Impact of Temperature Extremes on Climate Risks

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Abstract

This paper investigates the correlation between temperature variations and the Climate Risk Index (CRI) using machine learning models. It introduces the Temperature Sensitivity Score (TSS) to quantify the impact of temperature extremes on regional climate risks. The findings highlight significant variations in climate sensitivity across countries, underscoring the necessity of region-specific strategies in addressing extreme and detrimental climate events. The TSS emerges as a critical tool for guiding urban planning and emergency response, with implications for improving climate resilience.

1 Introduction

In the recent years, climate change poses a significant threat to global weather stability. Heatwaves and other unstable temperature events increase drastically in frequency and the destructions to the ecosystems and human societies. The Climate Risk Index (CRI) serves as a crucial indicator for assessing the vulnerability and exposure of regions to climate-related hazards. Understanding the influence of temperature extremes on the CRI is vital for developing adaptive strategies and informing policy decisions. This paper explores the predictive power of machine learning models in correlating temperature variations with the CRI, revealing the differential impact of climate extremes across countries.

2 Related Works

A body of work has focused on the characterization and prediction of extreme weather events, which are pivotal in understanding the broader implications of climate variability. For instance, the study by Paçal, A. titled *Detecting Extreme Temperature Events Using Gaussian Mixture Models* represents a significant contribution to the field, offering a statistical approach to identifying temperature anomalies that could presage severe climate disturbances [4]. This methodology aligns closely with our use of machine learning models to assess the relationship between temperature extremes and the Climate Risk Index (CRI). In parallel, the intersection of climate-induced events and their subsequent societal impacts has been explored in works such as *Predicting Food Crises Using News Streams* by Balashankar, A. et al. This study underscores the predictive capacity of data-driven models in preempting crises, particularly in the agricultural domain, where climate extremes manifest as either boon or bane [1]. The predictive modeling of food crises, often precipitated by erratic temperature behaviors, resonates with our objective of quantifying the impact of temperature variations on the CRI. These studies underpin the importance of temperature metrics in constructing comprehensive climate risk assessments.

The collective insights gleaned from these works enhance our understanding of the intricate dynamics between climate phenomena and risk indices. Our research aims to expand this growing knowledge base by specifically focusing on how machine learning can elucidate the differential impacts of climate extremes across diverse geographical landscapes.

3 Procedures

3.1 Data Collection

In this study, we chose to use the CRI data of year 2018 published on Germanwatch and the meteostat dataset in 2018.

The Climate Risk Index (CRI) is an empirical tool designed to quantify and communicate the exposure and vulnerability of nations to climatic impacts. Developed by Germanwatch, the CRI evaluates and ranks the extent to which countries have been affected by weather-related loss events, such as storms, floods, and heatwaves [2]. It serves as a critical barometer for policymakers and stakeholders, spotlighting regions most afflicted by climate change and necessitating urgent adaptive measures. By synthesizing data on fatalities, economic losses, and other indicators of climatic disruptions, the CRI furnishes a longitudinal perspective on climate-induced adversities, reflecting both short-term weather phenomena and long-term climate variability.

The Meteostat dataset provides a comprehensive repository of meteorological data, offering valuable insights into the climatic conditions governing our planet. As a robust aggregation of historical weather statistics and time-series data, Meteostat facilitates an in-depth analysis of climate dynamics across various geographies and temporal scales [3]. By availing datasets of temperature readings, precipitation patterns, and other pertinent climate variables, Meteostat acts as a pivotal resource for scientific research, enabling an accurate assessment of meteorological trends and anomalies.

The objective of harnessing these datasets lies in the critical assessment of how severe temperature extremes are impacting climate risk on a global scale. By correlating Meteostat's granular temperature data with the CRI's impact assessments, this project seeks to unveil the sensitivity of different regions to temperature fluctuations. In doing so, it aims to find out the extent to which temperature extremes contribute to the overall climate risk.

3.2 Data Processing

The data is processed to produce an aggregation of temperature data for each country. Using the comprehensive Meteostat dataset, we extracted key temperature metrics, namely 'Mean_Temperature', 'Variance_Temperature', 'Extreme_Hot_Frequency', and 'Extreme_Cold_Frequency'. For each nation, this data encapsulates the average temperature readings, the variability in these temperatures, and the frequency of both extremely high and low temperature occurrences.

The process involved identifying reliable data points corresponding to specific geographical coordinates and time frames. We ensured the representativeness of this data by focusing on extended periods, thus capturing both short-term fluctuations and long-term trends in temperature patterns.

3.3 Correlation Visualization

Without diving into prediction and analysis of CRI from the temperature data, we first visualize the correlation between the temperature metrics and the CRI scores. The objective was to discern whether regions with more pronounced temperature extremes exhibited correspondingly higher CRI scores, indicating greater vulnerability to climate-related risks.

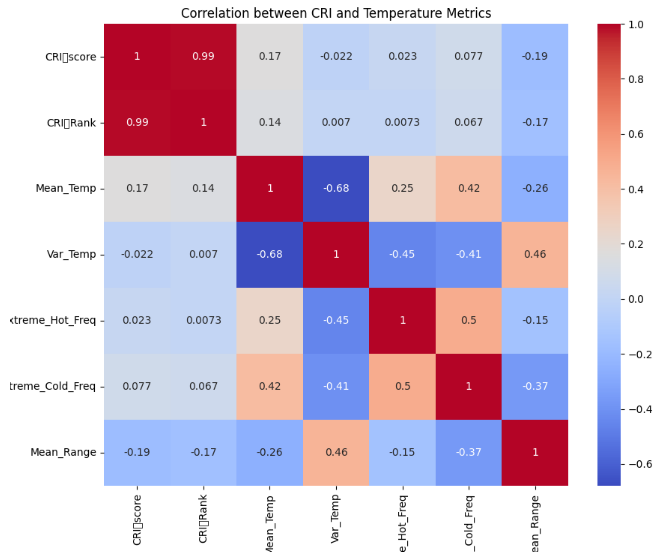

Figure 1: CRI score and CRI rank are to some extent related to the temperature and the extremeness of the temperature in different countries.

3.4 Predictive Modeling

Building upon the correlation analysis, we now look at predictive modeling to evaluate the capacity of temperature metrics to forecast CRI scores. We implemented models such as Linear Regression, Random Forest and Neural Networks, capitalizing on their ability to discern intricate patterns hidden within the data. The choice of models was driven by their ability to handle non-linear interactions and provide robust predictions.

The models were trained on a subset of the data and validated against a separate set to ensure robustness and generalizability. The effectiveness of these models was quantified through metrics such as R-squared and Mean Absolute Error, providing insights into their predictive accuracy.

3.4.1 Results

Model	R^2 Score
Linear Regression	-0.05
Random Forest	0.28
Random Forest with Feature Selection	0.22
Neural Network	-0.57

Table 1: Models and their R^2 Score on the predicting task. Linear regression producing a slightly negative score indicates that the relationship is likely nonlinear. Neural Network producing a very nagative score indicates that the data points are limited and the modeling is subject to overfitting. Feature selection doesn't help improve the score from random forest. And the best score we get here is Random Forest itself with R^2 score of 0.28.

3.5 By Country Temperature Sensitivity Score

As the models demonstrate a correlation between temperature extremes and CRI, we aim to find the varying levels of sensitivity across different regions. Here we propose a measurement, Temperature Sensitivity Score (TSS), that aims to show how large the impact of a country's temperature condition is on the CRI of the country.

3.5.1 Calculation of TSS

The TSS for each country is computed based on the deviation of its Mean Absolute Error (MAE) from the overall MAE obtained across all countries. The MAE is a standard metric in regression analysis that measures the average magnitude of errors in a set of predictions, without considering their direction. The formula for calculating the MAE is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

Where y_i represents the actual CRI score, $\hat{y}_i$ denotes the predicted CRI score using **random forest**, and n is the number of observations.

Based on this, the TSS is calculated using the following formula:

$$\text{TSS} = |\text{MAE}_{\text{country}} - \text{MAE}_{\text{overall}}| \tag{2}$$

Where $\text{MAE}_{\text{country}}$ is the MAE for a specific country, and $\text{MAE}_{\text{overall}}$ is the MAE calculated across the entire dataset. A higher TSS indicates a greater sensitivity of the CRI to temperature extremes, suggesting a more pronounced impact of climate variability on the respective region.

3.5.2 TSS by Country

With the calculation scheme from the above, we computed the TSS score for each country in our dataset.

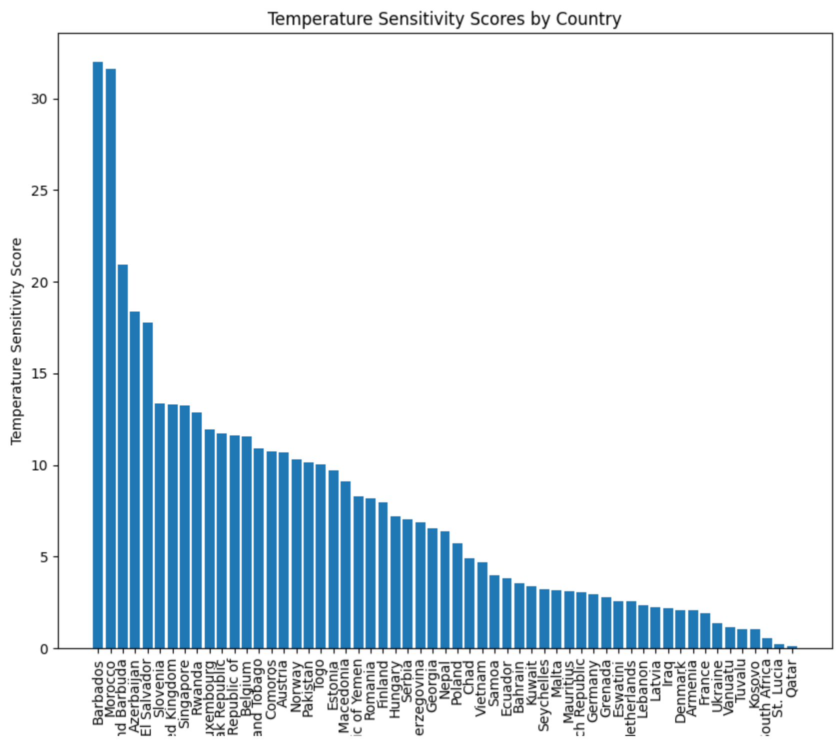

Figure 2: Plot of TSS by country

3.5.3 Global Heatmap of TSS

To make the result more interpretable, we also present the TSS score by country in a global heatmap. This aims to provide a visualization of how geographical location might impact TSS.

Further, we aim to see the mapping of average temperature and TSS in the countries.

Figure 3: Global heatmap illustrating the temperature sensitivity scores of countries. Darker shades represent higher sensitivity to temperature extremes.

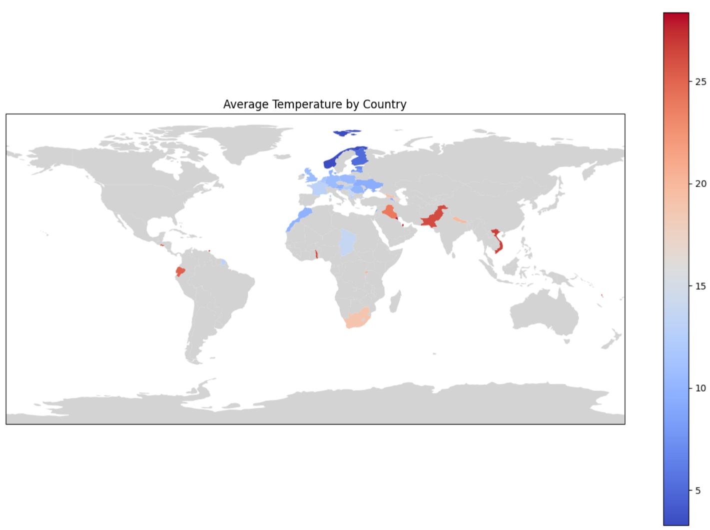

Figure 4: Global heatmap displaying average temperatures. The color gradient from blue to red indicates the spectrum from colder to warmer average temperatures.

4 Conclusion

This study's exploration of the relationship between temperature extremes and the Climate Risk Index (CRI) illuminates the varying impacts of temperature fluctuations on different regions. The findings underscore the significance of temperature extremes in influencing regional climate risks. Temperature Sensitivity Score (TSS) offers a novel metric for assessing regional vulnerability to temperature fluctuations, providing a guideline for global extreme weather risk control. Utilizing TSS in urban planning and disaster prevention infrastructure could significantly enhance preparedness for climate-induced risks, especially in high-sensitivity areas.

In the future, the work can keep on integrating a broader range of climate variables and employing advanced machine learning models for more nuanced predictions. Further research may also explore the causal mechanisms behind these correlations, paving the way for more targeted and effective climate resilience strategies.

References

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