

GRIDDED DISTRIBUTION OF DAILY NON-UNIFORM METEOROLOGICAL
STATION DATA OF TURKEY

by

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Turkey meteorological station data for temperature and precipitation from 1960 to 2016 had been studied to create a uniformly distributed high-resolution grid data. In this long and challenging journey, I would like to thank to my advisor Prof.Dr. M.Levent Kurnaz for his guidance and patience. He always supported me in this process. I would also like to thank to his team, especially to M.Tufan Turp and Aytaç Paçal; to my ex-company Enotek Engineering manager and colleagues for supporting my studies. Finally, I would like to thank to my friends and family who encourage and support me on every step of this study.

ABSTRACT

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The climate modeling is a complex area to work on. It is not easy to represent the atmospheric events in a model, because there are a lot of drivers and variables which affects the local and global climate. Even if, somehow, some meteorological phenomenon can be fully represented mathematically, it is even harder to do the calculation through a computer or a super computer with the current technological developments. So, some assumptions, optimizations and simplifications must be done to work on climate. This study will examine the climate measurement station data distributed in Turkey. The randomly distributed real station data all around Turkey gathered from the Turkish State Meteorological Service database. Our goal is to obtain uniformly distributed grid data for temperature and precipitation. We have used interpolation, one of the most ancient and common computational method with a scale that allows us to create a high-resolution temperature and precipitation map of Turkey. With the help of MATLAB build-in tools and functions, the scattered station data turned into a uniformly gridded data. The station data was very hard to work on, since the data begins from 1960. Meanwhile, the meteorology stations moved, closed, opened which caused a lot of incomplete and disconnected data. So, some normalization must be done, and the data become suitable for interpolation. To do the interpolation calculation, we used the MATLAB build-in function, `scatteredInterpolant`. It allowed us to calculate the scattered data into a gridded data. Once the interpolation completed, another MATLAB toolbox used to project the results on a regional map. The mapping toolbox is very powerful in printing the results on a map, in this case on Turkey regional map. Finally, we have managed to obtain Turkey temperature and precipitation station data map between 1960-2016 in daily basis.

ÖZET

TÜRKİYE DÜZENSİZ METEOROLOJİ İSTASYON VERİSİNİN DÜZENLİ GRİD HALİNDE DAĞITILMASI

İklim ve iklim modelleme üzerinde çalışması güç bir alandır. İklim, atmosferik olaylar sonucu oluşur ve bu atmosferik olaylar son derece kompleks ve içinde bir sürü değişken barındırır. Bu nedenle iklimi meydana getiren olayları matematiksel olarak modellemek zordur. Buna ek olarak bir şekilde tamamen bu olayları modelleyebilirsek bile, bu modeli çalıştırabilecek bir süper bilgisayar günümüz teknolojisinde bulmak oldukça zordur. Bu neden iklim olayları ve iklim verileri üzerinde bazı düzeltmeler, kabuller ve optimizasyonlar yapmak gerekmektedir. Bu çalışmada Tarım ve Orman Bakanlığı Meteoroloji Genel Müdürlüğü veritabanından alınana rasgele dağılmış istasyon verileri kullanılmıştır. Çalışmanın sonucundaki amacımız, Türkiye için, bu rastgele veriden düzgün dağılmış bir sıcaklık ve yağış haritası elde etmetir. Bu haritayı elde etmek için tarihteki en eski hesaplama yöntemlerinden biri olan interpolasyon yöntemini kullandık. MATLAB programının hazır fonksiyonları ve paketleri yardımıyla elimizdeki karmaşık dağınık data üzerinde interpolasyon hesaplamaları yaptık ve sonuç düzgün dağılmış ızgara şeklinde, yüksek çözünürlüklü bir Türkiye sıcaklık ve yağış haritası elde ettik. İstasyon dataları 1960'tan itibaren günlük şekilde tutulmuş verilerdi. Buna ek olarak bazı istasyonlar kapanmış, taşınmış ya da sonradan veritabanına eklenmişti. Bütün bu zorlukları gidermek için çalışmanın başında bazı normalizasyon teknikleri kullandık. Bu işlemin sonunda verilerimiz interpolasyon için uygun yapıya geldiler. Hesaplamalardan sonra elde ettiğimiz verileri Türkiye haritası üzerine basmak için yine MATLAB programının gömülü haritalama fonksiyonlarından yararlandık ve sonuçta 1960-2016 arası günlük istasyon verilerinin Türkiye haritasını elde etmeyi başardık.

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LIST OF SYMBOLS

\mathbf{h}	Altitude difference between inquiry and base data
\mathbf{P}_h	Inquiry precipitation data
\mathbf{P}_0	Base precipitation station data
\mathbf{S}	Variance
\mathbf{T}_h	Inquiry temperature data
\mathbf{T}_0	Base temperature station data
μ	Mean over all
σ	Standard deviation

LIST OF ACRONYMS/ABBREVIATIONS

GCM	General Circulation Model
GHG	Greenhouse Gas
IAM	Integrated Assessment Models
IPCC	Intergovernmental Panel on Climate Change
KCC	Köppen Climate Classifier
KTC	Köppen-Trewartha Climate Classifier
K-T	Köppen-Trewartha
NASA	National Aeronautics and Space Administration
RCP	Representative Concentration Pathways
SA90	Scientific Assessment
SRES	Special Report on Emissions Scenarios
UNFCCC	United Nations Framework Convention on Climate Change
UV	Ultraviolet

1. INTRODUCTION

1.1. Atmosphere

Climate is the most vital element on Earth that makes life, as we know it, possible. Without a suitable climate and atmosphere, Earth will be just another regular planet on a solar system which is monitored from outer space. Our solar system has two major types of planets and all of them have atmospheres: terrestrial planets like Mercury, Venus, Earth, Mars and gas giants like Jupiter, Saturn, Uranus, Neptune. Despite containing most of the same elements, these atmospheres are very different from Earth's. A celestial body's atmosphere, a planet or moon, must contain specific chemicals to support life as we know it. These chemicals include hydrogen, oxygen, nitrogen, and carbon. Our atmosphere has 78% nitrogen, 21% oxygen, 0.9% argon and 0.04% of carbon dioxide along with remaining 0.06% of trace gases like neon, ozone, helium, methane [8].

The atmospheres of the terrestrial planets are similar to Earth's. The closest planet to Sun, Mercury, has an atmosphere dominated by hydrogen, helium, and oxygen with only a thin layer exosphere. Its closeness to Sun makes it spin very slowly and because of its thin atmosphere the day and night temperature varies in between -173 to 427 degrees Celsius. The second planet, Venus has a very thick atmosphere, even much thicker than Earth's, preventing a clear view of the planet. Its thick atmosphere allows it to trap heat by the Greenhouse Effect and makes it dominated by carbon dioxide, which features swirling clouds of sulfuric acid. Even though Venus is not the closest planet to our Sun, it is the hottest planet in our Solar System with 465 degrees Celsius. The atmosphere on Mars is also dominated by carbon dioxide, but unlike Venus, it is quite thin. The temperature varies from -125 degrees Celsius up to 20 degrees Celsius. Gas giant planets are composed of gases. Their atmospheres are consisting of hydrogen and helium. The blue bright color is caused by the presence of methane in the atmospheres of Uranus and Neptune. In the lower atmospheres of Jupiter and Saturn, clouds of water, ammonia, and hydrogen sulphide

form clear bands. Fast winds separate light-colored bands, called zones, from dark-colored bands, called belts. Other weather phenomena, such as cyclones and lightning, create patterns in the zones and belts. Jupiter's Great Red Spot is a centuries-old cyclone that is the largest storm in the solar system. Most celestial bodies, including all the asteroids in the asteroid belt and our own moon, do not have atmospheres, but it is possible for some moons of other planets to develop their own atmospheres. The most famous of all is Saturn's largest moon, Titan, which has a thick atmosphere made mostly of nitrogen and methane. The way sunlight breaks up methane in Titan's ionosphere gives him the orange color. Although Venus, Mars, and Titan have similar atmospheric gases, there isn't any planet or moon in the solar system besides Earth that could support life. Venus' atmosphere is far too thick, Mars' far too thin, and Titan's far too cold. But the way a celestial body's atmosphere is structured and what it's made of allow astrobiologists to speculate what kind of life the planet or moon may be able to support. Atmospheres, then, are important markers in space exploration [9].

The lack of an atmosphere could have turned Earth into a lifeless celestial body like the Moon, which did not experience weather because has no atmosphere. The atmosphere protects and sustains its inhabitants. By absorbing the harmful solar rays in the ozone layer, it is filtering the ultraviolet radiation from the Sun, which can cause severe skin, eye and genetic damages. By its thickness, it is serving like a protective shield from the particles and meteors in space leftover from planet creations, collisions. The space is always defining as empty, but it contains a lot of randomly traveling celestial bodies. According to NASA, more than 100 tons of space debris strikes Earth every day, but they have been destroyed by the friction with the molecules in the atmosphere before reaching to the ground. With no protection, the surface of the Earth will be full of craters caused by meteor impact like on the Moon and with no wind or water to erode them, they have been stayed there for hundreds and even thousands of years. Another important benefit having an atmosphere is the maintaining the temperature in the habitable range. On the Moon, the temperature varies from 121 degrees Celsius to -157 degrees Celsius. However, on Earth the molecules in the atmosphere absorbs and spreads the sun ray's energy, and with the help of what we call the Greenhouse Effect, the temperature remains in the range [10]. The Greenhouse

Effect may sound as a bad phenomenon since we are currently facing the “dark side” of it; but this was not the case in the past. Right now, the warming influence is literally a matter of life or death, but in the beginning, it kept the average surface temperature of Earth at 15 degrees Celsius. Without this Greenhouse Effect, the average surface temperature would be -18 degrees Celsius; a temperature so low that all water on Earth would freeze, the oceans would turn into ice and life, as we know it, would not exist. The concept is first mentioned by Jean-Baptiste Joseph Fourier (1768-1830) in the 1820s. Fourier’s idea, still accepted today, is that the atmosphere lets some of the Sun’s radiation in, but it doesn’t let all the radiation back out, as a Greenhouse. The glass of a Greenhouse allows the sun’s radiation in, which warms the ground inside, then turns as heat radiation. The glass then acts like a barrier to prevent the warm air inside getting out. The Greenhouse Effect on Earth works approximately the same as shown in Figure 1.1. The sun’s energy enters the top of the atmosphere as shortwave (if the energy of a wave is high, the wavelength will be short) radiation and makes its way to the ground without reacting with the Greenhouse gases. Then the ground, clouds, and other earthly surfaces absorb this energy and release it back towards space as longwave radiation. As the longwave radiation goes up into the atmosphere, it is absorbed by the Greenhouse gases which by the way, mainly, are the very least components of the atmosphere like carbon dioxide and water vapor. The Greenhouse gases then emit their radiation (also longwave), which will often keep being absorbed and emitted by various surfaces, even other Greenhouse gases, until it eventually leaves the atmosphere. Since some of the re-emitted radiation goes back towards the surface of the earth, it warms up more than it would [11]. The problem in this process is too much Greenhouse warming raises global temperatures to a level that is significantly different. If the Earth’s Greenhouse gases increased in concentration and nothing else in the atmosphere changed, then the surface temperature would be expected to rise and eventually, the Earth’s energy will be adjusted to the new conditions. Unfortunately, the Earth has a complex climate system and increase in energy, resulting and merging with increased evaporation and cloud formation, melting of polar ice. This interaction in unexpected ways would cause irreversible changes in regional and global temperature and climate. In addition to all above, this trapping feature of the atmosphere allows

the vapor evaporated from the oceans, seas and other sources to stay in the atmosphere system by condensing and falling back as rain or snow. The water movement in this cycle provides life-giving moisture and simply allows creation of the weather and climate.

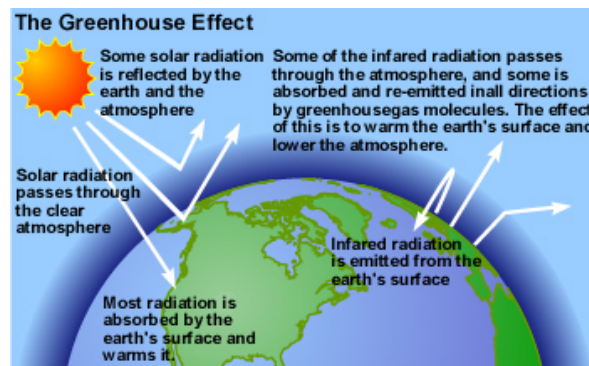


Figure 1.1. Greenhouse Effect [1]

All these different outcomes of atmosphere happen in different layers. The atmosphere has a layered structure with 4 main layers; the troposphere, stratosphere, mesosphere, thermosphere. Figure 1.2 shows the temperature in the layers sorted from Earth to space. The top layer which is not shown in the figure is called exosphere. This layer can expand and shrink with solar storms because it is directly in contact with solar rays. Many weather satellites use this layer to orbit Earth. The layer below exosphere is called thermosphere. It is the thickest and lightest layer. Gas molecules in this layer absorb x-ray and UV radiations, which gives them high temperature and speed. Even though they have very high temperature like 1.500 degrees Celsius, there is not much heat, the fact that heat is created when molecules get excited and transfer energy from one molecule to another. Gas molecules need high pressure or a small volume to encounter and transfer energy, and since thermosphere has not qualified for both, the heat transfer is very little. Despite high temperature of thermosphere, the lower layer, mesosphere, has the coldest temperatures in the atmosphere, with -120 degrees Celsius. It also hosts highest clouds in the atmosphere. They are called noctilucent clouds, or night-shining clouds and in a clear weather, can be observed shortly after sunset. The mesosphere is so cold that noctilucent clouds are literally frozen water vapor, ice clouds. Shooting stars, the fiery burnout of meteors, dust, and rocks from outer space are visible in the mesosphere. There is a sub-layer called ionosphere

starting from mesosphere up to exosphere. The free ions created by energetic particles from Sun and outer space gives the layer its name along with the free electrons. Its ionized structure allows conducting electricity and giving him the ability to reflect short wave radio signals. This feature used for long distance communication over a long time. The below layer is called stratosphere. The ozone layer which absorbs ultraviolet (UV) rays from the Sun, is in stratosphere and causing the temperature increases with height. The lowest and most important layer is the troposphere where we live and where weather happens. Temperature in this layer generally decreases with height because as in ozone layer, the ground is also absorbing most of the solar ray causing increase in temperature. The height of the troposphere varies with location, being higher over warmer areas and lower over colder areas. The structure of the atmosphere dictates the way the atmosphere behaves and controls how weather develops near the surface of the earth.

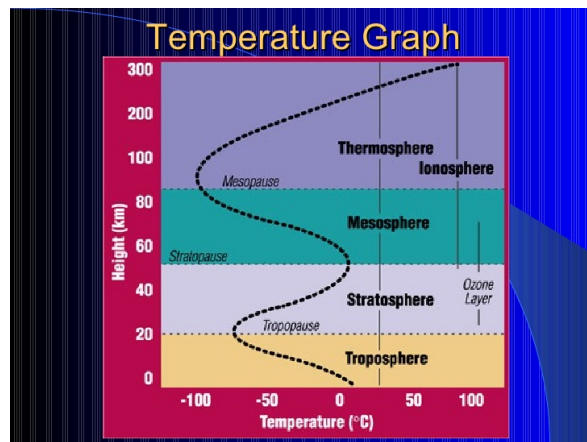


Figure 1.2. Temperature Graph of atmosphere layers [2]

The atmosphere, together with all the factors, that affect it to produce the climates of the world, constitutes the climate system. The system includes the oceans, lakes, rivers, and the hydrological cycle, the polar ice sheets, the solid Earth, and living organisms. The energy of system is derived from the Sun, and solar radiation, and periodic changes in it, is also included as a component of the system. The weather and climate are determined by factors called the climatic elements. These elements are temperature, precipitation, wind speed and direction, humidity, pressure, cloudiness,

sunshine [12], that are measured or calculated from observed data. The climate of an area is the average of weather conditions, determined by these elements, over a long period; where, the weather is day-to-day air conditions in a certain place. The climate of a place is determined principally by its latitude, distance from the ocean, and its elevation above sea level. It is characterized according to these varying elements and each one has different important impact. For example, latitude is one of the most important one, because it defines the amount of solar radiation the place receives. The proportions of the surrounding area that have surfaces of land and water are also important, because of their different heat capacities. All these characteristics of the climate make life on earth possible, but there is a balance to maintain in order to be friends with the climate. Because if we do not, life on earth can turn into a misery, may even come to an end. We might be ending up searching for new habitable planets with suitable atmosphere. Unfortunately, it seems very unlikely to find one in near and mid future. We need to realize it's worth and start protecting it before it is too late.

1.2. Global Warming

It will be naive to presume that the system, which had a crucial role in the creation of life, will not have an influence on our daily life. As mentioned above the climate of a region is determined by its system components like the atmosphere, hydrosphere, cryosphere, biosphere and land surface. The local atmosphere, the composition and movement of gases, can be affected by anthropogenic factors and nature itself. Hydrosphere and cryosphere have long-term effects on temperature most of the cases. But in marine environments like islands and coastal areas they can be very effective. Land surface of a region will impact on the vegetation which influence the evaporation amount and ambient temperature by determining the heat trapping capability. But it is better to consider land surface together with the biosphere of the region. Because for example forests through photosynthesis have a direct impact on the climate. Not only with producing oxygen, but also with trapping carbon, cooling the environment and regulating the Greenhouse gas flow on the region. These great ecosystems, forests, have much more contribution to the health of the climate system. In the past, Earth's

climate had been changed a lot. It had warmer and cooler times than these days but living creatures, plants, animals and humans always found a way to adapt. But this adaptation is not easy because the climate has so many effects on our way of live. The cultures, civilizations and industries developed and evolved with climate of their region. First thing, that comes up to mind when talking about weather, is how it is going to be hot, cold, rainy, etc. This is the case in the global level, too. The clothing of a region is depending on the climate of it. The Nordic, near to pole, civilizations of different continents like Canada, Sweden, Russia, all wear thick, isolated, long lasting, strong, most of the time waterproof, clothes and furs to keep them warm and dry to survive in challenging weather conditions. They usually use animal-skin based clothes to deal with both very low temperature and high precipitation. The opposite kind of clothing can be seen the equatorial/tropical regions like central America, Middle East, Africa, Australia. Their clothes are mostly light, thin, spacious to avoid high temperature. The similar effects can be seen in sheltering in different climates. The designs, engineering and materials used in construction differ whether preventing heat or not. For example, southern North American people built their house in tall cliff areas to benefit from the shade to avoid hot, dry climate. Another vital and direct influence of climate is on agriculture and animal husbandry which both is the direct resources for nourishment. Climate is the primary factor of agricultural productivity. All ancient civilizations and empires founded on very rich lands like Mesopotamia and India where they can culture the land every season. The soft climate of Mediterranean allowed Roman Empire and later Ottoman Empire people to become great farmers. Developed farming skills and techniques allowed them to cultivate all different kinds of crops like wheat, olive, grape. Like ancient Romans, ancient civilizations Azteks and Mayans also took advantage of their mild climate and become great farmers and introduced the world with potato, tomato, pepper, tropical fruits and cacao fruits. Even today the farmers are still depending on climate, some corps still cannot be cultivated in a Greenhouse. For example, filbert needs very specific heat, humidity and rain, so it can be cultivated in very specific altitudes and regions, one of the best quality nuts can be found in Turkey's east-north coast of Black sea in altitude 700-1500 meters [13]. Given the fundamental role of agriculture in human welfare, there has been

a lot of researches conducting on global level. A lot of crops are planting regarding the estimated precipitation amount of the season ahead, but when the weather conditions are not as expected, it is affecting the harvest and the cost in parallel. Most existing research has focused on the likely direct climate impacts on crop yields and agricultural output [14] [15] [16], but direct crop impacts in a given area provide only partial understanding of the consequences for human livelihoods. This is both because countries are inter-connected through trade, but also because different households are affected by these price changes in different ways. For instance, households selling their extra production in local markets could benefit if climate change causes food prices to rise, even as their non-farming neighbors are hurt by higher prices. Thomas Hertel's study presents important lessons for scientists and policy makers concerned with poverty responses to climate change. His results are concerned with the period until 2030. Although most studies focus on production impacts, these measures provide a relatively poor predictor of regional welfare impacts, because international trade is an important mediator between countries, which are differentially affected by climate change shocks to agricultural productivity. Despite experiencing significant negative yield shocks, some countries (e.g., Russia, Brazil) stand to gain from higher commodity prices. Indeed, the rise in price offsets the adverse impact of lower agricultural productivity in some cases. It is important to consider the full range of possibilities in designing policy responses, particularly given that these estimated potential price changes are well outside the range of changes predicted in the recent IPCC report for a similar level of warming [17].

The climate is also affecting the agriculture via carbon and water cycles (shown in Figure 1.3). Water cycle, also known as hydrologic cycle, is the continuous circulation of water in the Earth. Of the many processes involved in the water cycle, the most important ones are evaporation, transpiration, condensation, precipitation, and runoff. Although the total amount of water within the cycle remains essentially constant, its distribution among the various processes is always changing [3]. The cycle can be broken from time to time by natural causes, ending up with droughts. In the past, many civilizations faced with such problem, some of them survived and some did not. One of them is the First Empire of Mesopotamia, The Akkadian Empire. They faced one of the biggest droughts in ancient history, that led refugees from north

cities to move in south and eventually led to their collapse. After more than 4000 years same thing happened in the same region. In between 2006-2011, Syria faced with a drought, that decreased the agricultural production by 70% and animal husbandry by 85%. This led countryside people to immigrate to cities. The cities were also suffering from poverty caused by refugees from Iraq and Palestine, so the poverty escalated, merged with oppressive regime and became a civil war. Another example can be given from United States, California where half of the crop for the nation is harvested. The drought started in 2013 caused a serious outage in water that even the government placed mandatory restrictions of consumption in water by 25%. Serious production and plant life lost in the period. So, we should not be considering it as only a drought and water shortage. Climate change can cause serious political outcomes, which leads to wars and destruction of civilizations [18].

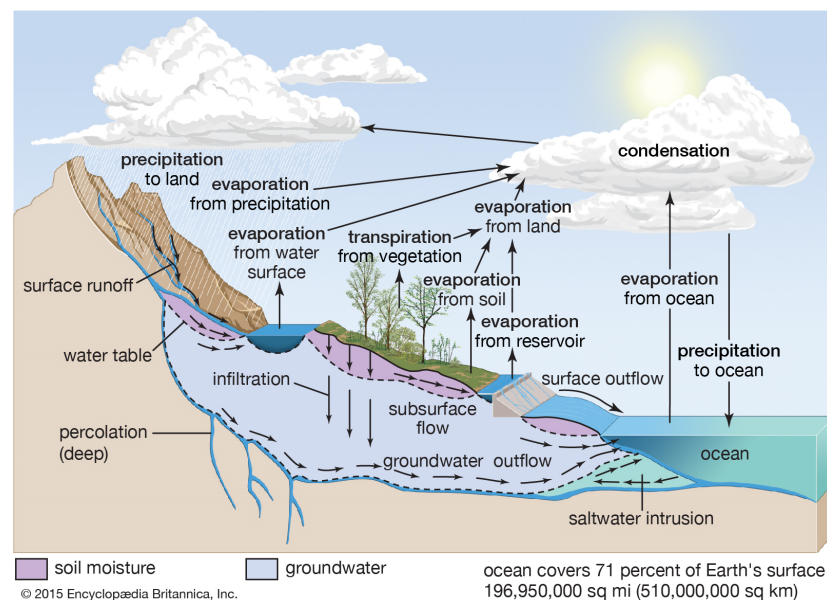


Figure 1.3. Scheme of Water Cycle [3]

The climate does change overtime, but it cannot be observed day by day like weather. It is a long period since the climate is a very huge and complex global system. The change in this complex climate system, that have vital effects on life, have serious effects. Climate change and Global Warming usually used instead of each other, but they are not the same. Climate change is the change in the weather patterns of climate that will not only change the temperature but also the precipitation

extremes, the winds, all the climate factors. On the other hand, Global Warming is the unnatural Earth's temperature increase with anthropogenic elements, which leads to climate change in a dangerous way for living creatures. Climate change is a natural phenomenon and in the past the people and other living being suffered from the consequences. For example, there was a time when Sahara Desert was part of the ocean, but it dried out and became the Earth's second biggest desert. Many natural reasons can cause a climate change like the change in distance between Earth and Sun, the tilt in the Earth's axis, increase or decrease in the amount of energy coming from the Sun, a volcanic eruption or tectonic movements. For example, after the volcanic eruption in Krakatau island in Indonesia in 1883, the ashes from the eruption blocked the sun which caused cold and dark winters and summers for Asia and Europe. The agriculture is also affected with shorter and weaker harvests. The period between 12th to 19th century was called "Little Ice Age" because of the climate change in that period. It was not a glacial period, but the climates were colder; frozen canals in Europe, severe winters in North America and snow-caped mountains and flooded rivers in Africa. All these were results of natural climate change in the past. Beginning with the Industrial Revolution, developed countries starting to pollute the air with burning fossil fuels and cutting down the forests to produce energy that released runaway Greenhouse gases like carbon and methane to the atmosphere with an irreversible flow. As previously explained, although Greenhouse gas effect is a natural and healthy mechanism for Earth to be warm to support life, this extra Greenhouse gas emissions result the atmosphere getting warmer more than enough. The increase in temperature disarrays the balance of nature and breaks down the carbon and water cycles. In parallel with the concerns, some organizations founded in the name of investigating and seeking solutions to Global Warming. The 2nd article of the United Nations Framework Convention on Climate Change (UNFCCC) states that the main goal is the stabilization of Greenhouse gas (GHG) concentrations in the atmosphere at a level that "would prevent dangerous anthropogenic interference with the climate system" [19]. While the definition of dangerous anthropogenic interference with the climate system is debated, the Intergovernmental Panel on Climate Change (IPCC) presented five reasons for concern, widely known as "burning embers diagram" [20]. These are; risks

to unique and threatened systems, risks from extreme climate events like hurricanes and typhoons in humid climates, distribution of impacts, aggregate impacts and risks from future large-scale discontinuities which we have already faced in some regions more vulnerable to climate change, like islands. Based on these reasons for concern and their relationship to global mean near surface temperature rise, it is now widely accepted that global warming needs to be limited to 2 degrees Celcius or less, as accepted in Paris Agreement 2015, compared to 1990s to prevent destructive anthropogenic interference with the climate system. The dominant cause of the observed warming since the mid-20th century can be credited to the human influence. When the GHG concentrations increase, they induce a radiative forcing, i.e. a change in the net radiative flux at top of the atmosphere, and the climate system warms. However, due to the large thermal reservoir of the ocean and slow processes in the cryosphere and land surfaces, the full surface response is not realized during the time of the radiative forcing. Instead, warming also includes a portion that will be realized after the radiative forcing is stabilized, for example when GHG concentrations stabilize. Moreover, the different subsystems of the climate system involve different response times. With the atmosphere reacting to stabilization of GHG concentrations within a few years and the upper ocean adjusting on a timescale of several decades, the ocean and ice-sheets involve longer response times up to millennia [21] [22]. Briefly what we can say is that even if we can stabilize the GHG concentration today, the damage is done. So, there will be an impact wave of what we have done until this time because of the different response time of the climate system elements. Looking the bright side, the damage done is repairable, if we react rapidly. The energy policies of countries should immediately change to carbon-free sources like wind, solar, hydro. The scientists are working every day to increase the efficiency of renewable energy sources. Transportation is another big source of carbon emission, so the vehicles also become carbon-free like electric vehicles. As the energy sources transform into renewables, as the extravagance in consuming should become retrenchment and recycling. The adaptation to the new climate and conditions is also critical. The glaciers have already melted and will continue to melt and rise which will cause the sea level to rise. Islands and coastal cities should be prepared. The ones in a humid climate should also be prepared to extreme weathers like hurricanes and

typhoons. Some of the islands in Maldives have already been forced to be abandoned because of such extreme phenomenon. The droughts will also be another serious issue that needs to be prepared for. The productivity in agriculture will have a serious hit with the change in weather patterns, but with new technological developments, like an efficient irrigation method, the damage can be weakened. The economy of the new order should be calculated carefully and fairly. The adaptation policies will definitely help along the way to a clean, cooler world without global warming.

1.3. Climate Factors and Variables

The climate has always been an issue to solve for humans from the ancient times. For example, Ancient Greeks, such as Aristotle, divide the known world into three zones (Torrid, Temperate and Frigid) based on their regional warmth [23]. The interest in climate continued incrementally over years. The scientist noted the variables affecting the climate and weather. Despite other weather variables, the most used ones are temperature and precipitation. Not only they are the earliest and simplest to measure, they also have the most direct effect on humans, animals, vegetation, soils and the forms of the landscape. This makes them the most effective weather elements to use. Additionally, they have the most significant observable traces of variations caused by the atmospheric controls. So, it is not a surprise that we have the most widely distributed and proper data of temperature and precipitation. The first meaningful and reliable data came after Galileo inventor of thermometer. Then, slowly, the measurements spread from Europe to their colonies, but to describe the climate of an area accurately, minimum of 30 years of data required. The routine was not set until mid-19th century. So, all these enormous meteorological data give scientists a start to work the climate. But to determine the climate temperature and precipitation is not enough by themselves. For example, San Francisco, U.S and Beijing, China have similar yearly temperature and precipitation. San Francisco has warmer and wetter winters and cooler and drier summers compared to Beijing, because of the daily and seasonal changes. According to temperature, which measured as minimum, maximum, lower ground and soil temperature, and precipitation and some additional param-

ters, it is possible to define different types of climate. Some additional parameters are windiness and wind speed, humidity, cloudiness, atmospheric pressure, vapor pressure, fogginess, solar radiation and average sunshine duration. There are some other factors which have great influences on regional climate like elevation, proximity to the ocean or freshwater, and land-use patterns. The climate of the region is the combination of all these factors and variables. For example, West Africa, located close to Equator, receives direct sunlight year-round and sits at an area called the intertropical convergence zone where moist trade winds meet. As a result, the region's climate is warm and rainy [24].

1.4. Climate Classification

A generalization is needed for this work to be meaningful and for scientists to have a common language. This common language is the climate classification, but to group things, you need to identify the main features, which are temperature and precipitation in our case. Classification of the climate of the Earth is an attempt to systematize enormous volumes of meteorological data on weather phenomena in different parts of the Earth. Climate classification is aimed at defining climatic types and to find similarity and distinctions in climatic patterns as observed in different regions of the world. The scientific and practical importance of climate classification is in both comprehension of physical mechanisms affecting climate and evaluation of climatic potentialities and aspects of their utilization in the various regions of the Earth. Climate classification assumes, on one hand, the identification of areas with distinctive climatic patterns. On the other hand, it provides the possibility of finding climatic similarities in different parts of the world. Modern science divides climatic classifications into two groups. The first group is the so-called genetic classifications, which are based on natural laws of climate formation, and not only covers characteristics of climatic types, but also explain the reasons for the existence of climatic patterns in different regions of the world. The second, that can be named descriptive, distinguish climatic types using criteria, which are not connected with genesis of climates. Descriptive classifications manipulate by formal criteria and often attribute climates of quite distinctive origins

to the same type. Among climatic classifications we shall pay particular attention to those which have well-expressed applications. There are many classifications developed for use in agriculture, the building industry, public health services and other domains. The classification, which we will use, is the second group, descriptive, because we can make mathematical models through it and simulate future change in climate. There has been a lot of different classifications on climate. The most common one in all is the Köppen Classification. Wladimir Köppen, a botanist and climatologist, who realized that vegetation in a region is the image of the climate of that area, found the most popular one of descriptive classification. His efficient work was built on the basis of five vegetation groups determined by the French botanist De Candolle referring to the climate zones of the ancient Greeks as mentioned before [25]. When the first attempts at classification made, the only reliable features available were temperature, precipitation, and vegetation types. Much more information has become available since then. It is now possible for a classification to include any kind of climate related data, for example, the crop growth or glacier movements, and data can be obtained from satellite readings and footage as well as from surface observations. Modern computing power also makes it possible to classify climates by means of extremely complex statistical analyses of the data within reasonable time scale. The five vegetation groups of Köppen distinguish between plants of equatorial zone A, the arid zone B, the warm temperate zone C, the snow zone D and the polar zone E. A second letter in the classification considers the precipitation (e.g. Df for snow and fully humid), a third letter the air temperature (e.g. Dfc for snow, fully humid with cool summer). We used the KTC defined in Trewartha & Horn (1980) in this study [4]. This scheme builds upon the original Köppen system and presents various modifications to make the climate types fit better with the observed boundaries of natural landscapes [26]. Despite all revisions, some the alterations still deal with the problem of certain haziness of the KCC formulations. The KTC defines 6 main climatic groups. Five of them (denoted as A, C, D, E, and F) are basic thermal zones. The sixth group B is the dry climatic zone that cuts through the other climate types, except for the polar climate F. The main climate types are, similarly to those of the KCC, determined regarding the long-term annual and monthly means of surface air temperature and amounts of precipitation.

The ultimate difference between the KTC and KCC is the characterizations of groups C and D, a newly defined E type, and different limits for identifying wet and dry climates. In the following, each group of climate types will be reviewed.

1.4.1. Group A: tropical humid climates

Trewartha & Horn (1980) call this type ‘killing frost absent’. The coldest months has an average air temperature of 18°C , which means all months must be warmer than 18°C . The annual cycle of precipitation determines the subtypes of this group (number of dry months, see Figure 1.4). Subtype Ar; tropical wet, sometimes called tropical rainforest climate, and subtype Aw; tropical wet and dry, called savanna climate are the two main subtypes of this group. Subtype As is quite rare. The ‘dry months’ have extremely low level of average precipitation totals, which is not more than 5,5 cm and where the average annual temperature is about 25 to 27°C as described by Trewartha & Horn [4].

1.4.2. Group C: subtropical climates

In this group of climate type, below 18 degrees Celcius is the coolest month temperature and the average air temperature should stay over 10 degrees Celcius for 8 to 12 months. As in the KCC, the letters s, w and f are similarly identified. Despite, the definition in the KCC, the conditions are due to the total precipitation during the winter/summer half year, not to the amount of precipitation in the wettest/driest month of the season. The definition of the subtype s, which is the average annual precipitation of less than 89 cm, is different for KCC. In addition, the driest summer month has not a precipitation more than 3 cm. The subtypes Cs, so-called Mediterranean, the subtropical dry-summer climate, and Cf, the subtropical humid climate, are the 2 main subtypes of this group. Another subtype Cw, which has subtropical dry winter, is not commonly seen (see Figure 1.5).

Type / subtype	Criteria Rainfall/temperature regime
A	$T_{\text{cold}} > 18^{\circ}\text{C}$; $P_{\text{mean}} \geq R$
<i>Ar</i>	10 to 12 mo wet; 0 to 2 mo dry
<i>Aw</i>	Winter (low-sun period) dry; >2 months dry
<i>As</i>	Summer (high-sun period) dry; rare in type A climates
B	$P_{\text{mean}} < R$
<i>BS</i>	$R/2 < P_{\text{mean}} < R$
<i>BW</i>	$P_{\text{mean}} < R/2$
C	$T_{\text{cold}} < 18^{\circ}\text{C}$; 8 to 12 months with $T_{\text{mo}} > 10^{\circ}\text{C}$
<i>Cs</i>	Summer dry; at least 3 times as much rain in winter half year as in summer half-year; $P_{\text{dry}} < 3$ cm; total annual precipitation < 89 cm
<i>Cw</i>	Winter dry; at least 10 times as much rain in summer half-year as in winter half-year
<i>Cf</i>	No dry season; difference between driest and wettest month less than required for <i>Cs</i> and <i>Cw</i> ; $P_{\text{dry}} > 3$ cm
D	4 to 7 months with $T_{\text{mo}} > 10^{\circ}\text{C}$
<i>Do</i>	$T_{\text{cold}} > 0^{\circ}\text{C}$ (or $> 2^{\circ}\text{C}$ in some locations inland) ^a
<i>Dc</i>	$T_{\text{cold}} < 0^{\circ}\text{C}$ (or $< 2^{\circ}\text{C}$) ^a
E	1 to 3 months with $T_{\text{mo}} > 10^{\circ}\text{C}$
F	$T_{\text{warm}} < 10^{\circ}\text{C}$
<i>Ft</i>	$T_{\text{warm}} > 0^{\circ}\text{C}$
<i>Fi</i>	$T_{\text{warm}} < 0^{\circ}\text{C}$
^a In the present study the boundary between subtypes <i>Do</i> and <i>Dc</i> is $T_{\text{cold}} = 0^{\circ}\text{C}$	

Figure 1.4. Climate types and subtypes by the K-T classification. T:mean annual Temperature (C); Tmo: mean monthly temperature (C); Pmean: mean annual rainfall (cm); Pdry: monthly rainfall of the driest summer month; R: Patton's precipitation threshold defined as $R = 2.3T - 6.4Pw + 41$ where Pw is the percentage of annual precipitation occurring in winter; Tcold (Twarm): monthly mean air temperature of the coldest (warmest) month [4]

		KTC												Sum
		<i>Ar</i>	<i>Aw</i>	<i>BW</i>	<i>BS</i>	<i>Cs</i>	<i>Cw</i>	<i>Cf</i>	<i>Do</i>	<i>Dc</i>	<i>E</i>	<i>Ft</i>	<i>Fi</i>	
KCC	<i>Af</i>	5.10												5.10
	<i>Aw</i>	0.38	11.17		2.09									13.63
	<i>Am</i>	1.92	1.74											3.66
	<i>BW</i>		0.01	16.76	1.08	0.50			0.01			0.11		18.47
	<i>BS</i>		0.01	2.52	6.36	0.27		0.23	0.22	0.39	0.02	0.13		10.15
	<i>Cs</i>					0.40		0.46	0.76	0.40	0.05			2.07
	<i>Cw</i>				1.46		0.77	2.71	0.38	0.26	0.02			5.59
	<i>Cf</i>				0.57			4.72	1.74	1.48	0.17			8.69
	<i>Ds</i>									0.48	0.14			0.62
	<i>Dw</i>			0.03	1.06					1.14	2.16			4.39
	<i>Df</i>				0.42					7.51	12.43			20.36
	<i>ET</i>											6.10		6.10
	<i>EF</i>												1.16	1.16
	Sum	7.40	12.93	19.31	13.04	1.17	0.77	8.12	3.11	11.65	14.99	6.34	1.16	

Figure 1.5. Percentage of continental area(without Antartica) covered by climate types according to the KTC and KCC. calculated from the Climate Research Units TS3.10 for the period 1961-1990 [4]

1.4.3. Group D: temperate climates

The D type climate must have 4 to 7 months a monthly average air temperature of over 10°C. Oceanic Do and continental Dc, are the most common subtypes. The average air temperature of the coldest month is separating them from each other.

1.4.4. Group E: boreal climates

The mandatory duration to have a monthly average air temperature of over 10°C is in between 1 to 3 months in group E type of climate. No subtypes are defined for group E, however there are some authors, who use the similar oceanic and continental subtypes as in D (e.g. [26]). When working with specific regions, this kind of separation can be helpful.

1.4.5. Group F: polar climates

Every month in group F of climate type could have a monthly average air temperature of maximum 10 degrees Celcius. There are two subtypes to be mentioned.

One with the minimum monthly air temperature 0 degree Celcius, called tundra or Ft and the other one which has no air temperature above 0 degrees Celcius, called Fi or ice cap.

1.4.6. Group B: dry climates

This group is the ultimate difference between the KCC and the KTC. As mentioned above, the definition of wet and dry climates is based on annual precipitation forms in KCC. According to Köppen (1936) this estimation was not troubling, while Trewartha & Horn found that this was a faulty approximation of degree accuracy when working with bigger units. The borderline between wet and dry climates is close when you consider lower average air temperature areas. In Köppen [27] [28] [29], when you say ‘rainfall resolution in summer/winter’ is not elaborated, however it is obvious seasonal rainfall and air temperature should be identified in detail. So, in KTC we use another, more detailed, formula that would minimize this problem.

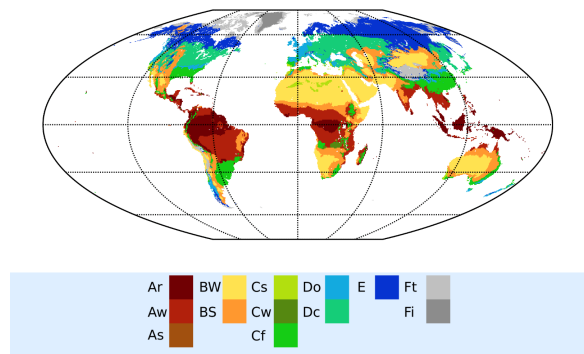


Figure 1.6. Köppen-Threwartha Classification - CRU TS 3.10.01 1976-2005 [4]

1.5. Climate Modelling and Scenarios

A broadly used climate classification is the modification of the Köppen system proposed by Trewartha [30] [4]. They modified original Köppen thermal and dryness criteria to make the climate types better correspond with the observed boundaries of natural landscapes and to eliminate certain vagueness of the KCC definitions. This

classification, sometimes referred to as Köppen-Trewartha or K-T classification (denoted as KTC in the following text), provides a more detailed description of climate type distributions than the original Köppen scheme, modifying the thresholds between types and adding a further level of division of types E and F ([31] for more details and a comparison of KCC and KTC). The KTC scheme was used by Feng [32] to analyze observed and projected climate changes and their impact on vegetation for the area north of 50° N over the period 1900–2099. They focused on the Arctic region, and in addition to the observed data, they incorporated the simulations of 16 AR4 GCMs under SRES scenarios B1, A1B, and A2. Another example of the application of KTC on the outputs of GCMs is the study by Guetter & Kutzbach [33], who investigated the last interglacial and glacial climates (126 000 and 18 000 year before present) using simulations of an atmospheric general circulation model.

A climate model is a mathematical representation of the climate where we can simulate the conditions that create or modify the weather and the climates of a region over a period. The climate models are also leading us to understand these conditions better and make more precise predictions about future weather and climate alterations. The model is a computer program based on the physical, chemical and biological laws driving the weather and gathered as mathematical equations. The scientists obtain a meaningful perception of past, current and future climate activities and its flexibilities from the models. Beginning from the first model, which developed as weather forecaster in 60s, the models evolve to become a complete climate tool. Stratospheric dynamics, atmospheric chemistry, oceanic circulation and the carbon cycles are included in some extremely unique climate models, some used further in Earth System models. Surface temperatures and rising sea levels are the results of increasing radiative force, which is caused by high GHG concentration, revealed in model simulations [34] [35]. It needed to take into account even if GHG concentrations are stabilized, there will be a late reaction of the climate system [34] [36] [35] [37], when setting target temperature limits for the future. Hence, scientists consider these facts when designing stabilization scenarios that will provide the ways to comprehend healthier both, fast adjustments to radiative forcing, like surface warming and melting glaciers, and the delayed response of climate change, like warming of the deep ocean, adjustment of the oceanic

circulation and sea level rise. Climate and climate change have been analyzing in the past 30 years and more by atmospheric general circulation models (GCMs) and joined atmosphere-ocean models. Commonly, certain model fields like temperature, pressure or wind are compared for validation of models regarding the observations with additional analysis of higher-order quantities like low and high frequency variability or the number of blocking events. The process is similar in climate change simulations. These direct model variables usually used with some additional assistants, which consist of long-term observational data, e.g. the classification that was introduced by Köppen (1923). He divided the observed climates into several climate zones, according to annual average surface temperature and precipitation, which above discussed in detail. His classification regards the vegetation distribution of the earth, too, which is why his classification is the most successful and commonly used. Thanks to scientists like Manable and Holloway [38] who applied the Köppen Classification to Geophysical Fluid Dynamics Laboratory GCMs, we could have enriched the GCMs, both in resolution and physical parameterization, which leads us to use Köppen's statistics in GCMs.

The model is always tested in an observed climate of a reference period in order to justify the performance of the simulation and estimation of the GCMs output for future climate changes. Climate classifications can define large range of features in a single characteristic which provide a considerable benefit in commonly used evaluation methods. Additionally, climate types and subtypes of classifications encapsulate the mean values of annual and monthly temperature and precipitation data. Because of the simplicity and clearness of rule-based climate classifications; they are commonly used in GCM validations and analysis to obtain easy interpretation which leads to the most important result of climate estimation, the future vegetation distribution. One of the most frequently used classifications of this kind was developed by Köppen (1923, 1931 and 1936) and modified by various authors [39] [4] [31]. In studies using rule-based classifications, such as KCC or KTC, it is sometimes not obvious which rules were applied first. A different approach to climate classification is represented by methods based solely on statistical techniques; most often cluster analysis [40] [41], but the physical interpretation of the results of such procedures might be complex and difficult.

When using climate models to project the future, the scientist needed different types of pathways or scenarios. In the first IPCC Assessment Report (IPCC FAR) in 1990, there were three types of scenarios discussed but they are based on CO₂ concentrations. Only Scientific Assessment (SA90) emission scenarios based on World Bank population predictions. In time these scenarios have widen up and with new generations, as the original SA90 scenarios were replaced by the IS92 emission scenarios of the 1990s, which were in turn succeeded by the Special Report on Emissions Scenarios in 2000 (SRES) and by the Representative Concentration Pathways in 2010 (RCPs). SA90, IS92, and SRES are all based on CO₂ emissions and population projections initially. By SRES, they got complicated, consistent demographics, international trade, flow of information and technology, and other social, technological, and economic characteristics of future worlds. Despite these developments helped built the latest scenarios, RCPs, they differ from previous sets of standard scenarios in many ways. RCPs are based on radiative forcing, not emissions. Each scenario is tied to one value: the change in radiative forcing at the edge of Troposphere by 2100 relative to preindustrial era. There are four different RCPs numbered according to the change in radiative forcing by 2100: +2.6, +4.5, +6.0 and +8.5 watts per square meter (W/m²). IAMs, Integrated Assessment Models, are working backwards starting from these radiative forcing values, to derive a range of emissions trajectories and corresponding policies and technological strategies for each RCP to achieve the same final impact on radiative forcing. From the multiple emissions pathways that could lead to the same 2100 radiative forcing value, an associated pathway of annual carbon dioxide and other anthropogenic emissions of Greenhouse gases, aerosols, air pollutants, and other short-lived species has been selected for each RCP to use as input to future climate model simulations [42] [43]. In addition, while none of the SRES scenarios involved a scenario with explicit policies and measures to limit climate forcing, all three lower RCP scenarios (2.6, 4.5, and 6.0) are climate-policy scenarios. The RCP8.5 scenario is the worst-case scenarios where GHG emissions continue growing as today, significant reduction in aerosols, and modest improvements in energy intensity and technology. GHG amounts reach more than 1200 ppm by 2100, and global temperature is increased by 5.4°–9.9°F (3°–5.5°C). Although RCP8.5 is worst scenario of all, it is not the upper

limit on possible emissions nor as a business-as-usual or reference scenario for the other three scenarios [44].

1.6. Importance of High Resolution and Complete Data on Climate Modeling

It is not possible to fully represent the climate system as it is, because of many reasons like the complexity and unreliability of human factors, complexity of climate system, lacking data and running the models over a very long period which in fact is beyond the limits of computers, etc. So, the climate models needed to be optimized. Computational methods are used for optimization of the models. The optimization and building a model start with determining the grid over the desired region. In most climate applications, the grid will be two dimensional, representing horizontal dimensions like latitude and longitude. But it could be three dimensional with placing two dimensional grids one above the other like a cage. Number of discrete grid points shapes the model's representation capability of atmosphere. The grid cell size and the spacing defines the resolution of the model. The accuracy of the model determined by the scale of the grid, the length of grid lines, and the size of the time steps. Although, reducing the distance between grid lines or time intervals may increases the accuracy, it will seriously affect the computation power of the model with increase in the number of calculations, which will lead to a need of powerful hardware. This can be an issue while working on a large area, but if the model has a finite region to run, it is better to a higher resolution, which means a smaller grid spacing and time step, to represent the regions atmospheric distribution. Models must be tested before they can be used to estimate the consequences of change. Testing usually begins by supplying the model with data from the recent past then running it to see how well it simulates the taken real weather data. If this is successful, the model is used to simulate conditions from the more distant past, partly as an aid to understanding how those conditions developed. Only if it passes these tests is the model used to estimate what may happen in the future. The most powerful supercomputers are used to construct and run the more complex models and the reliability of models is directly proportional to the amount of

computational power that is available to run them. Models that calculate the effect of releasing Greenhouse gases into the atmosphere estimate the climatic consequences at various times in the future [12]. The idea of using numerical methods on physically represented models in climate studies was first mentioned by Lewis Fry Richardson. He used his meteorology and mathematics knowledge to simplify the equations of motions presented by Abbe and later by Bjerknes. His idea was to represent Earth's surface with grids, with each one to be vertical column of the atmosphere which divided into several layer to become three-dimensional boxes. By the time the numerical models are too complex and sophisticated for the computers to solve, but with technological and theoretical improvements the models become more accurate and solvable. Development of different types of grids, grid-staggering and grid spacing results as high-resolution weather and climate predictions.

2. EXPERIMENTS AND RESULTS

Meteorological data is collected from the meteorology or weather stations strategically distributed all over the world to observe and examine the changes in the climate factors and variables discussed in the previous sections. These measurements are done via suitable instruments and technologies for the desired climate factor which can be soil or air temperature, humidity, precipitation, pressure, solar radiation, wind speed and direction and cloudiness according to the purpose of the station. In order to collect these measurements in a healthy way, the location of the weather station must meet some strict requirements. For example, it must be in an open environment, so that either the wind direction or speed is not deflected from local buildings and obstacles, or the shadow does not affect the temperature. The stations are collecting weather and environment measurements as per the measurement instruments, like thermometer for temperature or anemometer for wind, and sensors, like pressure and humidity sensors at the station. Anemometers are instruments to measure wind. The basic concept is that to measure the wind speed with a turning wheel and a cylindrical wheel to determine the direction. Thermometers are used for measuring ambient air temperature with simply using the thermal expansion rate of a liquid, mercury, in a tube. Barometers are measuring pressure by altering the flexible unit within a fixed volume air relative to pressure change. Hygrometers are used in measuring humidity or moisture with electronic sensors. The final main instrument in meteorological measurement is the rain gauges, which is used to measure precipitation. It simply tips their meter after a certain weight of water or over a period [45]. All these instruments must be carefully calibrated, and regularly serviced to maintain the reliability of the measurements. But not all stations could do all the measurements. There are dedicated stations for all purposes, for example, in Turkey there are more than a thousand station, only 400 of it can measure temperature. Station data can be used in weather forecasting and climate studies. The same data can also be used in analyzing the regional and global climate and classification change and shift.

It is also possible to observe the upper atmosphere meteorological data. Although

the ground climate measurements are important, the upper atmospheric measurements are equally important for climatologist to take a better picture of the climate. The most commonly used application in these measurements is with a weather balloon or kite. The studies started in 1800s with James Glaisher's balloon flight. Now the balloons can go up to 20-25 in general and in special applications it can be exceeded up to 35 km. With the development in technology the data stored in these balloons can be obtained through radio communication. There are instruments for the higher altitudes, too. Weather satellites, radars and rockets are used for measuring higher levels of the atmosphere. Additionally, they can provide images of the earth from a higher level, so that the scientist can a better view of atmospheric movements and earth's climate and weather.

2.1. Examined Data

We have surface minimum, maximum and average temperature, precipitation, pressure, humidity, vapor pressure, cloudiness, wind speed, sun radiation, sunshine duration, open surface evaporation and above ground temperature station data from Turkish State Meteorological Services, which is the only legal organization providing the meteorological data for Turkey. The data are daily based real station data from January 1st, 1960 until December 31th 2016. In this study, we will be focusing on particularly two main climate measurements; average temperature, precipitation data to examine the changes and shifts of climate types at Turkey land area since temperature and precipitation are the main indicators of climate change and distribution. Several observed monthly temperature and precipitation datasets were analyzed. The first dataset is from 1960 to 2016 for temperature, the second is the precipitation dataset from 1960 to 2016. Although it is a daily based dataset, both temperature and precipitation have enough amount of station data to create a uniformly distributed grid dataset from the non-uniformly distributed daily station data. The raw data from Meteorology Services has station numbers and names, dates and measurement values. To identify the locations of the stations, the coordinates are needed and there exists a database for the past and present station coordinates along with the altitude, region, city. Briefly we have two different databases; one with the station ID and meteorolog-

ical values, the other with the station ID and coordinates and other features.

The source database will be consisting of these two sets. The dataset can be merged using the station IDs as keys, so that a single database to be studied on, can be created. Merging data only using the station ID is not enough because there has been a lot of changes in the station database. Some of the stations were moved, some of them closed and new stations were added to the system. Without the coordinates of the station, it is not possible to conduct any computation like interpolation or extrapolation on the dataset. The position of the measurement must be known. To obtain the maximum station possible, we used both station ID and Station names to match the coordinates. But matching the names was not an easy task, since there were uppercases, lowercases, character mismatches, spaces in the ends and so. While merging the tables all these anomalies cleared out and almost every station passed this step. The database is consisting of 56 years daily temperature and precipitation data which is a big data. So, the efficiency concerns must be eliminated. Once this database created, the database should be organized to optimize and simplify the interpolation calculation and the analysis of the station data. Since there is a big data to be worked on, efficiency on calculations and analysis should be a major concern because of the hardware limitations that can be encountered by. The first step was to eliminate the duplicate and unnecessary and useless data. Then the table should be pivoted, so that every row has only one variable per day. Additionally, this process will allow us to create time filters. With the pivoting, we will be obtaining even bigger data in rows, but for interpolation purposes this must be done. So now, the data obtained is looking like Table 2.1. Since the data have more than 5 million rows, only the first 20 rows are shown.

Before starting to calculate the mid points by interpolation, 2 important operations must be done. The first one is the altitude correction for precipitation and temperature. As discussed in the previous section, the altitude a serious effect on both temperature and precipitation. The atmosphere pressure is also changing with altitude, but since we will be working on temperature and precipitation data this effect is not our main concern in this study. Mountains and hills increase the precipitation,

Table 2.1. Temperature Station Data.

Station No	Date	Latitude	Longitude	Altitude(m)	Temp(C)
970	01-Jan-1960	41.26	32.70	581	5
3015	01-Jan-1960	40.59	35.65	475	15
9030	01-Jan-1960	38.62	27.04	10	10
17015	01-Jan-1960	41.09	31.14	10	8
17020	01-Jan-1960	41.62	32.36	33	6
17022	01-Jan-1960	41.45	31.78	135	6
17024	01-Jan-1960	41.98	33.76	64	8.4
17026	01-Jan-1960	42.03	35.15	32	9.2
17030	01-Jan-1960	41.34	36.26	4	13.2
17034	01-Jan-1960	40.92	38.39	38	13.1
17037	01-Jan-1960	41.00	39.76	25	16.1
17040	01-Jan-1960	41.04	40.50	3	19.6
17045	01-Jan-1960	41.18	41.82	613	15.7
17046	01-Jan-1960	41.11	42.71	1827	3
17050	01-Jan-1960	41.68	26.55	51	7.5
17052	01-Jan-1960	41.74	27.22	232	9.8
17054	01-Jan-1960	41.18	27.82	145	4.6
17056	01-Jan-1960	41.96	27.50	4	5.7
17059	01-Jan-1960	41.25	29.04	38	7.3
17061	01-Jan-1960	41.15	29.05	59	7.4

because they catalyze the condensation and the formation of clouds which leads the air masses to elevate. In highlands precipitation distribution varies with the exposure conditions. The windy slopes get more rain than the lee sides. The wind carries the air mass upwards to cool which causes the rain, on contrary, at lee side it sinks and warm adiabatically. Precipitation increases with altitude in highlands. Temperature decreases with altitude and it becomes easier to reach out to the saturation temperature. It is not simple to mathematically represent the change in precipitation with altitude, because there is a lot of interference of different variables. But the below suggested formula, equation (2.1), is giving satisfying results for Turkey region where the study is conducted.

$$\mathbf{P}_h = \mathbf{P}_0 + 0.54 \times \mathbf{h} \quad (2.1)$$

P_h is the desired precipitation value, P_0 is the station precipitation value and h is the altitude difference between desired and station P . In this case we will use the station data as if they are in sea level, 0 altitude. Once the grid interpolation is done, the altitude effect will be reallocated. Precipitation increase with a direct proportion, but it has a limit. For tropical climates it is around 2000 meters because of the high humidity, but for the rest of the climates it is approximately 6000 meters, which is enough for Turkey since the highest location is Mount Ararat with 5137 meters [46]. The temperature is also changing with altitude and it is much easier to mathematically represent the change. It decreases 6,5 C in every 1000 meters which can be formulize as below, equation (2.2).

$$\mathbf{T}_h = \mathbf{T}_0 + 0.0065 \times \mathbf{h} \quad (2.2)$$

Inside the atmosphere, the temperature changes adiabatically. So, both temperature and precipitation altitude corrections are done before interpolation. The station data has values as if all the stations are in sea level. Since the altitudes of the new grid coordinates are known, the corrections equations will be re-applied to have the better results. The second operation that must be done is the creation of the desired grid. To

calculate our uniform grid, the edges of station data coordinate system is identified, and the new grid created with 0,08 steps for longitude and latitude. This should determine the points that would like to be calculated by interpolation.

2.2. Interpolation

Interpolation is one of the most common method within numerical methods of computational science which adds new points within a known range. It is used for estimating or determining the intermediary point(s) between this known range of dataset. This method helps smoothen the existing data or completing a missing piece of a dataset. The locations x , matching the values of v in a dataset can be interpolated to create a function like $f(x) = v$. This function can be used to identify the questioned inner points xq and the values corresponding vq in a specified range, $f(xq) = vq$. The function is single-valued, so there is only on vq for every xq . One of the interesting characteristics of interpolation is that the function is passing through the data points. Interpolation is distinguishing from curve fitting with this feature, in curve fitting, the function does not have to pass through the data points. The history of interpolation reaches up to ancient times. The Greek and Babylonian mathematicians and astro-physicists used interpolation to calculate the position of the celestial bodies like Sun, Moon and other known planets at that time. With the technological and scientific developments, the computers get involved in these calculations and now the modern computational science techniques can be used to interpolate any data including climate data.

MATLAB is a very powerful calculation and analysis tool. Like every software it has advantages and disadvantages, but with its wide calculation library, it is possible to calculate most of the known function and numerical method with a single command. With the latest user-friendly interface, plotting the values, analyzing the results is simply drag & drop and MATLAB will automatically allow to generate scripts of the process which can be used as a template and edited for future projects. This way, you can pinpoint the result of different researches with a single template and automatize or customize any desired process for the future studies. MATLAB has a lot of different

interpolation methods in its library and each one of them has different advantages over the others. The near data points are usually forming the base of the computation of the value v_q . There are various methods to calculate the interpolation. Since MATLAB will be used in this study, the interpolation can be done by the embedded functions in MATLAB library. There are a lot of different interpolation methods in MATLAB, some may take more time and memory than others. In order to meet with the acceptable smoothness and accuracy in results, sometimes more computing time and memory might be selected. Depending on the class and output format, many different methods can be used. Interpolation has 2 different classes depending on the database. The data can may be in the form of an axis-aligned grid (see figure 2.1) or randomly scattered (see figure 2.2). If the data is in grid form, the uniform structure will increase efficiency to determine the desired points. If it is in scattered format, it requires triangulation of the data points and needs a special care of computation.

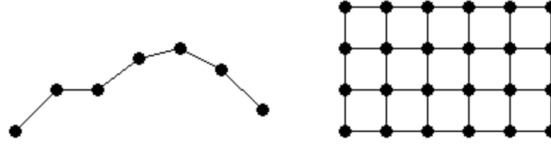


Figure 2.1. The Interpolating Gridded Data section covers 1-D interpolation, and the N-D ($N \geq 2$) interpolation of sample data in axis-aligned grid format [5].

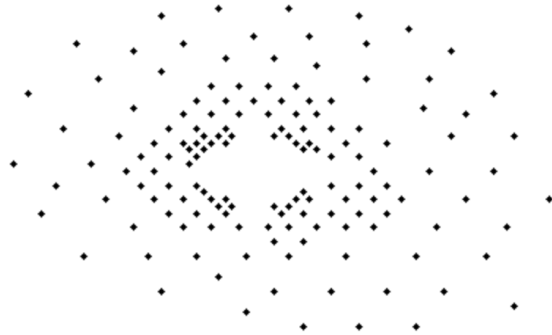


Figure 2.2. The Interpolating Scattered Data section covers the N-D ($N \geq 2$) interpolation of scattered data [5].

2.2.1. Gridded Data

Grid representation is a method of data storage of the matrices, it is a special structure. The idea is like matrices but the special adjacent arrangement in between points helps users in many applications, especially in grid-based interpolation. There are 2 types of grid representation, one is for Cartesian axis aligned with 2 and 3 dimensions and the other is for space aligned axis with N-dimensions. Both representations will create same kinds of grids in terms of input argument. The difference will be the output formats, depending on the user preferences both representations can be used. The grid-based interpolation methods will produce very efficient results in estimating points in focused range since the locations of the points are well-defined. MATLAB is using a binary search to locate the query point and this search can be done very quickly and efficiently when the data is ordered in grid format. A binary search (see figure 2.3) compares the query point with the middle point of the total range and continues until it locates the interval of the query point [6].

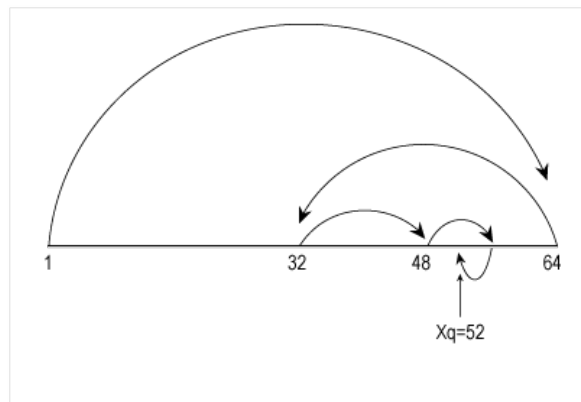


Figure 2.3. Binary Search [6].

2.2.2. Scattered Data

Opposite of gridded data, scattered data has no structure or arrangement in between the points of sample data. This disorder makes it very complex and tricky to compute the interpolation because it is very difficult to locate the interpoints of scatter data as in gridded data. There are several different methods to calculate the scattered

data interpolation. The most common method is to use a Delaunay triangulation of points, because of the beneficial geometric features. A circumcircle is a circle which passes from all the edges of a polygonal, which will be a triangle in this case. The most important one is that each triangle's circumcircle does not include any other point. In figure 2.4 note that both T1 and T2 are empty. This makes them examples of Delaunay triangles. Once the searched point located in traversed triangles, the corresponding value is calculated according to the chosen method. Nearest point of the neighborhood or weighted sum of the values could be the methods that can be selected. For more smoothness the natural neighbor method can also be selected [47].

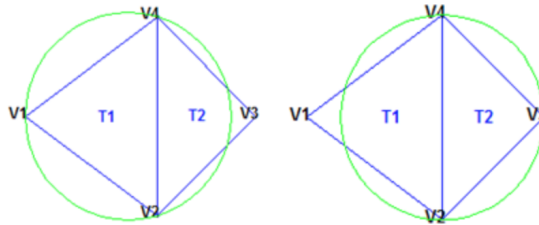


Figure 2.4. Delaunay Triangulation [7].

MATLAB has 2 different main functions for computing scattered data interpolation; `griddata` or `scatteredInterpolant`. The selection of either way depends on efficiency and application. The `griddata` function is used for 2-D or 3-D scattered data interpolation. For higher dimensions the function `griddata_n` can be used, but because of the triangulation method, it is not recommended to do the interpolation for more than 6-D. The function basically takes the coordinates $X/Xq, Y/Xq, Yq, Zq$, corresponding value V and the investigated coordinates $Xq/Xq, Yq/Xq, Yq, Zq$, then gives the interpolated result Vq for the questioned point. The function returns the interpolated values for preset gridded data. It may be used to query random points within the study range.

The `scatteredInterpolant` class, the second method, is more efficient than the `griddata` function in many ways and has less interpolation problems. The `scatteredInterpolant` class creates the background triangulation once, then do the interpolation through this triangulation. Once the triangulation done for the dataset, it allows you

to customize your interpolation as you wish. The interpolation method and the values of the dataset can be changed independently from the triangulation. New data can be added or removed without recalculation. This way, the interpolation can be efficiently computed, without unnecessary calculations and you can play with your data for further analysis easily.

2.3. Error Analysis

In every measurement and calculation, there is an error factor which is an accuracy and efficiency consideration. All measuring devices has some error margin that needs to be take into account when choosing equipment for an application. The criticality of the application usually determines the needed accuracy of the measurement; for more critical applications more accurate tools should be chosen. The accuracy of the equipment should be within the range of the acceptable error margin for the experimenter. Otherwise the results that has been collected from the equipment could be faulty and cannot be trusted. For example, suppose the error margin acceptable for an experiment is 0.5 degrees Celsius, but the thermometer has 1 degree Celsius. The temperature should stop at 10 degrees Celsius, so the experimenter is expecting it to be within range 9,5 – 10,5 degrees Celsius. When the thermometer is showing 10 degrees Celsius, it can be below expectations or exceeding the acceptable range. The existing error margin creates an uncertainty for the application or experiment. There are two main uncertainty sources; one is while taking measurement, second while computing. In measurement process to minimize or eliminate the uncertainty; the measurement can be repeated multiple times, the technique can be changed, or a more accurate device can be used. In computational methods, there can be an uncertainty, too. The mathematical method has to be chosen according to the application and expected outcome. Every computational method has an uncertainty because all the methods are some representations and approximation of complex mathematical problems. For some applications an approximate estimation could be acceptable, but for others the estimation must be very precise, so that the mathematical method should be satisfying. In every distribution problem, the variance and the standard deviation are the two

main concepts. They show how the data is distributed around the average of the variables (you can see the formula of variance below (2.3)). The relation between them is, the standard deviation is the square root of variance (see (2.4)). According to the application and simulation, variance or standard deviation can be used [48].

$$S^2 = \frac{\sum (X - \bar{X})^2}{n} \quad (2.3)$$

$$\sigma = \sqrt{\frac{\sum (X - \mu)^2}{N}} \quad (2.4)$$

X represents each separate number and μ represents the mean over all numbers. So, to be meaningful in terms of temperature and precipitation, a special MATLAB function, called moving standard deviation, used to identify the certainty. The function basically calculates the local standard deviation of a point, which is more valuable compared to looking at the deviation of the point with respect to entire longitude or latitude. So, the local or moving standard deviation of all the integrated points calculated through the latitude. The results are discussed and represented in next section. The moving standard deviation calculated in between the 4 adjacent station of the query point. The query point stayed in the center and the deviation calculated in between the 5 stations. If these 4 adjacent stations are not available, it is calculated in between the existing ones. For example, at the borders, the 2 stations before or after the query station is not available, so the deviation calculated in between the 3 stations.

2.4. Results and Discussions

Unfortunately, the data used in this study is a scattered data, and the benefits of gridded data can not be utilized during calculations. However, with the MATLAB's powerful interpolation function, the scattered data interpolation done with high accuracy. The daily based data interpolated for everyday from 01-Jan-1960 until 31-Dec-2016. The data used as it is provided, and all the results are based on this data. There has been more than 20.000,00 calculation done. To show the change in the tem-

perature and precipitation and to present the results, some days, months and years are randomly selected for both temperature and precipitation. For temperature data; 05 March selected as day, the average temperature for March and Spring season calculated through the years 1965, 1980, 1995 and 2010. Every temperature yearly calculation is followed by the moving standard deviation values. The results are presented with the standard deviation map. For precipitation data; 05 October selected as day, the average temperature for October and autumn season calculated through the years 1965, 1980, 1995 and 2010. Every precipitation yearly calculation is followed by the moving standard deviation values. The results are presented with the standard deviation map. According to dates and data type studied above from the Turkish Meteorological Services, the CRU and ERA data interpolated as explain in the previous sections and included in the study to compare the results.

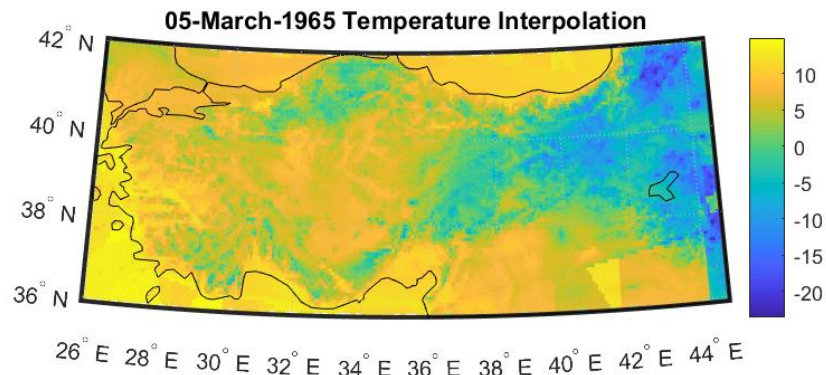


Figure 2.5. 05-Mar-1965 Temperature Data.

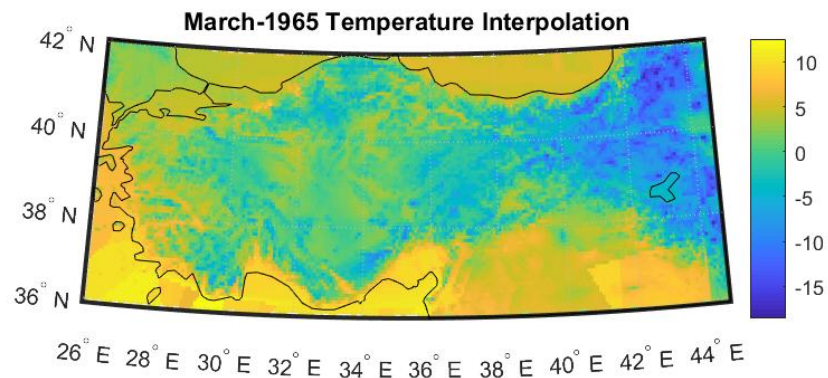


Figure 2.6. Mar-1965 Temperature Data.

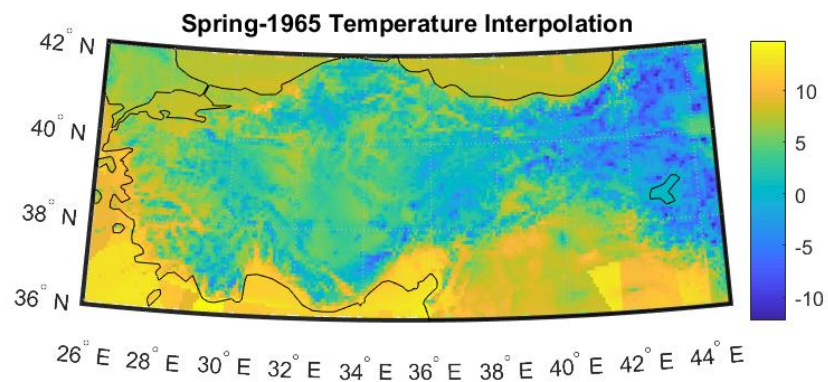


Figure 2.7. Spring-1965 Temperature Data.

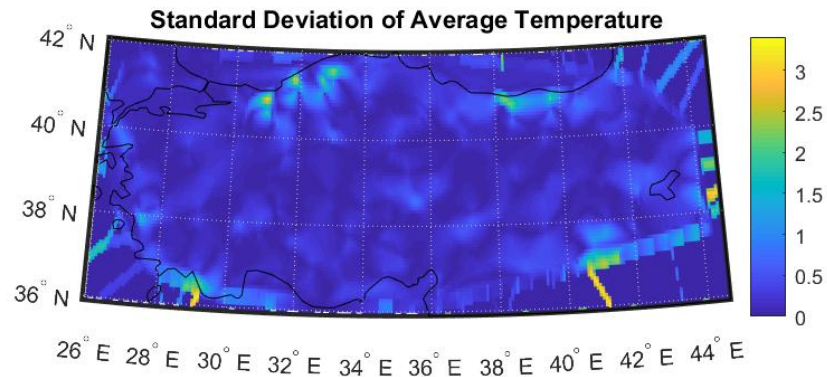


Figure 2.8. Standard Deviation-1965 Temperature Data.

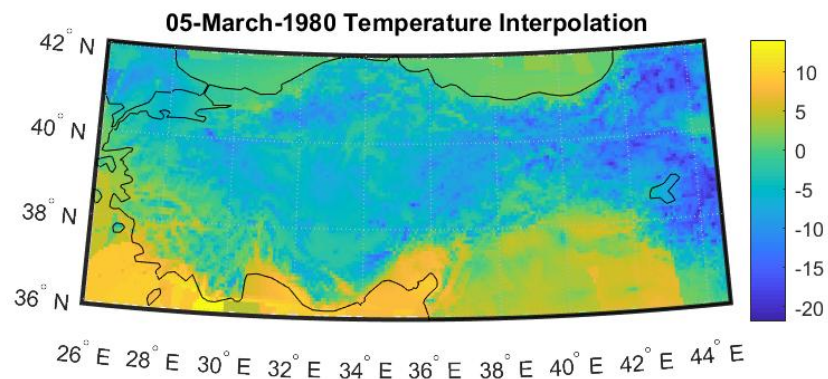


Figure 2.9. 05-Mar-1980 Temperature Data.

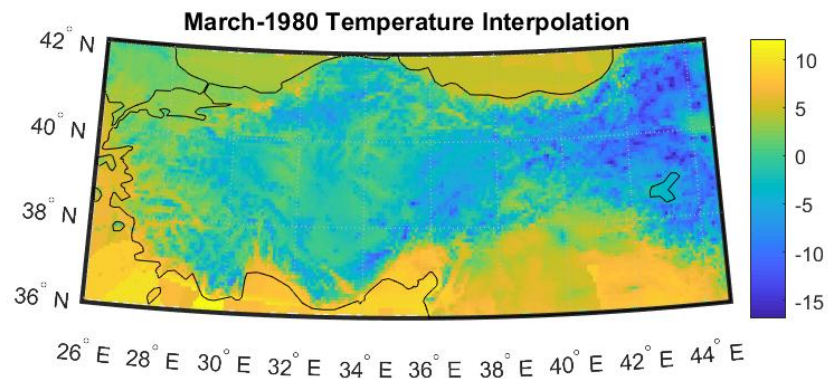


Figure 2.10. Mar-1980 Temperature Data.

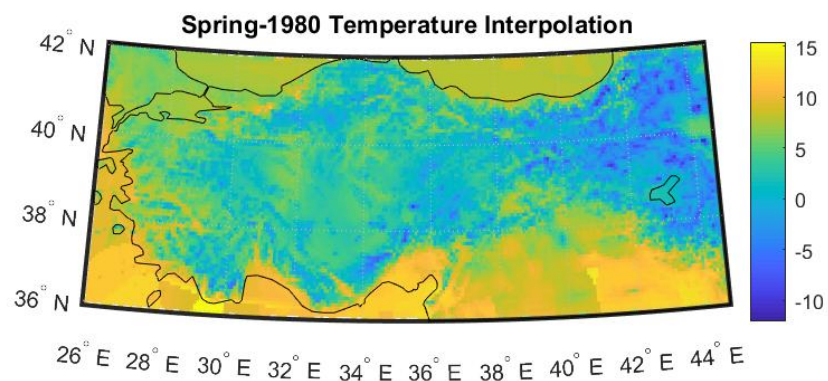


Figure 2.11. Spring-1980 Temperature Data.

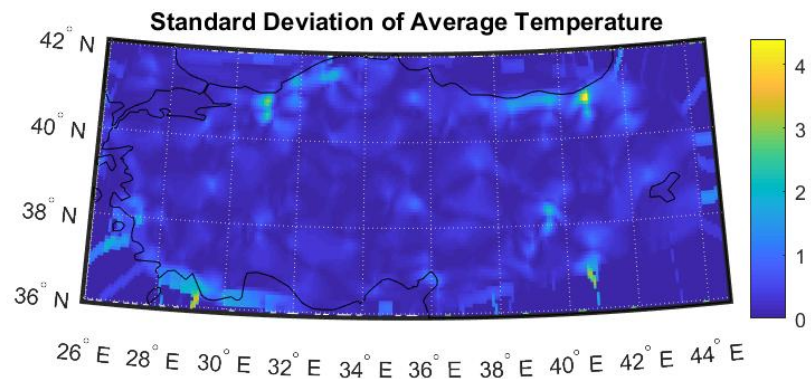


Figure 2.12. Standard Deviation-1980 Temperature Data.

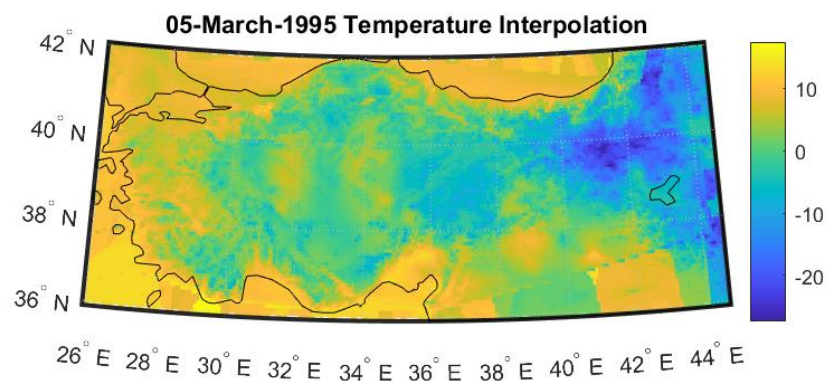


Figure 2.13. 05-Mar-1995 Temperature Data.

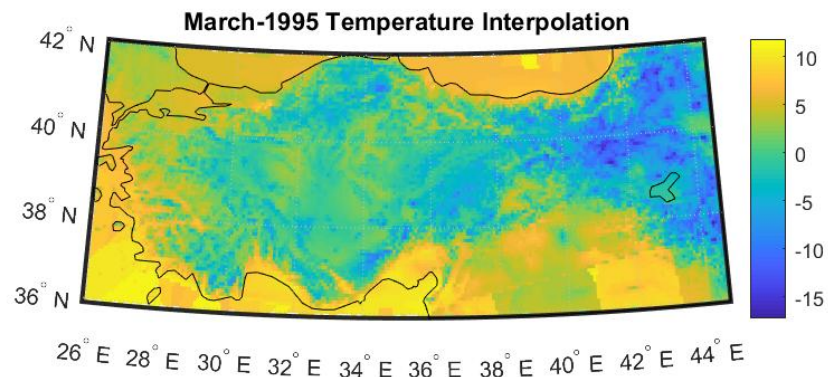


Figure 2.14. Mar-1995 Temperature Data.

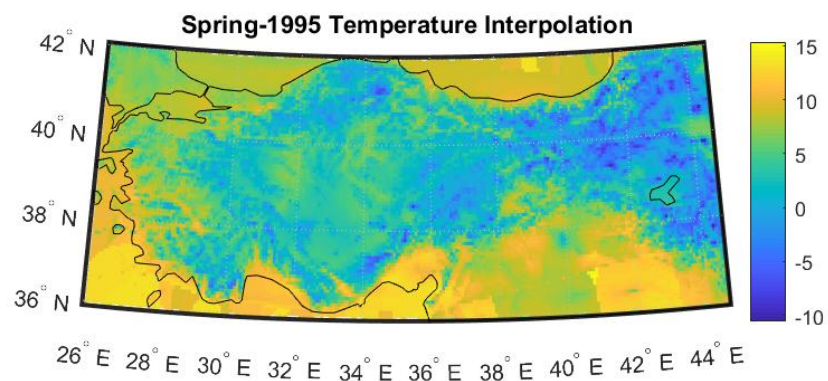


Figure 2.15. Spring-1995 Temperature Data.

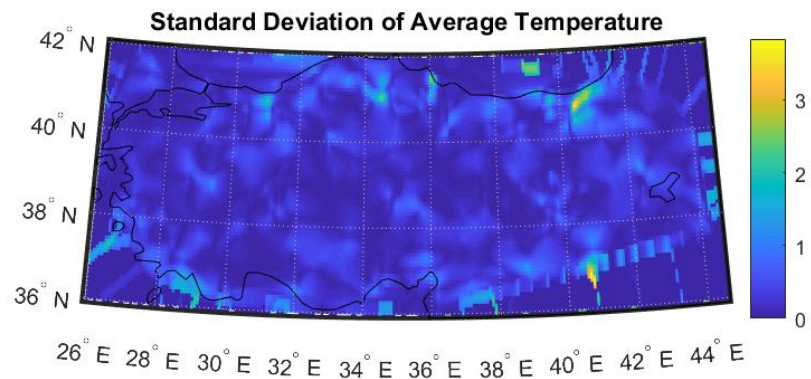


Figure 2.16. Standard Deviation-1995 Temperature Data.

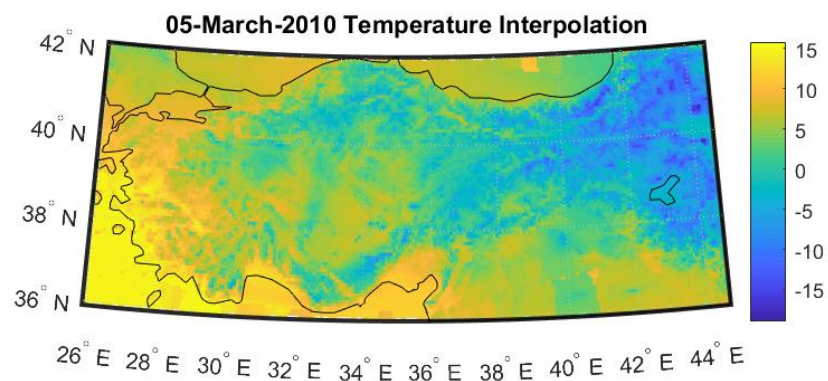


Figure 2.17. 05-Mar-2010 Temperature Data.

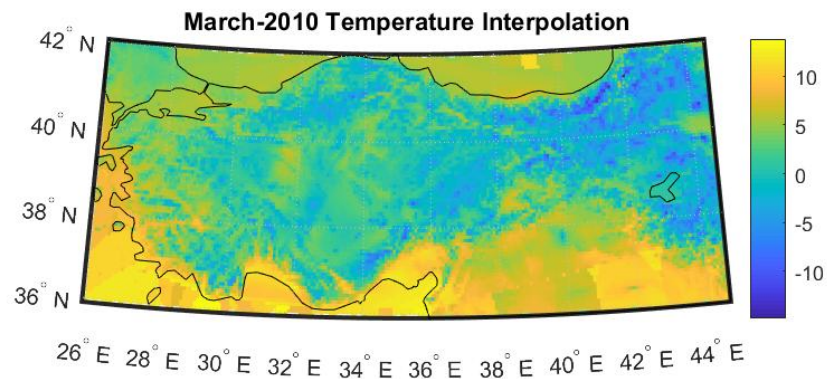


Figure 2.18. Mar-2010 Temperature Data.

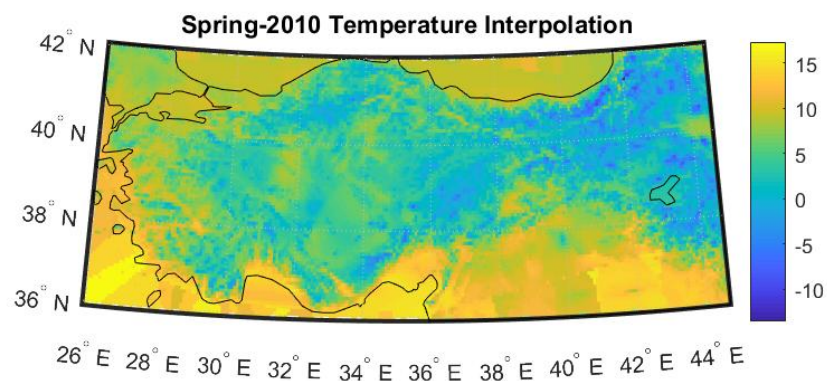


Figure 2.19. Spring-2010 Temperature Data.

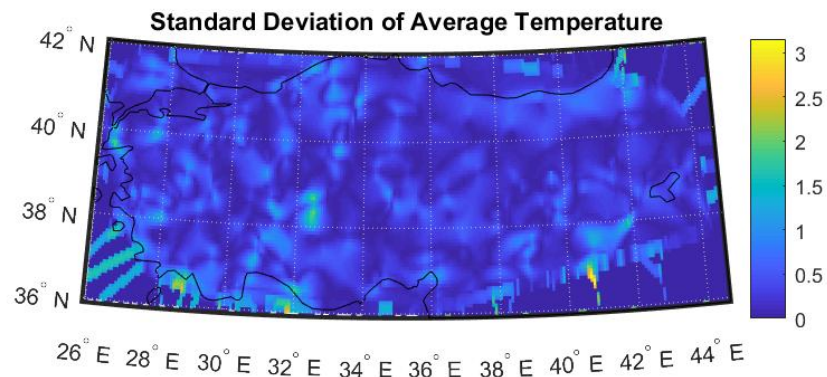


Figure 2.20. Standard Deviation-2010 Temperature Data.

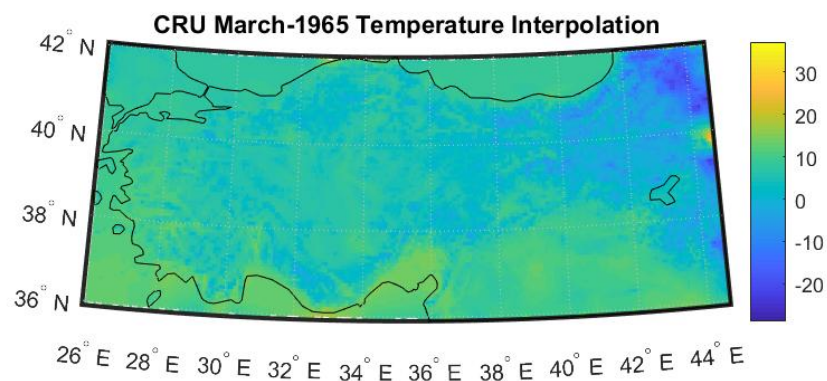


Figure 2.21. CRU Mar-1965 Temperature Data.

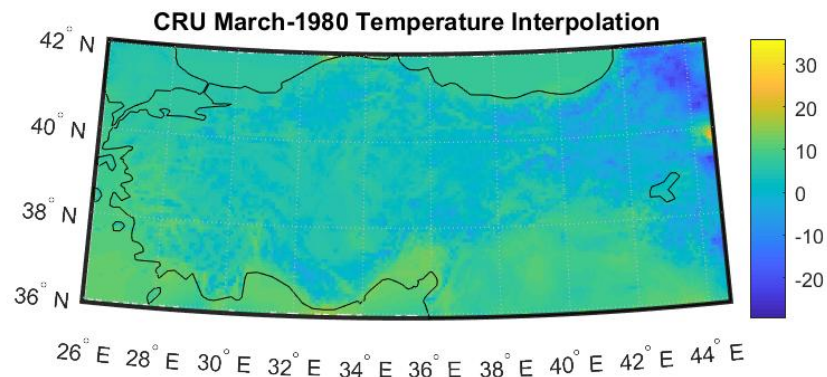


Figure 2.22. CRU Mar-1980 Temperature Data.

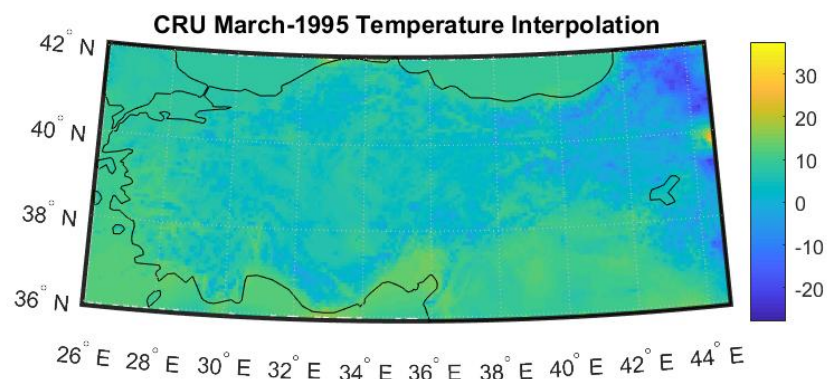


Figure 2.23. CRU Mar-1995 Temperature Data.

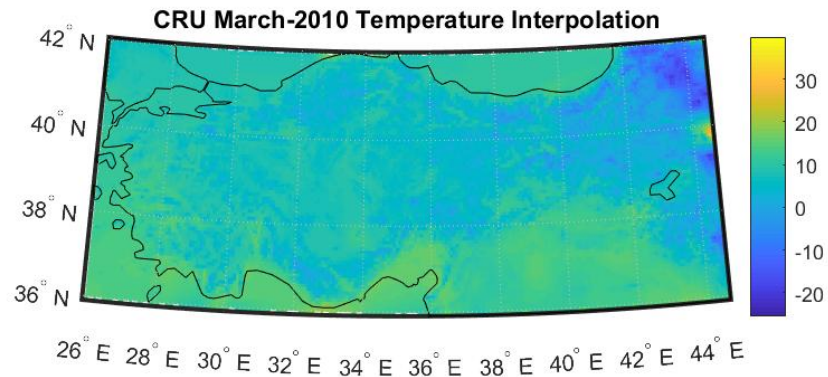


Figure 2.24. CRU Mar-2010 Temperature Data.

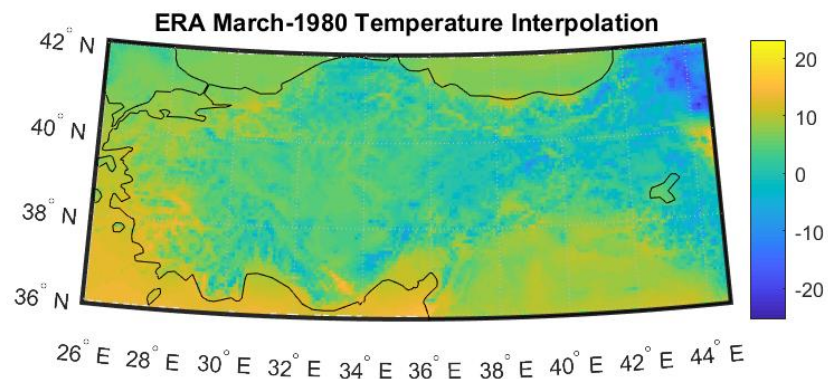


Figure 2.25. ERA Mar-1980 Temperature Data.

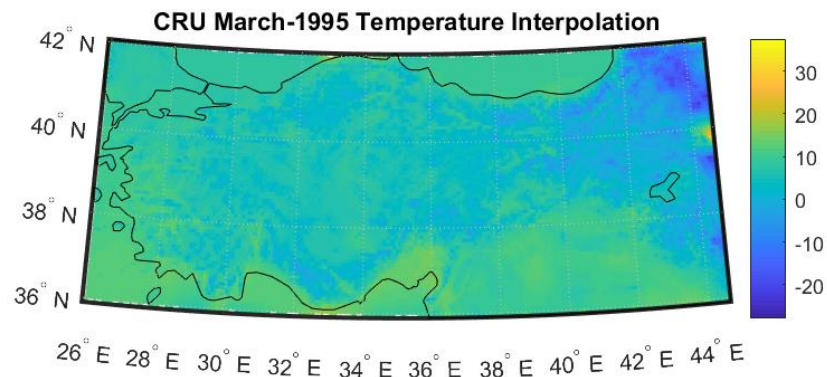


Figure 2.26. ERA Mar-1995 Temperature Data.

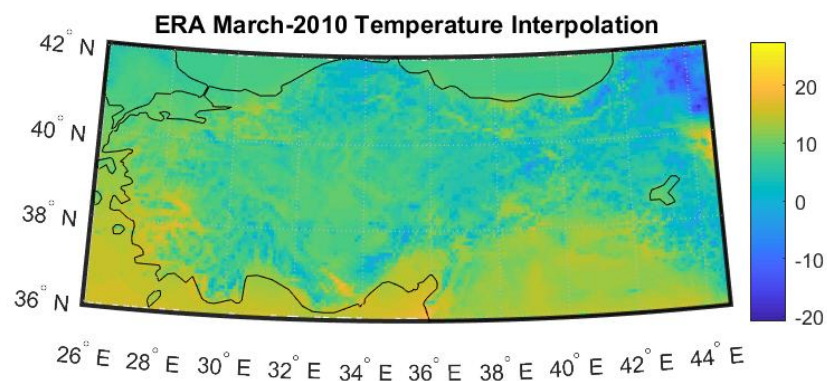


Figure 2.27. ERA Mar-2010 Temperature Data.

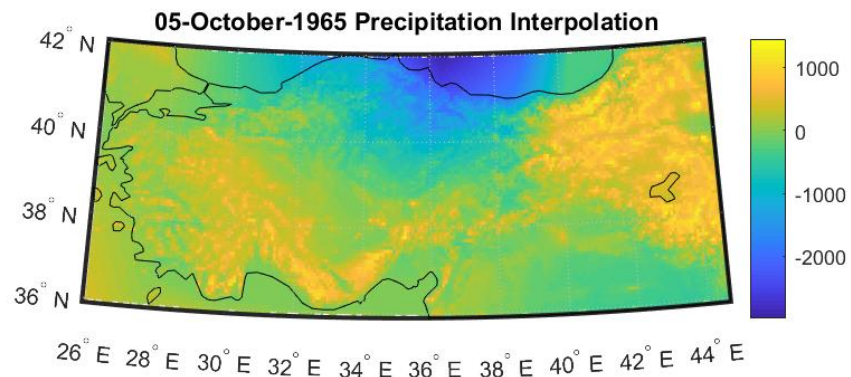


Figure 2.28. 05-Oct-1965 Precipitation Data.

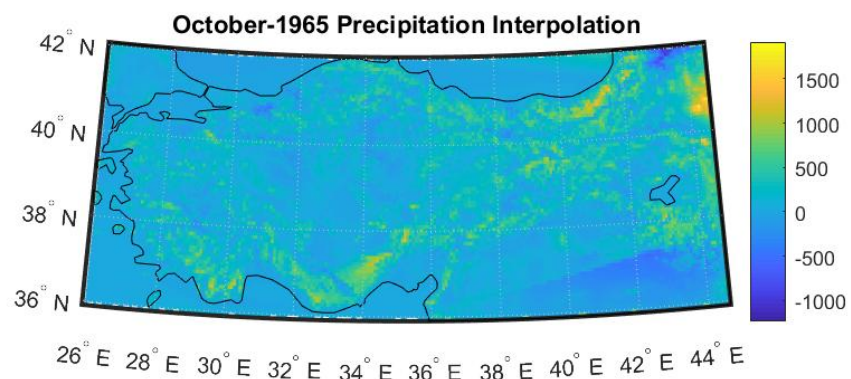


Figure 2.29. Oct-1965 Precipitation Data.

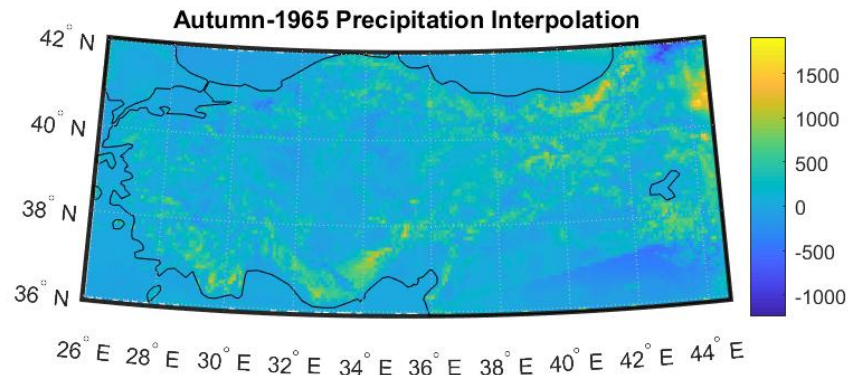


Figure 2.30. Autumn-1965 Precipitation Data.

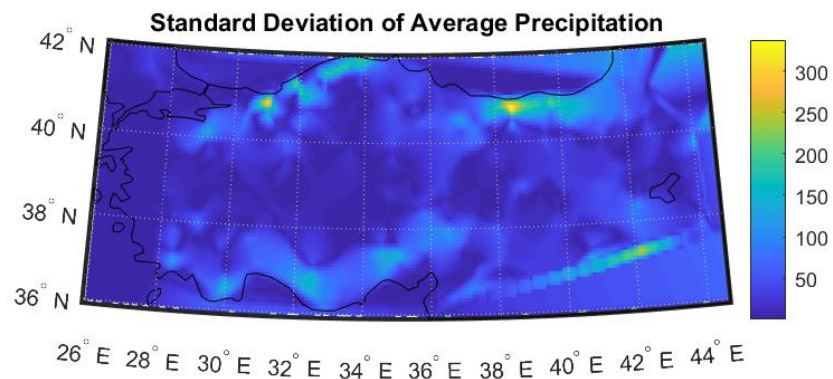


Figure 2.31. Standard Deviation-1965 Precipitation Data.

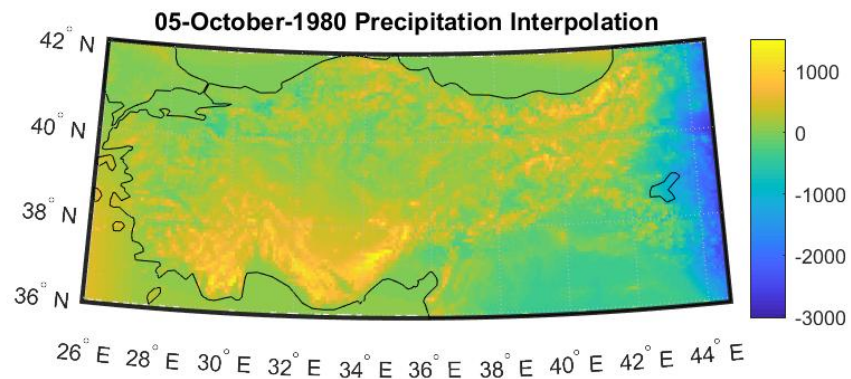


Figure 2.32. 05-Oct-1980 Precipitation Data.

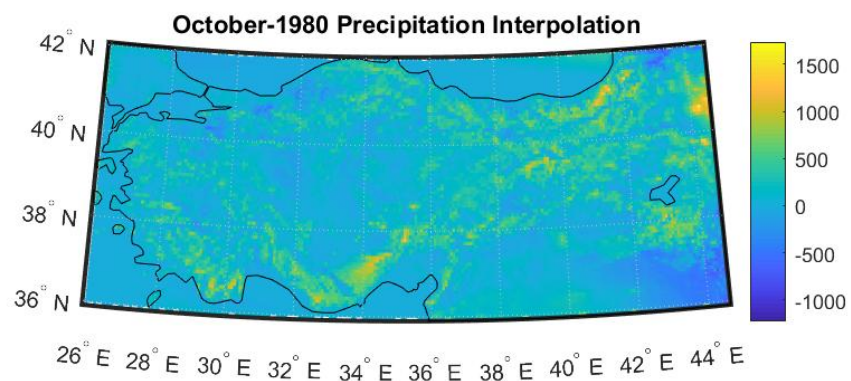


Figure 2.33. Oct-1980 Precipitation Data.

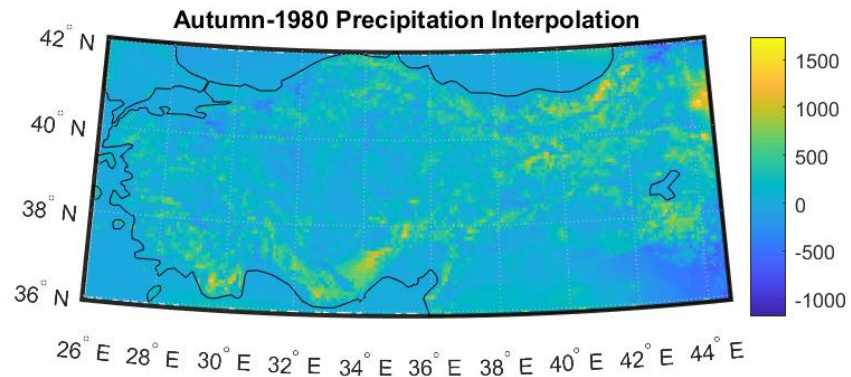


Figure 2.34. Autumn-1980 Precipitation Data.

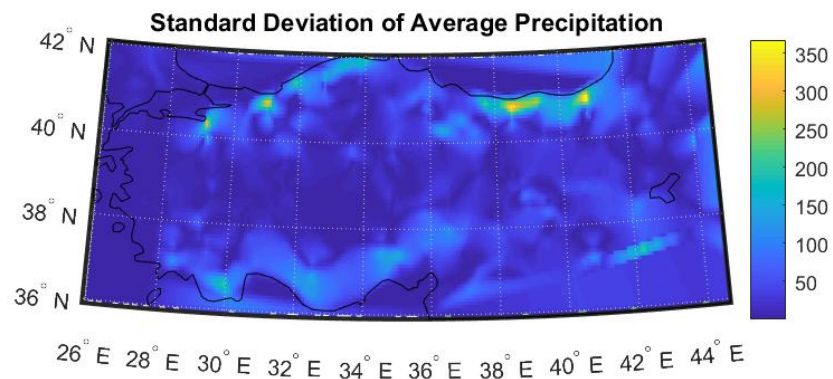


Figure 2.35. Standard Deviation-1980 Precipitation Data.

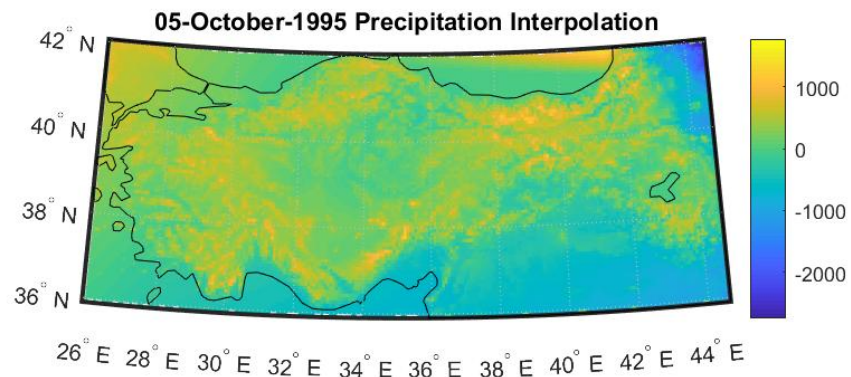


Figure 2.36. 05-Oct-1995 Precipitation Data.

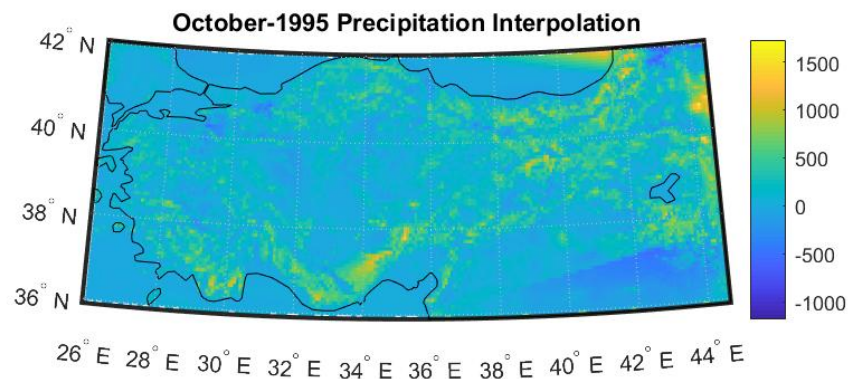


Figure 2.37. Oct-1995 Precipitation Data.

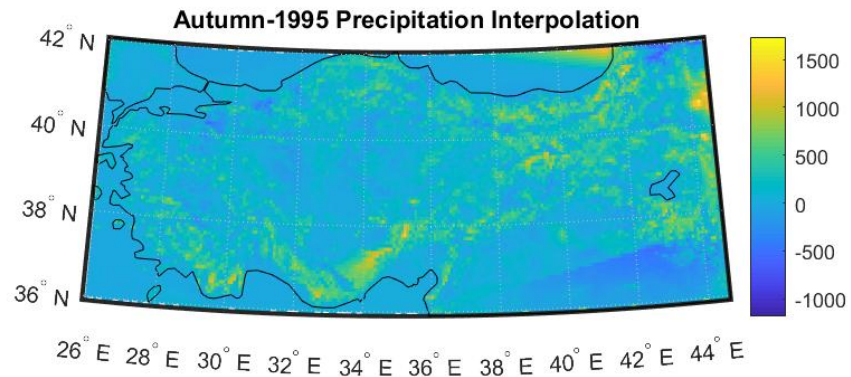


Figure 2.38. Autumn-1995 Precipitation Data.

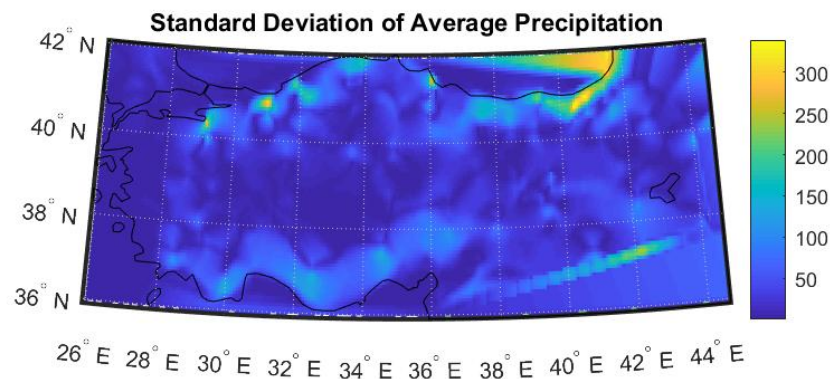


Figure 2.39. Standard Deviation-1995 Precipitation Data.

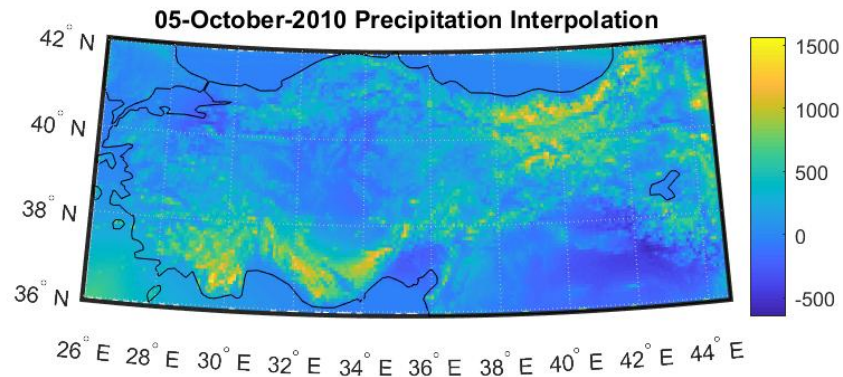


Figure 2.40. 05-Oct-2010 Precipitation Data.

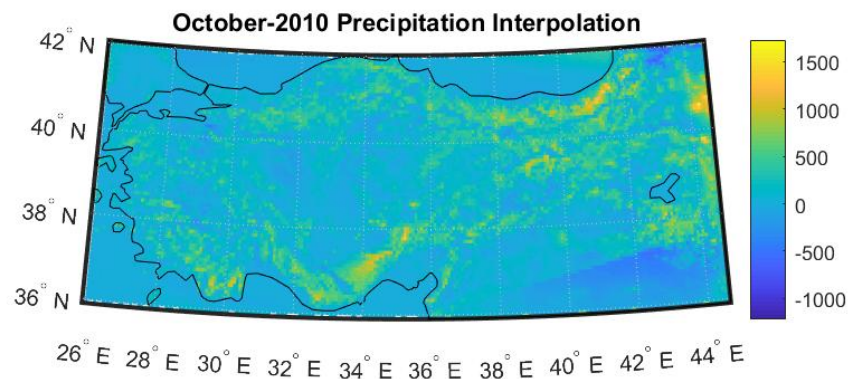


Figure 2.41. Oct-2010 Precipitation Data.

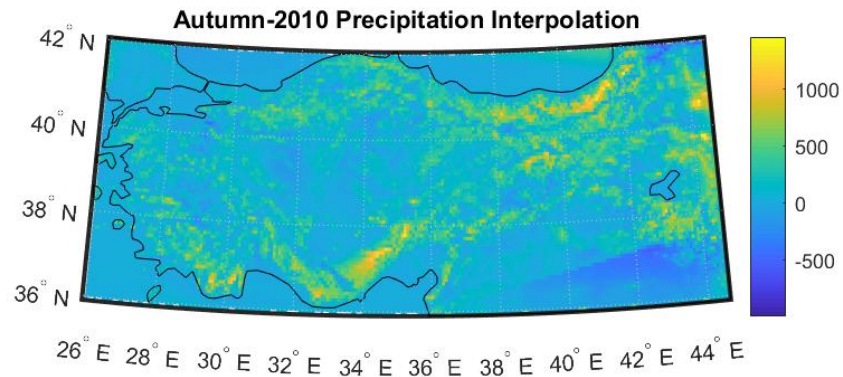


Figure 2.42. Autumn-2010 Precipitation Data.

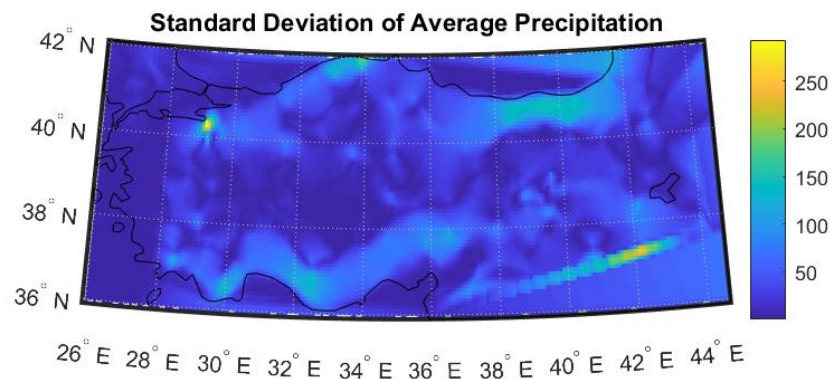


Figure 2.43. Standard Deviation-2010 Precipitation Data.

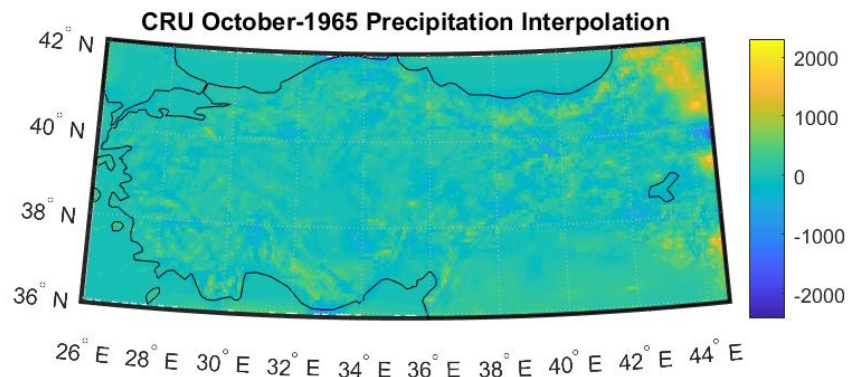


Figure 2.44. CRU Mar-1965 Precipitation Data.

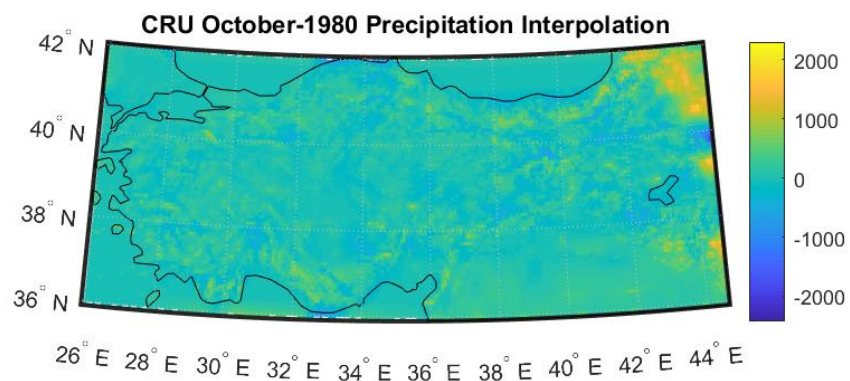


Figure 2.45. CRU Mar-1980 Precipitation Data.

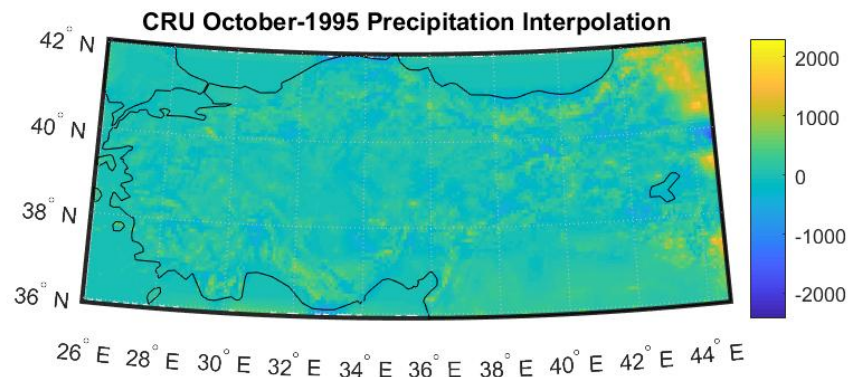


Figure 2.46. CRU Mar-1995 Precipitation Data.

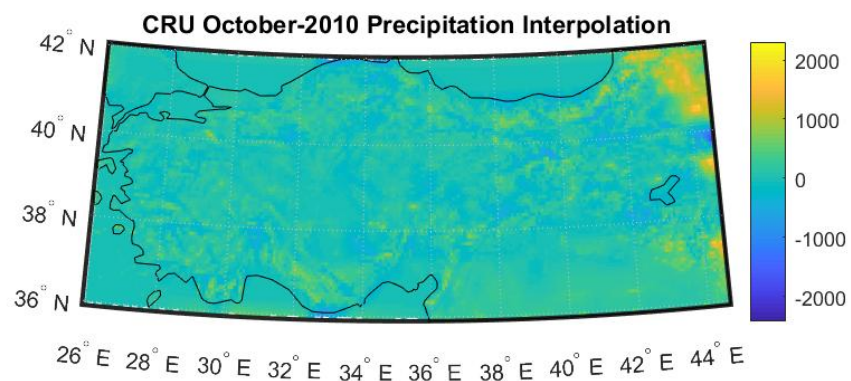


Figure 2.47. CRU Mar-2010 Precipitation Data.

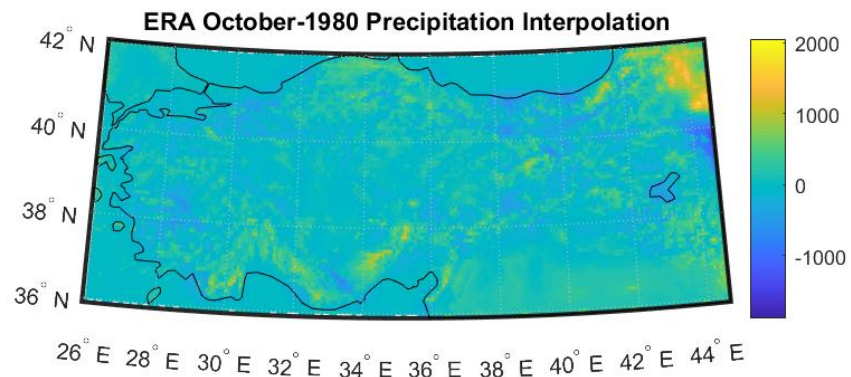


Figure 2.48. ERA Mar-1980 Precipitation Data.

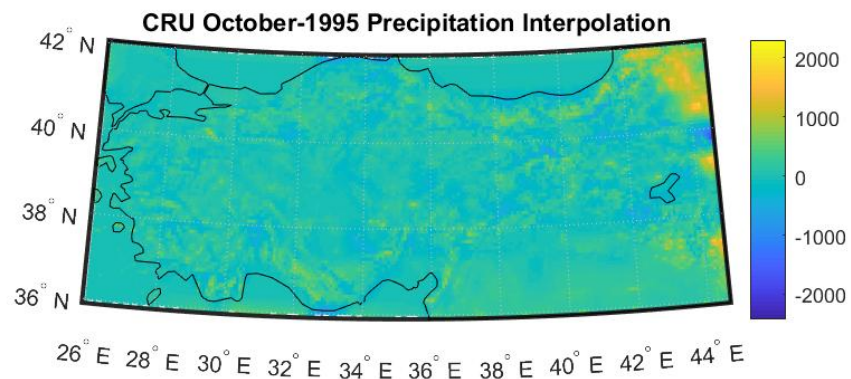


Figure 2.49. ERA Mar-1995 Precipitation Data.

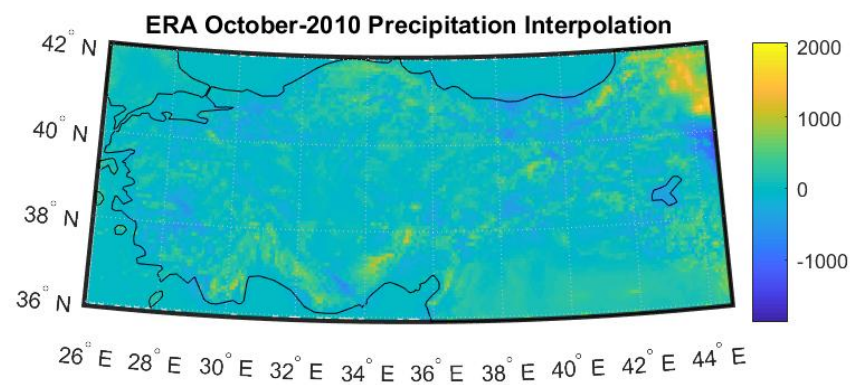


Figure 2.50. ERA Mar-2010 Precipitation Data.

As observed from the above figures from 2.7 to 2.20, over the years the average temperature increased all over Turkey. The maximum temperature value seems to be the same, but when you look at the distribution, it is clearly seen that the high temperature regions spread. We can see from the standard deviation map that the deviation kept in 1 degree Celsius, which is acceptable for the gridded data.

As observed from the above figures from 2.21 to 2.27, over the years the average temperature increased all over Turkey. The maximum temperature value seems to be the same, but when you look at the distribution, it is clearly seen that the high temperature regions spread. We can see from the standard deviation map that the deviation kept in 1 degree Celsius, which is acceptable for the gridded data. Also when we compare the CRU data with ERA data, the distribution seems better in ERA results. Also ERA data results are in parallel with the meteorological data that we gathered from Turkish Meteorological Services.

As for the precipitation data from above figures 2.28 to 2.43, through the years, especially after between 1995-2010 the precipitation values decreased. You can see the maximum average value dropped from 1500mm to 1000mm. When looked at the distribution, the overall value of 1000mm dropped to 500mm. The standard deviation maps are showing that across Turkey, the calculations are reliable.

As for the precipitation data from above figures 2.44 to 2.50, through the years, the precipitation values decreased. The standard deviation maps are showing that across Turkey, the calculations are reliable. When we compare the results of CRU and ERA data with Meteorological Service, we can say that monthly data better distributed than CRU and ERA data.

The temperature data is logged more properly than the precipitation data. When you compare the number of stations with data in daily basis, you can see that temperature stations have more data. This makes temperature data and the interpolation much more accurate and reliable than precipitation. But when we switch to monthly and seasonal basis, the precipitation data points are as good and healthy as tempera-

ture points. The precipitation stations must gather proper and continuous data, or the number of precipitation stations must be increased to obtain less variance and better quality. If we want a better picture of Turkey's climate for future applications, this can be applied for the other parameters like humidity, pressure, solar radiation, wind speed and direction and cloudiness, too. Also, it very important to keep the station IDs same as it was before or properly label the new ones to guide the future extensions of the Turkey meteorology database.

3. CONCLUSION

The local climate is following through the data coming from the meteorology stations in the specified region, which is Turkey for this study. The most significant drivers of climate, temperature and precipitation data, were used in interpolation. The real scattered station data successfully turned into a high-resolution gridded data at the end of this study. Temperature and precipitation data are the two most complete and reliable meteorological data. But since the altitude has bigger influence on precipitation and Turkey region has a lot of change in altitude, the temperature distribution has more reliable results. For the past data the CRU and ERA can be used for precipitation distribution, but for temperature since the station data are properly collected, it is better to use the Station Data. With the final phase of this study (the interpolation calculation for CRU and ERA data), we can clearly see the method used in this study, can be applied to various data for different regions and different resolutions. This shows the flexibility power of the calculation. According to data raw data type we have in the beginning like scattered or gridded, we can choose the method and acquire the results.

The results are showing that the temperature increased over the years and the high temperature regions spread as expected. For the precipitation, the maximum and the average precipitation decreased over the years. As a result, low precipitation regions spread. Even if the studies started earlier, the global warming is considered as a serious hazard in past 20 years. When combining both findings, it can be easily said that Turkey has already affected by the global warming. It has been suffering from the consequences and become hotter and drier over the years.

These effects are serious threats for agriculture and as a result, economy since Turkey's economy mainly depending on agriculture. There should be more studies and investigation for the future climate change and classification of Turkey. The new studies can predict the shift on the climate for near future and this can guide the decision makers to prepare for the future to minimize the hazard. This study can allow scientists to study the causes and effects of these results deeper. Having a high-

resolution data could give a better picture for the past data analysis and for the future studies and climate model analysis.

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APPENDIX A: MATLAB CODE FOR NORMALIZATION

```

clear
clc

% fid=fopen('TR_gunluk_minimum_sicaklik_(T-c).csv','r');
% fid=fopen('TR_gunluk_maksimum_sicaklik.csv','r');
% fid=fopen('TR_gunluk_ortalama_sicaklik_(T-c).csv','r');
    fid=fopen('TR_gunluk_toplam_yagis_(mm).csv','r');
% fid=fopen('TR_gunluk_toprak_ustu_minimum_sicaklik_(T-c).csv','r');

% fid=fopen('TR_gunluk_ortalama_nem.csv','r');
% fid=fopen('TR_gunluk_ortalama_basinc_(hpa).csv','r');
% fid=fopen('TR_gunluk_ortalama_buhar_basinci_(hpa).csv','r');
% fid=fopen('TR_gunluk_ortalama_bulutluluk.csv','r');
% fid=fopen('TR_gunluk_ortalama_ruzgar_hizi(m_sec).csv','r');
% fid=fopen('TR_gunluk_toplam_acik_yuzey_buharlasmasi_(mm).csv','r');
% fid=fopen('TR_gunluk_toplam_global_gunes_radyasyonu_(cal_cmT).csv','r');
% fid=fopen('TR_gunluk_toplam_guneslenme_suresi_(saat).csv','r');

if fid==-1
    disp('check the file name')
else
    headers=textscan(fid, '%s%s%s%s%s%s%s%s%s%s%s%s%s',1,
'delimiter',' ','');
    T=textscan(fid, '%s%s%d%d%f%f%f%f%f%f%f%f%f%f', 'delimiter',' ','');
    % import daily data to T

    Station_No=T{:,1};
    Station_Name=T{:,2};

```

```

Date(:,1)=T{:,4}+"."+T{:,3};
Jan=T{:,5};
Feb=T{:,6};
Mar=T{:,7};
Apr=T{:,8};
May=T{:,9};
Jun=T{:,10};
Jul=T{:,11};
Aug=T{:,12};
Sep=T{:,13};
Oct=T{:,14};
Nov=T{:,15};
Dec=T{:,16};
MaksT=[Station_No, "01"+"."+Date, Jan;
        Station_No, "02"+"."+Date, Feb;
        Station_No, "03"+"."+Date, Mar;
        Station_No, "04"+"."+Date, Apr;
        Station_No, "05"+"."+Date, May;
        Station_No, "06"+"."+Date, Jun;
        Station_No, "07"+"."+Date, Jul;
        Station_No, "08"+"."+Date, Aug;
        Station_No, "09"+"."+Date, Sep;
        Station_No, "10"+"."+Date, Oct;
        Station_No, "11"+"."+Date, Nov;
        Station_No, "12"+"."+Date, Dec;];
MaksT=rmmissing(MaksT);
% E=standardizeMissing(MaksT,-9999);
% E=rmmissing(E);
% MaksT=E;
% this should be done only for precipitation data
% pivottable and remove the missing data
MaksT(:,2)=datetime(MaksT(:,2),'InputFormat','MM.dd.yyyy');
% MaksT_year=year(MaksT(:,2));

```

```

% MaksT_year=unique(MaksT_year);
% Remove duplicates and sorts the array of years

MaksT=array2table(MaksT, 'VariableNames', {'Station_No' 'Date'
'Min_T'});
MaksT.Station_No=double(MaksT.Station_No);
MaksT.Min_T=double(MaksT.Min_T);
MaksT.Date=datetime(MaksT.Date);
% Variable type indication

% NewGrid=xlsread('TR_New_Grid_rev1.xlsx','Sayfa3','A2:B18332');
% Make it until 'C' when the altitude values ready
% use it as zeros for now

TR_Grid = xlsread('TR_Grid_rev2_Final.xlsx', 'Liste_Son', 'A2:E515');
TR_Grid = array2table(TR_Grid, 'VariableNames', {'Station_No'
'Staion_Name' 'Lat' 'Lon' 'Alt'});
TR_Grid = removevars(TR_Grid, {'Staion_Name'});
Maks_Temp = innerjoin(MaksT,TR_Grid);
Maks_Temp = movevars(Maks_Temp, 'Min_T', 'After', 'Alt');
Maks_Temp = sortrows(Maks_Temp,'Date','ascend');
A=unique(Maks_Temp.Station_No);
B=unique(MaksT.Station_No);
C=setdiff(B,A);
writetable(Maks_Temp, 'TR_gunluk_maksimum_sicaklik_out02.csv');
end

```

APPENDIX B: MATLAB CODE FOR INTERPOLATION AND MAPPING FOR STATION DATA

```

clear
clc

% importing the temp&precipitation data that we have created
Maks_Temp=readtable('TR_gunluk_minimum_sicaklik_out02.csv');
Tot_Prec=readtable('TR_gunluk_toplam_yagis_out02.csv');
Tot_Prec.Properties.VariableNames{end} = 'Tot_P';

% altitude correction for Temperature (New_Min_T) -> 6.5 degrees
% decrease in every 1000 meters; T=T0-0.00649*h
% altitude correction for Precipitation (New_Prec) -> 540 mm increase
% in every 100 meters; Yh=Y0+54
Maks_Temp.New_Min_T=Maks_Temp.Min_T+0.0065*Maks_Temp.Alt;
Tot_Prec.New_Prec=Tot_Prec.Tot_P-0.54*Tot_Prec.Alt;

% importing the empty Turkey grid to be filled by interpolation
% Longitude&Latitude&Altitude values
NewGrid=readtable('TR_New_Grid_rev3.xlsx');
NewGrid=rmmissing(NewGrid);
Lon=(min(NewGrid.New_Lon):0.08:max(NewGrid.New_Lon))';
Lat=(min(NewGrid.New_Lan):0.08:max(NewGrid.New_Lan))';
[NewLat,NewLon] = meshgrid(Lat,Lon);

% pivoted altitude values for reversing the correction in the end
A=xlsread('TR_New_Grid_rev4.xlsx','Altitude_Pivot');

% optimization and filtration of the temperature data for
interpolation

```

```

Maks_Temp.Year=year(Maks_Temp.Date);
Maks_Temp.Month=month(Maks_Temp.Date);

M1 = Maks_Temp(Maks_Temp.Date=={'01-Apr-2010'},
{'Station_No','Date','Lat','Lon','Min_T','New_Min_T'});

M2 = Maks_Temp(Maks_Temp.Date=={'01-Jan-1970'},
{'Station_No','Date','Lat','Lon','Min_T','New_Min_T'});

M3 = Maks_Temp(Maks_Temp.Date=={'01-Jan-1980'},
{'Station_No','Date','Lat','Lon','Min_T','New_Min_T'});

M12= Maks_Temp(year(Maks_Temp.Date)==2009 & month(Maks_Temp.Date)==03,
{'Station_No','New_Min_T'});

M_APR=varfun(@mean,M12,'GroupingVariables','Station_No');
M_APR = removevars(M_APR, {'GroupCount'});
M_APR.Properties.VariableNames{end} = 'T_Min';
M_APR_AVG = innerjoin(M_APR,Maks_Temp,'RightVariables',3:5);
M_APR_AVG = unique(M_APR_AVG);

% creating the scattered interpolant for temperature values
Ft_day = scatteredInterpolant(M1.Lon, M1.Lat, M1.New_Min_T,
'natural', 'nearest');

F_avg = scatteredInterpolant(M_APR_AVG.Lon, M_APR_AVG.Lat,
M_APR_AVG.T_Min, 'natural', 'nearest');

% to change the values of F interpolant
% F.Values=M2.New_Min_T;
% Evaluate the interpolant at (1.40,1.90).
% F(1.40,1.90)
% to change the method of F interpolant; 'linear' or 'nearest'
% F.Method = 'natural';
% vq3 = F(xq,yq);
% to add new points for example for X
% F.Points(end+(1:100),:) = X;
% F.Points(end+(1:100),:) = Y;
% F.Values(end+(1:100)) = V;
% F.ExtrapolationMethod = 'none';

```

```

% to remove extrapolation Method

% scattered interpolation
vq = Ft_day(NewLon,NewLat);
vq_avg = F_avg(NewLon,NewLat);
Mt=movstd(vq,5,0,2);
Mt_avg=movstd(vq_avg,5,0,2);
% reversing the altitude correction
vq = vq - 0.0065*A;
vq_avg = vq_avg - 0.0065*A;
% calculating the standard deviation and the means of the grid for
% error analysis
DevT=std(vq);
DevT2=std(vq,0,2);
DevT(2,:)=std(vq_avg);
DevT2(:,2)=std(vq_avg,0,2);
Avg_T=[mean(DevT(1,:)); mean(DevT2(1,:));mean(DevT(2,:));
mean(DevT2(2,:))];

% presenting the results on Turkey Map
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)],
[ min(NewGrid.New_Lon) max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.5 1 0.5])
tightmap
plot3(M_APR_AVG.Lon,M_APR_AVG.Lat,M_APR_AVG.T_Min,'o')
title('Apr-AVG Temperature Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Temperature')
hold on
pcolorm(NewLat,NewLon,vq_avg) % or surfm(NewLat,NewLon,vq) can be
used
% legend('Station data','Interpolated query data')
% mesh(NewLon,NewLat,vq)

```

```

figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)],
[ min(NewGrid.New_Lon) max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.5 1 0.5])
tightmap
plot3(M1.Lon,M1.Lat,M1.Min_T,'o')
title('01-Apr-2010 Temperature Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Temperature')
hold on
pcolorm(NewLat,NewLon,vq)
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)],
[ min(NewGrid.New_Lon) max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.5 1 0.5])
tightmap
plot3(NewLon,NewLat,Mt_avg,'o')
title('Standard Deviation of Average Temperature')
xlabel('Longitude'), ylabel('Latitude'), zlabel('movstd')
hold on
pcolorm(NewLat,NewLon,Mt_avg)
%%%%%%%%%% Temperature Part End %%%%%%%%%%%

% creating the scattered interpolant for precipitation values
P1 = Tot_Prec(Tot_Prec.Date=='02-Mar-2009', {'Station_No','Date',
'Lat', 'Lon', 'Tot_P', 'New_Prec'});
P12= Tot_Prec(year(Tot_Prec.Date)==2009 & month(Tot_Prec.Date)==03,
{'Station_No','New_Prec'});
P_APR=varfun(@mean,P12,'GroupingVariables','Station_No');
P_APR = removevars(P_APR, {'GroupCount'});
P_APR.Properties.VariableNames{end} = 'Prec';
P_APR_AVG = innerjoin(P_APR,Tot_Prec,'RightVariables',3:5);
P_APR_AVG = unique(P_APR_AVG);
P2 = Tot_Prec(Tot_Prec.Date=='01-Jan-1970',{'Station_No', 'Date',

```

```

'Lat', 'Lon', 'Tot_P', 'New_Prec'}));
    P3 = Tot_Prec(Tot_Prec.Date=={'01-Jan-1980'},{'Station_No','Date',
'Lat', 'Lon', 'Tot_P', 'New_Prec'}));

    % creating the scattered interpolant for precipitation values
    Pf = scatteredInterpolant(P1.Lon,P1.Lat, P1.New_Prec, 'natural',
'linear');
    Pf_avg = scatteredInterpolant(P_APR_AVG.Lon,P_APR_AVG.Lat,
P_APR_AVG.Prec,'natural','linear');

    % scattered interpolation
    pq = Pf(NewLon,NewLat);
    pq_avg = Pf_avg(NewLon,NewLat);
    Mp=movstd(pq,5,0,2);
    Mp_avg=movstd(pq_avg,5,0,2);
    % reversing the altitude correction
    pq = pq + 0.54*A;
    pq_avg = pq_avg + 0.54*A;
    % calculating the standard deviation and the means of the grid for
    % error analysis
    DevP=std(pq);
    DevP2=std(pq,0,2);
    DevP(2,:)=std(pq_avg);
    DevP2(:,2)=std(pq_avg,0,2);
    Avg_P=[mean(DevP(1,:)); mean(DevP2(1,:)); mean(DevP(2,:));
mean(DevP2(2,:))];

    % presenting the results on Turkey Map
    figure
    worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)],
[ min(NewGrid.New_Lon) max(NewGrid.New_Lon)])
    geoshow('landareas.shp','FaceColor',[0.5 1 0.5])
    tightmap
    plot3(P_APR_AVG.Lon,P_APR_AVG.Lat,P_APR_AVG.Prec,'o')

```



```

title('Apr-AVG Precipitation Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Precipitation')
hold on
pcolorm(NewLat,NewLon,pq_avg)
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)],
[min(NewGrid.New_Lon) max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.5 1 0.5])
tightmap
plot3(P1.Lon,P1.Lat,P1.Tot_P,'o')
title('01-Apr-2010 Precipitation Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Temperature')
hold on
pcolorm(NewLat,NewLon,pq)
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)],
[min(NewGrid.New_Lon) max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.5 1 0.5])
tightmap
plot3(NewLon,NewLat,Mp_avg,'o')
title('Standard Deviation of Average Precipitation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('movstd')
hold on
pcolorm(NewLat,NewLon,Mp_avg)

```

APPENDIX C: MATLAB CODE FOR INTERPOLATION AND MAPPING FOR CRU AND ERA DATA

```

clear
clc

CRU_coor=readtable('CRU_Coordinates.xlsx');
ERA_coor=readtable('ERA_Coordinates.xlsx');

pr_CRU_1965=readtable('prCRU1965Oct.csv');
pr_CRU_1965=standardizeMissing(pr_CRU_1965,9.969210000000000e+36);
pr_CRU_1965 = removevars(pr_CRU_1965, {'Var4'});
pr_CRU_1965.Properties.VariableNames={'LON','LAT','RAW_P'};
pr_CRU_1965=join(pr_CRU_1965,CRU_coor,'Keys',{'LON','LAT'});
pr_CRU_1965=rmmissing(pr_CRU_1965);
pr_CRU_1965.NEW_P=pr_CRU_1965.RAW_P-0.54*pr_CRU_1965.ALT;

pr_CRU_1980=readtable('prCRU1980Oct.csv');
pr_CRU_1980=standardizeMissing(pr_CRU_1980,9.969210000000000e+36);
pr_CRU_1980 = removevars(pr_CRU_1980, {'Var4'});
pr_CRU_1980.Properties.VariableNames={'LON','LAT','RAW_P'};
pr_CRU_1980=join(pr_CRU_1980,CRU_coor,'Keys',{'LON','LAT'});
pr_CRU_1980=rmmissing(pr_CRU_1980);
pr_CRU_1980.NEW_P=pr_CRU_1980.RAW_P-0.54*pr_CRU_1980.ALT;

pr_CRU_1995=readtable('prCRU1995Oct.csv');
pr_CRU_1995=standardizeMissing(pr_CRU_1995,9.969210000000000e+36);
pr_CRU_1995 = removevars(pr_CRU_1995, {'Var4'});
pr_CRU_1995.Properties.VariableNames={'LON','LAT','RAW_P'};
pr_CRU_1995=join(pr_CRU_1995,CRU_coor,'Keys',{'LON','LAT'});
pr_CRU_1995=rmmissing(pr_CRU_1995);

```

```

pr_CRU_1995.NEW_P=pr_CRU_1995.RAW_P-0.54*pr_CRU_1995.ALT;

pr_CRU_2010=readtable('prCRU2010Oct.csv');
pr_CRU_2010=standardizeMissing(pr_CRU_2010,9.969210000000000e+36);
pr_CRU_2010 = removevars(pr_CRU_2010, {'Var4'});
pr_CRU_2010.Properties.VariableNames={'LON','LAT','RAW_P'};
pr_CRU_2010=join(pr_CRU_2010,CRU_coor,'Keys',{'LON','LAT'});
pr_CRU_2010=rmmissing(pr_CRU_2010);
pr_CRU_2010.NEW_P=pr_CRU_2010.RAW_P-0.54*pr_CRU_2010.ALT;

pr_ERA_1980=readtable('prERA1980Oct.csv');
pr_ERA_1980 = removevars(pr_ERA_1980, {'Var4'});
pr_ERA_1980.Properties.VariableNames={'LON','LAT','RAW_P'};
pr_ERA_1980=join(pr_ERA_1980,ERA_coor,'Keys',{'LON','LAT'});
pr_ERA_1980=rmmissing(pr_ERA_1980);
pr_ERA_1980.NEW_P=pr_ERA_1980.RAW_P-0.54*pr_ERA_1980.ALT;

pr_ERA_1995=readtable('prERA1995Oct.csv');
pr_ERA_1995 = removevars(pr_ERA_1995, {'Var4'});
pr_ERA_1995.Properties.VariableNames={'LON','LAT','RAW_P'};
pr_ERA_1995=join(pr_ERA_1995,ERA_coor,'Keys',{'LON','LAT'});
pr_ERA_1995=rmmissing(pr_ERA_1995);
pr_ERA_1995.NEW_P=pr_ERA_1995.RAW_P-0.54*pr_ERA_1995.ALT;

pr_ERA_2010=readtable('prERA2010Oct.csv');
pr_ERA_2010 = removevars(pr_ERA_2010, {'Var4'});
pr_ERA_2010.Properties.VariableNames={'LON','LAT','RAW_P'};
pr_ERA_2010=join(pr_ERA_2010,ERA_coor,'Keys',{'LON','LAT'});
pr_ERA_2010=rmmissing(pr_ERA_2010);
pr_ERA_2010.NEW_P=pr_ERA_2010.RAW_P-0.54*pr_ERA_2010.ALT;

tas_CRU_1965=readtable('tasCRU1965Mar.csv');

```

```

tas_CRU_1965=standardizeMissing(tas_CRU_1965,9.969210000000000e+36);
tas_CRU_1965 = removevars(tas_CRU_1965, {'Var4'});
tas_CRU_1965.Properties.VariableNames={'LON','LAT','RAW_T'};
tas_CRU_1965=join(tas_CRU_1965,CRU_coor,'Keys',{'LON','LAT'});
tas_CRU_1965=rmmissing(tas_CRU_1965);
tas_CRU_1965.NEW_T=tas_CRU_1965.RAW_T+0.0065*tas_CRU_1965.ALT;

tas_CRU_1980=readtable('tasCRU1980Mar.csv');
tas_CRU_1980=standardizeMissing(tas_CRU_1980,9.969210000000000e+36);
tas_CRU_1980 = removevars(tas_CRU_1980, {'Var4'});
tas_CRU_1980.Properties.VariableNames={'LON','LAT','RAW_T'};
tas_CRU_1980=join(tas_CRU_1980,CRU_coor,'Keys',{'LON','LAT'});
tas_CRU_1980=rmmissing(tas_CRU_1980);
tas_CRU_1980.NEW_T=tas_CRU_1980.RAW_T+0.0065*tas_CRU_1980.ALT;

tas_CRU_1995=readtable('tasCRU1995Mar.csv');
tas_CRU_1995=standardizeMissing(tas_CRU_1995,9.969210000000000e+36);
tas_CRU_1995 = removevars(tas_CRU_1995, {'Var4'});
tas_CRU_1995.Properties.VariableNames={'LON','LAT','RAW_T'};
tas_CRU_1995=join(tas_CRU_1995,CRU_coor,'Keys',{'LON','LAT'});
tas_CRU_1995=rmmissing(tas_CRU_1995);
tas_CRU_1995.NEW_T=tas_CRU_1995.RAW_T+0.0065*tas_CRU_1995.ALT;

tas_CRU_2010=readtable('tasCRU2010Mar.csv');
tas_CRU_2010=standardizeMissing(tas_CRU_2010,9.969210000000000e+36);
tas_CRU_2010 = removevars(tas_CRU_2010, {'Var4'});
tas_CRU_2010.Properties.VariableNames={'LON','LAT','RAW_T'};
tas_CRU_2010=join(tas_CRU_2010,CRU_coor,'Keys',{'LON','LAT'});
tas_CRU_2010=rmmissing(tas_CRU_2010);
tas_CRU_2010.NEW_T=tas_CRU_2010.RAW_T+0.0065*tas_CRU_2010.ALT;

tas_ERA_1980=readtable('tasERA1980Mar.csv');
tas_ERA_1980 = removevars(tas_ERA_1980, {'Var4'});

```

```

tas_ERA_1980.Properties.VariableNames={'LON','LAT','RAW_T'};
tas_ERA_1980=join(tas_ERA_1980,ERA_coor,'Keys',{'LON','LAT'});
tas_ERA_1980=rmmissing(tas_ERA_1980);
tas_ERA_1980.NEW_T=tas_ERA_1980.RAW_T+0.0065*tas_ERA_1980.ALT;

tas_ERA_1995=readtable('tasERA1995Mar.csv');
tas_ERA_1995 = removevars(tas_ERA_1995, {'Var4'});
tas_ERA_1995.Properties.VariableNames={'LON','LAT','RAW_T'};
tas_ERA_1995=join(tas_ERA_1995,ERA_coor,'Keys',{'LON','LAT'});
tas_ERA_1995=rmmissing(tas_ERA_1995);
tas_ERA_1995.NEW_T=tas_ERA_1995.RAW_T+0.0065*tas_ERA_1995.ALT;

tas_ERA_2010=readtable('tasERA2010Mar.csv');
tas_ERA_2010 = removevars(tas_ERA_2010, {'Var4'});
tas_ERA_2010.Properties.VariableNames={'LON','LAT','RAW_T'};
tas_ERA_2010=join(tas_ERA_2010,ERA_coor,'Keys',{'LON','LAT'});
tas_ERA_2010=rmmissing(tas_ERA_2010);
tas_ERA_2010.NEW_T=tas_ERA_2010.RAW_T+0.0065*tas_ERA_2010.ALT;

NewGrid=readtable('TR_New_Grid_rev3.xlsx');
NewGrid=rmmissing(NewGrid);
Lon=(min(NewGrid.New_Lon):0.08:max(NewGrid.New_Lon))';
Lat=(min(NewGrid.New_Lan):0.08:max(NewGrid.New_Lan))';
[NewLat,NewLon] = meshgrid(Lat,Lon);

% pivoted altitude values for reversing the correction in the end
A=xlsread('TR_New_Grid_rev4.xlsx','Altitude_Pivot');

F_CRU = scatteredInterpolant(pr_CRU_1965.LON, pr_CRU_1965.LAT,
pr_CRU_1965.NEW_P, 'natural', 'linear');
F_ERA = scatteredInterpolant(pr_ERA_1980.LON, pr_ERA_1980.LAT,
pr_ERA_1980.NEW_P, 'natural', 'linear');

```

```

prq_CRU_1965 = F_CRU(NewLon,NewLat);
prq_CRU_1965 = prq_CRU_1965 + 0.54*A;
F_CRU.Values=pr_CRU_1980.NEW_P;
prq_CRU_1980 = F_CRU(NewLon,NewLat);
prq_CRU_1980 = prq_CRU_1980+ 0.54*A;
F_CRU.Values=pr_CRU_1995.NEW_P;
prq_CRU_1995 = F_CRU(NewLon,NewLat);
prq_CRU_1995 = prq_CRU_1995+ 0.54*A;
F_CRU.Values=pr_CRU_2010.NEW_P;
prq_CRU_2010 = F_CRU(NewLon,NewLat);
prq_CRU_2010 = prq_CRU_2010+ 0.54*A;

F_CRU.Values=tas_CRU_1965.NEW_T;
tasq_CRU_1965 = F_CRU(NewLon,NewLat);
tasq_CRU_1965 = tasq_CRU_1965 - 0.0065*A;
F_CRU.Values=tas_CRU_1980.NEW_T;
tasq_CRU_1980 = F_CRU(NewLon,NewLat);
tasq_CRU_1980 = tasq_CRU_1980 - 0.0065*A;
F_CRU.Values=tas_CRU_1995.NEW_T;
tasq_CRU_1995 = F_CRU(NewLon,NewLat);
tasq_CRU_1995 = tasq_CRU_1995 - 0.0065*A;
F_CRU.Values=tas_CRU_2010.NEW_T;
tasq_CRU_2010 = F_CRU(NewLon,NewLat);
tasq_CRU_2010 = tasq_CRU_2010 - 0.0065*A;

prq_ERA_1980 = F_ERA(NewLon,NewLat);
prq_ERA_1980 = prq_ERA_1980 + 0.54*A;
F_ERA.Values=pr_ERA_1995.NEW_P;
prq_ERA_1995 = F_ERA(NewLon,NewLat);
prq_ERA_1995 = prq_ERA_1995 + 0.54*A;
F_ERA.Values=pr_ERA_2010.NEW_P;
prq_ERA_2010 = F_ERA(NewLon,NewLat);
prq_ERA_2010 = prq_ERA_2010 + 0.54*A;

```

```

F_ERA.Values=tas_ERA_1980.NEW_T;
tasq_ERA_1980 = F_ERA(NewLon,NewLat);
tasq_ERA_1980 = tasq_ERA_1980 - 0.0065*A;
F_ERA.Values=tas_ERA_1995.NEW_T;
tasq_ERA_1995 = F_ERA(NewLon,NewLat);
tasq_ERA_1995 = tasq_ERA_1995 - 0.0065*A;
F_ERA.Values=tas_ERA_2010.NEW_T;
tasq_ERA_2010 = F_ERA(NewLon,NewLat);
tasq_ERA_2010 = tasq_ERA_2010 - 0.0065*A;

% CRU Precipitation
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.25 1 0.25])
tightmap
plot3(pr_CRU_1965.LON,pr_CRU_1965.LAT,pr_CRU_1965.RAW_P,'o')
title('CRU October-1965 Precipitation Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Precipitation')
hold on
pcolorm(NewLat,NewLon,prq_CRU_1965) % or surfm(NewLat,NewLon,vq) can be
used
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.25 1 0.25])
tightmap
plot3(pr_CRU_1980.LON,pr_CRU_1980.LAT,pr_CRU_1980.RAW_P,'o')
title('CRU October-1980 Precipitation Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Precipitation')
hold on
pcolorm(NewLat,NewLon,prq_CRU_1980) % or surfm(NewLat,NewLon,vq) can be

```

```

used

figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])
geoshow('landareas.shp', 'FaceColor', [0.25 1 0.25])
tightmap
plot3(pr_CRU_1995.LON, pr_CRU_1995.LAT, pr_CRU_1995.RAW_P, 'o')
title('CRU October-1995 Precipitation Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Precipitation')
hold on
pcolorm(NewLat, NewLon, prq_CRU_1995) % or surfm(NewLat, NewLon, vq) can be
used
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])
geoshow('landareas.shp', 'FaceColor', [0.25 1 0.25])
tightmap
plot3(pr_CRU_2010.LON, pr_CRU_2010.LAT, pr_CRU_2010.RAW_P, 'o')
title('CRU October-2010 Precipitation Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Precipitation')
hold on
pcolorm(NewLat, NewLon, prq_CRU_2010) % or surfm(NewLat, NewLon, vq) can be
used
% figure
% mesh(NewLon, NewLat, prq_CRU_1965)
% hold on
% plot3(pr_CRU_1965.LON, pr_CRU_1965.LAT, pr_CRU_1965.RAW_P, 'o')
% title('CRU-RAW October-1965 Precipitation Interpolation')

% CRU Temperature
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])

```



```

geoshow('landareas.shp','FaceColor',[0.25 1 0.25])
tightmap
plot3(tas_CRU_1965.LON,tas_CRU_1965.LAT,tas_CRU_1965.RAW_T,'o')
title('CRU March-1965 Temperature Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Temperature')
hold on
pcolorm(NewLat,NewLon,tasq_CRU_1965) % or surfm(NewLat,NewLon,vq) can be
used
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.25 1 0.25])
tightmap
plot3(tas_CRU_1980.LON,tas_CRU_1980.LAT,tas_CRU_1980.RAW_T,'o')
title('CRU March-1980 Temperature Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Temperature')
hold on
pcolorm(NewLat,NewLon,tasq_CRU_1980) % or surfm(NewLat,NewLon,vq) can be
used
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.25 1 0.25])
tightmap
plot3(tas_CRU_1995.LON,tas_CRU_1995.LAT,tas_CRU_1995.RAW_T,'o')
title('CRU March-1995 Temperature Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Temperature')
hold on
pcolorm(NewLat,NewLon,tasq_CRU_1995) % or surfm(NewLat,NewLon,vq) can be
used
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])

```

```

geoshow('landareas.shp','FaceColor',[0.25 1 0.25])
tightmap
plot3(tas_CRU_2010.LON,tas_CRU_2010.LAT,tas_CRU_2010.RAW_T,'o')
title('CRU March-2010 Temperature Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Temperature')
hold on
pcolorm(NewLat,NewLon,tasq_CRU_2010) % or surfm(NewLat,NewLon,vq) can be
used

% ERA Precipitation
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.25 1 0.25])
tightmap
plot3(pr_ERA_1980.LON,pr_ERA_1980.LAT,pr_ERA_1980.RAW_P,'o')
title('ERA October-1980 Precipitation Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Precipitation')
hold on
pcolorm(NewLat,NewLon,prq_ERA_1980) % or surfm(NewLat,NewLon,vq) can be
used
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.25 1 0.25])
tightmap
plot3(pr_ERA_1995.LON,pr_ERA_1995.LAT,pr_ERA_1995.RAW_P,'o')
title('ERA October-1995 Precipitation Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Precipitation')
hold on
pcolorm(NewLat,NewLon,prq_ERA_1995) % or surfm(NewLat,NewLon,vq) can be
used
figure

```

```

worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])

geoshow('landareas.shp', 'FaceColor', [0.25 1 0.25])

tightmap

plot3(pr_ERA_2010.LON, pr_ERA_2010.LAT, pr_ERA_2010.RAW_P, 'o')

title('ERA October-2010 Precipitation Interpolation')

xlabel('Longitude'), ylabel('Latitude'), zlabel('Precipitation')

hold on

pcolorm(NewLat, NewLon, prq_ERA_2010) % or surfm(NewLat, NewLon, vq) can be
used

% figure

% mesh(NewLon, NewLat, prq_ERA_1965)

% hold on

% plot3(pr_ERA_1965.LON, pr_ERA_1965.LAT, pr_ERA_1965.RAW_P, 'o')

% title('ERA-RAW October-1965 Precipitation Interpolation')


% ERA Temperature

figure

worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])

geoshow('landareas.shp', 'FaceColor', [0.25 1 0.25])

tightmap

plot3(tas_ERA_1980.LON, tas_ERA_1980.LAT, tas_ERA_1980.RAW_T, 'o')

title('ERA March-1980 Temperature Interpolation')

xlabel('Longitude'), ylabel('Latitude'), zlabel('Temperature')

hold on

pcolorm(NewLat, NewLon, tasq_ERA_1980) % or surfm(NewLat, NewLon, vq) can be
used

figure

worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])

geoshow('landareas.shp', 'FaceColor', [0.25 1 0.25])

tightmap

```

```

plot3(tas_ERA_1995.LON,tas_ERA_1995.LAT,tas_ERA_1995.RAW_T,'o')
title('ERA March-1995 Temperature Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Temperature')
hold on
pcolorm(NewLat,NewLon,tasq_ERA_1995) % or surfm(NewLat,NewLon,vq) can be
used
figure
worldmap ([min(NewGrid.New_Lan) max(NewGrid.New_Lan)], [min(NewGrid.New_Lon)
max(NewGrid.New_Lon)])
geoshow('landareas.shp','FaceColor',[0.25 1 0.25])
tightmap
plot3(tas_ERA_2010.LON,tas_ERA_2010.LAT,tas_ERA_2010.RAW_T,'o')
title('ERA March-2010 Temperature Interpolation')
xlabel('Longitude'), ylabel('Latitude'), zlabel('Temperature')
hold on
pcolorm(NewLat,NewLon,tasq_ERA_2010) % or surfm(NewLat,NewLon,vq) can be
used

```