LUISS

Degree Program in Management and Computer Science

Course of Artificial Intelligence and Machine Learning

AI and Climate Change

How AI can help enhance adaptation and mitigation strategies

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Introduction

In recent years, we have witnessed the emergence and flourishing of new technologies. Among these, the ones that have experienced the most growth are artificial intelligence and machine learning. Today, we live in a world saturated with these types of technologies, from the well-known ChatGPT to facial and voice recognition systems. Other examples include generative artificial intelligence and the various algorithms that power the social networks we use daily. However, these are not the only fields where artificial intelligence is having an incredible impact. Some of the most globally significant areas include scientific research, financial market predictions, and more.

A particularly important area where AI is starting to be applied is environmental issues, especially climate change. Many research organizations are developing their own AI models to assist in this domain, which, as we will see, requires a turning point in how we approach it.

This thesis focuses precisely on this topic, specifically climate change, and how these advanced technologies can become extremely useful in planning and improving strategies to better predict the consequences of this phenomenon and contribute to its contrasting.

Already several studies have been conducted before this work to discover various ways to introduce Artificial Intelligence and Machine Learning in this context, specifically in climate change *adaptation* and *mitigation*. Studies, examples of which were reported in the articles proposed in the following sections, highlighted the innovative potential of these technologies in predicting extreme events, climate pattern recognition, and enhancing resilience through improved decision-making based on data. However, we are only at the beginning of the research and the solutions proposed are very recent.

So, this thesis aims to bridge the gap between the development of data-driven technologies and their use in climate action. This is done by spreading knowledge about the problem of climate change, together with the current "state of the art" by analyzing some of the latest proposed solutions. Furthermore, this thesis presents the creation of a Machine Learning model, called Recurrent Neural Network, designed, in this specific case, to simulate future climate change effects based on historical data. This work may put a concrete basis that can be further developed in order to be more precise and to adapt to several datasets. It makes us able to gain insights about future scenarios and to plan effective strategies responding to the effects that we may face in the future.

Premised that this is only an initial basis, and the calculated values are approximations that do not take into account all the aspects that might affect changing future scenarios, with the development of technology and further versions, able to better analyze also these external factors, the insights derived by this model may be very useful when planning adaptation and mitigation strategies. By doing so, this thesis provides a concrete approach to the integration of Machine Learning in climate action.

The next chapters will follow this structure: the first chapter will describe the problem and its consequences, along with a general overview of the measures currently in place.

The second chapter will focus on artificial intelligence and machine learning, providing a description of the most widely used algorithms.

The third chapter will combine the topics of the first two, analyzing the context of using advanced technologies in this scenario, how they are being developed and applied, and the future prospects.

The fourth chapter will focus on the creation of a machine learning algorithm that will act as a simulation model for climate change, capable of analyzing historical data and making future predictions.

Finally, the results will be analyzed, and conclusions will be drawn that could serve as "guidelines" for understanding how to act in the future if we want to try to limit the duration and extent of this phenomenon. At the same time, the expectations for the future made by experts in this field will be analyzed.

The potential of the proposed work ranges from the prediction of *event* scenarios, useful for defining the future trends of climate change phenomenology (made more precise and realistic by the AI's and ML's elaboration of large quantity of multisectoral data), to the evaluation of the effectiveness of the proposed mitigation and adaptation measures (*damage* scenarios and their evolution depending on different mitigation/adaptation measures) that help decision makers to better define its contrasting strategies. Among them, a fundamental role is played by the *financial mechanism* where future actions will focus on promoting innovative financing for risk prevention/mitigation, especially to low-income countries. In this regard, future development of this work could also be devoted to assess the extent of vulnerability of the goods and assets exposed to climate risks, evaluate the effectiveness of existing DRM/DRR financial mechanisms and deploy innovative financial instruments including insurances.

1. Climate change

1.1. What is climate change?

Climate change, according to the definition given by the United Nations, is a phenomenon that consists in the progressive shifts in weather and temperature patterns. These shifts can be natural and can be seen as a normal consequence of the life of the planet.

However, since the 1800s, human activities have been the main driver of the climate change. In fact, the main reasons that lead to this shift are the burning of fossil fuels (coal, oil and gas). This generates gasses, such as, in particular, carbon dioxide (CO2) and methane (CH4), that enhance the greenhouse effect, described as the creation of an "invisible blanket" wrapped around the planet that traps the sun's rays and prevents the heat from exiting the atmosphere. The main causes of the release in the atmosphere of these types of gas are related mostly to industrial and agricultural practices, together with deforestation and animal breeding. Still, activities involved in everyday life of every person, such as driving, heating a building, energy uses and waste disposal, make an enormous contribution in the happening of these phenomena, also considering how numerous we are currently on earth.

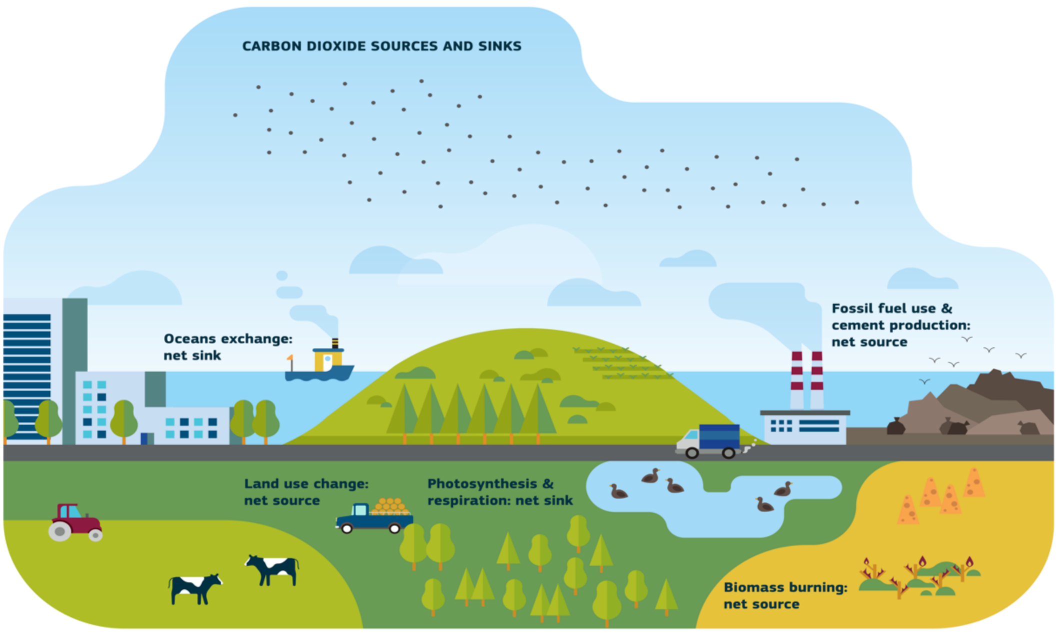


Fig. 1.1. Overview of the main natural and anthropogenic sources and sinks for CO_2. Credit: C3S/CAMS/ECMWF (www.copernicus.eu)

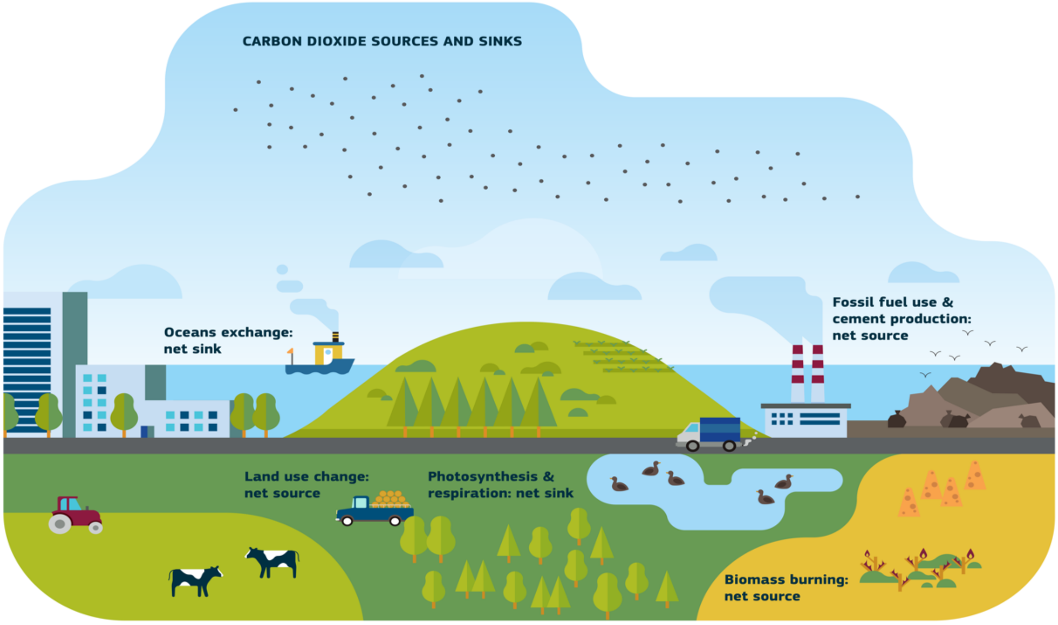


Fig. 1.2. Overview of the main natural and anthropogenic sources and sinks for CH_4. Credit: C3S/CAMS/ECMWF (www.copernicus.eu)

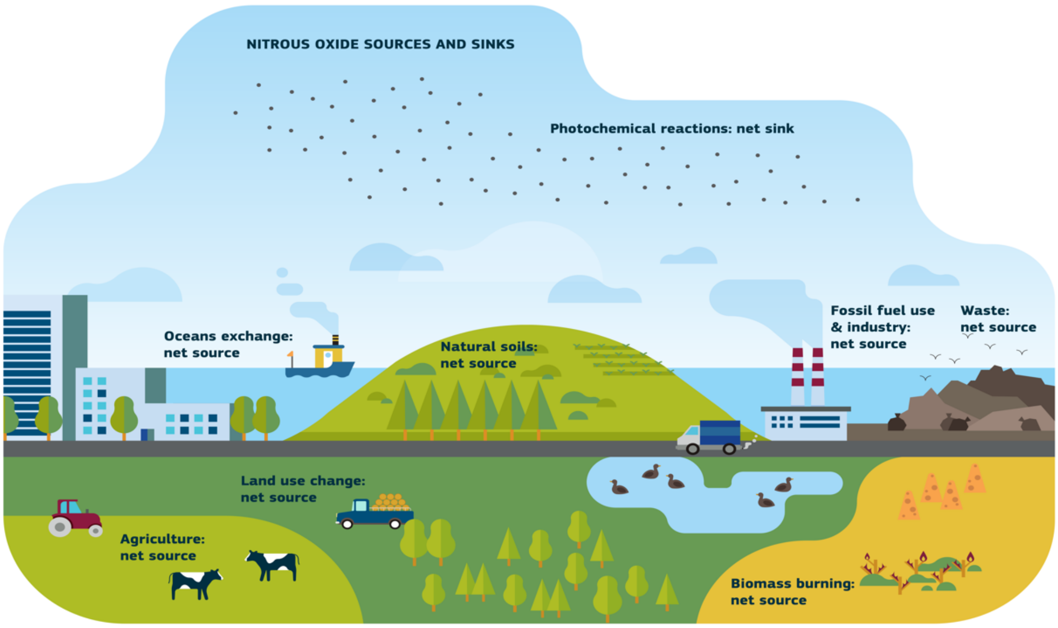


Fig. 1.3. Overview of the main natural and anthropogenic sources and sinks for N_2O. Credit: C3S/CAMS/ECMWF (www.copernicus.eu)

The effects of the climate change are obvious and under the eyes of all. What is most concerning is the fact that every year these effects become increasingly evident. Regarding last year 2023, the latest changes that happened, that have been recorded by Copernicus Climate Change Service, are summarised as follows:

- 2023 has been the warmest year on record, with a global average surface temperature of 14.98 °C;
- 2023 was almost 1.5 °C warmer than pre-industrial years;
- All days in 2023 were at least 1 °C warmer than pre-industrial levels;
- 2023 has seen both the highest absolute surface temperature, recorded in July, and the highest surface temperature relative to the annual cycle, recorded in November;
- Average air temperatures for 2023 were the warmest on record, or close to the warmest, over sizeable parts of all ocean basins and all continents except Australia.

Regarding, instead, the beginning of the current year, 2024:

- February 2024 was the warmest February on record globally, with an average temperature of 13.54 °C;
- European temperatures in February 2024 were 3.30°C above the 1991-2020 average for February, with much-above average temperatures experienced in central and eastern Europe;
- A record-breaking low temperature of -52.3°C was observed on 18th February 2024 in the Xinjiang region of China, highlighting the anomalies occurred during this period. Furthermore, in this regard...
- February 2024 was the month with the fifth-largest anomaly across all months, behind only the last months of 2023 (September, October, November and December);
- March 2024 was the warmest March on record globally, with an average temperature of 14.14°C;
- March 2024 is the tenth month in a row that is the warmest on record for the respective month of the year.

Resuming all, it is evident that the situation is critical and is getting constantly worse. However, what is most threatening is not only this constant warming of the whole planet, but the environmental consequences related to this phenomenon.

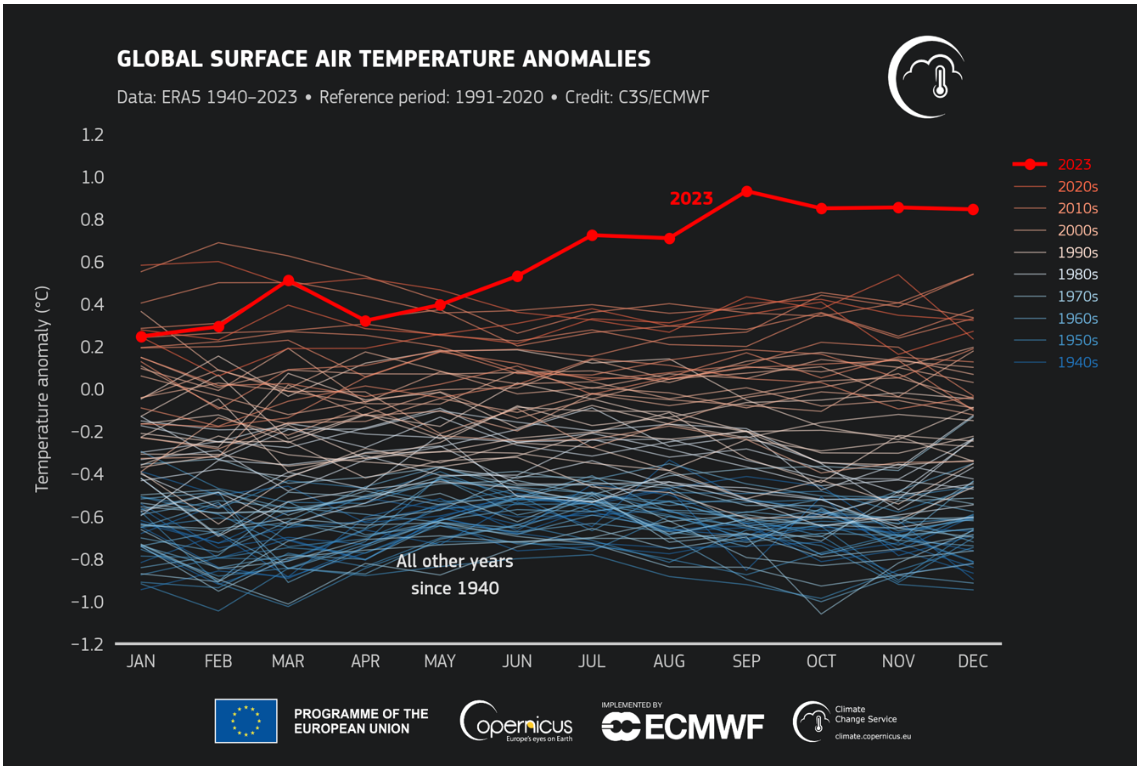
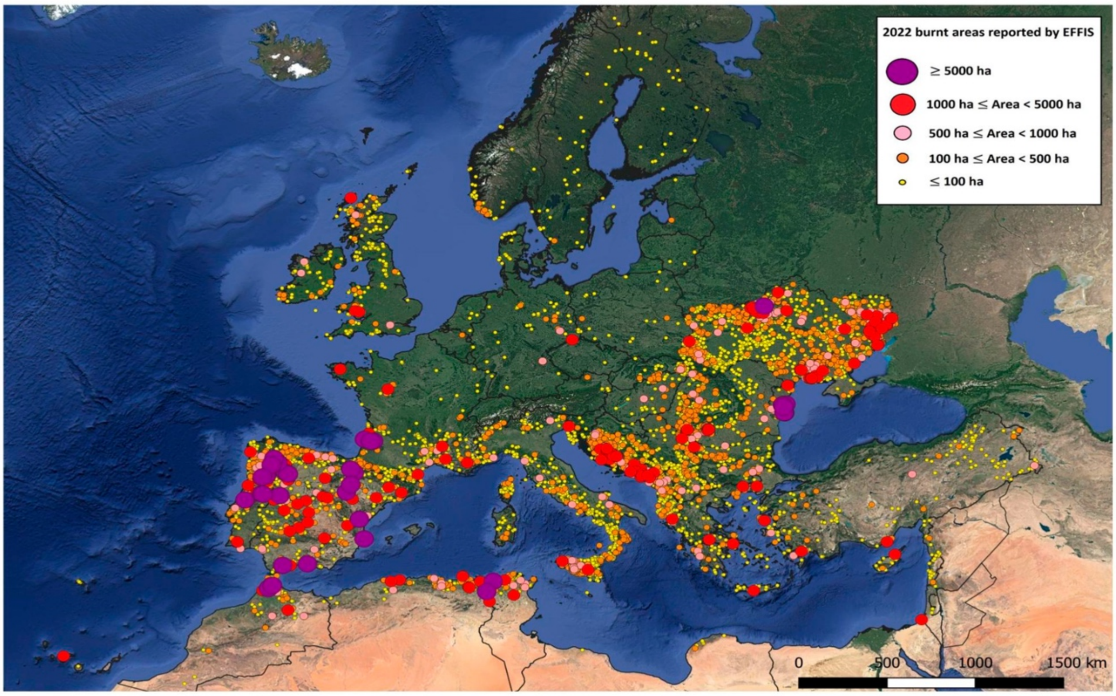


Fig. 1.4. Monthly global surface air temperature anomalies (°C) relative to 1991–2020 from January 1940 to December 2023, plotted as time series for each year. Credit: C3S/ECMWF (www.copernicus.eu)

In fact, the anomalous temperatures that every year we must face are only a facade problem, still being an issue that we must not overlook as every year we feel warmer than the preceding one and, at some point, it will surely become an unsustainable situation. Moreover, this constant growing heat increases the chance of getting ill and makes outside working very difficult, harming the economy.

However, behind that, there is a series of potential extreme events that, due to this shift of the temperatures, become more and more likely to happen.

First of all, being directly related to the constant warming of the planet, wildfires start more easily and spread more rapidly, as a consequence of the heat and of a dry and arid climate. These events harm ecosystems and actively participate in a worsening of the situation, due to the burning of trees, that, are not only a living and fundamental part of the ecosystem, but also, thanks to photosynthesis, consume carbon dioxide and emit oxygen, and to the larger spreading of damaging gasses in the atmosphere.



Copernicus Climate Change Service
European State of the Climate | 2022
PROGRAMME OF THE EUROPEAN UNION
IMPLEMENTED BY ECMWF

Fig. 1.5. Distribution and extent of burnt areas across Europe and the Mediterranean in 2022. Credit: EFFIS/Copernicus EMS (www.copernicus.eu)

Another consequence of the global warming is the fact that more moisture evaporates. This implies that destructive storms are more intense and more frequent in many regions, causing floodings and enormous damages to inhabited centres, potentially harming lives. In addition to this, rising temperatures cause oceans to become warmer, so great volumes of water evaporate more easily. As a consequence, cyclones, typhoons and hurricanes are becoming constantly more frequent, and can cause deaths and huge damages, which, then, require high costs to be fixed.

Related to the evaporation of great volumes of water, there is the problem of drought. In fact, global warming is leading to a more evident scarcity of water in regions in which the availability of water was already limited. This, first of all, is a major problem regarding less developed countries, in which people are already dying due to the shortage of water. In addition to this, ecosystems are getting damaged constantly and crops are less likely to grow healthy and, consequently, several agricultural systems all over the world get disadvantaged, being also a threat to economies and populations that rely on this type of sustain. Moreover, droughts may also stir destructive sand and dust storms that can move billions of tons of sand across continents, favouring desertification.

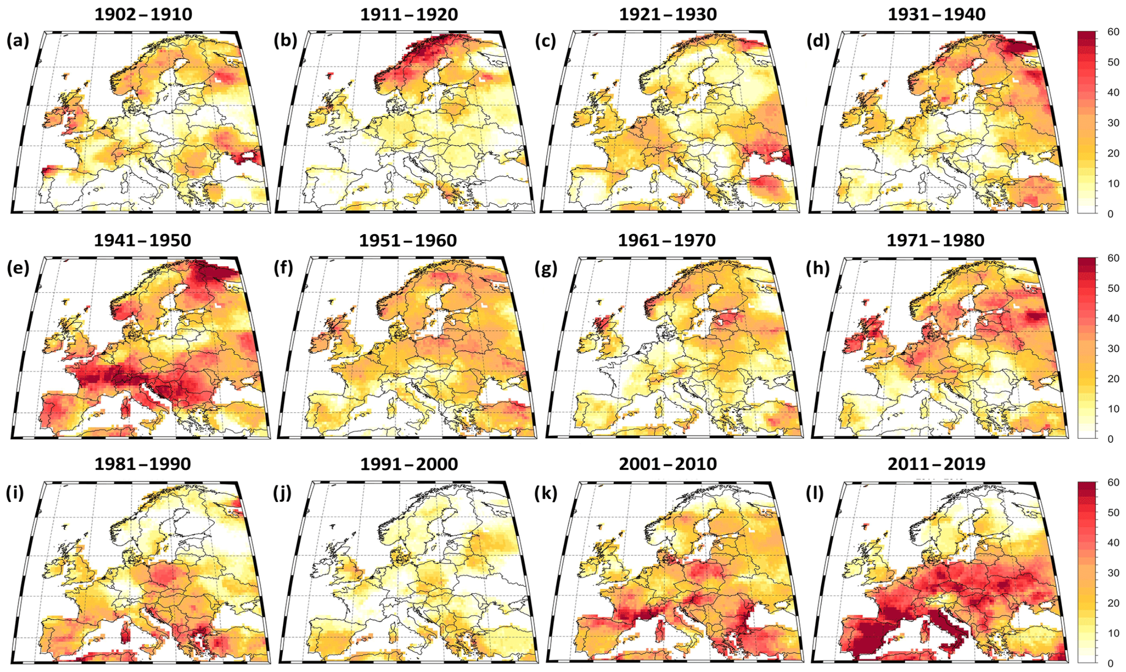


Fig. 1.6. Decadal frequency of drought duration for moderate drought (www.copernicus.eu)

Linked to the warming of oceans, there is the constant increase of their volumes. The rate at which oceans are warming is incredibly high, being a record over the past decades. Furthermore, this phenomenon is fed by the melting of ice sheets at the poles of the planet.

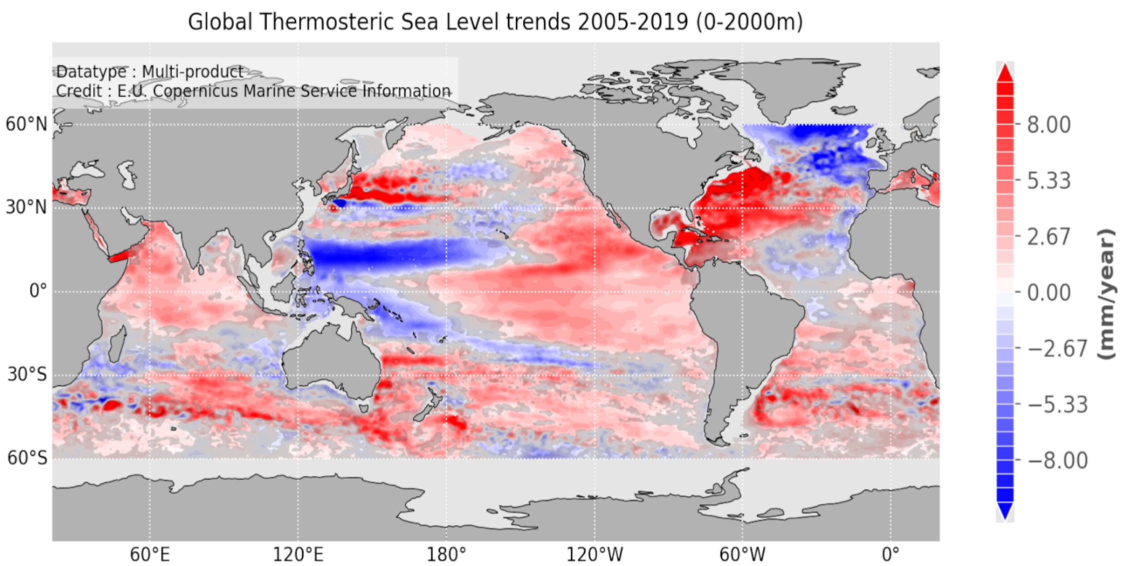


Fig. 1.7. Regional trends over the period 2005-2019 of thermosteric sea level (0-2000m) anomalies relative to the 2005-2019 (www.copernicus.eu)

This will lead to a rise of the sea levels, becoming a potential threat to a lot of coastal areas that, sooner or later, will be submerged by the water. In addition, the ocean absorbs a prominent part of the carbon dioxide present in the atmosphere, which makes it more acidic, and this can be fatal for several marine species and ecosystems, including coral reefs, already in danger due to ocean water pollution.

All these factors together contribute to the creation of very difficult living conditions both for us and for animal and plant species. The final consequences of this situation are many and terrible. First of all, the world is losing species at a rate 1,000 times higher than at any other time in the recorded human history, and this rate is getting higher and higher as the temperature increases. Currently, there are more than one million species at risk of becoming extinct in the next few decades, due to their inability to adapt to these rapid climate shifts, and this number is destined to rise.

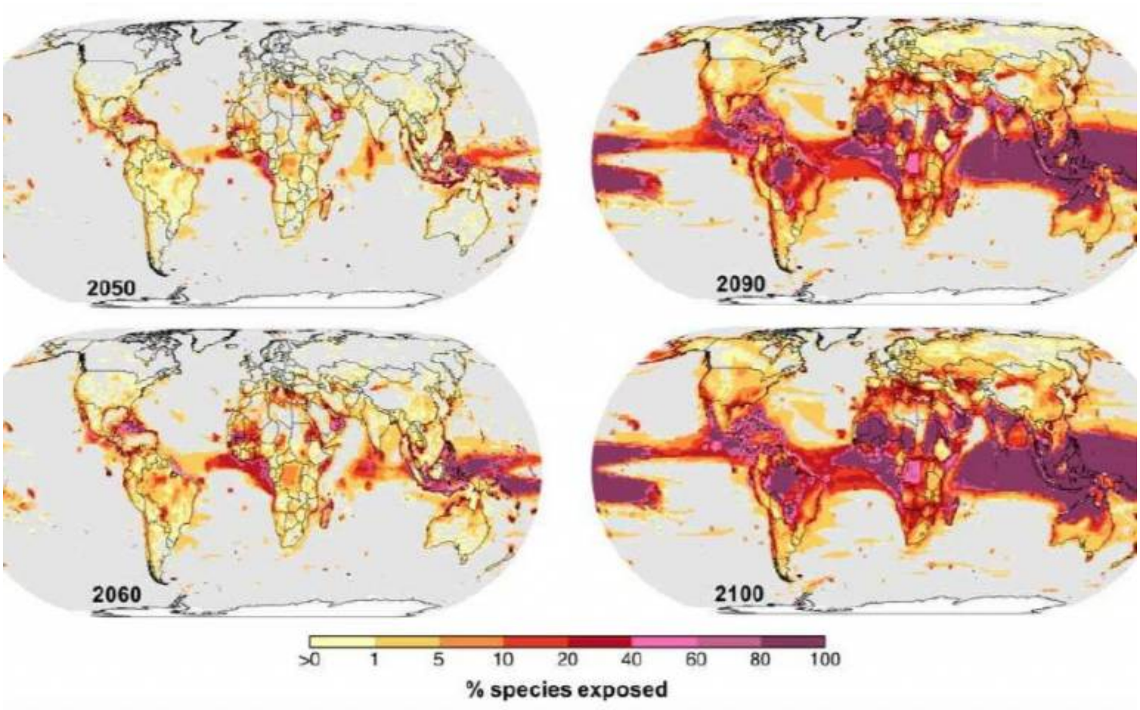


Fig. 1.8. Predicted threats to biodiversity over the course of the 21st century (Chris Trisos, Cory Merow & Alex Pigot, 2020)

Then, climate change encourages poverty and inequalities. Firstly because, as said before, outdoors working and agriculture become more difficult under these conditions. In addition, more acidic oceans are a substantial threat to fishing and environmental damages make also hunting more complicate. This harms a lot of economic systems all over the world. Secondly, extreme events, such as cyclones, wildfires and floodings, favoured by the climate change, destroy several homes and livelihoods. According to UN, over the past decade weather-related events displaced an estimated 23.1 million people on average each year, leaving many more vulnerable to poverty. In cases like this, especially in very poor countries, which are most vulnerable and least ready to adapt to the impacts of climate change, people are forced to leave to other more developed countries, favouring inequalities.

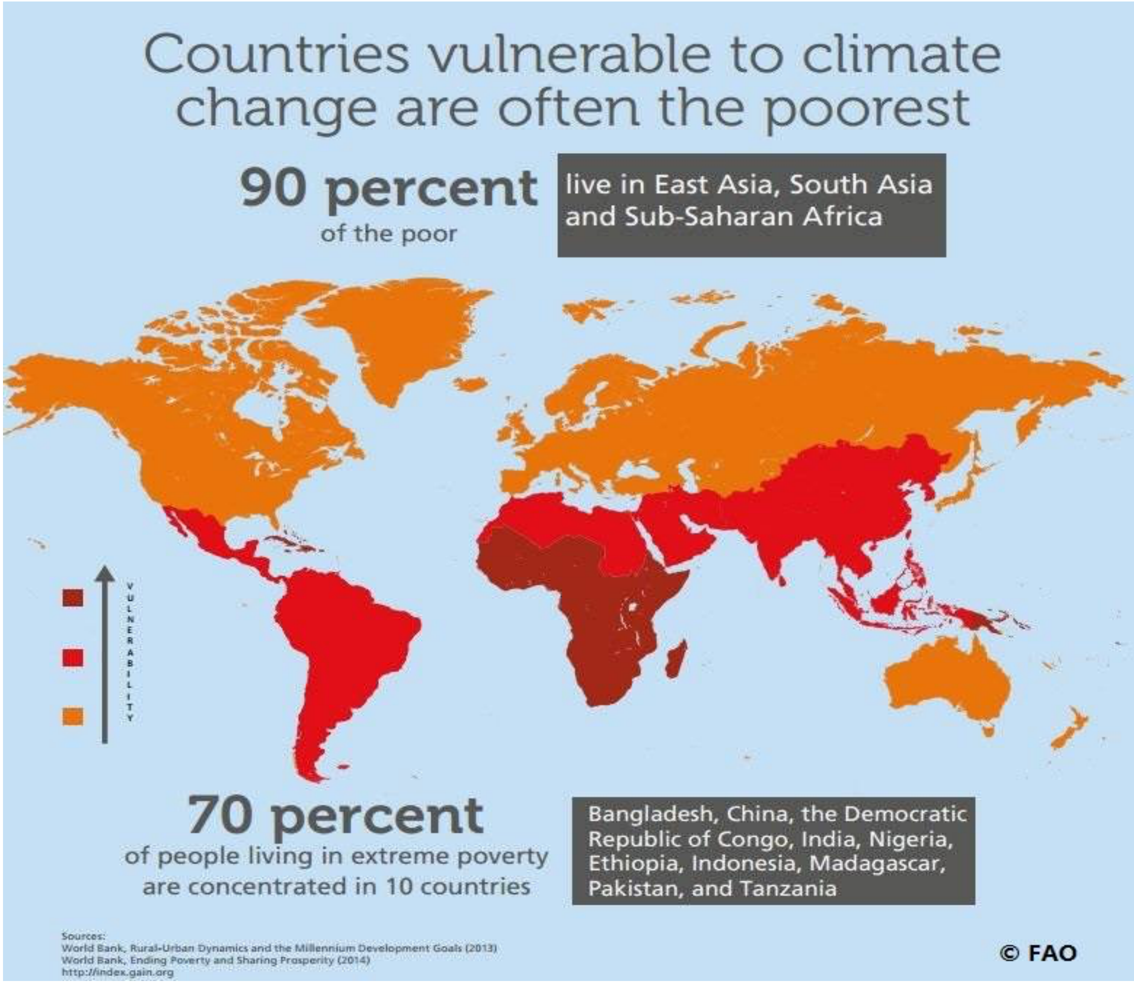


Fig. 1.9. Climate change disproportionately affects the world's poorest countries, where people are most dependent on natural resources (www.fao.org)

Last but not least, climate change is the single biggest health threat facing humanity. As reported by UN, every year environmental factors, such as air pollution, diseases, extreme events, forced displacements, increases hunger and poor nutrition, take the lives of around

13 million people. In fact, changing weather patterns are expanding diseases, and extreme weather events increase deaths and make it difficult for health care systems to keep up.

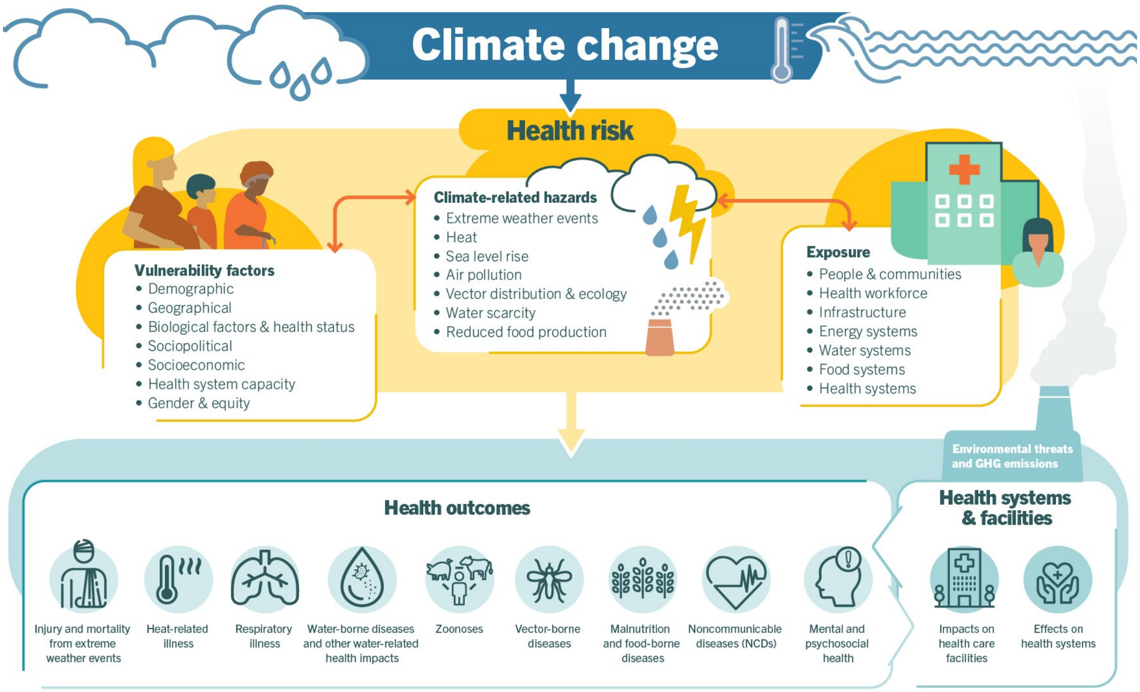


Fig. 1.10. Overview of climate-sensitive health risks, their exposure pathways and vulnerability factors (www.who.int)

1.2. The economic side

Obviously, the social and environmental consequences are not the only ones deriving from the climate change. Actually, only taking a look to the economic side too it is possible to understand how much damage this phenomenon has already caused and potentially will continue to cause.

The "European Environment Agency" conducted an analysis of the economic losses that there have been between 1980 and 2022 related to the climate change in the European Union Member States. According to the research, weather and climate-related extremes costed to the EU Member States economic losses of assets estimated at €650 billion, of which €59.4 billion only in 2021 and €52.3 billion only in 2022. This trend is increasing year over year, as shown in the following figure.

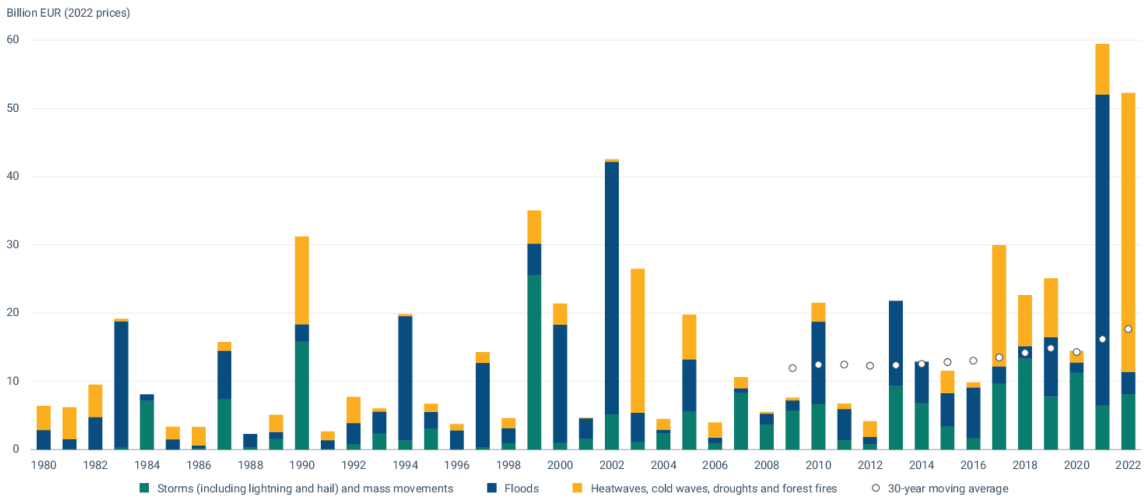


Fig. 1.11. Economic losses related to weather and climate extreme events (EEA, 2023)

Due to the climate change and the global warming, the occurrence of weather and climate-related extreme events is expected to increase and, with it, the number of losses. The phenomena that cost the most to the EU are hydrological hazards, such as floodings. In fact, these accounts for approximately 43% of the total losses. Following there are meteorological hazards (storms, typhoons, cyclones, hailstorms, etc.), accounting for 29% of the total. The remaining percentage includes heat waves, causing 20% of the total losses, and droughts, forest fires and cold waves together, causing 8% of the total losses. However, a consideration has to be done. In fact, a relatively small number of events is responsible for a big proportion of the economic losses: the most expensive climate-related hazards are responsible for a 59% of losses and 1% of the events caused 28% of losses. This results in very high variability from year to year. Reasons for this are multiple, but the main one is the increase in frequency and severity of these events due to the human-related climate change. The biggest losses were recorded in Germany and Belgium in 2021, after a flooding that hit western Europe, causing damage of €44 billion, as well as around 180 fatalities. The following biggest losses were recorded the next year, in 2022, after a period of intense heat and drought, that caused €40 billion-worth damage. This proves that the situation is always getting worse and that, potentially, in the near future there are going to be similar events, that could cost a huge amount of money. Unfortunately, also Italy was hit hard, as it is the third country with the highest number of losses in this period, after Germany and France. In Italy, indeed, there were losses amounting to around €111 billion and almost 22,000 fatalities were recorded. Although, if we shift our focus to a broader area, considering the global losses, the data are still more threatening. According to research conducted by the "World Meteorological Organization", between 1970 and 2021 weather, climate and water extremes caused over 2 million deaths and US $4.3 trillion in economic losses. The countries that came off worst are, obviously, the developing countries, in which there were the biggest numbers of human losses, accounting for over 90% of the total, and in which the damage was felt more, due to the restricted size of their economies. The number of people currently exposed to risks is enormous: around 3.3 and 3.6 billion people live in places highly vulnerable to climate change and weather-related events. This implies that better measures need to be taken.

1.3. Current measures against climate change

In practice, how are we fighting against the climate change? There are two main ways of action: "mitigation" and "adaptation". *Mitigation* is the one-word translation for "reducing climate change". It involves reducing the flow of heat-trapping greenhouse gases into the atmosphere.". Practically, the goal that is wanted to achieve by mitigation consists in avoiding as much as possible "*human interference with Earth's climate*" (NASA). This goal can be achieved either by reducing the sources of these harmful gases (for example, reducing the burning of fossil fuels in favour of renewable energy), or by enhancing their storage (for example, expanding the green spaces, such as forests). *Adaptation*, instead, means anticipating and adapting, as the word suggests, to the shifting conditions related to climate change. In practice, it means anticipating the changes that will be encountered in the future in order to take appropriate actions and measures, so that the damages they can cause will be minimised. Furthermore, adaptation also includes making the most of any potential beneficial opportunities related to climate change. Examples of adaptation measures could be reducing food waste in order to adapt against future food insecurities or creating safety plans and infrastructures to adapt to the potential increase in number of extreme events.

But what are the measures adopted by the various organizations currently in place against the climate change? Probably the most important global treaty about climate change entered into force on 4 November 2016: the Paris Agreement. It was adopted by 195 Parties (194 States plus the European Union) at the UN Climate Change Conference, held in Paris on 12 December 2015 (COP21). This agreement covers climate change mitigation, adaptation and finance. The aim of the agreement, as described in the Article 2, is to "*strengthen the global response to the threat of climate change, in the context of sustainable development and efforts to eradicate poverty*". Furthermore, it seeks to enhance the implementation of the UN Framework Convention on Climate Change through three important goals:

- Keeping the increase in the global average temperature well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase below 1.5°C above pre-industrial levels, as it would significantly reduce the risks and impacts of climate change (mitigation);
- Increasing the ability to adapt to the adverse impacts of climate change and foster climate resilience and low greenhouse gas emissions development, in a manner that does not threaten food production (adaptation);
- Making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development.

The Agreement provides a durable framework guiding the global effort to reach a net-zero emissions world. Moreover, the implementation of the Agreement is also essential for the achievement of the Sustainable Development Goals. The Agreement works on a five-year cycle of increasingly ambitious climate action carried out by countries. Since 2020, countries have been submitting their national climate action plans – known as Nationally Determined Contributions (NDCs). Each NDC has to reflect an increasingly higher degree of ambition with respect to the previous one. In their NDCs, countries communicate actions they will take to reduce their greenhouse gas emissions in order to reach the goals stated in the Paris Agreement, as well as the actions they will take to build resilience to adapt to the impacts of rising temperatures. Furthermore, the Agreement provides a framework for financial, technical and capacity building support to developing countries that need it:

- Finance: "*developed countries should take the lead in providing financial assistance to countries that are less endowed and more vulnerable, while for the first time also encouraging voluntary contributions by other Parties*.";

- Technology: "*the Paris Agreement speaks of the vision of fully realizing technology development and transfer for both improving resilience to climate change and reducing GHG emissions*.";
- Capacity-building: "*the Paris Agreement places great emphasis on climate-related capacity-building for developing countries and requests all developed countries to enhance support for capacity-building actions in developing countries.*".

After COP28, held in 2023 in Dubai, countries agreed that an acceleration in these processes is needed by 2030. How is EU acting within this framework? On 11 December 2019, the European Commission presented the European Green Deal, a set of policy initiatives aimed to reach the climate neutrality by 2050. Core points presented in the Deal are:

- No net emissions of greenhouse gases by 2050;
- Economic growth decoupled from resource use;
- No person and no places left behind.

The main objective is to reduce significantly (at least 55% less) the net greenhouse gases emission with respect to pre-industrial levels by the end of 2030, together with planting 3 million trees in European territories. One third of the €1.8 trillion investments from the "NextGenerationEU" recovery plan and EU's seven-year budget will be invested in reaching the aims stated in the European Green Deal.

2. Artificial Intelligence and Machine Learning

2.1. History and scope of AI & ML

Now, we seek to introduce the concepts of “Artificial Intelligence” and “Machine Learning”, looking forward to explaining how these powerful tools can be implemented and used in the fight against climate change.

AI is defined as the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. More specifically, the term is used to refer to the project of developing systems endowed with the intellectual processes characteristic of humans, such as the ability to reason, discover meaning, generalize, or learn from past experience.

The concept of “Artificial Intelligence” dates back to 1943, when the first work definable as artificial intelligence was created by McChulloch and Pitts. It was a system of artificial neurons that mimicked the functioning of a proper neural network thanks to the implementation of the two statuses “on” and “off” and a way to switch from “off” to “on” when a certain stimulus is received.

However, the birth of the idea of artificial intelligence that we know currently dates back to 1950, year in which Alan Turing, who can be considered as the “father” of theoretical computer science, published his article named “*Computing Machinery and Intelligence*”. The fundamental question underlying this article is “*Can machines think?*”, to which Turing provided an answer by introducing a criterion aimed to demonstrate whether a machine may or not exhibit an intelligent behaviour. This criterion is described as the Turing’s test, also known as the “Imitation Game”.

VOL. LIX. No. 236.] [October, 1950

MIND

A QUARTERLY REVIEW OF PSYCHOLOGY AND PHILOSOPHY

I.—COMPUTING MACHINERY AND INTELLIGENCE

BY A. M. TURING

1. *The Imitation Game.*

I PROPOSE to consider the question, 'Can machines think?' This should begin with definitions of the meaning of the terms 'machine' and 'think'. The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous. If the meaning of the words 'machine' and 'think' are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, 'Can machines think?' is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

Fig. 2.1. Extract from "Computing Machinery and Intelligence" by A.M. Turing (Mind, 1950)

This game consists in the presence of three people, a man (A), a woman (B), and a third person (C), who is the interpreter and their sex is irrelevant on the game. The interpreter stays in a different room with respect to the other two participants, known by the interpreter as "X" and "Y". The aim of the interpreter is to guess which one of the two other people is the male and who is the woman, instead. The only type of communication permitted between the interpreter and the other participants is by written text, or other means that do not give any suggestion about the sex of the interlocutor. Player A's aim is to trick the interpreter, while player B tries to help the latter one. Turing, at this point, proposed a modification of the game, involving a computer, asking "*What will happen when a machine takes the part of A in the game? Will the interrogator decide wrongly as often when the game is played like this as he does when the game is played between a* *man and a woman?*". These questions replace our original "*Can machines think?*". So, the game now involves two human participants, one of which is the interpreter. This one can interact with both the computer and the other human participant through a terminal, with these latter trying to convince the interpreter that is human. If the interpreter cannot state with certainty which one is the computer, then the machine wins the game. In this case, it would have demonstrated to be intelligent.

Some years later, in 1956, the field of AI research was founded in a workshop in Dartmouth College. During this time there was the creation of another important concept, that is "Machine Learning". The term was coined in 1959 by Arthur Samuel, an IBM employee and a pioneer of the field of artificial intelligence, to give a definition to the "*field of study that gives computers the ability to learn without being explicitly programmed*".

Machine learning is in fact a field of study in artificial intelligence. Although its first definition dates back to late 60s, it started to flourish only 30 years later. However, it has rapidly become the most popular and most successful branch of AI.

In 1997 the American computer scientist Tom Mitchell gave a more formal definition of the functioning of machine learning:" *A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E*". Practically, machine learning consists in training algorithms with a sample set of data, called training set, in a way that the machine can learn patterns, make prediction and correct itself to improve constantly.

Present-day machine learning has two objectives. The first one is to classify data based on models which have been developed. The other purpose is to make predictions to give future outcomes based on these models. There are several machine learning approaches that can be implemented. Usually, they are divided into three broad categories, that are going to be further analyzed in the following sub-sections and are the following:

- Supervised learning
- Unsupervised learning
- Reinforcement learning

2.2. Supervised Learning

In supervised learning the algorithm is trained using a known dataset (the "training set") with a known set of input data (called "features") and known output to make predictions. The training dataset includes labelled input data that pairs with desired outputs or response values. From it, the supervised learning algorithm seeks to create a model by discovering relationships between the features and the output. If the algorithm gives a correct answer, its learning mechanism is reinforced. Conversely, if the output is not the desired one, the machine "corrects" itself, by trying to minimize the deviation from the expected result. Once the algorithm is trained, a new dataset, called "test set", comes into play. Its function is to test the performance of the algorithm and to validate it. To obtain accurate results and a well-trained algorithm it is fundamental that both the training and the test set represent in a certain way the "reality". Supervised learning algorithms can be divided into two subcategories:

- Classification
- Regression

2.2.1. Classification

If we were to make an example of an algorithm pertaining to this category, we could think about the spam filter in our email. This filter learns from the emails already received, classified as "spam" or "regular", and it has to apply what learnt to classify new emails. Classification algorithms, more in general, are used when the outputs are restricted to a limited set of values and, hence, the algorithm has to "classify" new observations with respect to the training set.

2.2.2. Regression

Regression algorithms, instead, are used when the output is a numerical variable. The aim of these types of algorithms is to establish whether there is any correlation between the outcome and dependent variable and one or more independent variables. Then, based on this correlation, the algorithm is able to give a prediction for a new numeric value. To make an example, we can think to an algorithm predicting the price of a car, given a set of features, such as mileage, age, brand, etc., starting from a dataset containing a lot of data about cars, including both predictors and labels.

2.3. Unsupervised Learning

Conversely from Supervised Learning, in Unsupervised Learning the data is not labelled. So, basically, the algorithm has to learn from data without a "teacher". Mainly, unsupervised learning algorithms consist of classifying the input data, based on some common characteristics that the machine will learn autonomously during the process, without any human intervention.

During the process, the machine is able to "reason", predict and classify where the subsequent points of data will be placed. The classes are not known in advance by the algorithm but discovered automatically later.

The most common unsupervised learning algorithm is "clustering", which includes several types of models, such as "k-means" or "hierarchical clustering". Through clustering algorithms, hidden patterns and groupings in data are discovered. Usually, after having found such classes in data, supervised learning succeeds unsupervised learning, in a way that the labels necessary to carry out such a process are automatically discovered by the machine in this preceding step.

2.4. Reinforcement Learning

Reinforcement Learning is a branch of Machine Learning where software agents are designed to interact with an environment in order to maximize rewards.

In this approach, an agent takes actions and receives feedback from the environment, which helps shape its future decisions. Positive feedback encourages the agent to repeat certain actions, while negative feedback discourages them. Even though an action may seem beneficial at the moment, it could lead to problems later, and vice versa. The environment in which the agent operates is defined as "stochastic", meaning that the agent's future actions depend only on the current state and not on how it got there.

This is explained by the "Markov Property" of stochastic processes. In addition, the agent's way of action is "non-deterministic", meaning that it is influenced by the surrounding environment.

2.5. Deep Learning

In addition to the aforementioned ML techniques, it is fundamental to introduce “Deep Learning”, as it is the area in which we will operate in the following sections.

Deep Learning is a branch of Machine Learning which focuses on mimicking human brains. This is done through particular algorithms called “neural networks”. There are different types of neural networks, making them suitable for several tasks. Their main usage concerns image and face recognition. Their characteristic is the number of layers of “artificial neurons”, which can be infinite, of which they are composed. In fact, there can be created as many interconnected layers of neurons as needed. From this characteristic derives the adjective “Deep”. However, this is just a brief overview on this branch and these types of algorithms. The main concept will be explained more clearly and in the details in the section regarding the definition of a neural network model for timeseries analysis and forecasting.

These and other also more complicate algorithms are at the basis of the majority, if not the entirety, of the digital systems with which we come into contact every day. AI and ML found applications in every field of our lives, making our job easier and giving us a great hand in dealing with problems that are bigger than our solving capacity. One of them is exactly fighting against climate change and, more specifically, AI is giving a lot of help in enhancing mitigation and adaptation strategies, in order to deal with the problematics arising from such a shift in our living conditions.

However, it is just the starting point for something that in the future will surely become more and more developed and useful. In the following sections, we will go into more detail on how AI and, more generally, data-driven technologies are getting implemented in this scope and some examples of their already-existing applications.

3. How can AI aid in the context of climate change?

AI, together with ML, is increasingly assuming a vital role in managing the effects of climate change, especially in disaster risk reduction (DRR). It encompasses various aspects, such as predicting extreme events, developing hazard maps, real-time event detection, providing situational awareness, facilitating decision support, and more.

Priya Donti, an MIT professor and co-founder of Climate Change AI, a global nonprofit organization which has the aim to tackle climate change thanks to AI, together with many other experts in the sector, highlighted in the paper, "*Tackling Climate Change With Machine Learning*" (David Rolnick, Priya L. Donti et al, ACM Computing Surveys, 2022), several ways in which AI is currently helping scientists and policymakers to better address the problem of climate change. These ways are divided following the distinction between "*mitigation*" and "*adaptation*" strategies, already explained above.

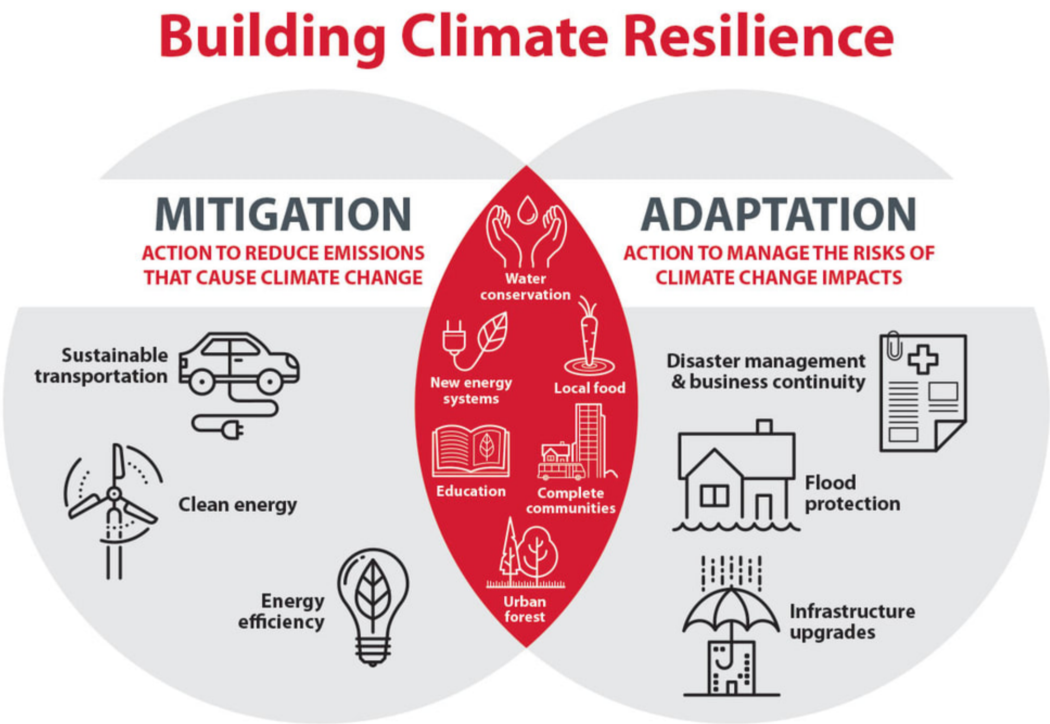


Fig. 3.1. Examples of climate change mitigation and adaptation actions (www.calgari.ca)

Let us introduce some of the applications that could have the greatest impact and that may be more likely to be deployed in short terms. Regarding the mitigation strategies, the paper focuses on the transformation of several aspects of our current societies towards a more climate-oriented approach. The first sector which needs to be transformed is the electricity one. Nowadays, most of electricity and energy systems rely on structures that spread a lot of greenhouse gases in the atmosphere, contributing a lot in threatening the whole planet. According to a statistic mentioned in the paper, "*electricity systems are responsible for about a quarter of human-caused greenhouse gas emissions each year*". In this field, AI and ML can give a great hand to developers, researchers and engineers in order to deploy cleaner energy technologies. In fact, these powerful tools can be used to upgrade and make "smarter" and more effective the already existing technologies, limiting also the usage of carbon sources and the spread of polluting gases. In this regard, another very important application of such tools can be forecasting energy supply and demand. Today, many system operators use basic forecasting techniques. Thanks to AI and ML, researchers are able to accurately understand and, consequently, schedule how much energy is needed based on the time period and on the area. In this way it is also possible to optimize the ways of dispatch of energy to inhabited centres and to plan more strategically the places in which new infrastructures have to be built. Moreover, these kinds of techniques reduce the waste of energy and materials, having a very positive impact on the environment. Finally, regarding this section, although being a project scheduled for a longer term, ML is helping researchers to find new materials and more sustainable ways of generating energy (for example, fusion reactors, that can make use of a virtually infinite source of hydrogen to work). This can also be a benefit for developing countries, ensuring a global framework in which access to clean energy is more available for everyone. However, there are still some trade-offs, such as the possibility that instead of reducing emissions, these new technologies would enhance them by making them cheaper to emit. So, development in this direction requires cautious decisions and a strong collaboration among involved parties.

Another very prominent sector in the contribution to climate change is the transportation one. Transportation systems "*account for about a quarter of energy-related CO2 emissions*". Differently from the previous sector, the transportation one is much harder to decarbonize. The opportunities that ML offers in this case are numerous. First of all, the paper describes how AI and ML techniques can be applied to traffic monitoring and designing efficient routes. All this information can be used to gather knowledge regarding behaviours of people and to understand which are the most trafficked routes. In this way, it could be possible to find alternative methods of transportation and also choose preferrable routes for long-distance transports. Another very important way in which these technologies can enhance decarbonization of transportation systems is through improving vehicle efficiency. The paper mentions as an example the aircraft engines, saying that "*aircraft carbon intensity is expected to decline by more than a third with respect to 2012, simply by virtue of newer models replacing aging jets*". In general, all the vehicles currently in circulation are not as efficient as they could technically be. AI and ML can help engineers to design better-performing and less-polluting vehicles. Together with them, although it is more a longer-term and uncertain project, these tools can be implemented into self-driving vehicles, that can be very useful, among the other reasons, in order to limit the consumption of energy, but, on the other hand, can create traffic jams. Finally, AI and ML technologies can have a great impact on modal shifts regarding fuels and means of transport. For what concerns about the first case, ML can give a lot of useful insights about the use of electric car, that have a way smaller carbon footprint. Apart from being able to give information about the correct design of such types of cars, these algorithms can also gain insights about their use patterns, their energy consumption and make able to create better and better batteries in terms of consumption and costs. Transportation systems are a big field in which ML can help a lot in reducing the greenhouse gases emissions, thing that until now has always been slow and complex. However, these solutions are prevalently technical and dependant on current infrastructure, so they require better understanding and studies.

Continuing, the paper describes how AI and ML can help in the construction of smart buildings and cities. This is another very impactful phenomenon as a large part of the polluting gases are emitted by buildings. According to the authors of the paper, "*a combination of easy-to-implement fixes and state-of-the-art strategies could reduce emissions for existing buildings by up to 90%*". So, the solution is already under our eyes, we only have to understand this and do everything to apply it. Also in this case, there are several ways of application of this solution, ranging from modelling data to optimize energy consumption to gather data to help policy makers in urban planning, or still to have the necessary information to complete the transition from cities to *smart* cities. However, there are still some limitations that are slowing down this process, such as the availability of high-quality data everywhere. Actually, this is restricted only to larger cities. Despite this, the project is well underway and realizing this potential can help both in mitigation terms and in improving the overall well-being of *smart* citizens. Next, the paper focuses on the industrial sector by saying that industries are one of the biggest sources of difficult-to-eliminate greenhouse gases emissions. An important fact is that this sector emits more pollutants than each country except US and China. So, there is a lot of work to be done, especially for these technologies. Indeed, there are several ways AI and ML can be utilized. In particular, as described in the paper, ML can be beneficial mainly "*by helping to streamline supply chains, improve production quality, predict machine breakdowns, optimize heating and cooling systems, and prioritize the use of clean electricity over fossil fuels*". The last aspects effectively attributable to the "mitigation" strategies regard ML applied to enhance land management by using advanced technologies, such as sensors as well as automated tools, and intelligent algorithms together with a better preservation of the forest environments, thanks to the identification of areas that could be threatened by deforestation or wildfires. A wrong land management is responsible for most of the greenhouse emissions globally. There is a need for an improvement in this aspect as soon as possible and AI and ML are powerful tools that can easily find fertile ground in this sector.

Changing the topic to the adaptation strategies, the most important one that needs to be mentioned regards climate modelling. These models are fundamental in order to raise general awareness of the problem and to bring to policy makers data and useful information that can be used to take the necessary measures. Several advancements in technology lead to the possibility of making a very impactful use of AI and ML in these situations. In particular, this possibility derives from the enormous number of advanced devices that foster the collection and gathering of numerous data, which, in turn, can be fed to such models, together with the fact that they are pretty easy and fast to train and test. Moreover, they can be generalized and applied to multiple situations without having to do a big number of adjustments. Of course, technology is on constant upgrade. Within some years, ML algorithms are going to be a lot more precise and capable of doing more complicated tasks. Currently, they are limited to work within already-existing climate models. However, they are being widely used in various helpful ways, particularly forecasting, monitoring and past trend analysis.

In this regard, it is impossible not to mention the paper entitled "*Innovation and Adaptation in the Climate Crisis: Technology for the New Normal*", written by Joseph Wegener, Fellow with the World Economic Forum in 2023, and published on the World Economic Forum in 2024, which explores the ways in which AI and ML can help us have a better response to the effects of climate change. Let us take a closer look to the concepts expressed in this paper. First of all, the paper describes a series of advanced data-driven technologies that are currently emerging as mission-critical tools for climate change adaptation. All these technologies, that include UAV drones, satellites, weather stations, advanced computing, IoT and AR/VR, have in common the synergy with AI and are being employed to enable leaders to enhance industry resilience, protect ecosystems and safeguard human well-being. These technologies have been selected, given the urgency due to climate change, thanks to their readiness for an immediate use and their vast potential for an impactful contribution. Moreover, all these types of technology co-operate in a unique "data life cycle", fostering the analysis and process of data. In fact, as described also in the report, these technologies can work alone, but their impact can be surely expanded if we use them in concert. The capabilities provided to leaders by such technologies are many and vary from the gathering, analysis and processing of complete datasets and, consequently, the enhancement of decision-making to nudging behaviour change towards a more adaptive and risk-reducing one. These technologies and capabilities need to be integrated into the climate adaptation cycle, consisting in comprehending risk and opportunities, building resilience and responding dynamically.

This challenge is the topic of the paper. Starting from the first phase of the adaptation cycle, which is comprehending risk and opportunities, organizations are called on to map the risk categories that may affect their assets and operations. Risks can be either physical or transition-related, such as a change in climate policy or in consumer's behaviour. After having assessed the risks, leaders must determine the level of exposure to these climate risks that threaten communities. Once the exposure is understood, organizations have to assess the extent to which their assets and supply chains are vulnerable. Finally, they have to estimate the cost of inaction to take the better decisions regarding investments and ways of action.

All these tasks can be enhanced thanks to the technologies described above. In particular, AI is fundamental in gathering and processing datasets and filling data gaps, as it is able to deal both with structured and unstructured data. This enormous quantity of data, provided by drones, Earth observation satellites (that alone collect more than 100 terabytes of imagery data every day) and IoT, can be used by AI to develop weather and climate models, that can be used to achieve several objectives. Firstly, they permit to have more accurate weather and climate simulations, that give better insights and make possible to have more precise predictions, also based on custom and localized inference. Secondly, thanks to such models, it is possible to have the probabilities of a particular event happening, or to state which communities or assets are exposed to a certain risk, or still to quantify potential damages and costs, constructing risk portfolios, considering various factors and scenarios.

Proceeding with the second stage of the adaptation cycle, which is building resilience in communities, businesses and environments, leaders, in this case, are required to use the data and predictions collected in the first phase to build real-life adaptation and resilience plans. Also in this phase, AI has a core role, finding a lot of possible ways of implementation. These vary from the development of early-warning systems and hazard monitoring to the optimization of supply chains and the creation of resilient infrastructures, such as smart sewer systems that optimize water flows.

Another very interesting field of application of AI mentioned in the paper is deep learning used to advance in the development of resilient design at molecular level, such as the design of drought resistant crops.

The third, and last, phase of the adaptation cycle consists in responding dynamically to climate effects in order to save lives, businesses and natural assets. In this regard, the paper mentions how fundamental it is to act in the first 72 hours after a crisis, which is the most critical time range in which it is possible to save numerous lives and minimizing damages if acted properly. AI can be employed in this phase of the adaptation cycle to gather and analyze humanitarian data, in order to pinpoint exactly where people are after an event and to distil key insights, such as how people are being affected during a crisis.

In addition, AI is fundamental in planning the best decisions to be implemented after a crisis, thanks to its ability to analyze vast datasets and find patterns to make recommendation for action.

Finally, another important case in which AI can find key applications is optimizing rescue and evacuations, as AI can find the best way to evacuate a zone affected by a crisis and to minimize the time needed for the transfer of people in a safer area.

However, the implementation of such kinds of technology is only at the beginning of its journey, but there is a huge need to have them functioning as soon as possible. This slowness in the deployment of technologies is due to several factors.

First of all, the lack of open-source data and analytical tools, that in a certain way limit the possibility of use of climate technologies, especially in the Global South. According to the IPCC, in fact, over 3 billion people are vulnerable to the effects of climate change. However, the majority of these people are not involved in the development of data-driven technologies. With an increase in openness, climate technology would become a public utility and their usefulness would be enhanced, together with cooperation between businesses or governments.

Secondly, there is a widespread lack of trust, especially in global leaders. As indicated by the "AI for the Planet Alliance", 67% of leaders lack confidence in AI data analysis. A trend that is seen also in users, as 52% of people are more concerned than excited about AI, as reported by the Pew Research Center. This lack of trust encompasses various dimensions, such as the quality of input data, the output of algorithms (the famous "black box problem") and the responsible use of these powerful means.

Thirdly, insufficient finance is continuing to slow processes. As UN stated, adaptation finance flows to developing countries are 10 to 18 times below estimated needs. This latter value is increasing year over year and slowing down the development processes can only worsen the situation. For this reason, several parties are trying to make their contribution through millionary fundings aimed at accelerating technological advances.

Finally, there is an absence of proper policies and regulations that may give a boost to the employment of advanced technologies in climate change. However, this situation is changing, as in the last years several policies and regulations focused on adaptation to climate change have been enacted in various countries of the world.

4. Future insights: building a model for climate forecasting

4.1. Introduction to the model

This chapter delves into an example of a practical application of an advanced Machine Learning model designed to interpret and extract meaningful insights from extensive historical climate records.

By leveraging the power of machine learning and data analytics, we aim to uncover patterns, trends, and anomalies that traditional analytical methods might overlook. Through a detailed exploration of the ML model's development, implementation, and performance, we demonstrate its potential to enhance our understanding of past climate behaviours, providing valuable perspectives that could inform future climate predictions and policy decisions.

Entering more into the details, the model that will be used for this application, as mentioned in the Chapter 2, is a Neural Network. First of all, let us introduce this type of model and explain how it works. A neural network is a program that in a certain way emulates the human brain. In fact, it uses processes that mimic the functioning of biological neurons in order to identify phenomena, weigh options and, based on this, derive conclusions. It consists of layers of interconnected units, called “nodes” or “neurons”.

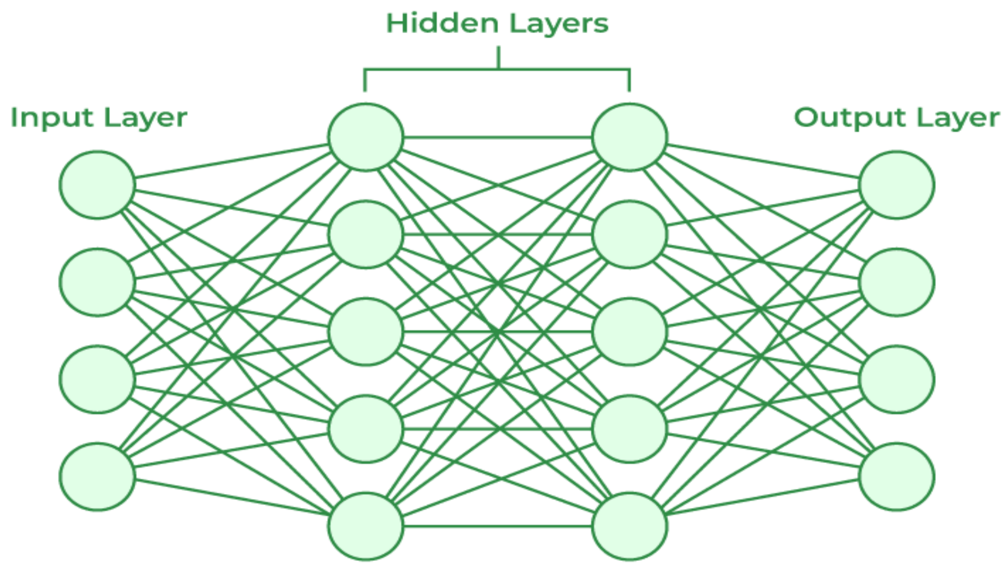


Fig. 4.1. Conceptual scheme of a Neural network

There is an initial input layer, which receives the input features from the data, a final output layer and, between them, one or more hidden layers, which are intermediate layers consisting of nodes performing computations and transformations on the input data.

As just said, there could be several hidden layers of nodes in a neural network, making it "deep", hence the term "deep learning". Each node can be seen as a distinct linear regression model and has its own weight and threshold, or bias. It receives the input from the previous layer and applies its own weight to adjust the input signal strength. Then, if the output of the individual neuron is above its threshold, it gets passed to the subsequent layer, otherwise no data is passed along. This process of passing the output data of a node to another one of a following layer, which, in turn, will use this data as its input, is called "forward propagation" and defines the neural network as "feedforward network". Most of neural networks act like this.

However, it is possible to train a model in the opposite way, which means from the output to the input. This way is called "backpropagation" and works by starting from the output to adjust weights and biases of the nodes, in order to minimize the so-called "loss function", or "cost function", which is the function used to evaluate the accuracy of the model.

The goal, in fact, is to minimize this loss function in order to ensure the correctness of fit for any observation. As the model adjusts its weights and biases, it uses the loss function and reinforcement learning, which was introduced in the previous chapters, to reach the local minimum. The process in which the algorithm does these adjustments is through gradient descent, allowing the model to determine the direction to take to minimize the loss function. There are several types of neural networks.

The model that will be used in the following practical application can be reconducted to the category of "Recurrent Neural Networks", or "RNNs". Algorithms of this type are primarily leveraged when using time-series data to make predictions about future outcomes, which, how we will see, is the aim of this application. In fact, these algorithms are distinguished by their "memory" as they take information from previous inputs to influence the current input and output.

4.2. Dataset

Delving straight into the practical application, let us start from the dataset that will be used. The data used for this example has been taken from the "Climate Change Knowledge Portal (CCLKP)". Data presented on this platform is disseminated by the World Bank under its Open Data Policy.

In this platform there are several options of spatially aggregated data. In our example we will be using a specific dataset, which is the historical climate reanalysis data from ERA5. ERA5 is the fifth generation European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis of the global climate. It uses a broad collection of observational data. The data are offered through the Copernicus Climate Change Service as a public good. CCKP holdings cover 1950-2022 and can be used to derive historical trends and variability, as we are going to do in this section. Our dataset, in particular, presents global data spatially aggregated (grouped by country, indeed). The climate indicators included in the dataset and that we will analyze more in depth during this practical application are listed as follows:

- **Year:** recorded from 1950 to 2022, data are aggregated yearly;
- **Cdd:** maximum number of consecutive dry days, which are days in which precipitation < 1mm;
- **Cdd65:** cooling degree days, which is the cumulative number of degrees that the daily average temperature over a given period is above a specific threshold (here 65°F, or, approximately, 18°C); this measure is very important in understanding the energy consumption in houses;
- **Cwd:** maximum number of consecutive wet days, in which precipitation >= 1mm;
- **Fd:** number of frost days, the average aggregated number of days in which the daily minimum temperature < 0°C;
- **Gslend:** growing season length end, annual series with the day of the year (1st Jan to June 30 in Southern Hemisphere, SH, and 1st July to 31st Dec in Northern Hemisphere, NH) that reflects the first span of at least 6 consecutive days with daily mean temperature T < 5°C;
- **Gslstart:** growing season length start, annual series with the day of the year (1st Jan to June 30 in Northern Hemisphere, NH, and 1st July to 31st Dec in Southern

Hemisphere, SH) that reflects the first span of at least 6 consecutive days with daily mean temperature T > 5°C;

- **Hd40:** number of hot days, the number of days with daily maximum temperature >= 40°C;
- **Hdd65:** heating degree days, **t**he cumulative number of degrees that the daily average temperature over a given period is below a specified threshold (here 65°F, or, approximately, 18°C); this measure is very important in understanding the energy consumption in houses;
- **Hi39:** number of days with Heat Index >= 39°C. The Heat Index is a measure of apparent temperature that includes the influence of atmospheric moisture; it is similar to the perceived temperature;
- **Hurs:** relative humidity, based on daily mean relative humidity at 2m as reported by climate models, or derived from specific humidity reported by climate models;
- **Id:** number of ice days, average aggregated number of days in which the daily maximum temperature < 0°C;
- **Pr:** precipitation, aggregated accumulated precipitation;
- **R20mm:** number of days in which accumulated precipitation >= 20mm (these days are called heavy precipitation days);
- **R50mm:** number of days in which accumulated precipitation >= 50mm (these days are called very heavy precipitation days);
- **R95ptot:** precipitation amount during wettest days, accumulated precipitation amounts during the 5% of yearly wettest days.
- **Rx1day:** the average largest precipitation in a 1-day period;
- **Rx5day:** the average largest precipitation amount over a consecutive 5-days period;
- **Sd:** number of summer days, that are days in which the daily maximum temperature >= 25°C;
- **Tas:** average mean surface temperature;
- **Tnn:** minimum of daily minimum temperature, which is the single-day minimum value of the daily minimum temperatures;
- **Tx84rr:** temperature-based excess mortality risk;

- **Txx:** maximum of daily maximum temperature, which is the single-day maximum value of the daily maximum temperatures;

4.3. Explanatory Data Analysis

Now that the attributes are listed, the research can start with an initial Explanatory Data Analysis, which is a preliminary study of the data available and the identification of some correlations among attributes or interesting features present in the data.

First of all, an important note to be mentioned, data can be downloaded from the Climate Change Knowledge Portal one feature at time. So, in order to have a complete dataset, including all the features listed above, it was necessary to download one dataset for each feature and then to combine them using as reference years and country codes, in order to have for each country the observations for each climate indicator and relative to the year in which they were recorded. Then, every column representing a climate indicator in the dataset was renamed as the appropriate aspect they measure. In this way, it is possible to better visualize data, without having to always look to the meaning of the acronyms to understand the values which are being used.

Once that the dataset is built, the practical application starts with the necessary libraries being loaded in our framework. The libraries that are going to be used are Pandas, Numpy, Sklearn, Matplotlib and, finally, Tensorflow. These libraries have as main features the possibility of creating specific dataframes that are very useful for data manipulation and visualization. This latter possibility is enhanced thanks to the Matplotlib library, which is designed specifically for creating plots and visualize data. The last library, which is Tensorflow, is very useful when dealing with Neural Network models, as it contains several methods and commands to understand better what is being done and simplify the work.

The first thing to be done, after having loaded the libraries, is loading the dataset, which, as said before, is going to be stored in a Pandas dataframe. After having done this, we can start having an overview of our dataset. There are some missing values, specifically in the two columns regarding growing season length. In order not to delete rows in the dataset, which may lead in having “holes” in the data and in losing probably relevant information, as we are working in year spans, the missing values are dealt with using the mean of the other values present in the same column. This because, the number of observations is very high, so we can assume that their mean can be pretty close to the actual value that would have been present in the dataset. In this way, it is also possible to reduce deviation. Once dealt with this problem, we can proceed with the EDA, starting with some data visualization to better understand the features of the dataset.

4.3.1. Histograms

Histograms are very useful types of plots, used mainly to understand the distribution of our data. Along the X-axis there is a range of values that can be assumed by the specific indicator that we are analyzing. Along the Y-axis, instead, there is the number of observations present in our dataset of every value placed along the X-axis. The most interesting features found thanks to histograms regard, for example, the column of number of days with heat index over 39°C, shown in the following figure.

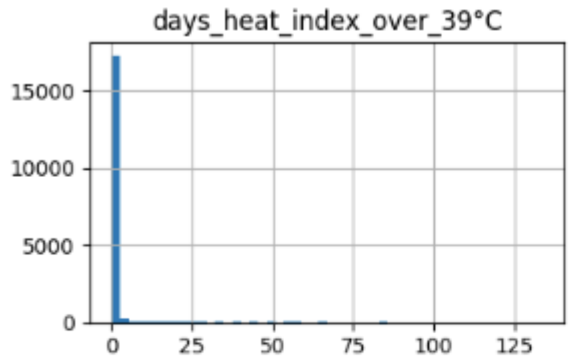


Fig. 4.2. Observations of number of days with heat index over 39°C

As it is possible to see, the distribution is highly right-skewed, indicating that most years have very few or no days surpassing this heat index. However, there are still some observations with significantly higher values. This is very important to notice, as they could be related to extreme heat events, which are becoming more common with climate change, so we could encounter an increase in the number of observations of higher values when we will gather future insights.

Other two histograms that can be mentioned, as they are pretty related, nevertheless they present some differences, are the ones regarding the indicators of cooling degree days and heating degree days.

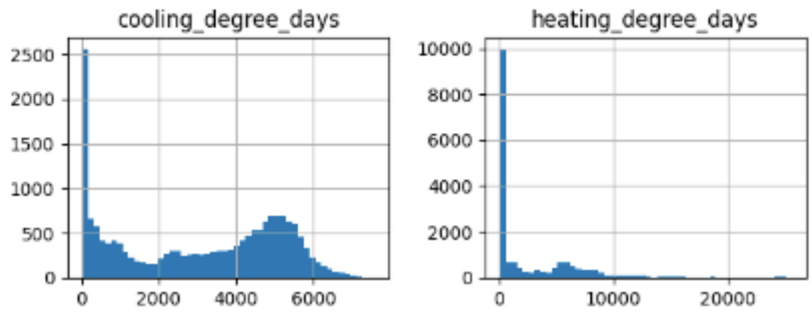


Fig. 4.3. Observations of cooling (on the left) and heating (on the right) degree days

The first histogram is more bimodal with respect to the second one, indicating a stronger presence of days in which the temperature is above the aforementioned threshold (approximately 18°C). So, we can state that the energy consumption is much more focused on cooling the buildings, rather than on heating them. This can be seen as a consequence of the climate change, that is bringing with it higher temperatures with milder winters, and this is important to know when stating and understanding seasonal patterns in energy consumption and demand.

Then, analyzing the histogram of the mean surface temperature, it shows consistencies in the occurrence of mild temperatures.

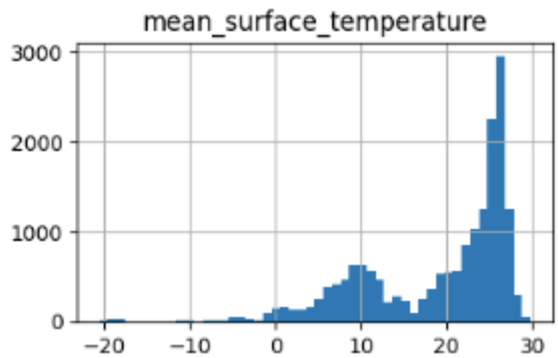


Fig. 4.4. Observations of mean surface temperatures

However, there are still some extreme observations, both in extreme cold and extreme heat ways.

Finally, analyzing the histogram related to the risk of excess mortality, also in this case it is possible to notice a right-skewed distribution, demonstrating a generally low risk of excess mortality.

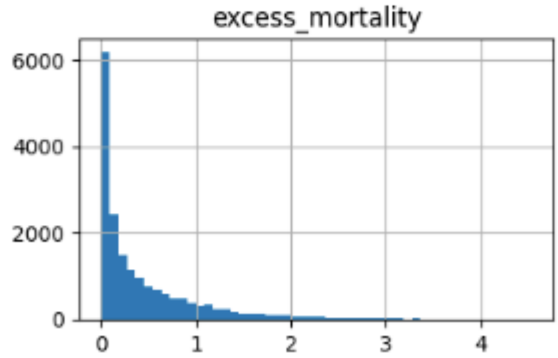


Fig. 4.5. Observations of excess mortality

However, there are still peaks of observations related to higher values of risk, so also this feature has to be kept on track, as it is anything but obvious that in future the level of risk may further increase.

4.3.2. Correlation matrix

After having completed this first analysis of the distributions of the observations present in the dataset thanks to histograms, another very important step of the EDA is the construction and analysis of a correlation matrix.

A correlation matrix is a table that displays the correlation coefficients between pairs of variables in a dataset. Each cell in the matrix shows the strength and direction of the linear relationship between two variables, with values ranging from -1 to 1. A value close to 1 indicates a strong positive correlation, meaning that as one variable increases, the other tends to increase as well. A value close to -1 indicates a strong negative correlation, where one variable increases while the other decreases. Values around 0 suggest no linear relationship between the variables.

The correlation matrix is a useful tool for identifying and understanding the relationships between multiple variables simultaneously. Once built the correlation matrix, we can try to analyze and explain some of the most interesting correlations present between our climate indicators.

The correlation matrix generated is shown in the picture below.

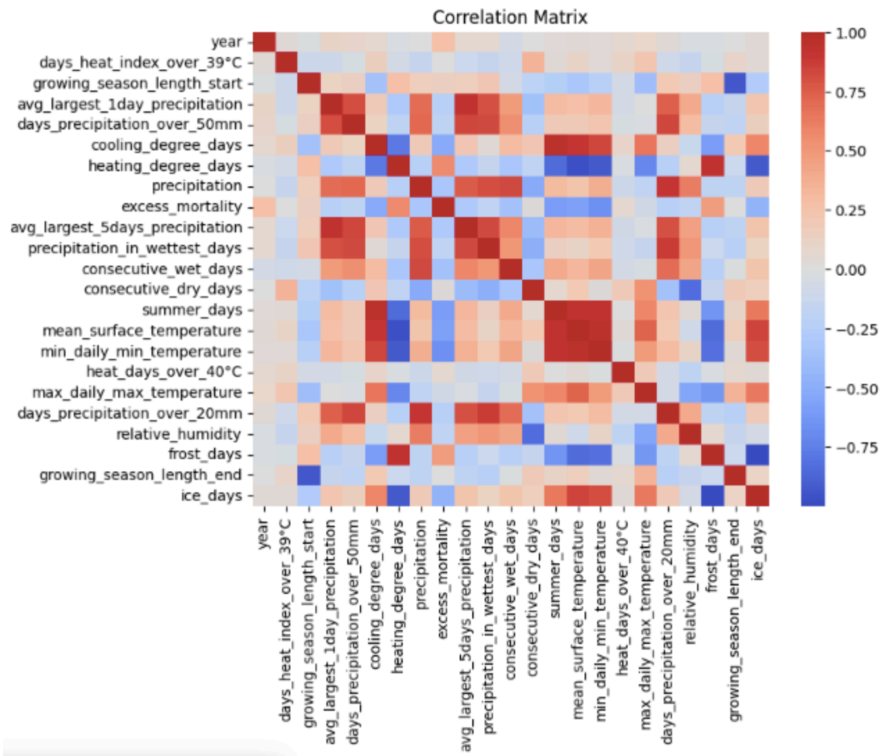


Fig. 4.6. Correlation matrix of the selected climate change indicators

Starting with the strong positive correlations that emerged, some of them regard indicators related to precipitation. The average largest single-day precipitation and the average largest cumulative precipitation over 5 days are strongly positively correlated, reflecting how extreme daily rainfalls significantly contribute to cumulative longer-lasting precipitation events. Days with precipitation exceeding 50mm are naturally a subset of those exceeding 20mm, resulting in a strong positive correlation between these two indicators. Additionally, the amount of precipitation on the wettest days shows a strong positive correlation with both the average largest single-day precipitation and 5-days cumulative precipitation, indicating that periods of extreme rainfall are crucial drivers of total precipitation during these wettest periods. These two latter indicators also strongly positively correlate to the number of heavy and very heavy precipitation days, as such strong events may be part, or even a cause, of these continuous rainfalls.

Then, cooling degree days and temperature levels, as well as summer days that indeed reflect the rise in temperatures, strongly positively correlate, as hot days imply a higher needing for cooling. This relationship, in particular, is important for understanding the energy demand dynamics in a warming climate. The contrary holds for heating degree days, that, instead, present a positive correlation with frost days (in which the minimum temperature is below 0°C).

Finally, one of the most interesting and important relationships is the one holding between excess mortality and heating degree days, together with frost days, highlighting that what represents a more threatening risk for human health and life are very low temperatures, rather than higher ones. This can be linked to the better adaptation and resilience of populations to rising temperatures, or, simply, in our dataset lower temperatures have a greater impact on excess mortality risk.

Proceeding with the most interesting moderate relationships, that are the one in the middle between strong and zero, the most evident and numerous ones are the moderate positive correlations present between temperature indicators and precipitation indicators. This is probably due to the fact that higher temperatures lead to greater evaporation of water masses, producing more precipitation events. However, there does not seem to be a proper correlation between temperature and relative humidity. Instead, a correlation exists between relative humidity and precipitation indicators, given its role in the atmospheric conditions that, actually, favor rainfall. Consecutive wet days also moderately positively correlate with cumulative precipitation indicators, as extended rainy periods contribute to higher rainfall totals. Consecutive wet days, as well as consecutive dry days, correlate to temperature indicators too, as, depending on the zone, higher temperatures can lead to more precipitation, but also to drought.

Finally, excess mortality, as highlighted before, shows moderate negative correlations with temperature indicators, but also with precipitation indicators. This suggests that, within the studied period, lower temperatures and lower precipitation are associated with higher mortality rates. As was noted before, the negative correlation with temperature may indicate that colder weather increases health risks, particularly for vulnerable populations, leading to higher mortality. Similarly, lower precipitation might coincide with drier, colder conditions that can exacerbate respiratory and cardiovascular issues, contributing to higher mortality. However, this does not necessarily mean that extreme high temperatures or heavy precipitation are harmless; rather, the data suggests that the more moderate or cooler and drier conditions present in the dataset have a more significant impact on mortality.

Concluding this part with strong negative correlations, the majority of them holds between pairs of indicators that are opposite to each other. Examples can include frost days and ice days, heating degree days and cooling degree days, growing season length start and growing season length end. The other ones are pretty trivial and imply pairs of variables in which an increase related to one of them will consequently lead to a decrease in the other one, such as, for example, heating degree days and temperature indicators.

4.3.3. Trend analysis

The last step of the EDA is fundamental in identifying historical patterns and visualize better the effect of the climate change. In fact, this preliminary data analysis ends with the trend analysis of our climate indicators. Trend analysis is a statistical technique used to identify patterns or directions in data over time. By examining historical data points, it helps in understanding how a particular variable has behaved in the past and predicting how it might behave in the future. Let us analyze and try to understand what each plot means:

- **Consecutive wet days and dry days:**

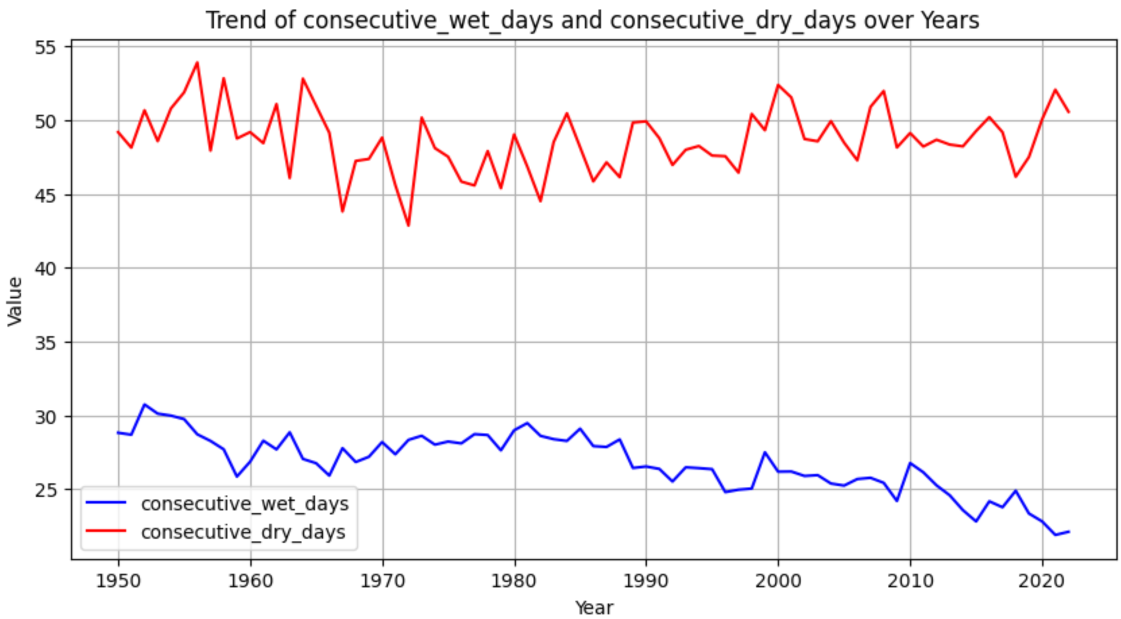


Fig. 4.7. Trends of wet and dry consecutive days over years

The two plots related to these variables show different trends; in fact, it is possible to notice that the trend of consecutive dry days has fluctuations over time with a slight overall increase in the most recent years, while the one of consecutive wet days shows an evident decrease. Trying to explain why these trends showed up, it can be said that, as the planet is getting warmer, in some regions it may be more likely to face prolonged dry periods, while, on the other hand, shifting climate conditions may lead to more frequent short but strong rainfalls; another thing to be noticed is the fact that consecutive dry days are almost double, or in some cases more than double, compared to wet days. This means that some countries experience and will continue to experience longer and more frequent periods of drought, while precipitations are becoming more and more variable, which can be harmful for people, ecosystems and agriculture;

- **Cooling and heating degree days:**

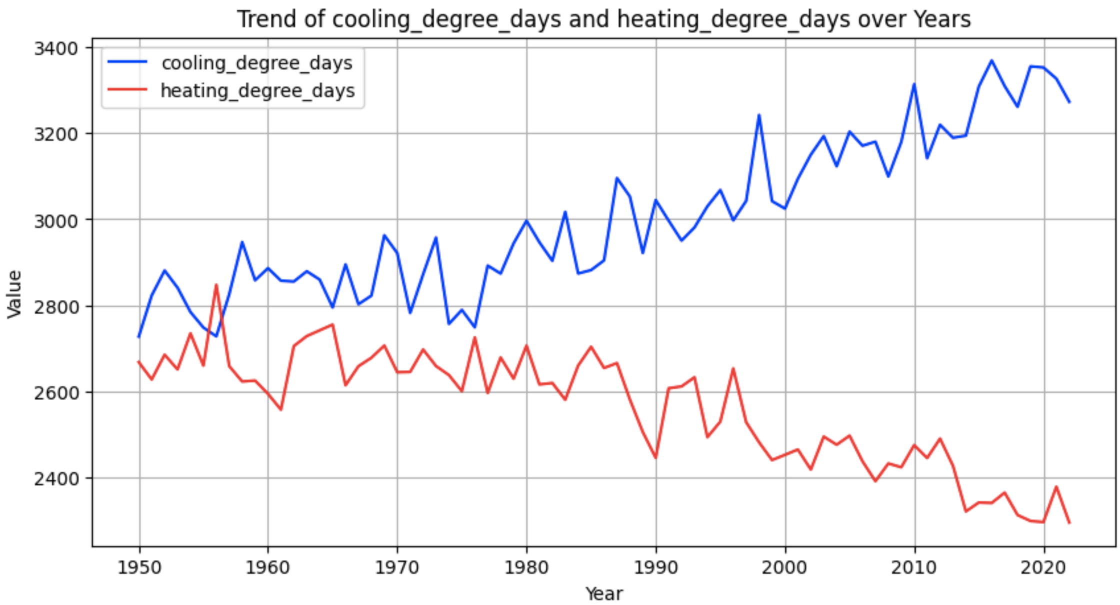


Fig. 4.8. Trends of cooling and heating degree days over years

The trend of cooling degree days has steadily increased over time, while, on the other hand, the trend of heating degree days is rapidly declining. It is important to notice that the number of cooling degree days has increased of approximately 600 globally since 1950, while the heating degree days has become approximately 350 less. This shows a growing trend in the cooling energy demand associated with climate change, together with the reduction in heating energy needing, due to the fact that winters are becoming milder. However, the increase in demand for cooling energy is way greater that the decrease in demand of heating energy, so this can lead, if not managed well, in very high energy consumption and, eventually, in more and more greenhouse gas emissions, consequently making the situation even worse;

- **Frost days and ice days:**

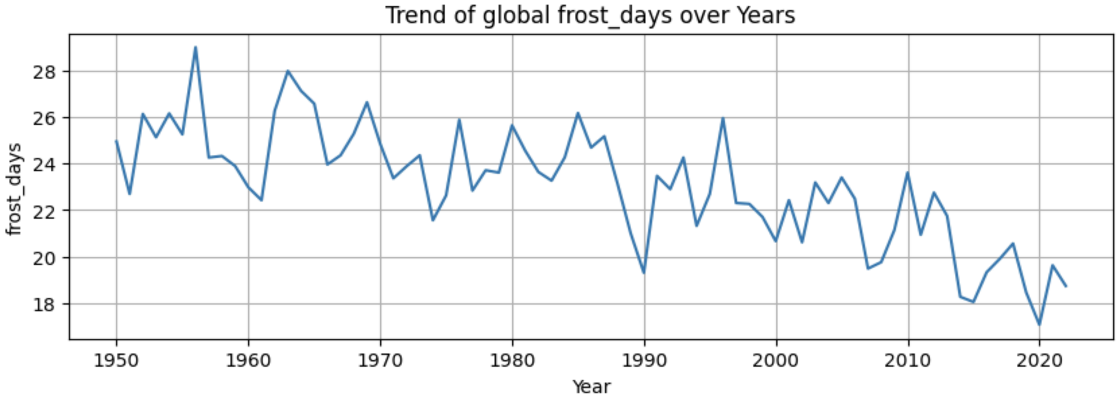


Fig. 4.9. Trend of global frost days over years

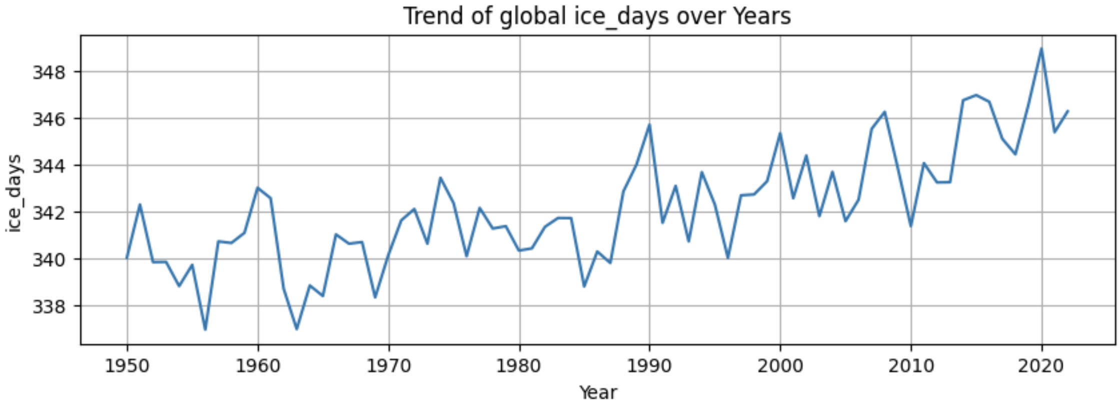


Fig. 4.10. Trend of global ice days over years

The two plots show opposite trends, with the first one related to frost days that has a decreasing nature, while the other one, related to ice days, demonstrates an increase over time;

- **Growing season length start and end:**

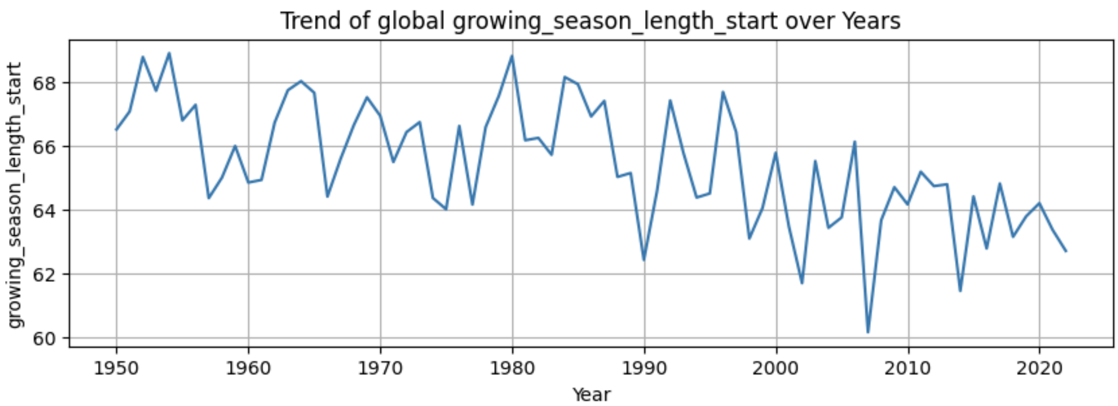


Fig. 4.11. Trend of growing season length start over years

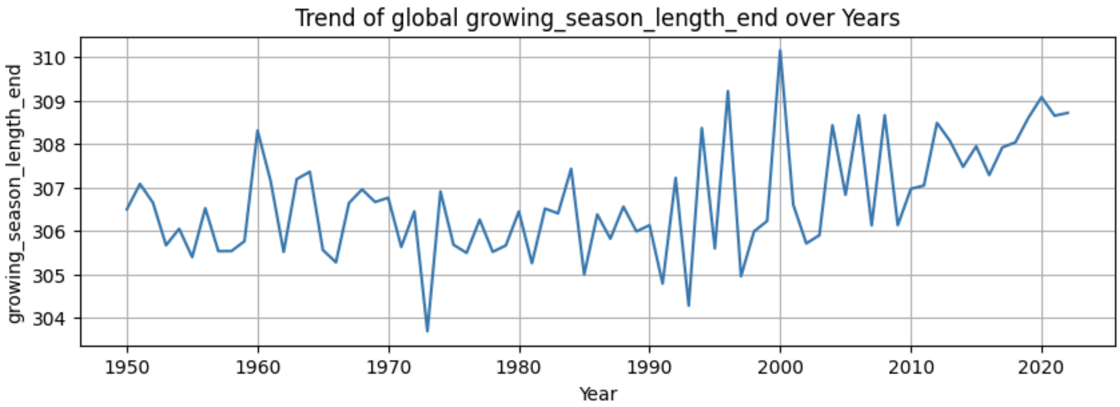


Fig. 4.12. Trend of global growing season length end over years

The first plot indicates that the growing season has been starting earlier, especially in the very last years. Combined with the second plot, that shows that growing season is also ending later, we can conclude that this longer-lasting growing season is a direct consequence of the climate change and of the warmer temperatures. This, while it could be a benefit for agriculture, may successively lead to water stress, particularly in regions already affected by water shortages, and increased presence of pests, that could affect crops, due to longer warm periods;

- **Hot days with maximum temperature > 40°C:**

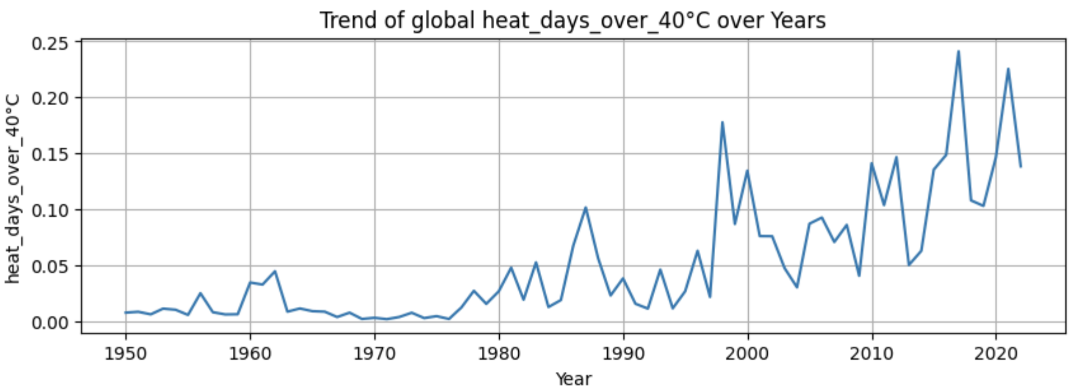


Fig. 4.13. Trend of global heat days over 40°C over years

A very interesting increasing trend that shows how hot days with daily maximum temperature over 40°C initially were 0 or slightly more, but over time became constantly more frequent, until very recent years in which were registered the peaks of occurrences of such hot days;

- **Days with Heat Index > 39°C:**

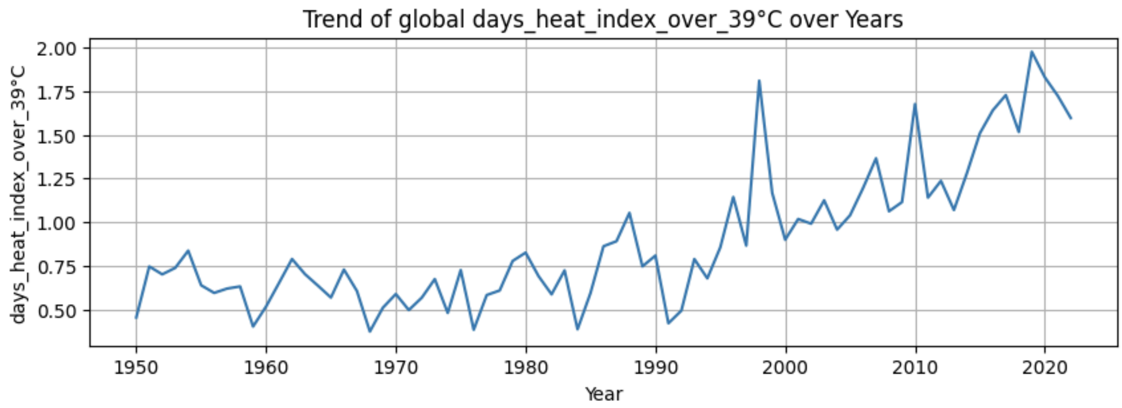


Fig. 4.14. Trend of global days heat index over 39°C over years

There is a clear upward trend, that starts to be steeper starting from 1990. The most extreme events happened in recent times, compared to the time span of our data. This trend suggests an increase in extreme heat events, which is a clear consequence of the global warming. This condition can potentially lead to high risks in public health, but also in working activities that require being outdoors and great physical efforts;

- **Relative humidity:**

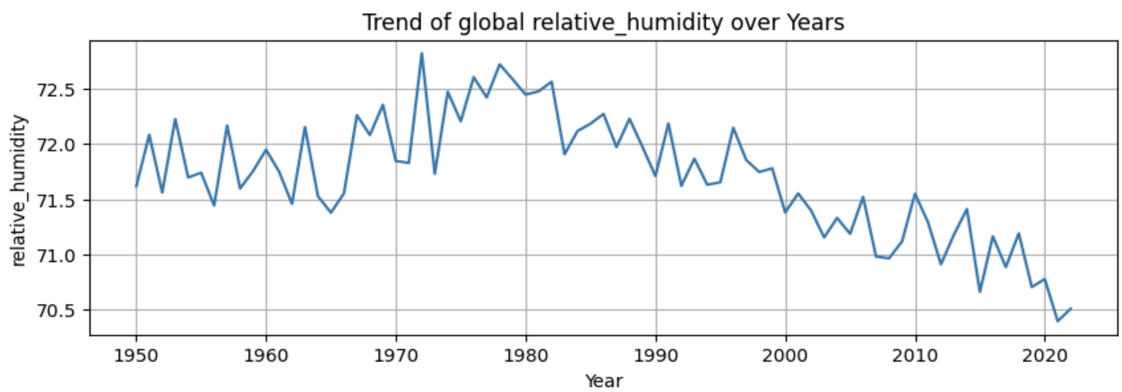


Fig. 4.15. Trend of global relative humidity over years

In the trend of relative humidity is observable a gradual decline, especially in the most recent years. This may be likely due to the fact that higher temperatures permit air to hold bigger volumes of water vapor, resulting in lower relative humidity unless the amount of moisture in the air increases proportionally. Another reason explaining this trend is the change in atmospheric patterns. With higher temperatures there is a greater percentage of moisture in the air. However, based on the areas, there could be prolonged drier periods or continuous periods of precipitation, as air circulates in different ways. So, globally, relative humidity decreased, but still some considerations regarding precises zones of the Earth have to be done. This reduction may be caused also by changes in land use. Activities, such as deforestation or urbanization, may alter the quantity of moisture present in the atmosphere, changing humidity observations.

- **Heavy and very heavy precipitation days:**

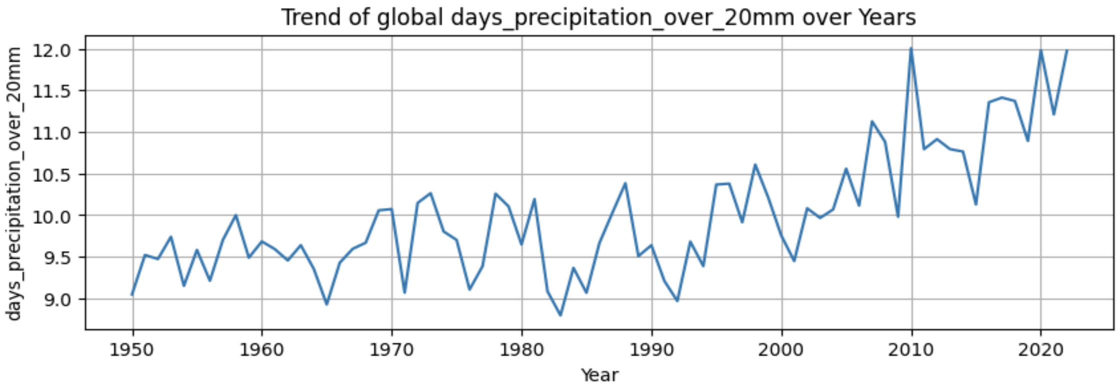


Fig. 4.16. Trend of global days precipitation over 20mm over years

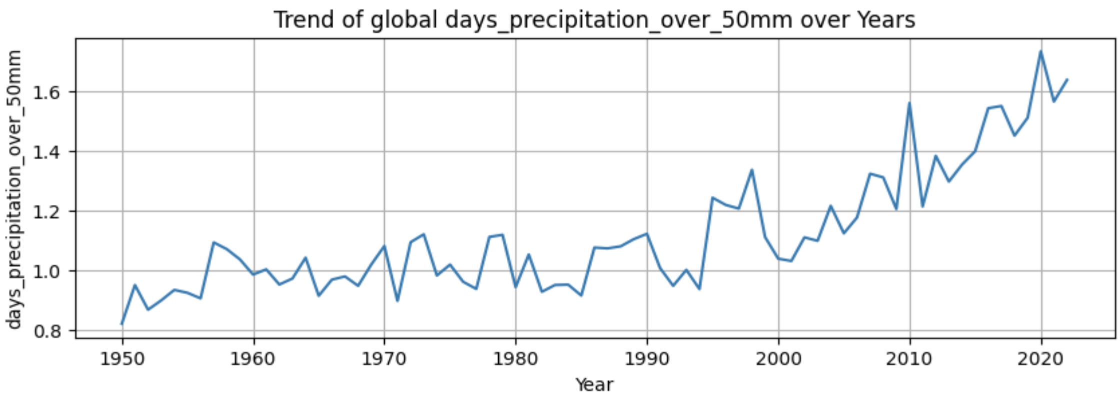


Fig. 4.17. Trend of global days precipitation over 50mm over years

Both the heavy precipitation indicators show upward trends. This up facing slope is more evident in the second plot, while the first one has various jumps, however still maintaining an increasing character. It is easy to notice that the most extreme events recorded for both the indicators happened in the very last years (in the range 2010-2022).

Moreover, the trend of rainfalls over 50mm has more than doubled since 1950. This indicates that extreme rainfall events are becoming more frequent and intense. Such events are really dangerous and can potentially lead to worse scenarios, so these trends are particularly worth keeping an eye on;

- **Precipitation in wettest days:**

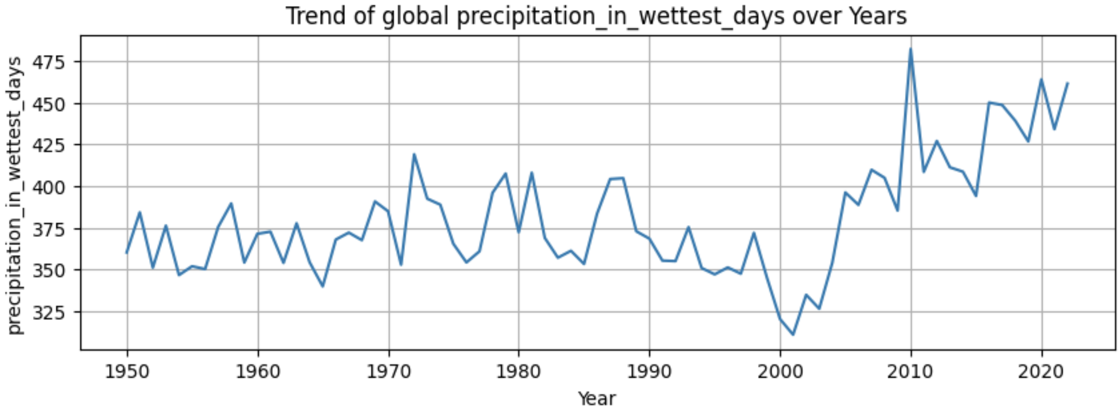


Fig. 4.18. Trend of global precipitation in wettest days over years

The plot shows a slight increase in the precipitation amount during wettest days. Also in this case, it can be an indicator of an increase of the extreme rainfall events, which is coherent with the fact that there is a more intense presence of moisture in the atmosphere;

- **Average largest 1-day and 5-days cumulative precipitation:**

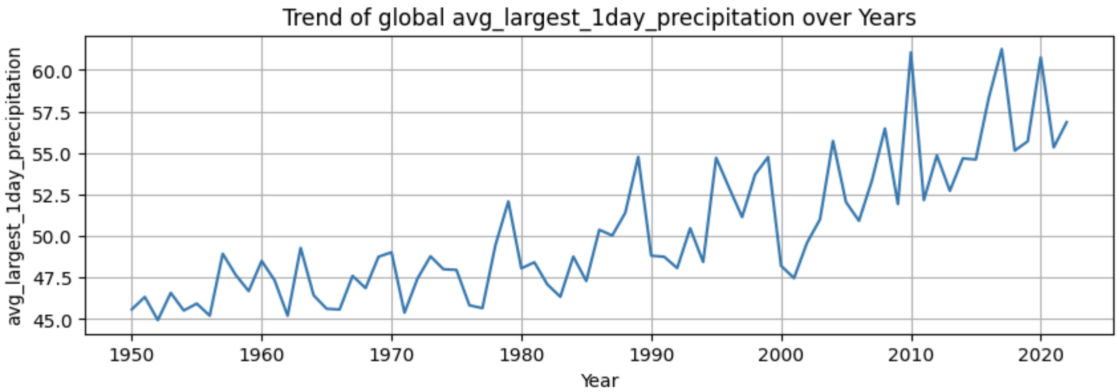


Fig. 4.19. Trend of global average largest 1-day precipitation over years

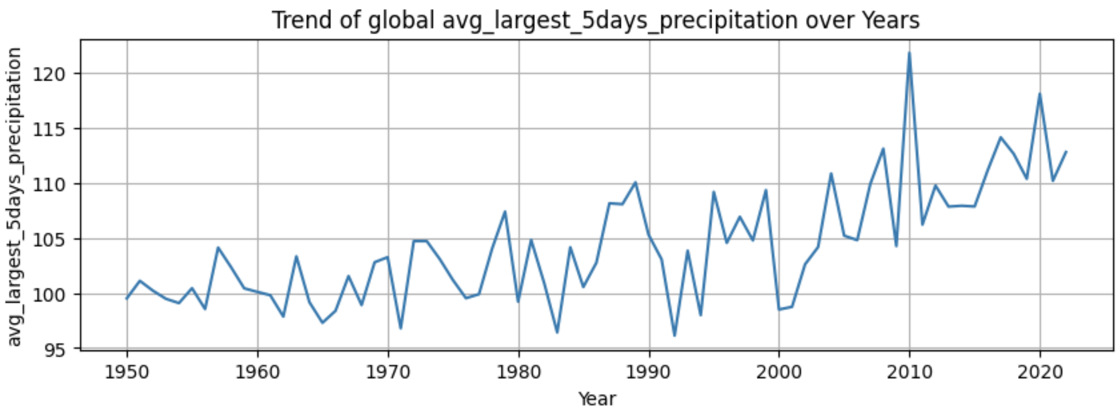


Fig. 4.20. Trend of global average largest 5-days precipitation over years

The two plots related to cumulative precipitations show upward trends. This can be seen better in the first plot, while the second one is a little more rapidly changing, but still maintains the same direction. Similar to what can be noticed looking at the heavy precipitation plots, the most extreme events recorded for both the indicators happened in the very last years. This proves the observations made above when talking about the other precipitation indicators;

- **Precipitation:**

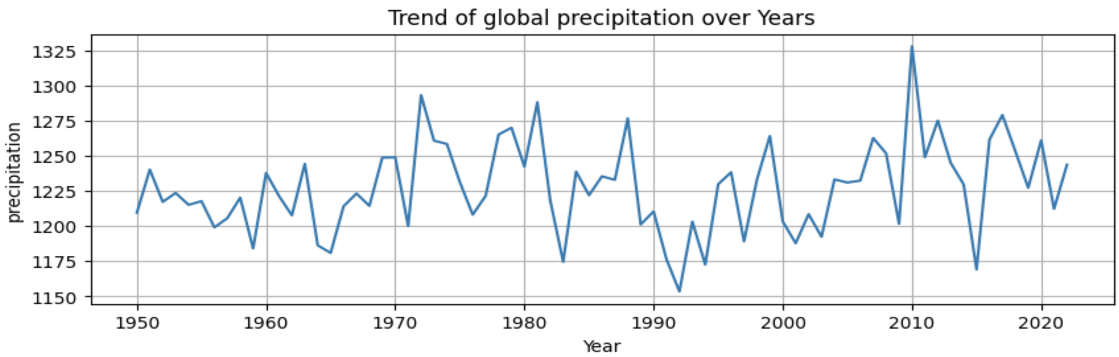


Fig. 4.21. Trend of global precipitation over years

The general trend of precipitation over the years shows variability, but there is not a strong increasing or decreasing trend, such as the ones encountered when analyzing the other precipitation indicators. However, this overall stability in average precipitation can mask the more extreme fluctuations that may have been happened. In fact, the average figures do not capture the increasing frequency and intensity of extreme precipitation events, such as heavy downpours or long periods of drought, that are very harmful for ecosystems and human activities and cannot be ignored when trying to understand the impact of climate change;

- **Summer days:**

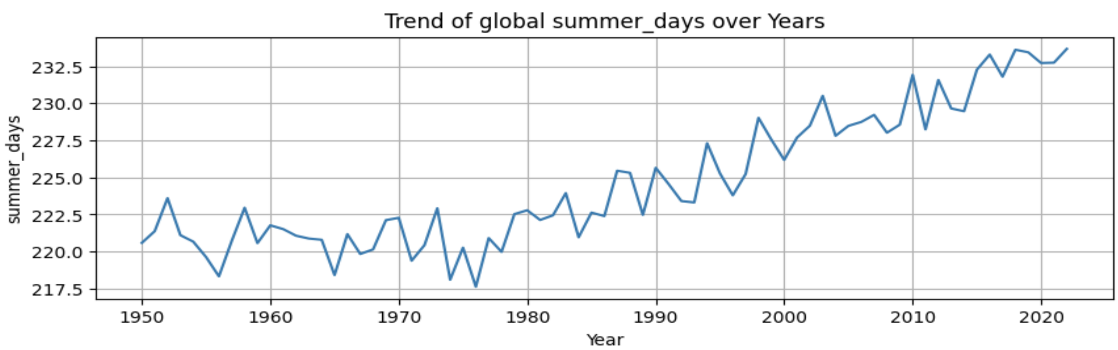


Fig. 4.22. Trend of global summer days over years

There is a clear upward trend in the number of summer days, which is direct evidence of the global warming, reflecting the overall rise in temperatures and the extended duration of the summer season;

- **Mean surface temperature:**

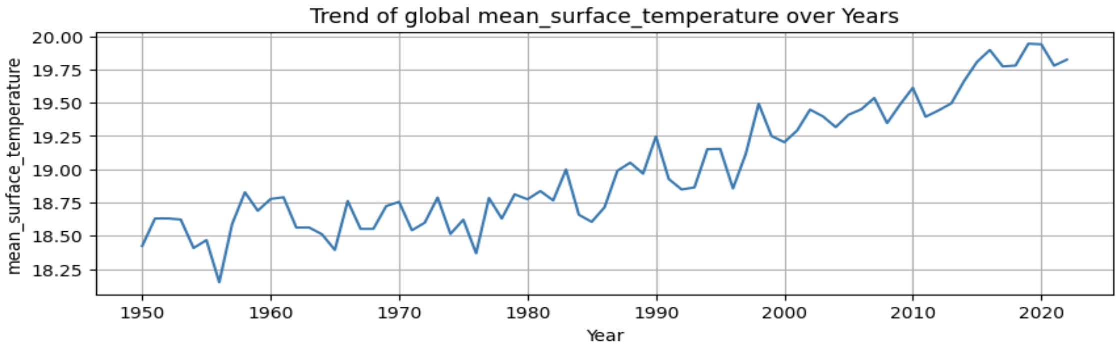


Fig. 4.23. Trend of global mean surface temperature over years

The plot shows very clearly a steep up facing trend. The global mean surface temperature passed from a mild 18.5°C dating back to 1950s becoming almost 20°C in the most recent years. This is probably the most evident effect of the climate change;

- **Minimum daily minimum and maximum daily maximum temperatures:**

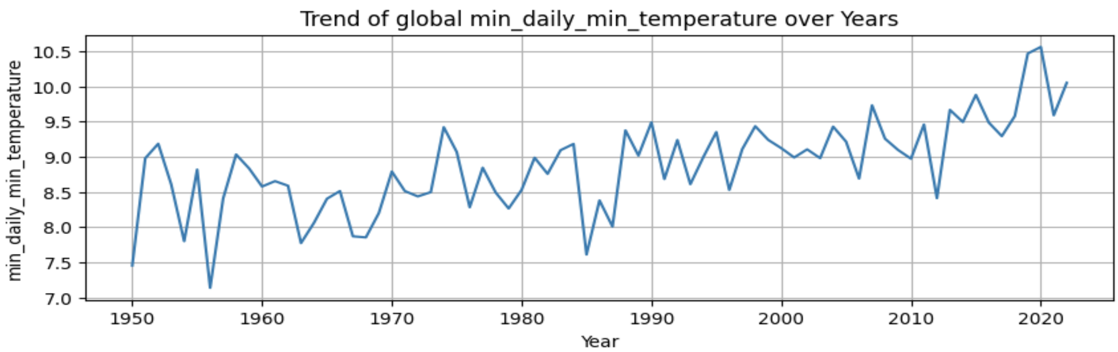


Fig. 4.24. Trend of global minimum daily minimum temperature over years

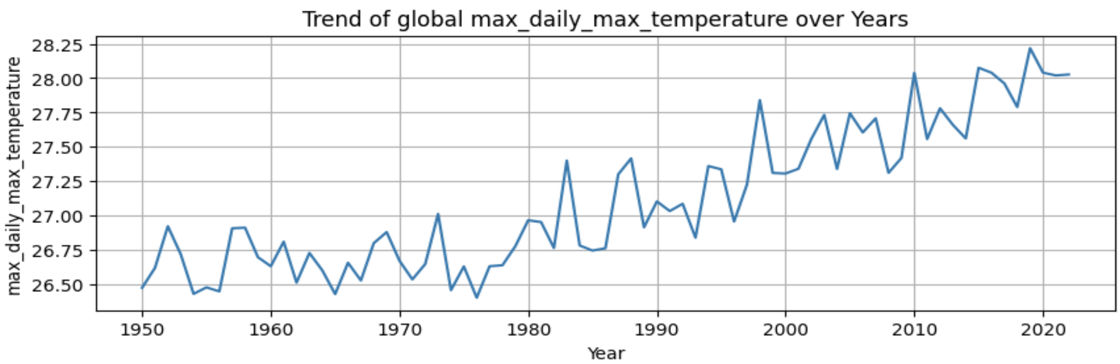


Fig. 4.25. Trend of global maximum daily maximum temperature over years

Both the trends of minimum daily minimum temperature and maximum daily maximum temperature are up facing. This can be noticed better in the second plot, that shows a more constant growth, while the other one shows more fluctuations, still keeping its upward direction. These two plots, as it is for the last two points, are the ones that highlight the most the effect of global warming;

- **Excess mortality risk:**

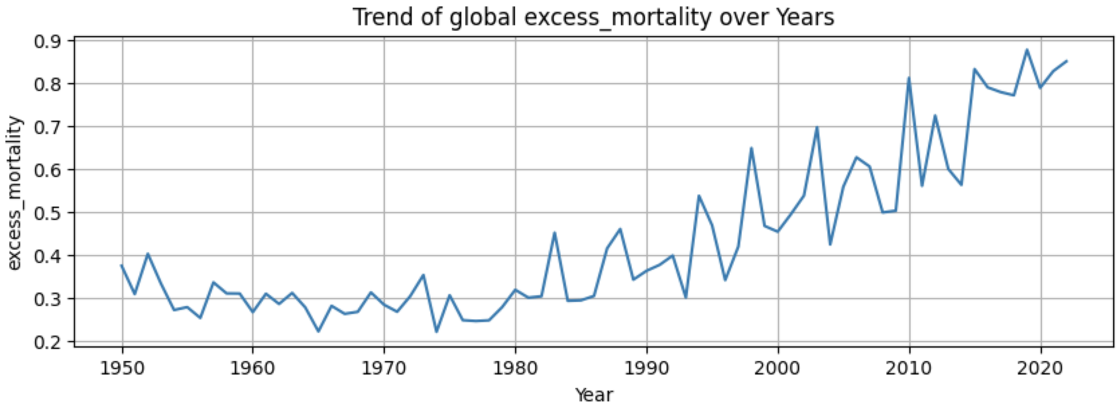


Fig. 4.26. Trend of global excess mortality over years

Also, the trend of excess mortality risk shows a gradual increase over the years. This can be interpreted as a response to various factors of the climate change and temperature shifts, such as more frequent heatwaves or cold spells or changes in disease vectors, that make living conditions worse and can have severe impacts on human health.

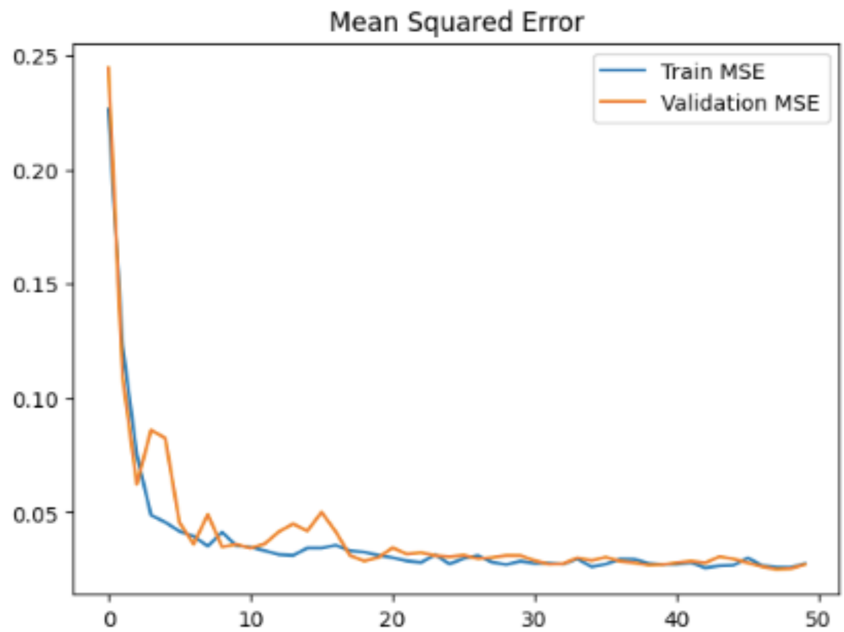
This last step concludes the EDA. Now we can shift our focus on defining, training and testing the model that will be later to gain some future insights thanks to the analysis of this time series data.

4.4. Model definition and training

In this section the focus is shifted on the definition of the model of recurrent neural network that we will use in our analysis. In particular, the aim of this analysis is expanding the trend analysis to future years thanks to the ability of these algorithms of learning from time series data and forecast future values. So, the data that will be utilized by this model is the one used just before, so the mean of data for all countries divided by years. Before doing this, having already analyzed every feature under different aspects during the EDA, now it is possible to do some feature engineering that may enhance the performance of the model. In fact, in the dataset are included all the most relevant climate indicators. However, some of them are pretty similar, so can be put together in order to remove redundant information and to reduce a bit the dimensionality, so that the model can learn faster and better. As just said, some columns are aggregated and replaced with these new generated columns. In particular, the columns that are replaced are:

- Cooling degree days are added to heating degree days forming the column "Energy consumption", in order to have a measure of the overall consumption in buildings related to temperature, both to heat and to cool;
- Minimum daily minimum temperatures are subtracted from the maximum daily maximum temperatures forming the column "Range of daily extreme temperatures", recording the range between the two extremes temperature recorded in a specific year;
- Growing season length end values are subtracted from growing season length start one forming the new column "Growing season length", which indeed measures the length of the season in which mean temperatures > 5°C. Negative values mean that, generally, in the places in which these values are recorded growing season length ends is greater than start, so occurrences of colder temperatures are most likely;
- Summer days are added to ice days forming the new column "Seasonal extremes", counting the number of days in which one of the conditions of the two indicators is verified. Indeed, a higher value means an increased number of both very hot and cold days in a year.

Now that the dataset is a bit leaner, we can proceed with the model definition. The first thing to do is to normalise the data. In order to do that, the MinMaxScaler imported from the "sklearn" library is used. This scaler simply restricts values between 0 and 1, using as guidelines the minimum and maximum extremes of every column. They are, respectively, converted to 0 and 1, while the other intermediate values are scaled based on this. Once having done this, which is fundamental to build the neural network, we can proceed with the second step of this part, which is defining sequences. RNNs are suitable for time series forecasting as they are able to learn patterns from sequential data. However, these sequences have to be created first. This is done through a function (create_sequences()), which takes as input the data wanted to be used for the time series forecasting. In order to do this, it is also necessary to specify the length of sequences, which, in this case, corresponds to a time span in years. But how does this function work in practice? It loops over the dataset and extracts consecutive “sequence_length”-sized subsets of data. These are, actually, the sequences. For each of them, the corresponding “target” is the data point immediately following in the time series. This is the value that the neural network will try to predict. This process is repeated, sliding across the dataset, until its end is reached. In this way we can fit also the two variables X and Y, which are, respectively, the independent, or “predictive”, variable and the dependent, or “predicted, variable. These two variables are, then, fitted into a, so called, “Random Forest Regressor” model. A Random Forest Regressor is an ensemble machine learning algorithm that builds multiple decision trees during training and averages their predictions to improve accuracy and control overfitting. Each tree in the forest is trained on a random subset of the data, making the model robust to noise and capable of handling complex, non-linear relationships in the data. In this case, this type of algorithm is used to select the most relevant features in the dataset. This, combined with the feature engineering previously executed, can improve the performance of the model and reduce overfitting. In this way, the RNN is able to generalize better and make more precise predictions. This new filtered dataset, then, is scaled as well, and divided in sequences, ready to fit in the model, whose definition is the following step. The model, precisely, is a Long Short-Term Memory (LSTM) Network, a particular type of RNN, particularly suitable for temporal patterns as it is designed to capture long-term dependencies. It is configured with two layers of LSTM units. The first layer has 150 units and is able to pass the output to the second layer, which has less units. Moreover, after each layer of LSTM units, there are the so-called “Dropout” layers, which are useful to prevent overfitting. This happens, as they drop a part of units in the training phase. The final layer, called “Dense”, has as many units as the input features and is used to produce the final predictions. After having constructed and declared the model, the following step consists in training it by fitting the previously prepared data into it. The training consists in two stages, which are the effective training and the testing. The training is done on a part of the data, which can be specified in the code of the model and in this case is equal to the 80% of the dataset, and is executed on data already known by the algorithm. The test is executed on the remaining part of the dataset, which is obscured to the algorithm, and it has to do predictions based on the pattern learnt during the training. The final performance is measured by the metric "Mean Squared Error" (MSE). In the following figure it is possible to see how the model learns during this process.




```
Final Train MSE: 0.027619419619441032, Final Validation MSE: 0.027216751128435135
```

Fig. 4.27. Mean squared error

The model is performing reasonably well, so it is ready to "predict the future". To do this, the model starts from the last sequence and goes further until the limit specified. In our case, the focus concerns a short/medium-term future, as we want to analyze the immediate consequence of a bad action. So, the predictions are calculated until year 2050. In addition to this, some noise is added to forecasting. Without the noise, we assume that the situation of external factors will remain the same for the following years. However, in reality, unfortunately, things are not like this. So, the noise represents this upcoming change in external factors (that could be an approximation of quantity of greenhouse gases in the atmosphere, overpopulation, land use, etc.). Finally, output data is re-scaled to the original form using the same scaler and used for plotting. Let us analyse and comment the output.

4.5. Analysis of the results

The results deriving from the RNN model are shown in the following plots. It is possible to see for each feature present in the output, indeed the ones selected through the application of the Random Forest, the real past trends together with the future outcomes predicted by the model. Let us analyse and try to explain each one of them.

- **Energy consumption:**

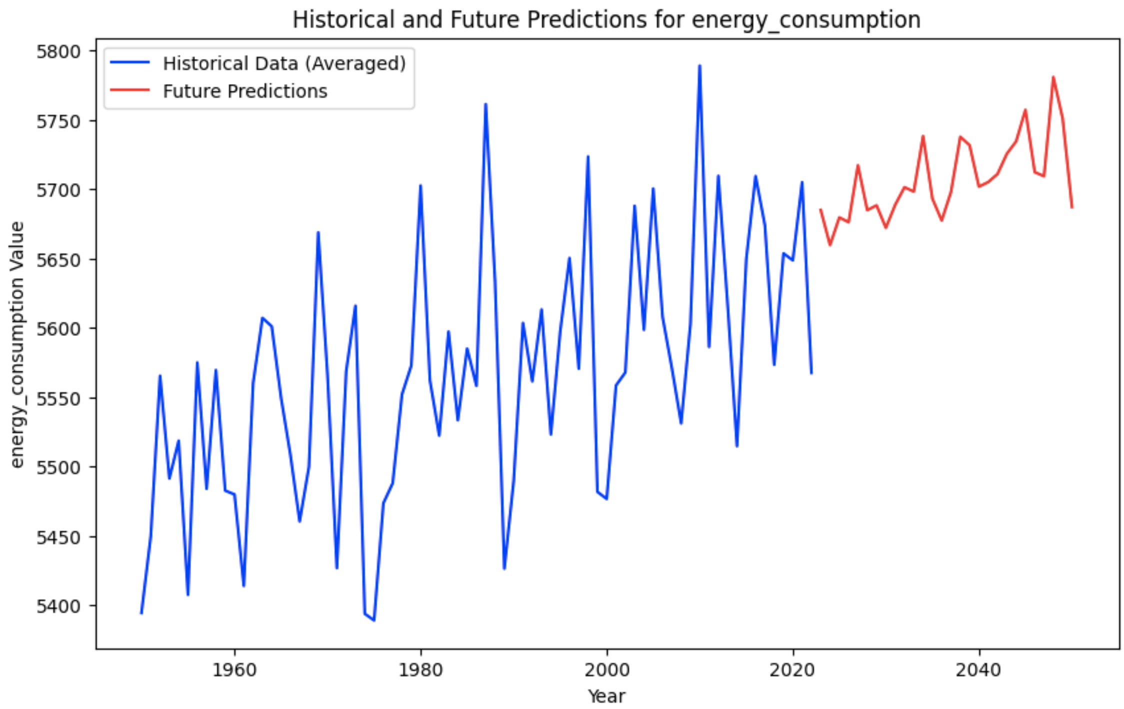


Fig. 4.28. Future trend of energy consumption

The model predicts a clear increase in the future trend of energy consumption. This may be very likely to happen, as one of the main consequences of climate change is the increase in occurrence of extreme temperatures, both in hot and cold directions. So, in the future, this effect may be further amplified, leading to higher and higher expenses and energy consumption, in order to heat or cool down buildings.

Referring, to the trend analysis addressed earlier, in which it was evident that cooling degree days are much higher in values with respect to heating degree days, we can state that most of the energy consumption forecasted for the future will be concentrated against hotter temperatures. This is a clear example of how the effects of climate change can arise problems to ordinary people not just in terms of health, but also economically. People are forced to use enormous quantities of energy. In turn, the production and delivery of such energy, if not managed well, feeds climate change and global warming. It is a vicious circle that absolutely must be ended as soon as possible;

- **Hot days with maximum temperature > 40°C:**

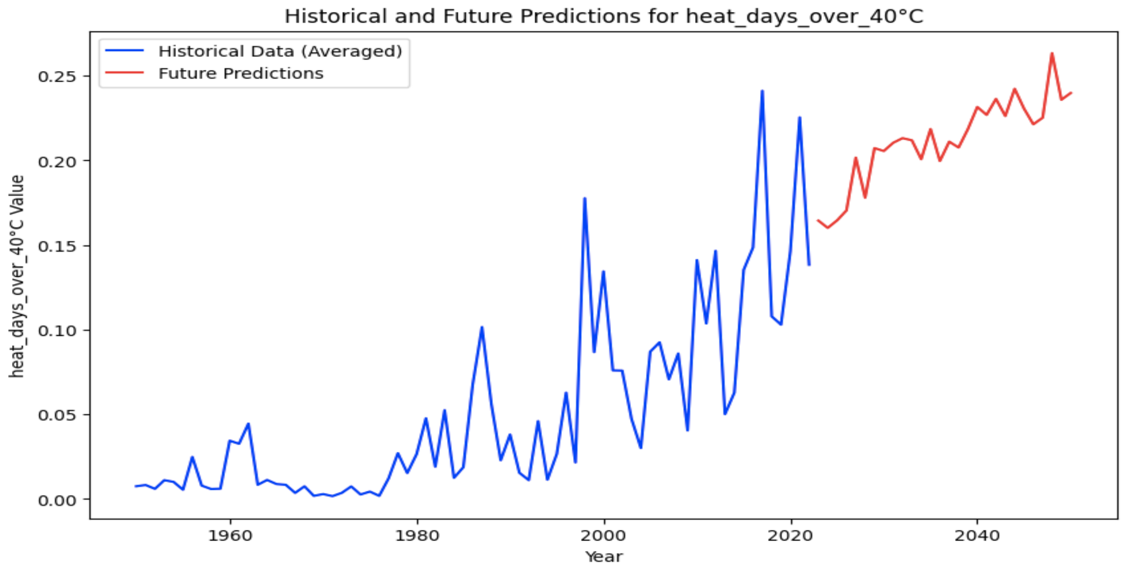


Fig. 4.29. Future trend of heat days over 40°C

The trend in number of days in which maximum temperatures surpassed 40°C had very high peaks in the last years. For what concerns the future predictions, they seem to follow this trend and reach the same levels of these peaks in the following 15/20 years, even surpassing them in the next future. This demonstrates the very high ratio at which temperatures are rising and how days with such extreme temperatures are more likely to happen;

- **Days with heat index > 39 °C:**

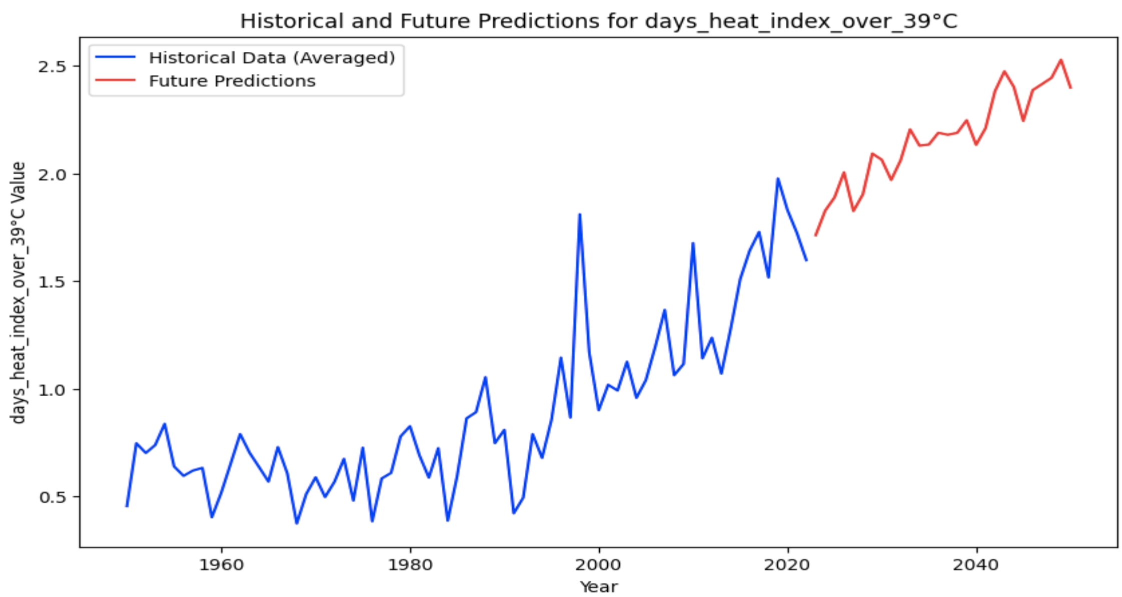


Fig. 4.30. Future trend of heat days over 40°C

The future predictions regarding days in which heat index surpasses 39°C show a more evident increase with respect to the previous indicator, which regarded very hot days. This difference derives from the fact that heat index considers the perceived temperature. So, we can conclude that, although the number of days in which the temperature effectively will be higher than 40°C will increase, the number of days in which we will perceive a such high temperature are going to be still more. This may be linked to the change in humidity present in the atmosphere. In fact, with hotter temperatures, evaporation of water will be enhanced. This phenomenon, together with increasing the amount of annual precipitation, as we will see next, contributes a lot in making us perceiving a hotter and more suffocating temperature. A mix of the increase in overall temperatures and of the levels of humidity in the atmosphere more or less explains the trend shown in the plot above;

- **Precipitation metrics:** all the plots regarding rainfall events follow the same trend that there has been in the past years.

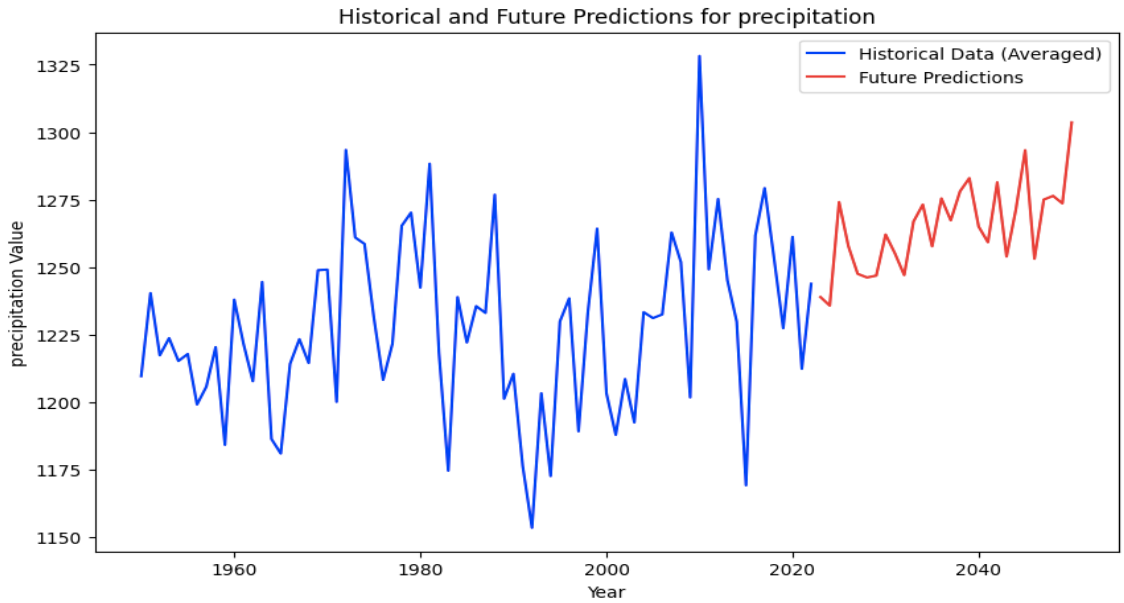


Fig. 4.31. Future trend of precipitation

The predictions regarding overall precipitation show that there will be an important increase in the amount of yearly rainfall in the short-term future. Together with it, there will be a higher probability of extreme rainfall events, such as typhoons or hurricanes, and the risk expands for a prolonged time, as can be seen in the plots regarding heavy (>20mm) and very heavy (>50mm) precipitation events and cumulative precipitation.

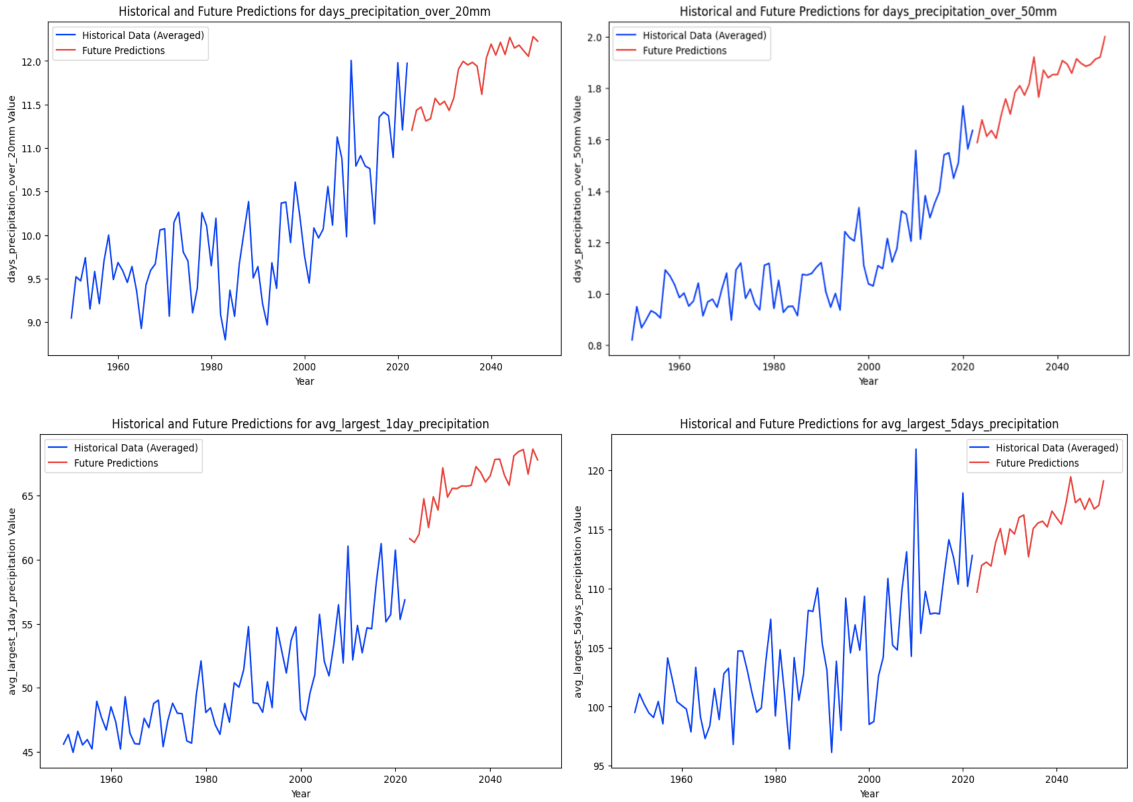


Fig. 4.32. Future trends of precipitation

The same identical trend is found in the plot regarding precipitation in wettest days.

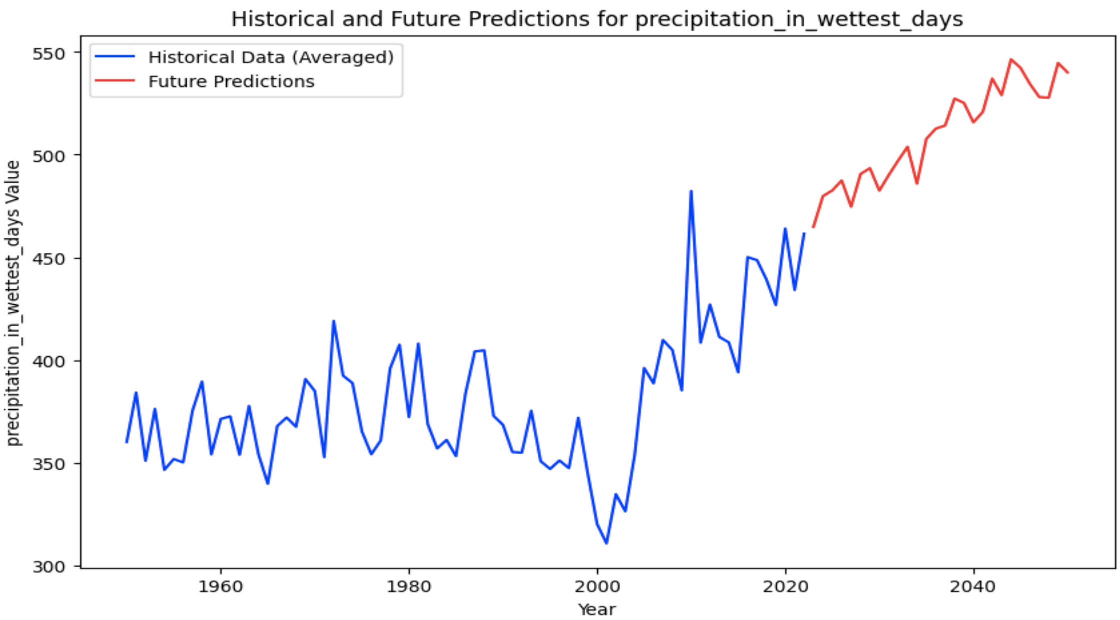


Fig. 4.33. Future trend of precipitation in wettest days

Such events threaten millions of lives every year. Connected to them and depending on the terrain type in some zones, there could be also a higher probability of floods or mudslides, which can be equally dangerous. These risks should absolutely not be underestimated. In cases like these ones, it is necessary to plan everything in advance. It is needed to identify the areas most exposed to risk, understand the nature and the most likely period in which these events may happen and study proper evacuation plans and protection measures. Remembering that this is only an approximation, when actually dealing with these types of analysis, the precipitation metrics, together with weather forecasts, are among the most important feature to treat;

- **Mean surface temperature:**

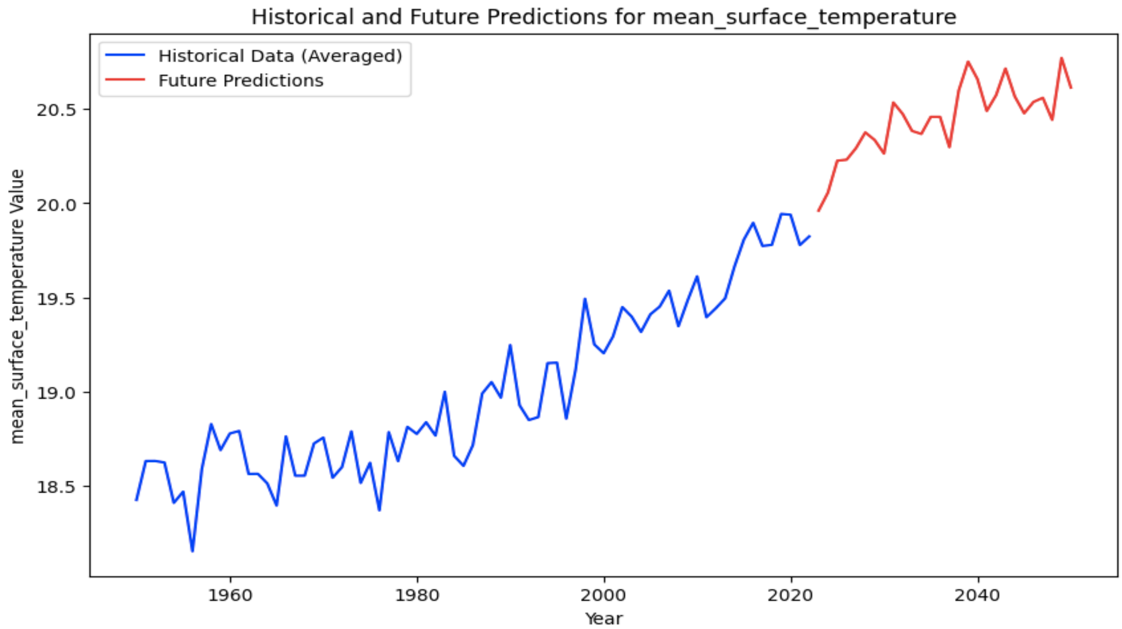


Fig. 4.34. Future trend of mean surface temperature

This is the most obvious trend. The plot shows what we already know is happening and will happen in the next years. What has been foreseen by the model is the inevitable overall rise in temperatures. This is, clearly, just an estimation. The actual temperatures that we will face in the next years could be slightly higher or lower.

However, there is no doubt that temperatures are rising without a hint of falling. At this rate, assuming with good hopes that it will not get worse, it cannot be ruled out that we might exceed the limit of 1.5°C above pre-industrial levels imposed by the Paris Agreement before than what we expected;

- **Range of daily extreme temperatures:**

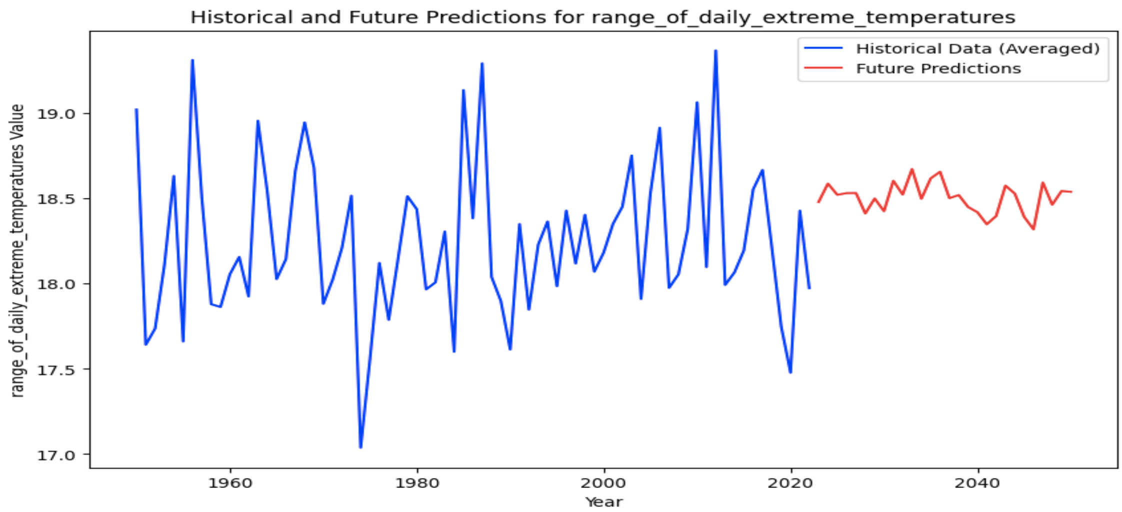


Fig. 4.35. Future trend of range of daily extreme temperatures

The plot shows how the predictions regarding this feature do not have the same fluctuations present in the historical data. This is due to the fact that we used a very basic model. More advanced models may be able to capture this variability, that we only approximated using predictions with some noise. However, the pattern of the future outcomes seems to re-create and follow the historical one. Although not having the most prominent peaks shown in the historical average, the predictions more or less stay on the same average of values, meaning that the ranges in between extremes of daily temperature may not vary a lot;

- **Consecutive dry days:**

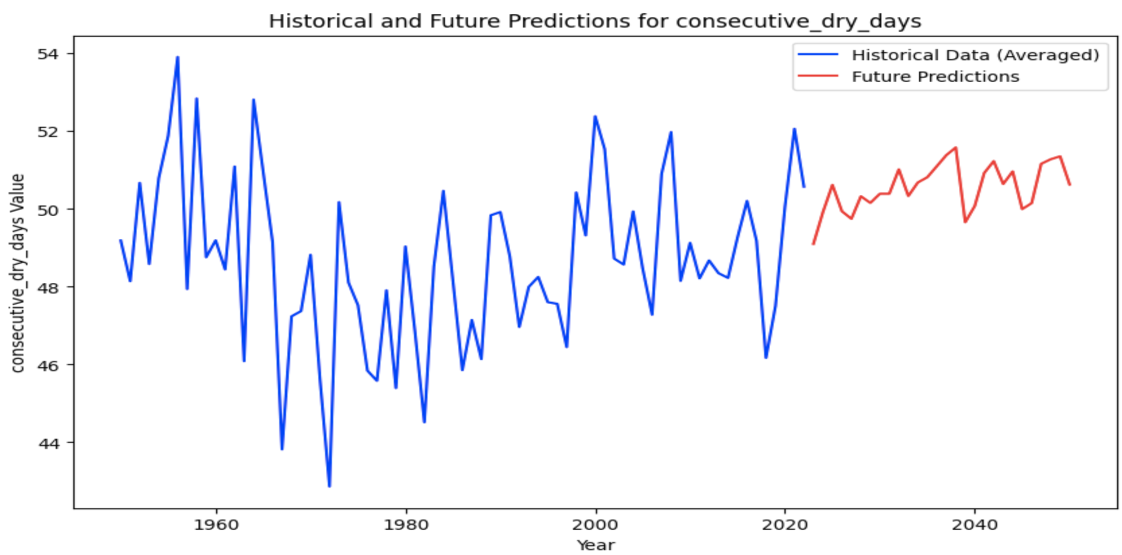


Fig. 4.36. Future trend of consecutive dry days

Also in this case, the future outcomes do not show a very important increase in the number of consecutive dry days. Instead, they remain on the same level, if not lower, with respect to the historical data. This can vary based on the areas of the planet. In fact, based on the biome of the different areas, these latter may be more likely to face periods of prolonged drought rather than cumulative precipitation events and vice versa.

4.6. Identifying crucial areas

The last part concerning the model just created consists in identifying, based on the results described above, the countries that face the highest risks in order to have an idea on where the priority of action should be focused. This is done by finding for each feature took in consideration for the model the 10 countries that, on average, have the highest values. This process takes only in consideration the historical data, as we can assume that the biggest consequences deriving by the future climate conditions are going to be suffered more in countries that already have to face extreme situations. Obviously, the main focus will be on precipitation features, as they are the most threatening event, especially if we think to cumulative and very heavy precipitation. In this regard, following there is shown the plot showing the 10 countries that on average have recorded the highest amount of overall precipitation, historically.

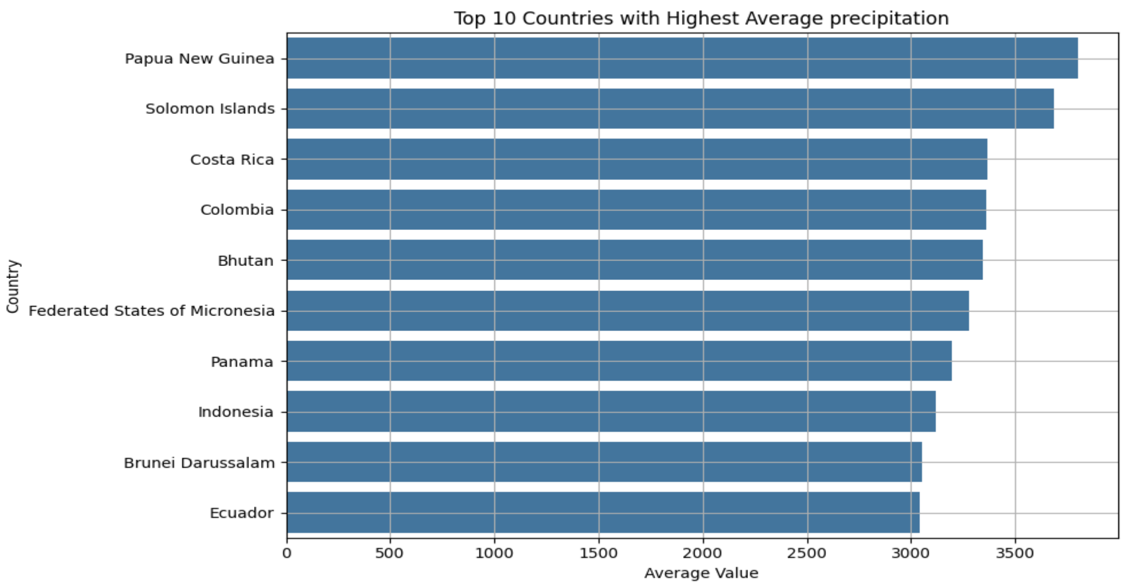


Fig. 4.37. Top 10 countries with highest average precipitation

The average values of precipitation are very high, considering they are around 3000mm, with peaks of over 3500mm in Papua New Guinea and in Solomon Islands. Just to make a comparison, the average precipitation recorded in Italy from 1901 until 2022 equal 829.27mm. So, we can conclude that these are the areas that in future may have problems in adaptation and mitigation related to rising amounts of precipitation. So, it should be correct to always keep an eye on these threatened zones. In particular, looking at the plots regarding heavy and very heavy precipitation, we can conclude that the countries that face the highest risks of facing extreme events are Bhutan, again Papua New Guinea and Costa Rica.

A complete analysis includes assessing the effective vulnerability of threatened countries. As these countries face these events almost every year, it could be possible that inhabitants are provided of safe infrastructures and eventual evacuation plans. However, we are not so sure about the efficiency of such aspects. Moreover, it is not sure whether the very likely we do not know whether the increase in the number of these events will be countered by an improvement in these systems or whether inhabitants will have difficulty in doing so. Another very important aspect to be considered is the energy consumption. As we already saw, the global average energy consumption is set to rise. Let us see the countries that, historically, have used the greatest amount of energy (actually, how many cooling and heating degree days together occurred).

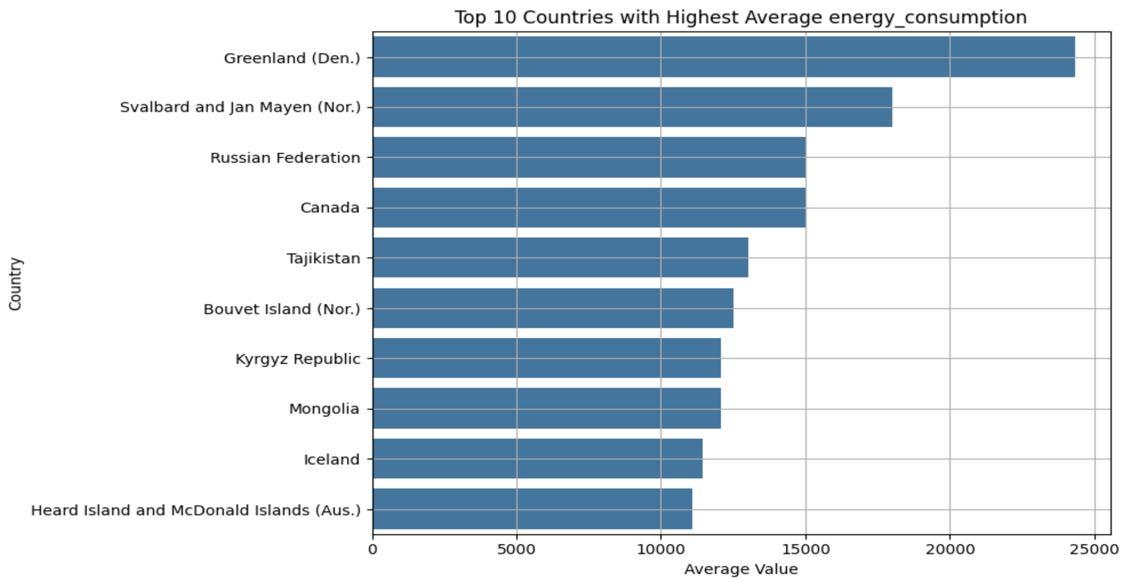


Fig. 4.38. Top 10 countries with highest average energy consumption

These countries face extreme temperatures depending on the season. So, it is normal they will have a higher energy consumption in future, with the increase in temperature anomalies. In this regard, it is fundamental to understand how much the energy consumption costs in these countries and how much it contributes to the emission of greenhouse gases in the atmosphere. So, it would be necessary to understand how the energy systems in these countries work and try to enhance them, together with trying to rely on "greener" sources of energy, but in a way that the need for this latter still remains satisfied. Finally, doing some general considerations about temperature indicators, following there are the plots regarding, respectively, mean surface temperatures and ranges between maximum daily maximum and minimum daily minimum temperatures.

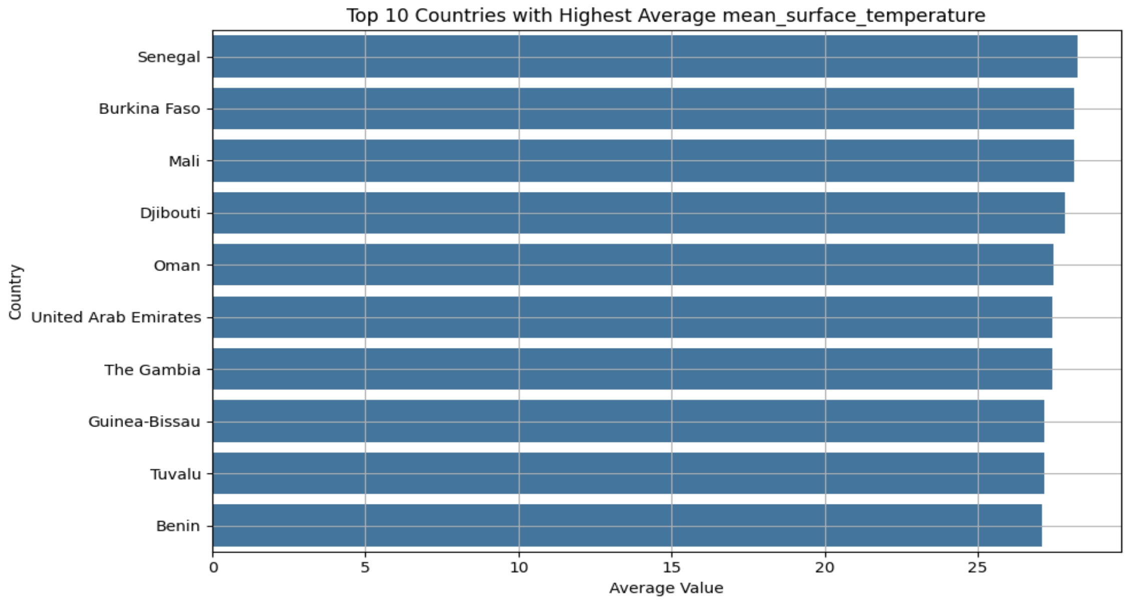


Fig. 4.39. Top 10 countries with highest average mean surface temperature

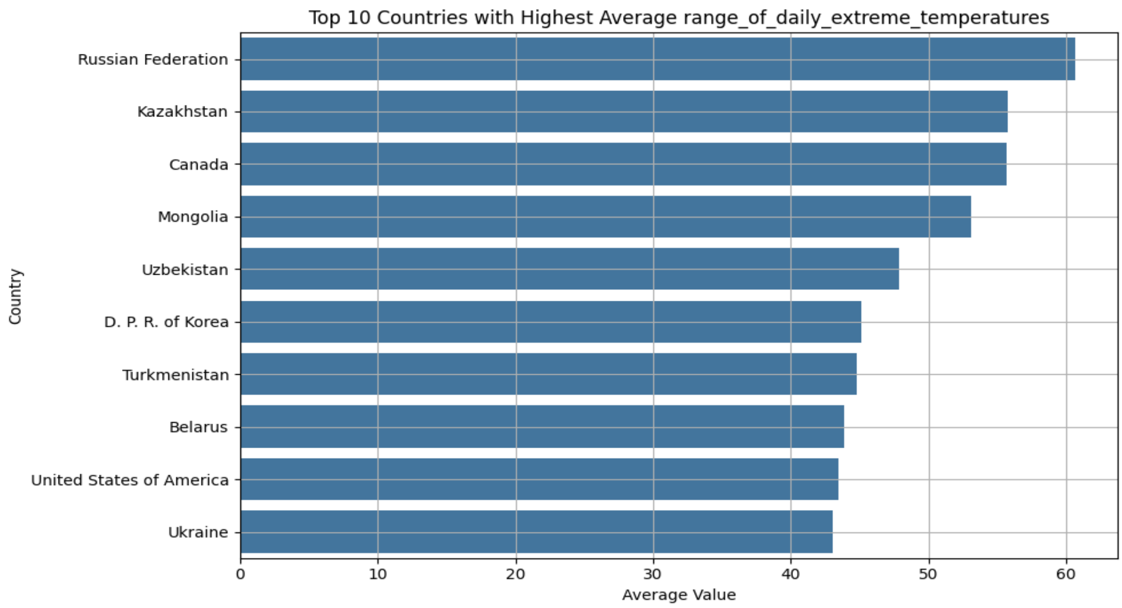


Fig. 4.40. Top 10 countries with highest average range of daily extreme temperatures

Looking at the first one, we can easily locate the countries shown. They are all African countries, more or less next to the equator. So, it is trivial to find such high values in countries like this. However, there is some uncertainty about the fact that the future rise in overall temperatures will not cause problems to people in these countries. Obviously, they are more used to such values than us that live in a different environment, however there is no certainty that a further increase will not jeopardise their living conditions. Switching to the other plot, which, instead, shows the countries that have recorded the biggest differences, on average, between maximum and minimum daily temperatures, we can notice that some of the countries shown (Russian Federation, Canada, Mongolia) were present in the energy consumption plot as well. This, at least partially, demonstrates that a higher energy consumption may be linked to greater temperature anomalies. Other countries, such as USA or Kazakhstan, are well-extended, so the temperature anomalies can be reconducted to different zones of the same country. What is certain is that in future these anomalies will be on the same level or, even, more frequent and, especially in these countries, the effect of this eventual increase in occurrences will be evident. So, people have to be prepared to adapt to these changes. This adaptation mainly relies on energy systems as the best way to do it is through cooling and heating. Consequently, energy supply and generation in these countries has to be well-functioning, as well as least polluting possible.

5. Future expectations of experts

Let us conclude this analysis with an overview of the actual future expectations of experts in this field. In this way, we can compare the results obtained from the model to understand if what emerged is reliable, together with assessing other possible future problematics and how to act to limit them. According to Copernicus Climate Change, the temperature limit set by the Paris Agreement of 1.5°C above the pre-industrial levels can be overcome within the next 10 years. If the temperature continues rising with the trend that has had until now, the limit could be surpassed in December 2032.

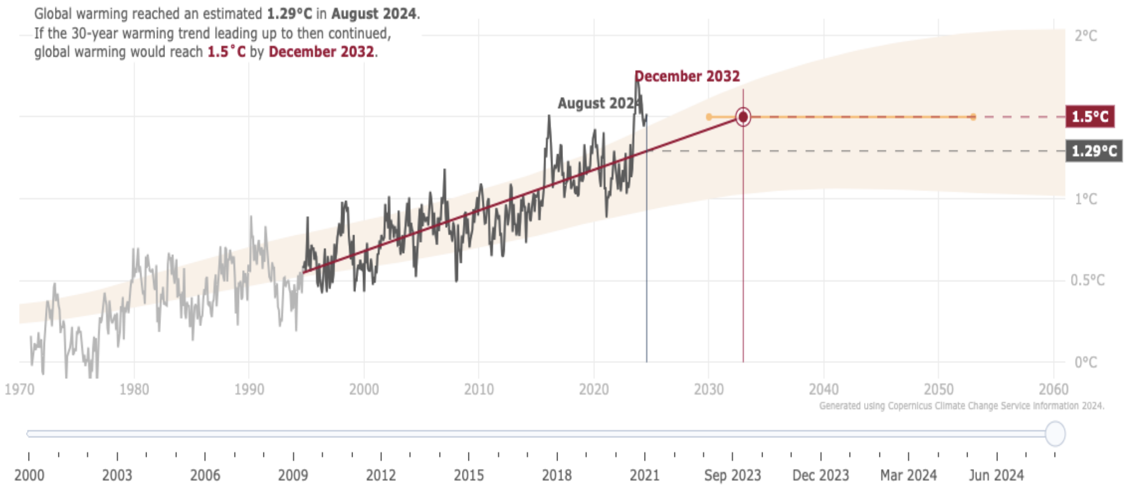


Fig. 5.1. Estimate of trend of global temperature

But what is more concerning is the fact that this trend is worsening with time, so it should not be excluded that this limit can be exceeded even before that date. And not only, according to various studies, the current policies can potentially lead to a future global warming exceeding by 3°C the pre-industrial levels, which is a threshold surpassed 3 million years ago for the unique time in history. If we think at the consequences of a 1.5°C warming, they are potentially very harmful for several ecosystems and economic systems around the world. Not to think to the consequences related to a far worse scenario. According to a report stated by IPCC, with this rate of warming, mid-latitude regions would experience extreme temperatures very frequently, associated with a substantial increase in occurrences of heatwaves, causing health risks to people in almost every continent in the world.

Moreover, as emerged also in the approximation above, there would be more frequent and intense precipitation, together with more powerful extreme events. In addition, the probability of severe droughts and risks associated with water availability increases with together with the increase of the temperature. This threatens especially developing countries, that could be more exposed to poverty and more vulnerable to extreme events. In fact, for global warming from 1.5°C to 2°C, risks across energy, food, and water sectors could overlap spatially and temporally, creating new hazards, exposures, and vulnerabilities that could affect increasing numbers of people and regions. However, these risks are faced also by well-developed countries, that must absolutely not underestimate them, and, on the contrary, act in advance to limit the potential damages. Always according to IPCC, another issue is associated to the loss of arctic ice. Direct consequence of this is the rise of sea levels, that can touch peaks of 0.04 up to 0.16 m, which, without sufficient adaptation measures, can be a severe threat for more than 10 million people.

Furthermore, ecosystems are already getting damaged, but with temperatures rising above the 1.5°C critical level, there would be much more severe damages, related especially to desertification. In fact, in particular, above 1.5°C, an expansion of desert terrain and vegetation would occur in our Mediterranean biome, causing changes unparalleled in the last 10,000 years. For what regards, instead, economic consequences, a recent study revealed a global GDP loss of 10% if the planet warms by 3°C. This study does not account for variability and extremes, that can further increase the global economic losses. Already limiting the global warming to 1.5°C we can reduce global losses related to climate change by two thirds. According to this study, only extreme rainfalls account, on average, for a 0.2% loss of global GDP, that currently would be equal to $200 billion. If we also consider all the other extreme consequences, limiting the climate change would be fundamental in order to save not only millions of lives, but also hundreds of billion dollars worldwide.

6. Conclusions

Finally, we have come to the conclusion of this thesis. Resuming all, climate change is probably the most impactful and continuous event on earth. It is something that is ongoing from the last century and whose consequences represent a constant threat to living beings on the planet.

The worst aspect of all this situation is that, although it has been going on for a long time, there have not been major improvements. In fact, it is getting worse by the day. There is an urgent need for a turnaround. Maybe this turning point can be represented by the Artificial Intelligence itself, together with the technological development deriving from it. All these new powerful technologies have an incredible potential, applicable in every field of our lives. So, they can be crucial in dealing such a big and worrying problem. We are only at the beginning of the technological revolution that sees at its core Artificial Intelligence and Machine Learning, so it is obvious that the biggest improvements are yet to be discovered and developed.

However, are we sure to still have time to act? The situation is already very critical and we are far from making it better. On the contrary, every year sets new records regarding each climate indicator and the predictions, as we proved even if approximately, follow this ascending line. All the studies and the conferences the institutions do demonstrates that there is a possible solution. All these technologies finally represent a mean thanks to which we can arrive at this solution. There is a need to act as soon as possible, before a no-return point is reached.

The new adaptation and mitigation strategies that have been developed, enhanced by the advent of these new technologies, are a good start as, if planned well, they are capable of preventing a huge number of losses, both in economical and vital terms. In this way, people in threatened areas are able to understand when there is a risk associated to their zones and act accordingly. At the same time, people should try to reduce their contribute to daily greenhouse gases emissions and energy consumption, even if in these conditions it may be difficult in some cases.

AI can be crucial when planning adaptation and mitigation strategies because, as we saw in the practical application, it is possible to identify temporarily and geographically the risks and the zone to which it is necessary to pay attention. Further developing makes possible to have a more precise climate model with enhanced functionalities. Thanks to Machine Learning models it is possible to assess different scenarios, based on the level of risk, and to plan in advance the measures to apply for each risk-based scenario (adaptation). Moreover, it is possible to make further predictions taking into account different climate indicators and also understand how the effects of climate change vary based on their variation. For example, policymakers are able to know by how much the temperature could fall or slow down the increase by limiting to a certain value local emissions or planning better energy consumption or land use as well (mitigation).

Artificial Intelligence, in this sense, is offering us the path to follow to do great improvements in climate action. However, there are still some hurdles to overcome.

The biggest ones are unavailability of advanced technologies and correct strategy planning in every area of the planet and inequalities, especially with developing countries. These latter, in particular, have to rely on richer countries to be included in global plannings and data gathering, as they do not have the means to act for themselves locally. In an interconnected world, countries that cannot rely on such technology remain disadvantaged compared to the other ones and this contributes to the slowdown in actions. Fighting against climate change, therefore, requires a lot of collaboration among countries and the contribute of every individual to make the situation better. The development and use of these technologies must be promoted worldwide. Policymakers should rely on them when they make decisions and governments should act locally to mitigate the effects and to adapt to the change.

Connected to these, there is the hope to see a future change in energy production, towards a more “environmental” way. At the same time, people have to be made aware of the issue, so that by adding up everyone's contributions, things will slowly start to improve.

What is certain is that if a breakthrough is needed, it is needed now. And it is good that it coincides with the beginning of a new technological era, driven by AI. If this latter is managed well, and not to foster inequalities, it has the potential to change the world.

It is up to us to seize the opportunity we have, make it our own and make the most of the immense potential of technology to try and change the situation in time.

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