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cand. M. Sc. Dhrumit Jignesh Upadhyay

Projection of greenhouse gases and air pollution emissions from coal powerplants in selected countries

Projektion der Treibhausgas- und Luftverschmutzungsemissionen von Kohlekraftwerken in ausgewählten Ländern

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University of Stuttgart
Institute of Combustion and
Power Plant Technology

ifk

Pfaffenwaldring 23 • 70569 Stuttgart • Germany • T +49 711 685-63487 • E-mail: ifk@ifk.uni-stuttgart.de

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Master Thesis No. 3780

Mr. cand. M.Sc. WASTE *Upadhyay, Dhrumit Jignesh*

Matriculation No.: 3574902

Projection of greenhouse gases and air pollution emissions from large point sources for selected countries

1. Problem definition

Coal-fired power plants are major contributors to greenhouse gas and air pollutant emissions globally, but knowledge gaps exist regarding emissions contributions of individual plants and the future makeup of the coal fleet. This impedes targeted emissions reduction strategies and sustainable energy planning. The problem is the lack of granular data on current emissions and sophisticated projections of the future coal fleet considering factors like plant retirements and technology shifts. This research will develop methodologies to construct a detailed emissions inventory, model coal fleet evolution, and integrate these to enable informed policymaking to mitigate emissions and transition towards sustainable energy systems. This master's thesis offers a unique opportunity to contribute to two crucial aspects of energy research: analyzing Greenhouse gas and air pollution emissions from coal-based energy generation and projecting the future composition of the global power plant fleet. By addressing both areas, the research aims to provide comprehensive insights for informed energy policy and sustainable planning. The study's comprehensive approach emphasizes the spatial relevance of air pollution emissions, extending beyond a mere country-level perspective to focus on emissions at the level of individual power plants. Beginning with a meticulous assessment of emissions from coal-based energy generation on a global scale, this analysis seeks to address a vital knowledge gap regarding the coal industry's impact on greenhouse gases and air pollutants. By integrating methodologies, data from various sources, and innovative modeling techniques, the research endeavors to construct an all-encompassing emissions inventory. This inventory will serve as a foundational resource for the development of targeted and effective emissions mitigation strategies. In parallel, the research delves into projecting the future composition of the global power plant fleet. This forward-looking analysis involves exploring existing point source databases and harnessing advanced modeling techniques to anticipate power plant developments, expansions, retirements, and technological shifts. By aligning projections with insights from Energy Scenarios such as Integrated Assessment Models (IAMs) and incorporating emission factors, this aspect of the study contributes to a comprehensive understanding of the energy landscape's trajectory. The overarching aim is to enable policy-makers, energy planners, and environmental stakeholders to make informed decisions that promote sustainable energy transition, reduce emissions, and shape a cleaner future.

2. Objectives

The master's thesis aims to achieve the following interconnected objectives, each consisting of specific tasks:

- **Emissions Inventory and Analysis:**

Develop a detailed emissions inventory for coal-based energy generation on a global scale. The inventory will contribute to understanding the coal industry's contribution to greenhouse gases and air pollutants.

- **Future Power Plant Fleet Projection:**

Create a comprehensive methodology for projecting the future composition of the global power plant fleet. This projection will consider factors such as expansions, retirements, and technological shifts, drawing insights from existing point source databases and advanced modeling techniques.

3. Task description

This section provides a preliminary overview of the research approach, including the selection of countries, the incorporation of established models, and the integration of relevant databases:

- **Selection of Countries for Focus in Emissions Analysis:**

The research will focus on a subset of countries that represent a diverse range of economic wealth classes. This selection aims to facilitate the creation of a tool capable of determining emissions from countries with varying economic indicators. The criteria for country selection will be based on economic development levels, energy consumption patterns, and contributions to global emissions.

- **Emission Factors and Activities for Emission Analysis:**

To estimate emissions from coal-based energy generation, country-specific emission factors will be determined. The GAINS model will be use to provide prospective emission factors at the country level. These factors will be informed by parameters such as energy mix, technology advancements, and emission control measures. Additionally, current power plant activities, including energy generation and emissions, will be gathered from existing databases and reports.

- **Future Power Plant Fleet Projection:**

The projection of power plant fleets, emissions, and activities will involve a multi-faceted approach. Future coal consumption data will be acquired from Integrated Assessment Models (IAMs), leveraging the average of the same scenario (e.g., 2, 3, 4 degrees warming) across different IAM models. The powerplant matching database will play a pivotal role in integrating data on power plant characteristics and operational aspects. The projection methodology will account for various factors, such as technological shifts, policy changes, and energy transition trends.

- ➢ **Current Power Plant Fleet, Emission Factors, and Activities:**
  This will detail the data sources, databases, and methodologies used to gather information on the current status of power plant fleets, emission factors, and activities. It will also explain the integration process of these factors to create a comprehensive baseline.
- ➢ **Projection of Power Plant Activities and Emissions:**
  Here, the methods for projecting future power plant fleets, emissions, and activities will be elucidated. The involvement of IAMs, coal consumption data, and the powerplant matching database will be highlighted.

Deliverables:

Upon successful completion of all these tasks, the following deliverables will be provided:

- Gridded Global Emission Inventory for the Energy Sector
- Methodology Documentation
- Powerplant Fleet Projection Results
- Activity and Emission Projections
- Strategic Policies and Recommendations

- Graph Trends and Analysis

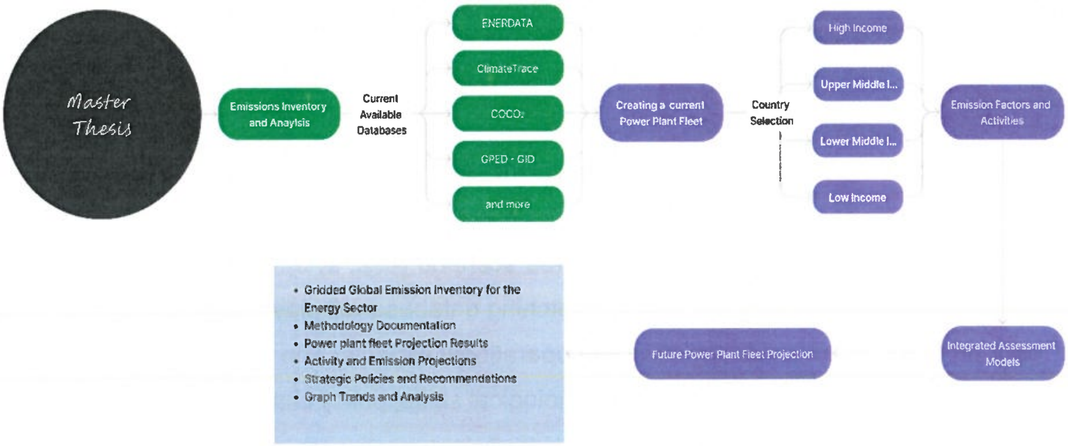

Figure 1: Flow Diagramm

The Master Thesis will be carried out at company: German Aerospace Center, Institute of Networked Energy Systems, Stuttgart super-vised by Mr Patrick Draheim Supervisor at IFK is Mr Dr.-Ing. Ulrich Vogt. The Guidelines for Student Projects/Papers at the IFK as well as the official notification on how to prepare a student thesis outside the University have to be considered, see „GKM Richtlinie_Abwicklung_externer_studentischer_Arbeiten.pdf “. Students also have to report on a regular basis (4-6 weeks).

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Ulrich Vogt

Dr.-Ing. Ulrich Vogt
(Examiner)

Address / contact details of external supervisor:	Student's address / contact details:
Name: Patrick Draheim	Name: Dhrumit Jignesh Upadhyay
Address: German Aerospace Center, Institute of Networked Energy Systems, Curiestraße 4, 70563, Stuttgart	Address: Allmandring 14C, Zimmer 53, 70569, Stuttgart
Email-Id: Patrick.Draheim@dlr.de	Email-Id: dhrumit.de@gmail.com; st179741@stud.uni-stuttgart.de
Phone: +4944199906157	Phone: +4915166192606

Abstract

This thesis presents a comprehensive spatial analysis of greenhouse gas and air pollutant emissions from coal power plants across five major countries: China, Germany, India, South Africa, and the United States. Leveraging a detailed emissions inventory of over 4,700 plants and integrated assessment modeling, the study uncovers key trends, projections, and policy implications associated with the coal power sector's environmental impact.A comparative analysis of emissions data from 2015 to 2023 reveals divergent trajectories among the studied countries. China's carbon dioxide (CO_2) emissions increased by 20%, while India experienced a substantial 76% rise. Conversely, Germany and the United States achieved reductions of 37% and 47%, respectively. Spatial mapping of 2023 emissions highlights regional disparities, with emission hot-spots concentrated in eastern and southern China, northern and eastern India, and the Midwestern and Eastern United States.

Future projections for 2025, 2030, 2035, and 2040 were generated using multiple Integrated Assessment Models (IAMs) under different climate policy scenarios. The 1.5°C warming pathway, aligned with the Paris Agreement, was emphasized as the most economically efficient and environmentally effective scenario. Under this pathway, all countries demonstrate potential for significant emissions reductions by 2040, with China and India projected to achieve (CO_2) emission reductions of 73% and 65%, respectively, compared to 2023 levels. However, the study highlights persistent challenges in managing (CO_2) and nitrogen oxide (NO_x) emissions across all countries. China's (NO_x) emissions are projected to decrease by 67%, while India shows a 56.1% reduction by 2040. However, the United States exhibits a unique convergence in sulfur dioxide (SO_2) emission projections, with a 67.8% decrease by 2040, indicating successful policy interventions and technological advancements in (SO_2) mitigation.

The thesis underscores the importance of transparent, comprehensive, and standardized emissions data at the unit level to inform targeted mitigation strategies and policy development. It emphasizes the need for collaborative efforts among nations to accelerate the transition towards cleaner energy sources while considering regional disparities, socioeconomic factors, and energy access issues. By providing a detailed spatial analysis of coal power emissions and future projections, this research contributes valuable insights to guide policymakers, researchers, and stakeholders in developing effective strategies for climate change mitigation and air quality improvement. The findings underscore the urgency of phasing out unabated coal power and transitioning to sustainable energy systems to reach nearby the Paris Agreement goals and protect public health.

Kurzfassung

In dieser Arbeit wird eine umfassende räumliche Analyse der Treibhausgas- und Luftschadstoffemissionen von Kohlekraftwerken in fünf großen Ländern vorgestellt: China, Deutschland, Indien, Südafrika und die Vereinigten Staaten. Auf der Grundlage eines detaillierten Emissionsinventars von über 4.700 Anlagen und einer integrierten Bewertungsmodellierung deckt die Studie wichtige Trends, Prognosen und politische Implikationen im Zusammenhang mit den Umweltauswirkungen des Kohlekraftsektors auf. Chinas Kohlendioxid (CO_2) - Emissionen stiegen um 20 Prozent, während Indien einen erheblichen Anstieg von 76% verzeichnete. Deutschland und die Vereinigten Staaten erzielten dagegen eine Verringerung um 37 bzw. 47% . Die räumliche Kartierung der Emissionen im Jahr 2023 macht regionale Unterschiede deutlich, wobei sich die Emissionsschwerpunkte auf Ost- und Südchina, Nord- und Ostindien sowie den Mittleren Westen und den Osten der Vereinigten Staaten konzentrieren.

Zukunftsprojektionen für die Jahre 2025, 2030, 2035 und 2040 wurden mithilfe mehrerer integrierter Bewertungsmodelle (IAMs) unter verschiedenen klimapolitischen Szenarien erstellt. Der 1,5°C-Erwärmungspfad, der mit dem Pariser Abkommen übereinstimmt, wurde als das wirtschaftlich effizienteste und ökologisch wirksamste Szenario hervorgehoben. Unter diesem Pfad weisen alle Länder ein Potenzial für erhebliche Emissionsreduzierungen bis 2040 auf, wobei für China und Indien Emissionsreduzierungen (CO_2) von 73% bzw. 65% im Vergleich zu den Werten von 2023 prognostiziert werden. Die Studie weist jedoch auf die anhaltenden Herausforderungen bei der Bewältigung der (CO_2)- und Stickoxid (NO_x) -Emissionen in allen Ländern hin. Für China wird ein Rückgang der (NO_x) - Emissionen um 67% prognostiziert, während Indien bis 2040 einen Rückgang um 56,1% verzeichnen wird. Die Vereinigten Staaten weisen jedoch eine einzigartige Konvergenz bei den Projektionen für die Schwefeldioxid (SO_2)-Emissionen auf, die bis 2040 um 67,8% sinken sollen, was auf erfolgreiche politische Maßnahmen und technologische Fortschritte bei der (SO_2)-Minderung hindeutet.

Die Arbeit unterstreicht die Bedeutung transparenter, umfassender und standardisierter Emissionsdaten auf der Ebene der einzelnen Einheiten, um gezielte Minderungsstrategien und die Entwicklung politischer Maßnahmen zu ermöglichen. Sie unterstreicht die Notwendigkeit der Zusammenarbeit zwischen den Nationen, um den Übergang zu saubereren Energiequellen zu beschleunigen und gleichzeitig regionale Ungleichheiten, sozio-ökonomische Faktoren und Fragen des Energiezugangs zu berücksichtigen. Mit einer detaillierten räumlichen Analyse der Emissionen aus der Kohleverstromung und mit Prognosen für die Zukunft trägt diese Studie zu wertvollen Erkenntnissen bei, die politischen Entscheidungsträgern, Forschern und Interessengruppen bei der Entwicklung wirksamer Strategien zur Eindämmung des Klimawandels und zur Verbesserung der Luftqualität helfen. Die Ergebnisse unterstreichen die Dringlichkeit des Ausstiegs aus der Kohleverstromung und des Übergangs zu nachhaltigen Energiesystemen, um die Ziele des Pariser Abkommens zu erreichen und die öffentliche Gesundheit zu schützen.

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Acronyms

IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
EDGAR	Emissions Database for Global Atmospheric Research
COP	Conference of the Parties
UNFCC	United Nations Framework Convention on Climate Change
G20	Group of 20
GHG	Greenhouse Gas or Greenhouse Gases
NDC	Nationally Determined Contributions
IAM	Integrated Assessment Models
U.S.	United States of America
HSPH	Harvard School of Public Health
EMEP/EEA	European Monitoring and Evaluation Programme/European Economic Area
CREA	Centre for Research on Energy and Clean Air
EF	Emission Factors
IGAC	International Global Atmospehric Chemistry
CARMA	Carbon Monitoring for Action
ECCAD	Emissions of atmospheric Compounds and Compilation of Ancillary Data
GCPT	Global Coal Plant Tracker
GEM	Global Energy Monitor
eGRID)	Emissions and Generation Resource Inte- grated Database
CoCO_2	Copernicus CO_2
GID-GPED	Global Innovation and Development Institute's - Power Emission Database
CEA	Central Electricity Authority
ID	Identification
EPA	Environmental Protection Agency
VS	Visual Studio Code
IDE	Integrated Development Environment
CSV	Comma-separated values
XLSX	Microsoft Excel Spreadsheet
JSON	JavaScript Object Notation
PPM	Powerplant Matching Tool
QGIS	Quantum Geographic Information System
LTR	Long Term Release
GDP	Gross domestic product
BECCS	Bioenergy with carbon capture and storage
DICE	Dynamic Integrated Climate-Economy model
GEM-E3	General Equilibrium Model - Energy-Environment-Economy
REMIND	REgional Model of Investment and Development
BAU	Business-as-usual
AIM/CGE	Asia-Pacific Integrated Modeling/Computable General Equilibrium
GAINS	Greenhouse Gas and Air Pollution Interactions and Synergies
FGD	Flue gas desulfurization
Kt and Mt	Kilo-tonnes and Million-Tonnes

1 Introduction

1.1 Background

Coal power plants are a major global source of greenhouse gas (GHG) emissions including carbon dioxide (CO_2), as well as air pollutants such as sulfur dioxide (SO_2), nitrogen oxides (NO_x), and particulate matter (PM) (H. Lockwood et al. 2009). Air pollutant emissions are a major concern for air quality, climate impacts, health and environmental effects. The main air pollutants covered in this study include (SO_2), (NO_x), (CO), ($NMVOC$), (NH_3), (PM_{10}), ($\mathrm{PM}_{2.5}$), black carbon (BC) and organic carbon (OC) (Crippa, Guizzardi, et al. 2018). Global energy demand is projected to rise driven by population and economic growth. According to the Intergovernmental Panel on Climate Change (IPCC 2006), International Energy Agency's (IEA 2023) Coal 2023 report and emissions inventories like EDGAR, electricity generation accounted for 42% of global (CO_2) emissions in 2019, with coal being the dominant energy source fueling this increasing consumption and providing over 36% of electricity generation globally.

As countries electrify other sectors like transportation and heating, the electricity sector is projected to be an even larger contributor to future emissions (IEA 2021). Tracking emission trajectories from electricity generation and other major emitting sectors via inventories is important to inform climate mitigation policy and action (Nascimento, Kuramochi, and Illenseer 2021). Coal power plants in particular are ripe for targeted policies and phase-out plans given their large contributions currently and going forward (Varadhan et al. 2023). Thus, developing detailed emissions inventories and projections specifically for coal power is crucial (IEA 2021).

1.2 Current Global Emissions

In 2019, coal power plants emitted over 13 billion metric tons of (CO_2) equivalents, as well as millions of tons of (SO_2), (NO_x), and PM (Crippa, Solazzo, et al. 2020). With many developing nations expanding coal capacity, emissions are expected to increase without targeted climate policies. Recognizing the environmental externalities related to unchecked coal usage, over 40 nations have committed to phase out unabated coal power plants under the COP26 agreement (United Nations Climate Change 2022). However, the IEA report highlights that tangible actions taken by the world's largest coal consumers towards reducing coal dependency have not progressed at the requisite pace. Global coal consumption and trading hit record highs in 2022. Current trajectory forecasts the share of coal in the global energy mix may marginally reduce from over 36% to about 30% by 2026, rather than witnessing an accelerated decline (IEA 2023).

According to Figure 1.1 (Gütschow et al. 2023), the developed countries like the United States and Germany have historically been the highest contributors cumulatively over the industrial era. However, developing economies now account for a growing share of current

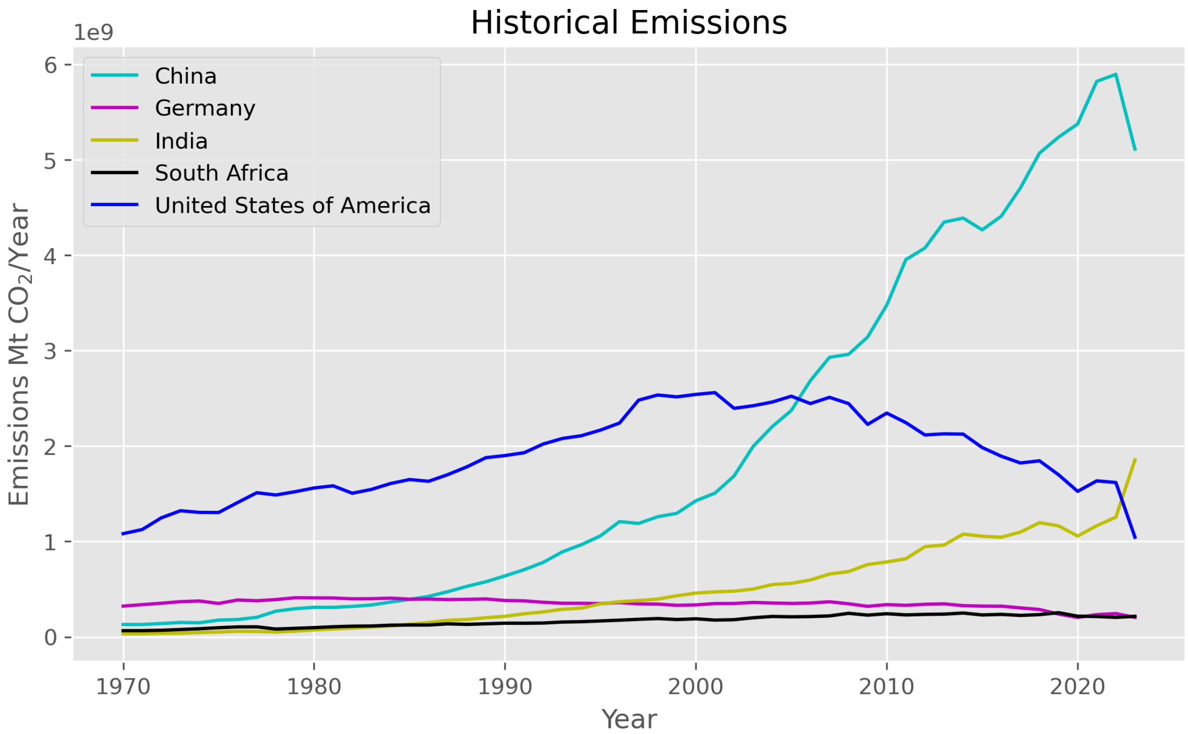


Figure 1.1: (CO_2) emissions by energy sector (1970 - 2022)

and future global emissions as they expand industries and electricity access (Lamb et al. 2021; Friedlingstein et al. 2019). For example, China emits over one-fourth of global fossil fuel CO_2 while India emits around 7%. But, per capita emissions in many developing nations remain below developed country levels (Gütschow et al. 2023) An analysis of national reports for G20 member states including China, Germany, India, South Africa, and United States reveals significant misalignment between pledged goals of phasing out fossil fuels consistent with Paris Agreement 1.5° C trajectories, versus the specificity and feasibility of interim targets and policies to meet these objectives (Varadhan et al. 2023). For instance, India lacks a firm timeline for winding down coal generation as committed at COP26 (World Economic Forum 2022), while China's plans entail further increasing the coal power fleet before initiating a gradual "phase-down" post-2025 (Climate Action Tracker 2023). Such G20 members, in conjunction with Indonesia, will constitute over 50% of global emissions by 2030 (Climate Transparency 2022).

1.3 Importance of Emissions Projection

(Fujimori et al. 2017) discussed projecting future greenhouse gas and air pollutant emission trajectories under various scenarios will quantify the magnitude of impacts from continued coal usage. (Nascimento, Kuramochi, and Höhne 2022) evaluated multi-scenario projections will enable nations to progress towards emissions reduction targets, such as those outlined under the Paris Agreement, and inform evidence-based policy decisions regarding coal phase-outs or abatement mechanisms. (Jewell et al. 2019) studied about comparing projected outcomes across countries using consistent frameworks also affords valuable insights into the global pace and direction of energy system transitions. Specifically, scenario analysis can delineate plausible upper and lower boundaries for coal energy's future role by region, along with associated climate and air quality implications (Jayarathna et al. 2022; Welsby et al. 2021). Overall, comprehensive projection studies are vital to understand the range of potential mitigation pathways and clarify the scale and nature of strategic interventions needed to curb coal emissions worldwide (Lamb et al. 2021).

1.4 Selected Countries and Time Span

This thesis focuses on projections for five countries with varied economic backgrounds - China, Germany, India, South Africa and United States. According to Figure 1.2 analysed by (Hamadeh Catherine et al. 2023), they represent diverse economies with different historical contributions and stages of development. The granular projections will elucidate the trajectory of emissions under different scenarios to inform national policy making and collective global climate action.

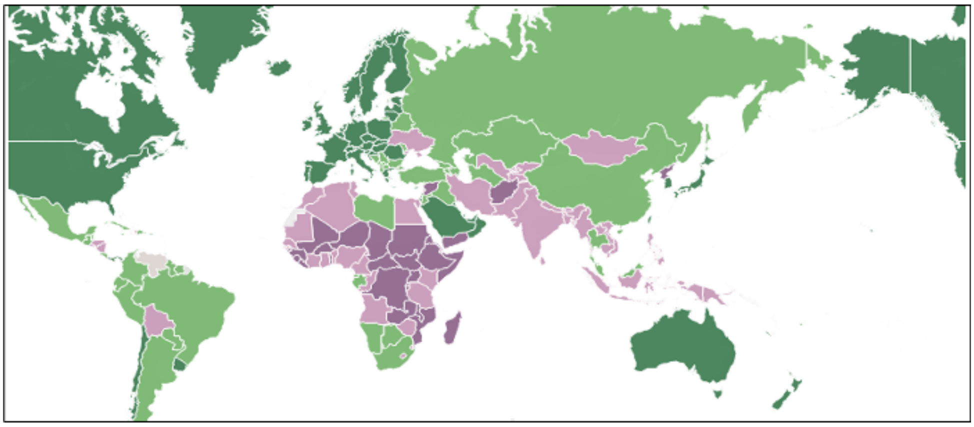


Figure 1.2: World Map - Country classification by income

China and India have developed rapidly in recent decades largely powered by domestic coal, United States and Germany represent post-industrialized or moving away from coal and South Africa is a developing country almost entirely reliant on coal for power is summarised in Table 1.1 (Hamadeh Catherine et al. 2023). This thesis will project GHG and air pollutant emissions from major coal point sources in selected countries from 2023 to 2040 under multiple scenarios (i.e Baseline, Nationally Determined Contribution (NDC), 1.5° C, and 2° C).

Table 1.1: Country classification by Income

Name	Income Classification
China	Upper Middle Income
Germany	High Income
India	Lower Middle Income
South Africa	Upper Middle Income
United States	High Income

1.5 Research Questions

This thesis utilizes historical emissions data and pursues detailed projections of future trajectories stemming from coal-fired electricity generation across key countries that collectively account for the majority of current global coal power output and associated impacts. The overarching aim is to delineate plausible upper and lower boundaries for coal power's climate and air quality through 2040 based on prevailing policy environments and under a range of assumptions around economic growth, technological developments, and potential additional policy actions. The analysis seeks to address the following research questions:

Q1. What are the current contributions of coal power plants from electricity generation to greenhouse gas and air pollutant emissions in the selected countries based on a detailed spatially-explicit inventory?

Q2. How will greenhouse gas and air emissions from coal power generation in the selected countries change over the next few decades based on projections of plant fleet evolution and Integrated Assessment Models (IAM's) energy policy scenarios?

Q3. Where are the technological and policy opportunities for reducing projected coal power emissions through 2040?

Q4. What are the most important projected shifts in the composition of coal power plant fleet in the selected countries, and what will drive these changes?

Q5. How do the projected emissions and plant fleet pathways vary between the selected countries, and what does this suggest about energy transitions in developed vs. developing economies?

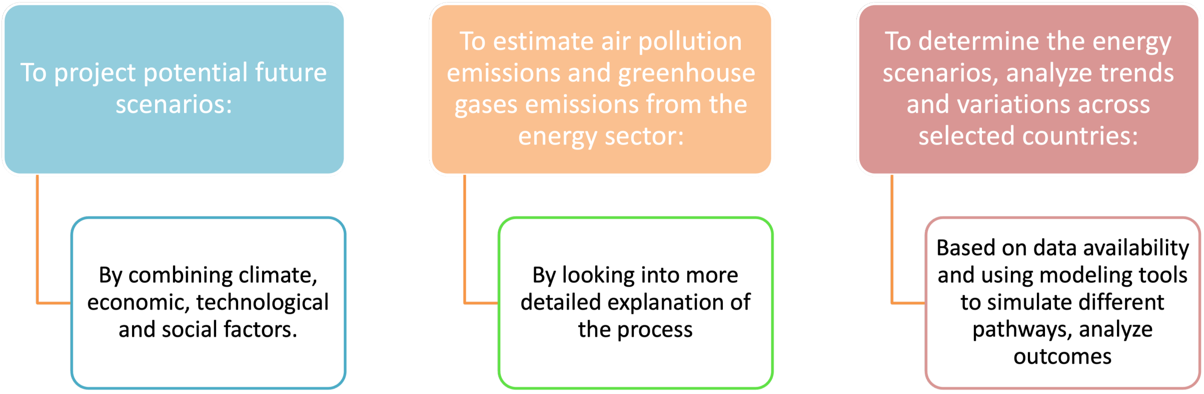


Figure 1.3: Approaches for objectives

2 Present State of Knowledge

2.1 Coal Power Emissions - Trends and Impacts

While coal combustion produces over 30% of global electricity, it accounts for over 40% of energy-related (CO_2) emissions - releasing waste heat and chemical byproducts that profoundly impact environmental quality. Beyond climate risks, coal emissions contain air pollutants imposing severe health burdens. As per the International Energy Agency's (IEA 2021) report, coal combustion constitutes the single largest source of global energy-related carbon dioxide (CO_2) emissions, responsible for over 40% in 2020.

An analysis by Harvard School of Public Health (HSPH) by (Henneman et al. 2023) directly attributes over 460,000 premature deaths in the U.S. since 1999 to particulate pollution exposure specifically from coal-based power generation - imposing a mortality risk twice that of pollution from other emission sources, underlining the associated socioeconomic costs. This indicates the immense public health burden stemming from coal's unique stack emissions chemistry.

Global satellite monitoring reveals aggregate sulfur dioxide emissions from aging coal power plants to be often underestimated, especially in developing countries, indicating deeper environmental and health ramifications (Ember 2023). As per reports, tighter emission controls and compliance enforcement has immense potential to reduce contamination levels by over 300,000 avoidable mortalities globally.

The (EEA/EMEP 2023) projections highlight that to align with stringent 1.5°C climate change mitigation pathways, coal power capacity and generation must fall steeply - over 80% by 2030 relative to recent historic peaks. This necessitates urgent multilateral collaboration enabling developing economies balance equitable and sustainable energy access alongside global climate priorities (EEA/EMEP 2023).

2.2 Emission Inventories Methodologies

Emission inventories form the foundation for air quality management by quantifying pollutant emissions from various sources. The (EEA/EMEP 2023) guidebook presents authoritative guidance on compiling inventories for major air pollutants including greenhouse gases and air pollutants through measurement data, emission factors, and activity levels. Methodologies for developing bottom-up emissions inventories involve source categorization, activity data collection, emission factor determination, and spatiotemporal allocation (Freeman et al. 2022). Based on plant-level parameters,(Y. Liu et al. 2007), demonstrated a GIS-based approach to develop high-resolution SO_2, NO_x and PM emissions inventory for the Chinese coal fleet incorporating capacity, technology, fuel use, and controls data. However, gaps in unit-specific information lead to usage of regional averages.

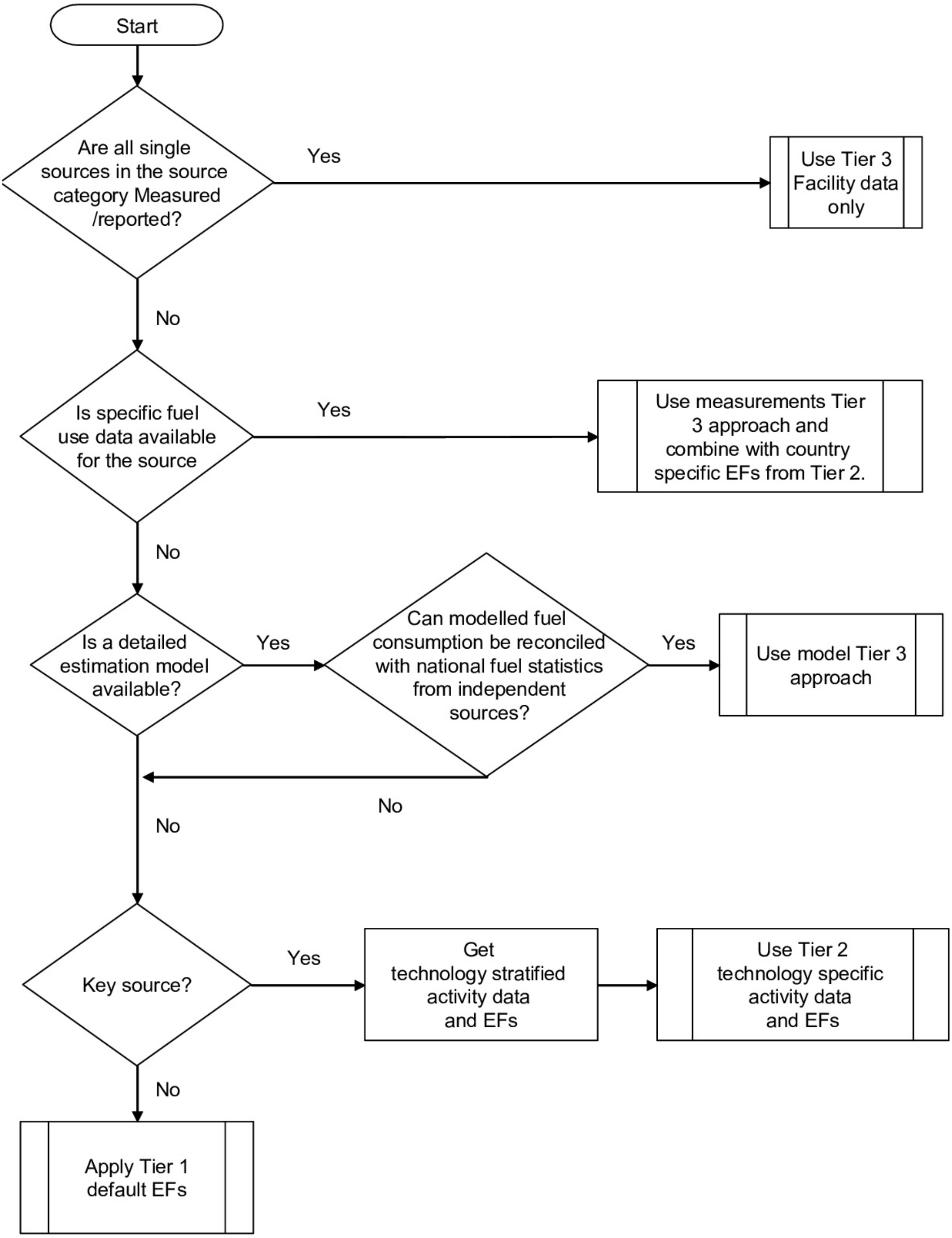


Figure 2.1: Emission Factor Tiers

As emission factors have inherent variability, the guidebook discusses tiered inventory approaches from simpler to complex modeling for completeness and accuracy (EEA/EMEP 2023). Figure 2.1 (EEA/EMEP 2023), delineates the tiered framework for categorizing emission factors and elucidates the selection criteria contingent on availability of ancillary data to compute cumulative emissions.

In (F. Liu et al. 2015a), strategies to estimate hazardous air pollutants from coal plants, underlining limitations around measurement data availability were reviewed. Advanced inventories also characterize uncertainty through statistical distribution functions, so, remote sensing data offers new means to develop or evaluate inventories (Guevara et al. 2023). (Xu et al. 2021), demonstrated a model fusing satellite observations and land-use information to construct high spatiotemporal resolution $PM_{2.5}$ concentration profiles. Such fusion can overcome ground monitoring limitations, validate emission inventories, and inform policy-making.

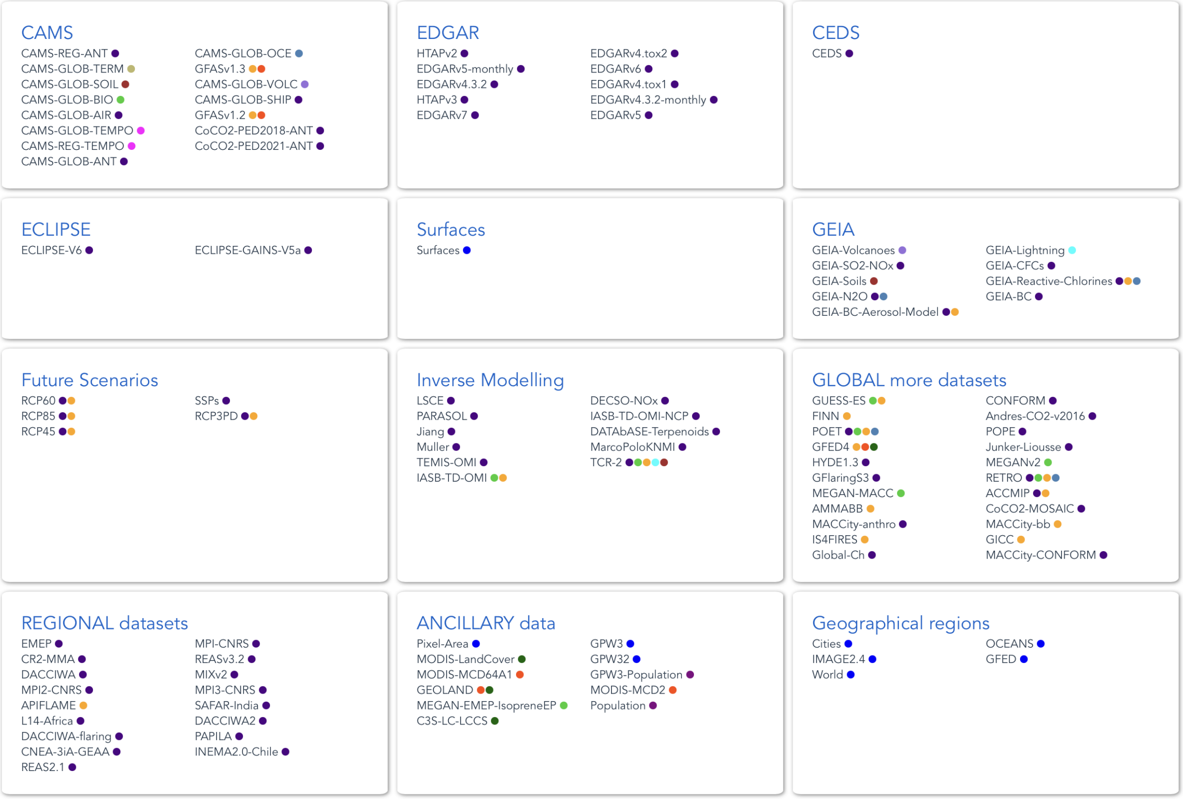
Overall, A combination of bottom-up inventory creation and validation of facility-level emissions is necessary for optimal spatial mapping. Recent researches like (Tong et al. 2018; F. Liu et al. 2015b; Oberschelp et al. 2019; Zhou et al. 2017) highlights the need for open access to plant-specific data on capacity, technology, controls, and fuel statistics to improve coal fleet inventories. Availability of validated, unit-level information promises to inform policy aligned with air quality goals through bench-marking, compliance tracking and auditing of coal power assets (Karplus et al. 2018; Tang et al. 2019).

2.3 Coal Power Plants Databases

Transparent, validated power plant data at unit level, forms the foundation for accurate, reproducible emission inventories. (Granier et al. 2018) in IGAC Newsletter, emphasized that open data access increases visibility of developer groups, enabling collaborative emission dataset usage and analysis. However, current global coal power-plant catalogs present limitations regarding data gaps and transparency.

CARMA (Carbon Monitoring for Action), used previously to represent plant locations in prominent inventories, excludes non-operating facilities. (Guevara et al. 2023), estimated coordinates can also be erroneous, with average displacements up to 79 km observed for Indian emitters. New plant additions across Asia also remain uncaptured. Besides incomplete capacity and technology details pose further constraints.

Developing open-access repositories, compiling validated unit details through regulatory reporting, surveys and licensing permits can bridge such data gaps. Figure 2.2 shows ECCAD (Emissions of atmospheric Compounds and Compilation of Ancillary Data) catalogue inventory interface, which interlinks extensive tabular/georeferenced emissions data inventories and analysis tools (Granier et al. 2018), facilitating harmonized comparisons, indicative of improved power sector analysis, supporting environmental goals. Fusing top-down observational constraints with collaborative bottom-up inventory creation practices can enhance realism and policy optimization.



CAMS

CAMS-REG-ANT ●
CAMS-GLOB-TERM ●
CAMS-GLOB-SOIL ●
CAMS-GLOB-BIO ●
CAMS-GLOB-AIR ●
CAMS-GLOB-TEMPO ●
CAMS-REG-TEMPO ●
CAMS-GLOB-ANT ●
CAMS-GLOB-OCE ●
GFASv1.3 ●●
CAMS-GLOB-VOLC ●
CAMS-GLOB-SHIP ●
GFASv1.2 ●●
CoCO2-PED2018-ANT ●
CoCO2-PED2021-ANT ●

EDGAR

HTAPv2 ●
EDGARv5-monthly ●
EDGARv4.3.2 ●
HTAPv3 ●
EDGARv7 ●
EDGARv4.tox2 ●
EDGARv6 ●
EDGARv4.tox1 ●
EDGARv4.3.2-monthly ●
EDGARv5 ●

CEDS

CEDS ●

ECLIPSE

ECLIPSE-V6 ●
ECLIPSE-GAINS-V5a ●

Surfaces

Surfaces ●

GEIA

GEIA-Volcanoes ●
GEIA-SO2-NOx ●
GEIA-Soils ●
GEIA-N2O ●●
GEIA-BC-Aerosol-Model ●●
GEIA-Lightning ●
GEIA-CFCs ●
GEIA-Reactive-Chlorines ●●●
GEIA-BC ●

Future Scenarios

RCP60 ●●
RCP85 ●●
RCP45 ●●
SSPs ●
RCP3PD ●●

Inverse Modelling

LSCE ●
PARASOL ●
Jiang ●
Muller ●
TEMIS-OMI ●
IASB-TD-OMI ●●
DECSO-NOx ●
IASB-TD-OMI-NCP ●
DATAbASE-Terpenoids ●
MarcoPoloKNMI ●
TCR-2 ●●●●●

GLOBAL more datasets

GUESS-ES ●●
FINN ●
POET ●●●●
GFED4 ●●●
HYDE1.3 ●
GFlaringS3 ●
MEGAN-MACC ●
AMMABB ●
MACCity-anthro ●
IS4FIRES ●
Global-Ch ●
CONFORM ●
Andres-CO2-v2016 ●
POPE ●
Junker-Liousse ●
MEGANv2 ●
RETRO ●●●●
ACCMIP ●●
CoCO2-MOSAIC ●
MACCity-bb ●
GICC ●
MACCity-CONFORM ●

REGIONAL datasets

EMEP ●
CR2-MMA ●
DACCIWA ●
MPI2-CNRS ●
APIFLAME ●
L14-Africa ●
DACCIWA-flaring ●
CNEA-3iA-GEAA ●
REAS2.1 ●
MPI-CNRS ●
REASv3.2 ●
MIXv2 ●
MPI3-CNRS ●
SAFAR-India ●
DACCIWA2 ●
PAPILA ●
INEMA2.0-Chile ●

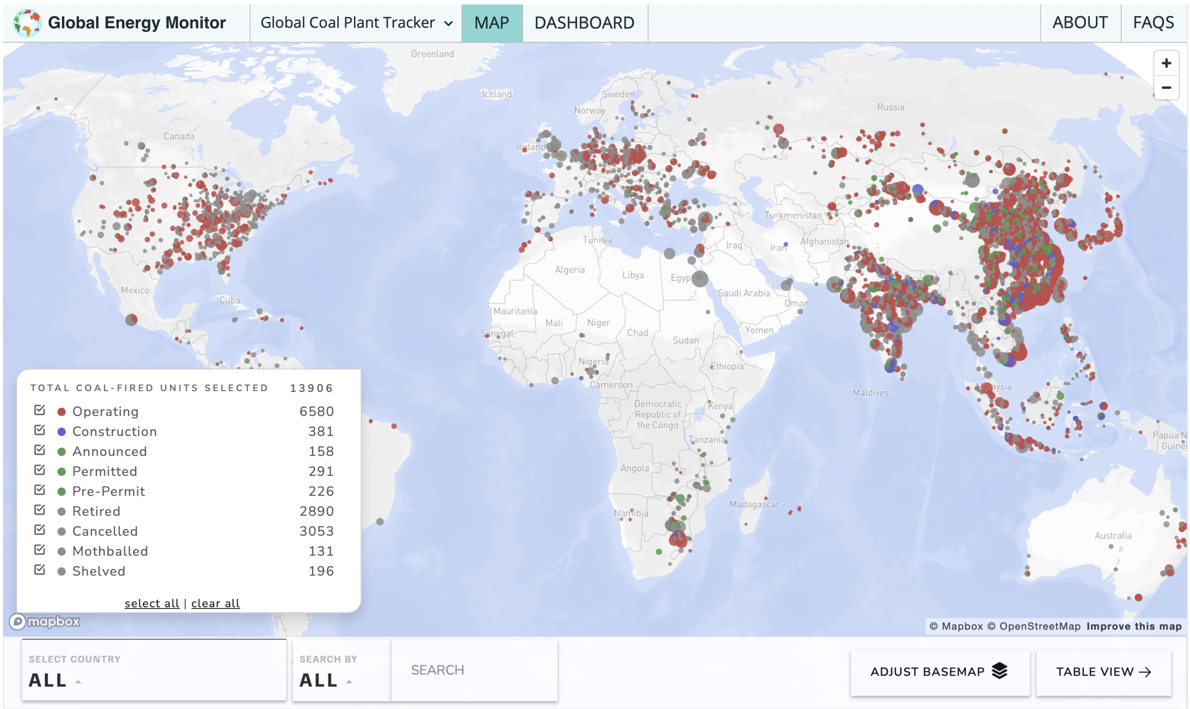
ANCILLARY data

Pixel-Area ●
MODIS-LandCover ●
MODIS-MCD64A1 ●
GEOLAND ●●
MEGAN-EMEP-IsopreneEP ●
C3S-LC-LCCS ●
GPW3 ●
GPW32 ●
GPW3-Population ●
MODIS-MCD2 ●
Population ●

Geographical regions

Cities ●
IMAGE2.4 ●
World ●
OCEANS ●
GFED ●

Figure 2.2: ECCAD Databases



TOTAL COAL-FIRED UNITS SELECTED	13906
☑ ● Operating	6580
☑ ● Construction	381
☑ ● Announced	158
☑ ● Permitted	291
☑ ● Pre-Permit	226
☑ ● Retired	2890
☑ ● Cancelled	3053
☑ ● Mothballed	131
☑ ● Shelved	196

select all | clear all

Figure 2.3: Global Coal Plant Tracker - Web Interface

Improvements in power plant inventories rely on comprehensive unit-level data with technological transparency. Recent efforts like the Global Coal Plant Tracker (GCPT) provided in figure 2.3 (*Tracker Map - Global Energy Monitor* 2024) has updated information on preconstruction, operating and retired units across regions. Developed by Global Energy Monitor (*Home - Global Energy Monitor* 2022), GCPT details individual boiler capacities, fuels, locations and technology deployment status . With 16000+ assets covered in 170+ countries and regular updates, it supports targeted emission reduction planning and policy.

U.S. Environmental Protection Agency's Emissions and Generation Resource Integrated Database (eGRID) is another example, compiling monitored American electricity, fuel and emissions data through continuous systems (US EPA, North-American 2021). This ensures current representation of the evolving power fleet and integration of renewable additions. eGRID thus aids regulatory analysis, allowing assessments of generation mix impacts on emissions. (Guevara et al. 2023) constructed under the Copernicus CO_2 Monitoring and Verification Support, the CoCO_2 point source catalog provides 2018 global power plant CO_2 and co-pollutant emissions at high spatiotemporal resolution. By combining reported energy statistics with unit-level combustion factors and technology penetration rates, CoCO_2 enables bottom-up emission inventory updates (Guevara et al. 2023). Its plant-specific temporal and vertical distribution profiles can inform atmospheric modelling.

The Enerdata Global Energy & CO_2 Database covers a wide array of energy-related topics, including energy supply and demand, electricity generation, renewable energy, energy prices, and CO_2 emissions (*ENERDATA* 2022). It provides detailed data on energy consumption by sector and source, as well as energy balances that offer a clear overview of energy flows from production to final consumption (*ENERDATA* 2022).

The Global Innovation and Development Institute's GID - Power Emission Database (GPED) integrates data across sources to map unit-level capacity age, technology trends and estimate multi-pollutant emissions from 1990-2020 globally (Qin et al. 2022; Tong et al. 2018). By incorporating satellite-validated locations, it supports rapid analysis of environmental goals. Extending the collaborative approach, ClimateTRACE aggregates surface, aerial and space-based sensors through AI to generate independent, daily CO_2 emissions quantification and interactive visualizations for global power infrastructure (Freeman et al. 2022). Regionally, gridded monitored particulate data and historic CO_2 emissions are integrated within India's CEA database to upgrade coal-fleet inventories with transparency (*Annual Report of CEA - Central Electricity Authority* 2023). Overall, unrestricted access and standardization of dynamic unit-level information on capacity, technology, fuels and emissions can catalyze iterative, multi-scale model refinements for the evolving power sector.

The efforts above demonstrate the value of collaborative data platforms in enabling power sector transparency. Integrating top-down observational constraints can further enhance inventory realism. Overall, open access unit-level details covering technology status, fuels, emissions and auxiliary factors support improved, rapid analysis for environmental goals.

2.4 Parameters for Emissions Projection

2.4.1 Data Transparency Needs

Despite extensive unit-level information encompassed in major power sector databases, unrestricted access and standardization remain lacking (Guevara et al. 2023) . Vast concealed details exist on core metrics like fuel characteristics, combustion modes, and control equipment (*Home - Global Energy Monitor* 2022). Such opacity constrains realistic, reproducible projections aligned to environmental targets (Guevara et al. 2023).

Recent emission transparency commitments by power generators indicate widening corporate recognition of collaborative data imperatives (Freeman et al. 2022). However, governmental mandates for unconstrained sharing of standardized dynamic details covering technology deployments and retrofits can catalyze extensive upgrades (Qin et al. 2022; Tong et al. 2018). Global decarbonization also necessitates unified missing data protocols using statistical, remote sensing and survey-based techniques (Guevara et al. 2023). Overall, open-sourced transparency of change-sensitive metrics can drive rapid analytical refinements.

2.4.2 Core Static Parameters

Fundamental facility details necessary for projection baselines include coordinates, distinct asset identifiers and technical capacities (Qin et al. 2022; Tong et al. 2018; *Home - Global Energy Monitor* 2022). Geospatial positioning ensures correct geographical allocation while inaccuracies from prior mapping approaches undermine local emission loads (Guevara et al. 2023).

Unique plant, unit and cluster designations also prevent misrepresentations within integrated datasets (US EPA, North-American 2021). Plant Name and net capacities help ascertain utilization levels during operations (Qin et al. 2022; Tong et al. 2018). Fuel and technology types determine applicable combustion parameters and removal efficiencies (Guevara et al. 2023). Table 2.1 from Multiple Databases enlists the parameters and their priorities. Together with locations, these foundation metrics establish the reference configurations for emission calculations.

Table 2.1: Basic Parameters (Database)

Key Parameters	**Priority Level**
Plant Name	High Priority
Net Capacities	High Priority
Fuel Type	Medium Priority
Longitude/Latitude	High Priority
Project ID	Low Priority

2.4.3 Dynamic Technology and Operations Data

Unlike intrinsic design details, dynamic technology, operations and fuel data require frequent updates for realistic projections (Guevara et al. 2023). New capacity additions, retrofits and retirements alter fleet-wide profiles continuously, necessitating sustained tracking (*Home - Global Energy Monitor* 2022). Temporal balancing of phase-ins, phase-outs and shifting utilization demands periodic validation of operational assumptions (Qin et al. 2022; Tong et al. 2018).

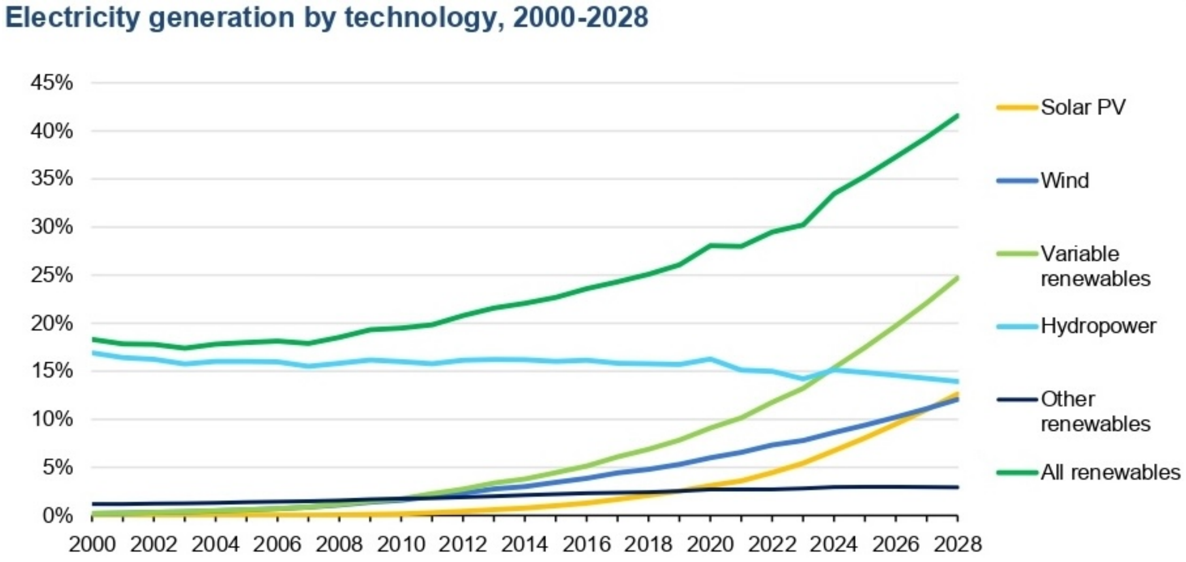


Figure 2.4: Energy Adaption (2008 - 2028)

Similarly, capital costs, energy investments, new equipment procurement and ancillary systems influence projections (Vrontisi et al. 2020). According to the figure 2.4 (IEA 2023), a distinct escalation is visible in Renewable adoption rates. Storage integration, automation upgrades and technology transfers alter facility-level emission factors (*Home - Global Energy Monitor* 2022). Regular calibration of such rapidly changing attributes via sharing recent survey, metering and licensing data hence boosts collective inventory refinement (Guevara et al. 2023).

2.5 Recent Coal Emissions Projections Studies

Recent studies projecting global coal emissions have yielded a wide range of potential future trajectories, largely due to differing assumptions about the stringency and effectiveness of air pollution control policies (Amann, Bertok, et al. 2011; Rafaj et al. 2013). In the absence of new control measures, some projections suggest that coal emissions could rebound after 2030, even if they decline in the near term (Amann, Kiesewetter, et al. 2020). This uncertain outlook can be understood in the context of the environmental Kuznets curve (EKC) hypothesis, which proposes an inverted U-shaped relationship between pollution and economic development (Grossman et al. 1995). However, empirical evidence for coal emissions provides only limited support for a universal EKC relationship (Rafaj et al. 2013). Instead, structural economic changes and targeted pollution control policies appear to be the primary drivers of emissions reductions, rather than income growth alone (Stern 2005). Consequently, dedicated policy interventions are likely to remain essential for reducing coal emissions in the future, as the EKC cannot be relied upon to automatically resolve the issue through economic development (Rafaj et al. 2013). A combination of technological improvements, transitions to cleaner energy sources, and robust air quality and climate policies will be necessary to ensure a long-term decline in coal emissions (Amann, Bertok, et al. 2011; Rafaj et al. 2013).

Building upon these insights, these literature (Chen et al. 2016; Zhang et al. 2021; Hirschhausen et al. 2020; The White House 2021; Burton et al. 2018; Jain et al. 2018) has delved into the specific challenges and opportunities for coal fleet transitions in the major coal utilizing countries - China, Germany, India, South Africa and United States - within national climate commitments, determining likely phaseout time frames and accompanying policies.

In China, (Chen et al. 2016) projected a combination of supercritical technology adoption, biomass blending and renewable displacement can collectively enable over 60% CO_2 reduction versus 2014 levels under moderate policy incentives by 2050. Long-term absolute decarbonization is however premised on commercialization and integration of carbon capture or storage innovations. (Zhang et al. 2021) determined 2060 as the economically optimal timeline for complete Chinese coal fleet retirement under moderate carbon pricing scenarios. The analysis highlights that near-term efficiency upgrades coupled with stable renewable growth can make graduation feasible, contingent on social security provisions for workforce transitions.

Germany legally enforces phase-out of all coal power without carbon capture by 2038, necessitating extensive early decommissioning of younger assets still within typical lifespan parameters (Hirschhausen et al. 2020). The legislation mandates intermediate targets before eventual ramp down. However, the phase-out pace needs accelerating for Paris-alignment. In the United States, under existing state-level commitments, (The White House 2021) found national coal capacity requires 87% reduction by 2030 for equitable phase-outs.

For emerging economies like South Africa and India, renewable adoption and old plant retirements face multiple barriers, including insufficient flexible modern capacity installations that can threaten grid reliability and stability (Burton et al. 2018; Jain et al. 2018). Both countries have situations of surplus yet financially ailing coal assets alongside electricity access shortfalls for lower-income consumers. As scenarios from (Burton et al. 2018; Jain et al. 2018) determined that premature closure of functioning capacity can sharply impact power availability amidst rising demands, transparent, planned coal transitions require synchronized renewable roll-outs with storage while re-purposing infrastructure for emerging load centers.

The studies also spotlight that early shutdowns often disproportionately impact poor, mining/worker communities relying on regional utilities (Burton et al. 2018; Jain et al. 2018). Hence, developing nations need to carefully balance coal phase-outs with accessible energy security through cross-subsidized tariff structures that eases equitable access. Targeted skill retraining, relocation stipends and seed investments into alternate sustainable livelihoods can further aid transition. Overall, country-specific cost buffers, execution capacity, demographic factors and cultural motivations govern complex retirement and transition road-maps requiring long-lead planning and support.

Such multidimensional, nationally-focused studies underscore the dependency on unit-level data that captures transition assumptions alongside technology, policy and cost drivers. Direct integration of observational constraints can refine outcomes. Overall, country-specific details are essential to phase down coal in sync with sustainable development priorities.

2.6 Thesis Statement

Coal combustion for power generation imposes immense global health burdens, accounting for over 40% of energy-related carbon emissions (IEA 2021) alongside substantial releases of sulfur and nitrogen oxides, and fine particulates linked to hundreds of thousands of premature deaths annually (Henneman et al. 2023). These impacts underscores coal's unique environmental emissions relative to other fossil fuels. Recent literature has called for accelerated retirement of unabated coal combustion in alignment with Paris climate goals (Chen et al. 2016; Zhou et al. 2017), necessitating extensive planning to balance grid stability, equitable energy access and workforce transition support. However, current long-term projections lack detailed representations of localized phase-out dynamics and infrastructure transitions for the evolving coal fleet.

This thesis develops high spatial resolution emissions projections for existing coal power generators in China, Germany, India, South Africa and the United States from 2025-2040. Detailed bottom-up projections of multi-pollutant trajectories under early retirement scenarios can delineate phase-down pathways consistent with air quality and 1.5°C climate policy ambitions. The analysis appraises unit-level retirement timelines, technology substitution risks, grid stability impacts and distributional consequences across affected communities. By exploring key regional tensions, findings aim to inform power systems planning towards managed coal transitions that synergies equitable, low-carbon energy access priorities. Overall, the projections provide a bridge from prevailing emissions baselines to mid-century goals.

3 Methodology

3.1 Software and Tools

3.1.1 Python

A variety of Python packages and libraries (*Python Package Index - PyPI* 2021) were leveraged to support the multi-faceted emissions analysis conducted in this research. The core methodology relied on Python for tasks ranging from data preprocessing to geographic analysis.

3.1.1.1 Packages

The data analysis and modeling code for this project was developed in Python version 3.11 (*Python Package Index - PyPI* 2021). Visual Studio (VS) Code (*Documentation for Visual Studio Code* 2021) is used as the main IDE to write and modify the code. Python was selected due to its specialized third-party libraries that enable complex climate modeling data workflows essential for scientifically rigorous emissions projections. While numerous programming language options exist for technical computing, Python provided an optimal balance of convenience, modification simplicity via its open source nature, and access to niche climate technology assessment capabilities through customizable packages. There are number of third party python packages used in this work, the ones that are standard for python development are listed here:

- Pandas (McKinney 2010) enabled loading the raw powerplant datasets from multiple formats such as CSV, XLSX and JSON. Once loaded, multi-index slicing, filtering, and transformations made it possible to wrangle the data into analysis-ready structures.

- geopandas (Jordahl et al. 2020) is with geographic data capabilities to pandas for working with geo-spatial data.

- matplotlib (Hunter 2007) is used to visualize and plot package to create publication-quality graphs and charts.

- numpy (Harris et al. 2020) for data representation and manipulation.

Operations like key data preparation tasks, including handling missing values, transforming data types, renaming variables, and filtering records by aggregation, were conducted using custom functions developed in the Powerplant Matching Tool (PPM) (Gotzens et al. 2019) Python package (Section 3.1.1.2). The PPM toolkit (Gotzens et al. 2019), created explicitly for this research, enabled programmatic consolidation of the multifaceted facility datasets into a unified emissions inventory foundation for subsequent modeling procedures.

3.1.1.2 Powerplant Matching Tool

A key preprocessing task involved combining numerous powerplant datasets from public and proprietary sources into a unified emissions inventory. To achieve this, the Powerplant Matching Tool (Gotzens et al. 2019) Python package was developed. This toolkit provided intersections and joins capabilities to merge records from multiple sources corresponding to the same facility. Custom functions compared plant characteristics such as fuel type, lat/long coordinates, electricity generation net capacities and dates of operation to algorithmically assess matches likelihood (Gotzens et al. 2019).

```python
                    #Global Coal Power Plant Database
def GCPT(raw=False, update=False, config=None):

    #filtering for required parameters
    config = get_config() if config is None else config
    #funtion to call for the raw database defined above
    fn = get_raw_file("GCPT", update=update, config=config)
    #Reading Excel database
    df = pd.read_excel(fn,sheet_name = "Units",header=[0],skiprows=[1])

    #filtering only power plants which are operational
    df = df[df['Status'] == 'operating']

    if raw:
        return df

    #Renaming variables according to required Emission Inventory
    RENAME_COLUMNS = {
        "Plant name": "Name",
        "Unit name": "Unit",
        "Country":"Country",
        "Subnational unit (province, state)":"Province",
        "Combustion technology": "Technology",
        "Fuel type": "Fueltype",
        "Coal type":"SubFueltype",
        "Capacity (MW)": "Capacity",
        "Latitude": "lat",
        "Longitude": "lon",
        "Start year": "DateIn",
        "Retired year": "DateOut",
        "GEM unit/phase ID": "projectID",
        "Annual CO2 (million tonnes / annum)": "CO2emissions",
        "Emission factor (kg of CO2 per TJ)":"EmissionFactorCO2",
        }
    df = (
        #renaming columns name according to RENAME_COLUMNS
        df.rename(columns=RENAME_COLUMNS)
        #Column name as the database acronyms
        .pipe(set_column_name, "GCPT")
        #filtering columns as per required parameters
        .pipe(config_filter, config)
        )
    return df
```

Listing 3.1: Python Code example of Global Coal Plant Tracker Database

The package also enabled projecting all merged plants to a common geographic coordinate reference system for consistent spatial analysis down the processing workflow. In the system architecture, Python enables ingesting varied powerplant datasets for standardization and merging. For example in the Listing 3.1, it exhibits the input specific code for Global Coal Plant Tracker inputs in Excel utilizing Pandas library (McKinney 2010) (Section 3.1.1.1). Hashtags provide the proper guidance for the Python code and functions used. This provides consistent Data Frame manipulation despite disparate raw storage.

3.1.1.3 Integrated Assessment Models (IAM's)

Integrated assessment models (IAMs) couple detailed energy system models with simplified representations of economic and climate systems to assess feasibility of climate goals (*Climate Analytics* 2018). IAMs applied in this research include both cost-optimal models that determine least-cost mitigation pathways and economic investments in energy sector along with constrained scenarios exploring accelerated transitions (*Climate Analytics* 2018). Numerous scenarios elaborated within this thesis to enable projections of emissions pathways, are enlisted below :

- **Business-as-Usual or Baseline** : The Baseline scenario serves as the core reference case reflecting projections of variables including population, economic growth, energy demand technologies, and emissions assuming the continuation of current trends and existing policy landscapes into the future over the modeling time horizon without additional climate mitigation efforts (*Climate Analytics* 2018).
- **Nationally Determined Contributions (NDC)**: The NDC scenario models the emissions outcomes of the Paris Agreement by incorporating the specific climate action pledges and timed targets communicated by individual signatory countries out to 2030 based on their unique national circumstances and capacities (*Climate Analytics* 2018).
- **1.5°C Scenarios**: The stringent 1.5°C mitigation scenarios model pathways to restrict future temperature rise to 1.5°C through rapid, global transformations requiring extensive decarbonization across all sectors. Scenarios also test sensitivity to uncertainties in technological advancement, fossil fuel availability outlooks, and economic evolution using stochastic modeling ensembles with varied seed input sets (*Climate Analytics* 2018).
- **2°C Scenarios**: The 2°C mitigation scenarios examine pathways to constrain global temperature rise to 2°C above pre-industrial levels through significant emissions reductions and societal transformations, though less stringent than the shifts required to reach 1.5°C. The 2°C scenario ensemble thus examines trajectories that are still highly ambitious historically, requiring profound changes to energy infrastructure deployment rates and capital allocation(*Climate Analytics* 2018).

3.1.2 QGIS

The data visualization and plotting powerplant coordinates for this thesis was carried out in QGIS-LTR (long term release) version 3.28 (QGIS Development Team 2023). It represents a free, open-source geographic information system leveraged to conduct spatial mapping and analyses of emissions distributions stemming from the powerplant inventory. Key attributes include native geospatial data representation, processing, and visualization capabilities as shown in 3.1 (QGIS Development Team 2023).

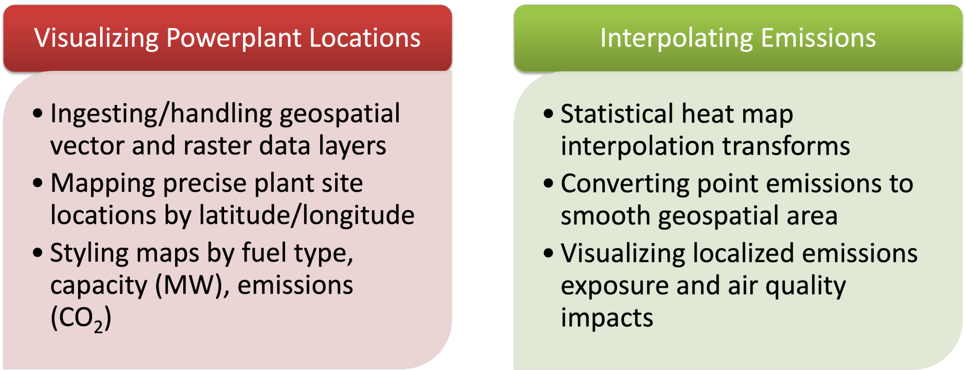


Figure 3.1: QGIS Features

3.1.3 Microsoft Excel

The emissions analysis leveraged Excel (Microsoft Corporation 2018) for centralized data organization, inventory compilation and integration across modules. Flexible workbook structures enabled multifaceted data consolidation capabilities tailored to methodological needs. In the figure 3.3 the work flow guides, from collating the emissions data to organizing Python outputs to feeding into QGIS for analysis.

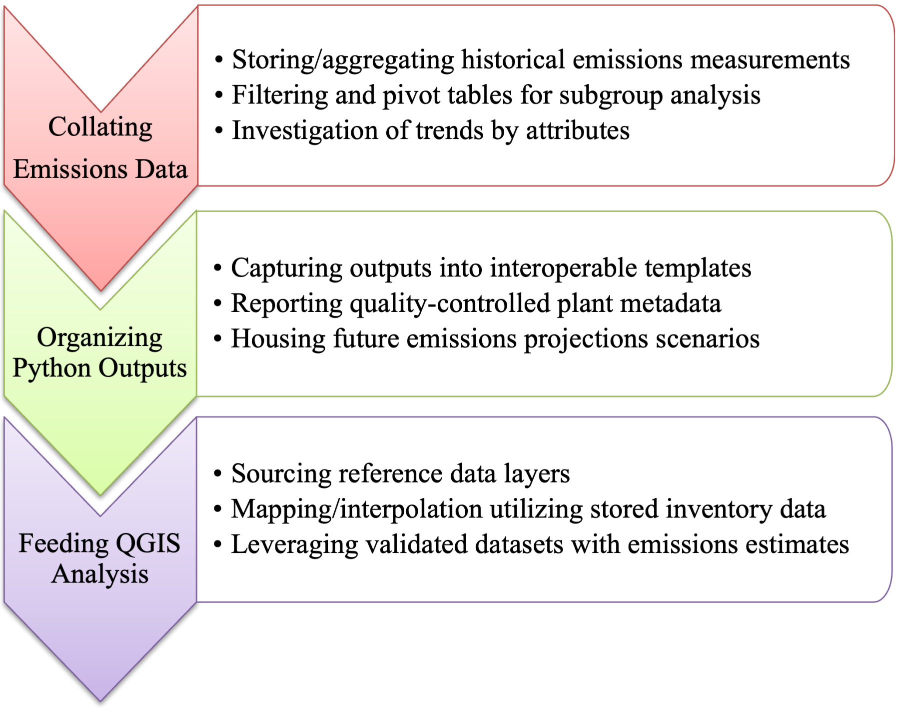


Figure 3.2: Work Flow

3.2 Data

3.2.1 Power-plants

Granular powerplant specifications provided the base data foundation, particularly plant name, generation capacity, fuel type, coordinates, technology classifications, along with plant activity for priority pollutants including (CO_2), (NO_x), (SO_2), and (PM) particulate matter. In the figure 3.3, these plant attributes were synthesized from the composite matching outputs of the Powerplant Matching Tool which consolidated information across public datasets along with proprietary sources. The aggregate emissions inventory established electricity sector profiles for the reference year 2023 across study countries.

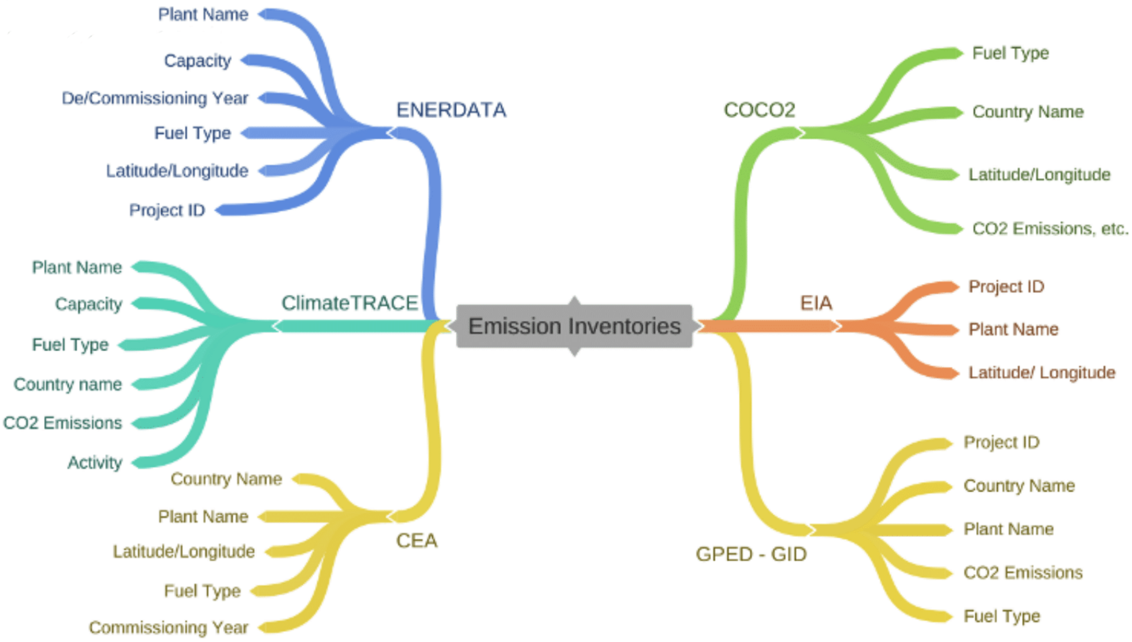


Figure 3.3: Various Power Plants Attributes Datasets

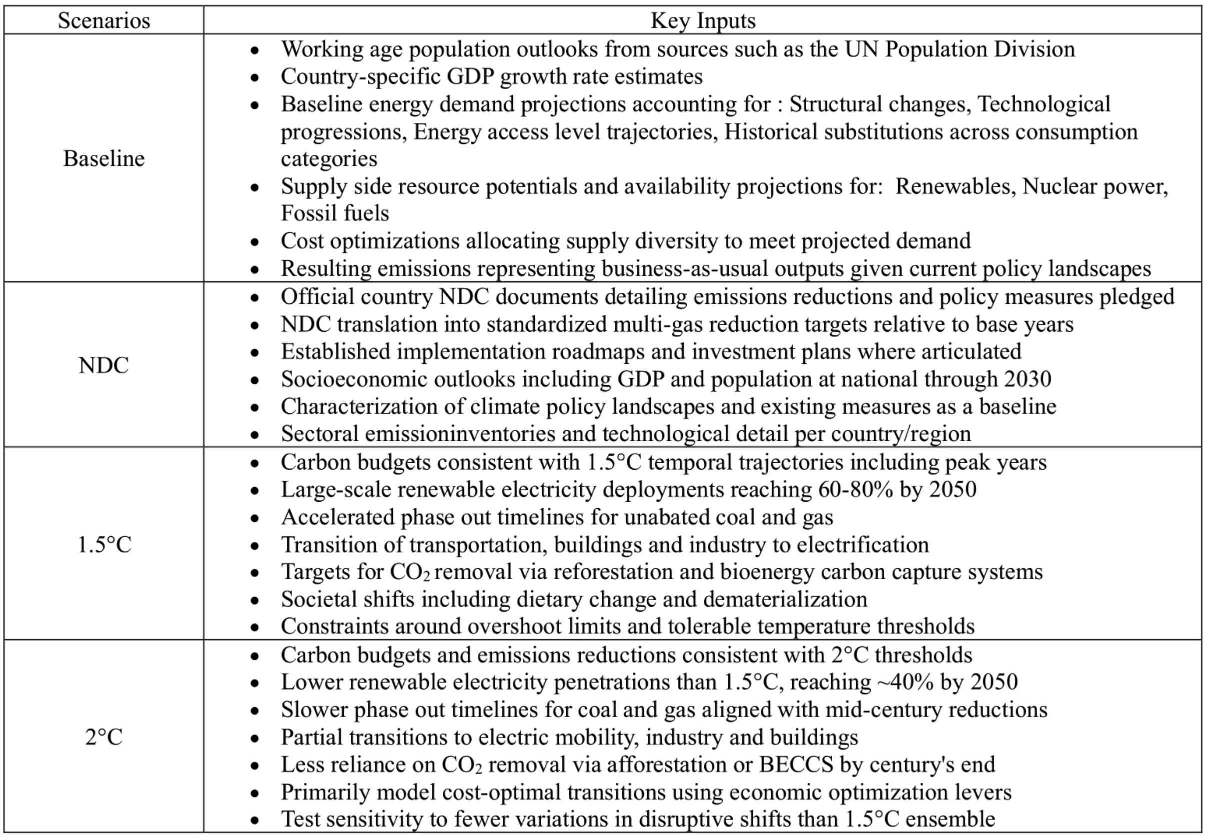
As in the section 2.3 discussed different powerplant database of GCPT, CoCO_2, GID-GPED, and ClimateTRACE. To enrich this collective, ENERDATA integrated to the given representation, as it collects annual electricity generation and capacity statistics for over 57 countries worldwide (*ENERDATA* 2022). Data is compiled from reliability score and best matching. Table 3.1, depicts the No. of coal power plants in each database.

Table 3.1: Database classification (Evaluated from Databases)

Database Name	**No. of Coal Power-plants**
GCPT	13786
CoCO_2	6256
GID-GPED	4710
ClimateTRACE	400 - 500
ENERDATA	6346

3.2.2 Emissions projections

Future emissions and technologies were projected through baseline, NDC, 1.5°C and 2°C scenarios from integrated assessment models (IAM's). As per the figure 3.4 (*Climate Analytics* 2018), The Baseline extrapolated population, GDP, and current energy policies. The NDC scenario translated climate pledges into emissions reductions by 2030. 1.5°C and 2°C scenarios applied carbon budget thresholds mandating renewable shares exceeding 60% and coal phaseouts accelerating through mid-century.



Scenarios	Key Inputs
Baseline	• Working age population outlooks from sources such as the UN Population Division • Country-specific GDP growth rate estimates • Baseline energy demand projections accounting for : Structural changes, Technological progressions, Energy access level trajectories, Historical substitutions across consumption categories • Supply side resource potentials and availability projections for: Renewables, Nuclear power, Fossil fuels • Cost optimizations allocating supply diversity to meet projected demand • Resulting emissions representing business-as-usual outputs given current policy landscapes
NDC	• Official country NDC documents detailing emissions reductions and policy measures pledged • NDC translation into standardized multi-gas reduction targets relative to base years • Established implementation roadmaps and investment plans where articulated • Socioeconomic outlooks including GDP and population at national through 2030 • Characterization of climate policy landscapes and existing measures as a baseline • Sectoral emissioninventories and technological detail per country/region
1.5°C	• Carbon budgets consistent with 1.5°C temporal trajectories including peak years • Large-scale renewable electricity deployments reaching 60-80% by 2050 • Accelerated phase out timelines for unabated coal and gas • Transition of transportation, buildings and industry to electrification • Targets for CO_2 removal via reforestation and bioenergy carbon capture systems • Societal shifts including dietary change and dematerialization • Constraints around overshoot limits and tolerable temperature thresholds
2°C	• Carbon budgets and emissions reductions consistent with 2°C thresholds • Lower renewable electricity penetrations than 1.5°C, reaching ~40% by 2050 • Slower phase out timelines for coal and gas aligned with mid-century reductions • Partial transitions to electric mobility, industry and buildings • Less reliance on CO_2 removal via afforestation or BECCS by century's end • Primarily model cost-optimal transitions using economic optimization levers • Test sensitivity to fewer variations in disruptive shifts than 1.5°C ensemble

Figure 3.4: Modelling Key Inputs

Key dimensions explored included fuel consumption, pollutant removal, and societal uncertainty constraints. The multivariate scenarios facilitate stress testing mitigate responses across economy-wide emissions, granular power substitutions, and policy sensitivities. Risk quantification enables targeting balanced interventions. Emission projections estimate potential future emission levels based on expected economic activities, energy use, technological developments, and policy impacts (EEA/EMEP 2023). Developing realistic emission trajectories is important for air quality management and tracking progress towards emission reduction commitments.

Projecting future emissions and air quality trends requires bringing together data and models across economic, energy, transportation, industrial, agricultural, and regulatory dimensions (EEA/EMEP 2023). Future emissions trajectories relied extensively on scenario outputs of Integrated Assessment Models (IAMs) with varied conceptual structures.

(Diemer et al. 2019) provided an overview of six major integrated assessment models (IAMs) for analyzing the linkages between energy, climate, and economics – World 3, DICE, MESSAGE, IMAGE, GEM-E3, and REMIND. It discusses how these models integrate different components into a common framework to assess climate impacts, mitigation pathways, and policy options. Key features like the core methodology, scale, dynamics, scenarios, and applications are compared across the models (Diemer et al. 2019). Challenges around expectations, financial sector representation, and technology detail are highlighted (Diemer et al. 2019). Overall, the review shows how IAMs have evolved from early system dynamics models like World 3 towards economy-energy-climate optimization frameworks (Diemer et al. 2019), yielding important insights for sustainable development planning despite limitations in fully capturing system complexities. The modular and collaborative nature of IAMs is identified as a strength for progressive model expansion and stakeholder engagement (Diemer et al. 2019).

As discussed in Section 3.1.1.3, future emission trajectories are commonly represented through alternate scenarios such as business-as-usual, emissions control legislation, accelerated technology adoption, sector investments and etc (EEA/EMEP 2023). The baseline scenario represents the case where only currently implemented legislation and policies continue without additional efforts (EEA/EMEP 2023). More ambitious control scenarios aim for cleaner technology shift and industrial modernization. Comparing such alternate futures provides insights into national priorities and pollution reduction potentials (EEA/EMEP 2023).

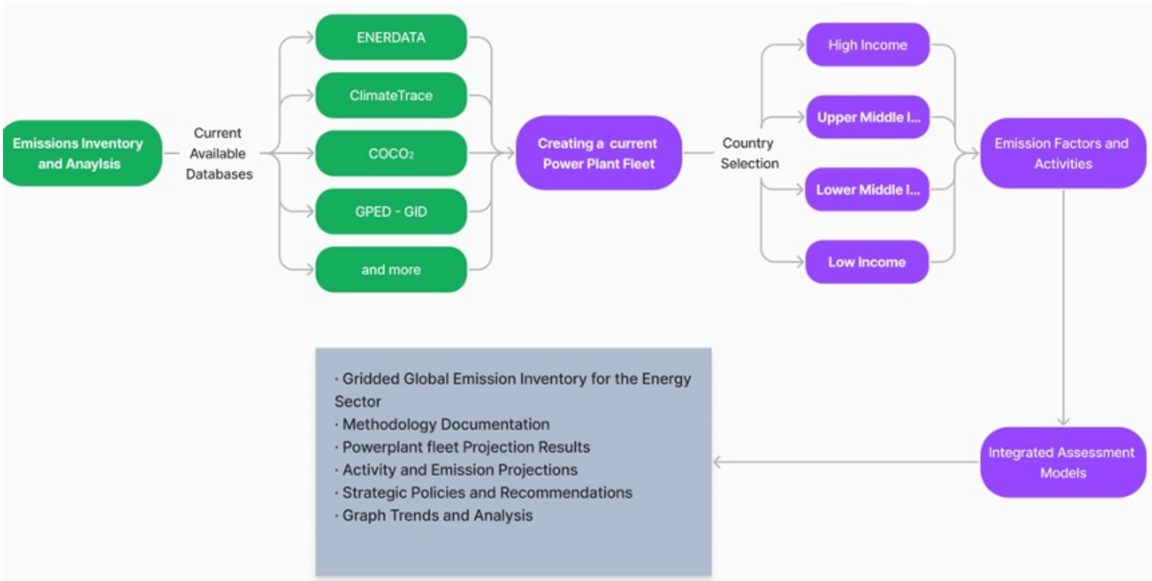
(O'Neill et al. 2014) coordinated by the International Institute for Applied Systems Analysis (IIASA), the Modeling groups operating top IAM frameworks including :

- AIM/CGE (Fujimori et al. 2017),
- GCAM (Wise et al. 2019),
- IMAGE (Stehfest et al. 2014),
- MESSAGEix-GLOBIOM (Fricko et al. 2017),
- REMIND-MAgPIE (Luderer et al. 2015),
- WITCH (Emmerling et al. 2016) and etc.

contributed Tier 1 results to the underlying multiple scenario ensemble within the Scenario Model Inter-comparison Project. Once established, the projections allow setting emission reduction targets, tracking progress, and strengthening policies if the desired trajectory is not achieved (EEA/EMEP 2023). Emission projections thus serve both as a benchmark for the future as well as a bridge between economic planning and environmental sustainability (EEA/EMEP 2023). Periodic updates incorporating the latest technical, regulatory and socio-economic data can enhance the accuracy and credibility of the projected emission trends (EEA/EMEP 2023).

3.3 Analysis Workflow

Multiple software tool-sets were leveraged for data flow across core analysis tasks (3.5). Python facilitated data standardization alongside inventory simulations while QGIS enabled critical geospatial examination.



- Gridded Global Emission Inventory for the Energy Sector
- Methodology Documentation
- Powerplant fleet Projection Results
- Activity and Emission Projections
- Strategic Policies and Recommendations
- Graph Trends and Analysis

Figure 3.5: Workflow

3.3.1 Data Preparation

Raw facility source data from over different powerplant databases enlisted in 3.1, underwent extensive rigorous scan and match through the Powerplant Matching Tool package.

```
# In PPM Tool file -> cleaning.py
def mode(x):
""" Get the most common value of a series """
return x.mode(dropna=False).at[0]
AGGREGATION_FUNCTIONS = {
    "Name": mode,
    "Fueltype": mode,
    "Unit": mode, "Set": mode,
    "Technology": mode,
    "Activity": set,
    "CO2emissions": mode,
    "Country": mode,
    "Capacity": mode,    #"mode" to evaluste values individual
    "lat": "mean",
    "lon": "mean",
    "DateIn": "min",
    "DateOut": "min",
    "projectID": set,
    }
```

Listing 3.2: Python code for sorting factors

GIS shape-files, Excel, along with proprietary formats were consolidated into process-ready structured tables. This involved rectifying diverse naming conventions, fuel type mappings, technology classifications, locating coordinates, and emission projections based on the aggregating function provided into the PPM Tool, as sample show below in Section 3.3.1. Resulting plant rosters at national through site-specific granularity feed subsequent phases as shown in Listing 3.3.1 below. The data preparation phase necessitated the computation of emissions levels by appropriate selection of emission factors, the methodology for which stands delineated in Section 2.1. The ultimate compiled set of preferred emission factors utilized within this thesis, differentiated based on researched national relevance, has been tabulated under Table 3.2. Specifically, the GAINS Asia dataset (Amann, Bertok, et al. 2011) proffered suitable values for application toward powerplant inventories across China along with India, whereas the GAINS Europe reference provided analogous figures corresponding to the geographic context of Germany (Amann, Bertok, et al. 2011). Alternatively, the Tier 2 (R. Gómez et al. 2006) standard emissions factor reference from the Intergovernmental Panel on Climate Change proved most pertinent for adoption considering the cases of the United States as well as South Africa - given lack of coverage present within the GAINS model in this category of country grouping (Amann, Bertok, et al. 2011).

Table 3.2: Emission Factor Selection 1.(Amann, Bertok, et al. 2011) 2.(R. Gómez et al. 2006)

Country	**Emission Factor**
China	country-specific^1
Germany	country-specific^1
India	country-specific^1
South Africa	fuel-specific^2
United States	fuel-specific^2

Through derivation by this structured hierarchical prioritization paradigm for factor selection, optimized accuracy and relevance gets infused into the emissions calculations scaffolding analysis. Salient pollutant emissions computations in 3.1 below, where $\mathrm{E_n}$ is the Emissions calculated for the year n, A is the Activity in the database, $\mathrm{EF_s}$ is the appropriate specific Emission Factor of the species s. have adopted the reference EMEP/EEA methodological equation transforming site-level activity data into emissions - enabling coherent modeled inventories supporting exploratory research interactions projecting atmosphere pollution referenced in Annex 7.1.

$$E_{\mathrm{n}} = A * EF_{\mathrm{s}} \tag{3.1}$$

The present work has adopted standard emissions factor methodological conventions as discussed above in Table 3.2, during constituent data preparation phases supporting greenhouse gas and air pollutant inventory compilation for Feeding into QGIS Analysis as per the work flows. As enumerated in Table 3.3, the precise subset of modeled gas species and particulates consists of carbon dioxide (CO_2), carbon monoxide (CO), sulfur dioxide (SO_2), nitrous oxides (NO_x), suspended fine particulate matter ($\mathrm{PM}_{2.5}$), coarse particulate matter (PM_{10}), particulate matter - Black Carbon (BC), and Volatile Organic Compunds (VOC) selected due to recognized dominance alongside wider availability of historical monitoring data at unit-level facility enabling robust bottom-up accounting scalable across localized through national levels requisite for multi-scope projection scenarios modeled. Standardization of constituent pollutant and gas variables proves essential for methodological consistency and comparability of computed emissions rates and associated climate impacts between geographic regions and across temporally dynamic projection horizons.

Table 3.3: Emissions (Inventory Compilation)

Greenhouse Gases	**Air Pollutants**
CO_2	CO
	SO_2
	NO_x
	$\mathrm{PM}_{2.5}$
	PM_{10}
	PM - Black Carbon
	VOC

3.3.2 Inventory

Annual historical emissions factors measurements have been compiled within a structured Excel computational workspace corresponding to (CO_2),(CO), (SO_2), (NO_x), ($\mathrm{PM}_{2.5}$), (PM_{10}), (BC), and (VOC) – as quantified via site-level monitoring instrumentation sensor data on a per annum basis per enlisted facility within scope boundaries. Python scripts conduct cleansing and aggregation preprocessing, as delineated in Code Listing 3.3.1, to produce consolidated country-differentiated emissions inventories – structured repositories constituting the xenith outputs scaffolding this thesis' modeling and simulation-centered analytical pursuits. Supplementary inventory parameters encompassing removal technology abatement classifications alongside compiled emission factors plus calculated emissions rates corresponding to all substances itemized within Table 3.3 undergo merging subsequently, thereby finalizing emission inventory assembly procedures.

According to the (EEA/EMEP 2023) Guidebook on Air Pollutant Emission Inventory 2019, energy industries including power plants burning fossil fuels are major contributors to air pollutant emissions.

Carbon Monoxide (CO): (CO) appears as an intermediate product of the combustion process, especially under sub-stoichiometric or poor combustion conditions. While (CO) emissions are lower compared to (CO_2) emissions from combustion plants, substantial (CO) emissions can still occur when combustion conditions are not properly controlled or optimized (EEA/EMEP 2023).

Sulfur Oxides (SO_x): In the absence of flue gas desulfurization (FGD) systems, (SO_x) emissions are directly related to the sulfur content of the fuel, with (SO_2) accounting for the majority of (SO_2) emissions. Small proportions of (SO_3) are also formed. Coal and oil fuels have higher sulfur contents and thus higher (SO_x) emission potential compared to natural gas (EEA/EMEP 2023).

Nitrogen Oxides (NO_x): NOx emissions, including nitric oxide (NO) and nitrogen dioxide (NO_2), arise from both nitrogen present in the fuel source as well as high temperature reaction between atmospheric nitrogen and oxygen during the combustion process. Combustion modifications, such as low-NOx burners, and post-combustion cleanup controls like selective catalytic reduction (SCR) are techniques that can minimize NOx emissions (EEA/EMEP 2023).

Non-Methane Volatile Organic Compounds ($NMVOCs$): Incomplete or imperfect combustion leads to emissions of NMVOCs like olefins, aldehydes and some unburnt fuel compounds like ethane. Large combustion plants tend to have lower NMVOC emission factors per unit energy input. VOC emissions including NMVOCs thus tend to decrease as plant capacity and thus combustion efficiency increases (EEA/EMEP 2023; Rentz et al. 1993).

Particulate Matter (PM) Emissions : The ash content and other solid residues present in fuels, especially coal, leads to particulate matter emissions including fly ash and bottom ash. PM emissions can be mitigated by particulate controls like fabric filters and electrostatic precipitators. Measurement and reporting of PM should account for both filterable and condensable PM fractions (EEA/EMEP 2023).

Black Carbon (BC) Emissions : BC emissions primarily result from incomplete combustion and are assumed to be equivalent to emissions of elemental carbon (EC). BC is a component of particulate matter emissions and thus the PM control techniques also reduce BC emissions proportionally (EEA/EMEP 2023).

The ultimate collated emissions database encoded in Excel format stands adequately equipped to serve as reference input source proffering geospatial emissions distribution layers for mapping tasks via the QGIS application module. Integrated assessment model results, as elaborated in Section 3.1.1.3, have generated multidimensional emissions projections across future scenarios for constituent power plants within the compiled baseline inventory. With cases tailored spanning policy, socioeconomic and technological uncertainties, outputs deliver streamlined inventory datasets mapping one-to-one with historical units across horizons through 2040. These structured model-derived future trajectories for facility ensembles, localized through economy-wide, stand equipped to inform downstream climate scoring plus impact assessments (7.3).

3.3.3 Modeling

In resonance with prior discourse presented in Section 3.1.1.3, elucidating myriad scenarios formulated to guide future emissions projections workflows alongside modeled ensemble variants across which individual scenarios stand parameterized, the current sub-section enumerates precise integrated assessment models leveraged toward country-specific projections objectives. In the (EEA/EMEP 2023) guidebook, Projecting Future Activity Based on Grade Levels section outlines good practices and steps involved in developing robust national-level emission projections. Three main grade levels are described for projecting future emissions – Grade 1, Grade 2, and Grade 3 shown in figure 3.6 (EEA/EMEP 2023). The grade level reflects the complexity and country-specificity of the methodology.

According to the EMEP/EEA Projection guidelines :

- Grade 1 projections are simplest using linear extrapolation.
- Grade 2 involves breaking down the source into sub sectors and estimating how emission controls will penetrate into the future.
- Grade 3 utilizes in-depth country-specific simulation models spanning the entire economic-emission landscape to provide "bottom-up" emission estimates.

Higher grade levels require more data, expertise and analysis but provide a more realistic picture of how emissions may evolve based on economic projections, policy impacts, and technological transformations over time. The grade utilized depends on national priorities and capacities (EEA/EMEP 2023).

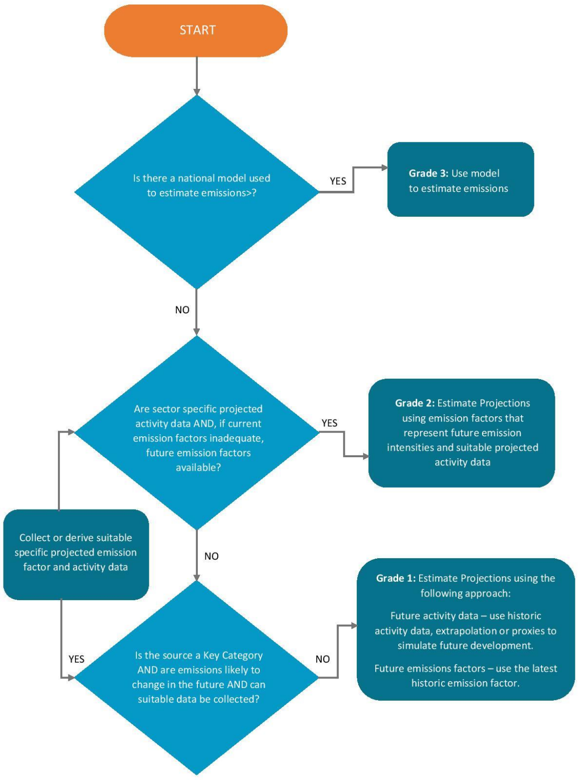


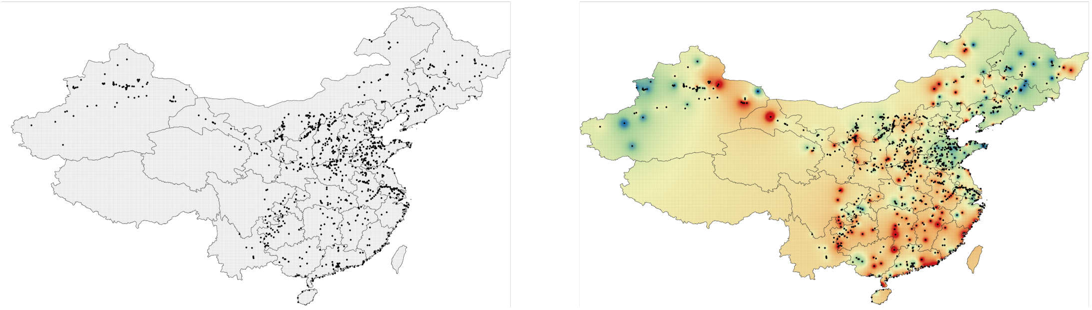
Figure 3.6: Approach for developing emission projection

Modeling emphasizes using historical inventory data as the starting point to ensure consistency (EEA/EMEP 2023). Formalizing periodic review processes with inventory teams can facilitate regular projection updates (EEA/EMEP 2023). Country-specific activity data from fields like energy planning offers greater relevance than international datasets (EEA/EMEP 2023). Projections necessitate assumptions regarding economic growth, technology evolution, infrastructure development etc. (EEA/EMEP 2023). It is critical to transparently document these in accompanying reports (EEA/EMEP 2023). Specifically, Section 3.2.2 notes foundational details regarding models encompassed within the umbrella emissions projections, with list in table 3.4 itemization presented herewith constitutes the definitive roster of models along with associated country linkages applied within the methodological schema of this thesis for future inventory compilation purposes aiding climate analytics.

Table 3.4: IAM Models (Relevant Rankings)

Countries	**Models**
China	IMAGE AIM/CGE MESSAGEix-GLOBIOM
Germany	REMIND-MAgPIE IMAGE WITCH
India	AIM/CGE IMAGE MESSAGEix-GLOBIOM
South Africa	IMAGE MESSAGEix-GLOBIOM WITCH
United States	GCAM IMAGE REMIND-MAgPIE

3.3.4 Spatial Mapping



a) Normal Mapping b) Spatial Mapping

Figure 3.7: QGIS Mapping for CO_2 Emissions

Geo-spatial representations and interpolations in figure 3.7 provide localized emissions exposure context. Interpolation feature converts plant greenhouse gas and other pollutant measurements into smooth coverage reflecting relative emissions for spatial variability and risk assessments.

3.3.5 Scenario Iteration

Configurable automation scenarios facilitates re-running integrated inventory, modeling and visualization pipelines for scientifically rigorous sensitivity analysis across exogenous forcing vectors and uncertainties ranges. As depicted within Figure 3.8, initial iterations encompassing the all the IAMs for that specific emission which contributed substantial result deviations - hence necessitating narrowed model sets to constrain variability.

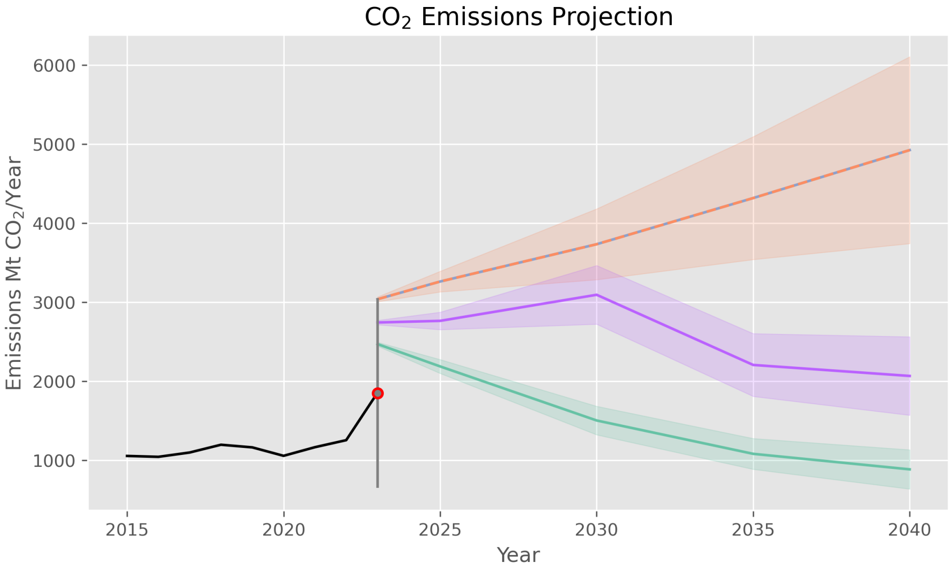


Figure 3.8: Initial Iteration of IAM Models

Final Iterations in the figure 3.9 leveraging the top 3 models with minimized variability factors ultimately provided enhanced consistency - giving rise to tightened scenario ranges bolstering reliability and policy applicability.

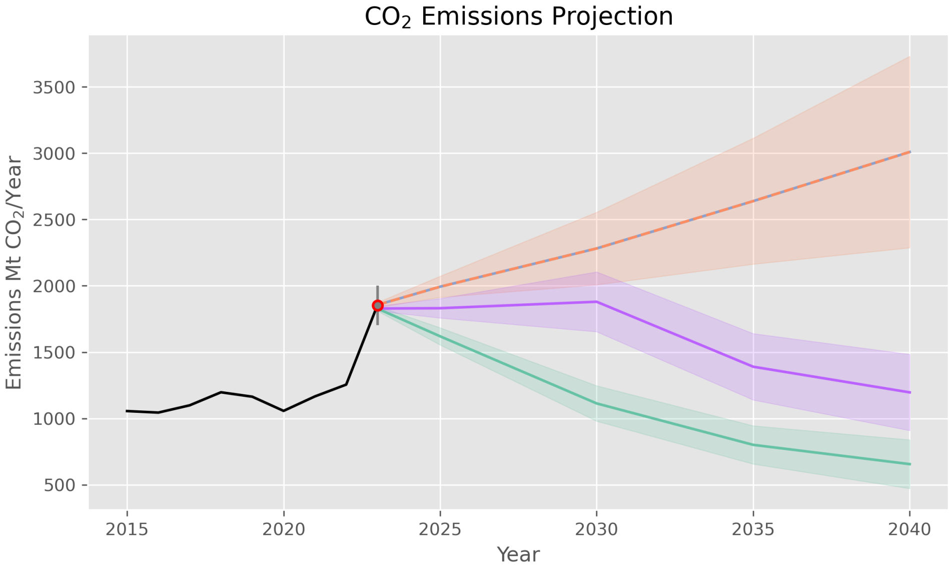


Figure 3.9: Final Iteration of IAM Models

4 Results

This section presents the findings from the inventory and projections of greenhouse gas and air pollutant emissions from coal power plants across 5 major countries. Using comparative analysis methodology, the study highlights significant current and future trends and country-specific outcomes related to coal-based emissions trajectories. Data synthesis integrated assessments model outputs which consists policy landscape analysis, and current technology assessment for emissions controls.

4.1 Current Emissions Trends

Compiled annual emissions inventory encompassing 4700+ power-plants across study geographies provides base historical context on emission outputs. Emissions were analyzed based on the discussed methodology in section 3.3.1 which correspond to the reference year 2023, with species including (CO_2), (CO), (VOC), (NO_x), (SO_2), $(\text{PM}_{2.5})$, (PM_{10}), (PM - Black Carbon). Country wise (CO_2) and other air pollutants emission inventories were compiled aligned to the baseline Paris Agreement year of 2015 for comparison with the 2023 reference data inventory compiled in this research. Over the 8-year interim period, divergent national trajectories emerged tied to varied energy infrastructure and decarbonization policy landscapes.

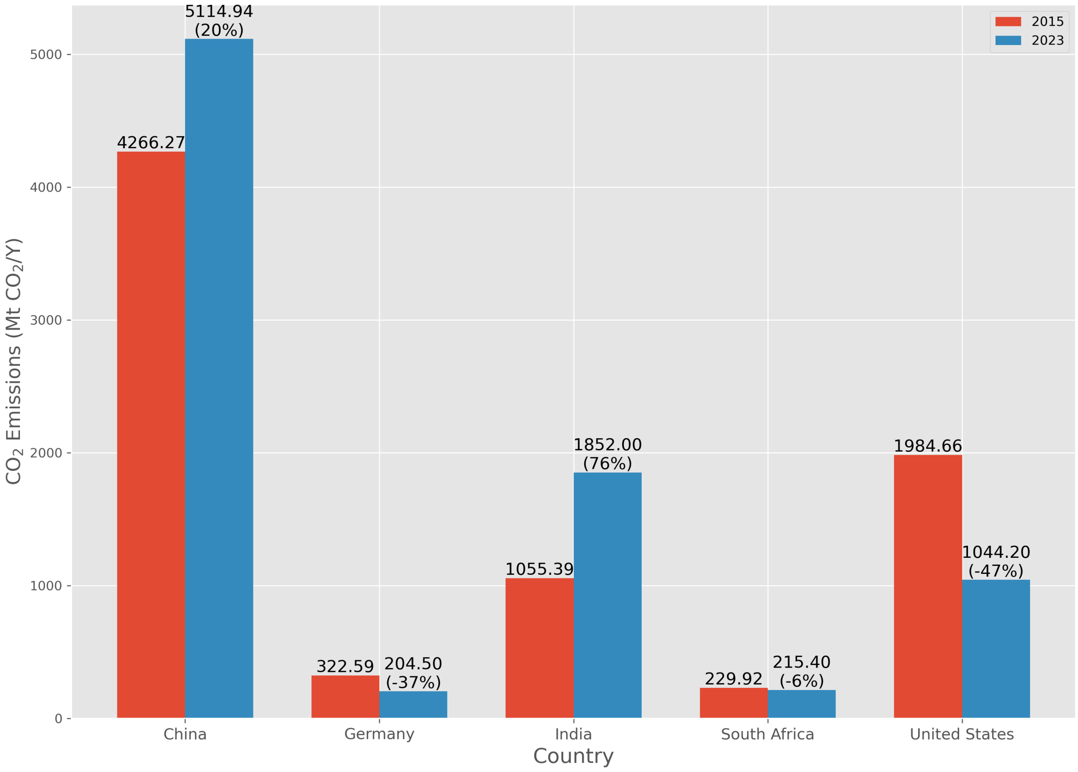


Figure 4.1: Relative Change in (CO_2) Emissions - 2015 vs 2023

Carbon Dioxide (CO_2): As Figure 4.1 indicates, China's carbon dioxide emissions have risen by 20% from 2015 to 2023, reflecting expanding industrialization and energy consumption. Germany exhibits a 37% reduction possibly attributable to a strategic transition toward renewable energy utilization. India's 76% escalation in emissions signifies rapid industrial and economic growth. South Africa displays a minor 6% dip, while the United States demonstrates a substantial 47% decrease, potentially resultant of decarbonization efforts across the energy sector.

Carbon Monoxide (CO): The dataset reveals a marginal 2% decline in China's carbon monoxide emissions, as shown in Figure 7.9. Germany exhibits an 82% plunge, indicating robust pollution control mechanisms. With a 39% drop, India has achieved appreciable reductions, signifying concerted mitigation actions. Conversely, South Africa denotes a concerning surge from 0.03 Mt to 0.25 Mt in carbon monoxide-generating processes. A notable 89% fall in the United States potentially reflects improvements in fuel economy and technological standards.

Sulfur Dioxide (SO_2): Figure 7.10 depicts that China's sulfur dioxide emissions have risen sharply by 5 times the value recorded in 2015, reflecting challenges in reducing high-sulfur fuel utilization. Germany's 17% drop signifies effective sulfur control strategies. India's emissions have climbed 24% likely tied to its coal-dependent energy paradigm. South Africa displays a 38% increase, pointing to a need for concerted mitigation efforts. The United States shows a considerable surge by double the recorded value in 2015, warranting targeted policy interventions.

Nitrogen Oxide - (NO_x) : From 2015 to 2023 in Figure 7.11, China has witnessed a significant 31% ascent in nitrogen oxide emissions, underlining the need for robust amelioration policies. Germany exhibits a minor 28% increase potentially indicating industry and transportation linked factors. India has accomplished a 36% plunge, suggesting impact pollution control actions. South Africa denotes a 52% dip, indicating constructive regulatory and technical progress. The 29% fall observed in the United States can potentially be ascribed to technological and policy-level advancements around mitigation.

Volatile Organic Compounds (VOC): Figure 7.12, illuminates both environmental policy successes and enduring challenges. China has witnessed a dramatic surge in VOC emissions, escalating from 0.16 Mt to 0.75 Mt, reflecting industrial expansion without commensurate pollution controls. Conversely, Germany has accomplished a sizable 90% plunge, decreasing from 0.03 Mt to 0.003 Mt, signifying impact environmental regulation. India displays a mount climb rising from 0.07 Mt to 0.28 Mt, indicating a need for enhanced industrial solvent and fuel emissions management. South Africa exhibits a 66% fall, while the United States has attained an 84% dip potentially due to stringent mitigation policy implementation.

Particulate Matter (PM_{10}): Analysis of (PM_{10}) emissions in the Figure 7.14, reveals variability across nations, symptomatic of diverse environmental and industrial realities. China denotes an exponential rise in (PM_{10}) emissions growth from 0.62 to 8.25 Mt, raising concerns regarding dust and particulate pollution. Germany displays an ascend surge from 0.015 Mt to 1.271 Mt, underscoring industrial coarse particulate sources management needs. India's (PM_{10}) emissions increment from 2.016 Mt to 7.305 Mt reflects ongoing construction and industrial dust mitigation challenges. In contrast, South Africa accomplished an 86% (PM_{10}) emissions dip from 0.125 Mt to 0.018 Mt through effective dust control. Similarly, the United States attained a 73% (PM_{10}) reduction from 0.32 Mt to 0.086 Mt, exemplifying impactful strategies targeting particulate pollution.

Particulate Matter ($PM_{2.5}$): Figure 7.13, indicates the relative change of ($PM_{2.5}$) over 2015 and 2023. China exhibits an exponential ($PM_{2.5}$) emissions rise from 0.11 Mt to 3.59 Mt, raising concerns regarding public health protections. Germany saw a scale increase from 0.008 Mt to 0.375 Mt, highlighting emerging fine particulate sources oversight needs. India displays an 84% climb in ($PM_{2.5}$) emissions from 1.356 Mt to 2.496 Mt, reflective of persisting urban air quality challenges. In contrast, South Africa achieved an 87% ($PM_{2.5}$) emission dip from 0.068 Mt to 0.009 Mt, signifying policy successes. The United States accomplished an 81% plunge from 0.191 Mt to 0.036 Mt, demonstrating impactful strategies diminishing exposures to fine particulate matter.

Particulate Matter - Black Carbon (BC): Black carbon (BC) emissions in the figure 7.15, indicates profound shifts globally, shedding light on variegated policy and industrial impacts. China exhibits an exponential rise from 4.85 kt to 334.92 kt, an approximate skyrocketing surge, emphasizing the need for stringent air pollution control. Germany accomplished a momentous 95% (BC) emission dip from 0.50 kt to 0.025 kt, exemplifying efficacy of regulations and technologies targeting particulate reduction. India achieved a substantial 72% (BC) emission decline from 48.20 kt to 13.54 kt, reflecting commitments to address major (BC) sources through cleaner fuel and efficiency improvements. South Africa displayed an 88% (BC) emission dip from 1.60 kt to 0.20 kt, underscoring policy effectiveness. The United States demonstrated a 90% plunge in (BC) emissions from 9.22 kt to 0.95 kt, indicative of regulatory and technological success.

4.1.1 Spatial Mapping : Year - 2023

China :

Figure 4.2 is a spatial map of China showing the locations of currently operating power plants and their corresponding (CO_2) emissions. China's spatial map of powerplant (CO_2) emissions utilizes a color-coded legend to represent the magnitude of emissions. The legend indicates that power-plants emitting less than 0.5 million tonnes (Mt) of (CO_2) are depicted in blue, while those emitting more than 1.5 Mt of (CO_2) are shown in red. However, the actual range of emissions from individual power-plants spans from 0.10 to 4.58 Mt of (CO_2), extending beyond the limits displayed in the legend. This suggests that the map provides a simplified visual representation of the emission levels, focusing on categorizing power-plants into low, medium, and high emission groups rather than capturing the full spectrum of emission values.

The spatial distribution of the power plants reveals a higher concentration of dots, representing power-plants with higher (CO_2) emissions, in the eastern and southeastern regions of China. This suggests that these areas have a greater number of power-plants with significant (CO_2) output compared to other parts of the country. The map effectively visualizes the geographic patterns and variations in (CO_2) emissions from power-plants across China. It highlights potential emission hot-spots, particularly in the densely populated and industrialized regions along the eastern coast. By presenting the data in a spatial context, the map enables a clearer understanding of the regional disparities in powerplant emissions. It can also facilitate further analysis of the factors contributing to higher emissions in certain locations, such as population density, economic activities, or the prevalence of coal-based power generation.

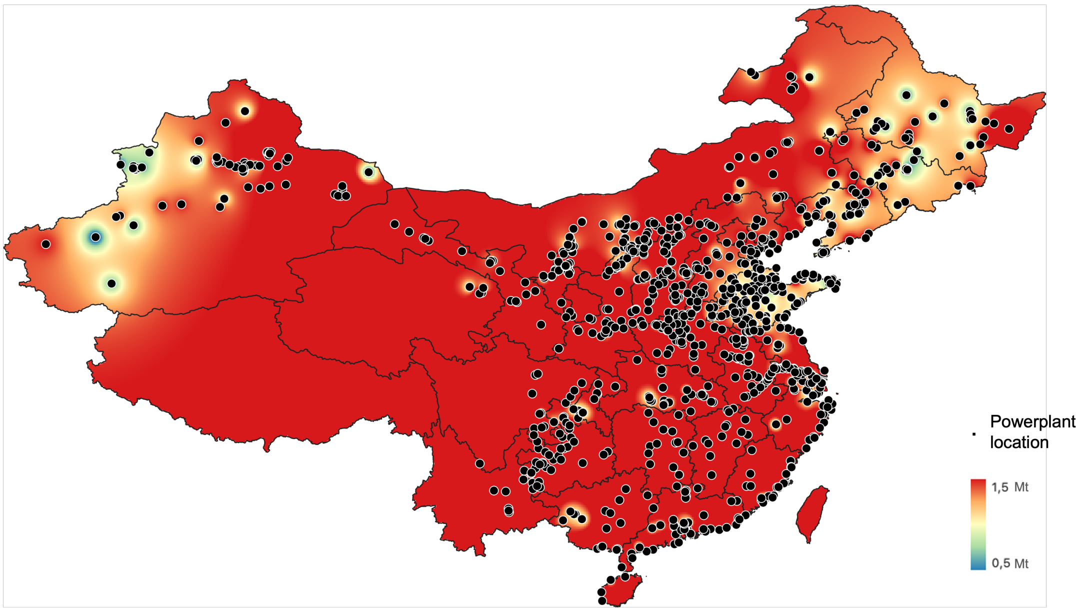


Figure 4.2: China (CO_2) Emissions - 2023

Germany :

Figure 4.3 presents a spatial map of Germany illustrating the geographic distribution of power plants and their corresponding (CO_2) emissions. The spatial map of Germany's powerplant (CO_2) emissions employs a color-coded legend to categorize the magnitude of emissions. The legend indicates that power-plants emitting less than 0.5 million tonnes (Mt) of (CO_2) are represented in blue, while those emitting more than 1.5 Mt of (CO_2) are depicted in red. However, it is important to note that the actual range of emissions from individual power-plants extends from 0.20 to 4.62 Mt of (CO_2), which goes beyond the boundaries shown in the legend. It offers a streamlined approach to visualizing powerplant emissions by classifying them into three broad categories: low (blue), medium, and high (red) emission levels.

By presenting the data in a spatial context, the map enables a clearer understanding of the regional variations in powerplant emissions within Germany. It highlights potential emission hot spots and areas where emissions are comparatively lower. This information can be valuable for policymakers and researchers in identifying regions that require targeted emission reduction strategies and assessing the effectiveness of existing policies at a regional level. It can also serve as a baseline for tracking changes in the spatial distribution of emissions over time, helping to monitor the progress and effectiveness of emission reduction initiatives in Germany.

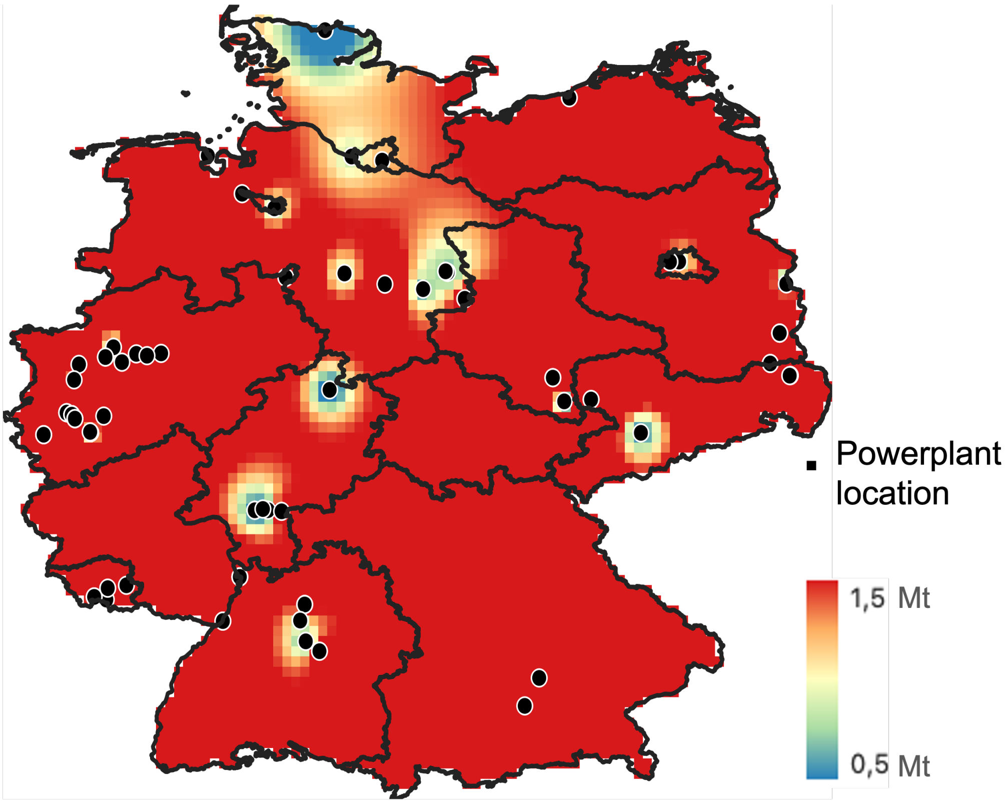


Figure 4.3: Germany (CO_2) Emissions - 2023

India:

In the figure 4.4, a spatial map of India is illustrated which depicts the geographic distribution of power-plants and their corresponding (CO_2) emissions. The map employs a color-coded legend to categorize the magnitude of emissions, with power-plants emitting less than 0.5 million tonnes (Mt) of (CO_2) represented by blue and those emitting more than 1.5 Mt of (CO_2) depicted by red. However, the actual range of emissions from individual power-plants in India extends from 0.20 to 3.19 Mt of (CO_2), which goes beyond the boundaries shown in the legend. The spatial distribution of the power-plants reveals a higher concentration of red, representing power-plants with higher (CO_2) emissions, in the northern and eastern regions of India. This suggests that these areas have a greater number of power-plants with significant (CO_2) emissions compared to other parts of the country. The map also shows a relatively sparse distribution of blue and yellow, indicating the presence of fewer power-plants with lower emissions across various regions.

The map serves as a powerful tool for visualizing and communicating the spatial distribution of powerplant emissions in India. It emphasizes the need for sustainable energy solutions and emission mitigation efforts across different regions of the country. By providing a clear visual representation of the geographic patterns of emissions, the map contributes to the growing body of research on the environmental impact of power-plants and can inform decision-making processes related to transitioning towards cleaner energy sources and reducing India's carbon footprint. Furthermore, the spatial map can facilitate comparative analysis with other countries or regions, allowing researchers to identify similarities, differences, and potential best practices in powerplant emission management. It can also serve as a baseline for tracking changes in the spatial distribution of emissions over time, helping to monitor the progress and effectiveness of emission reduction initiatives in India.

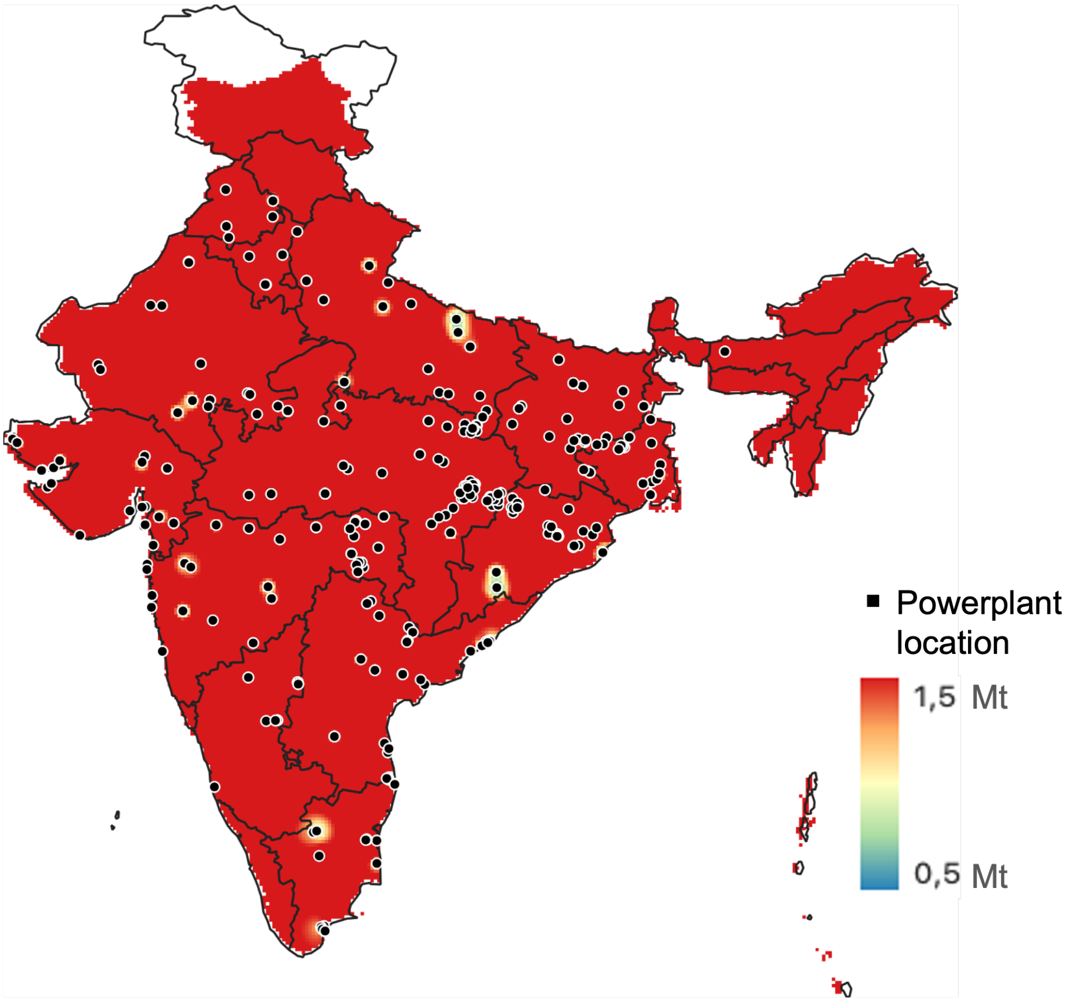


Figure 4.4: India (CO_2) Emissions - 2023

South Africa:

The spatial map in the figure 4.5, of South Africa's powerplant (CO_2) emissions reveals a distinct geographic distribution pattern compared to the maps of China, Germany, and India. The most striking feature is the concentration of black dots, representing powerplants with higher (CO_2) emissions, primarily in the northeastern region of the country. This suggests that the Mpumalanga province, known for its coal-rich deposits and intensive mining activities, is a significant hot-spot for powerplant emissions in South Africa. In contrast to the more evenly distributed emission patterns observed in China and India, South Africa's map shows a more localized concentration of high-emitting power-plants. This could be attributed to the country's heavy reliance on coal-based power generation and the spatial clustering of coal-fired power-plants near the coal mining areas.

The map also reveals a scarcity of power-plants in the western and central parts of South Africa, indicating lower electricity generation and consumption in these regions. This disparity in the spatial distribution of power-plants highlights the inequalities in energy access and infrastructure development across the country. Overall, the spatial map of South Africa's powerplant (CO_2) emissions underscores the need for targeted emission reduction strategies and a transition towards cleaner energy sources, particularly in the northeastern region where the majority of high-emitting power-plants are concentrated. It also highlights the importance of addressing regional disparities in energy access and promoting sustainable development across the country.

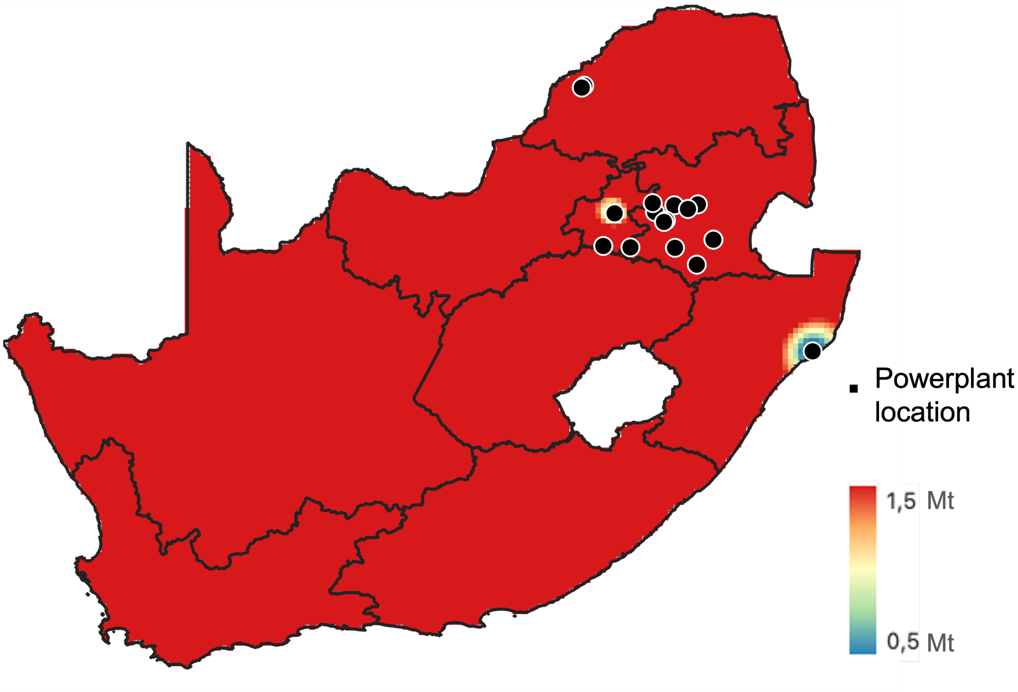


Figure 4.5: South Africa (CO_2) Emissions - 2023

United States:

Figure 4.6, shows a spatial map of the United States powerplant (CO_2) emissions presents a geographically dispersed distribution like the country maps of China, Germany, India, and South Africa. The map shows a concentration of black dots, representing power-plants, across various regions of the country, with notable clusters in the eastern half, particularly in the Midwest and along the East Coast. One striking feature of the U.S. map is the presence of a significantly higher number of power-plants compared to the other countries. This reflects the vast size of the United States and its extensive electricity generation infrastructure. The widespread distribution of power-plants suggests a more decentralized power generation system, with numerous facilities serving different regions and population centers.

In contrast, the western part of the country, particularly the Rocky Mountain and desert regions, has a lower density of power-plants. This could be attributed to factors such as lower population density, the presence of large-scale renewable energy projects (e.g., solar and wind farms), and the utilization of other energy sources like hydroelectric power in certain areas. Overall, the spatial map of the United States powerplant (CO_2) emissions provides a comprehensive view of the geographic distribution of power-plants and highlights the need for a multi-faceted approach to address the challenges of reducing emissions and transitioning to cleaner energy sources in a vast and diverse nation.

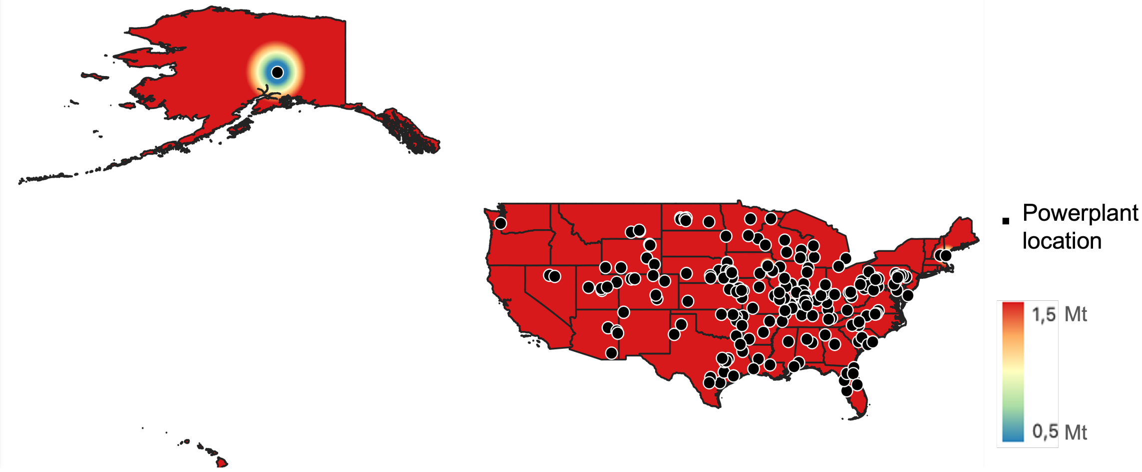


Figure 4.6: United States (CO_2) Emissions - 2023

4.2 Future Projection

With contemporary emissions quantification accomplished hitherto, analytical orientation progresses to exploratory projections for milestone years 2025, 2030 alongside 2035 and 2040 using Integrated Assessment Models (IAMs) from Table 3.4. These multi-model frameworks assimilate complex interplay of socio-economic determinants, abatement technological revolutions, regulatory transitions and energy-industry transformations to model multi-decadal emissions trajectories spanning both air pollutants and greenhouse gas.

Such geographic information system emissions mapping holds particular pertinence for centralized environmental planning agencies to identify likely pollution hot spots, transitional shifts and track intended abatement target fulfillment. Moreover, predictions enable strategic pro-activity whether locating pollution monitoring infrastructure density for upcoming station network expansions or individual establishments to minimize immediate exposure risks. Obtained visualizations geo-spatially interpolate such projections offering valued perspectives into localized dispersion forms and patterns. Projections for top emitting countries reveal varying climate action modeled pathways. Among the slate of future emissions projections comprising both air pollutants and greenhouse gas attained through Integrated Assessment modeling Pathways, the trajectories for Emissions are shown in Annex 7.3.

A brief synthesis of the modeled results on the study countries for (CO_2) emissions are analysed here:

- India could peak emissions with the current determined polices but soon a substantial decline is observed under 1.5°C and 2°C scenarios.
- China is trending toward stabilization and eventual reduction aligned with Paris targets
- Germany is on track for steep emissions cuts, nearing net-zero by 2040 under 1.5°C aims
- South Africa may initially increase emissions but could reverse under lower temperature scenarios
- The United States shows a pronounced downward shift from historical levels, especially meeting 1.5°C ambitions

Compared to weaker NDC commitments, these accelerated reductions for some countries under the 1.5 to 2 degree scenarios reflect more ambitious Paris Agreement goals. Considering different starting points, national policies, and constraints - the diversity of trajectories highlights the complex, collective effort needed to address climate change. While progress is uneven, the projections suggest that with stringent climate action and cooperation, peak emissions and decarbonization remain within reach for major economies.

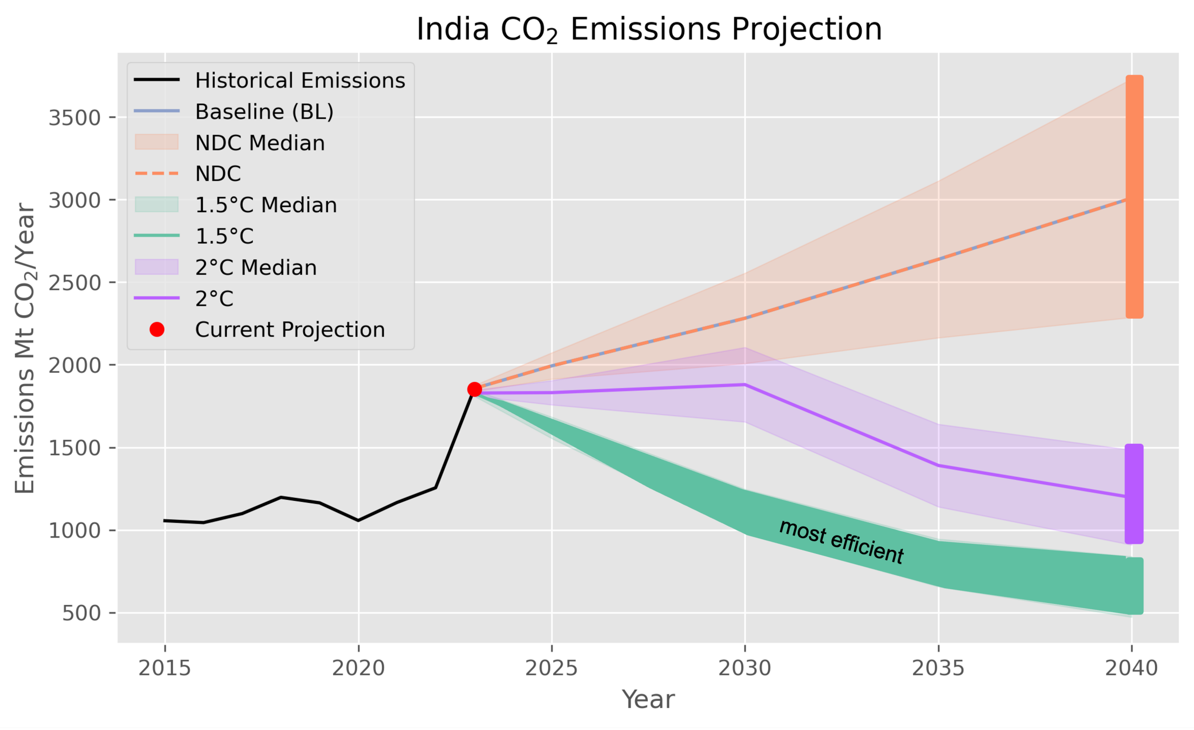


Figure 4.7: India (CO_2) Emissions - Model Analysis

For example in Figure 4.7, the multi-model scenarios illustrate different potential pathways for India's future carbon dioxide (CO_2) emissions under varying climate commitment levels. The current Nationally Determined Contributions (NDC) scenario, shown in orange, reveals that under India's existing targets, emissions are projected to rise steadily from a range of 0.1 - 3.5 Mt in 2023 to 0.16 - 5.7 Mt by 2040. In comparison, the

2°C scenario forecasts that with additional efforts, 2040 emissions could be constrained to 0.065-2.6098 Mt versus NDC levels - reflecting the postponing of net zero goals further into the future. More ambitiously, the 1.5°C scenario indicates that with strong, near-term mitigation actions, India could being reducing emissions straight away, declining to a 2040 range of just 0.0354 - 1.24 Mt. This lowest outcome in Table 4.1, across models underscores how pursuing the 1.5°C pathway could place India's emissions on a trajectory closely consistent with global net zero objectives in the coming decades. Overall, the multi-model analysis highlights that while India's emissions are currently rising, implementing more aggressive decarbonization policies swiftly by facilitated technology and knowledge transfers as well as appropriately directed clean energy investments could substantially curb projected growth and facilitate a transition to clean energy systems.

Table 4.1: Projected % reduction relative to Baseline

Scenario	**% Reduction Relative to Baseline**
Nationally Determined Contributions (NDC)	Same as Baseline
1.5°C	78-86 %
2°C	54-59 %

4.2.1 Key Takeaways from the Model Analysis

The reductions in projected emissions under the NDC, 2 degree, and 1.5 degree scenarios in Table 4.1 and Annex 7 section 7.3 exhibit nearly parallel decreasing trends across pollutants like (CO), (VOC), ($\mathrm{PM}_{2.5}$), (PM_{10}), (PM - Black Carbon) emissions - reflecting concerted past air pollution control efforts by the study countries are good. With emissions of these air pollutants steadily declining, attention shifts to the trajectories of carbon dioxide (CO_2), sulfur dioxide (SO_2) and nitrogen oxides (NO_x). Focus has narrowed to outcomes within the 1.5°C warming pathway alone given multiple sensitivities analyzed as this represents the most economically efficient abatement route congruent with Paris Agreement ambitions. While Annexure compiling tables chronicle additional pollutants and warming scenarios inclusive of all modeled emissions, main body analysis spotlights just the premier GHG and the two major air pollutants demonstrating maximum contemporary health and environmental detriment potential under the 1.5°C scenario.

The modeling analysis revealed that all countries included in the study faced significant challenges in managing their (CO_2) and (NO_x) emissions. These pollutants are major contributors to climate change and air quality deterioration, respectively. The widespread nature of these issues highlights the global scale of the problem and the need for concerted efforts from all nations to address these emissions effectively. Interestingly, the United States stood out as an exception when it came to (SO_2) emissions. The spatial analysis of (SO_2) emissions in the United States, as depicted in Figure 7.50, exhibits a distinct trajectory compared to other countries in the study. The projections from various models converge towards a common point, indicating a consistent trend in reducing (SO_2) emissions across the nation. This convergence suggests that the United States has implemented effective strategies and policies to mitigate (SO_2) emissions, setting it apart from the challenges faced by other countries in the analysis. This could be attributed to various factors, such as the implementation of successful (SO_2) reduction policies, shifts in energy sources, or technological advancements specific to the United States. Further investigation into the unique circumstances and strategies employed by the United States in managing (SO_2) emissions could provide valuable lessons for other countries facing similar challenges.

4.2.2 (CO_2), (NO_x) and (SO_2) Emissions: (2025 - 2040)

4.2.2.1 China :

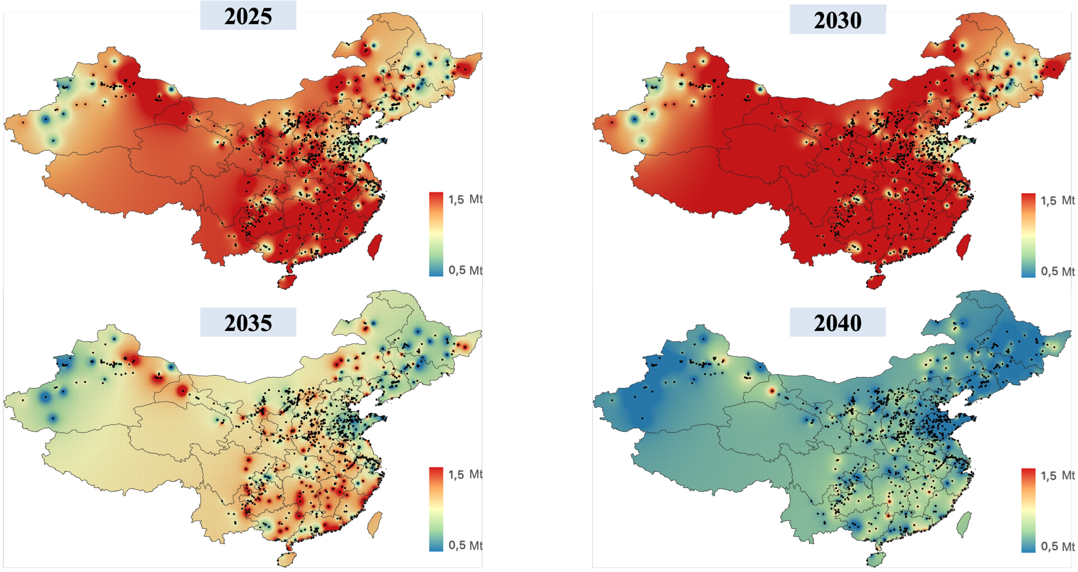


Figure 4.8: China (CO_2) Emission Projection : (2025 - 2040)

The spatial analysis of modelled pathway 1.5°C for (CO_2) emissions in China from 2025 to 2040 is carried out in the figure 4.8 which reveals a significant transition towards a low-carbon future. In 2023 figure 4.2, the emissions range from 0.10 Mt to 4.58 Mt, with the eastern and southern regions experiencing the highest emissions. By 2025, the upper limit slightly decreases to 3.94 Mt, indicating initial efforts to reduce emissions. The year 2030 marks a substantial reduction, with emissions ranging from 0.06 Mt to 2.62 Mt and a more even spatial distribution. This trend continues in 2035, as the emissions further decrease to a range of 0.04 Mt to 1.71 Mt, with a predominance of lower-emitting areas. Finally, in 2040, the emissions reach a range of 0.029 Mt to 1.23 Mt, showcasing a significant reduction of approximately 73% compared to 2023. The spatial map in 2040 exhibits a nearly uniform distribution of low emissions across the country. This transition helps to closely align with the goals of the Paris Climate Agreement and demonstrates China's commitment to decarbonizing its economy and contributing to the global fight against climate change.

In the figure 4.9, depicts (NO_x) emissions in China from 2023 to 2040 reveals a significant transition towards reduced (NO_x) emissions, contributing to improved air quality and supporting the reduction of emissions from the energy sector. In 2023, the (NO_x) emissions range from 0.109 Kt to 6.626 Kt, with the eastern and southern regions experiencing the highest emissions similar to (CO_2) emissions. By 2025, the upper limit decreases to

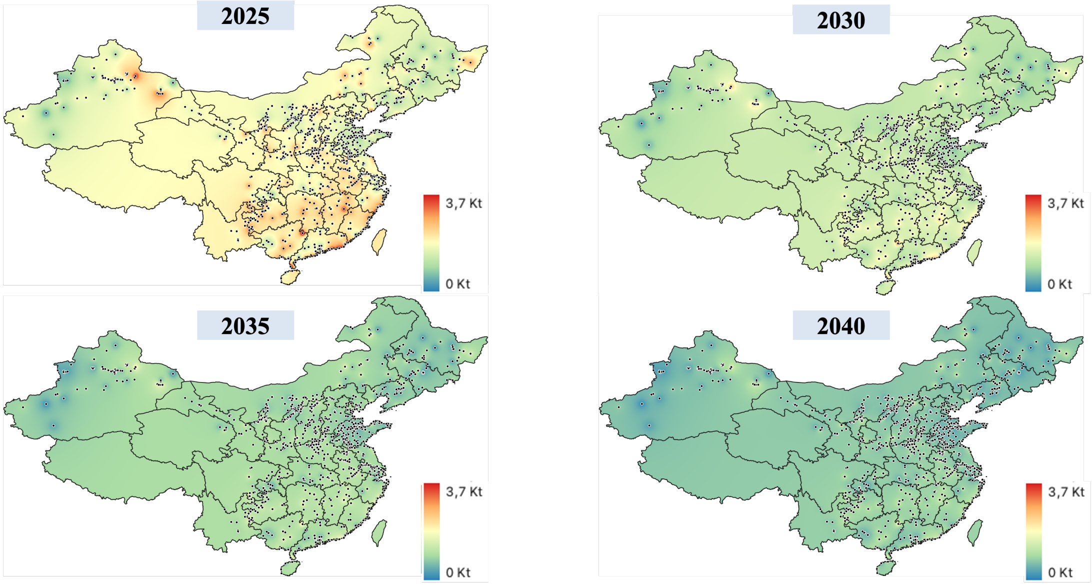


Figure 4.9: China (NO_x) Emission Projection : (2025 - 2040)

5.6636 Kt, indicating initial efforts to reduce emissions. The year 2030 marks a substantial reduction, with emissions ranging from 0.0621 Kt to 3.7904 Kt and a more balanced spatial distribution. This trend continues in 2035, as the emissions further decrease to a range of 0.0458 Kt to 2.7728 Kt, with a predominance of lower-emitting areas. Finally, in 2040, the emissions are projected to reach a range of 0.0366 Kt to 2.20706 Kt, showcasing a significant reduction of approximately 67% compared to 2023. This reduction is achieved, by assuming the technological adaptations, investments in the energy sector, and other measures aimed at mitigating emissions.

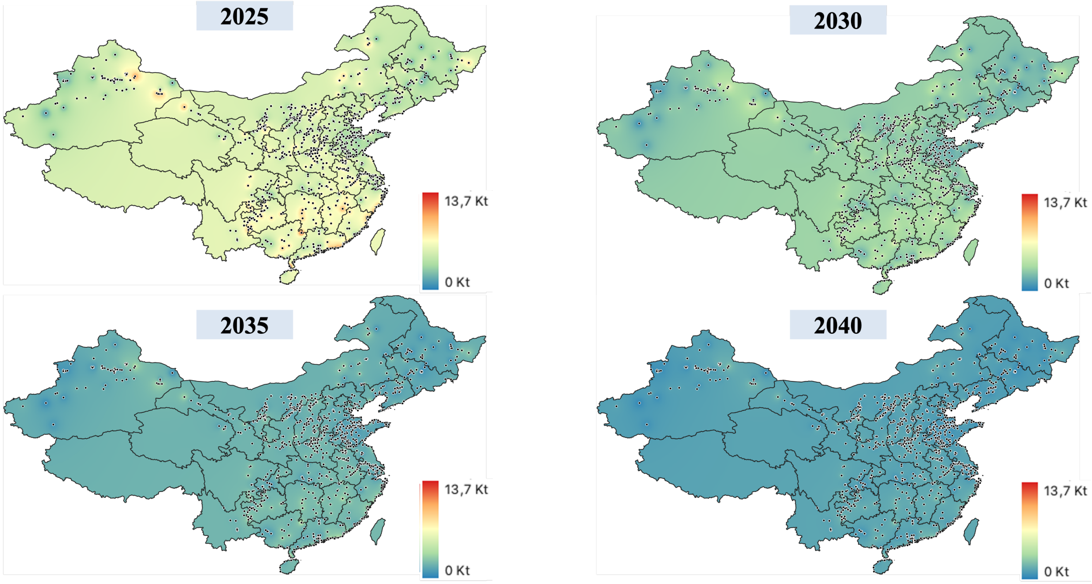


Figure 4.10: China (SO_2) Emission Projection : (2025 - 2040)

The spatial analysis of (SO_2) emissions, as illustrated in Figure 4.10, shows a significant transition towards reduced emissions using the same model. In 2023, the emissions range from 0.419 Kt to 22.910 Kt, with the same (eastern and southern) regions as stated in (CO_2) emissions. By 2025, the upper limit decreases to 16.1753 Kt, indicating progress in reducing emissions. The year 2030 marks a substantial reduction, with emissions ranging from 0.15 Kt to 8.68 Kt and a more balanced spatial distribution. This trend persists in 2035, as the emissions further decrease to a range of 0.09 Kt to 5.399 Kt, with a predominance of lower-emitting areas. Finally, in 2040, the emissions reach a range of 0.068 Kt to 3.723 Kt, showcasing a remarkable reduction of approximately 84% compared to 2023. The spatial map in 2040 exhibits a nearly uniform distribution of low emissions across the country.

4.2.2.2 Germany :

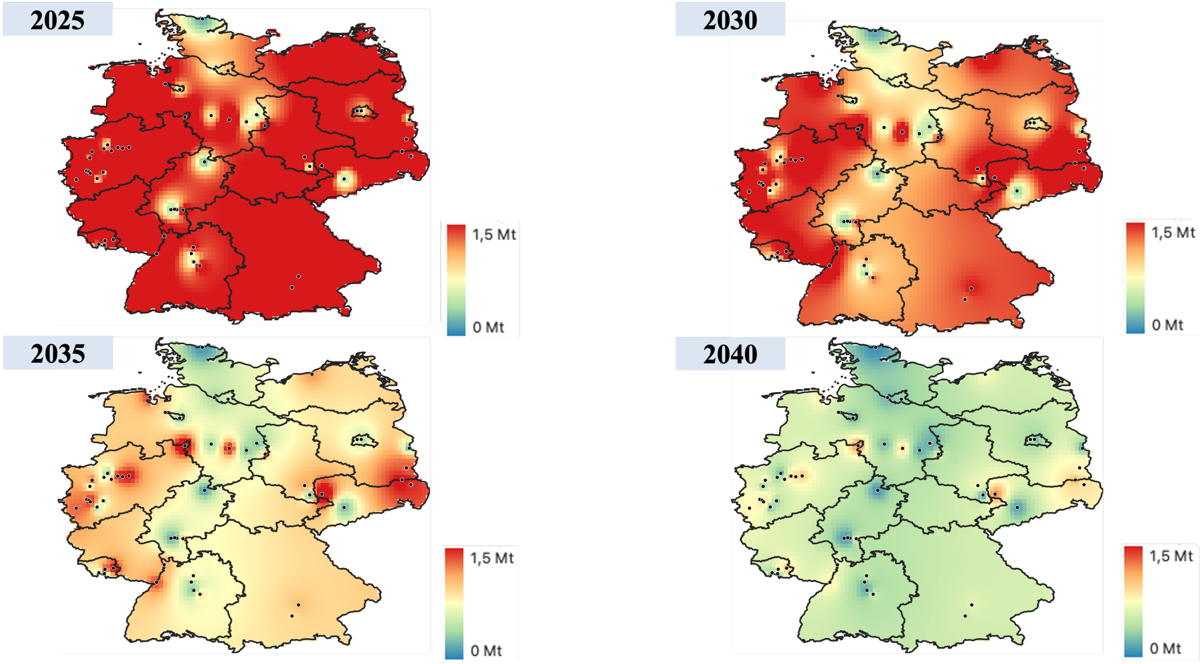


Figure 4.11: Germany (CO_2) Emission Projection : (2025 - 2040)

Spatial analysis of projected carbon dioxide (CO_2) emissions in Germany from 2025-2040 (Fig. 4.11) reveals a steady national-level decline. Emission ranges show a progressive drop, with maximum values falling from around 4.4598 Mt in 2025 to approximately 1.3540 Mt in 2040. The maps illustrate this shift, displaying a near ubiquitous transition towards lower emissions across regions by 2040. This trajectory highlights Germany's strong potential to deeply cut energy-related (CO_2), improving air quality while advancing Paris Agreement goals. Although the original 2030 emissions target may be missed, spatial trends indicate substantial decarbonization progress in the energy sector by 2040 - setting an example globally. Achieving these reductions will hinge on Germany's continued commitment to renewable energy and efficiency policies, creating economic growth and employment opportunities. As a leader in the EU, Germany's measurable success in driving down emissions can promote adoption of similar low-carbon strategies across member states. Collective action is key to achieving a carbon-neutral Europe.

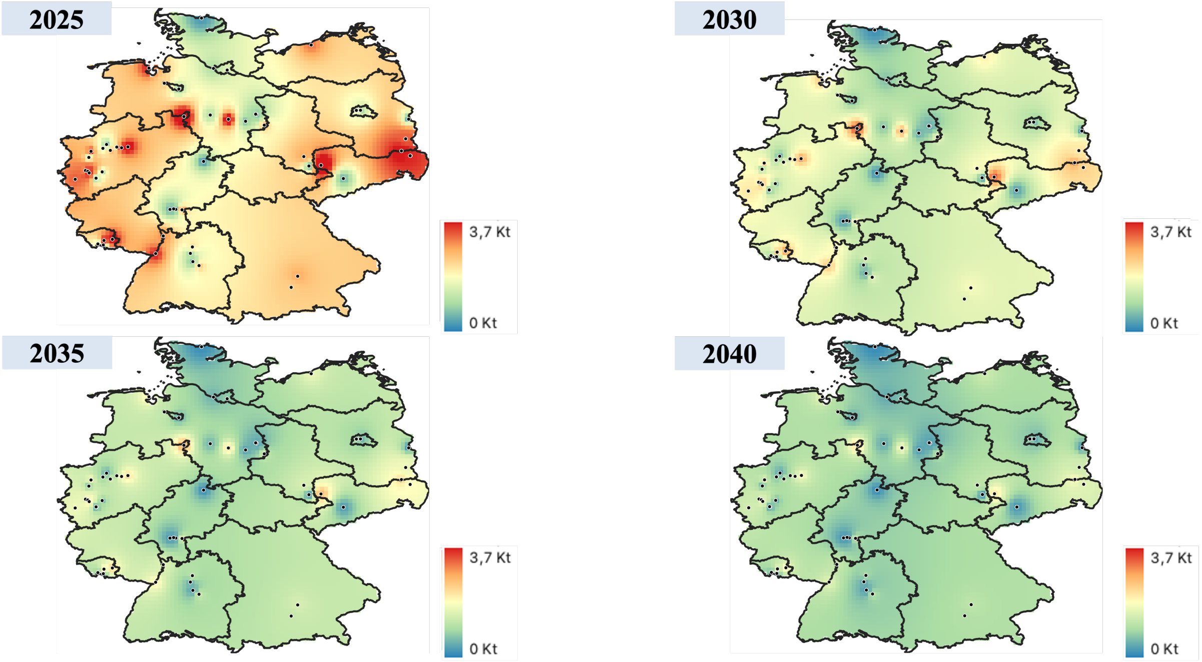


Figure 4.12: Germany (NO_x) Emission Projection : (2025 - 2040)

In the figure 4.12, the spatial analysis of (NO_x) emissions in Germany from 2025 to 2040 is demonstrated, which depicts a remarkable transition towards cleaner energy production and improved air quality. The maps reveal a substantial reduction in emissions across the country, with the highest values decreasing from 5.6207 Kt in 2025 to 2.3429 Kt by 2040. This significant decrease is attributed to Germany's implementation of advanced emission control technologies, adoption of cleaner fuel sources, and promotion of renewable energy alternatives. In 2025, most regions exhibit emission levels in the higher range, reaching up to 5.6207 Kt. However, by 2030, emissions have decreased considerably, with maximum values reaching only 3.6267 Kt. This trend continues in 2035, with a further reduction in emissions, as evidenced by the maximum value of 2.8802 Kt. By 2040, Germany demonstrates a remarkable achievement, with the highest emission levels not exceeding 2.3429 Kt, a 66.2% reduction from 2023, and most regions exhibiting values closer to the minimum of 0.0934 Kt. This analysis highlights the efficacy of Germany's strategies to mitigate (NO_x) emissions from the energy sector and serves as a valuable model for other nations seeking to reduce their emissions and combat climate change.

The figure 4.13 showcases the spatial distribution of (SO_2) emissions in Germany from 2025 to 2040, illustrating a remarkable decline that underscores the country's effective strategies to mitigate emissions from the energy sector and enhance air quality. The highest emission levels in 2023 stand at 37.4475 Kt, with the lowest at 1.4925 Kt. Over the course of 17 years, from 2023 to 2040, Germany achieves an impressive 69.4% reduction in both the maximum and minimum emission levels. By 2040, the peak (SO_2) emissions are capped at 11.4497 Kt, while the lowest values plummet to 0.4563 Kt. The spatial analysis visually represents the gradual transition towards reduced (SO_2) emissions nationwide. This substantial decrease can be ascribed to Germany's resolute actions, including the

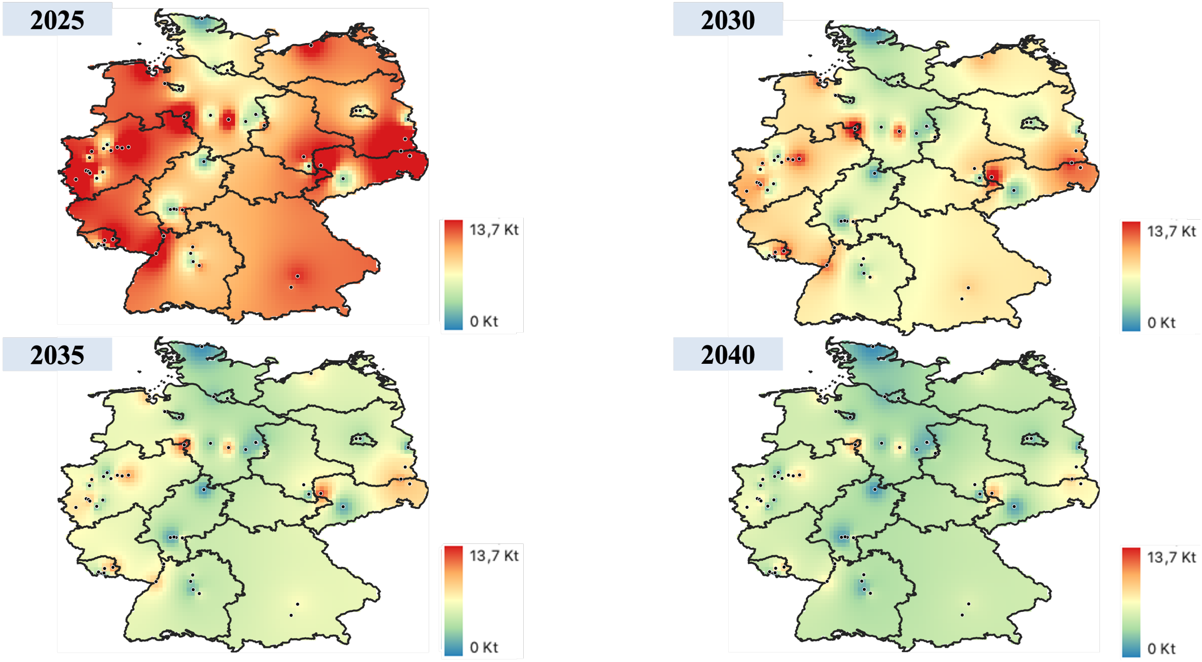


Figure 4.13: Germany (SO_2) Emission Projection : (2025 - 2040)

enforcement of more stringent emission regulations, the shift to cleaner energy alternatives, and the implementation of cutting-edge technologies to curb (SO_2) emissions from the energy sector.

4.2.2.3 India :

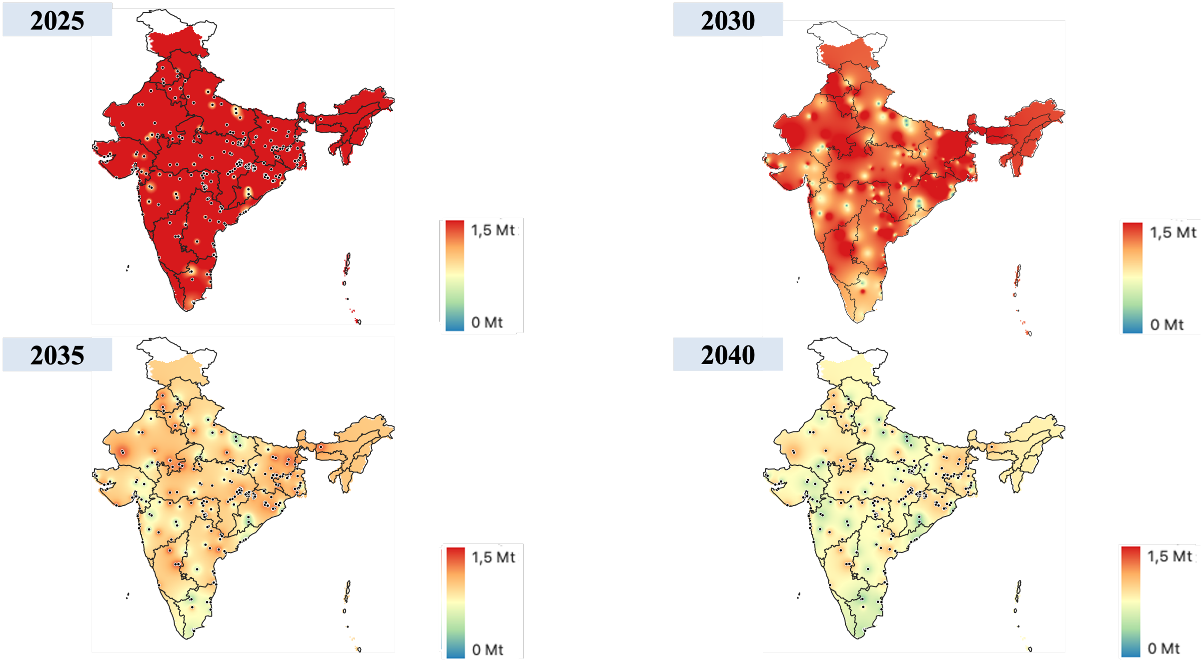


Figure 4.14: India (CO_2) Emission Projection : (2025 - 2040)

The spatial map in figure 4.14 depict a significant reduction in (CO_2) emissions across India from 2025 to 2040, with the maximum emission levels decreasing from 3.06 Mt in 2025 to 1.2386 Mt by 2040. Comparing the data from 2023 to 2040, the highest emission levels show a decline from 3.50 Mt to 1.2386 Mt, representing a 64.6% reduction over the 17-year period. Similarly, the lowest emission levels drop from 0.1 Mt in 2023 to 0.035 Mt in 2040, marking a 65% decrease. As the country transitions towards cleaner energy sources and implements effective emission reduction strategies, it not only contributes to global climate change mitigation efforts but also experiences significant improvements in air quality. The more homogeneous spatial distribution of emissions by 2040 suggests that these efforts are being undertaken across various regions, ensuring widespread benefits for public health and the environment.

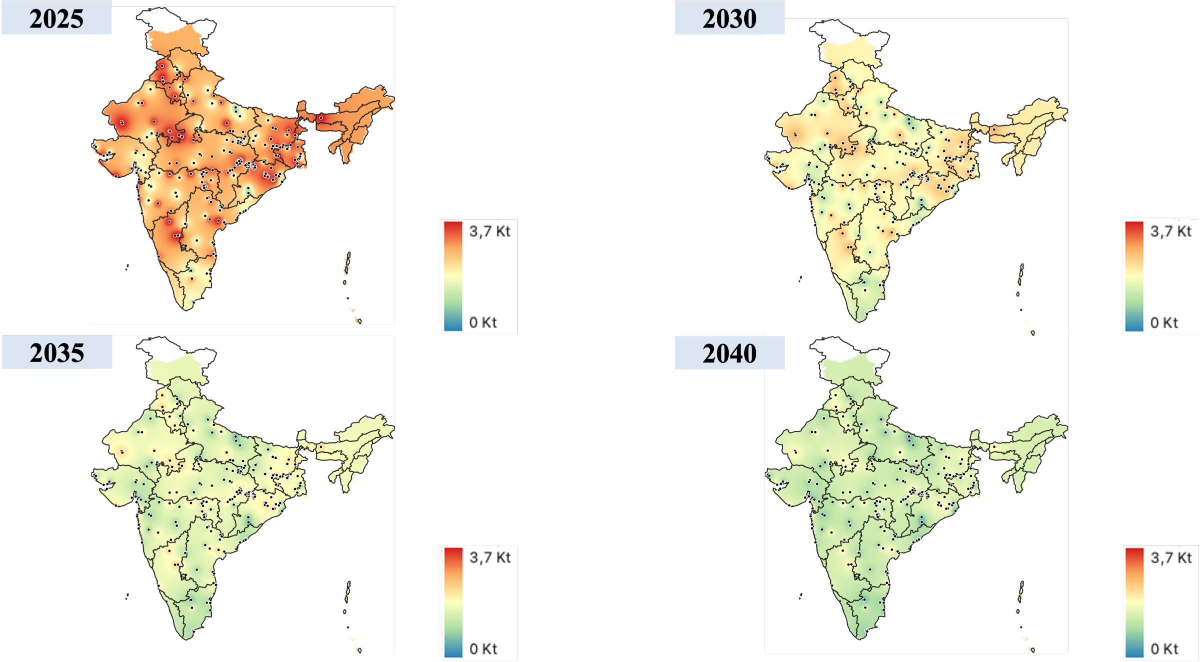


Figure 4.15: India (NO_x) Emission Projection : (2025 - 2040)

Figure 4.15 illustrate a spatial map which depicts notable decline in (NO_x) emissions across India between 2025 and 2040, reflecting the country's efforts to reduce air pollution and enhance air quality. In 2025, emissions range from 0.12603 to 4.41113 Kt, with higher concentrations in the northern and eastern regions. By 2030, a significant reduction is evident, with emissions spanning 0.09077 to 3.17700 Kt. This downward trend persists through 2035 and 2040, with emission levels decreasing to 0.07485 - 2.61971 Kt and 0.06370 - 2.22933 Kt, respectively. Comparing the data from 2023 to 2040, the highest emission levels exhibit a substantial 56.1% reduction, dropping from 5.0806 Kt to 2.22933 Kt. Similarly, the lowest emission levels decrease by 56.1%, from 0.1452 Kt in 2023 to 0.06370 Kt in 2040.

The spatial maps depict a remarkable reduction in (SO_2) emissions across India from 2025 to 2040 4.16, showcasing the nation's dedication to enhancing air quality and curbing pollution from the energy sector. In 2025, emissions span from 0.35181 to 12.31342

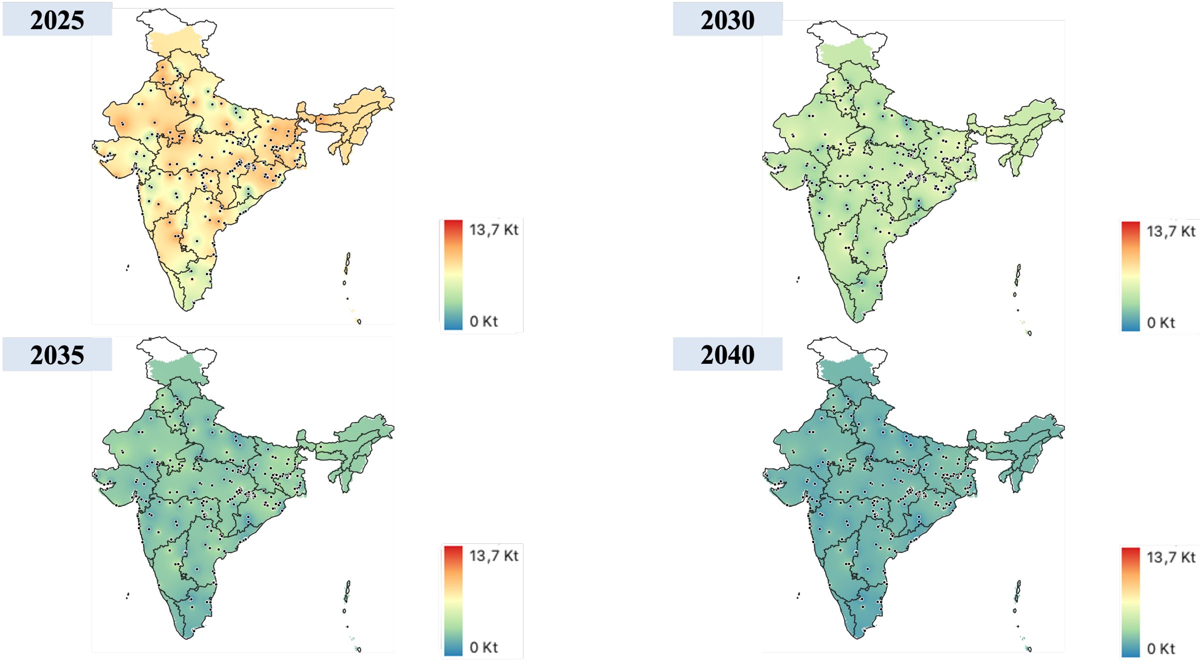


Figure 4.16: India (SO_2) Emission Projection : (2025 - 2040)

Kt, with elevated levels concentrated in the northern and eastern states. However, by 2030, a drastic decrease is observed, with emissions ranging from 0.20744 to 7.26045 Kt. This positive trajectory continues through 2035 and 2040, as emission levels plummet to 0.12433 - 4.35151 Kt and 0.09168 - 3.20889 Kt, respectively. Comparing the data from 2023 to 2040, the highest emission levels exhibit an astonishing 79.8% reduction, plunging from 15.8519 Kt to a mere 3.20889 Kt. Likewise, the lowest emission levels experience a dramatic 79.8% decrease, dropping from 0.4529 Kt in 2023 to 0.09168 Kt by 2040.

4.2.2.4 South Africa :

The spatial maps from 2025 to 2040 illustrate a significant transformation in (CO_2) emissions across South Africa in figure 4.17, reflecting the nation's efforts to progress towards the Paris Climate Agreement goals and enhance air quality. In 2025, emissions range from 0.1802 to 3.153 Mt, with the highest concentrations predominantly in the northeastern regions. By 2030, a notable reduction is evident, with emissions spanning 0.144 to 2.523 Mt, indicating progress towards the Paris Agreement targets, although not fully achieving them within this time-frame. However, the downward trajectory persists through 2035 and 2040, as emission levels decline to 0.1208 - 2.11410 Mt and 0.085 - 1.49535 Mt, respectively. Comparing the data from 2023 to 2040, the highest emission levels exhibit a substantial 57.3% decrease, dropping from 3.50 Mt to 1.49535 Mt. Similarly, the lowest emission levels experience a 57.5% reduction, falling from 0.2 Mt in 2023 to 0.085 Mt by 2040. These significant reductions in (CO_2) emissions underscore South Africa's resolute efforts to transition towards cleaner energy sources and implement effective carbon mitigation strategies, bringing the nation closer to aligning with the Paris Agreement goals by 2040.

Upon closer examination of the spatial maps and emission data from 2025 to 2040, it

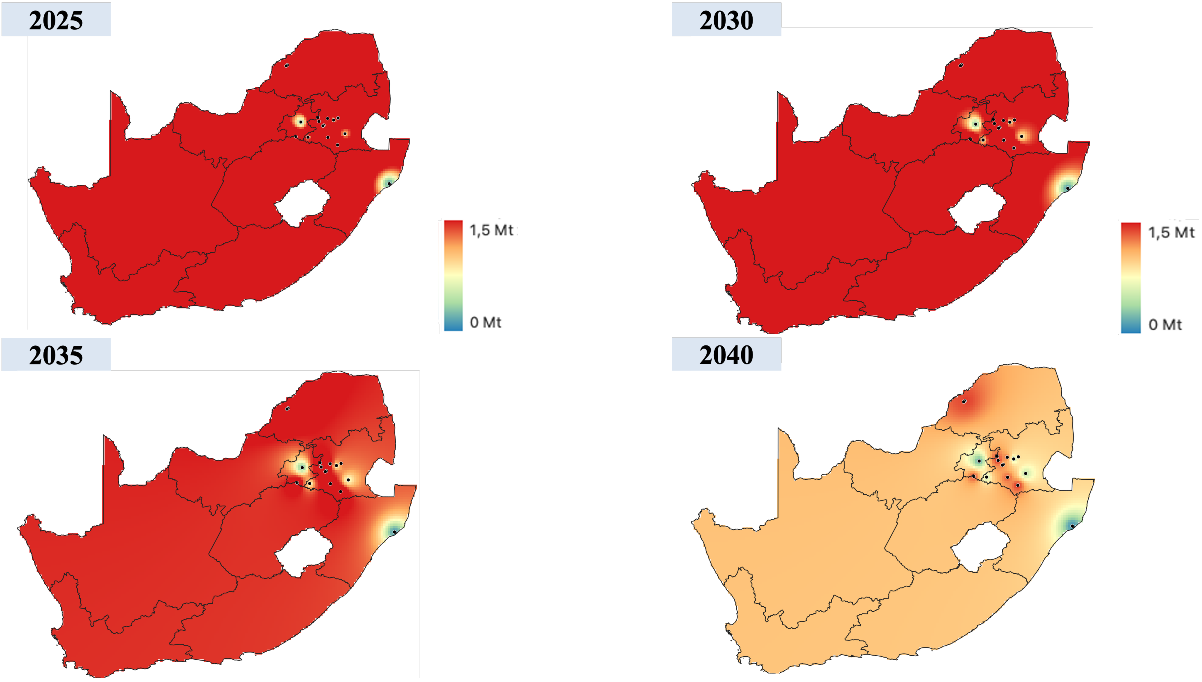


Figure 4.17: South Africa (CO_2) Emission Projection : (2025 - 2040)

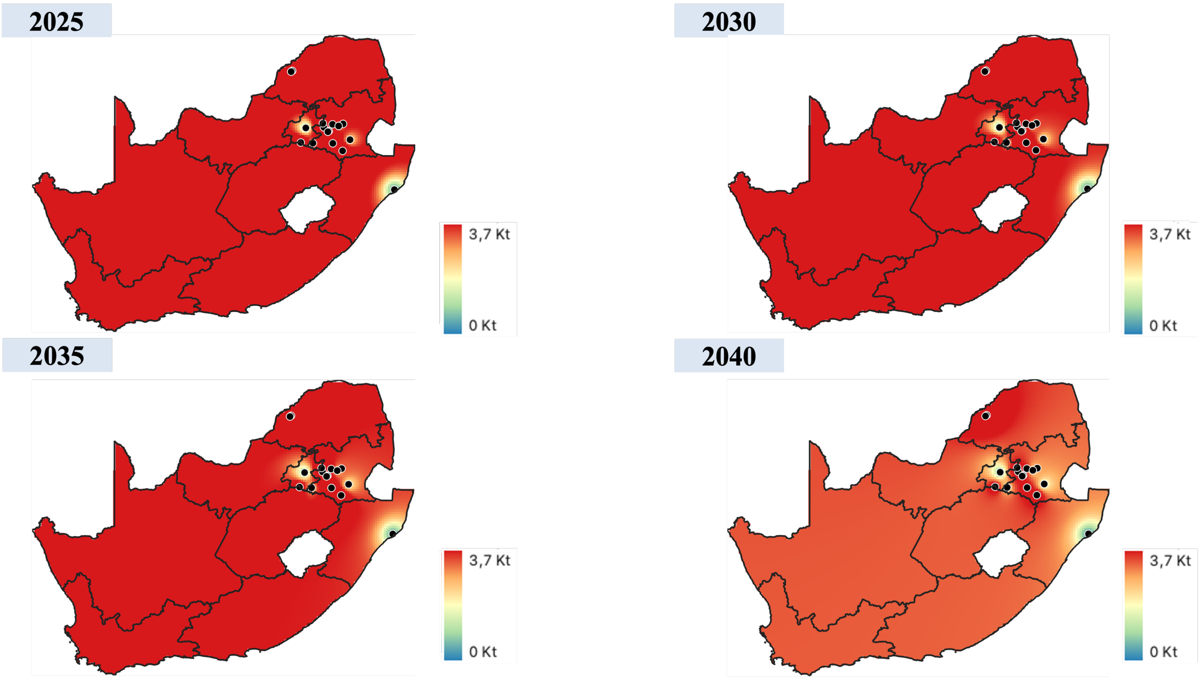


Figure 4.18: South Africa (NO_x) Emission Projection : (2025 - 2040)

becomes evident that the progress in reducing NOx emissions in South Africa is relatively slow in the figure 4.18, with an average annual reduction rate of only 1.83% over the 15-year period. While emissions decrease from 0.3588 - 6.3779 Kt in 2025 to 0.27101 - 4.81794 Kt by 2040, representing a 27.5% reduction, the pace of progress suggests that more aggressive measures and policies may be necessary to accelerate the transition towards cleaner energy sources. The spatial distribution of emissions remains relatively consistent throughout the years, with higher emission values persisting in the northeastern and southwestern regions, indicating a need for targeted interventions and infrastructure improvements. To expedite progress more rapidly, South Africa must prioritize the adoption of clean energy technologies, strengthen emissions regulations, and invest in sustainable infrastructure.

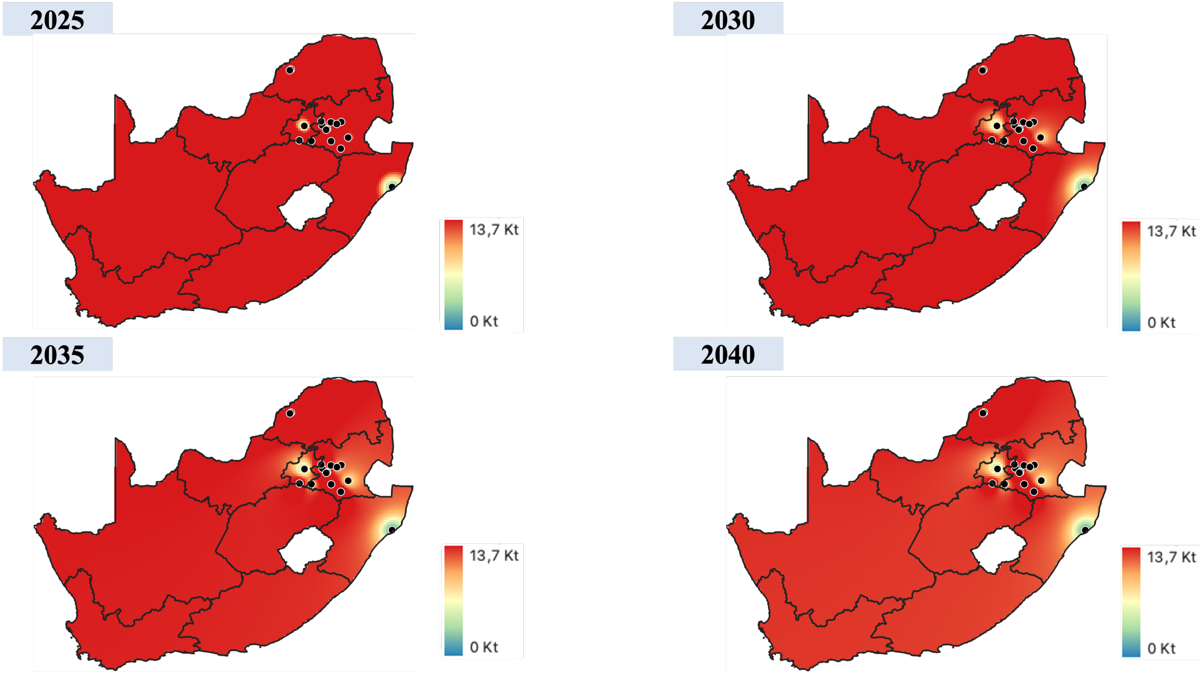


Figure 4.19: South Africa (SO_2) Emission Projection : (2025 - 2040)

From 2023 to 2040, South Africa is projected to experience a significant decrease in (SO_2) emissions from the energy sector. The spatial map in the figure 4.19, reveals that emissions are expected to decline from a range of 2.30 to 40.95 kilotons in 2023 to a range of 1.07 to 19.06 kilotons by 2040. This change represents a 53.4% reduction in the lower end of the emissions range and a 53.5% reduction in the upper end over the 17-year period. The consistent and substantial decrease in (SO_2) emissions across the country highlights the effectiveness of long-term strategies and policies aimed at improving air quality and mitigating the environmental impact of energy production. By maintaining this commitment to reducing (SO_2) emissions, South Africa can make significant progress in addressing atmospheric pollution, promoting public health, and fostering a more sustainable energy landscape.

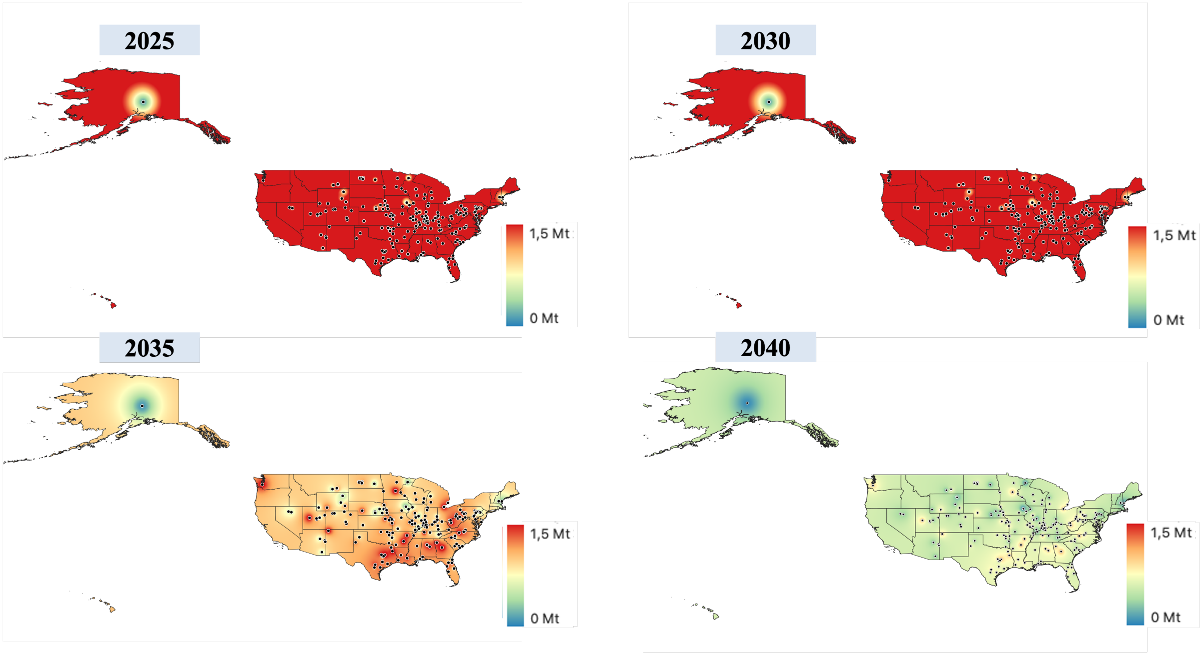


Figure 4.20: United States (CO_2) Emission Projection : (2025 - 2040)

4.2.2.5 United States :

Spatial maps presented in the figure 4.20 illustrate the projected decrease in (CO_2) emissions from the energy sector across the United States between 2025 and 2040. In 2025, emissions are expected to range from 0.1761 to 5.6364 Mt nationwide. The data indicates a consistent downward trend in (CO_2) emissions over the subsequent years. By 2040, the emissions are predicted to fall to a range of 0.0474 to 1.5163 Mt, representing a dramatic reduction of 76.3% to 73.1% compared to the 2023 levels, which span from 0.2 to 6.40 Mt. This significant decline in (CO_2) emissions underscores the efficacy of long-term strategies and policies aimed at mitigating the carbon footprint of the energy sector and enhancing overall air quality. By sustaining this commitment to reducing (CO_2) emissions, the United States can make substantial strides in combating climate change, promoting public health, and fostering a more sustainable energy landscape over the coming decades. The projected decrease in emissions serves as a testament to the potential for targeted initiatives and technological advancements to drive meaningful environmental change on a national scale.

In the figure 4.21 depict the anticipated reduction in (NO_x) emissions from the energy sector across the United States between 2025 and 2040. The data reveals a steady decline in emissions over this period, with the range falling from 0.3831 to 12.2577 kilo-tonnes (Kt) in 2025 to 0.1344 to 4.2994 Kt by 2040. This represents a substantial decrease of 71.7% to 64.9% compared to the 2023 levels, which span from 0.4745 to 15.1842 Kt. The spatial distribution of this reduction highlights the comprehensive impact of strategies and policies aimed at curbing (NO_x) emissions and enhancing air quality throughout the nation.

The spatial maps illustrate in the figure 4.22 projects the decrease in (SO_2) emissions

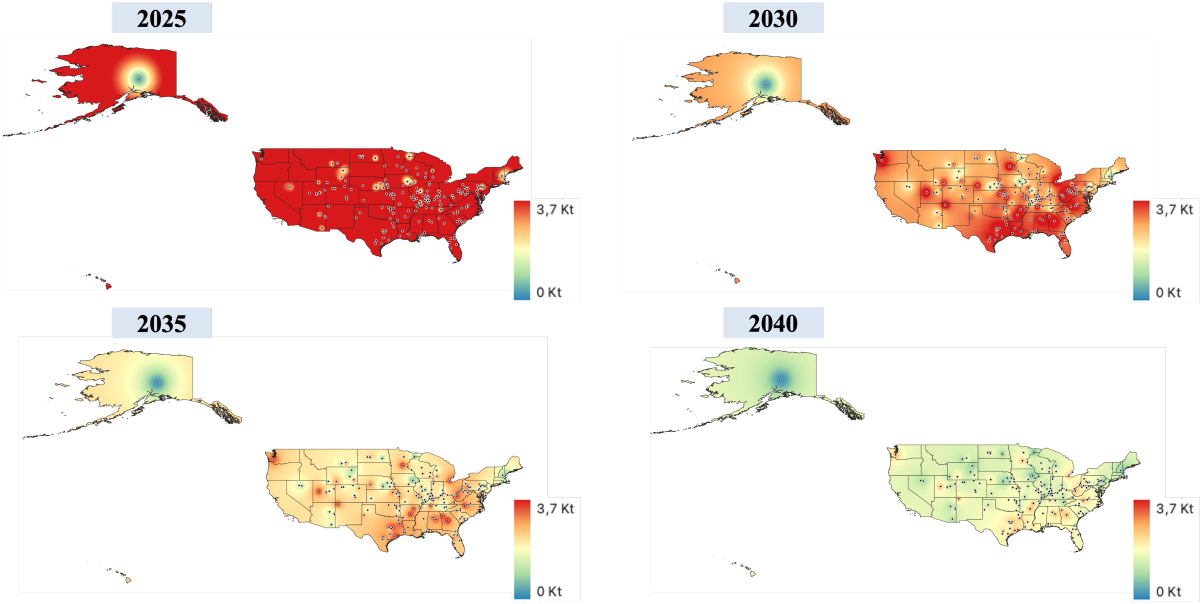


Figure 4.21: United States (NO_x) Emission Projection : (2025 - 2040)

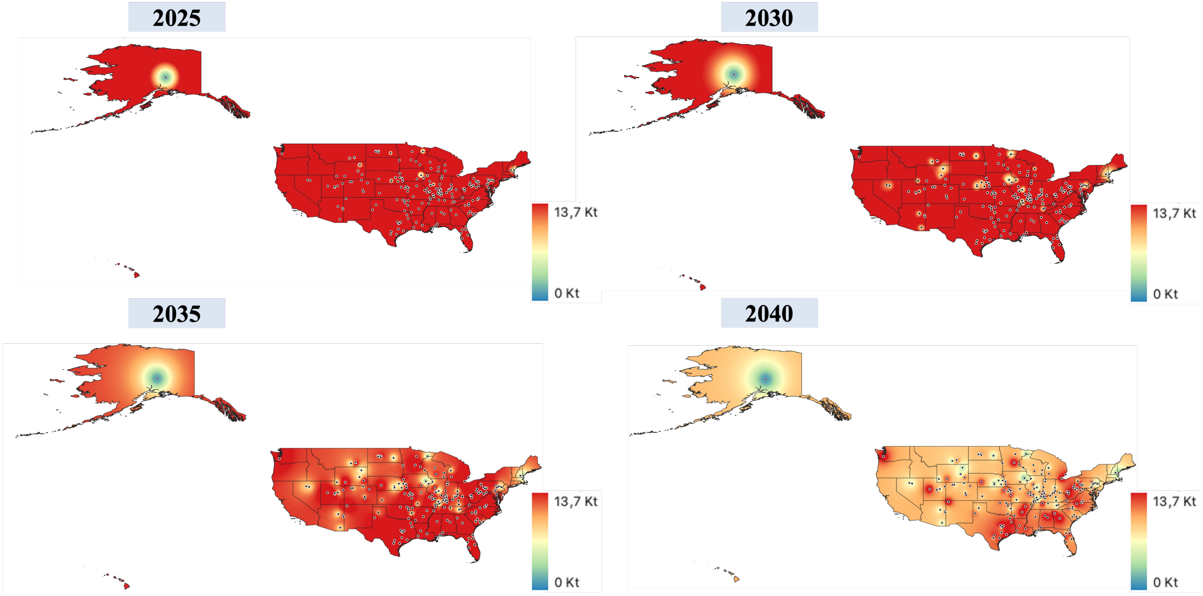


Figure 4.22: United States (SO_2) Emission Projection : (2025 - 2040)

from the energy sector across the United States between 2025 and 2040. The data indicates a consistent decline in emissions over this period, with the range dropping from 1.8560 to 59.3935 Kt in 2025 to 0.8375 to 26.8007 Kt by 2040. This represents a remarkable reduction of 67.8% compared to the 2023 levels, which span from 2.6015 to 83.2466 Kt. However, in comparison to other leading countries, the United States must continue improving adaptation of advanced (SO_2) control technologies across power generation and industrial facilities to sustain this downward trajectory. Additionally, although substantial reductions are observed, minimum (SO_2) levels remain higher than other peer countries - indicating difficulty in keeping pace with achieving the lowest benchmark values.

5 Discussion and Conclusion

This research analyzed current and projected future emissions from the coal powerplant sector across five major countries - China, Germany, India, South Africa and the United States. Leveraging an emissions inventory of more than 4,700 plants alongside integrated assessment modeling, key trends and outlooks associated with greenhouse gas and air pollutants emerge. This closing chapter synthesizes study findings, highlighting inter-country variations, best-performing geographies, challenges and limitations.

5.1 China

China's unchecked economic expansion has exacerbated coal sector emissions despite recent efficiency and environmental policies. While 2040 projections meeting Paris Agreement alignments reveal substantial abatement potential, immediate action is imperative.

5.1.1 Current and Projected Emissions

China's contemporary emissions reflect the complexities of balancing growth and sustainability objectives. Since the Paris Climate Agreement is signed, carbon dioxide emissions have climbed 20% indicating industrialization's energy expansion and demands. All other air pollutants except carbon monoxide display exponential increases, underscoring the atmosphere's rising contamination. Spatial distribution maps reveal higher emission coal facilities clustering in populous eastern & southern regions. Modeling suggests China can peak then drive down emissions under 1.5°C climate policy alignments. 1.5°C Scenario for 2040 emissions projections exhibit reductions from current levels, achieving around 70% carbon dioxide cuts. However, success hinges on urgent economy-wide upgrades (e.g. renewable switches, efficiency gains). Region-level hot-spots may require priority interventions. Stimulus policies also offer co-benefits like energy security and air quality for human health.

5.2 Germany

Germany has made demonstrable progress in reducing power sector emissions through clean energy investments - establishing reference deployment and policy mechanisms for other nations. But continued momentum is vital for realizing decarbonization roadmaps.

5.2.1 Current and Projected Emissions

Since 2015, Germany has notably reduced carbon dioxide and carbon monoxide from its power fleet by 37% and 82% respectively. These reflect Germany's ambitious sustainability pivot. But sulfur dioxide and nitrogen oxides have risen, indicating lingering fossil fuel reliance requiring stringent management. Spatial analysis reveals significant clustering near industrial centers and legacy infrastructure. Model projections exhibit sector-wide emission declines, affirming Germany's low-carbon transition is progressing albeit slower than road mapped. By 2040, carbon dioxide reductions up to 75% seem achievable if renewable energy, storage and efficiency adoption grow. Policies must also address remaining air pollutants while balancing energy security concerns during the transition. Germany's measurable progress can help guide regional neighbors.

5.3 India

India must integrate environmental objectives more strongly within its policy agenda to avoid reaching irreversible climate thresholds. But modeled outcomes give optimism that strategic reforms can flatten then decrease trajectories.

5.3.1 Current and Projected Emissions

All current emissions except sulfur dioxide have expanded since 2015, indicating industrialization's environmental imprint. But carbon monoxide and black carbon success showcase control feasibility. Coal-fired installations dominate the power mix, clustering near urban centers. This exacerbates air pollution, underscoring transition urgency. Emission projections exhibit decreasing profiles, affirming India can achieve substantial mitigation if climate considerations fully permeate governance. Carbon dioxide could fall 65% by 2040 per 1.5°C pathway modeled analysis, while sulfur dioxide may contract 80%. But near-term policy signals must clearly reshape energy investment flows towards efficiency and diversification. Early emissions peaking would also demonstrate leadership.

5.4 South Africa

South Africa must expedite its electricity transition to not just meet global climate obligations but enhance energy access and environmental justice nationally. Modeling suggests this is attainable if stakeholders unite behind clear decarbonization road-maps.

5.4.1 Current and Projected Emissions

Contemporary emissions trends showcase mixed success - with reductions in carbon monoxide and particulate matter but all other species rising. Spatial analysis also highlights geographic inequality in electricity availability versus traditional areas bearing the brunt of coal power powerplant. As a climate vulnerable developing economy, policy priorities must address these imbalances. Emission models indicate potential for substantial abatement by 2040 if South Africa progresses faster on just transition pathways. But obstacles around financing, vested interests and social outcomes must be reconciled. South Africa is well positioned for green industrial growth given ample renewable potential. But immediate policy clarity and implementation focus is essential or climate thresholds may be breached.

5.5 United States

The United States bears among the highest historical emissions, requiring continued climate policy leadership. Power sector modeling affirms the potential to reduce emissions markedly in coming decades through regulatory, technological and infrastructure transformation.

5.5.1 Current and Projected Emissions

Present analysis suggests recent reductions across most species excluding sulfur dioxide. This demonstrates progress from air quality regulation and energy shifts. But abundance of aging electricity assets necessitates strategic replacement programs, particularly in heartland industrial regions to consolidate gains. According to 1.5°C modeled outputs, the United States can build on reduction momentum to decarbonize its coal sector up to 75% by 2040. But this requires comprehensive policy signals to reshape investment flows, infrastructure and innovation priorities favoring renewable, storage and modernized grids. Success can re-establish the United States as a climate leader while delivering local environmental and health benefits.

5.6 Comparative Analysis

The multi-country analysis reveals differentiated starting points, policy landscapes and technological capabilities influencing emission outcomes. Certain best practices are evident across front-runners that could inform peer country initiatives:

- Germany's overall emission declines validate targeted policy incentives and infrastructure investments to enable renewable energy adoption can achieve measurable sustainability results
- The United States' sulfur dioxide emission convergence underscores potential for regulatory approaches to successfully drive specific industrial pollutant reductions.
- India's current lead reducing black carbon highlights that priorities addressing both near-term health and climate forcing impacts can align public and private action even amid broader fossil fuel reliance.
- South Africa's declining particulate matter emissions in recent years highlight that setting and enforcing ambient air quality standards can achieve public health co-benefits while laying the groundwork for further climate action.

Conversely, challenges faced by one state frequently resonate across others:

- Most countries display rising or high sustained carbon dioxide emissions - affirming economy-wide decarbonization remains a persistent roadblock requiring internal consensus-building and global cooperation.
- Many countries have to upgrade older electricity systems including aging power plants and grids. The institutions overseeing the electricity sector also face pressures to change - complicating transitions despite technological viability.

- Air pollution increases experienced across indicatives like sulfur dioxide showcase existing regulations and pollution equipment still have gaps. Tougher environmental oversight of fossil fuels is needed so health impacts and climate change risks keep declining all together.

Overall the cross-country analysis underscores that while realizing deep power sector decarbonization aligned to Paris Agreement targets is proving difficult, it remains attainable through policy prioritization, market reforms, financing and technological transformations enabling cleaner alternatives to take hold. But delays risk both destabilized climates and millions of avoidable pollution-linked deaths hence urgency is vital.

5.7 Limitations

While this analysis aimed to provide extensive insights into current emission status and future outlooks across focus countries, some limitations must be highlighted:

- The historical emissions trend analysis for air pollutants relied on the public EDGAR database for past inventory estimates until 2018. Since current year analysis focused on 2023, estimating emission levels for the intervening 2019-2022 period to link past trends required simplified assumptions to connect 2018 levels to the independently derived 2023 reference year inventories (Figure 7.33). This approximation introduces uncertainty into the precise progression of annual emissions between 2018-2023. With 5 year gaps in actual historical inventories, emissions fluctuations during events like the COVID-19 pandemic recovery cannot be captured accurately. More complete time series emission data would allow tracing step-wise changes across years with higher precision. However obtaining consistent annual country level emission statistics requires extensive ground data collection efforts.

- Integrating disparate power plant data sources posed cross-referencing difficulties, requiring extensive iterations within the matching tool to refine algorithms for accurately pairing facilities across databases with varying resolutions. While the recursive methodology helped improve linkages between records through coordinate, capacity and fuel type commonalities, some probability and uncertainty persists around precise plant mappings. Additionally, the iterative process contributed timeline delays. Composite inventory creation had to weigh trade-offs from manual verification for a consolidated facility-level dataset against residual gaps where linkages probabilities remain below absolute confidence thresholds.

- Using many different integrated assessment models to estimate future emissions created challenges in accurately projecting outcomes. Each model makes different assumptions about economic trends, policies, new technologies when looking ahead. This means there was wide variation in what different models forecast for the country's emissions in 2040 across pollutants. This made it hard to clearly compare projections for seeing where estimates match and finding the common range. Efforts to harmonize assumptions and link macro trends to micro impacts remain important areas for improvement.

6 Summary and Outlook

This research synthesized current and projected emissions across major coal power economies, revealing urgency for accelerated decarbonization. While Paris-aligned phase down is achievable, immediate action is vital.

6.1 Objectives and Approach

This research systematically analyzed current status and plausible phase-down pathways for coal power emissions across major economies representing over 70% of current global coal fleet outputs. Recognizing coal's disproportionate impact on climate and public health outcomes relative to other fossil fuels, the work traces potential transition trajectories aligned with ambitious temperature and sustainability goals. The multi-model assessment integrated plant-level emissions inventory creation, geospatial mapping, integrated scenario modeling spanning socio-technical uncertainties, and iterative analytics. By transparently quantifying current emission baselines from over 4700+ facilities and projecting alternates futures under policy, technology and cooperation assumptions, findings offer diagnostic and prescriptive utility for economy-wide decarbonization.

6.2 Key Imperatives

- **China and India** must peak coal power emissions within years, not decades - realizing approximately 70% decreases by 2040 through renewable switches and efficiency policies

- **South Africa** requires rapid transition from 87% coal reliance towards clean energy access and jobs

- **United States** must consolidate recent emission dips, incentivizing 75% coal power sector cuts

- **Germany** should accelerate its energiewende as a blueprint for further EU momentum

However, interim emission targets likely need greater ambition than projected outcomes still entailing phase-out delays against the pace of climate objectives. Near-term policy signals and systemic transition investments remain essential to reorient energy asset flows and consumption behaviors at scales demarcating existential climate thresholds. Targeted financing and knowledge transfer also stay vital for developing countries like India and South Africa to ensure socially just, economically equitable low-carbon growth pathways.

6.3 The Road Ahead

While vital near-term emission reductions remain contingent on complex policy, technology and investment redirection, this analysis has demonstrated that coal power peak and phase-down is achievable this decade through adequate coordinated action. However, commitments require backing by clear road-maps and financial incentives that restructure energy and growth pathways at scale towards sustainability. Accelerated progress calls for urgent cooperation - from knowledge exchange to consensus-building.

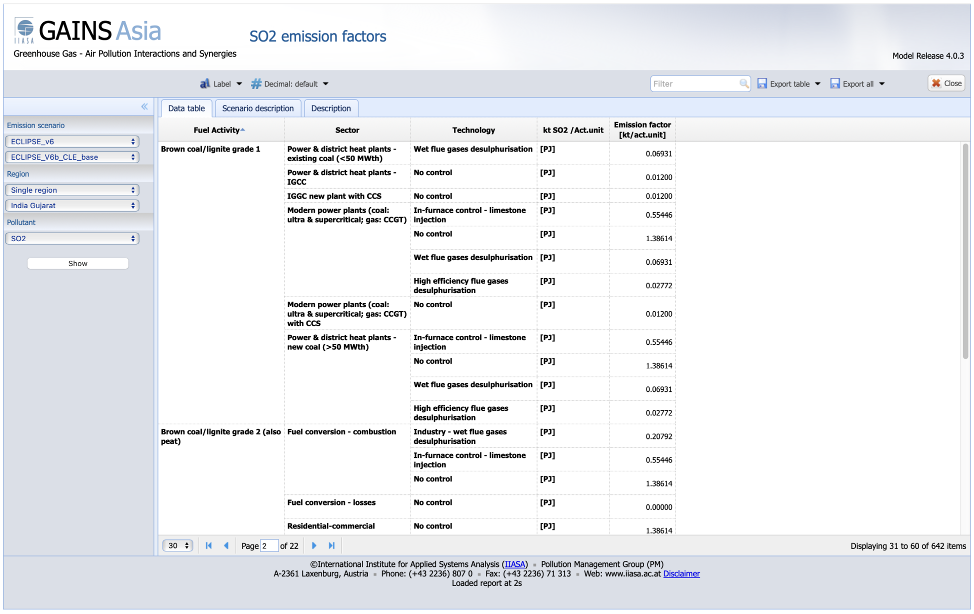
Further research can provide richer insights into solution priorities offering maximum societal benefit through:

- Contrasting above and below-average emitter commitments on decarbonization
- Expanding inventory and projections to transport, buildings and industry
- Modeling emission shifts against health and environmental co-benefits
- Relating renewable adoption potentials to grid-level emission changes
- Surveying diverse stakeholders from utilities to communities

In conclusion, this analysis has shown that while coal power emissions remain entrenched presently, modeled outcomes across contexts demonstrate that peak emissions can be achieved in coming years with adequate coordinated efforts that reshape infrastructure paradigms to favor sustainable alternatives. The stakes for public health and climate stability require nothing less. Commitments however must be backed by clear road-maps and policies that alter investment behaviors at scale. As top contributors wrestle with common and distinct adoption hurdles, sharing best practices around financial incentives, societal engagement processes and environmental regulation can help accelerate change multilaterally. With countries like India and South Africa pivoting development trajectories, the planet can yet transition emission norms from burden to begrudging necessity to source of innovation pride through determined leadership.

7 Annexes

7.1 Emission Factors



GAINS Asia — Greenhouse Gas - Air Pollution Interactions and Synergies

SO2 emission factors

Model Release 4.0.3

Emission scenario: ECLIPSE_v6, ECLIPSE_V6b_CLE_base
Region: Single region, India Gujarat
Pollutant: SO2

Fuel Activity	Sector	Technology	kt SO2 /Act.unit	Emission factor [kt/act.unit]
Brown coal/lignite grade 1	Power & district heat plants - existing coal (<50 MWth)	Wet flue gases desulphurisation	[PJ]	0.06931
	Power & district heat plants - IGCC	No control	[PJ]	0.01200
	IGGC new plant with CCS	No control	[PJ]	0.01200
	Modern power plants (coal: ultra & supercritical; gas: CCGT)	In-furnace control - limestone injection	[PJ]	0.55446
		No control	[PJ]	1.38614
		Wet flue gases desulphurisation	[PJ]	0.06931
		High efficiency flue gases desulphurisation	[PJ]	0.02772
	Modern power plants (coal: ultra & supercritical; gas: CCGT) with CCS	No control	[PJ]	0.01200
	Power & district heat plants - new coal (>50 MWth)	In-furnace control - limestone injection	[PJ]	0.55446
		No control	[PJ]	1.38614
		Wet flue gases desulphurisation	[PJ]	0.06931
		High efficiency flue gases desulphurisation	[PJ]	0.02772
Brown coal/lignite grade 2 (also peat)	Fuel conversion - combustion	Industry - wet flue gases desulphurisation	[PJ]	0.20792
		In-furnace control - limestone injection	[PJ]	0.55446
		No control	[PJ]	1.38614
	Fuel conversion - losses	No control	[PJ]	0.00000
	Residential-commercial	No control	[PJ]	1.38614

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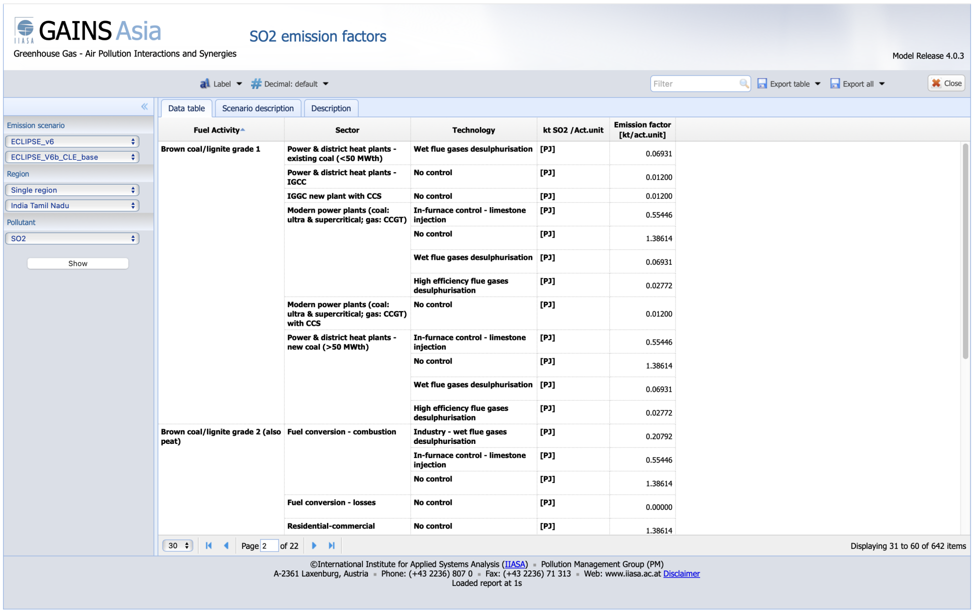
Figure 7.1: GAINS Asia (SO_2) Emission Factor - India (Gujarat)



GAINS Asia — Greenhouse Gas - Air Pollution Interactions and Synergies

SO2 emission factors

Model Release 4.0.3

Emission scenario: ECLIPSE_v6, ECLIPSE_V6b_CLE_base
Region: Single region, India Tamil Nadu
Pollutant: SO2

Fuel Activity	Sector	Technology	kt SO2 /Act.unit	Emission factor [kt/act.unit]
Brown coal/lignite grade 1	Power & district heat plants - existing coal (<50 MWth)	Wet flue gases desulphurisation	[PJ]	0.06931
	Power & district heat plants - IGCC	No control	[PJ]	0.01200
	IGGC new plant with CCS	No control	[PJ]	0.01200
	Modern power plants (coal: ultra & supercritical; gas: CCGT)	In-furnace control - limestone injection	[PJ]	0.55446
		No control	[PJ]	1.38614
		Wet flue gases desulphurisation	[PJ]	0.06931
		High efficiency flue gases desulphurisation	[PJ]	0.02772
	Modern power plants (coal: ultra & supercritical; gas: CCGT) with CCS	No control	[PJ]	0.01200
	Power & district heat plants - new coal (>50 MWth)	In-furnace control - limestone injection	[PJ]	0.55446
		No control	[PJ]	1.38614
		Wet flue gases desulphurisation	[PJ]	0.06931
		High efficiency flue gases desulphurisation	[PJ]	0.02772
Brown coal/lignite grade 2 (also peat)	Fuel conversion - combustion	Industry - wet flue gases desulphurisation	[PJ]	0.20792
		In-furnace control - limestone injection	[PJ]	0.55446
		No control	[PJ]	1.38614
	Fuel conversion - losses	No control	[PJ]	0.00000
	Residential-commercial	No control	[PJ]	1.38614

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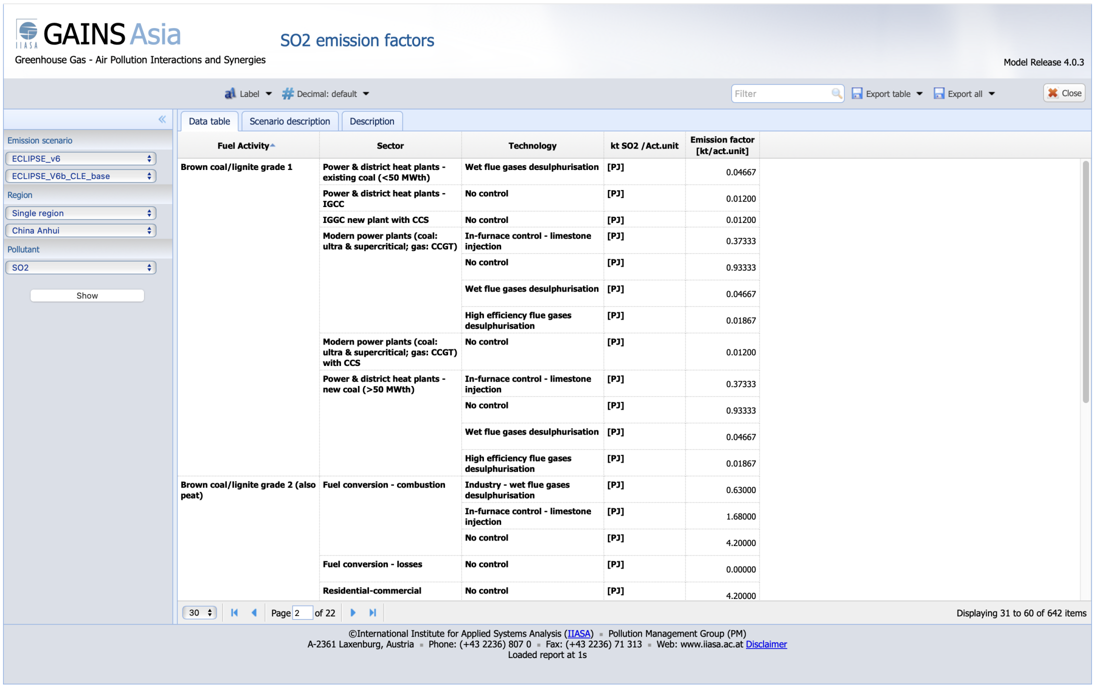
Figure 7.2: GAINS Asia (SO_2) Emission Factor - India (Tamil Nadu)



Emission scenario: ECLIPSE_v6, ECLIPSE_V6b_CLE_base
Region: Single region, China Anhui
Pollutant: SO2

Fuel Activity	Sector	Technology	kt SO2 /Act.unit	Emission factor [kt/act.unit]
Brown coal/lignite grade 1	Power & district heat plants - existing coal (<50 MWth)	Wet flue gases desulphurisation	[PJ]	0.04667
	Power & district heat plants - IGCC	No control	[PJ]	0.01200
	IGGC new plant with CCS	No control	[PJ]	0.01200
	Modern power plants (coal: ultra & supercritical; gas: CCGT)	In-furnace control - limestone injection	[PJ]	0.37333
		No control	[PJ]	0.93333
		Wet flue gases desulphurisation	[PJ]	0.04667
		High efficiency flue gases desulphurisation	[PJ]	0.01867
	Modern power plants (coal: ultra & supercritical; gas: CCGT) with CCS	No control	[PJ]	0.01200
	Power & district heat plants - new coal (>50 MWth)	In-furnace control - limestone injection	[PJ]	0.37333
		No control	[PJ]	0.93333
		Wet flue gases desulphurisation	[PJ]	0.04667
		High efficiency flue gases desulphurisation	[PJ]	0.01867
Brown coal/lignite grade 2 (also peat)	Fuel conversion - combustion	Industry - wet flue gases desulphurisation	[PJ]	0.63000
		In-furnace control - limestone injection	[PJ]	1.68000
		No control	[PJ]	4.20000
	Fuel conversion - losses	No control	[PJ]	0.00000
	Residential-commercial	No control	[PJ]	4.20000

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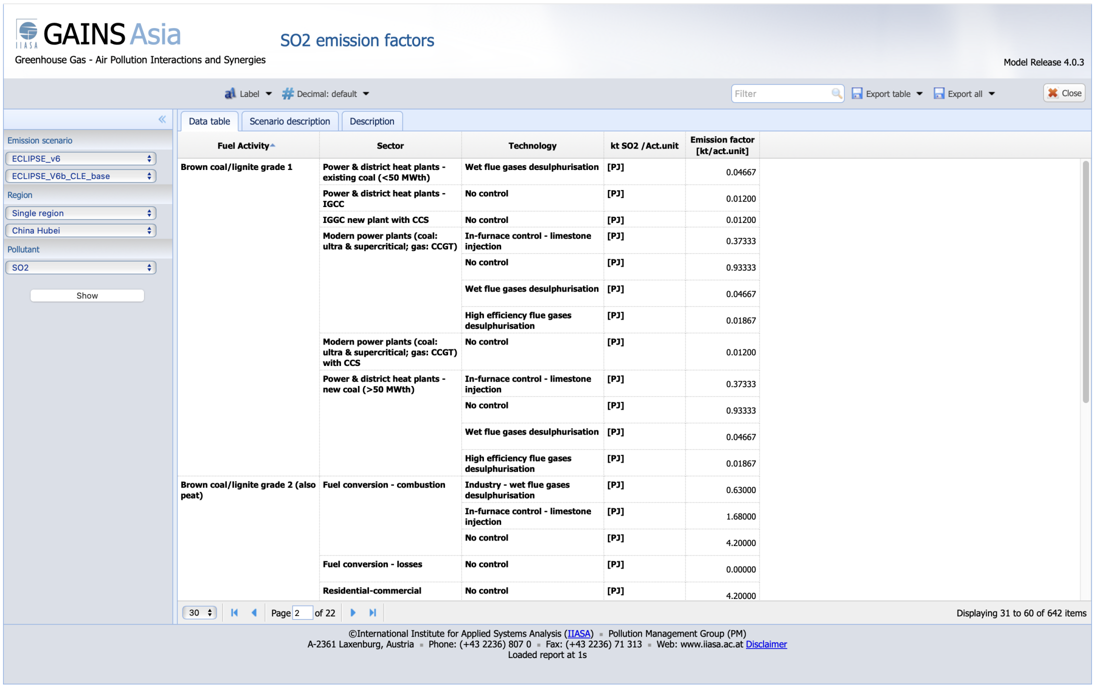
Figure 7.3: GAINS Asia (SO_2) Emission Factor - China (Hubei)



Emission scenario: ECLIPSE_v6, ECLIPSE_V6b_CLE_base
Region: Single region, China Hubei
Pollutant: SO2

Fuel Activity	Sector	Technology	kt SO2 /Act.unit	Emission factor [kt/act.unit]
Brown coal/lignite grade 1	Power & district heat plants - existing coal (<50 MWth)	Wet flue gases desulphurisation	[PJ]	0.04667
	Power & district heat plants - IGCC	No control	[PJ]	0.01200
	IGGC new plant with CCS	No control	[PJ]	0.01200
	Modern power plants (coal: ultra & supercritical; gas: CCGT)	In-furnace control - limestone injection	[PJ]	0.37333
		No control	[PJ]	0.93333
		Wet flue gases desulphurisation	[PJ]	0.04667
		High efficiency flue gases desulphurisation	[PJ]	0.01867
	Modern power plants (coal: ultra & supercritical; gas: CCGT) with CCS	No control	[PJ]	0.01200
	Power & district heat plants - new coal (>50 MWth)	In-furnace control - limestone injection	[PJ]	0.37333
		No control	[PJ]	0.93333
		Wet flue gases desulphurisation	[PJ]	0.04667
		High efficiency flue gases desulphurisation	[PJ]	0.01867
Brown coal/lignite grade 2 (also peat)	Fuel conversion - combustion	Industry - wet flue gases desulphurisation	[PJ]	0.63000
		In-furnace control - limestone injection	[PJ]	1.68000
		No control	[PJ]	4.20000
	Fuel conversion - losses	No control	[PJ]	0.00000
	Residential-commercial	No control	[PJ]	4.20000

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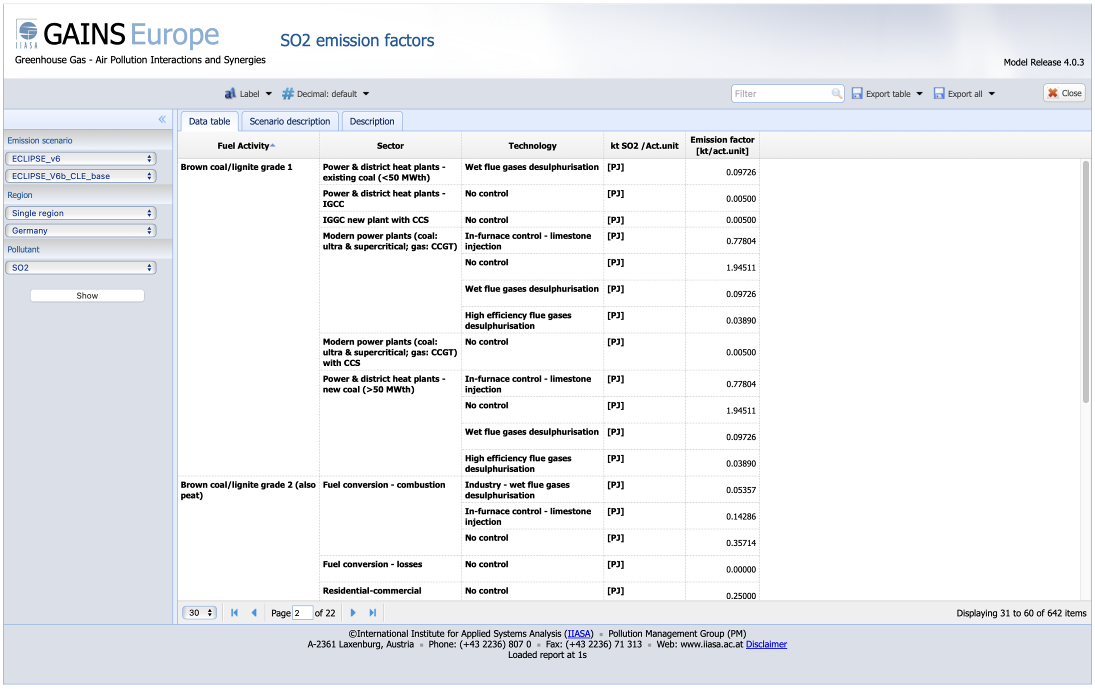
Figure 7.4: GAINS Asia (SO_2) Emission Factor - China (Anhui)



SO2 emission factors

Emission scenario: ECLIPSE_v6; ECLIPSE_V6b_CLE_base

Region: Single region; Germany

Pollutant: SO2

Fuel Activity	Sector	Technology	kt SO2 /Act.unit	Emission factor [kt/act.unit]
Brown coal/lignite grade 1	Power & district heat plants - existing coal (<50 MWth)	Wet flue gases desulphurisation	[PJ]	0.09726
	Power & district heat plants - IGCC	No control	[PJ]	0.00500
	IGGC new plant with CCS	No control	[PJ]	0.00500
	Modern power plants (coal: ultra & supercritical; gas: CCGT)	In-furnace control - limestone injection	[PJ]	0.77804
		No control	[PJ]	1.94511
		Wet flue gases desulphurisation	[PJ]	0.09726
		High efficiency flue gases desulphurisation	[PJ]	0.03890
	Modern power plants (coal: ultra & supercritical; gas: CCGT) with CCS	No control	[PJ]	0.00500
	Power & district heat plants - new coal (>50 MWth)	In-furnace control - limestone injection	[PJ]	0.77804
		No control	[PJ]	1.94511
		Wet flue gases desulphurisation	[PJ]	0.09726
		High efficiency flue gases desulphurisation	[PJ]	0.03890
Brown coal/lignite grade 2 (also peat)	Fuel conversion - combustion	Industry - wet flue gases desulphurisation	[PJ]	0.05357
		In-furnace control - limestone injection	[PJ]	0.14286
		No control	[PJ]	0.35714
	Fuel conversion - losses	No control	[PJ]	0.00000
	Residential-commercial	No control	[PJ]	0.25000

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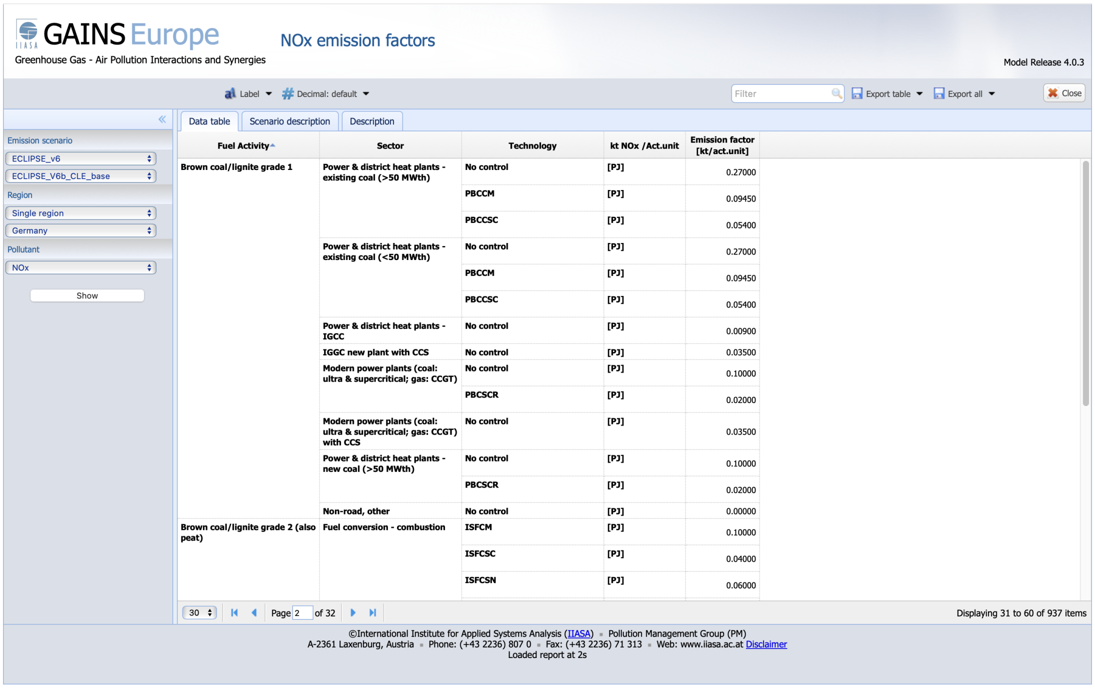
Figure 7.5: GAINS Europe (SO_2) Emission Factor - Germany



NOx emission factors

Emission scenario: ECLIPSE_v6; ECLIPSE_V6b_CLE_base

Region: Single region; Germany

Pollutant: NOx

Fuel Activity	Sector	Technology	kt NOx /Act.unit	Emission factor [kt/act.unit]
Brown coal/lignite grade 1	Power & district heat plants - existing coal (>50 MWth)	No control	[PJ]	0.27000
		PBCCM	[PJ]	0.09450
		PBCCSC	[PJ]	0.05400
	Power & district heat plants - existing coal (<50 MWth)	No control	[PJ]	0.27000
		PBCCM	[PJ]	0.09450
		PBCCSC	[PJ]	0.05400
	Power & district heat plants - IGCC	No control	[PJ]	0.00900
	IGGC new plant with CCS	No control	[PJ]	0.03500
	Modern power plants (coal: ultra & supercritical; gas: CCGT)	No control	[PJ]	0.10000
		PBCSCR	[PJ]	0.02000
	Modern power plants (coal: ultra & supercritical; gas: CCGT) with CCS	No control	[PJ]	0.03500
	Power & district heat plants - new coal (>50 MWth)	No control	[PJ]	0.10000
		PBCSCR	[PJ]	0.02000
	Non-road, other	No control	[PJ]	0.00000
Brown coal/lignite grade 2 (also peat)	Fuel conversion - combustion	ISFCM	[PJ]	0.10000
		ISFCSC	[PJ]	0.04000
		ISFCSN	[PJ]	0.06000

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Figure 7.6: GAINS Europe (NO_x) Emission Factor - Germany

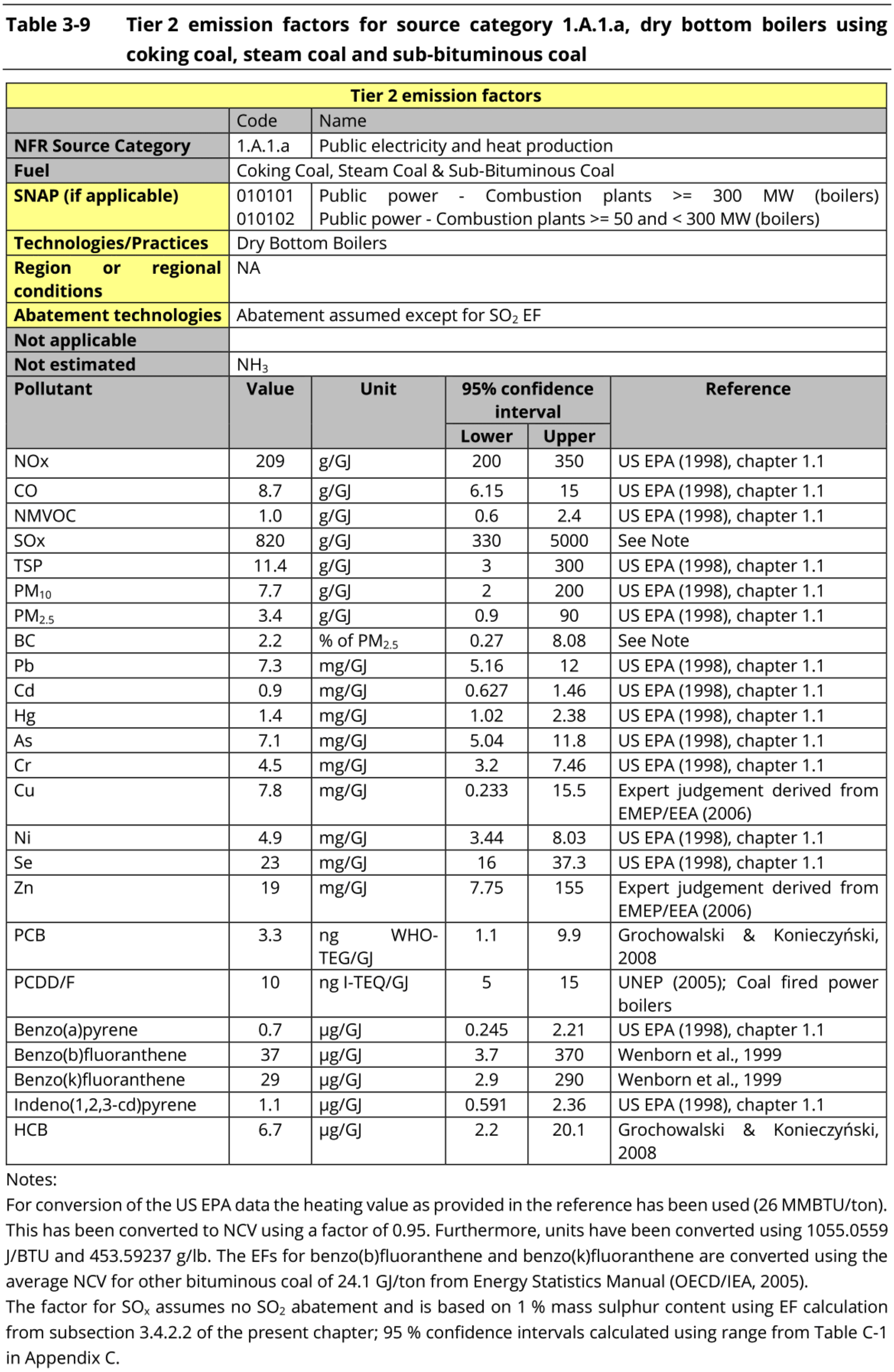

Table 3-9 Tier 2 emission factors for source category 1.A.1.a, dry bottom boilers using coking coal, steam coal and sub-bituminous coal

Tier 2 emission factors		
	Code	Name
NFR Source Category	1.A.1.a	Public electricity and heat production
Fuel	Coking Coal, Steam Coal & Sub-Bituminous Coal	
SNAP (if applicable)	010101 010102	Public power - Combustion plants >= 300 MW (boilers) Public power - Combustion plants >= 50 and < 300 MW (boilers)
Technologies/Practices	Dry Bottom Boilers	
Region or regional conditions	NA	
Abatement technologies	Abatement assumed except for SO_2 EF	
Not applicable		
Not estimated	NH_3	

Pollutant	**Value**	**Unit**	**95% confidence interval**		**Reference**
			Lower	**Upper**	
NOx	209	g/GJ	200	350	US EPA (1998), chapter 1.1
CO	8.7	g/GJ	6.15	15	US EPA (1998), chapter 1.1
NMVOC	1.0	g/GJ	0.6	2.4	US EPA (1998), chapter 1.1
SOx	820	g/GJ	330	5000	See Note
TSP	11.4	g/GJ	3	300	US EPA (1998), chapter 1.1
PM_{10}	7.7	g/GJ	2	200	US EPA (1998), chapter 1.1
$PM_{2.5}$	3.4	g/GJ	0.9	90	US EPA (1998), chapter 1.1
BC	2.2	% of $PM_{2.5}$	0.27	8.08	See Note
Pb	7.3	mg/GJ	5.16	12	US EPA (1998), chapter 1.1
Cd	0.9	mg/GJ	0.627	1.46	US EPA (1998), chapter 1.1
Hg	1.4	mg/GJ	1.02	2.38	US EPA (1998), chapter 1.1
As	7.1	mg/GJ	5.04	11.8	US EPA (1998), chapter 1.1
Cr	4.5	mg/GJ	3.2	7.46	US EPA (1998), chapter 1.1
Cu	7.8	mg/GJ	0.233	15.5	Expert judgement derived from EMEP/EEA (2006)
Ni	4.9	mg/GJ	3.44	8.03	US EPA (1998), chapter 1.1
Se	23	mg/GJ	16	37.3	US EPA (1998), chapter 1.1
Zn	19	mg/GJ	7.75	155	Expert judgement derived from EMEP/EEA (2006)
PCB	3.3	ng WHO-TEG/GJ	1.1	9.9	Grochowalski & Konieczyński, 2008
PCDD/F	10	ng I-TEQ/GJ	5	15	UNEP (2005); Coal fired power boilers
Benzo(a)pyrene	0.7	µg/GJ	0.245	2.21	US EPA (1998), chapter 1.1
Benzo(b)fluoranthene	37	µg/GJ	3.7	370	Wenborn et al., 1999
Benzo(k)fluoranthene	29	µg/GJ	2.9	290	Wenborn et al., 1999
Indeno(1,2,3-cd)pyrene	1.1	µg/GJ	0.591	2.36	US EPA (1998), chapter 1.1
HCB	6.7	µg/GJ	2.2	20.1	Grochowalski & Konieczyński, 2008

Notes:

For conversion of the US EPA data the heating value as provided in the reference has been used (26 MMBTU/ton). This has been converted to NCV using a factor of 0.95. Furthermore, units have been converted using 1055.0559 J/BTU and 453.59237 g/lb. The EFs for benzo(b)fluoranthene and benzo(k)fluoranthene are converted using the average NCV for other bituminous coal of 24.1 GJ/ton from Energy Statistics Manual (OECD/IEA, 2005).

The factor for SO_x assumes no SO_2 abatement and is based on 1 % mass sulphur content using EF calculation from subsection 3.4.2.2 of the present chapter; 95 % confidence intervals calculated using range from Table C-1 in Appendix C.

Figure 7.7: Tier 2 fuel specific - Emission factor USA and South Africa

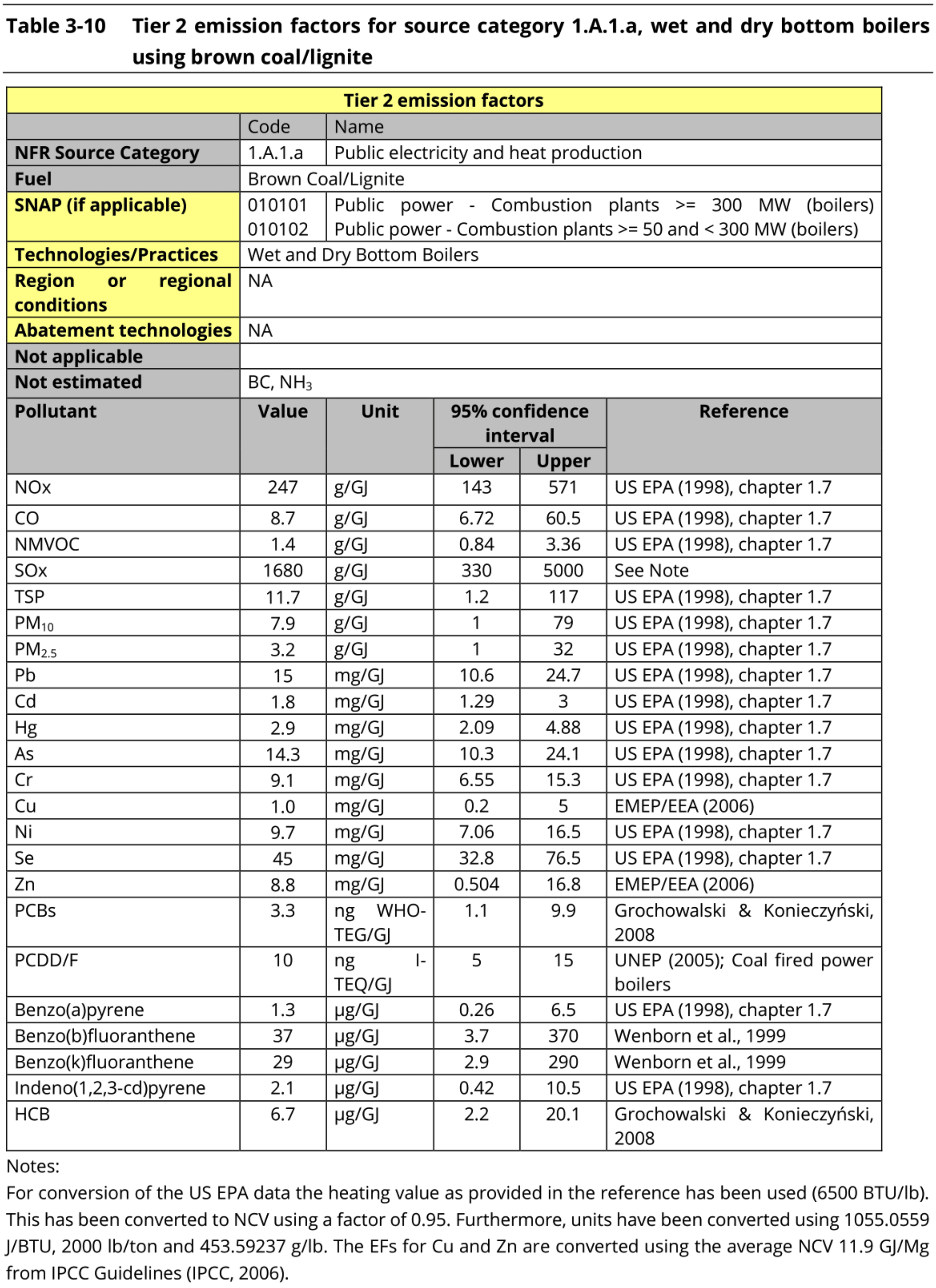

Table 3-10 Tier 2 emission factors for source category 1.A.1.a, wet and dry bottom boilers using brown coal/lignite

Tier 2 emission factors					
	Code	Name			
NFR Source Category	1.A.1.a	Public electricity and heat production			
Fuel	Brown Coal/Lignite				
SNAP (if applicable)	010101 010102	Public power - Combustion plants >= 300 MW (boilers) Public power - Combustion plants >= 50 and < 300 MW (boilers)			
Technologies/Practices	Wet and Dry Bottom Boilers				
Region or regional conditions	NA				
Abatement technologies	NA				
Not applicable					
Not estimated	BC, NH_3				
Pollutant	**Value**	**Unit**	**95% confidence interval**		**Reference**
			Lower	**Upper**	
NOx	247	g/GJ	143	571	US EPA (1998), chapter 1.7
CO	8.7	g/GJ	6.72	60.5	US EPA (1998), chapter 1.7
NMVOC	1.4	g/GJ	0.84	3.36	US EPA (1998), chapter 1.7
SOx	1680	g/GJ	330	5000	See Note
TSP	11.7	g/GJ	1.2	117	US EPA (1998), chapter 1.7
PM_{10}	7.9	g/GJ	1	79	US EPA (1998), chapter 1.7
$PM_{2.5}$	3.2	g/GJ	1	32	US EPA (1998), chapter 1.7
Pb	15	mg/GJ	10.6	24.7	US EPA (1998), chapter 1.7
Cd	1.8	mg/GJ	1.29	3	US EPA (1998), chapter 1.7
Hg	2.9	mg/GJ	2.09	4.88	US EPA (1998), chapter 1.7
As	14.3	mg/GJ	10.3	24.1	US EPA (1998), chapter 1.7
Cr	9.1	mg/GJ	6.55	15.3	US EPA (1998), chapter 1.7
Cu	1.0	mg/GJ	0.2	5	EMEP/EEA (2006)
Ni	9.7	mg/GJ	7.06	16.5	US EPA (1998), chapter 1.7
Se	45	mg/GJ	32.8	76.5	US EPA (1998), chapter 1.7
Zn	8.8	mg/GJ	0.504	16.8	EMEP/EEA (2006)
PCBs	3.3	ng WHO-TEG/GJ	1.1	9.9	Grochowalski & Konieczyński, 2008
PCDD/F	10	ng I-TEQ/GJ	5	15	UNEP (2005); Coal fired power boilers
Benzo(a)pyrene	1.3	µg/GJ	0.26	6.5	US EPA (1998), chapter 1.7
Benzo(b)fluoranthene	37	µg/GJ	3.7	370	Wenborn et al., 1999
Benzo(k)fluoranthene	29	µg/GJ	2.9	290	Wenborn et al., 1999
Indeno(1,2,3-cd)pyrene	2.1	µg/GJ	0.42	10.5	US EPA (1998), chapter 1.7
HCB	6.7	µg/GJ	2.2	20.1	Grochowalski & Konieczyński, 2008

Notes:

For conversion of the US EPA data the heating value as provided in the reference has been used (6500 BTU/lb). This has been converted to NCV using a factor of 0.95. Furthermore, units have been converted using 1055.0559 J/BTU, 2000 lb/ton and 453.59237 g/lb. The EFs for Cu and Zn are converted using the average NCV 11.9 GJ/Mg from IPCC Guidelines (IPCC, 2006).

Figure 7.8: Tier 2 fuel specific - Emission factor USA and South Africa

7.2 Current Emissions

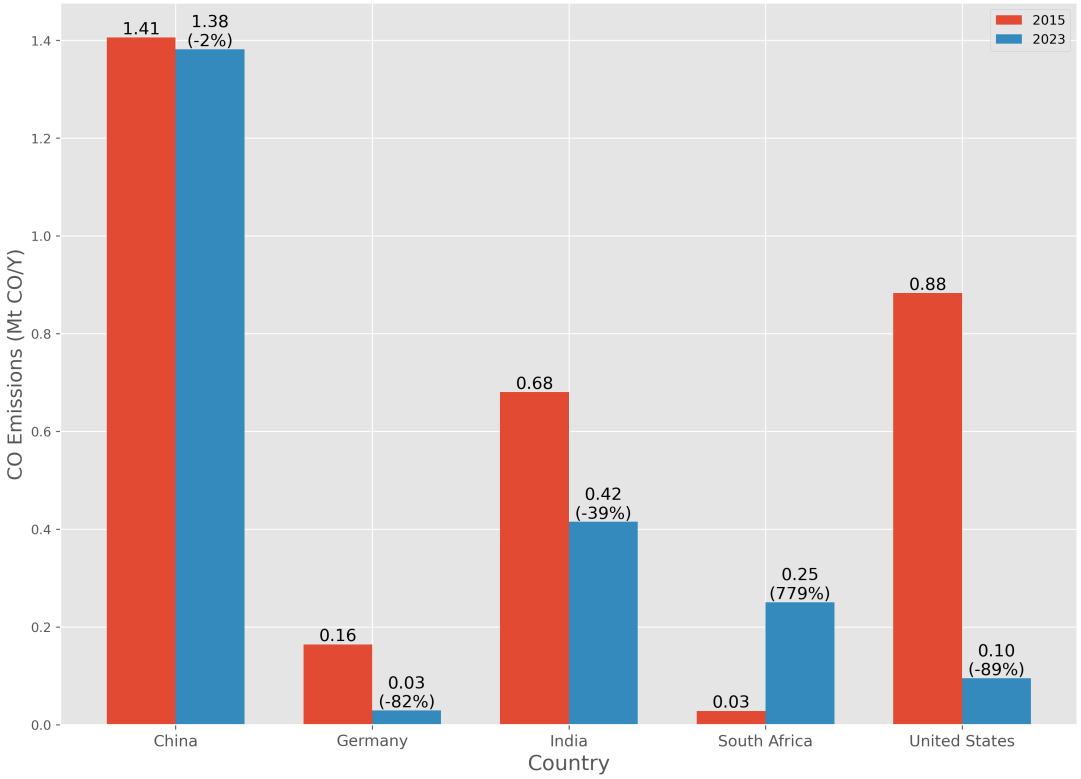

Figure 7.9: Relative Change in (CO) Emissions - 2015 vs 2023

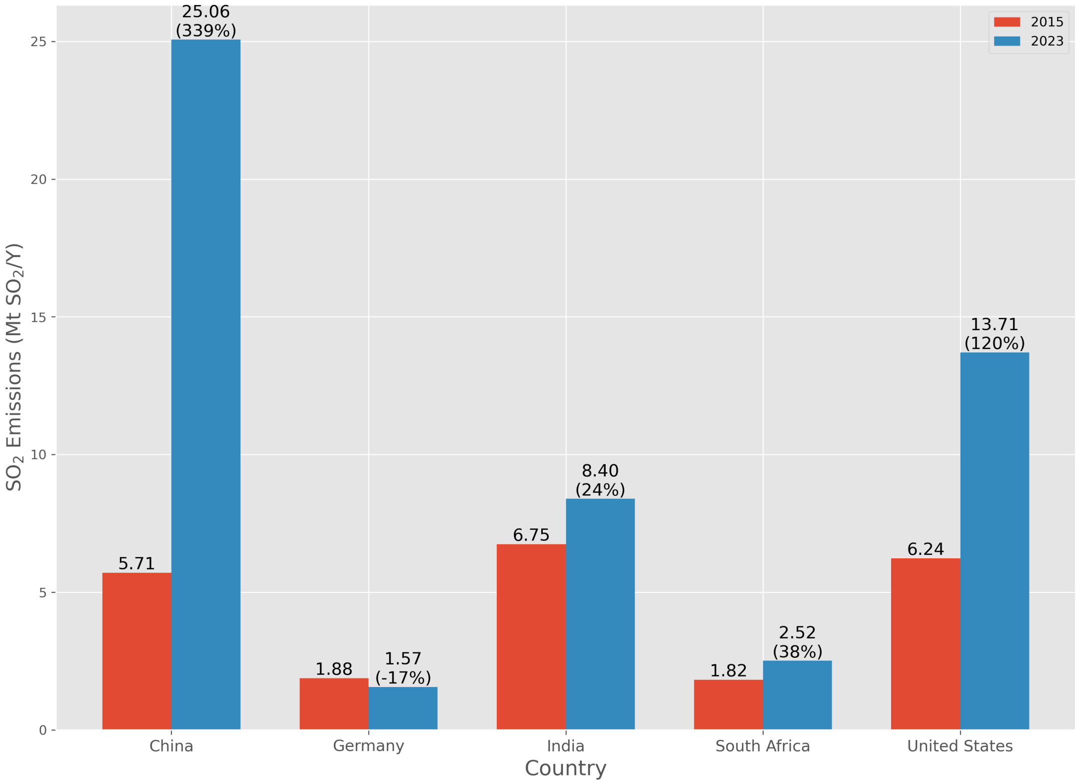

Figure 7.10: Relative Change in (SO_2) Emissions - 2015 vs 2023

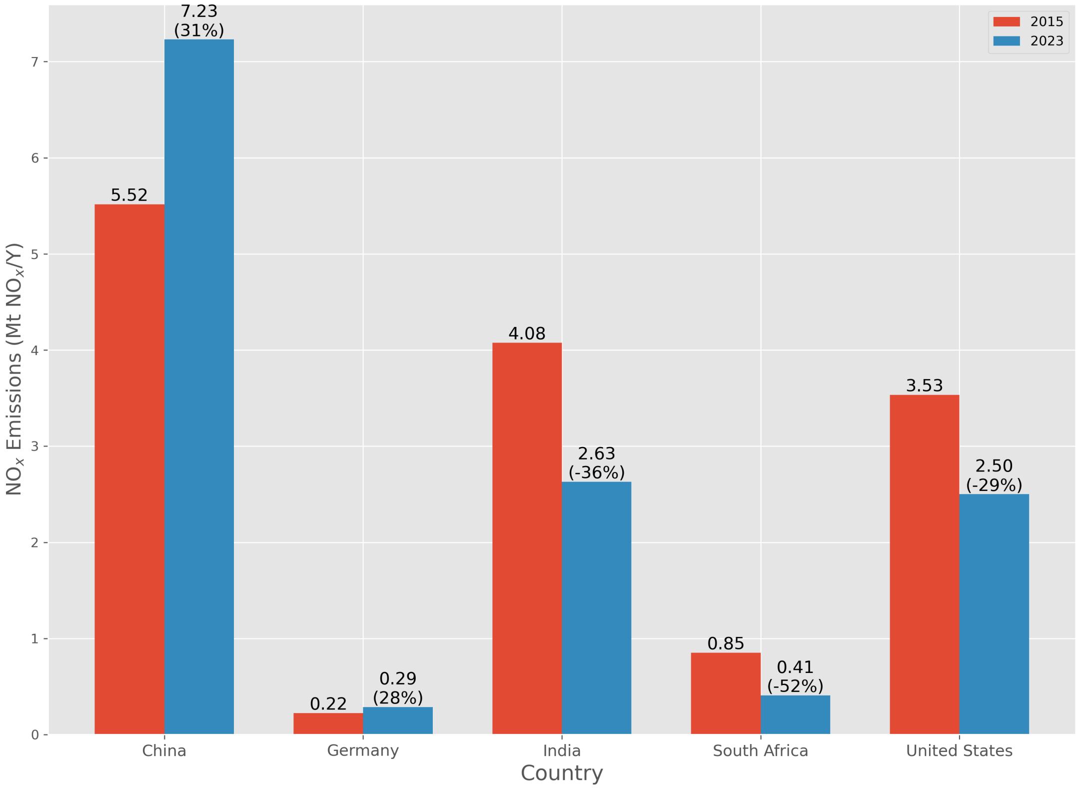

Figure 7.11: Relative Change in (NO_x) Emissions - 2015 vs 2023)

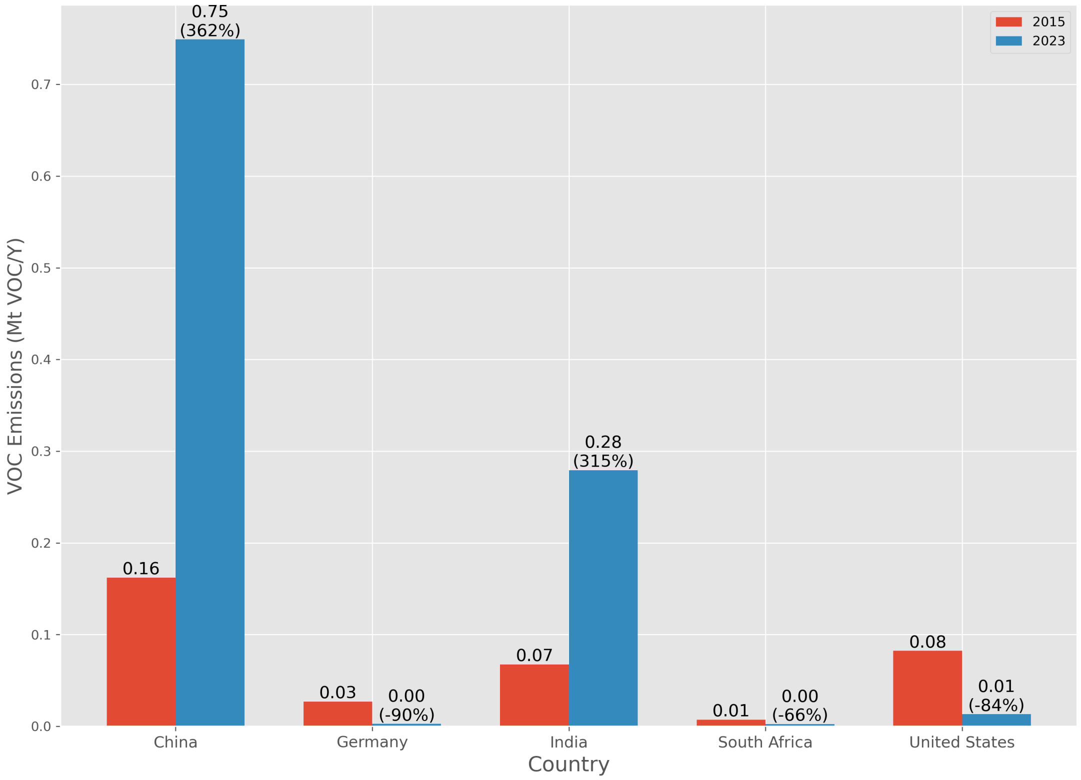

Figure 7.12: Relative Change in (VOC) Emissions - 2015 vs 2023

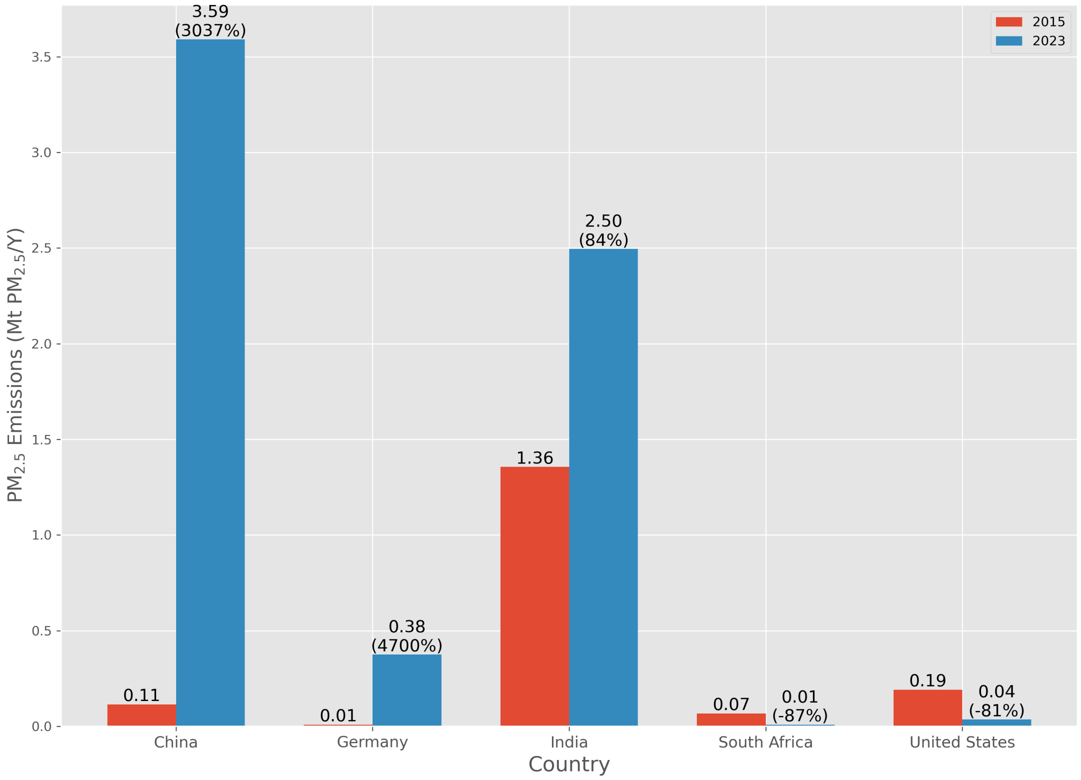

Figure 7.13: Relative Change in $(PM_{2.5})$ Emissions - 2015 vs 2023

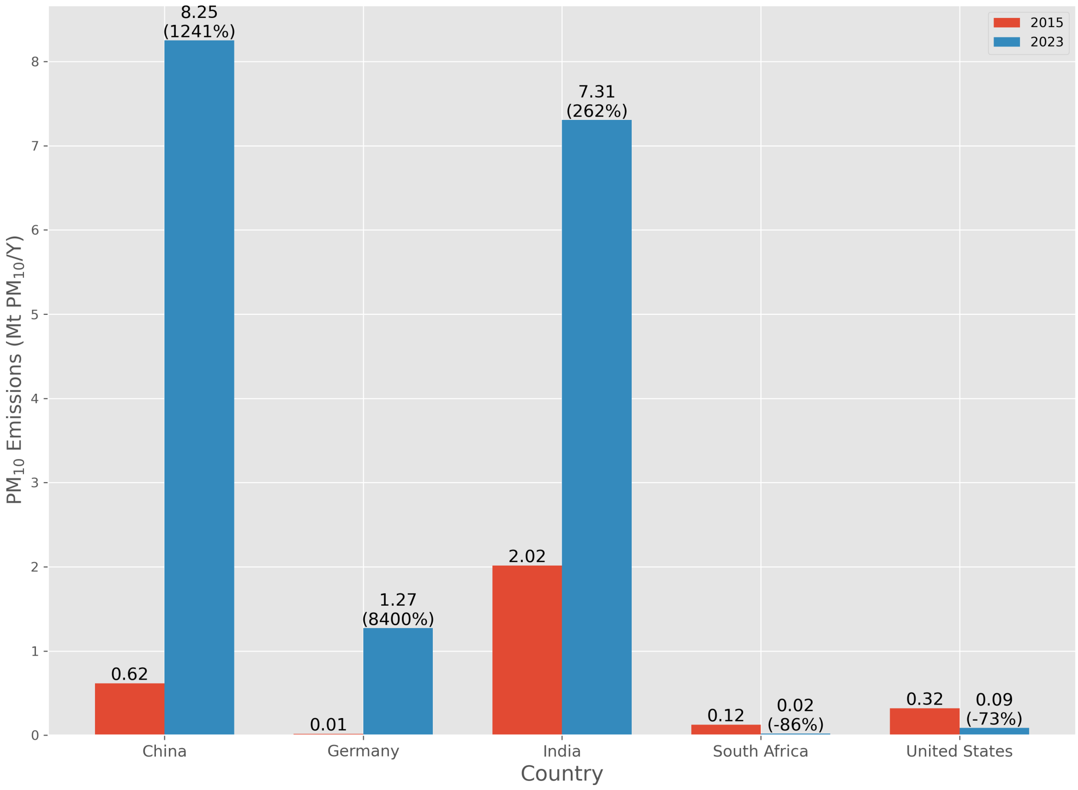

Figure 7.14: Relative Change in (PM_{10}) Emissions - 2015 vs 2023

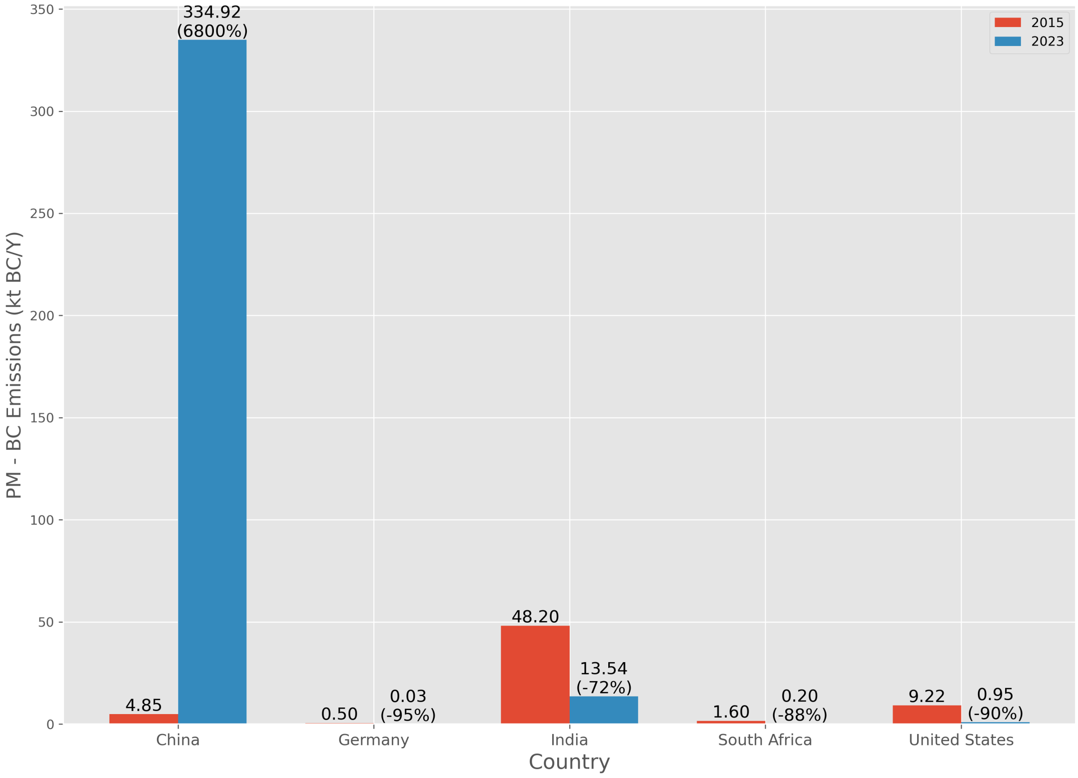

Figure 7.15: Relative Change in $(PM - BC)$ Emissions - 2015 vs 2023

7.3 Projection Model Results

7.3.1 China

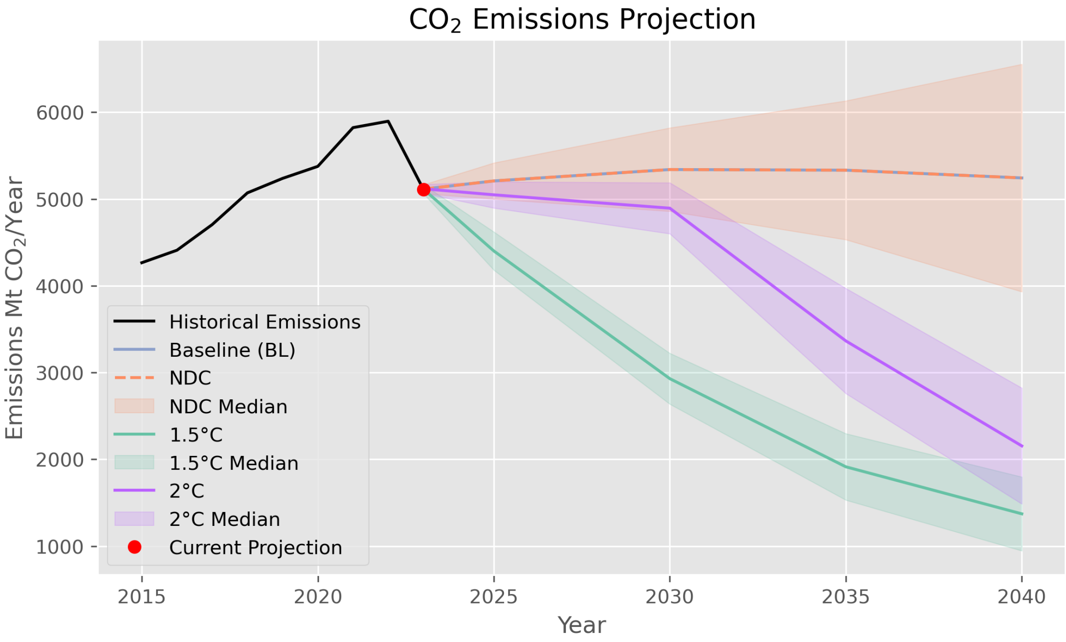

Figure 7.16: Projection Trends of (CO_2) Emissions to 2040

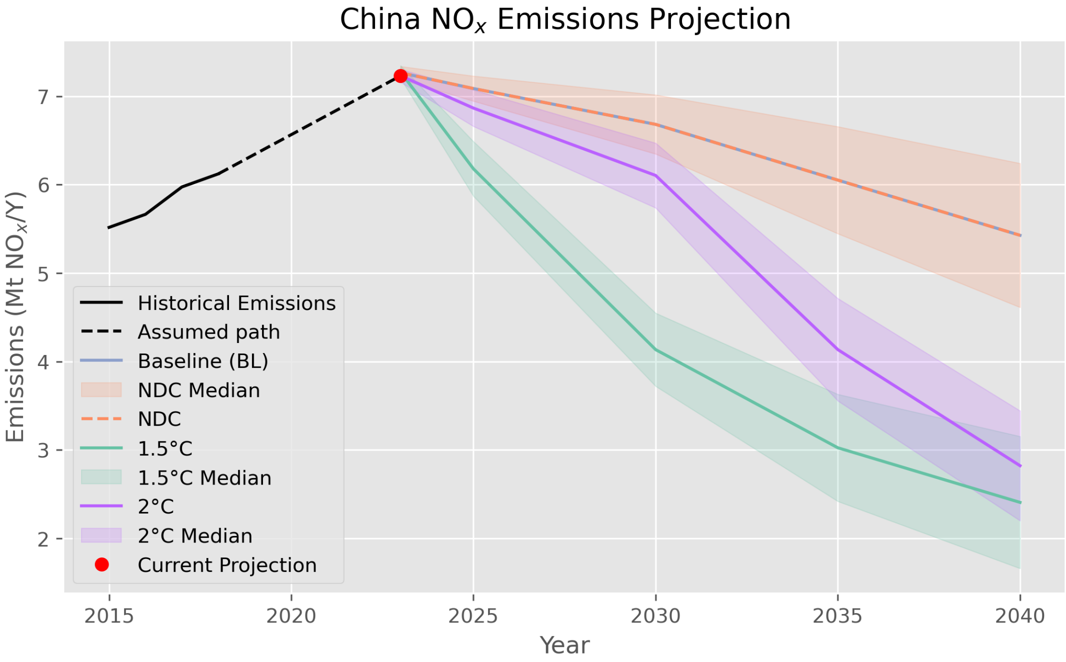

Figure 7.17: Projection Trends of (NO_x) Emissions to 2040

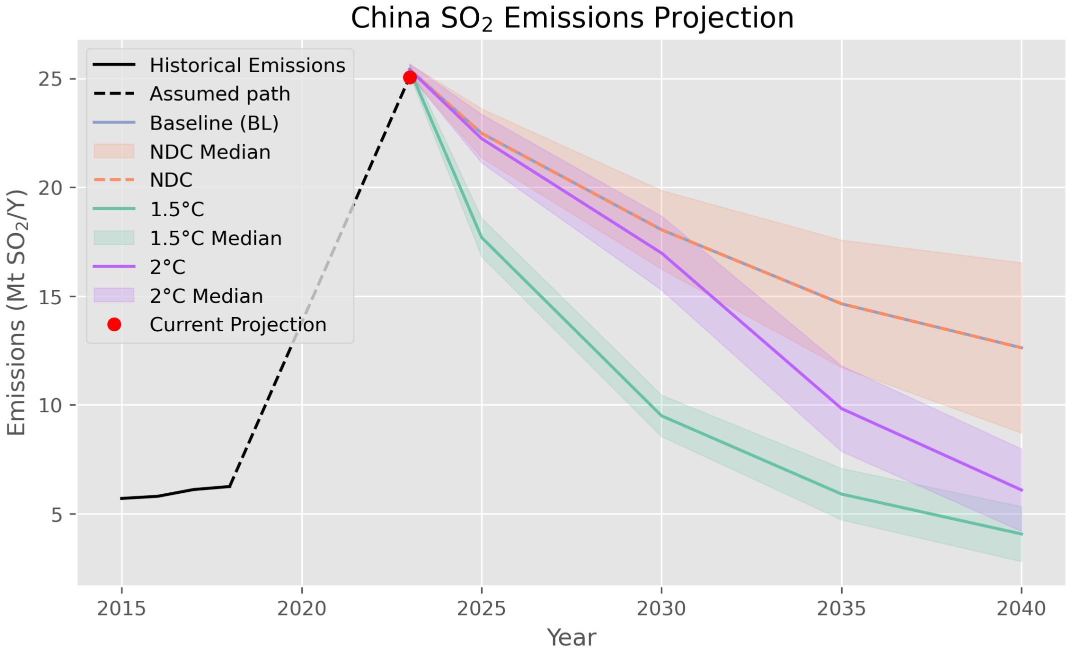

Figure 7.18: Projection Trends of (SO_2) Emissions to 2040

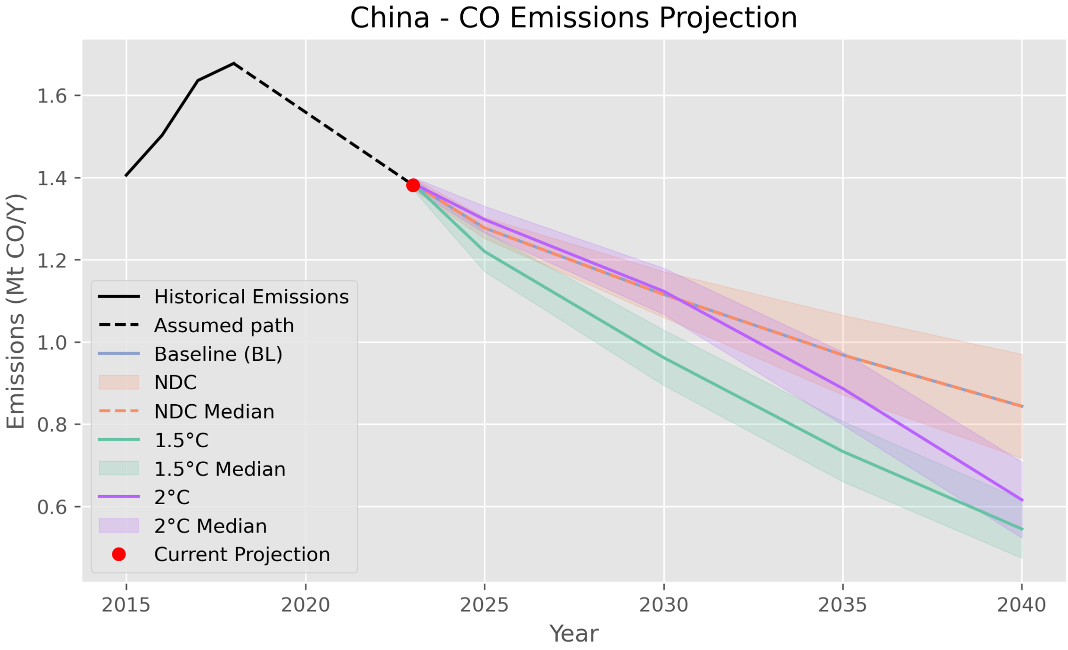

Figure 7.19: Projection Trends of (CO) Emissions to 2040

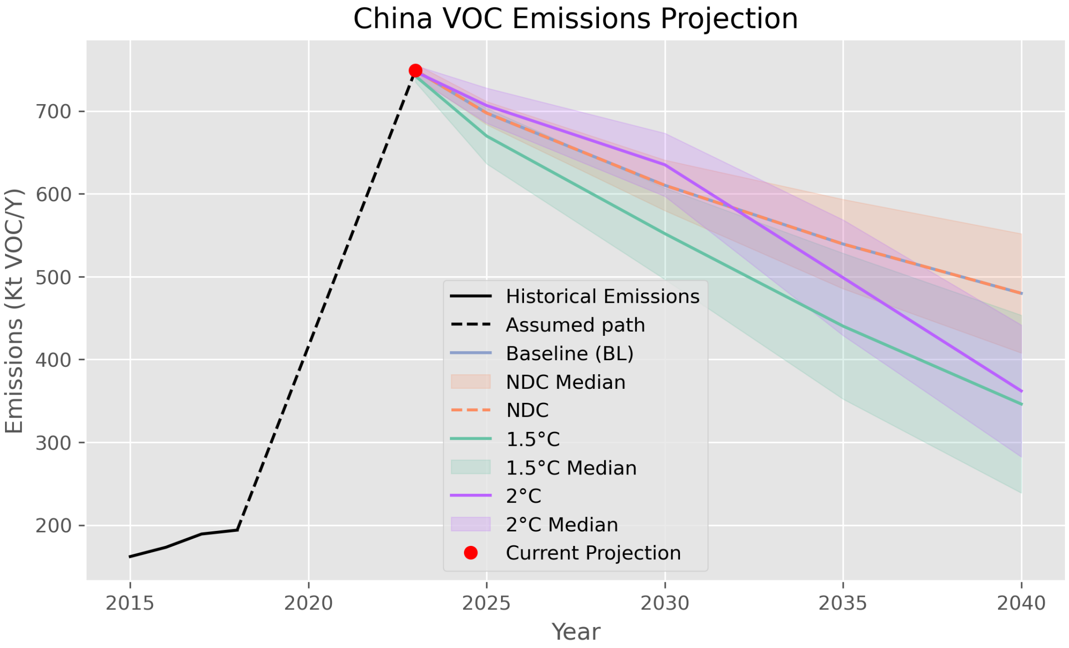

Figure 7.20: Projection Trends of (VOC) Emissions to 2040

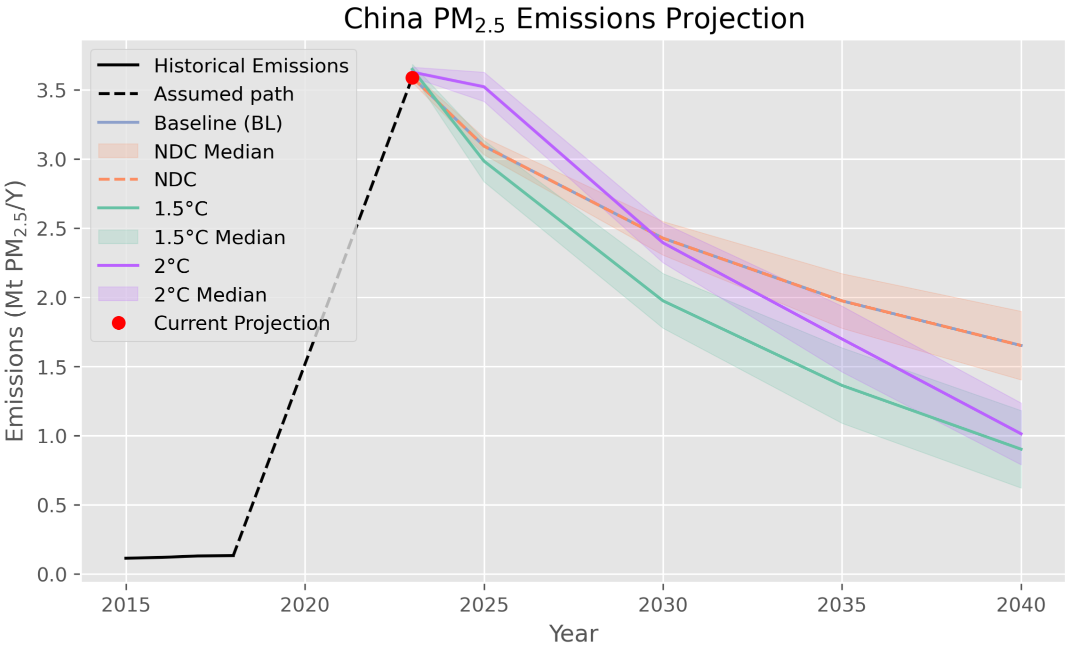

Figure 7.21: Projection Trends of ($PM_{2.5}$) Emissions to 2040

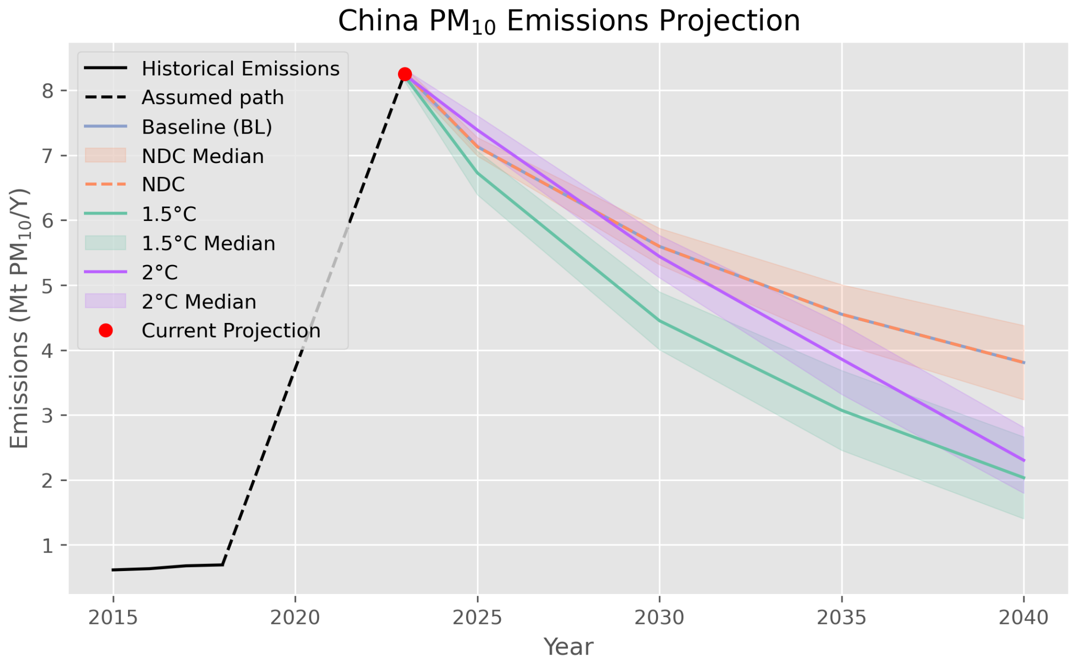

Figure 7.22: Projection Trends of (PM_{10}) Emissions to 2040

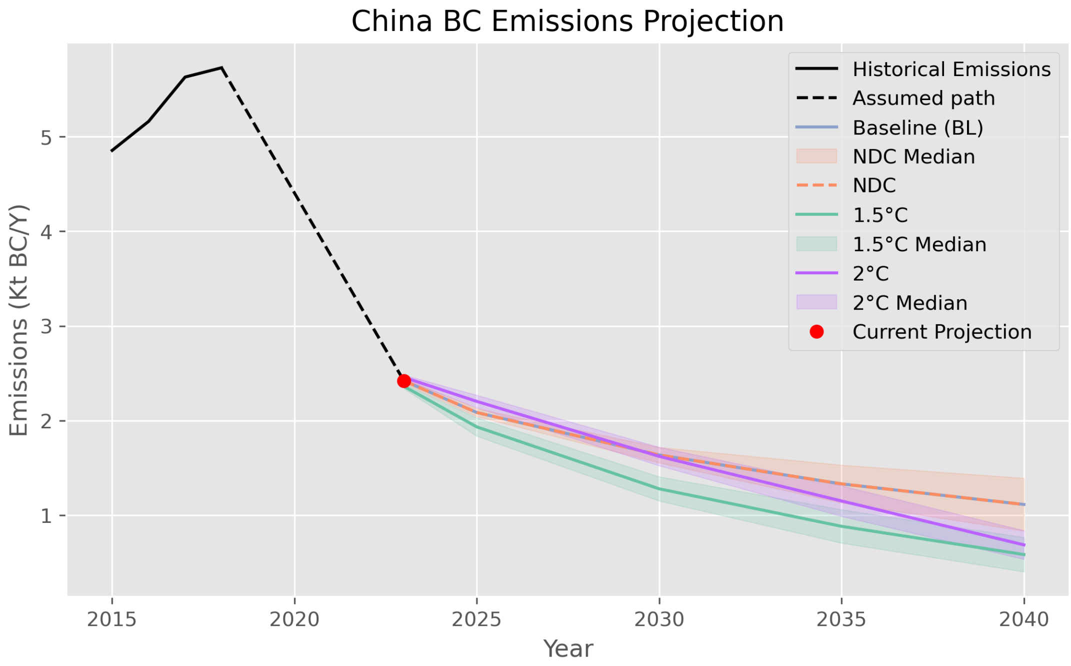

Figure 7.23: Projection Trends of (BC) Emissions to 2040

7.3.2 Germany

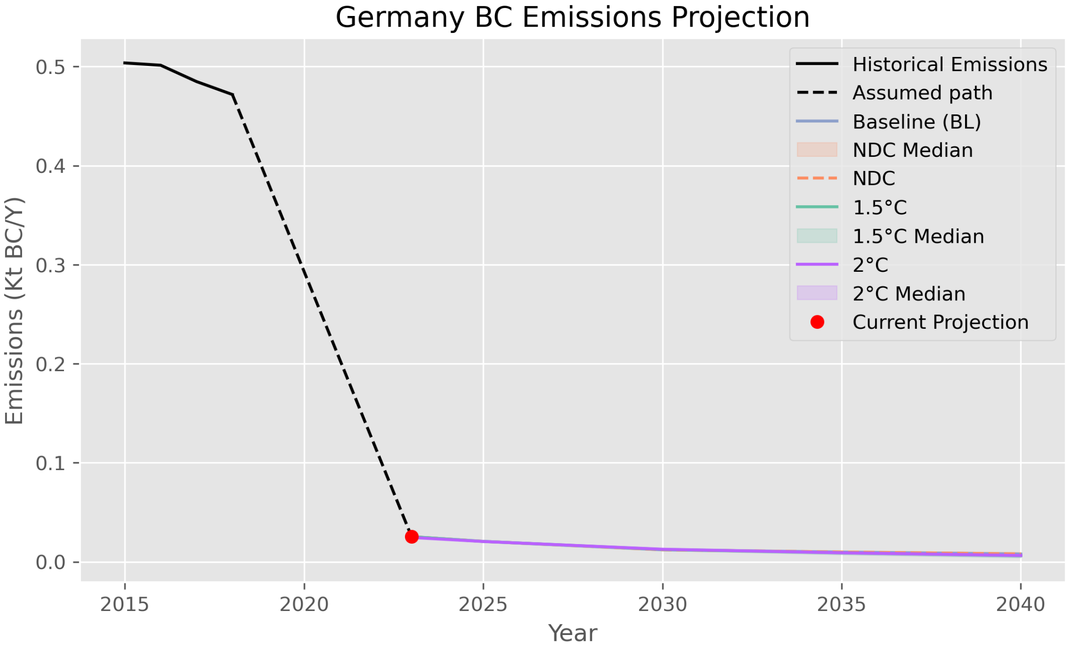

Figure 7.24: Projection Trends of (BC) Emissions to 2040

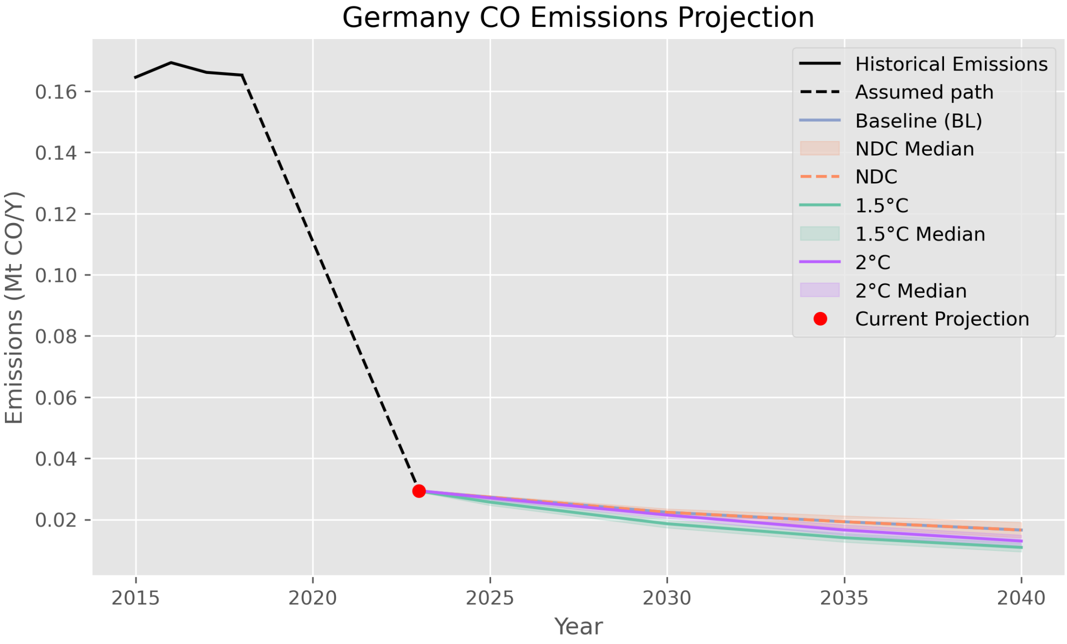

Figure 7.25: Projection Trends of (CO) Emissions to 2040

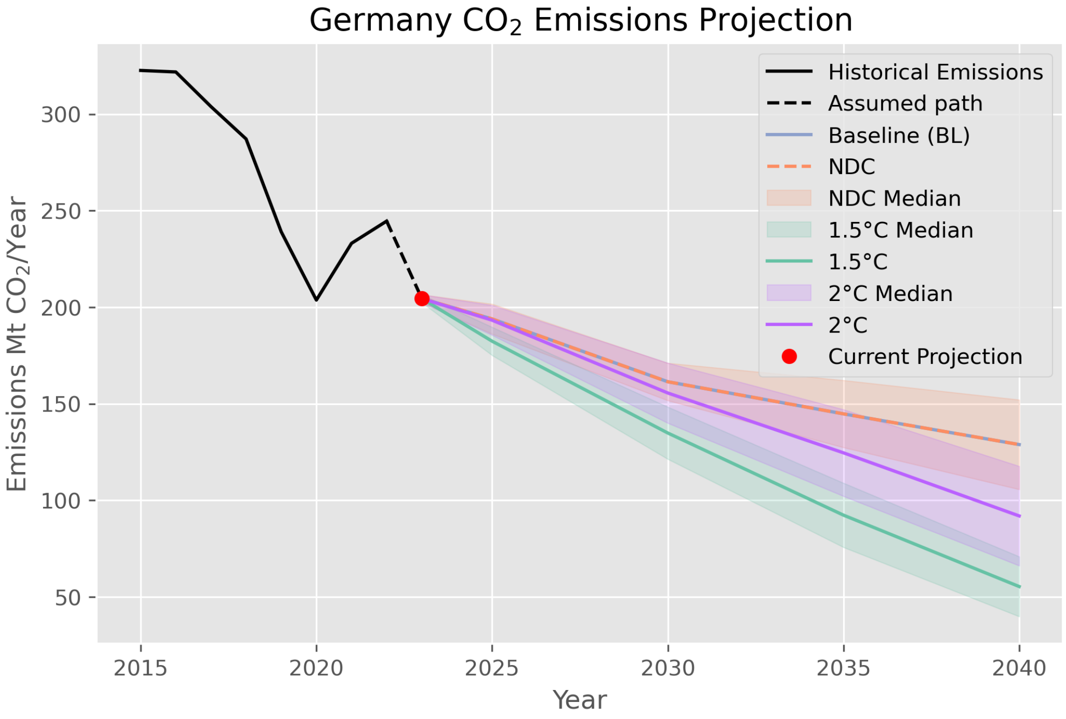

Figure 7.26: Projection Trends of (CO_2) Emissions to 2040

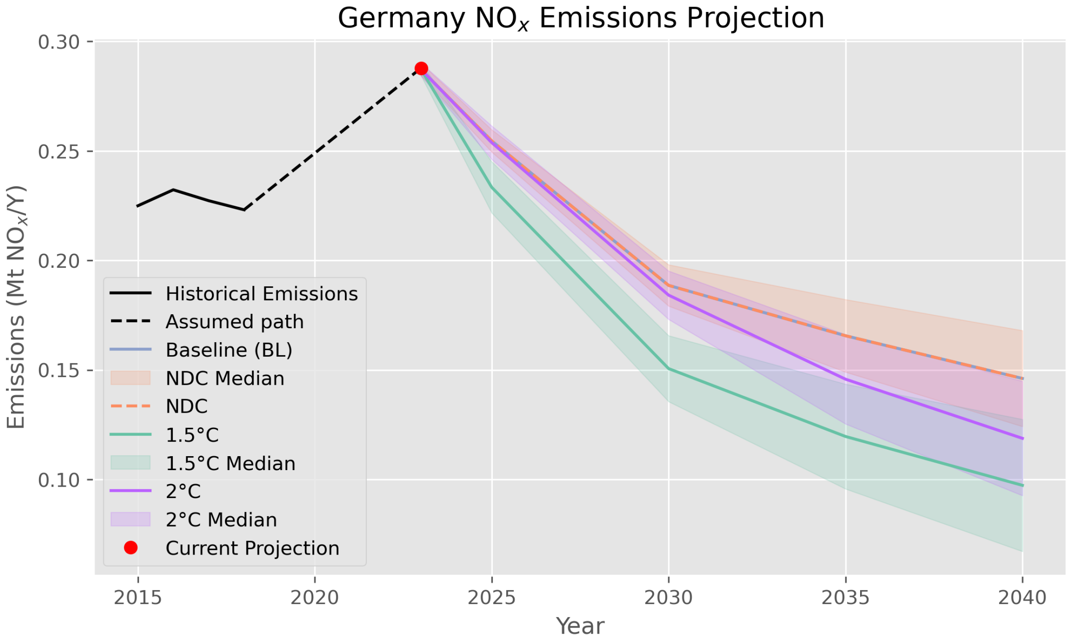

Figure 7.27: Projection Trends of (NO_x) Emissions to 2040

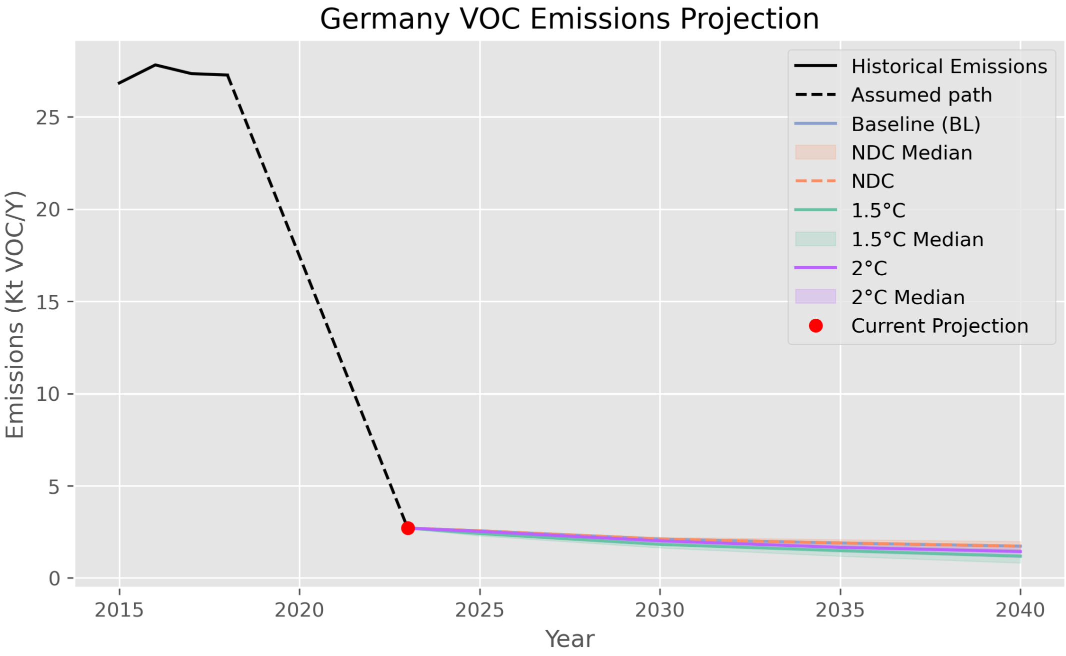

Figure 7.28: Projection Trends of (VOC) Emissions to 2040

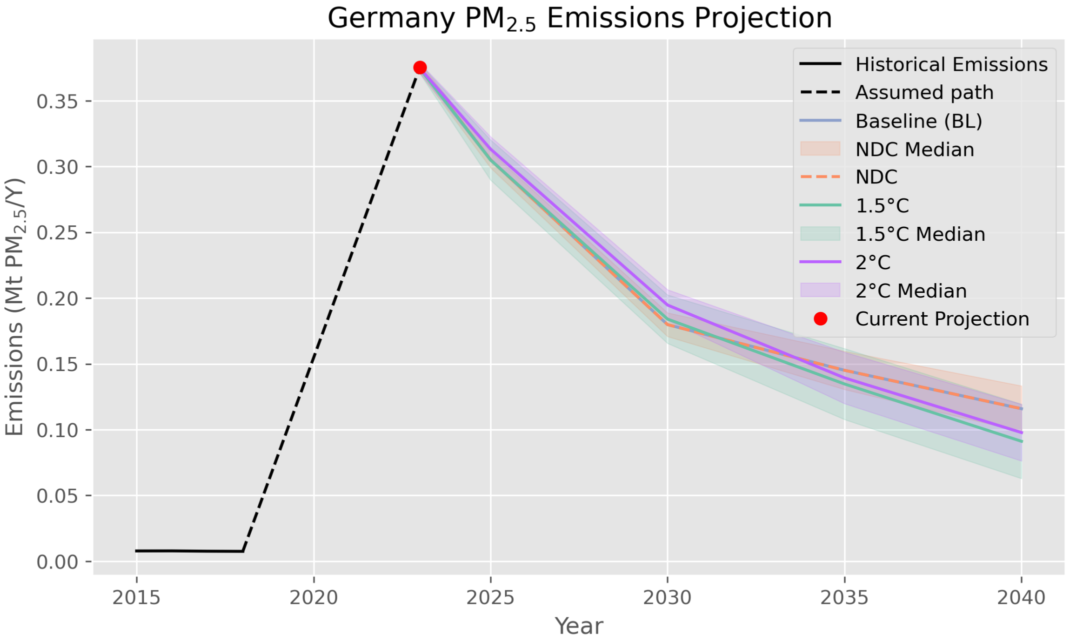

Figure 7.29: Projection Trends of $(PM_{2.5})$ Emissions to 2040

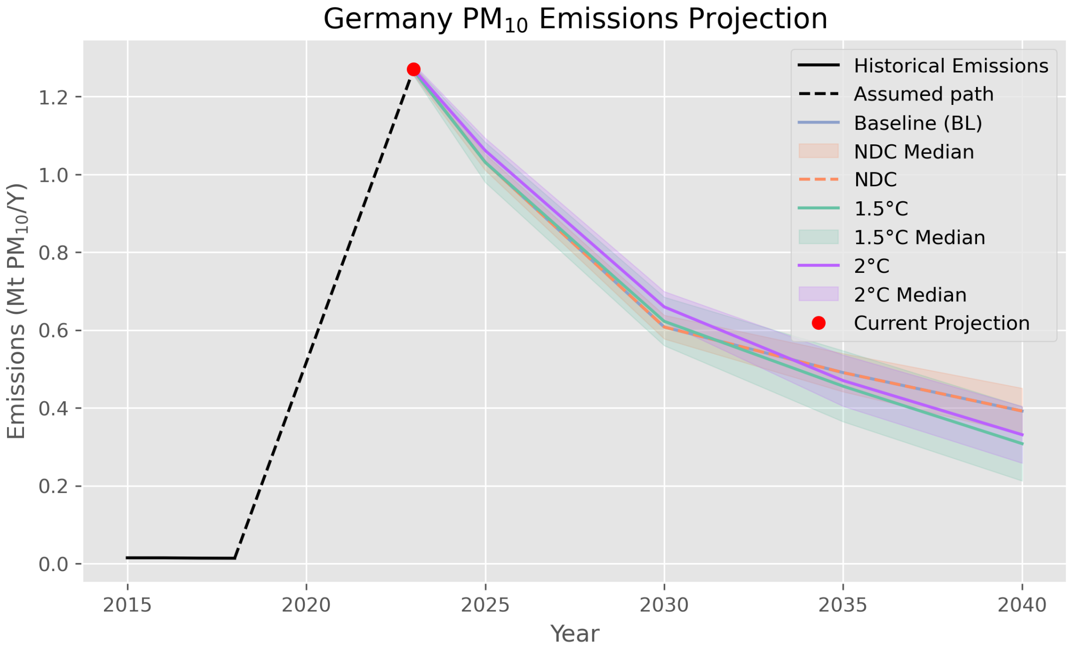

Figure 7.30: Projection Trends of (PM_{10}) Emissions to 2040

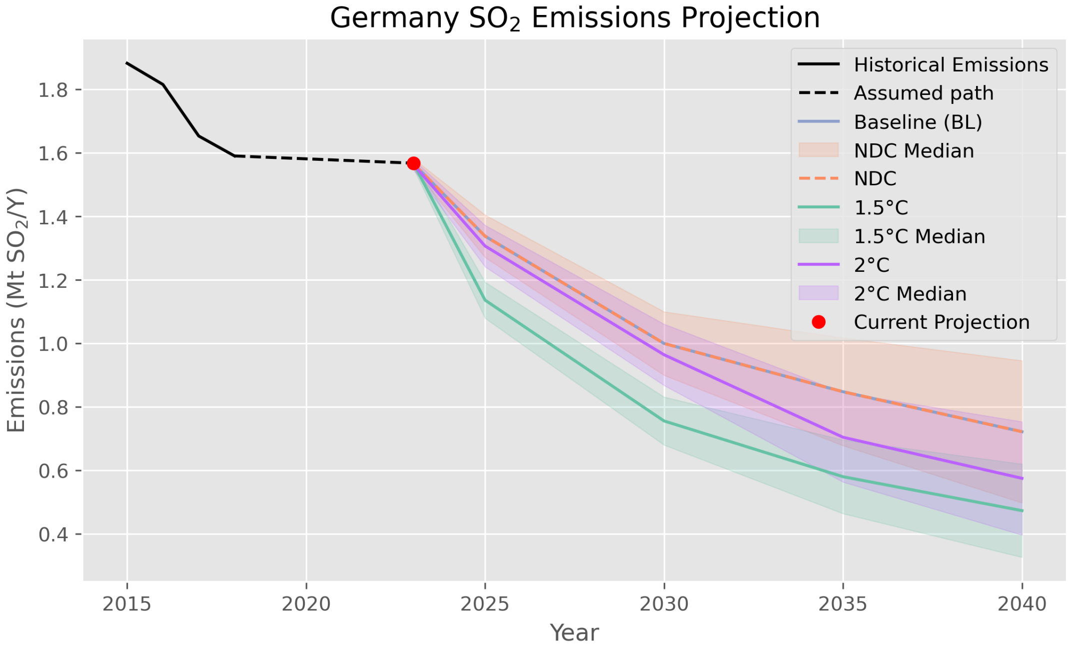

Figure 7.31: Projection Trends of (SO_2) Emissions to 2040

7.3.3 India

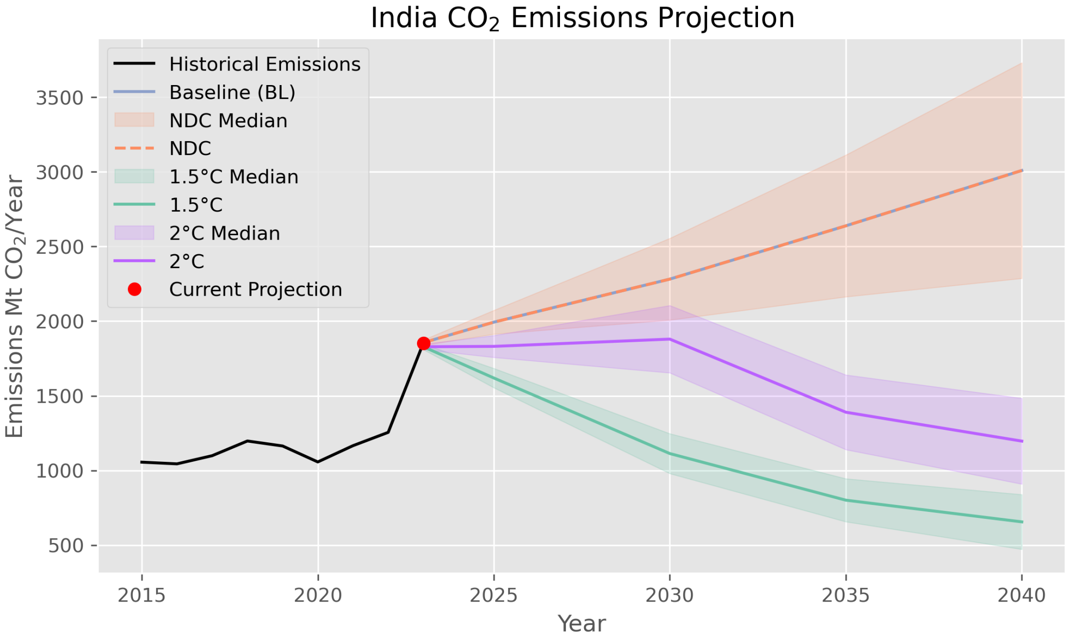

Figure 7.32: Projection Trends of (CO_2) Emissions to 2040

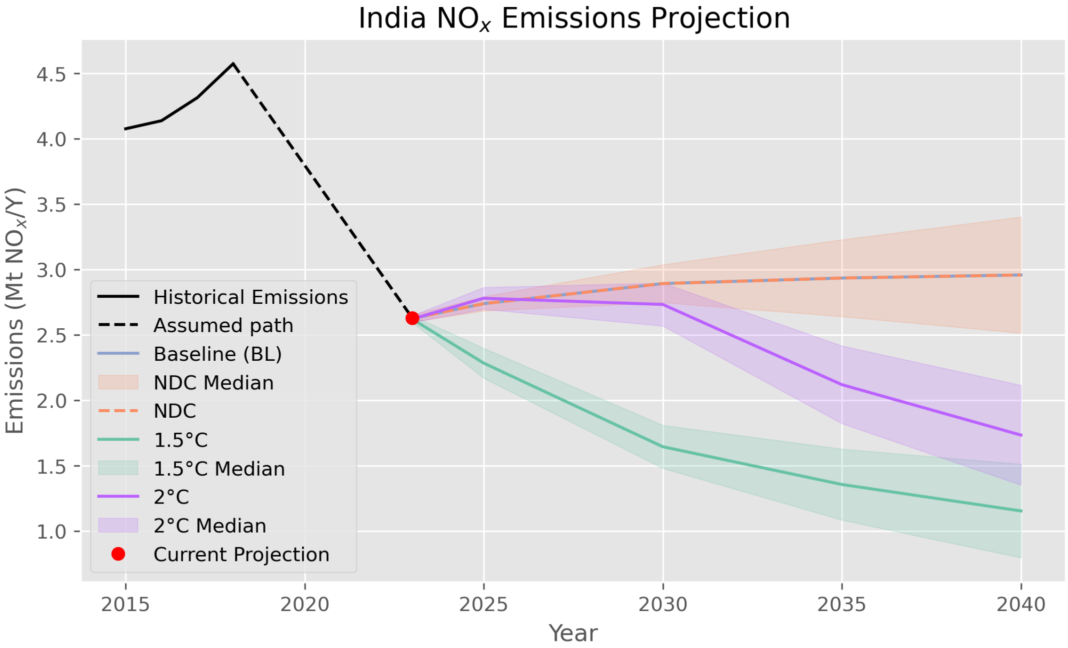

Figure 7.33: Projection Trends of (NO_x) Emissions to 2040

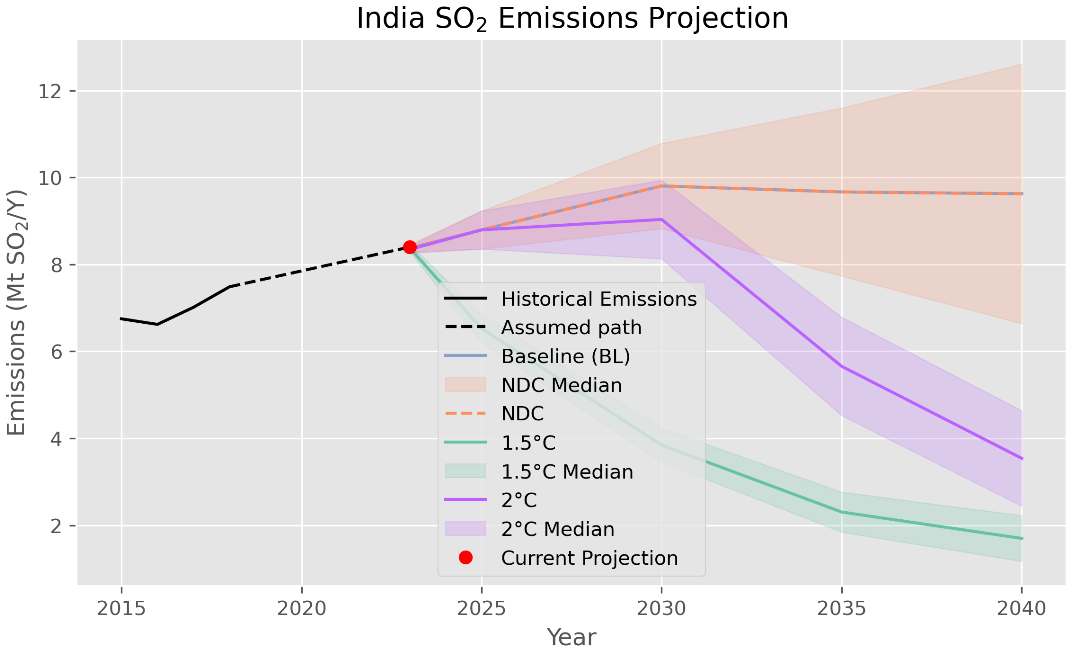

Figure 7.34: Projection Trends of (SO_2) Emissions to 2040

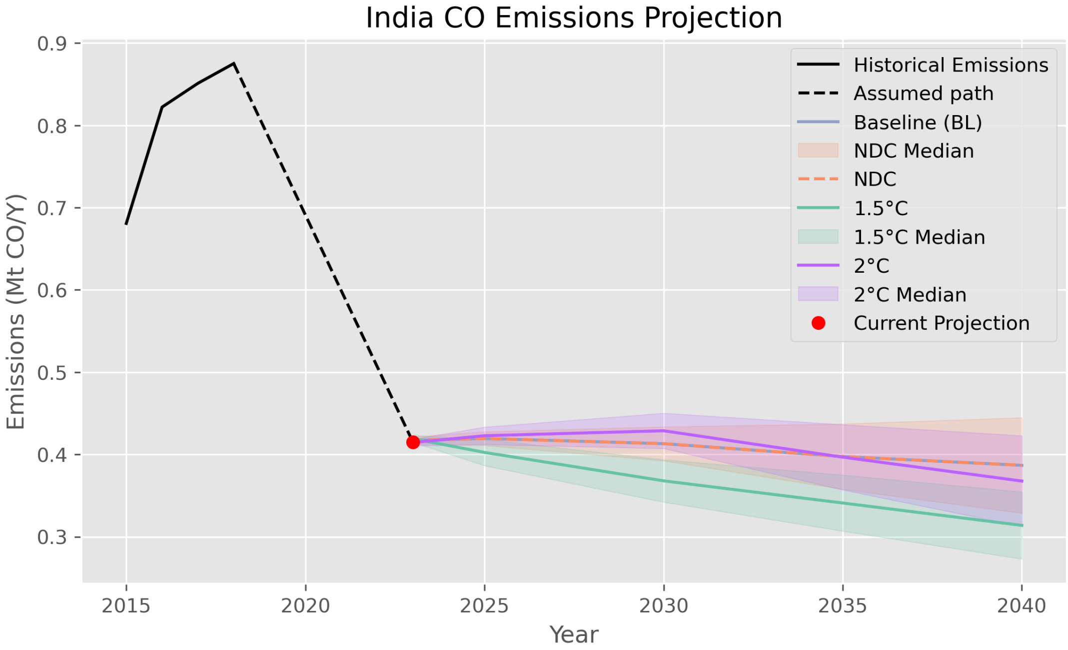

Figure 7.35: Projection Trends of (CO) Emissions to 2040

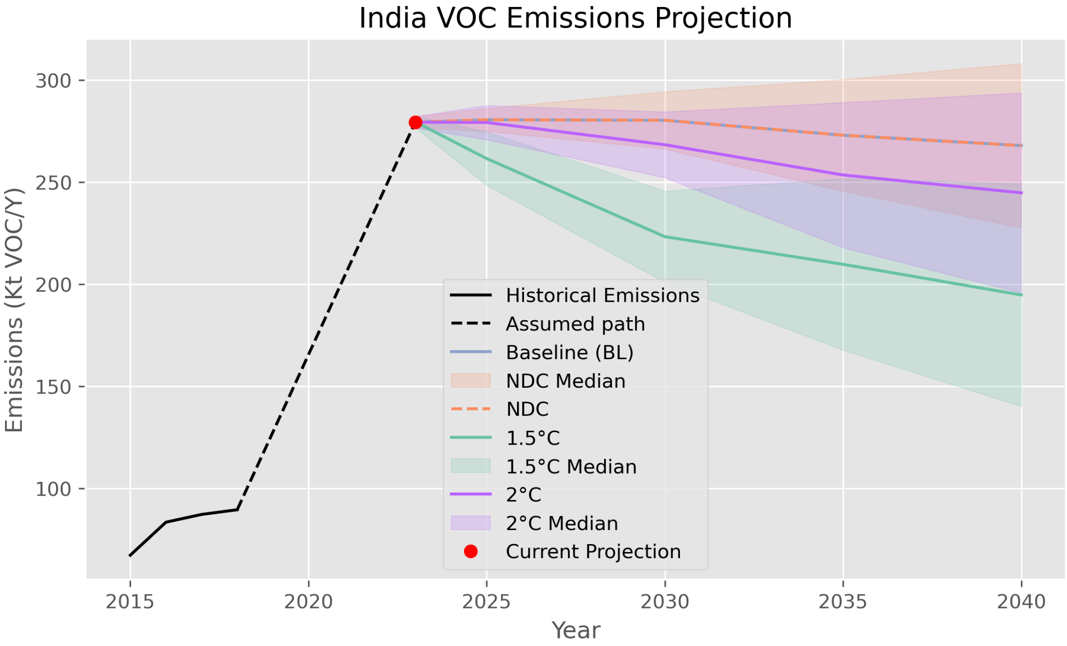

Figure 7.36: Projection Trends of (VOC) Emissions to 2040

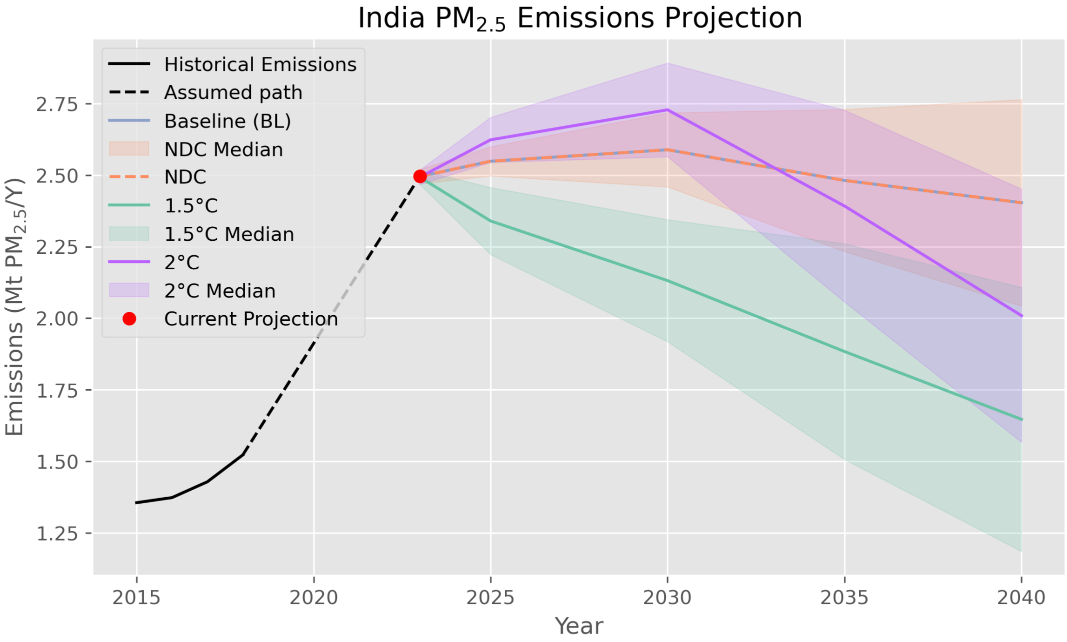

Figure 7.37: Projection Trends of $(PM_{2.5})$ Emissions to 2040

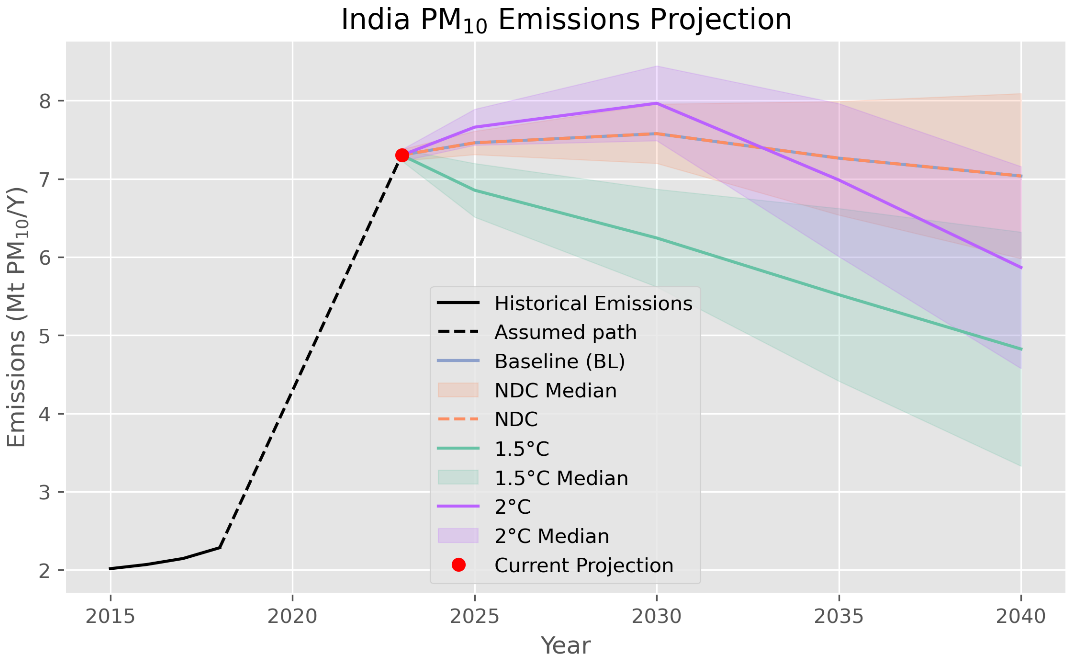

Figure 7.38: Projection Trends of (PM_{10}) Emissions to 2040

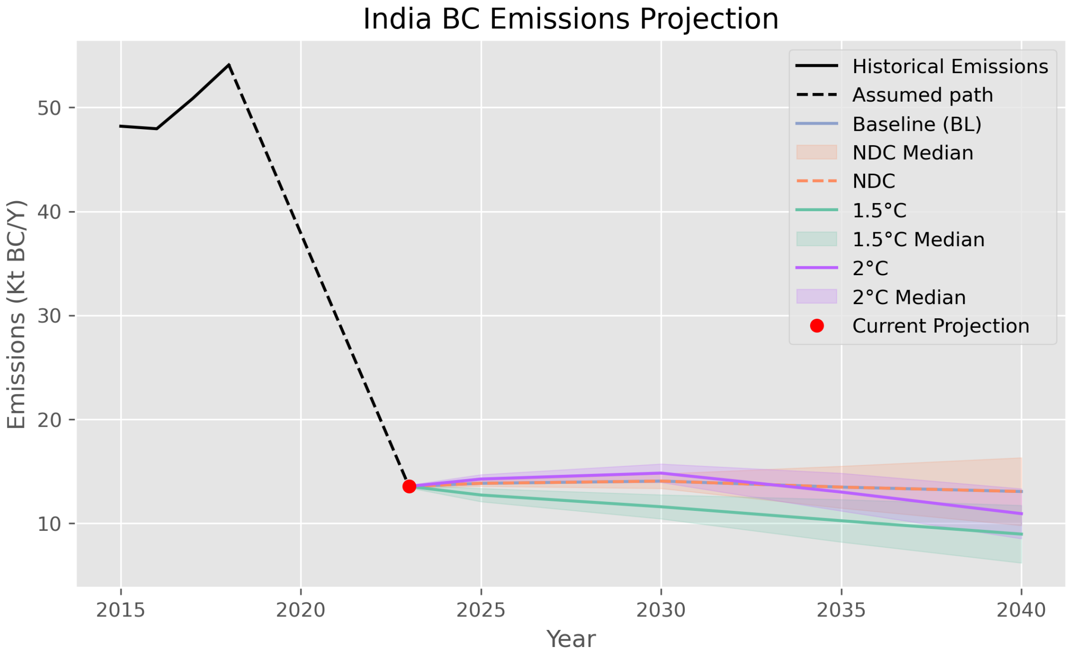

Figure 7.39: Projection Trends of (BC) Emissions to 2040

7.3.4 South Africa

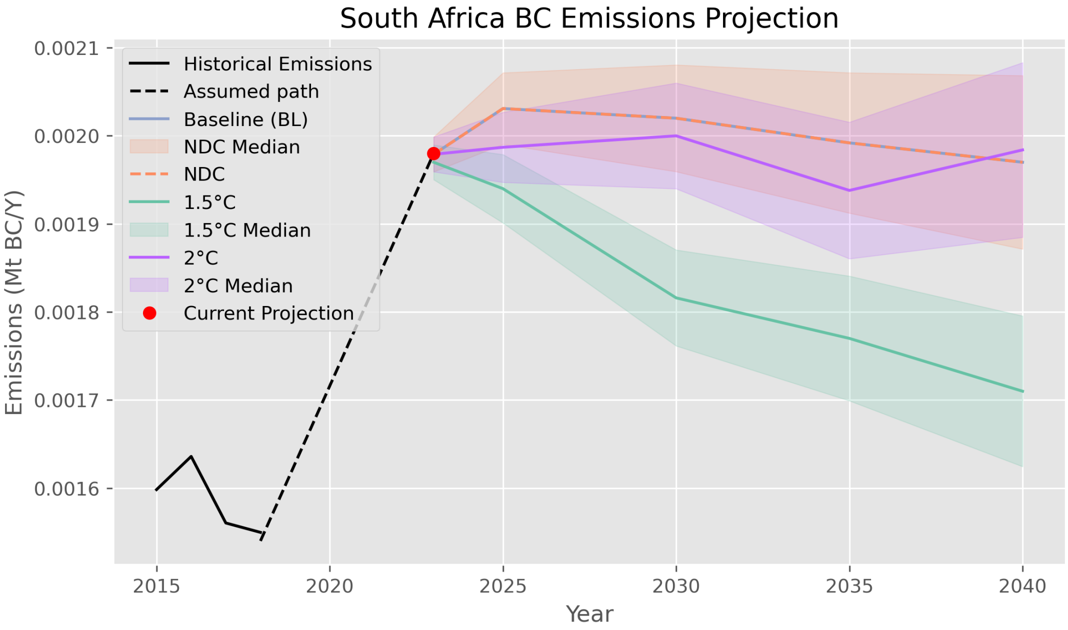

Figure 7.40: Projection Trends of (BC) Emissions to 2040

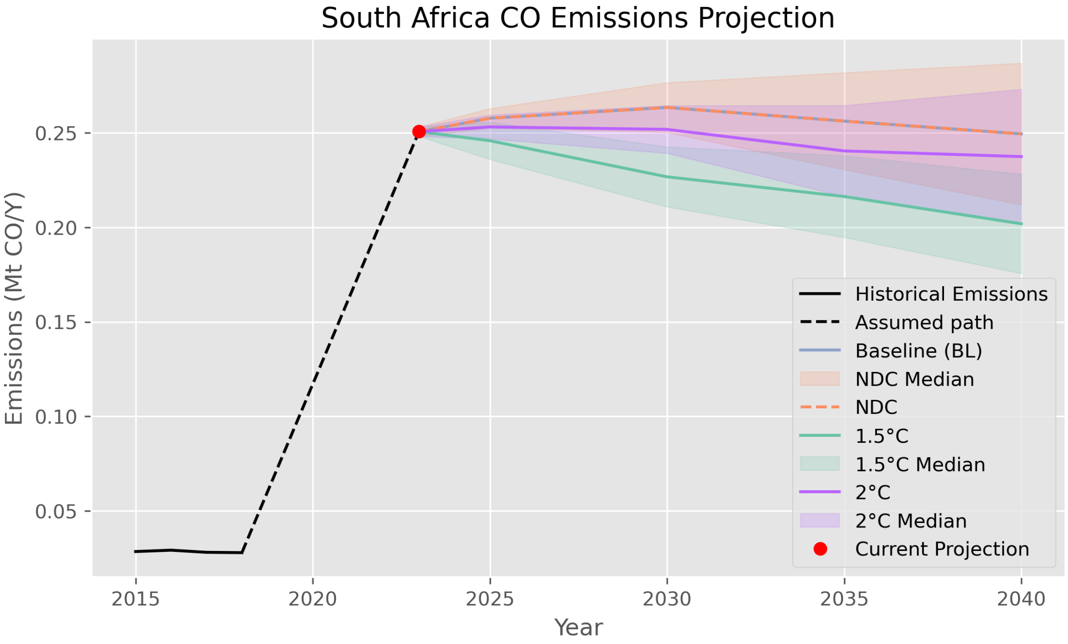

Figure 7.41: Projection Trends of (CO) Emissions to 2040

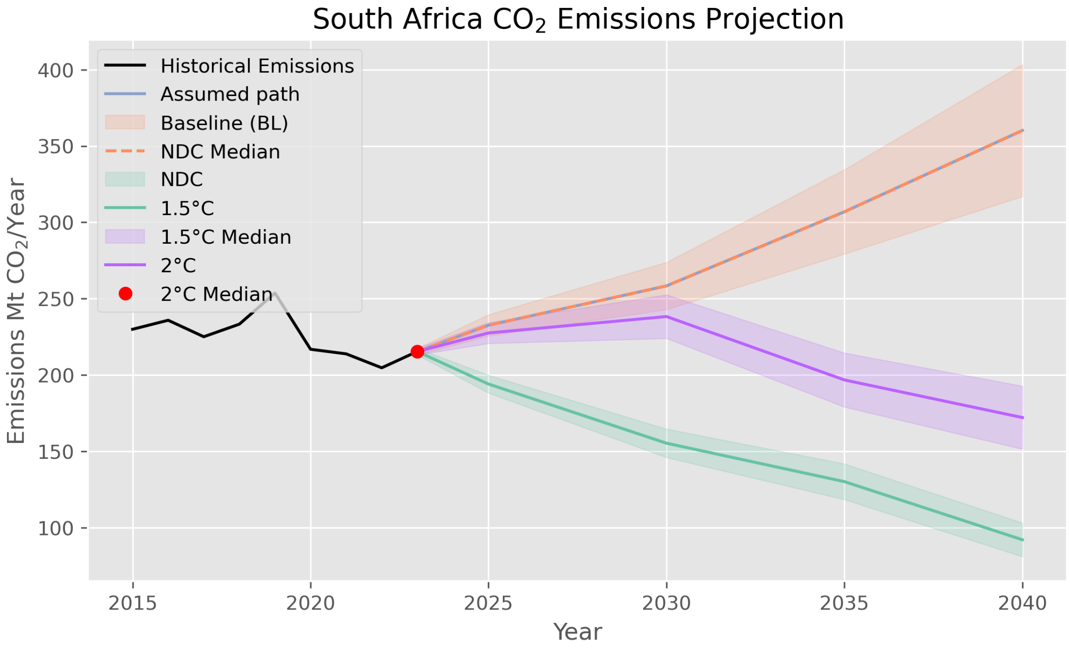

Figure 7.42: Projection Trends of (CO_2) Emissions to 2040

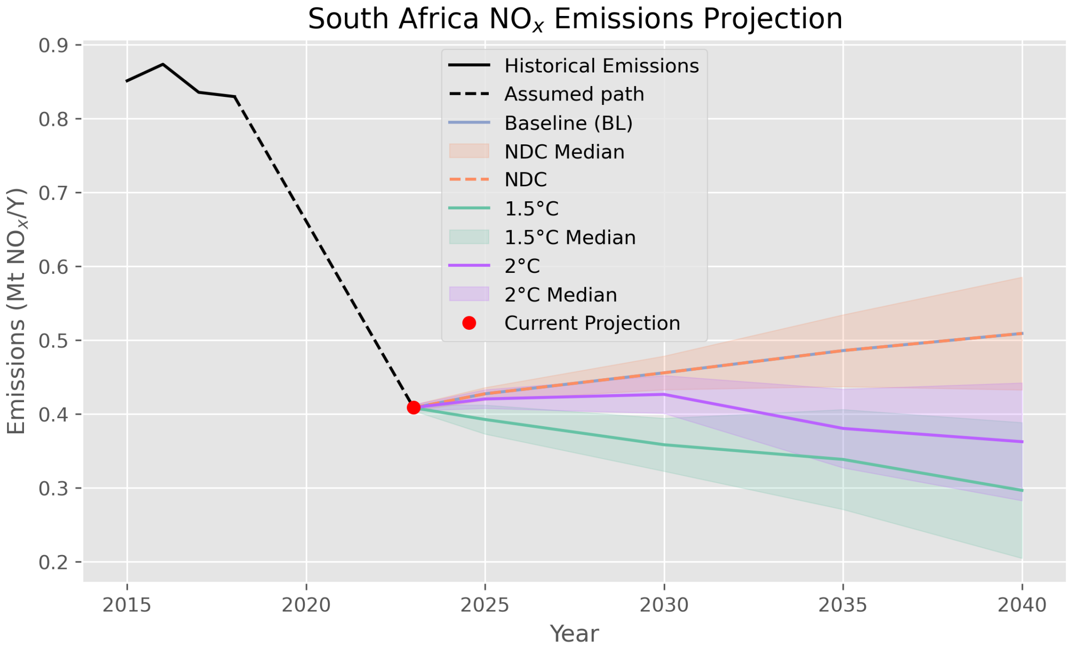

Figure 7.43: Projection Trends of (NO_x) Emissions to 2040

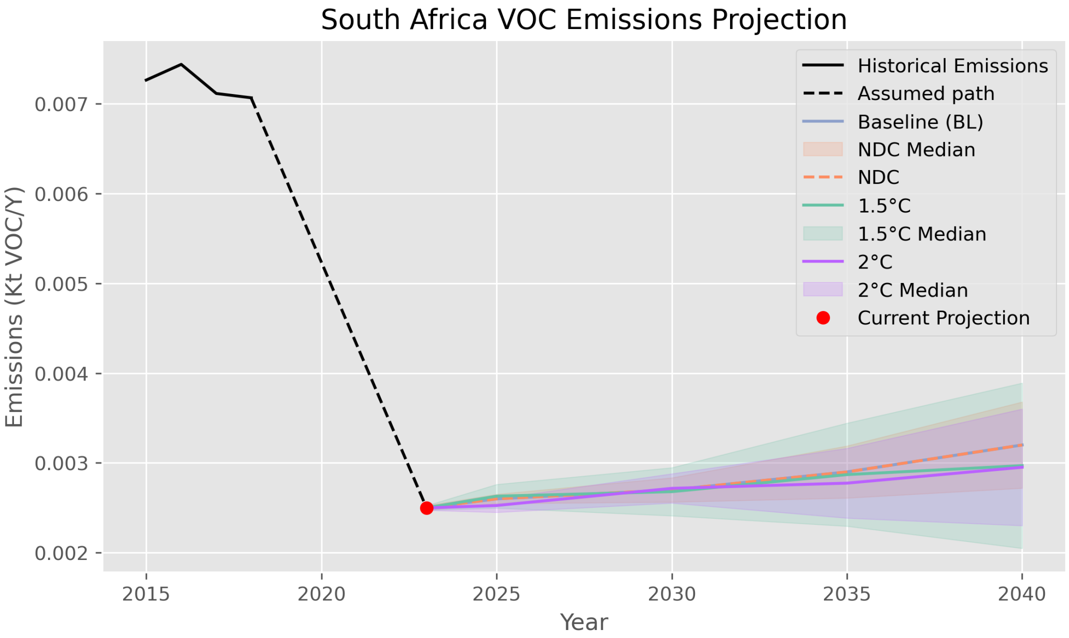

Figure 7.44: Projection Trends of (VOC) Emissions to 2040

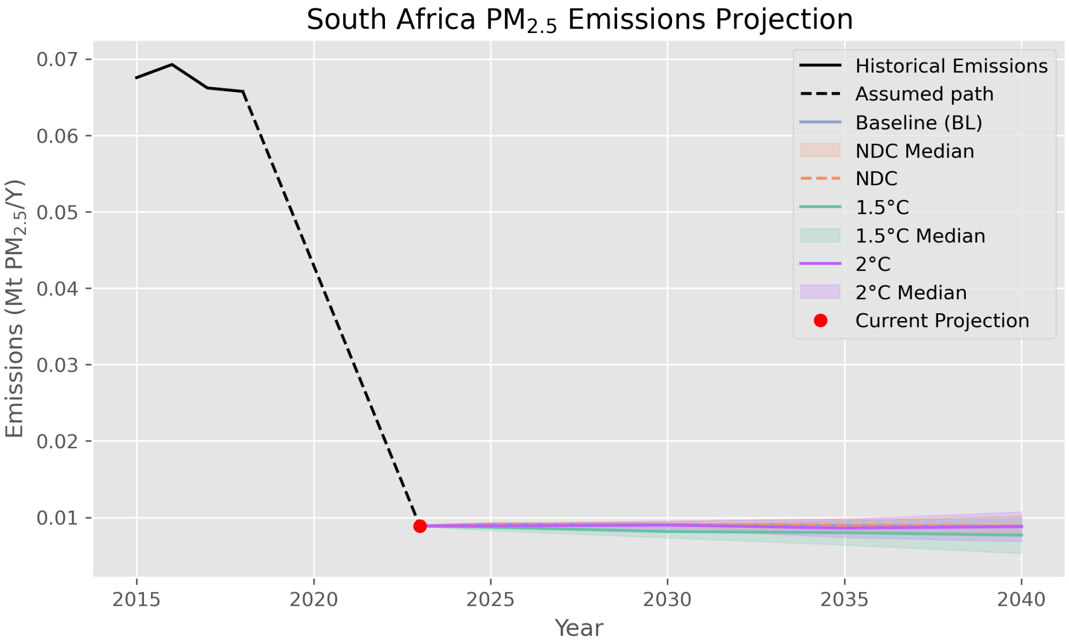

Figure 7.45: Projection Trends of $(PM_{2.5})$ Emissions to 2040

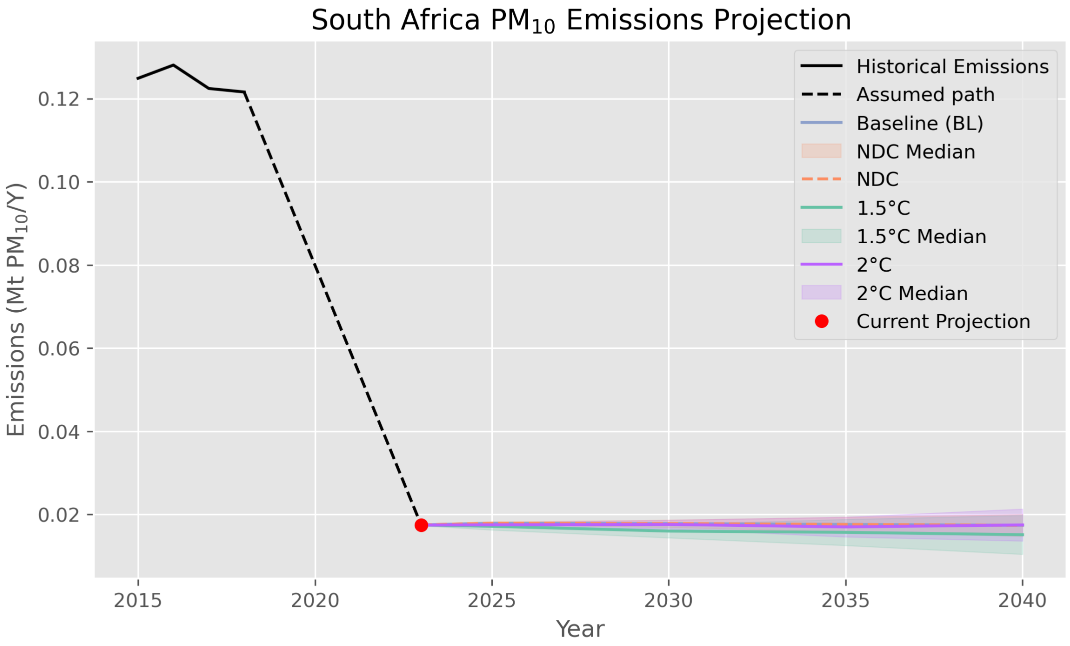

Figure 7.46: Projection Trends of (PM_{10}) Emissions to 2040

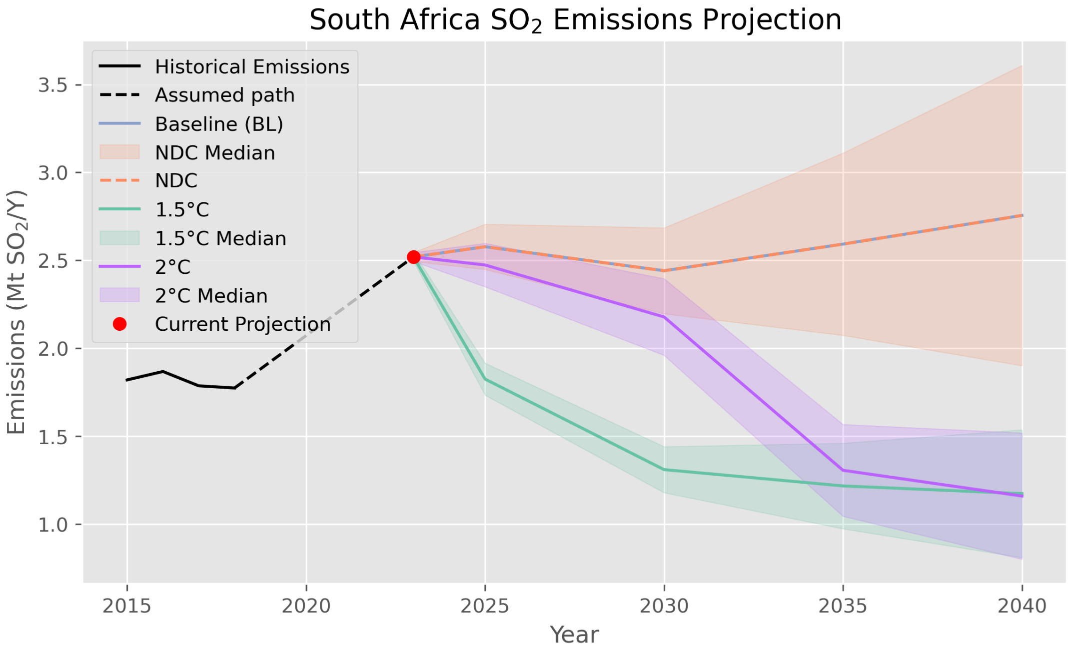

Figure 7.47: Projection Trends of (SO_2) Emissions to 2040

7.3.5 United States

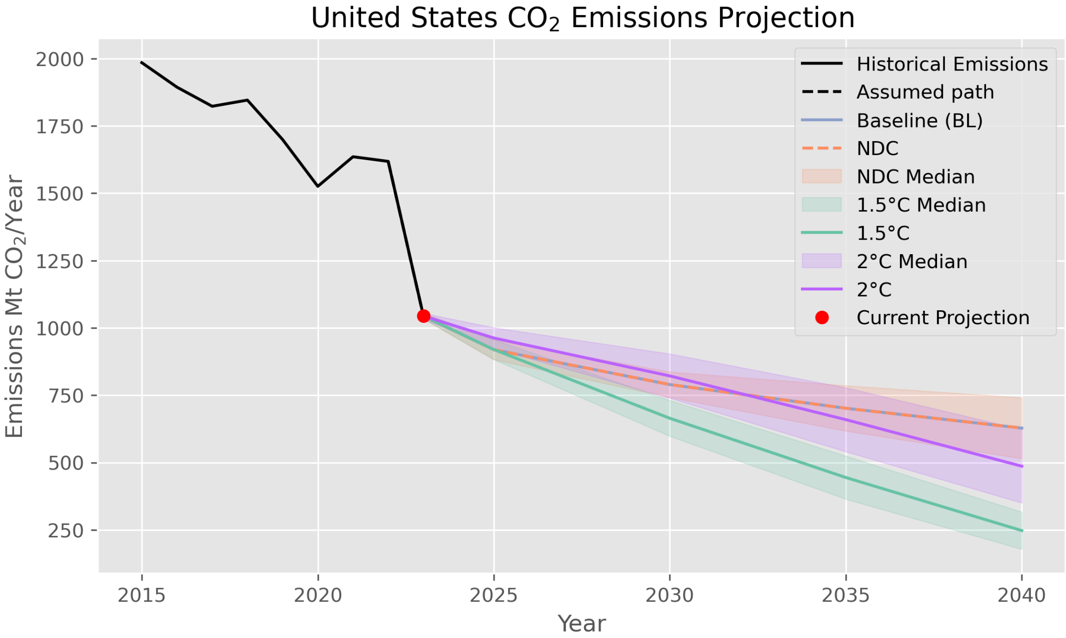

Figure 7.48: Projection Trends of (CO_2) Emissions to 2040

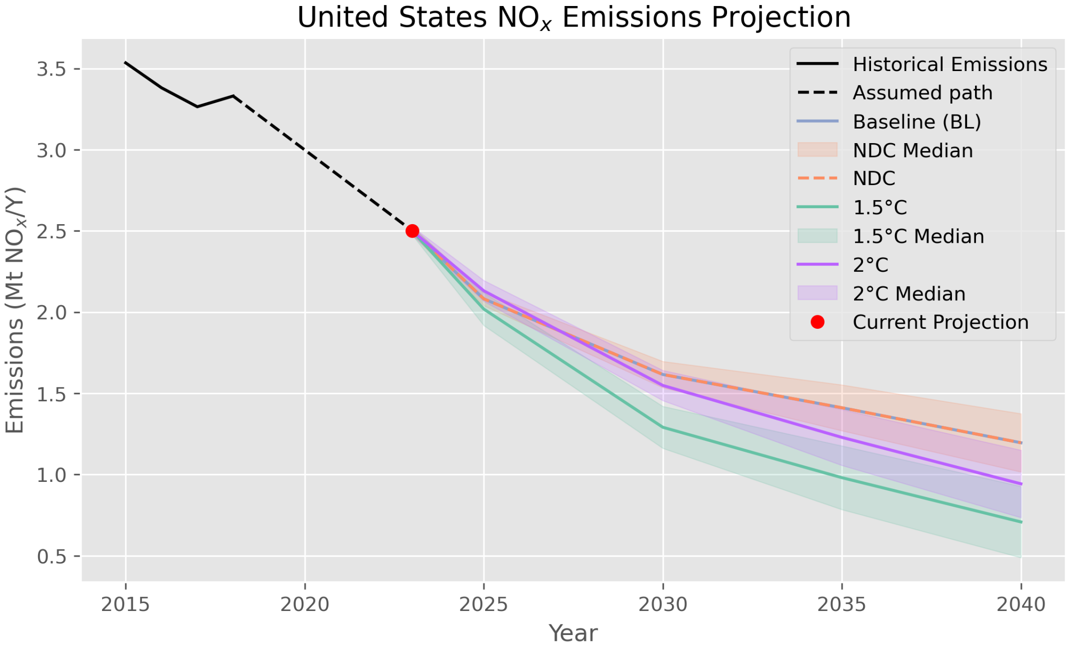

Figure 7.49: Projection Trends of (NO_x) Emissions to 2040

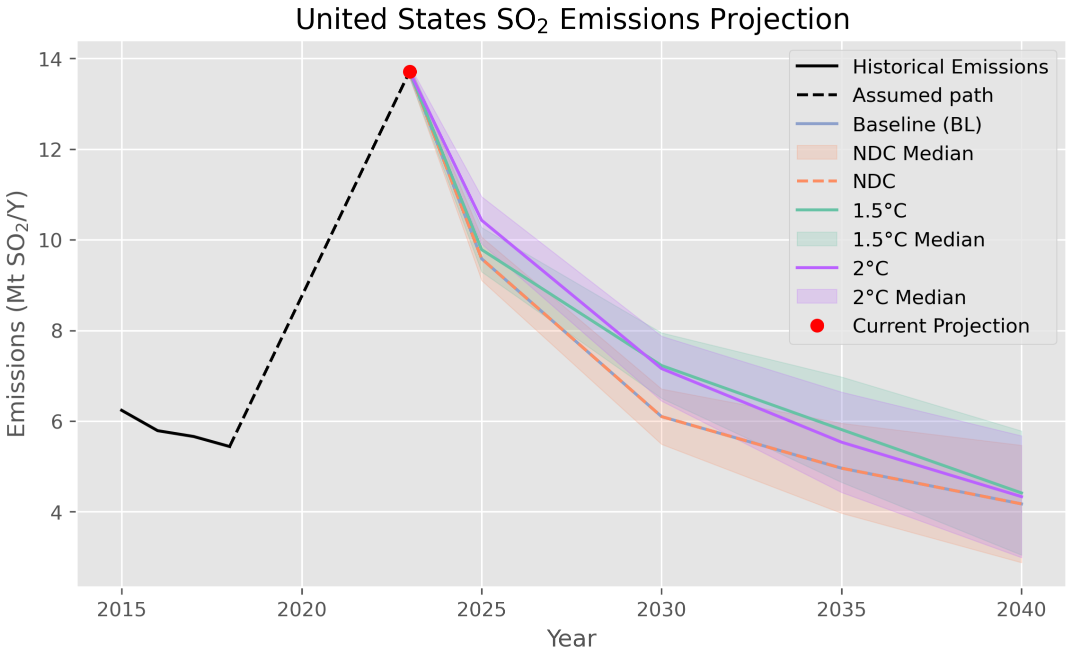

Figure 7.50: Projection Trends of (SO_2) Emissions to 2040

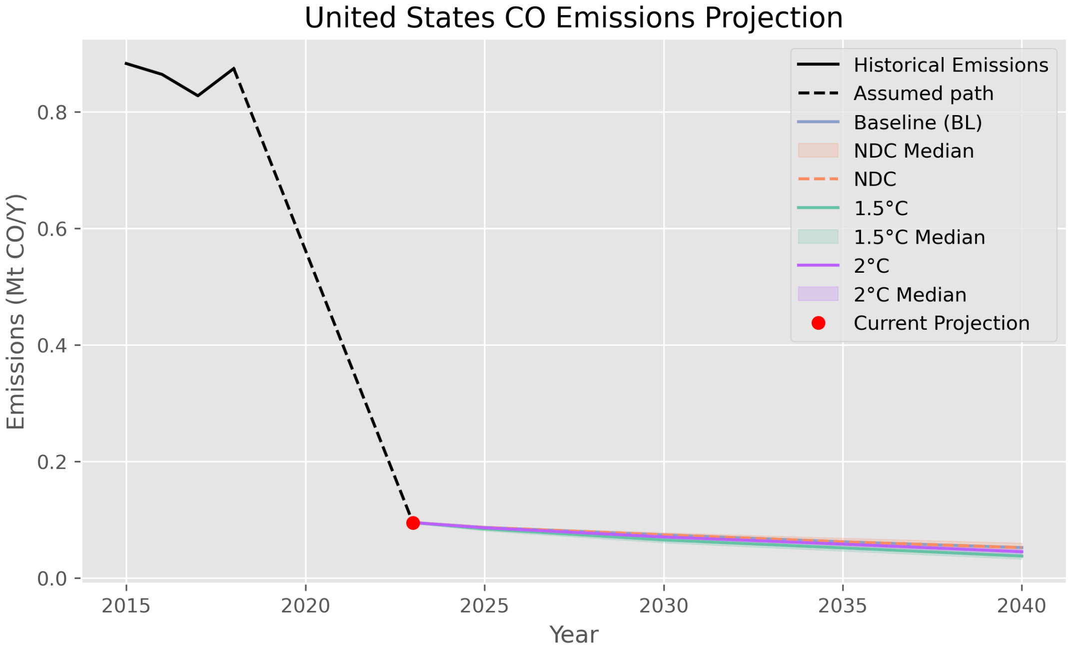

Figure 7.51: Projection Trends of (CO) Emissions to 2040

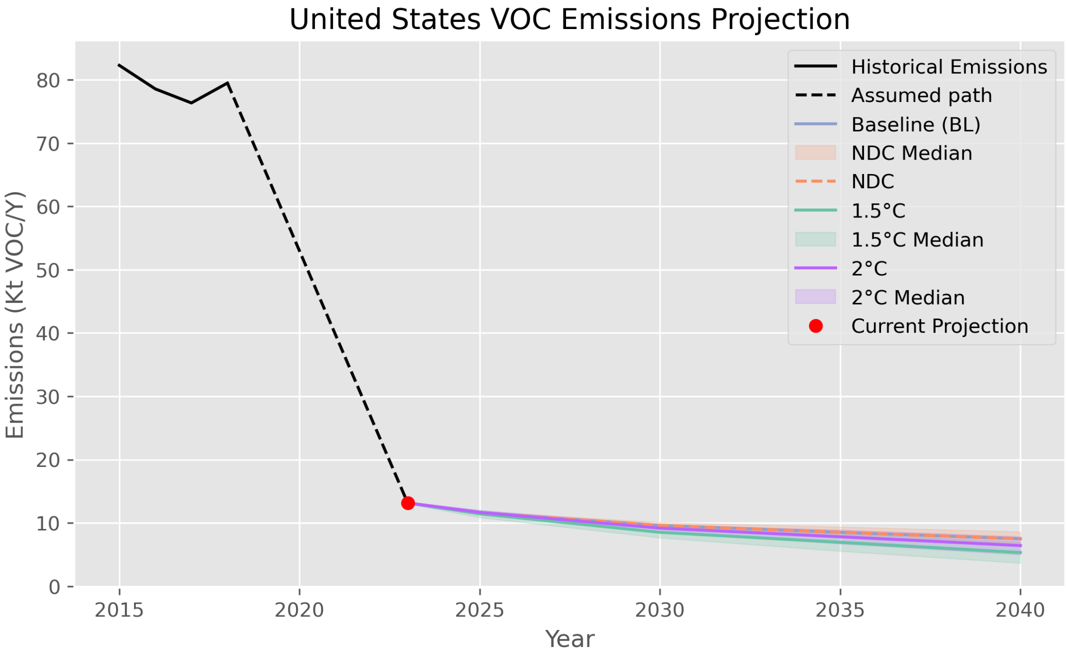

Figure 7.52: Projection Trends of (VOC) Emissions to 2040

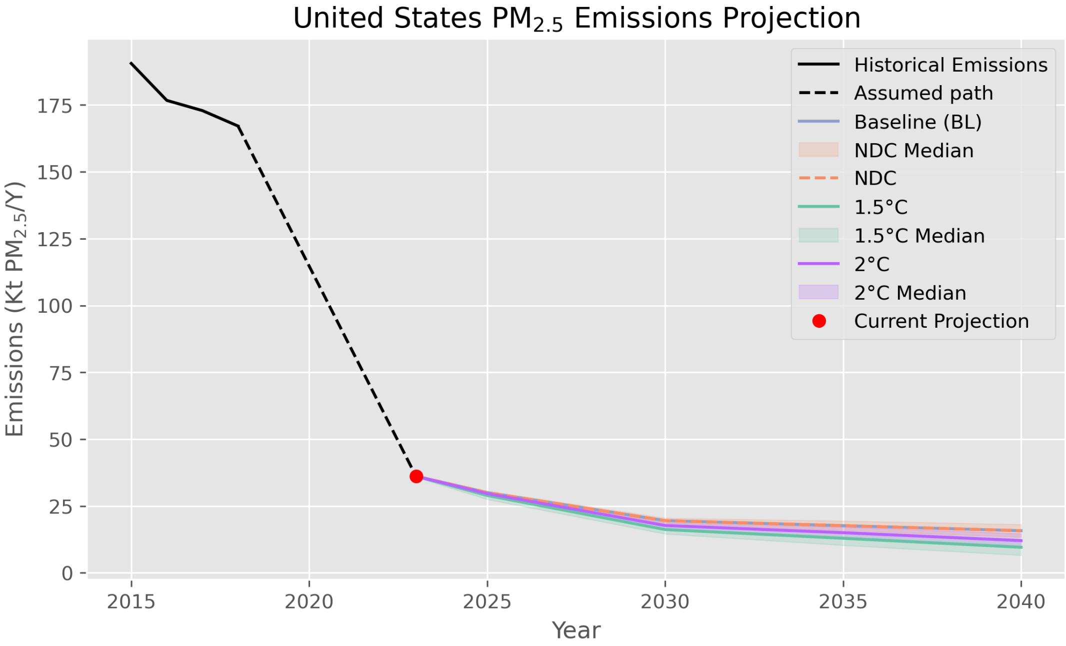

Figure 7.53: Projection Trends of $(PM_{2.5})$ Emissions to 2040

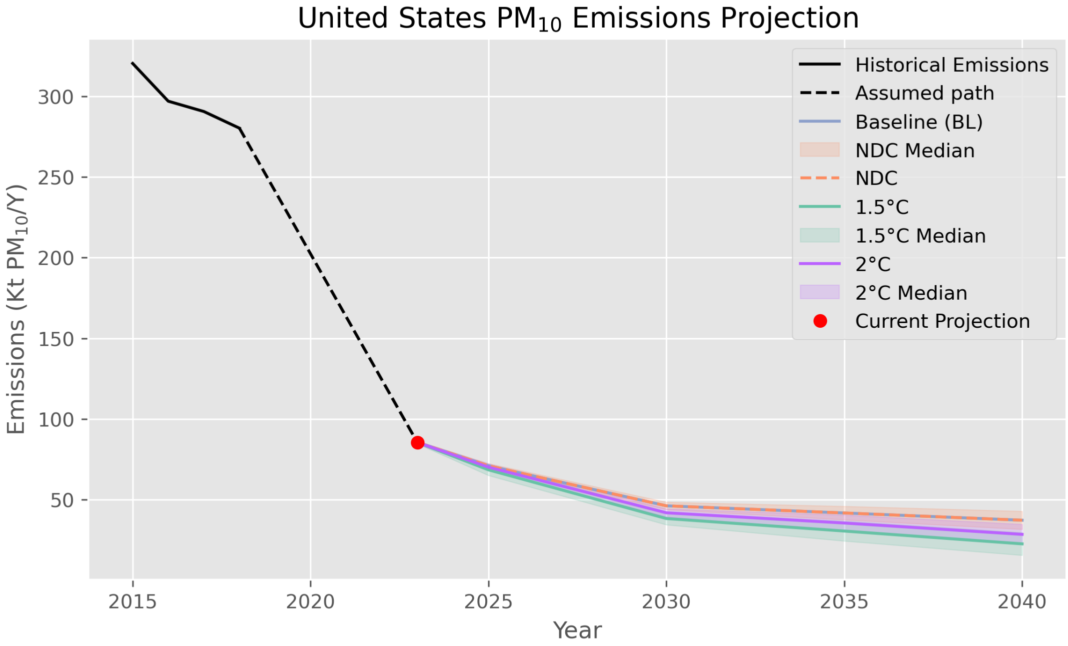

Figure 7.54: Projection Trends of (PM_{10}) Emissions to 2040

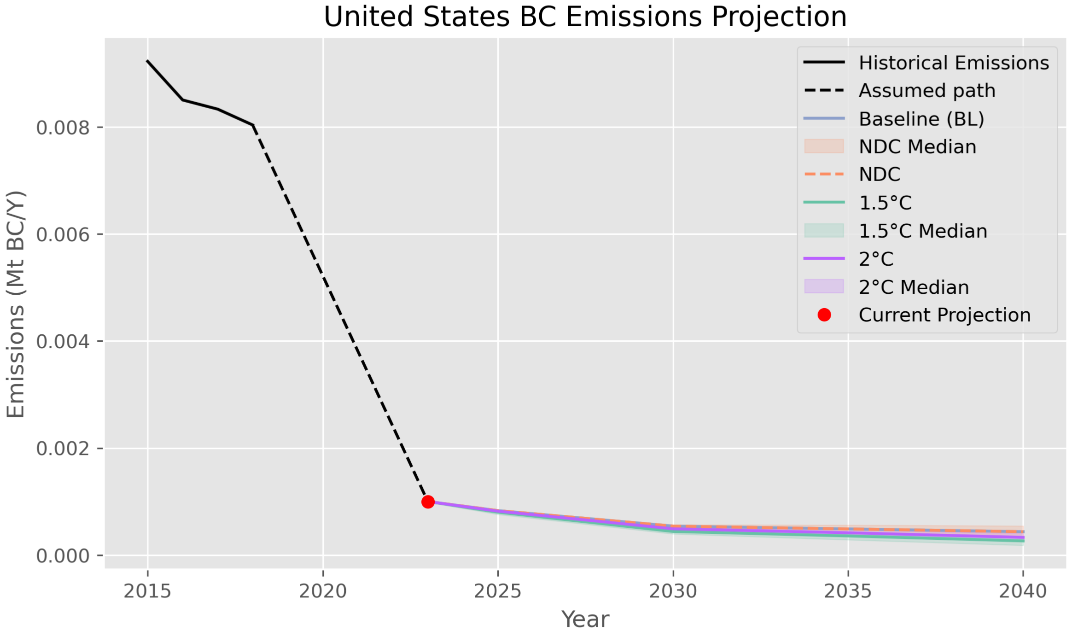

Figure 7.55: Projection Trends of (BC) Emissions to 2040

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