DEVELOPING AN ELECTRICITY SPECIFIC MULTI-REGIONAL INPUT-OUTPUT MODEL FOR ENERGY POLICY EVALUATION AND LIFE CYCLE ASSESSMENT

by

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Input-output (IO) models have been used in Life Cycle Assessment (LCA) to help understand the economy-wide impacts of goods and services, expanding the boundaries of more traditional process-based studies. IO models are particularly suitable for studies focusing on industries that are part of the supply chain of many other processes, as is the case with electricity generation. However, existing IO-LCA tools usually fail to account for the large variation in regional electricity consumption mixes within the economies they describe, providing only average emissions estimates for electricity use. Using average emissions estimates can lead to misleading results when studying a process that differs significantly from the economy-wide mix.

This dissertation addresses this shortcoming by creating a multi-region input-output model (MRIO) focusing on the power generation and supply (PGS) sector that features a mixed-unit PGS sector disaggregated by generation type. The sector disaggregation procedure is combined with region-specific electricity information as well as electricity trading data to yield a technologically and geographically disaggregated model. This method allows for better modeling of both regional supply chains and emissions, yielding for region specific estimates that can be used with process-based methods to build more accurate hybrid LCA studies. While the focus is on the U.S. economy, the methodology can be easily adapted to any region(s) for which the relevant data is available.

The model is used explored in two different cases studies. First, environmental effects of national and regional changes in electricity consumption are analyzed using electricity projections to the year 2030. This scenario examines changes to greenhouse gas (GHG) emissions and water consumption (WC) by state and industry given the projected changes. The results show that tradeoffs between GHG and WC emissions per MWh differ for specific states and industries. The second case study looks at the use of electricity by data centers, both at a regional scale and from a practical business perspective, and explores the possible tradeoffs related to switch from regional grid electricity to dedicated renewable sources for operating data centers. The results focus on the effect that geographic distribution of data centers in the U.S. have on their emissions.

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1.0 INTRODUCTION

1.1 MOTIVATION

Electricity generation is a critical industry in the U.S., representing about 2% of GDP in 2015 (U.S. Bureau of Economic Analysis 2017). Its importance extends beyond its direct economic output, as availability of electricity is a necessary input for most sectors in the economy, without which the availability of many goods and services would be severely impacted. Electricity generation is also one of the primary sources of many environmental burdens for most products and processes, representing 38% of CO_2 equivalent emissions (U.S. Environmental Protection Agency 2017) and 45% of water withdrawals (Maupin 2014) in the United States. The widespread need of electricity is met by many different electricity generation technologies, which use distinct primary inputs and thus have different supply chains and associated environmental impacts. This makes analysis of the economic and environmental impacts of power generation both vital for energy policy at national and regional scales, and challenging to perform.

Life cycle assessment (LCA) has become a standard method to evaluate environmental impacts of goods and services, and can be a useful tool to help us understand the impacts of electricity generation. However, performing a traditional process-based LCA can be an expensive and time-consuming task, with relatively narrow boundaries that cannot provide much information beyond the direct impacts of power generation (Lenzen 2000). An alternative approach is to use national economic accounts and environmental emissions data to produce fast, economy wide impacts of electricity generation; Economic Input-Output (IO) LCA is an example of this approach (Green Design Institute 2013). However, since IO models consist of aggregated data, they suffer from a different problem: the level of aggregation makes this approach inadequate for analyses of specific locations and/or processes difficult.

A way of dealing with the constraints of process-based and IO-LCA approaches is to combine them in what is called a hybrid LCA (Suh et al. 2004), using the IO model to help define the scope, boundaries and/or indirect impacts of power generation, while using a process based LCA to determine the more direct impacts. Still, combining the IO and process-based LCAs in a consistent manner may prove difficult, due to different functional units, geographic scales, and industrial processes represented by each approach. For power generation, this is especially true, given that this industry is represented by a single sector in the U.S. IO tables, but represents many diverse energy technologies. Such a broadly defined and aggregate sector limits the utility of the IO accounts for energy policy analysis, as it cannot distinguish the sources specific sources of emissions found in the grid.

In this work, national Input Output Accounts developed by the U.S. Bureau of Economic Analysis for the U.S. economy are supplemented with additional data for electricity generation to create an electricity focused multi-regional input-output model (MRIO). This model disaggregates the single sector electricity in the IO accounts using plant specific data that better represents the individual electricity generation technologies and makes it more compatible with electricity generation processes usually found in bottom-up approaches (Swiss Centre for Life Cycle Inventories 2010), thus facilitating the creation of hybrid models. Physical data, in the form of electricity flows, are introduced in the economic transactions of the MRIO tables to reduce the biasing effect that price can introduce in monetary models (i.e. making the physical quantity and price interaction inherent in economic models explicit). Finally, state-specific information that better represents the industries present in individual states as well as state-specific electricity generation mixes are included. The resulting MRIO model has the ability to estimate regional economic and environmental impacts of electricity consumption and individual electricity generation technologies, while still showing economy-wide monetary and energy flows associated with those impacts, a feature that process-based approaches lack.

The above steps constitute a useful framework for more than just modeling electricity generation. They can be adapted for any sector for which there is geographic, economic, and environmental data that can be included in the MRIO model (e.g., for mining sectors where there is data for each type of mine). They also allow for better modeling of hypothetical or projected policy scenarios since the supply chain demands and purchases of the new PGS technologies can be tailored to more detailed sectors, at the regional level, and without price distortions. The methods used here can be used for other commodities besides electricity generation so that they can be tracked in physical flows, using the unit that is most appropriate for the particular commodity under consideration given that price data is available (e.g. tracking natural gas flows in cubic feet for the Natural Gas Distribution sector). Finally, the addition of regional information and creation of a multi-regional model can add geographic context to any location-specific LCA study.

1.2 RESEARCH QUESTIONS

1. How can the MRIO model be used to evaluate the environmental impacts and energy flows associated with major nationwide changes to the electricity sector?

Introducing individual states as sectors in the model reduces the burden on the model user by removing their need to include or adjust for differences in regional electricity grids. States have considerable authority when implementing energy and environmental policy regarding electricity generation, which makes them the right spatial scale to address both region wide issues (when considered individually or as a combination of a few states) or nationally (when considering the aggregate effect of the individual state policies). While there are several Multi-Regional models for other countries and regions (Wiedmann et al. 2010; Lenzen et al. 2013c; Su and Ang 2014; Wood et al. 2015), there are fewer models that include distinct regions in the U.S. (Cicas et al. 2007; Caron et al. 2014). However, these do not represent the individual electricity generation technologies and their interactions with other sectors of the economy, and the PGS sector is not detailed at the state level. The model's capability of representing complex regional electricity scenarios and their effects on other economic sectors makes it a valuable tool that can be used on its own for screening analyses or in conjunction with other methods that focus more specifically on deployment of electric power generation technologies, such as the Regional Energy Deployment System (ReEDS) or MARKet Allocation (MARKAL) models (Short et al. 2011; Shay et al. 2008).

The MRIO model can be used to evaluate various scenarios ranging from future electricity production projections at the national level to impacts of electricity consumption for private industries. To explore this range of applications, two example scenarios were developed (and described in Chapter 4 in detail). The first scenario demonstrates how the MRIO model can be used to evaluate the potential impacts of national energy policies. EIA projections are used as a basis for developing a scenario of future electricity consumption at the state level in the year 2030. Impacts in terms of greenhouse gas (GHG) emissions and Water Consumption (WC) changes at both the national and state levels, as well as the effects that such changes have on other industries in the economy, are estimated. The second scenario demonstrates how the model can be used as a screening tool for exploring changes not only at the state level, but also by an individual industry committed to achieving ambitious sustainability goals. This scenario focuses on the GHG and water consumption impacts related to changes in electricity consumption for a single IO industry: data centers. The model is used to estimate emissions changes caused by a hypothetical relocation of data centers throughout the U.S., as well emissions reductions caused when privately owned data centers are powered using dedicated renewable electricity generation. These scenarios are two examples of the types of questions the model was designed to address, and provide an example of how the model can be used to explore effects of electricity policies at several different levels (national, state, individual industry and even company level).

2. How do emissions estimates change when flows are tracked in economic vs. physical flows in an IO framework?

By introducing energy units in the IO model, emissions are directly connected to the physical amount of consumed electricity rather amount of economic activity generated by electricity consumption, and decrease the uncertainty associated with fluctuating prices of commodity and produced electricity. This increases the confidence of impact estimates associated with life cycle assessments of power generation, and of different products, processes, and end-users of electricity. By having the IO model use energy units, model results are more directly compatible with process-based approaches, which measure impacts in terms of physical units. The increased compatibility and accuracy in PGS related results is beneficial for LCA practitioners and policy makers wishing to understand PGS's impact from cradle to grave by providing a screening tool that tracks electricity flows throughout the economy while still remaining less complex than other energy modeling efforts which usually rely on detailed optimization procedures (such as the National Energy Modeling System, NEMS).

3. How can we add resolution to IO models while maintaining its national (economy-wide) scope?

By disaggregating one sector into multiple constituent sectors in input-output life cycle assessment (LCA) models, we can introduce process-level detail into an IO context that allow more specific questions. In particular, by disaggregating the Power Generation and Supply sector into individual generation-specific sectors we can more easily investigate energy policy questions with the IO framework, such as what the economy-wide impacts of individual renewable generation technologies are. Further, we can make use of existing process level detail for individual PGS technology types to validate that the disaggregation process results in similar emissions estimates, as shown in Chapter 2. In this way the disaggregated model can be used for hybrid LCA studies since the emissions estimates are compatible with bottom-up approaches while still maintaining the economic connections of the PGS sectors to the rest of the economy, something that is rare for most process-level data sets (Majeau-Bettez et al. 2011).

1.3 BACKGROUND

1.3.1 Electricity

Electricity generation, distribution, and consumption plays an integral part in the U.S. economy. Directly, electricity consumption represents roughly 40% of total residential energy consumption (U.S. Energy Information Administration 2010a); over 80% of total energy consumption in commercial buildings (U.S. Energy Information Administration 2012); and over 13% of total energy consumption by manufacturing sectors (U.S. Energy Information Administration 2010b). However, the importance of electricity for the economy is greater than that suggested by its direct consumption, as can be surmised by the consequences of not having continuous access to electricity. The best example of this is the North East blackout of 2003, which remains the largest black out in U.S. history. It affected only 8 states in the U.S. for a period of only a few days, yet it is estimated to have cost up to $10 billion in lost productivity (EIA 2004). For comparison, the total profit of the electric power industry in 2003 was $29 billion (U.S. Energy Information Administration 2004). This indicates that the influence of power generation extends beyond its direct economic contributions, and that any policies that affect this industry have the potential to affect the many different consumers that rely on it.

In addition to being an important piece of the economy, the Power Generation and Supply (PGS) sector is equally or perhaps even more important from an environmental perspective. Due to the large scale of electricity generation as well as the many different power generation technologies that are part of the U.S. grid, the PGS sector produces many different types of pollutants, such as CO_2, NO_x, SO_2, P.M., etc. that have varied and adverse effects on the environment. This work focuses on two specific environmental effects of electricity generation:

greenhouse gas (GHG) emissions and water use. Electricity generation was responsible for as much as 38% of GHG emissions in the U.S. in 2015 (U.S. Environmental Protection Agency 2017) and up to 45% of all water withdrawals in 2010 (Maupin 2014). As one of the main drivers of climate change, GHG emissions are subject to national, regional, and local regulation (e.g., Renewable Portfolio Standards, Clean Power Plan, etc.), as well as corporate tracking and management efforts, while water use has come under increased scrutiny in recent years due to extreme droughts and limited water availability in southwestern U.S. states. In particular, water use for power generation is the focus of U.S. Department of Energy's Energy-Water nexus effort, which seeks to improve the modeling and analysis of power generation systems with the intent to assist in policy formulation with regards to climate change and energy security (U.S. Department of Energy 2014).

Besides regulations and policies set by various levels of government, there are other factors that are likely to cause the electricity industry to undergo considerable changes. These factors include variability in the prices and supplies of different fuels, such as natural gas and coal; the aging and decommissioning of baseload coal and nuclear power plants; and continued research and development of solar, wind, biomass, and other renewable electricity technologies. Given the potential for swift and extensive change to the power generation industry, it is important for policy and decision makers to analyze the system-wide impacts of their actions, since the implications of their choices could have long lasting effects.

1.3.2 Life Cycle Assessment

One tool that is ideally suited for comparing the various options in policies and technologies for power generation policies and deployment is life cycle assessment (LCA). LCA is a method which quantifies the environmental impacts throughout the life of a product, service or sector. This type of analysis is useful for understanding the environmental effects of a product or process in each part of its life cycle, from raw material extraction to disposal and end-of-life. A fundamental aspect of LCA is its requirement for a set of elements to ensure any comparisons of processes or technologies is intrinsically fair and “apples-to-apples”. This is crucial when considering impacts of electricity, given the significant differences in electricity generation technologies that make up the U.S. power grid. Additionally, LCA is flexible and broad enough that it can also be used to analyze not just individual products but also effects of policies (whether government or corporate), including the potential economic, environmental, and even social impacts (e.g. forced labor, health and safety conditions for workers, etc.) (Arcese et al. 2013). Several organizations have developed standards for LCA, including the Society for Environmental Toxicology and Chemistry (SETAC) (Fava 1991), the Environmental Protection Agency, and the International Standards Organization, as part of the ISO 14000 Environmental Management Systems standards (International Standards Organization 2006). Figure 1.1 shows common life cycle stages considered in LCA.

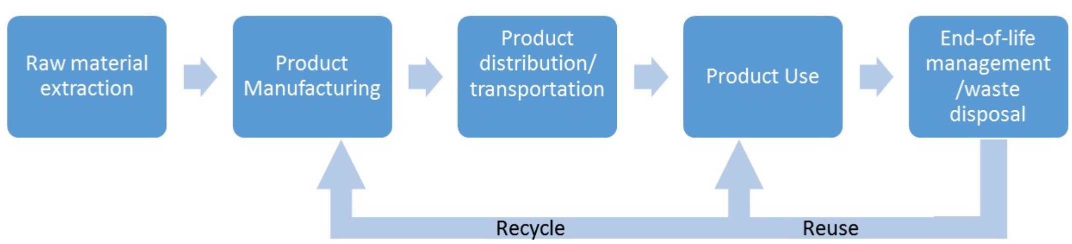

Figure 1.1: Common life cycle stages considered in LCA

1.3.2.1 Process Based LCA

Initially, the standards developed for LCA studies were focused mostly on individual products or services and focus on defining a product system with individual unit processes that described the transformation of inputs of the product system (e.g., barrel of oil) to outputs (e.g. diesel gas). This method is known as process-based LCA, and constitutes a bottom-up approach in which different types of data (e.g., energy, emissions, costs, etc.) are collected for each unit process needed to generate the product under study. There are two main ways data for process LCA are modeled: process-flow diagrams or using a process matrix. Figure 1.2 is an example of a process flow diagram of product system for coal generation, and shows how or how product systems and system boundaries are usually depicted for process LCA. The second main approach for modeling a process LCA is using process matrix, where the different processes in the product system are organized such that rows represent the physical balance of the different types of product outputs in the system (e.g., kWh, gallons of diesel, etc.) and each column represents a unique process. For either representation (diagrams or matrices), as the number of processes in a study increases, the LCA becomes more complex and the data requirements more onerous, requiring a boundary to limit the system to a manageable size.

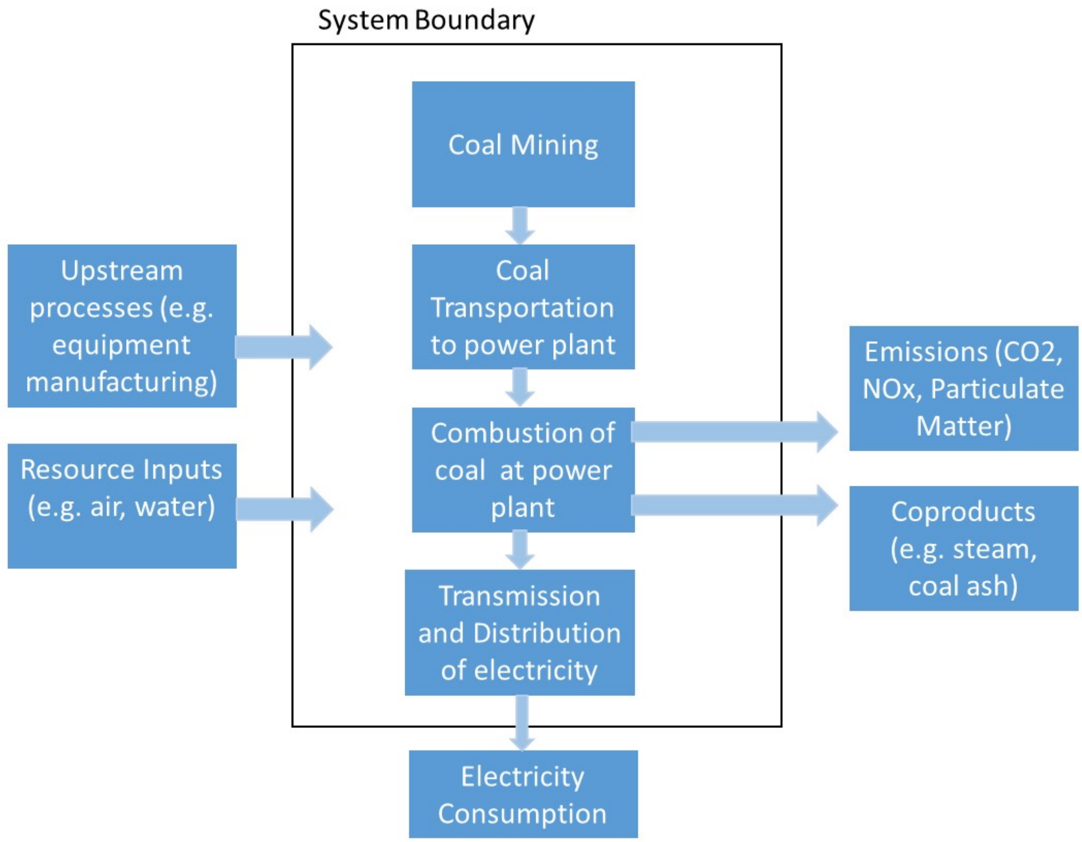

Figure 1.2 Conceptual representation of product system and system boundary for coal-based electricity production

Despite being addressed in the standards (e.g. using methods such as substitution of products and system expansion), these boundaries are often arbitrary and significant portions of the product's supply chain may be neglected leading to incomplete, inaccurate, or uncertain results (Lenzen and Dey 2000; Williams et al. 2009a; Matthews et al. 2008), normally referred to as truncation errors. Even for process LCAs that rely on large datasets with connected process flows, such as those conducted with proprietary software (PE International 2008; Pré Consultants 2008) and data (Swiss Center for LCI 2009), the boundary issue is a problem, as it is likely that certain sectors of the economy are underrepresented in such datasets (Majeau-Bettez et al. 2011) (Weinzettel et al. 2014) or that the assumptions and boundary choices are different between datasets and not transparent to those who view the results. For practitioners, choosing the right balance between completeness, practicality, transparency, and costs is difficult, and dissimilar boundaries for similar products cause problems for comparing across studies.

1.3.2.2 Environmentally Extended Input Output (EEIO) LCA

An alternate approach to LCA that compensates for the boundary selection problem, which can be used in conjunction with the process-based approach, is to use top-down economic IO methods for estimating environmental impacts. This approach is based on methods originally used for macroeconomic analysis (Leontief 1987; Leontief 1986; Leontief et al. 1970), and enables the expansion of the system boundary of process-based studies by using the monetary transactions of the economy as a way of measuring the production of goods and services. The Economic Input-Output Life Cycle Analysis (EIO-LCA) (Hendrickson et al. 1998; Lave et al. 1995; Horvath and Hendrickson 1997; Joshi and Lave 1998) and the Ecologically Based Life Cycle Assessment model (Eco-LCA) (Bakshi and Small 2011) are example implementations of this method. As this is the main focus of this work, this framework is explained in more detail in this section.

In the U.S., EEIO LCA models can be constructed from the U.S. Bureau of Economic Analysis survey data which records what industries produced and what they purchased to produce it; the latest data is for the year 2007 and covers approximately 390 distinct industries and commodities (U.S. Bureau of Economic Analysis 2013). The basic components of the IO model are the Supply and Use tables. The Supply table has commodities (types of goods and services produced) on the rows and industries (the different producing sectors) on the columns, and shows the sources of commodity production by industries. The Use table is similarly arranged, and shows the use of commodities by industries (i.e. each industry's supply chain). The Use table additionally has value-added rows, such as wages and taxes, and final demand columns. Together, these tables describe the monetary flows of the economy. Their use for input-output calculations follows. (Note that if the industry and commodity sectors are the same, the Use table is equivalent to the square input-output table).

Let U represent the inter-industry transactions part of the Use table with n commodities and m industries (i.e., excluding the value-added and final demand portions of the Use table). U is size $n \times m$ where u_{ij} represents the amount of commodity i used by industry j. Similarly, let V represent the $n \times m$ supply table where v_{ij} represents the amount of commodity i produced by industry j. Let g be a $1 \times m$ vector where g_i represents industry i's total output. Finally, let q be an $n \times 1$ vector where q_i represents the total amount of commodity i produced. Then the direct requirements (or technical coefficients) B matrix can be found as

$$B = U\hat{g}^{-1} \tag{1-1}$$

where $\hat{g}$ indicates a square matrix where the elements of the vector are on the diagonal. This matrix defines, for each industry, the amount of each commodity needed per unit output. Similarly, the market share matrix D, which defines the proportion of each commodity produced by each industry, can be found as

$$D = V'\hat{q}^{-1} \tag{1-2}$$

where V' indicates the matrix transpose. For the U.S. IO tables, the market share matrix is adjusted for the production of scrap by removing the value of scrap in each industry from the industry's total output; let W refer to this adjusted matrix. After this adjustment, we can find the industry by commodity total requirements matrix, L[1]:

$$L = W(I - BW)^{-1} \quad (1\text{-}3)$$

Note that there are several different approaches to constructing the model's total requirements tables, depending on what technology assumptions are used (i.e., industry-based vs. commodity-based technology assumptions) and how the final demand and total impacts need to be expressed (i.e., industry by industry, commodity by commodity, or industry by commodity). In this work we are using the industry by commodity, industry-based technology assumption. This is because we want to look at the impact that different prices of one commodity, PGS, have for different industries (thus necessitating industry by commodity total requirements), and the desire to keep the input structure of PGS consistent (thus necessitating an industry based technology assumption). More detail in the derivation and use of these different total requirements matrices and technology assumptions can be found in Miller and Peter D. Blair (1985).

[1] Note that this equation is the industry by commodity equivalent of the more commonly used square matrix representation of the Leontief Inverse:

$$L = (I - A)^{-1}$$

where A is the square direct requirements matrix.

This matrix can then be used in the standard Leontief equation,

$$X = L * Y \tag{1-4}$$

where Y is an $n \times 1$ vector of commodities representing the final demand and X is a $1 \times m$ vector of industry throughput necessary to meet that final demand.

This economic framework can be extended for use in LCA by creating a vector of emissions intensities per unit of output for each industry (e.g., Tonnes of CO_2 equivalent per $M of output). Let R be a $1 \times m$ vector containing these emissions intensities. Then we can use equation (1-5) to calculate the emissions associated with the production specified in the final demand vector Y:

$$E = R * L * Y \tag{1-5}$$

where E is a $1 \times m$ vector of resulting emissions. If R is expanded to represent k different pollutants, then R becomes a $k \times m$ matrix and the use of equation (1-5) results in E being a $k \times m$ matrix of emissions associated with the production specified in Y. Figure 1.3 shows the final components of the EEIO LCA framework.

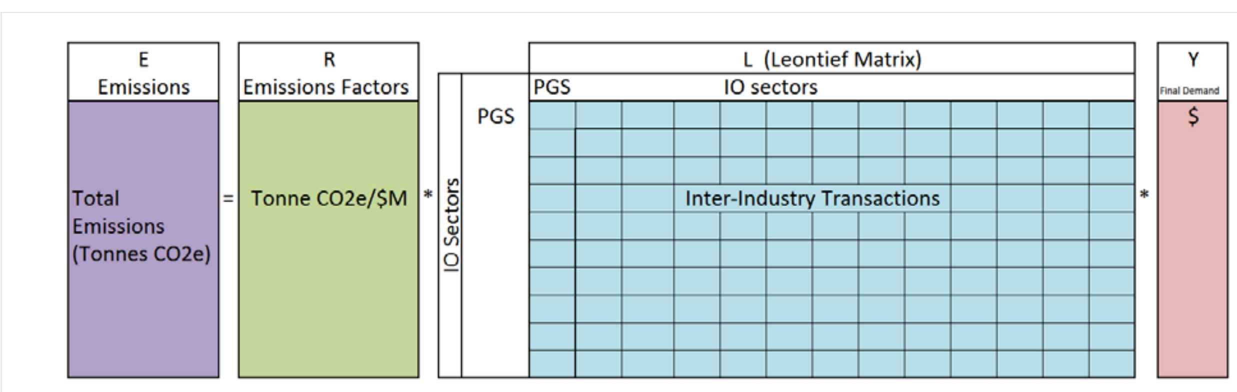

Figure 1.3: EEIO Framework for LCA

The EEIO framework as described above does not suffer from truncation errors due to system boundary constraints, as it effectively expands the boundary considered in an LCA to include the entire economy. However, this approach has its drawbacks as well. A trade-off for the increased scope is that individual processes cannot be considered at the same level of detail as with process LCAs, and instead process with similar products but possibly dissimilar production characteristics are grouped into the same sector, resulting in errors due to aggregation. Additionally, the data used to create these models are difficult to collect, and such work is often only done by governments at multi-year intervals, leading to a time lag in data. Finally, this same data is often only collected in terms of economic, rather than physical, outputs. While this is useful for comparing different products with a common unit, measuring outputs in economic subjects the estimates to economic alterations (e.g., price fluctuations, inflation) not encountered when accounting in physical units as is often done with process LCA.

1.3.3 Hybrid LCA Models

Since process LCA and EEIO LCA complement each other's main drawbacks (boundary selection limits and lack of process level detail, respectively), researchers have combined both methods, creating was is called hybrid LCA. There are several ways in which this is done; the most common approaches are outlined by Suh et al. (2004), and briefly described here.

The first approach is to produce a detailed process LCA for specific aspects of a particular product or system of interest, and use the EEIO framework to estimate the impacts of the rest of the system. This method is termed *tiered hybrid LCA*, as the process and EEIO frameworks constitute distinct tiers in the analysis, where the matrix coefficients of the EEIO framework are usually left unchanged. An example of this type of analysis was performed by Dong et al. (2013), where they used a process level detail to calculate the direct and downstream (e.g. construction, use, maintenance) impacts, while using EEIO to calculate the upstream (e.g. raw material extraction) impacts of the Shenyang Economic and Technological Development Zone industrial park in China.

A second approach is to disaggregate sectors in an EEIO model is *input-output based* hybrid analysis. In this approach, an original sector in the IO framework is divided into multiple sectors using more detailed monetary data than that used in the original model (or alternatively, process level data) to inform the disaggregation. Usually, the detailed data is used to derive weights by which to distribute the coefficients of the original sector in the direct requirements matrix. Joshi (2000) used this method to compare the environmental impacts of different types of automobile fuel tank systems. His method is explained in greater detail in Chapter 2, where we describe the similarities and differences between this type of hybrid approach and the disaggregation of the PGS sector in this work.

In a third type of hybrid LCA analysis, process level data is organized into a process matrix, as described above. Process matrices are conceptually similar to the EEIO Use and Supply tables and processes in the process matrices can be mapped to IO sectors in the EEIO tables that most closely represent each process creating flows that cross the border between the two systems. This type of analysis is called the *integrated hybrid* model, as it explicitly connects the process and IO level matrices in a single mathematical framework. An example of this approach is the study by Wiedmann et al. (2011), where they use an integrated hybrid model to estimate the potential environmental impacts of wind power in the U.K.

As a result of the use of multiple types of units and Input-Output elements in the model, integrated hybrid models can also be classified as type *Mixed-Unit Input-Output* (MUIO) model. More generally, however, MUIO models do not necessarily need distinct process IO matrices; an IO matrix that measures different sectors' outputs in different types of units can be considered to be a MUIO model. An early MUIO model was used by Bullard and Herendeen (1975) for wide scale energy analysis during the energy crisis in the 1970s. More recently, Hawkins (2007) created an MUIO model used to calculate and track the flows and environmental impacts of cadmium, lead, nickel and zinc, using detailed material data from the U.S. Geological Survey in conjunction with the BEA I.O. accounts. This approach is similar to the work described in this thesis, as we use process-and-plant level data as well as detailed price data for electricity and link electricity production in energy units with the rest of the economy for use with the MRIO model. This is described in more detail in Chapter 3.

1.3.4 Multi-regional Input-Output models

While the different types of hybrid LCA models address the issue of aggregation and truncation errors for individual processes and sectors, IO models in general are still limited in one important regard: they generally describe the entire economy as a single region. For an economy as extensive, both geographically and industrially as the U.S., this represents a different type of aggregation, one where regions as different as the arid southwestern states and the more temperate Midwest are lumped together. A way of addressing this issue in IO models is by creating Multi-Regional Input Output (MRIO) models.

There are two primary approaches to create MRIO models. The most common approach involves using data from existing IO tables for different regions and merging them together. This is usually done by deciding on specific set of IO sectors, adjusting the existing IO tables to include only sectors of the specified set, and linking the tables from different regions through their inter-regional trade by using import and export data between them as a way to reconcile the flows of goods between regions and balance the tables. Several studies follow this approach, including the EXIOPOL project in the European Union (Wood et al. 2013), the Global Trade Analysis Project or GTAP (Narayanan 2012), and the EORA project (Lenzen et al. 2013), among others.

The advantage of using independent IO tables for building the MRIO model is that the regional economies are well represented, as these tables form the basis on which the model is built. The downside is that if there are regions without IO accounts, they cannot be included in the model. An alternate approach, then, is to use the IO accounts for an existing economy and modify Use and Supply tables to include regional information. This is done by creating new, regional sectors in the IO model, modifying the existing values in the IO tables to match the regional economy using regional data, and linking the different regions using trade between regions and industries (i.e., inter-industry flows). This results in modified coefficients in the direct requirements and Leontief matrices that better represent regional supply chains. This is the approach that is used with the U.S. economy to create an MRIO model, as is done by RIMS II (Bureau of Economic Analysis 2014) and IMPLAN (IMPLAN Group), and that will be used in this dissertation due to the lack of independent IO accounts for different sub-regions of the U.S.

In this thesis, I present an MRIO model that includes individual PGS generation sectors, tracks the flow of electricity from these sectors in energy units, and represents the electricity mixes of individual U.S. states. To do this, data from the BEA's latest benchmark economic accounts will be combined with state-level electricity production and emissions data, as well as geographic data detailing the distribution of industries throughout the U.S. The intent is to create a model capable of estimating emissions for the entire U.S. economy and individual states within the U.S., while keeping track of the impact that individual states have on the larger economy. This will enable the model to provide an accurate estimate of electricity consumption, GHG emissions and Water Consumption for any type of electricity scenarios and energy policies.

The rest of this thesis is organized as follows. Chapter 2 discusses the disaggregation of the original electricity sector found in the BEA IO accounts into 10 electricity sectors that describe distinct generation technologies, as well as emissions factors for the newly disaggregated sectors. Chapter 3 describes the creation of a Mixed-Unit Input-Output model based on the disaggregated PGS sectors, using electricity price data at the industry level to enable the model to track flows of electricity in physical units (MWh) rather than monetary. Chapter 4 discusses the creation of the Multi-Regional Input-Output model by including state level electricity generation, consumption, and trading data. It also discusses application of the model on two different scenarios: a projection electricity consumption by different states in the year 2030, and a case study involving consumption of electricity at national and state levels. Chapter 5 summarizes the contributions of this dissertation and provides commentary on future work on the MRIO model, from the development of new emissions factors to additional components that could be incorporated into the model.

2.0 DISAGGREGATION OF POWER GENERATION AND SUPPLY FOR ENVIRONMENTALLY-EXTENDED INPUT-OUPUT MODEL

Context of disaggregation for the MRIO model

Before we can create an electricity specific MRIO model for the U.S., we need to introduce the individual power generation technologies in the base U.S. IO model. One of the most important reasons, as described in this chapter, is that aggregation bias is particularly egregious for PGS in the IO model. Both the requirements and emissions produced by different types of electricity generation technologies vary considerably, such that a single sector in the IO framework is a poor representation of an industry that plays a role in most other economic processes in the U.S. This is especially important given that the mix of generation technologies has changed significantly in the past few years, and is projected to continue to change in the coming decades (Energy Information Administration 2015). Additionally, to answer the types of research questions we want to explore with the full MRIO model, we need to provide this division between generation types. It is difficult to estimate the national or regional impacts of increased renewable generation, for example, if the IO model does include these sectors: even if electricity generation estimates are present for individual technologies at the process level (and this is not always the case), most such process flows lack the connections to the other sectors of the economy that are present in this framework, as there is a considerable lack of coverage in the areas process level datasets currently consider (Majeau-Bettez et al. 2011) and thus indirect impacts could be missed. This is explored in the context of economic activity and GHG emissions in this chapter, and in the context of Water Consumption in Chapter 4.0 .Finally, from a development perspective, performing disaggregation of the PGS sector as a first step allowed for the introduction of mixed units and individual regions with individual energy generation technologies, facilitating the implementation of the overall MRIO model. Figure 2.1 below shows a conceptual representation of the disaggregated EEIO framework (compare with Figure 1.3).

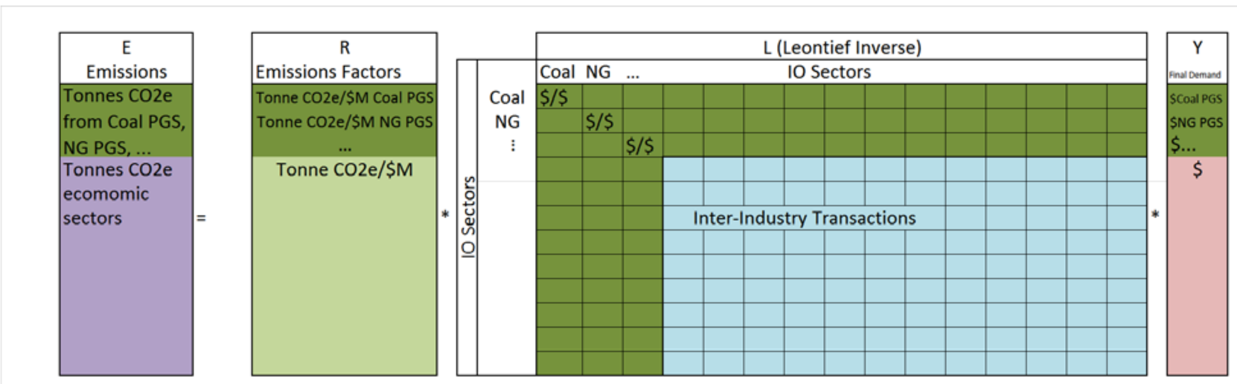

Figure 2.1: EEIO Framework with Disaggregated PGS Sectors

The disaggregation procedure presented here shares some similarities with the one built by Marriott (2007), but presents significant revisions (see Appendix A). In addition to using more recent economic and environmental data, we provide a more thorough, operational description of the disaggregation procedure than has been previously provided. The disaggregation procedure, and the algorithms implemented to carry them out, were redesigned to allow for a more refined allocation schemes for both the disaggregated PGS sectors and the non-PGS sectors affected by the disaggregation (e.g., allocation electricity production to both natural gas PGS and biomass PGS as secondary product by Paperboard Mills sector). Finally, this work provides validation of the disaggregation procedure by providing a comparison between process-based and the disaggregated IO estimates for GHG emissions.

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Vendries Algarin, J., Hawkins, T. R., Marriott, J., Matthews, H.S., and Khanna, V. (2015), Disaggregating the Power Generation Sector for Input-Output Life Cycle Assessment. Journal of Industrial Ecology, 19: 666–675. doi:10.1111/jiec.12207

2.1 INTRODUCTION

Over the past two decades, life cycle assessment (LCA) has become the standard method to estimate the environmental impacts of goods and services. The most popular LCA approach, called Process-LCA, defines a finite boundary by selecting the most important processes in a life cycle. However, such arbitrary and partial selection of life cycle boundaries is also susceptible to truncation error and conflicting conclusions by LCA practitioners (Lenzen 2000; Suh et. al 2004). Conversely, by using nation-wide economic and environmental emissions data, Environmentally Extended Input-Output life cycle assessment (EE IO LCA) allows practitioners to estimate impact inventories throughout the entire supply chains of goods and services. However, the level of aggregation inherent in IO data make it impossible to obtain the same level of detail for individual goods as can be achieved by process LCA. To address this limitation, we can disaggregate existing IO models by combining top-down economic information with bottom-up emissions data to better represent the underlying economic transactions, supply chains and emissions of goods and services, resulting in more detailed and accurate impact estimates.

In this work, we focus on the disaggregation of the U.S. power generation sector, from a single sector into multiple sectors that model electricity production to reflect different generation technologies. The power generation is particularly well suited for disaggregation: electricity generation is an enormous industry, representing about 2.5% of GDP in 2011(EIA 2013) (Bureau of Economic Analysis 2013b) as well as being primary component of environmental emissions for most products and processes, representing 38% of CO_2 equivalent emissions from the United States in 2011 (U.S. EPA 2013). Despite this economic and environmental importance, the functions of power generation and supply are often aggregated into a single sector in input-output tables, as is the case for the U.S. (Bureau of Economic Analysis 2008). A diverse set of technologies, supply chains and environmental and social impacts are represented in this single electricity sector (Bergerson and Lave 2004). We take a step towards rectifying this imbalance by disaggregating the power generation sector for use in input-output based life cycle assessment (LCA). We build a flexible framework for creating new disaggregated sectors, direct inputs and emission factors for the generation, transmission and distribution portions of the electric power industry. This disaggregation can then be used as a basis to introduce more detail to the electricity sector in future works, including incorporating physical electricity flow information and region specific mixes.

2.2 BACKGROUND

2.2.1 Motivation

During the data collection phase of the national economic accounts used for input-output models, industries with conceptually similar products but different production processes, input requirements and emission intensities are often combined in a single sector. This leads to a sector where the average emissions intensity may be significantly different from the individual process used to create it, making the sector not representative of any of its constituent processes and consequently has high aggregation uncertainty (Williams et al. 2009b; Lenzen 2000). It has been shown that even the most detailed input-output models will have sectors with significant aggregation error (Suh et al. 2004), and that this bias is more influential in modeling errors than the uncertainty introduced by sector disaggregation, even if done with limited data (Lenzen 2011).

Aggregation bias can easily be seen in the power generation sector. For example, representing an LCA of 1,000 megawatt-hours (MWh) of nuclear power at $0.02/kWh using the power generation and supply (PGS) sector in an unmodified version of an IO-LCA tool (Green Design Institute (2013)) results in 178 metric tons of direct CO_2e emissions. This can be contrasted with a process-based LCA of nuclear electricity, which results in about 0.2 tons of direct CO_2e emissions (Swiss Centre for Life Cycle Inventories 2010). However, using an IO-LCA tool, an uninformed practitioner assigns carbon from coal, petroleum and natural gas fired power plants to the nuclear power plant. This makes the PGS sector an excellent candidate for disaggregation.

Recent studies that deal with sector disaggregation do so in the context of multi-regional input-output (MRIO) models. For example, the EXIOPOL project expands number of sectors of the IO tables for the 27 EU member states. By combining IO and auxiliary data from different countries, they produce a more consistent and detailed set of sectors for the entire EU and selected non-EU countries (Wood et al. 2013). Similarly, the EORA database is used in for an MRIO model that harmonizes the published IO tables of 187 countries (Lenzen et al. 2013c). While these studies provide greater level of detail than the original IO tables offer, they do so in the context of regional transactions, where the main goal is the harmonization of international accounts.

Several studies have made use of IO models with disaggregated power sectors. Liu et al. (2012) and Lindner et. al (2013) disaggregated the electric power sector of Taiwan and China's IO tables, respectively, and used their expanded model to better estimate the emissions intensities using the updated coefficient matrix. While the aim of these studies is similar, their methodology relies on the symmetric input-output tables as a starting point. The U.S. publishes supply and use tables (SUT), which allow for a different approach to the disaggregation given that we can adjust the production of primary and secondary commodities by the different disaggregated industries.

In this regard, the study by Wiedmann et al. (2011) is more comparable, as they use the U.K.'s SUT framework as a starting point, though their focus is on the use of hybrid MRIO LCA to assess the feasibility of wind power for greenhouse gas reduction rather than the disaggregation procedure.

Previous disaggregation work on the U.S. electricity sector has focused on exploring the effect of different electricity generation and consumption mixes on carbon emissions. Marriott and Matthews (2005) disaggregated the generation mix used by the different economic sectors in the U.S. into 6 sectors, split by fuel type, and showed that inter-state trading of electricity produces an averaging effect on carbon emissions between different states and industries. However, they also showed that even with electricity trading there remains significant regional and industry variation with regards to consumption mixes, which can have substantial effects on the carbon emissions (Marriott et al. 2010). Choi et. al (2010) used a disaggregated PGS sector while keeping smaller size tables (31 sectors) to better track the physical flows of fossil fuels in the power generation sector in order to estimate the effects of a carbon tax on prices and emissions of carbon intensive industries. In this article, we focus on the disaggregation method itself rather than on the consumption mixes of the other sectors in the economy, using the detailed U.S. SUT framework (which contain over 400 sectors) and applying it to the PGS sector. We use plant level data to in order to both create more accurate emissions factors and show how bottom-up environmental datasets can be integrated with the newly disaggregated IO sectors as opposed to using point estimates found in the literature . By showing in detail how to apply this procedure to the PGS sector, we provide an example of how to reconcile top-down IO data with bottom-up process data to create a harmonized IO based hybrid LCA framework, as suggested by Majeau-Bettez et al. (2011) and Suh et al. (2004). We validate the disaggregation procedure and the emission factor calculation by comparing results from the disaggregated sectors to analogous process-level electricity LCI datasets.

2.2.2 Disaggregation Overview

Joshi (2000) describes three methods for performing an input-output LCA of an aggregated product or process not explicitly accounted for in the input-output tables The first of these is to assume that the process of interest is similar to an existing sector in the economy. We showed above, with our example of a nuclear power plant, that this can lead to significant errors, even if the power generation emissions vector were changed to zero for CO_2 – this would mean the entire economy used power with zero direct emissions.

The second method would add a new sector to the technical coefficients matrix of the economy representing the product or process of interest. This would reduce the error in our example by allowing for separate emissions vectors for nuclear power and all other power. However, this new sector will double count the impacts of nuclear power since it was not explicitly removed from the existing power sector, meaning additional steps are required to correctly represent the new nuclear power sector (Strømman et al. 2009).

The third method laid out by Joshi calls for multiplying each element in the row and column of the technical coefficients matrix of interest by a parameter *s*, where *s* is the percentage of that element associated with the product of interest and 1-*s* is the percentage associated with all other products in that sector. Mathematically, if:

$$A = \{a_{i,j}\} \tag{2-1}$$

where A is the direct requirements matrix; $a_{i,j}$ is the technical coefficient for row i, column j; and $i,j = \{1, 2, \ldots, n\}$, where n = 428, then consider

$$A^* = \{a^*_{i,j}\} \tag{2-2}$$

where now A^* and $a^*_{i,\mathrm{j}}$ refer to the expanded matrix and technical coefficients of the added sectors, respectively, and i,$j = \{1, 2, \ldots, n+m\}$, where m is the number of additional sectors. Further,

$$\mathrm{a}^*_{\mathrm{i,j}} = \mathrm{s}_{\mathrm{n+m}}\, \mathrm{a}^*_{\mathrm{i,n+m}} \tag{2-3}$$

where $s_{n,m}$ is the share of output from industry sector n allocated to new industry sector *nm.*

The trouble in this method, for the case of power generation, is that we need to come up with multiple *s* parameters, which have different values for each of the 428 row elements and 428 column elements. There is an additional difficulty working within the dollar per dollar fractions in the technical coefficients matrix, where there is no final demand for commodities, only inter-industry purchases. In our method, rather than try to obtain new technical coefficients $a^*_{i,j}$, which are unit-less amounts and difficult to conceptualize, we modify the supply and use tables by building new sectors using economic and environmental datasets. This allows a detailed disaggregation using the SUT framework based on monetary and emissions information rather than relying only on the weight factors (s_m). From these modified supply and use tables, we construct a new technical coefficients matrix and add new emissions vectors. An overview of the disaggregation method, as well as discussion of the BEA and eGrid datasets used in the creation of the disaggregated sectors, can be found in the first section of Appendix A.

2.3 METHODS

2.3.1 Selection of Disaggregated Sectors

The first issue that must be addressed is deciding which new sectors should be included to replace the original sector in the final model. The first requirement for disaggregation to be useful is that the sector represents a diverse set of processes. As discussed above, the PGS sector has high variability in generation technologies and emission intensities, fulfilling this requirement. The second constraint for disaggregation is data availability. For the PGS sector, quality data for the constituent power generation technologies can be found from several sources (U.S. EPA 2012b; EIA 2013).

The next step consists of gathering the data needed to create the disaggregated model, as well as the corresponding environmental emission factors. Table 2.1 summarizes the inputs required. The following subsections explain how each of these parameters are created and used from the inputs.

Table 2.1: Disaggregated Model Inputs

	Input	*Units*
1	U.S. Benchmark Supply & Use Tables	$
2	Electricity Generation Mix	%
3	CO_2e Emission Rates (per sector)	tonnes/kWh
4	CO_2e Emission Factors (per sector)	tonnes/$

2.3.2 Consolidation of Private, Federal, State, and Local Government Electricity Production

According to the entry in the supply table for the electricity commodity, six industries produce electricity, shown in Table 2.2. There are three industries in the use and supply tables whose primary commodity production is electricity: the main Power Generation and Supply (95% of total economic output); Federal Electric Utilities (99%); and State and Local Utilities (100%). Since the amount of secondary economic activity is negligible, and the data available for the electricity sector is not divided into private and public electricity generation sources but rather by generation technology, we can aggregate these three sectors into a single electricity production sector to simplify the system prior to the disaggregation. It should be noted that there are other industries that produce the electricity commodity as a secondary activity; however, this accounts for less than 2% of total production. Given that secondary production of electricity is such a small amount, we don't have to aggregate these industries with the three main power generation industries, and we can use the electricity grid mix as representative of their electricity generation mix.

Table 2.2: Structure of various electricity-related commodities and industries in 2002 prior to aggregation, all values in $M

	Industry Sector	*Industry Output*	*Commodity Produced*	*Commodity Output*
	PGS	$224,934	Electricity	**$214,207**
			Natural Gas distribution	$8,607
			Water, Sewage & Other	$2,107
			Other	$13
	Natural Gas Distribution	$83,255	Electricity	**$4,258**
			Other	$78,944
	Paperboard Mills	$21,101	Electricity	**$63**
			Other	$21,038
	Federal Electric Utilities	$9,820	Electricity	**$9,795**
			Other	$25
	State and local government electric utilities	$21,791	Electricity	**$21,791**
			Other	$0
	Other state and local government enterprises	$100,206	Electricity	**$17**
			Other	$100,189
				$250,158

Source: (Bureau of Economic Analysis 2008)

To aggregate the sectors at the use and supply table level, we added the values in the rows and columns of both the use and supply tables for the three sectors, replacing the original PGS sector with the aggregate values, and removing the two government sectors, following the aggregation procedure outlined by Miller and Blair (1985). A more detailed explanation can be found in Appendix A.

2.3.3 Allocation Methods for Disaggregation

In order to begin the disaggregation, we have to decide how to allocate the values found in the aggregated PGS sector rows and columns of the BEA use and supply tables among the disaggregated sectors. Since we cannot gather the data necessary from the industry to accurately assess these allocations, we can either allocate values manually, or we can use a default allocation method.

Manual allocations can be decided upon a sector-by-sector basis in cases where we have relevant information or can make reasonable assumptions. For example, consider the Natural Gas Distribution sector, as shown in Table 2.2. In the supply table, this industry produces around $4.2 billion of electricity. It is reasonable to assume that most of this electricity is produced using natural gas. Thus, we can allocate this electricity production to the newly disaggregated natural gas electricity commodity. In a similar fashion, the aggregated PGS industry produces about $8.6 billion of the Natural Gas Distribution commodity. It makes sense to allocate this production to the disaggregated natural gas electric power industry, since none of the other disaggregated sectors would produce such a large amount of a natural gas related commodity.

If there isn't relevant information to make decisions for manual allocations, we assign the values using a default allocation method. To create the allocation, we multiply the values in the original PGS sector by U.S. generation mix percentages for the different generation types (shown in Table 2.1). While there have been significant changes to the mix in the U.S. in recent years, such as the increased penetration of renewables, increased use of natural gas, and the corresponding decrease in use of petroleum and coal, we are trying to match the money spent in the 2002 tables with the generation that occurred that year. The percentages created by this allocation method are then adjusted by subtracting the manually allocated values in the rows and columns of the tables to preserve the correct commodity and industry output totals. This results in a distribution of dollar values to the disaggregated sectors, where the sum of the disaggregated sector throughputs equal the original, aggregate industry and commodity totals.

Table 2.3: 2002 U.S. generation mix (Aabakken 2005)

IO sector	*U.S. Grid Mix*
Coal	50%
NG	18%
Oil	2%
Nuclear	20%
Hydro	7%
Geo	0%
Bio	2%
Wind	0%
Solar	0%
Other	0%
Total	100%

By using the U.S. mix, we are effectively assigning a constant and equal price to the disaggregated sectors, which is useful as a first order approximation. Electricity prices vary by generation type, and calculating the price of electricity is a complicated process which takes into consideration different types of data, like the spot or long-term contract price of fuels, taxes and regulatory environment, transmission infrastructure, type of consumer, etc. (Stewart 1979), all of which can be difficult to obtain. In addition, the supply and use tables represent the electricity produced over a specific timeframe (2002 in this case), but the costs associated with that production are spread over different periods of time, and differently for different sectors (i.e., most of the cost for solar electricity is included in the construction of the PV cells, whereas for natural gas electricity the cost comes from the fuel itself). There are ways to address these issues, such as by building a construction supply chain (Marriott 2007) for the disaggregated sectors, but this is beyond the scope of this article.

Spending on transmission and distribution also needs to be taken into account, since those functions of the industry will be part of the disaggregation. The total amount spent on transmission and distribution in 2002 represent about 1.9% and 1.6% of total industry expenses (EIA 2013). In the default allocation, the percentages for generation are normalized to account for the industry dollars spent on these two transmission sectors.

2.3.4 Disaggregating the Use and Supply Tables

Using both the manual and default allocations methods described above, we can build the disaggregated use and supply tables. We broke down this process as follows:

Use table columns:

The use table columns represent the direct inputs to the electricity generation, or the ‘supply chain’ for electricity production. The allocations made along the columns represent the purchases each generation industry made from the other sectors for electricity production. Most of the manual allocations in the disaggregation were made here.

Use table rows:

A row in the use table represents purchases of a commodity by different industries. In our case, this means which type of electricity commodity (coal, natural gas, etc.) each industry purchases for its operations. Here we used the default allocation for all the disaggregated sectors, since to manually allocate these values, we would need to know which type of electricity generation each industry purchases and in what quantities, which is information that is not readily available.

Supply Table Columns

Allocations along the columns of the supply table represent production of electricity sector output (commodities) by generation type (e.g., Natural Gas Distribution commodity assigned to the natural gas electric power industry).

Supply Table Rows

Allocations along the rows of the disaggregated sectors represent assigning electricity produced by other industries besides PGS (i.e., secondary electricity production).

PGS Intersection

The intersection of PGS with itself in both tables merits special attention. For the supply table, this corresponds to the amount of electricity produced by the PGS industry. When doing the disaggregation, the assumption used for this analysis is that a generation type will only produce that type of electricity. Additionally, the amounts produced by each generation type are assumed to be proportional to the default allocation described above, resulting in no off-diagonal values along the disaggregated supply intersection. A similar assumption for electricity purchases by electricity sectors is applied in the use table, except for transmission and distribution, where it is assumed that all generation technologies purchase some amount of those services. These assumptions may not be strictly true, but they provide a good first order approximation. The result of these assumptions in the use table intersection, as well as more information on the manual default allocation procedures can be found in Appendix A.

2.3.5 Calculating Emissions Factors for the Disaggregated Sectors

In order to generate environmental output from an economic model, the data, which is normally available in units of mass per unit physical output, needs to be converted to mass per dollar output using electricity costs. For each new sector, we calculated the emission factors using equation (2-4):

$$Emission\ Factor = \ Ton\frac{CO_2e}{kWh} * \#kWh * \frac{1}{industry\ throughput} \tag{2-4}$$

The data for CO_2e emission rates was obtained from EPA's eGrid 2012 Database (U.S. EPA 2012b) (U.S. EPA 2012a), which contains national plant level data for each generation type. By looking at the net generation and net emissions of individual plants, we are able to screen out those which require more electricity from the grid than what they contribute to it (i.e., those with negative net generation), as well as plants with extremely high emission rates (i.e., positive low net generation but high emissions, which usually indicates that electricity generation is not the primary function of the plant). Appendix A has further information on how the plant level data was used to create an emissions estimate per kWh of electricity generated for each technology.

The electricity production by technology from NREL's Power Technologies Energy Data book (Aabakken 2005). While there is uncertainty in these numbers, we used point estimates that fell within the ranges shown in Table 2.4 (Bergerson 2005; Sathaye 2011; EIA 2011). The sector throughputs are the Supply table column sums (i.e., total industry output) of the disaggregated PGS sectors. Table 2.4 shows the CO_2 equivalent emission factors for each new electricity sector in tons per million dollars. Sectors that have no emission estimates (e.g., hydroelectric, wind, etc.) are assumed to have negligible direct CO_2 equivalent emissions during their operation.

It should be noted that the emission rates and resulting emission factors provided in Table 2.4 represent direct, operational discharges. This accounts for the high biomass emission factor. Ideally, the uptake of carbon during biomass growth should be accounted for in the sectors producing the biomass (which would be represented by negative emission factors). Currently there is no economic sector in the model that is specific to biomass growth for electricity production, but given the data is available such a sector could be added either as a new sector in the supply and use tables or through further disaggregation of the existing tables.

Table 2.4: **CO_2e emission rates and factors**

Technology	*Direct Emission Rates, g CO_2e / kWh*	*IO Emission Factors, Ton CO_2e/\$Million*
Coal	900 – 1,200	15,550
Natural Gas	410 – 680	6,230
Petroleum	800 – 1,000	13,600
Nuclear	0 – 10	90
Hydroelectric	-	-
Geothermal	0 – 30	470
Biomass	0 – 600	6,100
Wind	-	-
Solar	-	-
Transmission	-	-
Distribution	-	-

Sources: U.S. EPA 2012; EIA 2011; Bergerson 2005; Sathaye 2011
Note: Emission factors represents direct emissions estimates

2.3.6 Building the Model with the Disaggregated Tables

Once the use and supply tables have been disaggregated and the emission factors calculated, we can create the disaggregated electricity model following the procedure specified by the BEA (Bureau of Economic Analysis 2009). The model's main component is a new direct requirements matrix, which in turn is the primary component of the Leontief equation. This new matrix will have 9 additional rows and columns (12 new sectors less the three main electricity producing sectors in the original model), where each entry is the fraction of a dollar's worth of sector input needed to produce a dollar's worth of sector output.

To "run" the model, an additional vector or set of vectors is created to model the final demand of the scenario being run. This could be some future amount of kilowatt-hours of electricity demand converted to dollars, or a life cycle assessment represented by the final demand of a combination of electricity generation and other sectors. This vector and the vector of emission factors are multiplied using the Leontief equation:

$$E = R * L * Y \tag{2-5}$$

where

R is a vector of emissions factors, one for each sector;

L is the disaggregated total requirements (or Leontief Inverse) matrix;

Y is the final demand vector, which is user-specified, and

E is the model output, a vector of total emissions for each sector generated from the economic activity needed to meet the final demand.

2.4 RESULTS

As a test run, a final demand of $1 million worth of electricity (distributed among the disaggregated sectors as per the default allocation percentages) was compared with the same final demand using the original aggregate model. Figure 2.2 shows that given the same final demand vector, both models show an equivalent amount of economic activity needed to meet the final demand. This is a verification that the calculations are done correctly throughout the model. However, the disaggregated model additionally shows the contributions to both the total economic activity and CO_2e emissions from the different electricity sectors, which shows that the amount of economic activity is not the main driver in CO_2e emissions. For example, while electricity generation from coal is responsible for about one third of the total economic activity, it is responsible for over 70% of the emissions. It should be noted that the overall difference in GHG emissions between the two models is due to the use of different emission factors used in building them.

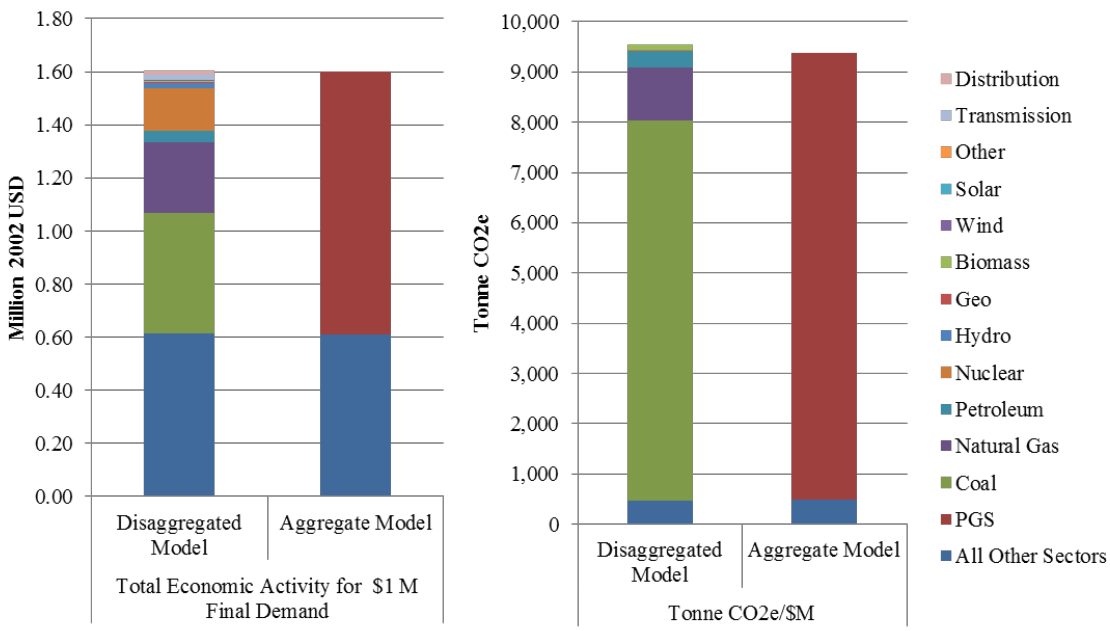


Figure 2.2: Total economic activity and total CO_2e emissions for $1M of electricity production.

The above results are useful to confirm that the IO model is built correctly. In order to further validate the results, we compared our model with results from other LCA studies by comparing the CO_2e emissions of producing 1 kWh of electricity from different generation technologies. In order to compare the IO results on a per kWh basis, we divided the total industry throughput of all the PGS sectors by the total electricity production in the U.S. in 2002. This way we obtain the constant price we assumed when using the default allocation when building the model. This implied production price comes out to be $0.063/kWh. We can then use this value as a final demand and run the model with this value for each of the individual electricity generation sectors. The results for the model are shown in Figure 2.3, labeled as USIO.

The IO results are compared to estimates obtained from several sources including process-based datasets. We used the Ecoinvent 2.2 database to simulate 1 kWh of electricity from the processes most analogous to the disaggregated sectors, using U.S. processes where available

(Swiss Centre for Life Cycle Inventories 2010). We also obtained life cycle GHG estimates from the National Renewable Energy Laboratory's LCA Harmonization Project (Sathaye 2011), a study from the National Technology Energy Laboratory (Skone 2013) (Schivley 2013), and Argonne National Laboratory's GREET Model. The results from these sources are labeled EI 2.2, NREL, NETL, and GREET in Figure 2.3, respectively.

This comparison is useful because it allows us to compare the accuracy of our top-down based hybrid approach with more traditional bottom-up estimates. Understanding where the differences between the different approaches are allows us to use them to complement each other in future studies. Several authors, including Lenzen (2000), Suh et al. (2004), Lenzen (2000) and (Wiedmann et al. 2011) describe the advantages of top-down vs. bottom-up LCA practices. Generally speaking, process-based approaches are more accurate for the process they describe, but suffer from systemic truncation errors due to the necessary application of system boundary selection. IO-based approaches expand the boundary by consideration all the interactions in the supply chain, but lack specificity with regards to specific products. The disaggregation of the PGS sector introduces more specificity in the supply chain of the disaggregated sectors as well as in the environmental data used to create the emissions factors with regards to the original model, making it more compatible with bottom-up approaches (see Appendix A for a comparison of LCA approaches).

The results in Figure 2.3 show that the IO emissions estimate for coal electricity falls within the estimates for the other sources, while the estimates for oil are about 5% higher than EI 2.2 estimate, the closest comparable study. The IO estimates for non-fossil technologies are generally lower than the estimates in the other studies. This is usually due to the use of direct emissions estimates for the sectors in the IO model. Despite these discrepancies, the results for these sectors are generally comparable to the results from the other studies.

The estimates for biomass and natural gas emissions from the IO model merit further attention. For natural gas, the lower estimate for the IO result when compared to the other sources is due to a couple of reasons. Part of the difference is the low direct emissions rate obtained from eGrid used in calculating the IO factor, which is comparable to NETL (about 10% higher) but lower than all the other sources. Additionally, the indirect gas emissions in the IO model represent the lowest percent of total gas emissions, which is comparable to the GREET model (14% for both) but lower than the other estimates. This discrepancy could be due to economic allocation inherent to IO models, as opposed to process estimates. For example, fugitive gas leaks along the supply chain, which can account for up to 30% of the indirect emissions (Skone 2013), produce no economic activity and are not taken into account by the IO model; however, they do contribute to global warming potential, thus explaining some of the difference. This combination of low total emissions and low percentage of indirect emissions accounts for the relatively low natural gas estimate.

The difference in the biomass estimates is due to the fact that in calculating the emissions factor we used direct emissions estimates (as is the case for the other IO sectors), which do not take into account avoided emissions like (for example) NREL's estimate (Moomaw 2011), since there is no sector(s) that could accurately be credited for the carbon uptake. Additionally, the IO biomass sector encompasses different types of biomass emission types, while other sources deal with specific biomass sources (e.g., wood or co-fired biogas for Ecoinvent). As a result, the biomass IO estimate is greater than the net emissions (direct plus indirect, minus carbon uptake) from Ecoinvent processes, but lower than the direct emissions estimates from these same sources, as shown in Figure 2.3. These differences highlight the need for top-down and bottom-up approaches to be used to complement each other, and the value that sector disaggregation adds to hybrid LCAs.

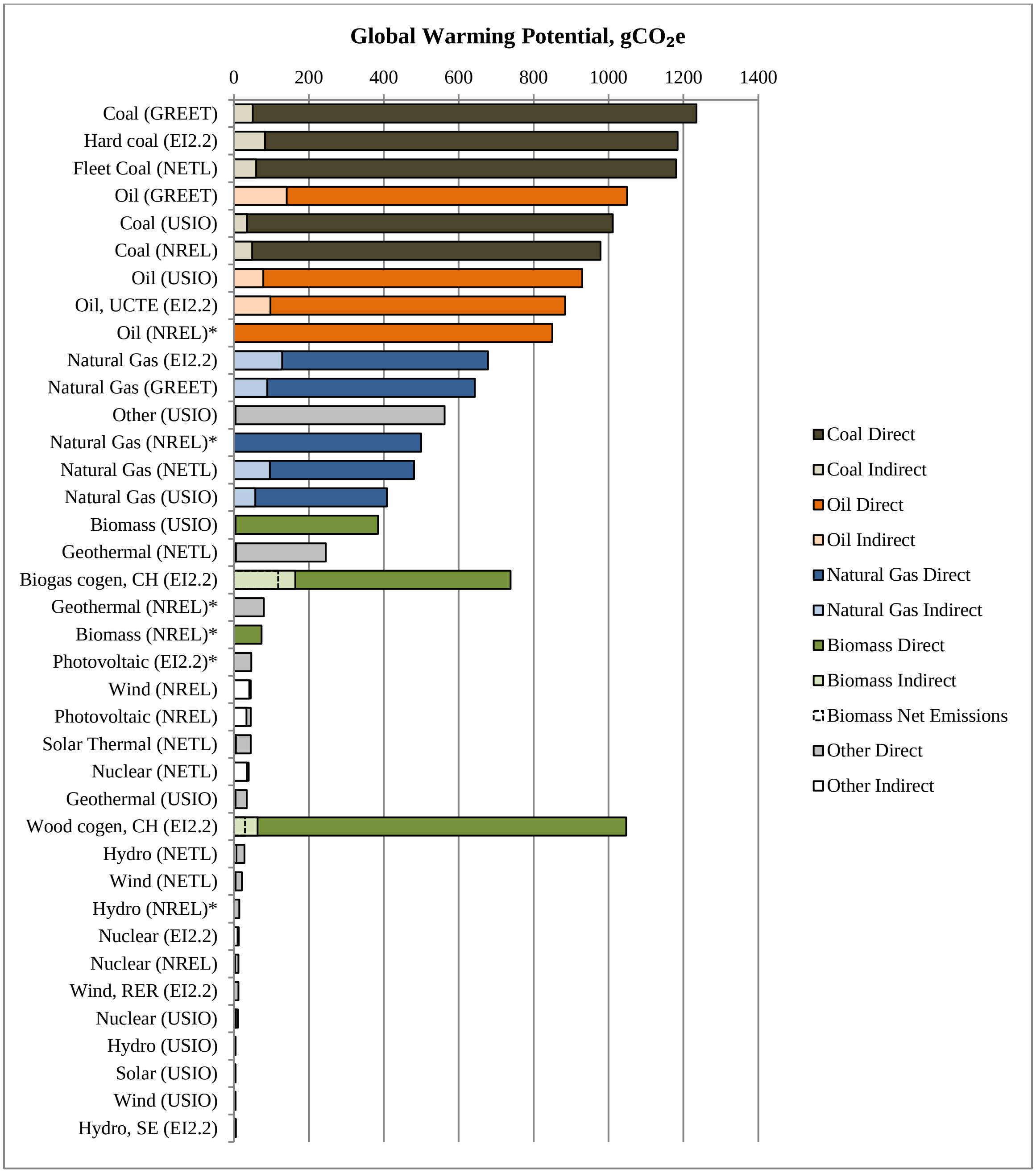


Figure 2.3: Emissions for 1 kWh of electricity produced, from selected sources. The region is U.S. average unless otherwise indicated (RER: European average, CH: Switzerland, SE: Sweden). *Note: Starred (*) entries indicate that the source does distinguish between direct and indirect emissions.*

While the above comparisons are useful for validation purposes, the utility of the disaggregated IO model can be better seen when applied to scenario analysis. As an example, we chose to compare the emissions resulting from an equal final demand of $1 million worth of electricity production using different consumption mixes. We chose to use the electricity mixes of the NERC regions defined by eGrid (2012a), since these are realistic consumption scenarios that an industry located in these regions might experience. The NERC regions and their PGS mixes are further described in Appendix A. We also used the U.S. average mix, as detailed in Table 2.3; the Indiana state mix, which is over 90% coal; and the Idaho state mix, which is about 80% hydroelectric. The CO_2e emissions for each grid are shown in Figure 2.4. Since we are using the national U.S. tables and applying the electricity consumption of the different regions as the final demand, we intrinsically assume that the regions have the same economic structure as the U.S. However, this example serves to illustrate how the model can be used.

The model results highlight the composition of the different grids. In most grids the majority of emissions are from coal based electricity, which is reflected in the national average results, most of the emissions of the Hawaiian and Alaskan grids (HICC and ASCC, respectively) are due to petroleum based electricity. When comparing individual states, the differences are even more apparent: while the U.S. mix results in about than 10,000 tonnes of CO2e emissions, the Indiana mix exceeds 16,000 tonnes, while the Idaho mix barely reaches 3,000 tonnes. These results show that having the option to tailor electricity consumption to the specific mix being used results in much more accurate models than what would be possible without the disaggregation. While this is just one example, the model could be used to create any number of scenarios, such as modeling the emissions resulting from achievement of the goals set by different states' renewable portfolio standards.

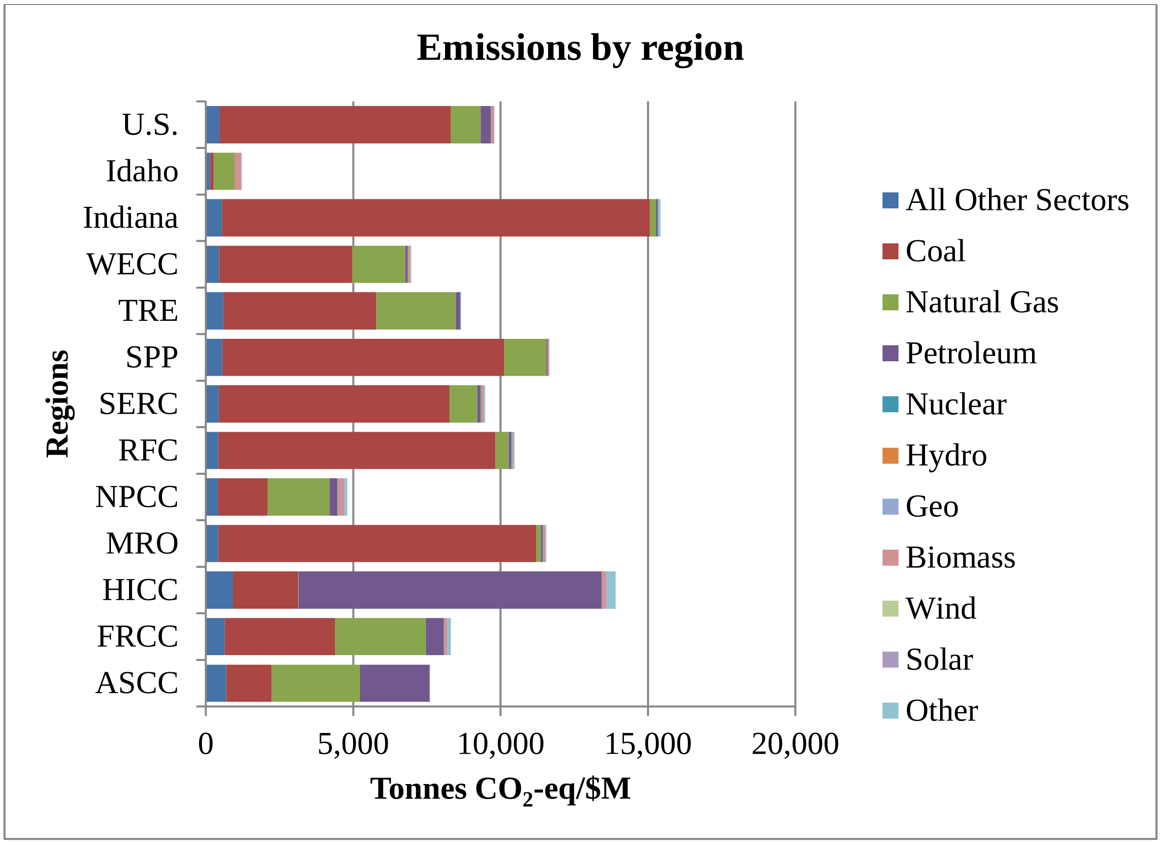


Figure 2.4: NERC, Indiana, Idaho, and U.S. total CO_2e emissions for $1M of electricity production (U.S. EPA 2012a)

2.5 CONCLUSIONS

The primary focus in this article is to expand the IO model using the SUT framework for disaggregation. While we recreate the 2002 U.S. electricity mix here, the disaggregation process to create is flexible and expandable. Specific power generation sectors can be added or modified to model to better reflect the consumption mix of a particular company or even product within a company, allowing increasingly detailed hybrid LCA studies.

Future research directions include developing more emission factors to allow for a more comprehensive analysis which allows for estimates for different impact categories (acidification, water consumption, etc.) as well as the building of a mixed unit IO model featuring energy and economic flows. Such a model could directly address the issue of price inhomogeneity in the PGS sector, and its resulting effects on the shift in the environmental burdens between consumer types (industrial, household, and service).

Building on the case study with the different grid mixes, future research could also focus on developing multi-region IO (MRIO) models which includes inter-regional trading as shown by Marriott (2005), to show how different scales of analysis represented by the aggregate national model, disaggregated MRIO model, and process-scale results affect federal and state level policies for meeting stated environmental standards. With industry sectors such as Power Generation & Supply, which are extremely important to many life cycle inventories, and for which a large amount of more process-specific data exists, this type of work can make the widespread use of hybrid LCA models easier. For practitioners, this work enables a greater level of detail for LCAs which include industry, and also provides a framework and case study for sector disaggregation.

3.0 USE OF MIXED UNITS FOR POWER GENERATION AND SUPPLY IN ENVIRONMENTALLY-EXTENDED INPUT-OUTPUT MODEL

Due to the large amount of data requirements, MUIO models remain difficult to create and maintain. Despite this difficulty, using mixed units in for PGS presents useful benefits in the conext of the overall MRIO model. Firstly, by using prices to convert economic units to physical, the MUIO model removes the allocation bias inherent to monetary models, where emissions are attributed to those sectors that pay more, rather than those that use more. Which allocation scheme to use is debatable, but most process level studies assume the second allocation (explicitly or not), and this change brings the IO model more in line with most process-level studies. This is explained in more detail in this chapter.

The second benefit of using physical units is that it removes the user's need to account for the monetary effects, such as price fluctuation and inflation, for analyses involving the physical unit. This is useful for electricity generation, where each technology type is subjected to different types of price pressures and different amounts of price volatility for the different fuel feedstocks. By incorporating mixed units directly into the model, the user can focus on obtaining results directly in terms of energy rather worry about using the correct adjustment factors.

Using physical units also removes the effects of prices from the coefficients that make up the supply chains in the direct and Leontief matrices. The resulting coefficients thus become more similar to process inputs in process LCAs (thus making this model a type of integrated hybrid model, as discussed earlier). This is a desirable quality: although the benchmark accounts used in creating the model represent a single year (2007 in this case[2]), these types of models are often used to extrapolate beyond their base year, as is done in one of the scenario analyses in this thesis. Given price fluctuations and inflation, it is usually the case that economic inputs vary considerably more than process inputs, as technologies tend to be developed and adapted more slowly. This in turns means that the economic production recipe or supply chain undergoes greater changes than the process-based recipe, making economic models less generalizable and in greater need of frequent updates. This is especially true for electricity generation, as prices fluctuate not only across time, but across customers, as alluded to previously. By including energy units for electricity in the MRIO model, we reduce these uncertainties tied to price fluctuation and end-user and put the focus back impacts of electricity generation rather than market allocations. Figure 3.1 below shows a conceptual representation of the mixed-unit EEIO framework (compare with Figure 1.3 and Figure 2.1).

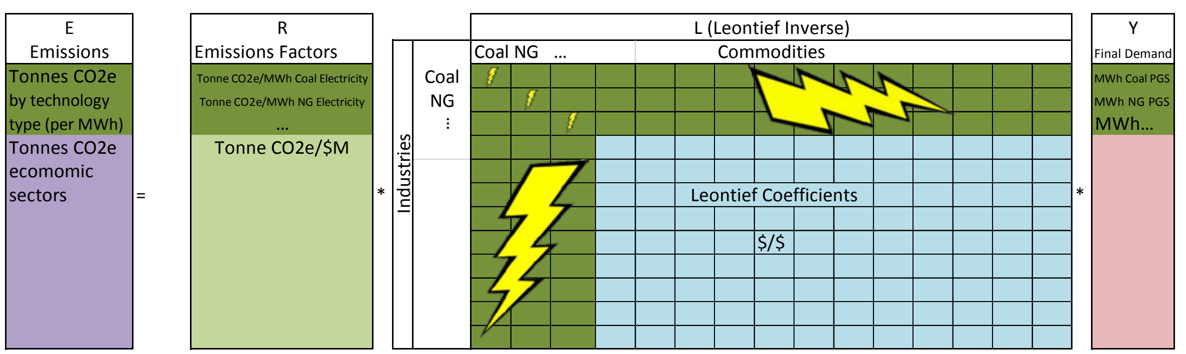


Figure 3.1: EEIO Framework with Disaggregated, Mixed-Unit PGS Sectors

[2] Note that while Chapter 1 uses the 2002 Benchmark accounts to describe the disaggregation procedure, this procedure was applied to the most recent Benchmark accounts (2007). Chapters 3 and 4 therefore use the disaggregated version of the 2007 tables.

This chapter is the peer reviewed version of the following article:

Vendries Algarin, J., Hawkins, T. R., Marriott, J. and Khanna, V. (2016), Effects of Using Heterogeneous Prices on the Allocation of Impacts from Electricity Use: A Mixed-Unit Input-Output Approach. Journal of Industrial Ecology. doi:10.1111/jiec.12502

3.1 INTRODUCTION

Input-output (IO) analysis is an economic technique that tracks the interactions between different sectors of an economy. Initially used as a method for evaluating the relationship between final demand and economy-wide production activities, this technique found additional applications when the economic framework was combined with other data, such as the use of energy data to estimate the embodied energy of goods and services (Bullard and Herendeen 1975). In recent years, IO analysis has been used with increasing frequency for life cycle assessment (LCA), allowing studies to focus on economy wide emissions of different products and services (Hendrickson 2005).

In creating an economy-wide input-output life cycle assessment (IO-LCA) model, it is common to combine environmental emissions data with the monetary data described in the economic accounts that form the basis of the IO tables (e.g., aluminum production). By using such a model to estimate supply chain emissions, a modeler makes the implicit assumption that the releases and associated impacts from each sector are proportional to each sector's monetary expenditures. In other words, the total environmental impact of a sector is allocated according to the monetary value of its output, which in turn is a function of both the quantity and price of the sector's physical output. This approach can be contrasted with many *bottom-up* process LCA studies where the outputs of processes are described in physical units (e.g., kilograms, megaJoules, etc.). In these studies, the implicit assumption is that the impacts of a process are assigned to a product or service solely on the basis of its output in physical terms, without considering price. This difference has been a source of debate between practitioners of the two methods and is often cited as one of the main reasons for the differences in results between them (Junnila 2006; Liang and Zhang 2013).

There is a fundamental question: should environmental impacts be allocated based on physical or monetary outputs? This debate will likely go on for some time; however, holding it out of the context of specific applications is somewhat unproductive. Here we ask a question we can make progress with: how much difference does it make whether we track the output of a sector in physical versus monetary (i.e., dollar-only) units? Similar questions regarding the effect that the choice of functional unit has on the results of LCA studies have been explored by others in the context of process based studies (Matheys et al. 2007; Choudhary et al. 2014), but we ask it here specifically in the context of the IO framework, where the functional unit is usually in monetary terms. It is worth noting that in this framework, the difference between physical and monetary terms is due to the implied prices assigned to each sector's output. That is, if a given sector's output is purchased at an equal price by all other sectors (i.e., the model assumes that each purchasing sector pays the same dollar value for a given unit of another sector's output), monetary and physical functional units can be considered equivalent (Weisz and Duchin 2006; Liang and Zhang 2013). This being the case, to understand the difference between the environmental impacts estimated by monetary and physical IO models, we investigate a case where the equal price assumption for each purchaser does not hold. In other words, we ask: *does the assumption of equal price paid by different purchasers for the same unit output affect the emissions estimates obtained with IO-LCA models?* And if so, *how does the introduction of heterogeneous prices paid by industry sectors for a given sector's output affect the emissions estimates of IO-LCA models?*

By introducing heterogeneous prices, and by extension, physical units and thus creating a mixed unit IO framework, the intent is to make the resulting IO model analogous to the use of a process-based LCI database where emissions in the supply chains are assigned based on energy use. To better understand the effects of introducing physical units on emissions estimates, we focus on a single IO commodity, electricity, in a one-region model of the U.S. The Power Generation and Supply (PGS) sector is one of the main sources of environmental impacts in the economy, as nearly all sectors use electricity for their operation. In addition, electricity is a commodity where impacts are dependent on the amount supplied, but where prices for equal amounts of electricity supply can vary considerably among different consumers. For example, in 2007 (the latest benchmark year for U.S. IO accounts) the average price for residential electricity was almost double the average price for industrial users (EIA 2013). Additionally, the price of electricity also varies considerably based on where that electricity was produced (EIA 2013), or even with the time of day. This variability in prices makes the PGS sector ideally suited to examine the implicit allocation bias in environmental burdens introduced by the homogeneous price assumption.

3.2 BACKGROUND

3.2.1 Monetary, Physical, and Mixed-Unit IO Models

Previous work has studied the effects of prices in IO models in the context of physical and mixed-unit input-output models (PIO and MUIO, respectively). These are often employed when tracking of physical products throughout the economy is required, such as in material flow analysis (MFA) or for the different life cycle stages in LCA. Physical IO models have been used for a wide variety of purposes, including calculating raw material consumption (Schoer et al. 2012) and waste management (Dietzenbacher et al. 2009; Liang and Zhang 2012). Analogous to EIO, PIO models replace flows measured in monetary values (e.g., dollars) with physical units (e.g., kg, joules, etc.);

by doing so, they avoid dealing with price explicitly, as transactions are recorded in physical units. However, it has been shown that when the assumption of price homogeneity within sectors holds for EIO and PIO models that track the same economic activities, the models are effectively equivalent (Weisz and Duchin 2006); (Hoekstra and van den Bergh 2006). Additionally, PIO models remain rare, mostly due to the difficulty in obtaining the raw data needed for their creation.

MUIO models are a middle ground between the purely monetary EIO and purely physical PIO models, as they have physical flows for some sectors and monetary flows for others. By combining economic information of sectors for which there is little physical data (such as service sectors) with physical flows for sectors where the data is available (such as mineral extraction sectors), MUIO are able to present a more complete picture of the transactions in the economy than either MIO or PIO can on their own. Examples of MUIO include the pioneering work by Isard (1969); a model for waste management (Nakamura et al. 2007); a model tracking heavy metal sectors use in the U.S. (Hawkins 2007); and a mixed unit energy model for China (Lindner and Guan 2014). More recently, Majeau-Bettez et al. (2015) proposed an alternative to MUIO tables that uses multi-layered IO tables, with each layer tracking the flows of individual commodity in a unique unit (e.g., monetary layer, energy layer, mass layer, etc.).

While the different models and approaches discussed above have the same ultimate goals of tracking economy-wide flows within the economy and their associated environmental impacts, the results they provide can be significantly different. Studies by (Giljum and Hubacek 2004), Weisz and Duchin (2006), and Liang and Zhang (2013), among others, argue that the differences arise due to several reasons In particular, they found that the level of aggregation, the way the models deal with service sectors (e.g., IT), accounting of waste, and the unique sectoral price assumption have a determining influence in the inter-sectoral relationships of the models and drive the differences between them. It is this last assumption that we seek to explore in this work, though there are other studies that have explored this issue. Merciai and Heijungs (2014) show that when performing impact analysis where purchasing sectors pay different prices for the same input, mass balances are violated for those sectors that use said input, since an equal monetary consumption by these sectors does not equate to an equal physical consumption. Zhang et al. (2014) compare fossil fuel consumption in the economy using demand side survey data, supply side data with homogenous prices and supply side data with heterogeneous prices, with results indicating that the energy balance of the IO model was violated when using the heterogeneous price dataset. Choi et al. (2010) used heterogeneous prices for energy commodities for select end-use sectors as well as the price model to estimate the effects of a possible carbon tax applied in the U.S.

3.2.2 Use of electricity prices in the U.S. IO Tables

The issue of price in IO models has also been studied in the context of price valuation, most recently due to price issues encountered when integrating IO tables from different regions to create a multi-regional model (Tukker et al. 2009) ;(Lenzen et al. 2013b) . Since we are interested in exploring what the effects of using monetary versus physical accounting in IO analysis are when estimating electricity related GHG emissions for different end-users, it is important to understand the price components for electricity. In reality, electricity prices are dynamic and fluctuate due to many different factors, including temporal (e.g. time of day) and geographical (e.g. by city), among others. Such variations occur at a resolution that is difficult to capture using an IO approach. Accordingly, we use electricity price data that better aligns with the economic data used to create the model: average electricity prices for 2007 (the benchmark IO year) for the different economic sectors present in the Use and Make tables (Energy Information Administration 2015) (U.S.

Census Bureau 2007) . Given this constraint, we proceed to examine how electricity price is handled in the benchmark tables, and how the price data we use to create the MUIO model relates to the tables.

It is usually not feasible to construct a physical IO table for electricity, as this physical data is not readily available for the detailed IO industry sectors. Using prices as a way of approximating physical flows is the next best approach. There are several different ways prices are handled in IO accounts. The U.S. BEA (U.S. Bureau of Economic Analysis 2013) publishes Use and Make (a transpose of the Supply table with some minor adjustments) tables in producer prices. Producer prices include taxes and subsidies, but exclude trade and transport margins. The Use table is also available in purchaser prices, which reflect the price paid by the final consumer, after expenses such as transportation, wholesale and retail margins are included in the price. Taxes and subsidies are included as a row in the value added section of the Use table for both producer and purchaser price versions. Product-related taxes are accounted for on the column of the producing industry or service sector. A third approach used in IO accounts is to use basic prices. This method, which has been used outside of the U.S. (KEMA Consulting GmbH 2005), mainly differs from producer prices in that taxes on production are included in producer prices, but not in basic prices, and that basic prices include transportation margins, whereas producer prices do not. Currently, there are no tables in basic price tables for the U.S. Converting between producer and basic price tables is a non-trivial task, since much of the data needed to perform the conversion is not publically available or not at the resolution needed for the BEA tables. As such, the use of basic prices is beyond the scope of this work.

In the BEA tables, electricity flows are represented as PGS commodity values consumed or produced by different industries (Use and Make tables, respectively). As this one sector includes transmission and distribution (i.e. what would constitute the transportation, wholesale, and retail margins; see section 2.2 in the S.I for more detail), the PGS values are indeed equal when considering purchaser or producer prices in the Use table. This allows us to use price data for end-users from EIA and the US Census, which are collected on the consumer side. Additionally, since the Make table is only available on a producer price basis, this price scheme is used for this analysis. It is worth noting that given the inclusion of transmission and distribution with generation in the PGS sector, the effect of choosing producer price over purchaser prices is limited to differences in total GHG estimates throughout the supply chain of non-PGS sectors. Since we compare the differences when using two versions of the same model (monetary vs. physical), the relative differences we explore in our analysis will not be affected by the choice or purchaser or producer price. Discussion of distinct electricity price components and their relation to the PGS sector in the IO tables is included in Appendix B.

Given the above constraints, we present a new mixed-unit IO (MUIO) model to explore the effects that heterogeneous sectoral prices have on environmental impacts of electricity production within an IO framework. This model of the U.S. economy tracks PGS in energy (MWh) units while leaving the rest of the sectors in economic terms, and includes specific electricity prices for the industry sectors. This allows us to track physical consumption on a per sector basis; investigate both the direct and indirect (supply chain) effects of different electricity pricing for distinct end users have on the way environmental burdens are assigned by the IO model; and provides insights as to whether physical or economic accounting is more appropriate for different types of consumers.

3.3 METHODS

We use the most recent, detailed Supply and Use (SUT) tables available for the U.S. economy in this analysis (U.S. Bureau of Economic Analysis 2013, 2009). Figure 3.2 contains a flow chart to serve as a visual aid to the method presented in the following section.

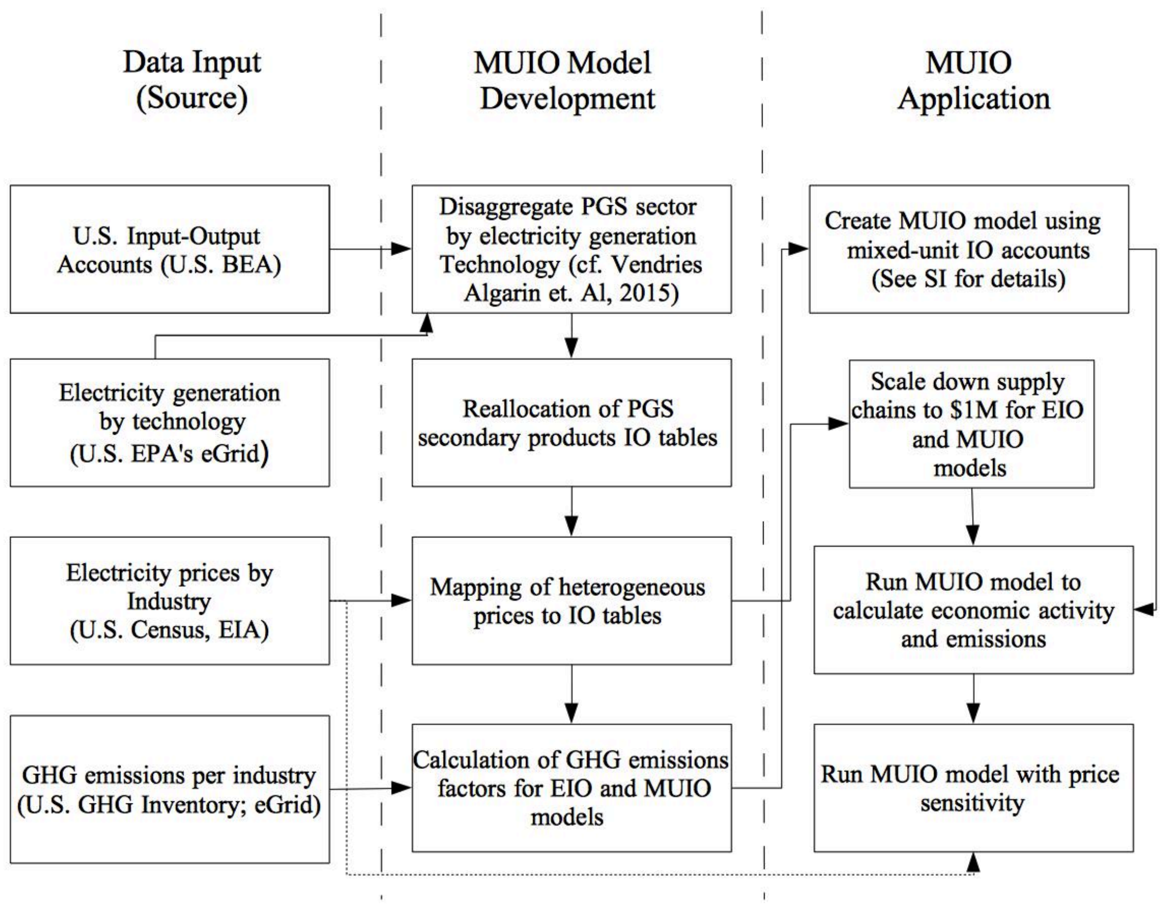


Figure 3.2: Detailed method diagram for creating the MUIO model. Parentheses denote data source or reference.

3.3.1 Modifying the IO Accounts

In Chapter 2, the IO Accounts were modified by disaggregating the original PGS sector into 10 Power Generation sectors, each representing a specific generation technology. To create the MUIO model we need to reallocate entries in the disaggregated PGS industry sectors of the Supply table that correspond to secondary products (i.e., commodities other than electricity produced by the PGS sectors). This is necessary due to modeling constraints imposed by the IO framework: to create the total requirements table, we need to sum the industry production of different commodities to obtain total industry output. Without reallocation, the PGS industries would have elements in both monetary and physical units, making summation of the industry totals impossible. By reallocating these values we can overcome this obstacle, ensuring that only the PGS industries produce electricity. Most of the values moved in these reallocations constitute less than 0.5% of the total industry output, ensuring their effect on model results is minimal. After making these changes in the Supply table, we adjust the Use table by moving the assumed inputs needed to produce the secondary commodities to match the reallocations performed in the Supply table. The reallocation necessary to create the MUIO is described in more detail in Appendix B.

While the reallocations described are small percentages of total industry production, such reallocations could still have the potential to change total requirements coefficients, thereby changing emissions estimates with respect to the original model. To analyze the effects of different electricity prices on emissions without fear of this distorting effect, we build a "base" monetary model, with all units in monetary terms but include the reallocations needed to create a MUIO model. As mentioned previously, Weisz and Duchin showed that when price is equal for all sectors, economic and physical input-output models are equivalent (2006). In the rest of this article, any reference to the EIO model is referring to the reallocated monetary model.

3.3.2 Creating Mixed-Unit model

Once the reallocations have been performed, the mixed unit model is created by combining physical electricity generation data and sector-specific electricity prices for different sectors of the U.S. economy with the IO Accounts. We use the U.S. EPA's eGrid database (2012) for the physical quantity of electricity produced in the year 2007. These values replace the monetary data in the Supply table for each PGS sector (e.g. coal electricity generation values in MWh replace the coal PGS commodity values in dollars). In the Use table, the prices paid by consumers of electricity are used to convert the dollar values to megawatt-hours (MWh). For manufacturing sectors, electricity prices for the BEA manufacturing sectors present in the IO model were obtained from the 2007 Economic Census (EC) conducted by the U.S. Census Bureau (2007) and mapped to their specific IO industry (e.g. the electricity price mapped to the Primary Aluminum Production industry is different than the price mapped to the Ferroalloy Manufacturing Industry) . Non-manufacturing industrial prices, as well as commercial, residential, and transportation electricity prices were not available at the same level of detail in the EC, and thus average prices were obtained from the (EIA (2014), 2013)). These prices were mapped more broadly (i.e., one price for all transportation sectors, including rail transportation, pipeline transportation, etc.). It should be noted that the prices provided by these sources are yearly average prices for the relevant sectors; in reality, electricity prices are variable even within the detailed industry sectors (e.g. Primary Aluminum Production), not to mention the more aggregate classifications (i.e., transportation sectors). To understand the effects of electricity price variability on the energy balance of the MUIO model, we perform a sensitivity analysis using high and low electricity prices provided by the EIA (2014). The sensitivity analysis is performed for the different end-use categories by varying electricity prices across the range of values for the different categories in different states. Details on the use of these prices to create the sensitivity estimates and the results can be found in Appendix B.

Using the sources mentioned above, we assign different prices to the different IO industry sectors that purchase electricity. This was accomplished by mapping the EC data by NAICS codes to their corresponding IO sectors, and mapping the EIA classifications for non-manufacturing sectors. A partial mapping is shown in Table 3.1, and a full mapping is provided in Appendix B. Using these prices, we multiply each element in the PGS sector rows by the appropriate price inverse to convert the monetary values to MWh in the Use table. That is,

$$U^{M} = U_{PGS,.} * P_{PGS}^{-1} \tag{3-1}$$

where U denotes the Use table; the first subscript denotes the row the operation is performed on, while the second denotes the column; P denotes the price mapping for each column of the Use table; and the dot (.) notation denotes that the multiplication operation is done along the entire dimension it replaces (in this case, the columns of the Use table).

Table 3.1: End-Use Classification to BEA mapping for select sectors. Prices in $/kWh for year 2007.

End-Use Classification	BEA Sector Code	Sector Description	Sector Average Price, $/kWh
Industrial	11-22	Agriculture, Mining, Utilities	0.064
Industrial	33131A	Primary Aluminum Manufacturing	0.042
Industrial	31-33	Other Manufacturing	Individually mapped
Commercial	42-49	Wholesale, Retail, Warehousing	0.097
Residential	F01	Private consumption	0.107
Commercial	531ORE	Other Real Estate	0.097
Commercial	51-92, F02-F09	Information, Finance, Public Administration, Exports, Gov. Consumption	0.097

3.3.3 MUIO Case Studies

To explore the effects of mixed units in our IO framework, we created a created a vector of commodity inputs for each industry and used them as final demand input for the MUIO model (Y in the standard Leontief equation). These vectors were populated using the Use table columns inputs of each industry, scaled to $1M, for both the EIO and MUIO models (i.e., divided every element in a given Use table column by the column sum). This gives us a sense of which sectors in the economy are most affected by a change in the price of electricity. For the MUIO model, the appropriate physical values were used (found by using the individual industry prices) for the electricity inputs for each industry to ensure that the total value was $1M for the entire column.

In addition, we examine the vectors of commodity inputs for three specific industries from the above run in more detail. These are the supply chains for the Private Consumption (PC), Alumina Refining and Primary Aluminum Production (Al), and Other Real Estate (ORE) sectors.

These were chosen because they each represent important sectors of the U.S. economy but their supply chain purchases are distinct from each other:

1) Private consumption represents expenditures by U.S. households. Direct consumption of electricity constitutes less than 2% of total private consumption in monetary terms, however electricity contributes significantly to the supply chains of the goods and services purchased. Private consumption also pays the highest price for direct electricity use compared with other sectors in the model.

2) Aluminum production is an industrial sector with high electricity requirements and low electricity prices. Electricity represents roughly 11% of aluminum production sector expenditures. Similar to other industrial and manufacturing sectors in the U.S., aluminum production experiences lower electricity prices than the transportation, service, and final demand sectors.

3) Other real estate is a sector with a relatively large percentage of its consumption expenditures for electricity (approximately 7%) and is an example of sector with a service commodity (i.e. non-manufacturing IO industry). This industry sector consists of establishments engaged in leasing and rental of non-residential real estate, such has office or storage space.

The supply chains of each of these sectors were scaled to $1M in order to allow for easier comparison of results across sectors. Demand for these sectors is also run with the MUIO model based on low and high electricity prices, to examine the sensitivity of results to changes in price *within* sectors. Results from this sensitivity analysis are discussed in Appendix B.

3.4 RESULTS

3.4.1 Results for all BEA sectors

Figure 3.3 shows the difference in total emissions for running the Use table column inputs of each BEA sector, scaled to $1M, between the MUIO and EIO models. Figure 3.4 shows the ratios between the two sets of results. For equivalent models, values would lie along the y = 0 and y = 1 lines, respectively. It is important to note that the further from these lines of equivalence the points are on the graph, the greater is the impact of the relative price differences between the models. In both figures, most values do not fall along the lines that indicate equivalence. The biggest differences can be observed in the BEA manufacturing, mining and drilling, and utility sectors, all of which lie above the equivalence lines, with aluminum production being the sector farthest from equivalence. As IO sectors, these industries on average pay lower electricity prices in the MUIO model than the average U.S. electricity price they pay in the EIO model; this is reflected in the MUIO model price mapping, which drives this difference. In contrast, non-manufacturing the sectors lie closer to or below the equivalence lines. Those that lie below have lower emissions estimates from the MUIO model, such as some commercial sectors or final users (e.g. warehousing and private consumption, respectively). These sectors are assigned higher electricity prices in the MUIO model than the U.S. average used in the EIO model, resulting in lower emissions estimates. Those that deviate the most below the line (i.e., real estate and warehousing) usually have electricity use as a large component in their supply chains. However, these sectors below the equivalence lines do not achieve differences as large as those above due to a combination of two factors: 1) they have a relatively smaller amount of electricity use when compared to manufacturing and mining sectors, meaning these high prices produce a smaller effect in decreasing emissions when compared to the effect that low prices paid by manufacturing sectors have in increasing emissions, and 2) most sectors in their supply chains pay either lower electricity prices or at least U.S. average prices, which drives emissions up, counteracting the effects of high, direct electricity prices.

Perhaps the most interesting observation from Figures Figure **3.3** and Figure **3.4** are that few sectors greatly deviate from the equivalence lines. Even among those sector groups where prices were mapped in most detail (e.g., manufacturing), under 10% of the sectors experience an increase in emissions greater than 20%, while over 80% of sectors experience a reduction in price of over 20% (this can be seen in Figure 3.4, as few sectors are outside the 0.9-1.1 ratio range). The few sectors that diverge significantly from the equivalence lines are those that have significant electricity consumption, both directly as a higher proportion of their supply chain, and indirectly, through a high demand of sectors that themselves require high electricity consumption. This is the case for the Aluminum production sector, which in both Figures Figure **3.3** and Figure **3.4** is the highest point in the graphs; this industry consumes significant amounts of electricity directly, as well as having a high proportion of mining sectors in its supply chain.

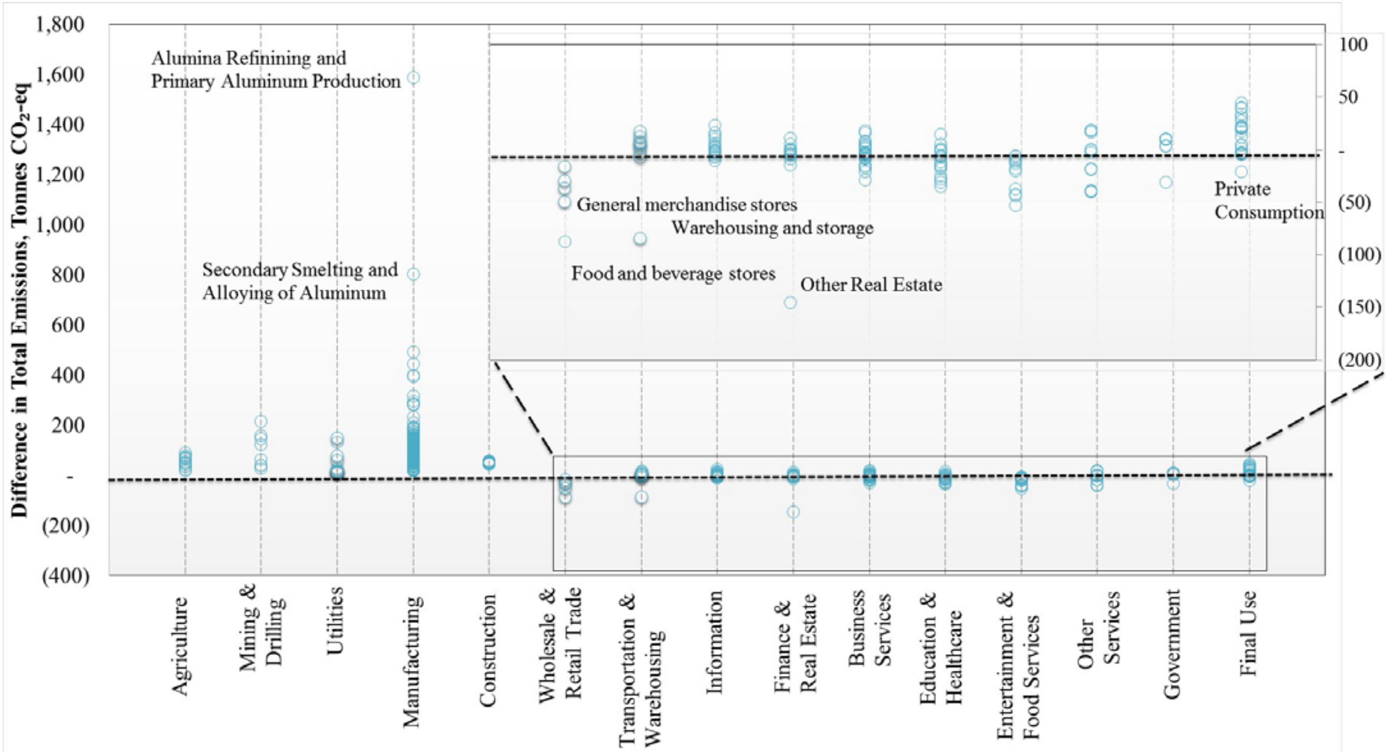


Figure 3.3: Difference in Total Emissions between MUIO and EIO model results (MUIO-EIO)

Each bubble represents the difference in total emissions from running the supply chain for a particular BEA sector, scaled to $1M. Bubbles are grouped by aggregate BEA sector labels. The bubbles starting with the Wholesale & Retail Trade label are expanded and shown in a lower scale in the box above them.

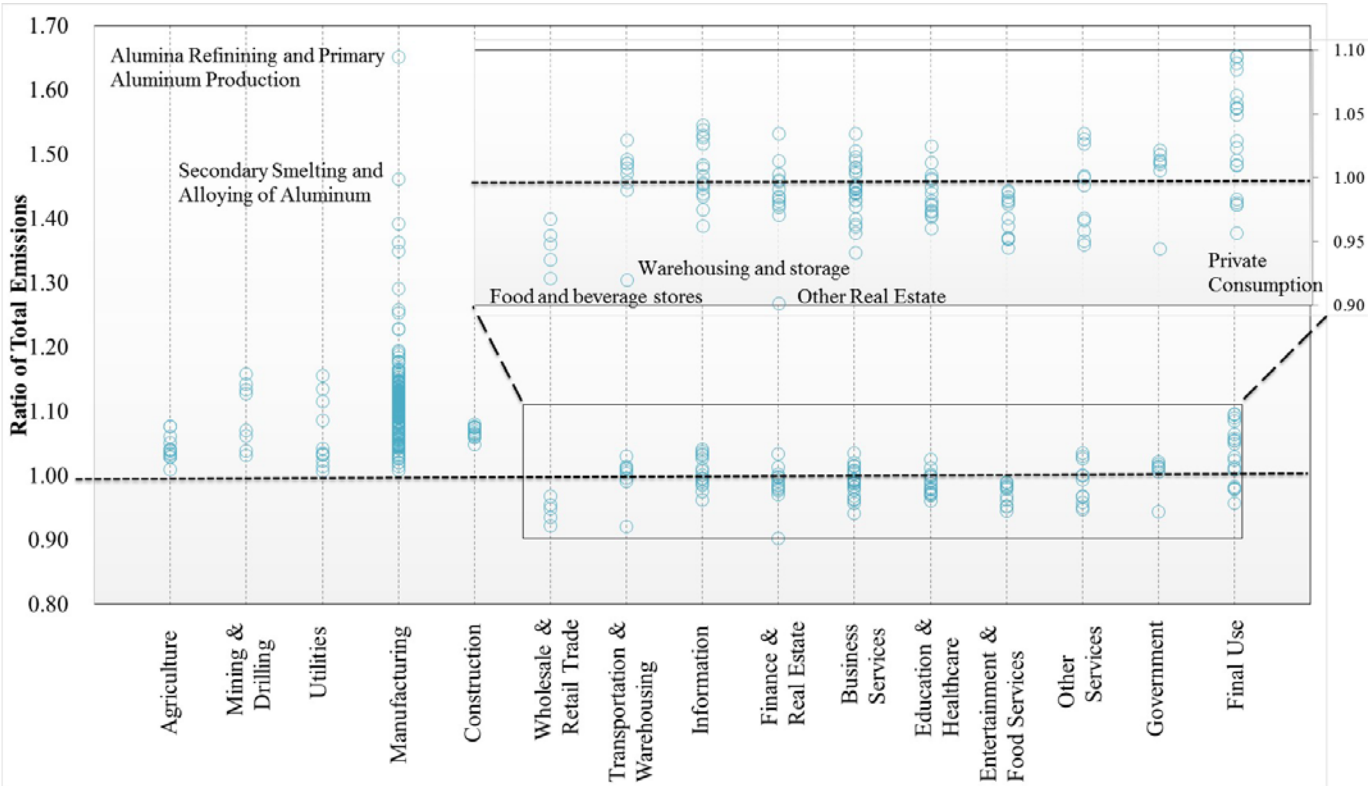


Figure 3.4: Ratio of Total Emissions between MUIO and EIO model results (MUIO/EIO)

3.4.2 Results for PC, AL, and ORE sectors

Figure 3.5 provides a comparison of life-cycle GHG emissions resulting from the supply chains of PC, Al, and ORE sectors for the EIO model and MUIO models in absolute terms. To highlight the differences between model results, each bar is divided into emissions from these sectors' direct electricity use, i.e. Scope 2, and emissions from all other supply chains, including electricity supply chains, i.e. Scope 3. Note that direct emissions, i.e. Scope 1 (WBCSD; WRI 2004) are equivalent in both models, as the only changes between models are related to electricity use being described in energy versus monetary terms. Accordingly, differences in the Other Emissions portions of the bars in Figure 3.5 (which corresponds to Scope 1 and 3 emissions) can unambiguously be attributed to the change in electricity prices along the supply chains of the selected sectors.

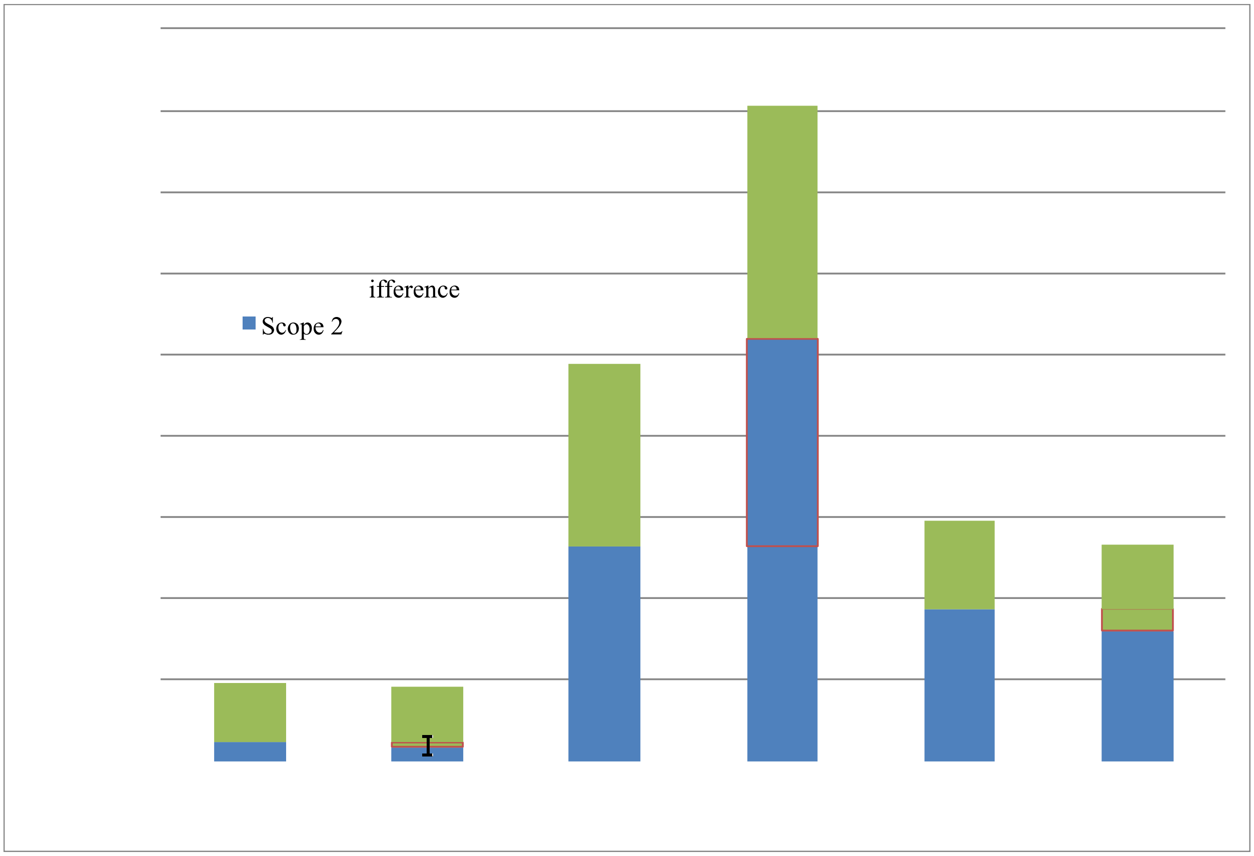


Figure 3.5: EIO vs. MUIO emissions differences
EIO vs. MUIO model for three supply chains: Private Consumption (PC), Primary Aluminum Production (Al), and Other Real Estate (ORE).
Scope 2: Direct emissions from electricity generation associated with direct purchases of electricity.
Scope 2 Difference: Difference in emissions between the MUIO and EIO models due to electricity purchases. The color inside the red lined box indicates which emissions were increased, whether scope 2 (blue, for AL) or scope 3 (green, for PC and ORE).
Other: Emissions caused by each sector's consumption of goods other than electricity in their operation (Scopes 1 and 3). Black error bars present the sensitivity of Scope 2 emissions due to high and low electricity price estimates for the MUIO model.

Figure 3.5 highlights a few results. First, for the MUIO model the amount of Scope 2 emissions change significantly for the Al sector, and less significantly for the PC sector and ORE sectors. The red-lined box shows the difference in electricity generation emissions between the EIO and MUIO models. As mentioned previously, this is due to the price mapping applied when creating the models. On average, the residential sector pays the highest price for electricity consumption (see Table 3.1). This higher price results in a reduction of MWh consumed by the PC sector in the MUIO model, leading to a decrease in Scope 2 emissions from residential use. The Scope 2 share of total emissions associated with PC has decreased by roughly 5%, a substantial amount considering purchases of electricity account for only 2% of total expenditures in monetary terms. Compared with the monetary model, Scope 2 emissions from private consumption are 20% lower in the mixed-unit model. A similar trend can be observed for the ORE sector, which pays a higher than average price (though not quite as high as PC); ORE Scope 2 emissions decreased by roughly 15%. Conversely, the lower price paid by the Al sector results an increase in the amount of electricity directly consumed by this industry as computed by the MUIO model, increasing the resulting emissions. For the Al sector, Scope 2 emissions almost doubled (from 1,322 to 2,593 Tonnes of CO_2-eq) when compared to the EIO model; however, there is also an increase in supply chain emissions, as Scope 2 emissions only increased by approximately 9% as share of total emissions (4,097 Tonnes CO_2-eq) in the MUIO model. These result highlights the fact that in monetary IO models, sectors that pay higher than average prices are allocated more Scope 2 emissions than physical accounting would suggest, while sectors that pay a lower than average price are assigned fewer Scope 2 emissions.

Second, the change from U.S. average prices in the EIO model to sector-specific prices in the MUIO results in the increase of Scope 1 and 3 emissions for sectors where indirect electricity consumption is prevalent throughout the supply chain. This is seen in the green portion of the bars in Figure 3.5, which are larger for the MUIO result of Al than they are for the EIO results (even after accounting for changes in Scope 2 emissions), resulting in an overall increase in emissions from this (and similar) sectors. For PC and ORE, the increased emissions along the supply chain are almost enough to offset the decrease in Scope 2 emissions, such that the net emissions from the MUIO and EIO models for PC are fairly similar. The decrease in total emissions is more notable for the ORE sector than PC since PGS consumption constitutes a larger percentage of the supply chain (7% vs. 2%, approximately).

The combination of these two effects – shifting Scope 2 emissions responsibility to different parts of the supply chain and potentially affecting the total emissions estimates – suggest that the choice of economic vs. physical models based on sector specific prices has the potential to significantly impact results of a study using the IO framework. Which is the better choice depends on the context of the study, as discussed in Section 5, below.

3.5 DISCUSSION AND CONCLUSIONS

The results presented in this analysis highlight that the choice of energy versus monetary units to represent the reference flow for electricity generation can have a significant effect on emissions results for specific IO sectors, ranging from a notable decrease in scope 2 emissions (20% decrease in scope 2 emissions for PC) to over 50% increase of total emissions (Aluminum sector). We have demonstrated that the difference in GHG emissions results is larger for sectors with a higher share of electricity expenditures and which pay a price that is significantly different from the economy-wide average, and that emissions for sectors with a higher share of electricity expenditures may be affected. These conditions occur most significantly in the case of industrial sectors that pay low electricity prices. Additionally, estimated emissions burdens along different parts of the supply chain can be affected as well when comparing EIO vs. MUIO models with sector-specific prices (i.e. changes in Scope 2 and Scope 3 emissions), as shown in the sectors chosen for detailed analysis in this study. These sectors have similar consumption profiles to several other sectors in the economy; that is, aluminum has a high share of electricity consumption in its supply chain, similar to other manufacturing sectors, whereas the opposite is true for ORE and other services sectors (these similarities can be seen in the trends in Figure 3.3 and Figure 3.4). The repercussions of this implicit bias depend on the intent with which the IO framework is used. For LCA and other studies that focus on estimating electricity emissions, whether the effort required to map electricity prices (and thus use a physical allocation for the IO framework) is warranted it depends on: 1) whether physical allocations reflect the driving motivations for electricity production and the related emissions, and, 2) if the price differences between end users of a commodity are enough to produce significant emissions or energy balance differences between the two approaches.

One way to determine which model to use is to consider the intent for which the electricity is used. Using a physical allocation for the electricity generation is a sensible approach when looking at a study that uses electricity as an input to another process (e.g., producing aluminum) rather than as commodity for end use consumption (e.g. to operate domestic appliances). In these cases, electricity use is a function of the production of the primary process, and the emissions resulting from that electricity production can be attributed to the end result of the process. In this regard, the MUIO model can be used to link physical processes with the rest of the supply chain to better estimate the electricity flows and emissions at a national level. Conversely, the economic allocation that is inherent in EIO models is better suited for studies where determining the cause of consumption (and thus the cause of emissions) of electricity by end-users is a main goal. It is these end use sectors that are ultimately responsible for the production of the commodity in the first place (e.g. electricity produced at higher prices for the PC sector would not be created without this user base, as industrial users would have used cheaper electricity). This is conceptually similar to the consumption-based approaches for carbon accounting used in other IO studies (Vetőné Mózner 2013).Several factors influencing electricity production, such as time of energy use (e.g. marginal electricity produced by peaking power plants) are not easy to physically relate to the amount of emissions produced, suggesting economic causality (and thus an EIO approach) is appropriate (Ardente and Cellura 2012). These differences in the two allocation approaches are similar to the ones discussed by Dietzenbacher et al. (2009), where different allocation schemes are proposed for wastes in physical IO tables based on where the responsibility of the waste produced for a given final demand lies.

Another factor that might affect which model is a better option is whether the price paid by a specific sector deviates significantly from the assumed average price. In this case, using the MUIO model will allow a better representation of emissions. Significant deviations might occur due to issues such as geography, or increasing price variability. Indeed, while all the prices used in this study are 2007 prices to match the BEA benchmark year IO Accounts, most recent electricity prices have greater variability, as shown in Table 3.2. This increase in price variability has the potential to exacerbate the differences between EIO and MUIO models presented in this work.

Table 3.2: Differences between 2007 and 2013 prices for different end-use sectors (i.e. customers) (EIA 2014). All prices in 2007 dollars. 2013 prices adjusted using the U.S. Bureau of Labor Statistics (2015) CPI inflation calculator.

	Average price	High Price	Low Price
Residential '07	10.65	24.12	6.36
Residential '13	10.79	32.91	7.74
Commercial '07	9.65	21.91	5.14
Commercial '13	9.15	26.74	6.56
Industrial '07	6.39	18.38	3.87
Industrial '13	6.09	26.59	3.76

The framework presented in this study can be expanded to other sectors beyond electricity generation in order to study the effects of price on those sectors, or to build a mixed unit model with additional unit types. For example, a suitable sector could be petroleum refineries, as this sector produces several commodities that vary in price in a manner similar to electricity (i.e., different end-users pay different prices for petroleum products). Choosing between the EIO vs. MUIO models should be done on a case-by-case basis, after considering what the intent of the study is and whether gathering the additional price data to include in the MUIO model is a reasonable investment. For this electricity focused MUIO model, the investment in finding additional data is better justified for studies focusing on manufacturing sectors, as these tend to be more sensitive to the choice between physical and economic allocation.

4.0 INTRODUCTION OF REGIONAL DATA IN THE EEIO FRAMEWORK – DEVELOPING THE MULTI-REGIONAL INPUT-OUTPUT MODEL

This chapter introduces the regional aspect to the IO model, along with the disaggregated (Chapter 2) and mixed-unit (Chapter 3) aspects of electricity generation to create the final electricity-specific Multi-Regional model. Bringing together these three different components aims to tackle some of the limitations inherent to input-output environmental analysis. The distinct electricity technology sectors tackle the technology aggregation bias in electricity. Introducing physical units by using detailed, sector-specific electricity pricing in the model to create a physical rather than monetary flow assumption for electricity generation and consumption reduces the uncertainty associated with monetary allocations, such as inflation and price fluctuations. Finally, including distinct regions addresses the geospatial uncertainty with regards to electricity generation and consumption, and can be used to estimate emissions at their point of release (due to generation) or at their point of probable cause (consumption).

Figure 4.1 shows a conceptual representation of the finalized MRIO framework. In this representation the electricity flows (in physical units) from the top left to the bottom right of the Leontief Inverse (or Total Requirements) table, as the individual PGS technologies inform the state consumption of electricity, which in turn drive the electricity use of the different industries in the economy. The rest of this chapter discusses the implementation of this framework given the components available from Chapters 2 and 3 plus the addition of geographical information.

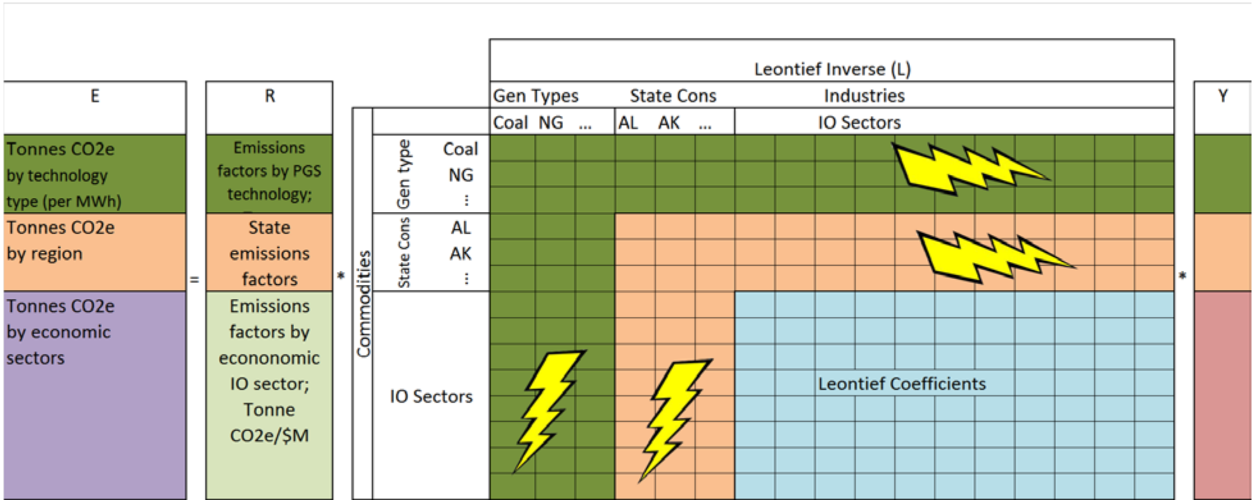


Figure 4.1: MRIO Framework with Disaggregated, Regional, Mixed-Unit PGS Sectors

4.1 INTRODUCTION

Continuous electric power generation is necessary for the normal operation of modern economies. In the United States, electricity production accounts for 39% of primary energy consumption (Energy Information Administration 2016b) and approximately 2% of economic activity (U.S. Bureau of Economic Analysis 2017). Such production requires vast use of resources; an interconnected grid to transmit the electricity from production centers to consumption sites; and creates significant environmental impacts. Given the interconnectedness between the economy, energy and the environment, it is critically important that policies regarding electric power generation be carefully evaluated to ensure that they fulfill their intended goals and that unintended consequences are not overlooked.

U.S. policies concerning electric power generation can be set at different regulatory levels. An example of a national policy is the Clean Power Plan, which was planned at the federal level and required a reduction in greenhouse gas (GHG) emissions from power plants by 30% by the year 2030 from 2005 emissions levels (U.S. Environmental Protection Agency 2015b). Even though such policies are aimed at national emissions reductions, their implementation is often executed at other regulatory levels. In particular, states often have considerable flexibility in the implementation of such policies within their borders, as they are the ones that set specific requirements that power generation companies must adhere to in order to meet national goals. In addition to carrying out federal mandates, states usually have individual goals that may not be directly tied to the national policy but interact with them in some way, such as specific Renewable Portfolio Standards (RPS) or energy efficiency targets (N.C. Clean Energy Technology Center 2016). Since electricity flows between states are linked through trading, both of electricity and other commodities, what happens in one state may affect other states, either directly or indirectly;

for example, electricity imported out of state leaves emissions impacts in the original exporting state. Given this reality, any analysis of national energy policy must consider the state level implementation of those policies to better capture the effects caused by the connections between states.

Environmentally Extended Input-Output (IO) models are often used to analyze both the environmental and economic impacts of policies at the national level, not only for the U.S. but also for many different countries. IO models and the corresponding data for individual countries can be connected to create Multi-Regional Input-Output (MRIO) models to provide a complete picture of the supply chain of goods and services in interlinked economies. Recent studies have used this approach to analyze and account for supply chain emissions related with particular products or services across international borders (Lenzen et al. 2013a; Wood et al. 2015). However, even though MRIO models are usually created to bridge gaps in flows between regions with existing IO models, they can also be created when there is sufficient data to transform a single region into multiple sub regions while maintaining the links between them.

In this study, we present a method for creating an environmentally-extended, electricity-focused MRIO model of the U.S., aimed at evaluating the environmental effects of electricity policy at both the national and state level, as well as understanding how changes in those policies affect the environmental impacts not only of states but also of non-electricity sectors in the economy. To explore the potential of the model, we developed two different scenarios. The first scenario aims to estimate the GHG and water consumption (WC) impacts related to projected changes in the U.S. electricity grid, according to EIA, and is intended to show the model's applicability as a tool for government policy evaluation at the state and national levels. The second scenario aims to demonstrate the utility of the model to analyze electricity consumption impacts due to a specific industry, data centers, both as an overall component of the U.S. economy, and as an plausible environmental impact analysis pursued by private corporations that rely on data centers for their business operations.

The MRIO model presented is capable of tracking electricity produced by several different technology types in megawatt-hours (MWh), resulting in electricity emissions estimates based on physical rather than economic basis. We also take into account electricity trading between states, which allows the model to report not only impacts due to production, but also consumption-based estimates, a concept that is gaining recognition as a key element in better understanding the embodied emissions in traded goods and services and thus useful for policy formulation (Vetőné Mózner 2013). The model takes into consideration the geographic distribution of the economic sectors it contains, so that each sector draws from their appropriate electricity generation technologies and can thus assess the upstream impact of changes to the electricity supply used by these sectors.. We focus on GHG emissions because, beyond its importance as an indicator for global warming potential, most clean power policies focus on GHG reductions. Additionally, GHG emissions are strongly correlated with other combustion related impacts, such as smog formation, respiratory effects and human health impacts, and even acidification, making it a good proxy indicator for these effects even though data collection for these impacts is beyond the scope of this work. We also focus on water consumption associated with electricity use, given its critical importance in electricity generation, the localized nature of water consumption impacts, and the growing awareness of the importance of the energy-water nexus (Bauer et al. 2014).

Section 4.2 provides a brief overview of recent literature concerning assessments of regional electricity impacts, as well as recent development and use of MRIO models. Section 4.3

provides an overview of the MRIO model creation. Sections 4.4 and 4.5 describe scenario development and results, while section 4.6 contains concluding remarks.

4.2 BACKGROUND

Recent studies have looked at the potential development and environmental impacts of U.S. electricity sector, focusing on different aspects of electricity production and using a variety of methods. A common approach is to use bottom-up, process-specific models that describe electricity generation in great detail. Such approaches often include methods for estimating changes in the grid due to renewable energy expansion, changing energy costs, and for diverse types of environmental impacts. Examples include the MARKAL (Shay et al. 2008) and ReEDs (Short et al. 2011), bottom-up linear optimization models that have been used to analyze the impacts of climate mitigation scenarios in the U.S. Regional and national policies are usually adapted for analysis by creating specific scenarios that explore their potential impacts, such as reductions in regional air quality (Rudokas et al. 2015) and possible technology pathways for electricity generation (and concomitant GHG emissions) in the near to midterm future (Sullivan et al. 2014). These studies rely on a comprehensive set of inputs and parameters that drive their calculations, and can produce detailed results concerning impacts of electricity production. However, while they may include non-electricity related data, they do not encompass the entire economic supply chain, and are usually focused on impacts of electricity production rather than consumption.

Another approach for analyzing impacts of electricity production is to use methods that rely on economic, material, and environmental data compiled by governments and used for analysis at the national level. MRIO models are an example of this type of approach. Recently, many different models have been built and used for policy assessment, usually emphasizing the impact of international trade on resources and embedded carbon flows (Steen-Olsen et al. 2012; Lenzen et al. 2013a; Wood et al. 2015; Aguiar et al. 2016). Though less common, MRIO models are also gaining use as tools to assess policies and environmental impacts of regions within individual countries (Wiedmann et al. 2010; Su and Ang 2014; Bachmann et al. 2015). In the U.S., MRIO models have been developed both with a focus on economic (Bureau of Economic Analysis 2014; IMPLAN 2016; Regional Economic Models 2016) as well as environmental analyses as main objectives. For example, Cicas et al. (2007) developed an 8-region model of the U.S. for regional policy assessment based on the BEA 1997 benchmark accounts, adjusting national totals for economic and environmental emissions with state and regional economic multipliers. Caron et al. (2014) created an MRIO model (using IMPLAN as a basis for the economic multipliers) to estimate the CO_2 content of consumption across regions of the U.S. Although regional electricity production and the related emissions is an important consideration for both of these studies, they do not distinguish between types of electricity generation technologies, nor estimate water use.

Taken together, the models currently available for estimating impacts of electricity in the U.S. are well suited for in-depth analyses of different electricity generation trends and impacts using highly detailed models and input requirements, or broader economic and environmental analyses that incorporate electricity in a more aggregate manner. However, it is more difficult to investigate regional environmental effects related to but not only consisting of changes in electricity consumption, issues that might not suit the scale of either approach: what are the environmental effects of changes in economic activity that depend on electricity consumption when they shift towards regions with cleaner electricity? What are the secondary (supply-chain) effects of these industries' cleaner electricity consumption? Are they comparable to effects caused by direct consumption changes? The MRIO model is ideally suited to tackle these questions, as it can estimate both regional and supply chain effects of by different end-users, and put the changes in environmental impacts in context with the rest of the economy. Additionally, it allows the evaluation of secondary effects of regional shifts, such as environmental impacts of employment and labor related to these shifts. Finally, it is created using publically available data, and the final model will also be publically available.

4.3 METHODS

4.3.1 Building the MRIO model

Figure 4.2 contains a flowchart that shows the data used to create the MRIO model; how those data are used; and the use of the completed model. Figure 4.3 shows a simplified representation of the original Use table (part A), and a representation of the final MRIO Use table (part B) after all the model development steps in Figure 4.2 have been implemented.

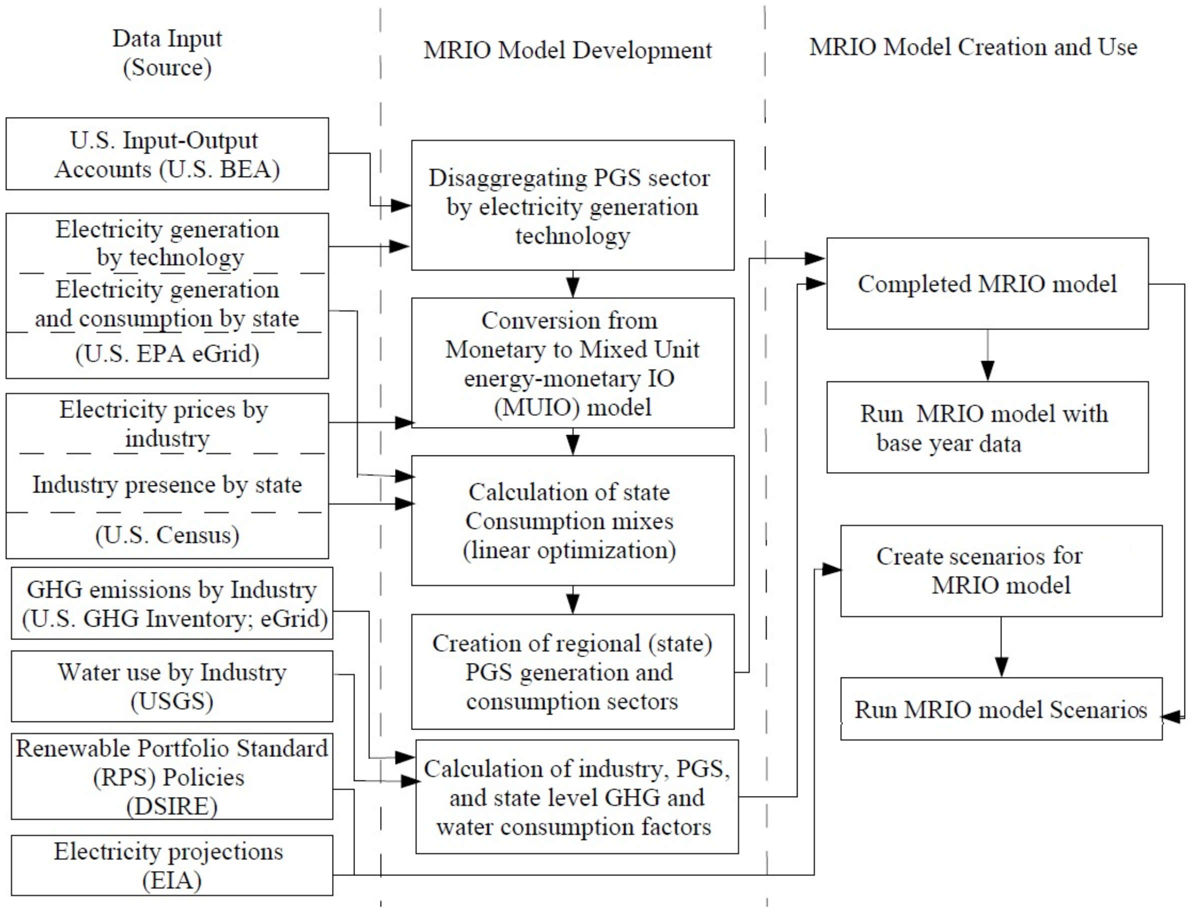


Figure 4.2: Flowchart for MRIO model creation
First column are data inputs; second column represent major model development steps; third column represents finalized model use.

A) Original IO Use Table

		Industries		
		Electricity Sector	Economic Transactions, excluding Electricity	Final Demand
Commodities	Electricity Sector ($)	Electricity Use ($) by Electricity Production	Electricity Use ($) by Industry Production	Non-Industrial Use of Electricity ($)
	Economic Transactions, excluding Electricity ($)	Economic Use ($) by Electricity Production	Economic Use ($) for Industry Production	Non-Electricity Final Demand ($)

B) MRIO Use Table

		Electricity Industries			Other Industries	
		Electricity Gen. by Technology	Electricity Gen. by State	Electricity Consumption by State	Economic Transactions, excluding Electricity	Final Demand
Electricity Commodities	Electricity Gen. by Technology (MWh)		State Gen. Mixes by Tech. (MWh)			
	Electricity Gen. By State (MWh)			Consumption Mixes by State (MWh)		
	Electricity Cons. by State (MWh)	Electricity Use (MWh) by Electricity			Electricity Use (MWh) by Industry Production	Non-Industrial Use of Electricity (MWh)
Other Commodities	Economic Transactions, excluding Electricity ($)	Economic Use ($) for Electricity Production			Economic Use ($) by Industry Production	Non-Electricity Final Demand ($)

Figure 4.3: Use table of the Model before (part A) and after (part B) of MRIO modifications. *Part A represents the original Use table with: one Electricity Sector in economic terms; all non-electricity sectors (approx. 400), represented by the Economic Transactions rows; and multiple Final Demand columns (represented here in one consolidated column); Part B represents the MRIO Use table that, in addition to the sections in Part A, also contains multiple (disaggregated) Electricity Technology Sectors, State Power Generation Sectors,, and State Power Consumption Sectors, all in energy terms. The areas in gray color have a value of 0. Tables are color coded according to row classifications.*

4.3.1.1 Introducing Regional Electricity Sectors

In this model, we include each U.S. state, the District of Columbia, Canada, and Mexico as individual regions for the reasons described as follow. First, energy policies are often set at the state level. Using a more aggregate geographic approach such as NERC regions would limit the ability of the model to represent individual state policies. Second, states are the highest geographic resolution for which we could obtain the data necessary to model regional electricity flows, their associated environmental impacts, and the interactions of regional electricity consumption with the rest of the economy (i.e. electricity supply chain) while still maintaining the IO framework at a reasonable size. Finally, including Canada and Mexico as states allows the model to contain the entirety of the electricity produced and consumed by the U.S. (even though trade accounts for less than 1% of U.S. electricity consumption), thus accounting for the international trade of electricity occurring in the North American grid. For simplicity, all regions are referred to as states going forward.

The MRIO model as shown in Figure 4.3B represents the interactions between generation technologies, state generation, state consumption, and industry consumption of electricity. These interactions are intended to flow from left to right, up to down in the figure. Thus, generation technologies flow into state generation mixes; generation mixes inform state consumption mixes; and consumption mixes are used to create industry consumption profiles. The rest of this section explains the creation of the MRIO model starting from the original IO model. Additional details relating to MRIO model creation can be found in the Appendix C.

4.3.1.2 BEA PGS sector disaggregation and use of mixed economic and energy units

To build the MRIO model, we combined data from several different sources. The main component of the model is based on the 2007 producer value BEA Benchmark Input-Output accounts (U.S. Bureau of Economic Analysis 2013), which contain the detailed Supply and Use tables for the U.S. economy. Each table is a Commodity by Industry matrix. For the Use table, each column represents the use of different commodities by each industry, while for the Supply table each column is the amount of commodity output from each industry.

The use of electricity by the economy is described by Power Generation and Supply (PGS) sector in the tables. We complemented the Use and Supply tables with electricity generation data, which was used to disaggregate the original BEA PGS sector into 10 distinct electricity generation technologies: coal, natural gas, oil, nuclear, hydroelectric, geothermal, biomass, wind, solar, and other. The disaggregation is described in detail in Vendries et al. (2015) and is represented in Figure 4.3 by the change from the Electricity Sector in part A to the Electricity Generation by Technology industries and commodoties sectors in part B.

The model tracks electricity flows in the economy in energy units. For this purpose we used electricity price information (U.S. Census Bureau 2007; EIA 2014) to convert the monetary data in the PGS sectors to energy units, in effect creating a Mixed-Unit Input-Output (MUIO) model. This step is necessary to reduce emissions estimates errors present in the IO model due to the implicit assumption that all economic sectors pay the same price for their electricity consumption, as well as allow the model to more easily track electricity trading between states. Additional details on this process can be found in (Vendries Algarin et al. 2015; Vendries Algarin et al. 2016). Again this is represented in Figure 4.3, as the Electricity sector changes from being tracked in dollars ($) in part A to MWh in part B.

4.3.1.3 Electricity Generation and Consumption by State

Electricity generation and consumption data by state for 2007 (the IO benchmark year) was obtained from U.S. EPA's eGRID database (2017). Import and export data to Canada and Mexico was obtained from EIA (2016a), Canadian, and Mexican government reports (Griffin 2017) (Secretaria de Energia 2015). These sources list net electricity generation and net consumption by state, which was used to create the first expansion to the MRIO model: the addition of Input-Output sectors that represent the amount of electricity generated in each state by each technology type. This is shown in "State Generation Mixes by Technology" block in Figure 4.3. Here, rows represent disaggregated electricity sectors and columns represent regions. The full-scale model contains 10 distinct electricity sectors, as well as rows and columns for regional generation mixes.

Electricity production values by state and generation type are based on eGRID (U.S. EPA 2017). The values are allocated such that the row totals match the national generation mix by technology type and the column totals match each region's share of total electricity production, making the sum of all values in the State Generation Mixes block match total U.S. electricity production.

Electricity consumption by state is shown in the "Consumption Mixes by State" block in Figure 4.3. This is the intersection of Electricity Generation by State row and Electricity Consumption by State column, which respectively correspond to all 53 generation and consumption regions in the full scale model. The difference between generation and consumption regions is that the latter incorporates the effects of electricity trading, and classifies states as net exporting or net importing. Interstate electricity trade was estimated using the net generation, net consumption, and net Export/Import data as inputs to a linear optimization model whose objective function minimizes the distance electricity must travel between net exporting states and net importing states (Marriott and Matthews 2005). This method is not meant to model all the individual interactions and transmissions between generation and consuming locations, but rather to provide an estimate of the net flows of electricity trading at the scope required by the MRIO model. Indeed, the difficulty in precisely tracking real time electricity flows from generation to consumption point translates to a lack of detailed electricity consumption data (Kodra et al. 2015) (Weber et al. 2009), making net import/export data the best estimates available at the state level.

4.3.1.4 Consumption by Industry

Electricity consumption by industry is allocated to the states where those industries are located. This allocation is created by aggregating County Business Patterns (CBP) data from the U.S. Census Bureau (2009) to the state level, and mapping the resulting state level employment data to the BEA IO Industry sectors. Some industries have no data available for mapping because data for these sectors is either classified (no estimate given) or aggregated in such a way that the CBP reports a range estimate for employment (e.g. small, medium, large businesses). For these sectors we found industries that were the most similar in their description or purpose in the BEA classification, and used their geographic distribution to replace the absent CBP estimates (see Table C.1) (Bureau of Economic Analysis 2009). Allocation by geographic distribution creates slight discrepancies between the row and column totals of the “Electricity Use by Industry Production” block, so a RAS procedure was used to rebalance them (Miller and Blair 1985). This procedure results in a state by industry matrix where each column describes the geographic distribution of a given industry in the U.S., represented by the blocks along the “Electricity Consumption by State” row in Figure 4.3. This row shows electricity consumption “commodities” for all 53 states. The “Electricity Use by Electricity” block represents the electricity required by the individual generation technologies to produce electricity; the “Electricity Use by Industry Production” block is the electricity required by all non-PGS industries for their operation. The final block on the row, “Non-Industrial Use of Electricity” is the different Final Demand sectors specified by the IO accounts, e.g. residential and government consumption of electricity, exports, etc. for each state (EIA 2016b).

Interindustry transactions other than electricity are included in the “Economic Transactions, excluding Electricity” rows in both the Original IO and MRIO Use tables. The “Economic Use for Electricity Production” block represents inputs to electricity technology sectors, including value added requirements (compensation for labor, taxes, operating surplus) based on Vendries Algarin et al. (2015). The “Economic use for Industry Production” block represents the economic requirements of the non-PGS sectors based on the BEA benchmark (Bureau of Economic Analysis 2013a).

4.3.1.5 GHG and WC Impact Factors & Running the MRIO model

In order for the model to be used for environmental impact assessments, the MRIO model needs impact factors for each individual sector for each type of impact category under consideration. The GHG emissions factors for the economic sectors were obtained from (Department of Defense 2015) and were developed for the disaggregated electricity sectors from a previous publication (Vendries Algarin et al. 2016). Water consumption estimates are developed based on Blackhurst et al. (2010) and updated to 2007 values (Maupin et al. 2014; Solley et al. 1998; Statistics Canada 2015; National Agricultural Statistics Service 2009). We used data from Torcellini et al. (2003), (Macknick et al. (2011); 2012), Mekonnen and Hoekstra (2012), Meldrum et al. (2013), and Diehl and Harris (2014) to create water consumption estimates for the individual PGS technologies.

The MRIO Supply table mirrors the structure of the Use table, but the values for the new blocks lie exclusively along the diagonal and are equal to the total commodity value (i.e. corresponding Use table row sum). To create the final MRIO model, the Use and Supply tables are combined with the Impact Factors as described in Chapter 1, and equation (1-5) is used to run the model.

4.4 MRIO SCENARIO: ELECTRICITY PROJECTIONS TO THE YEAR 2030

4.4.1 Modeling future electricity trends with the MRIO model

Electricity generation in the U.S. has undergone considerable changes in the past decade. Since 2007, electricity produced from coal has declined both in total generation and as a percentage of total electricity production, while natural gas and renewables have increased. These trends can be seen in Figure 4.4.

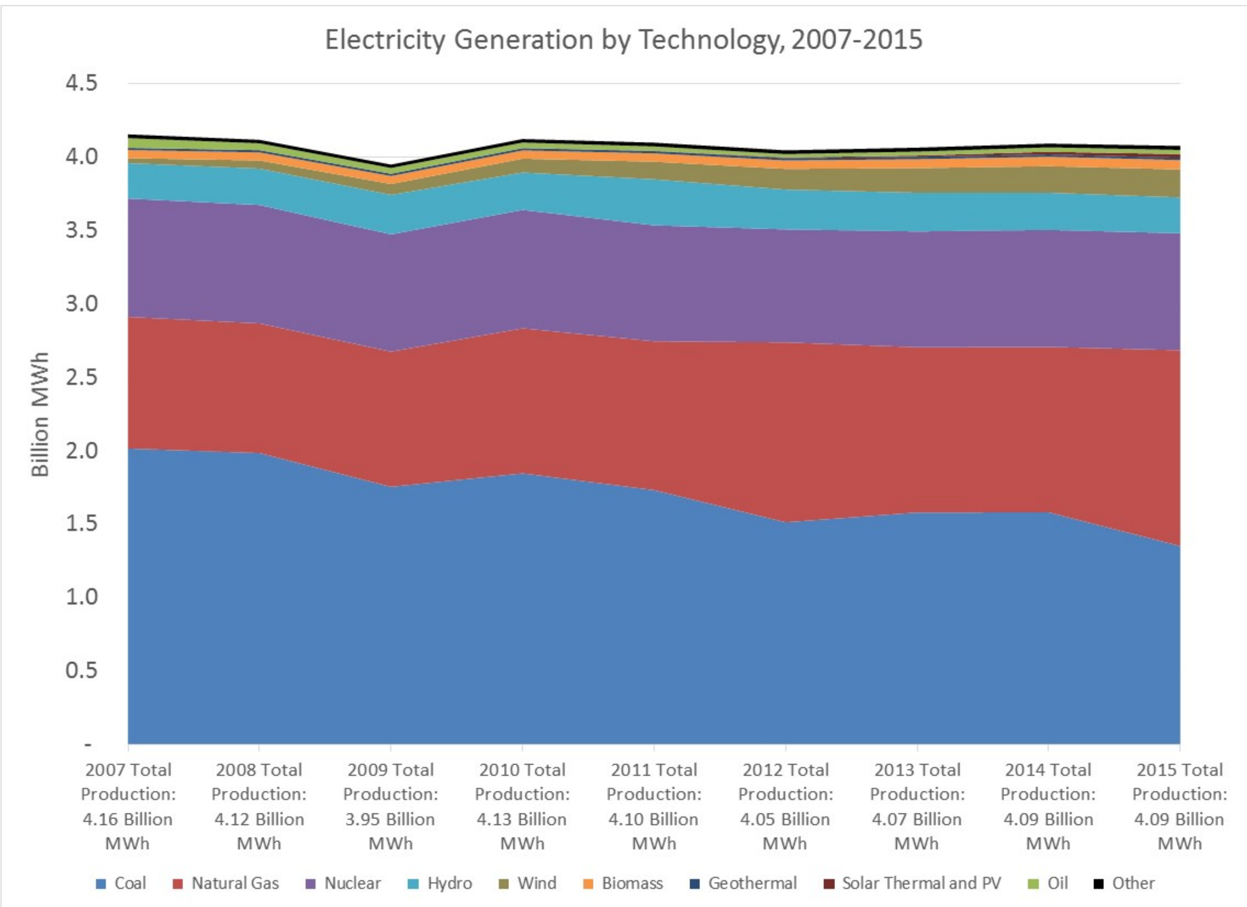


Figure 4.4: Yearly electricity production by Generation Technology, 2007-2015, EIA data

The goal of the MRIO model in this example is to evaluate regional electricity policies for both their regional and aggregate (national) effects, in terms of electricity flows and environmental impacts. We use recent trends in electricity production in the U.S. as well as EIA projections for electricity generation (Energy Information Administration 2017) to extrapolate a future electricity scenario for the year 2030. EIA data assumes trend improvement in known technologies, economic and demographic trends that reflect the central views of leading economic and demographic forecasts, and unchanging laws and regulations throughout the projection period (notably including the Clean Power Plan, as it was still the intended national policy at the time the data was published). This data provides a good guideline for future electricity production as they consider multiple energy technologies and have regional (but not state) specificity. Using EIA and eGRID data (U.S. EPA 2017) we build two new state generation mixes: one 2014 as a base year, reflecting the most up-to-date individual state generation data available for distinct PGS technologies, and another mix for 2030, reflecting the continuing increase in the use of shale gas for electricity generation, as well as moderate increase in renewable generation.

Some additional assumptions are made for this scenario, beyond the change in electricity generation mixes. The model still uses the BEA 2007 Input-Output accounts as a basis, as this is the most recent benchmark year data for the U.S. economy. It is also assumed that electricity trading patterns and industry distributions do not change, allowing the focus to remain on the effects of changes in generation mixes. However, a development that does influence supply chain emissions of the natural gas generation sector is increasing use of shale gas (Stephenson et al. 2011; Cooper et al. 2016) . Evolution of upstream emissions for natural gas are accounted for by modifying the GHG and WC factors for the Oil and Gas Extraction BEA sector shown in Table 4.1.

Table 4.1: Emissions factors for the Oil & Gas Extraction BEA sector, by year

Year	Shale gas production as percent of total gas production	GHG Emissions Factor, Tonnes CO2e/$M	WC Factor, kGal/$M
2007	10%	1,080	126
2014	48%	1,190	187
2030	69%	1,235	219

Once the generation mixes for 2014 and 2030 and emissions factors adjustments are finished, we create two MRIO models using the methods described in Section 3: the Base Case (2014 mix) and Projections Case (2030 mix). We then we ran a series of final demand vectors for each model and compared their supply chain GHG emissions and WC. The Final Demand Vectors are listed below.

1) 100 MWh of electricity consumption for each state;

2) One million dollars ($1M) in final demand for each non-PGS sector, as well as 100 MWh in final demand for each individual PGS technology (coal, natural gas, etc.), and

3) A private consumption vector, which represents the final demand of all commodities in the economy from residential users. It is important to note that the final demand for electricity in this vector is supplied by the state consumption sectors, rather than the individual PGS sectors (e.g. final demand for Coal PGS is zero; instead demand for Coal PGS is relayed through individual states).

4.4.2 Results for 2030 Projection Scenario

4.4.2.1 GHG and WC Results for 100 MWh of electricity consumption by State

Figure 4.5 shows the changes in emissions intensities resulting from 100 MWh of electricity consumption in each state with the Projected 2030 and Base 2014 MRIO models in terms of GHG emissions and WC. Each bar represents a single state. The left part of Figure 4.5 shows the differences in GHG emissions, while the right shows the differences in WC (Projected – Base).

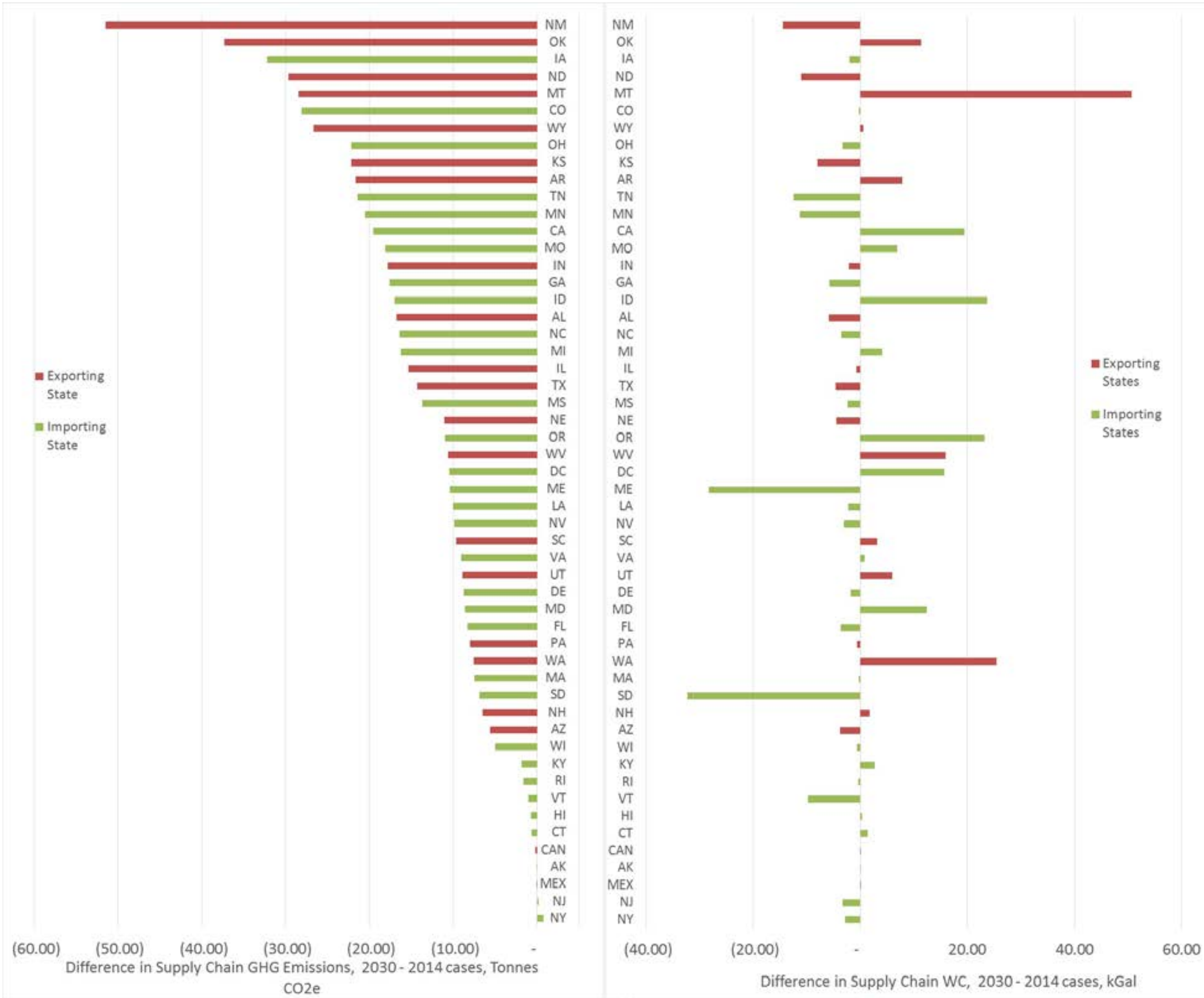


Figure 4.5: Difference between Projected (2030) and Base (2014) MRIO model results for 100 MWh of PGS consumption by state.
Negative values are shown in parenthesis, and indicate emissions reductions in the 2030 case with respect to 2014. States classified as net importing/exporting based on current electricity trading patterns.
Left: GHG emissions difference, Projected 2030 – Base 2014, Tonnes CO2e.
Right: WC difference, Projected 2030 – Base 2014, kGal.

There are several things to note from Figure 4.5. The first and most observable is that there is a decrease in GHG emissions per unit electricity consumption for most states. However, not all states' GHG emissions decrease equally, with states like New Mexico (NM) and Oklahoma (OK) registering the greatest decreases, while for two states, NJ and NY, emissions increase slightly. A closer look at the consumption mixes used in the 2014 and 2030 models gives a better understanding of these trends for these states.

Table 4.2 Consumption Mix Difference (Projected - Base) for select states.

State	'Coal'	'NG'	'Oil'	'Nuc'	'Hydro'	'Geo'	'Biomass'	'Wind'	'Solar'	'Other'
'NM'	-38%	-8%	0%	0%	0%	0%	0%	43%	3%	0%
'OK'	-27%	-8%	0%	0%	5%	0%	-1%	30%	0%	0%
'NJ'	-5%	13%	0%	-8%	0%	0%	-1%	0%	0%	0%
'NY'	0%	6%	-3%	-4%	0%	0%	-1%	1%	0%	1%

Positive values mean increase of that technology's share for that state. Row sums may not add to 0 due to rounding.

Table 4.2 suggests that the driving forces for the reduction in GHG emissions for NM and OK are the reduction in Coal and NG PGS, along with a marked increase in Wind PGS. As net exporting states, these changes exclusively represent shifts in the states' generation mix (i.e. net additions of wind farms and decommissioning of Coal and NG power plants within NM and OK). For NJ and NY, the situation is different; not only are the changes in their consumption mixes reflecting a net increase in NG consumption and virtually no changes in renewable generation, but as net importers their consumption mix is not solely dependent on in-state generation. NY imports approximately 9% of its total electricity consumption, while NJ imports 29%. Pennsylvania (PA) is the source of electricity imports to these states. PA has a higher share of Coal and NG PGS in the 2030 projection mix than either NY or NJ have in their 2014 Base mix, meaning that the GHG intensity of imports is higher than the generation mix in those states. These factors outweigh NJ's decrease in in-state Coal use, and add to NY's in-state generation increase of NG PGS production, resulting in a small net increase in GHG intensity for these two states.

In contrast to the GHG results, there is a roughly even split between states that show net decrease and net increase in WC intensity. There are several reasons for these differences. The most influential element for these results is the share of Hydro PGS used by each state's 2030 generation mix combined with the WC factor for Hydro PGS, which is considerably larger than the WC of other technology types (e.g. almost 10 times higher than Nuclear PGS, the second most water consumptive technology) (Macknick et al. 2011; Meldrum et al. 2013). While the overall U.S. mix of Hydro PGS does not increase substantially (from 6 to 8%), individual states' Hydro PGS generation shares can have larger variations between 2014 and 2030, either increasing or decreasing, depending on the state. For example, states like South Dakota (SD) and Maine (ME) have the greatest decrease in share Hydro PGS, at -7% and -5% respectively, which results in their overall decrease in WC per 100 MWh. On the other hand, Montana (MT) and Idaho (ID) have the largest increase in Hydro PGS share (13% and 6%, respectively) resulting in their higher rates of WC per 100 MWh. For these states, increases in Hydro PGS share outweigh any reductions obtained from gains from other low-water intensive alternatives (e.g. solar, wind, geothermal) or indeed even fossil power plants.

Although Hydro PGS is the technology driving most of the changes, for certain states' WC this is not the case. For example, the reduction of WC in New Mexico (NM) are due almost entirely to that state's decreased share of Coal PGS generation between 2014 and 2030, which is mostly replaced by Wind PGS. Conversely, Arkansas' increase in WC is driven mostly by increase in Nuclear PGS. It is important to note, however, that in these instances the changes in Hydro PGS are relatively small compared to the changes in shares of other PGS technologies (e.g., NM does not have any Hydro PGS generation in state and as an exporting state, does not import Hydro PGS). This combination of factors is rare, but it highlights the fact the decreasing share of fossil fuel technologies and use of renewables is a good combination for decreasing WC in electricity generation overall.

4.4.2.2 Results for $1M of final demand in non-PGS sectors, and 100 MWh of final demand for individual PGS technologies

Figure 4.6 shows projected changes in GHG and WC intensities (Tonnes CO2e/MWh, kGal/MWh respectively) for BEA IO sectors. Most sectors show reductions in GHG emissions associated with their operation for the Projected 2030 model. The reductions in absolute terms are greatest in the manufacturing sectors that are characteristically heavy users of electricity. For example, Primary Aluminum Manufacturing (labeled in Figure 5A) shows the greatest absolute reduction in GHG intensity in the 2030 projections, due to its high amount of electricity use for operations and its high presence in states with high reductions in GHG intensities (WA, OH, TX). This 275 Tonnes CO2e/MWh reduction corresponds to approximately a 10% decrease in emissions intensity, which represents about 70 million Tonnes of CO2e reductions (~1% of total U.S. GHG emissions in 2014) given primary aluminum production for 2014 (U.S. Geological Survey 2015; Burns 2009). However most sectors experience reductions in emissions intensities, not just manufacturing. For example, the Other Real Estate sector also benefits from having an overall less carbon intensive grid, as this is a sector present in most states. Reductions for most sectors are less than ten percent.

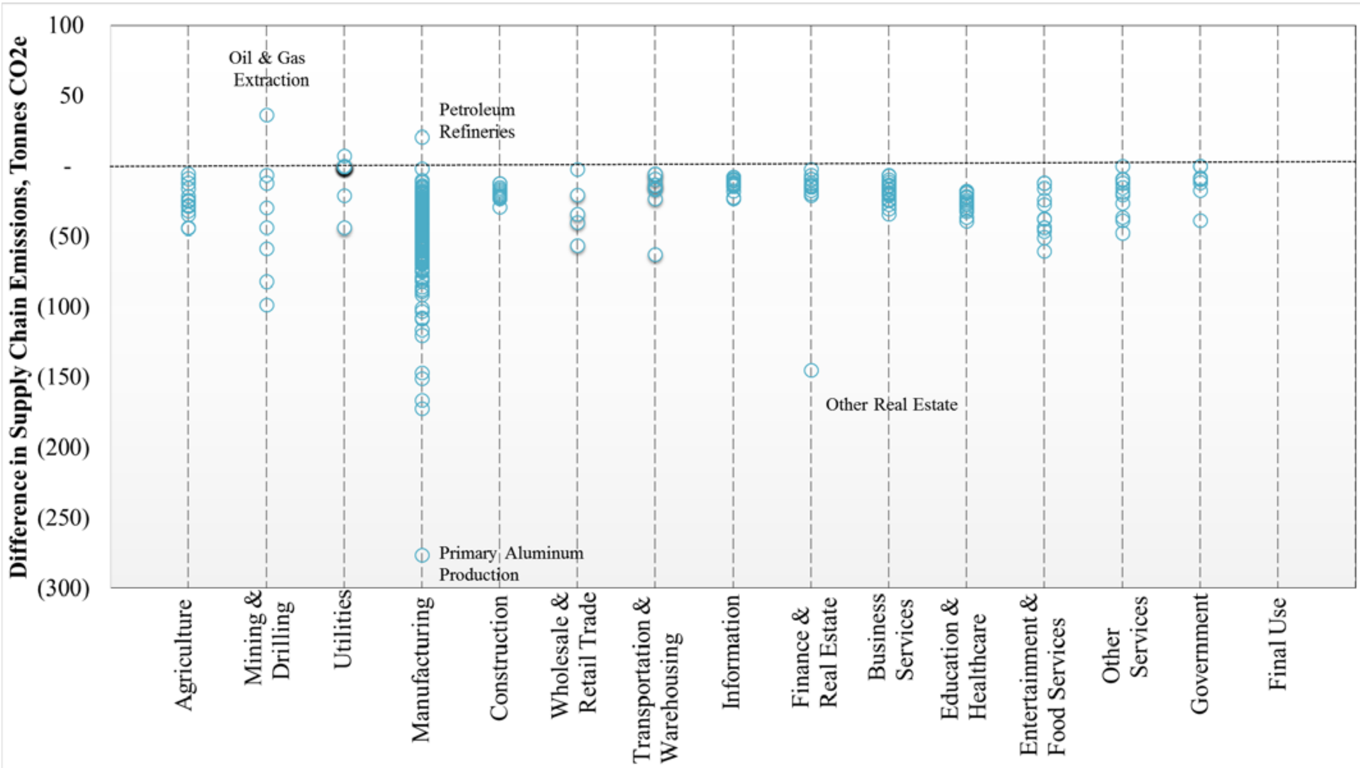
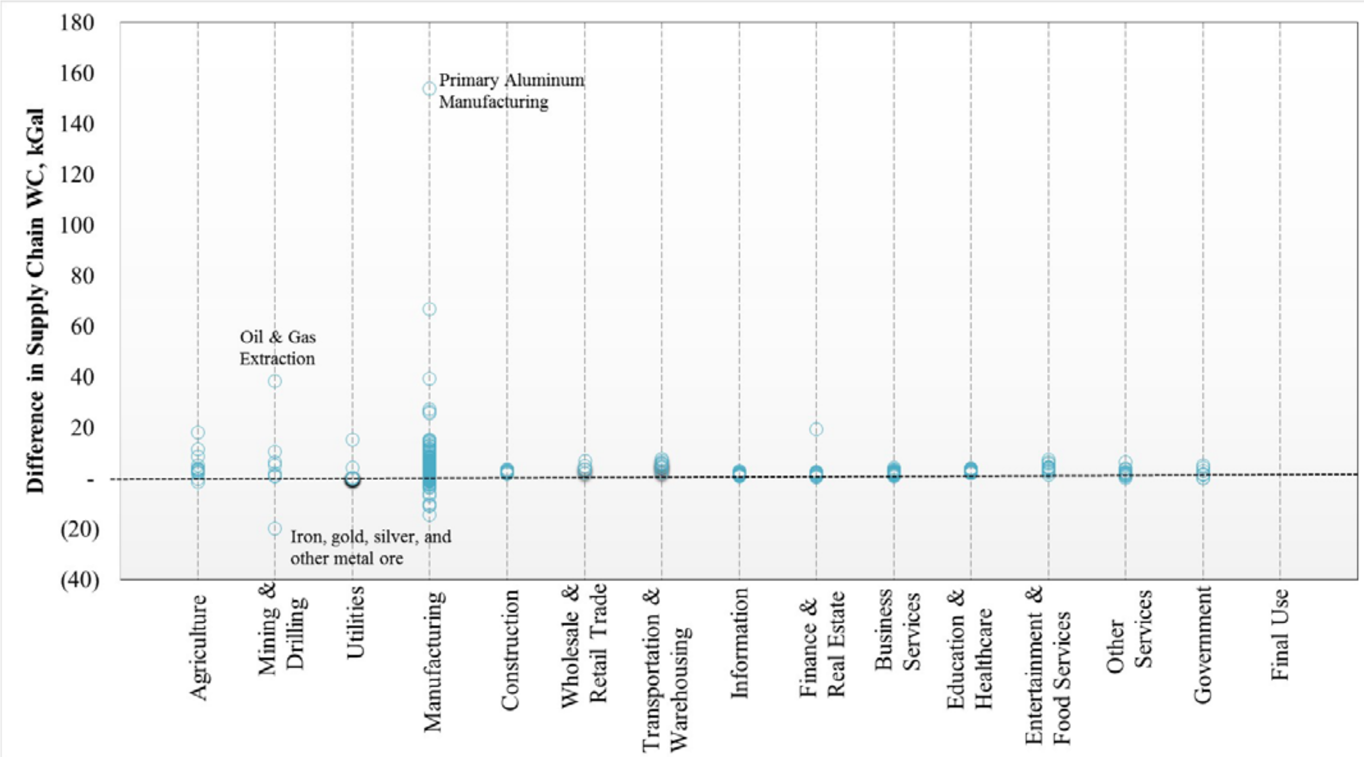


Figure 4.6: Comparison between Projected and Base MRIO model for $1M of final demand by each BEA IO sector.
Each bubble represents one BEA IO sector. Values above the dotted lines represent increase in emissions for that particular sector; values below represent decrease in emissions. Bubbles are clustered into the highest level economic categories described by the BEA.
Top (part A): GHG emissions difference, Tonnes CO2e.



Bottom (part B): WC Difference, kGal

An interesting observation is that the sector with the largest absolute decrease is not necessarily the sector with most reductions as a percentage of original emissions. In this case, Wind PGS is the sector with the largest relative decrease in emissions, with a decrease of about 25% in the Projected Scenario. Since Wind PGS has a direct GHG emissions factor of 0, its emissions are caused indirectly through its supply chain; accordingly the cleaner grid in the 2030 projection causes the decrease in supply chain emissions to have a greater effect on total GHG emissions in this sector than other sectors where total emissions are a combination of direct and indirect effects.

The only sectors with significant GHG emissions increase are Oil & Gas Extraction and Petroleum Refineries. This is caused by the change in the GHG emissions factor between the 2014 and 2030 models for Oil & Gas Extraction (shown in Table 4.1), which represents increased share of shale natural gas use. This change, which can be thought of as emissions at the extraction site, results in direct emissions increase for Oil & Gas extraction sector, and upstream emissions for Petroleum Refineries. For Oil & Gas Extraction sector, the results suggests that the projected increased in renewable electricity sources are likely to be comfortably offset by the emissions increase from extraction of shale gas sources. For the Petroleum Refineries sector, the increase may be overestimated. While petroleum refineries do use some amount of natural gas, their primary feedstock is crude oil, but this commodity is aggregated with natural gas in a single sector in the IO model.

Figure 4.6 shows that for most sectors there is a slight increase in water consumption from electricity use in the projected case. As with Figure 4.5, this can be traced to the slight increase in hydroelectric power use for most states. This, combined with the fact that most sectors are spread out across states, results in these slightly higher consumption values. The increase is most prominent in the manufacturing sectors. Interestingly, Primary Aluminum Manufacturing is the sector with the highest increase in water consumption, just as it was the sector with highest decrease in GHG emissions. On the other hand, the Iron Ore, gold, silver, and other metal ore sector exhibits the greatest decrease in WC. For both of these sectors, these trends are explained by their high electricity use and geographic distribution in the U.S. 87% of Primary Aluminum Manufacturing is spread across 11 states where Hydro PGS mix increased between the Base and Projected models, whereas 85% of Iron ore, gold, silver and other metal ore is concentrated in two states (MN and NV) where Hydro PGS mix decreased. Oil & Gas extraction presents an increase in WC as well due to the added extraction of shale gas. The results in Figure 4.6 corroborate the findings highlighted by Figure 4.5.

4.4.2.3 GHG and WC Results for Private Consumption (PC)

When running the PC final demand vector in the Base 2014 and Projected 2030 models, the assumption is that personal consumption expenditures remain fixed but the electricity sector evolves as expected. Figure 4.7 shows the differences in these two scenarios with the differences calculated as Projected 2030- Base 2014 results from the PC final demand vector for GHG and WC. GHG reductions come mostly from the decrease in emissions from Coal PGS, Oil PGS, and Coal Mining sectors as shown in Figure 4.7A. Most other sectors included in the PC final demand vector show negligible emissions changes (less than 0.01% difference between Projected and Base results). Emissions reductions from Coal and Oil PGS result from their decrease share in the U.S. mix (approximately 13% and 1% reduction, respectively). As the main sector providing fuel for Coal PGS, the Coal Mining sector decreases in economic output which results in the sector's decrease in emissions. There are some sectors with no GHG emissions either because of no (direct) demand from PC, or a GHG emissions factor of zero (e.g., Wind & Solar PGS). Finally, a few sectors increase in GHG emissions in the projections. NG PGS has the highest absolute and relative emissions increase, caused by an increase of approximately 5% of its share in the U.S. mix and higher share of shale gas use. This is followed by Oil & Gas Extraction, which is supplying more natural gas to meet the demands of NG PGS in addition to its increase use of shale gas. The other two sectors with a noteworthy increase are Geothermal PGS, which doubles its share in the U.S. mix (0.4 to 0.8%), and Pipeline Transportation, which is the main delivery system for natural gas to power plants and uses Oil and Gas Extraction's production as input to its operation, which drives its emissions up indirectly.

Figure 4.7B highlights the PC results with regards to WC, which mirror similar trends to GHG emissions. As with Figure 4.7A, a large number of sectors show negligible changes in water consumption. The Biomass, Oil, and Coal PGS show the largest decreases in water consumption, caused by their overall reduction in the U.S. mix. The increase in hydroelectricity in the U.S. mix (from 6.5 to 7.7%) also drives the increase Hydro PGS, while the increase in shale gas drives the WC increase for NG PGS and Oil & Gas extraction sectors Overall, the large drop in fossil based PGS technologies and slight increase in Hydro PGS largely cancel out WC changes nationally. The net effect is that, given constant private consumption patterns between the two periods, the projected changes in the electricity grid will result in a 1% increase in total WC and 9% decrease in total GHG emissions.

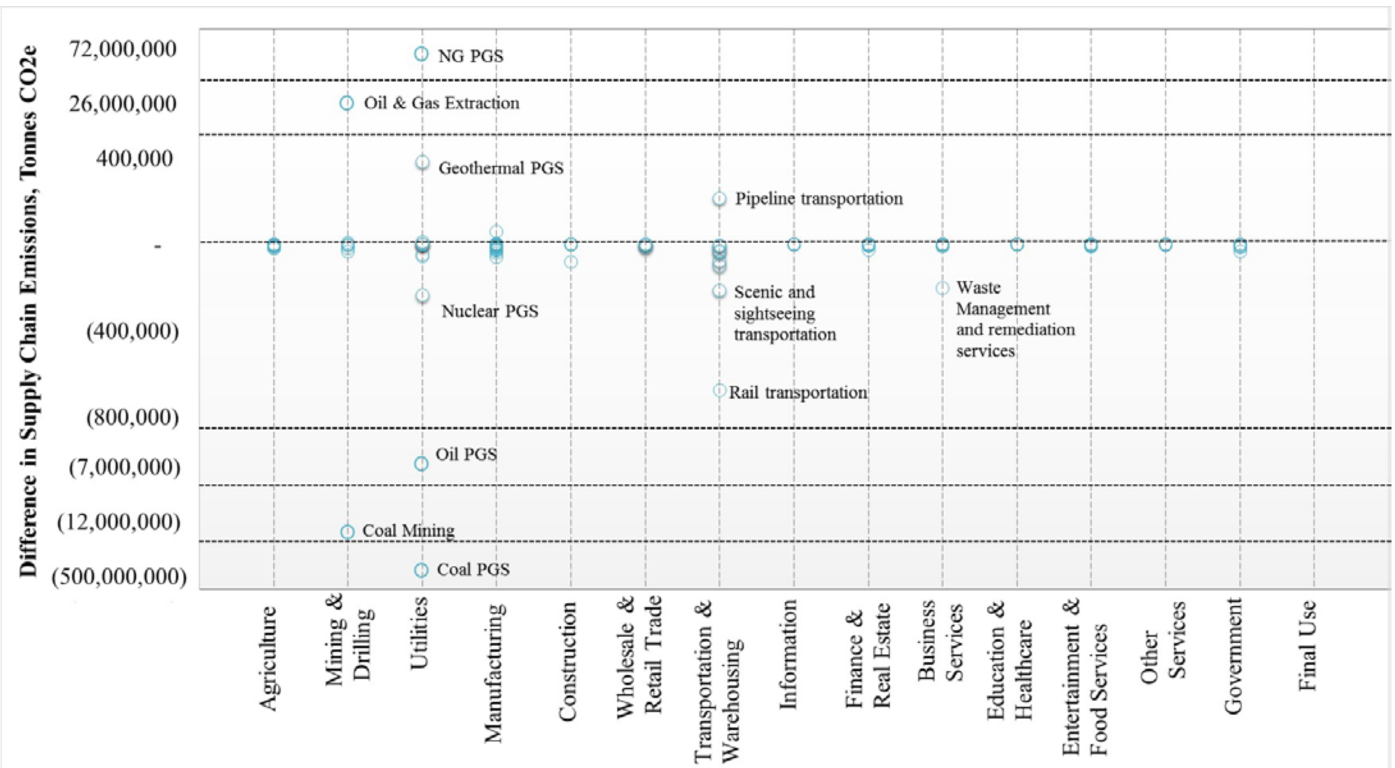
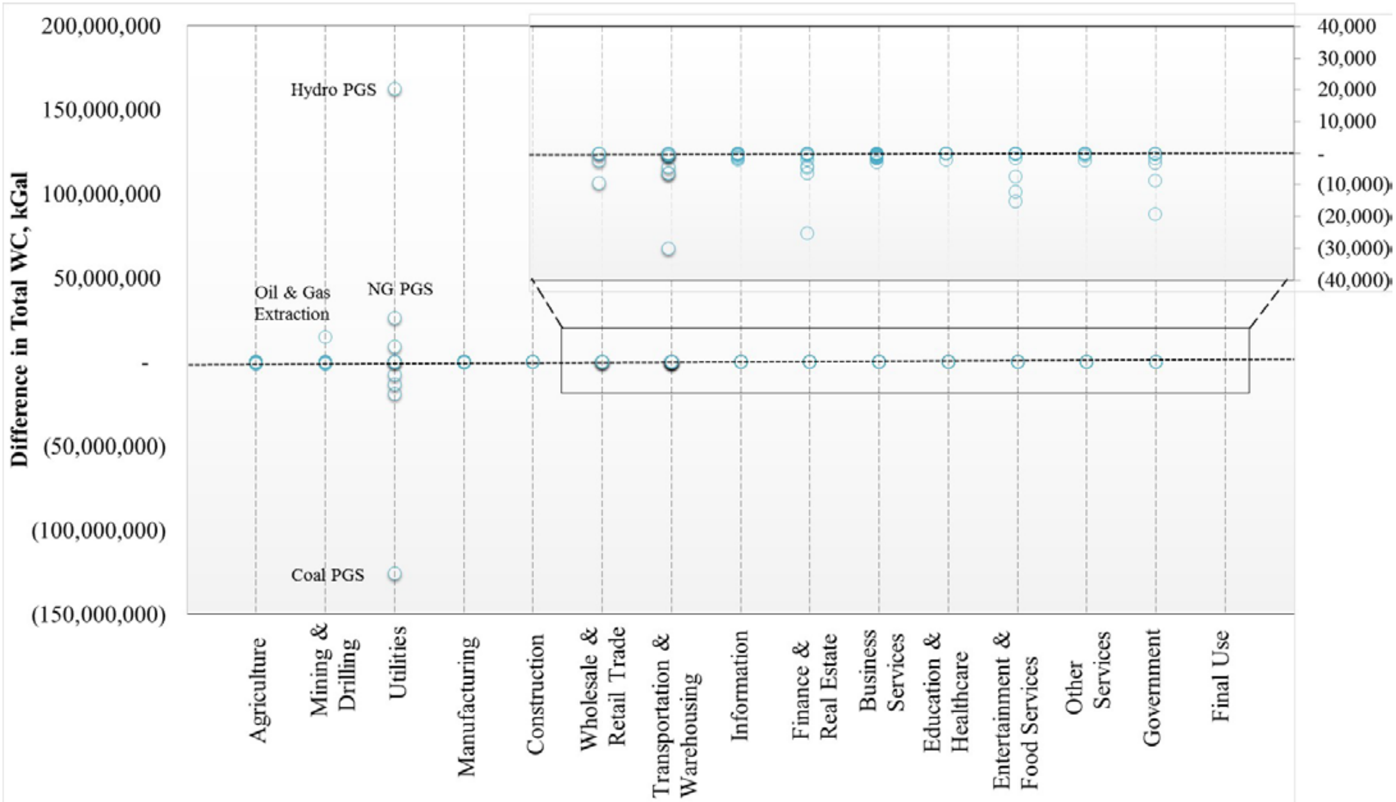


Figure 4.7: Emissions comparison for Private Consumption.
Note that the scale on the Y axis is not continuous, with jumps indicated by dotted lines towards the upper and lower portions of the figures.
Top (part A): GHG emissions difference, Tonnes CO2e



Bottom (part B): WC difference, kGal

4.5 MRIO SCENARIO: ENVIRONEMTNAL IMPACTS OF DATA CENTER ELECTRICITY CONSUMPTION

4.5.1 Data Centers and the MRIO model

Data centers present an excellent case study for demonstrating the utility of the MRIO model for several reasons. These are explained as follows. Data centers are energy intensive, and their environmental impacts are heavily related to their electricity use and thus local grid composition (Arushanyan et al. 2014) (Dandres et al. 2016). Data centers are one of the primary components of continued growth of the information and communication technologies industries (ICTs), as shown by the continued increase in economic output from the Data Processing, Hosting, and Related Services industry (NAICS sector 518200) in Figure 4.8. They can be installed in most regions in the U.S, as evidenced by sector 518200's presence in almost every state (U.S. Census Bureau 2009). Additionally, data center energy use and investment in clean electricity to operate them has become a focus for large ICT and information technology (IT) companies as they pursue their sustainability goals (Amazon Web Services 2017; Google Inc. 2016). The combination of continued growth potential and geographic flexibility make data centers an opportunity for regional economic development. Coupled with the increasing use of renewable technologies to power data centers due to corporate sustainability goals, regions with cleaner electricity grids could provide an incentive for companies to locate in these regions.

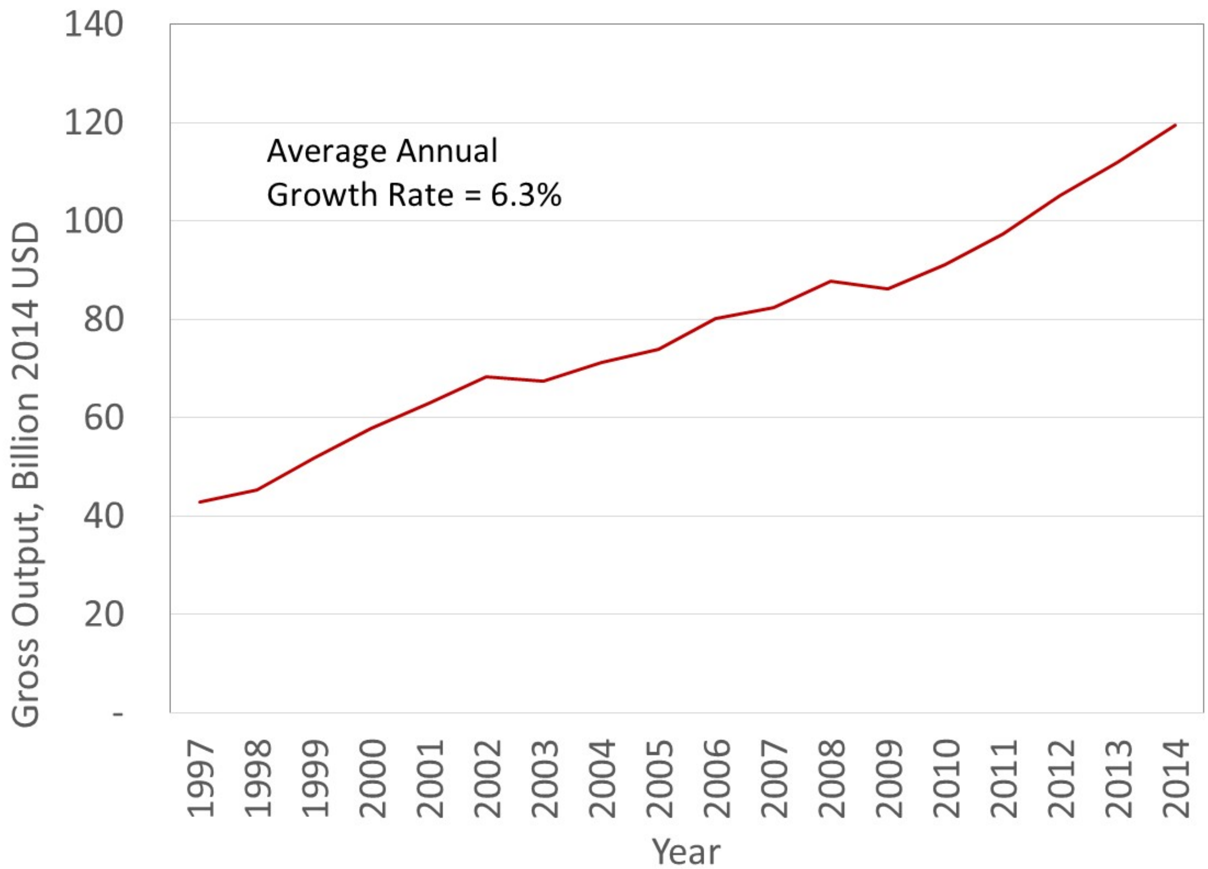


Figure 4.8: Economic output from the Data Processing, Hosting, and Related Services (NAICS 518200), 1997-2014, real 2014 USD (U.S. Bureau of Economic Analysis 2017)

In this section, two different scenarios regarding data center use are explored. The first scenario is based on the hypothetical question: what would the benefits be, in terms of GHG and WC reductions, of a wide-scale relocation of data center operations to states with the "cleanest" (i.e. low GHG intensity) grids, given current generation mixes in the U.S.? The second scenario is a look at the use of electricity by individual firms, where we adapt the stated data center sustainability goals of Amazon Web Services (AWS) and estimate the potential impacts of their electricity consumption goals for data centers in terms of GHG emissions and WC. Note that for these following scenarios, the emphasis is on changes in industry location only, not on projected changes to the U.S. grid (i.e. 2014 consumption mixes are used for these scenarios).

4.5.2 Data Center Relocation Scenario Implementation

While the economic value of ICTs is expected to continue to grow in the future, current efforts are underway to consolidate and optimize data center deployment, maintenance, and operations costs, and promote energy efficient and sustainable use of information technology. This trend can be seen from different types of data center users, including the U.S. government's Federal Data Center Consolidation Initiative (U.S. Department of Homeland Security 2011), as well as by private users' trend of moving to cloud-based computing rather than maintenance of their own infrastructure (International Data Corporation 2016). There are many factors that affect the ways in which data center consolidation and relocation is decided upon, such as the organization owning the data centers, cost and legal considerations, the extent of existing internet infrastructure, environmental factors that can impact operations (such as average temperature), etc. For the purposes of this work, we restrict our attention to considerations regarding GHG and WC reductions. As such, for the purposes of this scenario we assume the following:

1) Total economic output from sector 518200, and data centers in particular, does not change.
2) The main consideration is moving to the closest state with the cleanest grid. In this context, "closest" is considered to be the state in each NERC region with the cleanest grid; "cleanest" grid translates to the states with the highest share of Hydro, Geothermal, Biomass, Wind, and Solar PGS consumption. These states are shown in Table 4.3.
3) The trends of consolidation, optimization, closure, and implementation of sustainability initiatives with regards to data centers are modeled as a net change in location of data centers, reducing their locations from their original presence in many states (labeled 2014

distribution) to having a presence only in these “clean” states (labeled NERC Distribution). These distributions are shown in Table 4.4.

It is important to note that these considerations are not intended to result in a realistic new distribution of data centers in the U.S. Rather, they are intended to produce a distribution that results in data centers being relocated such that their electricity emissions were caused by operating locations where electricity consumption changed to match what are currently the cleanest available grid mixes in the U.S. In other words, the NERC distribution represents a “what if” case for environmental emissions using current generation technology mixes. Subsequent use of the term “data centers” in the context of scenario development refers to NAICS industry 518200, for simplicity.

Table 4.3: States with most renewable share of consumption by NERC region

NERC Region	"Most Renewable" State by Region	State Renewable Share
ASCC	AK	28.8%
FRCC	FL	3.1%
HICC	HI	15.1%
MRO	SD	46.7%
NPCC	ME	52.2%
RFC	WI	11.3%
SERC	TN	11.7%
SPP	KS	22.0%
TRE	TX	9.7%
WECC	WA	76.3%

Table 4.4 Distributions for the different data center scenarios.

State	2014	NERC	Amazon	State	2014	NERC	Amazon	State	2014	NERC	Amazon
AL	0.9%	0.0%	0.0%	KY	2.0%	0.0%	0.0%	ND	0.0%	0.0%	0.0%
AK	0.1%	0.1%	0.0%	LA	0.7%	0.0%	0.0%	OH	2.3%	0.0%	34.1%
AZ	1.9%	0.0%	0.0%	ME	0.3%	11.7%	0.0%	OK	0.8%	0.0%	0.0%
AR	1.2%	0.0%	0.0%	MD	1.9%	0.0%	0.0%	OR	1.1%	0.0%	0.0%
CA	15.9%	0.0%	0.0%	MA	4.3%	0.0%	0.0%	PA	3.4%	0.0%	0.0%
CO	2.6%	0.0%	0.0%	MI	1.8%	0.0%	0.0%	RI	0.2%	0.0%	0.0%
CT	0.9%	0.0%	0.0%	MN	1.8%	0.0%	0.0%	SC	0.5%	0.0%	0.0%
DE	0.4%	0.0%	0.0%	MS	0.2%	0.0%	0.0%	SD	0.0%	4.6%	0.0%
DC	0.4%	0.0%	0.0%	MO	1.9%	0.0%	0.0%	TN	1.0%	19.6%	0.0%
FL	5.8%	5.6%	0.0%	MT	0.2%	0.0%	0.0%	TX	10.3%	8.7%	0.0%
GA	4.1%	0.0%	0.0%	NE	0.6%	0.0%	0.0%	UT	2.1%	0.0%	0.0%
HI	0.2%	0.2%	0.0%	NV	0.3%	0.0%	0.0%	VT	0.3%	0.0%	0.0%
ID	0.3%	0.0%	0.0%	NH	0.4%	0.0%	0.0%	VA	3.5%	0.0%	21.6%
IL	3.7%	0.0%	0.0%	NJ	2.8%	0.0%	0.0%	WA	2.7%	27.2%	0.0%
IN	1.5%	0.0%	18.9%	NM	0.1%	0.0%	0.0%	WV	0.2%	0.0%	0.0%
IA	1.3%	0.0%	0.0%	NY	5.3%	0.0%	0.0%	WI	2.1%	18.7%	0.0%
KS	1.0%	3.7%	0.0%	NC	2.6%	0.0%	25.4%	WY	0.0%	0.0%	0.0%
								Total	100.0%	100.0%	100.0%

Three different spatial distributions shown for data center locations: 2014 distribution (base), NERC distribution (used in relocation scenario), and Amazon distribution (used in Amazon scenario).

Having established the different spatial distributions of the data centers before the relocation (2014 distribution) and after (NERC distribution), the next step is to estimate the changes in electricity related emissions caused by the relocation. These changes can be caused by the differences in electricity directly consumed by the data centers for their operations (e.g., electricity used to maintain the servers operational), termed here direct PGS effects, and by the differences in electricity consumed by those industries that service data centers (e.g. electricity used by employees, restaurants, and elsewhere in the supply chain), termed indirect PGS effects. It is important to emphasize that these estimates pertain only to electricity consumption of data centers and electricity consumption of the data center supply chain, rather than emissions estimates of all activities in the supply chain. As such, final demand vectors for these scenarios consist exclusively of PGS entries (as opposed to the final demand vector in the PC scenario, for example).

The Base 2014 model from the previous section was retained, and a new model was created using NERC distributions by changing the 518200 industry presence from the 2014 to the NERC distribution shown above; these are referred to here as the 2014 and NERC models). The two models are otherwise the same. To estimate the direct PGS effects, we ran a final demand vector that consists of the total electricity consumption (by state) of data centers in the U.S., spread geographically according to each distribution (U.S. Census Bureau 2009). Recent literature places the total electricity consumption by data centers in the U.S. in 2014 at approximately 70 million MWh, which is quite different from the BEA estimate. Since this source (Shehabi et. al 2016) is more recent and focuses specifically on data center activities, their reported value for direct data center electricity consumption is used in the direct final demand vector, and a scaling factor is used to adjust the values in the indirect final demand vector proportionally. Using this method and the distributions shown in Table 4.4, the direct PGS consumption from data centers in Texas, for example, is 7.21 and 6.09 million MWh for the 2014 and NERC models, respectively.

To estimate the indirect PGS effects, a final demand vector that contains the PGS consumption required by industries that service data centers was created. This is accomplished by finding the amount of monetary purchases that the 518200 industry purchased from all the industries along its supply chain, and for each of these industries, finding how much *they* spend on electricity consumption as a percent of their total purchases. Multiplying these values yield the electricity purchases by sectors in the supply chain for the purposes of meeting their sales obligations to sector 518200. Finally, these purchases are converted to energy units using the appropriate industry price (as discussed in Chapter 3) and adjusted using the scaling factor derived for the direct final demand vector.

After running the final demand vectors for direct and indirect effects using equation (1-5), the results are combined in a final estimate to show the total effects, as shown in the next section.

4.5.3 Data Center Relocation Scenario Results

The change in distributions, from 2014 to NERC, means that the states from which data centers draw their PGS consumption changes between models. This, in turn, means that the underlying PGS consumption mix changes to reflect the new data center locations. This is shown in Figure 4.9. As expected when moving to locations with more renewable consumption, Coal, Natural Gas and Nuclear PGS shares decrease from 2014 to NERC, with the shift occurring mostly to Hydro PGS, although Wind and Biomass show a slight increase as well.

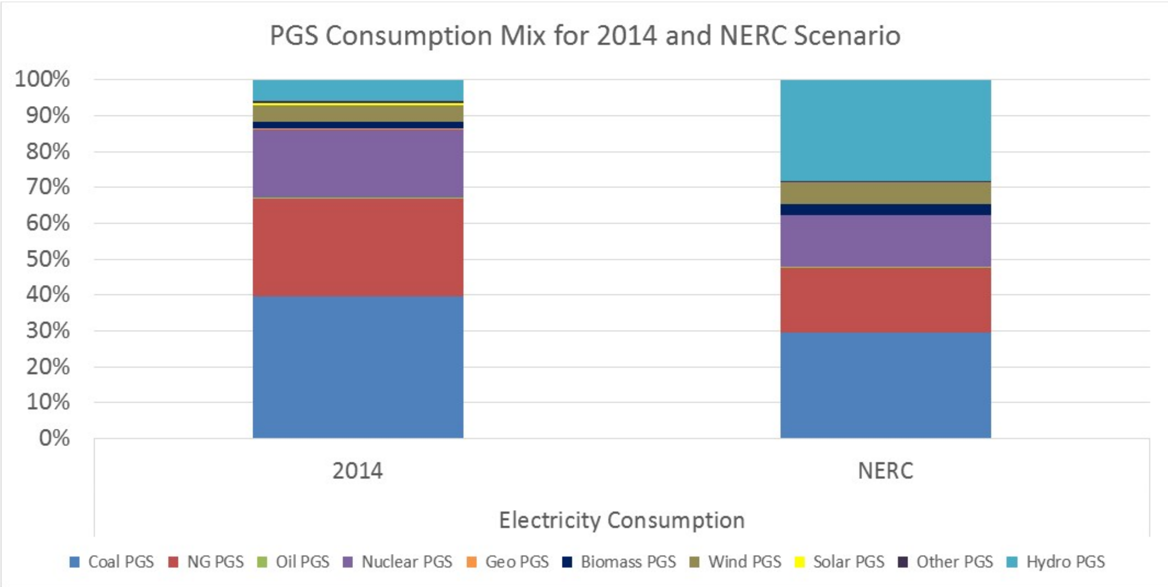


Figure 4.9: Comparison of electricity consumption mix, 2014 vs NERC distributions

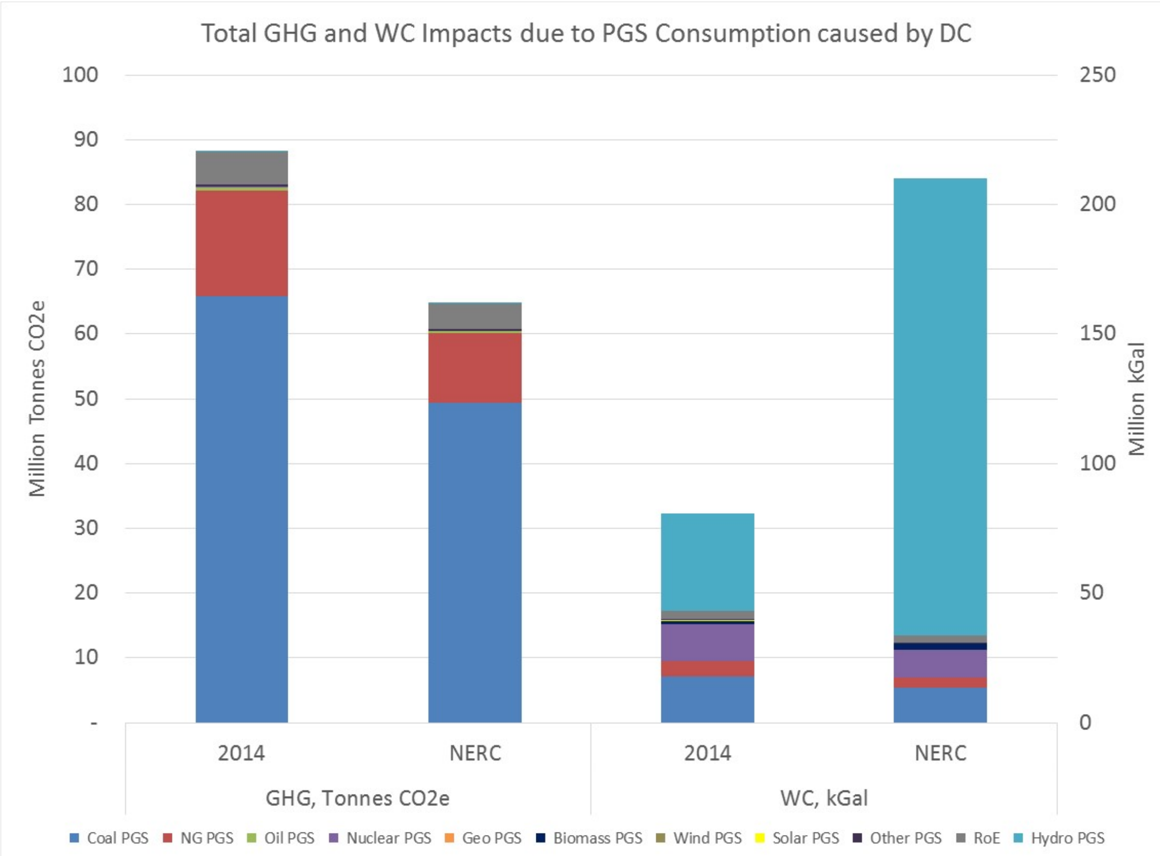


Figure 4.10: Comparison of total GHG and WC impacts due to PGS consumption of Data Centers, 2014 vs. NERC Distribution

The change in consumption mix drives the changes in GHG emissions and WC, as shown in Figure 4.10. For GHG emissions, the lower amount of Coal and Natural Gas PGS included in the mix explain the decrease in overall emissions. It is worth noting that direct and indirect PGS consumption contribute approximately equally in terms of total GHG and WC numbers seen in Figure 4.10; thus, for the 2014 estimate, approximately 45 million Tonnes of CO_2eq are caused directly by the electricity consumed by the data centers in the U.S. This estimate of direct CO_2eq emissions is comparable to other estimates in the literature (Brown et al. 2007). For WC, the 2014 estimate differs significantly from other estimates in the literature of direct water consumption by data centers, with the main difference being the assumed water consumption rate per MWh. For example, Shehabi et. al (2016) assume an average water consumption value for electricity generation of 2,000 gal/MWh, whereas the MRIO model has estimates for individual PGS technologies. In particular, the estimate for Hydro PGS is more than double at 4,500 gal/MWh, and the large increases in Hydro PGS share in the NERC scenario make this difference more relevant in the results. Again, these results serve to illustrate the tradeoff between GHG emissions reductions and WC increases, as was the case with the EIA projections scenario.

4.5.4 Amazon Web Services Scenario Implementation

The second data center focused scenario is aimed at showcasing the use of the MRIO model by a private business. Amazon Web Services (AWS) is a good option as they have ambitious sustainability goals related to electricity use by their data centers website (Amazon Web Services 2017); they have data centers located in different states; and their webhosting services are expected to continue to grow. The main question this scenarios asks is: how does changing from average state supplied electricity to dedicated renewable electricity affect GHG and WC of AWS's data centers? Additionally, this scenario is an example of a more localized application of the MRIO model: instead of focusing on the nationwide effects caused by state level changes, this example shows that the model can focus on regional issues.

To implement this scenario, AWS's sustainability goals for 2017 were adapted for use with the MRIO model. These goals can be found at AWS's sustainability website. In particular, they mention four states and two PGS technologies (Wind and Solar PGS) they are purchasing electricity from, rather than using the state grids. These locations will be the focus of this analysis, and are summarized in Table 4.5. Their main objective is to consume electricity for their data centers directly from the dedicated renewable sources in these areas.

Table 4.5: AWS PGS consumption goals for the new Data Center sites for 2017

State	Consumption/Year, MWh	Distribution	PGS tech
IN	500,000	18.9%	Wind
NC	670,000	25.4%	Wind
OH	900,000	34.1%	Wind
VA	570,000	21.6%	Solar
Total	**2,640,000**	**100.0%**	

State: IN = Indiana; NC = North Carolina; OH = Ohio; VA = Virginia
Distribution: For this scenario, AWS will purchase electricity in these 4 states, with the percent split shown in this column.
PGS Tech: The type of electricity purchased by AWS in each particular state

To run this scenario, again two different MRIO models are used: the Base 2014 distribution model, and an Amazon-specific distribution as specified in Table 4.5. The final demand for the 2014 distribution in this case is the amount of MWh specified for each specific state. For the Amazon distribution, the final demand is the amount of the specific electricity generation type, rather than by state as was the case for the NERC run. The direct PGS final demand vector for the Amazon scenario consists of a demand 2,070,000 MWh for Wind PGS and 570,000 MWh for Solar PGS.

The Indirect PGS final demand vector is created using the same steps as described in the NERC run, with the exception that the scaling factor is not applied. This is because the values in the Direct PGS final demand vector for this scenario did not exceed the BEA estimates of data center PGS consumption, and not applying the scaling factor preserves the linear relationship of the interindustry transactions in the model. Importantly, however, the final demand values are assigned not to individual electricity generation technologies, but to the states listed in Table 4.5.

4.5.5 Amazon Web Services Scenario Results

Figure 4.11 shows the electricity consumption mix for the Base 2014 and Amazon distributions given the final demand vectors discussed above. For the Base 2014 case, the consumption mix reflects the electricity generation technologies available in the four states under consideration. For the Amazon data centers, Wind and Solar PGS constitute a much larger proportion of their consumption mix given that they constitute the entirety of the direct PGS consumption; consumption of other electricity generation technologies is due to the indirect consumption from the state grids.

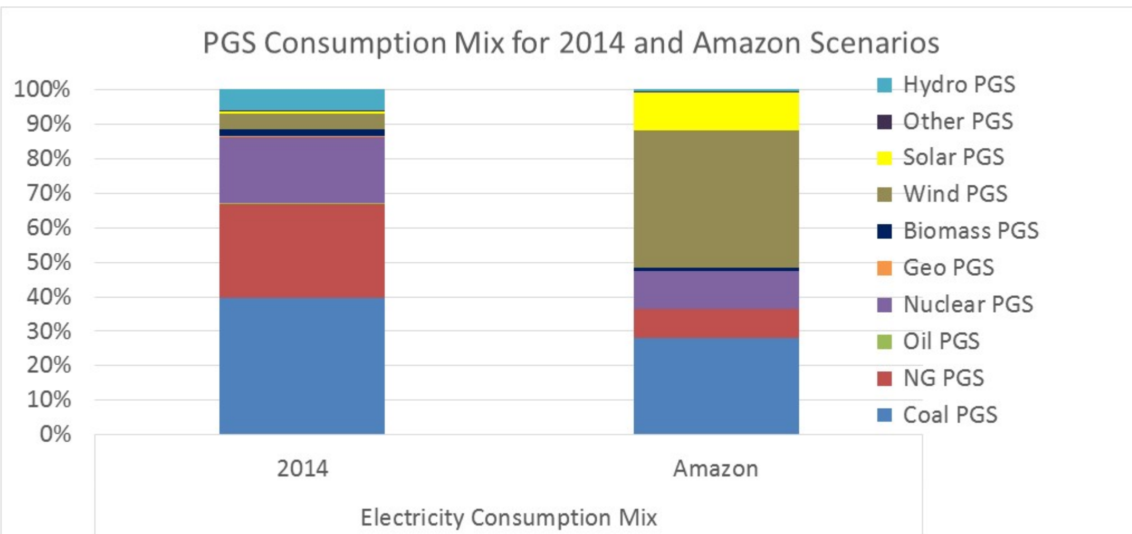


Figure 4.11: Comparison of electricity consumption mix, 2014 state vs Amazon scenarios.

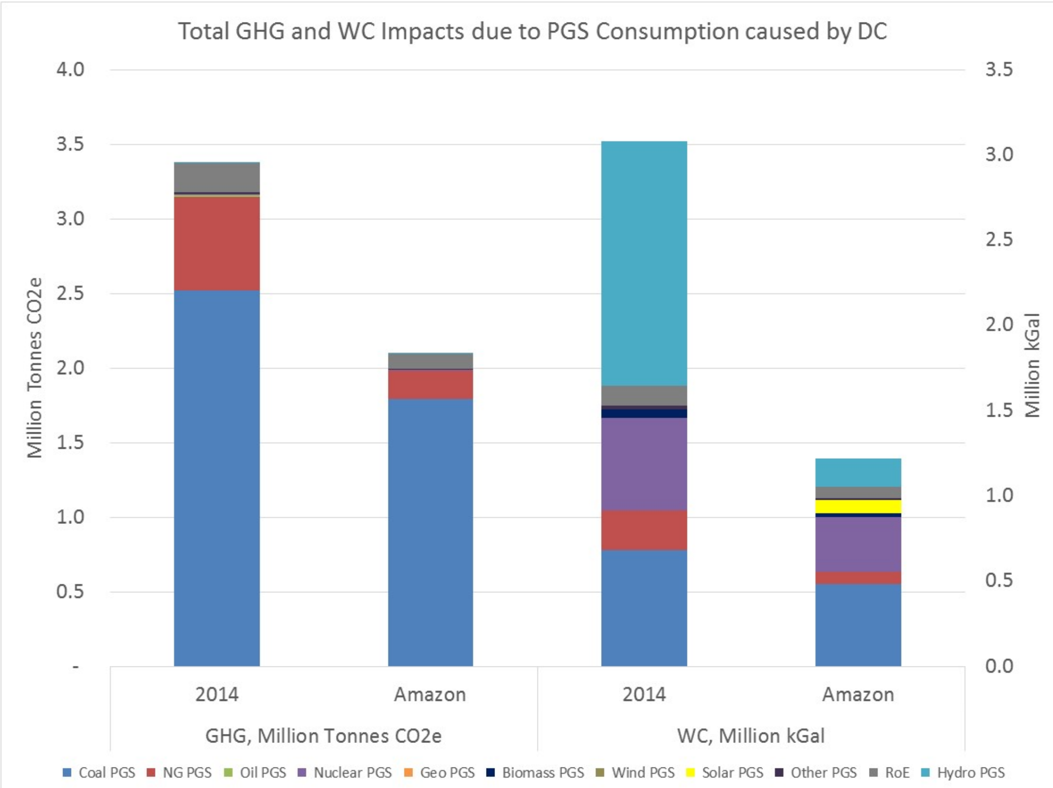


Figure 4.12: Comparison of total GHG and WC impacts due to PGS consumption of Data Centers, 2014 state vs Amazon Scenarios

Figure 4.12 shows the GHG and WC results for this run. As in the NERC case, consumption from the Amazon distribution display a reduction in total GHG emissions as compared to the Base distribution, again due to the reduction in fossil fuel based technologies. However, this scenario also shows a net reduction in WC. By substituting the entire direct electricity consumption of the data centers wind and solar electricity, Amazon can avoid the higher water consumption associated with state supplied hydroelectricity in favor of less WC intensive technologies. Additionally, *where* these emissions are coming from in the Amazon scenario also differs from the NERC scenario. Since emissions are reduced significantly in the direct portion of electricity consumed, the vast majority of emissions now come from the indirect sources in the supply chain (which uses state grid electricity). Emissions generated indirectly by employees and real estate services lead in both GHG and WC categories. This suggests that further reductions in emissions from direct data center consumption is unlikely for these locations. If additional reductions from electricity consumption are sought, the best route would be to purchase services from industries in these locations that also use renewable sources.

4.6 CONCLUSIONS

This article describes the development and implementation of an electricity-specific U.S. MRIO model. In particular, the model considers the state level electricity generation, interstate electricity trading and geographic industry distribution in the U.S. to estimate electricity consumption. This level of geographic detail combined with the potential to evaluate supply chain impacts makes the model useful to identify regional and national trends arising from state level electricity policies and their effects on specific industries. The model can be used to analyze the stated goals for reduction of carbon-intensive electricity sources and provide insight with regards to water consumption due to electricity, commonly referred to as the energy-water nexus, in a world with increasingly unpredictable weather patterns. Additionally, the model framework was developed such that it is able to accommodate changing underlying assumptions (i.e. changes in electricity trading) and possible policies, which can be done by modifying the individual model components and source data (shown in Figure 1). A beneficial feature of this model is that it can be extended with other types of electricity-related impacts beyond WC and GHG, provided that the appropriate electricity data are available. While electricity is regionalized, other sectors are not, which reduces the data burden usually required for multi-region models while providing an increased resolution with regards to electricity specifically.

Here the model is used to evaluate projected electricity trends in the U.S. out to the year 2030 and the consumption of electricity consumption by data centers. For the 2030 projections, overall results suggest that the 2030 U.S. grid will produce fewer GHG emissions, while slightly increasing the water consumption from electricity use for most states and industries. This could be a critical consideration for water scarce southern and western states. Electricity trading is also an important factor, as increases in water consumption due to electricity might not always be local. For example, California is a net importer of electricity; as such, while all of its electricity consumption happens within California, some of the water may actually be consumed in the states where the electricity is coming from, such as Arizona, another water constrained state. This highlights the difficulty in designing state level policies in isolation. More broadly, the result shows that while the expected trends are for reductions in GHG emissions, other potential impacts should not be ignored when developing policies at state or federal levels, as there may be important trade-offs that may otherwise be overlooked.

An important observation from the results presented in Section 5 is that in most instances Hydro PGS is the main driver of water consumption increases. While it may seem unusual that only one sector influences the results to such a degree, there is key difference between Hydro PGS and other PGS water use. While the other PGS technologies have comparable or even higher water withdrawal rates that Hydro PGS, most of the water is returned to the source. In contrast, the nature of most Hydroelectric power generation – the use of dams – means that the water withdrawn is exposed to larger retention periods in exposed, open air locations, which causes higher rates of evaporation. In our calculations, we used the lower estimates of water evaporation and consumption for Hydro PGS present in the literature (Mekonnen, M.M. and Hoekstra, A.Y. (2012); P. Torcellini, N. Long, and R. Judkoff (2003); Timothy H. Diehl and Melissa A. Harris (2014)), assuming that future additions would tend to be more water efficient than existing facilities, as most additions to Hydro PGS are expected to be in the form of expansion to existing dams or construction of new ones with smaller nameplate capacities (Clean Energy States Alliance, 2013). Even using this conservative approach, however, the fact remains that Hydro PGS is the most water consumption intensive from of electricity generation considered in this work.

While results from the model can provide valuable insight, the MRIO model does have several limitations. As with any input-output model, results from the MRIO model are not intended to be exact estimates of power generation needs or impacts. Despite the improvement in geographical resolution for electricity production, the data is still aggregate in nature, especially for non-PGS sectors, which means the model is better suited to identify hotpots and broader trends caused by policy decisions rather than for estimating individual power plant impacts. Another concern is the uncertainty in the data inputs to the model. For our analysis, we used comparative rather than absolute assessments from the model in an effort to minimize the effects of data uncertainty and model sensitivity. This is an area where future research identifying the sources of uncertainty would benefit the results and interpretations obtained from the model. In particular, coupling the MRIO model with more detailed network modeling approaches might improve the model's capacity to estimate the effects of electricity trading by allowing the model to regard all states as importers and exporters. With the exception of electricity, all other production technologies remain static as the supply chains for other sectors are likely to evolve as well. Finally, while we focus on GHG and WC in this study, it is possible to expand the model to include other environmental impacts, such as energy use, air particulates, and other pollutants relevant to national environmental policy.

5.0 CONCLUSIONS AND FUTURE WORK

5.1 SUMMARY

This model represents the first electricity focused, multi-regional input-output tool for LCA and policy analysis for the U.S. An overview of the contributions of this work is shown in Table 5.1.

Creation of an electricity focused Multi-Regional Input-Output Model

The detailed 2007 U.S. Benchmark Input-Output Accounts were combined with electricity price data, geographic distributions, and region specific generation and consumption mixes to create the MRIO model. The technologically and geographically disaggregated Use and Supply tables are used to create the Multi-Regional model with disaggregated electricity sectors. The additional electricity and regional sectors allow the model to assess changes by individual region, individual industry, or combinations of each for different types of emissions under consideration. Results from the model can be used to evaluate trends for electricity consumption and tradeoffs both nationally and for particular regions.

GHG and Water Consumption Factors

The MRIO model features updated GHG emissions intensities for all IO sectors in the original 2007 BEA IO Benchmark Accounts, in addition to GHG intensities developed specifically for the disaggregated electricity sectors. Additionally, Water Consumption factors for all IO sectors and electricity technologies were also developed. In addition to their use in this thesis, these factors can provide additional information to analyses performed with other EIO LCA or MRIO models of the U.S.

Table 5.1: Contributions of the MRIO model presented in this disseration

1	**Creation of Multi-Regional Input Output Model**	Creation of a 500+ sector Multi-Regional Input Output model of the U.S. electricity sector, with representation for individual electricity technologies and state generation and consumptions of electricity.
2	**GHG and Water Consumption Factors**	Updating GHG intensity vector for IO sectors in the 2007 U.S. Benchmark IO Accounts; creation of GHG emissions factors for PGS sectors. Creation of Water Consumption factors for all IO and PGS sectors.
3	**Validation of IO PGS results with process-based estimates**	Comparison of GHG Emissions estimates of IO PGS technologies with process-based analogues.
4	**Inclusion of mixed units for electricity**	Deatiled electricity prices for different end-users of electricity are used to convert monetary flows of electricity to physical flows in the model.
5	**Model Applicability (Case Studies)**	Model is used for two case studies: changes in GHG emissions and WC from projected changes in the U.S. grid to the year 2030;
6	**Model Availability**	Data used to create MRIO model is from public sources and model will be made publically available.

Validation of disaggregated IO PGS results with process-based estimates

The GHG emissions intensities of the disaggregated electricity sectors were compared against emissions intensities of process based models and found to be comparable. Additionally, the GHG and WC impacts caused by electricity consumption analyzed in the case studies were compared against existing literature estimates, when applicable (i.e. data center case study).

Inclusion of mixed units for electricity

The model includes specific electricity prices for over half of the detailed IO industry sectors, which were used to estimate physical flows of electricity throughout the economy. The choice of monetary vs. physical units for tracking commodity flows in IO models was investigated and found to have significant effects on emissions estimates for specific sectors, given that the industries that comprise a single IO sector have enough variation in the prices they pay for electricity. For electricity use, this is especially significant in the case of industrial sectors and residential users. Industrial sectors typically pay a lower than average price for electricity, which results in economic models implicitly assigning fewer emissions per kilowatt-hour, while the opposite is true for residential users. The inclusion of energy units for tracking electricity through sector-specific prices ensures that emissions are allocated based on the amount of electricity consumed.

Model Applicability

Two different scenarios were analyzed using the completed model. In the first scenario the MRIO model was used to estimate the changes in emissions intensities for individual states and industries arising from projected changes to the U.S. grid to the year 2030, showcasing the interconnectedness of electricity with every other sector in the economy. Results showed that reductions in GHG emissions intensity in the U.S. grid due to increased use of renewable electricity generation comes at the risk of increase in water consumption. This increase is primarily caused by increased share in hydroelectricity use, and can be a critical consideration for regions that consume electricity generated where water resources are scarce. The second scenario explores the effects of electricity use of data centers, first with a national and then with a business specific perspective. Results concerning GHG estimates caused by data center electricity consumption were found to be comparable to literature estimates. Conversely, results for water consumption estimates differed from the literature, which highlights the benefit of considering individual electricity generation technologies when analyzing electricity consumption by specific industries.

Model Availability

The model and results presented in this dissertation were achieved with data sources that are all publically available which allows for independent replication and evaluation of this work. The files used to create the model are available upon request by email to jav66@pitt.edu.

5.2 RECOMMENDATIONS FOR FUTURE WORK

5.2.1 Expanding vector of emissions intensities

The MRIO model developed in this work and the case studies explored focused on impacts related to changes in electricity consumption from different regions and PGS technologies. This is a greater level of resolution than was previously available for U.S. IO models, with the GHG and WC intensity (R) vectors representing the individual technologies more accurately. However, including additional information to represent variations in technologies according to location (state) in addition to technology type would further improve the conclusions drawn from the use in the model. In particular, renewable electricity generation technologies such as solar, wind, and hydro are more dependent on local conditions that more traditional technologies such as coal or nuclear generation. Indeed, it is likely that hydro PGS consumes less water per kWh in a state like Washington than a drier state like Arizona. Adding state-specific emissions intensity differences for these technologies would allow the model to provide greater accuracy for state level emissions estimates when using the MRIO model.

In addition to including state specific emissions intensities for renewable technologies, adding estimates for other types of emissions beyond GHG and WC would also expand the capabilities of the MRIO model, as it could be used to consider more types of tradeoffs between electricity generation technologies and the emissions they produce. Previous IO models such as EIO-LCA and Eco-LCA (Hendrickson 2005; Bakshi and Small 2011) include additional types of environmental intensities, including toxic releases, hazardous waste, exergy, or particulate matter. Including other types of types of emissions could be used to analyze scenarios similar to Rudokas et al. (2015), who analyzed GHG, SO_x, and NO_x emissions of the U.S. energy sector related to several climate mitigation scenarios. Unfortunately, creating emissions intensities for these types of pollutants for every IO sector in the 2007 Benchmark Accounts is a non-trivial and time consuming endeavor, which is why such vectors were not created.

Another addition that would benefit the model would be to include an "employment intensity" vector. The implementation would be similar to the GHG or WC vectors already developed for the model, except that instead of measuring environmental impacts per dollar worth of output for each IO sector (or MWh for PGS sectors), it would indicate the amount of employment required by each sector. This information would be beneficial because it could be used to provide estimates of employment changes in specific regions related to grid changes in said regions. For example, it could be used to augment the Amazon Data Center case study explored in this thesis. In addition to providing estimates on GHG and WC associated with the renewable electricity used by data centers in the states in which they are deployed, the model could also estimate the changes in employment related building those solar and wind farms. Such information could provide additional incentives for states to invest in renewable energy, as they could be seen as a way to attract employment for specific regions.

5.2.2 Including additional details on PGS sectors

Expanding the emissions intensities vector would benefit the MRIO model by providing additional information for all sectors included in the model. However, there is also additional data that could be included to further complement the PGS sectors. From the perspective of the disaggregated PGS sectors, data on the infrastructure and capital goods required to build these power generation sources could be included to form a construction layer in the MRIO model. Because IO models are often used for economic planning, analyses conducted with them do not usually focus on capital investments and their impacts. Currently, the MRIO model accounts for these impacts in one sector of the Use table, which describes all products or commodities purchased as capital investments. Future work can focus on expanding this sector by including results of LCA studies that describe the environmental impacts associated with the purchase of capital goods for the individual PGS technologies, and assign them to these sectors per kWh of electricity produced over the lifetime of each technologies' major components.

Finally, while the model does include trading of electricity between regions, the limited nature of the trading data available combined with the need to harmonize that data with the rest of the MRIO model components limits the insights that can be gained from trading at the state level.

Obtaining or estimating trading data that allow modeling of states and regions as both importing and exporting between each other, as is the case for the North American grid, would provide greater accuracy and detail when estimating production vs. consumption based accounting with the MRIO model.

APPENDIX A

SUPPLEMENTAL INFORMATION FOR CHAPTER 2: PGS DISAGGREGATION

This Appendix is the peer reviewed version of the Supplemental Information for the following article:

Vendries Algarin, J., Hawkins, T. R., Marriott, J., Scott Matthews, H. and Khanna, V. (2015), Disaggregating the Power Generation Sector for Input-Output Life Cycle Assessment. Journal of Industrial Ecology, 19: 666–675. doi:10.1111/jiec.12207

which has been published in final form at http://dx.doi.org/10.1111/jiec.12207. This article may be used for non-commercial purposes in accordance with Wiley Terms and Conditions for Self-Archiving.

A.1. Disaggregation Overview

The steps of the disaggregation method are described in Chapter 2. Here we provide additional details of the disaggregation as they pertain to the electric power generation sector.

Figure A.1 provides a conceptual overview of the disaggregation process.

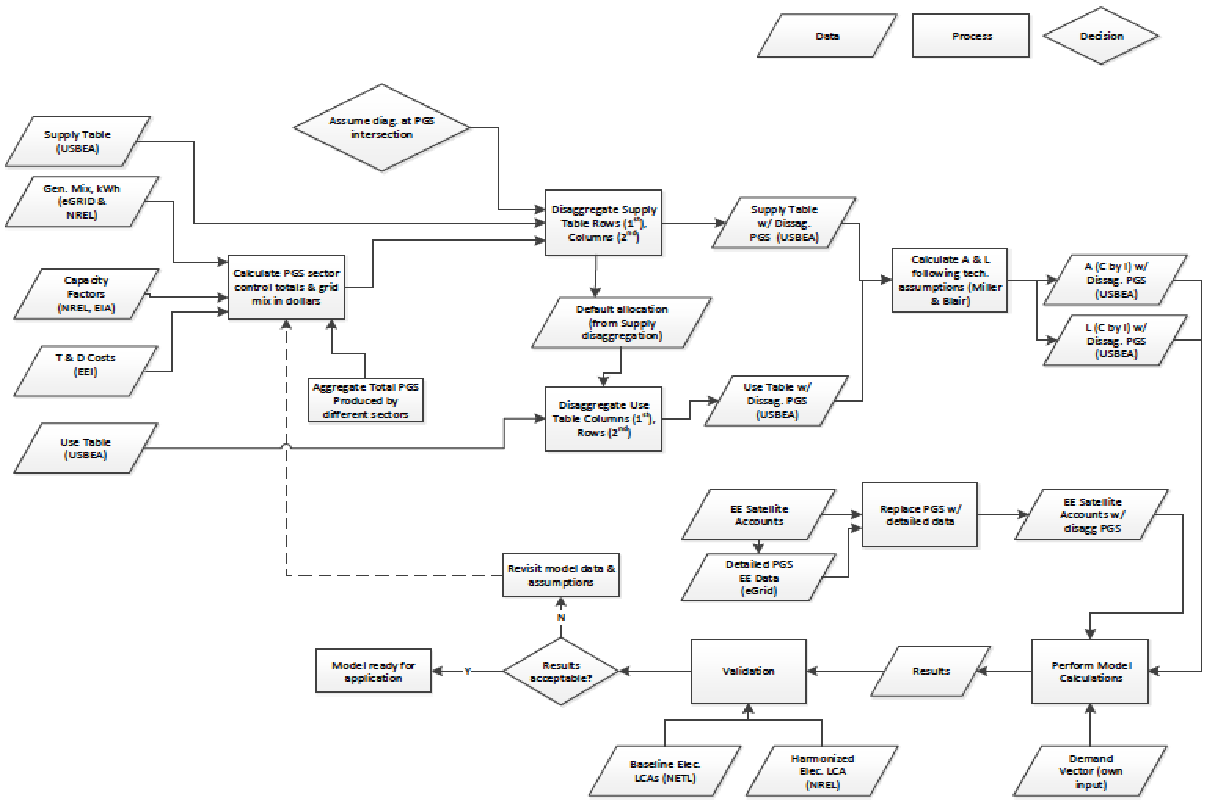


Figure A.1: Disaggregation of the power generation sector diagram

The disaggregation procedure highlighted in Chapter 2 and this Appendix has some similarities with the one built by Marriott (2007), but contains significant revisions. The most significant of these are:

-including multiple manual allocations in both the Use and Supply tables, along both the rows and columns for PGS and non-PGS sectors alike, and implementing said capability in the IO-LCA software;

-use of the updated 2007 BEA Benchmark Input-Output accounts;

-use of plant level emissions data for creation of GHG factors, and validation of those factors by comparing with other process-based emissions estimates;

-setting up the framework for inclusion of mixed units and individual regions

These revisions are described in more detail below.

A.1.1. Model Discussion and Data Selection

The U.S. Bureau of Economic Analysis (BEA) publishes the economic data used to create the IO model. BEA's input-output tables are created from the economic census done every five years in the United States. While there is some uncertainty in these numbers due to survey methods, assumptions made, etc., use of these data sources is widespread and accepted. The benchmark data are available for every five years (1992, 1997, and 2002), usually with a five-year lag (the 2007 input-output data should be available in late 2013). In order to build a new input-output model, we need to modify or replace the components of the benchmark data: the use and supply tables. It is worth noting that while the BEA uses the conventions established by Miller and Blair (1985), make and use tables, in this work we frame the disaggregation in terms of supply and use tables to be consistent with international standards (United Nations 2009).

While it would be preferable to use financial data obtained directly from the electric power industry to build the disaggregated model, such data is generally considered confidential and is not readily available. The federal government currently requires that utilities make some of this information publicly available, but the partially deregulated industry would like to have this financial reporting requirement removed, or at least made completely confidential (Raymond 2006). Additionally, there is variability in the way utilities report the data due to different accounting practices, the size of the utility, and the types and age of the generation assets the utility operates. The data in some cases is very general – like fuel purchases, which could be easily mapped to a sector like "coal mining" or "oil and gas extraction", or very detailed, like the purchase of a specific piece of environmental control equipment for a particular power plant, which is difficult to map to a specific sector. Finally, very few purchases, with the exception of fuel, are attributed to a particular plant or fuel type, making the information difficult to use in our model. Because of these problems with industry data, we chose instead to directly modify the use and supply table information.

Environmental emissions due to electricity generation are available from many different sources, which we use to calculate emission factors, or the output of a pollutant per unit output, for the disaggregated sectors. Emission factors can be based on top-down methods, where the amount of a pollutant is divided by the output of the process that created it, like those created by the U.S. EPA (U.S. EPA 2012b); some are bottom-up, where the input and efficiencies of a process are analyzed with a mass balance to calculate the emission factors. As a result, emission rates estimates vary considerably. Since we need average data for all power plants of a certain fuel type in the United States, a top-down approach works better. For the most part, the emission factors are adapted from the U.S. EPA's eGrid model, which are in turn based on the AP-42 emission factors (U.S. EPA 2012b).

A.2. Disaggregation Methodology

A.2.1. Number of Disaggregated Sectors

The choice of number of sectors to disaggregate to was mainly constrained by data availability. We chose the sectors that had a reasonable level of detailed data available in terms of electricity generation (EIA 2011) (Aabakken 2005) and fuel price information (EIA 2011) for the year 2002, the latest benchmark year for the BEA make and use tables (Bureau of Economic Analysis 2008).

The sectors are specified in Table A.1. We introduce a NAICS sector code appropriate to the technology in question. Italicized entries denote the disaggregated sectors implemented.

Table A.1: Disaggregated PGS sectors and code definitions

NAICS Code	*IO Model Code*	*NAICS Sector Definition*
2211	--	Power Generation and Supply
22111	--	Fossil Fuel Power Generation
221111	221101	*Coal*
221112	221102	*Natural Gas*
221113	221103	*Petroleum*
22112	--	Renewable Power Generation
221121	221105	*Hydroelectric*
221122	221106	*Geothermal*
221123	221107	*Biomass*
221124	221108	*Wind*
221125	221109	*Solar*
22113	--	Other Power Generation
221131	221104	*Nuclear*
221132	221110	*Other Power Generation*
22114	--	Power Supply
221141	221111	*Transmission*
221142	221112	*Distribution*

The technologies included in the sector definitions used here are the same as those used in Table 7.1 of NREL's Power Technologies Energy Data Book (Aabakken 2005) for the sectors with the same name, with the exception of the biomass power generation sector. In this work, the biomass sector combines NREL's Wood and Waste generation sources, which utilize the following generation feedstocks for electricity generation:

Wood: Wood, black liquor, and other wood waste.

Waste: Municipal solid waste, landfill gas, sludge waste, tires, agricultural byproducts, and other biomass.

A.2.2. Disaggregated Model Inputs

BEA Make and Use Tables

The main input to the model is BEA's make and use tables. In this work, we use the 2002 Benchmark Input-Output Make and Use tables at the detailed level, revised in 2008 (Bureau of Economic Analysis 2008).

U.S. Electricity Mix

Table A.2 shows the electricity mix used in this work. The electricity generation mix are derived from values in Table 7.1 from NREL's Power Technology Energy Data Book 2006 (Aabakken 2005). As part of the aggregated PGS sector, Transmission and Distribution need to be taken into account. Since we cannot directly compare the service performed by these two sectors with the physical electricity produced by generation sectors, we compare them on a monetary basis. To do so, we note that about 1.6~1.8% of operating expenses are spent on transmission and distribution (Table 8.1 in (EIA 2011)). Accordingly, we normalize the generation mix for the power generation technologies across the remaining 96%.

Table A.2: U.S. electricity generation mix, 2002

Sector	*2002 Gen Mix*	*2002 Gen Mix with Trans. & Dist.*
Coal	50.13%	48.36%
Nat. Gas	17.92%	17.29%
Petroleum	2.46%	2.38%
Nuclear	20.23%	19.51%
Hydroelectric	6.85%	6.60%
Geothermal	0.36%	0.35%
Biomass	1.61%	1.55%
Wind	0.26%	0.25%
Solar	0.03%	0.03%
Other	0.16%	0.15%
Transmission	-	1.88%
Distribution	-	1.65%

Emission Rates

Emission rates were calculated using EPA's Emissions and Generation Resource Integrated Database (eGrid) 2012 plant scale data for the U.S. (U.S. EPA 2012b). This data is presented in the main manuscript in table 4 and reproduced below for convenience. The point estimates represent the values used for the model runs presented in this work.

Table A.3: CO_2e emission rates

Technology	*Emission Rates Ranges, Ton CO_2e / GWh*	*Emission Rates Point Estimates, Ton CO_2e / GWh*
Coal	900 – 1,400	973.56
Natural Gas	410 – 1,100	428.42
Petroleum	800 – 1000	851.68
Nuclear	0 – 20	5.49
Hydroelectric	-	0.05
Geothermal	0 – 30	29.70
Biomass	0 – 600	380.24
Wind	-	0.00
Solar	-	-
Transmission	-	558.10
Distribution	-	-

A.2.3. Aggregation of Electricity Producing Sectors

Before the disaggregation of the new electricity sectors from the original PGS sector, we combine all the industries that have the PGS commodity as their main output. These sectors are PGS, Federal State Utilities, and State and local utilities (NAICS 221100, S00101, and S00202, respectively). The general procedure used was adapted from Miller and Blair (1985), and its application to the PGS sector is described below.

We define S as a *k* by *n* matrix of ones and zeros, where *k* is the desired number of sectors in the matrix to be created and *n* is the number of sectors in the original matrix. S is referred to as the aggregation matrix. The location of ones in row *i* of this matrix indicates which sectors will be combined as sector *i* in the aggregated table.

In our case, we need to create S matrices for the Use and Supply tables. However, the procedure for aggregating them is identical. In both cases, the S matrices are 428 by 430 (all sectors in the columns, and all sectors less S00101 and S00202 in the rows), and consist of zeros everywhere, with the following exceptions:

- The main diagonal, where all entries are one except for the intersections of S00101 and S00202 with themselves, which are 0, and
- The intersection of the PGS row with the Federal Utilities and State and Local utilities columns, which are one. These are the only off-diagonal entries, and their placement in this row indicates their incorporation into the main PGS sector.

Finally, if we denote the inter-industry transactions sections of the Use and Supply tables as Z, we can obtain aggregated version of both tables, denoted as Z^*, as follows:

$$Z^* = S * Z * S' \tag{A-1}$$

A.2.4. Disaggregation of Use and Supply Tables

In this section, manual allocations refer to how the values in the aggregate PGS rows and columns in the Use and Supply tables were distributed to the disaggregated PGS sectors. The main manuscript describes the motivations for using either a manual or a default allocation for each disaggregated sector either in the Use or Supply tables. Below we present these allocations in more detail.

Manual Allocations

Allocation of disaggregated Supply Table rows

Table A.4 shows the disaggregated Supply table rows that were manually allocated (i.e., allocation of commodity production to disaggregated PGS industries).

Table A.4: Supply table disaggregated PGS rows allocation

Industry / Commodity	*221200* NGD	*322130* Paper	*S00203* Gov.
Coal	0%	0%	50.1%
NG	100%	91.8%	17.9%
Oil	0%	0%	2.5%
Nuclear	0%	0%	20.2%
Hydro	0%	0%	6.9%
Geo	0%	0%	0.4%
Biomass	0%	8.2%	1.6%
Wind	0%	0%	0.3%
Solar	0%	0%	0.03%
Other	0%	0%	0.2%
Transmission	0%	0%	0%
Distribution	0%	0%	0%

Sector 221200 is Natural Gas Distribution (NGD), which was used as an example for manual allocation (and explained in) in the main manuscript.

Sector 322130 is the Paperboard mills. This sector is allocated manually on the assumption that the electricity generated by the paperboard mills industry is gas and biomass based. Percentages are the ratios of the national outputs of those two generation types. For example, electricity generated by natural gas in the paperboard mill sector was derived was follows:

$$\frac{\%\boldsymbol{Natural\ Gas}}{\%\boldsymbol{Natural\ Gas}+\%\ \boldsymbol{Biomass}} = \frac{.\mathbf{1792}}{.\mathbf{1792}+.\mathbf{0161}} = \text{.9175 or 91.75\%} \qquad \text{(A-2)}$$

where %Natural gas and % Biomass refer to the respective U.S. mix percentages. Similarly, the biomass percentage is .0161/(.1792+.0161) = 0.0825 or 8.25%.

Sector S00203 is Other state and local government enterprises. The percentages for this sector were generated by taking the national average for each sector and dividing by the sum of the national average of the other sectors, except transmission and distribution. This is equivalent to assuming that this sector produces electricity from all generation technologies, but does not distribute the electricity itself (i.e., for this it depends on the transmission and distribution sectors).

Allocation of disaggregated Supply Table columns

Table A.5 shows the disaggregated Supply table columns that were manually allocated (i.e., allocation of industry output to the disaggregated PGS commodities).

Table A.5: Supply table disaggregated PGS columns allocation

Commodity	Industry	*Coal*	*NG*	*Oil*	*Nuclear*	*Hydro*	*Geo*	*Biomass*	*Wind*	*Solar*	*Other*	*Trx*	*Dtx*
221200	NGD	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
221300	Water	0%	0%	0%	0%	100%	0%	0%	0%	0%	0%	0%	0%

Sector 221200 is Natural Gas Distribution (again refer to the example in the main manuscript). Sector 221300 is Water, sewage and other systems. The assumption here is that the commodity is water distribution, and that hydroelectric utilities are more likely to deliver this commodity.

Allocation of the disaggregated Use table columns

Table A.6 shows the disaggregated Use table columns that were manually allocated (i.e., allocation of commodity purchases by the disaggregated industries, or 'supply chain').

Table A.6: Use table disaggregated PGS columns allocation

Commodity	Industry	*Coal*	*NG*	*Oil*	*Nuclear*	*Hydro*	*Geo*	*Biomass*	*Wind*	*Solar*	*Other*	*Trx*	*Dtx*
211000	Extraction	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
221200	Mining	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
324110	Refining	0%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%
482000	Rail	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
486000	Pipeline	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Sector 211000 is Oil and Gas Extraction.

Sector 221200 is Coal Mining. We assume that all of the mined coal used in electricity generation is purchased by the coal power generation sector.

Sector 324110 is Petroleum Refineries. We assumed that all of the oil used in electricity generation is purchased by the oil power generation sector.

Sector 482000 is Rail Transportation. We assumed the only power generation sector in need of this service is coal power generation.

Sector 486000 is Pipeline Transportation.

Allocation of the disaggregated Supply Table intersection

We follow the assumption that all disaggregated power generation industries only produce their corresponding electricity commodity. That is, coal generation only produces coal electricity; nuclear plants only produce nuclear electricity, etc. This is represented by having no off-diagonal values in the Supply table intersection of the disaggregated PGS sectors, and 100% allocation along the main diagonal.

Allocation of the disaggregated Use Table intersection

The diagonal assumption is also followed in the Use table intersection, except for the Transmission and Distribution sectors. It is assumed that all of the other sectors will purchase services from these sectors in order to get the electricity they produce to costumers. We use the default price based allocation percentages here to determine how much each disaggregated PGS sector will purchase. The result is shown in Table A.7. Note that there were no manual allocations made to the use table rows, due to data constraints, the procedure is for allocation is similar as the one described for the supply table, and due to word count considerations. Accordingly, we assumed the average mix for the industries in the U.S. in this disaggregation. However, a general explanation of the physical meaning behind allocating the use table rows can be found under the subheading “Disaggregating the Use and Supply tables”.

Table A.7: Use table PGS Allocation ($M)

		Industries											
		Coal	Nat. Gas	Oil	Nuclear	Hydro	Geo	Biomass	Wind	Solar	Other	Trans	Dist
Commodities	Coal	37.46	-	-	-	-	-	-	-	-	-	-	-
	Nat. Gas	-	10.91	-	-	-	-	-	-	-	-	-	-
	Oil	-	-	1.11	-	-	-	-	-	-	-	-	-
	Nuclear	-	-	-	18.63	-	-	-	-	-	-	-	-
	Hydro	-	-	-	-	7.11	-	-	-	-	-	-	-
	Geo	-	-	-	-	-	0.33	-	-	-	-	-	-
	Biomass	-	-	-	-	-	-	1.48	-	-	-	-	-
	Wind	-	-	-	-	-	-	-	0.24	-	-	-	-
	Solar	-	-	-	-	-	-	-	-	0.02	-	-	-
	Other	-	-	-	-	-	-	-	-	-	0.14	-	-
	Trans	0.87	0.31	0.04	0.35	0.12	0.01	0.03	0	0	0	0.03	0.03
	Dist	0.76	0.27	0.04	0.31	0.1	0.01	0.02	0	0	0	0.03	0.03

Default Allocations

Most sectors were not allocated manually, either in the Supply or Use table. For these sectors (for both industries and commodities), we used a default allocation scheme. In order to perform the allocation correctly, we need to keep in mind two constraints to maintain the structure of the IO tables:

- The PGS industry and commodity totals must remain equal before and after aggregation. This ensures we are not shifting economic activity to or from the PGS sector.

- The disaggregated PGS commodity and industry totals must be equal in the Use and Supply tables. Equality of commodity and industry totals across tables is a characteristic present in the original BEA tables, and as such it should be maintained.

In order to abide by these constraints, we allocate the values in each of the sectors allocated by default using the equation below:

$$Allocation\ \% = \frac{(PGS_{Total} * GenMix_{Sector}) - ManAlloc_{Sector}}{PGS_{Total} - ManAlloc_{Sector}} \tag{A-3}$$

where:

PGS_{Total} is the aggregate total industry or commodity output (for column or row disaggregation, respectively);

$GenMix_{Sector}$ is the generation mix (including transmission and distribution) of each sector as indicated in Table A.2, and;

$ManAlloc_{Sector}$ is the sum of the manual allocations performed in this sector.

Table A.8 shows the result of applying this in order to perform the disaggregation of the PGS Supply row. The columns in Table A.8 are as defined for above; *Default Alloc* represents the amount allocated by applying equation (A-3). Note that the sum of the *ManAlloc* and *Default Alloc* totals equals the aggregate PGS commodity total, as shown in table 3 in the main manuscript (slight differences due to rounding). The same procedure is followed for the disaggregation of the PGS Supply column (industries), as well as the PGS Use row and column. By adjusting the allocation percentages for each step of the disaggregation, the disaggregated industry and commodity totals remain the same across tables, thus following the system constraints.

Table A.8: Default allocation for disaggregated rows (commodities) in the Supply table

PGS Sector	*Percent Mix*	*ManAlloc ($M)*	*% Allocation*	*Default Alloc($M)*
Coal	48.36%	8.42	49.21%	120,966.59
NG	17.29%	4,346.03	15.83%	38,899.56
Petroleum	2.38%	0.42	2.42%	5,945.07
Nuclear	19.51%	3.40	19.86%	48,812.18
Hydro	6.60%	1.15	6.72%	16,521.04
Geo	0.35%	0.06	0.36%	876.12
Biomass	1.55%	5.45	1.58%	3,874.77
Wind	0.25%	0.04	0.25%	625.80
Solar	0.03%	0.01	0.03%	62.58
Other	0.15%	0.03	0.15%	375.48
Trans.	1.88%	-	1.92%	4,710.44
Dist.	1.65%	-	1.68%	4,124.28
Total	**100%**	**4,365.01**	**100%**	**245,793.89**

A.2.5. Creating the disaggregated economic model

We followed the procedure described in chapter 12 of BEA's Concepts and Methods of the U.S. Input-Output Accounts (Bureau of Economic Analysis 2009) in order to create the new total requirements matrix (the main component of the IO model) from the disaggregated Use and Supply tables. We used the industry by commodity assumption in calculating the new total requirements table.

A.2.6. Calculating Emissions Factors

Direct Emissions

The emissions factors were calculated using data from eGrid's plant data for 2009 (U.S. EPA 2012b). The reasons for choosing this source are twofold: first, this is the closest data set to the year 2002 we could find that gives us detailed information by generation type; second, it allows us to view both general technology emission trends as well as individual plant outputs. By looking at the net generation and net emissions of individual plants, we are able to screen out those which require more electricity from the grid than what they contribute to it (i.e., those with negative net generation), as well as plants with extremely high emission rates (i.e., positive low net generation but high emissions, which usually indicates that electricity generation is not the primary function of the plant).

In order to calculate the average U.S. direct emissions rate for each generation type, we added the total CO_2e emissions for each type as defined by eGrid and which matched one of the disaggregated sectors (biomass, coal, gas, geothermal, hydro, nuclear, oil, other fossil, solar, and wind) and divided by the total net generation of those same plants. As mentioned above, some plants had negative emissions rates or very high emissions rates. This happened for coal, natural gas, and oil technologies. For these sectors, we established limits that ruled out extreme emissions rates (e.g., for coal generation we did not include plants with negative rates or rates above 1,600 gCO_2e). The upper limits were established by calculating the highest possible emissions rate for each technology, as follows:

$$Max\ CO_2e\ emissions\ rate = \frac{c_f}{h_f} * \frac{c_{CO_2}}{c_m} \qquad \text{(A-4)}$$

Where:

c_f = *specific carbon content in the fuel* (kg_C/kg_{fuel})

h_f = *specific energy content (kWh/kg$_{fuel}$)*

C_m = *specific mass Carbon (kg/mol Carbon)*

C_{CO2} = *specific mass Carbon Dioxide (kg/mol CO_2)*

These limits were compared to literature ranges (U.S. EPA 2012b; EIA 2013; Bergerson 2005; Sathaye 2011) to ensure they were reasonable. The remaining plants all have reasonable emission rates to net generation rations, as shown in Figures A.2-A.4 (data from eGrid (U.S. EPA 2012b)).

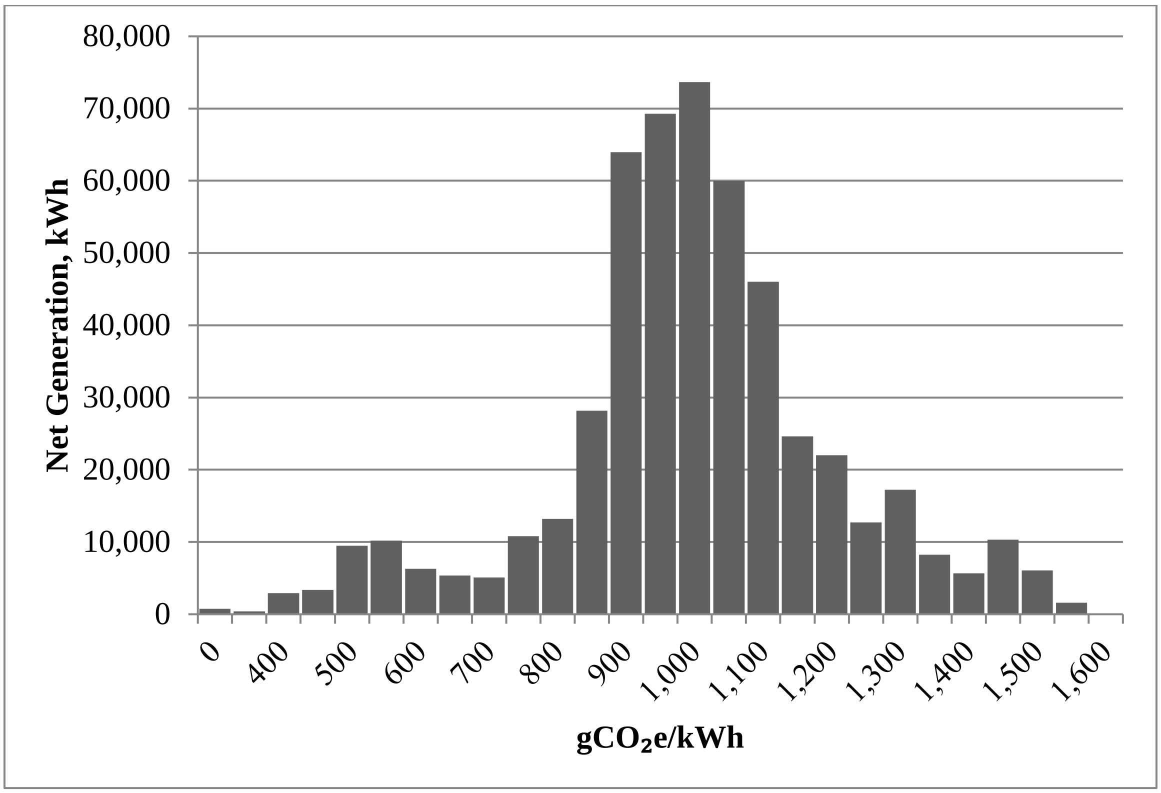


Figure A.2: Coal Plants emission rates vs. net generation

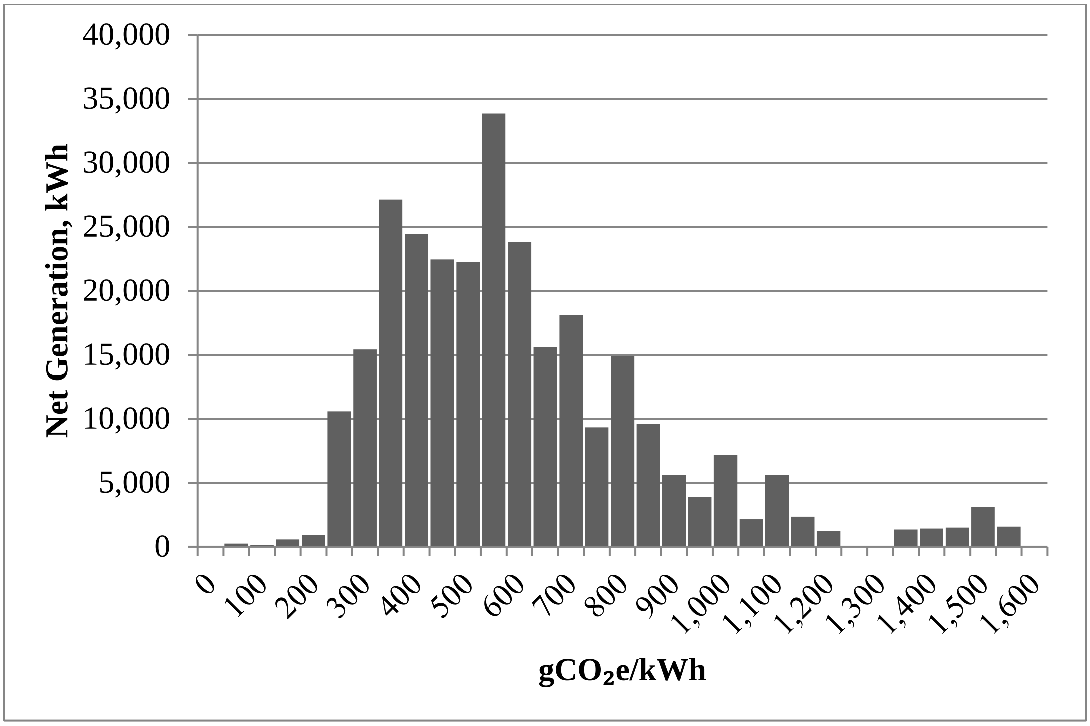


Figure A.3: Natural Gas Plants emission rates vs. net generation

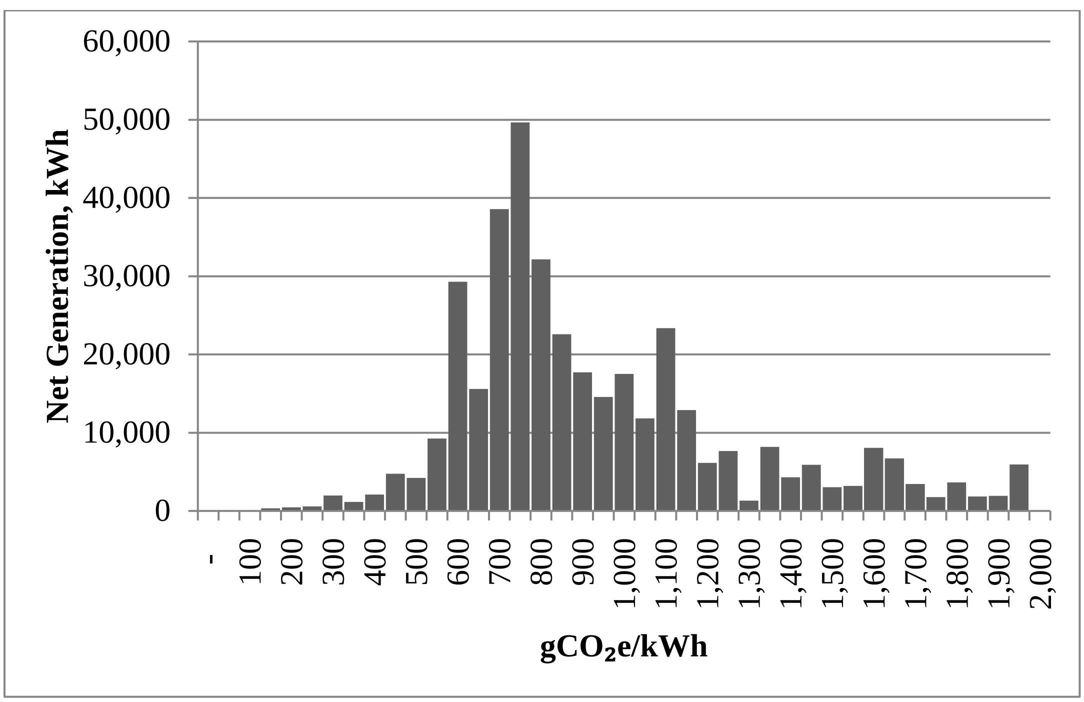


Figure A.4: Oil Plants emissions rates vs. net generation

Once these direct emissions rates were calculated, the IO emissions factors were obtained as described in Chapter 2.

A.3. Additional Information for Disaggregation Results

A.3.1. Comparison between the aggregate and disaggregated models using $1 million final demand in electricity

We ran both models as indicated in **(1-5**. For the aggregate model, we used a final demand of $1 million in the aggregate PGS sector. For the disaggregated model, we used a final demand of $1 million distributed in the disaggregated PGS sectors according to the U.S. generation mix with transmission and distribution shown in Table A.2. Results are shown in figure 2 of the main manuscript.

A.3.2. Comparison of 1 kWh of electricity generation between the disaggregated IO sectors and selected sources

Comparison of LCA methods

See Lenzen (2000), Suh et al. (2004), and (Wiedmann et al. 2011) for further information.

Table A.9: Comparison of IO-LCA approaches

Approach	Strength	Weaknesses
Input-Output LCA	*Includes the entire economy in the system boundary* *Accounts for service sectors, which are usually omitted in process-based studies*	*High sector aggregation* *Requires care in interpretation of results if sectors are highly inhomogeneous*
Process-based LCA	*Models system at a very detailed level* *Allows for direct comparison between products/systems*	*Usually has high truncation errors due to difficulty in incorporating all elements of the system within the system boundary*
Disaggregated Input-Output LCA	*Incorporates process –level data with nationwide system boundary* *Allows customization of product supply chain at the IO level*	*High data requirements needed in order to perform disaggregation accurately*

Data Sources for emissions estimates

In order to compare the IO on a kWh basis, we ran each disaggregated sector using a final demand value obtained as shown below:

$$\frac{Total\ Electricity\ Industry\ Generation\ Throughput}{Total\ kWh\ Produced\ in\ 2002} \tag{A-5}$$

$$= \frac{\$\ 241{,}324{,}180{,}000}{3{,}856{,}000{,}000{,}000\ kWh}$$

$$= \$0.063/kWh$$

The electricity production by technology was obtained from NREL's Power Technologies Energy Data book (Aabakken 2005). The results can be seen in Figure 2.3 in Chapter 2, labeled as USIO, and in Table A.10.

Table A.10: IO results emission results for 1 kWh for each disaggregated sector (gCO_2e/kWh)

	$0.063 final demand in									
Emissions from	*Coal*	*Nat. Gas*	*Oil*	*Nuclear*	*Hydro*	*Geo*	*Biomass*	*Wind*	*Solar*	*Other*
All Other Sectors	34.61	51.96	69.68	3.37	3.37	3.37	3.49	3.37	3.37	3.37
Coal	976.51	4.92	6.99	0.96	0.96	0.96	0.99	0.96	0.96	0.96
Natural Gas	0.47	351.66	1.42	0.15	0.15	0.15	0.16	0.15	0.15	0.15
Petroleum	0.12	0.21	852.00	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Nuclear	0.01	0.01	0.02	5.49	0.00	0.00	0.00	0.00	0.00	0.00
Hydro	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00
Geo	0.00	0.00	0.00	0.00	0.00	29.70	0.00	0.00	0.00	0.00
Biomass	0.04	0.06	0.09	0.01	0.01	0.01	380.34	0.01	0.01	0.01
Wind	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Solar	-	-	-	-	-	-	-	-	-	-
Other	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	558.23
Transmission	-	-	-	-	-	-	-	-	-	-
Distribution	-	-	-	-	-	-	-	-	-	-
Total	**1,011.75**	**408.83**	**930.21**	**10.04**	**4.60**	**34.25**	**385.03**	**4.55**	**4.55**	**562.77**

The results from the Ecoinvent unit processes were obtained by simulating 1 kWh of electricity production from each individual processes in Simapro 7.3, using TRACI 2 V3.01 characterization method. The processes are listed in Table A.11.

Table A.11: Ecoinvent emission results for 1 kWh for selected unit processes

Ecoinvent 2.2 Unit Process	*gCO_2e*
1 kWh Electricity, hard coal, at power plant/US U	1,185
1 kWh Electricity, nuclear, at power plant/US U	13
1 kWh Electricity, natural gas, at power plant/US U	678
1 kWh Electricity, production mix photovoltaic, at plant/US U	46
1 kWh Electricity, hydropower, at power plant/SE U	5
1 kWh Electricity, hydropower, at pumped storage power plant/US U	1,092
1 kWh Electricity, oil, at power plant/UCTE U	884
1 kWh Electricity, lignite, at power plant/UCTE U	1,231
1 kWh Electricity, industrial gas, at power plant/UCTE U	1,756
1 kWh Electricity, at wind power plant/RER U	12
1 kWh Electricity, at cogen 6400kWth, wood, allocation exergy/CH U	30
1 kWh Electricity, at cogen with biogas engine, allocation exergy/CH U	164

Values for GREET were obtained for coal, natural gas, and oil electricity using Model 1.8c (ANL 2009). Values for NREL (Sathaye 2011) and NETL (Skone 2013) were obtained from the referenced publications.

A.3.3. Comparison of NERC regions, Indiana, Idaho, and U.S. average generation mixes

We ran all results as indicated in **(1-5**. For the each mix, we used a final demand of grid mixes presented in Table A.14. The NERC region mixes were obtained from eGRID. The acronyms used in Figure 2.4 in Chapter 2 are expanded in Table A.12 (U.S. EPA 2012a). The different generation types from the NERC regions were mapped to the IO sectors as shown in Table A.13.

Table A.12: NERC acronyms and names

NERC Acronym	***Region NERC Name***
ASCC	Alaska Systems Coordinating Council
FRCC	Florida Reliability Coordinating Council
HICC	Hawaiian Islands Coordinating Council
MRO	Midwest Reliability Organization
NPCC	Northeast Power Coordinating Council
RFC	Reliability First Corporation
SERC	SERC Reliability Corporation
SPP	Southwest Power Pool
TRE/ERCOT	Texas Regional Entity
WECC	Western Electricity Coordinating Council

Table A.13: NERC generation types to IO sector mapping

IO sector	*NERC Gen Type*	*NERC Gen Type Abbrev.*
Coal	NERC region coal generation percent (resource mix)	NRCLPR
NG	NERC region gas generation percent (resource mix)	NRGSPR
Oil	NERC region oil generation percent (resource mix)	NROLPR
Nuclear	NERC region nuclear generation percent (resource mix)	NRNCPR
Hydro	NERC region hydro generation percent (resource mix)	NRHYPR
Geo	NERC region geothermal generation percent (resource mix)	NRGTPR
Bio	NERC region biomass generation percent (resource mix)	NRBMPR
Wind	NERC region wind generation percent (resource mix)	NRWIPR
Solar	NERC region solar generation percent (resource mix)	NRSOPR
Other	NERC region other fossil generation + other unknown/ purchased fuel generation percent (resource mix)	NROFPR+NROPR

Table A.14: NERC and select region mixes

Table S. 13: NERC and select region mixes (U.S. EPA 2012b)

	NERC Regions										*Select Mixes*		
IO sector	ASCC	FRCC	HICC	MRO	NPCC	RFC	SERC	SPP	TRE	WECC	Indiana	Idaho	U.S.
Coal	9%	24%	14%	69%	10%	60%	50%	61%	33%	29%	93%	1%	50%
NG	53%	55%	0%	3%	38%	8%	17%	26%	48%	32%	4%	13%	18%
Oil	17%	4%	75%	0%	2%	0%	1%	0%	1%	1%	1%	0%	2%
Nuclear	0%	14%	0%	14%	31%	28%	27%	4%	12%	9%	0%	0%	20%
Hydro	20%	0%	1%	4%	14%	1%	4%	4%	0%	23%	1%	80%	7%
Geo	0%	0%	2%	0%	0%	0%	0%	0%	0%	2%	0%	1%	0%
Bio	0%	2%	2%	1%	4%	1%	2%	1%	0%	1%	0%	4%	2%
Wind	0%	0%	2%	8%	1%	1%	0%	4%	5%	3%	2%	2%	0%
Solar	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Other	0%	1%	4%	0%	1%	1%	0%	0%	0%	0%	1%	0%	0%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

APPENDIX B

SUPPLEMENTAL INFORMATION FOR CHAPTER 3: MIXED UNITS FOR PGS

This chapter is the peer reviewed version of the Supplemental Information for following article:

Vendries Algarin, J., Hawkins, T. R., Marriott, J. and Khanna, V. (2016), Effects of Using Heterogeneous Prices on the Allocation of Impacts from Electricity Use: A Mixed-Unit Input-Output Approach. Journal of Industrial Ecology. doi:10.1111/jiec.12502

B.1. Creation of the MUIO Model

B.1.1. Reallocation of the Use and Supply Tables

In the supply table:

When moving values from non-PGS columns (i.e., industries) to the PGS columns, this means that no other industries produce electricity (i.e., there is no off-diagonal production of electricity). Using the notation introduced earlier, this means moving the value from its original location in the Supply table, $v_{i,j}$, from column j to column i, where i is one of the PGS sectors, such that $v_{i,j} = 0$. This value is added to a new location which is on the main diagonal of the Supply table, i.e., $v^*_{i,i} = v_{i,i} + v_{i,j}$, where $v_{i,i}$ is the original value at the intersection and $v^*_{i,i}$ the value after reallocation. Table B.1 shows which commodities were reallocated from non-PGS to PGS industries.

Table B.1: Values reallocated from non-PGS to PGS columns. Columns represent Industry sectors, while rows represent Commodity Sectors in the BEA Supply and Use tables.

Row Description	Row Code	Original Column Description	Original Column Code	Reallocated Column Description	Reallocated Column Code
Coal PGS	221101	Other state and local government enterprises	S00203	Coal PGS	221101
Natural Gas PGS	221102	Natural Gas Distribution	221200	Natural Gas PGS	221102
Natural Gas PGS	221102	Other state and local government enterprises	S00203	Natural Gas PGS	221102
Oil PGS	221103	Other state and local government enterprises	S00203	Oil PGS	221103
Nuclear PGS	221104	Other state and local government enterprises	S00203	Nuclear PGS	221104
Hydroelectric PGS	221105	Other state and local government enterprises	S00203	Hydroelectric PGS	221105
Geothermal PGS	221106	Other state and local government enterprises	S00203	Geothermal PGS	221106
Biomass PGS	221107	Other state and local government enterprises	S00203	Biomass PGS	221107
Wind PGS	221108	Other state and local government enterprises	S00203	Wind PGS	221108
Solar PGS	221109	Other state and local government enterprises	S00203	Solar PGS	221109
Other PGS	221110	Other state and local government enterprises	S00203	Other PGS	221110

When moving values from the PGS columns to non-PGS columns, this means assuming that PGS does not produce any other commodity. That is, we are moving the value $v_{i,i}$ in the Supply table from column i (a PGS sector) to column j (non-PGS), such that $v_{i,i} = 0$ and $v^*_{j,j} = v_{j,j} + v_{i,i}$.. Table B.2 shows which commodities were reallocated from PGS to non-PGS industries.

Table B.2: Values reallocated from PGS to non-PGS columns. Columns represent Industry sectors, while rows represent Commodity Sectors in the BEA Supply and Use tables.

Row Description	Row Code	Original Column Description	Original Column Code	Reallocated Column Description	Reallocated Column Code
Other Real Estate	531ORE	Coal PGS	221101	Other Real Estate	531ORE
Natural Gas Distribution	221200	Natural Gas PGS	221102	Natural Gas Distribution	221200
Other Real Estate	531ORE	Natural Gas PGS	221102	Other Real Estate	531ORE
Other Real Estate	531ORE	Oil PGS	221103	Other Real Estate	531ORE
Other Real Estate	531ORE	Nuclear PGS	221104	Other Real Estate	531ORE
Other Real Estate	531ORE	Hydroelectric PGS	221105	Other Real Estate	531ORE
Other Real Estate	531ORE	Geothermal PGS	221106	Other Real Estate	531ORE
Other Real Estate	531ORE	Biomass PGS	221107	Other Real Estate	531ORE
Other Real Estate	531ORE	Wind PGS	221108	Other Real Estate	531ORE
Other Real Estate	531ORE	Solar PGS	221109	Other Real Estate	531ORE
Other Real Estate	531ORE	Other PGS	221110	Other Real Estate	531ORE

In the Use table:

In the Use table, moving values from PGS columns to non-PGS columns (and vice-versa) means shifting parts of the supply chain from electricity industries to industries that produce other commodities (e.g., shifting the gas used to produce natural gas electricity to producing natural gas distribution). The Use table is reallocated based on the movements done on the Supply table to ensure that the column and row totals match. Using the nomenclature introduced in Section 1.3.2.2, the procedure used to do this is as follows:

1. When moving values in the Supply table, we calculate the percentage of the total column (industry) that the value to be moved represents. Using the notation introduced earlier, the column percent, C_p, is

$$C_p = \frac{v_{i,j}}{g_j} \tag{B-1}$$

2. In the Use table, multiply each element of column j by C_p to obtain r, the industry values to be reallocated. Note that the dot (.) notation in the subscripts indicates that this operation is done along the entire dimension it replaces (i.e., $u_{.,j}$ means the operation is done for each row of column j in the use table)

$$r_{.,j} = u_{.,j} * C_p \tag{B-2}$$

3. Subtract the percent fractions from column j:

$$u^*_{.,j} = u_{.,j} - r_{.,j} \tag{B-3}$$

4. Add r to the column (industry) that the value was moved to in the supply table, column k.

$$u^{*}_{.,k} = u_{.,k} + r_{.,j} \tag{B-4}$$

After this computation, the column and row totals are compared against the corresponding values in the Supply table to ensure that they are equal. This way, the constraints needed for the creation of the IO model are met.

The reallocations described above result in the creation of a “base” homogenous price model that allows us to explore the effects of heterogeneous prices more easily. However, when using the model for emissions estimates the changes introduced by the reallocations have to be taken into account. Fortunately, the reallocations performed on the SUT are minimal for the most part. Of the 22 reallocations performed, most consist of either moving the Other Real Estate (531ORE) commodity produced by the PGS industries to the Other Real Estate industry, or moving PGS commodity production from the Other state and local government enterprises industry (S00203) to the PGS industries. The values moved in these reallocations constitute less than 0.5% of the total production of the respective industries (i.e., less than 0.5% of the column total), meaning that the effects these changes have on emissions estimates are minimal. However, there is one reallocation that is significant: approximately 20% of Natural Gas PGS sector’s output, which corresponds to this sector’s Natural Gas Distribution commodity, is moved to Natural Gas Distribution sector. This has two noteworthy implications. First, the purchase values in the Use table are also changed, meaning the “production recipe” for each of these sectors is altered by the same amount for both sectors. Secondly, the emissions estimates for the Natural Gas Distribution sector may be underestimated, as a larger production value is used as a denominator to create the sector’s environmental emissions factor (emissions factors are computed as total sectoral emissions divided by total sector production value), while the opposite happens to the Natural Gas PGS sector's emissions (i.e., they may be overestimated). When the MUIO model is used to estimate emissions from these two sectors, care should be taken to properly assess the impact of this reallocation on their emissions intensities.

B.1.2. Electricity price components in the MUIO model

The MUIO model we are using is a producer price model with a PGS sector that encompasses generation and delivery of electricity (which makes the electricity sector effectively equal in both producer and purchaser prices). In this section we describe how electricity price components influence the prices used in the MUIO model.

Electricity prices are generally broken down into three major components: taxes, costs of energy production, and costs of grid use for delivery (KEMA Consulting GmbH 2005) (Energy Information Administration 2015). Fortunately, average electricity price data is available at a resolution adequate for many sectors in the IO model for broad categories of end users from several sources (Energy Information Administration 2015; U.S. Census Bureau 2007), as described in Section 3 of the main manuscript. Unfortunately, data for the price components of electricity for different end users is almost completely unavailable. Nevertheless, we can make a rough breakdown of how the major electricity price components are included in the BEA tables:

Taxes: As mentioned previously, taxes in the producer price model are included in the Use table value-added row "taxes on production and imports less subsidies". In the BEA tables the tax rates for commodities, such as PGS, are applied evenly to all transactions for items that are subject to tax (U.S. Bureau of Economic Analysis 2009). This means that the tax rate in the tables is equal for all end-users of electricity. It should be noted that none of the price sources used in this work explicitly mention tax rates for electricity; thus, we cannot ascribe tax burden differences to end-use sectors.

Costs of energy production: This constitutes the main portion of electricity costs (Energy Information Administration 2015), and the values that represent those costs are found in the Use table PGS row (commodity). However, as is the case for taxes, there is no readily available breakdown of costs of electricity production allocated to different end use sectors. While individual consumers may be able to arrange long term or large power draw contracts with specific utilities (mostly industrial consumers), most end-use sectors consume electricity available in the grid at large rather than obtaining their energy use from specific suppliers.

Costs of grid use for delivery: As with the energy production costs, the costs for transmission and distribution are found in the Use table PGS row. The Energy Information Administration (2015) indicates that the costs of transmission and distribution vary significantly between different types of consumers. Unfortunately they do not provide specific differences in transmission and distribution costs between consumers, just the differences in overall costs of electricity.

Given the limited data availability, it is impossible to produce a valuation that accurately describes the price components of electricity for each industry in the IO table. We can either produce a rough valuation for the different price components for all IO industries using national price data, similar to other studies (KEMA Consulting GmbH 2005), or assign a specific price to individual IO industries without considering the individual price components. For this analysis, we chose the latter approach. Since we are specifically interested in exploring differences in electricity emissions by different sectors, it is more important that we prioritize distinguishing between sectors than it is between price components of electricity. Additionally, it is likely the case that generation costs are relatively constant between different end-use categories (Energy Information Administration 2015), (2016a). This reinforces our approach as it enables us to treat the differences in price components and the difference in overall prices interchangeably, allowing us to use price differences between consumers as a way of distinguishing between monetary and mixed unit models.

B.1.3. Estimating Greenhouse Gas Emissions factors in physical units

The emissions intensity vector (R) derived in Chapter 2 is calculated by dividing total emissions by the total output of each sector, in monetary units for non-PGS sectors and in monetary and energy units for the PGS sectors. Their derivation is otherwise unchanged from the process described in Chapter 1.

B.2. Detailed MUIO price mapping

As explained in Chapter 3, the prices are mapped using the Detailed Industry Statistics for the 2007 Economic Census (EC) for manufacturing sectors (i.e., those sectors that begin NAICS Code 3) and EIA end-use classification for non-manufacturing sectors. The BEA industry sectors are not as detailed as the EC manufacturing sectors; accordingly, there is a one-to-many mapping between these data sets for certain BEA sectors. The full mapping can be seen in the tables below. Table B.3 shows the price mapping for the Input-Output non-industry sectors, based on EIA's end-use classification (EIA 2013). The numbers in parenthesis indicate the first digit of the NAICS code that has an assigned price. Table B.4 shows the U.S. Census Bureau (2007) Economic Census to BEA (2013) Input-Output manufacturing sector mappings, along with the electricity price assigned to the corresponding BEA sector.

Table B.3: End-Use sector pricing by EIA (2013) classification, used for non-industry sectors

End Use Sector	Price (cents/kWh), 2007 US Dollars
EIA Residential (Private Consumption)	10.65
EIA Commercial (NAICS CODE 44, 5-8)	9.65
EIA Industrial (NAICS CODE 1,2)	6.39
EC Industrial (NAICS CODE 3)	Individually Mapped (see below)
EIA Transportation	9.70

Table B.4: : BEA IO Industry Sector Codes for manufacturing to NAICS 6-digit Industry Codes for manufacturing price mapping. Prices in cents/kWh (2007 US Dollars)

BEA Industry Codes	NAICS 6-digit Industry Codes	Electricity Price per BEA Industry Code
321100	3211	5.77
321200	3212	5.55
321910	32191	6.14
3219A0	32192, 32199	5.95
327100	3271	6.16
327200	3272	5.77
327310	32731	5.72
327320	32732	6.27
327330	32733	6.63
327390	32739	6.52
327400	3274	5.79
327910	32791	6.63

Table B.4 (Continued)

BEA Industry Codes	NAICS 6-digit Industry Codes	Electricity Price per BEA Industry Code
327991	327991	6.08
327992	327992	6.17
327993	327993	5.80
327999	327999	6.82
331110	3311	4.57
331200	3312	5.52
33131A	331311-2	4.21
331314	331314	3.75
33131B	331315, 331316, 331319	4.93
331411	331411	4.60
331419	331419	4.16
331420	33142	6.11
331490	33149	5.56
331510	33151	5.63
331520	33152	5.59
33211A	332111-2, 332117	6.17
332114	332114	6.43
33211B	332115-6	6.43
332200	3322	6.74
332310	33231	6.39
332320	33232	6.53
332410	33241	6.18
332420	33242	6.43
332430	33243	6.57
332500	3325	6.75
332600	3326	6.43
332710	33271	6.58
332720	33272	7.06
332800	3328	6.56
33291A	332911-2, 332919	6.67
332913	332913	7.32
332991	332991	5.91
33299A	332992-5	6.81
332996	332996	6.37
33299B	332997-9	6.16
333111	333111	5.13
333112	333112	6.04
333120	33312	5.26
333130	33313	6.88
33329A	33321, 333291-4, 333298	6.62

Table B.4 (Continued)

BEA Industry Codes	NAICS 6-digit Industry Codes	Electricity Price per BEA Industry Code
333220	33322	6.34
333295	333295	7.89
33331A	333311, 333312, 333319	6.17
333313	333313	6.19
333314	333314	7.80
333315	333315	9.06
33341A	333411-2	6.61
333414	333414	6.71
333415	333415	5.82
333511	333511	6.48
33351A	333512-3	6.59
333514	333514	6.52
33351B	333515, 333516, 333518	6.60
333611	333611	5.50
333612	333612	5.80
333613	333613	6.46
333618	333618	5.62
33391A	333911, 333913	6.36
333912	333912	6.20
333920	33392	6.13
333991	333991	6.67
33399A	333992, 333997, 333999	8.26
333993	333993	6.76
333994	333994	6.05
33399B	333995-6	5.42
334111	334111	6.42
334112	334112	6.69
33411A	334113, 334119	6.12
334210	33421	7.18
334220	33422	8.42
334290	33429	4.52
334300	3343	6.18
33441A	334411, 334412, 334414-7, 334419	7.70
334413	334413	6.25
334418	334418	7.05
334510	334510	6.88
334511	334511	7.78
334512	334512	6.48
334513	334513	7.71

Table B.4 (Continued)

BEA Industry Codes	NAICS 6-digit Industry Codes	Electricity Price per BEA Industry Code
334514	334514	5.62
334515	334515	8.84
334516	334516	7.17
334517	334517	7.62
33451A	334518-9	6.94
334610	33461	6.38
335110	33511	5.59
335120	33512	6.37
335210	33521	5.95
335221	335221	5.26
335222	335222	5.54
335224	335224	5.54
335311	335311	5.52
335312	335312	5.77
335313	335313	6.45
335314	335314	6.68
335911	335911	5.36
335912	335912	5.61
335920	33592	6.45
335930	33593	6.73
335991	335991	4.90
335999	335999	8.35
336111	336111	5.39
336112	336112	4.97
336120	33612	6.45
336211	336211	6.02
336212	336212	6.05
336213	336213	5.06
336214	336214	5.91
336310	33631	5.52
336320	33632	5.63
3363A0	33633-4	5.38
336350	33635	5.37
336360	33636	5.03
336370	33637	5.94
336390	33639	5.63
336411	336411	6.48
336412	336412	6.49
336414	336414	7.23
33641A	336415, 336419	5.75

Table B.4 (Continued)

BEA Industry Codes	NAICS 6-digit Industry Codes	Electricity Price per BEA Industry Code
336500	3365	5.63
336611	336611	5.93
336612	336612	6.45
336991	336991	7.02
336992	336992	5.34
336999	336999	5.54
337110	33711	6.52
337121	337121	5.59
337122	337122	5.96
33712A	337124, 337125, 337129	4.95
337127	337127	6.70
33721A	337211, 337212, 337214	5.93
337215	337215	6.78
337900	3379	7.43
339112	339112	7.11
339113	339113	6.98
339114	339114	7.26
339115	339115	7.28
339116	339116	6.42
339910	33991	6.28
339920	33992	7.40
339930	33993	7.90
339940	33994	5.75
339950	33995	6.59
339990	33999	6.79
311111	311111	5.75
311119	311119	6.13
311210	31121	5.86
311221	311221	4.86
31122A	311222-3	5.14
311225	311225	5.64
311230	31123	5.54
311300	3113	6.28
311410	31141	6.00
311420	31142	6.91
31151A	311511-2	6.70
311513	311513	5.77
311514	311514	6.01
311520	31152	6.65
31161A	311611-3	5.85

Table B.4 (Continued)

BEA Industry Codes	NAICS 6-digit Industry Codes	Electricity Price per BEA Industry Code
311615	311615	5.70
311700	3117	6.87
311810	31181	6.92
3118A0	31182-3	6.56
311910	31191	6.19
311920	31192	6.89
311930	31193	7.57
311940	31194	6.86
311990	31199	6.71
312110	31211	7.14
312120	31212	6.59
312130	31213	10.04
312140	31214	5.29
312200	3122	8.22
313100	3131	5.03
313200	3132	5.14
313300	3133	6.39
314110	31411	5.22
314120	31412	6.16
314900	3149	5.41
315000	315	6.43
316000	316	6.21
322110	32211	5.00
322120	32212	4.73
322130	32213	4.96
322210	32221	6.83
322220	32222	6.24
322230	32223	6.05
322291	322291	5.84
322299	322299	6.53
323110	32311	6.57
323120	32312	6.96
324110	32411	6.20
324121	324121	7.01
324122	324122	7.03
324190	32419	5.52
325110	32511	5.92
325120	32512	5.00
325130	32513	5.21
325180	32518	4.54

Table B.4 (Continued)

BEA Industry Codes	NAICS 6-digit Industry Codes	Electricity Price per BEA Industry Code
325190	32519	5.42
325211	325211	6.11
3252A0	325212, 32522	5.49
325310	32531	4.82
325320	32532	5.85
325411	325411	7.01
325412	325412	6.68
325413	325413	8.72
325414	325414	7.20
325510	32551	6.29
325520	32552	6.64
325610	32561	6.48
325620	32562	7.25
325910	32591	6.57
3259A0	32592, 32599	6.29
326110	32611	5.89
326120	32612	5.99
326130	32613	6.20
326140	32614	6.26
326150	32615	6.31
326160	32616	6.60
326190	32619	6.21
326210	32621	4.99
326220	32622	5.54
326290	32629	6.22

The electricity price for each BEA manufacturing industry was calculated using the detailed electricity purchase data from the mapped EC manufacturing industry sectors, which is specified both in dollars and kilowatt-hours for each 6-digit NAICS manufacturing industry. For each of these sectors, we calculated an average price by dividing the total electricity purchase amount, in dollars, of the mapped sectors by the total megawatt-hours of those same sectors. As an example, BEA sector 321100 (Sawmills and wood preservation) is composed of the individual NAICS sectors 321113 and 32114 (sawmills, wood preservation, respectively), shown below.

Table B.5: Electricity purchase data for the Sawmills and Wood preservation sectors in the 2007 Economic Census (2007)

Sector Code	Industry Description	Electricity Purchased ($M)	Electricity Purchased (MWh)
321113	Sawmills	421	7,332
321114	Wood preservation	37	613

Using this data, the price for the BEA Sawmills and wood preservation industry is $M 458/ MWh 7,945, or 5.77 cents/kWh as shown in the first row of Table B.4.

Despite having detailed mapping for most industrial sectors, there was not equally detailed data for other sectors in the IO tables (agriculture, retail, etc.) publically available, which is why the broader mapping detailed in Table 3.1 was used for these sectors. However, even with the more detailed information, there is still some aggregation occurring, as these prices reflect the sector average. While this is more detailed than previous IO models, it is still not the case that every farm pays $0.06/kWh nor every sawmill pays $0.057/kWh for their electricity consumption, for example. This suggests that the approach used here, while reducing the overall price homogeity bias, does not completely eliminate it. One way to see the effects of this is to use a sensitivity analysis, as shown below. Including price information from individual businesses is not feasible, and moreover, is something that a process- or hybrid-based LCA approach focusing on a more limited product system would be more suitable for.

B.3. Comparing Total and Scope 2 Emissions between MUIO and EIO models

The main question we want to answer is "how do emissions change when tracked in physical vs. monetary units"? To answer this question, we need to carefully define what it is we want to measure in terms of outputs from the MUIO model. The main difference we want to explore is the changes in proportion of direct vs. total emissions for the final demand of a particular commodity (in this case electricity) caused by differences in prices. This implies two distinct comparisons of the EIO and MUIO models: 1) direct emissions from electricity consumption and 2) total emissions. In input-output terms, direct emissions are the first round of emissions produced by the given final demand of electricity (equivalent to Scope 2 emissions according the GHG protocol (WBCSD; WRI 2004)), while total emissions are those produced by the entire round by round effects produced by the entire final demand (not just electricity consumption). Total emissions from the electricity sector can be calculated using **(1-5**, using a Y vector composed on of all the purchases of the sectors under consideration (i.e., Private Consumption, Aluminum Production, and Other Real Estate). The direct emissions can be calculated using use the direct requirements table as shown below[3], and specifying only the PGS demand of the sectors under consideration:

$$E_{direct} = F * (WY + W * (BW) * Y) \tag{B-5}$$

[3] This is the industry by commodity formulation of the first round, direct effects of commodity production. The equivalent formulation for a square input-output tables is

$$E_{direct} = F * (Y + AY)$$

where A is the square direct requirements matrix. See Miller and Blair (1985) for a detailed derivation of the power series approximation of the Leontief equation and round by round effect estimates.

The results from these two equations for each final demand vector are found in Figure 4 in Chapter 3, as well as in Figure B.1 below for the PC, AL, and ORE scaled supply chains.

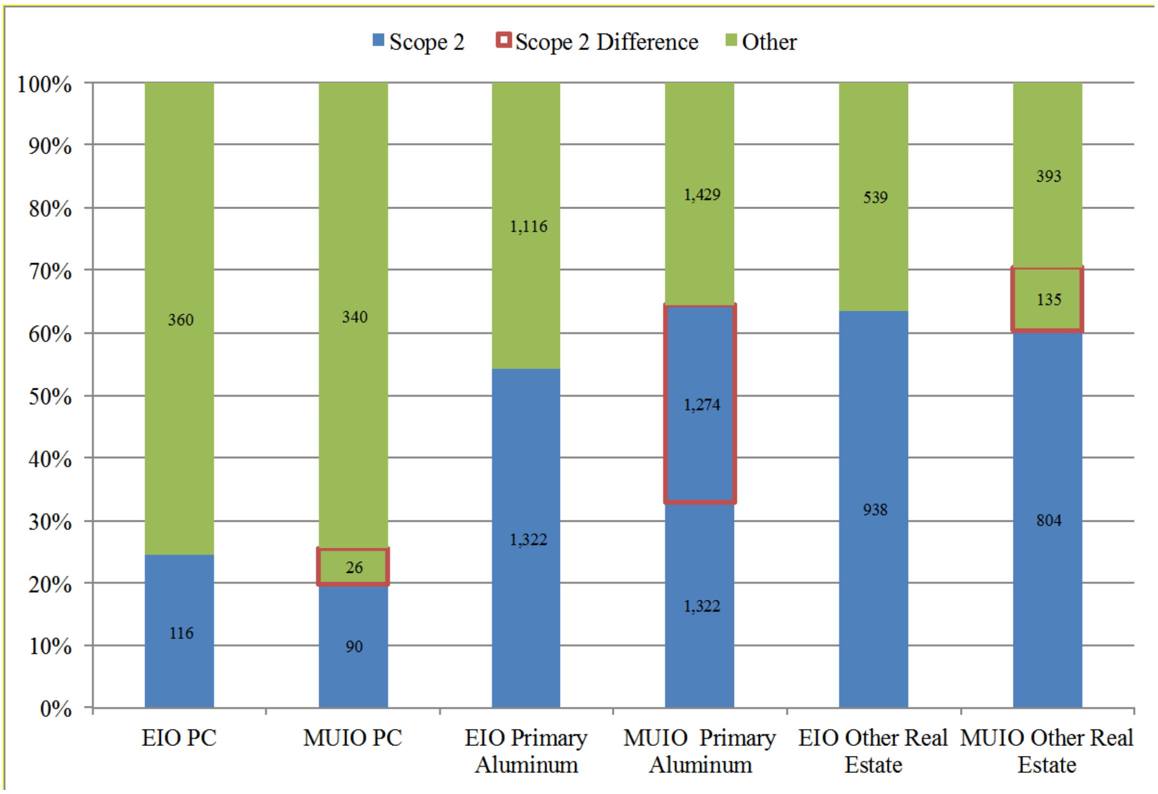


Figure B.1: Share of PGS Scope 2 CO2e Emissions as percent of total emissions for EIO and MUIO models.
The values in the blue part of the bars represents Scope 2 emissions. Values in the red-outlined box represent changes in scope 2 emissions, either increasing scope 2 (box colored blue) or decreasing scope 2 (box colored green). Values in the green part represent Other emissions. All values in Tonnes $CO_2eq/\$M$.

B.4. Price Sensitivity

We do not have information of the variability of electricity price for the detailed NAICS industry sectors. However, we do have price variability information in the form of state prices for the more general EIA end-use classification sectors (residential, industrial, commercial) (EIA

2014). We use the highest and lowest state electricity prices for each end-use sector and compare them with the average end-use electricity prices to create a percent increase and decrease, respectively. This average price for each end-use sector is then multiplied by the high and low percent change to create high and low price estimates. The results are shown in Table C.2. These values are then used to create high and low price estimates for the MUIO model, which creates the energy conservation imbalances described in the main text.

Table B.6: Average, Low, and High electricity prices, by end-use sector (EIA 2013). Price estimates in 2007 cents/kWh.

	Residential	Commercial	Industrial	Transportation
Average price	10.65	9.65	6.39	9.7
High price estimate	24.12	21.91	18.38	14.18
Low price estimate	6.36	5.14	3.87	5.74
High:Average price ratio	226%	227%	288%	146%
Low:Average price ratio	60%	53%	61%	59%

For BEA sectors that have no price mapping (i.e., they use the default price used in the EIO model), we used the percent change of all end-use sectors combined. For the manufacturing sectors that were mapped using the EC data, we use the same percent difference as for the BEA industrial sectors. We then multiply each price mapped to the BEA sectors by these percent changes to create high and low electricity price scenarios. These new price scenarios are run using the same vector of commodity inputs described in the main manuscript to obtain a high and low bound on emissions estimates and electricity flows with the MUIO model. These results are included in the error bars in Figure 4 in the main manuscript.

Effects of Low and high prices in MUIO models

In order to understand the effect of variation in electricity prices within the sectors of the detailed model, we perform sensitivity analysis using estimates for high and low prices for each mapped electricity price. We perform this analysis by modifying the physical value of electricity in the SUTs according to different electricity prices, re-creating the IOT using these modified SUTs, and then running the resulting IOT. The high and low price estimates are obtained from state-level electricity prices estimates for each end-use classification sector (EIA 2014). This helps us understand the effect of variability of electricity prices on both the energy flows and emissions when running IO models. When using these high and low price estimates to create the MUIO model, the equivalence in total physical output of the PGS sectors between the use and supply tables is not maintained. In other words, the overall energy balance in the economy is violated. Table 2 shows the amount of electricity, in megawatt-hours, represented by the different price assumptions used to build the MUIO models.

Table B.7: Physical electricity consumption implied by different price assumptions

Price used Model	Million MWh	MUIO Use:EIO Use ratio
EIO Use table	3,810*	100%
MUIO Use table average prices	3,643	96%
MUIO Use table low prices	6,355	164%
MUIO Use table high prices	1,744	47%

**The megawatt-hour value is what the monetary value represents in MWh using the U.S. average price of 8.5 cents per kWh.*

As seen above, variability in electricity prices can have a large impact in the amount of electricity represented in the MUIO model, which in turn impacts emissions estimates. When using average prices for the MUIO model, the total amount electricity represented is similar to that in the EIO model. PC consumes approximately 45% of the total PGS commodity and pays the highest electricity price of any sector. Conversely, the manufacturing, mining and utilities sectors (which pay lower prices for electricity) account for over half of all sectors in the BEA tables. This results in a counterbalancing effect between the high number of sectors that on average pay low electricity prices (increasing the total MWh represented in the economy), and the large amount of electricity consumed by the PC sector (decreasing the total MWh in the economy); this is consistent with the results shown in Figure 3.5. However, this is not the case when using the high and low prices for the MUIO model. The error bars in Figure 3.5 in the main manuscript show this imbalance: when using low prices in the MUIO model, the emissions estimates increase (represented by the top of the error bars in the figure) whereas for the high price model the emissions estimates decrease (represented by the bottom of the error bars). Table S.8 shows the underlying energy balance violation for the specific example of the PGS consumed by the PC sector for different prices. It should be noted that while the total monetary value remains the same ($1M), different electricity prices results in differences in total electricity flows.

Table B.8: PGS consumption in the Private Consumption supply chain ($1 million) when using different price assumptions.

Model	Price ($/kWh)	Private Consumption PGS demand ($ or MWh)
PGS Monetary Value ($)	N/A	$14,670
U.S. Average Electricity Price	0.085	171.94*
MUIO average price mapping	0.107	137.75
MUIO low price mapping	0.064	230.67
MUIO high price mapping	0.241	60.82

**The megawatt-hour value is what the monetary value represents in MWh using the U.S. average price of 8.5 cents per kWh.*

APPENDIX C

SUPPLEMENTAL INFORMATION FOR MRIO DEVELOPMENT

C.1. Data Requirements for the MRIO model and example model creation

The MRIO model requires several separate data inputs to operate correctly. Below is a brief description of the data sources required and how they are used for creating the model. This section illustrates how the different data sources are used to create the MRIO model with simple 2-sector example.

C.1.1. Data Uncertainty in the MRIO Model

Input-Output models have multiple sources of uncertainty, such as survey errors, temporal bias, aggregation errors, etc. (Williams et al. 2009b). While important, addressing all the different sources of uncertainty related to IO models generally is a non-trivial task, and beyond the scope of this work. In an effort to minimize the effects of data uncertainty, the scenarios and results shown in this work offer comparisons between different configurations of the MRIO model such that that external sources of uncertainty are included in equal measure in such thus less influential for the conclusions drawn.

Uncertainty associated with the data incorporated into the MRIO model during its creation is relevant and addressed throughout the different stages in which these data are added; a brief summary is these different sections is provided below, with references to other sections in this document (or other documents) where this is addressed, as appropriate.

C.1.2. BEA Use and Supply tables (Base EIO model)

The Use and Supply tables are the main components of the Economic Input-Output model of the U.S. These tables are economic accounts of the U.S., which describe the economic activity of a given year in terms of commodities used and produced by industries. For this work we use the most recent Benchmark Accounts, which correspond to the year 2007. The Use table is a commodity by industry matrix, where each column corresponds to the supply chain or production recipe for a given industry. The Supply table is an industry by commodity matrix, and shows which industries produce which commodities. Here we use the Supply table (which is essentially a transpose of the Make table as provided by the BEA) when creating the MRIO model, to be in alignment with the Supply and Use Table (SUT) formulation for creating IO models, which is common outside the U.S.

Here we focus on the modifications to the PGS sector to create the MRIO model; the Chapter 1 provides details on how to transform the SUT to a complete Input-Output model. Figure C.1 shows an example Supply and Use table that we will use to demonstrate the creation of the MRIO model. These example tables have a PGS sector, representing electricity flows, and a mining sector, which represents the treatment of all non-PGS sectors in the model. Additionally, the Use table shows the Final Demand and Exports columns. Final Demand represents purchasers by ultimate consumers, usually private households and governments; Exports represents commodities sold to customers outside the U.S.

Use table

	Industries → Commodities ↓	PGS 1	Mining 2	FD 3	Exports 4
1	PGS ($M)	40	60	90	10
2	Mining ($M)	70	15	15	0
3	VA ($M)	90	25		
	Industry Output	200	100	105	10

	Commodity Output
1	200
2	100
3	115

Economy Output
415

Supply Table

	Industries → Commodities ↓	PGS 1	Mining 2
1	PGS ($M)	200	0
2	Mining ($M)	0	100
	Industry Output	200	100

	Commodity Output
1	200
2	100

Interindustry Output
300

Figure C.1: Example 2-sector Supply and Use tables
The Use table is a commodity by industry matrix where columns specify the supply chain or "recipe" for each industry. The Supply table is a commodity by industry table where columns represent the amount of each commodity produced. The numbers next to the sector description denote row or column number (e.g., row 1 in the Use table corresponds to PGS commodity; column 1 to PGS industry; column 3 to the Final Demand sector, etc.).Total PGS commodity Output is $200M in this example

C.1.3. Electricity Generation by Technology (PGS Disaggregation)

The base EIO model created using the Use and Make tables contain only a single sector describing electricity use in the U.S.: the Power Generation, Transmission, and Distribution (PGS) Sector. We use electricity generation data from the U.S. EPA's eGrid database (2017), which contains data for the year 2007 by generation technology, to disaggregate the single BEA PGS sector into several sectors, each describing a unique power generation technology (coal, natural gas, solar, etc.). We use eGrid's data as a basis to allocate the values contained in the original PGS sector to the newly disaggregated sectors.

Details on this procedure can be found in Chapter 1 (Vendries Algarin et al. 2015), where discussion on the effect of disaggregation has on aggregation bias and discussion of the accuracy PGS emissions factor estimates (and comparisons to other model results) can be found (Appendix A). Applying this method to the 2 sector model example, and assuming a PGS technology mix consisting of 50% coal, 35% nuclear, and 15% wind power, the disaggregated version of the 2 sector economy is shown below.

Use table

	Industry -->	Coal	Nuclear	Wind	Mining	FD	Total	
	Commodity	11	12	13	2		Commodity	PGS Rows total
11	Coal ($M)	20			30	50	100	200 $M
12	Nuclear ($M)		14		21	35	70	
13	Wind ($M)			6	9	15	30	
2	Mining ($M)	35	24.5	10.5	15	15	100	
	VA ($M)	45	31.5	13.5	25		115	
	Total Industr	N/A			N/A			

Supply Table

	Industry -->	Coal	Nuclear	Wind	Mining	Total	
	Commodity	11	12	13	2	Commodity	PGS Rows total
11	Coal ($M)	100	0	0	0	100	200 $M
12	Nuclear ($M)	0	70	0	0	70	
13	Wind ($M)	0	0	30	0	30	
2	Mining ($M)	0	0	0	100	100	
	Total Industr	100	70	30	100	300	

Figure C.2: Example 2-sector Supply and Use tables disaggregation

C.1.4. Data Requirements for the Mixed-Unit (MUIO) model

Once the IO model has been disaggregated, the next step is to create a mixed-unit (MUIO) model that allows the tracking of electricity in the economy in physical terms. This transformation is accomplished by assigning a price to the electricity consumed by every industry in the Use table. This electricity consumption per sector is then divided by the individual industry price to obtain electricity use in energy units.

The electricity price data is obtained from the 2007 Economic Census (EC) conducted by the U.S. Census Bureau (2007) for manufacturing sectors, and from the (EIA (2014), 2013)) for all other sectors. The individual electricity prices per industry are used as a basis to convert from monetary to physical units.

Details on this process can be found in Chapter 2 (Vendries Algarin et al. (2016)), where discussion of the introduction of detailed price information on emissions can be found, as well as a sensitivity analysis on the prices used (Appendix B). Applying this method to the 2 sector model example, and assuming a uniform PGS price of $0.10/kWh, the mixed unit version of the 2-sector economy is shown below. Notice that the rows in the Use and the Supply Tables are now measured in physical units.

Use table

	Industry --> Commodity	Coal 11	Nuclear 12	Wind 13	Mining 2	FD	Total Commodity Output	PGS Rows total
11	Coal (GWh)	200			300	500	1000	2000 GWh
12	Nuclear (GWh)		140		210	350	700	
13	Wind (GWh)			60	90	150	300	
2	Mining ($M)	35	24.5	10.5	15	15	100	
	VA ($M)	45	31.5	13.5	25		115	
	Total Industry Output	N/A			N/A			

Supply Table

	Industry --> Commodity	Coal 11	Nuclear 12	Wind 13	Mining 2	Total Commodity Output	PGS Rows total
11	Coal (GWh)	1000	0	0	0	1000	2000 GWh
12	Nuclear (GWh)	0	700	0	0	700	
13	Wind (GWh)	0	0	300	0	300	
2	Mining ($M)	0	0	0	100	100	
	Total Industry Output	1000	700	300	100	2100	

Figure C.3: Example 2-sector Supply and Use tables disaggregation

C.1.5. State Electricity Generation Mixes

Electricity generation data by technology type was obtained from the eGRID database (U.S. EPA 2017) for the disaggregation of the PGS sector. eGRID also contains this information on a state-by-state basis. This enables the computation of generation mixes for each state by dividing the net negation by each technology type in each state by the total state generation. In addition to allowing the calculation of emissions caused by electricity generation by state, this data is also used (in conjunction with electricity trading and industry presence data) to calculate electricity consumption by state, and consequently emissions caused by electricity consumption on a state basis. For the 2 sector example, the assumed mixes are shown below for a 4 region economy.

	PGS Technology			
States	Coal	Nuclear	Wind	Total
MD	40%	40%	20%	100%
NJ	20%	50%	30%	100%
NY	35%	37%	28%	100%
PA	68%	30%	3%	100%

Figure C.4: Example Generation Mixes for the 2 economy sector for the 4 component states
Values chosen for ease of computation

C.1.6. Net electricity production, net import/export, and net consumption by state

In addition to net electricity generation totals for each U.S. state (plus Washington, D.C.), eGRID also compiles the net state consumption for each state, and calculates the net imports by state by subtracting net consumption from net generation. Thus, states that consume more than they generate have a positive net import value, while those that produce more than they consume have a negative net import value. For this work, the assumption is that states with positive net consumption values are net electricity importers, while states with negative net consumption are net electricity exporters. While both generation and import/export values are taken from eGRID, the total electricity production values are not equal due to assumptions regarding transmissions, distribution, and exports. In order avoid an inconsistency in the amount of electricity generation used in the model, the import/export numbers by state are scaled to match the U.S. total electricity produced by technology type.

The figure below shows the way this data is organized for use in the MRIO model, using the four sample regions and electricity totals introduced earlier.

States	Adj Net Gen	Estimated Net Imports	Net Consumption
MD	100	400	500
NJ	200	100	300
NY	700	-200	500
PA	1,000	-300	700
Total (GWh)	2,000	0	2,000

Figure C.5: Example State Generation and Import/Export data for 2 sector economy

C.1.7. State Import/Export optimization

The net generation, consumption, and net Export/Import data are used to calculate how electricity is traded between net exporting and net importing states. These data are used as inputs to a linear optimization whose objective function minimizes the distance electricity must travel between net exporting states and net importing states. To account for the reduced trading between different interconnects in the North American grid, the distances between states that belong to different interconnects is artificially increased such that trading between interconnects is reduced substantially but does not completely disappear. Constraints were also imposed such that only states border Canada/Mexico can trade with these countries. The optimization results in a state import-export (STIE) matrix, where states that have a net electricity surplus (rows) export that surplus to one or more states with a net electricity deficit (columns). Additional details for the procedure used to create this optimization can be found in (Marriott and Matthews 2005).

The figure below shows an example output from the optimization procedure suitable for building the MRIO table.

	Importers	
Exporters	MD	NJ
NY	25%	100%
PA	75%	0%

Figure C.6: Example State Import/Export (STIE) matrix result from trading optimization model

C.1.8. State Industry Presence Data

Data from U.S. Census Bureau (2009) was mapped to the MRIO BEA sectors to create industry distribution by state. There are some industries for which there was no data available for mapping. This is usually because data for these sectors is either classified (no estimate given) or aggregated in such a way that the CBP reports a range estimate for employment. For these sectors we found industries that were the most similar in their description or purpose in the BEA classification, and used their geographic distribution to fill in the absent CBP estimates. The sectors for which this was done, and the sectors whose distributions were used, are shown in Table C.1 below.

Table C.1: Sectors with no original geographic distribution

Original Sector without PGS presence	Copper, nickel, lead, and zinc mining	Primary smelting and refining of copper	Household refrigerator and home freezer manufacturing	Household laundry equipment manufacturing	Other major household appliance manufacturing	Primary battery manufacturing	Guided missile and space vehicle manufacturing	Housing Real Estate	Private households
	212230	331411	335222	335224	335228	335912	336414	'5310HS'	814000
Sector used to replace geographic distribution	Iron, gold, silver, and other metal ore mining	Copper rolling, drawing, extruding and alloying	Household cooking appliance manufacturing	Household cooking appliance manufacturing	Household cooking appliance manufacturing	Storage battery manufacturing	Propulsion units and parts for space vehicles and guided missiles		
	2122A0	331420	335221	335221	335221	335911	33641A		

Sectors with no original geographic PGS distribution after census mapping (top), and the sectors used to replace non-existent distribution (bottom). Note that blue highlighted sectors have no PGS use in the original BEA Use table (included for completeness).

The figure below shows the example distribution of the Mining sector for the 2 sector economy example.

States	Mining Dist.
MD	10%
NJ	30%
NY	0%
PA	60%

Figure C.7: Example distribution for the mining sector for the 2 sector economy

C.1.9. State Consumption Mixes

The result of the optimization is used along with state generation and industry presence data to build each industry's electricity consumption profile. Net exporting states are assumed supply all their electricity needs and thus have the same generation and consumption mix. Net importing states have a consumption mix calculated based on a weighted average of their own generation mix and the generation mix of the states they import electricity from.

State	% State Consumption	PGS Technology Coal	Nuclear	Wind	Total
NY	100%	35%	37%	28%	100%
PA	100%	68%	30%	3%	100%

Example consumption mix – net exporters

Imports	% State Consumption	Coal	Nuclear	Wind	Total-Check
NY	20%	7%	7%	6%	20%
PA	60%	41%	18%	2%	60%
In-State Generation	20%	8%	8%	4%	20%

Example consumption mix – net importer: MD

Imports	% State Consumption	Coal	Nuclear	Wind	Total-Check
NY	33%	12%	12%	9%	33%
In-State Generation	67%	13%	33%	20%	67%

Example consumption mix – net importer: NJ

Figure C.8: Example 2 sector economy consumption mixes by state

Top: Consumption mix of net exporter
Middle: Consumption mix of MD, a net importing state
Bottom: Consumption mix of NJ, a net importing state

C.1.10. Finalized MRIO Use and Supply Table

The data shown above is combined as described in Chapter 4 to build the MRIO Use and Supply tables.

For the 2 sector economy example, the result is shown in the figure below. The generation mixes are used to populate the intersection of rows 101-103 and columns 104-107. The consumption mixes are used to populate the intersection of rows 104-107 and columns 108-111. The consumption mixes combined with the industry presences are used to populate the intersection of rows 108-111 and columns 101, 102, 103, 2, and FD. The Mining and Value added rows are unmodified from Figure C.3. The values of the Supply table are assigned along the diagonal for SUT computation purposes.

	Use table	Electricity Generation Mixes				Electricity Consumption Mixes				Electricity Generation Technologies					
	Commodity/Industry -->	MD	NJ	NY	PA	MD	NJ	NY	PA	Coal	Nuclear	Wind	Mining	FD	Total Com
		104	105	106	107	108	109	110	111	101	102	103	2		Output
104	MD					100.0	-	-	-						100.0
105	NJ					-	200.0	-	-						200.0
106	NY					100.0	100.0	500.0	-						700.0
107	PA					300.0	-	-	700.0						1,000.0
108	MD									8.0	8.0	4.0	60.0	420.0	500.0
109	NJ									8.0	20.0	12.0	180.0	80.0	300.0
110	NY									49.0	51.9	39.1	-	360.0	500.0
111	PA									135.0	60.0	5.0	360.0	140.0	700.0
101	Coal (GWh)	40.0	40.0	245.0	675.0										**1,000**
102	Nuclear (GWh)	40.0	100.0	259.7	300.0										**700**
103	Wind (GWh)	20.0	60.0	195.3	25.0										**300**
2	Mining ($M)									35.0	24.5	10.5	15.0	15.0	100.0
	VA ($M)									45.0	31.5	13.5	25.0	-	115.0
	Total Industry Output									N/A			N/A		

Example Use table

Supply Table	on Mixes				Electricity Consumption Mixes				Electricity Generation Technologies				
Commodity/Industry -->	MD	NJ	NY	PA	MD	NJ	NY	PA	Coal	Nuclear	Wind	Mining	
	104	105	106	107	108	109	110	111	101	102	103	2	Total Commo
MD	100.0												100.0
NJ		200.0											200.0
NY			700.0										700.0
PA				1,000.0									1,000.0
MD					500.0								500.0
NJ						300.0							300.0
NY							500.0						500.0
PA								700.0					700.0
Coal (GWh)									1,000.0	-	-	-	**1,000.0**
Nuclear (GWh)									-	700.0	-	-	**700.0**
Wind (GWh)									-	-	300.0	-	**300.0**
Mining ($M)									-	-	-	100.0	100.0

Example Supply table

Figure C.9: Example 2 sector economy finalized Use and Supply tables

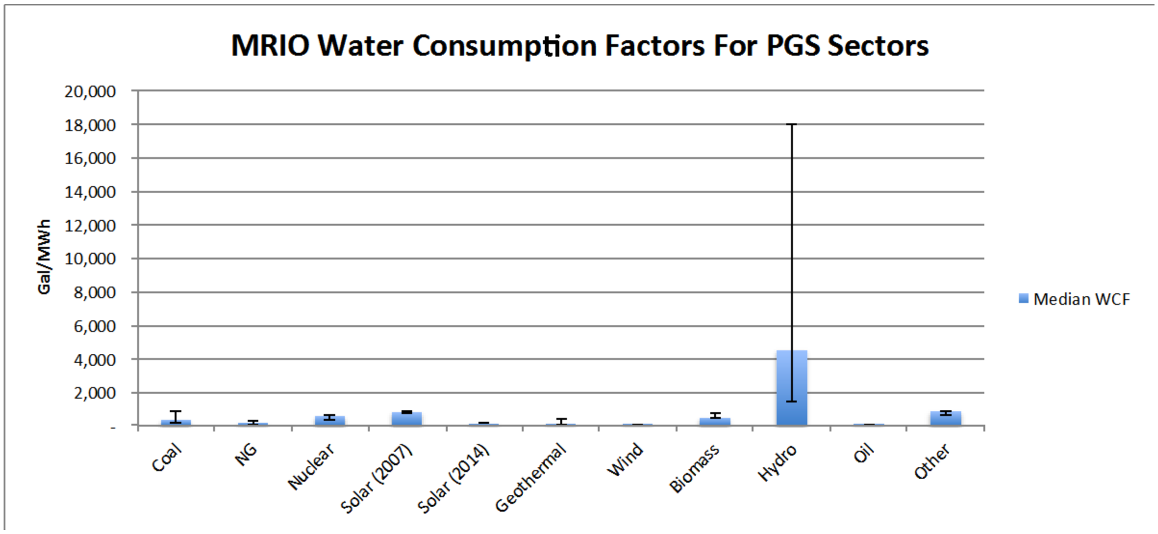
C.2. Emissions Factors

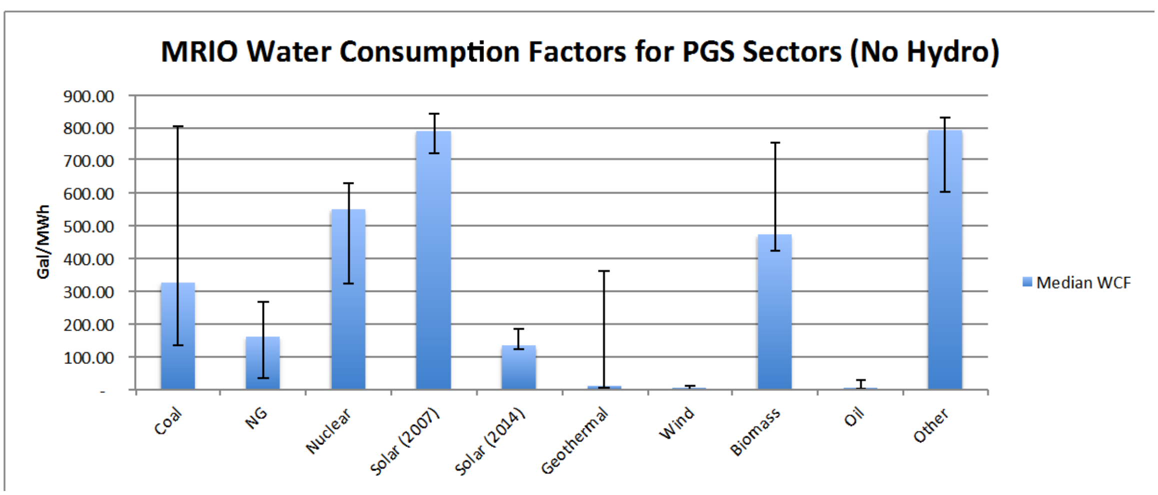
C.2.1. GHG emissions factors

Derivation of the GHG emissions factors for the PGS industries is described in detail in Chapter 2. Emissions factors for the rest of the BEA sectors are obtained from Department of Defense (2015).

C.2.2. PGS WC factors

Meldrum et al. (2013) provide an overview and harmonization for both consumption and withdrawals of water for different PGS technologies. For most technologies, the median water consumption and withdrawal estimates were created based on the harmonization data. For technologies were information is incomplete, unavailable, or unsuitable for MRIO, the data from this source was complemented with data from Torcellini et al. (2003), (Macknick et al. (2011); 2012), Mekonnen and Hoekstra (2012), Meldrum et al. (2013), and Diehl and Harris (2014).





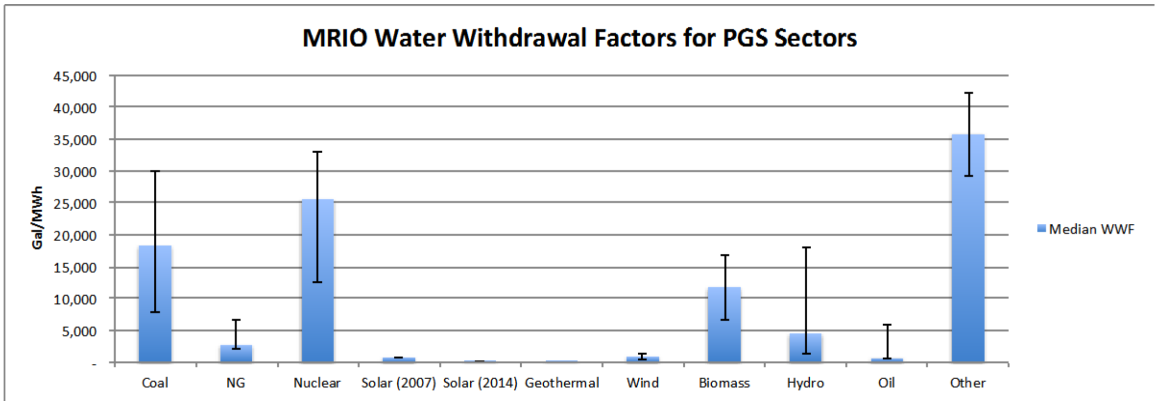


Figure C.10: Water Consumption and Withdrawal factors for PGS sectors.
Top: Water Consumption for all PGS sectors.
Middle: Water Consumption for all PGS sectors except Hydroelectricity.
Bottom: Water Withdrawal for all PGS sectors.

Notes for individual PGS sectors follow:

-For Coal, NG, and Nuclear PGS technologies, a weighted average for different cooling technologies was created using EIA statistics on the prevalence of these technologies and used to create a single IO water consumption estimate.

- Solar CSP produced most of the electricity in 2007, but since PV has greatly increased, becoming the dominant form of Solar PGS technology. Values for 2007 and 2014 Solar WC factor reflect their respective market share in those years, with the 2014 value used in the MRIO model.

- For Biomass PGS, it is worth noting that the values shown above are for power plant operation and do not include the water used for crop growth.

-For Hydropower, withdrawal values shown are evaporation estimates from hydropower reservoirs. All water evaporative losses are assumed to be consumption (Torcellini et al. 2003; Macknick et al. 2011; Mekonnen and Hoekstra 2012) making withdrawal and consumption factors equivalent. Water use per MWh produced by hydroelectricity vary widely in these sources. This work uses estimates on the lower end of the ranges, with the assumption that the lower estimates are representative of power generation from the more efficient hydroelectric sources, and that future expansion of hydroelectricity will tend to match these efficiencies. The net result is that the water consumption estimates may be underestimated for current generation, but is hopefully more reflective of future installed capacity, given limits imposed by regulation. For most states, these include a requirement for no new dams, but rather expansions to current production (either in reservoir size or generation capacity). Specific states have additional limitations, such as a maximum nameplate capacity for new dams (30 MW or less for most states), no pumped hydro, or meeting additional environmental regulations (Stori 2013).

C.2.3. WC factors for non PGS BEA sectors

The WC factors developed for this work follow the procedure from Blackhurst et al. (2010), updated for the latest available data. These factors are shown below.

Table C.2: Water Consumption factors for BEA IO Sectors

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
1111A0	Oilseed farming	41,637.87
1111B0	Grain farming	119,997.89
111200	Vegetable and melon farming	105,438.85
111300	Fruit and tree nut farming	93,665.66
111400	Greenhouse, nursery, and floriculture production	21,664.73
111900	Other crop farming	276,043.85

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
1121A0	Beef cattle ranching and farming, including feedlots and dual-purpose ranching and farming	21,159.31
112120	Dairy cattle and milk production	1,778.31
112A00	Animal production, except cattle and poultry and eggs	93,795.85
112300	Poultry and egg production	777.19
113000	Forestry and logging	4.37
114000	Fishing, hunting and trapping	35.47
115000	Support activities for agriculture and forestry	-
211000	Oil and gas extraction	125.70
212100	Coal mining	70.56
2122A0	Iron, gold, silver, and other metal ore mining	8,012.95
212230	Copper, nickel, lead, and zinc mining	3,275.57
212310	Stone mining and quarrying	16,990.14
2123A0	Other nonmetallic mineral mining and quarrying	17,247.95
213111	Drilling oil and gas wells	71.60
21311A	Other support activities for mining	459.87
221101	Coal PGS	0.33
221102	Natural Gas PGS	0.16
221103	Oil PGS	0.00

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
221104	Nuclear PGS	0.55
221105	Hydro PGS	4.49
221106	Geothermal PGS	0.01
221107	Biomass PGS	0.47
221108	Wind PGS	0.00
221109	Solar PGS	0.79
221110	Other PGS	0.83
221200	Natural gas distribution	0.37
221300	Water, sewage and other systems	304.01
230301	Nonresidential maintenance and repair	7.81
230302	Residential maintenance and repair	16.98
233210	Health care structures	9.03
233230	Manufacturing structures	7.80
233240	Power and communication structures	4.09
233262	Educational and vocational structures	8.88
233293	Highways and streets	8.15
2332A0	Commercial structures, including farm structures	14.92
2332B0	Other nonresidential structures	8.57
233411	Single-family residential structures	35.85

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
233412	Multifamily residential structures	16.45
2334A0	Other residential structures	15.97
321100	Sawmills and wood preservation	97.08
321200	Veneer, plywood, and engineered wood product manufacturing	155.44
321910	Millwork	135.27
3219A0	All other wood product manufacturing	127.55
327100	Clay product and refractory manufacturing	168.34
327200	Glass and glass product manufacturing	120.33
327310	Cement manufacturing	156.81
327320	Ready-mix concrete manufacturing	149.00
327330	Concrete pipe, brick, and block manufacturing	147.79
327390	Other concrete product manufacturing	168.53
327400	Lime and gypsum product manufacturing	110.56
327910	Abrasive product manufacturing	122.28
327991	Cut stone and stone product manufacturing	147.22
327992	Ground or treated mineral and earth manufacturing	102.79
327993	Mineral wool manufacturing	232.28
327999	Miscellaneous nonmetallic mineral products	122.34

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
331110	Iron and steel mills and ferroalloy manufacturing	512.10
331200	Steel product manufacturing from purchased steel	504.56
33131A	Alumina refining and primary aluminum production	504.40
331314	Secondary smelting and alloying of aluminum	540.04
33131B	Aluminum product manufacturing from purchased aluminum	482.42
331411	Primary smelting and refining of copper	281.58
331419	Primary smelting and refining of nonferrous metal (except copper and aluminum)	329.37
331420	Copper rolling, drawing, extruding and alloying	555.47
331490	Nonferrous metal (except copper and aluminum) rolling, drawing, extruding and alloying	428.74
331510	Ferrous metal foundries	651.47
331520	Nonferrous metal foundries	595.58
33211A	All other forging, stamping, and sintering	54.42
332114	Custom roll forming	47.93
33211B	Crown and closure manufacturing and metal stamping	43.06
332200	Cutlery and handtool manufacturing	44.51
332310	Plate work and fabricated structural product manufacturing	38.21

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
332320	Ornamental and architectural metal products manufacturing	46.94
332410	Power boiler and heat exchanger manufacturing	26.22
332420	Metal tank (heavy gauge) manufacturing	49.14
332430	Metal can, box, and other metal container (light gauge) manufacturing	41.90
332500	Hardware manufacturing	68.81
332600	Spring and wire product manufacturing	43.35
332710	Machine shops	50.05
332720	Turned product and screw, nut, and bolt manufacturing	44.07
332800	Coating, engraving, heat treating and allied activities	91.94
33291A	Valve and fittings other than plumbing	45.77
332913	Plumbing fixture fitting and trim manufacturing	52.15
332991	Ball and roller bearing manufacturing	37.63
33299A	Ammunition, arms, ordnance, and accessories manufacturing	33.30
332996	Fabricated pipe and pipe fitting manufacturing	56.38
33299B	Other fabricated metal manufacturing	54.63
333111	Farm machinery and equipment manufacturing	15.15
333112	Lawn and garden equipment manufacturing	7.89
333120	Construction machinery manufacturing	16.06

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
333130	Mining and oil and gas field machinery manufacturing	13.88
33329A	Other industrial machinery manufacturing	28.89
333220	Plastics and rubber industry machinery manufacturing	35.82
333295	Semiconductor machinery manufacturing	22.78
33331A	Vending, commercial laundry, and other commercial and service industry machinery manufacturing	17.11
333313	Office machinery manufacturing	4.10
333314	Optical instrument and lens manufacturing	22.46
333315	Photographic and photocopying equipment manufacturing	22.69
33341A	Air purification and ventilation equipment manufacturing	21.23
333414	Heating equipment (except warm air furnaces) manufacturing	29.64
333415	Air conditioning, refrigeration, and warm air heating equipment manufacturing	14.25
333511	Industrial mold manufacturing	19.74
33351A	Metal cutting and forming machine tool manufacturing	32.12
333514	Special tool, die, jig, and fixture manufacturing	34.22
33351B	Cutting and machine tool accessory, rolling mill, and other metalworking machinery manufacturing	28.02

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
333611	Turbine and turbine generator set units manufacturing	26.58
333612	Speed changer, industrial high-speed drive, and gear manufacturing	18.90
333613	Mechanical power transmission equipment manufacturing	30.69
333618	Other engine equipment manufacturing	26.71
33391A	Pump and pumping equipment manufacturing	24.71
333912	Air and gas compressor manufacturing	21.05
333920	Material handling equipment manufacturing	16.82
333991	Power-driven handtool manufacturing	4.39
33399A	Other general purpose machinery manufacturing	28.14
333993	Packaging machinery manufacturing	14.96
333994	Industrial process furnace and oven manufacturing	22.91
33399B	Fluid power process machinery	19.98
334111	Electronic computer manufacturing	22.96
334112	Computer storage device manufacturing	16.77
33411A	Computer terminals and other computer peripheral equipment manufacturing	28.34
334210	Telephone apparatus manufacturing	39.54
334220	Broadcast and wireless communications equipment	28.35

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
334290	Other communications equipment manufacturing	30.23
334300	Audio and video equipment manufacturing	36.57
33441A	Other electronic component manufacturing	48.11
334413	Semiconductor and related device manufacturing	28.96
334418	Printed circuit assembly (electronic assembly) manufacturing	30.90
334510	Electromedical and electrotherapeutic apparatus manufacturing	23.12
334511	Search, detection, and navigation instruments manufacturing	36.08
334512	Automatic environmental control manufacturing	46.17
334513	Industrial process variable instruments manufacturing	35.99
334514	Totalizing fluid meter and counting device manufacturing	12.15
334515	Electricity and signal testing instruments manufacturing	45.48
334516	Analytical laboratory instrument manufacturing	24.54
334517	Irradiation apparatus manufacturing	27.40
33451A	Watch, clock, and other measuring and controlling device manufacturing	28.03
334610	Manufacturing and reproducing magnetic and optical media	25.78
335110	Electric lamp bulb and part manufacturing	36.13

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
335120	Lighting fixture manufacturing	39.87
335210	Small electrical appliance manufacturing	30.69
335221	Household cooking appliance manufacturing	39.39
335222	Household refrigerator and home freezer manufacturing	30.88
335224	Household laundry equipment manufacturing	67.91
335228	Other major household appliance manufacturing	48.48
335311	Power, distribution, and specialty transformer manufacturing	25.82
335312	Motor and generator manufacturing	23.76
335313	Switchgear and switchboard apparatus manufacturing	30.71
335314	Relay and industrial control manufacturing	24.65
335911	Storage battery manufacturing	28.47
335912	Primary battery manufacturing	8.08
335920	Communication and energy wire and cable manufacturing	26.76
335930	Wiring device manufacturing	77.31
335991	Carbon and graphite product manufacturing	50.39
335999	All other miscellaneous electrical equipment and component manufacturing	35.93
336111	Automobile manufacturing	20.52
336112	Light truck and utility vehicle manufacturing	15.08

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
336120	Heavy duty truck manufacturing	12.85
336211	Motor vehicle body manufacturing	17.53
336212	Truck trailer manufacturing	26.29
336213	Motor home manufacturing	573.09
336214	Travel trailer and camper manufacturing	565.60
336310	Motor vehicle gasoline engine and engine parts manufacturing	20.36
336320	Motor vehicle electrical and electronic equipment manufacturing	30.73
3363A0	Motor vehicle steering, suspension component (except spring), and brake systems manufacturing	23.72
336350	Motor vehicle transmission and power train parts manufacturing	26.09
336360	Motor vehicle seating and interior trim manufacturing	15.69
336370	Motor vehicle metal stamping	22.79
336390	Other motor vehicle parts manufacturing	28.41
336411	Aircraft manufacturing	13.88
336412	Aircraft engine and engine parts manufacturing	40.52
336413	Other aircraft parts and auxiliary equipment manufacturing	58.70
336414	Guided missile and space vehicle manufacturing	12.82

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
33641A	Propulsion units and parts for space vehicles and guided smissiles	30.31
336500	Railroad rolling stock manufacturing	61.20
336611	Ship building and repairing	16.53
336612	Boat building	36.93
336991	Motorcycle, bicycle, and parts manufacturing	30.41
336992	Military armored vehicle, tank, and tank component manufacturing	22.33
336999	All other transportation equipment manufacturing	14.57
337110	Wood kitchen cabinet and countertop manufacturing	69.45
337121	Upholstered household furniture manufacturing	35.54
337122	Nonupholstered wood household furniture manufacturing	85.01
33712A	Other household nonupholstered furniture	69.12
337127	Institutional furniture manufacturing	54.76
33721A	Office furniture and custom architectural woodwork and millwork manufacturing	69.03
337215	Showcase, partition, shelving, and locker manufacturing	47.22
337900	Other furniture related product manufacturing	30.85
339112	Surgical and medical instrument manufacturing	30.12
339113	Surgical appliance and supplies manufacturing	27.42

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
339114	Dental equipment and supplies manufacturing	35.38
339115	Ophthalmic goods manufacturing	48.69
339116	Dental laboratories	44.16
339910	Jewelry and silverware manufacturing	23.76
339920	Sporting and athletic goods manufacturing	38.90
339930	Doll, toy, and game manufacturing	34.70
339940	Office supplies (except paper) manufacturing	61.66
339950	Sign manufacturing	52.01
339990	All other miscellaneous manufacturing	46.90
311111	Dog and cat food manufacturing	90.26
311119	Other animal food manufacturing	81.87
311210	Flour milling and malt manufacturing	91.73
311221	Wet corn milling	177.19
31122A	Soybean and other oilseed processing	79.42
311225	Fats and oils refining and blending	107.53
311230	Breakfast cereal manufacturing	101.59
311300	Sugar and confectionery product manufacturing	129.00
311410	Frozen food manufacturing	130.99
311420	Fruit and vegetable canning, pickling, and drying	125.70

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
31151A	Fluid milk and butter manufacturing	94.36
311513	Cheese manufacturing	79.57
311514	Dry, condensed, and evaporated dairy product manufacturing	81.19
311520	Ice cream and frozen dessert manufacturing	160.46
31161A	Animal (except poultry) slaughtering, rendering, and processing	91.15
311615	Poultry processing	134.42
311700	Seafood product preparation and packaging	120.52
311810	Bread and bakery product manufacturing	113.48
3118A0	Cookie, cracker, pasta, and tortilla manufacturing	90.45
311910	Snack food manufacturing	100.40
311920	Coffee and tea manufacturing	82.03
311930	Flavoring syrup and concentrate manufacturing	91.13
311940	Seasoning and dressing manufacturing	96.60
311990	All other food manufacturing	135.38
312110	Soft drink and ice manufacturing	133.70
312120	Breweries	117.38
312130	Wineries	142.08
312140	Distilleries	95.66

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
312200	Tobacco product manufacturing	75.31
313100	Fiber, yarn, and thread mills	83.59
313200	Fabric mills	90.28
313300	Textile and fabric finishing and fabric coating mills	135.59
314110	Carpet and rug mills	113.21
314120	Curtain and linen mills	81.14
314900	Other textile product mills	63.74
315000	Apparel manufacturing	59.16
316000	Leather and allied product manufacturing	46.01
322110	Pulp mills	2,051.78
322120	Paper mills	1,822.82
322130	Paperboard mills	1,685.45
322210	Paperboard container manufacturing	1,772.81
322220	Paper bag and coated and treated paper manufacturing	1,835.59
322230	Stationery product manufacturing	2,166.09
322291	Sanitary paper product manufacturing	1,750.15
322299	All other converted paper product manufacturing	1,938.39
323110	Printing	49.84
323120	Support activities for printing	41.59
324110	Petroleum refineries	343.16

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
324121	Asphalt paving mixture and block manufacturing	398.10
324122	Asphalt shingle and coating materials manufacturing	466.93
324190	Other petroleum and coal products manufacturing	382.70
325110	Petrochemical manufacturing	400.75
325120	Industrial gas manufacturing	580.80
325130	Synthetic dye and pigment manufacturing	418.12
325180	Other basic inorganic chemical manufacturing	465.88
325190	Other basic organic chemical manufacturing	599.27
325211	Plastics material and resin manufacturing	411.10
3252A0	Synthetic rubber and artificial and synthetic fibers and filaments manufacturing	400.37
325310	Fertilizer manufacturing	281.82
325320	Pesticide and other agricultural chemical manufacturing	409.85
325411	Medicinal and botanical manufacturing	470.47
325412	Pharmaceutical preparation manufacturing	393.35
325413	In-vitro diagnostic substance manufacturing	321.48
325414	Biological product (except diagnostic) manufacturing	322.08
325510	Paint and coating manufacturing	399.28
325520	Adhesive manufacturing	386.11

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
325610	Soap and cleaning compound manufacturing	363.75
325620	Toilet preparation manufacturing	377.01
325910	Printing ink manufacturing	378.27
3259A0	All other chemical product and preparation manufacturing	356.36
326110	Plastics packaging materials and unlaminated film and sheet manufacturing	45.98
326120	Plastics pipe, pipe fitting, and unlaminated profile shape manufacturing	53.75
326130	Laminated plastics plate, sheet (except packaging), and shape manufacturing	65.44
326140	Polystyrene foam product manufacturing	36.12
326150	Urethane and other foam product (except polystyrene) manufacturing	43.97
326160	Plastics bottle manufacturing	28.78
326190	Other plastics product manufacturing	52.67
326210	Tire manufacturing	61.65
326220	Rubber and plastics hoses and belting manufacturing	53.09
326290	Other rubber product manufacturing	43.94
420000	Wholesale trade	13.48
441000	Motor vehicle and parts dealers	20.43
445000	Food and beverage stores	42.13

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
452000	General merchandise stores	14.91
4A0000	Other retail	22.77
481000	Air transportation	3.95
482000	Rail transportation	3.77
483000	Water transportation	194.77
484000	Truck transportation	5.40
485000	Transit and ground passenger transportation	274.74
486000	Pipeline transportation	-
48A000	Scenic and sightseeing transportation and support activities for transportation	40.97
492000	Couriers and messengers	1.14
493000	Warehousing and storage	12.64
511110	Newspaper publishers	12.46
511120	Periodical Publishers	8.92
511130	Book publishers	5.27
5111A0	Directory, mailing list, and other publishers	3.69
511200	Software publishers	1.30
512100	Motion picture and video industries	5.03
512200	Sound recording industries	12.33
515100	Radio and television broadcasting	25.54

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
515200	Cable and other subscription programming	1.78
517110	Wired telecommunications carriers	26.19
517210	Wireless telecommunications carriers (except satellite)	33.13
517A00	Satellite, telecommunications resellers, and all other telecommunications	11.99
518200	Data processing, hosting, and related services	5.42
5191A0	News syndicates, libraries, archives and all other information services	4.78
519130	Internet publishing and broadcasting and Web search portals	5.30
52A000	Monetary authorities and depository credit intermediation	5.34
522A00	Nondepository credit intermediation and related activities	21.18
523A00	Securities and commodity contracts intermediation and brokerage	30.53
523900	Other financial investment activities	3.46
524100	Insurance carriers	0.96
524200	Insurance agencies, brokerages, and related activities	10.41
525000	Funds, trusts, and other financial vehicles	-
5310HS	Housing	-

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
531ORE	Other real estate	44.53
532100	Automotive equipment rental and leasing	6.28
532A00	Consumer goods and general rental centers	5.90
532400	Commercial and industrial machinery and equipment rental and leasing	3.16
533000	Lessors of nonfinancial intangible assets	19.00
541100	Legal services	3.02
541511	Custom computer programming services	1.18
541512	Computer systems design services	2.11
54151A	Other computer related services, including facilities management	2.80
541200	Accounting, tax preparation, bookkeeping, and payroll services	2.63
541300	Architectural, engineering, and related services	5.12
541400	Specialized design services	9.28
541610	Management consulting services	9.91
5416A0	Environmental and other technical consulting services	28.01
541700	Scientific research and development services	2.72
541800	Advertising, public relations, and related services	3.01

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
5419A0	Marketing research and all other miscellaneous professional, scientific, and technical services	3.81
541920	Photographic services	3.48
541940	Veterinary services	6.85
550000	Management of companies and enterprises	4.91
561100	Office administrative services	9.42
561200	Facilities support services	106.49
561300	Employment services	2.16
561400	Business support services	11.93
561500	Travel arrangement and reservation services	15.20
561600	Investigation and security services	19.23
561700	Services to buildings and dwellings	11.95
561900	Other support services	18.33
562000	Waste management and remediation services	36.13
611100	Elementary and secondary schools	121.14
611A00	Junior colleges, colleges, universities, and professional schools	736.72
611B00	Other educational services	3.74
621100	Offices of physicians	6.99

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
621200	Offices of dentists	12.99
621300	Offices of other health practitioners	0.53
621400	Outpatient care centers	17.84
621500	Medical and diagnostic laboratories	14.18
621600	Home health care services	5.78
621900	Other ambulatory health care services	7.83
622000	Hospitals	25.80
623A00	Nursing and community care facilities	44.72
623B00	Residential mental retardation, mental health, substance abuse and other facilities	25.65
624100	Individual and family services	10.32
624A00	Community food, housing, and other relief services, including rehabilitation services	23.20
624400	Child day care services	27.75
711100	Performing arts companies	12.65
711200	Spectator sports	9.71
711A00	Promoters of performing arts and sports and agents for public figures	33.60
711500	Independent artists, writers, and performers	6.84
712000	Museums, historical sites, zoos, and parks	33.25

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
713100	Amusement parks and arcades	59.69
713200	Gambling industries (except casino hotels)	25.50
713900	Other amusement and recreation industries	1,095.68
721000	Accommodation	100.05
722110	Full-service restaurants	56.60
722211	Limited-service restaurants	29.66
722A00	All other food and drinking places	8.21
811100	Automotive repair and maintenance	17.88
811200	Electronic and precision equipment repair and maintenance	3.30
811300	Commercial and industrial machinery and equipment repair and maintenance	5.90
811400	Personal and household goods repair and maintenance	7.55
812100	Personal care services	20.66
812200	Death care services	17.12
812300	Dry-cleaning and laundry services	131.58
812900	Other personal services	6.87
813100	Religious organizations	45.59
813A00	Grantmaking, giving, and social advocacy organizations	3.50
813B00	Civic, social, professional, and similar organizations	77.50

Table C.2 (Continued)

BEA Code	BEA Description	Water Consumption Factors kGal/$M for non PGS kGal/MWh for PGS
814000	Private households	-
S00500	Federal general government (defense)	38.52
S00600	Federal general government (nondefense)	26.16
491000	Postal service	90.97
S00102	Other federal government enterprises	322.30
S00700	State and local general government	112.81
S00201	State and local government passenger transit	35.50
S00203	Other state and local government enterprises	56.57

C.3. Additional Information for the 2030 projection scenario

The 2030 projection scenario uses two distinct mixes: a 2014 mix to represent the most up to date grid data, and a projected 2030 mix. The 2014 mix is obtained directly from the eGrid 2014 database, which has data on electricity generation by state, by technology. Creating the 2030 mix requires additional steps, as it is based on a combination of EIA projections for 2030 and eGrid regional generation data.

C.3.1. Creating the 2030 Mix for individual states

EIA projections data is organized according to Electricity Market Modules (EMMs), which are groups of states that are geographically connected. These modules usually contain a few states, with the largest module having 7. eGRID contains sub region data which maps almost 1-to-1 with the EIA EMM regions. eGrid's sub region categories and plant generation data, along with EIA's EMM regions, are used to create an appropriate mapping for each state. Additionally, the EIA projections contain data for the individual renewable PGS technologies for each EMM region. The procedure to create the EIA 2030 projection state mixes is as follows:

1) For states that have no projections the eGRID 2014 mixes were used (AK, HI).
2) For states that map one to one with the EIA EMM regions (i.e. there is only one state in an EIA EMM region), the projected mix for that region was used for the corresponding state.
3) For instances where multiple states map to one region, eGrid's plant data was used to create a contribution mix by state and by PGS technology to the region. For example, both EIA and eGRID contain a region which called MRO East. This region contains generation produced in 3 states, as seen in Table C.3. Using eGrid's generation values, 87% of EIA 2030's projected coal values for this EMM is assigned to WI and 13% to MI. This is done for each PGS tech and EMM/state combination. The resulting allocation produces the national mix shown in Table C.4, under EIA 2030 Projections.

Table C.3: MRO East sub region generation by PGS type

MRO East	COAL	GAS	OIL	NUCLEAR
Total MWh	**17,830,223.17**	**2,141,599.92**	**161,200.00**	**9,447,148.00**
IL	0%	0%	0%	0%
MI	13%	1%	0%	0%
WI	87%	99%	100%	100%

MRO East	HYDRO	GEOTHERMAL	BIOMASS	SOLAR	WIND	OTHF	Total
Total MWh	**1,193,339.00**	**-**	**1,482,685.15**	**-**	**1,265,100.00**	**32,208.00**	**33,553,503.24**
IL	1%	0%	0%	0%	0%	0%	0%
MI	22%	0%	46%	0%	0%	0%	10%
WI	78%	0%	54%	0%	100%	100%	90%

Table C.4: Percent of total U.S. generation by technology type, for 2014 and 2030 mixes

PGS tech	eGrid2014	EIA 2030 Projection
Coal	40%	25%
NG	26%	33%
Oil	1%	0%
Nuc	20%	19%
Hydro	6%	8%
Geo	0%	1%
Biomass	2%	1%
Wind	4%	12%
Solar	0%	3%
Other	1%	0%
Total	**100%**	**100%**
Renewables	**13%**	**24%**

C.4. Additional Results for the 2030 projection scenario

C.4.1. Additional results for $1M final demand of non PGS sectors, and 100 MWh final demand of PGS technologies

Figure C.11 complements Figure 4.6, showing the Projected 2030/Base 2014 ratios for GHG and WC. These ratios add context, showing that sometimes the sectors with the greatest absolute change in emissions (e.g. Primary Aluminum) are always the ones with the greatest relative change (e.g. Wind PGS). Likewise, Figure C.12 complements Figure 4.7.

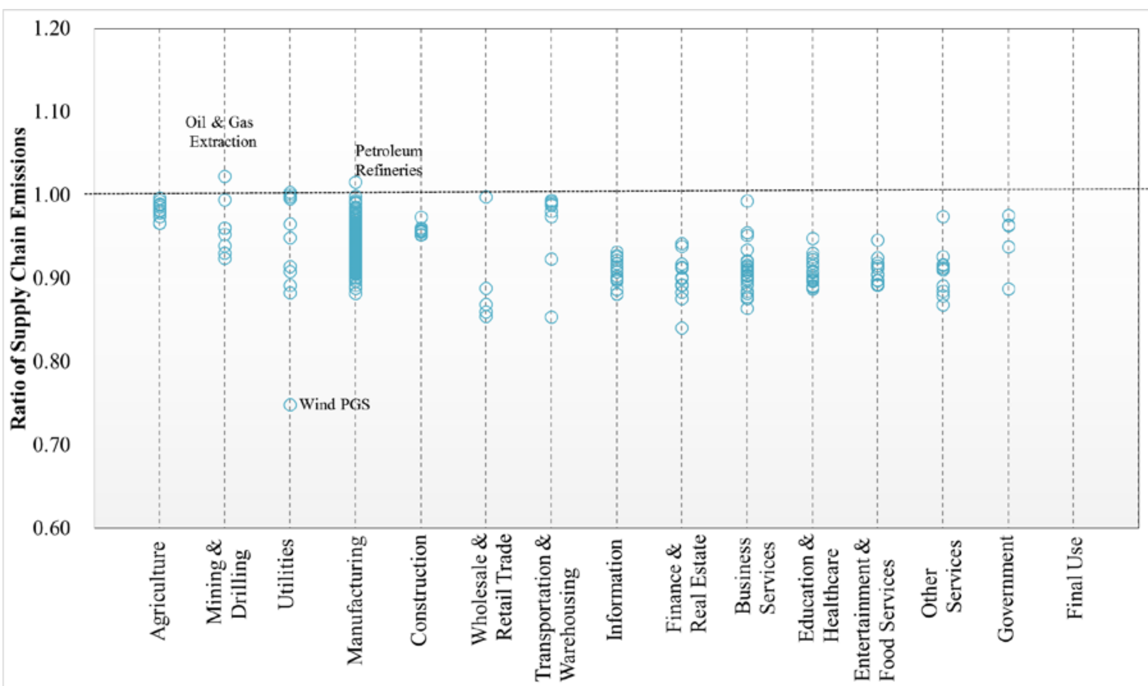
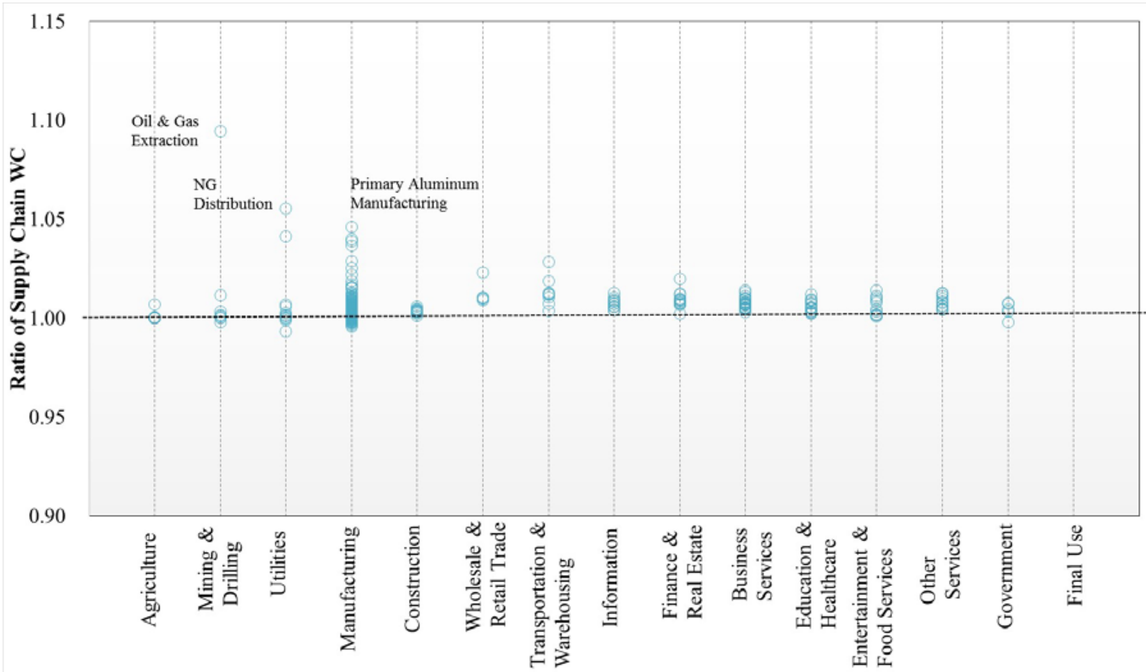


Figure C.11: Ratio Comparison between Projected and Base MRIO model for $1M of final demand by each BEA IO sector.
Each bubble represents one BEA IO sector. Values above the dotted lines represent increase in emissions for that particular sector; values below represent decrease in emissions. Bubbles are clustered into the highest level economic categories described by the BEA.
Top (part A): GHG Emissions ratio



Bottom (part B): WC ratio

C.4.2. Aluminum GHG reduction calculations

2.75 Tonnes CO2e/MWh reduction in the Projected 2030 scenario

1.72 Million Metric tons (Tonnes) of primary aluminum produced in the U.S. in 2014 (U.S. Geological Survey 2015)

Average of 15 MWh/Tonnes of Primary Aluminum produced (Burns 2009)

15 MWh/Tonne Primary Aluminum * 1,720,000 Tonnes Primary Aluminum * 2.75 Tonnes CO2e/MWh = 70,950,000 Tonnes CO2e

Total U.S. CO2e emissions in 2014 = 6,870,000,000 Tonnes CO2e (U.S. Environmental Protection Agency 2015a)

% reduction of total U.S. GHG emissions in 2014 would be 70,950,000/6,870,000,000 ~ 1% reduction in national GHG emissions.

C.4.3. Additional results for Private Consumption Run

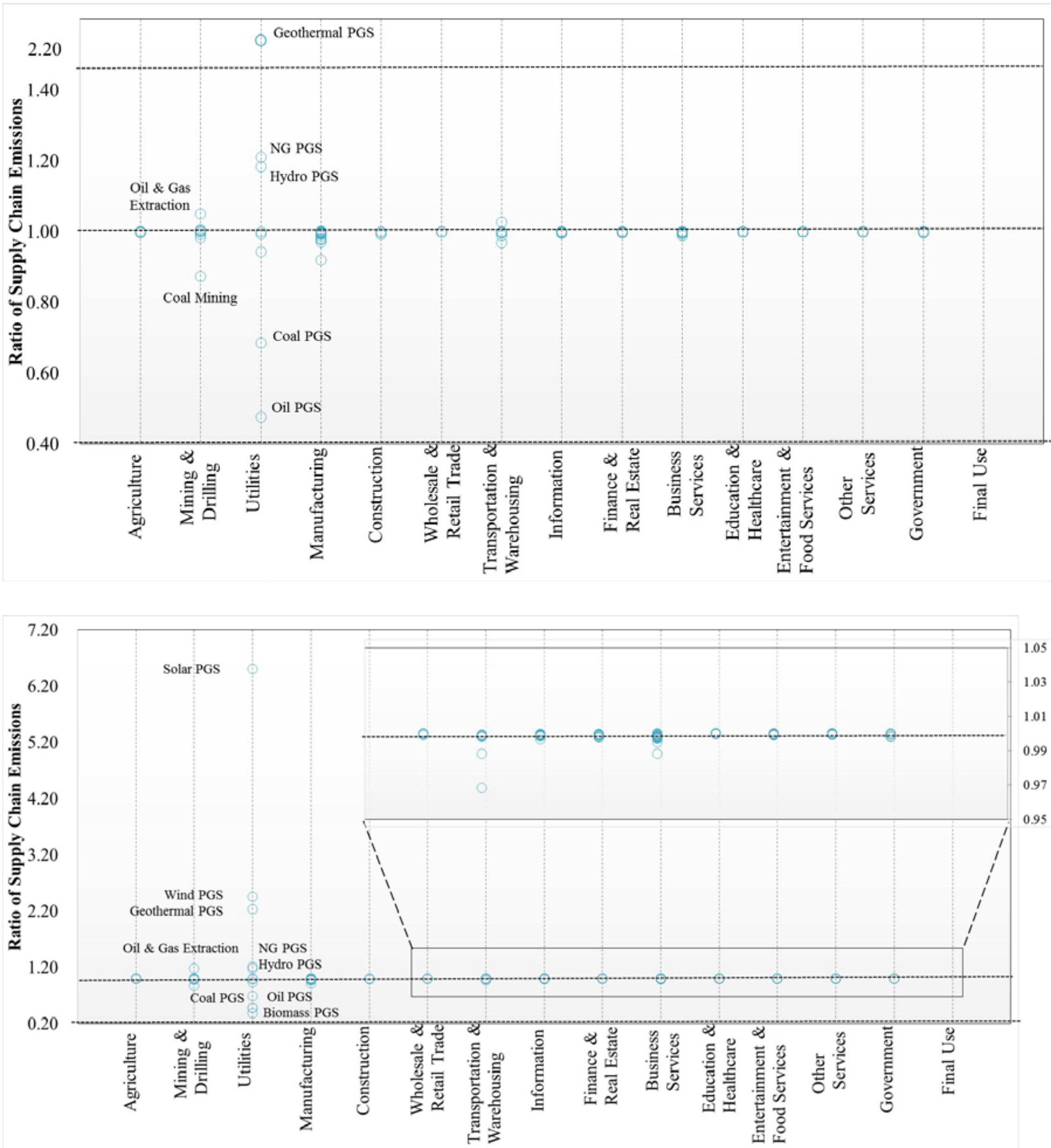


Figure C.12: Ratio comparison for PC.
Magnified part towards the right of the charts included for ease of reference due to different scales.
Top (part A): GHG emissions ratio.
Bottom (part B): WC ratio

C.5. Additional information for the Data Center Scenarios

C.5.1. Creation of the Direct PGS Final Demand vector for NERC run

The direct PGS final demand vector is based on the PGS consumption of the Data processing, hosting, and related services sector (518200) as found in the BEA IO accounts. However, the MWh value found when converting the monetary value found in the original accounts using the price conversion as per Chapter 3 (Vendries Algarin et al. 2016) is not comparable to more data center-specific estimates found in the literature for total electricity consumption by data centers in the U.S:

From BEA (Bureau of Economic Analysis 2013a)

The total use of PGS by 518200 is $M538 (from the original Use table) in 2007

This value results in a total of about 6.1 billion kWh in the MRIO model*.

Price: $0.095/kWh

From Report to congress by Berkeley National Lab (Brown et al. 2007)

Total electricity consumption estimate: 61 billion kWh in 2006.

Total electricity costs: $4.5 Billion

Implied price: $0.074/kWh

Berkeley National Lab report update (Shehabi et. al 2016)

Total electricity consumption estimate: 70 billion kWh in 2014.

*This assumes the price conversion as per Chapter 3 and allowing for adjustments due to RAS procedure when creating the MRIO table.

This discrepancy suggests that the electricity consumption by the 518200 sector is underestimated in the BEA IO accounts, as it does not compare well with more recent and dedicated sources and is unlikely that the electricity price used in creating the MRIO model is incorrect by approximately a factor of 10. Additionally, even considering other data center related sectors in the BEA IO accounts does not make up the difference, as the total kWh use of Information Technology sectors still underestimate the total consumption when compared to Shehabi et. al (2016):

PGS use by Information Sectors (NAICS 51), and other select industries tied with computer services (not manufacturing)		$M	Billion kWh
Newspaper publishers	'511110'	225	2.33
Periodical Publishers	'511120'	66	0.68
Book publishers	'511130'	34	0.35
Directory, mailing list, and other publishers	'5111A0'	35	0.36
Software publishers	'511200'	147	1.52
Motion picture and video industries	'512100'	163	1.69
Sound recording industries	'512200'	28	0.29
Radio and television broadcasting	'515100'	245	2.54
Cable and other subscription programming	'515200'	17	0.18
Wired telecommunications carriers	'517110'	940	9.74
Wireless telecommunications carriers (except satellite)	'517210'	477	4.94
Satellite, telecommunications resellers, and all other telecommunication	'517A00'	48	0.50
Data processing, hosting, and related services	'518200'	538	5.58
News syndicates, libraries, archives and all other information services	'5191A0'	22	0.23
Internet publishing and broadcasting and Web search portals	'519130'	23	0.24
Custom computer programming services	'541511'	218	2.26
Other computer related services, including facilities management	'54151A'	113	1.17
Total of Yellow Highlighted sectors		$M	Billion kWh
		909	9.42

Figure C.13: Electricity Consumption by IT sectors in the BEA IO accounts.
Yellow highlighted sectors are those most likely involved with data center operations (according the NAICS operational description). Assumes $0.095/kWh.

Given these differences, the determination was taken to preserve the structure of the IO model with regards to data center electricity consumption but rather use the estimate by Shehabi et. al (2016) in the MRIO scenarios. Further modifications to the BEA IO accounts to adjust the electricity consumption of data centers requires detailed data about overall industry expenditures and purchases that are not publically available and are beyond the scope of this work. However, to ensure that the direct and indirect effects remain proportional, a scaling factor was created to ensure that the linear relationships established in the IO accounts are upheld:

$$\text{Data Center Electricity consumption scaling factor}$$
$$= \frac{\text{Berkeley Data Center Electricity Consumption Estimate}}{\text{BEA IO Data Center Electricity Consumption Estimate}}$$
$$= \frac{70\ Million\ MWh}{6.1\ Million\ MWh} = 11.5$$

The Direct PGS Final demand vector, which represents the amount of electricity directly used for data center operations, thus consists 70 million MWh distributed throughout the 53 regions in the model according to the 2014 and NERC distributions.

C.5.2. Creation of Indirect PGS Final Demand Vector for NERC run

To create the Indirect PGS Final Demand vector, the following steps were followed:

1) For each commodity in the data center supply chain, the corresponding industry producing that commodity (as a main product) was found.

    a. For example, the largest expenditure in the data center supply chain is Employee compensation (Sector V00300), at $19.5 billion. As this “commodity” is value added, there is no corresponding industry sector. However, the Private

Consumption (PC) Use table column (Sector F00100) can be used to represent average expenditures by employees. Thus, the PC Use table column can be considered the industry, just as Employee compensation Use table row can be considered the commodity, and are thus mapped together.

2) The amount that each industry in data center's supply chain expends on its own electricity requirements, as a percent of total expenditures, is found.

    a. Continuing the above example, PGS represents approximately 1.52% of the total economic expenditure of the Private Consumption Use table column.

3) These two values – the amount that data centers spend on the different industries in its supply chain, and the percent that said industries spend on PGS consumption – are then multiplied together, to obtain an estimate of PGS consumption needed by industries supplying data centers.

    a. For Employees, this value is $19.5 billion * 1.52%, = $296 million.

4) The resulting value is converted to MWh using the same procedure and values used in the conversion of the MRIO model from monetary to physical units in Chapter 3 (Vendries Algarin et al. 2016), and distributed between states in the final demand vector using the corresponding distribution (2014 or NERC).

a. The assigned price for the PC sector for PGS consumption is $0.1065/kWh, this results in approximately 3.1 million MWh.

5) The Indirect PGS consumption value is multiplied by the Data Center Electricity Consumption Scaling Factor described above.

   a. For example, this increases the indirect MWh final demand from Employees from about 3.1 Million MWh to approximately 35 Million MWh.

C.5.3. Additional Results for Data Center Scenarios

The figures below compare the source of the emissions from the supply chain (i.e. whether emissions are caused by direct and indirect consumption of electricity) for both the NERC and Amazon runs. Note that emissions for the NERC run are split evenly between direct and indirect sources, whereas emissions for the Amazon run are almost entirely based on indirect electricity consumption.

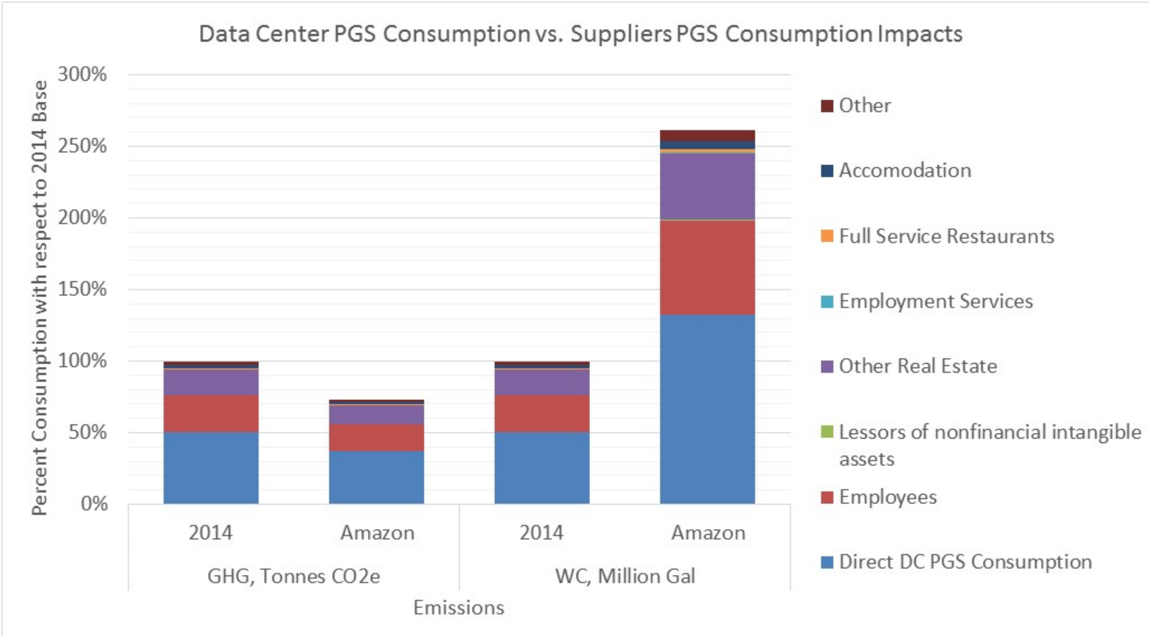


Figure C.14: Comparison of Direct vs Supply Chain Impacts, 2014 Base (state) vs NERC scenarios.

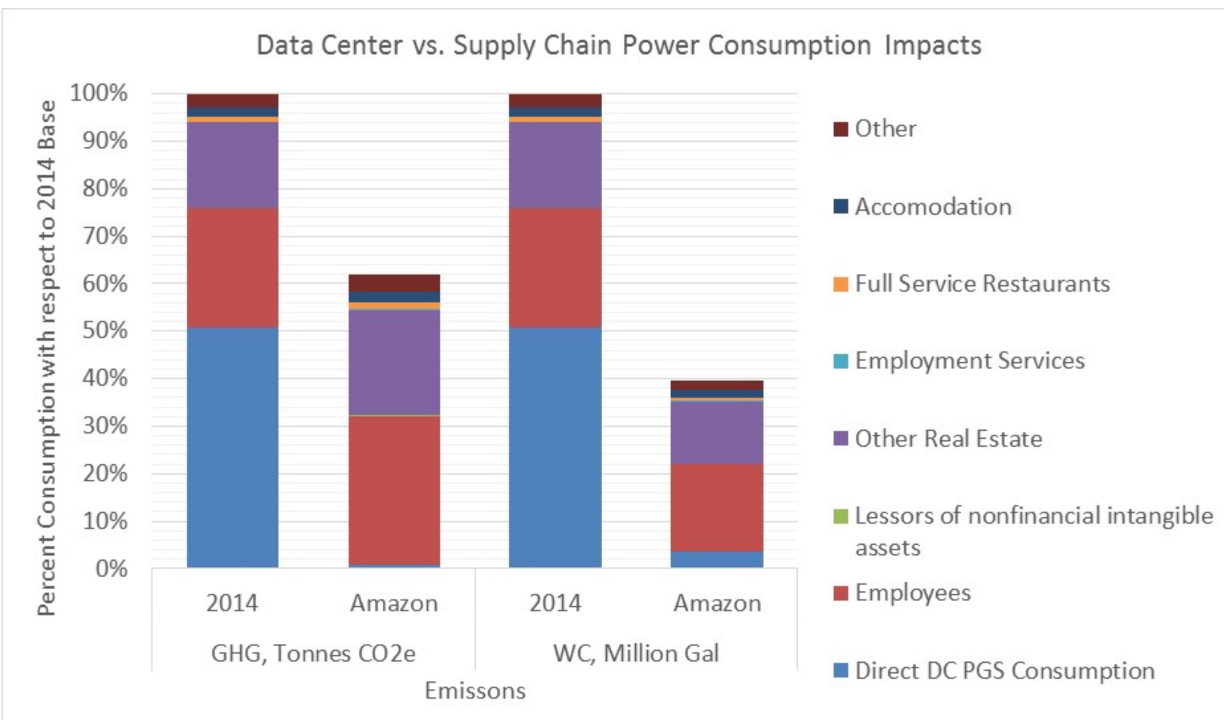


Figure C.15: Comparison of Direct vs Supply Chain Impacts, 2014 Base (state) vs Amazon scenarios.

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