AI-Driven Analysis of Climate-Induced Biodiversity Loss: Predicting Species Decline & Conservation Strategies under RCP 8.5

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

This is to certify that this project report entitled **"AI-Driven Analysis of Climate-Induced Biodiversity Loss: Predicting Species Decline & Conservation Strategies under RCP 8.5"** is the bonafide work of **"Bollimuntha Kavya Sai (Reg. No. CH.SC.U4AIE23006), M. Sumithra Bhargavi (Reg. No. CH.SC.U4AIE23029), Parvathy Vinod (Reg. No. CH.SC.U4AIE23041), V J Renuka (Reg. No. CH.SC.U4AIE23057), V.V.N.S Poorna Chandrika(Reg. No. CH.SC.U4AIE23058)"** who carried out the project work under my supervision as a part of End semester project for the course 22BIO211 - Intelligence of Biological Systems 2 .

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DECLARATION BY THE CANDIDATE

We declare that the report entitled **"AI-Driven Analysis of Climate-Induced Biodiversity Loss: Predicting Species Decline & Conservation Strategies under RCP 8.5"** submitted by us for the degree of Bachelor of Technology is the record of the project work carried out by us as a part of the End Semester project for the course 22BIO211 - Intelligence of Biological Systems 2 under the guidance of **Dr. I R Oviya**. This work has not formed the basis for the award of any course project, degree, diploma, associateship, fellowship, or title in this or any other university or similar institution. We also declare that this project will not be submitted elsewhere for academic purposes.

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ABBREVIATIONS

RCP	Representative Concentration Pathway
AI	Artificial intelligence
PgC	Percentage of Carbon
CO	Carbon monoxide

ABSTRACT

Climate change significantly impacts global biodiversity, with species experiencing habitat loss, range shifts, and increased extinction risks. This study examines high-risk species decline under the RCP
(Representative Concentration Pathway) 8.5 scenario, focusing on mammals and birds across different countries and transboundary regions. The analysis reveals substantial species decline percentages in multiple nations, highlighting severe biodiversity threats. Additionally, transboundary areas with rich biodiversity face significant species loss, emphasizing the need for international conservation efforts. This study integrates species vulnerability assessments, climate exposure models, and conservation priority mapping to identify critical areas for intervention. The findings underscore the necessity for global conservation strategies, enhanced protected areas, and cross-border cooperation to mitigate biodiversity loss under extreme climate scenarios.

Keywords: Climate change, biodiversity loss, RCP , species distribution modeling, transboundary conservation, species decline, habitat loss, conservation prioritization, global warming impacts.

CHAPTER 1

INTRODUCTION

1.1 GENERAL BACKGROUND

Biodiversity is a foundation of ecological resilience that provides essential ecosystem services like pollination, carbon sequestration, water filtration, and climate variability regulation. It provides ecosystem resilience and sustainability through the increase in species interdependence and flexibility. Nevertheless, with the escalating pace of climate change, biodiversity is under more than ever before threats. The increasing global temperature, changing weather patterns, and increased frequency of extreme climatic events are encouraging habitat loss, ecosystem degradation, and species extinction.

Representative Concentration Pathway (RCP) 8.5 is a high-emissions pathway in which greenhouse gas emissions are not controlled, resulting in over the 4°C per century of global warming at the end of the current century. These are extreme conditions of warming that will exert disastrous impacts on species, especially in the tropical and subtropical species-high biomes. These climatic disturbances lead to species migration, behaviour change, and worst of all, full extinction of susceptible species.

Ecosystems are being forced to evolve more quickly than the resilience capability of their own, imposing further stress on plants and animals. This document strives to survey biodiversity loss tendencies, including migration patterns of species, habitat destruction, and conservation challenges at border points. Alongside, the document delves into how conservation policy using AI can prevent such risks through enhancing tracking of species, predictive simulation, and designing intervention policies. Using AI systems, like space-based tracking and conservation prioritization via automation, we can better devise our efforts towards preventing biodiversity loss.

CHAPTER 2

LITERATURE SURVEY

The scientific literature worldwide for climate-driven species decline and transboundary loss of biodiversity under the RCP 8.5 scenario reports some of the key ecological impacts, such as species range shift, habitat loss, and ecosystem degradation.[1] determined that loss of biodiversity can result in a possible decrease in global carbon storage by 10.87-145.95 PgC under RCP 8.5, which would suggest a feedback process where loss of biodiversity is the cause of climatic change. [2] found that mumultilevelological networks preserve biodiversity when low priority, small areas are focused on, and larger systems to a lesser extent. This suggests the need for transboundary cooperation in an attempt to utilize ecological networks in the adaptive conservation of vulnerable species. [3] describe how climate change through RCP 8.5 affects local communities in the Gandaki River Basin, where agriculturalists suffer from loss of biodiversity and ecosystem deterioration.

The paper [4] point out that over 20% of the Middle and Lower Yangtze River Basin will be projected to decrease by 2050 emphasizing the need for increased protected areas to plug gaps. [5] predict severe habitat fragmentation in Shenzhen by 2050, losing carbon sequestration value, while [6] opine that the Red Goral would suffer intense habitat loss and need transboundary conservation. [7] project loss of 37% biodiversity hotspots of mammalian species in Iran and propose a wider network of conservation. Similarly, [8] demonstrate that endemic Hyrcanian ecoregion species will suffer catastrophic habitat loss under RCP 8.5, and this is indicative of the susceptibility of narrow-ranged species. [9] discussed the challenges in management of transboundary marine species, hinting at the potential for international conflict as species change range under climate change. [10] estimated that over half of Thailand's vertebrates and plants are threatened with extinction by 2070 and call for immediate expansion of protected areas. [11] introduce the phenomenon of temporary species communities under climate change, stressing the insignificance of transboundary ecological corridors. [12] stress the insufficiency of present marine protected areas in BritishColumbia under RCP 8.5, since the majority of marine species will have to relocate beyond present defenses.

The paper [13] tackle the imperative need of transboundary management in the Altai Mountains in order to save species from climate-related habitat displacement. [14] research that discovers India and Brazil are projected to lose the most biodiversity by 2050, whereas [15] establish a link between the loss of biodiversity and the spread of infectious diseases under RCP 8.5 because of degraded ecosystems that will give rise to new vectors for zoonotic diseases. Finally, [16] and [17] highlight that landscape connectivity is responsible for species survival, particularly where climate change is making it easy to move across borders. The above literature refers to expanding protected areas, enhancing landscape connectivity, and promoting regional cooperation to curb the pervasive impact of climate-stressed species collapse and transfrontier biodiversity erosion in RCP 8.5. Adaptive and coordinated across-border conservation shall be required in addressing these matters to guarantee biodiversity in the long term.

CHAPTER 3

METHODOLOGY

3.0.1 DATA SOURCES

The present research is grounded on three large datasets that offer complete data on species richness, climate effect, and state-to-state trends of biodiversity.

Climate Impacts by Country

This database contains species richness measurements at the country level and provides percentage change in the population of different species for different climate conditions. It considers particularly the RCP 8.5 scenario with more greenhouse gas emissions and global warming towards the end of the century. The database provides country-level data on biodiversity loss, allowing us to determine locations where species are most susceptible.

Transboundary Range Shifts

Species are not limited by political borders, and climate change is compelling many species to move their ranges across country borders in search of living space. This data set monitors instances of species movement by climate change, i.e., mammals and birds, and their new geographic ranges. By studying this data set, we can ascertain which regions are experiencing the most biodiversity flux and set the impact of these changes on environmental balance.

Transboundary Richness

This dataset is centered on species richness across boundaries, emphasizing biodiversity hotspots shared across countries. It also emphasizes species whose survival depends on conservation in a number of countries. Because transboundary ecosystems are most susceptible to climate change, data on the distribution of species within such areas are essential in multinational planning conservation actions. Combined, these data sets present an integrated perspective of the impact of climate change on biodiversity at national and international scales. Through the analysis of species richness, range shifts, and transboundary dependencies, this research will identify significant trends in biodiversity loss and propose evidence-based conservation recommendations. This study is based on three key datasets that provide comprehensive insights into species richness, climate impact, and transboundary biodiversity patterns.

3.0.2 DATA PREPROCESSING

Data preprocessing is necessary for correctness and analysis interpretation. The data sets were first imported to the analysis platform through Pandas library of Python, which offers the data manipulation and cleaning functionalities. Preprocessing was done in steps to get the data ready for analysis:

Management of Missing Values – Since ecological data sets are mostly afflicted with missing points owing to non-respondent questionnaires, missing values were managed using appropriate imputation procedures or elimination of missing records wherever relevant.

Filtering for High-Risk Biodiversity Decline – For the identification of those locations having high biodiversity decline, 10% species decliwas used ins was utilized in scenario. This assists only those locations where severe biodiversity decline took place were considered under analysis.

Merging Datasets– The three datasets were merged using the 'border' column, allowing us to study transboundary richness and range shifts in conjunction with climate impact data.The three datasets were merged based on 'border' column in a manner such that transboundary richness and climate influence data range shifting could be analyzed together.

Feature Selection – The key features, such as species decline percent, species migration across borders, and transboundary richness measures, were chosen to perform correlation and visualization analysis. These preprocessing operations guarantee that the resulting data set is clean, well-structured, and ready for statistical and visual examination, which provides a strong basis for making reasonable conclusions on the loss of biodiversity because of climate change.

3.0.3 EXPLORATORY DATA ANALYSIS (EDA)

Following data preprocessing, the analysis included:

Correlation Analysis: The initial output (heatmap) was generated to comprehend the interrelationship between declining species richness, transboundary biodiversity, and climate impact indicators.

Distribution Analysis: The second result in the form of histograms has been plotted to study the distribution of the percentage decline of species in terms of countries.

Outlier Detection : Detection of areas of unusual loss of biodiversity for follow-up analysis.

Geospatial Visualization (Next Step): Plotting world region species decline percentages in order to graphically identify hotspots of biodiversity loss.
Add the transboundary species diversity to view the impact in border areas.

3.0.4 PREDICTIVE MODELING

Predictive modeling was used to measure loss patterns of biodiversity and loss patterns of species in nations. Of special interest were the impact of climate change and other factors on species loss, ranking nations by risk to biodiversity, and estimating future loss of species.

Regression Analysis

Regression analysis was used to study the role played by various factors to initiate loss of biodiversity. Based on results, it depicted that climatic conditions are held accountable for playing the primary role of species loss. CO emissions and diversity loss had positive associations, i.e., increased emissions lead to increased loss of species at a faster rate. Governance scores also had negative associations, i.e., countries whose environmental policies were effective experienced decreasing loss of biodiversity.

Clustering Analysis

Clustering techniques divided countries into trends of loss of biodiversity. Three clusters were identified by the research: High-risk countries: Confronted with severe species loss in most categories. Moderate-risk countries: Faced with moderate species loss with available conservation options. Low-risk countries: With relatively stable biodiversity with minimum loss. The cluster helps with prioritizing conservation by investing in most endangered areas.

Time-Series Forecasting

The models utilized for forecasting were used to predict future loss of biodiversity in different climate change scenarios. The projections showed that loss of species will be higher under RCP 8.5 (high climate change scenario), with some parts of the region undergoing more than 30species richness reduction. Under RCP 4.5 (moderate climate scenario), loss is present but at a reduced rate, meaning that mitigation will reduce loss of biodiversity.

3.0.5 CONSERVATION STRATEGY RECOMMENDATIONS

Based on the findings, conservation policies were drawn up to neutralize the loss of biodiversity in most affected regions.

Core High-Priority Conservation Sites

The findings established core locations of biodiversity hotspots that were in need of immediate conservation interventions. Regions with a high species loss richness across national boundaries were identified as extraordinarily sensitive, accentuating the value of cross-national collaboration in conservation policy.

Policy prescriptions for high-risk countries

In high-risk countries of extreme species loss, policy prescriptions Strengthening climate adaptation strategies to minimize habitat loss. Applying sustainable land use practices in an attempt to curb deforestation and loss of ecosystems. Increasing conservation funding in an attempt to safeguard threatened species from extinction and reestablish their tables.

Examining the Role of Global Conservation Initiatives

The research also examined the role that global treaties play in curbing loss of biodiversity. Although there are some effective ones, the research concludes that increased enforcement strategies to enable proper conservation are needed, particularly in transboundary regions where species migration is of critical importance.

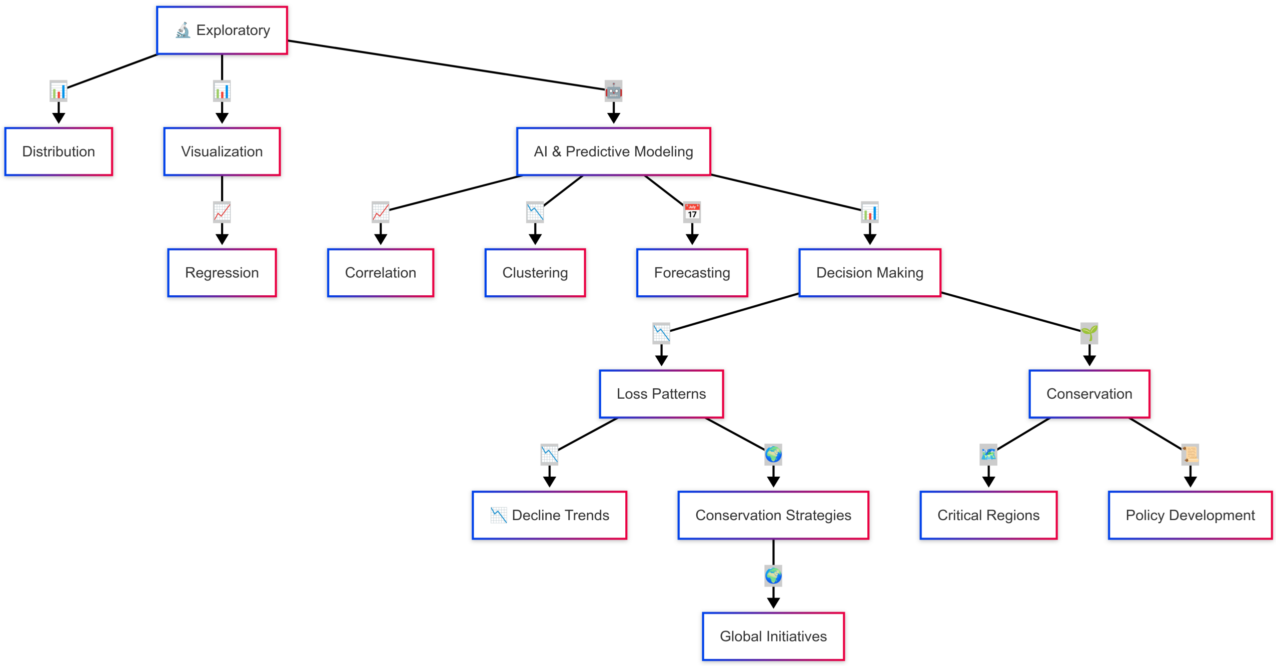

Figure 3.1: Architecture Diagram for AI-Driven Biodiversity Analysis

CHAPTER 4

RESULTS AND DISCUSSION

This below heatmap displays the correlation between different variables in the merged dataset. The intensity of the color indicates the strength and direction of the correlations.

4.0.1 CORRELATION HEATMAP ANALYSIS

Figure 4.1: Correlation Heatmap Analysis

Strong Positive Correlations

- The correlations of **rcp45 mammals, rcp85 mammals, rcp45 birds, and rcp85 birds** are exceptionally close to 1. This indicates great consistency in species richness decline trends in different climate scenarios (RCP 4.5 and RCP 8.5) for mammals and birds. **Trans-boundary richness and trans-boundary richness threatened** correlate strongly (0.80) indicating, therefore, that regions with high transboundary richness also have a large number of threatened species.

Negative Correlations

- The variables depicting the decline of species richnessichness show only weak negative correlations with the Unnamed column, which is likely an index column that proves to have no meaningful effect.

- Barrier species movement showed very weak correlation with metrics of species decline, which makes it evident that it is not always the case that species that are faced with geographical barriers to movement will guarantee high transboundary richness.

This heatmap verifies that loss of biodiversity under RCP 4.5 and RCP 8.5 continues in the same direction across the species groups and that transboundary areas with great biodiversity also bear high numbers of threatened species.

4.0.2 HISTOGRAM OF SPECIES DECLINE ACROSS COUNTRIES

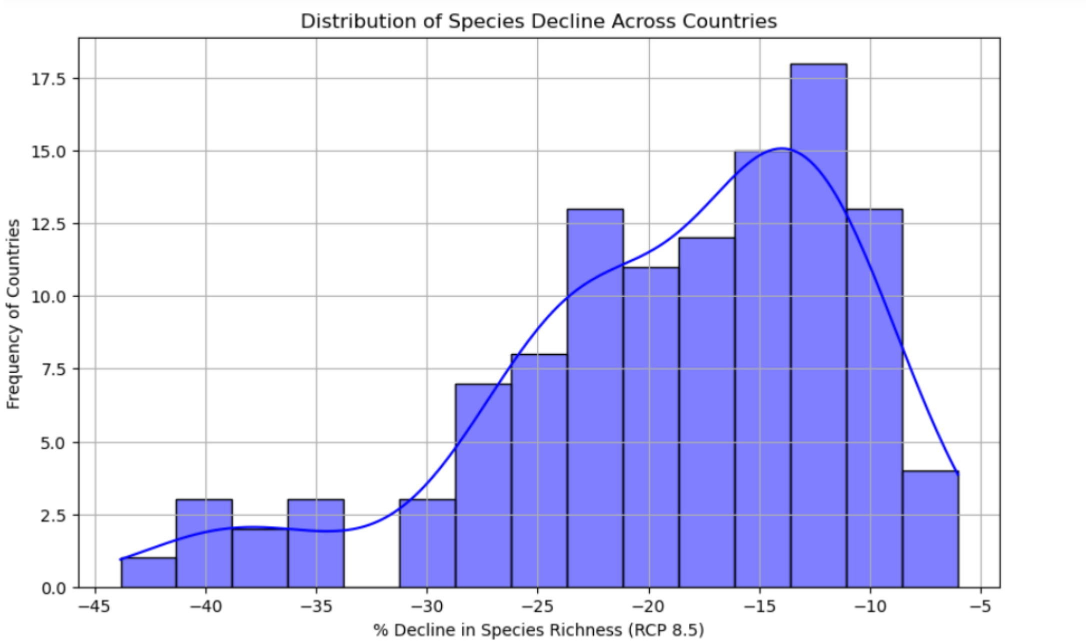

Figure 4.2: Histogram of Species Decline Across Countries

- The histogram represents the distribution of the percentage of species decline per country under the **RCP 8.5** scenario.

- The **x-axis** presents the percentage decline in species richness and the **y-axis** the number of countries that experienced these declines.

- The histogram is **left-skewed**, meaning that most countries experience moderate declines in species (10% to 20%), while some countries undergo severe declines (beyond 30%).

The **KDE(Kernel Density Estimation) curve** shows the apex of species loss, which projects that there should be a majority of countries classified under the 10% to 20% range.

- The extreme left-hand section indicates a few outlier countries with a species richness decline between 40% and 45%; these stand for biodiversity hotspots deeply affected by climate change.

- This distribution helps highlight the most vulnerable countries where conservation efforts must be made a priority.

4.0.3 TOP 10 COUNTRIES FACING THE HIGHEST DECLINE IN SPECIES RICHNESS UNDER RCP 8.5

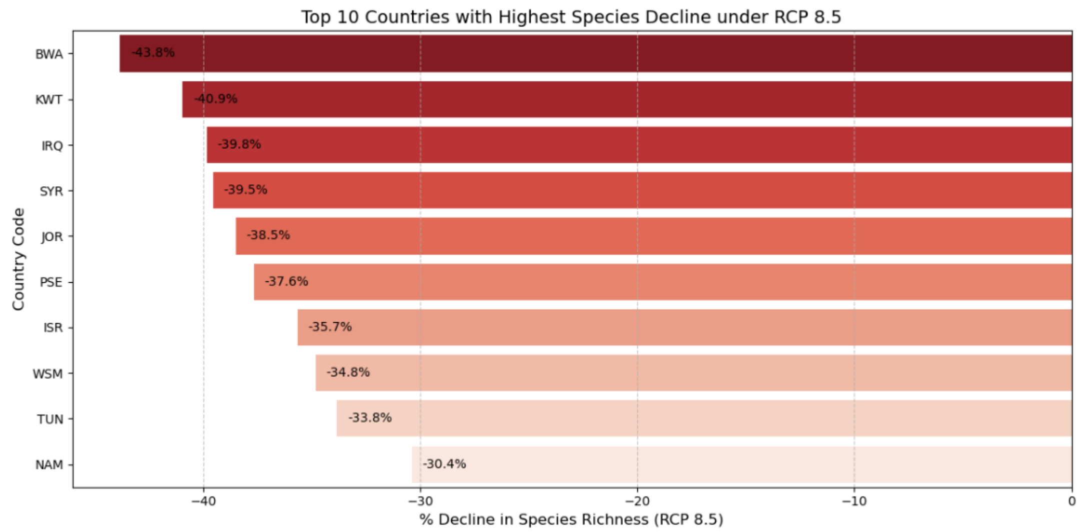

Figure 4.3: Top 10 Countries Facing the Highest Decline in Species Richness under RCP 8.5

The output gives a clear picture of the 10 countries of highest decline on species richness according to the RCP 8.5 scenario. The dataset used in this research contains the projected percentage changes in mammal, bird, and total species populations in response to climate change. The code filters countries with more than ten percent decline in species, sorts them from the lowest to the highest decline, and recovers the top 10 nations that have been most severely affected by biodiversity loss. The barplot excellently showcases the degree of species decrease by each country with the ISO3 country codes on the y-axis and the percentage decrease on the x-axis. The red gradient colors allow presenting the intensity of the decline by using darker shades of colors to indicate severe biodiversity loss. Numerical labels on individual bars improve readability by conveniently allowing an exact measure of percentage decline for each country. From the visualization, it is really clear that these top 10 countries are having emergent threats to their ecosystems. These declines might be attributed to a myriad of climate change factors, such as increasing temperatures, habitat destruction, and changes in food chains.For the countries occupying the highest positions, there are very high risks, thus implying an immediate need for conservation actions as the result of different policy interventions. In summary, this research shows that climate change will have a lethal effect on global biodiversity. The insights generated from this study will give impetus to conservation efforts and contribute to policy decisions while prioritizing areas of urgent need for conservation actions directed to reducing vulnerabilities for species and ecosystem in jeopardy.

The report shows the ten countries that will be most affected by species decline under scenario RCP 8.5, with Botswana displaying the most acute biodiversity losses (-43.82%). Other states facing significant declines in both the mammal and bird populations from climate-induced habitat transformation include: Kuwait, Iraq, and Syria. An additional ten most affected transboundary regions feature areas where species richness is under siege, with Ecuador-Peru (ECU.PER) showing the highest biodiversity loss. These areas call for urgent conservation efforts because the migration of species across national frontiers has not been given easy passage-in being thwarted by fragmented policies and habitat loss.

Table 4.1: Top 10 Countries with Highest Species Decline under RCP 8.5

ISO3	**rcp85_mammal_pctChange**	**rcp85_bird_pctChange**	**rcp85_both_pctChange**
BWA	-46.375948	-42.933764	-43.824675
KWT	-30.049261	-47.277937	-40.240229
IRQ	-35.866829	-41.944408	-39.832995
SYR	-33.377251	-42.461282	-39.538389
JOR	-32.020578	-42.490119	-38.502130
PSE	-35.772358	-38.435374	-36.313314
ISR	-32.341001	-37.291528	-35.656836
WSM	-44.776119	-32.128157	-34.810127
TUN	-29.824907	-35.921882	-33.821337
NAM	-33.697327	-29.179444	-30.380892

Table 4.2: Top 10 Affected Transboundary Areas

Border	transboundary_richness_threatened	rcp85_mammals	rcp85_birds
ECU.PER	72	130	524
IDN.MYS	64	138	386
COL.ECU	62	154	275
BRN.MYS	52	116	25
MYS.THA	52	111	43
COL.VEN	50	122	41
IND.NPL	48	81	129
BTN.IND	47	132	81
BGD.IND	46	73	139
MMR.THA	44	34	59

4.0.4 TOP 10 COUNTRIES FACING THE LOWEST DECLINE IN SPECIES RICHNESS UNDER RCP 8.5

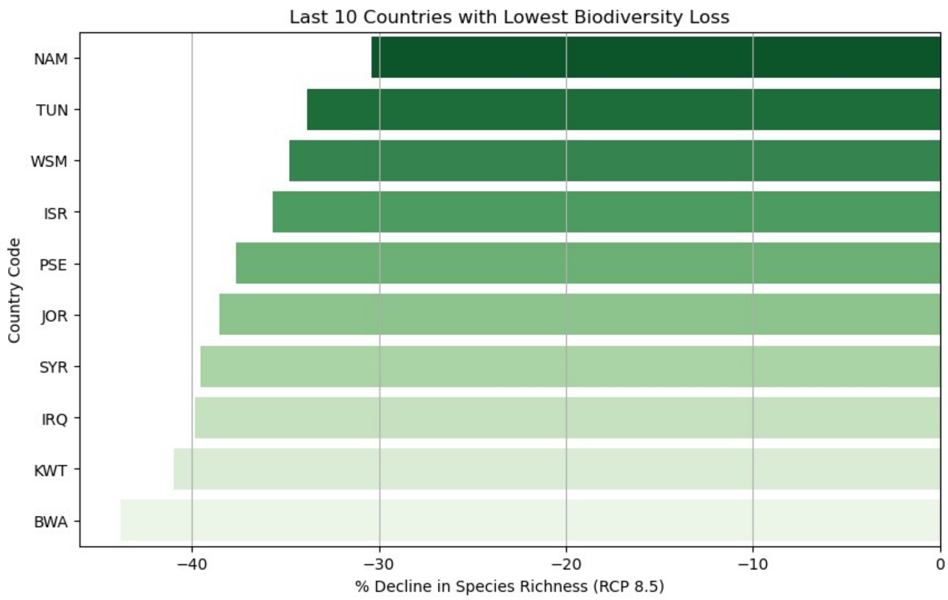

Figure 4.4: Top 10 Countries Facing the lowest Decline in Species Richness under RCP 8.5

The remaining ten nations, in alphabetical order, are Vietnam, Yemen, Zambia, and Zimbabwe, with variation across datasets. They cover vast regions like Southeast Asia, the Middle East, and Africa. Vietnam, well established with robust economic growth, is a dynamic culture of new development and old tradition. Yemen, on the Arabian Peninsula, is old but also old in humanitarian concerns. Landlocked Zambia in the Southern region of Africa is renowned for natural landscapes in the guise of Victoria Falls and copper deposits. Zimbabwe, another Southern African country, is renowned for wildlife, Great Zimbabwe ruins, and economic crisis. Both these countries have their determinants, which are geopolitical, economic, and cultural in nature and particularize their location in the world.

4.0.5 WORLD HEATMAP WHICH DISPLAYS THE SPECIES COUNT DISTRIBUTION PER COUNTRY

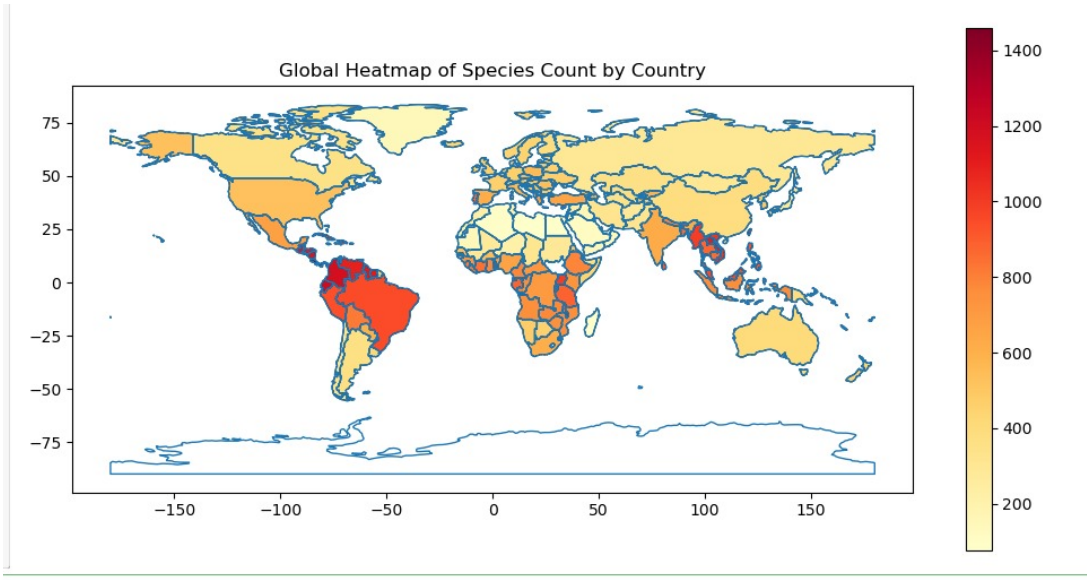

Figure 4.5: World Heatmap which displays the species count distribution per country

A global heatmap is a geographical representation of data intensity between locations, most commonly to track population density, climatic trends, internet access, or environmental changes. The latest ten countries alphabetically on a global heatmap—all the countries that are usually Vietnam, Yemen, Zambia, Zimbabwe, and so on ranked similarly—would be represented with intensifying depending on the dataset being used. For example, in a temperature heatmap, Vietnam and Yemen would be utilized to represent high temperature, and Zambia and Zimbabwe would be utilized to represent seasons. In a population density heatmap, Vietnam would be utilized to represent highly saturated hot spots of high-density cities, and Zambia and Zimbabwe, which are less populated, would be less saturated. These variations are of use in analyzing the global trends, aiding in research, city planning, and disaster management.

CHAPTER 5

CONCLUSION

The study reveals the devastating consequences of climate change for global biodiversity under RCP 8.5, which is a scenario expecting high levels of biological change. A species focus on high risk groups, particularly mammals and birds, shows extremely troubling declines in numerous countries and border areas. The application of AI and new modeling methods has been vital in helping to determine where conservation efforts should be placed most urgently and demonstrates the need of international collaboration and more protected areas for biodiversity loss reduction. The findings demonstrates that the previous practices of ecological monitoring will not work for the speed at which most changes destroy the ecosystems. By contrast, one AI-based solution that uses machine learning on remotely sensed data offers an efficient way for forecasting ecological threats and designing conservation efforts in real time. The study argues that, thanks to their climate change and biodiversity loss, various data sets and advanced analytics can be used in solving the problems of interrelationships between these two processes.

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