Downscaling Integrated Assessment Models for Energy Transition Policy Support

Exploring Trade-offs and Limitations

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by

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Preface

What is the most important thing a technical analyst can help climate policymakers, especially, to close the gap between top-down (usually national) and bottom-up (usually community or municipal-level) climate policies? This dissertation explores only one of many questions related to further improving model-based decision support for the energy transition. The greatest gap I attempted to gap was that between bottom-up and top-down decision-making, which sometimes also manifests as the two worlds of adaptation and mitigation policies. Each relies on the other to become successful just as a crew on a ship relies on a captain to guide its course but are the ones who carry out the orders. Narrowing down its scope was, as expected, perhaps the greatest challenge in the whole process. I am grateful for the guidance of my main supervisor, Dr. ir. Jan Kwakkel, and Dr. ir. Igor Nikolic in my efforts to sharpen my research purpose. A more complete discussion of my journey to formulate this purpose can be found online at `https://jrwang.ca/2020/03/05/thesis-journey-part-1/`. While the COVID-19 pandemic of 2020 proved to be an unexpected barrier in writing this, it also served as motivation to bring sharpen tools and ideas to help the world manage, recover, and develop from the crisis. We will still face the challenge of overcoming our climate, environmental, and social justice crises ahead. It is my hope that this thesis and the context surrounding it might inspire others to continue to search for ways to create the systemic changes human society needs, just as many have inspired me to do the same.

This research would not have been possible without the support of many people who have supported or encouraged me. I would like to thank my graduation committee for their support by lending their expertise, experience, and insights. Thanks to my main supervisor Jan for our discussions about modelling, philosophy, and climate challenges, and to my second supervisor Emile for sharp insights and pushing me to perform my best. Thank you as well to Prof. dr. Detlef van Vuuren for your work this area, and many other aspects of integrated assessment modelling, and offering external feedback. Working healthily through this unique year would not have been possible without my friends and family. To the sages Connor, Patrick, and Mikhail, I appreciate your advice, insights, humour, and serendipitous opportunities to challenge myself and to grow to solve these wicked grand challenges. Thanks Anja, Giorgios, and Kevin for your solidarity in persevering through long hours in Wijnhaven and, along with Daan, Irene, and Jason S., for reminding me to enjoy life in Europe, and Jochem, Pietro, and Ruchik for your worldly (but sometimes extraterrestrial) perspectives. Keita, you welcomed me to the Netherlands and helped me to enjoy all the small things different from Canada. You have all helped me make this beautiful city a second home. To my friends in Canada whose questions and feedback helped me succeed and relate my work outside of academia: Dayton, Jerry, Kabir, Ola, Sai, and many, many others, thank you. To my partner Natalie, thank you for your love, always making me laugh, and listening to all my musings. And of course, thank you to my parents 张利 (zhāng lì) and 王新葵 (wáng xīn kuí), and my brother, Albert 若宇 (ruò yǔ), for your decades of unconditional support.

Jason Ruochen Wang
王若宸 (wáng ruò chén)
Den Haag, August 2020

Summary

Under current policies, only two of global 197 countries meet their Paris Agreement obligations to keep global temperature rise well below 2°C. *Inter alia*, uncertainties about technological innovation, weariness of adverse economic impacts, and uncertain political support (including opposition lobbying) are barriers that hamper more ambitious policies. The first two of these barriers are often explored alongside actual environmental benefit by analysts using global Earth systems Integrated Assessment Models (IAMs) to support policymakers.

However, IAMs are limited in many ways. One main issue is that IAMs' complexity makes running them computationally expensive, so model builders aggregate their constituent components to save time and effort. But whereas IAMs often analyze global energy and economic systems in 10 or so subcontinental regions, climate policymakers need information at a national or subnational level. Nations or blocs like the European Union are interested in how each of their smaller regions might be affected in the future, and many climate policies are crafted at a subnational level too. This mismatch in IAMs outputs and where policy support is most needed limits the usefulness of these models.

This dissertation aims to explore how existing high-level IAM analysis approaches can be adapted to obtain higher resolution insights that are useful to support policymakers using downscaling methods. Specifically, it will focus on examining the electricity sector within a specific IAM, the Global Change Assessment Model (GCAM), to examine the usefulness of downscaled IAM results to policymakers who are trying to enable the energy transition. Modellers and analysts already use downscaling to localize weather, socioeconomic, and greenhouse gas emissions outputs – and policymakers heuristically in these and other domains like energy, so it is crucial for both analysts and policymakers to fully understand the limitations to the techniques that they employ. Downscaling methods themselves range in complexity from simple statistical methods to secondary local models that are coupled to the global IAMs (which build upon the statistical methods). While previous work as reviewed some downscaling approaches, none have done so for the energy sector.

Therefore, to initiate a first review of downscaling for a novel application to the energy domain, the main research question in this work is:

"*What are the limitations and trade-offs between statistical downscaling methods used with global Earth system integrated assessment models to provide model-based energy transition policy support?*"

Since other criticisms of IAMs exist elsewhere in the literature, this work will focus solely on the extent to which downscaling methods can bridge the gap between IAMs as they exist now and energy transition policymakers. While there are already a few implementations of energy demand downscaling in the literature, these works do not offer a comparison of trade-offs or comment on their overall usefulness for policymakers. This research will draw upon similar downscaling techniques used with greenhouse gas emissions within IAMs and apply them to examine electricity production. Electricity production was chosen to fill a gap in downscaling in the energy sector, where only demand has been implemented, and because the analysis is generalizable to energy demand. Using the EU-15 region defined in GCAM as a case study, I examine how these downscaling methods apply to each country within the EU-15 using criteria developed in this work to monitor internal consistency of the downscaled results to the parent model.

This work focuses on applying two statistical downscaling methods, the linear and convergence methods, because they have been used in the literature to downscaling emissions for countries, including those from the energy sector. They will be used in conjunction with the electricity sector outputs from the

GCAM model and then compared in two ways. Descriptive statistics will show the magnitude of differences between using variations of the two downscaling approaches on each country. Where these differences are large or inconsistent between methods, and across countries, they become limited in their usefulness for policy. Analyzing multiple countries in a region enables the exploration of the methods' robustness across heterogeneous contexts. The internal consistency of the methods will be examined more qualitatively. Since downscaling works to, in a way, create data where there was none, it must make assumptions to overcome information gaps. Some of these assumptions may prove harmless, but others could also limit the method's usefulness for actual decision-makers. In the discussion, the results of energy system downscaling methods deployed in other literature are contextualized to the ones that have been implemented.

The downscaling methods were compared across ten criteria in three categories: replicability, coherence to the parent model (the IAM), and handling of energy-specific insights. In general, the linear downscaling method was easier to implement and replicate for all countries and likely for other IAMs. However, it outputs a time series that is proportionally static to the parent model. Its policy usefulness is most directly related to whether another variable can act as a proportional proxy for energy use and whether the static nature of the proportions is acceptable. I find that while such proxies fit well for some countries, this approach is not generalizable to a wider set of nations. GDP is typically seen as a useful proxy for energy demand and is harder to link to energy production like in this case. However, any link between actual energy metrics and their proxies may change over time as nations' socioeconomic landscapes transform. Static proportions are perhaps acceptable for near-term policy insights and certainly not future ones.

The convergence method is harder to implement and less transparent. Its time series outputs are more dynamic than the linear's, but relies on imposing a continuous function to how a sector will grow over time. This work used an exponential function. Choosing the growth function has tremendous impact on the downscaled results, making the result very dependent on the analyst. Calculating the growth rate in the convergence process also has the potential to hugely distort downscaled results in some special cases, like where only a minority of countries use a resource now and the resource only grows in the short term and stagnates in the long term. In addition to this case, it cannot robustly handle similar ones where countries do not use a resource at all in the base year and easily deal with electricity production technologies that do not exist at all in the base year.

While the issue of introducing new technologies can be resolved and communicated transparently, the other above issue can only be resolved where all the countries within the parent model region standardize and couple their economic regulations. Such a reconciliation would allow a key assumption of both the linear and convergence methods, that heterogeneous states may act homogeneously now or become more so over time – subject to geographic limitations – to be true. This assumption represents a fundamental mismatch between the scales of IAM analysis and policymaking, and is highly unlikely to materialize throughout all the regions that GCAM and other IAMs analyze. Thus, while the linear IAM downscaling method might be useful for a select group of countries for short term policy support, it has no use in supporting energy transition policymaking, and the convergence method is also entirely irrelevant to support energy transition policymakers beyond a few short years.

These results are disappointing for analysts eager to support energy transition policymaking and policymakers who are looking for insights at a scale most relevant to them. Some key challenges lie ahead for IAM developers: to better support actual policymaking, they must accept the additional computational demands of increasing the resolution of geopolitical regions they examine, and they may need to adjust their model structures to better fit with downscaling methods. Further studies are necessary to use downscaling to provide appropriate energy system insights. For one, the generalizability of model-based downscaling approaches across domains must be explored. Downscaling still fundamentally holds the potential to mitigate the fundamental mismatch in analytical scales, especially since they have a proven record in other domains. Downscaling global circulation models to regional levels relies on using global outputs as boundary and forcing conditions, both of which are more generalizable outputs. On the other hand, factors like technology diffusion and alignment of institutional economics are not generalizable but could be either modelled separately or otherwise appended to the downscaling methods to contribute to enabling downscaling in the energy and other domains. Other statistical methods not yet envisioned can still prove useful, and further investigation could uncover better proxies for a region's energy preferences, though both are unlikely to emerge for energy production. Otherwise, the results from this study suggest that IAMs may be inappropriate to use in support for energy transition policymaking, though coupling many angles of analysis through some form of integrated assessment is still fundamentally necessary to understand how sectors interact. Such a conclusion demands that further reflection be given to how to then allow a mosaic of policymakers, scattered across the world and in multiple layers of governance, to be able to make decisions that are collectively sufficient and robust to meeting global climate and energy policy demands.

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Glossary

Acronym	Definition
CCS	Carbon capture and sequestration (or storage)
COP	(UNFCCC) Conference of the Parties
CGE	Computational general equilibrium (model)
DAPP	Dynamic adaptive policy pathway
DMDU	Decision making under deep uncertainty
IAM	Integrated Assessment Model
IPCC	Intergovernmental Panel on Climate Change
IPF	Iterative Proportional Fitting
GCM	Global/general circulation model
GHG	Greenhouse gas
LTS	Long Term Strategy (UNFCCC)
NDC	Nationally Determined Contribution (UNFCCC)
RDM	Robust decisionmaking
SSP	Shared Socioeconomic Pathway
UNFCCC	United Nations Framework Convention on Climate Change
Energy Technologies	
CSP	Concentrated Solar Power
IGCC	Integrated Gasifier Combined Cycle
conv pul	Conventional pulverized (coal)
CC	Combined Cycle
steam/CT	Direct combustion in boiler, engine, or turbine (Simple Cycle)
PV	Photovoltaic

I

Background

1

Problem Introduction

1.1. Climate Policy and Energy Transition

On June 1, 2020, the concentration of carbon dioxide gas (CO_2) reached 418.32 parts per million at the Mauna Loa observatory (Tans and Keeling, 2020), the highest in the last 20 million years (Foster and Rohling, 2013), when the Arctic and Antarctic ice sheets began to re-form in the Middle Miocene disruption. The recent rapid increase of $CO_2$and other greenhouse gases (GHGs) has led to an unprecedented rise in the Earth's geological history. The main cause of this rise has been the anthropogenic combustion of hydrocarbons, or fossil fuels, for use as energy (Stocker *et al.*, 2013, pp. 50, 53–54; Hausfather, 2017). To prevent or minimize irreversible environmental and economic damages due to today's atmospheric GHG concentration, several forms of policy have emerged or are emerging, but they vary by region. Still, an overarching policy objective of most nation-states is to decrease the global atmospheric concentration of GHGs – all United Nations member states are signatories to the United Nations Framework Convention on Climate Change (UNFCCC) that agrees as much. As a result, the world is undergoing a massive energy system transition to low-carbon or net-zero GHG emission energy technologies. In recent decades, renewable electricity options like from solar photovoltaics and wind energy have begun to displace traditional fossil fuels in human energy systems.

The extent to which the energy system needs to transform is not certain – even the terms transition and transformation are only loosely defined (Child and Breyer, 2017) – and there is disagreement on whether the transition necessitates a shift to 100% renewable energy (Heard *et al.*, 2017), whether biomass and nuclear energy should be a part of the energy mix, and the extent to which fossil fuel technologies can continue to participate. Röder *et al.* (2015) found that life-cycle assessments of using biomass in electricity can range from 83% better to 73% worse than coal. W. Liu *et al.*'s (2017) modelling work looked at actual GHG emissions from biomass use to typical biomass regrowth periods, noting that biomass from trees are not suitable for substituting fossil fuels, though perennial grasses could be useful. Some argue that since carbon capture and storage (CCS) systems are inevitably necessary to reach climate targets, betting that such techniques will succeed grant social license to continue burning GHG-intensive energy resources (Lenzi *et al.*, 2018). Regardless of the end objective, any form of systemic transformation for energy will require massive technological, behavioural, and policy changes in a complex and interconnected system.

Changes to energy use need to transcend geopolitical and governance structures. Citizens, companies, and governments must all undergo massive shifts in behaviour, attitude, and policy. Each of these actors bring differing perspectives to the objective, have different goals, and the solutions to the problem need to be both customized to local contexts and quickly implemented. For example, economists have a near-consensus that carbon pricing, preferably through a tax, should be used to disincentivize GHG emissions (Howard and Sylvan, 2015; Climate Leadership Council, 2019). Such pricing can be applied to both industries and to citizens but are often applied unevenly to both sectors – either in reality or in perception, leading to significant political opposition with the Yellow Vest movement in France and small businesses in Canada. These conflicting viewpoints, along with other attributes like the massive technical challenges of the energy transition and where many decisions may be technically or socially irreversible match the definition of a wicked problem (Rittel and Webber, 1973).

In such cases, policymakers rely on many forms of policy analysis and support, especially to forecast impacts of various policy options in the future (Enserink *et al.*, 2010, p. 15; Kwakkel, Walker, *et al.*, 2016). Models are one main way used to analyze the future, especially when exploring possibilities in complex systems (Auping, 2018) or the trade-offs between intervening actions (Liebman, 1976; Reed and Kasprzyk, 2009). However, all models are simplifications of reality. Thompson and L. A. Smith (2019) reminds us that models can create a false sense of certainty by quantifying and algorithmically calculating their nested components. Alongside the fact that models of open natural and social systems, like climate and energy transition studies, are impossible to verify and validate (Oreskes *et al.*, 1994), it is important for analysts and policymakers to understand the contexts of models and modelling choices when they craft and recommend policies.

- Problem Gap 1: *Models are commonly used in energy transition modelling, so it is important to understand their usefulness and limitations as much as possible.*

1.2. Integrated Assessment Modelling in Climate Policy Support

The complexity of the energy transition has naturally mobilized many researchers and analysts to use models to support crafting policies. The most commonly used type of models used in climate policymaking is the integrated assessment model (IAM). IAMs simply refer to models that attempt to collectively model multiple domains in tandem. In the climate sphere, this usually means that they have an atmospheric model of the greenhouse effect between GHGs and atmospheric temperatures, energy transformation and their associated GHG emissions, and an economic component that provides demand for energy (Bretschger and Karydas, 2019). These models vary in scope and complexity; some IAMs are strictly regional and others international.

Yet, these models are often criticized for the same reason that they exist at all. In their efforts to integrate various domains of considerations, they must simplify their analysis in each component. For example, one key issue is that these models often only examine global energy systems as around 20—30 large sub-continental regions (Carbon Brief, 2018), in contrast to geophysical systems that are more spatially dependent. An example of how the GCAM IAM draws its boundaries can be seen in fig. 1.1.

The aggregation of many nation-states into regions presents a gap for national or sub-national level policymakers, who need to make policies at their own level of governance. Model insights, whether they are pathways that variables of interest take or the policy and external variable parameters that lead to them reaching their objectives must be at the same scale at which they make decisions (Yeh *et al.*, 2016). Similarly, higher levels of government, like the EU or national governments in certain federal systems (e.g. Canada, China, India, USA), also want to understand the distribution of high-level policy on their constituent entities for planning and mediating negotiations.

- Problem Gap 2: *Policymakers cannot directly benefit from global level integrated assessment models because of their typical level of geopolitical aggregation.*

1.3. Aligning IAMs for Policy Support

How can analysts best support climate policymakers to make better decisions? Since the climate, economic, and political futures of the world are deeply uncertain and involve complex systems, much of climate policy is informed by modelled analysis, especially through the use of globally shared sustainable

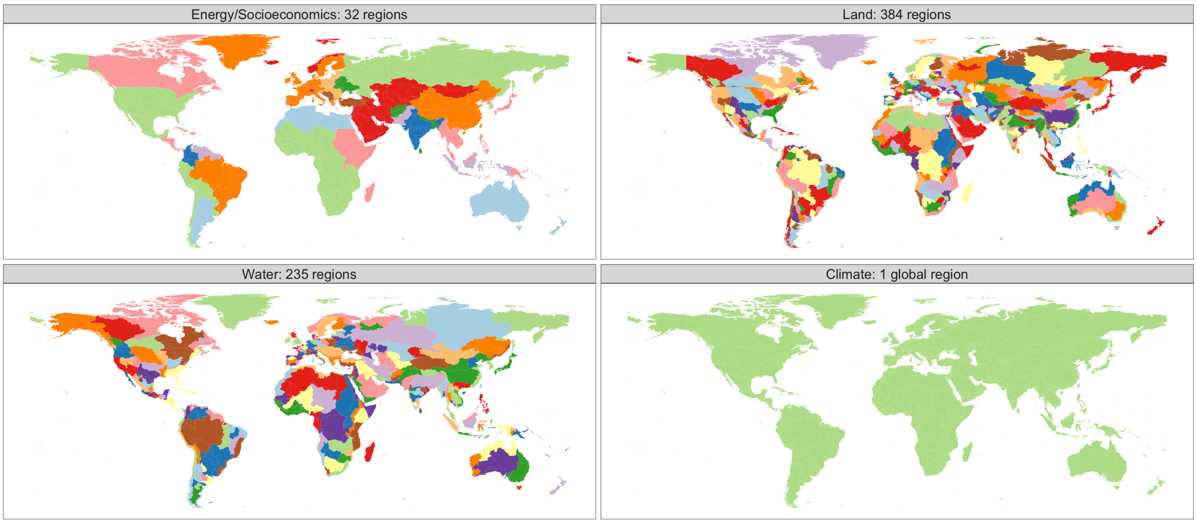


Figure 1.1: Exemplary separation of model regions in an IAM (figure from Joint Global Change Research Institute, 2019b).

development scenarios and (largely system dynamics) models like Integrated Assessment Models (IAMs) (Carbon Brief, 2018). Yet, IAMs have been criticized for a plethora of reasons. Ackerman *et al.* (2009) suggest that since the costs of environmental damages and futures are ethical decisions, IAMs cannot be run to optimize policies by cost. Burke *et al.* (2016) agree and also suggest and specific policies technologies be better represented in models. Another criticism is that climate models inherently deal with deep uncertainties and should not be used for forecasting (Pindyck, 2017). Still, they can be useful for exploring possible outcomes for policy support using decision-making under deep uncertainty methods (DMDU) (Weaver *et al.*, 2013). However, since they are tailored for global climate insights, IAMs provide little use for smaller countries or sub-national governments, especially because they lack outputs separated by economic sector (Sferra *et al.*, 2019).

Furthermore, the temporal window for policy action to limit the effects of global warming to the Paris Agreement's 1.5°C and 2°C targets is rapidly closing (Lamontagne, Reed, Marangoni, *et al.*, 2019). In such a world, it is critical that governments better understand the social, economic, and political impacts of rapid climate action that respect planetary boundaries and do not exacerbate the existing climate emergency. It is further politically and ethically important to ensure policy plans are just – that they fairly distribute both the positive and negative impacts of policies. With such insights, policymakers can plan to mitigate those impacts and pursue more ambitious climate policies than at present. Policymaking in this work refers to the policy-crafting process by government civil servants or academics. In contrast, the decision-making process is about political decisions made by the political party or parties that form a government.

While national and sub-national decision-makers sometimes have access to models geospatially relevant to their scope of governance, these are often unavailable. Moreover, these models are inherently more limited in scope and difficult to reconcile with the greater global climate policy domain. It is insufficient to analyze local policies without understanding their global impact. There are two approaches to bridge this gap: build more localized models and tie them together through upscaling, or downscale IAMs to bridge over these gaps.

Upscaling is essentially a process of inductive reasoning and relies on the principle that what is true for one region might be similar in other. On the other hand, downscaling is more deductive in assuming that insights for aggregated regions can be extended down to individual ones based on characteristics like each one's historical or forecasted biases. Both are forms of reasoning by analogy and rely on some form of extrapolation or interpolation of outcomes.

Upscaling is commonly used to turn successful local projects into regional policies (Larsen *et al.*, 2012), in econometrics studies (Chipman, 1975; Brandes, 1985), and inducing global weather effects from individual weather station samples – including to make global weather and climate models (Harvey, 2000). Downscaling is more common to forecasting, where models are often run for a region and results then extended downwards. High-level models using in downscaling are themselves products of upscaling. Weather and climate forecasts commonly rely on this approach (e.g. X. Liu and Coulibaly (2011) and Enke and Spekat (1997)), and by extension, IAMs.

Berrocal *et al.* (2012) showed that in weather forecasting, both upscaling and downscaling are valid approaches with small differences between each across various regions. However, upscaling policy conclusions from models is near impossible because it requires standardization of data, models, and policies from each region. A common fact base is often missing between all the regional actors and to supra-regional level. In the European Union (EU), two main energy-economy models are used for regional analysis: PRIMES and POTEnCIA. According to Duscha and Lehmann (2018), the former is viewed as a "black box" model where policymakers simply provide input to the modellers, who then report the model's outcomes. The latter model has been developed as a response and will be made available to all EU member states to run themselves, but requires "enhanced exchange" of input data and scenario development between member states (Climate Dialogue, 2019) to provide scientifically comparable outcomes (Wiese, 2018).

Downscaling is limited by treating these regions in aggregate or using proxy measures, like a flat carbon tax to represent all forms of possible carbon pricing. However, while a policy analyst can adapt a generic policy insight into a local context, they cannot pre-emptively standardize their possible future policy actions into a global standard that does not exist yet. The Deep Decarbonization Pathways Project is one response to this gap. 16 teams of academics around the world developed decarbonization pathways for their respective countries. In their work, they looked at global technology and policy trends and inferred how those trends might impact each country. Such an approach did not handle the dynamic interactions between countries for trade, technology diffusion, etc. Each country's scenarios were different (Deep Decarbonization Pathways Project, 2016). Canada looked at three oil price scenarios (Bataille *et al.*, 2015) and France the "efficiency" and "diversity" scenarios (Criqui *et al.*, 2015). While the project's mandate is to consider pathways that are compatible with the 2°C target in the Paris Agreement, it assumes that decarbonization is sufficient and does not comment on how it is certain that meeting the 2°C will be possible. It compiles carbon reduction possibilities between countries but does not ensure it matches what is globally asked.

Burton, Bizikova, *et al.* (2007) and Burton, Dickinson, *et al.* (2008) provide recommendations for upscaling successful local climate adaptation policies to a global level, but note that upscaling and downscaling are both necessary and complementary – any global inferences must be then downscaled to be region-specific.

It is clear that both can exist and should be studied. Choosing between the two eventually becomes a matter of which is more practical. Figure 1.2 shows a meta-model of the upscaling and downscaling approaches. Both rely on local data, but the global model is easier to narratives or scenarios than it is for all the local models to align. Similarly, interactions between the local regions in local models may be loosely defined, if at all, whereas global models more often consider these interactions. Whereas local energy transition models have been examined, there have been little to no efforts this author is aware of to upscale them to a global level. On the other hand, downscaling global models to local region is a more mature approach in other domains with both statistical algorithmic approaches and dynamical multi-modelling approaches. The latter of these build upon the simpler statistical techniques. It is nascent in the energy sector with recent work from Sferra *et al.* (2019) and Ahn *et al.* (2019), which only consider one downscaling method each and do not provide an overview of all possibilities these together.

- Problem Gap 3: *Downscaling has been used to increase the resolution of IAM outputs, but the limitations of their use in energy downscaling has not been reviewed.*

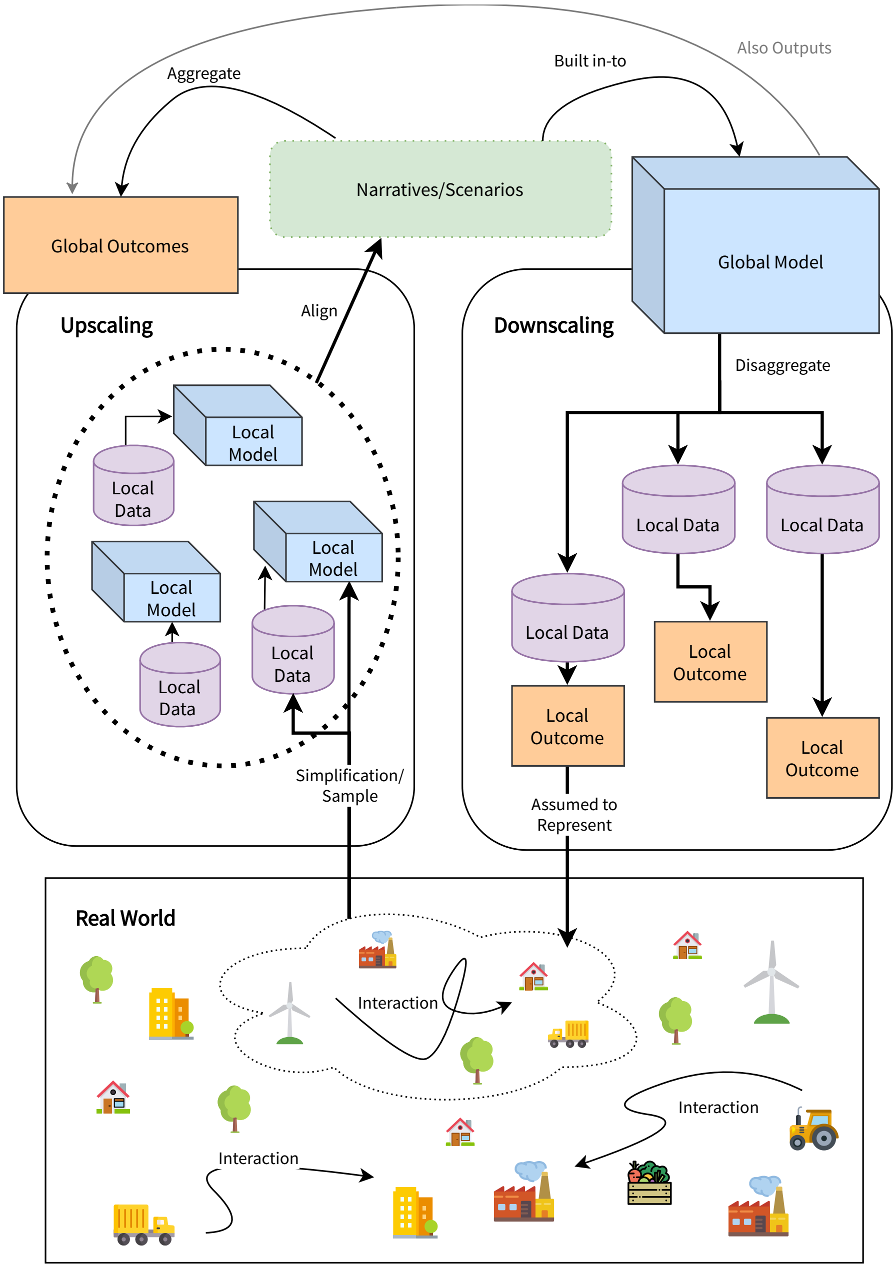


Figure 1.2: Meta-model of upscaling and downscaling approaches, showing similarities in components and dependencies. It is difficult to align many local models together to global narratives, especially since their structures are usually heterogeneous. Downscaling struggles with the heterogeneity of its constituent components. Note that global models are themselves a product of upscaling and also produce global outcomes. Icons by Freepik and Dinosoft Labs from `www.flaticon.com`.

1.4. Research Gap

The three problem gaps identified above illustrated how models are used to support energy transition policymaking and a conceptual gap in they are applied. There is clearly a research gap to be filled to understand the usefulness of all downscaling methods that have been or could be used in the energy domain.

1.5. Document Structure

The dissertation is structured as such: chapter 2 provides a definition to this thesis's research, and chapter 3 will review core concepts relevant to the work, including further details of the climate policy process, how models specifically fit, and how model downscaling has been used in the past. Chapter 4 then describes the technical implementation of modelling and downscaling, synthesized from the previous chapter's review. This section will also introduce a specific IAM that is used as a case study. Chapter 5 reports the results from downscaling and chapter 6 discusses the findings and the limitations to this work. These insights are compiled into the conclusion in chapter 7, which also lists recommendations to analysts, policymakers, and society; an academic reflection of this work; and suggests future work. Appendix A includes further details of the methodology and documentation of the analysis, and more details of results are appended in appendices B and C.

2

Research Definition

The introduction chapter reviewed three analytical problems and identified a research gap from these problems. This chapter formulates that research gap as a main and six sub-research questions, outlines an approach to answer those questions, and explains the methodologies that will be used to do so.

2.1. Research Questions

The main research question is "What are the limitations and trade-offs between statistical downscaling methods used with global Earth system integrated assessment models to provide model-based energy transition policy support?"

Note that this work will focus only on statistical methods because they are the foundational downscaling methods. Six sub-research questions can address the main research question:

1. How can the different geopolitical scales of global-level IAM analyses and local policymaking considerations be reconciled?
2. What downscaling methods are used with integrated assessment models to support climate policymaking?
3. How can downscaling be applied to the energy sector in integrated assessment models?
4. What are key criteria to evaluate the IAM downscaling methods in the energy transition?
5. How do the outputs from statistically downscaled IAMs differ?
6. How internally consistent are the outputs from statistically downscaled IAMs?

2.2. Research Approach

The exploratory research will take the EU-15 region within one specific IAM as a case study. Electricity production outputs from the IAM will be downscaled in each of the 15 countries to analyze their differences between them. The main goal is to verify and validate statistical downscaling approaches in the context of model-based energy transition policy support, not validate the specific number generated through the downscaling process. Emphasis is placed on statistical methods because more complex methods build upon their forms. Downscaling methods in the literature will be reviewed thoroughly in the next chapter.

The main research question proposed in section 2.1 includes two major concepts:

- Understanding how existing downscaling methods are applied, and
- Further exploring the trade-offs between these methods.

To fully address each of these sections in the scope of this analysis, different research methods need to be employed. The main issue that the research will address is the nature of trade-offs between established methodologies, but applied in a new context within the energy domain. While such approaches have been discussed in the literature, there is no theory that clearly exposes the nuances in choosing one method or another. Thus, this work will mostly be **exploratory** to understand the differences between downscaling methods.

To a small extent, since global-level IAMs have not been downscaled for energy production or consumption by sectors, this work may incorporate methodological design in that section. Any design work will draw upon downscaling methodology that is already applied to other sectors. As a whole, the work includes elements from modelling, deductive analysis, and techniques from case studies to address important elements of the overall research question while still retaining a clear focus.

The purpose of modelling here will not be to directly simulate the problem to make a policy recommendation, but rather improve the use of models in climate change policymaking. Some aspects of this research will require inductive and deductive reasoning, especially to test assumptions, but the goal will not be to determine an overall theory about trade-offs within models. Lastly, the insights from this work will be exemplified on small set of case-countries to provide a set of diverse countries to compare the usefulness of the implemented methods. Altogether, these approaches can fill a research gap that is relevant to analysts and policymakers. However, they are limited in that they cannot empirically generalize the usefulness of downscaling in general – other downscaling methods may arise and still be considered in the future to improve upon existing techniques.

2.3. Research Methods

Part 1

The first part of this analysis was to understand how a gap in the analysis between modelling global systems and local level policymakers can be bridged. Its sub-questions were:

1. How can the different geopolitical scales of global-level IAM analyses and local policymaking considerations be reconciled?
2. What downscaling methods are used with integrated assessment models to support climate policymaking?
3. How can downscaling be applied to the energy sector in integrated assessment models?

This section implemented a literature review to answer these questions. In all cases, ScienceDirect, WebofScience, Scopus, Google Scholar, and Semantic Scholar were used as search engines to discover literature. Other tools like VosViewer or CitNetExplorer, which use databases from the above sources to map out the network of referenced and referencing articles for a set of articles of interest, were also used to identify important or seminal literature.

To understand how downscaling is applied in general, various combinations of search terms like “integrated assessment”, “modelling”, “downscaling”, “multi-resolution”, “climate”, “meteorology”, and “hydrology” were used. The term “downscale” was also used instead of “downscaling” in each of these queries. To investigate downscaling in the energy domain, the following search terms were used:

- “energy AND downscaling”
- “energy AND downscaling AND model”
- “energy AND downscaling AND model AND IAM”
- “model downscaling typology”

To explore these downscaling methods in more depth, especially in the energy domain, an IAM was selected to downscale from. The Global Change Assessment Model (GCAM)[1] was picked for two main

[1]Note: as of June 25, 2020, GCAM has been renamed to the “Global Change Analysis Model”

reasons. Firstly, GCAM is easily accessible, documented online (Joint Global Change Research Institute, 2019d), and well-used in the climate science community. The model was started in 1980 and has been used in many major climate assessments, including to generate Representative Concentration Pathways for the IPCC Fifth Assessment Report and the SSPs more recently (Joint Global Change Research Institute, 2016; Calvin *et al.*, 2017). It is written in C++, documented extensively, and open-sourced for anyone to contribute. DeCarolis *et al.* (2012) found that few energy economy policy models are transparent or open source, making them hard to understand and for others to replicate results, and argue that these models are therefore useless to policy support. Wiese (2018) extends this argument to say non-open sourced models do not comply with science either. Though GCAM model includes other themes outside of just energy and economy, their argument is generalizable. Choosing GCAM allows the entirety of this work to be replicable. Secondly, choosing any other IAM would be functionally the same to compare downscaling methods. While each IAM may differ by how it implements policies, builds components, and measures outputs, the consistently have low geographic energy system resolution. Lastly, a unique specification of GCAM is that it is spatially explicit in its considerations of the land sector, including agriculture and agricultural trade. Though this benefit is not directly useful for the energy sector (it is still spatially implicit, aggregated by country-name), this design element positions the model well to be downscaled in these other domains and adds real-world credibility to the model.

GCAM is developed and maintained by the Joint Global Change Research Institute, a collaboration of the American Pacific Northwest National Laboratory and the University of Maryland, College Park. Version 5.2 of GCAM is used in this work, though a newer version, 5.3, was released in the course of the research.

Other IAMs include the Asia-Pacific Integrated Model (AIM), European Joint Research Centre GEM-E3 and POLES, American National Center for Atmospheric Research IPETS, World Induced Technical Change Hybrid (WITCH), The Integrated MARKAL–EFOM System (TIMES), Regional Model of Investments and Development (REMIND), and MESSAGE-GLOBIUM.

To follow the convention of other global-level climate research, GCAM will be run from a recent year where input data are available, 2018, until 2100. Many energy transition-specific models use 2050 as an end date, since reaching net zero by then would give higher probability of reaching the Paris Agreement's 1.5°C warming target. However, the 2°C target allows 2075 as a deadline for reaching net zero emissions (IPCC, 2018), so running until at least 2075 allows for a wider gamut of possibilities to emerge. In the context of this research question, the final date for this model is not important, since it seeks to only verify and validate the downscaling approaches for the narratives they provide, not their quantitative outputs.

Part 2

This chapter outlines how the results of downscaling will be analyzed.

The three sub-research questions that will be addressed in the remainder of the thesis are:

4. What are key criteria to evaluate the IAM downscaling methods in the energy transition?
5. How do the outputs from statistically downscaled IAMs differ?
6. How internally consistent are the outputs from statistically downscaled IAMs?

This exploratory phase of the research will mostly relate to analyzing differences in the outputs from the employed downscaling methods using descriptive statistics. The model used to generate climate outcomes across various scenarios will be downscaled across the identified methods using Python 3.8.1. Then, the results for each approach will be assessed in two ways. Firstly, the localized countries' set of outputs will be compared to the original overall region's. Statistical attributes like variance (including standard deviation and the coefficient of variation) can potentially highlight if the uncertainty space has been expanded or seemingly contracted.

The statistical methods themselves could be incomplete. Choosing the comparators must be well justified and are discussed further in the relevant section in section 4.3. Then, a set of criteria will be developed from the literature and used to evaluate the downscaling methods. Some key limitations to downscaling are “transparency, complexity, and effort” (Vuuren, S. J. Smith, *et al.*, 2010), which may be difficult to quantify, but could be described qualitatively. Internal consistency may have commensurability issues and uncertainties that propagate through downscaling will not be discussed rigorously. Permutations of terms like “comparison”, “internal consistency”, “IAM”, “scenarios”, and “downscaling ” will be used to search for literature to support this. Furthermore, in addition to the downscaling literature already identified, special attention will be given to review articles that have described downscaling.

The complexity of IAMs themselves might make analysis difficult; they make many structural, parametric, and model assumptions that this research may not be able to holistically identify. It might be easy to overlook every place where mismatches occur, since it may take many forms. Limiting the analysis to just the electricity production sector in the energy domain and choosing only the EU-15 serves as a boundary for this analysis. Typically, energy demand is considered in downscaling because it can presumably be linked better to other metrics like wealth. The purpose of this work is not to comment on validating the downscaled values, but rather to verify the approaches and understand limitations. Any approach can be validated against historical performance, but even when done, does not guarantee the same type of behaviour into the future. While other insights might be discovered if this approach is implemented for other sectors within the energy domain and in other regions, this approach should be sufficiently generalizable to downscaling for energy production and consumption.

The structure of this research, including where specific sub-research questions will be answered and with which methods, how the different research steps support each other, and more information is depicted in fig. 2.1.

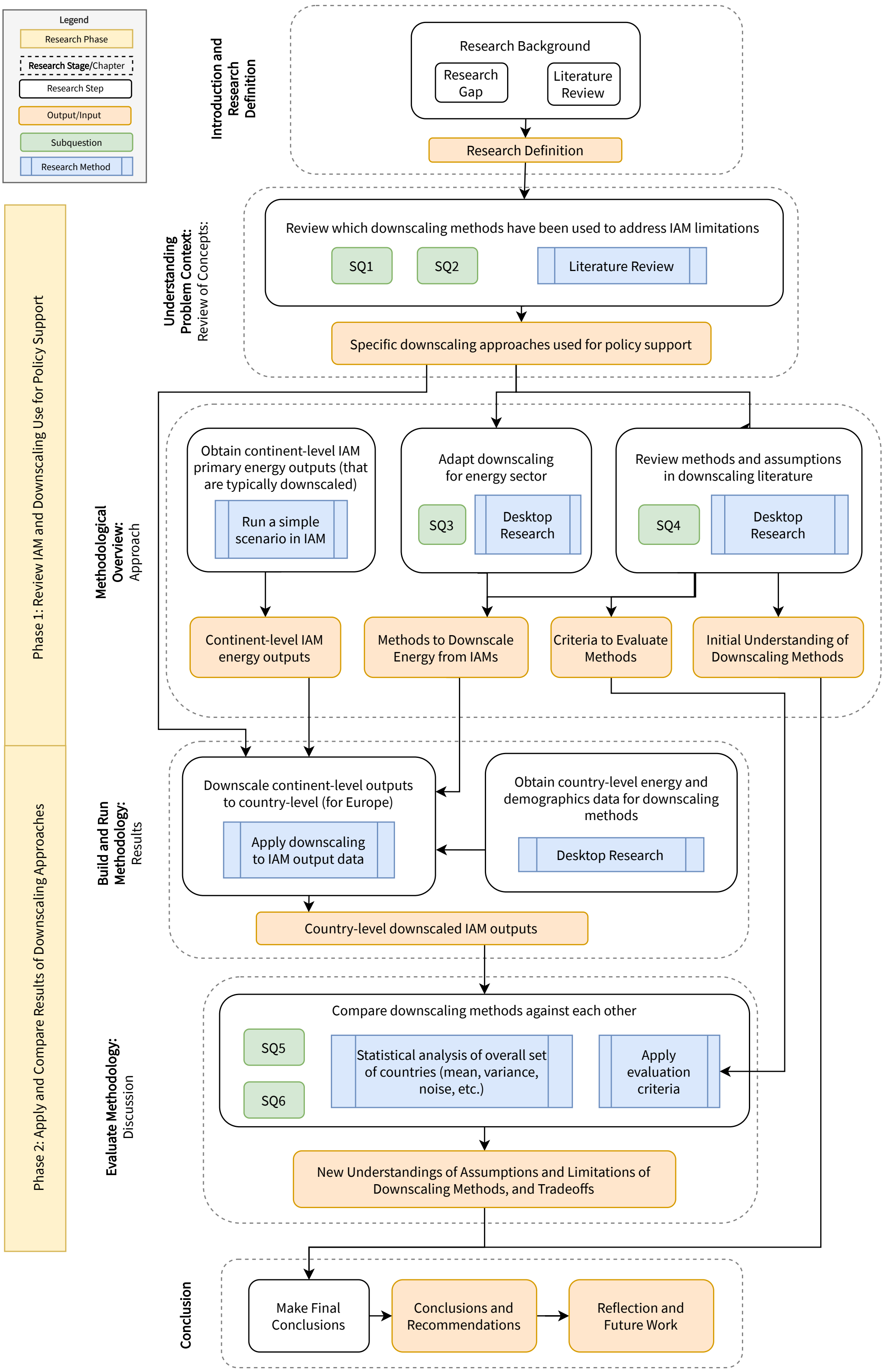


Figure 2.1: Research Flow depicting the stages and steps of the research, including which questions they will answer, what methods they will use, and each step's inputs and outputs.

3

Review of Concepts

The previous chapters identified a research gap and outlined a research approach to address the gap. This chapter will present a summary of four main concepts that define the main research question, the analytical methods to address the question, and review how those methods will be assessed. The four concepts are climate policymaking, modelling for policy-support, model downscaling, and frameworks to compare downscaled methods.

It attempts to answer the first two sub-research questions:

1. How can the different geopolitical scales of global-level IAM analyses and local policymaking considerations be reconciled?
2. What downscaling methods are used with integrated assessment models to support climate policymaking?

3.1. Climate Policymaking

3.1.1. International Climate Policy

Global decision-makers and diplomats look to IAMs directly and indirectly to inform their work. One main channel they rely on for scientific knowledge about climate change is through the Intergovernmental Panel on Climate Change (IPCC), which was formed in 1988 by the World Meteorological Organization and the United Nations Environment Programme to compile scientific knowledge to support global climate policymaking. Since its inception, the IPCC has coordinated or otherwise supported several initiatives to use IAMs to understand climate change[1]. As its mandate is global, the IPCC's scientific interest is also for global-level analyses, it has a special interest in IAMs and cited on many in its publications.

The main contributions of IAMs to global policymaking has been to explore possible futures and to explore the impact of (and sometimes optimize for) policy pathways. In these contexts, IAMs have been used extensively to develop climate scenarios like the Representative Concentration Pathways (RCPs) and Shared-Socioeconomic Pathways (SSPs) (Moss *et al.*, 2010; Nakicenovic *et al.*, 2014; B. C. O'Neill *et al.*, 2014; Vuuren, Kriegler, *et al.*, 2014). This work (e.g. Hare *et al.* (2010)) helped to set the explicit 1.5°C and 2°C temperature change targets in the 2015 Paris Agreement IPCC (2018). These temperature targets have then been taken by nations as guidance for their own policymaking.

There are two main and intertwined concepts relevant to national policies: a carbon budget (Knutti and Rogelj, 2015; Vuuren, Soest, *et al.*, 2016) and the Nationally Determined Contributions (NDCs). The total

[1] It has been criticized, and also acknowledged, that it both coordination and assessing climate scenarios is a conflict of interest (Pielke and Ritchie, 2020).

carbon budget describes how much cumulative GHGs can be released to maintain an acceptable probability to reach an overall global warming temperature. The interaction between these greenhouse gases and temperature are a core component of GCMs and, therefore, IAMs. IAMs directly show the relationship between human activities and possible harms to humans, like climate-induced economic impact (including from weather change) (e.g. Trenberth *et al.* (2014)), mortality (Vicedo-Cabrera *et al.*, 2018), conflict (Hsiang, Burke, *et al.*, 2013; Hsiang, Kopp, *et al.*, 2017; Kelley *et al.*, 2015).

NDCs are a policy component of the United Nations Framework Convention on Climate Change (UNFCCC) (more formally, the Paris Agreement), which is the main global channel for climate diplomacy and policymaking. Countries are expected to indicate to the global community how, and through which means, they plan to reduce their GHG emissions. Collectively, the NDCs paint a picture of how global emissions might shape over time and represent a written, though non-binding, commitment to tackle climate change from countries.

The level of commitment from each country in these NDCs (or the reduction "ambition") is determined purely politically. Richer industrialized countries are generally expected to reach net zero or near there by 2050, but many countries resist such demands by saying it would be too harmful for their economies. IAMs are used directly by decision-makers in international climate negotiations to discuss NDC commitments and other policies, exploring different sets of global policy options and how they might affect countries. The MIT "C-ROADs"[2] systems dynamics model has been used directly by American government officials, who "have developed an in-house capability to use the model" (Sterman *et al.*, 2013), and by numerous nations directly during UNFCCC negotiations (Raworth, 2017, p. 131). C-ROADs focuses on quickly exploring and communicating the outcomes of climate policies. It only provides simple outputs and does not allow users to easily explore scenarios or perform Scenario Discovery.

3.1.2. National Climate Policy

Countries are supposed to show how they will meet the agreed upon temperature targets by submitting their emissions reduction targets in the form of NDCs. Though the level of commitment from each country in these NDCs (or the reduction "ambition") is determined politically, often through heuristic downscaling relative to wealth or some development metric, countries individually often employ IAMs to compile their NDCs. They might use global level IAMs or ones built specifically for their country (or subnational regions) to explore the costs of enacting climate policies and determine what they are willing to implement, as well as gain insight into how other jurisdictions might react to their choices.

From the global level, both carbon budgets and NDC levels of ambition are allocated to countries as guidance for the amount of action expected from each country. However, both of these attributes are difficult to allocate. They are most often distributed relative to some other metric, like historical or current GHG emissions, or some attribute related to their ability to mitigate GHG emissions, like their wealth or level of development (e.g. Robiou du Pont *et al.* (2017)). NDCs are typically linked to the level of industrialization in a country. IAMs have been used to support negotiations that determined the categories of industrialization or development. The C40 cities coalition recommends carbon budgets be allocated for cities based on a convergence method where emissions per capita should converge to "a maximum of 3.2 tonnes of GHG emissions per capita" by 2030 and 0 and by 2050 City of Edmonton (2019). Regions that agree to these targets use localized IAMs to develop and share the possible "decarbonization pathways" they can adopt to mitigate climate change. The UNFCCC process encourages nations to submit Long Term Strategies (LTSs) with such details, which 20 nations and the EU have submitted as of August 2020. In fact, the EU mandated that all its member nations develop an LTS by 1 January, 2020 (Climate Dialogue, 2019). In total, the World Resources Institute found at least 67 long term strategies in June 2019 (Elliot *et al.*, 2019). The International Renewable Energy Agency also hosts a "Long-Term Energy Scenarios Network" to share insights and best practices from long-term energy modelling, especially those relevant for policymaking

[2]Available freely to run online or for download on https://www.climateinteractive.org/tools/c-roads/

(International Renewable Energy Agency, 2018).

Decarbonization pathways examine how sets of scenarios for changing technologies, energy prices, and geopolitics will shape their country's carbon footprint in the years to come, along with the economic costs of policies. They also signal possible policies the countries might implement if they find they are moving down one scenario or another, similar to the idea of dynamic adaptive policy pathways (DAPP) (Kwakkel, Haasnoot, *et al.*, 2015). The Deep Decarbonization Pathways Project is an example of an academic consortium that is supported and used by some governments to develop these pathways.

3.2. Modelling for Policy Support

3.2.1. Integrated Assessment Modelling

Global earth-system general circulation models (GCMs; also known as global circulation models) have been used for meteorology and climate science since at least 1956 (Phillips, 1956). They can be as simple as simply energy balance models (zero-dimensional Earth as one point, one-dimensional that looks at latitudes, Radiative Convective Models, General Circulation Models, coupled GCMs, Earth System Models, Regional Climate Models that are smaller GCMs (and require downscaling to the region), and IAMs that include societal aspects (McSweeney and Hausfather, 2018).

They have been coupled with economic and energy systems since the 1970s to understand climate change, including from Nordhaus (1979). Since then, IAMs have been used by academics and policymakers to collectively understand the interactions between the economy and the environment, especially the role of human policies and actions on pollution or climate change across multiple decision criteria (Hamilton *et al.*, 2015). They have been used within government cost-benefit analyses and by non-profit organizations and academics to bring attention to certain issues, such as understanding changes to ecosystem value or to quantify the value of biodiversity (Hamilton *et al.*, 2015). For a lay-person, IAMs are frequently used to provide narratives and graphics for science communication (Carbon Brief, 2018).

The EU Horizon 2020 NAVIGATE exists solely to improve IAMs to support the global climate policymaking. In a 2019 survey of European climate service (the entire family of climate-related activities) providers, 11% of responding firms implement some kind of modelling directly and 26% do some sort of downscaling, including through modelling, to connect results to the specific scope of focus (Cortekar *et al.*, 2020).

IAM Limitations

There are several forms of criticisms of IAMs. Firstly, the main issue relevant to this study is that IAMs aggregate attributes to save computational complexity. Geopolitical boundaries are usually at a continental level; stratifying more countries increases the computational cost more-than-linearly. Time is usually bundled into annual bins and social structures are usually viewed homogenously and with assumptions, like that actors are perfectly rational or even have perfect foresight of the future. Each of these aggregations can be "downscaled" into constituents to varying degrees of accuracy and precision. This thesis will study geopolitical boundary downscaling approaches used in the energy system.

The criticism of aggregating human systems is especially problematic to social scientists and some economists. Otto *et al.* (2020) discuss in depth how IAMs only implement human agency insofar as people are considered individually and as rational agents, questioning if such analytical approaches could ever understand social changes that could lead to systemic transformations in the very systems that IAMs study. Collective actions, like the impacts of energy transitions on the formation of social or political resistance, are completely neglected in contemporary IAMs. Incorporating agent-based modelling has been a key objective for some researchers (Donges *et al.*, 2018), especially for economic analysis (Burke *et al.*, 2016; Lamperti *et al.*, 2018a; Lamperti *et al.*, 2018b). Mercure *et al.* (2019) says that "Finding out whether carbon pricing is likely to reach its stated objective requires studying how agents take decisions, including how they take account of such incentives".

3

In policy analysis, problem formulation asks analysts to be very thoughtful in considering the approach they pick. As such, models are frequently very focused. Yet, the very *raison d'être* of IAMs conflicts with this idea (or at least challenges it by trying to integrate as much as possible). IAMs were originally built for coupling GHG outcomes with macro-economic activity, which has traditionally ignored material flows, and so IAMs do similarly (Pauliuk *et al.*, 2017). This is not to say these paradigms are inherently contradictory, but does suggest reasons why the academic community still sees much room for improvement in using IAMs.

Secondly, these computational constraints limit IAMs in *how* they are used. Modelling complex systems must inherently deal with "deep uncertainties", where analysts and stakeholders cannot know or agree upon the parameters, structure, or even evaluation criteria of a model (Lempert *et al.*, 2003). Such deep uncertainties prevent models from forecasting the future, which is often a key demand in top-down policymaking. The "Decision Making under Deep Uncertainty" (DMDU) field actively researches methods to manage deep uncertainties. Some argue that models are better used in bottom-up policymaking (e.g. climate adaptation) Dessai and Sluijs (2007) and Brown *et al.* (2019), and innovative methods like Dynamic Adaptive Policy Pathways (Kwakkel, Haasnoot, *et al.*, 2015) have been suggested to support these efforts. Weaver *et al.* (2013) and Auping (2018) offer a more generalizable approach to use models with climate policymaking, which can be applied to IAMs. DMDU processes can also help incorporate conflicting stakeholder views together in an analysis, an approach pertinent to climate policy and suggested by Roelich and Giesekam (2019). One DMDU approach is to use "scenario discovery" (Bryant and Lempert, 2010) to run models over a wide range of model policy and external parameters and then evaluate policies for efficacy and robustness *a posteriori*. Such a method minimizes bias from the analyst or stakeholders in choosing scenarios to run models over. Since scenario discovery requires a broad sweep of parameters, it intensifies the computation cost of analyzing models. However, such an approach has been applied to at least one IAM (Lamontagne, Reed, Link, *et al.*, 2018). Lempert (2018) argues that DMDU can be used to help countries build LTSs for their own exploration or to submit to the UNFCCC.

It is still unknown how downscaling IAMs propagate these deep uncertainties, though Stainforth *et al.* (2007) have suggested that using multi-modelling (ensemble) reasoning (Page, 2018) can be used to mitigate these uncertainties. However, the specific approach they describe is more relevant for downscaling in climate adaptation models.

Pindyck (2017) argues that optimization IAMs are limited beyond their "crucial flaws" and have deeper issues. Though this discussion was focused on optimization IAMs, the message is relevant for GESM-like IAMs. Mostly, IAMs give policymakers an illusion of knowledge and precision and are seen as forecasts. Instead, Pindyck suggests policymakers only rely on expert advice. They argue that even some sort of sampling-based exploratory work is misleading because of deep (parametric) uncertainties.

Lastly, IAMs are developed by academics for scientific comparison rather than directly giving policy insights (Doukas *et al.*, 2018; Carbon Brief, 2018). While they can support policymaking, they are generally too complicated to be used on a daily basis. The key point that Doukas *et al.* (2018) make, that these models should be crafted with their end-users and across more sets of scenarios, aligns with the view of the DMDU community.

3.2.2. Modelling Energy Transitions

Computational modelling is useful to support analysis for the complex energy system. They can account for the dynamics of large systems with non-linearities and feedbacks, unlike any human analyst.

Pfenninger *et al.* (2014) outlined four types of models used to understand and plan for energy system transitions: energy systems optimization models, energy systems simulation models, power systems and electricity market models, and qualitative and mixed-methods scenarios. Each of these approaches deals with a different perspective of energy systems. Energy systems are more focused on energy transformation and market models are directed at the dynamic economic contexts for actors or power generation facilities within these systems. There is no single modelling approach that can encompass all the aspects of modelling; modelling needs to address specific research questions (Nikolic *et al.*, 2019). The integrated assessment community has, as previously mentioned, attempted to pair some of these considerations together to address questions in tandem with one another. Crespo del Granado *et al.* (2018) reviewed how “top-down” and “bottom-up” modelling might be coupled in such a way, and the limitations to this were discussed into the introduction and extended briefly below in section 3.3. As discussed with IAMs, modularity within models can allow components, laden with their respective assumptions of the modelled system, to be changed with alternatives to provide a more holistic ensemble-like analysis of the system (Donges *et al.*, 2018). Hall and Buckley (2016) provide an overview of energy models used in the United Kingdom, including IAMs and more specific models, and Yue *et al.* (2018) review how uncertainty is considered within these models, including deep uncertainty.

Relevant Variables to Track

Energy is commonly stratified by two axes: level of processing and source or consumption. In the latter axis, both energy production and consumption are important to track, depending on the purpose of the analysis. The former axis is a more meta-level categorization of energy, which comes in two forms: primary and secondary. Primary energy refers to the raw form of energy that has not been processed, after which it is deemed secondary. Crude oil and wind energy are primary while gasoline and electricity are secondary. Oil that is burned to produce electricity is considered a primary to secondary energy transformation as well. Data for both primary and secondary energy supply and consumption are widely available, though to varying degrees. In the context of this study, the electricity production sector (which are also consumers of primary energies) will be the main focus. In many ways, it is the simplest and also intuitive to grasp. However, this analysis should be relevant to other stages of energy systems, like heating and transportation energy consumption. In northern hemisphere developed nations, electricity constitutes roughly 25% of energy consumption (Institution of Mechanical Engineers, 2014).

Pye *et al.* (2017) suggest that energy transitions need to be understood at at least a country level, and that there are four important criteria to examine: “the global carbon budget and its allocation; commercial availability of key energy system technologies; bioenergy resource, including its use for generating ‘negative’emissions; and demand levels for energy services.” The allocation aspect has already been discussed above. IAM outputs are useful in understanding the latter three.

It is important to note that IAM outputs are also limited by ethics. Though most economists agree that some form of carbon pricing, whether through direct pricing or a cap-and-trade system, is necessary to include the externalities (Howard and Sylvan, 2015), or impacts, of GHG emissions, the actual cost of those externalities is disputed. In fact, some argue that the cost of GHG pollution can never be known, since it must inherently consider damages on people now and on people in the future, thus demanding that a value-based weighting be applied (Pezzey, 2019; Howard and Sterner, 2017; Wang *et al.*, 2019). While other policies like electricity market reform, feed-in-tariffs, or a gross installation target of new technologies can also incentivize a transition (Department of Energy & Climate Change, 2011; Doorman and Vries, 2017), a carbon price is still most often used within energy transition modelling as an analogue for all types of policies. Setting a price on GHG emissions creates a market-based mechanism to support the deployment and innovation of renewable energy technologies and lower-emission fossil fuel technologies, including CCS technologies. Transparently communicating and testing how IAM outputs are calculated is important, but out of the scope of this research.

3.3. Model Downscaling

Climate and many other simulation arenas examine space and time at a low resolution to save computational cost. Model downscaling is used to thereby make low resolution analysis useful at a higher resolution. However, it is also used heuristically by decision-makers and analysts. This chapter will describe implementations of downscaling in other sectors, focusing on climate (including meteorology).

3

Climatology, Hydrology, and Meteorology

Contemporary weather forecasting also relies on downscaling to connect global analyses for regional meteorologists. An early implementation of downscaling is in Kim *et al.* (1984), who described this issue as the "climate inversion problem". For a set of 49 weather stations within one GESM grid, they calculated an average deviation for each relative to the grid value. Then, they applied those deviations to a parent model at the overarching level and compared their results to historical observations. Wood *et al.* (2004) compared six approaches for hydrology: linear interpolation, spatial disaggregation, bias-correction and spatial disaggregation, which were applied directly to a global model and also to an intermediary a regional dynamical downscaling model before arriving at their final resolution.

They found that the linear approaches were "unacceptably biased", the spatial aggregation method similar to the combination of the linear approach and the intermediary dynamical model, and the bias-correction and spatial disaggregation method to be best, noting that there was a trade-off where the intermediary model led to results more sensitive to climate change. Still, all the approaches have continued to be applied in the literature (without a second model: Storch *et al.* (1993), Enke and Spekat (1997), and Ahmed *et al.* (2013); with a second model: Bates *et al.* (1998) and Rummukainen *et al.* (2001)). Mearns *et al.* (1999) compared statistical and model-driven methods, finding that statistical methods perform worse when the model's parameters reach beyond historical performance in each location. In this space, McSweeney *et al.* quotes Dr. Dann Mitchell in saying that dynamical downscaling is more robust than statistical ones, but only if they "[capture] the relevant processes well and the data driving them is reliable." Wilby *et al.* (2002) proposed a tool to downscale GCMs to understand local climate effects, including a tool-kit for pre-screening and model calibration for original models, and Li *et al.* (2018) provide a Python package for just the water sector. West *et al.* (2014) used county-level data in the United States to spatially disaggregate land use change from the 0.5° resolution in GCAM to 0.05°, which is approximately 5 km.

Emissions and Climate Policy

Within the climate science and policy domain, the Coupled Model Intercomparison Project (CMIP) project (Taylor *et al.*, 2012) and various contributions to and with the IPCC assessment reports (Gaffin *et al.*, 2004; Walz *et al.*, 2014) have standardized and defined various downscaling approaches for its policy support (the narratives for the standardized scenarios for modelling, the latest of which are the SSPs, are done at roughly the continental level (Moss *et al.*, 2010; Nakicenovic *et al.*, 2014; B. C. O'Neill *et al.*, 2014; Vuuren, Kriegler, *et al.*, 2014)). To support this effort, Vuuren, Lucas, *et al.* (2007) provided an overview of downscaling approaches and short discussion of each of their qualitative limitations. In their review, Vuuren, S. J. Smith, *et al.* (2010) describe more applications. In neither of these did they directly compare the approaches.

These approaches have been applied for emissions downscaling (Shi *et al.*, 2017), including as a package for all the participants of the CMIP6 project (Gidden *et al.*, 2019). Outside of academia, policy makers also heuristically downscale using some variant of simple algorithms described by Vuuren, Lucas, *et al.* (2007). Without the support of high-resolution models to support analysis of complex systems, humans resort to using simple methods. For example, downscaling is also considered when attributing equity within climate policy (more specifically, allocating responsibility for climate action). Climate negotiations, whether at the international, national, or subnational level, are all plagued by the issue of distributing responsibility. For example, island nations that are most at risk to climate change damages in this century demand that wealthier nations in the northern hemisphere do more to both mitigate climate change and pay for their adaptation efforts. Robiou du Pont *et al.* (2017) provides an outline of five methods used to attribute responsibility, two of which rely directly on IAM outputs. Within a country, stakeholders commonly try to shift away responsibility: agriculture points to their cultural importance and towards fossil firms, fossil firms cite competitiveness as a reason to soften carbon pricing policy, *et cetera*. These arguments extend both up and down geospatially. In Canada, the province of Alberta is a fossil-driven economy that frequently interferes with its own or federal environmental policies (Adkin, 2016). Understanding how model analysis applies to Canadian provinces, rather than Canada as one entity, would support more precise policymaking.

Downscaling in the Energy Domain

At the time of writing, two other applications of downscaling energy use from global IAMs to the national level exist (Sferra *et al.*, 2019; Ahn *et al.*, 2019), and neither has any citations. Sferra *et al.* (2019) coupled a second reduced complexity model that used the global IAM as a boundary condition for its country-level calculations. In their work, they cited as a motivation for their approach the limitations Vuuren, Lucas, *et al.* (2007) and Vuuren, S. J. Smith, *et al.* (2010) previously described for approaches that are already used. In the second case, Ahn *et al.* (2019) used a "two-dimensional" statistical downscaling method, "Iterative Proportional Fitting" (IPF), that accounted for both the relative scales of countries and of energy demand sectors to downscale from a national to subnational level. They assumed that the GDP intensity and current energy demand mix in each subnational region will continue in the future. Using a forecast of GDP for each region and of energy intensity per technology, they calculate an initial energy consumption for the future. This value is then scaled using the Iterative Proportional Fitting, which iteratively assigns weights to proportions represented in a two-dimensional matrix by resource types in the total national mix and the local region's share of the national energy demand. These weights are scaled until the projections converge towards or match the parent model's national output, which is used as a boundary condition. Melnikov *et al.* (2017) applied a similar approach to obtaining household energy consumption profiles from a country-level dynamical computational general equilibrium (CGE) model.

Limits of Disaggregation and Upscaling

Instead of downscaling to provide local insights, it might be more worthwhile to frame the problem the other way: how can localized models support policymakers, and how can those models be considered alongside other regions' models to get a better overview of the global climate policy context? This upscaling approach has many limitations, but is similarly missing in the literature. Local models are often more complex with heterogeneous sectors. Aligning these sectors to provide regional or global outcomes also requires significant effort.

In economics, Leontief's Theorem supposes that the lowest level at which components can be aggregated is where its marginal rate of substitution is independent of other components. For example, food can be aggregated if the marginal rate of substitution between any two foods is not affected by anything that is not food (Fisher, 1987). In a world of imperfect and incomplete information, determining this boundary is impossible. But the theorem presents a generalizable point: the level of aggregation is most strictly related to the level of problem analysis and desirable resolution.

In considering how agent-based models of individual farms could be upscaled to represent the entire Swiss agricultural sector, Zimmermann *et al.* (2015) conclude that none of their approaches work consistently across a range of possible external scenarios - especially where ones that have worked are also not guaranteed to work in the future, and that aggregating agents in an upscaling method might be fundamentally flawed itself. They note that the interactions between agents at the pre-upscaling section cannot be generalized robustly since the one that is upscaled must be a sufficiently good sample, which is hard to determine *a priori* (Bertelmeier *et al.*, 2003). At the same time, treating individual and heterogeneous agents in groups leads to aggregation errors where the whole cannot show any useful information about actual constituents (Brandes, 1985, as cited in Zimmermann *et al.*, 2015).

As in other problem-solving cases, the main question about disaggregation is be whether it is important to have that additional layer of information or not. IAMs already aggregates resources. For example, the GCAM considers 16 types of fuels defined by the International Energy Agency as coal, including seven types of coal, and various cokes, peat, and blast furnace gas (Joint Global Change Research Institute, 2019a).

3

3.4. Summary of Downscaling Methods

The IAM community generally considers two main axes to view downscaling methods: statistical or dynamic (Ahn *et al.*, 2019). Vuuren, Lucas, *et al.* (2007) describe several general approaches to downscaling: statistical (including the linear, convergence, and external-input-based approaches), and dynamical models.

The linear approach assumes some bias in energy preferences that exists today will exist into the future. This bias is expressed through GDP, current GHG emission levels, and population size. The night-time light intensity approach in Doll *et al.* (2006) will not be employed here since, at this level of analysis, is analogous to the other three approaches. Whether lights offer a better characterization of energy preferences is discussed in their work and not in the scope of this dissertation. The external-input-based algorithm assumes that some other variable which is available at the downscaled level can be applied to the variable of interest. It is similar to the linear approach, but the proportions become dynamic.

The convergence method does similarly but assumes that the present mix will eventually converge to some regional average that is calculated in the parent model. The date of convergence could be farther in the future than either the model calculates or the analyst's period of interest. Yet, this method requires the parent model's outputs to be extrapolated into the future, which could be linear or any other shape. The exact method of convergence can also change shape: exponential, exponential with a change in direction of growth (i.e. maintains current inertia but eventually reverses), or some other method. Where the linear approach is static, the convergence approach is dynamic.

Ahn *et al.*'s (2019) Iterative Proportional Fitting approach sits in between the linear and the convergence methods. It is similar to the convergence approach in that it uses a forecast of an attribute of concern and energy intensity in the future for each localized region. Where it differs is that it normalizes the resultant energy use by both the proportional size of a local region within the larger set and of each resource type to the overall energy consumption.

In their review article, Vuuren, S. J. Smith, *et al.* (2010) extended their typology into four categories of algorithmic, intermediately complex methods, fully elaborated model at subnational level, and fully coupled models at national levels. Using the language of Vuuren, Lucas, *et al.* (2007), the first two are considered statistical and the latter are dynamic. However, they introduced the concept of "intermediate" approaches, which extend the statistical proportions in the linear method using small models. The authors give the Rostow growth models for economic growth, "gravity-based rules" for population data, and cellular automata models for urbanization.

It seems important to disentangle the concepts of time and holarchies[3] from the term *dynamic*. In this work, I stratify these methods along two dimensions. On one axis, I outline statistical and multi-model approaches. On the other, I differentiate between static and dynamical methods. Though these terms overlap with previous descriptions, they offer a better typology than exists in the literature.

Limits of Disaggregation and Upscaling

Instead of downscaling to provide local insights, it might be more worthwhile to frame the problem the other way: how can localized models support policymakers, and how can those models be considered alongside other regions' models to get a better overview of the global climate policy context? This upscaling approach has many limitations, but is similarly missing in the literature. Local models are often more complex with heterogeneous sectors. Aligning these sectors to provide regional or global outcomes also requires significant effort.

In economics, Leontief's Theorem supposes that the lowest level at which components can be aggregated is where its marginal rate of substitution is independent of other components. For example, food can be aggregated if the marginal rate of substitution between any two foods is not affected by

[3]For more on holarchies, see Dr. ir. Igor Nikolic's work on complex systems and the bizarre footnotes in his PhD dissertation.

anything that is not food (Fisher, 1987). In a world of imperfect and incomplete information, determining this boundary is impossible. But the theorem presents a generalizable point: the level of aggregation is most strictly related to the level of problem analysis and desirable resolution.

In considering how agent-based models of individual farms could be upscaled to represent the entire Swiss agricultural sector, Zimmermann *et al.* (2015) conclude that none of their approaches work consistently across a range of possible external scenarios - especially where ones that have worked are also not guaranteed to work in the future, and that aggregating agents in an upscaling method might be fundamentally flawed itself. They note that the interactions between agents at the pre-upscaling section cannot be generalized robustly since the one that is upscaled must be a sufficiently good sample, which is hard to determine *a priori* (Bertelmeier *et al.*, 2003). At the same time, treating individual and heterogeneous agents in groups leads to aggregation errors where the whole cannot show any useful information about actual constituents (Brandes, 1985, as cited in Zimmermann *et al.*, 2015).

This study already discussed the issue of aggregating the technologies of electricity production by resource type. GCAM itself aggregates resources. For example, it considers 16 types of fuels defined by the International Energy Agency as coal, including seven types of coal, and various cokes, peat, and blast furnace gas (Joint Global Change Research Institute, 2019a). As in other problem-solving cases, the main question about disaggregation is be whether it is important to have that additional layer of information or not.

Table 3.1: Taxonomy of Downscaling Methods

Method Family	**Temporal Treatment** Static	Dynamic
Statistical	Linear	Convergence Iterative Proportional Fitting Intermediately Complex Methods
Multi-model	–	Coupled-models

Two main approaches are compared in this work: the linear and convergence statistical archetypes, each of which can be applied to different variables. Between these, four types of trade-offs are immediately visible: dynamism, coherence to parent scenario, complicatedness of implementation, and transparency.

The most closely related implementation of these is in Gidden *et al.* (2019). In downscaling emissions for the energy sector (not energy use), they use the convergence method with the IPAT equation (Chertow, 2000), which calculates total emissions by multiplying together emissions intensity per GDP, and GDP per capita, and the size of the population.

Currently, the distribution of energy technologies in Europe is diverse and linked to geography, politics, institutional designs, and path dependencies. Within the transportation sector, this is not as prevalent. For example, France's electricity mix is nuclear-heavy, and some countries never shifted to nuclear at all. Within Canada, the territory of Nunavut relies entirely on diesel fuel for electricity, Alberta and Saskatchewan on coal, and Quebec on hydroelectricity, and Ontario mostly on nuclear power. The United Kingdom's success in moving away from coal has not been seen in ten years in continental Europe despite penetration of renewable technologies.

3.5. Chapter Summary

In summary, downscaling methods are already used, either mathematically or heuristically, with IAMs to support national and subnational policymaking. It is especially prevalent in the climatology domain (including meteorology and hydrology) and has also been used in for socioeconomic measurables like GDP. Only two published articles have applied downscaling to energy use directly. While previous work has briefly discussed why certain methods were used, there has been no direct comparison of these methods together or a thorough discussion of the trade-offs between these methods. Vuuren, Lucas, *et al.* (2007) proposed three key trade-offs but did not discuss them in-depth: “transparency, complexity, and effort”. Lastly, the typology of downscaling approaches does not sufficiently cover the recent advances in downscaling methods, especially to compare them.

The main research question, “What are the limitations and trade-offs between statistical downscaling methods used with global Earth system integrated assessment models to provide model-based energy transition policy support?”, would add to the literature on this subject. The first two sub-research questions in this analysis have now been covered and the latter two will be covered in the following chapters.

II

Approach and Results

4

Approach

This section will describe the analytical and technical methodologies used in this analysis. The following chapter reports the results from this process. The code used for the analysis is available in Jupyter Notebook format at: `https://gitlab.com/jasonrwang/downscaling-electricity`. The thirds and fourth sub-research questions are addressed here:

3. How can downscaling be applied to the energy sector in integrated assessment models?
4. What are key criteria to evaluate the IAM downscaling methods in the energy transition?

4.1. GCAM IAM Simulation Modelling Procedure

4.1.1. Energy System Specification within GCAM

The GCAM model covers energy technologies, land use, water, climate, and other socioeconomics surrounding it together. It implements global circulation climate modelling using the "Hector" or MAGICC modules. Its macroeconomic component is modelled as a dynamic–recursive partial equilibrium. The model assumes that its actors do not know the future and only make rational decisions relative to their contemporary perspectives. Input data for variables like cost and efficiency of specific technologies are static. Future population is an input, not an endogenous component. The only policy input is a carbon tax. It considers trade between nations for agricultural products and primary energy products, but not secondary ones like electricity or refined liquids (fossil and other oils). It is described in the literature of many domains due to its wide scope, but is best documented as an entity through its online documentation and the various workshops that its developers and affiliated institutes run (e.g. Joint Global Change Research Institute (2016)).

This work will only cover the most relevant aspects of GCAM to the energy downscaling analysis. Of particular interest from this model is that it the GCAM model endogenously includes energy use through not only resource type, but also the technologies that the resources are used with. Each of these technologies participate within markets in the model, so technologies that do not exist today may become available in the future.

GCAM separates the energy system into resources (depletable and renewable), energy transformation, and then final consumption. Figure 4.1 (Joint Global Change Research Institute, 2019a) provides an overview of which energy resources are used in GCAM for electricity and the other technological components, like cooling technologies, that are represented in the model. Depletable resources include oil, unconventional oil, natural gas, coal, and uranium. The total stock of these resources is tracked to feed the economic model that determines the resources' market prices. Renewable resources in GCAM are wind,

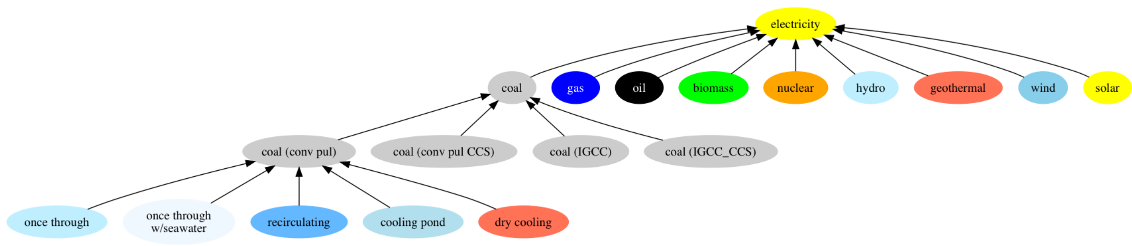


Figure 4.1: Simplified diagram of electricity resource structures within GCAM from Joint Global Change Research Institute (2019a).

solar, geothermal, hydro power, and biomass (including “traditional” biomass in some regions). These resources are provided with an annual rate alongside a cost curve that determines tracks the price to utilize them. Hydrogen is calculated as a by-product of industrial processes.

The specific energy resource and their technological implementation for electricity production are listed in table 4.1. Biomass and coal can both be directly burnt for steam generation in power plants (GCAM specifies that coal is pulverized in these cases; “conv pul”), in integrated gasification combined cycle (Brayton and Rankin) units (“IGCC”), or cogeneration, which is implemented through the industrial sector. Natural gas and refined liquids (fossil, biomass, or other oils) can generate electricity through direct combustion to heat steam, like in conventional coal plants, within internal combustion engines, or in simple cycle turbines (“Steam/CT”); combined cycle (again in Brayton and Rankin; “CC”) plants, or through cogeneration (“cogen”). Nuclear energy exists in second and third generator reactor designs. GCAM also considers electricity generators that utilize carbon capture and storage technologies. Carbon capture and storage (CCS) is available for pulverized conventional coal, IGCC coal, CC natural gas, conventional biomass, IGCC biomass, and CC refined liquids fuels. Apart from CCS, GCAM does not account for possible future energy technologies like Allam cycle for natural gas, fourth generation nuclear reactors, perovskite PVs, or other unknown technologies. The specific parameters defined for capacity factors, efficiencies, capital and operating costs, and other attributes in the electricity system are taken from Muratori *et al.* (2017). Storage in GCAM acts the same with the electricity market but is conceptually distinguished by the technology. Solar thermal plants (“CSP”) use thermal energy storage while solar photovoltaics (“PV”) and wind use battery storage. Residential PVs (“rooftop_pv”) is unable to use batteries here. Hydroelectricity is available simply as one entity without discriminating between dammed hydro, run of the river, or pumped hydro storage facilities. All of these parameters are calibrated *a posteriori* until 2010 in version 5.2 of GCAM, and sourced from the International Energy Agency.

Though the land use and climate models in GCAM solve at a 0.5° by 0.5° spatial resolution, it aggregates economic boundaries and energy systems into 32 geopolitical regions. GCAM outputs in the following regions: Global, Argentina, Africa (Eastern), Africa (Northern), Africa (Southern), Africa (Western), Asia (South), Asia (South-East), Australia and New Zealand, Brazil, Canada, Central America and the Caribbean, Central Asia, China, Colombia, EU-12, EU-15, Europe (Eastern), Europe (non-EU), European Free Trade Association, India, Indonesia, Japan, Mexico, Middle East, Pakistan, Russia, South Africa, South America (North), South America (South), South Korea, Taiwan, USA. A full table of these regions and the countries they contain is listed in table C.1.

4.1.2. Scenario Configuration Parameters

This analysis used GCAM version 5.2[1] released on November 4, 2019. The parent model in this case was run under the base reference scenario listed in a file called `configuration_ref.xml` (included in appendix A.2.1). Apart from changing the debug region from the USA to the EU-15, the file is unchanged

[1] `https://github.com/JGCRI/gcam-core/releases/tag/gcam-v5.2` and `https://doi.org/10.5281/zenodo.3528353`

4

Table 4.1: Electricity Resources and Technologies in GCAM

Energy Resource	Electricity Generation Technology	GCAM Variable Name
Biomass	Integrated gasification combined cycle	biomass (IGCC)
	Conventional boiler	biomass (conv)
	Cogeneration	biomass cogen
Coal	Integrated gasification combined cycle	coal (IGCC)
	Coal (conventional pulverized power plant)	coal (conv pul)
	Cogeneration	coal cogen
Natural Gas	Combined cycle	gas (CC)
	Direct combustion in boiler, engine, or turbine	gas (steam/CT)
	Cogeneration	gas cogen
Geothermal	Geothermal	geothermal
Hydro	Hydro	hydro
Hydrogen	Cogeneration	hydrogen cogen
Nuclear	Generation III	Gen_III
	Generation II Light water reactor	Gen_II_LWR
Refined Liquids	Combined cycle	refined liquids (CC)
	Direct combustion in boiler, engine, or turbine	refined liquids (steam/CT)
	Cogeneration	refined liquids cogen
Solar	Rooftop PV	rooftop_pv
	Concentrated solar plant	CSP
	Concentrated solar plant with storage	CSP_storage
	Utility PV	PV
	Utility PV with storage	PV_storage
Wind	Wind	wind
	Wind with storage	wind_storage

from the default reference scenario that comes with GCAM 5.2. This scenario takes runs the typical 2010 to 2100 time period and uses 1975 to 2005 as its calibration period. It is configured not to optimize for a policy target (by setting the parameter `find-path` to 0). The reference scenario assumes the SSP2 development pathway for its socioeconomic narrative, including for technological development and consumer elasticities for industry income, cement use, and negative emissions technologies. SSP2 is considered a "middle of the road" narrative, where contemporary social, economic, and technological trends perpetuate (Riahi *et al.*, 2017). In GCAM's implementation, this means they assume that the global the population in

2100 will be 9 billion and the GDP per capita $33,307. These specific parameters are discussed further in Table 2 of the GCAM online documentation SSP page (Joint Global Change Research Institute, 2019c).

4.2. Downscaling Methods

Section 3.4 described the various downscaling techniques that have been proposed in other sectors. The various methods are applied below to this study of energy.

The following section contains formulae with many variables. An overview glossary of each variable follows to help the reader understand the logic:

Table 4.2: Glossary of Downscaling Variables

Variable	**Meaning**
t	Time (year)
I	Energy intensity (per GDP)
E	Energy use
X	Downscaling driver parameter
GDP	Gross domestic product
β	Growth rate of energy intensity
t_i	Base (initial) year
t_f	Convergence (final) year (not the final year of simulation)
R	Region
c	Country
E^*	Energy use not yet normalized to model region data (for numeric consistency)

This work will primarily implement the linear and convergence methods described in Vuuren, Lucas, *et al.* (2007) and used to downscale emissions in Gidden *et al.* (2019).

4.2.1. Linear Downscaling

The linear approach will be used to allocate GCAM outputs proportionally to countries based on the following downscaling *drivers*:

- Emissions
- GDP
- Population

Each of these can be applied based on their current value with the following formula:

$$E_{t,c} = \frac{X_{i,c}}{X_{i,R}} \cdot E_{t,R} \tag{4.1}$$

Since GCAM outputs are at a five-year interval, this calculation also retains the same temporal resolution.

4.2.2. Convergence Downscaling

The convergence approach is more dynamic and assumes that a country's current preferences will eventually converge to a regional average. The following parameters need to be calculated, in the listed order, to apply the convergence method:

1. *Determine* the convergence year
2. Current energy intensity per country
3. Future energy intensity for the region
4. Growth rate between the base and future years
5. Energy intensity per country between base and future years
6. Actual energy use per country between base and future years
7. Normalize actual energy use to parent model's outputs

The convergence year is the date at which the country-level values will converge to a regional average. This will differ by scenario. Gidden *et al.* (2019) used 2125 for SSP1 and SSP5, 2150 for SSP2, and 2200 for SSP3 and SSP4.

Unlike the linear approach, the energy intensity will be calculated relative only to GDP and population, since this method requires a country-level forecast for the second variable, which does not exist for energy. A detailed breakdown of this step is listed below using GDP as an example downscaling driver.

$$I_t = \frac{E_t}{GDP_t} \tag{4.2}$$

Needs to be calculated for the region in the convergence year and for each country in the base year. The convergence year's value is extrapolated from the last period (2090–2100).

There are some special cases that require additional assumptions. Firstly, where a country has a zero value in the base year and the regional convergence value is non-zero, Gidden *et al.* (2019) takes one-third the value of the minimum non-zero value of the set. Secondly, some technologies do not yet exist in any country. Hydrogen is the clearest case. In this analysis, zeros will be replaced with a very small number (1×10^{-16}). Note here that technologies that do not yet exist are not accounted for. But since the approach is already fuel- and not technology-oriented, use cases like carbon capture and storage coupled to a coal plant are not treated well.

Then, the growth rate is found:

$$\beta_c = \frac{I_{R,t_f}}{I_{c,t_i}}^{\frac{1}{t_f - t_i}} \tag{4.3}$$

This approach assumes an exponential growth pattern with a constant rate of growth, except in a special case where some technologies are assumed to change the direction of growth.

Next, the growth rate is applied to find the interim energy intensities.

$$I_{c,t} = \beta_c I_{c,t-1} \tag{4.4}$$

By multiplying back the quantity the intensity is relative to, the interim values are found:

$$E^*_{c,t} = I_{c,t} X_{c,t} \tag{4.5}$$

The other quantity must come from an external source, since the parent model would, at best, carry these values at the regional-level . In this work, the GDP and population values in the interim (future) period comes from another model based on the same scenarios.

Finally, normalize the interim values by the parent model's regional values. This step ensures the downscaling approach is only a statistical approach and does not introduce values (i.e. informational mass is conserved, so to speak...)

$$E_{c,t} = \frac{E_{R,t}}{\sum_{c' \epsilon R} E^*_{c',t}} E^*_{c,t} \tag{4.6}$$

4.2.3. Data Requirements

This analysis requires the use of many data sources. This section below outlines the data that were used, including how data quality issues were resolved to implement downscaling. Table 4.3 lists all the external data sources and some metadata descriptions of what data they described, the temporal range they covered, the temporal and spatial resolution of the data, and the source. The discussion section of this thesis (chapter 6) covers data issues identified as a result of the actual downscaling or analyzing the results.

Table 4.3: Required Downscaling Data Overview

Acronym	Temporal Range	Temporal Resolution	Spatial Resolution	Source	URL or Code
External Data Sources					
Electricity production by resource type	2016 —2020	Month	Country	Eurostat	“nrg_cb_pem”
GDP	1975 —2019	Year	Country	Eurostat	“nama_10_gdp”
GDP	2010 —2100	Year	Country	OECD*	(Dellink *et al.*, 2017)^
Population	1990 —2019	Year	Country and subnational	Eurostat	“demo_r_d2jan”
Population	2010 —2100	Year	Country	IIASA WiC POP*	(KC and Lutz, 2017)^
Emissions by sector	1970 —2018	Year	Country	EDGAR (EU Joint Research Centre)	(Crippa *et al.*, 2019)
GCAM Model Outputs					
Population	1990 —2100	5 Years	Regional with some countries	GCAM	“total-population”
Emissions	1990 —2100	5 Years	Regional with some countries	GCAM	“emissions”
GDP	1990 —2100	5 Years	Regional with some countries	GCAM	“gdp-mer”
Electricity generation by resource and technology	1990 —2100	5 years	Regional with some countries	GCAM	See appendix A.2.2

*Modelled, based on authors’ interpretations of SSPs.
^Data directly accessed from IIASA Emissions Downscaling GitHub repository:
https://github.com/iiasa/emissions_downscaling/tree/master/input/SSP_pop_gdp

Data that were used were filtered for only the years and countries relevant to this analysis. The IIASA population (KC and Lutz, 2017) and OECD GDP (Dellink *et al.*, 2017) projections were used to stay consistent with Gidden *et al.* (2019), though the United Nations maintains another widely used projection[2].

The outputs of GCAM are stored in a boutique XML database format which can be accessed through queries defined in XML. GCAM comes with a Java-based tool called “ModelInterface” and offers a Python tool, `gcam_reader`[3], to apply these queries. The queries used in this work is listed in appendix A.2.2 and stored as “queries.xml”.

[2]Differences between these projections are listed on https://iiasa.ac.at/web/home/research/researchPrograms/WorldPopulation/Projections_2014.html

[3]Accessible online through https://github.com/JGCRI/gcam_reader.

4

Data Quality Limitations

Data quality is an important facet of modelling. Especially in models with complex components, like in the IAM case, where multiple data themes are used together, data quality can also act as a boundary for the quality of the model. For example, a key modelling issue is internal consistency (discussed further in chapter 6). Listed below are challenges in the available data to ensure internal consistency in the downscaling process.

Huang (2013) defines there are three main forms of data quality issues: syntactic, semantic, and pragmatic. The first category deals with how the data is digitally stored. The second examines whether the data refer to the same content (e.g. keys or indices have the same meaning). The third refers to the relevance of data to the intended use purpose.

Electricity Production Data Mismatch

Where GCAM endogenously considers electricity production by both fuel and technology type, real-world electricity production data is rarely distinguished by technology. EU Regulation 543/2013 Article 16, the regulation mandating the acquisition and publication of electricity market data in the EU, only defines that electricity producers must report by facility ("production unit") and fuel ("production type") (European Commission, 2013), for which the resource type is typically inferred by analysts. This mismatch presents a pragmatic data inconsistency, where the convergence downscaling method, which relies on base year data, is forced to only downscale by resource type. GCAM technologies will need to be aggregated by energy resource to match the Eurostat base data, and so the resolution of insight into technology is completely lost. Table 4.4 details a map of aggregate resource types to their GCAM category and the Eurostat name.

A semantic issue with the examined energy resource data is how those resources are categorized. The Eurostat historical electricity production category "combustible fuels – non-renewable" is not explicitly defined. Based on the definitions of non-renewable resources in the International Recommendations for Energy Statistics (United Nations, 2018, p. 145), which the Eurostat database categorizations are aligned with[4], this category likely refers to non-organic municipal wastes, industrial waste, or peat. In GCAM, these categories are treated as biomass, and so will be viewed the same in this analysis.

Country Categorizations

The various database sources used in this analysis also presented a pragmatic data issue regarding how countries are counted. Here, the Eurostat database does not include small nations like San Marino, Andorra, Monaco, and Vatican City as they are not part of the EU. However, the EDGAR GHG database includes San Marino and Vatican City with Italy, Andorra with Spain, and Monaco with France. These countries' energy and GHG footprints were similarly deemed negligible in this analysis as well and considered as just the larger state. For example, "France and Monaco" in the EDGAR data was treated as "France". Another issue in the data identified for this analysis is a common semantic (mapping) consistency issue between country names to regions and their codes. This work uses the Eurostat naming convention, which is tabulated in table C.2.

4.3. Criteria to Compare Downscaling Methods

Finally, three categories of ten key criteria will be used to compare the downscaling methods (tabulated in table 4.5)and the trade-offs between them. These categories are built upon the four identified for diagnosing IAMs proposed by Kriegler *et al.* (2015): identification of heterogeneity in model responses, diagnosis of relevant features for climate policy analysis, applicability to diverse models, and accessibility and ease of use; and on those Vuuren, Lucas, *et al.*'s (2007) suggestions that "transparency, complexity, and effort" are the key trade-offs between downscaling methods. Additionally, Doukas *et al.* (2018) mentions that results from modelling approaches must be robust to support climate policymaking. Beyond

[4]See 3.2 in `https://ec.europa.eu/eurostat/cache/metadata/en/nrg_quant_esms.htm`

Table 4.4: Map of Aggregated Resource Types to GCAM Category and Eurostat Name

Energy Resource	GCAM Name	Eurostat Name
Biomass	IGCC	Combustible fuels – renewable AND
	Conventional	Combustible fuels – non-renewable
	Cogen	*Idem*
Coal	Coal (conventional pulverized)	Coal and manufactured gases
	Cogeneration	Coal and manufactured gases
Natural Gas	Closed cycle	Natural gas
	Steam/CT	Natural gas
	Cogen	Natural gas
Geothermal	Geothermal	Geothermal
Hydro	Hydro	Hydro
Hydrogen	Cogen	Other renewable energies
Nuclear	Generation III	Nuclear fuels and other fuels n.e.c.
	Generation II Light water reactor	Nuclear fuels and other fuels n.e.c.
Refined Liquids	CC	Oil and petroleum products (excluding biofuel portion)
	Steam/CT	Oil and petroleum products (excluding biofuel portion)
	Cogen	Oil and petroleum products (excluding biofuel portion)
Solar	Rooftop PV	Solar photovoltaic
	Concentrated solar plant	Solar thermal
	Concentrated solar plant with storage	Solar thermal
	Utility PV	Solar photovoltaic
	Utility PV with storage	Solar photovoltaic
Wind	Wind	Wind
	Wind with storage	Wind
None	None	Other fuels n.e.c.

examining how IAMs are constructed, their work aimed to test how multiple IAMs' outputs can be characterized relative to changing carbon prices. In other words, they performed a sensitivity analysis on carbon pricing but viewed the qualitative outputs. The categories are:

- Replicability,
- Coherence to the parent model (the GCAM IAM), and
- How they manage the economic and technical nuances of the energy domain.

Replicability determines the ability for others to implement the downscaling method. Downscaling methods that are transparent and accessible are more useful for analysts to adopt and support decision-makers with. Especially in a downscaling context, having comparable results across localized regions can help provide a common fact base for discussions and negotiations. DeCarolis *et al.* (2012) argue that since energy optimization models (similar to IAMs) cannot be validated, it is critical for both scientific and policy contexts that their mechanisms and assumptions can be understood by users. The same issue applies here with downscaling methodology. Specifically, there are three qualities important here: ease of implementation, the types of data that are required, and the transparency of implementation. The types of data necessary could be historical data, future projections for the region or at a country level, or further calculations. Not all types of data are available for every part of the world and could therefore limit the use of a downscaling approach. For example, the convergence approach relies on OECD GDP forecasts for every country in the world based on the authors' (Dellink *et al.* (2017)) interpretation of SSPs. These forecasts are not available for every type of measure that might be used in a downscaling approach, and there may be a mismatch between a model's and forecast's scenarios.

The second point, coherence to the parent model, is concerned with the internal consistency of how the modelled aspects of the energy system – especially consistency to the parent IAM. There are two main criteria in this category: nature of time series behaviour and nature of energy system components. Since every downscaling approach attempts to fill in system changes at a country level that are not included in the parent model, it needs to introduce assumptions to how those countries change over time. The linear approach is clearly static, and the convergence approach leaves the choice of a growth function to the user, but usually uses an exponential growth function. Other methods implement more complex functions (e.g. cellular automata for population urbanization) or model specific changes more explicitly with relationships across domains (e.g. interactions between urbanization and technological innovation).

Similarly, the downscaling process may introduce a representation of energy system components. The new representation usually uses the parent model as a boundary, but approaches can even be fully coupled. For example, while most approaches, including those implemented in this study, statistically distribute aggregated outputs to each localized area, a method could take intermediate outputs from the parent model and allocate those directly to the smaller regions. An IAM that introduces electricity production facilities by discrete capacities could be downscaled by attributing individual facilities to specific countries. Likewise, electricity infrastructure (i.e. production, transmission, and distribution mechanisms) is discrete and encompass significant lock-in effects due to their size, which shapes how companies make decisions in building them. Nuclear energy facilities often need to be profitable over the course of two or more decades to be justifiable. This type of decision-making is built into GCAM and other IAMs, but the downscaling process might obfuscate the decision. Though micro-economic decisions are complex, this criterion will focus here on whether the approach can follow that of the parent model or introduces artefacts like sudden investment and divestment.

Another issue is that the energy categories used in an IAM may be different from those available for the downscaling methods. In many cases, some technologies may need to be subsumed by a larger category. For example, while models may consider the deployment of solar photovoltaics with and without electricity storage, electricity production reports do not make this distinction. A loosely coupled approach is like in the convergence method, where constructing facilities is considered independently in the method. Since the approaches all use the parent IAM's outputs as boundary conditions, there is no need to perform a scenario-based internal consistency check (like in (Schweizer and Kriegler, 2012; Schweizer and Kurniawan, 2016)). Even still, this can check for issues like the behaviour of local regions.

Thirdly, being aligned to the energy domain means three key attributes: recognizing the diverse and distributed allocation of energy resources, robustly and consistently deal with technologies that might not be used in the base year, and to do the same with technologies that do not exist commercially yet at all. Geography and energy are inextricably linked, where it can even entirely preclude some technologies' use in some areas entirely. As a low-lying country, the Netherlands will never see massive hydroelectricity facilities, and Sweden's northern locality means the output of solar photovoltaics is limited. Some countries do not have any historical precedence for a resource, which does not necessarily mean they will not in the future. Since many downscaling processes look precedence for projecting future patterns, the lack of historical data could distort the method. Similarly, there is little known about countries' preferences for technologies that do not exist yet. However, it could be possible to link some future technologies to attributes that are known. Hydrogen gas production could continue to come from places with abundant natural gas resources and carbon capture and sequestration potential, or places where there may be excess electricity production for electrolysis.

Table 4.5: Criteria Used to Evaluate Downscaling Methods

Criteria Category	**Criterion**
Replicability	Ease of implementation
	Data forms required
	Transparency of implementation
Coherence to Parent Model	Nature of time series behaviour
	Nature of energy system components (holarchy)
	Retains parent model categories
	Retains micro-economic decision-making
Treatment of Energy System Features	Handles geographic limitations
	Handles zero base year use robustly
	Handles technologies not commercialized yet

5

Downscaling Results

The interim calculations and final results from both downscaling methods are plotted and explored using a Jupyter notebook environment with Python through Altair (VanderPlas *et al.*, 2018). These data are depicted below, highlighting the most important insights. Tables containing the values to further numerical precision can be found in appendix C. However, it is an imcapportant point that these results are mostly seen qualitatively and not quantitatively. The results are listed below in the order of analysis.

5.1. Linear Downscaling

5.1.1. GCAM Outputs for EU-15 Region in Original Energy Categories

First, it is useful to examine the regional trend for the entire EU-15, which are outputs directly from GCAM. These values, faceted by resource type, are depicted in fig. 5.1 and provide some insight for what to expect from the downscaling results. There are broadly five categories of time series behaviour here: rising, fall, stagnation, rise and gradual fall, and other cases. Of the 24 resource-technology pairings, 12 rise, two fall, three rise quickly and stagnate, five rise and fall, and two form their own special cases.

Overall, this scenario sees energy consumption in the EU-15 rise from 11.5 to 16.9 EJ between 2020 and 2100, a 47% increase. Concentrated solar power (CSP) with and without thermal heat storage, third generation nuclear energy, solar photovoltaic with storage, biomass except for with cogeneration, coal with IGCC, natural gas in the combined cycle, hydrogen in cogeneration, refined liquids in combined cycle, and wind with and without storage fall into the first category. Second generation nuclear reactors and refined liquids in a direct combustion cycles are the only two technologies that only fall. Coal in conventional and with cogeneration are roughly stagnant, as is hydro power. Hydro power remains almost entirely constant except for a discrete rise of around 0.2 EJ around 2010, which could represent a large project of around 6.5 GW being completed (assuming it runs constantly throughout a year). Between 2014 and 2019, Europe installed around 10 GW of actual hydro power capacity (International Hydropower Association, 2020). It also matches the existing amount of energy production from hydro. Biomass in cogeneration, utility level and rooftop PV, gas in the direct fire methods, and refined liquids under cogeneration rise and then fall. The two other cases are geothermal energy, which rises quickly to 2040 and then stagnates, and gas in direct fire use, which rises almost linearly by 1 EJ around 2010 and then falls until it nears zero in 2100.

The dynamics of the technologies' development paths vary widely. Second generation nuclear energy phases out by 2070 in this base scenario while third generation rises from 2015 onward. Utility scale utility level PV has a rapid rise but then becomes very constrained past mid-century. While utility PV with storage continues to rise, it occurs at an order of magnitude lower than without storage. The sharp rise in direct fired natural gas power plants is somewhat matched in time by the decline of refined liquids in the same group and in conventional pulverized coal, suggesting direct fuel substitution.

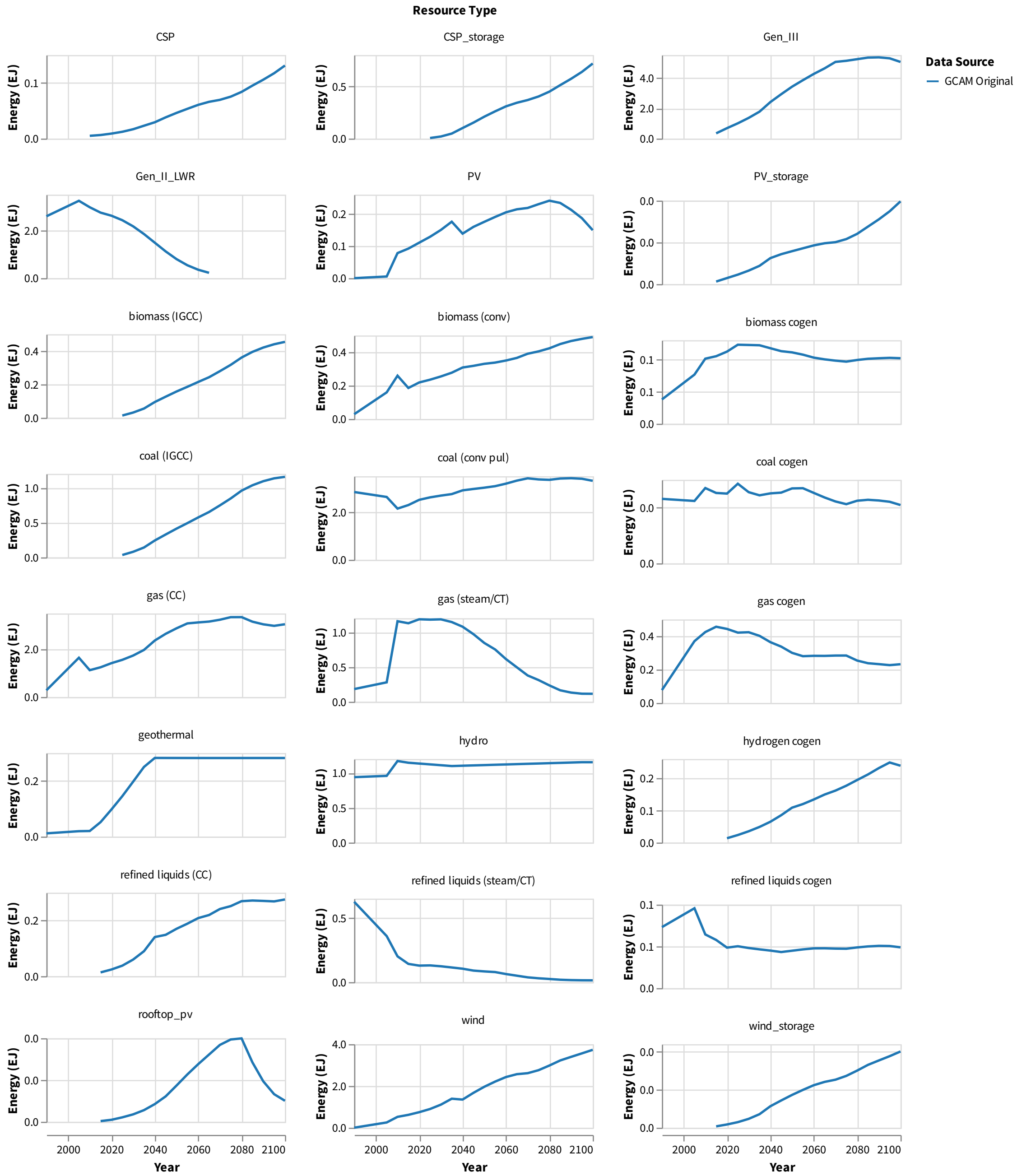


Figure 5.1: EU-15 Energy Use by Resource Type (from GCAM parent model)

5.1.2. Downscaled Results

The calculated proportions of each country via each of the three drivers, emissions, GDP, and population, are shown below in Figure 5.2 and tabulated to one decimal in in table C.3 with respect to each method. Though within each country, the proportions can vary greatly.

The linearly downscaled results are simply the regional values from GCAM (shown previously in fig. 5.1) divided by different scaling factors found in fig. 5.2. Though every country was downscaled, their results would look the same as just in the case of one country — three different paths separated by slightly different scaling values. Figure 5.3 shows the results for the Netherlands, as an example, in the original GCAM

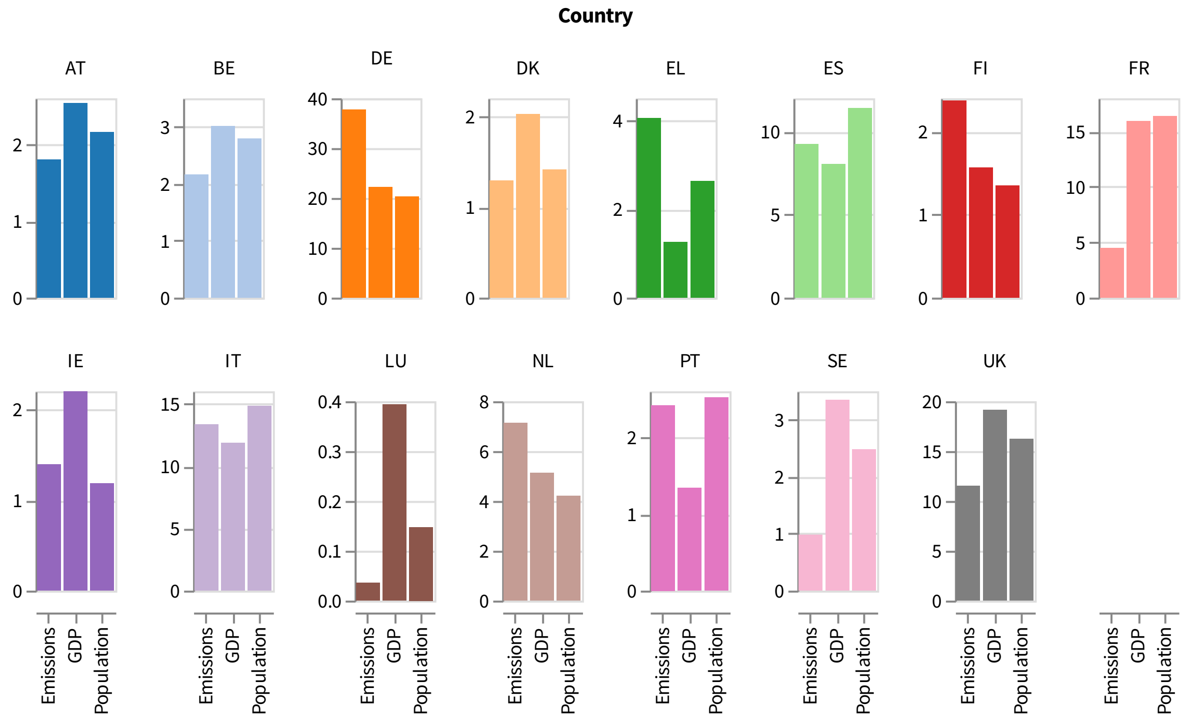
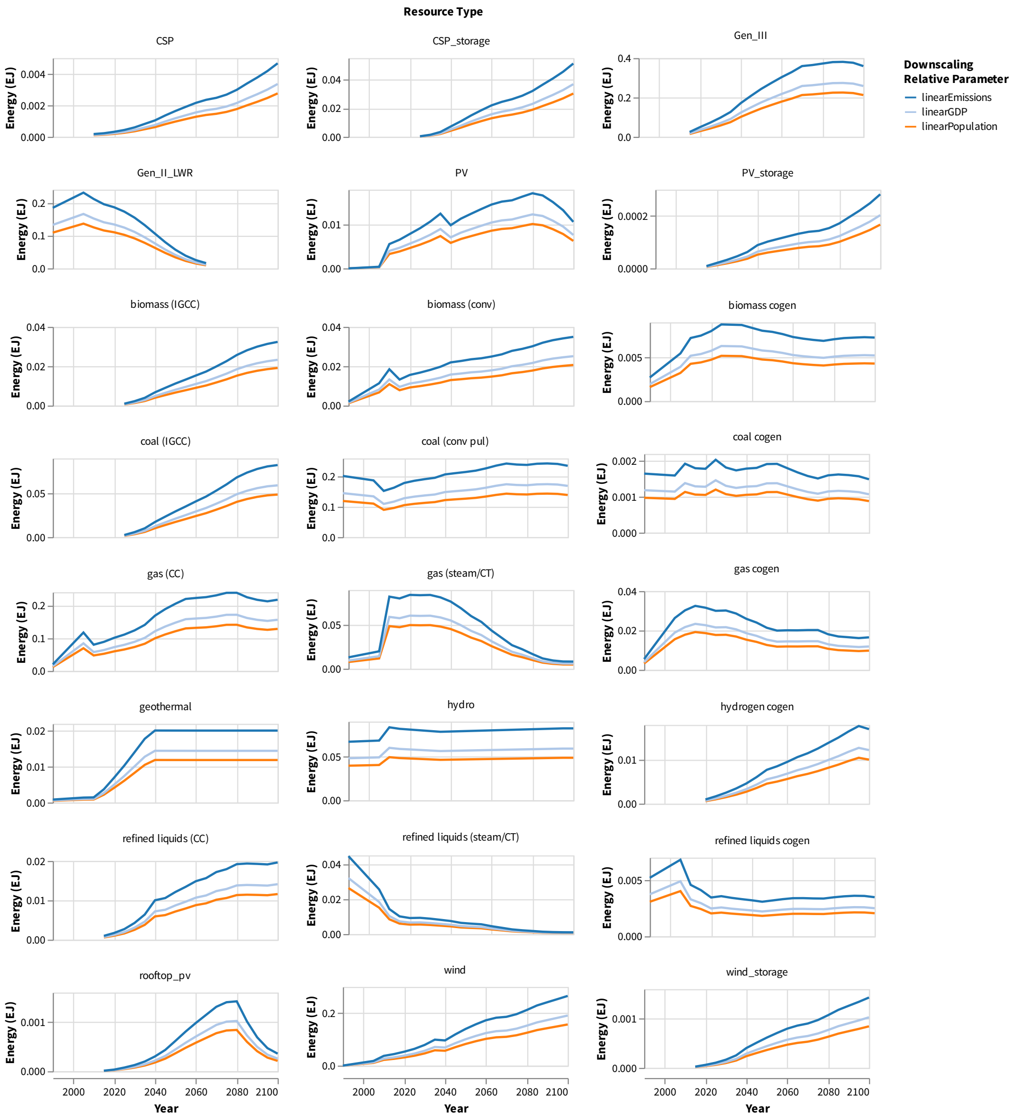


Figure 5.2: Linear Proportions for EU-15 Countries Relative to Emissions, GDP, and Population (by country)

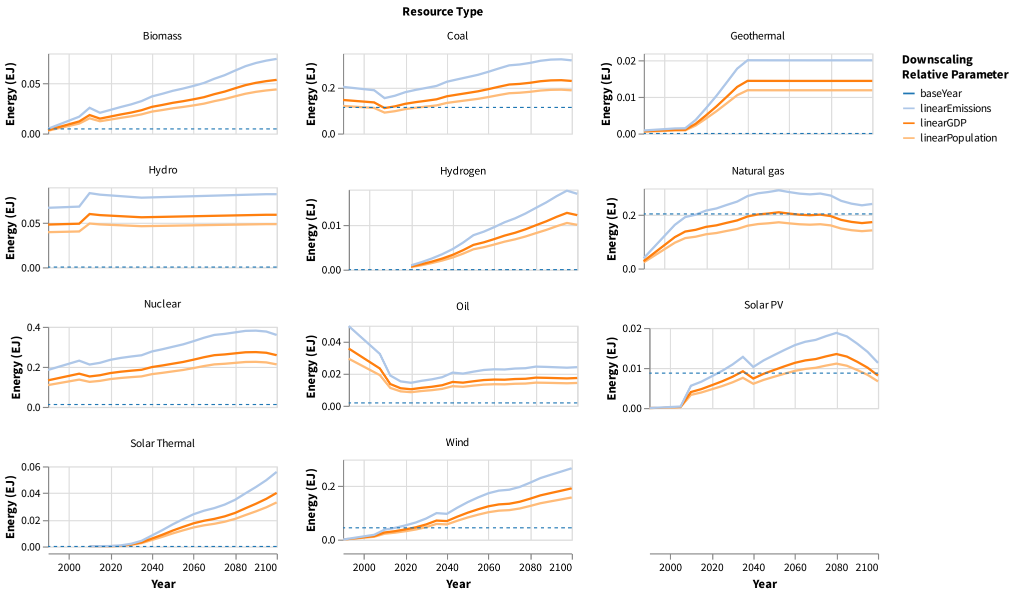
5

categories (fig. 5.3a) and the aggregated ones (fig. 5.3b, which also has 2018's actual values as the dotted horizontal line) that can be compared to the convergence method's results. The variance within each country of each driver's proportion cascades into discrepancies in the downscaled results. In the case of the Netherlands, its results driven by emissions are 70% as much as by population and 39% more than by GDP.

Compared to the criteria set forth to evaluate downscaling, the linear method is easy to implement, only requires historical data from one base year, and is very transparent to implement since it only has two main calculations to implement. Because the method is based on a static snapshot of preferences at some previous point in time, its time series, though non-linear, is a static representation. It is directly coupled to the parent IAM's energy system components, but distorts their disaggregation to each country; it assumes a homogeneous allocation of dynamic behaviour. The linear approach maintains the parent model categories, but not the micro-economic factors because it assumes its smaller regions are homogeneous. The linear approach clearly does not handle geographic limitations as it is implemented. The Netherlands sees hydroelectricity electricity production begin at 0.05 EJ and rise even more around 2010 despite its base year data being negligible (0.0003096 EJ). Conversely, this also means the linear method can handle zero use in base year robustly. Hydrogen, which is zero until 2020, is a better indicator of this ability, which also fills its performance in the last criteria for technologies that do not exist yet.



(a) GCAM Categories



(b) Aggregated Categories

Figure 5.3: Linearly downscaled energy use in the Netherlands. The order of the paths, from highest to lowest, is ranked by emissions, GDP, and then population, and are simply the GCAM regional results scaled by the proportions the Netherlands represents for each of these drivers – the relative differences between each time series is constant. Results are shown in GCAM energy-technology categories and aggregated resource type categories to align with the convergence method's results.

5.2. Convergence Downscaling

5.2.1. GCAM Outputs for EU-15 Region with Resources Recategorized

Like before, it is useful to first examine the regional trends to set a context for the further downscaling. Figure 5.4 shows the GCAM outputs for electricity production, aggregated into resource types only to match the base year data categories. They no longer distinguish the technologies that convert these resources into electricity. Overall, biomass, wind, hydrogen, and solar thermal energy appear to grow linearly in the EU-15 from near zero to 1, 4, 0.25, and 1 EJ, respectively. Hydrogen only starts to grow from 2020 and solar thermal similarly is stagnant until around 2030. Both roughly follow a linear growth trend, though hydrogen drops from its peak in 2095 to its 2090 level in 2100, and solar thermal slows slightly between 2050 and 2075 before accelerating.

Hydro power and geothermal are unchanged from the previous case, since it was not recategorized. Solar PV energy production rises from near zero to around 0.3 EJ between 2010 and 2080 with a sharp drop around 2035, and then gradually declines until 2100. Nuclear power production rises from its 2018 actual production at 2.7 EJ gradually until it doubles by 2090 and then declines slightly to 4.5 EJ. Fossil fuels will all grow between 2020 and 2100, though coal and oil (to a much greater extent) will first drop in 2010. Oil's growth is small but coal more than doubles in this period to just above 4 EJ while natural gas quadruples.

The comparisons between the GCAM results here and actual 2018 historical figures are only to illustrate the magnitude of changes and not to comment on validating GCAM. For example, solar PV is only half of what is already actually implemented in 2018. The discrepancy between these values is because GCAM 5.2 is calibrated only up to 2010 data from the International Energy Agency and the renewable energy sectors worldwide have grown faster than most models have anticipated (e.g. see Evans (2019)).

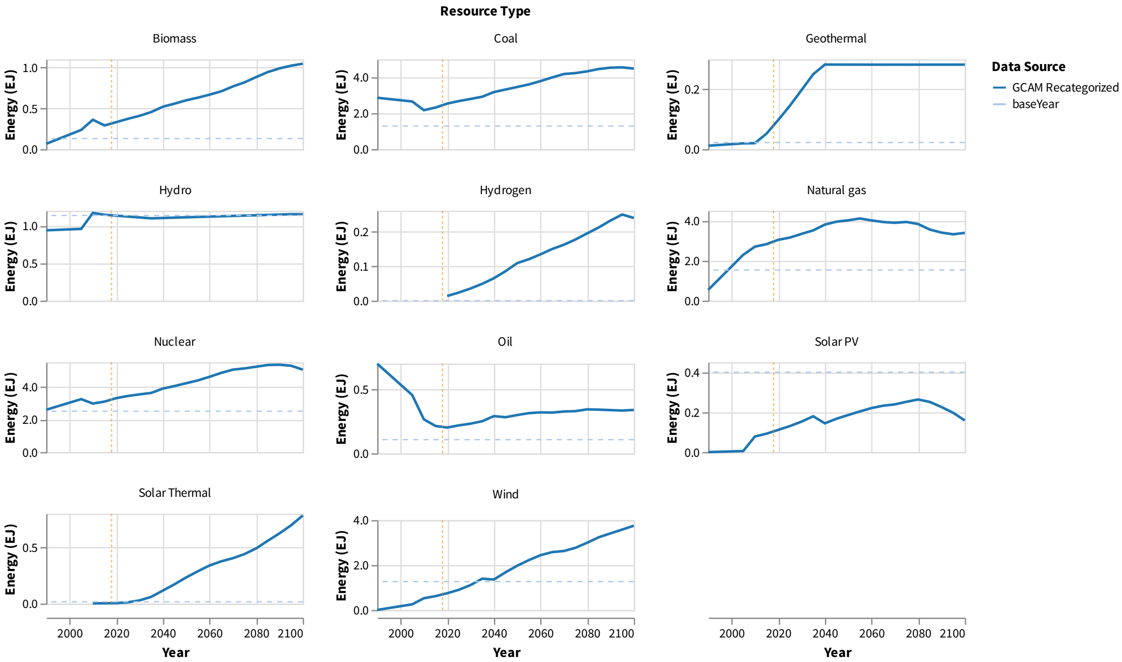
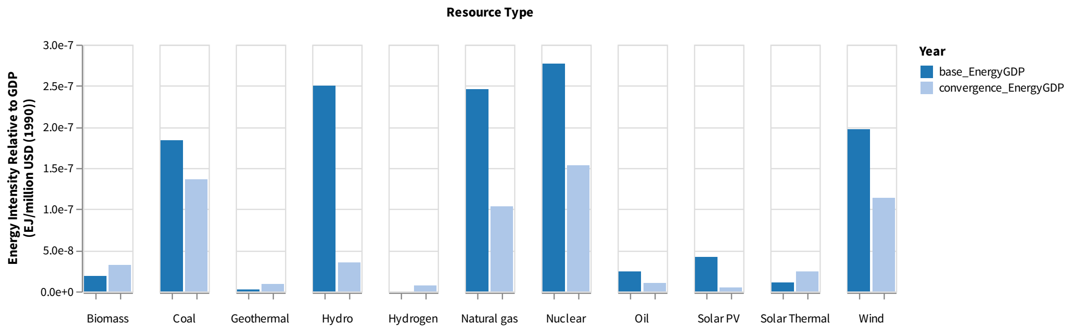


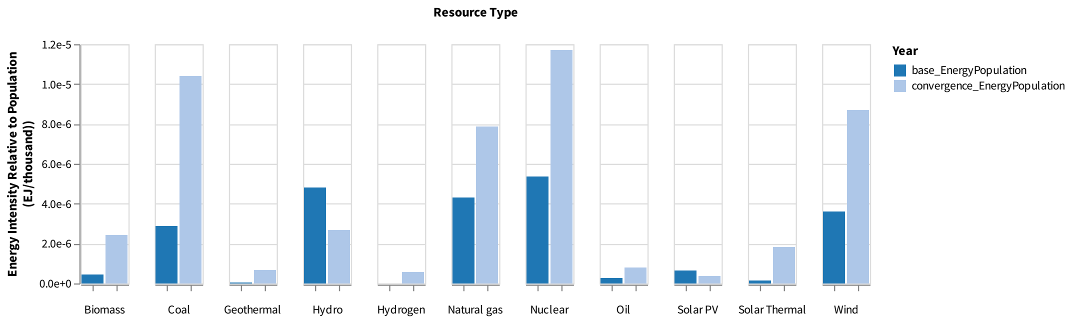
Figure 5.4: EU-15 Energy Use by Resource. These values are directly from the GCAM parent model but recategorized to be consistent with the 2018 base year electricity production data. The values along with the 2018 historical output shown in the dotted horizontal line and the year 2018 demarcated as the vertical one.)

5.2.2. Downscaled Results

The energy consumption intensities relative to both GDP and to population lead to different results. Firstly, fig. 5.5 shows how the initial and convergence energy intensities for each resource type in every EU-15 countries, respective to both these driver variables. In both the GDP and population cases, geothermal, hydrogen, and solar thermal intensities increase. Others renewable energy sources – hydro and solar PV – counter-intuitively decrease. While wind energy intensity increases when population is the downscaling driver, it decreases for the GDP metric. The other resource types, biomass, coal, natural gas, nuclear, and oil, similarly have divergent behaviour between the two downscaling metrics. Intensities decline relative to GDP for each of these and rise relative to population.



(a) Relative to GDP



(b) Relative to Population

Figure 5.5: EU-15 Regional Energy Intensity in Base and Convergence Years with both GDP and population as downscaling driver. In both cases, geothermal, hydrogen, and solar thermal intensities increase but hydro and solar PV decrease. With population as the driver, biomass, coal, natural gas, nuclear, oil, and wind energy intensity increase but decrease with GDP.

Intensities between the base and convergence year were interpolated assuming exponential growth. Figures 5.6a and 5.6b show the paths each country's energy intensity takes to reach the regional convergence value with both driver variables. While each value clearly converges by 2100, it is also easy to spot that countries' energy profiles are heterogeneous. There are four types of behaviours that can be seen:

1. The convergence year intensity is roughly in the middle of the countries' base year values. Some countries grow their energy use for the resource type, others degrow, and some are mostly stagnant. With GDP as a driver, biomass, coal, and wind fit this category; with population, natural gas and nuclear.
2. The convergence year intensity is slightly above all of the countries' base year values. Some countries trend towards 2100 almost linearly while others see growth from near-zero. This behaviour is only present with population driving for biomass, coal, and wind.
3. The convergence year intensity is much higher than most countries' base year data. This is the case for hydrogen fuel under both drivers and solar thermal with population. Solar thermal and geothermal under GDP behave almost in the same way, but Spain's intensity declines roughly linearly by around 30%.
4. The convergence year intensity is near-zero, so all countries decline. Hydro and solar fit this description in both cases, and nuclear and oil do so in the GDP case.

Viewed together, there also appear to be two classes of resource types: those that are used by all countries to varying extents and those that are not used by a majority with a few outliers. Coal, natural gas, wind, solar PV, and nuclear (to a lesser extent) fall into the first category. The other resource types hint at geographical or policy preferences. Austria and Sweden have strong preferences for hydroelectricity, France and Sweden for nuclear, Finland for biomass, and Spain for solar thermal.

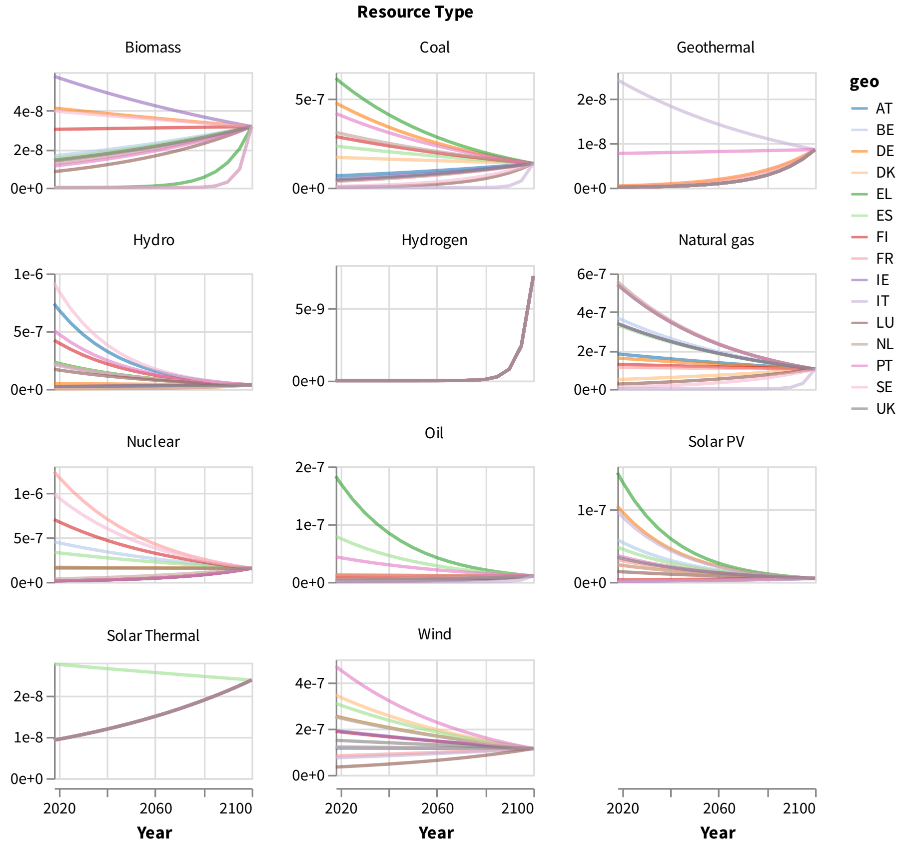
An interesting discrepancy between the two drivers is their influence on the shape of all countries' interim intensity paths viewed together. In some cases, like geothermal, the convergence intensity relative to GDP sits between many countries' but is entirely above them in the population case, which can also be seen in the views of the β plot above in figs. 6.4b and 6.4d. This difference suggests that the GDP and population approaches may lead to diverging outcomes for some energy types.

Next, figs. 5.7a and 5.7b show the interim gross energy values, from eq. (4.5), in the same period. Here, the general behaviour between the GDP and population approach look very similar. In the oil case, Spain's energy consumption is concave upward in the GDP case but slightly concave down in the population case. Interestingly, it, along with other values, like Germany's solar PV, have clearly different initial values. The general behaviour for all resource types can again be viewed as two sets: one where every country follows the same (de)growth direction, and another where many countries trend one way but a few outliers do the opposite. Biomass, hydrogen, solar PV, and solar thermal have distinctively similar trends between countries with both metrics as downscaling drivers. Every other resource type shows opposite trends.

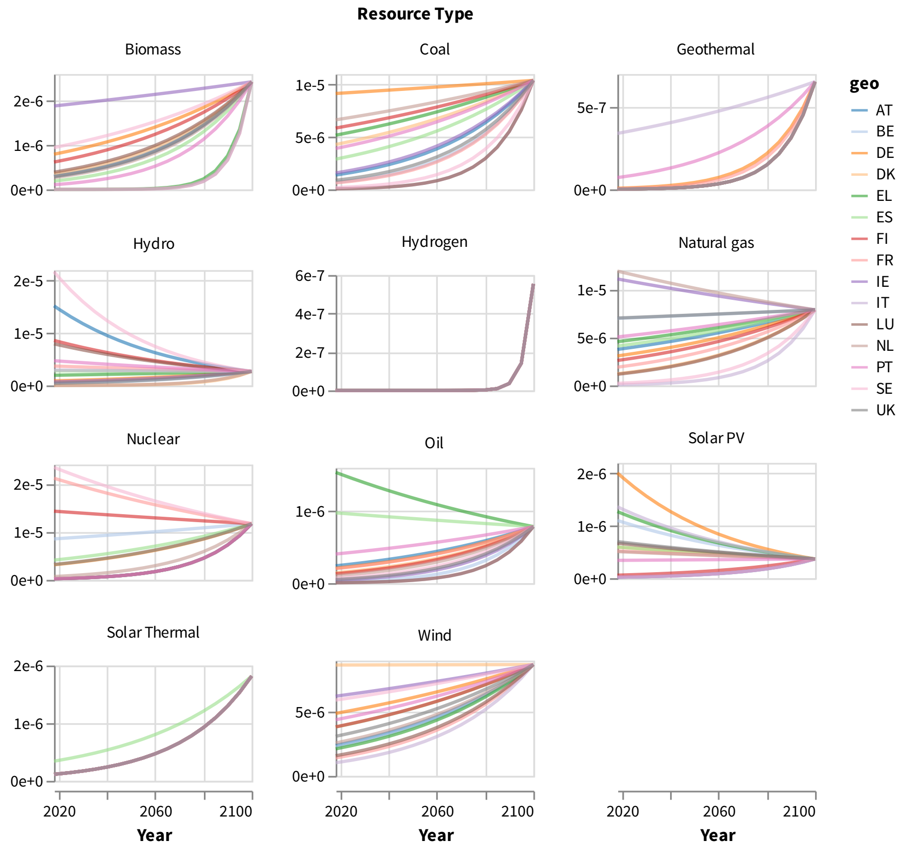
In the normalized final downscaling results in figs. 5.8a and 5.8b appear to match between using the two variables. Without looking closer, the general shapes of the two approaches are indistinguishable. There are small discrepancies, like where France's natural gas use exceeds Germany's around 2090 in the GDP case but does so a decade earlier when population drives the downscaling. Another divergence is where France's oil use decouples from Germany's around 2050 in the population case, whereas with GDP it remains intertwined.

With regard to the downscaling method evaluation criteria, the convergence method relies on a series of five calculations, one of which requires assuming some sort of growth function. This method is much more difficult to implement than the linear approach, but still easier than an approach like building a separate regional model. The process requires much more data. It needs the base year data, future projections of the downscaling drivers in each EU-15 countries (GDP and population here), which requires a consistent scenario narrative that should also be reflected in the parent IAM. Though not implemented here, the convergence approach may also require the parent model's outputs to be extrapolated to a convergence year beyond the range in the model. All of these assumptions can be clearly communicated, but exist as many layers that can be confusing, especially since the choices made here can contradict each other. Therefore, the transparency of implementing it is categorized as medium, since the approach is clearer than a black box.

The time series in the convergence approach is dynamic, but based on simple interpolation using an exponential function. Therefore, its representation of energy systems decouples slightly from the parent model. The normalization procedure (eq. (4.6)) keeps the results bounded by the parent model. Unfortunately, in this implementation, the technologies that use the various energy resources needed to be aggregated because the historical electricity production data only reports by resource type. The Italian geothermal case shows that micro-economic processes are likely not maintained, since facilities are rapidly built between 2020 and 2040 to an order of magnitude above the rest of the countries (0.22 vs. mean of 0.004 EJ), but then declines to meet them in 2100. From a technological lock-in perspective, this is inconsistent. This approach also ignores geographic limitations. Again, the Netherlands can be used as a clear example where the base year usage is near-zero, but goes to more than 0.05 EJ in both GDP and population driver cases. In Italy's oil and natural gas production cases, the rate of growth between using the GDP and population as downscaling drivers leads to distinct growth patterns (1.2880 vs. 1.0585 and 1.2523 vs. 1.0613 year over year). Clearly, it cannot handle zero use case in the base year robustly, and similarly struggles with technologies that do not exist yet.

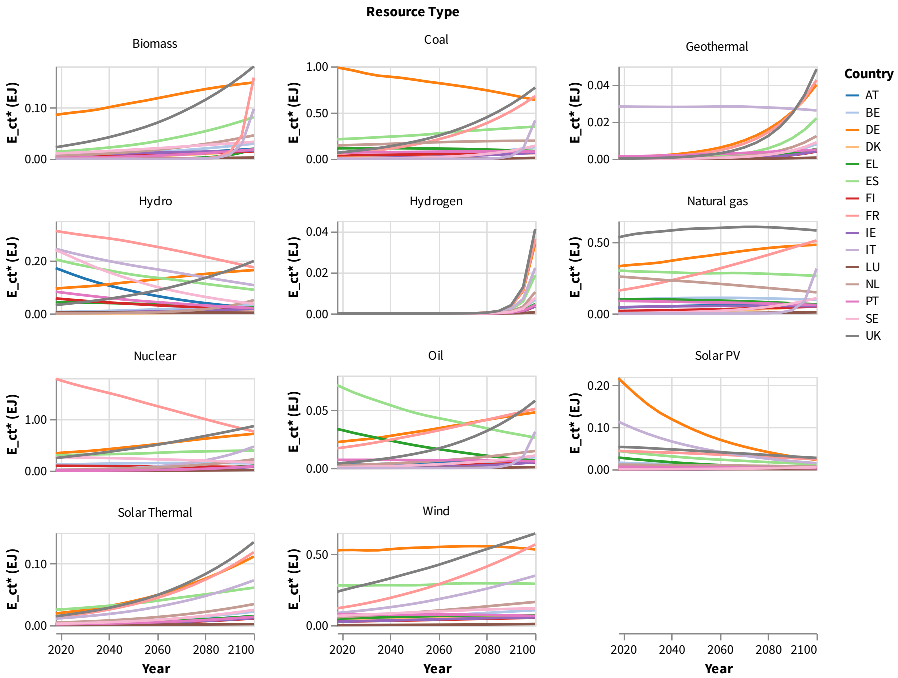


(a) Relative to GDP

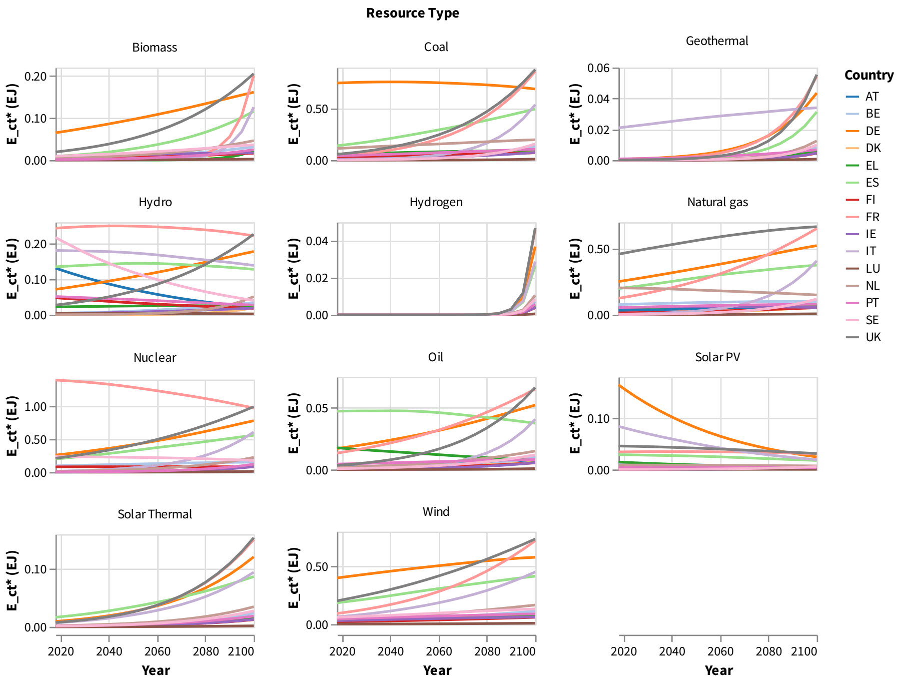


(b) Relative to Population

Figure 5.6: Energy intensity between base and convergence years by country and resource type. There are four distinct categories here, where the convergence year intensity is: roughly in the middle of (with GDP as a driver, biomass, coal, and wind; with population, natural gas and nuclear), slightly above (population driving for biomass, coal, and wind), and much higher than most countries' base year data (hydrogen in both cases and solar thermal with population); and near-zero (hydro and solar in both, nuclear and oil in GDP).

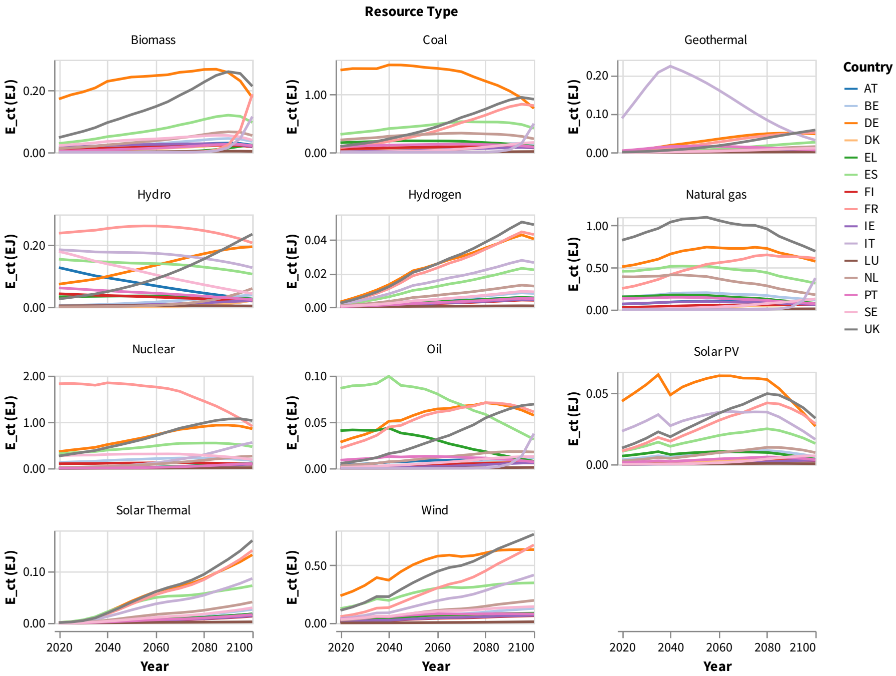


(a) Relative to GDP

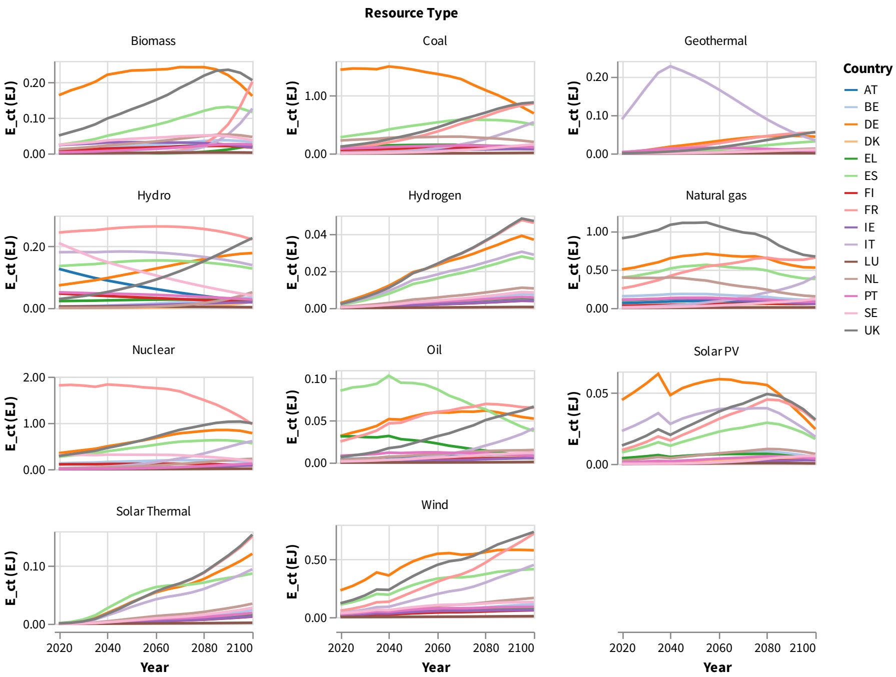


(b) Relative to Population

Figure 5.7: Energy use between base and convergence years by country and resource type. These values are very similar between countries, but there are some notable differences. France's nuclear and Germany's coal use declines linearly with GDP as a driver but looks more like a downwards concave parabola with population. Italy's geothermal use starts higher with GDP and is mostly stagnant, but then declines. Under population as a driver, it begins lower but then only rises.



(a) Relative to GDP



(b) Relative to Population

Figure 5.8: Normalized Energy Use Between Base and Convergence Years by Country and resource type. The two sets of figures are nearly indistinguishable between the two downscaling drivers, though France and Germany show discernible differences in natural gas and oil use in around 2080.

5.3. Discrepancies Between Approaches with Same Resource Recategorization

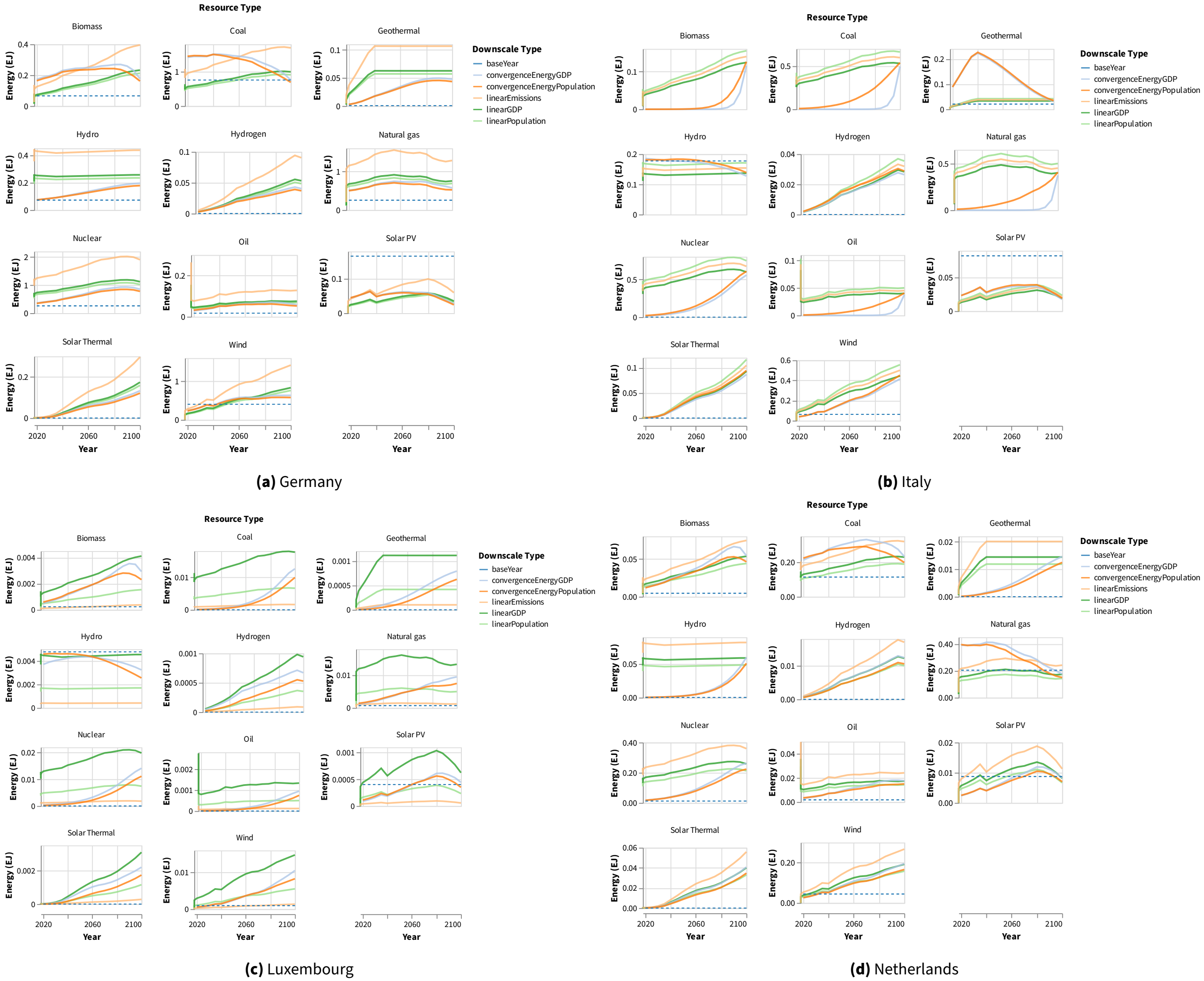
Finally, both of these methods are compared next to each other. Figure 5.9 shows all of the approaches together and the base year values for four countries. Germany is an industry-heavy country, Italy is mostly equivalent proportionally across emissions, GDP, and population; and Luxembourg has a uniquely intense service sector. The Netherlands is selected here as a country because its proportional contributions through emissions, GDP, and population are diverse (the earlier fig. 5.2 shows these distributions graphically). The other countries' downscaling results are shown in appendix B.

There are three main interesting results to point out with the Dutch case, which is somewhat exemplary of the other countries not shown here. Firstly, biomass, hydrogen, oil, solar PV, wind, and to some extent, coal, exhibit similar behaviour between the convergence and linear methods. As already seen, the variable that each approach uses to downscale relative can lead to a wide spread from each other. Secondly, the pathways for energy in the convergence downscaling method for hydro, geothermal, nuclear, and solar thermal (to a lesser extent) technologies are distinctly exponential. Lastly, the GDP and population variables sometimes lead to the same 2100 value using both the linear and convergence algorithms. This effect is seen with the geothermal, hydro, hydrogen, solar PV, solar thermal, and wind energy types. With coal, natural gas, and oil, the final values are close, but the convergence methods are all slightly positively offset. In biomass, the convergence methods are almost double those of the linear method.

The three other unique countries show a wider gamut of results. In many cases (i.e. solar thermal and hydrogen for Italy and Luxembourg, oil, hydrogen, solar PV, natural gas, solar thermal, wind, and nuclear for Germany), the paths that the convergence and linear methods take are similar. The only discrepancies here are due to the actual variable the downscaling is driven by. But in other cases, like coal for Germany, the two methods take opposing directions. Whereas the linear approaches show that coal consumption will increase, the convergence approach shows it halve. Italy's geothermal case also stands out by doubling between 2020 and 2040 to 0.2 EJ before converging roughly linearly to less than 0.05 EJ by 2100, where it matches the linear approach's conclusion. As previously noted, the linear method only shows a rise between 2020 and 2040 and stagnation after. This rapid change in direction is atypical of energy infrastructure investments and likely to be an artifact of the converging method itself.

Why the behaviour between approaches is consistent between some technologies is surprising. It is likely because, in these cases, the countries' growth is actually low (near 0%) and sit within the mean of the other countries' intensities. In other words, its path in fig. 5.6 is near-horizontal.

The criteria used to evaluate the two methods were discussed in their respective sections ahead. Between the criteria, some unique countries were distinctive outliers in general trends that illuminated issues with the downscaling methods. Neither of the approaches implemented here perform well in every category, and both are limited in their representation of geophysical limitations. Both approaches also ignore social or political effects of technological innovation and diffusion, treating regions within a block as homogeneous. Table 5.1 tabulates the findings in the previous section to offer a side-by-side comparison between the methods.



(a) Germany

(b) Italy

(c) Luxembourg

(d) Netherlands

Figure 5.9: Linear and convergence downscaled energy use in France, Italy, Luxembourg, and the Netherlands by resource type. The base year values are shown in the dotted horizontal line. The figure is truncated in the domain from the base year to 2100. Though the linear and convergence approaches agree in some areas, they vary widely in others. Italy's geothermal, biomass, and coal cases stand out, as does Germany's coal, where the linear and convergence methods show opposite trends. Luxembourg shows the methods varying widely. The Netherlands sees more agreement except for hydro and geothermal.

Table 5.1: Comparison of Linear and Convergence Downscaling Methods

Criterion	Linear	Convergence
Replicability		
Ease of implementation	High	Medium
Data forms required	Base year driver values	Base year driver values
		Future projection of drivers
		IAM outputs extrapolated to convergence year
		Scenario narrative
Transparency of implementation	High	Medium
Coherence to Parent Model		
Nature of time series behaviour	Static	Statistical dynamic (exponential growth)
Nature of energy system components (holarchy)	Coupled statically	Loosely coupled
Retains parent model categories	Yes	No
Retains micro-economic decision-making	Yes	Usually, but not always
Treatment of Energy System Features		
Handles geographic limitations	No	No
Handles zero base year use robustly	Yes	No
Handles technologies not commercialized yet	Yes	No

III

Discussion

6

Discussion

Following the results chapter from the linear and convergence statistical downscaling methods, the following chapter will discuss these results, the relevance for both modellers and policymakers alike, and the limitations of this analysis. It addresses the last two sub-research questions:

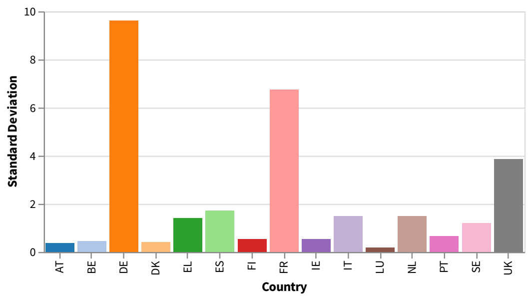
5. How do the outputs from statistically downscaled IAMs differ?
6. How internally consistent are the outputs from statistically downscaled IAMs?

6.1. Linear Downscaling

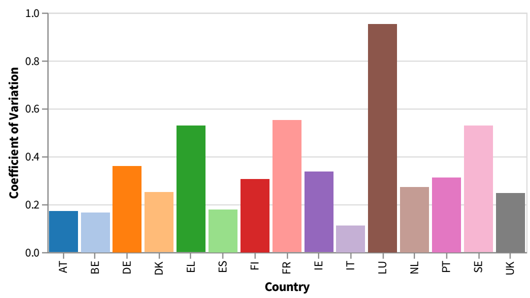
The linear downscaling approach simply scaled the regional GCAM IAM results to three driver attributes from each EU-15 country in 2018: total emissions, GDP, and population. Thus, its results were highly dependent on what these attributes were. In the previously shown fig. 5.2, the difference between individual countries' proportional contributions to the regional values clearly showed that most of the countries varied greatly, so choosing the right variable would be highly important to provide useful downscaling results. France's proportions by emissions were less than 5% to the EU-15 while its GDP and population contributions both exceeded 15%. Luxembourg was the most extreme case with emissions at less than 0.05%, GDP at 0.4%, and population at 0.1%. Italy looked to be the most consistent across metrics with the three metrics at 13, 15, and 12%. Looking at the absolute standard deviation (fig. 6.1a between the driver variables for each country shows one aspect of the absolute range of the dissimilarities. That is to say, the discrepancy between using the three variables to downscale relatively to affect some countries more than others. Germany saw the largest standard deviation with 9.6%, France had 6.8%, and the United Kingdom saw 3.9%. All other countries were below 1.7% with Luxembourg being the lowest at 0.2%. Austria, Belgium, and Denmark both saw only 0.4% standard deviation between the drivers. A federal analyst or policymaker who implemented linear downscaling might be interested in how large portions of the regional output are exchanged between countries based on the metric used, and realize that overall, Germany, France, and the United Kingdom would be very sensitive to the metric.

To look at the importance of choosing a metric for each country, the coefficient of variation fig. 6.1b, or the standard deviation divided by the mean, is a more useful metric because it shows the relative range of differences for each country. This metric is unitless. At a glance, there seem to be five clusters of countries based on the coefficient of variation with values at near 1 (only Luxembourg), around 0.55 (Greece, France, Sweden), around 0.3 (Germany, Finland, Ireland, the Netherlands, Portugal, and the United Kingdom), and between 0.15 and 0.2 (Austria, Belgium, Spain, and Italy). It is not quite clear why these clusters exist, though it could be a coincidence or over-analyzed. Both of these metrics are tabulated in table C.4.

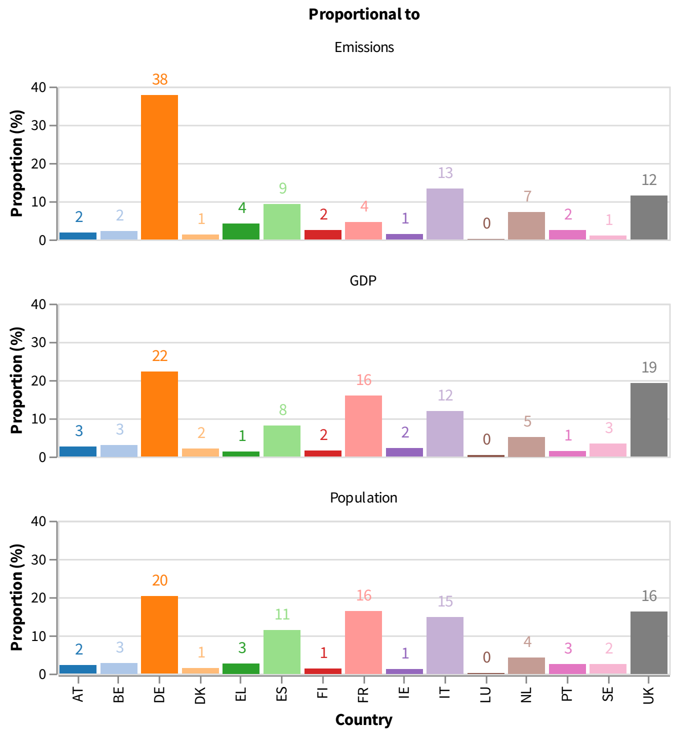
Clearly, linearly downscaling electricity outputs is highly dependent on the metric that is used. If one were to validate linear downscaling, understanding what the metric represents is very important. Figure 6.1c shows an overview of the proportions of each country faceted by the metric used to drive the downscaling. The disparity of how countries are represented via each metric shows that at least one of three metrics chosen here are not useful for downscaling electricity production, and this study does not investigate the validity of the metrics.



(a) Standard deviation between driver metrics



(b) Coefficient of variation between driver metrics



(c) Raw linear proportions per metric per country

Figure 6.1: Linear proportions for EU-15 countries relative to emissions, GDP, and population, including the raw proportions, the standard of deviation and the coefficient of variation for each country between its metrics.

Any metric that is chosen would need to account for the heterogeneity of a region's countries. The energy sector is linked to many sectors and use cases. Germany, being a large, industrial economy (relative to the EU-15) with lots of coal electricity generation sees itself represented more by emissions than GDP or population (though viewed in absolute terms, it is a regional heavyweight in both these regards). Since most of France's electricity system is nuclear, most of its emissions come from heating buildings, transportation, and industry (including agriculture). Its representation in emissions is accordingly low relative to through GDP and population. Luxembourg, being a financial and services hub with lots of hydroelectricity, sees this reflected as well.

A short investigation into the composition of EU-15 countries' GDP by sector illustrates these differences quantitatively. Figure 6.2 shows the Central Intelligence Agency (2017) estimates of the contribution of the agriculture, industry, and services sectors (a full list of values can be found in table C.5). That Luxembourg's coefficient of variation stood out is not surprising. Its economy is around 80% focused in the services sector and has very little agriculture or heavy industry, so such a disparity is reasonable. Ireland's services sector proportion is the lowest in the EU-15 at 60%, but its industry represents 39%, compared to Luxembourg's 13%. Greece's 4.1% agricultural representation is at least almost double that every other country. The Netherlands, Portugal, and Spain see 2.5, 2.2, and 2.6%, respectively. All other nations range between 0.3 to 1.7%.

This approach already shows that the electricity production resource and technology preferences of each nation are not easily quantifiable by using these metrics. Very few regional blocs have homogeneous constituents; each specialize in different industries and have developed in different ways. Arguably, any metric will struggle to capture electricity production preferences, but perhaps one can do so sufficiently.

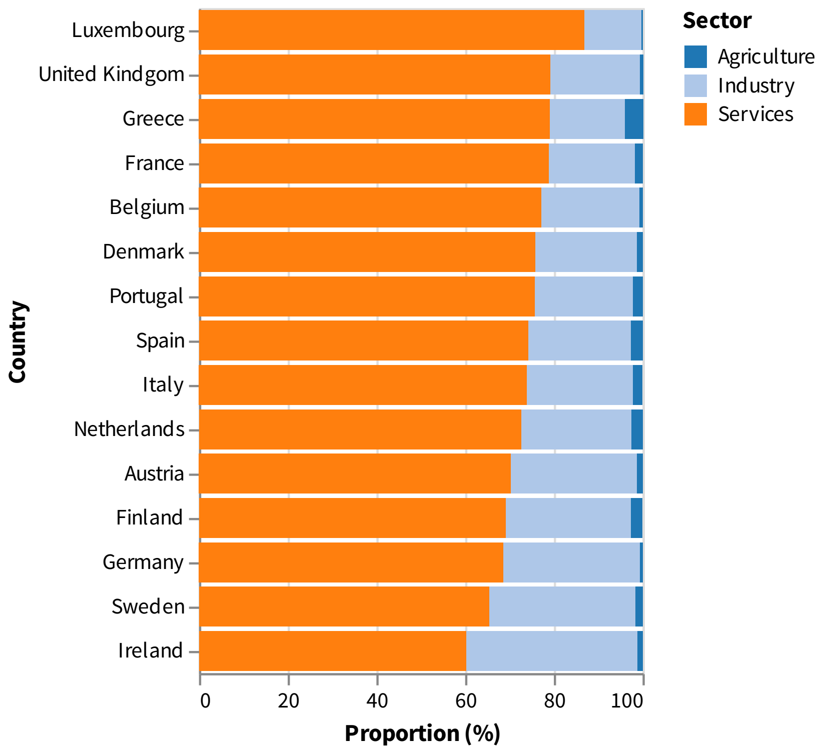


Figure 6.2: Heterogeneous Composition of GDP in EU-15 by Sector (Sorted by Services Sector). Source: Central Intelligence Agency (2017) estimates acquired through Ian Coleman's API at `https://github.com/iancoleman/cia_world_factbook_api`. Note that the composition of the Netherlands is based on 2013 data due to incomplete 2017 data.

In general, where the intent of downscaling is to handle the heterogeneity of constituents within a modelled region, that same heterogeneity limits the usefulness of the linear downscaling approach. As Vuuren, Lucas, *et al.* (2007) noted, the linear downscaling method is only useful where the preferences of the region's constituents can be discriminated. This is a key limitation to the method. Choosing which variable to downscale relative to is a big analytical choice that may not necessarily be consistent between countries; nothing other than tracking energy itself serves as a good analogue. In the ecological economics field, there have been attempts to relate GHG emissions to GDP. Most analyses find a general correlation (D. W. O'Neill *et al.*, 2018; Pollin, 2018), but these are not sufficiently strong links that it could be defensibly be used to downscale for all countries. The other main limitation of the linear method is its static nature, where it the preferences mapped here will stay constant over time. In the short term, preferences could be likely to stay constant, but the very nature of the change within an energy transition means that any initial preferences for technologies becomes outdated.

6.2. Convergence Downscaling

Unlike the linear method, the convergence approach is dynamic across time. The final downscaled values were similar between using the GDP and emissions drivers – nearly indistinguishable except for some special case: geothermal, biomass, and coal electricity production in Italy, coal in Germany, and Luxembourg wide range of results. The convergence approach has two main types of problems: the implementation of dynamics introduces new assumptions that are accompanied by internal consistency issues; and the normalization procedure (eq. (4.6)) that applies the parent model as a boundary condition for the local model distorts the energy transformation pathways.

Aggregation of Resources and Ignoring Technology

Additionally, while the downscaling itself is interesting, the categories it can handle also stand out. The convergence approach needs to aggregate energy sectors by resource type, unlike in the linear method, which means it cannot retain the resource–technology sectors from GCAM. For example, that the decline of second generation nuclear technology is visible in the linear approach is potentially important. While an amateur understanding of nuclear technologies might be able to look at nuclear as a resource and predict similarly, being able to distinguish them directly is an advantage for the linear method. Since GCAM actually also tracks the vintage year and cooling technologies used by each energy plant, the linear method could be used similarly to these attributes. This advantage to the linear downscaling method has not been discussed in the literature reviewed. Whether keeping resources and technologies separated is valuable depends on the users' interests. In the long term, it is likely that there will be technologies that the IAM does not consider, so keeping them separate might only be useful for short-term analyses. GCAM does not include technologies that do not exist. The more relevant problem is that these downscaling methods cannot deal with new technologies very well, though other methods could fare better.

6

Regional Average Intensity

While figs. 6.4a and 6.4c already show the base energy intensities relative to GDP and population, these figures serve better to compare intensities across resource types and countries. They do not show a key part of the convergence method — the actual mix of energy consumption of countries in the base year. Figure 6.3 shows the absolute energy consumption by resource type per country. It clearly highlights that the contemporary energy mix is quite heterogeneous. Germany's biomass, coal, solar PV, and wind electricity utilization stands far apart from other countries with 0.054, 0.563, 0.131, and 0.351 EJ of production in 2018 compared to the others' averages of 0.004, 0.028, 0.014, and 0.055, respectively. No one resource type is used ubiquitously, though natural gas and hydro power are relied on heavily in more than half of the countries. Interestingly, only wind electricity generators exist in every country. While Spain is the heaviest user of oil, it is also the only one with solar thermal power plants, and at half the total electricity output from their oil facilities. Geothermal and biomass are both nascent technologies with widespread adoption only in Italy and Germany, respectively.

The heterogeneity of the countries' initial energy portfolios contests the core concept of the convergence method, which is that the region will become more homogenous over time. If it is already so diverse now, there is no reason that it will ever converge. Homogeneity could perhaps hold for some technologies, but others are less likely. It would be useful to shape the amount or extent of convergence for each country by geographic limits. For most renewable energy resources, there exist estimates to the regional limits of power extraction. Incorporating limits for renewable systems could be more important too in scenarios that lead to more decarbonization, which remains a policy objective of many states. Such estimates could be used to direct the convergence paths or "intermediately complex methods" that could also be used in downscaling.

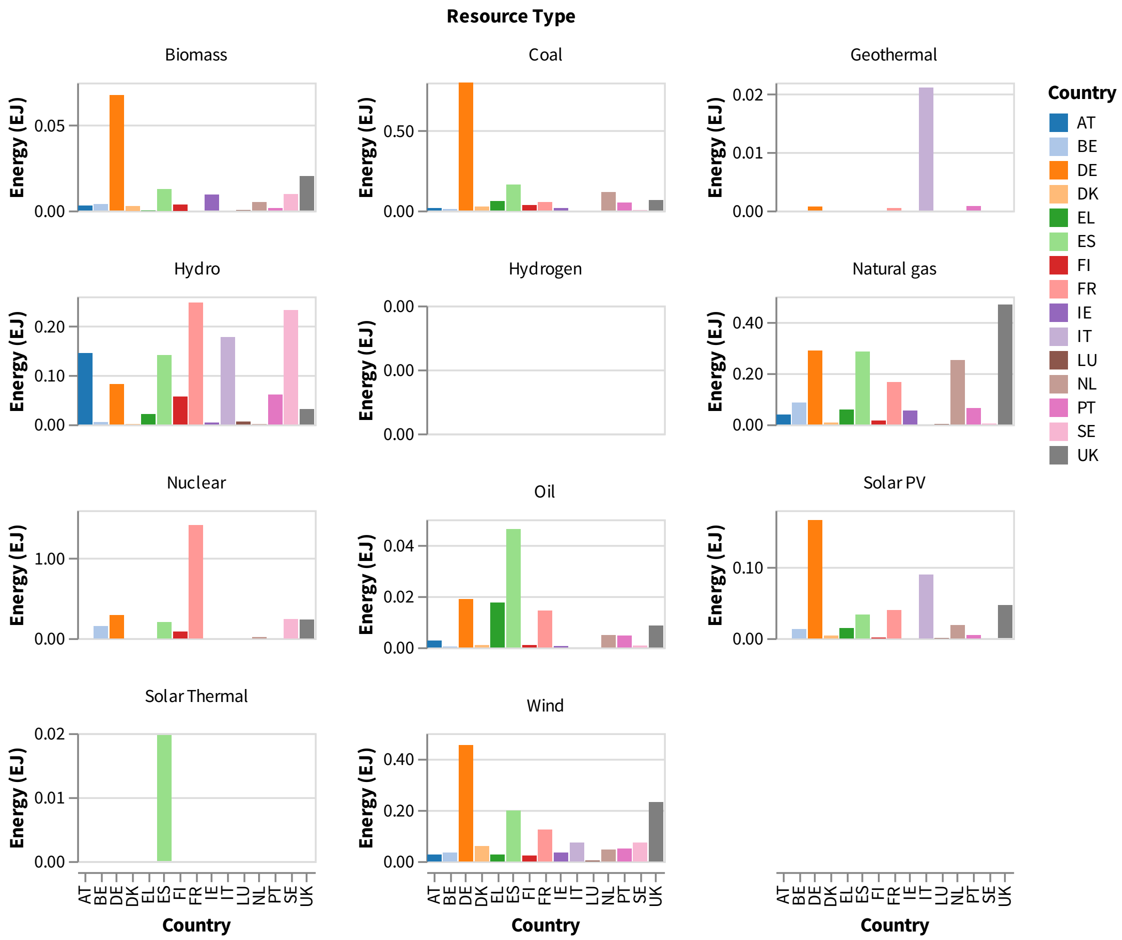
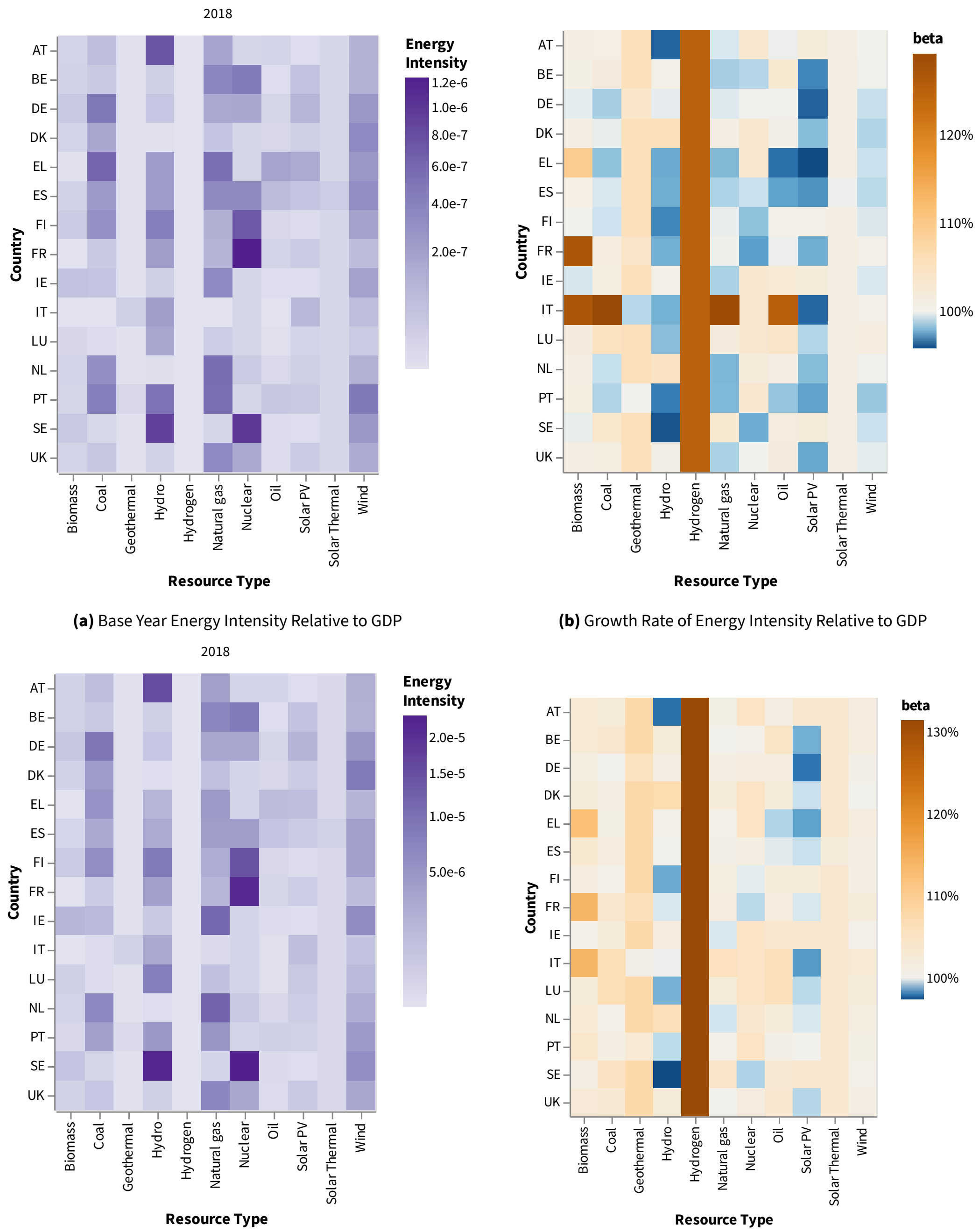


Figure 6.3: Base year energy use by country and resource type. Note that Spain is the only country that uses solar thermal, and Italy one of the only that uses geothermal.

Underlying Scenario Changes Direction of Intensity Change

In Italy’s oil and natural gas production cases, the rate of growth between using the GDP and population as downscaling drivers leads to distinct growth patterns (1.2880 vs. 1.0585 and 1.2523 vs. 1.0613). France’s biomass growth rate also stands out (section 6.2) The difference in trajectories can be explained by the divergent paths the GDP and population in these countries take, whose interim energy intensities took four distinct paths (fig. 5.6).



(a) Base Year Energy Intensity Relative to GDP

(b) Growth Rate of Energy Intensity Relative to GDP

(c) Base Year Energy Intensity Relative to Population

(d) Growth Rate of Energy Intensity Relative to Population

Figure 6.4: Energy intensity in base year and growth rate by country and resource type. Note that Italy and France’s biomass, coal, natural gas, and oil growth rates are much higher with GDP than with population, and that most countries decline in hydro under GDP as a driver but grow when population is used.

The discrepancies between the GDP and population variables used in implementing the convergence

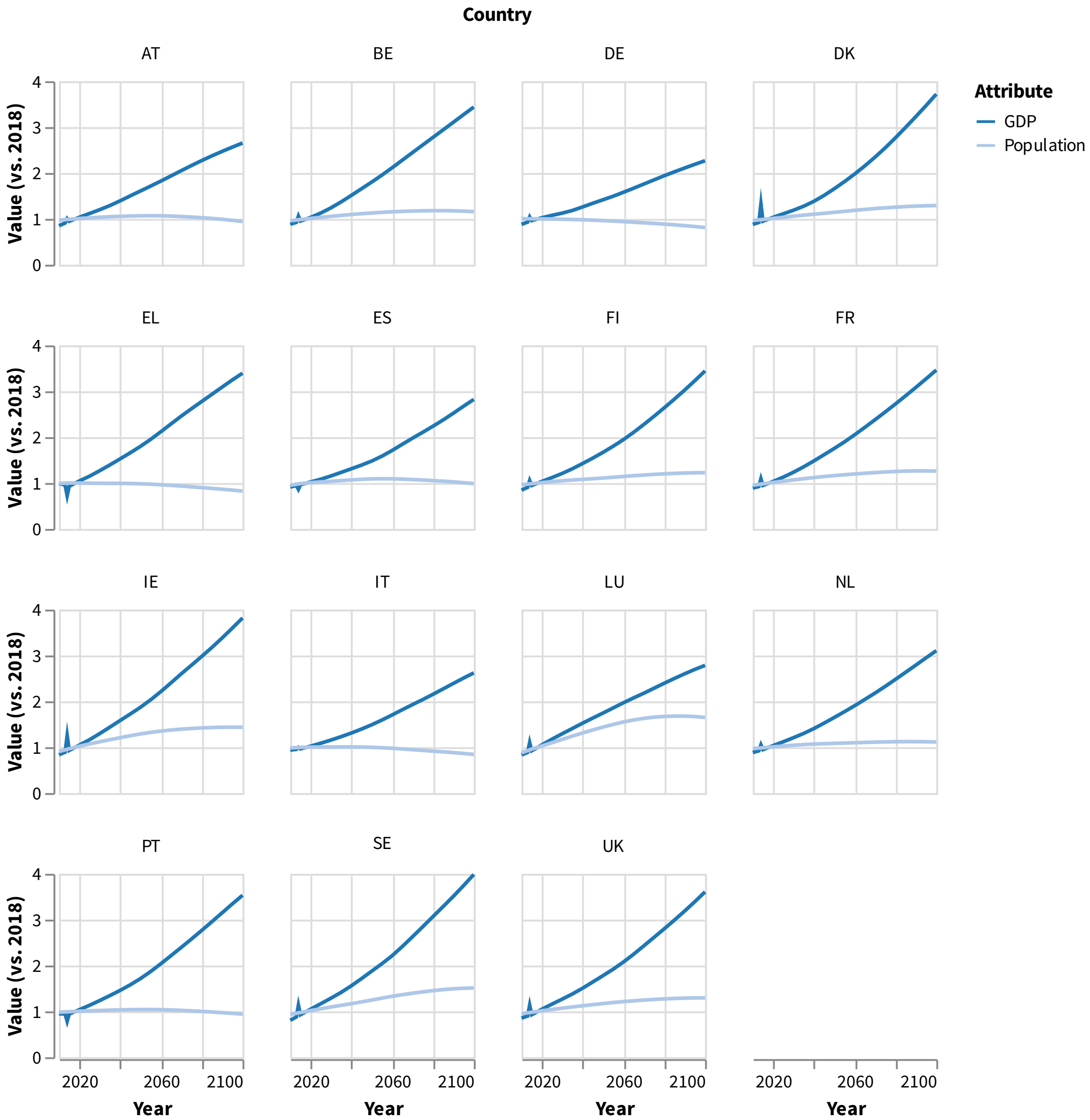


Figure 6.5: OECD/IIASA forecast of GDP and population to 2100 in EU-15 under SSP2 (Dellink *et al.*, 2017; KC and Lutz, 2017).

method might relate to could be understood as the different paths these metrics will take in SSP2. With the global GDP per capita at roughly $11,500 USD (2020), rising to $33,307 means approximately a 200% increase. On the other hand, 9 billion citizens globally means only an 18% rise. In the EU-15, the GDP is expected to grow fourfold, with population seeing a similar change under SSP2 (see fig. 6.5). The resource types that exhibit divergent intensity pathways can be mostly explained by this bifurcation in the denominator. The general decline of solar PV and hydro power can be related back to the regional energy overview in fig. 5.4, where solar PV is mostly stagnant. As GDP and population rise, these resource types' usage intensity will decline. Another explanation for this calculation could be the disproportionate distribution of these intensities. For example, few EU-15 countries actually generate hydroelectricity. Since the base intensities are calculated as a mean, it weighs each country the same by GDP and population whereas the convergence year value is agnostic to this weighting.

The differences between each path are clearly visible in fig. 6.6, which depicts the absolute and relative difference between the GDP and population methods over time for each country and resource type. The relative differences are calculated by dividing the absolute difference by the group sum of both methods over time (see eq. (6.1)).

$$x = \frac{E_{t,g,r,GDP} - E_{t,g,r,Population}}{\sum E_{t,g}} \tag{6.1}$$

where t is time, g is the country, r is the resource type, and the denominator aggregates over GDP and population.

Note that the offset between the approaches is as low as under 0.5% for some countries and up to 4% for Italy in coal, natural gas, and oil. Spain interestingly starts with a negative offset in wind, nuclear, hydro, biomass, coal, natural gas, and solar PV, before moving into a positive offset. A takeaway is that countries are again heterogeneous, and whichever population and GDP growth scenarios are picked greatly influence the relative paths taken. Due to the development of SSPs, the analysis here can claim to be internally consistent, but it is important to note that SSPs are *narratives* that must be interpreted in each model. GCAM's developers and the OECD team (Dellink *et al.*, 2017) who projected GDP and population operate at different resolutions and could have read and implemented SSP2 differently.

However, the absolute differences in this case are less alarming — for some countries and technologies. In fig. 5.9d, both the convergence methods, though offset from each other, eventually converge close to the linear GDP (and sometimes, population) method. In fig. 5.9, the results for Germany, Italy, and Luxembourg are shown. Italy's convergence and GDP approaches vary wildly in biomass, coal, natural gas, and oil. This was already seen above through the relative differences, but are more salient viewed here. Interestingly, these discrepancies were negligible in its geothermal and solar PV case, the latter of which also tracked the linear outputs well. The wide span of the convergence results here are worrying, but it is interesting to note that they only occurred in some technologies and only those where it started from zero. One explanation could be that filling in zeros with a "small" number to determine the base intensity in eq. (4.2) can distort the growth rate calculation (eq. (4.3)).

Indeed, if the denominator is smaller than the numerator (every case here), the right-hand side limit of this inversely exponential calculation as the denominator approaches 0 is infinity. Recall that $t_f > t_i$ (so $\frac{1}{t_f - t_i} > 0$) in this calculation and $I_{R,t_f} > 0$.

$$\lim_{I_{c,t_i} \to 0^+} \frac{I_{R,t_f}}{I_{c,t_i}}^{\frac{1}{t_f - t_i}} = \infty$$

Growth

The method implemented here used the exponential function to characterize the growth of technologies in each region over time. However, there are other mechanisms that could be implemented instead. Vuuren, S. J. Smith, *et al.* (2010) describe how methods of intermediate complexity, like using cellular automata, to

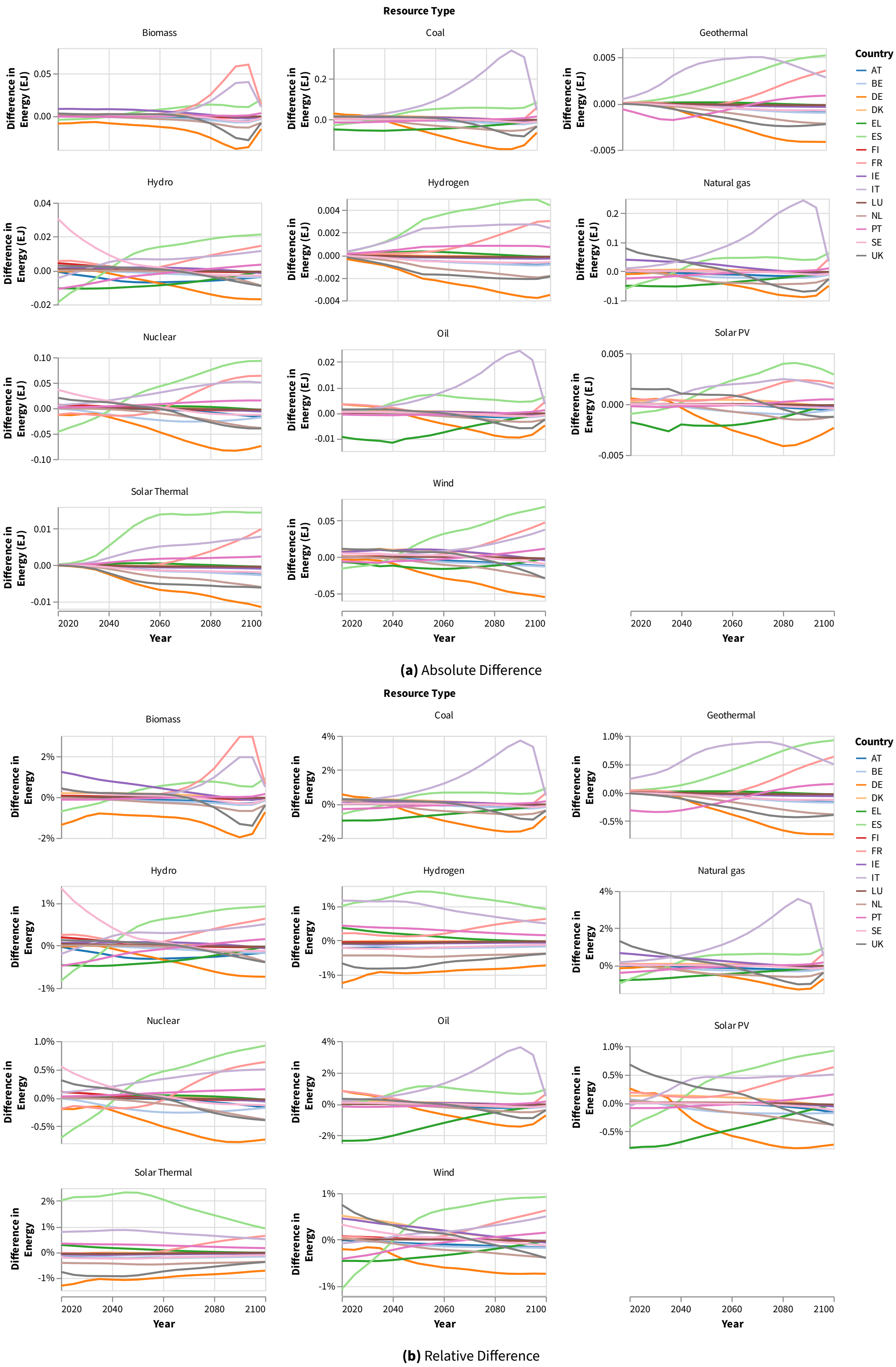


Figure 6.6: Difference in Energy Use between GDP and Population Convergence Downscaling Methods by Resource Type for EU-15 Countries

represent how population distributions may change over time. Ahn *et al.* (2019) extrapolate from trends in energy demand intensity changes over time using a log-linear method rather than using the IAM's outputs, though they still normalize to the IAM's output. Perhaps more defined meta-models of innovation and technological diffusion could also be used in this process, though they would add the complexity of the downscaling approach and sacrifice transparency. Changing IAMs structures could enable downscaling methods to couple to their decision structures. If IAMs were explicit about the types of electricity production facilities implemented down to a discrete facility level, then downscaling directly could disperse these facilities to various countries either statistically or through algorithms, like one based on technological diffusion theories. In the absence of these explicit declarations, downscaling could replicate a similar approach using typical facility sizes and technological adoption data. If implemented in accordance with factors like electricity prices from the IAM, and with the IAM as a boundary condition, this approach could remain fully coupled to the parent model and retain micro-economic decision processes, an improvement over all of the methods inspected here. Any of these approaches could be similarly fragile to the convergence method in some special cases, but warrant further exploration.

Resource Potentials

This analysis, as one of the first of its kind, relied on some methodological design to fill in gaps where others have not already published on the matter. Consequently, the implementation is only a first iteration of what could be possible. An obvious way to improve the convergence method is to implement resource potential estimates as boundaries, such as those provided for European countries in Enevoldsen *et al.* (2019). The same could be done with the linear method so that, for example, downscaling will not introduce massive hydroelectricity production to the Netherlands, where it is physically impossible. An issue with this approach is that there are inconsistencies with how research potential is calculated, including second order effects (i.e. crowding due to spacing design). An argument could be made that fuels without geographic limitations might also have other types of barriers, like economic, social, or political (e.g. nuclear fuel). While the future is uncertain and these conditions could change, the types of barriers that could be implemented are boundless. One core criticism of using IAMs is that their modelling characteristics and scenarios, while scientifically useful, have limited use in supporting policymaking (Donges *et al.*, 2018; Pielke and Ritchie, 2020). This criticism would not be resolved in this approach and could perhaps emphasize these limitations.

Convergence Date

The choice of convergence date can accelerate or decelerate the convergence outputs' paths. In other implementations of the convergence downscaling approach, the convergence year is dynamic based on the scenario. Gidden *et al.* (2019) used 2125 for SSP1 and SSP5, 2150 for SSP2, and 2200 for SSP3 and SSP4. By setting dates in the future beyond the end of the parent model's simulation year, the values must be further extrapolated, which in some ways defeats the purpose of the model. In their work, Gidden *et al.*linearly extrapolated the results from the last decade of model runs. Most of the models they used were like (and include) GCAM, which runs between 1975 (for calibration) and 2100, a span of 125 years. By 2150 as a convergence date, the values would be extrapolated for 40% of the time that the model itself actually ran. It could be better to just run the parent model to that future time instead. But the more a model is run in the future, the more deep uncertainties will take over. However, it could be more internally consistent to run the model for the future period instead of a linear extrapolation. In this work, neither approach was done as they do not significantly add to the analysis. The shape of the result would be the same regardless of the convergence date, and seeing the actual convergence of results is analytically useful.

Normalization Distortion

Lastly, Italy's geothermal case is a unique — the growth rate that the convergence method calculates only results in one value that should either lead to growth or degrowth. Yet, it first grows and then degrows. The main reason for this is that only four countries use geothermal energy in the base year, and Italy dwarfs the other nations; it is essentially the only country with any geothermal at all. Recall that eq. (4.6) normalizes the interim energy outputs for each country by the parent model (fig. 5.4). Geothermal energy rises sharply between 2015 and 2040 in GCAM and is then stagnant. Figure 5.6 shows that each country's intensities start low and eventually meet Italy's. This means that before 2040, the normalization effect amplifies Italy's downscaled value. After 2040, since the regional value no longer grows and other countries catch up, Italy's normalized value decreases. Solar thermal does not suffer from this issue since it continuously rises. This algorithm is ruthlessly tone-deaf to the economic effects that the GCAM model actually includes —there is no consideration of lock-in or capital cost recovery from implemented technologies. In the context of other technologies, this approach seems to work sufficiently well – even for hydrogen, which is a technology that does not exist yet. That this artifact only arises for technologies that stagnate means the method could be useful overall, but there are likely many scenarios were specific technologies plateau. A systemic exploration of results could identify this type of error, but it reduces the credibility of the approach in general.

6.3. Comparison to Other Downscaling Methods

This work implemented the linear and convergence downscaling methods in the energy domain. There are only two other examples of similar downscaling in the literature, where an iterative proportional fitting (IPF) method replaced the normalization process in this work (Ahn *et al.*, 2019), and a coupled regional meta-model (Sferra *et al.*, 2019). Both approaches examined aggregate energy demand by country, not electricity production. Some aspects are directly comparable across these two measures, but others are unclear. The meta-model, SIAMESE, is proprietary to Climate Analytics and not available open-source for analysis. Still, these works can be assessed under the same criteria introduced here.

The IPF approach is similarly complex and transparent as the convergence method. It requires the same data as in convergence, except it extrapolates energy intensity based on historical trends rather than extrapolating IAM outputs to a convergence year and then calculating that intensity. However, it does require local information about the types of resource technologies that are used, which was difficult to obtain in the electricity production case but available for energy demand. In terms of its behaviour over time, IPF remains a statistical approach, which means it similarly decouples from the parent IAM, but still uses it as a boundary. The fitting aspect replaces the IAM's micro-economic considerations, but it is unknown how the fitting might perform in regions other the South Korean cities and provinces covered in their work. Additional data could be available to keep technologies separated though. IPF likely needs to aggregate technologies based on resource types because it relies on historical data, like the convergence approach.

Overall, the IPF method performs better than the convergence approach in treating energy system features. IPF method handles the consistency issues that the convergence could not. The convergence normalization process created a major issue with geothermal use in Italy, while the IPF approach normalizes by both the proportion of a resource's use relative to a region and to all energy types. The latter aspect should be able to mitigate the issue seen with the convergence approach. It may also be able to detail to deal with technologies that do not exist yet, as long as the IAM can introduce those technologies. The IPF procedure treats growth by iteratively adjusted its technological allocations across sectors and local regions rather than relying on calculating a growth rate, so it avoids the "small number" issue described above. However, it is likely that it cannot robustly allocate new technologies, and to local regions that do not use them yet in the base year. Just like with the convergence approach, it would require some additional mechanism to introduce these technologies non-homogeneously, if doing so is deemed important. Otherwise, it may need to rely on integrating aspects of the linear downscaling approach. The iteration aspect of the procedure could possibly deal with geographic limitations, since it checks if the fitting matches the historical representation of energy resources in each local region relative to the others. Where this approach may fail is where one geographically limited country uses a little of a resource type and no or few other countries do because of political, economic, or social factors, so the country in question is represented well proportionally and is thus allocated more of the resource in the future.

Since the Sferra *et al.* regional meta-model is not available publicly, evaluating it is difficult. However, this approach is common in other downscaling domains, so this class of downscaling methods can still be assessed and will be referred to as "multi-modelling", since it attaches another model to the IAM.

Like all modelling approaches, it becomes harder to implement than a few statistical calculations. In their article, the authors described only three data sources needed for input: IAM outputs, base year data of the driver(s), and projections of those values in the future. They do not discuss data that are needed to construct the model. (Meta-)Modelling can range widely in complexity, and could require historical technological trends like in the IPF method or data that inform technological innovation or diffusion, like more specific population distributions or innovation metrics. For example, the regional model in Sferra *et al.* (2019) does not currently include energy trade between regions, which is important to assessing the actual location of energy consumption. If the authors implement this component, they will possibly need to incorporate data on the mechanisms for trade, like the capacity of energy transmission infrastructure. The transparency of the implementation is unique to each case. The SIAMESE model is likely not open-source because it may be used for commercial consulting – all of the authors in the publication are associated with Climate Analytics, private firm, in addition to some academic postings.

Modelling allows the time series of outputs to become fully dynamic, though the energy system will be decoupled from the IAM, like in the convergence and IPF methods. The IAM is likely to continue to be as a boundary; Sferra *et al.* do so. Micro-economic decisions are most likely replicated separately by the second model, but could be linked more directly to the IAM. Again, since it relies on historical data, it likely needs to aggregate technologies based on resource types. It is possible that additional data can be used to keep these aspects disentangled. Considering geographic limitations should be an integral part of specifying any regional model, unless a general model is made to be used in various regions. Generalizing the approach could be desirable and even necessary in the upscaling paradigm. For local regions that do not use a resource in the base year, the model could potentially include technology diffusion and adoption dynamics. Lastly, how the regional model handles technologies that do not exist yet depends again on how it implements diffusion of technology. It is likely that anyone who decides to use a model to perform downscaling will be interested in incorporating these components. Otherwise, the additional complexity of modelling is unnecessary.

Overall, none of these approaches distinctly stands out from others. Each have their benefits over others, and choosing between the options requires making preference judgements about their trade-offs. In general, both of the implemented approaches are somewhat transparent, as is the IPF method. Compared to multi-modelling, they can be implemented easily with few additional sets of data required. Yet, these attributes are difficult to describe. Complexity and effort also depend on the skill of the user, the specific tools they are using, the available data, and the scope of their study (e.g. one country or multiple?). The EU-15 electricity case has been straightforward, but the availability of data will likely plague the implementability of the convergence method in many use cases. Here, it may be tempting to just use the linear approach, but it should not be chosen because it is the only option without care. While the convergence approach ignores some micro-economic effects, the linear approach similarly overlooks geographical or regulatory environment and contexts. Intermediately complex methods not explored here could offer better representations of energy transition components, but more work needs to be done to understand how they might fit in the energy domain. An overview all of these approaches is tabulated in table 6.1.

Table 6.1: Comparison of Linear, Convergence, and Other Downscaling Methods

Criterion	**Linear**	**Convergence**	**Iterative Proportional Fitting** (Ahn *et al.*, 2019)	**Multi-Modelling** (e.g. Sferra *et al.* (2019))
Replicability				
Ease of implementation	High	Medium	Medium-Low	Low
Data forms required	Base year driver values	Base year driver values	Base year driver values	Base year driver values
		Future projection of drivers	Future projection of drivers	Future projection of drivers
		Extrapolate IAM to convergence year	Future projection of energy intensity	Scenario narrative
		Scenario narrative	Scenario narrative	More, depending on scope
Transparency of implementation	High	Medium	Medium	Low
Coherence to Parent Model				
Nature of time series behaviour	Static	Statistical dynamic (exponential growth)	Statistical dynamic (IPF)	Dynamic
Nature of energy system components (holarchy)	Coupled statically	Loosely coupled	Loosely coupled	Loosely coupled
Retains parent model categories	Yes	No (depends on base data; unlikely)	No (depends on base data; unlikely)	No (depends on base data; unlikely)
Retains micro-economic decision-making	Yes	Usually, but not always	Unknown	Possibly
Treatment of Energy System Features				
Handles geographic limitations	With modifications	With modifications	Yes, but perhaps not robustly	Part of model specification
Handles zero base year use robustly	Yes	With additional methods	With additional methods	Possibly
Handles technologies not commercialized yet	Yes	With additional methods	With additional methods	Yes

Historical Preferences May Not Hold

The convergence discussion covered the issue of growth patterns, and how other methods can fill in these gaps. Unfortunately, many of them suffer from a similar issue: basing future forecasts to historical preferences assumes that people and systems will not change their behaviours over time. Doing so is akin to calibrating a model of open (e.g. social) systems against historical performance, which does not guarantee it will perform well in the future (Oreskes *et al.*, 1994). The Ahn *et al.* (2019) Iterative Proportional Fit approach weighted downscaled results by historical preferences for each sector, which is similar to the weighting by energy approach implemented in this work, though to a more detailed extent. In the absence of further knowledge, analysts must assume the distribution of preferences is static even in other approaches. Adding further complexities like urbanization trends through methods of intermediate complexity (e.g. cellular automata) could make these preferences dynamic, but would reduce the transparency of downscaling. Similar to how Mearns *et al.* (1999) found that statistical methods perform worse when a parent model's behaviour is atypical of historical behaviour, this work shows the limitations of applying these downscaling methods to the future.

Disentangling CCS from Energy Could Support Sectoral Downscaling

The convergence downscaling method relies in eq. (4.3) on pairing current energy usage data with that within GCAM for 2100 (or a further date). However, the energy categories between these two datasets likely mismatch. In this case, GCAM distinguishes electricity production by both resource type and technology (in some cases). GCAM lists both second and third generation nuclear reactors, various thermodynamic cycles used with natural gas, and recognizes if CCS technology is built in or not. The Eurostat database for electricity production was used to set the base year values, but this dataset only distinguishes by resource type as noted in section 4.2.3. The reasons that this data might be aggregated could be to protect facilities' and overall market competitiveness. The GCAM data must therefore be aggregated by resource type to perform this calculation, thereby limiting the convergence method to only downscaling fuel use. Under such a limitation, users lose sight of another layer of detail. Whereas old technologies like second generation nuclear power plants might phase out and third generation ones are rehabilitated, the convergence method cannot allow such forms of insight. Similarly, if modellers want to see how the coal sector might adopt CCS technologies, the convergence method obfuscates this detail. GCAM's ability to endogenously solve for when CCS becomes commercially viable is an important outcome.

While the resource type obfuscation is unlikely to be resolved, the CCS one can be teased out. Whether CCS technologies become commercially viable in a coal or natural gas facility is mostly related to the cost of the entire process itself. Since both these types of facilities operate through combustion, the actual CO_2capture mechanism is largely the same — it would most likely be scrubbed from the exhaust (flue) gas stream. This approach is distinct from the other developing technology, which is direct air capture CCS. The relative concentration of CO_2in the flue gas can be around 6–15%(Rahaman *et al.*, 2011), which is much higher than the 0.042% found in atmospheric air. Therefore, tracking CCS as a separate component from the energy categories should be possible. Even if the economic decision to include CCS needs to be coupled to industrial and electricity facilities, it can be done so in parallel. GCAM's maintainers and other modellers can support the downscaling process by doing so.

6.4. Limitations

The main limitation of this work was that, as a novel exploratory approach, various methods were identified in the course of research to modify and improve the selected downscaling methods and not implemented. Consequently, some of the results say criteria can be met "with modifications". If implemented, the methods may have been evaluated differently than noted here and expand the usefulness of the results. Still, most of the criteria were addressed, and those listed as "with modifications" still show useful insight into trade-offs between the methods.

Likewise, the iterative proportional fitting and multi-modelling methods were not implemented for the same EU-15 region here, which would have created a common base to evaluate these methods. The analysis was only run for the EU-15 region, whereas two publications it compares to are focused strictly on Finland (Sferra *et al.*, 2019) and South Korea (Ahn *et al.*, 2019). In reviewing their work, it was not possible to determine how well the latter case could deal with the geographic limitations of different local regions when downscaling to their level. However, performing this analysis for a wider range of countries may not be necessary, since the results from the other regions were still sufficiently clear to generalize and compare with this study's results.

Basing the analysis only on one IAM also limits the extent of this analysis. Since downscaling is a top-down analytical approach where the IAM is used a boundary for all other parameters, it largely shapes the results from downscaling. Every IAM models interactions in the world differently, so any conclusions about downscaling might be sensitive to the IAM used. Those with more explicit components could perhaps be downscaled more easily, and those that are more implicit might render some of the results in this work to be inaccurate. For example, if an IAM treats all renewable electricity sources as a whole because they have historically produced almost negligible amount of electricity, then it would be difficult to disentangle different renewable energy sources. Especially since resource potentials in different locations differ, the downscaling itself may lose its ability to reasonably incorporate geographic limits. Most IAMs used for scientific analysis are not limited this way though.

A third notable limitation is that it did not consult with actual policymakers to validate the assumptions in this work, especially the criteria used to assess the methods. Instead, what was deemed relevant for supporting energy transition policymaking is limited to the author's experience and interpretation of issues. Similarly, though this work was concerned about the usefulness of downscaling for supporting model-based decision-making, it did not analyze any specific policies, and thus remains somewhat speculative of what information energy transition policymakers are actually looking for. An alternative approach could have been to simulate a few different scenarios from GCAM and run a policy search for each region, like sensitivity analysis based on a carbon tax (as implemented by (Kriegler *et al.*, 2015)), or through a Scenario Discovery process (Bryant and Lempert, 2010). The distribution of the resultant policies could then be used to explicitly show a spread in policy recommendations. Such an approach might not be generalizable to more forms of policies, but that is an issue with the scope of IAMs. The criteria developed here are quite broad, but the investigation in this work was sufficient to provide insight for every criterion.

As described in the convergence section, the convergence date in this work was set to 2100 instead of 2150, which Gidden *et al.* (2019) used in their work. Using 2150 as the convergence date would have required extrapolating the GCAM outputs to the future, which adds an additional layer of complexity to the approach, especially since the additional 50 years would have been 40% of the modelled period. The actual date of convergence will not affect the key insights seen here as much. In fact, they could hide some of the issues, like how normalization amplifies Italy's geothermal consumption before quickly then dropping it. In some cases, these artifacts could be seen to mitigate other forms of assumptions. The sensitivity of downscaling results could be explored further in the future.

Another limitation to this study is that it does not examine the applicability of the investigated downscaling methods to other energy system considerations and in other regions. Obviously, this can only be understood through deductive analysis; data that would be necessary for other considerations like final energy consumption is available and interoperable with GCAM's view of the world (i.e. its categories), so future work should be able to easily apply the same methodology to demand. By focusing on energy demand, this research would have been consistent with other literature, but would not have explored the application of downscaling to energy production, which is novel and interesting. Doing so could have provided a stronger link to the GDP and population downscaling drivers. However, the point was not to validate metrics, but rather to verify that it can represent areas at a higher resolution and validate the suitability of such an approach. The heterogeneity of countries and deep uncertainties about the future may still remain in such a case, especially as some resource types are phased out in some scenarios. Future work could expand the insights from this work to other contexts important for understanding the energy transition. Downscaling can be used with regional models to a municipal or even neighbourhood level, not just IAMs.

Lastly, Child and Breyer (2017) argue that the term transformation should be used instead in this case, reserving transition for sociotechnical considerations too. The word transition has been used in this work to describe mostly technical aspects. In this sense, I apologize for adding to confusion.

IV

Conclusion

7

Conclusion

This work has so far focused on three major elements: 1) reviewing how integrated assessment models fit within climate policymaking, and how downscaling can be relevant to supporting policymaking, 2) how integrated assessment models might be downscaled to support energy transition policymaking, including specific methods to do so and criteria to measure how useful they are, and 3) an analysis and discussion of the results of employing two of these downscaling methods, including the limitations to the work. This chapter will close the dissertation by reviewing how the research questions have been addressed and offer a reflection of the work, including its relevance for analysts and policymakers.

7.1. Main Conclusion

To contextualize the main conclusion, this section will first review how this work addressed the sub-research questions in section 2.1.

What downscaling methods are used with integrated assessment models to support climate policymaking? The climate and emissions outputs of integrated assessment models (IAM) have been downscaled extensively in the literature. In the case of climate outputs, spatially-explicit data has been important for researchers seeking to understand the impacts of climate change on water stress, drought, and flood risks throughout the world. The emissions sector has been downscaled for reasons similar to the goal here for energy – sub-national level policymakers wish to understand how global climate policy scenarios relate to their own region's economies, since emissions are highly correlated to economic activity. National or federal policymakers also want to know about the distribution of impacts within their conglomerate.

Previous literature has identified four families of downscaling methods: statistical, methods of intermediate complexity, fully elaborated (i.e. standalone and loosely coupled) models at a high-resolution, and models at a medium level of resolution fully coupled to the IAM. In reviewing the differences between these categories and their sub-methods, and the nature of each one's approach, this work created a typology for these models based on two axes: whether they use statistical algorithms or model-based approaches, and if the approaches treat components' behaviour over time statically or dynamically. Two statistical methods are used commonly: the linear and convergence methods. The linear approach statically allocates a region's IAM outputs to the constituents based on a proxy value, like each constituent's historical contribution of greenhouse gas emissions, GDP, or population to the region. The convergence approach is dynamic by interpolating (de)growth, usually with an exponential function, in an attribute's intensity between a base year and a final year. Intermediately complex methods combine statistical outputs with simple models, like using cellular automata to represent urbanization, so are still considered "statistical". A specific approach to downscaling energy demand was to replace the growth aspect of the convergence approach uses Iterative Proportional Fitting, a statistical regression method, that shows promise. Table 7.1 shows these categorizations in a table.

Table 7.1: Taxonomy of Downscaling Methods

Method Family	Temporal Treatment	
	Static	Dynamic
Statistical	Linear	Convergence Iterative Proportional Fitting Intermediately Complex Methods
Multi-model	–	Coupled-models

How can downscaling be applied to the energy sector in integrated assessment models? Two main methods were selected for further study, since the others have already been implemented in the literature for two specific cases – the results of which are also compared to the two in this study, and more complex approaches build upon the two used here. This thesis explored the linear and convergence statistical downscaling methods. Both methods have been applied to downscale IAMs' emissions outputs to a country-level. The linear approach assumes that some technological bias that exists in the base year will continue into the future. This bias in the literature has mostly revolved around population distributions across nations, but this work also implemented the approach using current GDP and emissions. On the other hand, the convergence approach assumes that the existing mixes of proportions will eventually converge at some future point to the regional average given by the parent IAM. Due to the limitations of existing base year data, this work focused on downscaling electricity sector resource use the GCAM IAM for the EU-15. However, it can be generalized to energy production or demand, so long as there is historical data at a local level that is sufficiently compatible with the IAM. The GCAM model was selected as a parent IAM because of its availability and accessibility as a documented open source nature, prevalence in the climate science literature, and its relatively high-resolution of geospatial outputs – in land use areas, it is spatially explicit down to a 0.5° resolution.

What are key criteria to evaluate the IAM downscaling methods in the energy transition? A literature review of downscaling methods only revealed brief discussions of how each family of downscaling method is often used and why. However, there is not a comprehensive examination of how methods would perform if they were applied to different areas, and there is no discussion with regards to energy. Therefore, three classes of criteria were determined from this review and of how energy is implemented in IAMs: replicability, coherence to the parent model (the IAM), and how they handle energy-specific insights. The first category deals with the pragmatic usefulness of the approach — it needs to be transparent, easy to implement, and have similarly easy-to-access data dependencies. Coherence to the parent model regards internal consistency of the model components between the downscaled results; a lack thereof limits the usefulness of the approach because the modelling scope boundaries becomes violated. The third category is related to how energy transition models need to be able to examine three key elements to be useful to support actual energy policymaking. Firstly, they need to be able to deal with the heterogeneous allocation of energy resources throughout nations and sub-national districts. Secondly, they should be able to robustly and consistently deal with technologies that a country does not use in the base year. Lastly, methods need to be able to provide insight into how technologies that do not exist yet will become introduced to the downscaled regions over time.

How do the outputs from statistically downscaled IAMs differ? *and* How internally consistent are the outputs from statistically downscaled IAMs? Using the criteria used to synthesize from quantitative (descriptive statistical) and qualitative methods (internal consistency checks), the two downscaling methods investigated directly in this study were evaluated and compared to each other. An evaluation was also performed for a multi-model downscaling method used in the literature. In brief, both downscaling approaches saw statistical differences vary widely for some countries and energy resource types between the different variables used to perform the downscaling. Neither approach was completely internally consistent, though the linear approach's assumptions are easy to understand and communicate. The convergence method implemented here struggled with internal consistency and in many areas forced an assumption on the system that not only neglects, but also displaces, the parent model's set of assumptions. Doing so is not always a problem *per se*, but limits the scientific consistency in this method to be actually deployed en masse for policy support.

Both downscaling approaches are algorithmic and somewhat simple to implement, though the linear approach is significantly easier than the convergence. The latter requires future projections for the denominator variable in its intensity calculation, the scenario narrative that drives that projection, and possibly needs to extrapolate the parent model to the future. The date of convergence could be farther in the future than either the model calculates or the analyst's period of interest. In choosing the method to extrapolate to this future point, the analyst must choose between forms, which introduces bias and uncertainty. Similarly, the path of convergence must also be chosen. Here, I used an exponential growth model, but it could also be more or less complex. These additional choices make the convergence approach less transparent than the linear. Where the linear approach takes a static proportion, the convergence one is dynamic over time – coupled to the chosen growth algorithm. Both algorithms in this study are overly simplistic in that they assume the regions are or will become homogeneous. Similarly, while the linear algorithm follows the constituent components of the parent model blindly (it is perfectly coupled), the convergence approach is agnostic towards it (it is loosely coupled). For example, while it normalizes its net energy at each time step to the parent model's value, this approach does not consider whether the normalization makes sense or not. This blind view of the parent model is particularly obvious when I downscaled geothermal energy use for Italy. The normalization procedure doubled Italy's geothermal energy production amount from around 0.1 EJ per year to 0.25 between 2020 and 2040, but then linearly drops it down to less than 0.5 EJ by 2100. It is highly unlikely that Italy would grow its geothermal sector so rapidly and then have it decline so similarly soon. This step holds no consideration for the technical and economic mechanisms, including lock-in, that underlie the parent model and could be included in multi-model downscaling.

Another drawback of the convergence approach is that it needs to match country-level base year data with regional-level future data from the parent model. Matching means that the categories of data must also match. Where the GCAM model distinguished energy by resources and technology, the base electricity data only reports by resource. As such, while the linear downscaling approach showed that second generation nuclear reactors would phase out by 2040, the convergence approach did not. Both methods were unable to cope with geographic limitations that form current technological biases. For example, both approaches assume that the Netherlands will eventually develop hydro power stations and that Sweden will have solar thermal power stations. Manipulating the convergence algorithm with conditional statements could mitigate this class of issue. The same could be done with linear algorithms, though it would then need to perform the same normalization step that the convergence does. While the linear method at least consistently handles countries that do not generate any electricity using a certain resource in the base year. The convergence approach requires these initial zero values to be set to a small number, like 1×10^{-16} in this case, to calculate a non-zero growth rate. Unfortunately, the growth rate is sensitive to the choice of the small number, so its application is problematic. In the future, a general premise could be to set this small number proportional to the smallest type of facility that could be built to use the relevant energy resource. Similarly, the linear method can handle technologies that do not exist yet and are introduced during the course of the parent model simulation. The convergence case, being so reliant on a base year, cannot deal with this. One modification can be to change the base year to that future date, based on the parent model, though this was not implemented in this study. Even if this is done, this approach would still leave a trivial case for downscaling: it is very difficult to determine the prior preference in a country a technology that does not already exist quantitatively.

Table 7.2: Comparison of Linear, Convergence, and Other Downscaling Methods Reviewed but Not Implemented

Criterion	**Linear**	**Convergence**	*Iterative Proportional Fitting* (Ahn *et al.*, 2019)*	*Regional Meta-Model* (e.g. Sferra *et al.* (2019))*
Replicability				
Ease of implementation	High	Medium	Medium-Low	Low
Data forms required	Base year driver values	Base year driver values	Base year driver values	Base year driver values
		Projection of drivers	Projection of drivers	Projection of drivers
		Extrapolated IAM outputs	Projections of energy intensity	Scenario narrative
		Scenario narrative	Scenario narrative	More, depending on scope
Transparency	High	Medium	Medium	Low
Coherence to Parent Model				
Time series behaviour	Static	Statistical dynamic	Statistical dynamic	Dynamic
Energy system components	Coupled statically	Loosely coupled	Loosely coupled	Loosely coupled
Aligned energy resource categories	Yes	No	No	No
Retains micro-economic decision-making	Yes	Usually, but not always	Unknown	Possibly
Treatment of Energy System Features				
Handles geographic limitations	With modifications	With modifications	Yes, but perhaps not robustly	Part of model specification
Handles zero base year use robustly	Yes	With additional methods	With additional methods	Possibly
Handles technologies not commercialized yet	Yes	With additional methods	With additional methods	Yes

*Note that the iterative proportional fit and multi-modelling methods were not implemented in this study, but were derived from a review of their work to downscale energy demand for South Korean and Finland, respectively. Moreover, while the Sferra *et al.* (2019) work used a loosely coupled regional meta-model, its descriptions for each criterion are combined with other multi-modelling techniques used in other domains.

7.2. Answering the Research Question

The main research question of this research was, "*What are the limitations and trade-offs between statistical downscaling methods used with global Earth system integrated assessment models to provide model-based energy transition policy support?*"

Answering the sub-research questions provided insight into what methods should be tested with downscaling energy systems within IAMs, the criteria that should be used to evaluate their usefulness, including limitations to the approaches and trade-offs between the methods that are used.

Overall, these techniques at present provide limited use to support policymakers understand and plan for the energy transition in their respective regions. The results from the downscaling study revealed that internal consistency is not maintained by these downscaling methods. In the linear approach, it is transparent how this consistency is broken, which somewhat maintains its usefulness in short term energy policymaking, but not long-term transition studies. The convergence approach is less transparent about its approach and breaks consistency is many forms from the parent model, rendering its connection to parent IAM almost meaningless for the purposes that energy policymaking is interested in. Specifically, this method leans heavily on the assumption that technologies will diffuse to all nations within an IAM region over time without barriers. This assumption overlooks the actual resource use potential in those nations, and regulatory, economic, and cultural environments.

A similar issue exists for both the convergence and linear methods. When the parent model determines that a new technology, like carbon capture and storage, becomes commercially viable in a region, both methods assume that the new technology will penetrate the markets in every nation at the same rate (subject to the proportionality constraints in the linear case). These assumptions are highly unlikely to hold, especially across all of the global regions that IAMs cover. For example, Canada – another region considered in GCAM – currently has a more complex system of trade tariffs between its 10 internal provinces than the nation does with the EU-15 (less the United Kingdom after Brexit).

7.3. Recommendations

The main recommendation in this work is for analysts to avoid the linear and convergence approaches for downscaling electricity production. Both of these approaches oversimplify the dynamics of technological adoption, but more complex methods exist as well. The iterative proportional fit approach shows promise but requires more analysis. Intermediately complex methods that model technological innovation and diffusion processes would be critical to study. Any use of multi-modelling must also incorporate these two aspects. Any approach needs to be at least open-source to be useful in science or policy support. A danger of modelling to support climate policy is that is tempting to apply one model, or one type of model, to many locations. In doing so, local contexts like geographic limitations must be incorporated.

The analytical methods evaluated here struggled the most with consistently handling technologies that do not exist commercially yet or that a country did not use in a base year, but might in the future. If one were insistent on using downscaling in the energy domain, they should focus on an approach that can characterize technological development and diffusion to overcome the main issues identified with the methods. It is easiest to implement these through multi-modelling, a method of intermediate complexity (such as some form of cellular automata), the IPF method, and then the convergence approach. The linear method ignores these dynamics completely. The typology of downscaling approaches and criteria to evaluate them can be useful in future cases to characterize any new downscaling methods that are suggested.

7.3.1. Relevance for Analysts, Modellers, and Scientists

More generally, analysts who seek to support energy transition policymaking should also reflect on the intent of modelling for policy support. The downscaling method itself attempts to cope with implementing national-level differences into an IAM's larger aggregated region. While this approach works well for physical systems, like climate, and sometimes aggregated economic attributes, like GDP, it is very difficult to do so for more complex sociotechnical systems, like the energy system.

IAMs only represent one angle of policy support, and other approaches exist. Electricity systems are complicated, and many types of granular policies are possible to implement, not just a carbon tax. Many of those are understood through modelling and can have the same type of issue as IAMs' low resolutions. However, local models are often more complex (Elliot *et al.*, 2019), since local decision-makers demand a very high-resolution of impacts many on heterogeneous sectors (Yeh *et al.*, 2016). Combining many specific models to upscale those insights is difficult, but perhaps achievable with some sort of modular, hierarchical, and multi-scale modelling.

A variety of theories are also used in understanding this complex system. Innovation theory brings some analytical perspectives of the future and how to facilitate the technological or social innovations needed to change the existing socio-technical system, and this work already showed the importance of implementing innovation and diffusion in IAMs and downscaling. Backcasting and the multi-level perspective illuminate possibilities for policy interventions. There are many policy pathways that can lead to this target, but we know little now about the feasibility of each of these pathways. The aforementioned technological uncertainties are indeed "deep". Even when new technologies become available, we know little about how quickly they will become implemented.

This is not to say that downscaling is entirely useless for energy systems. As already mentioned, it would be worthwhile to explore the extent to which methods of intermediate complexity can implement geographic rules, and how the ability to do so compares to borrowing the energy system component for the IAM and running it directly for the smaller region itself. Downscaling methods are used in many domains to create higher resolution outputs. IAM modellers could also consider increasing the resolution of IAMs instead of using downscaling. Since computational power is increasing quickly, the IAM itself could build in more of the considerations that underlie the downscaling method. They can still save time by identifying regions whose choices might influence the global system the most. Of course, the global energy system is vast and decentralized, but much of energy use exists in physical or political clusters (e.g. port or heavy industry areas; regions with high political institutional capacity).

If downscaling is to continue to be used, small changes to IAMs could likely support downscaling attempts in the future. For example, disentangling CCS from the energy and industrial sectors would provide insight into the actual CCS technology itself so that policymakers can more transparently see the policy drivers that would enable this technology specifically. While some argue that CCS is not necessary for an energy system transformation to meet climate objections (Jacobson *et al.*, 2017), this matter is still widely debated by others. Separating these choices could allow for a more thorough analysis that stakeholders with conflicting views can still use together (Roelich and Giesekam, 2019).

7.3.2. Relevance for Policymakers

In general, the results from this downscaling approach showed the immaturity of the approaches and may be alarming to policymakers because these methods are already used, to some extent, in their decision processes – especially heuristic ones. No one method appeared to be great contestants for policy use, and the linear and convergence approaches both shows critical limitations that add even more model uncertainty, leaving the question of how the numeric outputs are useful – if at all. Whereas good policy support requires robust methodologies, the downscaling approaches are not. Policymakers should be aware that while the two methods investigated here are not useful, other downscaling paradigms may exist and still help connect IAMs to the relevant types of information they need. On the other hand, the limits of the GCAM IAM's usefulness might not be new information at all.

As introduced in section 3.2.2, integrated modelling approaches are limited by how they pair different modelling paradigms and models created for different research questions together. This work does not resolve the inherent conflict with sufficiently characterizing social behaviours and unknown futures with integrated assessment, but does contribute one more element that both modellers and policymakers can consider as they review analysis from ensembles of models and permutations of model components. It is also tempting to consider if downscaling could be applied to social aspects like the diffusion of technology. Whereas diffusion has been discussed to stand in for technological growth, if the IAM included diffusion between sub-continental regions, then this attribute could potentially be downscaled to a national or subnational level. However, it is most likely that such downscaling would be even more difficult.

The issue of reconciling local and global concerns remains and raises the question of what role modelling should play. More importantly, policymakers themselves should reflect on the implications of the reversed question about the analytical gap posed above. Ensuring that a conglomerate of policy directions meets a global objective is an existing political science issue. The case of climate change and energy transition is wicked, and requires quick policy action. Closing the gap between local contexts and global assessments might require significantly more diplomacy than better modelling approaches. This is not to say they should put modelling aside, but that the priority of the elements to support climate and energy transition policy should be thoroughly examined.

7.4. Reflection

7.4.1. Scientific Contribution

The research conducted in this thesis first identified several problem gaps in climate and energy transition policymaking, suggested methods to overcome those issues, and then investigated the limitations of those methods. Overall, the process yielded scientifically interesting results and key insights for both analysts (including modellers) and policymakers alike about these methods. A significant portion of this study was dedicated to implementing the specific methods appropriately. The analysis of the outputs is both quantitative and qualitative. In both cases, they are largely influenced by my own interpretation of how useful they are to policymakers, drawing upon other literature, anecdotes in the news, and my personal experience working with carbon pricing policies. This work could have benefited from more feedback from experts in the field, and could have implemented a study of how the downscaling methods would change specific types of policy insights. However, I determined this was not actually necessary, since differences in the nature of IAM outputs themselves already illuminate the usefulness of these methods. Adding another layer of policy on top would provide a more complete view of downscaling GCAM using these methods, but I expect such an approach to offer limited further value.

The research contributes three new frameworks to the integrated assessment and downscaling communities:

1. A new typology of downscaling methods that disentangles time complexity,
2. Specific criteria to evaluate energy systems downscaling methods, and
3. An overview of four downscaling methods and the trade-offs in choosing between them.

Using GCAM and the EU-15 region as an example for linear and convergence downscaling uncovered limitations to downscaling not previously described in literature: how well the approaches can handle geographic limitations to local regions' resource use, how technologies not used in a local region in a base year are handled, and how technologies that do not exist yet are treated.

7.4.2. Relevance to the Problem Gaps and Society

The main goal of this work was to help analysts better support policymakers in tackling climate change, one of the greatest crises humanity has ever faced. Where models have been commonly used to provide analysis, the gap between measuring global outcomes (where climate change physically occurs) and more local decisions remains – none of the approaches reviewed in this work represented a breakthrough in analytical capacity. Yet, it contributed to the discussion of how and where models should be used to make decisions. The specific problem gaps identified in the introduced are addressed below.

Problem Gap 1

Models are commonly used in energy transition modelling, so it is important to understand their usefulness and limitations as much as possible. Through a literature review, this work examined the nature of recent global climate policymaking, including where it needs support and a conceptual overview of how models can be useful for supporting policymaking. Specifically, integrated assessment models (IAMs) were introduced and discussed, including how they have been used in policy support to-date and in which ways they are limited. One main gap is that they usually aggregate geopolitical regions into around 10 sub-continental regions, rather than more so in a nation-by-nation state, which is the focus of the second problem gap. Other issues, like how they treat deep uncertainties, were described briefly, but not investigated in the scope of this study.

Problem Gap 2

Policymakers cannot directly benefit from global level integrated assessment models because of their typical level of geopolitical aggregation. The issue of the gap between IAMs and where policy demands are met led to a review of how downscaling is used with IAMs to disaggregate sub-continental regions in IAMs into national or sub-national scopes. This review initially only considered how the geographic levels of quantitative analysis can connected, and did not cover the other types of information that actual policymakers consider – regulatory environments and economic and cultural contexts. Each of these localized considerations greatly affects how energy transition policy is actually implemented.

Perhaps this issue has been considered the wrong way. Instead of how IAMs can provide meaningful information to localized policymakers, the core issue is that local policymaking needs to be connected and contextualized in the global environment. This top-down method may need to be reversed into thinking about how bottom-up analyses can match top-down ones. Such an approach is most limited by aligning high-resolution localized analyses to global narratives, which may be more of a political issue than technical.

Problem Gap 3

Downscaling has been used to increase the resolution of IAM outputs, but the limitations of their use in energy downscaling has not been reviewed. Lastly, this work synthesized how IAMs can be downscaled for energy outputs. Though this was ostensibly completed, the methods themselves introduced new assumptions that broke the internal consistency of the method, rendering them ultimately limited in their usefulness. Specific types of limitations were discussed in-depth, and a new set of criteria were developed to analyze and compare downscaling approaches. These criteria can be used by other modellers and analysts as they consider how to best support policymaking. The issues presented here are not inherent flaws to downscaling in general, but highlight that there are major differences between downscaling physical elements like climate and complex sociotechnical systems. The work here identified future work for researchers and analysts to bridge the other problem gaps. In this sense, the work done to address this third problem gap has added value to the scientific discussion about modelling for policy-support.

7.5. Future Work

The exploration of downscaling methods for use in energy transition policymaking have uncovered future work for both the downscaling methods themselves, and for the use of models to support climate and energy transition policymaking in general.

Firstly, though the linear and convergence downscaling methods covered here were not useful to the objective, other downscaling methods are still possibly useful. While the novelty of these approaches in the literature limited this analysis to fully explore these other methods, they have been implemented and could be more rigorously examined and tested in one geographic region, like was done in this study. Slightly more complex methods, but not to the point of building completely separate models, could still potentially be used to improve this existing approach. Specifically, these methods could implement geographic resource use constraints and better rules for technological diffusion in light of heterogeneous regulatory, economic, and cultural contexts. Method of intermediate complexity could be implemented, especially paying attention to technological innovation, diffusion, and adoption theories. Extracting electricity and other energy prices from the model could facilitate these methods without raising internal consistency issues. This approach could become sufficiently "realistic" to become a larger part of policymakers' tool kits. The criteria that this work developed to evaluate the usefulness of downscaling methods can be used with the other methods as well.

Though this study only examined one IAM, its results should be similar in others – the main issues that arose were from the downscaling methods themselves and not how they interacted with the parent IAM. However, each other IAM has its own differences, and there may be benefits to using other IAMs that were not discovered in this research.

In this work, a key insight was that the choice of convergence year affects the path values take. Future studies could determine the sensitivity of downscaled outputs to the choice of convergence year. Moreover, convergence downscaling was implemented with 2100 as a convergence date, which differs from other work for the SSP2 scenario used that use 2150 as a date. This difference was not expected to be important and likely showed more insight about the limitations of the approach than without this decision. A sensitivity analysis could improve understanding of this choice.

As for the second theme, the gap between what energy transition policymakers need and what IAMs can provide is still left in this work. The previous chapter discussed how this gap identified here could be viewed another way. Instead of seeing IAMs as boundary conditions or drivers for information that local decision-makers need to know, more localized modelling could be *upscaled* and compared to IAMs' insights. The issues first identified in this thesis, like the capacity to develop such models likely diminishes as the resolution of analysis increases, remains a constraint. However, future work in this field could focus on how to model IAMs at the higher resolution more easily. Instead of trying to bridge the analytical gap by making IAM results useful and replace a model, models could be more easily implemented at a higher resolution. Doing so runs into issues already discussion in the literature about the composability of models, the necessary level of resolution (perhaps ultimately the per-person level), and will likely emphasize IAMs' weaknesses in handling social systems; the complexity of integrated assessment and energy transition might limit this approach's long term usefulness. Instead, IAMs could possibly modularize further. Instead of trying to analyze many domains in parallel at a global scale, more localized analysis could perhaps become inputs to the IAM process.

IAMs could also simply include more geopolitical sub-regions too, fitting boundaries to borders where global outcomes might be sensitive to policy decisions and prioritize validating the largest of those subregions. This approach would still be bound by the extents of IAM usefulness. The world's largest GHG emitters are already categorized by themselves – should the USA's biggest states be treated as their own? Determining global sensitivity to local policies could itself be a question best answered by an IAM, though expert judgement can surely contribute. If such an approach is taken, it would raise more questions about how model components interact with one another, like through trade. Still, it warrants further exploration.

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Vuuren, D. P. van, Smith, S. J., and Riahi, K. (May 2010). "Downscaling socioeconomic and emissions scenarios for global environmental change research: a review". In: *Wiley Interdisciplinary Reviews: Climate Change* 1.3, pp. 393–404. ISSN: 17577780. DOI: 10.1002/wcc.50.

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Yue, X., Pye, S., DeCarolis, J., Li, F. G., Rogan, F., and Gallachóir, B. (2018). "A review of approaches to uncertainty assessment in energy system optimization models". In: *Energy Strategy Reviews* 21.June, pp. 204–217. ISSN: 2211467X. DOI: 10.1016/j.esr.2018.06.003.

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V

Appendix

A

Replication Guide

A.1. Documentation of Procedure

There are two major sections to the analysis in this work: obtaining outputs from GCAM and analyzing them. GCAM version 5.2 (see `https://github.com/JGCRI/gcam-core/releases/tag/gcam-v5.2` and `https://doi.org/10.5281/zenodo.3528353`), released on November 4, 2019, was used to generate outputs. A default scenario, whose configurations are listed in appendix A.2.1 was run in macOS 10.15 on a quad-core Intel Coffee Lake mobile processor with a 28 W TDP and 16 GB of RAM. With the configuration file in place, the file `gcam-v5/exe/run-gcam.command` was launched from a Finder window. In total, this scenario took around 1 hour to be simulated.

Secondly, the outputs were extracted and analyzed in a Jupyter Lab environment using Python 3.8. The Python and Notebook code for this work is hosted online at `https://gitlab.com/jasonrwang/downscaling-electricity`, and has been implemented in a way that also retrieves the necessary external data automatically, except the IIASA and OECD GDP and population forecasts, which needed to be manually downloaded from the IIASA emissions downscaling toolbox used in (Gidden *et al.*, 2019) (`https://github.com/iiasa/emissions_downscaling/tree/master/input/SSP_pop_gdp`). There are four notebooks meant to be run in the order they are numbered. The necessary Python packages are also listed in this repository.

A.2. GCAM Configuration

A.2.1. GCAM Reference Scenario

This file, `configuration_ref.xml`, is given as an input to the GCAM API to query the database.

```
<?xml version="1.0" encoding="UTF-8"?>
<Configuration>
  <Files>
     <Value name="xmlInputFileName">../input/gcamdata/xml/modeltime.xml</Value>
     <Value name="BatchFileName">batch_ag.xml</Value>
     <Value name="policy-target-file">../input/policy/forcing_target_4p5.xml</Value>
     <Value name="GHGInputFileName">../input/magicc/inputs/input_gases.emk</Value>
     <Value write-output="1" append-scenario-name="0" name="xmldb-location">../output/database_basexdb</Value>
     <Value write-output="1" append-scenario-name="0" name="restart">./restart/restart</Value>
```

```xml
        <Value write-output="1" append-scenario-name="1" name="xmlDebugFileName">debug.xml</Value>
        <Value write-output="1" append-scenario-name="0" name="climatFileName">gas.emk</Value>
        <Value write-output="1" append-scenario-name="1" name="costCurvesOutputFileName">cost_curves.xml</Value>
        <Value write-output="1" append-scenario-name="0" name="batchCSVOutputFile">batch-csv-out.csv</Value>
        <Value write-output="0" append-scenario-name="0" name="supplyDemandOutputFileName">SDCurves.csv</Value>
        <Value write-output="0" append-scenario-name="0" name="flow-graph">gcam-flow-graph.dot</Value>
        <Value write-output="0" append-scenario-name="0" name="dependencyGraphName">DependencyGraph.dot</Value>
        <Value write-output="0" append-scenario-name="0" name="landAllocatorGraphName">LandAllocatorGraph.dot</Value>
    </Files>
    <ScenarioComponents>
        <Value name = "climate">../input/gcamdata/xml/hector.xml</Value>
        <Value name = "socioeconomics">../input/gcamdata/xml/socioeconomics_gSSP2.xml</Value>

        <Value name = "resources">../input/gcamdata/xml/resources.xml</Value>
        <Value name = "energy_supply">../input/gcamdata/xml/en_supply.xml</Value>
        <Value name = "energy_transformation">../input/gcamdata/xml/en_transformation.xml</Value>
        <!--Value name = "electricity">../input/gcamdata/xml/electricity.xml</Value-->
        <Value name = "elec_water_base">../input/gcamdata/xml/electricity_water.xml</Value>
        <Value name = "heat">../input/gcamdata/xml/heat.xml</Value>
        <Value name = "hydrogen">../input/gcamdata/xml/hydrogen.xml</Value>
        <Value name = "energy_distribution">../input/gcamdata/xml/en_distribution.xml</Value>
        <Value name = "industry">../input/gcamdata/xml/industry.xml</Value>
        <Value name = "industry_income_elas">../input/gcamdata/xml/industry_incelas_gssp2.xml</Value>
        <Value name = "cement">../input/gcamdata/xml/cement.xml</Value>
        <Value name = "cement_income_elas">../input/gcamdata/xml/cement_incelas_gssp2.xml</Value>
        <Value name = "fertilizer_energy">../input/gcamdata/xml/en_Fert.xml</Value>
        <Value name = "hddcdd">../input/gcamdata/xml/HDDCDD_constdd_no_GCM.xml</Value>
        <Value name = "building">../input/gcamdata/xml/building_det.xml</Value>
        <Value name = "transportation">../input/gcamdata/xml/transportation_UCD_CORE.xml</Value>
        <Value name = "carbon_content">../input/gcamdata/xml/Ccoef.xml</Value>
        <Value name = "carbon_storage">../input/gcamdata/xml/Cstorage.xml</Value>


        <Value name = "ag_base">../input/gcamdata/xml/ag_For_Past_bio_base_IRR_MGMT.xml</Value>
        <Value name = "ag_cost">../input/gcamdata/xml/ag_cost_IRR_MGMT.xml</Value>
        <Value name = "ag_prodchange">../input/gcamdata/xml/ag_prodchange_ref_IRR_MGMT.xml</Value>
        <Value name = "residue_bio">../input/gcamdata/xml/resbio_input_IRR_MGMT.xml</Value>
        <Value name = "animal">../input/gcamdata/xml/an_input.xml</Value>
        <Value name = "fertilizer">../input/gcamdata/xml/ag_Fert_IRR_MGMT.xml</Value>
        <Value name = "land1">../input/gcamdata/xml/land_input_1.xml</Value>
        <Value name = "land2">../input/gcamdata/xml/land_input_2.xml</Value>
        <Value name = "land3">../input/gcamdata/xml/land_input_3_IRR.xml</Value>
        <Value name = "land4">../input/gcamdata/xml/land_input_4_IRR_MGMT.xml</Value>
        <Value name = "land5">../input/gcamdata/xml/land_input_5_IRR_MGMT.xml</Value>
        <Value name = "protected_land2">../input/gcamdata/xml/protected_land_input_2.xml</Value>
        <Value name = "protected_land3">../input/gcamdata/xml/protected_land_input_3.xml</Value>
        <Value name = "demand">../input/gcamdata/xml/demand_input.xml</Value>
```

```
    <Value name = "bio_trade">../input/gcamdata/xml/bio_trade.xml</Value>
    <Value name = "ag_trade">../input/gcamdata/xml/ag_trade.xml</Value>

    <Value name = "ind_urb_proc">../input/gcamdata/xml/ind_urb_processing_sectors.xml</Value>
    <Value name = "nonco2_energy">../input/gcamdata/xml/all_energy_emissions.xml</Value>
    <Value name = "nonco2_fgas">../input/gcamdata/xml/all_fgas_emissions.xml</Value>
    <Value name = "nonco2_unmgd">../input/gcamdata/xml/all_unmgd_emissions.xml</Value>
    <Value name = "nonco2_aglu">../input/gcamdata/xml/all_aglu_emissions_IRR_MGMT.xml</Value>
    <Value name = "nonco2_aglu_prot">../input/gcamdata/xml/all_protected_unmgd_emissions.xml</Value>

    <Value name = "unlim_supply_water">../input/gcamdata/xml/unlimited_water_supply.xml</Value>
    <Value name = "water_supply">../input/gcamdata/xml/water_supply_constrained.xml</Value>
    <Value name = "water_mapping">../input/gcamdata/xml/water_mapping.xml</Value>
    <Value name = "ag_water">../input/gcamdata/xml/ag_water_input_IRR_MGMT.xml</Value>
    <Value name = "elec_water_coef">../input/gcamdata/xml/electricity_water_coefs.xml</Value>
    <Value name = "nonco2_elec_water">../input/gcamdata/xml/water_elec_emissions.xml</Value>
    <Value name = "ind_water">../input/gcamdata/xml/water_demand_industry.xml</Value>
    <Value name = "an_water">../input/gcamdata/xml/water_demand_livestock.xml</Value>
    <Value name = "municipal_water">../input/gcamdata/xml/water_demand_municipal.xml</Value>
    <Value name = "primary_ene_water">../input/gcamdata/xml/water_demand_primary.xml</Value>

    <Value name = "bio_feedstock_limit">../input/gcamdata/xml/liquids_limits.xml</Value>
    <Value name = "bio_elec_w_feed_limit">../input/gcamdata/xml/water_elec_liquids_limits.xml</Value>
    <Value name = "bio_neg_emiss_budget">../input/gcamdata/xml/negative_emissions_budget_gSSP2.xml</Value>
    <Value name = "solver">../input/solution/cal_broyden_config.xml</Value>

  </ScenarioComponents>
  <Strings>
    <Value name="scenarioName">Reference</Value>
    <Value name="debug-region">EU-15</Value>
    <Value name="MAGICC-input-dir">../input/magicc/inputs</Value>
    <Value name="MAGICC-output-dir">../output</Value>
    <Value name="AbatedGasForCostCurves">CO2</Value>
  </Strings>
  <Bools>
    <Value name="CalibrationActive">1</Value>
    <Value name="BatchMode">0</Value>
    <Value name="find-path">0</Value>
    <Value name="createCostCurve">0</Value>
    <Value name="debugChecking">0</Value>
    <Value name="simulActive">1</Value>
    <Value name="PrintValuesOnGraphs">1</Value>
    <Value name="ShowNullPaths">0</Value>
    <Value name="PrintPrices">1</Value>
  </Bools>
  <Ints>
    <Value name="numMarketsToFindSD">10</Value>
    <Value name="numPointsForSD">21</Value>
    <Value name="numPointsForCO2CostCurve">5</Value>
    <Value name="carbon-output-start-year">1705</Value>
    <Value name="climateOutputInterval">5</Value>
```

```
      <Value name="parallel-grain-size">50</Value>
      <Value name="stop-period">-1</Value>
      <Value name="restart-period">-1</Value>
   </Ints>
   <Doubles>
   </Doubles>
</Configuration>
```

Listing A.1: configuration_ref.xml

A.2.2. GCAM Output Queries

This file, `queries.xml`, is given as an input to the GCAM API to query the database.

```
<?xml version="1.0" encoding="UTF-8"?>
<queries>

   <aQuery>
      <region name="Canada"/>
      <region name="EU-15"/>
      <supplyDemandQuery title="Electricity generation by technology (inc solar roofs)">
         <axis1 name="technology">technology</axis1>
         <axis2 name="Year">physical-output[@vintage]</axis2>
         <xPath buildList="true" dataName="output" group="false" sumAll="false">*[@type = '
             sector' (: collapse :) and (@name='electricity' or @name='elect_td_bld' or @name
             ='industrial energy use')]//*[@type = 'technology' and not (@name='elect_td_bld'
              or @name='electricity')]/*[@type='output' (:collapse:) and (@name='electricity'
              or @name='elect_td_bld')]/physical-output/node()</xPath>
         <comments/>
      </supplyDemandQuery>
   </aQuery>

   <aQuery>
      <region name="Canada"/>
      <region name="EU-15"/>
      <gdpQueryBuilder title="GDP MER by region">
         <axis1 name="region">region</axis1>
         <axis2 name="Year">gdp-mer</axis2>
         <xPath buildList="true" dataName="gdp-mer" group="false" sumAll="false">GDP/gdp-mer/
             text()</xPath>
         <comments/>
      </gdpQueryBuilder>
   </aQuery>

   <aQuery>
      <region name="Canada"/>
      <region name="EU-15"/>
      <demographicsQuery title="population by region">
         <axis1 name="region">region</axis1>
         <axis2 name="Year">populationMiniCAM</axis2>
         <xPath buildList="true" dataName="total-population" group="false" sumAll="false">
             demographics/populationMiniCAM/total-population/node()</xPath>
         <comments/>
      </demographicsQuery>
   </aQuery>

   <aQuery>
      <region name="Canada"/>
      <region name="EU-15"/>
      <emissionsQueryBuilder title="CO2 emissions by region and sector">
         <axis1 name="sector">sector</axis1>
```

```xml
            <axis2 name="Year">emissions</axis2>
            <xPath buildList="true" dataName="emissions" group="false" sumAll="false">*[@type = 'sector' ]//CO2/emissions/node()</xPath>
            <comments/>
        </emissionsQueryBuilder>
    </aQuery>

</queries>
```

Listing A.2: queries.xml

A.2.3. GCAM Reference Scenario Socioeconomics

This file, `socioeconomics_gSSP2.xml`, is used to set the socioeconomic scenario in `configuration_ref.xml` (appendix A.2.3). This appendix only contains a snippet of the full document, focusing on the EU-15 region that was analyzed in this work. The other GCAM regions names are shown, but not their child XML nodes with their respective scenario data.

```xml
<?xml version="1.0" encoding="UTF-8"?>
<scenario>
    <world>
        <region name="USA">
        </region>
        <region name="Africa_Eastern">
        </region>
        ...
        <region name="EU-15">
            <demographics>
                <populationMiniCAM year="1975">
                    <totalPop>349576</totalPop>
                </populationMiniCAM>
                <populationMiniCAM year="1990">
                    <totalPop>364443</totalPop>
                </populationMiniCAM>
                <populationMiniCAM year="2005">
                    <totalPop>387381</totalPop>
                </populationMiniCAM>
                <populationMiniCAM year="2010">
                    <totalPop>397391</totalPop>
                </populationMiniCAM>
                <populationMiniCAM year="2015">
                    <totalPop>405921</totalPop>
                </populationMiniCAM>
                <populationMiniCAM year="2020">
                    <totalPop>412619</totalPop>
                </populationMiniCAM>
                <populationMiniCAM year="2025">
                    <totalPop>418915</totalPop>
                </populationMiniCAM>
                <populationMiniCAM year="2030">
                    <totalPop>424667</totalPop>
                </populationMiniCAM>
                <populationMiniCAM year="2035">
                    <totalPop>429939</totalPop>
                </populationMiniCAM>
                <populationMiniCAM year="2040">
                    <totalPop>434772</totalPop>
                </populationMiniCAM>
                <populationMiniCAM year="2045">
                    <totalPop>438964</totalPop>
```

```xml
            </populationMiniCAM>
            <populationMiniCAM year="2050">
               <totalPop>442269</totalPop>
            </populationMiniCAM>
            <populationMiniCAM year="2055">
               <totalPop>444611</totalPop>
            </populationMiniCAM>
            <populationMiniCAM year="2060">
               <totalPop>446215</totalPop>
            </populationMiniCAM>
            <populationMiniCAM year="2065">
               <totalPop>446769</totalPop>
            </populationMiniCAM>
            <populationMiniCAM year="2070">
               <totalPop>446694</totalPop>
            </populationMiniCAM>
            <populationMiniCAM year="2075">
               <totalPop>446140</totalPop>
            </populationMiniCAM>
            <populationMiniCAM year="2080">
               <totalPop>445013</totalPop>
            </populationMiniCAM>
            <populationMiniCAM year="2085">
               <totalPop>443217</totalPop>
            </populationMiniCAM>
            <populationMiniCAM year="2090">
               <totalPop>440454</totalPop>
            </populationMiniCAM>
            <populationMiniCAM year="2095">
               <totalPop>436701</totalPop>
            </populationMiniCAM>
            <populationMiniCAM year="2100">
               <totalPop>431684</totalPop>
            </populationMiniCAM>
         </demographics>
         <GDP>
            <baseGDP>4711007</baseGDP>
            <laborforce fillout="1" year="1975">0.5</laborforce>
            <laborproductivity year="1990">0.02379</laborproductivity>
            <laborproductivity year="2005">0.01709</laborproductivity>
            <laborproductivity year="2010">0.00189</laborproductivity>
            <laborproductivity year="2015">0.00385</laborproductivity>
            <laborproductivity year="2020">0.0139</laborproductivity>
            <laborproductivity year="2025">0.01212</laborproductivity>
            <laborproductivity year="2030">0.012</laborproductivity>
            <laborproductivity year="2035">0.01246</laborproductivity>
            <laborproductivity year="2040">0.01329</laborproductivity>
            <laborproductivity year="2045">0.01336</laborproductivity>
            <laborproductivity year="2050">0.01306</laborproductivity>
            <laborproductivity year="2055">0.01317</laborproductivity>
            <laborproductivity year="2060">0.01379</laborproductivity>
            <laborproductivity year="2065">0.0141</laborproductivity>
            <laborproductivity year="2070">0.01376</laborproductivity>
            <laborproductivity year="2075">0.01314</laborproductivity>
            <laborproductivity year="2080">0.01282</laborproductivity>
            <laborproductivity year="2085">0.01257</laborproductivity>
            <laborproductivity year="2090">0.01254</laborproductivity>
            <laborproductivity year="2095">0.01258</laborproductivity>
            <laborproductivity year="2100">0.01266</laborproductivity>
            <PPPConvert constRatio="1">0.89164</PPPConvert>
         </GDP>
```

A

```
        </region>
        ...
        <region name="Argentina">
        </region>
        <region name="Colombia">
        </region>
    </world>
</scenario>
```

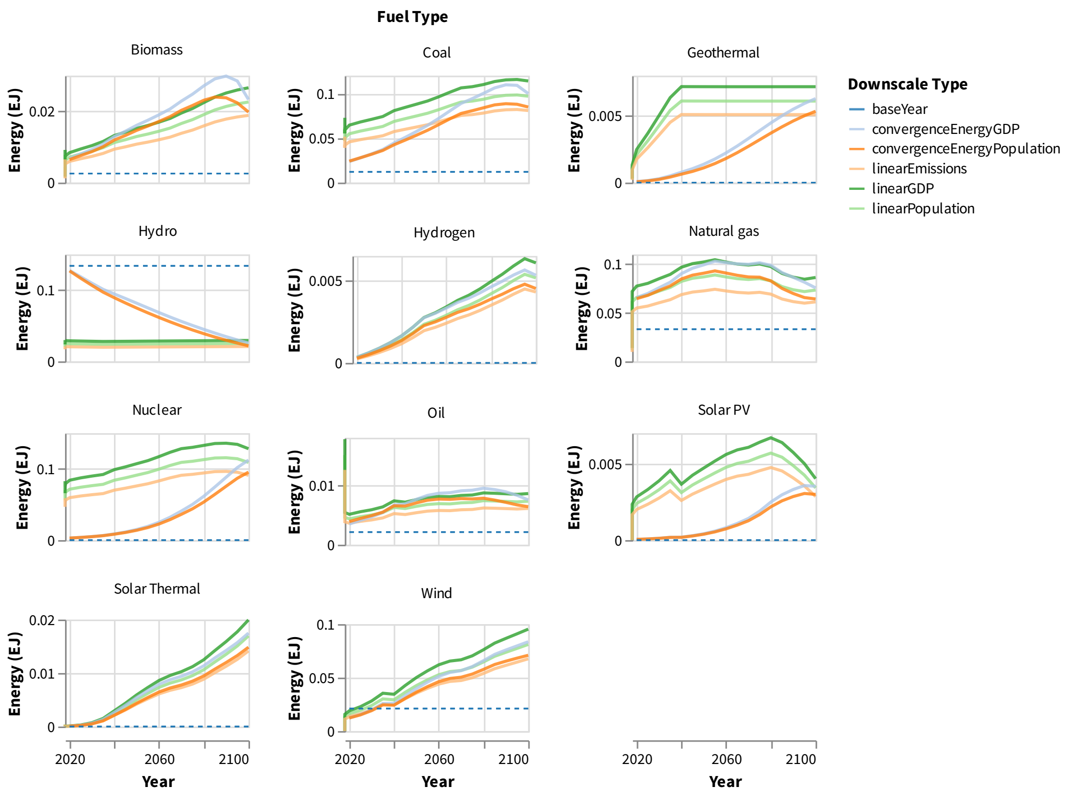
Listing A.3: socioeconomics_gSSP2.xml

B

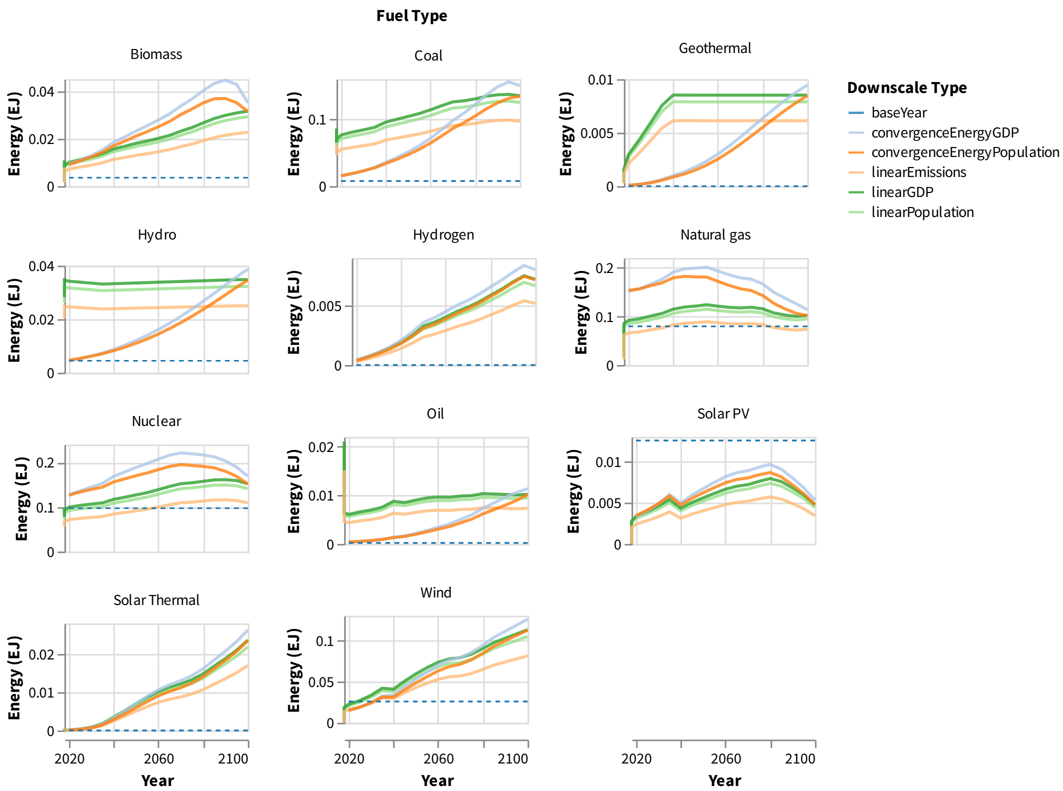
Linear and Convergence Downscaling Results by Country

This section shows the results from downscaling linearly and using the convergence method for each country that was not shown in the main text. The ones above are Germany (fig. 5.9a), Italy (fig. 5.9b), Luxembourg (fig. 5.9c), and the Netherlands (fig. 5.9d).

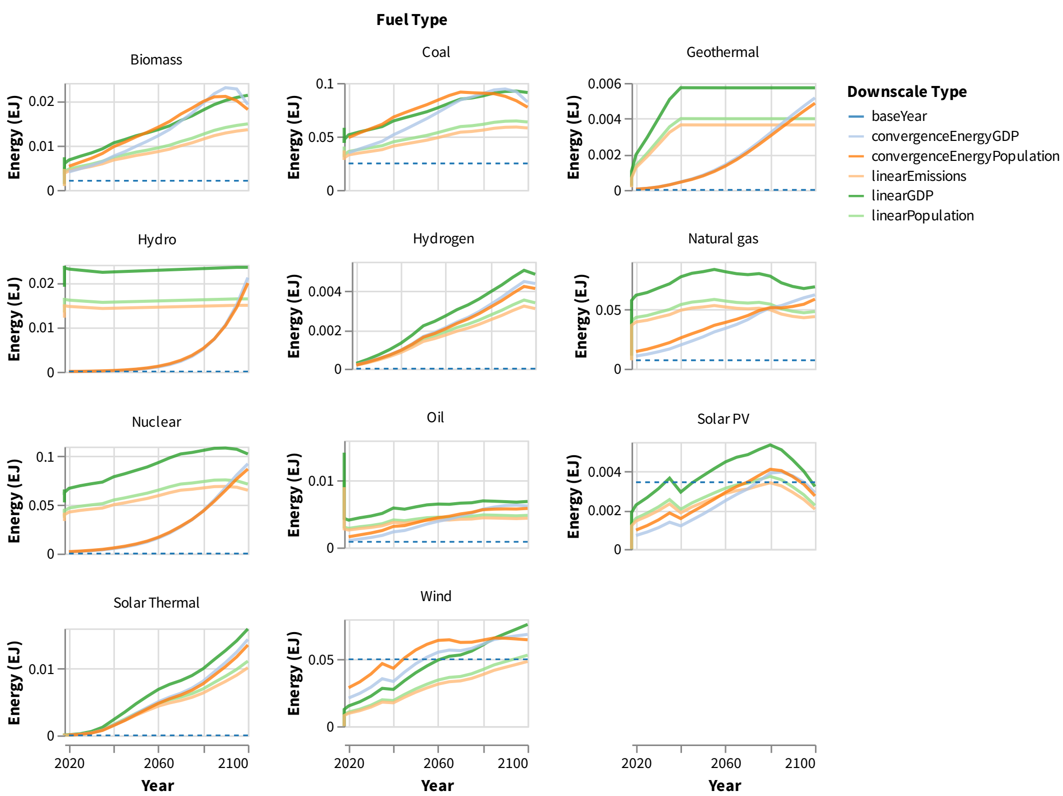
Austria



Belgium



Denmark



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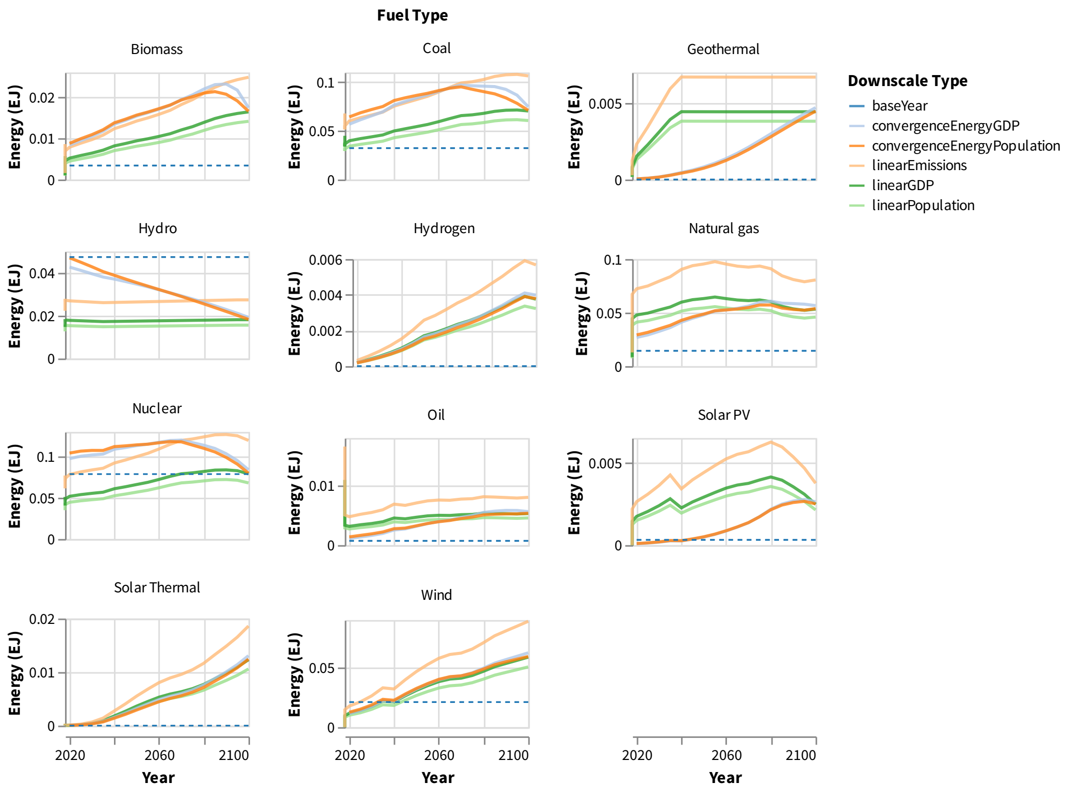

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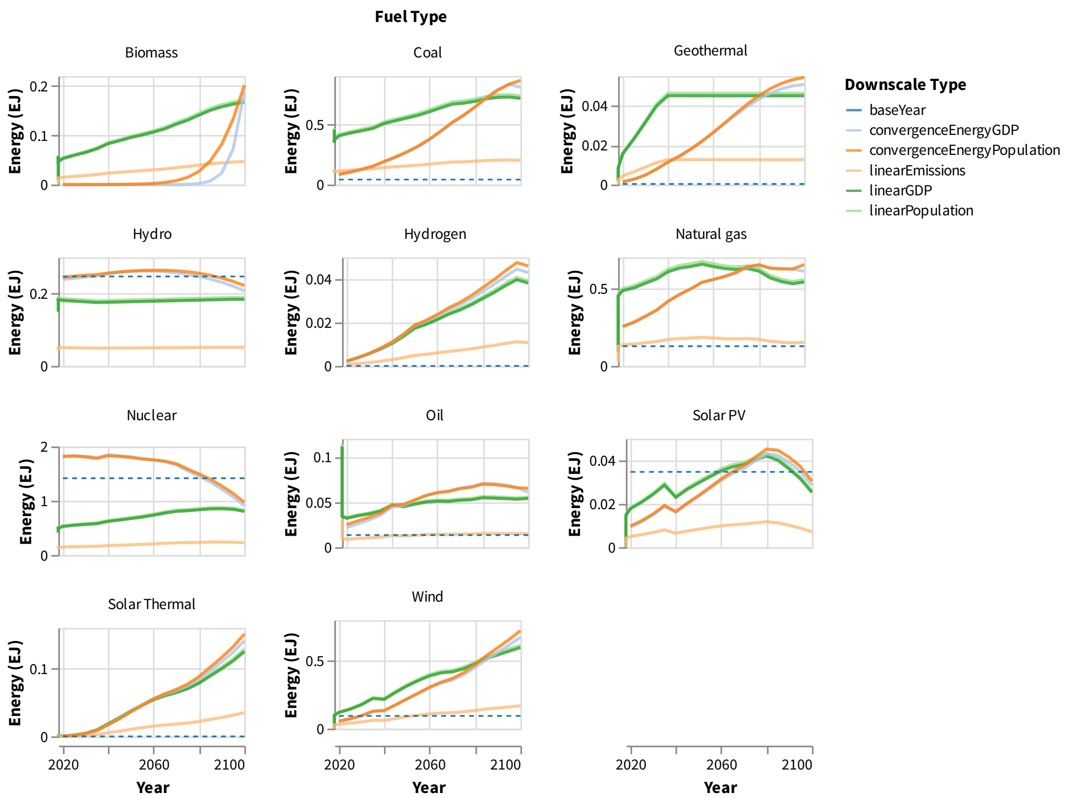

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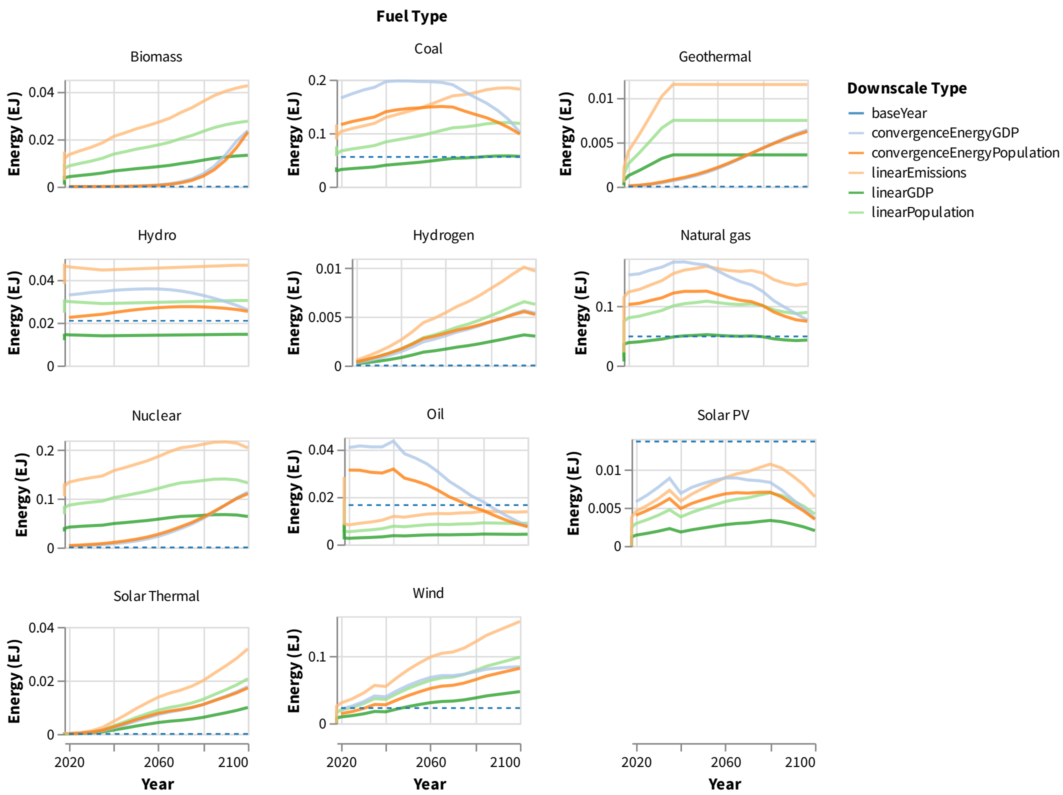

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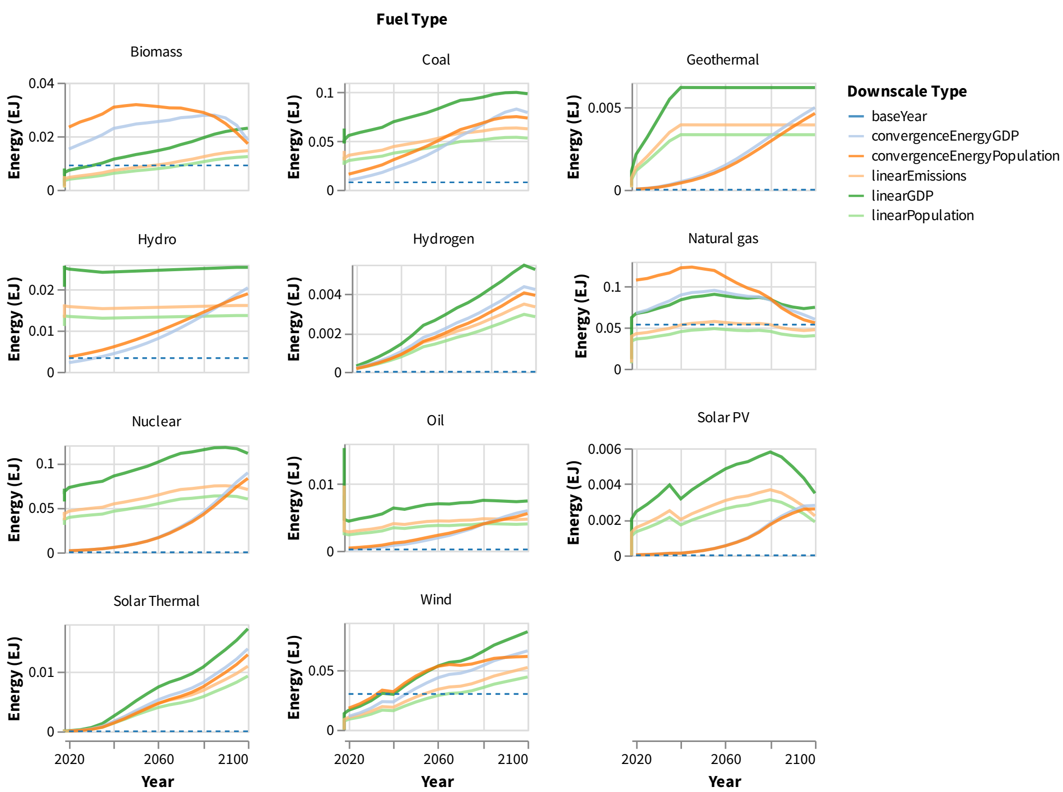

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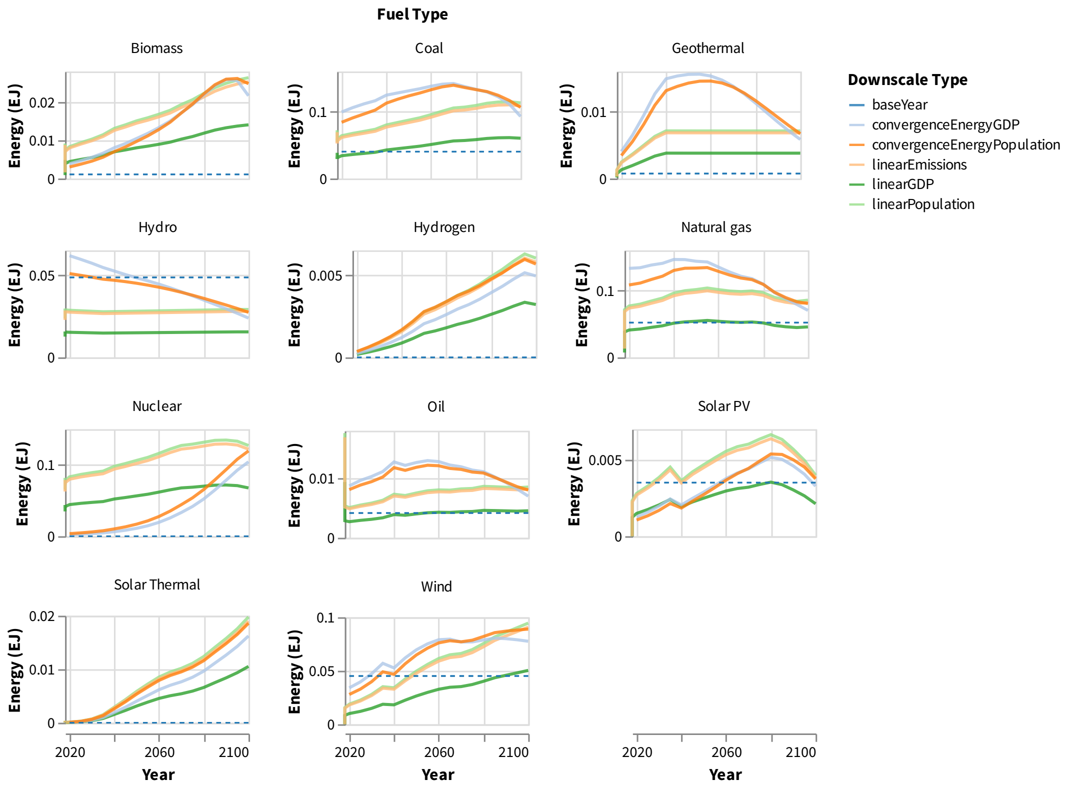
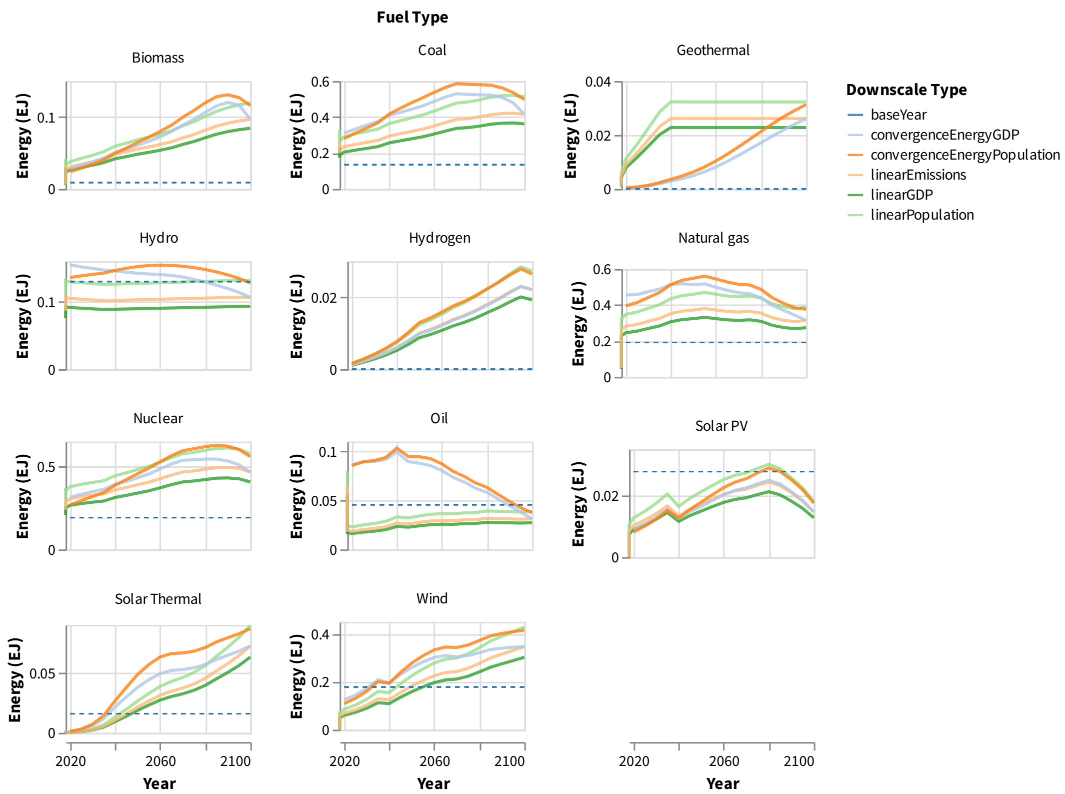
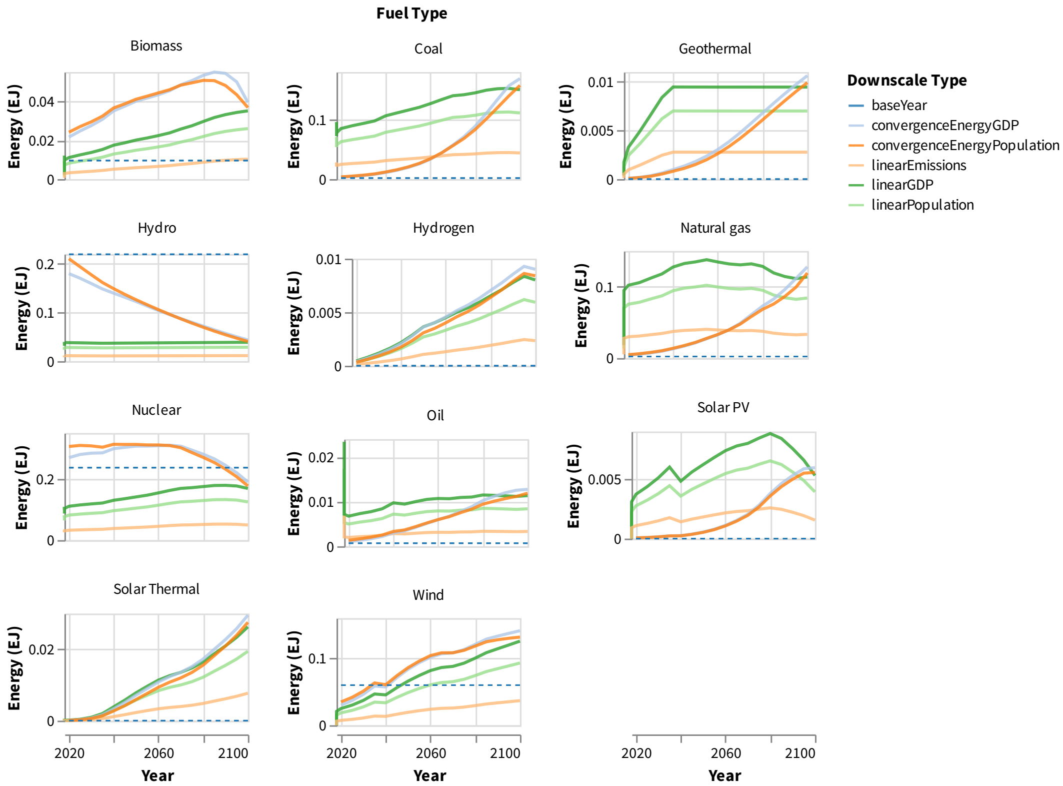


Spain

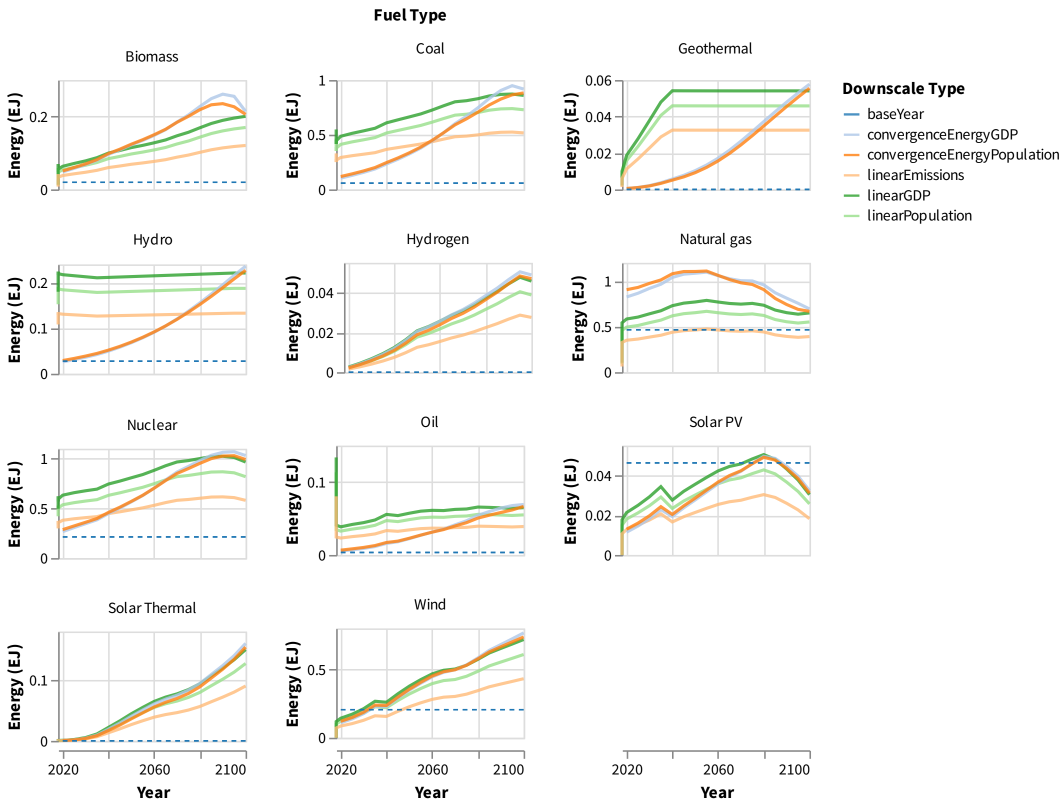


B

Sweden



United Kingdom



C

Supplementary Tables

C.1. GCAM Socio-economic Regions and Constituent Nation-States

Table C.1: GCAM Economic and Energy System Aggregate Regions and Mapped Countries

GCAM Region	**Countries**
Africa_Eastern	Burundi, Comoros, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Mauritius, Reunion, Rwanda, Sudan, Somalia, Uganda
Africa_Northern	Algeria, Egypt, Western Sahara, Libya, Morocco, Tunisia
Africa_Southern	Angola, Botswana, Lesotho, Mozambique, Malawi, Namibia, Swaziland, Tanzania, Zambia, Zimbabwe
Africa_Western	Benin, Burkina Faso, Central African Republic, Cote d'Ivoire, Cameroon, Democratic Republic of the Congo, Congo, Cape Verde, Gabon, Ghana, Guinea, Gambia, Guinea-Bissau, Equatorial Guinea, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Sao Tome and Principe, Chad, Togo
Argentina	Argentina
Australia_NZ	Australia, New Zealand
Brazil	Brazil
Canada	Canada
Central America and the Caribbean	Aruba, Anguilla, Netherlands Antilles, Antigua & Barbuda, Bahamas, Belize, Bermuda, Barbados, Costa Rica, Cuba, Cayman Islands, Dominica, Dominican Republic, Guadeloupe, Grenada, Guatemala, Honduras, Haiti, Jamaica, Saint Kitts and Nevis, Saint Lucia, Montserrat, Martinique, Nicaragua, Panama, El Salvador, Trinidad and Tobago, Saint Vincent and the Grenadines
Central Asia	Armenia, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Mongolia, Tajikistan, Turkmenistan, Uzbekistan

Table C.1 continued from previous page

GCAM Region	**Countries**
China	China
Colombia	Colombia
EU-12	Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Lithuania, Latvia, Malta, Poland, Romania, Slovakia, Slovenia
EU-15	Andorra, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Greenland, Ireland, Italy, Luxembourg, Monaco, Netherlands, Portugal, Sweden, Spain, United Kingdom
	Belarus, Moldova, Ukraine
European Free Trade Association	Iceland, Norway, Switzerland
Europe_Non_EU	Albania, Bosnia and Herzegovina, Croatia, Macedonia, Montenegro, Serbia, Turkey
India	India
Indonesia	Indonesia
Japan	Japan
Mexico	Mexico
Middle East	United Arab Emirates, Bahrain, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Palestine, Qatar, Saudi Arabia, Syria, Yemen
Pakistan	Pakistan
Russia	Russia
South Africa	South Africa
South America_Northern	French Guiana, Guyana, Suriname, Venezuela
South America_Southern	Bolivia, Chile, Ecuador, Peru, Paraguay, Uruguay
South Asia	Afghanistan, Bangladesh, Bhutan, Sri Lanka, Maldives, Nepal
Southeast Asia	American Samoa, Brunei Darussalam, Cocos (Keeling) Islands, Cook Islands, Christmas Island, Fiji, Federated States of Micronesia, Guam, Cambodia, Kiribati, Lao Peoples Democratic Republic, Marshall Islands, Myanmar, Northern Mariana Islands, Malaysia, Mayotte, New Caledonia, Norfolk Island, Niue, Nauru, Pacific Islands Trust Territory, Pitcairn Islands, Philippines, Palau, Papua New Guinea, Democratic Peoples Republic of Korea, French Polynesia, Singapore, Solomon Islands, Seychelles, Thailand, Tokelau, Timor Leste, Tonga, Tuvalu, Viet Nam, Vanuatu, Samoa
South Korea	South Korea
Taiwan	Taiwan
USA	United States

C.2. Eurostat Country Classifications

Table C.2: Eurostat Country Codes for EU-15 Nation-States

Country Code	**Country Name**
AT	Austria
BE	Belgium
DE	Germany
DK	Denmark
EL	Greece
ES	Spain
FI	Finland
FR	France
IE	Ireland
IT	Italy
LU	Luxembourg
NL	Netherlands
PT	Portugal
SE	Sweden
UK	United Kingdom

C.3. Linear Downscaling

Table C.3: Linear Proportions for EU-15 Countries Relative to Emissions, Population, and GDP

Country	**Proportional to (%)**		
	Emissions	Population	GDP
Austria	1.8	2.2	2.5
Belgium	2.2	2.8	3.0
Denmark	1.3	1.4	2.0
Finland	2.4	1.3	1.6
France	4.5	16.4	15.9
Germany	37.8	20.3	22.2
Greece	4.1	2.6	1.3
Ireland	1.4	1.2	2.2
Italy	13.3	14.8	11.8
Luxembourg	0.0	0.1	0.4
Netherlands	7.1	4.2	5.1
Portugal	2.4	2.5	1.3
Spain	9.2	11.4	8.1
Sweden	1.0	2.5	3.3
United Kingdom	11.5	16.2	19.1

Table C.4: Standard Deviation and Coefficient of Variation between Linear Proportions of Each EU-15 Country

Country	**Standard Deviation (%)**	**Coefficient of Variation (*Unitless*)**
Austria	0.4	0.2
Belgium	0.4	0.2
Germany	9.6	0.4
Denmark	0.4	0.3
Greece	1.4	0.5
Spain	1.7	0.2
Finland	0.5	0.3
France	6.8	0.6
Ireland	0.5	0.3
Italy	1.5	0.1
Luxembourg	0.2	1.0
Netherlands	1.5	0.3
Portugal	0.7	0.3
Sweden	1.2	0.5
United Kingdom	3.9	0.2

Table C.5: Composition of Economies in EU-15 Nations

Country	Contribution to GDP (%)		
	Agriculture	Industry	Services
Austria	1.3	28.4	70.3
Belgium	0.7	22.1	77.2
Denmark	1.3	22.9	75.8
Finland	2.7	28.2	69.1
France	1.7	19.5	78.8
Germany	0.7	30.7	68.6
Greece	4.1	16.9	79.1
Ireland	1.2	38.6	60.2
Italy	2.1	23.9	73.9
Luxembourg	0.3	12.8	86.9
Netherlands*	2.5	24.9	72.6
Portugal	2.2	22.1	75.7
Spain	2.6	23.2	74.2
Sweden	1.6	33.0	65.4
United Kindgom	0.7	20.2	79.2

Source: (Central Intelligence Agency, 2017)

*Note: 2017 data was incomplete so 2013 was used.

C.4. Convergence Downscaling

Table C.6: Base Year Energy Intensity Relative to GDP and Population in EU-15

Country	Year	Resource Type	Base Energy Intensity	
			GDP	Population
Austria	2018	Biomass	1.397e-08	2.876e-07
Austria	2018	Coal	6.644e-08	1.368e-06
Austria	2018	Geothermal	8.853e-11	1.508e-09
Austria	2018	Hydro	7.376e-07	1.519e-05
Austria	2018	Hydrogen	1.000e-16	1.000e-16
Austria	2018	Natural gas	1.820e-07	3.748e-06
Austria	2018	Nuclear	1.087e-08	2.314e-07
Austria	2018	Oil	1.170e-08	2.408e-07
Austria	2018	Solar PV	9.523e-10	1.937e-08
Austria	2018	Solar Thermal	9.220e-09	1.138e-07
Austria	2018	Wind	1.161e-07	2.390e-06
Belgium	2018	Biomass	1.653e-08	3.124e-07
Belgium	2018	Coal	3.568e-08	6.741e-07
Belgium	2018	Geothermal	8.853e-11	1.508e-09
Belgium	2018	Hydro	2.071e-08	3.914e-07
Belgium	2018	Hydrogen	1.000e-16	1.000e-16
Belgium	2018	Natural gas	3.696e-07	6.983e-06
Belgium	2018	Nuclear	4.512e-07	8.526e-06
Belgium	2018	Oil	9.477e-10	1.791e-08
Belgium	2018	Solar PV	5.832e-08	1.102e-06
Belgium	2018	Solar Thermal	9.220e-09	1.138e-07
Belgium	2018	Wind	1.200e-07	2.267e-06
Germany	2018	Biomass	4.136e-08	7.928e-07
Germany	2018	Coal	4.771e-07	9.146e-06
Germany	2018	Geothermal	3.749e-10	7.185e-09
Germany	2018	Hydro	4.546e-08	8.715e-07
Germany	2018	Hydrogen	1.000e-16	1.000e-16
Germany	2018	Natural gas	1.602e-07	3.071e-06
Germany	2018	Nuclear	1.640e-07	3.143e-06
Germany	2018	Oil	1.081e-08	2.071e-07
Germany	2018	Solar PV	1.048e-07	2.008e-06
Germany	2018	Solar Thermal	9.220e-09	1.138e-07
Germany	2018	Wind	2.545e-07	4.878e-06
Denmark	2018	Biomass	1.416e-08	3.552e-07
Denmark	2018	Coal	1.706e-07	4.279e-06
Denmark	2018	Geothermal	8.853e-11	1.508e-09
Denmark	2018	Hydro	3.706e-10	9.296e-09
Denmark	2018	Hydrogen	1.000e-16	1.000e-16
Denmark	2018	Natural gas	4.864e-08	1.220e-06
Denmark	2018	Nuclear	1.087e-08	2.314e-07
Denmark	2018	Oil	5.783e-09	1.451e-07
Denmark	2018	Solar PV	2.365e-08	5.934e-07
Denmark	2018	Solar Thermal	9.220e-09	1.138e-07

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Table C.6 continued from previous page

Country	Year	Resource Type	Base Energy Intensity	
			GDP	Population
Denmark	2018	Wind	3.450e-07	8.655e-06
Greece	2018	Biomass	2.037e-11	1.709e-10
Greece	2018	Coal	6.158e-07	5.169e-06
Greece	2018	Geothermal	8.853e-11	1.508e-09
Greece	2018	Hydro	2.317e-07	1.945e-06
Greece	2018	Hydrogen	1.000e-16	1.000e-16
Greece	2018	Natural gas	5.423e-07	4.551e-06
Greece	2018	Nuclear	1.087e-08	2.314e-07
Greece	2018	Oil	1.831e-07	1.537e-06
Greece	2018	Solar PV	1.514e-07	1.271e-06
Greece	2018	Solar Thermal	9.220e-09	1.138e-07
Greece	2018	Wind	2.516e-07	2.112e-06
Spain	2018	Biomass	1.522e-08	1.878e-07
Spain	2018	Coal	2.340e-07	2.887e-06
Spain	2018	Geothermal	8.853e-11	1.508e-09
Spain	2018	Hydro	2.256e-07	2.784e-06
Spain	2018	Hydrogen	1.000e-16	1.000e-16
Spain	2018	Natural gas	3.323e-07	4.101e-06
Spain	2018	Nuclear	3.331e-07	4.110e-06
Spain	2018	Oil	7.905e-08	9.756e-07
Spain	2018	Solar PV	4.822e-08	5.951e-07
Spain	2018	Solar Thermal	2.766e-08	3.414e-07
Spain	2018	Wind	3.094e-07	3.819e-06
Finland	2018	Biomass	3.030e-08	6.164e-07
Finland	2018	Coal	2.876e-07	5.849e-06
Finland	2018	Geothermal	8.853e-11	1.508e-09
Finland	2018	Hydro	4.224e-07	8.592e-06
Finland	2018	Hydrogen	1.000e-16	1.000e-16
Finland	2018	Natural gas	1.278e-07	2.599e-06
Finland	2018	Nuclear	7.027e-07	1.429e-05
Finland	2018	Oil	6.420e-09	1.306e-07
Finland	2018	Solar PV	2.857e-09	5.812e-08
Finland	2018	Solar Thermal	9.220e-09	1.138e-07
Finland	2018	Wind	1.881e-07	3.827e-06
France	2018	Biomass	1.000e-16	5.698e-11
France	2018	Coal	3.631e-08	6.185e-07
France	2018	Geothermal	2.656e-10	4.523e-09
France	2018	Hydro	2.170e-07	3.696e-06
France	2018	Hydrogen	1.000e-16	1.000e-16
France	2018	Natural gas	1.115e-07	1.900e-06
France	2018	Nuclear	1.242e-06	2.115e-05
France	2018	Oil	1.185e-08	2.019e-07
France	2018	Solar PV	3.049e-08	5.192e-07
France	2018	Solar Thermal	9.220e-09	1.138e-07
France	2018	Wind	8.255e-08	1.406e-06
Ireland	2018	Biomass	5.786e-08	1.881e-06

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Table C.6 continued from previous page

Country	Year	Resource Type	Base Energy Intensity	
			GDP	Population
Ireland	2018	Coal	4.834e-08	1.571e-06
Ireland	2018	Geothermal	8.853e-11	1.508e-09
Ireland	2018	Hydro	2.114e-08	6.871e-07
Ireland	2018	Hydrogen	1.000e-16	1.000e-16
Ireland	2018	Natural gas	3.410e-07	1.108e-05
Ireland	2018	Nuclear	1.087e-08	2.314e-07
Ireland	2018	Oil	1.234e-09	4.011e-08
Ireland	2018	Solar PV	9.523e-10	1.937e-08
Ireland	2018	Solar Thermal	9.220e-09	1.138e-07
Ireland	2018	Wind	1.915e-07	6.222e-06
Italy	2018	Biomass	1.000e-16	5.698e-11
Italy	2018	Coal	1.000e-16	5.760e-08
Italy	2018	Geothermal	2.428e-08	3.397e-07
Italy	2018	Hydro	2.096e-07	2.933e-06
Italy	2018	Hydrogen	1.000e-16	1.000e-16
Italy	2018	Natural gas	1.000e-16	7.411e-08
Italy	2018	Nuclear	1.087e-08	2.314e-07
Italy	2018	Oil	1.000e-16	5.969e-09
Italy	2018	Solar PV	9.736e-08	1.362e-06
Italy	2018	Solar Thermal	9.220e-09	1.138e-07
Italy	2018	Wind	7.367e-08	1.031e-06
Luxembourg	2018	Biomass	8.305e-09	3.883e-07
Luxembourg	2018	Coal	2.435e-09	5.760e-08
Luxembourg	2018	Geothermal	8.853e-11	1.508e-09
Luxembourg	2018	Hydro	1.696e-07	7.931e-06
Luxembourg	2018	Hydrogen	1.000e-16	1.000e-16
Luxembourg	2018	Natural gas	2.487e-08	1.163e-06
Luxembourg	2018	Nuclear	1.087e-08	2.314e-07
Luxembourg	2018	Oil	3.159e-10	5.969e-09
Luxembourg	2018	Solar PV	1.429e-08	6.679e-07
Luxembourg	2018	Solar Thermal	9.220e-09	1.138e-07
Luxembourg	2018	Wind	3.373e-08	1.577e-06
Netherlands	2018	Biomass	1.249e-08	2.659e-07
Netherlands	2018	Coal	3.115e-07	6.632e-06
Netherlands	2018	Geothermal	8.853e-11	1.508e-09
Netherlands	2018	Hydro	8.464e-10	1.802e-08
Netherlands	2018	Hydrogen	1.000e-16	1.000e-16
Netherlands	2018	Natural gas	5.588e-07	1.190e-05
Netherlands	2018	Nuclear	3.261e-08	6.943e-07
Netherlands	2018	Oil	4.862e-09	1.035e-07
Netherlands	2018	Solar PV	2.385e-08	5.077e-07
Netherlands	2018	Solar Thermal	9.220e-09	1.138e-07
Netherlands	2018	Wind	1.208e-07	2.573e-06
Portugal	2018	Biomass	1.122e-08	1.046e-07
Portugal	2018	Coal	4.182e-07	3.898e-06
Portugal	2018	Geothermal	7.694e-09	7.171e-08

Table C.6 continued from previous page

Country	Year	Resource Type	Base Energy Intensity	
			GDP	Population
Portugal	2018	Hydro	5.062e-07	4.719e-06
Portugal	2018	Hydrogen	1.000e-16	1.000e-16
Portugal	2018	Natural gas	5.416e-07	5.048e-06
Portugal	2018	Nuclear	1.087e-08	2.314e-07
Portugal	2018	Oil	4.339e-08	4.044e-07
Portugal	2018	Solar PV	3.655e-08	3.407e-07
Portugal	2018	Solar Thermal	9.220e-09	1.138e-07
Portugal	2018	Wind	4.703e-07	4.383e-06
Sweden	2018	Biomass	3.981e-08	9.419e-07
Sweden	2018	Coal	7.304e-09	1.728e-07
Sweden	2018	Geothermal	8.853e-11	1.508e-09
Sweden	2018	Hydro	9.169e-07	2.169e-05
Sweden	2018	Hydrogen	1.000e-16	1.000e-16
Sweden	2018	Natural gas	9.398e-09	2.223e-07
Sweden	2018	Nuclear	9.894e-07	2.341e-05
Sweden	2018	Oil	2.858e-09	6.762e-08
Sweden	2018	Solar PV	9.523e-10	1.937e-08
Sweden	2018	Solar Thermal	9.220e-09	1.138e-07
Sweden	2018	Wind	2.502e-07	5.919e-06
United Kingdom	2018	Biomass	1.432e-08	2.958e-07
United Kingdom	2018	Coal	4.199e-08	8.673e-07
United Kingdom	2018	Geothermal	8.853e-11	1.508e-09
United Kingdom	2018	Hydro	2.020e-08	4.171e-07
United Kingdom	2018	Hydrogen	1.000e-16	1.000e-16
United Kingdom	2018	Natural gas	3.395e-07	7.012e-06
United Kingdom	2018	Nuclear	1.554e-07	3.210e-06
United Kingdom	2018	Oil	2.506e-09	5.176e-08
United Kingdom	2018	Solar PV	3.382e-08	6.984e-07
United Kingdom	2018	Solar Thermal	9.220e-09	1.138e-07
United Kingdom	2018	Wind	1.497e-07	3.091e-06

Table C.7: Convergence Year Energy Intensity Relative to GDP and Population for EU-15 Countries

Resource Type	**Region**	**Year**	**Convergence Year Energy Intensity**	
			GDP	Population
Biomass	EU-15	2100	3.175e-08	2.425e-06
Coal	EU-15	2100	1.361e-07	1.040e-05
Geothermal	EU-15	2100	8.561e-09	6.540e-07
Hydro	EU-15	2100	3.501e-08	2.674e-06
Hydrogen	EU-15	2100	7.255e-09	5.542e-07
Natural gas	EU-15	2100	1.030e-07	7.866e-06
Nuclear	EU-15	2100	1.530e-07	1.169e-05
Oil	EU-15	2100	1.027e-08	7.847e-07
Solar PV	EU-15	2100	4.802e-09	3.669e-07
Solar Thermal	EU-15	2100	2.379e-08	1.818e-06
Wind	EU-15	2100	1.138e-07	8.691e-06

Table C.8: Growth Rate of Energy Intensity Relative to GDP and Population in EU-15

Country	**Growth Rate by Resource Type**										
	Biomass	Coal	Geothermal	Hydro	Hydrogen	Natural Gas	Nuclear	Oil	Solar PV	Solar Thermal	Wind
GDP											
Austria	1.0101	1.0088	1.0573	0.9635	1.2470	0.9931	1.0328	0.9984	1.0199	1.0116	0.9998
Belgium	1.0080	1.0165	1.0573	1.0064	1.2470	0.9845	0.9869	1.0295	0.9700	1.0116	0.9994
Germany	0.9968	0.9848	1.0389	0.9968	1.2470	0.9946	0.9992	0.9994	0.9631	1.0116	0.9902
Denmark	1.0099	0.9973	1.0573	1.0570	1.2470	1.0092	1.0328	1.0070	0.9807	1.0116	0.9866
Greece	1.0938	0.9818	1.0573	0.9772	1.2470	0.9799	1.0328	0.9655	0.9588	1.0116	0.9904
Spain	1.0090	0.9934	1.0573	0.9775	1.2470	0.9858	0.9906	0.9754	0.9723	0.9982	0.9879
Finland	1.0006	0.9909	1.0573	0.9701	1.2470	0.9974	0.9816	1.0057	1.0064	1.0116	0.9939
France	1.2696	1.0162	1.0433	0.9780	1.2470	0.9990	0.9748	0.9983	0.9777	1.0116	1.0039
Ireland	0.9927	1.0127	1.0573	1.0062	1.2470	0.9855	1.0328	1.0262	1.0199	1.0116	0.9937
Italy	1.2696	1.2924	0.9874	0.9784	1.2470	1.2880	1.0328	1.2523	0.9640	1.0116	1.0053
Luxembourg	1.0165	1.0503	1.0573	0.9809	1.2470	1.0175	1.0328	1.0434	0.9868	1.0116	1.0149
Netherlands	1.0114	0.9900	1.0573	1.0464	1.2470	0.9796	1.0190	1.0092	0.9806	1.0116	0.9993
Portugal	1.0128	0.9864	1.0013	0.9679	1.2470	0.9800	1.0328	0.9826	0.9756	1.0116	0.9828
Sweden	0.9972	1.0363	1.0573	0.9610	1.2470	1.0296	0.9775	1.0157	1.0199	1.0116	0.9904
United Kingdom	1.0098	1.0144	1.0573	1.0067	1.2470	0.9856	0.9998	1.0174	0.9765	1.0116	0.9967
Population											
Austria	1.0263	1.0250	1.0769	0.9790	1.3147	1.0091	1.0490	1.0145	1.0365	1.0344	1.0159
Belgium	1.0253	1.0339	1.0769	1.0237	1.3147	1.0015	1.0039	1.0472	0.9867	1.0344	1.0165
Germany	1.0137	1.0016	1.0566	1.0138	1.3147	1.0115	1.0161	1.0164	0.9795	1.0344	1.0071
Denmark	1.0237	1.0109	1.0769	1.0715	1.3147	1.0230	1.0490	1.0208	0.9942	1.0344	1.0001
Greece	1.1237	1.0086	1.0769	1.0039	1.3147	1.0067	1.0490	0.9918	0.9850	1.0344	1.0174
Spain	1.0317	1.0157	1.0769	0.9995	1.3147	1.0080	1.0128	0.9973	0.9941	1.0206	1.0101
Finland	1.0168	1.0070	1.0769	0.9859	1.3147	1.0136	0.9976	1.0221	1.0227	1.0344	1.0101
France	1.1388	1.0350	1.0625	0.9961	1.3147	1.0175	0.9928	1.0167	0.9958	1.0344	1.0225
Ireland	1.0031	1.0233	1.0769	1.0167	1.3147	0.9958	1.0490	1.0369	1.0365	1.0344	1.0041
Italy	1.1388	1.0654	1.0080	0.9989	1.3147	1.0585	1.0490	1.0613	0.9841	1.0344	1.0263
Luxembourg	1.0226	1.0654	1.0769	0.9868	1.3147	1.0236	1.0490	1.0613	0.9927	1.0344	1.0210
Netherlands	1.0273	1.0055	1.0769	1.0629	1.3147	0.9950	1.0350	1.0250	0.9960	1.0344	1.0150
Portugal	1.0391	1.0120	1.0273	0.9931	1.3147	1.0054	1.0490	1.0081	1.0009	1.0344	1.0084
Sweden	1.0116	1.0512	1.0769	0.9748	1.3147	1.0444	0.9916	1.0303	1.0365	1.0344	1.0047
United Kingdom	1.0260	1.0308	1.0769	1.0229	1.3147	1.0014	1.0159	1.0337	0.9922	1.0344	1.0127