Impact of Temperature Changes on Economic Productivity by Climatic Zone.

Muhammad Faiz Fuad

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Abstract

The escalating concerns of climate change and its implications on global economic productivity necessitate a thorough understanding of how temperature fluctuations influence economic outcomes across various climatic zones. This paper investigates the intricate relationship between average temperature variations and GDP per capita within the distinct environments delineated by the Köppen climate classification. Employing a rich dataset combining Berkeley Earth's temperature data with World Bank's economic indicators, the study provides an empirical examination of potential economic ramifications attributable to climate variability on a global scale.

Analytical methodologies, including multivariate OLS regressions and advanced machine learning models such as regression trees and Random Forest, are applied to a city-level dataset that encapsulates the direct and indirect effects of climatic factors on economic productivity. The nuanced approach of the regression tree model unveils complex interactions and nonlinear relationships, while the Random Forest model enhances the predictability and generalizability of the outcomes. The results underscore a varied impact of temperature changes on economic productivity across different climatic zones, highlighting the necessity of region-specific adaptation strategies and policies.

This research contributes to the body of knowledge in climate change economics by providing empirical insights and data-driven evidence, reinforcing the importance of considering the unique climatic conditions when devising economic policies aimed at fostering climate resilience and sustainable development. The findings of this study are of particular relevance to policymakers and stakeholders engaged in crafting responses to climatic transformations, emphasizing a proactive integration of climate adaptation into economic planning and development strategies.

1 Introduction

Climate change is a critical global issue, intricately linked to a myriad of ecological, societal, and economic systems. The core of my investigation delves into the dynamic interaction between climate variability and economic output. Specifically, my study scrutinizes the correlations between temperature variations and GDP per capita (Y_1) within the distinctive environments delineated by the Köppen climatic zones. This scholarly endeavor is driven by a singular aim: to unravel the complex relationship between climatic factors and economic productivity and to determine their connection with GDP per capita.

At the foundation of my analysis is a meticulously curated dataset that intertwines Earth's temperature data from Berkeley Earth with comprehensive economic indicators such as GDP per capita from the World Bank. The fusion of these diverse datasets facilitates a sophisticated exploration of the potential economic ramifications of temperature changes on a global scale.

The study employs the Köppen climate classification (Beck et al., 2018) as an analytical tool to stratify the planet into tropical (A), dry (B), temperate (C), and continental (D) zones, offering a methodical framework to assess the complex relationship between climate and economic productivity. The choice of climate and economic variables is grounded in the literature, drawing from influential studies such as those by Desmet and Rossi-Hansberg (2024) and Kahn et al. (2019), which explore the shifting economic landscapes in the face of climate change and the heterogeneous economic impacts experienced by different regions. These variables—including average temperature (X_1), temperature uncertainty (X_2), latitude (X_3), and population density (X_4)—are selected for their capacity to encapsulate direct climate effects and their moderating influences on economic output.

The regression tree model has unveiled intricate patterns of temperature impacts on economic productivity, highlighting nonlinear interactions and thresholds that a traditional OLS model could not capture. This analysis not only corroborates the differentiated vulnerabilities of regions to climate change but also advocates for climate policies that are attuned to regional idiosyncrasies. In light of these results, it becomes evident that economic vulnerability to temperature changes is not homogenous but rather varied across climatic zones, emphasizing the imperative for region-specific adaptation strategies to climate change.

The relationship between climatic factors and economic productivity is neither linear nor straightforward. In this study, I specifically observed how variations in temperature and climate zone influence GDP per capita, identifying a negative correlation in some zones and a positive correlation in others. For instance, initial findings suggest that temperate and continental zones demonstrate consistent economic performance across different temperatures, whereas tropical zones show variable outcomes. Such insights imply that economic activities are deeply intertwined with the climatic context, revealing a tapestry of interactions where no single factor operates in isolation. By elucidating these variable relationships, the study offers a nuanced understanding that challenges oversimplified assumptions and informs more targeted, climate-aware economic policies.

My work corroborates the view that an in-depth comprehension of the climate-economy nexus is pivotal for crafting sustainable development policies and shaping effective climate adaptation frameworks. The enriched dataset underpinning this research is poised to offer valuable empirical insights, contributing to the discourse on climate resilience and economic sustainability. Through this extensive empirical examination, I have expanded the corpus of knowledge in climate change economics, providing data-driven insights that are vitally relevant to policymakers and stakeholders tasked with navigating the future amid ongoing climatic transformations.

2 Data

2.1 Background

In my research, the primary dataset I employed originates from Berkeley Earth, which meticulously documents changes in average temperature across major global cities. This dataset was instrumental in my analysis, as it provided a granular view of how temperature variations could potentially impact economic outputs across different geographic locales. To augment the relevance and specificity of this dataset to my research question, I developed a code to categorize the cities listed in the data according to the Köppen climate classification system. The rationale behind this categorization was to leverage the Köppen system's nuanced understanding of climate zones, facilitating a more structured and meaningful analysis of climate's impact on economic productivity. Choosing to focus on the city-level dataset rather than a country-level dataset also enhances the granularity of the analysis. It allows for a more precise examination of the interplay between localized climatic conditions and economic output. This level of detail is particularly relevant because economic activities can vary significantly within a country, especially in larger and more diverse nations where multiple climatic zones are present. A city-level approach avoids the potential averaging out of data that could obscure the nuances of climate's impact on economic productivity. The Köppen system, with its comprehensive coverage of climate characteristics, enabled me to systematically explore the intersection between climatic conditions and economic outcomes. This methodological approach yielded a dataset encompassing 1470 observations across 31 cities, thereby establishing a robust foundation for my subsequent analyses.

To further refine my inquiry into the relationship between climate and economic productivity, I integrated this temperature data with GDP per capita data, which served as my primary dependent variable. The GDP per capita data, sourced from the World Bank, provided a standardized measure of economic output, allowing for comparative analysis across different climates and geographies.

In addition to temperature and economic output data, my research also incorporated several other variables to construct a comprehensive analytical framework. Specifically, I included CO2 per capita emission data and urbanization rates, obtained through web scraping, alongside data on energy consumption, population density, total population, and indicators of educational and health outcomes (e.g., life expectancy). These variables were meticulously chosen to illuminate the multifaceted relationships between climate change, urban development, and economic dynamics. By integrating these diverse datasets, my research aimed to offer a holistic understanding of how climatic factors, in conjunction with socio-economic and environmental variables, influence economic productivity.

The incorporation of CO2 emissions data allowed me to assess the environmental implications of economic activities, while urbanization rates offered insights into the transformative impact of urban growth on economic structures and environmental conditions. Energy consumption data further enabled me to explore the efficiency and intensity of energy use in relation to economic output, shedding light on the sustainability of economic growth patterns. Meanwhile, data on population density, total population, and life expectancy served to contextualize the economic analyses within the broader demographic and health landscapes, revealing the socio-economic dimensions of climate impacts. Lastly, educational attainment data provided an avenue to examine the role of human capital in economic resilience and adaptation to climate change.

The synthesis of these varied datasets underpinned my research with a rich empirical basis, allowing for a nuanced exploration of the intricate linkages between climate conditions and economic performance. Through this comprehensive methodological approach, my study sought to contribute to the burgeoning field of climate economics by elucidating the complex and dynamic interactions that define our collective pursuit of sustainable development in an era of profound climatic challenges.

2.2 Summary Statistics

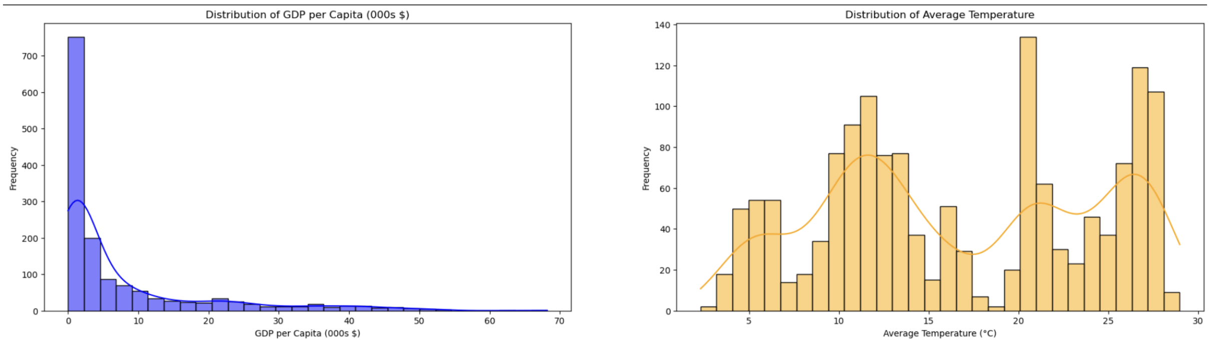

Figure 1: Global Distribution of Average GDP per Capita and Temperature Change Magnitude.

The histograms offer a visual summary of the GDP per capita and average temperature across various countries or regions. GDP per capita is a crucial indicator of a country's economic output and general prosperity, while average temperature is indicative of climatic conditions, with potential impacts on sectors such as agriculture, health, and energy usage—all vital to economic health.

In the histogram depicting GDP per capita, we can observe a right-skewed distribution. This suggests that most countries have a lower GDP per capita, with fewer countries achieving high economic output. This pattern might imply that higher economic performance is uncommon (Hsieh & Olken, 2014) and could be affected by various factors, including climatic conditions. The skewness could also reflect a broad range of economic development levels across different regions, which might be worth exploring in relation to climate variability.

Turning to the average temperature histogram, I notice a multimodal distribution. This indicates a diverse set of climates within the sample, which provides a rich basis for comparing economic performance against different climatic backgrounds. For example, I might hypothesize that regions with moderate climates could potentially have higher GDP per capita, suggesting that such climates are more conducive to economic activities.

By analyzing these histograms, I aim to identify any correlations between GDP per capita and average temperature. If I find a significant number of countries with higher GDP per capita within certain temperature ranges, it could point to a direct correlation between climate and economic performance. Conversely, a scattered or non-uniform distribution would indicate that the relationship between these variables is complex and potentially moderated by a variety of factors, with climate being just one.

This interpretive analysis, based on the observed trends in the histograms, serves as a preliminary step in hypothesizing about the possible mechanisms by which climate may affect economic performance. To confirm any hypotheses, a more detailed statistical investigation would be necessary.

The boxplot provided offers a comparative visual analysis of GDP per Capita across four distinct climatic zones, identified as A, B, C, and D. These variables—GDP per Capita and Climatic Zone—are chosen based on the hypothesis that economic performance might be influenced by climatic conditions. GDP per Capita is a critical economic indicator that reflects the average economic output per person, shedding light on the productivity and prosperity of a region. Climatic zones, which categorize regions based on their climatic characteristics, are understood to have significant effects on economic activities due to their influence on agriculture, energy needs, health, and general livability.

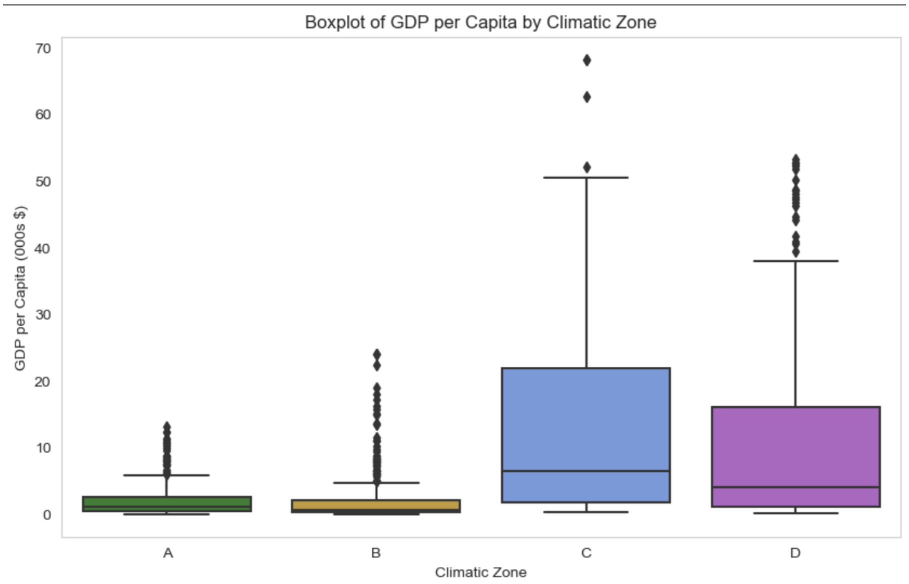

Figure 2: Boxplot of GDP per Capita by Climatic Zone.

In this boxplot, each box delineates the interquartile range (IQR) of GDP per Capita within a climatic zone, revealing the central tendency and dispersion of economic output. The median GDP per Capita is indicated by a horizontal line in each box, while the whiskers extend to the furthest data points within 1.5 times the IQR from the box, with outliers represented as individual points beyond the whiskers.

It seems that Climatic Zone C displays a higher median GDP per Capita and possesses a wider IQR, suggesting a broader variation in economic output within this zone. Conversely, Zones A and D show comparatively lower median GDP per Capita values and a narrower spread, hinting at less variability within these zones. Zone B presents a median GDP that is higher than A and D but lower than C, with a variability that appears moderate in comparison.

From these visual cues, there might be an association between climatic conditions and economic output per person. Nonetheless, it is imperative to recognize that a correlation does not establish causality. To confirm any cause-and-effect relationship, I would need to conduct more comprehensive statistical analyses, potentially controlling for confounding variables such as technological development, policy frameworks, infrastructure quality, and natural resource availability, which could influence economic performance independently of the climate.

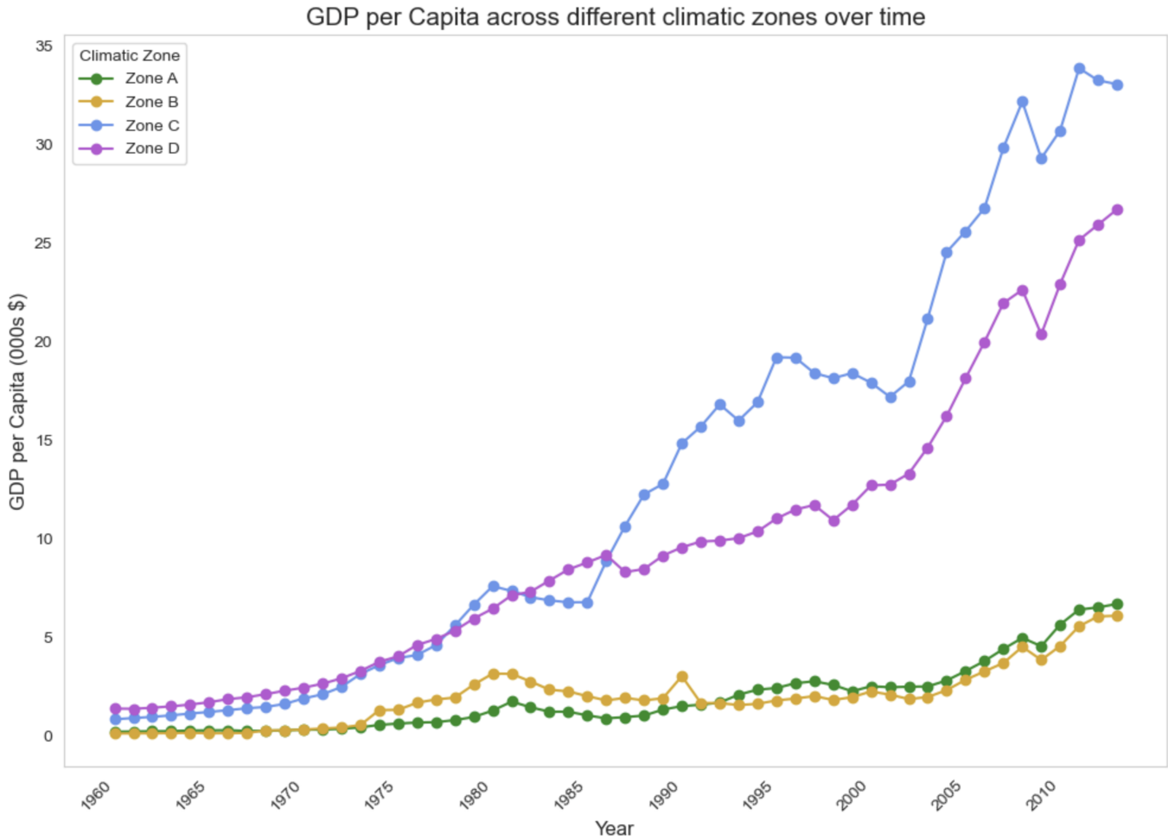

Figure 3: GDP per Capita Over Time by Climatic Zone.

The graph above presents a comparative analysis of economic performance measured in GDP per capita across four distinct climatic zones, labeled Zone A through Zone D, over a span of several decades. The choice of GDP per capita as a variable is pertinent to the research question, which probes the influence of climate on economic output, because it provides a standardized measure of economic activity that accounts for population size, enabling an apples-to-apples comparison across regions. The climatic zones are chosen based on distinct environmental characteristics that might affect economic activities, such as agriculture productivity, health outcomes, or the viability of various industries.

In relation to the research question, the plotted trends over time offer insights into whether and how climate may influence economic performance. For instance, a sustained increase or decrease in GDP per capita within a particular climatic zone may suggest that climatic factors either facilitate or hinder economic growth in that zone. The temporal dimension of the data allows for the observation of long-term trends, which are critical in distinguishing between transient economic shifts and more enduring, climate-related patterns.

Observations from the graph reveal that Zone C exhibits a pronounced upward trajectory in GDP per capita over time, suggesting that this climatic zone may possess favorable conditions for economic growth or has effectively adapted to its climate to foster economic development. In contrast, Zone A shows a more modest growth, while Zones B and D demonstrate relatively flat trends for a significant portion of the timeframe, followed by divergent paths in later years. These patterns may imply that climatic factors in Zones B and D have posed challenges to economic growth or that these zones have only recently begun to harness their climatic conditions to improve economic outcomes. Additionally, the sharp fluctuations in Zone B's GDP per capita, particularly the precipitous drop and subsequent recovery, may warrant further investigation into whether extreme climate events, such as droughts or floods, could be responsible for such volatility. The ability to maintain steady economic growth in the face of environmental stresses is critical for resilience, and the observed differences across zones could be indicative of varying levels of vulnerability to climate change.

In summary, the graph provides a foundation for exploring the complex interplay between climatic conditions and economic performance. It underscores the need for a nuanced analysis that considers a multitude of factors, including but not limited to, geographical location, access to technology, the structure of economies, and policy responses to climate change. The observed patterns suggest that the impact of climate on economic output is multifaceted and likely varies not only by region but also over time.

3 Results

3.1 How Temperature Variations Influence Economic Productivity in Different Climatic Zones

The investigation seeks to illuminate the influence of temperature variations on economic productivity within different Köppen climatic zones, aiming to discern if and how climate factors correlate with GDP per capita.

By observing the progression of economic metrics in relation to the climatic zones, categorized by distinct temperature and precipitation patterns, the investigation attempts to shed light on the role of climate in economic productivity. The Köppen classification system provides a framework for understanding the climate characteristics that define each zone.

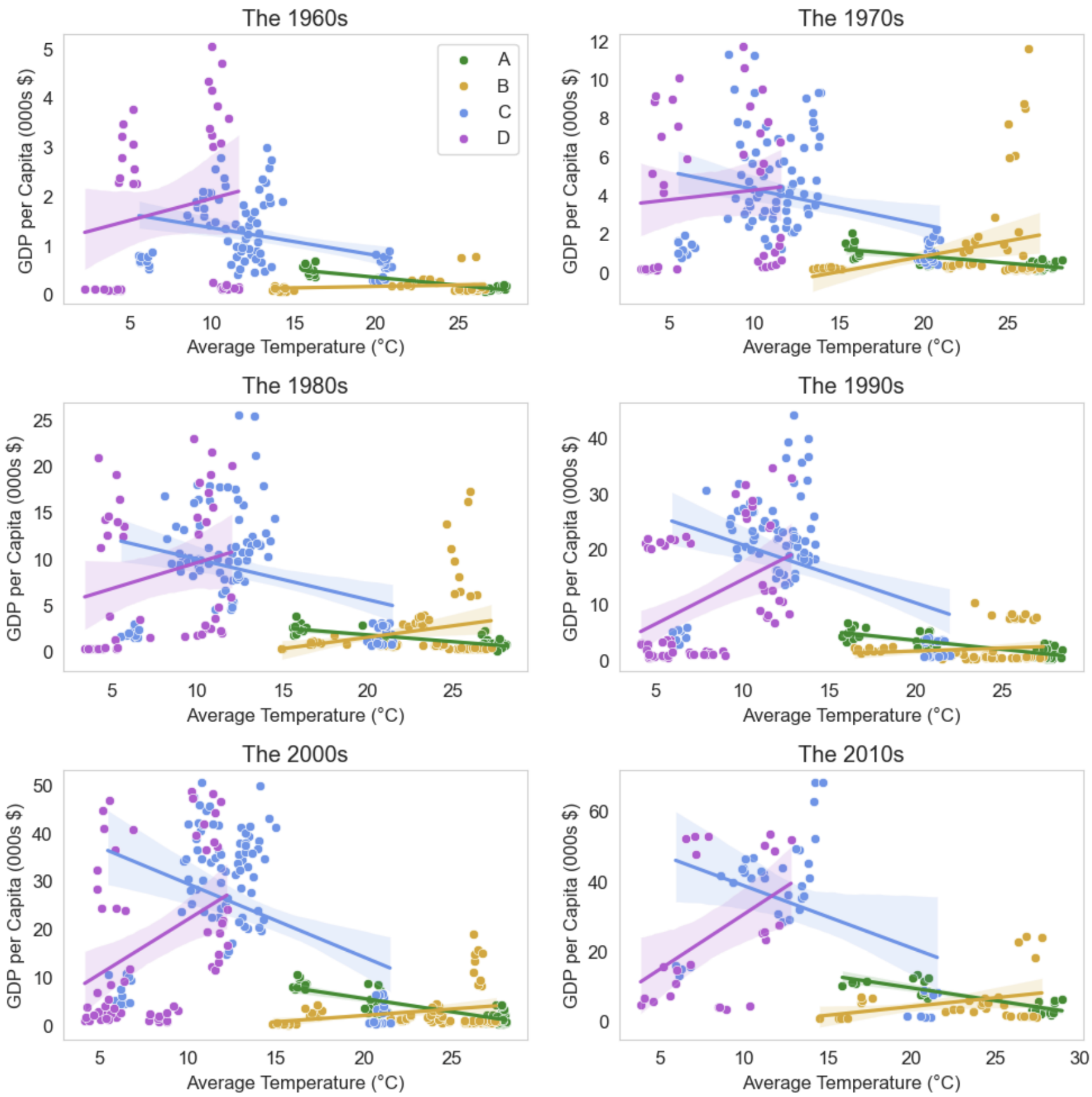

Figure 4: GDP per Capita vs Average Temperature Over Time by Climatic Zone.

The time-series graph above provides a longitudinal analysis of GDP per capita across four distinct climatic zones, identified as Zone A through Zone D, over several decades. GDP per capita is a valuable metric for this research, offering a standardized gauge of economic activity while accounting for population differences, thus facilitating direct comparisons across regions. The classification into climatic zones is based on the premise that unique environmental characteristics impact economic activities such as agricultural productivity, health, and industrial sustainability (Pretty, 2007). The justification for decadal grouping lies in capturing the long-term effects of climate on economic productivity. Shorter time frames might be influenced by transient economic factors or temporary climate anomalies. Decadal analysis helps smooth out these variations and reveals more enduring trends, providing a clearer picture of how average temperature impacts economic productivity over time.

The graph's temporal trends are crucial to understanding the potential influence of climate on economic performance. Persistent growth or decline in a specific climatic zone's GDP per capita might suggest the role of climate as either a catalyst or a barrier to economic prosperity. The extended timeline is particularly useful for discerning sustained economic patterns from short-term economic fluctuations and evaluating the long-term impact of climate on economic development.

In the 1960s, there is a discernible positive correlation between temperature and GDP per capita in Zone A (Tropical), suggesting that in this decade, warmer temperatures may have been associated with higher economic output, potentially due to the predominance of agriculture in tropical economies. This relationship appears to shift in subsequent decades, particularly in the 2000s and 2010s, where higher temperatures do not exhibit the same positive association with economic productivity. This could reflect structural changes in these economies over time, such as industrialization and the adoption of technology that may lessen the reliance on climate-sensitive sectors.

In contrast, Zones C (Temperate) and D (Continental) show a more consistent relationship across decades, with colder temperatures correlating with higher GDP per capita. This might indicate that temperate and continental climates, which can be more conducive to a diverse range of economic activities including advanced agriculture, industry, and services, contribute to higher economic productivity. Moreover, the data for Zones B (Dry) and D in later decades illustrate fluctuations that could be indicative of economic responses to environmental stressors, such as resource scarcity or the need for more robust infrastructure to deal with extreme weather, both of which can have profound economic implications.

Academic literature supports the notion that the relationship between climate and economic output is multi-faceted and may evolve over time as economies grow, diversify, and become more resilient to climate variability (Dell et al., 2012). The provided visualizations contribute to this body of knowledge by illustrating these shifts across climatic zones and over time, reinforcing the need for economic policies that are responsive to the unique challenges presented by different climatic conditions (Burke et al., 2015).

In light of these findings, further research is warranted to disaggregate the effects of other socio-economic factors and to understand the mechanisms through which climate affects economic productivity. This could include studies on infrastructure adaptability, technological innovation, and policy interventions that have been implemented in response to climatic challenges.

3.2 Mapping

In this section of the research paper, I aim to visually articulate the geographical dimensions of my research question, "Impact of Temperature Changes on Economic Productivity by Climatic Zone." Maps serve as an intuitive medium for presenting complex data, allowing for an immediate grasp of spatial relationships and patterns that might not be as evident in tabular data. Through the use of cartographic visualization, I intend to synthesize multifaceted datasets into a coherent narrative that underscores the spatial dynamics of climate's impact on economic productivity.

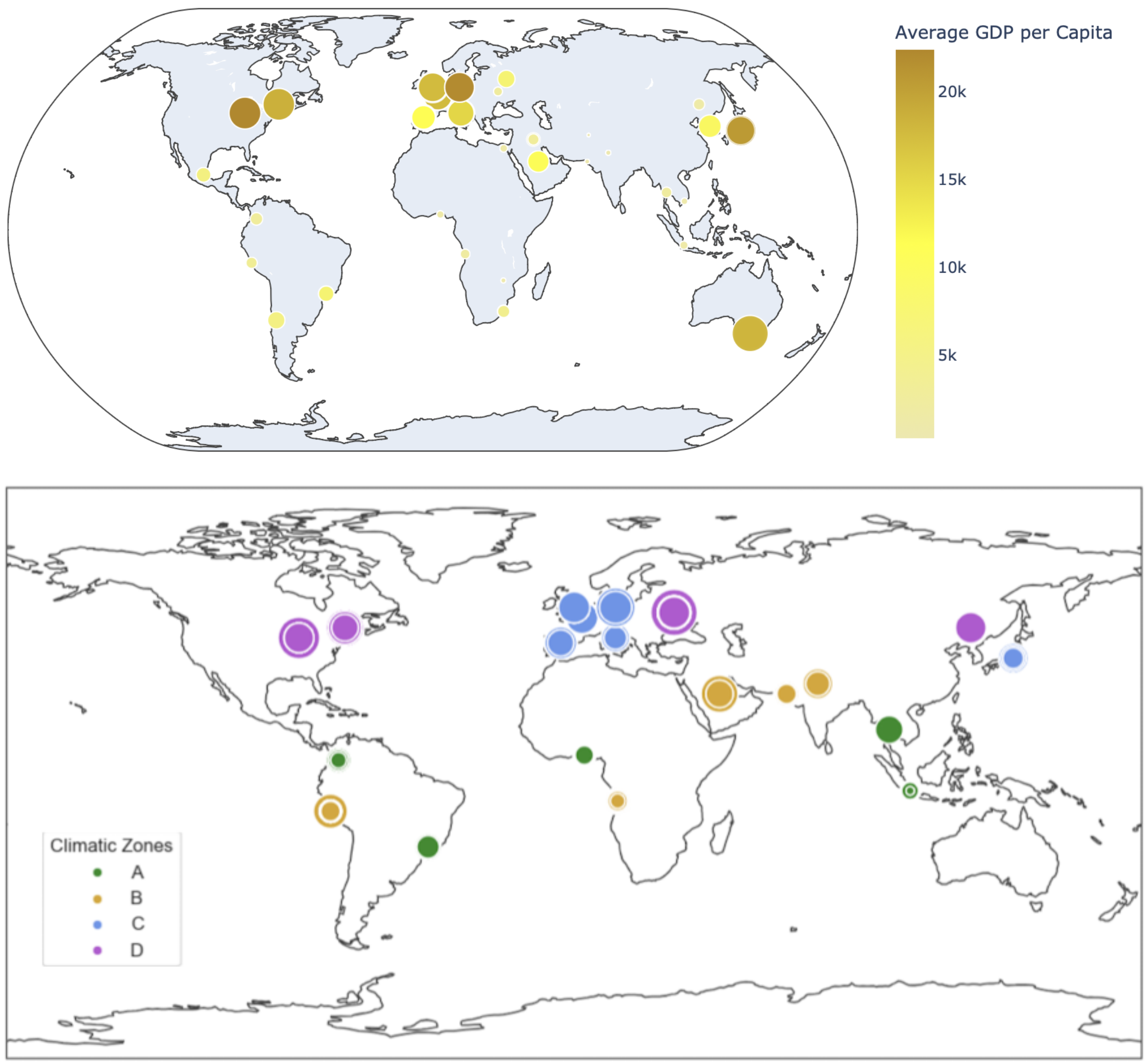

Figure 5: Maps Showing GDP Change Magnitude Across Various Cities and Variations in Average Temperature Changes Across Different Climatic Zones.

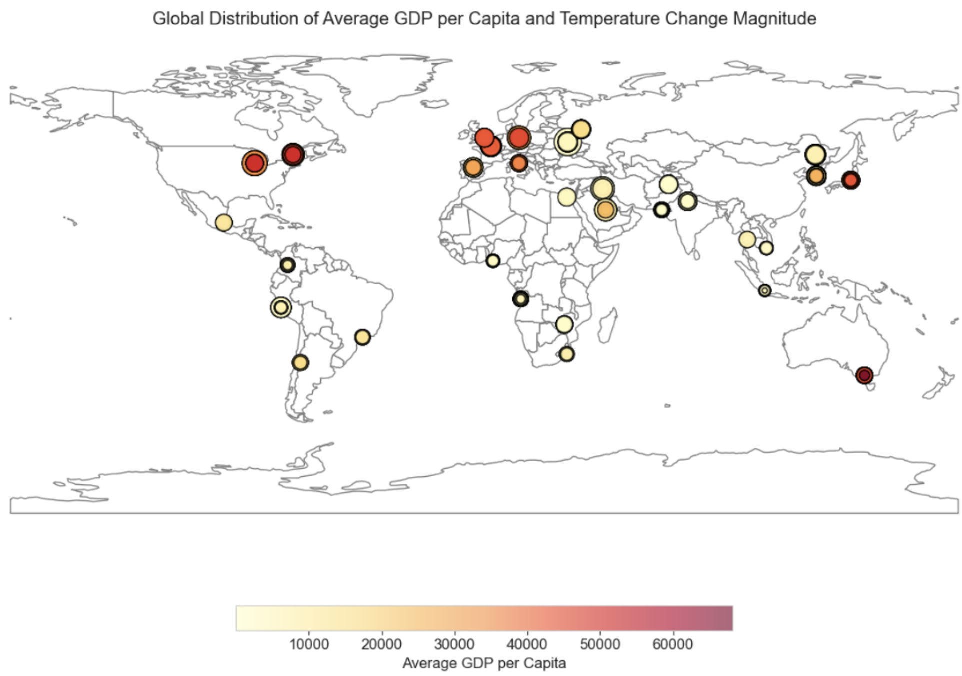

Figure 6: Map Showing Global Distribution of Average GDP per Capita and Temperature Change Magnitude.

The suite of visualizations presented offers a global perspective on the economic output and climatic changes across various cities, providing insights that speak directly to the relationship between temperature variations and economic productivity within different climatic zones.

The first visualization, "GDP Change Magnitude Across Various Cities," showcases the economic landscape of cities worldwide. The use of proportional symbols illustrates the vast disparities in economic productivity, revealing how wealth is distributed globally. Larger symbols in this map denote cities with a higher GDP per capita, highlighting regions of economic prosperity. Notably, these prosperous areas are not constrained by geographic or climatic boundaries, indicating that factors beyond climate—such as political stability, technological advancement, and access to global markets—may play a critical role in economic success.

The second map, "Variations in Average Temperature Changes Across Different Climatic Zones," depicts the extent of temperature changes experienced by cities within their respective climatic zones. The size of the symbols here correlates with the degree of temperature change, signaling the uneven impact of global warming. While this map does not provide a direct causal link to economic output, it emphasizes the areas most susceptible to climate change, which may in turn influence their economic conditions.

The third visualization, "Global Distribution of Average GDP per Capita and Temperature Change Magnitude," merges the climatic and economic data, highlighting the interplay between the two. The map uses color to indicate GDP per capita and symbol size to reflect temperature change magnitude. This dual representation allows for the examination of how economic productivity may align with or diverge from climatic shifts. Cities with larger, darker-colored symbols might suggest that despite significant temperature changes, they have managed to sustain or even enhance economic productivity, potentially due to effective adaptation measures or economic resilience. In synthesizing the insights from the third map, which overlays economic and climatic data, the complexity of the climate-economy relationship becomes even more pronounced. I can observe cities where significant temperature changes coincide with high GDP per capita, raising questions about the dynamics that enable economic robustness in the face of climatic adversity. Conversely, some cities with minimal temperature change exhibit lower economic productivity, suggesting the presence of other limiting factors at play.

These visual narratives underscore the importance of a multidimensional approach to understanding the climate-economy nexus. The maps provide a spatial representation of the data, which, when combined with quantitative analysis, enriches the understanding of the complex and variable relationship between climate and economic productivity.

However, these maps also come with limitations. The focus on city-level GDP per capita may not capture the full economic picture, particularly in countries where economic activity is more dispersed or not centrally located in urban areas. Additionally, while the visualizations effectively illustrate disparities and trends, they do not capture the underlying mechanisms driving these patterns nor do they address the distribution of wealth within cities or the socio-economic factors influencing climate vulnerability and economic resilience.

In terms of justifications, selecting cities as data points allows for a focused examination of how localized climate changes affect urban economic productivity, which is often at the forefront of climate impacts due to population density and infrastructure. The maps also serve as a visual prompt for policymakers and researchers to delve deeper into the nuances of climate impact, guiding targeted interventions and further study.

The combined analysis provided by these visualizations contributes to the existing body of research by offering a spatially-rich exploration of the relationship between climate and economic output. It aligns with the findings of previous studies which highlight the significance of geographical and socio-economic factors in climate adaptation and economic growth (Dell et al. 2012; Guivarch & Hallegatte, 2012). The insights drawn from these maps may aid in formulating strategies that account for the diverse impacts of climate change on global economic productivity.

3.3 Accounting for CO2 Emissions and Urbanization Rate

In the pursuit of extending the analytical depth of my study on the interplay between climatic conditions and economic productivity, I have identified an opportunity to enhance the dataset by incorporating data on CO2 emissions per capita and urbanization rates. This additional data was carefully chosen to provide a more nuanced understanding of the environmental impact of economic activities and the role of urban development in shaping economic productivity.

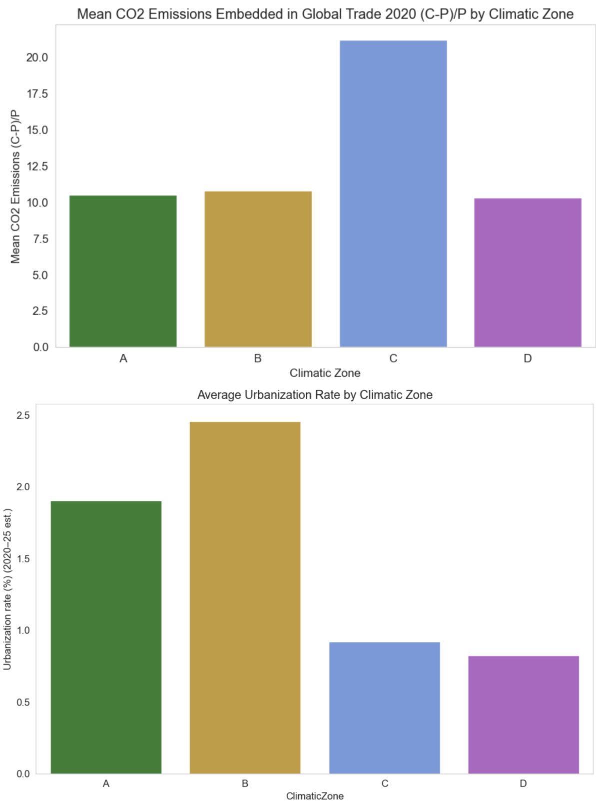

Figure 7: Bar Chart of Mean CO2 Emissions Embedded in Global Trade 2020 and Histogram of Urbanization Rates.

The graphical and statistical representation of CO2 emissions embedded in global trade, categorized by climatic zones, plays a critical role. The bar chart visually outline the mean values of the proportion of emissions due to consumption above production levels, relative to the production itself (C-P)/P, for each climatic zone. The bar chart depicted that Zone C has the highest mean value of (C-P)/P, strengthening the inference that consumption patterns in these regions might be leading to higher emissions compared to what their domestic production contributes. These findings align with the concepts described by Peters and Hertwich (2007) in "Post-Kyoto greenhouse gas inventories: Production versus consumption," where they discuss the relevance of considering trade-adjusted accounting for greenhouse gas emissions. They advocate for the importance of looking at consumption-based inventories to fully understand a country's or region's impact on global emissions.

In the bar chart showing the mean urbanization rates by climatic zone, Zone B stands out with the highest average urbanization rate, while Zone D remains the least urbanized.

This suggests that climatic conditions could influence the urban development of countries, which aligns with the findings from United Nations Development Programme (2005) that suggested in "World Resources: Managing Ecosystems to Fight Poverty" that geographic and climatic factors can significantly impact urban growth patterns.

However, the data also presents limitations. The sample size, particularly for Zone D, is small, which can limit the reliability of the statistics for this zone. This calls for a cautious interpretation and potentially suggests a need to investigate further or collect more data for robustness.

These findings are fundamental as they add a spatial dimension to the understanding of urbanization trends, which is crucial for policy formulation targeted at sustainable urban development. This spatial perspective is particularly relevant given the emphasis by the United Nations Human Settlements Programme (UN-Habitat) on the role of urbanization in sustainable development (UN Habitat, 2021). However, my findings challenge the notion that urbanization rates consistently increase as countries develop economically, as seen by the lower rates in some zones which could include countries at varying levels of development.

3.4 Ordinary Least Squares (OLS) Regression

In the pursuit of understanding the intricate dynamics between climatic conditions and economic productivity, this study proposes a multivariate OLS regression analysis with GDP per capita as the dependent variable (Y). The independent variables (Xs) chosen for analysis are '*Average Temperature*', '*Temperature Uncertainty*', '*Latitude*', '*Population Density*', '*CO2 Emissions Per Capita*', '*Urbanization Rate*', '*Greenhouse Gas Emissions*', and '*Fossil Fuel Consumption*'. These variables were selected based on their theoretical and empirical relevance to economic productivity within the context of climatic and environmental factors.

My analysis employs OLS regression to estimate the effect of various climate and economic variables on GDP per capita. The key advantage of using OLS is its ability to isolate the effect of individual predictors while holding other factors constant, thereby enabling us to understand the unique contribution of each variable.

Table 1: Direct Climate Effects

	Dependent variable: Log GDP per Capita			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Average Temperature	-0.111***	-0.117***	-0.115***	-0.115***
	(0.009)	(0.009)	(0.010)	(0.009)
Average Temperature Uncertainty	1.986***	1.849***	2.062***	1.811***
	(0.243)	(0.244)	(0.257)	(0.245)
Latitude	0.019***	0.017***	0.019***	0.007***
	(0.002)	(0.002)	(0.002)	(0.003)
Log Population density by city		-0.202***		
		(0.075)		
Log fossil fuel consumption				0.594***
				(0.144)
Log greenhouse gas emissions				-0.199**
				(0.086)
Urbanization rate			0.103	-0.207*
			(0.110)	(0.121)
Zone B	-1.198***	-1.196***	-1.217***	-0.502***
	(0.092)	(0.090)	(0.094)	(0.168)
Zone C	0.312**	0.118	0.383**	0.382***
	(0.134)	(0.150)	(0.154)	(0.143)
Zone D	0.125	0.006	0.194	-0.127
	(0.144)	(0.148)	(0.162)	(0.165)
const	9.882***	11.927***	9.773***	6.989***
	(0.231)	(0.797)	(0.260)	(0.648)
Observations	161	161	161	161
R^2	0.943	0.945	0.943	0.951
Adjusted R^2	0.940	0.943	0.940	0.948
Residual Std. Error	0.332 (df=154)	0.325 (df=153)	0.332 (df=153)	0.309 (df=151)
F Statistic	422.442*** (df=6; 154)	377.625*** (df=7; 153)	361.927*** (df=7; 153)	326.656*** (df=9; 151)
Note:				*p<0.1; **p<0.05; ***p<0.01

In the comparative analysis of regression models to discern the impact of temperature changes on economic productivity, **Model 4** emerges as the most comprehensive. This model integrates direct temperature effects and the interactions between climate conditions, energy use, and environmental factors, reflecting the intricate real-world interactions.

$$\begin{aligned} Log\_GDP\hat{\_}per\_Capita_i = {} & 6.989 - 0.115\text{AverageTemperature}_i \\ & + 1.811(\text{AverageTemperatureUncertainty})_i \\ & + 0.007\text{Latitude}_i - 0.207\text{Urbanization\_rate}_i \\ & - 0.199\text{Log\_greenhouse\_gas\_emissions}_i \\ & + 0.594\text{Log\_fossil\_fuel\_consumption}_i \\ & - 0.502\text{Zone\_B}_i + 0.382\text{Zone\_C}_i \\ & - 0.127\text{Zone\_D}_i + \varepsilon_i \end{aligned} \tag{1}$$

Statistical evaluations underline the strength of the models, with R-squared values around 0.943 to 0.955, indicating that the models explain a significant portion of GDP per capita variability. Adjusted R-squared values, providing a conservative measure of fit by accounting for the number of predictors, corroborate these findings. The consistently significant F-statistics across models confirm the collective influence of the variables.

The analysis of AIC and BIC aids in identifying the most parsimonious model without compromising the complexity of the data. The regression's standard error suggests the precision of the predictions, with lower values denoting greater accuracy.

This table presents a compelling quantitative examination of the direct climate effects on economic productivity, as evidenced by the log GDP per capita across various models. Each model incrementally integrates additional variables to dissect the complex interplay between climate and economic performance. The consistent negative coefficient of Average Temperature across all models suggests that higher temperatures may impede economic productivity, particularly in regions where climate-sensitive industries such as agriculture dominate. This is consistent with the literature indicating that excessive heat can reduce labor productivity and crop yields (Dell et al., 2012).

Furthermore, the positive and statistically significant coefficient of Average Temperature Uncertainty indicates that not just the mean temperature, but also the variability in temperature plays a crucial role. Economies might be suffering from unpredictability in climatic conditions, which could disrupt planning and stability in sectors sensitive to climate volatility. This aligns with the notion that uncertainty in climate conditions can have profound implications for economic planning and investment (Desmet & Rossi-Hansberg, 2024).

Interestingly, the positive coefficient for Latitude in Models 1, 2, and 3, which becomes less significant in Model 4, suggests a potential advantage for regions further from the equator, possibly due to less exposure to extreme heat. However, the diminishing significance in Model 4 could indicate that when controlling for other factors like fossil fuel consumption and greenhouse gas emissions, the latitude's influence wanes, suggesting that human-induced environmental changes might be overpowering natural geographic advantages.

The inclusion of urbanization rate and climatic zones adds another layer of nuance. The negative coefficient for urbanization rate in Model 4 highlights the complexities urban settings may face with respect to climate change, possibly due to the heat island effect or other urban-specific vulnerabilities.

The stark contrast in the coefficients for Zone B across the models suggests that areas with dry climates are experiencing the most significant negative impact from increasing temperatures, which could be due to water scarcity affecting agriculture and human habitation (Zone B's coefficient in Model 4). Conversely, Zones C and D exhibit varying degrees of resilience or vulnerability, implying that temperate and continental climates may have mixed impacts on economic productivity, likely because of diverse socio-economic structures and adaptive capacities.

Ultimately, these regression outcomes clarify the complex relationship between climate factors and economic output, particularly the distinct effects by climatic zone. These results provide a strong empirical basis for advocating region-specific economic policies to combat the economic challenges of climate change and promote sustainable growth tailored to regional climatic nuances. The evidence presents a clear response to the research question regarding the economic consequences of temperature fluctuations across climatic zones.

In the second suite of models, I delve into the indirect effects of climatic factors on GDP per capita to complement the direct effects analysis. Each model incorporates a unique combination of variables that capture different dimensions of climate's influence on economic activity, extending beyond the immediate impacts of temperature and climatic zones.

Table 2: Indirect Climate Effects

	Dependent variable: Log GDP per Capita			
	Model 5	**Model 6**	**Model 7**	**Model 8**
Percentage total of CO2 emission in 2022	0.932***			
	(0.218)			
Average Temperature			-0.077***	-0.060***
			(0.009)	(0.008)
CO2 emissions embedded in global trade 2020 (C-P)/P			0.018***	0.022***
			(0.003)	(0.002)
Change in per capita CO2 emissions			-0.005***	0.003***
			(0.001)	(0.001)
Education (Enrolment in primary school)	0.028***			-0.017***
	(0.005)			(0.003)
Health (Life expectancy)				0.178***
				(0.013)
Log carbon intensity elec		-0.105		0.021
		(0.078)		(0.036)
Log fossil fuel consumption		0.247***		0.487***
		(0.056)		(0.049)
Log$_{r}enewables_{e}nergy_{p}er_{c}apita$		0.405***		0.070**
		(0.051)		(0.030)
Urbanization rate	-0.265			
	(0.160)			
Zone B	-0.273*	-0.705***	-1.024***	0.083
	(0.149)	(0.146)	(0.089)	(0.103)
Zone C	1.113***	1.233***	0.312**	-0.499***
	(0.203)	(0.134)	(0.129)	(0.097)
Zone D	-0.496	1.417***	0.805***	-0.679***
	(0.413)	(0.151)	(0.134)	(0.148)
const	5.529***	4.644***	10.772***	-6.225***
	(0.736)	(0.722)	(0.219)	(0.918)
Observations	161	161	161	161
R^2	0.880	0.886	0.937	0.983
Adjusted R^2	0.876	0.881	0.934	0.982
Residual Std. Error	0.480 (df=154)	0.468 (df=154)	0.348 (df=154)	0.184 (df=149)
F Statistic	188.658*** (df=6; 154)	198.914*** (df=6; 154)	381.026*** (df=6; 154)	776.441*** (df=11; 149)
Note:				*p<0.1; **p<0.05; ***p<0.01

Model 8 stands out as the preferred specification, capturing the multifaceted impact of climate on economic productivity. This model underscores the integral role of health and education—variables that reflect human well-being—as they relate to the economic vigor of various climatic zones.

$$
\begin{aligned}
\widehat{Log\_GDP\_per\_Capita}_i = & -6.225 - 0.060\text{AverageTemperature}_i + 0.178\text{Health}_i \\
& + 0.083\text{Zone\_B}_i - 0.499\text{Zone\_C}_i - 0.679\text{Zone\_D}_i \\
& + 0.070(\text{Log\_renewables\_energy\_per\_capita})_i \\
& + 0.487(\text{Log\_fossil\_fuel\_consumption})_i \\
& + 0.821(\text{Log\_carbon\_intensity\_elec})_i \\
& + 0.022(\text{CO2\_emissions\_embedded\_in\_global\_trade})_i \\
& + 0.003\text{Change\_in\_per\_capita\_CO2\_emissions}_i \\
& - 0.017\text{Education}_i + \varepsilon_i
\end{aligned} \tag{2}
$$

The strength of Model 8 is evident in its R-squared value of 0.983, suggesting it explains a significant proportion of the variability in GDP per capita, more so than other models. The slightly lower Adjusted R-squared value continues to support its robustness, considering the number of predictors. Model 8's F-Statistic, the highest among the models, indicates a strong collective explanatory power of the included variables. Additionally, this model exhibits the lowest Residual Standard Error, implying that its predictions are more precise. The coefficients in Model 8 reveal intriguing relationships: a positive impact of life expectancy on GDP per capita hints at the economic benefits of a healthier population, while the negative coefficient for the combined enrollment rate might suggest diminishing returns to education or delayed economic benefits from educational investments.

The individual coefficients offer a window into the nuanced dynamics between climatic changes and economic productivity. The positive coefficient for life expectancy in Model 8 underscores the economic value of health, potentially capturing the increased labor productivity and reduced healthcare costs associated with a healthier workforce. Conversely, the negative coefficient for the combined enrollment rate raises intriguing questions about the timing and nature of education's economic returns. This unexpected finding might indicate that, while education is fundamentally valuable, its economic dividends may be long-term, or there could be a threshold beyond which additional education does not translate into immediate economic growth.

The negative coefficients for Average Temperature across Models 5 to 8 consistently suggest that rising temperatures may have a detrimental effect on economic productivity, corroborating a substantial body of literature that links adverse climate conditions to economic challenges. The model reveals that the indirect effects of climate, through health and education, are just as critical as direct impacts, such as those stemming from changes in agricultural yields or labor productivity due to temperature fluctuations. Interestingly, Model 8 does not show a significant relationship between urbanization rates and GDP per capita, which could imply that the economic benefits of urbanization are not uniform and may be contingent on other factors such as infrastructure, governance, and the urban-rural divide.

The analysis within Model 8 aligns with the research question by demonstrating that climate change's impact on economic productivity is multifaceted, with health and education acting as critical mediators. The insights gleaned from this model advocate for integrated policy solutions that simultaneously address climate resilience, public health, and education systems to foster sustainable economic growth in the face of climate change.

These findings advocate for policy frameworks that holistically integrate climate adaptation strategies with educational and health interventions. Such comprehensive policies are imperative for enhancing the economic resilience of different climatic zones to climate change. The insights from Model 8 offer a detailed answer to the research question and highlight the complexity of climate effects on economic output, emphasizing the need for multifaceted responses in policy-making.

3.5 Machine Learning

3.5.1 Regression Tree

A machine learning model such as a regression tree and Random Forest was considered in this research as a way to partition the dataset into subsets (nodes) based on the independent variables. Each split is chosen to reduce the sum of squared differences between the actual and predicted values within each node. The regression tree is attempting to divide the dataset into groups (partitions) where the GDP per Capita values are as close to each other as possible, within each group. Each split in the tree is determined by the variable and threshold that provides the largest reduction in this sum of squared differences. The goal is to create nodes that are as homogeneous as possible in terms of the dependent variable's value, thus minimizing within-node variance.

In a regression tree, the objective function can be expressed as follows:

$$\min_{j,s} \left[\sum_{i:x_{i,j} \leq s} (y_i - \hat{y}_{\text{left}})^2 + \sum_{i:x_{i,j} > s} (y_i - \hat{y}_{\text{right}})^2 \right]$$

where:

- j represents a particular independent variable or feature that I am are examining in my study. In this case, the explanatory variables such as AverageTemperature, Urbanization rate, Zone categories (B, C, D), etc.
- s is the threshold value that is used to split a node in the regression tree.
- $x_{i,j}$ is the value of the j-th feature for the i-th observation.

- y_i is the actual observed value of the dependent variable for the i-th observation.
- $\hat{y}_{\text{left}}$ and $\hat{y}_{\text{right}}$ are the mean values of the dependent variable for the observations in the left and right child nodes created by the split.

The algorithm seeks to partition the dataset into subsets (nodes) based on the independent variables. Each split is chosen to reduce the sum of squared differences between the actual and predicted values within each node. The regression tree is attempting to divide the dataset into groups (partitions) where the log GDP per Capita values are as close to each other as possible, within each group. Each split in the tree is determined by the variable and threshold that provides the largest reduction in this sum of squared differences. The goal is to create nodes that are as homogeneous as possible in terms of the dependent variable's value, thus minimizing within-node variance.

In lay terms, the regression tree algorithm will take the dataset and find the best split for the independent variables. Each split is chosen to create two groups that are as similar as possible in terms of log GDP per Capita. This process continues, creating a tree-like model of decisions, which ideally represents the complexity of the relationships in the data.

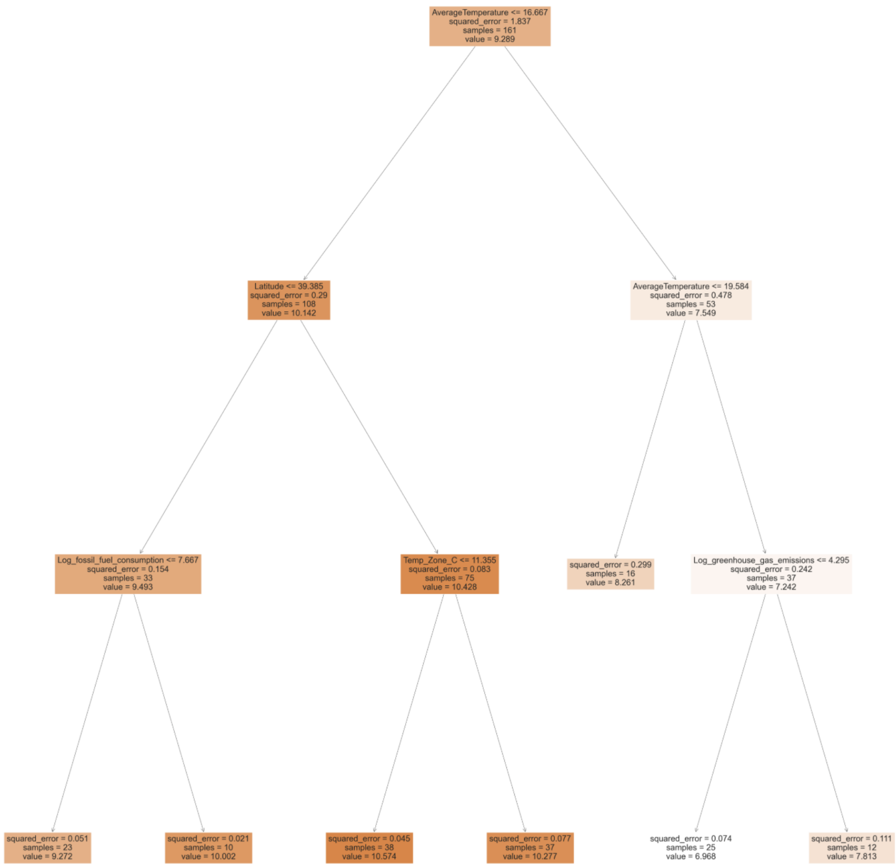

Figure 8: Regression Tree of Model 4

In my research, I employed a regression tree derived from Model 4 of my OLS regressions to explore the intricate dynamics between climate variables and economic productivity. This non-linear model complements the linear approach of OLS, potentially revealing complex interaction effects among the predictors.

The regression tree commences its analysis at the root node by selecting the most significant predictor of economic productivity, which in this case is the Average Temperature. The initial split is made at 16.667 degrees Celsius, suggesting a pivotal role of temperature in influencing economic outcomes. This threshold indicates that lower average temperatures generally correlate with higher economic productivity, likely due to favorable conditions for a range of economic activities that are adversely affected by excessive heat.

Subsequently, the tree branches into two main paths: one for cooler climates and another for warmer climates. In the cooler climate branch, the tree further divides data based on Latitude, with a critical point at 39.385 degrees. This split suggests that geographical positioning up to this latitude impacts productivity differently, potentially reflecting variations in agricultural zones or the distribution of industries.

Further down this branch, additional splits are based on environmental and consumption metrics such as '*Log Fossil Fuel Consumption*', with a threshold at 7.667. Regions with lower consumption within these climatic conditions are observed to have higher productivity, possibly due to more efficient energy use or a greater reliance on renewable resources. Another notable split in this branch is *'Temp Zone C'* $\leq$ 11.355, pointing to the economic influence of specific climatic zones that may have unique characteristics affecting productivity.

In the warmer climates branch, '*Urbanization Rate*' serves as a significant splitter at 1.65%, highlighting the influence of urban infrastructure on productivity. Lower urbanization rates in these warmer regions suggest challenges in maintaining productivity, likely due to less developed infrastructure or fewer economic opportunities. Deeper into this branch, a split by Log Greenhouse Gas Emissions at 4.295 further refines the analysis. This split reveals that lower emissions in these areas correlate with higher productivity, indicative of advanced technological adoption and efficient practices.

Throughout these branches, the regression tree identifies several non-linear relationships. For example, the interaction between temperature and latitude illustrates varying impacts on productivity based on geographical proximity to the equator. Additionally, the combined effects of urbanization and greenhouse gas emissions in warmer climates highlight complex dependencies where individual factors alone do not fully explain economic outcomes but together provide significant insights.

The tree's leaves, representing the culmination of each decision path, offer predictions for Log GDP per Capita based on specific conditions. These predictions reflect the nuanced impact of multiple converging climatic and socio-economic variables, providing a granular view of how different factors interact to shape economic productivity.

This detailed exploration of the regression tree underscores the model's utility in systematically illustrating the complex, non-linear interdependencies between climate-related factors and economic productivity across various geographic and climatic zones. Through this analysis, I have enhanced our understanding of the direct and combined effects of factors like temperature, urbanization, and environmental metrics on economic outcomes, offering valuable insights for future research and policy formulation.

3.5.2 Random Forest Regression

In this section, I delve into the Random Forest model — a machine learning algorithm that builds on the foundation of regression trees to provide a more robust analysis of the intricate relationship between climatic variations and economic productivity. Unlike a single regression tree, which might suffer from overfitting due to its sensitivity to the nuances of the training data, or an OLS regression which only allows us to estimate the dependent variable on a macro-level coefficients (Khazra, 2019) - a Random Forest model mitigates this risk by constructing a multitude of trees and aggregating their predictions, hence enhancing the generalizability of the results.

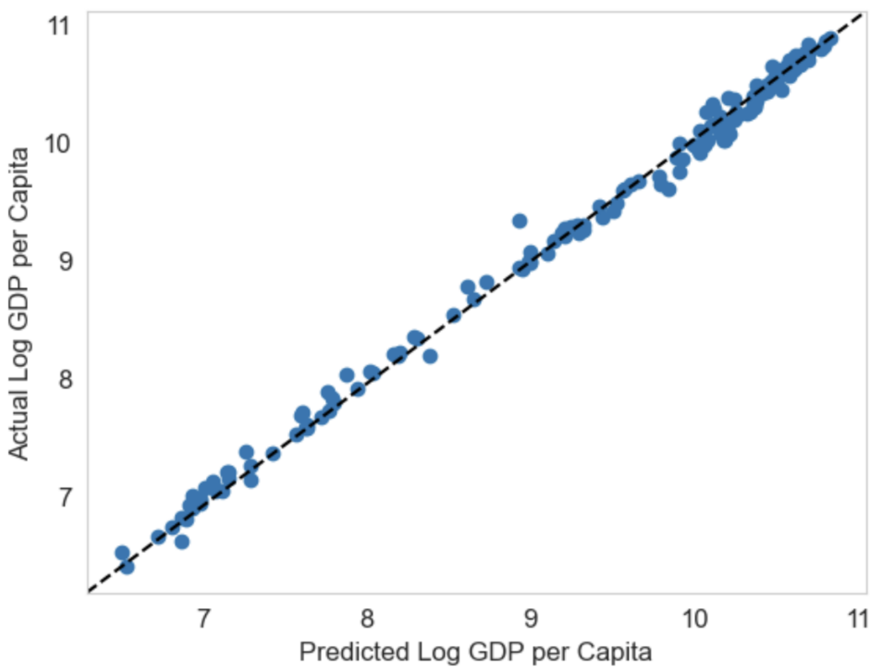

Figure 9: Random Forest Model

In the scatter plot in **Figure 7**, the MSE of my Random Forest model is depicted as 0.00726. This metric is pivotal in the context of my research as it quantifies the discrepancy between the actual GDP per capita values and those predicted by the model across diverse climatic zones. The proximity of this MSE to zero denotes an exceptional degree of accuracy in the model's predictions. Given that MSE evaluates the quality of an estimator, this notably low MSE value suggests that my model precisely estimates the GDP per capita based on the incorporated features, thereby confirming the robustness of the model's predictive capabilities.

Upon analyzing the results, I discerned a marked improvement in prediction error, with the Mean Squared Error (MSE) markedly reduced to 0.0073, indicating a more precise model compared to the regression tree previously discussed.

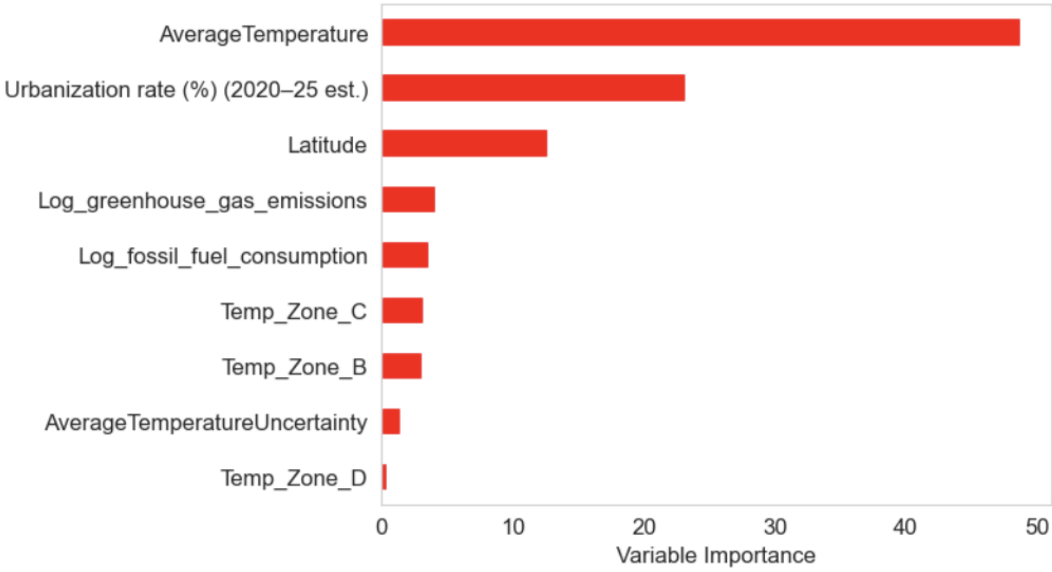

Figure 10: Importance Matrix

The importance matrix, a crucial output of the Random Forest, yields invaluable insights into the relative importance of each predictor variable within the model. In this matrix, '*Average Temperature*' emerges as the most influential variable, asserting its critical role in the prediction of log GDP per Capita. This result aligns with theoretical expectations and empirical evidence that temperature can exert substantial influence on various sectors of an economy, such as agriculture, health, and labor productivity (Dell, Jones, Olken, 2012).

The '*urbanization rate*' and '*latitude*' follow in significance, reinforcing my hypothesis about the multifaceted nature of economic productivity. Urbanization rates encapsulate the growth dynamics of economies, capturing shifts towards more service- and industry-based activities which are typically associated with increased economic productivity. Latitude serves as a proxy for geographic and climatic conditions, which has been shown to have a significant correlation with economic activity due to factors such as accessibility to sea routes, endowment of natural resources, and agricultural viability (Gallup, Sachs, and Mellinger, 1999).

Interestingly, '*greenhouse gas emissions*' and '*fossil fuel consumption*' also feature prominently in the importance matrix. Their significance suggests that the energy profile of a region – in terms of both consumption and emissions – is a key determinant of economic productivity, potentially due to its implications for sustainability and policy frameworks that govern economic activities (Auffhammer & Carson, 2008).

The Random Forest model's MSE and the derived importance matrix provide me with a robust analytical framework to further dissect the economic impacts of climatic variability. The reduced MSE underscores the efficacy of ensemble methods in capturing complex patterns that may not be apparent in linear models. Moving forward, I intend to delve deeper into the nuances highlighted by the importance matrix, exploring the intricate web of interactions between climate, geography, and economic dynamics. This line of inquiry is not only academically stimulating but also bears significant implications for policymakers striving to foster economic resilience in the face of climatic changes.

3.5.3 Comparing the results from OLS Regressions and Regression Tree

I undertake a comparative analysis of the outcomes derived from OLS regressions and the Regression Tree method to shed light on the nuanced impact of temperature changes on economic productivity across climatic zones. This comparison is vital as it allows me to contrast the linearity inherent in OLS with the non-linear, hierarchical decision-making process embedded within the Regression Tree approach.

The OLS regression models provide a foundational understanding of the relationship between climatic variables and economic productivity. In these models, the explanatory power, as gauged by the R-squared and adjusted R-squared statistics, was substantial, indicating that a significant proportion of the variation in Log GDP per Capita could be attributed to the model's independent variables. The OLS method, renowned for its simplicity and interpretability, offers clear insights into the direct linear associations between each independent variable and the dependent variable. In contrast, I employed the Regression Tree to capture potential non-linear interactions and to allow for more complex model structures. The hierarchical nature of this method offers an alternative view that can unveil the varying impact of predictors at different thresholds. This approach also addresses the possibility of non-linearity in the data, which OLS assumptions may overlook.

Upon reflection, the Regression Tree revealed intricate decision pathways, showcasing how different combinations of variables interact to predict economic productivity. Notably, the Regression Tree's MSE illuminated the method's predictive performance, serving as a benchmark for comparison with the MSE from the Random Forest model, which I found to be superior in predicting power.

The divergence in results between the two methods underscores the complexity of the relationship between temperature and economic productivity. While the OLS models provide a valuable baseline, the Regression Tree introduces an additional layer of depth to the analysis. For instance, variables that appeared less significant in the OLS models, such as 'Latitude,' assumed greater importance in the Regression Tree, suggesting non-linear effects that vary across different levels of other predictors.

Furthermore, the Regression Tree's ability to handle variable interactions inherently, which OLS models require explicit specification for, presents an advantage, particularly when theorizing about the underlying mechanisms of climate impact on economies. These non-linear interactions are critical in my research, as the impact of temperature on economic productivity is unlikely to be uniform across different climatic zones.

A thorough examination of methodological approaches must also account for the challenges inherent in the data being analyzed. In my case, the dataset comprises approximately 150 observations, which poses a limitation in terms of the variability and the complexity of the models that I can reliably estimate. This decision was informed by the belief that city-level analysis would yield more granular insights into the relationship between climatic variables and economic output.

While OLS regression is well-suited to small datasets and can provide robust estimates under such constraints, the limited number of observations restricts the inclusion of a large number of predictors due to the risk of overfitting and multicollinearity. These risks are exacerbated when interaction terms are considered, as they further consume degrees of freedom and can lead to less precise coefficient estimates. The Regression Tree, while adept at detecting non-linear relationships and interactions, also faces challenges with smaller datasets. Trees can become overly complex and may overfit the data, capturing noise rather than underlying patterns, which is particularly problematic when the number of observations is not sufficiently large to validate the complexity of the model structure.

The aforementioned limitation is also a crucial factor in the context of Random Forests. Despite their capacity to improve upon single trees by reducing variance through bagging, the scarcity of data can hinder the diversity of trees in the forest, potentially leading to correlated errors and thus diminishing the algorithm's effectiveness. Despite these limitations, I maintain that the city-level approach is valid and offers valuable insights. It can uncover specific climate-related economic effects that might be averaged out in national or regional data. However, it is crucial to acknowledge that expanding the dataset, perhaps by integrating more city-level data or by considering a multi-scale approach that combines city-level data with regional trends, could enhance the model's performance and the robustness of the conclusions drawn. In future work, I would consider exploring data at different levels of aggregation to compare how the scale of analysis impacts the results. The present study serves as a pivotal step that underscores the necessity of granularity in environmental economics research, and it opens avenues for more comprehensive investigations that build on the findings and methodological reflections derived from this research.

In conclusion, the juxtaposition of the OLS Regressions with the Regression Tree method has allowed me to appreciate the strengths and limitations of both approaches. While the OLS models offer clear interpretations within a linear framework, the Regression Tree provides a more nuanced understanding of the dataset's inherent complexities. In light of these findings, I advocate for a methodological pluralism in economic research on climate impacts, suggesting that a combination of linear and non-linear models can offer the most comprehensive insights into this multifaceted issue.

4 Conclusion

In summation, my paper's comprehensive analysis sheds light on the intricate connection between climatic dynamics, particularly temperature fluctuations, and economic productivity as gauged by GDP per capita within various Köppen climatic zones. The fusion of Earth's surface temperature data with economic metrics, enriched further by urbanization rates, energy consumption, and demographic factors, has offered insightful revelations into how climate may shape economic trajectories globally.

The methodological choice to utilize an outer merge in data integration, despite introducing a level of complexity, proved instrumental. It allowed the full breadth of the dataset to inform the analysis, thereby capturing a more complete picture of the climate-economy nexus. This approach was essential in acknowledging the nuanced interplay of climatic conditions with economic vitality.

Through additional analytical dimension with the use of regression trees and random forest models, tools not typically associated with traditional economic studies. This innovative step not only highlighted non-linear patterns and interactions but also revealed the significance of specific variables, such as urbanization rates and greenhouse gas emissions, which exhibit varying levels of influence on economic output when exposed to temperature changes. These findings are particularly crucial in understanding that the impact of temperature fluctuations is not uniform across climatic zones—rather, it is highly dependent on the unique socioeconomic and environmental contexts of each region.

Through this lens, my research addresses the central question: How do temperature changes impact economic productivity by climatic zone? The investigation confirms that temperature variations indeed have a discernible and diverse impact on GDP per capita, which varies from one climatic zone to another. In particular, regions with temperate climates exhibit a different economic response to temperature changes compared to those with tropical or dry climates. This variability accentuates the imperative for climate-specific economic strategies that can harness the potential of each region's unique climatic conditions.

Moreover, the machine learning techniques applied, specifically the regression tree analysis, have extracted additional nuances of the climate-economy relationship that traditional linear regression could not. For instance, these techniques identified thresholds and breakpoints in the data where shifts in temperature have proportionally greater or lesser impacts on economic productivity, suggesting areas of potential resilience or vulnerability within climatic zones.

As we confront the global challenge of climate change, this study not only enriches the discourse on climate resilience and economic sustainability but also provides actionable intelligence for policymakers and economic stakeholders. It advocates for the integration of climate adaptation into economic planning, highlighting that economic resilience can be enhanced through strategies that are sensitive to the differentiated impact of climate factors. The insights gleaned from this research pave the way for a paradigm where economic planning and development are not merely responsive to climatic conditions but are proactive in leveraging the distinct opportunities they present. This study, therefore, acts as a catalyst for further scholarly inquiry into adaptive measures that can buffer the economic ramifications of climate change, promoting sustainable economic growth in the face of an evolving global climate landscape.

References

[1] Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A., & Wood, E. F. (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific Data*, 5(1). Available: `https://doi.org/10.1038/sdata.2018.214`

[2] Berkeley Earth. (2017). Climate Change: Earth Surface Temperature Data. *Kaggle.com.* Available: `https://www.kaggle.com/datasets/berkeleyearth/climate-change-earth-surface-temperature-data`

[3] Borisov, S. (2019). World Cities by Climate. *Kudacity.com.* Available: `https://www.kudacity.com/cset/by_climate`

[4] Bren d'Amour, C., Reitsma, F., Baiocchi, G., Barthel, S., Güneralp, B., Erb, K.-H., Haberl, H., Creutzig, F., & Seto, K. C. (2016). Future urban land expansion and implications for global croplands. *Proceedings of the National Academy of Sciences*, 114(34), 8939–8944. Available: `https://doi.org/10.1073/pnas.1606036114`

[5] Burke, M., Hsiang, S. M., & Miguel, E. (2015). Climate and Conflict. *Annual Review of Economics*, 7(1), 577–617. Available: `https://doi.org/10.1146/annurev-economics-080614-115430`

[6] CIA. (2018). The World Factbook: Field Listing - Urbanization. *Cia.gov.* Available: `https://www.cia.gov/the-world-factbook/field/urbanization`

[7] Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics*, 4(3), 66–95. Available: `https://doi.org/10.1257/mac.4.3.66`

[8] Desmet, K., & Rossi-Hansberg, E. (2024). Climate Change Economics Over Time and Space. *SSRN Electronic Journal.* Available: `https://doi.org/10.2139/ssrn.4742035`

[9] European Comission. (2023). EDGAR - The Emissions Database for Global Atmospheric Research. *Europa.eu.* Available: `https://edgar.jrc.ec.europa.eu/report_2023`

[10] Glaeser, E. L., & Kahn, M. E. (2003). Sprawl and Urban Growth. *Harvard Institute of Economic Research Working Papers.* Available: `https://ideas.repec.org/p/fth/harver/2004.html`

[11] Grossman, G. M., & Krueger, A. B. (1991, November). Environmental Impacts of a North American Free Trade Agreement. *National Bureau of Economic Research Working Paper Series.* Available: `https://www.nber.org/papers/w3914`

[12] Guivarch, C., & Hallegatte, S. (2012). From Growth to Green Growth - a Framework. *SSRN Electronic Journal*. Available: https://doi.org/10.2139/ssrn.1988201

[13] Hammer, S. A., Mehrotra, S., Rosenzweig, C., & Solecki, W. D. (2009). Climate Change and Cities. *Cambridge University Press*. Available: https://doi.org/10.1017/cbo9780511783142

[14] Hsieh, C.-T., & Olken, B. A. (2014). The Missing "Missing Middle." *Journal of Economic Perspectives*, 28(3), 89–108. Available: https://doi.org/10.1257/jep.28.3.89

[15] Hussain, A., & Bangash, R. (2017). Impact of Climate Change on Crops' Productivity across Selected Agro-ecological Zones in Pakistan. *The Pakistan Development Review*, 56(2), 163–187. Available: https://www.jstor.org/stable/26875191

[16] Kahn, M. E., Mohaddes, K., Pesaran, M. H., Raissi, M., & Yang, J.-C. (2019). Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis. *International Monetary Fund*.

[17] Khazra, N. (2019). Heterogeneities in the House Price Elasticity of Consumption. *Social Science Research Network*. Available: https://doi.org/10.2139/ssrn.3483279

[18] Lenzen, M., Kanemoto, K., Moran, D., & Geschke, A. (2012). Mapping the Structure of the World Economy. *Environmental Science & Technology*, 46(15), 8374–8381. Available: https://doi.org/10.1021/es300171x

[19] Marcotullio, P. J., Hughes, S., Sarzynski, A., Pincetl, S., Peña, L. S., Romero-Lankao, P., Runfola, D., & Seto, K. C. (2014). Urbanization and the carbon cycle: Contributions from social science. *Earth's Future*, 2(10), 496–514. Available: https://doi.org/10.1002/2014ef000257

[20] Martinez-Zarzoso, I. (2008). The Impact of Urbanization on CO2 Emissions: Evidence from Developing Countries. *SSRN Electronic Journal*. Available: https://doi.org/10.2139/ssrn.1151928

[21] Mesgari, M., Okoli, C., Mehdi, M., Nielsen, F. Å., & Lanamäki, A. (2014). "The sum of all human knowledge": A systematic review of scholarly research on the content of Wikipedia. *Journal of the Association for Information Science and Technology*, 66(2), 219–245. Available: https://doi.org/10.1002/asi.23172

[22] Nordhaus, W. D. (2007). A Review of the "Stern Review on the Economics of Climate Change." *Journal of Economic Literature*, 45(3), 686–702. Available: https://www.jstor.org/stable/27646843

[23] O'Brien, P., O'Neill, P., & Pike, A. (2019). Funding, financing and governing urban infrastructures. *Urban Studies*, 56(7), 1291–1303. Available: https://doi.org/10.1177/0042098018824014

[24] OECD. (n.d.). The OECD Environment Programme: INDICATORS TO MEASURE DECOUPLING OF ENVIRONMENTAL PRESSURE FROM ECONOMIC GROWTH. Available: https://www.oecd.org/environment/indicators-modelling-outlooks/1933638.pdf

[25] Peters, G. P., & Hertwich, E. G. (2007). Post-Kyoto greenhouse gas inventories: production versus consumption. *Climatic Change*, 86(1-2), 51–66. Available: https://doi.org/10.1007/s10584-007-9280-1

[26] Peters, G. P., Minx, J. C., Weber, C. L., & Edenhofer, O. (2011). Growth in emission transfers via international trade from 1990 to 2008. *Proceedings of the National Academy of Sciences*, 108(21), 8903–8908. Available: https://doi.org/10.1073/pnas.1006388108

[27] Pretty, J. N. (2007). Agricultural sustainability: concepts, principles and evidence. *Philosophical Transactions of the Royal Society B*, 363(1491), 447–465. Available: https://doi.org/10.1098/rstb.2007.2163

[28] Ritchie, H., Rosado, P., & Roser, M. (2023, December 28). CO2 and Greenhouse Gas Emissions. *Our World in Data*. Available: https://ourworldindata.org/co2-and-greenhouse-gas-emissions

[29] Seto, K. C., Guneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences*, 109(40), 16083–16088.

[30] Stern, D. I. (1993). Energy and economic growth in the USA. *Energy Economics*, 15(2), 137–150. Available: https://doi.org/10.1016/0140-9883(93)90033-n

[31] Stern, D. I. (2016). The Role of Energy in the Industrial Revolution and Modern Economic Growth - David I. Stern, Astrid Kander, 2012. *The Energy Journal*. Available: https://journals.sagepub.com/doi/abs/10.5547/01956574.33.3.5

[32] The World Bank. (2022). World Bank Open Data. GDP per Capita (Current US$). Available: https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?view=map&year=2022

[33] Tol, R. (2009). The Economic Effects of Climate Change. *Journal of Economic Perspectives*, 23(2), 29–51. Available: https://doi.org/10.1257/jep.23.2.29

[34] UN Habitat. (2021). About Us — UN-Habitat. Available: https://unhabitat.org/about-us

[35] United Nations Development Programme. (2005). World Resources 2005 – The Wealth of the Poor. In *www.wri.org*. Available: https://www.wri.org/research/world-resources-2005-wealth-poor

[36] Wikipedia Contributors. (2019). List of countries by carbon dioxide emissions per capita. Wikipedia; Wikimedia Foundation. Available: https://en.wikipedia.org/wiki/List_of_countries_by_carbon_dioxide_emissions_per_capita

[37] Wikipedia Contributors. (2023). Urbanization by sovereign state. Wikipedia. Available: https://en.wikipedia.org/wiki/Urbanization_by_sovereign_state

[38] York, R. (2012). Asymmetric effects of economic growth and decline on CO2 emissions. *Nature Climate Change*, 2(11), 762–764. Available: https://doi.org/10.1038/nclimate1699

[39] Zhang, C., & Lin, Y. (2012). Panel estimation for urbanization, energy consumption and CO2 emissions: A regional analysis in China. *Energy Policy*, 49, 488–498. Available: https://doi.org/10.1016/j.enpol.2012.06.048