Decarbonisation in PyRICE:
Decomposing the Emission Output Ratio to Better Understand the Drivers Behind Low Carbon Futures

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Associated code is available at

https://github.com/maryamalki/PyRICE_2022/tree/sigma

Abstract

Climate Change continues to pose a considerable threat to the well-being of people and economies. Today, to avoid catastrophic and irreversible damage, decision-makers and policy advisers need to explore possible scenarios and enact mitigation and adaptation policies to curb the rise of global temperatures within the thresholds set by the Paris Agreement. However, avoiding a 1.5-degree warming seems already out of hand, and the last Conference of Parties in Glasgow (COP26) sparked a contentious debate surrounding the role of coal. Representatives rely on climate reports and models to understand the problem, including integrated assessment models that aim to encompass the whole process straightforwardly and transparently. One example is the RICE-2010 model developed by the 2018 Nobel Prize winner in economics William Nordhaus, used by the IPCC and known for its simplicity. However, the model does not include an explicit formulation of energy. This renders it hard to explore scenarios and policy questions directly tied to the diversification of the energy mix, a topic that has gained considerable attention with the Energy Crisis sparked by the Russian Invasion of Ukraine. Therefore, this thesis attempts to introduce energy intensity and carbon intensity to the model by decomposing the Emission Output Ratio. These parameters will allow the user to explore the drivers behind decarbonisation, whether it is related to an improvement in the energy efficiency of processes or a greener energy mix. The selected approach yielded surprising insights, such as the poor documentation and data quality of the RICE model, the over-simplistic design choices behind emissions and decarbonisation, and the under-representation of carbon intensity. These outcomes have highlighted potential, underestimations of future temperature rise, limited policy testing potential and a lack of transparency in data, methodology, and reproducibility.

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Acronyms

ACEI	Autonomous Carbon Efficiency Improvement
AEEI	Autonomous Energy Efficiency Improvement
BP	BP's Statistical Review
CDIAC	Carbon Dioxide Information and Analysis Centre
CI	Carbon Intensity
CO_2	Carbon Dioxide
DICE	Dynamic Integrated Climate-Economy (Model)
EDGAR	Emission Database for Global Atmospheric Research
EI	Energy Intensity
GDP	Gross Domestic Product
GNI	Gross National Income
GNP	Gross National Product
IAM	Integrated Assessment Model
IPCC	Intergovernmental Panel on Climate Change
K	Capital
L	Labour
NDC	Nationally Determined Contributions
OHI	Other High Income
OWD	Our World in Data
PE	Primary Energy
RICE	Regional Integrated Climate-Economy (Model)
UNFCC	United Nations Framework Convention on Climate Change

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1. Introduction

Climate change is a wicked problem that has taken centre stage in global diplomacy. During climate summits, decision-makers partake in negotiations to set forth plans to mitigate the impacts of global warming (Levin et al., 2012). In a most recent attempt, the Paris Agreement was adopted in 2015 by 196 parties under the United Nations Framework Convention on Climate Change (UNFCC), to limit the rise in temperature to “well below” 2 degrees Celsius, and ideally to 1.5 degrees compared to pre-industrial levels (UNFCC, 2015). Maintaining this threshold is meant to curtail the detrimental impacts of climate change, and avoid tipping points after which damage is irreversible (Lenton et al., 2019). However, it seems that the 1.5 degrees goal is out of reach (Jewell & Cherp, 2020), and the last Conference of Parties (COP26) exacerbated frustrations. In Glasgow, India and China led an effort to water down the language used for coal, pushing for a phasing-down instead of phasing-out of coal (Mathiesen, 2021). This brought up considerable ethical and political debates regarding the political economy of coal, the responsibilities of every nation-state towards the climate crisis, and the rights of emerging economies and the Global South in general.

Decision-makers rely on climate reports and models to reduce the complexity of this grand is and explore different scenarios and policy options (IPCC, 2022a). One type of model includes Impact Assessment Models (IAMs) known for being straightforward and transparent (Evans & Hausfather, 2018). One prominent IAM model is the Regional Integrated Climate Economy (RICE) model developed by Nobel Prize-winning economist William Nordhaus (Nordhaus & Yang, 1996). The RICE model is widely-used, including by the IPCC, because of its ability to encompass the major elements of the climate change process simply and transparently (Yang, 2008). However, it does not include an explicit component for energy, which makes it difficult to comment on the state of decarbonisation globally and regionally (Nordhaus, 1992), and answer questions such as those resulting from COP26.

Decarbonisation, generally defined as the reduction of carbon emissions, involves a few indicators. Most notably, Energy Intensity (EI) represents how energy-intensive the overall economy is, and Carbon Intensity (CI) represents the degree to which the energy mix is carbon-intensive. Understanding these indicators and comparing them across time and regions would allow the user to get a better understanding of how decarbonisation is occurring, what are the main drivers and what can be an improvement. It would also shed light on the relative importance of commitments adopted in international climate summits and their potential contribution.

2. Literature Review

In this section, the main concepts associated with the topic are introduced, along with the gap in literature and the main research question.

2.1. Integrated Assessment Models

i. Review of IAMs

Integrated Assessment Models (IAMs) are simple, transparent and easy-to-use climate models that integrate many aspects of the climate change process. They are widely used in international climate reports (Masson-Delmotte et al., 2018), where economists and climate scientists leverage them to make predictions about global warming, and estimate relevant variables to the climate debate, such as the Social Cost of Carbon (Harmsen et al., 2021).

A survey of main climate IAMs highlights a diversity in scope, method and complexity, as seen in Table 1 below:

Table 1: Survey of IAMs from the Literature

Model	Name	Regional Scope	Method	Complexity	Reference
DICE	Dynamic integrated model of climate and economy	Global	Neoclassical economic growth, Ramsey-type	Highly aggregated	(Nordhaus, 1992; Nordhaus, 2017)
RICE	Regional integrated model of climate and economy	12 regions (RICE-2010)	Neoclassical economic growth, Ramsey-type	Highly aggregated	(Nordhaus, 2010; Nordhaus & Yang, 1996)
FUND	Climate framework for uncertainty, negotiation, and distribution	16 regions	A non-general equilibrium model	Recursive model	(Anthoff & Tol, 2014; Tol, 1997)
GCAM	Global change assessment model	14 regions	Non-linear optimization with Negishi weights	Dynamically recursive	(Calvin et al., 2017; Edmonds & Reilly, 1983)
MERGE	Model for evaluating regional and global effects of GHG reduction policies	10 regions	Market oriented general equilibrium model		(Kypreos, 2007; Manne & Richels, 2005)
WITCH	World induced technical change hybrid	13 regions	Neoclassical economic growth, Ramsey-type		(Bosetti et al., 2007)

Despite them being widely adopted, IAMs garner a lot of criticism as well. They have been blamed for down-playing the climate crisis, reinforcing notions such as the ability for unlimited growth the inevitable correlation between mitigation and GDP reduction with an emphasis on richer regions, and the misleading illusion of full-integration (Asefi-Najafabady et al., 2021; Budolfson, 2021). Similarly, despite them being promoted as transparent, many design choices are instead opaque, such as what to count and who to count, the assumptions for the baseline scenarios, the model behind the feedback loops between submodules and the reasoning behind inter-temporal intergeneration equity (Weyant, 2017). However, despite the validity of many of these critiques, it is important to note that IAMs are designed to be a generalised simplification of the process. And even if some argue that leveraging them to quantify the impact of climate change policies is not fit for purpose (Naeini et al., 2020), they can still provide broader insights and advise policy-makers on optimal targets to reach climate goals .

ii. The DICE and RICE Models

For the sake of this analysis, the focus will be shifted to the DICE/RICE model family, developed by William Nordhaus. The models are known for their high level of aggregation and simplicity in combining the different elements of the earth and economy (Edmonds et al., 2012). The DICE model is the original IAM developed by Nordhaus in 1992, that explores the impacts of the economy on the environment by treating climate change as a stock externality from the perspective of a single global economy (Nordhaus, 1992). In 1996, the original RICE model was developed, as a regionally disaggregated counterpart to DICE, with six regions (Nordhaus & Yang, 1996). Later, Nordhaus & Boyer (2000) modified the methods behind the model, including the choice of control variables, and increased the regional specification to eight economic or politically similar regions with RICE-99. A few more iterations included RICE-2007 and RICE-2009, that introduced a longer time horizon, shorter timesteps and more detailed disaggregation (Yang, 2008). Those were followed by the RICE-2010 model, that was developed to assess the impact of the Copenhagen Climate Accords, by diving the world into twelve regions. Despite there being a new RICE-2020 model (Yang, 2022), this study will focus on the RICE-2010, refactored on Python as PyRICE-2022 by Tjallingii (2021) and Reddel (2022).

The DICE/RICE models are based on the integration of three submodules: the economy, the carbon cycle and the climate model. First, the economy submodule follows the neoclassical general equilibrium growth principles by Ramsey-Cass-Koopmans, where regions maximize utility by consuming a part of global output. This gross output is calculated using a Cobb-Douglas Production Function (Nordhaus, 2013b). Emissions are then computed as the sum of emissions from land and industry. Industrial emissions depend on the Emission Output Ratio and the gross output and are reduced by the Emission Control Rate. In turn, these emissions are either absorbed by the oceans or contribute to an increase in CO_2 concentrations in the atmosphere, resulting in an increase in radiative forcing. The latter induces an increase in both oceanic and atmospheric temperatures. And thus, as can be seen in Figure 1, due to the impact of climate change, a share of the global income is lost to damages caused by increased temperatures and sea level rise, as well as abatement costs to limit emissions.

Some of the assumptions presented in this model were criticized by climate economists, such as Keen (2021), who argues that the damages are not representative of reality, as they are assumed to impact only a fraction of GDP, thus painting mitigation measures as a considerably more costly option. Others criticize the inevitable negative feedback loop, connecting (marginal) abatement costs and global income, citing that the adoption of greener technology could reflect positively on the economy (Ji & Zhou, 2020). Despite these critiques, the model is still used by the IPCC for its insights on estimations of the social cost of carbon (Masson-Delmotte et al., 2018).

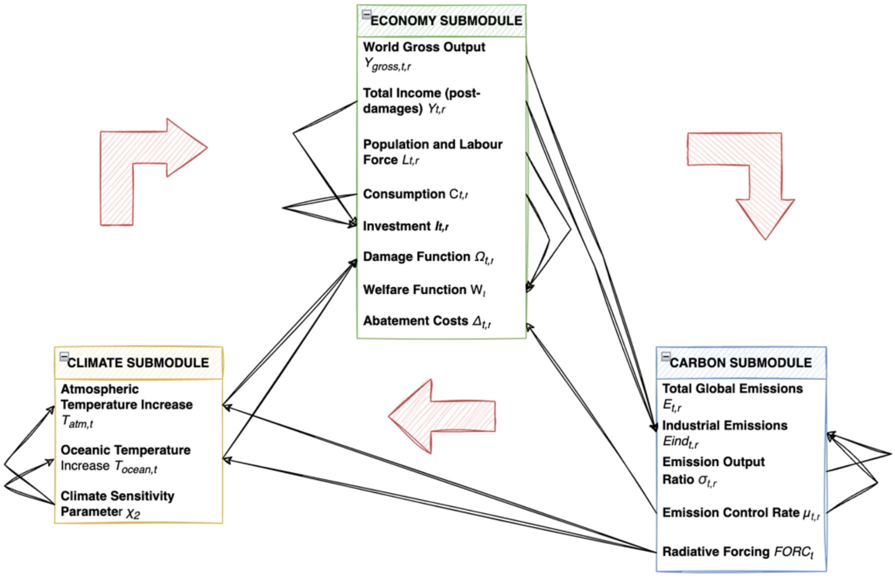


Figure 1: The Main Relationships in the DICE/RICE Models

Overall, IAMs have for aim to project trends, asses the cost and benefits of adopting certain climate policies and assess uncertainties in key parameters influencing climate change (Wilson et al., 2021). However, these models represent a reduction of complexity, and thus do not include all elements necessary to draw wide-scoped and detailed conclusions. Some expand their damage function to include different sectors, such as the new GIVE model that represents energy demand, agriculture, sea level rise and temperature mortality (Rennert et al., 2022), while others focused on endogenizing key parameters such as technological change (Pizer & Popp, 2008). One thing that is missing from the RICE-2010 model is an explicit consideration for the energy component (Nordhaus & Yang, 1996).

2.2. Energy System Models

Energy systems models are vital to determine the energy supply and demand, which are essential components of integrated assessment models. To date, a wide variety of energy systems models have been developed for different contexts and purposes. Pfenninger et al. (2014) divided these into four categories, according to their purpose and challenges. These are (1) Energy system optimization models, (2) Energy system simulation models, (3) Power system and electricity market models, and (4) Qualitative and mixed-methods scenarios.

i. Optimisation and Simulation Models

Most pertinent to this thesis are the first two categories. They can be seen as opposing ends of a continuous spectrum, encompassing all energy systems models, with the exact placement depending on the data, purpose, and context in which it is used.

The first category, "energy system optimization models", are aimed to help decision-makers and business planners make robust decisions under various scenarios. As such they require a highly detailed abstraction of the technical components of the energy system. Two influential model families that fall under this category are MARKAL/TIMES (Fishbone & Abilock, 1981) and MESSAGE (Schrattenholzer, 1981). Both serve a more general purpose, in that they try to represent possible evolutions of the energy system at a national, regional, or global scale over several decades, but are not necessarily capable of showing how probable these evolutions are. Both were originally conceived as linear optimization models with the minimization of total energy system cost as the central objective. Newer, more sophisticated versions also include non-linear and mixed integer linear formulations. For example, the MARKAL Elastic Demand version meets energy service demands with own-price demand elasticities and maximizes the sum of producer and consumer surplus (Dodds & McDowall, 2013).

Complementary to optimization models, the second category "energy system simulation models" are used in a more high-level strategic context. Instead of generating possible futures, the focus lies on predicting the system's most likely evolution, given a set of inputs. In contrast, to the more rigid mathematical formulation found in optimization models, simulation models are constructed in a modular fashion, meaning modules can incorporate a diverse set of methods. Thanks to this architecture, individual submodules can be implemented in different ways, which offers flexibility, but also makes the system highly complex and can make model results more difficult to understand.

Some prominent examples include NEMS (National Energy Modelling System) and PRIMES (Price-induced Market Equilibrium System). NEMS is used by the US Energy Information Administration to produce the Annual Energy Outlook, a cornerstone in U.S. energy policy (Gabriel et al., 2001). Similarly, The PRIMES model has long informed the EU's long-term energy policy decisions, including foundational underpinnings to the EU's Energy Roadmap 2050 (European Commission, 2011a). The model uses submodules to represent countries as independent agents and finds an equilibrium solution for energy supply, demand, cross-border energy trade, and emissions in all European member states (Kousoulidou et al., 2008).

Another important simulation model is LEAP (the Long-Range Energy Alternatives Planning system), in use since the late 1980s by both the private and public sectors (Roinioti et al., 2012). At its core, it provides an accounting system for energy supply with annual timesteps, but it also includes other methods e.g., to represent, e.g., demand using a macroeconomic model.

ii. Power Systems and Qualitative Mixed-Method Models

The third category, "Power systems and electricity models" deals with one segment of large energy models, the electricity market. These sorts of models are traditionally used within utility companies and other power sector businesses to make a wide range of decisions, from strategic investment planning to operational strategies such as generator dispatch (A. M. Foley et al., 2010).

Their range of applications fits under the optimization-simulation spectrum. Yet, specific to power systems models is the high temporal variation, since a constant balance between supply and demand is crucial for a well-functioning power system (Machowski et al., 2020). Two well-known commercial large-scale power systems models are WASP (Wien Automatic System Planner) used by the International Atomic Energy Agency (Bhattacharyya & Timilsina, 2010), and PLEXOS, a mixed-integer linear programming model with detailed modules for power plants, the transmission grid, market planning and capacity expansion. Given the proper data, it can perform analyses at up to 1-minute resolution, giving granular insight into supply and demand fluctuations (A. Foley & Díaz Lobera, 2013).

The last category, as identified by Pfenninger et al. (2014) concerns qualitative models. The previously described modelling approaches are mainly focused on technical and economic aspects. But these fail to capture human dimensions such as political circumstances, public acceptance, consumer behaviour, technological innovation, etc. The main purpose here is to capture these factors, to inform and complement quantitative models and analyses.

iii. Integrating Models

To understand the distributional impacts of climate policies, the various energy system models, macroeconomic models, and environmental models need to be integrated comprehensively. However, developing these so-called integrated assessment models poses enormous challenges, since each type of modelling paradigm tends to follow its own unique perspectives, formulations, and conventions. Integrating models is a precarious balance of closing the gap between models while preserving functionality and comprehensibility and mitigating the weaknesses of individual modelling techniques.

Montenegro et al. (2021) explicate different approaches toward integrated modelling. Coupling is the simplest method conceptually. It is a non-interventionist approach, in which minimal changes are applied to model formulations, and simply links models via variables, that are exchanged at specific points in time. Such an approach often results in longer model run times, depending on the number of variables exchanged. Results may also be of lesser quality if different modelling assumptions prove to be incommensurable. Hard linking is a more involved approach, where one model is adapted to another. The disadvantage of this approach is that it demands a high level of modelling skills and is very time intensive, as model objectives, source code, and underlying databases must be reformulated.

2.3. Explicit Introduction of Energy into RICE

Given that the RICE model is widely used for its simplicity, it becomes counterproductive to expand it based on complex energy system models, such as the ones surveyed above. A closer look into the model highlights how energy is implicitly considered in the model through the Emission Output Ratio (noted as Sigma) (Nordhaus, 2018). To make the introduction of energy more explicit, a few options were identified from the literature and compiled in Table 2 below.

One critique of IAMs, such as RICE, is that they are based on the traditional Cobb-Douglas equation that does not incorporate energy into the economic activity of a modelled economy (Stern, 2010). The factors of production represented by the equation are solely Capital and Labour because Energy is assumed to be negligible. According to economic equilibrium theory, the output elasticity of a particular factor is equal to the cost share of said factor, and with Energy's cost share being minimal, it is often omitted (Kümmel et al., 2010).

Table 2: Method Selection

Method	Motivation	Implementation	Reference
Introducing energy to the production function	The neoclassical Cobb-Douglas equation assumes that factors of production operate independently of energy needs	Modified Cobb-Douglas production function with constant return to scale (Refer to Eq. [1])	(Kümmel et al., 2010)
Incorporating energy to factors of production for a non-trivial representation	The above change renders energy trivial: a 10% fall in input → 0.7% fall in output	Energy-based Cobb-Douglas production function (Refer to Eq. [2])	(Keen et al., 2019)
Modifying emissions in the carbon cycle like the FUND model	Introduce carbon and energy intensity to reflect switching to RE, nuclear and less intensive industries	Replacing the CO2 emissions function with the Kaya Identity (Refer to Eq. [3])	(Wang & Teng, 2022; Anthoff & Tol, 2014)

Thus, one way of introducing energy into the RICE model would be through the introduction of a new production factor for energy, E, to the output function (represented by Q in this section only).

$$Q = A \times K^{\alpha} \times L^{\beta} \times E^{\chi} \qquad [1]$$

However, because of the elasticity of substitution associated with the energy component, the impact of energy may not be representative (Jorgenson et al., 2013). To remedy the situation and introduce energy in a non-trivial way, Keen et al. (2019) suggest incorporating energy into the production factors of Capital and Labour, using the Energy-based Cobb-Douglas production function. This interpretation relegates Labour to the background, giving energy a more prominent role in economic growth.

$$Q(t) = \left(K(t).E_X^K(t)\right)^{\alpha}.(L(t).E_X^L)^{\beta} \qquad [2]$$

Lastly, a different method of integrating energy into the RICE model involves modifying the emissions function rather than expanding the production function. As mentioned before, RICE has an Emission Output Ratio that is used as a proxy for Autonomous Energy Efficiency Improvement (AEEI) (Nordhaus, 2018). However, as it stands, the Sigma value does not distinguish between decarbonisation improvements due to less carbon-intensive industries (i.e., energy intensity) and less carbon-intensive energy mixes (i.e., carbon intensity). Therefore, decomposing the Emission Output Ratio into these two values, like in the FUND model (Tol, 1997), could help explore in more detail how regions develop less carbon-intensive economies to curb the impacts of climate change.

$$CO2\ Emissions = \frac{CO2\ Emissions}{Energy} \times \frac{Energy}{GDP} \times \frac{GDP}{Population} \qquad [3]$$

The first and second methods, based on the alteration of the production function, involve a range of changes to the economy submodule and new sets of data to represent the energy used in the economy. Despite representing a more holistic approach to expanding the model, and answering some recurring criticisms of the current DICE/RICE model family (Kümmel et al., 2010), these approaches require a thorough understanding of neoclassical theory and macroeconomics. Moreover, implementing any of these methods involves additional design choices, such as the type of return to scale, the role of Labour in the production function, the impact of damages on the modified output and assumptions surrounding the elasticities of substitutions (Jorgenson et al., 2013). Lastly, given that the focus of this thesis is on decarbonisation, additional structures need to be incorporated into the energy component to evaluate the decarbonisation rate affecting emissions. Thus, after surveying the three methods, the third and final approach was selected, as it incorporates energy in the context of regional decarbonisation, while being more straightforward to implement in the allocated timeframe for this research (Friedlingstein et al., 2022).

2.4. Exploring RICE-2010 and PyRICE-2022

To better understand PyRICE-2022, one must delve into the RICE-2010 model. Given that the energy consideration will primarily impact the energy submodule by changing the emissions function, the focus will be directed towards the major drivers of emissions, namely, GDP, Population, Energy Intensity and Carbon Intensity. However, while surveying the literature, we observed that there was little information regarding the regional disaggregation chosen for RICE-2010, with data only identified for RICE-99 (Nordhaus & Boyer, 2000). Moreover, the sources of data are unclear with missing references and a no indication of data collection and processing procedures (Nordhaus & Yang, 1996). And finally, while exploring the details of emissions in the model, we found that the choices in methodology vis-à-vis the representation of the emission output ration, the role of the decline rate and the growth models behind them are vague and lacked proper documentation (Nordhaus, 2010). And, given that these models, are used by the IPCC and decision-makers to decide on climate policy (IPCC, 2022a), it is important to delve into the claims of transparency and highlight the importance of reproducibility.

2.5. Research Question

This thesis attempts to introduce energy into the PyRICE Model by decomposing the Emission Output Ratio, posing the research question:

How does the introduction of an explicit energy consideration into the PyRICE model impact our understanding of the drivers behind decarbonisation?

The findings will support future users of the model in exploring more specific scenarios tied to the decarbonisation trends and plans of not only the global economy, but also important regions in the climate debate, such as emerging economies. The work presented in this thesis will also shed some light on the relatively undiscussed inner workings of the emission component of the economy model and highlight shortcomings of the DICE/RICE models family group that impact outcomes.

The next section, Section 3: Theory, will explore basic principles to better understand the reasoning behind the methods. Section4: Methods will expand on the approaches undertaken to clean and process relevant data and implement the decomposition. The main outcomes of the analysis are addressed in Section 5: Results and Discussion. Finally, concluding remarks, recommendations and suggestions for future work will be shared in the Section 6: Conclusion.

3. Theory

This section outlines a theoretical background necessary for a clear understanding of the adopted method.

3.1. Kaya Identity

As mentioned in the previous section, the selected method is inspired by the Kaya Identity decomposition. Kaya is a mathematical identity that represents CO2 emissions as the product of its constituent drivers.

The drivers of emissions are the population that consumes goods and services, the GDP per capita, showing that richer countries produce more CO_2 emissions, and the technology factors: Energy Intensity and Carbon Intensity (Ritchie et al., 2020a).

Energy Intensity represents the amount of energy per unit of GDP, reduced by improvements in energy efficiency and structural changes to the economy. On the other hand, Carbon Intensity represents the amount of CO2 that is produced per unit of energy, and that can be reduced by switching to cleaner fuels (e.g., from Coal to Gas or RE) and adopting carbon capture and storage technology (Peters et al., 2017).

The Kaya Identity is presented by Equation 3 above. It has already been adopted by some IAMs such as the FUND Model, with the AEEI and ACEI representing EI and CI (Anthoff & Tol, 2014). The Kaya decomposition is also widely used to explore global and regional decarbonisation paths (Friedlingstein et al., 2022).

3.2. The PyRICE Model

For the sake of this analysis, the PyRICE 2022 model is used. The Python model was refactored by Tjallingii (2021) and Reddel (2022), and is based on RICE-2010 (Nordhaus, 2010) that includes 12 regions. To better understand the steps taken for this method, the relevant model equations are presented below. For a more complete reference to the RICE model, refer to Appendix II.

The total CO2 emissions are based on the sum of 'industrial' CO2 emissions from energy-related activities and exogenous CO2 emissions related to land-use.

$$E_{total,t} = \sum_{r=1}^{R} E_{ind,t,r} \times E_{land,t} \quad [4]$$

The 'industrial' CO2 emissions function is based on the product of the Emission Output Ratio, reduced by the endogenously calculated emission-control rate, and the gross output. Given that the emission control rate is an optimisation lever in the PyRICE model, the implementation of Kaya will be focused on decomposing the Sigma parameter, rather than modifying the entire emissions equation.

$$E_{ind,t,r} = \sigma_{t,r} \times Y_{gross,t,r} \times (1 - \mu_{t,r}) \qquad [5]$$

Where:

- $\sigma_{t,r}$ is the Emission Output Ratio per region per timestep
- Y_gross is gross output
- μ is the emission-control rate
- t is for the time step
- r is for the region

In turn, in the PyRICE model the Emission Output Ratio changes based on the following equation, with Δt representing a step size of 10 years. The initial value for σ (i.e., for 2005), is calculated based on the ratio between the 'industrial' CO2 emissions for 2005 per region and the GDP in 2005 per region (in 2005$ prices). The calculated Emission Output Ratio from this equation is then used to implicitly update the 'industrial' CO2 emissions at each timestep.

$$\sigma_{t,r} = \sigma_{t-1,r} \times e^{\Delta t \times g_r(t-1)} \quad [6]$$

Where:

- Δt is the step size
- $g_r(t)$ is the growth rate of σ at timestep t

The growth rate of σ has been calculated in multiple ways throughout the development of the RICE model. In the RICE-99 model, the growth rate was itself based on exponential decay, with the decay rate constant being the sum of two parameters that determine the rate of decarbonisation (i.e., decline rates) (Nordhaus & Boyer, 2000). In later iterations, the exponential decay function was passed on to the CO2-to-Ouput ratio equation, resulting in a growth rate as seen in Equation 7 (Gazzotti, 2022).

$$g_r(t) = g_r(t-1) \times (1+d)^{\Delta t} \qquad [7]$$

Where:

- d is the global annual decline rate

In the PyRICE model, the growth rate is calculated differently. It is based on a few variables, including the decline rate and the so-called "trend Sigma growth", a constant of 0.25% for each timestep across all regions. The origin of this value and what it represents is unclear, as it is not documented. Therefore, the growth rate identified by Gazzotti (2022) was used for this thesis.

There is very little information regarding the last two equations in the literature. Initially, the Sigma variable was computed as CO2-to-GNP, considering the gross national product rather than the gross domestic product (Nordhaus, 1992). Unlike the GDP, the GNP excludes the output produced by multi-nationals that is sent overseas and includes income generated by nationals abroad, and has grown less relevant in the climate debate (Abildtrup et al., 2006). According to Nordhaus (1992), the growth rate estimates for Sigma are based on two unreferenced graphs depicting the changes in energy-GNP and CO2-GNP changes from 1929 to 1989 and the forecasts on models that are not explained. In most papers referring to the DICE and RICE models, Sigma and its growth are barely discussed (Nordhaus, 2010, 2013a, 2013b; Nordhaus & Boyer, 2000; Nordhaus & Yang, 1996). Moreover, the growth rate of σ is also referred to as the "cumulative improvement in energy efficiency" (Diaz, 2015), which reinforces the idea that the Emission Output Ratio in the RICE model is designed to represent energy intensity specifically.

The last equation that is relevant in the context of this analysis is the emission control rate. It represents a functional reduction in emissions and is determined through optimization as a result of policies to reduce emissions in different regions (Nordhaus, 1992).

$$\mu_{t,r} = \mu_{0,r} + \frac{(\mu_{max} - \mu_{t,r})}{\mu_{period,r}} \quad [8]$$

Where:

- $\mu_{t,r}$ is the control rate per region per timestep
- μ_{max} is the maximum control rate per region set globally
- μ_{period} is the period where the control rate reaches the maximum value

In the PyRICE model, the emission control rate is presented as a target year, 2135, where emissions will be equal to zero.

4. Methods and Preliminary Results

This section describes the approach used to decompose the Emission Output Ratio (Sigma) in PyRICE. The sub-questions that frame the research plan are:

> **Sub-question 1** How does the choice of CO_2 emission, GDP and Population data influence the Emission Output Ratio?
> **Sub-question4** What is the role of the decline rate in decarbonisation?
> **Sub-question 2** How do emission drivers grow over time?
> **Sub-question 3** How can transparency be improved in the model?

4.1. Data Collection, Analysis and Processing

To decompose Sigma, energy intensity (EI) and carbon intensity (CI) components need to be introduced. Initially, EI and CI data was collected from Our World in Data's (OWD) Emissions Drivers that includes per country information for every Kaya Identity element. However, after inspecting the data, a large deviation between Nordhaus' initial Sigma (i.e., for 2005) and the OWD product of EI and CI for 2005 was identified. This was due to different CO_2 emissions adopted from each dataset (for details refer to Appendix III).

i. Carbon Emissions

The OWD data's carbon emissions are based on values from the Global Carbon Project 2021 (Friedlingstein et al., 2022). They account for "energy-related" carbon emissions, i.e., CO_2 emissions that are a result of energy production and industry. They are around three times greater than the CO_2 emissions values reported in Nordhaus' dataset. In fact, Nordhaus & Boyer (2000) use what they define as 'industrial' CO_2 emission, because according to them, these account for 90% of cumulative CO_2 emissions. And although that may have been true last century, things seem to be changing. According to the (EIA, 2020), the share of transportation in total CO_2 emissions has grown since the 1990s and currently exceeds industrial emissions, as can be seen in the Figure 2 below.

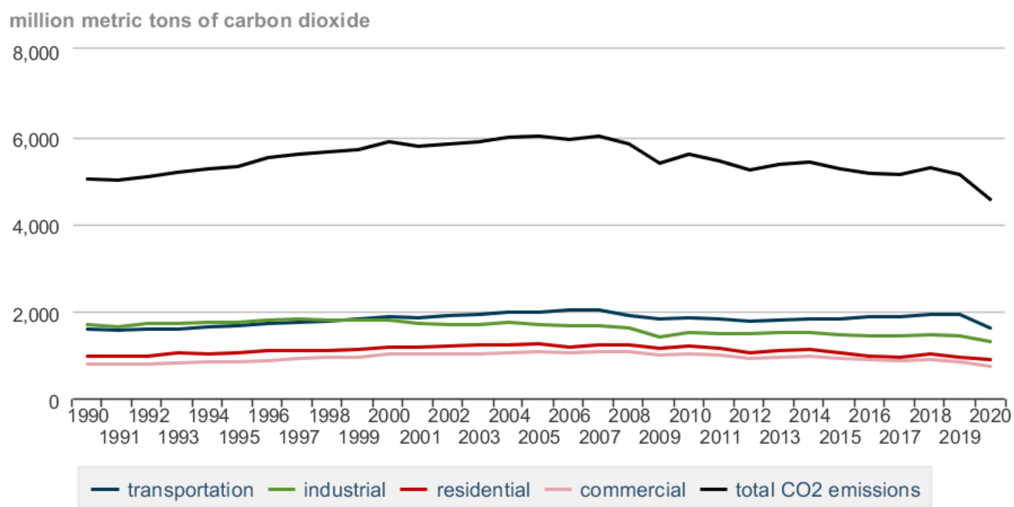


Figure 2: Energy-related Carbon Emissions in the US

This trend can also be observed on a global level, with the World Resource Institute reporting that emissions from energy use in industry accounts for 33% of energy-related CO_2 emissions in 2016 (with the industry sector, i.e., cement and chemicals, accounting for 5.2% of total CO_2 emissions) (Ritchie et al., 2020b). Similar conclusions can be drawn from datasets tied to other countries, such as China (Wan et al., 2021) and India (IEA, 2021). However, direct comparisons cannot be drawn between multiple sources because the definition of 'industrial' CO_2 emission differs between authors and datasets. Nordhaus & Boyer (2000) define 'industrial' CO_2 emissions as a mix of the industry sector and power generation for industry, whereas other sources defined industry as simply cement and flaring.

Some other IAMs such as GCAM, MERGE and EEPA, that cite the DICE and RICE models, also use similar values for CO_2 emissions. In fact, Wilkerson et al. (2015) state that these relatively smaller values of CO_2 emissions account for "energy-related emissions" and cites the (EIA, 2012). However, according to the EIA's Annual Energy Outlook for 2012, "energy-related emissions" are akin to the values used by the Global Carbon Project 2021, and only the "industrial" emissions are like the GCAM, MERGE and EEPA values. This highlights a sort of confusion in reporting and interpreting the data at hand, but also a lack of consistency in CO_2 emissions used.

Given the shortcomings, a new dataset was used for the CO_2 emissions that includes all energy-related CO_2 emissions. Based on the (IPCC, 2022a), the dataset of choice is the European Commission's Emission Database for Global Atmospheric Research (EDGAR). The values in this dataset are comparable to many widely used CO_2 emissions data sources (BP, 2022; EIA, 2021; Friedlingstein et al., 2022; IEA, 2022b), as well as the up-to-date CDIAC data (IPCC, 2022a). Naturally, there are few deviations with the values between different datasets due to inclusion and exclusion criteria (for cement, flaring and bunker fuels) and different methodologies (Minx et al., 2021), as can be seen in the Figure 3 below.

The EDGAR dataset was thus cleaned and aggregated into the RICE-2010 regions to change the initial Sigma value. However, this next step was not without its challenges.

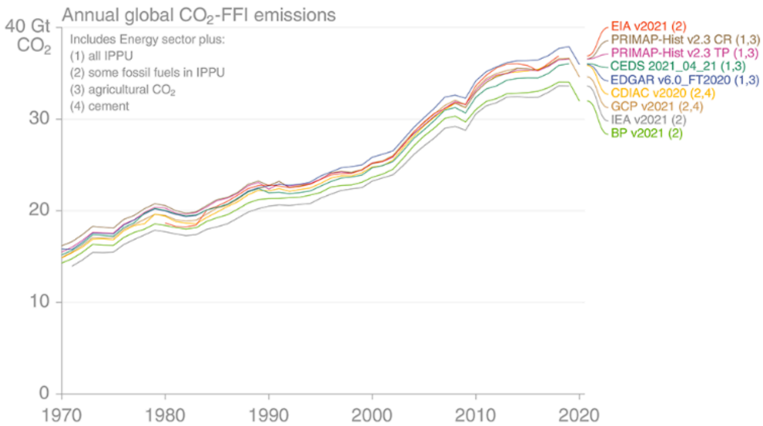


Figure 3: Annual Global CO2 emission from Fossil Fuels and Industry from Minx et al. (2021)

ii. Regional Specification

After surveying every paper published by Nordhaus about the RICE model, no details on the regional specification were available for the RICE-2010 model. Given that these groupings are vague, aggregating the regions is no longer an objective task and thus there is quite some room for interpretation vis-à-vis what country goes where. This includes unclear descriptions, such as the case of the Middle East, which often includes Turkey and Israel. But, Turkey has been a member of OECD-Europe since 1961, and Israel, who joined in 2010, is counted as part of Europe for statistical purposes (EIA, 2021). Moreover, countries in North Africa, are often grouped with other Arabic-speaking countries in the Middle East. Another challenge is outdated information regarding which countries are members of OECD-Europe (e.g., Latvia and Lithuania joined in 2016 and 2018 respectively (OECD, 2021)) and countries with gross national incomes (GNI) per capita that have risen beyond the World Bank's high-income classification threshold of $ 13,205, such as South Korea (World Bank, 2021). Other issues arise from the fact that different datasets have their own regional aggregation level for smaller countries and island nations. For example, in the Primary Energy (BP, 2022) dataset, Caribbean countries with a high GNI would go under OHI, but they cannot be separated from the Central and South America group. However, given the size of these nations and their corresponding CO_2 emissions, Primary Energy use and GDP, the impact of this limitation can be negligible.

After attempting multiple configurations of the regional specification, and drawing inspiration from the RICE-99 region aggregation (Nordhaus & Boyer, 2000), the FUND model's classification (Anthoff & Tol, 2014) and EIA's Regional Reference (EIA, 2021), the PyRICE's regions could not be exactly replicated. Given that comparisons could not be made to the CO_2 emissions (as those too could not be replicated), regions were compared based on their share of CO_2 emissions, as seen in Figure 15, and GDP in Figure 16 in Appendix IV. Ultimately, the suggested regional specification was established and can be found in Appendix I. It is worth mentioning that this classification is primarily based on economic similarities rather than strictly regional and climactic ones, which might lead to some limitations in interpretating results from the climate submodule.

iii. CI and EI Initial Values and Internal Consistency

When looking into the 2005 CI and EI data from the OWD dataset (Ritchie et al., 2020a), a challenge was identified. The CI and EI data are presented per country. After grouping the values per region, the values for region groups were faulty. This is because the sum of EI across multiple countries is not equal to the sum of Primary Energy divided by the sum of GDPs across countries. Therefore, it was necessary to decompose both EI and CI elements. For CI, the carbon emission was already calculated based on the Edgar Dataset. The OWD data uses the Global Carbon Budget 2021 dataset, but the values are similar. Next, the Primary Energy data could be extracted from the BP Statistics Review dataset. However, BP (2022) has a more aggregated classification of countries, resulting in a loss of granularity. Therefore, the Maddison Project 2021 GDP dataset, the same dataset used by OWD was used to calculate the GDP of each country. This was done by multiplying the population data by the GDP per capita. One thing to keep in mind is that the data presented in the Madison Project dataset is in 2011$ price. To maintain consistency with the rest of the PyRICE model, the values were converted to 2005$ prices to adjust for inflation by dividing by 1.15 (U.S. Bureau of Labour Statistics, 2022). After calculating both CO_2 and GDP, PE was inferred from both CI and EI data and the values per region were aggregated.

This step highlighted the importance of maintaining internal consistency across the model. Variables like GDP and population are impacted by changes to the CO_2 dataset and the regional specification. Moreover, the implicit use of new GDP datasets to calculate EI and CI contributes to additional inconsistencies if not addressed. Therefore, Nordhaus' initial population and GDP data were replaced by the Madison Project values aggregated to the new regional specification. With this step, internal consistency is maintained for all the kaya identity emission drivers.

4.2. Implementation in PyRICE

i. Modified Equations

After updating the relevant initial datasets, we start by decomposing Sigma into its constituent intensities: EI and CI.

$$\sigma_{t,r} = CI_{t,r} \times EI_{t,r} \qquad [9]$$

Where:

- $EI_{t,r}$ is the energy intensity
- $CI_{t,r}$ is the carbon intensity

This product is then used in Equation 5, with the 'industrial' emission functions.

As highlighted in the Data Collection and Analysis sections, the data has been modified to account for the changes and lack of reproducibility in the original Nordhaus data. The initial values for CI and EI were calculated as follows:

$$CI_{t=initial,r} = \frac{CO2_{initial,r}}{PE_{initial,r}} \qquad [10]$$

Where:

- $CO2_{initial,r}$ is based on the EDGAR dataset
- $PE_{initial,r}$ is based on the Our World in Data and Maddison Project datasets

$$EI_{t=initial,r} = \frac{PE_{initial,r}}{GDP_{initial,r}} \qquad [11]$$

Where:

- $PE_{initial,r}$ is based on the Our World in Data and Maddison Project datasets
- $GDP_{initial,r}$ is based on the Maddison Project dataset

As for the change in Sigma, it is decomposed into:

$$CI_{t,r} = CI_{t-1,r} \times e^{\Delta t \times gCI_r(t-1)} \qquad [12]$$

$$EI_{t,r} = EI_{t-1,r} \times e^{\Delta t \times gEI_r(t-1)} \qquad [13]$$

Where growth rates of CI and EI are:

$$gCI_r\,(t) = gCI_r(t-1) \times (1 + d_{CI}\,)^{\Delta t} \qquad [14]$$

$$gEI_r\ (t) = gEI_r(t-1) \times (1 + d_{EI})^{\Delta t} \qquad [15]$$

ii. CI and EI Growth

Nordhaus' growth model is poorly backed in the RICE and DICE papers (Nordhaus, 1992, 2010, 2010, 2013a, 2013b, 2018; Nordhaus, 2017; Nordhaus & Boyer, 2000; Yang, 2008), and criticized in literature (Gazzotti, 2022). However, due to time constraints associated with this thesis project, the exponential model was retained to represent the change in CI and EI over time. This introduces limitations, especially considering that even though Nordhaus' Sigma is intended to represent the product of CI and EI, it has been simplified to be a proxy of the Autonomous Energy Efficiency Improvement (AEEI), designed to focus on improvements in energy efficiency. Therefore, using this model for CI and even Sigma is questionable, and more fitting models for EI have already been used for a while (Metcalf, 2008). Suggestions to improve this method can be found in Section 6.1 Future Works.

Initial values for growth were calculated based on Nordhaus' approach of taking the average from 1996 to 2005. The data was selected from Section 4.1.3.

iii. CI and EI Decline Rates and Experiments

The decline rate represents the rate of decarbonisation of the economy and energy mix. In the RICE-2010 model, it is assumed that one constant decline rate is used across all regions and for all periods. According to Nordhaus & Boyer (2000), it is based on the change in Sigma value in the last ten to fifteen years. The value of 1% represented the trend between 2000 and 2010 (Nordhaus, 2010), and therefore, Nordhaus (2017) later recommended increasing the value to 1.5% to reflect more recent data. This decline rate, despite being attributed to Sigma, in reality reflects the decline rate of energy intensity. More recently, the IPCC recorded a decrease of 2% for EI and 0.3% for CI (Friedlingstein et al., 2022; IPCC, 2022a). The focus on EI back when the RICE model was conceived could be due to the fact that CI was marginal at the time. However, the decline in carbon intensity in recent years has been exerting more downward pressure on carbon emissions and is projected to keep doing so (Peters et al., 2017). The change in carbon intensity was slower in the past with a 0.1% decline, but has improved with time (Ritchie et al., 2020b). It does however, fluctuate with time, with years that witness improvements and other deteriortion. Most recently, a decline of 0.5% was recorded (Enerdata, 2022).

The decline rate is a source of great uncertainty in this model, and for that reason the values for CI and EI decline rates were varied between more conservative and more optimistic values reported in literature, and mentioned above. Nine experiments were run to encompass a full factorial design, including low (L), medium (M) and high (H) values of decline, as seen in Figure 4 below.

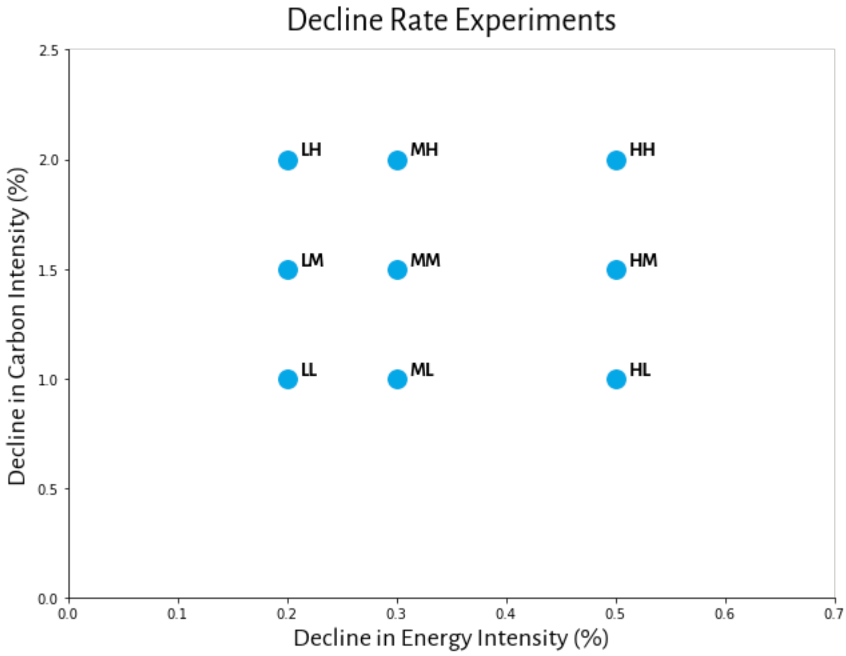


Figure 4: Decline Rate Experiments

The experiments are run using the Nordhaus policy in the model, while maintaining the Standard model specificaion, the Nordhays damage function and the Utilitarian ethical principle.

5. Results and Discussion

This section presents results from the data analysis and model runs and discusses main insights. For the full set of results, refer to Appendix VI.

5.1. Model Outcomes

i. Comparing Outcomes before and after the introduction of harmonized datasets for CO2, GDP and Population

After finalising the regional specification and implementing the changes in CO2, GDP and population data, the model was run to explore how the new datasets would impact the model projections. As seen in the consumption vs. damage graphs, global damages have increased considerably from around 100 billion US$ to near 400 billion US$ by 2300. Noting that the EDGAR CO2 emission data, consistent with the IPCC recommendation, is around three times larger than the Nordhaus dataset, damages are expected to increase proportionally.

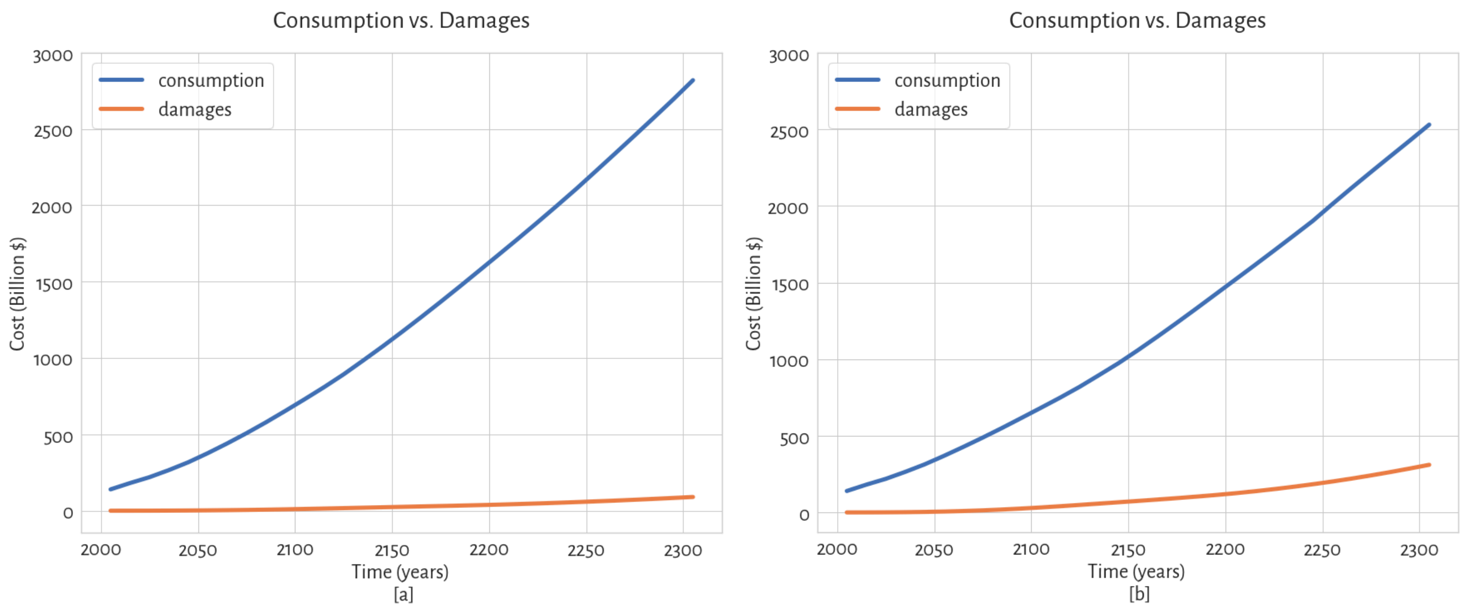


Figure 5: Comparison of Consumption vs. Damages between Nordhaus' Data [a] and EDGAR and MDP Data [b] for CO2, GDP and Population

One reservation anticipated before changing the datasets was that the model would go out of bounds when the CO2 emissions were greatly increased. However, as can be seen in Figure 5, the model maintains its behaviour after the change, but requires further calibration. The same can be said of other indicators found in Appendix IV, such as the Damages over Consumption per region (see Figure 17).

Increasing the CO2 emissions will also inevitably impact the change in atmospheric temperature. As can be seen in these graphs, using the EDGAR emissions dataset has resulted in a doubling of peak temperature increase from 3 degrees to 6 degrees C by 2150, a finding that is consistent with literature (Valone, 2021), and a common critique of IAMs for downplaying the increase in temperature (Ackerman et al., 2009; Keen, 2021). Moreover, the temperature offshoot occurs a lot earlier with the new dataset, to around 2025, an outcome that has already been identified in literature for China using the RefCM3 model (Lang & Sui, 2013), and that continues to be a possibility globally. The IPCC (2022) warns that if drastic action to cut CO2 emissions is not taken now, maintaining global warming below 2 degrees C by 2030, as proposed by the Paris Agreement, will be impossible.

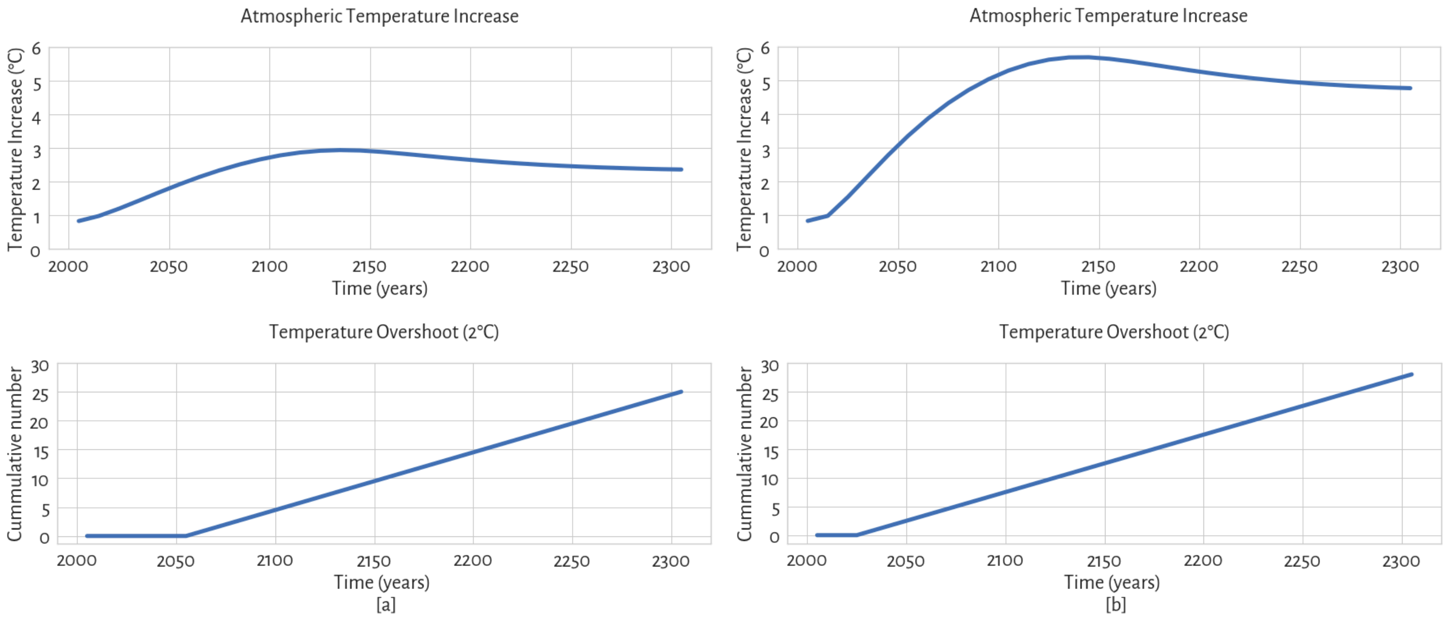


Figure 6: Comparison of Temperature Increase and Overshoot between Nordhaus' Data [a] and EDGAR and MPD Data [b] for CO2, GDP and Population

In the RICE-2010 model, emissions are endogenous and dependent on the Emission Output Ratio represented by Sigma. As can be seen in Figure 7, the overall trend in Sigma before and after modifying the datasets is maintained, however, the values increase significantly. Taking the US as an example, the value presented with the modified datasets, around 0.45 kg/$ for 2010, is more in line with data from literature (Ritchie et al., 2020a), than the value obtained from Nordhaus' dataset (around 0.13kg/$ in 2010). Moreover, as can be noticed while comparing both graphs, the value of Sigma for certain regions changes relative to the others. For instance, assuming a descending order, the rank of the Middle East decreases. This is probably because the values for initial GDP and emissions for the region could not be replicated, even after adding North Africa to the specification, leaving the regional proportion of emissions and GDP lower than in the original model. Similar conclusions can be drawn for other re-defined regions, such as Latin America and OHI. More interestingly, the cases of Africa and Non-Russia Eurasia highlight some of the limitations of adopting 'industrial' emissions to calculated Sigma, as these countries' industrial share of emissions is minimal compared to the bulk of energy-related emissions (African Development Bank Group, 2020).

Finally, in both graphs, sharp inflections can be observed at the first timestep after initialisation, in 2015, where the growth model and Sigma calculation functions kick in (instead of the initial variables). This then begs the question, of whether the models selected to represent the change in Sigma are adequate for this application.

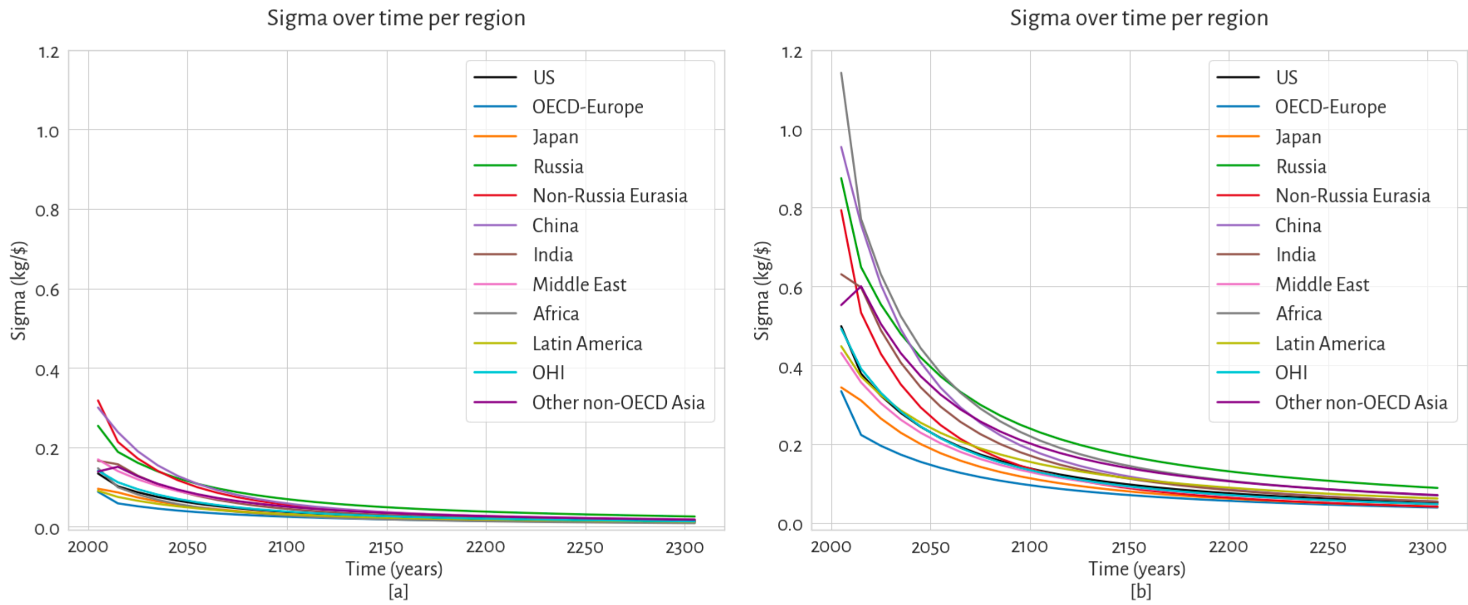


Figure 7: Comparison of Sigma between Nordhaus' Data [a] and EDGAR and MPD Data [b] for CO2, GDP and Population

ii. Comparing Outcomes Before and After Decomposing Sigma

In the next step, Sigma was decomposed into its constituent parts: EI and CI. This was achieved by decomposing the decline rates representing the rate of decarbonisation, the growth rates of CI and EI, and the values themselves to track the change in EI and CI across time. However, in the rest of the model, Sigma was kept as the product of EI and CI, a step that can be improved in future work.

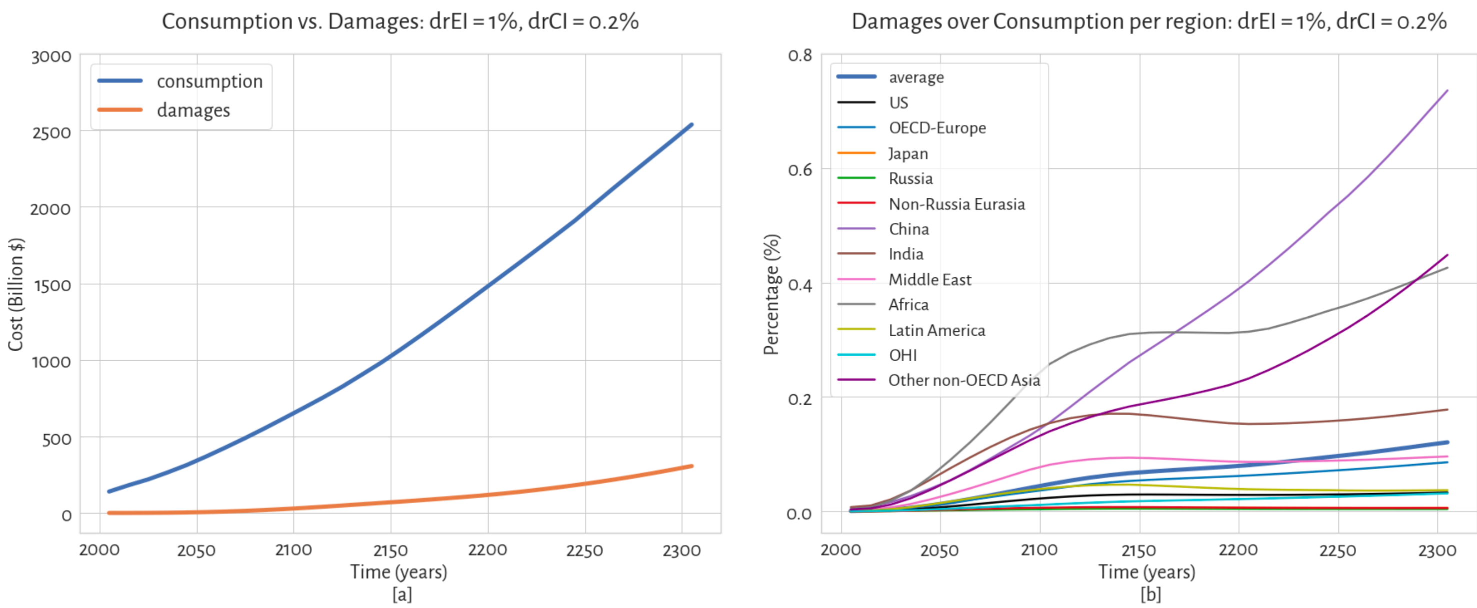
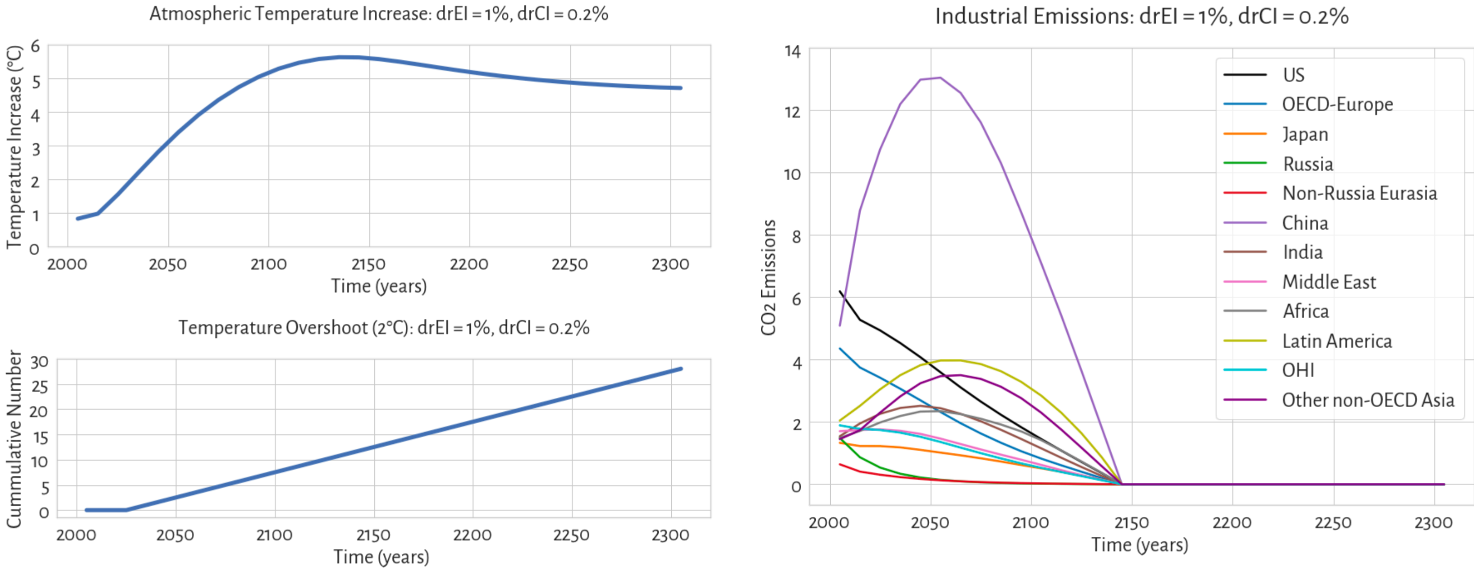


Figure 8: Consumption vs. Damages [a] and Damages over Consumption per region [b] with decline rates of 0.2% for CI and 1% for EI

As mentioned in Section 4.2.3, a total of nine experiments were run to explore the impact of decomposing EI and CI with different decline rates. The pair of decline rates that is most in line with current predictions is the MM experiment with decline rates of 1.5% for EI and 0.3% for CI (IPCC, 2022a; Nordhaus, 2017). However, for the sake of comparing Sigma to the decomposed EI and CI, the LL experiment with decline rates of 1% for EI and 0.2% for CI was selected, as it most closely resembles the 1% Sigma decline rate adopted by the original model (Nordhaus, 2010).



[a] [b]

Figure 9: Atmospheric Temperature Increase and Temperature Overshoot [a] and Emissions [b] with decline rates of 0.2% for CI and 1% for EI

As can be seen in the figures above, the behaviour observed in Figures 5 and 6 is maintained after splitting Sigma. However, this is not to be said of all indicators, such as CO2 emission over time. Even though they are overall consistent with the model outcomes pre-decomposition (refer to Figure 18 in Appendix IV), with the net-zero year selected as 2135 (μ), significant differences can be identified. First, as seen, China is set to more than double its emissions between 2005 and when it peaks in 2050. Even though this is not in accordance with previous PyRICE results, the growth is in line with current trends (IEA, 2022a). However, given the current policies that China is implementing, it is likely that emissions will peak earlier, between 2022 and 2026 with a probability of over 80% (Zhou et al., 2020), and more certainly before 2030 (IRENA, 2022). This forecast is not reflected in this experiment because the decline in carbon intensity required to achieve such a goal is well above 0.2%. In fact, in 2021, China's carbon intensity declined by 3.8%, resulting in a total change of -50.8% since 2005, with a goal of reaching -65% in 2030 as indicated in their Nationally Determined Contribution (UNFCC, 2022). This, however, is highly contingent on China' s ability to increase the penetration of renewables into their energy mix, a step that will be difficult to achieve if the country continues to commission new capacity for coal-fired power plants (Normile, 2020).

On the other hand, the emissions of Global North countries such as the US and OECD-Europe are the fastest to decrease, with Japan and OHI slowly following the trend. These results are consistent with previous findings in Figure 18, and generally in line with forecasts, with some regions having similar EI and CI values as set by the experiments, where others have slightly higher values(IPCC, 2022a). Other countries like Latin America and Other non-OECD Asia are expected to increase their emission until around 2070, before experiencing a decrease, while India and Africa are expected to peak earlier between 2050 and 2060, according to this graph. Similar to China, India's current improvements in EI and CI are greater than the experiments suggest, with a decline of -3.9% and -3.5% respectively for 2021 (Enerdata, 2022). These values can be explained by India's commitment to improve energy efficiency and their competitively rapid uptake of renewables, despite the country's leading role in watering down language in COP26 and plans to continue expanding coal capacity in the long-term (Climate Action Tracker, 2022; Jiang et al., 2019).

To avoid optimistic overestimations, it is important to remember that these values represent improvements for one year, and not over the average of a decade, and that the last couple of years have been marked by the COVID-19 pandemic, that saw global output drop, (something that is not represented in the model) which negatively impacts CO_2 emissions. Nevertheless, this highlights a considerable underestimation of CI in these experiments, and more importantly, an underestimation of CI as a driver in the RICE-2010 model, given that the growth of sigma is based on the improvement in energy efficiency. Moreover, the adoption of one decline rates across regions renders region-specific conclusions difficult to draw, especially when it comes to emerging economies with growing CI and EI decline rates.

iii. Comparing EI, CI and Sigma After Decomposition

After comparing the outcomes stemming from the decomposition of Sigma into EI and CI, we now compare Sigma itself, as the product of the newly defined Energy and Carbon Intensities. As can be seen in Figure 10, the values of the decomposed Sigma are similar in range to the Sigma values before decomposition. The overall behaviour is also maintained; however, interesting deviations can be observed. The sharp inclinations noticed in Figure 7 are no longer present, probably because in the decomposition process, the growth rate function was modified to follow Equations 14 and 15, removing constants that were set to adjust EI and CI growth values.

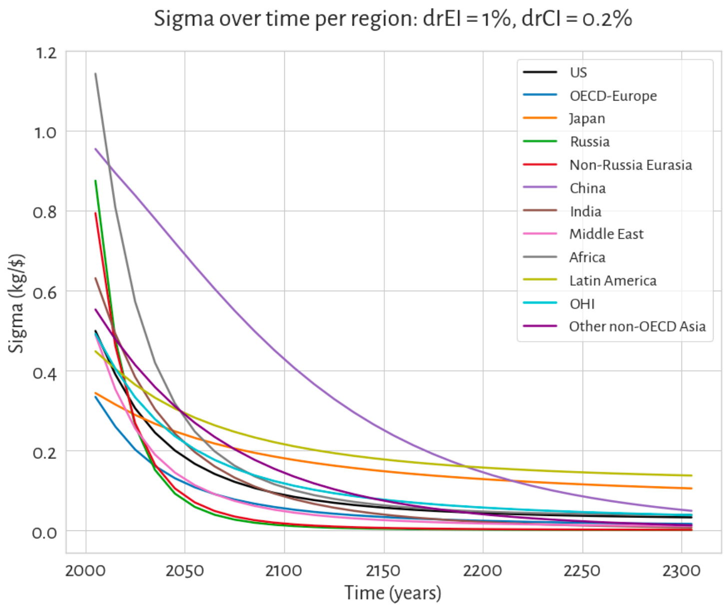


Figure 10: Sigma calculated as the product of EI and CI, with decline rates of 1% and 0.2% respectively

Moreover, the change in Emission Output Ratio for China is considerably slower. This is due to China's positive change in EI, as seen in Figure 11. However, this is not in accordance with recent data (Enerdata, 2022).

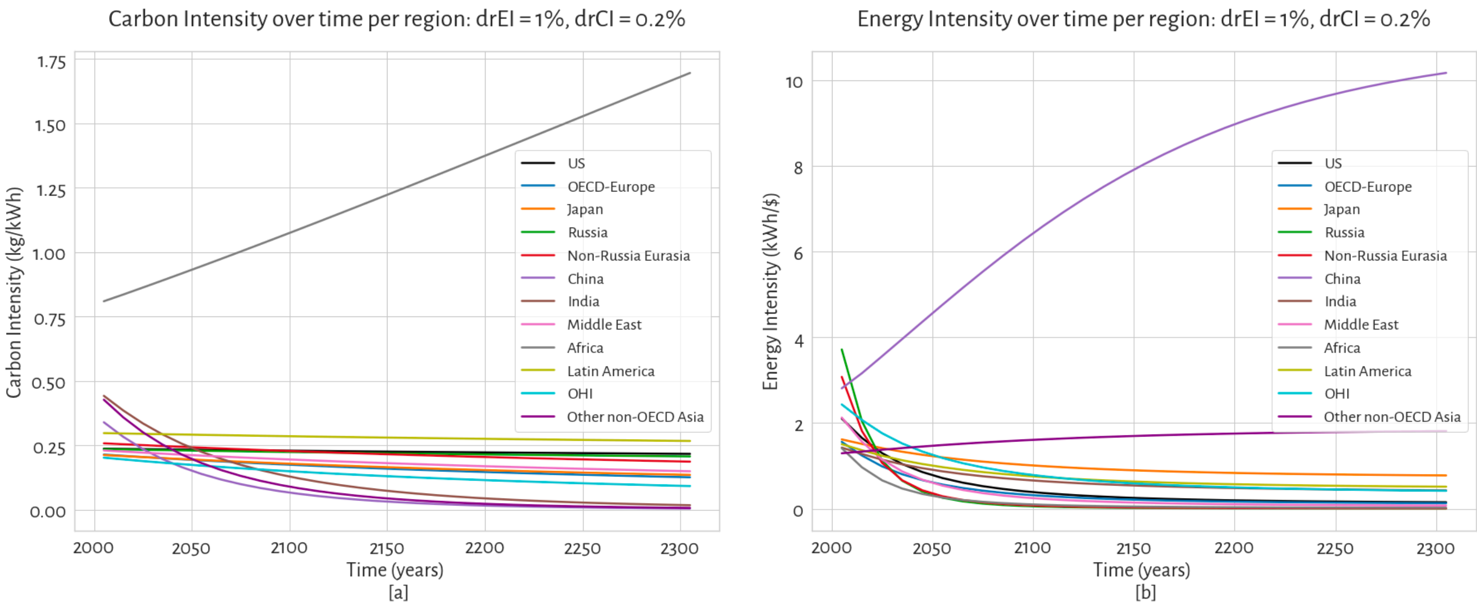


Figure 11: CI [a] and EI [b] with decline rates of 0.2% and 1% respectively

Another interesting result is in the change of Africa's CI over time. Unlike the growth in China's EI, Africa's CI is expected to grow in the near future, with increased access to electricity generated by fossil fuel (UN Department of Economic and Social Affairs, 2018). In fact, CI in Africa has increased in the last decade between 2010 and 2019 by 2.6% (IPCC, 2022a). However, it is not expected to continue increasing as shown in the graph above. Overall, when comparing the graphs for EI and CI, it is clear that EI is dropping faster, as technological advancement has been at the forefront of climate debates (Masson-Delmotte et al., 2018). Even though renewables have become cheaper and more accessible, regulatory and geopolitical barriers have stood in the way of wide-spread adoption (IEA, 2021), limiting a targeted decline of CI.

iv. Comparing Decline Rates

After contrasting the outcomes of decomposing Sigma using the decline rates of 1% and 2% for or EI and CI respectively, we now move to compare the different experiments defined in Section 4.2.3, with three different decline rates per emission driver.
Values for the decline rate are highly uncertain and there is no consensus estimates about their uncertainty (Nordhaus, 2018). Multiple values have been suggested to modifications of the DICE/RICE models (Gazzotti, 2022), for other data sources (Global Carbon Project, 2021) and for the RICE and DICE models themselves. Nordhaus (2010) originally suggested a decline rate of 1% based on estimations between 2000 and 2010. However, according to new values from 2000 – 2015, Nordhaus (2017) highlights that the decline rate is now around 2%, while suggesting the use of a decline rate of 1.5% in the most recent DICE-2016R model to avoid overestimation. To explore this uncertainty, the experiments were run.

We expect higher decline rates to result in lower increases in global temperature, as well as lower values for EI and CI, and consequently Sigma. However, this was not represented in the outcomes of the experiments. Instead, as can be seen in Figure 12, the opposite occurs. To understand what is happening, the equation used to calculate the growth of CI and EI (defined by Equations 14 and 15) was inspected. Given the scarce information regarding relations in the model, the growth equation was adopted from Gazzotti (2022), who identified it as the growth rate equation used in the recent iterations of the DICE/RICE family. Given the exponential decay function used to calculate CI and EI, the behaviour observed in the graphs below can be expected. To compare the result with the PyRICE-2022 model pre-decomposition, the original model was run for all experiments with the new EDGAR and MDP data. For reference, growth rates in this model include constants such as "trend sigma growth" with a value of -0.25% across all regions and "total growth rate sigma" with values ranging between -4.5% and 2% depending on the region. These constants that can be found in the RICE Data Excel sheet are not documented nor explained and the Sigma growth rate equation is never defined (Reddel, 2022; Tjallingii, 2021). Therefore, it is difficult to estimate what these constants would be in the case of the decomposition. However, given that the purpose of running this version of the model is only to explore the impact of increasing decline rates, this limitation is trivial.

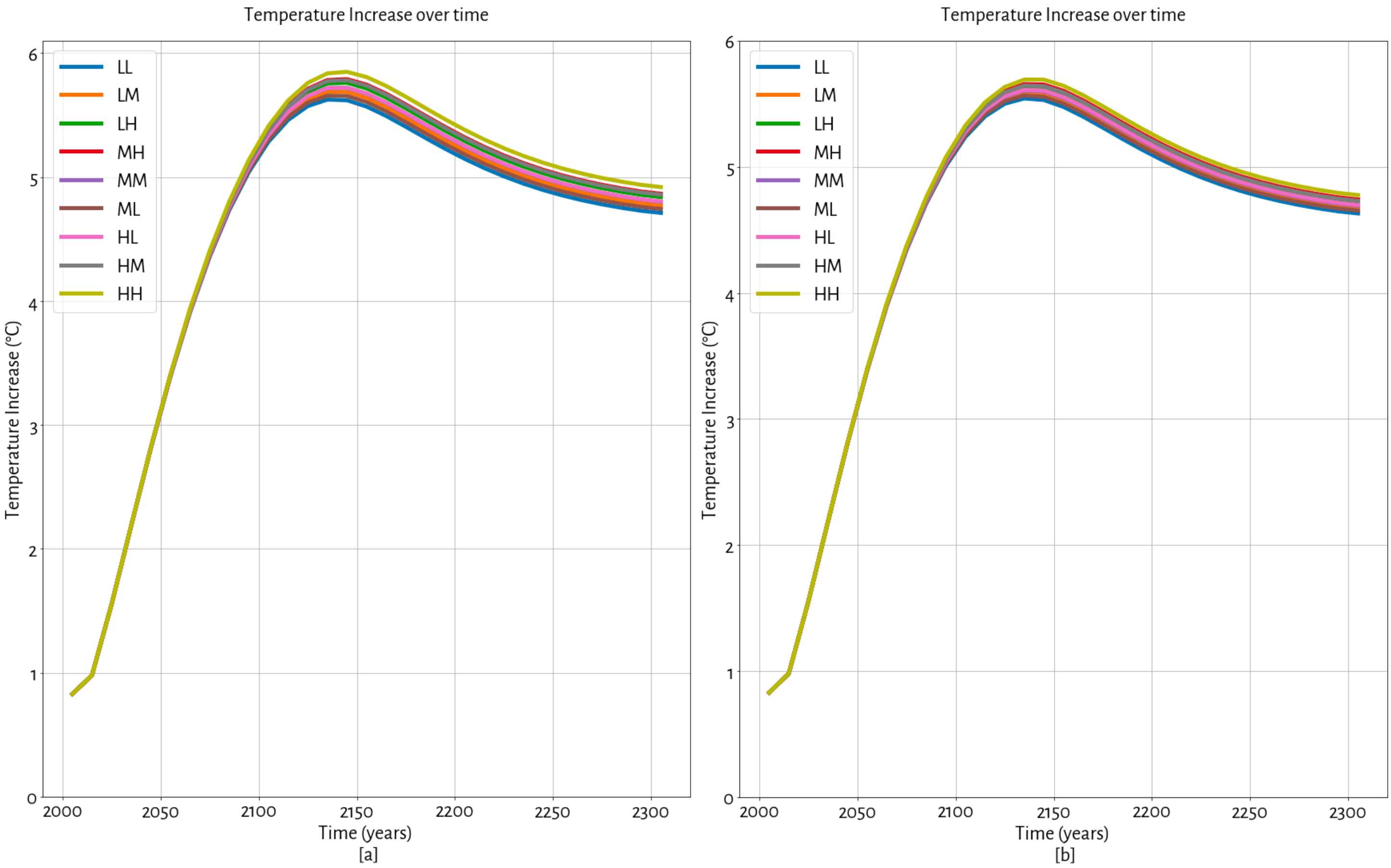


Figure 12: Temperature Increase using Gazzotti (2022)'s definition of EI and CI growth [a] and Temperature Increase using the original definition of EI and CI growth [b] across all experiments

As observed in the figure above, both growth rates yield similar results, with higher decline rates yielding higher temperature increases. The same can be said about Sigma, chosen here to represent both drivers to highlight the results of each experiment. As seen, most regions show that higher decline rates translate into higher Sigma values, with a few notable exceptions: China, Africa and Other non-OECD Asia.

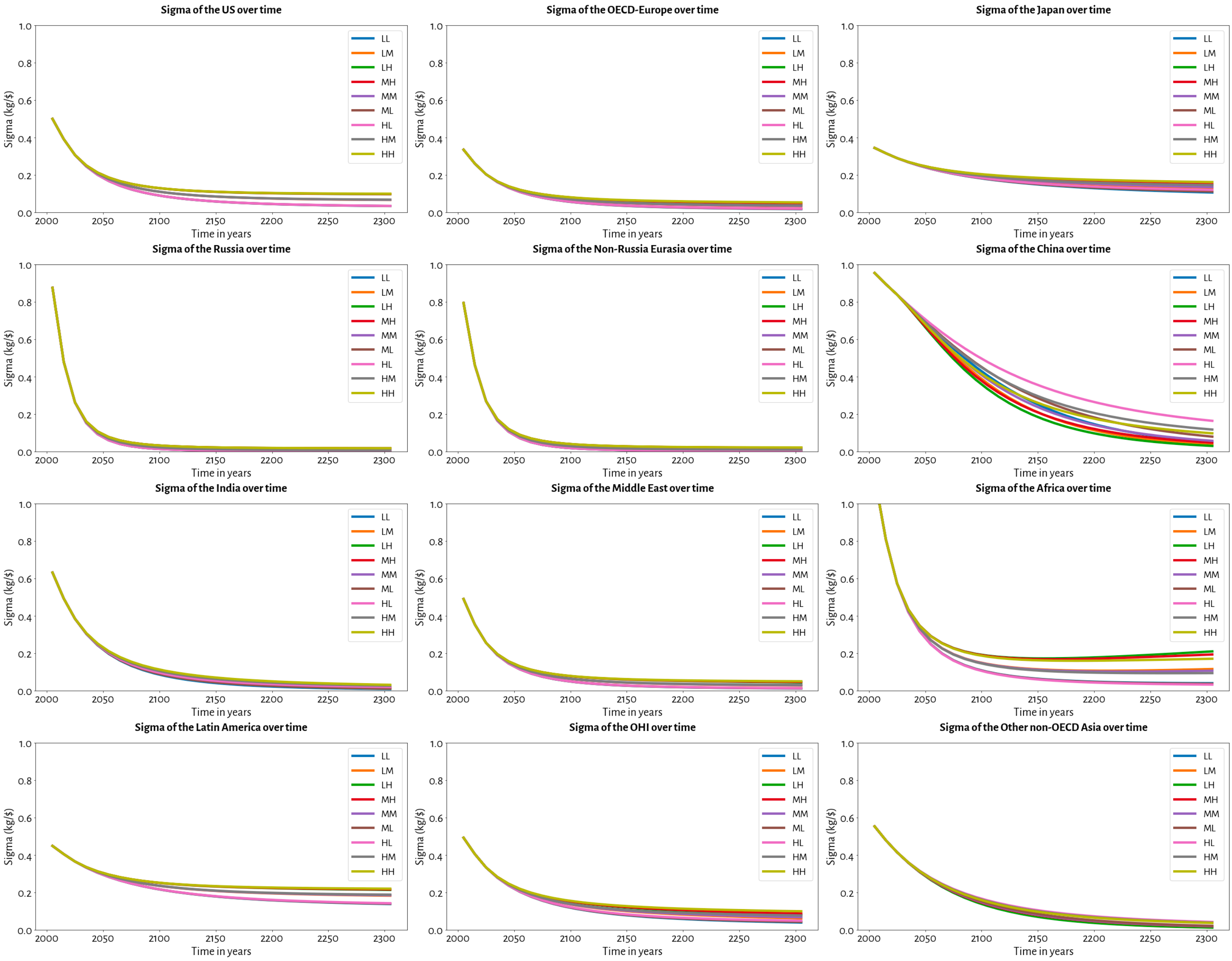


Figure 13: Evolution of Sigma over Time for Every Region Across All Experiments

When looking at the experiment outcomes for CI in Figure 19, we notice that instead of decreasing, Africa's CI increases. And while an increase in CI is expected in the region with growing electrification (African Development Bank Group, 2020), it is unclear if the growth will be as significant in magnitude. Moreover, according to experiment outcomes for EI in Figure 20, values for China and Non-OECD Asia are also expected to grow. Given the current projections for China, however, this seems highly unlikely (Zhou et al., 2020). A few hypotheses can be made as to why this behaviour is occurring. However, given the obscurity of the growth function, as well as the many variables and submodules influencing output, emissions and the control rate, it is difficult to pinpoint the source of the problem, especially given how the rest of the input data is introduced.

An additional step was taken to better understand the growth rate equations presented in the DICE/RICE family. Looking into earlier versions of the models, we identified different equations for Sigma and its growth function, as seen in Equations 16 and 17. Interestingly, in this version, the exponential decay is used to calculate the growth of Sigma, rather than Sigma itself, while relying on the initial growth in each step, rather than the growth at the step before. The calculation also relies on “parameters that determine the rate of decline” without any additional information on what they represent, but unlike the decline rate in RICE-2010, they change over time. Even though these steps did not yield additional clarity regarding the growth rates, the findings highlight the changes made to the growth rate over time, and the modifications that need to be made to adequately use this decomposed model. In fact, setting aside some odd behaviours, these experiments shed light on the important of the decline rate in defining the Emission Output Ratio and consequently the impact on global temperature increases. Moreover, despite being marginally addressed in the RICE model, the influence of CI on the decarbonisation paths of some regions is clear and should be better represented moving forward.

v. The Role of Carbon Intensity in DICE/RICE models

Even though Sigma is meant to represent the product of CI and EI it is often called carbon intensity (of output) resulting in some confusion. This confusion is further exacerbated by the fact that the RICE Model seems to use Sigma as a proxy for energy intensity solely. Nordhaus (1992) argues that energy use and CO2 emissions per unit output form Sigma but focuses on the trend of Energy/GNP. Moreover, as mentioned earlier, Sigma has been used synonymously with AEEI (Nordhaus, 2018; Yang, 2022), further contributing to the idea that Sigma does not properly incorporate CI. This could be due to the fact that CI has been historically much smaller than EI, with a global change in energy per unit GDP of -2% vs. -0,3% for carbon per unit energy (IPCC, 2022b). EI has seen improvement due to considerable energy efficiency improvements in the last decades. This trend, however, is expected to slow down as a threshold is reached in terms of technological improvement. CI on the other hand has not improved as greatly, especially given that the trend of decarbonising the energy mix is volatile and influenced by political events, such as the 2008 financial crisis, the 2014 Fukushima disaster and potentially the current Energy Crisis (Friedlingstein et al., 2022). Overall, global energy intensity has improved in transport, buildings and industry, whereas carbon intensity has not (IPCC, 2022a).

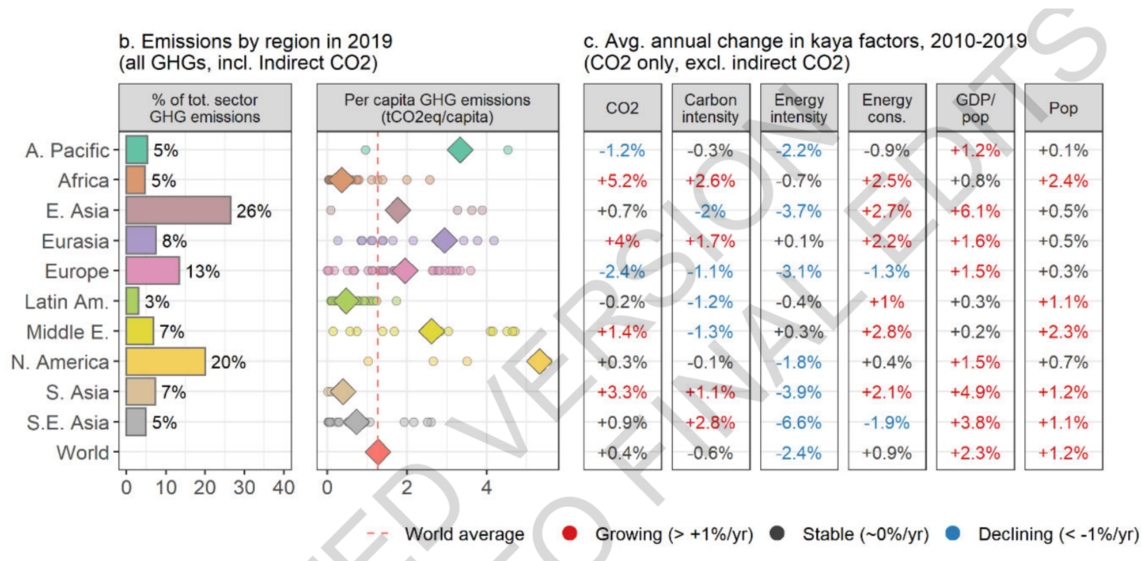


Figure 14: Emissions by Region in 2019 and the Average Annual Change in Kaya Factors (2010-2019). Source: IPCC (2022)

However, when taking a closer look at the changes in these kaya factors across regions (see Figure 14), we can see that using an average to account for global carbon intensity decline greatly skews the value towards zero, with countries experiencing a considerable increase in CI versus a decrease. And even though regional disaggregation would improve results, the most recent values presented in the IPCC report are not enough to maintain temperature increase below 2 degrees C, as stipulated by the Paris Agreement. In fact, in literature the improvements in both CI and EI are not consistent as the structure of the RICE model would suggest. Instead, decline has slowed down compared to historical trends, created a wider gap between current change levels and the 3.5% yearly decrease in EI necessary to reach the Paris goals (Enerdata, 2022).

5.2. Limitations

This research project has been challenging, and difficult decision were made to account for time and scope. That said, a few limitations should be mentioned.

Despite best efforts, there was not enough data in literature to replicate the regional specification thought-out for the RICE-2010 model. An approximation was instead used and adopted across the model (see Appendix II). This regional aggregation mostly gave priority to economic similarities between regions, rather than focusing on climactic and/or geographic characteristics. Even though this fits better into the context of the economy sub-module modified in this thesis, some of these choices may impact outcomes from the carbon and climate sub-modules.

Updating input data was a major contribution to this work. The EDGAR CO2 dataset was selected because it has been adopted by the IPCC (IPCC, 2022a). However, many CO2 datasets are available, and they vary based on estimation methods and inclusion criteria (Minx et al., 2021). Since initial CO2 emissions represent the foundation of the Emission Output Ratio calculation, varying the values will have an impact on the results. This is because the Emission Output Ratio is used to endogenously represent the change of energy-related carbon emissions in the model, which in turn drives the increase in temperature, and eventually, the damages to the economy.

Maintaining internal consistency was also a main concern in this project. For this reason, after updating the regional specification and CO2 emissions, GDP and Population data were modified to ensure all the emission drivers are consistent with respect to each other. However, the model is large and is built in such a way that most of the input data derives from static excel sheets. Updating inputs for each variable to reflect changes in regional specification or GDP, CO2 and Population is tedious and time consuming, but will be necessary for this model to be used for future applications.

Furthermore, the RICE model uses a single constant global decline rate based on the average of the regions. According to Peters et al. (2017) and the IPCC (2022), decarbonisation is considerably different from region to region, meaning that aggregating this value would result in less granularity, and deepen the focus on the Global North in the climate debate (Blicharska et al., 2017). Moreover, the decline was initially computed based on the average trend observed between 2000-2010, and later based on observations from 2010-2020. The decline rate is assumed to persist from the start of the model in 2005 to the end in 2305, which results in considerable uncertainty in the results. Finally, the decline rate is influenced by a multitude of factors, including trends in the use of power sources, carbon taxation policies, technological advancements and historical events, rendering difficult to forecast the rate (Nordhaus & Boyer, 2000).

Another source of limitation is the growth approach used for the CI and EI parameters. Following the RICE model growth equation is highly conjectural, especially since there is little information as to why this approach was selected. With many iterations of this function available in literature and practice, it is challenging to find a detailed application. Moreover, as it stands, it does not adequately reflect the impacts of changing the decline rate on the system. Moreover, the growth model was initially designed to serve as an indicator for "cumulative improvement in energy efficiency", i.e., an indicator for the improvement in energy intensity, calling into question whether it is even suitable for carbon intensity growth calculations. And given that there is great discontinuity in historical data for improvements in energy efficiency (Nakata, 2004) , this growth model is not ideal to represent changes in energy intensity. Finally, the projected growth of these parameters is sensitive to future scenarios and adopted policies, something that is not reflected in the current definition. Improvements to growth of Sigma have already been introduced to some iterations of the model, such as Gazzotti (2022) who improved the equation and made it vary across all five shared socioeconomic pathways (SSP) (Riahi et al., 2017).

As meticulous attention was drawn to the Emission Output Ratio and its constituent parts, other variables such as the Emission Control Rate μ (defined in Equation 8) were not addressed. Given that this analysis focused on the Kaya decomposition, the optimization variable μ was considered out of scope. However, μ does play a significant role in determining the energy-related emissions, as it reduces the value of said emissions until a target year is attained where the economy reaches net-zero. The Emission Control Rate is thus a lever in the XLRM model of the PyRICE-2022 model (Reddel, 2022), and exploring how it is impacted by the changes made to the model in this thesis is key to better understanding decarbonisation pathways.

Finally, despite observing similar behaviours to the original PyRICE-2022 when running the modified version, the values obtained need to be taken with a grain of salt as the new model was not calibrated to account for these changes.

6. Conclusion

In summary, the RICE-2010 model lacked an explicit consideration for energy, one that can be leveraged to explore how regions decarbonize to mitigate the impacts of climate change. Energy was explicitly introduced to the Python version of the model, PyRICE-2022, by decomposing the Emission Output Ratio, Sigma, into Energy Intensity (i.e., indicating how energy-intensive the economy is) and Carbon Intensity (i.e., indicating how carbon-intensive the energy mix is). Leveraging the Kaya identity to achieve this goal, shifted our understanding of the drivers behind decarbonisation by highlighting the different roles of CI and EI, their respective impacts on decarbonisation paths and the importance to explore them separately. Decarbonisation is an umbrella term designating a decrease in carbon emissions per unit output. However, whether decarbonisation is driven by a cleaner energy mix or more efficient processes is relevant, as it highlights different behaviours between regions and the need to define separate objectives to achieve climate goals. Interestingly, CI continues to be under-represented at a time where crucial decisions in climate summits, such as the phase-down vs. phase-out debates in COP26, rely heavily on its impact on carbon emissions. And whereas the decline in EI is expected to slow down, as it is limited by technological change, CI can theoretically reach zero with an energy mix that is 100% based on green energy, shedding light on the importance of using adequate and up-to-date methods before evaluating climate policies.

Throughout the process, data quality and transparency issues have been identified, resulting in considerable data work being done. This includes updating the initial CO_2 emissions, the regional aggregations, the definition of the Emission Output Ratio and the growth rate of said ratio. These obstacles were tackled by researching for and validating quality data, basing choices on other applications of the RICE and DICE models, and dynamically introducing the data to maximize transparency (instead of relying on static excel sheets). Naturally, as mentioned before, these steps were not without their limitations, and a few suggestions for improvements and future work have been researched and suggested. These findings can help improve the current refactored RICE-2010 model, to make reproducibility more accessible and set the basis for evaluating future low-carbon pathways using more specific technological advancements in energy sources, energy industries and carbon capture and storage.

6.1. Future Works

Decomposing Sigma into EI and CI constitutes the first step in rendering the RICE model better suited for energy-related policy questions. The approaches undertaken in this thesis are not without their limitations, as mentioned in the sub-section above. To overcome these drawbacks and improve the model a few steps can be taken. For a to-do list format of this sub-section, refer to Appendix V.

First, the data quality and transparency of the model should be improved further. The regional specification defined in Appendix I should be reconsidered. It is based on economic and or political similarities between countries, similar to how the regions in RICE-99 were defined (Nordhaus & Boyer, 2000). However, given the scope of the model, it would also be helpful to assess the impact of prioritising geographic and/or climactic similarities between regions instead, and update the specification accordingly. Another important step is to go through the PyRICE model and ensure that it is consistent with the RICE-2010 model and adequately refactored. This includes getting rid of unused variables that can be misleading and ensuring that the relationships between variables are correct. Moreover, given that data processing and documentation have been key challenges throughout this research, updating static data found in the Excel files would greatly improve the quality of the results. This could be done by identifying what data is introduced through *data_sets.py* and replace it in case it is outdated or impossible to replicate. Later, all the inputs should be introduced in a transparent and clear way to facilitate reproducibility. The introduction of new data should be done carefully, while upholding internal consistency cross the model. Special attention needs to be given to exogenous variables as they rely heavily on the RICE Excel datasheets. To streamline this process, a more detailed version of Figure 1 can be used to observe how inputs, variables, equations and outputs are intertwined in the model.

The implementation of the decline rate and consequent growth in EI and CI should be amended. As it stands, the decline rate is a constant across region and time, based on the average of the previous decade. This makes the analysis susceptible to issues regarding the discontinuity in growth for EI and CI, and key historical events. Since the decline rate represents the rate of decarbonisation, it is important to find a better way to represent it. For instance, this can be achieved through the adoption of an adjusted average that accounts for global events like the 2008 financial crisis and COVID-19 or by adopting forecasts from reliable models that take into account the uncertainty range of the variable (Peters et al., 2017). Moreover, to push forward the regional disaggregation of the RICE model compared to DICE, the decline rates should be specified on a regional level, as regions have considerably different rates of decarbonisation as seen in Figure 14. Furthermore, as mentioned in Section 4: Methods, instead of using the RICE Model's exponential growth rate for Sigma, a simple but more representative regression model can be used for each of CI and EI (Gazzotti, 2022; Metcalf, 2008; Nakata, 2004) highlighting expected slowing trends in EI, and the need for larger decreases in CI. These growth models need to account for a few things. First, the growth of EI should consider the limits of technological advancement, as improvements in the structure and energy efficiency of the economy slow down over time. One simple way of representing this behaviour is using an S-shaped curve. Second, CI should not be modelled the same way as EI, as it involves the change in the energy mix, that can theoretically become a 100% green (i.e., from non-emitting sources). Lastly, in this simplified version of the model, CI and EI depend on a decline rate and are not directly impacted by policies taken on scenarios experienced. Given that the development of these drivers of emission is heavily influenced by the context in which they calculated, it would be useful to adapt these values to multiple scenarios, such as the different SSPs, similar to what was done by (Gazzotti, 2022).

In this research, introducing an explicit consideration for energy was translated into decomposing the Emission Output Ratio (σ), into its constituent parts. The decline rates, growth rates and the calculation of EI and CI themselves were decoupled from σ, allowing for the exploration of these variables across time and region. However, in every other part of the model, σ was maintained and updated as the product of EI and CI. Therefore, it helpful to fully decompose σ across the model, such as when calculating the cost for the backstop. This will bring forth a few conceptualization and implementation questions as to when the product of EI and CI are necessary and when the focus is on energy efficiency or energy mix. Similarly, with the introduction of more detail to emission drivers, the role of the Emission Control Rate (μ) in the emissions function should be reconsidered, especially considering that it is a singular value across regions.

Finally, to use the model in more complex policy context, additional steps can be undertaken. This includes, making the model more adaptable to questions about energy-related technological change, an extension of Kaya can be further introduced to check for fuel switching (e.g., from coal and gas) as suggested by (Peters et al., 2017). Furthermore, to delve deeper into the role of energy, both energy and carbon intensity, which are based on primary energy, can be further decomposed into primary and final energy, to better understand the drivers behind decarbonisation and look deeper inside the black box models (Koomey et al., 2019). And finally, to test out the question behind the phase out and phase down debate, better compare the mitigation pathways of various regions and account for the deep uncertainty in the CI and EI parameters, it is helpful to run many-objective robust decision making (Bartholomew & Kwakkel, 2020; Kwakkel et al., 2016).

6.2. Recommendations and Reflection

Even though the advice from this work is not a comment on the decisions made in COP26, it tackles a larger scope that is increasingly common. With COP27 happening a few weeks from when this section is written, it is important to remember that all models are wrong (Sterman, 2002), but it is the job of modelers to make them useful. The RICE model is an important tool, that simplifies the complex challenge of climate change. However, the data quality and transparency in data processing and methodology are opaque, resulting in a model with results that cannot be reproduced or expanded on. Therefore, it is crucial to provide this model, and other climate IAMs, with proper documentation and theoretical backing, to begin the process of using them for climate policy making.

On that note, the improvements introduced to the PyRICE model in this research allow for some recommendations to be made. First, the prioritisation of EI should be shifted to include CI as well, as it is not enough to rely on improvements in energy efficiency, that will eventually plateau due to limits in technological advancement. Moreover, as decline rates stand, even when disaggregating them across regions, we are still far from reaching the decline rates needed to meet the goals set by the Paris Agreement, including the 2 degrees warming above industrial levels. And finally, policy makers should re-evaluate the way they use models such as this one. The strength of the DICE/RICE models family is that they are simple and straightforward to understand and utilise. Many critiques, although well-founded, can be out of scope. Models like these are not meant to be used to quantify policy levers, but instead, they are meant to serve as an ideal to strive for, given the better understanding of social, economic and climatic processes they confer, such as decarbonisation.

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Appendices

I. Regional Aggregations

The regional specification selected for this analysis is based on a collection of data from (Anthoff & Tol, 2014; EIA, 2021; Nordhaus & Boyer, 2000).

Table 3: Suggested Regional Specification

Regions	Countries
United States	United States
OECD-Europe	Austria, Belgium, Turkey, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom
Japan	Japan
China	China
Russia	Russia
India	India
Non-Russia Eurasia	Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Faroe Islands, Georgia, Gibraltar, Kazakhstan, Kosovo, Kyrgyzstan, North Macedonia, Malta, Moldova, Montenegro, Romania, Serbia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan.
Middle East	Israel, Bahrain, Iran, Iraq, Jordan, Kuwait, Lebanon, Oman, Palestinian Territory, Qatar, Saudi Arabia, Syria, United Arab Emirates, Yemen,Egypt, Algeria, Tunisia, Libya, Morocco
Latin America	Anguilla, Antigua and Barbuda, Argentina, Aruba, Bahamas, Barbados, Belize, Bolivia, Brazil, British Virgin Islands, Cayman Islands,Chile, Colombia, Costa Rica, Cuba, Curacao, Dominica, Dominican Republic, Ecuador, El Salvador, Falkland Islands, French Guiana, Grenada, Guadeloupe, Guatemala, Guyana, Haiti, Honduras, Jamaica, Martinique, Mexico, Montserrat, Nicaragua, Panama, Paraguay, Peru, St. Kitts and Nevis, St. Lucia, St. Pierre and Miquelon, St. Vincent and the Grenadines, Suriname, Trinidad and Tobago, Turks and Caicos Islands, Uruguay, Puerto Rico, Venezuela, Netherlands Antilles
Africa	Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo, Democratic Republic of Congo, Cote d'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Reunion, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, South Sudan, St. Helena, Sudan, Tanzania, Togo, Uganda, Zambia, Zimbabwe
OHI	Canada, Australia, New Zealand, South Korea, Singapore, Taiwan, Hong Kong, Greenland, Andorra
Other Non-OECD Asia	Afghanistan, Bangladesh, Bhutan, Brunei, Myanmar, Cambodia, Cook Islands, Fiji, French Polynesia, Indonesia, Kiribati, Laos, Macau, Malaysia, Maldives, Mongolia, Nauru, Nepal, New Caledonia, Niue, North Korea, Pakistan, Papua New Guinea, Philippines, Samoa, Solomon Islands, Sri Lanka, Thailand, Timor-Leste, Tonga, Vanuatu, Vietnam

II. Model Equations

For the overall model equations for the RICE-2010 model, refer to Tjallingii (2021).

Additionally, the earlier iteration of the Sigma and Sigma growth equations as defined by Nordhaus & Boyer (2000) in RICE-99.

The Emission Output Ratio (Sigma) was defined as:

$$\sigma_t = \frac{\sigma_{t-1}}{1+g\sigma(t)} \quad [16]$$

Where:

σ_t is Sigma at time t
$g\sigma(t)$ is the growth rate of Sigma as defined by the equation below

$$g\sigma(t) = g\sigma(t=0) \times e^{(-\delta_1^\sigma(t)-\delta_2^\sigma(t))} \quad [17]$$

Where:

$g\sigma(t)$ is the growth rate of Sigma at time t
$\delta_1^\sigma(t)$ and $\delta_2^\sigma(t)$ are parameters that determine the rate of decarbonisation

III. CO_2 Emissions Check

This section highlights an example calculation conducted to understand the discrepancy in CO2 emission values.

Example 2005 United States

Based on Our World in Data (OWD)
Energy Intensity = 1.83 kWh/$
Carbon Intensity = 0.23 kg/kWh

Computing the product of Energy Intensity x Carbon Intensity:

1.83 kWh/$ x 0.23 kg/kWh = **0.42 kg/$**

Step 1: Validating OWD Data with other sources

Energy Intensity: Primary Energy / GDP

From BP Dataset: Primary Energy

$$Primary\ Energy = 96.88\ exajoules\ \times \frac{2.778\ \times 10^{11}\ kWh}{1\ exajoules} = 269.13 \times 10^{11}\ kWh$$

From World Bank Dataset

$$GDP = 13.04\ trillion\ \$$$

Calculation

$$Calculated\ Energy\ Intensity = \frac{Primary\ Energy}{GDP} = \frac{269.13\times10^{11}}{13.04\times10^{12}} = 2.06\ kWh/\$$$ ≈ 1.83 kWh/$ from OWD

Carbon Intensity: CO_2 Emission / Primary Energy

From the BP Dataset: CO_2 Emissions from Energy

$$CO2\ emissions = 5873\ million\ tons = 5873 \times 10^6\ tons \times \frac{10^3 kg}{1\ ton} = 5873 \times 10^9\ kg$$

Calculation

$$Calculated\ Carbon\ Intensity = \frac{CO2\ emissions}{Primary\ Energy} = \frac{5873\times10^9\ kg}{269.13\times10^{11}\ kWh} = 0.218\ kg/kWh$$ ≈ 0.23 kg/kWh from OWD

Step 2: Comparing to Emission Output Ratio (σ) in PyRICE mode

From the RICE_PARAMTER.xlsx from the model inputs:

As seen above, the initial Sigma (CO2/GDP) is **0.134** $\neq$ **0.42** (from the OWD data).

When checking how the 0.134 was computed, it's based on:

$$\frac{CO2\ emission}{GDP} = \frac{1.662}{12.3979\ trillion\ \$} = 0.134$$

The GDP = 12.3979 trillion $ is sound $\approx 13.04\ trillion$ $ from the World Bank data, but CO2 emissions of 1.662 does not:

- The unit is unclear in the dataset, but it's found to be 1662 million metric tons (thus, the order of magnitude checks out)
- 1662 million metric tons **< 5873-6007 million metric tons** (acc. to BP and EIA)
- The PyRICE CO_2 emissions is only 27% of the amount reported by other sources for "energy-related CO_2 emissions"
- Checking the original source of the dataset, the CDIAC, shows carbon emissions from "Fossil Fuel and Cement Production" is equal to **1579 MMtC $\approx$ 1662 MMtC.**

The data was inspected based on Nordhaus & Yang (1996)'s original source, the Carbon Dioxide Information and Analysis Centre (CDIAC). However, the sum of the per country CO2 emissions for 2005 from the CDIAC did not match the sum of the regional CO2 emissions present in the *RICE_Parameter.xlsx* dataset inputted into PyRICE. In fact, the PyRICE data was 336.000.000 tons larger than the CDIAC dataset. Moreover, the unit of the CO2 emissions in the PyRICE dataset is not clearly documented, resulting in some unnecessary confusion. Finally, when trying to identify where the data is imported from, it was found that it is inputted into the dataset from an unknown private Dropbox link. This highlights a lack of transparency in the data, how it is defined and where it comes from, making it impossible to replicate.

IV. Comparing Datasets and Supplementary Results

This appendix includes additional results that are relevant to better understanding the results presented in Section 5: Results and Discussion.

i. Modifying CO2 Emissions and Regional Specification

After introducing the new CO2 emissions data for 2005, collected from the European Commission's EDGAR Dataset, and given that detailed regional specification is not provided for this model, the regional share of CO2 emissions for 2005 for every region was calculated to validate the regional aggregation. As can be seen, for single countries and OECD-Europe the share is somewhat similar. However, bigger deviations are observed for grouped regions, especially the Middle East, Africa and Latin America and non-OECD Asia.

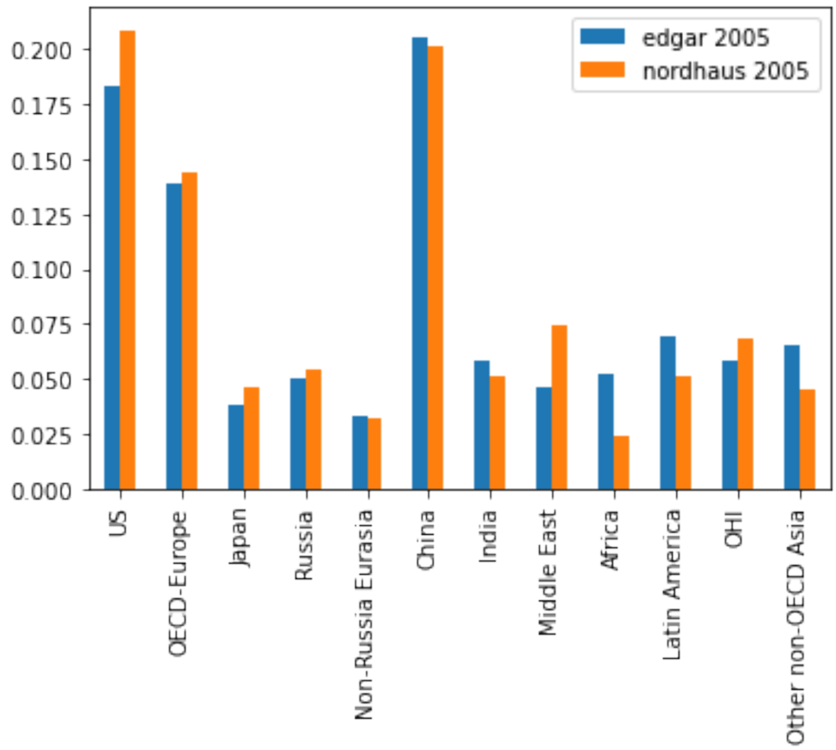

Figure 15: Comparison of regional share of CO2 emissions between the Nordhaus PyRICE data and regional specification and EDGAR data for 2005

For instance, the share of the Middle East is much higher in the Nordhaus dataset. This could be due to the fact than in this graph, the Middle East did not include North Africa. However, the potential introduction of North Africa into the Middle East, along with its larger players such as Algeria, Egypt and Morocco, could tilt the scales for the region. Moreover, Latin America's share is much higher in the EDGAR dataset, potentially because some of the Caribbean islands and overseas territories in Latin America fall under OHI. With trial and error, the regions were amended to try and capture Nordhaus' initial specification, but in vain.

Even moving North Africa to the Middle East did not improve the share of CO2 emissions considerably for that region. To test out the theory differently, the GDP of the Middle East, the Middle East and North Africa (MENA) and (Sub-Saharan) Africa were compared based on data from the World Bank (World Bank, 2020). As can be seen the overall GDP of the entire MENA region is still well below the GDP for Nordhaus' Middle East region. As for Sub-Saharan Africa, it is comparable with Nordhaus' Africa, resulting in a decision to move North Africa to the Middle East dataset, despite the discrepancy.

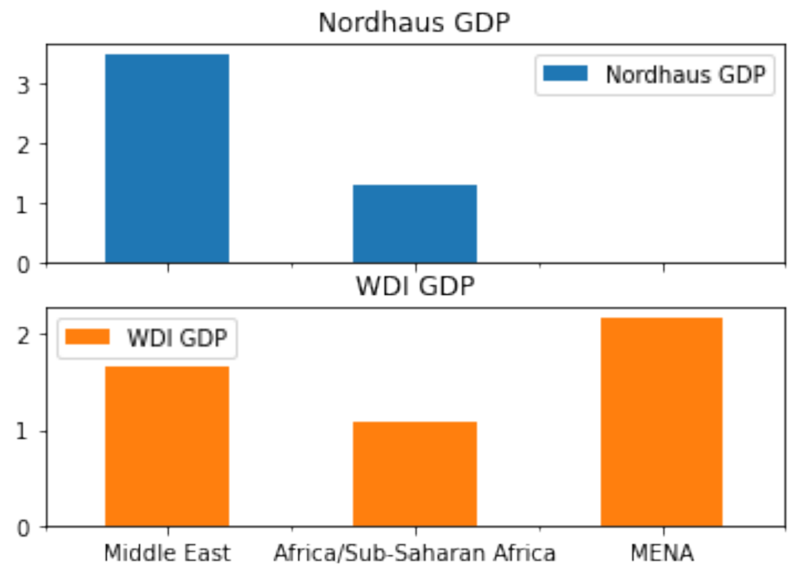

Figure 16: Comparison of regional GDP (in trillion $ for 2005$ price) between Nordhaus PyRICE data and regional specification and WDI data for 2005

This poses a new question regarding the quality and transparency of the data presented by the RICE-2010 model and its PyRICE counterpart.

ii. Experiments: Modifying Nordhaus' Datasets

To explore whether the model maintained its behaviour after changing the CO_2, GDP and Population datasets, comparisons were drawn between both Nordhaus' and EDGAR & MDP datasets.

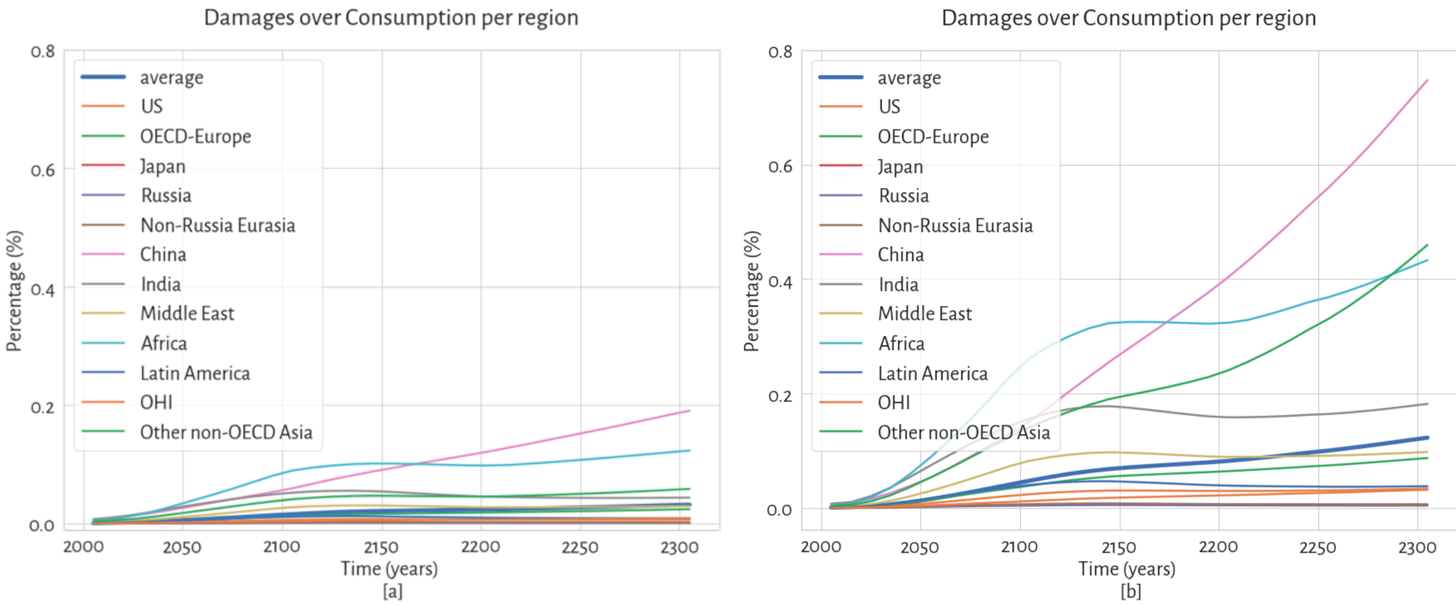

Figure 17: Comparison of Damages over Consumption between Nordhaus' Data [a] and EDGAR and MDP Data [b] for CO2, GDP and Population

Given that Sigma has been used as a proxy for CO_2 emissions, industrial emissions were also graphed using the new datasets to explore how they change over time.

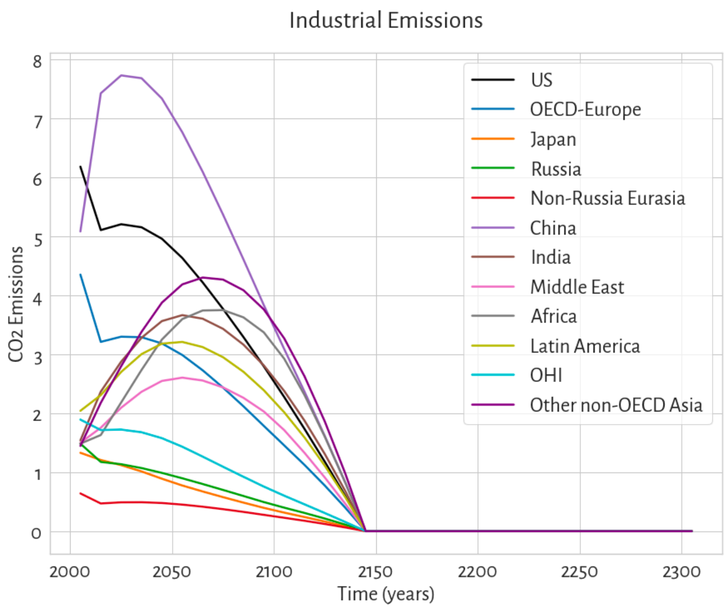

Figure 18: Emissions using EDGAR and MPD data (before Sigma decomposition)

iii. Experiments: Modifying CI and EI Decline Rates

One of the goals of this research is to decompose Sigma to better understand the role of CI and EI individually in the process of decarbonising regional economies. As seen from the figures below, some regions still register an increase in Carbon Intensity, such as in Africa, and an increase in energy intensity such as China and Non-OECD Asia.

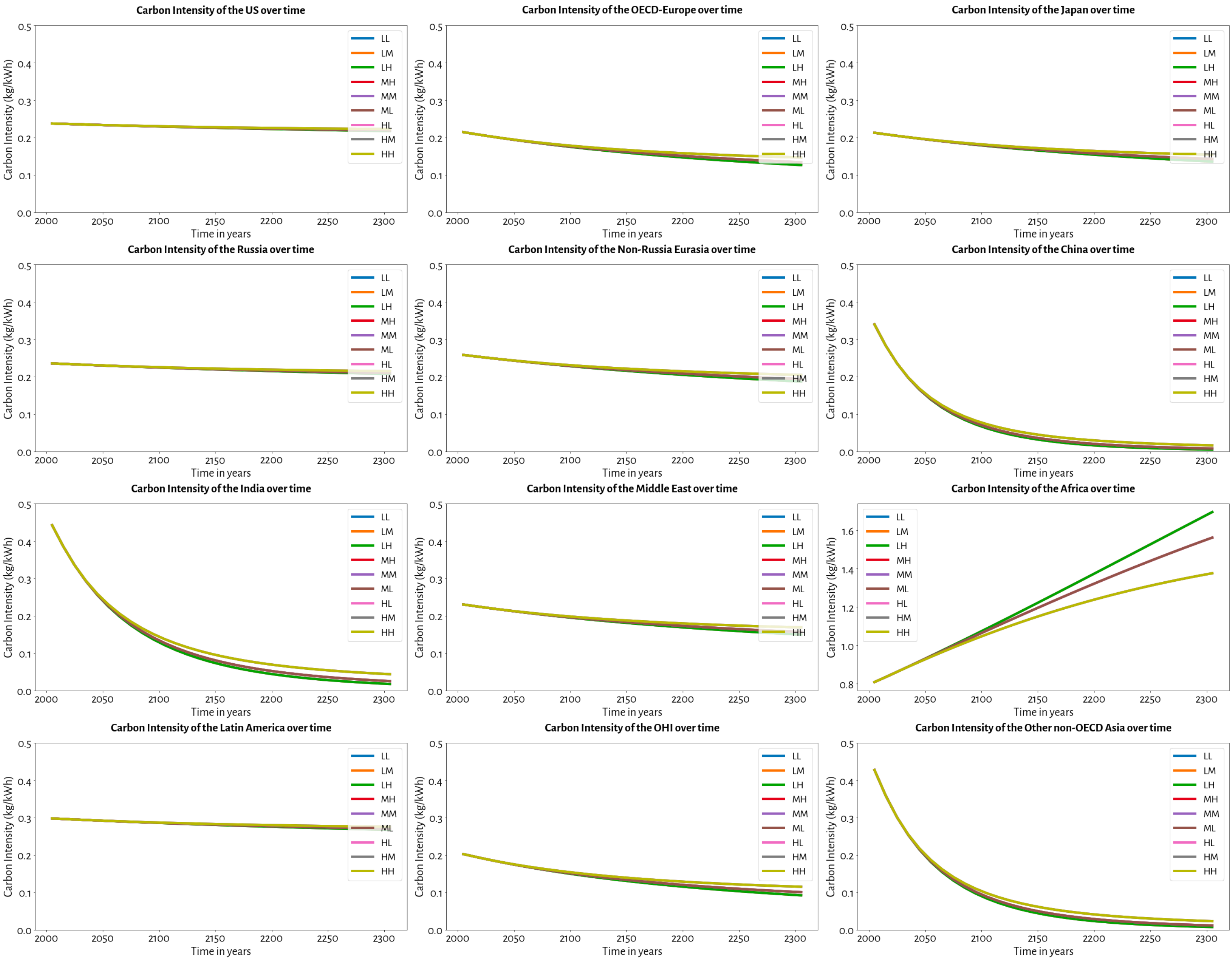

Figure 19: Evolution of CI over Time for Every Region Across All Experiments

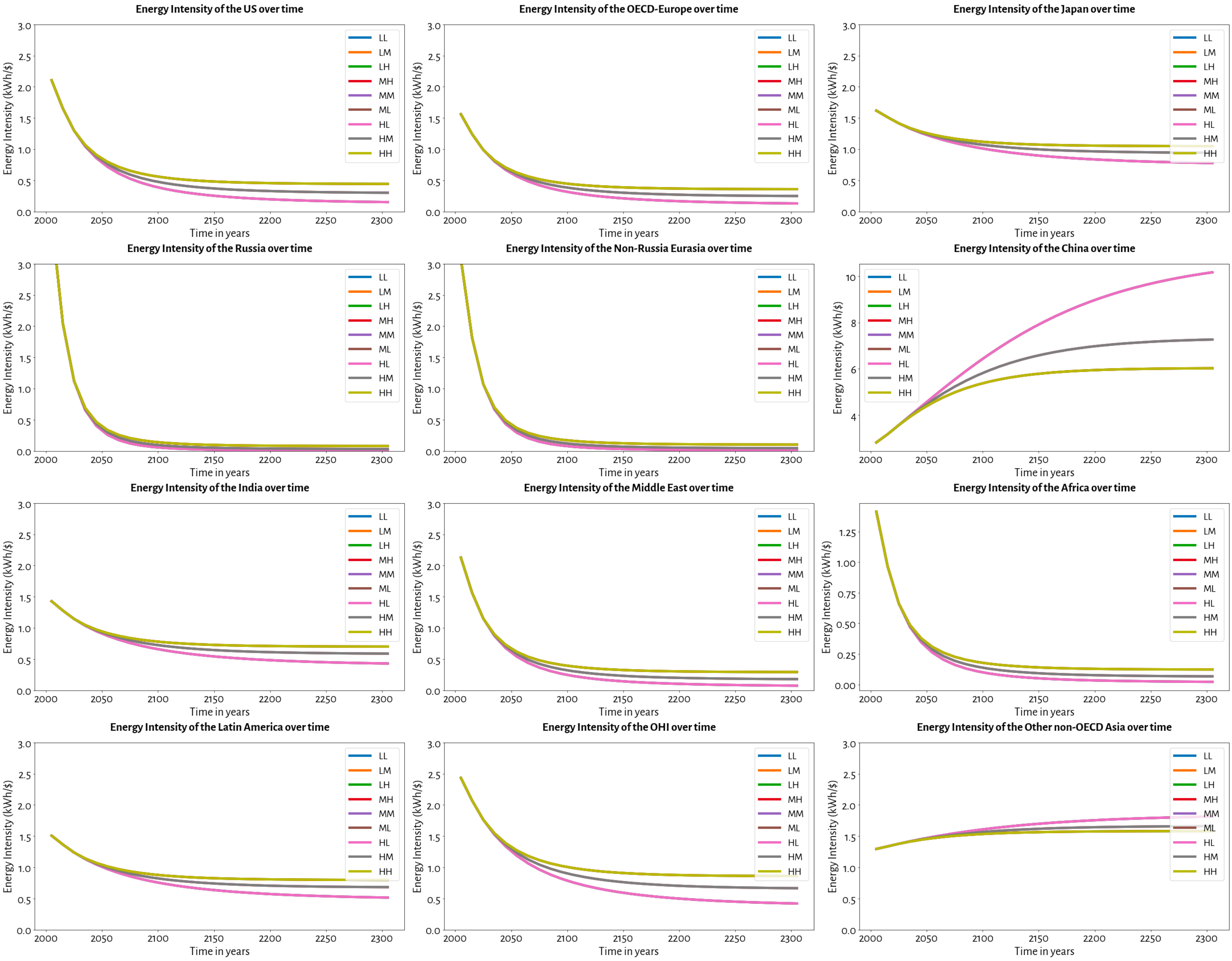

Figure 20: Evolution of EI over Time for Every Region Across All Experiments

V. Future Work List

Below is presented a more list version of future works that would greatly improve the work presented in this thesis:

i. Assess the impact of basing regional specifications on geographic and climatic similarities, versus economic and political similarities, and update the regions accordingly.

ii. Revise the PyRICE-2022 model as it includes a few inconsistencies, such as calculating Sigma at time t based on the Sigma growth from the time $t-1$ instead of t, and the use of misleading variables (e.g., *self.decl_Sigma_gr* that is never used and is inconsistent with the decline rate presented in the original Sigma growth equation).

iii. Go through the excel sheets that are used in the model and identify static introductions of input data. Either find the dataset or replace them in case of inability to replicate or outdated data. Introduce the data into the model by making processing and input transparent, clear and reproducible.

iv. Check for internal consistency along the entire model, to assess whether other, less obvious, especially exogenous variables are impacted by the changes (e.g., population growth). This could be facilitated using detailed diagram that highlights how equations related to each other in the model.

v. Completely decompose EI and CI throughout the entire model, getting rid of Sigma. This includes yearly emissions and the cost for backstop.

vi. Identify a more representative way of defining decline rates, rather than just averaging the last decade, to account for discontinuity and/or specific historical events. To start small, this could include an adjusted average that accounts for incidents (e.g., the 2008 financial crash and the COVID-19 pandemic) or predictions from other well-regarded models and or reports (Peters et al., 2017).

vii. Specify decline rates for each region, as decarbonisation takes very different forms and rates across the world, as can be seen in Figure 11, from the IPCC (2022). It would also be helpful to set up a sensitivity analysis, to evaluate how changes in these highly uncertain variables will impact the model.

viii. Changing the growth rate function used for EI and CI. For EI, adopt a function that reflects the limits of the improvement of energy efficiency (e.g., sigmoid curve). For CI, find a function that represents CI's ability to reach 100% green energy. For both EI and CI, modify the growth functions in a way to reflect different scenarios (e.g., the SSPs, such as Gazzotti, (2022)) and allow for testing various policies that would impact the growth or decline of these variables (e.g., phasing-out policies).

ix. Given the split of the Emission Output Ratio (σ), and the potential introduction of other details to the drivers of emissions, review the role of the Emission Control Rate (μ) in the emissions function.

For further steps:

x. Implement an extension of the Kaya Identity (Peters et al., 2017), by introducing decomposition that allow for the evaluation of fuel switching (e.g., from coal to gas).
xi. Decompose primary energy into primary energy and final energy, to better understand where and how decarbonisation is occurring (Koomey et al., 2019).
xii. Run an optimization to explore decarbonisation can be achieved through changes in emission drivers, under different scenarios and by leveraging different policies.

VI. Other Results from Experiments

The full set of results can be found in this repository:
https://github.com/maryamalki/PyRICE_2022/tree/sigma

They are organised as follows:

a. Under the 'master' branch we have the code for the original model, with both the Nordhaus datasets and the updated EDGAR and MDP Datasets. Results are saved under *results_original*, with:
    - *original_data* for the Nordhaus dataset results
    - *new_data* for the EDGAR and MDP datasets results

b. Under the 'sigma' branch we have the code for the decomposed Sigma model, with two versions of growth:
    - *results_PyRICE_growth* for the growth rate defined in the PyRICE-2022 model
    - *results_RICE50+_growth* for the growth rate defined by (Gazzotti, 2022)

Both these growth rates are intended to represent the original RICE-2010 model growth rates for sigma (or "cumulative improvement in energy efficiency"). The growth rate defined by Gazzotti (2022) is the one adopted for the main discussion of results.