A SYNTHETIC APPROACH TO THE HOLIDAY CLIMATE INDEX FOR THE MEDITERRANEAN COAST OF TURKEY

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A SYNTHETIC APPROACH TO THE HOLIDAY CLIMATE INDEX

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DECLARATION OF ORIGINALITY

I, Başak Bilgin, certify that

- I am the sole author of this thesis and that I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution;
- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
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ABSTRACT

A Synthetic Approach to the Holiday Climate Index for the Mediterranean Coast of Turkey

Climate change has an impact on the comfort level of tourists visiting coastal areas. Researching these impacts is important for a more comprehensive understanding of climate change and for developing effective solutions. The study first derives the Holiday Climate Index (HCI:Coast, HCI:Urban, and HCI:Combined) in the Mediterranean provinces of Turkey for the 1976-2000 period. Second, it examines how comfort patterns could change during the 2026-2050 period using the RCP8.5 global warming scenario. Third, utilizing the derived indices, the effects of climate-related holiday comfort on the number of tourist arrivals as well as on overnight stays between 1976 and 2020 are estimated by panel data analysis. It is detected that the comfort level has a significant and positive impact on the number of arrivals and overnight stays of tourists. Besides, comfort levels are found to deteriorate in the 2026-2050 period compared to the reference period, 1976-2000. As the comfort conditions get worse, the number of tourist arrivals and overnight stays is expected to decline in the future. Since regional analyses of climate change, holiday comfort, and tourism activity are rare in the literature, the study intends to fill the gap in this area. It is envisaged that the results of the study can be very useful for tourists, tourism professionals, operators, other stakeholders, and policymakers.

ÖZET

Türkiye'nin Akdeniz Kıyısı için Tatil İklimi İndisine Bütünleşik Bir Yaklaşım

İklim değişikliğinin kıyı bölgelerini ziyaret eden turistlerin konfor düzeyi üzerinde etkisi vardır. Bu etkilerin araştırılması, iklim değişikliğinin daha kapsamlı anlaşılması ve etkili çözümler geliştirilmesi açısından önemlidir. Çalışmada ilk olarak Türkiye'nin Akdeniz illerinde 1976-2000 dönemi Tatil İklim İndisi (Holiday Climate Index) (HCI:Coast, HCI:Urban ve HCI:Combined) elde edilmiştir. İkinci olarak, RCP8.5 küresel ısınma senaryosunu kullanarak 2026-2050 döneminde konfor kalıplarının nasıl değişebileceğini inceler. Üçüncüsü, türetilmiş indisler kullanılarak, iklimle ilgili tatil konforunun 1976 ile 2020 yılları arasında gelen turist sayısı ve geceleme üzerindeki etkileri panel veri analizi ile tahmin edilmektedir. Konfor düzeyinin turistlerin geliş ve geceleme sayıları üzerinde anlamlı ve pozitif bir etkiye sahip olduğu tespit edilmiştir. Ayrıca, 2026-2050 döneminde, 1976-2000 referans dönemine göre konfor düzeylerinin bozulduğu tespit edilmiştir. Konfor koşulları kötüleştikçe, gelecekte turist gelişlerinin ve gecelemelerin azalması beklenmektedir. Literatürde iklim değişikliği, tatil konforu ve turizm aktivitesine ilişkin bölgesel analizlere az yer verildiğinden, çalışma bu alana katkı sunmayı amaçlamaktadır. Çalışma sonuçlarının turistler, turizm profesyonelleri, işletmeciler, diğer paydaşlar ve politika yapıcılar için oldukça faydalı olabileceği öngörülmektedir.

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ABBREVIATIONS

BCI	Beach Climate Index
CIT	Climate Index for Tourism
CO_2	Carbon Dioxide
GCM	General Circulation Model/Global Climate Model
GDP	Global Domestic Product
HadGEM2	Hadley Centre Global Environment Model version 2
HCI	Holiday Climate Index
ICTP	International Center for Theoretical Physics
MCIT	Modified Tourism Climate Index
MPI-ESM	Max Planck Institute Earth System Model
RCI	Relative Climate Index
RCM	Regional Climate Model
SME	Small and Medium-Sized Enterprise
TCI	Tourism Climate Index

CHAPTER 1

INTRODUCTION

The atmospheric accumulation of greenhouse gases caused by human activities has been on the rise since the onset of the industrial revolution. Global warming refers to the observed rise in temperature on Earth and in the lower layers of the atmosphere. This phenomenon is attributed to the intensification of the natural greenhouse effect, which is further exacerbated by urbanization. The accumulation of greenhouse gases in the atmosphere, resulting from various human activities such as burning of fossil fuels, deforestation, agricultural practices, and industrial processes, is a major contributor to this trend. Climate changes are a consequence of the phenomenon of global warming.

The majority of projections suggest a rise in the probability of detrimental impacts of climate change on both ecosystems and human populations. As per the (IPCC) report of 2021, the impacts related to climate change are currently observable and seem to be escalating and diversifying. Climate change has direct and indirect impacts on human health and comfort. Direct effects include exposure to extreme weather conditions such as heat, cold, drought, heavy rains, and cyclones. Indirect effects include changes in food supply and quality, air pollution, and alterations in social and cultural environments. The potential hazards of climate change are expected to have a considerable impact on the environment and communities in the Mediterranean region. The phenomenon of climate change has significant impacts on various sectors, including but not limited to health, agriculture, energy, and tourism. The tourism industry is vulnerable to the impacts of climate change due to its reliance on climatic factors, including temperature, precipitation, wind, humidity, and their changes. Numerous tourist destinations, particularly those that offer sea, sand, and sun-oriented products, owe their widespread appeal to the warm weather and favorable climatic conditions that prevail during the holiday season. Climate change poses significant impacts on mass tourism, primarily through the heightened risk of inundation of tourist facilities and beaches due to sea level rise and the potential disappearance of beach areas due to coastal erosion. Furthermore, desertification and the depletion of clean water resources may also limit access to necessary amenities for tourists. Additionally, extreme weather events such as floods, storms, and droughts may increase in frequency, leading to further health and comfort issues for tourists.

Climate change is a global issue that impacts numerous industries, with tourism being particularly susceptible due to its reliance on weather and climatic conditions. The unpredictability of weather resulting from alterations in climate patterns poses a challenge for tourists in terms of trip planning and reduces their level of comfort. The potential effects of climate change on the comfort of visitors can be substantial. With the increase in temperatures, the frequency of heat waves has also risen, causing inconvenience for travelers engaging in outdoor activities and intensifying thermal discomfort. Variations in precipitation can impact the level of comfort experienced by tourists.

The anticipated impacts of climate change are likely to present considerable risks to both the environment and communities situated in the Mediterranean region. The phenomenon of climate change has a discernible impact on the level of comfort experienced by individuals who visit coastal regions for diverse purposes. Given the aforementioned impacts, it is imperative for researchers to investigate the impacts of climate change on the comfort level of tourists who visit coastal regions in order to gain a more comprehensive comprehension of these concerns and develop effective solutions. The utilization of this approach has the potential to aid both communities and government organizations in the creation of strategies for adaptation and mitigation. Additionally, it can serve as a valuable tool for informing policy and decision-making processes at the local, national, and international levels. The ultimate goal of these efforts is to minimize the adverse effects of climate change on coastal tourism. The correlation between the climatic attributes of a location and the tourism sector is unequivocal. It is essential for tourists, tour organizers, and tourism coordinators to possess dependable knowledge regarding the influence of weather and climate. Consequently, it is imperative to evaluate the appropriateness of the climatic conditions for tourism, thereby enabling tourists to utilize the data to make well-informed decisions within the tourism sector. The aim and motivation of this study are to conduct an assessment of the top 10 provinces of Turkey that attract the highest influx of tourists during the summer season. In line with this purpose and motivation, the study has three main goals. Accordingly, three research questions related to these goals are presented.

The first objective is to examine how human comfort patterns have changed from 1976 to 2020 in the Mediterranean provinces of Turkey. The second aim is to investigate the effect of human comfort in terms of climatic characteristics on tourism activities for the 10 provinces of Turkey (Adana, Antalya, Aydın, Balıkesir, Çanakkale, Edirne, Hatay, İzmir, Mersin, Muğla) analyzed in the study. The indices derived for the Mediterranean provinces of Turkey (HCI:Coast, which analyzes the districts to see the effect on the coastline, HCI:Urban to analyze the other touristic activities that can be done in the city, and HCI:Combined to analyze the average impact of climate change on comfort throughout the province) will be regressed according to the number of tourist arrivals and overnight stays using the fixed effects model and panel data analysis. The third objective is to analyze the future (2026-2050) trends in HCI for the 10 selected provinces.

In this context, the research questions and hypotheses of the thesis are as follows:

Q1: How did human comfort patterns change from 1976 to 2020 in the Mediterranean provinces of Turkey?

H1: It is expected that comfort levels will decrease with increasing temperatures from the past to the present. However, the improvement of comfort conditions in some provinces and in some months is also an expectation.

Q2: What is the result of the analysis when the climate-related comfort across the province with the indices derived for the Mediterranean provinces of Turkey (HCI:Coast, HCI:Urban, and HCI:Combined) is regressed on the number of tourist arrivals and overnight stays using the fixed effects model and panel data analysis?

H2: When the comfort conditions improve, it is expected that the number of tourist arrivals and the number of overnight stays of the tourists will increase.

Q3: What are the future trends in HCI indices for the selected 10 provinces?

H3: As climate change gets worse in the future, comfort levels are expected to decline due to extreme weather events such as extreme temperatures, heavy rainfall, drought, and floods. However, the improvement of comfort conditions in some provinces and in some months is also an expectation.

Insufficient research has been conducted on local approaches to human thermal comfort thresholds in Mediterranean climates. Regional analysis is an important tool for scientists, researchers, and decision-makers due to the latitudinal differences that characterize the effects of global warming. Over the past decade, there has been a significant increase in interest in the relationship between climate and tourism due to concerns about climate change. However, there are relatively few studies that focus on the local context. The main objectives of this study are to assess how climate change shapes the holiday comfort of tourists visiting the Mediterranean coast and how holiday comfort affects tourism activity in the region. The HCI has been calculated for the top 10 coastal tourism destinations in Turkey during their peak tourism season as part of climate change projections. To effectively protect ourselves from the harmful effects of climate change and mitigate associated risks, we must first accurately define the risks and identify our specific needs for adaptation. This will enable us to develop appropriate strategies to adapt to the changing climate. Accurately and promptly identifying risks is crucial, beginning with prioritizing the sectors. This research will be beneficial and contribute to the literature for a wide range of individuals, stakeholder groups, and policymakers.

CHAPTER 2

LITERATURE REVIEW

2.1 Climate change

Climate change is the long-term changes in the world's climate system that occur under the influence of natural and/or anthropogenic factors. These changes may include changes in temperature, precipitation, air movements, and sea level (IPCC, 2021). The climate has changed before. Humans have transformed the world for thousands of years; however, the effects of changes over the past centuries have become noticeable on a global scale. There is remarkable evidence that the global climate is altering at an accelerated rate. It is widely acknowledged that climate change is an anthropogenic phenomenon initiated and perpetuated by human industrial activities that generate immense quantities of greenhouse gas emissions (for example, carbon dioxide and methane). After the Industrial Revolution, the increase in greenhouse gas emissions in the atmosphere because of the massive use of fossil fuels such as oil, coal, and natural gas has revealed many problems, such as environmental pollution and climate change. Even if greenhouse gas emissions are stopped immediately, temperatures are expected to remain high for centuries due to the effects of current emissions of greenhouse gases in the atmosphere (IPCC, 2013). Limiting global warming to 1.5 °C, which is the target of the Paris Agreement (UNFCCC, 2015), urging countries to take action to minimize greenhouse gas emissions to prevent global warming, has seven years to halve global net carbon emissions before the most major impacts occur. Achieving this goal has become even more difficult (IPCC, 2023). Yet, even if this goal is reached, the possible effects of warming will likely endure for years or even centuries (Nicholls et al., 2018).

Climate change contributes to fundamental changes in the earth's system, such as alterations in ice cover, sea level, ecosystems, ocean acidification, seasonal timing, species distributions, and extreme events such as extreme temperatures and extreme precipitation (IPCC, 2021). These effects on nature also bring important effects on various sectors of the economy and society. Decreased agricultural production, deterioration of settlements and infrastructures, increasing mortality rates, dangers for water and food security, decreasing physical and mental health and comfort, problems with food and water, the spread of vector-borne diseases, loss of livelihoods and culture, economic losses, service interruptions, and poor welfare are among its effects (IPCC, 2022). Climate change can have a range of effects on agriculture, including changes in crop yields, changes in the geographic range of crops, and changes in pest and disease incidence (Bindi and Olesen, 2011; Iglesias, Mougou, Moneo, and Quiroga, 2011; Tanasijevic, Todorovic, Pereira, Pizzigalli, and Lionello, 2014; Saadi et al., 2015). They can have significant impacts on food security and the livelihoods of people in several parts of the world (FAO, 2015; IPCC, 2022). Climate change can influence the quantity, accessibility, and distribution of water resources, leading to changes in the timing and volume of runoff and changes in the occurrence of droughts and floods. They can have critical impacts on the availability of fresh water for human consumption, irrigation, and hydroelectric power generation (USGCRP, 2016; IPCC, 2022) and can lead to water shortages in various regions, mostly in the southern and eastern parts of the Mediterranean (Iglesias, Garrote, Flores, and Moneo, 2007; García-Ruiz, López-Moreno, Vicente-Serrano, Lasanta-Martínez, and Beguería, 2011). Climate change can cause sea levels to rise. Rising sea levels can also lead to coastal flooding and erosion. This situation can have significant impacts on coastal communities and infrastructure such as roads, buildings, and ports (USGCRP, 2016; IPCC, 2022). Climate change causes changes in the distribution and abundance of species and the timing of biological events such as flowering. They can have significant impacts on ecosystems and the services they provide, such as pollination and pest control (IPBES, 2019; IPCC, 2022). Climate change can affect the availability and cost of energy, as well as the reliability of energy systems. For example, extreme weather events such as heatwaves and storms can disrupt the operation of power plants and transmission lines, leading to blackouts (IPCC, 2022). Furthermore, climate change can have various effects on human health, such as increased heat stress, respiratory problems, and infectious diseases (WHO, 2016; IPCC, 2022).

Besides, climate change has significant effects on human comfort levels, as rising temperatures, increased humidity, and changes in the occurrence and intensity of extreme weather events all contribute to increased discomfort in many parts of the world. For example, rising temperatures can lead to increased heat stress and discomfort, especially during hot weather events. Similarly, rising temperatures can cause increased humidity, making people feel overwhelmed and uncomfortable. In addition, climate change may cause an increase in air pollution, which may have adverse effects on human health and comfort (WHO, 2016). Finally, climate change increases the frequency and intensity of extreme weather events such as heatwaves, storms, and hurricanes, which can disrupt daily life and make people feel less comfortable (IPCC, 2022).

2.2 Climate change and tourism relationship

2.2.1 Impacts of climate change on tourism

The term "tourism" refers to the practice of going to and staying in a foreign location for the purpose of recreation, business, or other reasons. The tourism industry encompasses a wide range of sectors, such as accommodation, transportation, attractions, and catering, which play a vital role in supporting and facilitating tourism activities. Tourism is an important global economic sector that has grown tremendously, and its contribution to the global economy continues to increase. In 2019, international tourist arrivals reached 1.5 billion. This number increased by 4% compared to the previous year. However, the COVID-19 pandemic in 2020 caused a significant drop in international tourist arrivals, with a 58% drop compared to 2019. Despite this decline, the tourism sector continues to make a significant contribution to the global economy, accounting for 10% of global GDP and supporting one in ten jobs worldwide (UNWTO, 2021). In 2019, its sectoral contribution to the global economy was $9.2 trillion (10.4% of global GDP [decreased to 5.5% in 2020 due to the pandemic]) and 334 million jobs (10.6% of jobs worldwide) (WTTC, 2021). In 2022, the tourism sector contributed 7.6% to the global GDP. This rate is 22% higher than in 2021 but 23% below 2019 levels. 22 million new jobs were created in 2022, up 7.9% from 2021 (WTTC, 2022).

In 2020, 62 million jobs were lost due to the COVID-19 pandemic, and only 272 million people were employed across the industry worldwide. This decrease of 18.5% compared to the previous year was felt in all components of the tourism sector, including small and medium-sized enterprises (SMEs), which account for 80% of global businesses in the sector (WTTC, 2021). The impacts of COVID-19 have highlighted the enormous significance and contributions of tourism. The sector offers unique opportunities to women, minorities, and youth who are more disadvantaged in business life. It creates jobs, reduces poverty, improves well-being, and aids socio-economic development. With these features, it provides important positive social effects.

Weather serves as a facilitator for enabling and enhancing tourism activities (Gómez Martín, 2005), or conversely, it can hinder participation and result in the cancellations of trips (Tervo, 2008). Individuals can adapt to the atmospheric effects of the weather by giving behavioral responses. Examples of these reactions are avoiding adverse weather conditions, changing activities according to these conditions, using structural or mechanical aids such as umbrellas, and adjusting the thermal insulation of the body by changing clothes (de Freitas, 2003). Weather conditions can also affect tourists through transportation delays, cancellations, and accidents (Koetse and Rietveld, 2009). Extreme weather events, such as heatwaves (Scott and Lemieux, 2010) and tropical cyclones (Becken, Wilson, and Hughey, 2011), have been linked to tourist safety. Climate change will exacerbate these risks in the future (Nyaupane and Chhetri, 2009). Climate and weather refer to different temporal scales of the same phenomenon. The climate is the average weather conditions over the years. It affects tourists at different times in their travels. For example, climate comes to the fore in travel planning stages. However, the weather becomes more important during the trip (Scott and Lemieux, 2010).

Tourism, one of the world's fastest-growing industries, is particularly vulnerable to climate change due to its close ties to the environment and climate, being strongly influenced by many factors, namely the state of the natural environment, perceptions of personal safety, and the capacity to cover travel expenses. For example, the climate has a direct impact on tourism and the resources available to participants (for example, weather perception, thermal comfort, and safety) (Scott, Hall, and Gössling, 2012). Mora et al. (2018) state there are 10 types of climate change impacts, namely, warming, heat waves, precipitation, flood, drought, fires, sea level, storms, natural cover change, and ocean climate change. These types affect 89 attributes of six different aspects of human systems (i.e., human health, food, water, infrastructure, economy, and security). Among these 89 attributes, a comprehensive review asserts that tourism is one of only five features affected by all 10 types of climate impacts. Other features are transport, agriculture, water quality, and diseases (Mora et al., 2018). Tourism-based economies are particularly vulnerable. Ensuring the long-term sustainability of the tourism sector depends on the protection and development of its environment. Climate change affects various services of the tourism sector thanks to ecosystems (Cheer and Lew, 2017; Franzoni, 2015; Kaján, Tervo-Kankare, and Saarinen, 2015). For example, more frequent and severe heat waves may occur, or sea levels may rise. Because of these factors, beach availability may decrease, impacting the value of the recreational experience in the destination. All these factors affect tourism demand and expenditures (Arabadzhyan et al., 2021).

To Scott, Hall, and Gössling (2012), tourism is one of the economic sectors that are least prepared for the risks and opportunities brought by climate change. Almost all tourism destinations and businesses are climate-sensitive, and climate plays a key role in travel planning and travel experience. For this reason, it is extremely important to determine the effects and risks of weather variability in this sector, to design contemporary economic policies and risk management strategies effectively, and to evaluate the potential economic effects of future climate change. The negative and positive effects of climate change on the tourism sector vary from region to region. Therefore, all tourism facilities must adapt to climate change. They must seek to minimize risks and take advantage of new opportunities in an economically, socially, and environmentally sustainable way (UNWTO and UNEP, 2008).

It is expected that the increase in temperatures will have some positive effects in the short term for the tourism sector in some regions. Geographic regions such as Northern Europe, Scandinavia, and Alaska are likely to be more attractive and more popular with visitors as temperatures rise (IPCC, 2014). There are other studies that indicate that the zone with beautiful summer conditions will shift geographically from the Mediterranean region to the north or near the poles and to high latitudes and altitudes as a result of climate change (Hamilton, Maddison, and Tol, 2005; Amelung and Viner, 2006; Bigano, Hamilton, Maddison, and Tol, 2006; Hamilton and Tol, 2007; Amelung and Moreno, 2012).

The tourism industry and its stakeholders should unequivocally work on climate change. The volume of relevant literature is increasing rapidly. There has been significant interest in the interactions between climate, weather, and tourism in recent years. This situation can be explained in response to climate change concerns (Becken and Wilson, 2013). Critically, the accumulating evidence indicates that climate change, particularly high emissions scenarios, will be an important issue influencing the medium- and long-term future of tourism development and management. As a result, the scale of climate change is increasing and confidence in previous experience is decreasing. It can be deduced from this that the need for climate services will increase throughout the twenty-first century (Scott, Hall, and Gössling, 2012). Tourism and all kinds of activities that are far from reducing greenhouse gas emissions in the climate example will continue to cause climate change, and this change will increase the need for adaptation efforts by causing effects on different types of tourism and travel flows (Demiroglu, 2017).

2.2.2 Impacts of tourism on climate change

Anthropogenic activities are accepted as the main causes of climate change in the scientific literature (IPCC, 2021). Tourism contributes substantially to the global GDP. Global tourism is a trillion-dollar industry that represents a substantial portion of global exports and contributes significantly to global GDP. Obviously, economic activities of this scale are bound to have a significant impact on the environment. These impacts include more specific point-of-effects and sources of pollution, such as tourism infrastructure (resorts, roads, attractions), tourism demands on local resources such as water and energy, and the subsequent impacts of tourism on habitats.

Moreover, the tourism industry triggers environmental change by contributing to the production of carbon emissions. Greenhouse gas emissions arise as a result of the mobility required to happen between a tourism source area and a destination. In particular, transportation, a key component of travel, is energy- and carbon-intensive, making tourism a possible contributory factor to climate change (Lenzen et al., 2018). Due to its high carbon intensity and continued growth, the sector accounts for an increasing share of the world's greenhouse gas emissions and will carry on doing so in the future. Carbon dioxide (CO_2) emissions from tourism are estimated to increase by at least 25% by 2030 compared to 2016 (UNWTO and ITF, 2019). In the tourism sector, which continues to grow rapidly, a recovery in greenhouse gas emissions has begun to be seen during the COVID-19 pandemic (Gössling, Balas, Mayer, and Sun, 2023). Carbon management (CO_2 and other greenhouse gases) has emerged as a significant management challenge for the tourism sector as a result of the important development rates that are anticipated in the sector (Gössling, 2011).

In the Mediterranean Basin, sustainable development faces additional obstacles. There are some challenges with water availability and quality. There are also other challenges arising from factors such as new industries, urbanization, growth of the tourism sector, migrations, and population growth in coastal regions. These problems are the intrusion of salty waters into freshwater sources and the increase of water pollution on the coasts (Ludwig, Bouwman, Dumont, and Lespinas, 2010). The number of international tourists coming to countries in the Mediterranean Basin was over 400 million in 2019 (UNWTO, 2022). This extremely high number of international visitors (estimated to reach 174 million by 2025) (UNEP, 2015) is expected to place tremendous, unanticipated pressure on the coastal ecosystems of the Mediterranean, including the local population living in coastal areas. Coastal tourism has various effects on the Mediterranean marine environment, such as marine litter (UNEP/MAP, 2015), inadequate sewage treatment capacity (Kent, Newnham, and Essex, 2002), and biodiversity loss (Habibullah, Din, Chong, and Radam, 2016).

In order to achieve the international community's goal of keeping global warming at 1.5 °-2.0 °C, tourism needs to reduce emissions in line with other economic sectors. This would require the industry to halve its emissions by 2030 and reach net zero by the mid-century (Gössling, Balas, Mayer, and Sun, 2023).

2.3 Coastal systems

Coasts are the transition zones between the oceans and the lands. The extension of the coastal zones towards the land and the coast is not clearly described, but the area extending in the sea up to the limit of the continental influence and on the land up to the limit of the oceanic influence is called the coastal zone (Carter, 1988). About 37% of the global population is part of coastal communities and is dependent on coastal or marine resources as well as the ocean to afford the expenses of living (UN Ocean Conference, 2017).

Coastal areas, which are the most densely populated areas of the world, are under the threat of global climate change. Even in the most optimistic scenario, a 1.5 °C increase in global atmospheric temperature will have critical effects on future vulnerable coastal areas and put global coastlines at risk. Coastal areas are affected by changes in the ocean, terrestrial landforms, and upper atmosphere. In addition, interactions between the three components also have an effect on coastal areas. Some of these changes are sea level rise, changes in precipitation and storm intensity, changes in ocean temperature and chemistry, and changes in coastal ecosystems (Vinayachandran, Seng, and Schmid, 2022). To explain these changes, as the earth's temperature rises, the polar ice caps melt, which raises sea levels. This can present problems such as coastal flooding, erosions, and loss of coastal habitats. 37% of coastal areas are at medium or high risk due to coastal erosion and flooding (Satta, Puddu, Venturini, and Giupponi, 2017). Rising sea levels may increase the risk of coastal flooding, despite possible slight reductions in sea storms (Lionello, Conte, Marzo, and Scarascia, 2017; Vousdoukas, Mentaschi, Voukouvalas, Verlaan, and Feyen, 2017). In addition, rising sea levels can increase beach erosion (Bitan and Zviely, 2019; Rizzetto, 2020), exaggerating coastal degradation and pollution (Enríquez, Marcos, Álvarez-Ellacuría, Orfila, and Gomis, 2017; Gössling, Hall, and Scott, 2018). Second, climate change can affect the frequency and intensity of storms, which can have a significant impact on coastal systems. For example, more intense storms can cause more coastal erosion, while changes in precipitation patterns can affect freshwater availability in coastal areas (IPCC, 2022). As another effect, as the earth's temperature rises, the oceans get warm. It can lead to coral bleaching, the death of marine species, and changes in species distribution. The chemistry of the oceans is also changing due to the absorption of carbon dioxide from the atmosphere, which can have adverse effects on marine life. Finally, climate change can affect the distribution and abundance of species in coastal ecosystems, leading to changes in the structure and function of these systems. In addition, human activities such as infrastructure development, tourism and recreational activities, aquaculture, freshwater, and raw material exploration and exploitation also affect coastal systems.

2.4 Tourism and climate change in the Mediterranean Basin

The Mediterranean Basin is renowned for its exceptional sociocultural and environmental diversity. It consists of the semi-enclosed Mediterranean and European, Asian, and African countries and regions. All three continents have extraordinary biological and cultural diversity. Due to human activities, the region has witnessed continuous transformation for several thousand years. With its high-density urban settlements and industrial infrastructure, it is currently home to over 500 million people. The region is the most popular tourist destination in the world and one of the busiest shipping routes. The Mediterranean Basin receives one-third of all international tourists. International arrivals during 2019 to the countries in the Mediterranean region reached over 400 million in total: France (90 million), Spain (83.5 million), Italy (64.5 million), Turkey (51.1), Greece (31,3 million), Croatia (17.3 million), Egypt (13 million), Morocco (12.9 million), Tunisia (9.4 million), Albania (5.9 million), Slovenia (4.7 million), Israel (4.5 million), Cyprus (3.9 million), Malta (2.7 million), Montenegro (2.5 million), Algeria (2.4 million), Bosnia-Herzegovina (1.2 million), and Monaco (0.3 million) (UNWTO, 2022). Before the COVID-19 crisis, it was assumed that international tourist arrivals would increase by 60% between 2015 and 2030, exceeding 500 million (UNEP/MAP, 2012). France, Spain, Italy, Turkey, and Greece are the most popular tourist destinations (UNWTO, 2021). However, from 1995 to 2015, Turkey, Croatia, and Albania experienced the greatest growth (MGI, 2017). In the majority of socioeconomic sectors, climate change threatens all Mediterranean countries. As a consequence of a 1 °C increase in temperature, the GDP of the basin's countries with low per capita incomes may fall by 1.1% (Radhouane, 2013).

The tourism industry is very sensitive to climate change, and the effects of climate change are inevitable in the Mediterranean Basin, where tourism is widespread and located in a coastal system. Over several millennia, human society and the natural environment in the Mediterranean Basin have co-evolved in response to significant climatic changes. The region is in a transition zone between mid-latitude and subtropical atmospheric circulation patterns. With the high regional sensitivity and exposure observed in the Mediterranean Basin, the predicted increase in climate hazards exceeds global trends for most variables, and the region is defined as a hot spot with this feature (Giorgi, 2006; Lionello et al., 2006, 2012; Giorgi and Lionello, 2008; Lelieveld et al., 2012; Zittis and Hadjinicolaou, 2017; Cramer et al., 2018; Zittis, Hadjinicolaou, Klangidou, Proestos, and Lelieveld, 2019; Zittis et al., 2022). It is anticipated that the Mediterranean region's future warming will exceed global rates by more than 20%, with summer warming being 40% faster than the global average (Lionello and Scarascia, 2018). Across the basin, average annual temperatures are 1.4 °C above late nineteenth-century levels, especially in summer. Heat waves are now occurring more frequently, and droughts have increased in frequency and intensity since 1950 (Vicente-Serrano et al., 2014; Kelley, Mohtadi, Cane, Seager, and Kushnir, 2015; IPCC, 2021). Drought levels will reach unprecedented intensities in the last 10 thousand years in global warming of 1.5 °C and above (Hoegh-Guldberg et al., 2018). Also, for the Mediterranean Basin, climate models consistently predict less precipitation (-12% for global warming of 3 °C) (IPCC, 2022). A 2 °C increase in global atmospheric temperature will reduce summer precipitation by 10 to 15% in southern France, northwest Spain, and the Balkans, and by up to 30% in Turkey and Portugal (Vautard et al., 2014). A temperature increase of 2 °-4 °C is expected for Southern Europe in the 2080s. It means widespread reductions in precipitation of up to 30% (especially in spring and summer) and no frost season in the Balkans (Forzieri et al., 2014). For every 1 °C of global warming, average precipitation over most of the region will likely decrease by about 4% (Lionello and Scarascia, 2018). An average global warming of 1.5 °C, especially in the south, will extend the duration of dry periods by 7% (Schleussner et al., 2016). Heavy precipitation events are anticipated to become 10-20% more intense in all seasons except summer (Toreti et al., 2013; Toreti and Naveau, 2015). The scientific literature tends to agree that in the twenty-first century, the climate of the Mediterranean Basin will experience a reduction in precipitation and widespread warming in most of its regions (Planton et al., 2012; Gualdi et al., 2013; Ulbrich et al., 2013; Cherif et al., 2020).

Tourism demand in the Mediterranean is anticipated to decline as a result of rising temperature extremes (Dos Santos, Moncada, Elia, Grillakis, and Hilmi, 2020; IPCC, 2022). Tourism in the Mediterranean region is at risk due to the unpredictability of the timing, duration, and intensity of extreme climate events (Kutiel, 2019; IPCC, 2022). These issues will lead to negative situations in the tourism sector, including economic losses. For example, in countries located in the Mediterranean Basin, decreased rainfall may affect the water supply (Philandras et al., 2011), and costs related to issues such as water management may increase (Martínez-Ibarra, 2015). Recently, accelerating climate change has increased environmental problems such as changes in land use, increased pollution, and decreased biodiversity in the Mediterranean Basin (Cramer et al., 2018). It is a region whose rural/natural land has been damaged, has the lowest percentage of natural vegetation among the hot points that will be most affected by climate change in the world, and is rapidly urbanizing (Leka, Lagarias, Panagiotopoulou, and Stratigea, 2022). There is also the problem of overconsumption of resources, especially in coastal and marine parts of the countries in the region (Stratigea, Leka, and Nicolaides, 2017). Tourism has been widely accepted in the region and is one of the main economic resources of several countries. However, it is also a very sensitive sector to the effects of climate change, and identifying these effects is important for adaptation and mitigation studies.

2.5 Tourism, climate change, and human discomfort: Tourism climatic indices

Climate change is a worldwide issue that affects numerous sectors, with tourism leading the way due to its sensitivity to weather and climate. Changes in climate patterns result in unpredictability in the weather, making it difficult for tourists to plan their travels and diminishing their level of comfort. The impact of climate change on visitors' comfort can be significant. As temperatures rise, heat waves become more frequent, making outdoor activities unfavorable for travelers, and exacerbating thermal discomfort (Zinzi and Carnielo, 2017; IPCC, 2021). Changes in precipitation patterns can also affect the comfort level of tourists. The effects of climate change on human health and comfort are either direct (by heat, cold, drought, heavy rains, cyclones, and other forcings) or indirect (by changes in the availability and quality of food, air pollution, and other factors influencing social and cultural settings). These aspects of climate change are anticipated to pose significant dangers to Mediterranean communities and the environment. Along the coasts and densely populated urban areas are the regions with the most intense heat waves in the Mediterranean Basin (Kuglitsch et al., 2010). The majority of the population of the Mediterranean region is accustomed to relatively high temperatures. However, the increases in the intensity and frequency of heat waves or the changes in seasonality pose significant health risks for vulnerable population groups such as those with limited access to inadequate shelter and air conditioning and those living in poverty (Paz, Negev, Clermont, and Green, 2016).

Researchers are interested in how climate change will affect the comfort level of people who visit coastal places for a number of reasons. To further elaborate on the above-mentioned points, first, rising sea levels, increased coastal flooding, and eroding coastlines have a negative impact on the comfort of tourists in many coastal destinations (IPCC, 2014). In addition, extreme weather events such as cyclones and hurricanes that are becoming more frequent and intense as a result of climate change (IPCC, 2014) can disrupt coastal tourism and make some tourist destinations less comfortable. Second, climate change may have significant economic effects, including employment losses in the tourism industry (UNWTO, 2008). These impacts can have a substantial effect on the viability and sustainability of coastal tourism enterprises and communities. Third, climate change may have social effects on coastal tourism, such as the displacement of communities and the loss of livelihoods (UNWTO, 2008). These impacts can have significant effects on the well-being and quality of life of people whose livelihoods depend on coastal tourism. In light of these effects, it is crucial that researchers investigate the effects of climate change on the comfort levels of tourists visiting coastal areas to better understand and address these problems. It can help inform policy and decision-making at the local, national, and international levels, as well as assist communities and governments in developing adaptation and mitigation strategies to minimize the negative effects of climate change on coastal tourism.

There are other factors that influence tourism besides weather and climate, but these characteristics are crucial to the financial success of tourism operators and the satisfaction of visitors. It is a fact that the climatic characteristics of a destination and tourism are intertwined in a variety of ways, and tourists, tour organizers, and tourism coordinators must have reliable information regarding the role of weather and climate. Climate has a substantial impact on tourism demand and satisfaction, and tourists, who are typically unconcerned with a destination's annual climate, are primarily concerned with the weather during their visit. Therefore, it is necessary to evaluate climate suitability for tourism so that travelers can use the information to make decisions based on information in the tourism industry. Numerous attempts have been made to identify the climatic conditions that are optimal for tourism in general and for specific tourism activities. Due to the complexity of weather and its multifaceted characteristics in which weather variables combine to make sense of climate in relation to tourism, an index approach is beneficial for this purpose. Tourism-specific climate indices have evolved from the more general development of climate indices in sectors such as health (e.g., comfort indices) and agriculture (e.g., numerous drought indices). In the 1960s and 1970s, the international tourism industry grew tremendously. With this development, a number of studies began to explore the relationship between destination climate and tourism demand (Perry, 1972; Mieczkowski, 1985; de Freitas, 1990; Smith, 1990). Several attempts have been made to quantify the climatic comfort of visitors from a biometeorological perspective, i.e., an estimation of weather parameters and outdoor thermal comfort. de Freitas (2003) identified three climate-related resources for the tourism industry. The thermal component considers the combined effects of ambient temperature, wind, solar radiation, humidity, metabolic rate, clothing, and activity to determine the thermal comfort of visitors. The physical component is comprised of elements such as wind and precipitation that can function as physical disturbances or limit tourist activities. The aesthetic component refers to climatic characteristics, such as sunlight, blue sky/cloud cover, visibility, and day duration, that can influence the preference or quality of a landscape among travelers. While the thermal and physical components are fundamental to tourism infrastructure design and significant operating cost determinants, all three are essential to the actual visitor experience as well as the destination's image and marketing (de Freitas, 2003). It is important that an index is created using these components.

Mieczkowski (1985) was the first to recognize the need for an index that evaluates tourist destinations' climatic conditions. In order to evaluate favorable and unfavorable climatic conditions, he devised the Tourism Climate Index (TCI), the first index for the relationship between tourism and climate. TCI is computed using seven monthly climate variables (daily maximum and minimum air temperature, daily minimum relative humidity, daily average relative humidity, precipitation, daily sunshine, and average wind speed). These components define the sub-indices for daily thermal comfort, daily thermal comfort, precipitation, sunshine hours, and wind speed. In Mieczkowski's proposed formula, the daytime comfort index is given the most weight to reflect the fact that travelers are typically the most active during the day. The second-highest weights are assigned to the quantity of sunlight and precipitation, followed by daily temperate comfort and wind speed. Since its development nearly 40 years ago, TCI has been widely used to determine whether a climate is suitable for tourism. It has been used extensively in several locations around the world, such as Europe (Nicholls and Amelung, 2008; Perch-Nielsen, Amelung, and Knutti, 2010; Kovács and Unger, 2014), Mediterranean (Amelung and Viner, 2006), Turkey (Aygün Oğur and Baycan, 2023), South Africa (Noome and Fitchett, 2019), Australia (Amelung and Nicholls, 2014), and China (Fang and Yin, 2015; Zhong, Yu, and Zeng, 2019; Qiang, 2020).

Subsequent research discovered a number of theoretical weaknesses in TCI. These weaknesses include its inapplicability to certain climatic conditions required for beach/coastal tourism. For example, the optimal temperatures for tourism in the TCI do not correspond with the stated preferences of coastal visitors (Scott, Rutty, Amelung, and Tang, 2016; Rutty et al., 2020; Demiroglu, Saygili-Araci, Pacal, Hall, and Kurnaz, 2020). It does not reflect any empirical data regarding what specific visitor groups want from specific destinations. Despite having a basis in scientific knowledge, the equation's weights are ultimately subjective. The weighting scheme overemphasizes thermal comfort (Dubois, Ceron, Dubois, Frias, and Herrera, 2016). The main weakness of TCI is that the ranking and weighting scheme of sub-indices is subjectively based on Mieczkowski's opinion. Also, it has not been empirically evaluated based on travelers' preferences or other measures of tourism performance. In the last four decades after the development of TCI, other indices have been developed to assess the suitability of the climate for tourism activities. According to the results from the surveys, tourists adopt a wider range of climatic conditions than those determined subjectively by Mieczkowski (1985).

Morgan et al. (2000) created a slightly modified version of the TCI to assess sun, sea, and sand tourism. The Beach Climate Index (BCI) was derived from field research conducted with 1354 individuals in Wales, Malta, and Turkey. Since Northern Europe is the most significant tourism market in the Mediterranean Basin (Rutty and Scott, 2010), the index was designed to take the preferences of Northern European beachgoers into consideration. BCI was created by improving TCI's daytime comfort index ratings, as indicated by participant responses. The relative significance of the numerous TCI factors was determined by the beachgoers' responses in accordance with their prioritization. This index is weak in terms of its reliance on responses from beachgoers in Northern Europe, and it cannot be applied to beachgoers in other regions because their thermal preferences differ from those described in other studies (Demiroglu, Saygili-Araci, Pacal, Hall, and Kurnaz, 2020). In addition, the BCI was designed for beach use only (3S - sun, sea, sand) and cannot serve for other daytime activities among beach users or other touristic activities in general (Morgan et al., 2000). Furthermore, the BCI has methodological limitations (Moreno and Amelung, 2009).

The Climate Index for Tourism (CIT), another index designed in 2008, establishes thresholds for precipitation and wind speed and considers factors such as clear skies and light breezes (de Freitas, Scott, and McBoyle, 2008). The study asserts that for a tourism climate index to be comprehensive and universal, it must incorporate the effects of all climate factors and be theoretically sound, straightforward to calculate, user-friendly, and easily understood by tourism industry users. In contrast to other indices, they discovered that dispersed clouds were preferred over clear skies, and a light breeze was valued by numerous respondents. However, CIT lacks cross-cultural understanding because all the respondents in the study were from a single country, and the survey sample had a narrow age distribution (331 university students, i.e., young adults), so it can only be used for 3S tourism, just in the case with BCI (de Freitas, Scott, and McBoyle, 2008; Demiroglu, Saygili-Araci, Pacal, Hall, and Kurnaz, 2020).

Yu, Schwartz, and Walsh (2009) revised the CIT and created the Modified Tourism Climate Index (MCIT) with substantial modifications. MCIT offers two different climate variants. They are visibility and important weather conditions (such as rain, lightning, hail, and snow) that can hinder various tourist activities. It also removes sunshine and cloud cover components, as they are not indicative of whether or not an activity is going to occur. MCIT uses hourly data instead of daily data to achieve high temporal resolution. In this manner, MCIT can demonstrate the significant difference in tourist comfort between the rain falling in 1 hour and the same amount of drizzle for 10 hours. However, MCIT did not utilize the previously published research on tourist preferences to construct variable rating scales and weightings of climatic variables or to determine whether added variables play a significant role in tourist decision-making. In addition, the scarcity of hourly data for several locations around the globe is a significant barrier to the application of this index (Demiroglu, Saygili-Araci, Pacal, Hall, and Kurnaz, 2020).

Li, Goh, Hung, and Chen (2018) developed the Relative Climate Index (RCI), which employs a push and pull framework to assess the relative attraction of a destination compared to the tourist's country of origin. According to the study, travelers are more likely to visit a hot destination when their country of origin is cold, and vice versa, because people desire new experiences. The aforementioned study uses the TCI of the destination and the TCI of the tourist's country of origin. It does so to calculate a relative tourism climate index that measures the climatic differences between the destination and the tourist's home country. It is stated that tourists can visit less comfortable destinations because they also seek novelty in their destination selection. However, RCI employs a variant of TCI, so it is not yet operational (Ma, Craig, Scott, and Feng, 2021).

HCI was developed in light of the fact that these indices have limitations and TCI is highly subjective (Tang, 2013; Scott, Rutty, Amelung, and Tang, 2016; Rutty et al., 2020). HCI does not rely on subjective opinions, as rating scales and weights for sub-indices are determined using available literature on visitors' climate preferences (Demiroglu, Saygili-Araci, Pacal, Hall, and Kurnaz, 2020). Furthermore, numerous studies demonstrate that HCI overcomes certain TCI shortcomings and is more consistent with the visiting patterns observed in various urban and beach destinations (Scott, Rutty, Amelung, and Tang, 2016; Demiroglu, Saygili-Araci, Pacal, Hall, and Kurnaz, 2020; Rutty et al., 2020). More detailed information about HCI will be discussed in the next section.

CHAPTER 3

DATA AND METHODOLOGY

3.1 Data

3.1.1 Domain: Climatic characteristics of the region

Climatic conditions can be defined from local to global scale. The geographic pattern of contemporary climate is influenced by latitude and proximity to oceans, other large bodies of water, and mountains, as well as other factors such as dominant winds and ocean currents. It can be represented globally in classification schemes such as the Köppen-Geiger system (Peel, Finlayson, and McMahon, 2007; Türkeş, 2022), which includes 25 different categories according to temperature, precipitation, and dominant vegetation type. In the Köppen-Geiger climate classification system, the major climate groups in the world, namely the five main climate clusters, are denoted by the letters A, B, C, D, and E. These are the tropical (A), the arid (B), the temperate (C), the cold (D), and the polar (E) groups. In this classification, 10 provinces in the Aegean and Mediterranean regions analyzed in this thesis are in the temperate (C) climate class. In this group, generally humid climatic features are seen. These are the climates where the average temperature of the coldest month is above 0 °C and below +18 °C, and the average temperature of the warmest month exceeds +10 °C. Considering the main climate types classified under these five main climate groups, 10 provinces, which are the subject of the thesis, have a Mediterranean climate with arid and very hot summers (Türkeş, 2022). The 10 provinces examined in the study are located in the south-southwest and west of Turkey (Figure 1).

When we look at the climatic characteristics of the regions, while the winter season is generally warm in the Mediterranean and Aegean coasts, there are days with high temperatures (above 25 °C) in the coastal areas throughout the day (Doğanay and Zaman, 2021). In addition, the average daily sunshine duration in summer along the entire Mediterranean and Aegean coasts are 12-13 hours. While the annual sunshine duration is 3000-3200 hours on the Mediterranean coast, it is around 3000 hours on the Aegean coast. The existence of coves and gulfs with clean beaches and the rich cultural potential attractions that support them explain how the Mediterranean and Aegean coasts have become summer tourism attraction areas (Doğanay and Zaman, 2021). In addition, in the Mediterranean and Aegean coasts, where the annual sea water temperatures are above 18-20 °C, the summer season is above 20 °C. It is possible to do swimming, sea or sand bathing, and water sports for 200-250 days on the Mediterranean and South Aegean coasts and for 150-180 days on the North Aegean coasts (Doğanay and Zaman, 2021).

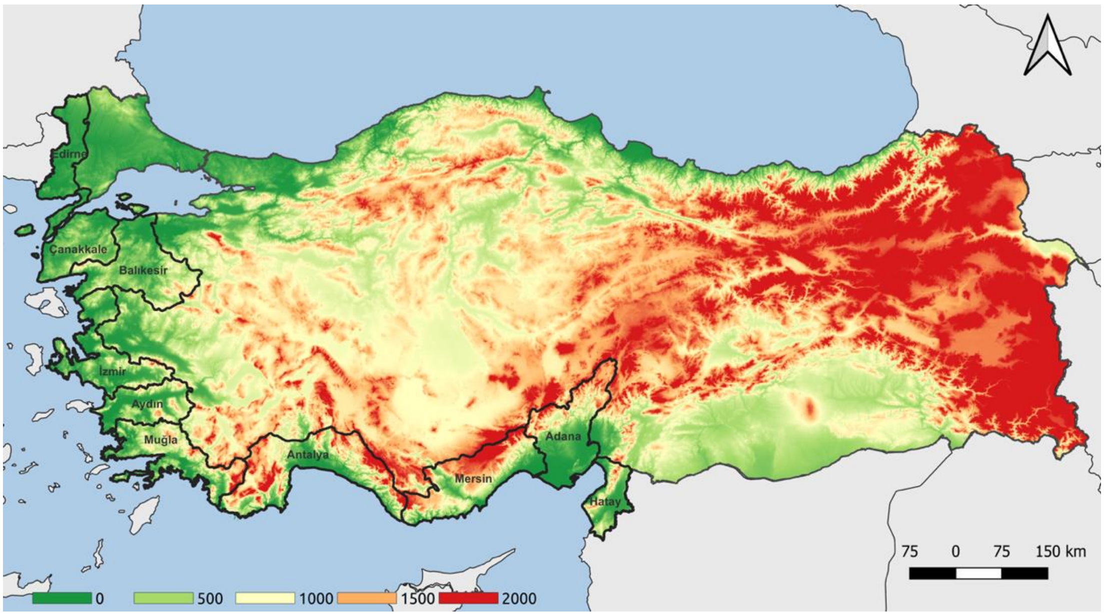

Figure 1. The elevation map showing the Mediterranean and Aegean regions with 10 provinces

3.1.2 Climate data

3.1.2.1 Climate models

Determining and estimating the potential direct or indirect effects of climate change, which is one of the greatest challenges facing the globe today, is crucial for adapting to climate change and mitigating its effects. In this discipline, model studies for future climate projections have been the primary focus of research for the past quarter century. Today, numerous research centers and scientists from around the world conduct individual and collaborative climate forecasting projects. Modeling the climate permits the estimation of past and prospective climatic conditions.

Using "quantitative" (observable and measurable) methods, climate models illustrate the relationship between climate system components (atmosphere, lithosphere, biosphere, hydrosphere, and cryosphere). All climate models incorporate the energy emitted by the sun in the form of short-wave radiation and the energy emitted by the earth in the form of long-wave radiation. Any deviation from this equilibrium will result in a change in temperature.

3.1.2.1.1 General circulation models

General circulation models, also global climate models (GCM), are the most sophisticated climate models. These models evaluate atmospheric and oceanic movements on a global scale and incorporate atmospheric-ocean interactions. These models divide the world horizontally and vertically into a series of cells (grids), allowing climate data for any location on Earth to be obtained. Using multiple simulation experiments and a variety of emission scenarios for greenhouse gases, they are used to project future climatic conditions. GCMs are used to simulate the future reactions of the climate system to emissions of greenhouse gases and sulfate aerosols, as well as other human activities that influence the climate.

A disadvantage of GCMs was their inability to resolve small-scale features. The first models were comparatively simple (IPCC, 2007). With the advancement of computational capacity, the horizontal resolution of the models has steadily increased, allowing for the creation of increasingly detailed products. Increased computing power enables the addition of new components to models (a more accurate representation of initial conditions), thereby decreasing uncertainty. Climate models produced between 1970 and 2007 accurately predicted the observed global surface warming, according to a study analyzing 17 projections from 14 models (Hausfather, Drake, Abbott, and Schmidt, 2020); therefore, they are quite valuable. In this thesis, the Earth System Model from the Max Planck Institute and the Global Environment Model version 2 from the Hadley Center were used as GCMs; more information about these models was provided below.

Max Planck Institute Earth System Model (MPI-ESM) includes a set of coupled general circulation models consisting of atmosphere, surface, and ocean submodules. These submodules are ECHAM6 for the atmosphere, MPIOM for the ocean, JSBACH for land and vegetation, and HAMOCC5 for the marine biogeochemistry (Figure 2). MPI-ESM-MR, a mixed resolution (MR) version of MPI-ESM, was used in this thesis. This version has higher vertical resolution in the atmosphere and higher horizontal resolution in the ocean.

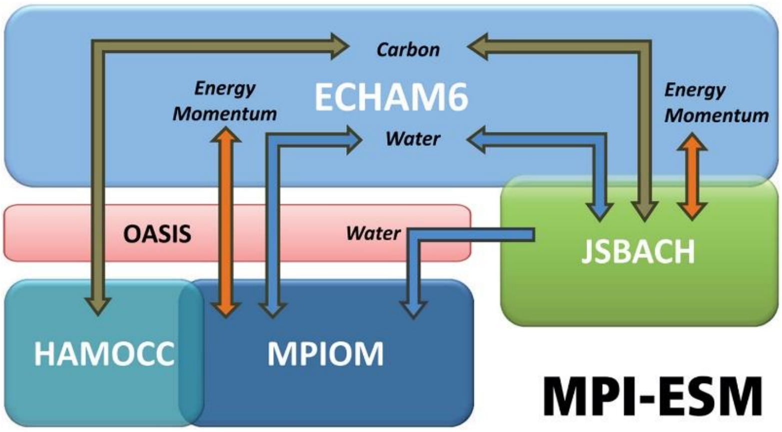

Figure 2. Schematic view of MPI-ESM

Source: Giorgetta et al. (2013)

The Hadley Centre Global Environment Model version 2 (HadGEM2) comprises components for the atmosphere, ocean, and sea ice (Figure 3). The Earth-system configuration encompasses various components such as dynamic vegetation, ocean biology, and atmospheric chemistry that interact with one another in a complex manner. The atmospheric component adheres to a standard that encompasses 38 levels, reaching an altitude of 40 kilometers. The horizontal resolution is 1.25 degrees of latitude by 1.87 degrees of longitude, which yields a global grid of 192 x 145 grid cells. The aforementioned values denote a resolution of roughly 208 km x 139 km when situated at the Equator and 120 km x 139 km at a latitude of 55 degrees. A version with 60 levels extending to an altitude of 85 kilometers is also used to study stratospheric processes and their impact on the global climate (Martin et al., 2011) The HadGEM model assumes that each month has 30 days.

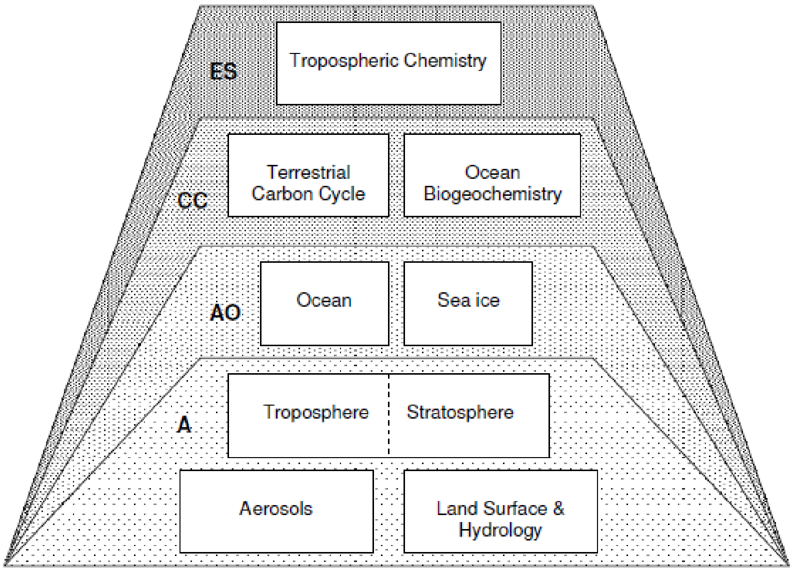

Figure 3. Processes included in the HadGEM2 model

Source: Martin et al. (2011)

3.1.2.1.2 Regional Climate Model: RegCM

Due to their coarse resolution, GCMs run at various grid sizes (resolution) are valuable but not beneficial for high-resolution analyses of regional climate variability. GCMs can be performed for the entire planet; thus, the grid size is coarser, the output information from GCMs has a lower resolution, and simulations take a long time due to their complex systems. Present models have a typical resolution of 150 km. Although this resolution is an improvement over earlier models, regional and local studies necessitate data with a higher resolution. In regions with complex orographic or climatic conditions, they cannot provide the high-resolution regional climate data required by researchers, stakeholders, and policymakers (Leung, Qian, and Bian, 2003).

Using Regional Climate Models (RCMs), the output of the global model is dynamically downscaled to higher resolutions (10-50 km). In other words, the results of the global models serve as the input for the regional models, which then produce the most relevant datasets for the region of interest. Dynamic downscaling techniques using data from GCMs for RCMs have been extensively used to derive this information (Giorgi and Gutowski, 2015). Using climate models to simulate climate systems is known as dynamical modeling or downscaling (Figure 4).

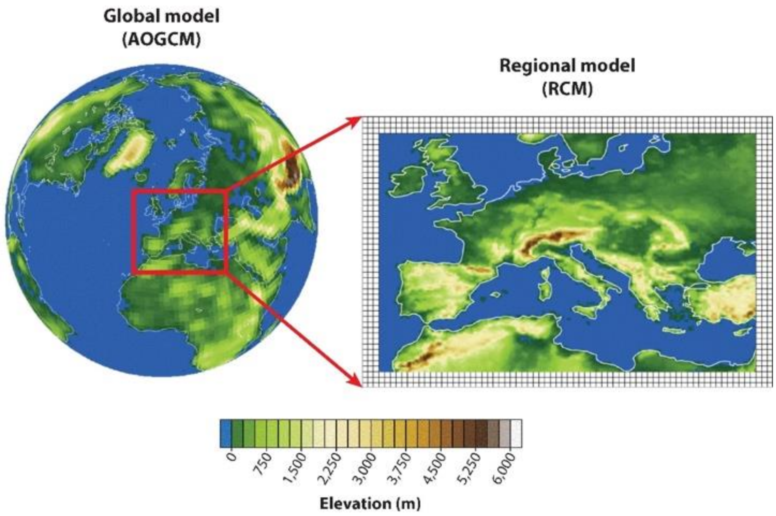

Figure 4. The concept of dynamical downscaling

Source: Giorgi and Gutowski (2015)

RCMs are climate models that utilize complex mathematical equations similar to those used in GCMs. However, unlike GCMs, RCMs are designed to simulate climate processes for a specific region of interest. In order to conduct impact assessment studies pertaining to phenomena such as the ramifications of climate change on water resources, agriculture, and urban planning, it is imperative that we obtain data of a heightened resolution. In order to achieve this objective, it is imperative to employ regional climate modeling techniques that can furnish climate data at elevated resolutions. In order to evaluate the impact of climate change on intricate phenomena such as crop yield and hydrological systems, climate models with high resolution spanning 10-50 kilometers are necessary. RCMs utilize GCM output as an input parameter and integrate intricate topographical, land-sea distribution, and surface features to generate climate outputs with an enhanced spatial resolution that are more authentic. Modern RCMs can be operated with a resolution of 10 km or higher due to the swift advancement of computing technology. Even if climate parameters are known, and projections can be made for as little as ten years, the ability to predict regional climate change is constrained by unpredictability. Nonetheless, such studies are extremely useful for estimating the maximal quantity of carbon dioxide that must be present in the atmosphere to achieve a certain level of surface warming. RCMs exhibit enhanced proficiency in replicating climatic characteristics when finer resolutions are employed in surface topography, vegetation, and land-sea distributions (Giorgi and Bates, 1989; Rummukainen, 2010; Arritt and Rummukainen, 2011).

In this thesis, RegCM4.4 was used to generate regional climate model outputs for the study region. RegCM started to be developed starting with version 1 in the 1980s. It has reached version 4 today. It was created through the collaborative efforts of a heterogeneous group and made available as an open-source and adaptable programming language. The coordination of its distribution and maintenance is managed by the Earth System Physics section of the Abdus Salam International Center for Theoretical Physics (ICTP). It has been utilized extensively in climate-related research across the globe (Turp, Ozturk, Türkeş, and Kurnaz, 2014; Sylla, Pal, Wang, and Lawrence, 2016; Ozturk, Ceber, Türkeş, and Kurnaz; 2015; Ozturk, Turp, Türkeş, and Kurnaz, 2017, 2018; An, Turp, Türkeş, and Kurnaz, 2020).

3.1.2.1.3 Representative concentration pathways

The most crucial aspect of climate models is how to predict the future climate. Therefore, it should be projected how the greenhouse gas emissions, which are the primary cause of the current climate change, will change in the future, as well as how much the concentrations in the atmosphere will increase and how much the energy will warm the earth. To model and predict the future climate, assumptions must be made about the changes in economic, social, and physical aspects of the environment that will influence climate change. Climate research employs socio-economic and emissions scenarios to offer credible interpretations of future developments, considering various factors such as socio-economic and technological changes, energy and land use, and greenhouse gas and air pollutant emissions. These inputs are utilized in climate model studies and serve as a foundation for assessing potential climate impacts, mitigation strategies, and associated expenses (van Vuuren et al., 2011). Representative Concentration Pathways (RCPs) are a method for documenting these assumptions and assessments within a variety of prospective greenhouse gas concentration scenarios. RCPs provide a spectrum of optimistic and pessimistic future projections, ranging from low to high greenhouse gas emissions. With the aid of global models, the future climate of many different regions of the globe is thus predicted using RCP scenarios.

RCPs represent a broad spectrum of climate outcomes and are neither forecasts nor policy recommendations (Moss et al., 2010; van Vuuren et al., 2011). RCPs provide a range of greenhouse gas concentrations and emission pathways to facilitate research on the effects and potential policy measures for addressing climate change. There are numerous assumptions regarding attitudes toward population growth, economic growth, technological innovation, and social and environmental sustainability. In the process of simulating possible future climate evolution, each scenario’s conditions are utilized. RCPs indicate greenhouse gas concentrations that will increase total radiative forcing (the alterations in the balance of incoming and outgoing radiation in the atmosphere due to variations in atmospheric constituents, such as carbon dioxide) by a specified amount by 2100 relative to pre-industrial levels. The total radiation forcing equals the difference between incoming and emitted radiation at the top of the atmosphere. These targets are reflected in the terminology of the RCPs as RCP2.6, RCP4.5, RCP6.0, and RCP8.5 (van Vuuren et al., 2011). Each path results in a distinct spectrum of 21st-century global average temperature rise. RCP2.6, RCP4.5, RCP6.0, and RCP8.5 scenarios presume 2100 CO2-eq concentrations of approximately 490, 650, 850, and 1370 ppm, respectively (Moss et al., 2010).

In this thesis, projection studies were carried out using RCP8.5, a scenario where greenhouse gas emissions continue to increase unabatedly, and the average global temperature rises by 4.3 °C by 2100 (van Vuuren et al., 2011). The recent research on the impacts of future climate change has predominantly centered on RCP8.5. The scenario with high emissions indicates a potential outcome if society fails to take collective action to decrease greenhouse gas emissions. The RCP8.5 is a valuable resource for assessing physical climate risks, especially for policy planning in the short and medium-term. The emissions that align with RCP8.5 are closely in line with the total cumulative CO_2 emissions from the past. RCP8.5 is the most appropriate for the mid-century period, given the current policies and stated objectives, as it maintains CO_2 emission levels at a reasonable level even in 2100 (Schwalm, Glendon, and Duffy, 2020). This study chose RCP8.5, the most pessimistic scenario, to analyze the effects of climate change in the near future. The study is based on risk analysis to provide tourism professionals, hotel/facility owners, stakeholders, and policymakers with valuable insights. The worst-case scenario has been selected to ensure that the results are useful to these groups.

3.1.3 Tourism indicators for the Mediterranean coast of Turkey

3.1.3.1 Characteristics of provinces as tourism centers

The coasts are the areas where both domestic and international tourism in Turkey are mostly directed, and the coastal areas where the demand is concentrated are in the southern and western parts of the country. With the Tourism Encouragement Law No. 2634 in Turkey, the list of "Tourism Centers and Culture and Tourism Conservation and Development Zones" was announced by the Ministry of Culture and Tourism. There are 236 tourism centers and cultural and tourism protection and development zones on the list (Ministry of Culture and Tourism, n.d.). 79 of them are coastal-themed centers and zones, and it is the most crowded one in the group. 64 of these coastal tourism regions are within the borders of the provinces examined within the scope of the thesis. The following information has been compiled from this list of the ministry (Ministry of Culture and Tourism, n.d.).

There is 1 coastal tourism region in Adana, and it is Yumurtalık. Since 1976, Adana has received approximately 500,000 tourists annually. The average number of days of overnight stays of these tourists varies between 1.5-1.65. There are 19 tourism regions in Antalya. These are Alanya Alara Çayı Güneyi, Alanya Batısı, Alanya Çenger, Alanya İncekum, Arapsuyu, Belek, Demre (Kale) Kıyı Bandı, Demre, Gazipaşa, Kaleiçi, Kaş Kalkan Kıyı Bandı, Kemerağzı-Kundu, Kent Merkezi, Konyaaltı, Serik Çolaklı, Serik Manavgat Kıyı Kesimi, Side No. II tourism center and Antalya Side. Antalya has received approximately 4,000,000 tourists annually since 1976. The average number of days of overnight stays of these tourists varies between 3.36-8.52. There are 3 tourism regions in Aydın. These are Akbük, Kuşadası Çamlimanı and Kuşadası Marina. Since 1976, Aydın has received approximately 370,000 tourists annually. The average number of days of overnight stays of these tourists varies between 2.5-4.69. There is 1 tourism region in Balikesir, and this is Balikesir-Marmara Güneyi Islands. Since 1976, Balıkesir has received approximately 400,000 tourists annually. The average number of days of overnight stays of these tourists varies between 1.81-4.48. There are 3 tourism regions in Çanakkale, and these are Behramkale Kadırga Bay, Geyikli, and Küçükkuyu. Since 1976, Çanakkale has received approximately 260,000 tourists annually. The average number of days of overnight stays of these tourists varies between 1.08-1.73. Saros Bay, which is a coastal tourism center in Edirne, is within the borders of Edirne-Çanakkale. Since 1976, Edirne has received approximately 120,000 tourists annually. The average number of days of overnight stays of these tourists varies between 1.2-1.61. There are 3 tourism regions in Hatay, and these are Arsuz Samandağ, Belen Güzel Yayla, and İskenderun Kıyı Bandı. Since 1976, Hatay has received approximately 230,000 tourists annually. The average number of days of overnight stays of these tourists varies between 1.2-1.99. There are 16 tourism regions in İzmir. These are Alaçatı Çakabey, Alaçatı Güvercinlik, Alaçatı Mersin Bay, Alaçatı, Alaçatı Yumru Bay, Çeşme Altınkum North, Çeşme Altınkum, Çeşme Ayasaranda, Çeşme, Çeşme Paşalimanı, Çeşme Reisdere, Çeşme Şifne, İnciraltı, Özdere Kesre, Selçuk Pamucak No. II tourism center and Selçuk Pamucak. Since 1976, İzmir has received approximately 730,000 tourists annually. The average number of days of overnight stays of these tourists varies between 2-4.42. There are 8 tourism regions in Mersin. Kargicik, Melleç, Narlikuyu Akyar, Ortaburun, Ovacik, Tarsus Coastal Area, Tarsus and Taşucu Boğsak. Since 1976, Mersin has received approximately 440,000 tourists annually. The average number of days of overnight stays of these tourists varies between 1.5-2.08. Finally, there are 19 tourism regions in Muğla. These are Bodrum Adalıyalı, Bodrum Karaada, Bodrum Kızılağaç İçmeler, Bodrum

Marina, Bodrum Torba and its surroundings, Bodrum Türkbükü Doğusu, Bodrum Yalıçiftliği, Bodrum Yalıkavak Gündoğan Göltürkbükü, Bodrum Yalıkavak Port, Marmaris, and its surroundings, Milas Akbük Kazıklı Koyu Kıyı Şeridi, Milas Akbük, Milas Çam Port, Milas Çökertme, Milas Güvercinlik Bay, Milas Kazıklı Koyu, Ölüdeniz Belceğiz Kıdırak, Sarıgerme, and Muğla-Milas-Bodrum-Tuzla Lake. Since 1976, Muğla has received approximately 750,000 tourists annually. The average number of days of overnight stays of these tourists varies between 2.77-6.66.

3.1.3.2 Exploratory statistics for tourist arrivals and overnight stay in the selected tourism regions

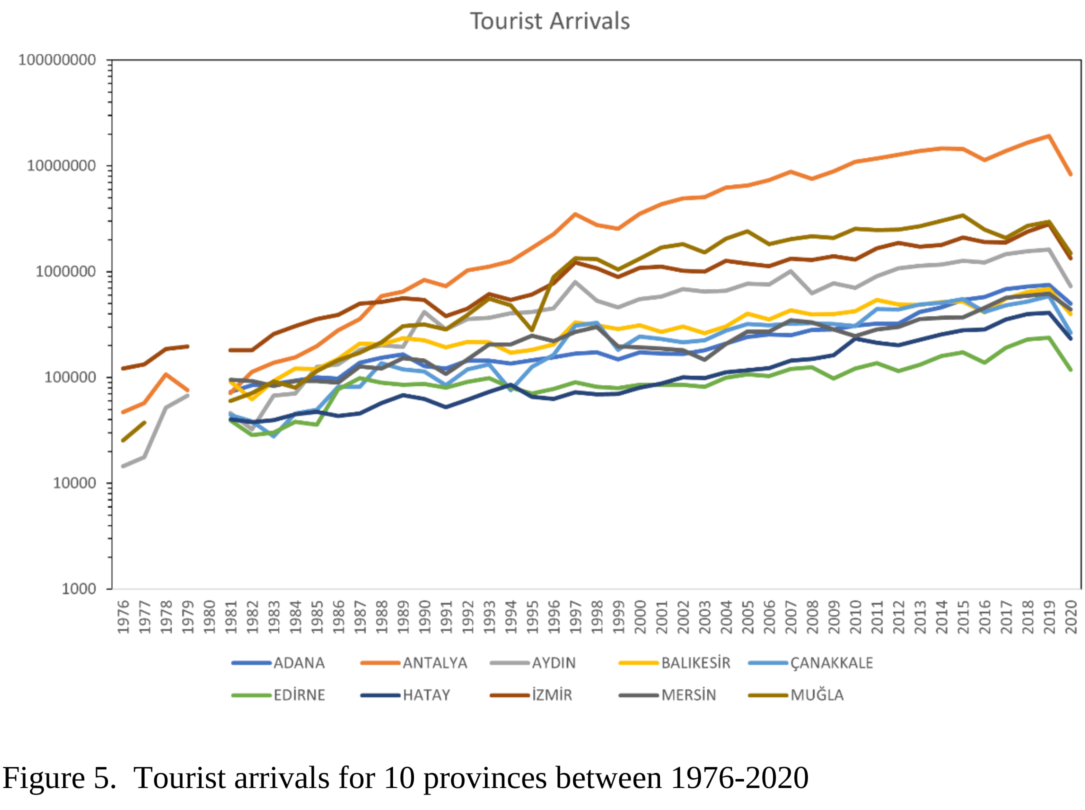

Figure 5. Tourist arrivals for 10 provinces between 1976-2020

As can be seen in Figure 5, there is an increase in the number of tourists from 1976 to 2020 in 10 provinces. It is important to note that the data are in logarithmic scales. Data entry could not be made for 1980 due to lack of data for all provinces. In addition, sharp declines in tourist arrivals due to the COVID-19 pandemic in 2019 and 2020 were noticed.

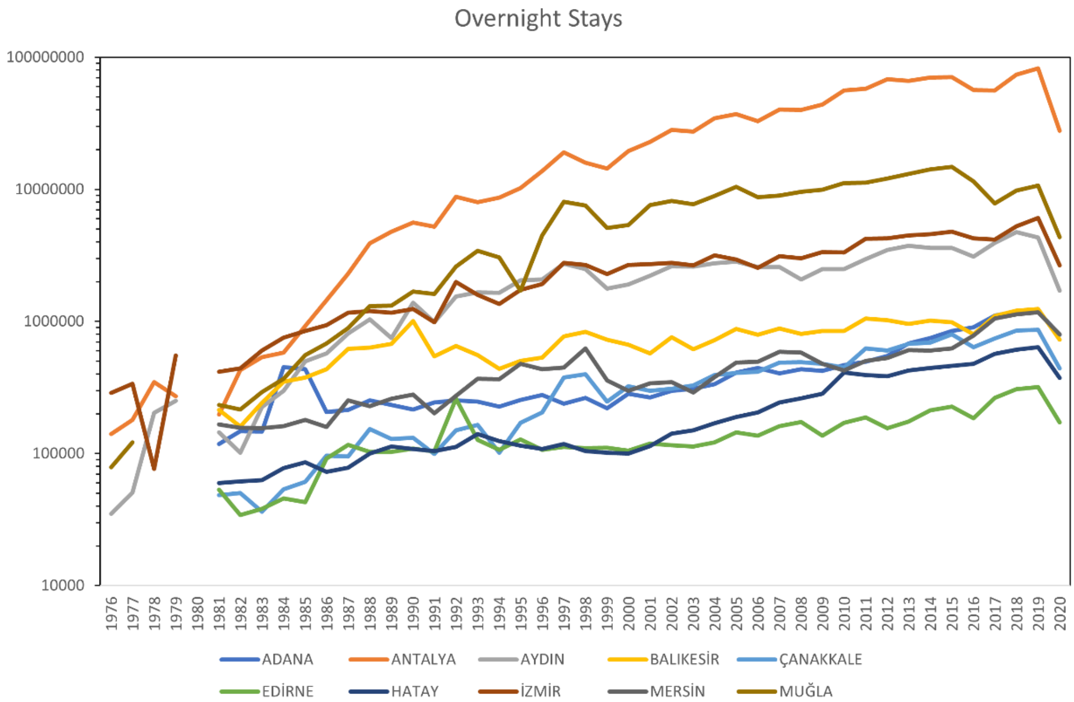

Figure 6. Overnight stays for 10 provinces between 1976-2020

As can be seen in Figure 6, there is an increase in the number of overnight stays of tourists from 1976 to 2020 in 10 provinces. It is important to note that the data are in logarithmic scales. Data entry could not be made for 1980 due to lack of data for all provinces. In addition, sharp declines in the number of overnight stays due to the COVID-19 pandemic in 2019 and 2020 were noticed.

3.2 Methodology

3.2.1 Deriving the HCI for the Mediterranean coast of Turkey

The Holiday Climate Index (HCI) was created in 2013 to address the inadequacies of previously established tourism climate indices, particularly the TCI (Tang, 2013). Eventually, Scott, Rutty, Amelung, and Tang (2016) improved the index. In order to decide the rating scales and weights of sub-items, HCI utilizes the existing literature on tourists' climate preferences obtained from recent surveys (Tang, 2013; Scott, Rutty, Amelung, and Tang, 2016; Rutty et al., 2020). Therefore, unlike TCI, it is not based on subjective opinions. Tang (2013) created the index based on three published studies (Scott, Gössling, and de Freitas, 2008; Moreno, 2010; Rutty and Scott, 2010). In these studies, the market segment consisted primarily of young adults. Scott, Rutty, Amelung, and Tang (2016) benefited from further studies that allowed the market segment to expand further. Additionally, the HCI:Beach form was created later (Rutty et al., 2020). There are two types of HCI, namely HCI:Urban and HCI:Beach. These indices have distinct weights for thermal comfort and cloud cover to accommodate the climatic needs of various tourism segments. HCI:Urban was developed to study urban tourism (Tang, 2013; Scott, Rutty, Amelung, and Tang, 2016). HCI:Beach has been developed using studies on the climate preferences of coastal tourists (Rutty et al., 2020). In this study, the index was modified as HCI:Coast to express the coastlines more comprehensively. However, to avoid confusion, it was referred to as HCI:Beach when citing studies in the literature.

Low temporal resolution is one of the limitations of TCI; however, HCI employs daily data as opposed to monthly data to fix this issue. HCI identifies the dominant effects of physical aspects by designating 0 or even negative ratings when predetermined thresholds are exceeded. HCI was analyzed by examining in contrast average monthly HCI:Urban scores to hotel occupancy in Paris (Scott, Rutty, Amelung, and Tang, 2016) and confirming average monthly HCI:Beach scores with Canadian visitor arrivals to three Caribbean destinations (Antigua and Barbuda, Barbados, and Saint Vincent) (Rutty et al., 2020). The authors presented a methodological framework to optimize HCI for improved clarification of climate preferences for particular destinations. These essential characteristics make HCI a comprehensive and universal index.

While calculating the HCI for the provinces analyzed in this thesis (Adana, Antalya, Aydın, Balıkesir, Çanakkale, Edirne, Hatay, İzmir, Mersin, Muğla) the HCI:Coast formula was applied to the grid points corresponding to the coastal districts of each province. For districts that do not have a coastline, the HCI:Urban formula was applied. Then, HCI:Combined was calculated by taking the average of all grid points within the borders of this province. This extra calculation was made to see the provincial average. HCI:Combined was calculated because considering an entire province as just an urban or just a coastal region would not yield healthy and accurate results.

3.2.1.1 Components

HCI employs four climate variables related to three tourism-relevant factors.
They include thermal comfort (TC), aesthetic (A), and physical (A) aspects. The four climate variables are comprised of humidity for thermal comfort, cloud cover for aesthetics, precipitation, and wind for the physical components. Each climate variable is rated on a scale from 0 to 10, and the HCI index score ranges from 0 to 100. The HCI:Urban, HCI:Coast and HCI:Combined were calculated as follows:

$$HCI: Urban = 4(TC) + 2(A) + 3(P) + (W)$$

$$HCI: Coast = 2(TC) + 4(A) + 3(P) + (W)$$

$$HCI: Combined = HCI: Urban \times c_1 + HCI: Coast \times c_2$$

There is a fundamental distinction between urban and beach tourists. The majority of beach visitors consider cloud cover to be the most essential climate resource (40%), while thermal comfort ranks third (20%) (Tang, 2013; Scott, Rutty, Amelung, and Tang, 2016; Rutty et al., 2020). Given that beach tourism is predominantly a daytime activity and that air conditioning is a ubiquitous feature in tourist lodgings, the aspect of evening comfort was not factored in as a distinct weighted element in HCI:Coast (Rutty et al., 2020). The comparison of the sub-index weights by climate index adopted in this study is shown in Table 1.

Table 1. Comparison of the Sub-Index Weights

Index Component	Weather Variables	HCI:Urban (Tang, 2013; Scott, Rutty, Amelung, and Tang, 2016)	HCI:Coast (Rutty et al., 2020)
Thermal comfort (TC)	Temperature and Relative humidity	40%	20%
Aesthetic (A)	Cloud cover (%)	20%	40%
Precipitation (P)	Total precipitation (mm)	30%	30%
Wind (W)	Mean wind speeds (km/hr)	10%	10%

3.2.1.1.1 Thermal comfort

Effective temperature, a combination of maximum air temperature and average relative humidity, was used to determine thermal comfort in the first HCI (Tang, 2013). Scott, Rutty, Amelung, and Tang (2016) applied the same methodology. However, Rutty et al. (2020) utilized Humidex, a heat index used by Canada's official weather office, instead of effective temperature because it highlights the additional effects of relative humidity on perceived temperature (Environment and Climate Change Canada, n.d.).

As stated previously, TCI's overemphasis on thermal comfort is one of its most criticized characteristics. Nevertheless, this emphasis on thermal comfort may understate the effects of other climatic factors on the overall vacation experience and neglect the potential effects of physical dimensions (Tang, 2013). Physical appearance (precipitation and wind) and thermal comfort are given sufficient weight to ensure that a high HCI score cannot be attained if the physical appearance rating is low. It is due to the fact that unfavorable physical climatic conditions (such as heavy rainfall, strong winds, and thunderstorms) precede pleasant thermal and aesthetic conditions (de Freitas, 1990; Moreno, Amelung, and Santamarta, 2009; Martínez-Ibarra, 2011). This equal weight also diminishes the significance of thermal comfort, which is less significant in regions where physical climate variables predominate (Scott, Rutty, Amelung, and Tang, 2016) (Tables 2 and 3).

3.2.1.1.2 Aesthetic

Regarding the aesthetic component, HCI:Urban employs percentage cloud cover as a variable in place of sunshine hours, as data on sunshine hours may not be collected by regular weather stations. The highest score for the aesthetic scheme of HCI:Urban reflects the preferences of tourists as determined by surveys. Contrary to expectations, tourists prefer 11-20% cloud cover to clear skies (i.e., 0% cloud cover) as the “ideal” aesthetic experience for urban tourism (Tang, 2013; Scott, Rutty, Amelung, and Tang, 2016). As for the lowest aesthetic appearance rating, TCI scores less than one hour of sunlight per day with a score of 0. Nevertheless, survey results found in the literature indicate that tourists tolerate all cloud cover conditions (i.e., even 100% cloud cover) (Tang, 2013; Scott, Rutty, Amelung, and Tang, 2016). The HCI:Urban index analyzes the potential of climate to support various forms of tourism where cloud cover is less significant than thermal comfort. Thus, on the HCI:Urban scale, there is no score of 0 (Tables 2 and 3).

The rating scheme for the HCI:Coast aesthetic aspect allocates the highest score to days with 15 to 25% cloud cover. Beach tourists give preference to marginally more cloud cover than urban tourists (Rutty et al., 2020). In light of this, slightly higher rankings are assigned. As mentioned previously, there is no 0 score on the HCI:Coast aesthetic scale as there is in the HCI:Urban example, and survey results in the literature indicate that travelers tolerate all cloudy conditions, even with a cloud cover of 100% (Scott, Rutty, Amelung, and Tang, 2016; Rutty et al., 2020) (Tables 2 and 3).

3.2.1.1.3 Precipitation

In accordance with the survey findings in the relevant literature regarding the preferences of tourists, in both HCI: Urban and HCI:Coast the weight of is increased to 30% (see, for example; Rutty and Scott, 2010; Georgopoulou et al., 2019). The prevalence of air conditioning in many locations is likely to increase in the future. As a result of this, the Daily Comfort Index (CIA) component of Mieczkowski's TCI (1985) is eliminated (Tang, 2013; Scott, Rutty, Amelung, and Tang, 2016; Rutty et al., 2020).

HCI:Urban examines the reported impacts of precipitation on the holiday experience. Since the HCI employs daily quantities, each rating category is divided by 30 and converted to daily precipitation (mm) (Scott, Rutty, Amelung, and Tang, 2016). By using daily data, monthly data usage is limited. HCI:Coast and HCI:Urban exhibit similarities, albeit with the sole distinction of ratings pertaining to moderate precipitation (6-11 mm). This difference is due to the fact that beach tourists are more resistant to precipitation than urban tourists (Rutty et al., 2020). This result is attributable to the cooling influence of afternoon rainfall in the tropics, where the majority of studies on coastal tourism are conducted (Rutty and Scott, 2014). Using data with a daily resolution is crucial for all variables, but especially for precipitation. This is due to the fact that travelers are interested in both the quantity and intensity of precipitation in a particular month (Rutty et al., 2020). For instance, surveys and some markets research indicate that tourists prefer a lack of precipitation over a comfortable temperature (Maddison, 2001; Gössling, Bredberg, Randow, Svensson, and Swedlin, 2006; Moreno, 2010; Jacobsen, Denstadli, Lohmann, and Forland, 2011; Dubois, Ceron, Dubois, Frias, and Herrera, 2016) (Tables 2 and 3).

3.2.1.1.4 Wind

HCI employs a single rating system for wind because the physical effects of wind are more likely to irritate tourists (e.g., blowing clothing and hair, prohibiting dining outdoors, blowing sand) than the wind's significant impact on thermal comfort. As with precipitation, destructive winds influence tourism demand due to the wind variable's dominant effect on HCI.

Other sub-indices already account for temperature (thermal comfort) and aesthetics. Therefore, both HCI:Urban and HCI:Coast share a single wind speed rating scheme with eight categories (Tang, 2013; Scott, Rutty, Amelung, and Tang, 2016; Rutty et al., 2020) (Tables 2 and 3).

Table 2. The Ratings of Thermal Comfort (Based On Humidex), Aesthetic (Based on Cloud Cover), Precipitation, Wind, and HCI:Coast Scores

Thermal Comfort (TC)		Aesthetic (A)		Precipitation		Wind		HCI:Coast Score	
Humidex		Cloud Cover							
	Rate	%	Rate	mm	Rate	(km/hr)	Rate		Rate
(-∞, 10)	-10	[0, 1)	8	[0, 0.01)	10	[0, 0.6)	8	[0, 20)	Dangerous
[10, 15)	-5	[1, 15)	9	[0.01, 3)	9	[0.6, 10)	10	[20, 40)	Unacceptable
[15, 17)	0	[15, 26)	10	[3, 6)	8	[10, 20)	9	[40, 50)	Marginal
[17, 18)	1	[26, 36)	9	[6, 9)	6	[20, 30)	8	[50, 60)	Acceptable
[18, 19)	2	[36, 46)	8	[9, 12)	4	[30, 40)	6	[60, 70)	Good
[19, 20)	3	[46, 56)	7	[12, 25)	0	[40, 50)	3	[70, 80)	Very Good
[20, 21)	4	[56, 66)	6	[25, ∞)	-1	[50, 70)	0	[80, 90)	Excellent
[21, 22)	5	[66, 76)	5			[70, ∞)	-10	[90, 100)	Ideal
[22, 23)	6	[76, 86)	4						
[23, 26)	7	[86, 96)	3						
[26, 28)	9	[96, 100]	2						
[28, 31)	10								
[31, 33)	9								
[33, 34)	8								
[34, 35)	7								
[35, 36)	6								
[36, 37)	5								
[37, 38)	4								
[38, 39)	2								
[39, ∞)	0								

Source: Tang (2013), Scott, Rutty, Amelung, and Tang (2016), Rutty et al. (2020), Demiroglu, Saygili-Araci, Pacal, Hall, and Kurnaz (2020)

Table 3. The Ratings of Thermal Comfort (Based On Humidex), Aesthetic (Based on Cloud Cover), Precipitation, Wind, and HCI:Urban Scores

Thermal Comfort (TC)		Aesthetic (A)		Precipitation		Wind		HCI:Urban Score	
Humidex		Cloud Cover							
	Rate	%	Rate	mm	Rate	(km/hr)	Rate		Rate
(-∞, -6)	1	[0, 1)	8	[0, 0.01)	10	[0, 0.01)	8	[0, 20)	Dangerous
[-6, 0)	2	[1, 11)	9	[0.01, 3)	9	[0.01, 10)	10	[20, 40)	Unacceptable
[0, 7)	3	[11, 21)	10	[3, 6)	8	[10, 20)	9	[40, 50)	Marginal
[7, 11)	4	[21, 31)	9	[6, 9)	5	[20, 30)	8	[50, 60)	Acceptable
[11, 15)	5	[31, 41)	8	[9, 12)	2	[30, 40)	6	[60, 70)	Good
[15, 18)	6	[41, 51)	7	[12, 25)	0	[40, 50)	3	[70, 80)	Very Good
[18, 20)	7	[51, 61)	6	[25, ∞)	-1	[50, 70)	0	[80, 90)	Excellent
[20, 23)	9	[61, 71)	5			[70, ∞)	-10	[90, 100)	Ideal
[23, 26)	10	[71, 81)	4						
[26, 27)	9	[81, 91)	3						
[27, 29)	8	[91, 100)	2						
[29, 31)	7	100	1						
[31, 33)	6								
[33, 35)	5								
[35, 37)	4								
[37, 39)	2								
[39, ∞)	0								

Source: Tang (2013), Scott, Rutty, Amelung, and Tang (2016), Rutty et al. (2020), Demiroglu, Saygili-Araci, Pacal, Hall, and Kurnaz (2020)

3.2.2 Modeling the impacts of comfort on tourist arrivals and overnight stay: Panel fixed effects model

In this section, the aim is to explore the impact of human comfort in regard to climatic characteristics on tourism activity in the Mediterranean provinces of Turkey. Specifically, the coastal, urban, and combined HCI indices derived for the Mediterranean provinces of Turkey will be regressed on the number of tourist arrivals and days of overnight stay using panel data analysis with the fixed effects specification.

Panel data is a set of data in which the behavior of entities (i) over time (t) is observed. These units may consist of individuals, families, businesses, or nations. If the same observation units from a cross-section sample are examined twice or more, the resulting observations constitute a panel or longitudinal data set (Dougherty, 2016). The analysis of panel data incorporates cross-sectional and time series data. It facilitates the control of individual heterogeneity by allowing for the examination of variation and involving less linear correlation between variables. Consequently, it offers more illuminating data, more variability, a less linear connection between variables, more degrees of freedom, and greater efficiency (Gujarati, 2022).

The panel structure of the data used in this study enables to examine the effects of holiday climate indices on tourism activity both on a provincial level and over a long-time span (1976-2020). We include the provinces with the greatest number of tourists in Turkey's Aegean and Mediterranean regions based on a predetermined threshold (10 provinces with the highest number of tourists in the Aegean and Mediterranean Regions).

The model can be expressed as follows:

$$y_{it} = \alpha + X_{it}^{'}\beta + u_{it}$$

In this formula, for $i= 1,..., N$ and $t= 1,..., T$, where y_{it} is the dependent variable, $X_{it}^{'}$ is the vector of independent variables, α is the constant term, β is the coefficient of HCI, and u_{it} is the error term, in the following form:

$$u_{it} = \mu_{it} + v_{it}$$

where μ_{it} is the *unobservable* individual-specific effects (i.e., fixed effects), and v_{it} is the remainder disturbance. μ_{it} is time-invariant, and it takes into account any individual-specific impact that is left out of the regression. v_{it} differs from individual to individual and time and can be considered the usual disturbance in the regression. The fixed effects μ_{it} are not directly predictable. Each μ_{it} is a discrete constant associated with a particular group or cross-section; therefore, the genuine constant term for every cross-section is $\beta_0 + \mu_{it}$. The remaining disturbances v_{it} are stochastic, independent, and uniformly distributed (*iid*). The explanatory variables are independent of v_{it}. The fixed effects model is preferred when all independent variables are conditionally related to individual effects, whereas the random effects model can be applied when all independent variables are exogenous to random individual effects (Mundlak, 1978). If the sample consists of *N* randomly selected observations from a large population, a random effects model can be appropriate.

A 2023 version of the Gretl program was used for analysis (https://gretl.sourceforge.net/osx.html). Gretl is a software package that has been designed to facilitate econometric analysis and is compatible with multiple operating systems. It is free and open-source software. Using the program, an analysis was made using the number of tourists and overnight stays in 10 provinces from 1976 to 2020, as it is the longest period for which data was available. An annual analysis of the HCI:Coast (the average of districts with a coast to the sea) and HCI:Urban (the average of the counties excluding the counties with a coastline) was carried out.

Also, an examination of HCI:Combined, which is the average of the two indices, was carried out in order to see the average effects across the provinces (HCI:Coast and HCI:Urban average in order to make an evaluation across the province). In addition, the sea water temperature reaches 20-28 °C during May-October, especially on the Mediterranean and Aegean coasts, which have a long holiday season (Zengin, 2006). Therefore, 6 months (May, June, July, August, September, October) with the highest number of tourist visits and which can be called the tourism season for the Mediterranean and Aegean coasts in Turkey (Gao and Giorgi, 2008; Türkeş, Koç, and Sariş, 2009; Rutty and Scott, 2010; Cook, Anchukaitis, Touchan, Meko, and Cook, 2016; Demiroglu et al., 2017) were also examined with the MPI-ESM-MR and HadGEM2 models, together with the annual analysis. In the analysis analyzed under the HCI:Coast, HCI:Urban and HCI:Combined indices, the number of tourist arrivals and overnight stays were dependent, HG-6-month, HG-annual, MPI-6-month and MPI-annual were independent variables (Table 4).

3.2.3 Analysis of future HCI trends

Temperatures are already high in the provinces in the Mediterranean and Aegean regions studied in this study. This situation prompted a curiosity for analysis and further research on the future, where we can see the values above a certain threshold after seeing the relationship between the number of tourist arrivals and overnight stays and the indices of HCI:Coast, HCI:Urban and HCI:Combined. Proper measurement of human exposure to extreme temperatures is a necessary basis for studying the effects of extreme temperatures on human comfort. It can also help identify future steps to be taken regarding the tourism sector in the 10 provinces in the analysis. In this context, this part of the study aims to examine the changes that future extreme temperatures can make on tourist comfort by using climate change projections in 10 provinces that attract millions of visitors as a coastal tourism destination in Turkey and to comment on the potential effects of this situation on the number of tourist arrivals and overnight stays. It also aims to draw attention to the effects of extreme heat on summer coastal tourism in terms of tourist comfort.

For this purpose, high resolution climate data was obtained from RegCM4.4 regional climate model by using the outputs of low-resolution global climate models as input. The study covered the future period 2026-2050 compared to the 1976-2000 reference period under the RCP8.5 scenarios. By using the Holiday Climate Index (HCI), future changes in the comfort levels of tourists were estimated for the next period (2026-2050). All input variables were derived directly from the regional climate model RegCM4.4. Dynamically calculated variables were used in the model, which minimizes the uncertainties that may arise from extra calculations.

RegCM version 4.4 (RegCM4.4) dynamically downscaled the low-resolution (200 km x 200 km) outputs of the global climate models MPI-ESM-MR and HadGEM2. High-resolution (10 km x 10 km) climate data under the RCP8.5 (pessimistic) scenario was produced. Since the aim of this analysis was to compare the last quarter of the last century and the quarter after 2025 (near future period) of this century, 25-year periods were preferred. The reason for examining only the near future is that investment plans for tourism are made for the short term. Another advantage of choosing this reference period is to be able to show the change more clearly in the 21st century, when the temperature increases began to become evident, compared to the 20th century.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 HCI trend analysis of 1976-2020

In this section, a trend analysis was performed to evaluate the changes in the HCI:Urban, HCI:Coast, and HCI:Combined indices between 1976 and 2020.

Looking at the trend analysis of the comfort conditions for HCI:Urban between 1976-2020, there are lower comfort conditions in Adana, Mersin and Antalya in both annual and 6-month analyzes. In the 6-month analyzes including the months of May-October, comfort scores are generally higher when all of the MPI-Annual, MPI-6-Month, HG-Annual and HG-6-Month analyzes are considered (Figure 7).

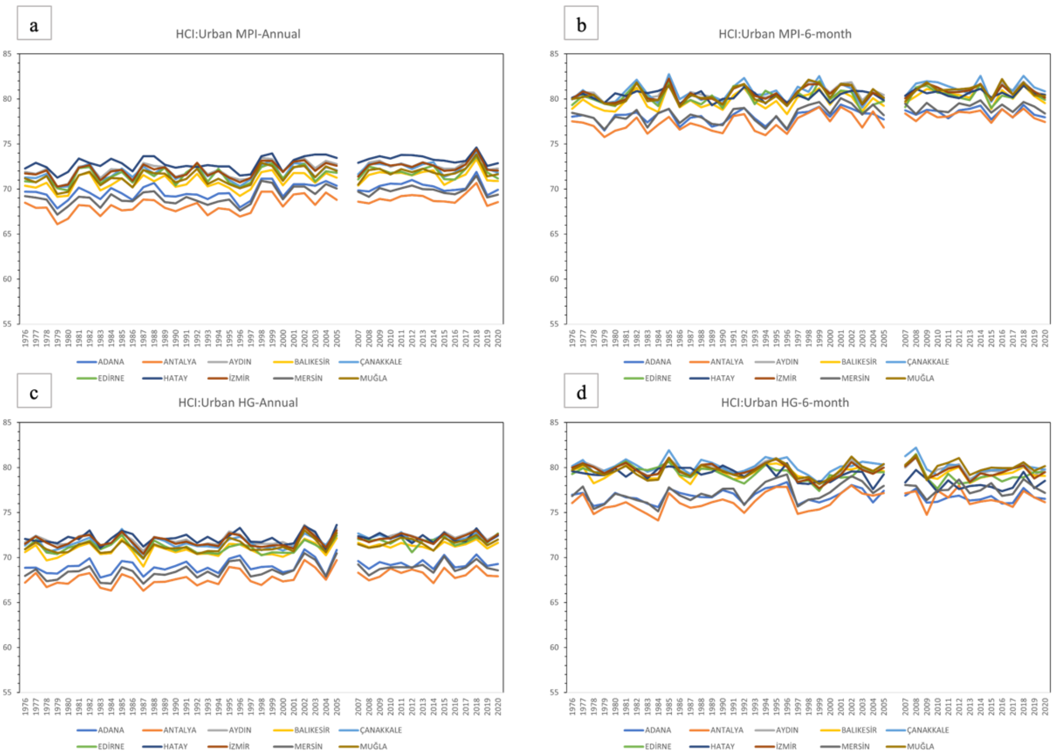

Figure 7. HCI:Urban trend analysis a) MPI-Annual, b) MPI-6-Month, c) HG-Annual, d) HG-6-Month

When we look at HCI:Coast, it is seen that Mersin has the lowest comfort score. In both annual and 6-month analyzes, it is seen that the best comfort conditions are in Adana and Aydın. However, MPI-Annual and HG-Annual analyzes show that the difference between these two months and the other months is greater. As in HCI:Urban, comfort scores in 6-month analyzes including May-October are generally higher when looking at all analyzes of MPI-Annual, MPI-6-Month, HG-Annual and HG-6-Month (Figure 8).

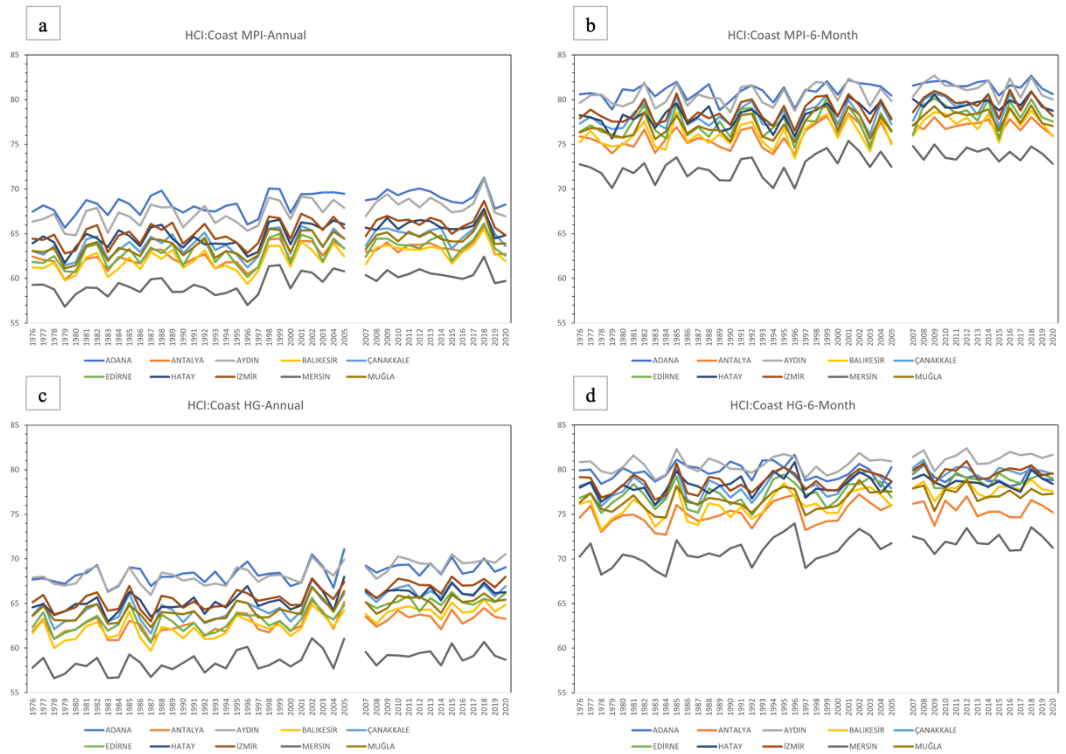

Figure 8. HCI:Coast trend analysis a) MPI-Annual, b) MPI-6-Month, c) HG-Annual, d) HG-6-Month

When we look at HCI:Combined, it is seen that the province with the least comfort conditions is Mersin. In MPI-Annual and HG-Annual analyzes, it is seen that Antalya and Muğla have lower scores than other provinces. In the MPI-6-Month and HG-6-Month analyzes, the scores of these provinces were closer to the other provinces (Figure 9).

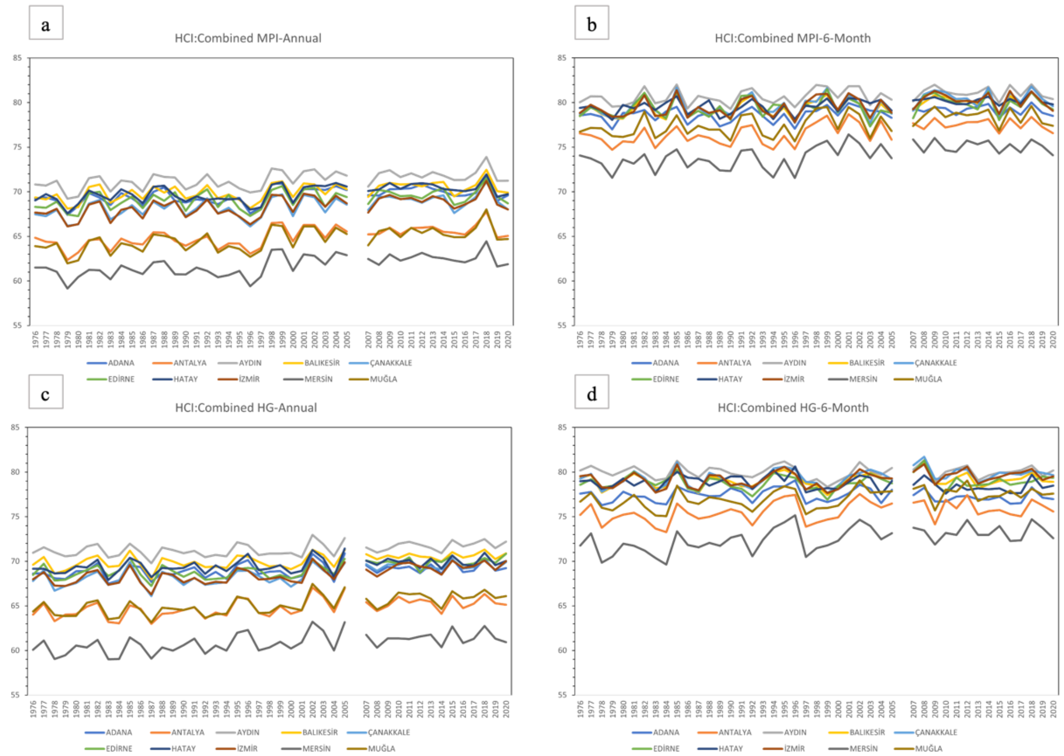

Figure 9. HCI:Combined trend analysis a) MPI-Annual, b) MPI-6-Month, c) HG-Annual, d) HG-6-Month

In general, since there was no noticeable decrease in comfort conditions between 1976 and 2020, the first hypothesis of the study, “Comfort levels are expected to decrease from the past to the present,” was not fully confirmed. In the 6-month analyzes performed for HCI:Urban, HCI:Coast and HCI:Combined in Aydın, Balıkesir, Çanakkale, Hatay and İzmir, decreases of 1-2 points were noticed between 1976 and 2020.

4.2 Results of the panel data analysis

The results of the panel data analysis are summarized in Table 4. Each row in Table 4 represents a single regression equation where the dependent variable is *Arrivals* or *Overnight stays*, and there is only one independent variable that stands for the HCI in the corresponding context (coast, urban, or combined). Hence, the effects of holiday comfort on arrivals and overnight stays are separately examined in each regression using various specifications of the HCI (i.e., *HG-6-month, HG-annual, MPI-6-month,* and *MPI-annual*) one at a time.

Table 4. Results of the Panel Fixed Effects Analysis for Arrivals and Overnight Stays

	HCI:COAST		HCI:URBAN		HCI:COMBINED	
	Dependent variable: Arrivals	*Dependent variable:* Overnight stays	*Dependent variable:* Arrivals	*Dependent variable:* Overnight stays	*Dependent variable:* Arrivals	*Dependent variable:* Overnight stays
Independent variable						
HG-6-month	0.399214***	0.285411***	0.0201439	0.0249142	0.284532**	0.176227*
	(0.0648793)	(0.0693395)	(0.164345)	(0.144356)	(0.108336)	(0.0879703)
HG-annual	0.295060***	0.209762***	0.299709***	0.216766***	0.324008***	0.162905***
	(0.0357107)	(0.0395575)	(0.0650180)	(0.0651156)	(0.0461290)	(0.0471146)
MPI-6-month	0.393414***	0.291711***	0.457794***	0.357312**	0.454280***	0.265394***
	(0.0724480)	(0.0771619)	(0.120510)	(0.121140)	(0.0887818)	(0.0705967)
MPI-annual	0.495255***	0.369180***	0.650364***	0.486967***	0.588650***	0.351897***
	(0.0728887)	(0.0796245)	(0.103466)	(0.115467)	(0.0833335)	(0.0799702)

Note. Standard errors in parentheses. Detailed regression outputs are presented in the Appendix A and B.

4.2.1 Arrivals

4.2.1.1 HCI:Coast analysis

Our analysis shows that the comfort variables, which were abbreviated as HG-6-month, HG-annual, MPI-6-month and MPI-annual in this thesis, positively affect the number of tourists visiting the coastal areas of the selected regions. It shows that climatic conditions are effective on the comfort of tourists, and moreover, the comfort factor is effective in the arrival of tourists to the coastal part of the provinces within the scope of the research. The coefficient of the MPI-annual variable is much higher than the coefficient of the other comfort variables; in other words, the increase in the MPI-annual level increases the number of tourists more than the other comfort variables.

4.2.1.2 HCI:Urban analysis

The analysis shows that the HG-annual, MPI-6-month and MPI-annual variables each positively affect the number of tourists arriving in the urban areas of the selected regions. However, the coefficient of the HG-6-month variable is not statistically significant. This result shows that the comfort factor is effective in the arrival of tourists to the urban areas within the scope of the research, since climatic conditions are also effective on the comfort of tourists. As in the HCI:Coast analysis, it is seen that MPI-annual variable is more effective than other comfort variables due to its higher coefficient.

4.2.1.3 HCI:Combined analysis

Our analysis shows that HG-annual, MPI-6-month and MPI-annual variables all positively affect the number of tourists coming to the analyzed provinces. This shows that the comfort factor is effective in the arrival of tourists to the provinces within the scope of the research, and as the comfort increases, more tourists come. As in the HCI:Coast and HCI:Urban analyzes, it is seen that the MPI-annual variable affects the number of tourists more because of its higher coefficient than the others.

4.2.2 Overnight stays

4.2.2.1 HCI:Coast analysis

Our analysis shows that the variables HG-6-month, HG-annual, MPI-6-month and MPI-annual all positively affect the number of overnight stays of tourists in the coastal areas of the selected provinces. This result shows that climatic conditions are effective on the comfort of tourists and the comfort factor is effective in the number of days tourists spend in their visit to the provinces within the scope of the research. It is seen that MPI-annual variable is more effective than other comfort variables.

4.2.2.2 HCI:Urban analysis

Our analysis shows that HG-annual, MPI-6-month and MPI-annual variables all increase the number of overnight stays of tourists coming to urban areas. These results show that the comfort factor is effective in the number of days tourists spend visiting these provinces. However, the coefficient of the HG-6-month variable is not statistically significant, that is, HG-6-month does not affect the overnight stays. It seems that the MPI-annual variable is more effective than the others.

4.2.2.3 HCI:Combined analysis

Our analysis shows that the HG-annual, MPI-6-month and MPI-annual components all positively affect the number of overnight stays by tourists for HCI:Coast. This result shows that climatic conditions are effective on the comfort of tourists and the comfort factor is effective in the number of days tourists spend in their visit to the provinces within the scope of the research. However, the statistical significance level of the coefficient of the HG-6-month variable was lower. It is seen that the MPI-annual variable is more effective than the others in increasing the overnight stays.

4.3 Robustness checks for panel data analysis

In this part of the study, a robustness check is performed using the MPI series derived as the comfort indicator and including an additional independent variable, the gross domestic product per capita (GDPPC) (USD) of provinces, which is an economic measure of a province's per capita economic output. It is included in the analysis to stand for the socioeconomic determinant of the provinces' tourism activity. However, GDPPC data on a provincial basis are only available between 2004 and 2020 (TURKSTAT, 2022). Thus, the robustness checks are conducted only for the 2004-2020 period.

Table 5. Results of the Panel Fixed Effects Analysis for Arrivals and Overnight Stays Using GDP per Capita as an Additional Independent Variable

	HCI:COAST		HCI:URBAN		HCI:COMBINED	
	Dependent variable Arrivals	*Dependent variable* Overnight stays	*Dependent variable* Arrivals	*Dependent variable* Overnight stays	*Dependent variable* Arrivals	*Dependent variable* Overnight stays
Independent variables						
MPI-6-month	0.0498010**	0.00885040	0.106266***	0.0437591***	0.0722029***	0.0276724***
	(0.0154377)	(0.00815917)	(0.0170260)	(0.0105498)	(0.0220520)	(0.00844397)
GDPPC	0.971671***	0.743357***	0.945180***	0.718073***	0.958321***	0.725617***
	(0.103375)	(0.0960810)	(0.106314)	(0.102388)	(0.106989)	(0.0996754)
MPI-annual	0.0364520	0.0259722	0.0805944***	0.0458250**	0.0563382**	0.0377706*
	(0.0215545)	(0.0162130)	(0.0244887)	(0.0197553)	(0.0237045)	(0.0171737)
GDPPC	1.04524***	0.762932***	1.05796***	0.768416***	1.04959***	0.765338***
	(0.108468)	(0.0995607)	(0.105803)	(0.0999729)	(0.107238)	(0.0998015)

Note. Standard errors in parentheses. Detailed regression outputs are presented in the Appendix C and D.

Each two rows present the coefficient estimates of a multivariate regression, where the independent variables are an MPI indicator and GDP per capita, respectively (Table 5). The results show that the coefficients of most MPI specifications are still significant and positive when the GDP per capita levels of the provinces are controlled for. Besides, GDP per capita also affects tourist arrivals and overnight stays positively in the examined period.

4.4 Results for future HCI projections

In order to study the effects of extreme temperatures on human comfort, it was aimed to appropriately measure the effects of human exposure to extreme temperatures. In the analysis, using climate change projections in 10 provinces, the possible effects of future extreme temperatures (2026-2050) on tourist comfort and the possible effects of this on tourist arrivals and overnight stays were interpreted. First, a monthly analysis was performed, and monthly average HCI:Coast, HCI:Urban, and HCI:Combined values were examined. With this analysis, it was aimed to see the changes that may occur in tourist comfort levels in the summer tourism season and other months in the future. The previously mentioned thresholds were indicated again with the color scale used in the analysis (Table 6).

Table 6. HCI Color Scale

0	0-20	Dangerous
20	20-40	Unacceptable
40	40-50	Marginal
50	50-60	Acceptable
60	60-70	Good
70	70-80	Very Good
80	80-90	Excellent
90	90-100	Ideal

4.4.1 Adana

Looking at the results for Adana, the conditions that were excellent for May, June, July, August, and September in the HCI:Coast index for the MPI-ESM-MR model in the past (1976-2000), will be in the same category in the future (2026-2050). However, it is seen that the scores increase in May and June and decrease in July and August. For the category, which was very good for October, the score increased slightly and approached the excellent threshold. There is an increase of 2 points in January, April and December, and an increase of 4 points in February, March and November, but there is no category change. Looking at the HadGEM2 model, a category change is seen with an increase of 3 points in May, which is during the tourist season months, that is, the comfort conditions, which were very good, will become excellent in the future. There is a decrease of 3 points in June, but the comfort conditions are still excellent. However, the point drops in July and August indicate that conditions that were excellent will become very good. Despite 1 point decrease in September and increase in October, no categorical change is observed. With an increase of about 6 points in March, acceptable conditions will become good. Although the increase of 5 points in November does not provide a categorical change in the month, it can be said that the comfort conditions will improve. In January marginal comfort conditions will become acceptable in the future. Although there is no categorical change in February and December, the scores will increase.

Looking at the HCI:Urban index, some categorical changes will be seen in 2026-2050 compared to some 1976-2000 periods for the MPI-ESM-MR model in the months with tourism season. For example, for July and August, there will be a transition from excellent to very good, with decreases of 2 and 1 points, respectively. There will be an increase of 3 points for May. Categorical change will not be observed in June, September and October. There will be increases in points for January, February, March, April, November and December, but no categorical change will be observed in terms of comfort. For the HadGEM2 model, a categorical change will be seen with the increase in points for April and October, and while the comfort conditions are good in these months, they will be very good. In addition, there will be a transition from acceptable conditions to good conditions with an increase in points in February. Despite the increase or decrease in points for May, June, July, August and September, categorical changes will not be observed and very good comfort conditions will continue. There will also be increase in points for January, November and December, but no categorical change will be observed.

Considering the HCI:Combined index, although there are increases in points for the MPI-ESM-MR model for January, February, April, May, June, September, October, November and December, no category change will be observed. January, February and December will maintain acceptable comfort conditions, April and November good conditions, May and October very good conditions, and June and September will maintain excellent conditions. In March, acceptable comfort conditions will be good with an increase of about 3 points, and excellent comfort conditions for July and August will be very good. For the HadGEM2 model, categorical changes will not be observed despite the increase in points in January, February, March, May, July, September, October, November and December. January, February and December will maintain acceptable comfort conditions, March and December good conditions, and May, July, August and September very good conditions. With an increase of 3 points in April, good conditions will move into the category of very good comfort conditions. For June and August, the excellent comfort conditions will regress to the very good category (Table 7).

Table 7. Comparison of Monthly Projected HCI Scores for Adana

Index Type	Model	Period	January	February	March	April	May	June	July	August	September	October	November	December
HCI:Coast	MPI-ESM-MR	1976-2000	47,3517	49,6334	54,7222	67,3358	75,1543	82,6707	83,6494	83,5521	83,5012	75,9144	60,2933	50,6636
		2026-2050	49,9394	53,0287	58,8699	69,132	78,5793	83,5304	81,8323	81,5544	83,6166	78,694	64,5903	52,7272
	HadGEM2	1976-2000	48,7618	51,0794	56,7715	67,7275	78,121	83,3035	80,8293	81,1927	82,2246	73,3279	61,3201	51,5771
		2026-2050	52,5224	55,7963	62,4095	72,6692	81,2865	80,6179	75,5381	76,5663	81,0364	76,0159	66,5326	55,8382
HCI:Urban	MPI-ESM-MR	1976-2000	56,2008	57,8886	60,8719	68,859	73,8685	79,7122	80,072	80,4589	80,0342	73,5726	63,4394	57,9981
		2026-2050	57,2813	59,742	63,3704	69,7778	76,4915	79,8285	78,9846	79,0302	80,5732	75,3579	65,5161	59,0721
	HadGEM2	1976-2000	56,8635	58,4805	61,7985	67,6722	74,2617	79,3515	79,4746	79,8449	77,7927	69,9793	63,1548	57,8298
		2026-2050	57,9993	60,337	64,5164	70,1949	76,1181	78,0063	76,1495	77,4146	79,085	72,8488	65,7805	59,6698
HCI:Combined	MPI-ESM-MR	1976-2000	54,3907	56,2001	59,614	68,5475	74,1315	80,3174	80,8037	81,0916	80,7434	74,0516	62,7959	56,4979
		2026-2050	55,7796	58,3688	62,4499	69,6457	76,9185	80,5857	79,5671	79,5465	81,1957	76,0403	65,3267	57,7743
	HadGEM2	1976-2000	55,2063	56,9666	60,7702	67,6835	75,0511	80,1599	79,7517	80,1206	78,6992	70,6642	62,7795	56,5509
		2026-2050	56,879	59,4082	64,0854	70,701	77,1753	78,5405	76,0244	77,2411	79,4842	73,4966	65,9344	58,8861

4.4.2 Antalya

Looking at Antalya, categorical changes in the HCI:Coast index for the MPI-ESM-MR model in the period of 2026-2050 versus the 1976-2000 period draw attention. For example, for March, May, and June, marginal comfort conditions will become acceptable, good comfort conditions will become very good, and very good comfort conditions will become excellent, respectively. For January, February, and December, marginal conditions will not change. There will be an increase in points in April and November, but good comfort conditions will not change categorically. There will be an increase in points in July and August, but the excellent conditions will not change. Despite the increase in points for September and October, very good and good comfort conditions will continue, respectively. Looking at the HadGEM2 model, marginal comfort conditions will become acceptable for March, acceptable conditions for April will become good, and good conditions for May will become very good. There will be an increase in points for January, February, and December, but it will not cause a categorical change. June and September will maintain very good comfort conditions. For July and August, there will be a decrease in points, but the excellent comfort conditions will continue. Finally, there will be no categorical change in October and good comfort conditions will continue.

For the MPI-ESM-MR model in the HCI:Urban index, there will be increase in points in January, February and December in the next period of 2026-2050 compared to the 1976-2000 period, but there will be no categorical change and acceptable conditions will continue. There will be no categorical change in good conditions in April and November, but comfort conditions will increase as the points increase. In May, September, and October, the index will increase in points, but the very good category will not change. For July and August, excellent comfort conditions will continue in the future. On the other hand, a 2-point increase in March will make acceptable conditions good, and a 1-point increase in June will make very good conditions excellent. In the HadGEM model, the categorical change will be seen only in March, and the acceptable comfort conditions will be good. In January, February, and December, there will be no categorical change despite the increase in points. There will be an increase in points in April, October, and November, but the good comfort conditions will not change. For May, June, and September, there will be no change in the very good category. Despite the decrease in points in July and the increase in points in August, the excellent category will not change.

When we look at the HCI:Combined index, a categorical change will be observed in the MPI-ESM-MR model in the period of 2026-2050 compared to the 1976-2000 period. In February and December, marginal comfort conditions will be acceptable. Good comfort conditions in May will be very good, and very good conditions in June will be excellent. Marginal comfort conditions will continue in the future for January. Acceptable conditions in March and November and good conditions in April and October will continue in the future. There will be an increase in points in September, but very good comfort conditions will continue. Excellent conditions will continue in July and August. In the HadGEM2 model, for January, comfort conditions that were marginal in the past will be acceptable in the future, and comfort conditions that were good in May will be very good. On the other hand, despite the increase in points in February, March, November, and December, acceptable conditions will remain the same. There will be an increase in points in April and October, but the good conditions will continue. Very good comfort conditions will continue in June and September. In July and August, despite the slight decrease in points, the excellent conditions will continue (Table 8).

Table 8. Comparison of Monthly Projected HCI Scores for Antalya

Index Type	Model	Period	January	February	March	April	May	June	July	August	September	October	November	December
HCI:Coast	MPI-ESM-MR	1976-2000	43,0364	44,5338	47,6974	57,9863	66,7259	77,8517	82,6416	82,4479	77,3285	66,4245	51,7842	45,0451
		2026-2050	44,5632	47,329	50,6609	59,3774	71,3727	80,1079	83,367	83,0979	79,6847	68,5683	55,1441	47,4377
	HadGEM2	1976-2000	45,0566	46,4704	49,9191	58,2499	68,5832	78,5581	82,3936	81,7696	74,5243	62,3745	53,1872	46,0163
		2026-2050	46,2702	48,4482	53,4703	62,4591	73,6146	79,9124	80,5711	80,4947	77,6524	67,2778	56,6785	48,9125
HCI:Urban	MPI-ESM-MR	1976-2000	54,5688	55,8789	58,603	65,9484	71,5238	79,0031	82,1136	81,966	78,1718	70,2156	60,3409	56,0682
		2026-2050	55,5157	58,0245	60,589	66,7684	74,706	80,2803	82,634	82,6281	79,7734	71,2938	62,1789	57,6073
	HadGEM2	1976-2000	55,4836	56,7848	59,6473	65,1453	71,618	78,6669	82,286	81,9483	75,1624	65,912	60,7836	56,0583
		2026-2050	56,0363	58,0195	61,4824	67,3504	74,7359	79,8686	81,6821	82,0236	78,6144	69,1232	62,3219	57,7078
HCI:Combined	MPI-ESM-MR	1976-2000	47,6377	49,0604	52,0486	61,1631	68,6402	78,3111	82,4309	82,2556	77,6649	67,9371	55,1982	49,4432
		2026-2050	48,9331	51,5964	54,6221	62,3264	72,7026	80,1767	83,0745	82,9105	79,7201	69,6557	57,9509	51,4952
	HadGEM2	1976-2000	49,2169	50,5858	53,8006	61,0011	69,7941	78,6015	82,3507	81,8409	74,7789	63,7859	56,218	50,0229
		2026-2050	50,1668	52,2671	56,6671	64,4107	74,062	79,8949	81,0144	81,1048	78,0362	68,0141	58,9302	52,4217

4.4.3 Aydın

Looking at Aydın, there is a categorical change in the HCI:Coast for the MPI-ESM-MR model in two months in the period of 2026-2050 versus the 1976-2000 period, and point increases and decreases in the other months. It is seen that marginal comfort conditions will be acceptable with point increases in February. It is also seen that with the increase in points in November, the comfort conditions will change from acceptable to good category. On the other hand, it is seen that marginal conditions will continue despite the increase in points in January. Similarly, despite the increase in points in March and December, there will be no categorical change and acceptable comfort conditions will continue. Good conditions in April and very good comfort conditions in May and October will continue in the future. Looking at June, July, August and September, it is seen that the excellent conditions will continue in the future despite the increase in points or the continuation of the same conditions. In the HadGEM2 model, categorical changes draw attention in January and May. In January marginal conditions will become acceptable and in May very good conditions will become excellent. On the other hand, despite the increase in points in February, March and December, it is seen that acceptable comfort conditions will continue. High score increases also draw attention in April and November, but these score increases will not cause a categorical change and good comfort conditions will continue. It is seen that the excellent comfort conditions will continue in the future in June, July, August and September. However, the decrease of 5 points in July and 3 points in August draws attention. Although there is no categorical change, it can be said that comfort conditions will decrease even more in the future.

For the MPI-ESM-MR model in the HCI:Urban index, a categorical change is seen in only one month in the 2026-2050 period versus the 1976-2000 period, and this month is January when the comfort conditions turn from acceptable to good. Despite the increase in points in February, March, November and December, good comfort conditions will continue in the future. In April, May and October, the comfort conditions will continue to be very good despite the increase in points. Excellent comfort conditions will continue in June, July, August and September, but similar to HCI:Coast, points decrease in July and August draw attention. In the HadGEM2 model, on the other hand, categorical changes are noticeable in three months. Very good comfort conditions in May will become excellent in the future. In July and August, the excellent comfort conditions will become very good with points declining in the future. Compared to other provinces, good comfort conditions will continue in the future as in the past, even in winter months such as January, February and December. There will be an increase in points in March and November, but good comfort conditions will continue in the future. There will also be an increase in points in April and October, but very good comfort conditions will continue in the future without any categorical change. There will be a decrease in points in June and an increase in points in September, but the comfort conditions in these months will continue to be excellent in the future.

In the HCI:Combined index, there will be no categorical change in any month in the 2026-2050 period versus the 1976-2000 period for the MPI-ESM-MR model. Comfort conditions that were acceptable in January, February, and December will remain the same in the future. Good comfort conditions will continue in the future in March, April, and November. There will also be an increase in points in May and October, but no categorical change will be observed, and very good comfort conditions will continue in the future. In June and September, the index scores will not change much, and also the points will decrease in July and August, but the comfort conditions will remain in the excellent category in these months. In the HadGem2 model, on the other hand, categorical changes draw attention. For example, comfort conditions that were acceptable in the past in February and December will become good in the future. Comfort conditions, which were good in April, will move to the very good category in the future with an increase in points. The comfort conditions, which were very good in May, will be excellent in the future. On the other hand, comfort conditions, which were excellent, will become very good with the decrease in points in July and August. There will be a decrease in points in June and an increase in points in September, but the comfort conditions in these months will remain excellent in the future (Table 9).

Table 9. Comparison of Monthly Projected HCI Scores for Aydın

Index Type	Model	Period	January	February	March	April	May	June	July	August	September	October	November	December
HCI:Coast	MPI-ESM-MR	1976-2000	46,9637	48,1872	51,6368	62,4184	72,8111	82,8914	84,8658	84,7687	82,6591	73,8623	59,0633	50,8144
		2026-2050	49,2736	51,3662	54,8919	63,9799	76,8008	83,7746	84,1494	83,5249	83,0052	75,3205	63,1644	53,1122
	HadGEM2	1976-2000	49,6395	50,1512	53,8797	63,8493	75,475	83,3712	85,0776	85,7084	81,7129	71,0047	61,19	51,9073
		2026-2050	52,7548	54,1143	58,5897	68,7352	80,513	83,5794	80,7892	82,1852	83,2816	76,1103	66,0254	56,3029
HCI:Urban	MPI-ESM-MR	1976-2000	59,0564	60,3686	63,0391	70,6615	76,8512	82,769	82,7913	83,0222	82,3415	75,8449	65,4048	60,4359
		2026-2050	60,0911	61,9383	64,8846	71,063	79,1011	82,1875	80,7344	80,613	82,7686	76,8671	67,7837	61,6054
	HadGEM2	1976-2000	60,3057	61,077	63,9369	70,5981	77,8279	82,0313	80,9729	82,9439	81,9105	73,1128	66,4251	61,0627
		2026-2050	60,8878	62,5986	65,9657	72,7349	80,519	80,8592	75,2219	77,9441	82,9927	77,2226	69,0277	62,7649
HCI:Combined	MPI-ESM-MR	1976-2000	56,7007	57,9956	60,8178	69,0557	76,0642	82,7929	83,1954	83,3624	82,4034	75,4587	64,1694	58,5616
		2026-2050	57,9838	59,8788	62,938	69,6831	78,653	82,4966	81,3997	81,1802	82,8147	76,5658	66,8839	59,9508
	HadGEM2	1976-2000	58,2279	58,9486	61,9777	69,2834	77,3696	82,2923	81,7725	83,4824	81,872	72,7021	65,4053	59,2792
		2026-2050	59,3034	60,9458	64,5289	71,9557	80,5178	81,3891	76,3064	78,7703	83,049	77,0059	68,4428	61,5061

4.4.4 Balıkesir

Looking at Balıkesir, a categorical change in the HCI:Coast index for the MPI-ESM-MR model in two months in the 2026-2050 period compared to the 1976-2000 period draws attention. Good comfort conditions in May will be very good and very good comfort conditions in June will be excellent. On the other hand, marginal comfort conditions will continue in the future despite the increase in points in January, February, March and December. Similarly, points will increase in April and November, but acceptable comfort conditions will continue. There will be an increase in points in September but very good comfort conditions will continue in the future. Finally, the excellent comfort conditions will continue in the future, despite the slight increase in points in July and August. In the HadGEM2 model, there will be a categorical change in five months. March will move from the marginal category to the acceptable category. In April, comfort conditions will change from acceptable to good. May will move from the good category to the category with very good comfort conditions, with an increase of 6 points. In June and September, the comfort conditions will change from the very good category to the excellent category with points increase. Marginal conditions in January, February and December will continue into the future. There will be an increase of 7 points in October, but the comfort conditions will continue to be good. Acceptable conditions in November will remain in the same category in the future, despite point increases. There will be a decrease in points in July and August, but the comfort conditions will remain in the excellent category.

In the HCI:Urban index, a categorical change is noticeable only in December in the 2026-2050 period compared to the 1976-2000 period for the MPI-ESM-MR model. The comfort conditions acceptable this month will be good in the future.

Despite the increase and decrease in points in other months, no categorical change will be observed. For example, comfort conditions in January and February will continue to be acceptable in the future. Good comfort conditions in March, April and November will continue in the future. There will also be an increase in points in May and October, but there will be no transition from the very good category to the next category. There will also be increases and decreases in points in June, July, August and September, but the comfort conditions in these months will continue to be excellent in the future. In the HadGEM2 model, there will be a categorical change in five months. Acceptable comfort conditions in February and December will be good in the future. Conditions that are good in April will move to the next category, very good. On the other hand, the comfort conditions which were excellent in July and August will be very good in the future as the points decrease. Comfort conditions, which were acceptable in the past, will remain in the same category in the future. Comfort conditions that were good in the past in March and November will remain in the same category in the future. May and September will remain in the very good category in the future, but it is noteworthy that the point increases are high. Despite the increase in points in June and decrease in points in September, comfort conditions will remain in the excellent category in these months as well.

In the HCI:Combined index, a categorical change is remarkable in only one month in the 2026-2050 period compared to the 1976-2000 period for the MPI-ESM-MR model. This month is March when acceptable comfort conditions will be good in the future. Comfort conditions that were acceptable in the past in January, February and December will remain in the same category in the future. Good comfort conditions in April and November will remain in the same category in the future. May and October will continue to have very good comfort conditions in the future.

There will also be increases and decreases in points in June, July, August and September, but the comfort conditions in these months will continue to be excellent in the future. In the HadGEM2 model, on the other hand, categorical changes in more months draw attention. For example, with the decrease in points in July and August, comfort conditions will move from excellent to very good in the future. On the other hand, comfort conditions that are very good in September will be excellent in the future, and comfort conditions that are acceptable in December will be good in the future. In December, comfort conditions that were acceptable in the past will be good in the future. Comfort conditions that were acceptable in the past in January and February will remain in the same category in the future. In March, April and November, points will increase, but comfort conditions will remain in the good category in these months as in the past. Although the comfort conditions in May and October will remain in the very good category in the future, high point increases are noteworthy (Table 10).

Table 10. Comparison of Monthly Projected HCI Scores for Balıkesir

Index Type	Model	Period	January	February	March	April	May	June	July	August	September	October	November	December
HCI:Coast	MPI-ESM-MR	1976-2000	42,4172	43,3057	45,6274	55,7233	66,9866	79,1538	83,1019	82,6694	77,5801	66,3463	51,1815	44,4589
		2026-2050	43,6374	45,2353	48,4315	57,2284	71,3992	80,5548	83,8409	83,3664	79,3011	67,8415	54,6765	47,1101
	HadGEM2	1976-2000	43,9883	44,3709	47,3535	55,8808	69,3097	79,5633	83,5966	83,0513	75,6899	62,3767	52,5098	44,9268
		2026-2050	45,7097	47,0819	51,4759	60,9821	75,2042	81,7753	81,9824	82,877	80,2757	69,1071	57,4276	48,6294
HCI:Urban	MPI-ESM-MR	1976-2000	57,8098	58,8382	61,1071	68,4694	74,9801	82,0069	83,3239	83,1056	80,9068	73,8327	63,4602	59,1016
		2026-2050	58,5592	59,9708	63,0497	68,8963	77,5026	82,0508	82,0216	81,5413	81,3552	74,6316	65,5806	60,3079
	HadGEM2	1976-2000	58,6326	59,2912	62,0349	67,9039	76,2556	81,9319	82,4453	83,6474	80,3845	71,3515	64,6009	59,7178
		2026-2050	59,7297	61,0802	64,0727	70,3151	79,4455	80,7436	76,3087	79,2626	82,0652	75,7922	67,5271	61,5291
HCI:Combined	MPI-ESM-MR	1976-2000	56,1121	57,125	59,3998	67,0636	74,0985	81,6922	83,2994	83,0575	80,5399	73,007	62,1059	57,4866
		2026-2050	56,9135	58,3456	61,4374	67,6094	76,8294	81,8858	82,2223	81,7426	81,1287	73,8827	64,378	58,8522
	HadGEM2	1976-2000	57,0175	57,6456	60,4156	66,5778	75,4895	81,6707	82,5723	83,5816	79,8668	70,3616	63,2673	58,0864
		2026-2050	58,1833	59,5363	62,6834	69,2857	78,9777	80,8574	76,9345	79,6613	81,8678	75,0549	66,4132	60,1064

4.4.5 Çanakkale

Looking at Çanakkale, the category change in the HCI:Coast index for the MPI-ESM-MR model in three months in the 2026-2050 period versus the 1976-2000 period draws attention. Marginal comfort conditions in the past for March will be acceptable in the future. It is seen that good comfort conditions in May and October will pass into the very good category in the future. On the other hand, despite the increase in points in January, February and December, it is seen that the marginal comfort conditions will continue in the future. With the increase in points in April and November, comfort conditions will improve, but these increase in points will not lead to a change in category and comfort conditions will remain acceptable in these months. It is seen that the comfort conditions, which were excellent in the past in June, July, August and September, will continue in the same way in the future. In the HadGEM2 model, a categorical change is observed in the five months of the year. For example, with the increase in points in March and December, comfort conditions that were marginal in the past will become acceptable in the future. In April, comfort conditions that were acceptable in the past will become good in the future. Comfort conditions that were very good in the past for September will be excellent in the future, and good comfort conditions in the past for October will become very good in the future. On the other hand, conditions that were marginal in the past in January and February will continue in the future. Although there is no category change for May, a 6-7 point increase in comfort conditions draws attention. Despite the increase and decrease in points in June, July and August, excellent comfort conditions will continue in the future. Finally, in November, as in the past, the comfort conditions will continue to be acceptable in the future, but the increase in points draws attention.

In the HCI:Urban index, the categorical changes in March, May and October in the 2026-2050 period for the MPI-ESM-MR model over the 1976-2000 period draw attention. Comfort conditions, which were marginal in the past in March, will become acceptable in the future with point increases. Good comfort conditions in the past for May and October will become very good in the future. For the marginal comfort conditions of the past in January, February and December, there will be future increases in points, but they will remain in the same category. In the past, April and November in the acceptable category will still have acceptable comfort conditions, despite the increase in points. For the months of June, July, August and September, the comfort conditions, which were excellent in the past, will continue to be the same in the future. In the HadGEM2 model, the categorical changes in March, April, September, October and December draw attention. It can be seen that in March and December it will move from the marginal category to the acceptable category in the future. There will be a transition from the acceptable category in April to the good category in the future, and the comfort conditions will improve further. It is seen that there will be a transition from the very good category to the excellent category for September and from the good category to the very good category for October. On the other hand, the comfort conditions for January and February will continue to be marginal in the future. May will continue to maintain very good comfort conditions in the future. However, an increase of 6-7 points is noticeable, indicating that the comfort conditions for May will improve further in the future. June, July and August will have excellent comfort conditions in the future as in the past. However, the decrease in points is remarkable for July and August.

In the HCI:Combined index, a categorical change is seen for the MPI-ESM-MR model in the period of 1976-2000 versus the period 2026-2050 only in

November, and this is the transition of the acceptable category to the good category in the future. January, February, March and December will have acceptable comfort conditions in the future as in the past. Good comfort conditions will remain for April in the future. In May and October, the comfort conditions will improve with the increase in points. However, their categories will remain very good. There will be increases and decreases in points in June, July, August and September, but comfort conditions will continue to be excellent in the future. In the HadGEM2 model, acceptable comfort conditions will continue in the future in January, February and December. For April and November, there is no categorical change in the future and these months will have good comfort conditions in the future, but the point increases are noteworthy. There is no categorical change in May either, but the increase in points draws attention. Very good comfort conditions will continue for this month in the future. The acceptable comfort conditions in the past in March will become good in the future. The comfort conditions for October will change from the good category to the very good category with a significant increase in points. In addition, a category change is seen in July, and it is noteworthy that the comfort conditions in the excellent category will switch to the very good category in the future. June, August and September will continue to be in the excellent category in the future. However, a decrease of 4 points for August draws attention (Table 11).

Table 11. Comparison of Monthly Projected HCI Scores for Çanakkale

Index Type	Model	Period	January	February	March	April	May	June	July	August	September	October	November	December
HCI:Coast	MPI-ESM-MR	1976-2000	43,9842	44,6894	46,5122	57,3143	69,0245	80,8137	84,6675	84,5206	80,0211	69,1047	53,2579	46,6597
		2026-2050	45,3023	46,571	50,1525	59,3753	73,4686	82,1982	84,9612	84,5014	81,235	70,3161	57,0875	49,2182
	HadGEM2	1976-2000	45,4077	45,6438	48,8975	57,6562	71,7553	81,6845	85,1083	84,9469	78,3823	65,1589	54,5234	46,8103
		2026-2050	47,9289	49,2241	54,0361	63,5647	78,1152	83,1508	82,2633	83,6813	82,3367	71,8861	59,9086	51,0608
HCI:Urban	MPI-ESM-MR	1976-2000	58,9905	60,0189	61,8521	69,0636	75,8323	82,8935	84,2311	84,0453	82,3305	74,8034	64,4622	60,5069
		2026-2050	59,8064	61,0284	63,9345	69,9088	78,4752	82,7545	82,3352	81,7472	82,4695	75,6377	66,6247	61,9212
	HadGEM2	1976-2000	59,6419	60,1743	62,9375	68,5132	76,964	82,6976	82,8374	84,3725	81,5783	72,1341	65,2179	60,6744
		2026-2050	60,9594	62,2429	65,4119	71,5861	80,5475	80,6702	75,3866	78,557	82,6873	77,1071	68,4085	62,662
HCI:Combined	MPI-ESM-MR	1976-2000	52,0645	52,9438	54,7722	63,6408	72,6902	81,9336	84,4325	84,2646	81,2646	72,1732	59,291	54,1159
		2026-2050	53,1122	54,3557	57,5735	65,0472	76,1645	82,4978	83,5472	83,0184	81,8997	73,1816	62,2229	56,0583
	HadGEM2	1976-2000	53,0723	53,4679	56,4575	63,5023	74,56	82,23	83,8855	84,6376	80,1032	68,9148	60,282	54,2755
		2026-2050	54,9453	56,2342	60,1616	67,8839	79,4249	81,8151	78,5605	80,9221	82,5255	74,6974	64,4855	57,3076

4.4.6 Edirne

Looking at Edirne, the comfort conditions that were marginal in the past for the months of January, February, March and December in the period of 2026-2050 for the MPI-ESM-MR model in the HCI:Coast index will continue in the future, as opposed to the 1976-2000 period. Considering April and November, despite the increase in points, the comfort conditions that were acceptable in the past will remain the same in the future. June, July and August will maintain excellent comfort conditions in the future as well as in the past. On the other hand, it is seen that very good comfort conditions will occur in the future for May, which had good comfort conditions in the past. It is also noteworthy that September, which had very good comfort conditions in the past, will see excellent comfort conditions in the future. Considering the HadGEM2 model, the comfort conditions for January, February and December, which were marginal in the past, will continue in the future. Looking at October and November, it is seen that they will maintain the good and acceptable comfort conditions in the future, respectively. Looking at May, it is seen that the comfort conditions will remain in the very good category in the future, but an increase of 6 points draws attention. It is seen that excellent comfort conditions will continue in the future in June, July and August, but the decrease in points in July and August is remarkable. Looking at the category changes, it is seen that March will switch from the marginal category to the acceptable category, and April will switch from the acceptable category to the good category. It is also noteworthy that there will be a transition from the very good category to the excellent category in September.

In the HCI:Urban index, the marginal comfort conditions of the past for January for the period 2026-2050 compared to the period 1976-2000 for the MPI-

ESM-MR model will continue in the future. Good comfort conditions in the past for March, November and December will continue in the future. Looking at May and October, it is seen that the very good comfort conditions in the past will remain the same in the future. In June and September, the comfort conditions scores will decrease, but the excellent category will not change. Acceptable comfort conditions in February will be good in the future and good comfort conditions in April will be very good in the future. On the other hand, with the decrease in points in July and August, the category with excellent comfort conditions will turn into the very good category. In the HadGEM2 model, the category change is observed for six months. The comfort conditions that were good in the past for February, March and November will remain the same in the future. The comfort conditions for September, which were excellent in the past, will be the same in the future. Although the category has not changed in July and very good comfort conditions will continue in the future, a decrease of 6-7 points draws attention. The comfort conditions, which were very good in the past, will continue to increase in the future for October. The comfort conditions for September, which were excellent in the past, will be the same in the future. Looking at the category changes, it is striking that the comfort conditions that were acceptable in the past in January will turn into good in the future, and the comfort conditions that were good in April will be very good in the future. The comfort conditions for May will become better and excellent in the future. With a category change for June and August, excellent comfort conditions seem to be very good in the future.

Looking at the index HCI:Combined, comfort conditions that were acceptable in the past for January, February, and December in the 2026-2050 period compared to the 1976-2000 period for the MPI-ESM-MR model will continue into the future.

While point increases for April are noteworthy, good comfort conditions will continue in the future as in the past. A change in category is not expected for May and October, and it is seen that the very good comfort conditions of the past will continue. Point decreases for June, July, August and September are noteworthy, but it is seen that the excellent comfort conditions will continue in the future. Comfort conditions that were acceptable in the past for March and November will be good in the future. In the HadGEM2 model, the comfort conditions that were acceptable in the past for January, February and December will continue in the future. Good comfort conditions will continue in the future for April and November. For May and September, very good and excellent comfort conditions will continue in the future. Comfort conditions that were acceptable in the past for March will be good in the future, and comfort conditions that were good in the past for October will be very good in the future. The comfort conditions for June, July and August, which were excellent in the past, will be very good in the future (Table 12).

Table 12. Comparison of Monthly Projected HCI Scores for Edirne

Index Type	Model	Period	January	February	March	April	May	June	July	August	September	October	November	December
HCI:Coast	MPI-ESM-MR	1976-2000	43,3207	43,9202	45,8363	56,6638	68,6354	80,4435	84,3107	84,0709	78,8772	66,5249	50,4237	45,4448
		2026-2050	43,9031	45,4298	49,206	58,8817	73,0757	81,8061	84,4879	84,1855	80,006	67,5083	53,9708	47,1177
	HadGEM2	1976-2000	44,0691	44,6978	48,0003	56,8714	71,4488	81,2963	84,7189	84,4014	77,2013	62,6882	51,3818	44,9466
		2026-2050	46,1612	48,0926	53,5364	62,5685	77,4496	82,1593	81,8361	83,5184	81,749	69,909	56,9032	48,8915
HCI:Urban	MPI-ESM-MR	1976-2000	58,7631	59,8525	62,131	69,805	76,8872	82,6559	82,3723	82,8438	82,0817	74,5717	63,6072	60,2413
		2026-2050	59,1452	60,9157	64,3417	70,6874	78,9429	81,4978	79,9524	79,9608	81,8316	75,3503	65,8123	60,8963
	HadGEM2	1976-2000	58,9748	60,0228	63,2575	69,683	78,3525	81,8181	79,8938	82,4508	81,7855	72,1849	64,1151	59,7651
		2026-2050	60,4866	62,5184	66,3299	72,7443	80,7312	77,6965	72,3186	77,0236	82,2049	77,5469	67,8391	62,1411
HCI:Combined	MPI-ESM-MR	1976-2000	54,3926	55,3434	57,5193	66,0858	74,5517	82,0298	82,9209	83,1911	81,1748	72,2943	59,876	56,0536
		2026-2050	54,8314	56,5329	60,058	67,3461	77,2824	81,5851	81,2361	81,1565	81,3149	73,1309	62,4609	56,9967
	HadGEM2	1976-2000	54,7562	55,6856	58,9394	66,057	76,3986	81,6704	81,2594	83,0029	80,4881	69,4971	60,5113	55,5712
		2026-2050	56,4322	58,4356	62,7091	69,8644	79,8024	78,9595	75,0122	78,8617	82,0759	75,3853	64,7441	58,3912

4.4.7 Hatay

Looking at Hatay, it is seen that the past marginal comfort conditions of January, February and December will continue in the future for the MPI-ESM-MR model in the HCI:Coast index in the 2026-2050 period versus the 1976-2000 period. It is seen that the good comfort conditions in the past for April will remain the same in the future. Although the very good comfort conditions in the past for October will continue in the future, the increase in points draws attention. In July, August and September, it is seen that the excellent comfort conditions in the past will remain the same in the future. On the other hand, looking at March, it is seen that the marginal conditions of the past will become acceptable in the future. Good comfort conditions in the past for May will become very good in the future with increasing points. Finally, it is seen that very good comfort conditions in June will become excellent in the future. In the HadGEM2 model, it is seen that the marginal comfort conditions of January will continue in the future. In April, the good comfort conditions in the past will continue in the future. However, the point increase is noticeable. May will maintain the very good comfort conditions of the past in the same way in the future. However, there will be improvement in points showing increased comfort conditions. The comfort conditions for June will remain the same in the future with little change in points and will be excellent. It appears that past marginal comfort conditions for February and December will become acceptable in the future. The excellent conditions of July and August in the past will become very good in the future. The very good comfort conditions in the past for September will become excellent in the future. Good comfort conditions in the past for planting will become very good in the future. Finally, the acceptable comfort conditions in the past for November will become very good in the future with the increase in points.

In the HCI:Urban index, it is seen that the good comfort conditions in the past for February, March and December will continue in the future for the MPI-ESM-MR model in the period of 2026-2050 versus the period 1976-2000. It is seen that the very good comfort conditions in the past for April, May and October will continue in the future. It is seen that the excellent comfort conditions in the past for June and September will continue in the future. It is seen that the acceptable comfort conditions in the past for January will turn into good in the future. It is seen that the good comfort conditions in the past for November will turn into very good in the future. On the other hand, the excellent comfort conditions in the past for July and August will become very good in the future due to the decrease in points. Looking at the HadGEM2 model, it is seen that the good comfort conditions in the past for January, February, March and December will continue in the same way in the future. The very good comfort conditions in the past for April, July, August and October will continue in the future. However, point increases for April and October and decreases for July and August are noteworthy. It is seen that the excellent conditions in the past for September will continue in the same way in the future. The past very good comfort conditions for May will become excellent in the future and the past good comfort conditions for November will become very good in the future. Finally, it is seen that the excellent comfort conditions of June in the past will become very good in the future.

For the MPI-ESM-MR model in the HCI:Combined index, the acceptable comfort conditions of the past in January, February and December in the 2026-2050 period compared to the 1976-2000 period will continue into the future. For May and October, the good comfort conditions in the past will continue in the same way with the increase in points. The excellent comfort conditions in the past for June, July and

September will continue in the future. Conditions that were good for November will remain the same in the future, but the increase in points is noticeable. The acceptable comfort conditions in the past for March will become good in the future. For April, conditions that were good in the past will become very good. On the other hand, looking at August, it is seen that the excellent comfort conditions in the past will be very good in the future. In the HadGEM2 model, looking at January, February and December, it is seen that the comfort conditions that were acceptable in the past will remain the same in the future. The comfort conditions that were good in the past for March and November will remain the same in the future, but the increase in points draws attention. It is seen that the same situation will continue in the future for May and October, where the comfort conditions in the past were very good, but the increase in points draws attention. Looking at September, it is seen that the future comfort conditions will be excellent as in the past. On the other hand, it can be said that April, whose comfort conditions were good in the past, will have very good comfortable days in the future. However, it is seen that the excellent comfort conditions of June, July and August in the past will turn into a subcategory of very good comfort conditions in the future (Table 13).

Table 13. Comparison of Monthly Projected HCI Scores for Hatay

Index Type	Model	Period	January	February	March	April	May	June	July	August	September	October	November	December
HCI:Coast	MPI-ESM-MR	1976-2000	43,5342	45,7997	49,9247	61,7942	69,7698	79,3884	82,9981	83,386	81,1327	70,9529	54,917	46,572
		2026-2050	46,0748	48,7539	53,8928	63,7388	73,9928	81,762	83,3878	83,5502	82,8749	74,5058	58,9817	48,1337
	HadGEM2	1976-2000	45,6274	47,5659	51,9831	61,9187	73,0572	82,0734	83,0341	82,6427	79,7154	68,1174	55,291	46,9555
		2026-2050	48,2155	51,1636	57,4472	67,622	78,1145	82,0049	79,2401	79,048	80,9051	72,2715	60,5193	50,962
HCI:Urban	MPI-ESM-MR	1976-2000	59,5712	61,7738	65,0237	73,2492	78,0432	81,7476	80,8322	80,783	82,6204	77,9569	67,8001	61,548
		2026-2050	61,1714	63,663	67,7649	74,3492	79,6297	81,208	78,2241	77,5282	82,0686	79,9818	70,3188	62,6039
	HadGEM2	1976-2000	60,1319	62,187	65,9797	72,4049	78,7255	81,5	79,0732	79,6611	82,3037	75,2193	66,8476	60,8482
		2026-2050	61,8419	64,557	69,1947	75,4967	80,691	77,9128	71,0846	72,1124	80,4004	78,2606	70,1482	63,4498
HCI:Combined	MPI-ESM-MR	1976-2000	53,3528	55,5798	59,169	68,8075	74,8351	80,8328	81,6721	81,7923	82,0435	75,2411	62,8046	55,7409
		2026-2050	55,3176	57,8819	62,3859	70,2349	77,444	81,4228	80,2264	79,8632	82,3812	77,8584	65,9228	56,993
	HadGEM2	1976-2000	54,5077	56,5176	60,5524	68,3388	76,5276	81,7223	80,6091	80,8172	81,3001	72,4655	62,3665	55,4613
		2026-2050	56,5582	59,3636	64,6395	72,4432	79,6919	79,4995	74,2469	74,8017	80,5961	75,9383	66,4146	58,6076

4.4.8 İzmir

Looking at İzmir, it is seen that the marginal comfort conditions for January and February in the period of 2026-2050 for the MPI-ESM-MR model in the HCI:Coast index will remain the same in the future, as opposed to the 1976-2000 period. It seems that good comfort conditions in the past for April will remain the same in the future. Looking at May and October, it is seen that the comfort conditions, which were very good in the past, will remain the same in the future. However, the increase in points especially in May draws attention. Looking at the months of June, July, August and September, it is seen that the excellent comfort conditions in the past will continue in the future. Looking at November, it is seen that the comfort conditions that were acceptable in the past will continue in the same way in the future. On the other hand, when we look at March and December, it is seen that the comfort conditions that were marginal in the past will become acceptable in the future. Looking at the HadGEM2 model results, it is seen that the comfort conditions, which were marginal in the past in January, will remain the same in the future. It is seen that the acceptable comfort conditions in the past for March will also remain the same in the future, but the increase in points draws attention. Likewise, looking at April, it is seen that good comfort conditions in the past will be the same in the future, but there will be an increase in points. When May is examined, it is seen that the comfort conditions, which were very good in the past, will be very good in the future. However, a significant increase in points is noticeable, indicating that comfort conditions will improve. It is seen that the comfort conditions which were excellent in the past in June, July and August will remain the same in the future. On the other hand, looking at February and December, it is seen that the comfort conditions that were marginal in the past will become acceptable in the future. For September, it is seen that the comfort conditions, which were very good in the past, will be excellent in the future. In October, it is seen that good comfort conditions in the past will become very good in the future. Finally, it is seen that the comfort conditions that were acceptable in the past for November will become very good in the future.

It is striking that there will be no categorical change in any month in the 2026-2050 period versus the 1976-2000 period for the MPI-ESM-MR model in the HCI:Urban index. Comfort conditions, which were acceptable in the past for January, will continue in the future with a slight increase in points. Good comfort conditions in the past for February, March, November and December will also remain in the same category in the future. Comfort conditions for April, May and October, which were very good in the past, will also be in the same category in the future. Finally, the comfort conditions for June, July, August and September, which were excellent in the past, will continue to be the same in the future. However, it is noteworthy that there will be a decrease in points in July and August. Looking at the analysis results of the HadGEM2 model, it is noteworthy that the months of January, February, March, November and December, which were in the good category in the past, will be in the same category in the future. The same conditions will continue in the future for the months of April and October, where the comfort conditions in the past were very good. The comfort conditions will remain the same in the future for the months of June and September, where the comfort conditions in the past were in the excellent category. On the other hand, it is seen that May, which was in the very good category in the past, will move to the excellent category with an increase in points in the future. In addition, it is seen that the months of July and August, which were in the excellent category in the past, will switch to the very good category in the future with the decrease in points.

In the HCI:Combined index, it is seen that for the MPI-ESM-MR model, there will be a categorical change only in November in the 2026-2050 period compared to the 1976-2000 period, and the comfort conditions that were acceptable in the past will become gold in the future. It is seen that the months of January, February, March and December, which had acceptable comfort conditions in the past, will have the same comfort conditions in the future. It is seen that April, which had good comfort conditions in the past, will remain in the same category in the future. It is seen that the months of May and October, which were in the very good category in the past, will be in the same category in the future, but there will be an increase in points. Finally, June, July, August and September, which were in the excellent category in the past, will have the same comfort conditions in the future. However, the decrease in points in July and August draws attention. Looking at the HadGEM2 model, it can be said that they will have the same comfort conditions in the future for January, February and December, which were in the acceptable category in the past. It is seen that the months of April and November, which were in the good category in the past, will also be in the same category in the future, but the increase in points draws attention and this indicates that the comfort conditions will improve. It can be said that May, which had very good comfort conditions in the past, will have the same comfort conditions in the future, but the increase in points draws attention. It is seen that for June, August and September, which had excellent comfort conditions in the past, they will be in the same category in the future, but the decrease in points in August is remarkable. July will undergo a categorical change with a decrease in points and the excellent comfort conditions will become very good in the future. Finally, October, which was in the good category in the past, will switch to the very good category in the future with the increase in points (Table 14).

Table 14. Comparison of Monthly Projected HCI Scores for İzmir

Index Type	Model	Period	January	February	March	April	May	June	July	August	September	October	November	December
HCI:Coast	MPI-ESM-MR	1976-2000	45,2988	46,3104	49,2355	60,1111	70,768	81,5466	84,0627	83,7382	80,4334	70,5988	55,5508	48,1904
		2026-2050	46,8355	48,9282	52,3384	61,6049	74,9343	82,4984	83,8704	83,3149	81,4894	72,0936	59,3816	50,7117
	HadGEM2	1976-2000	46,7895	47,3988	50,9189	60,4706	73,1552	81,886	84,3098	84,5689	79,1592	67,1371	56,9187	48,616
		2026-2050	49,443	50,8068	55,5455	65,5653	78,4319	82,7602	81,2498	82,6008	82,0275	72,9318	61,8558	52,69
HCI:Urban	MPI-ESM-MR	1976-2000	59,0336	60,3449	62,8957	70,3289	76,5948	82,8336	82,7894	82,8288	82,0751	75,741	65,2859	60,3638
		2026-2050	59,88	61,7599	64,6803	70,6989	78,8736	82,1219	80,654	80,2384	82,3675	76,7219	67,6286	61,7011
	HadGEM2	1976-2000	60,1499	60,9638	63,7598	70,2775	77,739	82,0014	80,644	82,8186	81,7718	73,0305	66,4401	60,9771
		2026-2050	60,8902	62,6214	66,002	72,6445	80,6599	80,3045	74,1664	77,1153	82,5278	77,107	69,207	62,9078
HCI:Combined	MPI-ESM-MR	1976-2000	51,3899	52,5344	55,2935	64,6425	73,3521	82,1173	83,498	83,3349	81,1615	72,8793	59,8681	53,589
		2026-2050	52,6204	54,6188	57,8118	65,6379	76,6813	82,3314	82,444	81,9505	81,8789	74,1462	63,0389	55,5853
	HadGEM2	1976-2000	52,7146	53,4146	56,6136	64,8198	75,188	81,9371	82,6841	83,7927	80,3178	69,7507	61,1412	54,0979
		2026-2050	54,5196	56,0464	60,1827	68,7047	79,42	81,6712	78,1085	80,1681	82,2493	74,7834	65,1159	57,2214

4.4.9 Mersin

For Mersin, it is seen that January, February, March, and December, which were in the marginal category in the past, will be in the same category for the MPI-ESM-MR model in the HCI:Coast index for the period of 1976-2000 versus the period of 2026-2050. Nisan, which had acceptable comfort conditions in the past, will have the same comfort conditions in the future. May and October, which had good comfort conditions in the past, will be in the same category in the future; however, the increase in points draws attention. Looking at June and September, which were in the very good comfort category in the past, they will be in the same category in the future. However, there is an increase in scores, indicating that the comfort conditions have improved. It is seen that they will be in the excellent category in the future with the increase in points in July and August, which were in the very good category in the past. Finally, November, which had marginal comfort conditions in the past, will have acceptable comfort conditions in the future. Looking at the analysis result of the HadGEM2 Model, January, February, March, and December, which were in the marginal category in the past, will be in the same category in the future, similar to the previous model. Similar to the previous model, it seems that April, which had acceptable comfort conditions in the past, will have the same conditions in the future, but there will be an increase in points. May, which had good comfort conditions in the past, will be in the same category in the future. Looking at June, it will be in the very good category in the future as it was in the past. However, there will be an increase in comfort points. July will be in the category of excellent comfort in the future as in the past. On the other hand, the very good comfort conditions in the past in August will become excellent in the future. Looking at September, the comfort conditions that were good in the past will become very good with a high point increase. Comfort conditions that were acceptable in the past in October will be good in the future, and marginal comfort conditions in November will become acceptable in the future.

For the MPI-ESM-MR model in the HCI:Urban index, January, February and December, which had acceptable comfort conditions in the 2026-2050 period versus the 1976-2000 period, will have the same comfort conditions in the future. It is seen that the months of April and November, which had good comfort conditions in the past, will have the same comfort conditions in the future. May and October, which were in the very good comfort category in the past, will continue to be in the same category in the future. July and August, which were in the excellent comfort category in the past, will have the same comfort conditions in the future. On the other hand, March, which had acceptable comfort conditions in the past, will have good comfort conditions in the future. Also, June and September, which had very good comfort conditions in the past, will be in the excellent category in the future. Looking at the analysis results of the HadGEM2 model, it is striking that there will be no categorical change in any month. It is seen that January, February, and December, which had acceptable comfort conditions in the past, will have the same comfort conditions in the future. March, April, October, and November, which were in the good category in the past, will be in the same category in the future. May and September, which were in the very good category in the past, will also be in the same category in the future but will experience an increase in points. June, July, and August, which were in the excellent category in the past, will be in the same category in the future.

It is concluded that there will be a categorical change in the HCI:Combined index for the MPI-ESM-MR model in just one month in the 2026-2050 period compared to the 1976-2000 period. This categorical change is that March, which had marginal conditions in the past, will have acceptable comfort conditions in the future. January, February, and December, which had marginal comfort conditions in the past, will have the same comfort conditions in the future. April and November, which had acceptable comfort conditions in the past, will be in the same category in the future, but they will experience an increase in points. May and October, which was in the good category in the past, will be in the same category in the future. However, point increases draw attention, indicating that comfort conditions will improve. June and September, which were in the very good category in the past, will be in the same category in the future, but there will be increases in points. July and August, which were in the excellent category in the past, will be in the same category in the future. When the results of the HadGEM2 model are analyzed, it draws attention that there will be a categorical change in three months. March, which had marginal comfort conditions in the past, will have acceptable comfort conditions in the future. On the other hand, June, which had very good comfort conditions in the past, will have acceptable comfort conditions, and October, which had acceptable comfort conditions in the past, will have good comfort conditions in the future. On the other hand, January, February, and December, which had marginal comfort conditions in the past, will be in the same category in the future. April and October, which had acceptable comfort conditions in the past, will have the same comfort conditions in the future. However, increases in points indicate that comfort conditions will improve slightly. The same is true for the month of May, which was in the good category in the past. June and September, which had very good comfort conditions in the past, will be in the same category in the future. However, especially for September, a very high score increase draws attention. July, which was in the excellent category in the past, will be in the same category in the future (Table 15).

Table 15. Comparison of Monthly Projected HCI Scores for Mersin

Index Type	Model	Period	January	February	March	April	May	June	July	August	September	October	November	December
HCI:Coast	MPI-ESM-MR	1976-2000	40,9666	42,2458	45,0953	55,0495	63,2299	74,6642	79,9039	79,7368	73,8875	61,6377	47,3152	42,2038
		2026-2050	41,9623	44,5038	47,9124	56,522	68,0529	77,2843	81,3646	81,2625	76,814	64,8299	50,4281	43,7283
	HadGEM2	1976-2000	41,8767	43,3959	46,2553	53,7042	63,56	74,9304	80,1831	78,9989	69,33	55,9762	46,9385	41,9099
		2026-2050	41,8582	44,2935	49,5099	57,434	68,3529	77,4404	80,5485	80,2675	74,5676	60,7855	50,2411	43,3419
HCI:Urban	MPI-ESM-MR	1976-2000	55,4207	56,8221	59,6496	67,3403	72,8182	79,9603	82,6959	82,6428	79,0429	71,1848	61,113	56,9277
		2026-2050	56,4372	58,7392	61,9077	68,2885	75,9175	81,2691	83,1287	83,0507	80,8001	73,0587	63,4168	58,1962
	HadGEM2	1976-2000	55,8743	57,4093	60,2342	66,0488	72,5301	80,0284	83,3409	82,9572	76,0021	66,7404	60,9847	56,7999
		2026-2050	56,5804	58,6247	62,4176	68,0782	75,435	81,1502	82,4582	83,1909	79,8795	69,7522	62,9821	58,0398
HCI:Combined	MPI-ESM-MR	1976-2000	44,2212	45,5279	48,3725	57,817	65,3888	75,8567	80,5326	80,3912	75,0483	63,7874	50,422	45,5191
		2026-2050	45,2216	47,7091	51,0637	59,1714	69,8238	78,1816	81,7618	81,6651	77,7115	66,6827	53,3527	46,986
	HadGEM2	1976-2000	45,0284	46,5512	49,4029	56,4838	65,5798	76,0783	80,8941	79,8902	70,8323	58,3999	50,1012	45,2626
		2026-2050	45,1731	47,5204	52,4163	59,8307	69,9476	78,2757	80,9785	80,9258	75,7636	62,8045	53,1099	46,6513

4.4.10 Muğla

When the analysis results for Muğla are examined, it is seen that the marginal comfort conditions in the past in January, February, and December will continue in the future in the 2026-2050 period for the MPI-ESM-MR model in the HCI:Coast index compared to the 1976-2000 period. Looking at April and November, the acceptable comfort conditions in the past will continue in the future. The increase in points in November is remarkable. The excellent comfort conditions of July and August in the past will continue in the future. On the other hand, March, which had marginal comfort conditions in the past, will have acceptable comfort conditions in the future. May and October, which had good comfort conditions in the past, will have very good comfort conditions in the future. Finally, June and September, which had very good comfort conditions in the past, will have excellent comfort conditions in the future. Looking at the analysis results of the HadGEM2 model, January, and February, which had marginal comfort conditions in the past, will have the same comfort conditions in the future. March and November, which had acceptable comfort conditions in the past, will also be in the same category in the future; however, the comfort points will increase in these months. May and September, which were in the very good category in the past, will be in the same category in the future. However, comfort conditions will improve with the increase in points in these months. The decrease in points for July and August attracts attention, but they will continue to have the same comfort conditions in the future. On the other hand, April, which had acceptable comfort conditions in the past, will have good comfort conditions with a high increase in points. June with very good comfort conditions in the past will be excellent in the future, and October, with good comfort conditions in the past, will have very good comfort conditions in the future. Finally, December, which had marginal comfort conditions in the past, will have acceptable comfort conditions in the future.

For the MPI-ESM-MR model in the HCI:Urban index, January, which had acceptable comfort conditions in the 2026-2050 period versus the 1976-2000 period, will have the same comfort conditions in the future. March, April and November, which had good comfort conditions in the past, will have the same comfort conditions. May and October, which had very good comfort conditions in the past, will have the same comfort conditions in the future. June, July, August, and September, which had excellent comfort conditions in the past, will remain in the same category in the future. However, decreases in points are noteworthy in July and August. February and December will continue to have good comfort conditions in the future. Looking at the analysis results of the HadGEM2 model, January, which had acceptable comfort conditions in the past, will have the same comfort conditions in the future. As in the previous example, March and November, which had good comfort conditions in the past, will have the same comfort conditions in the future. May and October, which had very good comfort conditions in the past, will also have the same comfort conditions in the future, similar to the previous model. June, August, and September, which had excellent comfort conditions in the past, will have the same comfort conditions in the future. However, it is noteworthy that there will be a decrease in points, especially in August. February and December, which had acceptable comfort conditions in the past, will have good comfort conditions in the future. Finally, July, which had excellent comfort conditions in the past, will have very good comfort conditions by experiencing a decrease in points in the future.

In the HCI:Combined index, January, February, and December, which had marginal comfort conditions in the 2026-2050 period compared to the 1976-2000 period for the MPI-ESM-MR model, will have the same comfort conditions in the future. July and August, which had excellent comfort conditions in the past, will remain in the same category. November, which was in the acceptable category in the past, will remain in the same category in the future, but the increase in points draws attention. March, which had marginal conditions in the past, will have acceptable comfort conditions in the future. Nisan, which had acceptable comfort conditions in the past, will have good comfort conditions. May and October, which had good comfort conditions in the past, will have very good comfort conditions. June and September, which had very good comfort conditions in the past, will have excellent comfort conditions. When the analysis results of the HadGEM2 model are examined, it is seen that January, which had marginal comfort conditions in the past, will have the same comfort conditions in the future. March, which had acceptable comfort conditions in the past, will experience an increase points in the future but will remain in the same category. April, which had good comfort conditions in the past, will remain in the same category in the future, but there will be an increase in points. May and September, which had very good comfort conditions in the past, will remain in the same category in the future, but the increase in points especially for May is remarkable. July and August, which had excellent comfort conditions in the past, will remain in the same category in the future, but there will be a decrease in points. On the other hand, February and December, which had marginal comfort conditions in the past, will have acceptable comfort conditions in the future. Having very good comfort conditions in the past, June will have excellent comfort conditions in the future. Having good comfort conditions in the past, October will have very good comfort conditions in the future. Finally, November, which had acceptable comfort conditions in the past, will have good comfort conditions in the future (Table 16).

Table 16. Comparison of Monthly Projected HCI Scores for Muğla

Index Type	Model	Period	January	February	March	April	May	June	July	August	September	October	November	December
HCI:Coast	MPI-ESM-MR	1976-2000	43,8575	45,2588	48,4373	58,5857	68,1099	79,2902	83,2626	83,1046	78,8994	68,5908	53,8984	46,2877
		2026-2050	45,4973	48,1719	51,3819	59,8661	72,3706	80,9991	83,466	83,1732	80,4227	70,1561	57,1719	48,6202
	HadGEM2	1976-2000	46,8153	47,3707	50,8229	59,7201	70,3746	79,4652	83,0377	83,0755	76,8562	64,8022	55,5729	47,6305
		2026-2050	48,0095	49,8554	54,4739	64,0458	75,4167	80,68	80,5111	81,0311	79,4523	70,1026	59,5173	51,0377
HCI:Urban	MPI-ESM-MR	1976-2000	57,8666	59,0789	61,6	69,0689	75,4233	82,3313	83,7144	84,0198	81,8957	74,6967	63,9387	59,0595
		2026-2050	58,7964	60,672	63,3534	69,5297	77,998	82,5569	82,5362	82,4473	82,7471	75,5731	66,056	60,3666
	HadGEM2	1976-2000	59,3246	59,864	62,5412	68,9958	76,3019	81,9233	82,9538	84,1584	80,7532	71,1955	64,8046	59,7287
		2026-2050	59,3176	61,1682	64,3195	71,3211	79,4872	82,2392	78,3318	80,5938	82,9469	75,514	67,0149	61,0583
HCI:Combined	MPI-ESM-MR	1976-2000	45,3145	46,6961	49,8063	59,676	68,8705	79,6065	83,3096	83,1997	79,211	69,2258	54,9426	47,6159
		2026-2050	46,8804	49,472	52,6269	60,8711	72,9559	81,1611	83,3693	83,0977	80,6644	70,7195	58,0958	49,8418
	HadGEM2	1976-2000	48,1162	48,67	52,0416	60,6847	70,991	79,7209	83,0289	83,1881	77,2615	65,4671	56,533	48,8887
		2026-2050	49,1855	51,0319	55,4978	64,8024	75,84	80,8422	80,2845	80,9856	79,8158	70,6654	60,2971	52,0798

4.4.11 Summary results for future HCI projections for the 10 provinces

The findings on the future HCI trends of 10 provinces were given in time series. The red and green lines represent trend graphs presenting projections for MPI-ESM-MR and HadGEM2, respectively. 1976-2020 is presented on the left axis, and 2026-2050 is presented on the right axis. The period 1976-2020 was analyzed to show the trend comparison with the number of tourist arrivals and overnight stays until 2020.

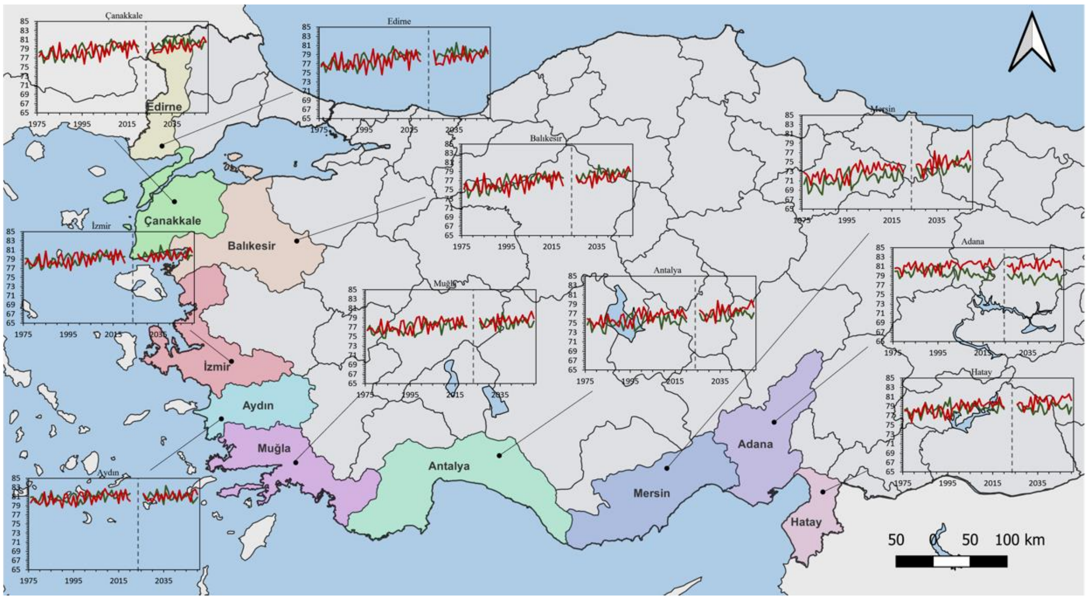

Figure 10. 6-Month time series of HCI:Coast for the MPI-ESM-MR and HadGEM2

When the annual trend of the 6-month HCI averages is analyzed for HCI:Coast, a 1-point decrease is predicted for HadGEM2 in Adana, while a slight increase is seen for MPI-ESM-MR. An increase of 1 point for MPI-ESM-MR and 2 points for HadGEM2 is expected in Çanakkale, Edirne, İzmir, and Balıkesir. An increase of 1 point is expected for MPI-ESM-MR and HadGEM2 in Muğla. There is a similar situation in Aydın and Antalya. Unlike other provinces, Mersin is expected to increase by 2 points in both MPI-ESM-MR and HadGEM2. In Hatay, a slight increase is expected for HadGEM2, and a 1-point increase is expected in HCI values for MPI-ESM-MR (Figure 10).

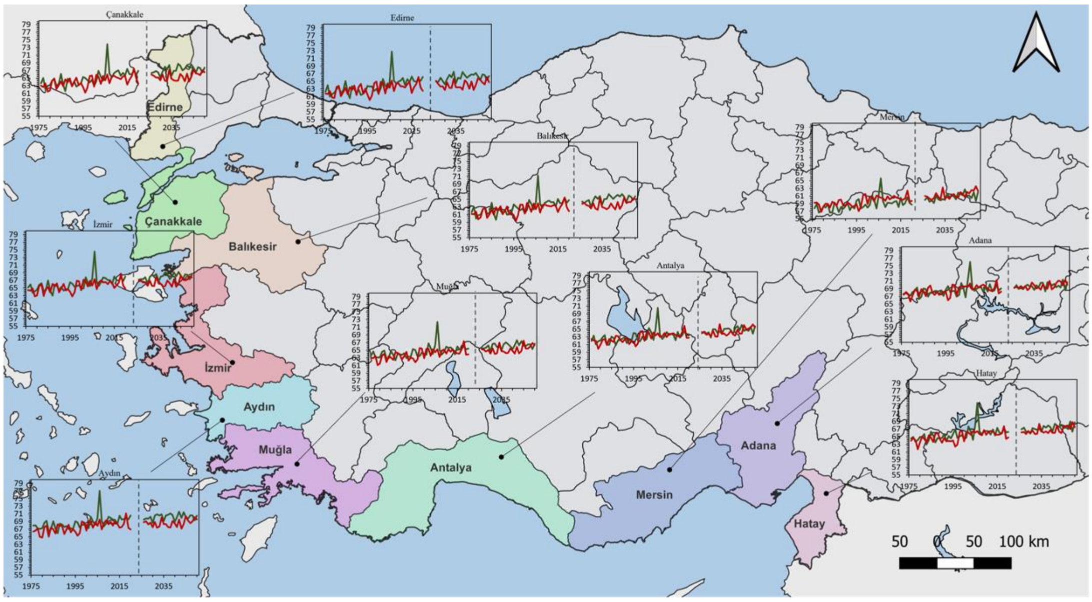

Figure 11. Annual time series of HCI:Coast for the MPI-ESM-MR and HadGEM2

When the annual trend of the 6-month HCI averages is analyzed, according to the HCI:Coast calculation, the HCI values for HadGEM2 and MPI-ESM-MR differ in all 10 provinces. In Adana, 1 point increase is foreseen for both HadGEM2 and MPI-ESM-MR. An increase of 1 point for MPI-ESM-MR and 2 points for HadGEM2 is expected in Çanakkale. While the same is the case for MPI-ESM-MR in Edirne, an increase of 3 points is expected for HadGEM2. An increase of 1 point is expected for MPI-ESM-MR and HadGEM2 in İzmir. While there is a similar situation for MPI-ESM-MR in Balıkesir, an increase of 2 points is expected for HadGEM2. An increase of 2 points is expected for MPI-ESM-MR and HadGEM2 in Muğla. There is a similar situation in Antalya and Mersin. In Aydın, an increase of 1 point for MPI-ESM-MR and 2 points is expected for HadGEM2. In Hatay, an increase of 1 point for MPI-ESM-MR and 2 points is expected for HadGEM2 (Figure 11).

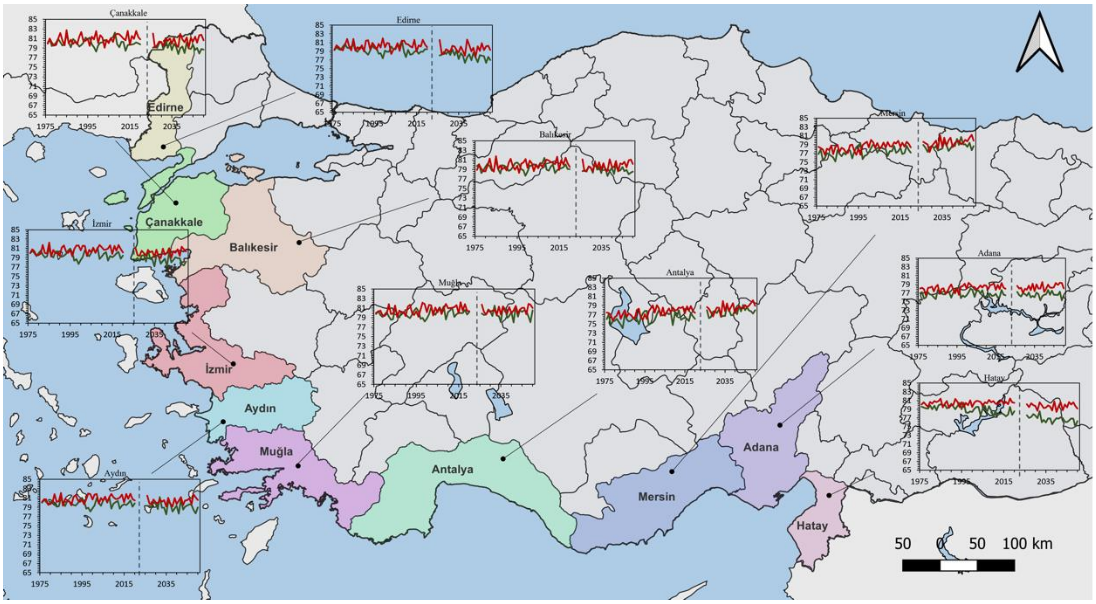

Figure 12. 6-Month time series of HCI:Urban for the MPI-ESM-MR and HadGEM2

When the annual trend of the 6-month averages of HCI is analyzed, HadGEM2 shows lower HCI values than MPI-ESM-MR in all 10 provinces according to the HCI:Urban calculation. In Çanakkale, HCI values are expected to decrease by approximately 1 point for HadGEM2 and half a point for MPI-ESM-MR. In Edirne, 1.5 points and 1-point decreases are expected for HadGEM2 and MPI-ESM-MR, respectively. Similar to Çanakkale, a decrease of 1 point and half a point is projected in İzmir for HadGEM2 and MPI-ESM-MR. A more stable HCI value is expected in Balıkesir, but a slight decrease is projected. Muğla is similarly almost stable, but little increase is expected. While a decreasing trend of half a point is expected in Aydın, an increase in HCI scores is expected in Antalya and Mersin. In addition, a slight decrease is predicted for Adana for HadGEM2, while a slight increase is predicted for MPI-ESM-MR. In Hatay, the greatest decrease is expected (Figure 12).

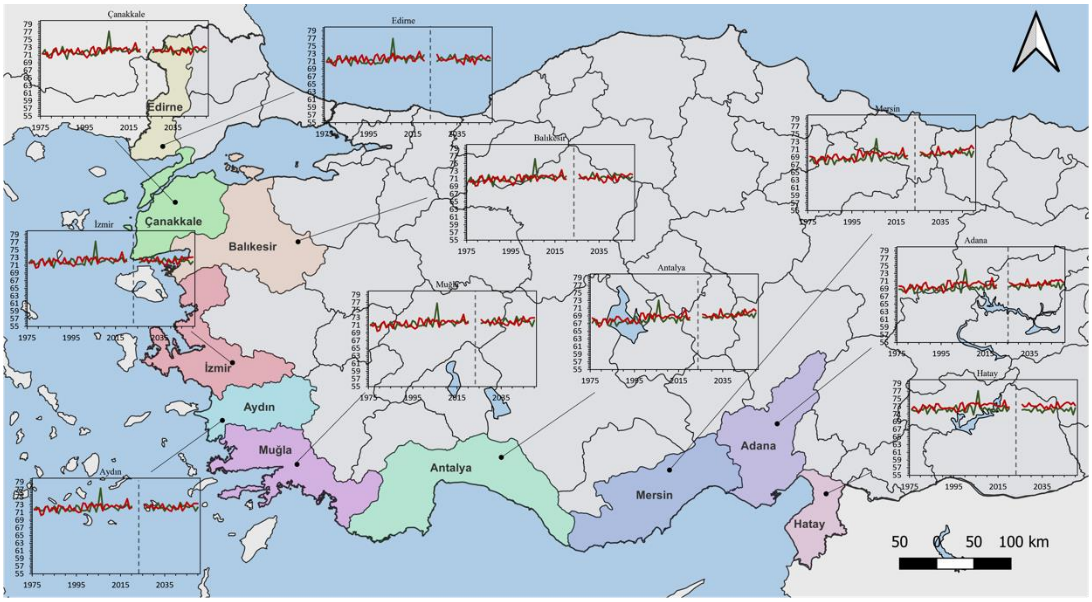

Figure 13. Annual time series of HCI:Urban for the MPI-ESM-MR and HadGEM2

HCI values for the annual trend are similar in HadGEM2 and MPI-ESM-MR in all 10 provinces, according to the HCI:Urban calculation. A slight decrease is predicted for HadGEM2 in Adana, while an increase of 1 point is expected for MPI-ESM-MR. For both MPI-ESM-MR and HadGEM2, a slight increase in HCI values is expected in Çanakkale. In Edirne, likewise, a slight increase is expected for HadGEM2 and MPI-ESM-MR. There is a similar situation in İzmir. There was also a slight increase in Balıkesir. Muğla is similarly almost stable, but little increase is expected. A slight increase is expected in Aydın. Contrary to other provinces, Antalya and Mersin are expected to increase both MPI-ESM-MR and HadGEM2 HCI points. In Hatay, a slight decrease is expected for HadGEM2, while an increase in HCI values is expected for MPI-ESM-MR (Figure 13).

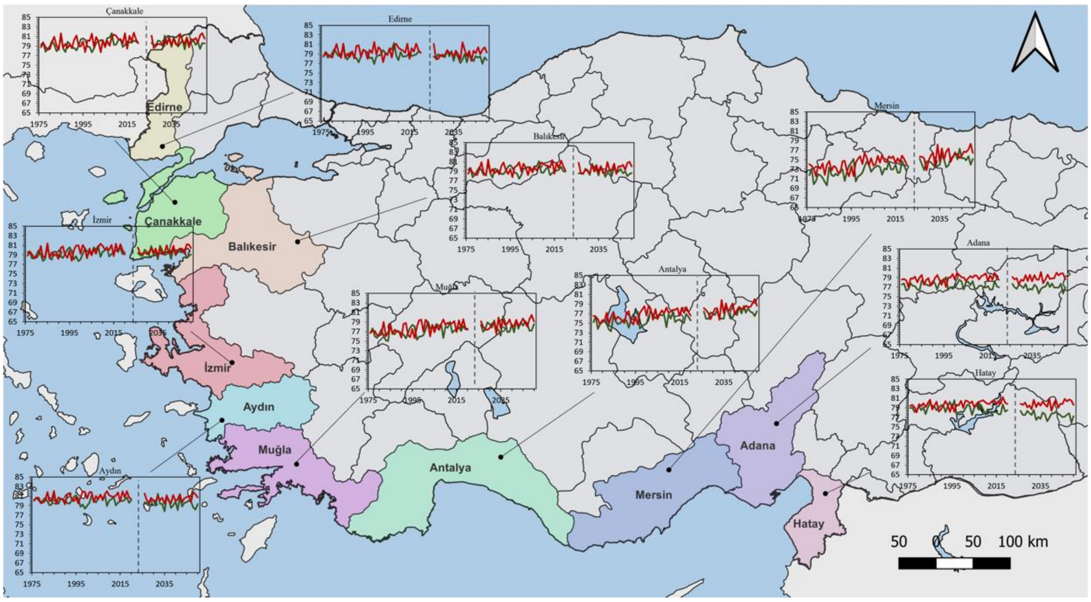

Figure 14. 6-Month time series of HCI:Combined for the MPI-ESM-MR and HadGEM2

When the annual trend of 6-month HCI averages is analyzed, the HadGEM2 model shows lower hci values than MPI-ESM-MR in many provinces according to the HCI:Combined calculation. There appears to be a slightly increasing trend in HCI in Çanakkale. A slight downward trend is predicted towards the end of 2050 in its northern neighbor Edirne, while a stable trend is foreseen in its southern neighbor Balıkesir. Similar to Çanakkale, a slightly increasing HCI trend is foreseen in İzmir. While a decrease of half a point is expected in Aydın, one of the provinces on the southwest coast of Turkey, an average increase of 1 point is expected in Muğla. Similar to Muğla, an upward trend of up to 2 points is projected in the southern coastal provinces of Antalya and Mersin. On the other hand, decreasing HCI trend was noticed in Adana and Hatay (Figure 14).

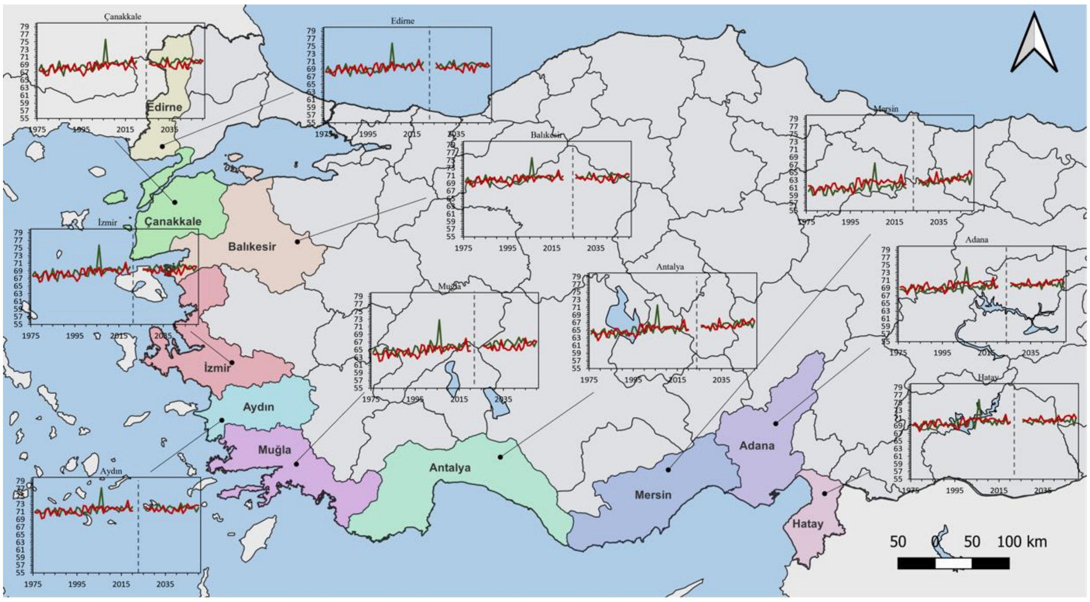

Figure 15. Annual time series of HCI:Combined for the MPI-ESM-MR and HadGEM2

When the trend of annual HCI averages is examined, the HadGEM model shows similar HCI values with the MPI-ESM-MR model in all 10 provinces according to the HCI:Combined calculation. When the HCI trends of the provinces on the western and northwest coasts of the country are examined, HCI in the provinces of Edirne, Çanakkele, Balıkesir, İzmir and Aydın shows an increasing trend over time. In addition, increases of up to 2.5 points are predicted for both models in the provinces of Muğla, Antalya, Mersin, Adana and Hatay on the southern coasts. Compared to the HCI changes in the 6-month summer period, the increases in annual averages indicate that the previously unfavorable or less favorable periods for tourism will become more favorable in the future (Figure 15).

CHAPTER 5

CONCLUSIONS

The Mediterranean Basin, a prominent tourist destination, is subject to a range of environmental issues stemming from urbanization, land use alteration, overfishing, pollution, biodiversity depletion, and degradation of both terrestrial and marine ecosystems. These issues are closely linked to climate change (IPCC, 2021).

In this thesis, using the 1976-2020 data for 10 provinces (Adana, Antalya, Aydın, Balıkesir, Çanakkale, Edirne, Hatay, İzmir, Mersin, Muğla) the indices of HCI:Coast, HCI:Urban and HCI:Combined were analyzed annually and on a 6-month basis. The econometric analysis of the effects of comfort on tourist arrivals and overnight stays is performed using the panel fixed effects model. According to the results of the HCI:Coast analysis, in which the coastal districts are analyzed, the comfort variables positively affect the number of tourists visiting the coastal areas of the selected regions and the number of overnight stays of these tourists in the destinations. A similar result was obtained for HCI:Urban, except for the HG-6-month analysis. This shows that comfort variables are also effective in activities such as walking in the provinces. The HCI:Combined index analysis also indicates that the comfort variables, as a province average, positively affect the number of tourists visiting the selected provinces and the number of overnight stays in these destinations. The findings of the research confirm the studies in the literature that examine the effects of climate change on tourist comfort and find positive correlations between arrival data and tourist comfort indices (Demiroglu, Saygili-Araci, Pacal, Hall, and Kurnaz, 2020; Aygün Oğur and Bağcan, 2023). Tourism climate indices as a concept arose from the idea of gaining more general information about the impact of climate conditions on the well-being of tourists. The results of the present research also confirm this information.

After examining the relationship between the number of tourist arrivals and the number of overnight stays of these tourists and the HCI:Coast, HCI:Urban, and HCI:Combined indices and finding a positive relationship between holiday comfort and tourism activity, an analysis was conducted using climate change projections in 10 provinces to examine the effects of climate change on human comfort. In the analysis, the possible effects of future climate change (2026-2050) on tourist comfort and its possible effects on tourist arrivals and overnight stays were interpreted (but not econometrically analyzed). First, monthly average HCI:Coast, HCI:Urban, and HCI:Combined values were calculated in the 10 provinces for the 2026-2050 period. With this analysis, the changes that may occur in tourist comfort levels during the summer tourism season and in the rest of the months were examined. As a result of the analysis, it was found that projected comfort levels decreased in these provinces, especially in July and August. On the other hand, it was seen that comfort conditions would improve in May and October. In addition, it was noticed that comfort conditions could improve in some provinces in April and November, indicating that there may be shifts in the tourism season. Secondly, the general findings on the future HCI trends of 10 provinces were presented in time series. Trend graphs were plotted providing forecasts for MPI-ESM-MR and HadGEM2, and the 1976-2020 period was analyzed to show a trend comparison with the number of tourist arrivals and overnight stays up to 2020. As a result of the analysis, it was seen that tourist comfort tended to increase slightly in some provinces, especially for the 6-month analysis. In the 6-month and annual analysis, some provinces with a decrease in comfort score were also noticed.

The climate is a major driver of seasonality in tourism demand, which is a defining feature of global tourism, as well as being an important factor in determining the suitability of a place for touristic activities (Butler, 2001). While tourism businesses focus on tourism activities with a limited activity period, whether it is winter or summer, they have to make a profit in a limited time. Therefore, in tourism destinations, the climate is also very important economically, as it is one of the most important factors determining the attractiveness of the region in terms of its suitability for tourism (de Freitas, 2003; Yu, Schwartz, and Walsh, 2009). Examining the current and potential climatic conditions for tourism is important for future planning and regional investments. With substantial evidence showing the intrinsic importance of climate in tourist decision-making processes, projected changes in climate conditions are expected to have significant consequences on tourism demand (Gómez-Martín, 2005; Amelung, Nickolls, and Viner, 2007; Gómez-Martín, Armesto-López, and Martínez-Ibarra, 2014). Climate change has the potential to change the distribution of climate conditions among coastal tourism destinations with its impact on tourism seasonality, demand, and travel patterns (Amelung and Viner, 2006) because it is known that climate change changes the climate characteristics of tourism destinations, such as sunshine duration, precipitation, humidity, wind speed, and average temperature. If current climate projections turn out to be correct, it is argued that by the 2050s, popular destinations in the Mediterranean will become less attractive due to the very hot climate during the summer months, when the holiday activity is at its highest, and the ideal number of days for vacation will decrease. In addition, climate change scenarios point to possible changes, such as the Mediterranean becoming a more pleasant place in spring and autumn (Amelung and Viner, 2006). Aygün Oğur and Baycan (2022), who associate the changes in climate comfort levels between the past and future periods with the number of international tourists using TCI and a regression model, predict extreme decreases in demand in the tourism sector, seasonal changes, and the emergence of new alternative destinations as a result of climate change.

The energy balance of the human body alone is insufficient to fully account for the thermal comfort experienced by individual tourists, as it is subject to the influence of psychological and behavioral factors, as well as the countries of origin of said tourists (Lin and Matzarakis, 2008; Lin, de Lear, and Hwang, 2011). Notwithstanding the ambiguities surrounding the precise delineation of indices, extant literature has demonstrated a strong association between tourism indices and the number of overnight stays in various destinations (Amelung and Moreno, 2009; Rossell’o-Nadal, 2014). Empirical evidence suggests that these measures are efficacious in assessing the overall climate appropriateness of tourist destinations.

Adaptation is viewed as an appropriate response for reducing the tourism industry's sensitivity to climate change (Patterson, Bastianoni, and Simpson, 2006). Adaptation to climate change is a necessity, but it cannot be said that the tourism industry truly comprehends this requirement. When the prospective effects of climate change are understood, it may be simpler and more effective to concentrate on adaptation strategies (Dubois and Ceron, 2006). This threshold is the difference between an impact study and an adaptation study. Examining the effects of climate change on a system is crucial for studies that evaluate and comprehend vulnerabilities and associated adaptation measures (IPCC, 2022). Examining the effects of climate change on a system must give way to evaluating and comprehending the system’s vulnerabilities and associated adaptation measures.

A growing number of publications predicting climate change-induced shifts in travel patterns seek to assist the industry in planning its future operations and adapting to shifting environmental conditions (Gössling and Hall, 2006). The most frequently mentioned adaptation strategies are efforts to diversify products or change destinations. Diversification of tourism products has been proposed as a potential adaptation mechanism and is widely recognized as an effective adaptation strategy that can reduce vulnerability to economic and other crises (Dubois and Ceron, 2006; Gómez-Martín, Armesto-López, Cors-Iglesias, and Muñoz-Negrete, 2014).

People who are especially vulnerable to the effects of climate change in terms of comfort require improved monitoring and management systems. There is a need for educational programs that provide information on the risks of exposure to high temperatures and how to manage them, particularly for the most vulnerable populations (Linares et al., 2020). It is essential to collaborate with other sectors and institutions to promote urban green infrastructure suitable for countries in the Mediterranean Basin and to reduce heat and solar exposure and associated discomfort (Shashua-Bar, Tsiros, and Hoffman, 2012). In conclusion, the health, environment, and ecological hazards that rising temperatures may create in relevant locations should be developed in an integrated manner, not only with the tourism industry but also with other sectors related to the tourism industry, particularly health. For instance, the capacity of the health system, which must serve a larger population than usual during the summer tourism season, is an area that must be developed first.

Given the hazards associated with climate change, planned adaptation may be the best course of action. On the other hand, the planned adaptation process should include risk management planning, adaptation process financing, prioritizing research and development activities, education and effective communication, and taking responsibility for all stakeholders, from local residents to government agencies. Tourism stakeholders state that government leadership is needed in adapting to climate change (Scott, Hall, and Gössling, 2012).

The study has some limitations. Data on tourist arrivals and overnight stays are available from 1976, obtained from the Ministry of Culture and Tourism. However, there is no data for periods before 1976. Additional analyzes are made using gross domestic product (GDP) data for provinces, but these data are only available since 2004. As a result, robustness analyzes are made specifically for the post-2004 period. The study accepts that there are no reliable data on tourism activity for the 10 selected provinces, except for the number of tourists and overnight stays. Consequently, a more comprehensive analysis of the past and future would have been possible if other tourism indicators were included. These are the limitations of the study.

On the other hand, the study also has suggestions for future research. Regional analyzes of climate change, holiday comfort and tourism activity are rarely included in the literature. This study aims to fill the gap in this field. However, it is necessary to increase impact studies in order to focus on harmonization-oriented studies in this area. Additional validation against tourism performance measures, including visitor satisfaction, should be encouraged. Since near-term planning is more important in the tourism sector, a near future analysis has been made, but a more distant future, for example the end of the century, can also be analyzed. It is anticipated that research results such as this study can be very useful for tourists, tourism professionals, operators, other stakeholders and policy makers.

APPENDIX A

TOURIST ARRIVALS DATA

Table A1. HadGEM2 6-Month and Annual Analysis for HCI:Coast

Model 4: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−17.9847	5.02786	−3.577	0.0060	***
HCI_HG_6month	0.399214	0.0648793	6.153	0.0002	***

Mean dependent var	12.95269	S.D. dependent var	1.477727
Sum squared resid	531.0335	S.E. of regression	1.146490
LSDV R-squared	0.412601	Within R-squared	0.149966
Log-likelihood	−640.0179	Akaike criterion	1302.036
Schwarz criterion	1346.347	Hannan-Quinn	1319.558
rho	0.789223	Durbin-Watson	0.365344

Joint test on named regressors -
Test statistic: F(1, 9) = 37.8616
with p-value = P(F(1, 9) > 37.8616) = 0.000168075

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.8) = 21.3034
with p-value = P(F(9, 164.8) > 21.3034) = 1.38163e-23

Model 2: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−6.18600	2.31633	−2.671	0.0256	**
HCI_HG_annual	0.295060	0.0357107	8.262	<0.0001	***

Mean dependent var	12.95269	S.D. dependent var	1.477727
Sum squared resid	514.8303	S.E. of regression	1.128863
LSDV R-squared	0.430524	Within R-squared	0.175903
Log-likelihood	−633.5880	Akaike criterion	1289.176
Schwarz criterion	1333.487	Hannan-Quinn	1306.698
rho	0.757812	Durbin-Watson	0.433560

Joint test on named regressors -
Test statistic: F(1, 9) = 68.2689
with p-value = P(F(1, 9) > 68.2689) = 1.70867e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.7) = 24.4824
with p-value = P(F(9, 164.7) > 24.4824) = 2.95865e-26

Table A2. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Coast

Model 3: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−17.7113	5.64683	−3.136	0.0120	**
HCI_MPI_6month	0.393414	0.0724480	5.430	0.0004	***

Mean dependent var	12.95269	S.D. dependent var	1.477727
Sum squared resid	520.0165	S.E. of regression	1.134535
LSDV R-squared	0.424788	Within R-squared	0.167601
Log-likelihood	−635.6677	Akaike criterion	1293.335
Schwarz criterion	1337.647	Hannan-Quinn	1310.858
rho	0.710675	Durbin-Watson	0.522777

Joint test on named regressors -
Test statistic: F(1, 9) = 29.4881
with p-value = P(F(1, 9) > 29.4881) = 0.000416213

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.8) = 22.6583
with p-value = P(F(9, 164.8) > 22.6583) = 9.52304e-25

Model 1: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−18.9360	4.69319	−4.035	0.0030	***
HCI_MPI_annual	0.495255	0.0728887	6.795	<0.0001	***

Mean dependent var	12.95269	S.D. dependent var	1.477727
Sum squared resid	470.9365	S.E. of regression	1.079669
LSDV R-squared	0.479077	Within R-squared	0.246165
Log-likelihood	−615.0968	Akaike criterion	1252.194
Schwarz criterion	1296.505	Hannan-Quinn	1269.716
rho	0.658152	Durbin-Watson	0.608386

Joint test on named regressors -
Test statistic: F(1, 9) = 46.1677
with p-value = P(F(1, 9) > 46.1677) = 7.95295e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.7) = 24.1479
with p-value = P(F(9, 164.7) > 24.1479) = 5.53139e-26

Table A3. HadGEM2 6-Month and Annual Analysis for HCI:Urban

Model 4: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	11.3658	12.9467	0.8779	0.4028	
HCI_HG_6month	0.0201439	0.164345	0.1226	0.9051	

Mean dependent var	12.95269	S.D. dependent var	1.477727
Sum squared resid	624.6053	S.E. of regression	1.243404
LSDV R-squared	0.309097	Within R-squared	0.000184
Log-likelihood	−673.6941	Akaike criterion	1369.388
Schwarz criterion	1413.699	Hannan-Quinn	1386.910
rho	0.931917	Durbin-Watson	0.112935

Joint test on named regressors -
Test statistic: F(1, 9) = 0.0150236
with p-value = P(F(1, 9) > 0.0150236) = 0.90514

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.7) = 21.8415
with p-value = P(F(9, 164.7) > 21.8415) = 4.73846e-24

Model 2: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−8.29093	4.60852	−1.799	0.1056	
HCI_HG_annual	0.299709	0.0650180	4.610	0.0013	***

Mean dependent var	12.95269	S.D. dependent var	1.477727
Sum squared resid	582.6070	S.E. of regression	1.200873
LSDV R-squared	0.355554	Within R-squared	0.067412
Log-likelihood	−659.2506	Akaike criterion	1340.501
Schwarz criterion	1384.812	Hannan-Quinn	1358.023
rho	0.863172	Durbin-Watson	0.240481

Joint test on named regressors -
Test statistic: F(1, 9) = 21.2488
with p-value = P(F(1, 9) > 21.2488) = 0.00127295

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.7) = 19.924
with p-value = P(F(9, 164.7) > 19.924) = 2.30141e-22

Table A4. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Urban

Model 3: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−23.5947	9.62076	−2.452	0.0366	**
HCI_MPI_6month	0.457794	0.120510	3.799	0.0042	***

Mean dependent var	12.95269	S.D. dependent var	1.477727
Sum squared resid	565.7132	S.E. of regression	1.183334
LSDV R-squared	0.374240	Within R-squared	0.094454
Log-likelihood	−653.1448	Akaike criterion	1328.290
Schwarz criterion	1372.601	Hannan-Quinn	1345.812
rho	0.807808	Durbin-Watson	0.338944

Joint test on named regressors -
Test statistic: F(1, 9) = 14.431
with p-value = P(F(1, 9) > 14.431) = 0.00422508

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.7) = 20.7372
with p-value = P(F(9, 164.7) > 20.7372) = 4.33738e-23

Model 1: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−33.3584	7.36763	−4.528	0.0014	***
HCI_MPI_annual	0.650364	0.103466	6.286	0.0001	***

Mean dependent var	12.95269	S.D. dependent var	1.477727
Sum squared resid	510.8005	S.E. of regression	1.124437
LSDV R-squared	0.434982	Within R-squared	0.182354
Log-likelihood	−631.9574	Akaike criterion	1285.915
Schwarz criterion	1330.226	Hannan-Quinn	1303.437
rho	0.717265	Durbin-Watson	0.483677

Joint test on named regressors -
Test statistic: F(1, 9) = 39.5107
with p-value = P(F(1, 9) > 39.5107) = 0.000143392

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.7) = 19.4372
with p-value = P(F(9, 164.7) > 19.4372) = 6.34917e-22

Table A5. HadGEM2 6-Month and Annual Analysis for HCI:Combined

Model 4: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−9.22500	8.43577	−1.094	0.3026	
HCI_HG_6month	0.284532	0.108336	2.626	0.0275	**

Mean dependent var	12.93065	S.D. dependent var	1.469641
Sum squared resid	589.0887	S.E. of regression	1.207535
LSDV R-squared	0.341194	Within R-squared	0.046471
Log-likelihood	−661.5464	Akaike criterion	1345.093
Schwarz criterion	1389.404	Hannan-Quinn	1362.615
rho	0.887800	Durbin-Watson	0.190018

Joint test on named regressors -
Test statistic: F(1, 9) = 6.89794
with p-value = P(F(1, 9) > 6.89794) = 0.027521

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.7) = 19.86
with p-value = P(F(9, 164.7) > 19.86) = 2.63053e-22

Model 2: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−9.07709	3.13324	−2.897	0.0177	**
HCI_HG_annual	0.324008	0.0461290	7.024	<0.0001	***

Mean dependent var	12.93065	S.D. dependent var	1.469641
Sum squared resid	539.9632	S.E. of regression	1.156089
LSDV R-squared	0.396133	Within R-squared	0.125988
Log-likelihood	−643.4782	Akaike criterion	1308.956
Schwarz criterion	1353.267	Hannan-Quinn	1326.478
rho	0.805063	Durbin-Watson	0.349014

Joint test on named regressors -
Test statistic: F(1, 9) = 49.336
with p-value = P(F(1, 9) > 49.336) = 6.15985e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.7) = 18.8153
with p-value = P(F(9, 164.7) > 18.8153) = 2.36339e-21

Table A6. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Combined

Model 3: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−22.8273	6.98834	−3.266	0.0097	***
HCI_MPI_6month	0.454280	0.0887818	5.117	0.0006	***

Mean dependent var	12.93065	S.D. dependent var	1.469641
Sum squared resid	530.1182	S.E. of regression	1.145502
LSDV R-squared	0.407143	Within R-squared	0.141924
Log-likelihood	−639.6600	Akaike criterion	1301.320
Schwarz criterion	1345.631	Hannan-Quinn	1318.842
rho	0.753380	Durbin-Watson	0.443442

Joint test on named regressors -
Test statistic: F(1, 9) = 26.1817
with p-value = P(F(1, 9) > 26.1817) = 0.000630685

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.7) = 20.3252
with p-value = P(F(9, 164.7) > 20.3252) = 1.00614e-22

Model 1: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−27.0586	5.66117	−4.780	0.0010	***
HCI_MPI_annual	0.588650	0.0833335	7.064	<0.0001	***

Mean dependent var	12.93065	S.D. dependent var	1.469641
Sum squared resid	478.5426	S.E. of regression	1.088353
LSDV R-squared	0.464823	Within R-squared	0.225406
Log-likelihood	−618.4213	Akaike criterion	1258.843
Schwarz criterion	1303.154	Hannan-Quinn	1276.365
rho	0.685124	Durbin-Watson	0.551958

Joint test on named regressors -
Test statistic: F(1, 9) = 49.8971
with p-value = P(F(1, 9) > 49.8971) = 5.89605e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.7) = 17.8915
with p-value = P(F(9, 164.7) > 17.8915) = 1.72908e-20

APPENDIX B

OVERNIGHT STAYS DATA

Table B1. HadGEM2 6-Month and Annual Analysis for HCI:Coast

Model 8: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−8.60449	5.37351	−1.601	0.1438	
HCI_HG_6month	0.285411	0.0693395	4.116	0.0026	***

Mean dependent var	13.51366	S.D. dependent var	1.674569
Sum squared resid	410.3196	S.E. of regression	1.007791
LSDV R-squared	0.646560	Within R-squared	0.104508
Log-likelihood	−586.5060	Akaike criterion	1195.012
Schwarz criterion	1239.323	Hannan-Quinn	1212.534
rho	0.798289	Durbin-Watson	0.325639

Joint test on named regressors -
Test statistic: F(1, 9) = 16.9426
with p-value = P(F(1, 9) > 16.9426) = 0.00261293

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.5) = 69.175
with p-value = P(F(9, 164.5) > 69.175) = 2.52659e-51

Model 6: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−0.0922808	2.56585	−0.03597	0.9721	
HCI_HG_annual	0.209762	0.0395575	5.303	0.0005	***

Mean dependent var	13.51366	S.D. dependent var	1.674569
Sum squared resid	402.6677	S.E. of regression	0.998350
LSDV R-squared	0.653151	Within R-squared	0.121208
Log-likelihood	−582.5999	Akaike criterion	1187.200
Schwarz criterion	1231.511	Hannan-Quinn	1204.722
rho	0.777368	Durbin-Watson	0.373127

Joint test on named regressors -
Test statistic: F(1, 9) = 28.1187
with p-value = P(F(1, 9) > 28.1187) = 0.000492094

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.5) = 77.7379
with p-value = P(F(9, 164.5) > 77.7379) = 1.28109e-54

Table B2. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Coast

Model 7: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−9.22322	6.01425	−1.534	0.1595	
HCI_MPI_6month	0.291711	0.0771619	3.780	0.0043	***

Mean dependent var	13.51366	S.D. dependent var	1.674569
Sum squared resid	400.6395	S.E. of regression	0.995832
LSDV R-squared	0.654898	Within R-squared	0.125634
Log-likelihood	−581.5521	Akaike criterion	1185.104
Schwarz criterion	1229.415	Hannan-Quinn	1202.626
rho	0.745875	Durbin-Watson	0.429134

Joint test on named regressors -
Test statistic: F(1, 9) = 14.2922
with p-value = P(F(1, 9) > 14.2922) = 0.00434568

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.5) = 72.3952
with p-value = P(F(9, 164.5) > 72.3952) = 1.34426e-52

Model 5: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−10.2573	5.12690	−2.001	0.0765	*
HCI_MPI_annual	0.369180	0.0796245	4.637	0.0012	***

Mean dependent var	13.51366	S.D. dependent var	1.674569
Sum squared resid	372.7524	S.E. of regression	0.960549
LSDV R-squared	0.678919	Within R-squared	0.186496
Log-likelihood	−566.5814	Akaike criterion	1155.163
Schwarz criterion	1199.474	Hannan-Quinn	1172.685
rho	0.707783	Durbin-Watson	0.486672

Joint test on named regressors -
Test statistic: F(1, 9) = 21.4973
with p-value = P(F(1, 9) > 21.4973) = 0.0012253

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.5) = 77.4095
with p-value = P(F(9, 164.5) > 77.4095) = 1.69868e-54

Table B3. HadGEM2 6-Month and Annual Analysis for HCI:Urban

Model 8: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	11.5510	11.3721	1.016	0.3363	
HCI_HG_6month	0.0249142	0.144356	0.1726	0.8668	

Mean dependent var	13.51366	S.D. dependent var	1.674569
Sum squared resid	458.0296	S.E. of regression	1.064771
LSDV R-squared	0.605463	Within R-squared	0.000385
Log-likelihood	−609.3305	Akaike criterion	1240.661
Schwarz criterion	1284.972	Hannan-Quinn	1258.183
rho	0.896598	Durbin-Watson	0.154896

Joint test on named regressors -
Test statistic: F(1, 9) = 0.0297866
with p-value = P(F(1, 9) > 0.0297866) = 0.866794

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.5) = 77.2005
with p-value = P(F(9, 164.5) > 77.2005) = 1.99618e-54

Model 6: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−1.85091	4.61544	−0.4010	0.6978	
HCI_HG_annual	0.216766	0.0651156	3.329	0.0088	***

Mean dependent var	13.51366	S.D. dependent var	1.674569
Sum squared resid	436.1763	S.E. of regression	1.039059
LSDV R-squared	0.624287	Within R-squared	0.048078
Log-likelihood	−599.1863	Akaike criterion	1220.373
Schwarz criterion	1264.684	Hannan-Quinn	1237.895
rho	0.843994	Durbin-Watson	0.252707

Joint test on named regressors -
Test statistic: F(1, 9) = 11.0819
with p-value = P(F(1, 9) > 11.0819) = 0.00881382

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.6) = 63.0755
with p-value = P(F(9, 164.6) > 63.0755) = 8.90538e-49

Table B4. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Urban

Model 7: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−15.0119	9.67102	−1.552	0.1550	
HCI_MPI_6month	0.357312	0.121140	2.950	0.0162	**

Mean dependent var	13.51366	S.D. dependent var	1.674569
Sum squared resid	422.2590	S.E. of regression	1.022348
LSDV R-squared	0.636275	Within R-squared	0.078451
Log-likelihood	−592.4576	Akaike criterion	1206.915
Schwarz criterion	1251.226	Hannan-Quinn	1224.437
rho	0.799762	Durbin-Watson	0.326705

Joint test on named regressors -
Test statistic: F(1, 9) = 8.70009
with p-value = P(F(1, 9) > 8.70009) = 0.0162317

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.6) = 66.4267
with p-value = P(F(9, 164.6) > 66.4267) = 3.37561e-50

Model 5: Fixed-effects, using 415 observations
Included 10 cross-sectional units
Time-series length: minimum 40, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−21.1623	8.22217	−2.574	0.0300	**
HCI_MPI_annual	0.486967	0.115467	4.217	0.0022	***

Mean dependent var	13.51366	S.D. dependent var	1.674569
Sum squared resid	394.3374	S.E. of regression	0.987969
LSDV R-squared	0.660326	Within R-squared	0.139388
Log-likelihood	−578.2621	Akaike criterion	1178.524
Schwarz criterion	1222.835	Hannan-Quinn	1196.046
rho	0.740169	Durbin-Watson	0.413784

Joint test on named regressors -
Test statistic: F(1, 9) = 17.7862
with p-value = P(F(1, 9) > 17.7862) = 0.00224817

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 164.6) = 57.3972
with p-value = P(F(9, 164.6) > 57.3972) = 3.15337e-46

Table B5. HadGEM2 6-Month and Annual Analysis for HCI:Combined

Model 9: Fixed-effects, using 315 observations
Included 10 cross-sectional units
Time-series length: minimum 17, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−0.215368	6.84757	−0.03145	0.9756	
HCI_HG_6month	0.176227	0.0879703	2.003	0.0762	*

Mean dependent var	13.50204	S.D. dependent var	1.734971
Sum squared resid	204.4593	S.E. of regression	0.820100
LSDV R-squared	0.783682	Within R-squared	0.038962
Log-likelihood	−378.8936	Akaike criterion	779.7871
Schwarz criterion	821.0654	Hannan-Quinn	796.2794
rho	0.857168	Durbin-Watson	0.252589

Joint test on named regressors -
Test statistic: F(1, 9) = 4.01302
with p-value = P(F(1, 9) > 4.01302) = 0.0761525

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 106.9) = 403.07
with p-value = P(F(9, 106.9) > 403.07) = 3.25788e-78

Model 7: Fixed-effects, using 315 observations
Included 10 cross-sectional units
Time-series length: minimum 17, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	2.46908	3.19090	0.7738	0.4589	
HCI_HG_annual	0.162905	0.0471146	3.458	0.0072	***

Mean dependent var	13.50204	S.D. dependent var	1.734971
Sum squared resid	195.8251	S.E. of regression	0.802597
LSDV R-squared	0.792817	Within R-squared	0.079546
Log-likelihood	−372.0979	Akaike criterion	766.1958
Schwarz criterion	807.4741	Hannan-Quinn	782.6880
rho	0.809844	Durbin-Watson	0.345515

Joint test on named regressors -
Test statistic: F(1, 9) = 11.9552
with p-value = P(F(1, 9) > 11.9552) = 0.00718758

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 107.0) = 409.683
with p-value = P(F(9, 107.0) > 409.683) = 1.16925e-78

Table B6. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Combined

Model 8: Fixed-effects, using 315 observations
Included 10 cross-sectional units
Time-series length: minimum 17, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−7.38532	5.55620	−1.329	0.2165	
HCI_MPI_6month	0.265394	0.0705967	3.759	0.0045	***

Mean dependent var	13.50204	S.D. dependent var	1.734971
Sum squared resid	190.5809	S.E. of regression	0.791777
LSDV R-squared	0.798365	Within R-squared	0.104196
Log-likelihood	−367.8225	Akaike criterion	757.6450
Schwarz criterion	798.9233	Hannan-Quinn	774.1372
rho	0.762296	Durbin-Watson	0.427947

Joint test on named regressors -
Test statistic: F(1, 9) = 14.1323
with p-value = P(F(1, 9) > 14.1323) = 0.00448992

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 106.8) = 395.606
with p-value = P(F(9, 106.8) > 395.606) = 9.81914e-78

Model 6: Fixed-effects, using 315 observations
Included 10 cross-sectional units
Time-series length: minimum 17, maximum 44
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−10.3203	5.41375	−1.906	0.0890	*
HCI_MPI_annual	0.351897	0.0799702	4.400	0.0017	***

Mean dependent var	13.50204	S.D. dependent var	1.734971
Sum squared resid	176.6705	S.E. of regression	0.762334
LSDV R-squared	0.813082	Within R-squared	0.169580
Log-likelihood	−355.8856	Akaike criterion	733.7711
Schwarz criterion	775.0494	Hannan-Quinn	750.2634
rho	0.705207	Durbin-Watson	0.512085

Joint test on named regressors -
Test statistic: F(1, 9) = 19.3631
with p-value = P(F(1, 9) > 19.3631) = 0.00171951

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 106.9) = 367.476
with p-value = P(F(9, 106.9) > 367.476) = 4.10529e-76

APPENDIX C

TOURIST ARRIVALS AND GDP DATA

Table C1. HadGEM2 6-Month and Annual Analysis for HCI:Coast

Model 8: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	8.26268	1.31144	6.300	0.0001	***
l_GDPPCUSD	1.07071	0.119752	8.941	<0.0001	***
HCI_HG_6month	−0.0507050	0.0212140	−2.390	0.0405	**

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.70337	S.E. of regression	0.353136
LSDV R-squared	0.917654	Within R-squared	0.239693
Log-likelihood	−58.04382	Akaike criterion	140.0876
Schwarz criterion	177.7172	Hannan-Quinn	155.3573
rho	0.630395	Durbin-Watson	0.746741

Joint test on named regressors -
Test statistic: F(2, 9) = 47.5488
with p-value = P(F(2, 9) > 47.5488) = 1.64289e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 54.9355
with p-value = P(F(9, 65.1) > 54.9355) = 5.51511e-27

Model 6: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	6.60944	0.857212	7.710	<0.0001	***
l_GDPPCUSD	0.991173	0.101848	9.732	<0.0001	***
HCI_HG_annual	−0.0239859	0.00627714	−3.821	0.0041	***

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.60879	S.E. of regression	0.352287
LSDV R-squared	0.918049	Within R-squared	0.243343
Log-likelihood	−57.63479	Akaike criterion	139.2696
Schwarz criterion	176.8992	Hannan-Quinn	154.5392
rho	0.603737	Durbin-Watson	0.797022

Joint test on named regressors -
Test statistic: F(2, 9) = 47.3642
with p-value = P(F(2, 9) > 47.3642) = 1.66937e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 51.558
with p-value = P(F(9, 65.1) > 51.558) = 3.29121e-26

Table C2. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Coast

Model 7: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	1.29321	1.64047	0.7883	0.4508	
l_GDPPCUSD	0.971671	0.103375	9.400	<0.0001	***
HCI_MPI_6month	0.0498010	0.0154377	3.226	0.0104	**

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.56810	S.E. of regression	0.351921
LSDV R-squared	0.918219	Within R-squared	0.244913
Log-likelihood	−57.45822	Akaike criterion	138.9164
Schwarz criterion	176.5460	Hannan-Quinn	154.1861
rho	0.644172	Durbin-Watson	0.723848

Joint test on named regressors -
Test statistic: F(2, 9) = 45.8645
with p-value = P(F(2, 9) > 45.8645) = 1.905e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 52.8089
with p-value = P(F(9, 65.1) > 52.8089) = 1.67373e-26

Model 5: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	2.16489	1.90365	1.137	0.2848	
l_GDPPCUSD	1.04524	0.108468	9.636	<0.0001	***
HCI_MPI_annual	0.0364520	0.0215545	1.691	0.1251	

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.77398	S.E. of regression	0.353768
LSDV R-squared	0.917359	Within R-squared	0.236968
Log-likelihood	−58.34789	Akaike criterion	140.6958
Schwarz criterion	178.3254	Hannan-Quinn	155.9654
rho	0.664019	Durbin-Watson	0.687047

Joint test on named regressors -
Test statistic: F(2, 9) = 46.6961
with p-value = P(F(2, 9) > 46.6961) = 1.76967e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 49.352
with p-value = P(F(9, 65.1) > 49.352) = 1.12357e-25

Table C3. HadGEM2 6-Month and Annual Analysis for HCI:Urban

Model 8: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	15.2423	1.41479	10.77	<0.0001	***
l_GDPPCUSD	0.976180	0.0997588	9.785	<0.0001	***
HCI_HG_6month	−0.127913	0.0230370	−5.552	0.0004	***

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	18.45102	S.E. of regression	0.341729
LSDV R-squared	0.922888	Within R-squared	0.288018
Log-likelihood	−52.46185	Akaike criterion	128.9237
Schwarz criterion	166.5533	Hannan-Quinn	144.1934
rho	0.540257	Durbin-Watson	0.916432

Joint test on named regressors -
Test statistic: F(2, 9) = 48.3407
with p-value = P(F(2, 9) > 48.3407) = 1.53496e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 47.082
with p-value = P(F(9, 65.1) > 47.082) = 4.20064e-25

Model 6: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	8.56800	1.01205	8.466	<0.0001	***
l_GDPPCUSD	0.964542	0.0976866	9.874	<0.0001	***
HCI_HG_annual	−0.0462409	0.0124426	−3.716	0.0048	***

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.36827	S.E. of regression	0.350120
LSDV R-squared	0.919054	Within R-squared	0.252624
Log-likelihood	−56.58576	Akaike criterion	137.1715
Schwarz criterion	174.8011	Hannan-Quinn	152.4412
rho	0.581540	Durbin-Watson	0.837895

Joint test on named regressors -
Test statistic: F(2, 9) = 48.7881
with p-value = P(F(2, 9) > 48.7881) = 1.47782e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 43.7265
with p-value = P(F(9, 65.1) > 43.7265) = 3.20024e-24

Table C4. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Urban

Model 7: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−3.06455	1.63226	−1.877	0.0932	*
l_GDPPCUSD	0.945180	0.106314	8.890	<0.0001	***
HCI_MPI_6month	0.106266	0.0170260	6.241	0.0002	***

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.22551	S.E. of regression	0.348827
LSDV R-squared	0.919651	Within R-squared	0.258133
Log-likelihood	−55.95690	Akaike criterion	135.9138
Schwarz criterion	173.5434	Hannan-Quinn	151.1834
rho	0.632854	Durbin-Watson	0.744135

Joint test on named regressors -
Test statistic: F(2, 9) = 61.7802
with p-value = P(F(2, 9) > 61.7802) = 5.53643e-06

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 42.424
with p-value = P(F(9, 65.1) > 42.424) = 7.2483e-24

Model 5: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−1.34868	2.16993	−0.6215	0.5497	
l_GDPPCUSD	1.05796	0.105803	9.999	<0.0001	***
HCI_MPI_annual	0.0805944	0.0244887	3.291	0.0094	***

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.53393	S.E. of regression	0.351614
LSDV R-squared	0.918362	Within R-squared	0.246231
Log-likelihood	−57.30969	Akaike criterion	138.6194
Schwarz criterion	176.2490	Hannan-Quinn	153.8890
rho	0.660044	Durbin-Watson	0.695021

Joint test on named regressors -
Test statistic: F(2, 9) = 50.7167
with p-value = P(F(2, 9) > 50.7167) = 1.25933e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 43.0042
with p-value = P(F(9, 65.1) > 43.0042) = 4.9798e-24

Table C5. HadGEM2 6-Month and Annual Analysis for HCI:Combined

Model 9: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	12.5877	1.89603	6.639	<0.0001	***
l_GDPPCUSD	1.03063	0.109697	9.395	<0.0001	***
HCI_HG_6month	−0.101394	0.0288543	−3.514	0.0066	***

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.05518	S.E. of regression	0.347279
LSDV R-squared	0.920363	Within R-squared	0.264705
Log-likelihood	−55.20051	Akaike criterion	134.4010
Schwarz criterion	172.0306	Hannan-Quinn	149.6707
rho	0.578648	Durbin-Watson	0.843586

Joint test on named regressors -
Test statistic: F(2, 9) = 46.1261
with p-value = P(F(2, 9) > 46.1261) = 1.8611e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 51.4065
with p-value = P(F(9, 65.1) > 51.4065) = 3.60435e-26

Model 7: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	7.41097	0.933216	7.941	<0.0001	***
l_GDPPCUSD	0.979271	0.100029	9.790	<0.0001	***
HCI_HG_annual	−0.0331456	0.00985127	−3.365	0.0083	***

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.51851	S.E. of regression	0.351475
LSDV R-squared	0.918426	Within R-squared	0.246826
Log-likelihood	−57.24258	Akaike criterion	138.4852
Schwarz criterion	176.1147	Hannan-Quinn	153.7548
rho	0.594765	Durbin-Watson	0.813568

Joint test on named regressors -
Test statistic: F(2, 9) = 47.9254
with p-value = P(F(2, 9) > 47.9254) = 1.59044e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 53.9516
with p-value = P(F(9, 65.1) > 53.9516) = 9.17977e-27

Table C6. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Combined

Model 8: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−0.386759	1.93516	−0.1999	0.8460	
l_GDPPCUSD	0.958321	0.106989	8.957	<0.0001	***
HCI_MPI_6month	0.0722029	0.0220520	3.274	0.0096	***

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.47743	S.E. of regression	0.351105
LSDV R-squared	0.918598	Within R-squared	0.248411
Log-likelihood	−57.06349	Akaike criterion	138.1270
Schwarz criterion	175.7566	Hannan-Quinn	153.3966
rho	0.640846	Durbin-Watson	0.729984

Joint test on named regressors -
Test statistic: F(2, 9) = 47.814
with p-value = P(F(2, 9) > 47.814) = 1.60574e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 50.5344
with p-value = P(F(9, 65.1) > 50.5344) = 5.7458e-26

Model 5: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Touristarrivals
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.639765	2.06076	0.3105	0.7633	
l_GDPPCUSD	1.04959	0.107238	9.788	<0.0001	***
HCI_MPI_annual	0.0563382	0.0237045	2.377	0.0415	**

Mean dependent var	14.02141	S.D. dependent var	1.189886
Sum squared resid	19.67393	S.E. of regression	0.352872
LSDV R-squared	0.917777	Within R-squared	0.240829
Log-likelihood	−57.91671	Akaike criterion	139.8334
Schwarz criterion	177.4630	Hannan-Quinn	155.1031
rho	0.660795	Durbin-Watson	0.693596

Joint test on named regressors -
Test statistic: F(2, 9) = 47.9507
with p-value = P(F(2, 9) > 47.9507) = 1.58699e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 55.296
with p-value = P(F(9, 65.1) > 55.296) = 4.52841e-27

APPENDIX D

OVERNIGHT STAYS AND GDP DATA

Table D1. HadGEM2 6-Month and Annual Analysis for HCI:Coast

Model 16: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	8.12682	1.03977	7.816	<0.0001	***
l_GDPPCUSD	0.761747	0.108310	7.033	<0.0001	***
HCI_HG_6month	−0.0100748	0.0162564	−0.6197	0.5508	

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.95542	S.E. of regression	0.275077
LSDV R-squared	0.974440	Within R-squared	0.210575
Log-likelihood	−15.57737	Akaike criterion	55.15473
Schwarz criterion	92.78432	Hannan-Quinn	70.42438
rho	0.691072	Durbin-Watson	0.585457

Joint test on named regressors -
Test statistic: F(2, 9) = 34.8029
with p-value = P(F(2, 9) > 34.8029) = 5.81496e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 104.51
with p-value = P(F(9, 65.2) > 104.51) = 3.23748e-35

Model 14: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	8.37485	0.770743	10.87	<0.0001	***
l_GDPPCUSD	0.733626	0.0988576	7.421	<0.0001	***
HCI_HG_annual	−0.0118154	0.00384875	−3.070	0.0134	**

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.88217	S.E. of regression	0.274233
LSDV R-squared	0.974596	Within R-squared	0.215412
Log-likelihood	−15.05499	Akaike criterion	54.10998
Schwarz criterion	91.73956	Hannan-Quinn	69.37962
rho	0.682609	Durbin-Watson	0.597591

Joint test on named regressors -
Test statistic: F(2, 9) = 29.1046
with p-value = P(F(2, 9) > 29.1046) = 0.000117669

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 94.9382
with p-value = P(F(9, 65.2) > 94.9382) = 5.85238e-34

Table D2. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Coast

Model 15: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	6.81240	1.39391	4.887	0.0009	***
l_GDPPCUSD	0.743357	0.0960810	7.737	<0.0001	***
HCI_MPI_6month	0.00885040	0.00815917	1.085	0.3062	

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.95310	S.E. of regression	0.275050
LSDV R-squared	0.974445	Within R-squared	0.210728
Log-likelihood	−15.56089	Akaike criterion	55.12178
Schwarz criterion	92.75136	Hannan-Quinn	70.39142
rho	0.688746	Durbin-Watson	0.590624

Joint test on named regressors -
Test statistic: F(2, 9) = 47.3141
with p-value = P(F(2, 9) > 47.3141) = 1.67664e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 102.575
with p-value = P(F(9, 65.2) > 102.575) = 5.69947e-35

Model 13: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	5.63947	1.09533	5.149	0.0006	***
l_GDPPCUSD	0.762932	0.0995607	7.663	<0.0001	***
HCI_MPI_annual	0.0259722	0.0162130	1.602	0.1436	

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.87536	S.E. of regression	0.274154
LSDV R-squared	0.974611	Within R-squared	0.215861
Log-likelihood	−15.00629	Akaike criterion	54.01258
Schwarz criterion	91.64216	Hannan-Quinn	69.28222
rho	0.686263	Durbin-Watson	0.595514

Joint test on named regressors -
Test statistic: F(2, 9) = 41.4133
with p-value = P(F(2, 9) > 41.4133) = 2.8889e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 87.5753
with p-value = P(F(9, 65.2) > 87.5753) = 6.54502e-33

Table D3. HadGEM2 6-Month and Annual Analysis for HCI:Urban

Model 16: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	11.7525	1.29620	9.067	<0.0001	***
l_GDPPCUSD	0.730939	0.101601	7.194	<0.0001	***
HCI_HG_6month	−0.0524464	0.0189388	−2.769	0.0218	**

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.71303	S.E. of regression	0.272274
LSDV R-squared	0.974958	Within R-squared	0.226580
Log-likelihood	−13.83638	Akaike criterion	51.67276
Schwarz criterion	89.30234	Hannan-Quinn	66.94240
rho	0.678202	Durbin-Watson	0.606749

Joint test on named regressors -
Test statistic: F(2, 9) = 26.4023
with p-value = P(F(2, 9) > 26.4023) = 0.000171593

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.1) = 81.5834
with p-value = P(F(9, 65.1) > 81.5834) = 5.47029e-32

Model 14: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	9.20373	0.733571	12.55	<0.0001	***
l_GDPPCUSD	0.722884	0.0982355	7.359	<0.0001	***
HCI_HG_annual	−0.0211751	0.00656247	−3.227	0.0104	**

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.84301	S.E. of regression	0.273780
LSDV R-squared	0.974680	Within R-squared	0.217998
Log-likelihood	−14.77438	Akaike criterion	53.54876
Schwarz criterion	91.17834	Hannan-Quinn	68.81841
rho	0.679407	Durbin-Watson	0.602976

Joint test on named regressors -
Test statistic: F(2, 9) = 27.7661
with p-value = P(F(2, 9) > 27.7661) = 0.000141284

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 80.0286
with p-value = P(F(9, 65.2) > 80.0286) = 9.57882e-32

Table D4. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Urban

Model 15: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	4.23271	1.42947	2.961	0.0159	**
l_GDPPCUSD	0.718073	0.102388	7.013	<0.0001	***
HCI_MPI_6month	0.0437591	0.0105498	4.148	0.0025	***

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.84218	S.E. of regression	0.273771
LSDV R-squared	0.974682	Within R-squared	0.218052
Log-likelihood	−14.76846	Akaike criterion	53.53691
Schwarz criterion	91.16649	Hannan-Quinn	68.80656
rho	0.673373	Durbin-Watson	0.617522

Joint test on named regressors -
Test statistic: F(2, 9) = 26.9277
with p-value = P(F(2, 9) > 26.9277) = 0.000159056

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 78.3495
with p-value = P(F(9, 65.2) > 78.3495) = 1.77713e-31

Model 13: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	3.99903	1.27362	3.140	0.0119	**
l_GDPPCUSD	0.768416	0.0999729	7.686	<0.0001	***
HCI_MPI_annual	0.0458250	0.0197553	2.320	0.0455	**

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.83038	S.E. of regression	0.273634
LSDV R-squared	0.974707	Within R-squared	0.218831
Log-likelihood	−14.68370	Akaike criterion	53.36740
Schwarz criterion	90.99698	Hannan-Quinn	68.63704
rho	0.677664	Durbin-Watson	0.610335

Joint test on named regressors -
Test statistic: F(2, 9) = 51.9728
with p-value = P(F(2, 9) > 51.9728) = 1.13809e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 84.9517
with p-value = P(F(9, 65.2) > 84.9517) = 1.63134e-32

Table D5. HadGEM2 6-Month and Annual Analysis for HCI:Combined

Model 17: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	9.87473	1.17259	8.421	<0.0001	***
l_GDPPCUSD	0.753509	0.103019	7.314	<0.0001	***
HCI_HG_6month	−0.0314937	0.0179006	−1.759	0.1124	

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.87877	S.E. of regression	0.274194
LSDV R-squared	0.974604	Within R-squared	0.215636
Log-likelihood	−15.03069	Akaike criterion	54.06137
Schwarz criterion	91.69095	Hannan-Quinn	69.33102
rho	0.685829	Durbin-Watson	0.593095

Joint test on named regressors -
Test statistic: F(2, 9) = 30.5994
with p-value = P(F(2, 9) > 30.5994) = 9.67408e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 94.6658
with p-value = P(F(9, 65.2) > 94.6658) = 6.40953e-34

Model 15: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	8.72229	0.793724	10.99	<0.0001	***
l_GDPPCUSD	0.728686	0.0991071	7.353	<0.0001	***
HCI_HG_annual	−0.0157588	0.00521079	−3.024	0.0144	**

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.86745	S.E. of regression	0.274063
LSDV R-squared	0.974628	Within R-squared	0.216384
Log-likelihood	−14.94959	Akaike criterion	53.89919
Schwarz criterion	91.52877	Hannan-Quinn	69.16884
rho	0.681639	Durbin-Watson	0.599194

Joint test on named regressors -
Test statistic: F(2, 9) = 27.1787
with p-value = P(F(2, 9) > 27.1787) = 0.000153464

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 102.899
with p-value = P(F(9, 65.2) > 102.899) = 5.18529e-35

Table D6. MPI-ESM-MR 6-Month and Annual Analysis for HCI:Combined

Model 16: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	5.47901	1.34872	4.062	0.0028	***
l_GDPPCUSD	0.725617	0.0996754	7.280	<0.0001	***
HCI_MPI_6month	0.0276724	0.00844397	3.277	0.0096	***

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.89564	S.E. of regression	0.274388
LSDV R-squared	0.974568	Within R-squared	0.214522
Log-likelihood	−15.15130	Akaike criterion	54.30260
Schwarz criterion	91.93218	Hannan-Quinn	69.57225
rho	0.680970	Durbin-Watson	0.604465

Joint test on named regressors -
Test statistic: F(2, 9) = 26.5004
with p-value = P(F(2, 9) > 26.5004) = 0.000169162

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 102.003
with p-value = P(F(9, 65.2) > 102.003) = 6.75077e-35

Model 14: Fixed-effects, using 170 observations
Included 10 cross-sectional units
Time-series length = 17
Dependent variable: l_Overnightstay
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	4.72146	1.09436	4.314	0.0019	***
l_GDPPCUSD	0.765338	0.0998015	7.669	<0.0001	***
HCI_MPI_annual	0.0377706	0.0171737	2.199	0.0554	*

Mean dependent var	14.25237	S.D. dependent var	1.663630
Sum squared resid	11.84069	S.E. of regression	0.273754
LSDV R-squared	0.974685	Within R-squared	0.218151
Log-likelihood	−14.75773	Akaike criterion	53.51547
Schwarz criterion	91.14505	Hannan-Quinn	68.78511
rho	0.680564	Durbin-Watson	0.606061

Joint test on named regressors -
Test statistic: F(2, 9) = 51.1971
with p-value = P(F(2, 9) > 51.1971) = 1.21118e-05

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(9, 65.2) = 113.29
with p-value = P(F(9, 65.2) > 113.29) = 2.81632e-36

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