

EVALUATION OF DIFFERENT DOWNSCALING APPROACHES FOR
VERY-HIGH-RESOLUTION CLIMATE DATA

by

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ABSTRACT

EVALUATION OF DIFFERENT DOWNSCALING APPROACHES FOR VERY-HIGH-RESOLUTION CLIMATE DATA

Climate change leads to widespread changes in atmospheric and oceanic conditions, increasing the frequency of climate anomalies and negatively impacting ecosystems and human communities. It is crucial to understand climate change and make accurate predictions about it. Climate change studies focus on tools like General Circulation Models (GCMs); however, GCMs cannot accurately represent local climates, leading to uncertainties due to their coarse resolution. Statistical and dynamical downscaling techniques improve local climate projection accuracy. This study compared statistical and dynamical downscaling techniques for evaluating Turkey's climate change projections, using the MPI-ESM-MR as the main GCM, RegCM4.7.0 regional climate model for dynamical downscaling and the spatial delta method for statistical downscaling. 17 datasets were analyzed to investigate spatio-temporal correlations at resolutions of 1km, 5km, 10km, and 20km. Evaluated spatial correlation of precipitation and temperature showed low to moderate correlation coefficients with negative correlations and near-zero values for precipitation but higher correlation results for temperature. 10 and 20km resolution downscaling data showed more favorable results. The temporal correlation of precipitation showed superior consistency with reduced standard deviations and improved correlation coefficients. The study highlighted the temporal correlation of temperature, exhibiting exceptional precision due to its nature and alignment with annual seasonal cycles. This study's findings will significantly enhance understanding of the optimal methodology for downscaling climate change projections and the impacts of climate change on local communities.

ÖZET

ÇOK YÜKSEK ÇÖZÜNÜRLÜKLÜ İKLİM VERİLERİ İÇİN FARKLI ÖLÇEK KÜÇÜLTME YAKLAŞIMLARININ DEĞERLENDİRİLMESİ

İklim değışikliğı, atmosferik ve okyanus koşullarında değışikliklere yol açarak iklim anomalilerinin sıklığını artırır ve ekosistemleri ve insan topluluklarını olumsuz etkiler. İklim değışikliğini anlamak ve bu konuda doğru tahminlerde bulunmak çok önemlidir. İklim değışikliğı çalışmaları, Küresel İklim Modelleri gibi araçlara odaklanır; ancak, bu modeller iklim bileşenlerini bölgesel düzeyde doğru bir şekilde tahmin edemez ve bu da düşük çözünürlükleri nedeniyle belirsizliklere yol açar. İstatistiksel ve dinamik ölçek küçültme teknikleri, bölgesel iklim projeksiyonu doğruluğunu artırır. Bu çalışma, ana GCM olarak MPI-ESM-MR'yi, dinamik ölçek küçültme için RegCM4.7.0 bölgesel iklim modelini ve istatistiksel ölçek küçültme için alansal delta yöntemini kullanarak, Türkiye'nin iklim değışikliğı tahminlerini değerlendirmek için istatistiksel ve dinamik ölçek küçültme tekniklerini karşılaştırdı. 1km, 5km, 10km ve 20km çözünürlüklerde alansal ve zamansal korelasyonları araştırmak için 17 veri seti analiz edildi. Yağış ve sıcaklığın değerlendirilen alansal korelasyonu, yağış için negatif ve sıfıra yakın değerlerle düşük ila orta korelasyon katsayıları gösterirken, sıcaklık için daha yüksek korelasyon sonuçları gösterdi. 10 ve 20km çözünürlük küçültme verileri daha olumlu sonuçlar gösterdi. Yağışın zamansal korelasyonu, daha düşük standart sapmalar ve daha yüksek korelasyon katsayıları ile üstün tutarlılık gösterdi. Çalışmada incelenen sıcaklığın zamansal korelasyonu, doğası ve mevsimsel döngülerle uyumu nedeniyle oldukça yüksek korelasyon sergiledi. Bu çalışmanın bulguları, iklim değışikliğı tahminlerini ve iklim değışikliğinin yerel topluluklar üzerindeki etkilerini azaltmak için en uygun metodolojinin anlaşılmasını önemli ölçüde artıracaktır.

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LIST OF SYMBOLS

$i_1(t, x)$	Grid values of first data
$i_2(t, x)$	Grid values of second data
$o(t, 1)$	Spatial correlation coefficient of datasets
$o(1, x)$	Temporal correlation coefficient of datasets
$S(t)$	Grid location of non-missing value point
$w(x)$	Area weights obtained by the input streams

LIST OF ACRONYMS/ABBREVIATIONS

CDO	Climate Data Operators
CO ₂	Carbon Dioxide
CPU	Central Processing Unit
GCM	General Circulation Models
GRIB	Gridded Binary
ICBC	Initial Condition and Boundary Conditions
Km	Kilometer
LECZ	The Low Elevation Coastal Zone
MGM	Turkish State Meteorological Service
MPI-ESM	Max Planck Institute for Meteorology Earth System Model
MPI-ESM-MR	MPI-ESM Mixed Resolution
netCDF	Network Common Data Form
NOAA	National Oceanic and Atmospheric Administration
ppm	Parts per million
RAM	Random-Access Memory
RCM	Regional Climate Model
RegCM	ICTP Regional Climate Model
UNIX	Uniplexed Information Computing System
USA	United States of America
USD	United States Dollar

1. INTRODUCTION

The problem of global warming has become one of the most talked-about issues of our time. Changes in atmospheric and oceanic conditions result in transformations across multiple weather parameters [1]. The greenhouse effect, caused by human actions such as carbon dioxide (CO_2) and other greenhouse gas emissions, is the primary cause of climate change [2, 3]. The changing climate triggers frequent climate anomalies, threatening natural habitats and human populations [4, 5].

The far-reaching consequences of climate change are a crucial consideration. The temperature rise accelerates melting, leading to sea level rise and flooding along coasts [6, 7]. Crop failures and insufficient availability of food occur because climate change affects agricultural production negatively while also impacting food security through alterations in temperature and precipitation patterns [8]. These events have become even more severe by climate change, resulting in extensive damage to buildings and facilities, forced migration of people, and fatalities [9].

Climate change has far-reaching effects on human welfare and the environment, affecting future generations. It threatens food security, agriculture, and community well-being with its complex impact on human life [10]. Therefore, it is crucial to understand the complexities of climate change, accurately predict future changes, and implement strategies to mitigate and adapt to its impacts.

Given the dire consequences of climate change, policymakers must monitor and address its effects. The accuracy of future climate forecasts is crucial to planning effective mitigation and adaptation strategies. Global climate models, which simulate Earth's climate system and its reactions under various scenarios, are crucial in this context. These models provide valuable insights into changing climate conditions, guiding policymakers to make informed decisions and develop effective strategies to address climate change [11].

In recent years, there has been an increased focus on studying the dynamics of climate change and developing tools to understand its various impacts. One area of study involves the use of general circulation models (GCMs) as tools for analysis. GCMs are used to simulate the complex climate systems of the Earth, providing valuable information about future climate scenarios [12]. However, these models often have limitations in accurately representing the complexities of localized climate patterns, which leads to uncertainties in their predictions [13]. Various statistical and dynamical downscaling methods have been developed to improve the accuracy of climate change predictions at a smaller scale. Dynamical downscaling provides high-resolution datasets to simulate the effects of climate change in more detail. Although this approach can provide more realistic data results, it requires a substantial amount of computational resources because of its high computational complexity [14]. On the other hand, statistical downscaling methods rely on statistical techniques to adjust GCM projections to fit local scales. Although computationally less demanding and easier to implement, these methods may not accurately capture the detailed local climatic variations as the dynamic approaches [15].

This study aims to evaluate the strengths and limitations of statistical and dynamical downscaling techniques. For this reason, statistical downscaling and dynamical downscaling climate change projections for Turkey are compared. The MPI-ESM-MR global climate model is used as input data, the RegCM4.7.0 model is used for dynamical downscaling and spatial delta method is used for statistical downscaling in specific regions. Ultimately, the research has examined how similar statistical downscaling is to dynamical downscaling.

The results of this study are expected to provide valuable insights into the best way to downscale climate change projections. It will help us better understand how climate change affects local communities. The findings clearly demonstrate that the 'spatial delta method' allows for the collection of detailed climate data using limited computational resources. This method provides advantages for researchers who have limited computational resources, allowing them to obtain detailed climate data without

requiring a large amount of computational power. Moreover, it provides a convenient opportunity for researchers with powerful computers who want to accelerate their research by improving computational efficiency. By effectively applying the spatial delta method, researchers may improve and accelerate their investigative processes, leading to the achievement of their objectives more efficiently.

2. LITERATURE REVIEW

2.1. Climate Change

Climate change refers to long-term changes in the Earth's climate, involving noticeable changes in average and/or varying conditions over decades or more. It arises from natural and human-made factors [16]. The sun is the primary energy source impacting climate. The amount of sunlight reaching Earth depends on factors like solar energy fluctuations, Earth's orbit, surface reflectivity (albedo), and atmospheric particles like aerosols that can block radiation [17]. Sunlight, including visible light, reaches Earth, and about one-third is reflected away. The rest is absorbed by elements like the atmosphere, oceans, ice, land, and biota. This absorbed energy is counterbalanced by outgoing radiation, mostly invisible infrared radiation. The intensity of this radiation relates to the Earth's temperature. Earth's average temperature results from a balance between absorbed solar energy and emitted infrared radiation, as shown in Figure 2.1.

Natural factors can disrupt the balance, causing changes in energy absorption and emission, which influence climate [18]. Greenhouse gases in the atmosphere, especially water vapor and carbon dioxide, cannot completely absorb sunlight but are effective at capturing infrared radiation from the surface. They then re-radiate some of this energy back downward, contributing to warming, as illustrated in Figure 2.2. This effect makes today's average surface temperature more than 33°C warmer than if there were no atmosphere [19].

It can be stated without question that the detectable rises in the levels of greenhouse gases (GHGs) that have been observed since the late 1700s are directly attributed to human actions [16]. Furthermore, these concentrations have continued their upward trend and currently exhibit yearly averages of 410 parts per million (ppm) for CO₂ [16]. The examination of observational data has indicated a continual increase in atmospheric CO₂ concentrations from year to year (Figure 2.3). This increase has been

found to be the result of human activities disrupting the natural carbon cycle on a global scale. Further research conducted by 1970 revealed a widespread elevation in CO_2 concentration, which can be largely considered as irrefutable evidence of its correlation with the combustion of fossil fuels [20].

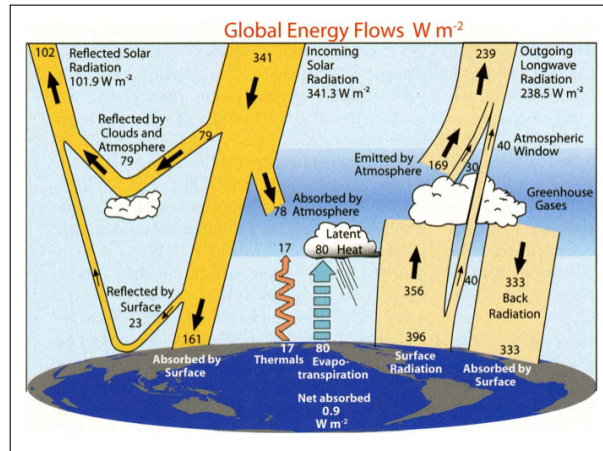


Figure 2.1. The representation of the average annual energy budget of the Earth on a global scale (W/m^2) [21].

Over the past four decades, temperatures have been consistently higher in each successive decade. Analysis of global surface temperature between 2001 and 2020 reveals a 0.99°C increase compared to the period from 1850 to 1900 [16].

Human influence has shaped the planet for millennia, but the recent changes brought about in the last few centuries are now evident worldwide. The pace of global climate transformation has become more apparent. Countries have seven years, as stipulated by the Paris Agreement [22], to halve their net carbon emissions to achieve the goal of limiting global warming to under 1.5°C and avert severe consequences. This objective has become even more challenging to attain [23]. Yet, even if this goal is met, the effects of warming are likely to endure for centuries [24]. Climate change is fundamentally reshaping the Earth's systems, leading to changes like extreme weather events, rising sea levels, and changes in glacier masses.

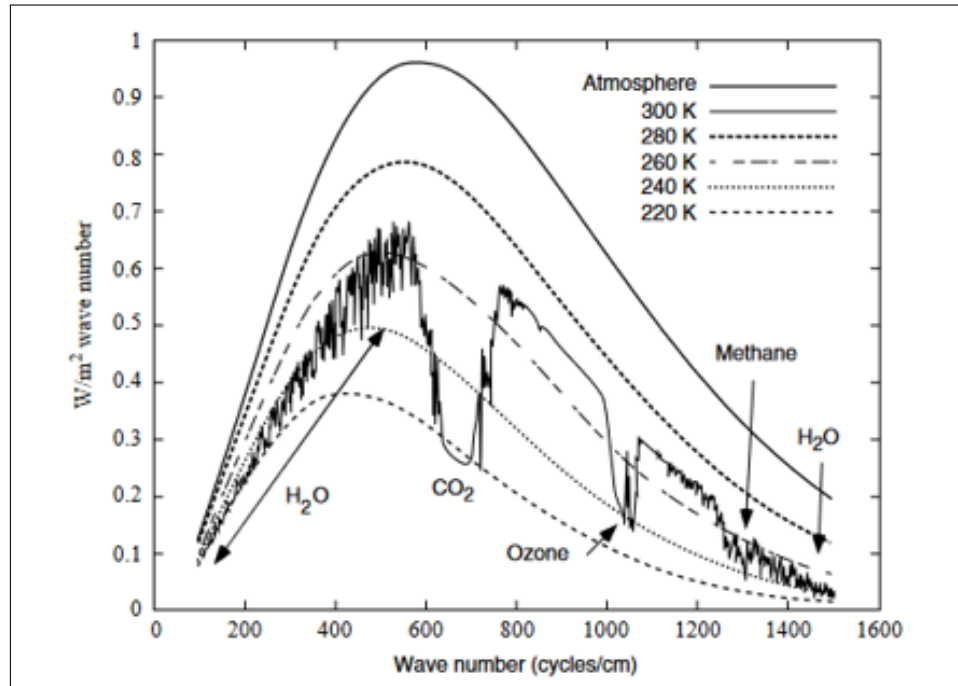


Figure 2.2. The spectrum of light leaving the Earth going into space [25].

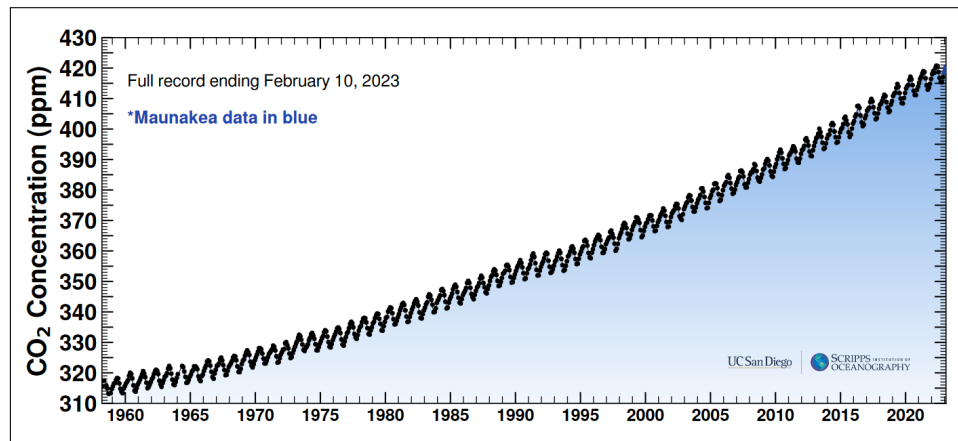


Figure 2.3. CO₂ concentration at Mauna Loa Observatory [26].

2.1.1. Rising Temperatures

Due to the characteristics and considerable heat capacity of Earth's oceans, a slight rise in the yearly average surface temperature would require a substantial amount of heat energy. The increase of around 1 °C in the average global surface temperature since the pre-industrial era (1880-1900) represents a significant increase of heat.

One significant result of climate change is the rise in global temperatures, which has wide-ranging and dangerous consequences. The period following the industrial revolution resulted in an increase in global warming, leading to higher average surface temperatures. As a result, this phenomenon leads to an increased occurrence and heightened intensity of heatwaves, which present significant risks to human welfare. The rising sea levels, caused by the melting of arctic ice and glaciers as a result of higher temperatures, present dangers to people living along the coastlines and to the diversity of plant and animal life. The increased temperature of oceanic conditions also leads to occurrences of coral bleaching and other disruptions in marine ecosystems. Changes in weather patterns, such as alterations in rainfall and increased intensity of storms, have significant effects on agriculture, water resources, and ecosystems. Additionally, the stability of permafrost is negatively affected by increasing temperatures, resulting in the release of powerful greenhouse gases like methane. The urgent resolution of these challenges necessitates the worldwide embrace of renewable energy sources, conservation of natural ecosystems, and the enactment of policies that can decrease the impacts of climate change.

The three decades before the present have been identified as the warmest period since 1850 [27]. This period of warmth aligns with the significant increase in the emission of greenhouse gases. In 2022, the average global temperatures experienced a rise of 1.24 °C compared to the temperatures recorded between 1850 and 1900. This time period is commonly used as a reference period to establish global temperature benchmarks before the industrial revolution [28]. According to a study conducted by Berkeley Earth ([28]), which examined climate data from various regions, the average global temperature in 2022 was 0.91 °C higher than the average temperature recorded between 1951 and 1980, which is commonly used as a reference period for comparisons. Turkish State Meteorological Service (MGM) determined that the average temperature in Turkey for the year 2022 was observed to be 0.6 °C higher than the average temperature recorded between 1991 and 2020 [29]. Furthermore, the continuous pattern of increased temperatures has persisted throughout the summer of 2023. As stated by National Oceanic and Atmospheric Administration (NOAA), there has been a gradual

increase in the ocean’s surface temperature since 1880, with a rate of 0.06 °C per decade [30]. According to projections, it is anticipated that the average surface temperature worldwide may increase by 0.2 to 0.5 °C in the next decade, even if all human-caused emissions are ceased immediately [31].

2.1.2. Extreme Weather Events

Extreme weather and natural disasters are rising in frequency, intensity, and length as a result of global warming. Extreme weather events refer to instances of exceptional meteorological conditions. These events are distinguished by the presence of meteorological or climatological variables that exceed a previously established threshold value, which is in close proximity to the upper bounds of the observed range of the respective variables [32]. The effects of extreme weather events are mainly connected with the concept named “risk” [33]. With regard to the global climate change issue, the potential for risk stems from the complex interconnections between the hazards brought about by climatic changes and the vulnerability and exposure of human populations and ecological systems. Vulnerability refers to the susceptibility to harm and encompasses a multitude of concepts and factors, including sensitivity to adverse impacts and an absence of capacity for mitigation and adaptation [34]. The ability of a human system to adapt shows its potential to lower its social vulnerability and decrease the risk connected to a specific hazard. Several elements will affect the system’s ability to adjust to different hazards that are present now or could occur in the future [35]. The effects of climate change on human society are substantial. The extreme weather events also cause financial loss (Figure 2.4). There may be a rise in the frequency of floods, storms, and droughts. Heatwaves, storms, and hurricanes are becoming more often and severe as a result of climate change [34].

It is well known that human-induced climate change is increasing the frequency and intensity of many extreme weather events. Implementing effective strategies to mitigate the potentially catastrophic effects of extreme weather events requires a comprehensive understanding of their potential occurrences and timing [36]. On a global

scale, cold days and nights have decreased while warm days and nights have increased. Continental-scale temperature shifts have been observed in North America, Europe, and Australia [32].

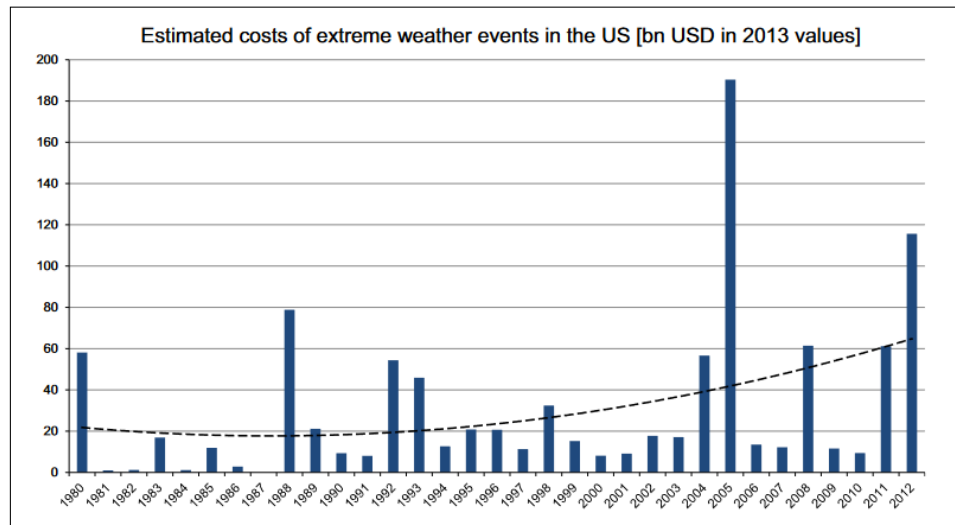


Figure 2.4. The estimated cost of extreme weather events in the USA from 1980 to 2012, presented in billions of USD. Only events with a cost exceeding 1 billion USD have been taken into consideration [33].

2.1.3. Melting in Glaciers and Sea Level Rise

Over the course of the last century, glaciers have experienced a significant reduction in their mass. Between 1800 and the present day, approximately 35-50% of the observed increase in sea levels can be attributed to the melting of glaciers and ice caps [37]. During the 20th century, the most prominent contributor to the rise in sea levels was the loss of mass from glaciers, and it is considered a critical contributor [38, 39]. It also influences the instability of slopes in high-elevation mountainous regions and leads to modifications in the seasonality and the volume of river flows [40, 41]. These phenomena have important implications for natural and human systems, such as changes in the availability of freshwater, ecosystem dynamics, and impacts on infrastructure and livelihoods [42].

Glaciers tend to expand towards lower elevations when they experience positive mass balances, while negative mass balances cause glaciers to retreat towards higher elevations. This process creates a negative feedback mechanism, allowing glaciers to adjust their distribution of elevation and area in response to atmospheric influences [43].

One of the most noticeable results of climate change is the increase in sea levels. The present sea level is experiencing a rise, and it is predicted to persist in the forthcoming centuries (Figure 2.5), irrespective of the reduction of greenhouse gas emissions and their stabilization in the atmosphere. One of the significant factors of climate change and subsequent sea-level increase is the increasing ocean heat content, which results in the expansion of the ocean [44]. Also, the increase in ocean mass due to the melting of land-based ice, which includes glaciers, ice caps, and the major ice sheets of Antarctica and Greenland, is another primary cause [45]. The oceanic temperature measurements gathered in recent decades indicate a significant increase in the thermal expansion of the ocean during the second half of the 20th century [46]. However, the impacts of this rise are locally experienced and determined by the relative sea level at particular locations. The global sea level has been observed by satellites since 1993, and it has been seen to increase by an average of 30 millimeters every decade [44](Figure 2.6). Anthropogenic subsidence is a significant factor that impacts the response to sea level rise, as it can result in relative sea level rise rates that exceed those caused by climate-induced sea level rise by up to tenfold, particularly in delta regions and urban areas. In these subsiding areas, managing and mitigating anthropogenic subsidence is an appropriate response to prepare for future climate-induced sea level rise [45].

Sea level rise can have different effects. Because of inundation and coastal erosion, countries, particularly those in low-lying regions and small islands, are concerned that their land area will decrease. There is also concern that a significant portion of their population may be compelled to migrate to other countries [47]. As the effects of climate change become visible, this issue has consequently received increased international attention.

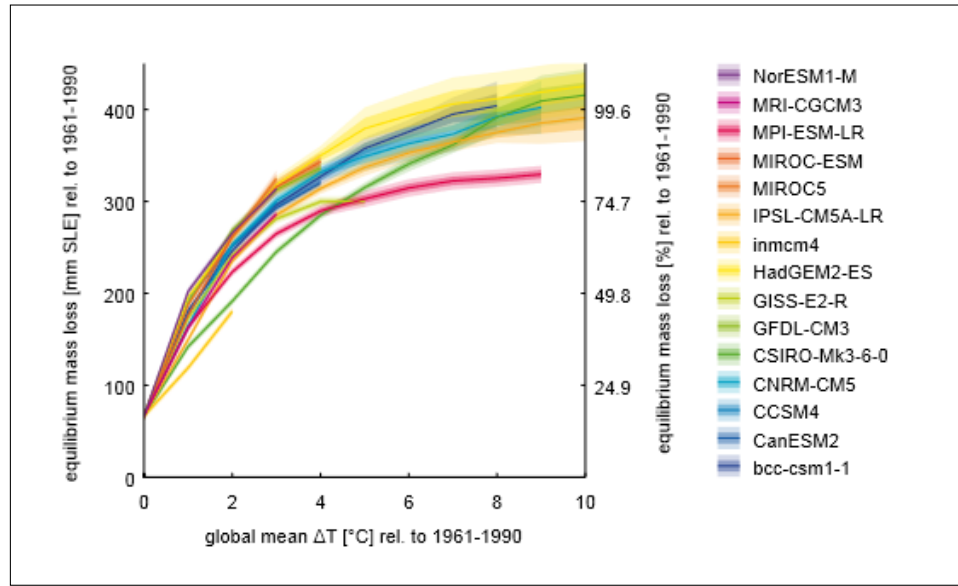


Figure 2.5. According to CMIP5 models, equilibrium mass loss of glaciers as a results of global mean temperature anomaly [43].

Coastal urban areas are particularly vulnerable to climate change impacts, including sea-level rise, storm surges, and coastal erosion. However, numerous urban areas that are experiencing the most rapid population growth are close to coastal zones [48]. Currently, around 300 million people in the world live in areas directly vulnerable to sea level rise, and by the end of the century, this number is expected to increase to 480 million [49]. The Low Elevation Coastal Zone (LECZ) is a geographic area that extends up to 10 meters above sea level and is located within 100 kilometers of the coastline. Despite covering only 2% of the Earth's land area, this zone is inhabited by a significant proportion of the global population, with 10% of the world's total population and 13% of its urban population residing within these boundaries [50]. Although sea level rise is not predicted to exceed 10 meters, there are numerous ways in which people living in the LECZ may be impacted, such as the salinization of groundwater due to intrusion of saltwater from the ocean [51].

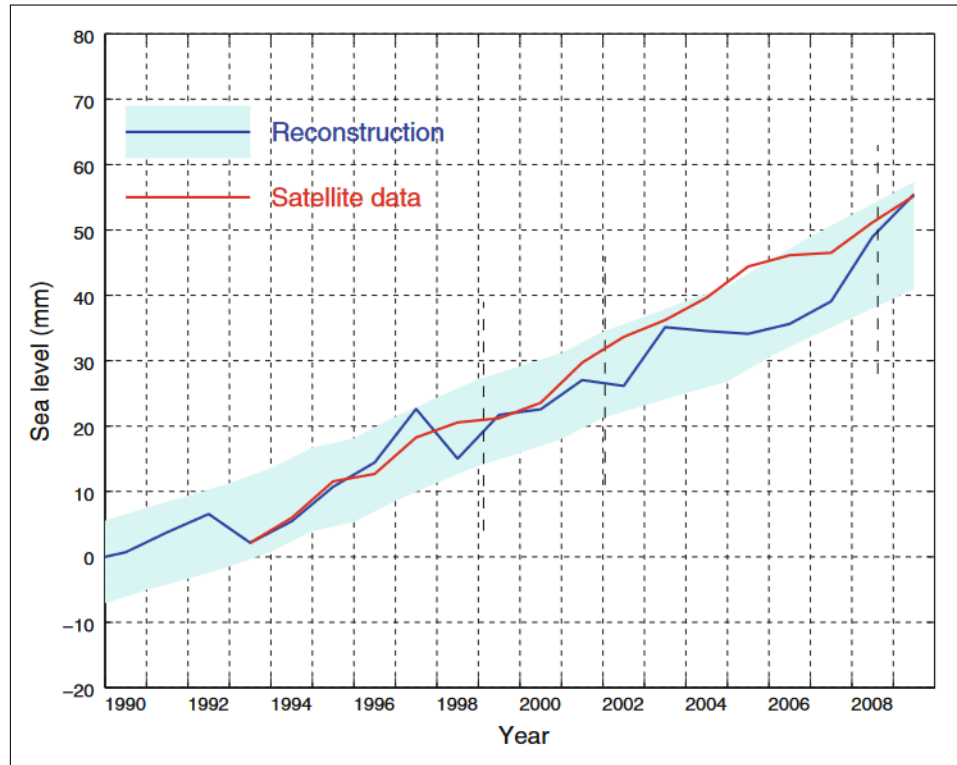


Figure 2.6. Global mean sea level from 1990 to 2009 [44].

2.1.4. Ocean Acidification

The increase in CO_2 in the atmosphere has led to an increase in the amount of CO_2 dissolved on the sea surface. It has been noted that the pH value of ocean water has decreased by 0.1 units since the Industrial Revolution (it was 8.2 before), and it is predicted that this decrease will continue [52].

The high amount of CO_2 released into the atmosphere, which is the cause of global warming, also causes an increase in the amount of CO_2 absorbed by the oceans [53]. The oceans absorb one-third of the CO_2 in the atmosphere, thereby reducing this gas in the atmosphere. However, the concentration of CO_2 , which was 280 ppm in the atmosphere before the Industrial Revolution, has increased as a result of human activities. The global average atmospheric CO_2 reached 417.06 ppm in 2022, setting a new record [54]. This increase in the atmosphere also causes an increase in the amount of CO_2 absorbed by the ocean surface. A decrease of 0.1 units in the logarithmically

increasing pH scale means an increase of approximately 30% in acidity [55]. This phenomenon is called “ocean acidification”.

Ocean acidification is becoming an increasingly important environmental problem due to increased anthropogenic carbon emissions. It causes a number of adverse effects on marine ecosystems and organisms. One of the most serious effects of ocean acidification relates to the life cycles of organisms composed of calcium carbonate minerals, particularly coral reefs [56]. Acidified waters cause the calcium carbonate to dissolve, which forms the shells and skeletons of these organisms. It leads to the bleaching of coral reefs and the deterioration of their structural integrity, contributing to the reduction of biodiversity in reef ecosystems. Likewise, shellfish, mussels, and other organisms are adversely affected by the damage to their calcium shells in acidified water conditions [57].

Ocean acidification also has a significant impact on the physiology of marine organisms. Acidified waters can reduce the growth rate and reproductive capacity of some marine organisms [58]. Its effects, especially on essential food sources such as plankton, can have serious consequences on the food chain of marine ecosystems [59, 60]. It can cause the balance of the food chain to be disturbed, from marine invertebrates to fish and ultimately to marine mammals. In addition, ocean acidification contributes to the degradation of habitats in marine ecosystems and the overall structure of ecosystems [61]. The decline or disappearance of some marine organisms may also affect the species that these organisms hunt or prey on. These changes may affect the entire marine ecosystem and cause the deterioration of natural balance, resulting in adverse effects on biodiversity.

2.1.5. Loss of Biodiversity

Climate change presents a significant danger to biodiversity and disrupts ecosystems, thereby diminishing the likelihood of species’ survival [62]. Biodiversity encompasses the wide range of living organisms, including plant and animal species, as well

as the various ecosystems that exist on our planet. Nevertheless, the decline in biodiversity is occurring at an alarming rate due to anthropogenic actions. The destruction of habitats and endangerment of numerous species are attributed to various factors, including deforestation, expansion of agricultural lands, urbanization, and pollution of land and marine ecosystems [63]. Consequently, such occurrences give rise to ecological imbalances and the eventual extinction of certain species.

The loss of biodiversity leads to the disruption of ecosystem functions, impacting crucial ecosystem services such as pollination [64], soil fertility [65], and the water cycle [66]. Consequently, this phenomenon adversely impacts individuals' means of subsistence and disrupts the ecological balance within the food chain [67]. The adverse impacts of climate change and biodiversity loss on ecological integrity are of significant concern. Hence, it is imperative to acknowledge the significance of international cooperation and sustainability measures in effectively tackling these challenges.

3. DATA AND METHODOLOGY

3.1. General Circulation Models

GCMs are complex computational framework used to simulate and analyze the complicated dynamics of the climate system on Earth. The GCMs consist of several crucial components, such as atmospheric models, ocean models, land surface models, and sea ice models. These components are based on well-established principles of physics, fluid dynamics, and thermodynamics, as well as other relevant scientific disciplines [68]. The Earth is partitioned into a three-dimensional grid (Figure 3.1), and the GCMs attempt to replicate the behavior of atmospheric phenomena, oceanic currents, energy exchanges, moisture transport, and other variables across these grid cells.

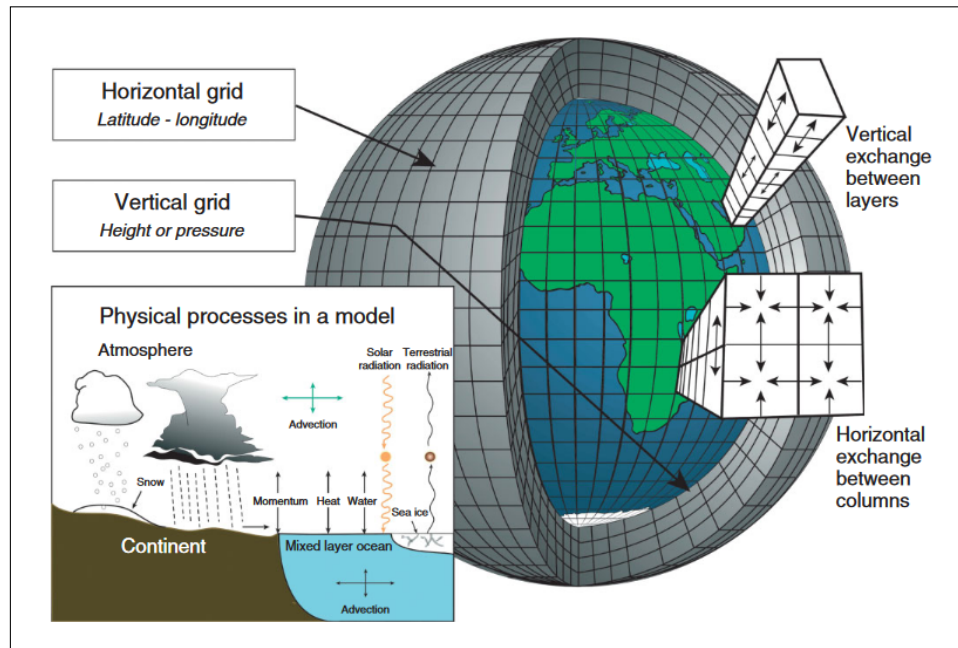


Figure 3.1. The finite-difference general circulation model employs a Cartesian grid structure [69].

3.2. Max Planck Institute for Meteorology Earth System Model

In this thesis, a well-known climate model known as the “Max Planck Institute Earth System Model” (MPI-ESM) is utilized. The MPI-ESM is a comprehensive model used to simulate and investigate the Earth’s climate system. It incorporates multiple components, including the atmosphere, ocean, land surface, and sea ice, to provide a holistic view of the climate of the Earth and its interactions. The model consists of coupled GCMs (Figure 3.2) for the atmosphere and ocean, ECHAM6 and MPIOM, in addition to subsystem models for land and vegetation, JSBACH, and marine biogeochemistry, HAMOCC5, respectively. By integrating these process models into the model system, the carbon cycle has been incorporated. For this research, institute’s mixed resolution of the earth system model (MPI-ESM-MR) that provides higher horizontal resolution in the ocean and greater vertical resolution in the atmosphere was used [70]. The MPI-ESM-MR model has a resolution of 1.9° on land, 0.4° on ocean, and 95 levels in vertical [70, 71].

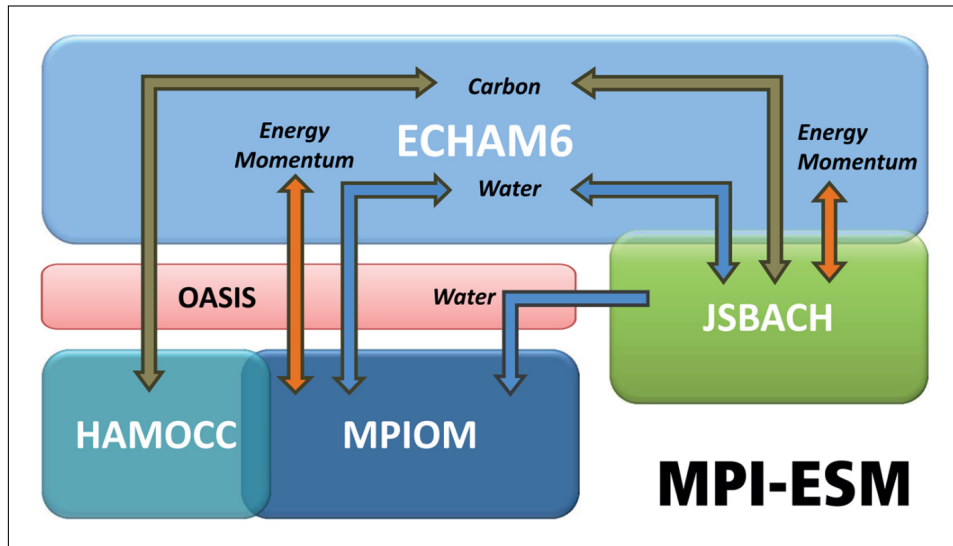


Figure 3.2. Schematic view of MPI-ESM [70].

3.3. Domain

This study focuses on Turkey, a transcontinental country between Europe and Asia. Turkey covers 783,562 square kilometers between 35° and 42° N and 25° and 45° E. The country has territorial boundaries with a combined total of eight neighboring countries. Countries located in the northwest are Greece and Bulgaria. In the northeast are Georgia, Armenia and Azerbaijan. Iran is located to the east and Iraq to the southeast. Finally, Syria is in the south. Turkey is surrounded by the Mediterranean Sea in the south and the Aegean Sea in the west. Turkey's northern border runs along the Black Sea coast.

Turkey has coastal plains, plateaus, and mountains. This location is ideal for studying the interaction between climate patterns and elevation changes (Figure 3.3). The research area includes the Anatolian Plateau, Taurus Mountains, Pontic Mountains, and Eastern Anatolian Mountains. Turkey is bisected by significant rivers such as the Euphrates, Tigris, and Kızılırmak, which impact regional climate patterns.

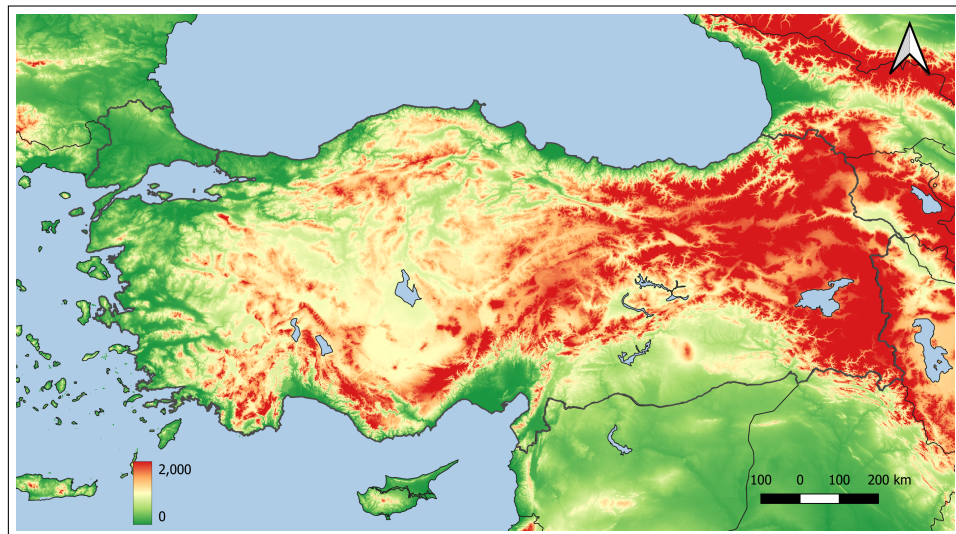


Figure 3.3. Elevation map of the study area.

The climate in Turkey displays a diverse range of variations as a result of its geographical diversity. The country has a variety of climatic zones, including Mediterranean, Aegean, Continental, Black Sea, Central Anatolian, Eastern Anatolian, and Southeastern Anatolian as categorized by the Köppen climate classification (Figure 3.4). The distribution of climate zones is determined by several factors, such as latitude, elevation, presence of water bodies, and wind patterns.

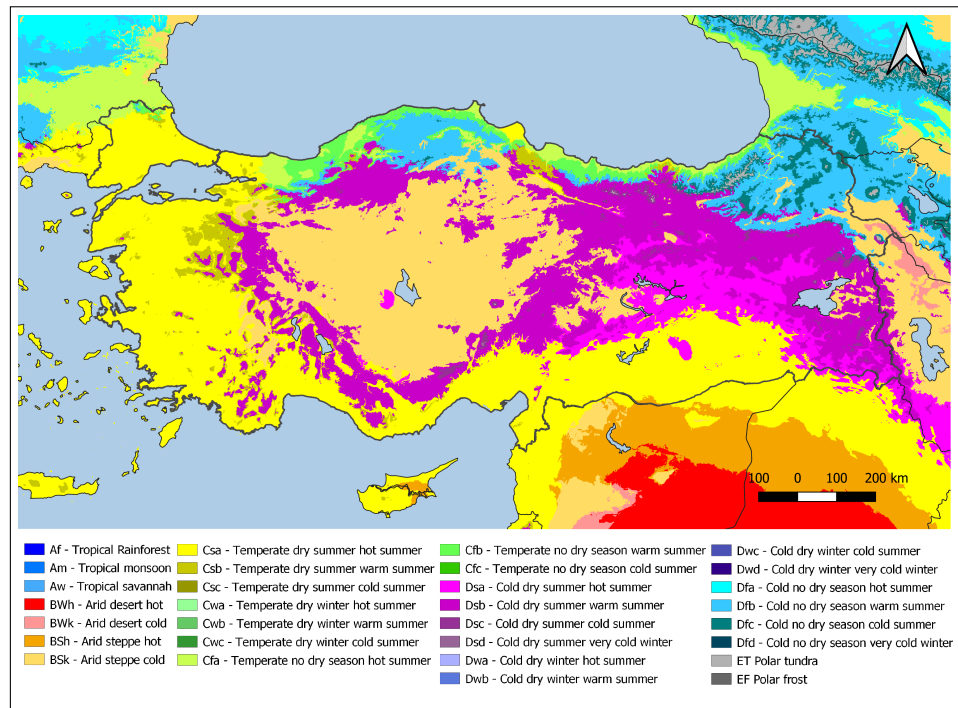


Figure 3.4. Köppen climate classification of study area [72, 73].

This thesis employed six distinct datasets, including two sets of 1km resolution data that covered specific regions, two sets of 5km resolution data representing different areas, and one dataset covering the whole country for both 10km and 20km resolution datasets. The decision to select specific areas for analysis at resolutions of 5km and 1km, rather than utilizing the entire geographic extent of Turkey, is caused by computational limitations. The rationale behind choosing these specific regions was driven by the objective of examining the impact of mountainous topography on the evaluation of downscaling techniques. The initial selection was made in favor of the Konya plain (Figure 3.5 a,b), which is recognized as the geographically least mountain-

ous area in Turkey. This region is centrally located within the Anatolian region. The second area was chosen as a representative of the highly mountainous regions situated in eastern Anatolia (Figure 3.5 c,d). Furthermore, the geographical regions chosen for the 5km resolution were characterized by larger dimensions in comparison to the areas designated for the 1km resolution.

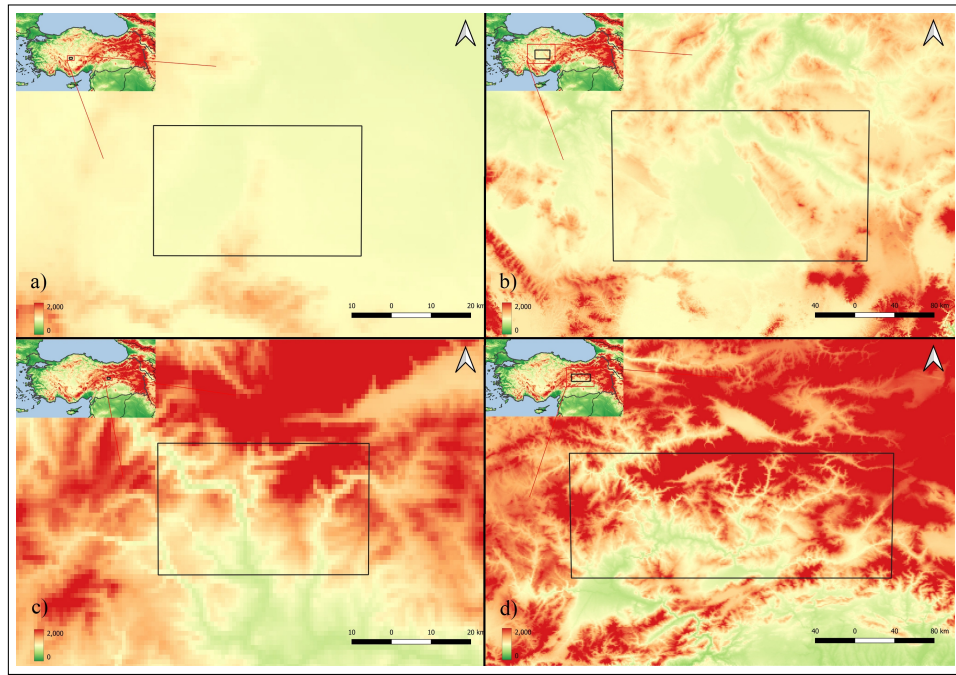


Figure 3.5. Study areas of (a) 1km resolution flat location, (b) 5km resolution flat location, (c) 1km resolution mountainous location, (d) 5km resolution mountainous location.

3.4. Downscaling Techniques

Due to their coarse horizontal resolution, GCMs are incapable of accounting for the complex and localized variations in climate variability and change. Numerous landscape features, such as mountains, aquatic bodies, infrastructure, and land-cover characteristics, as well as climate system components such as convective clouds and coastal winds, have dimensions much smaller than the 100–500 kilometer resolution typically employed by GCMs. These fine-scale heterogeneities play a crucial role for

decision makers who require precise information regarding potential impacts on crop production, hydrology, species distribution, and other factors at scales ranging around 10 kilometers [74]. Hence, atmosphere-ocean GCM outputs must be downscaled to depict climate changes at regional and local scales in order to enhance their utility for environmental degradation impact and adaptation research [75]. It entails the use of additional methodologies and models to refine the output of GCMs at a higher spatial resolution, typically between tens and a few hundred kilometers. There are two primary kinds of downscaling techniques: dynamical and statistical.

3.4.1. Dynamical Downscaling

Dynamical downscaling is an advanced technique used to improve the spatial resolution of climate model simulations for specific regions of interest. It overcomes the limitations of GCMs, which have a coarse resolution and cover extensive areas, by employing regional climate models (RCMs) that can simulate climate processes on a much finer scale.

In the process of dynamical downscaling, an RCM is nested within the GCM output. The GCM provides the boundary conditions to RCM, including large-scale atmospheric variables [76]. In turn, the RCM refines and downscales this information within its defined domain to generate high-resolution climate simulations for the area of interest (Figure 3.6).

An RCM with the designation RegCM4.7.0 was used during the course of this investigation. The Abdus Salam International Centre for Theoretical Physics is responsible for the development of the hydrostatic regional climate model known as RegCM4.7.0. It was designed with the purpose of addressing the interactions and dynamics of atmospheric processes within a constrained geographical area, making it possible to conduct an in-depth research of local effects of climate change.

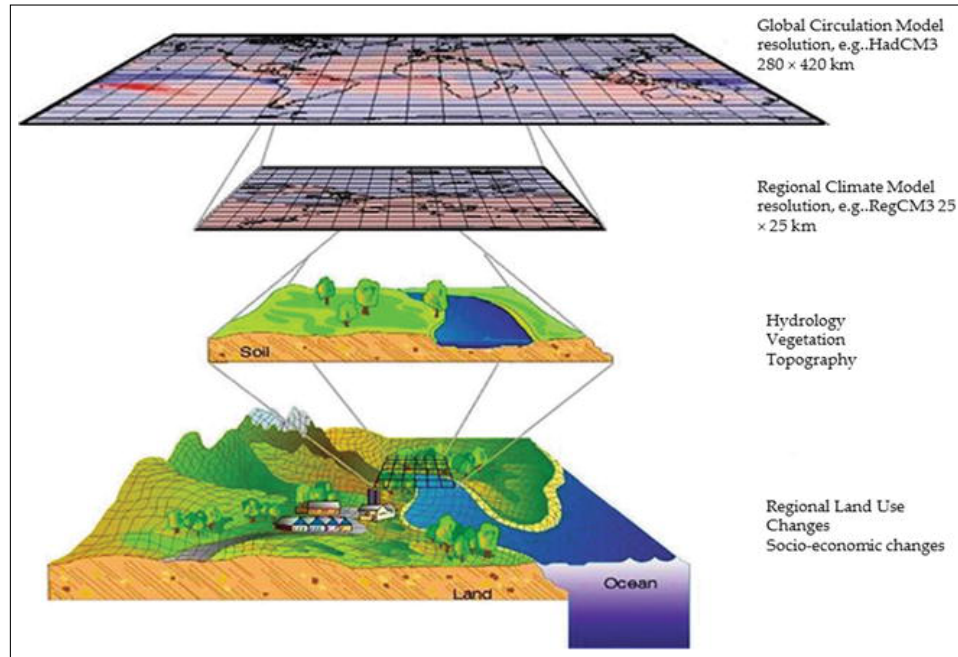


Figure 3.6. Schematic representation of regional climate modeling to obtain climate data at a finer resolution from coarser resolution [77].

The primary components of the RegCM modeling system are Terrain, Initial Condition and Boundary Conditions (ICBC), RegCM, and Postprocessor. Terrain and ICBC are two crucial components within the RegCM preprocessor. The preprocessor is in charge of preparing the necessary data and conditions for the RegCM simulation. In this context, three-dimensional meteorological data and terrestrial variables such as elevation, land use, and sea surface temperature are horizontally interpolated to a higher-resolution domain from a latitude-longitude mesh. In addition, the preprocessor manages vertical data interpolation. It entails transforming atmospheric variables from the GCM levels' vertical coordinate system to the RegCM's vertical coordinate system. This step assures compatibility and consistency between the data obtained from the GCM and the RCM, allowing for the simulation's seamless integration and accurate representation of atmospheric processes [78].

3.4.2. Statistical Downscaling

Statistical downscaling is an alternative method for generating high-resolution climate data for specific regions based on the outputs of GCMs. In contrast to the complexities involved in dynamical downscaling, statistical downscaling employs an empirical method to derive the necessary data. This feature significantly reduces the computational resources necessary for the downscaling process, making statistical downscaling a computationally efficient method.

Utilizing statistical downscaling methods has the primary advantage of requiring less computation. Researchers conducting high-resolution climate research can benefit from this method because it eliminates the need for advanced computational power, extensive storage capacity, and significant time investments to obtain the desired climate data. Using empirical relationships and historical observations, statistical downscaling transforms coarse-scale GCM outputs into fine-scale climate information, thereby facilitating detailed analyses of local and regional climate patterns without imposing excessive computational burdens.

Delta downscaling method is one of the statistical spatial downscaling methods. The method requires two primary inputs: a time series with a lower resolution and high-resolution climatology data. The high-resolution climatology should include a realistic and precise distribution of the meteorological variable across the landscape. The Delta method is preferred to direct interpolation of low spatial resolution data to a higher spatial resolution because it accounts for the intricate orographic effects present in high-resolution input grids that are absent in low-resolution input grids.

In other words, the Delta downscaling process offers a more sophisticated approach by taking into account fine-scale topographic influences, such as elevation variations and local terrain characteristics, which play a significant role in determining the local climate conditions. By incorporating these orographic effects at high resolution, the Delta method improves the accuracy and reliability of the downscaling process, re-

sulting in more accurate and realistic representations of climate patterns at the desired higher spatial resolution. It makes the Delta downscaling method a valuable tool for researchers seeking to capture fine-scale climate variations and comprehend the effect of regional topography on climate conditions [79].

3.5. WorldClim

WorldClim consists of spatially interpolated gridded climate data, derived from monthly averages of climate variables measured at weather stations and derived from a wide variety of global, regional, national, and local datasets [80]. The data relies primarily on 1970–2000 period and satellite-based information. Using the thin-plate smoothing spline algorithm employed in ANUSPLIN [81], satellite-derived data and other covariables were utilized to perform data interpolation. As a result, global climate surfaces for a variety of monthly parameters, such as precipitation, minimum, mean, and maximum temperatures, solar radiation, wind speed, and vapour pressure, were effectively generated. The WorldClim data is available in $0.008\bar{3}^\circ$, $0.041\bar{6}^\circ$, $0.08\bar{3}^\circ$, and $0.1\bar{6}^\circ$ resolutions which are approximately 1km, 5km, 10km, and 20km respectively at equator. The Delta method statistical downscaling process needs the high resolution sample data in corresponding resolution. WorldClim datasets have all high to middle resolution datasets for precipitation and temperature which are obtained by station data. Because of the suitability for use, WorldClim version 2.1 was used in this research.

3.6. Climate Data Operators

In this thesis, Climate Data Operators (CDO) were used to work with the climate files in Network Common Data Form (netCDF) format. CDO is a large collection of various operators designed to standardize the output processing of climate and prediction models. The functionality of these operators ranges from fundamental statistical and arithmetic operations to sophisticated spatial interpolation techniques. The ability of CDO to manage Gridded Binary format (GRIB) and netCDF datasets simultaneously within the same software package is a significant point. CDO's notable

characteristics include a large library of over 700 operators, a modular design that facilitates the simple integration of innovative operators, and an uncomplicated Uniplexed Information Computing System (UNIX) command line interface. CDO also facilitates efficient data processing by enabling the application of multiple operators to a dataset without requiring intermediate result storage. An important aspect of its reliability and robustness is its capacity to efficiently manage datasets with missing values. Its reputation as a potent resource for analyzing climate and prediction data is supported by the software’s capacity to efficiently process large datasets and adapt to various grid types [82].

The present study aims to compare dynamical and statistical downscaling techniques by evaluating the field and time correlations of two distinct datasets. To achieve this objective, two specific CDO operators, “fldcor” and “timcor,” are utilized. The “fldcor” operator enables a thorough examination of the correlation between time-averaged data resulting from statistical and dynamical downscaling techniques. In contrast, the “timcor” operator is used to evaluate the correlation between field-averaged data derived from statistical downscaling and dynamical downscaling. Utilizing these CDO operators, a rigorous and systematic investigation of the performance and dependability of downscaling methods is conducted.

On the basis of the field correlation and time correlations of two datasets, comparisons were conducted between dynamical and statistical downscaling methods. fldcor and timcor operators from CDO were employed for this purpose. To determine the field correlation value, the fldcor operator was first applied, followed by the calculation of time averages for all time steps, each containing the field correlation value. Similarly, the timcor operator was applied prior to computing field averages for all grid points, with each grid point containing the time correlation value.

3.6.1. Spatial Correlation

Field correlation, also referred to as spatial correlation, is a metric used to evaluate the similarity or relationship between two datasets over a given domain. Comparing the spatial distribution of the variable at each grid point or location in the two datasets yields the field correlation. The correlation coefficient, which ranges from -1 to 1, is a commonly employed metric for expressing the strength and direction of the relationship. A correlation value close to 1 is indicative of a strong positive relationship, signifying that the patterns of the variable in the two datasets tend to move in the same direction. A negative correlation value close to -1, on the other hand, indicates a strong negative relationship, demonstrating that the patterns move in opposite directions. A correlation value near zero signifies a weak or nonexistent relationship between the datasets. “fldcor” operator correlates all gridpoints of two fields for each timestep with following formula:

$$S(t) = \{x, i_1(t, x) \neq missval \wedge i_2(t, x) \neq missval\}, \quad (3.1)$$

$$o(t, 1) = \frac{\frac{\sum_{x \in S(t)} i_1(t, x) i_2(t, x) w(x) - \overline{i_1(t, x)} \overline{i_2(t, x)} \sum_{x \in S(t)} w(x)}{\sqrt{(\sum_{x \in S(t)} i_1(t, x)^2 w(x) - \overline{i_1(t, x)}^2 \sum_{x \in S(t)} w(x))}}}{\frac{\sqrt{(\sum_{x \in S(t)} i_2(t, x)^2 w(x) - \overline{i_2(t, x)}^2 \sum_{x \in S(t)} w(x))}}{1}}, \quad (3.2)$$

where $w(x)$ are the area weights obtained by the input streams.

3.6.2. Temporal Correlation

Temporal correlation, or time correlation, is a statistical measure used to compare two time series. The correlation coefficient, having values from -1 to 1, is frequently employed as a measure of temporal correlation. The temporal patterns of the variable in the two datasets likely follow a similar trend and tend to vary together over time if the correlation value is close to 1. An inverse association between the temporal patterns in the two datasets is indicated by a negative correlation value near to -1. There is little to no temporal connection between the datasets if the correlation value is near to zero. “timcor” operator correlates each gridpoint of two fields over all timesteps with

following formula:

$$S(x) = \{t, i_1(t, x) \neq missval \wedge i_2(t, x) \neq missval\}, \quad (3.3)$$

$$o(1, x) = \frac{\sum_{t \in S(x)} i_1(t, x) i_2(t, x) - \overline{ni_1(t, x) i_2(t, x)}}{\sqrt{\left(\sum_{t \in S(x)} i_1(t, x)^2 - \overline{ni_1(t, x)}^2\right) \left(\sum_{t \in S(x)} i_2(t, x)^2 - \overline{ni_2(t, x)}^2\right)}}, \quad (3.4)$$

where $w(x)$ are the area weights obtained by the input streams.

3.7. Data Preparation

Frequently, it is common practice to employ a combination of dynamical and statistical methodologies in various scientific disciplines. The process of dynamical-statistical downscaling encompasses the utilization of a RCM to downscale GCM output. This initial downscaling step is followed by the application of statistical equations to further downscale the RCM output to a finer resolution. By combining the dynamical and statistical approaches, this downscaling methodology aims to enhance the accuracy and resolution of climate projections at a local or regional scale [74]. The use of a dynamical downscaling approach has proven to be effective in improving the accuracy of climate model simulations. By incorporating high-resolution regional climate models, the dynamical downscaling technique enhances the spatial heterogeneity of trends and the long-term time evolution predicted by the GCMs. This partial correction is achieved by downscaling the GCM outputs to a finer resolution, which allows for a more detailed representation of local climate processes and topographic features. Consequently, the dynamical downscaling approach provides a more realistic depiction of regional climate patterns and their changes over time. The optimal outcomes were achieved by employing a synergistic integration of both the deterministic and stochastic approaches. [83].

In this thesis, a combination of both statistical and dynamical downscaling methods was employed in response to the findings. The years between 1970 and 2000 were used by the WorldClim dataset. In the focus of the study, a particular five-year period

in the middle of this range, spanning from 1984 to 1988, was selected. Additionally, data for the year 1983 was generated as spin-up year, although it was excluded from the analysis. The objective of this study is to assess the level of similarity between the outcomes derived from the integrated downscaling techniques and those obtained through direct dynamical downscaling at corresponding resolutions. To achieve this objective, various combinations of downscaling were utilized, including 1km, 5km, 10km, and 20km resolutions (Table 3.1). Dynamical downscaling was performed for the whole Turkey at 50km, 20km, and 10km resolutions, while selected regions were run at 5km and 1km resolutions. Following this, the process of statistical downscaling was implemented on these resolution levels utilizing the outcomes derived from lower resolution dynamical downscaling, and subsequently, a comparative analysis was conducted.

Table 3.1. Dynamical and statistical downscaling runs.

Dynamical Downscaling	Statistical Downscaling					
50km	1km first area	1km second area	5km first area	5km second area	10km	20km
20km	1km first area	1km second area	5km first area	5km second area	10km	
10km	1km first area	1km second area	5km first area	5km second area		
5km first area	1km first area					
5km second area		1km second area				
1km first area						
1km second area						

In this study, a total of seven dynamical downscaling processes and 17 statistical downscaling processes were employed. The statistical downscaling methodology involved the application of the spatial delta downscaling method, which aimed to generate climate datasets with a specific spatio-temporal resolution. The process began with the preparation of dynamically downscaled data, which were then interpolated to a standard latitude-longitude coordinate system.

To further refine the data, in step-1, the WorldClim dataset was upscaled to match the resolution of the dynamically downscaled data (Fig. 3.7). This upscaling was achieved by averaging the grid cells of the WorldClim data within each grid cell of the lower resolution data. The resulting upscaled WorldClim data were then subtracted

from the low-resolution dynamically downscaled MPI-ESM-MR data in next step (Fig. 3.7).

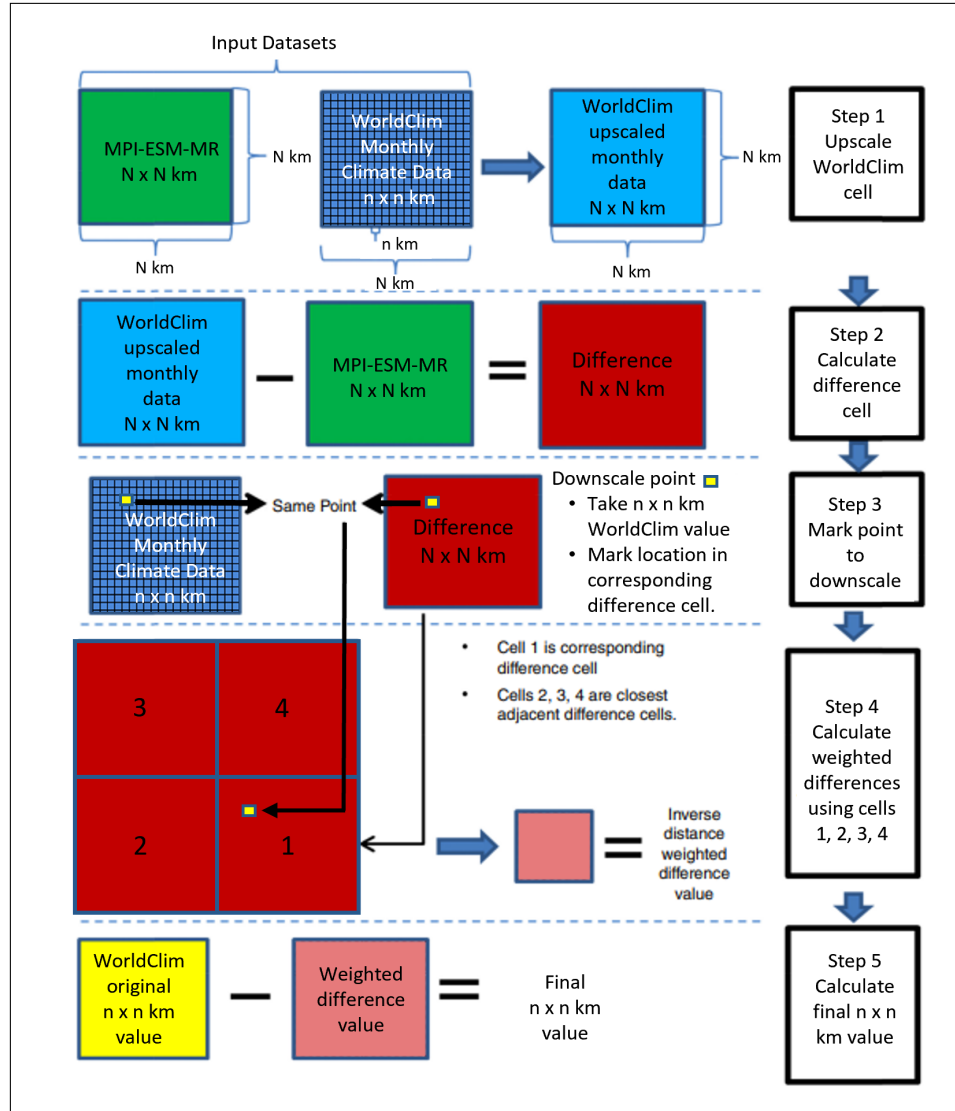


Figure 3.7. Flowchart of the delta downscaling method's methodology (Adapted from [84]).

In step-3, the coordinates of original WorldClim grids were assigned in difference data (Fig. 3.7). Subsequently, the difference data obtained from the subtraction was interpolated using the inverse distance weighting method, aligning it with the original WorldClim data's grid points in step-4 (Fig. 3.7). In the final step, the interpolated difference data was subtracted from the original WorldClim data, which shared the

same resolution and grid points (Fig. 3.7). The outcome of this subtraction provided the statistically downscaled climate data using the delta method.

It is noteworthy that the spatial delta downscaling method leveraged climate datasets with varying spatio-temporal resolutions to derive the desired high-resolution climate data, employing a step-by-step process as illustrated in Figure 3.7.

3.8. Materials

In this thesis, three different computers were used for dynamical downscaling. Each of these computers include 16GB of Random-Access Memory (RAM) and featured an Intel Xeon Central Processing Unit (CPU). The first computer utilized an E5-2620 v4 model CPU that operating at 2.10GHz and 32 cores. The other two computers employed an E5-2680 model CPUs that running at 2.70GHz, one with 32 cores and the other with 48 cores. 5km first area, 5km second area, and 50km dynamical downscaling were progressed in first computer. 1km second area data was created by second computer with 32 CPU and other datasets were prepared by third computer with 48 CPU.

To quantify the computational efficiency, the required times to compute one grid point for a single month using a single CPU were measured. For the 50km resolution, it took averagely 10.1 seconds per grid point. This time increased to 12.6 seconds for a 20km resolution, 15.1 seconds for a 10km resolution, 29.3 seconds for the 5km resolutions in first and second area, 108.2 seconds for the 1km resolution in the first area, and 124.8 seconds for the 1km resolution in the second area. These variations in computation time between similar resolutions can be attributed to the differences in the computational capabilities of the three computers.

According to these findings, dynamically downscaling the same region in different resolutions, such as a 100x100km region, it was observed that 40.4 seconds were required for 50km resolution, 315 seconds for 20km resolution, 1510 seconds for 10km resolution, 11720 seconds for 5km resolution, and 1160000 seconds for 1km resolution needed. It can be concluded that downscaling to a 1km resolution demands approximately 28712 times more computational time compared to downscaling to a 50km resolution for the same area.

4. RESULTS

4.1. Spatial Correlation of Precipitation

The spatial correlation of the precipitation results provide insight into the similarity of spatial distribution between the dynamical and statistical downscaling methods (Figure 4.1). The diverse outcomes observed in downscalings with the same resolution can be attributed to variations in geographical characteristics across different regions. The analysis of spatial correlation patterns in precipitation reveals that the second area, which is situated in a mountainous region, demonstrates slightly better performance in comparison to the first area located in a flat region.

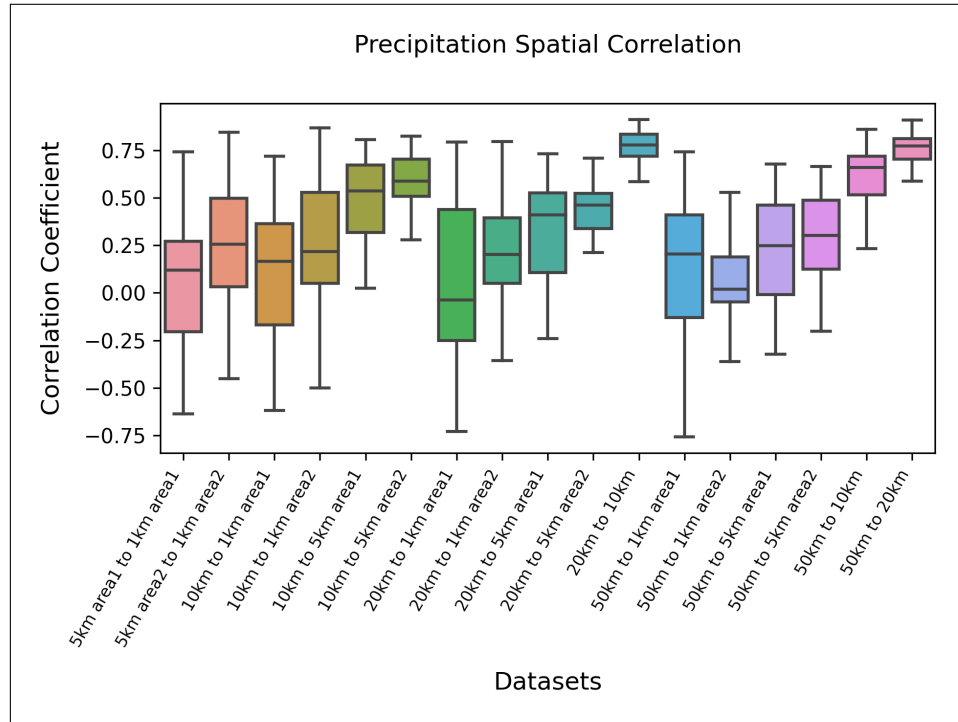


Figure 4.1. Temporal distribution of spatial correlation of precipitation as box plot without outliers. The plot displays the median, quartiles, and data range.

Additionally, the investigation demonstrates that downscaling from low-resolution to low-resolution yields more favorable outcomes compared to downscaling from high-

resolution to high-resolution and from low-resolution to high-resolution. The temporal distribution results show that downscaling from a resolution of 20km to 10km and from 50km to 20km yield the most favorable outcomes, as indicated by a median correlation coefficient of 0.75. The observed correlation coefficient demonstrates a strong positive correlation. Nevertheless, when downscaled at higher resolutions, there is a notable decrease in correlation coefficients. These coefficients range from no correlation to moderate correlation, and in some cases, even exhibit negative values. The median values for higher resolution downscaling exhibit correlation levels that range from low to moderate. Table 4.1 presents the descriptive statistics, including minimum, maximum, mean, and standard deviation values, for all downscale data.

Table 4.1. Statistical values of spatial correlation of precipitation.

Datasets	Minimum	Mean	Maximum	Standard Deviation
5km area1 to 1km area1	-0.636	0.059	0.742	0.326
5km area2 to 1km area2	-0.451	0.243	0.846	0.305
10km to 1km area1	-0.620	0.108	0.719	0.352
10km to 1km area2	-0.500	0.253	0.868	0.336
10km to 5km area1	0.024	0.503	0.805	0.213
10km to 5km area2	0.280	0.595	0.824	0.125
20km to 1km area1	-0.731	0.046	0.793	0.394
20km to 1km area2	-0.357	0.216	0.797	0.255
20km to 5km area1	-0.240	0.323	0.732	0.276
20km to 5km area2	-0.202	0.435	0.710	0.155
20km to 10km	0.519	0.775	0.913	0.082
50km to 1km area1	-0.758	0.137	0.743	0.365
50km to 1km area2	-0.362	0.062	0.621	0.200
50km to 5km area1	-0.324	0.206	0.679	0.273
50km to 5km area2	-0.202	0.290	0.666	0.239
50km to 10km	0.023	0.615	0.862	0.161
50km to 20km	0.416	0.757	0.910	0.084

The multi-year monthly mean of spatial correlation results for precipitation reveals distinct patterns between the first and second areas, as well as variations across different downscaled resolutions. In the first area, when downscaled to 1km resolution, there appears to be less correlation, and even negative correlation, during the summer months, which represent the driest period for the region (Figure 4.2). In February, the 50km and 20km to 1km datasets yield the most favorable results, yet still fall within the moderate correlation range. Conversely, in the second area at 1km downscaled resolution, the correlation during summer months shows more positive results compared to the spring and autumn seasons (Figure 4.3). For this area, all datasets, except for the 50km to 1km downscaled data, exhibit similar outcomes within the moderate correlation range for all months.

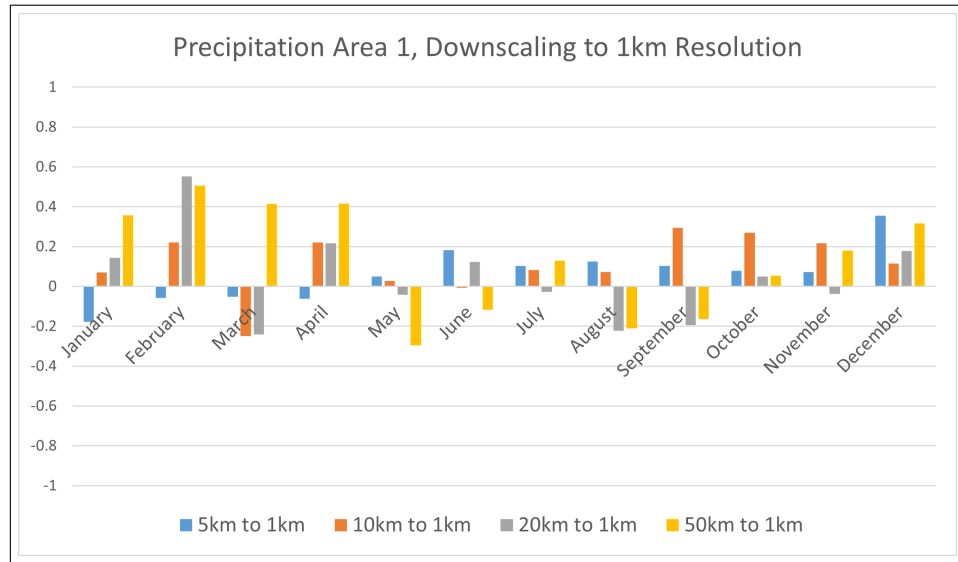


Figure 4.2. Multi-year monthly mean of spatial correlation of precipitation for the area 1 and 1km resolution.

When considering the 5km downscaled resolution datasets, the first area demonstrates better results respectively with 10km, 20km, and 50km to 5km resolutions (Figure 4.4). The months of May, June, July, and August show the most favorable outcomes, whereas the winter months exhibit lower to moderate degree correlations, while the summer months display moderate to high degree correlations. Similarly, for the second area, the 10km, 20km, and 50km to 5km downscaled resolutions yield improved results respectively, with consistent outcomes across all months for the 10km

and 20km datasets, while the 50km to 5km dataset shows no correlation for March and April (Figure 4.5).

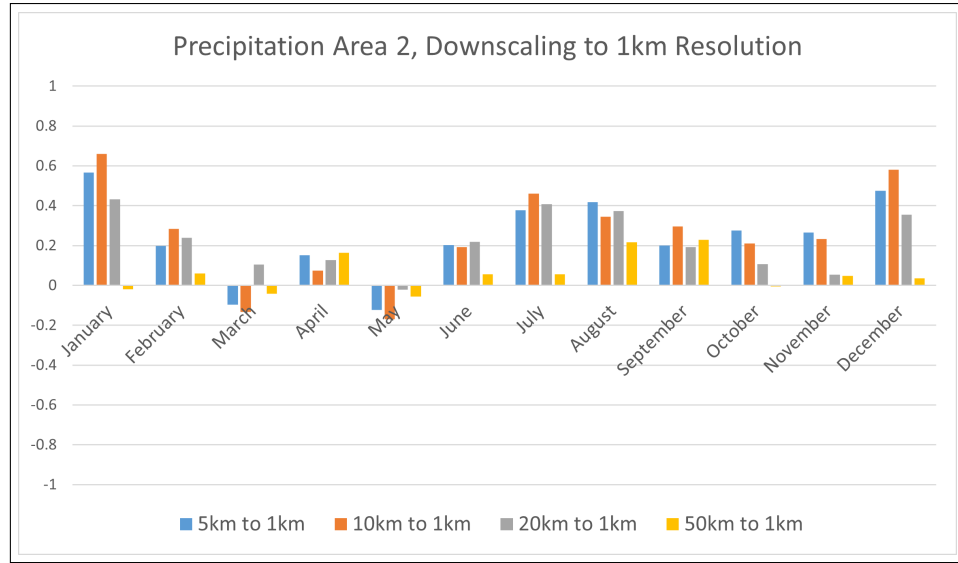


Figure 4.3. Multi-year monthly mean of spatial correlation of precipitation for the area 2 and 1km resolution.

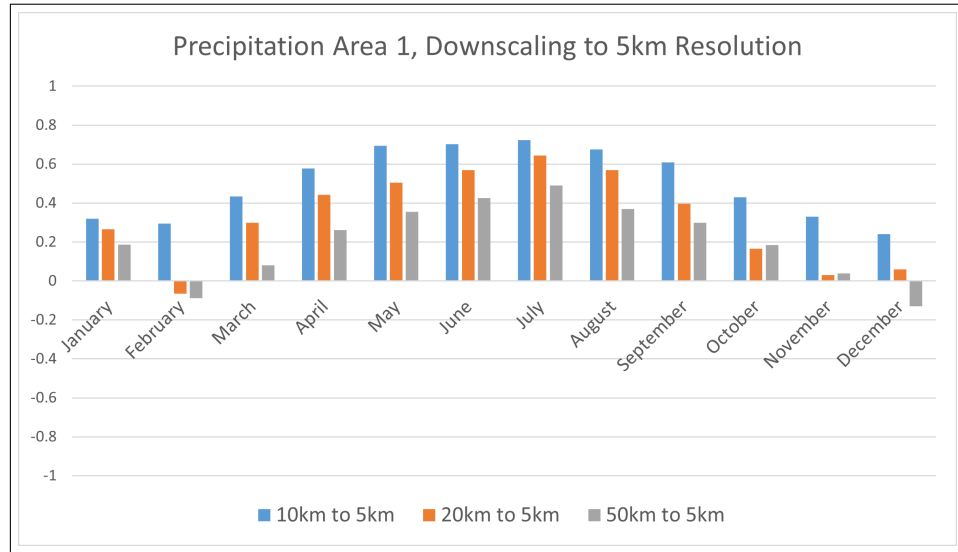


Figure 4.4. Multi-year monthly mean of spatial correlation of precipitation for the area 1 and 5km resolution.

On a broader scale encompassing the entire Turkey region, downscaling to 10km from 20km and 50km resolutions proves to be more effective than higher resolution

downscaling datasets. The 20km to 10km downscaling consistently performs better for all months compared to the 50km to 10km downscaling (Figure 4.6). Each month exhibits similar outcomes, with moderate to high degree correlations. Notably, the 50km to 20km downscaling yields very similar results to the 20km to 10km downscaling, following the same pattern across all months (Figure 4.7). Overall, the results indicate a high spatial correlation for the Turkey.

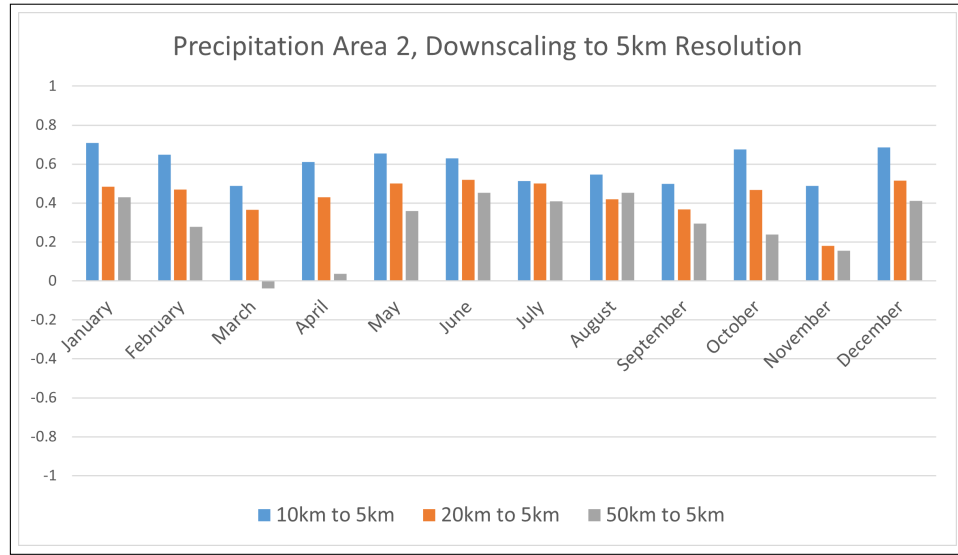


Figure 4.5. Multi-year monthly mean of spatial correlation of precipitation for the area 2 and 5km resolution.

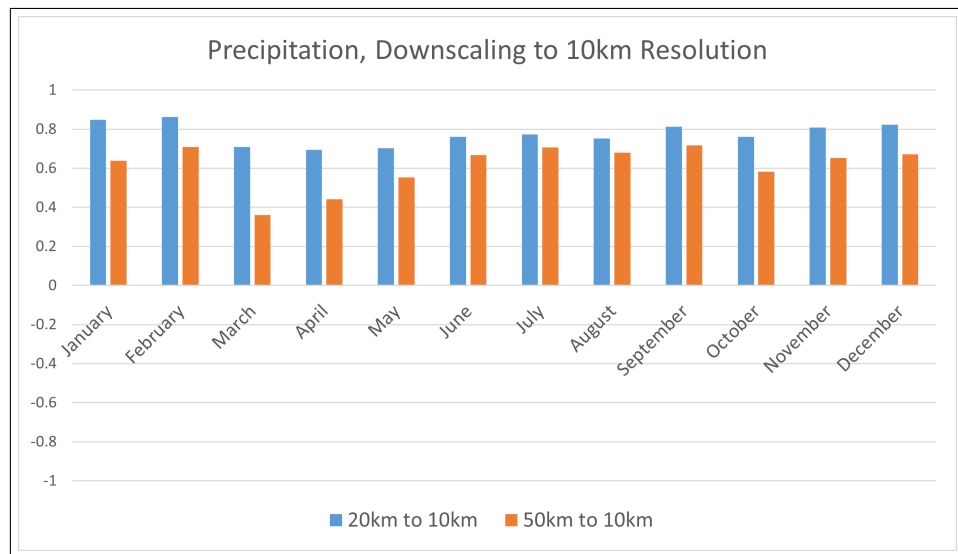


Figure 4.6. Multi-year monthly mean of spatial correlation of precipitation for the 10km resolution.

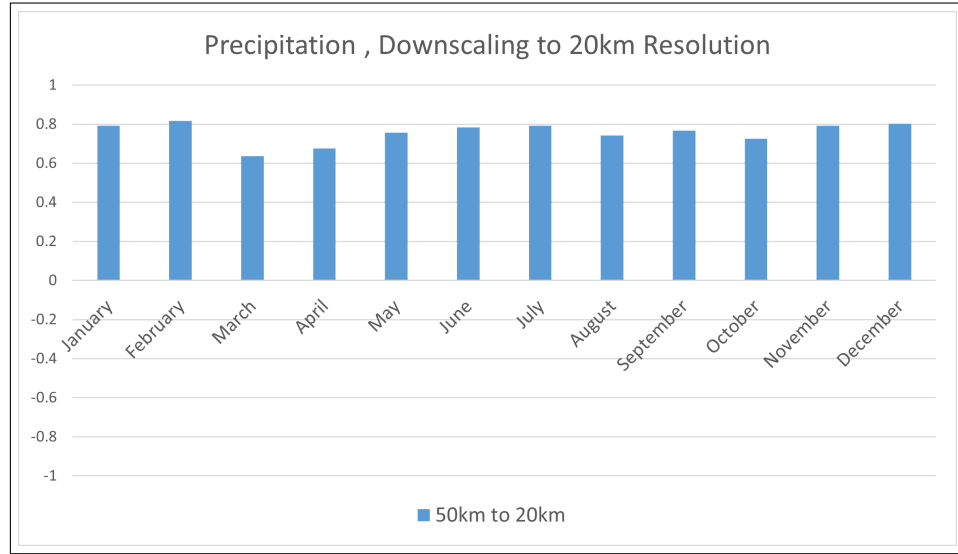


Figure 4.7. Multi-year monthly mean of spatial correlation of precipitation for the 20km resolution.

4.2. Spatial Correlation of Temperature

The spatial correlation of the temperature results provides insight into the similarity of spatial distribution between the dynamical and statistical downscaling methods (Figure 4.8). The diverse outcomes observed in downscalings with the same resolution can be attributed to variations in geographical characteristics across different regions. The analysis of spatial correlation patterns in temperature reveals that the first area, which is in a flat region, demonstrates highly worse performance in comparison to all other datasets. Since temperature is directly affected by the elevation, mountainous areas show better correlations between statistical and dynamical downscaling data.

Additionally, the investigation demonstrates that downscaling from low-resolution to low-resolution yields more favorable outcomes compared to downscaling from high-resolution to high-resolution and from low-resolution to high-resolution. The temporal distribution results show that downscaling from a resolution of 20km to 10km yield the most favorable outcome, as indicated by a median correlation coefficient of 0.98. The observed correlation coefficient demonstrates a perfect positive correlation. Although,

when downscaled at higher resolutions, there is a decrease in correlation coefficients, all results show high degree and perfect correlation except downscalings to 1km of first area. Coefficients for first area 1km downscaled datasets range from low to high correlation, and in some cases, close to no correlation. Table 4.2 presents the descriptive statistics, including minimum, maximum, mean, and standard deviation values, for all downscale data.

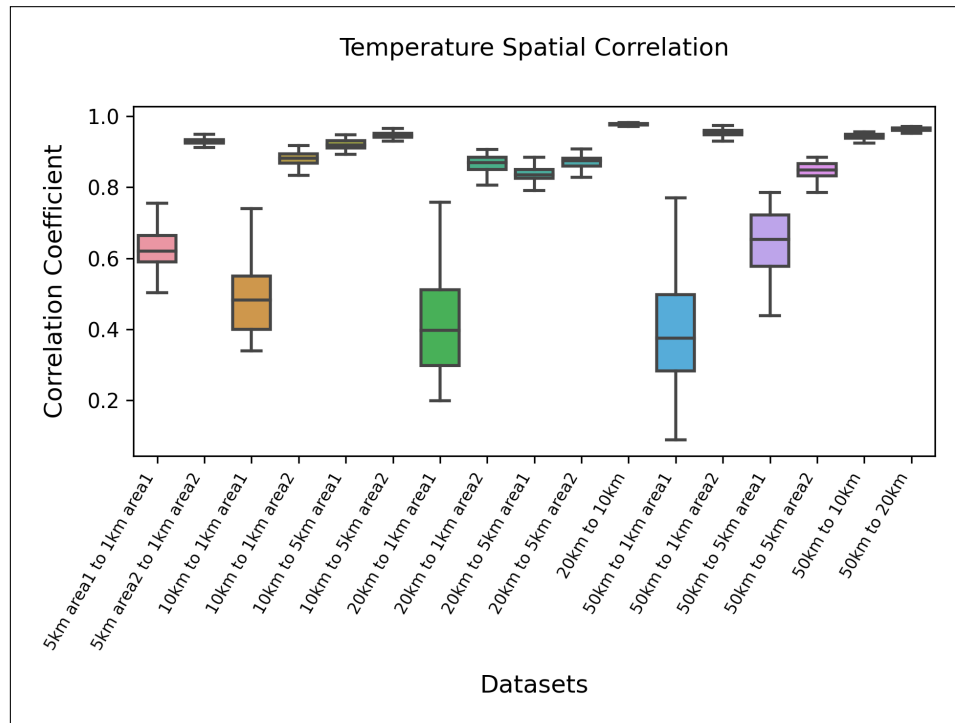


Figure 4.8. Temporal distribution of spatial correlation of temperature as box plot without outliers. The plot displays the median, quartiles, and data range.

The multi-year monthly mean of spatial correlation results for temperature reveals distinct patterns between the first and second areas, as well as variations across different downscaled resolutions. In the first area, when downscaled to 1km resolution, there appears to be slightly less correlation during the summer months, which represent the driest period for the region (Figure 4.9). 5km to 1km downscaling shows similar and high correlation results for all months while other downscaling datasets are in the range of low and moderate degree correlation range for the multi-year monthly means. In December, all datasets yield the close and high results, yet still fall within the moderate-high correlation range. Conversely, in the second area at 1km downscaled

resolution, the correlation values show much more positive results compared to the first area (Figure 4.10). For this area, all datasets, exhibit similar outcomes within the high and perfect correlation range for all months.

Table 4.2. Statistical values of spatial correlation of temperature.

Datasets	Minimum	Mean	Maximum	Standard Deviation
5km area1 to 1km area1	0.444	0.622	0.756	0.061
5km area2 to 1km area2	0.906	0.929	0.949	0.009
10km to 1km area1	0.339	0.489	0.740	0.093
10km to 1km area2	0.833	0.881	0.918	0.020
10km to 5km area1	0.893	0.920	0.948	0.013
10km to 5km area2	0.922	0.946	0.966	0.009
20km to 1km area1	0.200	0.415	0.757	0.130
20km to 1km area2	0.807	0.867	0.906	0.022
20km to 5km area1	0.781	0.837	0.896	0.023
20km to 5km area2	0.819	0.870	0.908	0.018
20km to 10km	0.969	0.977	0.983	0.003
50km to 1km area1	0.089	0.400	0.870	0.164
50km to 1km area2	0.917	0.953	0.973	0.012
50km to 5km area1	0.438	0.652	0.786	0.084
50km to 5km area2	0.785	0.848	0.885	0.022
50km to 10km	0.917	0.943	0.956	0.009
50km to 20km	0.946	0.964	0.972	0.006

When considering the 5km downscaled resolution, the first area demonstrates better results respectively with 10km, 20km, and 50km to 5km resolutions (Figure 4.11). Although 10km and 20km to 5km downscalings show high and perfect correlation results, 50km to 5km downscaling data demonstrates moderate for summer months. Similar to 1km downscaling datasets, second area results for 5km downscaling show higher correlation. For the second area, the 10km, 20km, and 50km to 5km downscaled resolutions yield improved results respectively, with consistent outcomes across all months for the all datasets, with the high correlations (Figure 4.12).

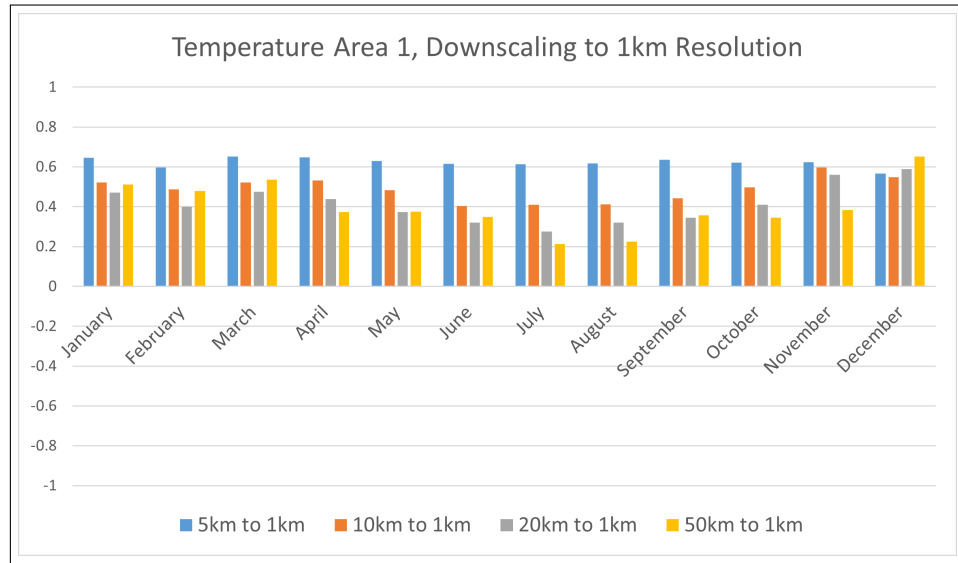


Figure 4.9. Multi-year monthly mean of spatial correlation of temperature for the area 1 and 1km resolution.

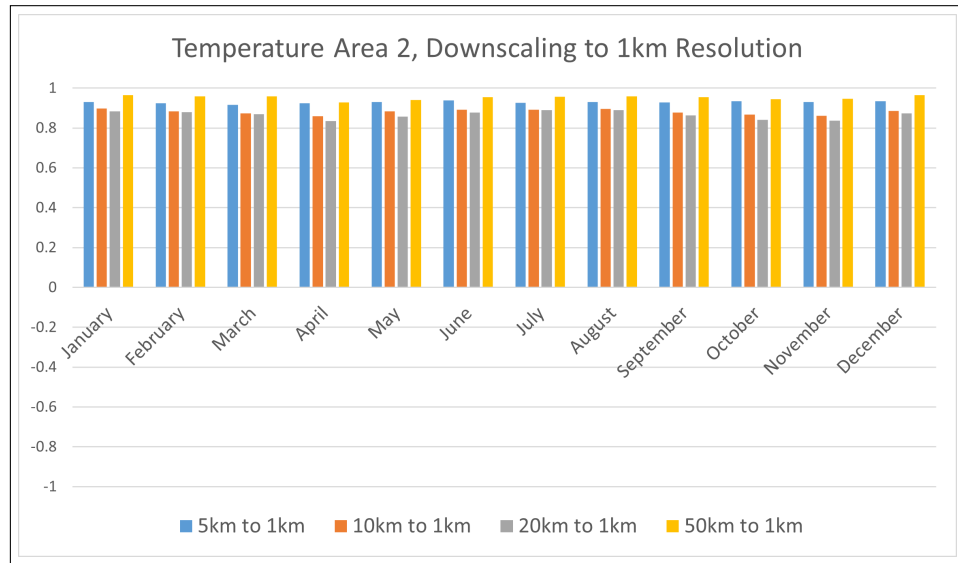


Figure 4.10. Multi-year monthly mean of spatial correlation of temperature for the area 2 and 1km resolution.

On a broader scale encompassing the entire Turkey region, downscaling to 10km from 20km and 50km resolutions proves to be more effective than higher resolution downscaling datasets. The 20km to 10km downscaling consistently performs slightly better for all months compared to the 50km to 10km downscaling (Figure 4.13). Each month exhibits similar outcomes, with perfect degree correlations. Notably, the 50km

to 20km downscaling yields very similar results to the 20km to 10km downscaling, following the same pattern across all months (Figure 4.14). Overall, the results indicate a perfect spatial correlation for the Turkey.

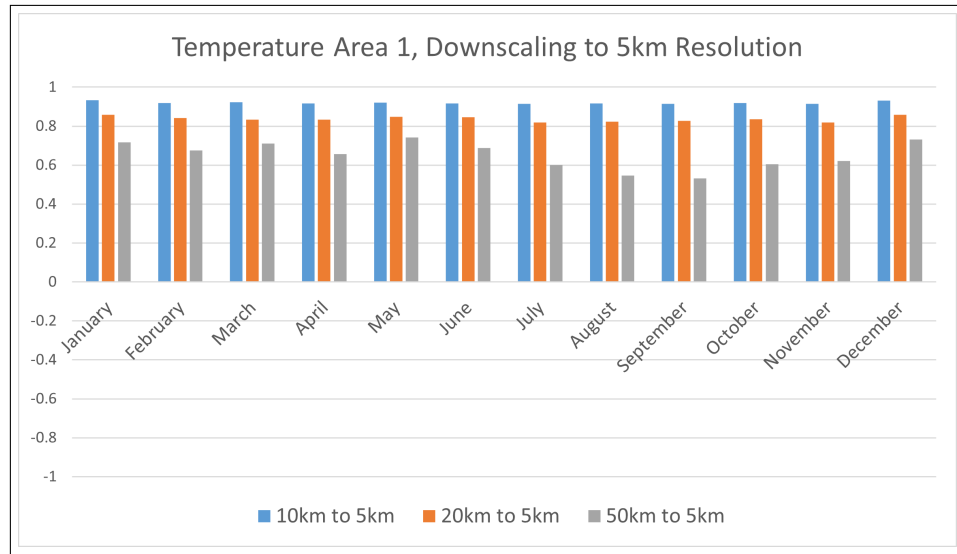


Figure 4.11. Multi-year monthly mean of spatial correlation of temperature for the area 1 and 5km resolution.

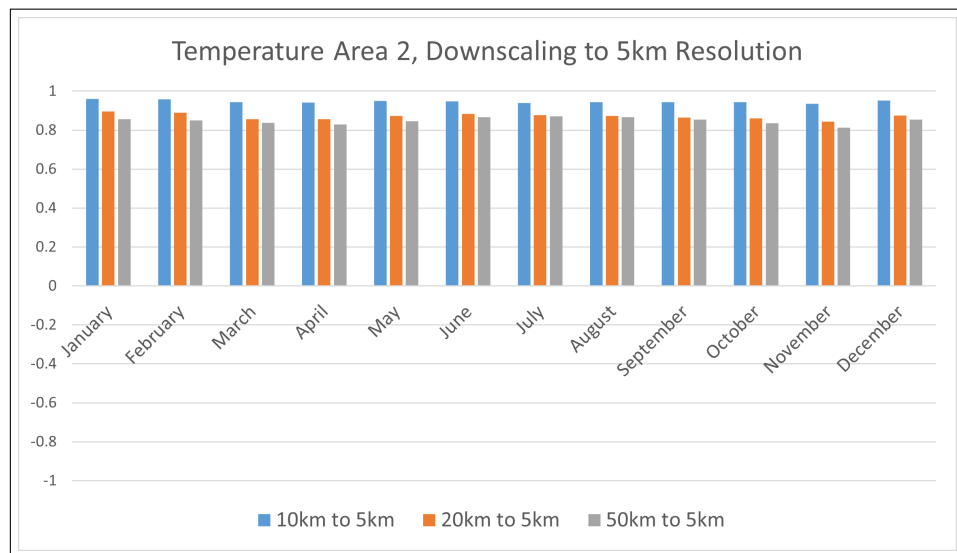


Figure 4.12. Multi-year monthly mean of spatial correlation of temperature for the area 2 and 5km resolution.

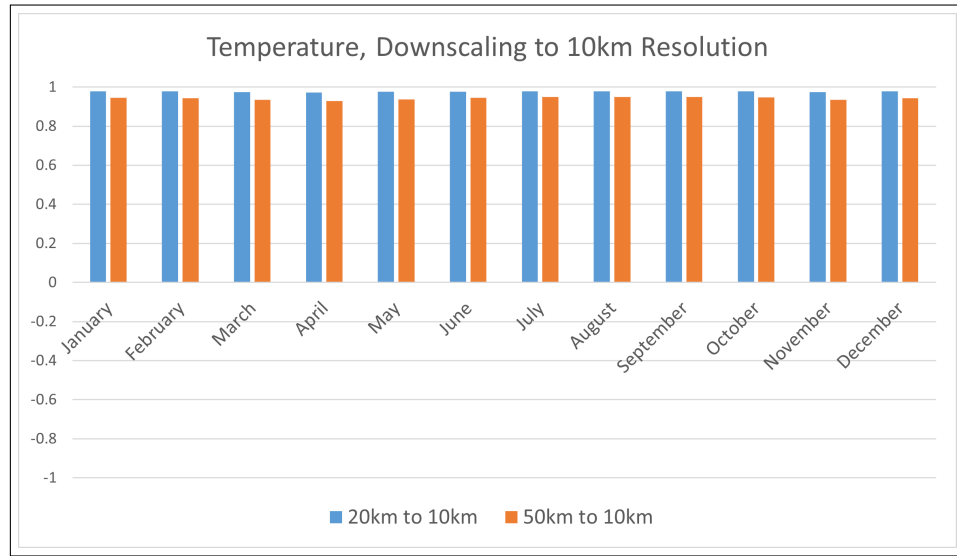


Figure 4.13. Multi-year monthly mean of spatial correlation of temperature for the 10km resolution.

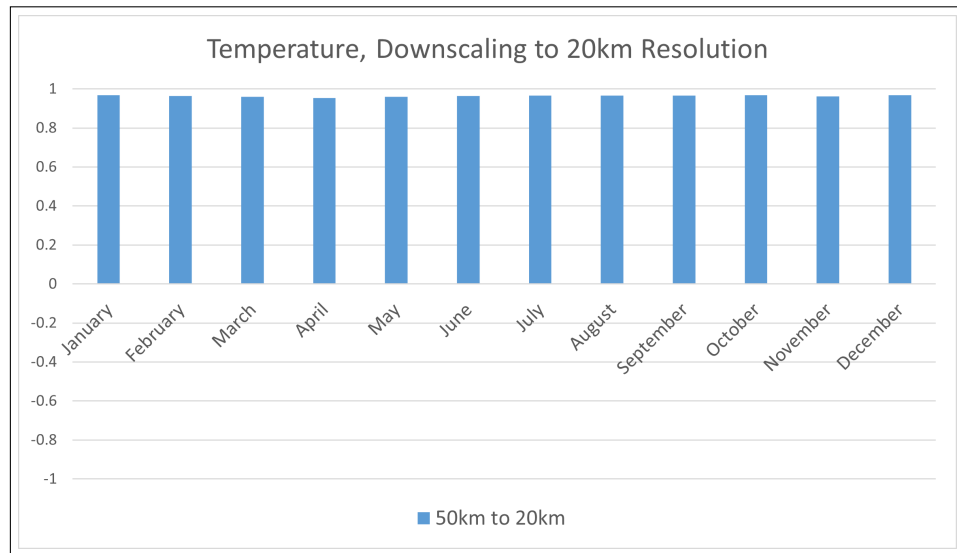


Figure 4.14. Multi-year monthly mean of spatial correlation of temperature for the 20km resolution.

4.3. Temporal Correlation of Precipitation

The temporal correlation of the precipitation results provides insight into the similarity of temporal distribution between the dynamical and statistical downscaling methods (Figure 4.15). The diverse outcomes observed in downscalings with the same

resolution can be attributed to variations in geographical characteristics across different regions. The analysis of temporal correlation patterns in precipitation reveals that the first area, which is in a flat region, demonstrates slightly better performance in comparison to the second area located in a mountainous region.

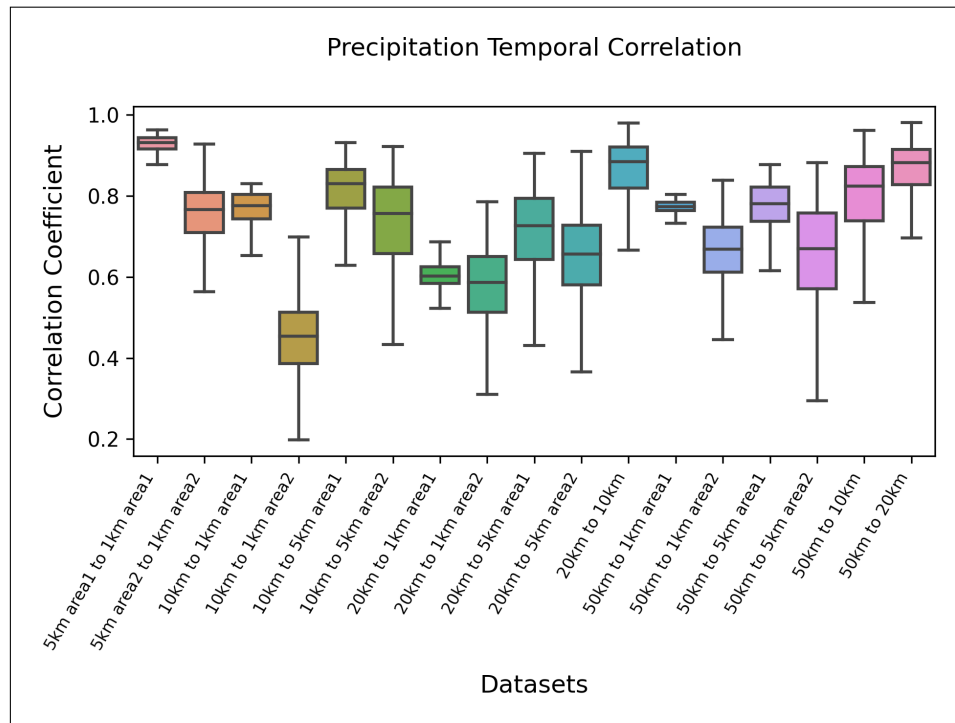


Figure 4.15. Spatial distribution of temporal correlation of precipitation as box plot without outliers. The plot displays the median, quartiles, and data range.

Additionally, the investigation demonstrates that there is no direct correlation between the temporal correlation results and downscaling resolutions. The temporal distribution results show that downscaling from a resolution of 5km to 1km in first area yield the most favorable outcome, as indicated by a median correlation coefficient of 0.93. The observed correlation coefficient demonstrates a very high positive correlation. Nevertheless, in some downscaled datasets, there is a notable decrease in correlation coefficients. These coefficients range from very low correlation to high correlation. Table 4.3 presents the descriptive statistics, including minimum, maximum, mean, and standard deviation values, for all downscale data.

Table 4.3. Statistical values of temporal correlation of precipitation.

Datasets	Minimum	Mean	Maximum	Standard Deviation
5km area1 to 1km area1	0.873	0.928	0.963	0.019
5km area2 to 1km area2	0.455	0.758	0.928	0.078
10km to 1km area1	0.567	0.767	0.831	0.046
10km to 1km area2	0.132	0.447	0.751	0.103
10km to 5km area1	0.559	0.815	0.931	0.065
10km to 5km area2	0.227	0.734	0.922	0.115
20km to 1km area1	0.443	0.603	0.702	0.036
20km to 1km area2	0.286	0.575	0.785	0.098
20km to 5km area1	0.431	0.714	0.905	0.095
20km to 5km area2	0.057	0.646	0.909	0.120
20km to 10km	-0.004	0.853	0.979	0.103
50km to 1km area1	0.684	0.771	0.804	0.019
50km to 1km area2	0.374	0.662	0.839	0.087
50km to 5km area1	0.584	0.777	0.877	0.054
50km to 5km area2	0.096	0.650	0.882	0.142
50km to 10km	0.106	0.791	0.962	0.114
50km to 20km	-0.039	0.852	0.982	0.104

The map of temporal correlation for precipitation reveals distinct patterns between the first and second areas, as well as variations across different downscaled resolutions. In the first area, when downscaled to 1km resolution, there appears mostly homogeneously distributed values (Figure 4.16). As the area is mostly flat, there are no significant changes for precipitation in close regions. 5km to 1km downscaling shows best and very high correlation results for all region while other downscaling datasets are in the range of low to high degree correlation range. The south edge of the region shows slightly different correlation coefficients because of the small elevation changes at that part. Conversely, in the second area at 1km downscaled resolution, the correlation values show more non-homogeneous distribution compared to the first area (Figure 4.17). For this area, all exhibit similar spatial distributions driven by the mountains at the region. The second area shows less favorable results than the first area.

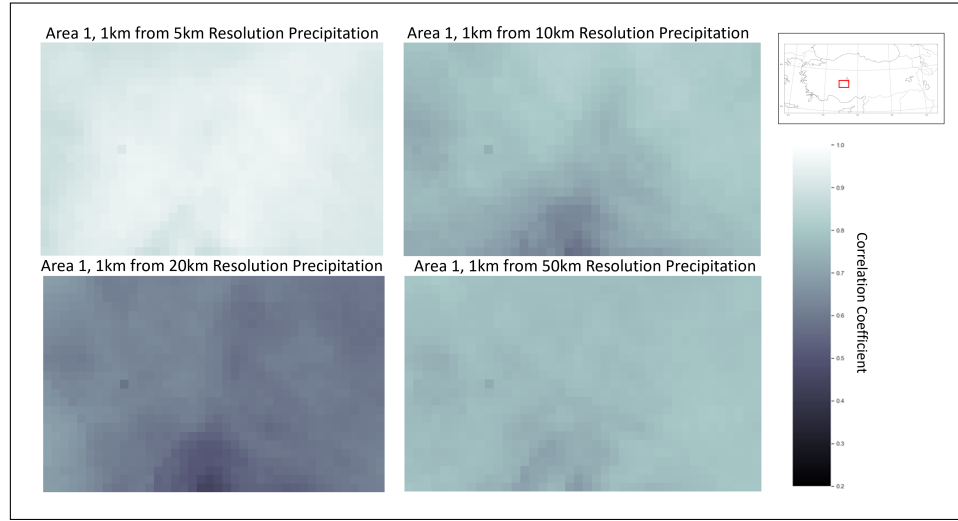


Figure 4.16. Map of temporal correlation of precipitation for the area 1 and 1km resolution data.

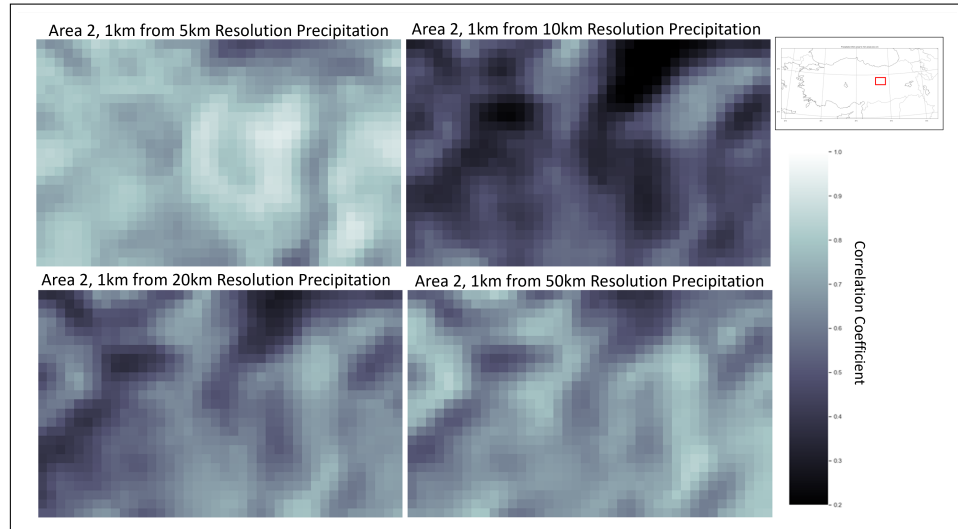


Figure 4.17. Map of temporal correlation of precipitation for the area 2 and 1km resolution data.

When considering the 5km downscaled resolution datasets, each area demonstrates spatial distribution that driven by the elevation changes. Similar to 1km downscaling datasets, first area shows more equally distributed values (Figure 4.18) while the second area has sharp changes on values within short distances (Figure 4.19). In addition to the changes in elevation, water masses also effect the results. For the first area, Lake Tuz is one of the important factors that effects the results and Keban Dam

is effective for the second area. Especially, in the first region, 10km to 5km resolution map shows obvious effect of Lake Tuz with decreasing correlation values of grids inside the lake.

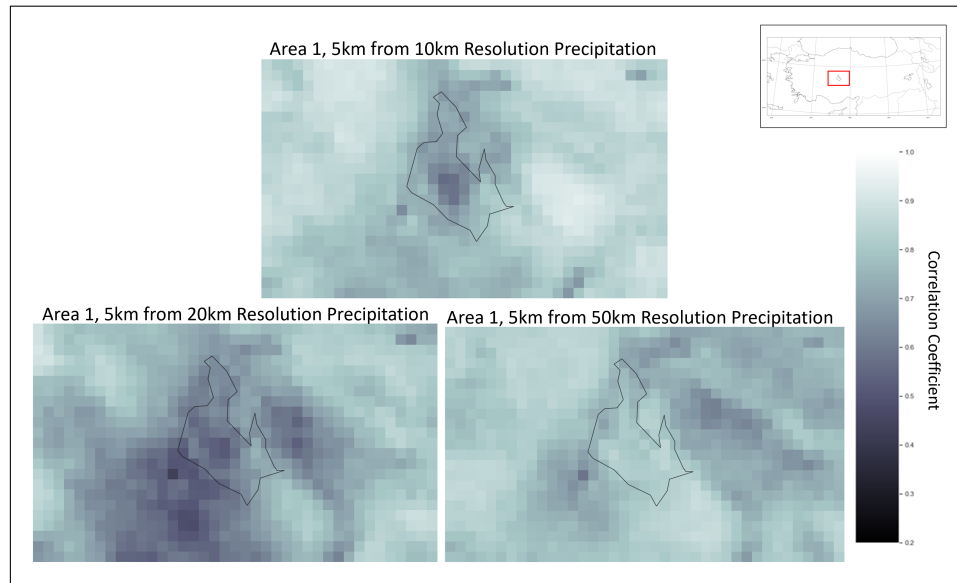


Figure 4.18. Map of temporal correlation of precipitation for the area 1 and 5km resolution data.

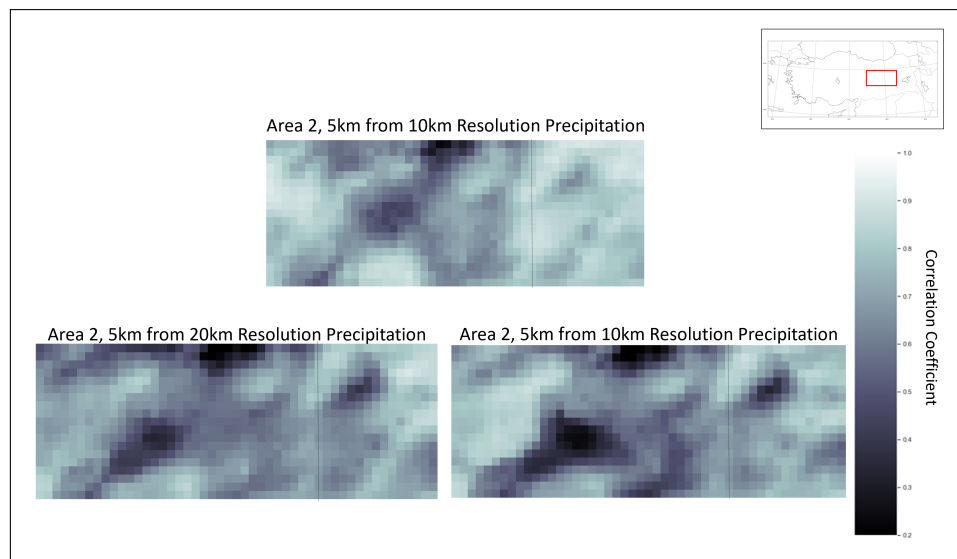


Figure 4.19. Map of temporal correlation of precipitation for the area 2 and 5km resolution data.

On a broader scale encompassing the entire Turkey, downscaling to 10km from 20km and 50km resolutions shows the effects of topography and water mass on temporal correlation values. The 20km to 10km downscaling consistently performs slightly better for all region compared to the 50km to 10km downscaling (Figure 4.20). Regionally, correlation degrees range from low to high degree for both datasets. Notably, the 50km to 20km downscaling yields very similar results to the 10km downscaled datasets, following the same pattern across all regions (Figure 4.21). Especially Caucasus Mountains and Eastern Black Sea coasts show the worst results. Overall, the results indicate a moderate to high temporal correlation for the Turkey region.

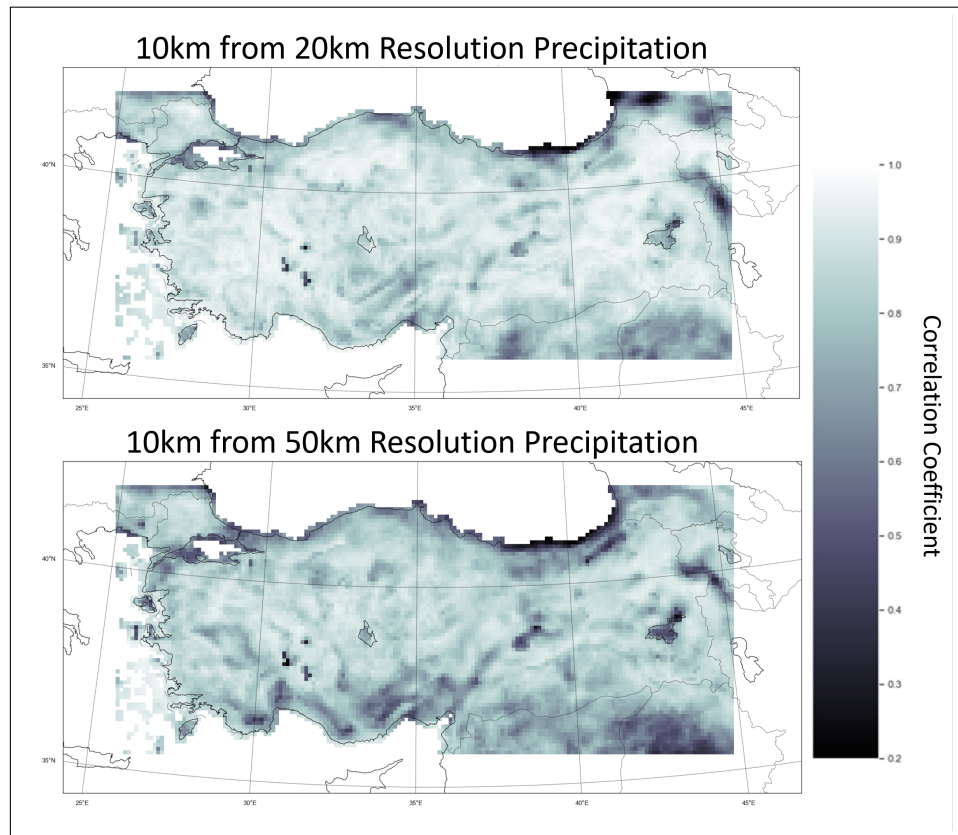


Figure 4.20. Map of temporal correlation of precipitation for the 10km resolution data.

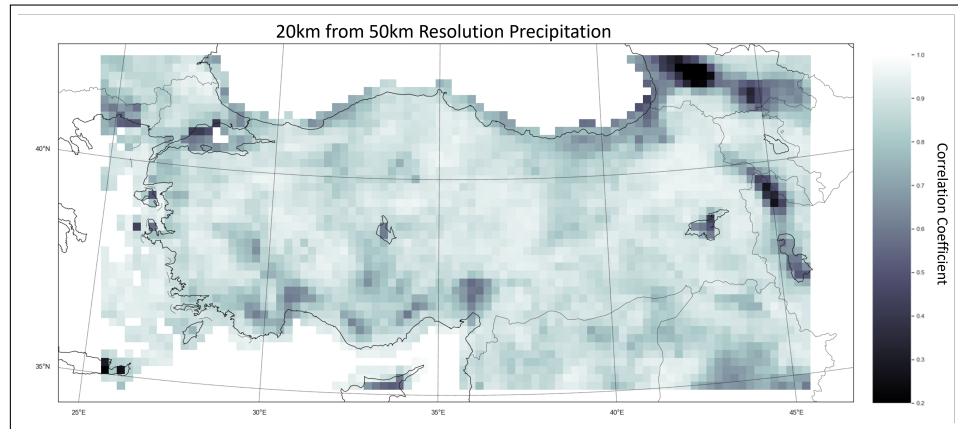


Figure 4.21. Map of temporal correlation of precipitation for the 20km resolution data.

4.4. Temporal Correlation of Temperature

The temporal correlation of the temperature results provides insight into the similarity of temporal distribution between the dynamical and statistical downscaling methods (Figure 4.22). The diverse outcomes observed in downscalings with the same resolution can be attributed to variations in geographical characteristics across different regions. The analysis of temporal correlation patterns in temperature reveals that all datasets have great performance. The results are all above the 0.99 correlation coefficient values which gives perfect temporal correlation for all grid points.

Additionally, the analysis demonstrates that except for 5km, other datasets that downscaled to 1km resolution for the first area have slightly lower values in comparison to others. Generally, low-to-low resolution downscalings have better results. The temporal distribution results show that downscaling from a resolution of 20km to 10km yield the most favorable outcome, as indicated by a median correlation coefficient of 0.999. The observed correlation coefficient demonstrates a perfect positive correlation. Besides 20km to 10km downscale dataset, all other downscaled datasets show perfect correlation. These coefficients range from 0.993 to 1 correlation coefficient values. Table 4.4 presents the descriptive statistics, including minimum, maximum, mean, and standard deviation values, for all downscale data.

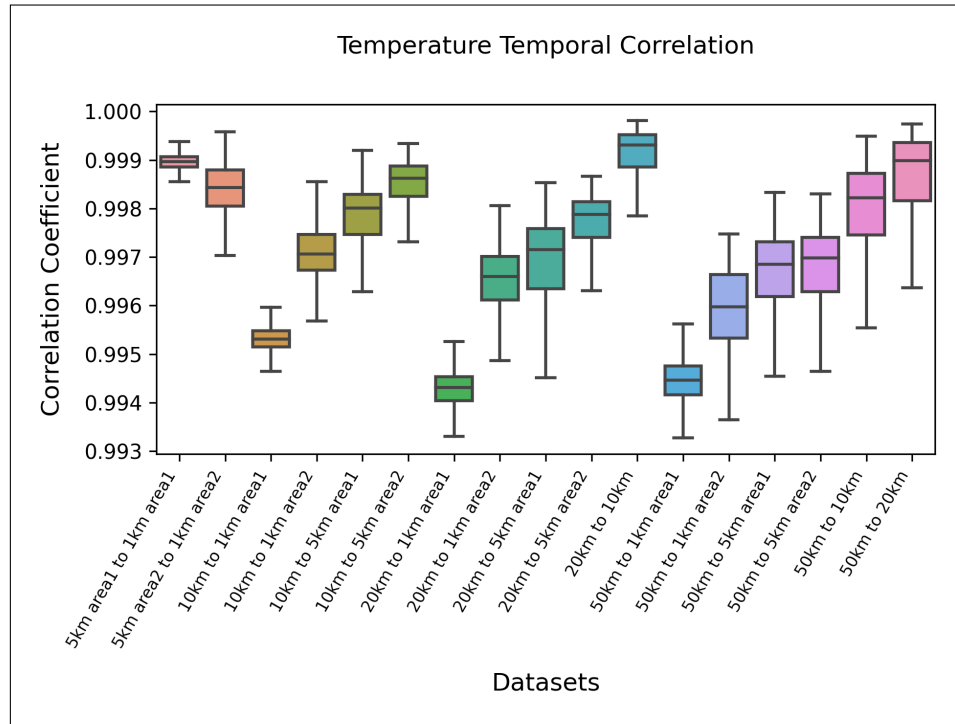


Figure 4.22. Spatial distribution of temporal correlation of temperature as box plot without outliers. The plot displays the median, quartiles, and data range.

The map of temporal correlation for temperature reveals distinct patterns between the first and second areas, as well as variations across different downscaled resolutions. In the first area, when downscaled to 1km resolution, there appears mostly homogeneously distributed values (Figure 4.23). Since the area is mostly flat, there are no significant changes for temperature in close regions. 5km to 1km downscaling shows best correlation results for entire region like other downscaling datasets. In the second area at 1km downscaled resolution, the correlation values show slightly less homogeneous distribution compared to the first area (Figure 4.24). For this area, all datasets, exhibit similar spatial distributions which driven by the mountains at the region. Most striking point for the second area is that the grid points inside the Keban Dam indicates less temporal correlation which can be recognized easily in Figure 4.24. Besides, these lower values are in the perfect correlation range.

Table 4.4. Statistical values of temporal correlation of temperature.

Datasets	Minimum	Mean	Maximum	Standard Deviation
5km area1 to 1km area1	0.999	0.999	0.999	0.000
5km area2 to 1km area2	0.993	0.998	1.000	0.001
10km to 1km area1	0.994	0.995	0.996	0.000
10km to 1km area2	0.990	0.997	0.999	0.001
10km to 5km area1	0.988	0.998	0.999	0.001
10km to 5km area2	0.992	0.998	0.999	0.001
20km to 1km area1	0.993	0.994	0.996	0.000
20km to 1km area2	0.989	0.996	0.998	0.001
20km to 5km area1	0.987	0.997	0.999	0.002
20km to 5km area2	0.993	0.998	0.999	0.001
20km to 10km	0.967	0.999	1.000	0.002
50km to 1km area1	0.993	0.994	0.996	0.000
50km to 1km area2	0.990	0.996	0.997	0.001
50km to 5km area1	0.986	0.996	0.998	0.002
50km to 5km area2	0.992	0.997	0.998	0.001
50km to 10km	0.958	0.998	0.999	0.002
50km to 20km	0.965	0.998	1.000	0.003

When considering the 5km downscaled resolution datasets, each area demonstrates spatial distribution that is driven by the water mass. Similar to 1km downscaling datasets, first area shows more equally distributed values except the Lake Tuz (Figure 4.25) while the second area has sharper changes on values within short distances (Figure 4.26). The effects of water masses can be seen obviously in 5km downscaled maps. For the first area, Lake Tuz is one of the important factors that effects the results and Keban Dam is for the second area. Especially, in the first region, maps show obvious effect of Lake Tuz with decreasing correlation values of grids inside the lake.

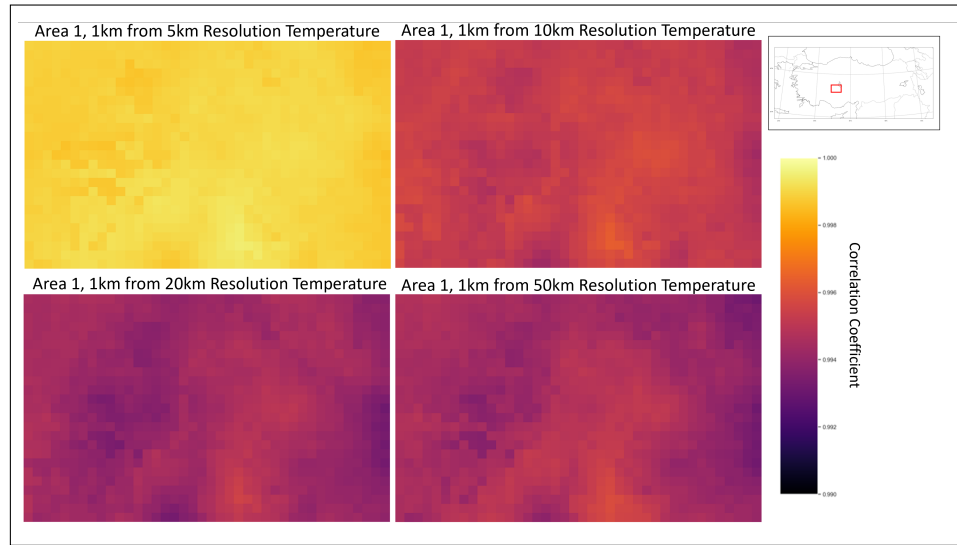


Figure 4.23. Map of temporal correlation of temperature for the area 1 and 1km resolution data.

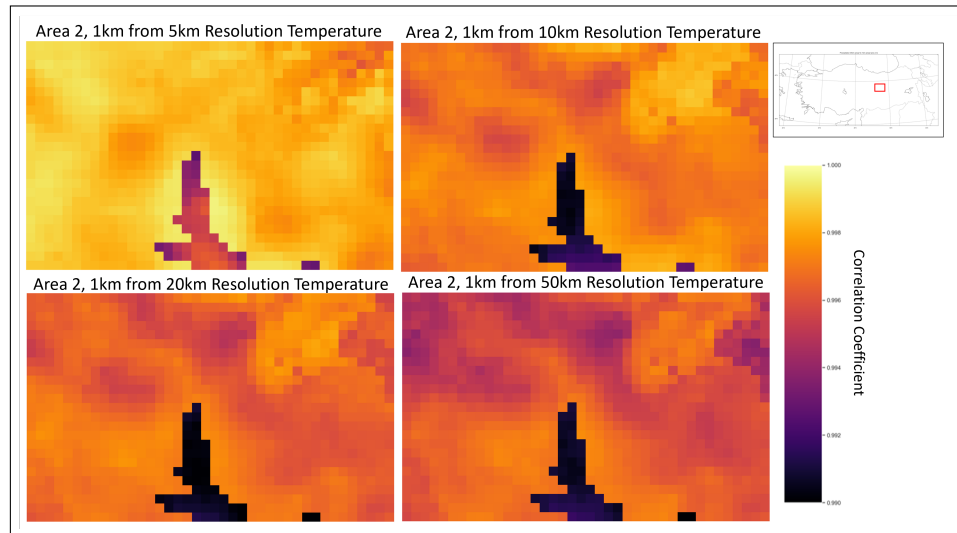


Figure 4.24. Map of temporal correlation of temperature for the area 2 and 1km resolution data.

On a broader scale encompassing the entire Turkey, downscaling to 10km from 20km and 50km resolutions shows the effects of topography and water mass on temporal correlation values. The 20km to 10km downscaling consistently performs slightly better for all region compared to the 50km to 10km downscaling (Figure 4.27). Regionally, correlation degrees are in the range of perfect correlation for both datasets. Notably, the

50km to 20km downscaling yields very similar results to the 10km downscaled datasets, following the same pattern across all regions (Figure 4.28). In these three datasets, especially Aegean and Mediterranean Sea coast lines show the worst results with the Lake Van and Lake Tuz. Overall, the results indicate perfect temporal correlation for the Turkey.

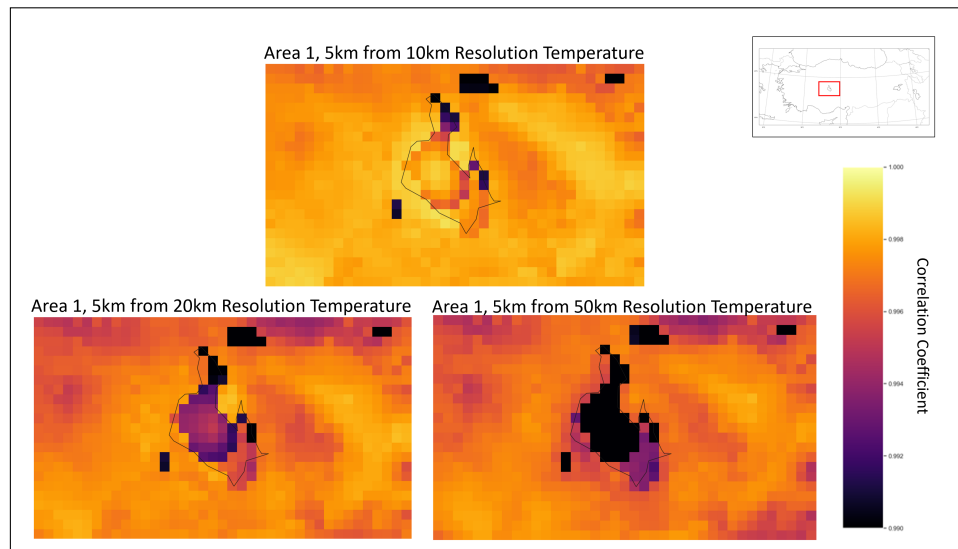


Figure 4.25. Map of temporal correlation of temperature for the area 1 and 5km resolution data.

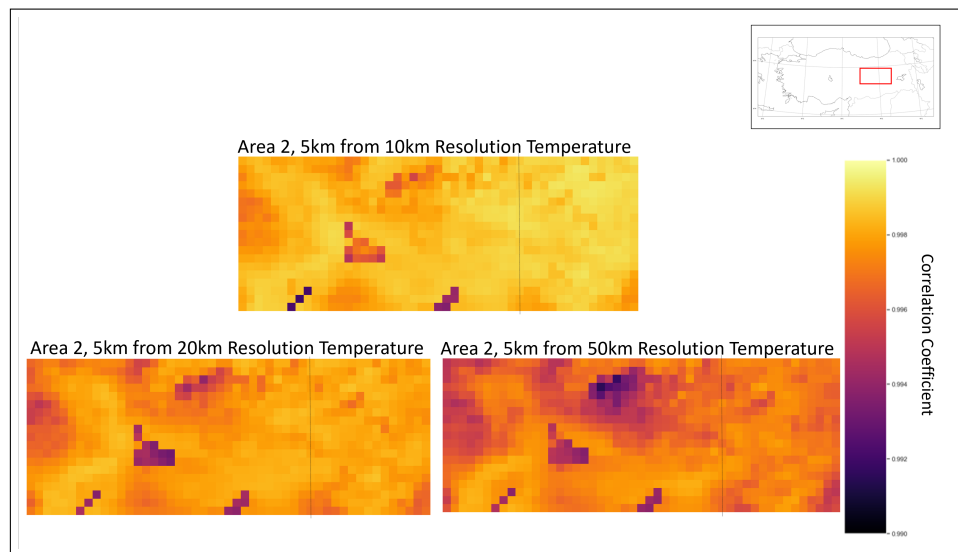


Figure 4.26. Map of temporal correlation of temperature for the area 2 and 5km resolution data.

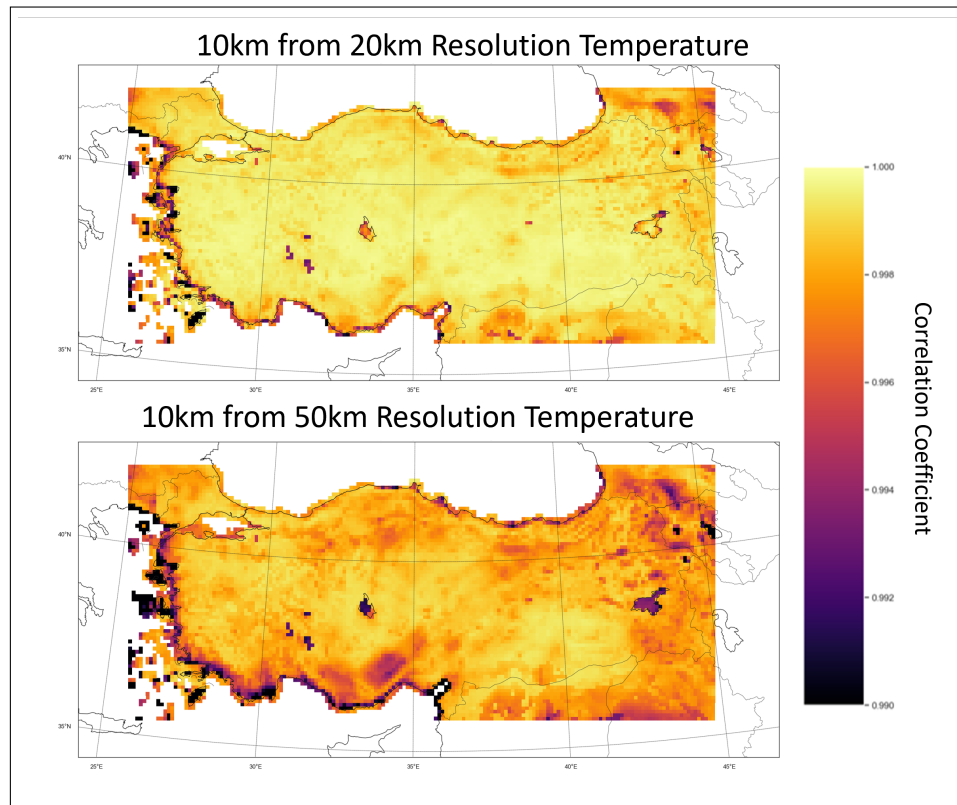


Figure 4.27. Map of temporal correlation of temperature for the 10km resolution data.

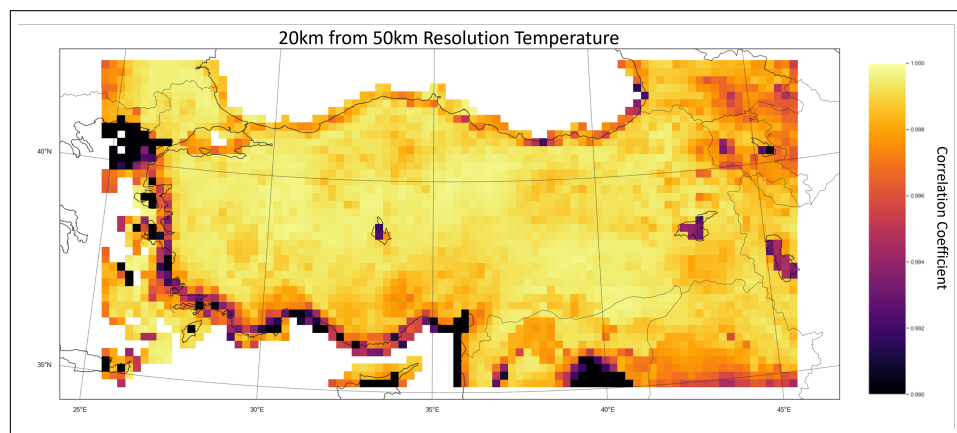


Figure 4.28. Map of temporal correlation of temperature for the 20km resolution data.

5. DISCUSSION AND CONCLUSION

In conclusion, this thesis aimed to conduct an analysis that focuses on comparing and evaluating the spatial and temporal correlations evident within two downscaled datasets. The focal points of investigation were the statistical and dynamical downscaled datasets, with the former involving a two-step process of initial dynamic downscaling followed by statistical downscaling to achieve higher resolutions. The RegCM4.7 regional climate model was employed for dynamical downscaling, while the delta spatial downscaling method was employed for statistical downscaling of precipitation and temperature data. A total of 17 datasets were derived and meticulously examined, focusing on spatial correlations at resolutions of 1km, 5km, 10km, and 20km. The study primarily centered on the geographic region of Turkey, though due to computational limitations, the 1km and 5km resolutions were scrutinized within distinct topographical terrains, encompassing both flat and mountainous areas.

The evaluation of spatial correlation of precipitation unveiled a spectrum of outcomes, wherein correlation coefficients predominantly ranged from low to moderate values, punctuated by instances of negative correlations and near-zero values. Although mean values are ranged between 0.059 to 0.775, minimum values reach up to -0.758 which shows high negative correlation for that specific timestep. Intriguingly, lower resolution downscalings exhibited relatively more favorable results. 20km to 10km downscaling shows the highest mean correlation value which is 0.775 and the 50km to 20km shows second highest mean correlation values as 0.757. Even the mean correlations of low resolution downscaling datasets are best and it can be concluded that the spatial downscaling does not perform well in precipitation according to comparison of spatial correlations. The outcomes of spatial correlation of temperature revealed a good results, with the 1km resolution first area displaying less favorable results. Since the temperature directly linked to altitude, it can be expected to find lower spatial correlation in flat regions. Conversely, the remaining downscalings exhibited robust results, characterized by high correlation coefficients and minimal standard deviation.

Except the first area datasets, minimum mean correlation value is 0.848 and maximum standard deviation of correlations is 0.022. The results show good correlation between statistical and dynamical downscalings. It can be suggested that the statistical downscaling can be used instead of dynamical downscaling as the aspect of spatial distribution except for very flat areas.

Temporal correlation of precipitation displayed notable trends, with the results from Area 1 and 1km resolutions showing superior consistency with up to 0.928 mean value, marked by reduced standard deviations with minimum 0.019 and relatively improved correlation coefficients which means are ranged between 0.447 to 0.928. Although the overall results were not without imperfections, the average correlation coefficients predominantly inhabited the moderate to high correlation range. Notably, except for Area 1 at 1km resolution, other scenarios displayed relatively higher standard deviations in the range of 0.036 to 0.142. In contrast, temporal correlation of temperature emerged as the highlight of the study, exhibiting exceptional precision. The consistently high correlation values which has minimum 0.994 along all datasets and markedly low standard deviations with maximum 0.003, can be attributed to the nature of temperature data, which aligns closely with the annual seasonal cycles.

In summary, this master thesis illuminated the intricacies of spatial and temporal correlations within the context of downscaled climate datasets and compares how close results will be obtained by easy-to-apply statistical downscaling instead of hard-to-compute dynamical downscaling. According to findings, for the studies that need high resolution temperature data, Delta method statistical downscaling technique can be used instead of dynamical downscaling. The comparison of temperature values showed high correlation both spatially and temporally. The literature also agrees with the result that statistical downscaling appears to provide results very close to those of dynamical downscaling, while requiring fewer computational resources, so there is no need to dynamically downscale the model temperatures [85]. On the other hand, in researches, using statistical downscaling for precipitation can cause different outcomes than dynamical downscaling. Also this result agrees with the existent literature. One

of the study that compares the different dynamical and statistical methods for precipitation in European Alps region conclude that there are large differences between statistical downscaling models and regional climate models outputs [86]. The outputs of this thesis do not provide information about which technique gives better results according to historical observations but the study underscores the critical influence of resolution, topography, and climatic variables on correlation outcomes. The findings herein enrich our understanding of downscaled datasets, offering valuable insights for refining downscaled climate data for diverse applications.

Because of the computational limitations, 1km and 5km resolution data studied only limited area of Turkey and only 5 years period is investigated in this thesis. Working with greater areas and longer periods can provide more accurate correlation results. Also in the future, developed regional climate models can have better high-resolution results than RegCM4.7.0.

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