MODELING THE CURRENT AND FUTURE RANGES OF TURKISH PINE (*PINUS BRUTIA*) AND ORIENTAL BEECH (*FAGUS ORIENTALIS*) IN TURKEY IN THE FACE OF CLIMATE CHANGE

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submitted by **SEMRA YALÇIN** in partial fulfillment of the requirements for the degree of **Master of Science in Geodetic and Geographic Information Technologies, Middle East Technical University** by,

Prof. Dr. Canan Özgen
Dean, Graduate School of **Natural and Applied Sciences** __________

Assoc. Prof. Dr. Ahmet Coşar
Head of Department, **Geodetic and Geographic Inf. Tech.** __________

Assoc. Prof. Dr. C. Can Bilgin
Supervisor, **Geodetic and Geographic Inf. Tech. Dept., METU** __________

Prof. Dr. H. Şebnem Düzgün
Co-Supervisor, **Geodetic and Geographic Inf. Tech. Dept., METU** __________

Examining Committee Members:

Prof. Dr. Zeki Kaya __________________
Biology Dept., METU

Assoc. Prof. Dr. C. Can Bilgin __________________
Geodetic and Geographic Inf. Tech. Dept., METU

Prof. Dr. H. Şebnem Düzgün __________________
Geodetic and Geographic Inf. Tech. Dept., METU

Prof. Dr. Nüzhet Dalfes __________________
Eurasia Institute of Earth Sciences, ITU

Dr. Uğur Zeydanlı __________________
General Manager, Nature Conservation Centre

Date: 06.12.2012

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name: SEMRA YALÇIN

Signature:

ABSTRACT

MODELING THE CURRENT AND FUTURE RANGES OF TURKISH PINE (*PINUS BRUTIA*) AND ORIENTAL BEECH (*FAGUS ORIENTALIS*) IN TURKEY IN THE FACE OF CLIMATE CHANGE

Yalçın, Semra
M.Sc., Department of Geodetic and Geographic Info. Technologies
Supervisor: Assoc. Prof. C. Can Bilgin
Co-Supervisor: Prof. Dr. H. Şebnem Düzgün

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Climate change is widely recognized to have potential impacts on global biotic and abiotic systems. One of the major impacts is expected on species distributions. Species distribution models (SDMs) are used for estimating the relationship between species occurrences at sites and environmental and/or spatial characteristics of those sites. SDMs can be used to understand possible responses of species to climate change. Despite some sources of uncertainty, projections onto future climate are useful and cost-effective tools for managers, especially given the increasing urgency to inform management authorities under the pressure of climate change. This thesis aims to model current and potential future distributions of two economically and ecologically important tree species, Turkish pine and oriental beech, in the face of climate change, and to assess the effect of using different data sets and modeling methods in model setups on SDM accuracy.

The BIOMOD 2 framework, implemented in the open source software R (version 2.15.1) was used to build the distribution models. In model calibrations, different data sets of response variables were used with eight different modeling methods. Moreover, ensemble forecasting was carried out by using a proportional weighted average of each model's predictions (trained models) based on the AUC scores. Performances of the current predictions were compared to 1/25.000 scale forest stand maps and evaluated using various metrics. Future distributions for each species were projected according to IPCC SRES emission scenarios A2 and B2 of the HadCM3 global circulation model. Based on the results of the ensemble models, climatically suitable areas of Turkish pine trees were predicted to shift to higher altitudes and toward the north and northeastern regions of Turkey. Potentially suitable areas for oriental beech were expected mainly to be lost and its overall distribution was predicted to be narrower in the future. While Turkish pine was likely to gain large climatically suitable areas by 2080, expansion into suitable areas by oriental beech in the future was predicted to be very limited. An important proportion of habitats where Turkish pine and oriental beech currently occur were predicted to become unsuitable in the future.

Overall, climate change is expected to have significant impacts on the distributions of Turkish pine and oriental beech forests in Turkey. Depending on whether fast dispersal to newly occurred suitable habitats will be possible or not, it can be stated that serious ecological, economic and social consequences will probably come out.

Keywords: Climate Change, Species Distribution Models, BIOMOD, MAXENT, Turkish Pine, Oriental Beech

ÖZ

TÜRKİYE'DEKİ KIZILÇAM (*PINUS BRUTIA*) VE KAYIN (*FAGUS ORIENTALIS*) ORMANLARININ MEVCUT VE GELECEKTEKİ YAYILIŞLARININ İKLİM DEĞİŞİKLİĞİNE GÖRE MODELLENMESİ

Yalçın, Semra
Yüsek Lisans, Jeodezi ve Coğrafi Bilgi Teknolojileri
Tez Yöneticisi: Assoc. Prof. C. Can Bilgin
Ortak Tez Yöneticisi: Prof. Dr. H. Şebnem Düzgün

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Küresel iklim değişikliğinin biyotik ve abiyotik sistemler üzerindeki potansiyel etkileri genişçe kabul görmektedir. Bu etkilerden başlıcalarından birisinin de tür dağılımları üzerinde olduğu beklenmektedir. Tür dağılım modelleri (TDM) türlerin alanlarda var oluşları arasındaki ilişkileri ve bu alanların çevresel uzamsal karakteristiklerini tahmin etmek için kullanılmaktadır. Ayrıca TDM'ler türlerin küresel iklim değişikliğine karşı olası tepkilerini anlamak için de kullanılabilmektedir. Özellikle, küresel iklim değişikliğinin oluşturduğu baskıdan dolayı artan yönetici mercilerin bilgilendirilmesi ihtiyacının zorunluluğu düşünüldüğünde, bazı belirsizlik kaynaklarına rağmen, TDM'ler gelecekteki iklim durumları üzerinde yapılabilecek tahminler açısından yararlı ve yöneticiler için uygun maliyetli araçlar haline gelebilmiştir. Bu tez, ekonomik ve ekolojik olarak önemli değerlere sahip iki ağaç türünün, kızılçam ve kayının, şimdiki ve gelecekteki olası dağılımlarının küresel iklim değişikliği karşısında nasıl değişeceğini modellemeyi ve model kurulumlarında değişik veri setlerini ve modelleme yöntemleri kullanmanın TDM doğruluğunun üzerine etkilerini incelemeyi hedeflemektedir.

Tür dağılım modelleri çalıştırılmasında bir açık yazılım olan R (versiyon 2.15.1) üzerinde çalışan BIOMOD 2 uygulaması kullanılmıştır. Model kalibrasasyonlarında, farklı yanıt değişken setleri sekiz farklı modelleme yöntemiyele kullanılmıştır. Ayrıca, topluluk tahminini AUC (ROC eğrisi altında kalan alan büyüklüğü) değerlerine orantılı ağırlıklı ortalama (eğitimli modeller) kullanılarak gerçekleştirilmiştir. Güncel model değerlendirmeleri 1/25.000 ölçekli sayısal meşçere haritaları ile karşılaştırılmış ve farklı ölçültlerle sınanmıştır. Türlerin gelecek yayılışları IPCC SRES A2 ve B2 emisyon senaryoları ile üretilmiş HadCM3 küresel iklim modelleri kullanılarak projeksiyonları üretilmiştir. Topluluk tahmin modellerine göre, 2050 ve 2080 yıllarında öngörülen kazanç/kayıp habitat büyüklükleri haritalandırılmış ve değeşen alan büyüklükleri her veri seti ve emisyon senaryolarına göre hesaplanmıştır.

Topluluk modellerinin sonucuna gore, kızılçam ağaçlarına iklimsel olarak uygun alanların daha yüksek irtifalara, Türkiye'nin kuzey ve kuzeydoğu bölgelerine, kayacağı tahmin edilmiştir. Kayın ağaçları içinse potansiyel olarak uygun alanların çoğunlukla yok olacağı ve toplam dağılımlarının gelecekte daralacağı/küçüleceği tahmin edilmiştir. 2080'de kızılçam ağaçlarının iklimsel olarak uygun alanlara sahip olabileceği öngörülürken, kayın ağaçlarının gelecekte bulabileceği uygun alanların çok sınırlı olacağı ön görüldümüştür. İki ağaç türünün de günümüzdeki habitatlarının gelecekte önemli bir kısmının uygun olmayan hale geleceği tahmin edilmiştir.

Genel olarak, küresel iklim değişikliğinin Türkiye'deki kızılçam ve kayın ormanları üzerinde önemli derecede etkili olacağı düşünülmüştür. Gelecekte, yeni oluşabilecek uygun habitatlara bu türlerin yayılımlarının hızlı olup olamayacağına dayanarak, ciddi ekolojik, ekonomik ve sosyal sonuçlar doğabileceği belirtilmiştir.

Anahtar Kelimeler: İklim Değişikliği, Tür Dağılım Modellenmesi, BIOMOD, MAXENT, Kızılçam, Kayın

To my parents

Essentially, all models are wrong, but some are useful.
George E. P. Box

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ANN:	Artificial Neural Network
AUC:	Area Under Curve
CCSM3:	Community Climate System Model version 3
CTA:	Classification Tree Analysis
DEM:	Digital Elevation Model
EM:	Ensemble model
FAO:	Food and Agriculture Organization of the United Nations
FDA:	Flexible Discriminant Analysis
fvGCM:	Finite Volume General Circulation Model
GAM:	Generalized Additive Model
GBM:	Generalized Boosting Model
GCM:	General Circulation Model
GHG:	Greenhouse gases
GLM:	Generalized Linear Model
HadCM3:	Hadley Centre Coupled Model, version 3
IPCC:	Intergovernmental Panel on Climate Change
MAXENT:	Maximum Entropy
PA:	Pseudo-absence
RegCM3:	Regional Climate Model version 3
RF:	Random Forest
ROC:	Receiver Operating Curve
SDM	Species Distribution Modeling
SRE:	Surface Range Envelope
SRTM:	Shuttle Radar Topography Mission
TSS:	True Skill Statistic
TWI:	Topographic Wetness Index
UTM:	Universal Transverse Mercator
WGS84:	World Geodetic System 1984

CHAPTER I

INTRODUCTION

1.1. Climate change in Turkey

The whole Mediterranean Basin, including the Anatolian Peninsula, is considered as one of the most vulnerable zones to climate change (IPCC, 2007). Climate change will affect Turkey through diminishing water resources and increasing rates of climate-related natural disasters and ecological degradation, such as frequent forest fires, drought, floods, desertification, and erosion (Talu *et al.*, 2011). Therefore, many sectors, including forestry, energy, tourism and agriculture, will likely experience the impacts of climate change.

1.1.1. Observed Changes in Climatic Variables

Advances in weather and climate observation systems, and the availability of long-term climate data sets provide information to understand the climate change. With this aim, Tayanç *et al.* (2009) conducted a study using temperature and precipitation data of Turkish stations in the period of 1950–2004. They found that Turkey experienced a general cooling trend in mean annual and seasonal surface air temperatures from early 1960s until the mid-1990s, generally with the lowest temperature values on 1992–1993 owing to the eruption of Mount Pinatubo. A significant warming trend has been observed since 1993, whereas maximums of temperature in the recorded history were observed in recent years (Tayanç, 2009) (Figure 1).

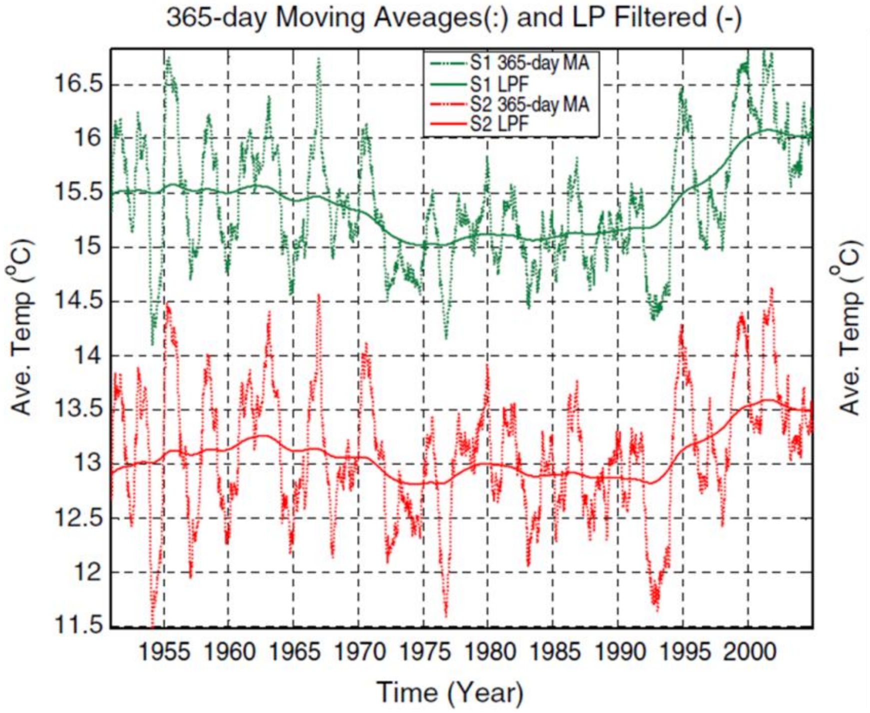

Figure 1 *Mean temperature in the period of 1950–2004 (S1 = rural and suburban stations, S2 = large urban stations; LPF = low pass filter; 365-day MA= moving average signals, 365-day) (Tayanç, 2009)*

Toros (2012) showed that a higher increase has been observed in temperatures of the warm period compared to the temperatures of the annual and cold periods (Figure 2). Moreover, since the sixties, the intensity and frequency of heat waves have increased six to sevenfold than previously known for the eastern Mediterranean region (Kuglitsch *et al.*, 2010).

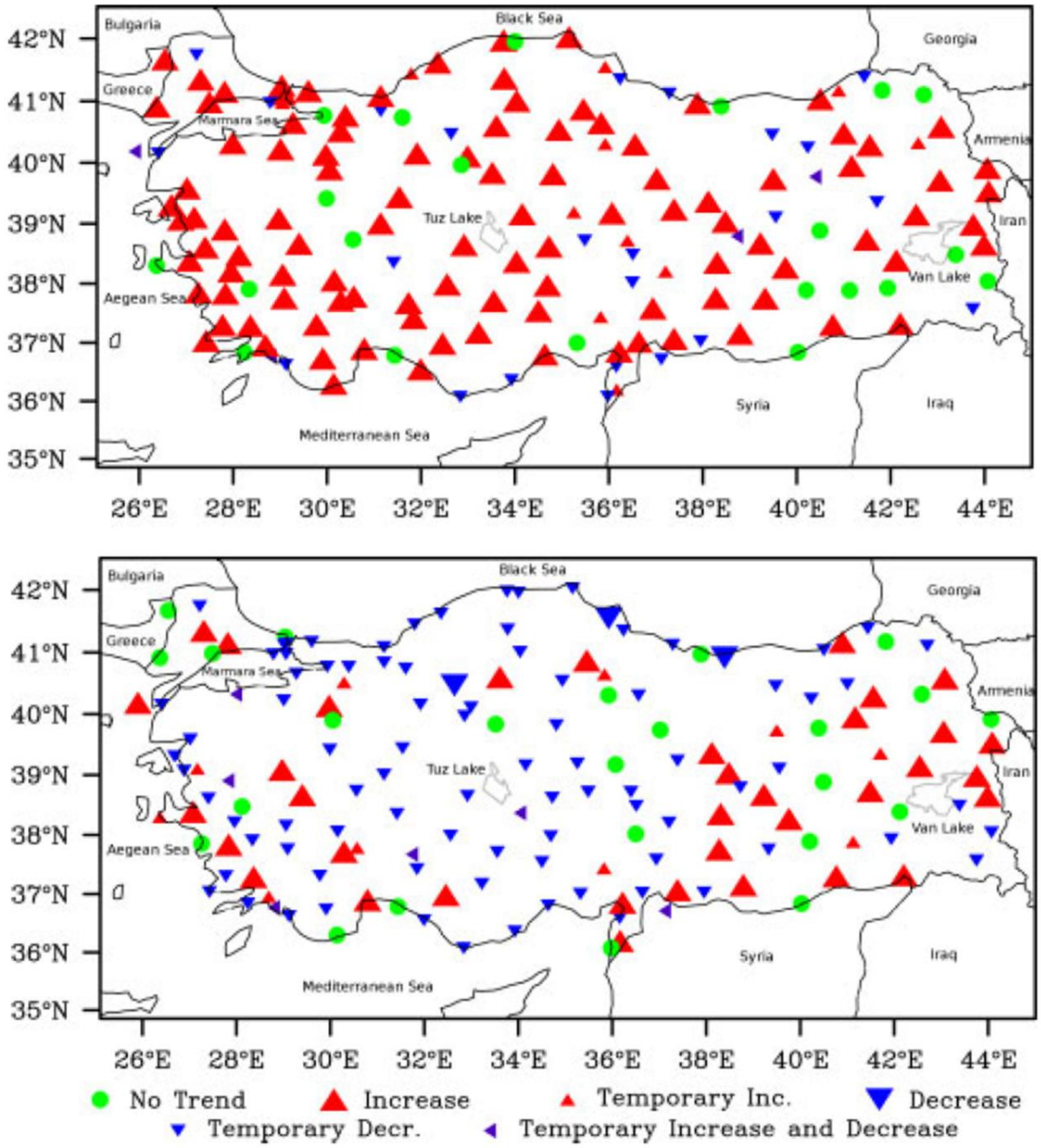

Figure 2 *Statistically significant trends in average maximum temperature for warm period (top) and average maximum temperature for cold period (down) over Turkey in the period 1961–2008 (Toros, 2012)*

A recent study also demonstrated a general decrease in the annual number of frost days at most stations over Turkey in the 1950–2010 periods (Erlat *et al.*, 2012). A significant decrease particularly between 2000 and 2010 indicates a stronger warming during the first decade of the 21th century (Figure 3).

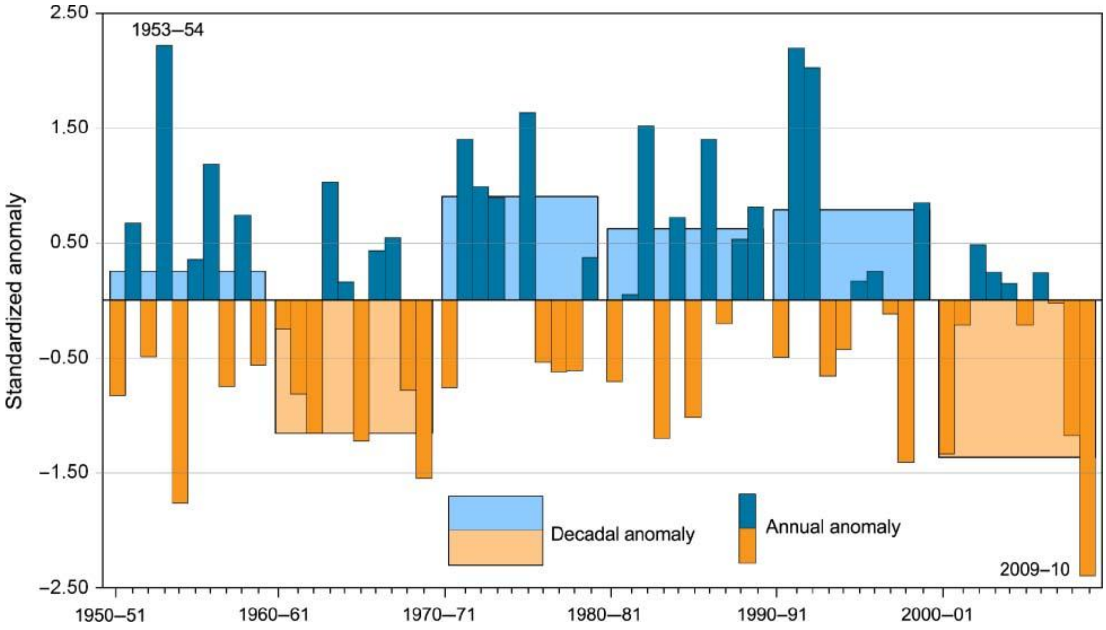

Figure 3 *Inter-annual and inter-decadal variations in numbers of frost days over Turkey during the period 1950-2010 relative to the long-term average (Erlat et al., 2012)*

In the period of 1951–2004, winter precipitation in the western provinces of Turkey has declined significantly, whereas fall precipitation has increased at stations that mostly lie in the northern parts of central Anatolia (Dalfes *et al.*, 2007). Consistent with local studies, according to García-Ruiz *et al.* (2011), precipitation has decreased in the western coastline of Turkey, despite an observed positive trend in northern Turkey between 1950 and 2002 (Figure 4).

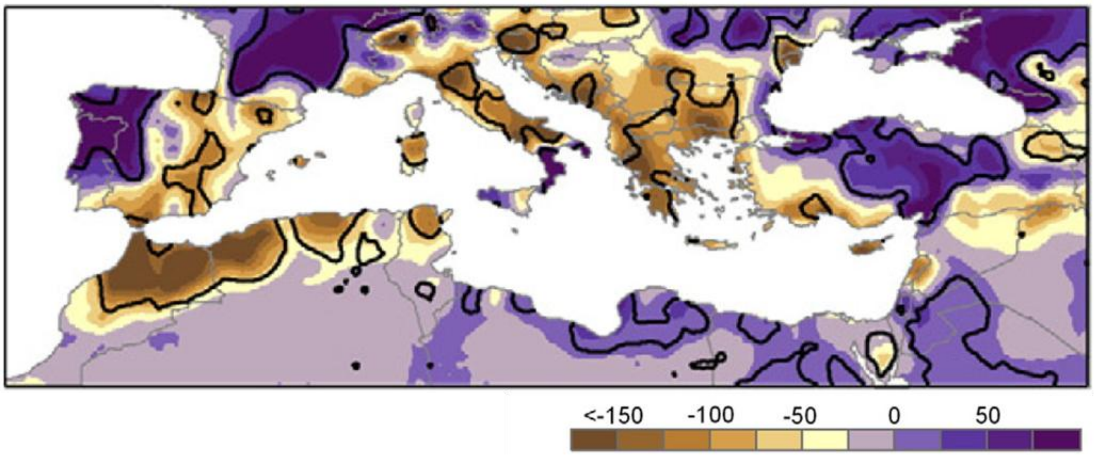

***Figure 4** Annual precipitation changes in the Mediterranean region between 1950 and 2002. Colors show the magnitude of changes in precipitation, in mm. Black isolines: areas with significant trends ($p < 0.05$) (García-Ruiz et al., 2011)*

Additionally, in the period of 1989-2009, the amount of water potential of Turkey was reduced from 178.15 billion to 163.79 billion m^3 due to a decrease in surface flows (Yıldız, 2010). Besides, 30% of glaciers of Mount Ağrı have been lost since 1976 (Sarıkaya & Bishop, 2010).

1.2.2. Climate Change Projections in Turkey

In *Turkey's National Climate Change Adaptation Strategy and Action Plan* (2010), projected seasonal precipitation change (%) and seasonal temperature change (°C) were examined according to regional climate models based on A2 simulations of ECHAM5, HadCM3 and CCSM3, the A1FI simulation of CCSM3 and the B1 simulation of CCSM3 in the 2071-2100 period compared to the 1961-1990 period (Talu *et al.*, 2010).

The increases in temperature estimated by three GCMs for the same scenario (A2) are relatively close to each other for all seasons (Table 1). Simulations mostly indicate larger increases in temperature in eastern Turkey than in western Turkey.

Increases of 5.2- 6.8 °C in mean summer temperatures are expected by three GCMs for A2 scenarios in eastern Turkey. The predictions of the CCSM model by different scenarios show an increase of 3.4 °C in average summer temperature by the B1 scenario, whereas A2 and A1FI simulations indicates even higher increases in summer temperatures.

Table 1 *Projected seasonal surface temperature changes (°C) in 2017-2099 period over 1961-1990 period based on different scenario simulations. W indicates the western half of Turkey and E indicates the eastern half of Turkey (Talu et al., 2010)*

		Winter		**Spring**		**Summer**		**Autumn**	
Scenario	GCM	*W*	*E*	*W*	*E*	*W*	*E*	*W*	*E*
A2	ECHAM5	2.9	3.4	3.1	4.1	4.7	5.2	4.0	4.4
	HadCM3	3.4	3.8	3.7	4.1	6.9	6.1	4.0	4.3
	CCSM3	2.5	2.9	3.6	3.5	6.4	6.8	4.9	5.9
A1FI	CCSM3	3.5	4.0	4.8	4.9	6.9	7.3	5.5	6.8
B1	CCSM3	1.3	1.5	1.7	1.7	3.3	3.4	2.5	3.0

According to SRES A2 simulation, for the period of 2000-2100 with a reference period of 1961-1990, regional climate models show that while winter temperatures will show a linear increasing trend after 2030, reaching up to 3°C, the trend in summer temperatures is much more significant and reaches up to 5°C at the end of the century (Özdemir *et al.*, 2011) (Figure 5).

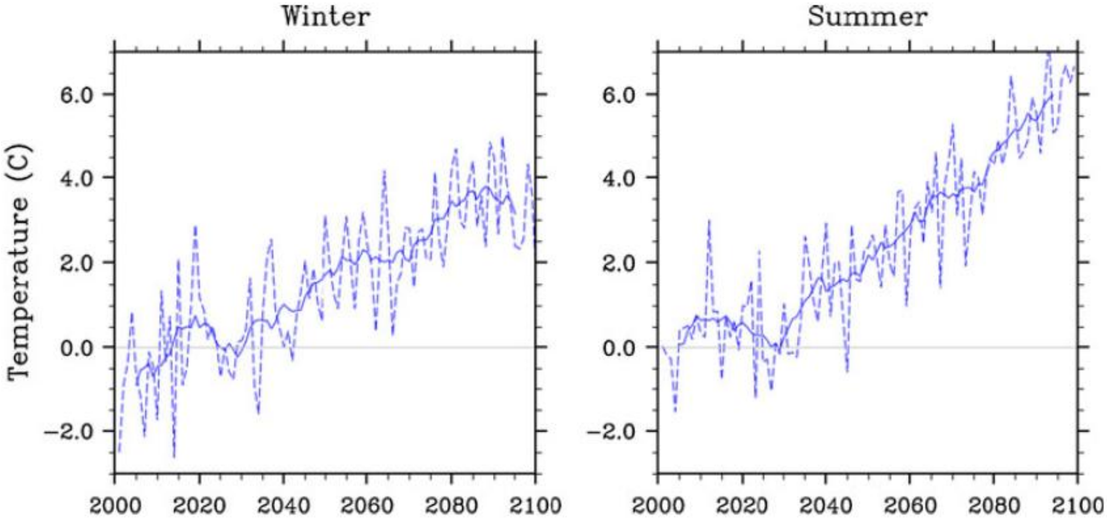

Figure 5 *Mean temperature anomaly of the Anatolian Peninsula in the period of the period of 2000-2100 (Özdemir et al., 2011)*

In the face of climate change, precipitation can be subject to high inter annual and seasonal variability, with long and intense dry periods, or extreme rainfall and floods (IPCC, 2007). Table 2 shows the projected seasonal precipitation change (%) according to the five different simulations in 2071-2100 period compared with the 1961-1990 period (Talu *et al.*, 2010). Simulations mainly agree that there will be less annual precipitation in future compared to the present day. Northern half of Turkey is expected to experience a much bigger decrease in summer precipitation than the southern half.

Table 2 *Projected seasonal precipitation changes (%) in 2071-2099 period over 1961-1990 period based on different scenario simulations. N indicates the northern half of Turkey and S indicates the southern half of Turkey (Talu et al., 2010)*

		Winter		**Spring**		**Summer**		**Autumn**	
Scenario	GCM	*N*	*S*	*N*	*S*	*N*	*S*	*N*	*S*
A2	ECHAM5	13.0	-17.0	1.5	-23.0	-23.0	-30.0	-4.0	4.0
	HadCM3	-2.5	-26.0	-1.0	-28.0	-48.0	-61.0	3.0	21.0
	CCSM3	-6.0	-32.0	-21.0	-36.0	-33.0	-62.0	-6.0	-23.0
A1F	CCSM3	-0.6	-35.0	-30.0	-47.0	-57.0	-70.0	-1.5	-10.0
B1	CCSM3	-0.6	-14.0	-10.0	-28.0	-19.0	-40.0	-7.0	-16.0

Future simulations with RegCM3, forced by the general circulation model fvGCM and based on the SRES A2 emission scenario (Dalfes, 2007), showed that in the period 2071-2100 precipitation will likely decrease along the Aegean and Mediterranean coasts and increase along the Black Sea coast of Turkey whereas Central Anatolia shows little or no change (Figure 6-a, and 6-b). Most significant decline in precipitation will be observed on the southwestern coast while the Caucasian coastal region is expected to receive substantially more precipitation. Winter precipitation is projected to decrease along the Mediterranean coast.

The annual temperature of Turkey in the period 2071-2100 will increase over the whole country; especially the Aegean Region is expected to experience temperature increases up to 6 °C. Additionally, winter temperature increase was estimated to be higher in the eastern half of the country during this period (Dalfes *et al.,* 2007) (Figure 6-c and 6-d).

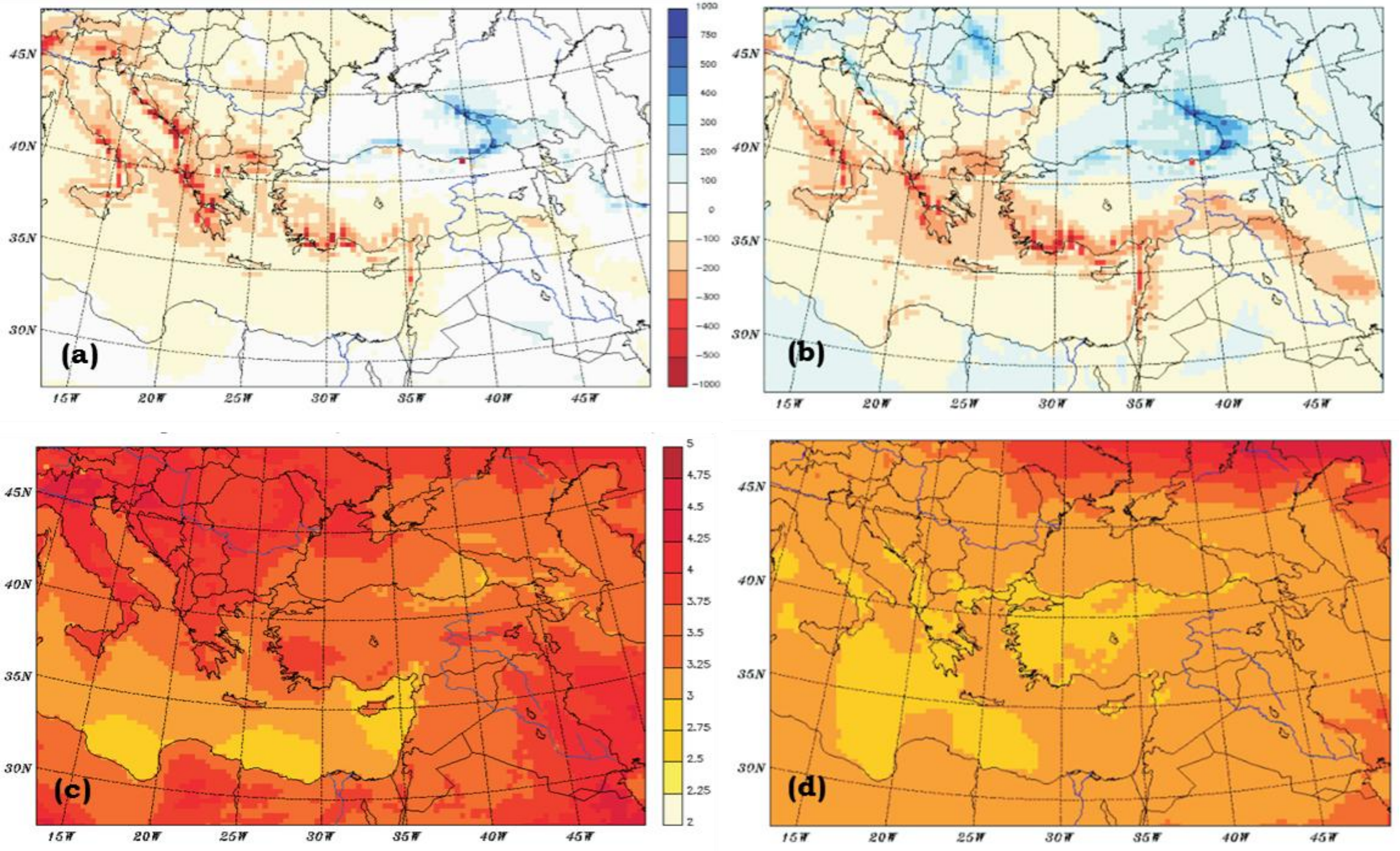

Figure 6 *Differences in (a) total annual precipitation and (b) winter precipitation; differences in (c) annual mean temperature and (d) winter mean temperature between A2 run (2071-2100) and control run (1961-1990) (Dalfes et al., 2007)*

1.2. Climate Change Impacts on Forest Ecosystems

Forests are significant terrestrial ecosystems globally, covering over 30 percent of the total land area of Earth, and providing habitat for many species and numerous goods, benefits and services to people (FAO, 2010).

Climate plays an essential role in forest ecosystems. Observations, experiments and models strongly indicate that climate change will alter the functioning and structure of forest as well as forest location, composition, and productivity (Gunderson *et al.*, 2012; Allen et al., 2010; Linder et al., 2010; Dawson et al., 2011; Bellard *et al.*, 2012). Forests are specifically sensitive to climate change because the long-life time of trees does not allow them to adapt for abrupt change (Lindner *et al.*, 2010). Therefore, local extinctions and loss of important functions and services are predicted (Keene, 2012).

Furthermore, threats to forest ecosystems such as pest outbreaks, fires, storm damage, and drought will likely become worse due to climate change (Seidl *et al.*, 2011). Prieto *et al.* (2009) conducted an experiment about effects of droughts and warming on recovery process of a plant community after fire disturbances. They found that drought and warmer temperature in Mediterranean areas may affect recovery after a disturbance due to lower level of plant establishment and reduced growth rates. Moreover, it is expected that fire regimes will trigger more intense attacks of insects such as bark beetles (Hernandez, *et al.* 2012).

As a result, climate change is expected to have negative consequences for organisms and people that depend on forest ecosystems. It is particularly urgent to develop adaptation strategies, since current forest stands will suffer from changes in climatic conditions that are projected to change extremely throughout their lifetime (Kolström *et al.*, 2011).

There have been few studies examined climate change effects on forests in Turkey. One of the research, which was conducted by Nature Conservation Centre, aimed to determine the impacts of climate change on forest areas in Seyhan Basin located in the south of Turkey and to designate the vulnerabilities of forest ecosystems where detrimental effects of climate change are expected to occur (Zeydanlı *et al.*, 2010). Other research based on dynamic vegetation models aimed to model possible effects of climate change major tree species of natural Turkish forests (Fer, 2011). Moreover, Beton (2011) conducted a study about effects of climate change on distribution of four endemic plant species in Anatolia.

1.3. Species Distribution Modeling

One of major impacts of climate change is predicted to be on species distributions (IPCC, 2007). Climate is an important determinant of species distributions. It sets the limits to the distribution of species at the regional to global levels (Meier *et al.*, 2012). Thus, changing climate has a profound influence on species ranges (Pearson & Dawson, 2003). Under changing climatic conditions, species may adapt to new conditions on site, shift their distributions, or go extinct (Parmesan 2006; Massot et *al.* 2008).

Species distribution models (SDMs) estimate the relationship between species presence records at sites and the environmental and/or spatial characteristics of those sites (Franklin, 2009). They have become an important tool in ecology, biogeography, evolution, and conservation biology (Guisan & Thuiller 2005). SDMs have been used to project the potential effect of climate change on species distributions for more than a decade now (Eeley *et al.*, 1999; Beaumont & Hughes, 2002; Neilson *et al.*, 2005; Renwick *et al.*, 2012).

There are four steps followed in the modeling process for SDMs (Figure 6). The first step is to collect, process, error-check and format the data that are necessary as input. After preparation of occurrences and environmental variables, the next step is to use a modeling algorithm to describe the species' ecological niche as a function of environmental variables. In this step, model calibration, including selecting suitable model parameters, evaluating trained models with statistical methods and setting threshold for binary prediction, takes place.

The next step is to project the prediction and to evaluate how well the model predicts independent data. The last step is to transfer modeled conditions to predict environmental suitability across a new region or for a different time period (e.g. under future climate simulations) (Peterson *et al.*, 2011).

Many habitat modeling methods are available to simulate spatial distribution of a species (Table 3). Deciding on which modeling method to use in any given situation should be based on the available biological and environmental data and the end use purpose of the model (Wintle *et al.*, 2005).

There are three main levels of biological data used in species distribution modeling: presence-only, presence–absence and presence-pseudo absence data. Presence-only data are the most common form of observation data, and are usually available from museums and herbaria, atlases, species lists, incidental observation databases and radio-tracking studies (Pearce & Boyce, 2006). The problem of the 'presence-only' data is that observations are unplanned and tend to be biased toward towns and roads and the variation in survey effort between different environments and geographical areas cannot be controlled or adjusted in model fitting (Wintle *et al.*, 2005). Since reliable absence data often are not available, 'pseudo-absences' data are used instead. Pseudo-absence data is a set of localities chosen from the study area that are used in place of real absence data (Pearson, 2007).

Table 3 *Some of modeling methods and key features. ML = machine learning; P* = for these models, pseudo-absences need to be provided to model presence-only data (P = presence-only, PA = presence-absence); L= low, M= medium, H = high. (Elith & Leathwick, 2009)*

Name	**Category (for algorithm)**	**Type(s) of species data**	**Complexity of fitted functions**	**Predictive performance**
Habitat suitability index	Expert	Expert	L-H	L
Kriging	Interpolation	P	L	L
BIOCLIM	Envelope	P	L	L
DOMAIN	Similarity	P	L-M	M
ENFA (Ecological Niche Factor Analysis)	Factor analysis	P	L-M	M
Resource Selection Function	Regression	P*, PA, count	L-H	M-H
GLM (Generalized Linear Model)	Regression	P*, PA, count	L-H	M-H
GAM (Generalized Additive Model)	Regression	P*, PA, count	L-H	M-H
Decision tree	ML/Tree	P*, PA, count	L	L-M
SVM (Support Vector Machines)	ML/Kernel	P*	L-H	M-H
Neural nets	ML/Regression	P*, PA	L-H	M-H
BRT (Boosted Regression Trees)	ML/Tree/Regression	P*, PA, count	M-H	H
RF (Random Forests)	ML/tree/Ensemble	P*, PA, count	M-H	H
Bayesian methods	Bayesian	P*, PA, count	L-H	M-H

Modeling algorithms used commonly in species distribution modeling are classified into three main groups: envelope, machine learning and regression based algorithms. Examples of climate envelope methods are BIOCLIM and surface range envelope (SRE). BIOCLIM is an envelope method that identifies all areas that exhibit similar climate profiles to the occurrence locations of the species (Pearson, 2007). SRE is similar to BIOCLIM. It produces a climatic envelope based on data within defined percentiles (e.g. 5-95 % percentile) of the maximum and minimum range for each predictor variable (Beaumont & Hughes 2002). In both BIOCLIM and SRE, variable interactions are not considered; thus they are primarily useful for estimation of ranges but not for more detailed maps of species distribution (Beaumont *et al.*, 2005). Moreover, all envelope methods are sensitive to missing data and spatial error (Wintle *et al.*, 2005).

Examples of machine learning techniques are artificial neural networks (ANN), classification tree analysis (CTA), generalized boosting model (GBM), random forest ensemble classifier (RF), and maximum entropy (MAXENT). Artificial neural networks (ANN) is an advanced and powerful rule-based modeling technique, inspired from the structure, processing and learning ability of the brain (Manel *et al.*, 1999). An ANN contains an input layer, predefined hidden layers (intermediate) and an output layer, composed of independent neurons and connected each other (Ripley, 1996). In a feed-forward neural network, each layer use previous layer as inputs of multivariate functions to generate the outputs (Marmion *et al.*, 2009). To avoid overfitting in neural networks, a predefined cross-validation method is implemented. Once the complete network is built, different weighting factors of the multivariate linear functions are chosen by minimizing the quadratic error of the estimate (Marmion *et al.*, 2009). Their robustness to noisy data and their ability to represent linear and non-linear functions are some of the advantages of ANN. However, tuning the parameters requires great knowledge and effort that make ANNs difficult to use (Lorena *et al.*, 2011).

Classification tree analysis (CTA) is a rule-based method that generates a binary tree through a recursive data-splitting technique, iteratively creating homogenous subgroups (Breiman *et al.*, 1984; Venables & Ripley, 2002).

Each split is based on a single variable, while the goal is to minimize variance within each group (Roberts & Hamann, 2012). Cross-validation is used to prune the tree by balancing the number of terminal nodes and the explained variance (Breiman *et al.*, 1984; Miska & Jan, 2005). The advantage of CTA is that it allows capturing of non-additive behavior and complex interactions (Marmion *et al.*, 2009). However, CTA has a tendency to produce overly complex models that lead to spurious interpretations (Breiman *et al.*, 1984).

Random forest (RF) (Breiman, 2001) is a machine learning method that generates multiple trees with bootstrapping technique using randomly selected subsets of the observation and predictor variables. Final predictions either average probabilities over multiple classification trees or tally them using a voting system (Prasad *et al.* 2006). A selective algorithm limits the number of implemented parameters in each tree. Despite the number of trees employed in the combination, RFs do not overfit (Breiman, 2001). RFs have been successful in a wide range of applications (Cutler *et al.*, 2007).

Generalized boosting method (GBM) is a non-parametric technique that is highly efficient in fitting the data (Ridgeway, 1999; Friedman, 2001). It used boosting technique that is a numerical optimization for minimizing a loss function (such as deviance) by adding at each step a new tree that best reduces the loss function (Ridgeway, 1999; Elith *et al.*, 2008). Environmental variables are input into a first regression tree, which maximally reduces the loss function. For each following step, the focus is on the residuals. For example, at the second step a tree is fitted to the residuals of the first tree. The model is then updated to contain two trees, and the residuals from these two trees are calculated. The sequence is repeated as long as necessary (Elith *et al.*, 2008).

MAXENT uses the principle of maximum entropy on presence-only data to estimate a set of functions that relate environmental variables and habitat suitability in order to approximate the species' niche and potential geographic distribution (Phillips *et al.* 2006). It is a discriminative modeling technique, meaning it fits species occurrences relative to available habitat in a model as uniform as possible between two probability densities (the single constraint that the mean of the function for each variable and the mean of the observed data defined in feature space (Elith *et al.* 2011). Although MAXENT was designed to use presence-only data, it also performs well when compared to presence–absence procedures that utilize both real and pseudo-absence data (Elith *et al.* 2006).

Examples of regression based techniques are flexible discrimination analysis (FDA), generalized linear model (GLM) and generalized additive model (GAM). FDA is a supervised discriminant analysis and an extension of the well-known linear discriminant analysis (Hastie *et al.*, 1994). It uses a nonparametric regression method for classification of predictors and a mixture of normals for obtaining a density of estimation for each class. In contrast to linear discriminant analysis, it uses a mixture of Gaussians to model a class rather than a single Gaussian (Hastie *et al.*, 1994).

Generalized linear models (GLM) are mathematical extensions of linear models which are capable of capturing nonlinear relationships via a link function (Guisan & Zimmermann, 2000). They provide a less restrictive form than classic multiple regressions by providing error distributions for the dependent variable. In the case of nonlinearity of the response with a predictor variable, a transformation takes place where polynomial terms allow for the simulation of skewed and bimodal responses, functions or hierarchical sets of models. An automatic forward stepwise procedure is used to compute the best model by minimizing the Akaike information criterion (AIC) value or the Bayesian information criteria (BIC) to reduce redundancy in variables and (most of time) multicollinearity (Thuiller, 2003).

Generalized additive models (GAM) are nonparametric extensions of GLM, using smoothing equations to generalize the data and fit to local data subsets (Guisan & Zimmermann, 2000). The smooth functions are computed independently for each explanatory variable and added to construct the final model. The step forward variable selection of GAM is generally based on AIC (Thuiller, 2003).

1.3.1. Ensemble Modeling

One difficulty with the use of species distribution models is that the number of techniques available is large and is increasing steadily, making it difficult to select the most appropriate methodology for research needs (Elith *et al.*, 2006; Heikkinen *et al.*, 2006; Marmion *et al.* 2009). The performance of individual SDMs varies widely among methods and species (Elith *et al.* 2006). For those reasons, when models are used to project distributions of species into independent situations, which is the case for projections of species distributions under future climate change scenarios, making the choice of an appropriate model is even more difficult (Pearson *et al.*, 2006; Thuiller, 2004, Araújo et al., 2005).

A solution for this inter-model variability is to use ensembles of forecasts by simulating across more than one set of initial conditions, model classes, model parameters, and boundary conditions (Araújo & New, 2007) and analyze the resulting range of uncertainties with bounding box, consensus and probabilistic methodologies rather than lining up with a single modeling outcome (Araújo & New, 2007). Consensus methods that integrate results of different methods, alternative parameterizations of the same method, or multiple iterations of stochastic methods provide a composite robust estimate of potential species' distributions (Araújo & New 2007; Marmion *et al.* 2009).

1.3.2. Evaluation of Models

One fundamental issue in the development of distribution models is the assessment of predictive accuracy (Guisan & Thuiller 2005; Barry & Elith 2006). An assessment of model performance can also provide a basis for comparing alternative modeling techniques (Loiselle *et al.* 2003; Segurado & Araujo 2004; Pearson *et al.* 2006) and enables the user to investigate how different properties of the data and/or the species affect the accuracy of predictive maps generated by the model (Kadmon *et al.*, 2003; Segurado & Araujo 2004; Reese *et al.* 2005). There are different evaluation methods of SDMs which are currently used in SDMs studies.

Confusion Matrix**:** Models generating presence–absence are usually evaluated by comparing the predictions with a set of validation sites and constructing a confusion matrix that records the number of (a) true positive, (b) false positive, (c) false negative and (d) true negative cases predicted by the model (Table 4).

***Table* 4** *Confusion matrix (n is the overall number of cases).*

		Validation data set	
		Presence	*Absence*
Model	*Presence*	a	b
	Absence	c	d

Overall accuracy**:** One simple measure of accuracy that can be derived from the confusion matrix is the proportion of correctly predicted sites (eqn. 1).

$$Overall\ accuracy = \frac{a+d}{n} \tag{1}$$

Sensitivity & Specificity**:** Two alternative measures that are often derived from the confusion matrix are sensitivity and specificity. Specificity is calculated as the ratio of correctly predicted absences to the total number of absences (eqn. 2), and sensitivity as the ratio of correctly predicted presences to their total number (eqn. 3).

$$Specificity = \frac{d}{b+d} \tag{2}$$

$$Sensitivity = \frac{a}{a+c} \tag{3}$$

False Positive Rate (Type I Error): False positive rate is calculated as the proportion of false positive predictions versus the number of actual negative sites, which equals to 1- specificity (eqn. 4).

$$False\ positive\ rate\ = \frac{d}{c+d} \tag{4}$$

Receiver Operating Characteristic Curve: The area under the ROC curve (AUC) is often used as a single threshold-independent measure for model performance (Fielding & Bell 1997). ROC curves are constructed by using all possible thresholds to classify the scores into confusion matrices, obtaining sensitivity and specificity for each matrix, and then plotting sensitivity against the corresponding proportion of false positives (equal to 1 − specificity) . The AUC value is independent from prevalence and considered a highly effective measure for the performance of ordinal score models (Allouche *et al.*, 2006). The range of AUC is from 0 to 1. A model providing excellent prediction has an AUC higher than 0.9, a fair model has an AUC between 0.7 and 0.9, and a model is considered poor if its AUC is below 0.7 (Swets, 1988).

True Skill Statistic: The true skill statistic (TSS), an established approach for assessing the accuracy of weather forecasts, compares the number of correct forecasts, minus those attributable to random guessing, to that of a hypothetical set of perfect forecasts (eqn.5).

$$TSS = sensitivity + specificty\ - 1 \tag{5}$$

It takes into account both omission and commission errors and success as a result of random guessing, and ranges from -1 to +1, where +1 indicates perfect agreement and values of zero or less indicate a performance no better than random.

1.4. Aim of the Study

Forest ecosystems are one of the most important terrestrial ecosystems. However, climate change is anticipated to affect forests by altering both forest processes and biodiversity and in doing so change forest location, composition, and productivity. It is urgent to integrate possible effects of climate change on forest ecosystems into conservation plans/strategies. In order for this integration to occur, reliable information on how species will be affected from climate change is required.

This study aims to model current and potential future distributions of two economically and ecologically important tree species, Turkish pine (*Pinus brutia,* in Turkish *Kızılçam*) and Oriental beech (*Fagus orientalis,* in Turkish *Kayın*), in the face of climate change, and to assess the effect of using different data sets and modeling methods in model setups on species distribution models accuracy.

CHAPTER II

MATERIAL AND METHODS

2.1. Studied Species

2.1.1. Turkish Pine (Pinus brutia)

Turkish Pine, *Pinus brutia*, is a fast growing tree species found especially in Eastern Mediterranean region: Turkey, Greece, Cyprus, Syria and Lebanon. A few small populations can be found in Iran and Iraq and around the Black Sea: Georgia, Russia and Ukraine (Figure 7). Moreover, one of the variety (var. *eldarica*) is found in Afganistan. Most of its distribution is found in Turkey (Boydak *et al.*, 2006).

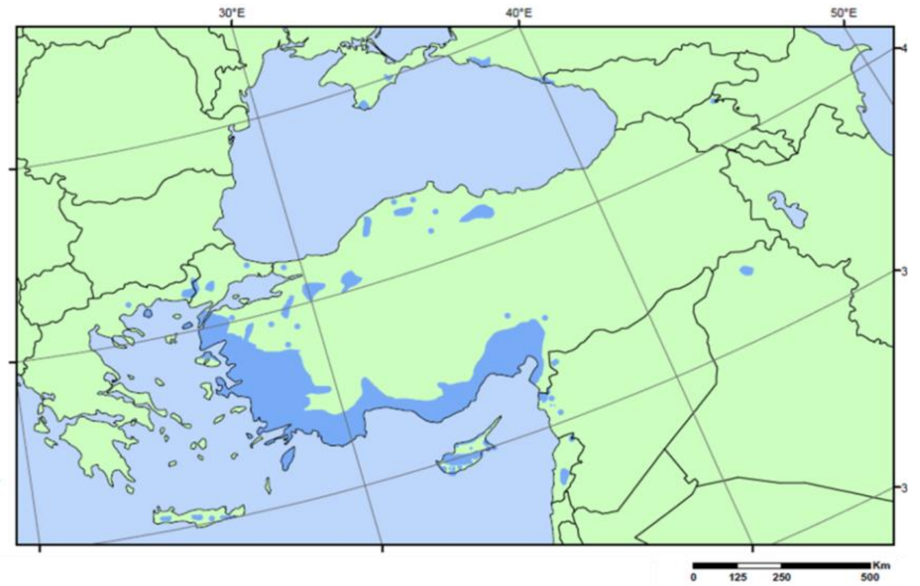

***Figure 8** Current distribution of Turkish pine (source: EUFORGEN 2009, www.euforgen.org.)*

In Turkey, Turkish pine forms extensive forests, especially in regions where the Mediterranean climate prevails. Main distribution of Turkish pine lays out the areas where hot/very hot summers and mild winters, year-round temperate effect of the sea air and moderate rainfall concentrated in the winter months are. Moreover, it is commonly found in fire-related ecosystems of the eastern Mediterranean region. It has not any soil type preferences; it can grow all on all types of soil. Generally it is found in pure stands, besides some regions it is also found in mixed stand with cedar, black pine and juniper (Boydak *et al.*, 2006; Atalay *et al.*, 1998).

In Mediterranean region of Turkey, it is distributed from Muğla to Antakya where it is generally found below 1300 m a.s.l. with some exceptions; for example in Anamur-Sarıdana region, it is found up to 1500-1650 m. In southern aspects of Taurus Mountains, it can be found in areas where the sea maritime influences reach through valleys; for example through Seyhan Valley to north Feke, or through Göksu River to Mut. Furthermore, it spreads locally in parts of Southeastern Anatolia, for instance in Kahramanmaraş, Gaziantep, and Adıyaman (Boydak *et al.*, 2006, Atalay *et al.* 1998). In the Aegean region, it shows a wide distribution from sea level up to 800-1000 m. Following Gediz, Büyük Menderes, and Küçük Menderes valleys, the species reaches inner west Anatolia. In Thrace, it is found along the northern coast of the Marmara Sea (Keşan and Gelibolu) where it grows up to 400 m (Boydak *et al.*, 2006, Atalay *et al.* 1998). Along the coasts and valleys of the Black Sea region, it is found up to 800-1000 m altitude. Especially it occurs along the Kelkit, Yenice and Sakarya valleys. In Kelkit valley, it is found as pure stands up to 600 m altitude and as mixed stands between 600-800 m altitudes (Boydak *et al.*, 2006). Overall, the elevation range of Turkish pine varies according to the region: in the Mediterranean region, 0–1500 m; in the Aegean region, 0–1000 m; and in the Black Sea region, 0–600 m (Boydak *et al.*, 2006, Atalay *et al.* 1998).

Turkish pine is the most widely distributed coniferous species in Turkey, covering 5.4 million hectares (OGM, 2006). It is an important forest tree species in Turkey for both economic and ecological reasons. It is valuable for its timber products as well as for soil stabilization and as wildlife habitat.

The wood of these Mediterranean pines is used for many purposes: construction, industry, carpentry, firewood and pulp.

There are different common names used for *Pinus brutia* such as Turkish red pine, Turkish pine and Calabrian pine. Throughout this study, Turkish pine is used for refering *Pinus brutia*.

2.1.2. Oriental Beech (Fagus orientalis)

The oriental beech, *Fagus orientalis*, is a temperate deciduous tree in the beech family Fagaceae. It is a shade tolerant climax species that occur in Turkey, the Caucasus, northern Iran and the parts of south-eastern Europe (Figure 8). Its core distribution starts near the Bulgarian-Turkish border, expands eastward through the Northern Anatolian Mountains and extends north along the coastline of the Black Sea until the Crimean Peninsula (Atalay, 1992).

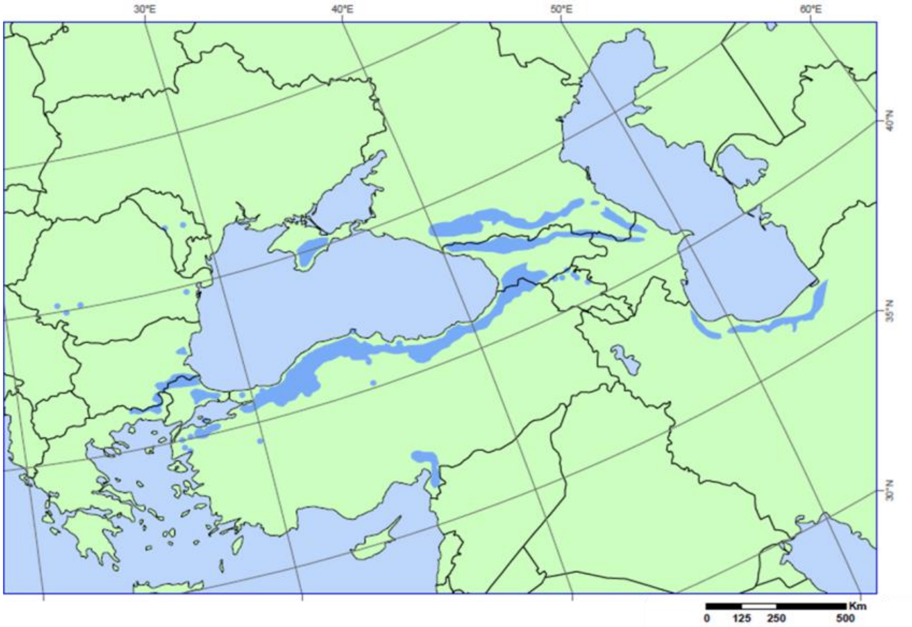

***Figure 9** Distribution of Oriental beech (Source: EUFORGEN 2009, www.euforgen.org.)*

In Turkey, the species is distributed in northern Thrace and south of the Marmara Sea, and throughout the Black Sea Region, where it is possible to find oriental beech both in pure and mixed stands with conifers and other deciduous broadleaved trees.

There are also isolated natural populations on the northern aspects of the Murat Mountains in the inner Aegean Region as well as in the Amanos Mountains in the eastern Mediterranean Region (Atalay, 1992).

The optimum elevation for oriental beech is between 700 and 1200 m whereas it can be found between 0 and 2000 m a.s.l. Aspect is an important topographic factor for oriental beech as it usually occurs in northern and north-eastern aspects with a medium slope. It is vulnerable against extremes of low and high temperatures. Therefore, dry summer months and early/late frost are the main constraints for its distribution (Atalay, 1992). Furthermore, the other constraint for its distribution is Rhododendron, a competitive species in the Black Sea Region where human caused disturbances have enhanced its spreads, further constraints the occurrence of beech (Yıldız & Esen, 2006). Especially in its early years, oriental beech cannot compete with a layer of dense rhododendron.

This species covers some 1.7 million ha in Turkey, and is an economically important tree species with more than 6 million m^3 annual wood production increment (OGM, 2006). As a one of the dominant forest species in Turkey, oriental beech has a wide range of uses in forest industry (Atalay, 1992).

2.2. Spatial Scale: Extent and Resolution

Spatial extent of this study encompasses the whole of Turkey, placed between 26° – 45° E longitude and 36° – 42° N latitude. Turkey covers 783,562 km^2 of land surface with highly diverse geographical and environmental features. The spatial resolution used was 1 km^2, a value that is considered sufficiently fine to identify environmental differences and forest distributions at the regional scale (Pearson *et al.*, 2003). The cell (pixel) size for all GIS raster datasets was set as 1×1 km.

2.3. Data Collection and Preparation

Two types of data are required to build species distribution models: species occurrence/absence data and raster formatted GIS datasets summarizing environmental variables. This section outlines the steps for collecting and processing data used in the models. All data preparation was carried out with ArcGIS Desktop v: 10.1 (ESRI Inc., Redlands, CA).

2.3.1 Species Occurrence Data

Species occurrence data, also called response variables, are point localities defined by x and y coordinates that specify the geographical distribution of a species. It is used in the training and testing of the species distribution models that were sampled on the principle that selected samples should represent all environmental diversity of targeted species distribution and they should be far enough to one another to exclude possible auto-correlation between them.

1:25.000 scale digital forest stand maps for Turkish pine and oriental beech were obtained from the General Directorate of Forestry, and used for extracting response variables. These maps are highly accurate and rely on 1:15,000 scale air photos and field observations by forestry personnel. They show a species as present when it has 10% or more crown closure (which approximates abundance) in a stand.

The following working scheme was used for the both Turkish red pine and oriental beech (Figure 9). Polygons of stand maps were converted to raster data to avoid unequal sampling intensity of species occurrence. Firstly, all polygons of stand maps were aggregated for reducing processing time. After this, stand maps were intersected with a vector grid that was snapped with the raster data at a resolution of 1×1 km.

For each grid cell, areas occupied by each species were calculated and grids that were covered by a species on more than 50% of their area (≥ 50 ha) were selected. Those selected grids were assigned as presence of the respective species.

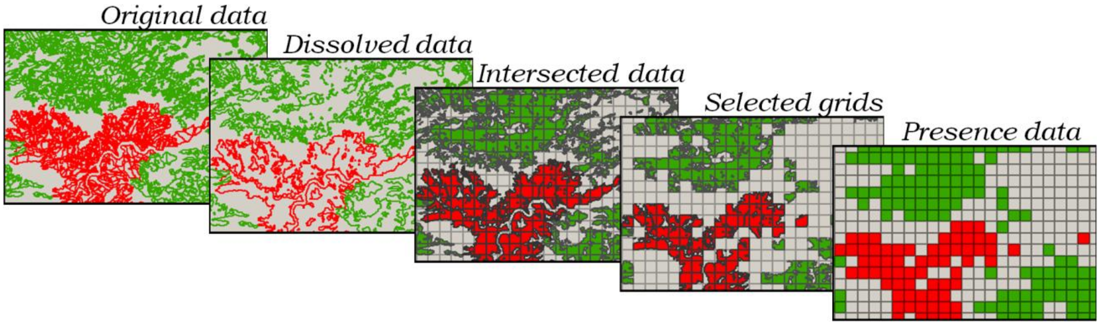

Figure 10 *Converting stand polygons into a raster layer*

Occurrence data were derived from the presence data as randomly selected 500 points for each species. The selection of points was adjusted to be at least 5 km apart for eliminating the autocorrelation between points (Figure 10).

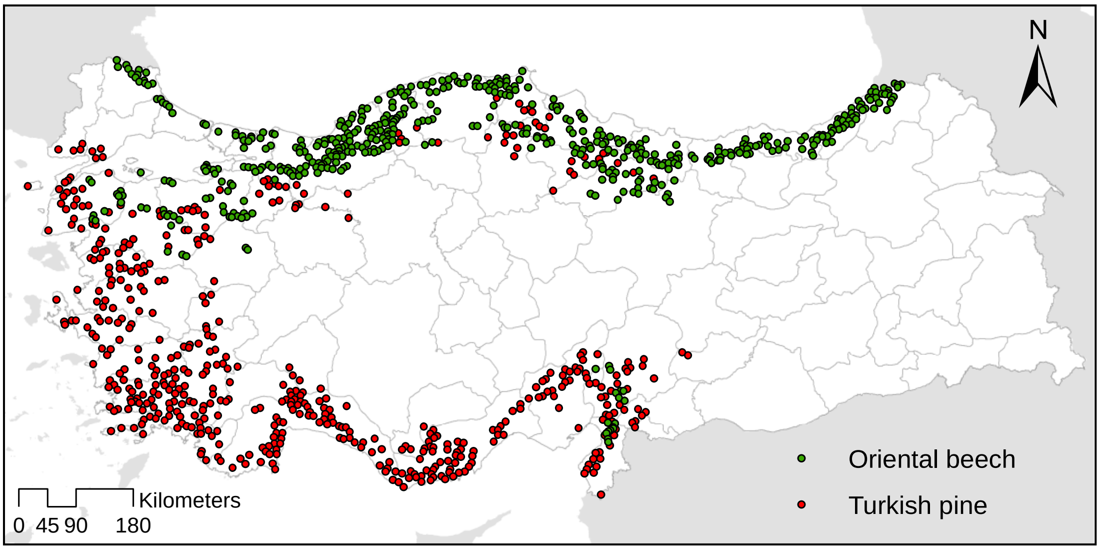

Figure 11 *Randomly selected presence data of both species*

2.3.2. Species Pseudo-Absences Data

If the true absence of a species is unknown, there are two approaches in species distribution modeling. They are generating either background or pseudo-absence data. Background data is a sample which characterizes the environmental conditions present across the study area. Whereas, pseudo-absence data is a sample of points selected from areas or sites where the species has not been detected (Peterson *et al.*, 2011).

There are four reasons for a species to be absent at a particular site. First, the physiology and life history traits of a species may not allow it to get established and/or grow under the particular climate and soil conditions found at that site. Second, even though it may be able to survive the conditions, the species may never have been able to reach that site either since there has not been enough time for it to disperse from its source, or because barriers such as mountains or water bodies avoided such dispersal.

Third, even though a few individuals are actually present, their occurrence at less than 10% crown closure would be reflected in stand maps as absence. Fourth, humans might have historically destroyed previous stands at a site and the current “absence” of the species may be a recent event. The first two reasons would lead to true absences, while the last two to false absences (within the temporal and spatial scales of this study).

Therefore, even using accurate stand maps as input, it is not possible to safely determine true absences. As a result, generated background and pseudo-absence datasets were used in this study. Background data was generated by selecting 10,000 points randomly from the whole study area; it is called “random pseudo-absence” data throughout this study. Two strategies were used for selecting the pseudo-absence data.

First one was SRE strategy in which pseudo-absences were selected outside of the defined environmental conditions for the species found by surface range envelope (SRE) model within 2.5-97.5 % percentile range of these maximum and minimum limits of all environmental variables for each input species presence.

The second was disk strategy, which was defined by minimum and maximum distance to presence points for selecting the pseudo-absences. A distance of 20 km from presence points was used to build a buffer zone; outside of this zone 10,000 pseudo-absence points were selected. This buffer zone was used to omit probable presence areas for the species from the selection because it was assumed that areas adjoining the actual distribution of species are likely suitable for the species. All selections were replicated 5 times for eliminating bias in the selection.

2.3.3. Environmental Variables

2.3.3.1. Topographic Features

Digital Elevation Model

SRTM version 4 with a resolution of ~90 m was obtained from CGIAR-CSI GeoPortal. It was clipped by the study area extent, projected to WGS84 UTM zone 36 with a resampling of pixel size to 1×1 km resolution. Bilinear interpolation, which determines the new value of a cell based on the four nearest pixel values which are located in diagonal directions from a given pixel, was used as the resampling algorithm and causes some smoothing of the data.

Aspect and Slope

Aspect and slope data were derived from SRTM raster data by ArcGIS Desktop Spatial Analyst Tool. The inclination of slope was calculated in degrees.

Topographic Wetness Index

Topographic wetness index is a calculation of the ratio of the slope to the specific catchment area (Beven & Kirkby 1979), defined as TWI=ln(As/tan b), where As is the specific catchment area (the cumulative upslope area draining through a cell divided by the contour width) and b is the local slope (Beven & Kirkby 1979).

Specific catchment area is a grid that is calculated according the contributing area value for each cell taken as its own contribution plus the contribution from up-slope neighbors that drain into it. Topographic wetness index is used to describe spatial soil moisture patterns (Kopecky, 2010) and was calculated from SRTM raster data with ArcGIS Desktop v: 10.1 under Spatial Analyst Tools- Map Algebra.

2.3.3.2. Climatic Features

Raster grids of the global current (1960-1990 averaged) climate data with a spatial resolution of 30 Arc-seconds (~1 km^2) were obtained from the WorldClim database. This database provides 19 layers of bioclimatic variables compiled from monthly data collected from 1950 to 2000 (Hijmans *et al.*, 2005).

Raster grids of the global future climate data were obtained from CIAT-GCM (Centro Internacional de Agricultura Tropical-Global Climate Model) database (Ramirez & Jarvis, 2010). The Hadley Centre Coupled Model version 3 (HadCM3) GCM for IPCC SRES scenarios A2 and B2 for the years 2050 and 2080 were used in this study. These two IPCC SRES scenarios differ mainly in the amount of carbon emission from energy and industrial sources by 2100. The A2 scenario involves a continuous increase in the human population, regionally oriented economic development and semi-intensive use of fossil fuels. On the other hand, B2 involves slower growth of the human population, local solutions on economic, social, and environmental sustainability, and lower CO_2 emissions (IPCC, 2007). Thus, one can state that the A2 SRES scenario is more pessimistic than the B2 scenario. Climatic data were clipped by study area and projected onto WGS-UTM Zone 36 system.

2.3.3.3. Selection of Environmental Variables for Modeling

Quite a lot of different variables are available to use in species distribution modeling; however, many are also highly correlated to each other. It is better to only use one variable among many such correlated variables since using highly correlated variables causes multicollinearity between predictor variables, which can result in model overfitting (Peterson et al. 2007).

Pearson correlations were calculated between all environmental variables that can potentially be used in the models. Selection was based on both ecological relevance to life history of the species and on the calculated correlation coefficients. Highly correlated variable pairs (correlation coefficient > 0.60) were omitted from the data set. In all the models, 8 environmental variables are used (Table 5).

Table 6 *Pearson's correlation matrix of used variables in the models (Wetness: topographic wetness index, Aspect: aspect, Tsea: Temperature seasonality, MaTWM: max temperature of warmest month, MiTCM: min temperature of coldest month, AP: annual precipitation, PDM: precipitation of driest month)*

	Wetness	**Aspect**	**Tsea**	**MaTWM**	**MiTCM**	**AP**	**PDM**
Wetness	1						
Aspect	0.02	1					
Tsea	0.00	- 0.02	1				
MaTWM	0.21	- 0.03	0.31	1			
MiTCM	0.14	- 0.01	- 0.52	**0.6**	1		
AP	- 0.22	0.03	- 0.23	0	0.33	1	
PDM	- 0.15	0.03	- 0.42	**- 0.6**	- 0.11	0.35	1

Temperature seasonality is the coefficient of variation of temperature, i.e. the standard deviation of the monthly mean temperatures expressed as a percentage of the annual mean (Hijmans *et al.*, 2005).

2.3.4. Summary of Model Inputs

For each species and for each SRES scenario, 7 environmental and 500 response variables were used in the model setups with background and pseudo-absence datasets (Figure 11).

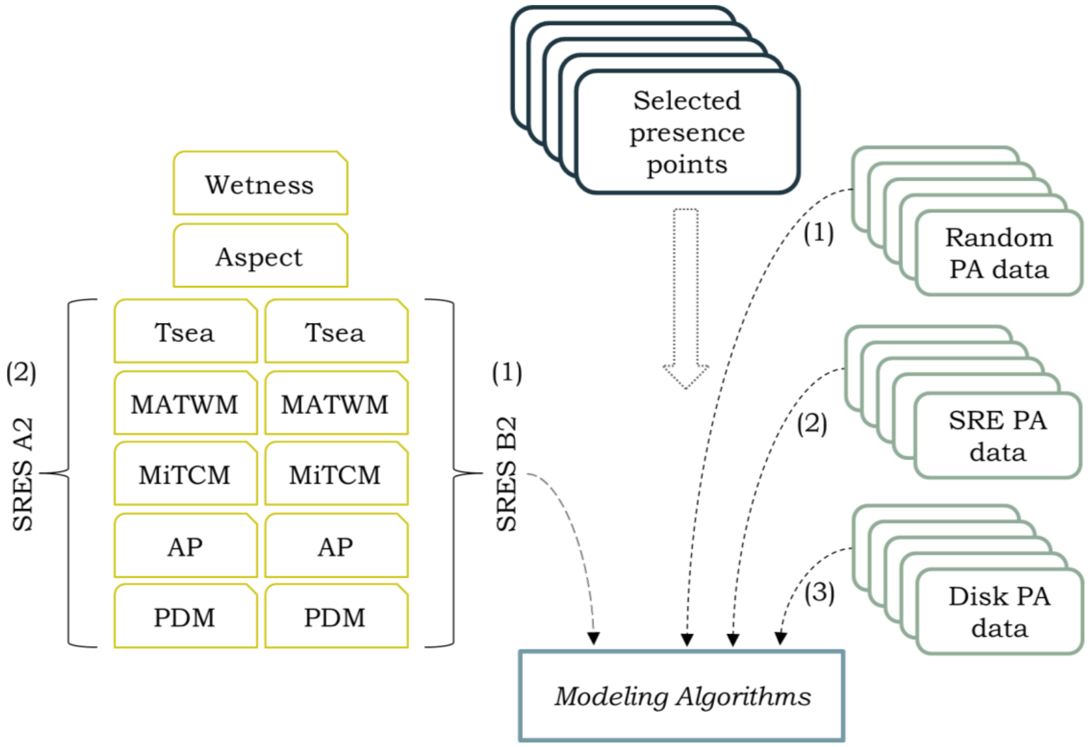

Figure 12 *Inputs used in the models (Wetness: topographic wetness index, Aspect: aspect, Tsea: Temperature seasonality, MaTWM: max temperature of warmest month, MiTCM: min temperature of coldest month, AP: annual precipitation, PDM: precipitation of driest month)*

2.4. Model Calibration

Modeling algorithms were used to characterize the species distribution as a function of environmental variables by using species occurrence data and environmental variables prepared as explained in the previous section.

The BIOMOD 2 framework (Thuiller, 2003), implemented in the open source R version 2.15.1 software (R Development Core Team), was used to build the distribution models. It offers multiple algorithms for modeling and provides an ensemble of spatial projections of the models obtained.

For each species, the following modeling approaches were used to compute predictions: artificial neural networks (ANN), classification tree analysis (CTA), generalized additive models (GAM), generalized linear models (GLM), generalized boosted regression modeling (GBM), flexible discriminant analysis (FDA), maximum entropy (MAXENT), and classification and regression with random forest (RF).

The following arguments were set up for parameterization of the models: ANNs were fitted as 200 maximum iterations with 5 cross-validations. CTAs were fitted as class method with 5 cross-validations. GAMs were fitted as binomial family error distribution as an automatic stepwise procedure with a smoothing term of 2. GLMs were fitted as binomial (logit link) family error distribution type (i.e. logistic regression) with quadratic terms, and an automatic stepwise procedure with AIC. GBMs were fitted by using Bernoulli family error distribution with total number of trees at 500 and with performing 5 cross-validation folds at the learning rate 0.01. FDAs were fitted with multi-response regression method used in optimal scaling. MAXENT were set up as 200 maximum iterations with linear, quadratic, product, threshold, hinge features used. RFs were computed as classification random forest with 500 trees grown.

There were a total 1440 model calibrations for 2 study species, 3 types of background/absence data with 5 randomizations, 8 different modeling approaches and 6 replications. For the background/absence data, random background points, “SRE” pseudo-absence points and “disk” pseudo-absence points were designated as Set 1, Set 2 and Set 3, respectively.

2.5. Model Validation

For each species and for all models, the original data set was split randomly into two: 70% of the total data were used for calibration (training) and 30% to evaluate of the models (i.e. for validation). This procedure was repeated five times to make sure the model predictive accuracy was not influenced by the random-splitting procedure. For each replication, the area under curve (AUC) and the true skill statistic (TSS), sensitivity and specificity values were calculated using selected test data.

2.6. Model Projections

After calibrating the models, results were projected onto the current, 2050 (A2, B2) and 2080 (A2, B2) time periods by using the same environmental variables used in the training model steps. There were a total of 7200 model projections (1440 model calibrations x 5 climate settings listed above).

2.7. Model Outputs Analysis

2.7.1. Ensemble Modeling

Ensemble methods can pull out the correctly predicted areas from several models and indicate areas of uncertainty by averaging and measuring variation in the predictions of multiple modeling techniques (Thuiller *et al.* 2009).

The ensemble process was carried out by using a proportional weighted average of each model's predictions (both different model algorithms and single model repetitions) based on the AUC in the BIOMOD 2 framework. Models with an AUC score lower than 0.75 were excluded from the ensemble process.

After the model ensemble process, results were projected onto the current, 2050 (A2, B2) and 2080 (A2, B2). The projected ensemble models were converted into binary presence-absence using a threshold maximizing the AUC.

2.7.2. Binary Maps

Binary presence/absence maps are generated from the probability maps by using a threshold to by maximize the percentage of presence and absence correctly predicted for present conditions (Thuiller, 2003). This threshold reduces the risk of identifying areas not environmentally suitable for a species (Parker-Allie *et al.* 2009). These maps show a binary map of predicted "habitat" and "non habitat" for the current, 2050, and 2080 projections, and were used further in performance evaluation of model predictions. They were compared with the raster layers of species stand maps, and overall accuracy, sensitivity, specificity, precision, F-score and false positive rate were calculated.

2.7.3. Gain/Loss of Habitats

Grids that are suitable for the species both at current and future climates are called stable areas/habitat. Whereas if areas are suitable under current climate conditions and predicted be become unsuitable under future climate conditions, these are called loss areas/habitat. Conversely, gain areas/habitats are defined as habitat that is unsuitable in the present but predicted to become suitable under future scenarios.

To define stable/gain/loss areas, two analyses were carried out under full dispersal and null dispersal hypotheses. Under the full dispersal hypothesis, we assumed species would be able to move through the landscape without physiological or environmental impediments (i.e. the species can occupy any habitat that is suitable, regardless of its location). Under the null dispersal hypothesis, we assumed species would not disperse at all. These two hypotheses are at two opposite extremes of predicted dispersal behavior of species in the future. Therefore, they are useful to estimate optimistic and pessimistic results of species distributions in the future. Analyses were made on ArcGIS Desktop v: 10.1 under Spatial Analyst Tools.

2.8. Testing Effects of Different Subsets of Response Variables on the Models of Turkish Pine

Turkish pine is distributed widely where ecological conditions within that range are expected to be diverse. We assumed that populations at different parts of Turkey react differently to ecological conditions (i.e. they are different ecotypes). To test this hypothesis, different subsets of response variables were used for calibration the models. The localities in the north were reclassified as Set-a, and the rest as Set-b (Figure 12). We tested whether modeling of those two populations separately provides better prediction than a single model for the whole range.

By using these two sets of occurrence data (Set-a and Set-b) as well as all points together, the MAXENT model was rerun with randomly selected 10,000 background points. 5 replicate runs were used for cross-validation. After calibration of the models, the results were projected onto the current conditions. The projection results were converted to binary maps by using a threshold that maximizes the percentage of presence and absence correctly predicted. Afterwards, binary maps of Set-a and Set-b were overlaid and a single result was produced.

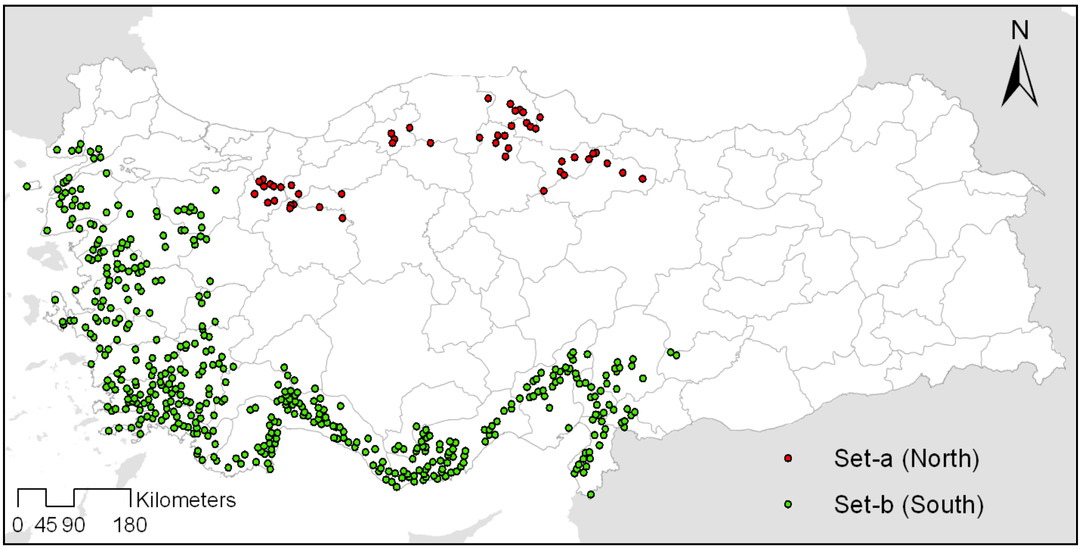

Figure 13 *Classification of Turkish Pine's occurrence data*

The results of overlaid sets and models with all points were compared according to the correct classification rates. The actual stand maps were used in this comparison as the true distribution of the species. The correct classification rate was calculated by dividing total numbers of true positive and true negative pixels by the total number of all pixels.

CHAPTER III

RESULTS

3.1. Turkish Pine

3.1.1 Modeled Current Distribution and Evaluation of Models

3.1.1.1. Evaluation of Model Success by BIOMOD

The mean and standard deviations of AUC, TSS, sensitivity, and specificity values for all model runs are presented in Table 6.

Mean AUC values range between 0.85 and 0.98, and AUC values for the ensemble model for all three pseudo-selection (PA) strategies are higher than those for individual modeling algorithms. The AUC and TSS values are higher when SRE and disk PA selection strategies are used compared to random strategy results. The result of ensemble model for disk PA selection strategy shows the highest sensitivity and specificity.

Table 7 *Mean and standard deviation of true skill statistic (TSS), area under curve value (AUC), sensitivity and specificity values of all repetition runs for random PA selection, SRE PA selection, disk PA selection strategy and ensemble model (EM)*

	Model	**TSS**	**AUC**	**Sensitivity**	**Specificity**
Random	ANN	0.63 ± *0.15*	0.85 ± *0.08*	79.03 ± *18.80*	80.93 ± *15.52*
	CTA	0.69 ± *0.02*	0.86 ± *0.02*	87.15 ± *4.81*	79.68 ± *3.58*
	FDA	0.68 ± *0.02*	0.90 ± *0.01*	82.88 ± 0.99	82.84 ± *0.90*
	GAM	0.69 ± *0.02*	0.91 ± *0.01*	83.31 ± 1.01	83.29 ± *10.90*
	GBM	0.72 ± *0.02*	0.91 ± *0.01*	84.64 ± 0.85	84.83 ± *0.84*
	GLM	0.63 ± *0.03*	0.86 ± *0.02*	78.77 ± 2.60	78.90 ± *2.50*
	MAXENT	0.71 ± *0.02*	0.92 ± *0.01*	83.92 ± 1.09	84.15 ± *1.07*
	RF	0.73 ± *0.01*	0.91 ± *0.01*	85.15 ± 1.47	87.84 ± *5.57*
	EM	**0.75**	**0.94**	**86.60**	**86.58**
SRE	ANN	0.82 ± *0.03*	0.94 ± *0.01*	90.57 ± *1.61*	90.35 ± *1.42*
	CTA	0.83 ± *0.02*	0.92 ± *0.01*	91.07 ± *1.69*	91.06 ± *1.89*
	FDA	0.83 ± *0.02*	0.96 ± *0.01*	90.85 ± *0.93*	90.88 ± *0.78*
	GAM	0.84 ± *0.01*	0.97 ± *0.00*	91.36 ± *0.95*	91.34 ± *0.74*
	GBM	0.85 ± *0.02*	0.97 ± *0.00*	92.13 ± *0.90*	92.13 ± *0.88*
	GLM	0.85 ± *0.01*	0.97 ± *0.00*	91.39 ± *0.81*	91.48 ± *0.74*
	MAXENT	0.86 ± *0.02*	0.98 ± *0.00*	92.59 ± *1.02*	92.60 ± *0.98*
	RF	0.87 ± *0.02*	0.97 ± *0.01*	93.23 ± *1.34*	93.14 ± *0.87*
	EM	**0.89**	**0.99**	**94.4**	**94.30**
Disk	ANN	0.70 ± *0.24*	0.89 ± *0.13*	87.81 ± 18.61	80.06 ± *18.69*
	CTA	0.81 ± *0.01*	0.91 ± *0.01*	95.65 ± 0.91	85.56 ± *1.50*
	FDA	0.81 ± *0.02*	0.96 ± *0.01*	90.08 ± 1.22	90.10 ± *1.18*
	GAM	0.84 ± *0.02*	0.97 ± *0.00*	91.20 ± 0.98	91.19 ± *0.99*
	GBM	0.85 ± *0.02*	0.97 ± *0.00*	91.36 ± 0.87	91.45 ± *0.91*
	GLM	0.84 ± *0.02*	0.97 ± *0.00*	90.61 ± 0.98	90.60 ± *0.88*
	MAXENT	0.85 ± *0.02*	0.98 ± *0.00*	91.97 ± 0.78	91.99 ± *0.80*
	RF	0.91 ± *0.01*	0.98 ± *0.01*	95.36 ± 0.91	95.31 ± *0.96*
	EM	**0.90**	**0.99**	**94.80**	**94.83**

Within repetitions, most of the modeling methods show a consistent range in their AUC values. However, artificial neural network (ANN) shows high variations for each repetition. Similarly, the AUC values of classification tree analysis have a wide range for random and SRE PA selection strategies (Figure 13).

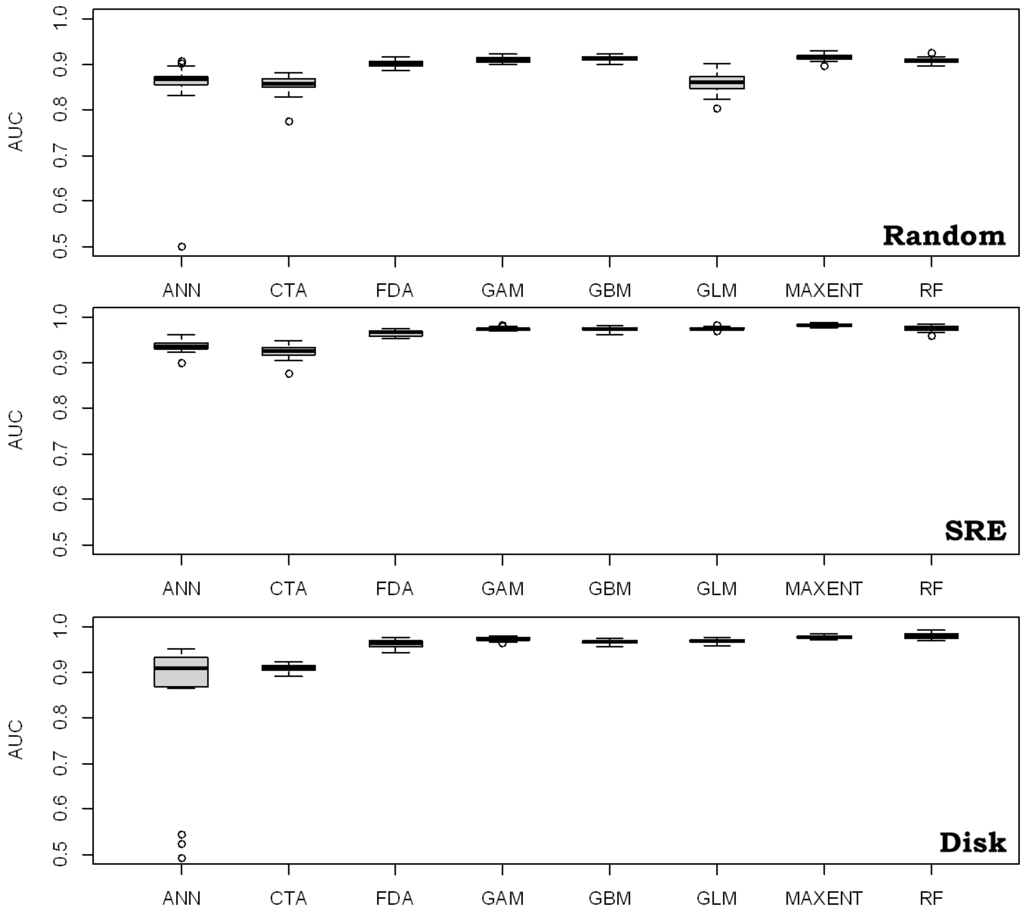

***Figure 14** Boxplot of the area under curve values of each run based upon model method of each PA selection strategy*

3.1.1.2. Evaluation of Model Success by Comparing Current Stand Map

Since there were a large number of model results, model runs with the highest AUC values across all repetitions of a single modeling method were selected. They could also be called as the “best model” result of a modeling algorithm (Table 7). In some cases, the AUC values of the repetition runs of a single model were the same. In that case, TSS values were checked, and a model run with a higher TSS value was selected.

Table 8 *Highest area under curve values (AUC) of each model methods across all PA selection strategies*

		PA Strategy		
	Model	**Random**	**SRE**	**Disk**
AUC	ANN	0.91	0.96	0.95
	CTA	0.88	0.95	0.92
	FDA	0.92	0.97	0.98
	GAM	0.92	0.98	0.98
	GBM	0.92	0.98	0.98
	GLM	0.90	0.98	0.98
	MAXENT	0.93	0.99	0.98
	RF	0.92	0.98	0.99

Table 3 shows the overall accuracy, sensitivity (recall), specificity, precision, F-score, false positive rate (type I error) of best models and ensemble model predictions according to current stands for all three PA selection strategies.

Table 8 *Statistical evaluations of best run of a modeling method and ensemble model (EM) for all PA selection strategies*

		ANN	**CTA**	**FDA**	**GAM**	**GBM**	**GLM**	**MAXENT**	**RF**	**EM**
Random	*Overall accuracy*	0.866	0.855	0.866	0.875	0.882	0.858	0.892	0.891	0.896
	Sensitivity	0.848	0.858	0.82	0.826	0.83	0.846	0.805	0.847	0.808
	Specificity	0.868	0.855	0.869	0.878	0.885	0.859	0.897	0.893	0.901
	Precision	0.272	0.257	0.267	0.283	0.296	0.259	0.313	0.316	0.322
	F- score	0.412	0.396	0.403	0.422	0.436	0.397	0.451	0.460	0.461
	False positive rate	0.132	0.145	0.131	0.122	0.115	0.141	0.103	0.107	0.099
		ANN	**CTA**	**FDA**	**GAM**	**GBM**	**GLM**	**MAXENT**	**RF**	**EM**
SRE	*Overall accuracy*	0.817	0.827	0.812	0.819	0.829	0.812	0.819	0.845	0.832
	Sensitivity	0.906	0.899	0.893	0.915	0.885	0.915	0.900	0.911	0.910
	Specificity	0.812	0.823	0.807	0.813	0.826	0.806	0.815	0.841	0.827
	Precision	0.219	0.228	0.216	0.222	0.229	0.216	0.221	0.251	0.235
	F- score	0.353	0.364	0.348	0.357	0.363	0.349	0.354	0.393	0.374
	False positive rate	0.188	0.177	0.193	0.187	0.174	0.194	0.185	0.159	0.173
		ANN	**CTA**	**FDA**	**GAM**	**GBM**	**GLM**	**MAXENT**	**RF**	**EM**
Disk	*Overall accuracy*	0.670	0.754	0.818	0.833	0.831	0.830	0.840	0.864	0.846
	Sensitivity	0.979	0.971	0.89	0.889	0.904	0.881	0.909	0.926	0.92
	Specificity	0.651	0.741	0.814	0.83	0.826	0.827	0.836	0.861	0.841
	Precision	0.141	0.180	0.218	0.234	0.233	0.229	0.244	0.279	0.253
	F- score	0.246	0.303	0.35	0.370	0.370	0.363	0.385	0.429	0.397
	False positive rate	0.349	0.259	0.186	0.170	0.174	0.173	0.164	0.139	0.159

It is found that the best individual model runs of the random forest models are as successful as the ensemble model results, especially with the SRE and disk PA selection strategies.

The range of overall accuracy of ensemble model results is between 0.832 and 0.896. The sensitivity measure, i.e. the proportion of correctly predicted area, is higher than 0.80 for all best model and ensemble model predictions, which means 80 % of the stand map extent, is found in all modeling methods at least once.

The total area of predictions varies among modeling methods and depending on the pseudo-absence selection strategy used. The main reason for the observed variation is the varying proportion of false positive predictions. Table 9 shows that how much larger an area than the current distribution was found by the best and ensemble model predictions. For example, MAXENT modeling algorithm finds as suitable an area 1.8 times bigger than actual distribution of Turkish pine under a random PA selection strategy.

Table 9 *Rate of false positive predictions of best run of modeling methods and ensemble model for all PA selection strategies, with respect to the current stand map.*

	ANN	CTA	FDA	GAM	GBM	GLM	MAXENT	RF	EM
Random	2.3	2.5	2.3	2.1	2.0	2.4	1.8	1.8	1.7
SRE	3.2	3.0	3.3	3.2	3.0	3.3	3.2	2.7	3.0
Disk	6.0	4.4	3.2	2.9	3.0	3.0	2.8	2.4	2.7

3.1.1.3. Spatial Success and Failure of Models

The predictions of false positive, false negative, true positive locations were mapped for the best results of each modeling method, and also for the ensemble model, for all three PA selection strategies (Figure 14; 15; 16). In the figures, false positive areas represent areas predicted by the models outside the current stand map, false negative areas represent where models failed to find current stands, and true positive areas show where models correctly predicted occurrences of the studied species.

Some current occurrences of the Turkish pine were not predicted within all PA selection strategies and by all modeling methods. 3091 km^2 area occupied by Turkish pine today, in other words 7.17% of its current distribution, was not predicted in any best model or the ensemble model using any pseudo-absence selection strategy.

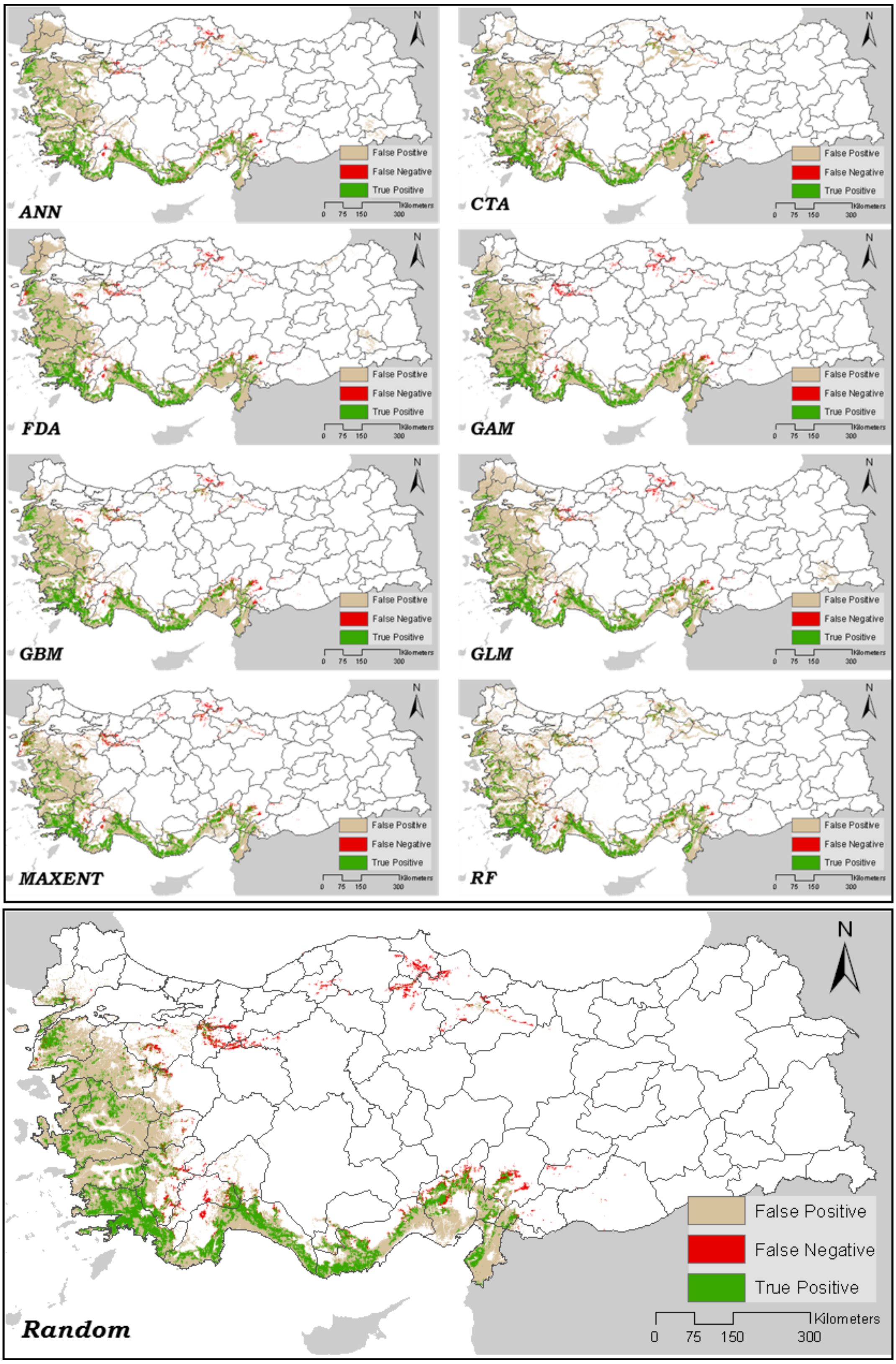

Figure 15 *Prediction accuary and error of best model runs of random PA selection strategy in the current models (top: 8 single best models, bottom: ensemble model)*

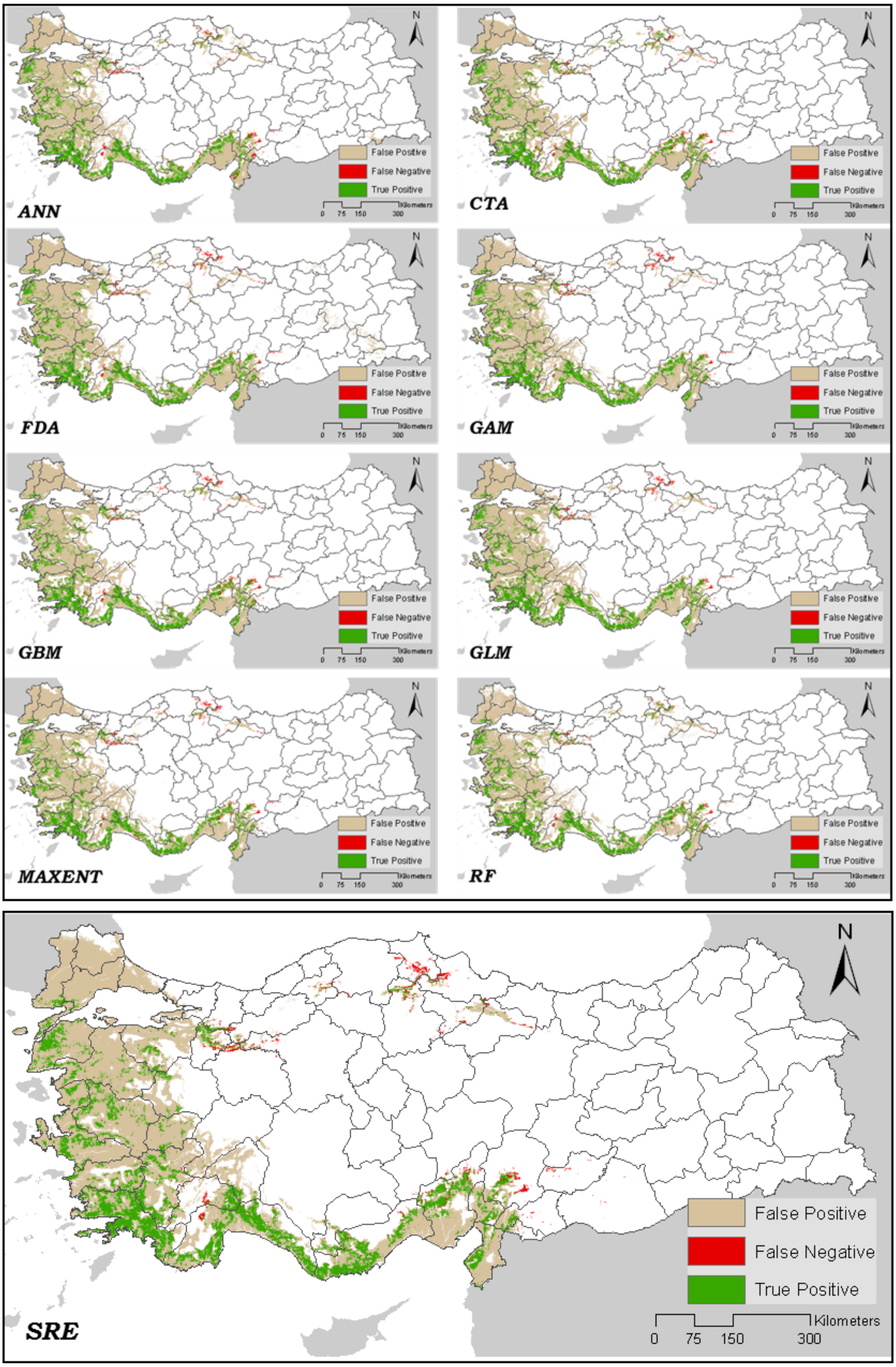

Figure 16 *Prediction accuracy and error of best model runs of SRE PA selection strategy in the current models (top: 8 single best models, bottom: ensemble model)*

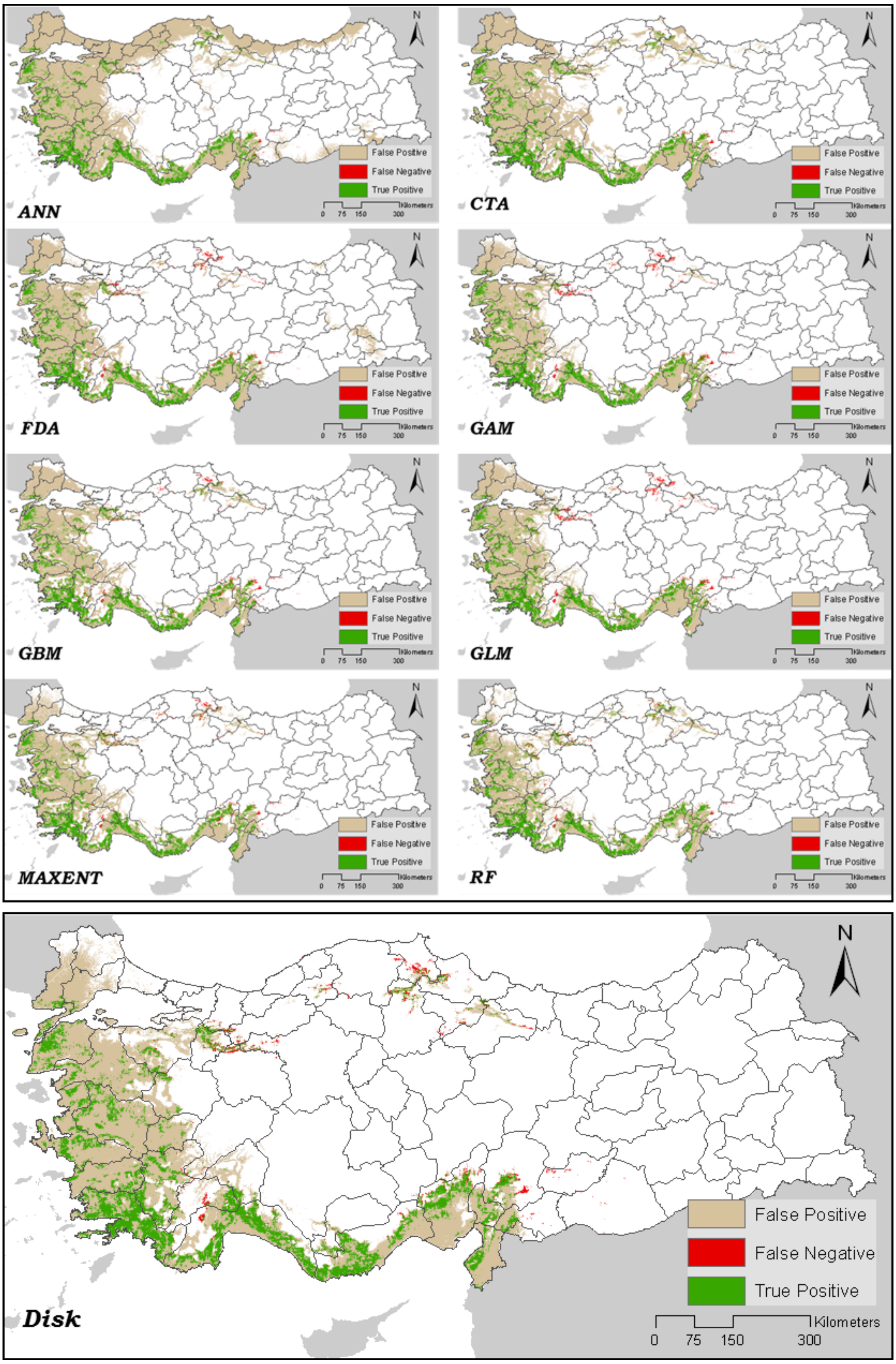

***Figure 17** Prediction accuracy and error of best model runs of Disk PA selection strategy in the current models (top: 8 single best models, bottom: ensemble model)*

3.1.2 Future Projections

Current model predictions were projected to the 2050 and 2080 for two SRES scenarios: A2 and B2. The projection of all modeling methods were used to obtain consensus model outcomes; i.e. ensemble models with a particular pseudo-absence selection strategy. Binomial maps of the predictions created using the set threshold are given in Figures 17, 19, and 21. In addition, the gain/loss areas in the future are mapped with regards to the current distribution of Turkish pine (Figures 18; 20; 22).

Predicted suitable areas of Turkish pine in the 2050 and 2080 are given separately for SRES A2 and B2 scenarios under full migration hypotheses (Table 10). All but the 2080 A2 scenario with disk pseudo-selection strategies predict a decrease in total suitable area in the 2080 with respect to the current area of Turkish pine forests.

Table 10 *Predicted future areas of different PA selection strategy of SRES A2 and B2 scenarios under full migration hypothesis; square kilometer*

	Current (modeled)	**2050 A2**	**2080 A2**	**2050 B2**	**2080 B2**
PA strategy	km^2	km^2		km^2	
Random	107,963	75,425	58,256	83,504	33,816
SRE	166,896	137,416	99,800	147,124	62,803
Disk	156,295	206,053	192,359	210,933	133,540

Future suitable habitat and percentages of these areas with regard to current distribution under the null migration hypothesis are given in Table 11. B2 scenario results are found to be more pessimistic than A2 scenario results. The percentage of the current distribution predicted suitable in the future ranges from 7% to more than 70 % of current distribution, depending on the pseudo-absence selection strategy, climate change scenario and the predicted year. Again, the disk pseudo-absence selection strategy predicts much larger future suitable habitat than the other two selection strategies.

Table 11 *Predicted preserved areas in future with respect to current stand map; square kilometer and percentage of current distribution*

	2050 A2		**2080 A2**		**2050 B2**		**2080 B2**	
PA strategy	*km²*	*%*	*km²*	*%*	*km²*	*%*	*km²*	*%*
Random	16102	**37.36**	3382	**7.85**	18918	**43.89**	10198	**23.66**
SRE	20054	**46.52**	3020	**7.01**	22951	**53.25**	9325	**21.63**
Disk	34955	**81.09**	20304	**47.10**	35710	**82.85**	30782	**71.41**

Geographically, climatically suitable areas of Turkish pine are expected to shift to higher altitudes (or largely disappear) in the Mediterranean region, expand toward inner valleys in the Aegean region, and in parts of the Black Sea and Marmara regions, regardless of the various methods and parameters used in the models.

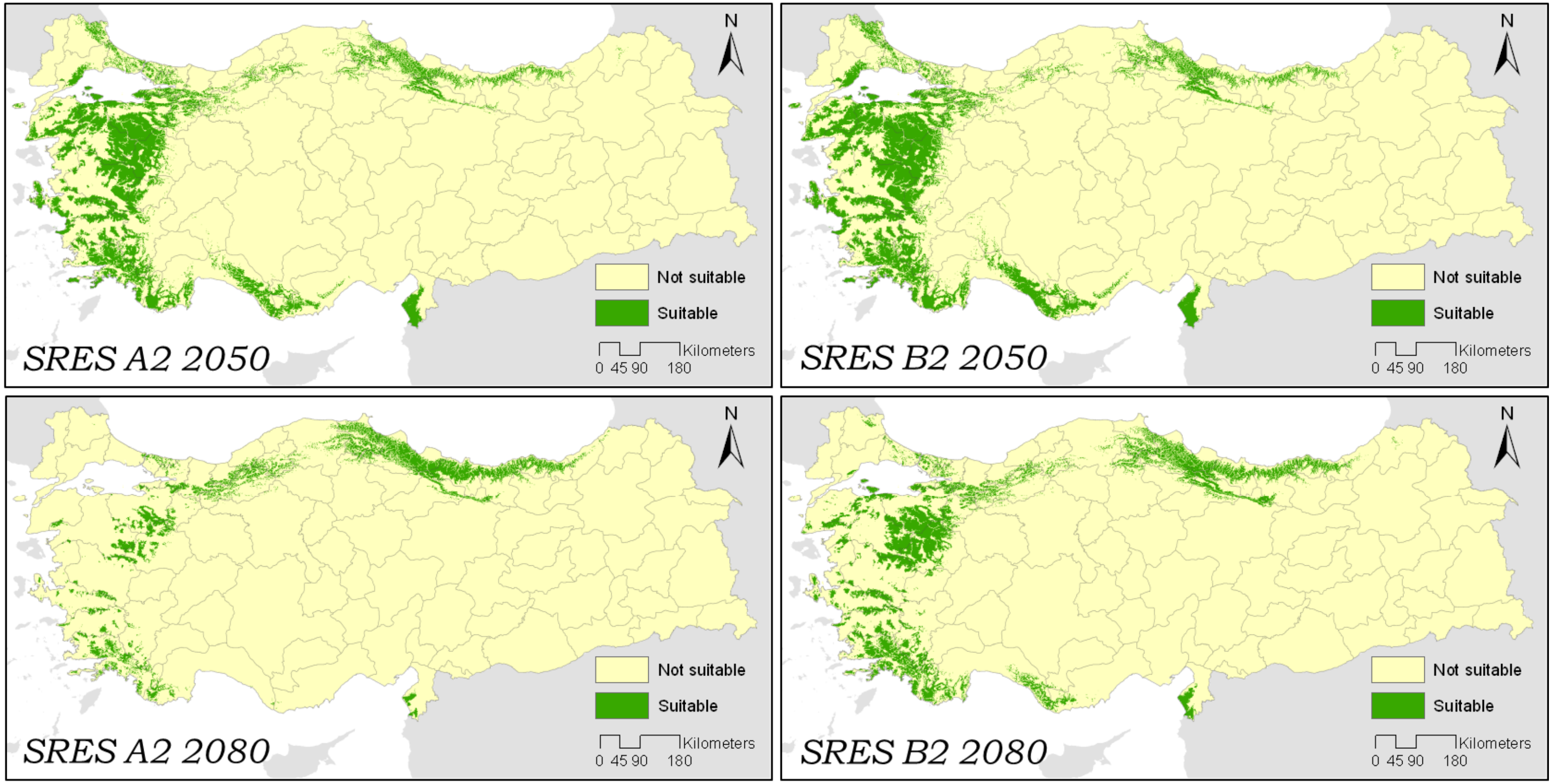

Figure 18 *Future projections (2050 & 2080) of random PA selection strategy of SRES A2 (left) and B2 (right)*

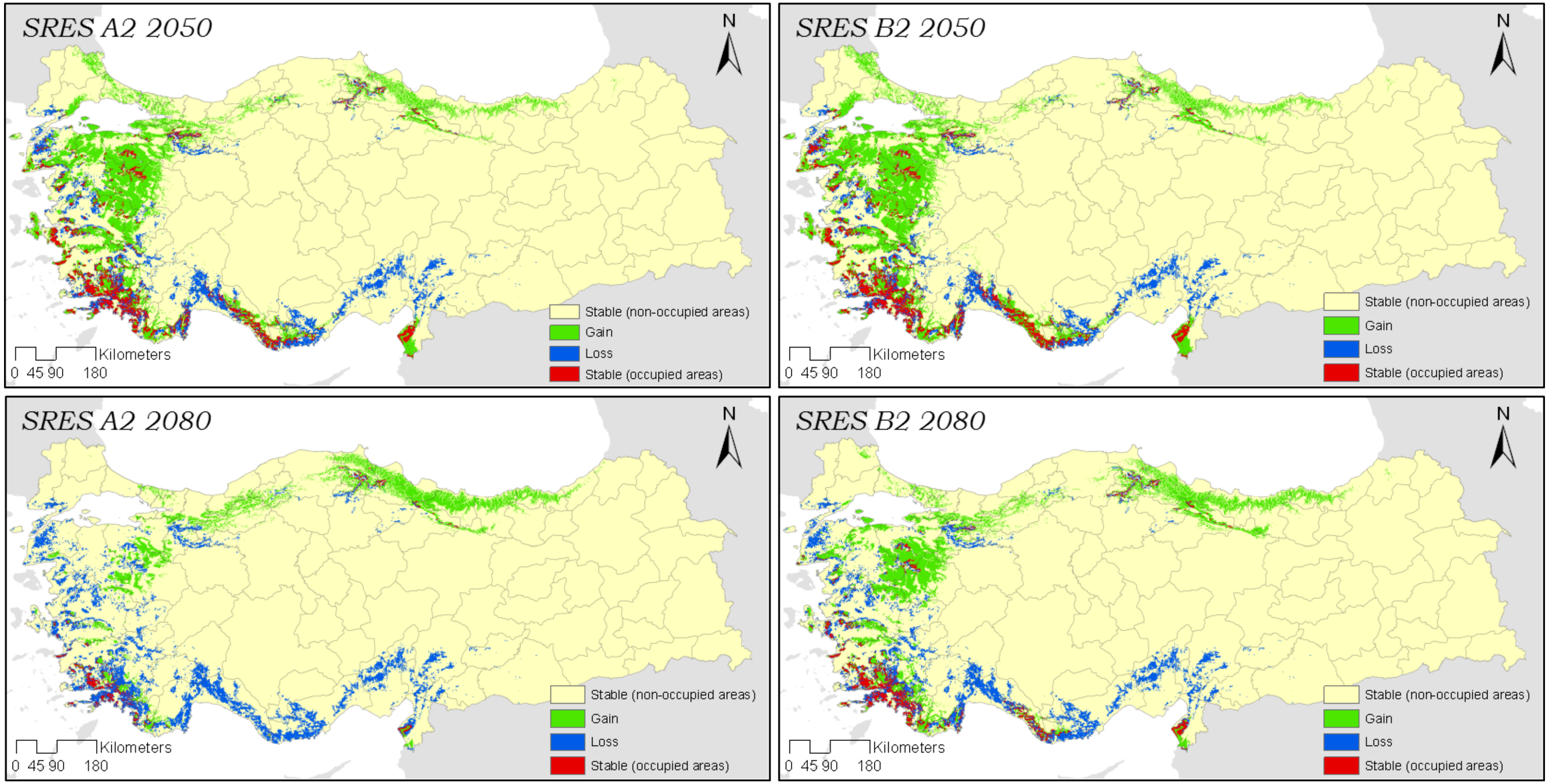

Figure 19 Gain/loss maps of future projections of random PA selection strategy of SRES A2 (left) and B2 (right)

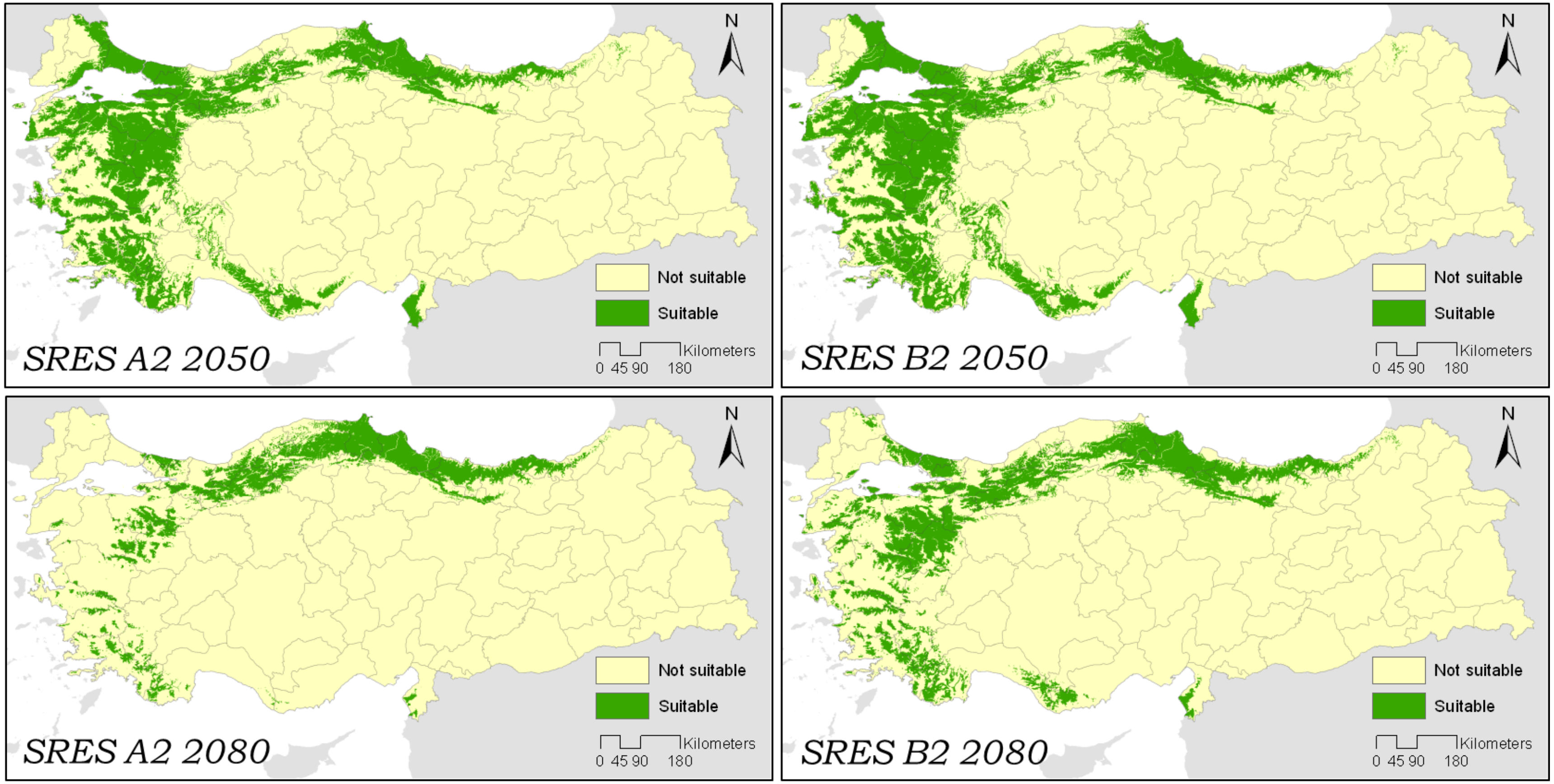

Figure 20 *Future projections (2050 & 2080) of SRE PA selection strategy of SRES A2 (left) and B2 (right)*

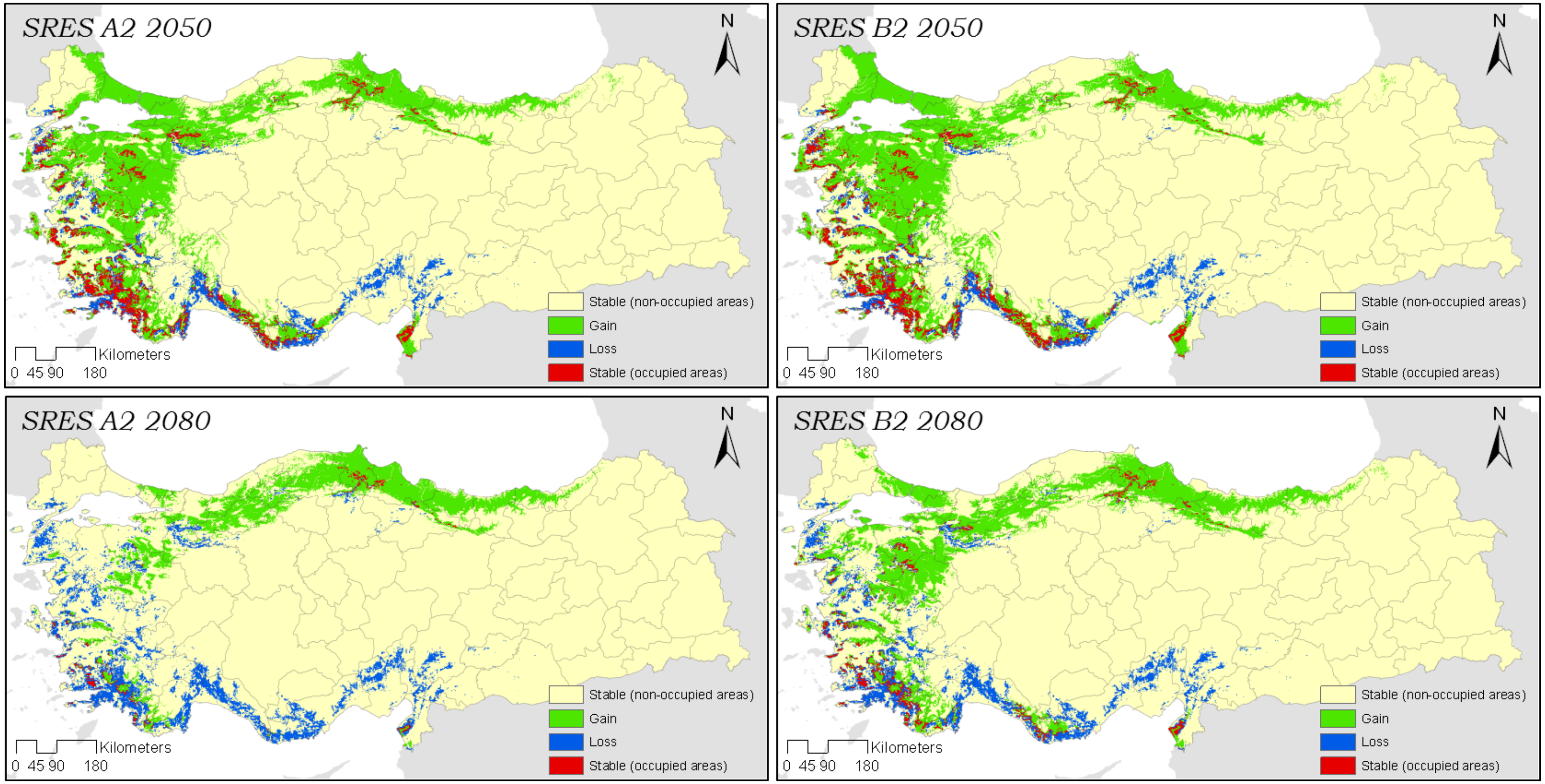

Figure 21 *Gain/loss maps of future projections of SRE PA selection strategy of SRES A2 (left) and B2 (right)*

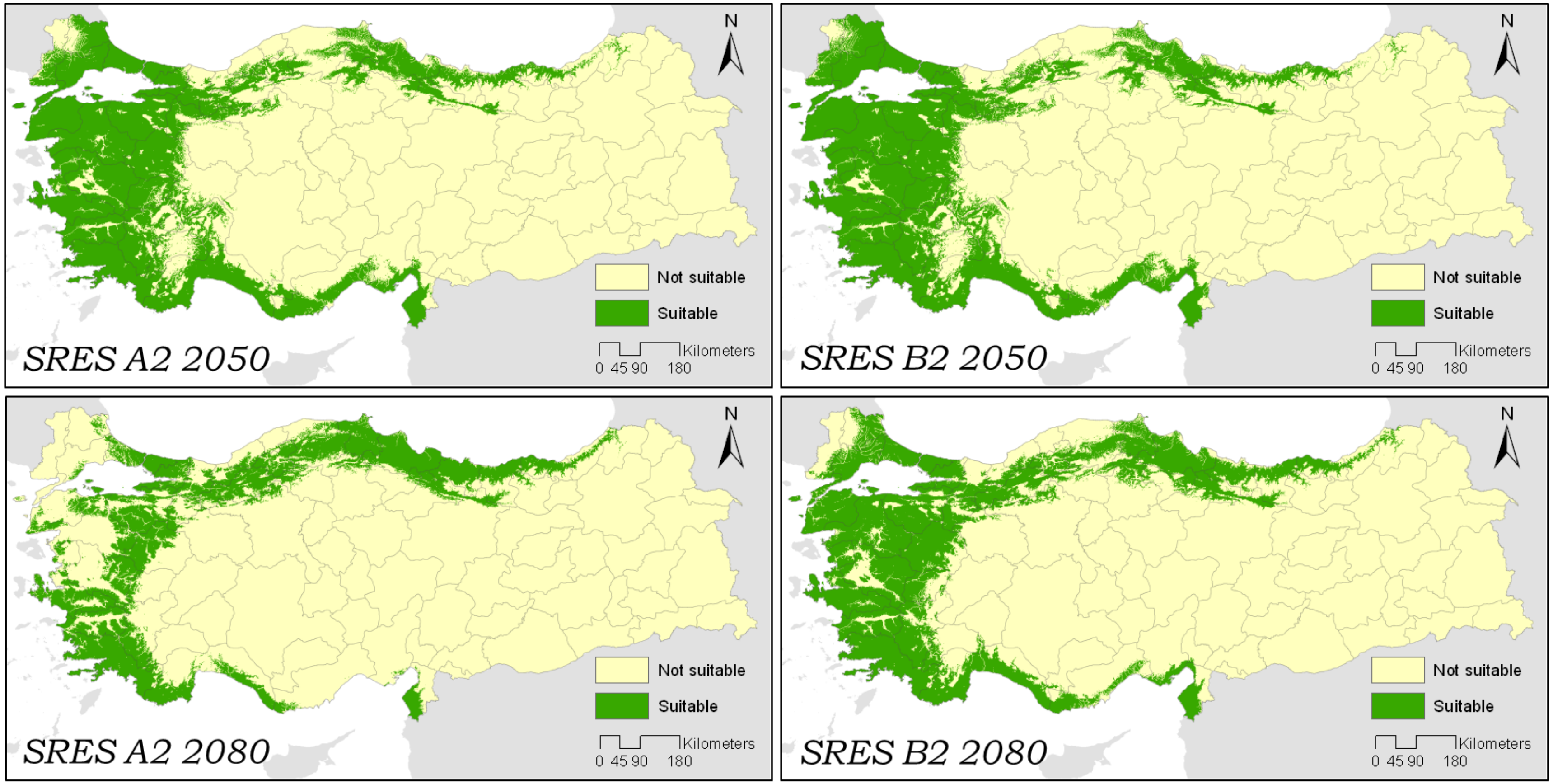

Figure 22 *Future projections (2050 & 2080) of disk PA selection strategy of SRES A2 (left) and B2 (right)*

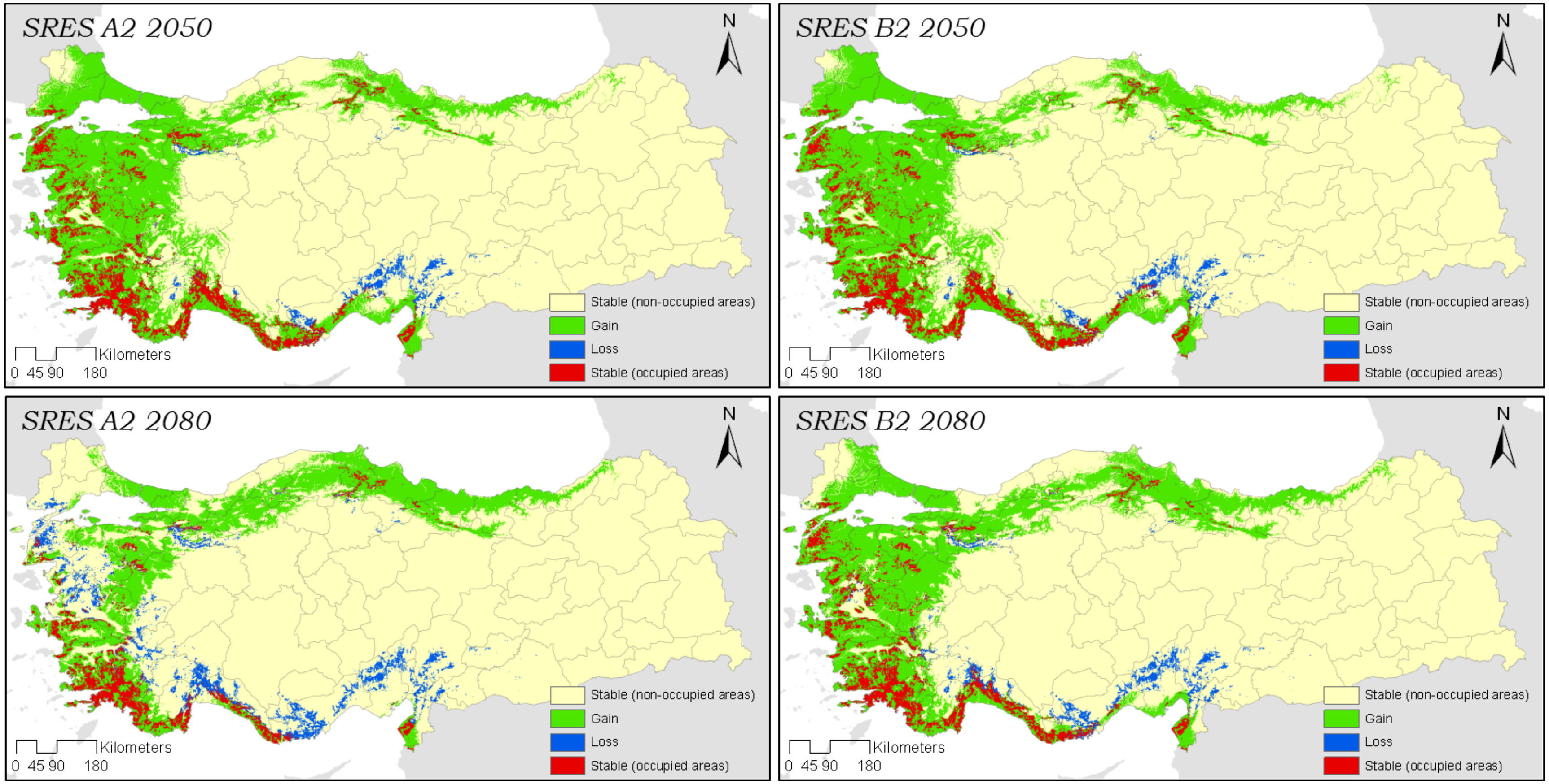

Figure 23 *Gain/loss maps of future projections of disk PA selection strategy of SRES A2 (left) and B2 (right)*

3.1.2. Testing Effects of Different Subsets of Response Variables

Different subsets of response variables of Turkish pine were used to build models separately. Overlaid binary results of these sets were overlaid and are mapped in Figure 23 (upper). While Set-a (north) predicted the suitable areas more widely distributed, Set-b (south) model predicted a more compact area. When comparing the overlaid result with the current distribution of Turkish pine (Figure 10, lower), it is found that 16.5 % of current distribution of species was not predicted by any sets of response variable.

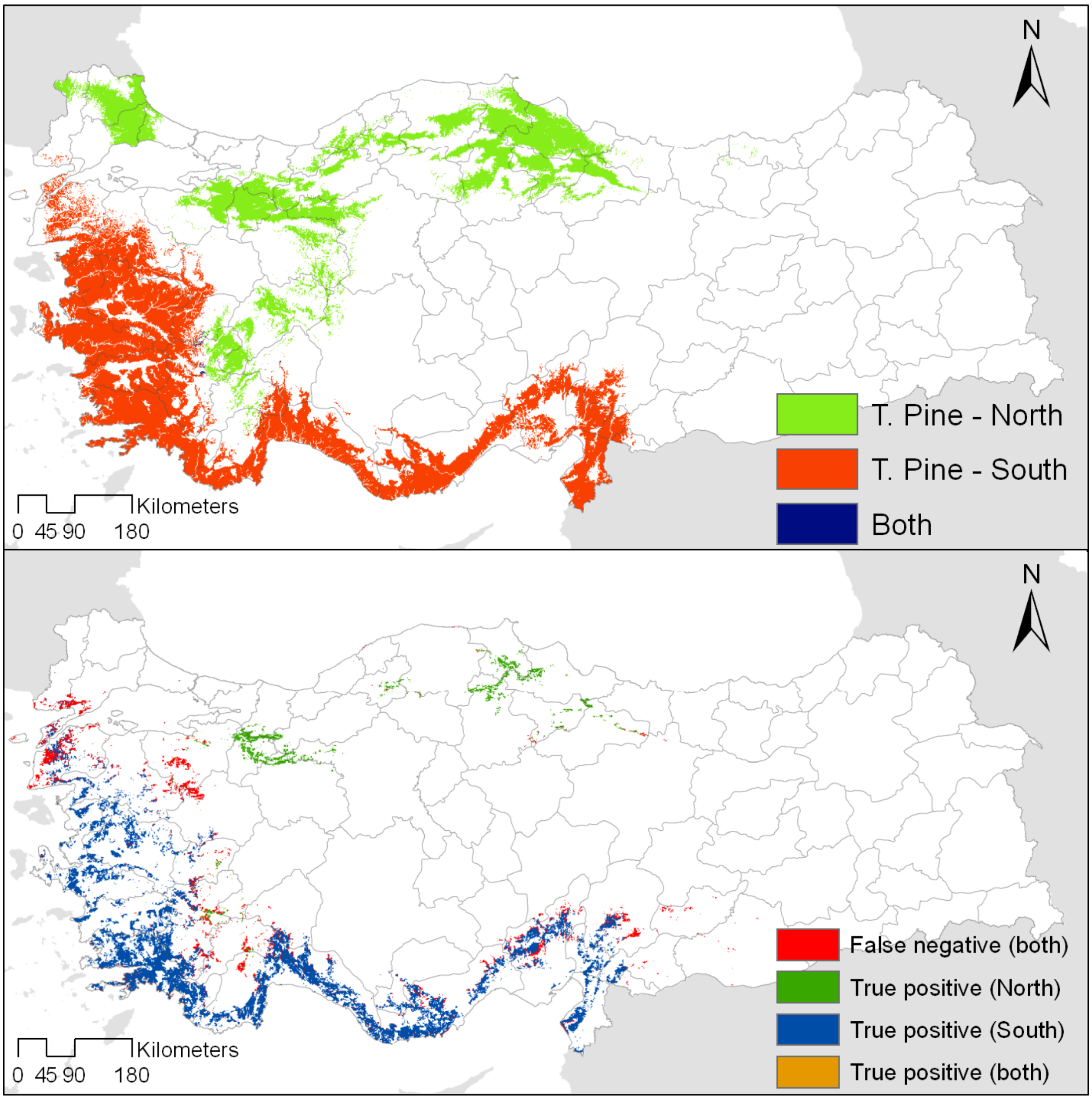

Figure 24 *Consensus model results of north and south datasets of Turkish pine, upper: current distribution of model results, lower: intersection of model results with current stand map*

3.2. Oriental Beech

3.2.1 Modeled Current Distribution and Evaluation of Models

3.2.1.1. Evaluation Tests of Model Success by BIOMOD

The mean and standard deviation of the area under curve (AUC), true skill statistics (TSS), and sensitivity and specificity measurements for each repetition run of modeling algorithms are presented in Table 12.

The mean AUC values of the single model algorithm range between 0.75 and 0.94; 0.89 and 0.99; 0.82 and 0.98 for random, SRE and disk pseudo-absence selection strategies, respectively. Ensemble model shows higher AUC, TSS, sensitivity and specificity values than single model algorithms for every pseudo-absence selection strategy. Sensitivity values for ensemble models are bigger than 90, which mean that 90% of test data is always found by models.

Table 12 *Mean and standard deviation of true skill statistic (TSS), area under curve value (AUC), sensitivity and specificity values of all repetition runs for random PA selection, SRE PA selection, disk PA selection strategy and ensemble model (EM)*

	Model	**TSS**	**AUC**	**Sensitivity**	**Specificity**
Randm	ANN	0.45 ± 0.31	0.75 ± 0.17	88.30 ± 11.62	55.40 ± 35.76
	CTA	0.68 ± 0.01	0.84 ± 0.01	96.99 ± 1.58	71.34 ± 2.24
	FDA	0.75 ± 0.02	0.92 ± 0.01	86.19 ± 1.01	86.16 ± 1.00
	GAM	0.75 ± 0.02	0.93 ± 0.01	85.81 ± 0.95	85.79 ± 0.97
	GBM	0.74 ± 0.02	0.92 ± 0.01	85.23 ± 1.03	85.42 ± 1.00
	GLM	0.77 ± 0.02	0.93 ± 0.01	86.27 ± 0.88	86.36 ± 0.88
	MAXENT	0.77 ± 0.02	0.94 ± 0.01	87.15 ± 1.03	87.15 ± 0.97
	RF	0.77 ± 0.02	0.93 ± 0.01	87.71 ± 1.28	87.92 ± 0.86
	EM	**0.83**	**0.97**	**91.00**	**90.99**
SRE	ANN	0.74 ± 0.23	0.89 ± 0.12	89.11 ± 8.97	82.61 ± 21.01
	CTA	0.84 ± 0.02	0.92 ± 0.01	95.25 ± 2.13	88.17 ± 1.88
	FDA	0.86 ± 0.02	0.96 ± 0.01	92.45 ± 1.08	92.43 ± 1.09
	GAM	0.88 ± 0.02	0.98 ± 0.00	93.68 ± 0.77	93.66 ± 0.71
	GBM	0.88 ± 0.02	0.98 ± 0.01	93.55 ± 0.92	93.51 ± 0.92
	GLM	0.89 ± 0.02	0.98 ± 0.00	93.92 ± 1.01	93.93 ± 0.92
	MAXENT	0.89 ± 0.02	0.99 ± 0.00	94.08 ± 0.68	94.10 ± 0.69
	RF	0.90 ± 0.02	0.98 ± 0.01	94.48 ± 1.01	94.60 ± 0.91
	EM	**0.93**	**0.99**	**96.00**	**95.99**
Disk	ANN	0.59 ± 0.32	0.82 ± 0.17	77.70 ± 29.53	80.68 ± 22.81
	CTA	0.80 ± 0.02	0.91 ± 0.01	95.00 ± 3.48	84.72 ± 3.79
	FDA	0.85 ± 0.02	0.96 ± 0.01	92.27 ± 1.11	92.58 ± 0.99
	GAM	0.85 ± 0.01	0.98 ± 0.00	92.21 ± 0.88	92.24 ± 0.83
	GBM	0.85 ± 0.02	0.97 ± 0.01	91.97 ± 0.73	91.96 ± 0.74
	GLM	0.86 ± 0.01	0.97 ± 0.00	92.03 ± 0.68	92.03 ± 0.62
	MAXENT	0.88 ± 0.02	0.98 ± 0.00	93.79 ± 0.88	93.76 ± 0.84
	RF	0.91 ± 0.02	0.98 ± 0.00	95.25 ± 0.89	95.30 ± 1.00
	EM	**0.92**	**0.99**	**96.00**	**95.99**

Some model algorithms show higher deviations in their AUC values within repetitions. In all pseudo-absence selection strategies, artificial neural network (ANN) results show a much larger range of AUC values (Figure 24).

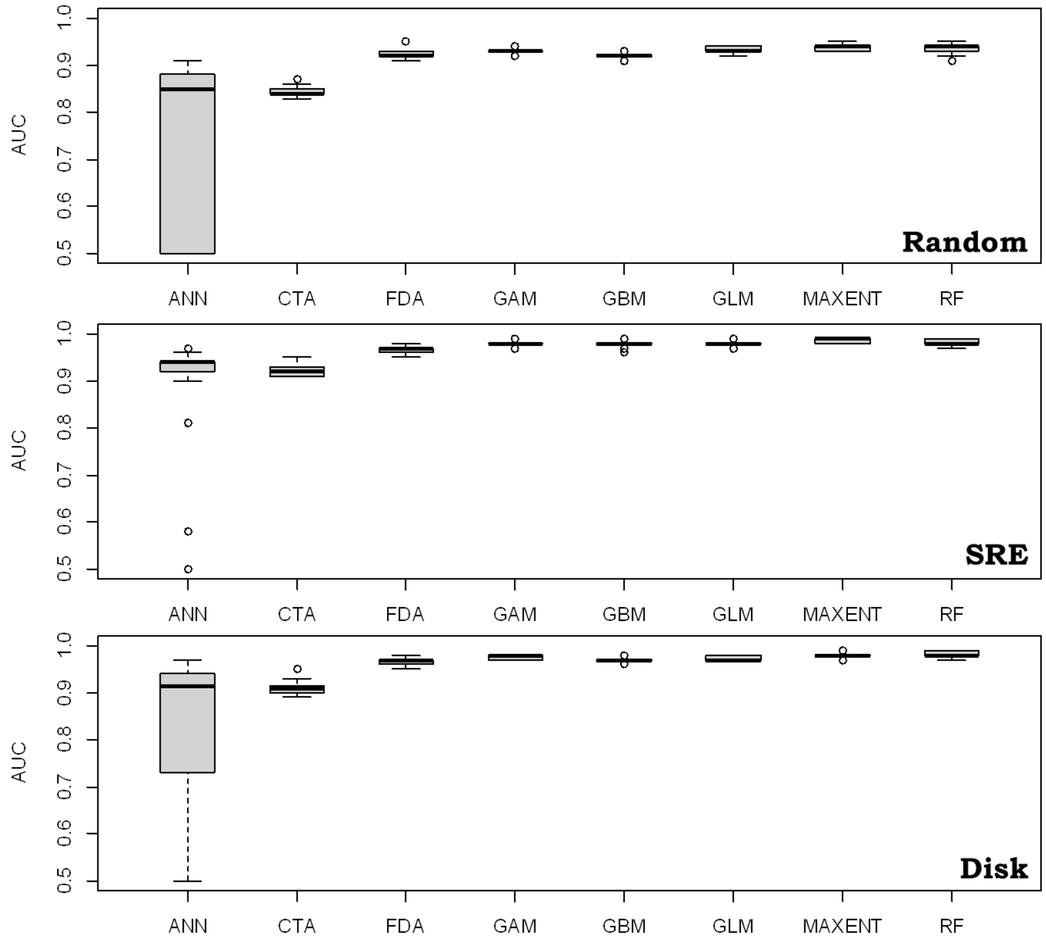

Figure 25 *Boxplot of the area under curve values of each run based upon model method of each PA selection strategy*

3.1.1.2. Evaluation of Model Success by Comparing Current Stand Map

The current stand map was used in comparing model success. Firstly, model runs with the highest AUC values across all repetitions of a model algorithm were selected (Table 13). In some cases, the AUC values of the repetition runs of a single model were the same. In that case, TSS values were checked, and a model run with a higher TSS value was selected.

Table 13 *Highest area under curve values (AUC) of each model methods across all PA selection strategies*

		PA Strategy		
	Model	**Random**	**SRE**	**Disk**
AUC	ANN	0.91	0.97	0.97
	CTA	0.87	0.95	0.95
	FDA	0.95	0.98	0.98
	GAM	0.94	0.99	0.98
	GBM	0.93	0.99	0.98
	GLM	0.94	0.99	0.98
	MAXENT	0.95	0.99	0.99
	RF	0.95	0.99	0.99

Table 14 shows the overall accuracy, sensitivity (recall), specificity, precision, F-score, false positive rate (type I error) of best models and ensemble model predictions according to current stands for all three PA selection strategies.

Table 14 *Statistical evaluations of best run of a modeling method and ensemble model (EM) for all PA selection strategies*

		ANN	**CTA**	**FDA**	**GAM**	**GBM**	**GLM**	**MAXENT**	**RF**	**EM**
Random	*Overall accuracy*	0.813	0.795	0.896	0.883	0.889	0.886	0.897	0.913	0.924
	Sensitivity	0.953	0.971	0.882	0.86	0.859	0.869	0.901	0.913	0.871
	Specificity	0.81	0.791	0.897	0.884	0.89	0.886	0.897	0.913	0.925
	Precision	0.1	0.094	0.159	0.141	0.147	0.145	0.162	0.189	0.205
	F- score	0.182	0.171	0.27	0.243	0.252	0.249	0.275	0.313	0.331
	False positive rate	0.19	0.209	0.103	0.116	0.11	0.114	0.103	0.087	0.075
		ANN	**CTA**	**FDA**	**GAM**	**GBM**	**GLM**	**MAXENT**	**RF**	**EM**
SRE	*Overall accuracy*	0.848	0.782	0.854	0.84	0.824	0.85	0.814	0.865	0.842
	Sensitivity	0.951	0.966	0.94	0.946	0.936	0.935	0.95	0.953	0.951
	Specificity	0.846	0.778	0.852	0.838	0.822	0.848	0.811	0.863	0.839
	Precision	0.121	0.088	0.124	0.115	0.105	0.12	0.101	0.133	0.116
	F- score	0.214	0.162	0.219	0.205	0.188	0.213	0.182	0.234	0.207
	False positive rate	0.154	0.222	0.148	0.162	0.178	0.152	0.189	0.137	0.161
		ANN	**CTA**	**FDA**	**GAM**	**GBM**	**GLM**	**MAXENT**	**RF**	**EM**
Disk	*Overall accuracy*	0.837	0.833	0.839	0.846	0.842	0.856	0.859	0.876	0.875
	Sensitivity	0.959	0.941	0.951	0.93	0.943	0.928	0.961	0.972	0.959
	Specificity	0.834	0.831	0.836	0.844	0.84	0.855	0.857	0.873	0.873
	Precision	0.114	0.11	0.114	0.117	0.115	0.124	0.13	0.146	0.143
	F- score	0.204	0.197	0.204	0.208	0.206	0.219	0.229	0.253	0.249
	False positive rate	0.166	0.169	0.164	0.156	0.16	0.145	0.143	0.127	0.127

The best model runs of the random forest method are as successful as the ensemble model results. The range of overall accuracy of ensemble models is between 0.842 and 0.924 for all pseudo-absence selection strategies. Moreover, sensitivity measurement, i.e. the proportion of correctly predicted area, is higher than 0.87 for all best model and ensemble model predictions, which means 87 % of the stands, occur in all ensemble models.

There false positive rates vary among modeling methods and depending on the PA selection strategy used. Table 15 shows that how much larger an area that the current distribution was found by the best and ensemble model predictions. Ensemble models predict least false positive predictions at the random strategy.

Table 15 Rate of false positive predictions of best run of model and ensemble model (EM) method for all PA selection strategies.

	ANN	CTA	FDA	GAM	GBM	GLM	MAXENT	RF	EM
Random	8.5	9.4	4.7	5.2	5.0	5.1	4.7	3.9	3.4
SRE	6.9	10.0	6.6	7.3	8.0	6.8	8.5	6.2	7.2
Disk	7.5	7.6	7.4	7.0	7.2	6.5	6.4	5.7	5.7

3.1.1.3. Spatial Successes and Failures of Models

For the best results of each modeling method, and also for the ensemble model, the predictions of false positive, false negative, true positive locations were mapped for all three PA selection strategy (Figure 25; 26; 27). In the figures, false positive areas represent areas where predicted by the models outside the current stand map, false negative areas represent where models failed to find current stands, and true positive areas represent where models correctly predicted occurrences of the studied species.

Some current occurrences of the oriental beech were not predicted in any modeling methods. 583 km^2 area occupied by oriental beech today, in other words 3.43% of its current distribution, was not predicted in any best model ot the ensemble model using any PA selection strategy.

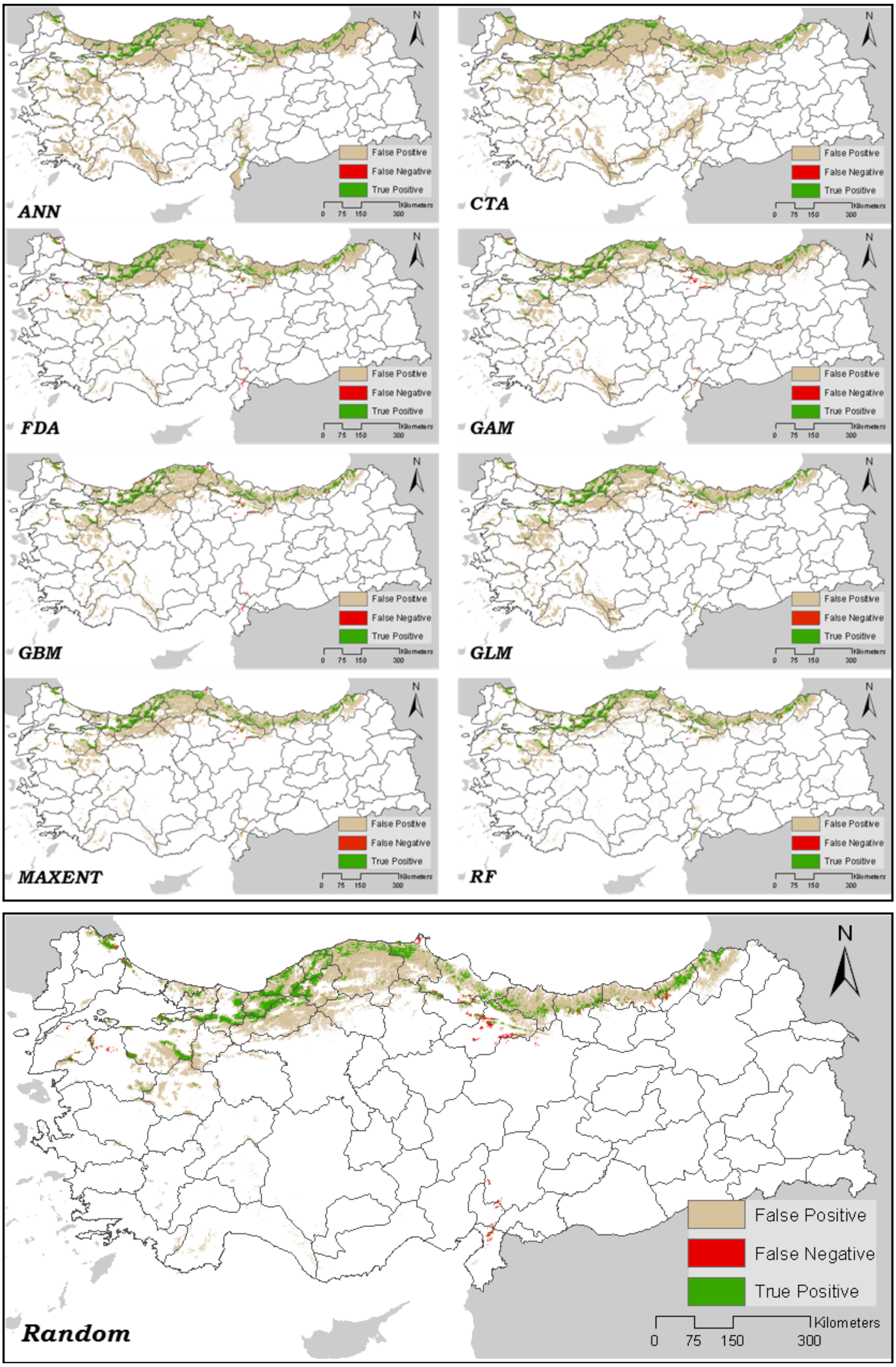

Figure 25 *Prediction accuracy and error of best model runs of random PA selection strategy in the current models (top: 8 single best models, bottom: ensemble model)*

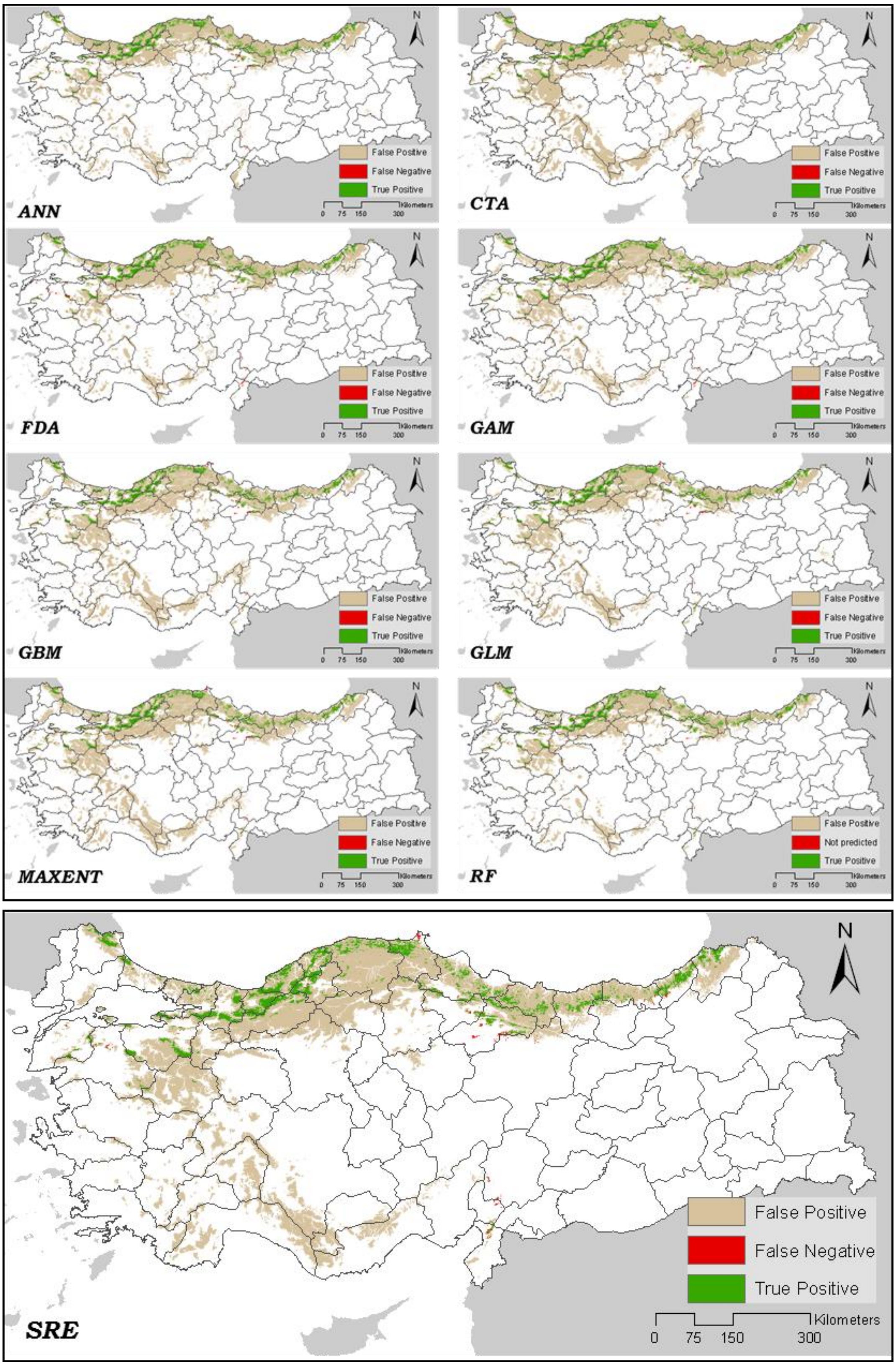

Figure 26 *Prediction accuracy and error of best model runs of SRE PA selection strategy in the current models (top: 8 single best models, bottom: ensemble model)*

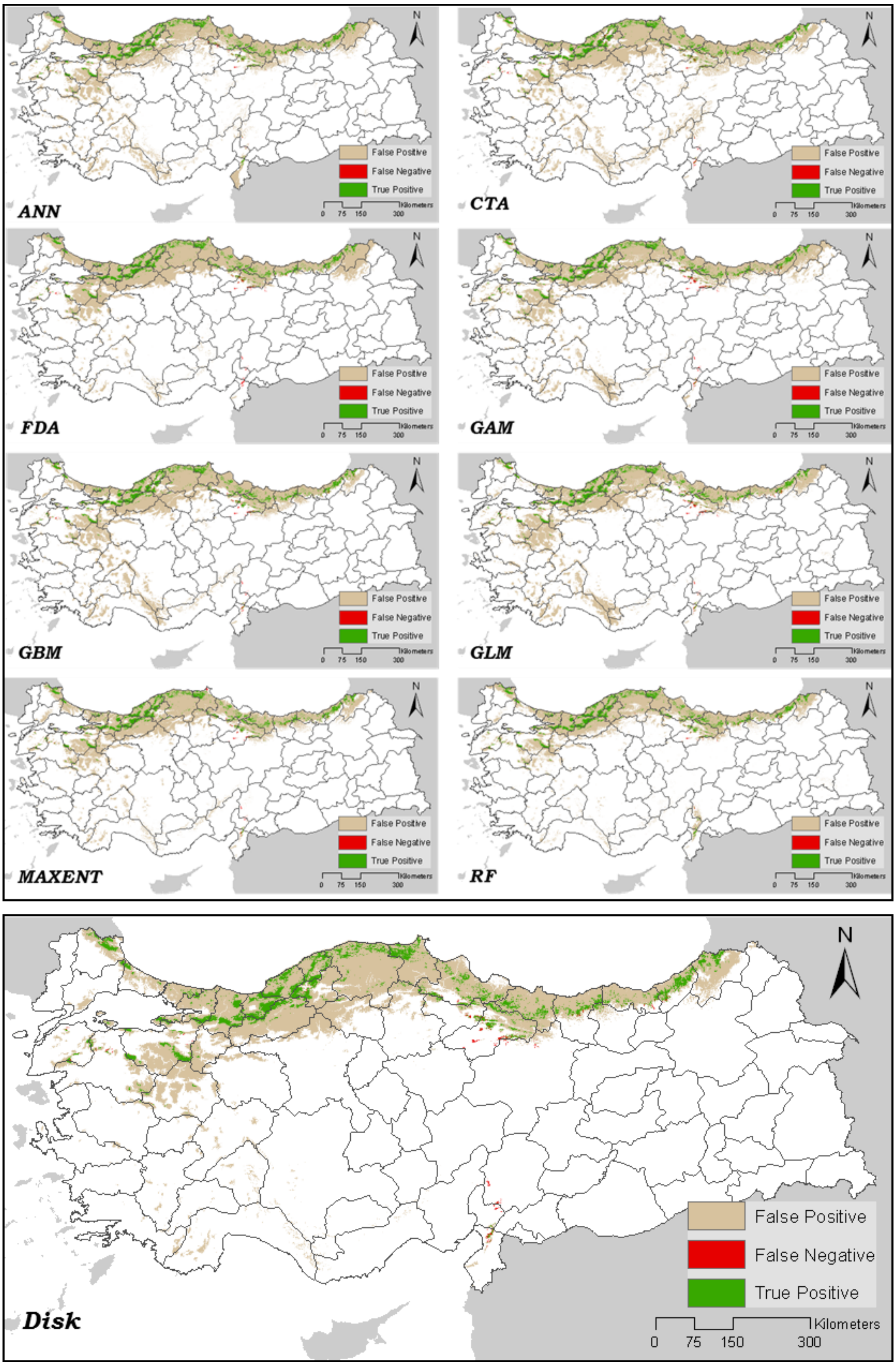

Figure 27 *Prediction accuracy and error of best model runs of Disk PA selection strategy in the current models (top: 8 single best models, bottom: ensemble model)*

3.1.2 Future Projections

Current model predictions were projected to the 2050 and 2080 for two SRES: A2 and B2. The projection of all modeling methods were used to obtain consensus model outcomes; i.e. ensemble models with a particular PA selection strategy. Binomial maps of the predictions created using the set threshold are given in Figures 28, 30, 32. In addition, the gain/loss areas in the future are mapped with regards to the current distribution of oriental beech (Figures 29; 31; 33).

Under full migration hypothesis, predicted suitable areas of oriental beech in the 2050 and 2080 were given separately for SRES A2 and B2 scenarios (Table 16). There are differences in predictions of suitable areas among PA selection strategy used. The SRE strategy predicts the largest current and future areas. Two SRES scenarios predict a sharp decline in suitable area of oriental beech by 2080 for all three PA selection strategies.

Table 16 *Predicted future areas of different PA selection strategy of SRES A2 and B2 scenarios; square kilometer*

	Current (modeled)	**2050 A2**	**2080 A2**	**2050 B2**	**2080 B2**
PA strategy	*km^2*	*km^2*		*km^2*	
Random	72,431	4,376	303	3,569	1,281
SRE	139,137	14,480	1,034	14,103	3,666
Disk	113,720	9,235	853	8,639	3,217

Future suitable habitat and percentages of these areas with regard to current distribution under the null migration hypothesis are given in Table 17. Most of the current distributions of oriental beech are predicted to be loss by all PA selection strategy and climate change scenario.

Table 17 *Predicted preserved areas in future with respect to current stand map; square kilometer*

	2050 A2		**2080 A2**		**2050 B2**		**2080 B2**	
PA strategy	km^2	%	km^2	%	km^2	%	km^2	%
Random	1857	**10.92**	187	**1.10**	1538	**9.04**	579	**3.40**
SRE	3760	**22.11**	420	**2.47**	3601	**21.17**	1226	**7.21**
Disk	3354	**19.72**	386	**2.27**	3006	**17.68**	1229	**7.23**

Geographically, the current suitable areas for oriental beech are expected largely to be lost and its overall distribution is predicted to be much narrower in the future.

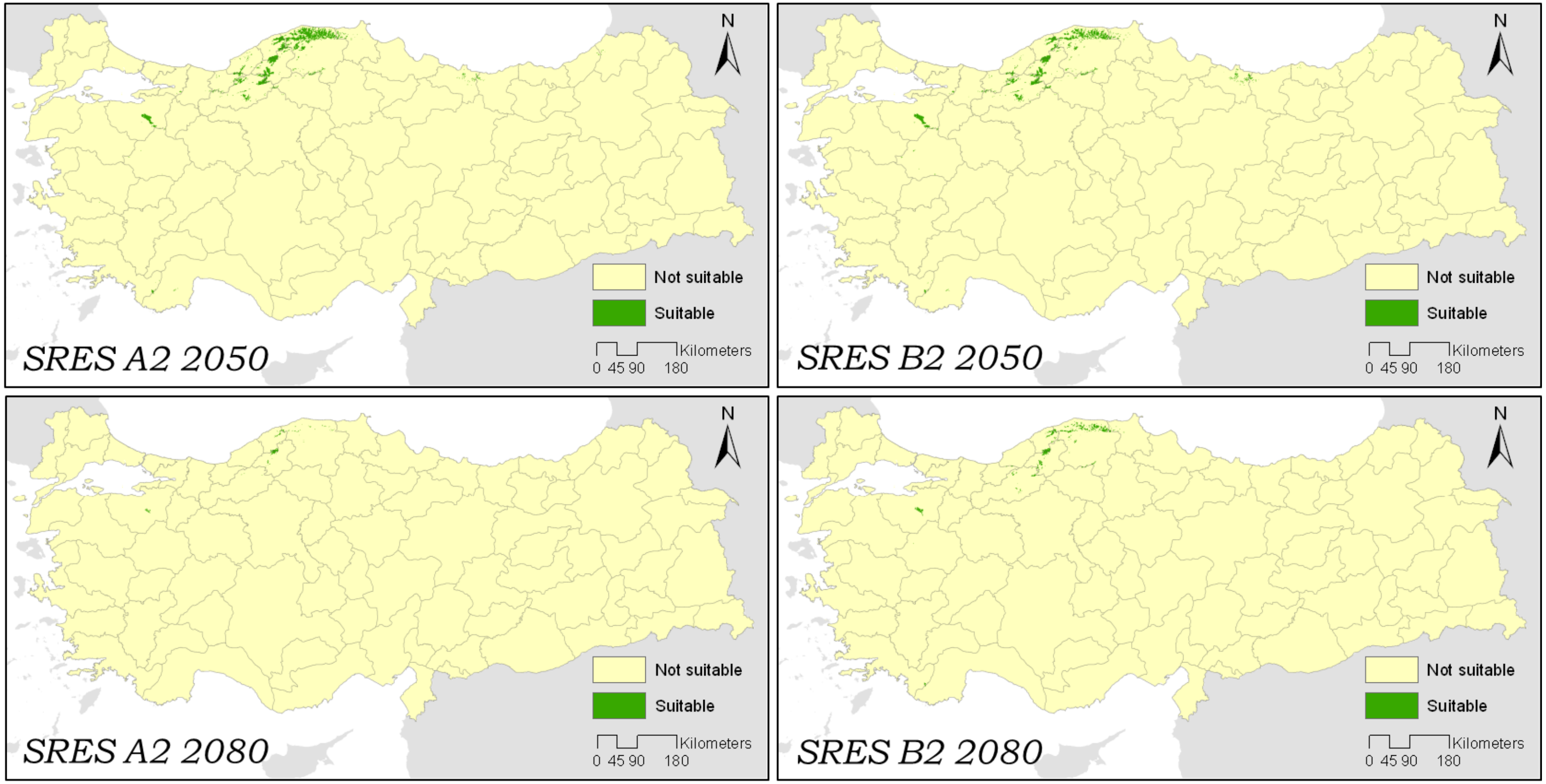

Figure 29 *Future projections (2050 & 2080) of random PA selection strategy of SRES A2 and B2 scenarios*

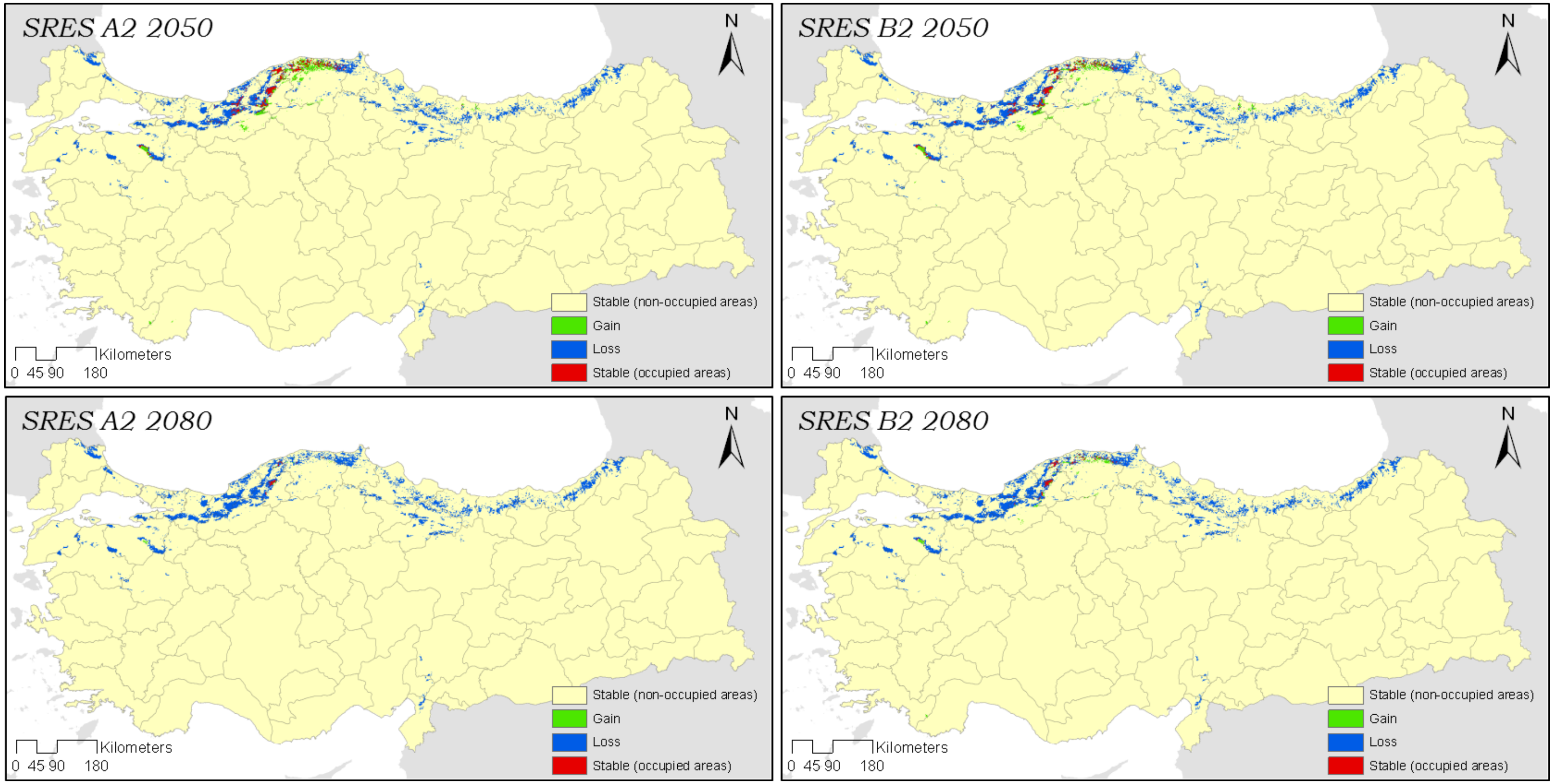

Figure 30 *Gain/loss maps of future projections of random PA selection strategy of SRES A2 (left) and B2 (right)*

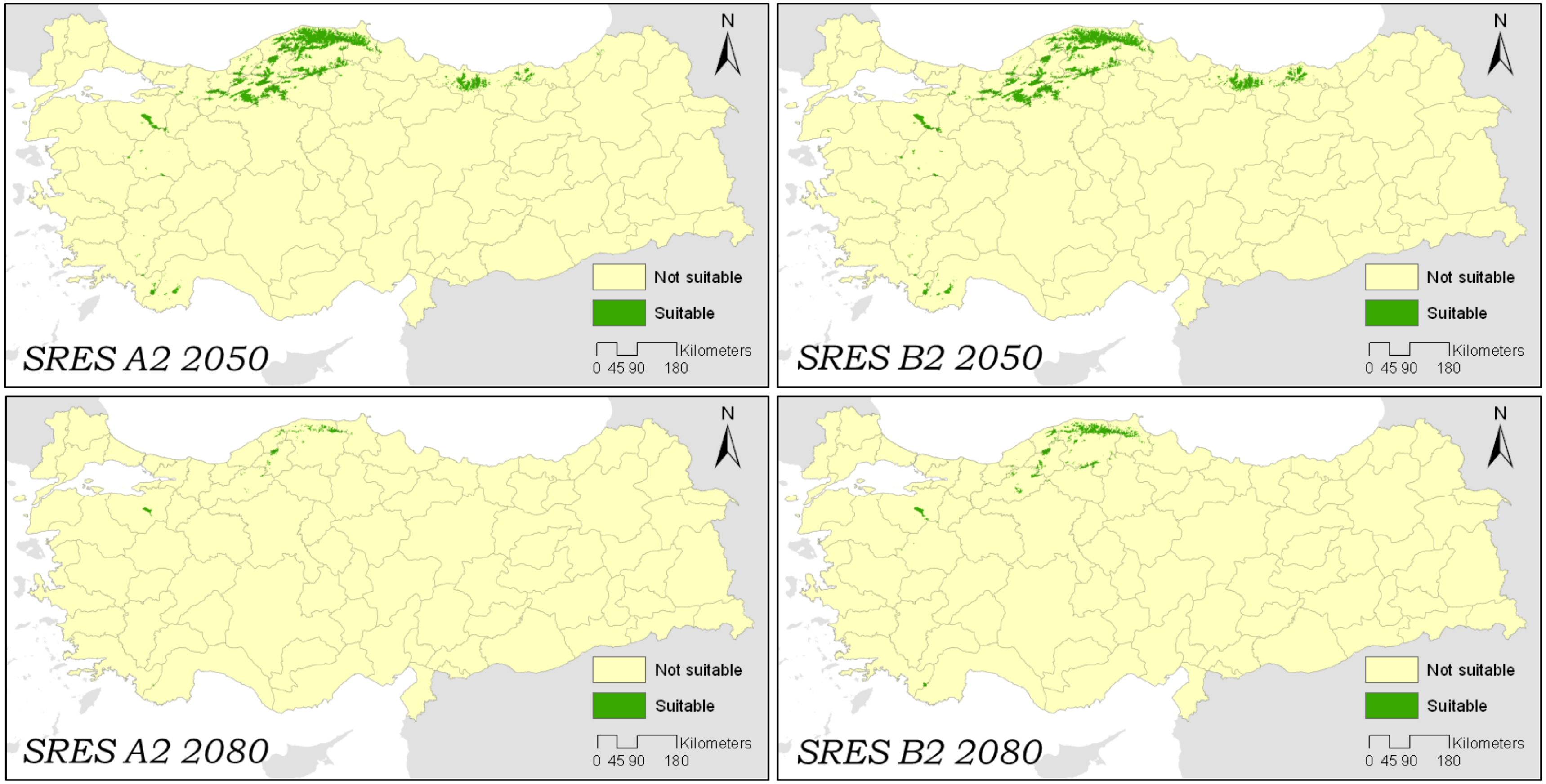

Figure 31 *Future projections (2050 & 2080) of SRE PA selection strategy of strategy of SRES A2 (left) and B2 (right)*

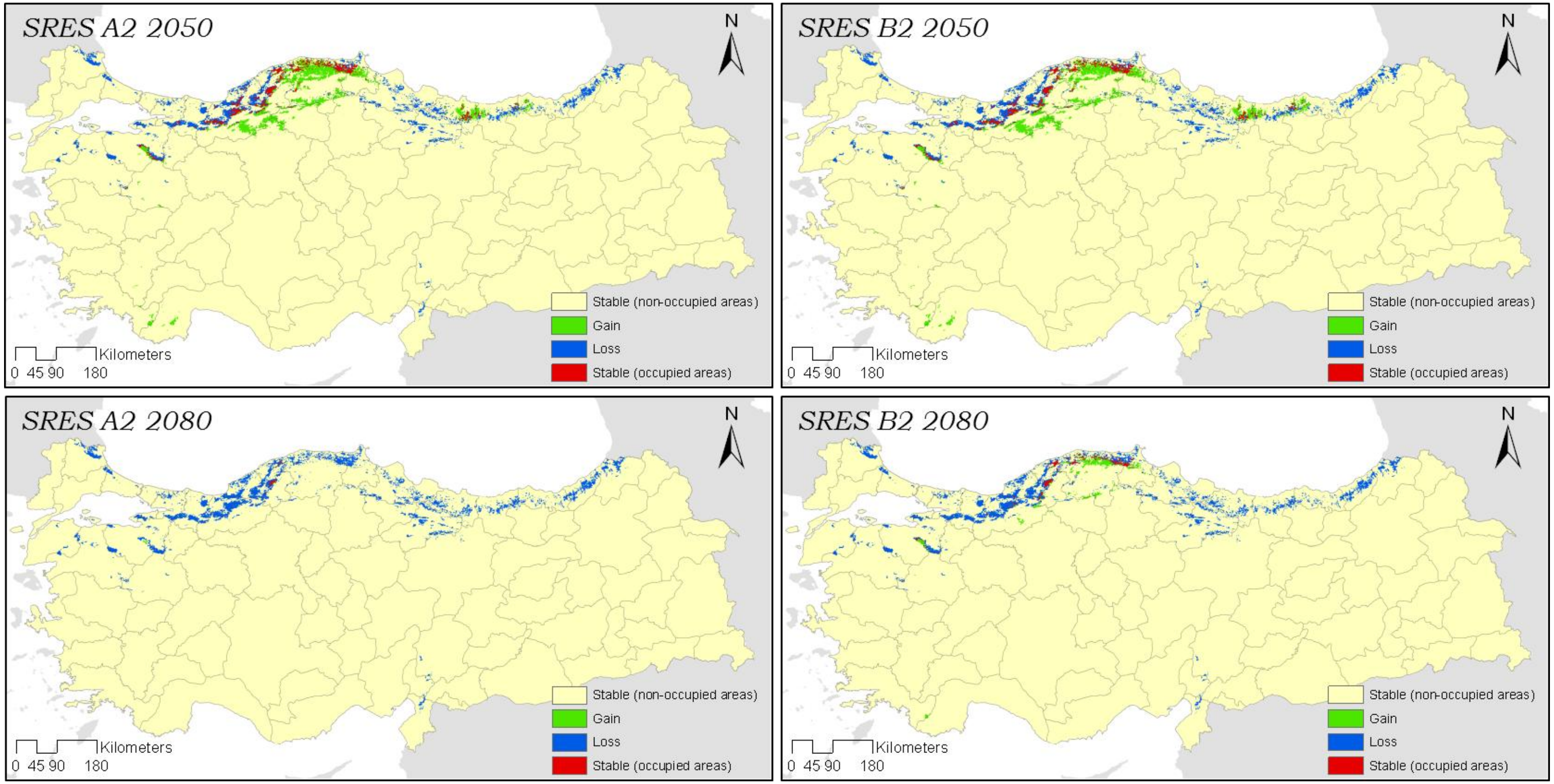

Figure 32 Gain/loss maps of future projections of SRE PA selection strategy of SRES A2 (left) and B2 (right)

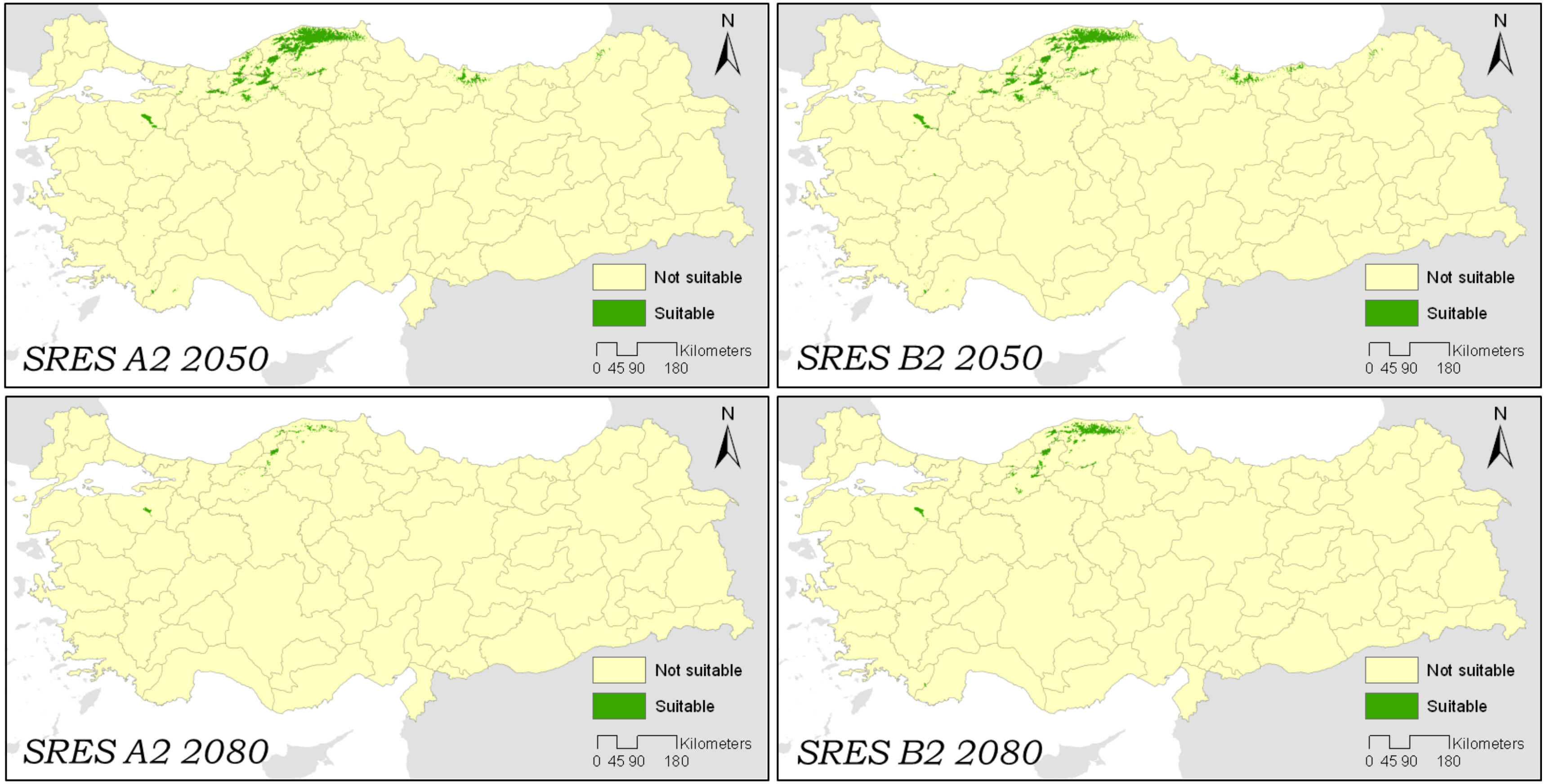

Figure 33 *Future projections (2050 & 2080) of disk PA selection strategy of strategy of SRES A2 (left) and B2 (right)*

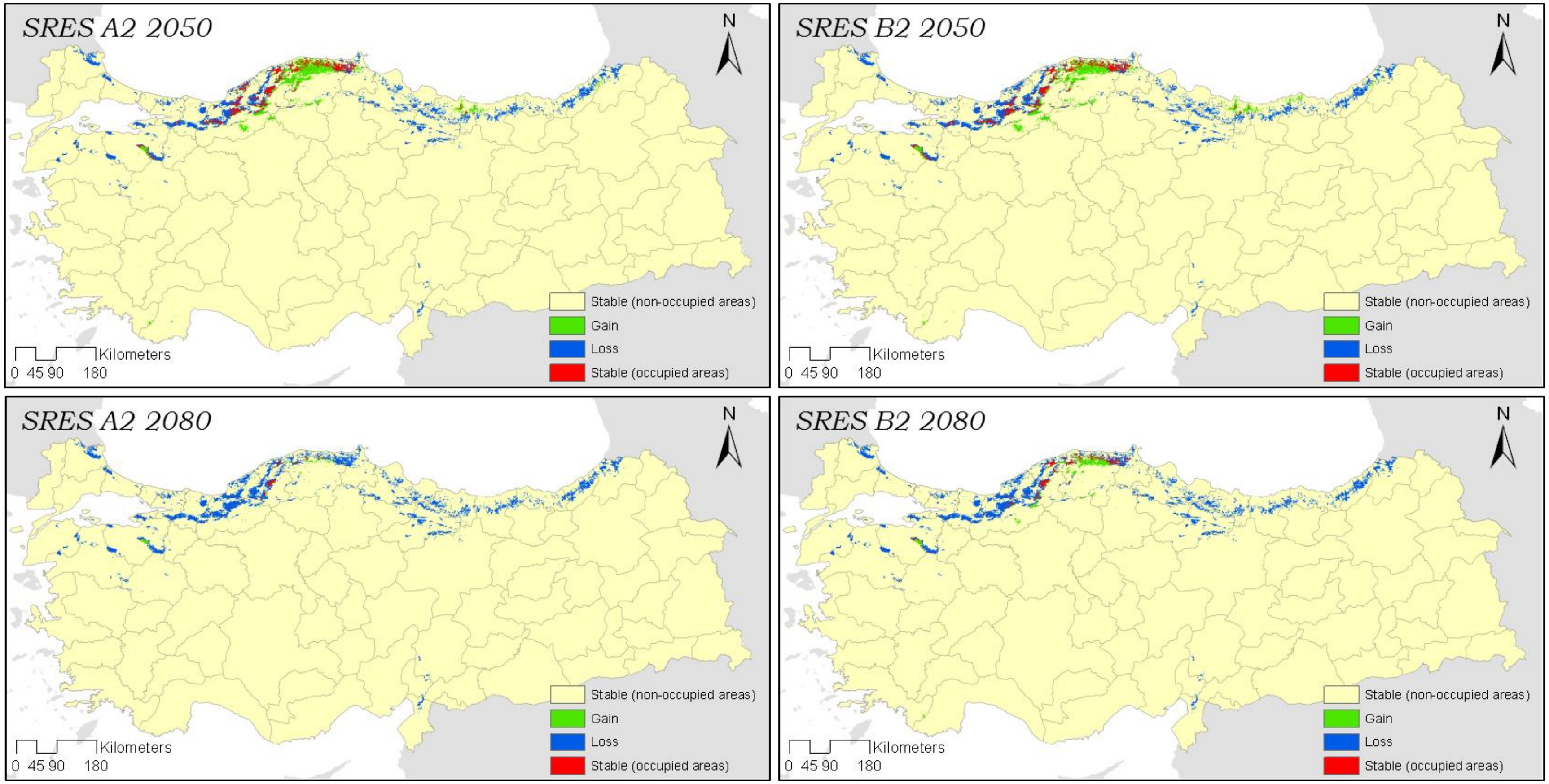

Figure 34 *Gain/loss maps of future projection of disk PA selection strategy of SRES A2 (left) and B2 (right*

CHAPTER IV

DISCUSSION

4.1. Assumptions and Uncertainties

In this study, we focused on the possible changes in the ranges of two tree species in Turkey in the face of climate change. Our methodology was based on species distribution modeling under some assumptions. Since models are just an image of the reality, they can have present uncertainties leading to variations in the outputs of SDMs. Quantification of uncertainties in projections is vital for integrating climate change considerations into conservation action plans.

Our first assumption is that abiotic and biotic variables influence species distribution at different spatial and temporal scales, in line with the hierarchical theories of ecosystems. These theories suggest that abiotic factors influence species distributions at a global, continental or regional scale, whereas biotic factors such as intraspecific or interspecific interactions affect species ranges within a local or micro environment (i.e. they are at the bottom of the hierarchy) (Pearson & Dawson, 2003; Meier *et al.*, 2010). Since our study covers the whole of Turkey, hence at the regional scale, we use only climatic and topographic variables to model ranges of Turkish pine and oriental beech. We used variables at 1 km resolution, which we assume a pixel size capable to capture variations of environmental factors affecting species distribution at the regional scale, but large enough to exclude biotic variables. Accordingly, it is adequate for our study aim, which is to model climatically suitable areas of species at the current time and future.

Inaccurate species presence and/or absence data is another source of uncertainty in SDMs (Phillips *et al.*, 2009). We used high resolution (1/25.000) forest stand maps for both species, so one claim that the presence points used in this study are accurate. However, as mentioned previously, we generated pseudo-absences (PA) from under certain assumptions. We used three strategies to generate PA namely, random, SRE and disk. In the random strategy, it was possible to select real presence points as absence. In the SRE strategy, we excluded environmental space defined by used training presence data set. In the disk strategy, we put a distance limit around the training presence points. Therefore, in the SRE and disk strategies, we minimized the selection probability of a true presence as PA. The drawback of SRE or disk strategy is that their choice is directly linked to presence data set. To reduce the effect of an atypical presence data set, we repeated PA selection five times in all strategies.

Another source of uncertainty is the model algorithms used. Each algorithm has strengths and weaknesses that can be difficult to interpret (Elith *et al.*, 2006). Variability in predictions from alternative modeling methods is observed; moreover, it is not possible to decide a “best” technique for predicting potential species ranges. Consequently, selection of an adequate modeling method from a diverse collection of techniques is a critical step. To circumvent this problem, we used eight different modeling techniques to compare each model’s ability to simulate observed presences and absences, and then built up a consensus (or ensemble) model using them. The main advantage of the ensemble approach is that the strength of each model is combined to create a new output. Moreover, the ensemble approach allows us to observe the variability within different model projections.

A further source of uncertainty in SDMs is the selection of thresholds (cut-offs) to transform modeled probabilities of suitability into binary (present/absent) predictions. There are potentially as many rules for setting thresholds as modeling methods and the choice is often made arbitrarily since no guidelines for selection exist (Nenzén *et al.*, 2011). We used a threshold that maximizes the prediction percentage of presence and absence correctly. It reduces the risk of excluding true occupied areas (omission errors) or including false presence areas (commission errors).

To project future species distribution in the face climate change, the most important input is the future climate models. However, inherently, an unknown fraction of the uncertainties in future conditions are introduced to SDMs. These uncertainties were sourced from the equations that formalize the global climate and circulation system, limitations of computing power and regarding climate sensitivity. Moreover, downscaling process of climate models used is another source of climate models. There is no single best climate model, they vary spatially and temporally in their ability to simulate current climate in one variable or region (Beaumont *et al.*, 2008). We used only one climate model, Hadley Centre Coupled Model version 3 in this study. There are two reasons to use this climate model. First, this climate model results have been used in many previous SDM studies. The other reason is that the data of climate model is accessible in high resolution for any region and any time period. Therefore, we admit that some uncertainties in our study might stem from this particular climate model. The choice of future climate scenarios for species distribution modeling is important. On the other hand, by using two different SRES scenarios, it was possible to investigate the range of possible climate change uncertainties due to future GHG emissions.

There is also some uncertainty about the reactions of forest ecosystems to climate change. The intensity of human disturbance, the frequency and intensity of extreme events, presence of possible invasive species, forestry applications, possible dispersal barriers and future biotic interactions in the future remain unclear today.

4.2. Performance Measurement of Trained Models

All trained models were compared in terms of discrimination to assess performance measures. Performance measures are informative for determining the suitability of the model results for specific applications and for identifying weaknesses of the models. We carried two performance measurements at the different modeling stage.

First, after training the models, BIOMOD calculated AUC, TSS, sensitivity and specificity values by using a set of test data (the first performance measurement). Secondly, after projection to current conditions, all probability maps of suitability were transformed to binary maps by using a set threshold. The success of model predictions was compared with the current distributions. In other words, binary maps of predictions were tested with all points of presence and absence gathered from the raster stand maps (the second performance measurement). Accordingly, sensitivity, specificity, AUC and TSS values were calculated by using test data, while overall accuracy, precision, F-score, and false positive rate were calculated during performance measurements. Since these two types of measurements use different datasets for evaluation, their results may be different for the same modeling method. In both performance measurements, sensitivity and specificity were calculated and therefore constituted a link between the two measurements.

4.2.1. Effects of Different Pseudo-absences Selection Strategy

Based on the first performance measurement, ensemble model results of both Turkish pine and oriental beech show the highest AUC value in SRE and/or disk strategy, and the lowest in random strategy. The case same order was observed for TSS scores too. Sensitivity scores for Turkish pine models are ranked, from highest to lowest, as disk, SRE and random. The lowest sensitivity score for oriental beech is observed with random strategy too, while SRE and disk have the same sensitivity score. The specificity scores show the same pattern as sensitivity for both species. However, the second performance measurement indicates that the results of random strategy show the highest overall accuracy in both species. Moreover, sensitivity and specificity evaluations present different scores. The reason behind these conflicting observations might be because the sample size of test data (both assigned true presence and absence) used for evaluation was different in each type of performance measurement. In the second performance measurement, a larger dataset was used to test the performance of the models that led to sensitivity and specificity scores for ensemble models varying under different strategies.

These differences in performance measurements also revealed critical information on the effects of different PA selection strategies on model predictions. In contrast to first performance measurements, the random strategy results always showed the highest specificity score with the lowest false positive rate under the second performance measurements for both species. Therefore random strategy could be considered to be more “conservative” because it attempts to predict fewer suitable areas than SRE and disk strategies. Consequently, its sensitivity values were smaller but its specificity values were higher across all strategies. On the other hand, ensemble models with SRE and disk strategies cover larger areas as suitable for each species, which leads to higher sensitivity but also higher false positive rates. Consequently, the decision of which PA selection strategy to use in the training of models is directly linked to the aim of the study. For finding future ranges of species (like in our study), to find all suitable areas correctly is more important. Since prediction of suitability at a site where species has not been observed can be associated with non-climatic factors (e.g. human disturbance) that limit the actual distribution. On the other hand, failure to predict an existing (i.e. occupied) habitat as suitable leads to possible errors in future predictions.

The possible reason why PA selection strategies behave differently is that there are differences among strategies in the aspect of bearing information to the models. In random PA selection strategy, there is a higher chance to select true presence as absence (i.e. false absence), which could lead to narrower predictions of suitable areas. On the other hand, in both SRE and disk strategies selected PA are more accurately representative of absence. Therefore, their predictions are likely to find all suitable areas to minimize the percentage of false absences.

4.2.2. Single Modeling Methods and Ensemble Models

Our results were examined as three classes according to which PA selection strategies had been used.

(1) Random PA data selection strategy

Turkish pine: Except ANN and CTA, other modeling methods had mean AUC values higher than 0.90 with small deviation, which means models provide excellent predictions of Turkish pine. CTA result showed highest mean sensitivity result. This is because CTA overestimated the presence of species; in other words it found more suitable area than other methods. Therefore its sensitivity score is not an indicator of its success as a method. According to the second performance measurements, the highest false positive rate was seen in the result of CTA. It should be noted that CTA behaves similarly in disk PA selection strategy too, possibly again due to overestimation of suitable areas. The highest overall accuracy, precision and F-score, and the lowest false positive rate were seen in the ensemble model. We conclude that for Turkish pine, when using pseudo-absence generated randomly, the ensemble model show highest best performance compared to using a single modeling algorithm.

Oriental beech: All modeling methods have mean AUC values higher than 0.75. When ANN and CTA models are removed, this score rises to 0.91. The AUC value for ensemble model is 0.97, which means a perfect prediction. Similar to Turkish pine results, the highest sensitivity score was obtained with CTA. We assume that the explanation is similar to that of Turkish pine case, an overestimation of presence of the species. When comparing best models with respect to current stand map, the highest overall accuracy is found for the ensemble model.

(2) SRE PA data selection strategy

Turkish pine: The mean AUC values were higher than for random strategy for all modeling methods and ensemble models. The minimum mean AUC value was 0.92 for CTA and the highest mean AUC value was 0.98 for MAXENT, and the AUC value of ensemble model was 0.99.

Additionally, TSS scores for all modeling method increased accordingly. These increases in TSS are linked to increases in sensitivity and specificity scores under the SRE strategy. The highest sensitivity and specificity was found in the result of the ensemble model, which were higher than 94, which means 94% of test data were found correctly either as presence or absence. The first performance measurements show that the ensemble model approach is much more successful than single modeling methods. In contrast, best runs of single modeling methods show equal or better scores for the second performance test. For instance, the overall accuracy of the ensemble model is 0.83, whereas it is 0.83 for CTA, 0.83 for GBM and 0.84 for RF best runs. Moreover, some modeling algorithms (such as GAM, GLM, MAXENT, RF) have similar sensitivity scores with the ensemble model. Although this situation appears that the second and first performance measurements disagree, we believe this a bias due to the fact that the best runs of methods (i.e. which has the highest AUC value) were used to calculate the evaluation metrics in the second evaluation step. Therefore, the first performance measures should be considered for comparing each modeling algorithm with one other and for analyzing the performance of the ensemble model over single modeling methods. Whereas, the second performance measurements could be used for comparing best runs of single modeling methods among themselves and for comparing effects of using different PA selection strategies on the ensemble models.

Oriental beech: All model results show very high AUC values. Additionally, the ensemble model got a 0.99 AUC value, a near perfect outcome in the first performance measurements. On the other hand, similar to Turkish pine result, the evaluation metrics of second measurements did not indicate ensemble model as the best method. Instead, the random forest results show the highest scores in all metrics among single modeling methods.

(3) Disk PA data selection strategy

Turkish pine: The single modeling methods have very high AUC values, such that they could be accepted as perfect predictions. The ensemble model has the highest AUC values, 0.99, over all modeling methods.

The sensitivity and specificity scores of ensemble model were higher than random and SRE PA selection strategies. However random forest showed higher specificity score than the ensemble model, similar to other PA selection strategies. Furthermore, in second performance test best run of random forest showed lowest false positive rate and the highest overall accuracy among all methods.

Oriental beech: Again the mean AUC values of each modeling methods were high enough to consider model results excellent. The increases of TSS values are bigger than for AUC due to increased sensitivity and specificity values. Although the ensemble model showed highest evaluation scores in the first performance test, random forest achieved almost equal scores of evaluation metrics with the ensemble model, in terms of overall accuracy, specificity, precision, F-score and false positive rate.

4.3. Current Projections: Failures and Successes

The size of predicted suitable areas was differently in each PA selection strategy, but for both species they show same pattern in extent. The random PA selection strategy, as discussed previously, shows narrower distributions of suitable areas for both Turkish pine and oriental than SRE and disk strategies. Thus correct predictions of actual distribution were highest for the results of SRE and disk strategies. Random strategy could not predict 19.23 % of Turkish pine stands, whereas this value was reduced to 4.88 % and 4.13 % in SRE and disk strategies, respectively. This pattern also seemed in oriental beech results: SRE and disk strategies did not predict 4.88 % and 4.18 % of current beech distribution, while random strategy left out 12.89 % of current oriental beech stands. However, not only sensitivity but also specificity rates are important to assess the results of models. The level of discrimination should be considered carefully. If models overestimate the suitability of species, it yields high sensitivity but low specificity. Therefore the main goal should be getting a prediction which balances sensitivity and specificity.

Some of the current presences (7.17 % of Turkish pine stands and 3.43 % of oriental beech stands) were not predicted in any modeling methods. One reason might be that these stands are found in sites which deviate climatically from the general climate pattern but climate models we used are not of high enough resolution to detect those. For instance, models of Turkish pine did not predict areas at the outermost regions of its extent, such as the northern parts of Feke (Adana) or the Kelkit Valley (Tokat), a region known as a microclimatic enclave.
The climatic profiles of these "left out" areas were analyzed with respect to climatic constraints of the species concerned. Minimum temperature of the coldest quarter and precipitation of the driest quarter were used as limiting factors for Turkish pine and oriental beech, respectively. The minimum temperature of areas not correctly predicted Turkish pine is 2.33 ± 1.44°C, whereas 6.88 ± 2.28 °C for the correctly predicted areas. Similarly, precipitation of the driest quarter of areas not correctly predicted for oriental beech is 50.86 ± 24.47 mm, whereas 108.19 ± 37.68 mm for the correctly predicted areas. Therefore, the current stands that the models could not predict appear to be in areas with suboptimal climatic character (colder for Turkish pine and drier for oriental beech).

The forest structure of Turkish pine sites that were not predicted in any model, were classified as pure (48%), mixed (13%) and degraded (39%). For oriental beech, percentages were 21% pure stand, 48% mixed and 31% degraded. Both Turkish pine and oriental beech typically occur as pure, undegraded stands due to their dominant nature. The observed low proportions of such pure stands at "failed to predict" sites probably indicate they are at the edge of their environmental tolerances. Moreover, models of oriental beech failed to find the isolated populations in Amanos Mountain (Hatay). This may be either to the wetter than expected local climate there or due to the relict feature of these stands (i.e. they are the remnants of a historical period with more suitable climate than today).

4.4. Future Projections: Where and Why

In this study, we examined two extreme cases of possible migration of species: full migration and no migration. This approach assumes that as climate changes species either migrate to all suitable areas without any obstacles or they cannot disperse at all and try to survive within their current extent; there is no intermediate scenario. This perspective is useful for understanding the emergency of climate change action. For instance, under the 2080 B2 assumptions with no migration, oriental beech forests will cover only 7.23% of their current area; even under full migration they will cover 21.55% of their current range.

The two species studied are expected to behave differently in the future. The main findings indicate that Turkish pine will expand its range northward and into higher elevations although it will lose most of its suitable habitat at the south. For example, in the south there will be a compact forest area (higher than 1200 m) around Anamur Uplands at the conjunction of West and Central Taurus Mountains, where they are expected to receive more precipitation than surrounding areas because of western winds. Similarly, Sandras Mountains/ Muğla (2294 m) will become suitable for Turkish pine growth. In the Aegean region, there will be also a shift to higher elevations but not much as in the Mediterranean region. Aydın Mountains (1831 m), Bozdağlar (2159 m) and Spil Mountains (1517 m) will become largely suitable for Turkish pine. Moreover, the whole of Kazdağı (1174 m) will become suitable too. In the inner northwestern regions of Turkey, areas through Alaçam Mountains to along Köroğlu Mountains (Bolu) will become suitable for the first time. The northern slopes of Canik Mountains will become suitable along the coastline of Black Sea.

However, the change in suitable areas of oriental beech is more dramatic than that of Turkish pine. Most of the current suitable area will be lost at the end of 2050. According to optimistic predictions, only 3 – 7 % of current stands will remain suitable in 2080.

There will be distinct gain and preserved areas in Kastamonu, particularly along the Küre Mountains. For instance, most of the oriental beech forest found in Küre Mountains National Park will be preserved. Moreover, there will be some gain along Ilgaz Mountains. Another compact area will remain on the higher altitude areas (above 1000m) of Yenice Forests. However, most of the current distribution of beech around Uludağ Mountains will be lost, and areas at the higher altitude, where forest cover is not found today, will become suitable for beech in the future.

The impact of climate change can change according to ecological and geographical characteristics of a species (Broennimann *et al.*, 2006). Turkish pine is a generalist species which has a large niche breadth; it is also adapted to a relatively dry and warm climate. Therefore, it shows more range expansion than oriental Beech. In contrast, oriental beech is a specialist species whose environmental preferences are on the wetter end, especially depended dependent on summer precipitation. As a result, it shows large range contractions in its current distribution.

4.5. Possible Improvements of Modeling

Our models only focused on climatic and topographic variables, since our aim was to analyze possible changes in forest range at the regional scale. We used only 2050 and 2080 as time slices due to the lack of appropriate data for other dates, although to use in conservation assessments/ planning, shorter time periods such as ten years slices might be better.

One improvement could be to model the change at local scales to better understand effects of climate change on species distribution. Such studies could focus on integration of important processes such as mortality, dispersal, regeneration, biotic interactions and disturbance, as well as other predictor variables such as future land use and fire regimes to be included in future projections.

4.6. Use of Model Outputs in the Conservation Management

Climate change is expected to have significant impacts on the distributions of Turkish pine and oriental beech forests in Turkey. Depending on whether fast dispersal to newly available suitable habitats will be possible or not, serious ecological, economic and social consequences are probable. SDMs can be used to understand possible responses of species to climate change. Despite some sources of uncertainty, projections onto future climate are useful and cost-effective tools for managers, especially given the increasing urgency to inform management decisions under pressure from climate change.

SDMs can use to identify both vulnerable areas to climate change and possible refuge areas in future. Consequently, conservation plans and also forest management plans can be prepared to protect/strengthen these areas. The strategies to protect these areas against human disturbance should be developed to minimize habitat loss and fragmentation for improving species resilience to climate change. For example, Turkish pine will preserve its suitability in the upper regions on Marmaris Peninsula. Those areas should be protected from further threats caused by people such as fragmentation to ensure species occurrences in future.

Moreover, SDMs can be used for evaluation of current protected areas in the manner of their areas, places, size, layout and design (Araujo *et al.* 2011). The outputs of modeling studies can be used for enhancing connectivity between suitable areas in different time frame for increasing a species' chances for dispersal (Hannah *et al.* 2007). For instance, the current distribution of oriental beech in Kure Mountains National Parks will preserve suitability and around this core area new habitat will appear for the species. The size and layout of Kure Mountains National Park could be reviewed to cover all suitable areas or at least, the connectivity between national park and these newly emerged habitats could be established.

Furthermore, maintaining genetic diversity of a species is crucial to adapt climate change. Range reductions are likely to lead to loss of genetic diversity (Alsos *et al.*, 2012). Particularly oriental beech is going to lose some genetic diversity loss.

To conserve genetic diversity, seeds could be collected from distinct populations likely to become extinct in the future and used in forest regeneration efforts or new stands constituted with these seeds in different regions.

Moreover, the current marginal populations are important to conserve genetic diversity in future. They have already adapted different climatic conditions than optimum which is defined with respect to main distribution of species. One of the examples of these sites is Turkish pine forests along northern border of Adıyaman Province. It is necessarily important to protect and manage this type sites for improving habitat quality and reducing other non-climate related threats such as human disturbance in order to enhance forest resilience against climate change. Furthermore, seeds collected from that type of sites could be used in the ex-situ conservation activities such as planting in seed orchards or using for transfer of species to newly emerging suitable areas.

Another strategy should be to look for possible ways to control invasive and pest outbreaks. It is expected that pest outbreaks will occur more frequently and intensely in future. Therefore, improving and expanding risk assessments and protocols for screening and detection of pests and invasive species are emergency issues.

Monitoring populations at the limits of their bioclimatic suitability will provide more information about species responses to climate change. A network of such monitoring stations should be immediately set up. Last but not least, not only mitigating and adapting to effects of climate change is important but also slowing down climate change itself should be a priority in conservation actions.

CHAPTER V

CONCLUSION

The study was set out to model the current and future potential distribution of Turkish pine and oriental beech by using single-based and ensemble modeling methods and has tested the effects of using different pseudo-absence data on the model predictions.

This study demonstrated that ensemble models have more accurate model predictions than single-based models for both species according to accuracy measurements of models. Moreover, using different sets of pseudo-absence data have apparent effects on the model predictions. According to model evaluations, “disk” strategy showed the highest scores of evaluation metrics and predicted 92.01 % of current Turkish pine forest and 95.82 % of current oriental beech forest correctly.

This study established that there will be might dramatic changes in climatically suitable habitats of both pine and beech in future due to climate change. Turkish pine habitats will expand northward and into higher elevations, whereas suitable areas of oriental beech will become narrower. According to the optimistic scenario, in 2080, only 3217 ha will be climatically suitable for beech, covering a mere 7% of its current distribution.

These projections provide information on potential distribution of species in space and time. Therefore, they are very useful tools which can be integrated into conservation planning. It is imperative to develop further research by coupling distributional models with other methods such as ecosystem modeling to conserve forests ecosystems in the face of climate change.

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