsberg et al.,1997 [33]), different coefficients (0.48 for broadleaf trees and, 0.51 for needleleaf trees) were used here, as both the MC and JC approaches consider the trees according to their leaf structures and wood types. After calculating the carbon in each measured tree, using each method, the average carbon pool within respective plot areas was calculated by equation 2.3.

$$C_{mean} = \frac{\sum_{k=1}^{n}}{n} \tag{2.3}$$

where C_{mean} is the mean carbon among the measured trees (kgC), T is the tree and n is the total number of measured trees within a plot. The aim to calculate mean tree carbon among measured trees is to find average carbon production of any tree in a given plot. Then, total carbon produces by living trees in each plot can be calculated by multiplying this value with number of trees per ha (kgC ha^{-1}) obtained from MFWA. These values then can be converted to kg carbon per m^2 after adding other carbon pools in a forest. MODIS NPP product includes three basic carbon stocks, (i) carbon fixed by living tissues (steams, branches, leaves, roots), (ii) carbon in dead parts (dead foliage (above ground litter fall), dead wood), and (iii) soil carbon (He et al., 2012 [21]; Heinsch et al., 2003 [23]). After calculation of above ground biomass using three different methods (MC, JC and AEI), dead foliage and soil carbon were added using pre-determined ministry coefficients. Malhi et al., 2011 [36] give the relation between NPP and the carbon pools stated above for many accepted NPP models. CASA (Carnegie-Ames-Stanford Approach) model, for example, accepts each pool as 0.33 of NPP. However, ministry coefficients were based on the structure of the tree and the closeness of the forest (Table 2.2), and they were considered as more suitable for the study. Moreover, it is stated that these coefficients include all carbon pool including fine root turnover. It is important to use area specific coefficients to increase the accuracy. Finér et al., 2011 [13] and Liu et al., 2004 [35] showed the difference in production in different ecosystem in fine root production and above ground litter fall, respectively. Dead wood carbon, on the other hand, was calculated using one coefficient (0.01) for all types of ecosystems. This coefficient was used to consider the dead wood biomass (mortality) as one of the carbon pool (He et al., 2012 [21]; Asan et al., 1995 [4]).

2.2.3 MODIS Data

MODIS MOD17A3 NPP product is an annual 1 km $\times$ 1 km spatial resolution data product. It uses monthly intervals to calculate total annual production. Basic inputs for the product, other than the satellite images, are climate data sets from NASA Data Assimilation Office (DAO-NASA) and MODIS land cover product (Zhao et al., 2005 [78]; Heinsch et al., 2003 [23]). For this study, the MODIS NPP product was downloaded from the University of Montana database system (ftp://ftp.ntsg.umt.edu). These data are rectified for cloud contamination, climate grid consistency with the original MODIS images, improved biome parameters look-up table and quality assessment control (Zhao et al., 2005 [78]). MODIS NDVI (Normalized Difference Vegetation Index) products were downloaded from NASA-EODIS (http://reverb.echo.-nasa.gov/reverb/redirect/wist). All images were converted into the standard geographic coordinate system, Geographic Latitude/Longitude, WGS84 (World Geodetic System 1984) datum, using the MODIS Reprojection Tool (MRT) to have a common coordinate system with the MFWA filed data.

Table 2.2: Dead foliage (Above Ground Litter Fall) and soil carbon coefficients taken from MFWA (Soil carbon amount of the area is linearly related with the age of the forest).

Tree structure	Volume to agb	Agb to tagb	Tagb to tagc	Dead wood carbon (mortality)	Bgc (closeness >= 10%)	Bgc (closeness <= 10%)
Broadleaf trees	0.541	1.310	0.48	0.0047	0.24	0.46
Needleleaf trees	0.446	1.212	0.51	0.0047	0.29	0.40

Tree structure	Soil carbon (t C $^{h}-1$/age) (closeness >= 10%)	Soil carbon (t C $^{h}-1$/age) (closeness <= 10%)	Dead foliage carbon, (foliage turnover) (t C $^{h}-1$/year) (closeness >= 10%)	Dead foliage carbon, (foliage turnover) (t C $^{h}-1$/year) (closeness <= 10%)
Broadleaf trees	84.82	21.20	3.75	0.93
Needleleaf trees	76.56	19.14	7.46	1.86

2.2.4 Determining the Contribution of Forest NPP to Each MODIS Pixel

Previous studies have found that image spatial resolution, land cover type (Heinsch et al., 2003 [23]; Thomlinson et al., 1999 [67]) within a pixel, and algorithm uncertainty associated with LUE, and FPAR are significant source of uncertainty in the calculation of MODIS NPP (Turner et al., 2006 [70]). These three components are also considered to drive differences between ground-based/flux towers, NPP measurements, and satellite based estimations (Donmez et al., 2011 [8]; Running et al., 1999a [60]). For the evaluation of the MODIS data using ground-based measurements performed here, the first two of these components, spatial resolution and heterogeneous land cover, were carefully considered to decrease the uncertainties during the upscaling. A key problem in upscaling the field NPP measurements to the scale of a MODIS pixel was to determine the mix of nearby land-cover types. As a result, the calculated NPP is the function of those land cover types. Thus, first, each CORINE land cover type in a 1 km $\times$ 1 km MODIS NPP pixel was recorded to its corresponding ministry plot point to determine the total contribution of each land cover to MODIS NPP. Net primary productivity (NPP) of each pixel was calculated monthly, and summed to an annual product (Zhao et al., 2005 [78]; Heinsch et al., 2003 [23]). For a given MODIS pixel, for example, the NPP contribution will be zero from the agricultural areas but nonzero from forested areas. However, for the growing season, the agricultural contribution might be more than that from any other land cover type. Because of this effect, it is important to understand the changes of the NPP contribution of each land cover types during the year. Although NDVI was used to estimate the satellite based NPP (Zhao et al., 2005 [78]; Turner et al., 2004 [69]), inter-annual variations may affect the relation between NDVI and NPP (Zhao et al., 2005 [78]; Briggs et al., 1998 [5]). However, to decrease the heterogeneity within a pixel area and be consistent with the CORINE data, 250 m $\times$ 250 m (Figure 2.2) 16 day MODIS NDVI dataset (MOD13Q1) was used to create a ratio among the LC types. In order to calculate these ratios, first MODIS NDVI values were summed up to calculate total annual NDVI, and then 10000 random points were selected within Turkey's geographical area. Because the seasonal and geographical variations may alter the annually calculated NDVI-NPP relationships (Zhao et al., 2005 [78]; Briggs et al., 1998 [5]), the study area was divided into 4 different zones according to the climatological properties (i.e. mean annual temperature (MAT), mean annual precipitation (MAP)), and natural vegetated areas using Evrendilek and Berberoglu (2008) [9] (Figure 2.3). An NDVI ratio for each land cover type during each year was then calculated for each zone using random points. Next, the total effect of the forest in that particular pixel was calculated as a function of LC and NDVI ratio using equation 2.4.

$$\begin{aligned} P_F = (P_M/((R_U \times N_U) + (R_A \times N_A) + (R_F \times N_F) + \\ (R_S \times N_S) + (R_L \times N_L) + (R_W \times N_W))) \times NF \end{aligned} \tag{2.4}$$

where P_F is the forest net primary productivity within a pixel, P_M is NPP from MODIS product, $R_U, R_A, R_F, R_S, R_L, R_W$ are the NDVI ratios of artificial, agricultural, forest, semi-natural, wetland and water areas, respectively. N_U, N_A, N_F, N_S, N_L, N_W are the number of the pixels of artificial, agricultural, forest, semi-natural, wetland and water areas, respectively in one MODIS pixel according to CORINE LC data. As the main goal of the study is to validate MODIS forest NPP estimation, the forest ratio was defined as "1" and other land cover types were calculated relative to this constant value. The calculated forest NPP values were then used to evaluate MODIS product using field data.

2.2.5 Statistical Analysis

After calculation of the forest NPP contribution to each MODIS pixel, a simple linear regression (SLR) model was applied using the R statistical software (Version 3.3.2) to find the correlation between MODIS forest NPP and field forest NPP. The contribution of forest in a MODIS pixel was considered as equivalent to the forest field NPP. Because, after the calculation, the contribution is found in $kgCm^{-2}$, which refers to its productivity to a square meter, regardless of where the forest is in that pixel. Furthermore, the ministry plots are assumed to be exactly in a forest area. The R^2, RMSE (Root Mean Square Error) and intersection of the model with respect to a hypothetical perfect (1:1) model were evaluated.

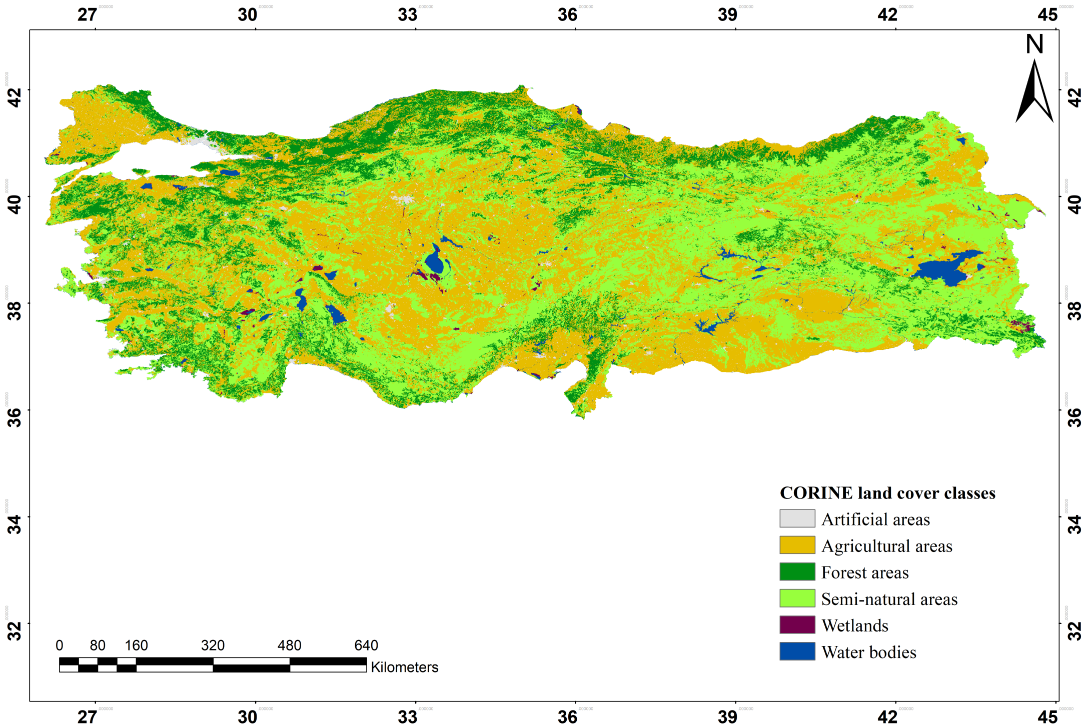


Figure 2.2: The CORINE Land Cover Map for Turkey (EEA, 2006 [1]).

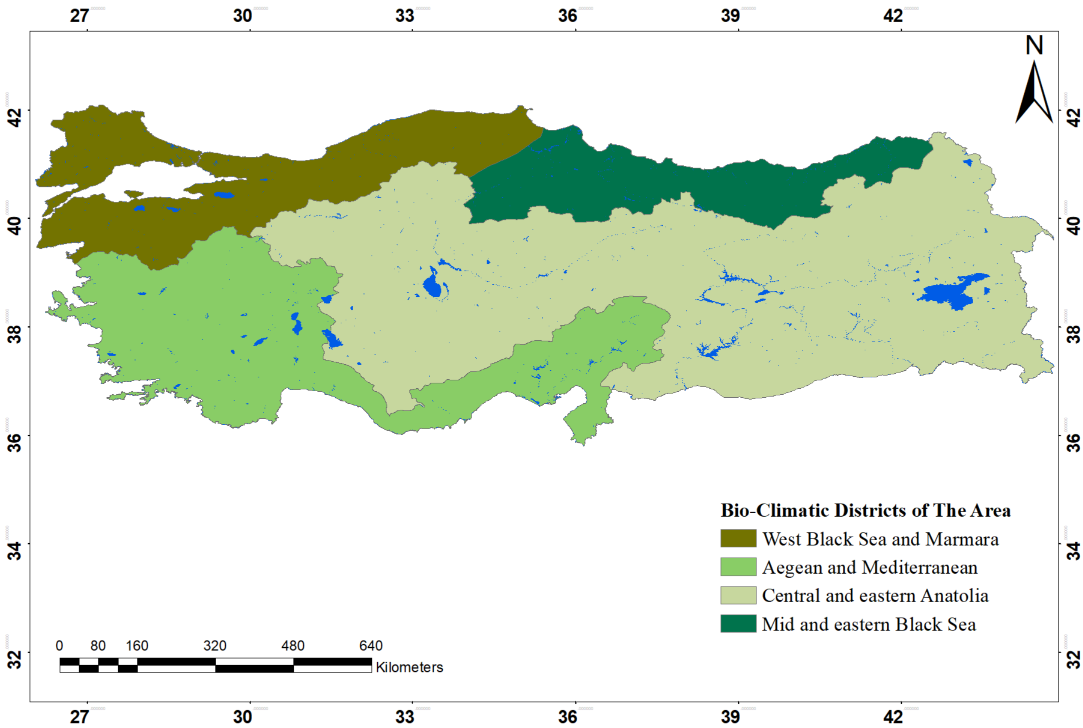


Figure 2.3: Regions of the study area used to calculate the NDVI ratios described in the text. Altered from original according to Evrendilek and Berberoglu (2008) [9].

2.3 Results

2.3.1 NDVI Ratio

All calculated NDVI values for each year and for the period of 2008-2013 were compared with respect to the regions in order to evaluate the regional differences. The results do not show any significant change for temporal variation; no significant difference were observed between individual years. However, differences between the regions (Figure 2.4) are statistically significant and therefore they are considered during the evaluation process (Table 2.3).

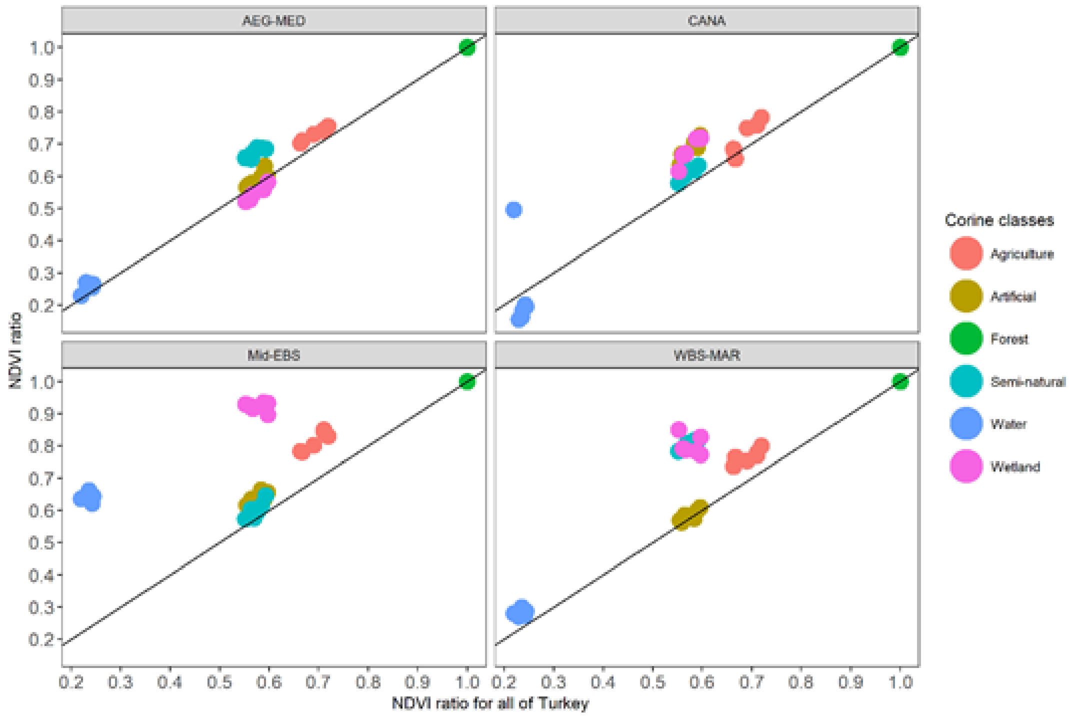


Figure 2.4: Regional NDVI ratio vs. Turkey's overall NDVI ratio. AEG-MED, CANA, Mid-EBS and WBS-MAR is; Aegean and Mediterranean, Central and eastern Anatolia, Mid and eastern Black Sea and West Black Sea and Marmara regions, respectively.

Table 2.3: Calculated NDVI ratios, normalized to Forest Areas = 1.0. The ratio for each land cover type was calculated separately for each region, to decrease the spatial effects caused by the climate and land cover properties of the regions.

Regions / **Land Cover**	**West Black Sea & Marmara region**	**Aegean & Mediterranean region**	**Central & eastern Anatolia region**	**Mid & eastern Black Sea region**
Artificial areas	0.583	0.588	0.675	0.634
Agricultural areas	0.767	0.730	0.732	0.810
Forest areas	1	1	1	1
Semi-natural areas	0.801	0.674	0.613	0.595
Wetlands	0.801	0.552	0.684	0.922
Water bodies	0.283	0.256	0.175	0.634

2.3.2 Comparison of MODIS NPP with Field NPP

i. Ministry Coefficient (MC) Method

Average MODIS forest NPP was calculated as 0.74 kgC m^{-2} $(5years)^{-1}$ (0.148 kgC m^{-2} $year^{-1}$) for the region of Aegean and Mediterranean,1.07 kgC m^{-2} $(5years)^{-1}$ (0.214 kgC m^{-2} $year^{-1}$) for Central and Eastern Anatolia, 0.8 kgC m^{-2} $(5years)^{-1}$ (0.16 kgC m^{-2} $year^{-1}$) for the region of Middle and Eastern Black Sea and 1.2 kgC m^{-2} $(5years)^{-1}$ (0.24 kgC m^{-2} $year^{-1}$) for the region of West Black Sea and Marmara. Aegean and Mediterranean region and Central and Eastern Anatolia regions showed the best and the least agreements between MODIS and field forest NPP respectively (50%, 15%). The low correlation between MODIS NPP and field forest NPP for Central and Eastern Anatolia region might be the result of having less number of measurements over this area. It should be noted here that, the lack of measurements is not only due to the number of the plot measured by the ministry, but also due to the selection process explained in section 2.2.1. MODIS forest NPP showed 34% agreement with field forest NPP over the entire study area. However, as it can be seen in Figure 2.5, there is significant variability in the relation (RMSE = 1.51 kgC m^{-2} $(5years)^{-1}$), suggesting a high potential for estimation error of MODIS NPP values over areas with high geographical and inter-annual changes (Zhao et al., 2005 [78]). On the other hand, there is a clear relation (R^2 = 0.34) between field data and MODIS NPP estimation, although average MODIS NPP values are twice as large as field values (Figure 2.5), which can be the result of the bias in model and/or parameters used to estimate MODIS NPP.

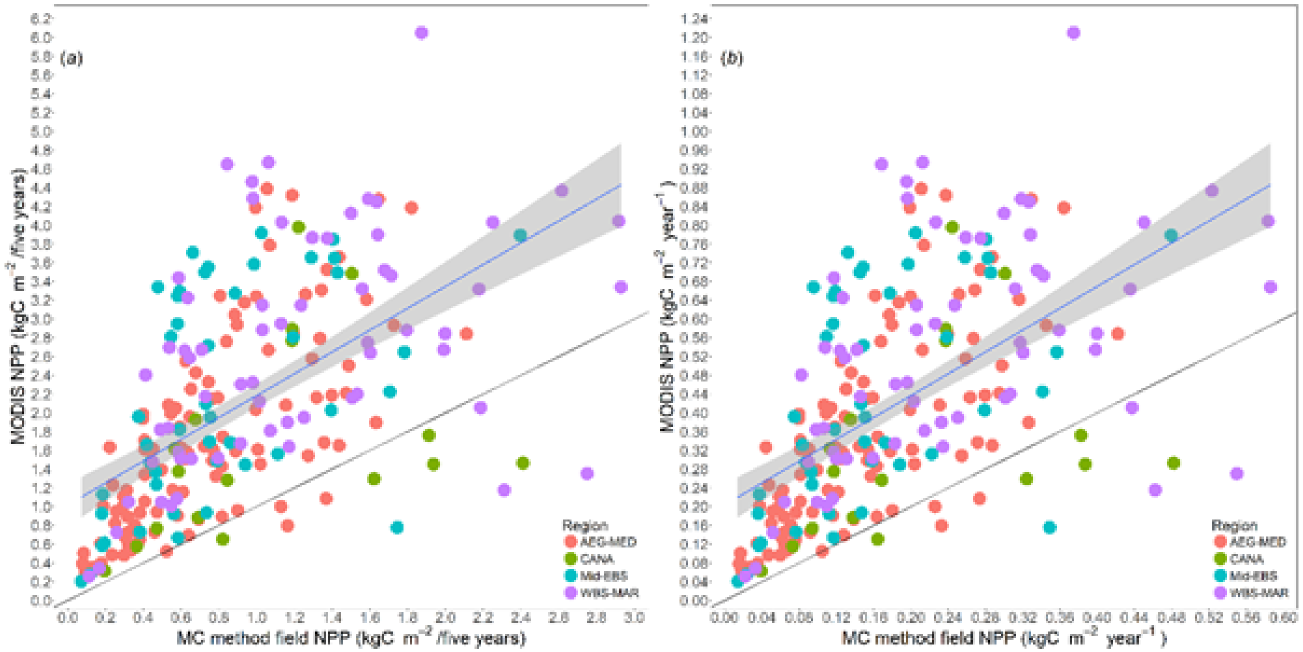


Figure 2.5: Field net primary production (NPP) vs. the MODIS NPP product. The X-axis shows the MC based field NPP and Y-axis shows the MODIS NPP. A best-fit regression line (R^2 = 0.34, RMSE = 1.51, Regression Function = 1.019 + 1.164(MC NPP)) is shown with a shaded error region. (Figure 2.5-a shows 5 years total NPP values and Figure 2.5-b shows yearly averages). AEG-MED, CANA, Mid-EBS and WBS-MAR is; Aegean and Mediterranean, Central and eastern Anatolia, Mid and eastern Black Sea and West Black Sea and Marmara regions respectively.

ii. Jenkins Coefficient (JC) Method

Jenkins method (Jenkins et al., 2003 [28]) used in this study was developed for the tree species of Northern America. Although the genus is the same, the difference in species may create errors. JC based NPP was tested with MC based NPP to understand how well the coefficients can reflect the reality over Turkey's forest ecosystems. The NPP based on the JC coefficients method showed good agreement (R^2 =0.76, RMSE = 0.39 kgC m^{-2} $(5years)^{-1}$) with ministry based NPP (Figure 2.6). JC based calculated NPP compared with MODIS forest NPP (Figure 2.7), resulted in relatively lower correlation (R^2 = 0.31). The root mean square error (RMSE) of this regression (JC vs MODIS) shows a variation close to the MC based calculation with respect to the regression line (RMSE =1.77 kgC m^{-2} $(5years)^{-1}$).

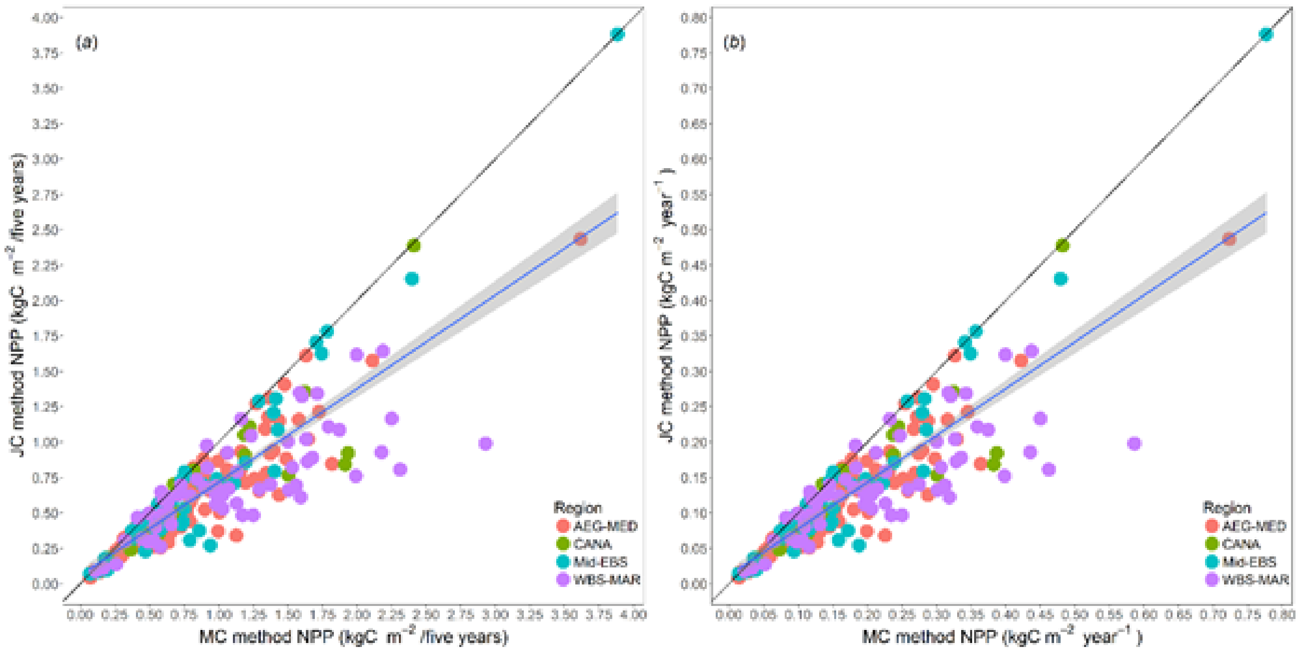


Figure 2.6: Ministry Coefficients (MC) based above ground carbon vs. Jenkins Coefficients (JC) based above ground carbon. A best-fit regression line (R^2 = 0.76, RMSE= 0.39, Regression Function= 0.05797 + 0.65998(MC NPP)) is shown with a shaded error region. (Figure 2.6-a shows 5 years total NPP values and Figure 2.6-b shows yearly averages). AEG-MED, CANA, Mid-EBS and WBS-MAR is; Aegean and Mediterranean, Central and eastern Anatolia, Mid and eastern Black Sea and West Black Sea and Marmara regions respectively.

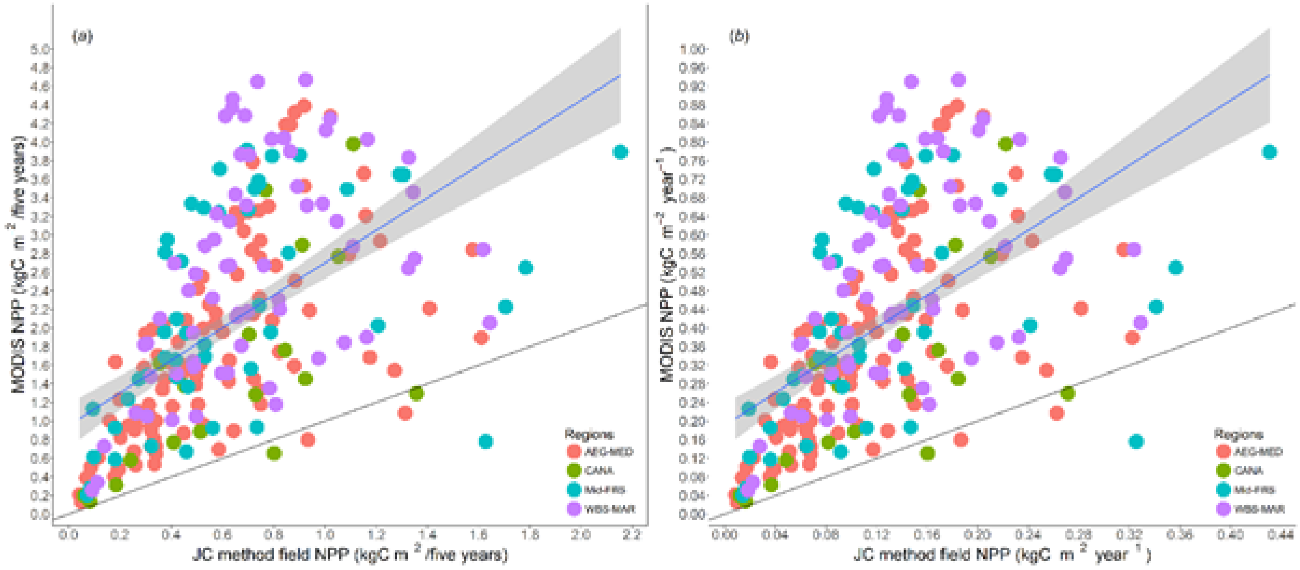


Figure 2.7: JC based NPP vs. MODIS NPP. A best-fit regression line (R^2 = 0.31, RMSE = 1.73, Regression Function = 0.9551 + 1.7471(JC NPP)) is shown with a shaded error region. (Figure 2.7-a shows 5 years total NPP values and Figure 2.7-b shows yearly averages). AEG-MED, CANA, Mid-EBS and WBS-MAR is; Aegean and Mediterranean, Central and eastern Anatolia, Mid and eastern Black Sea and West Black Sea and Marmara regions respectively.

iii. Annual Expected Increment (AEI) Method

Many studies indicate that, MODIS NPP product can be used to understand general conditions of the globe (Zhao and Running, 2010 [79]; Zhao et al., 2005 [78]; Heinsch et al., 2003 [23]). However, it cannot reflect the actual conditions at the country and local scale, especially for the areas having abrupt geographical and climatic changes (Neumann et al., 2016 [42]; Zhao et al., 2005 [78]). Due to this reason, MODIS NPP product has a higher correlation with AEI compared to the actual conditions (Figure 2.8). Moreover, it has relatively low residual error (RMSE = 0.26 m^{-2} $year^{-1}$) with respect to the actual NPP values.

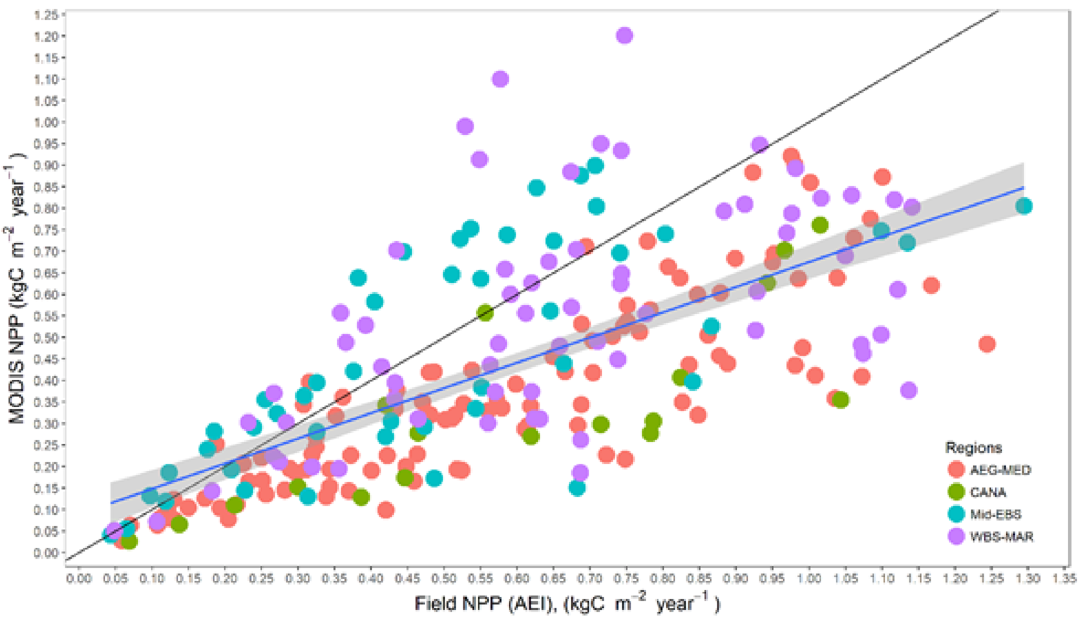


Figure 2.8: MODIS 2009 NPP vs. AEI 2009. A best-fit regression line (R^2 = 0.48, RMSE = 0.26 m^{-2} $year^{-1}$, Regression Function = 0.08995 + 0.58542(AEI NPP)) is shown with a shaded error region. AEG-MED, CANA, Mid-EBS and WBS-MAR is; Aegean and Mediterranean, Central and eastern Anatolia, Mid and eastern Black Sea and West Black Sea and Marmara regions respectively.

2.4 Discussion for the results

In this chapter, MODIS NPP product was evaluated for the forest ecosystems in Turkey. The analysis showed that MODIS NPP has a higher correlation with AEI (R^2 =0.48, slope = 0.58). However, it reaches a certain saturation point (Figure 2.8). This saturation might be the result of the climate data used to create BPLUT (Biome Parameters Look-Up Table) as a model input (Zhao et al., 2005 [78]). MODIS uses a BPLUT table as a scalar to mitigate certain input variables such as LUE, specific leaf area, leaf longevity (Heinsch et al., 2003 [23]). This scalar changes within a range from 0 to 1 and it may cause the final product to reach a saturation point for certain areas. The saturation effect might also be related to differences in stand density. In a closed stand the dominant trees assessed by the field crews probably well cover forests NPP. In an open stand with shrubs, grass and young trees, the mismatch between field NPP and MOD17 NPP is probably larger (Neumann et al., 2016 [42]). Although there are many saturation point in all parts of the study area, this is mostly common in regions with relatively less vegetative variability such as Northwest Turkey and Central and eastern Anatolia. Northwest Turkey is richly covered by the dense forested area but with relatively less diversity. The BPLUT may be the most significant reason for the saturation of MODIS NPP in this area. However, Central and eastern Anatolia has less forest areas and most of them are not closed stands. Since ministry does not measure the understorey plants in a forest area, this may result in the saturation of MODIS NPP mentioned in this section. In most cases, MODIS has higher NPP values than the field NPP calculations. These differences may be the results of (i) the errors in the field data, and (ii) regional accuracy of input data used in the MODIS algorithm and (iii) mismatching of actual conditions of the area with remotely sensed data used in the evaluation process such as land cover data and (iv) effects of coarse resolution climate data. In this study, forest field data from the Ministry of Forest and Water Affairs of Turkey were used. Field data includes DBH measurements of two different years (2008 and 2013). First, the ministry measurement protocol is not well known, (i.e. which side is the ground level for a tree on a hill, which compass direction the tree is measured) and both measurements and recordings are subject to human error. Second, the quality and the quantity of the field data as model input, has a great effect on the result, and selection of the same trees decreases not only number of the measured trees but also number of the sampled plots. Finally, the ministry only measures dominant trees within a plot. Understorey vegetation is not included to any of the plot measurements. This may result in estimating NPP less than actual amount. One of the basic inputs for the NPP products is land cover data. MODIS MOD17A3 NPP product uses global land cover data MOD12Q1 (500 m $\times$ 500 m) (Heinsch et al., 2003 [23]). The MODIS land cover product shows high (65-80%) accuracy especially in large homogeneous areas (Heinsch et al., 2006 [24]; Hansen et al., 2000 [19]). Although this might be correct for global studies, MODIS products may not have the same accuracy at regional scales. For example, the land cover product of MODIS (MOD12Q1), an input to the NPP algorithm has certain misclassification errors over Turkey (e.g. deciduous needleleaf forest and savannahs) (Evrendilek and Gulbeyaz, 2011 [10]), which can affect LUE directly as well. The CORINE land cover data was used for the study, to minimize the errors due to the land cover changes in a 1 km $\times$ 1 km MODIS pixel. However, not all ministry forest plot points are classified as forest areas in the CORINE data, and these points were excluded from the data set. This situation was found when comparing the MODIS land cover product and field data, even for higher number of plots. This situation causes a misestimation of MODIS forest NPP for Turkey, and thus error in calculating the forest NPP contribution for each MODIS pixel. CORINE is a European Union based data set, and thus its model has a smaller region with respect to the MODIS land cover product (a global model). As stated above, global models tend to misestimate local properties especially in areas with abrupt physical changes; a prime example of this is the MODIS's misclassification of deciduous needleleaf trees in Turkey. Thus many mismatching properties and estimation were identified over Turkey, not only with respect to MODIS data set but also with respect to actual on-the-ground data. The other obvious mismatch with the CORINE data is related to the NDVI ratio. As can be seen from Table 2.3, Middle and Eastern Black Sea region's NDVI ratio for water surfaces and wetlands are higher than expected. It was thought that three main reasons might cause this problem. First of all, misclassification of the CORINE land cover product. Second, the spatial resolution of the land cover product. If a pixel was mostly covered by water, it would be assigned as a water surface although the rest is forest or any other land cover type. Since the closeness of the forested areas in this region is higher than the other (>75%) this may affect the NDVI values of these areas. Third and most probable reason is the high density of the green vegetation over the water surfaces during the vegetative period.

Finally, the coarse resolution climate data ($1.00^o \times 1.25^o$) may create bias since each pixel is the average of covered area. For instance, if a pixel covers a sea and a mountain area together, the condition in both areas would be altered from both sites condition. Moreover, it is important to emphasize that all climate data, used in MODIS NPP product, are assimilated data not measured (Zhao et al., 2005 [78]; Heinsch et al., 2003 [23]).

CHAPTER 3

UNDERSTANDING AND MODELLING NET PRIMARY PRODUCTIVITY (NPP) OVER SEMI-NATURAL AREAS: A CASE STUDY OF CASA MODEL FOR TURKEY'S FOREST ECOSYSTEMS

3.1 Introduction

One of the basic accuracy problem of the global NPP models, such as MODIS MOD17-A3 NPP product, is the accuracy of the input data. Global models mostly use global data sets as input parameter (i.e. land cover maps). Moreover, the input data used to estimate NPP might be assimilated datasets, not the measurements, such as climate data used in providing MOD17A3. Turkey is one of the countries, having many different eco-regions. These regions are the results of abrupt geographical and climatic changes. Because of this richness in ecosystem, global models mostly have low accuracy over Turkey such as MODIS land cover and NPP (Net Primary Productivity) product. MODIS land cover product have 85% consistence only over large homogeneous areas (Heinsch et al., 2006 [24]; Heinsch et al., 2003 [23]). For example, MODIS land cover product misclassified some areas as deciduous needleleaf forest and savannahs over Turkey. In addition, MODIS NPP product also has low accuracy (R^2 = 0.34) over Turkey's forest ecosystem. Using local data, such as meteorological measurements, to improve the accuracy of a model is a widely used approach. In this part of the study, CASA (Carnegie Ames Stanford Approach) NPP model was used to estimate net primary productivity over Turkey. CASA NPP model uses basic principle presented by Monteith (1972) [39]. This approach suggests that, the productivity of a well irrigated cropland is linearly related to the quantity of incoming solar radiation. However, this approach is valid only for optimum conditions. To reflect the actual conditions, stress coefficients are added to the equation as mitigation factors (Equation 3.1).

$$NPP = APAR \times LUE \times T_{\varepsilon_1} \times T_{\varepsilon_2} \times W_{\varepsilon} \tag{3.1}$$

where NPP is Net Primary Productivity, APAR is Absorbed Photosynthetically Active Radiation and LUE is the Light Use Efficiency. $T\varepsilon_1$, $T\varepsilon_2$ and $W\varepsilon$ are temperature effects at very high and low temperatures, temperature stress above and under optimum temperature, and water stress factor respectively (Potter et al., 1993 [51]).

In this part of the study;

i. NPP of Turkey's forest ecosystems was tried to be explained using local data as input variable to CASA NPP model.

ii. The accuracy of the CASA model was tried to be improved based on the basic adaptation process of the plants.

It should be noted here that, no-changes on the formulation of the model was made. However, a new approach was tried for the calculation by means of data usage. In this study, CASA (Carnegie Ames Stanford Approach) was used as the base NPP model and two different APAR calculation methods (based on Potter et al., 1993 [51]; and Yu et al., 2009 [77]). Previously, in many studies scientist tried to estimate NPP of different land cover types (especially natural areas) using different modelling approaches (Yu et al., 2009 [77]; Zhao et al., 2005 [78]; Haxeltine and Prentice, 1996 [20]; Running and Hunt, 1993 [61]; Potter et al., 1993 [51]; Parton et al., 1993 [48]; Ruimy et al., 1996 [57]). Most of these studies created new models to explain NPP, and their findings are close to each other's (Cramer et al., 1999 [7]). Yu et al. (2009) [77], on the other hand presented a new calculation approach implemented to CASA NPP model to improve the accuracy. The ideas behind their modelling are (i) to calculate APAR (Absorbed Photosynthetically Active Radiation) directly from NDVI (Normalized Difference Vegetation Index), not from pre-determined aggregated ecosystem groups and their coefficient (Potter et al., 1993 [51]; Sellers et al., 1996a [65]; Sellers et al., 1996b [66]). This study presents a new calculation approach to improve the accuracy of CASA NPP model. It should be noted here that, the contribution of the study is not changing the equations but the understanding of natural process and by that means, changing the selection of the suitable data sets for the model.

3.2 Materials and Methods

3.2.1 Remote Sensing Data

MODerate resolution Imaging Spectroradiometer (MODIS), MOD13A3 MODIS/Terra Vegetation Indices 16-Day L3 Global 1 km SIN Grid V006, images were used for the study (Figure 3.1). 1 km resolution was used because (i) the study covers all forest area of Turkey, (ii) 1 km resolution is compatible with MODIS global NPP product (MOD17A3). The MODIS data uses an integerized coordinate structure and Hierarchical Data Format (HDF) extensions. All data were converted into geotiff file format and latitude/longitude coordinate system with WGS84 datum, using MODIS reprojection tool (MRT). The latitude/longitude coordinate system was selected to have a common format with the ministry data.

3.2.2 Meteorological Data

The meteorological data used for the study were obtained from Ministry of Forest and Water Affairs (MFWA) Turkish State Meteorological Service (TSMS) division. TSMS in average has over 300 and 200 measurement points for temperature and precipitation, respectively (Figure 3.2 - 3.3) data and between 65 and 80 points for the solar radiation data. All meteorological measurements are in monthly intervals and cover the years between 2008 and 2013. We used IDW (Inverse Distance Weighted) interpolation method to create surface maps for the meteorological data. IDW was chosen to acknowledge the importance of the measurements.

3.2.3 Calculation of Field NPP

Field NPP values were calculated using ministry measurements for each plot. First of all DBH values were converted into volume values using ministry DBH-volume table.

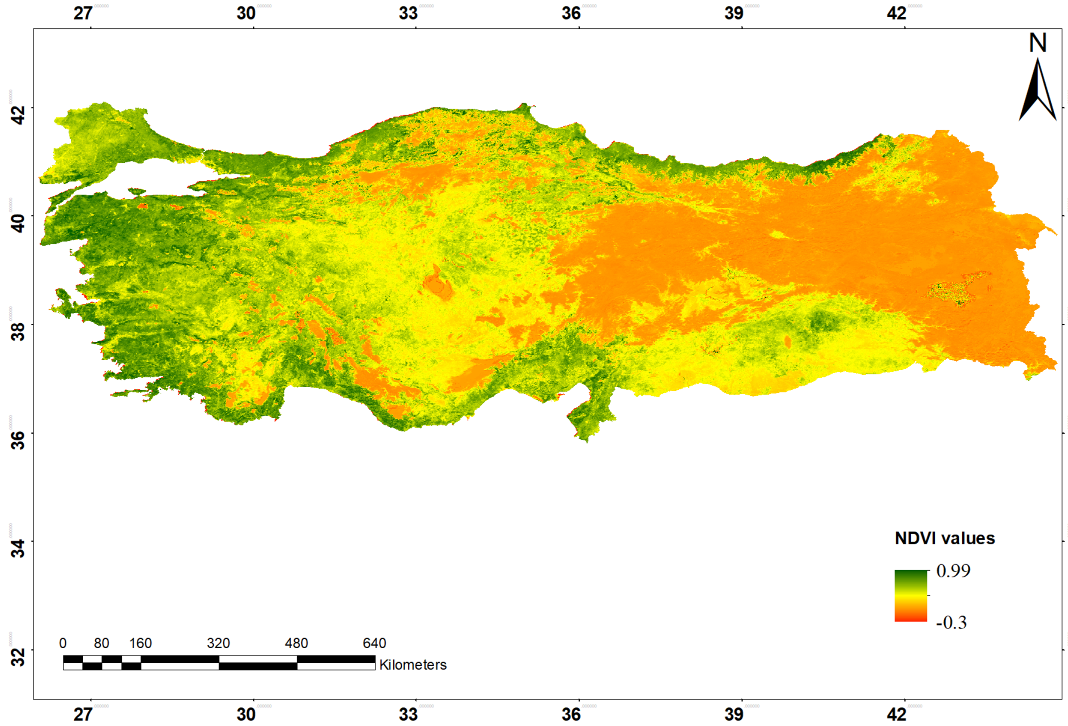


Figure 3.1: An example to MODIS MOD13A3 image. 2009 January NDVI image of the area (https://www.nasa.gov/).

Then using these volume, biomass of each tree was calculated based on ministry coefficients. Finally, carbon content of each tree was calculated. After calculation of the NPP of each tree, these values were averaged to find the average carbon stock of any tree within a plot area.

Ministry of Forest and Water Affairs of Turkey general administration structure has many sub-sections such as regional managements and chieftaincies. Each chieftaincy has the information about number of trees per hectares. Using this information, total NPP over a hectare was calculated in the units of tones carbon. Then these results were converted into kilogram carbon per square meter (kgCm^{-2}). It should be noted here that, it is not possible to measure NPP directly (Clark et al., 2001 [6]). All the calculations are based on hypothetical approximations using measured quantities.

The calculation of field NPP only covers the forested areas. The MODIS pixels, on the other hand are the composition of many land cover types. To overcome this mixed pixel problem, an NDVI based ratio was used to calculate the NPP contribution of forested areas to each pixel. More information about calculation forest NPP can be found in Gulbeyaz et al., 2018 [18].

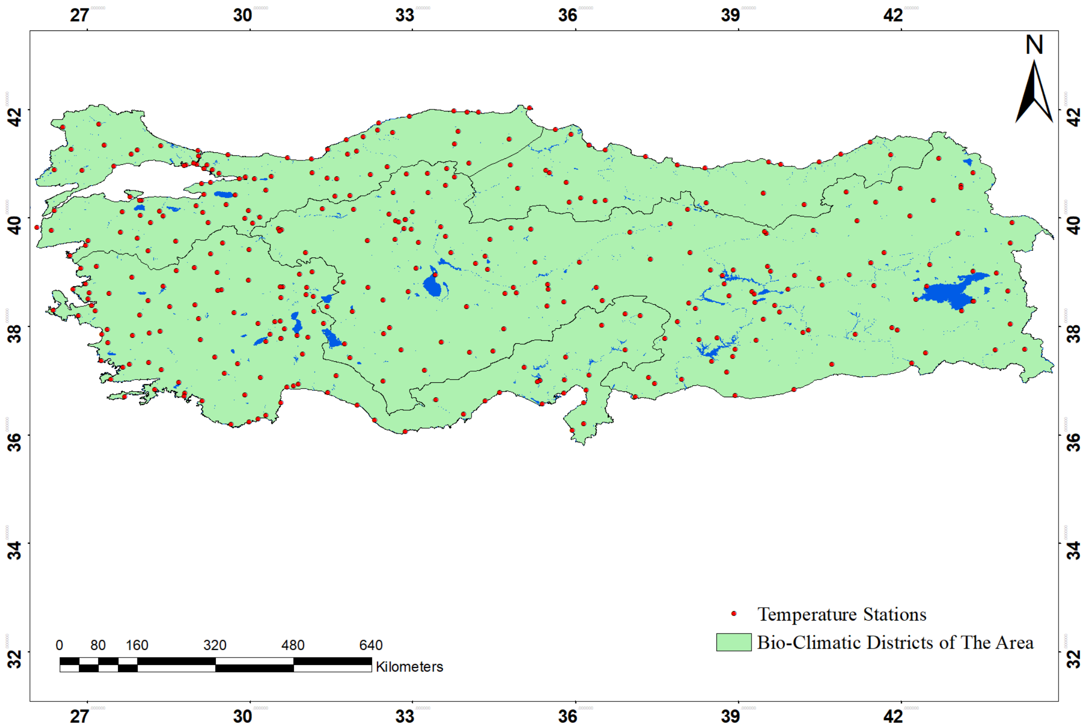


Figure 3.2: Distribution of temperature measurement stations in Turkey (TSMS).

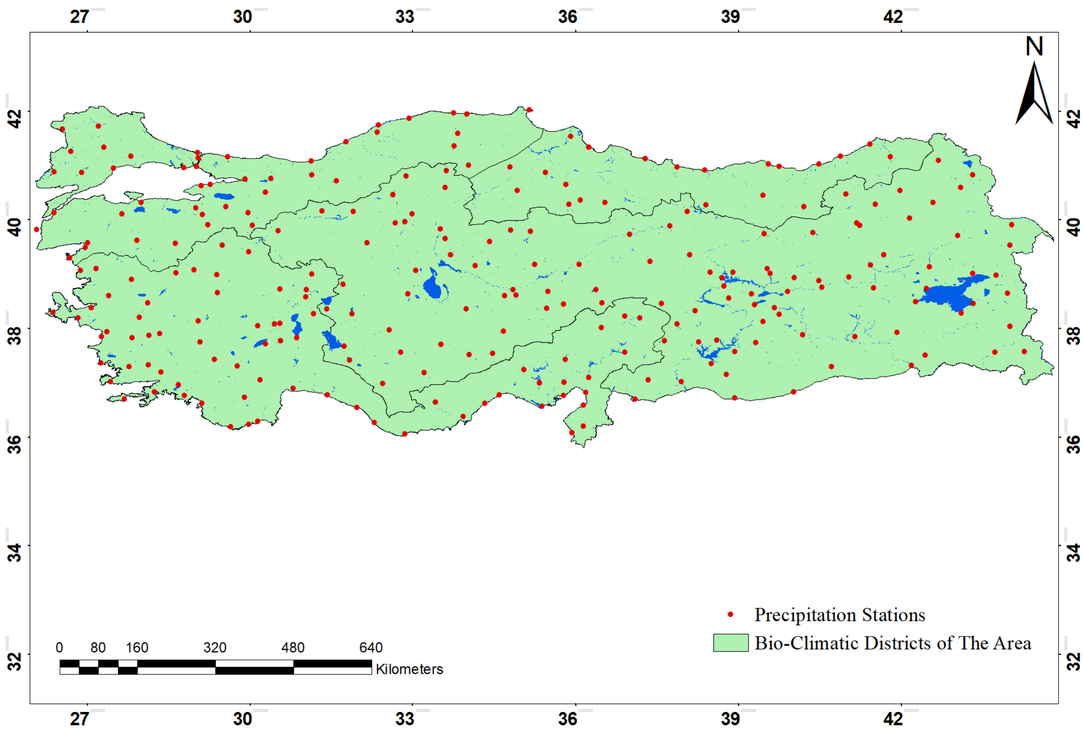


Figure 3.3: Distribution of precipitation measurement stations in Turkey (TSMS).

3.2.4 Calculation of APAR (Absorbed Photosynthetically Active Radiation)

APAR is calculated by the function of solar radiation (SOL) and FPAR (Equation 3.2) (Yu et al., 2009 [77]; Potter et al., 1993 [51]). Since the solar radiation is a measured quantity, it is important to estimate FPAR with a high accuracy.

$$APAR = SOL \times FPAR \times 0.5 \quad (3.2)$$

where APAR is absorbed photosynthetically active radiation, SOL is solar radiation and FPAR is the fraction of photosynthetically active radiation (Yu et al., 2009 [77]; Potter et al., 1993 [51]). In this study, CASA (Carnegie-Ames-Stanford Approach) NPP model was used. Original article (Potter et al., 1993 [51]) suggest an FPAR calculation (Equation 3.3) based on Simple Ratio (SR) (function of NDVI) and maximum possible values of simple ratio with respect to aggregated land cover types classified by Sellers et al. (1996a) [65] and Sellers et al. (1996b) [66]. Same maximum FPAR values presented in Potter et al. (1993) [51] were used. However, the land cover types do not exactly overlap with Turkey's land cover. It was needed to exclude or modify some of the LC types according to corresponding LC types over Turkey (Table 3.1).

$$FPAR = min\{SR/[SR_{max} - SR_{min}] - SR_{min}/[SR_{max} - SR_{min}], 0.95\} \quad (3.3)$$

where SR is simple ratio (Equation 3.4), SR_{max} and SR_{min} are minimum and maximum simple ratio, respectively. Possible minimum simple ratio is set to 1.08. 0.95 is the upper limit value for the FPAR (Potter et al., 1993 [51]).

$$SR = (1 + NDVI)/(1 - NDVI) \quad (3.4)$$

Yu et al. (2009) [77] suggested another approach to estimate FPAR using NDVI. According to their approach, instead of calculation of simple ratio, they calculated the probability distribution function of NDVI values with respect to the LC types. The statistical minimum (0.5) and maximum (0.95) of the function gives the minimum and maximum of each LC types FPAR values. They also set a possible minimum (0.001) and maximum (0.95) FPAR values independent of land cover types (Equation

3.5). Finally, calculation of APAR takes place using equation 3.2.

$$
\begin{aligned}
FPAR = \{[(NDVI - NDVI_{min}) \times (FPAR_{max} - FPAR_{min})]/ \\
[NDVI_{max} - NDVI_{min}]\} + FPAR_{min})
\end{aligned}
\tag{3.5}
$$

Both methods were used to estimate/calculate APAR values of each pixel for the study. Possible reasons of the results with respect to APAR differences were also discussed in section 3.4.

3.2.5 Selection of Light Use Efficiency (LUE) values

Light use efficiency (LUE) (gC/MJ) is the ability to turn inorganic matter into organic using incoming solar radiation. Previously some studies used single LUE value for all LC types (Heimann and Keeling, 1989 [22]). However, recent studies showed that, each plant functional types (vegetation types) has its unique LUE value related with the tree species, climatic and edaphic conditions (Potter et al., 1993 [51]). LUE coefficients were selected based on literature survey (Table 3.2) although it is possible to calculate LUE values of each forest types over Turkey using ministry field data. Calculated LUE values were not used because (i) the field data only covers forest area and there is no information about other land cover types and (ii) the calculation of forest NPP contribution is an approximation based on NDVI values, and it might create uncertainties.

3.2.6 Calculation of Stress Coefficients

i. Water Stress

The water stress depresses the LUE values with respect to the aridity condition around the vegetation and it changes from 0.5 (very dry conditions) to 1 (wet conditions) (Potter et al., 1993 [51])(Equation 3.6). The calculation process presented by Potter et al. (1993) [51], requires too many detailed input data such as relative drying rate of the soil. Yu et al. (2009) [77], suggested a new approach to calculate water stress (Figure 3.4) based on Thornthwaite (1948) [68], (Equation 3.7), potential evapotranspiration (PET) model (Yu et al, 2009 [77]; Pereira and Pruit, 2004 [49]; Thornthwaite, 1948 [68]). However, it should be noted that, Thornthwaite PET model is valid only between 0 and 26^{o}C and calculated for 12 hours of sunshine for a month with 30 days (Pereira and Pruit, 2004 [49]; Thornthwaite, 1948 [68]). A regression model is applied for the temperature values above 26^{o}C (Equation 3.10), and for the days with sunshine hour above or below 12 hours for the month with total numbers of days less or more than 30, an adjustment factor must be applied (Equation 3.11).

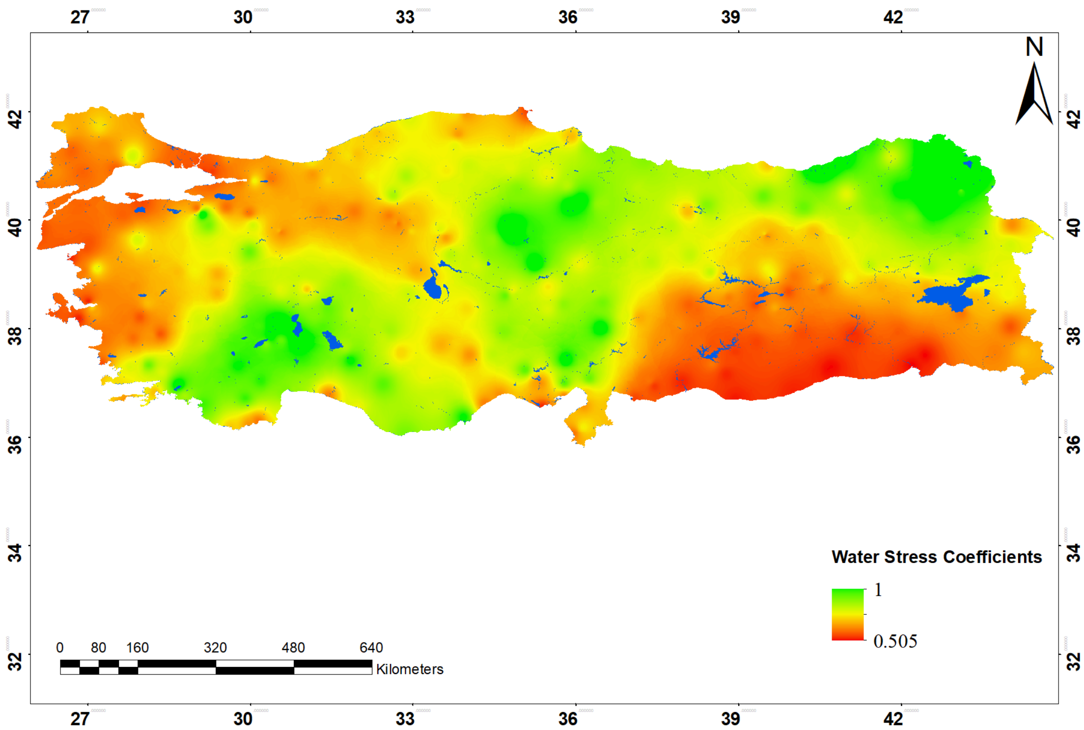


Figure 3.4: An example of water stress (May 2009) conditions. Higher values states less water stress.

$$Ws = 0.5 + 0.5 \times (EET/PET) \tag{3.6}$$

where Ws is Water Stress, EET is Estimated Evapotranspiration and PET is the Potential Evapotranspiration, calculated by using Thornthwaite equations.

$$PET = 16 \times (10 \times T/I)^{\alpha} \qquad 0^oC <= T <= 26^oC \tag{3.7}$$

where PET is Potential Evapotranspiration, T is the temperature and I is thermal heat index. α is a function of I (Pereira and Pruit, 2004 [49]). I and α are calculated as shown (Equation 3.8 and 3.9) below;

$$I = \sum_{k=1}^{12} (0.2 \times T_n)^{1.514}, \quad T_n > 0 \tag{3.8}$$

$$\alpha = 6.75 \times 10^7 \times I^3 - 7.71 \times 10^{-5} \times I^2 + 1.7912 \times 10^{-2} \times I + 0.49239 \tag{3.9}$$

where T is the temperature and n is the number of the month. Temperature below 0^oC is set to 0.

If the temperature becomes more than 26^oC, Willmott et al. (1985) [75] equation (Equation 3.10) is used (Pereira and Pruit, 2004 [49]).

$$PET = -415.85 + 32.24 \times T - 0.43 \times T^2, \quad T > 26^o C \tag{3.10}$$

where PET is Potential Evapotranspiration and T is the temperature. An adjustment factor (AF) is also added to the original equation for the days with different than 12 hours of sunshine duration and for the months with number of days different than 30 days (Equation 3.11).

$$AF = (SH \times DM)/(12 \times 30) \tag{3.11}$$

where AF is the adjustment factor, SH is sunshine hours in a day, DM is number of days in a month (Yu et al., 2009 [77]; Pereira and Pruit, 2004 [49]).

According to the approach presented by Yu et al. (2009) [77], EET is a function of net solar radiation and precipitation (Equation 3.12).

$$EET = (PPT \times SOL_{net} \times [P^2 + (R^2 + P + R)])/([P + R] \times [P^2 + R^2]) \tag{3.12}$$

where EET is estimated evapotranspiration, PPT is monthly total precipitation and SOL_{net} is monthly net solar radiation. However, if monthly total precipitation is higher than the calculated PET, then EET is set to the same value as PET (Yu et al., 2009 [77]).

ii. Estimation of Optimum Temperature

The main goal of this study is to improve NPP estimation using CASA model. The main structure of the modelling is the Monteith's solar radiation based approach proposed in 1972. (Monteith (1972) [39]; Monteith and Moss (1977) [40]) suggest that under optimum condition (a well irrigated and fertilized area), productivity of a cropland is linearly related to the incoming solar radiation. However, since the stress factors are more likely to occur over natural ecosystems, it is important to calculate them precisely. In this study, a new approach has been used to improve the accuracy of the temperature stress calculation. Calculation of temperature stress for CASA NPP model is referred to the optimum temperature (T_{opt}) of the area. Optimum temperature is the function of annual temperature and annual NDVI values. The temperature of the month with the maximum NDVI values during the year is set as the optimum temperature of the area (Yu et al., 2009 [77]; Potter et al., 1993 [51]). However, many studies showed that (Holdridge, 1967 [26]), adaptation of a plant to temperature conditions is not an annually changing process. It is a result of long term temperature regime and adaptation of the tree to the given conditions instead. The optimum temperature of a given area was estimated using long term monthly average temperature values. Original model estimated different optimum temperature for each year for a given area. The approach used in this part of the study, on the other hand, estimates single optimum temperature value for a given area for the study period. Here the annual temperature based on optimum temperature was compared with long term temperature based optimum temperature. CASA model uses two different temperature stress coefficients calculated using optimum temperature of the area. The first temperature stress (T_{ε_1}) shows the effect of extreme temperature (very high or low) on light use efficiency (LUE), and the second temperature stress factor (T_{ε_2}) depicts LUE when the temperature is around the optimum conditions. After estimation of the optimum temperature, the same equations proposed in Potter et al. (1993) [51] were used, because (i), it was a proven, widely used equation (Yu et al., 2009 [77]; Potter et al., 1993 [51]), and (ii), in this part of the study, only the effect of the optimum temperature estimation on the model was evaluated.

3.2.7 Statistical Analysis

Evaluation process of the NPP estimation result of all models were compared using R statistical computing software (Version 3.3.2). The correlation coefficients between the models were considered for the evaluation process using linear regression models. RMSE (Root Mean Square Error), R^2 were assessed for the model accuracy. A sensitivity analysis was also used to assess the accuracy of the model with respect to the best possible result.

Table 3.1: Maximum Simple Ratio (SR_{max}) coefficients for Turkey modified from Sellers et al. (1996a) [65] according to CORINE Land Cover Classification (2006).

CORINE Class Name	**CORINE Class Code**	**SR$_{max}$ Values**
None Vegetated Urban Areas	1 to 9	1.08
Vegetated Urban Areas and Agricultural Areas	10 to 22	5.13
Deciduous Broadleaf Forests and Mixed Forest	23 and 25	6.17
Evergreen Needleleaf Forests	24	5.43
Grasslands and Shrubs	26 to 29	4.14
Dunes – Sands - Beaches and Bare Rocks	30 and 31	1.08
Sparsely Vegetated Areas	32	5.13
Burnt Areas - Glacier and Perpetual Snow	33 and 34	1.08
Inland Marshes – Peat Bogs – Salt Marshes	35 to 37	5.13
Salines – Intertidal Flats	38 and 39	1.08
Water Bodies	40 to 45	9999

Table 3.2: LUE values for the study area (Wei et al., 2017 [74]; Running and Zhao, 2015 [64]; Ogutu and Dash, 2013 [46]; Yu et al., 2009 [77]; Ruimy et al., 1999 [58]; Medlyn, 1998 [38]; Nayak et al., 2010 [41])

Vegetation Type	**Light Use Efficiency (LUE) gC/MJ**
Artificial Areas	0.110
Non-Irrigated Arable Lands	0.498
Permanently Irrigated Lands	0.770
Lands Principally Occupied by Agriculture with Significant Areas of Natural Vegetation	0.452
Agro-Forestry Areas	0.376
Other Agricultural Areas	0.573
Broadleaf Forests	0.620
Needelleaf Forests	0.506
Mixed Forest	0.563
Natural Grasslands	0.234
Moors and Heatlands and Sclerophyllous Vegetation	0.272
Transitional Woodland – Shrub	0.345
Other Semi-Natural Areas	0.210
Wetlands	0.41
Water Bodies	0.100
Minimum	0.100
Maximum	0.770

3.3 Results

3.3.1 Calculation of APAR (Absorbed Photosynthetically Active Radiation)

APAR values of the study area were calculated based on two different approaches. For the first approach simple ratio (SR) values were calculated in monthly intervals, based on NDVI ratio (Equation 3.4). Calculated SRs were used to estimate FPAR of given pixel for the given month (Equation 3.5). Modified maximum simple ratio values proposed in Potter et al. (1993) [51] (Sellers et al., 1996a [65]) were modified for the study (Table 3.1). The second method was proposed by Yu et al. (2009) [77], based on probability distribution function of NDVI. This method does not require any fixed land cover type based coefficients since all data are obtained from NDVI values based on given land cover properties. It makes the model more suitable to areas having various land cover. The comparisons of two models, based on more than 3700 random points, showed that, although they have high correlation (R^2 = 0.88, RMSE = 75) (Figure 3.5), Potter et al. (1993) [51] proposed model shows better result according to the NPP calculations, if the aggregated land properties are to define accurately. Yu et al. (2009) [77] proposed model, on the other hand, shows higher amount of APAR values in most cases over the study area, except dense forest cover areas. it is believed that, this might be the result of backscattering properties of the NDVI.

3.3.2 Calculation of Stress Coefficients

i. **Water Stress**

   Thornthwaite [68] PET equation based water stress coefficients offers a unique calculation opportunity if the available data set is limited with the meteorological measurements. However, it is believed that, this method underestimates the water stress conditions especially over arid and semi-arid areas such as Turkey. To understand the relation between water stress coefficients proposed by Yu et al. (2009) and actual condition over the study area, a potential evapotranspiration (PET) and precipitation (PPT) based aridity ratio was created. First, PET values for all meteorological stations were calculated using Thornthwaite

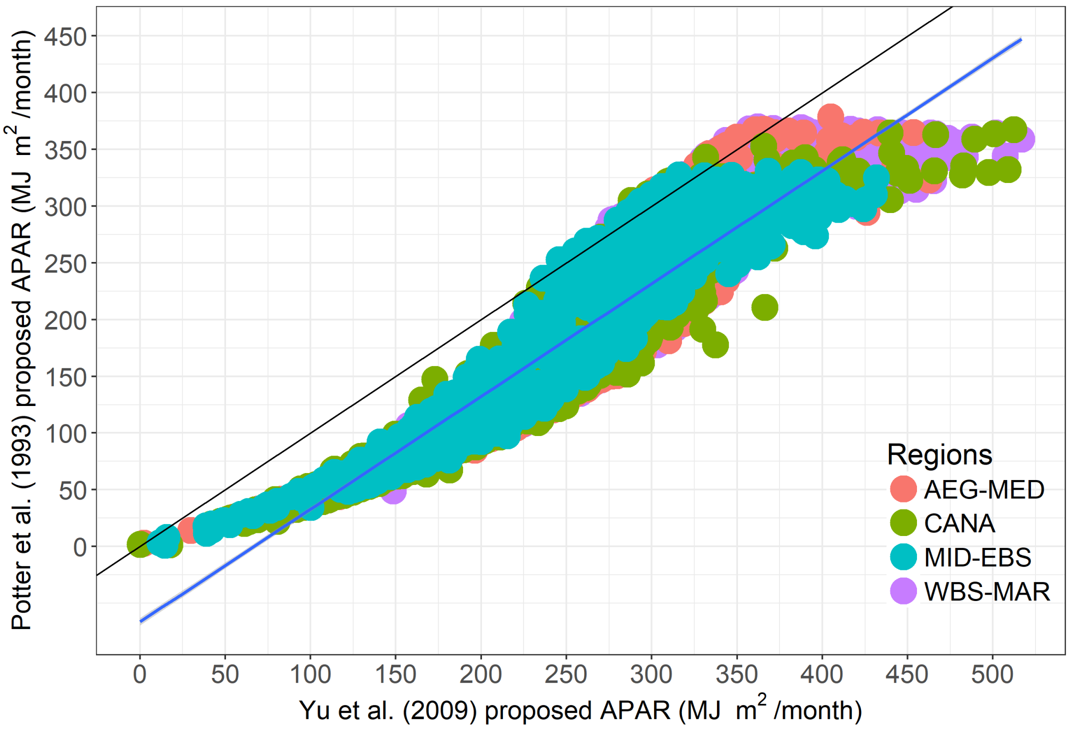


Figure 3.5: APAR calculation based on Potter et al. (1993) [51] ($APAR_{Potter}$) vs. Yu et al. (2009) [77] ($APAR_{Yu}$). R^2 = 0.88, RMSE = 75 MJ/m^2/month. Blue line shows the regression line between two quantities and black line is 1:1 line. Regression function: $APAR_{Potter}$ = -66.478 + 0.994 $\times$ $APAR_{Yu}$

PET equation using long term and monthly data. Second, a ratio between PET values and precipitation values were calculated. In this point, long term and monthly aridity ratio was obtained. However, for both conditions, it was not possible to understand whether the aridity conditions are in plants' toleration range. Finally, to understand this, a ratio between long term aridity index values and monthly values were created. The results were expected to show the deviation from the normal condition of the ecosystem (Figure 3.6).

As it can be seen in Figure 3.6, the aridity ratio shows more changes during 6 years' period, than Yu et al. (2009) [77] proposed water stress values (modelled).

ii. **Temperature Stress**

The main contribution of this study is to improve the accuracy of CASA NPP model, using a new approach to estimate optimum temperature for a given area.

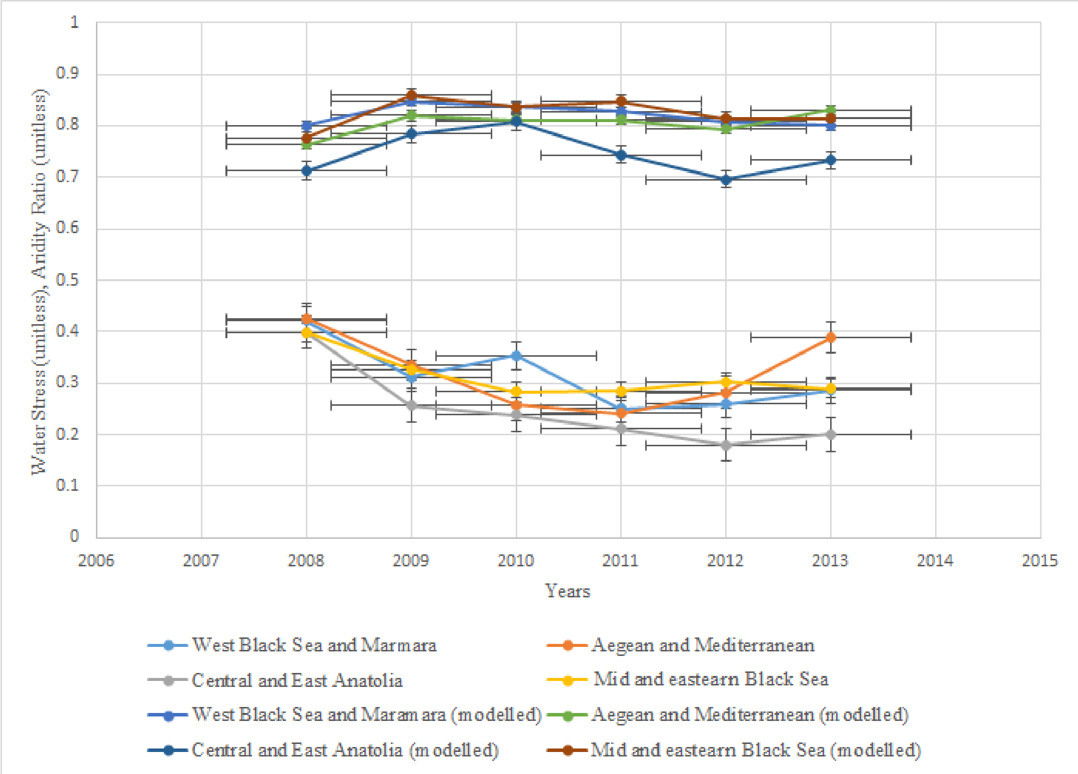


Figure 3.6: CASA model (proposed by Yu et al. (2009) [77]) water stress coefficients (modelled) vs. Precipitation and PET (Potential Evapotranspiration) ratio based aridity index.

Original study (Potter et al., 1993 [51]) suggests an annual based temperature and NDVI relation. However, adaptation of a tree (plant) to the climatic condition of its environment is a long term process. The adaptation process is not affected by the annual fluctuations. Under this assumption, long term meteorological measurements (temperature), and NDVI values were used for the calculation. It was observed that, long term measurements based optimum temperature estimation (Figure 3.7) has more precise result when comparing each pixel with the neighbourhood pixels, especially for the open areas. For the forested areas, on the other hand, the correlation between two estimations is higher. The basic problem with the annual estimations is that, due to properties of NDVI, the optimum conditions may occur during the cold seasons. Which results in very low optimum temperature estimations such as minus (-) degrees (Figure 3.8).

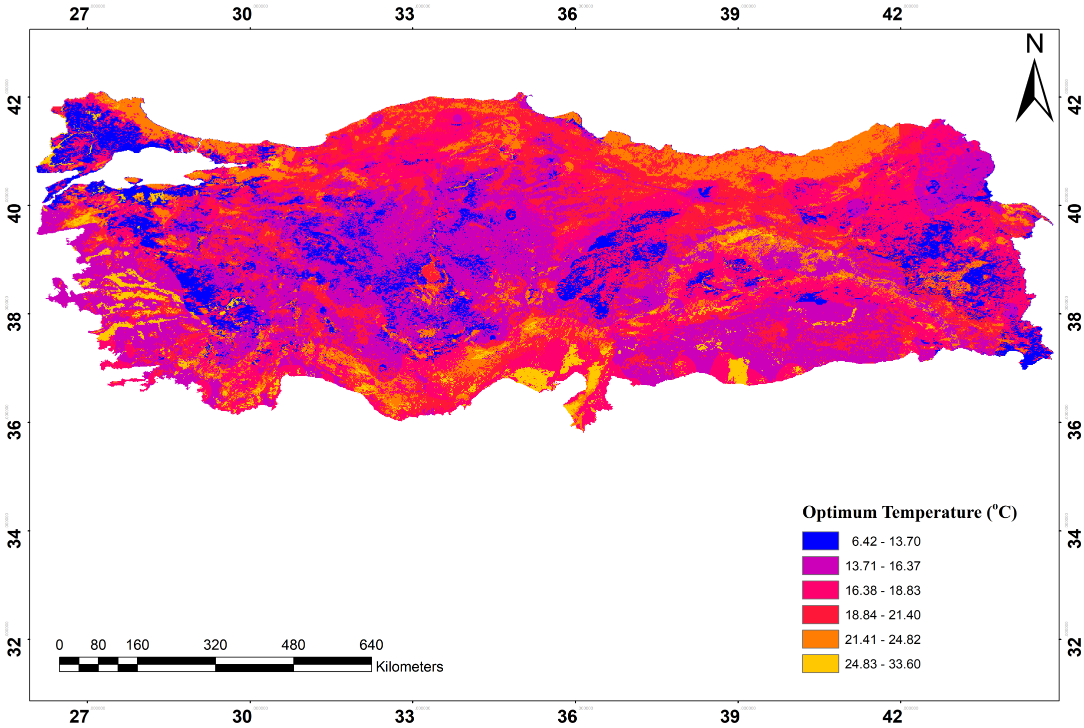


Figure 3.7: Optimum temperature conditions of the area based on long term temperature measurements.

3.3.3 Comparisons of NPP Results

The ability of a global model (MODIS MOD17A3 NPP product) to estimate forest production over Turkey is 34% (Gulbeyaz et al., 2018 [18]). It was suggested that, this result is mostly due to the input data sets such as land cover and meteorological data (Zhao et al., 2005 [78]). In this study, first, this accuracy was tried to be improved using local data sets. CASA model was chosen because of its application of simplicity, and its wide usage.

Four different models (i) original CASA model optimum temperature approach with APAR estimation proposed by Potter et al. (1993) [51], (ii) original CASA model optimum temperature approach with APAR estimation proposed by Yu et al. (2009) [77], (iii) long term optimum temperature approach with APAR estimation proposed by Potter et al. (1993) [51], and (vi) long term optimum temperature approach with APAR estimation proposed by Yu et al. (2009) [77] outputs were compared. All four models use locally measured meteorological data.

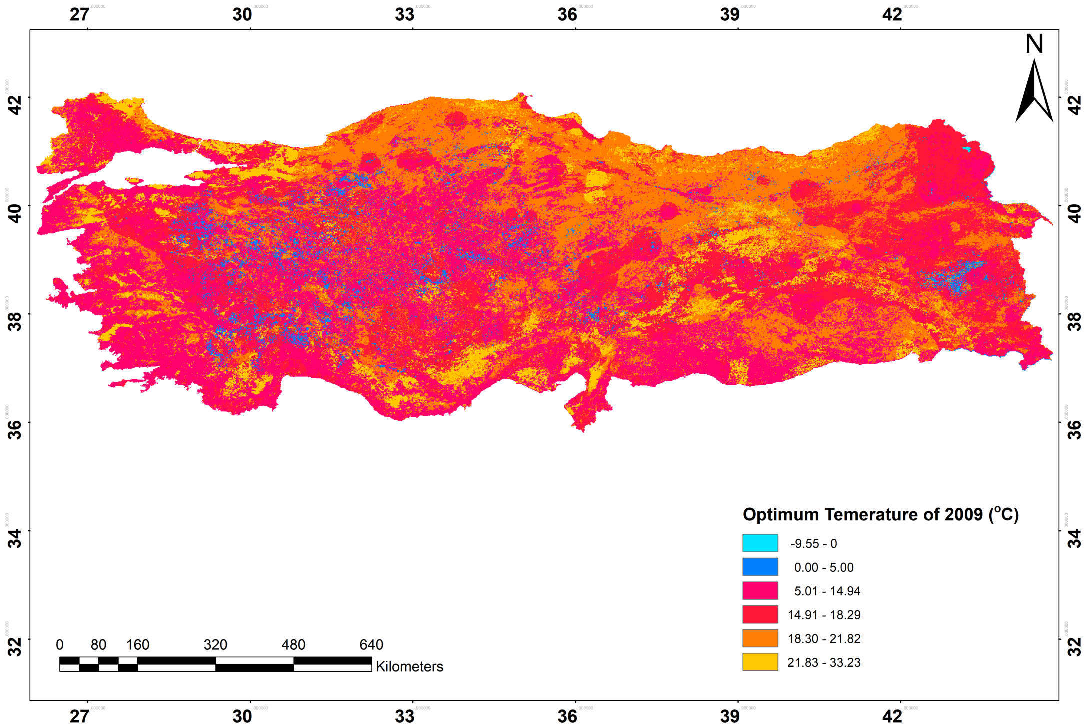


Figure 3.8: Optimum temperature conditions of the area based on annual temperature measurements.

i. **Annual based Temperature Stress**

CASA NPP model was originally proposed by Potter et al. (1993) [51]. This model is based on Monteith light use efficiency and solar radiation related approach. The key point in Monteith's model is to understand and estimate the factors that cause reduction effect on maximum light use efficiency (LUE_m) of the plant. LUE_m is the maximum possible ability of the plant to turn the light into organic matter. These reduction factors are mainly depending on water availability and temperature stress. One of the assumptions of this study were to improve accuracy of the model using local data. Results show that, usage of local data such as meteorological variables explains the NPP over the area 35% and 39% for $APAR_{Yu}$ and $APAR_{Potter}$, respectively (Figure 3.9 and 3.10). Results state that, $APAR_{Potter}$ based NPP estimation can explain the area with a higher accuracy with respect to $APAR_{Yu}$.

ii. **Long Term based Temperature Stress**

The main goal of this part of study is to create a new approach to improve

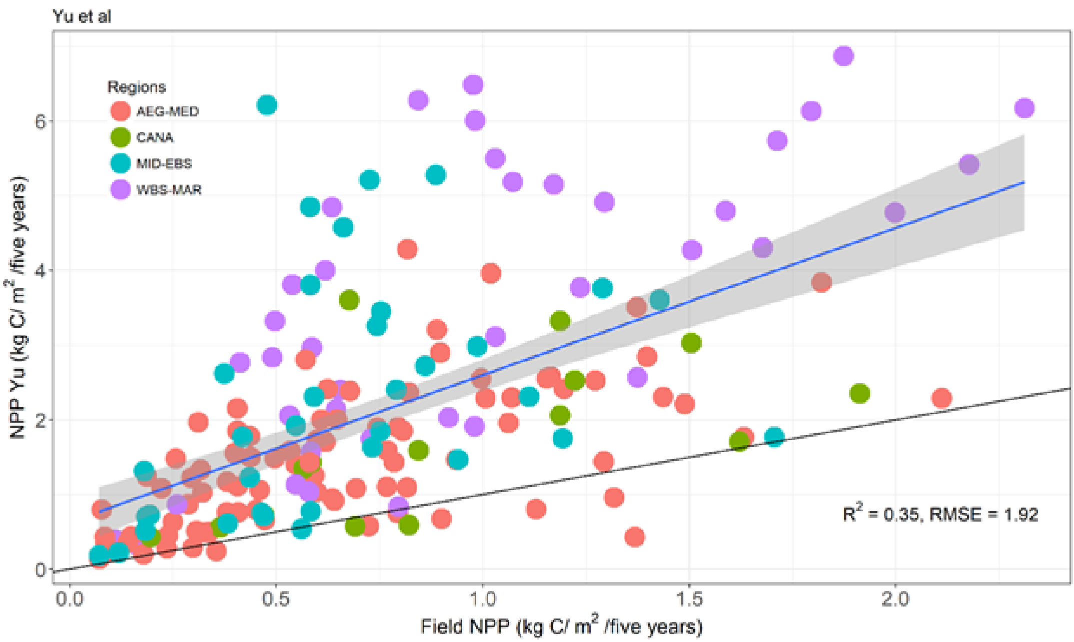


Figure 3.9: NPP calculation based on annual optimum temperature using $APAR_{Yu}$. R_2 = 0.35, RMSE = 1.92. Blue line is the regression line and black line is 1:1 regression line.

the accuracy of a NPP model. As it was stated previously, the adaptation of a plant to an environment is a long term based process. Under this assumption, optimum temperature values of the study area was estimated using long term monthly mean temperature. Results show that, usage of long term data improves the model accuracy from 35% to 43% for $APAR_{Yu}$, and from 39% to 43% for $APAR_{Potter}$ (Figure 3.11 and 3.12).

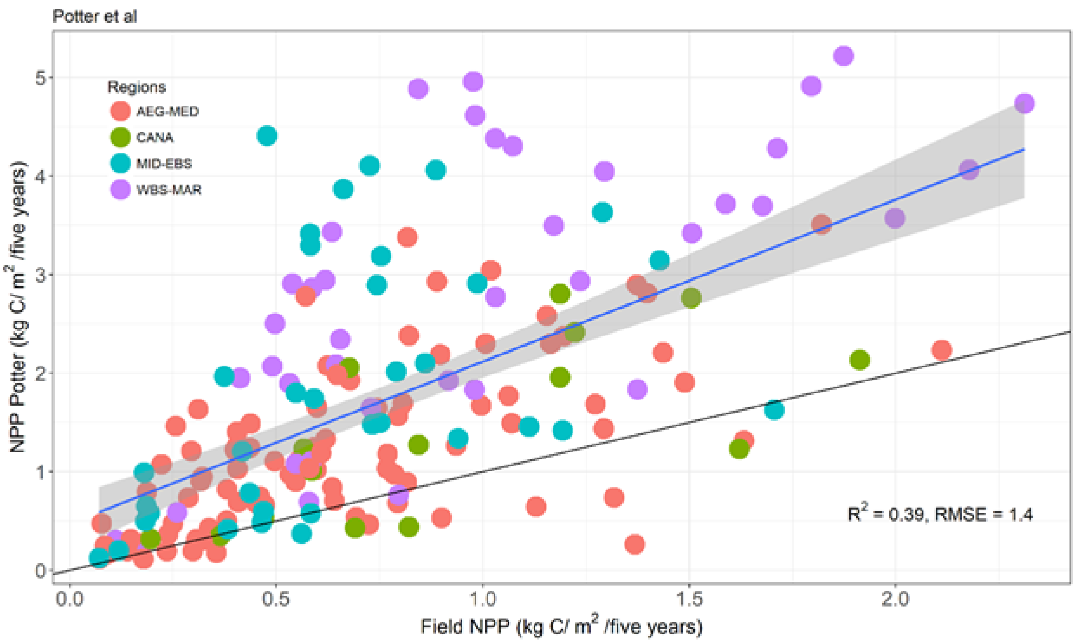


Figure 3.10: NPP calculation based on annual optimum temperature using $APAR_{Potter}$. R_2 = 0.39, RMSE = 1.4. Blue line is the regression line and black line is 1:1 regression line.

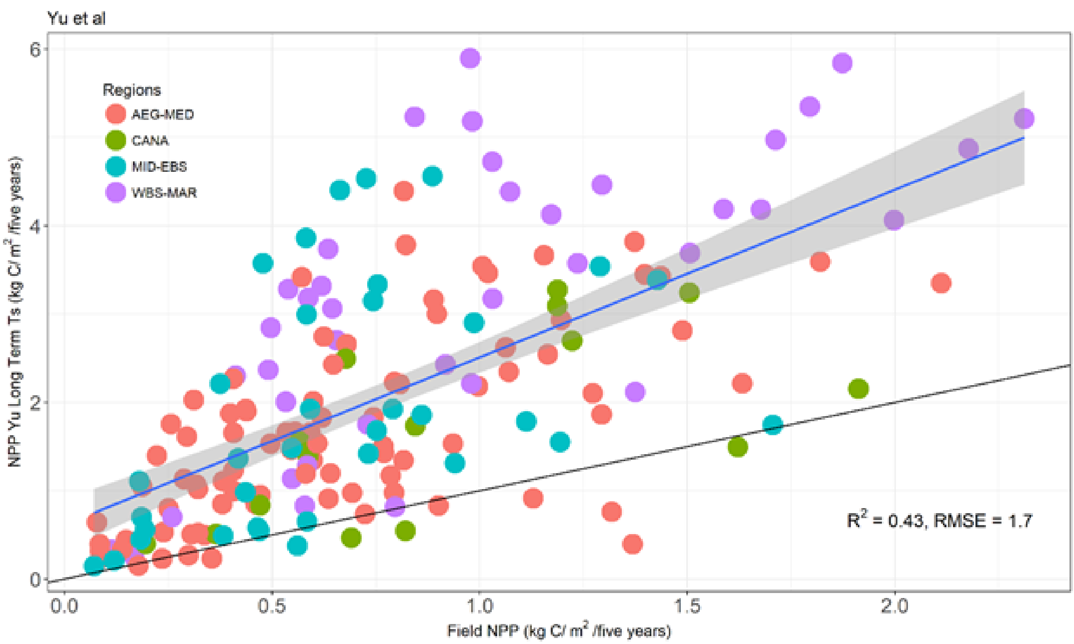


Figure 3.11: NPP calculation based on long term optimum temperature using $APAR_{Yu}$. R_2 = 0.43, RMSE = 1.7. Blue line is the regression line and black line is 1:1 regression line.

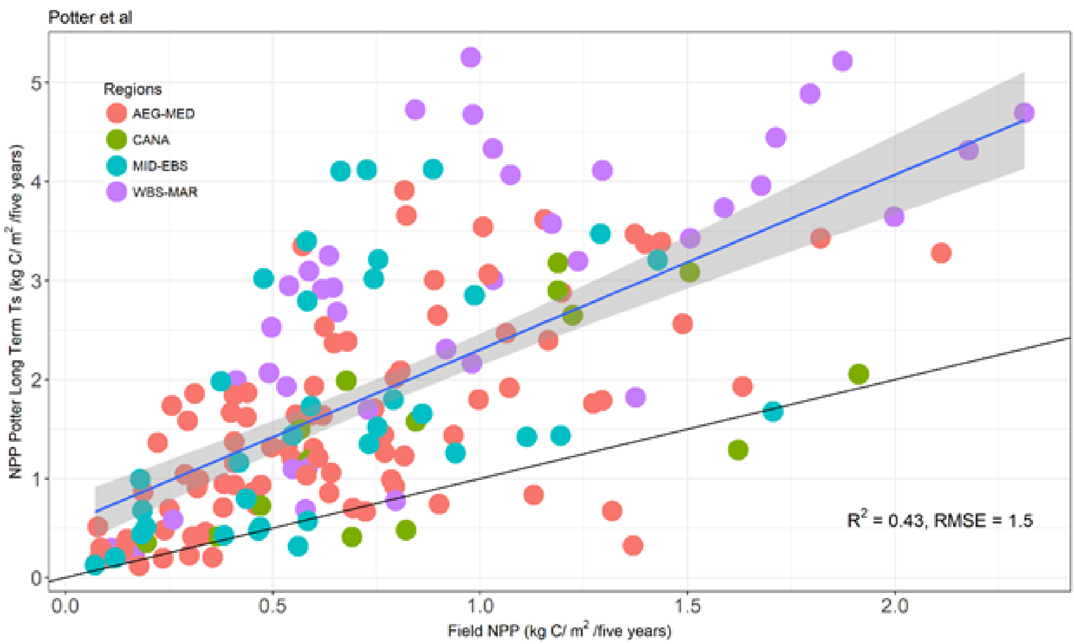


Figure 3.12: NPP calculation based on annual optimum temperature using $APAR_{Potter}$. R_2 = 0.43, RMSE = 1.5. Blue line is the regression line and black line is 1:1 regression line.

3.4 Discussion for the results

This study intended to (i) improve the accuracy of a NPP model with respect to the global model using local data and (ii) improve the overall model accuracy using a new approach. The results prove that; the usage of local data has a significant effect on the accuracy of the model (Table 3.3) especially for $APAR_{Potter}$ with respect to global models such as MODIS NPP product (MOD17A3). It is acknowledged here that, the improvement using $APAR_{Yu}$ is not as significant as $APAR_{Potter}$. However, it is believed that, this is caused by the main properties of NDVI (i.e. back scattering), since all variables are obtained from vegetation index in this approach. Moreover, it is believed that the main reason for the model cannot to be improved to a higher accuracy is due to the mathematical formulation used to calculate stress factor (section 3.2.6). The formulas used for the stress factors are general approaches to simulate the conditions over the globe (study area). However, they may not be suitable for the local conditions especially for arid and semi-arid areas. Finally, the quality of the measurements also affects the accuracy. The ministry field measurement protocol is not known. Thus the quality and the accuracy of the measurements are in question. To check the explainibility of the measurements, a sensitivity analysis was run. The basic principle behind this analysis was to change some variables between their minimum and maximum values. In this part, APAR is considered as calculated correctly. However, LUE, water stress, temperature stress (1 and 2) were changed. It is believed that, this analysis would help to understand how much it is possible to explain all measurements using an NPP model. The results show that; best model can explain the field measurements with 0.51 R^2 and 0.34 RMSE. Moreover, some of the measurement points cannot be explained at all (Figure 3.13).

Table 3.3: Accuracy of different modelling approaches.

NPP calculation	R^2	RMSE (kgCm^2/years)
$APAR_{Yu}$ annual temperature stress	0.35	1.92
$APAR_{Potter}$ annual temperature stress	0.39	1.4
$APAR_{Yu}$ long-term temperature stress	0.43	1.7
$APAR_{Potter}$ long-term temperature stress	0.43	1.5

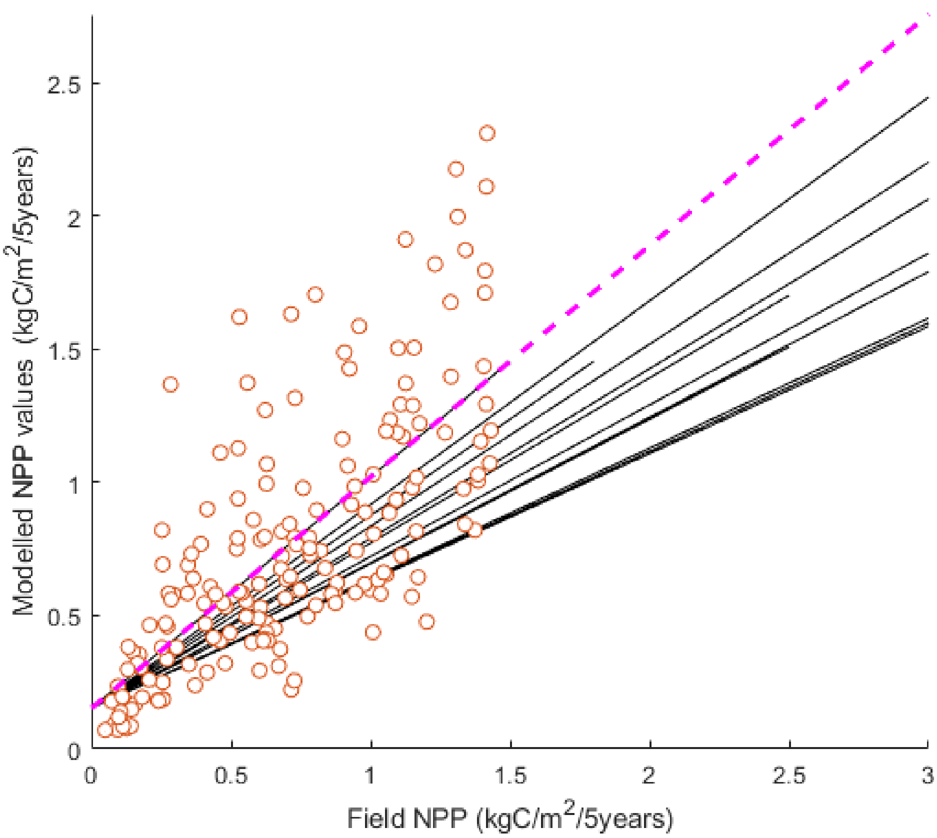


Figure 3.13: Different model coefficients to explain field measurements. Dashed purple line shows the best fit line for the model with respect to the observations.

CHAPTER 4

UNDERSTANDING THE SPATIO-TEMPORAL CHANGES IN NET PRIMARY PRODUCTIVITY OVER TURKEY BETWEEN 2000 AND 2015

4.1 Introduction

Climate change has become one of the major concepts and concerns among environmental scientists since last decades. The effect of climate change, especially global warming, has a great impact on natural ecosystems. Primary productivity (PP) is one of the key components of natural cycles to understand and create solutions to these conditions in particular for the terrestrial ecosystems. Net Primary Productivity (NPP), total amount of stored carbon (C) after plant respiration, can be used to monitor changes in climate and their effects. It is important to understand that; such short period is not enough to understand the effect of the climate change on the ecosystems. However, these datasets (meteorological, land cover, NPP models) can help scientist to understand the relation between these quantities. Many institutions such as NASA (National Aeronautics and Space Administration) and World Meteorological Organization (WMO), reported that the last decade (2000 to 2010) was the warmest decade since meteorological variables started to be measured instrumentally (Zhao and Running, 2010 [79]). Although it affects the productivity of ecosystems, it is also an opportunity to understand the direct effects of global warming on the globe. Zhao and Running (2010) [79] estimated that, there is 0.55 petagrams of decrease in total amount of produced NPP during this period. The effects of changing climate are not only limited factor by itself but the combination of different factors and their indirect relations. The relation between water availability and energy determines the evaporation over an area (Ragab and Prudhomme, 2002 [54]). Evaporation may decrease with respect to decreasing energy although there is enough water in the system, or vice versa. Lavee et al. (1998) [34], studied the change in geomorphological pattern and desertification on Mediterranean arid zones. The climate classification used in the study was Köppen (1984) [31]; [32] climate model, according to which, Mediterranean area considered as semi-arid zone with rainfall 450 mm to 700 mm per year. Their results show, if climate change causes a reduction in water availability, the area will lose its tree composition and most of the shrub cover. Another study states that, Turkish pine tree will be shift to northern areas where the areas are normally covered by oriental beech (Yalcin, 2012 [76]). This conclusion is a result of climatic change scenarios until the year 2080. In this study, the change in net primary productivity over Turkey's forest ecosystem with respect to change in precipitation and temperature regime was studied. Moreover, the spatial distribution of the NPP is analysed. This is the first study for Turkey to understand the relation between climate variable and NPP. This is also the first study to analyse spatial distribution of net primary productivity over Turkey.

4.2 Materials and Methods

4.2.1 Calculation of Net Primary Productivity

The Carnegie-Ames-Stanford approach (CASA) Net Primary model suggested by Potter et al. (1993) [51] was used for the study. The model has 4 basic calculation parameters, (i) Absorbed (incident) Photoseynthetically Active Radiation, (ii) Light Use Efficiency (LUE), (iii) Water Stress, (iv) temperature stress. Temperature stress is composed of two different parameters. The first temperature stress shows the effect of very high and very low temperature on LUE. The second temperature stress factor mitigates the LUE when the temperature is around the optimum temperature. The same formulation as described in the original paper for the temperature stress was used. However, to estimate the optimum temperature for an area, Potter et al. (1993) [51], suggested to use annual temperature measurements related to annual NDVI values. In this study, long term monthly temperature averages related with long term monthly NDVI composites were used to estimate optimum temperature values of each pixel location (Figure 3.7). Another different calculation method relative to original paper was applied to estimate water stress factor by Yu et al. (2009) [77]. The estimation method for water stress used in Potter et al. (1993) [51] requires complex calculations and detailed soil data. To overcome this problem, Yu et al. (2009) [77] suggested to use Thornthwaite (1948) [68] Potential Evapotranspiration (PET) method. According to Yu et al. (2009) [77], water stress can be estimated as the function of temperature, precipitation and net solar radiation (section 3.2.6). Calculation of APAR was done using the same method and equations stated in Potter et al. (1993) [51]. The only difference is the adaptation of aggregated land cover types to Turkey (Sellers et al., 1996a [65]). All calculations were done in ArcGIS version 10 ArcMap environment licensed to Middle East Technical University, using ArcGIS Python programming interface ArcPy.

4.2.2 Statistical Analysis

The relation between NPP (16 years - 2000-2015) and meteorological variables and spatial conditions were evaluated. The meteorological variables used here were precipitation and temperature data since they are considered as basic significant variables for NPP, according to Monteith (1972) [39] modelling algorithm. Results of the NPP calculation were evaluated also with respect to the climatic regions. To analyse the results, 1000 random points were created over study area. The points were grouped and yearly averaged according to the climatic regions with respect to related data set.

4.3 Results

i. Net Primary Productivity

   The analysis showed that, there is a significant increment for each region between 2007 and 2008 (Figure 4.1). Moreover, through 2007 to 2014, estimated NPP values of each region is more than previous years. As it can be seen from Figure 4.1, West Black Sea and Marmara region is the most productive and Central and eastern Anatolia is the least productive regions relative to others. The same results were obtained for monthly median values of NPP as well (Figure 4.2). It should be noted here that, due to the pixel resolution and the

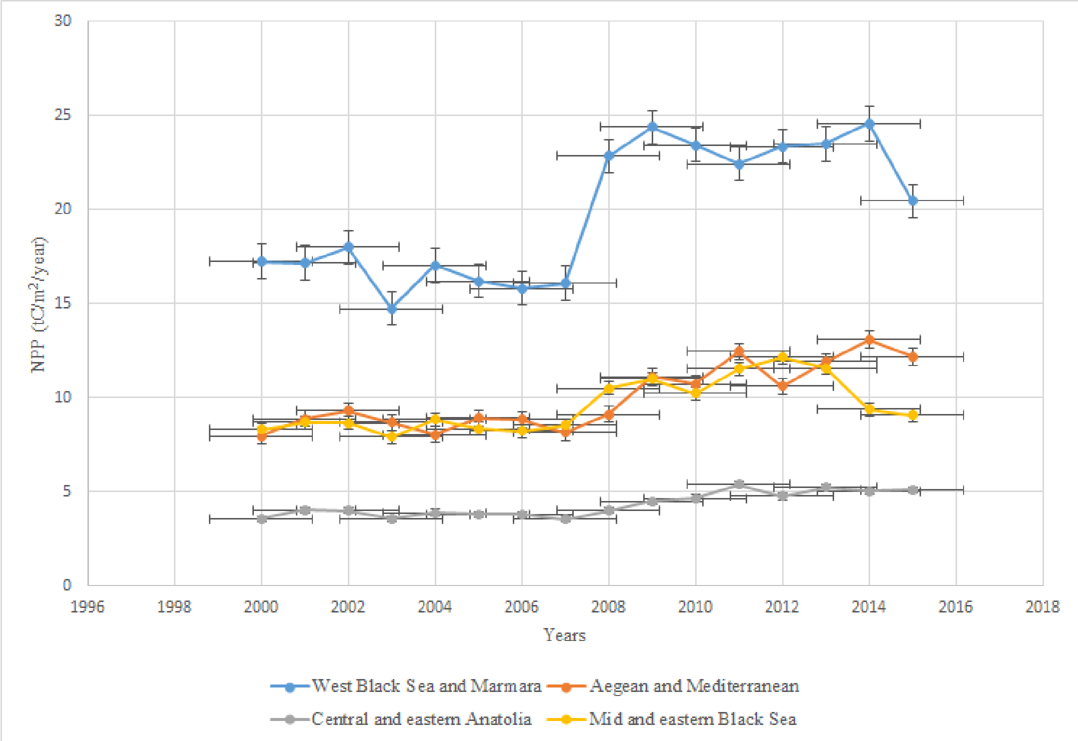


Figure 4.1: Total Annual NPP with respect to climatic regions between 2000 and 2015. The vertical error bars show the deviation of the NPP value of the point among the data set. The horizontal bars show the deviation of the point among the years

projection of the image, the total area of the study area and forested areas can change with respect to other sources. The monthly change in NPP was also evaluated. Starting from 2000 to 2015, median values of each month were calculated (Figure 4.2).

The climatic regions used in this study was created by using results from Evrendilek and Berberoglu (2008) [9]. Their results show that Turkey basically has 7 different bio-climatic zones. However, due to forest cover, east Anatolia region, southeast Anatolia region and central Anatolia region were considered as one region.

This classification is similar to phytogeographical regions of Turkey. These three regions are together called Irano-Turanian zone. Due to the climatic and ecological similarities, Aegean and Mediterranean regions were also merged. Karadeniz region was first divided into two main parts, west Black Sea and mid and eastern Black Sea regions due to the climatic and phytological proper-

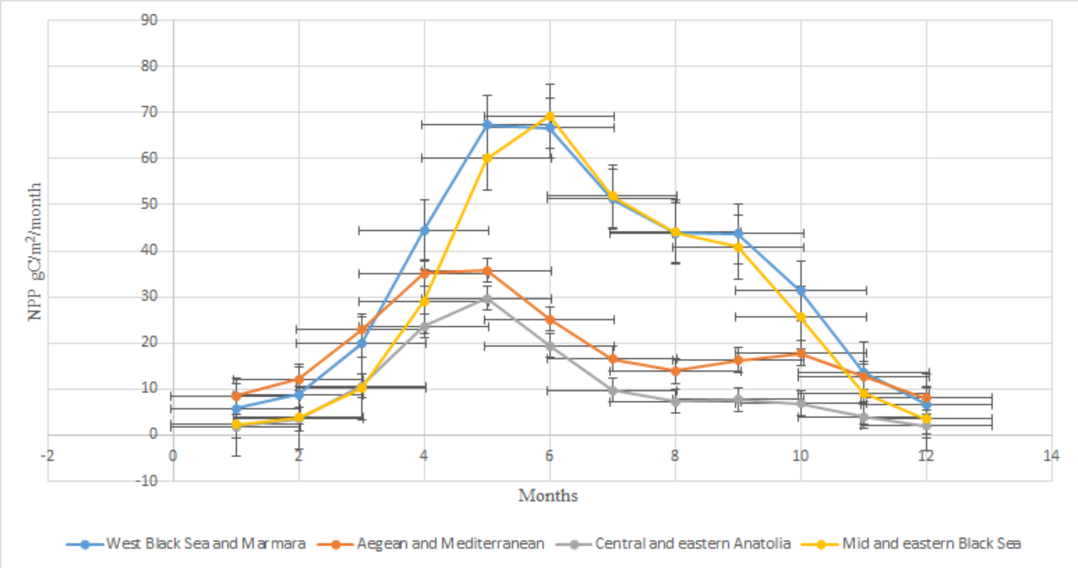


Figure 4.2: Monthly median values of NPP from 2000 to 2015. The vertical error bars show the deviation of the NPP value of the point among the data set. The horizontal bars show the deviation of the point among the years

ties. However, because as they are transition zones, west Black Sea region and Marmara region were merged. According to 1 km resolution CORINE classification, the highest amount of forest exists over Marmara region (Table 4.1). The ratio of the forest to the total area is also higher in the region with respect to the others.

According to the Figure 4.2, the most productive months are May for West Black Sea and Marmara, Aegean and Mediterranean, Central and eastern Anatolian regions and June for Mid and eastern Black Sea region. The monthly median precipitation (PPT) values (Figure 4.3) and monthly median potential evapotranspiration (PET) values (Figure 4.4) were also evaluated. The results shows a decreasing rate in PPT values between the months January and July. The PET values, on the other hand, show an increasing rate between same months. This might be the result of temperature increment between these months.

ii. Bioclimatic Regions of the Study Area

Here, each region was evaluated with its total area, forest cover, and meteorological variable. As stated previously, Marmara region has the highest amount

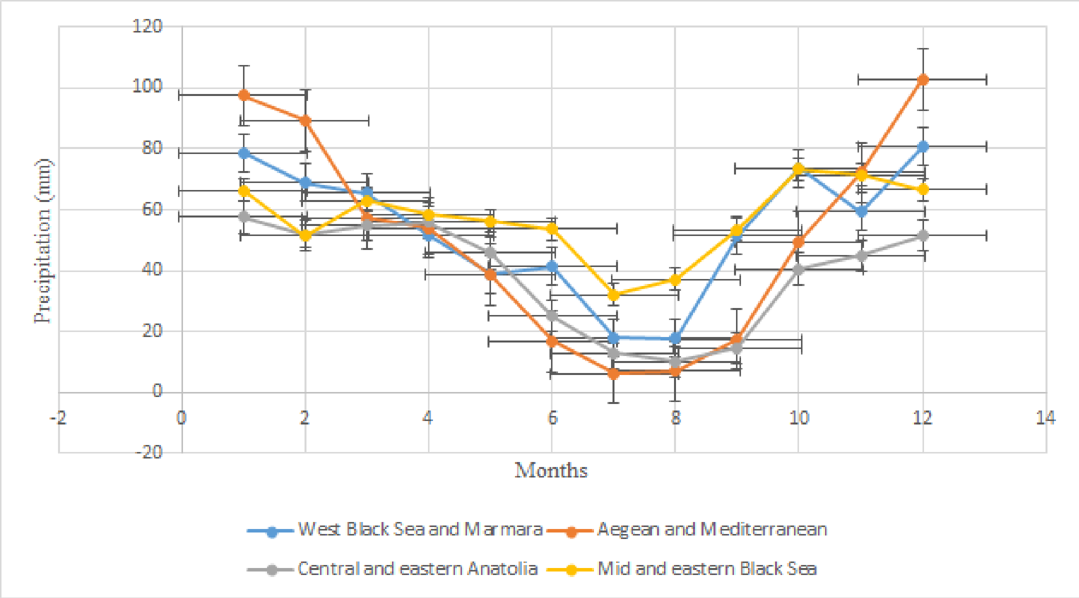


Figure 4.3: Monthly median precipitation (PPT) values according to the climatic regions.

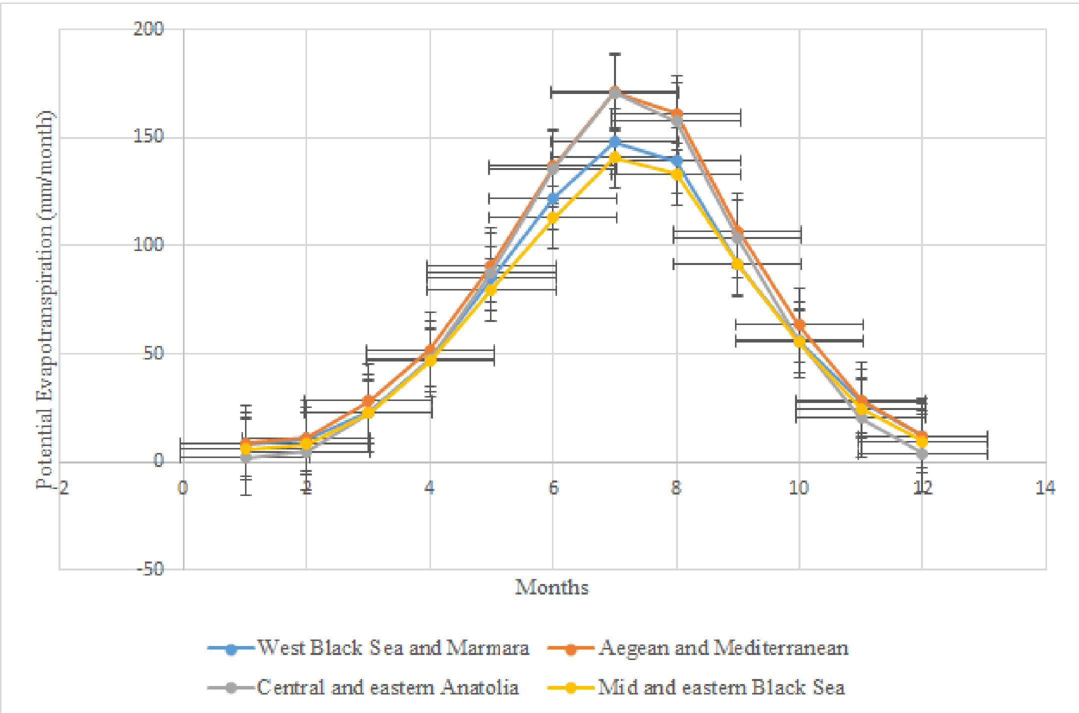


Figure 4.4: Monthly median Potential Evapotranspiration (PET) values according to the climatic regions.

of NPP production (Figure 4.5). The amount of forest, or ratio of forest to the total area is higher in Marmara than the other region (Table 4.1).

Table 4.1: Total area of each regions and their forest covers according to CORINE 2006 (converted to 1 km resolution).

Regions	**Total Area (km^2)**	**Forest Areas (km^2)**	**Ratio**
West Black Sea and Marmara	101402	38896	0.383
Aegean and Mediterranean	154198	30778	0.200
Central and eastern Anatolia	359640	18147	0.050
Mid and eastern Black Sea	68844	19600	0.285
Total	684084	107421	0.157

West black Sea and Marmara region's annual average NPP production is 440 gC/m^2/year. Minimum production occurred in 2003 with 318 gC/m^2/year, and maximum production is in 2009 with 554 gC/m^2/year.

Aegean and Mediterranean region covers the west and south cost of Turkey. The area is described as semi-arid. The main forest cover of the area is red pine, Lebanese cedar and oak. Area has 30778 km^2 of forest cover (Figure 4.6(a)). The region was most productive in 2011 (329 gC/m^2/year) and least productive in 2007 (185 gC/m^2/year). The average production of the area is 243 gC/m^2/year (Figure 4.6(b)).
Central and eastern Anatolia region is the region with least amount of forest coverage (18147 km^2) according to CORINE map used in this study (Figure 4.7(a)). Moreover, due to the security issues, not all forest covers of the region was studied. The region is mostly covered by agricultural areas. The regions highest and lowest productivities are in 2011 (208 gC/m^2/year) and in 2000 (108 gC/m^2/year) respectively (Figure 4.7(b)).
Mid and west Black Sea region lays on the north-east of the study area. The region is well known with its dense forest ecosystems (Figure 4.8(a)). However, its total forest coverage is less than of Marmara region. Region's average production is 344 gC/m^2/year. 2011 was the most productive year (443

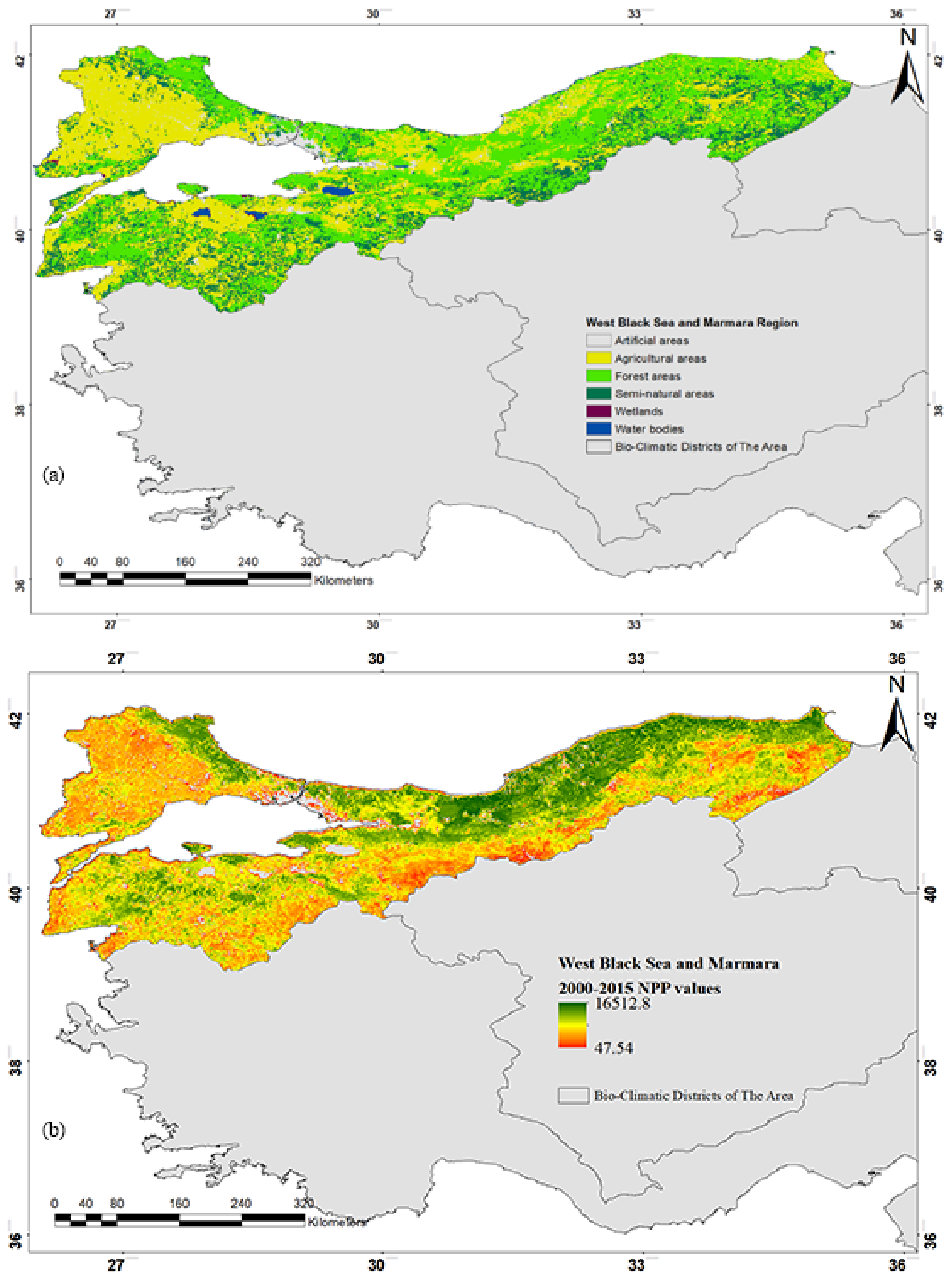


Figure 4.5: Land cover (a) and total NPP (gC/m^2/year)(b) between 2000-2015 of West Black Sea and Marmara region according to CORINE 2006.

gC/m^2/year) for the area, and 2003 was the least productive (270 gC/m^2/year)(Figure 4.8(b)).

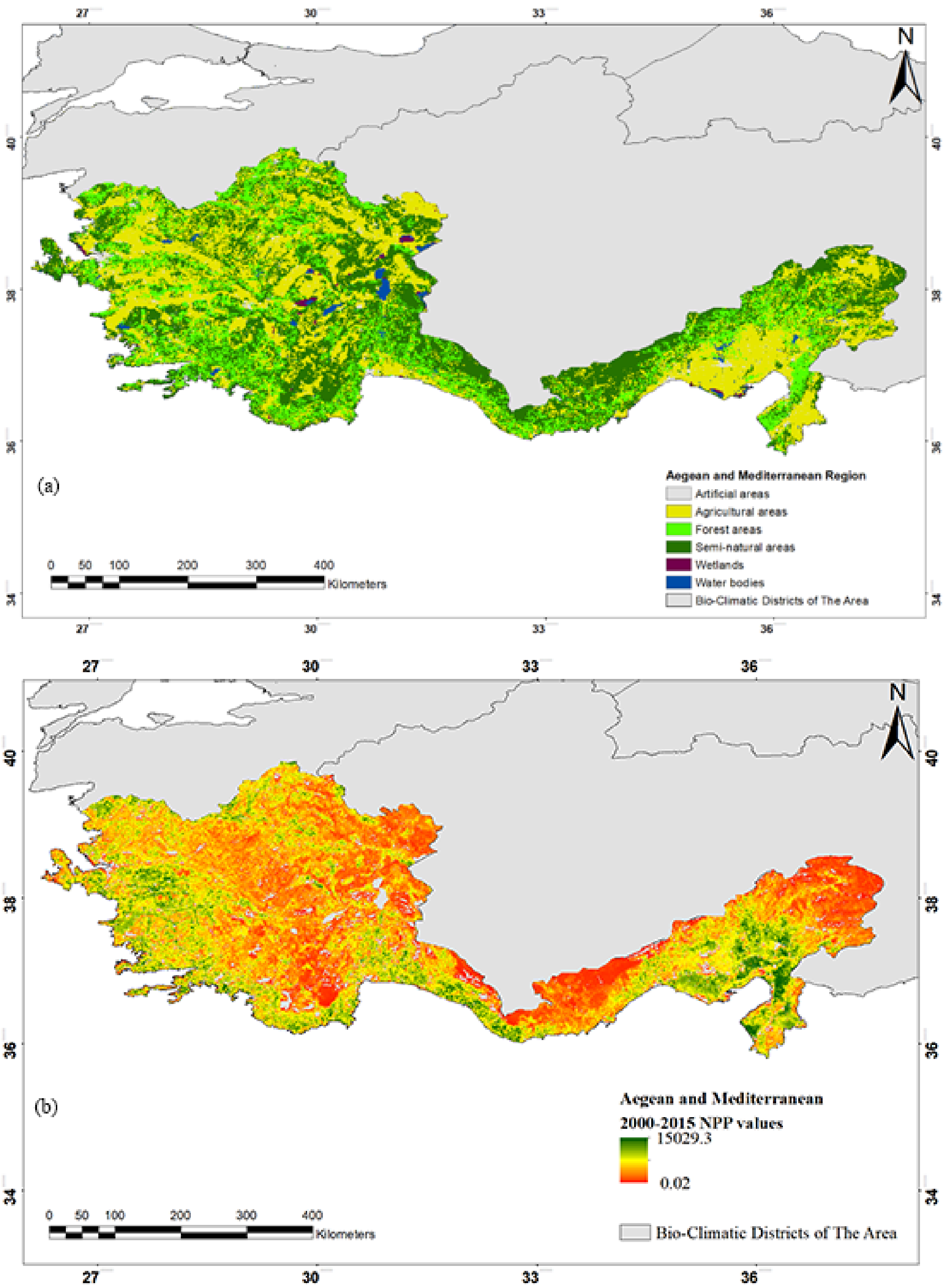


Figure 4.6: Land cover (a) and total NPP (gC/m^2/year)(b) between 2000-2015 of Aegean and Mediterranean region according to CORINE 2006.

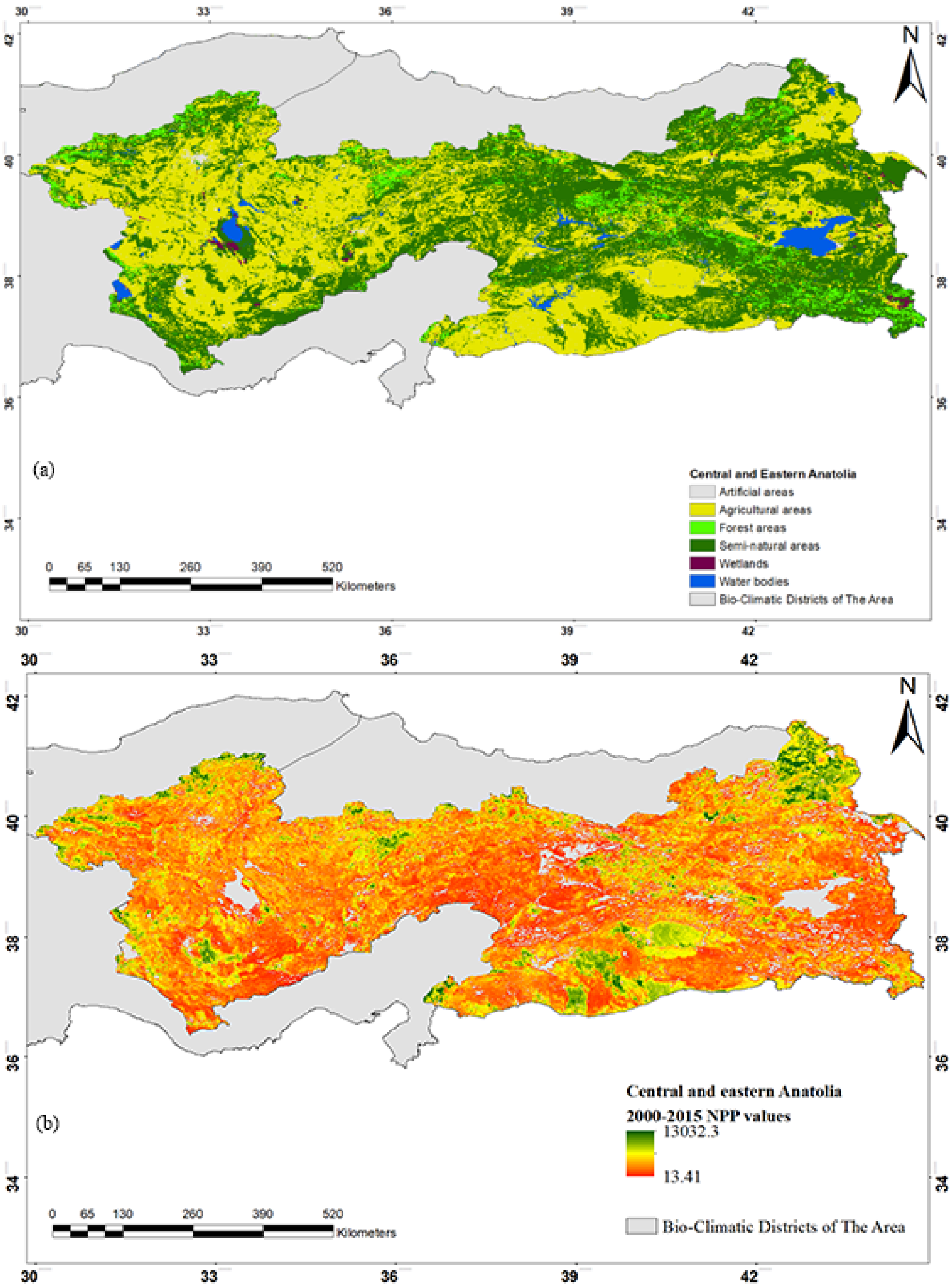
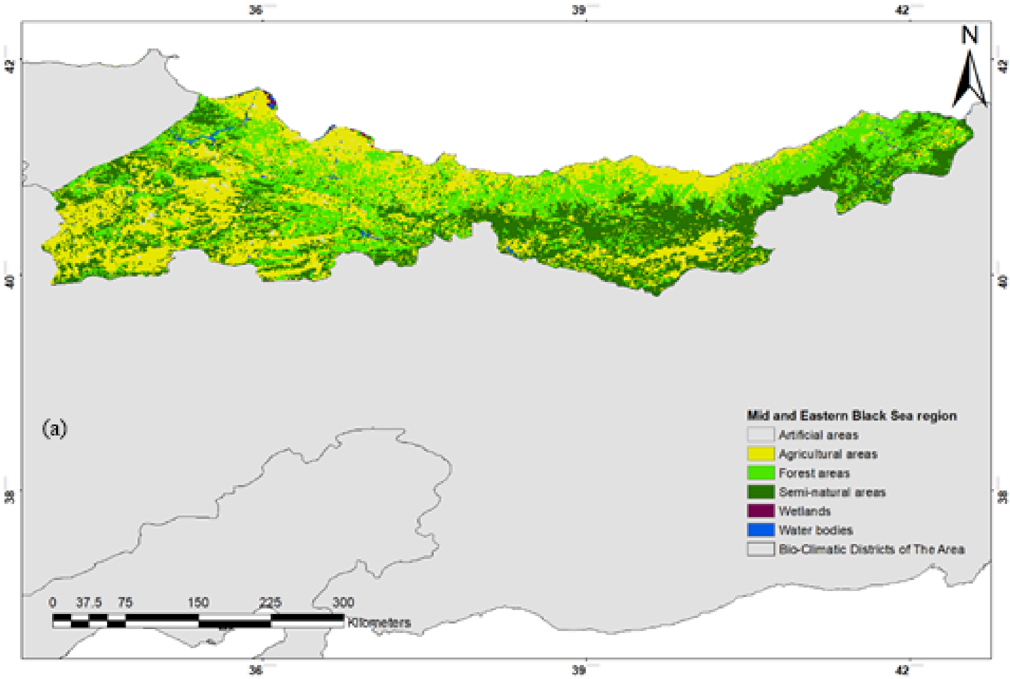


Figure 4.7: Land cover (a) and total NPP (gC/m^2/year)(b) between 2000-2015 of Central and Eastern Anatolia region according to CORINE 2006.



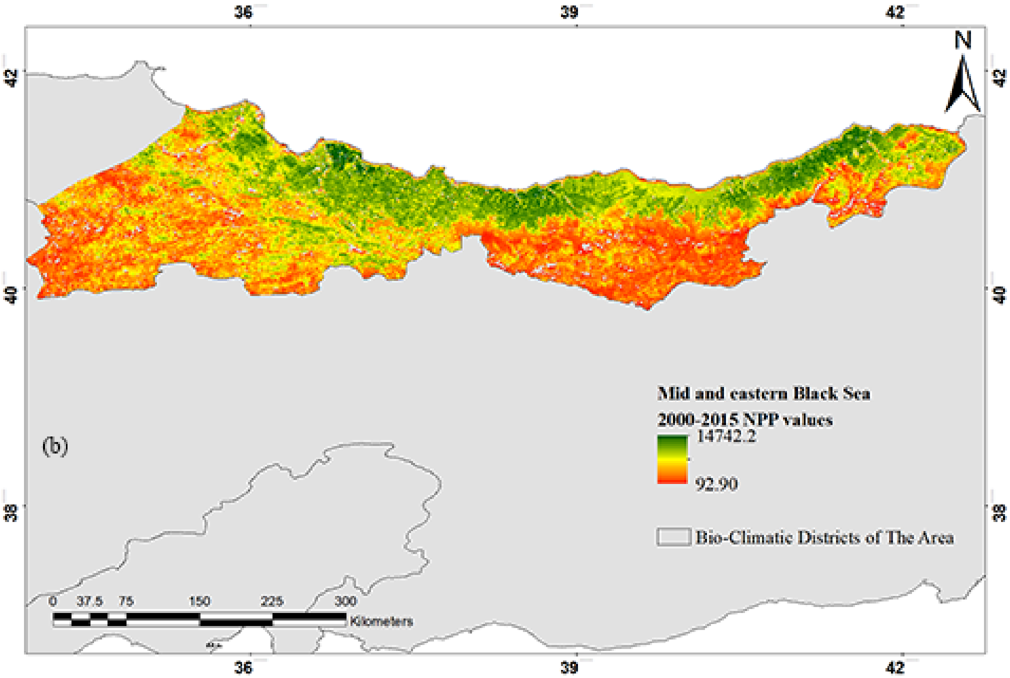


Figure 4.8: Land cover (a) and total NPP (gC/m^2/year)(b) between 2000-2015 of Mid and Eastern Black Sea region according to CORINE 2006.

4.4 Discussion for the Results

Estimated NPP values using remotely sensed data were evaluated by field measurements from Ministry of Forest and Water Affairs. Due to lack of forest ecosystems and security issues, some regions had less number of field data. Moreover, the distance between the meteorological stations affects the interpolation results. These conditions might affect overall results of the final NPP maps. It should also be noted here that, all the evaluations in this section were done on pixel scale. The forest areas were not considered individually. As a result, the productivity of the forest areas for each region may be higher or lower. The study was carried out on pixel scale, because number of the field data points were too few to make a comparison only for the forested areas. Moreover, although it was possible to calculate forest NPP using a finer resolution image (i.e. CORINE 250 m), it was not possible to calculate the temperature difference, for example, of the forest from its surrounding. The CORINE land cover classification map which is a vector based data, is converted into raster format with 100 m and 250 m resolution which may alter the land cover composition of the area. Despite some misclassifications, the data reflect the general conditions over Turkey. However, since there is no CORINE data with 1 km resolution, the existing maps were scaled up to create such data. This scale change may have affected the land cover classes over the area and this change results in changing the number of pixels (or area coverage) of any land cover classes. The meteorological data were interpolated using IDW method. Due to the distance between each measurement point the interpolation may alter the actual conditions. However, the general trend of the study area for each region reflects expected results. In this part of the study, a trend analysis was also performed. Mann-Kendal trend analysis was performed for all data sets. According to this analysis "p" value is calculated. If the calculated p values are less then theoretical value ($p < 0.005$), the null hypothesis is rejected. As a result, it is accepted that there is a trend in the data set. The results show that, although there is a certain increasing trend (Figure 4.9) in forest NPP values between 2000 and 2015, there is no related trend in temperature (Figure 4.10) and precipitation (Figure 4.11).

Zhao and Running (2010) [79] stated that, last decade (2000-2010) was the most

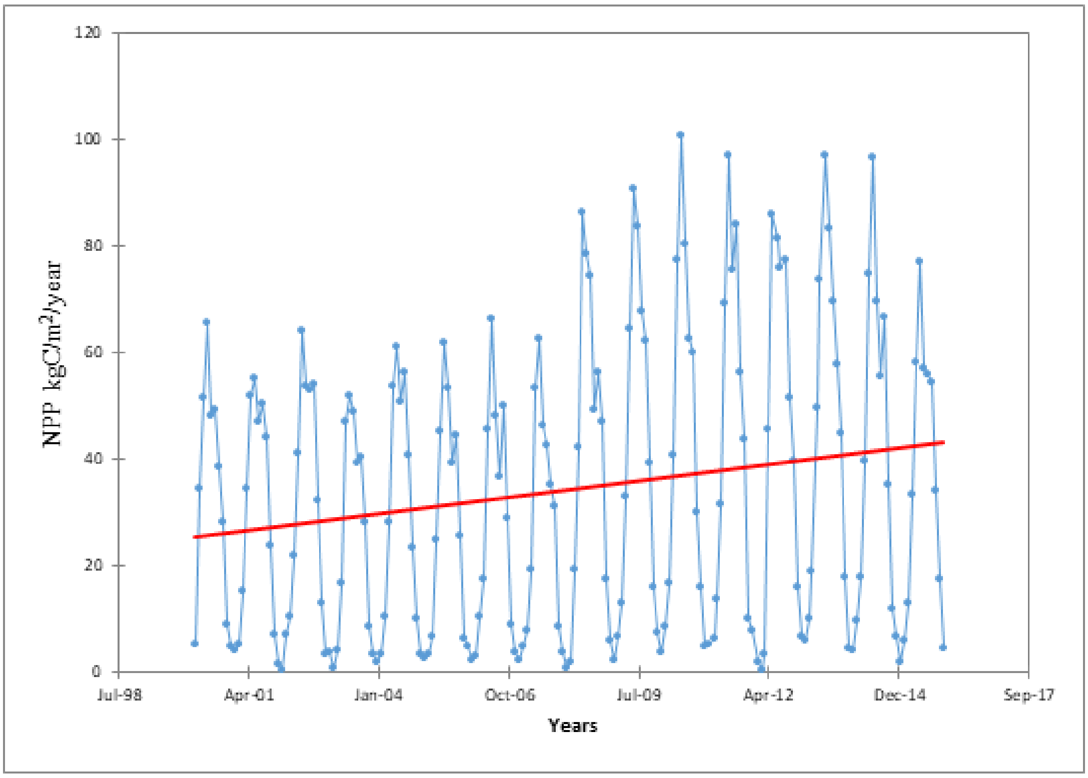


Figure 4.9: Trend analysis of forest NPP values for West Black Sea and Marmara region (p-values = 0.0246).

drought decade since the instrumental measurements has begun. There is no decreasing trend in NPP values over Turkey, although the precipitation values have fluctuations between this period especially showing a significant decrease in 2008 (Figure 4.12). These results show that, a single meteorological value does not affect overall process. Holdridge (1967) [26] stated that, the ratio between meteorological parameters are more important for the ecosystem than the value of single parameter. Another reason for increasing NPP might be the pixel resolution of the study. The study uses 1 km pixel resolution. Each pixel may consist of many different land cover types. Even the forest areas' productivity remains the same, the productivity of the surrounding land cover types (such as agricultural areas) may increase the modelled NPP of the pixel.

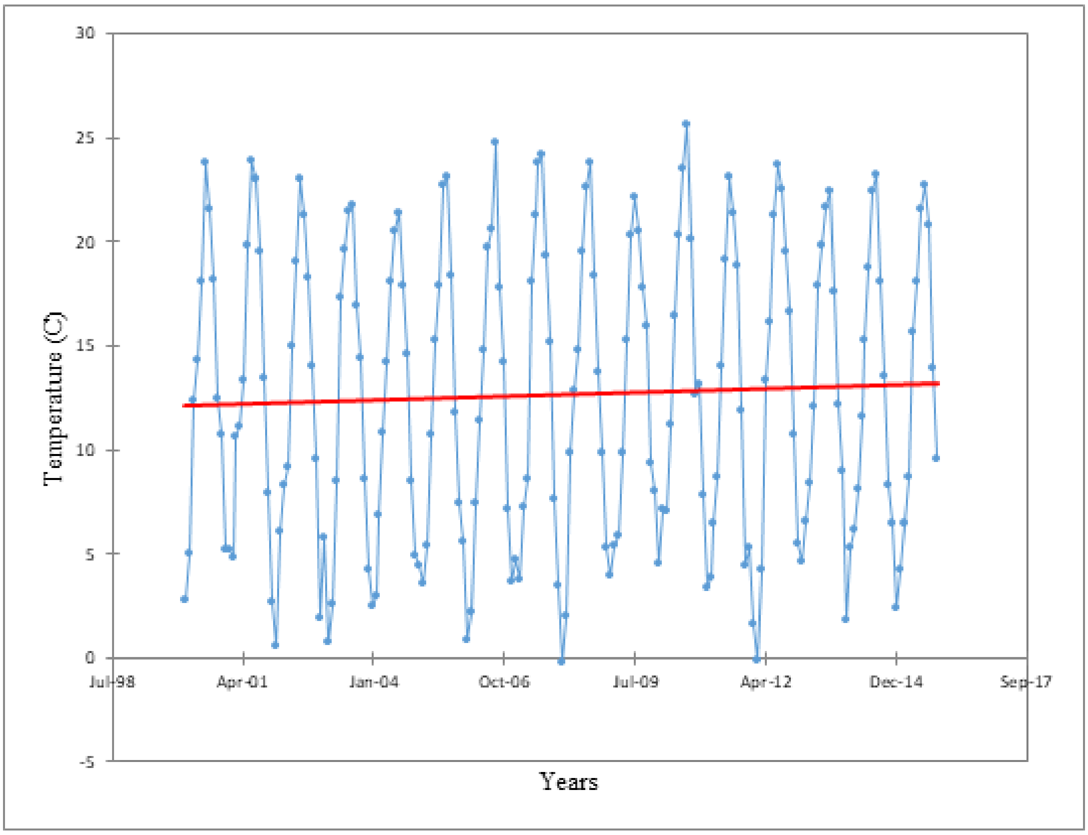


Figure 4.10: Temperature trend analysis for West Black Sea and Marmara region (p-values = 0.047).

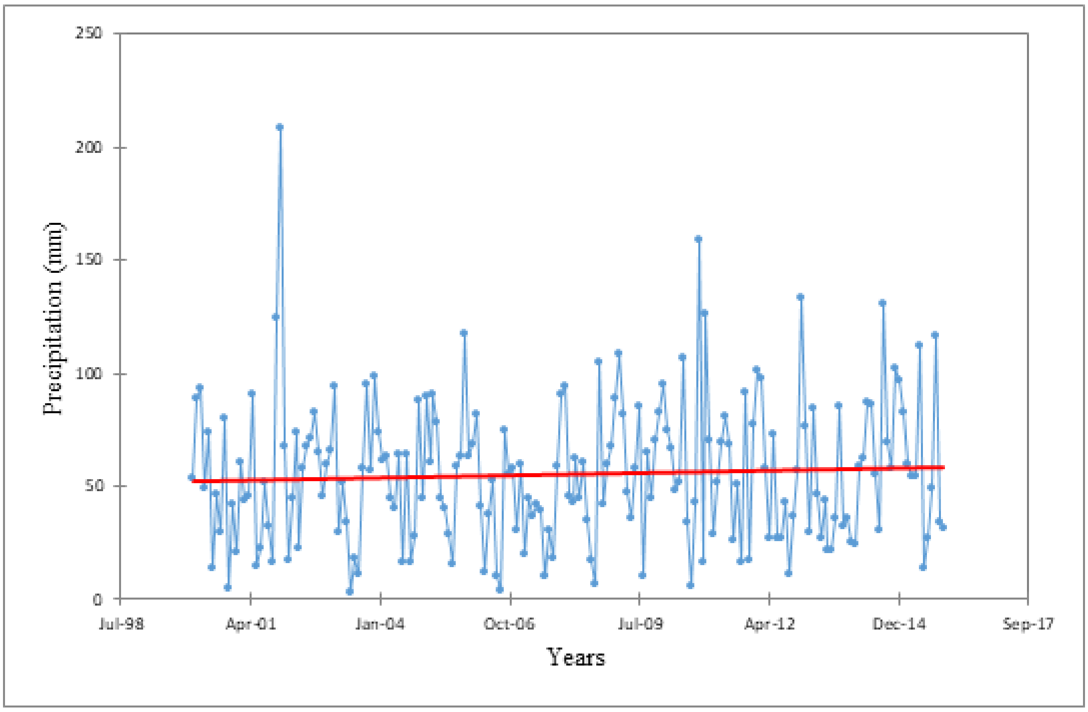


Figure 4.11: Precipitation trend analysis for West Black Sea and Marmara region (p-values = 0.05).

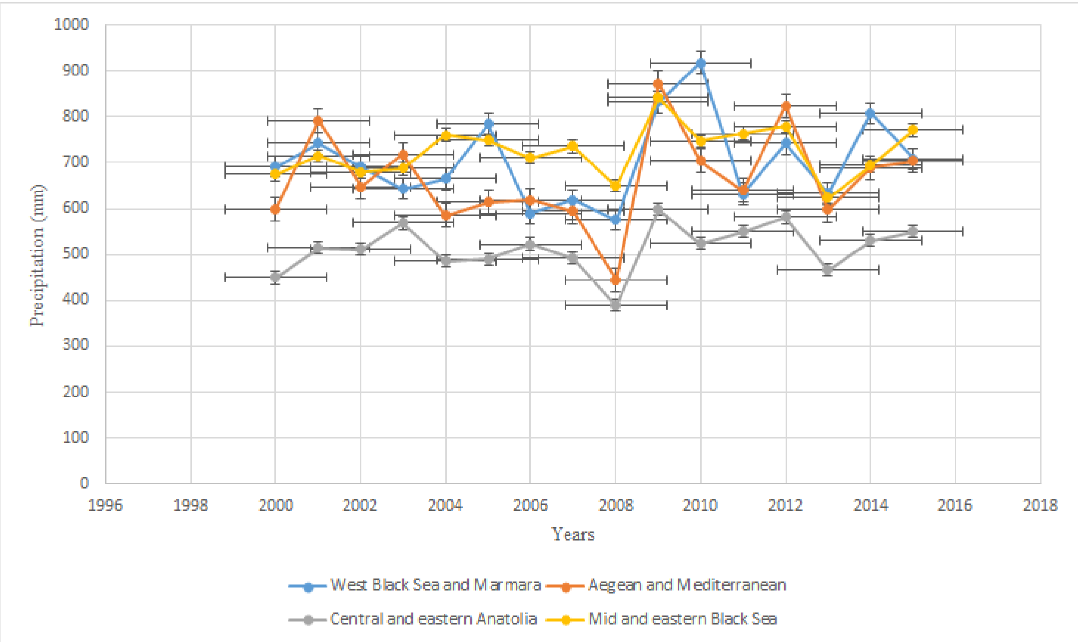


Figure 4.12: Annual average precipitation between 2000 and 2015.

CHAPTER 5

CONCLUSIONS

In the first part of the study (Chapter 2), a global NPP product was evaluated using field data from Turkey's forest ecosystems. The MODIS NPP product is important for the understanding of the global carbon cycle and has been shown to have good global accuracy. However, its accuracy at regional scales, especially in areas with high heterogeneity is less certain. It is important to create a country scale database compatible with the global data. Moreover, these datasets can help scientists to understand and model global conditions. The Ministry of Forest and Water Affairs of Turkey started to measure the DBH values of the trees in predetermined plot, in 2008. According to this protocol, ministry will run measurements in the same plots with the same trees every 5 years. This study is the first effort to create a remote sensing based reliable national forest NPP database for Turkey using ministry forest inventory, which, in return, can be used to increase the accuracy of the global products. Finally, the approach used in this study can be used for other areas, and aimed to decrease the uncertainties over heterogeneous areas and strengthen evaluation efforts of remote sensing products. The results of evaluation process showed that, although MODIS has a good accuracy over large homogeneous areas, it is lack of reflecting the actual condition on regional/country scale, especially for the areas with high topographical and climatic changes. To overcome this situation, (i) more evaluation/validation sites should be established around the world representing different ecosystem types, (ii) the importance of the local measured data sets should be acknowledged and used, (iii) basic coefficients, such as light use efficiency, values should be researched for different ecosystems around the world.

In the second part of the study (chapter 3), a new approach was developed to improve the accuracy of the NPP model. This improvement was carried out using (i) local data and (ii) a new optimum temperature approach. The analysis showed that, usage of the long term based optimum temperature can increase the accuracy of the model with respect to annual optimum temperature approach. However, the temporal resolution of the satellite data (MODIS images are available starting from February 2000) is a limitation factor to estimate optimum temperature. It is highly suggested to use satellite images with finer temporal resolution such as Landsat. For longer period temperature measurements, especially NDVI relation may reveal more precise optimum temperature values for the areas.

It is important to state that, this study is not only the first effort to estimate net primary productivity of Turkey's forest ecosystems, but also it is the first in the world to present a new calculation approach for the temperature stresses. The last part of the study (chapter 4) covers 16 years (2000-2015) of NPP calculation and its spatio-temporal variations. The analysis show that, there is a significant trend (increment) in NPP during the period. However, the same trend could not be found in meteorological data. It is important to acknowledge that, it is not possible to understand the effect of the climate change in such short period. However, it is important to understand the relation between each meteorological variable and NPP. Moreover, last decade was reported as the most drought decade since the instrumental measurements (Zhao and Running, 2010) [79]), this period can help to understand this relation (the effect of meteorological variables on NPP). Although Zhao and Running (2010) [79] reported a decrease in the global NPP, the analysis in the last section of the study show that, total annual NPP has an increasing rate over the study area (Figure 4.1). There can be two basic explanation for this result. First reason might be the resolution of used land cover data. If for a given area, due to the spatial resolution, forest areas might be merged with other land cover types such as agriculture although it is classified as forest. This may increase the estimated NPP value of the pixel. Second, the areas under the jurisdiction of the Ministry of Forest and Water Affairs include none forested areas. Most of these areas might be converted into agricultural lands by the locals. This may lead to increase the estimated NPP values.

Overall, this study confirms (i) importance of the local data as model input, (ii) usage of long term temperature values to improve the modelling approach, (iii) this study presents a new approach to scale up local data to evaluate/validate global models.

Moreover, monitoring and managing natural areas (i.e. forest areas) may help scientists and decision makers to create rapid solutions to the problems. Estimation of country scale productivity for the forest is not only time and money consuming job but also resulting data mostly face with out-of-date problems. This approach offers researchers an opportunity to analyse data in near-real time scale with less time and money consumption.

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PUBLICATIONS

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