Unveiling Climate Vulnerability

How Economic Strength, Demographic Dynamics,
Geographical Factors Shape Environmental Resilience

STA 220 Final Project Report
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[1] Abstract

This project aims to analyze and compare key economic, geographic, demographic, and geo-environmental indicators across countries with differing levels of climate vulnerability, as defined by the ND-GAIN Vulnerability Score [2]. Focusing on the top 10 least vulnerable and bottom 10 most climate-vulnerable countries [1], the study seeks to identify critical trends and underlying factors that influence national resilience to climate change and global challenges. Using systematic web scraping techniques, comprehensive data were collected from authoritative sources such as ClimateWatch [8] and FAOSTAT [9], capturing a diverse set of indicators, including economic, demographic, and geographical. Through rigorous statistical and comparative analysis, the project highlights significant disparities between the two groups and explores how economic stability, geographical features, and demographic attributes contribute to climate vulnerability. The findings provide valuable insights to inform sustainable development strategies and climate-resilient policy planning [5].

Contributions:

- **Shaik Haseeb Ur Rahman** was primarily responsible for the data acquisition and analytical components of the project. He worked on the static crawling process *(Scraping Phase 1 [A-C])* to collect the initial foundational **four datasets** and also executed the last part of the dynamic crawling *(Scraping Phase 2 [B])* using Selenium to extract structured data from the Climate Watch data website [8]. He also carried out the end-to-end data analysis, including data cleaning, formatting, preprocessing, statistical modeling, inference formulation, and the complete analytical workflow for ***Research Questions #1, #3, and #4***, encompassing metric selection, visualization, and result interpretation.
- **Shaoor Munir** contributed significantly to the project by managing data acquisition and analysis for key components. He was responsible for handling the **final five datasets**, ensuring accurate integration, and preprocessing for subsequent analysis. During *Scraping Phase 1 [D]*, he worked in the structured extraction of static data from the UN Website, while in *Scraping Phase 2 [A]*, he led dynamic scraping tasks and REST API integration to retrieve real-time and structured datasets. Additionally, he conducted the complete analytical workflow for ***Research Questions #2 and #5***, including metric formulation, data cleaning, visualization, and interpretation of results.

- **Aditi Agarwal** contributed to the dynamic crawling (*Scraping Phase 2)* of the project, the formulation of key metrics, and inference modeling. She managed intermediate data transformation tasks, including preprocessing workflows, data normalization, and seamless data integration across the analytical pipeline using libraries such as Pandas and Numpy. Additionally, she actively contributed to the analytical execution of ***Research Questions #5 and #6***, leveraging Matplotlib and Seaborn for data visualization and assisting in the interpretation of statistical patterns to extract meaningful insights.

[2] Introduction

[2.1] Background

Climate change poses a significant and growing threat to global development, with countries, e.g., the United States of America [4], experiencing varying degrees of vulnerability based on their socio-economic conditions, geographic characteristics, and environmental resilience [3]. Understanding these disparities is critical for formulating effective mitigation and adaptation strategies. The Notre Dame Global Adaptation Initiative (ND-GAIN) [2] vulnerability score provides a standardized measure to assess a country's exposure, sensitivity, and capacity to adapt to climate-related hazards, making it a reliable benchmark for evaluating climate vulnerability. Despite the growing availability of global climate and development data, there remains a gap in comparative studies that integrate multiple dimensions—economic, demographic, geographic, and environmental—into a single analytical framework. This project seeks to bridge that gap by conducting a comprehensive analysis of key indicators across countries at opposite ends of the climate vulnerability spectrum. By selecting the top 10 most and least vulnerable countries as classified by the ND-GAIN Vulnerability Score, the project enables a focused, data-driven comparison to uncover the drivers behind national resilience or susceptibility to climate change.

[2.2] Objective

The primary objective of this project is to conduct a comprehensive, multi-dimensional analysis of the key economic, demographic, and geographical indicators influencing climate vulnerability among countries classified as highly vulnerable versus those deemed least vulnerable by the ND-GAIN Vulnerability Score. Specifically, the project aims to:

- Identify and quantify the relationships between economic factors (such as GDP per capita and environmental expenditure), demographic characteristics (including population density, urbanization, and birth rates), and geographical variables (such as land temperature changes and environmental areas) in shaping national climate vulnerability.
- Generate actionable insights to guide policymakers and stakeholders toward developing targeted and proactive climate adaptation and mitigation strategies.

By leveraging systematic web scraping and data integration from multiple authoritative sources, the project intends to fill existing research gaps, thereby enhancing the understanding of climate vulnerability drivers and contributing to global resilience planning.

[2.3] Scope

The scope of this research includes:

- **Geographical Focus:** Comparative analysis between two distinct groups identified by the ND-GAIN Vulnerability Score—specifically, the 10 most vulnerable and the 10 least vulnerable countries globally.
- **Temporal Coverage:** Recent historical and current data, primarily spanning from 2000 to the most recent available year (2023-2024), provide a robust temporal context for identifying evolving trends.
- **Analytical Dimensions:** Multi-dimensional analysis encompassing economic, demographic, and geographical indicators, with a clear delineation of ground truth as established by the ND-GAIN Vulnerability Score and corroborated through trusted global data repositories.
- **Methodological Approach:** Integration of static and dynamic web scraping methods to construct a unified dataset from authoritative sources, including UN Data, World Population Review, Country Demographic Data, FAOSTAT Data, and Climate Watch Data.

The project explicitly excludes predictive modeling or forecasting beyond the scope of descriptive, correlation-based analysis. Ground truth definitions and benchmarking rely upon established methodologies cited from the Notre Dame Global Adaptation Initiative (ND-GAIN, 2024) and Germanwatch (2025). Global Climate Risk Index 2025 [1-2].

[3] Research Questions

We divided our research questions into three different categories based on the type of indicators:

[3.1] Research questions based on economic indicators

1. Do countries with higher GDP per capita tend to exhibit lower climate vulnerability?
2. How does a country's expenditure on environmental protection, relative to its GDP, influence its climate vulnerability?

[3.2] Research questions based on demographic indicators

3. Do countries with higher birth rates or younger populations have greater climate stress?
4. How do population density and the degree of urbanization jointly influence a country's climate vulnerability, and do highly urbanized yet densely populated regions experience compounded climate stress?

[3.3] Research questions based on geographical indicators

5. How does the change in land surface temperature differ between countries most affected by climate change and those least affected, and what insights does this reveal about climate vulnerability patterns?
6. How do geo-environmental indicators like forest area, inland water reserves, protected land, land area, and average temperature change influence a country's ND-GAIN vulnerability score?

[4] Dataset

4.1 Key Metrics

The project comprised a set of quantitative indicators to assess and compare climate vulnerability across selected countries. These metrics were carefully curated to capture critical dimensions spanning economic, demographic, geographic, and geo-environmental domains. At the core of the analysis was the *ND-GAIN Vulnerability Score*, a metric reflecting a country's exposure, sensitivity, and adaptive capacity to climate change. Complementary indicators such as *GDP per Capita*, *Government Expenditure on Environmental Protection*, *Population Density*, *Urban Population (%)*, and *Average Temperature Change* provided additional layers of insight into national resilience profiles. Furthermore, key geo-environmental land indicators—including *Land Area*, *Forest Area*, *Water Reserves*, *Agricultural Land Use*, and *Protected Land*—were integrated to assess ecological capacity and environmental buffers. Together, these metrics enabled a robust multidimensional analysis framework, facilitating meaningful statistical modeling, comparative assessment, and inference development in alignment with the project's research questions.

4.2 Data Retrieval

GitHub Links: Scraping Phase 1 & **Scraping Phase 2**

Our data retrieval process was strategically divided into static and dynamic crawling, based on the nature of content rendering on the source websites. Static crawling involved direct access and parsing of HTML content using tools such as Requests, Lxml, and BeautifulSoup, which proved efficient for extracting structured data from web pages with minimal client-side rendering. This method was effectively applied to extract datasets from sources like UN Data, World Population Review, and ISO Codes, where the content was readily accessible in the static HTML structure.

However, several data sources, including FAOSTAT and Climate Watch Data, rely heavily on JavaScript-rendered content, making traditional static scraping techniques inadequate. To address this, we employed dynamic crawling using Selenium, a web automation tool that simulates user interactions, executes JavaScript, and navigates web pages like a typical browser. Selenium enables the extraction of fully rendered HTML content by waiting for dynamic elements to load—often requiring deliberate delays (e.g., time.sleep(5)) to ensure completeness before parsing. This approach allowed us to capture complex datasets and maintain data integrity across all sources.

4.3.1 Static Crawling [Scraping Phase 1]

[A] Population Data [HTML Parsing using BeautifulSoap]
Website URL: World Population Review
Libraries Used: BeautifulSoup (bs4), requests, pandas
Methodology:

- HTTP requests were used to fetch HTML content from the World Population Review webpage.
- BeautifulSoup parsed the <table> elements to extract population, area, density, growth rate, global population share, and rank per country.
- The data was cleaned using custom parsing logic to handle units like K/M and percentages.
- Cleaned records were stored in a structured Pandas DataFrame.

Why These Tools?

- The HTML content was static and well-structured, making bs4 optimal for table parsing.
- Pandas was efficient for data cleaning, transformation, and final storage.

Challenges Faced:
- Handling units (K/M) and special characters like < in raw HTML values.
- Stripping, converting, and normalizing values across different data formats.

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End Result: The cleaned dataset was saved as **1-population-data.csv** and contains 7 key indicators per country, serving as a base demographic reference for subsequent analysis.
Final Dataset: Population Data

[B] ISO Codes Data [HTML Parsing using LXML]
Website URL: ISO Codes
Libraries Used: lxml, requests, pandas
Methodology:

- HTTP requests fetched the Wikipedia page content.
- lxml was used to parse HTML with XPath for precise extraction of country names and their corresponding ISO Alpha-3 codes. Extracted data was organized into a Pandas DataFrame.

Why These Tools?
- Wikipedia's list format and clean HTML structure made lxml ideal for speed and accuracy.
- XPath-based parsing was more efficient than traditional tag parsing for this structured content.

Challenges Faced:
- Ensuring proper handling of Unicode characters and formatting inconsistencies in country names.
- Matching these ISO codes accurately with other scraped datasets.

End Result: Final dataset saved as **2-countries-iso-codes.csv**, which served as a reference file for country identification and uniform mapping in later analysis stages.
Final Dataset: ISO Codes Data

[C] Country Demographics Data [RESTful API Based Scraping]
Web URL: [World Population Review - Demographics]
Libraries Used: BeautifulSoup (bs4), requests, pandas
Methodology:

- Using ISO-mapped country names, dynamic URLs were formed for each country's demographics page.
- HTTP requests retrieved HTML content for each country.
- BeautifulSoup parsed structured <div> blocks containing metrics such as Births/Deaths per Day, Immigration, Net Change, and 2025 Population Change.
- Data was stored in a pandas DataFrame with country-wise aggregation.

Why These Tools?
- The site used static content with JavaScript-driven structuring, but not full AJAX; hence bs4 and requests sufficed.
- Custom logic handled varied formatting of data blocks within country pages.

Challenges Faced:
- The structure of content blocks varied slightly across country pages.
- Class names were not always consistent; fallback logic was needed to locate label-value pairs.

End Result: Cleaned dataset saved as **3-countries-demographic-stats.csv**, with multiple daily change indicators per country used in demographic correlation analysis.
Final Dataset: **Country Demographics Data**

[D] Social, Economic, and Environmental Indicators [RESTful API Based Scraping]
Web URL: **UN Data**
Libraries Used: BeautifulSoup (bs4), requests, pandas
Methodology:

- Created dynamic URLs for each country by first crawling the homepage
- HTTP requests retrieved HTML content for each country.
- BeautifulSoup parsed structured data in tables for each country; each type of indicator was divided based on a summary tag in HTML.
- Data was stored in a pandas DataFrame with country-wise aggregation.

Why These Tools?
- There was no dynamic element in the webpage, and the data was also structured in HTML elements such as tables.
- Custom logic handled varied formatting of data blocks within country pages.

Challenges Faced:
- Not every country had all the indicators, which resulted in inconsistent data.

End Result: Cleaned dataset saved as **5-general_data.csv, 6-economic_data.csv, 7-social_data.csv,** and **8-environmental_data.csv** with multiple daily change indicators per country used in demographic correlation analysis.
Final Dataset: **General Data**, **Economic Data**, **Social Data**, **Environmental Data**

4.3.2 Dynamic Crawling [Scraping Phase 2]

[A] Food and Agricultural Organization [Selenium based Scraping]
Website URL: FAO
Libraries Used: Selenium, webdriver_manager, BeautifulSoup (bs4), requests, zipfile, io
Methodology:

- Selenium WebDriver launched a headless Chrome browser using webdriver_manager to handle dynamic JavaScript-rendered content. Navigated to the FAO statistics webpage URLs.
- Introduced explicit delays (time.sleep()) to ensure complete content loading.
- Extracted fully rendered HTML content with Selenium, subsequently parsed by BeautifulSoup to locate required elements such as download URLs. Utilized requests, zipfile, and IO for downloading, extracting, and organizing large datasets from dynamically generated links.

Why These Tools?

- Selenium was used to render JavaScript-loaded content and access complete HTML structures for accurate data extraction.
- Webdriver Manager ensured seamless ChromeDriver integration, while BeautifulSoup efficiently parsed the rendered HTML to extract key elements.

Challenges Faced:

- Handled JavaScript-rendered content using headless browser solutions to ensure complete data extraction. Implemented request delays, retry logic, and error handling to manage rate limiting and dynamic HTML variability.
- Managed ~40 GB dataset, including individual CSV files over 8 GB, by selectively downloading files, storing in Google Drive, and importing only relevant subsets for analysis.

End Result: Large dataset crawled and selectively downloaded; relevant data imported and used for final analysis.
Final Dataset: FAO Dataset

[B] Climate Watch Data [HTML parsing using LXML and Selenium-based web scraping]
Web URL: Climate Watchdata
Libraries Used: Selenium, lxml, pandas
Methodology:

- Selenium WebDriver was used to automate browser navigation to each country page via dynamic ISO URL.
- Required wait times and XPath-based locators were used to identify metric cards on the page.
- Each metric (e.g., Total Emissions, Emissions per Capita, ND-GAIN Score, GDP per Capita) was parsed and stored. Data was appended to a final list and exported to Pandas for storage.

Why These Tools?

- The Climate Watch website renders key metrics cards via JavaScript, necessitating Selenium.

- lxml and Pandas provided efficient content parsing and data storage once the page was loaded.

Challenges Faced:

- Handling asynchronous content loading was challenging, which necessitated the use of Selenium with explicit wait conditions to ensure reliable data extraction.
- Class names were auto-generated (e.g., *country-header-styles__cardContent__Y6vBv*), requiring fragile but necessary XPath navigation. Class names were not always consistent; fallback logic was needed to locate label-value pairs.
- Handling load times, retries, and browser compatibility issues.

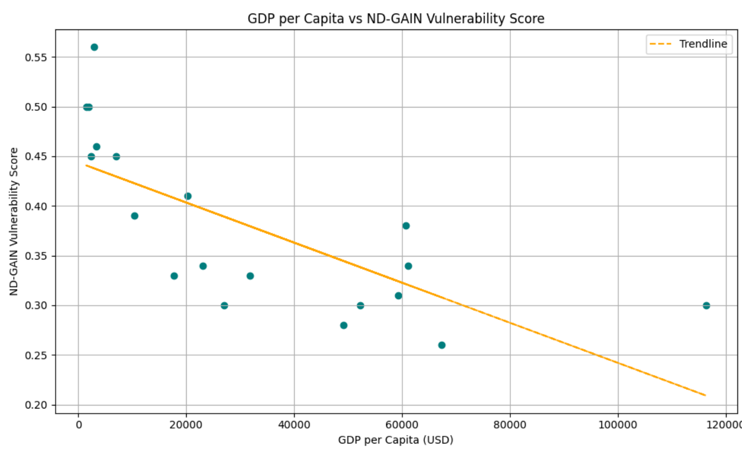
End Result: A final structured dataset **4-countries-climate-watchdata.csv**, including 7 critical metrics per country, used in multiple research questions and correlation models in the project.

Final Dataset: **Climate Watchdata**

[6] Results Analysis

GitHub: **Results Analysis**

[RQ#1] Do countries with higher GDP per capita tend to exhibit lower climate vulnerability?

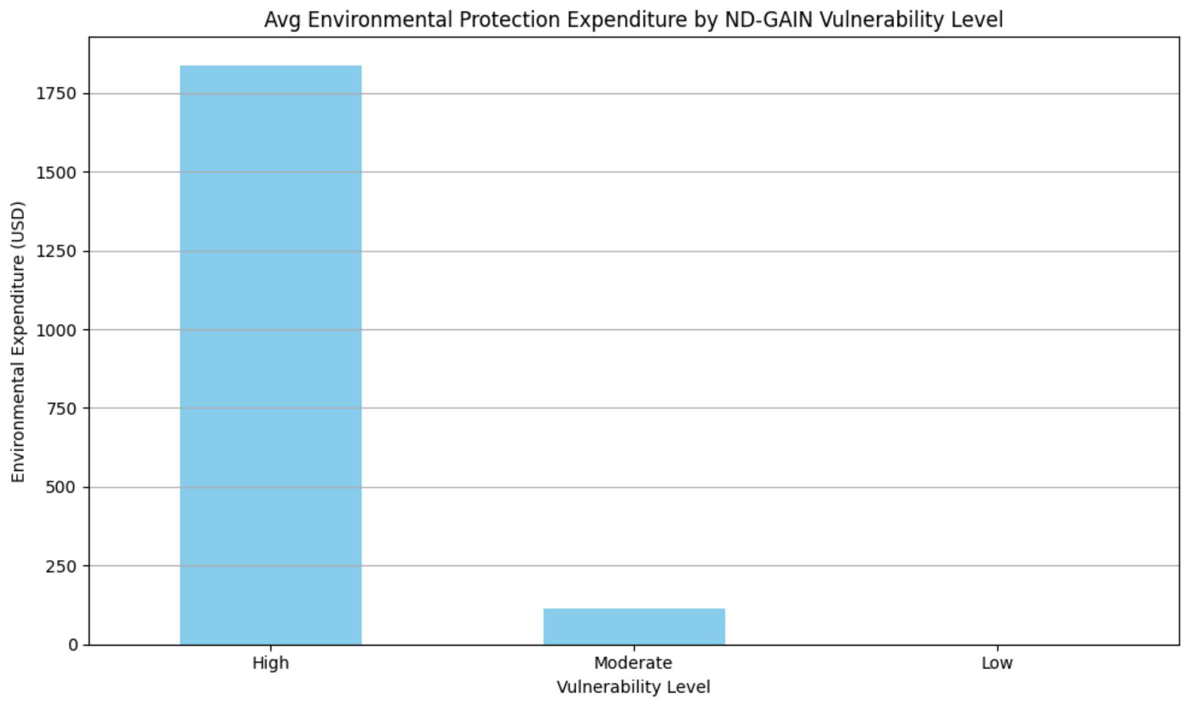


Results: The analysis revealed a clear inverse relationship between GDP per Capita and the ND-GAIN Vulnerability Score, indicating that economically stronger countries tend to have lower climate vulnerability. This suggests that wealthier nations are better equipped to invest in adaptive infrastructure and climate-resilient policies. Conversely, lower-income countries face higher vulnerability due to limited resources. However, outliers in the trend indicate that GDP alone is not a definitive predictor of climate resilience—factors like governance, geography, and institutional readiness also play a critical role.

Discussion:

- Higher GDP per capita is associated with lower climate vulnerability, reflecting stronger adaptive capacity and resource availability.
- Economic strength facilitates investments in climate infrastructure, risk mitigation strategies, and governance systems.
- Despite the trend, deviations indicate that a holistic climate resilience framework must incorporate factors beyond GDP, such as institutional quality, geographic exposure, and environmental policies.

[RQ#2] How does a country's expenditure on environmental protection, relative to its GDP, influence its climate vulnerability?

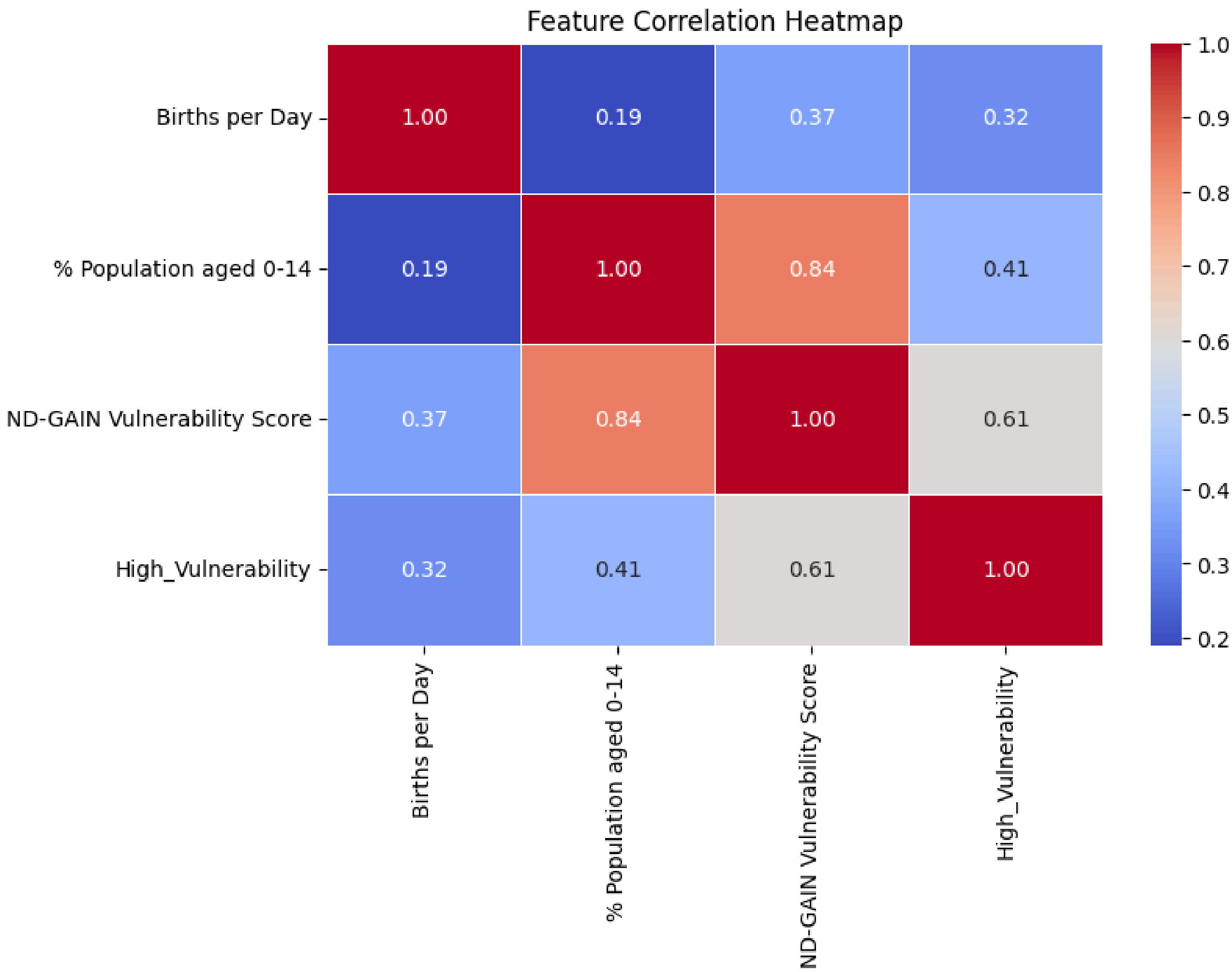


Results: The analysis indicates that countries with higher ND-GAIN vulnerability scores tend to allocate significantly greater funding toward environmental protection. This trend suggests a reactive approach, where governments facing heightened climate risks prioritize environmental expenditure as a mitigation strategy. In contrast, countries with moderate or low vulnerability exhibit substantially lower investment levels, implying that perceived risk levels may directly influence policy-driven environmental spending.

Discussion:

- **Reactive vs. Proactive Spending:** The high-vulnerability group's elevated spending suggests a reactive approach, where greater funding is funneled into environmental protection after vulnerability levels have escalated.
- **Early Mitigation Advantage:** The comparatively lower expenditure among low-vulnerability countries may indicate proactive policies or better preparedness, reducing the current need for large-scale environmental investments.
- **Policy Implications:** A shift from reactive to proactive investment strategies could help reduce future climate risk. Allocating resources early—toward sustainability, clean technology, and resilient infrastructure—may be more cost-effective and impactful in the long run.

[RQ#3] Do countries with higher birth rates or younger population have greater climate stress?

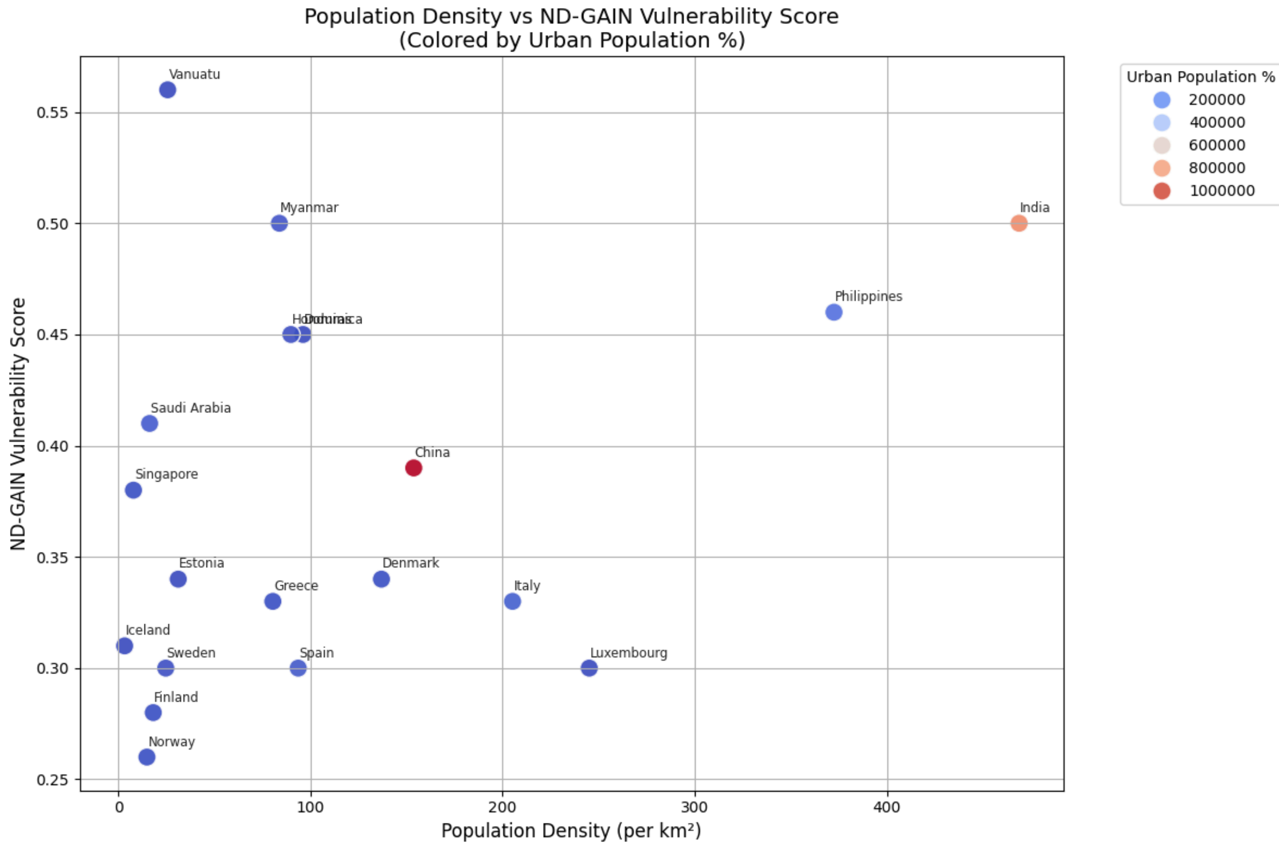


Results: The correlation analysis revealed that ND-GAIN Vulnerability Score has a strong positive correlation (0.84) with the percentage of population aged 0–14, indicating that countries with a younger population tend to be more climate vulnerable. The ND-GAIN Score also demonstrated a solid correlation (0.61) with the High_Vulnerability classification, reinforcing its reliability as an indicator of climate risk. Additionally, births per day showed a moderate correlation (~0.32) with high vulnerability, while % population aged 0–14 also correlated moderately (0.41) with vulnerability status. These findings underscore the significant role of demographic composition in influencing a country's sensitivity to climate impacts.

Discussion:

- A younger population profile strongly correlates with higher climate vulnerability, suggesting that age structure is a critical socio-demographic determinant of climate risk.
- The strong alignment between ND-GAIN Score and High_Vulnerability classification confirms the effectiveness of ND-GAIN as a comprehensive measure of climate sensitivity.
- Although Births per Day is moderately correlated, it is less impactful compared to age-based population distribution, highlighting the need for targeted policy planning that incorporates demographic dynamics into resilience strategies.

[RQ#4] How do population density and the degree of urbanization jointly influence a country's climate vulnerability, and do highly urbanized yet densely populated regions experience compounded climate stress?



Results:

The analysis revealed no strong linear correlation between population density and ND-GAIN Vulnerability Score, indicating that both low- and high-density countries can exhibit varying levels of climate vulnerability. Countries such as India, Myanmar, Vanuatu, and the Philippines demonstrate higher vulnerability despite differing population densities, emphasizing the role of other structural and socio-economic factors. Furthermore, Urban Population %—used as a color gradient in the visualization—showed no consistent alignment with ND-GAIN scores, suggesting that urbanization alone does not strongly influence a country's climate resilience.

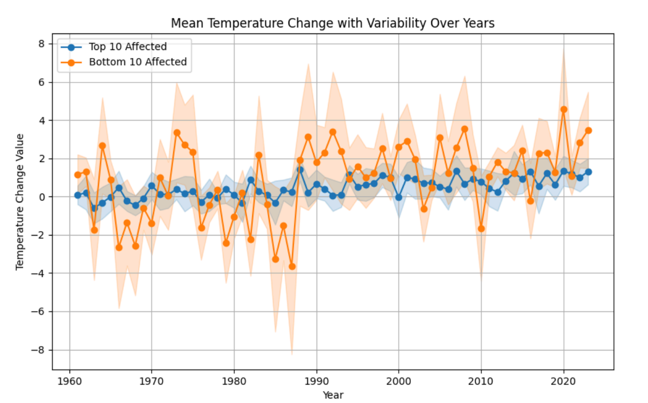
Discussion:

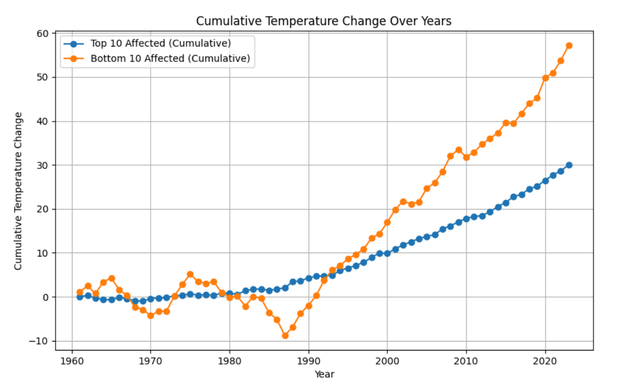
- Population density and urbanization are not definitive predictors of climate vulnerability, as countries with varying profiles show inconsistent vulnerability levels, highlighting the limited standalone impact of these factors.
- Climate resilience is influenced by a complex interplay of factors, including infrastructure quality, economic capacity, governance, and adaptive readiness—beyond just demographic or urban characteristics.

[RQ#5] How does the change in land surface temperature differ between countries most affected by climate change and those least affected, and what insights does this reveal about climate vulnerability patterns?

Results:

- **Cumulative Temperature Change Over Years:** The "Bottom 10 Affected" countries (orange line) show a larger net cumulative temperature change over the observed period. In contrast, the "Top 10 Affected" countries (blue line) exhibit a lower—but still steadily increasing—cumulative change.
- **Mean Temperature Change with Variability:** The "Top 10 Affected" countries (blue line) tend to have lower average temperature changes, maintaining values consistently above zero and showing a gradual rise. Meanwhile, the "Bottom 10 Affected" (orange line) demonstrates more pronounced fluctuations and often registers higher mean temperature changes in many years.





Discussions:

- The Bottom 10 (least vulnerable) countries exhibit higher net temperature increases and greater year-to-year variability compared to the Top 10 group.
- The Top 10 (most vulnerable) countries show lower raw temperature anomalies, indicating a more stable but steady warming trend.
- These findings suggest that vulnerability classification extends beyond temperature change alone, factoring in socio-economic exposure, infrastructure resilience, and adaptive capacity.

[RQ#6] How do geo-environmental indicators such as forest density, protected land use, inland water resources, and average temperature change correlate with national climate vulnerability (ND-GAIN score) across different regions?

Map Plots: Interactive Maps [Refer APPENDIX(A) for map plots]
The interactive maps can be accessed through the attached GitHub link above, and the plot has been attached in the appendix section as well.

Results:
The spatial analysis using interactive choropleth maps revealed strong associations between key geo-environmental indicators and climate vulnerability, as measured by the ND-GAIN Score. Countries with higher normalized values of forest area, protected land, and inland water resources per km^2 generally exhibited higher ND-GAIN scores, indicating lower climate vulnerability. For instance, nations like Finland, Sweden, and Norway demonstrated strong environmental richness paired with higher resilience. Meanwhile, countries with lower protected land coverage and limited inland water reserves, such as Honduras and Myanmar, reflected higher vulnerability levels. Interestingly, even some of the least vulnerable countries, like Russia and Iceland, showed significant average temperature changes, suggesting that environmental richness must be supported by robust governance, infrastructure, and economic capacity to fully mitigate climate risk.

Discussions:
- Higher forest density, protected land, and inland water reserves per km^2 tend to correlate with lower climate vulnerability, reinforcing their role in enhancing ecological resilience and adaptive capacity.
- However, geo-environmental richness alone is insufficient; anomalies like Italy and Spain reveal that institutional capacity, socioeconomic development, and governance quality are equally vital for resilience.
- Significant temperature anomalies in low-vulnerability countries indicate that adaptive infrastructure and strategic governance can offset environmental stress, emphasizing the need for a multidimensional approach to climate resilience.

[8] Conclusion

This study provides a comprehensive analysis of the multifaceted drivers of climate vulnerability, using the ND-GAIN Score as a benchmark across diverse countries. The results highlight that while higher GDP per capita generally correlates with lower climate vulnerability, economic strength alone is insufficient—factors like infrastructure quality, institutional readiness, and governance are equally critical. Environmental expenditure tends to rise with vulnerability, reflecting a reactive policy response rather than proactive planning. Demographics, particularly a younger population profile, significantly influence vulnerability, emphasizing the need for socially inclusive climate strategies. Conversely, population density and urbanization do not show a direct correlation, underscoring the complex interplay of structural and contextual factors. Although temperature change patterns vary, they do not directly define vulnerability—adaptive capacity matters more. Similarly, geo-environmental richness (forest cover, protected land, inland water) contributes to resilience only when supported by strong governance and economic stability. In essence, this study reaffirms that climate vulnerability is not shaped by singular factors but by an intricate nexus of economic, environmental, demographic, and institutional dimensions. A multidimensional and proactive policy framework, rather than reactive spending or isolated metrics, is essential for building long-term national climate resilience.

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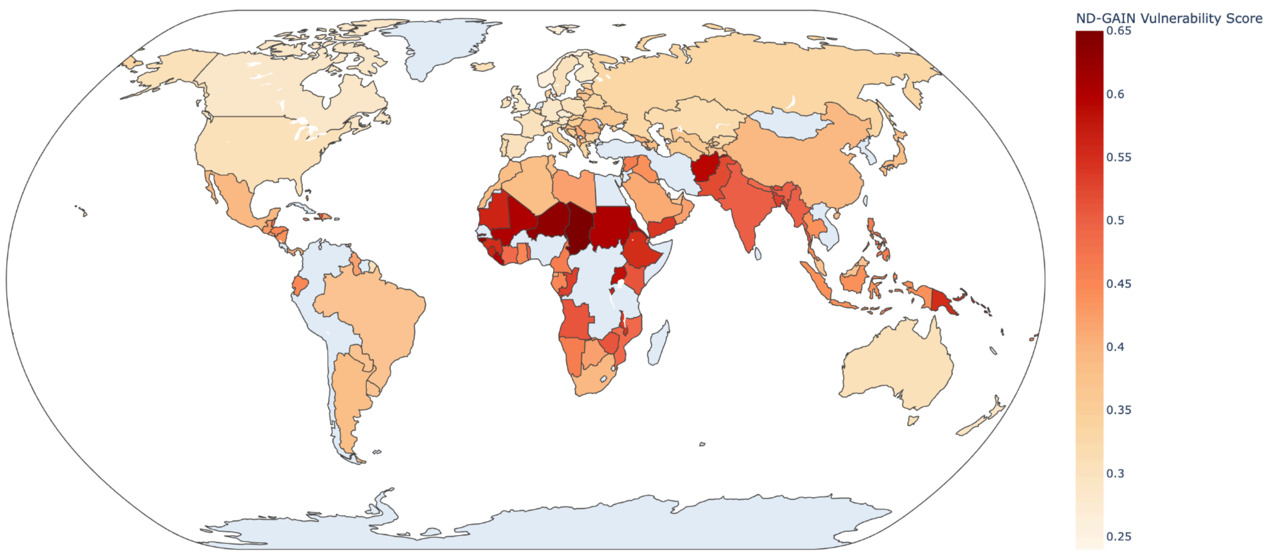
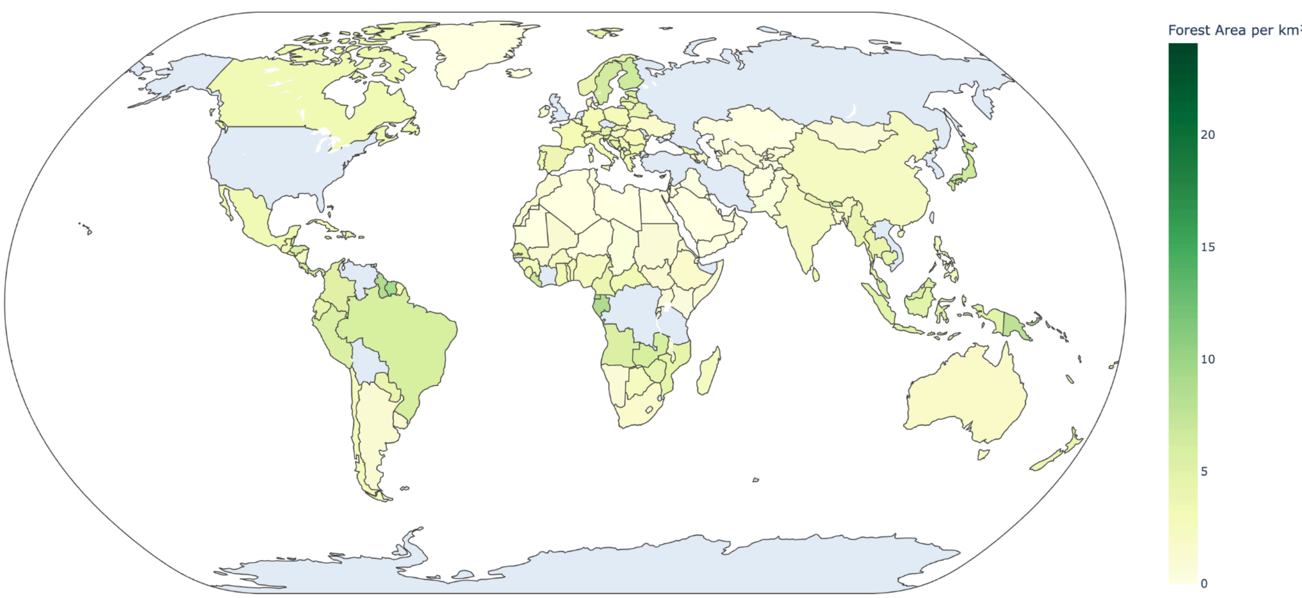
APPENDIX

[A] MAPS

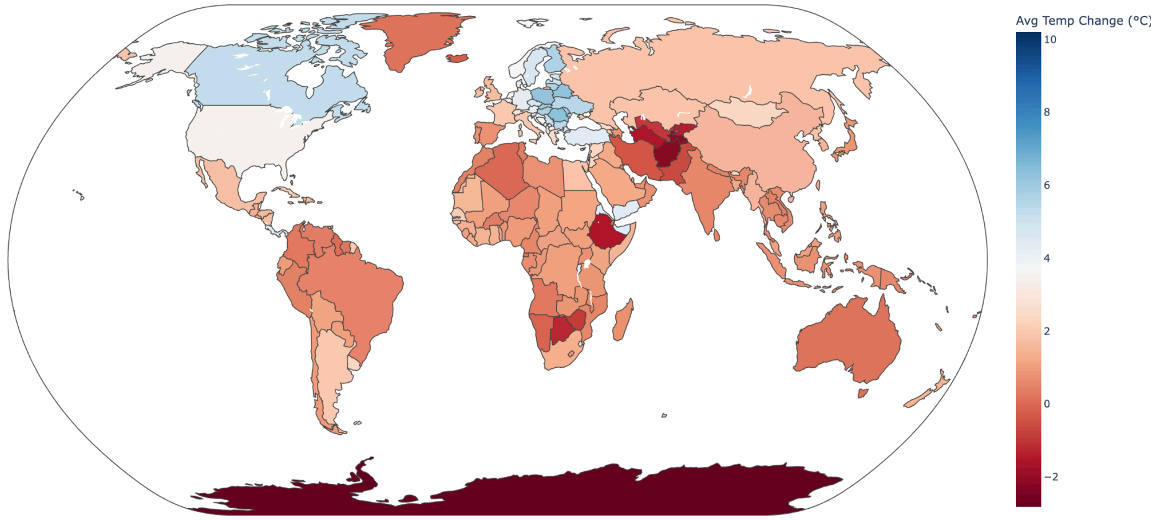
- **ND-GAIN Vulnerability Score by Country**



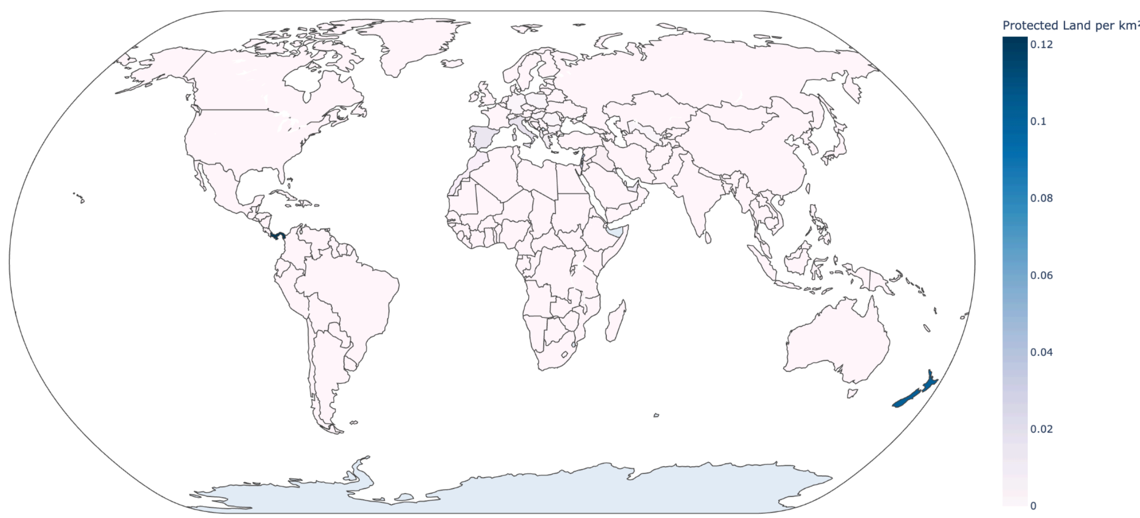
- **Normalized Forest Area/km^2 of Land by Country**



- **Avg. Temperature Change (in C) by Country**



- **Normalized Protected Land/km^2 by Country**



- **Normalized Inland Waters/km^2 by Country**