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# Building a Strategy for Key Energy Transitions: Modeling Biophysical Economics

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# Building a Strategy for Key Energy Transitions: Modeling Biophysical Economics

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John Sherwood
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# Abstract

Economists rarely model the economy as explicitly bound by Earth's ecological systems. However, ecological systems act as constraints on the economy — constraints that have historically been too far away from economic productivity to seriously consider. These ecological or biophysical constraints have been growing closer and more prominent as natural resources are depleted and environmental impacts increase. Modeling these constraints is what defines the emerging subdiscipline of biophysical economics, BPE. The goal of this dissertation is to map out and extend current biophysical economics modeling strategies. BPE provides the ideal framework to holistically understand energy transitions towards sustainability.

In Chapter 2, we examine and classify 110 biophysical models of the economy. Although BPE modelling approaches are varied, grouping the research by common characteristics reveals several active research areas. Gaps also exist. We identify which of those gaps could be promising avenues for future research.

In Chapter 3, we integrate US food production data into the environmental-input–output life cycle assessment (EIO-LCA) model. The extended model is used to characterize the food, energy, and water (FEW) intensities of every US economic sector, and is applied to every metropolitan statistical area (MSA) within the U.S. Results of this study enable a more complete understanding of food, energy, and water as key ingredients to a functioning economy.

Chapter 4 analyzes datasets from multiple sources to build a detailed picture of the $CO_2$-eq emissions generated by coal rail transportation. The results show that rail transportation distances range from 0 km to over 3500 km. Transportation emissions can be as high as 35% of a power plant's operational emissions — a number significantly higher than previous literature estimates. Additionally, implementation of post-combustion Carbon Capture and Storage (CCS) at existing plants may further increase transportation emissions.

Chapter 5 uses an agent-based model to demonstrate the potential economic impacts of a resource supply shock. Economic "agents" mine resources and invent technology in order to grow their economy. Economic growth, however, comes with a cost. Unexpected, large economic collapse can arise from a shock to even a single resource, due to each resource's interdependent role in the economy.

# Dedication

As I reflect on my dissertation, I am struck by just how much support I've received. A PhD is as much a communal effort as a personal endeavor. This work is dedicated to those who have continually encouraged, supported, and motivated me along the PhD journey.

**Michael Carbajales-Dale** has been an incredible advisor and mentor, constantly displaying kindness and empathy during times of self-doubt while also encouraging service and skill-building through teaching opportunities. **Becky Haney** has been a true mentor and friend. She has been an excellent guide through academia - through encouragement of rigorous research, setting the foundations of papers and giving me a launch pad, and by discussing the roles of teaching and research. **Matt Heun** first inspired me to attend graduate school, and first introduced me to the links between energy and economics. His careful and measured approach to problems has had a lasting impact. The **E3SA research group**, members past and present, were a great source of encouragement and comradery. The **Clemson Center for Geospatial Technologies** and **Patricia Carbajales-Dale** provided some awesome opportunities to learn how to teach and build into an academic community. My own **Department of Environmental Engineering and Earth Sciences**, and various professors within, have been incredibly supportive and have demonstrated how a community of researchers ought to function. The **Calvin College Engineering Department** trained me to think deeply on multidisciplinary issues, and instilled a sense of problem solving and perseverance. **My family** has been extremely encouraging and supportive. Finally, **Sammy**, **Steve**, and **Bridget Blood** have been a ceaseless source of joy and laughter which has kept me sane.

Thank you to everyone who has believed in me, encouraged me, worked with me, or otherwise just put up with me during this five year journey.

# Acknowledgments

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I would like to thank all reviewers whose insights and comments improved the quality of the these chapters.

# Table of Contents

# List of Tables

# List of Figures

# Chapter 1

# Introduction

## 1.1 Thesis in three minutes

Bob Ross and I painted Figure 1.1 about halfway through my doctoral studies; I am quite proud of it. Painting is a lot of fun, but it is challenging — it takes creativity and effort and attention to detail to come out looking like a perfect model of reality. Painters aren't the only ones that model reality, though: scientists do that too.

Figure 1.1: A painting by John Sherwood, inspired by the work of Bob Ross. A two inch brush and script liner brush are pictured.

A few scientists work on modeling the reality of climate change and its interplay with economics and energy systems. In broad strokes, they do this by stitching together climate, energy, and economic models. Often, models assume an economic growth rate of a few percent for the next hundred years and try to project energy production to meet that growth. The models have a few different scenarios, but the structures of the algorithms are all the same — they tend to be macro oriented or top-down.

In a way, the equations used are a bit like the two inch brush on Figure 1.1. I used that brush to paint the entire picture. It is difficult to use that big of a brush to paint the details of those trees, because the brush was originally designed for big strokes — not detail work. But by understanding the brush well enough, a painter can get it to generate what seem to be smaller details.

For energy forecasting, scientists tend to use a two inch brush. Often, models tend to simplify the entire world energy system into a small set of equations and treat it like an optimization problem. Models use these broad strokes to create rough projections that are loaded with assumptions. And if you look closely, the models might fall apart in the details.

For all his skill, Bob Ross's happy little trees fall apart in the details. While they approximate reality, they do not function like reality.

Is there a better way to paint? Unfortunately for Bob Ross, there is. Rather than use a massive brush, what if we used a tiny brush? Rather than focus on the macro picture, what if we focused on the details in the hopes that a picture might emerge? Artists might recognize this suggestion as pointillism art. Scientists might see it as bottom-up modeling, or potentially agent-based modeling.

If we focus on the microeconomic interactions of energy systems and use a different set of assumptions, can we avoid the current pitfalls of energy and climate models? What might the alternate projections look like? What additional information will they provide?

This dissertation is a step towards the smaller brush. It recognizes the importance of holistically modeling energy, economics, and environmental impacts while also pointing out limitations to current modeling practices. The dissertation shows that using a smaller brush is feasible for many paintings. Ultimately this work shows that, for an effective transition towards sustainability, a better and more detailed picture of the world is necessary.

## 1.2 Objectives

The goal of this dissertation is to map out and extend current biophysical economics[1] modeling strategies. Biophysical economics, by putting energy and material resources at the center of economic production and wellbeing, is best suited to fully model the coming energy transitions towards sustainability. The objectives of this work are to:

1. Fully characterize the current landscape of biophysical economic models
2. Identify potential research gaps within the field
3. Implement and extend upon three modeling frameworks to demonstrate their use and advance the field of biophysical economic modeling

This work is both highly relevant and urgent. While economic growth has proceeded relatively unchecked throughout the 19$^{\text{th}}$ and 20$^{\text{th}}$ centuries, there is reason to believe that continued growth may be in jeopardy. The Earth has already crossed many "planetary boundaries," thresholds of various environmental factors that, when crossed, Earth-systems may be substantially (and likely negatively) altered (Steffen et al., 2015; O'Neill et al., 2018). Simultaneously, scientists have expressed concerns about declines in fossil-fuel energy return on investment (Hall et al., 2014; King and Van Den Bergh, 2018; Sers and Victor, 2018). We may be facing depletion of easily accessible fuels in the coming decades, or at the very least, have less of an energetic surplus with which to fuel the rest of the economy. It seems that the world cannot continue for long in a business-as-usual economic loop. A transition towards a more circular economy fueled through renewable energy systems seems necessary, regardless of it being prompted by either a declining resource base or increasing environmental impacts.

### 1.2.1 Limitations of common models

Unfortunately, many mainstream energy-economic models tend to only represent energy systems and energy transitions in terms of a financial optimization problem. The recent "2035 Report" demonstrates this (Phadke et al., 2020). The report is a projection of achieving a 90% clean electricity grid by 2035 and is written by multiple organizations with leadership from the

[1] Biophysical economics is more fully defined in Chapter 2, but incorporates energy and physical resources into the study of economic systems.

Goldman School of Public Policy, University of California Berkeley. It is meant to inform and prompt policymakers to support the type of transition projected.

The 2035 report optimizes, based on least-cost, power producers across 134 regions of the U.S. electric grid. The optimization is subject to various constraints, such as achieving a 90% clean grid by 2035. The report finds that a 90% clean grid nearly achieves a cost parity with a business-as-usual model, and is much more cost effective when incorporating environmental externalities.

While an impressive modeling effort, the model and subsequent report face certain limitations. Chief among these limitations is a reliance on assumed continued cost decreases in renewable technology, despite more than doubling the amount of renewable capacity installations to an average of 70 GW per year for the next 15 years. The report's cost data comes from the National Renewable Energy Laboratory's Annual Technology Baseline 2019 report (NREL (National Renewable Energy Laboratory), 2019), but it is unclear if these cost projections account for upstream supply changes or constraints prompted by such a massive increase in renewable energy systems demand. In life cycle assessment[2] terms, the cost data is likely attributional in nature (i.e. data based on the current industry structure) rather than consequential (i.e. taking into account structural changes within the industry prompted by large changes in demand). Of course, if the upstream supply chain of renewable energy systems cannot adapt to such a large demand increase (such as encountering trouble sourcing large quantities of various components and materials), the entire 2035 report may be far too optimistic.

The 2035 report represents only one of several energy-economic models that have required certain modeling assumptions to be tractable. Many of these modeling assumptions, that while necessary at the time of model construction, present a stylized view of reality that miss important components or feedback loops. These missed feedback loops could seriously alter model output and policy recommendations. Both Palmer (2018b) and Pauliuk et al. (2017) describe how common Integrated Assessment Models (IAMs, that among other uses help inform Intergovernmental Panel on Climate Change (IPCC) reports) miss physical material flows and the interrelationship between GDP and energy requirements. Palmer (2018b) states, "...IAMs insufficiently describe the energy-economy nexus ..." and may be overly optimistic in their projections because of it.

This dissertation, by describing, extending upon, and building new models that place phys-

[2]Life cycle assessment is more fully defined within Chapter 3, it is a method used to fully account for the environmental impacts of a product or service.

ical resource concerns at their center, is a much-needed step towards proper planning of a renewable energy transition. Only through holistic modeling of the energy-economy system can we develop a strategy for a transition towards sustainability.

## 1.3 Chapter overviews

The dissertation is composed of four main chapters (Chapter 2–5), each of which has been published as a journal article over the course of this doctoral research. Chapter 2 covers a literature review and fulfills the objectives: 1. Fully characterize the current landscape of biophysical economic models, and 2. Identify potential research gaps within the field. Chapters 3–5 each contain a model that, together, fulfill the third objective: 3. Implement and extend upon three modeling frameworks to demonstrate their use and advance the field of biophysical economic modeling. The next sections will provide a brief overview of each chapter.

It is important to note that, even though I was the primary author on each of these journal articles, each article was developed as a collaborative effort among several co-authors. Because much of the work was collaborative, each chapter overview below contains a statement outlining the contributions and responsibilities of every co-author. I am grateful for their excellent support, contributions, and insights which helped further develop each of these projects.

These chapters do not necessarily stand alone. They build upon each other to illustrate the main goal of this dissertation: to map out and extend current biophysical economics modeling strategies in order to showcase its effectiveness at holistically modeling a transition towards sustainability.

### 1.3.1 Chapter 2

Chapter 2, titled "Putting the Biophysical (back) in Economics: a taxonomic review of modelling the Earth-bound economy," describes a comprehensive literature review of the biophysical economics modeling landscape. It provides a brief history of the field and identifies areas of high research activity. The chapter effectively answers the question *What types of biophysical economics models exist?* To answer the question, though, we first need to define biophysical economics. Briefly, the contrast between conventional and biophysical economics can be seen in Figure 1.2 (This also appears as Figure 2.1).

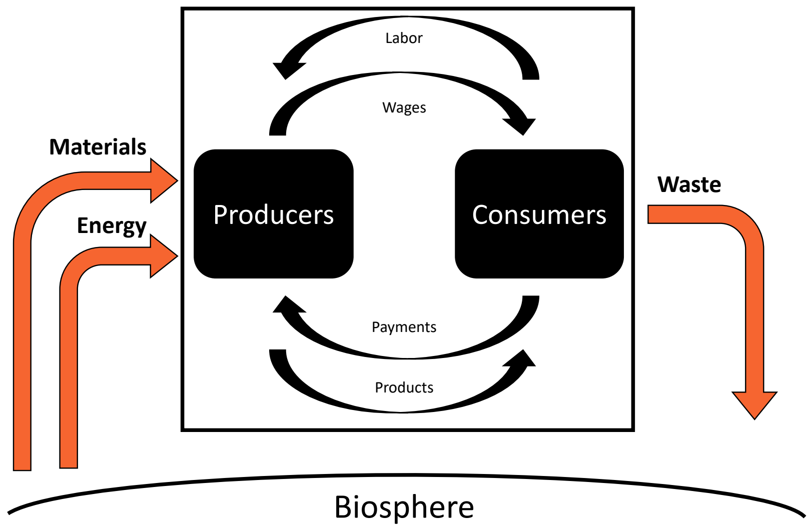


Figure 1.2: Biophysical economics' Circular Flow Model. Adapted from Heun et al. (2015); Hall et al. (1986)

The conventional economic circular flow model is still included, but is clearly embedded and enmeshed within the biosphere. The diagram not only recognizes the necessity of material and energy as inputs to a functioning economy, but also recognizes the inevitability of outputs — presently waste deposited back to the biosphere. The non-monetary flows of natural resources, energy, and waste that are intrinsic to the economy are made visible alongside the monetary flows and flows of economic goods and services. This coupling between economy and biosphere is critical to holistically understand constraints to economic opportunities and the impacts of economic activity upon the natural environment.

Ultimately, this figure and perspective frame the rest of the dissertation. Subsequent chapters investigate various aspects of the biophysical circular flow model.

Chapter 2 goes on to develop a modeling taxonomy with which to characterize 110 selected models. This taxonomy informs what types of models have been popular, but also helps determine if any modeling gaps exist within the literature. Briefly, these modeling characteristics are:

1. Framework: does action in the model flow from the top-down or bottom-up?
2. Spatial scale: is the model more local or global in scale?
3. Time horizon: is the time frame short or long term?

4. Ethos: is the model more empirical or theoretical?

5. Origins: does the model emerge primarily from natural sciences or from social sciences?

6. Mechanism: does the model rely on statistical inference or simulated outcomes?

Figure 1.3 shows the results of mapping 110 models to these modeling characteristics. Darker shaded characteristics indicate more models that fit the characteristic.

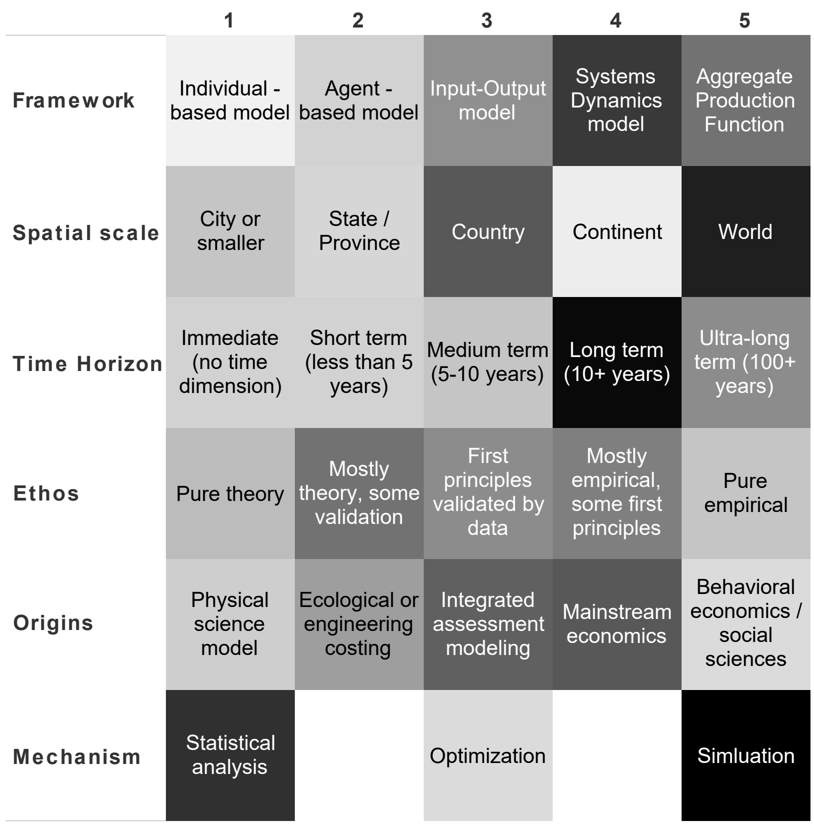


Figure 1.3: Results of categorizing 110 biophysical economics models across these 6 characteristics. Darker shaded areas of the taxonomy indicate more models fall within that category. Here, a black box represents 57 models.

From this analysis, we see potential research gaps in the field. These include (among others) few agent-based models, few city or state-level models, and few shorter term models. Essentially, this means that the biophysical economics research community may be missing important research questions.

The combination of Figures 1.2 and 1.3 provide a framework with which to understand the rest of this dissertation; subsequent chapters, each representing a biophysical economics model, can be linked back to these lenses. Each model reinforces the importance of a biophysical perspective (i.e. the importance of physical flows and holistically studying the economy) while also expanding the range of models used in the field. By the conclusion of this dissertation, we will have studied and extended upon a wide swath of the biophysical economics modeling taxonomy.

#### 1.3.1.1 CRediT authorship statement & citation information

Though this chapter was a collaborative effort, the primary and original contributions by the main author (John Sherwood) include data collection, analysis, writing, and much of the planning of the paper. Other co-authors helped primarily with the framing of the paper (e.g. introduction and conclusion) and with editing. The co-authors also helped guide the project. Full details of tasks and responsibilities are included in the CrediT statement below (Allen et al., 2019).

**John Sherwood:** Conceptualization, Methodology, Analysis, Validation, Data Curation, Writing — Original Draft, Writing — Review & Editing, Visualization. **Becky Haney:** Conceptualization, Writing — Original Draft (primarily within Section 2.1), Writing — Review & Editing, Supervision. **Michael Carbajales-Dale:** Conceptualization, Methodology, Writing — Original Draft, Writing — Review & Editing, Supervision.

This chapter was originally published in 2020 within the *Journal of Biophysical Economics and Sustainability* (formerly the *Journal of Biophysical Economics and Resource Quality*).[3] The chapter has been edited for clarity and format.

### 1.3.2 Chapter 3

Chapter 3, titled "An extended environmental input–output lifecycle assessment model to study the urban food–energy–water nexus" answers the question *what are the food, energy, and water requirements of every industry, and every metropolitan statistical area within the U.S.?* It describes an extended environmental input-output life cycle assessment model. The model traces the flow of goods, resources, and environmental impacts through the entire U.S. economy, and can be used to find the total environmental impacts (including impacts from upstream its supply chain) of any particular product.

[3]Sherwood, J., Carbajales-Dale, M., and Haney, B. R. (2020b). Putting the Biophysical (Back) in Economics: A Taxonomic Review of Modeling the Earth-Bound Economy. *Biophysical Economics and Sustainability*, 5(1):1–20, published as Open Access under the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/)

While this model existed previously, the novel contribution of this chapter is quantifying food as an input to many economic sectors. With this addition, food can also be traced through the U.S. economy just like previous indicators such as energy and water requirements. The application of this model to metropolitan statistical areas is also novel. Ultimately, the goal of this paper is to demonstrate how various industries and cities are reliant on natural resources (the primary inputs to a biophysical economy, as in Figure 1.2). Some of the results of this analysis are shown in Figure 1.4.

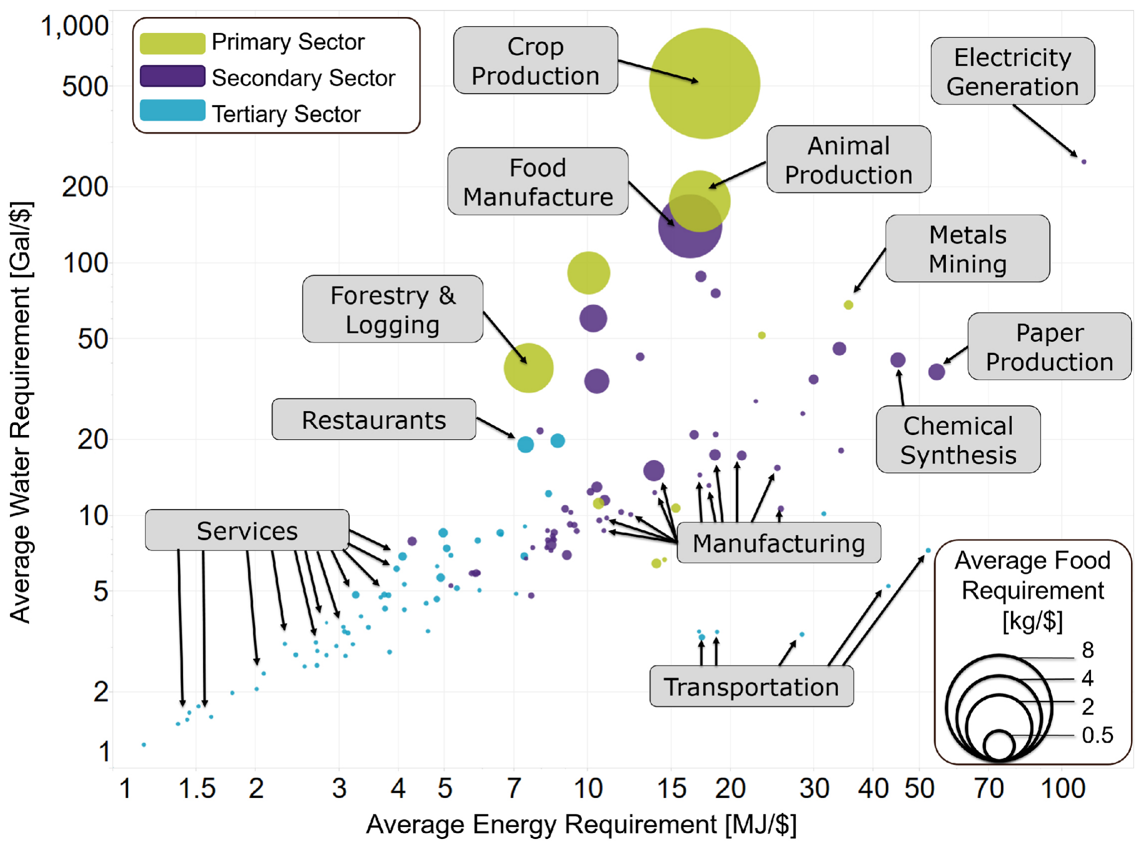


Figure 1.4: Resource requirements per dollar of final demand output for 133 industry groups.

Within Figure 1.4, 133 different U.S. industries representing the full range of businesses in the U.S. economy are plotted as dots against their respective food, energy, and water requirements needed to make $1M USD of final demand (that is, consumer product). Each industry, even many service industries, require physical resources to function. As such, viewing the economy through a biophysical lense seems critical to a holistic understanding of economic growth and wellbeing.

The chapter concludes by identifying correlations between these resources and economic output. A key piece of this chapter is that energy, food, and water resource requirements are correlated — it may be difficult to decouple these resources from each other or from economic growth. A transition towards sustainability on the energy front may not mean a holistic transition towards sustainability if food and water inputs continue to cause undue environmental stress. Therefore, energy transitions studies should be aware that they might not solve all problems and much more work needs to be done along other resource fronts.

#### 1.3.2.1 CRediT authorship statement & citation information

Though this chapter was a collaborative effort, the primary and original contributions by the main author (John Sherwood) include conceptualization, data collection, analysis, writing, and much of the planning of the paper. While the model was prexisting, the main author focused on extending it to include food resources and applied it to metropolitan statistical areas. Other co-authors helped primarily with the framing of the paper (e.g. Introduction and conclusion) and with editing. Raeanne Clabeaux took on the Los Angeles longitudinal study and also helped with the broader analysis. Michael Carbajales-Dale provided guidance throughout the project. Full details of tasks and responsibilities are included in the CrediT statement below (Allen et al., 2019).

**John Sherwood:** Conceptualization, Methodology, Analysis, Validation, Data Curation, Writing — Original Draft, Writing — Review & Editing, Visualization. **Raeanne Clabeaux:** Analysis, Validation, Writing — Original Draft (primarily Section 3.3.5), Writing — Review & Editing, Visualization. **Michael Carbajales-Dale:** Conceptualization, Methodology, Writing — Review & Editing, Supervision.

This chapter was originally published in 2017 within *Environmental Research Letters*.[4] The chapter has been edited for clarity and format.

### 1.3.3 Chapter 4

Chapter 4, titled "Rolling Coal: The Greenhouse Gas Emissions of Coal Rail Transport for Electricity Generation" answers the question *can highly disaggregated energy data be used to build a better picture of the energy sector's environmental impacts?* It describes a GIS-based model of coal

[4] Sherwood, J., Clabeaux, R., and Carbajales-Dale, M. (2017a). An extended environmental input–output lifecycle assessment model to study the urban food–energy–water nexus. *Environmental Research Letters*, 12(10):105003, published as Open Access under the Creative Commons Attribution 3.0 License (http://creativecommons.org/licenses/by/3.0/)

rail transportation from nearly every mine to nearly every coal power plant within the U.S. This model was developed from the ground up and is based on several disparate datasets.

The chapter opens by describing the differences in coal quality; eastern U.S. coal has a high sulfur content, but is close to many power plants. In contrast, western U.S. coal has a minimal sulfur content, but is farther from many power plants. As such, there may be a tradeoff between (regulated) sulfur emissions and (currently unregulated) transportation emissions.

The model assumes a shortest-path route between all coal mines and power plants, and traces coal shipment information along these routes. The results are shown in Figure 1.5 — significant quantities of coal flow from the western U.S. towards eastern power plants.

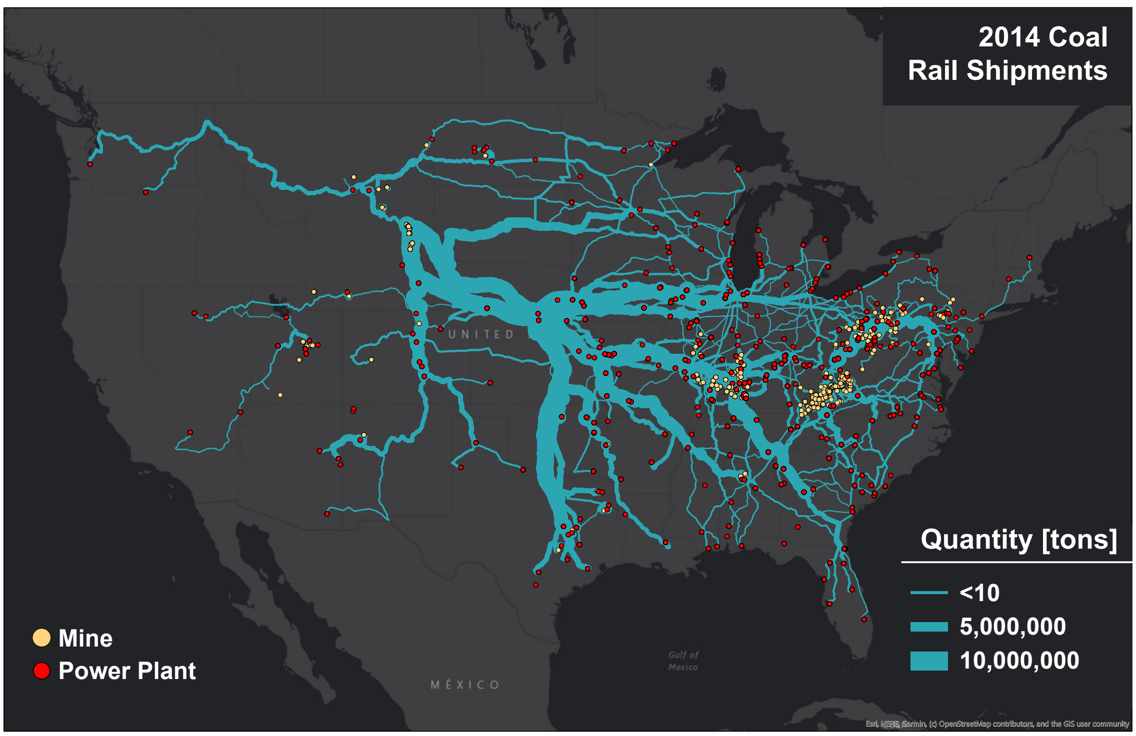


Figure 1.5: 2014 power plant-destined coal rail shipments along the U.S. rail network.

The chapter concludes by comparing the greenhouse gas emissions from transporting coal to the emissions from burning coal. For most coal plants, the transportation emissions are a minimal percentage of the plant's operational emissions (emissions resulting from burning coal). However, this study demonstrates that, though the Clean Air Act restricted sulfur emissions, it resulted in greater transportation emissions from transporting coal. As such, the environmental benefit may not be quite as good as initially expected. A holistic understanding of the supply chain is needed.

The call for a holistic understanding is emphasized in the chapter's final analysis piece — that of carbon capture and storage (CCS). Many energy-economy models call for significant investment in CCS technology, though it is not clear if they trace and account for CCS externalities. A power plant operating a CCS system will incur an energy penalty. Effectively, this means that the power plant will need more coal to produce the same net amount of energy. Therefore, installing CCS may increase the amount of emissions arising from transporting coal.

Through this study, we again see the interconnection of material, energy, and waste flows as factors of an economic system. Coal as a resource must be shipped around. Understanding not just "what" and "how", but where resources come from is critical for tracing a path towards sustainability. Does the example 2035 report and model account for the impacts of sourcing the vast quantities of raw materials that would build out a clean grid? This author believes the geospatial and upstream elements are vital, but currently missed. GIS ought to be used much more in biophysical economics studies to better plan for energy transitions.

#### 1.3.3.1 CRediT authorship statement & citation information

Though this chapter was a collaborative effort, the primary and original contributions by the main author (John Sherwood) include data collection, all analysis and visualization, writing, and much of the planning of the paper. Robert Bickhart conceived of the idea and curated much of the data, in addition to helping write the original draft. Emily Murawski primarily worked on locating coal mines, and provided data curation assistance. Zemin Dhanani and Blake Lytle assisted with the GIS components. Both Patricia and Michael Carbajales-Dale provided supervision and guidance. Full details of tasks and responsibilities are included in the CrediT statement below (Allen et al., 2019).

**John Sherwood:** Methodology, Visualization, Formal analysis, Validation, Writing — original draft, Writing — review & editing. **Robert Bickhart:** Conceptualization, Methodology, Data curation, Writing — original draft. **Emily Murawski:** Methodology, Data curation, Validation. **Zemin Dhanani:** Software, Formal analysis. **Blake Lytle:** Software, Methodology. **Patricia Carbajales-Dale:** Supervision, Project administration. **Michael Carbajales-Dale:** Supervision, Project administration, Writing — review & editing.

This chapter was originally published in 2020 within the *Journal of Cleaner Production*.[5] The chapter has been edited for clarity and format.

### 1.3.4 Chapter 5

Finally, chapter 5, titled "Resource Criticality in Modern Economies: Agent-Based Model Demonstrates Vulnerabilities from Technological Interdependence" answers the question *what would happen if industrial society faced a sudden resource supply constraint?* It describes a theoretical agent-based model of resource-based technological evolution and economic development.

A motivation for this chapter is the idea of resource criticality — that certain resources are elements are critical to the modern economy and may not have substitutes. The work of Graedel and others on resource criticality indicates that several materials have limited to no substitutability, effectively "decoupling materials substitution from price signals" (Graedel et al., 2015a,b). Furthermore, technological advances often use increasingly unique and varied material requirements to improve designs. These concerns fuel the current model configuration. Agents invent and use technology that is based on a supply of distinct resources. Some time into the simulation, a resource is cut off from the agents to simulate a sudden supply shock. We study how the agents' economy reacts in Figure 1.6.

Figure 1.6 shows five types of economies, ranging from no technology to the fully advanced technology of tier 4 devices [6]. The vertical axis displays the economy's average "utility" or measure of economic wellbeing. Every level of technological advancement takes an economic "hit" by the resource constraint imposed at time-step 600. It is important to note that the more advanced economies face a much larger collapse.

Ultimately, this model shows that while technological innovation allows for higher levels of utility and economic wellbeing, it also increases the economy's vulnerability to a supply shock. The deep levels of interdependence encountered in the advanced economies cause a worse economic collapse.

The chapter concludes by calling for fresh thinking related to macroeconomic modeling —

[5] Sherwood, J., Bickhart Jr, R., Murawski, E., Dhanani, Z., Lytle, B., Carbajales-Dale, P., and Carbajales-Dale, M. (2020a). Rolling coal: The greenhouse gas emissions of coal rail transport for electricity generation. *Journal of Cleaner Production*, page 120770. Elsevier (the publisher) grants authors the rights to reproduce this work, in full or in part, within a thesis or dissertation provided that it is not commercially published. For more information, see: `www.elsevier.com/about/policies/copyright`

[6] Each tier of technology is built using devices of a lower tier. The first tier of devices are built using resources directly.

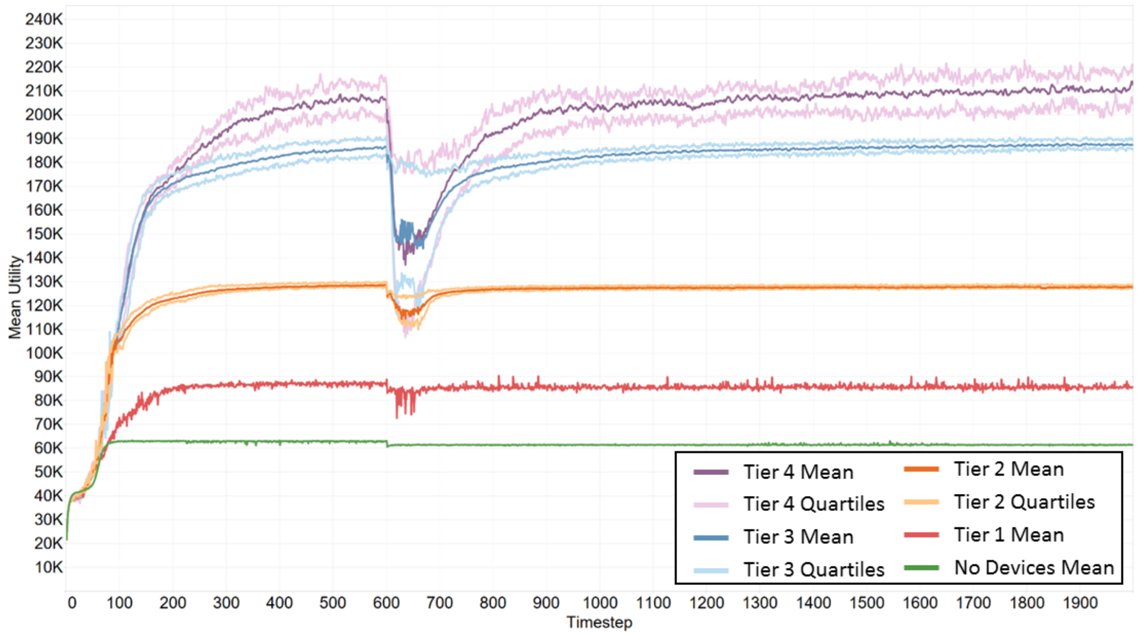


Figure 1.6: Model output, collapse scenario.

many assumptions built into more common economic models mask or ignore important facets that could lead to vulnerabilities across the economy. In relation to the biophysical economics version of the circular flow model, the physical availability of energy and material resources is a critical component to model in order to better understand future energy transitions. As mentioned above, more traditional energy-economy models such as the 2035 report seem to inadequately take into account the material requirements of their proposed energy transition.

#### 1.3.4.1 CRediT authorship statement & citation information

Though this chapter was a collaborative effort, the primary and original contributions by the main author (John Sherwood) include the analysis and visualization, writing, and data management. Anthony Ditta, Becky Haney, and Loren Haarsma are responsible for designing and coding the SOCIETIES model. Becky Haney helped frame the paper and wrote much of the introduction and conclusion. Michael Carbajales-Dale provided supervision and guidance. Full details of tasks and responsibilities are included in the CrediT statement below (Allen et al., 2019).

**John Sherwood:** Analysis, Validation, Data Curation, Writing — Original Draft, Writing — Review & Editing, Visualization. **Anthony Ditta:** Methodology, Software. **Becky Haney:**

Conceptualization, Methodology, Software, Analysis, Data Curation, Writing — Original Draft (primarily Section 5.1.2), Writing — Review & Editing, Supervision. **Loren Haarsma:** Conceptualization, Methodology, Software. **Michael Carbajales-Dale:** Analysis, Writing — Original Draft, Writing — Review & Editing, Supervision.

This chapter was originally published in 2017 within the *Journal of Biophysical Economics and Resource Quality*.[7] The chapter has been edited for clarity and format.

The original SOCIETIES resource and technology trading agent-based model was developed by Becky Haney and Loren Haarsma, with the programming and research assistance of Tony Ditta and Jiaming Jiang. Haney, et al. (2016)[8] used SOCIETIES v1.0 to examine the effects of technological growth on income inequality, even in the presence of unlimited resources.

## 1.4 Summary of themes

In addition to the research objectives listed above, each of these chapters contains three common, underlying themes. These themes are:

1. Biophysical economics modeling allows deeper insights into how the economy is reliant on resources
2. Models are better informed and constructed with granular and detailed data
3. Detailed, high resolution models enhance decision-making capability

While more fully described in chapters 2 and 5, the first theme emphasizes the importance of natural resources (such as oil, lithium, water, or food) to an advanced economy. Resources fuel economic growth, and it may prove difficult to fully decouple resource and energy usage from growing an economy. Biophysical economics is well suited to explore these issues by explicitly modeling the role of resources within the economy. In order to best strategize future energy system transitions, the biophysical reality of society must be taken into account.

[7] Sherwood, J., Ditta, A., Haney, B., Haarsma, L., and Carbajales-Dale, M. (2017b). Resource Criticality in Modern Economies: Agent-Based Model Demonstrates Vulnerabilities from Technological Interdependence. *BioPhysical Economics and Resource Quality*, 2(3):9, published as Open Access under the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/)

[8] Haney, B. R., Haarsma, L., and Ditta, A. (2016). Income inequality & technology: What can agent-based models tell us? *Calvin University Department of Economics working paper*, available at: `https://github.com/bhaney22/SocietiesABM/blob/master/Haney%202016%20Income%20Inequality%20and%20Technology%20ABM%20working%20paper.pdf`

The second theme shows that the rising amounts of data (particularly accessible data) being generated across the world enables studies and models that would have been difficult to build a decade ago. Each model presented in this dissertation utilizes (or could be capable of utilizing) highly granular data. This utilization points towards the third theme - detailed datasets enable high resolution modeling (that is, modeling many components of a larger picture). High resolution modeling enables more detailed results and discussions compared to previous modeling strategies. Ultimately, this allows for enhanced decision making by policymakers because of the more detailed view of a system.

The combination of these themes, and the evidence provided by each of these chapters, point towards new modeling directions which can explicitly account for the biophysical basis of the economy. We can best plan coming resource and energy transitions only by holistically studying the interactions between economy and biosphere.

# Chapter 2

# Putting the Biophysical (back) in Economics: a taxonomic review of modelling the Earth-bound economy

## Prelude

This chapter was originally published in 2020 within the *Journal of Biophysical Economics and Sustainability* (formerly the *Journal of Biophysical Economics and Resource Quality*).[1] The chapter has been edited for clarity and format. Additionally, the conclusion has been expanded to better place the chapter within the broader dissertation.

[1]Sherwood, J., Carbajales-Dale, M., and Haney, B. R. (2020b). Putting the Biophysical (Back) in Economics: A Taxonomic Review of Modeling the Earth-Bound Economy. *Biophysical Economics and Sustainability*, 5(1):1–20, published as Open Access under the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/)

## Abstract

Economists rarely model the economy as explicitly bound by Earth's ecological systems. Modelling the dynamic interactions of both human and non-human systems is admittedly a challenging task, as it requires expertise from multiple disciplines. Within the last ten years, a wide variety of research papers have been published that include some biophysical aspects in a model of the economy. These papers all have one thing in common: the model of the economy includes physical and/or energetic exchanges, as well as monetary exchange. This theme is what defines the emerging sub-discipline of biophysical economics, BPE. BPE models of the economy originate from a variety of disciplines, and thus BPE research articles are published across a wide spectrum of academic journals. As inter-disciplinary researchers ourselves, we want to understand what BPE modelling approaches have been used so far. In this paper, we examine and classify over one hundred published articles that use biophysical models of the economy. Although BPE modelling approaches are quite varied, grouping the research by common characteristics reveals several active research areas. We highlight recent papers that are helpful examples of the most popular BPE modelling strategies. Gaps also exist. Several modelling approaches have not been used in published works yet. We identify which of those gaps could be promising avenues for future research. We conclude by suggesting which BPE modelling approach might be particularly appropriate for a variety of research questions.

## 2.1 Introduction

Biophysical constraints are largely ignored in conventional economic models. Of course these popular models do not explicitly deny the biophysical reality that the economy depends on the availability of natural resources, or even that the economy takes advantage of ecosystem services such as water purification, carbon sequestration, and erosion control. However, these realities are often not considered limiting enough to be of concern.

To be fair, instances of natural resource depletion leading to economic contraction are rare in the modern era and early attempts by economists to model or account for biophysical limits on the economy were unsuccessful. In 1798, economist Thomas Malthus' modeled the economy as bound by the quantity of agricultural land. And, because the quantity of land available to feed the population could only grow linearly, but the population would grow exponentially, he predicted catastrophic outcomes (Malthus, 1878). What Malthus' model missed was the impact of technology. Human ingenuity would be able to improve the quality of land, rendering the physical quantity of land a seemingly non-binding constraint. Indeed, the subsequent increase in the quantity and quality of food production ushered in one of the greatest eras of improvement in human health and well-being.

In 1866, renowned mathematical economist William Stanley Jevons' predicted that the rebound effect from England's improvements in energy technology would outstrip the available reserves of coal. He called for policy to restrain economic growth and keep the economy from an unsustainable path. (Jevons, 1866). However, his policy suggestions went unheeded and his predictions were proved wrong as well. Again, the economy skirted looming constraints through technological innovation. Thus, this more sophisticated biophysical model of the economy model proved lacking as well.

These failures may have inadvertently led economists to believe that technological innovation will always allow the economy to ignore biophysical limits. And to be fair, that is a possibility, though an unlikely one. As the Industrial Age enters its fourth century, there is reason to believe that past technological advances did not abolish biophysical constraints, but instead merely postponed them. For example, while diminishing reserves of underground coal in the UK and Eastern US were replaced with coal mined from near surface resources (e.g. in Wyoming's Powder River Basin), the less obvious depletion of CO2 sequestration capacity (through deforestation) continued. Similarly, as diminishing conventional oil reserves are being supplemented with 'unconventional oil' from oil sands or tight oil resources, the increasing amounts of energy required to provide energy may becoming unsustainable. These and other substitutions allow economies to skirt obvious natural resource limits in the short-run, but economies will be subject to less obvious ecological limits in the long-run. Thus, the urgency to understand the relationship between economic and the ecological systems might be more apparent to those outside the economics discipline.

As Malthus and Jevons demonstrated, developing a useful biophysical model of the economy is challenging. Biophysical models of the economy require knowledge from a variety of additional disciplines, including Earth and environmental science, biology, and ecology; as well as industrial and mechanical engineering, to name a few. Development of biophysical models of the economy is necessarily multi-disciplinary. Unsurprisingly, most of the biophysical models of the economy have been developed outside of the economics discipline because ecosystem services are not traded in the market, nor are ecological systems necessarily well-understood by economists.

The field of biophysical economics provides a named space for the diverse body of research that is linked by a common goal: to elucidate the physical reality of the Earth-based economy. BPE models must capture complex interactions between human and natural systems. Many focus particularly on modelling thermodynamics and energy as part of the economic systems of extraction, production, distribution, consumption, and disposal. The advantage of BPE models is that researchers from a wide variety of backgrounds can work together to understand these systems. The disadvantage is that emerging, multi-discipline research fields such as BPE can be a daunting landscape to navigate. It is not easy to understand the full range of BPE research that already exists, let alone identify potential openings for new BPE research questions. Given the urgency of the questions that biophysical economics research can address, coupled with the widely diverse set of approaches used by practitioners, a way to understand the current biophysical economics modelling landscape is a necessity.

The contribution of this paper is to develop a taxonomy for biophysical models of the economy and classify a sample of over 100 BPE articles published in the last ten years using the taxonomy. This taxonomy classifies articles based on six characteristics:

1. Framework: does action in the model flow from the top-down or bottom-up?
2. Spatial scale: is the model more local or global in scale?
3. Time horizon: is the time frame short or long term?
4. Ethos: is the model more empirical or theoretical?
5. Origins: does the model emerge primarily from natural sciences or from social sciences?
6. Mechanism: does the model rely on statistical inference or simulated outcomes?

Each characteristic is described in detail in Section 2.3.3.

Classifying BPE research through this taxonomy helps to identify approaches that have attracted high levels of research activity. The taxonomy also reveals under-utilized approaches that could be successful new avenues of future research. Gaps within the modelling taxonomy may indicate open niches, or room for new biophysical economic models. Preliminary analysis of the gaps in the modelling landscape suggests that promising openings for future research include for example, how the geographic distribution of people and resources affect biophysical constraints. Or, what policy interventions might be necessary to transition smoothly to a renewable energy based economy.

This chapter proceeds as follows. We first provide a brief history of biophysical economics as it emerged from within economics and other disciplines. We identify additional reviews of BPE literature as well. We then describe the wide variety of modelling approaches that have appeared so far in the field of biophysical economics. We describe each of the six characteristics that are used to categorize them and show how four examples of recent research are classified using the taxonomy. Classifying 110 BPE articles according to the taxonomy allows researchers interested in biophysical economics an opportunity to see the broad landscape of modelling approaches that have been published so far. The chapter concludes with suggestions of areas that are ripe for additional research.

## 2.2 What makes a model of the economy a biophysical model?

Mainstream environmental economic models examine the markets and market failures related to natural resources, energy, and waste. These models perceive natural resources, energy, and waste through the lens of financial flows. In contrast, biophysical models of the economy also account for the physical flows of natural resources, energy, and waste through the economy. In most cases, resources, energy, and waste are viewed as central players in BPE models of the economy. Palmer's (2018a) *Energies* article provides an especially clear definition of biophysical economics.

> Biophysical economics is the study of the ways and means by which human societies procure and use energy and other biological and physical resources to produce, distribute, consume and exchange goods and services, while generating various types of waste and environmental impacts. Biophysical economics builds on both social sciences and natural sciences to overcome some of the most fundamental limitations and blind spots of conventional economics. It makes it possible to understand some key requirements and framework conditions for economic growth, as well as related constraints and boundaries.

Conventional economics models the economy as a separate and distinct entity. The economy is modeled as a circular flow of goods and services in one direction, and monetary flows in the other. In conventional economics textbooks, the circular flow economy is presented as disembodied and disconnected from the Earth upon which it is based.

The contrast between BPE and conventional economics is made clear in the BPE version of the circular flow model as depicted in Figure 2.1.

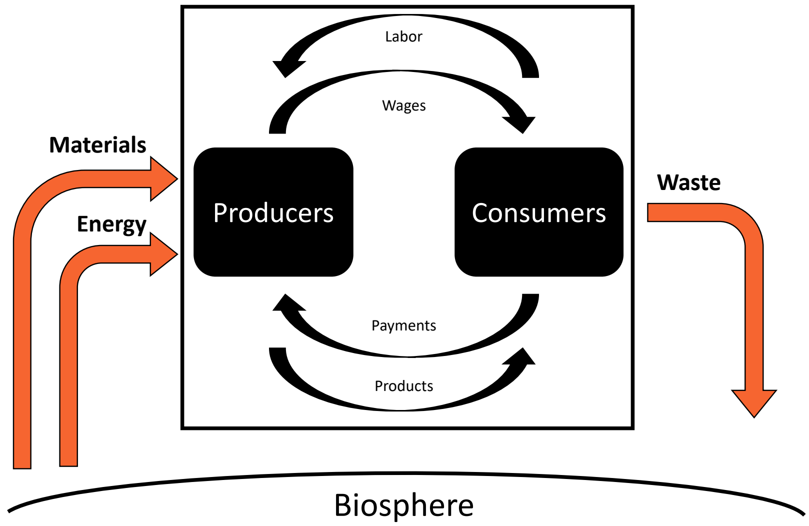


Figure 2.1: BPE's Circular Flow Model. Adapted from Heun et al. (2015); Hall et al. (1986)

The conventional economic circular flow model is still included, but is clearly embedded and enmeshed within the biosphere. The diagram not only recognizes the necessity of material and energy as inputs to a functioning economy, but also recognizes the inevitability of outputs — presently waste deposited back to the biosphere. The non-monetary flows of natural resources, energy, and waste that are intrinsic to the economy are made visible alongside the monetary flows and flows of economic goods and services. This coupling between economy and biosphere is critical to holistically understand constraints to economic opportunities and the impacts of economic activity upon the natural environment.

### 2.2.1 The biophysical economics renaissance

As mentioned above, biophysical economics is not new. In fact, the name "economist" was coined by the the Physiocrats, arguably the first biophysical economists in the modern era (Miller and Blair, 2009). The Physiocrats were led by French physician Francois Quesnay and advocated that agriculture was the source of a country's wealth. This rivaled earlier ideas of mercantilism (led by Sir William Petty, the first econometrician) that described a country's wealth as coming from the accumulation of silver and gold.

Francois Quesnay is likely most known for his Tableau Economique, an economic model depicting the flow of goods through economic sectors. Most notably, Quesnay saw no "value-added" in manufacturing or service industries — agriculture and land output was the sole source of wealth (Quesnay et al., 1972). Despite this flaw, the Tableau Economique went on to influence the foundations of national accounts and input-output economics and Quesnay is known as one of the first economists who valued an economy's reliance on natural resources.

Outside the field of economics, the scientific work of Sadi Carnot, Rudolf Clausius, and Lord Kelvin formalized the laws of thermodynamics. These laws describe the nature of energy, but the second law is of particular importance to economics. The second law of thermodynamics roughly states that isolated systems tend toward an equilibrium at which point no useful work can be done. For a system to maintain a non-equilibrium state and continue to do work, it requires a continual flow of low entropy (high quality) energy. That is, the system must be open (i.e. have inputs) to perform tasks and/or grow. The economy is such a system. The goal of biophysical economics is to stay true to these thermodynamic principles.

Scientists outside the field of economics began to see the implications of these laws on the economy — because economies exist in a physical reality, they must have fundamental physical limits or constraints. Cleveland (1987, 1999) go into more detail concerning this early theory development phase. Some notable researchers include Lotka, who linked energy quality to biological life (Lotka, 1922), Cottrell, who studied "surplus energy" (a precursor to Energy Return on Investment, EROI) and its role in societal development (Cottrell, 1955), M. K. Hubbert, who developed the theory of peak oil (Hubbert, 1949), and Odum, who posited an energy theory of value and developed systems ecology (Odum, 1994). Additionally, Cleveland et al. (1984) studied the relationship between energy use and GNP.

Within the economics discipline, Nicholas Georgescu-Roegen and Herman Daly pioneered the modern biophysical approach to economic theory. In 1971, Georgescu-Roegen's *The Entropy Law and the Economic Process* introduced the implications of entropy for an economy (Georgescu-Roegen, 1971). An economy relies upon low entropy (high quality) resources to fuel the production of goods. Furthermore, economies emit high-entropy (low quality) wastes (e.g. waste-heat). Georgescu-Roegen is one of the first economists in the modern era to acknowledge the biophysical constraints of the global economy (Kåberger and Månsson, 2001; Ayres, 1999). And, although somewhat controversial, Georgescu-Roegen even went so far as to suggest that the second law might apply to physical matter as well as energy — economies consume highly concentrated ores (e.g. copper or lithium) and then dispose of materials in a low concentration waste-stream (e.g. landfills).

Herman Daly built on Georgescu-Roegen's biophysical approach as he developed the concept of steady-state economics. In contrast to mainstream economic theory that requires ever-increasing levels of economic output to maintain growth in standards of living, Daly posits that a steady-state economy, in combination with significant recycling programs, can maintain growth in standards of living, while also acknowledging and incorporating the biophysical limitations of the economy (Daly, 1991). The implications and pathways towards a steady-state is a growing research thrust that has recently gained popularity (Ghisellini et al., 2016).

Arguably the first holistic biophysical model of the economy in the current era is the seminal *Limits to Growth* work by Meadows et al. (1972). Advances in computer technology opened the door for their (at the time) highly sophisticated model, which produced simulated outcomes of the interaction between economic and biophysical systems. Their model explored the impacts of population growth, resource depletion, and pollution on societal growth. Harking back to Malthus and Jevons, their simulations resulted in growth patterns that exhibited overshoot and collapse. Only scenarios of concerted and sustained efforts to mitigate damaging effects of overconsumption were able to avoid unplanned collapse. The study's findings generated controversy within the academic and popular literature, however as the decades have unfolded since their work, the predicted patterns of the model have not been proven inconsistent with reality. Malthus and Jevons' theories may be proven correct after all (discounting their timeline), although that would not be a win to celebrate.

Since Daly and his contemporaries' work, many BPE researchers have turned to solidifying, building out, and fine-tuning the theoretical framework that was largely outlined in the 20$^{\text{th}}$ century. Hall and Klitgaard (2011), for example, wrote *Energy and the Wealth of Nations*, an introductory textbook to biophysical economics. Now, more research activity is trending towards quantitative modelling rather than qualitative theorizing. A few researchers have been at the forefront of this modelling effort. Many researchers have worked on analytical and statistical models. Ayres and Warr (2010); Heun et al. (2017b); and others have worked on including energy in aggregate production functions . Murphy and Hall (2010); Brandt et al. (2011); Dale et al. (2011); and others have worked on modelling EROI for various fuels and society. King (2016); Brand-Correa et al. (2017); Heun et al. (2018); and others have explored using input-output tables to better understand the role of energy in economies. Other researchers have focused on simulations of longer-term trends. Dale et al. (2012b); Sverdrup et al. (2017a); Motesharrei et al. (2014); and others have developed systems-dynamics models of society to study long term energy transitions & resource scarcity. Voudouris et al. (2011); Sherwood et al. (2017b); and others have been developing agent-based models to study biophysical economics . These various modelling approaches are usually modifications or adaptations of the models used in similar disciplines. For more about the history of biophysical economics, see for example Dale et al. (2012a); Cleveland (1987, 1999); Røpke (2004).

### 2.2.2 Biophysical, environmental, and ecological economics

The economics discipline does model aspects of the natural environment. Biophysical economics articles published in economics journals usually categorize their subject matter under the subject code for "Agricultural and Natural Resource Economics; Environmental and Ecological Economics."

Environmental and ecological economics articles make up about 7% of all economics articles. This proportion remained constant throughout the years spanning 1969 to 2007 (Kelly and Bruestle, 2011). What did change during that time period was a proliferation of specialized journals in economics. Of the 842 journals in economics, 605 are specialty journals. The diffusion of research journals is particularly common for BPE subjects. More than 80% of environmental and ecological economics articles are published in specialty journals, a higher percentage than any other subject in economics (Kelly and Bruestle, 2011, Table 6). [2]

BPE models also appear in macroeconomics, energy economics, natural resource economics, and complexity economics. Table 2.1 provides a concise description of each of these subfields of economics and discusses the particular ways within them that BPE models are used.

Table 2.1: Summary of economic fields related to Biophysical Economics.

| Field | Description | BPE Distinction |
|---|---|---|

[2] Specialty journals are defined as journals where over 50% of their articles use the same major subject code. (Kelly and Bruestle (2011))

| | | |
|---|---|---|
| Macroeconomics (ME) | Study of the economy as a whole (national or multi-national level), often through aggregate indicators such as GDP or sectoral-level performance characteristics. | BPE often leans towards long-term, macroeconomic perspectives of the physical flow of energy and materials. BPE can use macro models such as aggregate production functions or Input-Output tables, which are two ways of characterizing an economy. Often, BPE extends these to include energy or physical flows. |
| Energy Economics (EE) | A broad field that tends to apply traditional economic models to energy markets, suppliers, and utilities. Typically focuses on short- or medium-term models (<10 year timeframe), such as the impact of increasing gasoline prices on consumers or the effects of deregulating an electricity market. | BPE tends to have a larger scope than EE models — rather than model short-term effects of a gasoline price hike, BPE might model long-term economic effects of crude oil availability (e.g. over a 50 year period). BPE also tends to question some assumptions of EE (some EE practitioners refute peak oil, for example). |
| Natural resource Economics (NRE) | Study of how natural resource markets differ from other tradable goods, due to the nature of physical resource stocks. NRE particularly focuses on determining the optimal extraction rate of one or more resources. Tends to focus on models of individual suppliers. | BPE certainly incorporates NRE models and techniques, such as understanding effort to extract resources. However, NRE models tend to be open or semi-open systems. In contrast, BPE often studies the flow of a resource throughout an entire economy (e.g. "cradle-to-grave"), or, takes into account global depletion and non-substitutability. |
| Environmental Economics (EnE) | EnE performs Cost-benefit analyses of non-tradeable goods, such as pollution or natural beauty. EnE often calculates or utilizes the shadow price to study or optimize the effects of environmental policies. Typical scope ranges from local to national. | BPE tends to adopt stronger concepts of sustainability compared to EnE. Also, EnE tends to convert everything to price or dollar amounts to perform analyses, implying that a single (economic) unit can be representative. BPE instead has a perspective of physical materials and flows might not be distilled into simple prices when studying the full costs and benefits of policies. |

| | | |
|---|---|---|
| Ecological Economics (EcE) | EcE is similar to EnE, but views the economy as a "wholly owned subsidiary of the ecosystem" (Daly, 2005a). That is, the economy lies inside the the larger system of the biosphere. As a consequence, EcE recognizes the fundamental limits of the biosphere and its impacts on the economy. These fundamental limits are absent in EnE due to assumed substitution or because EnE tends to focus on smaller, isolated systems. | BPE is similar to EcE in the belief that economics needs a paradigm shift (from small, isolated systems to large systems interconnected to the biosphere). BPE shares EcE's underlying theory, perspective, and historical literature, but differs in the primary research thrust. While EcE is focused on expanding economic modelling to account for the ecosystem (i.e. natural capital), BPE is much more focused on placing the need and flow of energy and critical materials as primary drivers within the larger economy. |
| Complexity Economics (CE) | CE applies complexity science to economics, which implies that the economy is best modeled as a dynamic, self organizing, adapting system rather than an equilibrium-seeking system. CE relaxes the normal economic assumptions, allowing for heterogeneous agents, imperfect knowledge, and multiple markets. | Currently, there is not significant overlap between CE and BPE modelling. However, BPE and CE share some theory, such as the idea that equilibrium or comparative statics analysis may not account for the full picture of an economy — complex networks might better represent the importance of energy and resource flows. BPE could see growth in network analysis to better align with work in the CE field. |

Surprisingly, biophysical economics has appeared in a similar number of publications over the last decade as the traditional field of natural resource economics. Figure 2.2 shows the number of BPE research articles published as compared to the number published in each of the economic fields listed in Table 2.1. These numbers were tabulated based on literature searches using each field as a search term.[3]

### 2.2.3 Additional surveys of biophysical economics

The literature analyzed in this paper is only comprised of BPE modelling efforts published within the last 10 years. This paper does not discuss the details of each model, or weave together an understanding of a specific group of models. The strength of this paper lies in its comprehensive categorization of various BPE models to understand the modelling landscape. BPE modelling ap-

[3] In Figure 2.2, bioeconomic research articles were included as BPE. However, bioeconomics tends to study the microeconomics of fisheries and forestry and could instead be grouped with natural resource economics (Clark, 2010). In either case, biophysical economics is emerging as a growing field.

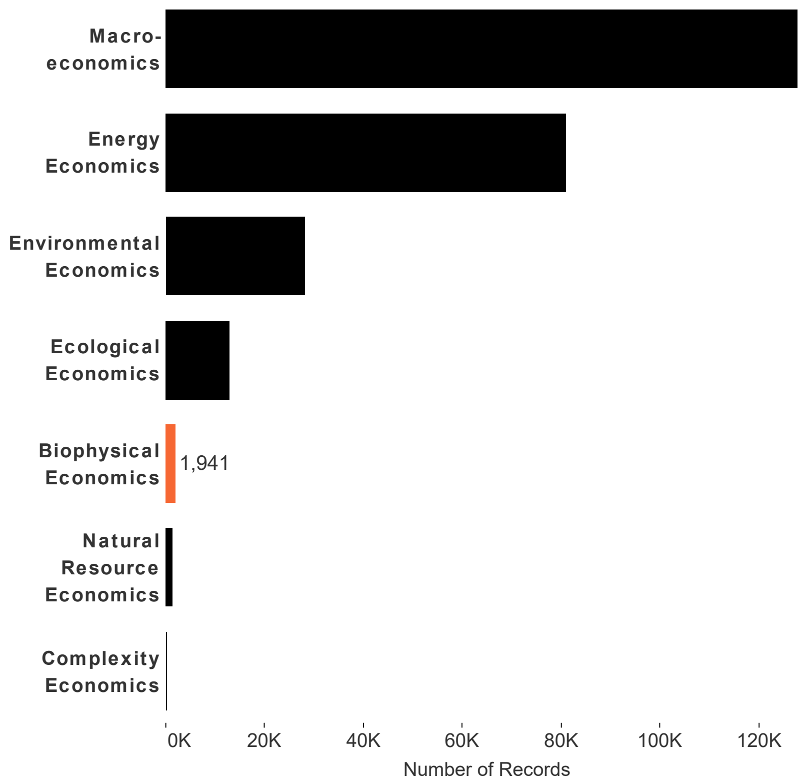


Figure 2.2: Relative size of relevant economic fields based on peer-reviewed literature search on EBSCO's Academic Search Complete using all databases. Search terms included [subject] Econ* within Title OR Subject terms OR Abstract.

proaches appear in a variety of other disciplines' publications as well, including industrial ecology, geology, engineering disciplines, and environmental science. Other recent and more traditional BPE and BPE-related reviews go into more detail for their respective subject areas, and are summarized in Table 2.2 for the interested reader.

## 2.3 The biophysical economic modelling landscape

In addition to overlapping and interacting with several disciplines, biophysical economic studies use similar, though often modified, modelling strategies. These include aggregate production functions, input-output tables, system dynamics, life cycle assessment, and many others. The choice of model depends partially on the modelling goal, but also on data availability and domain knowledge (North and Macal, 2007; Hamill and Gilbert, 2015; Sterman, 1991). An interesting example is

Table 2.2: Additional BPE or BPE-related literature surveys.

| Reference | Title | Description |
|---|---|---|
| Dale et al. (2012a) | Global energy modelling - A biophysical approach (GEMBA) part 1: An overview of biophysical economics | Provides a historical review of BPE and outlines some prominent BPE models |
| Hardt et al. (2017) | Ecological Macroeconomic Models: Assessing Current Developments | Reviews 22 ecological macroeconomic models and their ability to handle post-growth scenarios |
| Palmer (2018a) | A Biophysical Perspective of IPCC Integrated Energy Modelling | Critiques current integrated assessment models from a biophysical perspective. |
| Rye and Jackson (2018) | A review of EROEI-dynamics energy-transition models | Historical review of EROEI-related models. Focuses on systems-dynamics rather than I-O approaches |
| Earles and Halog (2011) | Consequential life cycle assessment: a review | Reviews cLCA literature with focus on opportunities to better bridge LCA studies with economic models at a macro scale. |
| Li et al. (2015) | A review of socio-technical energy transition (STET) models | Reviews a number of IAM or similar models that focus on energy transitions |
| Hansen et al. (2019) | Agent-based modelling and socio-technical energy transitions: A systematic literature review | ABM specific review of energy transition modelling. |
| Melgar-Melgar and Hall (2020) | Why ecological economics needs to return to its roots: the biophysical foundation of socio-economic systems | Provides historical summary of Ecological Economics and BPE, and describes various BPE methodologies |

provided by the World3 model, developed during the seminal *Limits to Growth* study (Meadows et al., 1972). The goal of the model was "to identify different possible futures" by "sketching alternative scenarios for humanity as we move toward 2100." (Meadows and Randers, 2012, p.xvii). This meant that models results were not meant to be treated as *predictions*, but instead "merely indicate the general direction our system, as it is currently structured, is taking us." (Meadows et al., 1972, p.43). This however, did not stop many critics from rebuffing the model by pointing out that "predictions" did not come to pass in any particular year (Bardi, 2011). That is, some readers of the model results assumed a different modelling goal than the designers intended.

We postulate that biophysical economic models can be categorized in many ways (described in Section 2.3.3). The categorization of models may elucidate several things about the field: 1. What topic areas have been addressed? 2. What modelling types have researchers focused on? 3. What modelling goals are prominent? And, categorization may help point out potential gaps in the current modelling landscape. Is the current landscape of BPE models missing any important areas of research that can be identified through a taxonomic analysis?

For this paper, we have selected 110 articles containing biophysical economic models to analyze based on their topics addressed and model characteristics.

### 2.3.1 Article selection criteria

In order to capture as representative a sample of recent models as possible without generating too large of a potential set, we developed a set of search and screening criteria in our literature search. For our initial search, we included the journals: *Biophysical Economics and Resource Quality*, *Ecological Economics*, *Ecological Modelling*, *Energy Economics*, *Energy Policy*, and *Resource and Energy Economics*. We acknowledge that BPE researchers publish elsewhere as well, but we believe these journals provide a representative cross-section of the field (the journals *Energy*, *Applied Energy*, and *Energy Policy* all receive similar BPE models, for example). We also added 20 known BPE models published elsewhere. These models were categorized when developing the categorization criteria, but were outside the final defined scope of the literature search. We additionally added 7 papers recommended by reviewers. Our search process followed the following steps:

1. Using ScienceDirect, filter to only include research articles from 2009-2019. (results are provided in the supporting materials.)
2. For each journal, search with keywords:
    - Model, input-output
    - Model, systems dynamics
    - Model, production function
    - Model, agent-based
3. Perform first screening of 1366 results

We limited the initial search with certain modelling framework keywords to attempt to avoid articles discussing conceptual or qualitative models or reviews. We acknowledge that, by focusing specifically on these keywords, we may miss other BPE models that do not fall into one of these categories, such as a generic analytical model defined by a few equations (though, the search did pick up some of these models, usually under the "production function" search query). The initial search provided a total of 1366 papers to screen.

Our initial screening process consisted of reading the title of the paper to determine if it fit a broad definition of "BPE model". Our primary guide here is the definition of biophysical economics referenced in Section 2.2. To align with the definition of BPE, we kept articles that hinted at including both an economic component, and physical resources or environmental flows within industrialized society. A BPE model either explicitly accounts for physical limits in non-monetary units of physical substances in or around an economy (in addition to some economic component), or a BPE model frames the interpretation of a monetary-based model through a BPE perspective (such as a model critiquing the cost-share of energy and its impacts on GDP). For this first screening process, our aim was to be inclusive rather than exclusive. That is, we only excluded papers that clearly were *not* a BPE model. An article was discarded if:

1. The article only mentioned emissions, $CO_2$, or carbon footprinting in the context of climate change, such as "Structural decomposition analysis and input-output subsystems: Changes in $CO_2$ emissions of Spanish service sectors (2000-2005)" (Butnar and Llop, 2011).
   - Excluded because short-term environmental concerns, without much discussion of physical limits or the root causes of climate change, align closer to environmental economics than biophysical economics.
2. The article was overly focused on land use or agriculture, such as "The role of farmers' property rights in soil ecosystem services conservation" (Foudi, 2012).
   - Excluded because, while a macroscopic land-use or agriculture study could fit within BPE, a microeconomic or small-scale / local perspective rarely fits within the BPE definition of "...the ways and means by which human *societies* procure and use energy and other biological and physical resources." Here, the title does not imply investigating fundamental limits or constraints on soil at a societal level.
3. The article only referenced pricing externalities, such as "Pricing emission permits in the absence of abatement" (Hintermann, 2012).

- Excluded because pricing externalities and emissions abatement fall within the realm of energy economics, and do not necessarily examine physical limits or the root cause of emissions (economic output & resource usage).

4. The article focused on non-humans (often within the journal Ecological Modelling), such as "Evaluating impacts of intensive shellfish aquaculture on a semi-closed marine ecosystem" (Han et al., 2017).

    - Excluded because the definition of BPE limits the field to human societies.

5. The article had no clear link to economics, such as "Foodweb modeling for polychlorinated biphenyls (PCBs) in the Twelvemile Creek Arm of Lake Hartwell, South Carolina, USA" (Rashleigh et al., 2009).

    - Excluded because, while PCBs are a pollutant generated by humans, BPE models must include an economic component.

Screening article titles reduced the pool to 207 potential BPE models. These 207 articles were then screened based on the abstract and conclusion. This second stage followed all of the discard criteria above, but additionally looked for commentary on the physical nature of resources or potential ecological constraints on the economy. Lack of BPE specific commentary often meant the article better aligned with one of the neighboring economic disciplines described in Table 2.1. Additionally, the paper needed to include a quantitative model. Abram and Dyke (2018), for example, did not pass the second screening. Though the title "Structural Loop Analysis of Complex Ecological Systems" and abstract hint at BPE commentary and a quantitative model, the paper itself details a specific tool used to analyze system dynamics models and does not focus on a specific BPE model. This second screening reduced the pool to 110 articles that were categorized according to the criteria outlined in Section 2.3.3. A full list of all models considered is found in the supporting materials.

### 2.3.2 Topic & keyword analysis

To better understand the diversity of selected models, we collected and analyzed all of the articles' keywords. Figure 2.3 displays a word-cloud of the keywords. Keywords that occur more frequently throughout the dataset have a larger font. From this word-cloud, we can determine that many papers used keywords such as "system dynamics" and "EROI," while other keywords such as "resource criticality" occur infrequently. Note that we adjusted certain keywords to better align within this analysis, such as combining "EROI," "EROEI," and "energy return on investment."


Figure 2.3: Word-cloud of keywords for all 110 papers. Larger words indicate more occurrences across the papers.

Additionally, Figure 2.4 shows the number of occurrences for the top 20 keywords. By viewing both Figure 2.3 and 2.4, we can see that both methodology-based keywords (such as "net energy analysis" or "input-output model") and application-based keywords (such as "EROI" or "mining") are popular. Researchers writing papers within biophysical economics may want to include at least one of these popular keywords in their manuscript for more visibility, if possible.

Based on trends within the keyword analysis, we then mapped the articles to seven topic areas to further understand common trends in biophysical economics modelling. These topic areas were selected by identifying common, but discrete themes among the papers. The topic areas include: 1. "Energy Economy" - macroeconomic models such as an economy-wide EROI or rebound-effect study; 2. "Energy Resources & Technology" - models focused on a specific sector or technology

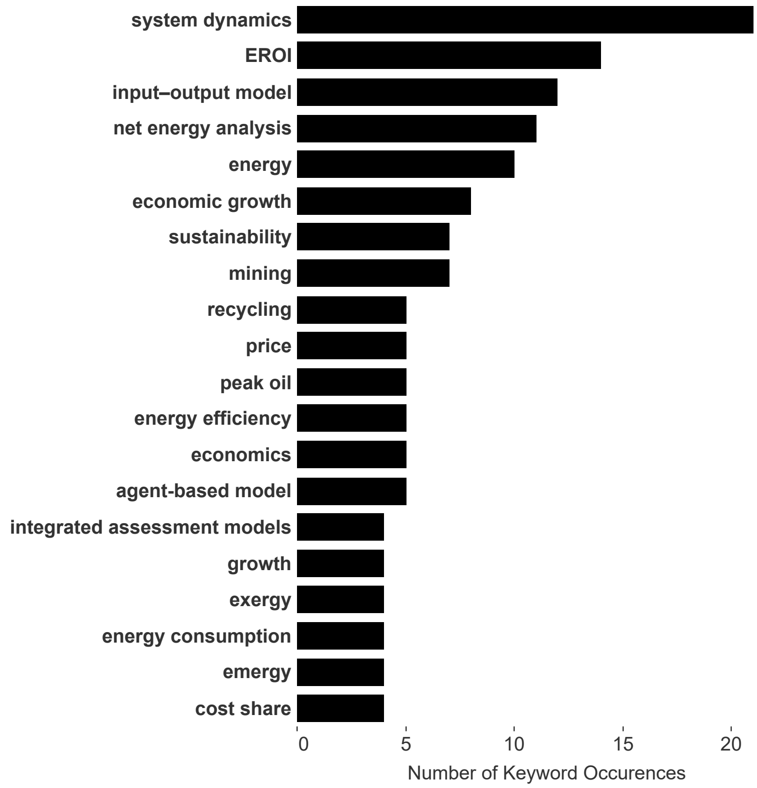


Figure 2.4: Number of occurrences of the top 20 keywords from all 110 papers.

such as peak oil or solar PV; 3. "Materials" - models studying the depletion of non-energetic, non-renewable substances, particularly industrial feed-stocks, such as lithium or iron; 4. "Resources" - models studying renewable resources, or resources in the context of ecology rather than industry. These include agriculture, water, or land-use; 5. "Interconnections" - models of a holistic nature that capture multiple categories, such as the Human and Nature Dynamics (HANDY) model (Motesharrei et al., 2014); 6. "Climate" - models focused on the relationship between biophysical economics and climate change; and 7. "Policy" - models focused on policy and stakeholder action, such as a dynamic ecological footprint model to examine the impact of different policy scenarios (Jin et al., 2009).

Figure 2.5 displays the number of papers within each of these broad categories. The figure shows that the majority of models investigate energy-related subjects. Indeed, much of biophysical economics has been focused on questions related to energy return on investment and the role of energy in the economy. However, there are also a significant number of models that focus on non-energetic materials and resources. These models hit the "materials" economy-biosphere link present on Figure 2.1, the biophysical circular flow diagram. Figure 2.5 also seems to indicate that there are

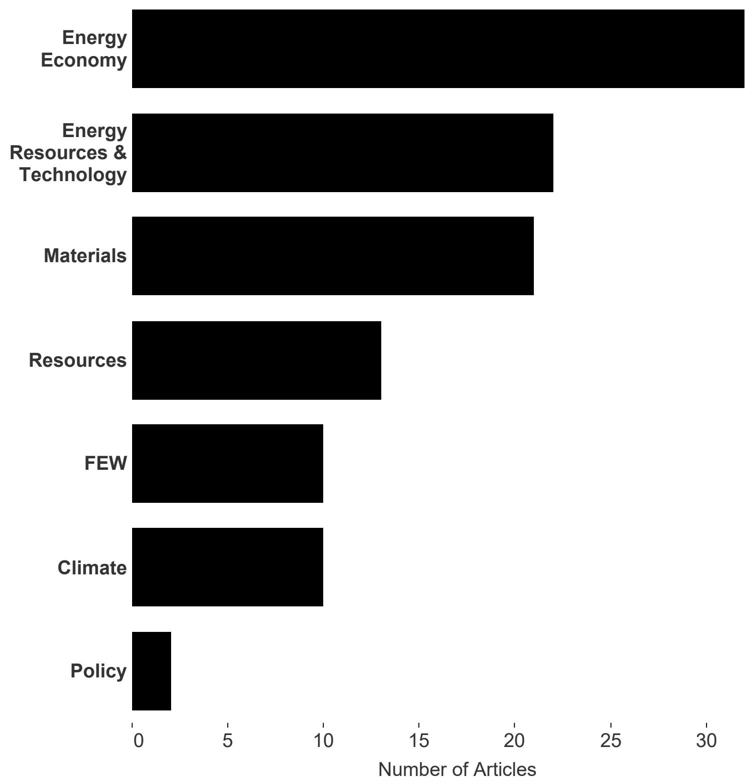


Figure 2.5: Topic grouping of all 110 BPE models.

relatively few models focused on interconnections, climate, and policy. These categories seem ripe for future growth.

In addition to a topical analysis, we create a taxonomy, or model classification scheme, to categorize models according to characteristics of the models themselves, outside of the topics they address.

### 2.3.3 Taxonomy

In general, different models can be qualitatively mapped according to different characteristics. These characteristics are: Framework, Spatial scale, Time horizon, Ethos, Origins, and Mechanism. For each characteristic, we use an ordinal 1-5 scale to designate the potential categories of that characteristic. Note that though we use a 1-5 scale, we make no value or effectiveness judgments. Neither 1 nor 5 is "the best" —the quality of a specific model is wholly dependent on how well it aligns with its intended application. Additionally, the categories may not be evenly spaced

– they are merely a logical ordering. That is, a category of three is not necessarily directly halfway between two and four, but the order 2-3-4 is logical.

#### 2.3.3.1 Framework

The framework characteristic is the big-picture structure of a model type. The categories are Individual-based Model, Agent-based Model, Input-Output Model, Systems Dynamics, and Aggregate Production Function. The framework characteristic describes something broader than "model structure." Two systems dynamics models may have vastly different structures. But, as systems dynamics models, they will have the same overall rules, mathematical concepts, and types of algorithms governing them.

In the taxonomy, a 5 represents models similar to aggregate production functions — simple, highly aggregated analytical models that collapse highly distinct and variable real-world phenomena into a minimal number of variables.

Systems dynamics models or similar are given a category of 4, as they can capture more details of the dynamics of a system. As system dynamics models are one of the most prevalent approaches we find, here we provide further description of this approach. A systems dynamics model identifies stocks and flows within a system and determines feedback loops in order to build system-level equations that relate various parameters. An example systems dynamics model might be of the world economy, such as the WORLD3 model in *Limits to Growth* (Meadows et al., 2004b). Often (though not a requirement), the equations describe aggregated flows at the economy or sector level, such as lumping all production, emissions, or energy use into a single parameter. These parameters might miss important details of what they represent, like limitations of specific energy technologies. Furthermore, the design and structure of a systems dynamics model is static throughout its runtime. Stocks and flows representing portions of the economy do not spontaneously switch trading partners or alter their supply chain.

Input-output modelling or similar are given a category of 3, because they can be highly disaggregated with numerous distinct industries or processes (assuming data availability).

A category of 2 represents agent-based models. Agent-based models (ABM) are relatively new modeling approaches and we provide further description of them here. ABM often model micro-economic behavior at the level of the individual or firm. Macroeconomic outcomes (desired indicators) emerge from agents' interactions. While also incorporating feedback loops, an agent-based model is adaptive in ways that system dynamics cannot be, in part because the major driver within the model is an individual rather than system. Social networks and relationships can form or dissolve because of agents' changing behavior. Intra-system, emergent, macro-level dynamics, such as income inequality and technological adoption, are more able to represent realistic variability because they need not be constrained by a static set of functions. For example, Rai and Robinson (2015) developed an agent-based model of household solar panel adoption within Austin, Texas. The model simulated both economic and social influences (such as geographic neighbors installing PV systems) on the decision to invest in solar panels, and accurately simulated city-wide solar adoption trends (the emergent behavior being studied).

Lastly, a category of 1 for the framework characteristic represents true individual-based models, where an agent is a specific person or entity, rather than an industry or country (a country might often be the "agent" in ABMs, such as Voudouris et al. (2011)) The Rai and Robinson (2015) example would be categorized as an individual-based model, as the "agent" is a specific household, the lowest level of analysis for household solar adoption.

In summary, this characteristic captures a modelling framework's flexibility and ability to model varying levels of real-world phenomena.[4]

Table 2.3: Framework taxonomy criteria.

| Characteristic | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Framework | Individual-based Model | Agent-based Model | Input-Output Model | Systems Dynamics | Aggregate Production Function |

#### 2.3.3.2 Spatial scale

This dimension characterizes the overall scope or intended application of a model. A systems dynamics model may represent the global economy, a specific country's economy, or one city's economy using the same equations. However, each scale still encounters the limitations of the modelling framework. A coarse- or fine-grained systems dynamics model will always treat its object of analysis as a system of stocks and flows. For the modeler, it is important to ensure assumptions

[4]Here, ability does not relate to a specific model's success or failure at modelling its intended application. We use ability here to mean that some models are better suited to model, for example, very detailed complex systems than others. The structure or framework of aggregate production functions are unable to capture many phenomena that an IO or agent-based model may seek to investigate.

built into the modelling framework align with the represented scope. An aggregate production function model might not fit a rapidly evolving city well, as the framework abstracts away from many of the details that defines a "rapidly evolving city". On a practical level, an individual-based model of the world would create significant computing costs.

The choice of scale also impacts model interpretation and policy implications. What is the modeler trying to say with their model? A peak-oil model of a single oil well has a significantly different impact than a continent or world model. The scale dictates how "open" or "closed" a model can be. Spatial scale is a key component to the story behind an analysis — it's the setting upon which characters act.

For the taxonomy, a category of 1 represents a city or smaller and a category of 5 represents models that have a global scope.

Table 2.4: Spatial scale taxonomy criteria.

| Characteristic | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Spatial scale | City or smaller | State / province | Country | World region | World |

#### 2.3.3.3 Time horizon

The time horizon characteristic evaluates the length of time a model represents. Some models, such as the *Limits to Growth* systems dynamics model, are intended to represent 200+ years. Some models are designed to represent hours or days (e.g. electric utility day-ahead or weekly energy balancing models) but would be computationally expensive and/or incapable of running for a longer time horizon. The model framework or spatial scale does not inherently dictate model runtime: rather, the modeler choses a runtime based on their resources or extrinsic criteria.

Here, a category of 1 is reserved for models that evaluate immediately — that is, there is no time dimension. A category of 2 represents short term models, or less than a 5 year timeframe. An input-output model that uses one year's data would rank here. A category of 3 captures models that run in range of 5-10 years. Many models run long term scenarios, defined as more than 10 years. These include many integrated assessment models (IAMs) that model up to 2100. Finally, ultra-long term models, such as those capturing the industrial revolution and continuing through 2100, span time periods in excess of 100 years; these are categorized as a 5.

Table 2.5: Time horizon taxonomy criteria.

| Characteristic | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Time horizon | Immediate (less than one year) | Short term (1-5 years) | Medium term (5-10 years) | Long term (10+ years) | Ultra-long term (100+ years) |

#### 2.3.3.4 Ethos

The ethos characteristic describes how directly relatable the model is to reality, or to a specific application.[5] Some models are intended to only explore concepts and theory, without direct links to an explicit dataset. These models do not provide prediction capabilities, but elucidate the consequences of theory (like the *Limits to Growth* model as discussed at the start of Section 2.3). Pure theory models are designed to understand and develop general theories without explicitly modelling a specific place or time period (Sherwood et al., 2017b; Motesharrei et al., 2014; Epstein and Axtell, 1996). At the other end of the spectrum are complete empirical and applied models that directly correlate to a specific location, time, and technology, but leave little room for making general observations. Ethos captures that characteristic spirit of the model's interpretation intentions. Many models fall between these two extremes — they are built with some links to a specific, real instance, but are based on theory or contain stylized elements. Often the specific & real data is used to validate theory (or at least the model), which may enable further model projection past the original dataset (i.e. hindcasting to prove model legitimacy).

Some researchers have suggested that, at least for certain modelling frameworks, few should fall in the middle of this characteristic. Sun et al. (2016) have suggested that modelers should stick to first-principles or wholly rely on empirical research to limit the difficulty in model validation and acceptance. An applied model that contains stylized elements will be difficult to justify.

For the taxonomy, a category of 1 represents a purely theoretical model with no empirical input from the real world. A key example would be Sugarscape, an ABM that models the migration behavior of agents in a society that mines two generic resources (Epstein and Axtell, 1996). A category of 5 would be a purely empirical or econometric model, similar to many EROEI studies(Heun and de Wit, 2012). In the middle are IAMs — these are often developed from first-principles and

[5] An abridged definition of ethos is "the characteristic spirit of a community as manifested in its aspirations." Here, we use ethos to mean "the characteristic spirit of a model as manifested by how the modeler interprets it." That is, researchers may have designed a model to be directly related to the real world, or merely to explore the implications of a theory.

a combination of economic & engineering principles, but are calibrated and validated on real-world data.

Table 2.6: Ethos taxonomy criteria.

| Characteristic | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Ethos | Pure theory, no connection to real world) | Mostly theory, limited validation | First principles validated by real data (e.g. IAMs) | Mostly empirical, some first principles | Pure empirical (e.g. econometric) |

#### 2.3.3.5 Origins

While somewhat different from other characteristics, origins is a categorical characteristic to evaluate how similar a given model is to traditional science and engineering techniques, or traditional economic or social models. As mentioned previously, many biophysical economic models have arisen from a combination of mainstream economics and science & engineering disciplines. These two broad disciplines often have their own language, assumptions, and nuanced understanding of complexities that may not be apparent to the other. Each field's perspectives influence their models. Therefore, the modelling framework origins influence the (apparent or hidden) assumptions and capabilities of current biophysical economic models.

For the taxonomy, a category of 1 indicates a pure science or engineering model without any economic influence. A category of 2 might be more of an engineering costing approach, techno-economic analysis, ecological model, or similar. A category of 3 represents a true blend of disciplines which often arises in integrated assessment models. A category of 4 represents mainstream economic models such as aggregate production functions. Finally, a category of 5 indicates models originating in behavioral economics or other social sciences — often agent-based models.

Table 2.7: Origins taxonomy criteria.

| Characteristic | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Origins | Physical science model | Ecological or engineering costing | IAMs | Mainstream economics | Behavioral economics / social sciences |

#### 2.3.3.6 Mechanism

Finally, the last characteristic stems from multiple interpretations of "model." Often, a scientific model is a simulation (either static, steady-state, or dynamic) that has to "run." This type of model is constructed with a set of equations and/or algorithms, often forming a computer program or script that must be executed to generate data. These simulation models are distinct from statistical models and optimization models. An optimization model is much stricter than a simulation, and attempts to find the best set of parameters for a given objective, subject to constraints. While also constructed with equations and/or algorithms, a statistical model is purely analysis of already-existing data, often to draw out relationships between variables (Sterman, 1991).

For the taxonomy, a category of 1 indicates a statistical model, a category of 3 indicates an optimization model, and a category of 5 indicates a simulation.[6]

Table 2.8: Modelling mechanism taxonomy criteria.

| Characteristic | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Mechanism | Simulation (model has to "run") | | Optimization | | Analysis (i.e. statistical modelling) |

## 2.4 Using the taxonomy

In this section, we classify four recently published biophysical economics models to demonstrate the use of this taxonomy. We chose one model for each level of the model framework characteristic (excluding individual-based modelling), to show how a specific combination of characteristics applies to a research topic. These combinations of characteristics are deliberate, and gaps between potential combinations and actualized combinations may point towards topics or research questions that may not have been modeled yet.

### 2.4.1 Energy rebound (Brockway et al., 2017)

This article uses a modified aggregate production function to estimate national-level energy rebound for three countries (the US, UK, and China) over 30 years. This study extends a line of

[6] Because there are only three categories for this characteristic, spaces two and four are unused in the taxonomy and analysis.

research that seeks to incorporate energy parameters into a standard macroeconomic model (Ayres and Warr, 2010; Heun et al., 2017b). In this paper, the objective is to determine how effective energy efficiency programs are at reducing energy use. The authors accomplish this by modifying a model that originated in macroeconomics, then econometrically fitting their equations to obtain their results. As such, this model can be categorized according to Table 2.9.

Table 2.9: Taxonomy characterization applied to Brockway et al. (2017)

| Characteristic | Category | Rationale |
|---|---|---|
| Framework | 5 | Aggregate Production Function |
| Spatial scale | 3 | Country level analysis |
| Time horizon | 4 | 30 year timeframe |
| Ethos | 3 | First principles validated by data |
| Origins | 4 | Mainstream economics |
| Mechanism | 5 | Statistical analysis |

### 2.4.2 Mineral extraction (Sverdrup et al. 2017, 2018)

Sverdrup et al. (2017a,b); Sverdrup and Olafsdottir (2018) are working to develop the WORLD6 systems dynamics model — a heavily extended and modified version of the same model used in *Limits to Growth*. These specific papers represent the development of a submodule that simulates global cobalt extraction and market dynamics. The model represents a global scale and simulates 500 years (1900-2400). The model was built using a combination of economic, geologic, and systems theory, and incorporates real-world data. As such, the model was categorized according to Table 2.10.

Table 2.10: Taxonomy characterization applied to WORLD6 (Sverdrup et al., 2017a,b; Sverdrup and Olafsdottir, 2018)

| Characteristic | Category | Rationale |
|---|---|---|
| Framework | 4 | Systems Dynamics |
| Spatial scale | 5 | World |
| Time horizon | 5 | 500 year timeframe |
| Ethos | 2 | Mostly theory, informed by data |
| Origins | 2 | Systems science |
| Mechanism | 1 | Simulation |

### 2.4.3 Oil production (Voudouris et al., 2011)

The ACEGES model was developed by Voudouris et al.,who designed it for exploratory energy policy (Voudouris et al., 2011). They used the model to study oil production and peak oil. In this model, agents are countries (rather than individual oil companies or oil wells, which would make it an individual-based model). Each agent has a demand for oil, and may produce oil based on certain behavioral rules. In this way, the model avoids specific market-maximizing equations or an optimization of the supply-demand curve, which may better represent reality. The model is initialized with year 2001 data, allowing for 10 years of real-world data for validation (the paper was published in 2011). With that said, model calibration did not seem to be a central focus of the article, so the model was categorized as a 2 on the modelling ethos characteristic. The model was run for 60 years, which was enough to simulate a peak oil and decline scenario. Because of this, the model was categorized according to Table 2.11. This model demonstrates the viability of using ABM to study biophysical economics. The nature of the modelling framework allowed for deep insight into indicators that are normally highly aggregated, such as production and consumption of oil for every country.

Table 2.11: Taxonomy characterization applied to ACEGES (Voudouris et al., 2011)

| Characteristic | Category | Rationale |
|---|---|---|
| Framework | 2 | Agent-based model |
| Spatial scale | 5 | World |
| Time horizon | 4 | Long term, 10+ years |
| Ethos | 2 | Mostly theory, limited validation |
| Origins | 5 | Behavioral economics |
| Mechanism | 1 | Simulation |

### 2.4.4 EROI (Palmer, 2017)

Palmer combines Input-Output (IO) methodology with net-energy analysis to calculate the economy-wide energy-return-on-investment (technically the gross external power ratio) of Australia for the 2013-14 year. IO methodology originated in mainstream economics as a way to track economic output and linkages across industries. Palmer and many others have recently begun to utilize environmentally-extended input-output models to study biophysical economics indicators (King et al., 2015; King, 2016; Brand-Correa et al., 2017; Heun et al., 2018). This paper was categorized as Table 2.12.

Table 2.12: Taxonomy characterization applied to Palmer (2017)

| Characteristic | Category | Rationale |
|---|---|---|
| Framework | 3 | Input-Output model |
| Spatial scale | 3 | Country level analysis |
| Time horizon | 2 | One year timeframe |
| Ethos | 5 | Empirical |
| Origins | 4 | Mainstream economics |
| Mechanism | 5 | Analysis |

### 2.4.5 Summary of example categorization

These examples represent a range of biophysical economic modelling frameworks, objectives, and mechanisms. The differences in modelling approach allow for different insights into the field. Each model was constructed to answer a specific hypothesis or research question - typically, that question, or the goal and scope of a research project, dictates many or all of a model's characteristics. So, a new question arises; are there currently research gaps within the field, indicated by unfilled combinations of these characteristics? If certain model characteristic patterns are unused, is it due to a legitimate research gap, or some inconsistency between the pattern's characteristics? We investigate this next.

## 2.5 Qualitative analysis of modelling space

### 2.5.1 Results by characteristic

Figure 2.6 shows the results of this analysis. The taxonomy shows each characteristic and its categories, and the shading of each box represents the number of models categorized within that category. This taxonomy indicates that most BPE models analyzed are either simulations or a statistical analysis with a time horizon longer than 10 years. Most models have a spatial scale at the country or world scale. There is a fairly even mix among modelling frameworks and modelling ethos, though individual-based models are rarely represented. Most models tend to have at least some validation and theory — there are few pure theory or pure empirical models within the dataset.

This taxonomy indicates that there may be gaps in the current modelling landscape —

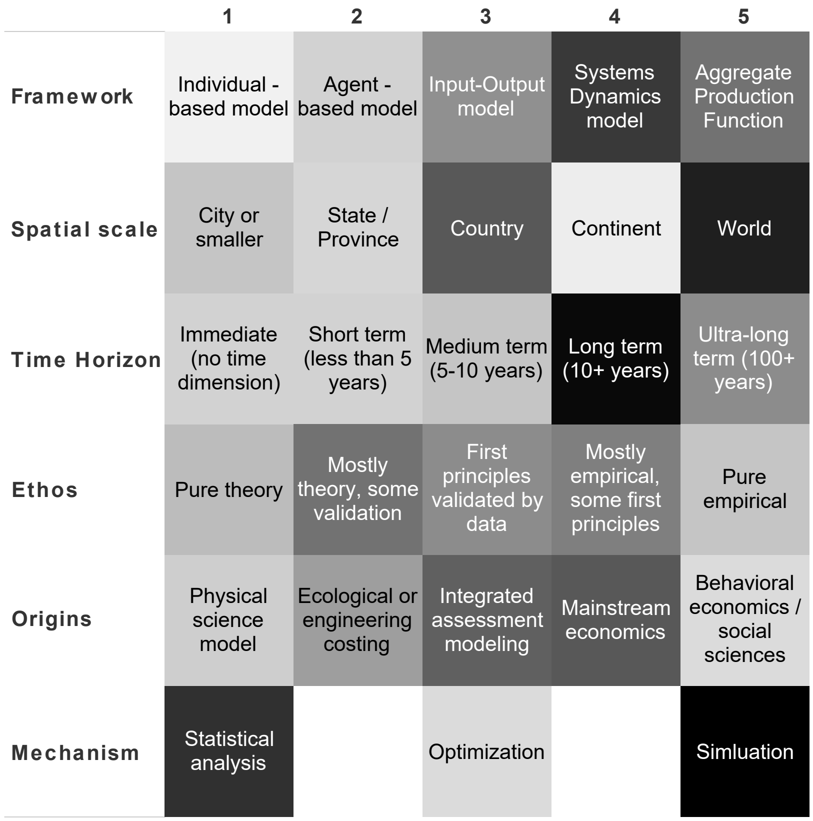


Figure 2.6: Results of categorizing 110 BPE models across these 6 characteristics. Darker shaded areas of the taxonomy indicate more models fall within that category. Here, a black box represents 57 models.

continent scale models are rare, as are medium term models. Few models arise from the behavioral economics or social science fields. And, there are few optimization models.

### 2.5.2 Identifying gaps

To get a clearer picture of the BPE modelling landscape, we can plot the six characteristics within a correlation matrix to refine our understanding of research gaps. Figure 2.7 shows this correlation matrix. Here, each row (or column) represents a rating on a characteristic. Each box shows the number of models that were categorized according to that specific intersection of ratings. For example. the far left column shows how all individual-based models were categorized. The top-left box shows that there are two individual-based models in the dataset. Moving down the far left column, we note that these two models were both at the State/Province spatial scale and at the long term time horizon. We see that one of these two individual-based models is at the "pure theory"

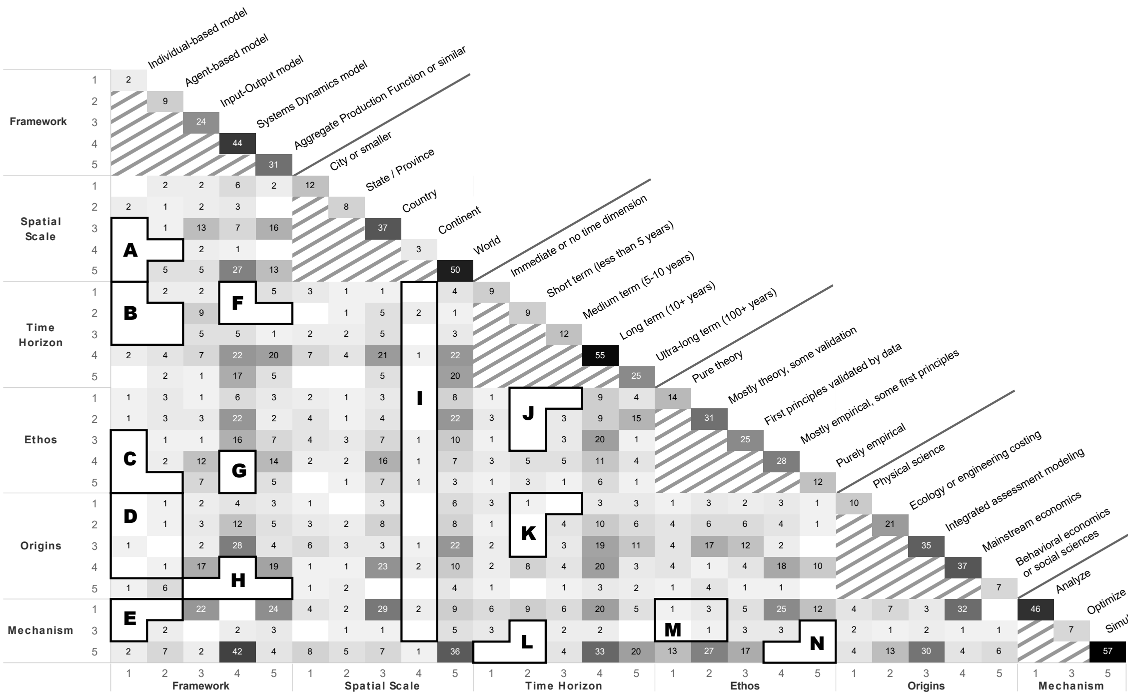


Figure 2.7: Correlation matrix of 110 categorized BPE models across six characteristics. Darker cells indicate a greater number of models fall within that category. Gaps within the correlation matrix are outlined and labeled.

ethos, while the other is "mostly theory, some validation." At the bottom of the far left column, we note that both individual-based models are simulations (there are no analysis or optimization individual-based models.)

The main diagonal of the matrix, where characteristics intersect with themselves, shows the same information as Figure 2.6. The top left of the matrix shows that there are two individual-based models and eight agent-based models, for example. These diagonal boxes show the total number of models categorized in a single characteristic. Looking at the bottom right of the matrix, there are 57 simulation models. These 57 simulation models are distributed across each of the other characteristics — reading the last row of this matrix, we see that of the 57 simulations, 42 are systems dynamics models. 36 of the 57 are at the world spatial scale. 33 of the 57 have a long term time horizon, and so on.

The correlation matrix indicates several gaps within the modelling landscape. These gaps are areas of the matrix in which few, if any, models were categorized. Each gap has been highlighted on Figure 2.7 and labeled with a letter. We break down these modelling gaps and provide commentary based on the columns of Figure 2.7, from left to right. For each gap, we conclude whether or not future research might be able to fill it and provide a potential research question if possible. Some gaps may be "open" but unfillable due to inherent modelling limitations or conflict within the characteristics (such as a systems dynamics statistical analysis).

#### 2.5.2.1 Agent-based modelling gaps

**Box A** shows that there are no individual-based models at the country, continent, or world scale. This is likely a computational limitation — instantiating enough individuals to fill a world model would be prohibitively expensive. In contrast, agent-based models might be able to model the world if agents are appropriately defined, such as "country" agents. Or, if only a small segment of the world is modeled, such as an agent-based model of the world's oil extraction (Voudouris et al., 2011). **Gap possible to be filled,** if agents are appropriately defined. *How might local or "global" policies help economically competing countries within Africa overcome future energy shortages while maintaining or improving quality-of-life?*

**Box B** indicates that individual-based and agent-based models tend to extend across a long term time horizon. Few agent-based models occur in short- or medium-term timeframes. **Gap possible to be filled.** *What short-term social dynamics, including international trade agreement or supplier contract structure, limit resiliency in the face of sudden physical supply shocks?*

**Box C** indicates that individual-based and agent-based models are usually theoretical. Due to the nature of agent-based modelling, it might be impossible to build a purely empirical model. Agent-based models require significant modelling assumptions (ideally based on theory) that extend beyond a pure data-based analysis. **Gap unlikely to be filled.**

**Box D** indicates that agent-based models are grounded in behavioral economics or social science. This is because agent-based models originated in the social sciences, and the framework is significantly dependent on social dynamics and interactions.**Gap unlikely to be filled.**

**Box E** shows that an agent-based model by definition is a simulation. It cannot be a statistical analysis. An agent-based model could potentially be constrained by an optimization framework but these are rare. **Gap unlikely to be filled.**

#### 2.5.2.2 System dynamics gaps

**Box F** shows that there are no short term systems dynamics models. So far, system dynamics models have been used to study long term and ultra-long term time horizons. It may be easier to use an input-output model or other model structure to study short term time horizons. **Gap possible to be filled,** if the systems dynamics model is built appropriately. *Is there enough rare-earth element mining capacity for the European Union to dramatically ramp-up energy storage technologies in the short term (<5 years)? How might prices and supply react?*

**Boxes G** and **H** indicate that systems dynamics models are not purely empirical, and are a mix of engineering, systems thinking, and economics. Similar to agent-based models, this gap appears to be a byproduct of the systems dynamics framework. **Gap unlikely to be filled.**

#### 2.5.2.3 Continent spatial scale gap

**Box I** shows that across all other modelling characteristics, continent-scale models are rare. It is interesting to note that most simulation models work at the world scale, while most statistical analysis models work at the country scale. An apparent gap exists in scaling these modelling mechanisms to alternate spatial scales. This might be attributed to low data availability at the continent scale; country or worldwide data may be easier to obtain. There seems to be much room for models of a specific continent, particularly if there is an emphasis on ocean- vs land-based trade or supply routes. **Gap possible to be filled.** *Does one continent have an inherent advantage over others for an energy resource transition due to distribution of resources? How has geographic distance between suppliers & manufacturers affected EROI & costs for various energy technologies?*

#### 2.5.2.4 Time horizon gap

The majority of time horizon gaps occur for the short-term (less than 5 years) time horizon models. **Boxes J, K,** and **L** show that only Input-Output models currently model the short-term. As input-output models usually work with a single year of economic data, this makes sense. However, the gap indicates that short-term simulations (Box L) do not exist. This may be because economies are not facing fundamental physical constraints in the short-term, and so a short term biophysical model might reduce down to a standard economic model. However, there is potential for sudden supply shocks within the short term. This might require a biophysical model to understand. We believe this is certainly a research gap that ought to be further studied. **Gap possible to be filled.** *What short-term economic and environmental effects would occur due to a repeat of the 1973 oil crisis in today's economy?*

#### 2.5.2.5 Ethos gap

**Box M** indicates that few statistical analysis or optimization models are purely theoretical. Conversely, Box N indicates that few simulations are purely empirical. This makes sense — a certain level of abstraction is necessary to create a tractable simulation. That is, simulations rely on theory. In parallel, analytic models rely on empirical data. Analytic models may incorporate theoretical underpinnings (such as the concept of EROI), but they tend to be far more empirical than theory. As such, these research gaps make sense and seem to be a product of the modelling mechanism, rather than an underdeveloped area of the landscape. **Gap unlikely to be filled.**

#### 2.5.2.6 Other observations

Few optimization models were found in the literature. This might be a consequence of the requirements for optimization - biophysical economics tends to be complicated and complex in a way ill-suited for an optimization routine. Optimization requires a well-specified objective and well-specified constraints. Within the context of economics, an optimization model might also require economic actors to maximize their utility and perfectly value everything — a contentious assumption.

## 2.6 Conclusion & future research

Biophysical models of the economy are necessarily multi-disciplinary because they model both human and natural systems, as well as the relationships between them. Because of the multi-disciplinary nature, biophysical economics modelling approaches are published across a large spectrum of academic journals. The primary contribution of this study has been to develop a taxonomy of biophysical economics models as a way to understand the current landscape of this diverse body of work. Using the taxonomy to classify the last ten years of published studies reveals which approaches have been used more than others. The more densely populated cells of the taxonomy include systems dynamics models, global models, long time horizon, and those originating from either integrated assessment modeling or mainstream economics. Several gaps in the taxonomy suggest that some modelling approaches have yet to be explored in the published literature. Some of the gaps are expected, and are not likely to be productive areas to explore. For example, the Ethos gaps are a natural result of the context of how models are developed. On the other hand, the lack of agent-based models, and models at the city, state, or continental scale are likely to be promising avenues for the future. That these gaps exist indicates that certain research questions have yet to be addressed. We believe there is merit to building models in these gaps. By expanding the application of these biophysical modelling approaches we can deepen the understanding of how the economy can work within its biophysical constraints.

## Relation to broader dissertation

The three themes of this dissertation are woven into and throughout this chapter. These themes are:

1. BPE modeling allows deeper insights into how the economy is reliant on resources
2. Models are better informed and constructed with granular and detailed data
3. Detailed, high resolution models enhance decision-making capability

The history of biophysical economics showed that theme 1 was present at the beginning of the field (see Section 2.1). BPE has always meant to describe and model the implications of energy and material resources usage (including depletion or other constraints) on economic growth and societal wellbeing. As we will see in the chapters ahead, individual BPE models may have much to say to a specific resources, their connections, or resource constraint scenarios.

While not quite as apparent, theme 2 has also been present here. As more countries and organizations track their energy data, modeling possibilities open up. The past ten years of BPE modeling have seen many more detailed models that are better informed by real-world data compared to older and seminal models (such as *Limits to Growth*). Constructing BPE-related datasets and databases should be a top priority of the research community — doing so allows for more intensive model validation while also allowing for a larger base of data with which to start modeling. Validation through more detailed data also positively affects model credibility. Eker et al. (2018) presents a survey of resource management modelers' views on model validation and credibility; survey results show a common perception that decisionmakers trust models that match historical data. As the

BPE community continues to develop models, they ought to take advantage of the explosion of data within the world today to inform and validate models.

Theme 3 follows theme 2 within this chapter. If decisionmakers care about model credibility then they may more likely trust the implications of models that are validated. In this chapter, we have seen that many models have some validation component (see the Ethos characteristic in Figure 2.6). As such, the BPE research community is already taking steps towards providing better decision-making capability to policymakers through their modeling efforts.

These three themes will be present within the next chapters as well. Each of the following chapters will describe a BPE model demonstrating these themes. These chapters will open by placing the model on the taxonomy developed in this chapter, as a signpost to the reader. The intention is to show how each of the models fits within the BPE modeling landscape. At the conclusion of this dissertation, much of the landscape will have been investigated and moved forward through novel modeling strategies to better describe the relationship between energy, materials, economics, and the environment.

# Chapter 3

# An extended environmental input–output lifecycle assessment model to study the urban food–energy–water nexus

## Prelude

This chapter was originally published in 2017 within *Environmental Research Letters*.[1] The chapter has been edited for clarity and format. Additionally, the conclusion has been expanded to better place the chapter within the broader dissertation.

This chapter describes an analytical model with characteristics as shown in Figure 3.1. The model is an extended input-output model and so fits in the input-output framework. Because this model is applied to every metropolitan statistical area, it fits into the "city or similar" spatial scale. As with most input-output models, the majority of this chapter deals with a single year of data, so the model exists within the short term time horizon. The model's Ethos characteristic was

[1]Sherwood, J., Clabeaux, R., and Carbajales-Dale, M. (2017a). An extended environmental input–output lifecycle assessment model to study the urban food–energy–water nexus. *Environmental Research Letters*, 12(10):105003, published as Open Access under the Creative Commons Attribution 3.0 License (http://creativecommons.org/licenses/by/3.0/)

chosen because the model is mostly data analysis, although some first-principles or stylized elements were utilized to make the model tractable. This chapter originates from mainstream economics, as input-output modeling is a primary tool of many economists. Finally, the model is a statistical analysis.

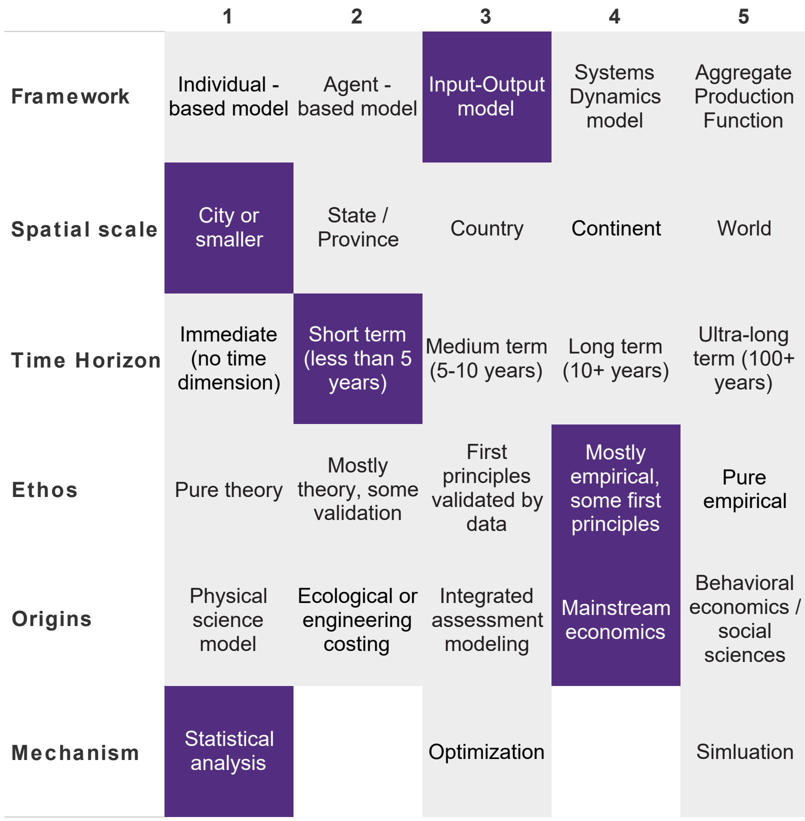


Figure 3.1: The extended EIO-LCA model mapped to Chapter 2's biophysical economics modelling characteristics.

Note that, although this chapter is relevant to biophysical economics, it is not explicitly discussed in part due to the original publishing venue.


## Abstract

We developed a physically-based environmental account of US food production systems and integrated these data into the environmental-input–output life cycle assessment (EIO-LCA) model. The extended model was used to characterize the food, energy, and water (FEW) intensities of every US economic sector. The model was then applied to every Bureau of Economic Analysis

metropolitan statistical area (MSA) to determine their FEW usages.

The extended EIO-LCA model can determine the water resource use (kGal), energy resource use (TJ), and food resource use in units of mass (kg) or energy content (kcal) of any economic activity within the United States. We analyzed every economic sector to determine its FEW intensities per dollar of economic output. This data was applied to each of the 382 MSAs to determine their total and per dollar of GDP FEW usages by allocating MSA economic production to the corresponding FEW intensities of US economic sectors. Additionally, a longitudinal study was performed for the Los Angeles–Long Beach–Anaheim, CA, metropolitan statistical area to examine trends from this singular MSA and compare it to the overall results.

Results show a strong correlation between GDP and energy use, and between food and water use across MSAs. There is also a correlation between GDP and greenhouse gas emissions. The longitudinal study indicates that these correlations can shift alongside a shifting industrial composition. Comparing MSAs on a per GDP basis reveals that central and southern California tend to be more resource intensive than many other parts of the country, while much of Florida has abnormally low resource requirements.

Results of this study enable a more complete understanding of food, energy, and water as key ingredients to a functioning economy. With the addition of the food data to the EIO-LCA framework, researchers will be able to better study the food–energy–water nexus and gain insight into how these three vital resources are interconnected. Applying this extended model to MSAs has demonstrated that all three resources are important to a MSA's vitality, though the exact proportion of each resource may differ across urban areas.

## 3.1 Introduction and background

### 3.1.1 Introduction to urban sustainability and food–energy–water (FEW) nexus

Urbanization is one of the defining characteristics of the 21st century. People continue to be attracted to growing metropolitan areas for economic opportunities and social advantages. In 1950, 30% of the world's population was urban, and by 2014 more than half of the global population lived in cities (UN, 2015). Population growth and urbanization are projected to add 2.5 billion people to the world's urban population by 2050, meaning that two-thirds of people will be living in urban areas (UN, 2015).

This urbanization affects sustainable development, as urban residents have higher consumption patterns than their rural counterparts. For instance, in 2011 US urban households spent $7808 (18%) more on consumer expenditures compared to rural households (Hawk, 2013). Urban households also generally use more energy per square foot than rural households (Muratori, 2014). From 2000 to 2010 the US urban population increased by 12.1%, which was higher than the nation's overall growth rate of 9.7% during that same period (Bureau, 2012). Metropolitan areas cannot be sustainable if their consumption of food, energy, and water (FEW) continues to increase with their growing population.

The production and use of FEW are distinctly interconnected. Water is essential for the growing, cleaning, and processing of food. Energy is vital for food production as it powers farm machinery and allows the transportation of the field goods. Energy is also utilized to obtain potable water for drinking and agricultural irrigation by powering water extraction, treatment, and transportation. As metropolitan areas grow rapidly, the effects of growing economic activity are reflected in the amplified demands, both direct and indirect, for food, energy, and water.

This study evaluates the FEW requirements of every Bureau of Economic Analysis (BEA) metropolitan statistical area (MSA) using an input–output (I–O) lifecycle analysis approach. As global urbanization continues, gaining insight to the FEW nexus is invaluable for sustainable development.

### 3.1.2 Introduction to life cycle assessment (LCA)

LCA is a comprehensive framework for analyzing environmental impacts associated with the provision of goods and services within the economy (Guinée and Lindeijer, 2002). There are four stages to carrying out an LCA, which are undertaken iteratively: (1) goal and scope definition; (2) inventory analysis; (3) impact assessment; and (4) interpretation. The fundamental principle is to define a functional unit (e.g. one gallon of fuel) and define the boundary of the product system (often called the foreground system) necessary to deliver the functional unit through all relevant life cycle stages: materials extraction (e.g. pumping oil from the ground); transportation; materials processing; manufacture; operation; and disposal. Exchanges between the product system and the background system—the broader economy (e.g. steel for oil well) are traced back to their elementary exchanges between the economy and the environment (e.g. iron ore).

### 3.1.3 Introduction to environmental input–output (EIO) LCA

Life cycle assessment also distinguishes between two common methodological approaches: bottom-up, process-based, which builds an engineering-type model of the physical production system; and top-down, I–O, which extends economic tables of inter-industry monetary flows by adding a vector of exchanges (e.g. water withdrawals or greenhouse gas emissions) between some industries and the environment (Majeau-Bettez et al., 2011). While the bottom-up method allows much finer resolution of impacts down to the level of specific products (a problem for the I–O method, since it assumes only one highly aggregated product per industry), it loses out on comprehensively capturing the full breadth of processes within the economy (called the truncation problem, within LCA (Reap et al., 2008)) and can underestimate impacts (by as much as 50%, depending on the product and impact (Lenzen, 2000)) compared with I–O methods.

The EIO-LCA model was initially developed in the mid-1990s by the Institute (2008). The model relies on an economic I–O table, a snapshot of the structure of an economy within a given year. The most recent model relies on year 2002 I–O tables and can characterize several environmental impacts including energy requirements, greenhouse gas emissions, water withdrawals, and land use. Researchers and businesses often use the model as a screening tool—the cost of a specific product (e.g. a computer) is assigned to a sector (e.g. computer terminal manufacturing) as input to the model to estimate its environmental impact from material extraction up through manufacturing and assembly. Therefore, the tool is typically used for consumption-based accounting, meaning all upstream environmental impacts are applied to a product being consumed. At a city, state, or national level, consumption-based accounting allocates all up-stream emissions to final consumption (Mi et al., 2016; Mózner, 2013).

However, this paper uses the tool slightly differently to analyze MSAs. Because the MSA dataset specifies GDP in terms of value-added rather than final use, the model output represents all upstream emissions associated with the final production of industries within an MSA (using value-added as a proxy), whether the produced commodity is consumed within the MSA or in another region. This differs from production-based accounting as described in Larsen and Hertwich (2009) (in that production-based accounting only looks at direct, or operational, emissions rather than lifecycle emissions), because a portion of intermediate, up-stream emissions are assigned to an industry's final production output. Therefore, our approach most closely resembles transboundary infrastructure supply chain (TBIS) footprinting as developed by Ramaswami et al. (2008). The TBIS approach is primarily process-based and attempts to account for a region's key indirect emissions, like electric and fuel supply, which might be produced outside the region. More details can be found in Chavez and Ramaswami (2011). While TBIS only accounts for key transboundary flows, our I–O model accounts for all indirect flows, though at the expense of specificity due to the nature of I–O modeling.

An overview of the EIO-LCA methodology is presented in Section 3.2. We include sections detailing the food data extensions (Section 3.2.2) and methodology used to analyze MSAs (Section 3.2.3). Within Section 3.3, we first present the EIO-LCA results by industry (Section 3.3.1) before analyzing the MSAs (Sections 3.3.2–3.3.3). We compare MSAs to US national data (Section 3.3.4) and present a longitudinal study of a single MSA (Section 3.3.5). Finally, we address limitations and potential future work in the conclusion (Section 3.4).

## 3.2 Methodology

### 3.2.1 EIO-LCA methodology

Process-based and I–O-based LCA share similar computational frameworks, shown in Figures 3.2 and 3.3 (Heijungs and Suh, 2013; Hendrickson et al., 2006). The $A$ matrix represents the total products each industry requires to produce one unit of output. The final demand vector $f$ represents the functional unit. In I–O analysis, $f$ is usually the final-use GDP of an economy. Typically, $f$ is used in conjunction with $A$ to find the scaling vector, $s$, through equation 3.1. The scaling vector represents the total number of each product needed to produce the functional unit, and is often total industry output for I–O analysis

$$A^{-}1f = s \tag{3.1}$$

The B matrix represents exchanges between the economy and the environment for each industry. B is multiplied by the scaling vector s to determine the total environmental impact, g, in equation 3.4. These flows include energy, food, water use, and other flows of interest[2]

$$Bs = g \tag{3.4}$$

#### 3.2.1.1 EIO-LCA model data

The EIO-LCA model and data formed the basis of the study by providing detailed 428 sector BEA IO tables and a list of environmental flows. All environmental flows used (except for the new food flows) come from the model (Institute, 2008). These flows include: conventional air pollutants, greenhouse gases, energy, toxic releases, water withdrawals, transportation, land use, and the flows contained in the TRACI Impact Assessment. This paper focuses on the water withdrawals, energy, and greenhouse gases flows. These flows, along with the new food flows developed in Section 3.2.2, form the B matrix within the standard LCA matrix framework.

The EIO-LCA model determines the energy usage and water withdrawals for all economic activity required to produce the final demand vector. This includes both direct and indirect usage. For example, manufacturing steel in a foundry might directly require natural gas in its processes, which counts as direct energy usage. A foundry might also require electricity from a natural gas power plant—an indirect energy usage because the power plant is the process burning natural gas.

Similarly, a foundry might use water directly within its internal processes or indirectly, such as water used within the power plant's fuel cycle. Note that the EIO-LCA model counts any water withdrawal, even if water is returned to the watershed after use (this often occurs in power plant cooling cycles).

[2] In some economic I–O literature, the matrix may be denoted differently (Institute, 2008). The matrix may use economic flows to and from industries known as $X_{ij}$ where $i$ is the flow from industry $i$ and $j$ is the flow to industry $j$. The sum of a row is $X_i$, representing the total direct output of an industry. The vector of total direct outputs, $x_direct$, can be diagonalized, forming matrix $\hat{X}$. The $X_{ij}$ matrix is multiplied by $\hat{X}^{-1}$, essentially normalizing the matrix to a per dollar total output. This is the direct requirements matrix, represented by $X\hat{X}^{-1}$. The total requirements matrix is $[I - X\hat{X}^{-1}]$ and is equivalent to the A matrix in equation 3.1. This is also known as the Leontief matrix. The Leontief Inverse, $[I - X\hat{X}^{-1}]^{-1}$ is used to find the total economic output through equation 3.2

$$[I - X\hat{X}^{-1}]^{-1} y = x \tag{3.2}$$

Here, $y$ is the final demand vector, equivalent to $f$ in equation 3.1. $x$ is the total economic output, equivalent to $s$ in equation 3.1. This $x$ can be used to find the total environmental burden, $e$, through equation 3.3, where $R$ is the environmental burden matrix

$$R[I - X\hat{X}^{-1}]^{-1} y = Rx = e \tag{3.3}$$

Note that $e$ is equivalent to $g$ in equation 3.4 and $R$ is equivalent to $B$.

Table 3.1: New B vectors, based on UNFAO and Pimentel and Pimentel (2007). All unlisted sectors have values of zero.

| Mass intensity [kg USD-1] | Calorie intensity [kcal USD-1] | BEA IO code | BEA sector description |
|---|---|---|---|
| 5.60 | 24,906.11 | 1111A0 | Oilseed farming |
| 10.32 | 36,876.70 | 1111B0 | Grain farming |
| 2.22 | 540.24 | 111200 | Vegetable and melon farming |
| 2.77 | 1062.07 | 1113A0 | Fruit farming |
| 1.27 | 5693.36 | 111335 | Tree nut farming |
| 0.071 | 226.24 | 111400 | Greenhouse, nursery, and floriculture production |
| 29.57 | 108,266.19 | 1119A0 | Sugarcane and sugar beet farming |
| 1.01 | 793.61 | 1119B0 | All other crop farming |
| 1.85E–4 | 0.59 | 113A00 | Forest nurseries, forest products, and timber tracts |

### 3.2.2 Towards the new food environmental flows

We supplemented the EIO-LCA model by using United Nations Food and Agriculture Organization (UNFAO) data from 2002 (the same year as the core EIO-LCA model) to generate two new environmental flow vectors, namely embedded food mass and embedded food calories as described below (Division, 2002b,a).[3] Additional methodology details can be found in the supplementary material available at `stacks.iop.org/ERL/12/105003/mmedia`.

The UNFAO collects statistics about agriculture production across the world. Their FAOSTAT webpage provides an interactive dashboard to explore and download the data. Food production and caloric value data from the US were combined in order to generate an averaged mass and calorie intensity per dollar of production for each of the BEA industries that produce food from the environment.

All the UNFAO data is aggregated into nine BEA agriculture sectors, shown in Table 3.1.[4] The total UN crop production for each sector was divided by the total industry output to obtain that sector's production intensity. Although it is possible to obtain intensity factors for other sectors such as cattle production or coffee manufacturing, these sectors do not directly pull inputs from nature. Rather, they take inputs from the sectors listed below, which are responsible for all

[3]We supplemented the UNFAO dataset with some caloric value data from Pimentel and Pimentel (2007).

[4]We only track primary crops suitable for human consumption — forage, roughage, and other naturally occurring animal feedstocks are not accounted for (pure grass-fed cattle and wild game do not enter our model). Additionally, aquaculture that is not reliant on agriculture crops (e.g. fish feed) do not enter our model. These exclusions are due to lack of data.

primary agriculture.[5] Note that sugarcane farming and grain farming produce the most mass and calories per dollar.

As with the water and energy flows, the new food environmental flow enable counting both direct and indirect food requirements for economic activity. Foundries might purchase food for employees at a company picnic, so the foundry is responsible for some of its own workers' food requirements as well as some portion of the food intake of miners from whom the foundry buys its iron.

A limitation of the food data is that the model aggregates all food types into a single mass or calorie indicator without regard to nutritional value. These highly aggregated food types limit a full understanding of a specific food's importance to specific economic sectors or regions. Another limitation lies in the base year of the data—corn based ethanol has significantly increased corn supply and the price of corn has risen since 2002 (USDA, 2002). These vectors model food supply circa 2002 and the I–O tables model the food supply chain circa 2002.

This extended model was used to determine the food, energy, and water intensities (defined as unit per million dollars of GDP) for every industry within the I–O tables.[6] This data is shown in Section 3.3.1. Once the industry intensities were computed, they can be scaled by any GDP vector to find total resource requirements for that GDP. In this paper, metropolitan statistical area GDP data is utilized.

### 3.2.3 Metropolitan statistical area analysis

The United States Office of Management and Budget uses Census Bureau data to define metropolitan statistical areas (MSAs). A MSA is defined as a county or counties that have at least one urbanized area with a population of 50,000 or more, plus adjacent territory that has a high degree of social and economic integration with the urban core as measured by commuting ties (U.S. Office of Management and Budget, 2013). This classification applies to about 85% of the US population which resides in one of 382 metropolitan statistical areas. Using the environmental flows generated from the EIO-LCA model, the FEW intensities of each MSA can be characterized and compared.

[5] The model views a steak as a collection of processed grains rather than its own unique food item. A 500 calorie, 250 g steak actually represents and requires roughly 13,000 calories or 8 kg of primary grains — cows are inefficient at converting feed into meat.

[6] For our analysis and model results, we choose to only track food mass and omit calorie requirements because the results are redundant.

#### 3.2.3.1 Methodology

The BEA compiles yearly, sectoral GDP data for each MSA.[7] Our analysis uses 2013 GDP data because it is the most recent and most complete. We converted the 2013 nominal GDP to real GDP in 2002 chained-dollars to align with the EIO-LCA model, which uses a 2002 I–O table and environmental flows. This conversion was done using MSA-specific quantity indexes for each industry, which are provided in the dataset. Each MSA's sectoral GDP is multiplied by that sector's national average FEW intensities (Section 3.3.1) and summed to determine the MSA's total FEW usages.[8] Additional details are provided in the supplementary material.

While real sectoral FEW intensities vary by region, this model does not account for regional differences. However, the model does provide a general screening tool that can indicate if further detailed analysis is warranted from an MSA's irregular FEW requirements. This methodology can also be thought of as querying the national IO table with feasible US production mixes—each MSA's output. How do FEW requirements vary between the different production mixes? We discuss this further in the results and conclusion.

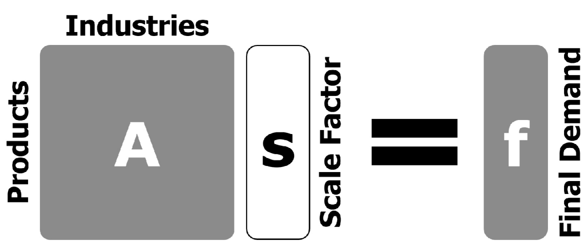


Figure 3.2: Economic portion of the LCA matrix methodology.

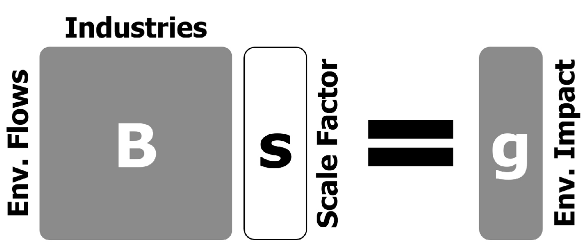


Figure 3.3: Environmental portion of the LCA matrix methodology.

[7]While GDP commonly refers to Gross Domestic Product for the US, it can also refer the gross domestic product of smaller areas, such as a state or MSA GDP.

[8]Note that we did not calibrate the I–O model to each MSA using physical flows (e.g. the total water used in an MSA), though some researchers have studied this for individual regions by using hybrid LCA models (Ramaswami et al., 2008; Cohen and Ramaswami, 2014; Erickson and Lazarus, 2012).

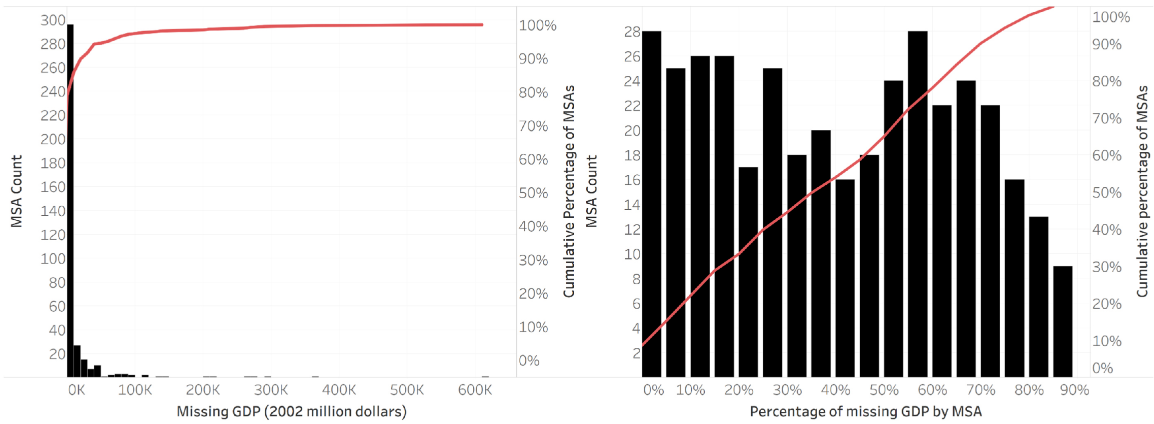


Figure 3.4: Histogram of 'missing' sectoral GDP due to undisclosed data for each MSA. The left shows 'missing' GDP in absolute terms while the right shows 'missing' GDP as a percentage of an MSA's total GDP.

In most MSAs, certain sector values were undisclosed to protect specific companies. These sectors were represented by a (D), for undisclosed, within the data. To approximate these unknown values, the summation of known sectoral GDP values was compared to the city-wide aggregated GDP value. The difference represents the 'missing' GDP of all undisclosed sectors. In order to more accurately allocate the 'missing' GDP to each undisclosed sector, we compared each sector to a national average. Luckily, the BEA produces an 'All US MSA' sectoral GDP dataset, which is the sum of all MSA GDP for each sector and has no undisclosed values. We calculated each sector's percentage of total GDP for the 'All US MSA' data, and used this as a weight to allocate each MSA's 'missing' GDP to the undisclosed sectors.

For example, the San Diego MSA is missing $422 million of GDP and has 'Rail-', 'Water-', 'Pipeline Transport', and 'Funds, trusts, and other financial vehicles' as undisclosed industries. The 'All US MSA' data gives the average percentage of GDP for these sectors as 0.16%, 0.33%, 0.11%, and 0.35% respectively. These percentages are used as weights to distribute the missing $422 million, with $71 million to rail-, $145 million to water-, $49 million to pipeline-transportation, and $156 million to funds and trusts. This method ensures all aggregate GDP is accounted for within the disaggregated sectors. Figure 3.4 shows a histogram of MSAs binned by the amount of 'missing' GDP. Roughly half of the MSAs have 40% or less GDP missing, and 109 MSAs have less than 20% GDP missing. Many MSAs have a significant amount of missing data because they are smaller city centers with few companies for each sector. In general, most MSAs are disproportionately missing

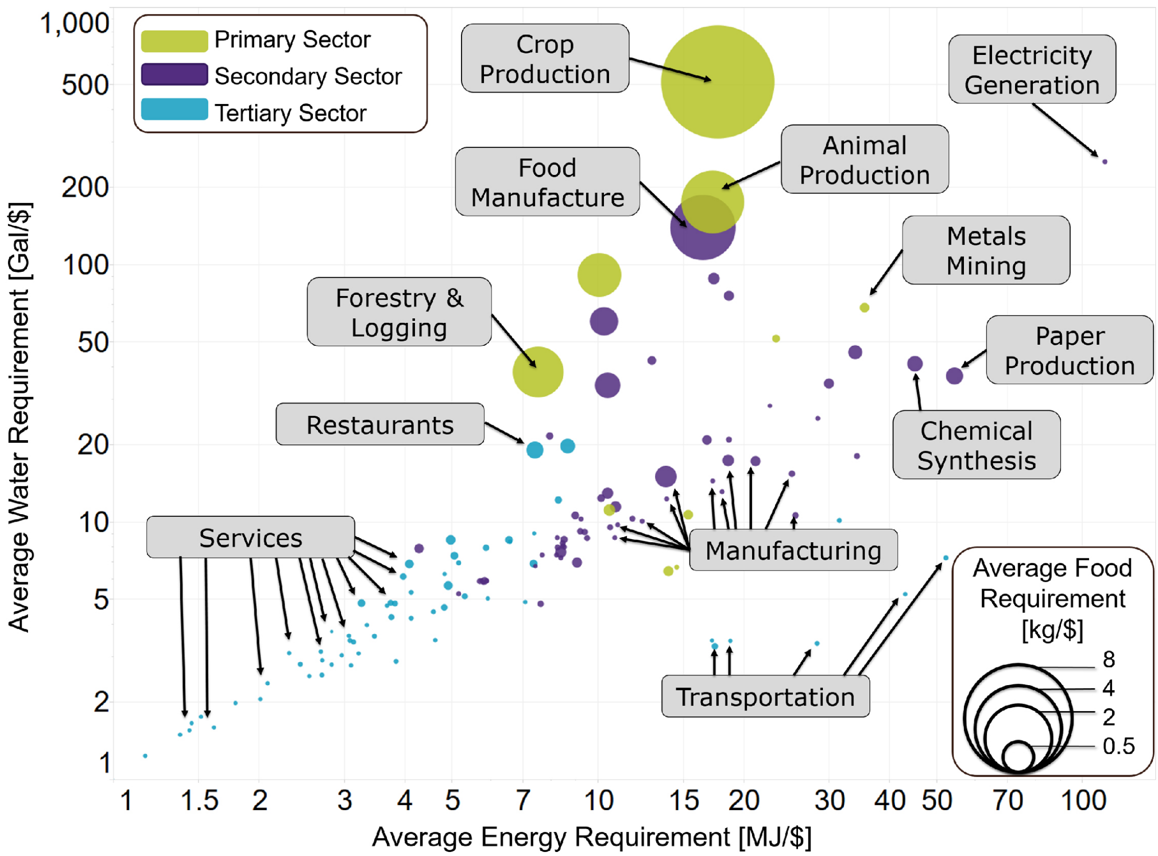


Figure 3.5: Resource requirements per dollar of final demand output for 133 industry groups.

manufacturing data (28% of sectors within the dataset are manufacturing). Manufacturing industries tend to have somewhat above average resource intensities, though most are within the same order of magnitude. Because of this, incorrectly distributing GDP between manufacturing sectors should not drastically change the results.

Some MSAs also had some sector values listed as (L) for values less than \$500,000 in nominal GDP. This value was assumed to be \$250,000; the center of the range. Note that because these are such a small percentage of an MSA's GDP, they have little to no effect on the overall analysis.

Throughout the rest of the paper, all MSAs are displayed in graphs regardless of data quality. However, we have produced each of the graphs using only MSAs with less than 20% of 'missing' GDP. These are available in the supplementary material. The overall results remain similar regardless of excluding low data quality MSAs.

## 3.3 Results and discussion

### 3.3.1 Industry resource intensities

The first step of our analysis was to characterize the resource intensities of every industry within the national I–O tables. These resource intensities represent the average intensity of that industry across the US. The results are displayed in Figure 3.5. The circle colors represent one of three economic sectors in a three sector economy model (Goodwin et al., 2013). The primary sector, represented by green circles, consists of all raw material extraction including mining, oil extraction, and crop and animal production. The secondary sector, represented by purple circles, consists of all manufacturing including paper production, car manufacturing, and food processing. Finally, the tertiary sector is represented by light blue circles, and consists of all service industries. All three axes (including food requirement as circle size) are defined as the cradle-to-gate lifecycle requirements of a resource per dollar of final demand output.

Figure 3.5 indicates that in general, the primary sector industries require significant water and food resources, and about average energy to produce one dollar of final demand. The secondary sector industries require about average food and water, and above average energy. Finally, the services within the tertiary sector require below the average of each resource. This would indicate that MSAs which have primarily service industries will have low resource requirements, while MSAs that are primarily agriculture or manufacturing might have high resource requirements.

### 3.3.2 Metropolitan statistical area analysis

Figure 3.6 shows the top 50 MSAs ranked by GDP and their food, water, and energy requirements. Greenhouse gas emissions are also estimated through the EIO-LCA model. The FEW usages are greater for MSAs with higher GDP, although there are some exceptions. This is expected, as the model scales resource requirements by the MSA's GDP. Additionally, the fact that all resources scale similarly would indicate that most MSAs have evenly mixed economies. In some cases, an MSA has a larger GDP but lower resource requirements. For example, the Washington DC MSA (Rank #4) has a larger GDP compared to the Dallas MSA (Rank #5), but lower FEW requirements. This is due to a difference in sectoral composition—Washington DC's economy is more service based, and therefore less resource dependent, than Dallas.

We can also look at resource required per dollar of GDP, a measure of resource intensity.

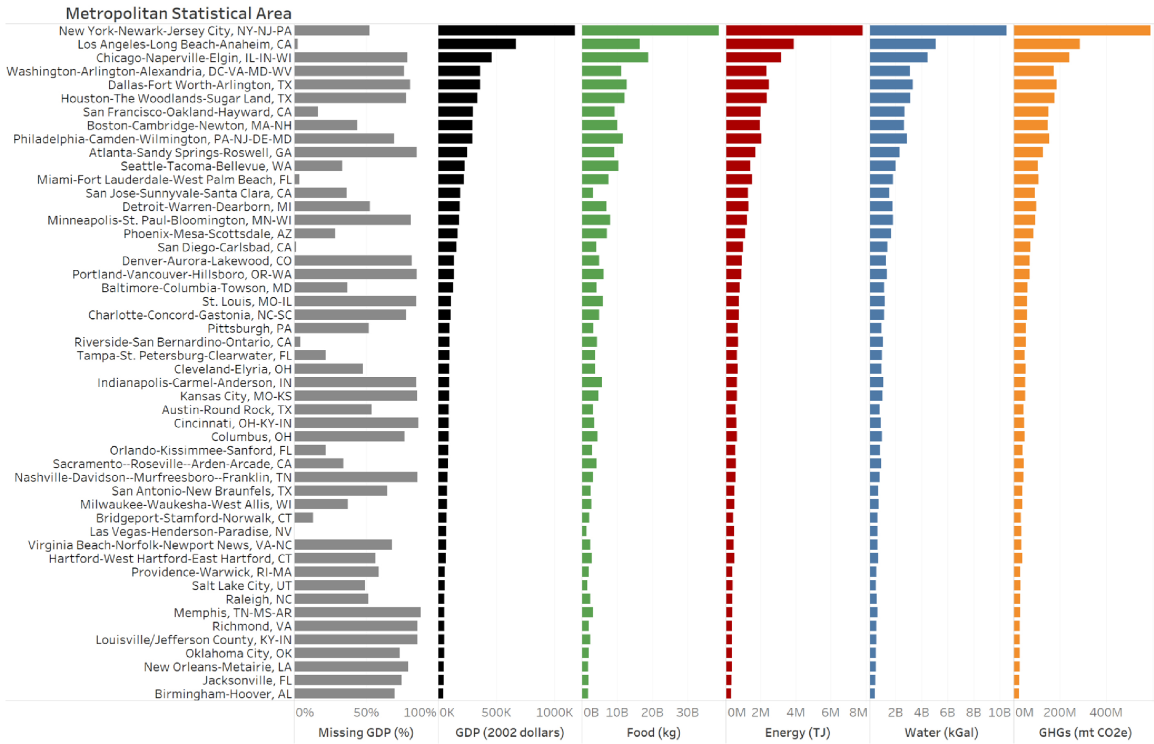


Figure 3.6: Top 50 MSAs ranked by GDP (black) and corresponding food (green), energy (red), and water (blue) requirements. Estimated greenhouse gas emissions (tan) are also shown.

Figure 3.7 shows the top 25 and bottom 25 MSAs ranked by GDP per capita (PC), and their corresponding resource and GHG intensities. Here, we use GDP per capita as a measure of economic productivity. Note that many smaller MSAs, such as Midland, TX (PC rank #2, population 156,800) or Trenton, NJ (PC rank #8, population 370,400) have higher productivity than the largest MSAs from Figure 3.6. However, none of the top 50 MSAs in terms of total GDP are in the bottom 25 in terms of per capita GDP. Ideally, an MSA would have high economic productivity with low resource intensities.

Most MSAs, such as San Jose, CA (PC rank #1, population 1,919,600) or Minneapolis, MN (PC rank #25, population 3,459,100) have comparatively larger energy requirements than food or water requirements. Other MSAs, such as Madera, CA (PC rank #358, population 152,400) or Visalia, CA (PC rank #361, population 454,100) have abnormally high food and water requirements without a significant increase in energy requirements. In general, there are more high food and water intensity outliers than high energy intensity outliers. This again is due to the industry composition

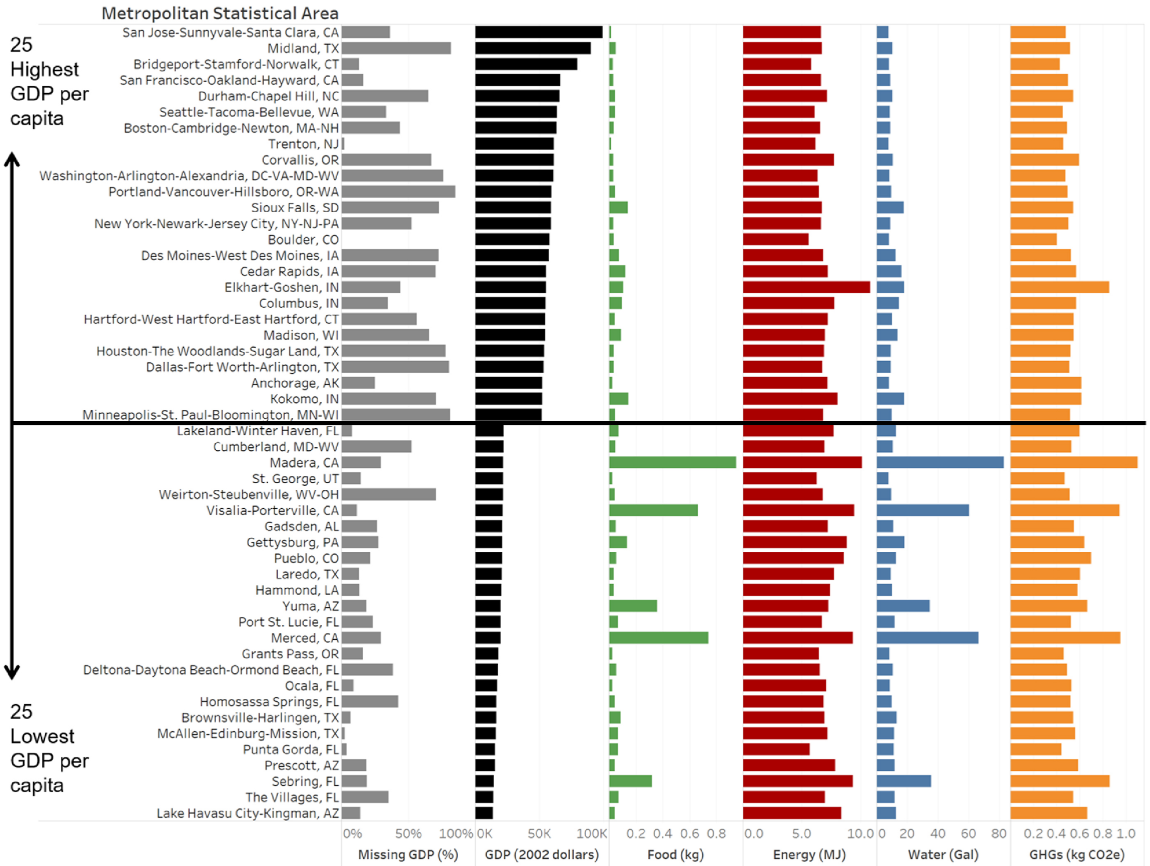


Figure 3.7: Top 25 and bottom 25 MSAs ranked by GDP per capita (black) and corresponding food (green), energy (red), and water (blue) requirements per dollar of GDP. Estimated greenhouse gas emissions dollar of GDP (orange) is also shown.

of each MSA. Some MSAs such as Madera, CA have much larger agriculture or food processing industries (requiring a significant amount of food) than heavy manufacturing industries (which require a significant amount of energy). Overall, the majority of MSAs fall near the US MSA average for all indicators, which may in part be due to low data quality for individual MSAs. All data can be viewed geographically on maps provided within the supplementary material. In general, Florida has abnormally low resource intensities while southern California tends to have above average resource intensities.

Table 3.2: Coefficient of variation for the FEW and GHG parameters. The left column contains all MSAs while the right filters out low data quality MSAs: those with more than 20% missing GDP. There are 382 MSAs total and 109 high data quality MSAs.

| Indicator | Unit | Coefficient of variation | CV, excluding low data quality MSAs |
|---|---|---|---|
| Food intensity | $\frac{kg}{\$}$ | 1.26 | 1.40 |
| Energy intensity | $\frac{MJ}{\$}$ | 0.159 | 0.210 |
| Water intensity | $\frac{Gal}{\$}$ | 0.680 | 0.805 |
| GHG intensity | $\frac{kgCO_2e}{\$}$ | 0.193 | 0.252 |

### 3.3.3 MSA FEW correlations

Each MSA can be treated as a data point to study correlations between the FEW resource intensities and GHG emission intensities. This perspective can be interpreted as querying the US economic structure with different possible output mixes—each MSA's GDP—to understand correlations between resources. The question becomes 'are there clear correlations between resource requirements for different feasible representations of the US economy?' Figure 3.3.5 shows scatter plots for each possible correlation. The opacity of each point is set at 25%, so if at least four MSAs overlap, the color is black.

There is a strong correlation between food and water intensity (plot B). Note that the outliers with abnormally high GHG emissions in plot E are also the MSAs with high food intensities, indicating that GHG emissions are a combination of energy and food production data. There is surprisingly little correlation between water intensity and energy intensity (plot C), though the major outliers are associated with high food intensities.

In addition to studying correlations between these variables, we can also study the variation within each intensity variable to understand how correlated resource requirements are to GDP (the denominator in each intensity metric). We use the coefficient of variation (CV) to measure the relative variability of each parameter. Table 3.2 displays the CVs. Both energy and GHG intensities have small CVs, indicating that they are correlated to GDP. However, food and water intensities vary comparatively more than energy and GHG, indicating less of a correlation with GDP.

These results suggest that food and water requirements within a region are coupled, while energy, GDP, and GHG emissions are also coupled. If an MSA pursues economic growth strategies, it will likely require additional energy supply and unless clean energy systems are sought after, GHG

Table 3.3: MSA comparison to total US resource requirements data. US national data from U.S. Bureau of Economic Analysis (2002); U.S. Office of Management and Budget (2013); Food and Agriculture Organization of the United Nations (FAO) (2016); US Geological Survey (2016); Environmental Protection Agency (2015)

| Indicator | Units | All MSAs | US national data | Percent of US accounted for by MSAs |
|---|---|---|---|---|
| Population | | 269,912,876 | 316,128,839 | 85.4% |
| 2013 real GDP | million 2002 dollars | 11,807,432 | 13,276,414 | 88.9% |
| Food requirement | $kg$ | 613,800,000,000 | 691,100,000,000 | 88.8% |
| Food intensity | $\frac{kg}{\$}$ | 0.0520 | 0.0521 | - |
| Energy | $TJ$ | 81,559,000 | 102,590,000 | 79.5% |
| Energy intensity | $\frac{MJ}{\$}$ | 6.9 | 7.7 | - |
| Water use | $kGal$ | 124,950,000,000 | 129,570,000,000 | 96.4% |
| Water intensity | $\frac{Gal}{\$}$ | 10.58 | 9.75 | - |
| Greenhouse gas emissions | $mtCO_2e$ | 6,231,000,000 | 6,673,000,000 | 93.4% |
| GHG intensity | $\frac{kgCO2e}{\$}$ | 0.53 | 0.51 | - |

Table 3.4: Historical Los Angeles data quality.

| Year | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 'Missing' GDP [%] | 3.51 | 4.12 | 4.34 | 4.88 | 5.04 | 4.91 | 4.11 | 3.98 | 2.75 | 2.49 | 3.95 | 60.9 | 2.48 |

emissions would also increase. If an MSA is facing water scarcity, it might make sense to advocate for limiting food waste in its agriculture systems in addition to water conservation policies.

### 3.3.4 Comparison to US national data

Finally, we can compare the sum of all MSAs to national data to both gauge the accuracy of the results and determine the percentage of total US resources required by MSAs. Because we used year 2002 resource intensity values to determine MSA resource requirements, it is possible that we are under- or overestimating resource requirements for the 2013 MSA GDP data. A quick way to check is to compare the MSA results to national data. The MSAs' share of GDP and resource requirements should all be similar because of the correlations identified above; any significant outlier could indicate an issue. Table 3.3 displays this data.

About 85.4% of the US population lives within an MSA. MSAs also account for about 88.9% of all US GDP. With these two numbers in mind, we can examine the other indicators. According to our model, MSA energy requirements account for roughly 79.5% of all energy 'consumed' in the US This seems reasonable given the strong correlation between energy and GDP and the MSA percentage of US GDP. MSAs also account for 93.4% of all US GHG production, which seems reasonable or slightly higher than expected given the population and GDP values.

MSAs require about 88.9% of all food production in the US, matching the GDP share almost exactly. Water use is likely overestimated, with MSAs apparently accounting for 96% of all water used in the US. However, the reference data is from a 2010 USGS survey which appeared to be a low year in terms of total water withdrawals. When compared to 2005 or 2000 USGS data, the MSA percentage drops to about 84%. The next USGS report containing data for 2015 is not yet available for comparison.

Particularly for water intensity, another source of potential error comes from applying national I–O tables to a regional analysis. In Blackhurst et al. (2010), the authors responsible for the EIO-LCA water data, cautioned against regional analyses because water usage varies significantly across the country. Similarly, there are also regional differences between food production and energy resources that may cause error. This certainly limits the accuracy of a specific MSA's results, though the qualitative trends and comparison to national statistics still provide insight even if specific MSA values are off.

### 3.3.5 Longitudinal Los Angeles–Long Beach–Anaheim MSA study

Historically, the Los Angeles MSA has experienced environmental problems that motivated regulation and altered the area's resource use. The Industrial Revolution spurred manufacturing and utility sector growth which caused increased greenhouse gas emissions and smog events throughout the 1940s. Over time, the origins of smog were discovered. The discovery led California to pass regulations which minimized smog formation, resulting in much cleaner air.

We will use the Los Angeles MSA dataset to examine potential decoupling of economic growth from food, energy, or water resource usage. This MSA has the second highest population and GDP in the United States, and particularly good data quality across the full dataset—2001 to 2013. The Los Angeles MSA has previously adapted and decoupled economic growth from smog emissions; will the pattern repeat within the FEW nexus?[9]

Currently, Los Angeles' economy is mixed with 'heavy and light industries, including two major ports, oil production and refining, steel production, aerospace manufacturing, and coal-fired power plants' Watson and Zhao (2007). According to the Los Angeles Department of Water and Power, coal and natural gas are the main contributors to the area's electricity mix (Wisland and Haya, 2012). In 2014, 84% of the total amount of US greenhouse gases emitted were energy-related and 92% of those energy-related gases were CO2 emissions from fossil fuel combustion (U.S. Energy Information Administration, nd). This directly connects higher energy usage to greenhouse gas emissions. While future growth in renewable energy from the California Renewables Portfolio Standard[10] may begin to decrease current trends in GHG emissions, our model will investigate if a shift to low-energy industries might help to decouple greenhouse gases from GDP.

The Los Angeles–Long Beach–Anaheim MSA also has an issue with water scarcity; the area has experienced a period of historic drought which began in 2007 and continued until 2009 (Christian-Smith et al., 2011). During this time, water restrictions and other policies were implemented with severity increasing annually. Then, in 2011 California began another historic drought which continues past our dataset (Public Policy Institute of California, nd). Has the drought had a measurable effect

[9] Our longitudinal analysis is inherently limited. The individual industry emissions intensities do not change over time—only the industrial mix within the MSA will change. As such, the model will not detect any within-industry technical change that reduces resource use or pollution—akin to smog's reduction from catalytic converters and other technology. Instead, the model will screen for a shift in industrial makeup, similar to partial CO2 decoupling due to economy-wide shifts towards services (Tietenberg and Lewis, 2016; Jackson et al., 2016).

[10] The California Renewables Portfolio Standard was established in 2002 and requires investor-owned utilities, electric service providers, and community choice aggregators to increase procurement from eligible renewable energy resources to 33% of their total procurement by 2020 (California Public Utilities Commission, nd).

on economic output?

As seen in Table 3.4, for most years between 2001 and 2013, the percentage of missing GDP was relatively low. Note that in 2012 about 61% of the data was undisclosed. For the following graphs, we averaged 2011 and 2013 data for the 2012 data points.

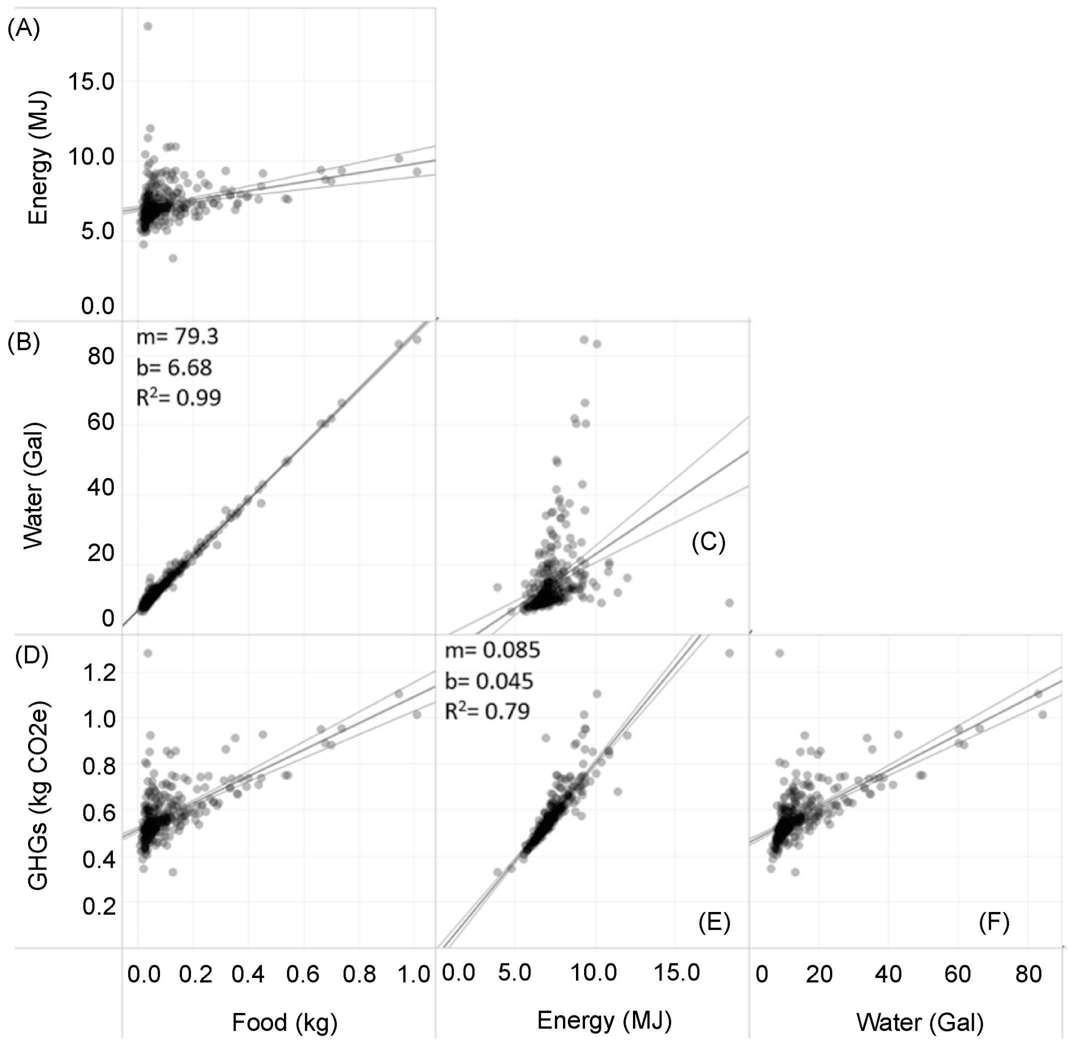


Figure 3.8: Correlations between food, energy, water, and greenhouse gas emissions per dollar of GDP. Each MSA is a data point with 25% opacity. The trend lines are of the form $Y = mX + b$, with parameters listed for the top two correlations.

In Figure 3.3.5 we see the GDP per capita and FEW and GHG intensities on a per dollar of GDP basis for the period 2001–2013. While this analysis cannot capture specific regional details of resource intensities because of the national I–O table used, the MSA can still be generally screened

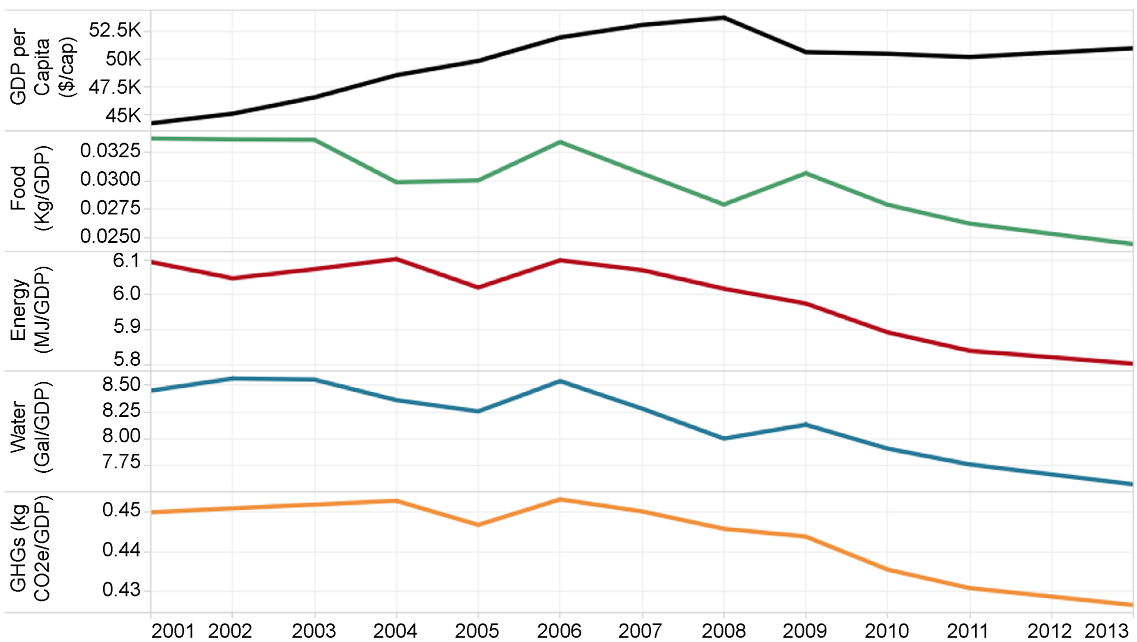


Figure 3.9: Los Angeles–Long Beach–Anaheim, CA MSA trends for GDP per capita, followed by food, energy, water and GHGs per dollar of GDP.

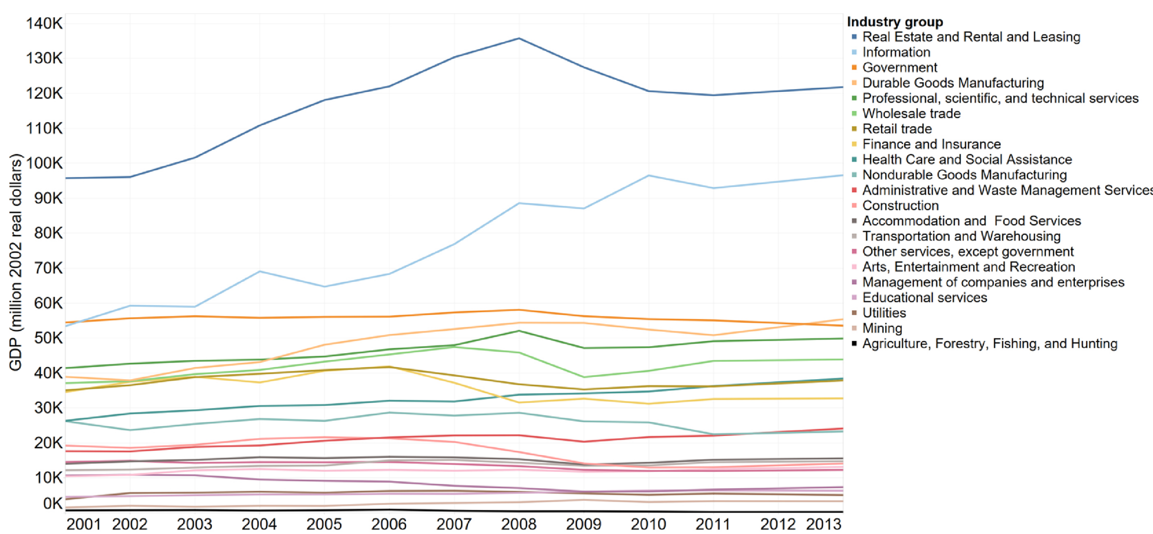


Figure 3.10: Los Angeles–Long Beach–Anaheim, CA MSA GDP by sector.

for its FEW requirements and trends. These trends can be attributed to variations in the MSA's GDP and sectoral composition.

Food and water requirements appear highly correlated over time in the LA MSA, matching the high correlation we saw across all MSAs for 2013. The LA region experienced a long period of historic drought which began in 2007 and is reflected in the decreased water resource intensity. Agriculture's contribution to the MSA's GDP dropped by 50% between 2006 and 2008.

Another trend to note is that GDP steadily rises from 2001 to 2008, then decreases after the 2008 housing crisis. From 2009 to 2013, GDP for the MSA is fairly constant. However, all resource intensities decrease from 2009 onwards, indicating a restructuring of the economy after the housing crisis. The steady GDP from 2009–2013 is quite useful for analyzing the resource intensities. All resource intensities decrease throughout that period, which indicates a structural shift in the LA economy that also reduces total resource requirements. We can examine specific industry groups to understand the influences of these trends better. Examining Figure 3.3.5, we see each industry group's contribution to the MSA's GDP.

The real estate industry faced a significant decrease in GDP following the 2008 recession. Relatedly, the construction industry also declined. Other notable declines include nondurable goods manufacturing, and wholesale trade. While many industries saw constant contributions to GDP, some industries experienced sudden growth or decline. The LA MSA's information technology sector grew significantly from 2008 onwards, counteracting the decline in real estate to create a steady aggregate GDP from 2008–2013. This influenced the MSA's decrease in energy and GHGs as GDP remained constant from 2008–2013.

The longitudinal analysis shows that an MSA's industrial composition affects its resource requirements, and that altering the industrial mix will have an impact on resource use. In the LA MSA case, resource intensities decreased as it shifted towards services.

## 3.4 Conclusion

We have presented an extension to the EIO-LCA model by adding embodied food flows. This allows us to assess FEW interactions, which we have done for metropolitan statistical areas within the United States. We found strong correlations between energy and GDP, energy and GHG emissions, and food and water requirements across the different industrial mixes represented by MSAs. We then presented the results of a longitudinal study for the Los Angeles–Long Beach–Anaheim MSA for the years 2001–2013, finding that the major correlations hold despite change in the MSA's economy. We found that it is possible to reduce resource requirements within a region by altering the industry mix.

There are many assumptions and limitations on using this technique. Many of the limitations are the same as any other I–O study, which include (i) assuming a completely linear model of the economy, (ii) only accounting for domestic production, (iii) excluding capital investments, and (iv) that the I-O table is a steady-state snapshot of the economy (Reap et al., 2008; Lenzen, 2000; Joshi, 1999; Casler and Wilbur, 1984).

A large limitation for this model is using a national input-output table to study regional resource requirements, as noted in Section 3.3.4. The model assumes that regional production generates the national average FEW intensities for each sector. The only regional differences are caused by a difference in the mix of industries within a region, not differences in industries themselves. Southern California may be more efficient in terms of water use than the rest of the country, but this would not be taken into account within our modeling process. This could lead to underestimations or over estimations for specific regions, particularly for water which is typically region specific.

However, future research could incorporate regional I–O tables and calculate regional industry resource intensities to better characterize MSAs. To improve the longitudinal study, yearly resource intensities could be utilized to better track changes over time. This could provide insight into how the implementation of the California Renewables Portfolio Standard may decouple GHGs from energy within the Los Angeles–Long Beach–Anaheim MSA. By utilizing yearly regional resource intensities, it would be possible to directly examine the effects of various environmental policies within a region.

Since FEW are all interconnected, policies pertaining to one of these subjects inevitably affects the others. A better understanding of the relationships across the FEW nexus can help assess the feasibility and impacts of resource policies in one sector. More insight may also be gained through further examination of specific sectors and their correlations with the FEW nexus, such as the strong relationship between food production and water usage. The US is experiencing growing water scarcity even in areas that once had abundant water resources, such as in the Los Angeles–Long Beach–Anaheim MSA. Understanding which industries use water and how those industries contribute to an MSA's GDP and economic wellbeing is critical to developing appropriate policy measures.

Further research may be conducted to evaluate connections between water scarcity and the GDP decline of various economic sectors such as nondurable goods manufacturing within the Los Angeles–Long Beach–Anaheim MSA. Future studies could also conduct a policy analysis of water restrictions and their broader effect on food production and other economic sectors, assuming yearly resource intensities could be calculated. It is important to note that a change in economic production will likely affect other regions or MSAs that require Californian food and goods to produce economic output. Not only are food, water and energy interconnected, but so too is each MSA through its direct and indirect requirements of products from all over the country and world.

## Relation to broader dissertation

The three themes of this dissertation are woven into and throughout this chapter. These themes are:

1. BPE modeling allows deeper insights into how the economy is reliant on resources
2. Models are better informed and constructed with granular and detailed data
3. Detailed, high resolution models enhance decision-making capability

Life cycle assessment is an excellent tool with which to study biophysical economics and biophysical impacts. By design, life cycle assessment traces the flows of energy and materials from the biosphere, through the economy, and often through waste — this touches every piece of the biophysical economics circular flow diagram presented in Figure 2.1. This chapter's work of introducing new food resource flows has extended LCA modeling to take into account yet another resource and way that the economy is reliant on the biosphere: it deeply aligns with theme 1.

Theme 2 was also deeply connected to this chapter. Without detailed, sectoral-level datasets on food, energy, and water usage across the country, the EIOLCA model would not exist. Without the Bureau of Economic Analysis MSA-level GDP data, this analysis could not happen. Detailed datasets enable better and more detailed models. The trend of increased, and increasingly detailed, data ought to be harnessed by biophysical economics practitioners.

This model enables interesting conversations for policymakers at the city level (theme 3). The comparisons between MSAs could prompt competition across different FEW indicators. The MSA level values allow policymakers to see where their region stands and could be a first-step towards targeting resource efficiency efforts. Finally, Figure 3.5 may play a part in tax incentives for new businesses. If a specific MSA is resource constrained (e.g. facing water scarcity issues), policymakers may be able to target lower water-use industries for economic growth.

This chapter showcases these three themes and foregrounds their importance in understanding the relationship between the economy and the biosphere. These themes, and this specific modeling strategy, advance and enable key insights that will better equip policymakers to handle coming resource transitions.

# Chapter 4

# Rolling Coal: The Greenhouse Gas Emissions of Coal Rail Transport for Electricity Generation

## Prelude

This chapter was originally published in 2020 within the *Journal of Cleaner Production*.[1] The chapter has been edited for clarity and format. Additionally, the conclusion has been expanded to better place the chapter within the broader dissertation.

This chapter describes an analytical model with characteristics as shown in Figure 4.1. Because the main environmental impact equations used in this model are at a highly aggregated scale, it is similar to an aggregated production function model framework despite being highly detailed geospatially. One of the main model takeaways is displayed in Figure 4.7 and Table 4.2, which provide mean coal transportation distances for each regional electric grid. Therefore, the spatial scale is best characterized as being similar to a state or province (that is, regions within a country). The model takes into account nearly a decade of data, fitting with the medium term time

[1] Sherwood, J., Bickhart Jr, R., Murawski, E., Dhanani, Z., Lytle, B., Carbajales-Dale, P., and Carbajales-Dale, M. (2020a). Rolling coal: The greenhouse gas emissions of coal rail transport for electricity generation. *Journal of Cleaner Production*, page 120770. Elsevier (the publisher) grants authors the rights to reproduce this work, in full or in part, within a thesis or dissertation provided that it is not commercially published. For more information, see: `www.elsevier.com/about/policies/copyright`

horizon. The model's Ethos characteristic was chosen because the model is mostly data cleaning and analysis, although some first-principles or stylized elements were utilized to make the model tractable. This chapter originates from the physical sciences - environmental engineering and life cycle assessment. Finally, the model is a statistical analysis, though it could be extended into an optimization model.

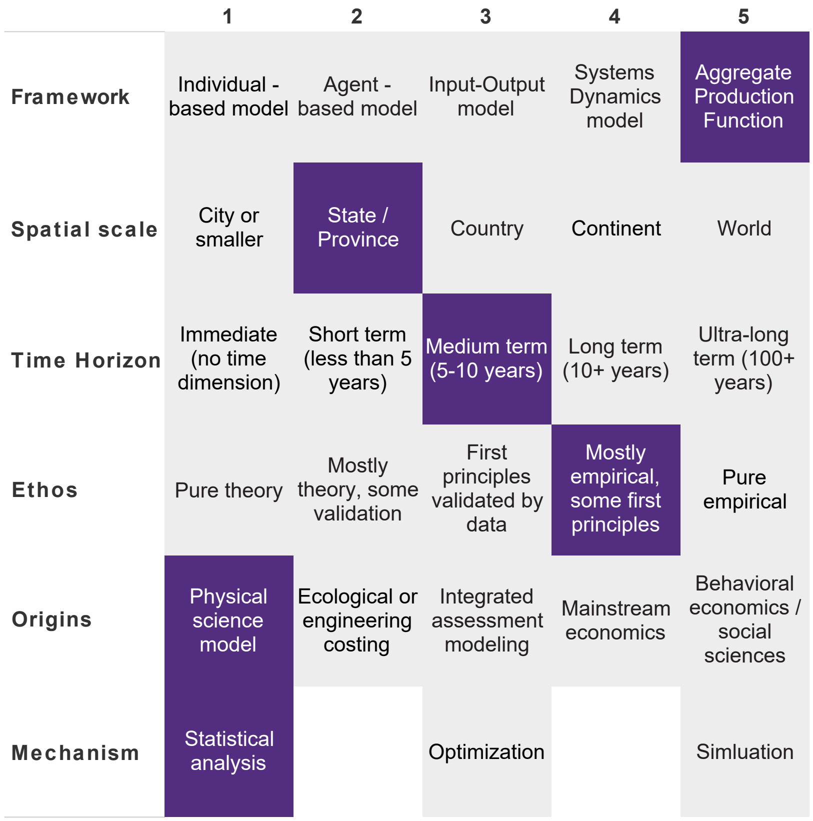


Figure 4.1: The Rolling Coal model mapped to Chapter 2's biophysical economics modelling characteristics.

Note that, although this chapter is relevant to biophysical economics, it is not explicitly discussed in part due to the original publishing venue.

# Abstract

This study analyzes datasets from the Energy Information Administration, Environmental Protection Agency, and the U.S. Geological Survey to build a detailed picture of the $CO_2$-eq emissions generated by coal rail transportation over the past decade. We use a GIS-based network

analysis to illustrate how coal transportation routes and shipments have changed since 2008. Coal basins are characterized by type and emission intensities, and the scale of transportation emissions are compared to power plant operational emissions. The results show that rail transportation distances range from 0 km to over 3500 km. Transportation emissions can be as high as 35% of a power plant's operational emissions — a number significantly higher than previous literature estimates. Additionally, implementation of post-combustion Carbon Capture and Storage (CCS) at existing plants may further increase transportation emissions. We conclude by recommending using at least regionalized distance factors rather than US-wide averages to more accurately account for transportation emissions within life cycle assessments and carbon footprints of coal power.

## 4.1 Introduction and background

Electricity has fundamentally changed the modern world, but not without cost. Emission-producing fossil fuels provide the primary means of electricity generation within the United States. According to the Energy Information Administration (EIA), approximately 30% of all U.S. electricity in 2017 was generated using coal. This percentage is down from a peak of 56.9% in 1988, a decline largely brought about by an increased use of natural gas (Energy Information Administration, 2018). Since 2008, the share of coal as a power producer has decreased by 35%. The shale boom and the extraordinary recent drop in the cost of producing solar panels and wind turbines has steered power producers away from relatively expensive coal (Kolstad, 2017). Even with the market share decrease, the total amount of coal shipped from mine to power plant has remained consistent (U.S. Energy Information Administration, 2016). A major variable, though, is the mining location of purchased coal. Using geographic information systems (GIS) techniques, we analyze thermal coal transportation routes during the period 2008-2016 and the associated transportation emissions. Our dataset was generated by combining U.S. Geological Survey (USGS) information with EIA and Environmental Protection Agency (EPA) data.

### 4.1.1 Understanding U.S. coal

Conversations, reports, or articles mentioning coal often consider it a single homogenous fuel or feedstock. However, there is significant variation in coal quality and impurities. Most notably, there are variations in heat content, sulfur content, other hazardous air pollutants, or other minerals or impurities (Schweinfurth, 2009). These variations can exist within a single mine, but broad variation is more apparent across different coal basins. The American Society for Testing and Materials (ATSM) describes these variations in coal quality as four broad ranks – Anthracite, Bituminous, Subbituminous, and Lignite coal. These ranks correspond to steps in the coalification process – the natural progression of coal formation (ATSM, 2005).

Anthracite coal tends to be the oldest while Lignite tends to be the youngest. Anthracite coal is typically used in metallurgy (not power generation), and represents 0.2% of all U.S. coal mined in 2016 (U.S. Energy Information Administration, 2016). Because it is not widely used for power generation, this chapter will ignore Anthracite. Of the remaining ranks, Bituminous coal has the highest heat content and sulfur content and is mined mainly in the Eastern United States. Lignite has the lowest heat content and is mined in or near Texas and North Dakota. Subbituminous coal has a heat content between the other ranks, and, at least within the U.S., has the lowest sulfur content. Subbituminous comes from relatively few mines in and around Wyoming.

Figure 4.2 shows coal basins across the continental United States using geospatial data obtained from the U.S. Geological Survey (USGS) (East, 2013). Here, the basins' coal rank is denoted by color. Figure 1 also shows the locations of individual coalmines as white points. The point size is dependent on the total amount of coal shipped to power plants from 2008-1016 (the timeframe of our dataset). These mine locations were determined through methodology described later in this chapter.

Figure 4.3 shows the variation of coal properties within the regions of the United States that are annotated on 4.2. Each data point is the average heat content (or sulfur content) of coal produced by a specific mine within a given region. The data point color represents the rank of coal.

In general, Figures 4.2 and 4.3 indicate that there are many small mines in the Eastern U.S. and a few large mines in the Western US. The Western mines produce significantly more coal primarily because of the differences in mining technologies – Western mines tend to be open pit mines. In fact, the total output from the Western region overtook the East's total output at the end of the 1990s (Kolstad, 2017). Aside from the increased productivity, another benefit to Western coal is its low sulfur content, shown in Figure 4.3. This low sulfur content is beneficial to power plants, as it means lower $SO_2$ emissions.

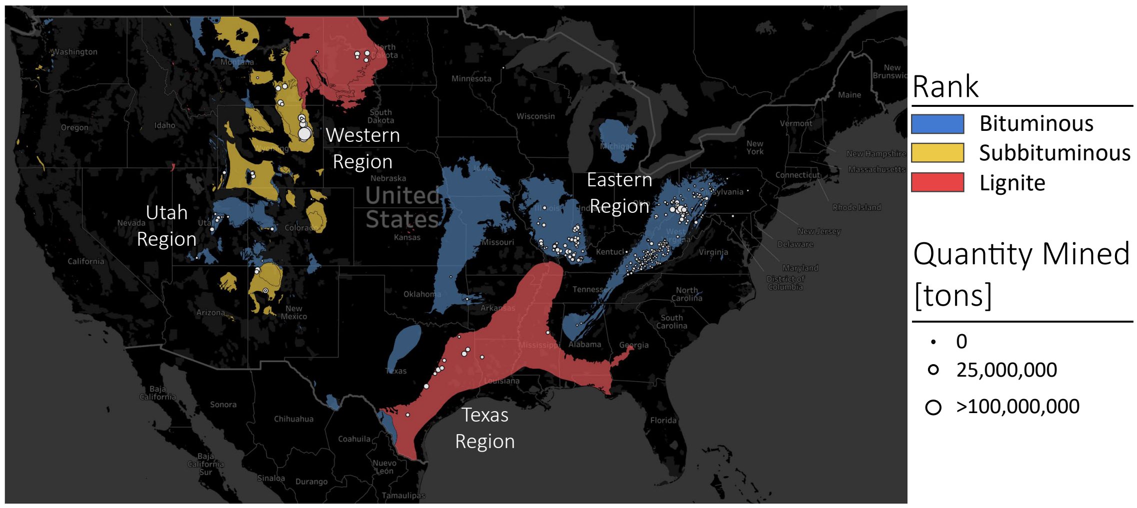


Figure 4.2: Map of Coal Basins and mines. The coal basin geospatial data is courtesy of USGS (East, 2013) while the mine locations were geolocated as described in Section 4.2. The size of the mines' point corresponds to the quantity of coal shipped to power plants over the 2008-2016 period.

### 4.1.2 Historical and environmental concerns

A significant drawback of using coal to produce electricity are the emissions generated during combustion, particularly smog created from sulfur dioxide ($SO_2$) and nitrogen pollutants ($NO_x$). In the 1970's, smog was becoming a serious problem in many of U.S. cities. It was such a problem, in fact, that Congress amended the Clean Air Act to address these issues (EPA, 2018). The act provided an economic incentive for coal-fired power plants to reduce emissions by installing pollution control systems, burning lower sulfur coal, or to produce less electricity. In 1990, the Clean Air Act was further revised to establish threshold limits on $SO_2$ emissions. These revisions were primarily motivated by growing concerns over acid rain, caused downwind by sulfur dioxide from Midwest power plants (Schmalensee and Stavins, 2013). Specifically, Title IV of the 1990 Clean Air Act amendments established a cap-and-trade program intended to reduce annual $SO_2$ emissions significantly below a baseline year of 1980 (EPA, 2018). The cap-and-trade program worked by assigning emissions allowances to each facility, such that exceeding the allowance would result in a fine. Facilities could trade or "bank" allowances, creating a market-based mechanism intended to reduce emissions through a lowest-cost approach. Total $SO_2$ emissions were capped at approximately 10 million tons of $SO_2$ per year, reducing emissions by about 6.3 million tons compared to the baseline (Busse and Keohane, 2007).

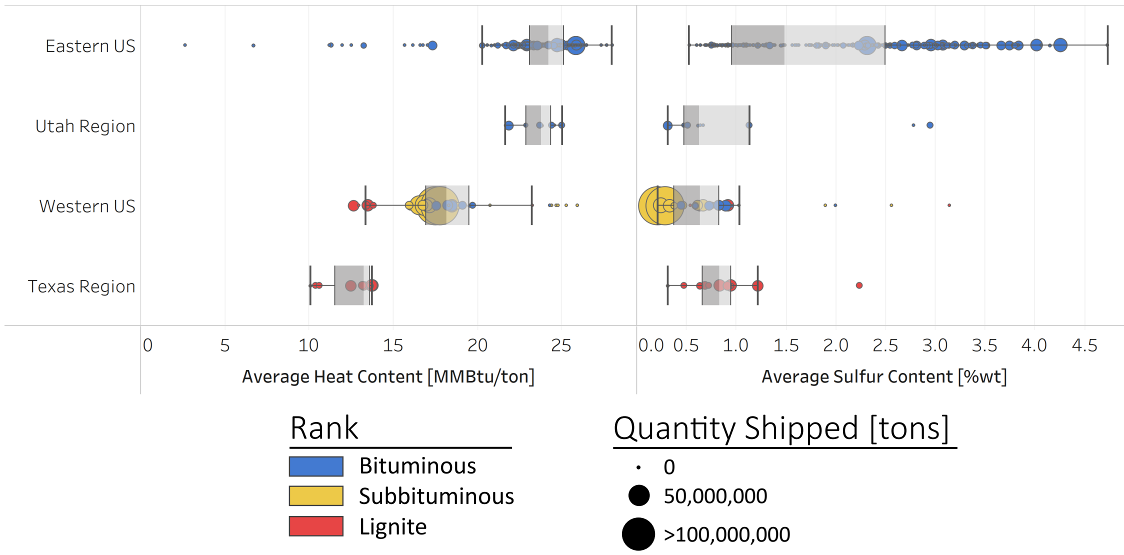


Figure 4.3: Coal properties of specific mines (data points) for four different regions of the US. Each dot represents a specific coal mines' average coal properties over the 2008-2016 period. Utah is separated from the rest of the Western United States, as it is a large bituminous basin atypical of other Western basins.

The Title IV amendment was in part a success because low sulfur coal ended up being cheap, abundant, and relatively close to major Midwest power plants. Because rail transportation accounts for a large portion of the cost of extracting and delivering coal, a power plant's geographical location is a determinant in the cost of limiting sulfur emissions (Busse and Keohane, 2007). For many Midwestern plants in particular, a switch to low sulfur coal was the option that provided the lowest overall cost, compared to installing scrubbers or purchasing other plants' allowances.

While the transition to low sulfur coal suppliers did reduce $SO_2$ emissions at individual power plants, it also increased transportation distances. This increased transportation distance implies an increase of transportation emissions, particularly $CO_2$e emissions resulting from the burning of diesel fuel in train engines. These emissions are an additional externality, and one that was not explicitly accounted for in the Clean Air Act. Furthermore, coal transportation emissions have not received significant attention in many environmental research communities. The purpose of this paper is to develop methodology and produce preliminary results of the total $CO_2$e impact of coal transportation within the U.S.

### 4.1.3 Relation to post-combustion Carbon Capture & Storage (CCS)

Carbon Capture & Storage, broadly defined, is a system of technologies that captures, transfers, and stores $CO_2$ (International Energy Agency, 2009). Typically, CCS is discussed in the context of fossil fuel-based electricity generation, though systems are also being developed for biofuel electricity generation and various industrial use-cases (International Energy Agency, 2019). In the context of this paper, we focus on possible CCS retrofitting of existing power plants. Any implementation of post-combustion Carbon Capture & Storage (CCS) at existing power plants may have additional unforeseen impacts along the upstream supply chain. Some CCS designs incur an energy penalty at the power plant as CCS equipment takes energy to run (Sanpasertparnich et al., 2010).

If a power plant installs post-combustion CCS, it could maintain the same gross electricity output resulting in a lower net output caused by the CCS energy requirements. Or, it could produce more gross electricity to maintain a similar net electricity output relative to its prior production. In the first case, fuel requirements would stay the same. The implication is that transportation $CO_2$e emissions would stay constant, but operational $CO_2$e emissions would decrease – transportation $CO_2$e emissions would become a more significant part of the overall environmental impact. In the second case, the fuel requirements would increase. This would result in even more transportation $CO_2$e emissions, further compounding the significance of transportation impacts.

Many studies and organizations have called for an increase in CCS technologies, particularly within the energy sector. The impacts of these technologies on the upstream supply chain warrant further study. A detailed dataset and understanding of coal transportation and its $CO_2$e emissions would be beneficial.

### 4.1.4 Need for study

While there are a few papers that study coal transportation (either directly or as part of a broader study), they often only use an average distance or do not explicitly provide an analysis of the transportation component. An overview of relevant studies is supplied in Table 4.1.

In a major coal life cycle assessment (LCA) harmonization study (a meta-analysis of 53 papers), Whitaker et al. state that "one parameter that was not harmonized due to lack of consistently available disaggregated data was GHG emissions associated with the transport of coal from the mine

Table 4.1: Selected coal transportation literature.

| Author | Distance Used | Comments |
|---|---|---|
| Steinmann et al. (2014) | Rail Distance is equivalent to Road Distance | Uses Google map API |
| Whitaker et al. (2012) | Not provided | Transportation is 2-3% of total greenhouse gas emissions |
| Odeh and Cockerill (2008) | 100 km | - |
| Jaramillo et al. (2007) | 1M ton-miles | Uses the EIO-LCA tool |
| Spath et al. (1999) | Average 483 km<br>Maximum 1538 km | - |
| Bergerson and Lave (2005) | 1000 miles — a new rail line | Compares coal to electric transmission & gas pipeline |
| Mutchek et al. (2016) | - | Total transport (including oceanic) accounts for 2.0% to 6.7% of emissions |
| Szabo (1978) | 985 km | Discusses the environmental impacts of a specific unit train transport |
| U.S. Department of Transportation (2015) | Average of 140 km | US Commodity Flow Survey |

to the power plant." And that, when reported, the "average contribution was 2% to 3% of life cycle GHG emissions, with the largest reported contribution for the long-distance, transoceanic transport of coal, at approximately 8%." (Whitaker et al., 2012) The lack of accessible data indicates a gap in the literature that warrants study.

A recent study by Mutchek et al. states that transportation GHG emissions from exporting coal out of the U.S. account for 2.0% to 6.7% of the total life cycle emissions (Mutchek et al., 2016). The rail transport portion is roughly one third of these emissions. However, Mutchek et al. only look at coal coming out of the Powder River Basin (Wyoming) and traveling through West-Coast ports – they do not study within-U.S. transportation.

Another article by Steinmann et al. performed a similar analysis to this paper as part of studying LCA uncertainty and variability (Steinmann et al., 2014). However, they used Google maps to map road distances between mines and power plants. While a good estimate for their broad study on uncertainties in an LCA, we seek to improve on their findings by focusing exclusively on transportation, explicitly using the U.S. rail network, and validating each mine location.

In summary, articles that have analyzed coal transport emissions tend to analyze either a specific use-case (e.g. Mutchek et al.) or have a different overall objective than studying transportation in detail (e.g. Steinmann et al.). Therefore, there is a need for a comprehensive study of the total coal transportation network within the U.S.

There is also a methodology gap in the literature – few life cycle assessment or environmental footprint studies describe an explicit use of geographic information systems (GIS) in their data collection when studying a supply chain. Using GIS output within a life cycle assessment has become more common in recent years; several papers use GIS to study land use, particularly for agricultural systems. Hiloidhari et al. provides a literature review of many GIS studies related to biomass and bioenergy (Hiloidhari et al., 2017). Other papers, such as Liu et al. and Nitschelm et al. use GIS to help inform and localize environmental impacts (Liu et al., 2014; Nitschelm et al., 2016). However, the goal and scope of these studies do not focus on transportation. Two papers, Gilmore et al. and Goswein et al. do utilize a GIS analysis of transportation routes to accurately understand the environmental footprint of transportation (Gilmore et al., 2014; Göswein et al., 2018). Both papers focus on roads – Gilmore studied trucking water to shale gas wells while Goswein studied truck transport of raw materials for concrete production. The novel aspect of this paper is analyzing transportation routes across every coal rail shipment to power plants, studying the variance, and providing regional $CO_2$-eq emission factors for the U.S.

## 4.2 Methodology

Our method followed three steps. First, we used geospatial network analysis to estimate which routes might be used to transport coal for electricity generation throughout the United States. Data from the Energy Information Administration shows that 70% by mass of all U.S. coal destined for a power plant has rail as the primary transport mode designation (U.S. Energy Information Administration, 2016). Because of this, we focused this analysis on the railroad shipments. Secondly, this information was combined with actual data on coal purchases by power plants to obtain the total rail transport service (per unit mass-distance) required for the transport of coal for electricity generation in the US. Thirdly, this was combined with data on both direct and indirect rail transport GHG emissions (again per unit mass-distance) to then calculate total emissions associated with rail transport of coal. This was then analyzed for regional and temporal variations.

### 4.2.1 Network analysis

The primary tool used to analyze the U.S. coal rail transportation system is a network. A network consists of a series of edges joined by nodes. Nodes can be origins (i.e. a mine), destinations (a power plant), forks or intersections, or used to facilitate curving an edge. For this study, the network's edges are all railroad links within the U.S. rail system. Because our data is inherently geospatial (in contrast to a social network), we use a GIS software package, ArcGIS Pro. Geographic information systems are purpose-built to handle and interpret geographic data. These systems allow for mapping, categorizing, storage, and analysis of datasets that contain a geographic component, such as latitude and longitude. ArcGIS Pro provides these tools and many others to facilitate geographic data analysis.

One feature of a network is the lowest cost path between nodes. The "lowest cost" may be in terms of distance, time, monetary value, or some other impedance factor. The most common approach to determine this path is credited to Dijkstra; an algorithm follows a network path (starting at a specific origin node) and records the impedance to each neighboring node. Then, it selects the lowest impedance neighbor and again records the impedance to the new neighbors. Once the destination is a neighbor, the algorithm can trace a shortest path back to the origin (Dijkstra et al., 1959). For this analysis, the impedance is the geographic distance between nodes, measured in kilometers. ArcGIS Pro has the Origin-Destination Cost Matrix tool to run such an analysis. This tool takes in a network (here, the U.S. rail network), a set of origins (coal mines), and destinations (power plants) and produces a lowest cost distance (which in this case is the shortest path distance) through the network for every combination of origin and destination.

#### 4.2.1.1 Network data

The Origin-Destination Cost Matrix tool required three distinct sets of information: origin locations (coal mines), destination locations (power plants), and a network connecting them (the U.S. rail system). We pieced together datasets to fill each set of information.

The Energy Information Administration (EIA) 923 data files provided power plant address and specification data, and also included monthly mine-power plant transaction data. Each 923 data file only contains information for a specific year – these files were collated to create a master transaction table ranging from 2008 (the earliest date available) to 2016 (the latest year available at the time of analysis). We then created two supplementary data tables – one with power plant information (location, nameplate capacity, etc.), and one with coalmine information.

The coalmine information was collected from a variety of sources. The EIA 923 files included information on coal quality for each shipment, but only included county-level location data for each mine. This analysis required more precise locations. The EIA 923 file also included a Mine Health and Safety Administration (MSHA) ID, which was used in conjunction with an MSHA address database to locate the mine headquarters (Mine Data Retrieval System, 2017). Many of the addresses, however, were not of the mine itself. In a few cases, the headquarters were in a different county or across state lines from the actual mine. To validate each mines' location, we utilized Google Maps satellite imagery and Google Streetview to locate mines. Usually, the mines had signage visible on Google Streetview to verify a location. These signs were either a typical outdoor business sign with a company logo, or a plain traffic-style sign listing property ownership and MSHA ID. In cases where signs were absent, we assumed the closest mine to MSHA address was the correct mine (and, based on the mines with visible signs, this seemed to be a correct assumption). We excluded the mines we were unable to locate, which accounted for 1.17% of all coal shipments within the dataset. A full list of these excluded mines is in the supporting materials.

With mines and power plants located, the next piece of necessary information was the

U.S. railroad network. The Environmental Systems Research Institute (ESRI) has many geographic datasets available, including a U.S. railroad network. This network originated from the 2012 U.S. Census Bureau TIGER geographic database. The network needed some modifications in order to be used in this analysis – the mines and power plants needed to be connected as nodes to the network. We connected each mine and power plant to the rail network by appending the shortest line possible to the closest existing railroad, and creating a new node (railroad junction) at this intersection. Effectively, this created a short, artificial rail line between each mine or power plant and the U.S. rail network. The result is a single network between all mines and power plants, which could then be used to find routes through ArcGIS' Origin-Destination Cost Matrix tool.

### 4.2.2 Coal transactions

The endpoint for the geospatial analysis is the total rail transport service (in ton-kilometers) of coal for each power plant. The first step was to run the Origin-Destination Cost Matrix tool and record each shortest distance between every mine and power plant. The second step to these transport service values is to calculate the amount of coal shipped from each mine to each power plant.

As mentioned previously, the EIA 923 files contained information on monthly mine-power plant transactions, including the quantity shipped (in tons). Each transaction was assigned a unique path ID variable, generated by combining the mine ID and power plant ID (provided within the dataset). Each path ID was matched to its shortest distance route, which provided the distance travelled (in kilometers) for every transaction. For each transaction, the quantity shipped was multiplied by the distance travelled to determine the rail transport service (in ton-kilometers). These transactions were then aggregated for each power plant and for each year, to determine the total yearly rail transport service for each plant.

### 4.2.3 Transportation GHG emissions

The last step was to combine the total rail transport service data with data on per unit mass-distance transportation emissions. This would allow for analysis of total rail transportation GHG emissions for each coal power plant, and to compare the transportation emissions to each power plant's operational emissions.

We utilize two types and sources of GHG emissions information. The first is the transportation related emissions from diesel trains used to transport coal. We utilized the Ecoinvent database, commonly used in life cycle assessments, to find these emissions on a per unit mass-distance transportation basis. To clarify, these GHG emissions are the sum of all greenhouse gases, converted to $CO_2$ equivalents using IPCC 100-year global warming potential characterization factors. The Ecoinvent database contains a multitude of environmental emissions for many unit processes – it is a primary tool used by LCA practitioners to characterize the emissions caused by many production processes, including mineral extraction, manufacturing, and transportation (among others). This analysis pulled data from the "transport, freight train, diesel, US" unit process from the Ecoinvent 3.01 database (Wernet, G. and Bauer, C. and Steubing, B. and Reinhard, J. and Moreno-Ruiz, E. and Weidema, B., 2016). This unit process supplies the direct and indirect lifecycle $CO_2$e emissions of transporting 1 metric ton, 1 kilometer (See Section 4.2.4 and Figure 4.4 for the difference between direct and indirect emissions).

The second piece of emissions data is used for comparing the transport $CO_2$-eq emissions to a power plant's operational emissions. We used the Environmental Protection Agency eGRID database, which contains emissions information for every power plant in the U.S. (US Environmental Protection Agency, 2007). This dataset is compiled every other year, with some lag in publishing data. At the time of the analysis, the 2014 dataset was the latest available and so 2014 is used as a baseline for this paper's analysis across all data sources.

### 4.2.4 Assumptions and system boundary

Our analysis contains two main assumptions. 1) That all trains will take the shortest distance route along the rail network. It may be the case that a train might avoid areas of congestion in and around certain cities or have contracts with specific rail companies to use specific lines. Without detailed rail traffic data, the shortest distance is a reasonable assumption to make. 2) That all trains have the same emissions factor as specified in the Ecoinvent 3.01 database. This is a relatively common critique of life cycle assessments in general, though the Ecoinvent database is used quite often in many analyses. We believe this $CO_2$-eq emissions data provides a best estimate of train emissions. Results are provided in units of ton-kilometers in the supporting materials; researchers are welcome to use a more specific emissions factor for their own studies if needed.

The system boundary for this paper is shown in Figure 4.4. We only consider rail transport from mine to power plant (distribution, shaded in the diagram) during our primary analysis (the blue dashed boundary in the diagram). The $CO_2$-eq emissions from transporting coal to a specific power plant is also compared to that power plant's operational $CO_2$-eq emissions (also shaded) — the emissions from burning fuel for power generation as reported in the EPA's eGRID dataset. Finally, we incorporate the indirect emissions from transportation during the last segment of our analysis (the green dotted boundary in the diagram). These include the emissions from train production, and train & track maintenance. These indirect emissions are added to the direct emissions in Section 4.3.3 to get a complete picture of the transportation $CO_2$-eq emissions caused by shipping coal.

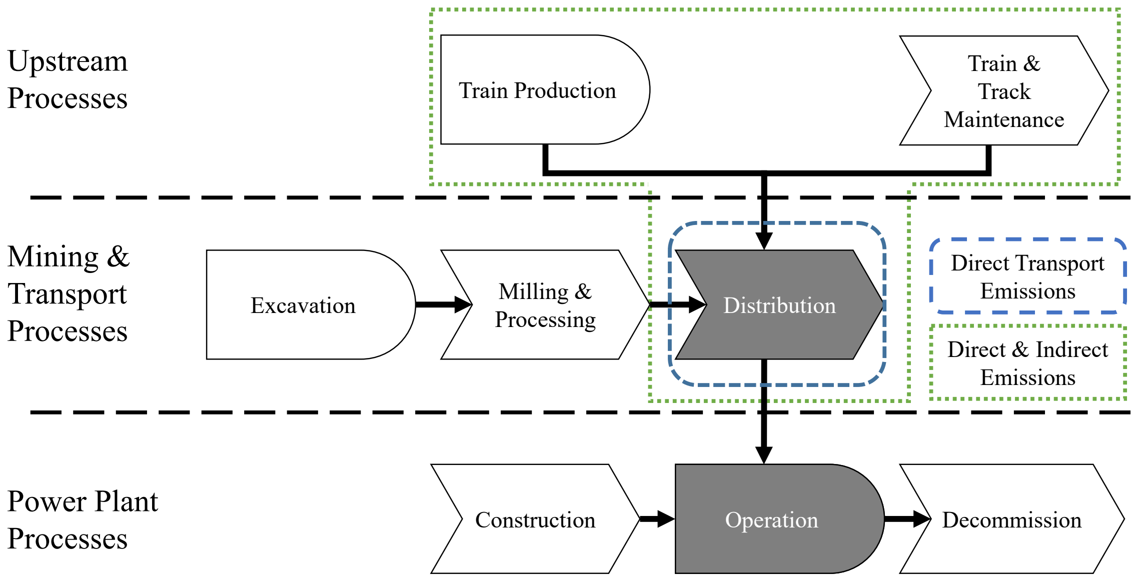


Figure 4.4: Simplified system boundary of the analysis.

## 4.3 Results and discussion

A main goal is to quantify and understand the variation in coal transportation emissions. To better understand the distances involved, we mapped all of the transportation routes used in 2014, along with the quantity shipped on each route, as a Sankey diagram in Figure 4.5.

The width of each line represents the quantity shipped along that rail segment. The map shows that a significant portion of U.S. coal travels out of a few Wyoming mines and reaches Texas, the Midwest, and the eastern United States. Looking at individual routes, many eastern mines do not ship far west (e.g. past Wyoming.)

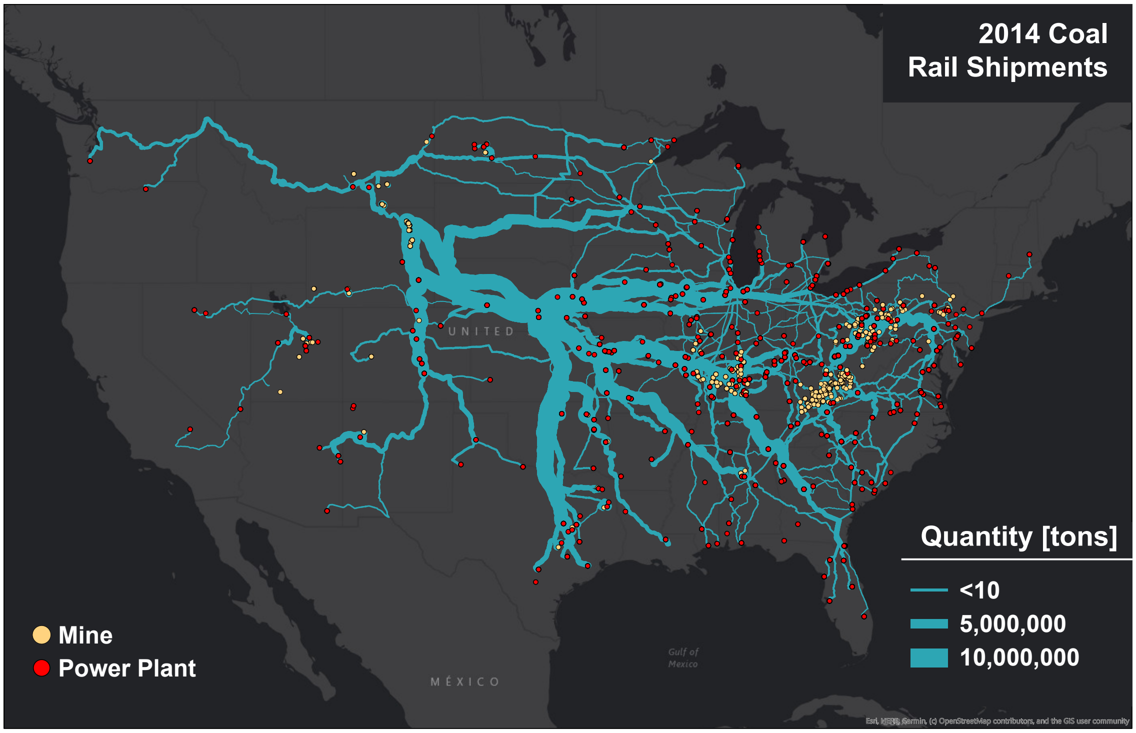


Figure 4.5: 2014 power plant-destined coal rail shipments along the U.S. rail network.

Section 4.1.1 hints towards why this shipment distribution is the case – Wyoming mines are low unit-cost surface mines that have minimal sulfur content. Eastern mines tend to have higher unit-costs and greater sulfur content. Therefore, a power plant located in the eastern U.S. may be inclined to purchase cheaper, low sulfur coal if they wish to avoid investing in sulfur-scrubbing technology or other emissions penalties.

### 4.3.1 Transport distance variation

Next, we study the variation in transport distances. Most coal-emission studies and life cycle assessments tend to assume an average coal transportation distance, usually at a national level. However, we demonstrate that there is significant variation that can alter the results of these studies. Figure 4.6 displays the variation in transport route's distance for each year in the dataset. For 2014, the transport distances ranged from effectively zero kilometers to just over 3,500 km. Even the median transportation distance (arguably the most representative value since the distribution is not normal) ranges between 700-1000 km, dwarfing any of the distances used in previous studies listed in Table 4.1.

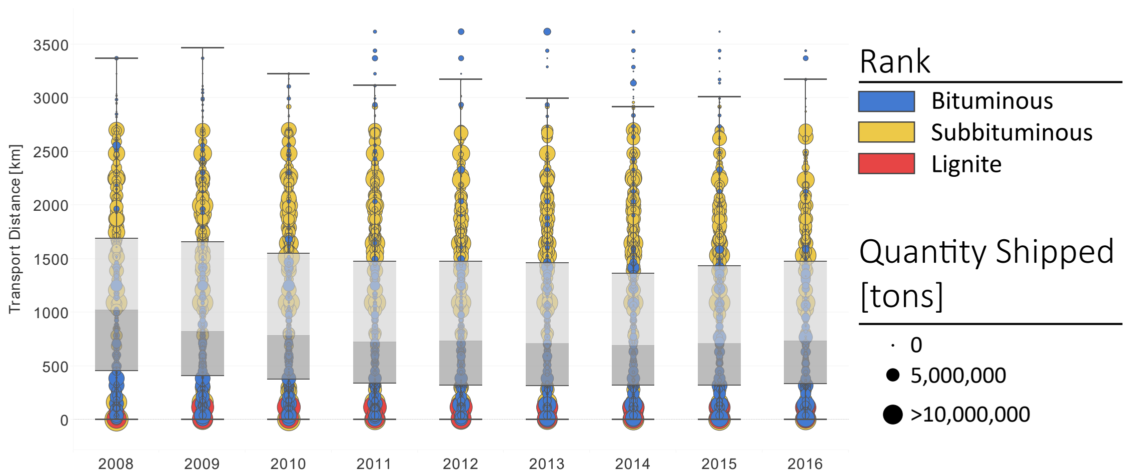


Figure 4.6: Transport distances across the dataset. Each dot represents a specific mine-plant route. The data points are sized by the quantity shipped along that route for the year. The color corresponds the rank of coal shipped. Median and quartile values provided in supporting materials.

To aid in future studies, we also aggregate the routes to specific North American Reliability Corporation (NERC) regions of the national electric grid to determine regional transportation distances. (We group routes into NERC regions according to the location of the power plant – the endpoint of a route.) Figure 4.7 shows the distances of all routes ending in each NERC region for the year 2014. The data shows that there are significant variations in the transportation distance (ranging from 600-1600 km) across different NERC regions (see Table 4.2). Therefore, location of a coal power plant matters. We recommend using at least these regional distances, rather than a national average, when incorporating coal transportation into a research project. Using the exact power plant and transportation data is preferred; this data is included in the supplemental materials.

### 4.3.2 Direct (D) transportation emissions

Next, we studied how transportation $CO_2$-eq emissions compare to the emissions generated from burning coal. Specifically, we utilized the Ecoinvent life cycle assessment database to estimate the $CO_2$ emissions caused during coal transportation. We used the U.S. specific diesel freight train unit process, which contained a direct emission factor of 4.42E-5 short tons $CO_2$e per ton-km. This value was multiplied by the total ton kilometers of each power plant's coal supply to determine the

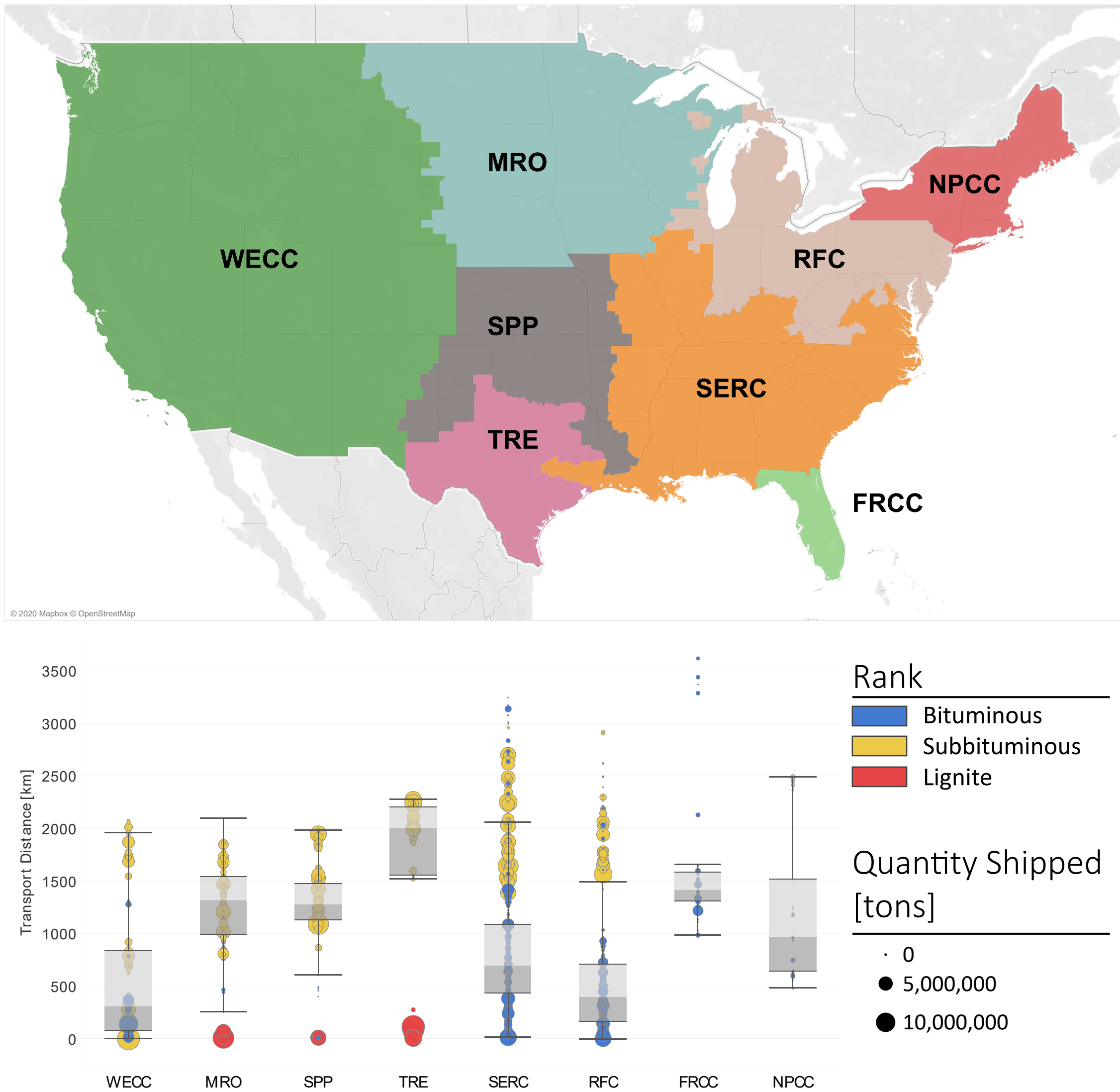


Figure 4.7: Transport distances across the dataset, aggregated to the NERC region codes. Each dot represents a specific mine-plant route. The data points are sized by the quantity shipped along that route in 2014. The color corresponds the rank of coal shipped. Median and quartile values provided in supporting materials.

total transportation emissions attributed to each power plant. The total transportation emissions were compared to each power plant's direct operational emissions using data from the EPA's eGRID database. The comparison for 2014 (the latest eGRID year available at the time of the analysis) is shown in Figure 4.8:

This histogram shows the significance of transportation emissions for all power plants within the U.S. In general, the histogram follows what appears to be an exponential distribution. For most

Table 4.2: Mean coal rail transportation distance and weighted Mean distance by mass of shipped coal for each NERC region.

| NERC Region | Mean Distance [km] | Weighted Mean Distance by Mass [km] | Standard Deviation |
|---|---|---|---|
| WECC | 612 | 472 | 657 |
| MRO | 1221 | 965 | 474 |
| SPP | 1,239 | 1,249 | 408 |
| TRE | 1,631 | 1,153 | 816 |
| SERC | 891 | 1,314 | 695 |
| RFC | 603 | 728 | 632 |
| FRCC | 1,544 | 1,534 | 545 |
| NPCC | 1,260 | 1,384 | 708 |
| U.S. Wide | 880 | 1,003 | 703 |

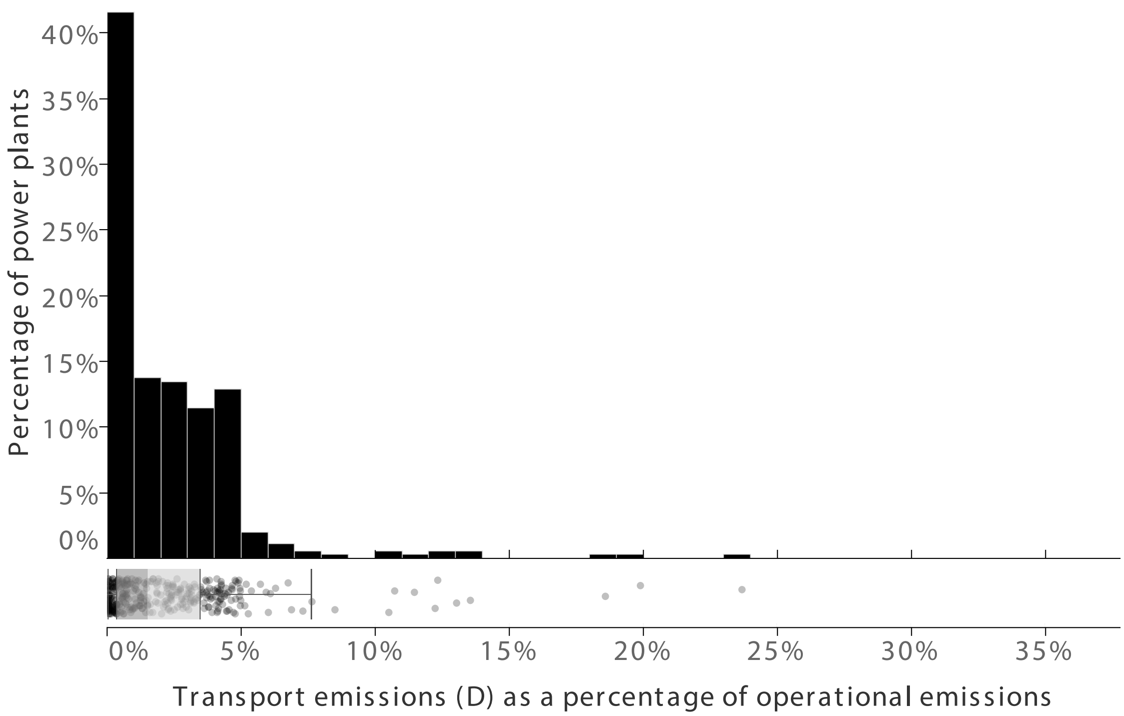


Figure 4.8: Comparison of direct transportation emissions to a power plant's operational emissions for each rail-supplied coal power plant in the U.S. Bin sizes are set to 1% increments.

power plants, the transportation emissions are less than 5% of their operational emissions. The median value is 1.5%, which is consistent with assumptions and provided estimates in previous studies. However, there are several plants whose transportation emissions are much higher. Based on the variation of distances shown earlier in Figure 4.5 and Figure 4.7, the high emissions are to be expected – some power plants are outliers distance-wise, and so these power plants also have higher transportation emissions. These outliers have been mostly ignored in previous literature.

### 4.3.3 Direct plus indirect (D+I) transportation emissions

Figure 4.8 only incorporates direct transportation $CO_2$-eq emissions. That is, the emissions directly released from burning diesel to move trains. Including indirect transportation emissions increases the emissions factor to 6.62E-5 short tons $CO_2$-eq per ton-km, a roughly 50% increase. These indirect emissions include all the upstream $CO_2$-eq emissions from activities such as manufacturing rail cars or track maintenance (refer to the system boundary in Figure 4.4). Figure 4.9 shows an updated histogram using this comprehensive transportation $CO_2$e emission factor.

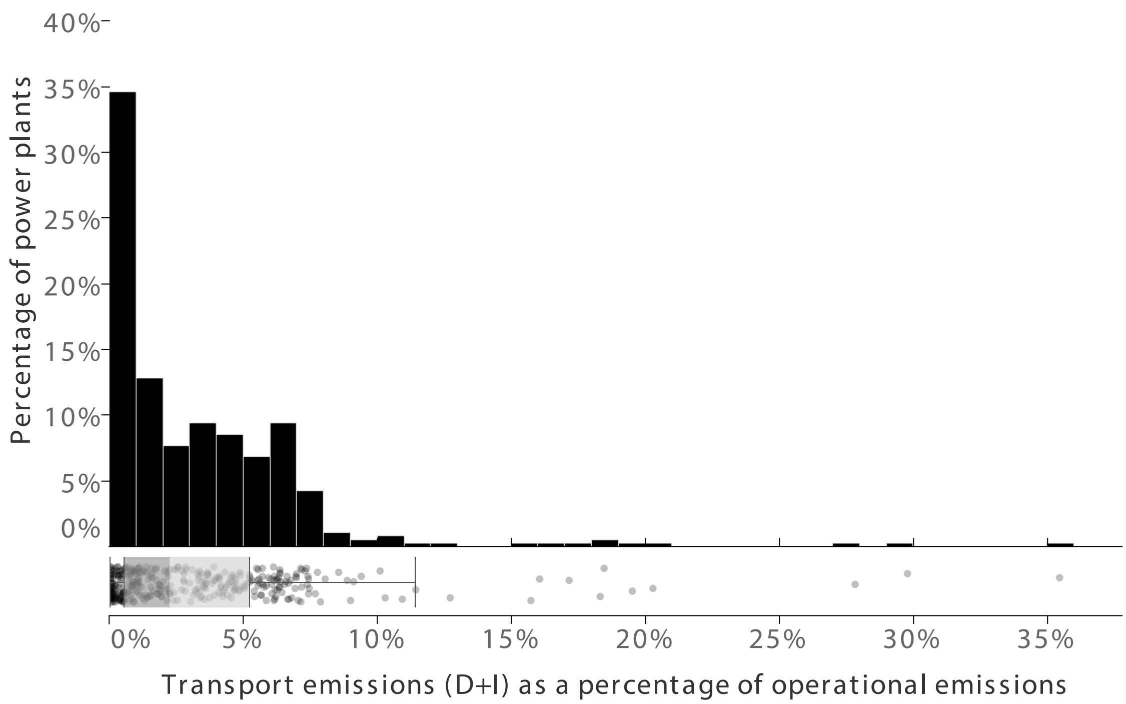


Figure 4.9: Comparison of direct plus indirect transportation emissions to a power plant's operational emissions for each rail-supplied coal power plant in the U.S. Note the axes are identical to Figure 4.8.

The comprehensive (D + I) transportation distribution shifts to the right. The median value shifts to 2.2% and the upper quartile jumps to 5.2%. In the most extreme case, transportation emissions were just higher than 35% of the power plant's operational emissions. Such high transportation emission power plants (greater than 10%) are usually small generators – most generated less than 10 million MWh in 2014. It is likely that these facilities are used as peaking plants rather than for baseload electricity generation. They also primarily receive coal from Wyoming, though they are located in Texas, Illinois, and California (among other states), so their transportation distances tend to be high. In 2014, the two most productive coal power plants in the U.S. were the Scherer plant in Georgia and the James H. Miller Jr. plant in Alabama. For reference, Scherer generated nearly 19 million MWh in 2014. Scherer's D + I transportation emissions were 9% of its operational emissions, while Miller's were 7% of its operational emissions. Both power plants seem to exclusively buy their coal from Wyoming coalmines. These numbers are particularly concerning because they are above previous literature estimates and these power plants burn significant quantities of coal. Note also that this analysis only contains the transportation emissions for rail transport, which only account for 70% of coal shipments to power plants. These graphs would likely shift even farther right if other transportation emissions, such as emissions from trucks or barges, were included.

### 4.3.4 Transport and sulfur tradeoffs

As mentioned earlier, a draw of Wyoming coal is its low sulfur content and therefore ability to meet sulfur-emission targets. We therefore compare the transportation distances for each route to the sulfur content of the coal in Figure 4.10.

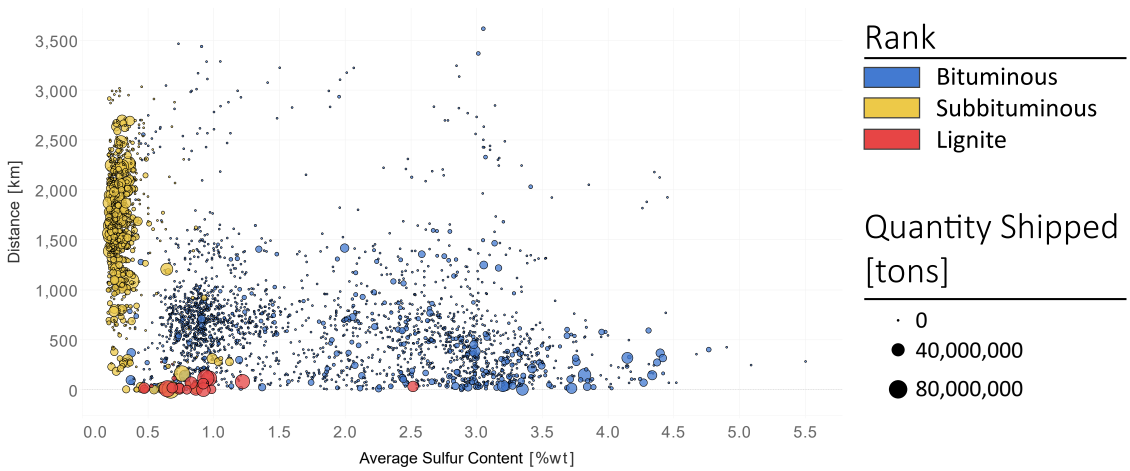


Figure 4.10: Comparison of transportation distance to average sulfur content of the transported coal. Each point is a specific shipment route within the dataset. The points are sized by the total amount of coal transported on that route from 2008-2016. The points are colored by coal rank.

Each point is a unique mine-to-power-plant route present in the dataset and is sized by the total quantity of coal shipped along that route. There seems to be a tradeoff between direct sulfur content (potential sulfur emissions) and emissions arising from transportation. This is because most high sulfur coal comes out of the eastern U.S. near power plants, and most low-sulfur coal comes out of Wyoming – far from many power plants. If power plants wanted to reduce their transportation emissions, many would have to purchase higher sulfur coal from closer mines. We believe this tradeoff warrants further investigation, particularly in relation to the Clean Air Act. Currently, transportation emissions are an externality for coal plants, and it appears plant operators are choosing coal near the top left of Figure 4.10 (low sulfur, large distance) rather than the bottom right (high sulfur, low distance). Incorporating this externality may shift coal markets and alter the emissions profile of coal power. More work is needed to better understand and model all economic considerations that feed into these decisions.

### 4.3.5 Implications for Carbon Capture & Storage (CCS)

The analysis of transportation routes & shipments allows for a unique perspective on carbon capture & storage (CCS) technology. If CCS is installed at existing power plants, the transportation emissions relative to operational emissions may increase drastically. Consider the Scherer plant, which had 9% transport to operational emissions. Assuming 80% of the operational emissions are captured post-combustion, the transportation emissions jump to 46.9% of the new operational emissions (assuming no energy losses from CCS).

Sanpasertparnich et al. demonstrate that running post-combustion carbon capture systems incurs an energy penalty. The authors estimate that for subbituminous coal (which Scherer uses), capturing 80% of the carbon emissions results in an energy penalty of about 0.44 kWh per kg $CO_2$ captured (Sanpasertparnich et al., 2010). If Scherer installs this technology and wishes to maintain the same net energy output, it must burn an additional 37.5% of its coal input. Assuming Scherer buys this additional coal from the same suppliers, it will create additional transportation emissions. Scherer's transportation emissions would increase to 64.5% of the now reduced operational emissions (calculation in the Supporting Materials). Therefore, policymakers favoring CCS systems should be aware of the upstream impacts of installing such systems. Total transportation emissions may increase significantly if power plants choose to produce the same net output. After CCS is installed, transportation may be the next biggest emitter in the coal supply chain.

## 4.4 Conclusion

This paper presented an analysis of datasets from the EIA, EPA, and USGS, which were combined to present a detailed and comprehensive picture of coal mines, rail network, power plants, and $CO_2$ emissions from coal rail transport for the past decade. Despite relatively little attention on this subject so far, our results show large variation in transportation distances, and therefore emissions, for coal rail transportation across the US. For many power plants, the emissions from transporting coal are a significant percentage of their operational emissions – as high as 35%. Two of the largest coal power plants in the U.S. have transport emissions above 5% of their operational emissions.

Environmental footprint studies and life cycle assessments that simply use a US-wide average transport distance may be mischaracterizing the emissions profile of coal power. We recommend at least using an average transportation distance within a NERC region (Figure 4.7) when performing a life cycle assessment. The average transportation distance may vary by up to 1,064 km depending on the NERC region under analysis (compare FRCC to WECC in Table 4.2). Using the proper regional transportation distance will reduce uncertainty in a life cycle assessment.

Our results also point towards the limits of clean coal. Intrinsically clean coal (coal with low sulfur content) only exists at high quantity in the Western coal basins. Unfortunately, the majority of U.S. coal power plants are in the Midwest and Eastern US. Any further push towards sourcing low sulfur content coal will shift emissions into transportation externalities. This tradeoff warrants future study. It may be possible for utility companies to optimize routing of shipments across all their power plants to reduce transportation emissions.

It is important to note that our results present a conservative estimate. The analysis was only completed for rail transportation (capturing 70% of all coal shipments). If some power plants received coal by barge or truck in addition to rail, their transport emissions would increase as those forms of transportation are currently left unaccounted. Furthermore, the main assumption of this analysis was that trains would use the shortest route along the rail network. If trains deviate from this shortest path, possibly to stay on a specific company's rail line, the transportation distance would increase.

Furthermore, if carbon capture and storage solutions (CCS) are retrofitted onto existing coal power plants, their transportation emissions as a percentage of operational emissions will increase significantly. Additionally, their absolute transportation emissions will increase if power plants choose to produce a similar net energy output due to the energy penalty associated with CCS. We believe that, in the case of CCS, transport emissions deserve scrutiny and ought to be minimized so that CCS provides the largest net benefit possible.

This paper lays the groundwork for future research directions. With the new coal shipment network, it may be possible to better understand the resilience of the coal power sector. If portions of the network become inoperable (caused by natural disaster or malfunctions), what cascading effects might occur? What are the most critical nodes and pathways? The dataset also provides future possibilities for understanding emissions. What are the environmental impacts of different transfer terminals and other transportation processes? What are the localized effects of coal dust and other emissions from these coal trains? This analysis is a first step towards answering these questions that we intend to pursue.

## Relation to broader dissertation

The three themes of this dissertation are woven into and throughout this chapter. These themes are:

1. BPE modeling allows deeper insights into how the economy is reliant on resources
2. Models are better informed and constructed with granular and detailed data
3. Detailed, high resolution models enhance decision-making capability

Theme 1 presented itself through this model's treatment of emissions data. By taking a more holistic approach to understanding coal emissions, the model particularly elucidated implications for CCS technology. It also underscored the importance of policy — the Clean Air Act was meant to reduce emissions. Here, we have shown some of those emissions were merely shifted from $SO_2$ to $CO_2$ through increased transportation.

Of course, this chapter is explicit in its connection to theme 2. The point of this chapter was to use granular data to build a more detailed model of transportation emissions than previous literature. Furthermore, this level of data enables significantly more and more detailed analyses hinted at within the conclusion. Using this detailed data provides a great level of fidelity to the study of energy systems. Therefore, BPE modelers ought to take advantage of increased data resources to fully inform their models.

Theme 3 is mainly present in the future research directions. This dataset and model presented a preliminary study of how CCS technology affects transportation emissions. This research avenue ought to be further explored to inform policy decisions surrounding CCS. Other tools meant to inform policy have also been hinted at throughout the chapter, such as optimization modeling or resilience studies. Only with this level of detail of the coal transportation network could these studies take place. These future research directions must be investigated.

# Chapter 5

# Resource Criticality in Modern Economies: Agent-Based Model Demonstrates Vulnerabilities from Technological Interdependence

## Prelude

This chapter was originally published in 2017 within the *Journal of Biophysical Economics and Resource Quality*.[1] The chapter has been edited for clarity and format. Additionally, the conclusion has been expanded has been added to better place the chapter within the broader dissertation.

The original SOCIETIES resource and technology trading agent-based model was developed by Becky Haney and Loren Haarsma, with the programming and research assistance of Tony Ditta and Jiaming Jiang. Haney, et al. (2016)[2] used SOCIETIES v1.0 to examine the effects of

[1] Sherwood, J., Ditta, A., Haney, B., Haarsma, L., and Carbajales-Dale, M. (2017b). Resource Criticality in Modern Economies: Agent-Based Model Demonstrates Vulnerabilities from Technological Interdependence. *BioPhysical Economics and Resource Quality*, 2(3):9, published as Open Access under the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/)

[2] Haney, B. R., Haarsma, L., and Ditta, A. (2016). Income inequality & technology: What can agent-based models tell us? *Calvin University Department of Economics working paper*, available at: `https://github.com/bhaney22/SocietiesABM/blob/master/Haney%202016%20Income%20Inequality%20and%20Technology%20ABM%20working%20paper.pdf`

technological growth on income inequality, even in the presence of unlimited resources.

The chapter describes an agent-based model with characteristics as shown in 5.1. Although purely theoretical, the model describes a self-contained world and is therefore at the world spatial scale. The model describes technological advancement from a period of no inventions to a period of maximum technological innovation — it most closely resembles an ultra-long term time horizon. The model's Ethos characteristic was chosen because the model is pure theory. This chapter originates from behavioral economics and social science because it describes the behavior of individual agents. Finally, the model is a simulation.

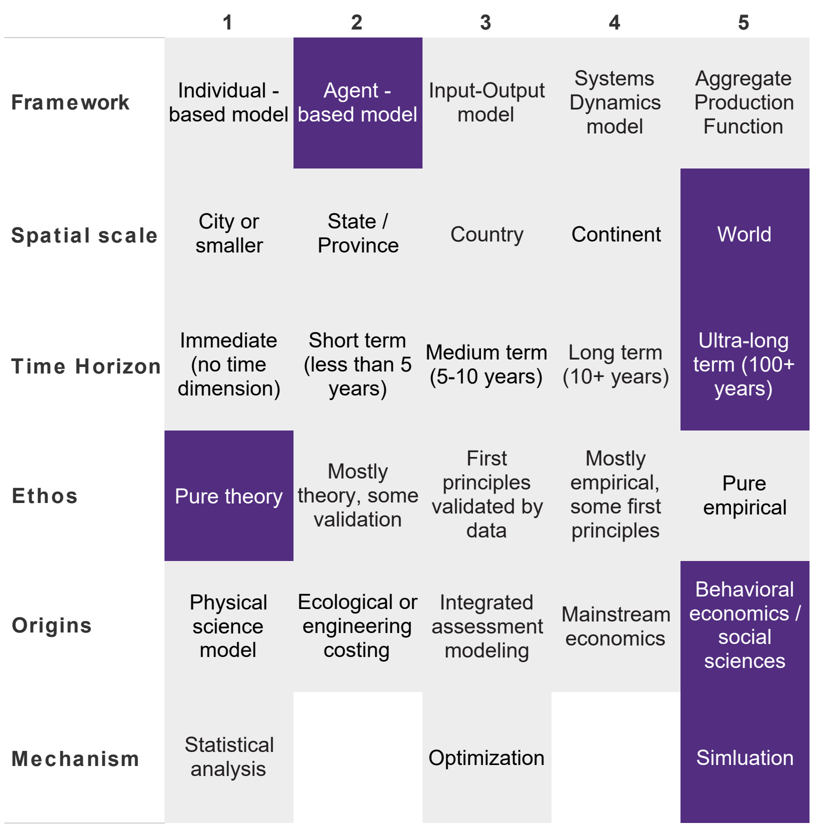


Figure 5.1: The SOCIETIES model mapped to Chapter 2's model characteristics.

## Abstract

Industrialized society will transition away from dependence on non-renewable resources (fossil fuels, in particular) sometime in the foreseeable future. How disruptive this transition will be

to the economy and societal well-being is unknown, particularly if there are any sudden resource supply constraints. However, the effects of resource supply constraints on an economy, or models of the interdependent relationship between the economy and natural capital overall have not been thoroughly developed. One problem is that traditional models of the economy assume linear growth, while highly interdependent industrialized economies may behave more like a complex adaptive system with non-linear, path-dependent, and unexpected growth trajectories. Agent-based models have been shown to successfully model important aspects of a complex adaptive economy. This paper uses an agent-based model to demonstrate potential economic impacts for industrialized economies in the face of a sudden resource supply constraint. Economic "agents" mine resources and invent technology. Through trade and specialization, the economy evolves from a collection of self-sustaining, resource-poor agents to a society with a high degree of interdependence and wealth. Economic growth, however, comes with a cost; the interdependence that arises from specialization and trade also leads to a less resilient economy. Unexpected, large economic collapse can arise from a shock to even a single resource, due to each resource's interdependent role in the economy.

## 5.1 Introduction and background

### 5.1.1 Resource depletion and criticality concerns

Despite a strong historical record of societies facing resource supply constraints, relatively little analysis of the relationship between exhaustible or constrained resources and the economy appears in the mainstream economics literature. Notable exceptions include Hotelling (1931), Hartwick (1977), Hartwick (1978), and Nordhaus (1979). However, their models do not place natural resources as the driver of economic activity. Instead, pricing systems and well-functioning markets insulate the economy from resource constraints.

Conversely, an economy's dependence on natural resources is the center piece of an interdisciplinary, biophysical approach to economics. This approach goes beyond environmental economics, which simply examines the markets and market failures related to natural resources. Instead, the biophysical approach starts with ecology and understands the economy as "a wholly owned subsidiary of the ecosystem," as economist Herman Daly has been often quoted as saying (Daly, 2005b). Seeing the economy as a system wholly dependent on and ultimately tied to the health of a larger natural system brings questions related to sustainability to the fore rather than as an afterthought, and particularly after a crisis.

Near-complete socioeconomic collapse appears to have occurred several times in history due to natural resource (mis)management. Examples include the inhabitants of Easter Island, and the Minoan, Mayan, and Anasazi societies, although there is not full agreement on the exact causes of collapse (Tainter, 1988, 2006). Conversely, in more recent and recorded history, predictions of imminent collapse due to natural resource supply constraints have rarely materialized and most industrialized societies have weathered a variety of transitions through innovation. Yet, collapse is not outside the realm of possibility. Cuba experienced a severe collapse in GDP when it lost access to a significant portion of its energy imports upon the dissolution of the Soviet Union in 1989, as seen by the large drop in the dashed line in Fig. 5.2. In large part due to this constrained supply of energy resources, Cuba soon experienced a 35% drop in GDP. The Cuban electric grid experienced severe supply disruptions which, along with the loss of imports from the Soviet Union, contributed to significantly reduced economic output. Cuba faced starvation and potential societal collapse during what Cubans call the "Special Period." Strong communities, social cohesion, and policy measures gradually transitioned Cuban society to a new normal (Piercy et al., 2010; Friedrichs, 2010). Cuba's industrial output recovered eventually, despite energy imports remaining low. This advanced economy experienced first-hand the potential effects of a natural resource supply constraint: a severe collapse and painful, slow but eventual recovery.

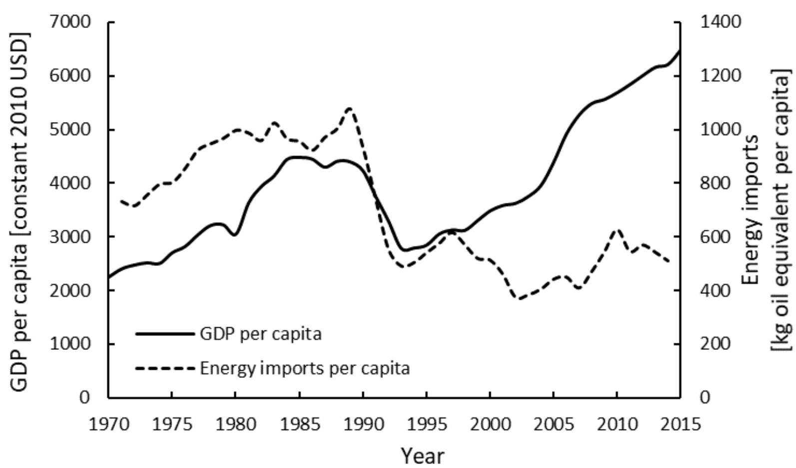


Figure 5.2: Cuba historical GDP per capita and energy imports per capita. Data from The World Bank (World Bank, 2016b).

Though Cuba adapted, the fact that the country needed drastic measures highlights how dependent modern-day society is on a supply of natural resources, and that a constrained supply may prompt drastic shifts throughout an economy. Additionally, the chances of encountering a supply constraint can increase as more people desire and consume more resources, particularly if resource acquisition technology fails to keep pace with demand. Vaclav Smil has stated that, as the world population continues to grow, the absolute rate of resource consumption will increase – even while accounting for diminishing per capita resource consumption in OECD countries (Smil, 2016).[3]

Furthermore, globalization continues to forge economic connections across continents – most economies were affected by the 2008 U.S. housing crisis and subsequent recession (Claessens et al., 2010). Therefore, if a supply constraint is encountered, it will likely affect the entire world economy.

### 5.1.2 Where are resources in macro-economic growth models?

Despite the potential for painful, global economic collapse due to natural resource constraints, economic implications of resource constraints as a research topic receives relatively little attention. One reason for this is that macro-economic models rely on assumptions that downplay or eliminate the role of natural resources. The predominant models used to examine economic output fall into two general categories: 1. Aggregate growth accounting models, such as the Solow growth model, and 2. Computational general equilibrium models, such as dynamic stochastic general equilibrium (DSGE) heavily used by the Federal Reserve for economic and policy analysis (Del Negro et al., 2013). These two categories of approaches exist because they make different assumptions about the structure underlying the dynamics of macro-economic aggregate measures. However, both approaches have been heavily criticized for failing to account for biophysical reality and failing to acknowledge binding biophysical constraints on economic growth (Kümmel et al., 1985; Hall et al., 2001; Hoel and Kverndokk, 1996; Hirsch, 2005). The failure of both approaches to account for the relationship of the environment and the economy can be traced to four problematic assumptions regarding resources:

1. **Factor Substitution**: Most economic models assume natural resources and built capital are substitutable inputs into production. Resource scarcity is not a significant concern long-term because price signals will guide economic actors away from increasingly scarce natural

[3]Theoretically, it is possible to have a decline in total material consumption at the same time as population growth. This would occur if the rate of population growth is less than the rate of dematerialization per capita. However, as Smil (2016) points out, this has not been observed empirically and is unlikely to happen.

resources and toward innovations to replace them. However, the work of Graedel and others on resource criticality indicates that several materials have limited to no substitutability, effectively "decoupling materials substitution from price signals" (Graedel et al., 2015a,b). Furthermore, technological advances often use increasingly unique and varied material requirements to improve designs. Some economists, such as Stern, have begun to recognize the limits of substitution when the economy is viewed as a complex adaptive system (Stern, 1997).

2. **Cost-share Theorem**: The Solow growth model, and certain extensions that include materials and/or energy, assume that factors of production influence economic growth based on their overall cost-share (Gullickson and Harper, 1987; Ayres and Warr, 2005). Because the cost-share of energy and raw materials are relatively low, the implicit assumption is that a resource supply constraint will have a minimal effect on the overall economy. Ayres et al. argue that resources like energy are much more important than their cost-share, such that a small drop in supply will have drastic effects on the overall economy (Ayres et al., 2013). The authors state that cost-shares undervalue resources because cost is only related to extraction and not the intrinsic value of a resource (Ayres et al., 2013).

3. **Perfect Knowledge and Foresight**: In economic models of resource allocation, such as in the Hotelling or Ricardian models, it is assumed that the resource allocators accurately know the level of resource scarcity (Hotelling, 1931). However, Norgaard (1990) criticizes this. The theoretical models require perfect information about resource deposits, while much empirical work implicitly assumes that at least the resource allocators have perfect information regarding their deposits. Neither the theoretical or empirical approach correlate particularly well with history. Norgaard comments that economists' "theoretical models do not readily explain economic history with respect to the most basic patterns and hence are not likely to be useful..." to understand resource scarcity Norgaard (1990).

4. **Representative Agents**: General equilibrium models attempt to link macro-economic output to the underlying behavior of a few, representative agents. Each agent stands in for a multitude of heterogeneous economic agents. Deep interdependencies that result from specialization and path-dependent trade networks cannot be captured in even the most advanced representative agent model (Del Negro et al., 2013). The failure of representative agent models to predict the massive global collapse in the international banking system reveals the severity of this

limitation (Squazzoni, 2010). Resource supply constraints can cause cascading collapse similar to that of the global financial crash due to the interconnectedness of technologies and agents.

This paper claims that to understand how a seemingly wealthy, advanced economy could experience an unexpectedly severe collapse and possible recovery scenario, a model cannot be limited by any of the above four assumptions. A growing body of diverse research, predominantly outside the mainstream of economics, has been able to relax at least one, but not all of these assumptions. Significant examples include:

1. **Factor Substitution**: Mainstream economists such as Hotelling, Hartwick, and Nordhaus have developed theoretical models of natural resource depletion and economic growth when factor substitution is limited (Hotelling, 1931; Hartwick, 1977, 1978; Nordhaus, 1979). More recently, Smulders et al. (2014), and Brock and Taylor (2005) have attempted to extend computable general equilibrium models to include interactions with the environment.

2. **Cost-share Theorem**: A robust interdisciplinary literature exists that ignores the cost-share assumption and adds energy as a primary input factor to growth accounting models, including the work of Ayres and Warr (2005), Kümmel et al. (1985), and more recently Heun et al. (2017a).

3. **Perfect Knowledge and Foresight**: Systems dynamics models have examined the effect of resource depletion on the macro economy when economic agents do not have perfect foresight, or do - but are limited in their ability to act on it, including Meadows and Randers' World3 model (Meadows et al., 2004a), used in Limits to Growth, and Nordhaus' DICE integrated assessment model (Nordhaus, 1993).

4. **Representative Agents**: Agent-based models (ABM) of the economy are designed specifically to alleviate the need for representative agents. A growing body of research that uses ABM to study the economy exists. However, Balint et al. (2017) provides a recent, comprehensive review of environmental macro-economic models and identifies few, if any, ABM that also include resource dependency and technological innovation in their framework.

None of these models, however, use a resource-dependent economic framework and explicitly model the relationship between technological innovation, technological interdependency, resource criticality and the dynamics of macro-economic outcomes. The primary contribution of this paper is to demonstrate that underlying technological interdependencies, emerging over time from trade networks of heterogeneous economic agents, can lead to both exponential growth in output and increasing resource criticality.

### 5.1.3 Why use agent-based models to understand resource criticality?

The model developed in this paper belongs to a growing class of agent-based models used to examine how economic agents interact and develop trade networks (Balint et al., 2017). In our case, agents also interact with their natural environment and develop technology. The agents' underlying economic decisions form trade networks, capital infrastructure, and draw down natural resources. Macro-economic aggregate outcomes emerge as an explicit result of economic behavior. As an economy grows increasingly interdependent from these interactions, it has been shown to behave as a complex adaptive system (Andersen, 1996; Anderson and Arrow, 1988; Arthur, 1999; Durlauf, 2012; Kirman, 2016; Colander and Kupers, 2016). Agent-based models are a particularly appropriate methodology for examining an economy as a complex adaptive system.

Interdependence can be simulated through an agent-based model, a relatively new modeling technique based on defining rules for individual agent behavior. Agents' interactions with each other and the macro-economy that they create generate macro-economic time series that can trace out trajectories similar to those that result from Solow growth models or dynamic stochastic general equilibrium models (Tesfatsion and Judd, 2006). Agent-based models (ABM) provide a 'laboratory' to model the outcomes of alternative policies, behavioral assumptions and social norms (Holland and Miller, 1991). For example, Epstein and Axtell's Sugarscape ABM can replicate neoclassical comparative statics models of commodity trade price equilibrium. The initial conditions of the model can be set to mimic the neoclassical behavioral assumptions of agents (full information, rational, self-interested) and show that such an economy left to its own devices can lead to a "socially optimal" outcome where commodity trade prices reflect actual utility of the commodities. That is, they can reproduce the evidence that is used to make the case for laissez-faire economic policies. However, they also generate several counterfactuals by making the agents "progressively less neoclassical" such as having culturally-conditioned preferences, and show that under different assumptions, laissez-faire policies can lead to less efficient outcomes accompanied by greater inequality (Epstein and Axtell, 1996).

A number of ABMs 'grow' economies "from the bottom up" and model bilateral exchanges between agents in ways that are useful to examine the dynamic and complex nature of the modern economy (Epstein and Axtell, 1996; Hamill and Gilbert, 2016). While all of them model certain aspects of the modern economy, none of them explicitly model the deep level of technological interdependence that has emerged since the industrial revolution. Thus, while previous models are complex adaptive systems, they do not include the interdependence arising from invention of technology.

The model presented here is called Self Organizing Complex Interdependent Evolving Technology In an Economic System, or SOCIETIES.[4] It is one of the first ABM that directly simulates resource-dependent technological innovation and capital formation in order to study the interdependence found within the economy. By building a virtual resource-dependent economy from the bottom up, we study both the increased economic production and vulnerability to collapse and recovery that come with resource criticality. Because the simulation explicitly models resource and technological development pathways, it can provide much needed insight into the effect of resource supply constraints on technologically advanced economies.

## 5.2 Model description

### 5.2.1 Overview

SOCIETIES is based on four basic elements: agents, resources, devices, and trade. Agents represent firms, communities, or regions who increase their utility by extracting resources. Agents can construct devices that speed up resource extraction and thus increase utility gains, however the devices require resources to build. The agents gain experience extracting specific resources or building devices, which increases the efficiency of those tasks. This allows for specialization and creates incentives to trade. The agents can trade resources or devices with one another through random bi-lateral trade pairings that occur once per time-step.

All agents start out homogenous, and only begin to differentiate themselves through stochastic choices. The initial homogeneity of agents guards against specifying particular producers or consumers for a certain device or resource. Any resource criticality due to trading relationships will emerge from the nature of the model. Additionally, all resources are homogenous with identical utility curves (see Section 5.2.3.1). This ensures that any sort of resource criticality only emerges

[4]The software is available as open source under the GPL license and is available for download and extension by the research community at https://github.com/bhaney22/SocietiesABM

through the nature of technology rather than by generating desirability of a resource due to some intrinsic resource property.

### 5.2.2 A day in the life of an agent

Agents cycle through six phases each time-step, shown in Figure 5.3. All agents progress through the phases in parallel, allowing them to interact during the trade phases (represented by dashed boxes in Figure 5.3).

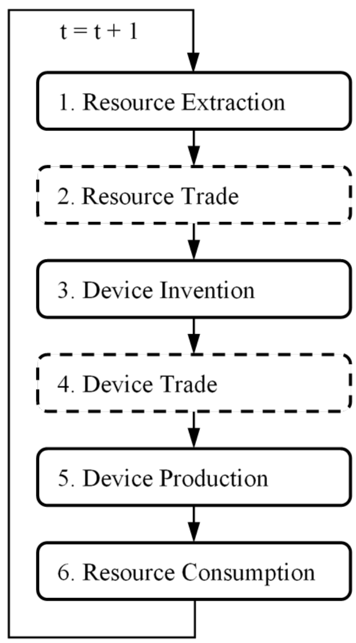


Figure 5.3: Overview of agent phases per time-step. Dashed boxes represent social interaction phases.

#### 5.2.2.1 Agents

Agents are initially homogenous, self-interested, and fully rational economic actors. They cannot die, do not procrastinate, and can switch between tasks with no transaction costs. They perfectly calculate costs and benefits to decide which resource to extract or which device to make based on utility gains. Agents make decisions that optimize their extraction efficiency and thus utility gain each time-step. When trading, they have no strategic or information advantage over each other and barter/trade honestly and only when both parties benefit.

However, their rationality is bounded. The agents have limited memory and only a certain amount of foresight. They do not anticipate gains from trade when deciding which resource to extract. They can only communicate pair-wise during barter. The only information they can use for trading resources is the value they themselves put on each resource. When trading devices, they factor in how efficiently they can use the device based on the previous time-step. They also remember the last few days of trades. Agents are not able to anticipate gains from future trades when calculating the benefit of producing a device; they only consider the benefit it provides them in extracting resources for themselves. 24 agents exist in the current model. This is enough to ensure heterogeneity but also relatively smooth aggregated model outputs. For more information on the number of agents, see the appendices.

### 5.2.3 Resources

Resources are homogenous, differentiated only by agents' experience with them. Each resource has a utility curve that reflects its value. Agents consume a constant proportion of each of their resources every time-step. This accounts for resources being used, wearing out, or breaking down over time. 24 resources exist in the current model – enough so that each agent can uniquely specialize if they choose to. The choice of number of resources is also discussed in the appendices.

#### 5.2.3.1 Resource extraction

The SOCIETIES model contains nested time-steps. Each high-level time-step represents every agent progressing through each phase in Figure 5.3. For clarity in the model description, we call these global time-steps "days", though they do not represent a day to society on Earth. Within each "day", agents have a fixed number of "minutes" that can be used to extract resources or build devices (see Section 5.2.7). Extracting a resource takes a number of minutes, dependent on the agent's experience level. An agent gains experience for a specific resource every time the agent extracts it. At higher resource experience levels, it takes fewer minutes to extract a resource. The exact relationship is shown in the resource effort curve as Figure 5.4 below.

The sigmoid represented in Figure 5.4 is produced by the Gompertz function (a generalized logistic function) shown to the right of the curve. This is one of many choices of functions that can be employed to model a learning a task. Following Pan and Koehler (2007), we chose this type of function to model learning-by-doing that results initially in minimal gains for experience, then

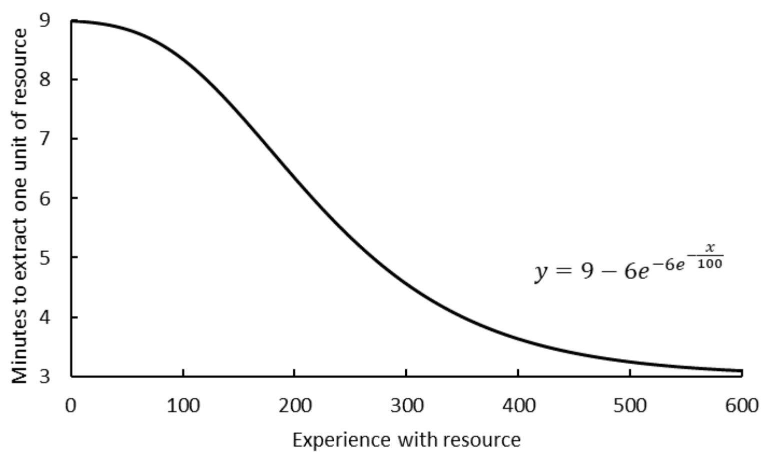


Figure 5.4: Resource effort curve.

significant gains from experience, then finally no gains due to physical limitations which cannot be overcome with further experience. It is ideal for the purposes of our model in that it rewards specialization and promotes trade in resources and technology. The parameters that define the particular shape of the sigmoid were chosen so that agents would require several days to reach maximum experience. This allows the economy to change in small increments each time-step, but to change significantly in just a few hundred time-steps.

Each resource could have a different effort curve in principle, though for this paper the curves will be homogenous to limit any inherent resource uniqueness or criticality. The effort curve does, however, provide a reward for an agent to specialize in a specific resource. But, if an agent does not extract a specific resource during a day, they lose 3 experience for that resource. This simulates losing unused skills.

Agents decide which resource to extract by the amount of "utility" it provides them. Utility curves are defined as $U(x) = Dx^(1/n)$, where $D$ is the utility of the first unit, $x$ is the number of units owned,[5] and $n$ is a control parameter to adjust the curvature, causing diminishing returns, as shown in Figure 5.5. Resources are restricted to discrete units, so the marginal utility of the $k$th unit is $MU(k) = U(k) - U(k-1)$. The marginal utility of resource $i$ eventually falls below the initial marginal utility of resource $j$, such that all resources are extracted.

Agents choose to extract the resource that provides the most utility gain per minute. If an

[5]As such, the utility of a particular resource may increase as an agent's stock of that resource is depleted.

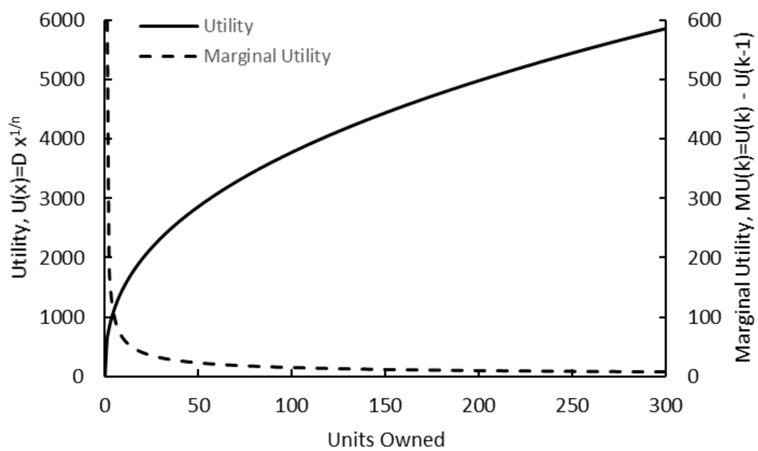


Figure 5.5: Utility (left axis) and marginal utility (right axis) as a function of resource units owned by an agent. Here, D = 600 and n= 2.5 which were used in all model runs presented.

agent has $x$ units of resource $r$, the utility gain per minute is:

$$Gainperminute(GPM) = MU(x_r + 1)/e_r \tag{5.1}$$

Where $e_r$ is the effort required to extract resource $r$, which is further reduced by a factor of $3^{\tau}$ when using devices of tier $\tau$ for resource $r$.[6] The agent performs this calculation for each resource before each time (minute) investment. Note that this is the only decision heuristic for resource extraction; agents do not anticipate future gains from trade when making extraction decisions.

A process diagram for resource extraction is shown in Figure 5.6.

#### 5.2.3.2 Resource trade

Agents pair to trade resources multiple times. For this paper, all agents go through twelve trade rounds. The rounds are simple bi-lateral trades between honest agents; strategic bartering behavior is not explored. The agents follow the process diagram shown in Figure 5.7. When agents are randomly paired, each one ranks their resource holdings from most to least valuable based on their MU from the last unit received. Note that agents only look back at previous MU when calculating gains from trade; they do not account for future resource extraction. The agent may

[6] Effort is a function of experience extracting a resource, shown in Figure 2, and device tier. The equation to calculate effort is:$e_r = (9 - 6e^{(} - 6e^{(} - x_r/100)))/3^{\tau}$ $x_r$ is the amount experience with resource $r$ and $\tau$ is the device tier, 1-4. $\tau = 0$ when no devices are used to extract a resource.

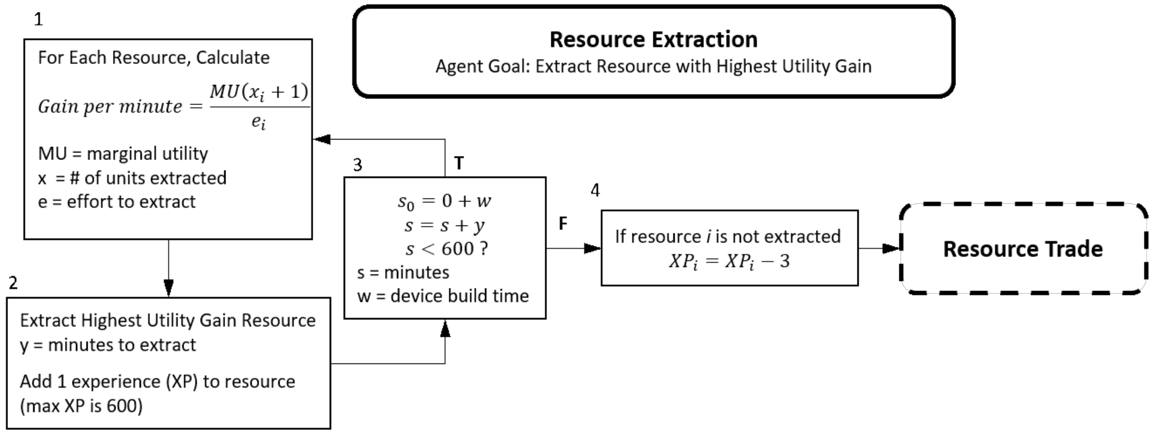


Figure 5.6: Resource extraction phase process diagram.

benefit by trading low MU resources for high MU resources. If there is a net utility gain, defined by $\sum MU(buying) - \sum MU(selling)$, then an agent will agree to trade.

When agents are paired, they offer to trade their five least valuable resources. One agent is randomly assigned as the "buyer" or decision-maker (agent **A**). Agent **A** chooses a pair of resources to maximize its net utility gain. Agent **B**, the "seller", calculates its net utility for the chosen pair. If both **A** and **B** benefit from the potential trade, a price is determined as the integer rounded geometric mean of the agents' valuations, following Epstein and Axtell (1996).

Next, **A** chooses the quantity to trade that maximizes its net utility gain. **B** accepts if **B** still gains from the trade. If **B** does not gain from the offered quantity, **B** makes a counter-offer using its maximizing quantity. **A** either accepts the counter-offer, or restarts the trade round with switched roles (**A** will try being the "seller"). Regardless of completing a trade, the two agents swap roles five times before the round of trading ends. Once all trade rounds are complete within the resource trading phase, agents advance to the device invention phase.

### 5.2.4 Devices

Devices are inventions that speed the extraction of resources. Initially, agents have no devices. As agents gain experience with resources, they become increasingly likely to invent a device for that resource because they learn how to extract it better. The first devices invented are simple, made from a combination of resources. As agents gain experience with simple devices, they begin to invent more complex devices by combining lower-level devices, each level offering more efficient

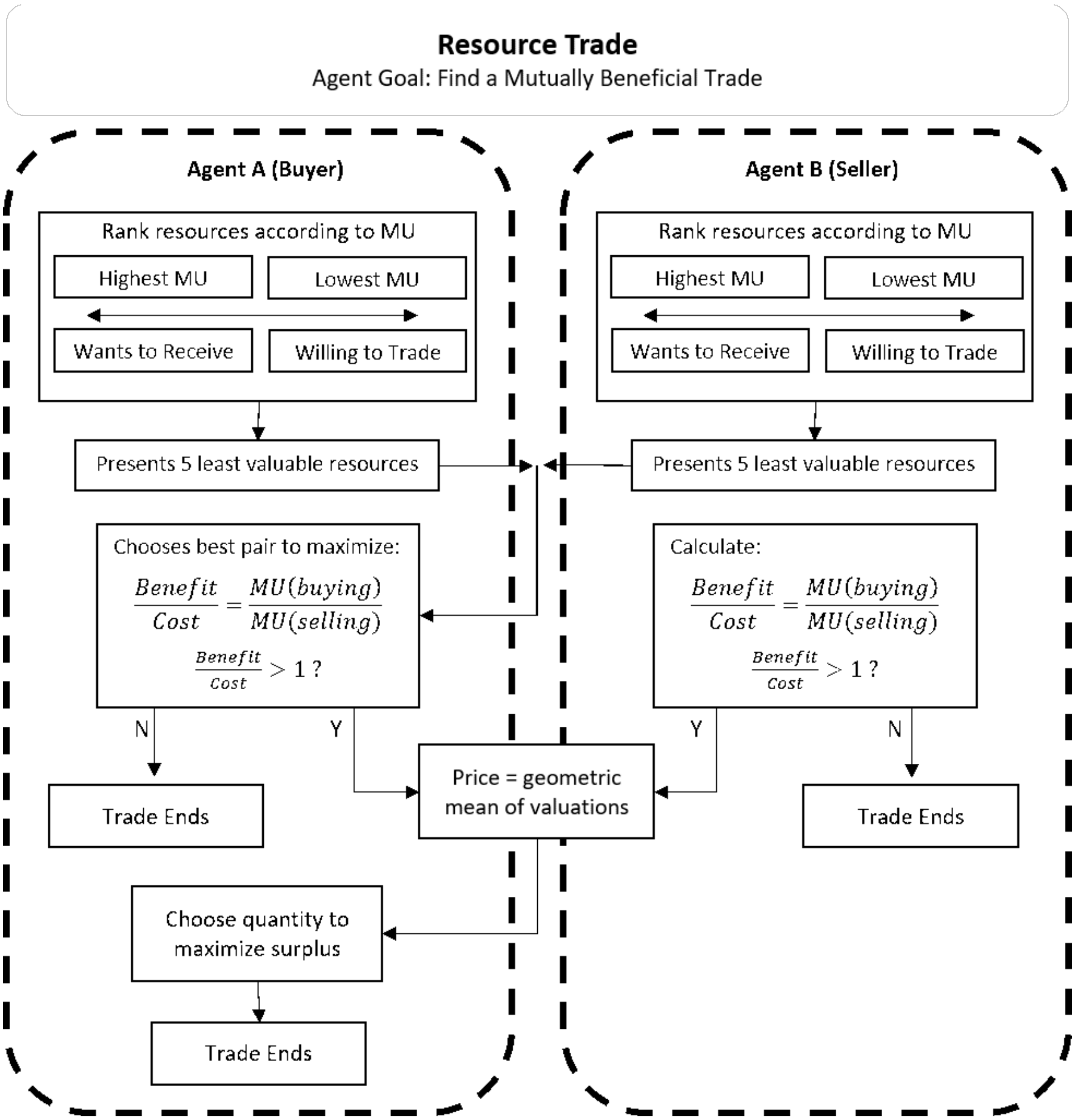


Figure 5.7: Resource trade phase process diagram.

resource extraction. Each device has a finite lifetime and wears out more quickly through use.

### 5.2.5 Device invention

Once resource trading ends, agents have an opportunity to invent a device. Tier 1 devices are invented by combining four resources: two random and the two highest experience resources for the agent. If a tier 1 device has already been invented for all four resources, the agent attempts to invent a tier 2 device by combining four tier 1 devices. The probability of successfully inventing a device is proportional to the sum of experience from all underlying components, and is always less than one.

When a device is invented, the combination of components is considered that device's formula or recipe. Every device of the same type will follow that recipe – other agents learn the recipe by purchasing the device from the inventor. This behavior allows for a certain "patent" length on a device type and creates a diffusion of technology within the society. See Figure 5.8 for the process diagram of device invention, and Figure 5.9 for an example device recipe tree for a tier 4 device.

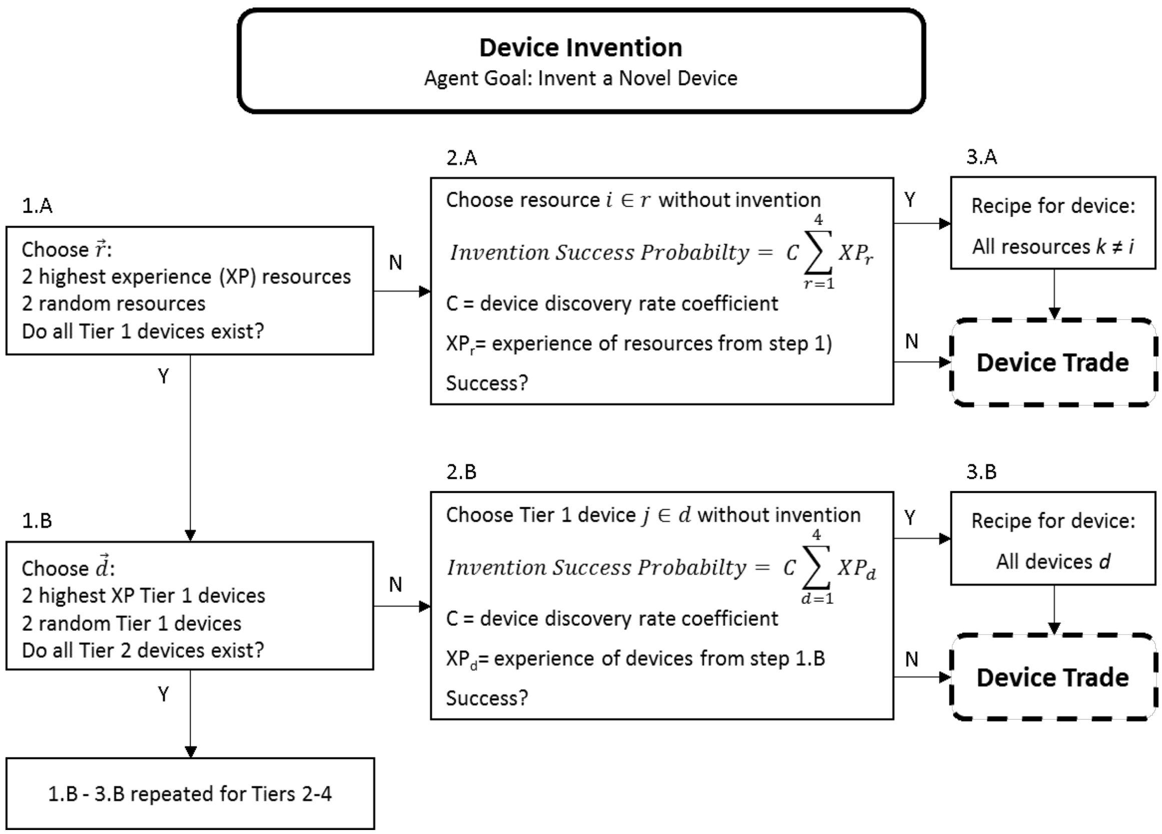


Figure 5.8: Device invention phase process diagram.

Devices reduce the effort required to extract a resource (by a factor of $3^{\tau}$, where $\tau$ is the device tier) but have a finite lifetime and wear out through use. The lifetime is measured in minutes used during the resource extraction phase. Devices have a lifetime of 150, 300, 600, and 1200 minutes for tiers 1-4 respectively. These lifetimes correspond to 1/4, 1/2, 1, and 2 days. So, higher order

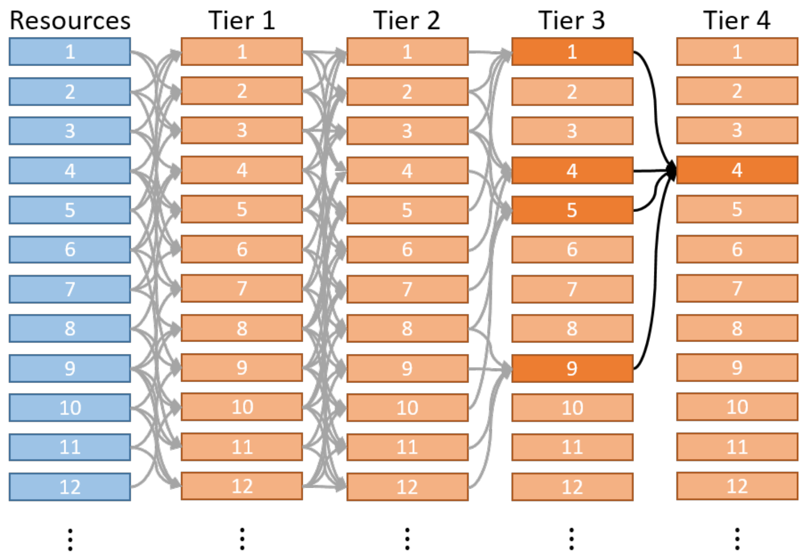


Figure 5.9: Example recipe tree for a tier 4 device. The tier 4 device for resource four is highlighted, along with its direct dependencies. While only 12 resources (and subsequent devices) are shown, the model contains 24 resources. In this example only resources 1-12 are used to build tier 4 device four, though numerous combinations are possible (including dependencies on resources 12-24).

devices are both more efficient and more durable. We chose these values to create quick capital changeover while still ensuring a device would be worth the cost of its construction. If device lifetimes were too long, it would take more computing resources for essentially the same result —- a shift in the structure of an economy.

### 5.2.6 Device trade

Agents trade devices after the invention phase, so that they can both invent and trade within the same day. Device trade is very similar to resource trade, though with a few differences. "Buyer" agents are randomly selected, but they choose a "seller" from a pool of successful trade partners (if none exist, an agent is randomly selected). We allow this agent memory in order to form device trade networks. A trade network approach is much more successful than relying on random agent pairing because devices are initially scarce and require significant resource inputs. The process flow diagram is shown in Figure 5.10.

The pair of agents goes through twelve trade rounds, just as in resource trading. Within a round, the "buyer" (agent **A**) calculates its potential benefit from each device the "seller" (agent

**B**) can produce.[7] The potential benefit is measured in utility gained by using the device compared to not using it:

$$Benefit = [U(z) - U(x)] - [U(y) - U(x)] \tag{5.2}$$

Here, $z$ is the final amount of a resource after using the device if purchased, $x$ is the starting amount of a resource (after any currently held devices are used up), and $y$ is the final amount of a resource if it were extracted using the same amount of minutes without the device. Agent **A** then calculates the cost of producing the same device for itself, allowing for a "make-or-buy" decision. If agent **A** could make the device (production requires device experience, see Section 5.2.7), the device cost is the sum of component costs plus the opportunity cost of spending minutes to produce it rather than extract something. This extraction opportunity cost is calculated using the highest final GPM in the previous day.

The component costs are calculated differently for tier 1 and for higher tier devices. Because tier 1 devices are directly built with resources, the cost is the sum of the marginal utility of all resources used to build the tier 1 device. For higher order devices, the cost can be calculated two ways: through direct production or old trade data. The direct production cost is the summed marginal utility of all resources used to build all components that are used to build the device. However, if agent **A** purchased a component in the past 5 days, it will substitute the purchase price for the production cost of that component if the purchase price is lower. For this paper, trade data older than 5 days is forgotten by agents.

Agent **A** then determines the value of the device, which is the minimum of potential benefit and production cost. If a buyer paid more than the benefit or the production cost, it would lose out on utility. So, this value is the maximum price agent **A** is willing to pay. Agent **B** also determines its valuation of the device, which is equal to **B**'s production cost. For a trade to occur, **B**'s value must be less than **A**'s value.

The price is determined is in a similar way as resource trade, with resources being used as the currency. The device buyer (**A**) offers one unit of a resource it wants to trade away (its least valuable resource) and adds it to a list. Then the seller (**B**) chooses one unit of a resource it wants the most (**B**'s most valuable that **A** possesses) and adds it to a list. Each continues to add resources

[7] Devices are made to order. The selling agent does not need inventory for the buyer to place an order, though the seller must spend minutes in the next day to produce the ordered device.

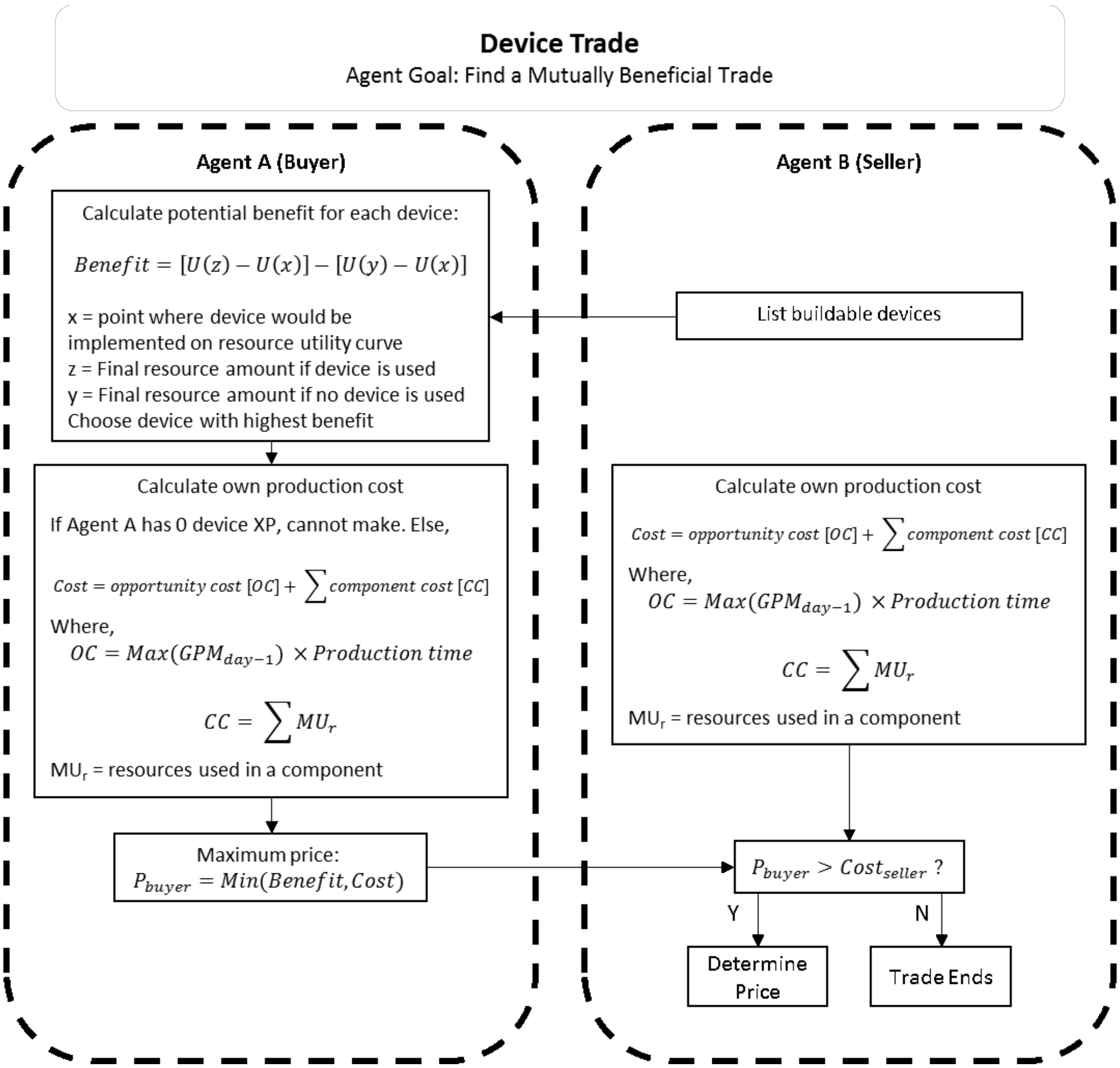


Figure 5.10: Device Trade Process Flow Diagram

to their list until the list's value is at least the value of the device up for trade. Then, they split the difference of their lists.

Agent **A** technically places an order for the device: agent B still needs to produce it. **B** reserves the minutes required to produce it in the next day. If **B** doesn't already own a component for the device to be produced, **B** will attempt to buy it in subsequent trade rounds.

Finally, this phase ends with all agents determining if they will make devices for themselves. They follow similar logic as above – agents calculate a benefit and cost of production for every device they can produce. If the benefit outweighs the production cost, the agent will reserve the needed minutes and produce the device in the next day.

### 5.2.7 Device production

Within the device production phase, agents build the devices on order from other customers or for themselves. The agents start building tier 1 devices and end with tier 4 devices so that lower tiers can be combined into higher tiers. For every device made, the agent subtracts the components from its holdings and reserves minutes to build it in the next day.

Devices take minutes to produce, but the amount varies depending on the device experience. Note that each device has separate experience. Each time an agent makes a tier 1 device, the agent receives 1 experience for that device. Producing tier 2-4 devices generates 2, 4, and 8 experience respectively. The required minutes vary based on Figure 5.11 below. To model technological learning-by-doing, the sigmoid-shaped Device Effort Curve is produced using a generalized logistic (Gompertz) function, shown to the right of the curve in Figure 5.10.

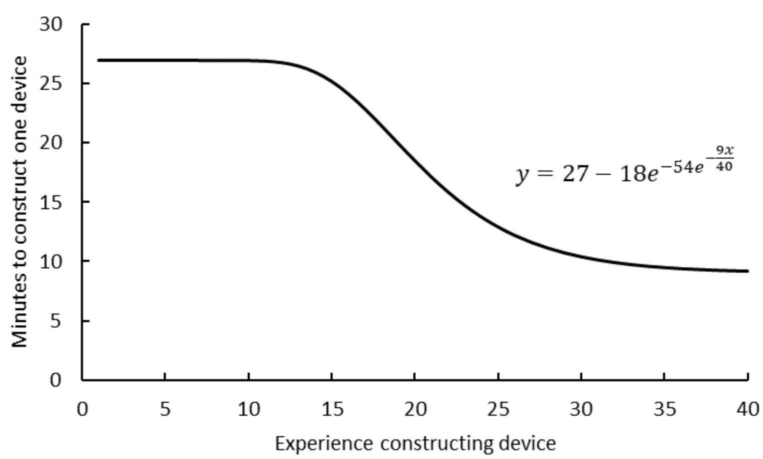


Figure 5.11: Device Effort Curve.

If an agent does not make a device during this phase, it will lose 1 experience for that device. So, agents lose proficiency at skills that are not actively used. If an agent has less than 2 experience for a device (newly invented devices, for example) but purchases it, the device experience will be set to 2. This is a reverse engineering mechanism that gives a slight initial boost to agents that trade for new devices.

### 5.2.8 Resource consumption

The final phase in each time-step is resource consumption. Resources are consumed to account for depreciation, decay, and to create biophysical requirements for the agents. In this paper, agents consume an average of 25% of each resource in their possession. Specifically, a resource unit is drawn from a binomial distribution with probability of consumption equal to 0.25.

Devices also depreciate in this phase, regardless of utilization. Every device held by an agent loses 3 minutes of its lifetime.

## 5.3 Results and discussion

A main simulation choice is the number of agents and resources. The results in this paper are based on 24 agents and 24 resources. These numbers are large enough that both aggregated wealth and technological interdependence change slowly and smoothly over time, but small enough for simulations to run in a reasonable amount of computational time. Note that the model is robust to variations in these values; more details are in the appendices.

This model assumes natural resources are unlimited to see how social and economic structures form without constraints. We can also inject a supply shock by suddenly removing a resource to study how SOCIETIES react. As a reminder, agents do not account for a potential supply shock or depletion of a resource during their economic activity.

### 5.3.1 Technological innovation with unlimited resources

For the initial model runs, resources are unlimited in order to focus on technological innovation. We focus on five parameter variations – limiting the maximum device tier to 1, 2, 3, or 4, and completely disabling devices. Figure 5.12 shows the mean agent utility for these runs. Because this is a stochastic model, each parameter set is run 30 times.[8]

Here the dark colored lines show the average output for a max device tier, while the light colored lines show the quartiles for tiers 2, 3 and 4. Note that, for tier 1 and no devices, the quartiles are omitted because the lines almost perfectly overlap the mean.

The society starts with no devices and over time increase utility through resource extraction aided by gaining experience and the efficiency gains from using devices. For the tier 1 limit, the

[8]We determined that 30 runs was an appropriate number through analysis provided in the appendix.

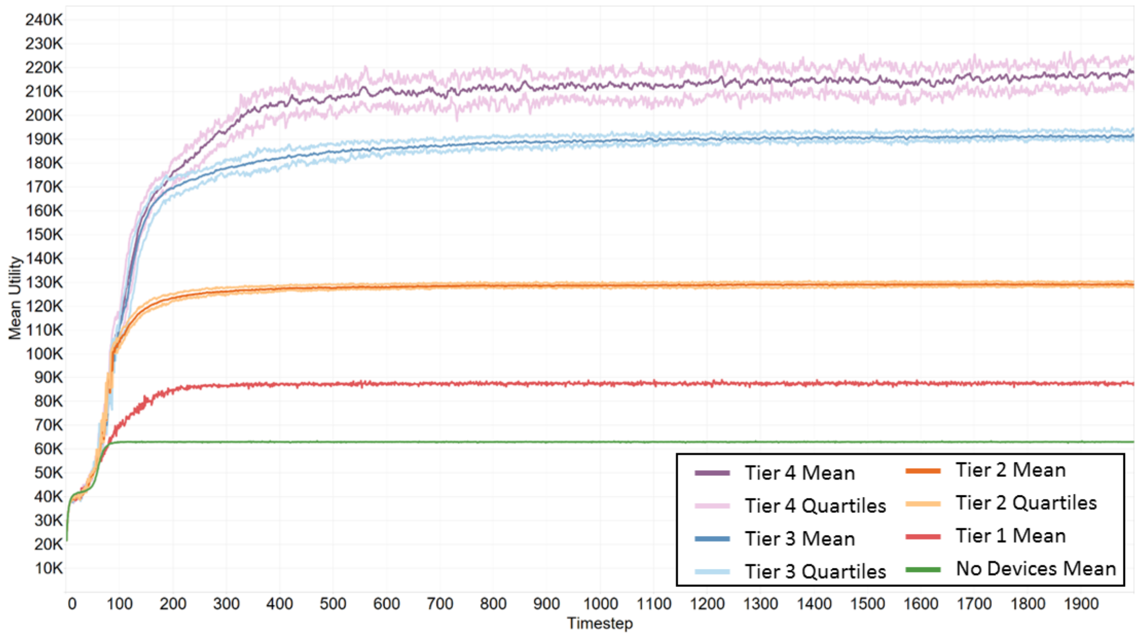


Figure 5.12: Model output with unlimited resources.

agents discover and build devices up to time-step (day) 300. By day 300, they have discovered a device for every resource and reach the upper limit of technological development – there can be no more productivity gains which results in a per capita steady-state. The same pattern holds for every additional device tier, although it takes slightly longer to reach saturation because agents can invent more complex devices.

### 5.3.2 Modeling resource supply constraint

In the next scenario, one resource is deleted from the environment at time-step 600. Agents can no longer extract the deleted resource.[9] The average agent quickly loses a portion of its utility (see Figure 5.13) as devices wear out and new ones cannot be built using the old recipes. Agents work around the missing resource by reinventing devices, but the rate of utility growth is slower. They again reach a pseudo steady state (roughly time-step 1,000 for tier 3 & 4), but the level is slightly lower than before because there is one less resource to draw utility from. Note that lower tier runs face very little collapse while the higher tier runs face significant collapses. Exact numbers

[9]We modeled two variations of deleting a resource: deletion from only the environment, or global deletion including all agents' inventories of the resource. Both variations produce functionally identical results. This is because it only takes a few days to deplete resource reserves by building devices or through the resource consumption stage.

Table 5.1: Collapse characteristics.

| Device level | Utility before collapse [units] | Utility after collapse [units] | Utility during collapse [units] | Collapse severity [%] | Time to initial steady state [days] | Recovery time [days] |
|---|---|---|---|---|---|---|
| Tier 1 | 88,000 | 85,000 | 79,500 | 9.7 | 300 | 100 |
| Tier 2 | 130,000 | 125,000 | 110,000 | 15.4 | 400 | 200 |
| Tier 3 | 190,000 | 185,000 | 142,000 | 25.3 | 500 | 600 |
| Tier 4 | 209,000 | 210,000 | 143,000 | 31.9 | 500 | 800 |

are provided in Table 5.1.

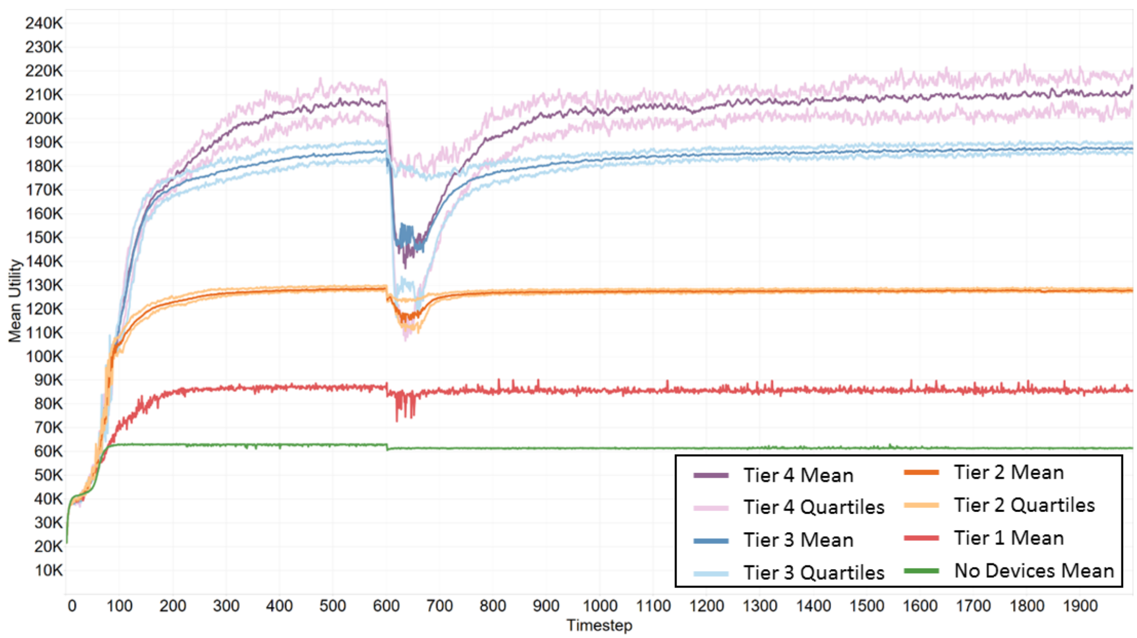


Figure 5.13: Model output, collapse scenario.

We quantify the collapse severity by comparing the lowest utility reached during collapse to the pre-collapse steady state values. The basic tier 1 society experiences a small collapse of 9.7% and has a quick recovery time. As device tiers increase, the collapse severity increases to 31.9% for tier 4. Both tier 3 and 4 societies experience recovery times longer than the initial time it took to build the economy. Tier 4 society initially took 500 time-steps to invent every device, but takes roughly 800 time-steps to reinvent all devices and reach a steady state after the resource supply shock.

In every collapse scenario involving devices, the collapse severity was larger than the individual cost-share of the lost resource. On average, a resource's cost-share is roughly 4.2% (each of the 24 resources are, on average, extracted evenly due to homogenous utility curves). Therefore, every resource within the SOCIETIES model has a greater impact within the economy than its cost-share would suggest.

### 5.3.3 Comparing mean utility to resources gathered

We can compare the agent utility to the number of resources gathered per time-step, seen in Figure 5.14. These values differ because of the diminishing marginal utility of resource extraction. Agents must extract more and more of a resource to maintain the same rate of utility generation because they gain less utility for each additional resource unit.

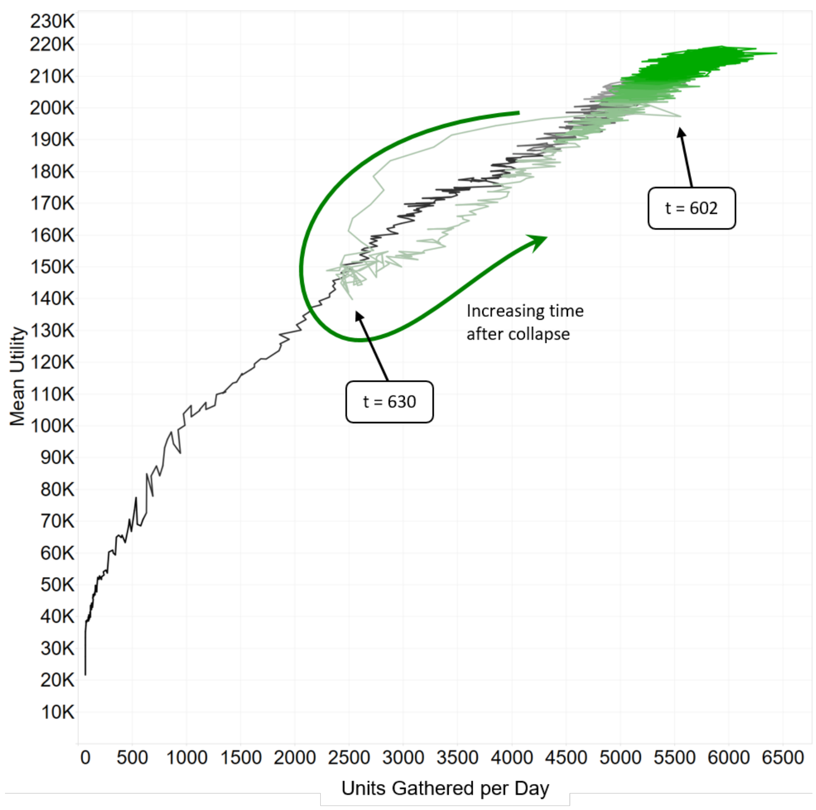


Figure 5.14: The effect of resource extraction on mean utility generation, with a resource removed at time-step 600 and Tier 4 devices available. The color shift occurs at time-step 600 and the green becomes more saturated towards the end of the simulation.

Figure 5.14 shows the diminishing marginal utility through a decreasing slope. Note that the line is colored green after a resource is removed at time-step 600. Right after time-step 600, agents can no longer produce devices with the removed resource. They also have not yet reinvented devices that were reliant on the removed resource. As a consequence, agents spend many more minutes each day extracting resources rather than building devices. This corresponds to an increased number of units gathered until the old devices begin to wear out (time-step 602). As their old devices wear out, the amount of units gathered each day significantly drops. The agents' mean utility doesn't change, however, until they start inventing and building new devices (corresponding to a drop in mean utility). They spend a few days building inventory, then begin to proceed as normal at roughly time-step 630. The new path follows the same initial trajectory, which indicates a similar technological development pathway to the original economic development.

### 5.3.4 Sensitivity analysis

A major parameter is the number of different resources required to construct a tier 1 device. Because tier 1 devices are subcomponents of all higher tier devices, varying the required number of resources has compound effects throughout all types of capital formation.

The default setting is 4 components per device. We ran the model with variations of 2, 4, 6, and 8 components per device. We also placed limits on the highest device tier for a given parameter set, similar to the main analysis. Each set of parameters ran 30 times, resulting in Figure 15.

As the number of device components increases, the agents require a larger supply chain and resource base to construct devices. Increasing the tier limit affects the complexity of devices. These parameters essentially control the level of resource-interdependence embedded within technology. Here, we define interdependence as the average number of resources required to extract one more unit of a resource. As this interdependence increases, there is a tendency to experience more resource criticality and collapse. Figure 5.15 shows the observed collapse severity for each parameter set. Here, collapse severity is calculated by comparing the mean utility before a collapse and at the minimum of the collapse, just as in Table 5.1.

Within Figure 5.15, data points gain edges as the number of device components increases. In general, there is a positive correlation between interdependence and collapse severity. Note that the square series is the primary parameter set within this paper and follows a highly correlated trend. Other parameter sets tend to have underlying behavior that deviates from this trend. For example, the tier 2-4 star points all have roughly the same level of interdependence.

To help understand these behaviors, we look at the collapse through a different lens. Table 5.2 lists the collapse severity in terms of lost interdependence – the number of resources used to

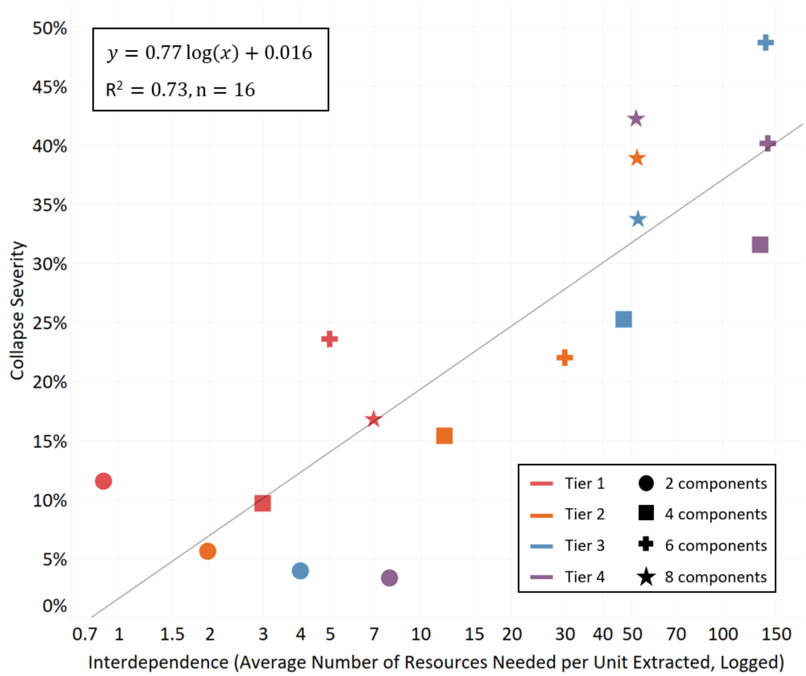


Figure 5.15: Economic collapse severity as a function of interdependence. The trend line is calculated using all data points.

extract a resource. We term this a technical collapse because it is an indicator of agents shifting towards lower tier devices rather than an indicator of dropping utility. By directly viewing the technical collapse, it is easier to decipher how agents interact with technology (though at the expense of understanding economic impacts).

Regardless of device components, Tier 1 societies experience similar technical collapse severities because their supply chains are all shallow with basic devices. There is not enough interdependence to drastically affect the economy. The collapse severity increases with device complexity, though 8 device components plateaus at roughly 70%. Because so many components are required for each subsequent tier, it is uneconomical to construct tier 3 and 4 devices with 8 components each - limiting the complexity. The agents simply stop building devices beyond tier 2, which is why tier 2-4 star points have similar interdependence levels in Figure 5.15. Nevertheless, more resource-interdependent agents tend to face larger collapses along with greater economic development.

To gain insight into economic development pathways, we return to comparing mean utility and resources gathered for all parameter sets (Figure 5.16).

When limited to tier 1 or 2 devices, economic development is roughly the same regardless

Table 5.2: Technical Collapse severity sensitivity analysis. Darker colored cells indicate more severe collapse. Note that 2 device components is a lower limit of the model.

| Device Components | Tier 1 | Tier 2 | Tier 3 | Tier 4 |
|---|---|---|---|---|
| 2 | 4.5% | 0.5% | 2.5% | 6.3% |
| 4 | 4.0% | 10.0% | 31.1% | 55.0% |
| 6 | 4.1% | 27.3% | 85.0% | 83.0% |
| 8 | 4.6% | 73.1% | 70.9% | 70.9% |

of the number of components per device. Development begins to vary by introducing tier 3 and tier 4 devices. The tier 4, 2 components case is abnormal behavior considered outside the limits of the model. As the number of components increases, the available minutes for resource extraction decreases because more lower-tier devices and more resources are needed to produce a device. The tier 4, 4 components case is the default for our analysis because it reached the highest levels of mean utility and units gathered. This allows for better study of a resource depletion due to more pronounced negative effects.

## 5.4 Conclusion

This paper presents an economic modeling framework that demonstrates ways that advanced economies can be susceptible to severe collapse and lengthy recovery scenarios, even in the presence of extraordinarily high levels of economic output. The industrial revolution produced great leaps in material well-being in large part through harnessing the power of fossil fuels and incorporating natural resources with highly specific properties into manufacturing processes. This extraordinary material wealth, however, has come with a hidden cost. The same technology and resource-dependence that produces high levels of output can also create latent vulnerabilities within the system (Graedel et al., 2015a,b; Chen and Graedel, 2015). A seemingly small disruption in the complex network of resource and technological interdependencies can lead to an unexpected cascading collapse in productivity and severe drop in societal well-being. When hidden system vulnerabilities exist, historical patterns of smooth, exponential growth in economic output are not necessarily the best predictors of the future. Production may suffer a sudden collapse and lengthy recovery period unlike anything experienced before (Stern, 1997).

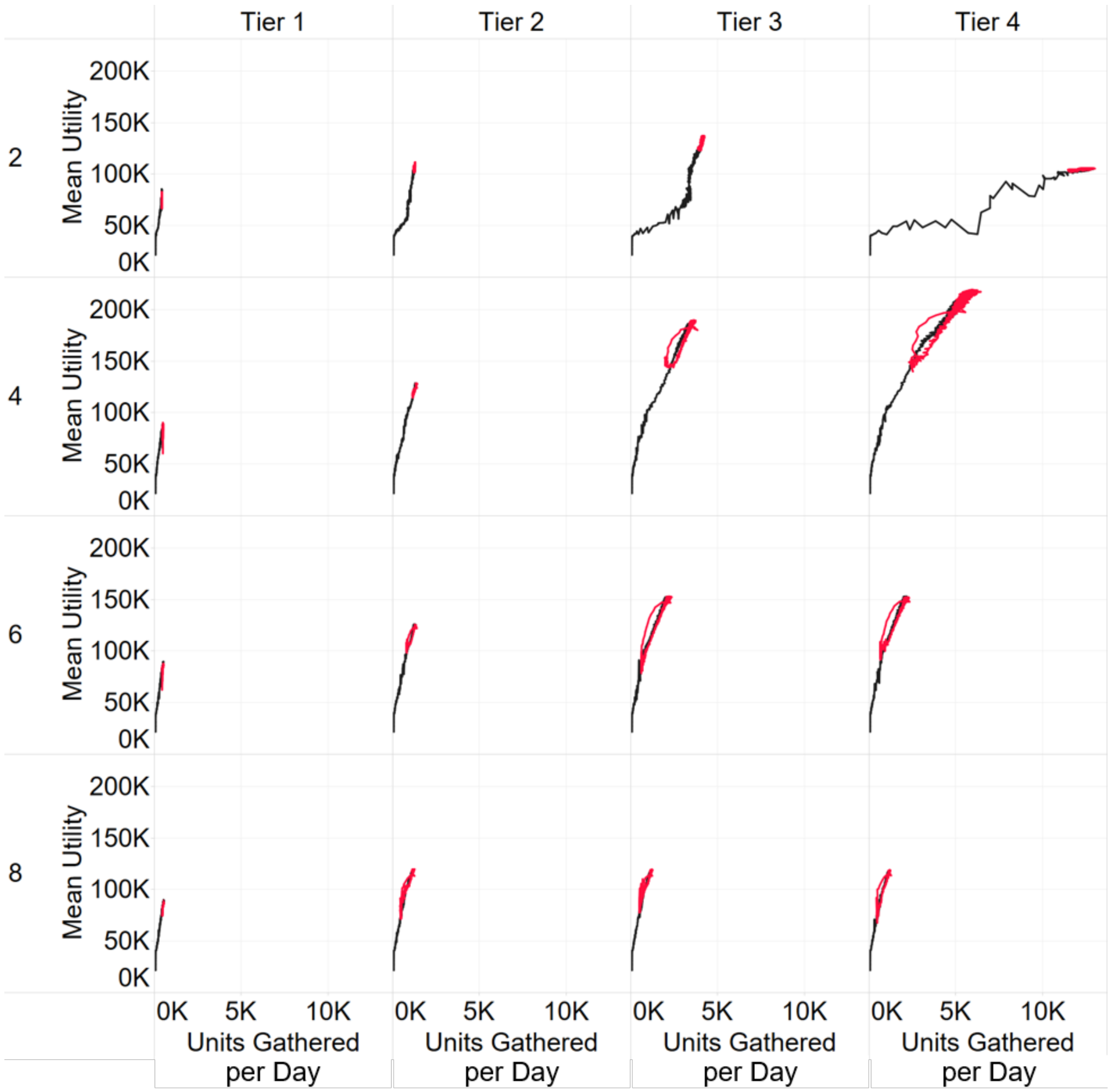


Figure 5.16: Model parameter sweeps. The vertical axis represents number of sub-components per device. The horizontal axis represents the highest device tier available. The color shifts to red after a resource is depleted at time-step 600.

As levels of resource criticality and technological interdependence have increased in recent decades, traditional macroeconomic models have begun to show signs of wear. Policy-makers and others have called for fresh thinking (Colander and Kupers, 2016; Simpson, 2013; Vriend, 2002). Interest in and development of alternative macroeconomic models has increased. Several new approaches are currently being explored that examine different facets of the macro-economy. One category of these new models explores how an economy might behave as a complex adaptive system. The economy is created "from the bottom up" as a network of interdependent economic agents (Colander and Kupers, 2016; Epstein and Axtell, 1996; Arthur, 1999). Another category of approaches examines the dependence of the built economy on natural resources. These often extend traditional Solow growth type models to include natural resources or energy in the pursuit of demonstrating biophysical constraints (Brock and Taylor, 2010; Arbex and Perobelli, 2010).

The approach taken in this paper models both of these important facets of the macroeconomy: technological growth as a complex adaptive system and binding biophysical constraints on macro-economic growth. In SOCIETIES, heterogeneous economic agents interact with the natural environment and with each other to form trading networks, innovate, and build increasingly advanced technological devices. Levels of output from this simulated economy grows exponentially, producing trajectories of macroeconomic outcomes similar to those generated by traditional economic models and observed in historical time series. However, the underlying framework of SOCIETIES also allows an economy to suffer collapse and recovery scenarios when it encounters a binding biophysical constraint. This alternative framework demonstrates that potentially devastating macroeconomic outcomes are indeed possible when the simplifying assumptions used in traditional macroeconomic models are removed. These potential vulnerabilities are not taken seriously as real possibilities because the assumptions that undergird traditional economic models do not allow for them.

Collapse and recovery scenarios are explicitly ruled out in Solow growth models and other traditional modeling frameworks. These models assume and require that macroeconomic outcomes follow a smooth trajectory, modeled best by a twice differentiable function (Solow, 2007). The seemingly innocuous assumption of smooth growth results from four underlying assumptions detailed in Section 5.1.2. Assumption 1 (**Factor Substitution**) is that substitutes for resources and technology exist – or will exist in a short enough time frame that transitions occur smoothly. This explicitly rules out resource criticality.

Assumption 2 (**Cost-share Theorem**) is that cost shares drive derivatives. That is, models use cost shares of inputs to production to determine their relative impact on production, if their input levels were to change. The cost shares of energy and natural resource inputs are relatively small compared to labor and capital cost shares, which have remained virtually constant at 70% and 30% over time. Thus, modelers expect that production output levels will not be impacted by a natural resource supply shock. Graedel and others argue against this expectation – resource criticality and technological interdependence has likely de-coupled the importance of an input from its cost share

(Graedel et al., 2015a,b; Chen and Graedel, 2015). A supply shock to a natural resource can have a disproportionate, cascading effect on production, despite its relatively small cost share.

Assumption 3 is that economic agents act with **Perfect Knowledge and Foresight**. That is, agents are aware of potential supply shocks, understand the potential impact on production of a supply shock, and take all of this into account in pricing and technological decisions. Thus, it is assumed that the price of a critical, potentially constrained resource results from a perfectly competitive market and that the price will rise proportionately and just in time to signal development of a substitute before resource criticality would impact output. However, this assumption can be unrealistic because the behavior of a complex, interdependent economy may not be as predictable as traditional models suggest. Information needed to allocate resources efficiently or plan for capital investment may be unavailable or incorrect.

Lastly, Assumption 4 is that the economy consists of **Representative Agents** rather than interactions of a multitude of heterogeneous agents. Deep interdependencies that result from specialization accompanied by path-dependent trade networks cannot be captured in even the most advanced dynamic stochastic general equilibrium (representative agent) model (Del Negro et al., 2013). The rich tapestry of economic behavior that leverages specialization and trade for economic growth is celebrated in the economics discipline and is assumed to be occurring in traditional economic models. But, this celebrated trade and innovation must occur in the background. It remains off-stage in traditional economic models for tractability. Trading relationships modeled in such simplified terms cannot capture increasing vulnerabilities to supply shocks.

The strength of the SOCIETIES agent-based model presented here, is that it does not require any of these four problematic assumptions. First, it does not need to assume homogeneity in order to use **Representative Agents** (Assumption 4). Agent-based models can explicitly model the dynamic, interdependent networks that emerge as a result of specialization, trade, and technological innovation decisions of multitudes of heterogeneous agents. This allows for path-dependent, nonlinear trajectories of macroeconomic outcomes that might occur in collapse and recovery scenarios.

Second, SOCIETIES does not have to assume **Perfect Knowledge and Foresight** (Assumption 3). As agents interact, trajectories of macroeconomic outcomes emerge endogenously rather than as a result of predictable calculations. This allows supply shocks to be unexpected and for production to be hampered by over-investment in now defunct capital infrastructure that took place in previous time-steps.

Third, agent-based models in general can allow relationships between inputs and macroeconomic outcomes to emerge endogenously rather than resulting from a pre-defined functional form and estimated parameters. SOCIETIES' framework takes advantage of this and explicitly models how trade and technology drives derivatives rather than **cost shares** (Assumption 2). SOCIETIES models the dynamic relationship between output and all inputs, including capital, labor, technology and natural resources. Thus, the effect on output of a shock to the supply of one seemingly insignificant resource can be traced out over several simulated time-steps by the model.

Lastly, the design of SOCIETIES allows for the possibility that **substitutes for resources or technological devices** may not be available in a short enough time frame to prevent collapse in the face of a supply shock (Assumption 1). This framework is designed to explicitly allow some resources and technology to have disproportionate impacts on production and demonstrate the potential for collapse and recovery scenarios in advanced economies.

The collapse and recovery scenarios examined in this paper demonstrate two important results for understanding the behavior of advanced economies.

First, resource criticality and economic collapse can occur even with generic, homogenous natural resources.[10] In the simulated economies with high levels of technological interdependence, removing any resource led to a large decline in economic output. Our model's largest collapse severity was 31.9% despite an average resource cost-share of just 4.2% (Section 5.3.2). Similarly, Cuba faced a GDP reduction of 35% after losing its oil imports, despite spending a relatively small amount on oil.[11] Therefore, this paper reinforces the biophysical perspective that natural resources have a disproportionate impact on macroeconomic outcomes, not tied to their cost-share. Cuba's economy faced huge productivity losses because they lost portions of their energy supply, a requirement for most economic activity. Just as in our model, Cuba's GDP eventually started to recover as they implemented new policies and altered the structure of their economy. Agents in SOCIETIES needed to restructure their economy and redesign technology away from the removed resource. Qualitatively, the Cuba collapse and recovery in Figure 5.2 is similar to our model's collapse and recovery in Figure 5.13.

[10]Every resource has the same initial properties, though they cannot be directly substituted in device recipes.

[11]Ideally, we could compare the total Cuban oil spending to our model's resource cost-share. However, there is poor or missing data availability for Cuban imports. Additionally, the USSR heavily subsidized Cuba which skew import and export prices (Purcell, 1991). We know that Cuba imported roughly 10-12 million tonnes of oil equivalent (mtoe) in 1989, the start of their collapse (World Bank, 2016b,a). Cuba's GDP was 27 billion USD (nominal), and both the WTI and Brent spot price of oil was roughly $18 per barrel (nominal). Assuming Cuba paid this spot price for its imports (a cost of 1.3 billion USD) and all energy imports were oil, their cost-share of oil would have been roughly 5%.

Second, the intensity of a potential economic collapse may be unexpected. As technological advancement leads to exponentially higher levels of observed economic output, it is also creating increasing levels of unobserved vulnerability. This idea parallels Graedel's comments on material use. As products become more optimized for their given task, each material "is carefully chosen to enable exquisite performance, precise physical and chemical properties essentially become requirements", leading to a varied mix of resources used to create a final product (Graedel et al., 2015b). Intel, for example, increased the number of elements within computer chips from 12 in the 1980s to roughly 60 by 2000 (Council et al., 2008). As technological interdependence continues to increase, traditional models of macroeconomic behavior will increasingly miss the mark. Agent-based models and other approaches to understanding the behavior of a complex economy should continue to be validated against the empirical record.

### 5.4.1 Model assumptions and limitations

A drawback to agent-based models is that they require several assumptions, often of a different nature than traditional assumptions used in mainstream economic models. This section identifies several assumptions related to each of the elements of the model (agents, resources, trade, and technology) and discusses the impact of these assumptions on the results.

Two key economic assumptions undergird the model and create the conditions for collapse and recovery: (1) learning-by-doing (diminishing effort curves); and (2) diminishing marginal utility. Together, these two assumptions lead to specialization and trade, and increasing levels of technological interdependence. These assumptions are rarely disputed in the vast majority of economics literature, although a variety of functional forms to model them could be used. The general functional forms chosen for this paper are common to the mainstream literature. The simulation results are robust to a wide range of specific parameter values used in them. However, full parameter sweeps, and exploration of other functional forms, is planned for future work.

While traditional macro-economic models may err on the side of assuming too much factor substitutability, this paper errs in the opposite direction. This model assumes resources have no direct substitutes. Resource substitution abounds in reality, although there is debate on the degree of substitutability. Jewelry, for example, can be crafted out of many different metals that all use similar refining and manufacturing processes. However, cars cannot run on coal – a type of energy resource – without a significant redesign. SOCIETIES treats all devices more like the car than the jewelry; redesigns are always needed in the model. Thus, this model assumption biases the results toward greater collapse and recovery scenarios than would occur in reality.

SOCIETIES also assumes that there is no technological redundancy. But, redundancy is quite common for many technologies. Several alternative ways to produce electricity currently exist side-by-side in the economy. Within the model, only one device exists for each resource at each technology tier. That is, a device in SOCIETIES more closely represents an entire class of real devices (of the same complexity level) which all provide the same function, such as producing electricity. At this level of abstraction, the assumption is that everything within a class of devices is built from the same materials or components – all electronics rely on silicon, for example. Adding technological redundancy and factor substitutability to the model might reduce or even eliminate collapse and recovery scenarios. We intend to explore this in future work.

The assumption that the resource supply shock is exogenous, instantaneous, and unforeseen, also biases the results toward greater collapse and recovery scenarios. In real-world economies, agents might take preventative measures to reduce or prevent collapse. However, the bias toward more severe collapse and recovery scenarios is offset by assumption of infinite resources for all but the constrained resource.

The assumptions regarding agent behavior also bias the results against severe collapse and recovery because they intentionally stack the deck against the formation of specialization, trade, and technological interdependence. For example, agents are endowed with equal access to resources and have the same level of bargaining skills and power.

Much of the ABM literature has focused on examining the macroeconomic effects that emerge from the interaction of agents that exhibit these more realistic micro-behaviors. The evidence suggests that incorporating these assumptions diminishes the resilience of the economy and increases vulnerability (Tesfatsion and Judd, 2006; Epstein and Axtell, 1996; Hamill and Gilbert, 2016). Thus, the fact that the model on balance is biased against producing collapse and recovery scenarios means that the simulation results in this paper are likely to understate the potential collapse and recovery scenarios in the real economy.

### 5.4.2 Future work

The purpose of this paper was to demonstrate the capacity of an agent-based model to shed light on the relationship between resource criticality and technological interdependence. Despite each of the limitations outlined in the previous section, we believe SOCIETIES is on a promising path to model biophysical economics problems. Agent-based models provide a significant number of advantages over traditional economic approaches, and a good deal of future biophysical economics research lies in areas that traditional economic approaches cannot adequately capture. Agent-based computational economics in general, and SOCIETIES in particular, is more readily able to capture the complexity of our economic systems leading to insights regarding system behavior that has previously been inaccessible.

In addition to the future work testing the current model's limits outlined in the previous section, extensions to the model are planned. First, by creating specific resource types, SOCIETIES can examine how constrained supplies of energy, water, or materials, for example, might have different impacts on economic output. We can also create types of environmental pollution, stemming from the use of certain resources, which negatively impact the economy. Second, by introducing limited resources and providing agents some knowledge about resource stocks, SOCIETIES can examine various policy strategies for preventing or attenuating collapse due to resource depletion.

Finally, future plans also include using real-world data to validate the model. The current paper is purely a theoretical exercise, although it is encouraging that the simulated time series appear consistent with empirical time-series.

By incorporating these model extensions, we hope to build an empirically grounded agent-based model of society's economic & technical development that will help inform energy, economic, and environmental policy decisions.

## Relation to broader dissertation

The three themes of this dissertation are woven into and throughout this chapter. These themes are:

1. BPE modeling allows deeper insights into how the economy is reliant on resources
2. Models are better informed and constructed with granular and detailed data
3. Detailed, high resolution models enhance decision-making capability

This biophysical economics model is built from the ground up to showcase how resource-based technology may cause economic constraints in the face of a supply shock. As such, it is nearly the epitome of theme 1. Because of the way the model was constructed, it is able to capture the complexity of an industrial economy's reliance on technology in ways that most mainstream economic models fail to consider. Only by relying on biophysical economic principles can the insights regarding resource criticality be considered.

Theme 2 is likely weakest within this chapter. Indeed, a purely theoretical model is not reliant on data, let alone the granular and detailed kind. However, this chapter could be expanded on to include real world data, such as resource estimates. International trade data could help calibrate trading between agents. Agent-based modeling as a framework is well suited to take advantage of granular data to inform agent behavior.

The SOCIETIES model also showcases theme 3. The benefits of fallback technology and stockpiles manifests itself within this model of stochastic technology innovation. A resource supply constraint could potentially happen to many different resources (Graedel et al., 2015b), but how widespread the effects of a constraint spread has rarely been modeled. A key takeaway for policymakers is that resource constraints could have deep, lasting effects to economic wellbeing, and that more work ought to be done on both substitutable technology (even if that technology is less efficient and only exists as a fallback option) and stockpile capacity.

# Chapter 6

# Conclusion

The goal of this dissertation was to map out and extend current biophysical economics modeling strategies. Specifically, the objectives were to:

1. Fully characterize the current landscape of biophysical economic models

2. Identify potential research gaps within the field

3. Implement and extend upon three modeling frameworks to demonstrate their use and advance the field of biophysical economic modeling

Many of the results of these objectives can be observed in Figure 6.1. The biophysical modeling landscape was characterized in Chapter 2 with research gaps identified. The biophysical economics modeling landscape was "filled in" by chapters 3,4, and 5. The resulting image in Figure 6.1 shows how much of the biophysical economics landscape has been investigated and extended by this dissertation.

Additionally, the dissertation contained three underlying themes. These themes were:

1. BPE modeling allows deeper insights into how the economy is reliant on resources

2. Models are better informed and constructed with granular and detailed data

3. Detailed, high resolution models enhance decision-making capability

These themes were showcased throughout each chapter. Theme 1 appeared within: 1. Chapter 2 though the history of biophysical economics modeling; 2. Chapter 3 through the accounting of

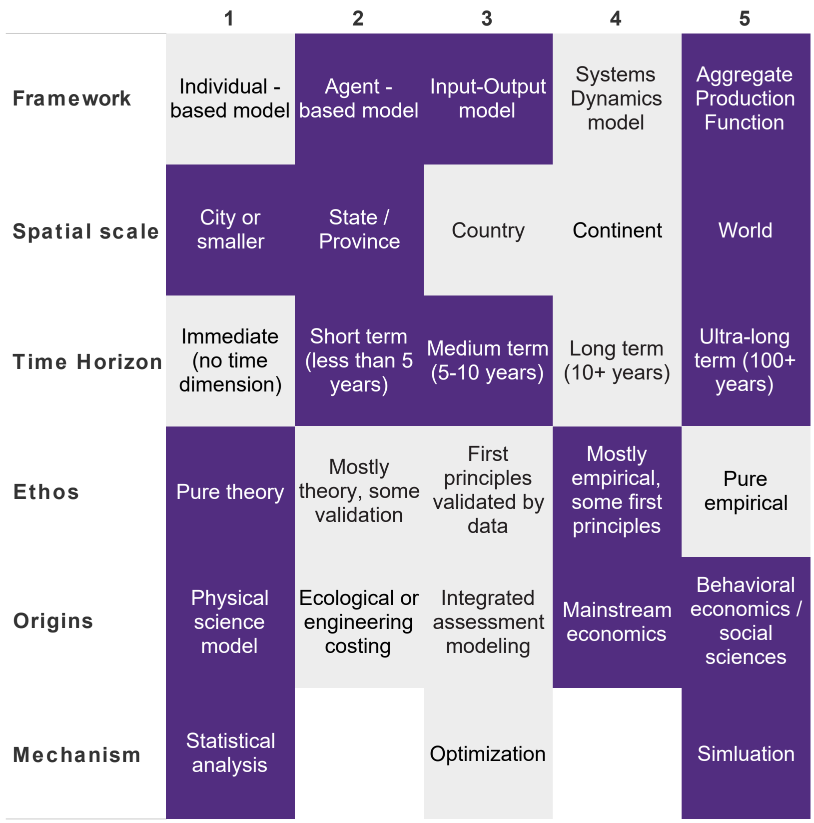


Figure 6.1: Models from Chapters 3, 4, and 5 mapped to Chapter 2's model characteristics. A large portion of the modeling space has been covered.

food, energy, and water and their relationship to GDP; 3. Chapter 4 through the impacts of policy through the Clean Air Act and the accounting of emissions; 4. Chapter 5 through the economic consequences of resource criticality.

Theme 2 appeared within: 1. Chapter 2 though call to take advantage of increased data for validation; 2. Chapter 3 through the use of detailed resource and economic data; 3. Chapter 4 through the use of granular, mine-to-power plant shipment data; 4. Chapter 5 through the potential capability of agent-based models to take advantage of highly granular datasets.

Theme 3 appeared within: 1. Chapter 2 though commentary on model credibility; 2. Chapter 3 through the possible policy actions at the city level; 3. Chapter 4 through future research opportunities such as optimization and CCS studies; 4. Chapter 5 through highlighting the importance of resource criticality to policymakers.

The combination of these themes, and the evidence provided by each of these chapters, point towards new modeling directions which can explicitly account for the biophysical basis of the economy. We can best plan coming resource and energy transitions only by holistically studying the interactions between economy and biosphere.

# Appendices

# Appendix A Appendix to Chapter 2

## A.1 BPE model publishing across journals

Figure 2 shows the number of results from our initial literature search described in Section 2.3.1. The colors represent whether or not an article made it through the entire screening process; the black bars represent the BPE models categorized and included in the results of this paper. The grey bars represent all other papers that were screen out of our analysis.

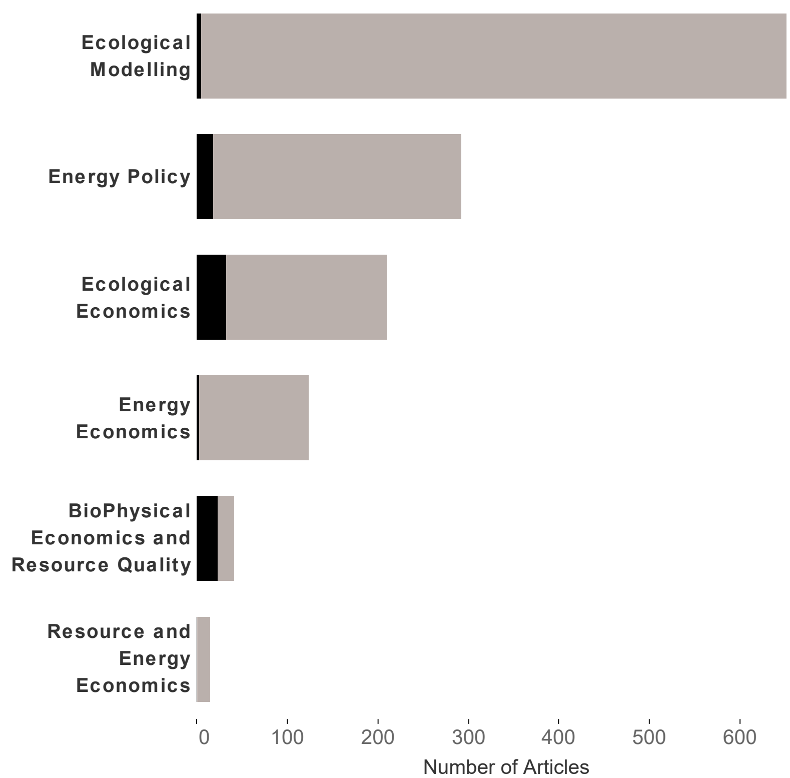


Figure 2: Number of articles from initial literature search for each journal. The grey color represents articles that were excluded from categorization. The black color represents articles that made it through the screening process and were categorized.

The majority of articles were from the journal Ecological modelling, possibly because the name of the journal included the "model" keyword, one of our search parameters. Ecological modelling also had the lowest percentage of BPE models within the journal, suggesting that BPE does not align well with the goal and scope of the journal (the same might be said of Resource and Energy Economics, which is surprising to the authors).

The largest number of BPE models were found in the journal Ecological Economics. This suggests a certain amount of overlap between Ecological Economics and BPE. The journal Biophysical Economics and Resource Quality (BERQ) has the largest percentage of BPE models, followed by Ecological Economics and Energy Policy. BERQ's high percentage indicates that its scope fully aligns with BPE and the editors filter models appropriately. Although BERQ was launched in 2016, the rate of non-BERQ BPE models has remained fairly steady during the time period under review (2009-2019). This indicates that field has grown over the past three years, and BERQ has captured this growth without negatively affecting publishing rates in other journals.

## A.2 Full taxonomy scheme

For reference, the full taxonomy scheme is supplied in Table 1.

Table 1: Full model taxonomy scheme.

| **Characteristic** | **Category** | | | | |
|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** |
| Framework | Individual-based Model | Agent-based Model | Input-Output Model | Systems Dynamics | Aggregate Production Function |
| Spatial scale | City or smaller | State / province | Country | Continent / world region | World |
| Time horizon | Immediate (less than one year) | Short term (1-5 years) | Medium term (5-10 years) | Long term (10+ years) | Ultra-long term (100+ years) |
| Ethos | Pure theory, no connection to real world) | Mostly theory, limited validation | First principles validated by real data (e.g. IAMs) | Mostly empirical, some first principles | Pure empirical (e.g. econometric) |
| Origins | Physical science model | Ecological or engineering costing | IAMs | Mainstream economics | Behavioral economics / social sciences |
| Mechanism | Simulation (model has to "run") | | Optimization | | Analysis (i.e. statistical modelling) |

# Appendix B Appendix to Chapter 5

## B.1 Optimal number of model runs

Because SOCIETIES is a stochastic model, it is important to determine how many model runs provide an accurate representation of the probability space. There is a tradeoff between this accuracy and required computing time. SOCIETIES requires a nontrivial amount of computing time, so determining the optimal number of runs was a worthwhile exercise.

We followed Lee et al. (2015)'s approach towards determining the optimal number of runs for the main analysis of SOCIETIES. Because the tier 4, 4 components case saw the most variation (see Section 3), we ran that case 100 times. The steady state utility values (see Table 1) were determined for each run in order to create a population for a bootstrap analysis. Sets of 5, 10, 15, etc. were sampled 100 times each. A coefficient of variation was generated for each set, and the distribution of all 100 coefficient of variations is shown in Figure 16.

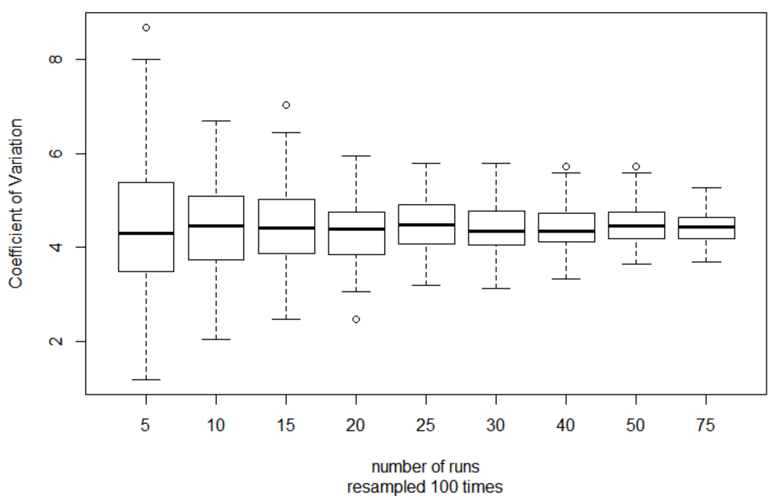


Figure 3: Determining the optimal number of model runs through bootstrapping. The vertical axis shows percentages. Note that the horizontal axis is not a continuous number line.

The variation between sets decreases as the set size increases. However, increasing the set size has a diminishing payoff. Past a set of 30 runs, there is little reduction in sample variation. Therefore, the default number of runs was chosen to be 30 in order to balance capturing model stochasticity and required computational resources.

## B.2 Number of agents and resource variations

Two key parameter choices for SOCIETIES is the number of agents and number of resources. The number of agents should fulfill these objectives:

1) There ought to be enough agents to produce relatively smooth model outputs. Too few agents lead to large day-to-day variations in outputs such as mean agent utility or units gathered. If all agents decide to build devices for their entire day, the "units gathered", and other indicators, would go to zero. Increasing the number of agents reduces the probability of this happening. 2) Too many agents would take too much computing time, a relatively small number is computationally efficient. 3) An even number means that pairing up to trade would work nicely. Numbers within the range of roughly 10-50 would work well; we chose 24 for the main analysis. While it is somewhat arbitrary, 24 is easily divisible – it is easy to do diagnostic runs with 1/2, 1/3, 1/4, or 1/6 the number of agents.

Regarding resources, there ought to be enough for distinct recipes of high-tier devices. Looking at Figure 8 (the example recipe tree), if there are too few resources, recipes for devices might begin to significantly overlap. While less than 24 resources would still work, 24 provides a good amount of recipe variability. Additionally, high-tier devices should be dependent on nearly all resources in order to appropriately model the interdependencies of advanced technology; too many resources would undermine this desired effect.

We varied the number of agents and resources to determine how influential the choices were on model results; this is shown in Figure 17 below.

The results are similar across parameter sets, although the collapse tends to be slightly less severe with a large number of resources. In these scenarios, agents have too many resource options to extract or use in devices. They do not specialize as quickly, reach a higher utility (due to more high-utility resource options), and face a smaller collapse because the importance of the removed resource is diluted - a tier 4 device might not be dependent on every resource. So, despite increased computational time, adding more resources does not provide more information about tracing interdependencies throughout the economy.

Similarly, adding more agents than resources results in unnecessary redundancies. In these cases, each resource may have many agents specializing in its extraction. Agents begin to lose their heterogeneity, and modeling two nearly identical agents adds computational time without adding

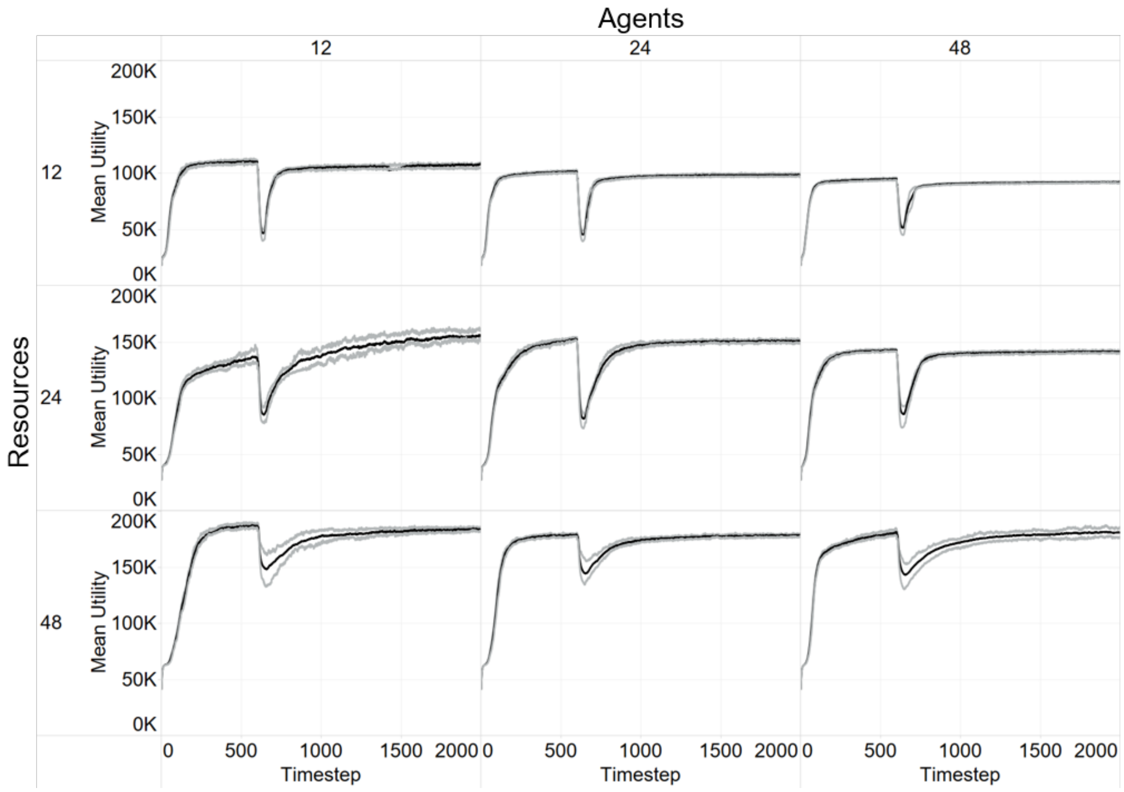


Figure 4: Mean Utility for collapse scenarios as a function of number of agents and resources. The black line represents the average of 30 runs while the grey lines represent quartiles. These runs have the maximum device tier set to 4 and components per device set to 6.

information relevant to the study of technological interconnectedness. Therefore, we chose to model 24 agents and 24 resources, giving each agent an opportunity to uniquely specialize in a resource.

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