KULLIYYAH OF INFORMATION & COMMUNICATION TECHNOLOGY

CSCI 3303 MATHEMATICS FOR COMPUTING III

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SECTION 01

TITLE: THE MOST PROMINENT FACTORS IN INCREASING THE RATES OF CLIMATE CHANGE

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1.0 OVERVIEW

1.1 INTRODUCTION

Our project topic is about analyzing the change of the climate and the most prominent factors of it . Climate change has become one of the most urgent and complex challenges faced by humanity today. From rising sea levels to extreme weather events, the evidence of a warming planet is becoming more visible and more difficult to ignore. At the core of this global crisis is the excessive release of greenhouse gases into the atmosphere, particularly **carbon dioxide (CO_2)**, which is largely emitted through human activities such as burning fossil fuels, deforestation, and industrial operations.

While the Earth has naturally experienced cycles of warming and cooling throughout its long history, such as during the Ice Ages, the current rate of climate change is unprecedented. For instance, after the last Ice Age around 20,000 years ago, global temperatures increased gradually over thousands of years. In comparison, the industrial revolution, which began just over 150 years ago, has caused a rapid and dramatic spike in atmospheric CO_2 levels. Since the 1850s, concentrations of CO_2 have risen by more than 48%, a change driven almost entirely by human behaviour.

In addition to carbon dioxide, other synthetic greenhouse gases have also contributed significantly to global warming. These include **hydrofluorocarbons (HFCs)**, which are commonly used as refrigerants; **perfluorocarbons (PFCs)**, often emitted during aluminium production and semiconductor manufacturing; **sulphur hexafluoride (SF_6)**, an extremely potent gas used in the electrical industry as an insulator; and **nitrogen triflouride (NF_3)**, used in semiconductor and solar panel production. Although these gases are released in smaller quantities than CO_2, their heat-trapping abilities are much greater, making them important factors in climate studies.

In this project, we aim to analyze the emissions of CO_2 & other greenhouse gases like HFCs, PFCs, and SF_6 across ten selected countries: Australia, Ukraine, Malaysia, the United Kingdom, Russia, India, France, Japan, Germany, and Canada. Using historical data and mathematical modelling, particularly the *Markov Chain method*, we will explore which of these factors plays the most prominent role in accelerating climate change. Our analysis will also compare how these gases have evolved over time in each country, helping us understand the global and regional contributions to this critical issue. Through this research, we hope to highlight the most impactful factors in climate change and support efforts to reduce emissions effectively.

1.2 MARKOV CHAIN

A Markov chain is a stochastic model that considers several alternative outcomes, with the probability of each occurrence being determined solely by the condition met in the first instance. It's a cycle that occurs in a series of time-steps, each of which involves an erroneous decision between a finite (or enumerable) set of states.; since both the index set and the state space are discrete, XnX(TN) is denoted; the probability of transition can then be expressed by a matrix P=(pij), where pij is the probability of going from the state I to state j: pij=Prob[Xn+1=j|Xn=i].

The Markov chain method is used to predict the expected outcome of the factors that lead to climate change. How much is it changing, and which one is the most common factor? Based on the given and calculated results from the statistics on all factors, we can use the Markov chain method to predict the percentage value of all factors, which we then compare to get the best factor that contributes to our objective.

1.3 PROBLEM STATEMENT

The world's climate is changing rapidly. There are many factors that contribute to climate change. In our project, we will conduct an analysis based on 10 different countries: Australia, Ukraine, Malaysia, the United Kingdom, Russia, India, France, Japan, Germany, and Canada. We will do mean, median and hypothesis. The two most important influencers of climate change are emissions of carbon dioxide and other greenhouse gases (GHG) which are methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulphurhexafluoride (SF6) from the energy, industry, waste, and agriculture sectors, standardized to carbon dioxide equivalent values. This measure excludes GHG fluxes caused by Land Use Change, Land Use and Forestry (LULUCF), as these fluxes have larger uncertainties. The measure is standardised to carbon dioxide equivalent values using the Global Warming Potential (GWP) factors of IPCC's 5th Assessment Report (AR5). In this report, we will compare which are the major factors of climate change.

1.4 OBJECTIVE

The objective of this research is as below:

- To determine whether the rate of climate change is increasing or decreasing.
- To find out the best factor which is causing more harm to our environment.
- We will calculate the CO_2 rate in different countries and decide which country is causing the most global warming effects.
- We will take data globally, and we will compare it with countries. Since climate change is a big problem throughout the whole world. We aim to prove that.

2.0 RELATED WORK

2.1 **Estimating the Emissions Reductions Needed to Meet the 2°C Warming Target** (Liu & Raftery, 2021)

The article is about figuring out how much we need to cut emissions to keep global warming below 2°C. It found that big polluters like the USA (2% chance) and China (16% chance) probably won't meet their climate goals. Right now, there's only a 5% chance of staying under 2°C. While the article doesn't go into detail about the math, this type of analysis, dealing with probabilities and future predictions, often uses linear algebra and statistical methods. For example, it might involve Markov chains to model how our emissions "transition" from one state to another, or regression analysis to predict future emission trends based on current data. These tools are commonly used in many fields to understand systems that change over time, from economics to biology.

2.2 **Hidden Markov Models for Presence Detection Based on CO2 Fluctuations** (Karasoulas et al., 2023)

This article investigates using Hidden Markov Models (HMMs), a linear algebra-based approach, and CO_2 concentration fluctuations to detect human presence indoors. It addresses the limitations of traditional motion and camera sensors by proposing CO_2 sensors as a low-cost, non-intrusive alternative. The authors developed a simple Markov Chain Model, which relies on transition probability matrices and emission probability matrices, core linear algebra concepts to infer hidden states (presence or absence) from observed CO_2 levels. This method achieved high accuracy (up to 97%) in detecting occupancy in both experimental and real-world data, demonstrating the practical efficacy of using probabilistic models derived from linear algebra for real-time applications like HVAC and lighting control.

2.3 **An Algorithm for Predicting Carbon Emission Trends Based on Adaptive Hidden Markov Models** (Wan et al., 2024)

This article proposes an algorithm for predicting carbon emission trends using an adaptive Hidden Markov Model (HMM), a powerful linear algebra-based statistical framework. Recognizing the complex interplay of factors influencing emissions, the authors construct an index system of influencing factors, such as energy structure and industrial population size, to serve as the hidden state parameters of the HMM. The algorithm leverages core linear algebra concepts, including transition probability matrices (describing the likelihood of moving between hidden states) and observation probability distributions (relating hidden states to observed carbon emission levels). By incorporating time complexity and adaptive attributes, the model learns from historical data to dynamically update these probabilities and generate future carbon emission prediction sequences, demonstrating high accuracy with prediction errors consistently within 2.0×10^4 tons, thus showcasing the HMM's robust capability for complex time-series forecasting.

2.4 **Optimizing Climate-Related Global Development Pathways in the Global Calculator Using Monte Carlo Markov Chains and Genetic Algorithms** (Garcia et al., 2022)

This article explains how a tool called the 'Global Calculator', which predicts future energy, food, and land use, is being optimized to reach global climate goals. Because this tool has a huge number of possible settings, researchers used advanced computing methods based on linear algebra: Monte Carlo Markov Chains (MCMC) and genetic algorithms. MCMC helps explore many different options efficiently by moving through possibilities based on probabilities, similar to how a random walk works. Genetic algorithms, inspired by natural selection, 'evolve' better solutions over time by combining and selecting the best settings, much like how species adapt and improve. These methods, which rely on mathematical operations to navigate complex search spaces, allowed them to find the best settings in the Global Calculator to both reduce CO_2 emissions significantly and boost economic growth (GDP), proving they can create effective and customized plans for a sustainable future.

2.5 How do green energy investment, economic policy uncertainty, and natural resources affect greenhouse gas emissions? A Markov-switching equilibrium approach (Hassan et al., 2022)

This study investigates how green energy investment, economic policy uncertainty, and natural resources impact greenhouse gas (GHG) emissions in China. To do this, they used a sophisticated method called a Markov-switching equilibrium correction model. This model, a type of Hidden Markov Model (HMM) based on linear algebra, is like having different 'modes' or 'states' for the economy, such as times of high or low policy uncertainty, and it allows the relationships between these factors and emissions to change depending on which mode the economy is in. These 'switches' between modes happen based on probabilities, which are represented by transition matrices. This approach allowed them to discover that green energy investment helps the environment, while natural resources and economic uncertainty hurt it, ultimately pushing for more green energy investment.

2.6 Greenhouse Gas Emissions from Heavy-Duty Vehicles in Ireland (Middela et al., 2024)

This study looked at CO_2 emissions from large trucks in Ireland, a key area for cutting overall pollution. Researchers used a special tool called VECTO, but they made it more accurate by creating new driving patterns based on real Irish roads. They found that using these Irish-specific patterns changed the estimated CO_2 emissions, showing the importance of local conditions. The study also highlighted how factors like the truck's weight, road hills, and idling time affect fuel use and emissions, noting that ignoring hills can lead to underestimating fuel consumption by over 7%. This research provides important information for Irish policymakers to help reduce truck pollution.

2.7 Compound extremes in a changing climate – a Markov chain approach (Sedlmeier et al., 2016)

This article applied a Markov chain model to forecast the probability of heatwaves in Iran. The model was trained using a dataset of daily maximum temperatures from 1980 to 2010. The study found that the model could predict heatwaves with high accuracy. According to the researchers, the Markov chain model is a promising method for predicting heatwaves and could be used to develop early warning systems for such events.

2.8 Applications of Markov Chain in Forecast (Xia Yutong, 2021)

This article introduces the concept of the Markov chain and its practical applications, particularly in business forecasting. The author explains the theory using two daily life examples to illustrate that in a Markov process, the probability of a future state depends solely on the immediately preceding state. By constructing transition probability matrices, the study demonstrates how mathematical models for market and weather forecasting can be built, analyzed, and computed using Markov chains. Through data analysis and calculation verification, the article concludes that the Markov chain is a scientific, effective, and convenient method for prediction, applicable to solving various daily issues.

2.9 Analysis of Air Quality Parameters on Climate Change Phenomenon Using Markov Autoregressive Model (VijayaShanthy et al., 2024)

This research developed a portable device to monitor air pollution and harmful gas emissions, like NOx, in real-time. It uses an Internet of Things (IoT) system to send data every 2 seconds to smart devices, comparing it against standard air quality levels. The goal is to use this data with a Markov autoregressive model to predict climate conditions and give early warnings for pollution, helping us take action to protect the environment.

2.10 Modeling the Spatio-Temporal Dynamics of Air Pollution Index Based on Spatial Markov Chain Model (Alyousifi et al., 2020)

This study used a spatial Markov chain model to analyze how air pollution levels in one location affect, and are affected by, neighboring areas in Peninsular Malaysia. The research found that a station's air quality is significantly dependent on its neighbors' pollution states, with cleaner neighbors increasing the probability of a station remaining clean.

2.11 Research on the Methodology of Carbon Emission Prediction Under Dual Carbon Target Based on Improved Gray Markov Model (Zhu et al., 2025)

This paper proposes a carbon emission prediction method that utilizes an improved gray Markov model. The approach involves calculating carbon emissions at various times using the carbon emission factor method, then creating a cumulative sequence. The state transition for the Markov process is determined by analyzing the relative error of gray prediction results. Finally, carbon emission prediction values are calculated, with their arithmetic average taken as the final prediction result. Experimental findings indicate that the predicted outputs from this method are closer to the actual values, demonstrating its effectiveness for carbon emission forecasting under dual carbon targets.

2.12 Locating and Quantifying Methane Emissions by Inverse Analysis of Path-Integrated Concentration Data Using a Markov-Chain Monte Carlo Approach (Weidmann et al., 2022)

This article presents a novel area monitoring approach to locate and quantify methane emissions, a significant challenge in reducing greenhouse gas pollution. The method utilizes laser dispersion spectroscopy to measure path-averaged methane concentrations across multiple beams. By integrating this data with a Gaussian plume gas dispersion model and employing a Markov-chain Monte Carlo (MCMC) analysis, the system identifies source locations and emission rates. The approach was tested with 19 calibrated methane releases in a 175m x 175m area, demonstrating high accuracy: it correctly located sources within 9 meters in over 75% of cases and achieved better than 30% accuracy for mass emission rates in 70% of cases, with discrepancies typically less than 2 kg/h. This method provides a promising tool for precisely identifying and measuring methane leaks.

3.0 METHODOLOGY

3.1 General introduction/overview of the linear algebra method.

A Markov chain is a mathematical framework used to model sequences of events in which the likelihood of moving to a future state depends only on the present state, not on the sequence of events that happened before it. This type of process is called *stochastic*, meaning it involves *randomness.*

Markov chains are defined by a set of possible states and the probabilities of transitioning between them. These probabilities are organized into a square matrix known as the *transition matrix* or *stochastic matrix,* where each row represents a current state and each column shows the probability of moving to a next state. By multiplying this matrix by itself repeatedly (raising it to a power), one can determine the probability of transitioning between states over several steps. This allows for analysis of the system's behavior over time, including identifying the *steady-state distribution*, which represents the long-term probability of being in each state. Markov chains are widely used to study and predict the behavior of systems governed by probabilistic rules.

3.2 General types of problems Markov Chain rule is used to solve.

Markov chains are applied in a wide range of fields to solve various types of problems. They are especially valuable in probabilistic modeling, where they help represent the behavior of systems influenced by randomness, such as fluctuations in stock markets, climate variations, population growth, and the transmission of diseases. Additionally, Markov chains are effective in modeling random walks, studying queueing systems, addressing optimization challenges through Markov decision processes (MDPs), and supporting natural language processing tasks like text generation and prediction. These diverse applications demonstrate the flexibility and usefulness of Markov chains in analyzing, forecasting, and improving systems that exhibit probabilistic characteristics.

3.3 Write the general formulation of the equations from the textbook.

We examine a discrete-time, discrete-space stochastic process denoted as

$$X(t) = X_t \text{ , for } t = 0,1,....$$

The state space S is discrete—either finite or countably infinite—so we can represent it as a set of integers, such as:

$$S = \{1,2,...,N\} \text{ or } S = \{1,2,...\}$$

The sequence $X(t) = X_0,X_1,X_2,...$ is considered a discrete-time Markov chain if it satisfies the Markov property:

$$P(X_{n+1} = s \mid X_0 = x_0, X_1 = x_1, \dots , X_n = x_n) = P(X_{n+1} = s \mid X_n = x_n)$$

This property means that the future state depends only on the present state and not on the sequence of past states.

The values $P(X_{n + 1} = j \mid X_n = i)$ are referred to as **transition probabilities** and are generally dependent on the current state iii, the next state jjj, and the time step nnn. For convenience, these probabilities are denoted as:

$$p_{ij} (n) = P(X_{n + 1} = j \mid X_n = i)$$

The collection of these probabilities at time nnn forms the **transition matrix** $P(n) = (p_{ij} (n))$, where the entry in the i-th row and j-th column corresponds to $p_{ij} (n)$.

This matrix satisfies two key conditions:
(i) $p_{ij}(n) \geq 0 \ \forall \ i, j$ (the entries are non-negative)
(ii) $\sum_j p_{ij}(n) = 1 \ \forall \ i$ (the rows sum to 1)

Any matrix that meets these two conditions is known as a **stochastic matrix**, so the transition matrix $P(n)$ is stochastic.

A Markov chain $X(t)$ is said to be **time-homogeneous** if the transition probabilities are independent of time n; that is,

$$\boldsymbol{P(X_{n + 1} = j \mid X_n = i) = P(X_1 = j \mid X_0 = i)}$$

In this case, we write

$$\boldsymbol{p_{ij} = P(X_1 = j \mid X_0 = i)}$$

to denote the one-step transition probability from state i to state j, and define the transition matrix as $P=(p_{ij})$.

In this , we will focus solely on time-homogeneous Markov chains, though we may occasionally comment on how certain results extend to the time-inhomogeneous case.

4.0 VARIABLE & DATA SOURCES

Total greenhouse CO2 gas emissions (kt of CO2 equivalent) (Excluding LULUCF)

Country Name	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979
Australia	160.3769	162.1077	167.9569	177.3185	186.8463	193.595	196.384	209.6638	205.9886	211.8454
Ukraine	477.2242	476.8572	502.4115	532.108	556.1456	582.1754	600.1396	610.5376	653.2175	667.0468
Malaysia	26.8826	27.2778	14.3218	14.8103	17.8525	19.2436	21.2425	21.1059	27.1876	31.2059
United Kingdom	673.4202	668.6714	657.7172	690.031	644.6402	623.6572	629.8113	638.3125	636.4771	672.6636
Russia	1307.9918	1308.9747	1377.0903	1460.8889	1536.3042	1620.8224	1681.8341	1719.5681	1841.6854	1867.6469
India	213.9344	214.4281	222.9632	221.9373	237.6409	253.2017	270.6936	276.0218	271.347	291.7332
France	469.4414	481.5545	499.1043	535.7473	517.0076	476.4954	521.9985	503.433	521.4465	529.0211
Japan	848.7516	846.4521	893.0016	1006.6245	1003.1882	948.6801	980.7332	1005.7789	1006.3741	1030.144
Germany	1084.6575	1077.4192	1105.2903	1157.7203	1122.5066	1060.5661	1122.9347	1101.4441	1139.317	1189.4771
Canada	358.1272	365.7851	383.0355	401.9821	410.0579	400.2143	413.3629	427.8718	431.0299	445.1962

Country Name	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
Australia	222.0147	222.9747	229.2624	217.7334	223.519	237.9354	238.3953	249.5845	258.3833	274.1612
Ukraine	684.8723	674.3338	672.4168	672.9621	676.0755	678.3837	692.5807	713.9627	722.0811	718.2876
Malaysia	32.3916	33.0891	35.7918	41.0466	43.1615	42.7145	43.9599	44.7952	47.9098	56.6283
United Kingdom	608.3254	589.021	573.101	566.2653	549.9603	576.5427	590.5337	595.1847	592.8904	579.2874
Russia	1929.3114	1923.5418	1951.446	1985.1133	2020.4148	2059.49	2126.7823	2189.1639	2241.0717	2252.9505
India	303.5765	333.9885	351.9038	374.5973	412.8617	431.4118	468.5979	501.4341	532.2986	570.1243
France	507.05	456.7116	435.6642	416.5339	404.9673	394.7068	382.601	375.7727	375.8439	390.36
Japan	1003.1434	981.5855	939.7607	943.2447	1011.0488	983.4576	980.48	987.784	1060.6681	1090.4943
Germany	1135.5984	1099.9653	1054.0401	1069.5505	1085.7373	1086.3402	1080.194	1072.2524	1065.9799	1050.769
Canada	450.4307	431.7735	413.774	407.4239	426.7784	426.65	416.5804	429.3182	460.3398	475.4707

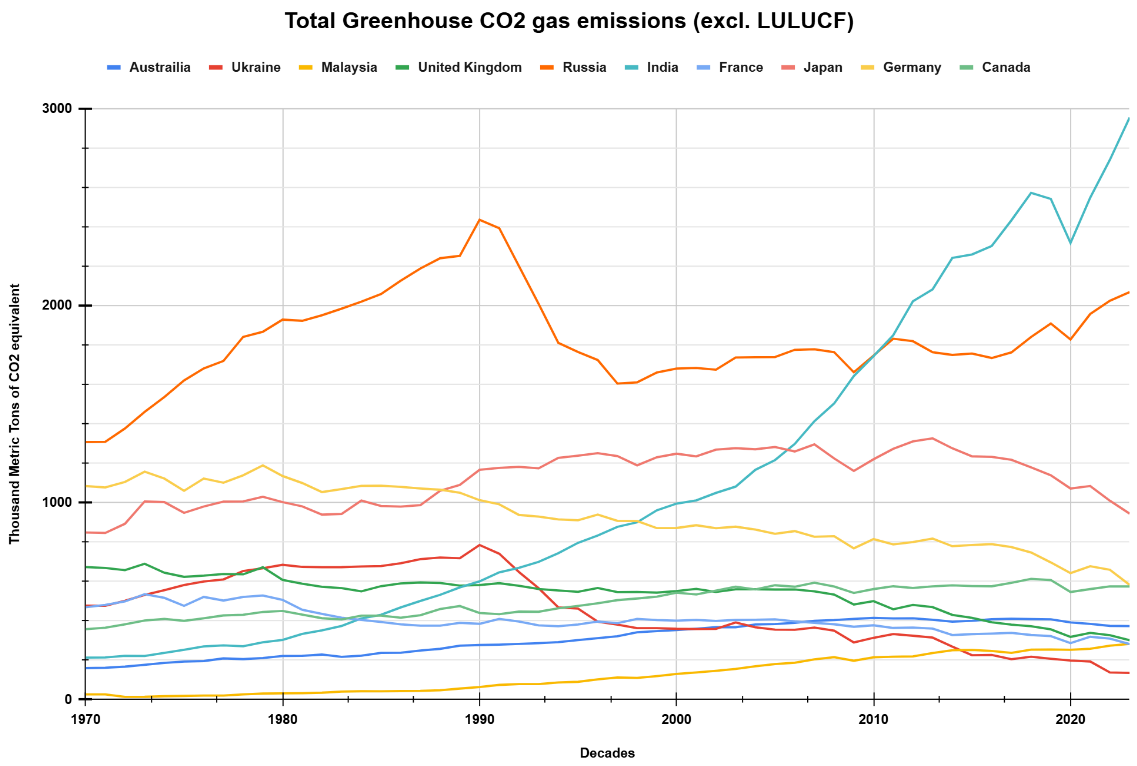
Country Name	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Australia	277.7123	279.7336	283.1129	287.0239	292.3756	302.6923	312.6713	322.3709	342.1087	348.1127
Ukraine	785.5447	741.0614	648.3748	565.9997	468.4401	462.6363	396.2374	380.9966	363.5368	363.2923
Malaysia	64.4223	75.3034	79.2844	79.4983	87.5645	90.9385	103.4302	113.2578	110.6673	119.6946
United Kingdom	582.349	591.4813	578.1824	562.1317	554.6245	548.0823	567.3642	546.492	547.1041	543.7186
Russia	2436.2592	2393.5273	2200.8303	2008.7494	1811.1206	1765.1898	1724.2331	1604.8446	1611.1046	1660.9052
India	600.6873	646.3888	669.6642	699.7562	743.8583	796.4639	833.512	877.7065	900.6255	961.6311
France	385.272	410.3361	396.929	377.283	373.0042	382.0537	396.7419	388.4739	410.4713	404.1642
Japan	1166.8237	1176.8604	1181.8812	1174.7455	1227.961	1238.6398	1251.4624	1236.9539	1189.7637	1230.7275
Germany	1013.0316	992.0353	938.1013	929.647	915.6041	910.8205	939.6957	907.821	906.9508	871.0236
Canada	440.4753	434.5216	447.282	446.6273	463.8531	475.9147	489.835	505.6071	513.8019	523.3953

Country Name	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Australia	353.8697	360.4081	368.6209	368.115	381.942	384.0857	390.1513	400.6653	404.2851	410.2594
Ukraine	360.0221	359.0635	359.6469	392.02	367.8053	356.0703	355.3087	366.3142	350.633	290.6597
Malaysia	130.7796	138.4076	146.5554	156.576	169.6248	181.1517	187.7708	204.9404	216.1782	197.9811
United Kingdom	551.6797	562.9085	546.9059	560.427	560.9379	559.3283	559.7568	550.2287	533.7479	483.3614
Russia	1681.1439	1684.2625	1675.2806	1737.2379	1738.8498	1739.2783	1776.173	1779.0046	1764.31	1662.0566
India	995.6526	1011.8047	1049.8801	1081.7852	1166.8166	1216.5339	1298.3951	1413.8648	1503.6111	1643.0647
France	401.2112	405.3435	399.9106	404.8426	405.9175	408.1656	397.4259	390.2734	383.0041	370.3759
Japan	1248.8068	1235.2221	1269.4295	1276.7113	1271.3841	1283.0176	1260.2992	1296.2507	1224.9593	1161.4121
Germany	871.7357	885.8183	870.3116	878.2763	863.7247	842.0993	855.8555	826.9926	830.3551	768.5531
Canada	543.0448	534.3097	554.0309	573.6839	559.7293	581.0957	573.5411	594.0202	574.5625	541.8042

Country Name	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Australia	415.2731	412.8096	413.3193	405.6523	396.2575	400.5424	408.5061	410.8371	409.2067	407.8604
Ukraine	314.3313	333.2225	324.8218	315.1852	269.2522	226.0362	227.1896	205.5392	218.3518	207.8431
Malaysia	215.5746	218.3287	219.8784	237.2457	251.4646	252.9286	247.5683	237.8645	254.3612	255.2071
United Kingdom	500.6285	459.0174	481.19	470.1718	430.4962	415.856	393.3439	381.2854	373.2205	357.3326
Russia	1746.8481	1832.562	1819.7501	1764.1938	1750.144	1757.0574	1734.5602	1763.1528	1841.4417	1909.8166
India	1743.6929	1850.3319	2022.7648	2083.2109	2242.8409	2260.1314	2303.3619	2433.7831	2573.1194	2542.0351
France	377.7598	364.3139	366.1388	360.9924	328.0879	332.9749	335.7678	339.3458	328.6302	322.7523
Japan	1220.4535	1273.3455	1311.2998	1326.7101	1276.2555	1235.4187	1232.8769	1217.8484	1179.2176	1139.4974
Germany	815.3784	788.5477	800.4648	818.2784	779.2231	785.3872	789.7138	774.9482	747.2145	697.0085
Canada	561.6033	575.8915	567.2705	575.2453	580.4828	577.1296	575.8711	593.0442	613.6582	607.2496

Country Name	2020	2021	2022	2023
Australia	392.5191	384.6772	374.8785	373.6164
Ukraine	198.6575	194.0549	138.3356	136.1979
Malaysia	253.3934	258.9144	274.3424	283.3235
United Kingdom	319.0147	339.4953	327.4607	302.1033
Russia	1828.7967	1957.9274	2025.1436	2069.502
India	2318.9477	2548.4833	2740.8206	2955.1817
France	287.3243	319.4248	310.4579	282.4275
Japan	1072.1695	1084.9216	1009.9787	944.7586
Germany	642.552	677.8039	659.5018	582.9506
Canada	546.6751	561.6259	575.3213	575.012

Country Name	Mean	Median
Australia	309.6725815	279.7336
Ukraine	455.6759685	502.4115
Malaysia	125.1303907	75.3034
United Kingdom	536.9989278	567.3642
Russia	1826.987967	1765.1898
India	1101.575998	646.3888
France	402.6492389	404.1642
Japan	1123.693685	1166.8237
Germany	928.5034444	992.0353
Canada	496.8966389	450.4307



Co2 gas

Country	Class 1 (Low)	Class 2 (Medium)	Class 3 (High)
Australia	< 253.896	253.896 - 374.853	> 374.853
Ukraine	< 357.537	357.537 - 565.803	> 565.803
Malaysia	< 46.3214	46.3214 - 180.921	> 180.921
United Kingdom	< 546.695	546.695 - 578.15	> 578.15
Russia	< 1738.03	1738.03 - 1867.13	> 1867.13
India	< 516.558	516.558 - 1215.54	> 1215.54
France	< 377.517	377.517 - 405.336	> 405.336
Japan	< 1010.5	1010.5 - 1227.9	> 1227.9
Germany	< 848.84	848.84 - 1053.97	> 1053.97
Canada	< 442.789	442.789 - 559.615	> 559.615

Total Greenhouse (excl. LULUCF & CO2) gas emissions. (Thousand metric tons of CO2 equivalent)

Country Name	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979
Australia	154.6501	159.1969	165.4939	163.4756	168.628	171.2756	171.605	165.0431	159.6786	158.0262
Ukraine	129.901	133.9423	139.0019	144.4937	149.3799	153.1501	157.291	160.3692	164.7599	166.2948
Malaysia	18.4245	18.788	19.227	19.0168	18.6067	19.1405	19.9368	20.1324	19.3555	22.0629
United Kingdom	181.6536	182.0735	172.8469	181.0465	176.5802	186.1481	187.1488	184.0116	183.8887	187.7576
Russia	415.1676	428.9727	443.9357	461.7499	477.766	491.3836	506.5772	517.2852	531.9103	540.2773
India	578.877	582.3815	584.2862	592.6964	598.3737	613.4236	618.3659	631.677	639.6889	646.722
France	167.2087	165.7817	164.9418	165.8687	165.9095	164.4412	163.6471	164.7335	164.2727	165.5208
Japan	167.5319	159.7026	156.2509	156.1245	154.7456	151.185	155.2111	158.1504	151.8672	153.8203
Germany	241.174	240.7372	237.0205	239.5346	240.9663	238.6106	239.3703	236.7816	240.6494	243.983
Canada	108.2327	110.111	114.7027	123.3336	124.0506	118.9361	117.2138	123.783	127.4291	127.8604

Country Name	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
Australia	155.0498	157.2378	158.2462	156.773	163.1264	164.6655	169.2986	169.0553	169.0627	176.6502
Ukraine	169.5129	169.2835	170.5226	173.101	175.6731	176.4025	179.7917	182.6123	180.327	181.193
Malaysia	21.8775	21.5365	21.8883	22.9235	23.9781	24.3293	25.0825	25.345	26.2049	27.1517
United Kingdom	187.2449	186.076	185.4479	185.2091	157.3173	173.1042	182.5292	177.8188	176.7544	174.2275
Russia	547.6246	549.8561	559.7154	573.9782	588.1578	595.2092	604.7923	614.5769	619.8926	622.0119
India	658.6685	676.6578	681.3131	706.9399	721.1731	731.2744	755.3699	754.9887	791.5142	809.869
France	164.4991	163.7791	164.7012	168.0553	167.5113	162.1544	161.3396	158.0601	155.0722	148.6831
Japan	151.2335	146.0891	145.1546	145.3724	150.5873	150.4199	148.9803	144.0854	145.5117	146.3412
Germany	244.2057	242.8523	238.1827	235.5819	236.4631	236.048	230.8689	227.1727	225.5768	227.8454
Canada	127.7925	126.3566	125.2788	132.8871	134.8529	130.5435	126.9778	130.2512	133.3558	140.4354

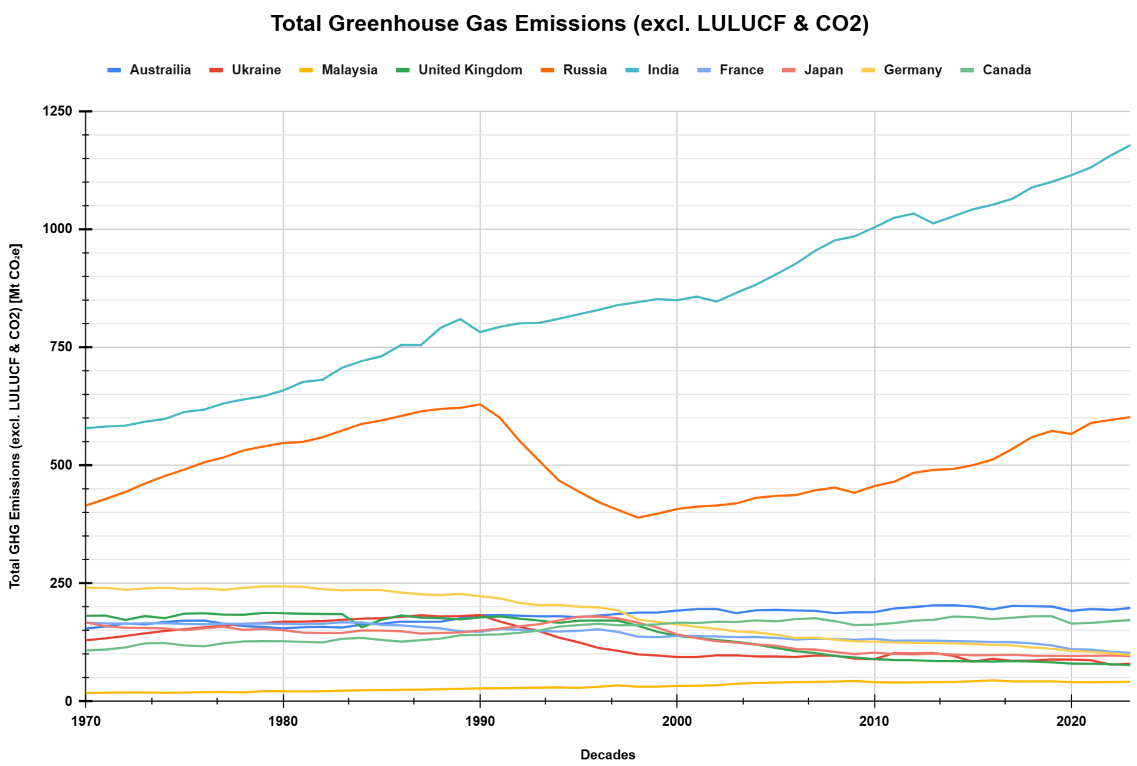
Country Name	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Australia	182.5836	183.307	181.7357	180.6641	181.0077	178.755	182.1412	185.5247	188.4313	188.7807
Ukraine	182.982	169.5441	158.3714	149.02	135.4672	125.5187	113.7688	107.5378	99.9512	97.5196
Malaysia	27.9137	28.2699	28.8354	29.5042	30.1376	28.9997	31.1962	34.3581	31.5543	31.8348
United Kingdom	178.2595	180.4899	175.6261	171.5761	166.5355	171.2918	171.8284	171.4073	160.7775	147.786
Russia	629.4372	601.4706	552.0366	509.8671	468.0081	444.8696	422.7229	405.8859	389.5317	397.8967
India	782.3765	793.3869	800.9554	801.9557	810.7025	820.1452	829.2578	839.7351	845.8733	852.2992
France	147.7418	153.5097	152.2143	149.3892	148.1503	149.7334	153.0634	147.4739	137.6944	136.3502
Japan	150.3943	154.8085	159.5771	163.9031	171.8252	179.7094	180.4467	176.1504	167.3727	156.6843
Germany	222.8419	218.5519	209.0949	204.1167	204.3024	201.0475	199.4715	193.0509	173.9074	168.4669
Canada	141.4375	142.3277	145.8409	150.4697	158.9438	161.9299	164.8088	161.5945	162.069	163.4276

Country Name	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Australia	192.6407	195.8103	196.2276	187.2294	193.4365	194.1612	193.1569	192.0409	187.0982	189.2289
Ukraine	94.5086	94.449	97.7823	97.8234	95.6097	95.5334	94.4156	97.6094	97.2081	90.9627
Malaysia	33.1811	33.5739	34.6443	37.8157	39.6504	40.1531	41.256	41.6458	42.5089	43.5868
United Kingdom	139.3621	135.1786	130.5537	126.3745	121.0078	113.6158	106.962	102.7328	96.6763	93.3779
Russia	407.958	412.9241	415.4149	419.5637	431.5988	435.4624	437.1168	447.2917	453.0917	442.2705
India	849.7996	857.5049	847.0594	865.4942	882.6749	904.359	926.7081	954.4633	976.5274	985.2069
France	139.0296	139.0718	137.8877	136.3426	136.6046	134.8009	131.5469	132.8981	132.6107	130.7271
Japan	142.3145	134.1027	127.7971	124.8391	120.8039	118.391	111.386	110.1283	105.0733	100.4963
Germany	163.6426	158.1728	154.1477	148.6754	146.5313	141.5988	134.5138	135.4187	131.1995	127.7435
Canada	167.3287	166.3117	169.2873	168.5628	171.8509	169.8527	174.6697	176.3821	170.2017	162.0224

Country Name	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Australia	189.3309	197.2203	200.0743	203.7421	203.7756	201.516	195.3419	202.5931	202.1146	201.3094
Ukraine	89.8381	102.5758	101.7328	102.8197	96.8336	84.5783	90.6705	86.4099	86.8477	89.0123
Malaysia	40.9826	40.4037	40.5815	41.3517	41.5399	43.117	44.878	42.7179	42.6766	42.6797
United Kingdom	89.9523	88.0396	87.5207	86.0478	85.6221	85.2223	84.8962	85.7573	84.9194	83.2641
Russia	456.4066	465.416	484.4093	490.7665	492.5281	500.5797	512.3797	535.0389	560.0525	573.0174
India	1003.9249	1024.1499	1033.4479	1012.7032	1027.5293	1042.3562	1052.286	1064.619	1088.7464	1100.3753
France	133.0706	128.9305	129.2613	129.0749	128.0805	127.4047	126.1914	125.673	123.2398	118.8784
Japan	103.772	100.6947	99.9662	101.2636	99.5786	98.165	98.4729	98.9629	97.2967	96.9947
Germany	127.148	125.1735	124.2622	123.6365	123.3072	122.1329	120.3045	118.9422	114.6747	111.7812
Canada	163.0218	166.3552	171.2035	173.1763	179.9368	178.7761	174.7298	177.4325	180.5155	180.7581

Country Name	2020	2021	2022	2023
Austrailia	192.0524	196.0606	194.1318	198.2234
Ukraine	88.8946	87.4895	78.1392	79.8949
Malaysia	41.273	40.8721	41.4461	42.0823
United Kingdom	80.5889	80.1389	79.0588	77.2153
Russia	566.8189	590.028	596.3744	602.5374
India	1114.6713	1131.3785	1156.3884	1178.3727
France	111.027	110.0625	105.6543	103.0926
Japan	96.5839	96.848	97.5971	96.2542
Germany	107.2477	105.6847	102.4817	98.8597
Canada	165.2562	166.642	169.9238	172.666

Country Name	Mean	Median
Australilia	181.6238241	180.6641
Ukraine	126.2652463	139.0019
Malaysia	31.70797037	28.2699
United Kingdom	141.6397796	172.8469
Russia	504.474313	468.0081
India	845.0313907	800.9554
France	144.3085778	152.2143
Japan	134.7596167	150.4199
Germany	181.5881074	218.5519
Canada	151.3721778	142.3277



Other gasses

Country	Class 1 (Low)	Class 2 (Medium)	Class 3 (High)
Australia	< 171.437	171.437 - 192.052	> 192.052
Ukraine	< 97.3607	97.3607- 149.373	> 149.373
Malaysia	< 25.7664	25.7664- 40.143	> 40.143
United Kingdom	< 110.222	110.222- 175.598	> 175.598
Russia	< 454.716	454.716- 547.478	> 547.478
India	< 768.603	768.603- 903.925	> 903.925
France	< 133.918	133.918- 155.041	> 155.041
Japan	< 114.818	114.818- 151.233	> 151.233
Germany	< 138.447	138.447- 227.141	> 227.141
Canada	< 134.089	134.089- 166.636	> 166.636

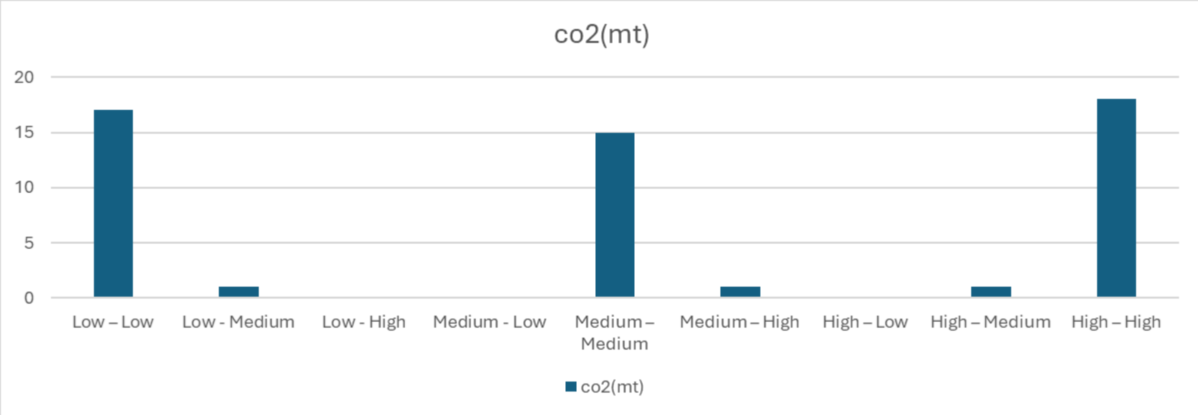
5.0 RESULTS

5.1.1 Australia Gas Emissions (CO_2)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	160.3769	Low	1997	322.3709	Medium
1971	162.1077	Low	1998	342.1087	Medium
1972	167.9569	Low	1999	348.1127	Medium
1973	177.3185	Low	2000	353.8697	Medium
1974	186.8463	Low	2001	360.4081	Medium
1975	193.595	Low	2002	368.6209	Medium
1976	196.384	Low	2003	368.115	Medium
1977	209.6638	Low	2004	381.942	High
1978	205.9886	Low	2005	384.0857	High
1979	211.8454	Low	2006	390.1513	High
1980	222.0147	Low	2007	400.6653	High
1981	222.9747	Low	2008	404.2851	High
1982	229.2624	Low	209	410.2594	High
1983	217.7334	Low	2010	415.2731	High
1984	223.519	Low	2011	412.8096	High
1985	237.9354	Low	2012	413.3193	High
1986	238.3953	Low	2013	405.6523	High
1987	249.5845	Low	2014	396.2575	High
1988	258.3833	Medium	2015	400.5424	High
1989	274.1612	Medium	2016	408.5061	High
1990	277.7123	Medium	2017	410.8371	High
1991	279.7336	Medium	2018	409.2067	High
1992	283.1129	Medium	2019	407.8604	High
1993	287.0239	Medium	2020	392.5191	High
1994	292.3756	Medium	2021	384.6772	High
1995	302.6923	Medium	2022	374.8785	High
1996	312.6713	Medium	2023	373.6164	Medium

Transition of state for Australia Gas Emissions (CO_2)

State	Total Transition
Low – Low	17
Low - Medium	1
Low - High	0
Medium - Low	0
Medium – Medium	15
Medium – High	1
High – Low	0
High – Medium	1
High – High	18

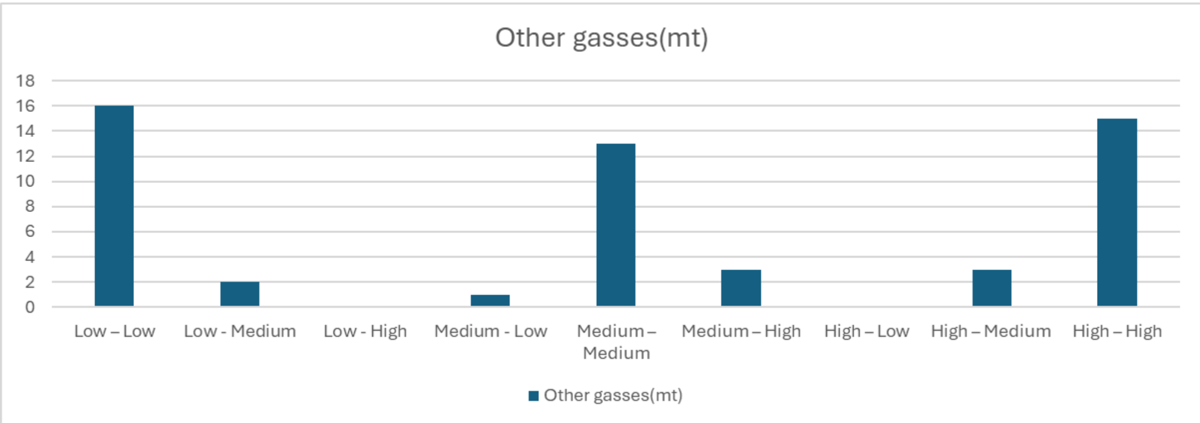


5.1.2 Australia Gas Emissions (HFC, PFC, and SF6)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	154.65	Low	1997	185.5247	Medium
1971	159.1969	Low	1998	188.4313	Medium
1972	165.4939	Low	1999	188.7807	Medium
1973	163.4756	Low	2000	192.6407	High
1974	168.628	Low	2001	195.8103	High
1975	171.2756	Low	2002	196.2276	High
1976	171.605	Medium	2003	187.2294	Medium
1977	165.0431	Low	2004	193.4365	High
1978	159.6786	Low	2005	194.1612	High
1979	158.0262	Low	2006	193.1569	High
1980	155.0498	Low	2007	192.0409	Medium
1981	157.2378	Low	2008	187.0982	Medium
1982	158.2462	Low	209	189.2289	Medium
1983	156.773	Low	2010	189.3309	Medium
1984	163.1264	Low	2011	197.2203	High
1985	164.6655	Low	2012	200.0743	High
1986	169.2986	Low	2013	203.7421	High
1987	169.0553	Low	2014	203.7756	High
1988	169.0627	Low	2015	201.516	High
1989	176.6502	Medium	2016	195.3419	High
1990	182.5836	Medium	2017	202.5931	High
1991	183.307	Medium	2018	202.1146	High
1992	181.7357	Medium	2019	201.3094	High
1993	180.6641	Medium	2020	192.0524	High
1994	181.0077	Medium	2021	196.0606	High
1995	178.755	Medium	2022	194.1318	High
1996	182.1412	Medium	2023	198.2234	High

Transition of state for Australia Gas Emissions (HFC, PFC, and SF6)

State	Total Transition
Low – Low	16
Low - Medium	2
Low - High	0
Medium - Low	1
Medium – Medium	13
Medium – High	3
High – Low	0
High – Medium	3
High – High	15

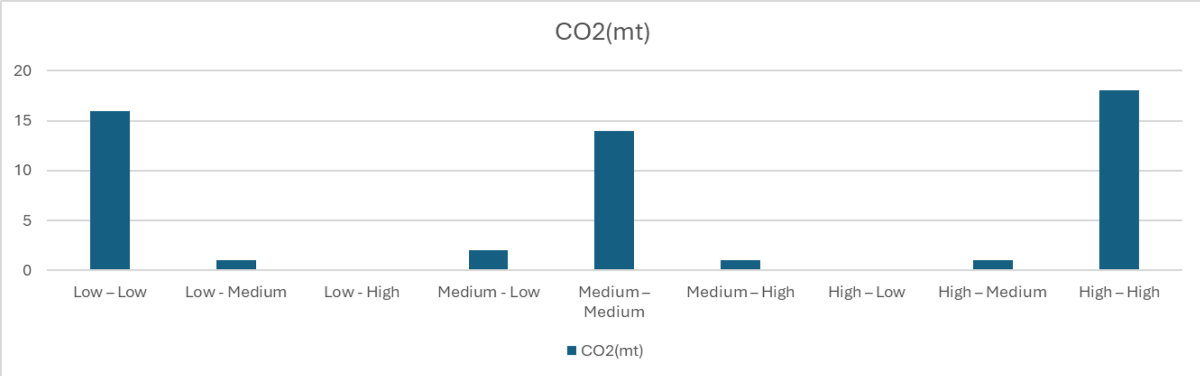


5.2.1 Ukraine Gas Emissions (CO_2)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	477.2242	Medium	1997	380.9966	Medium
1971	476.8572	Medium	1998	363.5368	Medium
1972	502.4115	Medium	1999	363.2923	Medium
1973	532.108	Medium	2000	360.0221	Medium
1974	556.1456	Medium	2001	359.0635	Medium
1975	582.1754	High	2002	359.6469	Medium
1976	600.1396	High	2003	392.02	Medium
1977	610.5376	High	2004	367.8053	Medium
1978	653.2175	High	2005	356.0703	Low
1979	667.0468	High	2006	355.3087	Low
1980	684.8723	High	2007	366.3142	Medium
1981	674.3338	High	2008	350.633	Low
1982	672.4168	High	2009	290.6597	Low
1983	672.9621	High	2010	314.3313	Low
1984	676.0755	High	2011	333.2225	Low
1985	678.3837	High	2012	324.8218	Low
1986	692.5807	High	2013	315.1852	Low
1987	713.9627	High	2014	269.2522	Low
1988	722.0811	High	2015	226.0362	Low
1989	718.2876	High	2016	227.1896	Low
1990	785.5447	High	2017	205.5392	Low
1991	741.0614	High	2018	218.3518	Low
1992	648.3748	High	2019	207.8431	Low
1993	565.9997	High	2020	198.6575	Low
1994	468.4401	Medium	2021	194.0549	Low
1995	462.6363	Medium	2022	138.3356	Low
1996	396.2374	Medium	2023	136.1979	Low

Transition of state for Ukraine

State	Total Transition
Low – Low	16
Low - Medium	1
Low - High	0
Medium - Low	2
Medium – Medium	14
Medium – High	1
High – Low	0
High – Medium	1
High – High	18

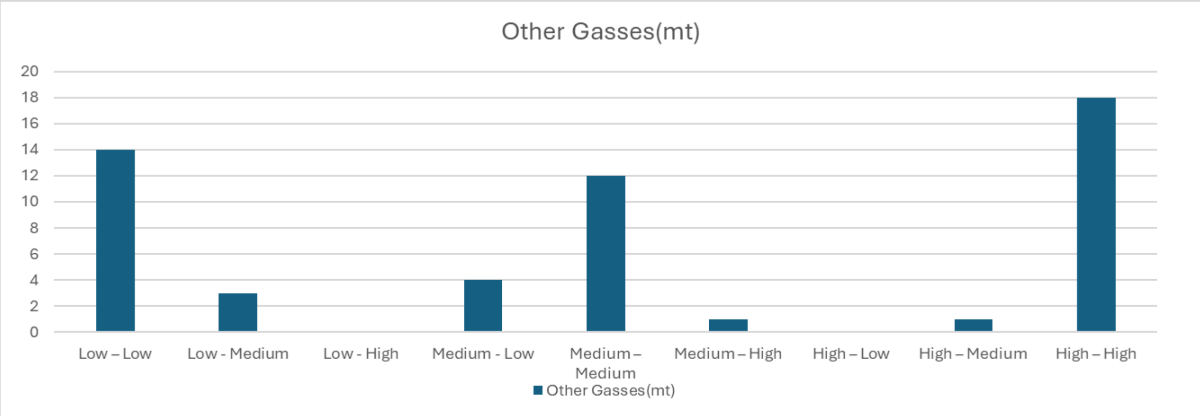


5.2.2 Ukraine Gas Emissions (HFC, PFC, and SF6)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	129.901	Medium	1997	107.5378	Medium
1971	133.9423	Medium	1998	99.9512	Medium
1972	139.0019	Medium	1999	97.5196	Medium
1973	144.4937	Medium	2000	94.5086	Low
1974	149.3799	High	2001	94.449	Low
1975	153.1501	High	2002	97.7823	Medium
1976	157.291	High	2003	97.8234	Medium
1977	160.3692	High	2004	95.6097	Low
1978	164.7599	High	2005	95.5334	Low
1979	166.2948	High	2006	94.4156	Low
1980	169.5129	High	2007	97.6094	Medium
1981	169.2835	High	2008	97.2081	Low
1982	170.5226	High	2009	90.9627	Low
1983	173.101	High	2010	89.8381	Low
1984	175.6731	High	2011	102.5758	Medium
1985	176.4025	High	2012	101.7328	Medium
1986	179.7917	High	2013	102.8197	Medium
1987	182.6123	High	2014	96.8336	Low
1988	180.327	High	2015	84.5783	Low
1989	181.193	High	2016	90.6705	Low
1990	182.982	High	2017	86.4099	Low
1991	169.5441	High	2018	86.8477	Low
1992	158.3714	High	2019	89.0123	Low
1993	149.02	Medium	2020	88.8946	Low
1994	135.4672	Medium	2021	87.4895	Low
1995	125.5187	Medium	2022	78.1392	Low
1996	113.7688	Medium	2023	79.8949	Low

Transition of state for Ukraine

State	Total Transition
Low – Low	14
Low - Medium	3
Low - High	0
Medium - Low	4
Medium – Medium	12
Medium – High	1
High – Low	0
High – Medium	1
High – High	18

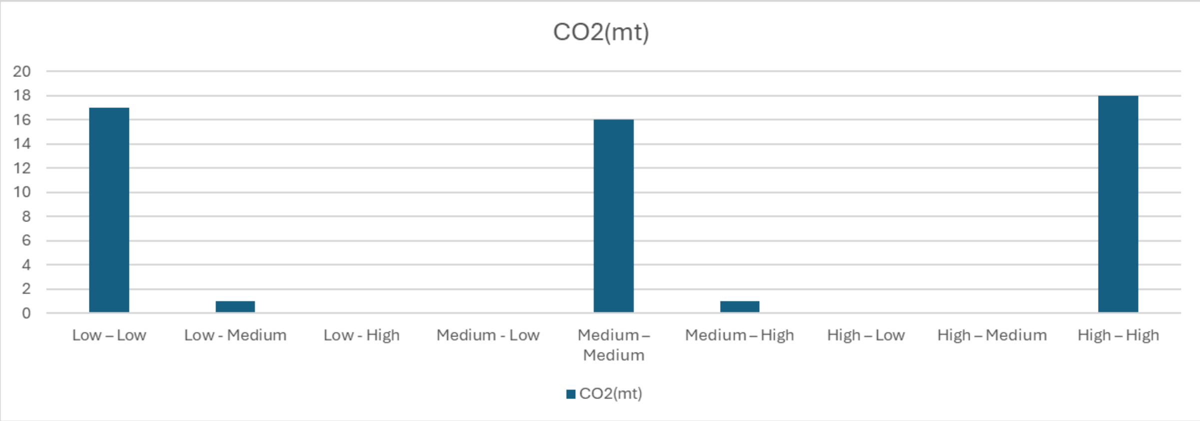


5.3.1 Malaysia Gas Emissions (CO2)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	26.8826	Low	1997	113.2578	Medium
1971	27.2778	Low	1998	110.6673	Medium
1972	14.3218	Low	1999	119.6946	Medium
1973	14.8103	Low	2000	130.7796	Medium
1974	17.8525	Low	2001	138.4076	Medium
1975	19.2436	Low	2002	146.5554	Medium
1976	21.2425	Low	2003	156.576	Medium
1977	21.1059	Low	2004	169.6248	Medium
1978	27.1876	Low	2005	181.1517	High
1979	31.2059	Low	2006	187.7708	High
1980	32.3916	Low	2007	204.9404	High
1981	33.0891	Low	2008	216.1782	High
1982	35.7918	Low	2009	197.9811	High
1983	41.0466	Low	2010	215.5746	High
1984	43.1615	Low	2011	218.3287	High
1985	42.7145	Low	2012	219.8784	High
1986	43.9599	Low	2013	237.2457	High
1987	44.7952	Low	2014	251.4646	High
1988	47.9098	Medium	2015	252.9286	High
1989	56.6283	Medium	2016	247.5683	High
1990	64.4223	Medium	2017	237.8645	High
1991	75.3034	Medium	2018	254.3612	High
1992	79.2844	Medium	2019	255.2071	High
1993	79.4983	Medium	2020	253.3934	High
1994	87.5645	Medium	2021	258.9144	High
1995	90.9385	Medium	2022	274.3424	High
1996	103.4302	Medium	2023	283.3235	High

Transition of state for Malaysia

State	Total Transition
Low – Low	17
Low - Medium	1
Low - High	0
Medium - Low	0
Medium – Medium	16
Medium – High	1
High – Low	0
High – Medium	0
High – High	18

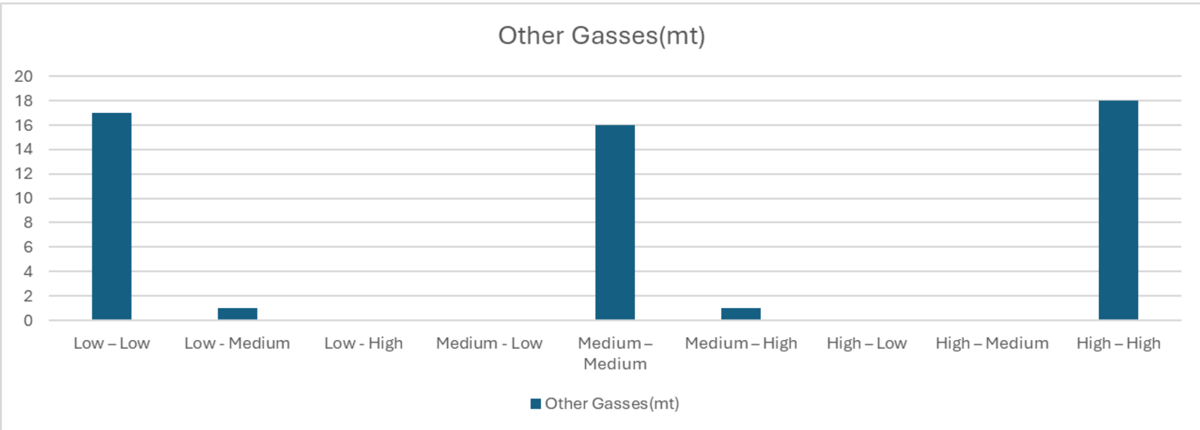


5.3.2 Malaysia Gas Emissions (HFC, PFC, and SF6)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	18.4245	Low	1997	34.3581	Medium
1971	18.788	Low	1998	31.5543	Medium
1972	19.227	Low	1999	31.8348	Medium
1973	19.0168	Low	2000	33.1811	Medium
1974	18.6067	Low	2001	33.5739	Medium
1975	19.1405	Low	2002	34.6443	Medium
1976	19.9368	Low	2003	37.8157	Medium
1977	20.1324	Low	2004	39.6504	Medium
1978	19.3555	Low	2005	40.1531	High
1979	22.0629	Low	2006	41.256	High
1980	21.8775	Low	2007	41.6458	High
1981	21.5365	Low	2008	42.5089	High
1982	21.8883	Low	2009	43.5868	High
1983	22.9235	Low	2010	40.9826	High
1984	23.9781	Low	2011	40.4037	High
1985	24.3293	Low	2012	40.5815	High
1986	25.0825	Low	2013	41.3517	High
1987	25.345	Low	2014	41.5399	High
1988	26.2049	Medium	2015	43.117	High
1989	27.1517	Medium	2016	44.878	High
1990	27.9137	Medium	2017	42.7179	High
1991	28.2699	Medium	2018	42.6766	High
1992	28.8354	Medium	2019	42.6797	High
1993	29.5042	Medium	2020	41.273	High
1994	30.1376	Medium	2021	40.8721	High
1995	28.9997	Medium	2022	41.4461	High
1996	31.1962	Medium	2023	42.0823	High

Transition of state for Malaysia

State	Total Transition
Low – Low	17
Low - Medium	1
Low - High	0
Medium - Low	0
Medium – Medium	16
Medium – High	1
High – Low	0
High – Medium	0
High – High	18

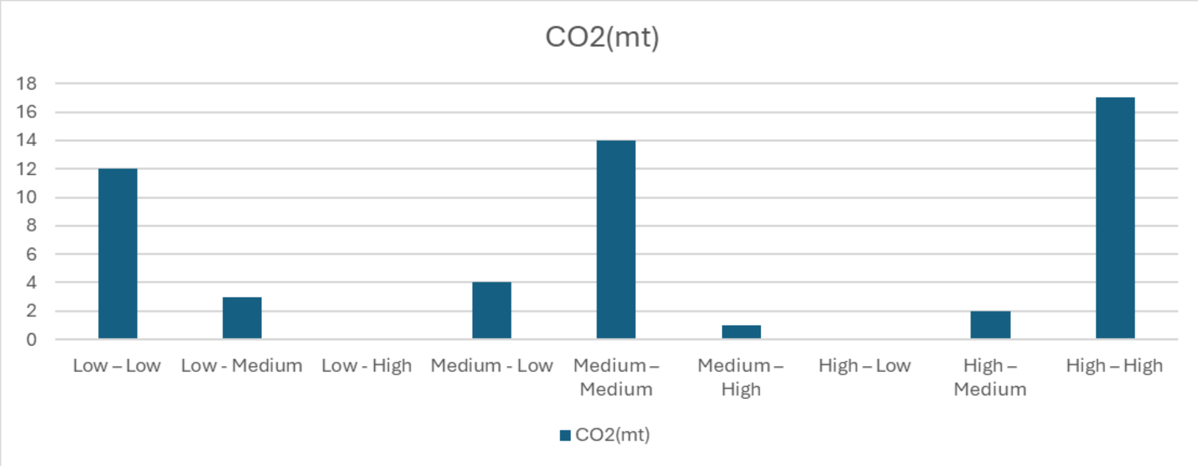


5.4.1 United Kingdom Gas Emission (Co2)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	673.4202	High	1997	546.492	Low
1971	668.6714	High	1998	547.1041	Medium
1972	657.7172	High	1999	543.7186	Low
1973	690.031	High	2000	551.6797	Medium
1974	644.6402	High	2001	562.9085	Medium
1975	623.6572	High	2002	546.9059	Medium
1976	629.8113	High	2003	560.427	Medium
1977	638.3125	High	2004	560.9379	Medium
1978	636.4771	High	2005	559.3283	Medium
1979	672.6636	High	2006	559.7568	Medium
1980	608.3254	High	2007	550.2287	Medium
1981	589.021	High	2008	533.7479	Medium
1982	573.101	Medium	2009	483.3614	Low
1983	566.2653	Medium	2010	500.6285	Medium
1984	549.9603	Medium	2011	459.0174	Low
1985	576.5427	Medium	2012	481.19	Low
1986	590.5337	High	2013	470.1718	Low
1987	595.1847	High	2014	430.4962	Low
1988	592.8904	High	2015	415.856	Low
1989	579.2874	High	2016	393.3439	Low
1990	582.349	High	2017	381.2854	Low
1991	591.4813	High	2018	373.2205	Low
1992	578.1824	High	2019	357.3326	Low
1993	562.1317	Medium	2020	319.0147	Low
1994	554.6245	Medium	2021	339.4953	Low
1995	548.0823	Medium	2022	327.4607	Low
1996	567.3642	Medium	2023	302.1033	Low

Transition of state for United Kingdom

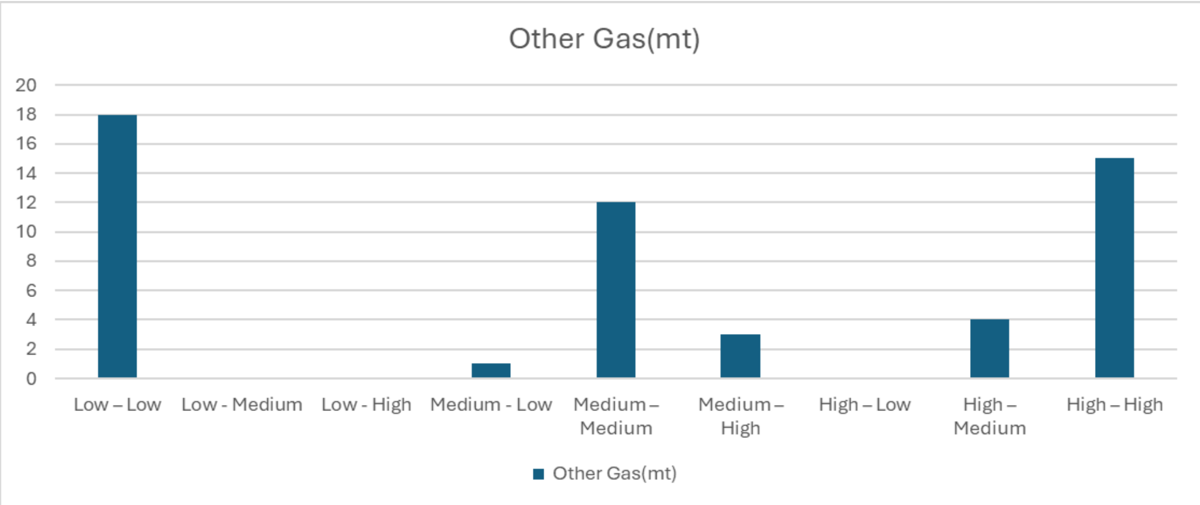
State	Total Transition
Low – Low	12
Low - Medium	3
Low - High	0
Medium - Low	4
Medium – Medium	14
Medium – High	1
High – Low	0
High – Medium	2
High – High	17



5.4.2 United Kingdom Gas Emissions (HFC, PFC, and SF6)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	181.6536	High	1997	171.4073	Medium
1971	182.0735	High	1998	160.7775	Medium
1972	172.8469	Medium	1999	147.786	Medium
1973	181.0465	High	2000	139.3621	Medium
1974	176.5802	High	2001	135.1786	Medium
1975	186.1481	High	2002	130.5537	Medium
1976	187.1488	High	2003	126.3745	Medium
1977	184.0116	High	2004	121.0078	Medium
1978	183.8887	High	2005	113.6158	Low
1979	187.7576	High	2006	106.962	Low
1980	187.2449	High	2007	102.7328	Low
1981	186.076	High	2008	96.6763	Low
1982	185.4479	High	2009	93.3779	Low
1983	185.2091	High	2010	89.9523	Low
1984	157.3173	Medium	2011	88.0396	Low
1985	173.1042	Medium	2012	87.5207	Low
1986	182.5292	High	2013	86.0478	Low
1987	177.8188	High	2014	85.6221	Low
1988	176.7544	High	2015	85.2223	Low
1989	174.2275	Medium	2016	84.8962	Low
1990	178.2595	High	2017	85.7573	Low
1991	180.4899	High	2018	84.9194	Low
1992	175.6261	High	2019	83.2641	Low
1993	171.5761	Medium	2020	80.5889	Low
1994	166.5355	Medium	2021	80.1389	Low
1995	171.2918	Medium	2022	79.0588	Low
1996	171.8284	Medium	2023	77.2153	Low

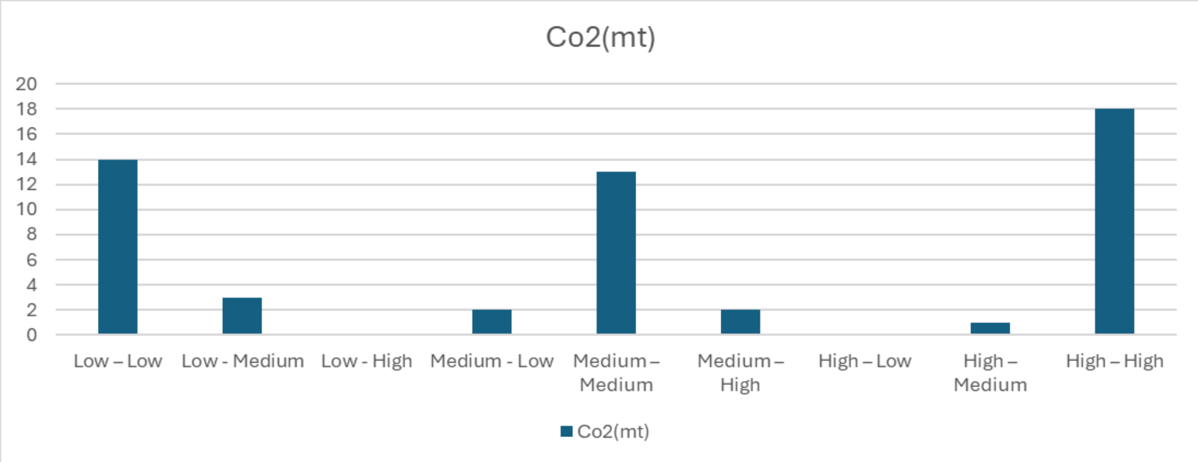
State	Total Transition
Low – Low	18
Low - Medium	0
Low - High	0
Medium - Low	1
Medium – Medium	12
Medium – High	3
High – Low	0
High – Medium	4
High – High	15



5.5.1 Russia Gas Emissions (CO_2)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	1307.9918	Low	1997	1604.8446	Low
1971	1308.9747	Low	1998	1611.1046	Low
1972	1377.0903	Low	1999	1660.9052	Low
1973	1460.8889	Low	2000	1681.1439	Low
1974	1536.3042	Low	2001	1684.2625	Low
1975	1620.8224	Low	2002	1675.2806	Low
1976	1681.8341	Low	2003	1737.2379	Low
1977	1719.5681	Low	2004	1738.8498	Medium
1978	1841.6854	Medium	2005	1739.2783	Medium
1979	1867.6469	High	2006	1776.173	Medium
1980	1929.3114	High	2007	1779.0046	Medium
1981	1923.5418	High	2008	1764.31	Medium
1982	1951.446	High	2009	1662.0566	Medium
1983	1985.1133	High	2010	1746.8481	Medium
1984	2020.4148	High	2011	1832.562	Medium
1985	2059.49	High	2012	1819.7501	Medium
1986	2126.7823	High	2013	1764.1938	Medium
1987	2189.1639	High	2014	1750.144	Medium
1988	2241.0717	High	2015	1757.0574	Medium
1989	2252.9505	High	2016	1734.5602	Low
1990	2436.2592	High	2017	1763.1528	Medium
1991	2393.5273	High	2018	1841.4417	Medium
1992	2200.8303	High	2019	1909.8166	High
1993	2008.7494	High	2020	1828.7967	High
1994	1811.1206	Medium	2021	1957.9274	High
1995	1765.1898	Medium	2022	2025.1436	High
1996	1724.2331	Low	2023	2069.502	High

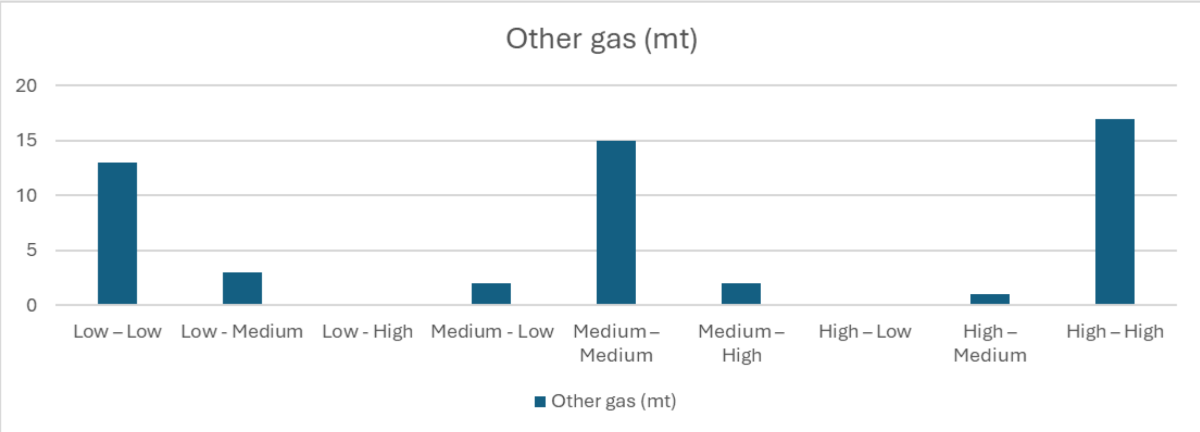
State	Total Transition
Low – Low	14
Low - Medium	3
Low - High	0
Medium - Low	2
Medium – Medium	13
Medium – High	2
High – Low	0
High – Medium	1
High – High	18



5.5.2 Russia Gas Emissions (HFC, PFC, and SF6)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	415.1676	Low	1997	405.8859	Low
1971	428.9727	Low	1998	389.5317	Low
1972	443.9357	Low	1999	397.8967	Low
1973	461.7499	Medium	2000	407.958	Low
1974	477.766	Medium	2001	412.9241	Low
1975	491.3836	Medium	2002	415.4149	Low
1976	506.5772	Medium	2003	419.5637	Low
1977	517.2852	Medium	2004	431.5988	Low
1978	531.9103	Medium	2005	435.4624	Low
1979	540.2773	Medium	2006	437.1168	Low
1980	547.6246	High	2007	447.2917	Medium
1981	549.8561	High	2008	453.0917	Medium
1982	559.7154	High	2009	442.2705	Low
1983	573.9782	High	2010	456.4066	Medium
1984	588.1578	High	2011	465.416	Medium
1985	595.2092	High	2012	484.4093	Medium
1986	604.7923	High	2013	490.7665	Medium
1987	614.5769	High	2014	492.5281	Medium
1988	619.8926	High	2015	500.5797	Medium
1989	622.0119	High	2016	512.3797	Medium
1990	629.4372	High	2017	535.0389	Medium
1991	601.4706	High	2018	560.0525	High
1992	552.0366	High	2019	573.0174	High
1993	509.8671	Medium	2020	566.8189	High
1994	468.0081	Medium	2021	590.028	High
1995	444.8696	Low	2022	596.3744	High
1996	422.7229	Low	2023	602.5374	High

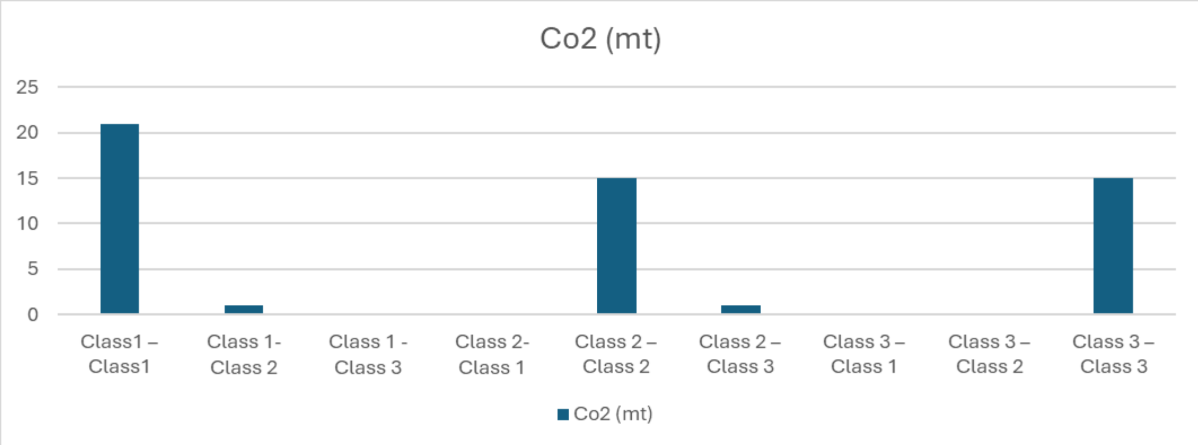
State	Total Transition
Low – Low	13
Low - Medium	3
Low - High	0
Medium - Low	2
Medium – Medium	15
Medium – High	2
High – Low	0
High – Medium	1
High – High	17



5.6.1 India Gas Emissions (CO_2)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	213.9344	Low	1997	877.7065	Medium
1971	214.4281	Low	1998	900.6255	Medium
1972	222.9632	Low	1999	961.6311	Medium
1973	221.9373	Low	2000	995.6526	Medium
1974	237.6409	Low	2001	1011.8047	Medium
1975	253.2017	Low	2002	1049.8801	Medium
1976	270.6936	Low	2003	1081.7852	Medium
1977	276.0218	Low	2004	1166.8166	Medium
1978	271.347	Low	2005	1216.5339	High
1979	291.7332	Low	2006	1298.3951	High
1980	303.5765	Low	2007	1413.8648	High
1981	333.9885	Low	2008	1503.6111	High
1982	351.9038	Low	2009	1643.0647	High
1983	374.5973	Low	2010	1743.6929	High
1984	412.8617	Low	2011	1850.3319	High
1985	431.4118	Low	2012	2022.7648	High
1986	468.5979	Low	2013	2083.2109	High
1987	501.4341	Low	2014	2242.8409	High
1988	532.2986	Medium	2015	2260.1314	High
1989	570.1243	Medium	2016	2303.3619	High
1990	600.6873	Medium	2017	2433.7831	High
1991	646.3888	Medium	2018	2573.1194	High
1992	669.6642	Medium	2019	2542.0351	High
1993	699.7562	Medium	2020	2318.9477	High
1994	743.8583	Medium	2021	2548.4833	High
1995	796.4639	Medium	2022	2740.8206	High
1996	833.512	Medium	2023	2955.1817	High

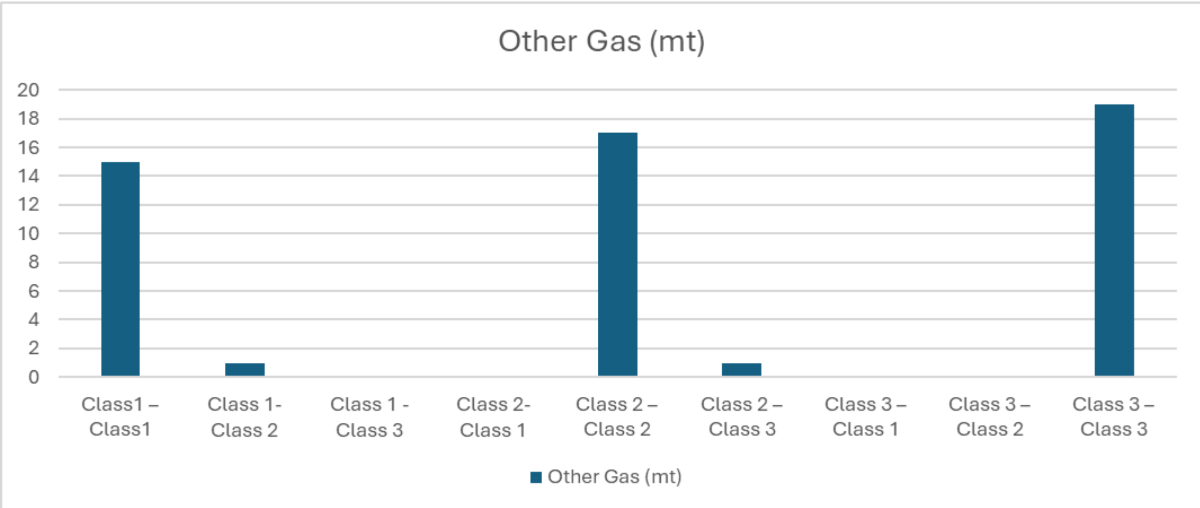
State	Total Transition
Low – Low	21
Low - Medium	1
Low - High	0
Medium - Low	0
Medium – Medium	15
Medium – High	1
High – Low	0
High – Medium	0
High – High	15



5.6.2 India Gas Emissions (HFC, PFC, and SF6)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	578.877	Low	1997	839.7351	Medium
1971	582.3815	Low	1998	845.8733	Medium
1972	584.2862	Low	1999	852.2992	Medium
1973	592.6964	Low	2000	849.7996	Medium
1974	598.3737	Low	2001	857.5049	Medium
1975	613.4236	Low	2002	847.0594	Medium
1976	618.3659	Low	2003	865.4942	Medium
1977	631.677	Low	2004	882.6749	Medium
1978	639.6889	Low	2005	904.359	High
1979	646.722	Low	2006	926.7081	High
1980	658.6685	Low	2007	954.4633	High
1981	676.6578	Low	2008	976.5274	High
1982	681.3131	Low	2009	985.2069	High
1983	706.9399	Low	2010	1003.9249	High
1984	721.1731	Low	2011	1024.1499	High
1985	731.2744	Low	2012	1033.4479	High
1986	755.3699	Low	2013	1012.7032	High
1987	754.9887	Low	2014	1027.5293	High
1988	791.5142	Medium	2015	1042.3562	High
1989	809.869	Medium	2016	1052.286	High
1990	782.3765	Medium	2017	1064.619	High
1991	793.3869	Medium	2018	1088.7464	High
1992	800.9554	Medium	2019	1100.3753	High
1993	801.9557	Medium	2020	1114.6713	High
1994	810.7025	Medium	2021	1131.3785	High
1995	820.1452	Medium	2022	1156.3884	High
1996	829.2578	Medium	2023	1178.3727	High

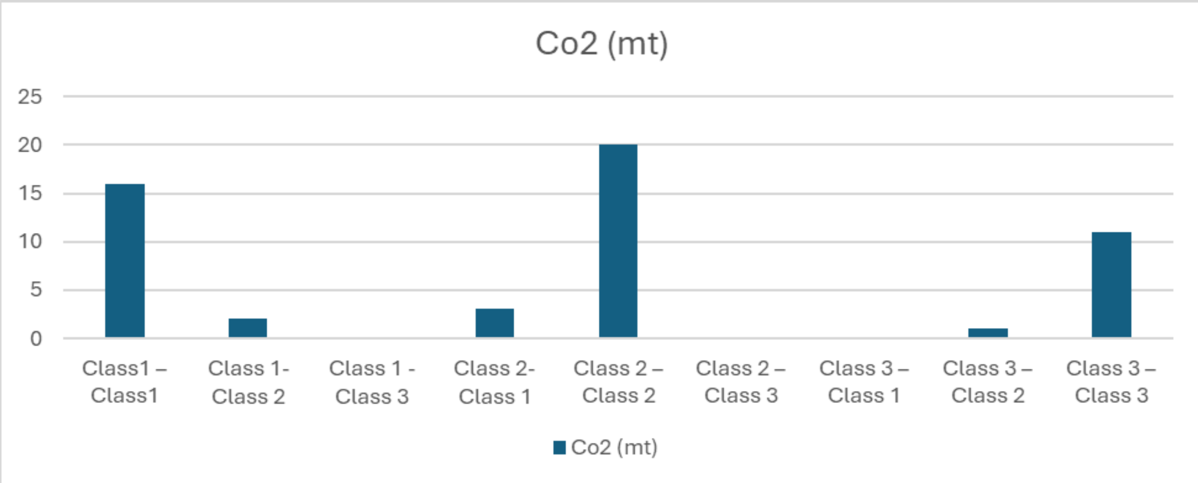
State	Total Transition
Low – Low	15
Low - Medium	1
Low - High	0
Medium - Low	0
Medium – Medium	17
Medium – High	1
High – Low	0
High – Medium	0
High – High	19



5.7.1 France Gas Emissions (CO_2)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	469.4414	High	1997	388.4739	Medium
1971	481.5545	High	1998	410.4713	High
1972	499.1043	High	1999	404.1642	Medium
1973	535.7473	High	2000	401.2112	Medium
1974	517.0076	High	2001	405.3435	Medium
1975	476.4954	High	2002	399.9106	Medium
1976	521.9985	High	2003	404.8426	Medium
1977	503.433	High	2004	405.9175	Medium
1978	521.4465	High	2005	408.1656	Medium
1979	529.0211	High	2006	397.4259	Medium
1980	507.05	High	2007	390.2734	Medium
1981	456.7116	High	2008	383.0041	Medium
1982	435.6642	High	2009	370.3759	Low
1983	416.5339	High	2010	377.7598	Medium
1984	404.9673	Medium	2011	364.3139	Low
1985	394.7068	Medium	2012	366.1388	Low
1986	382.601	Medium	2013	360.9924	Low
1987	375.7727	Low	2014	328.0879	Low
1988	375.8439	Low	2015	332.9749	Low
1989	390.36	Medium	2016	335.7678	Low
1990	385.272	Medium	2017	339.3458	Low
1991	410.3361	Medium	2018	328.6302	Low
1992	396.929	Medium	2019	322.7523	Low
1993	377.283	Low	2020	287.3243	Low
1994	373.0042	Low	2021	319.4248	Low
1995	382.0537	Medium	2022	310.4579	Low
1996	396.7419	Medium	2023	282.4275	Low

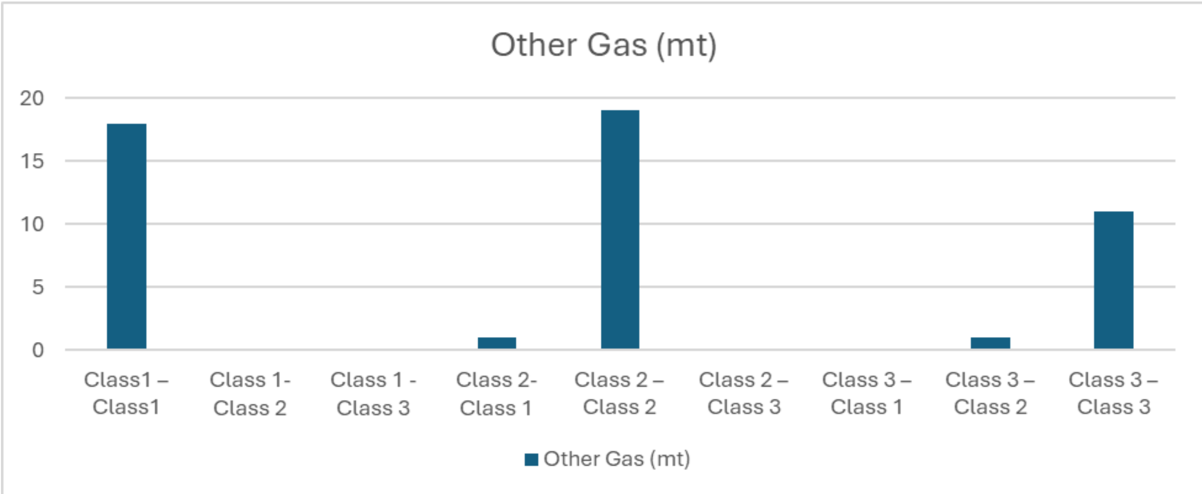
State	Total Transition
Low – Low	16
Low - Medium	2
Low - High	0
Medium - Low	3
Medium – Medium	20
Medium – High	0
High – Low	0
High – Medium	1
High – High	11



5.7.2 France Gas Emissions (HFC, PFC, and SF6)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	167.2087	High	1997	147.4739	Medium
1971	165.7817	High	1998	137.6944	Medium
1972	164.9418	High	1999	136.3502	Medium
1973	165.8687	High	2000	139.0296	Medium
1974	165.9095	High	2001	139.0718	Medium
1975	164.4412	High	2002	137.8877	Medium
1976	163.6471	High	2003	136.3426	Medium
1977	164.7335	High	2004	136.6046	Medium
1978	164.2727	High	2005	134.8009	Medium
1979	165.5208	High	2006	131.5469	Low
1980	164.4991	High	2007	132.8981	Low
1981	163.7791	High	2008	132.6107	Low
1982	164.7012	High	2009	130.7271	Low
1983	168.0553	High	2010	133.0706	Low
1984	167.5113	High	2011	128.9305	Low
1985	162.1544	High	2012	129.2613	Low
1986	161.3396	High	2013	129.0749	Low
1987	158.0601	High	2014	128.0805	Low
1988	155.0722	High	2015	127.4047	Low
1989	148.6831	Medium	2016	126.1914	Low
1990	147.7418	Medium	2017	125.673	Low
1991	153.5097	Medium	2018	123.2398	Low
1992	152.2143	Medium	2019	118.8784	Low
1993	149.3892	Medium	2020	111.027	Low
1994	148.1503	Medium	2021	110.0625	Low
1995	149.7334	Medium	2022	105.6543	Low
1996	153.0634	Medium	2023	103.0926	Low

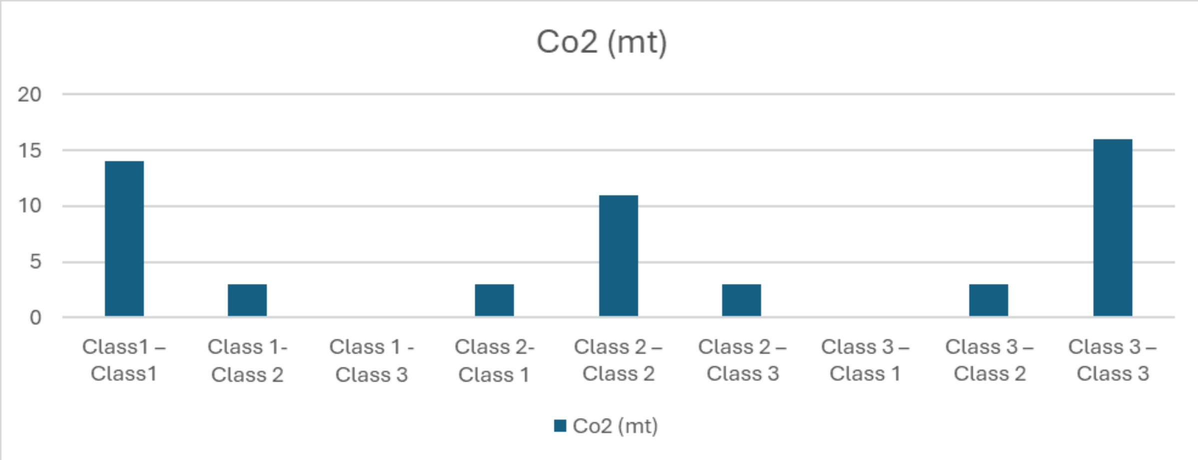
State	Total Transition
Low – Low	18
Low - Medium	0
Low - High	0
Medium - Low	1
Medium – Medium	19
Medium – High	0
High – Low	0
High – Medium	1
High – High	11



5.8.1 Japan Gas Emissions (CO_2)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	848.7516	Low	1997	1236.9539	High
1971	846.4521	Low	1998	1189.7637	Medium
1972	893.0016	Low	1999	1230.7275	High
1973	1006.6245	Low	2000	1248.8068	High
1974	1003.1882	Low	2001	1235.2221	High
1975	948.6801	Low	2002	1269.4295	High
1976	980.7332	Low	2003	1276.7113	High
1977	1005.7789	Low	2004	1271.3841	High
1978	1006.3741	Low	2005	1283.0176	High
1979	1030.144	Medium	2006	1260.2992	High
1980	1003.1434	Low	2007	1296.2507	High
1981	981.5855	Low	2008	1224.9593	Medium
1982	939.7607	Low	2009	1161.4121	Medium
1983	943.2447	Low	2010	1220.4535	Medium
1984	1011.0488	Medium	2011	1273.3455	High
1985	983.4576	Low	2012	1311.2998	High
1986	980.48	Low	2013	1326.7101	High
1987	987.784	Low	2014	1276.2555	High
1988	1060.6681	Medium	2015	1235.4187	High
1989	1090.4943	Medium	2016	1232.8769	High
1990	1166.8237	Medium	2017	1217.8484	Medium
1991	1176.8604	Medium	2018	1179.2176	Medium
1992	1181.8812	Medium	2019	1139.4974	Medium
1993	1174.7455	Medium	2020	1072.1695	Medium
1994	1227.961	High	2021	1084.9216	Medium
1995	1238.6398	High	2022	1009.9787	Low
1996	1251.4624	High	2023	944.7586	Low

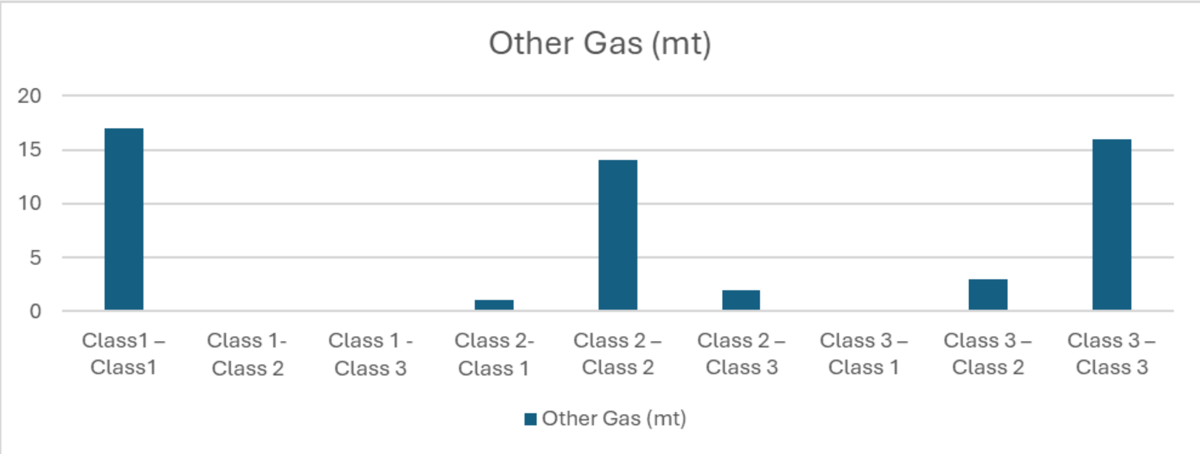
State	Total Transition
Low – Low	14
Low - Medium	3
Low - High	0
Medium - Low	3
Medium – Medium	11
Medium – High	3
High – Low	0
High – Medium	3
High – High	16



5.8.2 Japan Gas Emissions (HFC, PFC, and SF6)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	167.5319	High	1997	176.1504	High
1971	159.7026	High	1998	167.3727	High
1972	156.2509	High	1999	156.6843	High
1973	156.1245	High	2000	142.3145	Medium
1974	154.7456	High	2001	134.1027	Medium
1975	151.185	Medium	2002	127.7971	Medium
1976	155.2111	High	2003	124.8391	Medium
1977	158.1504	High	2004	120.8039	Medium
1978	151.8672	High	2005	118.391	Medium
1979	153.8203	High	2006	111.386	Low
1980	151.2335	High	2007	110.1283	Low
1981	146.0891	Medium	2008	105.0733	Low
1982	145.1546	Medium	2009	100.4963	Low
1983	145.3724	Medium	2010	103.772	Low
1984	150.5873	Medium	2011	100.6947	Low
1985	150.4199	Medium	2012	99.9662	Low
1986	148.9803	Medium	2013	101.2636	Low
1987	144.0854	Medium	2014	99.5786	Low
1988	145.5117	Medium	2015	98.165	Low
1989	146.3412	Medium	2016	98.4729	Low
1990	150.3943	Medium	2017	98.9629	Low
1991	154.8085	High	2018	97.2967	Low
1992	159.5771	High	2019	96.9947	Low
1993	163.9031	High	2020	96.5839	Low
1994	171.8252	High	2021	96.848	Low
1995	179.7094	High	2022	97.5971	Low
1996	180.4467	High	2023	96.2542	Low

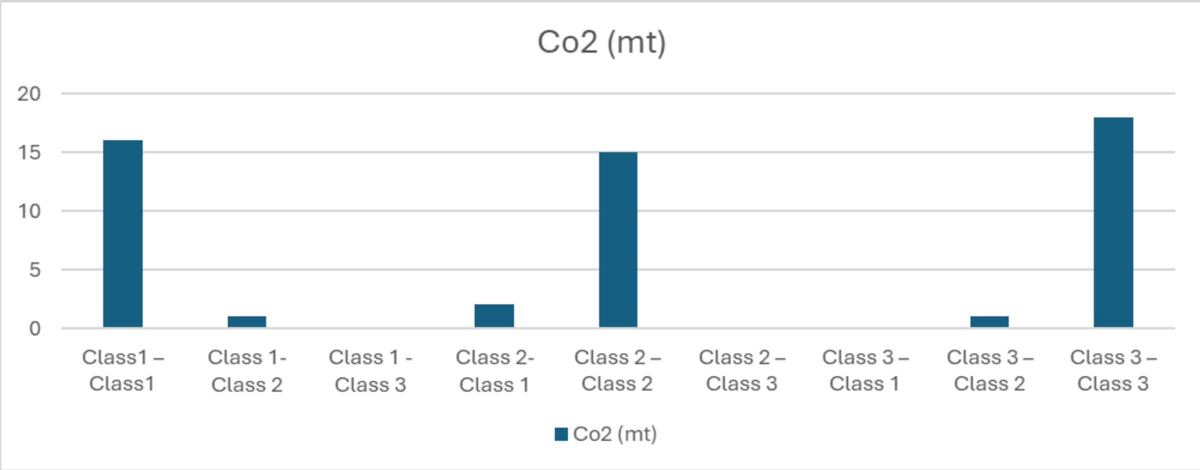
State	Total Transition
Low – Low	17
Low - Medium	0
Low - High	0
Medium - Low	1
Medium – Medium	14
Medium – High	2
High – Low	0
High – Medium	3
High – High	16



5.9.1 Germany Gas Emissions (CO_2)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	1084.6575	High	1997	907.821	Medium
1971	1077.4192	High	1998	906.9508	Medium
1972	1105.2903	High	1999	871.0236	Medium
1973	1157.7203	High	2000	871.7357	Medium
1974	1122.5066	High	2001	885.8183	Medium
1975	1060.5661	High	2002	870.3116	Medium
1976	1122.9347	High	2003	878.2763	Medium
1977	1101.4441	High	2004	863.7247	Medium
1978	1139.317	High	2005	842.0993	Low
1979	1189.4771	High	2006	855.8555	Medium
1980	1135.5984	High	2007	826.9926	Low
1981	1099.9653	High	2008	830.3551	Low
1982	1054.0401	High	2009	768.5531	Low
1983	1069.5505	High	2010	815.3784	Low
1984	1085.7373	High	2011	788.5477	Low
1985	1086.3402	High	2012	800.4648	Low
1986	1080.194	High	2013	818.2784	Low
1987	1072.2524	High	2014	779.2231	Low
1988	1065.9799	High	2015	785.3872	Low
1989	1050.769	Medium	2016	789.7138	Low
1990	1013.0316	Medium	2017	774.9482	Low
1991	992.0353	Medium	2018	747.2145	Low
1992	938.1013	Medium	2019	697.0085	Low
1993	929.647	Medium	2020	642.552	Low
1994	915.6041	Medium	2021	677.8039	Low
1995	910.8205	Medium	2022	659.5018	Low
1996	939.6957	Medium	2023	582.9506	Low

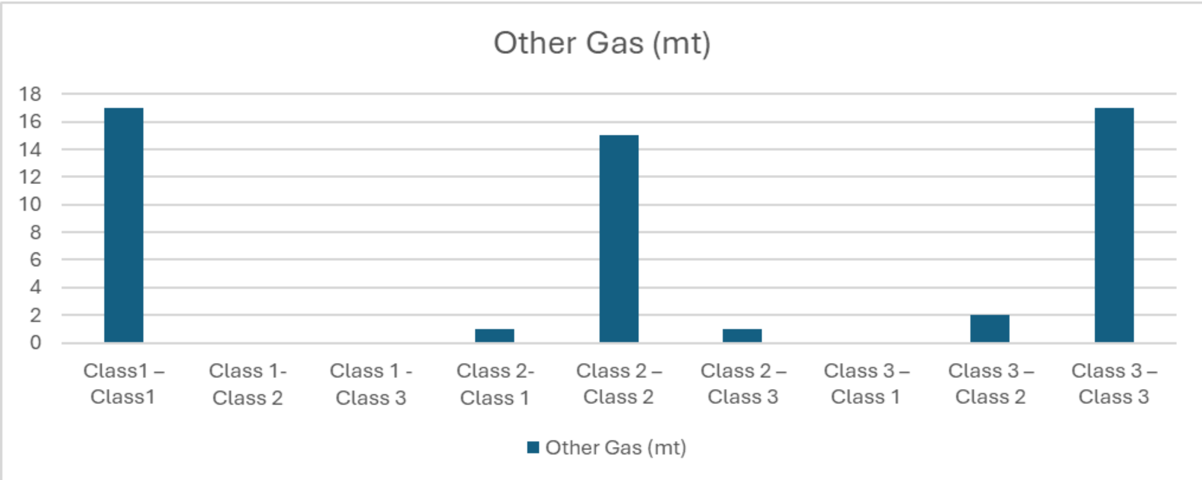
State	Total Transition
Low – Low	16
Low - Medium	1
Low - High	0
Medium - Low	2
Medium – Medium	15
Medium – High	0
High – Low	0
High – Medium	1
High – High	18



5.9.2 Germany Gas Emissions (HFC, PFC, and SF6)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	241.174	High	1997	193.0509	Medium
1971	240.7372	High	1998	173.9074	Medium
1972	237.0205	High	1999	168.4669	Medium
1973	239.5346	High	2000	163.6426	Medium
1974	240.9663	High	2001	158.1728	Medium
1975	238.6106	High	2002	154.1477	Medium
1976	239.3703	High	2003	148.6754	Medium
1977	236.7816	High	2004	146.5313	Medium
1978	240.6494	High	2005	141.5988	Medium
1979	243.983	High	2006	134.5138	Low
1980	244.2057	High	2007	135.4187	Low
1981	242.8523	High	2008	131.1995	Low
1982	238.1827	High	2009	127.7435	Low
1983	235.5819	High	2010	127.148	Low
1984	236.4631	High	2011	125.1735	Low
1985	236.048	High	2012	124.2622	Low
1986	230.8689	High	2013	123.6365	Low
1987	227.1727	High	2014	123.3072	Low
1988	225.5768	Medium	2015	122.1329	Low
1989	227.8454	High	2016	120.3045	Low
1990	222.8419	Medium	2017	118.9422	Low
1991	218.5519	Medium	2018	114.6747	Low
1992	209.0949	Medium	2019	111.7812	Low
1993	204.1167	Medium	2020	107.2477	Low
1994	204.3024	Medium	2021	105.6847	Low
1995	201.0475	Medium	2022	102.4817	Low
1996	199.4715	Medium	2023	98.8597	Low

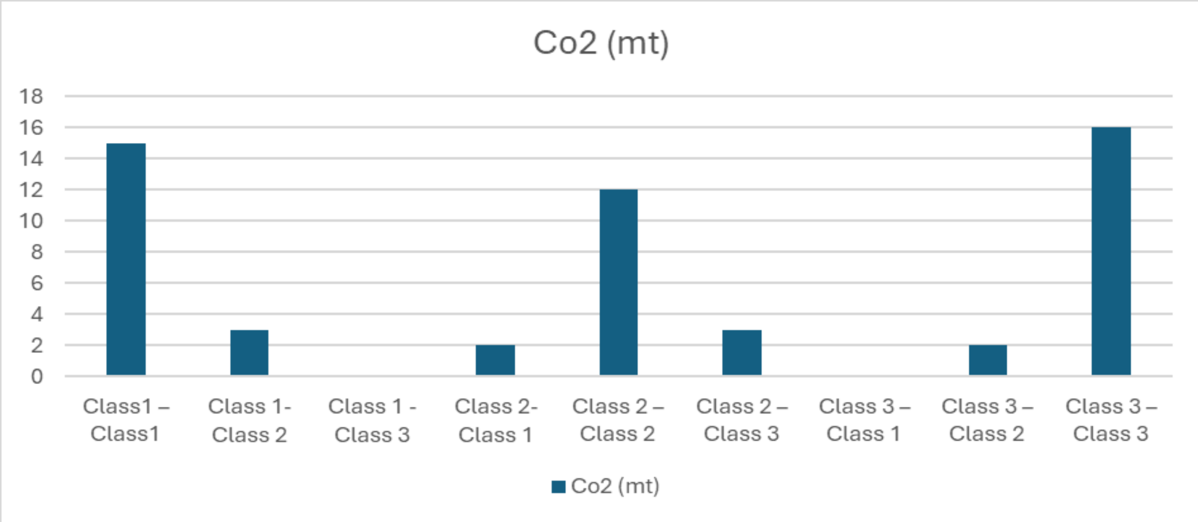
State	Total Transition
Low – Low	17
Low - Medium	0
Low - High	0
Medium - Low	1
Medium – Medium	15
Medium – High	1
High – Low	0
High – Medium	2
High – High	17



5.10.1 Canada Gas Emissions (CO_2)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	358.1272	Low	1997	505.6071	Medium
1971	365.7851	Low	1998	513.8019	Medium
1972	383.0355	Low	1999	523.3953	Medium
1973	401.9821	Low	2000	543.0448	Medium
1974	410.0579	Low	2001	534.3097	Medium
1975	400.2143	Low	2002	554.0309	Medium
1976	413.3629	Low	2003	573.6839	High
1977	427.8718	Low	2004	559.7293	High
1978	431.0299	Low	2005	581.0957	High
1979	445.1962	Medium	2006	573.5411	High
1980	450.4307	Medium	2007	594.0202	High
1981	431.7735	Low	2008	574.5625	High
1982	413.774	Low	2009	541.8042	Medium
1983	407.4239	Low	2010	561.6033	High
1984	426.7784	Low	2011	575.8915	High
1985	426.65	Low	2012	567.2705	High
1986	416.5804	Low	2013	575.2453	High
1987	429.3182	Low	2014	580.4828	High
1988	460.3398	Medium	2015	577.1296	High
1989	475.4707	Medium	2016	575.8711	High
1990	440.4753	Low	2017	593.0442	High
1991	434.5216	Low	2018	613.6582	High
1992	447.282	Medium	2019	607.2496	High
1993	446.6273	Medium	2020	546.6751	Medium
1994	463.8531	Medium	2021	561.6259	High
1995	475.9147	Medium	2022	575.3213	High
1996	489.835	Medium	2023	575.012	High

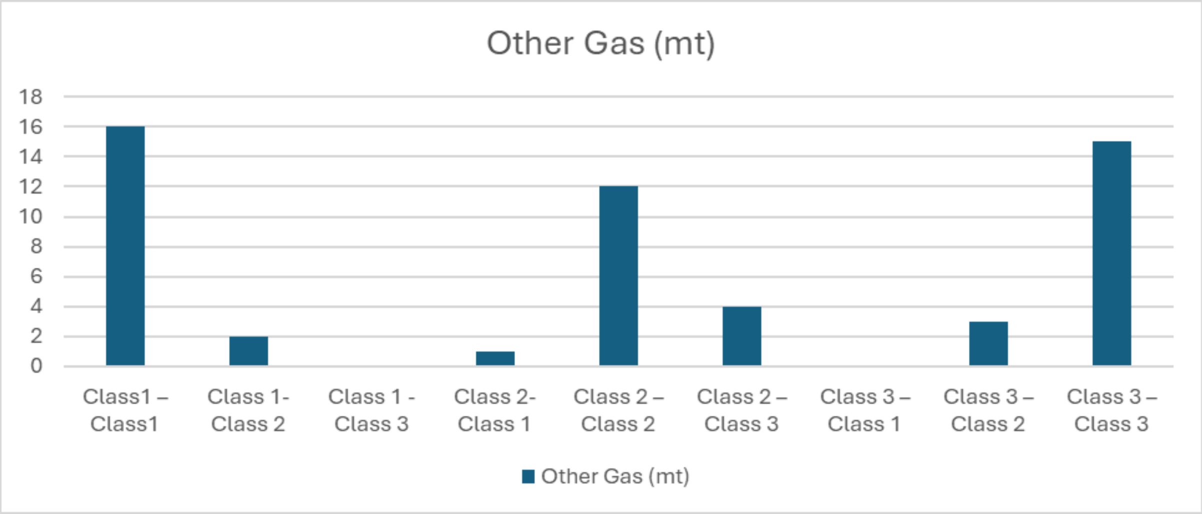
Class	Total Transition
Low – Low	15
Low - Medium	3
Low - High	0
Medium - Low	2
Medium – Medium	12
Medium – High	3
High – Low	0
High – Medium	2
High – High	16



5.10.2 Canada Gas Emissions (HFC, PFC, and SF6)

Years	Emission (mt)	State	Years	Emission (mt)	State
1970	108.2327	Low	1997	161.5945	Medium
1971	110.111	Low	1998	162.069	Medium
1972	114.7027	Low	1999	163.4276	Medium
1973	123.3336	Low	2000	167.3287	High
1974	124.0506	Low	2001	166.3117	Medium
1975	118.9361	Low	2002	169.2873	High
1976	117.2138	Low	2003	168.5628	High
1977	123.783	Low	2004	171.8509	High
1978	127.4291	Low	2005	169.8527	High
1979	127.8604	Low	2006	174.6697	High
1980	127.7925	Low	2007	176.3821	High
1981	126.3566	Low	2008	170.2017	High
1982	125.2788	Low	2009	162.0224	Medium
1983	132.8871	Low	2010	163.0218	Medium
1984	134.8529	Medium	2011	166.3552	Medium
1985	130.5435	Low	2012	171.2035	High
1986	126.9778	Low	2013	173.1763	High
1987	130.2512	Low	2014	179.9368	High
1988	133.3558	Low	2015	178.7761	High
1989	140.4354	Medium	2016	174.7298	High
1990	141.4375	Medium	2017	177.4325	High
1991	142.3277	Medium	2018	180.5155	High
1992	145.8409	Medium	2019	180.7581	High
1993	150.4697	Medium	2020	165.2562	Medium
1994	158.9438	Medium	2021	166.642	High
1995	161.9299	Medium	2022	169.9238	High
1996	164.8088	Medium	2023	172.666	High

Class	Total Transition
Low – Low	16
Low - Medium	2
Low - High	0
Medium - Low	1
Medium – Medium	12
Medium – High	4
High – Low	0
High – Medium	3
High – High	15



6.0 RESULT ANALYSIS

6.1 Which Country Is Contributing More to Climate Changing

Analysis of your results/output from your chosen method(s) Markov, Discrete Dynamic System, Least Square, Game Theory, Optimisation:

Australia co2

Class 1 (Low)

- Total from Class 1 = 17 (to Low) + 1 (to Medium) + 0 (to High) = 18
- Low – Low = 17 / 18 = 0.9444
- Low – Medium = 1 / 18 = 0.0556
- Low - High= 0 / 18 = 0

Class 2 (Medium)

- Total from Class 2 = 0 (to Low) + 15 (to Medium) + 1 (to High) = 16
- Medium - Low= 0 / 16 = 0
- Medium – Medium = 15 / 16 = 0.9375
- Medium – High = 1 / 16 = 0.0625

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 1 (to Medium) + 18 (to High) = 19
- High – Low = 0 / 19 = 0
- High – Medium = 1 / 19 = 0.0526
- High - High = 18 / 19 = 0.9474

Transition Matrix

	Low	Medium	High
Low	0.9444	0	0
Medium	0.0556	0.9375	0.0526
High	0	0.0625	0.9474

Eigenvalues (rounded): [1.0000 0.8849 0.9444]

Eigenvectors (rounded):

[[0.00 0.00 0.69]
[0.64 0.71 0.03]
[0.77 -0.71 -0.72]]

Steady-State Probabilities: [0.00 0.45 0.55]
Convergence Time (years): 53.0
Verification (Pπ ≈ π): True

In the long run, there is a 45.00% chance that CO_2 and other gas emissions in Australia will remain at a moderate level, and a 55.00% chance that they will reach a high level, with almost no likelihood of staying at a low level.

Ukraine – CO_2

Class 1 (Low)

- Total from Class 1 = 16 (to Low) + 1 (to Medium) + 0 (to High) = 17
- Low - Low = 16/17 = 0.9412
- Low - Medium = 1/17 = 0.0588
- Low - High = 0/17 = 0

Class 2 (Medium)

- Total from Class 2 = 2 (to Low) + 14 (to Medium) + 1 (to High) = 17
- Medium - Low = 2/17 = 0.1176
- Medium - Medium = 14/17 = 0.8235
- Medium - High = 1/17 = 0.0588

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 1 (to Medium) + 18 (to High) = 19
- High - Low = 0/19 = 0
- High - Medium = 1/19 = 0.0526
- High - High = 18/19 = 0.9474

Transition Matrix

	Low	Medium	High
Low	0.9412	0.1176	0
Medium	0.0588	0.8235	0.0526
High	0	0.0588	0.9474

Eigenvalues (rounded): [0.7667 1.000 0.9454]

Eigenvectors (rounded):
[[0.54 0.8 -0.69]
[-0.8 0.4 -0.02]
[0.26 0.45 0.72]]

Steady-State Probabilities: [0.48 0.24 0.27]
Convergence Time (years): 54.0
Verification ($P\pi \approx \pi$): True

In the long run, there is a 48.00% chance that CO_2 emissions in Ukraine will remain at a low level, a 24.00% chance of stabilizing at a medium level, and a 27.00% chance of persisting at a high level.

Malaysia – CO_2

Class 1 (Low)

- Total from Class 1 = 17 (to Low) + 1 (to Medium) + 0 (to High) = 18
- Low - Low = 17/18 = 0.9444
- Low - Medium = 1/18 = 0.0556
- Low - High = 0/18 = 0

Class 2 (Medium)

- Total from Class 2 = 0 (to Low) + 16 (to Medium) + 1 (to High) = 17
- Medium - Low = 0/17 = 0
- Medium - Medium = 16/17 = 0.9412
- Medium - High = 1/17 = 0.0588

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 0 (to Medium) + 18 (to High) = 18
- High - Low = 0/18 = 0
- High - Medium = 0/18 = 0
- High - High = 18/18 = 1.0

Transition Matrix

	Low	Medium	High
Low	0.9444	0.0	0.0
Medium	0.0556	0.9412	0.0
High	0.0	0.0588	1.0

Eigenvalues (rounded): [1.0000 0.9412 0.9444]

Eigenvectors (rounded):

[[0.00 0.00 0.04]
[0.00 0.71 0.69]
[1.00 -0.71 -0.73]]

Steady-State Probabilities: [0.00 0.00 1.0]
Convergence Time (years): 53.0
Verification ($P\pi \approx \pi$): True

Gas emissions are projected to ultimately stabilize in the high state. The steady-state distribution [0, 0, 1] confirms that, over time, all probability mass accumulates in the high-emission state, making it an absorbing state. This suggests that without intervention, emission levels will become permanently high.

United Kingdom – CO_2

Class 1 (Low)

- Total from Class 1 = 12 (to Low) + 3 (to Medium) + 0 (to High) = 15
- Low - Low = 12/15 = 0.8
- Low - Medium = 3/15 = 0.2
- Low - High = 0/15 = 0

Class 2 (Medium)

- Total from Class 2 = 4 (to Low) + 14 (to Medium) + 1 (to High) = 19
- Medium - Low = 4/19 = 0.2105
- Medium - Medium = 14/19 = 0.7368
- Medium - High = 1/19 = 0.0526

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 2 (to Medium) + 17 (to High) = 19
- High - Low = 0/19 = 0
- High - Medium = 2/19 = 0.1053
- High - High = 17/19 = 0.8947

Transition Matrix

	Low	**Medium**	**High**
Low	0.8	0.2105	0.0
Medium	0.2	0.7368	0.1053
High	0.0	0.0526	0.8947

Eigenvalues (rounded): [0.5514 1.0000 0.8802]

Eigenvectors (rounded):
[[0.64 0.69 -0.57]
[-0.76 0.65 -0.22]
[0.12 0.33 0.79]]

Steady-State Probabilities: [0.41 0.39 0.20]

Convergence Time (years): 24.0

Verification ($P\pi \approx \pi$): True

In the long run, there is a 41.00% chance that CO_2 emissions in the United Kingdom will remain at a low level, a 39.00% chance of stabilizing at a medium level, and a 20.00% chance of persisting at a high level.

Russia – CO_2

Class 1 (Low)

- Total from Class 1 = 14 (to Low) + 3 (to Medium) + 0 (to High) = 17
- Low - Low = 14/17 = 0.8235
- Low - Medium = 3/17 = 0.1765
- Low - High = 0/17 = 0

Class 2 (Medium)

- Total from Class 2 = 2 (to Low) + 13 (to Medium) + 2 (to High) = 17
- Medium - Low = 2/17 = 0.1176
- Medium - Medium = 13/17 = 0.7647
- Medium - High = 2/17 = 0.1176

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 1 (to Medium) + 18 (to High) = 19
- High - Low = 0/19 = 0
- High - Medium = 1/19 = 0.0526
- High - High = 18/19 = 0.9474

Transition Matrix

	Low	Medium	High
Low	0.8	0.2105	0.0
Medium	0.2	0.7368	0.1053
High	0.0	0.0526	0.8947

Eigenvalues (rounded): [0.6349 0.9008 1.0000]

Eigenvectors (rounded):

[[0.5 0.49 0.26]
[-0.81 0.32 0.39]
[0.3 -0.81 0.88]]

Steady-State Probabilities: [0.17 0.25 0.58]

Convergence Time (years): 29.0

Verification (Pπ ≈ π): True

In the long run, there is a 17% probability that Russia's annual CO_2 emissions will remain in the Low state, a 25% probability of remaining in the Medium state, and a 58% probability of staying in the High emission state. This steady-state distribution suggests that, without intervention, Russia is more likely to experience persistently high levels of CO_2 emissions in the future.

India – CO_2

Class 1 (Low)

- Total from Class 1 = 21 (to Low) + 1 (to Medium) + 0 (to High) = 22
- Low - Low = 21/22 = 0.9545
- Low - Medium = 1/22 = 0.0455
- Low - High = 0/22 = 0

Class 2 (Medium)

- Total from Class 2 = 0 (to Low) + 15 (to Medium) + 1 (to High) = 16
- Medium - Low = 0/16 = 0
- Medium - Medium = 15/16 = 0.9375
- Medium - High = 1/16 = 0.0625

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 0 (to Medium) + 15 (to High) = 15
- High - Low = 0/15 = 0
- High - Medium = 0/15 = 0
- High - High = 15/15 = 1.0

Transition Matrix

	Low	Medium	High
Low	0.9545	0.0	0.0
Medium	0.0455	0.9375	0.0
High	0.0	0.0625	1.0

Eigenvalues (rounded): [1. 000 0.9375 0.9545]

Eigenvectors (rounded):

[[0.0 0.0 0.21]
[0.0 0.71 0.57]
[1.0 -0.71 -0.79]]

Steady-State Probabilities: [0. 0. 1.]

Convergence Time (years): 65.0

Verification (Pπ ≈ π): True

Gas emissions are projected to ultimately stabilize in the high state. The steady-state distribution [0, 0, 1] confirms that, over time, all probability mass accumulates in the high-emission state, making it an absorbing state. This suggests that without intervention, emission levels will become permanently high.

France – CO_2

Class 1 (Low)

- Total from Class 1 = 16 (to Low) + 2 (to Medium) + 0 (to High) = 18
- Low - Low = 16/18 = 0.8889
- Low - Medium = 2/18 = 0.1111
- Low - High = 0/18 = 0

Class 2 (Medium)

- Total from Class 2 = 3 (to Low) + 20 (to Medium) + 0 (to High) = 23
- Medium - Low = 3/23 = 0.1304
- Medium - Medium = 20/23 = 0.8696
- Medium - High = 0/23 = 0

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 1 (to Medium) + 11 (to High) = 12
- High - Low = 0/12 = 0
- High - Medium = 1/12 = 0.0833
- High - High = 11/12 = 0.9167

Transition Matrix

	Low	Medium	High
Low	0.8889	0.1304	0.0
Medium	0.1111	0.8696	0.0833
High	0.0	0.0	0.9167

Eigenvalues (rounded): [1. 0 0.7585 0.9167]

Eigenvectors (rounded):

[[0.76 -0.71 -0.63]
[0.65 0.71 -0.13]
[0.00 0.00 0.76]]

Steady-State Probabilities: [0.54 0.46 0.00]

Convergence Time (years): 35.0

Verification (Pπ ≈ π): True

In the long run, there is a 54% probability that France's annual CO_2 emissions will remain in the Low state,and a 46% probability of remaining in the Medium state. This steady-state distribution suggests that, without intervention, France is more likely to experience persistently low levels of CO_2 emissions in the future.

Japan – CO_2

Class 1 (Low)

- Total from Class 1 = 14 (to Low) + 3 (to Medium) + 0 (to High) = 17
- Low - Low = 14/17 = 0.8235
- Low - Medium = 3/17 = 0.1765
- Low - High = 0/17 = 0

Class 2 (Medium)

- Total from Class 2 = 3 (to Low) + 11 (to Medium) + 3 (to High) = 17
- Medium - Low = 3/17 = 0.1765
- Medium - Medium = 11/17 = 0.6471
- Medium - High = 3/17 = 0.1765

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 3 (to Medium) + 16 (to High) = 19
- High - Low = 0/19 = 0
- High - Medium = 3/19 = 0.1579
- High - High = 16/19 = 0.8421

Transition Matrix

	Low	Medium	High
Low	0.8235	0.1765	0.0
Medium	0.1765	0.6471	0.1579
High	0.0	0.1765	0.8421

Eigenvalues (rounded): [0.4796 0.833 1.00]

Eigenvectors (rounded):

[[0.42 0.69 0.55]
[-0.82 0.04 0.55]
[0.4 -0.72 0.62]]

Steady-State Probabilities: [0.32 0.32 0.36]

Convergence Time (years): 17.0

Verification (Pπ ≈ π): True

In the long run, there is a 32% probability that Japan's annual CO_2 emissions will remain in the Low state, a 32% probability of remaining in the Medium state, and a 36% probability of staying in the High emission state. This steady-state distribution suggests that, without intervention, Japan is more likely to experience persistently high levels of CO_2 emissions in the future.

Germany – CO_2

Class 1 (Low)

- Total from Class 1 = 16 (to Low) + 1 (to Medium) + 0 (to High) = 17
- Low - Low = 16/17 = 0.9412
- Low - Medium = 1/17 = 0.0588
- Low - High = 0/17 = 0

Class 2 (Medium)

- Total from Class 2 = 2 (to Low) + 15 (to Medium) + 0 (to High) = 17
- Medium - Low = 2/17 = 0.1176
- Medium - Medium = 15/17 = 0.8824
- Medium - High = 0/17 = 0

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 1 (to Medium) + 18 (to High) = 19
- High - Low = 0/19 = 0
- High - Medium = 1/19 = 0.0526
- High - High = 18/19 = 0.9474

Transition Matrix

	Low	Medium	High
Low	0.9412	0.1176	0.0
Medium	0.0588	0.8824	0.0536
High	0.0	0.0	0.9474

Eigenvalues (rounded): [1. 0 0.8236 0.9474]

Eigenvectors (rounded):

[[0.89 -0.71 -0.69]
[0.45 0.71 -0.04]
[0. 00 0.00 0.72]]

Steady-State Probabilities: [0.66 0.34 0.00]

Convergence Time (years): 56.0

Verification (Pπ ≈ π): True

In the long run, there is a 64% probability that Germany's annual CO_2 emissions will remain in the Low state, and a 34% probability of remaining in the Medium state. This steady-state distribution suggests that, without intervention, Germany is more likely to experience persistently low levels of CO_2 emissions in the future.

Canada – CO_2

Class 1 (Low)

- Total from Class 1 = 15 (to Low) + 3 (to Medium) + 0 (to High) = 18
- Low - Low = 15/18 = 0.8333
- Low - Medium = 3/18 = 0.1667
- Low - High = 0/18 = 0

Class 2 (Medium)

- Total from Class 2 = 2 (to Low) + 12 (to Medium) + 3 (to High) = 17
- Medium - Low = 2/17 = 0.1176
- Medium - Medium = 12/17 = 0.7059
- Medium - High = 3/17 = 0.1765

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 2 (to Medium) + 16 (to High) = 18
- High - Low = 0/18 = 0
- High - Medium = 2/18 = 0.1111
- High - High = 16/18 = 0.8889

Transition Matrix

	Low	Medium	High
Low	0.8333	0.1176	0.0
Medium	0.1667	0.7059	0.1111
High	0.0	0.1765	0.8889

Eigenvalues (rounded): [0.57 0.8581 1.00]

Eigenvectors (rounded):

[[0.36 0.63 0.35]
[-0.81 0.13 0.5]
[0.45 -0.76 0.79]]

Steady-State Probabilities: [0.21 0.3 0.48]

Convergence Time (years): 20.0

Verification ($P\pi \approx \pi$): True

In the long run, there is a 21% probability that Canada's annual CO_2 emissions will remain in the Low state, a 30% probability of remaining in the Medium state, and a 48% probability of staying in the High emission state. This steady-state distribution suggests that, without intervention, Canada is more likely to experience persistently high levels of CO_2 emissions in the future.

Australia – Other Gases

Class 1 (Low)

- Total from Class 1 = 16 (to Low) + 2 (to Medium) + 0 (to High) = 18
- Low - Low = 16/18 = 0.8889
- Low - Medium = 2/18 = 0.1111
- Low - High = 0/18 = 0

Class 2 (Medium)

- Total from Class 2 = 1 (to Low) + 13 (to Medium) + 3 (to High) = 17
- Medium - Low = 1/17 = 0.0588
- Medium - Medium = 13/17 = 0.7647
- Medium - High = 3/17 = 0.1765

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 3 (to Medium) + 15 (to High) = 18
- High - Low = 0/18 = 0
- High - Medium = 3/18 = 0.1667
- High - High = 15/18 = 0.8333

Transition Matrix

	Low	Medium	High
Low	0.8889	0.0588	0
Medium	0.1111	0.7647	0.1667
High	0	0.1765	0.8333

Eigenvalues (rounded): [0.6097 0.8772 1.00]

Eigenvectors (rounded):

[[0.16 0.77 0.34]
[-0.77 -0.15 0.65]
[0.61 -0.62 0.68]]

Steady-State Probabilities: [0.2 0.39 0.41]

Convergence Time (years): 23.0

Verification (Pπ ≈ π): True

In the long run, there is a 20% probability that Australia's annual HFC, PFC, and SF6 emissions will remain in the Low state, a 39% probability of remaining in the Medium state, and a 41% probability of staying in the High emission state. This steady-state distribution suggests that, without intervention, Australia is more likely to experience persistently high levels of HFC, PFC, and SF6 emissions in the future.

Ukraine – Other Gases

Class 1 (Low)

- Total from Class 1 = 14 (to Low) + 3 (to Medium) + 0 (to High) = 17
- Low - Low = 14/17 = 0.8235
- Low - Medium = 3/17 = 0.1765
- Low - High = 0/17 = 0

Class 2 (Medium)

- Total from Class 2 = 4 (to Low) + 12 (to Medium) + 1 (to High) = 17
- Medium - Low = 4/17 = 0.2353
- Medium - Medium = 12/17 = 0.7059
- Medium - High = 1/17 = 0.0588

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 1 (to Medium) + 18 (to High) = 19
- High - Low = 0/19 = 0
- High - Medium = 1/19 = 0.0526
- High - High = 18/19 = 0.9474

Transition Matrix

	Low	Medium	High
Low	0.8235	0.2353	0
Medium	0.1765	0.7059	0.0526
High	0	0.0588	0.9474

Eigenvalues (rounded): [0.5476 1.00 0.9292]

Eigenvectors (rounded):

[[0.64 0.66 -0.55]
[-0.76 0.5 -0.25]
[0.11 0.56 0.8]]

Steady-State Probabilities: [0.38 0.29 0.33]

Convergence Time (years): 41.0

Verification ($P\pi \approx \pi$): True

In the long run, there is a 38% probability that Ukraine's annual HFC, PFC, and SF6 emissions will remain in the Low state, a 29% probability of remaining in the Medium state, and a 33% probability of staying in the High emission state. This steady-state distribution suggests that, without intervention, Ukraine is more likely to experience persistently low levels of HFC, PFC, and SF6 emissions in the future.

Malaysia – Other Gases

Class 1 (Low)

- Total from Class 1 = 17 + 1 + 0 = 18
- Low - Low = 17/18 = 0.9444
- Low - Medium = 1/18 = 0.0556
- Low - High = 0/18 = 0

Class 2 (Medium)

- Total from Class 2 = 0 + 16 + 1 = 17
- Medium - Low = 0/17 = 0
- Medium - Medium = 16/17 = 0.9412
- Medium - High = 1/17 = 0.0588

Class 3 (High)

- Total from Class 3 = 0 + 0 + 18 = 18
- High - Low = 0/18 = 0
- High - Medium = 0/18 = 0
- High - High = 18/18 = 1.0

Transition Matrix

	Low	Medium	High
Low	0.9444	0	0
Medium	0.0556	0.9412	0
High	0	0.0588	1

Eigenvalues (rounded): [1.0 0.9412 0.9444]

Eigenvectors (rounded):

[[0.00   0.00   0.04]
[0.00   0.71   0.69]
[1.0   -0.71   -0.73]]

Steady-State Probabilities: [0. 0. 1.]

Convergence Time (years): 53.0

Verification (Pπ ≈ π): True

Gas emissions are projected to ultimately stabilize in the high state. The steady-state distribution [0, 0, 1] confirms that, over time, all probability mass accumulates in the high-emission state, making it an absorbing state. This suggests that without intervention, emission levels will become permanently high.

United Kingdom – Other Gases

Class 1 (Low)

- Total from Class 1 = 18 + 0 + 0 = 18
- Low - Low = 18/18 = 1.0
- Low - Medium = 0/18 = 0
- Low - High = 0/18 = 0

Class 2 (Medium)

- Total from Class 2 = 1 + 12 + 3 = 16
- Medium - Low = 1/16 = 0.0625
- Medium - Medium = 12/16 = 0.75
- Medium - High = 3/16 = 0.1875

Class 3 (High)

- Total from Class 3 = 0 + 4 + 15 = 19
- High - Low = 0/19 = 0
- High - Medium = 4/19 = 0.2105
- High - High = 15/19 = 0.7895

Transition Matrix

	Low	Medium	High
Low	1	0.0625	0
Medium	0	0.75	0.2105
High	0	0.1875	0.7895

Eigenvalues (rounded): [1.00 0.5701 0.9694]

Eigenvectors (rounded):

[[1.0 0.11 0.82]
[0.0 -0.76 -0.4]
[0.0 0.65 -0.42]]

Steady-State Probabilities: [1. 0. 0.]

Convergence Time (years): 97.0

Verification (Pπ ≈ π): True

Gas emissions are projected to ultimately stabilize in the high state. The steady-state distribution [1, 0, 0] confirms that, over time, all probability mass accumulates in the low-emission state, making it an absorbing state. This suggests that without intervention, emission levels will become permanently low.

Russia – Other Gases

Class 1 (Low)

- Total from Class 1 = 13 (to Low) + 3 (to Medium) + 0 (to High) = 16
- Low - Low = 13/16 = 0.8125
- Low - Medium = 3/16 = 0.1875
- Low - High = 0/16 = 0

Class 2 (Medium)

- Total from Class 2 = 2 (to Low) + 15 (to Medium) + 2 (to High) = 19
- Medium - Low = 2/19 = 0.1053
- Medium - Medium = 15/19 = 0.7895
- Medium - High = 2/19 = 0.1053

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 1 (to Medium) + 17 (to High) = 18
- High - Low = 0/18 = 0
- High - Medium = 1/18 = 0.0556
- High - High = 17/18 = 0.9444

Transition Matrix

	Low	Medium	High
Low	0.8125	0.1053	0
Medium	0.1875	0.7895	0.0556
High	0	0.1053	0.9444

Eigenvalues (rounded): [0.649 0.8974 1.00]

Eigenvectors (rounded):

[[0.52 0.45 0.25]
[-0.81 0.36 0.45]
[0.29 -0.82 0.86]]

Steady-State Probabilities: [0.16 0.29 0.55]

Convergence Time (years): 28.0

Verification ($P\pi \approx \pi$): True

In the long run, there is a 16% probability that Russia's annual HFC, PFC, and SF6 emissions will remain in the Low state, a 29% probability of remaining in the Medium state, and a 55% probability of staying in the High emission state. This steady-state distribution suggests that, without intervention, Russia is more likely to experience persistently high levels of HFC, PFC, and SF6 emissions in the future.

India – Other Gases

Class 1 (Low)

- Total from Class 1 = 15 + 1 + 0 = 16
- Low - Low = 15/16 = 0.9375
- Low - Medium = 1/16 = 0.0625
- Low - High = 0/16 = 0

Class 2 (Medium)

- Total from Class 2 = 0 + 17 + 1 = 18
- Medium - Low = 0/18 = 0
- Medium - Medium = 17/18 = 0.9444
- Medium - High = 1/18 = 0.0556

Class 3 (High)

- Total from Class 3 = 0 + 0 + 19 = 19
- High - Low = 0/19 = 0
- High - Medium = 0/19 = 0
- High - High = 19/19 = 1.0

Transition Matrix

	Low	Medium	High
Low	0.9375	0	0
Medium	0.0625	0.9444	0
High	0	0.0556	1

Eigenvalues (rounded): [1.0   0.9444 0.9375]

Eigenvectors (rounded):

[[0.0   0.0 0.08]
[0.0   0.71 -0.74]
[1.0   -0.71   0.66]]

Steady-State Probabilities: [0. 0. 1.]

Convergence Time (years): 53.0

Verification ($P\pi \approx \pi$): True

Gas emissions are projected to ultimately stabilize in the high state. The steady-state distribution [0, 0, 1] confirms that, over time, all probability mass accumulates in the high-emission state, making it an absorbing state. This suggests that without intervention, emission levels will become permanently high.

France – Other Gases

Class 1 (Low)

- Total from Class 1 = 18 + 0 + 0 = 18
- Low - Low = 18/18 = 1.0
- Low - Medium = 0/18 = 0
- Low - High = 0/18 = 0

Class 2 (Medium)

- Total from Class 2 = 1 + 19 + 0 = 20
- Medium - Low = 1/20 = 0.05
- Medium - Medium = 19/20 = 0.95
- Medium - High = 0/20 = 0

Class 3 (High)

- Total from Class 3 = 0 + 1 + 11 = 12
- High - Low = 0/12 = 0
- High - Medium = 1/12 = 0.0833
- High - High = 11/12 = 0.9167

Transition Matrix

	Low	Medium	High
Low	1	0.05	0
Medium	0	0.95	0.0833
High	0	0	0.9167

Eigenvalues (rounded): [1.0   0.95   0.9167]

Eigenvectors (rounded):

[[1.0   -0.71 0.49]
[00.   0.71 -0.81]
[0.0   0.0   0.32]]

Steady-State Probabilities: [1. 0. 0.]

Convergence Time (years): 59.0

Verification (Pπ ≈ π): True

Gas emissions are projected to ultimately stabilize in the low state. The steady-state distribution [1, 0, 0] confirms that, over time, all probability mass accumulates in the low-emission state, making it an absorbing state. This suggests that without intervention, emission levels will become permanently low.

Japan – Other Gases

Class 1 (Low)

- Total from Class 1 = 17 + 0 + 0 = 17
- Low - Low = 17/17 = 1.0
- Low - Medium = 0/17 = 0
- Low - High = 0/17 = 0

Class 2 (Medium)

- Total from Class 2 = 1 + 14 + 2 = 17
- Medium - Low = 1/17 = 0.0588
- Medium - Medium = 14/17 = 0.8235
- Medium - High = 2/17 = 0.1176

Class 3 (High)

- Total from Class 3 = 0 + 3 + 16 = 19
- High - Low = 0/19 = 0
- High - Medium = 3/19 = 0.1579
- High - High = 16/19 = 0.8421

Transition Matrix

	Low	Medium	High
Low	1	0.0588	0
Medium	0	0.8235	0.1579
High	0	0.1176	0.8421

Eigenvalues (rounded): [1.0 0.6962 0.9694]

Eigenvectors (rounded):

[[1. 0.15 0.82]

[0. -0.77 -0.42]

[0. 0.62 -0.39]]

Steady-State Probabilities: [1. 0. 0.]

Convergence Time (years): 97.0

Verification (Pπ ≈ π): True

Gas emissions are projected to ultimately stabilize in the low state. The steady-state distribution [1, 0, 0] confirms that, over time, all probability mass accumulates in the low-emission state, making it an absorbing state. This suggests that without intervention, emission levels will become permanently low.

Germany – Other Gases

Class 1 (Low)

- Total from Class 1 = 17 + 0 + 0 = 17
- Low - Low = 17/17 = 1.0
- Low - Medium = 0/17 = 0
- Low - High = 0/17 = 0

Class 2 (Medium)

- Total from Class 2 = 1 + 15 + 1 = 17
- Medium - Low = 1/17 = 0.0588
- Medium - Medium = 15/17 = 0.8824
- Medium - High = 1/17 = 0.0588

Class 3 (High)

- Total from Class 3 = 0 + 2 + 17 = 19
- High - Low = 0/19 = 0
- High - Medium = 2/19 = 0.1053
- High - High = 17/19 = 0.8947

Transition Matrix

	Low	Medium	High
Low	1	0.0588	0
Medium	0	0.8824	0.1053
High	0	0.0588	0.8947

Eigenvalues (rounded): [1.0 0.8096 0.9675]

Eigenvectors (rounded):

[[1. 0.25 0.81]
[0. -0.8 -0.45]
[0. 0.55 -0.36]]

Steady-State Probabilities: [1. 0. 0.]

Convergence Time (years): 91.0

Verification (Pπ ≈ π): True

Gas emissions are projected to ultimately stabilize in the low state. The steady-state distribution [1, 0, 0] confirms that, over time, all probability mass accumulates in the low-emission state, making it an absorbing state. This suggests that without intervention, emission levels will become permanently low.

Canada – Other Gases

Class 1 (Low)

- Total from Class 1 = 16 (to Low) + 2 (to Medium) + 0 (to High) = 18
- Low - Low = 16/18 = 0.8889
- Low - Medium = 2/18 = 0.1111
- Low - High = 0/18 = 0

Class 2 (Medium)

- Total from Class 2 = 1 (to Low) + 12 (to Medium) + 4 (to High) = 17
- Medium - Low = 1/17 = 0.0588
- Medium - Medium = 12/17 = 0.7059
- Medium - High = 4/17 = 0.2353

Class 3 (High)

- Total from Class 3 = 0 (to Low) + 3 (to Medium) + 15 (to High) = 18
- High - Low = 0/18 = 0
- High - Medium = 3/18 = 0.1667
- High - High = 15/18 = 0.8333

Transition Matrix

	Low	Medium	High
Low	0.8889	0.0588	0
Medium	0.1111	0.7059	0.1667
High	0	0.2353	0.8333

Eigenvalues (rounded): [0.5488 0.8793 1.0]

Eigenvectors (rounded):

[[0.13 0.76 0.29]
[-0.76 -0.12 0.55]
[0.63 -0.64 0.78]]

Steady-State Probabilities: [0.18 0.34 0.48]

Convergence Time (years): 24.0

Verification ($P\pi \approx \pi$): True

In the long run, there is a 18% probability that Canada's annual HFC, PFC, and SF6 emissions will remain in the Low state, a 34% probability of remaining in the Medium state, and a 48% probability of staying in the High emission state. This steady-state distribution suggests that, without intervention, Canada is more likely to experience persistently high levels of HFC, PFC, and SF6 emissions in the future.

6.2 Best Factor for Climate Change

To determine the best (i.e., most impactful) factor contributing to climate change, we analyzed the long-term steady-state probabilities of carbon dioxide (CO_2) and other greenhouse gases (HFCs, PFCs, and SF_6) across ten countries using the Markov Chain method. The steady-state probabilities help us understand the likely emission levels (Low, Medium, High) that each country will settle into over time.

After comparing the data, we observed the following key trends:

CO_2 Emissions:

- **Malaysia** and **India** show a 100% steady-state probability in the High emission state.
- **Russia** and **Australia** also demonstrate high likelihoods of remaining in the High emission state at 58% and 55%, respectively.
- In contrast, countries like **France** and **Germany** are projected to maintain Low emission levels (54% and 66%, respectively).

Other Gases (HFCs, PFCs, SF_6):

- **Malaysia** and **India** again show a 100% probability of stabilizing in the High emission state.
- **Russia** and **Canada** have high probabilities of remaining in the High state (55% and 48%, respectively).
- However, more countries—including **France**, **Japan**, **Germany**, and the **United Kingdom**—show a **100% probability** of stabilizing in the Low emission state, making their contribution to climate change from these gases less concerning.

Overall Comparison:

- CO_2 emissions tend to remain high in a larger number of countries and are less likely to transition back to lower states once high levels are reached.
- Other gases, although extremely potent in their warming effect (per molecule), are more controlled or decreasing in several countries.

Based on the Markov steady-state probabilities, CO_2 is the most impactful and consistent driver of long-term climate change across the majority of the analyzed countries. While other greenhouse gases are significant, CO_2 consistently shows higher and more persistent emission levels, especially in industrializing countries. Therefore, carbon dioxide is identified as the best (most influential) factor in accelerating climate change, highlighting the critical need for CO_2-focused mitigation strategies globally.

6.3 Prediction for Climate Change

6.3.1) Worst-Case Prediction:

Co2 emission

A. Australia

The worst-case prediction for the Co2 emission in Australia is, there are 0% chances remaining in the low state.

B. Ukraine

The worst-case prediction for the Co2 emission in Ukraine is, there are 24% chances remaining in the Medium state.

C. Malaysia

The worst-case prediction for the Co2 emission in Malaysia is, there are 0% chances of transitioning from the high state back to low or medium.

D. United Kingdom

The worst-case prediction for the Co2 emission in Ukraine is, there are 20% chances remaining in the High state.

E. Russia

The worst-case prediction for the Co2 emission in Russia is, there are 17% chances remaining in the Low state.

F. India

The worst-case prediction for the Co2 emission in India is, there are 0% chances of transitioning from the high state back to low or medium.

G. France

The worst-case prediction for the Co2 emission in France is, there are 0% chances of transitioning from the low or medium state back to high .

H. Japan

The worst-case prediction for the Co2 emission in Japan is, there are 32% chances remaining in the Low and Medium state.

I. Germany

The worst-case prediction for the Co2 emission in Germany is, there are 0% chances of transitioning from the low or medium state back to high .

J. Canada

The worst-case prediction for the Co2 emission in Canada is, there are 21% chances remaining in the Low state.

Other gasses emission

a. **Australia**

The worst-case prediction for the Other gas emission in Australia is, there are 20% chances remaining in the Low state.

b. **Ukraine**

The worst-case prediction for the Other gas emission in Ukraine is, there are 29% chances remaining in the Medium state.

c. **Malaysia**

The worst-case prediction for the Other gas emission in Malaysia is, there are 0% chances of transitioning from the high state back to low or medium.

d. **United Kingdom**

The worst-case prediction for the Other gas emission in United Kingdom is, there are 0% chances of transitioning from the low state back to high or medium.

e. **Russia**

The worst-case prediction for the Other gas emission in Russia is, there are 16% chances remaining in the Low state.

f. **India**

The worst-case prediction for the Other gas emission in India is, there are 0% chances of transitioning from the high state back to low or medium.

g. **France**

The worst-case prediction for the Other gas emission in France is, there are 0% chances of transitioning from the low state back to high or medium.

h. **Japan**

The worst-case prediction for the Other gas emission in Japan is, there are 0% chances of transitioning from the low state back to high or medium.

i. **Germany**

The worst-case prediction for the Other gas emission in Germany is, there are 0% chances of transitioning from the low state back to high or medium.

j. **Canada**

The worst-case prediction for the Other gas emission in Canada is, there are 18% chances remaining in the Low state.

6.3.2) Best-Case Prediction:

Co2

a. **Australia**

The best-case prediction for the Co2 emission in Australia is, there are 55% chances remaining in the high state.

b. **Ukraine**

The worst-case prediction for the Co2 emission in Ukraine is, there are 48% chances remaining in the low state.

c. **Malaysia**

The best-case prediction for the Co2 emission in Malaysia is, there are 100% chances of transitioning from the low or medium state back to high.

d. **United Kingdom**

The best-case prediction for the Co2 emission in Ukraine is, there are 41% chances remaining in the low state.

e. **Russia**

The best-case prediction for the Co2 emission in Russia is, there are 58% chances remaining in the high state.

f. **India**

The best-case prediction for the Co2 emission in India is, there are 100% chances of transitioning from the low or medium state back to high.

g. **France**

The best-case prediction for the Co2 emission in France is, there are 54% chances remaining in the Low state.

h. **Japan**

The best-case prediction for the Co2 emission in Japan is, there are 36% chances remaining in the high state.

i. **Germany**

The best-case prediction for the Co2 emission in Germany is, there are 66% chances remaining in the low state.

j. **Canada**

The best-case prediction for the Co2 emission in Canada is, there are 48% chances remaining in the Low state.

Other gasses

a. **Australia**

The best-case prediction for the Other gas emission in Australia is, there are 41% chances remaining in the high state.

b. **Ukraine**

The best-case prediction for the Other gas emission in Ukraine is, there are 38% chances remaining in the low state.

c. **Malaysia**

The best-case prediction for the Other gas emission in Malaysia is, there are 100% chances of transitioning from the low or medium state back to high.

d. **United Kingdom**

The best-case prediction for the Other gas emission in the United Kingdom is, there are 100% chances of transitioning from the high or medium state back to low.

e. **Russia**

The best-case prediction for the Other gas emission in Russia is, there are 55% chances remaining in the high state.

f. **India**

The best-case prediction for the Other gas emission in India is, there are 100% chances of transitioning from the low or medium state back to high.

g. **France**

The best-case prediction for the Other gas emission in France is, there are 100% chances of transitioning from the high or medium state back to low.

h. **Japan**

The best-case prediction for the Other gas emission in Japan is, there are 100% chances of transitioning from the high or medium state back to low.

i. **Germany**

The best-case prediction for the Other gas emission in Germany is, there are 100% chances of transitioning from the high or medium state back to low.

j. **Canada**

The best-case prediction for the Other gas emission in Canada is, there are 48% chances remaining in the high state.

6.3.3) Do general comparison of the scenarios, individual variable, several variables, and overall variables, to see different view. You may present in tables for comparison.

Co2 emission

Steady-State in Australia [0.0 0.45 0.55]	Steady-State in Ukraine [0.48 0.24 0.27]	Steady-State in Malaysia [0.0 0.0 1.0]	Steady-State in United Kingdom [0.41 0.39 0.2]
Steady-State in Russia [0.17 0.25 0.58]	Steady-State in India [0.0 0.0 1.0]	Steady-State in France [0.54 0.46 0.0]	Steady-State in Japan [0.32 0.32 0.36]
	Steady-State in Germany [0.66 0.34 0.0]	Steady-State in Canada [0.21 0.3 0.48]	

Other Gasses

Steady-State in Australia [0.2 0.39 0.41]	Steady-State in Ukraine [0.38 0.29 0.33]	Steady-State in Malaysia [0.0 0.0 1.0]	Steady-State in United Kingdom [1.0 0.0 0.0]
Steady-State in Russia [0.16 0.29 0.55]	Steady-State in India [0.0 0.0 1.0]	Steady-State in France [1.0 0.0 0.0]	Steady-State in Japan [1.0 0.0 0.0]
	Steady-State in Germany [1.0 0.0 0.0]	Steady-State in Canada [0.18 0.34 0.48]	

7.0 CONCLUSION

This project provided an in-depth mathematical and statistical analysis of climate change contributors specifically CO_2 and other greenhouse gas emissions (HFCs, PFCs, and SF_6) across ten countries using the Markov Chain model. Our findings highlight critical patterns and long-term predictions about emission trends for each country, revealing substantial variation in both the current states and projected futures of greenhouse gas levels.

The analysis showed that countries such as **Malaysia** and **India** are projected to stabilize at high CO_2 and other gas emission levels, indicating a pressing need for immediate intervention. On the other hand, countries like **France**, **Germany**, **Japan**, and the **United Kingdom** showed more promising trends, with their emissions either stabilizing at low levels or being likely to reduce over time. Notably, **Malaysia** and **India** demonstrated absorbing states in the high-emission category for both CO_2 and other gases, posing significant environmental risks if mitigation measures are not enforced.

The use of Markov Chains allowed us to model the probability of future emission states, assess convergence times, and understand the steady-state behavior of emission trends. Through steady-state probability distributions and eigenvalue analysis, we identified which countries are on a sustainable path and which are moving toward irreversible high-emission futures.

Overall, the **most damaging factor contributing to climate change is CO_2 emissions**, as it appears more frequently in high steady states across the analyzed countries. Our predictions emphasize the urgent need for global cooperation, stricter environmental regulations, cleaner energy adoption, and emission reduction strategies, particularly in rapidly industrializing nations.

The study also proves the effectiveness of **mathematical modeling**, such as Markov Chains, in environmental studies. It not only provides data-driven insights but also forecasts the future impact of present policies and trends. Therefore, the findings of this research are intended to aid in both awareness and informed policy-making to combat the global climate crisis effectively.

8.0 Appendix

Coding that was used in this project.

```
import numpy as np
import numpy.linalg as la

# change this matrix(column-stochastic) for each country
P1 = np.matrix([
    [0.8889, 0.0588, 0.0000],
    [0.1111, 0.7059, 0.1667],
    [0.0000, 0.2353, 0.8333]
])
print("P1:\n", P1)
#print the matrix

# Compute eigenvalues and eigenvectors
eigenvalues, eigenvectors = la.eig(P1)
eigenvalues_rounded = np.round(eigenvalues, decimals=4)
eigenvectors_rounded = np.round(eigenvectors, decimals=2)

# Steady-state probabilities
idx = np.argmax(abs(eigenvalues))
steady_state = eigenvectors_rounded[:, idx] / np.sum(eigenvectors_rounded[:,
idx])
steady_state = np.round(steady_state, decimals=2)

# Convergence time
lambda_2 = sorted(abs(eigenvalues), reverse=True)[1]
t = np.ceil(np.log(0.05) / np.log(lambda_2))

print("Eigenvalues (rounded):", eigenvalues_rounded)
print("Eigenvectors (rounded):\n", eigenvectors_rounded)
print("Steady-State Probabilities:", steady_state)
print("Convergence Time (years):", t)
print("Verification (Pπ ≈ π):", np.allclose(P1 @ steady_state, steady_state,
atol=1e-2))
```

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