ISTANBUL TECHNICAL UNIVERSITY ★ EURASIA INSTITUTE OF EARTH SCIENCES

MODELING SPATIAL DISTRIBUTION OF ORIENTAL BEECH (*Fagus orientalis)*: PAST, PRESENT AND FUTURE

M.Sc. THESIS

Ayşegül Dilşad DAĞTEKİN

Climate and Marine Sciences

Earth System Sciences Programme

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DOĞU KAYINI (*Fagus orientalis)* AĞACININ ALANSAL DAĞILIM MODELLEMESİ: GEÇMİŞ, GÜNÜMÜZ VE GELECEK

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ABBREVIATIONS

AIC : Akaike Information Criteria
ANN : Artificial Neural Network
App : Appendix
AUC : Area Under Curve
EUFORGEN : European Forest Genetic Resources Program
GAM : Generalized Linear Model
GBIF : Global Biodiversity Information Facility
GCM : Global Climate Model
GDF : General Directorate of Forestry
GIS : Geographic Information Systems
GLM : Generalized Linear Model
LGM : Last Glacial Maximum
MaxEnt : Maximum Entropy
MH : Mid Holocene
RCP : Representative Concentration Pathways
RF : Random Forest
ROC : Receiver Operating Characteristic
SDM : Species Distribution Model

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MODELING SPATIAL DISTRIBUTION OF ORIENTAL BEECH (*Fagus orientalis)*: PAST, PRESENT, AND FUTURE

SUMMARY

Climate change affects forest biomes more severely than ever, even with the ~1°C temperature warming so far. Geographical distributions of these biomes are linked to warming temperatures and decreasing precipitation. Species try to adapt to this change by changing these geographical barriers. Recent warming not only impacted the survival rates of most tree species, also increased risks in handling extreme events. *Fagus orientalis* is a temperate, deciduous, broad-leaved species, which covers a wide area from the eastern Balkans through Turkey, Caucasia, Crimea and northern Iran, including the Amanos Mountains in the south, with a large elevational distribution from sea level to 2100 m. Beech has an important role in terms of dominating forests and creating new ecosystems, also it is used by many industries. Several research indicate that these species are disturbed by changing the climate in terms of increasing temperature and decreasing precipitation. Because of its importance in forestry, industry and ecosystem *Fagus* sp. were the focus of interest in this study. We conducted species distribution model simulations with five different algorithms embedded in biomod2 R package – BIOCLIM, GAM, GLM, RF, MaxEnt – and with environmental data from the climate of the present, past, and future from Wordclim version 1.4, as well as digital elevation model for altitude from NASA. Our simulations covered an area in Eurasia where *Fagus* sp. is seen, exact coordinates of 18 – 62 East and 33 – 51 North. We verified our model with present-day classifications, which fitted well the distributional data obtained from General Directorate of Forestry and EUFORGEN project. These models were used to ‘predict’ distributions through climate changes spanning Last Glacial Maximum (21,000 bp), Mid-Holocene (6,000 bp), 2050 and 2070 obtained from two global climate models, MIROC-ESM and CCSM4. We observed that *F. orientalis* distribution is toward the northeast from its present distribution, where mountainous regions are intense, colder and wetter climates are available according to future conditions. These results led us to verify that drier

climate and higher temperatures are considered as limitations to these species. Additionally, we could identify refugia areas for this particular species in the past which might lead to new studies. We believe that the outcomes of this study would help improving management and conservation plans for *Fagus orientalis* in order to protect it from severe effects of climate change.

DOĞU KAYINI (*Fagus orientalis)* AĞACININ TÜR DAĞILIM MODELLEMESİ: GEÇMİŞ, GÜNÜMÜZ VE GELECEK

ÖZET

İklim değişikliği, şimdiye kadar ~ 1 ° C'lik sıcaklık ısınmasıyla bile orman biyomlarını her zamankinden daha ciddi şekilde etkilemektedir. Bu biyomların coğrafi dağılımları, artan sıcaklık ve azalan yağışlarla ilişkilendirilmektedir. Türler bu coğrafi bariyerleri kaydırarak bu değişikliğe uyum sağlamaya çalışırlar. Global ölçekteki son ısınma, çoğu ağaç türünün hayatta kalma oranını etkilemekle beraber, aynı zamanda ekstrem olayların türler üzerindeki risklerini de arttırmış oldu. Bu türlerden biri olan *Fagus orientalis* (doğu kayını), Doğu Balkanlardan itibaren, Türkiye, Kafkasya, Kırım ve Kuzey İran ile güneydoğudaki Amanos Dağları da dahil olmak üzere, geniş bir alana yayılan, aynı zamanda geniş bir yükselti dağılımına da sahip (deniz seviyesinden 2100 metrelere kadar), ılıman iklimlerde yaşayan, yaprak döken, geniş yapraklı bir türdür. Kayın, ormanları domine eden ve yeni ekosistemler yaratan bir tür olmasından ötürü bulunduğu yaşam alanında önemli bir role sahiptir, bunun yanında birçok endüstri tarafından kullanıldığından ekonomik etkisi de oldukça fazladır. Yapılan araştırmalardan bazıları, iklim değişikliğinin sebep olduğu sıcaklık artışı ve yağışların azalamasıyla beraber gelen kuraklık riskinin doğu kayınının büyümesini kısıtladığını göstermektedir. Kayın ağacının, ormancılık, endüstri ve ekosistemdeki önemi nedeniyle Türkiye coğrafyasına daha çok hakim olan *Fagus orientalis* türü bu çalışmada ilgi odağı olmuştur. Bunun için biomod2 R paketine gömülmüş beş farklı algoritma - BIOCLIM, General Additive Model (GAM), General Linearized Model (GLM), Random Forest (RF), Maximum Entropy (MaxEnt) - ile alansal tür dağılım modeli simülasyonları gerçekleştirilmiştir. Bu simülasyonlar için gerekli olan çevresel etmenler iklim ve yükselti olarak kararlaştırılmış, günümüz, geçmiş ve gelecek iklim verisi WordClim'den (versiyon 1.4), yükselti verisi alışma alanına özel olarak NASA'dan dijital yükseklik modeli şeklinde alınmıştır. Modeller için çalışma alanı, Avrasya'da *Fagus* sp.'nin görüldğü yerler baz alınarak tanımlanmıştır, tam olarak belirtmek gerekirse 18 - 62 Doğu ve 33 - 51 Kuzey koordinatları bu alanı

kapsamaktadır. Çevresel verilere ek olarak modelin gerektirdiği bir diğer veri olan dağılım verileri, Orman Genel Müdürlüğü ve EUFORGEN projesinden elde edilen verilerin birleşimi ile elde edilmiştir. Günümüz şartlarıyla yürütülen ilk simülasyon bu dağılım verisi ile alansal olarak çakıştığından , modelin güvenilirliği doğrulanmıştur. Sonrasında bu modeller, iki küresel iklim modeli ile, MIROC-ESM ve CCSM4, elde edilen Son Buzul Maksimumu (21.000 g.ö.), Orta Holosen (6,000 g.ö.), 2050 ve 2070 zaman dilimlerini kapsayan iklim değişikliğini yansıtan parametrelerle, türün ilerideki alansal dağılımının tahmini için kullanılmıştır. *F. orientalis* dağılımının bugünkü dağılımından kuzeydoğuya doğru kaydığı görülmüştür ve bu bölgelerin dağlık alanların yoğun görüldüğü yerler (genellikle Kafkasya) olduğu saptanmıştır. Ek olarak türün, gelecekte soğuk ve yağışlı iklim şartları beklenen alanlara yöneldiği gözlemlenmiştir. Kullanılan algoritmalar istatiksel olarak eğri altında kalan alan (AUC) değerleri ile karşılaştırılmış ve girdilere göre en iyi modelin RF (AUC = 0.99) olduğu görülmüştür. Literatüre göre, RF algoritması etkin sınıflandırma prensibi ile daha kesin ve daha güvenilir tahminler yapmaktadır, bu çalışmada bunun doğruluğu görülmüştür. İlk tür dağılım modeli algoritması ve ilkel istatiksel hesaplamaları sebebiyle BIOCLIM (AUC = 0.79) ise en kötü model olmuştur. Öte yandan GAM algoritmasının geçmiş dönemlerdeki simülasyonlarında aşırı yorumlamaya sebebiyet verdiği görülmüş ve buna çalışma alanının büyüklüğünün, algoritmanın hesaplama istatistiklerinde sebebiyet verdiği hatanın neden olduğu tespit edilmiştir. Bazı simülasyonların sonucunda günümüzde görülmeyen alanlarda, özellikle iç Ege ve Avrupa, *F. orientalis* dağılımı tespit edilmiştir. İç Ege'deki dağılımın sebebinin insan etkisiyle beraber, ekosistemdeki bitki ve diğer canlılar ile olan kompetisyon olabileceği şeklinde yorumlanmıştır. Tür dağılım modellerinin biyolojik faktörleri girdi olarak kabul etmemesi bu konuda yapılabilecek bir tahmini bu çalışma için engellemektedir. Modeller sadece abiyotik faktörleri kabul etmektedir ve bu çalışmmada sadece bunlardan iki tanesi (iklim ve yükselti) kullanılmıştır. Avrupa'daki dağılım ise *F. orientalis*'in yakın akrabası olan *F. sylvatica* ile ilişkilendirilmiştir. İki türün fizyolojik benzerliği, birbirine yakın şartlar ve ekosistemlerde yaşamalarını sağlamaktadır, modelin bu bölgelerde uygun iklim şartları gördüğü yerlerde *F. orientalis* bireylerinin olabileceğini düşünmesi bu açıdan beklenilebilir olarak görülmüştür. Her küresel iklim modeli kendi içinde farklı değerlere sahip olduğundan, MIROC-ESM ve CCSM4 kendi aralarında karşılaştırılmış ve MIROC-ESM'in daha sıcak ve yağışlı olduğu saptanmıştır. İki modelle aynı dönemlerde yapılan tahminlerde

CCSM4 simülasyonlarının daha fazla popülasyon yoğunluğuna sahip olduğu görülmüştür, bu sonuç ve iki model arasındaki karşılaştırma, *F. orientalis* üzerindeki asıl limitleyici faktörün sıcaklık olduğunun düşünülmesine yol açmıştır. Simülasyonların doğrulukları aynı zamanda dönemler arasındaki iklim şartlarının karşılaştırılması ile de doğrulanmıştır. Geçmişteki daha soğuk ve kurak dönemler ile, gelecekte daha sıcak ve kurak olması beklenen alanlarda türün dağılımı oldukça az gözlenmiştir. Bu sonuçlar ile daha kuru ve daha yüksek sıcaklıkların bu türlere sınırlama olarak görüldüğü doğrulanmıştır. Ayrıca, geçmiş simülasyonları ile bu türlerin sığınak alanlarını kabaca tanımlanmış olup, tür özelinde bu alanda yeni çalışmaların ilk adımı atılmıştır. Bu çalışmanın sonuçlarının, *Fagus orientalis* türünü iklim değişikliğinin ağır etkilerinden koruyabilmek için amenajman ve koruma planlarının iyileştirilmesine yardımcı olacağına inanıyoruz. Buna ek olarak, çalışmayı geliştirmek amacı ile IPCC'den farklı iklim senaryoları ve korelasyon analizi yapılmış iklim parametreleri ile simülasyonlar yapılmaya, ayrıca dendrokronoloji ile palinoloji alanlarından destek alınmaya çalışılmaktadır.

1. INTRODUCTION

Climate change was always an issue in Earth's history. However, this time, its impacts are observed more severely than ever, even with the ~1°C temperature warming so far (IPCC, 2013). One of the most obvious impacts is on living organisms worldwide, they try to adapt to this change by changing their behaviors, physical features, and also geographical distributions (Scheffers et al., 2016; Parmesan, 2006). The distribution barriers are linked to warming temperatures and decreasing precipitation (IPCC, 2013). In all of the biomes, forests are the ones which are affected the most by the recent warming. These changes not only unbalance the survival rate of tree species, also increased risks will force them to handle extreme events, such as severe droughts, floods, wildfires etc. (Lindner, 2010). Since trees are the dominant species of forest ecosystems, any influence on them would leave marks on the environment in terms of resource supply, shelter, local and regional climate, as well as ecosystem services. Changes in dominant tree species would force the whole ecosystem and dependent organisms to alter their lifestyle and even die (Dyderski, 2017). Climate is the basic factor that is responsible for trees' growth and survival. Changing in climate is causing many tree species to be at the edge of relocation or extinction, this would result in the decreased endemism in an area. Also, climate dependent factors, such as a shift in time frames of biological processes, drought, lack of resources, become the foundation of many disturbances and limiting the growth of tree species. Thus, any effect on a forest environment would be a collaboration of many factors especially ignited by climate change.

1.1 Climate Change in Turkey and Surrounding

The Anatolian plate was formed in the Oligocene, which makes it an aged zone with lots of changes in its environments, especially with the effects of climate (Aral, 2008). This region is rich in providing paleoclimatic information that also helps to construct future predictions. In the present day, impacts of global warming can be seen in Turkey significantly because of its diverse and endemic biodiversity, vegetation characteristic and different climatic zones (Şekercioğlu et al., 2011). For this reason, it is important to understand the consequences of climate change around Turkey and try to predict its possible outcomes on biodiversity. The study region in this study focuses on the northern part of Turkey (Black Sea region) and also the nearest surroundings such as Caucasus, Crimea and northern Iran. The study region is determined by the present-day distribution of the tree species of concern, Eastern beech, *Fagus orientalis* L., which belongs to *Fagus* genus that is widely distributed across Eurasia. *F. orientalis* can be seen widely and *F. sylvatica* can be seen locally in the above-mentioned area (Yaltırık, 1982a; Caudullo et al., 2017). Recent studies propose that these two species should be considered as subspecies of *Fagus sylvatica* as *F. sylvatica* L. subsp. *sylvatica* and *F. sylvatica* subsp. *orientalis* L., they can be distinguished by morphological characteristics of their leaves and cabin (Figure – 1.1). (Denk, 2003; Greuter et al., 1984; Akkemik, 2014).

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Figure – 1.1: Fagus sylvatica (left) and Fagus orientalis (right) (Akkemik, 2014).

Nevertheless, both are ecologically and economically highly important (Pastorelli et al., 2003). Beech has an important role in its own niche in terms of dominating forests and creating new ecosystems. Also, beech wood can be used as fuel, paper, furniture etc. Because of its importance in forestry, industry, and ecosystem, *Fagus* was the focus of interest in many species across Eurasia. Several studies indicate that *F. orientalis* species are disturbed by changing the climate in terms of increasing temperature and decreasing precipitation (Köse and Güner, 2012; Haghshenas et al., 2016). The outcomes of these studies with the importance of *F. orientalis* to its environment and ecosystem services led to a need of understanding the current situation and future of these species in terms of conservation and management plans according to climate change as well as maintaining the biodiversity around it.

1.2 Species Distribution Models (SDMs)

Since climate change is the main driven factor of geographical distributions, this issue has been studied by many researchers via various models, either with climate, ecosystem or vegetation models. Nevertheless, currently, the most used approach to investigate the impacts of climate change on distributions is species distribution models (SDMs). SDMs are also called as bioclimatic models, climate envelopes, ecological niche models, habitat models, range maps, and resource selection functions. SDM is the most commonly used term, yet it can cause confusion from time to time, still, the modeling process is the same for all. These models help to identify areas in an area that have similar environments to localities where the species has been observed. For this purpose, models use mapped observation data (mostly in presence/absence format) and environmental (such as climate, among others) data provided for the interested area (Elith and Leathwick, 2009; Pearson, 2007). SDMs provide predictions of distributions of the given species by using the abiotic factors such as environmental data, so it is mostly a tool for understanding the fate of a species in the future in terms of ecology and conservation purposes. These models also help to understand current and possible interactions between species, organisms, environmental parameters and richness in the area (Elith et al., 2006). SDMs can be considered as the evolved form of predictive habitat distribution models, described by Guisan and Zimmermann in 2000. Many of the known statistical classification algorithms which are already in use for prediction of distribution, can also be applied to SDM, such as generalized linear models (GLM, Nelder and Wedderburn, 1972; McCullagh and Nelder, 1989), generalized additive models (GAM, Hastie and Tibshirani, 1990), machine-learning algortihms (maximum enthropy) (Phillips et al., 2006), neural networks (Hopfield, 1982), regression trees (Breiman et al., 1984), and random forest (Breiman, 2001a). Distribution modeling with the help of climate parameters is going back to the 1920s, to attempts by Johnston, the first use of a computer for this purpose was in 1971, by Austin, earliest SDM trial was done by Henry Nix in 1977 (Guisan and Thuiller, 2005). From that time until now, this tool has been improved and advanced which made it significant for answer tons of questions in ecology, evolution, biodiversity, conservation, and now also climate change research. Improvements on SDMs are continuing day by day by incorporating of external and non-climatic factors (Hijmans and Graham, 2006), comparing different model algorithms (Li and Wang, 2013), advancing modeling methods and parameters (Elith et al., 2006) and by focusing on model variables and parameters (Jiménez-Valverde, Lobo and Hortal, 2008; data to be occurrence/absence/pseudo-absence, VanderWal et al., 2009; importance of accessible area concept, Barve et al., 2011). This helps to understand the underlying mechanism of change in forest ecosystems caused by climate change and let us predict a certain aspect of what will happen in the future, how will species react and what would be the costs of it.

1.3 Hypothesis

In this study, for the reasons given above, we ran different SDM algorithms on one particular tree species, eastern beech, *Fagus orientalis* L. which can be found across the northern Anatolia, Caucasus and Iran. We used past, present and future climatic conditions to observe how the species respond to the climate change throughout its history. Köse and Güner made a detailed tree ring study on *F. orientalis* in 2012 to identify the most important climate factors that affect the growth and found out that the species are vulnerable in high temperature and low precipitation conditions. Also, it is observed in the field that there are some biological problems on beech populations that are found in the low altitudes can be caused by altering climate. We tested the species distribution to explore these two points and expect its distribution zone to be shifted to higher altitudes and the areas with wetter and milder climatic conditions.

2. MATERIALS AND METHODS

2.1 Study Species

Fagus orientalis is a temperate, deciduous, broad-leaved species that belong to the family Fagaceae that is widely distributed across Northern Hemisphere (Feng and Lechowicz, 2006; Denk, 2003). In Eurasia when *F. sylvatica* is found only in regions such as Thrace (Turkey), small populations in Black Sea Region, Bulgaria, southern Russia; *F. orientalis* cover a much wider area from the eastern Balkans, northeastern Turkey (Black Sea region), small population around Amanos Mountains (Turkey), Caucasia, Crimea and northern Iran. Some hybridization zones between two species have been observed around Europe and Asia border, where two species actually separating (Feng and Lechowicz, 2006; Kandemir and Kaya, 2009; Akkemik, 2014; Caudullo et al., 2017). Considering the distribution area of the species, we defined an extent with coordinates of 18 – 62 East and 33 – 51 North (Figure – 2.1). The species has several synonyms, including consideration as a subspecies of *F. sylvatica* mentioned before (The Plant List, 2013). *F. orientalis* has a wide elevational distribution from sea level to 2100 m (Şanlı, 1978). It is a wind-pollinated species with an average growth temperature ranges from 6.5 °C to 10.2 °C (Feng and Lechowicz, 2006). European beech is distributed in a wide area as mentioned above, however, it shows different growth rates depending on its location by means of climate, aspect, and elevation (Akkemik and Demir, 2003).

2.2 Data Collection

2.2.1 Environmental data

Climate is the main factor shaping species distributions (Pearson & Dawson, 2003) and with SDM, climate predictors may provide an effective approach for handling the environmental sustainability (Bucklin et al., 2015), thus 19 bioclimatic variables (Table – 2.1) (Hijmans et al., 2005) and altitude were used as environmental input and other factors, such as soil type and land use were not taken into account.

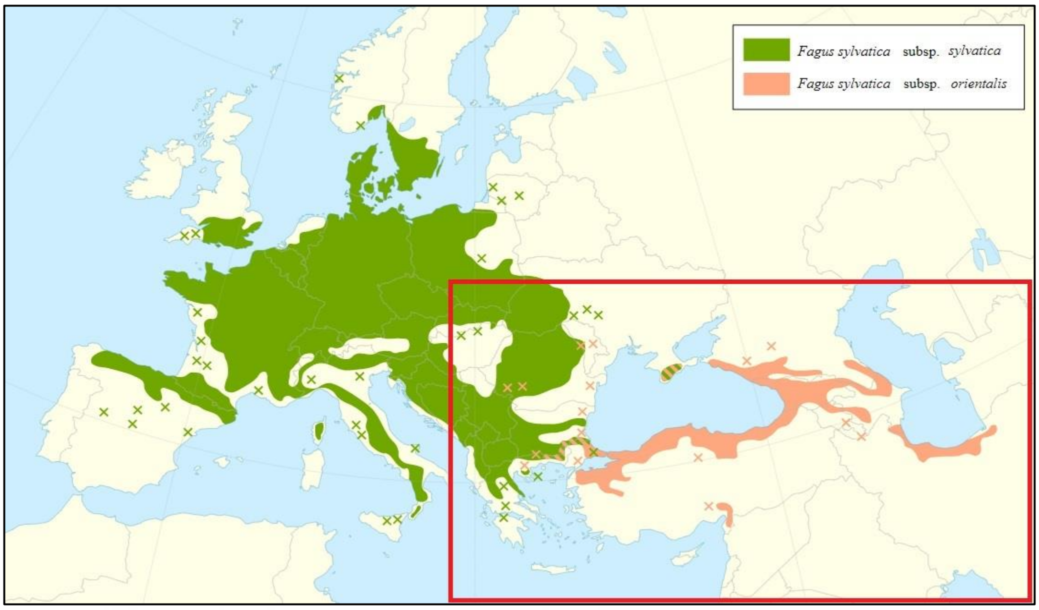

Figure – 2.1: Distribution of F. sylvatica and F. orientalis adapted from Caudullo et al., 2017. Here, F. orientalis is indicated as subspecies of sylvatica and hybridization zones can be seen clearly. Our study site is the region in the red box.

Table – 2.1: Bioclimatic variables from WorldClim database.

Abbreviation	**Bioclimatic variables**
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3	Isothermality (BIO2/BIO7) (* 100)
BIO4	Temperature Seasonality (standard deviation *100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

Past and future climate data were also available on WorldClim version 1.4 database as Last Glacial Maximum (LGM), Mid-Holocene (MH) for past, and 2050 (average for 2041–2060) and 2070 (average for 2061–2080) for future as downscaled global climate model (GCM) output from CMIP5. From these options MIROC-ESM (Watanabe et al., 2011) and CCSM4 (Gent et al., 2011) were selected. For each GCM representative concentration pathway (RCP) 8.5, which is the pessimistic scenario of

IPCC, 5th Assessment Report was applied. The pessimistic scenario assumes 1,350 ppm CO_2 and 2.6–4.8°C increase by 2100, and refers to the A1F1 scenario of IPCC AR4 guidelines (Harris et al., 2014; van Vuuren et al., 2011) 2100 relative to to pre-industrial (Weyant et al., 2009). Raster maps of current (1960–1990) and projected (2041–2060 & 2061–2080) bioclimatic variables at 2.50 resolution were obtained from the WorldClim version 1.4 dataset (http://www.worldclim.org/; Hijmans et al., 2005).

Additionally, in order to integrate the altitude in the models, 30 seconds resolution of GMTED2010 digital elevation model from NASA's USGS website was downloaded according to our coordinates (https://earthexplorer.usgs.gov/), merged and resampled into 2.5 arc minutes resolution. All environmental data was cropped according to our defined extent of 18 – 62 East and 33 – 51 North. Entire conversions, operations, and formatting on environmental data were done on ArcGIS 10.3 and/or QGIS 2.15.

2.2.2 Distribution data

Distribution data of *Fagus orientalis* was obtained from European Forest Genetic Resources Program (EUFORGEN distribution maps, http://www.euforgen.org/species/fagus-orientalis/) for areas outside Turkey (since the data given to EUFORGEN for Turkey was too coarse) and from Turkey's General Directorate of Forestry (GDF) for areas within Turkey, two occurrence data is merged together in QGIS (version 2.14) providing 10,399 presence points in total across the study area. Data from GDF includes all the mixed forests in Turkey according to the latest management plans, forests that contain Eastern beech species were selected and extracted by QGIS. Because the distribution data sources differed in the form we merged and transformed all of them into one single raster map at 2.50 resolution in a WGS-84 spatial coordinates system, then obtained spatial points from this final raster map when needed.

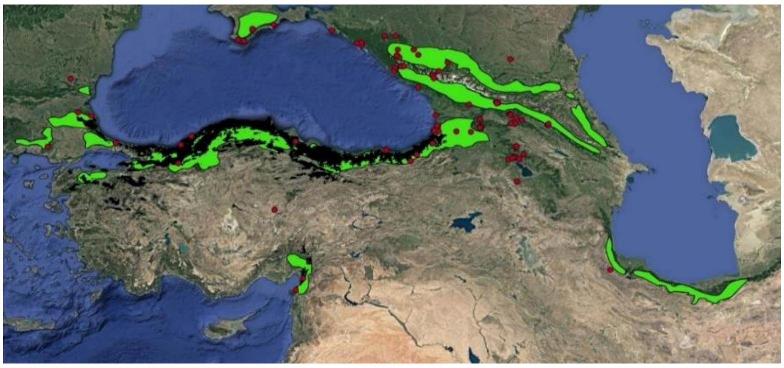

Figure – 2.2: Fagus orientalis distribution data from EUFORGEN (green), GDF (black), and GBIF (red).

We are aware that some data provided by Global Biodiversity Information Facility (GBIF) database too, yet it was insufficient and containing slightly biased data. In Figure – 2.2, all distribution data from these 3 sources can be seen.

2.3 The Model

Among all of the algorithms of SDM (Pearson, 2007), we applied five of them for our research which are General Linearized Model (GLM), General Additive Model (GAM), Random Forest (RF), BIOCLIM, and Maximum Entropy (MaxEnt) (Figure – 2.3). All these models were applied by using R with the **biomod2** package, which is mainly designed for species distribution modeling, calibration, evaluation, and an ensemble of models by Thuiller et al., 2007. As input, our distribution data and 19 bioclimatic variables were given. Input data was formatted with default settings, 80% as training sample and randomly 20,796 background points as pseudo-absence were created.

MaxEnt is also used from its open source Java platform designed by Phillips et al., 2006, with randomly selected 10,000 pseudo-absence points, with 70% of data as a training sample. Background points lead more conservative models through shaping the model for an equal proportion of presences and pseudo-absences (Elith et al., 2011), giving more reliable results.

As evaluation criterion of model performance, we used the area under receiver operator curve (AUC) because it depends on true positive and true negative overlapping rates between the current and projected models.

All analyses were applied using R software, code sheets, modeling and evaluation scripts are given in appendices (App A).

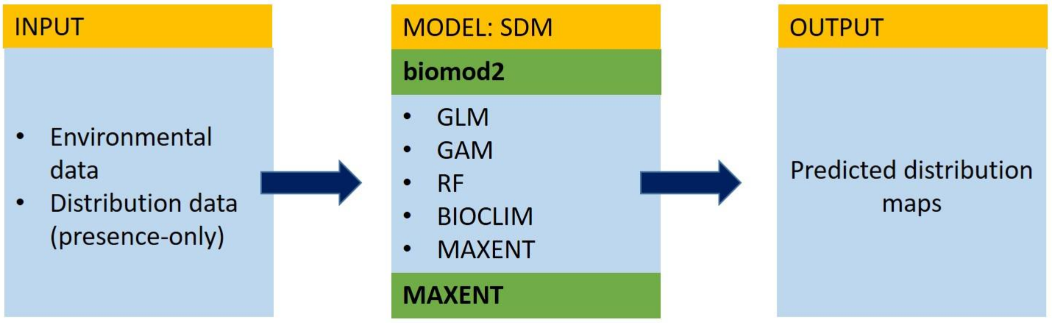

Figure – 2.3: Representation of model workflow with input and output parameters.

3. RESULTS

3.1 Model Outputs

Performance of models was measured by AUC, ranged from 0.76 to 0.99 (Table – 3.1) since all were above 0.7, the runs were successful (Elith et al., 2011).

Table – 3.1: AUC values of all the models.

Algorithm	AUC
BIOCLIM	0.79
GAM	0.98
GLM	0.96
RF	0.99
MaxEnt (biomod2)	0.96
MaxEnt (open source java)	0.76

All algorithms differed in projected range changes among different time zones, LGM, MH, present and average values for 2050 and 2070 with the pessimistic scenario. The model outcomes were analyzed with RStudio, following figures show the prediction maps of *Fagus orientalis* distribution in the study area. All of them contain also distribution data and present time projection – in the first row left and right respectively – to compare with the predictions.

The first figure shows the present time distribution projections with all the algorithms (Figure – 3.1). Green areas mark the most expected distribution areas of *F. orientalis*, with this information the most distributed projection is BIOCLIM while the least one is RF. The closest one to our distribution data (observation data) is also RF.

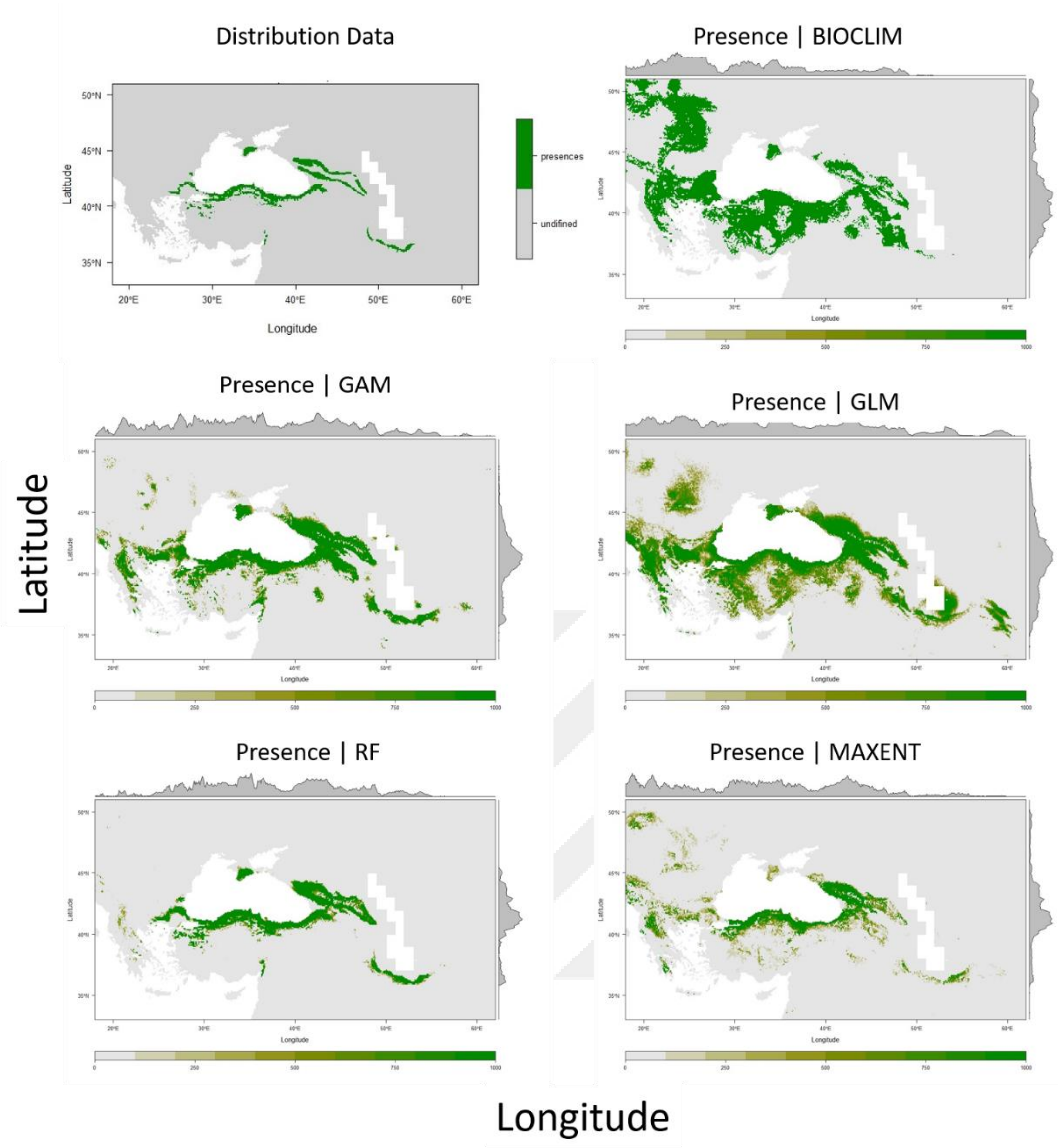

Figure – 3.1: Present time projection distribution maps according to the distribution data as input. The top row shows distribution data (left) and BIOCLIM projection (right), middle row shows GAM (left) and GLM (right) projections, and the bottom row shows RF (left) and MAXENT (right) projections. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0, absent, to 1, presence.

Rest of the figures demonstrate a particular algorithm, with MIROC – ESM and CCSM4 models, respectively. All of these have distribution data (left) and present time projection (right) in the first row, past projections, LGM (left) and MH (right) in the middle row, and future projections, 2050 (left) and 2070 (right) in the bottom row. Figure – 3.2 shows the BIOCLIM projections of MIROC – ESM model with all time zones. There are certain decreases between different time zones in terms of population density and distribution area. The geographical shift is observed to the northeast from the present distribution, assuming to the higher altitudes.

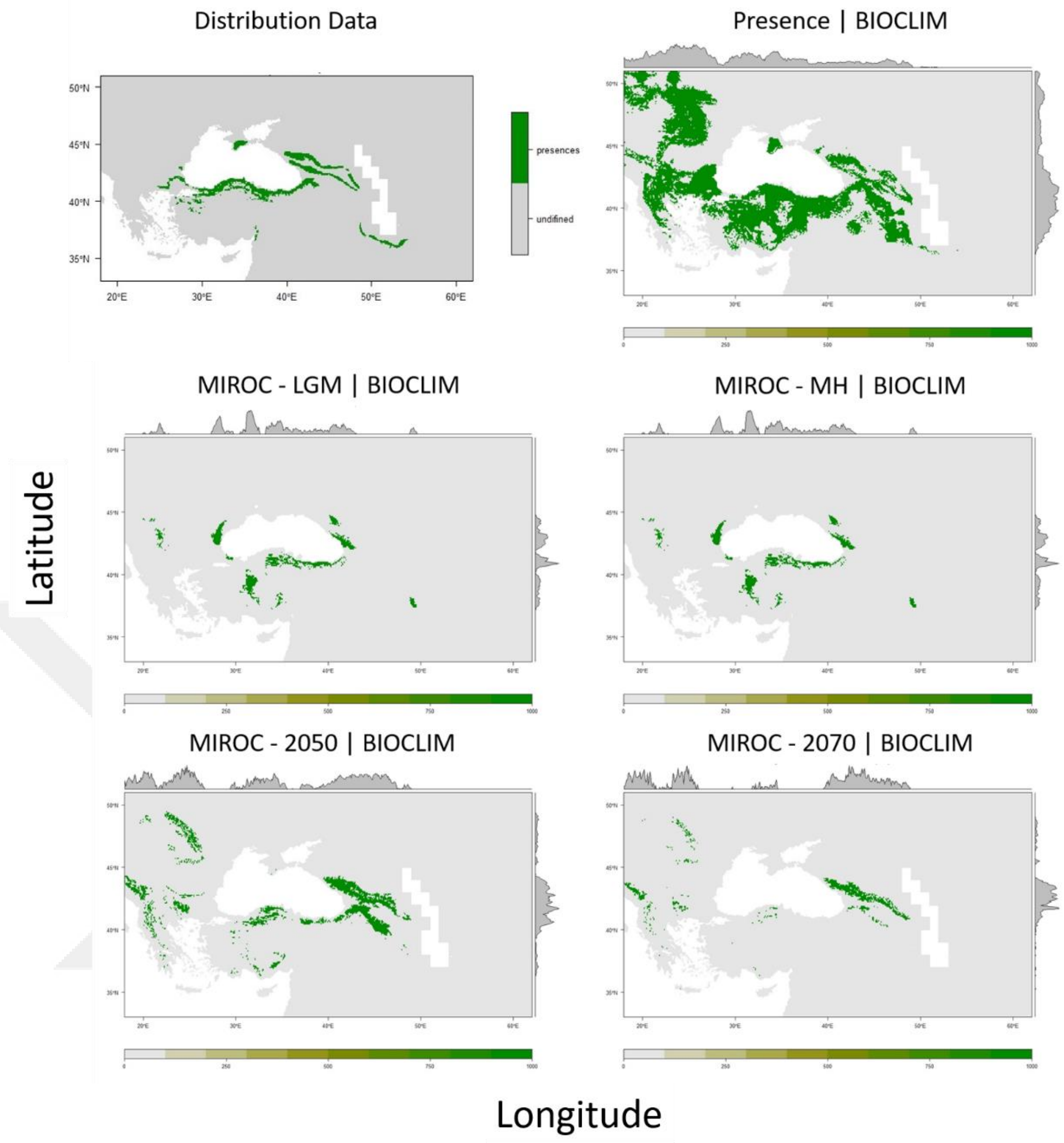

Figure – 3.2: MIROC – ESM BIOCLIM projection distribution maps. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0, absent, to 1, presence.

Figure – 3.3 shows GAM projections with MIROC – ESM model. As it can be seen from the maps, GAM predicts an overfitted distribution area during LGM and MH time zones, which will be discussed in the next section. From past to future projections, it is obvious that density and distribution area decrease again. In future projections, species shift to the inner Anatolia, and northeast of Black Sea region.

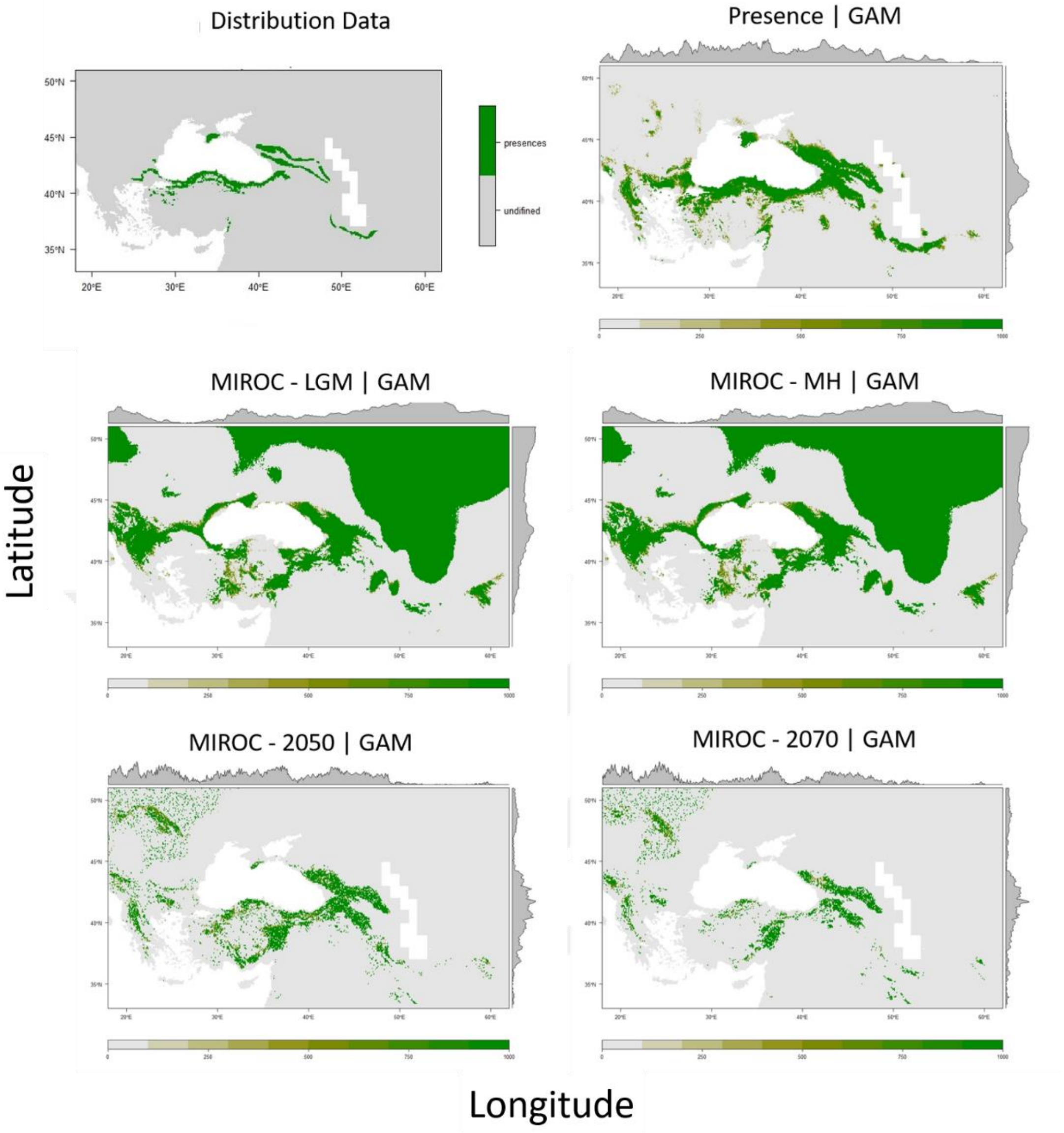

Figure – 3.3: MIROC – ESM GAM projection distribution maps. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0 to 1, absence to presence.

GLM projections of MIROC – ESM model can be seen in Figure – 3.4. Again distribution areas differ from past to future, however this time there is no obvious decrease in the population density. Also, it is important to point out that, GLM revealed the distribution around Amanos Mountains from the input data also in the projections (slightly in present time, LGM and MH). Past projections indicate that the species were denser in Iran and future projections predict that it will shift to northern parts of its present distribution, to the Crimea and Ukraine in 2050 and eastern Russia in 2070.

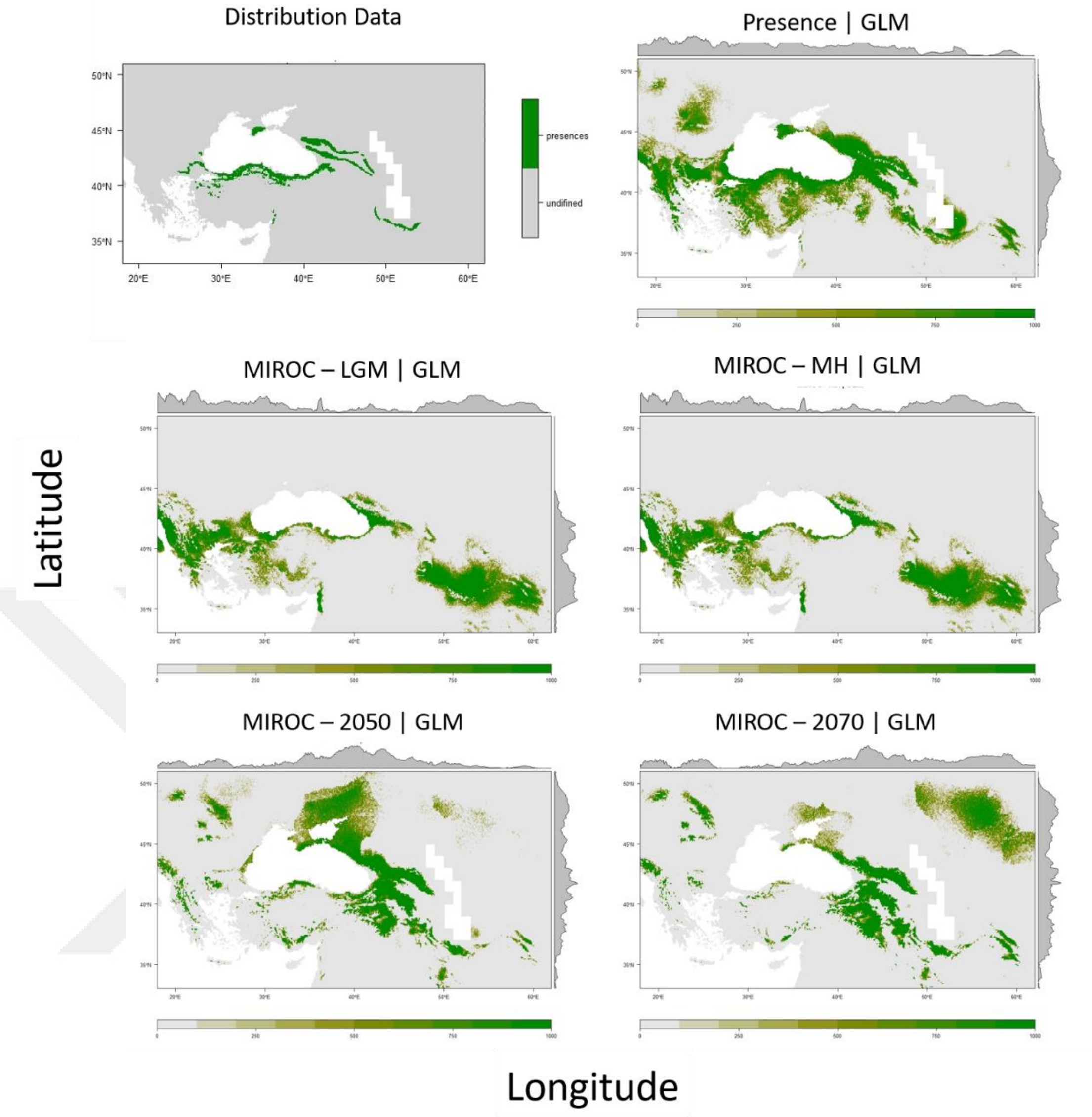

Figure – 3.4: MIROC – ESM GLM projection distribution maps. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0, absent, to 1, presence.

From Figure – 3.5 RF projections of MIROC – ESM model can be seen. According to this algorithm, there is a significant decrease in population density in the projections. Also, RF's present time projection (top row, right) is the best-fitted one to the distribution data among all of the prediction maps, even the sensitive distribution around Amanos Mountains can be seen fully in this algorithm. Iran region was denser in the past and future predictions show a shift to the northeastern parts from the present distribution, assuming to the higher altitudes.

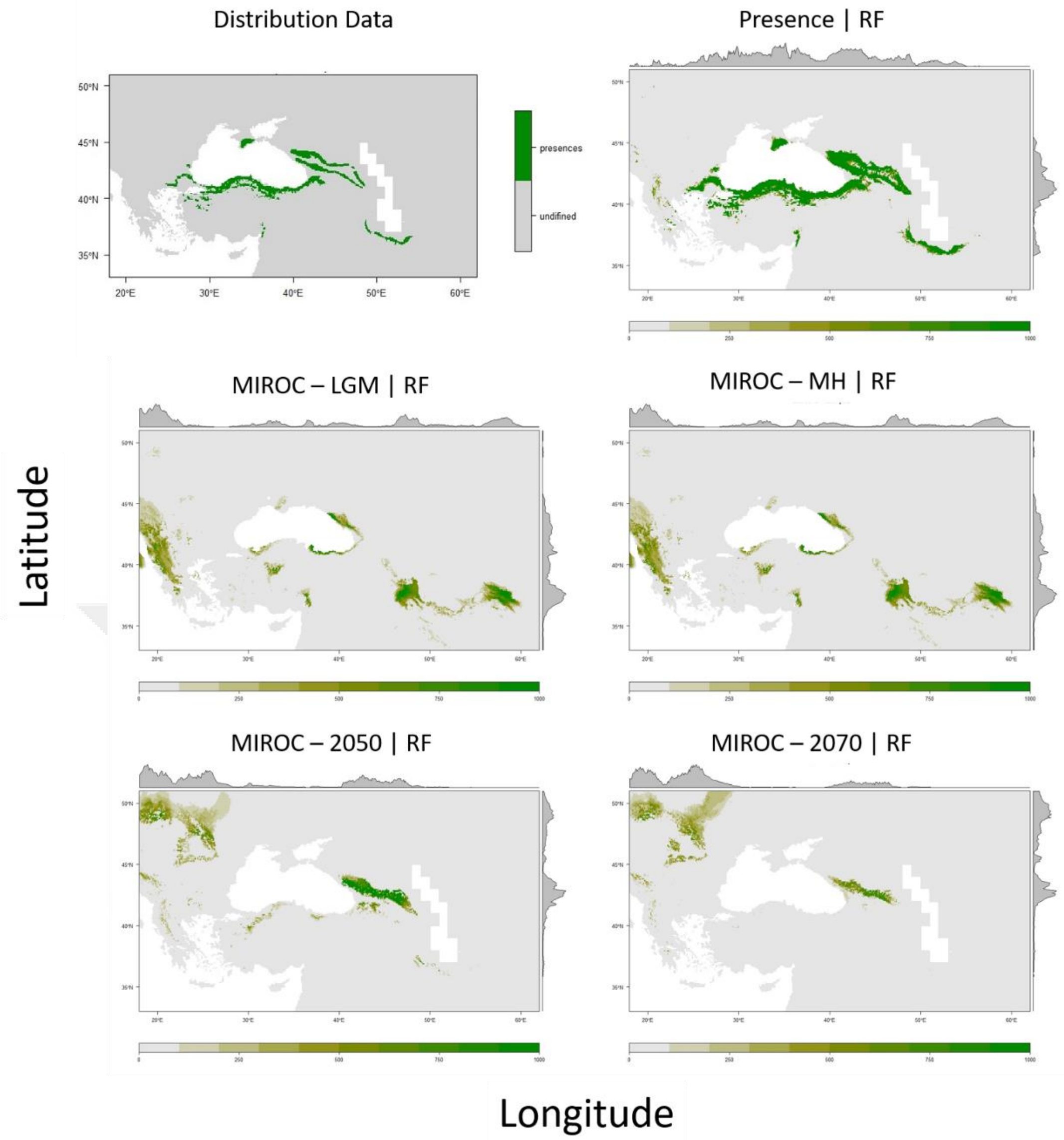

Figure – 3.5: MIROC – ESM RF projection distribution maps. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0, absent, to 1, presence.

Final one for MIROC – ESM model is Figure – 3.6, which shows MaxEnt projections. There is a certain decrease again in population density and distribution area in time. There was more beech in the inner and southern Anatolia in the past, also the future predictions show a shift to the northeast of the present distribution, again with higher altitudes.

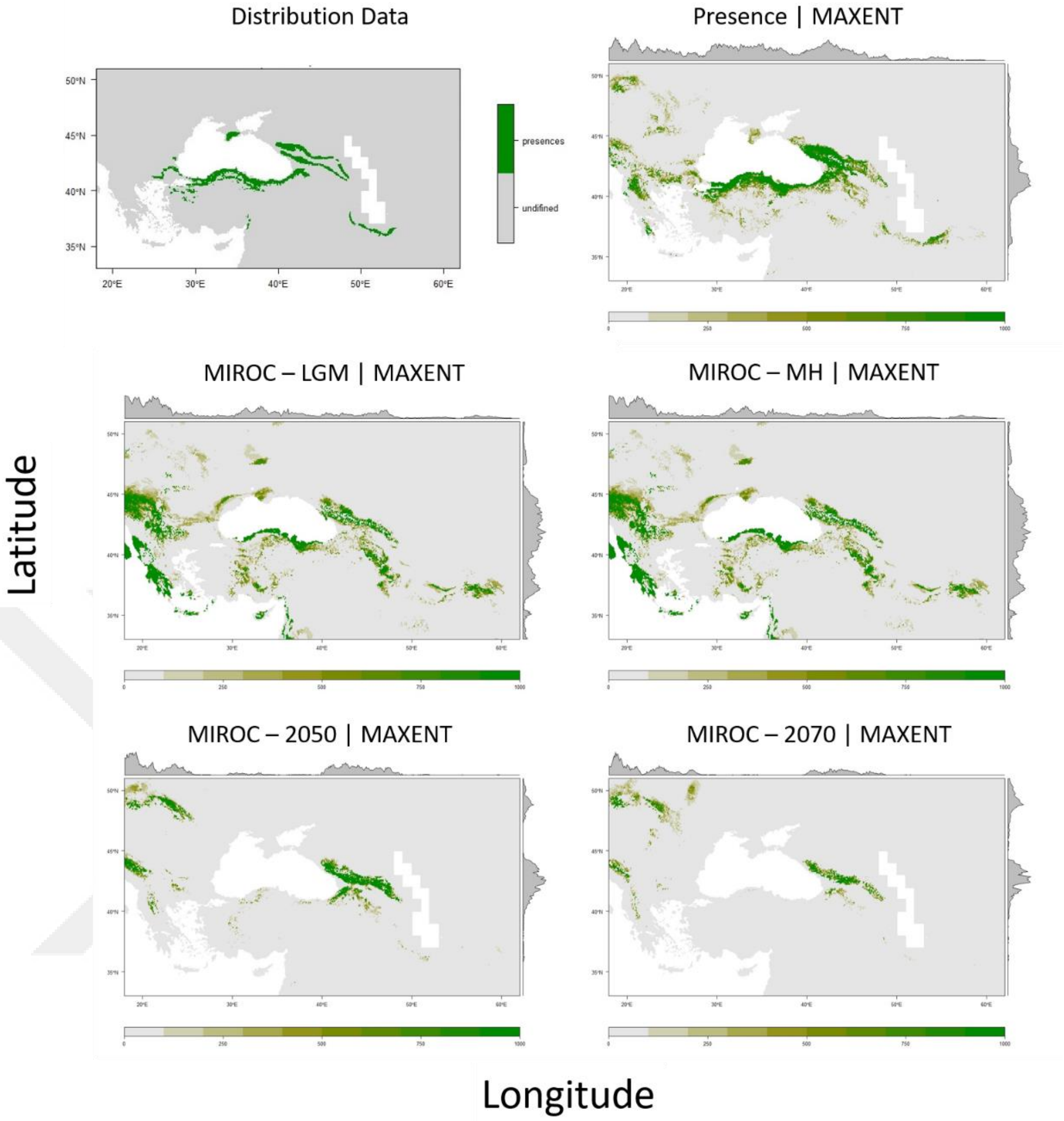

Figure – 3.6: MIROC – ESM MAXENT projection distribution maps. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0, absent, to 1, presence.

The second part of the outputs focuses on CCSM4 model. Figure – 3.7 shows BIOCLIM projections. This time, with respect to distribution data, no significant decrease in population density or distribution area is observed. However, according to present time prediction (top row, right), there are declines in the population density of past and future. There are no obvious shifts in the future predictions, except some regions in the southern Anatolia.

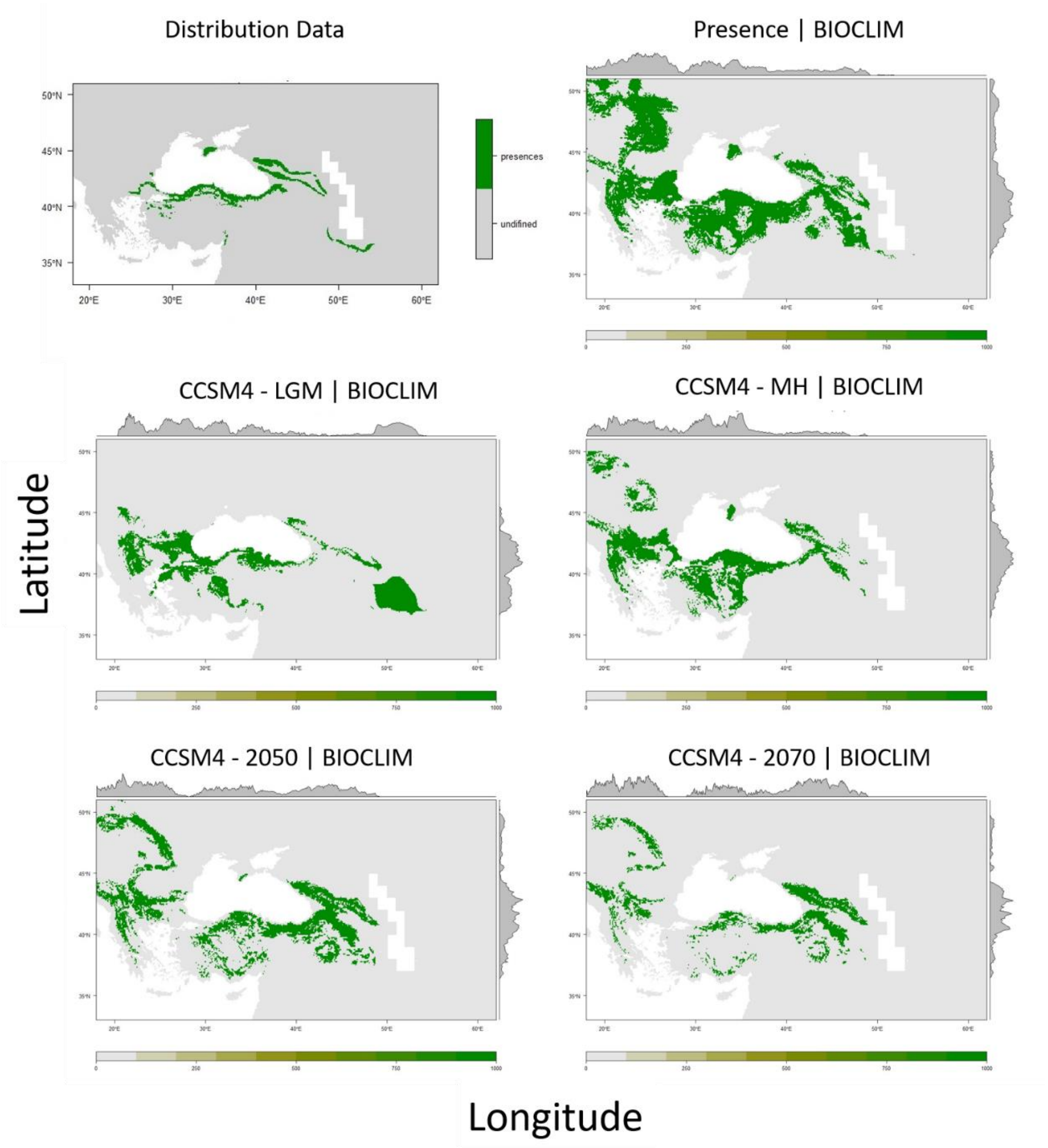

Figure – 3.7: CCSM4 BIOCLIM projection distribution maps. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0, absent, to 1, presence.

Figure – 3.8 shows the GAM projections of CCSM4 model. Similar to MIROC – ESM outputs overfitted distribution area during LGM and MH time zones are observed again. There are significant areas in Europe in the past, also future predictions show a shift towards there. According to this algorithm, inner Anatolia regions will be covered with beech in the future as well.

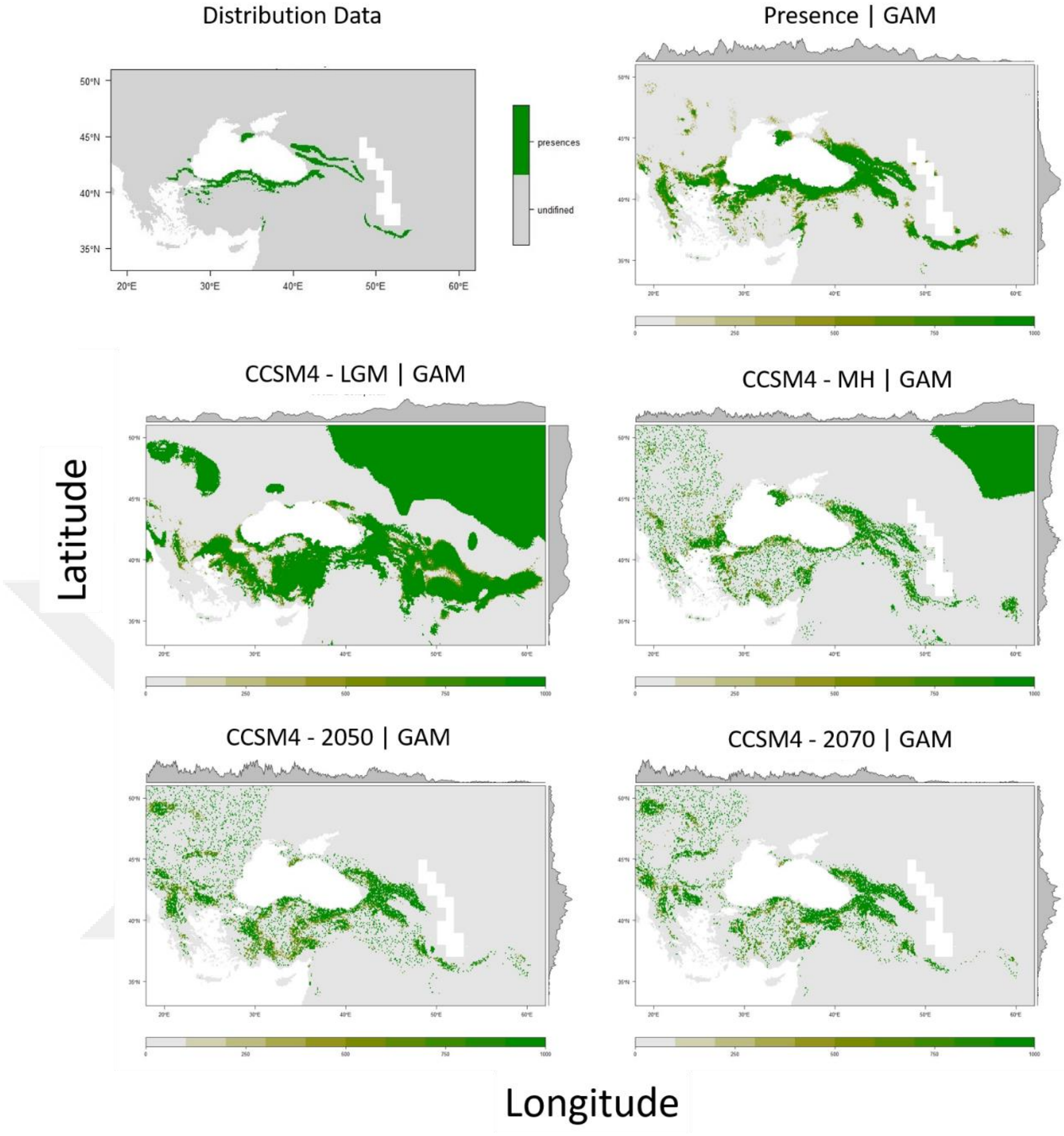

Figure – 3.8: CCSM4 GAM projection distribution maps. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0, absent, to 1, presence.

GLM projections of CCSM4 model are seen in Figure – 3.9. During LGM, Iran and Azerbaijan were covered with beech, yet they lost this cover through time. There are no obvious shifts in the future, except inner and southern Anatolia.

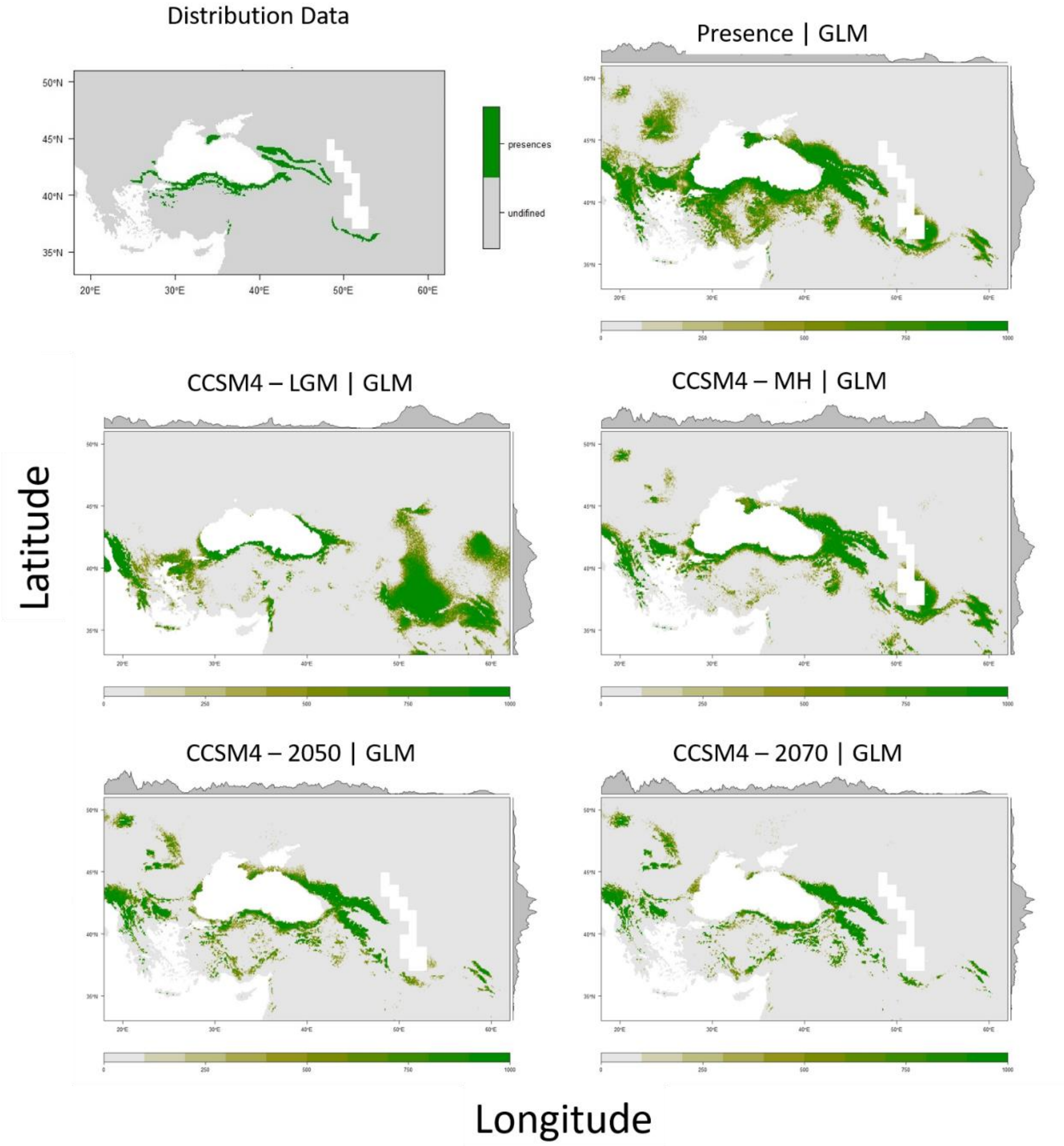

Figure – 3.9: CCSM4 GLM projection distribution. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0, absent, to 1, presence.

Figure – 3.10 shows the RF projections of CCSM4 model. Again this algorithm is overlapping with the distribution data in the Amanos Mountains, which is sensitive. The population density and distribution area decrease in time according to future predictions. The shift is observed around northeast of the present distribution, concentrated on higher altitudes.

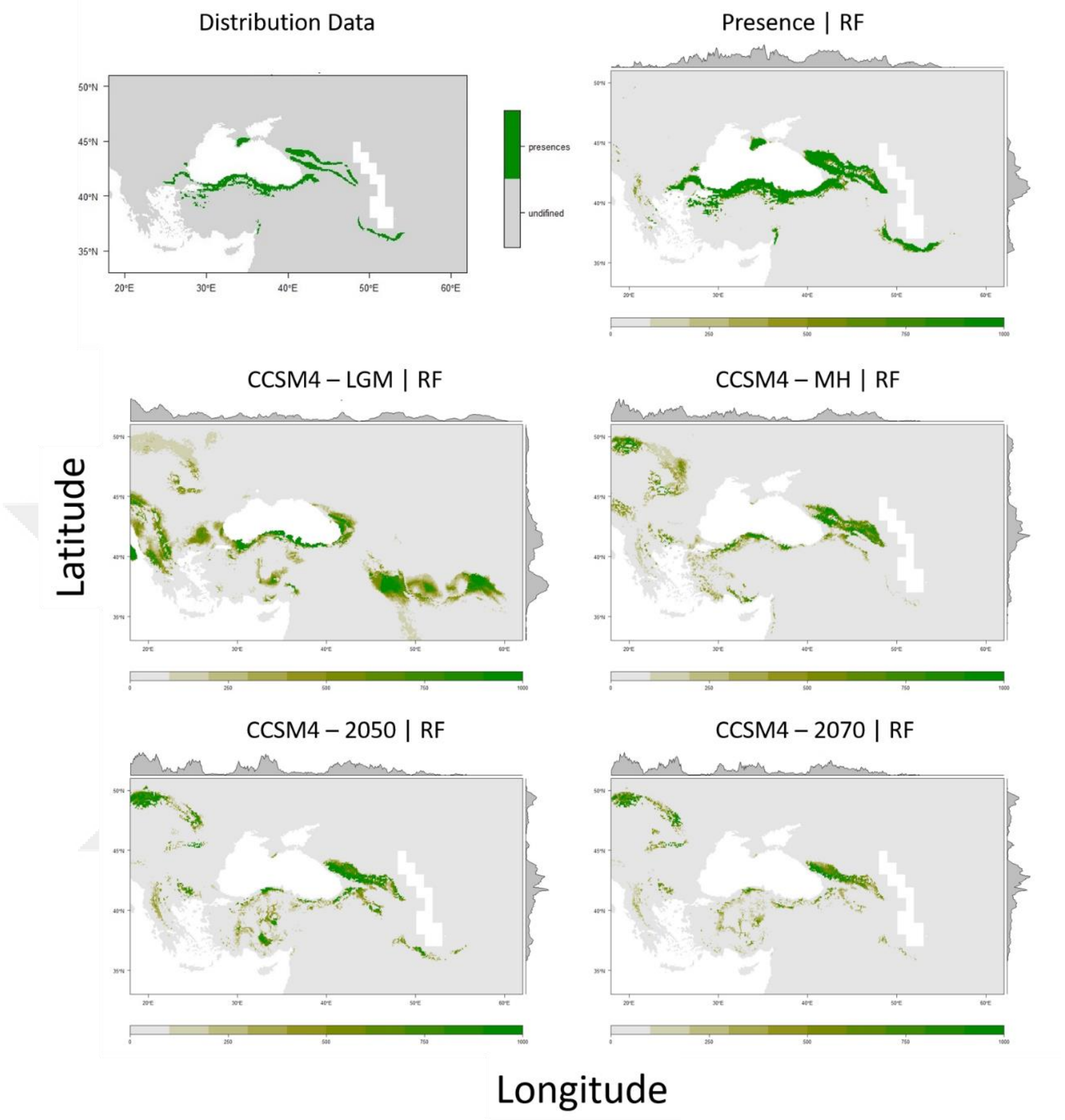

Figure – 3.10: CCSM4 RF projection distribution maps. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0, absent, to 1, presence.

Finally, Figure – 3.10, shows MaxEnt projections of CCSM4. It can be said that the population density was lower in the past and it will be even lower in the future, also there will be a certain shift in the northeast of present distribution.

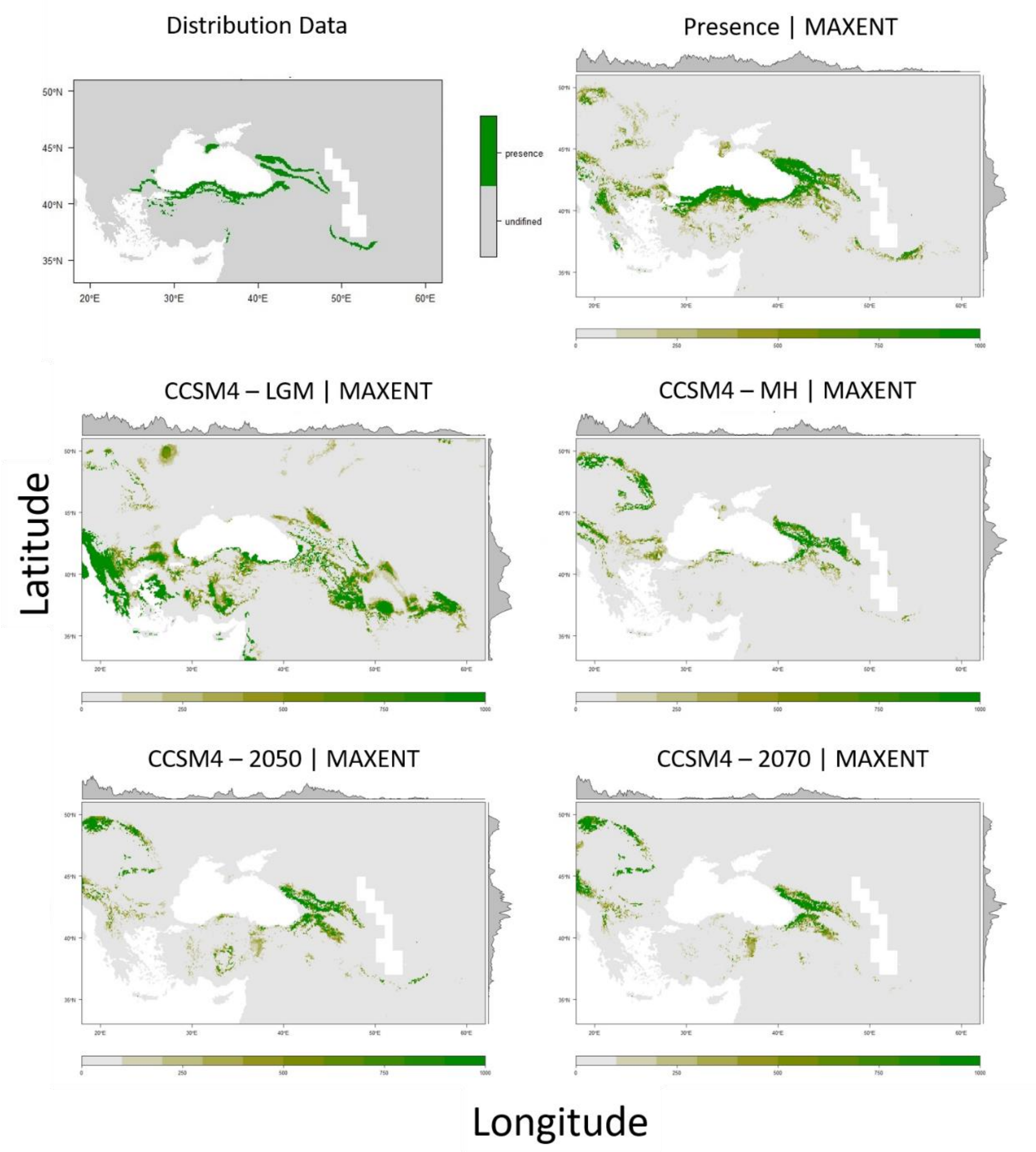

Figure – 3.11: CCSM4 MAXENT projection distribution maps. Grey curves indicate the density of species distribution latitude and longitudewise, whereas color scale meaning the possibility of distribution from 0, absent, to 1, presence.

In total it can be said that mainly all outputs agree with the direction of the shift of *Fagus orientalis* in the future, which will be northwest of its present distribution, accumulating mainly in the mountainous regions around the borders of Turkey, Russia, and Georgia. This leads us to make inferences that in the future *F. orientalis* will prefer higher altitudes with milder, slightly colder regions with wetter conditions.

3.2 GCM Difference

In this study, as it is mentioned before, two different GCMs were used, MIROC – ESM, and CCSM4. Since they are two different models, there are differences between values of 19 bioclimatic variables (Table – 2.1). This difference between values affect the model predictions as well. To show that, we combined MaxEnt model projections (from original MaxEnt open source Java platform, Phillips et al., 2006) in one figure with QGIS to see all time zones and two GCMs at once (Figure – 3.12). As it can be seen from below, two GCMs have obvious differences in their distribution maps. The predicted shift is again, northeast of the present distribution as the other model outputs, yet they differ in the predicted distribution area size and population density.

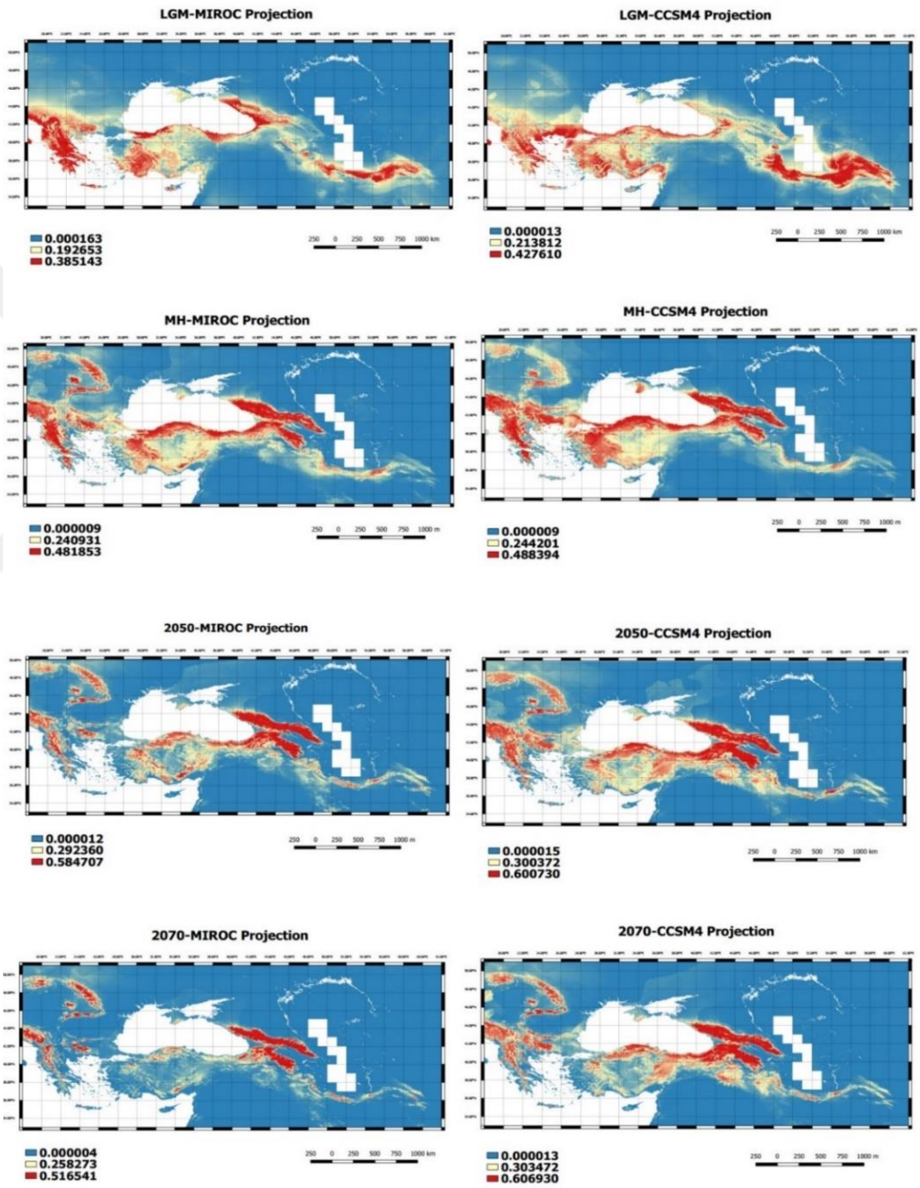

Figure – 3.12: MaxEnt projection distribution maps with all time zones and two different GCMs. The right column shows MIROC – ESM projections, left columns shows CCSM4 projections. First two rows show past distributions, LGM and MH respectively, whereas last two rows show future distributions, 2050 and 2070 respectively. The blue, yellow and red areas indicate the distribution possibilities from low to high, according to the threshold obtained from ROC curve (with 0.76 AUC value) of projections.

Additionally, with Figure – 3.6, Figure – 3.10 and Figure – 3. 12 the two MaxEnt model methods, from biomod2 and the original java platform, can be compared. There are no significant differences between outcomes of both methods, they are also both reliable according to their AUC values (Table – 3.1), thus they fit well with each other and MaxEnt run with biomod2 R package is reliable to use.

4. DISCUSSION

SDM simulations provided the predicted distribution maps of past, present, and future according to the given distribution data and environmental parameters. From the distribution maps obtained there are three main things to point out. First one is the unusual predicted distribution of *F. orientalis* in the inner Aegean region. Present distribution of beech species is not overlapping with this region. SDM mainly works with abiotic factors, and also from these abiotic factors only temperature, precipitation and elevation are used in this study. This led us to think the reason that we see distribution around Aegean region can be possible human influences and inter-/intraspecies competition effects on *Fagus* sp.. Second is slightly predicted distributions across Europe. As we mentioned before, *Fagus sylvatica* and *Fagus orientalis* are very close species with similar physiological characteristics, it is a possibility that the models interpret the *F. sylvatica* habitat, mainly Europe, as suitable habitat for *F. orientalis* because of this similarity. Lastly, in input data (distribution data), Amanos Mountains were considered as unexpected since the climate conditions around that region are not suitable for *F. orientalis* to grow. However, Amanos Mountains has a microclimate that is providing many species an extraordinary habitat and being a connection from the Eastern Mediterranean region to the mountain ranges, thus being in the center of the Anatolian diagonal, and serving as one of the important biodiversity hotspots of the area (Yılmaz, 1997; Şekercioğlu et al., 2011). Since this is a highly specific and unordinary environmental condition, this explains why the distribution around the Amanos Mountains did not appear in all of the projections, but only in MIROC – ESM model’s GLM, GAM (Figure – 3.4, 3.5) and CCSM4 model’s RF (Figure – 3.10).

In addition to these points, we compared model algorithms, GCMs, and climate conditions in different time zones.

4.1 Model Algorithm Comparisons

As it was mentioned before all of the models ran successfully, according to their AUC values (Table – 3.1). The most successful one among the algorithms is RF, least successful one is BIOCLIM. When we also compare the original MaxEnt software and MaxEnt embedded in the biomod2 package, they are both successful as indicated on their distribution maps above. RF works with a combination of classification trees to produce more accurate classifications, create complex interactions with model predictors and data, perform several statistical data analysis, such as regression, classification, survival and unsupervised learning (Cutler et al., 2007). Comparing the other algorithms, we assumed that this accuracy and verification by different statistical data analysis in RF (Figure – 3.5, 3.10) led this algorithm to be the most successful one. On the other hand, BIOCLIM algorithm is the primitive one in SDM studies. It was the first developed model to apply the spatial analysis of species. It was expected to from other algorithms to give better results than BIOCLIM (Figure – 3.2, 3.7) with their advanced characteristics and calculations.

In addition to that, present time projections fitted well with the present distribution data, thus our model is verified by the observation data, this means trained model is reliable to do further projections for past and future. Also, all future predictions agree well with the prediction distribution of *Fagus orientalis*, northeast from its present time distribution, towards mountainous regions with higher altitudes.

The only critical problem with the model outputs is seen in GAM algorithm (Figure – 3.3,3.8) with its overfitted distribution in the past projections. In order to check the *Fagus orientalis* presence in the LGM and MH, European Pollen Database was used (www.europeanpollendatabase.net), no records were found for *F. orientalis* in these time zones. Even GAM is seen as the second best model with its AUC value (Table – 3.1), its present time projection perfectly matched with the distribution data, and future predictions are seen as expected, we interpreted its past projections as an error in calculations. It is known that GAM algorithm is highly sensitive to large sample size since the fitted functions are not constrained to any particular functional form when sample size increases. Our study area is considered as a very large sample for a default SDM, thus it is likely that GAM results would be biased (Perce & Ferrier, 2000; Hijmans et al., 2008).

4.2 GCM Difference

Figure – 3.12 in the results section is indicating the main differences between MIROC – ESM, and CCSM4. It can be said that GCM difference did not affect the geographical shift, yet it caused a higher population density and wider distribution area, both in past and future. Tı further investigate this we analyzed mean annual temperature and annual precipitation bioclimatic parameters (bio1 and bio12 respectively, according to Table – 2.1) for both GCMs during LGM (time zone is selected randomly). Figure – 4.1 shows the mean annual temperature (top row) and annual precipitation values (bottom row) for the models and their difference. Difference values are obtained simply subtracting CCSM4 from MIROC values. This analysis points out, MIROC – ESM model is wetter but warmer than the CCSM4. Results show that *Fagus orientalis* prefers wetter climate, thus it was expected to see a wider distributional area and denser population in the MIROC – ESM projections. However, MIROC – ESM has also higher temperatures, this is a strategic limitation to the growth of beech species. With this information, it is logical to see wider distribution and denser population in CCSM4.

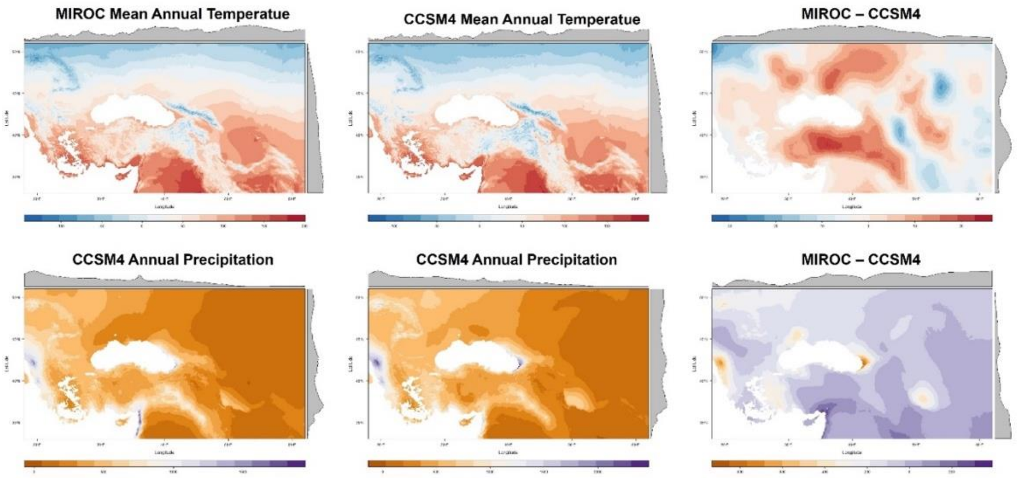

Figure – 4.1: Mean annual temperature (bio1) and annual precipitation (bio12) maps of MIROC – ESM model (left column), CCSM4 model (middle column) and the difference between them (right column). Within each map red color indicates warmer regions, whereas purple color indicates wetter regions.

4.3 Past-Present-Future Climate Comparison

Since SDM is a great tool to predict past and future distributions of particular species with present time information, it is important to point out the difference between climatic conditions through time zones. For this purpose, LGM, present, and 2070 climatic conditions from MIROC – ESM model (randomly selected) were compared again to annual mean temperature (bio1) and annual precipitation (bio12) parameters. In Figure – 4.2, present and LGM conditions were shown. Their difference was taken by subtracting LGM values from present values. According to this, LGM was colder, 4°C to 16°C, and drier, ~500 mm increase, thus it is compatible with the SDM results and predicted distribution maps. For past projections, distribution regions in LGM can be considered as refuge areas for *Fagus orientalis*.

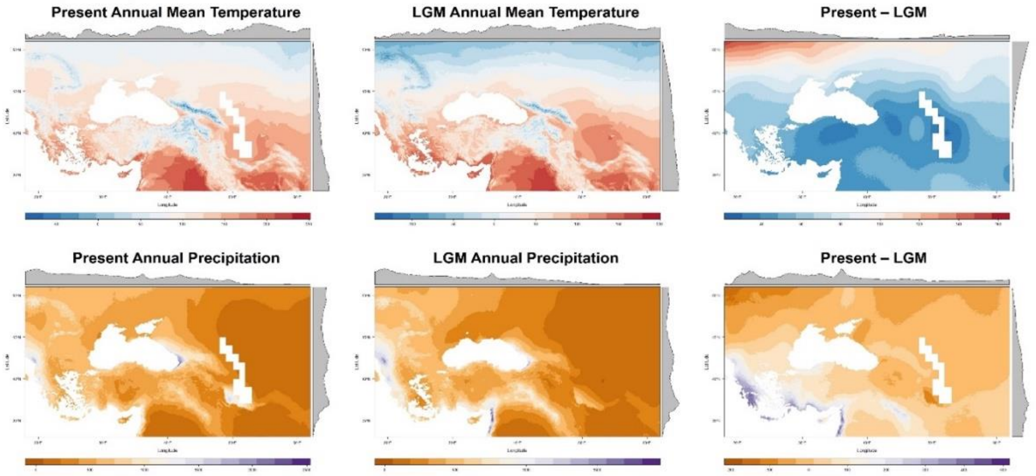

Figure – 4.2: Mean annual temperature (bio1) and annual precipitation (bio12) maps of the present (left column), past – LGM – (middle column) and the difference between them (right column). Within each map red color indicates warmer regions, whereas purple color indicates wetter regions.

Figure – 4.3, on the other hand, points out the difference between presence and 2070 climates. This time, the difference between them was calculated by subtracting present conditions from 2070 values.

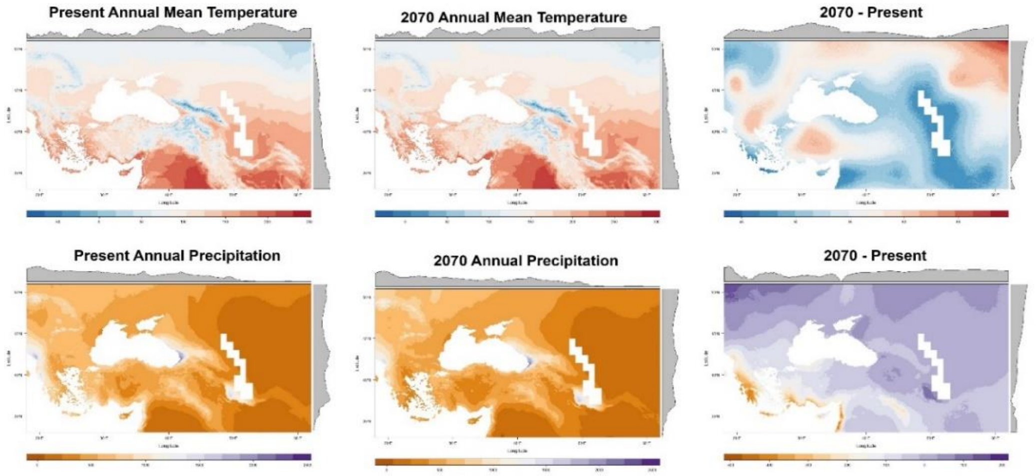

Figure – 4.3: Mean annual temperature (bio1) and annual precipitation (bio12) maps of the present (left column), future – LGM – (middle column) and the difference between them (right column). Within each map red color indicates warmer regions, whereas purple color indicates wetter regions.

We obtained that in 2070 climate will be warmer, 4.5°C to 6.5°C, and drier, ~300 mm decrease, so it is expected for *F. orientalis* to shift its range to drier regions where the colder temperature is available. This was provided from our prediction maps. When we compare the distribution maps with this climate difference, the regions that beech is accumulating in the future predictions are overlapping with the dry and colder areas in future climatic conditions.

5. CONCLUSION AND FUTURE STEPS

In conclusion, from the SDM simulations, we obtained past and future distribution maps. By comparing our present time projections with distribution – observation – data, we were able to validate our models' performance. We showed that *Fagus orientalis* species will be found in colder and drier climate in the future(2041-2080), northeast from its present distribution and higher altitudes. Additionally, by our past simulations, we had an idea of possible refuge areas of *F. orientalis*. As future steps, this study can be improved by selecting more precise bioclimatic parameters, mainly by principal component analysis, since there is a correlation between them that affects the model algorithms. Also, other possible scenarios from IPCC can be compared with our pessimistic scenario outputs. Finally, this study can be supported by additional dendrochronology and palynology studies for past and future predictions, as well as present observations.

Species tried to adapt to this climate change in the past and they are trying currently too. However, the problem is, with the continuing climate change in the future extinction risks will increase, since there will be limited suitable habitat for them to survive because climate is also changing spatially and many species are having a hard time to keep up with this fast change. This study showed the response of *Fagus orientalis* to climate change through SDM, which is a tool to visualize the species is growing and to answer "is there any other suitable regions for it to grow?". Lastly, this study can help to improve conservation and management plans in the future.

REFERENCES

Akkemik, Ü., Demir, D. (2003) Tree ring analysis on eastern beech (*Fagus orientalis* Lipsky.) in the Belgrad Forest. Istanb Univ Orman Fak Derg 53: 33-36.

Akkemik, Ü. (2014). Türkiye’nin Doğal-Egzotik Ağaç ve Çalıları. I. *Cilt. Orman Genel Müdürlüğü Yayınları*.

Aral, I. O. (2008)“Geology of Turkey: A Synopsis”. Anschnitt, 21. 19-42.

Barve, N., Barve, V., Jiménez-Valverde, A., Lira-Noriega, A., Maher, S. P., Peterson, A. T., ... & Villalobos, F. (2011). The crucial role of the accessible area in ecological niche modeling and species distribution modeling. *Ecological Modelling*, *222*(11), 1810-1819.

Breiman, L. (2001a). Random forests. Machine Learning 45, 5–32.

Breiman, L. Friedman, J.H., Olshen, R.A., Stone, C.J. (1984). Classification and Regression Trees. Chapman and Hall, New York.

Bucklin, D. N., Basille, M., Benscoter, A. M., Brandt, L. A., Mazzotti, F. J., Romanach, S. S., ... & Watling, J. I. (2015). Comparing species distribution models constructed with different subsets of environmental predictors. *Diversity and distributions*, *21*(1), 23-35.

Caudullo, G., Welk, E., & San-Miguel-Ayanz, J. (2017). Chorological maps for the main European woody species. Data in brief, 12, 662-666.

Cutler, D. R., Edwards, T. C., Beard, K. H., Cutler, A., Hess, K. T., Gibson, J., & Lawler, J. J. (2007). Random forests for classification in ecology. *Ecology*, *88*(11), 2783-2792.

Denk, T. (2003). Phylogeny of Fagus L.(Fagaceae) based on morphological data. *Plant Systematics and Evolution*, *240*(1-4), 55-81

Dyderski, M. K., Paź, S., Frelich, L. E., & Jagodziński, A. M. (2018). How much does climate change threaten European forest tree species distributions?. Global change biology, 24(3), 1150-1163.

Elith, J., & Leathwick, J. R. (2009). Species distribution models: ecological explanation and prediction across space and time. *Annual review of ecology, evolution, and systematics*, *40*, 677-697.

Elith, J., Graham, C. H., Anderson, R. P., Dudík, M., Ferrier, S., Guisan, A., ... & Li, J. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, 129-151.

European Forest Genetic Resource Programme: *Fagus orientalis* distribution map (no date). *Retrieved May 2, 2018, from* *www.euforgen.org/species/fagus-orientalis/*

Gent, P. R., Danabasoglu, G., Donner, L. J., Holland, M. M., Hunke, E. C., Jayne, S. R., ... & Worley, P. H. (2011). The community climate system model version 4. *Journal of Climate*, *24*(19), 4973-4991.

Greuter, W., Burdet, H. M., & Long, G. (2008). *Med-Checklist: a critical inventory of vascular plants of the circum-mediterranean countries*. OPTIMA:[puis] Conservatoire et Jardin botaniques de la Ville de Genève; Secrétariat Med Checklist Botanischer Garten und B.

Guisan, A., & Thuiller, W. (2005). Predicting species distribution: offering more than simple habitat models. *Ecology letters*, *8*(9), 993-1009.

Guisan, A., & Zimmermann, N. E. (2000). Predictive habitat distribution models in ecology. *Ecological modelling*, *135*(2-3), 147-186.

Haghshenas, M., Mohadjer, M. R. M., Attarod, P., Pourtahmasi, K., Feldhaus, J., & Sadeghi, S. M. M. (2016). Climate effect on tree-ring widths of Fagus orientalis in the Caspian forests, northern Iran. *Forest Science and Technology*, *12*(4) 176-182.

Harris, R. M. B., Grose, M. R., Lee, G., Bindoff, N. L., Porfirio, L. L., & Fox-Hughes, P. (2014). Climate projections for ecologists. *Wiley Interdisciplinary Reviews: Climate Change*, *5*(5), 621-637.

Hastie, T. J., & Tibshirani, R. J. (1990). Generalized additive models, volume 43 of Monographs on Statistics and Applied Probability.

Hijmans, R. J., & Graham, C. H. (2006). The ability of climate envelope models to predict the effect of climate change on species distributions. *Global change biology*, *12*(12), 2272-2281.

Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the national academy of sciences*, *79*(8), 2554-2558.

Jiménez-Valverde, A., Lobo, J. M., & Hortal, J. (2008). Not as good as they seem: the importance of concepts in species distribution modelling. *Diversity and distributions*, *14*(6), 885-890.

Kandemir G., &. Kaya, Z. (2009) EUFORGEN Technical Guidelines for genetic conservation and use of oriental beech (Fagus orientalis). Biodiversity International, Rome, Italy. 6 pages.

Köse, N., & Güner, H. T. (2012). The effect of temperature and precipitation on the intra-annual radial growth of Fagus orientalis Lipsky in Artvin, Turkey. *Turkish Journal of Agriculture and Forestry*, *36*(4), 501-509.

Li, X., & Wang, Y. (2013). Applying various algorithms for species distribution modelling. *Integrative Zoology*, *8*(2), 124-135.

Lindner, M., Maroschek, M., Netherer, S., Kremer, A., Barbati, A., Garcia-Gonzalo, J., ... & Lexer, M. J. (2010). Climate change impacts, adaptive capacity, and vulnerability of European forest ecosystems. *Forest ecology and management*, *259*(4), 698-709.

McCullagh, P., & Nelder, J. A. (1989). Binary data. In Generalized linear models (pp. 98-148). Springer US.

Myhre, G., Shindell, D., Bréon, F. M., Collins, W., Fuglestvedt, J., Huang, J., ...& Nakajima, T. (2013). Climate change 2013: the physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. *K., Tignor, M., Allen, SK, Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, PM, Cambridge University Press Cambridge, United Kingdom and New York, NY, USA.*

Nelder, J. A., & Baker, R. J. (2004). Generalized linear models. *Encyclopedia of statistical sciences*, *4*.

Parmesan, C. (2006). Ecological and evolutionary responses to recent climate change. *Annu. Rev. Ecol. Evol. Syst.*, *37*, 637-669.

Pastorelli, R., Smulders, M. J. M., Van't Westende, W. P. C., Vosman, B., Giannini, R., Vettori, C., & Vendramin, G. G. (2003). Characterization of microsatellite markers in Fagus sylvatica L. and Fagus orientalis Lipsky. *Molecular Ecology Resources*, *3*(1), 76-78.

Pearce, J., & Ferrier, S. (2000). An evaluation of alternative algorithms for fitting species distribution models using logistic regression. *Ecological modelling*, *128*(2-3), 127-147.

Pearson, R. G. (2007). Species' distribution modeling for conservation educators and practitioners. *Synthesis. American Museum of Natural History*, *50*.

Pearson, R. G., & Dawson, T. P. (2003). Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful?. *Global ecology and biogeography*, *12*(5), 361-371.

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological modelling, 190(3-4), 31-259.*

Scheffers, B.R., Meester, L.D., Bridge, T.C.L., Hoffmann, A.A., Pandolfi, J.M., Corlett, R.T., . . . Watson, J.E.M. (2016). The broad footprint of climate change from genes to biomes to people. Science, 354, aaf7671.

Seidl, R., Schelhaas, M.-J., Rammer, W., & Verkerk, P. J. (2014). Increasing forest disturbances in Europe and their impact on carbon storage. Nature Climate Change, 4, 806–810.

Şanlı, İ. (1977). Doğu kayını (Fagus orientalis Lipsky.) nin Türkiye'de çeşitli yörelerde oluşan odunları üzerine anatomik araştırmalar. *Journal of the Faculty of Forestry Istanbul University| İstanbul Üniversitesi Orman Fakültesi Dergisi*, *27*(1).

Şekercioğlu, Ç. H., Anderson, S., Akçay, E., Bilgin, R., Can, Ö. E., Semiz, G., ... & Sağlam, İ. K. (2011). Turkey's globally important biodiversity in crisis. *Biological Conservation*, *144*(12), 2752-2769.

The Plant List (2013). Version 1.1. *Retrieved May 2, 2018 from* *http://www.plantlist.org/*

Thuiller, W., Lafourcade, B., Engler, R., & Araújo, M. B. (2009). BIOMOD–a platform for ensemble forecasting of species distributions. Ecography, 32(3), 369-373.

Van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., ... & Masui, T. (2011). The representative concentration pathways: an overview. *Climatic change*, *109*(1-2), 5.

VanDerWal, J., Shoo, L. P., Graham, C., & Williams, S. E. (2009). Selecting pseudo-absence data for presence-only distribution modeling: how far should you stray from what you know?. *ecological modelling*, *220*(4), 589-594.

Watanabe, S., Hajima, T., Sudo, K., Nagashima, T., Takemura, T., Okajima, H., ... & Ise, T. (2011). MIROC-ESM 2010: Model description and basic results of CMIP5-20c3m experiments. *Geoscientific Model Development*, *4*(4), 845.

Weyant, J., Azar, C., Kainuma, M., Kejun, J., Nakicenovic, N., Shukla, P. R., ... & Yohe, G. (2009). Report of 2.6 versus 2.9 Watts/m2 RCPP evaluation panel. Integrated Assessment Modeling Consortium.

Wisz, M. S., Hijmans, R. J., Li, J., Peterson, A. T., Graham, C. H., Guisan, A., & NCEAS Predicting Species Distributions Working Group. (2008). Effects of sample size on the performance of species distribution models. *Diversity and distributions*, *14*(5), 763-773.

Yaltırık, F., & Eliçin, G. (1982a). Trees and Shrubs in European Turkey. *İstanbul Üniversitesi Orman Fakültesi Dergisi A*, *32*(2).

Yilmaz, K. T. (1997). Ecological diversity of the Eastern Mediterranean region of Turkey and its conservation. *Biodiversity & Conservation*, *7*(1), 87-96.

APPENDICES

APPENDIX A: R code sheet for modeling with the biomod2 package.

APPENDIX A

```
library(biomod2)
setwd("C:/Users/dilsa/Desktop")
#load the data
fagus <- read.csv("presence25.csv", header = TRUE, sep = ",")
head(fagus)
#getting presence values from data
myRespName <- 'Fagus_orientalis'
myResp <- as.numeric(fagus[,myRespName])
#getting presence coordinates from data
myRespXY <- fagus[,c("X", "Y")]
#environmental layers as explanatory variables
bio1 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio1.tif")
bio2 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio2.tif")
bio3 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio3.tif")
bio4 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio4.tif")
bio5 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio5.tif")
bio6 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio6.tif")
bio7 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio7.tif")
bio8 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio8.tif")
bio9 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio9.tif")
bio10 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio10.tif")
bio11 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio11.tif")
bio12 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio12.tif")
bio13 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio13.tif")
bio14 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio14.tif")
bio15 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio15.tif")
bio16 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio16.tif")
bio17 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio17.tif")
bio18 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio18.tif")
bio19 <- raster("C:/Users/dilsa/Desktop/current_2.5_tif/bio19.tif")
current_bioclim =
stack(bio1,bio2,bio3,bio4,bio5,bio6,bio7,bio8,bio9,bio10,bio11,bio12,bio13,bio14,bio15,bio16,bio17,bio18,bio19)
myBiomodData <- BIOMOD_FormatingData(resp.var = myResp,
                                      expl.var = current_bioclim,
                                      resp.xy = myRespXY,
                                      resp.name = myRespName,
                                      PA.nb.rep = 1,
                                      PA.nb.absences = 20796,
                                      PA.strategy = 'random',
                                      na.rm = TRUE)
plot(myBiomodData)
#modeling
myBiomodOption <- BIOMOD_ModelingOptions()
myBiomodModelOut <- BIOMOD_Modeling(
  myBiomodData,
  models = c('GLM','GAM','RF','SRE','MAXENT.Phillips'),
  models.options = myBiomodOption,
  NbRunEval=3,
  DataSplit=80,
  Prevalence=0.5,
```

```
  VarImport=3,
  models.eval.meth = c('TSS','ROC'),
  SaveObj = TRUE,
  rescal.all.models = TRUE,
  do.full.models = FALSE,
  modeling.id = paste('Fagus orientalis',"FirstModeling",sep=""))
myBiomodModelOut
#get all models evaluation
myBiomodModelEval <- get_evaluations(myBiomodModelOut)
myBiomodModelEval
# print the ROC scores of all models
myBiomodModelEval["ROC","Testing.data",,,]
# variable importances
get_variables_importance(myBiomodModelOut)
# Model Projection
# Firstproject our current conditions (the globe) to visualize them.
myBiomodProj <- BIOMOD_Projection(
  modeling.output = myBiomodModelOut,
  new.env = current_bioclim,
  proj.name = 'current',
  selected.models = 'all',
  binary.meth = 'TSS',
  compress = 'xz',
  clamping.mask = F,
  output.format = '.grd')
myBiomodProj
# files created on hard drive
list.files("Fagus.orientalis/proj_current/")
# make plots sub-selected by str.grep argument
plot(myBiomodProj, str.grep = 'RUN1_GLM')
plot(myBiomodProj, str.grep = 'RUN1_GAM')
plot(myBiomodProj, str.grep = 'RUN1_RF')
plot(myBiomodProj, str.grep = 'RUN1_SRE')
plot(myBiomodProj, str.grep = 'RUN1_MAXENT.Phillips')
myCurrentProj <- get_predictions(myBiomodProj)
myCurrentProj
#CLIMATE CHANGE PROJECTIONS#
# MIROC #
#Last Glacial Maximum MIROC
a_bio1 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio1.tif")
a_bio2 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio2.tif")
a_bio3 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio3.tif")
a_bio4 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio4.tif")
a_bio5 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio5.tif")
a_bio6 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio6.tif")
a_bio7 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio7.tif")
a_bio8 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio8.tif")
a_bio9 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio9.tif")
a_bio10 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio10.tif")
a_bio11 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio11.tif")
a_bio12 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio12.tif")
a_bio13 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio13.tif")
a_bio14 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio14.tif")
a_bio15 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio15.tif")
```

```
a_bio16 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio16.tif")
a_bio17 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio17.tif")
a_bio18 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio18.tif")
a_bio19 <- raster("C:/Users/dilsa/Desktop/lgm_miroc_2.5_tif/bio19.tif")
a_bioclim <-
stack(a_bio1,a_bio2,a_bio3,a_bio4,a_bio5,a_bio6,a_bio7,a_bio8,a_bio9,a_bio10,a_bio11,a_bio12,a_bi
o13,a_bio14,a_bio15,a_bio16,a_bio17,a_bio18,a_bio19)
# projection under lgm_miroc conditions
LGM_MIROC_Proj <- BIOMOD_Projection(
  modeling.output = myBiomodModelOut,
  new.env = a_bioclim,
  proj.name = 'LGM_MIROC',
  selected.models = 'all',
  binary.meth = 'TSS',
  compress = 'xz',
  clamping.mask = F,
  output.format = '.grd')
LGM_MIROC_Proj
# files created on hard drive
list.files("Fagus.orientalis/proj_LGM_MIROC")
# make some plots sub-selected by str.grep argument
plot(LGM_MIROC_Proj, str.grep = 'RUN1_GLM')
plot(LGM_MIROC_Proj, str.grep = 'RUN1_GAM')
plot(LGM_MIROC_Proj, str.grep = 'RUN1_RF')
plot(LGM_MIROC_Proj, str.grep = 'RUN1_SRE')
plot(LGM_MIROC_Proj, str.grep = 'RUN1_MAXENT.Phillips')
myLGMMProj <- get_predictions(LGM_MIROC_Proj)
myLGMMProj
# Do this part again for all climate conditions: MIROC-MH, MIROC-2050, MIROC-2070, CCSM4-LGM,
CCSM4-MH, CCSM4-2050, CCSM4-2070.
```

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- **Bektas, B., Dagtekin, A. D., Fer, I., Dalfes, H. N.** 2017: Explain the Late Holocene tree-cover reduction in West Anatolia in Ecological. Society of America Annual Meeting - August 6-11, 2017 Portland, OR, USA.
- **Bektas, B., Dagtekin, A. D., Fer, I., Dalfes, H. N.** 2017: Explain the Late Holocene tree-cover reduction in West Anatolia in Ecological. Society of America Annual Meeting - July 11-13, 2017 Istanbul, Turkey.