Spatial and compound dependencies in drought and heatwaves in the climate of South-Western Europe

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Abstract

The South-Western Europe (Iberian Peninsula) has been highlighted for the escalating occurrence and severity of droughts and heatwaves during the last decades. However, the statistical interdependencies between these extremes remain largely understudied, which makes effective climate adaptation and mitigation strategies compromised as a result. In this study, ERA5 reanalysis of daily mean temperature and accumulated precipitation data is used to examine the statistical interdependencies that exist between drought conditions and heatwaves in the Iberian Peninsula from 1950 to 2022. Markov chain models are applied to establish the probability of transitions among the four states monthly, event-free, drought, heatwave and compound states. The connection of these extremes between pairs of grid points by the use Hamming distance technique is also explored by analysing the similarities in decades and seasons. The results confirm that there is a rise in extreme events in the Iberian Peninsula, the magnitude is increasing and the connections of occurrences of extreme events between grid points are gradually becoming weaker which shows that the statistical similarities are changing significantly in time.

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Chapter 1

Introduction

The Intergovernmental Panel on Climate Change (IPCC) sixth assessment report defines "Climate change" as "the state of the climate that can be identified by changes in the mean and/or the variability of its properties and that persists for an extended period, typically like decades or longer" [1]. Long-term alterations in the Earth's average temperature, precipitation patterns, weather events caused by human activities such as burning fossil fuels, deforestation, industrial processes, greenhouse gas emission, and some natural factors such as volcanic eruption and changes in solar radiation [2, 3] are the main causes of the climate change (Figure 1.1). However, the effect of natural factors on climate change is relatively minimal compared to human activities [4]. Although climate change is expected to have a global impact, cities should be prioritized for assessment because of their high population density, abundance of resources, and economic activity, which makes them more vulnerable to the effects of climate change [5]. According to Giannakis and Bruggeman [6], over 75% of people in the European Union live in urban areas, and by 2050, this percentage is expected to rise to 82%.

Unprecedented heatwaves have occurred in recent years all over the world [8]. Examples include the heatwave in Western Europe in 2003, which claimed over 70,000 lives [9], and the heatwave in Eastern Europe and Russia in 2010 that is estimated to have killed 55,000 people [10]. Amid simultaneous heatwaves and droughts in the summer of 2017, the Mediterranean region had the 'Lucifer' heatwave in late July and early August, while Portugal saw devastating wildfires in June that claimed 65 lives [11, 12]. According to earlier estimates conducted in Europe, heatwave frequency is predicted to increase, especially in southern Europe [13]. The study by Molina et al. [14] uses the EURO-CORDEX RCP8.5 model ensemble and finds strong and significant increases in heatwaves across a range of definitions, from nine to forty-five times. With estimates ranging from 2 days to 27–67 days, Sánchez-Benítez et al. [15] calculated significant changes in the number of heatwave days, especially in Iberia and the Mediterranean region. Sánchez-Benítez et al. [15] also observed a notable increase in the intensity of heatwaves, particularly in south-central Europe. Heatwaves impact vegetation, air quality, and human

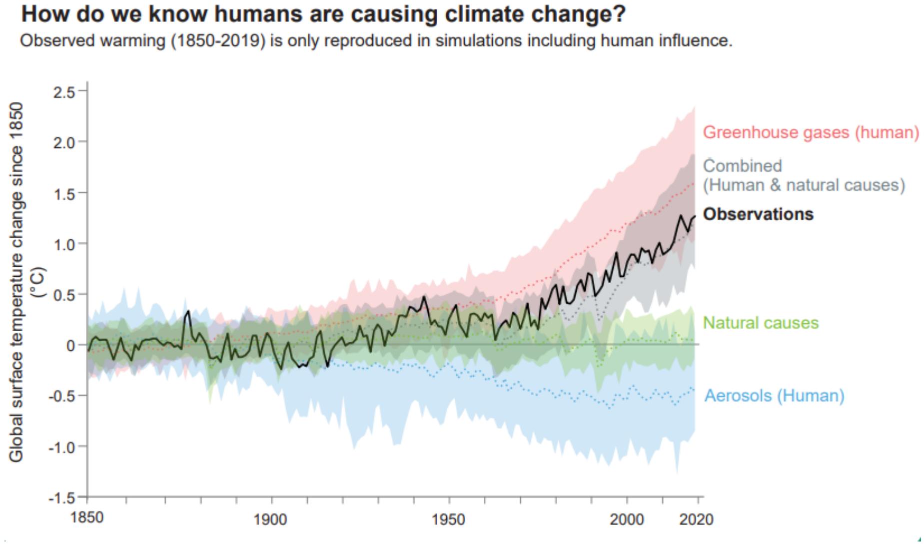

Figure 1.1: Change in global surface temperature as results of human and natural influence [7].

health, among other aspects of society and the environment. For example, the 2003 heatwave in Europe caused high levels of ozone to build up and serious health problems that killed almost 15,000 more people in France alone [9]. Heatwaves can have a variety of repercussions, such as higher evapotranspiration rates, lower agricultural yields, higher energy consumption, lower power plant efficiency, air pollution, and negative health effects[16]. Heatwaves have also been connected to wildfires becoming longer, bigger, and more intense, which has had disastrous effects on the ecosystem and caused significant financial losses [17]. The European heatwave, which was aggravated by concurrent drought conditions, was named by the United Nations Environment Programme in 2003 as the most expensive weather-related disaster globally [9].

Droughts also have major negative effects on the environment and civilization, such as sharp declines in gross primary productivity, which result in shortages of food and higher food prices worldwide [18]. Droughts are thought to cost $7 billion in economic harm each year worldwide, with possible effects on livestock, river transportation, hydropower generation, bioenergy, and energy consumption [19]. The type of drought being considered (e.g., meteorological, agricultural, hydrological) and the selected drought index are important factors to consider when evaluating changes in drought patterns [20]. However, as Ojeda et al. [21] point out, estimates point to longer and more frequent droughts in central Europe and the Mediterranean region, as well as in the Iberian Peninsula. According to Jaagus et al. [18], there will likely be substantial changes in river discharge in the future, with rises expected in northern Europe and declines in southern Europe. Drought pattern changes are dependent on the observational methods, and changes in precipitation extremes show heterogeneity over space [22].

The effects on the environment and society are exacerbated when extreme weather events happen together [23]. Environmental risks often result from the interaction of multiple climate events occurring at different time and space scales [24]. For example, a day that is windy, hot, and dry may result in a wildfire, even if these factors by themselves might not be deemed extreme. A compound event is defined as the conjunction of numerous climate extremes, according to Avila-Diaz et al. [25, 26] study on managing the risks of extreme events and disasters. Additionally, there appears to be a tendency for winter to last shorter and summer to last longer. According to forecasts from climate models, as long as anthropogenic emissions keep piling up, further warming is expected [27].

Considering the expected ongoing climatic changes, static definitions of seasons (such as astronomical and meteorological) are insufficient for adequately determining seasonal timing and duration [28]. The study emphasizes how metropolitan areas are becoming more and more susceptible to extreme weather events, especially heatwaves and droughts, because of the negative effects they have on both the environment and civilization. The huge financial losses and detrimental health effects linked to these events highlight how urgent it is to comprehend their statistical connections and how they vary over time [29]. Furthermore, the impact of seasons on climatic systems emphasizes how important it is to evaluate trends in seasonal transition dates, especially in areas that are vital to agricultural productivity [30]. To tackle these concerns, the study analyze the statistical dependencies between droughts and heatwaves in climate systems in Iberian Peninsula.

1.1 Problem statement

The study emphasizes how important it is to have a thorough understanding of the statistical correlations and temporal dynamics between heatwaves and droughts throughout time. A complete understanding of the long-term interactions between heatwaves and droughts is lacking, even though much prior research has concentrated on specific extreme weather occurrences [31–34]. The study bridges a knowledge gap on long-term climate variability and its consequences for future climate projections by examining the temporal dynamics and shifts in the statistical relationship between these occurrences. Although the impact of seasons on climate variability is widely acknowledged [35, 36], a more thorough examination of how seasons impact the frequency and severity of extreme weather events, such as heatwaves and droughts, is still necessary. The study fills this knowledge gap and sheds light on the seasonal drivers of extreme weather occurrences by looking at the seasonal patterns in the study region. Assessing climate risk and developing adaptation plans require an understanding of the probability of changing climatic states, including those with and without extreme events [37].

The probabilistic character of transitions has often been overlooked in favor of deterministic correlations between climate variables in earlier research [5]. The study fills this research gap by using Markov Chain analysis, which offers a probabilistic framework for examining climatic shifts [38]. The regional distribution of climate events is not uniform, and a deeper comprehension of the spatial link between extreme weather occurrences across regions is necessary [39]. The study fills this knowledge gap by examining the spatial clustering of heatwaves and droughts in the study region and offering insights into the underlying mechanisms governing spatial patterns of climatic variability. Assessing the efficacy of climate models and determining how transferable adaption techniques are required comparing the similarity of extreme climate occurrences across different places. The regional and temporal variations in similarity patterns have been overlooked by previous studies, which frequently relied on simplistic criteria to compare the similarities of climate events [40]. The study fills this gap by employing the Hamming distance metric, which offers a more sophisticated method of evaluating similarities between climate events.

The frequency, severity, and geographical distribution of extreme weather events are changing due to climate change; however, it is yet unclear how exactly these changes will affect heatwaves and droughts [41]. However, the research addresses this knowledge gap by analyzing historical data to identify statistical dependencies between heatwaves and droughts. By understanding these relationships, the study offers insightful projections about future occurrences of these events. This information is crucial for stakeholders and policymakers who are developing strategies to address and mitigate the impacts of these phenomena in the study region. The intricate relationships between heatwaves, droughts, and other climatic variables in the Iberian Peninsula can be better understood by looking into these issue statements. Additionally, they emphasize how crucial it is to take temporal and spatial aspects into account to comprehend climate dynamics and guide the formulation of climate-related policies and decision-making procedures [40].

1.2 Objectives

The main goal of this study is to analyze the statistical dependencies between droughts and heatwaves in the Iberian Peninsula. To achieve this, the study has laid out these objectives:

1. **Identify the Nature of the Statistical Relationship:** This objective focuses on discerning the types of statistical relationships that exist between droughts and heatwaves within the region, and how these relationships have evolved.

2. **Seasonal Influence on the Climate System:** Here, the aim is to determine how different seasons affect the climate dynamics of the region, particularly the occurrence of droughts and heatwaves.

3. **Probabilities of Extreme Event Transitions:** This involves calculating the likelihood of transitions between various climatic condi-

tions—ranging from normal to extreme events. The study seeks to understand the conditions under which such transitions occur.

1.3 Research questions

This study proposes to answer to three important research questions, which are:

1. What is the nature of the statistical relationship between droughts and heatwaves in the Iberian Peninsula, and how has this relationship changed over time?
2. How do different seasons influence the climate system in the Iberian Peninsula, particularly in terms of affecting the likelihood and severity of droughts and heatwaves?
3. What are the probabilities or likelihood of transitioning from one climatic condition to another, for example; from normal conditions to extreme events or vice versa?

1.4 Significance of the thesis

This thesis adds to our understanding of the intricate relationships between heatwaves and droughts in climate systems [42]. Through the identification of the statistical relationship between heatwaves and droughts and their temporal variations, the study contributes to our understanding of the fundamental dynamics of climate systems and it is essential for forecasting future patterns in climate change and creating workable plans for both adaptation and mitigation [43].

Having a better understanding of the statistical relationships between these occurrences helps stakeholders better target initiatives and distribute resources, strengthening society's ability to withstand the effects of climate change [23]. For instance, if the findings indicate that a severe drought is ongoing, stakeholders can preemptively allocate resources like water supplies and cooling centres in anticipation of a subsequent heatwave. This proactive approach allows for more effective distribution of aid, reducing the strain on emergency services and infrastructure during peak times. By using sophisticated statistical and computational methods to evaluate climate data, the study advances scientific understanding of the subject of climatology. The study's approaches and conclusions can be used as a foundation for additional investigation into climatic variability and extreme occurrences in different places through modelling and research. Research on the statistical relationships between heatwaves and droughts in climate systems is important because it helps us understand climate dynamics, guides the development of risk management plans, directs the creation of policies, and advances our understanding of climatology. Considering continuing climate change, its conclusions have applications for strengthening climate resilience and adaptation initiatives [5].

1.5 Organization of the thesis

The thesis is organized into five sessions. Chapter one presents the background, problem statement, aim, objectives, research questions and significance. Chapter two presents the literature review on the statistical dependencies between droughts and heatwaves in climate systems at the Iberian Peninsula. Chapter three presents the study methodology on how the study was conducted and analysed. Session four presents the analysis and results of the study. Chapter five presents the conclusion, recommendations, and future works.

Chapter 2

Background and state of the art

This chapter provides a comprehensive background of the current literature focusing on droughts and heatwaves and their interplay in climate systems. The state of the art section aims to identify the current state of knowledge on the relationship between these extreme weather events and to highlight areas for further research.

The chapter begins by providing a detailed definition of compound events, Hot-dry extremes, droughts and heatwaves and drivers of extreme events. Some concepts from statistical learning will be highlighted, and finally, the current state of the related studies will be pinpointed and how they would be applied to the study. It then explores the historical background of research in this area, starting from early studies that focused on individual extreme events to recent research that has shifted towards examining the statistical dependencies between these events.

Additionally, different statistical methods used to study the relationship between droughts and heatwaves and the various associated drivers, including classification and regression analyses, will be presented.

2.1 What are Extreme Events?

Severe weather conditions including heatwaves, droughts, and floods cause fatalities as well as substantial property damage and financial losses [41]. According to projections, over this century, there will likely be an increase in the frequency, duration, and intensity of these extremes across several European regions, impacting previously vulnerable areas such as the Mediterranean and new ones in mid-latitudes [44]. Comprehending the existing conditions and anticipated shifts in these extremes is essential for gaining scientific understanding as well as assisting society in devising adaptation and mitigation strategies [45]. As a result, a quick and easy-to-use tool is required to determine extreme occurrences, susceptible areas, and crucial seasons [41]. For this reason, several extreme indices have been created, such as the Palmer Drought Index (PDI) and Effective Drought Index (EDI) for droughts, the Universal Thermal Climate Index (UTCI) for heatwaves, and the Standardized Precipitation Index (SPI) for droughts [46]. These indexes are used to create extreme event catalogues, like the ones the European Drought Observatory publishes [47], and to identify and characterize extreme events. It is crucial to remember that these indices differ greatly in terms of their timeframes, thresholds, approaches, and intended uses. As a result, there are differences in what the various indexes consider to be extraordinary [48].

Extreme heat events have increased noticeably in recent years, and some of these events have had major effects on economies, society, and agriculture [48]. These extreme circumstances may result from the interaction of several drives and processes, or they may develop from a single underlying reason [49]. Furthermore, it is commonly known that forcing by greenhouse gases (GHGs) influences not only the mean climate state but also the variability of the climate, the likelihood and severity of weather extremes, and the climate [50]. Gaining a greater knowledge of these contributing factors specifically, the underlying physical mechanisms in the current climate context—is crucial to improve forecasting accuracy and revise future estimates [49]. Since preindustrial times, there has been a shift in the probability of severe occurrences due to changes in land use and land-cover, as well as climate change, which is mostly caused by anthropogenic greenhouse gas emissions [51]. Although it is difficult to link a particular event to climate change alone, it is possible to assess and measure the impact of different causes on shifts in the probability of an event or a certain class of events [52]. A probabilistic attribution approach was used in early studies of extreme occurrences to evaluate the change in likelihood ascribed to greenhouse gas (GHG) forcing [53]. Using this strategy, one can compare the probability of an event under hypothetical conditions (also known as "counterfactual") with that under actual conditions (also known as "factual") [54].

On the other hand, a complementary but more modern method uses "storylines" to calculate how much anthropogenic forcing contributed to a certain occurrence [55]. This method provides a more thorough knowledge of the reasons of the event by identifying a series of circumstances that led up to it and evaluating the significance of each [56]. Taking a more mechanical approach, this framework can also be expanded to consider the attribution of extreme events to different atmospheric, oceanic, and land variables. Sea surface temperature (SST) anomalies have an impact on local and worldwide weather and climate patterns, indicating that the ocean is a major contributor to climate variability [57]. Through changes in atmospheric circulation known as teleconnections, these anomalies, which are frequently linked to climate events like the El Niño Southern Oscillation (ENSO), can affect global patterns of temperature and precipitation [58]. It has been suggested that specific sea surface temperature (SST) trends in northern Eurasia increase the likelihood of heatwaves via changing air circulation [59]. SSTs can have varying effects on various occurrences, though; in the case of the Russian heatwave in 2010, for instance, their significance was less clear [10]. Anomalies in the atmospheric circulation are often linked to heatwaves. Hot extremes frequently occur in conjunction with extended high-pressure systems in the northern mid-latitudes [57] and also in southeast Australia [60]. Although oceanic circumstances can have an impact on these high-pressure systems, internal variations in air circulation can also give rise to them [61, 62].

In a changing climate, feedback from land surface conditions, especially soil moisture availability, can greatly increase the intensity and length of heatwaves [63]. Because of soil moisture memory and interactions with the atmospheric boundary layer, reduced soil moisture can decrease evaporative cooling and prolong heatwave episodes [64]. Because of the close connection between the land and the atmosphere in these locations, severe heatwaves and droughts frequently occur together, particularly in places with transitional climates [65].

2.1.1 Heatwaves

A heatwave is defined as a string of consecutively hot days that the temperature exceeds a particular threshold [9]. Heatwaves can have a substantial impact on several factors, such as energy consumption, the environment, water resources, agricultural production, and human health [10]. Prominent heatwaves, such those that occurred in Europe in 2003 and Russia in 2010, claimed a significant number of lives—over 56,000 and 70,000, respectively [9, 10]. An additional two days during heatwaves was found to dramatically enhance the chance of mass heat-related mortality events by 78% between 1978 and 2006, according to research conducted in India [66]. High temperatures have the potential to desiccate soil, which puts plants under more stress and increases the need for watering. Heatwaves increase demand and decrease efficiency, which puts additional strain on the electrical infrastructure [13]. Because urban structures both absorb and reemit solar radiation, they increase energy consumption and greenhouse gas emissions, which worsens the consequences of heatwaves [14]. For example, France had a sharp decline in electricity exports during the 2003 European heatwave because of the tremendous demand on its internal energy infrastructure [67]. Scientists predict that water and energy consumption will rise in tandem with global temperature increases and the growth of urban regions [15]. Still, there is a lack of knowledge on the specific effects of rising temperatures on consumption rates and the anticipated rise in peak energy demand. By the end of the century, projections show that peak energy consumption in the US might increase by 7.2% (under the moderate emission scenario known as Representative Concentration Pathway (RCP) 4.5) to 18% (in the high emission scenario known as RCP 8.5) [66]. RCPs outline different future possibilities for land use and emissions [68]. Urbanization is predicted to be a major factor in this regard since it increases local temperature extremes through the urban heat island effect. To fully understand the anticipated interaction between socioeconomic elements and local climate extremes, more research is required [17]. Heatwaves have become more frequent, prolonged, and intense on a global scale [69]. Records for temperature set in the 1930s have been exceeded by recent heatwaves, like those that occurred in Texas and the midwestern United States in 2011 and 2012 [70]. The Iberian Peninsula (IP) experienced an excess mortality rate of 3.5% in Portugal and 8% in Spain due to the August 2003 heatwave [71–73] and in June 2007 [15]. Record-breaking temperatures have also been experienced in California, aggravating the drought, and raising the possibility of wildfires [74]. Records for hot temperatures are being broken more quickly than records for low temperatures.

Furthermore, the minimum daily temperature is rising faster than the highest temperature [23]. This means that the body will be less able to disperse heat during heatwaves and will be less able to cool down at night, which will increase the risk of heat-related illnesses and deaths [75]. Projections suggest that throughout the course of the next century, heatwaves will continue to increase [15]. Even though there are international attempts to keep global warming to 1.5 or 2°C by 2100, regional variations are anticipated in local temperature extremes [13]. By the end of the century, maximum temperatures are expected to rise by at least 3°C in several regions, including the Northern Hemisphere, Central America, and South Africa [76, 77]. In the Arctic, for example, annual minimum temperatures are predicted to rise by 5.5°C over preindustrial levels. According to climate projections, there might be more than thirty additional heatwave days in the tropics and roughly ten to fifteen more days in the mid to high latitudes, which includes parts of North America, Europe, and Russia, for every degree Celsius that temperatures rise [9, 10]. The variety of physical circumstances from year to year and feedback loops between soil moisture and temperature are the factors driving the intensification of intense heatwaves brought on by rising global temperatures [14]. Since there is still a great deal of uncertainty regarding the length and intensity of local extreme heat episodes as a result of global warming, more research is necessary.

Many heatwave research ignore the connections between different heatwave characteristics like intensity and duration in favor of concentrating on single indicators [64]. It is essential to look at these traits at the same time because they are interconnected. Furthermore, elements such as humidity, airflow, and sun radiation can intensify the effects of heatwaves, resulting in heat stress and associated health hazards, especially for vulnerable groups [23]. It is still difficult to comprehend the cumulative consequences of extended exposure to extremely high temperatures and heat stress on human health [24]. Research on heatwave detection and attribution has connected human factors and global warming to the strongest heatwaves and their rising frequency in recent years [31]. In fact, in certain areas, emissions caused by humans have increased the likelihood of the worst-case scenarios by up to ten times [34]. There are not many studies that concentrate on attribution, which emphasizes the need for more research to determine how much human activity affects instances of extreme heat as well as how human-induced warming affects different elements of heatwaves, such as their length and intensity [9, 13, 15]. Warming temperatures brought on by climate change frequently set off a domino effect that makes other extreme events, such as wildfires or droughts, worse [66]. For example, there is a reciprocal relationship between heatwaves and droughts: heatwaves intensify drought conditions, and severe droughts raise the risk of even more violent heatwaves [34, 78, 79].

2.1.2 Drought

One of the problems identified by many when studying droughts is the definition of drought itself. It is difficult to define drought since different drought indices measure different aspects of water constraint [11] and different definitions have been used by different studies. The IPCC report 2022 [80] defines drought as "An exceptional period of water shortage for existing ecosystems and the human population (due to low rainfall, high temperature and/or wind". Another study also described drought as prolonged periods of abnormally dry weather conditions, reducing water availability for human activities and natural ecosystems [81].

Recent studies have concentrated on identifying and understanding drought patterns in a rising climate as knowledge of anthropogenic climate change develops [20, 22]. Research has shown changes in localized patterns of precipitation and snow cover, and forecasts point to a worldwide reallocation of precipitation that may have a substantial effect on areas that are vulnerable to variations in soil moisture [21]. The influence of land surface moisture on local drought occurrences may change due to shifts in transitional zones brought about by changes in global climate patterns [18]. To understand how localized feedback mechanisms and systems may respond to changes in surface moisture, regional investigations will be essential. There is a lack of understanding regarding changes in drought occurrences despite efforts to resolve inconsistencies in research caused by variations in observational data and approaches accounting for natural climatic events (such as the El Niño–Southern Oscillatio) [58]. For instance, Naumann et al. [19] found that the area of the world impacted by droughts grew by 8% between the 1980s and the 2000s, although Gaitán et al. [82] found no evidence of a recent global trend in the frequency of droughts. This discrepancy highlights how crucial it is to improve the consistency between observational data and drought indices so that different studies can get to comparable findings [83]. Furthermore, to handle different features of dry situations, like snow droughts or deficits in snow water equivalent (SWE), additional drought characterizations must be created [23]. Because of the observed and anticipated decreases in snowpack, snow droughts have become more significant, especially in areas like the western United States [84]. Margulis et al. [85], for example, found that between 1985 and 2016 in the Sierra Nevada in the United States, historical winter warming of 1 to 2°C increased the risk of below-average April 1 SWE quantities from 20% to 40%, respectively [86]. It is important to keep a watchful eye out for drought conditions in areas that are vulnerable to temperature changes and likely to experience snow droughts [87]. To better prepare for a warmer future climate, it is therefore essential to build global frameworks and indicators for monitoring and describing snow droughts [88].

In terms of future projections, Cook et al. [89] projected that by the end of the twenty-first century, compared to the twentieth, soil moisture drought events will become more frequent and severe, covering roughly twice the land area under moderate (based on simulations with CO2 concentrations peaking at 720 ppm) and high emissions scenarios (peaking at 850 ppm) emissions [90]. Global aridity, or the difference between precipitation and potential evapotranspiration, is expected to increase by 3.4% for every degree Celsius that land temperatures rise [91]. This would result in less water being available in drier locations [92]. Global drylands are predicted to expand by 10–23% between 1961–1990 and 2071–2100 because of the advent of a warmer climate, making up 50–56% of the planet's land surface [93]. According to Tigkas et al. [94], there will be a significant increase in the number of communities suffering from extended water stress due to this spread of aridity and drylands. The predicted increase in aridity and the spread of areas vulnerable to drought will probably increase the frequency of dust storms [95]. These dust storms can cause health problems and change the hydrology of neighboring and distant areas. As per Strzepek et al. [96], the existence of dust on snow or ice can have an impact on the time and pace of melting processes, as well as the interactions between the ground and atmosphere. Feedback interactions between the land surface, atmosphere, and biosphere impact the predicted increase in global aridity and the growth of dryland areas. Dubrovsky et al. [97] separated the effects of long-term soil moisture trends on temperature, relative humidity, and precipitation in a changing climate, highlighting the relevance of land-atmosphere interactions in causing the expected doubling in aridity. Furthermore, it is anticipated that the spread of drylands and the frequency of droughts would reduce soil and vegetation's ability to absorb carbon, raising atmospheric CO2 levels and accelerating the processes of desertification [98]. Large-scale deforestation, especially in tropical areas, may also influence the frequency and intensity of droughts [99]. Nevertheless the above mentioned, it is still unclear how precisely global warming and natural variability affect the frequency of droughts [29], particularly on a regional basis. Therefore, studies targeted at improving our understanding of droughts and natural variability would improve our understanding of past and future patterns of drought [30]. Additionally, research must be deepened to understand how human endeavours like farming, deforestation, and increased water use affect the frequency and intensity of drought occurrences [32]. Tripathy and Mishra [100] emphasized the dearth of research on the effects of human activity on water stress and the importance of comprehending how human activity affects water availability. Like this, Akhtar et al. [47] stressed how important it is to consider how humans both contribute to and mitigate drought circumstances. Understanding the proportional effects of natural variability, climate change, and human activity on drought occurrences is crucial to improving regional and global drought management techniques [101].

2.1.3 Compound Events

Compound events are the combinations of two or more events involving physical processes that occur simultaneously or in close succession resulting in great impacts that would be expected from individual events occurrences [102, 103]. These combined effects have gained significant interest because, when multiple natural disasters occur in succession, the effects are often more devastating [41].

Compound drought and heatwaves (CDHWs) pose a serious threat to socioecological systems and have often more detrimental effects than isolated events [104]. Socioeconomic crises, wildfires, agricultural losses, and an increase in heat-related mortality are some of these effects [105]. Globally, CDHWs have been more common in recent years, impacting areas like Europe, the US, South America, Australia, and Asia [106]. Due to changes in land and vegetation cover, increased sensible heat flux, and other factors, linked variations in temperature and precipitation are frequently the result of droughts and heatwaves being interconnected [107]. Although natural variability contributes to the occurrence of CDHW, human-induced warming has made these occurrences more intense, resulting in more widespread and long-lasting heatwaves and droughts [108]. Due to their substantial effects on socioecological systems, such as crop production losses, heat-related mortality, and wildfires, CDHW occurrences have drawn a lot of attention [100]. Several places in the world, including portions of China, Western Russia, the USA, Australia, and Europe, have recently experienced heatwaves and compound droughts during summer months [109].

Summers 2003, 2010, 2015, 2017 and 2018 in Europe and western Russia, 2012–2014 in the USA, 2013 in Australia, and 2006, 2009–2010, and 2014 in southwestern and northern China were all recorded for these events [9, 10, 109]. Numerous land surface processes contribute to the formation of droughts and heatwaves, resulting in varied spatial patterns because of regional differences in precipitation, anomalies in temperature, and hydrological changes [34]. These land surface processes are also shaped by variables like human activity, background aridity, and large-scale climate trends.

Awareness, adaptations, and resilience are essential for coping with such compound events [110]. Early warning models, systems, and effective communication strategies can be very useful in creating more awareness and avoiding potential disasters and discomfort. People's awareness, education, and knowledge can be important factors in reducing the impacts of compound events.

According to Zscheischler et al. [111] in analysing compound events, there is no single method dedicated to analyzing compound events because the type of analysis and approach will depend on the specific situation and the nature of the compound event. However, depending on the goal, there may be a need for a combination of many methods/approaches. In the above paper, some methods/approaches that can be used to analyse compound events are: regression, multivariate probability distribution, correlation coefficient, copula-based approaches, poison process, external coefficient and the semivariogram, and others were discussed as a possible way to analyse compound events.

2.2 Concepts from statistical learning

It becomes more difficult for algorithms to find solutions to problems as the problems they are trying to solve become more complex. In this research, we shall use one aspect of Artificial Intelligence (AI) known as Machine Learning (ML) to explore knowledge about the statistical dependencies between drought and heatwaves in the Iberian Peninsula sub-region.

Artificial Intelligence is the way of developing computer systems to perform simple to complex problems that require high human intelligence to solve, such as pattern recognition, decision-making, and problem-solving [112, 113]. AI systems can be programmed to identify patterns in data and learn from experience and subsequently improve performance with time. AI has so many systems and techniques, including Machine Learning (ML), Computer Vision (CV), and robotics.

Machine Learning (ML) has solved many complex problems across various industries, including healthcare, finance, and transportation [114]. Some of the critical problems that ML has addressed include image and speech recognition, natural language processing, fraud detection, and recommendation systems, to name a few. Machines can now mimic human cognitive functions thanks to the development of the concept of learning and the ability to solve complex problems [115]. ML has contributed much to the studies related to the Earth's Climate. Building more accurate and efficient models by researchers [116]. Weather forecasting using satellites sensor and weather stations data sources [117]. Prediction of natural disasters such as hurricanes, floods, and wildfires by analyzing data from sources.

2.2.1 Markov chain analysis

After the states have been determined, the following step is to develop a transition matrix to describe the probability of changing from one state to another within a certain amount of time. Utilizing the sequence of state changes that were observed in the dataset from 1950 to 2022, this matrix is constructed through the process of analysis. It is possible to calculate transition probabilities based on the relative frequency of each transition by recording the transition from the starting state to the succeeding state for each pair of successive observations. This allows for the computation of transition probabilities.

These assumptions are established to guarantee that the analysis is conducted by the principles of a Markov Chain [118]:

The property of Markov: There is a presumption that the future state is solely dependent on the current state, and not on the sequence of events that came before it.

Time Homogeneity: The transition probabilities are considered constant throughout the analysis. While this simplifies the model, it is acknowledged that climate dynamics may introduce time-dependent variations.

A directed graph is used to show the transition probabilities. The nodes of the graph represent the states, while the edges of the graph reflect the transitions. To provide a graphical depiction of the Markov Chain, each edge is given a weight that is determined by the chance of migrating from one specific state to another. By showing the most likely routes and potential stable states or cycles within the system, this representation contributes to a better understanding of the dynamics of climatic state changes. To illustrate short-term dynamics, the graphs are constructed for six months, with each subplot representing the transitions that occur during a single full month. The ability to observe seasonal trends and the influence of temporal granularity on transition probabilities is made possible by this temporal resolution.

Through the use of Markov Chain analysis on climate data, this approach provides a mathematical framework that may be utilised to comprehend and forecast changes in climatic conditions. This method offers insights into the chance of several different climatic states occurring, which enables improved preparedness and response plans for threats associated with climate change.

By tracking simultaneously the derived series of binary states for both heatwaves and droughts, we then calculate the frequency of all possible transitions between the four possible states, $(S_H, S_D) = \{(0,0); (0,1); (1,0); (1,1)\}$. These frequencies are mapped into conditional probabilities.

$$P((S_H(t+\Delta t), S_D(t+\Delta t))|(S_D(t), S_D(t))) = \frac{P((S_H(t+1), S_D(t+1)); (S_H(t), S_H(t)))}{P((S_H(t), S_D(t)))} \tag{1}$$

where Δt is the time within which the transition occurs. Here we consider $\Delta t = 1, 2, 3, 4, 5$, and 6 months.

2.3 Hamming Distance

The analysis starts with defining states from heatwave and drought conditions as depicted by SPI-12, employing binary states for computation. The '00' state signifies a normal day without heatwaves or droughts; '10' indicates the presence of a heatwave; '01' represents a drought, and '11' denotes a compound state of both heatwaves and droughts.

Data transformation is a critical step, where the binary states '00', '01', '11', and '10' are mapped into '0' and '1' states for simplification. "00" is mapped to '0', indicating the absence of heatwave or drought, and any other value is mapped to '1', signifying the presence of these conditions. This mapping is applied across all grid points in the 'State_hamming' column.

To facilitate focused comparison and incorporate spatial context in the analysis, the dataset is grouped by unique pairs of latitude and longitude.

This spatial grouping is essential for comparing binary sequences across different geographic locations.

The generation of unique pairs of grid points is achieved through Python's `'itertools'` combination function, ensuring a comprehensive pairwise comparison across all grid points.

For the computation of Hamming distance, it is essential to ensure that the sequences being compared are of equal length, truncating them if necessary. The Hamming distance, calculated using the `'hamming'` function from the `'scipy.spatial.distance'` module, indicates the proportion of differing bits between sequences. This proportion is converted to an absolute count of differing bits, providing a quantitative measure of sequence dissimilarity. The computed distances and their counts are collected for subsequent analysis.

We take into consideration the Hamming distance[119] between the heatwave series of binary states and the drought series of binary states. The Hamming distance is defined for each pair of locations, l_1 and l_2, and it is given by:

$$H_{total}(l_1, l_2) = \sqrt{H_d^2(l_1, l_2) + H_h^2(l_1, l_2)} \tag{2}$$

$$\text{where } H_d(S_1^{(d)}, S_2^{(d)}) = \frac{1}{N}\sum_{i=1}^{N} |S_1^{(d)}(i) - S_2^{(d)}(i)| \tag{3}$$

$$\text{and} \quad H_h(S_1^{(h)}, S_2^{(h)}) = \frac{1}{N}\sum_{i=1}^{N} |S_1^{(h)}(i) - S_2^{(h)}(i)| \tag{4}$$

with $S_2^{(d)}(i)$ and $S_2^{(h)}(i)$ the binary state (0 or 1) with respect to heatwave ("h") or drought ("d") at location $l1$ in day i, and similarly for location $l2$. To put it another way, the Hamming distance is a quantitative measure of sequence dissimilarity that is derived from the proportion of bits that are different between sequences.

In summary, the concepts from statistical learning, including ML, Markov chain models, and Hamming distance approaches, provide valuable tools for analyzing and understanding the complex relationships between climatic events. These methods not only enhance our understanding of climate impacts on agriculture, ecosystem vulnerability, and resource management but also facilitate the development of adaptation and mitigation strategies. By enabling precise comparisons and identifications of climate patterns, these statistical tools serve as valuable assets in the study of climate adaptation and mitigation strategies.

2.4 State of the art

A study relies on the examination of the relationship between precipitation and temperature, proposing a new method based on dynamical systems theory to measure the persistence and co-occurrence of these events [120]. They analysed data from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis dataset from 1979 to 2018 for the Mediterranean region. The authors found that specific regions and processes influence the relationship between temperature and precipitation, not always reflecting the entire region. Additionally, the study found that the relationship is sensitive to non-extreme events and can be used to understand potential future seasonal climate changes in the Mediterranean region. The authors also identified specific factors that drive changes in this relationship, such as surface warming.

In another study, Geirinhas et al. use ERA5 reanalysis data to assess the historical evolution of southeast Brazil's compound summer drought heatwave events between 1980-2018. The studies aimed to thoroughly analyze the surface and weather conditions and the interactions between the land and the atmosphere that cause single and compound dry and heat extremes [104]. Daily and hourly periodic meteorological data were extracted from the European Centre of Medium-range Weather Forecast ERA5 reanalysis dataset and soil moisture data from the Global Land Evaporation Amsterdam Model (GLEAM v3.3a). The authors considered the 80th, 90th, and 95th percentiles, as well as days between 3-4 days, 5-7 days, and 7+ days, for periods of consecutive by applying a 1st-degree polynomial to resolve the linear trend to isolate Tmax values from the global warming effect. A non-parametric Wilcoxon Rank sum test was computed to assess the importance between data pairs to be tested. It was discovered that Southeast Brazil, which is the most populated, has experienced extremely dry and hot conditions. The summers of 2013/14 and 2014/15 demonstrated a clear association between drought and heatwaves. The interrelationship was influenced by two soil atmosphere coupling regimes that predominated at different times in both summer seasons and were characterized by strong evaporative demands, unequal evaporation levels, and soil moisture availability.

Similarly, with ERA5 reanalysis datasets, [121, 122] were used to conduct different studies but [121] added more datasets into the studies (AVHRR satellite data, the European Space Agency's land cover data set, leaf area index data, and the ESA-CCI land cover data set). The study focuses on determining the dangers CHDES poses to vulnerable populations and assets. A topology-based selection of the case study to emphasise six common recommendations for studying compound events. The study concludes that the effects of hot and dry summers on crops could be intensified by the preceding impacts of dry and bright springs. The study guidelines will aid in advancing the study of compound events across multiple fields and industries.

On the other hand, the study examines the different types, common locations, patterns over time, and changes in location of concurrent and cascading extreme events in the drylands of Eurasia [122]. The study used a combination of empirical values and percentile-based indicators to identify the types, locations, and patterns of these extreme events and found that the most common types and locations of concurrent and cascading extreme events are similar. The study found that in high-latitude regions, extreme winter events are dominated by cold-hot events, making up more than 85 out of 100 of extreme winter events in that area, concurrent extreme events have a wider geographic range, and cascading extreme events have a longer duration.

Compound dry and hot extremes going into significant augmentation has been a fact for recent decades; it has been a concern for the escalation of highly unusual anomalies over the southern and northeastern regions of the United States [123]. By using the Mann-Kendal and Moran's I to determine the monotonic trend in relevant variables and the spatial autocorrelation of the composite extreme occurrences, respectively, the Cramanalyzedises test was used to assess the changes in distribution as well. It was known that significant increase in compound dry-hot extremes in the CONUS over the previous 50 years, compound dry-hot extremes are mostly caused by heat surplus, and also vigorous emission reduction can reduce the risks brought on by their rising frequency.

Climate Research Unit (CRU) TS 4.01 global climate data and European Climate Assessment Data (E-OBS version 14) were used by [124] to examine the correlation between the frequency of hot days and nights in the region's warmest months and a drought indicator from prior months. Characterized drought was performed using the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evaporation Index (SPEI) in 3, 6, and 9-month time frames. To assess the extent to which spring and early summer droughts antecede the appearance of extreme heat months in the Mediterranean. Additionally, the evolution of droughts in the Mediterranean was thoroughly characterised. There were clear findings that high (low) NHD/NHN follows negative (positive) SPEI/SPI warnings. The results imply a certain degree of predictability of drought indicators and soil moisture data by pinpointing hotspots that could anticipate a heightened likelihood of extreme events occurring during the summer heat.

ECAD-EOBS v14 daily dataset and CRU TS4.01 database were used to calculate NHD and SPEI, respectively. NHD and SPEI joint probability was calculated by using copula theory. It was shown from the study by [125] shows that there is spatial heterogeneity over the IP when characterizing the influence of water deficits on summer temperature in some regions and also a relation between NHD andprevious SPEI increases from May to July. Mukherjee et al. [103] employs a cascade modelling framework to analyze and quantify the complex interactions and cascading effects between dry and hot climate extremes across global hotspots with GLEAM v3.3a, ERA5, and NSIDC datasets, enhancing our understanding and predictive capabilities of these increasingly impactful events.

Other researchers have used machine learning algorithms to investigate the association between drought and heatwaves [126] and to identify global hotspots of drought and heatwaves [127]. Random Forest and Gradient Boosting regression and other machine learning models to predict the probability of concurrent drought and heatwave events and discovered that the occurrence of drought and heatwave events was highly dependent on the geographical location and that machine learning algorithms were effective in predicting these events [126].

Cardoso Pereira et al. [128] utilize high-resolution climate simulations to forecast a significant reduction in annual precipitation and altered precipitation patterns on the Iberian Peninsula, potentially exacerbating drought conditions and impacting water resource management under the RCP8.5 scenario, Barbosa & Scotto analysed ERA5-Land reanalysis compared to station data from European Climate Assessment (ECA&D) data to describe extreme temperature events in the Iberian Peninsula using an extreme value model with normal distribution for the bulk distribution and Generalized Pareto Distribution for the upper tail estimation at each point [129]. However, the researchers ignored the spatial dependencies and also considered short-length time series data. García-Valdecasas Ojeda et al. [21] used the Weather Research and Forecasting (WRF) model driven by two global climate models (GCMs), CCSM4 and MPI-ESM-LR, to simulate future climate scenarios. They analyzed drought characteristics on the Iberian Peninsula using two drought indices—the Standardized Precipitation Evapotranspiration Index (SPEI) and the Standardized Precipitation Index (SPI)—over different time scales and under two Representative Concentration Pathways (RCP4.5 and RCP8.5). This comprehensive approach allowed them to project changes in drought frequency, duration, and severity across various future periods.

The studies utilize various methodologies, such as threshold and indicator methods, Mann-Kendal, Moran's I, and copula theory, Metrics R, Lagrangian Analysis, copula theory, machine learning algorithms and several estimations criteria to investigate various relationships, occurrences, correlations, and interactions among many climate events such as drought, heatwaves, rainfall, and others. There have been several studies, and few are considered above, which investigate various events separately and some combined. The papers also utilize different datasets, including CRU, UDEl, GLEAM, PGF, ERA5 reanalysis, AVHRR satellite data, and land cover data, to examine the occurrence and impacts of concurrent extreme events.

Most of the studies use ERA5 [103, 104, 120–122, 130], CRU [124, 125, 131], and GLEAM datasets in their investigations. All of the studies show how physical processes like weather patterns, precipitation, soil moisture-temperature feedback, and modes of variability can cause multiple extreme events to happen at the same time. It is also important to think about the duration and dynamics of multivariate processes when figuring out what effects they have. Additionally, the studies emphasize the need for further research on concurrent extreme events and their dependencies to improve understanding and preparedness for their impacts.

Although several machine learning methods have been used by many researchers to analyse the climate and proved to be very effective such of the methods that have been applied are Random Forest and Gradient Boosting regression [126], Convolutional Neural Network (CNN) [132], Support Vector Machine (SVM) [133] and others. Other researchers have used other methods, such as probabilistic approaches like the Markov chain models and hamming distance approaches. Markov chain models, extensively used to analyze the dynamics and probabilistic nature of climate events, have been effectively applied in various contexts. Yeh et al. [134] analyzed drought characteristics in southern Taiwan using SPI

References	Data	Study Area
(Barbosa & Scotto, 2022) ([129])	*ERA5-Land reanalysis*	*Iberian Peninsula*
(De Luca et al., 2020) ([120])	*ERA5 reanalysis*	*Mediterranean*
(Geirinhas et al., 2021) ([104])	*ERA-5 reanalysis*	*Southeast Brazil*
(Bevacqua et al., 2021) ([121])	*ERA-5 reanalysis*	—
(Alizadeh et al., 2020) ([122])	*ERA5 reanalysis*	*Eurasian*
(Alizadeh et al., 2020) ([123])	*Climate Divisional*	*Contiguous United States*
(Russo et al., 2019) ([124])	*Climatic Research Unit (CRU)*	*Mediterranean*
(Ribeiro et al., 2020) ([125])	*ECAD-EOBS v14 daily t*	*Iberian Peninsula*
(Tuel et al., 2022) ([130])	*ERA5 reanalysis, EOBS*	*Europe*
(Mukherjee et al., 2023) ([103])	*ERA5 reanalysis, Gleam*	*Global*
(Zhang et al., 2020) ([126])	*Bio-ORACLEand GMED*	*China*
(Cardoso Pereira et al., 2020) ([128])	*ECA&D*	*Iberian Peninsula*

Table 2.1: Key research papers considered in state of the art

and RDI, similarly Markov chain models have been used in analyzing drought class transitions, using a case study with rainfall data from Southwest China to demonstrate spatial heterogeneity, though it finds no clear evidence of spatial dependency [135]. Alam et al. [136] forecasted agricultural droughts in the Barind region through spatial mapping. These studies illustrate Markov chains' utility in modelling climate dynamics. Hidden Markov Models (HMM) have provided a more probabilistic understanding of drought transitions compared to traditional indices, as demonstrated by Yoo et al. [137]. Markov Chain Monte Carlo (MCMC) methods have outperformed bootstrapping in estimating the uncertainty of multivariate quantiles for hydrometeorological extremes, showing significant benefits in small sample scenarios [138] Further research includes the assessment of ecosystem impacts due to heatwaves and droughts, where heatwave dynamics were explored in the eastern Mediterranean, indicating high intrinsic predictability by Hochman et al. [139]. Studies like Cao and others [140] used multiple Markov chains for drought prediction in the U.S., highlighting the importance of Markov models in drought management. A comprehensive review of compound extremes involving droughts and heatwaves was conducted by Afroz et al. [141] using probabilistic quantifications in examining the variables, drivers, and impacts of these events, providing a holistic view of climate extremes. Javadinejad et al. [142] employed Markov chain models to forecast drought occurrences in southeast Iran, demonstrating their practical utility in arid climate management.

Hamming distance, a measure of similarity, has been extensively used in various climate studies to analyze weather station data [143], identify regions with similar heatwave patterns, and assess ecosystem vulnerability to climate changes. This section consolidates the usage of Hamming distance across multiple studies, highlighting its role in understanding and adapting to climate-related challenges. The methods have been applied in many fields such as biological, chemical, energy and biochemical [144] fields as well, Pirot et. al. [145] used the same method in topology as a low-scale topological indicator to quantify dissimilarities between geological models by summing the absolute differences in their adjacency matrices, aiding in the assessment of uncertainty and variability in geological predictions. In another study by Raoult and others [146] to compare the bit vectors of wavelet-based fingerprints of meteorological fields, determining their similarity to facilitate the fast retrieval of weather analogues from a multi-petabyte archive. In Identifying Heatwave Patterns by Kalu et al. [147] utilizes Hamming distance as a similarity measure to cluster weather station data. This method identifies regions with similar heatwave patterns, crucial for understanding the impacts of heatwaves on agricultural productivity, thereby aiding in the development of targeted agricultural strategies.

On the other side, another study on drought with satellite data employs Hamming distance to analyze the temporal profiles of the Vegetation Condition Index (VCI) time series. This application allows for the effective identification of drought-affected regions, enabling timely interventions and drought management strategies [148]. The same method is applied as a measure of similarity to evaluate comprehensive drought in the Qucun Yellow River Irrigation Region by comparing different drought assessment models and integrating relative membership degrees in a fuzzy decision framework, enhancing the accuracy and reliability of drought level evaluations [149].

A study was conducted to assess ecosystem vulnerability by using Hamming distance to quantify the dissimilarity between current and future climate conditions. This assessment helps in evaluating the vulnerability of ecosystems to climate change, including the impacts of droughts and heatwaves, thus facilitating the development of adaptation and mitigation measures [150]. The hamming distance was used in measuring the dissimilarity between two products by calculating the number of differing positions in their binary representations of snow presence, providing a normalized value that reflects the degree of agreement or discrepancy between these satellite observations in monitoring wet snow coverage [151]. Hamming distance was applied directly to compare vegetation index time series across different regions. This facilitates the identification and monitoring of drought patterns, providing essential data for drought response planning and resource allocation [148]. The application of Hamming distance across these studies demonstrates its versatility and effectiveness in enhancing our understanding of climate impacts on agriculture, ecosystem vulnerability, and resource management. By enabling precise comparisons and identifications of climate patterns, Hamming distance serves as a valuable tool in the arsenal of climate adaptation and mitigation strategies.

2.5 Conclusion

Researchers emphasized the significance of physical processes, atmospheric patterns, precipitation, and soil moisture-temperature feedback in shaping these events. They stressed the need for continued research to enhance preparedness and understanding of concurrent extreme events and their dependencies. In this tale of scientific exploration, researchers from various disciplines joined forces to uncover the intricate web of compound extreme events, pinpointing the importance of an interdisciplinary approach. The collective efforts shed light on the complex relationship between weather phenomena, identified vulnerable regions, and offered vital insights for better preparedness and mitigation strategies. Through numerous studies, researchers have made much effort to explore the effects and relationship between extreme weather events, such as droughts and heatwaves, and the factors driving them. Although much effort has been made, understanding these relationships and various extreme events continues to be a challenge needing a continued and clear explanation. Utilising various datasets and methodologies, they have identified specific regions, processes, and physical factors that influence these events. The studies highlight the need for further research to understand and prepare for the impacts of compound extreme events. By unravelling the complexities of these events, scientists strive to protect communities and assets in the face of a changing climate.

Chapter 3

Data and Methodology

3.1 Data

3.1.1 Data Download

The first stage of our analysis involved acquiring the necessary data. The data was downloaded from the ERA5 dataset using the CDS API. The dataset contains daily means of total precipitation and 2m temperature from 1950 to 2022 for the Iberian region.

The ERA5 dataset - a global atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF)- provides a wealth of meteorological variables, including temperature and precipitation, at a daily resolution. The Climate Data Store (CDS) API, an ECMWF service enabling users to programmatically access and download the datasets, was used. To automate this process, a Python function which specifies the years, months, days and hours for the request to be sent was created. The function initiates a new instance of the CDS API client and generates a list of years to retrieve data. The default range from 1950 to 2022 was set with a fine spatial resolution of 0.25 degrees, which can be easily adjusted by changing the function's parameters. The function then sends a data retrieval request to the ERA5 dataset. The data for the 'total_precipitation' and '2m_temperature' variables for each month of the specified years was then retrived. For each day, each hourly data is downloaded and requested in 'netcdf' format. The geographical area was also specified, setting the boundaries to encompass the Iberian Peninsula, with coordinates [44, -10, 36, 4] representing the North, West, South, and East boundaries, respectively. Upon successful retrieval, the data is saved as a NetCDF file named "ERA5_daily_data_Iberian_Peninsula_year_month.nc". Each file contains data of each year's unique month records. These files contain all the requested data and are the starting point for our subsequent analysis.

After successfully downloading the ERA5 dataset, the next step in the analysis was to load and preprocess the data. A Python function, 'load_data()', is created to automate this process. This function begins by loading the data from the NetCDF files 'ERA5_temperature_data_iberian.nc' using the 'xr.open_dataset()' function from the xarray library. This function reads the file and returns an xarray. Dataset object, which is a multi-dimensional, in-memory, array-based dataset. After loading the data, the function checks if the dataset is empty. If the dataset is empty, it raises a ValueError with a message indicating that the dataset is empty and suggesting checking the file path or content. Next, the function converts the xarray.Dataset object to a pandas DataFrame using the 'to_dataframe()' method. This method flattens the multi-dimensional dataset into a 2D table, making it easier to manipulate and analyze the data. Finally, the function checks if the resulting DataFrame is empty. If the DataFrame is empty, it raises a ValueError with a message indicating that the DataFrame is empty and suggesting to check the dataset. If all checks pass, the function returns the DataFrame. This Dataframe contains all the data from the ERA5 dataset, ready for further analysis.

3.1.2 Data Preprocessing

After acquiring the necessary data, the next step was to preprocess the data to ensure it was in a suitable format for analysis. A Python function, 'preprocess_data(data)' was created to automate this process. Since the interest of the study is based on daily means, daily means were calculated from the hourly means, which gives a true representation of daily means.

Temperature Conversion

The ERA5 dataset provides temperature data in Kelvin. However, for ease of understanding and analysis, we converted the temperature data to Celsius using the formula 'C = K - 273.15', where 'C' is the temperature in Celsius and 'K' is the temperature in Kelvin.

Outlier Detection and Handling

We assumed that the temperature data follows a Gaussian distribution and used the Z-score method for outlier detection. A Z-score measures how many standard deviations an element is from the mean. Any data point with a Z-score greater than 3 was considered to be an outlier.

If any outliers were found, they were replaced with NaN and then the forward fill method to fill them. If no outliers were found, a message was printed to confirm this.

3.1.3 Nature of Data

Descriptive statistics, histograms, and correlation calculations were performed on the data. A scatter plot for temperature vs total precipitation was also plotted.

3.2 Heatwaves

In the context of this comprehensive climate study using the ERA5 dataset, we conducted an in-depth analysis of heatwave conditions. Heatwaves, characterised by extended periods of excessively hot weather, often accompanied by high humidity, have significant implications for both the environment and public health [152].

This section provides a detailed methodological approach for identifying heatwave events within a climate dataset. This process is well-designed to capture heatwave occurrences based on temperature anomalies, employing a series of computational steps tailored to refine the detection criteria. Below, each step is explained and rationalized within the context of the study:

Calculation of Daily 90th Percentile Temperatures

A key step in the method is the calculation of the 90th percentile temperature for each day of the year across all included years. This is achieved by finding the 90th percentile temperature for each day of the year. The resultant series represents the 90th percentile temperature for each unique day, serving as a threshold to identify unusually high temperatures, indicative of extreme weather events.

Calculation of the 90th Percentile Threshold Over a Rolling Window on the Daily 90th Percentile

The initial step involves calculating a dynamic threshold for heatwave detection by employing a rolling window technique on the `Daily_90th_percentile` temperature data [153]. The choice of a 31-day window, centered around each day enables the inclusion of a broader temporal context in setting the threshold. This method adjusts for seasonal and interannual variability, ensuring the 90th percentile threshold reflects the climatological norms and anomalies for each period. The quantile calculation at 0.9 within this window identifies the temperature above which only the top 10% of extreme temperature values fall, setting a rigorous benchmark for heatwave conditions.

Identification of Days Above the 90th Percentile

By comparing daily average temperatures (`temperature`) against the calculated 90th percentile threshold, the function flags days where temperatures exceed this critical value. This binary classification (`is_above_90th`) serves as a preliminary filter for potential heatwave days, isolating instances of abnormal heat.

Calculation of Rolling Sum to Identify Sequences of Abnormal Temperature Days

There is a further refinement of the identification process by calculating a rolling sum of days flagged as exceeding the 90th percentile threshold over a 5-day window, with a minimum of three days required (`min_periods=3`). This step ensures that only sustained periods of abnormal temperatures are considered, aligning with the definition of heatwaves as events that persist for several days.

Heatwave Day Identification

A critical part of the function is the determination of actual heatwave days. This is achieved by evaluating whether the rolling sum of abnormal temperature days equals 5 within the predefined window, indicating a continuous sequence of high temperatures typical of a heatwave. This condition ensures the detected heatwaves reflect significant and prolonged periods of heat stress.

Adjustment for Brief Interruptions in Heatwave Conditions

Recognizing the dynamic nature of heatwaves, the function includes a mechanism to account for brief interruptions in heatwave conditions. It retrospectively assesses sequences where a heatwave might be interrupted by one or two days of relatively cooler temperatures but is immediately followed by a return to heatwave conditions. This adjustment ensures the continuity of heatwave identification, accounting for minor fluctuations in temperature that do not significantly break the overall pattern of a heatwave.

Final Classification and Cleanup

The last step concludes by mapping the boolean `heatwave` flags to a more descriptive 'yes'/'no' format, facilitating easier interpretation and analysis of the results. Additionally, the DataFrame is cleaned by removing intermediate calculation columns no longer needed for further analysis, streamlining the dataset for subsequent use.

This sequence of operations represents a comprehensive and scientifically grounded approach to heatwave detection, emphasizing the importance of both intensity and duration in defining such events. Each step is carefully calibrated to ensure the accurate and meaningful identification of heatwave occurrences, contributing valuable insights into the study of climate patterns and extremes. Figure3.1 below shows the time series of average temperature at a single grid-point indicating heatwaves as well and Figure3.2 throws more emphasizes on the 2003 climate year.

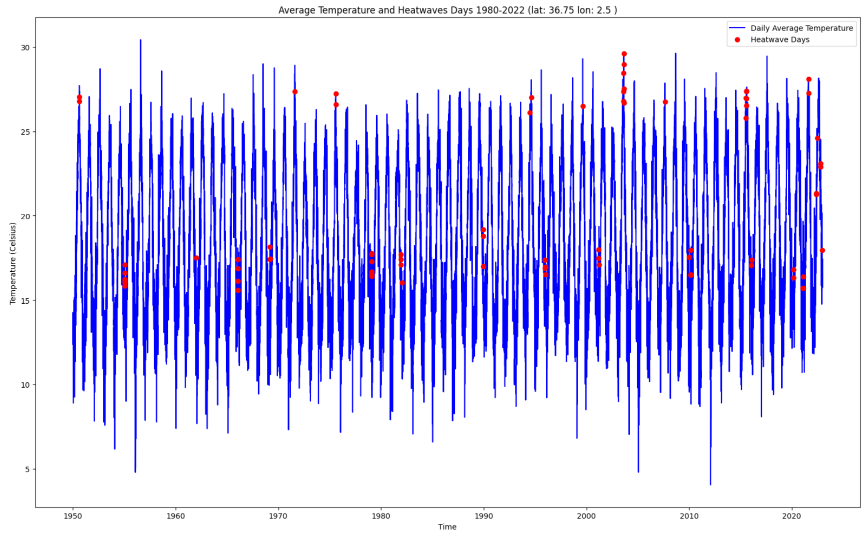

Figure 3.1: Temperature Trend with Heatwave Indicator using 31-day moving window (1950 to 2022).

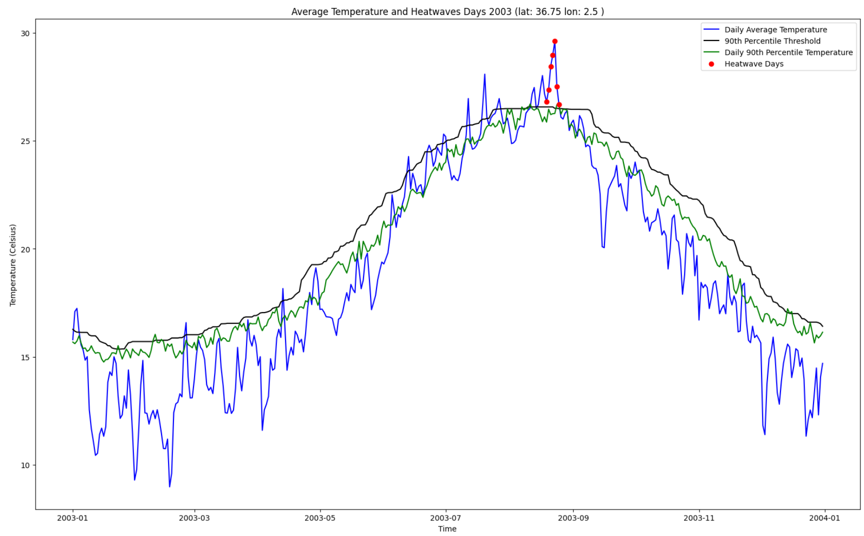

Figure 3.2: Temperature and Heatwave trends in 2003.

3.3 Drought

In our analysis of the ERA5 dataset, we conducted a drought analysis to identify periods of abnormally low rainfall. Drought is typically characterised as a prolonged period of significantly below-average precipitation, leading to water shortages [81]. To quantify the drought, we used the Standardized Precipitation Index (SPI) and Standardized Precipitation-Evapotranspiration Index (SPEI), widely accepted indices that measure to measure drought conditions. The SPI/SPEI indices can be calculated in different time scales (e.g., 1,2,3,6,12, and 24 months) and each time scale can be used to represent a different type of drought as follows:

3.3.1 SPI/SPEI time scales

- 1-Month Scale (SPI-1 and SPEI-1): Reflects immediate moisture conditions, sensitive to short-term precipitation anomalies and meteorological events. SPEI-1 additionally accounts for potential evapotranspiration (PET), making it sensitive to both precipitation deficits and temperature-induced increases in evaporation.

- 2-Month Scale (SPI-2 and SPEI-2): Useful for monitoring short-term drought conditions, these indices integrate precipitation and PET over two months, providing a detailview of recent weather impacts on moisture levels.

- 3-Month Scale (SPI-3 and SPEI-3): Aimed at assessing seasonal or short-term drought impacts, particularly in agricultural settings. While SPI-3 focuses solely on precipitation, SPEI-3 includes PET to better reflect the effects of both rainfall and evaporation trends.

- 6-Month Scale (SPI-6 and SPEI-6): Indicates medium-term trends in moisture conditions, essential for planning in agriculture and water resource management. This scale is particularly valuable for understanding moisture availability across growing seasons.

- 12-Month Scale (SPI-12 and SPEI-12): Captures long-term trends in moisture conditions, integrating a year's worth of precipitation and evapotranspiration data. These indices are crucial for analyzing hydrological drought and its broader impacts on water systems, making them particularly relevant for long-term water resource management and policy planning.

- 24-Month Scale (SPI-24 and SPEI-24): Provides insights into extended moisture and precipitation trends over two years, essential for assessing the impact of climate variability and change on hydrological conditions.

The SPI values were computed with 3, 6, and 12 month windows, resulting in a time series of SPI-3, SPI-6, and SPI-12 values. After getting the SPI-12 values, the values are classified into various drought conditions. The Table 3.1 gives the details of the drought categories based on the SPI values.

For example, SPEI-12 can record long-term moisture patterns, which consider both decreased rainfall and increasing evaporation. This is an extremely important factor to consider when dealing with changing climatic circumstances. Due to this, SPEI is especially important in regions where the circumstances of drought are being made worse by rising temperatures. When the SPEI values are classified into drought categories, it provides a comprehensive assessment of the severity of the drought by taking into consideration both the reduced amount of precipitation and the increased amount of evapotranspiration. Within the current context of global warming, this dual concern is of the utmost importance.

Class	SPI/SPEI Values
Extremely wet	2.0 or more
Very wet	1.5 to 2.0
Moderately wet	1.0 to 1.5
Mild wet	0 to 1.0
Near normal	-1.0 to 0
Moderately dry	-1.5 to -1.0
Severely dry	-2.0 to -1.5
Extremely dry	-2.0 or less

Table 3.1: Drought Classifications

3.3.2 Drought Classifications

The values in the Table 3.1 are used to classify the severity of drought or wet conditions based on SPI/SPEI values:

- Extremely wet (2.0 or more): This indicates an exceptionally high amount of precipitation much greater than the average.

- Very wet (1.5 to 2.0): This shows a very high amount of precipitation significantly above the average.

- Moderately wet (1.0 to 1.5): This signifies an above-average amount of precipitation.

- Mild wet (0 to 1.0): This represents a slightly higher than average amount of precipitation.

- Near normal (-1.0 to 0): This category indicates a near-average amount of precipitation.

- Moderately dry (-1.5 to -1.0): This shows a slightly below-average amount of precipitation, suggesting a mild drought.

- Severely dry (-2.0 to -1.5): This indicates a significant lack of precipitation, indicating a severe drought.

- Extremely dry (-2.0 or less): This shows an extreme lack of precipitation, indicating an extremely severe drought.

The SPI and SPEI are crucial in drought monitoring and early warning systems, both are very in drought analysis and this work puts more attention to use SPI. As such, the measures and their classification play a significant role in understanding climate variability and its impacts.

3.4 Markov Chain

3.4.1 Application of Markov Chains to Analyze Climate State Transitions

This section provides an overview of the use of Markov Chain analysis to the study of transitions between specified climatic states, with a particular emphasis on heatwaves and drought situations. The analysis and prediction of state transitions based on observed climate data is accomplished through the utilisation of a Markov Chain, which is a stochastic model that describes a sequence of possible events in which the probability of each event is purely dependent on the state that was attained if came before it.

Our dataset comprises records of heatwave occurrences and drought conditions, quantified using the Standardized Precipitation Index (SPI) and also the Standardized Precipitation Evapotranspiration Index (SPEI) over intervals of 3, 6, and 12 months, alongside timestamps. The initial step involves mapping these records to discrete states based on the presence or absence of heatwaves as well as drought. A method is designed to classify each record into one of four states: '00' (no heatwave, no drought), '01' (no heatwave, drought), '10' (heatwave, no drought), and '11' (heatwave and drought). The creation of a finite state space, which is required for Markov Chain analysis, is made possible by this categorization. This space enables the study of transitions between various states over time.

Chapter 4

Results

This chapter presents the findings of the analysis aimed at understanding the climate patterns of the Iberian region, with a particular focus on drought and heatwave events from 1950 to 2022. This study began on a methodological journey, applying advanced statistical and computational approaches to explore the relationship between climatic extremes. The dataset that was used for this study was the ERA5 dataset. The objectives presented in the earlier sections served as a guide for the analytical procedures throughout this study. The primary objective was to discover the temporal dynamics and the relationship between the most important climatic variables, namely temperature and precipitation, and how these variables contribute to extreme compound weather events. Some of the things that are talked about in this chapter are drought analysis using the Standardised Precipitation Index (SPI) and the Standardised Precipitation-Evapotranspiration Index (SPEI), heatwave detection using temperature anomalies, and Markov Chain analysis to look at how the climate changes over time. A structured narrative that integrates theoretical notions with empirical findings is presented in each section of this chapter. Several levels of complexity are present in climate data, and the purpose of each part of the process is to discover those layers.

This analysis lays the groundwork for more in-depth research into climatic phenomena. The first portion provides a foundational understanding of the climatic conditions that are present in the Iberian region by focusing on the general features of the data on temperature and precipitation. In the following step, the findings of the drought analysis are provided, which provide information on the frequency, length, and intensity of drought events as measured by the SPI and SPEI indices. This section investigates the incidence of heatwaves and their temporal distribution and severity to provide light on the continuously shifting dynamics of situations characterised by severe temperatures. Following that, the chapter moves on to the results of the Markov Chain analysis, which is a novel approach in this study. The purpose of this analysis is to gain an understanding of the probabilistic transitions that occur between various climatic states, with a particular emphasis on the interaction between temperature extremes and drought conditions. Using this technique, one may gain a forward-looking view of the possibility of projecting climate alterations within the region. The section also contributes to a more complex knowledge of climatic variability and extreme weather events that occur on the Iberian Peninsula. The findings that are reported are examined in the context of their consequences for climate science, the design of policies, and adaptive measures in response to the effects of global climate change.

4.1 Descriptive Statistics

After acquiring the data, a preliminary analysis was performed to understand the basic characteristics of our dataset. We used the 'describe()' method in Python, which provides a summary of the central tendency, dispersion, and shape of the dataset's distribution, excluding 'NaN' values.

The 'describe()' method was applied to the dataframe, which contains two variables: 'Total Precipitation' (in m) and 'Temperature' (in °C) of the daily data of the study area. The method returned the following statistics:

Description	**Precipitation (mm)**	**Temperature (°C)**
Count	50,153,100	50,153,100
Mean	1.8754	14.9257300
Standard Deviation	4.8024	6.3889400
Minimum Value	0.0000	-21.8978300
25th Percentile (Q1)	0.0000	10.7760800
Median (50th Percentile, Q2)	0.0424	14.9534700
75th Percentile (Q3)	1.2006	19.4715900
Maximum Value	203.1700	38.6434300

Table 4.1: Statistical Summary of Daily Average Temperature and Accumulated Precipitation

Description	**Precipitation (mm)**	**Temperature (°C)**
Count	26,663	26,663
Mean	1.3273	17.863832
Standard Deviation	4.2425	4.810658
Minimum Value	0.0000	1.490685
25th Percentile (Q1)	0.0000	13.792804
Median (50th Percentile, Q2)	0.0177	17.057856
75th Percentile (Q3)	0.5734	22.319162
Maximum Value	129.8086	29.713526

Table 4.2: Statistical Summary of Average Daily Temperature and Accumulated Precipitation Latitude:40.0 Longitude:2.0

The average daily temperature is estimated to be around 14.93°C, suggesting the possibility of a temperate climatic zone or a composite of other climate zones that have been averaged. With a standard deviation of around 6.39°C, temperature variation is substantial. This may be the result of seasonal variations in the data, which is extremely wide in temperature, ranging from a minimum of -21.90°C to a maximum of 38.64°C. The existence of these exceedingly high temperatures implies that the dataset potentially encompasses many seasons. The average precipitation is an extremely meagre 1.88 millimetres. Although the standard deviation for precipitation is 4.80 mm, it remains below the mean value, suggesting minimal unpredictability in precipitation. The precipitation ranges between a low of 0.00 mm and a maximum of 0.20317 mm in magnitude. The observed peak value deviates considerably from the average, indicating the possible existence of exceptional precipitation occurrences. The 75th percentile for precipitation is established at 1.20 mm, which signifies that the 75th percentile of the records has precipitation of little more than or equal to this amount. This further supports the notion that the climate is usually arid or that the dataset has several dry spells.

This is important as it can provide insights into how these two variables interact, which is fundamental in climate studies. To achieve this, the correlation is calculated between the 'Temperature (°C))' and 'Total Precipitation (m)' columns in our dataset. The correlation was computed using the corr() method, which provides the Pearson correlation coefficient, a measure of the linear relationship between two variables. The result of our correlation computation is -0.1581. This value indicates a weak negative relationship between temperature and total precipitation. In the context of our dataset, this suggests that as the temperature slightly increases, the accumulated precipitation slightly decreases, and vice versa.

In the continued elaboration of the ERA5 dataset, we sought to understand the temporal trends in temperature and total precipitation. This involved examining how the average temperature and total precipitation changed every year.

Comparative Analysis

The mean temperature at a single grid point (latitude 40 and longitude 2) is higher (17.86°C) compared to the whole region's mean (14.93°C), this shows that the area data has variability in nature. The standard deviation of temperature at the single grid point is lower (4.81°C) than that of the whole region (6.39°C), indicating less variability in temperature and potentially a more stable climate at this grid point. Particularly noticeable in the region-wide data are the temperature extremes, including the minimum temperature (-21.90°C), which is far lower than the lowest temperature recorded at a single grid point (1.49°C). The somewhat lower average precipitation at the single grid point compared to the region may indicate that this grid point is, on average, drier than the region. At the single grid point, the standard deviation of precipitation is somewhat smaller, suggesting a reduced degree of unpredictability in precipitation quantities in comparison to the entire region. The fact that the highest precipitation value at the single grid point is lower than that of the entire region indicates that other areas of the region experience more extreme precipitation occurrences. In comparison to the general region, the temperature and precipitation at the single grid point appear to be less variable, rendering it warmer and drier. The diversity of climatic conditions across all grid points is reflected in the broader range of temperature and precipitation values for the whole region. This includes places characterised by cooler temperatures and more severe precipitation occurrences. This comparison may serve as an indication of microclimate influences specific to the individual grid point, or it may be a result of the location's geographical attributes (e.g., proximity to a city, coastline, or higher elevation) in contrast to the entire region. Similarly, the correlation computation for the single grid point is computed and it is -0.1080 which is a little higher compared to -0.1581 for the whole region.

Scatter Plots of Temperature and Precipitation

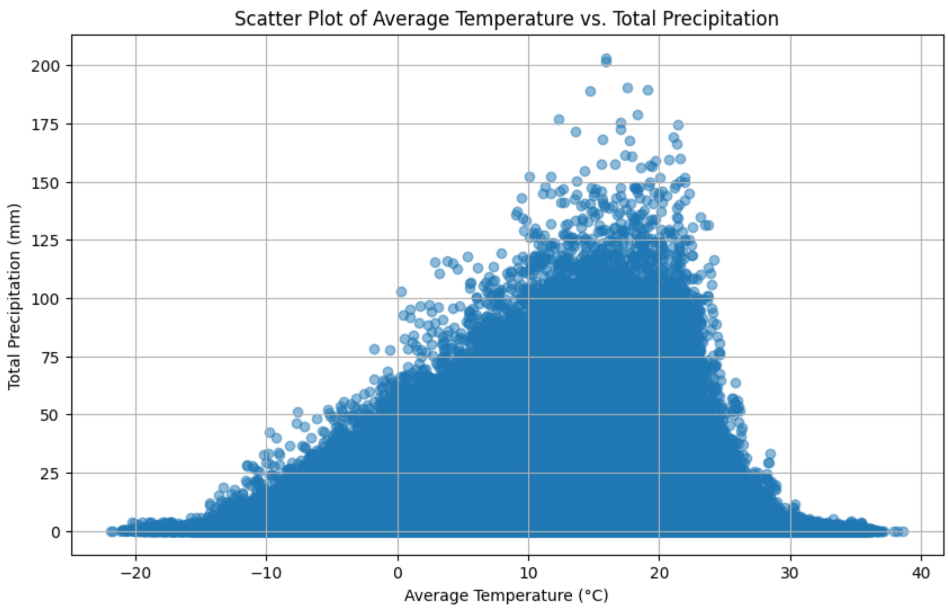

Figure 4.1: Scatter Plot of Average Temperature vs Total Precipitation

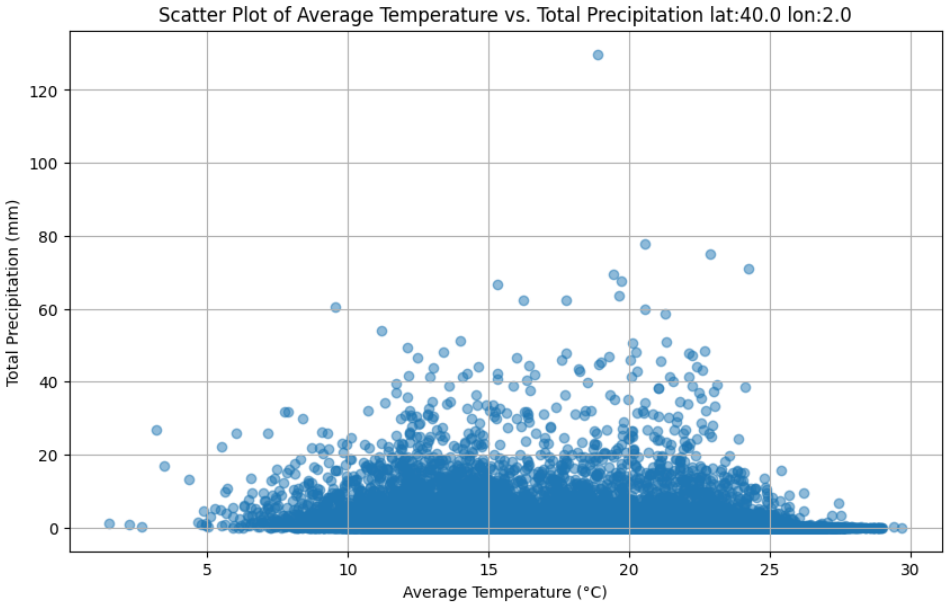

Figure 4.2: Scatter Plot of Average Temperature vs Total Precipitation for a single grid point

The scatter plot illustrates the correlation between the total precipitation and the average temperature. The graphic portrayal prompts the following observations:

- The data point density is significantly greater in the vicinity of lower temperatures and precipitation levels. This indicates that a considerable proportion of observations correlate less precipitation with lower temperatures.

- Most of the precipitation values exhibit a concentration at the lower extremity of the scale, accompanied by a limited number of occurrences with greater precipitation. This may suggest a reduced frequency of heavy precipitation occurrences.

- A limited number of data points exhibit high precipitation levels that deviate significantly from the overall trend observed in most of the data. These may symbolise severe meteorological phenomena, such as heavy rainfall or storms.

- At the specific grid location (add location here), lower precipitation levels are seen more often, as shown by the single grid scatter figure. The single grid scatter plot has fewer data points over the temperature range than the total region, indicating less temperature fluctuation.

- The grid point scatter plot shows reduced precipitation with fewer high values. This matches the data summary showing a lower grid point mean and maximum precipitation.

- In contrast, the plot for the entire region scatter plot revealed more precipitation values, including greater extremes as expected.

- Temperature does not appear to be linearly related to precipitation in either scatter plot. The grid-point-specific plot revealed less precipitation variability than the region-wide plot, which indicated a modest rise with higher temperatures.

Yearly Average Temperature Over Time

The first part of this analysis involved plotting the yearly average temperature over time for the all region. This was done by grouping the data by year and calculating the mean temperature for each year for all the region. The resulting time series was then plotted using a line plot, with each data point represented by a circle marker.

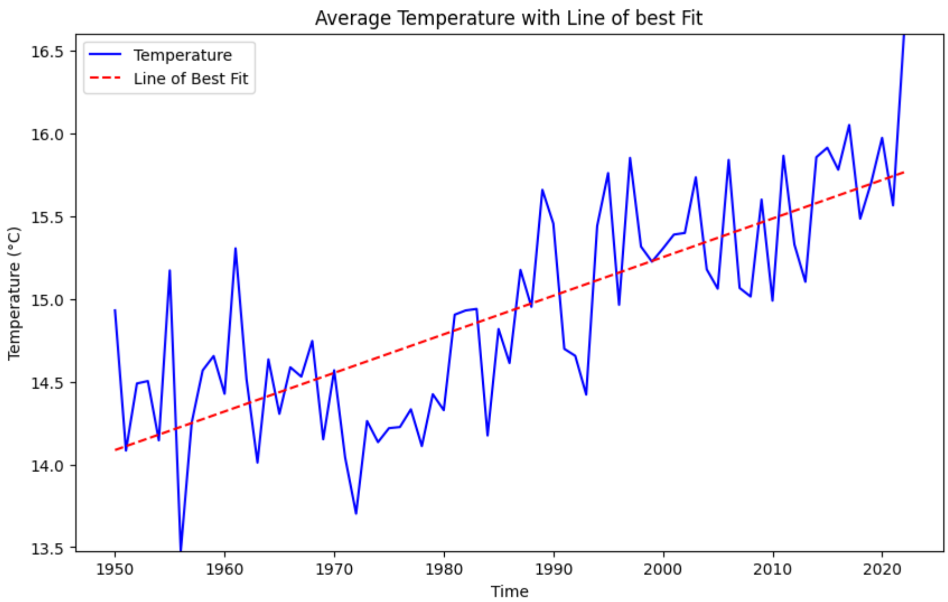

Figure 4.3: Yearly Average Temperature Over Time, ΔT= 1.673

The resulting plot provides a clear visual representation of how the average temperature has changed over time. The x-axis represents time (in years), and the y-axis represents the average temperature (in degrees Celsius). ΔT= 1.673 shows that with time the average temperature in the Iberian Peninsula is significantly getting higher.

Total Precipitation Over Time

A similar analysis was performed for the daily mean precipitation over time.

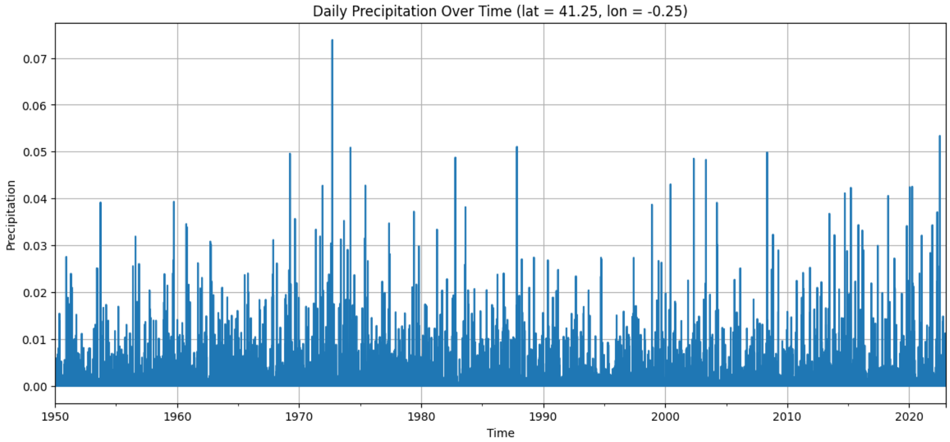

Figure 4.4: Daily Total Precipitation Over Time

4.2 SPI/SPEI Climatology

The resulting plot provides a clear visual representation of how the daily precipitation has changed over time. The x-axis represents time (in years), and the y-axis represents the daily precipitation (in millimetres).

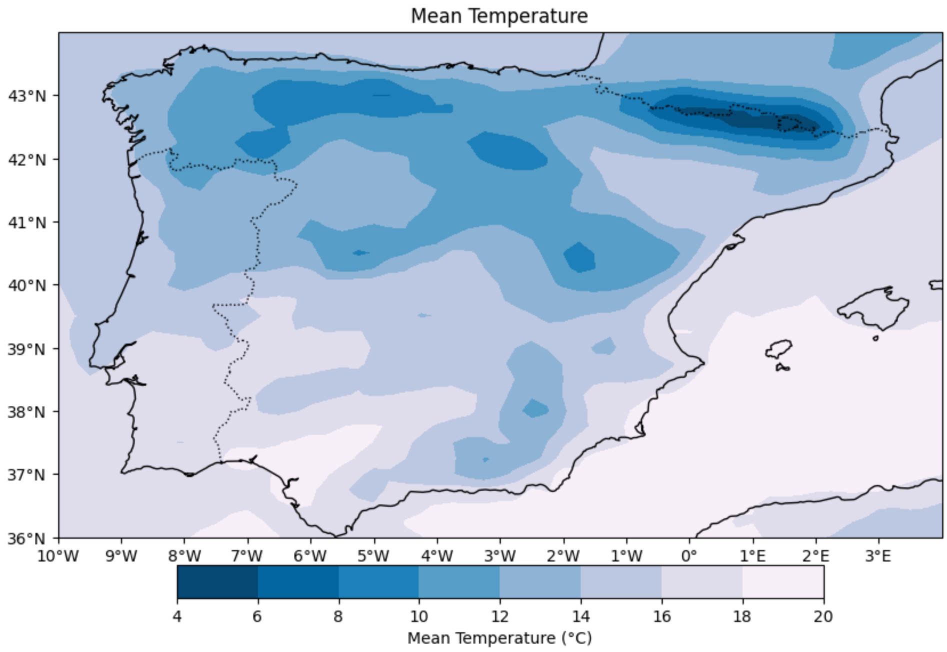

Figure 4.5: Temperature Climatology of the Iberian Peninsula

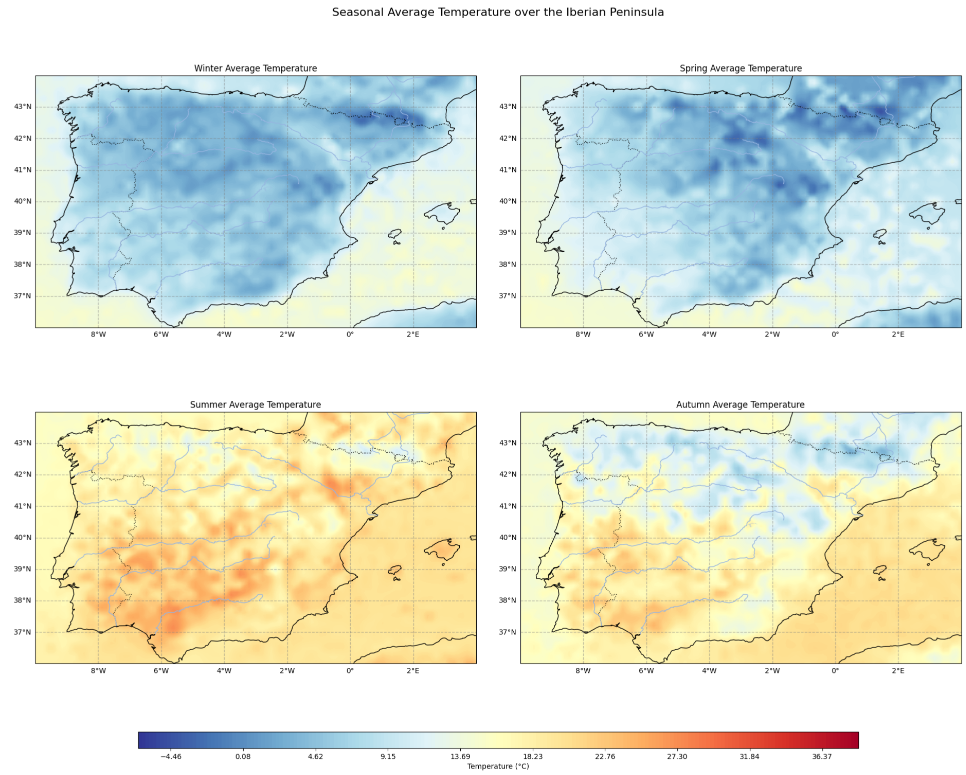

Figure 4.6: Seasonal Temperature Climatology of the Iberian Peninsula

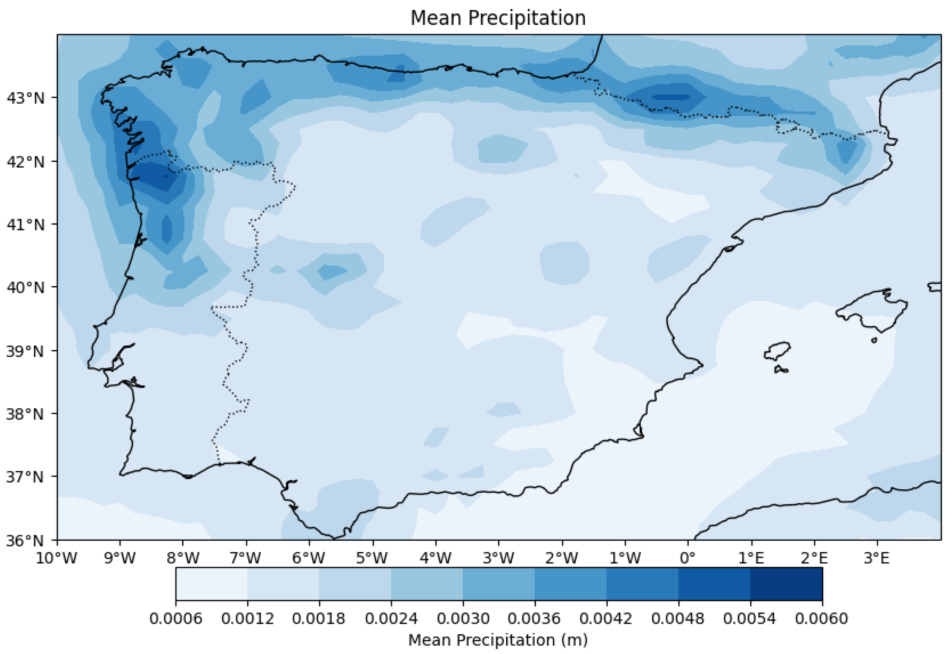

Figure 4.7: Precipitation Climatology of the Iberian Peninsula

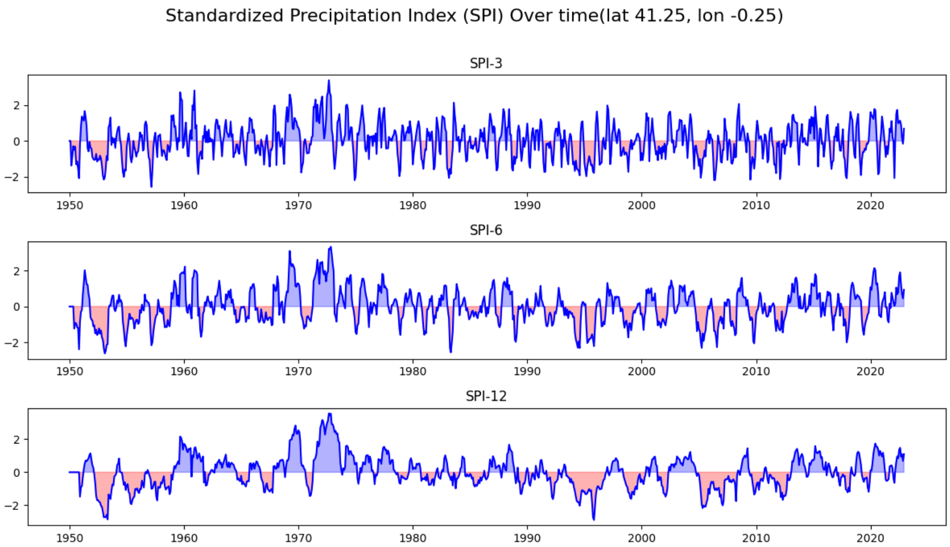

Figure 4.8: Standardized Precipitation Index (SPI-3,6,12) of a Selected grid point in the Iberian Peninsula Over Time using.

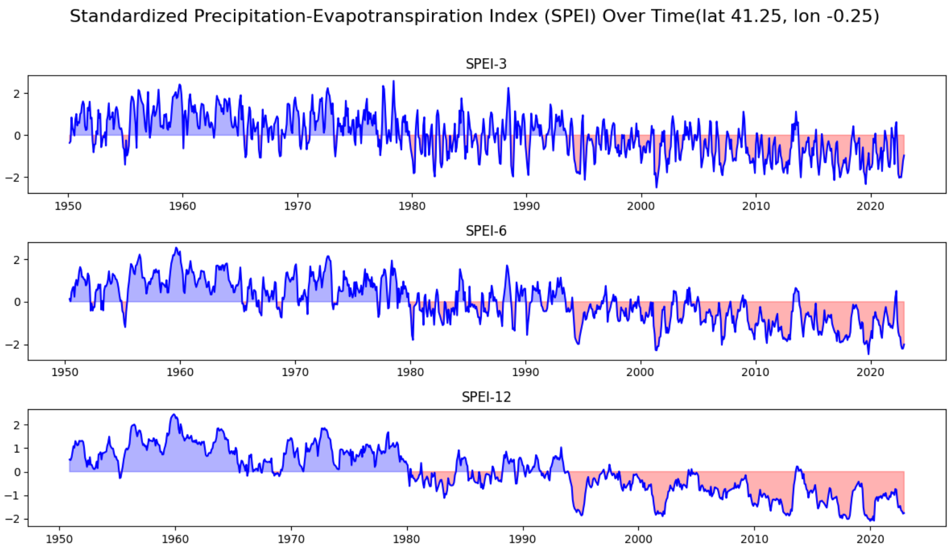

Figure 4.9: Standardized Precipitation-Evapotranspiration Index (SPEI-3,6,12) Over Time using.

Figure4.8 and 4.9 are time series graph of the Standardised Precipitation Index (SPI 3,6,12) and Standardized Precipitation-Evapotranspiration Index (SPEI 3,6,12)for a specific location (latitude 41.25, longitude -0.25). Drought monitoring and climate studies use these indices to quantify precipitation deficits over time. The graphs show fluctuations from 1950 to 2022. Blue areas indicate positive values, where precipitation was above the median for the period and red areas indicate negative values, where precipitation was below the median. The y-axis shows the SPI/SPEI value scale from -2 to +2. Positive SPI values indicate higher precipitation (wetter conditions), while negative values indicate lower precipitation (drier conditions). Multiple years of negative SPI values indicate a drought. Similar clusters of positive SPI values indicate wet periods as well as the SPEI.

4.3 Monthly states of random grid points

The following figures provide a detailed visual representation of the temporal pattern of heatwaves and droughts from 1951 to 2022 in specific regions monthly. By observing data from selected grid points, the figures offer valuable insights into climate variability and changes over the years. Each figure represents data from different periods and geographical coordinates, with various extreme events illustrated using distinct markers. Yellow squares represent heatwaves, dotted squares indicate drought months, and red squares with asterisks symbolize compound events - the simultaneous occurrence of heatwaves and droughts. Trends, seasonality of events, frequency, duration and the variability of these extreme climate conditions can be observed.

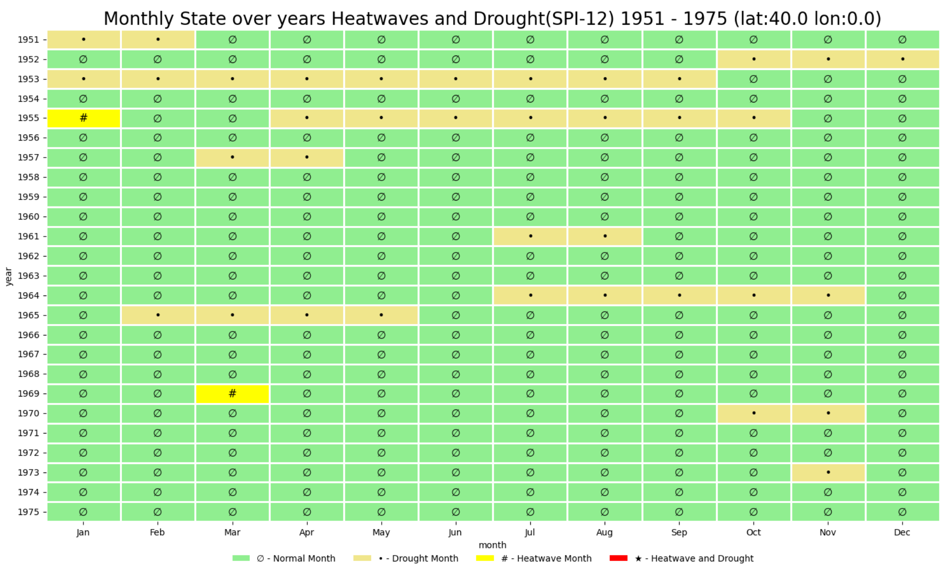

Figure 4.10: Monthly State values over years Heatwaves and Drought (SPI-12) 1951 - 1979 latitude: 37.0 longitude: -6.0

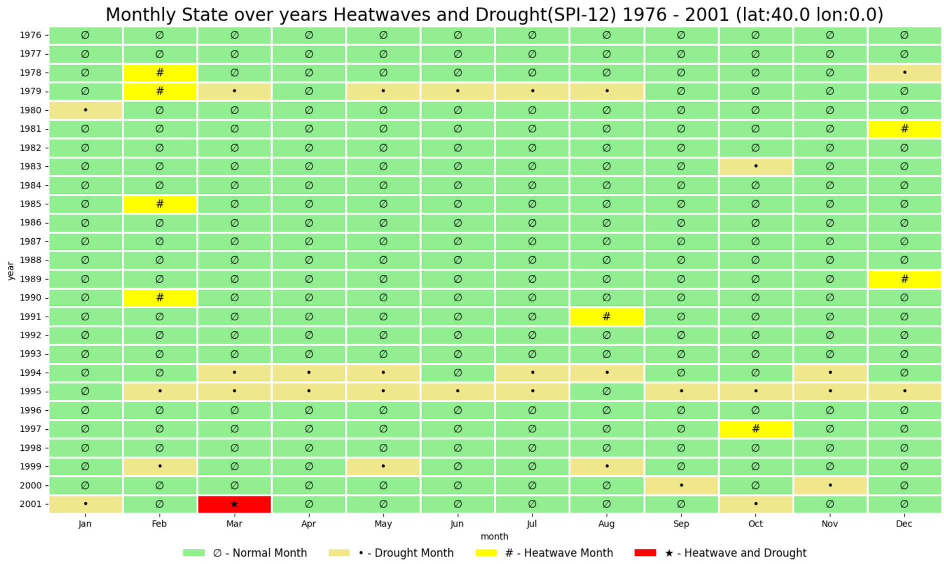

Figure 4.11: Monthly State values over years Heatwaves and Drought (SPI-12) 1975 - 1999 latitude: 37.0 longitude: -6.0

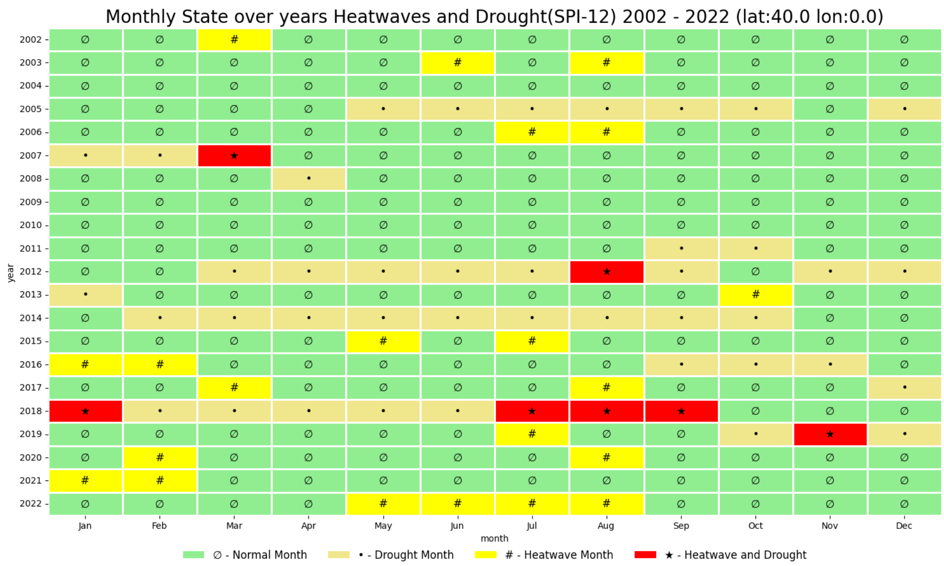

Figure 4.12: Monthly State values over years Heatwaves and Drought (SPI-12) 2001 - 2022 latitude: 37.0 longitude: -6.0

The Figure 4.10 - 4.12 show the the temporal pattern of heatwaves and droughts between 1951 and 2022 in the region, taking some random grid points, providing important information on climate variability and change. The data reveals important patterns with substantial implications for environmental management and policymaking. Heatwaves, shown by yellow squares in the visualizations, have noticeably increased throughout the years, especially in the late 20th century and the first two decades of the 21st century. This observation is consistent with worldwide patterns and strengthens the story of a globe experiencing rising temperatures [154].

Heatwaves exhibit a distinct pattern of seasonality, mainly happening during the summer months, with occasional occurrences in spring and fall, aligning with the anticipated seasonal occurrence of these events.

The frequency and duration of drought months, represented by dotted squares, show some variability but demonstrate a noticeable increase towards the end of the data run. This may indicate a rising pattern in drought conditions that may be associated with both natural climatic cycles and human impacts. Compound events (Heatwaves and droughts), represented by red squares with asterisks, keep increasing over time, especially since the 1980s. The simultaneous occurrence of these phenomena is especially worrying, as they increase the likelihood of negative effects on ecosystems and human society. The visual data shows that some years had consecutive occurrences of high heat or drought, while other years were comparatively mild. Interannual variability is crucial for resource management, emphasising the necessity for strong adaptive techniques to deal with extreme conditions and unpredictability.

4.4 Markov chains of extreme climate events

4.4.1 Markov Chain transitional probabilities

An in-depth comprehension of the state transitions that occur between heatwaves and drought conditions is being obtained through the application of Markov Chains in the analysis of climatic data. The calculation of Markov chain Transitional Probabilities allows for a systematization of the results reached in the previous section for the all area. In each of the states ('10', '01', '11', and '00'), the presence of a heatwave, drought, both, or neither is the binary representation of the situation. The odds of transitioning from one climatic condition to another have been computed using transition matrices, which provide a descriptive and predictive perspective on the dynamics of climate. The graphs represent transitions from the first month sixth months. For example, transitions to the '11' state (both heatwave and drought) are not frequent, which means the occurrence of these two conditions known as compound events does not occur frequently. Conversely, transitions to the '00' state (no heatwave, no drought) are more frequent. The state stability analysis uncovers those certain states, like '00', exhibit a higher degree of stability, with a greater likelihood of remaining in the same state over consecutive time steps. This suggests a natural climatic resilience against extreme events such as heatwaves and droughts. Across all the state transitions, certain paths are not common. In 4.14 the transition between heatwave month and compound event month is very weak in the if even there is existence. If the current month is in either the '10' or '11' state the next closet transition, 3rd, and 5th transitions have no probability of moving between these two states.

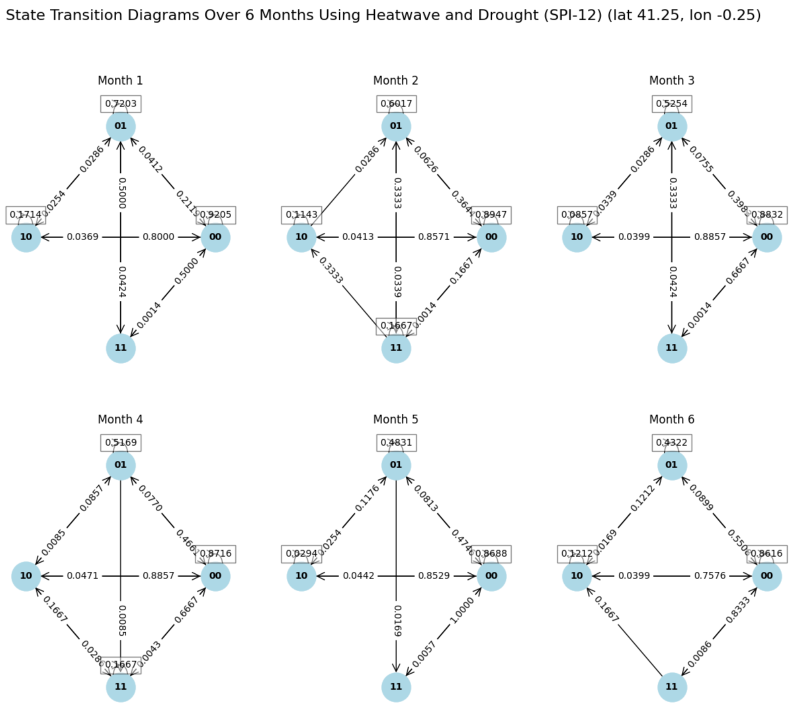

Figure 4.13: Markov chain demonstrating probability of changing to another state Heatwaves and SPI-12

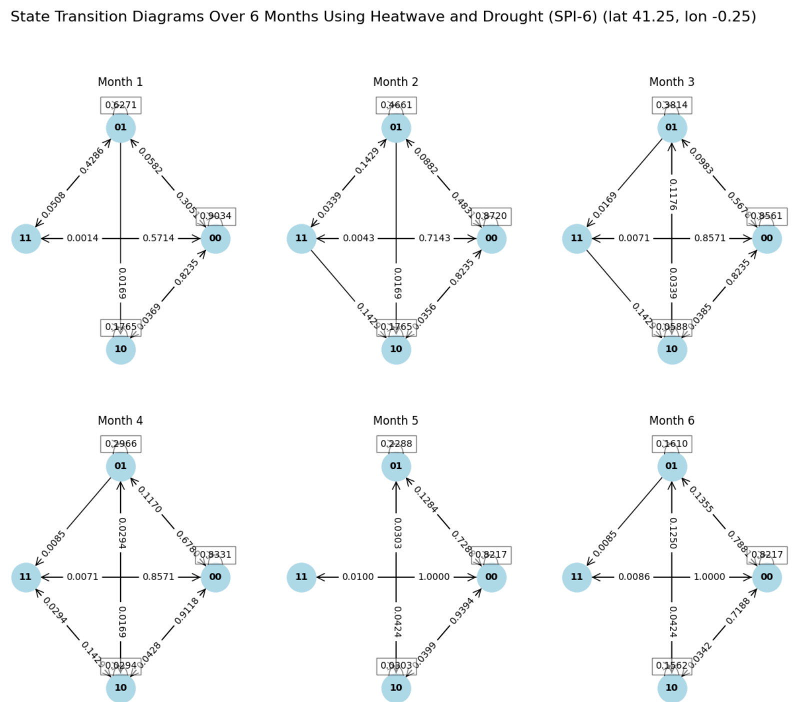

Figure 4.14: Markov chain demonstrating probability of changing to another state Heatwaves and SPI-6

Figure 4.13 presents the in-depth analysis of the SPI-12 six-month Markov chain transition probabilities provided significant insight into the climate system's shifts between various states which encompass '00' (no heatwave/no drought), '01' (drought without heatwave), '10' (heatwave without drought), and '11' (both heatwave and drought). While the '00' state, indicative of no extreme weather conditions, is the most favourable for living, the primary focus of this analysis lies in understanding the dynamics and probabilities of the system transitioning to the other. The system has a strong tendency to remain in the '00' state, indicating a high level of natural resilience and stability. In the first month, the probability of maintaining this state is exceptionally high at 0.9205 if the current state is '00'. This reflects a robust starting point of stability. Although this probability exhibits a slight decrease over the six-month transitions, it remains consistently high, settling at 0.8616 by the end of the sixth month. This enduring trend towards the '00' state signifies the system's inherent resilience and a strong tendency to remain in the most favourable state, despite potential disruptions to shift to other states. The current month with no extreme effect tries to maintain itself with a high probability between 0.9205 and 0.8616, showing that when the current state is '00' the is a higher probability of maintaining the same state in the upcoming months.

The system shows several vulnerabilities to transitioning to other states, each of which represents more severe climate conditions. In the case of the '01' state, which represents drought conditions without a heatwave, the first-month transition presents a relatively significant probability of transitioning from the '00' state, standing at 0.0412. This suggests an initial vulnerability to drought within the system. However, as the months progress, this vulnerability appears to increase, with the transition probability to the '01' state dropping to 0.0899 by the sixth month. This trend could indicate if the current is not experiencing any extreme climate conditions, there is a bit of a chance of close to 9 percent in the sixth month.

Transitions to the '10' state from the normal month condition, representing heatwave conditions without a drought, were less prevalent initially but showed a gradual increase as time progressed. Notably, by the end of the sixth month, the probability of the system transitioning to the '10' state from the '00' state reached 0.0399. The transition probabilities for the compound event state, '11', representing both heatwave and drought conditions, remained consistently low throughout the six-month transitions. Starting from a mere risk of 0.0014 in the first month, the probability remained low, reaching 0.0086 by the end of the sixth-month transition. These show that it is almost not possible for the climate conditions to transit from '00' states to compound events '11' and needs some intermediate transitions which are '01' and '10'. For the current state to be '01', the system starts with a probability of 0.7203 in the first month to remain in the same state. However, this probability decreases to 0.4322 by the sixth month. Transitions within state '10' are initially less common, with a probability of 0.1714 in the first-month shift. However, this probability increases over time, reaching a significant 0.1212 by the sixth month. This trend indicates that heatwave months do not show a higher probability of maintaining the same climate conditions with time but maintaining the extreme event with a probability between 0.1714 and 0.1212 is still a threat due to the consequence of this event.

The transition probabilities within state 11, representing the simultaneous occurrence of both heatwave and drought, also fluctuate. Starting from a 0 probability in the first month, the probability reaches 0.1667 in the fourth and sixth months, indicating sporadic occurrences of both conditions. In terms of transitions between these states ('10','01','11'), the probabilities vary. For instance, the probability of transitioning from state 01 to state 10 in the first month is 0.0254, which decreases to 0.0169 by the sixth month. The transition from state 10 to state 11 sees an increase from 0 in the first month to 0.0286 in the fourth month, before dropping to 0 again by the sixth month. This analysis follows similar pattern as in the SPI-6 Figure4.14

4.4.2 Spatial correlation of Markov states

Heatmaps of state transitions

It is less likely that a heatwave will occur if the same heatwave condition is maintained exclusively inside the shift throughout any of the succeeding six months. There are geographical locations that are comparable to one another that demonstrate a strong sign of transition throughout the first two months of the transition and during the final month of the transition. Throughout the remainder of the month, there are few dispersed regions that display strong transitional signals, and the indicators are weak. On the other hand, when it comes to the transition to other states, the drought that occurred during the heatwave month demonstrates only relatively minor and noticeable alterations during the first month of transition, while the next months exhibit clear indications of transition.

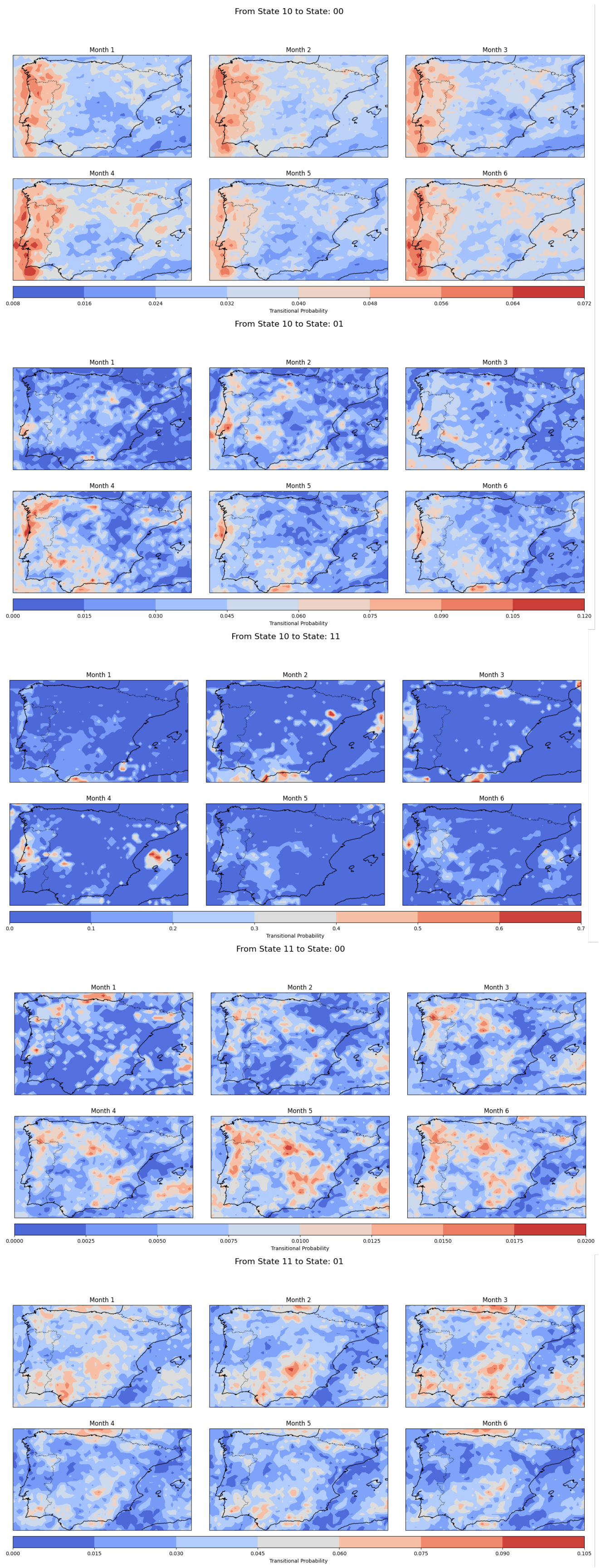

Figure 4.15: Heatmaps of State Transitions.

The transition from compound events to heatwave events without drought has a very low probability of occurring in geographical areas that are geographically distant from one another and that exhibit strong signals of change. On the heatmap, the first and second months of transition show absolutely no sign of transition. However, as the number of transition months grows, the density of changes shows a little increase. During the transformations that occurred in the late months, only a few areas indicated a stronger transition. During the shift, the change from months with only drought from the same compound event month to months with drought is relatively similar throughout all of the months. On the other hand, the transitions are not particularly powerful, but the most recent three months appear to be stronger than the months that came before them. Generally speaking, with regard to Figure 4.15 and from State ’11’ to ’00’ the probability of transitioning from a month with compound events to a month with normal events and no severe events is extremely low. Additionally, some random places can display these transitions. In the first two months, this adjustment appears to be quite difficult to accomplish.

4.5 Hamming distance to assess spatial conditions of extreme events

After applying the Hamming distance to assess how each pair of grid points is strongly connected, their pattern simultaneously occurs. The weight of each line between the pairs of grid points is determined by how strong they behave similarly which is the inverse of the hamming distance since it measures dissimilarity.

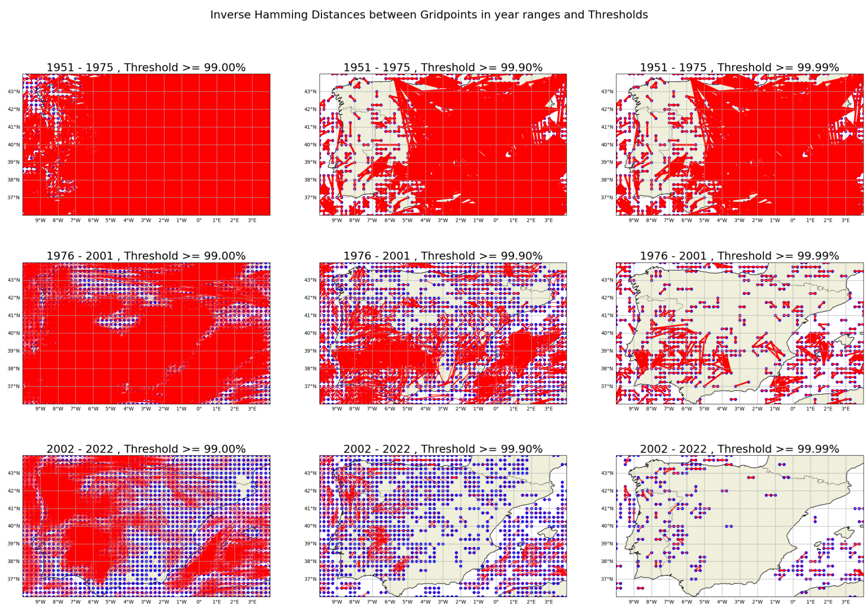

Figure 4.16: Inverse of Hamming distance between pairs of grid-points grouped by years

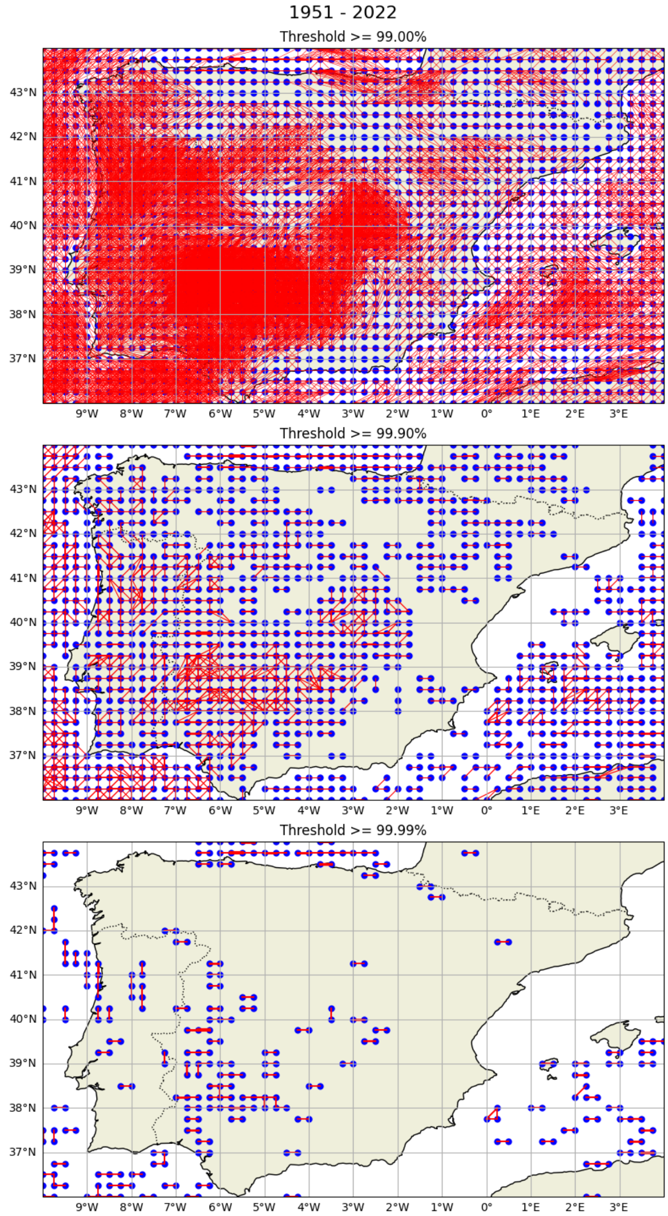

Figure 4.17: Inverse of Hamming distance between pairs of grid-points from 1951-2022

Figure 4.16 assesses the similarity of extreme climate events, between different regions in the Iberian Peninsula. (Row 1, Left) Graph with the cumulative similarities between 1951 and 1975, (Row 2) between 1976 and 2001, (Row 3) between 2002 and 2022, and 4.17 the total time 1951-2022. (First col, Top) Graphs showing the 99.00% highest similarities, (2nd col) the 99.9% highest similarities and (3rd col) the 99.99% highest similarities. Figure 4.18 assessing the similarity of extreme climate events, between different regions in the Iberian Peninsula in decades. (Row 1) Graph with the cumulative similarities between 1951 and 1960, (Row 2) between 1961 and 1970, (Row 3) between 1971 and 1980, (Row 4) between 1981 and

1990, (Row 5) between 1991 and 2000, (Row 6) between 2001 and 2010 and (Row 7) between 2011 and 2022. (First Col.) Graphs showing the 99.00% highest similarities, (2nd Col. Mid) the 99.90% highest similarities and (3rd Col., Last) the 99.99% highest similarities. Figure 4.19 has similar positions in terms of the degree of similarities and it is assess the extreme climate event similarity in terms of seasons (Row1: Winter, Row2: Spring, Row3: Summer and Row4: Fall) The similarities are measured by the inverse of the corresponding Hamming distance between each two geographic locations. Blue dots represent grid points, whereas red edges represent the similarity "strength" between pairs of points. The collection of visual data in the graphs represents a profound analytical observation of the evolution and interconnection of extreme climate event similarities across the Iberian Peninsula, spanning over seven decades. This dataset is instrumental in illustrating not only the distribution of these events across distinct geographical nodes but also in deciphering the temporal shifts in climatic patterns. Using the inverse Hamming distance as a measure of similarity between geographic locations offers a quantifiable and scientific method to explore these intricate relationships in climate variability.

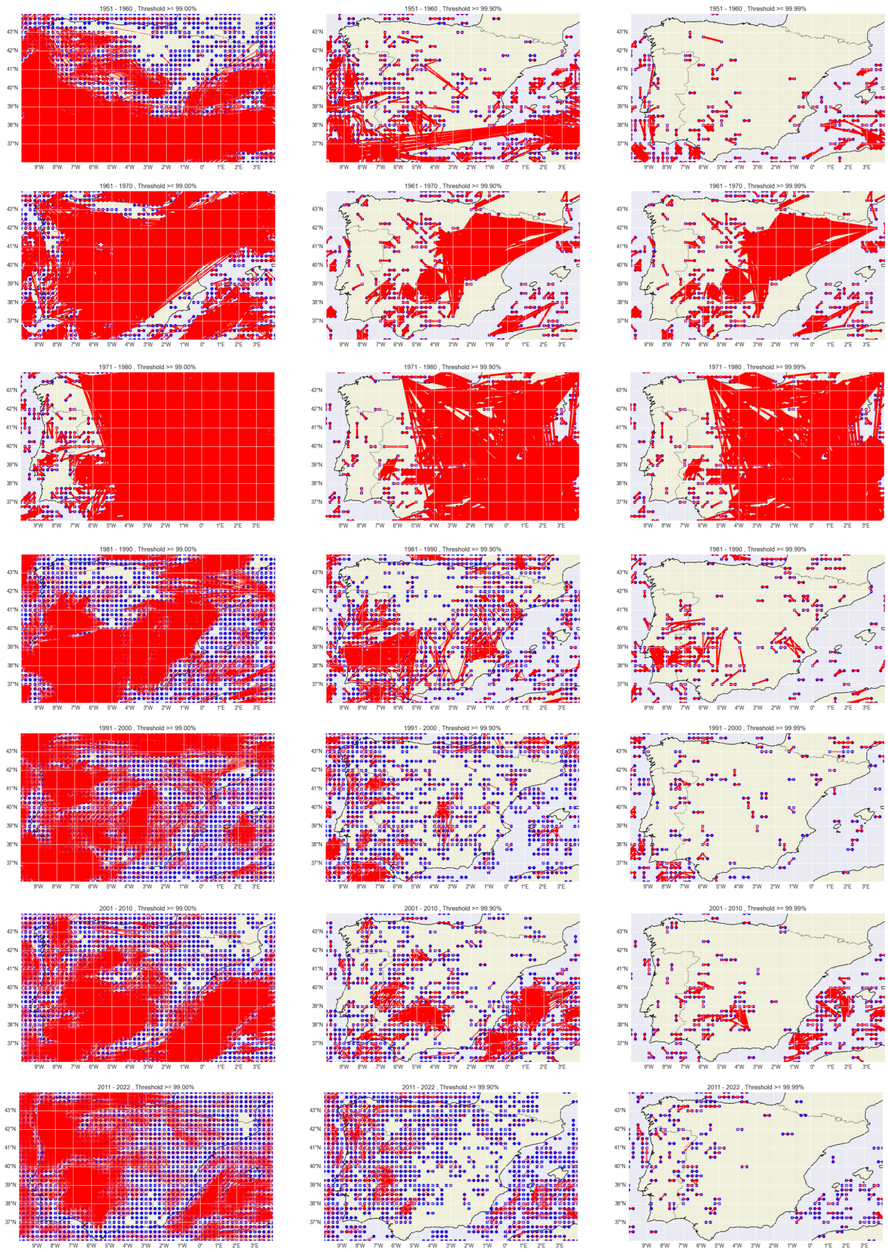

Figure 4.18: Inverse of Hamming distance between pairs of grid-points of Different Decades

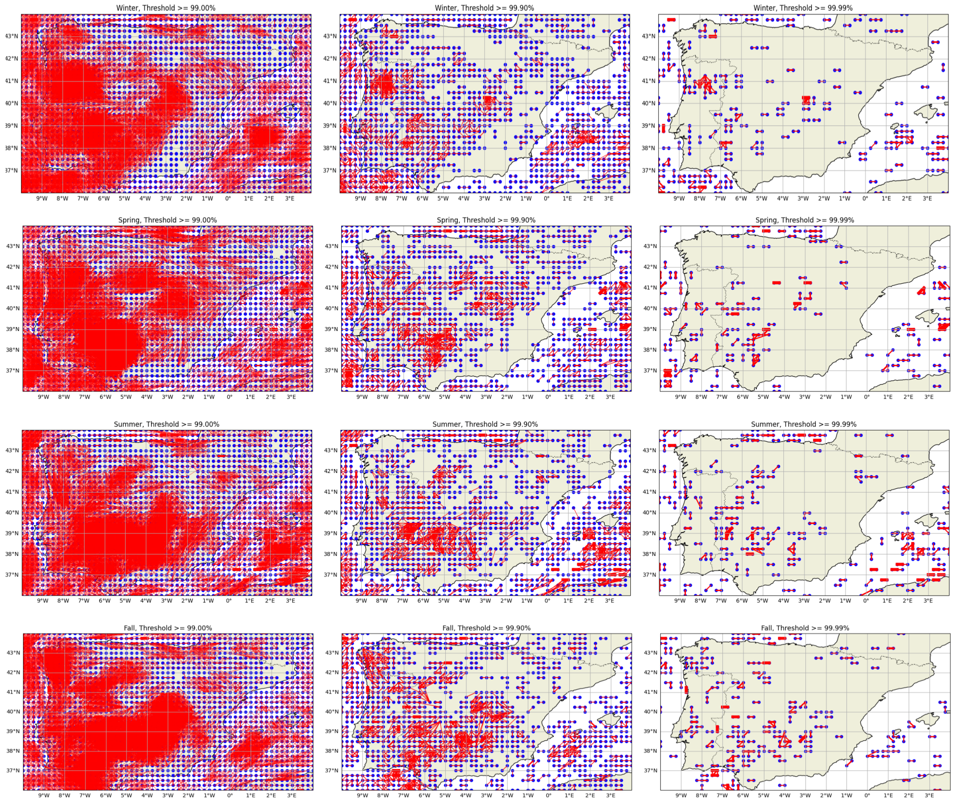

Figure 4.19: Inverse of Hamming distance between pairs of grid-points Different Seasons

The spatial and temporal dynamics of climate event similarities depicted in the figures underline three notable trends: close proximity correlations, the expansion of similarity clusters over time, and a decreasing intensity of these similarities. Figure 4.18 shows extremely strong connections in pattern in the earlier decades, there is a likelihood of creating discontinuities at the transition points because the ERA5 historic data was produced by running several parallel experiments for each different period, which is then sliced into the final product [155].

Close Proximity Correlation and Its Implications

The observed trends across all time frames are noticeable for the strong climate event similarities in areas within close geographic proximity. This underlines the principle that close grid points often share microclimatic elements and localized environmental factors, such as topography, vegetation, and soil types, which have a direct impact on climate events. The intensity of these events, ranging from heatwaves to drought, is thus closely interlinked within these zones.

Expansion of Similarity Clusters Over Time

A remarkable expansion of similarity clusters from early (1951) to recent (last decade) periods is noted. Initially, clusters were small and localized; however, they have progressively spread to cover larger regions. This pattern suggests a significant shift in the behaviour of extreme climate events, potentially due to changes in regional weather patterns, alterations in global atmospheric circulation, or the effects of climate change. The increased spread might also reflect improvements in data gathering and observational techniques, allowing us to recognize climate event similarities that were previously undetected.

Decreasing Intensity of Similarities and Diversification

Despite the growing geographical coverage of climate event similarities, their intensity seems to be diminishing. This implies a diversification in climate behaviour and a more heterogeneous climate system. Various factors could contribute to this shift, such as diverse local responses to global warming, human alterations of land surfaces, and changes in sea surface temperatures influencing weather patterns.

Graph Density and Degree of Similarity Analysis

Considering the graph density, the initial decades (1951-1980) show an intense network of climate correlations, as illustrated by the 99% similarity threshold. This density denotes synchrony in climate events across numerous locations, possibly due to overarching climatic influences. As we progress towards the 99.9% and 99.99% thresholds, a clear reduction in graph density emerges. These levels filter out all but the most pronounced climatic correlations, indicating either persistent microclimates or areas exhibiting heightened resilience to climate variability.

Evolving Climate Event Patterns

The 99% threshold initially displays the most extensive climatic connections. Over time, these connections spread but become less dense, indicating a broadening impact of extreme climate events within a more complex and interconnected climate system. At the 99.9% threshold, extreme climate events become less common, pointing towards a climate system with less predictability and increased variability in the occurrence of extreme events. Finally, within the strict 99.99% threshold, the figures show that while the frequency of extreme similarities decreases, the geographical spread of such events increases. This suggests that extreme events are not only becoming more geographically widespread but also more unique in their characteristics. In summary, these results show changing patterns of similarity in extreme events. Early periods were characterized by localized, intense climate event similarities, which have since evolved into a more complex web of climate dynamics with broader impacts and less predictability. This highlights the importance of adapting our understanding and response to climate variability in the face of ongoing environmental changes.

A changing climate in the Iberian region is characterized by the observed increase in number of heatwaves and droughts over the research period. Global trends of rising temperatures are consistent with the considerable increase in heatwaves, especially in the last two decades of the 20th century and the first two of the 21st [29, 32]. This temporal trend points to a possible escalation of catastrophic weather occurrences in the area, which might have profound effects on human communities and ecosystems [40]. The unique seasonality of heatwaves, which mostly happen in the summer, is in line with predictions derived from climatological norms. The sporadic events in the spring and fall, however, suggest that seasonal trends are not always consistent. A possible change in seasonal precipitation patterns may be indicated by the rising frequency and length of drought months, especially near the conclusion of the data set [16]. This could have an impact on agricultural practices and the management of water resources.

The Markov Chain analysis highlights the relationship between temperature extremes and drought conditions and offers insightful information about the probabilistic transitions between various climatic states. Policymakers and stakeholders can improve resilience and adaptive capacity by anticipating and preparing for future climate fluctuations by knowing the possibility of shifting between these states. The visualizations highlight areas more vulnerable to extreme weather events by showing the spatial distribution of heatwaves and droughts throughout the region. The spatial clustering of these phenomena that have been observed emphasizes the necessity of focused interventions and tailored adaptive techniques to lessen the effects of these phenomena on communities and ecosystems. Compounded events heatwaves and droughts occurring simultaneously are becoming more common, which presents unique difficulties for environmental management and policy [39]. These occurrences intensify the detrimental impacts on human societies and ecosystems, highlighting the significance of multi-sectoral adaptation strategies and integrated risk assessment.

With a special emphasis on the connection between heatwaves and droughts, the Markov Chain approach provides insightful information about the probability transitions between various climatic states. These transition probabilities between different climatic states drought without heatwaves ('01'), heatwaves without drought ('10'), and both heatwaves and droughts ('11') are shown by the analysis. The system is naturally resilient and stable despite adverse weather conditions, as evidenced by the high probability of staying in the '00' state. This implies that the climate in the area is generally steady, with little tendency toward extreme occurrences [40]. However, there are clear signs of susceptibility to changing into more extreme climate states ('01', '10', or '11'). The analysis in time indicates a possible escalation of drought risk in the region by showing that the initial vulnerability to drought conditions ('01') gradually grows. As a further illustration of the growing likelihood of heatwaves, the probability of changing to heatwave conditions ('10') likewise rises with time.

According to the data, the likelihood of moving towards compound events ('11'), in which heatwaves and droughts occur at the same time, is consistently low during the study. This implies that although isolated severe occurrences might happen, compound events happen less frequently. The transition probabilities exhibit temporal fluctuations, signifying changes in the probability of encountering distinct environmental conditions throughout time. It is essential to understand these temporal dynamics to plan for future climate fluctuations and to create adaptive methods that lessen the effects of catastrophic weather occurrences [42]. The results of the Markov Chain analysis have significant ramifications for efforts to increase resilience and adapt to climate change. Policymakers and other stakeholders can improve adaptation capacity and lower the risks connected with extreme weather occurrences by identifying vulnerabilities and possible trajectories of climate states.

The heatmaps of state transitions illustrate the results of the spatial correlation analysis of Markov states, which provides information about the geographic patterns of transitions between various climatic states. The analysis focuses on the shift from heatwaves to droughts and vice versa. It is less likely for a heatwave to last for the entire six months that follow, according to the heatmap showing state transitions from one heatwave month to the next. This implies that the persistence of heatwave conditions exhibits some degree of variable and spatial variation [43]. Heatwaves are more likely to persist or fade over time in geographic areas with significant transitional signals during the first and last months of the transition period [104]. The transitional signals, on the other hand, are less strong and more scattered during the intermediate months, indicating higher variability in heatwave persistence [16]. When looking at changes from months of heatwaves to months of droughts, the heatmap shows comparatively small but noticeable changes in the first month of the shift, with more distinct signs of transition in the months that follow. Therefore, implies that the change from heatwave to drought conditions can happen gradually over time, with the first month acting as the start of the transition and the subsequent months showing more noticeable alterations.

The results demonstrate that there is extremely little chance of moving from compound events both heatwave and drought to single extreme events either heatwave or drought, especially in remote locations. According to the heatmap, there are not many changes during the first two months of the transition phase, with the density of changes gradually rising. This suggests that the shift from compound occurrences to single severe events could be difficult and less frequent, particularly in the early phases of the shift.

Understanding the trends and development of extreme climatic events throughout the Iberian Peninsula is made possible by analyzing the spatial-temporal distribution of similar climate events and the Hamming distance. The great degree of climate event similarity between adjacent locations that have been found highlights the important significance that geographic proximity plays. These relationships are influenced by specific environmental conditions and shared microclimatic features, which can affect occurrences such as severe rains and heatwaves [105]. The results show that similarity clusters have grown over several decades, suggesting a change in the behaviour of extreme weather events. This extension shows that weather-related extremes are caused by variables that go beyond traditional territorial borders. These factors may include shifting regional weather patterns and global atmospheric circulation [106, 107]. Similarities between climate events become more spatially widespread, but their strength diminishes over time, indicating a change in the patterns of climate. This implies a wider range of intensities for climate events, perhaps impacted by different local climate reactions to global warming and alterations in land surfaces because of human activity [108].

A decrease in graph density is observed as similarity thresholds are raised, suggesting a transition toward a climate system with more isolated but strong similarities between climate events. This implies a process of selection in which only the strongest climate associations hold true, indicating regions that are resilient to shifting climate conditions or persistent microclimates [8]. The filter isolates the most extreme climate events, which become less frequent over time, at higher thresholds. This suggests that the climate system is changing such that extreme event manifestations are becoming less predictable and more variable.

Chapter 5

Conclusion

5.1 Introduction

This concluding chapter provides an opportunity to reflect on the findings of this research and discuss their implications. It brings together the major insights gleaned from the research, reflecting on the connections between heatwaves and droughts in the Iberian Peninsula. Furthermore, it delves into the potential impacts of these findings on climate adaptation and risk management strategies. This chapter also acknowledges the limitations of the study, proposes recommendations for future research, and discusses the potential directions for future work. Through this synthesis, this chapter aims to underscore the value and relevance of this research in contributing to our understanding of climate patterns and their impacts.

5.2 Summary of Findings

The thesis has offered a wealth of knowledge regarding the statistical relationships between heatwaves and droughts in the Iberian Peninsula. Some of the key insights obtained from the analysis of the data are as follows:

- The relationship between droughts and heatwaves in the Iberian Peninsula is characterized by a complex interplay, with both extremes showing a tendency to increase over time, especially noted in the later decades of the 20th century and early 21st century. This relationship is emphasized by the rising frequency and intensity of heatwaves, aligning with global warming trends, and an increase in the duration and frequency of drought conditions, possibly driven by changes in precipitation patterns and increased evapotranspiration.

- Seasonally, the influence on the climate system in the Iberian Peninsula varies, with heatwaves predominantly occurring during the summer months, as expected, but also showing sporadic instances during spring and fall. This suggests a broadening of the window in which heatwaves can occur, potentially linked to the overall rise in temperatures. Drought conditions, similarly, appear to be influenced by seasonal shifts, with potential implications for water resource management and agricultural scheduling.

- In terms of transitioning probabilities between climatic conditions, the Markov Chain analysis illustrates that while the baseline state (normal conditions) is relatively stable, there are clear pathways to more extreme states. Transition from normal to drought or heatwave conditions shows a gradual increase in likelihood over time, indicating a shifting baseline towards more frequent extreme conditions. Conversely, transitions from compound extreme events (simultaneous droughts and heatwaves) back to normal conditions are relatively rare, suggesting that once extreme conditions set in, they can be particularly persistent and challenging to revert. This understanding of transition probabilities is crucial for developing adaptive strategies and resilience planning in response to climate variability and change in the Iberian Peninsula.

5.3 Implications of the Research

The findings of this study not only contribute to the existing body of knowledge but also have potential implications for a broader context. These implications could affect policy decisions, shape future research, or even alter current practices. In this section, we will delve into the possible applications of our research findings for both practitioners and policymakers in the field.

The insights generated from this study can be leveraged by policymakers and planners to enhance the resilience of infrastructures and communities, enabling them to withstand extreme climatic events more effectively. The probabilistic models developed in this research can be instrumental in forecasting and preparing for potential future scenarios of droughts and heatwaves. A deeper understanding of the interaction between these extreme events can contribute towards more efficient water resource management and agricultural planning during periods of risk.

5.4 Recommendations

Considering the findings of this study, the following recommendations are proposed:

- Future studies should aim to build on this research by incorporating additional climatic variables that could potentially influence or be influenced by heatwaves and droughts.

- There is a necessity for the development of localized models that can predict extreme weather events for specific regions within the Iberian Peninsula, considering their unique geographical features.

- Investment in climate data collection and monitoring tools should be increased to enhance the accuracy and reliability of future studies. Which can be amplified to a larger area.

5.5 Limitations of the thesis

Despite the rigorous methodologies and substantial findings, this study, like all research, is not without its limitations. It is important to acknowledge these constraints as a guide for future research and a lens through which to view the results. The following are some of the limitaions:

- The research was limited to the analysis of reanalysis data, which may contain inherent biases or errors. The ERA5 historical data was generated through parallel experiments for different periods, which were later combined, potentially leading to discontinuities at the transition points, especially from the earlier years to 1979 [155].

- A notable constraint of this index mainly used (SPI) is its considerable sensitivity to variations in the duration of distinct statistical periods [156, 157].

- Although the Markov Chain provides a good basis for understanding the transitions between various states, it assumes that past conditions are reliable predictors of future states. This assumption may not always be valid, especially in the context of rapidly changing climate conditions.

5.6 Future Work

While this study has provided valuable insights into the relationship between heatwaves and droughts in the Iberian Peninsula, it also opens up new avenues for future research. These potential directions are not only extensions of this research but also opportunities to delve deeper into unexplored aspects or address questions that have arisen from our findings. Some of the potential areas that future studies could explore to further enhance our understanding of this complex climatic interplay are:

- Investigate the impact of global climate change trends on the frequency and intensity of droughts and heatwaves.

- Consider integrating more sophisticated statistical methods or machine learning models to predict extreme events with higher accuracy.

- Conduct a detailed examination of the socio-economic impacts of these extreme events on the Iberian Peninsula, with a particular focus on sectors such as agriculture and public health.

- Also to find the mechanisms that drive the relationship between droughts and heatwaves, and how can this be used to develop adaptation and mitigation strategies.

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