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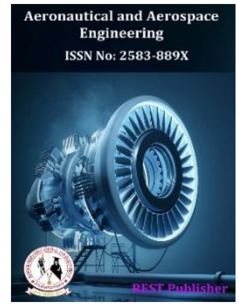

Evaluating Global Warming Trends Using TOPSIS an Analysis of Global Surface Air Temperatures (2014–2016)

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Abstract: *On the basis of five datasets of historical observational records of surface temperature, we present a study of the worldwide annual mean surface temperature anomaly in 2014, 2015, and 2016. These gases cause an increase in global temperatures by trapping heat in the Earth's atmosphere, a process known as the greenhouse effect. The consequences of global warming are wide-ranging and can have severe impacts on both human societies and natural ecosystems. Increased heat waves, droughts, and wildfires can all be brought on by rising temperatures, posing dangers to agriculture, human health, and water supplies. Changes in precipitation patterns can result in more frequent and intense storms, floods, and hurricanes, further threatening communities and infrastructure. In addition to extreme weather events, global warming can disrupt ecosystems and biodiversity. Many species are experiencing shifts in their habitats, altered migration patterns, and changes in their life cycles. Sea levels may rise as a result of glaciers and polar ice caps melting as a result of rising temperatures. This poses a significant threat to coastal regions, increasing the risk of flooding and erosion, and potentially displacing millions of people. Reducing greenhouse gas emissions is crucial for preventing global warming. Many tactics can be used to accomplish this. Switching to sustainable energy sources like solar and wind power, can help reduce carbon dioxide emissions from fossil fuel combustion. Improving energy efficiency in industries, transportation, and buildings can also contribute to emission reductions. Another critical aspect is addressing deforestation and promoting sustainable land management practices. A portion of the heat radiation can be trapped and re-emitted by greenhouse gases like carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), and chlorofluorocarbons (CFCs) in the Earth's atmosphere, preventing it from escaping into space. Global warming is the process by which this phenomena causes an increase in the average surface temperature of the Earth. Infrared (IR) radiation is produced when solar radiation strikes the Earth's surface and is absorbed before being reemitted as thermal radiation. Greenhouse gases, particularly CO2 and CH4, are transparent to solar radiation that enters the atmosphere but absorb some of the IR radiation that leaves the atmosphere. Similar to how a greenhouse retains heat inside, this absorption and re-emission process traps heat in the atmosphere. The greenhouse effect has been exacerbated by the increased atmospheric greenhouse gas concentrations brought on by human activity, particularly the burning of fossil fuels, deforestation, and industrial operations. This has resulted in an enhanced trapping of heat and an overall rise in global temperatures. Utilizing the remaining four datasets, similar outcomes were attained. The longer-term warming trend and the bigger contribution from the DM component suggest that warmer years like 2014-2016 may occur more frequently in the near future. We draw the conclusion that the alleged warming hiatus has ended.*

Keywords: *greenhouse effect, TOPSIS method, Surface temperature anomalies (STA)*

1. INTRODUCTION

It's crucial to remember that the greenhouse effect is a natural phenomenon that has played a crucial role in keeping the Earth's average temperature within a range that is suitable for habitation. However, an excessive buildup of greenhouse gases in the atmosphere throws the natural order off, resulting in global warming and a corresponding change in the climate. It is essential to cut greenhouse gas emissions in order to reduce the greenhouse effect and stop global warming. the employment of sustainable farming and land-use practices, the transition to cleaner and renewable energy sources, and the promotion of laws that support the reduction of greenhouse gas emissions. Additionally, efforts to capture and store carbon dioxide from power plants and industrial facilities are being explored as a means to reduce CO2 emissions. Similarly, initiatives to reduce methane emissions from agriculture, landfills, and fossil fuel extraction can contribute to mitigating the greenhouse effect. By understanding the basic science behind global warming and the role of greenhouse gases, we can make informed decisions and take effective actions to address this critical environmental challenge. The balance can be restored through an increase in the Earth's surface temperature. The effect was first recognized by the French scientist Fourier in A British scientist, John Tyndall around 1860 measured the absorption of infrared radiation by carbon dioxide and water vapour and suggested that a cause of the ice ages might be a decrease in the greenhouse effect of carbon dioxide. Yes, you are correct. Svante Arrhenius, a Swedish chemist, was one of the early scientists to calculate the potential impact of increasing greenhouse gas concentrations on global temperatures. You're right that a greenhouse has a similar impact to the Earth's atmosphere in terms of transmitting solar energy from the outside and trapping thermal heat from the inside. Climate change mitigation entails taking steps and implementing policies to cut greenhouse gas emissions and improve sinks that absorb these pollutants. Mitigation measures can range from individual efforts, such as energy conservation and lifestyle changes, to large-scale initiatives like implementing renewable energy infrastructure and promoting sustainable transportation. Implications for technology in the context of climate change refer to the need for developing and implementing fresh technological developments that can reduce greenhouse gas emissions and aid in climate adaptation. This covers, among other things, developments in energy storage, carbon capture and storage, renewable energy technology, and sustainable farming methods. The future problem of combating climate change calls for international cooperation, technological innovation, and policy interventions. It involves transitioning to a low-carbon economy, promoting sustainable development, and putting adaptation measures in place to reduce how much the changing climate affects human communities, ecosystems, and economies. It is worth noting that specific details and strategies for climate change mitigation and adaptation can vary depending on regional contexts, national policies, and scientific advancements. Ongoing research and collaboration among scientists, policymakers, and various stakeholders are crucial in addressing the complex challenges posed by climate change. By absorbing carbon dioxide from the atmosphere, forests serve as carbon sinks. Implementing sustainable agriculture methods and protecting and restoring forests can reduce greenhouse gas emissions and maintain biodiversity. In addition to mitigation efforts, adaptation strategies are necessary to cope with the impacts that are already occurring or are inevitable due to past emissions. This includes developing resilient infrastructure, implementing disaster preparedness measures, and promoting sustainable water management practices. International cooperation is vital in addressing global warming. The Paris Agreement and the United Nations Framework Convention on Climate Change (UNFCCC) offer a framework for international cooperation to lower greenhouse gas emissions and assist adaptation measures. It is crucial for countries to work together, set ambitious emission reduction targets, and provide financial and technological support to developing nations. Individual actions also play a role in combating global warming. Reducing personal carbon footprints by conserving energy, using public transportation, and adopting sustainable lifestyle choices can contribute to the overall efforts. In conclusion, global warming is a serious environmental problem that will have a wide range of effects. We may fight to lessen the effects of global warming and create a more sustainable future for future generations by lowering greenhouse gas emissions, supporting sustainable behaviors, and putting adaption measures into action.

The 20-year return value of the summer daily maximum has amplitude of more than 4 C, which indicates an increase in extreme heat episodes. This indicates that extreme heat waves during the summer would be significantly hotter compared to historical records. These heat waves can have severe implications for human health, agriculture, and infrastructure. Scandinavia experiences an even larger warming for extreme cold daily minima in winter. This suggests that while the overall average temperatures may rise, extreme cold events during winter can become less frequent but more intense. This indicates a higher frequency and intensity of heavy rainfall events, which can lead to increased flood risk, soil erosion, and damage to infrastructure. Southern Europe's lack of significant increase in summer precipitation suggests a potential increase in dry conditions and associated drought risks. In parts of Central Europe, there is a modest and marginally robust increase in extreme winds during winter. This implies a potential for stronger winter storms that can impact various sectors. However, the changes in wind extremes during summer are not as robust, indicating less certainty in summer wind patterns. Sensible and latent heat fluxes exhibit strong seasonality. There is an increase in spring, indicating higher rates of water evaporation from the surface and plant transpiration. This can affect water availability and agricultural productivity. Conversely, in Southern and Central Europe, decreases, which can have implications for water resources and ecosystem functioning. This suggests an increased exchange of heat between the surface and the atmosphere, potentially leading to higher temperatures in these regions, particularly during summer. The reduced cloud cover in Southern and Central Europe during summer allows for more intense net radiation, contributing to higher sensible heat fluxes. This indicates a greater heating effect and potential for heat-related impacts in these areas. Overall, these patterns highlight the diverse and complex changes in temperature, precipitation, wind, and heat fluxes across Europe. For the purpose of reducing the effects of climate change, it is essential to comprehend these geographical variances.

FIGURE 1. Atmosphere change

The atmosphere would lead to a significant increase in global average temperatures. While his estimate was not precisely accurate, it provided an initial understanding of the relationship between greenhouse gas concentrations and global warming. Apart from the issue of global warming, there have long been concerns about air pollution caused by local sources, such as emissions of nitrogen oxides and sulfur dioxide These contaminants may negatively impact the environment, human health, and air quality. As a result of the negative impacts of air pollution, efforts have been made to aggressively minimize it, especially in major cities. To limit and minimize emissions from industrial facilities, power plants, transportation, and other pollution sources, governments and regulatory agencies have put numerous laws and regulations into place. These measures include the use of cleaner technologies, implementation of emission standards, and promoting the adoption of renewable energy sources. Additionally, efforts have been made to improve monitoring and enforcement to ensure compliance with pollution control measures. The aim of reducing local air pollution aligns with broader environmental goals, including mitigating climate change. Numerous methods and tools used to lessen local air pollution also help to cut greenhouse gas emissions. This synergy allows for integrated approaches that address multiple environmental challenges simultaneously. It is important to continue pursuing efforts to reduce both local air pollution and greenhouse gas emissions to protect human health, preserve ecosystems, and lessen the effects of global warming. We can work toward cleaner air and a healthier environment by embracing cleaner technologies, supporting sustainable practices, and putting in place efficient legislation. I'm sorry if I've been unclear, but as an AI text-based model, I don't have access to the particular statistics or portions you specified. However, I can still provide you with a general overview of the topics you mentioned. Global warming, as a result of increased greenhouse gas emissions, can be considered a form of global pollution. The long lifespan of greenhouse gases, like carbon dioxide, in the atmosphere means that their effects are not limited to specific regions but impact the entire planet. Consequently, addressing global pollution requires global solutions and collaborative efforts. Climate models are valuable tools used to simulate past and current climate conditions and help us understand the complex interactions within the climate system. Climate models are used in projections of climate change for the twenty-first century. and various scenarios to estimate potential future climate conditions based on different levels of greenhouse gas emissions. These projections provide insights into possible effects of climate change on different aspects, including ecosystems, agriculture, water resources, and human communities. Climate change has a wide range of effects on human societies, including an increase in the frequency and severity of extreme weather events, sea level rise, changes in the availability of water, effects on food security, and hazards to human health. International policy and action regarding global warming are addressed through international agreements and initiatives. Key international frameworks that seek to reduce greenhouse gas emissions include the United Nations Framework Convention on Climate Change (UNFCCC) and the Paris Agreement, support adaptation efforts, and promote sustainable development. These agreements encourage countries to set emission reduction targets, enhance climate resilience, and provide financial and technological support to developing nations. While I can provide general information on these topics, if you have specific questions or require more detailed information, please let me know, and I'll be happy to assist you further.

2. MATERIALS AND METHODS

A multi-criteria decision-making methodology called TOPSIS (methodology for Order Preference by Similarity to Ideal Solution) is used to choose the best option from a group of alternatives based on many factors. Since its creation in 1981 by Hwang and Yoon, it has found widespread application across a range of industries, including engineering, operations research, and strategic management. The following steps are part of the TOPSIS method:

1. Identification of the relevant criteria: List the criteria that will be used to assess the alternatives. These requirements ought to be quantifiable, impartial, and directly relevant to the decision-making issue.
2. Create a decision matrix with a row for each choice and a column for each criterion. This process is known as "normalizing" the decision matrix. To remove scale inconsistencies between the criteria, normalize the decision matrix's value entries. Techniques like standardization or min-max normalization can be used for this.
3. Establish the weights: Give each criterion a weight to represent its relative importance or priority. Subjective assessments, professional judgments, or quantitative techniques like the Analytic Hierarchy Process (AHP) can all be used to calculate the weights.
4. construct the normalized choice matrix: To construct a weighted normalized decision matrix, multiply each of the decision matrix's normalized values by its corresponding weight.
5. Identify the ideal and undesirable ideal solutions: The ideal and undesirable ideal solutions are determined in this stage. The best performance for each criterion is represented by the ideal solution, whilst the lowest performance is represented by the negative ideal solution. The positive ideal solution is produced by choosing the minimal value for each criterion, whereas the ideal solution is produced by choosing the greatest value for each criterion.
6. Calculate the distances between each alternative and the ideal and contra-ideal solutions using the Euclidean distance or another method. The distance stands for how similar or how close each alternative is to the ideal and non-ideal solutions.
7. Calculate each alternative's proximity to the ideal solution by dividing its distance from the negative ideal solution by the total of its distances from the ideal and negative ideal solutions. 7. Calculate the relative closeness. Each choice is given a relative proximity score between 0 and 1, with a larger value indicating a higher ranking.
8. 8. Arrange the options in ascending order based on relative closeness values. The option with the greatest relative proximity value is regarded as the ideal option.

The TOPSIS method provides a systematic and quantitative approach to decision-making when there are multiple criteria involved. It allows decision-makers to consider trade-offs among criteria and identify the most preferred alternative based on their relative performance.

Based on the information provided, it seems that Table 1 includes evaluation parameters related to different organizations or methods used in climatic research. The parameters and their corresponding descriptions are as follows:

1. CRU (Climatic Research Unit): It represents the evaluation parameter associated with the Climatic Research Unit. The specific details or criteria being evaluated under this parameter are not provided in the given information.
2. GISS (Goddard Institute of Space Studies): It represents the evaluation parameter associated with the Goddard Institute of Space Studies. Similarly, the specific details or criteria being evaluated under this parameter are not mentioned.
3. NCDC (National Climatic Data Center): It represents the evaluation parameter associated with the National Climatic Data Center. Again, the specific criteria or details being evaluated under this parameter are not provided.
4. BE_air: This evaluation parameter refers to the first version of a method or approach called "BE_air." It involves deriving surface temperature values by extrapolating land surface temperature anomalies. This parameter likely pertains to the evaluation of the accuracy, reliability, or performance of the BE_air method in predicting or estimating surface temperature using land surface temperature anomalies.

5. BE_water: This evaluation parameter represents the second version of the method or approach called "BE_water." In contrast to BE_air, BE_water extrapolates sea-surface water temperature anomalies to derive surface temperature values. Similar to BE_air, this parameter likely relates to the evaluation of the accuracy, reliability, or performance of the BE_water method in predicting or estimating surface temperature using sea-surface water temperature anomalies.

Please note that the specific criteria or details being evaluated under the parameters CRU, GISS, and NCDC are not provided in the given information. Additional context or information would be required to understand the evaluation dimensions or criteria associated with these parameters.

3. RESULTS AND DISCUSSION

TABLE 1. evaluation parameters

CRU	Climatic Research Unit
GISS	Goddard Institute of Space Studies
NCDC	National Climatic Data Center
BE_air	the first version (“BE_air”) derives surface temperature values by extrapolating land surface temperature anomalies
BE_water	he second version (“BE_water”) instead extrapolates sea-surface water temperature anomalies

TABLE 2. Surface temperature anomalies (STA; unit: °C) over the world for the years 1998, 2014, 2015, and 2016 in the datasets from CRU, GISS, NCDC, BE_air, and BE_water.

	CRU	GISS	NCDC	BE_air	BE_water
2016	0.83	0.98	0.92	0.95	0.84
2015	0.82	0.84	0.88	0.81	0.76
2014	0.63	0.74	0.72	0.67	0.61
1998	0.59	0.63	0.61	0.59	0.53

Table 2 provides annual mean surface temperature anomalies (STA) in degrees Celsius for the years 1998, 2014, 2015, and 2016. The data is presented for five datasets: CRU, GISS, NCDC, BE_air, and BE_water. Here are the temperature anomaly values for each dataset in the respective years: Each value represents the annual mean surface temperature anomaly for the corresponding dataset and year. The units for the temperature anomalies are degrees Celsius (°C).

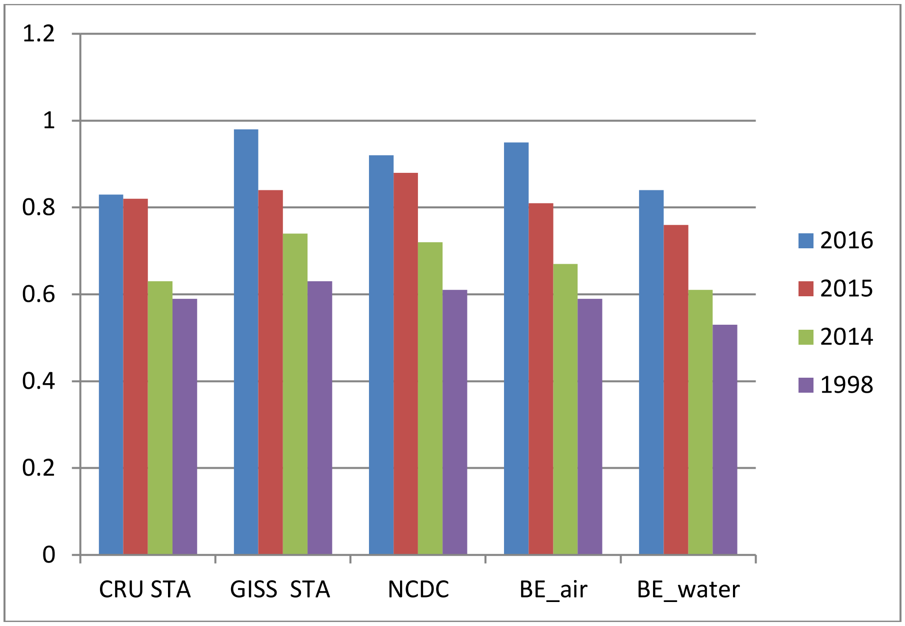

FIGURE 1. Data set graph

Figure 2 Surface temperature anomalies (STA; unit: °C) over the world for the years 1998, 2014, 2015, and 2016 in the datasets from CRU, GISS, NCDC, BE_air, and BE_water.

TABLE 3. Normalized Data

	CRU	GISS	NCDC	BE_air	BE_water
2016	0.5719	0.6065	0.5805	0.6190	0.6037
2015	0.5650	0.5199	0.5553	0.5278	0.5462
2014	0.4341	0.4580	0.4543	0.4365	0.4384
1998	0.4065	0.3899	0.3849	0.3844	0.3809

Table 3 presents the normalized data for the annual mean surface temperature anomalies in the CRU, GISS, NCDC, BE_air, and BE_water datasets. The values in the table represent the normalized scores for each dataset and year. Here are the normalized data values: In each dataset, the values have been normalized to lie between 0 and 1, with 0 denoting the lowest value and 1 the highest. The normalization process aims to eliminate the scale differences among the datasets, allowing for better comparison and evaluation of the temperature anomalies across different years and datasets.

TABLE 4. Weight

year	CRU	GISS	NCDC	BE_air	BE_water
2016	0.20	0.20	0.20	0.20	0.20
2015	0.20	0.20	0.20	0.20	0.20
2014	0.20	0.20	0.20	0.20	0.20
1998	0.20	0.20	0.20	0.20	0.20

Table 4 presents the weights assigned to each dataset for each year. The weights represent the relative importance or priority given to each dataset when evaluating the annual mean surface temperature anomalies. In this case, an equal weight of 0.20 is assigned to each dataset for every year. This indicates that all datasets are considered equally important in the evaluation of the annual mean surface temperature anomalies across the years.

TABLE 5. Weighted normalized decision matrix

	CRU	GISS	NCDC	BE_air	BE_water
2016	0.1144	0.1213	0.1161	0.1238	0.1207
2015	0.1130	0.1040	0.1111	0.1056	0.1092
2014	0.0868	0.0916	0.0909	0.0873	0.0877
1998	0.0813	0.0780	0.0770	0.0769	0.0762

The weighted normalized decision matrix, which is produced by multiplying the normalized data values, is shown in Table 5 (from Table 3) by the corresponding weight values (from Table 4). The values in Table 5 represent the weighted and normalized scores for each dataset and year.

These values represent the scores obtained by multiplying the normalized data values (from Table 3) by the corresponding weight values (from Table 4) for each dataset and year. The weighted normalized decision matrix allows for a more comprehensive evaluation of the temperature anomalies, considering both the importance assigned to each dataset and the relative performance indicated by the normalized scores.

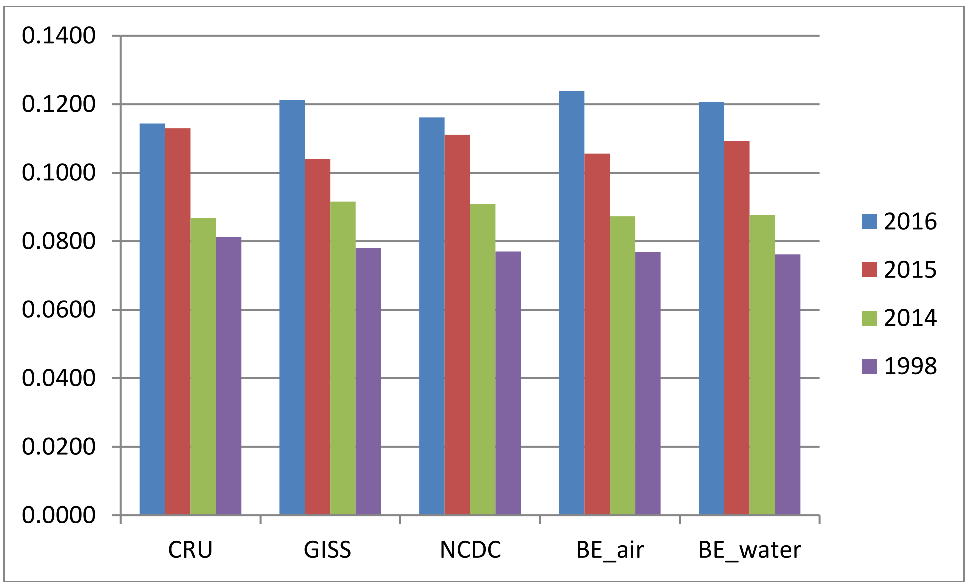

FIGURE 2. Weighted normalized decision matrix

The weighted normalized decision matrix graph is shown in Figure 3. From 1998 to 2016, values increased.

TABLE 6. Positive Matrix

year	CRU	GISS	NCDC	BE_air	BE_water
2016	0.1144	0.1213	0.1161	0.1238	0.1207
2015	0.1144	0.1213	0.1161	0.1238	0.1207
2014	0.1144	0.1213	0.1161	0.1238	0.1207
1998	0.1144	0.1213	0.1161	0.1238	0.1207

Table 6 represents the positive matrix; this is obtained by choosing the highest value for each dataset across all years from the weighted normalized choice matrix (from Table 5). The values in Table 6 represent the maximum scores for each dataset. In this case, the positive matrix simply retains the same values as the weighted normalized decision matrix (Table 5) since each dataset has the same maximum value across all years. This indicates that there is no variation in the maximum scores among the datasets, and they all have the same highest value across the evaluated years.

TABLE 7. Negative Matrix

Year	CRU	GISS	NCDC	BE_air	BE_water
2016	0.0813	0.0780	0.0770	0.0769	0.0762
2015	0.0813	0.0780	0.0770	0.0769	0.0762
2014	0.0813	0.0780	0.0770	0.0769	0.0762
1998	0.0813	0.0780	0.0770	0.0769	0.0762

Table 7 represents the negative matrix, This is obtained by choosing the highest value for each dataset across all years from the weighted normalized choice matrix (from Table 5) by selecting the minimum value for each dataset across all years. The values in Table 7 represent the minimum scores for each dataset. In this case, the negative matrix retains the same values as the weighted normalized decision matrix (Table 5) since each dataset has the same minimum value across all years. This indicates that there is no variation in the minimum scores among the datasets, and they all have the same lowest value across the evaluated years.

TABLE 8. SI Plus, Si Negative and Ci

	SI Plus	Si Negative	Ci
2016	0.0000	0.0932	1.0000
2015	0.0282	0.0690	0.7101
2014	0.0686	0.0255	0.2709
1998	0.0932	0.0000	0.0000

Table 8 provides the values for SI Plus, Si Negative, and Ci. These numbers are computed using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method based on the positive and negative matrices (Tables 6 and 7).

- SI Plus depicts the degree of similarity between each dataset and the successful ideal solution. Higher resemblance to the ideal solution is indicated by a lower SI Plus score. The dataset most closely resembles the positive ideal solution in this situation has the lowest SI Plus value for each year.
- Si Negative is a measure of how similar each dataset is to the unfavorable ideal solution. A better resemblance to the negative ideal solution is indicated by a lower Si Negative value. The dataset that most closely resembles the negative ideal solution in this situation has the lowest Si Negative value for each year.
- • Ci is a measure of how closely each dataset comes to the ideal outcome. The ratio of Si Negative to the total of Si Plus and Si Negative is used to compute it. A greater Ci value denotes a closer proximity to the optimal solution. The dataset that comes closest to the optimum solution in this situation is the one that has the highest Ci value for each year.

Please be aware that the presented information does not include the precise weights or criteria used to define the positive and negative ideal solutions. The TOPSIS method relies on the definition of these ideal solutions based on the decision-maker's preferences or criteria.

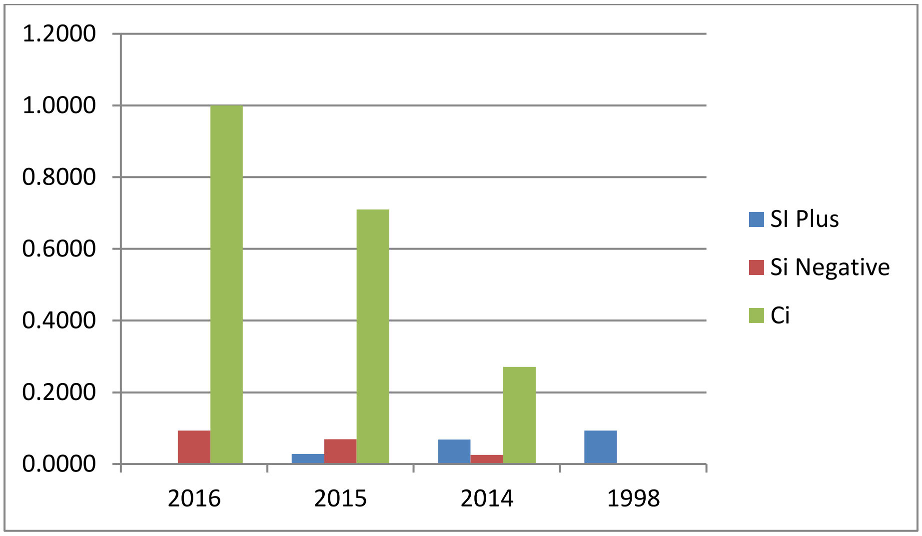

FIGURE 3. SI Plus, Si Negative and Ci

Figure 4 shows that the SI Plus, Si Negative and Ci values.

TABLE 8. Ranking

year	Rank
2016	1
2015	2
2014	3
1998	4

Table 8 provides the ranking of the datasets based on the TOPSIS analysis. The datasets are ranked in Table 8 according to the TOPSIS analysis. The ranking indicates the order of preference or performance of the datasets in relation to the ideal solution. Based on the TOPSIS analysis, the dataset ranked 1 is considered the most preferable or performs the best, followed by the dataset ranked 2, and so on. In this case, the dataset for the year 2016 is ranked 1, indicating that it is the most preferable or performs the best among the evaluated years. The dataset for the year 1998 is ranked 4, indicating that it is the least preferable or performs the worst among the evaluated years. From 1998 to 2016, ranking decreased so year to year increased surface temperature anomalies. As seeing ranking figure 5.

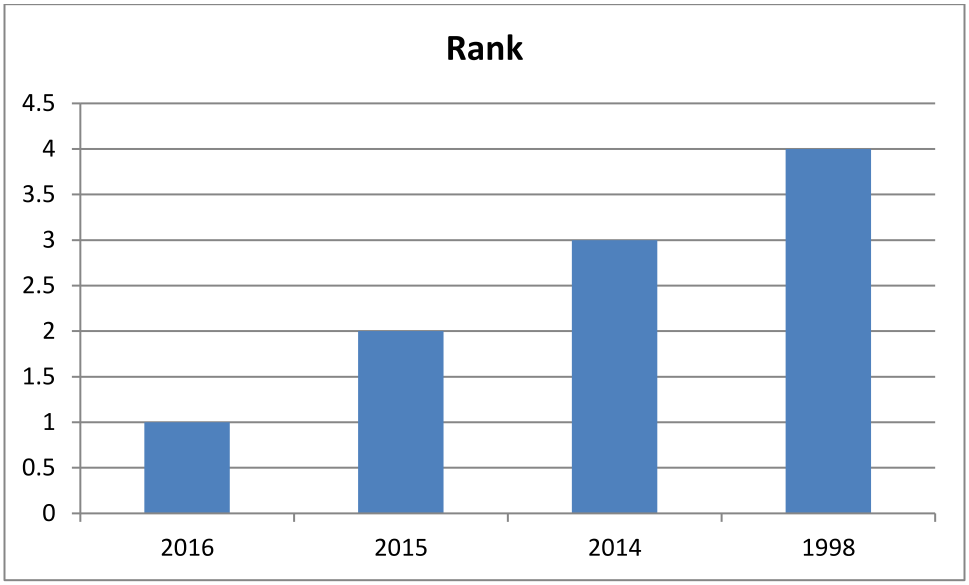

FIGURE 4. Ranking

CONCLUSION

There are a number of explanations for why Europe has suffered more warming than the rest of the world on average. The placement of Europe geographically is one of the important reasons, with many regions being closer to the North Pole and experiencing amplified warming due to polar amplification. Additionally, Large-scale atmospheric circulation patterns like the North Atlantic Oscillation (NAO) have an impact on Europe's climate. and the Arctic Oscillation (AO), which can affect temperature and precipitation patterns. The distributional pattern of warming across Europe is influenced by regional climate characteristics and local factors. North-Western Europe generally experiences stronger warming due to the influence of the North Atlantic Drift, which brings warm water and air currents from the Gulf Stream. This leads to milder winters and less extreme temperature variations compared to other regions. Northern and Eastern Europe experience more intense warming in winter, which can be attributed to reduced snow cover and sea ice extent, leading to decreased and enhanced heat absorption. In contrast, Southern Europe experiences more intense warming in summer, which is influenced by factors such as increased solar radiation, decreased cloud cover, and changes in atmospheric circulation patterns. Changes in precipitation patterns across Europe are also notable. Central and Northern Europe experience increased precipitation in winter, which can be associated with a warmer atmosphere holding more moisture and changes in atmospheric circulation patterns. This can lead to more frequent and intense winter rainfall events. In summer, precipitation decreases in Central and Southern Europe, which can contribute to drought conditions and increased risk of wildfires. The increased variability of extreme events is a significant concern for Europe. Heat waves are projected to become more frequent and severe, posing risks to human health, agriculture, and ecosystems. Heavy rainfall events can lead to flooding and infrastructure damage. Droughts can impact water resources, agriculture, and ecosystems. These extreme events can have socio-economic implications and require adaptation strategies to mitigate their impacts. It's important to note that the information provided here is based on general trends and projections. Climate change is a complex and dynamic process, and there can be regional variations and uncertainties in specific locations.

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