EVALUATION OF WIND POWER PLANT ELECTRICITY GENERATION AT THE MARMARA BASIN BASED ON CLIMATE CHANGE PROJECTIONS

MARMARA HAVZASINDA RÜZGÂR SANTRALLERI ELEKTRİK ÜRETİMİNİN İKLİM DEĞİŞİKLİĞİ PROJEKSİYONLARINA BAĞLI OLARAK DEĞERLENDİRİLMESİ

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To my family…

ABSTRACT

EVALUATION OF WIND POWER PLANT ELECTRICITY GENERATION AT THE MARMARA BASIN BASED ON CLIMATE CHANGE PROJECTIONS

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Projections indicate a continuing rise in greenhouse gas emissions until 2100, exhibiting an influence on several aspects of climate, such as temperature and wind speed. This research aims to develop recommendations aligning with Türkiye's renewable energy strategies, evaluating the possible impacts of changing wind energy-related parameters on wind power plants. The study focuses explicitly on wind energy-based electricity generation in the Marmara Basin, which accounts for 48% of the installed wind power capacity in the Marmara Region. Machine learning and statistical methods are used to develop models to predict future wind energy-based electricity generation. These models consider wind speed and temperature estimates derived from RCP4.5 and RCP8.5 between 2016-2098. The findings suggest an anticipated decrease in electricity generation from wind power plants in the Marmara Basin, with a predicted fall ranging from -6% to -4% by 2098. This loss is expected to impact about 87 to 144 thousand households' electricity demand, which may require establishing additional wind power facilities.

Keywords: climate change, climate adaptation, renewable energy, wind energy, wind power plant, artificial neural network, multiple linear regression

ÖZET

MARMARA HAVZASINDA RÜZGÂR SANTRALLERI ELEKTRİK ÜRETİMİNİN İKLİM DEĞİŞİKLİĞİ PROJEKSİYONLARINA BAĞLI OLARAK DEĞERLENDİRİLMESİ

Buse Nur HAYTA

Yüksek Lisans, Çevre Mühendisliği Bölümü
Tez Danışmanı: Prof. Dr. Merih AYDINALP KÖKSAL
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Projeksiyonlar, sera gazı emisyonlarının 2100 yılına kadar artmaya devam edeceğini ve sıcaklık ve rüzgar hızı gibi iklim parametreleri üzerinde etkili olacağını göstermektedir. Bu araştırma, rüzgar enerjisi ile ilgili parametrelerdeki değişimin rüzgar santralleri üzerindeki olası etkilerini değerlendirerek Türkiye'nin yenilenebilir enerji stratejileri ile uyumlu öneriler geliştirmeyi amaçlamaktadır. Çalışma, özellikle Marmara Bölgesi'ndeki kurulu rüzgâr enerjisi kapasitesinin %48'ini oluşturan Marmara Havzası'ndaki rüzgâr enerjisine dayalı üretimine odaklanmaktadır. Gelecekteki rüzgar enerjisine dayalı elektrik üretimini tahmin edecek modelleri geliştirmek üzere makine öğrenimi ve istatistiksel yöntemler kullanılmıştır. Bu modeller, 2016-2098 yılları arasında RCP4.5 ve RCP8.5'ten türetilen rüzgar hızı ve sıcaklık tahminlerini dikkate almaktadır. Bulgular, Marmara Havzası'ndaki rüzgar enerjisi santrallerinden elde edilen elektrik üretiminde 2098 yılına kadar %4 ile %6 arasında değişen bir düşüş ortaya koymaktadır. Bu kaybın yaklaşık 87 ila 144 bin hanenin elektrik talebini etkilemesi beklenmektedir ve bu da ilave rüzgar enerjisi tesislerinin kurulmasını gerektirebilir.

Anahtar Kelimeler: iklim değişikliği, iklim uyumu, yenilenebilir enerji, rüzgar enerjisi, rüzgar santrali, yapay sinir ağı, çoklu doğrusal regresyon

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LIST OF SYMBOLS AND ABBREVIATIONS

Symbols

°	Degree
°C	Degree Celsius
E	East
K	Kelvin
ms^{-1}	Meter per second
MWh	Megawatt-hour
N	North
R^2	Coefficient of Determination
V	Speed

Abbreviations

ANN	Artificial Neural Network
C3S	Copernicus Climate Change Service
CMIP	Coupled Model Intercomparison Project
CORDEX	Coordinated Regional Climate Downscaling Experiment
ECMWF	European Centre for Medium-Range Weather Forecasts
EMRA	Energy Markets Regulatory Authority
EPİAŞ	Enerji Piyasaları İşletme A.Ş.
ERA	ECMWF Re-Analysis
ESM	Earth System Model
GCM	Global Climate Model
GFDL	Geophysical Fluid Dynamics Laboratory
GHG	Greenhouse Gas

HadGEM	Hadley Centre Global Environment Model
IPCC	International Panel on Climate Change
MAPE	Mean Absolute Percentage Error
MGM	The General Directorate of Meteorology
ML	Machine Learning
MPI	Max Plank Institute
NOAA	The National Oceanic and Atmospheric Administration
PBIAS	Percent Bias
RCM	Regional Climate Models
RCP	Representative Concentration Pathways Scenarios
RMSE	Root Mean Square Error
SEE	Standard Error of the Estimate
SM	Statistical Model
SRES	Special Report on Emission Scenarios
SSP	Shared Socioeconomic Pathways Scenario
WPP	Wind Power Plant
YEKDEM	Renewable Energy Resources Support Mechanism

1. INTRODUCTION

General information on wind energy and climate change is provided in this chapter. Following general information, the problem statement, the thesis's aim and objective, and the study's scope and structure are outlined, respectively. The thesis will be continued with climate change and the interaction between climate change and wind energy.

1.1. Background Information

The International Panel on Climate Change, in its Sixth Assessment Report [1] confirms that human activities are undeniably causing the climate to warm at an unprecedented pace due to greenhouse gas (GHG) emissions. The report has stated that climate change is likely to lead to a deterioration in the resilience and adaptive capacity of cities, infrastructure such as energy and transport systems due to extreme weather conditions, and will become "faster and more severe," with likely negative social and economic impacts in eleven regions (Africa, Asia, Australia, Central and South America, Europe, North America, Small Islands, Poles, Seaside Cities, Mediterranean Region, and Mountain Regions), including Türkiye. The report suggests that climate-related risks should be tackled by implementing adaptation and mitigation measures to enhance the resilience of assets. It also highlights that the energy sector is susceptible to the impacts of climate change if it is not designed to accommodate changing climate conditions. Climate change may impact the energy industry by reducing the efficiency of power plants due to rising temperatures and changes in wind density and patterns. It could also affect fuel supply and the resilience of energy infrastructure, leading to network disruptions or electricity demand overload during periods of high temperatures [2].

Adaptation to climate change, which is directly related to goal 13 and indirectly connected to the other Sustainable Development Goals established by the United Nations, is increasingly becoming a top issue for governments. In line with the Paris Agreement, the Turkish Government, as stated in the 12th National

Development Plan [3], intends to consistently pursue the efficient and effective utilization of renewable energy resources. This includes minimizing reliance on fossil fuels by increasing electricity generation from renewable sources and developing resilient cities that can withstand disasters and promote a sustainable environment. The ultimate goal is to achieve net zero emissions by the year 2053. Consequently, it may be inferred that investments in wind power plants (WPPs) and other forms of renewable energy might be augmented under Türkiye's 2053 vision.

Türkiye's total installed capacity as of December 2023 is 106,668MW. The installed wind energy capacity accounts for 11.1% of the total installed capacity in Türkiye [4]. The Marmara Region has the greatest proportion of installed wind energy capacity compared to other areas in Türkiye. The 12th National Development Plan of Türkiye aims to increase the installed capacity of wind energy by 58% in relation to the installed capacity in 2022 [3]. Thus, it may be inferred that the Marmara Region will maintain its significance in the realm of wind energy.

However, based on climate change projections obtained from open sources [5], it is expected that Türkiye, including the Marmara Region, will experience substantial increases in average temperature, average maximum temperature, and extreme weather events until 2100. These changes could potentially impact the efficiency of energy plants.

Previous studies on analyzing climate change impacts on wind energy have revealed that wind energy is affected by climate change.

1.2. Problem Statement

Owing to the concerns above, decision-makers (both national and municipal governments), practitioners (including investors, contractors, and consultants), and financiers need to prioritize the adaptation to climate change and the reduction of climate-related risks by boosting the resilience of cities. Investment in renewable energy, such as WPPs, and lowering reliance on fossil fuels are key focus areas in climate change adaptation and risk reduction within the energy industry. Nevertheless, several studies indicate that climate change might impact wind energy generation.

Given Türkiye's strategic goal of increasing renewable energy investments, it is important to analyze the impact of climate change on electricity generation, the potential deviation of existing WPP capacities from planned generation capacities, and the extent to which the growing population, rising temperatures, and electrification of transport can meet the electricity demand.

1.3. Aim and Objective of the Thesis

This study aims to assess the impact of climate change on the electricity generation of WPPs in the Marmara Basin. It seeks to provide an analysis of electricity generation under future climate projections and develop recommendations aligning with Türkiye's climate objectives.

The objectives of the proposed study can be listed as follows:

1. Determining the current WPPs generation shares in the Marmara Basin;
2. Gathering present and projected climate data in the Marmara Basin;
3. Analyzing the impact of climate change on the electricity generation of the currently in-operation WPPs within the borders of the Marmara Basin, based on current climate projections, using models created with statistical and machine learning (ML) approaches;
4. Developing applicable and precise suggestions;
5. Better understanding of climate change impacts specific to Türkiye's electricity sector in the bigger picture and better analysis of medium and long-term strategies for Türkiye's adaptation to climate change.

The project aims to create outputs that are particularly useful for electricity producers, transmission providers, sellers, and institutions and organizations involved in shaping our energy policy. This research will enable institutions and organizations responsible for the energy strategy to assess the long-term electricity generation potential of WPP and examine the effects of climate change stress on electricity generation in the Marmara Basin.

1.4. Scope of the Thesis

The study is based on modeling wind power generation under climate change scenarios using both statistical analysis and ML methods. The Marmara region, accounting for 39% of the overall wind power capacity, is also the most densely inhabited area in Türkiye [6] and exhibits a significant energy demand. Additionally, it is under considerable strain due to the effects of climate change. Therefore, the Marmara region has been selected as the research area to comprehend the susceptibility of wind energy.

Furthermore, the area has been scrutinized in several scholarly publications, maps, and forecasts specifically focused on Eastern Europe and the Black Sea. Selecting this location might minimize the lack of data for comparison and enhance the effectiveness of the analysis.

The study will analyze the installed power and actual electricity generation data of existing and planned WPPs in the Marmara Region. This data will be obtained from Enerji Piyasaları İşletme A.Ş. (EPİAŞ) [7]. The analysis will be conducted using forecasted climate parameters provided by the General Directorate of Meteorology. These parameters will be based on the HadGEM scenario for the Marmara Basin from 2020 to 2099.

The basin map of Türkiye and the coordinates of the WPPs registered in YEKDEM in the Marmara Region are analyzed and compared using Google Earth to align the basin-based climate projections of the General Directorate of

Meteorology. The WPP List in the Marmara Region consists of WPPs registered with YEKDEM and the Energy Markets Regulatory Authority (EMRA) [8].

The research will employ statistical analysis and Artificial Neural Networks (ANN) approaches to examine the correlation between climatic factors and wind energy output. Subsequently, models will be developed based on these approaches. SPSS will be utilized for statistical analysis, while MATLAB will be employed for ANN tasks.

The electricity generation of WPPs in the Marmara Basin is projected using the developed models. The actual output is then compared to the projected generation to quantify the developed models' performance. Recommendations are developed by considering the potential alterations in power generation.

1.5. Structure of the Thesis

This thesis has a total of six chapters. Chapter 1 of the paper presents a comprehensive review of the research. Chapter 2 provides an overview of the fundamental concepts and relevant empirical information about the correlation between wind energy and climate change. Chapter 3 presents previous studies on the analysis of the influence of climate change on wind energy. Chapter 4 presents collecting and analyzing data, developing a model, applying future scenarios, and conducting analyses. Chapter 5 includes the findings and discussion. Chapter 6 provides the final findings and suggestions derived from the investigation.

2. BACKGROUND INFORMATION

This chapter provides an overview of climate change, including radiative forcing, greenhouse gas scenarios, different climate models (global, earth system, and regional), and the Coupled Model Intercomparison Project. Furthermore, the relationship between wind energy and climate change is also addressed. The chapter also discusses wind energy, machine learning applications in wind energy projections, and climate reanalysis.

2.1. Climate Change

Climate change refers to significant long-term changes in historical patterns of climate parameters. Global climate parameters have been changing since the beginning of the Industrial Revolution due to the additional increase in radiative forcing from anthropogenic GHGs [9].

2.1.1. Radiative Forcing

The Sun's energy that reaches the Earth's atmosphere is reflected by the Earth via various means, such as clouds, snow, ice, and heat in the form of infrared radiation [10]. However, not all of the incoming energy is reflected back from Earth, as it is partially absorbed by the oceans, land, and GHGs. This absorption leads to an imbalance between the incoming and outgoing energy, known as radiative forcing. This disparity may lead to fluctuations in the Earth's average temperature, resulting in higher or lower temperatures [11]. The summary illustration of radiative forcing is demonstrated in Figure 2.1.

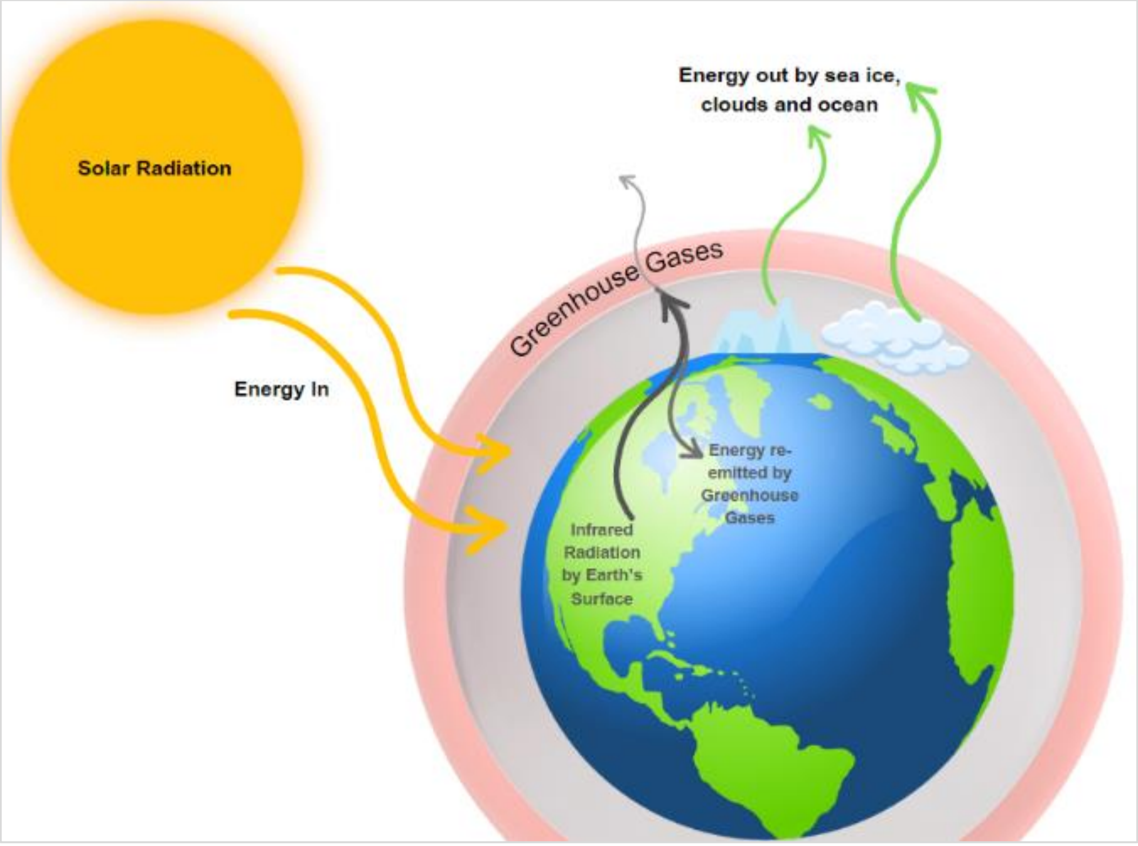


Figure 2.1. Radiative Forcing – Summary Illustration

Following the Industrial Revolution in 1760, human activities have altered the preexisting radiative forcing via the emission of GHGs. The study of IPCC [12] has shown that the abundance of gases relevant to the radiative forcing in 1750 has notably increased in 1998.

2.1.2. Greenhouse Gases

GHGs (carbon dioxide, methane, ozone, nitrous oxide, chlorofluorocarbons, and water vapor) are present in the atmosphere naturally and contribute to the radiative balance of the Earth's surface. Each of them has a different lifetime in the atmosphere. For instance, nitrous oxide could be present in the atmosphere for 109 years, whereas the lifetime of methane is 11.8 years [13].

Human activities such as fossil fuel use, transport and combustion, deforestation or land use change, and fluorinated gases have increased the global concentration of GHG, thereby changing the radiative forcing [14].

The following figure illustrates the GHG amount from 1750 to 2015 calculated by The National Oceanic and Atmospheric Administration (NOAA) [15].

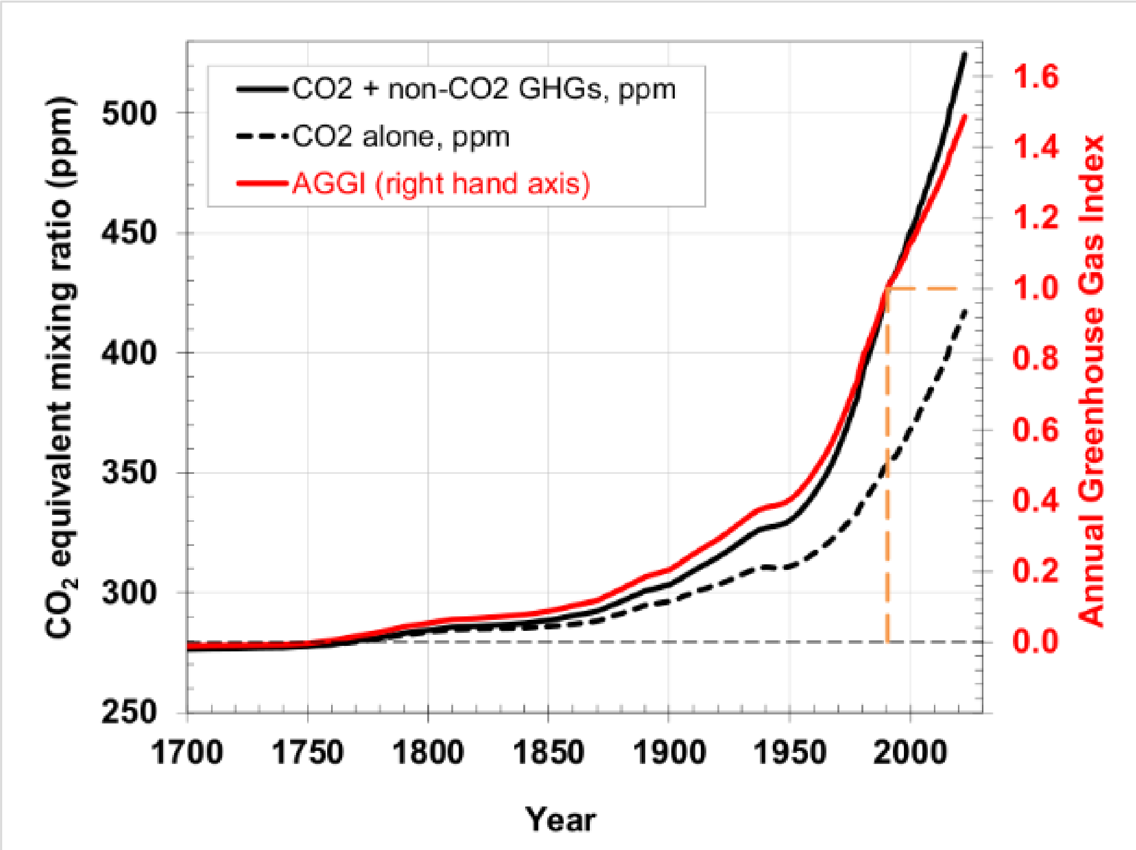


Figure 2.2. The GHG Amount between the years 1750 – 2015 [15]

As seen in Figure 2.2., GHG have increased significantly since the 1900s. Transportation, energy generation, and usage are responsible for the majority of global emissions [16]. The augmentation of GHG causes the increase of radiative forcing. The radiative forcing increased by 45% between 1990 and 2019 [14].

The increase in radiative forcing leads to a rise in the global temperature. The upward trend in the average world temperature leads to changes in climate-related factors such as precipitation, sea level, temperatures, hydrogeological cycles, and so on [9].

The Sixth Assessment Report of the International Panel on Climate Change [1] unequivocally affirms that human activities are indisputably responsible for the extraordinary acceleration of global warming, mostly owing to the generation of GHGs.

2.1.3. Greenhouse Gas Scenarios

Forecasting future GHG concentrations may enhance comprehension of climate change. However, the estimation of the GHG quantity in the atmosphere is influenced by several factors, including population increase, socioeconomic development, technical advancements, and the type of industrialization. In light of this complicated framework, scientists have devised scenarios such as "Special Report on Emission Scenarios", "Representative Concentration Pathways", and "Shared Socioeconomic Pathways Scenarios" to illustrate vulnerabilities to climate change and formulate adaptive strategies to combat it.

2.1.4. Special Report on Emission Scenarios

“Special Report on Emissions Scenarios (SRES)” consists of six scenario groups, A1F1, A1B, A1T, A2, B1, and B2 in accordance with the fossil fuel uses. A1F1 describes a fossil fuel-intensive scenario, whereas B2 represents environmental, social, and economic sustainability on a local basis. Figure 2.3 demonstrates the output CO_2 patterns of the SRES scenario [17].

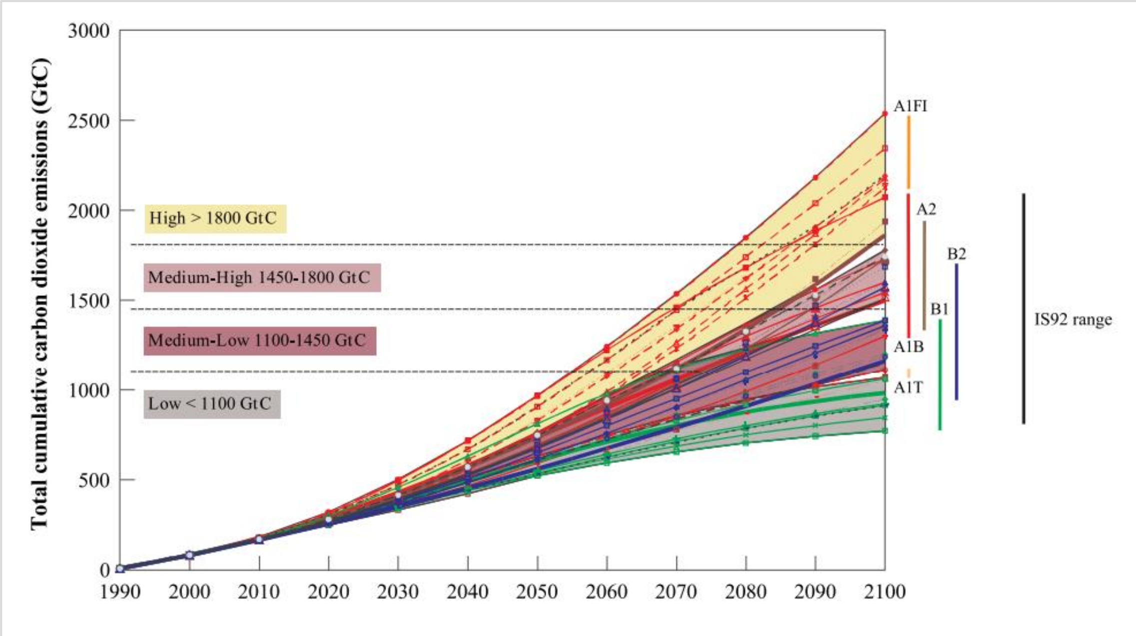


Figure 2.3. The output CO_2 patterns of SRES [17].

2.1.5. Representative Concentration Pathways Scenarios

The developed SRES are based on the policy differences in fossil fuels. However, policies on land use also affect the amount of GHG in the atmosphere. The IPCC has therefore developed a new scenario, “Representative Concentration Pathways (RCPs)”, based on those used in academic studies. The scenario covers both radiative forcing and land use. The RCP includes four different pathways to 2100, which have been identified according to radiative forcing levels: 2.6, 4.5, 6, and 8.5 Wm^{-2} [18].

The RCP2.6 scenario comprises GHG emissions at a low level. RCP4.5 consists of low GHG emissions and low mitigation activities, while RCP 6 has a high mitigation level but medium-level GHG emissions. RCP 8.5 is designated at high-level radiative forcing [19].

The figure of demonstration of RCP scenario patterns is given below:

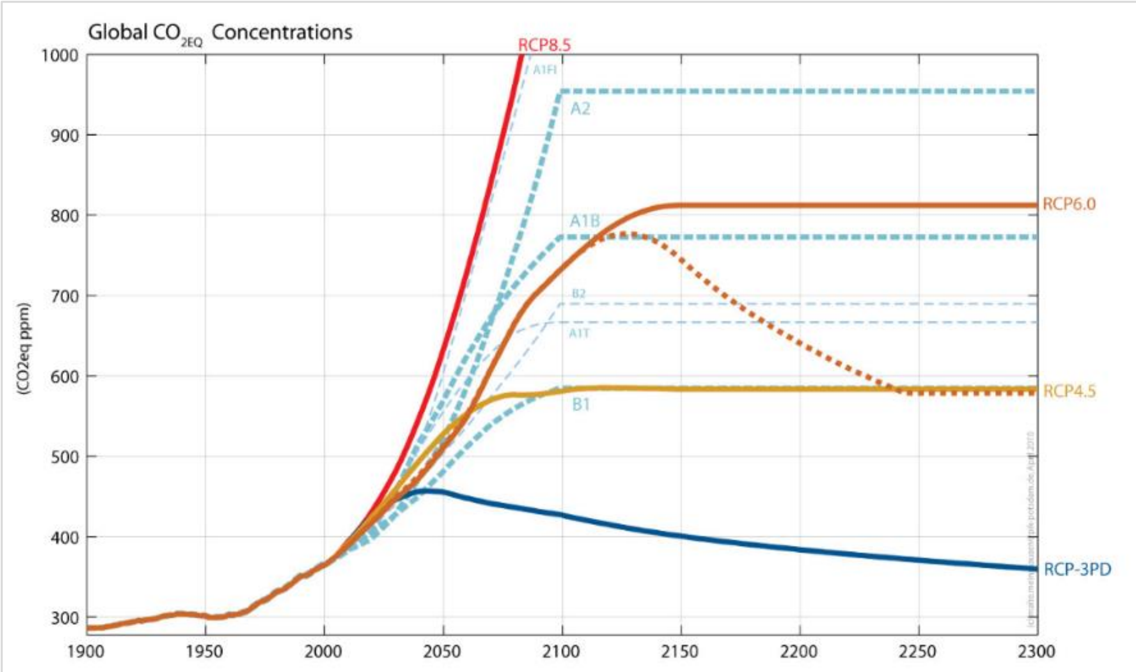


Figure 2.4. CO_2eq Emission Estimation of the RCP [18]

Figure 2.4 demonstrates that the scenarios differ from the SRES, except for the RCP 8.5 and RCP 4.5 scenarios. The RCP 8.5 pathway is almost similar to A1F1, whereas the RCP4.5 has a similar pattern to the B1 scenario of SRES.

2.1.6. Shared Socioeconomic Pathways Scenarios

The "Shared Socioeconomic Pathways" (SSP) examines five distinct scenarios, SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5. The SSP assesses the potential reduction of emissions based on the level of action taken to combat climate change. Factors such as population size, economic expansion, educational attainment, urbanization, and technological advancement are considered [20]. The SSPs are detailed in Figure 2.5 [21].

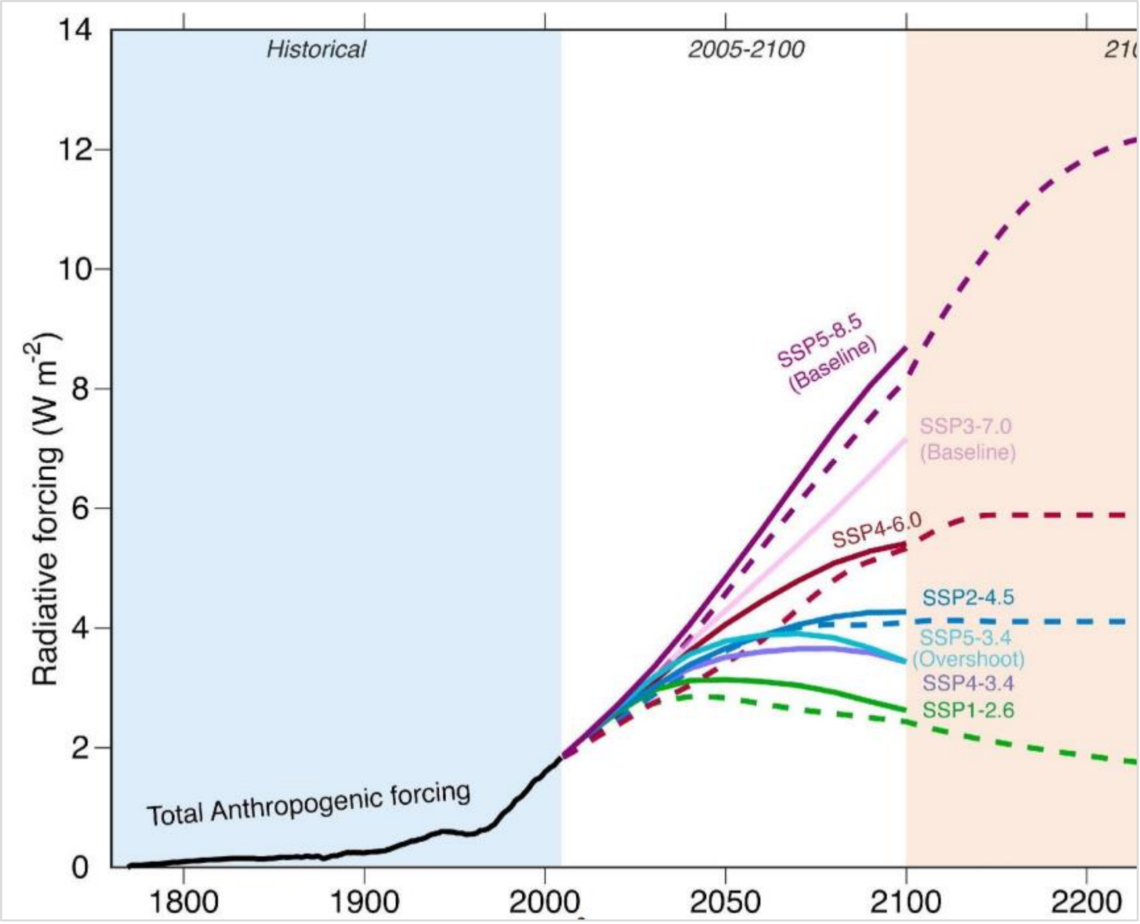


Figure 2.5. CO_2eq Emission Estimation of the SSP (Dashed curves represent RCP scenarios while solid curves represent SSPs.) [21]

The climate models are combined with the scenarios mentioned earlier to understand future climate change trends. The following section elucidates these models.

2.2. Climate Models

Climate models are advanced computational simulations that aim to forecast and comprehend Earth's future climate. They achieve this by incorporating complex interactions among the atmosphere, oceans, land surface, and other elements. These models help evaluate potential consequences and provide insights for strategies to reduce and adapt to climate change.

2.2.1. Global Climate Models

Global Climate Models (GCMs) are computer programs replicating extended weather trends. They analyze the interlinkages of the atmosphere with land, ocean, and sea ice, considering physical laws such as energy and ideal gas laws and different parameters such as air temperature, pressure, density, water in gas form, and wind, as well as GHG amounts [22].

2.2.2. Earth System Models

Earth System Models (ESMs) have been developed for climate models to include interactions of biological components of the Earth. This is because the biological components are also natural producers of GHGs. ESMs include additional features compared to Global Climate Models, such as atmospheric features, the hydrosphere, the biosphere (including vegetation-soil interaction), the carbon cycle, ocean circulation, and biogeochemistry. After the Coupled Model Intercomparison Project 3 phase (refer to Section 2.2.3), this approach has been widely adopted by global institutes and projects, such as the Hadley Centre Global Environment Model (HadGEM), Max Planck Institute (MPI), Geophysical Fluid Dynamics Laboratory (GFDL), Earth System Grid Project, and Earth System Grid Federation [23].

Climate models aid in comprehending the behavior of climate parameters over the long term by considering various GHG emission levels in the atmosphere. Despite uncertainties arising from atmospheric interactions such as clouds [24], these models are the primary tools for illustrating the response of the climate system to increasing GHG emissions [25]. CMs operate using 3D grid boxes with a resolution of 500 km, as shown in Figure 2.6 [26].

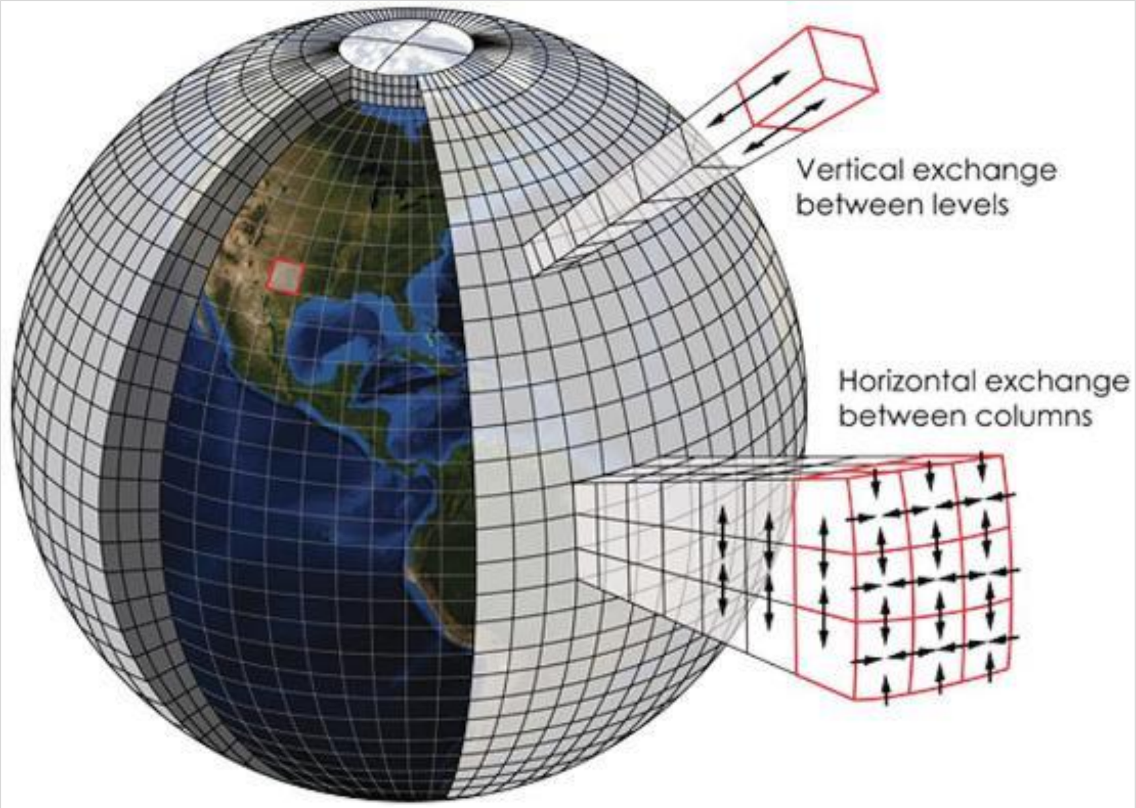


Figure 2.6. An Example for Grids of Climate Models [26]

2.2.3. Coupled Model Intercomparison Project

The World Climate Research Programme initiated the Coupled Model Intercomparison Project (CMIP) in 1995 to compare the results of various climate models. This comparison has led to a better understanding of uncertainties, model performance, and climate change parameters. The project has undergone several phases throughout its history, including [27];

- CMIP1 in 1995 ran with 21 models,
- CMIP2 in 1997 ran with 18 models,
- CMIP3 in 2003 that could define climate change problems by A1, A1B, B1 scenarios, and the results has been assessed in IPCC AR4 Report,
- CMIP5 in 2006-2013 that could define climate change problems in near-term and long-term phases by RCP2.6, 4.5, 6, and 8.5 scenarios. The results have been assessed in the IPCC AR5 Report, and

- CMIP6 in 2013-2019 used Shared Socio-Economic Pathways with 48 model groups. The results have been assessed in the IPCC AR6 Report.

2.2.4. Regional Climate Models

As discussed in Section 2.2.2, the global climate models used for forecasting have low resolution, approximately 500 km. Therefore, they cannot accurately represent specific regional analyses due to the model's inefficiency in reflecting the region's topographical, coastal, and land areas. Regional Climate Models (RCMs) have been developed with higher resolutions to conduct regional assessments and analyze climate change more effectively. For example, the World Climate Research Programme has developed an RCM called the Coordinated Regional Climate Downscaling Experiment (CORDEX) for smaller scales [28]. In addition, the National Center for Atmospheric Research has developed another regional climate model known as the Regional Climate Model System [29]. Dynamic Downscaling Techniques are another RCM that could be used to create continental projections for adaptation measures on a smaller scale for individual countries [25]. The figure below demonstrates the difference in resolution between climate and regional climate models.

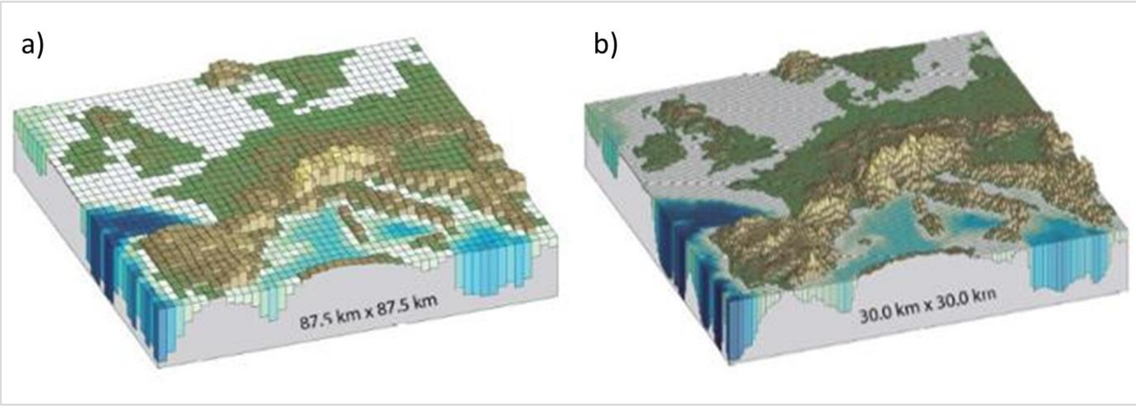


Figure 2.7. The Resolution Difference of Climate Models and Regional Climate Models [25]

As seen in Figure 2.7, the regional models (represented as b) could reflect borders, topography, etc., more precisely than global climate models (represented as a).

The CORDEX data, created for Europe, Africa, South Asia, Middle Asia, Mediterranean, and MENA areas, includes limited coverage of Türkiye. However, the Turkish State Meteorological Service has performed a downscaling analysis using regional and global climate models to illustrate forecasts for the country [25].

The national study mentioned above was conducted using the HadGEM2-ES model developed by Hadley Center, the MPI-ESM-MR model developed by Max Planck Institute, and the GFDL-ESM2M model developed by Geophysical Fluid Dynamics Laboratory models, which are the most preferred globally. The study has produced climate projections between 2016 and 2100, with a resolution of 20 km, considering the RCP4.5 and RCP8.5 scenarios [25].

HadGEM2-ES and MPI-ESM-MR are two models used in the IPCC and CMIP studies. HadGEM2-ES covers physical laws and Earth system configuration, such as land and ocean carbon cycles and dynamic vegetation [30]. Meanwhile, MPI-ESM-MR includes circulations of energy, momentum, water, and carbon dioxide and uses the atmosphere, ocean, and land in the model [31].

GFDL-ESM2M was developed by GFDL, affiliated with NOAA, and includes lake, atmosphere, and land components [32]. Like other models, it incorporates ocean ecology and biochemistry, land vegetation, and the carbon cycle and is referenced in IPCC and CMIP studies [33].

2.3. Climate Change Parameters and Wind Energy Interaction

Wind energy-based electricity generation depends on various factors such as wind speed, ambient temperature, height, and air density [34], [35]. Climate change could cause changes in wind speed and increase maximum and average temperatures [1], which could affect the climate-related parameters of wind energy-based electricity generation. A study has shown that renewable energy power potentials, particularly hydroelectric, solar, and wind energy, are visibly affected by climate change [36]. In 2018, Tobin et al. [37] reported that in most countries, electricity generation would be negatively affected by 1.5°C, 2°C, and 3°C warming, and solar photovoltaic and wind energy potential would decrease by approximately 10%. Another study analyzed the impact of climate change on wind energy potential in the Black Sea Region, focusing on RCP4.5 and RCP8.5 scenarios [38]. The results indicate that wind resources in the region are affected by climate change.

The average and maximum air temperatures are expected to increase between 2080 and 2099 for the SSP4.5 and SSP8.5 scenarios, according to the projections for Türkiye [5].

Figure 2.8 shows that the projected mean annual surface air temperature and maximum annual surface air temperature are likely to increase by 4-10^{o}C. The same parameters' June, July, and August averages are likely to increase by 7-9^{o}C for the Marmara Region, as shown in the figure below.

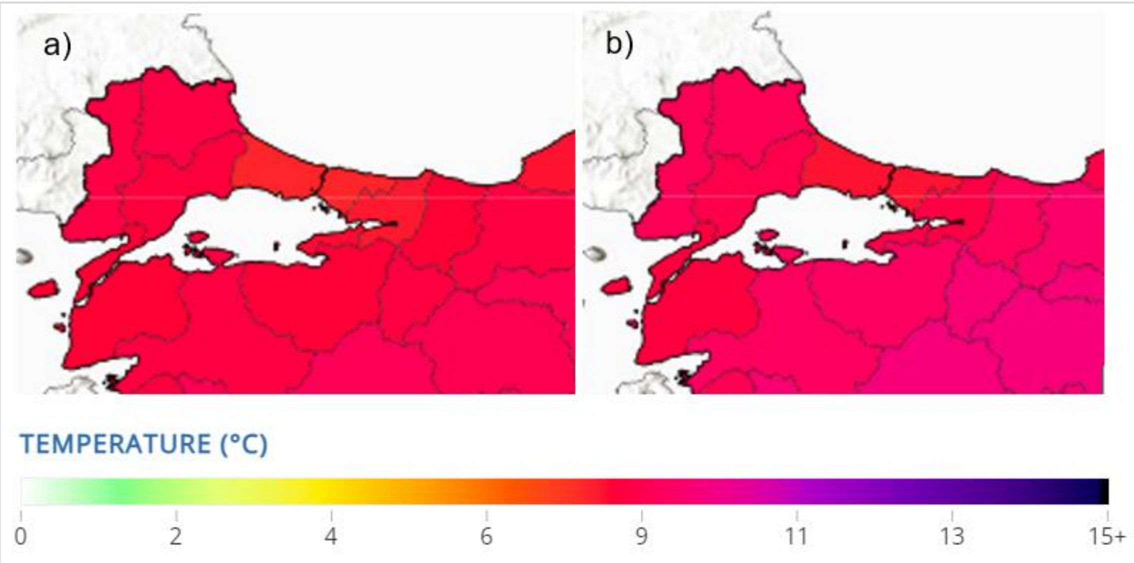


Figure 2.8. a) Projected Average Mean Surface Air Temperature Anomaly for 2080-2099 (Jun-Jul-Aug) b) Projected Average Maximum Surface Air Temperature Anomaly for 2080-2099 (Jun-Jul-Aug) [5]

It can be inferred that wind energy-based electricity generation in Türkiye may be affected by climate change, considering potential temperature, wind speed, and air density alterations. Hence, it is important to assess these climate variables for the energy generation of WPPs in Türkiye, in line with climate change forecasts.

2.4. Wind Energy

Wind energy is a highly favored renewable energy source in the fight against climate change. Its growth has been significant over the past decade, thanks to regulatory support and decreasing installation costs worldwide [39]. This chapter has two sections: wind energy installed capacity change and modeling techniques for wind energy-based electricity generation.

2.4.1. Wind Energy Installed Capacity Change in the World and Türkiye

The research conducted by Oxford Martin School [39] shows that the worldwide cumulative installed wind energy capacity, including both onshore and offshore wind sources, has increased by 396% since 2010 (181.08 GW), reaching 898.82 GW in 2022.

Between 2010 and 2022, wind energy installation in Türkiye increased by 728%, from 1,376 MW to 11,396 MW, parallel with the global trend [40]. As of December 2022, the total installed capacity of Türkiye is 103,809 MW. Figure 2.9 shows the distribution of electricity installed capacity based on fuel type.

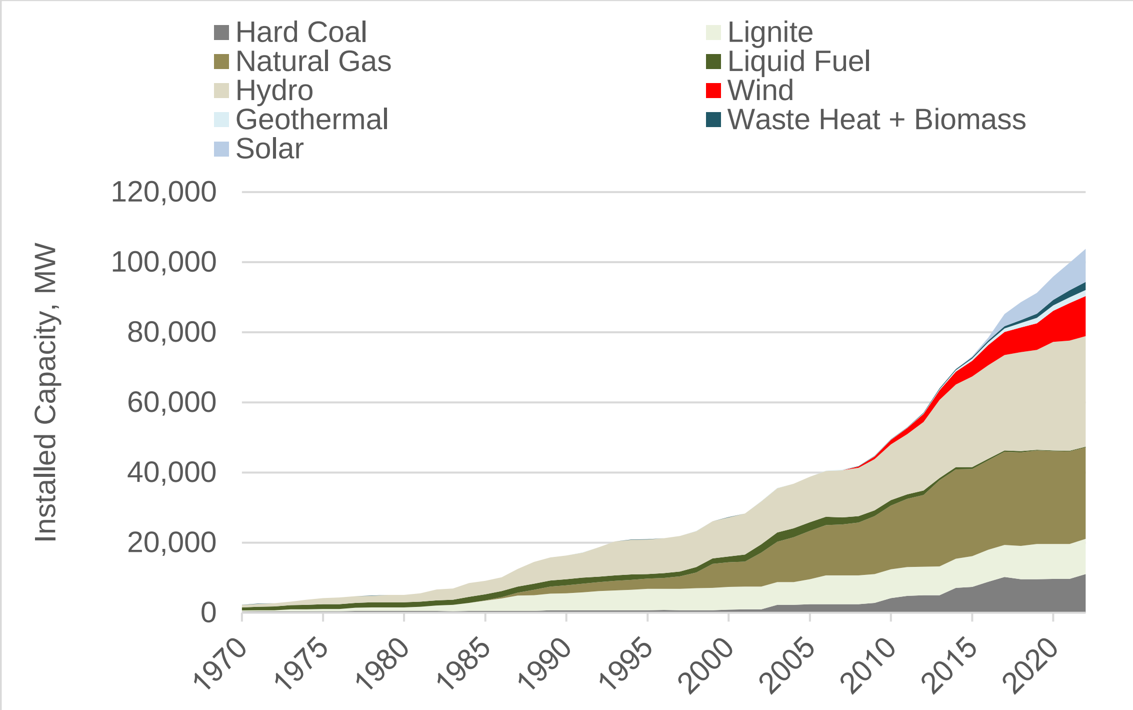


Figure 2.9. Installed Capacity of Türkiye in terms of fuel type [41]

The figure shows that, after hydro, wind power is the second most invested renewable energy type in the last five years. The charts in Figure 2.10 illustrate the regional distribution of installed and constructed WPPs in Türkiye. It is seen from the figure that the Marmara Region has the largest portion of the installed and constructed capacity compared to other areas.

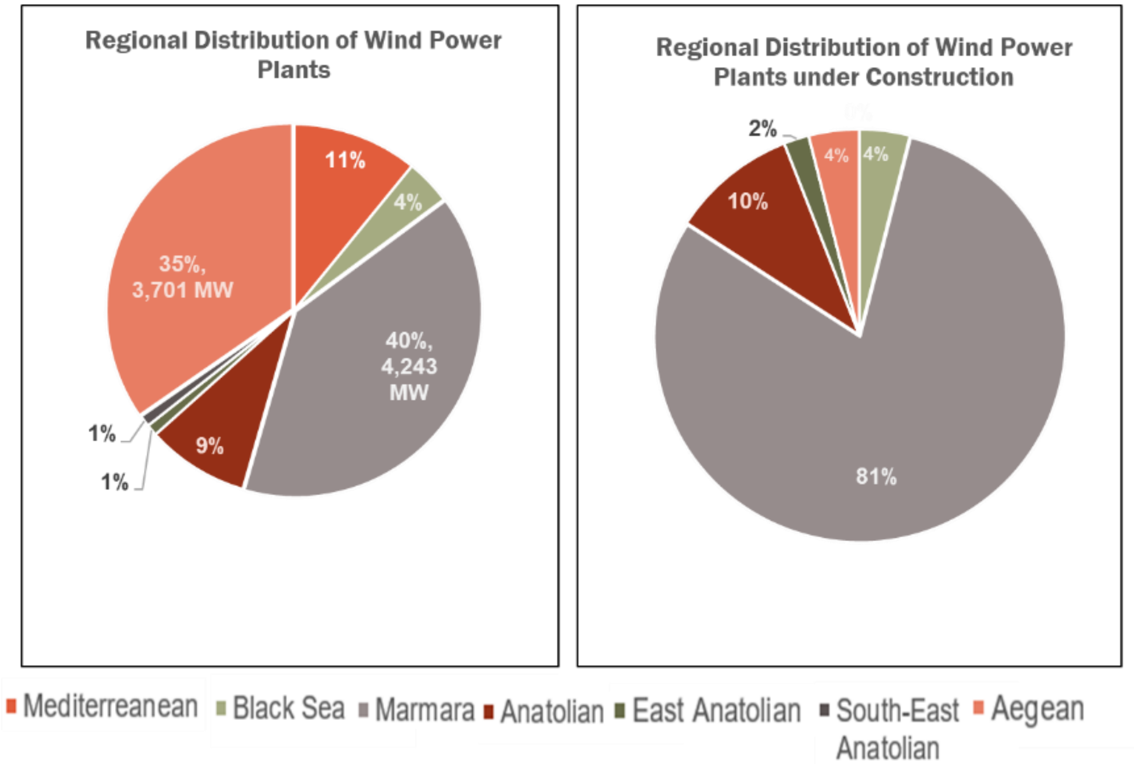


Figure 2.10. Regional Distribution of Installed and Constructed WPPs in Türkiye [42]

The 12th National Development Plan of Türkiye aims to increase the installed wind energy capacity by 58% compared to the 2022 installed capacity [3]. Therefore, it can be inferred that the Marmara Region will remain significant for wind energy.

According to TÜİK, Türkiye's population is projected to reach 107.1 million by 2080 [43]. This growth will inevitably increase electricity demand. Furthermore, the electricity sector is struggling to meet the additional demand caused by the increased need for cooling due to extreme temperatures exacerbated by climate change [44]. According to the International Energy Agency (IEA), air conditioning and electric fans account for 20% of total electricity consumption in buildings and 10% of global electricity consumption. The IEA predicts that this consumption will increase due to the growing availability of air conditioning units, expected to be installed in two-thirds of homes worldwide by 2050 [45]. In summary, the increasing use of air conditioners and other coolers due to climate change, in addition to current population growth, is likely to place an additional burden on existing electricity demand in the coming years. Furthermore, the electrification of cars as part of green investments in cities could also lead to additional electricity demand.

The chart below presents the actual electricity consumption until 2022 and the estimated electricity demand for electricity until 2031 for Türkiye.

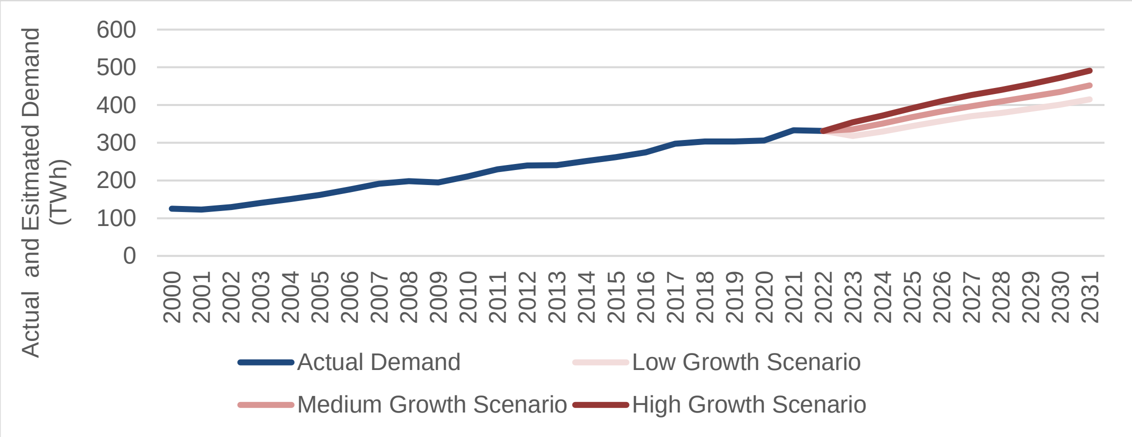


Figure 2.11. Actual and Estimated Electricity Demand of Türkiye [46]

It is necessary to discuss whether future electricity generation will be able to keep up with the increasing demand to ensure the resilience of energy systems, as shown in Figure 2.11.

2.4.2. Wind Energy-Based Electricity Generation Modelling Methods

Wind energy-based electricity generation is generated using turbines that operate based on a simple principle: the force of wind causes the rotor blades to rotate, hence driving a generator that produces electricity. Wind energy can be collected through the installation of turbines in various locations, including onshore, offshore, and distributed wind systems (such as local and small wind turbines for residential and educational use) [47] [48] [49].

Predictive techniques that rely on mathematical models and ML methods can be used to calculate wind energy output. It is important to note that the amount of electricity produced by wind turbines may change in the long term due to the impact of climate change on climate parameters, particularly wind speed, temperature, and air density. The amount of electricity that can be produced with changing climate parameters in the long term can be estimated with statistical and ML approaches such as ANN [50].

2.5. Machine Learning and Wind Energy Predictions

ML is a specialized branch of artificial intelligence that concentrates on creating computer algorithms that improve their performance through experience and data. ML models can forecast numerical values by analyzing historical data, classifying occurrences as either true or false, and grouping data points based on shared characteristics. ML could be conducted by supervised, unsupervised, or reinforcement learning methods [51].

Figure 2.12 illustrates the main stages of the ML analysis.

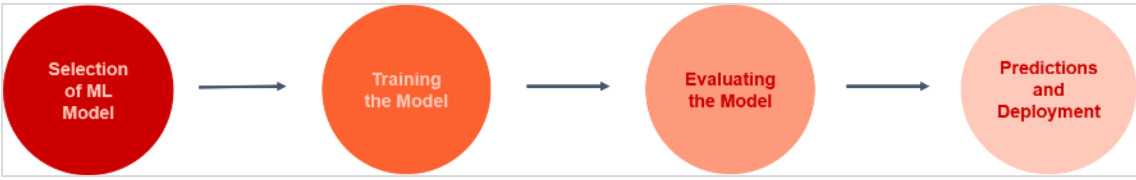


Figure 2.12. Major Steps of The ML [51]

A subfield of ML known as "deep learning" is devoted to techniques that use multi-layered ANN. The structure of these networks is similar to that of the human brain. A range of models are available for selection, including linear regression, decision trees, and neural networks [52].

Linear regression is a type of supervised ML technique that generally uses linear relationships for small data sets. At the same time, a decision tree is another supervised ML technique that generally uses a decision tree structure to make predictions of large data sets [53].

Neural networks, inspired by the structure of the human brain, are made up of multiple interconnected processing nodes, which can number from hundreds to millions. A node assigns a numerical value, called a "weight", to each incoming connection [54]. A summary of the network structure is shown in Figure 2.13.

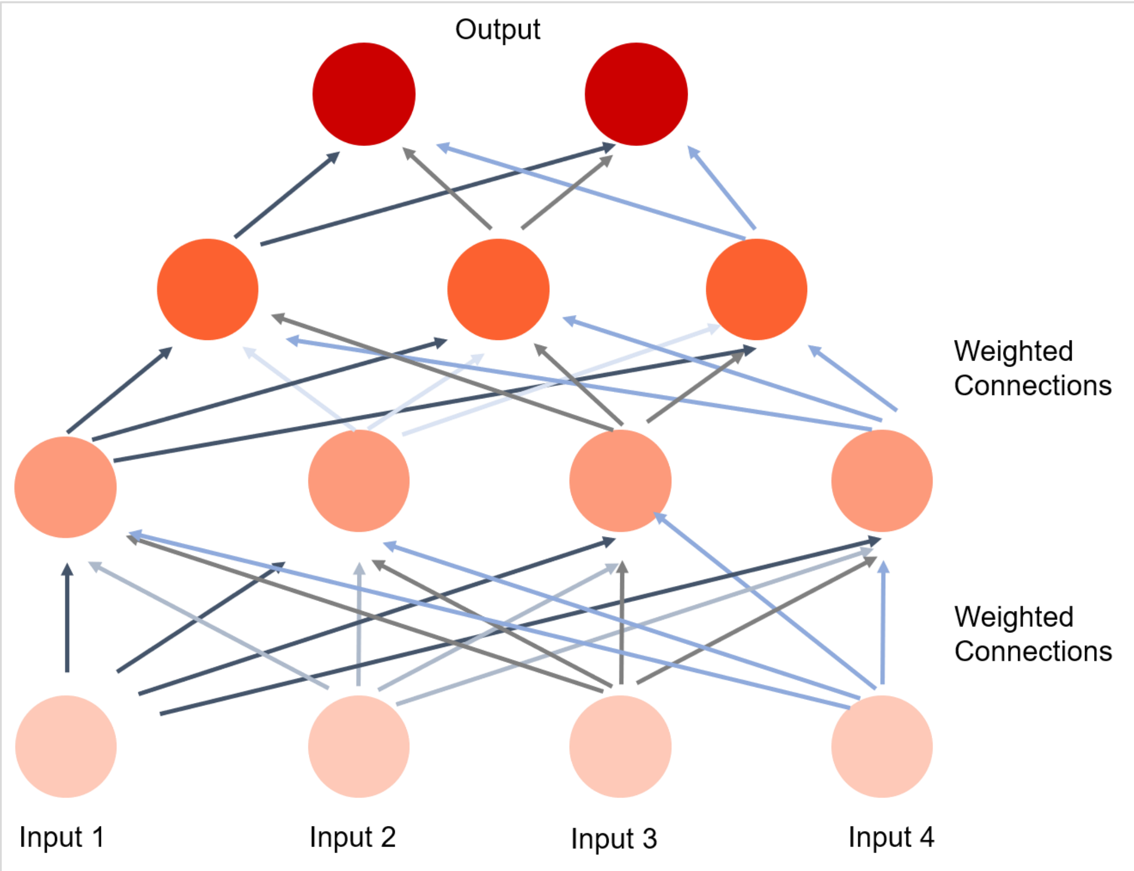


Figure 2.13. ANN Structure Summary [55]

There are several neural networks that use different algorithms, such as Multi-Layer Perception, which is used for pattern categorization, recognition, prediction, and approximation; Convolutional neural networks, which is preferred in image classification; Recurrent Neural Networks, such as Elman Neural Network, which is used for modeling sequential data; Restricted Boltzmann

Machines for dimensionality reduction, classification, and regression; Deep-belief networks; Generative adversarial networks, etc. [56] [57].

Several academic studies have focused on understanding wind energy-based electricity generation under changing climate conditions by analyzing it using ML and statistical analysis. The most preferred statistical modeling approaches can be listed as AutoRegressive Moving Average (ARMA), AutoRegressive (AR), AutoRegressive Exogeneous Variable (ARX), and Non-Linear Autoregressive Neural Network [58] [59] [60] [61] [62]. Multi-Layer Perceptron (MLP) is considered to be the most preferred ANN modeling technique in wind turbine power generation [63] [64] [65] [66] [67] [68] [69].

2.6. Climate Reanalysis

Reanalyses integrate historical data with models to provide a consistent time series of climate variables. Reanalyses are extensively employed in the field of geophysics. They utilize 3D grids with sub-daily time intervals to depict the documented climate, including its fluctuations throughout the decades.

The Copernicus Climate Change Service (C3S), on behalf of the European Centre for Medium-Range Weather Forecasts (ECMWF), is serving long-term climate reanalysis data sets, namely ECMWF Reanalysis (ERA). There are three climate reanalyzes: ERA-Interim, ERA5, and ERA5-Land. ERA5 is the latest climate reanalysis providing hourly data on a range of atmospheric, land surface, and ocean state indicators, together with uncertainty estimates. The Climate Data Store provides ERA5 data on grids with a resolution of $0.25^{o} \times 0.25^{o}$ and encompasses 37 pressure levels. The daily updates for ERA5 are delayed by 5 days compared to real-time data starting with 1940 to date [70].

ERA5 allows the monitoring of the climate over time. It is used for a variety of purposes, such as studying specific historical events, analyzing low-frequency variability and extreme weather events in climate research, and as input for initialization, boundary conditions, or driving other models. ERA5 is increasingly used as a large dataset for ML applications [71].

2.7. Closing Remarks

Global climatic conditions have shifted since the 1950s because of the increased radiative forcing caused by human-produced greenhouse gases. The greenhouse gas scenarios indicate that GHG emissions are expected to rise across various radiative forcing levels until 2100. Global and regional climate models have lately examined the relationship between climate change and wind energy. The findings indicate that wind energy is impacted by climate change, particularly changes in wind speed, ambient temperature, and air density. The Marmara Region in Türkiye has over 40% of the total wind energy capacity and faces challenges due to changing climatic conditions affecting wind energy generation. Wind energy forecasts under climate change may be studied using machine learning, numerical techniques, and statistical analysis. Long-term changes in climatic characteristics may be used to predict the potential power generation using statistical and machine learning methods. ERA-5 data is suitable for historical data inputs.

3. PREVIOUS STUDIES ON ANALYZING CLIMATE CHANGE IMPACTS ON WIND ENERGY

Extensive studies have been conducted on the influence of climate change on wind energy generation, while there has been relatively less focus on this topic in Türkiye. Research has shown that anticipated climatic conditions are expected to result in alterations in the possibilities for harnessing wind energy.

3.1. Summary of Previous Studies

The first study found that climate change projections indicate that wind resources would shift from the mid-latitudes of the Northern Hemisphere to polar and tropical regions by 2100. The study interprets that this shift might provide challenges, especially in the Northern Hemisphere's mid-latitudes, where the majority of global energy consumption occurs. The predicted increase in wind resources in tropical regions offers new opportunities for industrial expansion [72].

Another study conducted for the assessment of wind energy changes underneath climate change presents the main discoveries on offshore wind resources in the following manner: The average wind speeds in the Black Sea are forecasted to rise by over 20%, while the projected changes in the Marmara Sea are minimal [73]. The same study also states that the projected winter wind speed changes for onshore WPPs are mostly negative, except for the Aegean, Marmara, and Mediterranean areas. Mesoscale model results show a projected long-term rise in wind speeds near the WPPs in the Marmara, Anatolia, Black Sea, and Aegean regions. Specifically, the estimated increases are 10%, 6.9%, 9%, and 6.1%. Anticipated reductions in wind speeds are likely to occur near the WPPs located in the Black Sea region. The research suggests enhancing downscaling studies to improve the depiction of wind climatology in the region.

The research conducted by Lia Rapella et al. [74] quantifies the patterns of strong winds throughout Europe between 1950 and 2020 to analyze their impact on the overall weather systems and their effect on wind energy-based electricity generation in offshore locations. The incidence of strong winds, both high and low, has significantly increased, indicating that either climate change or long-term internal climatic variability has impacted the generation of offshore wind power. Studies on weather regimes have shown that Europe may see simultaneous occurrences of both high and low strong winds.

Furthermore, Yang et al. conducted a thorough study to determine how climate uncertainties affect renewable energy prediction in five European climatic zones. The research examined the long-term consequences of climate uncertainty on solar and wind energy. Researchers found that climate change has little effect on solar radiation across situations and time; however, wind energy-based electricity generation was reduced by 25% [75].

Zakari et al. emphasized that climate change impacts wind output by altering the daily and seasonal patterns of wind speed and temperature. This underscores the need to conduct impact studies for future wind and solar energy projects [76].

Carvalho et al. [77] have focused on wind energy sources in Europe and found that the CMIP6 study predicts a substantial decrease in most parts of Europe by the end of the century.

In addition, Hübler et al. evaluated the impact of increased wind speeds on wind turbine lifespans and generation costs. They suggested that the anticipated alterations are evident but rather minor compared to other uncertainties [78].

Another study conducted by Li Delei et al. has projections indicating a substantial increase in the intensity of interannual and intra-annual variations in wind power density throughout the study region [79].

Wang et al. proposed an ensemble approach to assess the sustainability of wind energy in the face of climate change. They highlighted the need to conduct directional analysis to identify energy hotspots and inform wind turbine design and installation in future climate change scenarios. The findings demonstrated a significant alteration in the average yearly wind energy inside the examined region, highlighting its crucial significance for promoting sustainable advancements [80].

Two studies have been conducted focusing on the Black Sea. The first study revealed that the analysis showed a rise in the average wind power levels up to 2050, followed by a decline of 3% between 2071 and 2100 [81]. The second study concluded that the Black Sea does not possess significant potential, particularly in comparison to coastal ocean regions [82].

Davy et al. conducted research on the European domain, specifically focusing on the Black Sea, and found that climate change did not have any noticeable detrimental impact on wind resources in the study location, even when considering multiple warming scenarios [38].

Moemken et al. discovered that future climatic circumstances may result in a little augmentation of wind energy potentials in northern Europe and a slight reduction in southern Europe [83].

3.2. Summary of the Methodologies of the Previous Studies

The summaries of the previous studies are given in Table 3.1.

Table 3.1. Methodology Summary of Previous Study

Study No.	Reference	Region	Sources of Data for Model Estimation	Climate Change Model	Climate Change Scenario	Time Horizon	Model Used to Predict Wind Energy
1	Martinez et al., 2024 [72]	Global and regional for North America, Europe, and East and Southeast Asia	ERA5	18 CMIP6 models for global analysis and EC-Earth3, GFDL-CM4, NorESM2-MM, CESM2-WACCM and GFDL-ESM4 models for regional analysis	SSP2-4.5 and SSP5-8.5	2051–2060 and 2091–2100	Multi-model ensemble for wind power density (NorESM2-MM, CESM2-WACCM, EC-Earth3, IPSL-CM6A-LR and ACCESS-CM2)
2	Çetin, İrem Işık, 2023 [73]	Türkiye	ERA5, MERRA2	28 CMIP6 models	SSP2-4.5 and SSP5-8.5	2014-2045, 2045-2075, and 2075-2100	Random Forest Multiple Linear Regression
3	Lia Rapella et al., 2023 [74]	Europe	ERA5	N/A	N/A	1950 – 2020	Numerical Method
4	Yang et al., 2022 [75]	Europe	Information is not available.	(1) CNRM-CM5, (2) ICHEC-EC-EARTH, (3) IPSL-5CM5A-MR, (4) MOHC-HadGEM2-ES, and (5) MPI-ESM-LR	RCP 2.6, RCP 4.5, and RCP 8.5	2010–2039, 2040–2069, 2070–2100	Numerical Method by Calculation of Wind Power Density

Study No.	Reference	Region	Sources of Data for Model Estimation	Climate Change Model	Climate Change Scenario	Time Horizon	Model Used to Predict Wind Energy
5	Zakari et al., 2022 [76]	India	ERA5	CMIP5, CORDEX WAS-22	RCP 2.6 and RCP 8.5	2025 to 2055 and 2065 to 2095	Linear regression and the Theil–Sen nonparametric method
6	Carvalho et al. 2021, [77]	Europe	ERA5	CMIP6	SSP2-4.5 and SSP5-8.5	2046–2065 and 2081–2100	Numerical Method by Calculation of Wind Power Density
7	Clemens Hübler et al., 2020 [78]	North Sea	Actual Site Data for a representative turbine	Uses existing estimations	Special scenarios (Increasing median and extreme (99th percentile) wind speeds and increasing air temperatures)	2071-2100	Uses Existing Estimations
8	Delei Li et al., 2020 [79]	East Asia	Three-hourly ERA5 wind speeds	CORDEX-East Asia CNRM-CM5, EC-EARTH, HadGEM2-ES, and MPI-ESM-LR	RCP 8.5	2021–2050 and 2070–2099	Numerical Method

Study No.	Reference	Region	Sources of Data for Model Estimation	Climate Change Model	Climate Change Scenario	Time Horizon	Model Used to Predict Wind Energy
9	Shengjin Wang et al., 2020 [80]	Persian Gulf	ERA-Interim	CORDEX	RCP4.5	2081–2100	Numerical Method by Calculation of Wind Power Density
10	L Rusu et al., [81]	Black Sea	RCA4	CMIP5, CORDEX	RCP4.5	2021–2050 and 2071-2100	Numerical Method by Calculation of Wind Power Density
11	E Rusu et al., 2021 [82]	Coasts of Black Sea	RCA4	CMIP5, CORDEX	RCP4.5 and RCP 8.5	2021–2050	Numerical Method by Calculation of Wind Power Density
12	Davy et al., 2018 [38]	Black Sea	RCA4	CMIP5, CORDEX	RCP4.5 and RCP8.5	2021-2050 and 2061 – 2090	Numerical Method by Calculation of Wind Power Density
13	Moemken et al., 2018 [83]	Europe	ERA Interim	CNRM-CM5, EC-EARTH, HadGEM2-ES, MPI-ESM-LR, and IPSL-CM5A-MR	RCP4.5 and RCP8.5	2021-2050 and 2071-2100	Numerical Method for a Specific Wind Turbine

3.3. Closing Remarks

Overall, the literature review suggests that climate change could substantially affect wind energy-based electricity generation. Studies have primarily examined alterations in wind energy potentials, evaluated the consequences for future installations, and emphasized the necessity of comprehensive frameworks to assess the sustainability of wind energy in the face of climate change scenarios.

4. METHODOLOGY AND DATA SOURCES

The methodology of this study consists of five main steps: data gathering and analysis, model development, model performance comparison, projections of electricity generation, and visualization. The flowchart of the methodology is illustrated in the flowchart given in Figure 4.1.

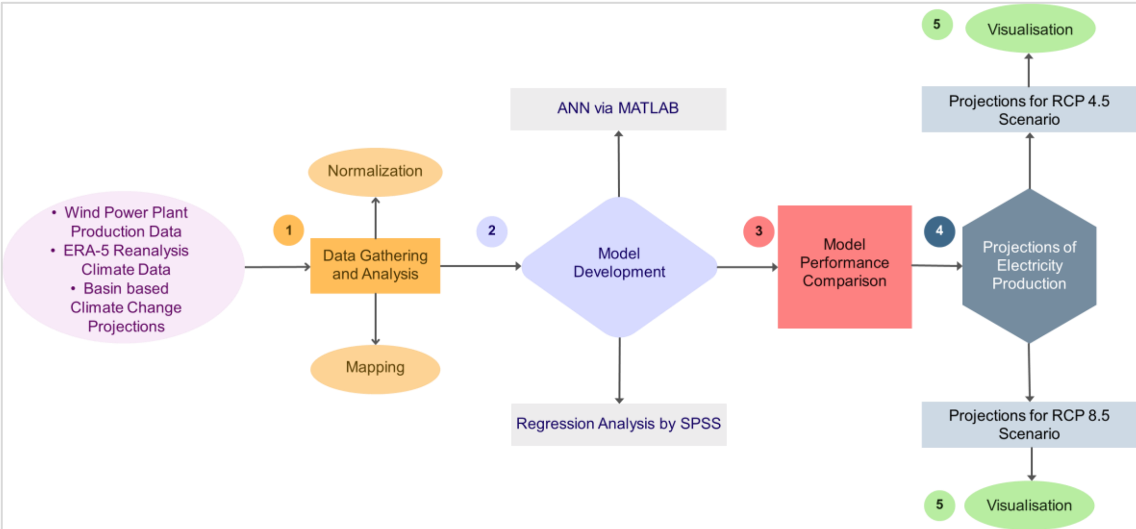


Figure 4.1. Flowchart of the Methodology of the Study

4.1. Data Gathering and Analysis

The data on the electricity generation of WPPs in the Marmara Basin, as well as the historical climate data and climate change forecasts, are collected from several sources and are detailed below.

4.1.1. Wind Power Plant Electricity Generation Data

The operational data on the WPP located in the Marmara Region is gathered from the list of WPPs registered with YEKDEM.

Table 4.1. Comparison of the WPPs in The Marmara Region with Türkiye [8]

Region \ WPP	Number of WPPs	Installed Capacity of WPPs (MW)
Marmara Region	88	3,450
Türkiye	224	8,755
Ratio (Marmara Region/Türkiye)	39%	39%

As seen in Table 4.1, there are 88 WPPs registered to YEKDEM in the Marmara Region. The ratio of 88 WPPs' total installed capacity to Türkiye's WPP installed capacity is 39%. The list of existing WPPs registered to YEKDEM in the Marmara Region is prepared with installed power information. In line with the list, hourly electricity generation data of each WPP between 2014-2023 is obtained from EPİAŞ and converted into daily and monthly generation data.

In addition, the coordinate data of each WPP determined to be located in the Marmara Region are listed. The coordinates of the WPPs are obtained from the Google Maps database.

The Türkiye basin map and the coordinates of the WPPs in the Marmara Region are analyzed and compared using Google Earth to ensure accurate alignment between the basins and the WPPs. The comparison map is given in Figure 4.2.

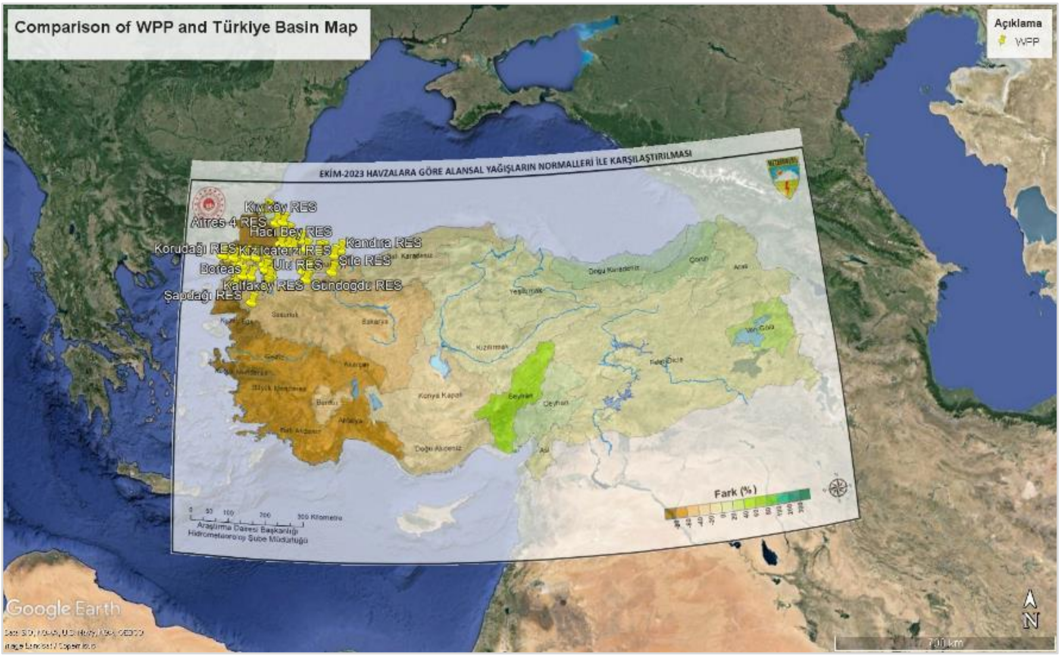


Figure 4.2. Comparison of WPP in the Marmara Region and Türkiye Basin Map

The Marmara Basin is determined to be the most significant portion of the basin data set in terms of quantity and capacity, as shown in Figure 4.3. Consequently, the study proceeded using data obtained from the Marmara Basin.

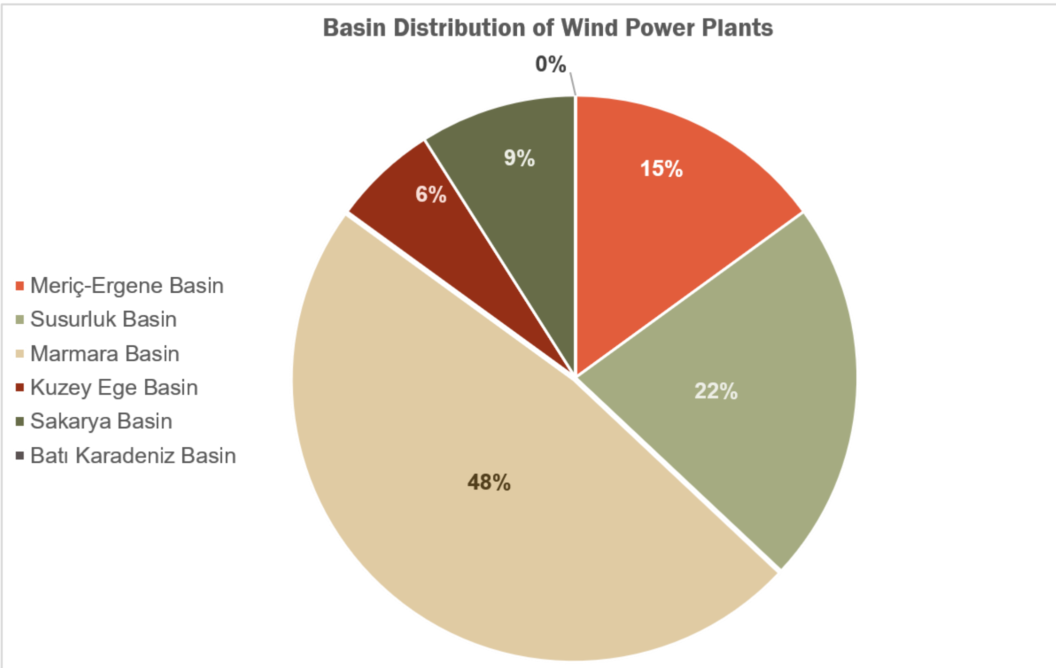


Figure 4.3. Basin Distribution of WPPs in the Marmara Region

Figure 4.4 below is the map illustrating the distribution of WPPs in the Marmara Basin. The list of WPPs in the Marmara Region is given in APPENDIX 1.

Figure 4.4. WPPs in the Marmara Basin

Actual electricity generation data between 2014 and 2023 from WPPs in the Marmara Basin is collected from EPİAŞ and transformed into monthly generation statistics. Figure 4.5 displays the total power generated by WPPs in the Marmara Basin during the last ten years.

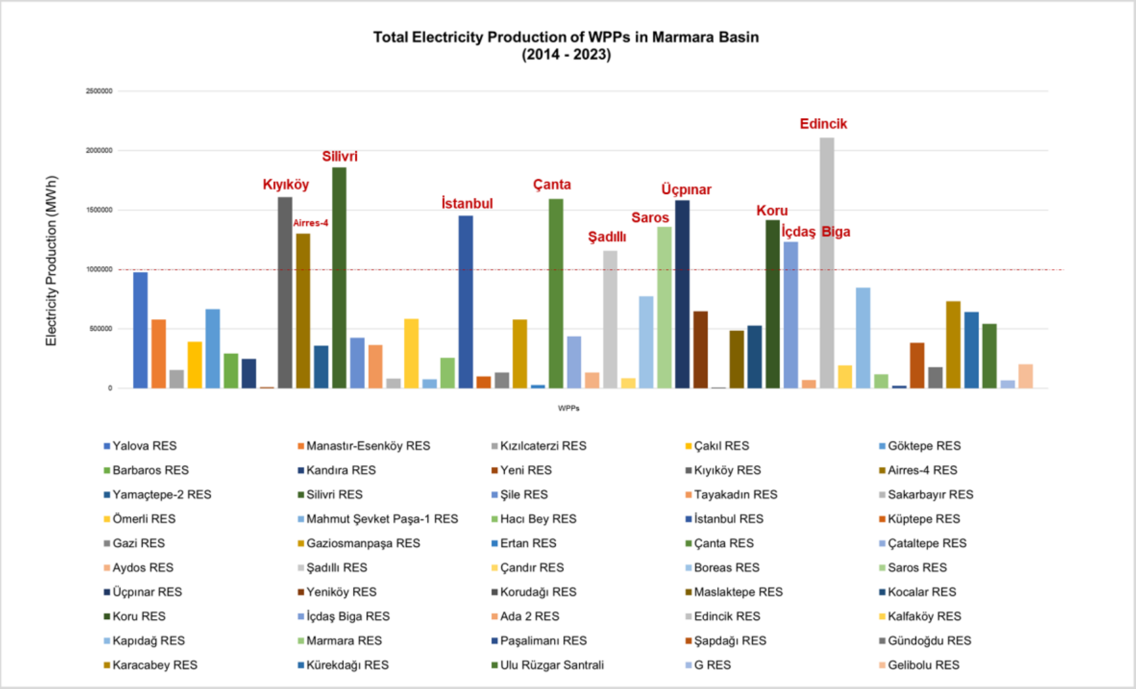


Figure 4.5. Electricity Generation of WPPs in the Marmara Basin

The figure above shows that 11 WPPs generated more than 100,000 MWh of electricity in 10 years. Edincik, Kıyıköy, and Silivri (highlighted in red in the figure) have the highest cumulative electricity generation among the WPPs.

Figure 4.6 demonstrates that electricity generation increased 136% between 2014 and 2023.

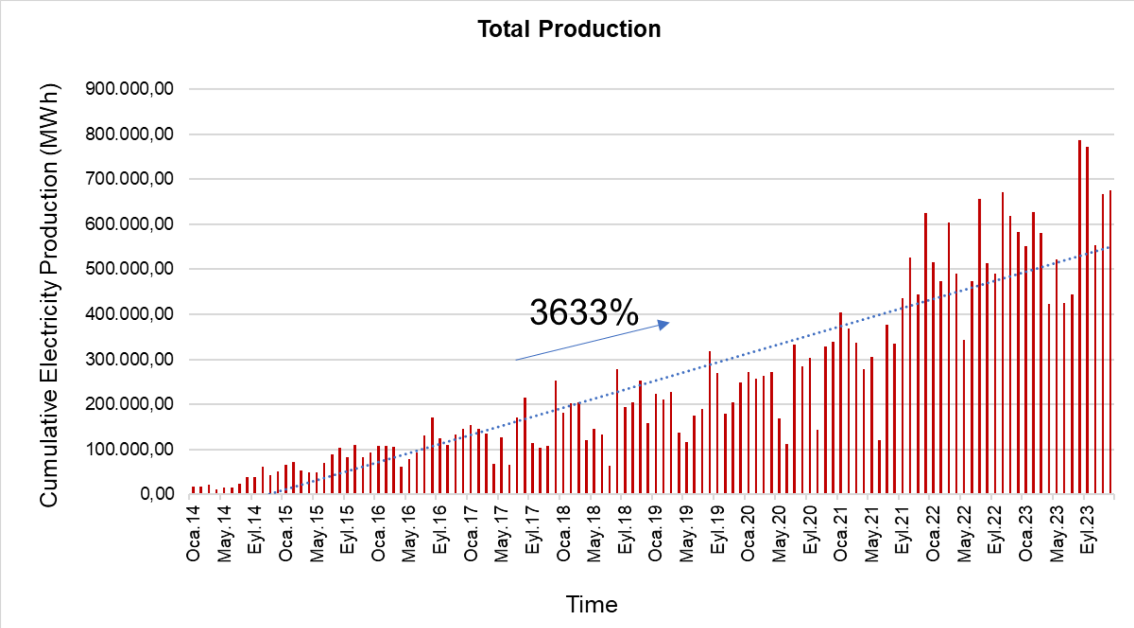


Figure 4.6. Electricity Generation Increase of WPPs in the Marmara Basin

APPENDIX 2 lists the locations, installed capacities, and yearly generations of WPPs in the Marmara Region between 2014 and 2023.

Since not all 50 facilities commenced generation in 2014 and underwent capacity expansions in subsequent years, not all 50 plants were included in the modeling process. The present study utilizes the aggregate electricity generation of 10 power plants that have consistently maintained continuous and efficient operation since 2016. The facilities mentioned above include Silivri WPP, Çanta WPP, Çataltepe WPP, Şadıllı WPP, Boreas WPP, Koru WPP, İçdaş Biga WPP, Edincik WPP, Paşalimanı WPP, and Gündoğdu WPP. Figure 4.7 demonstrates the generation patterns of WPPs chosen for the model development.

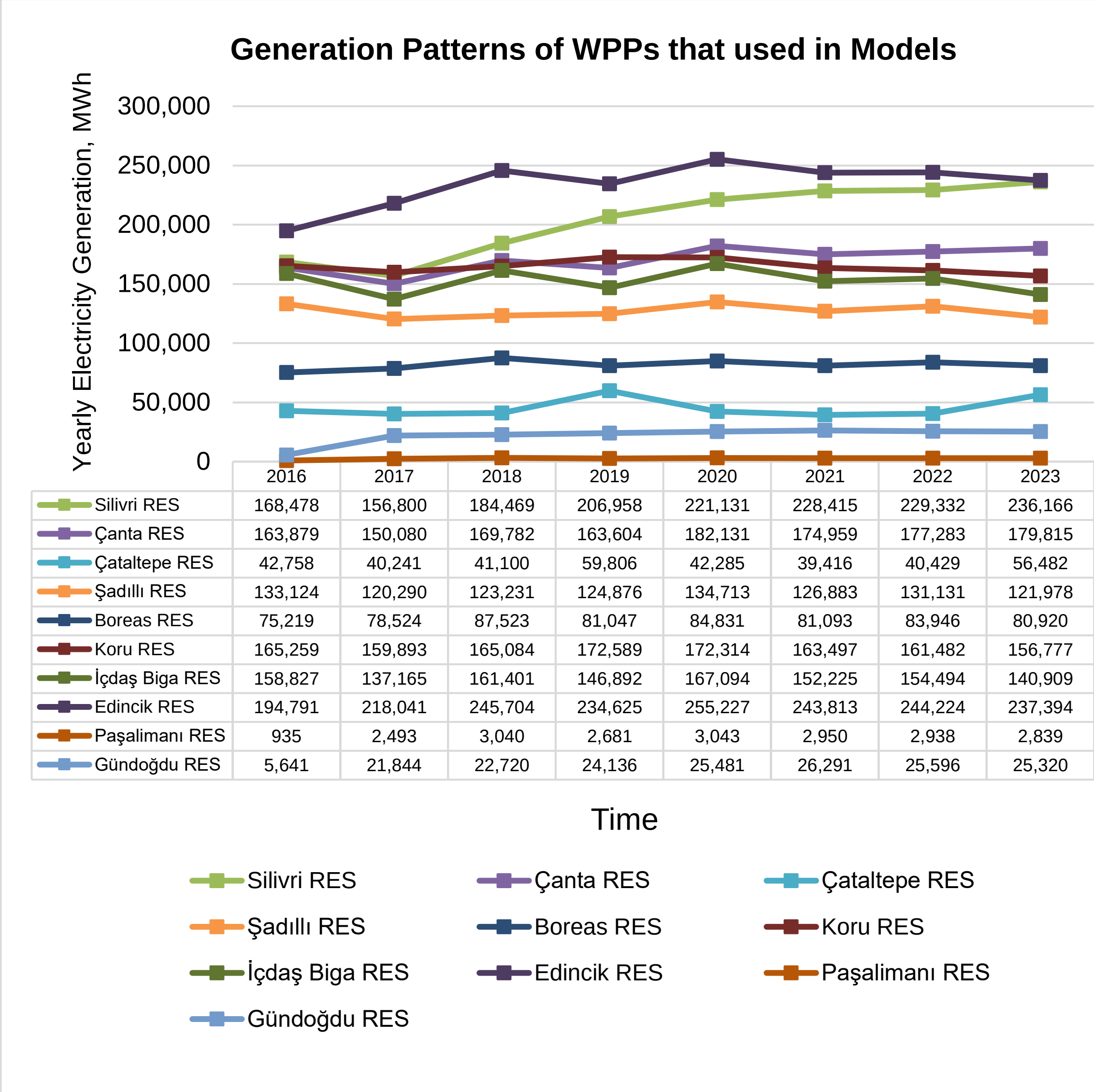


Figure 4.7. Generation Patterns of WPPs That Are Used in Models

4.1.2. Historical Data

As discussed in Chapter 2.3, wind speed, ambient temperature, height, and air density are the climate parameters that may affect wind energy generation.

According to the United States Department of Energy, the average hub height of wind turbines is 100 m [84]. Since the average wind speed from the MGM includes the wind speed at 10 m (V_{10m}), research has been carried out for statistical approaches that can be used to calculate the wind speed at the level of wind turbines. It is found that there are numerical approaches to calculate wind speed at different heights [85] [86]. However, ERA5 shows less bias and a higher correlation with observed winds [73].

Therefore, 100m u-component of wind (in ms^{-1}) and 2m temperature (K) with a 0.25°x0.25° horizontal resolution are obtained from the "ERA5 monthly averaged data on single levels from 1940 to present" dataset via the Climate Data Store of C3S [87]. The chosen product type is a monthly averaged reanalysis from 2020 to 2023. A sub-region extraction is performed for the Marmara Basin coordinates, which are around latitudes of 39-42 °N and longitudes of 26-30.5 °E.

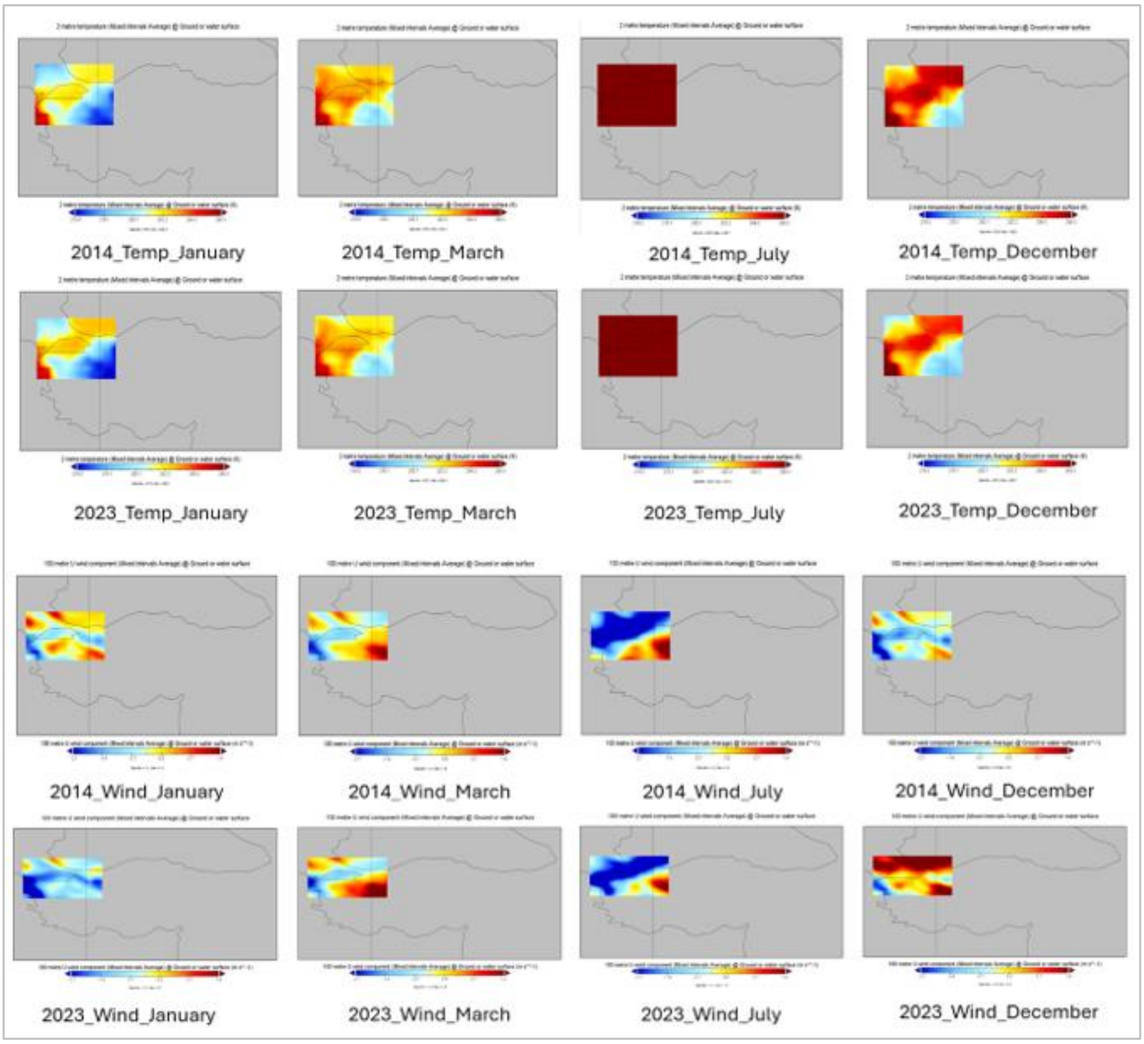


Figure 4.8. Samples from ERA-5 Data gathered for 2014-2023

The information that has been downloaded consists of values organized in a 19x13 grid, including Marmara Basin coordinates for each month. The data are consolidated by calculating the averages of the grid.

The following graph demonstrates the historical wind speed that converted to its absolute value between 2014 and 2023.

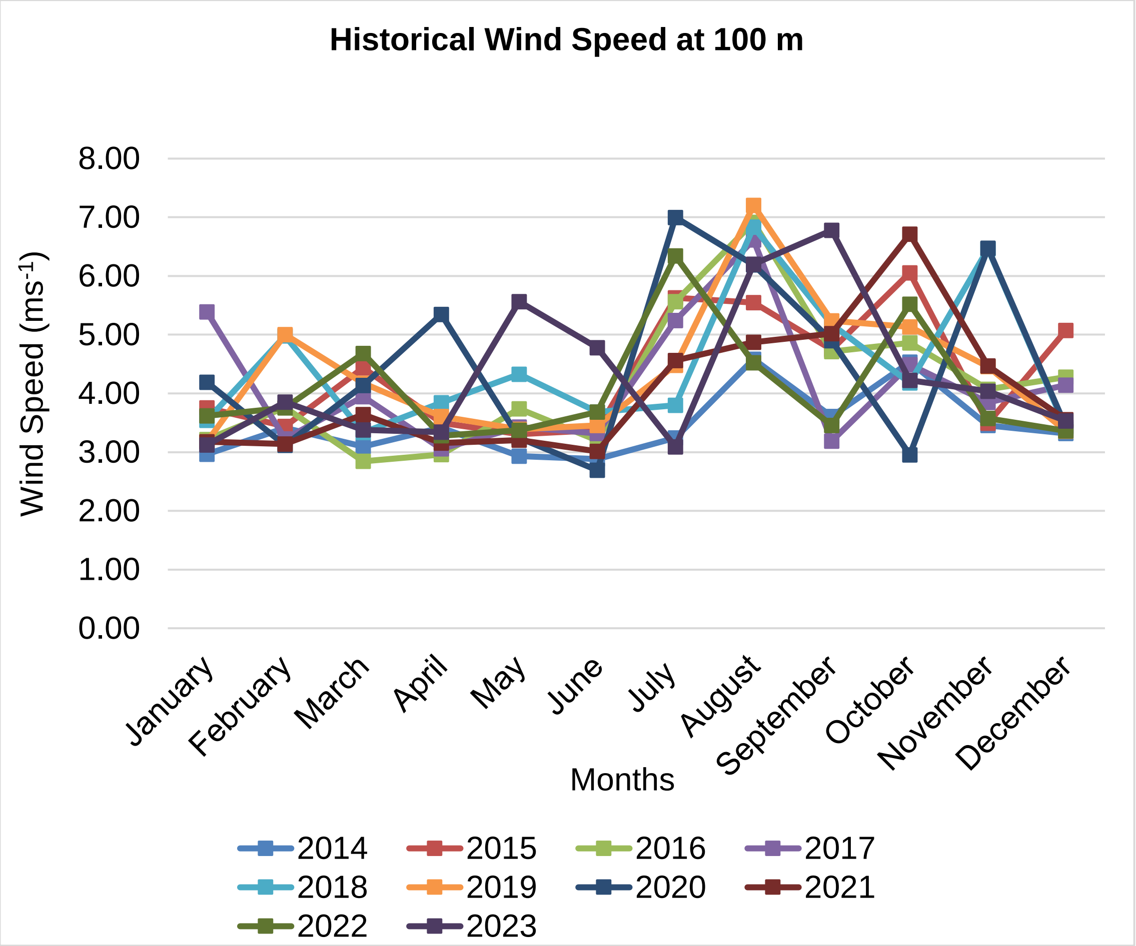


Figure 4.9. Historical Wind Speed at 100 m – ERA5 Reanalysis Data

It is seen from Figure 4.9 that the wind speed increased between July and December. The highest wind speed occurs in August. The minimum wind speeds happen in April.

The temperature data is translated into the Celsius system. The following graph demonstrates the historical temperature between 2014 to 2023.

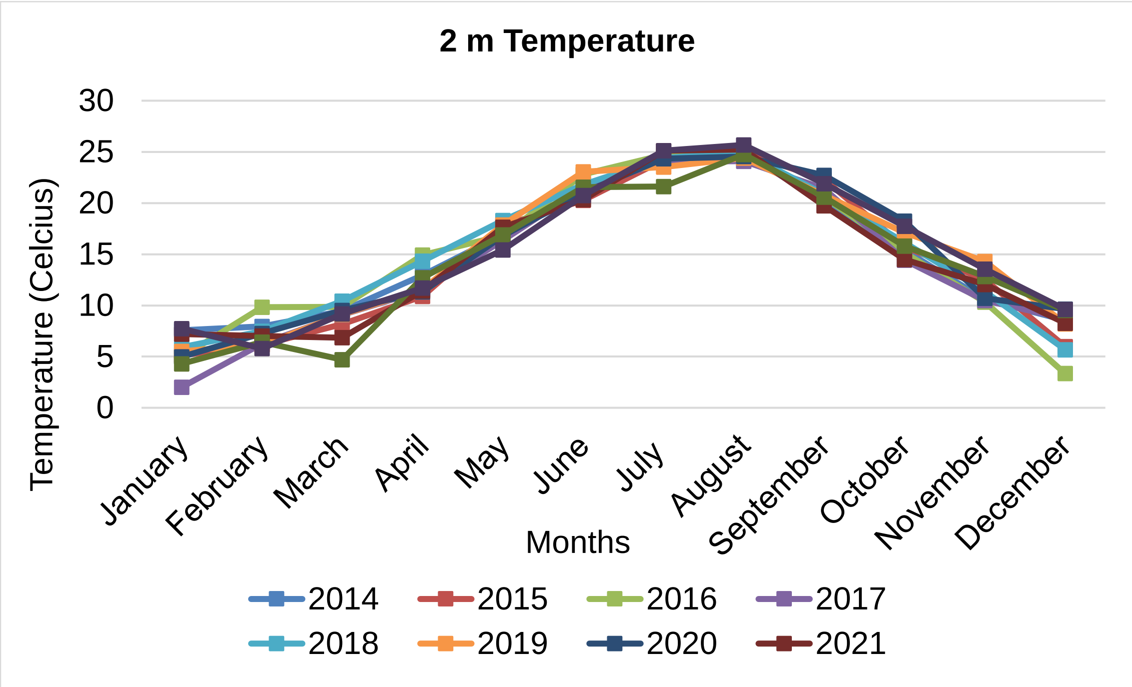


Figure 4.10. Historical Temperature at 2 m – ERA5 Reanalysis Data

It is seen in Figure 4.10 that the temperature is high in summer while it is low in winter. Also, August temperatures in the last three years (2021, 2022, and 2023) are the highest in the ten years.

Since the generation data is consistent after 2016, the historical data between 2016 and 2023 is used for the model development. APPENDIX 3 contains the definitive version of the historical data collection.

4.1.3. Climate Change Projections

The climate forecasts are also gathered from C3S to maintain the integrity of the data. The sub-country level data is acquired for monthly “wind speed at 100 m” and “2 m air temperature” forecasts from "Climate and energy indicators for Europe from 2005 to 2100 derived from climate projections" [88]. The RCA4 regional climate model and HadGEM2-ES global climate model (since the HadGEM2-ES model was used in common in many studies as discussed in Table 3.1) are used together with the RCP4.5 and RCP8.5 scenarios.

The collected data include projections from 2016 to 2098, categorized under the Nomenclature of Territorial Units for Statistics-2 [89]. The dataset extracts predictions for TR10, TR21, TR22, TR41, and TR42 territorial units. The historical data and projection data are combined in the graphs below. The projection data is given in the APPENDIX 4.

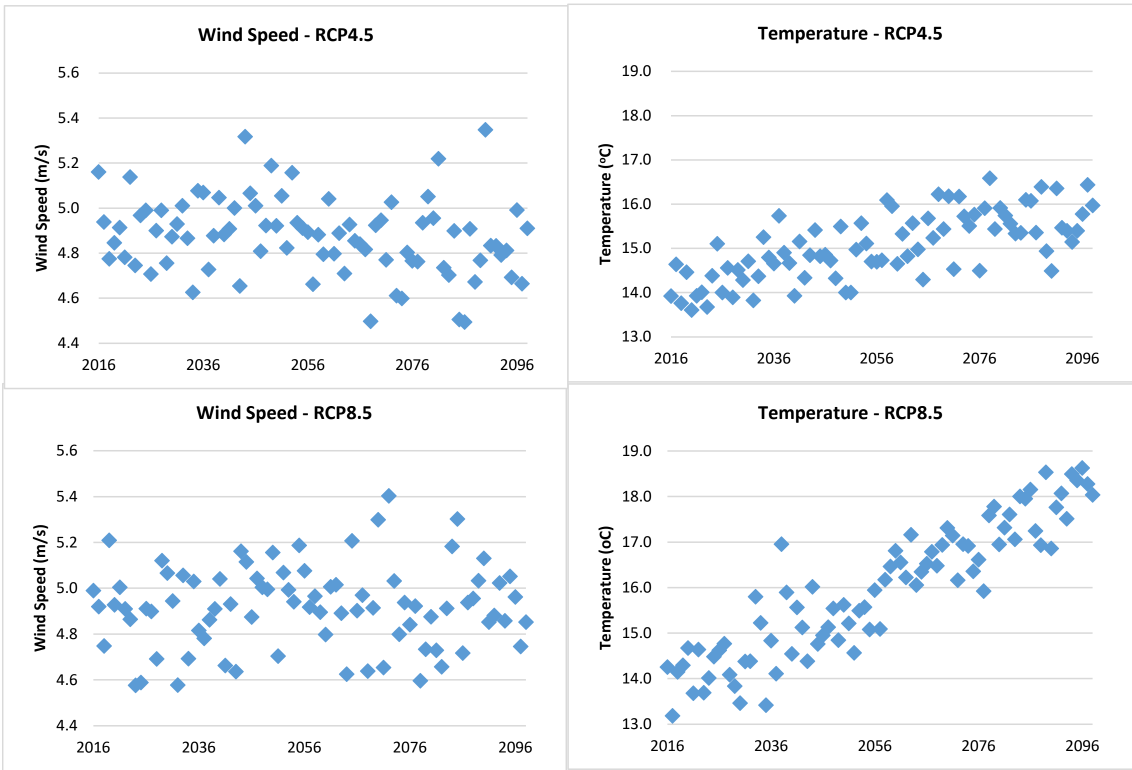


Figure 4.11. Combination of projection data for 2 m temperature and 100 m wind projection based on RCP 4.5 and RCP8.5

It is seen in Figure 4.11 that the air temperature will likely increase until 2098, especially based on the RCP8.5 scenario. Hereinafter, 2 m temperature will be mentioned as “temperature” and wind speed at 100 m will be mentioned as “wind speed”.

4.2. Model Development

As mentioned, the models are developed using statistical and ANN approaches with the same data set. The following sections give details of the models' development steps.

4.2.1. Development of Statistical Model

The development of a statistical model is performed via IBM SPSS Statistics 23. The analysis is conducted using the method of "Multiple Linear Regression".

The dataset includes cumulative empirical data on ten wind power generation from 2016 to 2023 (refer to Chapter 4.1.1), as well as measurements of air temperature at 2 m and wind speed at 100 m, which were gathered from C3S within the same time frame. The dataset includes monthly values for 96 months throughout 2016 – 2023. The dependent variable is the actual wind generation. The independent variables are the temperature and the wind speed at 100 m.

For the cumulative monthly electricity output data discussed in 4.1.1, WPPs with missing monthly electricity generation data are excluded from the dataset to eliminate outliers. This also enables the elimination of generation increases from commissioning additional WPP investments.

The dataset used in modeling is demonstrated in Table 4.2.

Table 4.2. Dataset for Statistical Modelling

Years	**Months**	**Wind Speed (ms^{-1})**	**Temperature (°C)**	**Actual Electricity Generation (MWh)**
2016	1	3.22	4.95	89,840.76
2016	2	3.76	9.83	86,995.40
2016	3	2.84	9.87	86,242.60
2016	4	2.96	14.92	51,674.37
2016	5	3.74	16.83	64,605.85
2016	6	3.20	22.79	77,489.41
2016	7	5.57	24.71	108,680.60
2016	8	6.92	24.73	137,959.11

Years	Months	Wind Speed (ms^{-1})	Temperature (°C)	Actual Electricity Generation (MWh)
2016	9	4.72	20.59	100,261.59
2016	10	4.86	15.13	90,217.75
2016	11	4.07	10.32	102,611.30
2016	12	4.28	3.34	112,331.17
2017	13	5.39	2.01	124,105.92
2017	14	3.23	6.28	109,128.90
2017	15	3.94	9.09	91,307.06
2017	16	3.06	11.48	47,788.02
2017	17	3.43	16.36	81,767.60
2017	18	3.32	21.53	43,835.29
2017	19	5.24	24.01	109,131.02
2017	20	6.62	24.10	140,449.16
2017	21	3.19	21.38	70,549.19
2017	22	4.49	14.43	64,073.29
2017	23	3.85	10.48	61,938.64
2017	24	3.54	8.69	141,296.93
2018	25	4.98	5.92	103,310.74
2018	26	3.33	7.48	119,202.83
2018	27	3.84	10.43	111,687.43
2018	28	4.32	14.32	65,400.37
2018	29	3.50	18.31	81,745.12
2018	30	3.80	21.79	76,220.50
2018	31	6.83	24.39	35,856.80
2018	32	5.18	24.95	156,151.61
2018	33	4.18	20.85	109,868.88
2018	34	6.46	16.15	112,503.64
2018	35	3.40	11.37	145,682.43
2018	36	3.40	5.68	86,423.44
2019	37	3.17	5.53	127,401.03
2019	38	5.01	6.14	122,879.71
2019	39	4.18	9.10	116,461.74
2019	40	3.61	11.57	71,584.68
2019	41	3.39	17.87	52,411.44
2019	42	3.45	23.05	83,554.88
2019	43	4.48	23.52	89,305.50
2019	44	7.20	24.40	151,089.93
2019	45	5.24	20.78	124,728.59
2019	46	5.14	17.10	81,602.06
2019	47	4.46	14.29	87,239.32
2019	48	3.36	8.21	108,956.31
2020	49	4.19	4.98	123,118.98
2020	50	3.12	7.25	108,391.76
2020	51	4.14	9.53	112,639.66
2020	52	5.34	11.34	119,951.28
2020	53	3.74	16.80	68,838.74
2020	54	3.19	21.02	44,143.84
2020	55	7.00	24.32	142,100.38
2020	56	6.19	24.54	121,971.64
2020	57	4.90	22.71	130,284.36
2020	58	3.86	18.24	60,266.07
2020	59	6.47	10.70	135,768.08

Years	Months	Wind Speed (ms^{-1})	Temperature (°C)	Actual Electricity Generation (MWh)
2020	60	3.43	9.64	120,777.05
2021	61	3.18	7.22	127,261.73
2021	62	3.14	7.02	113,441.72
2021	63	3.77	6.85	99,933.83
2021	64	3.16	11.42	77,154.25
2021	65	3.70	17.65	86,051.69
2021	66	3.51	20.35	33,726.08
2021	67	4.56	25.11	102,582.03
2021	68	4.87	25.23	92,255.33
2021	69	5.02	19.74	113,727.23
2021	70	6.71	14.48	142,930.13
2021	71	4.50	12.04	106,542.09
2021	72	3.26	8.26	143,937.38
2022	73	3.62	4.30	109,825.45
2022	74	3.00	6.44	93,328.35
2022	75	4.68	4.69	124,076.45
2022	76	3.73	12.70	95,244.63
2022	77	3.38	16.90	70,931.66
2022	78	3.68	21.56	93,108.35
2022	79	6.34	21.61	128,015.12
2022	80	4.52	24.75	102,433.38
2022	81	4.12	20.57	88,428.32
2022	82	5.52	15.79	130,500.46
2022	83	3.58	12.84	114,725.41
2022	84	3.07	9.52	100,235.49
2023	85	3.12	7.73	102,780.89
2023	86	3.10	5.78	110,427.47
2023	87	3.51	9.17	102,088.69
2023	88	3.79	11.70	69,937.51
2023	89	5.56	15.41	98,698.98
2023	90	4.78	20.73	82,043.66
2023	91	3.09	25.13	74,513.48
2023	92	6.20	25.68	146,995.65
2023	93	6.78	21.91	146,073.74
2023	94	5.13	17.74	90,950.02
2023	95	4.04	13.54	106,191.85
2023	96	3.53	9.60	107,897.79

The statistical analysis of the model input data is given in Table 4.3.

Table 4.3. Statistical Analysis of the Model Input Data

Statistical Data	Parameters (2016-2023)		
	Temperature (°C)	Wind Speed (ms^{-1})	Actual Electricity Generation (MWh)
Mean	4.29	14.83	100,341.65
Median	3.85	14.45	102,596.67

Statistical Data	Parameters (2016-2023)		
	Temperature (°C)	Wind Speed (ms^{-1})	Actual Electricity Generation (MWh)
Min	2.84	2.01	33,726.08
Max	7.20	25.68	156,151.61
St.Dev.	1.14	6.77	27,679.41

4.2.2. Development of Artificial Neural Network Model

For the ANN model, the dataset is normalized to correct the different scale differences in the generation and installed power data of WPP facilities and climate data. This is made to ensure better model performance. For the normalisation of the data sets, 0-1; 0.5-1; 0.1-0.9 interval values are tested, and 0.1-0.9 interval is selected as the most suitable data interval for the characteristics of the study data.

Development of ANN is performed via MATLAB R2023a. First, a MATLAB code is developed to create a regression equation using an ANN. The primary objective of the code is to simulate the correlation between a dependent variable (target) and independent variables (input) in the dataset using a neural network. It aims to elucidate this correlation by ANN, as described in Chapter 2.5.

The code has two primary components: Section 1 – Training and Section 2 – Regression Equation. Within Section 1, the input and target data are extracted from the dataset and used to construct a feedforward neural network using the feedforward net function. This network consists of 2 levels, with each layer containing 10 neurons. The 'trainlm' technique is used to train the neural network using the training data ('train function'). The output of the trained network is reacquired using the input data. Section 2 calculates the regression equation coefficients (b) that represent the relationship between the input data (inputData) and the target data (targetData). The normalized dataset used in ANN modeling is demonstrated in Table 4.4.

Table 4.4. Dataset for ANN Modelling

Years	Months	Wind Speed (ms^{-1})	Temperature (°C)	Actual Electricity Generation (MWh)
2016	**1**	0.193	0.199	89,840.76
2016	**2**	0.290	0.364	86,995.40
2016	**3**	0.127	0.366	86,242.60
2016	**4**	0.148	0.536	51,674.37
2016	**5**	0.286	0.601	64,605.85
2016	**6**	0.190	0.802	77,489.41
2016	**7**	0.610	0.867	108,680.60
2016	**8**	0.849	0.868	137,959.11
2016	**9**	0.459	0.728	100,261.59
2016	**10**	0.485	0.543	90,217.75
2016	**11**	0.345	0.381	102,611.30
2016	**12**	0.382	0.145	112,331.17
2017	**13**	0.579	0.100	124,105.92
2017	**14**	0.195	0.244	109,128.90
2017	**15**	0.322	0.339	91,307.06
2017	**16**	0.165	0.420	47,788.02
2017	**17**	0.231	0.585	81,767.60
2017	**18**	0.212	0.760	43,835.29
2017	**19**	0.552	0.844	109,131.02
2017	**20**	0.796	0.847	140,449.16
2017	**21**	0.189	0.755	70,549.19
2017	**22**	0.419	0.520	64,073.29
2017	**23**	0.305	0.386	61,938.64
2017	**24**	0.357	0.326	141,296.93
2018	**25**	0.250	0.232	103,310.74
2018	**26**	0.506	0.285	119,202.83
2018	**27**	0.214	0.385	111,687.43
2018	**28**	0.304	0.516	65,400.37
2018	**29**	0.390	0.651	81,745.12
2018	**30**	0.276	0.769	76,220.50
2018	**31**	0.296	0.856	35,856.80
2018	**32**	0.835	0.875	156,151.61
2018	**33**	0.541	0.737	109,868.88
2018	**34**	0.364	0.578	112,503.64
2018	**35**	0.769	0.416	145,682.43
2018	**36**	0.226	0.224	86,423.44
2019	**37**	0.186	0.219	127,401.03
2019	**38**	0.510	0.240	122,879.71
2019	**39**	0.363	0.339	116,461.74
2019	**40**	0.263	0.423	71,584.68
2019	**41**	0.224	0.636	52,411.44
2019	**42**	0.235	0.811	83,554.88
2019	**43**	0.418	0.827	89,305.50
2019	**44**	0.900	0.857	151,089.93
2019	**45**	0.551	0.734	124,728.59

Years	Months	Wind Speed (ms^{-1})	Temperature (°C)	Actual Electricity Generation (MWh)
2019	**46**	0.533	0.610	81,602.06
2019	**47**	0.413	0.515	87,239.32
2019	**48**	0.218	0.309	108,956.31
2020	**49**	0.366	0.200	123,118.98
2020	**50**	0.175	0.277	108,391.76
2020	**51**	0.356	0.354	112,639.66
2020	**52**	0.570	0.415	119,951.28
2020	**53**	0.198	0.600	68,838.74
2020	**54**	0.100	0.743	44,143.84
2020	**55**	0.864	0.854	142,100.38
2020	**56**	0.721	0.862	121,971.64
2020	**57**	0.492	0.800	130,284.36
2020	**58**	0.146	0.649	60,266.07
2020	**59**	0.771	0.394	135,768.08
2020	**60**	0.231	0.358	120,777.05
2021	**61**	0.186	0.276	127,261.73
2021	**62**	0.180	0.269	113,441.72
2021	**63**	0.268	0.263	99,933.83
2021	**64**	0.183	0.418	77,154.25
2021	**65**	0.191	0.629	86,051.69
2021	**66**	0.157	0.720	33,726.08
2021	**67**	0.431	0.881	102,582.03
2021	**68**	0.487	0.885	92,255.33
2021	**69**	0.512	0.699	113,727.23
2021	**70**	0.813	0.521	142,930.13
2021	**71**	0.416	0.439	106,542.09
2021	**72**	0.253	0.311	143,937.38
2022	**73**	0.264	0.177	109,825.45
2022	**74**	0.289	0.250	93,328.35
2022	**75**	0.453	0.191	124,076.45
2022	**76**	0.204	0.461	95,244.63
2022	**77**	0.221	0.603	70,931.66
2022	**78**	0.276	0.761	93,108.35
2022	**79**	0.747	0.762	128,015.12
2022	**80**	0.425	0.869	102,433.38
2022	**81**	0.235	0.727	88,428.32
2022	**82**	0.602	0.566	130,500.46
2022	**83**	0.257	0.466	114,725.41
2022	**84**	0.219	0.354	100,235.49
2023	**85**	0.176	0.293	102,780.89
2023	**86**	0.306	0.227	110,427.47
2023	**87**	0.222	0.342	102,088.69
2023	**88**	0.215	0.428	69,937.51
2023	**89**	0.609	0.553	98,698.98
2023	**90**	0.470	0.733	82,043.66
2023	**91**	0.171	0.881	74,513.48

Years	Months	Wind Speed (ms^{-1})	Temperature (°C)	Actual Electricity Generation (MWh)
2023	**92**	0.722	0.900	146,995.65
2023	**93**	0.825	0.773	146,073.74
2023	**94**	0.372	0.631	90,950.02
2023	**95**	0.339	0.490	106,191.85
2023	**96**	0.249	0.357	107,897.79

4.3. Model Performance Comparison

The methods mentioned above are replicated to build several models. The models constructed using statistical and ML methodologies are compared based on their prediction capabilities evaluated using the Standard Error of the Estimate (SEE), Root Mean Square Error (RMSE), Percent Bias (PBIAS), Mean Absolute Percentage Error (MAPE), Pearson Correlation, Mann-Kendall Test, and Spearman Rank Correlation, and R Square (R^2) parameters. These factors are used to ascertain the model with the greatest predictive efficacy.

4.4. Projections of Electricity Generation and Visualisation

The wind turbine electricity generation forecasting model with the most accurate forecasting performance is chosen. The chosen model is integrated with long-term climate change estimates and used to predict power generation. The generation projections are compared and analyzed in relation to the generation estimates that do not consider climate change. The studies undertaken in this research are visualized using Google Earth, excel, and other tools.

4.5. Closing Remarks

The methodology used in this research includes the collection and analysis of data, the building of a model, the comparison of model performance, and the prediction of electricity generation. Actual electricity generation data of WPPs in the Marmara Basin (which accounts for 48% of the WPPs in the Marmara Region) are collected for the period spanning from 2014 to 2023. The climatic parameters include “wind speed at 100 m” and “2 m temperature”. The ERA5 reanalysis data of C3S is used to acquire historical climate data. Climate change projection is obtained from C3S for RCP4.5 and RCP8.5 scenarios with HadGEM2-ES and

RCA4 climate models. Two models are identified through Multiple Linear Regression and ANN. The multiple linear regression model utilizes the original dataset, while the ANN model uses a normalized dataset ranging from 0.1 to 0.9. The dataset is restricted between 2016 and 2023 to minimize missing values and increases due to additional WPP investments. The models are compared by assessing their predictive capacities using statistical methods such as R^2, RMSE, PBIAS, correlation analysis method, and others. The optimal models are selected to forecast forthcoming power generation from wind turbines. Results are displayed using various techniques.

5. RESULTS AND DISCUSSION

This chapter presents the outcomes of the developed models, the comparison of model performances, and the estimates of energy output for the RCP4.5 and RCP8.5 projections in line with the methodology detailed in Chapter 33.

5.1. Statistical Analysis of Input Data

A correlation study was performed to examine the association between temperature and wind speed and to get insight into the relationship between the inputs of the statistical models. During the correlation analysis, the Pearson Correlation [90], Mann-Kendall Test [91] and Spearman Rank Correlation [92] techniques were used. The p-values for the Pearson Correlation, Mann-Kendall Test, and Spearman Rank Correlation are 0.000, 0.001, and 0.001, respectively. In light of the findings, the null hypothesis positing no link is refuted, indicating the presence of an interaction between wind speed and temperature. Therefore, the null hypothesis of no correlation is rejected, which means there is an interaction between wind speed and temperature.

The Pearson Correlation, Mann-Kendall Test, and Spearman Rank Correlation coefficients for the relationship between temperature and wind speed are 0.374, 0.210, and 0.310, respectively. This signifies a positive correlation, where when one measure grows, the other variable tends to increase, however weak. The monthly wind speed and temperature interaction between January 2015 and December 2023 is demonstrated in Figure 5.1.

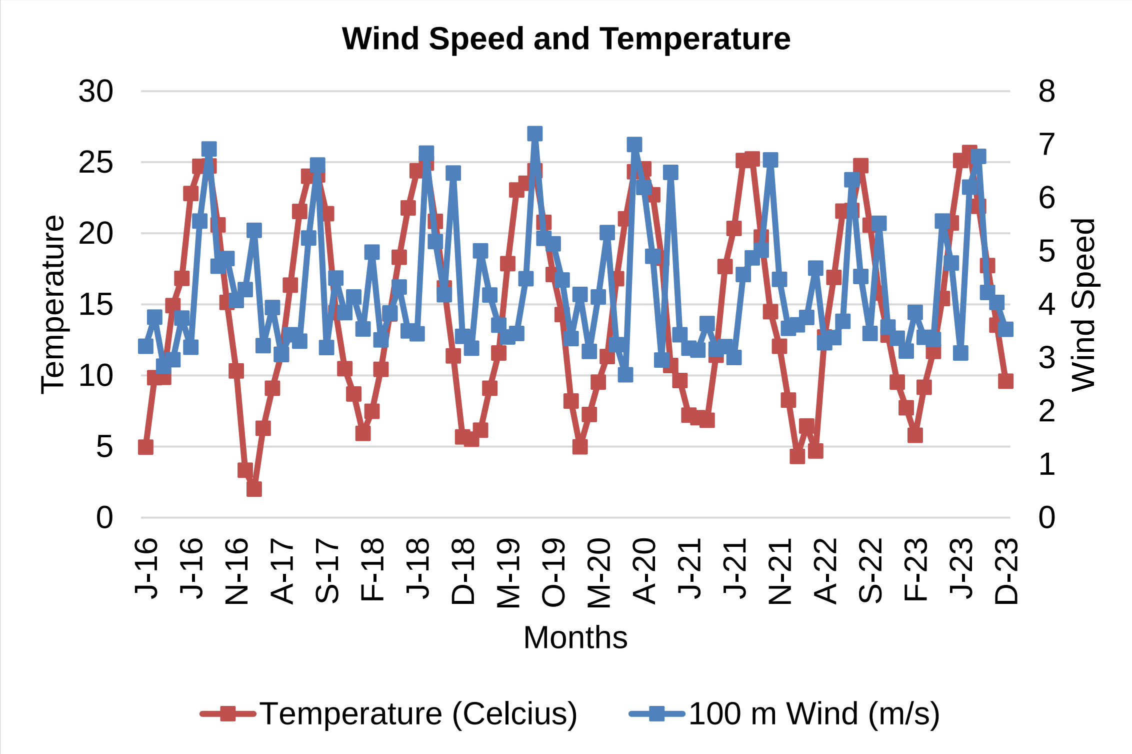


Figure 5.1. Monthly Temperature and Wind Speed between January 2016 and December 2023

The abovementioned method was applied to temperature - actual electricity generation and wind speed - actual electricity generation.

The temperature and actual electricity generation have p-values for the Pearson Correlation, Mann-Kendall Test, and Spearman Rank Correlation of 0.139, 0.069, and 0.101, respectively. Based on the sample data, this result indicates that there is insufficient evidence to establish a statistically significant association between temperature and actual electricity generation since the correlation coefficient exceeds 0.05. The Pearson Correlation, Mann-Kendall Test, and Spearman Rank Correlation coefficients for the relationship between temperature and actual electricity generation are -0.112, -0.103, and -0.131, respectively. This indicates a negative but weak correlation between temperature and actual electricity generation. This result aligns with the findings of Yang et al. [75] about a negative association between ambient temperature and wind generation. In addition, their findings also confirm that there is a statistically significant correlation between ambient temperature and wind turbine power generation. Figure 5.2

demonstrates the interaction between monthly temperature and actual electricity generation between January 2016 and December 2023.

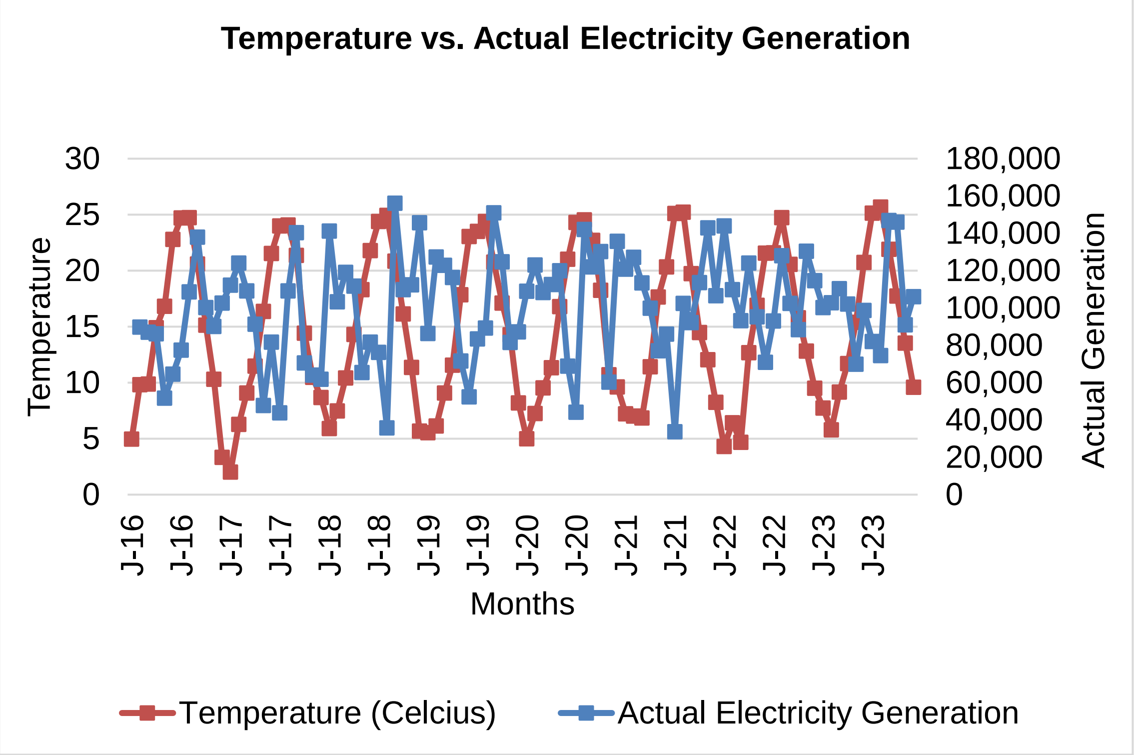


Figure 5.2. Monthly Temperature and Actual Electricity between January 2016 and December 2023

The wind speed and actual electricity generation have p-values for the Pearson Correlation, Mann-Kendall Test, and Spearman Rank Correlation of 0.000. The Pearson Correlation, Mann-Kendall Test, and Spearman Rank Correlation coefficients for the relationship between wind speed and actual electricity generation are 0.668, 0.446, and 0.607, respectively. This shows a positive correlation. The monthly wind speed and actual electricity generation interaction between January 2016 and December 2023 is demonstrated in Figure 5.3.

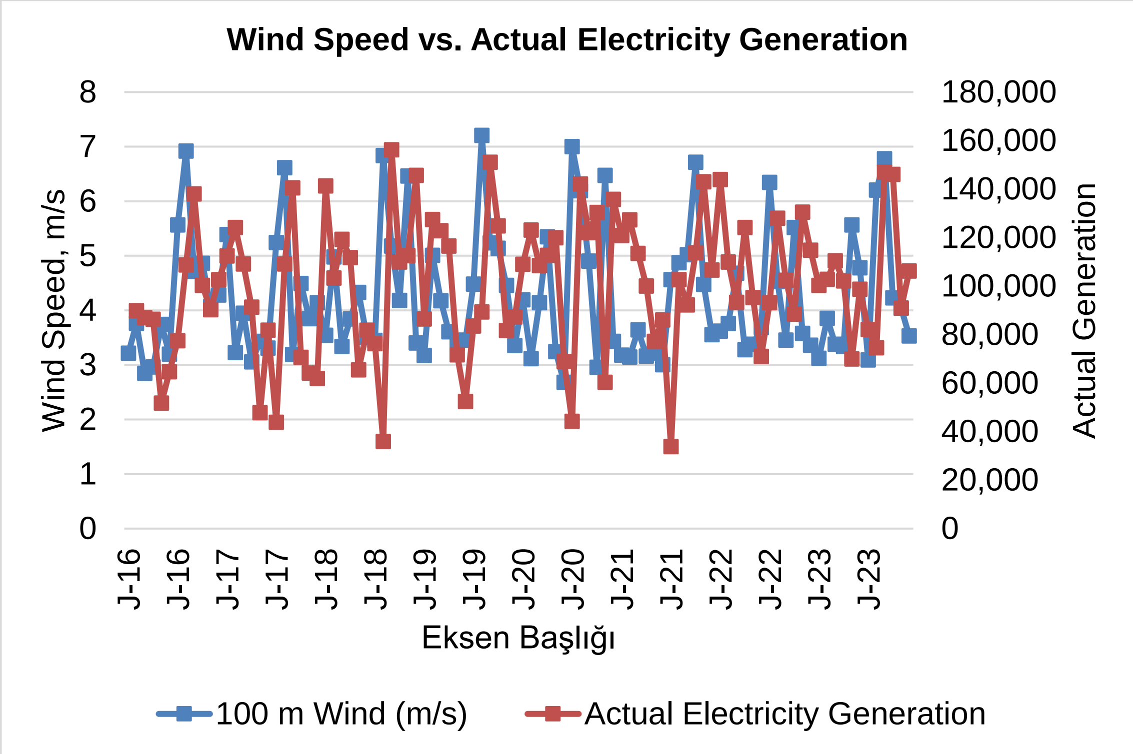


Figure 5.3. Monthly Wind Speed and Actual Electricity Generation between January 2016 and December 2023

5.2. Model Development

The models are developed based on the methodology presented in Section 4.2. Three statistical and four ANN models were created and explained in the following sections.

5.2.1. Statistical Model Development

The multiple linear regression analysis was carried out using the data given in Table 4.2, where the dependent variable is actual electricity generation, and the independent variables are wind speed and temperature. Three different combinations are tested to develop models: i) temperature and actual electricity generation, ii) wind speed and actual electricity generation, and iii) wind speed, temperature, and actual electricity generation. Table 5.1 displays the models' equations, R^2, and p values.

Table 5.1. R^2 and p Values of the Statistical Models

Model No.	Model Versions	Model Equation	R^2	P value
SM-1	Independent Variable: Temperature (T) Dependent Variable: Actual electricity generation (y)	y = 107,132.47 - 458.04 x **T**	0.013	0.277
SM-2	Independent Variable: Wind speed (W) Dependent Variable: Actual electricity generation (y)	y = 32,004.21 + 16041,65 x **W**	0.446	0.000
SM-3	Independent Variables: Temperature and wind speed Dependent Variable: Actual electricity generation (y)	y=41,412.69 + 19,827.06 x **W** – 1,722.29 x **T**	0.599	0.000

These results indicate that wind generation generally increases as wind speed rises. Conversely, wind generation tends to decrease with temperature.

5.2.2. ANN Model Development

The ANN analysis was carried out using the data in Table 4.4, where the dependent variable is normalized actual electricity generation, and the independent variables are wind speed and temperature. Three different combinations are tested to develop models: i) temperature and actual electricity generation, ii) wind speed and actual electricity generation, and iii) wind speed, temperature, and actual electricity generation.

Different structures, training, and test percentages are used to obtain the best performance. The structures used were [10 10], [10 5], [5 10], [5 5], [20 10], and [20 20]. The training percentages used for the model development were 70-30, 75-25, 80-20, and 85-15 for training and testing, respectively. In total, 72 models (6 structures x 4 different training percentages x 3 different inputs) were developed. The models and their R^2 values are given in Table 5.2.

Table 5.2. Summary of the ANN Model Structures and their R^2

Structure	Training Percentage (%)	R^2		
		Input: T	Input: W	Inputs: T, W*
10 10	70 (Training) - 30 (test)	<0.10	0.591	0.608
	75 (Training) - 25 (test)	<0.10	0.513	0.611
	80 (Training) - 20 (test)	0.184	0.369	0.275
	85 (Training) - 15 (test)	<0.10	0.613	0.688
10 5	70 (Training) - 30 (test)	<0.10	0.465	0.700
	75 (Training) - 25 (test)	<0.10	0.519	0.690
	80 (Training) - 20 (test)	0.194	0.616	0.689
	85 (Training) - 15 (test)	<0.10	0.615	0.672
5 10	70 (Training) - 30 (test)	<0.10	0.513	0.121
	75 (Training) - 25 (test)	<0.10	0.447	0.647
	80 (Training) - 20 (test)	0.132	0.215	0.707
	85 (Training) - 15 (test)	<0.10	0.454	0.704
5 5	70 (Training) - 30 (test)	<0.10	0.442	0.708
	75 (Training) - 25 (test)	<0.10	0.465	0.652
	80 (Training) - 20 (test)	<0.10	0.449	0.698
	85 (Training) - 15 (test)	<0.10	0.447	0.652
20 10	70 (Training) - 30 (test)	<0.10	0.461	0.706
	75 (Training) - 25 (test)	<0.10	0.565	0.682
	80 (Training) - 20 (test)	0.158	0.469	0.762
	85 (Training) - 15 (test)	<0.10	0.587	0.638
20 20	70 (Training) - 30 (test)	<0.10	0.447	0.670
	75 (Training) - 25 (test)	<0.10	0.469	0.755
	80 (Training) - 20 (test)	0.183	0.582	0.589
	85 (Training) - 15 (test)	<0.10	0.587	0.811

*T: Temperature, W: Windspeed

Four representative models were chosen based on their R^2 values to compare the performances of the ANN models. According to the data shown in Table 5.2, it can be seen that the [10 5] structures with a training percentage of 80% exhibit better average R^2 values (0.69) (green colored) than others. However, the [20 10] structure has the highest R^2 value. Hence, a comparative analysis was conducted between the [10 5] structure, which had three distinct input kinds. Besides, the [20 10] structure had a single input type: temperature and windspeed, as elaborated upon in Chapter 4.3. The compared models are listed in Table 5.3.

Table 5.3. Properties and R^2 values of the Best Four ANN Model Structures

Model No.	Model Versions	R^2
ANN-1	Temperature vs. Actual Generation - with [10 5] structure and 80% training	0.1937
ANN-2	Wind vs. Actual Generation - with [10 5] structure and 80% training	0.6162
ANN-3	Temperature, Wind vs. Actual Generation - with [10 5] structure and 80% training	0.6888
ANN-4	Temperature, Wind vs. Actual Generation - with [20 10] structure and 80% training	0.7622

5.3. Model Performance Comparison

Model performance comparison is addressed in the following sections for the statistical and ANN models.

5.3.1. Statistical Model Performances

According to R^2 values, the SM-3 has the highest R^2 value, which is the closest to 1, as presented in Table 5.1. This indicates that the SM-3 model performs a better model fit to the data than others. The predictors and actual electricity generation correlate regarding p values of the SM-2 and SM-3. However, there is no statistically significant correlation between temperature and actual electricity generation in line with the p-value of SM-1. Similar to the correlation analysis explained in Chapter 5.1, there is not enough evidence to conclude that there is a statistically significant correlation between temperature and actual electricity generation at a 95% confidence level.

The SM-1, SM-2, and SM-3 models are used to predict electricity generation via model equations given in Table 5.1. Actual electricity generation and predicted electricity generation comparisons of the SM-1, SM-2, and SM-3 are presented in Figure 5.4, Figure 5.5, and Figure 5.6, respectively.

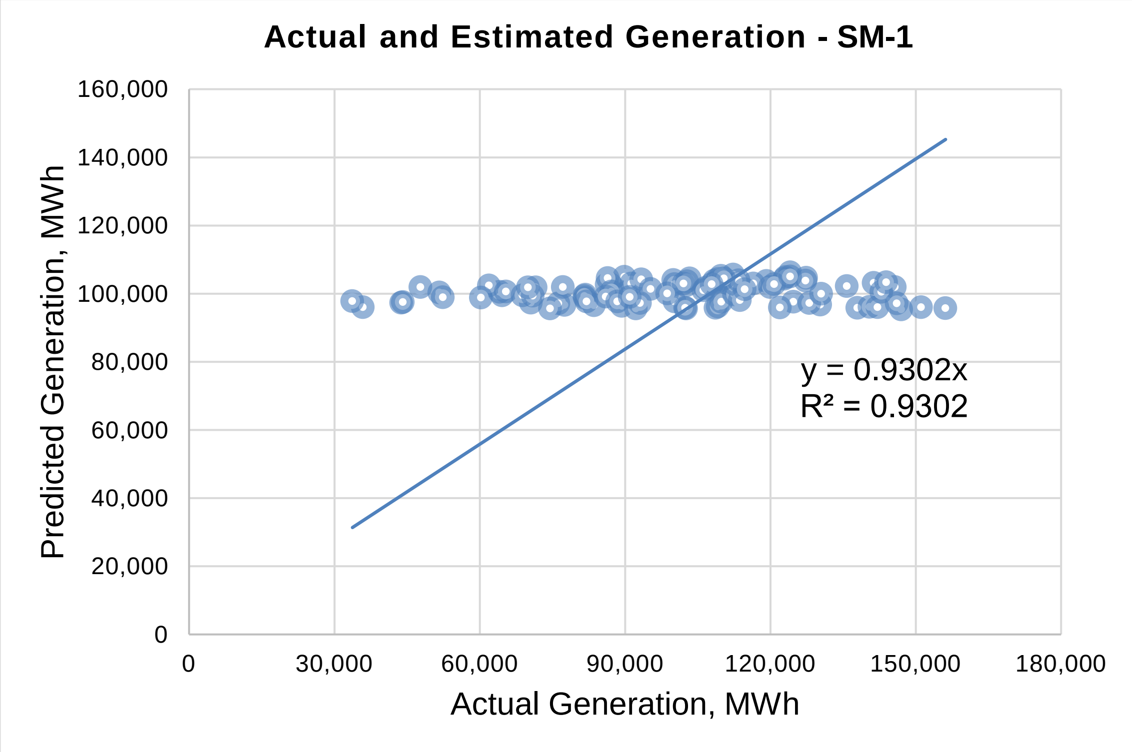


Figure 5.4. SM-1 Actual and Estimated Generation Comparison

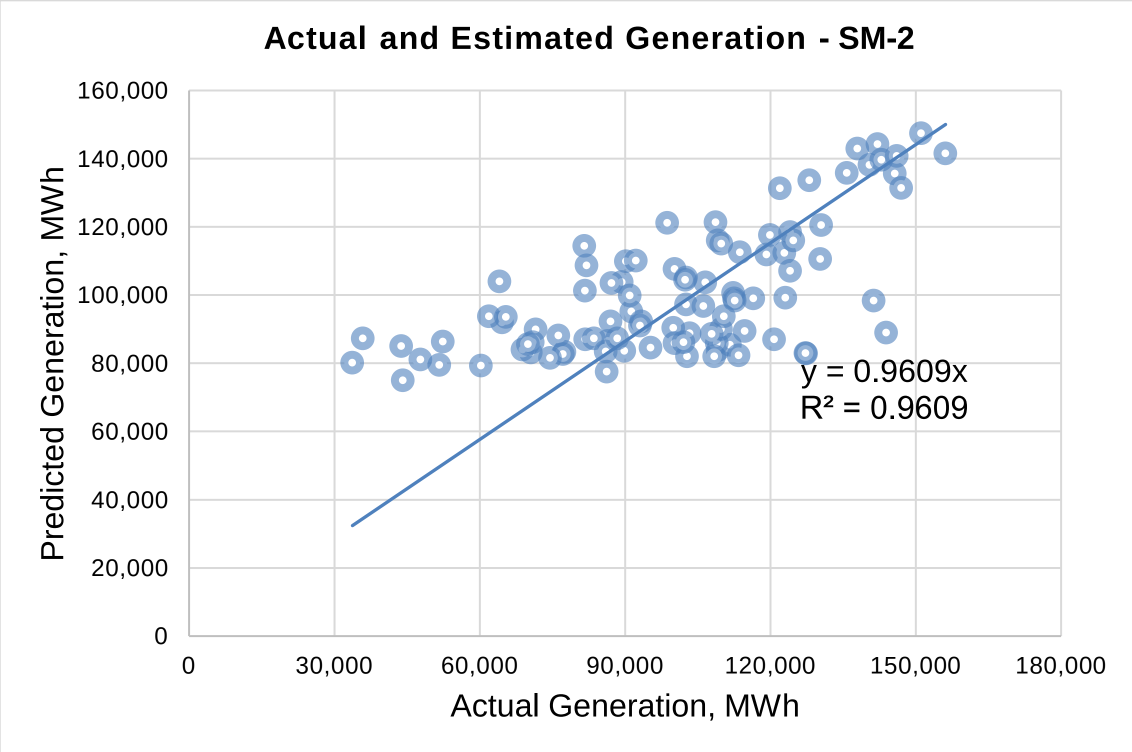


Figure 5.5. SM-2 Actual and Estimated Generation Comparison

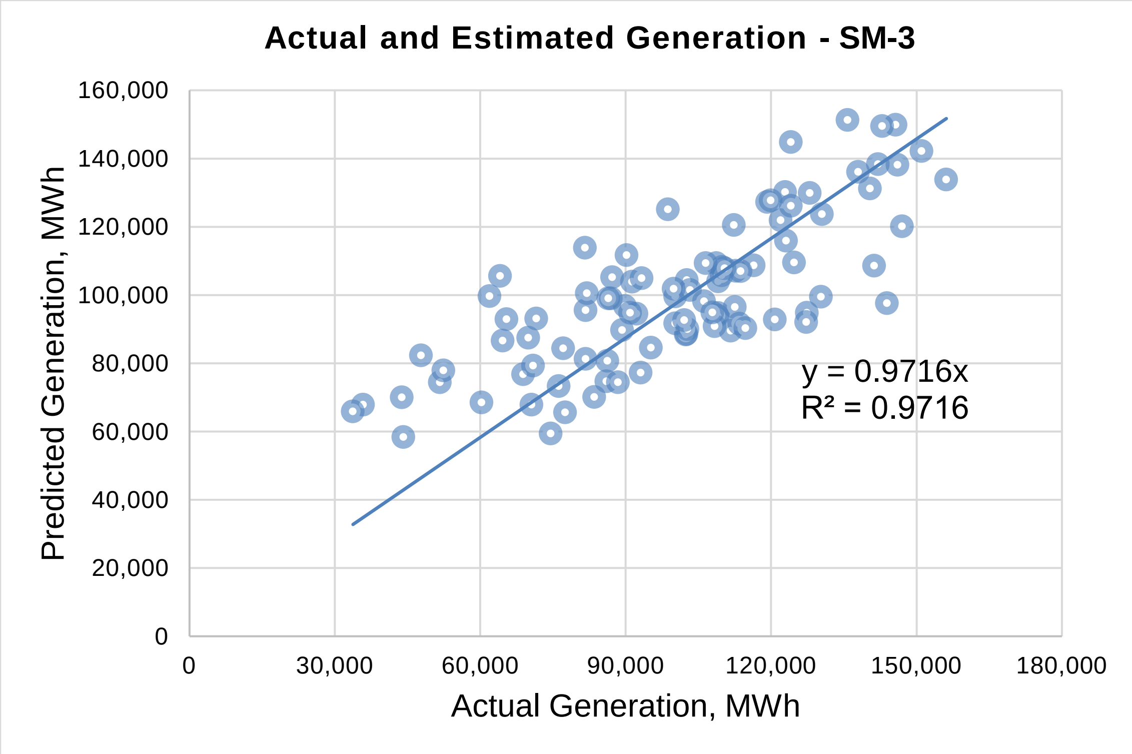


Figure 5.6. SM-3 Actual and Estimated Generation Comparison

As identified with the comparison of the R^2 values in the paragraph above, the comparison graphs indicate that the best fit belongs to SM-3, while the weak fit belongs to SM-1. It is seen that the SM-3 has better performance than the SM-2.

5.3.2. ANN Model Performances

Actual electricity generation and predicted electricity generation comparisons of the ANN-1, ANN-2, ANN-3, and ANN-4 (refer to Table 5.3) are given in Figure 5.7, Figure 5.8, Figure 5.9, and Figure 5.10, respectively.

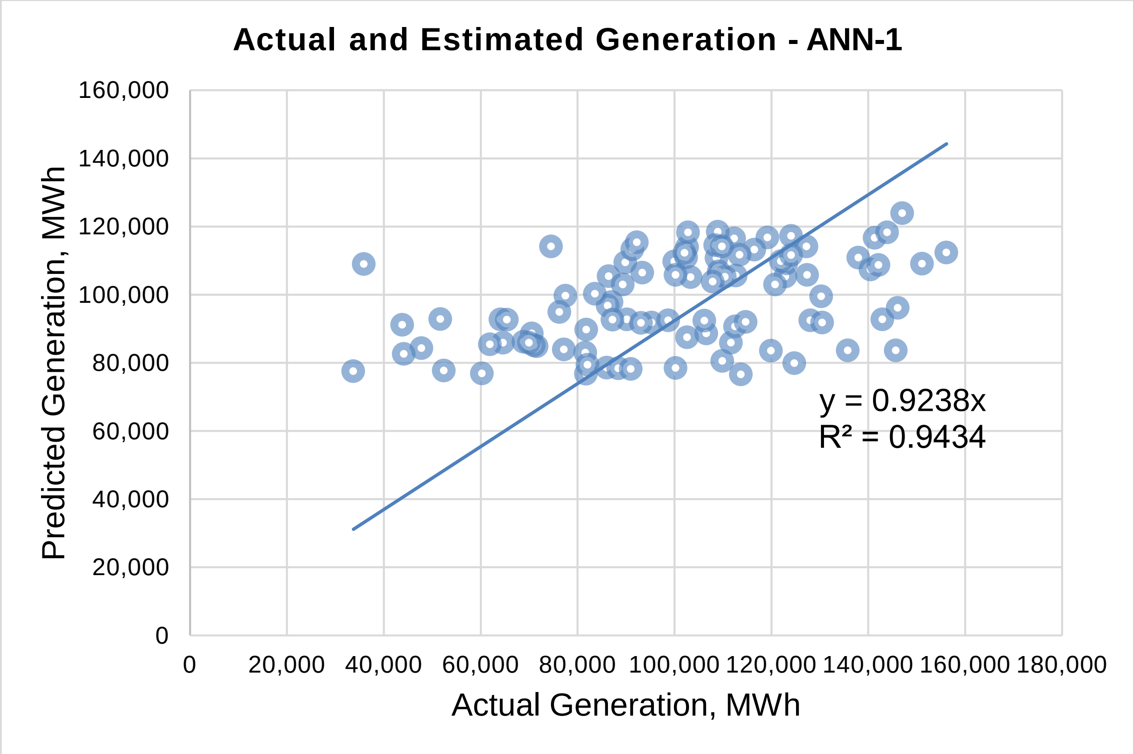


Figure 5.7. ANN-1 Actual and Prediction Generation Comparison

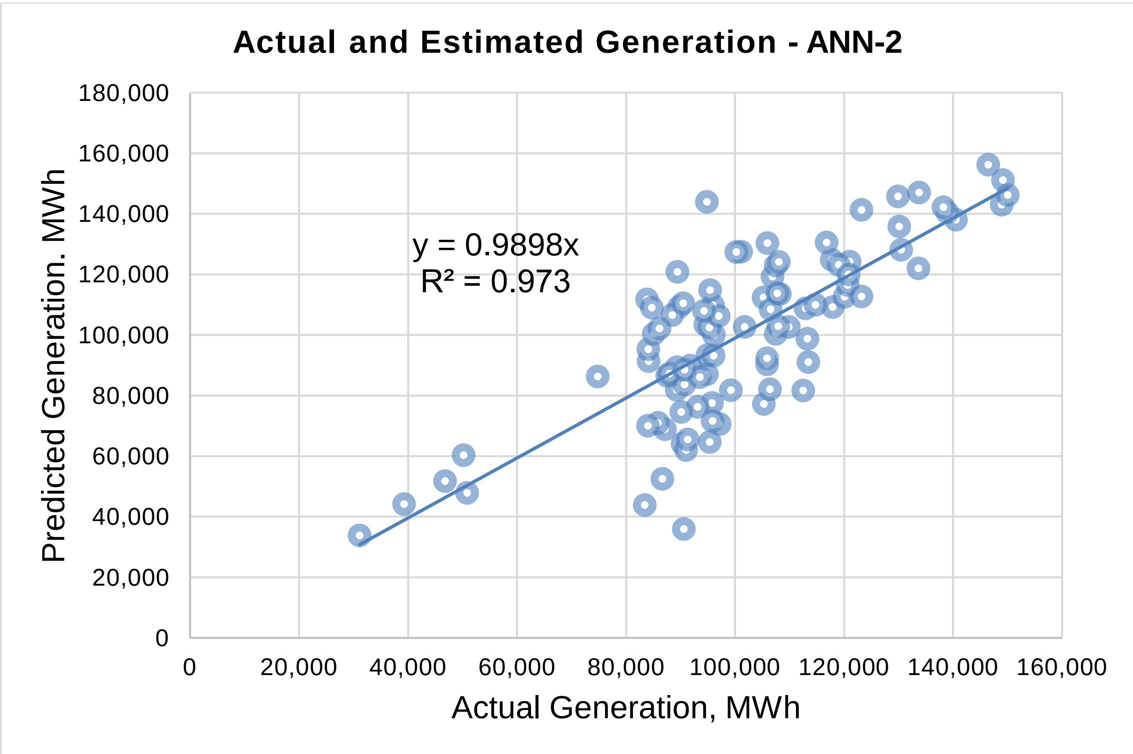


Figure 5.8. ANN-2 Actual and Prediction Generation Comparison

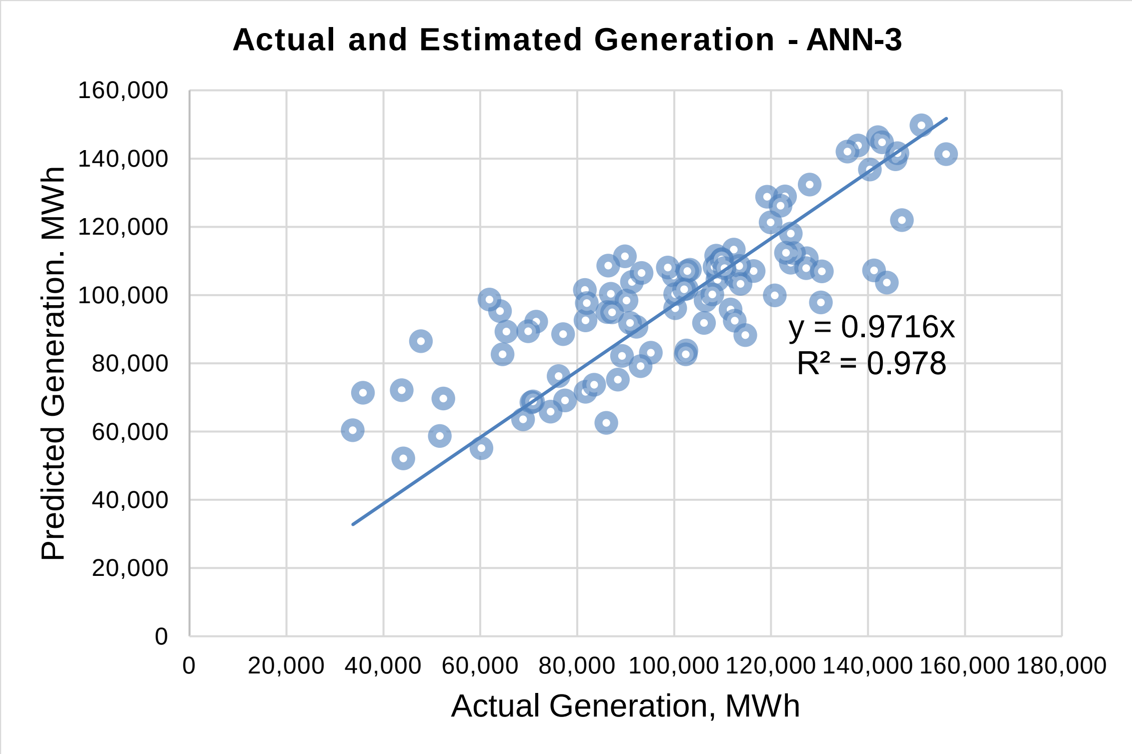


Figure 5.9. ANN-3 Actual and Prediction Generation Comparison

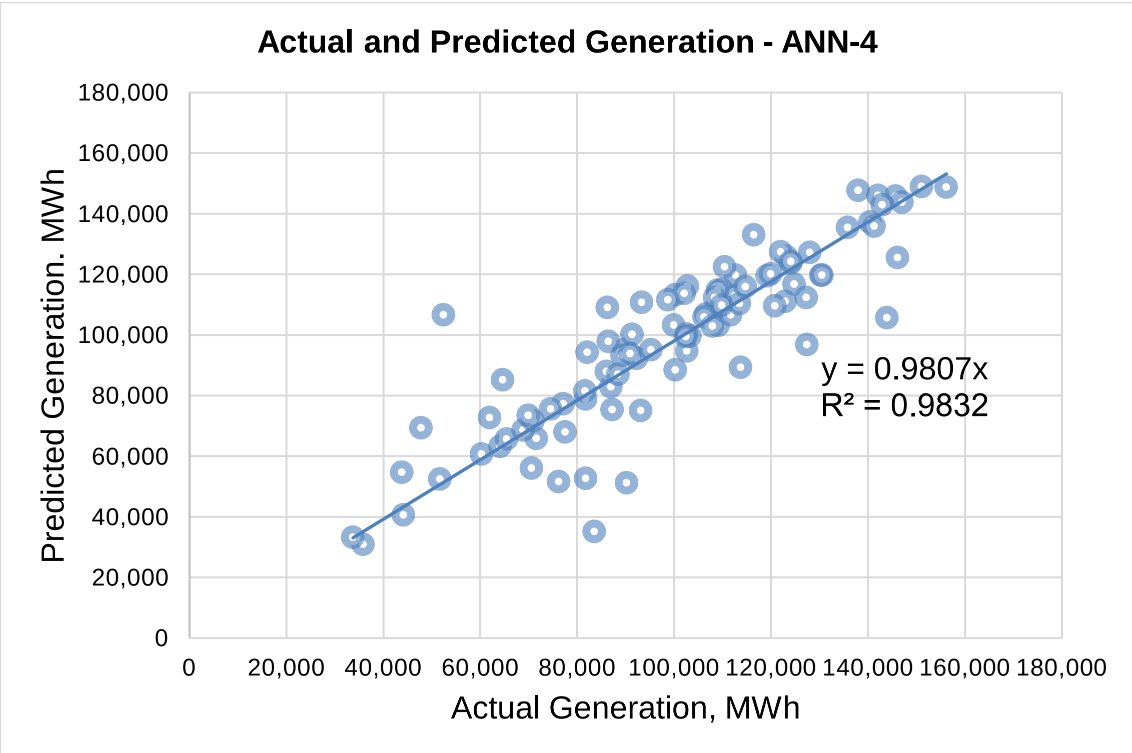


Figure 5.10. ANN-4 Actual and Prediction Generation Comparison

5.3.3. Statistical Parameters of Models

SEE, RMSE, PBIAS, MAPE, Pearson Correlation, Mann-Kendall Test, and Spearman Rank Correlation were performed to investigate statistical performances of the seven best models. The statistical results in Table 5.4 show that the most optimal models are those run with temperature and wind speed, namely SM-3 and ANN-4.

Table 5.4. Statistical Parameters of Models – SEE, RMSE, PBIAS, and MAPE

Model No.	R2	SEE	RMSE	PBIAS	MAPE
SM-1	0.01	27,796	27,505	-1.04	27.2%
SM-2	0.45	20,811	20,593	-0.70	20.3%
SM-3	0.60	17,807	17,527	-0.54	16.9%
ANN-1	0.19	25,117	24,854	-0.69	23.4%
ANN-2	0.62	17,329	17,148	-0.93	16.1%
ANN-3	0.69	15,605	15,442	-0.68	14.6%
ANN-4	0.76	13,641	13,498	0.41	9.7%

These models exhibit the lowest SEE, RMSE, and MAPE values and stronger correlations than others; the PBIAS values are closer to zero. The models with only wind speed, SM-2, and ANN-2, exhibit the second-highest performances.

The models executed only using temperature, SM-1 and ANN-1, exhibit the least favorable performance, aligning with the findings presented in Sections 5.3.1 and 5.3.2. This could result from the nonlinear effect of temperature on wind electricity generation. The efficiency of energy generation is mostly influenced by wind speed. At the same time, temperature may also affect the operation of wind turbines, although there is no direct relationship between temperature and power output [93] [94]. The complex connection among these variables underscores the difficulties in establishing a definitive relationship between temperature and energy generation from wind-generating facilities [95].

5.4. Projections of Electricity Generation and Visualisation

The models with the highest prediction performances, SM-3 and ANN-4 as presented in Section 5.3, were used to forecast power generation, considering temperature and wind speed forecasts based on the RCP4.5 and RCP8.5 scenarios. The following sections provide a comprehensive analysis of the statistical and ANN model predictions using RCP4.5 and RCP8.5 scenarios. The results were assessed considering short-term (2024-2048), medium-term (2049-2073), and long-term (2074-2098).

5.4.1. Projections of the Statistical Model

The total generations were predicted using the SM-3 model, with temperatures and wind speeds estimated based on RCP4.5 and RCP8.5. APPENDIX 5 presents the estimates corresponding to the quantity of power generated between 2016 and 2023. The results for short-term (2024-2048), medium-term (2049-2073), and long-term (2074-2098) are given in Table 5.5.

Table 5.5. Projected Electricity Generation Based on SM-3.

Period	Electricity Generation (MWh)		Change	
	RCP4.5	**RCP8.5**	**RCP4.5**	**RCP8.5**
2016 - 2023	1,376,374	1,383,000	base data	
2024 - 2048	1,364,861	1,351,800	-0.8%	-2.3%
2049 - 2073	1,342,639	1,345,881	-2.5%	-2.7%
2074 - 2098	1,322,114	1,299,757	-3.9%	-6.0%

SM-3 predicts a negative trend in electricity generation between 1-2% in the short term, 2.5% in the medium term, and 4-6% in the long term. Figure 5.11 shows electricity generation projections and weather data based on RCP4.5 and RCP8.5 from 2016 to 2098 using SM-3.

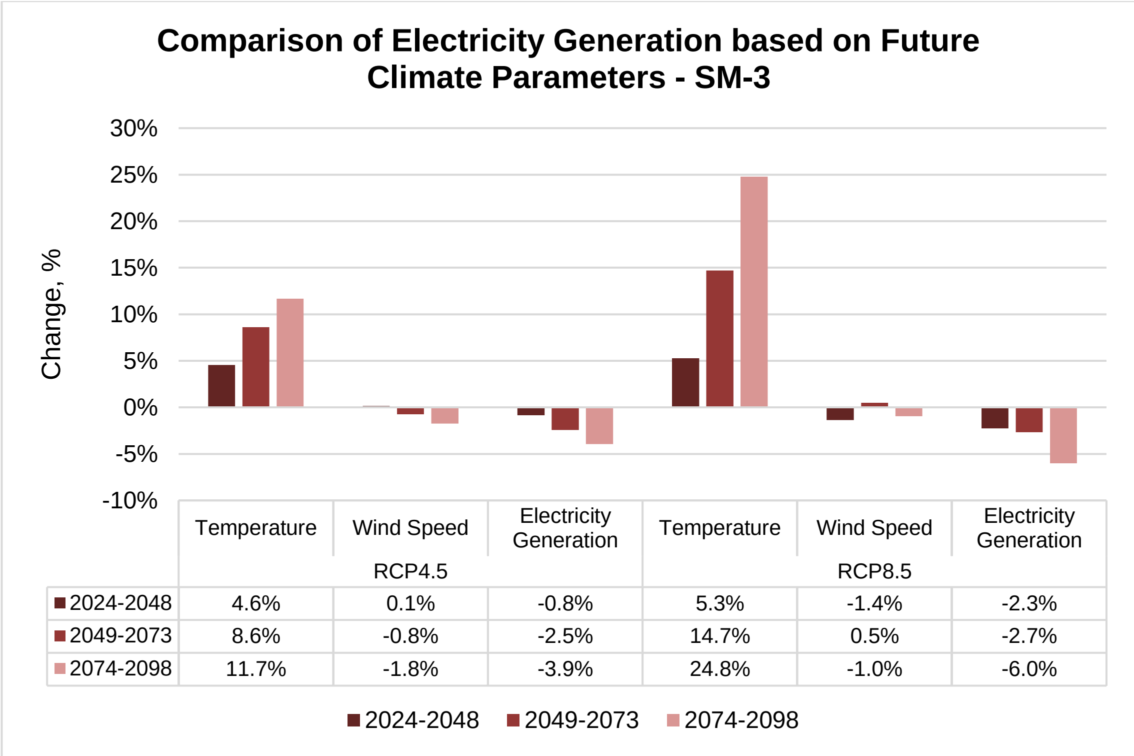


Figure 5.11. Comparison of Electricity Generation Based on Future Climate Parameters

Figure 5.11 illustrates that electricity generation will likely decrease gradually, based on the decrease in wind speed and temperature increase. Although there is a probable medium-term growth in wind speed for the RCP8.5 scenario, the electricity generation is projected to decline by around 3% after 2048.

5.4.2. Projections of the ANN Model

The total normalized generations were predicted using the ANN-4 model, with normalized temperatures and wind speeds estimated based on RCP4.5 and RCP8.5. APPENDIX 6 presents the estimates corresponding to the quantity of power generated between 2016 and 2023. Table 5.6 presents the data corresponding to the quantity of power generated and the corresponding percentage change in electricity generation.

Table 5.6. Projected Electricity Generation – ANN -4

Period	Electricity Generation (MWh)		Change	
	RCP4.5	RCP8.5	RCP4.5	RCP8.5
2016 - 2023	1,271,050	1,247,341	base	
2024 - 2048	1,269,973	1,279,724	-0.1%	2.6%
2049 - 2073	1,284,684	1,206,349	1.1%	-3.3%
2074 - 2098	1,198,301	1,202,286	-5.7%	-3.6%

ANN-4 predicts a 4-6% decrease in electricity generation by 2098, similar to SM-3. Figure 5.12 shows electricity generation projections from 2016 to 2098 via ANN-4 and projected weather data based on RCP4.5 and RCP8.5 from 2016 to 2098.

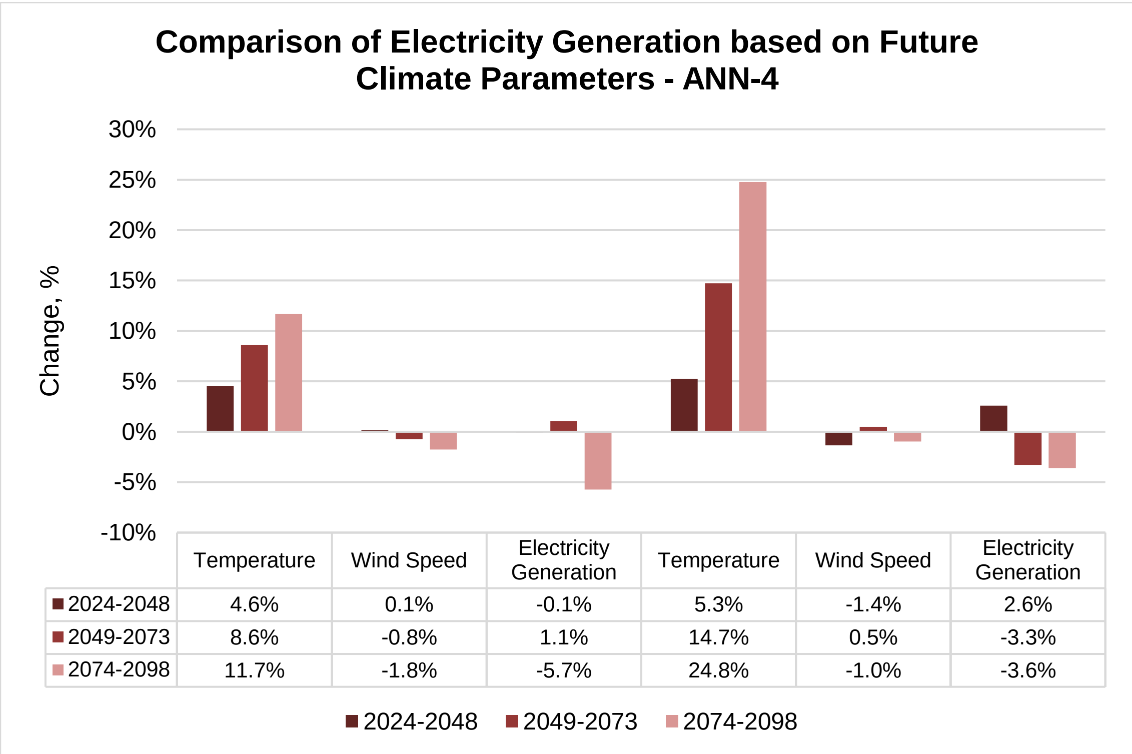


Figure 5.12. Forecasted Electricity Generation – ANN Models

Figure 5.12 demonstrates that ANN-4 displays a declining pattern by 2098 while the temperature rises and wind speed decreases. However, the model run with RCP4.5 scenario forecasted a higher decrease than the one with RCP8.5.

5.4.3. Comparison of Results

The predicted electricity generation change for the chosen next years, considering short-term (2024-2030), medium-term (2030-2050), and long-term (2080-2098), is shown in Figure 5.11 and Figure 5.12. These figures indicate that the energy generation linked to wind power facilities in the Marmara Basin has been negatively affected by climate change for three periods. The generation is expected to decrease by 4-6%, except for the short-term prediction of ANN-4 based on RCP8.5 and the medium-term prediction of ANN-4 based on RCP4.5. According to ANN-4, there is a projected 2.6% increase in power generation in the near term based on RCP8.5 and a 1.1% rise in the medium term based on RCP4.5. However, the anticipated changes can be considered insignificant in the long term.

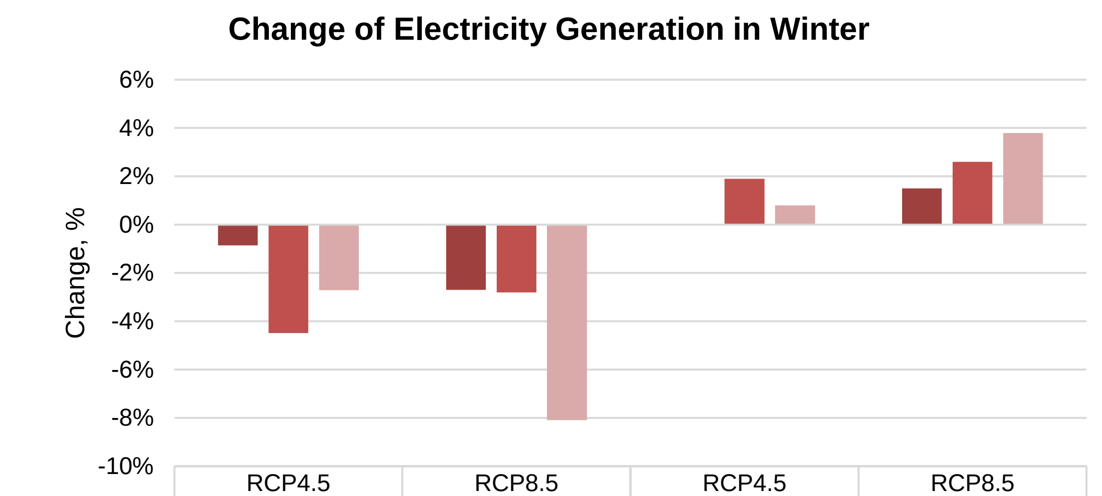
Yang et al. [75] reveal that there is no overarching pattern indicating a consistent growth or reduction in wind energy potential throughout time. The RCP 8.5 of studied cities had a marginal increase of about 1–2% in wind turbine potential. Martinez et al. [72] reported a 5% rise in the Marmara Region between 2091 and 2100 based on SSP8.5. According to Davy et al. [38] the wind power density may vary by around 0-5% in the RCP4.5 and RCP8.5 scenarios from 2061 to 2100. Moemken et al. [83] projected long-term growth of 0-6% in wind energy generation under the RCP4.5 and RCP8.5 scenarios, as analyzed by RCA4. Carvalho et al. [77] reported that the wind power density in the Marmara area is expected to rise by around 10-20% under the SSP4.5 scenario and decline by 0-10% under the SSP8.5 scenario in the long future. Furthermore, the research conducted by Çetin [73] suggests a significant likelihood of climate change impacting wind energy resources in Türkiye. The predictions made by the above investigations were mainly in line with the results obtained from the SM-3 and ANN-4 models, indicating a lack of statistical significance. Nevertheless, the projected direction of the influence differs significantly from the other research since both SM-3 and ANN-4 anticipate a decline, whereas the other studies anticipate an increase. This study's change ratio is consistent with the change ratio established by Carvalho et al. [77] using SSP8.5 in the long term.

Table 5.7, which is listed below, illustrates how the predictions of the developed models vary with the seasons.

Table 5.7. Seasonal Change of Models for Selected Years

Model	**Scenario**	**Season**	**Change of Electricity Generation**		
			2024-2048	**2049-2073**	**2074-2098**
SM-3	RCP4.5	DJF	-0.9%	-4.5%	-2.7%
		MAM	-2.5%	-3.1%	-5.0%
		JJA	2.3%	0.3%	-4.3%
		SON	-1.9%	-1.8%	-4.0%
	RCP8.5	DJF	-2.7%	-2.8%	-8.1%
		MAM	-4.8%	-4.7%	-6.4%
		JJA	-1.0%	-3.0%	-7.4%
		SON	-0.2%	-0.1%	-1.8%
ANN-4	RCP4.5	DJF	0.0%	1.9%	0.8%
		MAM	-2.6%	-4.1%	-11.5%
		JJA	3.1%	1.4%	-9.9%
		SON	-0.6%	5.4%	-3.4%
	RCP8.5	DJF	1.5%	2.6%	3.8%
		MAM	-0.6%	-12.4%	-8.9%
		JJA	-3.7%	-11.9%	-19.0%
		SON	14.9%	9.2%	10.0%

There are variations among the models during the winter season (DJF, i.e., December, January, and February). The SM-3 projected a downward trend, 2.7% for RCP4.5 and 8.1% for RCP8.5, until 2098. Conversely, ANN-4 projected an upward trend of 0.8% based on RCP4.5 and 3.8% based on RCP8.5. Changes based on the winter of 2023 are illustrated in Figure 5.13.

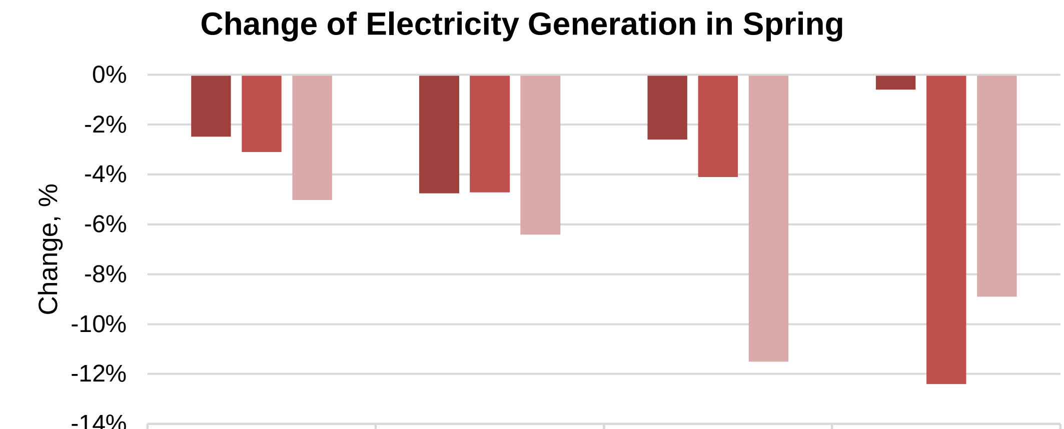


	SM-3 RCP4.5	SM-3 RCP8.5	ANN-4 RCP4.5	ANN-4 RCP8.5
2024-2048	-0.9%	-2.7%	0.0%	1.5%
2049-2073	-4.5%	-2.8%	1.9%	2.6%
2074-2098	-2.7%	-8.1%	0.8%	3.8%

Figure 5.13. Summary Illustration of Changes for Winter

The long-term winter electricity generation of this study has a decreasing trend for SM-3, around 3% based on RCP4.5 and 8% based on RCP8.5. It aligns with the study of Çetin [73] regarding the decreasing trend. In addition, Martinez et al. [72] interpreted a 0-15% increase for the Marmara Region in the winter season for the SSP4.5 scenario in the long term, whereas it is a 0-25% decreasing trend for the SSP8.5 scenario. Carvalho et al. [77] predicted a 0-20% increase in wind power density under SSP4.5 and a 20-30% decrease under SSP8.5. The results of these studies under SSP8.5 are comparable with the results of SM-3. The studies based on SSP4.5 align with the ANN-4 results regarding the increase.

The models consistently demonstrate a decrease in power generation throughout March, April, and May (spring). The short-term decrease ratio varies between 2.5% for RCP 4.5 and 4.8% for RCP 8.5 across the models. The medium-term decrease ratio ranges from 3.1% to 12.4% for RCP4.5 and RCP8.5. The range of long-term changes spans from 5% to 11.5% for RCP 4.5 and RCP 8.5. Changes based on the spring of 2023 are illustrated in Figure 5.14.



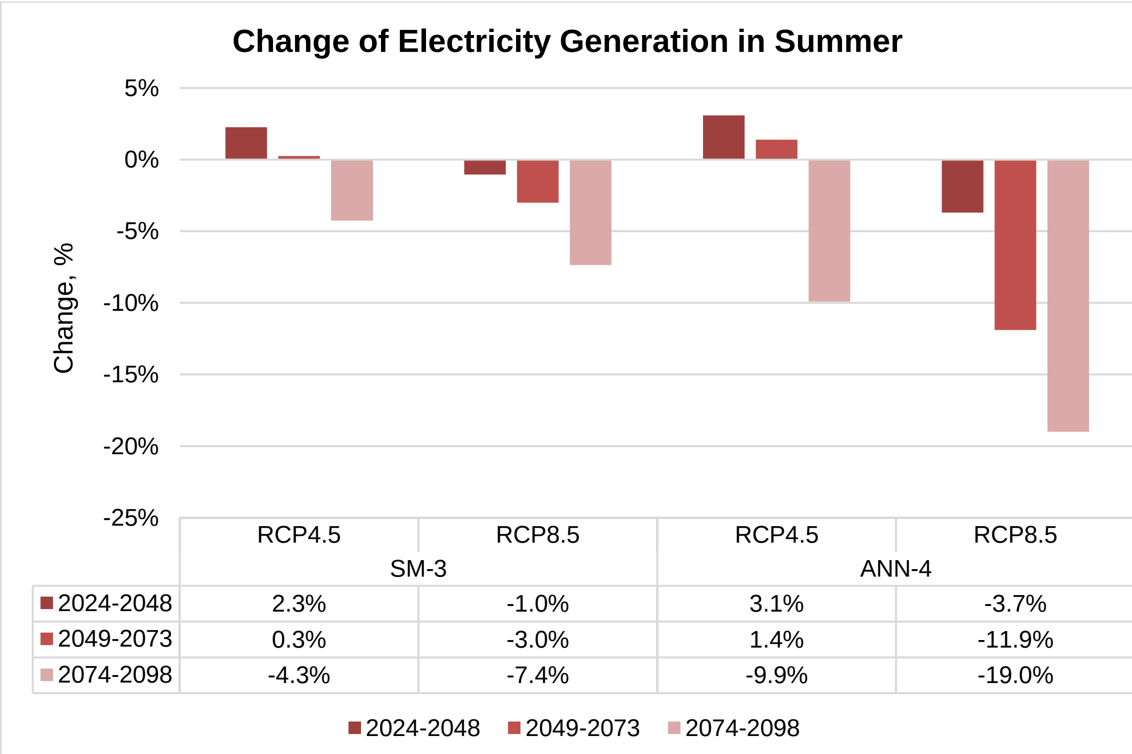
	SM-3 RCP4.5	SM-3 RCP8.5	ANN-4 RCP4.5	ANN-4 RCP8.5
2024-2048	-2.5%	-4.8%	-2.6%	-0.6%
2049-2073	-3.1%	-4.7%	-4.1%	-12.4%
2074-2098	-5.0%	-6.4%	-11.5%	-8.9%

Figure 5.14. Summary Illustration of Changes for Spring

The research conducted by Çetin [73] predicted that the wind power density in the Marmara Region and Marmara Sea Offshore may see a 2-3% rise during the spring season from 2080 to 2100. Therefore, this research is inconsistent with the findings of Çetin's study on the rise in wind power generation.

In their study, Martinez et al. [72] found that in the long future, Türkiye had a 0-20% rise in wind power density in the spring season under the SSP4.5 scenario, whereas the SSP8.5 scenario showed a declining trend of 0-25%. Carvalho et al. [77] predicted the wind power density in the Marmara Basin would see a 0-10% rise for SSP4.5 and a 0-10% drop for SSP8.5. So, the findings of SM-3 and ANN-4 for the spring season based on RCP4.5 and RCP8.5 align with the downward trajectory shown in the SSP8.5 scenario of the studies.

The summer season estimates exhibit a low stability level between RCP4.5 and RCP8.5 scenarios, but the projection patterns shown by SM-3 and ANN-3 are similar. According to SM-3 and ANN-4 prediction based on RCP4.5, there is an increase in the near term and a reduction in the long term. It is projected that electricity production will likely increase around 2-3% in the short term and 0.3-1.4% in the medium term. However, SM-3 and ANN-4 predict a decrease of around 4-10% in the long term. There is no forecasted increase by SM-3 and ANN-4 based on the RCP8.5 scenario. The predictions show a declining trend of 7.4-19% by the end of 2098. Changes based on the summer of 2023 are illustrated in Figure 5.15.



	SM-3 RCP4.5	SM-3 RCP8.5	ANN-4 RCP4.5	ANN-4 RCP8.5
2024-2048	2.3%	-1.0%	3.1%	-3.7%
2049-2073	0.3%	-3.0%	1.4%	-11.9%
2074-2098	-4.3%	-7.4%	-9.9%	-19.0%

Figure 5.15. Summary Illustration of Changes for Summer

The research conducted by Çetin [73] reveals that the summer season has the most significant growth rate, ranging from 30% to 48% between 2080 and 2100. According to Martinez et al. [72], the Marmara Region had a 0-25% rise during the summer season in the long-term scenarios of SSP4.5 and SSP8.5. Carvalho et al. [77] projected 10-20% rise for the SSP4.5 and SSP8.5 scenarios. The short- and medium-term predictions of the models based on RCP4.5 are consistent with these outcomes. However, a decreasing trend of the SM-3 and ANN-4 is inconsistent with the compared studies. Nevertheless, the SM-3 and ANN-4 show a reverse pattern between temperature and electricity generation, as described in Chapter 5.1. According to RCP8.5, the temperature is rising in the summer term by 5.5% in the short term, 14.5% in the medium term, and 20.8% in the long term, while the windspeed is decreasing by 1.7% in the short term, and increasing 1.6% and 0.8% in the medium and long terms, respectively (please also refer to Figure 5.11 and Figure 5.12). Therefore, the decreasing trend in electricity generation in the summer season predicted by SM-3 and ANN-4 seems reasonable.

The findings of SM-3 for September, October, and November (autumn) show a consistent downward trend. However, the predictions of ANN-4 do not show the same pattern. Changes based on the autumn of 2023 are illustrated in Figure 5.16.

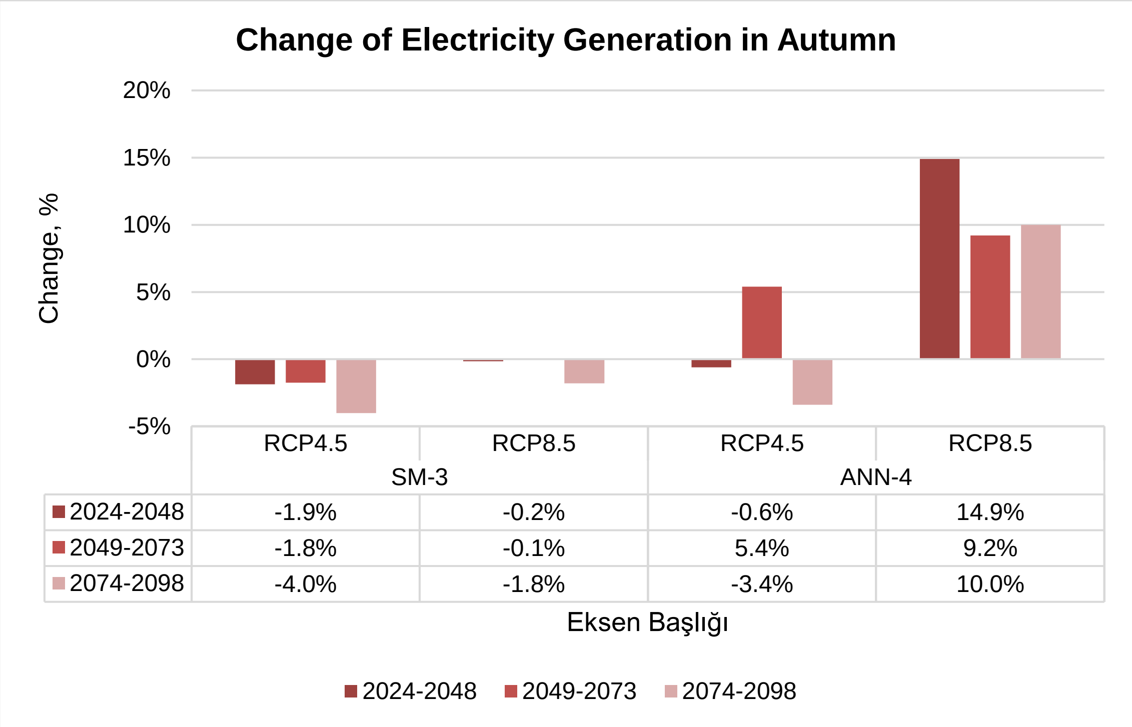


Figure 5.16. Summary Illustration of Changes for Autumn

SM-3 model in this research forecasted a gradual decrease in wind power generation in the long term throughout the autumn. In contrast, the ANN-4 forecasted a 3.4% decrease based on RCP4.5 and a 10% increase based on

RCP8.5. The study of Çetin [73] predicted an increasing trend in wind power density between 15% and 22% for autumn. In their research, Martinez et al. [72] also found that the Marmara Region experiences a 0-10% rise in the autumn season under the SSP4.5 scenario, whereas the long-term trend under the SSP8.5 scenario was a 0-5% increase. Carvalho et al. [77] identified a projected rise for the Marmara Basin of 10-20% with SSP4.5 and an increase of 0-10% with SSP8.5. So, the findings of these studies align only with the prediction of ANN-4 based on RCP8.5, but they are not consistent with SM-3 findings.

5.4.4. Evaluation of Results

The actual electricity generation of 50 WPP in Marmara Basin is 7,028,723 MWh for 2023. The percent changes predicted for the short, medium, and long terms using the models SM-3 and ANN-4 shown in Table 5.5 and Table 5.6 are used to estimate the total wind-based electricity generation by 50 WPP, as given in Table 5.8.

Table 5.8. Estimated Electricity Generation of 50 WPPs in Marmara Basin

Period	SM-3		ANN-4	
	RCP4.5	RCP8.5	RCP4.5	RCP8.5
2024-2048	6,972,493	6,867,062	7,021,694	7,211,470
2049-2073	6,853,005	6,838,947	7,106,039	6,796,775
2074-2098	6,754,603	6,607,000	6,628,086	6,775,689

According to the reference, household electrical consumption in Türkiye amounts to 8 kWh/day [96]. Table 5.9 shows the potential impact on residential power consumption resulting from changes in electricity generation.

Table 5.9. Potential Impact on Residental Power Consumption

Terms	SM-3		ANN-4	
	RCP4.5	RCP8.5	RCP4.5	RCP8.5
2024-2048	19,257	55,363	2,407	62,585
2049-2073	60,177	64,992	26,478	79,434
2074-2098	93,877	144,426	137,205	86,655

The change in electricity generation can potentially impact 87-144 thousand households by 2098. The anticipated decrease in energy output might be offset by constructing a second wind power station with a capacity of about 132 MW and 40% efficiency.

6. CONCLUSIONS AND RECOMMENDATIONS

Human-induced GHG emissions have escalated radiative forcing, hence inducing changing the global climate since the 1950s. Wind energy-based electricity generation is one of the energy sectors that could be impacted by climate change, particularly in wind speed, ambient temperature, and air density. More than 40% of Turkey's wind energy capacity is located in the Marmara Region, and 50 out of 99 wind power plants in the Marmara Basin are now facing challenges due to changing climatic conditions.

The literature assessment indicated that climate change has the potential to impact power generation from wind energy significantly. Previous research has mostly focused on investigating changes in wind energy capacities, assessing the implications for future infrastructure, and highlighting the need for comprehensive frameworks for evaluating the long-term viability of wind energy in the context of climate change scenarios.

The objective of this project was to gather and examine data, construct a model, evaluate the performance of the models, and forecast electricity generation. The power generation data of WPPs in the Marmara Basin account for 48% of the WPPs in the Marmara Region. The historical climate-related parameters consist of the wind speed at 100 m and the temperature at 2 m from C3S ERA5. The projections utilize data from HadGEM2-ES and RCA4 models to provide climate change estimates for the RCP4.5 and RCP8.5 scenarios. Two models are identified using ANN and Multiple Linear Regression. Statistical methods such as R2, RMSE, PBIAS, correlation analysis, and others are used to compare the predictive capabilities of models. The optimal model is selected to forecast wind turbine power generation. The findings are presented using various methodologies.

The comparison of statistical models indicates that the best fit belongs to SM-3 (temperature and windspeed were used as inputs), while the weak fit belongs to SM-1 (temperature was used as input). It is seen that the SM-3 has better performance than the SM-2 (wind speed was used as input). The ANN-4 (temperature and wind speed were the inputs with [20 10] structure) model has the highest performance among the ANN models.

The findings of this study indicate that the energy generation linked to 10 wind power plants in the Marmara Basin is influenced by climate change, with a range of -6% to -4% from 2023 to 2098. The long-term changes predicted by this study align with similar studies yearly.

The analysis reveals a declining tendency in the long-term winter power production for SM-3, with a decrease of around 3% according to RCP4.5 and 8% according to RCP8.5. These results partly align with other studies.

The investigation of seasonality across all models revealed a notable decrease in wind power generation during the spring season, with a range of 5% to 11.5% between 2023 and 2098. The findings are consistent with the conclusions drawn from prior research on wind power density.

The summer season predictions show a 7.4-19% decline by the end of 2098. The model's short- and medium-term predictions are based on RCP4.5 and are consistent with the previous studies.

This study predicted a fluctuating pattern for autumn, ranging from -4 to +10%. Prior research has shown a 0-22% rise in wind power density. The results of the previous studies align with the forecast made by ANN-4 using RCP8.5; however, they do not correspond with the conclusions of SM-3.

The observed disparities with the previous studies may be attributed to variations in historical values, predictions, GCM models used, and numerical disparities resulting from the wind power density equation.

The possible effect of the shift in power production extends to a total of 87-144 thousand homes. The potential reduction in energy production might be mitigated by establishing additional wind power facilities.

This study has limitations on data synchronization for developing an extensive dataset for better analysis of ANN models since the electricity generation of 50 WPPs has gaps between 2014 and 2023. In addition, WPPs in Marmara Basin no longer generate electricity before 2014. Another limitation was taking monthly and regional raw data averages to estimate basin-based changes since the dataset was smoother than the raw data. Considering these limitations, future recommendations for this study include detailed studies on a specific WPP using location-based daily data.

Future recommendations can be listed as follows:

- Conducting a detailed study on a specific wind power plant, collecting all relevant information such as location-based daily data, height, turbine models, and quality of recorded data.
- Utilizing up-to-date data to minimize the occurrence of missing data in reanalysis.
- It may be worth considering the study of climate change on solar power plants due to the increasing temperature that may affect the efficiency of cells [97].
- Studying the climate resilience of a wind power plant can provide valuable insights into the causes of shut-downs and shortages resulting from maintenance and repair needs. This includes examining the impact of heavy rain, storms, and extreme temperatures on the mechanical equipment of wind power plants (which could affect real-time electricity generation).

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APPENDICES

APPENDIX 1 – LIST OF WPPs IN THE MARMARA REGION

No.	Basin No.1	Basin No.2	Basin No.3	Basin No. 4	Basin No. 12
	Meriç Ergene Basin	**Marmara Basin**	**Susurluk Basin**	**Kuzey Ege Basin**	**Sakarya Basin**
1	Kıyıköy WPP	Yalova WPP	Balıkesir WPP	Ilgardere WPP	Pamukova WPP
2	Karatepe WPP	Manastır-Esenköy WPP	Çaypınar WPP	Hasanoba WPP	Geyve WPP
3	Balabanlı WPP	Kızılcaterzi WPP	Günaydın WPP	Alibey WPP	Adapazarı WPP
4	Zeliha WPP	Çakıl WPP	Kavaklı WPP	Gazi-9 WPP	Gökdağ WPP
5	VİZE-2 WPP	Göktepe WPP	Ortamandıra WPP	Gelibolu WPP (Ayvacık)	Dikili WPP
6	Karadere WPP	Barbaros WPP	Pazarköy WPP	Gülpınar WPP	Bozüyük WPP
7	Evrencik WPP	Kandıra WPP	Poyraz WPP	Ayvalık – I WPP	Meryem WPP
8	Kanije WPP	Yeni WPP	Poyrazgölü WPP		Metristepe WPP
9	Hamzabeyli WPP	Kıyıköy WPP	Tatlıpınar WPP		
10	Süloğlu WPP	AirWPP-4 WPP	Umurlar WPP		
11		Yamaçtepe-2 WPP	AlaWPP 2 WPP		
12		Silivri WPP	Güney 1 WPP		
13		Şile WPP	Harmanlık WPP		
14		Tayakadın WPP	Taşpınar WPP		
15		Sakarbayır WPP			
16		Ömerli WPP			
17		Mahmut Şevket Paşa-1 WPP			
18		Hacı Bey WPP			
19		İstanbul WPP			
20		Küptepe WPP			
21		Gazi WPP			

No.	Basin No.1	Basin No.2	Basin No.3	Basin No. 4	Basin No. 12
	Meriç Ergene Basin	Marmara Basin	Susurluk Basin	Kuzey Ege Basin	Sakarya Basin
22		Gaziosmanpaşa WPP			
23		Ertan WPP			
24		Çanta WPP			
25		Çataltepe WPP			
26		Aydos WPP			
27		Şadıllı WPP			
28		Çandır WPP			
29		Boreas WPP			
30		Saros WPP			
31		Üçpınar WPP			
32		Yeniköy WPP			
33		Korudağı WPP			
34		Maslaktepe WPP			
35		Kocalar WPP			
36		Koru WPP			
37		İçdaş Biga WPP			
38		Ada 2 WPP			
39		Edincik WPP			
40		Kalfaköy WPP			
41		Kapıdağ WPP			
42		Marmara WPP			
43		Paşalimanı WPP			
44		Şapdağı WPP			
45		Gündoğdu WPP			
46		Karacabey WPP			
47		Kürekdağı WPP			
48		Ulu WPP			
49		G WPP			
50		Gelibolu WPP			

APPENDIX 2 – LIST OF LOCATION, INSTALLED CAPACITY AND ACTUAL GENERATİON DATA OF WPPS IN THE MARMARA BASIN

No.	Name of WPP	Location		Installed Capacity (MW)	Total Electricity Generation (MWh)									
		Latitude	Longitude		2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
1	Yalova RES	40.58377269	28.93098806	53.2	0	0	32523	93732	127546	136982	149891	151969	142654	140314
2	Manastır-Esenköy RES	40.58289901	29.00811503	32.4	0	0	0	17610	85572	92909	97813	96671	94035	94707
3	Kızılcaterzi RES	40.69865303	26.55074891	13.6	0	0	0	0	0	6918	35792	36830	37927	36641
4	Çakıl RES	40.60643399	29.10682337	42	0	0	0	0	0	3287	80864	103459	104287	99926
5	Göktepe RES	40.53136627	28.88116019	45.5	0	0	0	0	0	0	599	27609	287874	348842
6	Barbaros RES	40.7630131	27.28327582	12.45	0	0	0	25696	43282	41736	46044	44418	46027	45098
7	Kandıra RES	41.11242469	30.02876122	24.9	0	0	0	0	0	0	0	22456	107957	117564
8	Yeni RES	41.941282	27.454262	3.6	0	0	0	0	0	0	0	0	4968	5261
9	Kıyıköy RES	41.6704512	28.05129825	100	0	27962	153814	141696	166679	150667	114167	282172	298088	273639
10	Airres-4 RES	41.63453578	27.82679624	60.8	0	0	0	128011	205684	187859	206601	184058	193930	194695
11	Yamaçtepe-2 RES	41.31178555	28.24445632	33	0	0	0	0	0	12545	77316	96215	76914	97061
12	Silivri RES	41.17029112	28.25644319	63	55489	169749	168478	156800	184469	206958	221131	228415	229332	236166
13	Şile RES	40.98390381	29.82445791	51.2	0	0	0	0	0	0	0	105816	155521	162365
14	Tayakadın RES	41.27821571	28.70184873	40.8	0	0	0	0	0	0	2372	87724	130780	142905
15	Sakarbayır RES	41.17327441	28.30336637	3.45	0	0	0	0	1251	24336	20759	11356	12060	11578
16	Ömerli RES	41.06609805	29.43779933	4.8	0	0	0	0	0	0	338	20559	232495	329895
17	Mahmut Şevket Paşa-1 RES	41.03724074	29.29395586	9.6	0	0	0	0	0	0	0	19927	28257	29207
18	Hacı Bey RES	41.09863448	28.47766543	3.6	0	0	0	0	0	0	0	0	59677	197840
19	İstanbul RES	41.41473989	28.26425438	115.2	0	0	0	0	0	0	0	125273	645285	681111
20	Küptepe RES	41.24513786	28.47070107	11.7	0	0	0	0	0	0	2443	29382	33219	33918
21	Gazi RES	41.14310677	28.31718297	6.9	0	0	0	0	1197	28142	32825	23333	23405	24696
22	Gaziosmanpaşa RES	41.07655003	28.90064454	54	0	0	0	0	0	0	5885	174706	196692	200749
23	Ertan RES	41.2433662	28.12269017	4.2	0	0	0	0	0	0	0	4888	11120	11286
24	Çanta RES	41.14063748	28.05348325	54.7	73292	158033	163879	150080	169782	163604	182131	174959	177283	179815
25	Çataltepe RES	41.22359324	28.44352155	12	31356	42741	42758	40241	41100	59806	42285	39416	40429	56482
26	Aydos RES	41.2696	28.3898	16.6	0	0	0	0	0	0	0	17624	51196	63024
27	Şadıllı RES	40.69683675	26.83988613	33	13805	125713	133124	120290	123231	124876	134713	126883	131131	121978
28	Çandır RES	40.672052	26.304012	10	0	0	0	0	0	0	0	8444	38674	38608
29	Boreas RES	40.72107267	26.18021542	21.6	51340	69458	75219	78524	87523	81047	84831	81093	83946	80920
30	Saros RES	40.06208522	26.7088212	132.886	0	0	0	0	0	0	8041	372070	506425	471469
31	Üçpınar RES	40.1527784	26.71427481	112.2	0	0	0	0	0	192005	343494	352887	353604	338127
32	Yeniköy RES	40.46285889	26.5854528	50.4	0	0	0	0	0	0	29214	205233	209426	202863
33	Korudağı RES	40.77561056	26.95057761	3.4	0	0	0	0	0	0	0	0	0	6715
34	Maslaktepe RES	40.55788237	26.85696181	23.4	0	0	0	0	0	13822	86819	82888	108365	192091
35	Kocalar RES	40.11383103	26.76964134	30.6	0	0	0	0	0	78857	112719	110697	114173	111966

No.	Name of WPP	Location		Installed Capacity (MW)	Total Electricity Generation (MWh)									
		Latitude	Longitude		2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
36	Koru RES	40.23827475	26.76315414	52.8	0	98699	165259	159893	165084	172589	172314	163497	161482	156777
37	İçdaş Biga RES	40.29046809	27.19618879	60.8	0	11765	158827	137165	161401	146892	167094	152225	154494	140909
38	Ada 2 RES	40.62181351	27.62106253	4.6	0	0	0	0	9977	11373	10408	12762	13512	12423
39	Edincik RES	40.31774848	27.79669542	77.4	82790	151488	194791	218041	245704	234625	255227	243813	244224	237394
40	Kalfaköy RES	40.090015	27.70933203	10.2	0	0	0	0	21542	33711	36388	34170	35460	33202
41	Kapıdağ RES	40.5021131	27.68491411	42.4	51274	66301	67765	63168	73697	67575	70136	127122	135624	124928
42	Marmara RES	40.62131038	28.95629337	9.6	0	0	0	0	0	0	969	38116	41313	38966
43	Paşalimanı RES	40.48721657	27.64278017	0.8	0	1261	935	2493	3040	2681	3043	2950	2938	2839
44	Şapdağı RES	39.667098	27.311464	30.4	0	0	0	0	0	0	1770	39888	146176	194694
45	Gündoğdu RES	40.33932344	28.9969396	9.6	0	0	5641	21844	22720	24136	25481	26291	25596	25320
46	Karacabey RES	40.61819505	29.0607111	33.3	0	0	10640	91588	102888	99951	107769	100397	109178	109689
47	Kürekdağı RES	40.5243278	29.03496816	36	0	0	0	14529	96636	104169	107144	108127	104981	104773
48	Ulu Rüzgar Santrali	40.57405933	29.81691876	28	0	0	0	0	0	0	0	27160	185316	329040
49	G RES	40.44353258	26.6106646	7.2	0	0	0	0	0	0	1002	19532	22369	24230
50	Gelibolu RES	40.28140444	26.91291753	10.8	0	0	0	0	0	0	0	9186	82552	111993

APPENDIX 3 – HISTORICAL CLIMATE DATA

Years	Months	100 m U Wind ($m.s^{-1}$)	Temperature (°C)
2016	January	3.22	4.95
	February	3.76	9.83
	March	2.84	9.87
	April	2.96	14.92
	May	3.74	16.83
	June	3.20	22.79
	July	5.57	24.71
	August	6.92	24.73
	September	4.72	20.59
	October	4.86	15.13
	November	4.07	10.32
	December	4.28	3.34
2017	January	5.39	2.01
	February	3.23	6.28
	March	3.94	9.09
	April	3.06	11.48
	May	3.43	16.36
	June	3.31	21.53
	July	5.24	24.01
	August	6.62	24.10
	September	3.19	21.38
	October	4.49	14.43
	November	3.85	10.48
	December	4.14	8.69
2018	January	3.54	5.92
	February	4.98	7.48
	March	3.33	10.43
	April	3.84	14.32
	May	4.32	18.31
	June	3.50	21.79
	July	3.45	24.39
	August	6.83	24.95
	September	5.18	20.85
	October	4.18	16.15
	November	6.46	11.37
	December	3.40	5.68
2019	January	3.17	5.53
	February	5.01	6.14
	March	4.18	9.10
	April	3.61	11.57
	May	3.39	17.87
	June	3.45	23.05
	July	4.48	23.52

Years	Months	100 m U Wind ($m.s^{-1}$)	Temperature (°C)
	August	7.20	24.40
	September	5.24	20.78
	October	5.14	17.10
	November	4.46	14.29
	December	3.36	8.21
2020	**January**	4.19	4.98
	February	3.12	7.25
	March	4.14	9.53
	April	5.34	11.34
	May	3.74	16.80
	June	3.19	21.02
	July	7.00	24.32
	August	6.19	24.54
	September	4.90	22.71
	October	3.86	18.24
	November	6.47	10.70
	December	3.43	9.64
2021	**January**	3.18	7.22
	February	3.14	7.02
	March	3.77	6.85
	April	3.16	11.42
	May	3.70	17.65
	June	3.51	20.35
	July	4.56	25.11
	August	4.87	25.23
	September	5.02	19.74
	October	6.71	14.48
	November	4.50	12.04
	December	3.26	8.26
2022	**January**	3.62	4.30
	February	3.00	6.44
	March	4.68	4.69
	April	3.73	12.70
	May	3.38	16.90
	June	3.68	21.56
	July	6.34	21.61
	August	4.52	24.75
	September	4.12	20.57
	October	5.52	15.79
	November	3.58	12.84
	December	3.07	9.52
2023	**January**	3.12	7.73
	February	3.10	5.78
	March	3.51	9.17
	April	3.79	11.70
	May	5.56	15.41
	June	4.78	20.73

Years	Months	100 m U Wind ($m.s^{-1}$)	Temperature (°C)
	July	3.09	25.13
	August	6.20	25.68
	September	6.78	21.91
	October	5.13	17.74
	November	4.04	13.54
	December	3.53	9.60

APPENDIX 4 – FORECASTED CLIMATE DATA

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
2016	January	5.52	4.22	6.48	4.12
	February	4.96	3.02	5.41	3.35
	March	5.91	11.11	6.23	7.94
	April	4.58	12.14	4.29	11.17
	May	4.64	16.59	4.28	19.31
	June	4.36	22.56	3.79	20.87
	July	4.33	24.49	4.73	23.43
	August	6.50	23.42	4.60	24.65
	September	5.65	20.59	4.85	19.78
	October	5.03	13.78	4.75	16.09
	November	4.64	10.61	4.65	12.78
	December	5.81	4.54	5.80	7.52
2017	January	6.33	3.69	4.67	4.17
	February	4.18	7.70	3.92	0.99
	March	5.15	9.97	5.04	6.47
	April	4.01	13.37	4.06	14.63
	May	4.42	17.10	4.86	16.38
	June	4.72	22.89	4.80	21.45
	July	5.05	23.59	5.56	23.74
	August	5.36	24.30	5.86	23.83
	September	5.13	20.21	4.40	20.14
	October	5.03	15.18	5.50	14.10
	November	4.13	9.27	5.43	5.92
	December	5.75	8.43	4.94	6.37
2018	January	4.22	5.97	4.18	4.86
	February	5.36	4.27	5.21	3.28
	March	5.03	6.65	3.99	5.73
	April	4.58	9.29	4.88	12.93
	May	3.73	13.83	5.98	17.46
	June	3.76	21.90	3.81	20.90
	July	6.55	23.63	5.31	25.96
	August	5.76	23.60	6.80	24.69
	September	4.46	21.87	4.42	22.82
	October	4.24	16.30	4.73	16.38
	November	4.23	10.73	3.29	7.62
	December	5.38	7.11	4.40	7.13
2019	January	4.93	5.17	5.79	2.66
	February	4.36	4.04	5.58	9.68
	March	4.73	8.77	3.97	8.46
	April	4.97	13.13	4.42	12.67
	May	3.81	18.18	4.24	17.13
	June	4.18	21.86	3.52	22.43
	July	5.38	24.30	6.14	24.22

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	August	4.91	24.88	6.40	24.51
	September	4.66	20.67	4.24	19.87
	October	5.68	14.65	5.84	16.50
	November	5.29	11.13	5.46	9.80
	December	5.24	6.78	6.90	3.61
2020	January	6.71	6.55	5.10	5.32
	February	4.20	4.09	4.85	5.76
	March	5.60	5.97	6.00	7.55
	April	4.83	9.92	4.15	12.55
	May	4.78	16.53	3.71	16.47
	June	4.85	20.85	3.71	20.90
	July	4.77	25.48	5.15	24.74
	August	5.29	24.82	5.87	23.86
	September	4.78	21.34	4.46	20.50
	October	3.72	13.95	5.25	18.64
	November	4.70	8.92	4.84	12.31
	December	4.74	4.89	6.03	7.48
2021	January	4.47	7.22	5.09	5.69
	February	5.30	8.14	4.86	8.52
	March	5.22	6.96	6.39	4.99
	April	4.31	12.58	4.85	9.31
	May	4.10	15.49	4.35	16.64
	June	4.17	21.03	3.99	22.10
	July	5.28	23.66	5.31	23.71
	August	3.95	25.81	6.49	22.23
	September	4.72	18.09	5.24	20.19
	October	5.42	12.81	4.53	17.03
	November	5.33	7.38	4.37	10.59
	December	5.12	7.99	4.57	3.15
2022	January	5.64	6.51	4.94	5.42
	February	5.87	6.39	5.99	7.51
	March	6.81	7.07	4.73	9.32
	April	4.65	8.93	5.63	15.13
	May	3.98	16.48	5.23	17.31
	June	4.09	21.47	4.14	20.97
	July	5.55	23.55	4.43	24.69
	August	5.71	24.59	4.94	25.08
	September	4.63	19.45	4.54	19.06
	October	5.01	17.91	4.40	13.87
	November	4.35	11.46	4.48	11.63
	December	5.38	4.32	5.47	5.68
2023	January	4.06	3.45	4.43	3.93
	February	5.13	5.25	5.12	5.59
	March	5.64	7.92	5.79	8.48
	April	4.18	11.75	4.37	12.29
	May	4.10	16.98	4.87	14.55

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	June	3.92	21.12	3.71	20.75
	July	5.64	23.77	5.51	22.61
	August	4.91	24.67	4.69	22.52
	September	5.64	20.59	4.72	21.10
	October	4.58	15.61	4.68	16.74
	November	4.77	8.55	5.35	9.02
	December	4.38	4.46	5.13	6.71
2024	January	6.01	4.22	4.41	2.83
	February	4.72	5.84	4.57	4.32
	March	5.18	9.07	4.77	8.00
	April	4.87	14.59	4.38	14.12
	May	4.06	16.88	3.69	16.77
	June	4.29	22.71	4.45	22.10
	July	6.01	23.85	5.64	24.46
	August	5.22	24.37	5.85	24.09
	September	5.02	20.25	4.21	21.99
	October	4.26	15.65	3.76	13.30
	November	4.59	10.19	4.07	8.23
	December	5.38	4.93	5.11	7.94
2025	January	5.23	6.68	4.19	5.84
	February	5.89	9.05	4.55	7.45
	March	5.04	11.90	4.34	10.23
	April	5.02	14.52	4.37	13.10
	May	4.89	19.44	4.47	18.55
	June	4.28	21.70	5.13	22.12
	July	5.41	23.72	4.74	25.77
	August	5.16	25.62	5.00	24.09
	September	4.35	20.33	5.50	18.08
	October	4.88	14.42	4.49	16.18
	November	4.01	9.21	4.02	9.00
	December	5.76	4.67	4.25	3.35
2026	January	4.00	6.16	5.08	2.16
	February	4.95	7.19	5.55	7.87
	March	4.34	8.01	4.70	9.09
	April	4.45	11.83	4.33	13.61
	May	4.12	16.91	5.13	16.15
	June	4.67	20.69	3.75	21.16
	July	4.89	24.81	5.17	25.80
	August	5.39	25.12	5.49	25.90
	September	5.11	20.75	5.01	20.04
	October	3.87	14.24	4.40	17.47
	November	4.67	7.27	5.65	9.45
	December	6.04	5.07	4.67	6.77
2027	January	5.65	5.26	5.24	6.00
	February	5.07	4.05	5.26	5.45
	March	4.95	8.65	4.26	11.59

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	April	4.18	13.35	5.15	11.58
	May	4.90	18.71	4.39	17.75
	June	3.67	22.71	4.06	21.34
	July	4.85	24.24	4.24	25.68
	August	6.20	23.60	6.12	23.53
	September	5.25	19.43	4.03	21.47
	October	3.83	13.78	6.25	14.06
	November	5.10	11.76	5.13	12.81
	December	5.14	9.18	4.65	5.91
2028	January	6.35	5.54	4.80	8.21
	February	5.93	3.31	4.20	4.49
	March	4.88	6.09	4.15	7.00
	April	4.38	13.82	4.33	13.15
	Haz	3.55	18.16	3.27	18.03
	June	4.20	22.08	4.10	22.83
	July	5.18	24.28	5.70	25.16
	August	5.80	23.04	5.21	23.40
	September	4.66	20.28	5.63	19.19
	October	5.43	13.68	4.64	12.83
	November	5.34	9.13	5.07	10.94
	December	4.19	7.27	5.21	3.79
2029	January	5.45	7.37	5.69	4.25
	February	5.07	6.40	4.75	5.49
	March	4.28	6.96	5.14	6.41
	April	5.59	12.60	5.48	10.38
	Tem	3.91	20.40	3.97	16.87
	June	4.27	20.35	4.27	21.57
	July	4.10	23.73	5.09	24.81
	August	6.11	24.73	5.09	24.58
	September	4.27	21.35	5.56	20.34
	October	4.34	16.64	5.38	15.37
	November	5.16	11.18	5.09	11.92
	December	4.54	2.41	5.92	4.06
2030	January	5.95	4.69	5.84	3.43
	February	4.68	6.27	5.88	5.49
	March	5.71	10.19	5.62	7.19
	April	4.35	12.93	4.81	11.20
	Ağu	4.44	16.54	3.97	15.60
	June	4.91	21.55	4.69	21.94
	July	4.42	25.34	6.20	24.52
	August	5.27	23.54	5.16	23.47
	September	3.95	19.85	4.94	19.32
	October	5.84	14.33	4.53	11.82
	November	4.82	9.05	4.28	9.38
	December	4.13	7.13	4.86	8.15
2031	January	6.26	7.65	3.73	6.24

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	February	4.98	8.46	5.23	5.92
	March	6.24	7.74	5.03	8.11
	April	4.30	13.27	4.14	13.51
	Eyl	4.07	16.61	4.54	18.76
	June	3.99	23.04	4.49	22.00
	July	5.57	25.26	5.25	25.02
	August	5.93	24.44	6.04	24.62
	September	4.37	19.39	5.26	19.32
	October	4.60	13.71	4.98	12.74
	November	4.30	9.77	5.57	11.19
	December	4.55	7.15	5.07	5.07
2032	January	5.23	3.79	4.29	6.53
	February	5.44	3.26	5.27	5.05
	March	4.10	4.76	6.10	8.77
	April	4.53	12.46	4.12	10.34
	Eki	5.17	16.35	4.02	18.84
	June	4.26	21.46	3.76	23.51
	July	5.09	25.43	4.62	22.93
	August	5.54	26.27	4.40	23.74
	September	5.62	17.98	4.68	18.61
	October	4.34	14.79	4.65	16.07
	November	5.53	12.62	4.52	12.03
	December	5.27	6.70	4.49	6.14
2033	January	6.28	5.43	5.37	7.41
	February	5.21	8.91	5.52	8.90
	March	7.09	8.17	5.66	8.93
	April	4.45	10.77	4.69	12.72
	Kas	3.64	17.39	4.49	17.48
	June	3.65	22.04	4.67	22.89
	July	5.44	23.86	5.11	26.24
	August	5.27	23.13	5.93	25.67
	September	4.50	19.91	3.39	21.86
	October	4.38	17.41	4.87	16.97
	November	4.85	9.27	5.64	12.19
	December	3.63	6.13	5.33	8.29
2034	January	3.74	5.68	5.80	4.00
	February	4.39	3.42	3.90	6.67
	March	4.39	7.29	4.55	6.52
	April	4.55	13.92	3.99	11.70
	Ara	5.11	18.34	4.37	18.24
	June	4.00	23.85	4.26	23.20
	July	5.20	25.57	5.00	26.10
	August	5.61	26.12	6.26	25.99
	September	4.61	22.51	4.82	20.20
	October	4.51	18.12	3.87	18.37
	November	4.86	10.14	5.18	11.03

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	December	4.56	8.09	4.33	10.67
2035	January	5.40	5.59	5.04	6.98
	February	5.63	7.83	4.95	5.32
	March	5.64	7.56	4.83	7.89
	April	4.29	14.20	5.22	9.78
	Oca	4.14	16.58	4.38	16.61
	June	3.39	22.45	4.41	20.52
	July	5.88	24.04	6.38	23.80
	August	7.59	26.29	5.94	24.87
	September	4.60	20.05	4.04	19.71
	October	5.09	16.38	3.69	12.21
	November	4.64	11.60	5.72	10.72
	December	4.63	4.93	5.76	2.58
2036	January	5.12	4.97	4.67	4.10
	February	6.32	6.43	5.99	7.79
	March	4.20	8.83	5.30	8.79
	April	4.20	13.18	3.68	12.84
	Şub	3.93	17.39	4.17	16.55
	June	4.55	20.94	4.08	23.34
	July	5.92	25.26	4.66	26.40
	August	5.15	24.47	5.67	25.28
	September	4.69	20.73	4.28	20.36
	October	5.37	16.78	3.79	18.28
	November	5.59	8.76	5.63	7.60
	December	5.79	8.17	5.87	6.72
2037	January	5.52	7.80	5.66	3.94
	February	5.42	8.04	4.01	3.30
	March	5.11	11.49	4.40	9.07
	April	4.52	14.59	5.27	10.61
	Mar	4.41	18.04	4.06	18.72
	June	4.10	23.74	3.60	22.63
	July	4.43	25.89	5.88	25.61
	August	6.19	24.93	6.19	22.91
	September	4.36	20.32	4.91	21.51
	October	3.79	16.69	4.94	13.72
	November	4.73	10.10	3.77	8.24
	December	4.15	7.17	4.68	9.02
2038	January	4.25	7.83	5.72	7.62
	February	5.88	7.96	5.51	9.79
	March	4.52	7.72	5.09	14.08
	April	4.56	13.35	4.86	17.55
	Nis	4.58	17.73	3.90	17.99
	June	5.25	23.13	4.75	23.97
	July	5.50	25.81	5.07	26.62
	August	5.17	24.58	6.24	26.16
	September	4.82	17.92	4.13	23.98

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	October	5.58	15.33	3.90	18.03
	November	4.03	9.12	4.67	9.16
	December	4.42	8.34	4.49	8.52
2039	January	4.95	5.70	4.50	7.92
	February	5.87	9.73	5.40	8.66
	March	5.72	6.89	5.87	10.54
	April	4.63	11.03	5.75	13.41
	May	4.77	16.82	3.76	18.54
	June	4.49	20.69	4.51	23.00
	July	5.28	24.23	6.14	25.54
	August	6.64	25.05	5.13	25.26
	September	4.12	20.93	5.04	22.28
	October	4.12	17.29	3.43	17.63
	November	4.74	10.58	4.13	12.14
	December	5.23	7.09	5.26	5.77
2040	January	5.20	2.88	6.01	2.04
	February	4.77	3.98	5.29	3.42
	March	6.21	4.64	5.62	8.69
	April	4.49	13.10	4.44	14.10
	Haz	3.87	20.45	3.74	17.55
	June	4.10	21.44	4.86	22.37
	July	4.68	25.35	4.75	26.48
	August	5.75	24.17	5.16	25.41
	September	4.68	20.33	5.31	22.96
	October	5.24	15.81	6.18	17.53
	November	4.24	9.33	4.57	7.43
	December	5.37	5.64	4.57	6.56
2041	January	5.45	6.53	4.86	4.63
	February	5.26	6.74	4.20	6.96
	March	5.19	6.99	4.80	8.52
	April	4.14	13.38	3.83	14.64
	Tem	3.99	18.36	4.25	17.80
	June	4.30	22.42	4.02	22.56
	July	4.12	25.56	4.99	27.33
	August	6.80	23.65	5.79	26.49
	September	5.01	20.30	5.64	21.05
	October	4.60	17.56	4.95	16.68
	November	4.50	12.11	4.16	11.24
	December	5.53	8.27	4.45	8.85
2042	January	5.00	3.55	5.51	7.79
	February	4.36	5.58	4.73	6.25
	March	5.25	6.55	4.97	9.20
	April	4.68	11.96	4.78	13.29
	Ağu	4.34	17.70	4.98	17.08
	June	4.05	23.55	4.41	21.98
	July	6.08	24.73	5.91	25.68

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	August	5.96	25.35	5.69	23.68
	September	4.44	22.22	4.90	22.35
	October	4.49	13.83	4.50	16.29
	November	6.21	9.50	4.77	9.95
	December	5.14	7.50	4.02	7.95
2043	**January**	6.52	7.74	4.65	4.81
	February	4.39	3.23	5.60	1.59
	March	4.79	8.15	4.17	6.91
	April	4.90	15.13	4.80	12.16
	Eyl	4.73	17.00	3.71	18.08
	June	3.21	22.55	4.11	22.20
	July	4.98	25.19	4.62	26.27
	August	5.75	24.85	5.34	25.79
	September	4.78	20.33	4.60	20.40
	October	3.48	14.56	5.79	15.59
	November	3.92	11.80	3.91	11.53
	December	4.40	7.64	4.32	7.28
2044	**January**	5.79	7.91	5.64	7.64
	February	5.46	9.20	6.43	9.03
	March	6.31	7.63	5.35	7.91
	April	5.09	13.36	4.64	12.48
	Eki	3.54	17.95	3.63	17.98
	June	5.64	22.86	3.25	24.26
	July	5.79	24.58	5.70	26.65
	August	5.54	25.13	7.10	25.03
	September	4.58	19.85	5.67	23.98
	October	5.96	15.41	5.68	18.83
	November	5.21	13.77	4.16	11.35
	December	4.89	7.29	4.68	7.04
2045	**January**	5.89	5.74	6.20	7.78
	February	5.08	5.17	5.01	6.84
	March	4.86	6.30	5.90	8.24
	April	4.30	13.52	4.59	14.14
	Kas	5.63	19.22	3.99	18.34
	June	3.97	21.82	4.43	22.75
	July	6.10	25.47	5.10	24.55
	August	6.18	26.71	5.42	25.88
	September	5.25	23.03	5.52	21.20
	October	5.26	14.00	5.13	12.90
	November	4.42	11.00	4.62	10.13
	December	3.86	5.91	5.47	4.37
2046	**January**	5.24	5.04	5.32	3.06
	February	5.27	6.29	6.01	9.45
	March	4.52	10.53	5.23	8.29
	April	4.62	14.72	4.82	13.38
	Ara	5.37	18.67	4.73	18.64

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	June	4.25	22.02	3.86	25.20
	July	4.95	25.31	4.13	26.83
	August	5.99	25.41	5.12	24.97
	September	5.12	21.38	4.65	20.41
	October	5.07	13.67	4.98	13.51
	November	4.70	8.89	4.83	10.55
	December	5.03	6.34	4.80	5.17
2047	January	4.80	7.65	5.77	4.36
	February	5.13	7.34	4.81	5.72
	March	4.82	7.98	4.81	7.80
	April	4.11	13.08	4.74	11.82
	Oca	4.43	16.94	4.99	17.45
	June	5.58	21.61	3.38	23.02
	July	5.42	26.11	5.21	25.27
	August	5.47	25.35	6.25	26.12
	September	3.93	23.18	5.17	20.47
	October	4.96	17.29	3.79	17.66
	November	4.51	7.78	5.50	12.08
	December	4.55	2.39	6.09	9.74
2048	January	4.42	3.26	5.86	6.42
	February	4.71	4.52	5.60	10.45
	March	4.95	7.98	5.95	10.26
	April	3.99	11.88	5.09	16.21
	Şub	4.42	18.10	4.21	16.66
	June	3.98	23.64	4.58	22.45
	July	5.82	26.63	5.35	25.04
	August	6.32	25.40	4.61	25.83
	September	5.03	19.47	4.47	21.68
	October	5.85	14.57	4.23	16.93
	November	5.27	11.48	4.90	9.84
	December	4.31	4.97	5.17	4.73
2049	January	5.53	4.24	4.73	6.84
	February	4.75	7.55	4.63	8.23
	March	5.82	9.97	5.35	6.23
	April	4.57	16.65	4.36	11.85
	Mar	5.02	22.40	3.76	17.09
	June	4.13	25.12	4.14	24.15
	July	5.55	24.71	6.45	25.35
	August	7.02	26.48	5.74	26.45
	September	5.49	21.82	5.71	21.15
	October	5.38	14.58	5.08	16.28
	November	4.75	7.21	5.12	10.61
	December	4.27	5.22	4.85	3.89
2050	January	4.76	4.67	3.98	6.47
	February	5.13	3.18	4.98	5.45
	March	6.28	9.32	5.90	10.46

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	April	4.17	13.32	4.69	14.87
	Nis	4.07	17.70	4.07	19.36
	June	4.48	21.17	5.25	21.80
	July	5.04	22.74	5.36	25.49
	August	5.29	24.99	5.85	25.14
	September	5.39	21.84	5.04	22.61
	October	4.80	16.17	4.59	16.42
	November	5.53	9.09	5.40	11.78
	December	4.12	3.88	6.75	7.61
2051	**January**	5.06	3.45	4.32	6.38
	February	4.78	5.06	4.84	5.24
	March	4.94	6.79	4.25	11.36
	April	4.58	9.85	4.76	14.32
	May	3.96	17.07	4.58	18.92
	June	4.75	20.91	4.55	22.82
	July	4.87	24.01	5.53	27.18
	August	5.41	24.95	5.07	25.38
	September	5.49	20.22	5.28	21.59
	October	6.51	16.11	4.09	14.60
	November	5.95	12.66	4.27	11.16
	December	4.36	6.91	4.90	3.58
2052	**January**	4.61	5.57	5.86	6.22
	February	5.20	3.24	5.47	5.77
	March	5.56	9.17	4.74	6.73
	April	4.77	12.57	4.39	14.17
	Haz	3.74	17.72	4.33	16.56
	June	3.97	23.31	5.64	22.11
	July	5.26	27.10	4.90	26.69
	August	5.23	26.56	5.50	24.80
	September	5.14	20.15	5.21	21.21
	October	4.20	15.65	4.65	15.19
	November	4.54	13.02	5.96	9.97
	December	5.68	5.59	4.18	5.38
2053	**January**	6.18	5.56	5.57	6.64
	February	4.76	7.59	4.52	7.29
	March	4.87	9.59	5.08	8.43
	April	4.85	12.30	5.14	11.62
	Tem	4.36	19.39	4.47	18.89
	June	4.68	22.96	4.35	23.49
	July	5.83	26.50	5.50	25.94
	August	5.72	24.67	4.90	25.58
	September	6.29	22.63	5.35	21.38
	October	4.08	18.19	4.82	13.44
	November	4.95	12.29	5.76	13.92
	December	5.30	5.16	4.45	9.25
2054	**January**	5.23	8.22	5.26	8.07

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	February	4.97	6.69	4.73	3.99
	March	4.36	7.02	5.93	8.55
	April	4.69	11.74	4.62	16.45
	Ağu	4.71	18.14	4.12	18.06
	June	4.92	22.26	5.66	23.65
	July	4.97	26.26	5.31	28.16
	August	5.29	25.07	5.61	26.91
	September	5.09	19.86	4.31	22.69
	October	5.60	17.11	5.43	16.44
	November	4.95	11.97	4.55	10.46
	December	4.45	6.96	3.75	3.39
2055	January	5.04	6.40	5.93	6.83
	February	5.34	6.92	5.91	6.14
	March	5.05	8.59	6.08	7.59
	April	5.27	12.05	4.68	11.65
	Eyl	3.65	17.78	4.12	17.56
	June	5.06	22.30	4.71	22.70
	July	5.38	24.16	5.58	25.87
	August	5.36	25.24	5.20	27.13
	September	5.50	19.61	4.57	22.32
	October	4.14	16.21	4.91	17.54
	November	4.55	12.21	5.70	11.47
	December	4.59	4.97	4.85	4.15
2056	January	5.41	9.36	5.60	7.74
	February	5.35	7.27	5.24	5.69
	March	5.09	6.73	6.13	8.75
	April	3.73	14.75	4.43	14.45
	Eki	4.61	18.45	5.19	18.17
	June	5.22	23.44	3.91	24.40
	July	5.24	24.73	5.26	27.94
	August	6.09	25.85	5.49	26.24
	September	3.63	19.47	3.90	22.89
	October	4.22	15.11	4.99	15.47
	November	5.64	6.38	4.93	12.75
	December	4.49	4.77	5.83	6.81
2057	January	4.36	4.91	5.74	4.86
	February	4.41	8.58	5.63	2.71
	March	5.44	9.90	4.65	7.65
	April	4.91	11.18	3.91	14.00
	Kas	4.23	17.89	3.96	21.33
	June	4.91	21.11	3.98	24.28
	July	5.83	23.52	5.86	26.90
	August	5.25	24.57	5.20	25.89
	September	5.17	20.13	5.19	20.66
	October	3.63	14.89	5.27	15.60
	November	3.41	13.25	4.77	11.67

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	December	4.39	6.86	4.85	5.55
2058	January	4.28	6.82	4.55	5.62
	February	4.42	9.64	4.01	6.71
	March	5.42	7.76	5.03	10.29
	April	4.59	15.09	4.81	16.04
	Ara	3.68	19.59	4.46	19.21
	June	4.31	24.14	4.64	24.46
	July	5.45	26.59	5.39	27.86
	August	6.05	27.24	5.35	28.08
	September	5.00	22.21	4.73	23.96
	October	5.26	15.58	5.82	17.94
	November	5.03	11.66	5.43	9.30
	December	5.08	6.81	5.37	4.59
2059	January	5.47	7.30	4.76	4.91
	February	5.47	8.82	5.13	8.49
	March	4.88	8.41	5.34	11.40
	April	4.46	15.00	4.85	16.48
	Oca	4.95	18.80	5.32	17.82
	June	3.80	23.68	4.49	22.59
	July	5.31	27.34	4.35	28.58
	August	5.24	25.66	5.90	27.58
	September	4.90	21.96	4.22	22.05
	October	4.10	17.70	4.42	17.40
	November	5.29	10.76	4.52	14.12
	December	3.69	6.00	5.44	6.12
2060	January	4.58	4.39	4.35	7.67
	February	4.25	7.27	6.24	7.86
	March	5.60	3.91	5.18	7.85
	April	3.86	13.39	5.04	11.86
	Şub	5.40	19.70	4.02	20.11
	June	5.16	23.51	3.54	25.45
	July	5.21	25.97	5.00	29.12
	August	5.75	25.74	5.29	26.97
	September	5.81	22.48	4.38	23.30
	October	5.89	12.80	5.79	18.06
	November	4.15	8.96	4.10	14.96
	December	4.82	7.69	4.64	8.50
2061	January	4.45	5.40	4.65	6.24
	February	5.17	4.73	4.80	6.04
	March	4.79	6.90	5.16	7.65
	April	4.27	15.02	4.48	14.57
	Mar	4.76	17.48	5.05	17.53
	June	4.92	23.25	4.22	24.53
	July	4.82	25.96	5.22	27.33
	August	5.20	26.31	5.96	26.67
	September	5.38	21.99	5.09	24.53

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	October	4.48	16.97	4.85	17.69
	November	4.15	13.11	4.73	15.21
	December	5.19	6.83	5.86	10.67
2062	January	4.29	4.32	5.29	7.40
	February	5.90	6.93	4.44	6.82
	March	5.06	6.42	4.94	8.92
	April	4.17	13.54	4.74	14.87
	Nis	4.71	18.65	4.31	20.18
	June	4.65	23.78	4.33	25.60
	July	4.87	26.18	5.29	27.13
	August	5.09	25.63	6.04	28.42
	September	5.90	21.24	5.50	23.03
	October	5.29	15.17	5.86	16.42
	November	4.71	10.51	4.82	8.56
	December	4.04	5.53	4.62	7.35
2063	January	5.39	6.40	5.33	7.35
	February	3.75	6.65	6.40	10.77
	March	4.67	7.87	4.82	11.21
	April	4.12	16.04	4.86	15.70
	May	4.52	20.66	3.86	20.38
	June	4.45	22.92	4.28	26.95
	July	6.42	26.19	4.74	28.19
	August	4.97	25.76	6.22	27.44
	September	4.45	20.61	4.19	22.61
	October	4.40	15.07	4.60	19.40
	November	4.71	10.50	4.84	10.29
	December	4.67	8.18	4.53	5.61
2064	January	5.59	3.26	3.93	5.27
	February	5.84	9.55	5.09	9.67
	March	5.98	9.74	5.14	7.20
	April	5.83	11.97	4.22	15.33
	Haz	4.36	15.26	4.67	20.17
	June	3.45	21.72	4.31	26.39
	July	5.63	25.18	4.49	27.07
	August	5.13	25.15	4.68	26.76
	September	4.55	21.76	4.04	21.88
	October	3.98	16.69	4.35	17.68
	November	4.31	12.22	4.55	8.48
	December	4.47	7.27	6.05	6.78
2065	January	5.04	6.59	6.84	5.70
	February	5.69	3.56	5.74	8.30
	March	4.96	6.84	5.63	9.11
	April	4.75	13.54	4.45	12.38
	Tem	4.02	18.25	4.23	19.11
	June	4.13	21.58	4.09	26.18
	July	5.48	25.06	5.62	26.45

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	August	5.22	23.43	5.59	27.16
	September	4.24	22.19	5.26	21.87
	October	4.48	15.61	5.15	15.15
	November	5.32	11.13	4.18	13.52
	December	4.92	3.74	5.70	11.19
2066	**January**	4.26	4.16	4.72	3.72
	February	5.88	7.97	6.48	9.46
	March	4.74	6.56	4.51	13.10
	April	4.41	13.05	5.06	13.68
	Ağu	4.42	19.02	5.27	18.54
	June	5.06	23.37	3.54	25.49
	July	5.39	25.30	5.07	26.73
	August	5.58	26.70	6.20	27.34
	September	4.36	22.26	5.25	23.43
	October	4.43	18.19	4.69	14.95
	November	4.82	13.62	3.62	11.69
	December	4.75	7.94	4.40	10.18
2067	**January**	4.47	5.66	4.12	9.06
	February	5.51	7.04	4.95	7.24
	March	5.22	6.33	5.22	9.47
	April	5.36	13.28	4.27	12.69
	Eyl	3.72	19.59	4.02	21.30
	June	4.44	23.03	4.43	26.63
	July	5.34	27.44	4.89	28.39
	August	5.25	27.62	6.21	26.19
	September	4.81	21.06	4.98	23.43
	October	4.11	14.77	5.78	18.33
	November	4.75	9.43	5.92	11.80
	December	4.83	7.58	4.85	6.90
2068	**January**	4.20	5.97	5.09	8.27
	February	4.47	9.82	4.76	7.31
	March	4.27	10.24	4.29	11.35
	April	4.67	15.25	4.60	13.60
	Eki	3.76	21.89	3.93	20.88
	June	3.81	24.14	5.09	24.86
	July	4.36	25.54	4.82	28.23
	August	6.24	24.80	4.75	27.04
	September	4.74	21.28	4.74	21.58
	October	4.20	17.34	4.32	17.35
	November	5.61	10.26	3.93	9.73
	December	3.65	8.14	5.33	7.59
2069	**January**	5.16	8.46	5.08	8.43
	February	4.85	6.62	5.23	9.54
	March	4.92	8.41	5.50	10.14
	April	5.22	14.12	4.39	14.48
	Kas	5.81	18.04	5.22	21.00

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	June	3.80	21.90	4.62	25.38
	July	4.84	27.54	4.89	28.28
	August	5.01	26.34	4.26	28.55
	September	4.48	23.93	5.69	24.87
	October	4.89	15.27	4.31	15.34
	November	5.07	8.96	4.50	11.30
	December	5.04	5.65	5.28	5.97
2070	January	5.03	8.00	5.78	9.59
	February	4.73	7.75	6.64	6.14
	March	4.99	9.08	4.74	9.93
	April	4.04	14.33	4.61	15.28
	Ara	4.32	21.76	4.09	20.37
	June	4.16	23.83	4.36	26.19
	July	5.87	26.48	6.41	27.71
	August	6.23	25.44	6.63	28.31
	September	5.62	23.43	5.93	23.43
	October	4.56	17.99	5.48	17.42
	November	4.40	10.98	4.43	15.12
	December	5.42	5.05	4.48	8.24
2071	January	4.50	5.98	4.87	7.00
	February	5.44	5.85	4.27	9.09
	March	4.93	7.63	5.04	9.71
	April	4.84	10.76	3.82	16.04
	Oca	4.33	18.00	4.23	19.94
	June	3.82	23.59	4.20	26.06
	July	4.84	25.59	5.03	26.91
	August	6.10	25.86	6.17	25.94
	September	5.34	21.00	3.91	24.54
	October	4.26	13.87	4.89	19.00
	November	4.32	11.12	3.74	14.14
	December	4.55	5.17	5.67	7.37
2072	January	5.76	6.51	6.52	7.12
	February	5.85	5.97	5.52	4.70
	March	4.14	8.29	6.27	9.33
	April	4.37	12.50	4.77	13.49
	Şub	4.76	19.47	3.54	18.43
	June	4.77	24.57	3.95	27.62
	July	5.15	26.47	6.21	27.12
	August	6.06	25.87	5.71	27.27
	September	4.84	22.83	6.44	22.77
	October	5.31	19.28	5.14	19.15
	November	4.10	15.67	5.44	10.05
	December	5.21	6.67	5.33	6.87
2073	January	5.10	8.80	5.57	7.12
	February	5.66	10.27	4.42	5.86
	March	5.40	11.61	5.34	13.50

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	April	4.68	14.28	5.31	14.65
	Mar	3.47	19.52	5.41	20.31
	June	3.77	23.02	4.07	26.35
	July	4.91	25.80	4.97	28.05
	August	5.36	24.90	5.80	24.80
	September	4.28	22.98	4.95	22.49
	October	5.22	15.22	4.09	18.90
	November	3.70	6.88	5.20	14.08
	December	3.78	5.42	5.27	7.32
2074	**January**	5.14	6.96	4.59	5.23
	February	4.89	8.30	4.55	8.40
	March	5.60	9.98	3.84	11.18
	April	4.17	16.08	5.01	14.80
	Nis	4.50	18.20	4.16	19.44
	June	3.67	21.32	4.74	24.43
	July	4.73	23.59	5.71	28.42
	August	4.74	26.43	5.43	28.18
	September	4.65	22.02	5.29	23.09
	October	4.72	13.52	3.98	19.25
	November	3.55	12.84	5.20	12.99
	December	4.83	6.83	5.09	7.53
2075	**January**	5.80	5.38	4.67	8.37
	February	4.31	3.70	4.69	2.24
	March	4.71	9.06	6.74	12.47
	April	3.79	16.87	4.32	14.49
	May	3.95	20.56	4.88	18.72
	June	4.51	24.85	4.11	25.41
	July	5.43	26.20	4.92	27.65
	August	4.66	25.89	5.97	27.54
	September	4.80	21.89	5.34	24.13
	October	4.88	16.73	4.57	15.58
	November	5.17	10.31	4.40	11.90
	December	5.64	7.71	4.65	7.77
2076	**January**	5.25	5.90	5.53	7.94
	February	5.42	8.21	5.49	5.63
	March	5.07	9.39	4.43	9.14
	April	5.18	12.21	4.92	13.87
	Haz	3.81	16.01	4.52	18.03
	June	4.19	22.01	5.02	23.11
	July	5.26	25.54	4.56	28.71
	August	4.78	25.15	5.04	26.21
	September	5.22	19.34	3.83	22.67
	October	4.30	16.62	5.27	19.09
	November	3.87	9.80	4.89	14.34
	December	4.84	3.74	4.59	10.63
2077	**January**	5.20	6.93	5.25	7.95

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	February	5.42	8.35	5.01	10.16
	March	5.01	7.76	5.39	7.52
	April	3.74	12.75	5.23	15.41
	Tem	4.12	18.77	4.86	17.82
	June	4.38	24.00	3.72	24.55
	July	6.32	26.48	5.39	27.05
	August	5.31	26.49	5.21	27.39
	September	3.83	21.87	5.13	24.48
	October	5.36	15.08	4.79	13.24
	November	5.06	13.28	4.71	8.77
	December	3.40	9.11	4.36	6.73
2078	**January**	6.39	9.98	4.36	9.12
	February	4.57	7.23	4.43	6.55
	March	5.45	11.29	5.77	12.03
	April	4.17	13.85	4.04	18.26
	Ağu	4.41	20.03	4.01	20.49
	June	4.42	24.69	5.05	26.11
	July	4.71	28.38	4.47	28.80
	August	5.39	26.64	4.97	28.93
	September	5.26	23.09	4.33	21.41
	October	5.38	17.63	4.45	17.46
	November	5.12	8.98	4.73	12.12
	December	3.95	7.25	4.53	9.72
2079	**January**	5.76	8.50	4.54	9.15
	February	4.78	5.52	4.47	6.89
	March	5.09	9.42	4.26	11.14
	April	4.70	15.98	4.48	16.21
	Eyl	4.87	18.56	3.79	20.90
	June	4.41	23.23	3.70	25.06
	July	4.51	27.58	6.85	29.27
	August	6.01	25.46	4.94	28.77
	September	5.33	22.41	4.82	23.34
	October	6.64	15.41	5.43	18.01
	November	3.91	8.68	4.49	12.94
	December	4.60	4.54	5.02	11.67
2080	**January**	5.20	7.20	4.83	7.13
	February	5.99	9.51	5.58	9.50
	March	4.87	8.83	5.22	7.73
	April	4.10	14.06	4.57	14.11
	Eki	4.41	20.47	3.68	19.69
	June	5.04	24.08	3.93	25.42
	July	5.32	26.79	4.59	28.19
	August	5.90	25.68	6.17	27.44
	September	5.81	22.19	4.95	24.80
	October	3.59	16.46	5.11	20.85
	November	4.64	10.39	4.90	10.92

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	December	4.57	5.32	4.97	7.58
2081	January	6.17	5.34	4.70	9.57
	February	5.66	6.38	3.82	10.78
	March	5.48	8.05	4.94	11.58
	April	4.80	12.44	5.37	14.93
	Kas	5.04	18.93	4.75	19.97
	June	4.34	24.05	4.94	25.95
	July	6.11	24.37	5.05	29.79
	August	5.19	25.54	4.77	29.85
	September	4.51	22.30	4.23	22.87
	October	5.15	18.44	4.36	15.70
	November	4.52	13.59	4.58	10.80
	December	5.65	9.48	5.24	6.04
2082	January	5.22	6.04	4.16	7.71
	February	4.30	6.66	4.56	11.48
	March	4.45	9.70	4.49	11.39
	April	4.63	10.48	4.53	14.02
	Ara	3.55	20.48	3.83	20.13
	June	3.89	24.45	4.05	25.86
	July	5.43	25.00	5.03	29.93
	August	5.29	26.66	5.56	30.35
	September	4.47	22.44	4.40	23.55
	October	4.49	16.48	5.13	17.15
	November	6.03	13.64	4.77	11.32
	December	5.08	4.66	5.39	8.38
2083	January	4.37	7.71	5.65	5.74
	February	4.94	4.39	4.33	6.50
	March	4.94	10.22	5.15	11.58
	April	4.39	14.97	5.84	13.67
	Oca	5.07	17.51	4.81	19.41
	June	3.94	24.34	4.40	26.15
	July	4.53	27.40	5.11	27.94
	August	5.00	27.43	6.60	28.78
	September	4.93	21.59	4.45	23.81
	October	5.08	15.74	4.50	17.67
	November	4.96	9.22	4.09	12.43
	December	4.29	3.47	4.01	11.05
2084	January	5.95	5.27	5.52	8.40
	February	5.43	7.98	4.67	6.32
	March	5.81	10.36	5.71	9.59
	April	4.50	12.79	4.24	18.59
	Şub	4.08	18.14	5.05	21.36
	June	4.90	23.13	4.86	27.61
	July	5.44	24.50	5.57	29.08
	August	5.19	25.59	5.59	29.81
	September	5.19	22.55	6.77	25.75

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	October	4.69	16.56	4.54	17.21
	November	3.51	10.20	4.77	13.29
	December	4.09	7.17	4.90	9.05
2085	January	4.58	5.82	5.81	8.89
	February	6.09	5.19	6.09	11.81
	March	5.09	10.17	6.08	11.99
	April	4.70	14.39	4.79	15.02
	Mar	4.19	20.39	4.34	21.05
	June	3.99	25.49	4.98	24.28
	July	4.00	26.39	4.97	28.11
	August	4.15	27.33	5.41	28.80
	September	4.39	21.23	5.32	24.11
	October	4.26	17.53	4.37	16.90
	November	4.24	11.28	5.76	13.38
	December	4.40	7.98	5.71	11.09
2086	January	4.33	6.93	4.06	6.97
	February	3.82	6.54	5.52	8.25
	March	5.38	9.43	5.00	11.00
	April	3.89	15.20	4.71	15.44
	Nis	4.37	18.10	5.10	19.93
	June	4.19	23.90	4.43	25.98
	July	5.51	25.57	4.78	29.14
	August	4.72	26.58	5.22	29.59
	September	5.30	21.35	6.09	26.05
	October	4.14	16.75	4.19	20.76
	November	3.91	13.57	3.53	16.17
	December	4.37	8.98	3.94	8.54
2087	January	5.24	5.01	6.12	9.03
	February	5.21	8.12	4.70	9.61
	March	5.01	8.69	5.49	11.32
	April	4.32	11.79	4.50	12.29
	May	3.52	19.33	4.56	19.71
	June	3.63	23.91	4.37	25.77
	July	4.40	27.03	4.08	29.38
	August	6.39	26.25	4.97	27.09
	September	5.40	20.92	4.80	22.65
	October	5.07	15.83	5.16	18.95
	November	5.49	9.86	4.83	12.07
	December	5.18	7.56	5.67	9.06
2088	January	5.32	8.07	4.85	8.57
	February	5.87	8.85	5.72	8.08
	March	4.92	9.40	4.99	7.67
	April	4.83	15.25	3.69	14.00
	Haz	4.51	19.76	5.27	18.94
	June	4.30	23.66	4.33	24.84
	July	4.19	27.45	4.06	29.34

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	August	4.88	27.27	6.63	28.59
	September	3.88	23.18	5.08	23.43
	October	4.18	16.12	5.06	19.79
	November	5.33	9.44	5.11	12.17
	December	3.85	8.25	4.66	7.74
2089	January	4.53	7.01	4.34	6.43
	February	5.80	7.35	5.43	6.97
	March	6.11	8.29	5.15	12.61
	April	4.38	12.32	4.13	19.26
	Tem	4.72	17.23	5.70	22.74
	June	4.38	20.55	4.48	27.16
	July	4.92	24.17	5.45	31.29
	August	5.94	26.25	4.75	30.42
	September	3.81	22.86	5.38	24.98
	October	4.56	17.51	5.30	17.83
	November	3.46	11.41	4.81	14.79
	December	4.63	4.33	5.47	7.96
2090	January	6.00	1.77	5.20	6.86
	February	5.14	1.38	5.07	12.31
	March	6.14	7.13	5.32	9.32
	April	4.25	12.35	4.95	13.34
	Ağu	4.77	16.70	4.24	18.27
	June	4.31	23.06	4.03	25.76
	July	6.66	27.78	6.44	26.76
	August	6.43	25.85	5.17	28.80
	September	5.66	21.75	4.84	24.30
	October	4.34	18.69	6.14	17.21
	November	5.41	11.23	5.42	11.61
	December	5.08	6.21	4.76	7.76
2091	January	5.56	5.81	4.09	4.23
	February	4.90	10.00	4.42	9.82
	March	4.44	8.69	4.49	9.43
	April	4.00	12.91	4.47	16.52
	Eyl	4.55	17.85	3.80	21.45
	June	5.05	22.75	4.77	26.93
	July	4.09	26.34	6.42	29.11
	August	5.10	26.98	6.20	29.98
	September	4.97	24.51	5.80	25.87
	October	5.38	16.96	4.96	19.06
	November	5.74	14.85	4.71	11.87
	December	4.23	8.64	4.10	8.89
2092	January	4.85	4.72	4.45	8.03
	February	5.76	4.77	5.22	7.57
	March	5.34	6.15	4.39	11.96
	April	3.79	14.34	5.70	17.85
	Eki	3.30	19.54	4.60	21.34

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	June	4.02	25.34	3.98	26.71
	July	4.63	27.49	4.16	30.77
	August	4.92	25.99	5.60	28.68
	September	5.02	23.59	5.08	23.62
	October	5.11	16.84	4.90	19.99
	November	5.60	9.76	5.19	12.43
	December	5.64	7.07	5.29	7.87
2093	January	4.80	4.60	5.34	9.08
	February	6.51	4.96	5.66	6.97
	March	4.23	9.65	5.22	11.63
	April	4.50	14.54	4.90	15.68
	Kas	4.63	20.22	3.96	18.71
	June	4.73	24.17	4.37	25.92
	July	3.86	27.87	4.93	30.69
	August	5.56	26.16	5.12	29.94
	September	4.91	23.10	5.48	25.81
	October	4.50	14.71	6.27	17.38
	November	3.99	9.47	4.82	9.37
	December	5.29	5.34	4.20	8.95
2094	January	5.31	5.00	4.30	8.64
	February	5.08	4.81	4.53	5.93
	March	5.78	8.51	4.44	10.58
	April	3.92	11.44	5.38	17.67
	Ara	4.82	17.01	4.83	23.86
	June	5.06	23.10	4.54	27.34
	July	5.03	26.01	5.20	29.71
	August	4.99	25.61	5.95	28.61
	September	5.18	22.52	4.88	24.86
	October	4.72	17.90	4.42	20.71
	November	3.97	11.82	4.27	14.76
	December	3.89	8.04	5.56	9.24
2095	January	4.74	4.55	4.88	8.38
	February	4.45	8.67	5.96	8.53
	March	4.84	9.03	5.28	13.62
	April	4.95	13.25	5.14	16.00
	Oca	4.69	19.35	3.93	20.66
	June	4.34	24.40	4.08	25.83
	July	5.17	26.57	4.63	30.35
	August	4.98	26.15	5.10	28.66
	September	4.20	21.42	6.26	23.90
	October	4.33	15.28	5.81	18.98
	November	5.00	11.14	5.26	14.76
	December	4.65	4.97	4.27	10.62
2096	January	5.24	7.18	4.86	8.37
	February	6.01	7.28	4.60	8.42
	March	5.47	9.37	5.32	10.92

Years	Months	RCP4.5		RCP8.5	
		100 m Wind (ms^{-1})	Temperature (°C)	100 m Wind (ms^{-1})	Temperature (°C)
	April	4.11	15.07	5.11	14.00
	Şub	4.43	21.01	3.63	20.31
	June	4.01	24.15	4.95	28.12
	July	5.19	25.58	5.77	29.98
	August	6.06	24.09	5.38	29.63
	September	5.57	20.70	4.26	27.68
	October	4.40	17.44	4.48	19.36
	November	4.84	9.29	5.98	15.35
	December	4.58	8.12	5.20	11.42
2097	January	5.10	8.73	6.13	8.55
	February	5.14	10.07	5.15	7.56
	March	5.36	9.38	5.71	13.02
	April	4.01	13.58	4.32	16.31
	Mar	4.02	19.94	3.75	23.00
	June	3.85	23.56	4.51	26.82
	July	5.76	24.35	4.78	29.56
	August	5.37	27.26	5.38	28.45
	September	4.07	23.93	4.70	23.60
	October	4.31	18.61	4.52	17.89
	November	4.49	14.18	4.17	14.42
	December	4.51	3.65	3.83	10.10
2098	January	4.96	6.17	4.20	7.33
	February	5.47	4.49	5.64	9.87
	March	4.43	6.17	4.78	12.88
	April	4.53	15.69	4.16	16.22
	Nis	4.64	20.16	4.62	21.78
	June	4.81	24.91	4.16	26.42
	July	5.87	25.64	5.91	28.40
	August	6.16	27.02	5.59	29.08
	September	4.91	22.34	4.45	24.46
	October	4.60	15.53	4.87	19.43
	November	4.47	13.55	4.92	14.07
	December	4.08	10.00	4.95	6.45

APPENDIX 5 – ELECTRICITY GENERATION FORECASTS OF SM-3

Year	Electricity Generation (MWh)		Year	Electricity Generation (MWh)	
	RCP4.5	RCP8.5		RCP4.5	RCP8.5
2016	1,184,497	1,184,497	2058	1,325,827	1,344,146
2017	1,193,611	1,193,611	2059	1,308,293	1,321,430
2018	1,235,149	1,235,149	2060	1,393,592	1,291,157
2019	1,228,942	1,228,942	2061	1,321,555	1,345,950
2020	1,248,820	1,248,820	2062	1,353,863	1,354,932
2021	1,156,726	1,156,726	2063	1,295,766	1,305,985
2022	1,176,184	1,176,184	2064	1,359,659	1,265,570
2023	1,208,870	1,208,870	2065	1,356,647	1,398,024
2024	1,381,667	1,296,276	2066	1,324,581	1,321,670
2025	1,372,262	1,289,376	2067	1,327,995	1,332,452
2026	1,327,669	1,363,225	2068	1,231,820	1,259,975
2027	1,362,004	1,357,259	2069	1,349,525	1,316,144
2028	1,397,170	1,322,163	2070	1,339,585	1,399,852
2029	1,328,601	1,429,236	2071	1,331,708	1,249,865
2030	1,361,143	1,424,025	2072	1,358,626	1,448,404
2031	1,365,863	1,376,153	2073	1,269,191	1,343,870
2032	1,403,564	1,288,678	2074	1,270,733	1,289,092
2033	1,357,800	1,373,370	2075	1,314,067	1,333,683
2034	1,282,504	1,298,874	2076	1,331,364	1,305,226
2035	1,399,271	1,416,302	2077	1,301,469	1,338,777
2036	1,400,262	1,336,121	2078	1,328,398	1,226,987
2037	1,296,638	1,342,975	2079	1,379,627	1,255,738
2038	1,349,546	1,303,234	2080	1,347,081	1,306,554
2039	1,394,625	1,336,772	2081	1,413,358	1,264,198
2040	1,371,022	1,395,606	2082	1,302,221	1,241,118
2041	1,351,427	1,284,707	2083	1,299,084	1,313,066
2042	1,390,322	1,357,636	2084	1,345,322	1,357,808
2043	1,297,396	1,302,648	2085	1,236,266	1,387,412
2044	1,443,498	1,393,833	2086	1,233,939	1,243,974
2045	1,395,866	1,408,812	2087	1,347,192	1,315,325
2046	1,382,227	1,347,550	2088	1,269,913	1,325,954
2047	1,336,892	1,384,001	2089	1,322,801	1,311,415
2048	1,372,293	1,366,164	2090	1,469,894	1,369,109
2049	1,411,414	1,378,644	2091	1,308,885	1,284,232
2050	1,378,456	1,400,756	2092	1,327,137	1,284,748
2051	1,410,357	1,301,742	2093	1,318,939	1,330,152
2052	1,335,263	1,401,740	2094	1,328,951	1,270,471
2053	1,402,189	1,364,592	2095	1,295,357	1,319,405
2054	1,358,937	1,350,655	2096	1,358,627	1,292,505
2055	1,361,607	1,419,299	2097	1,267,174	1,248,338
2056	1,357,690	1,375,242	2098	1,335,056	1,278,647
2057	1,301,837	1,354,932			

APPENDIX 6 – ELECTRICITY GENERATION FORECASTS OF ANN-4

Year	Electricity Generation (MWh)		Year	Electricity Generation (MWh)	
	RCP4.5	RCP8.5		RCP4.5	RCP8.5
2016	1,274,853	1,143,486	2058	1,326,337	1,256,243
2017	1,373,222	1,150,781	2059	1,142,564	1,032,016
2018	1,356,251	1,335,424	2060	1,435,808	1,224,787
2019	1,280,694	1,353,438	2061	1,233,924	1,068,676
2020	1,255,446	1,220,159	2062	1,279,336	1,340,984
2021	1,154,925	1,359,442	2063	1,327,436	1,172,686
2022	1,239,472	1,230,606	2064	1,275,966	1,170,739
2023	1,233,540	1,185,393	2065	1,196,997	1,147,659
2024	1,302,246	1,303,265	2066	1,179,214	1,094,706
2025	1,123,362	1,363,174	2067	1,263,497	1,380,205
2026	1,360,192	1,258,661	2068	1,154,091	1,165,202
2027	1,239,342	1,178,504	2069	1,253,769	1,205,558
2028	1,317,430	1,395,233	2070	1,307,738	1,388,864
2029	1,271,468	1,303,318	2071	1,301,900	1,066,931
2030	1,361,362	1,346,597	2072	1,290,947	1,234,706
2031	1,275,503	1,267,724	2073	1,148,297	1,165,965
2032	1,278,180	1,124,466	2074	1,226,938	1,179,100
2033	1,289,976	1,143,630	2075	1,205,305	1,260,549
2034	1,206,449	1,299,428	2076	1,196,464	1,107,260
2035	1,270,415	1,306,843	2077	1,252,231	1,134,497
2036	1,370,293	1,305,000	2078	1,300,993	1,184,420
2037	1,226,317	1,281,678	2079	1,177,098	1,263,341
2038	1,287,767	1,300,748	2080	1,282,455	1,178,868
2039	1,262,729	1,380,016	2081	1,180,509	1,130,816
2040	1,265,783	1,425,365	2082	1,246,174	1,172,959
2041	1,192,741	1,230,346	2083	1,196,774	1,271,407
2042	1,301,543	1,271,370	2084	1,250,337	1,305,556
2043	1,100,158	1,331,399	2085	936,683	1,232,689
2044	1,289,283	1,350,700	2086	1,288,521	1,118,961
2045	1,392,071	1,217,080	2087	1,235,232	1,152,872
2046	1,236,004	1,014,879	2088	1,063,489	1,273,875
2047	1,259,124	1,294,074	2089	1,144,791	1,153,273
2048	1,269,592	1,299,603	2090	1,324,854	1,296,308
2049	1,329,368	1,365,522	2091	1,303,422	1,393,211
2050	1,268,355	1,218,840	2092	1,122,983	1,139,480
2051	1,451,000	1,189,761	2093	1,090,772	1,224,625
2052	1,228,509	1,249,984	2094	1,088,284	1,306,085
2053	1,332,281	1,280,278	2095	1,252,537	1,100,356
2054	1,388,894	1,241,841	2096	1,249,908	1,274,621
2055	1,376,436	1,237,887	2097	1,124,320	1,036,849
2056	1,273,208	1,046,427	2098	1,216,443	1,165,168
2057	1,351,216	1,212,267			