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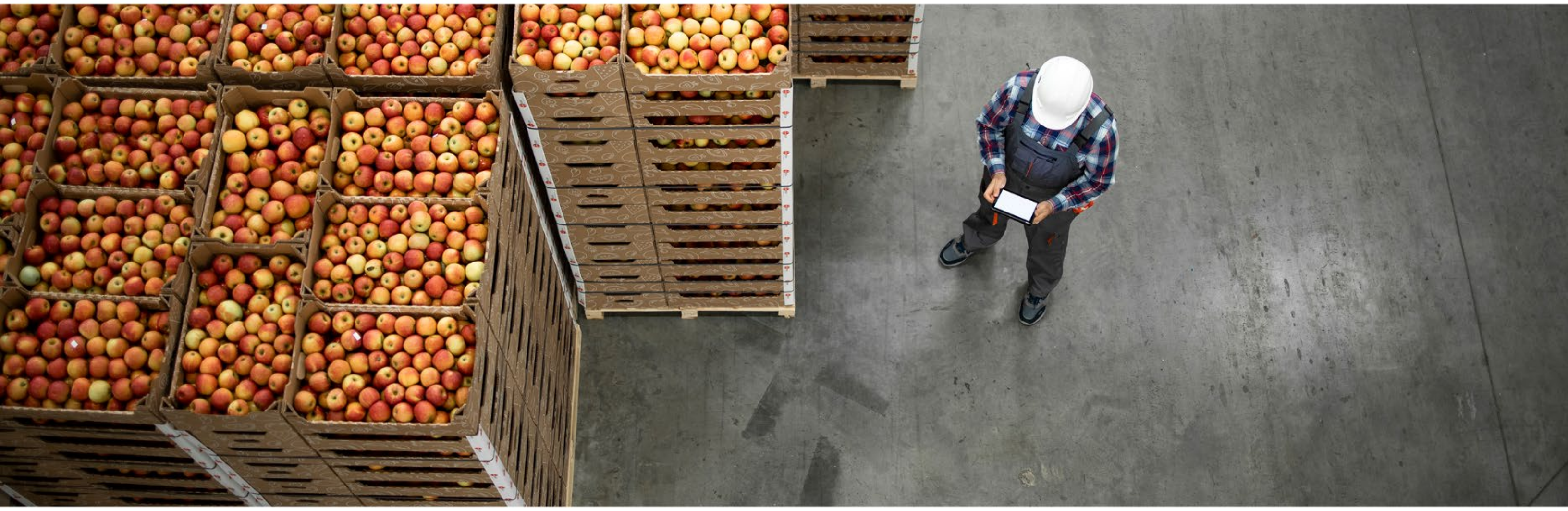
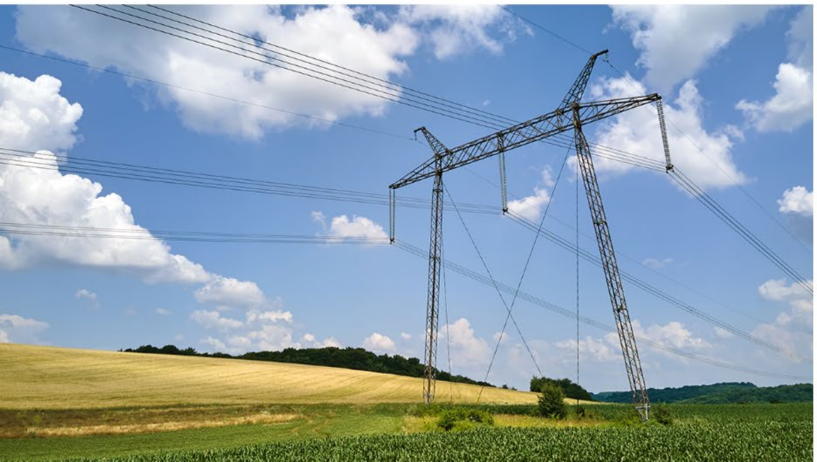
Linking Resource Flows to Economic Sectors in the United States

Sarah Rehkamp, Patrick Canning, Miguel I. Gómez, James Chandler Zachary, and Quinton Baker





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Abstract

The production of goods and services throughout an economy requires the use of resources and materials. Linking resource flows to economic sectors is challenging because of the varying data availability and heterogeneity in the dataset dimensions, such as geography, activity scale, or time. This technical bulletin presents a flexible accounting structure to measure annual resource use throughout the U.S. economy by production activity. This research builds on past work by presenting an annual time series and advancing allocation metrics. Both natural resources (i.e., energy and freshwater) and human resources (i.e., employment) are considered. These data quantify resource use and identify the resource intensity or efficiency of sectors but also offer opportunities for macroeconomic modeling and applications.

Keywords: U.S. economy, resource flows, employment, energy, freshwater

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Linking Resource Flows to Economic Sectors in the United States

Introduction

The production of goods and services throughout an economy requires the use of resources and materials. Economic activity in the United States continues to grow over time, measured by real Gross Domestic Product (GDP) (U.S. Department of Commerce, Bureau of Economic Analysis (BEA), 2024e), and relies on the country's domestic resources, some of which are nonrenewable and scarce. In agriculture, for example, crude oil is refined to produce diesel fuel used by tractors to plant seed, freshwater resources are used to irrigate crops, and employees are hired to harvest the crops. However, it is challenging to measure these inputs because the data describing the economy and resources are heterogeneous in their dimensions and characteristics. Natural and economic boundaries and measurements differ (e.g., geographic boundaries, such as countries, versus hydrological units based on a region's hydrologic features) and data collection periods vary (e.g., USDA, National Agricultural Statistics Service releases Census of Agriculture data every 5 years, whereas the U.S. Department of Commerce, Bureau of Economic Analysis estimates each quarter's GDP over 3 consecutive months).

This report documents how we build out a resources module, or link resources to economic data for analysis to better understand anthropogenic dynamics. We comprehensively map resource flows to economic sectors or distribute resource use to annual production activities in the U.S. economy. This has been referred to as sectoral attribution modeling (Birney et al., 2022; Ingwersen et al., 2022), differing from natural capital accounting, an area of related work that also captures stocks (for more information, see figure 1 in Bagstad et al., 2021). "In general, a flow is a variable that measures a quantity over a time period, whereas a stock is a variable that measures quantity at a point in time" (United Nations Environment Programme (UNEP), 2021, p. 10).

A benefit to developing data in this way is that there are clear, consistent boundaries across all resources for comparison and comprehensiveness. In this report, the coverage is annual U.S. economywide production and associated resource use. This contrasts with other methods that measure resources, such as a process-based, life-cycle assessment where the researcher may make different decisions on boundaries of the analysis (e.g., which parts of the supply chain are included) and the functional unit (i.e., the basis for comparison). Additionally, the data are typically compiled from multiple sources or multiple counties (Heller et al., 2013; Majeau-Bettez et al., 2011; Sherwood et al., 2017).

Popular U.S. based tools that explore linkages between U.S. economic sectors and resources include the Flow Sector Attribution (FLOWSA) Python Package and the fee-based impact analysis for planning (IMPLAN) (Birney et al., 2022; IMPLAN, 2024). For other countries, the Eora Global Supply Chain Database contains data on many materials (Lenzen et al., 2012; Lenzen et al., 2013) as well as FABIO (Food and Agriculture Biomass Input-Output Model) (Bruckner et al., 2019), and EXIOBASE, a global multi-regional, input-output database from the Exiopol Database/EXIOPOL project (Merciai & Schmidt, 2018; Tukker et al., 2013).

In recent years, USDA, Economic Research Service (ERS) has provided foundational analyses that identified data and developed a flexible accounting structure to measure resource use throughout the U.S. economy and linked to the U.S. food system. This report builds on previous research that either focused on several resources in one time period (Canning et al., 2020) or one resource over several time periods (Canning et al., 2017; Rehkamp et al., 2021). We built out national, economywide resource flows and extended past work by first developing an annual time series because the data had not been previously available as frequently or as timely. Second, we developed advanced methods to allocate resources to economic sectors. We filled data gaps by estimating unsuppressed datasets[1] to use as allocation metrics and also improved the accuracy of allocation by developing a weighting matrix, allocating resources at the subnational level when possible, and emphasizing the detail for agricultural sectors' allocation (Su et al., 2010). The methodology follows the U.N.'s System of Environmental Economic Accounting (SEEA) Central Framework (2012), the first set of international statistical standards for resource flows.

The resulting data, representing resource use by activity in the U.S. economy, were informative to quantify resource use or explore the varying resource intensities of production which may inform where interventions could be most effective. Additionally, the time series could inform how resource use varies in different time periods. This report's focus has been on both natural (i.e., energy and freshwater) and human resources (i.e., labor), but the coverage could be expanded to additional flows following a similar methodology.

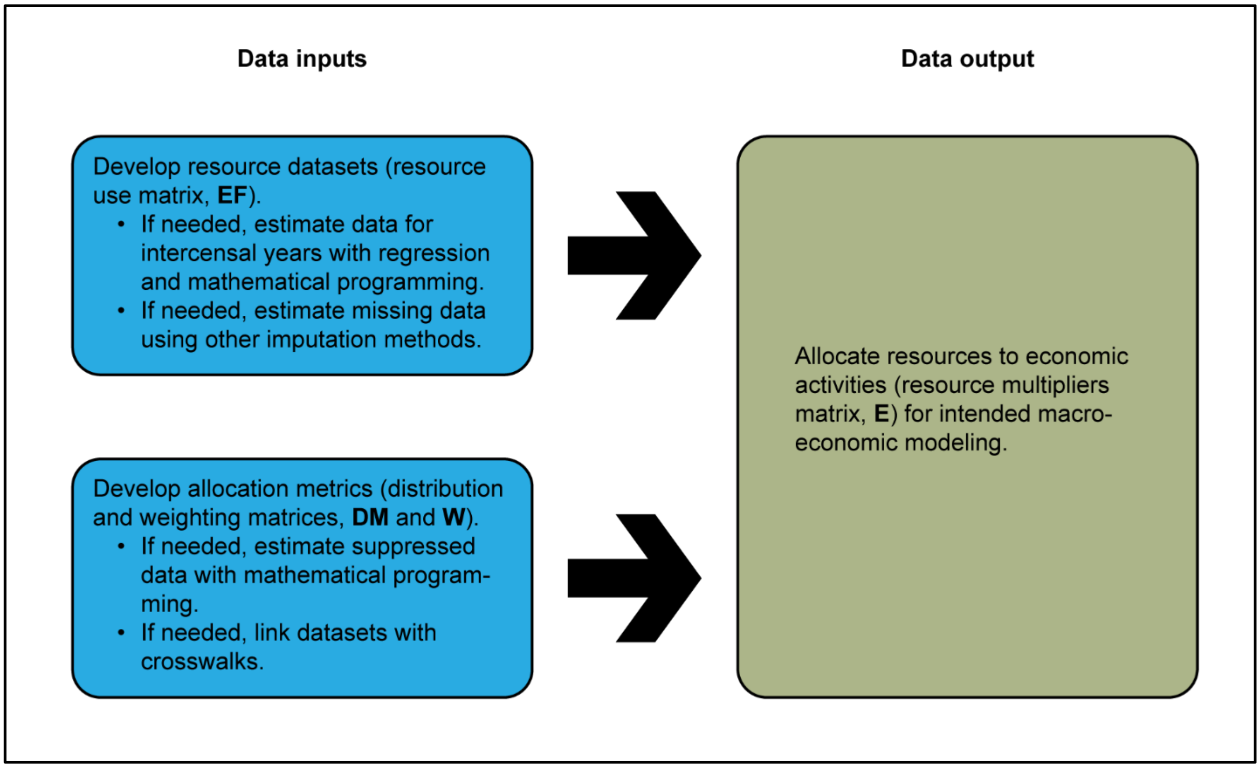
A potential use for this data system could be model-derived analysis. For example, the resulting data could be used with macroeconomic models, such as a multiplier model or a computable general equilibrium (CGE) model. These models could allow researchers to estimate direct and indirect resource use or introduce policy shocks to see how the system and resource use would change in response. Similar data systems and models, such as the U.S. Environmentally-Extended Input-Output (USEEIO) models, have been used extensively by both public and private stakeholders for assessments (Environmental Protection Agency (EPA), 2024). For this report, we presented a flexible framework and a modularized data system that can be expanded, adapted, and used by a diverse group of stakeholders.

Data and Methods

This research was conducted using many data sources and modeling techniques. Figure 1 summarizes the major steps toward the linking of resource data to economic activities. We developed annual datasets on resource use and then additional datasets to allocate the resources to economic activities using several types of software for data preparation and modeling, including General Algebraic Modeling System (GAMS), Microsoft SQL Server Management Studio (SSMS), and R.

[1] Data suppression is commonly used by federal statistical agencies to protect data confidentiality, but it poses challenges for research purposes (Yi et al., 2023).

Figure 1
Summary of analysis steps



EF = Resource use matrix. **DM** = Distribution matrix. **W** = Weighting matrix. **E** = Resource multipliers matrix.
Source: USDA, Economic Research Service.

Matrix Algebra Linking Economic and Resources Data

There are four primary matrices to document (resource use matrix (**EF**); distribution matrix (**DM**); weighting matrix (**W**); and resource multipliers matrix (**E**)) (figure 1). We started with resources data from different sources and aggregation levels and then linked these data to economic activities using the **DM** matrix, the **W** matrix, and additional data sources, which resulted in the **E** matrix.

Table 1

Matrix algebra convention and equation element definitions

Equation element	Description or definition	Example
Bold, uppercase letter	Matrix	$\mathbf{A}$
Bold, lowercase letter	Vector	$\mathbf{a}$
Italics, uppercase letter	Set	A
Italics, lowercase letter	Set element(s)	a
vec	A vectorized matrix	vec($\mathbf{A}$)
Superscript	Indicates dimension	$\mathbf{A}^t$, where t represents year
Parentheses to the right of a vector or matrix	Indicates dimensions of vector or matrix	$\mathbf{A}(B,C)$
Subscripts to the right of an omega	Indicates dimensions of matrix	$\mathbf{\Omega}_{A,B}$, where A indicates the rows and B indicates the columns
Double prime (″)	Diagonalizing a vector (a square diagonal matrix with zeros except for the main diagonal)	$\mathbf{a}''$
$\{\}^{-1}$	Inverting a matrix	$\mathbf{A}^{-1}$
Premultiply with an omega	Collapses or expands rows of a vector or matrix	$\mathbf{\Omega}_{A,B} \times \ldots$
Postmultiply with an omega	Collapses or expands columns of a matrix	$\ldots \times \mathbf{\Omega}_{A,B}$
d	Distribution vector; identifies the shares to apply to the **EF** matrix	
DM	Distribution matrix; identifies the data to distribute the resource to economic activities	
E	Resource multipliers matrix; reports the resources per quantum/unit of output	
EF	Resource use matrix; source data on resource use by activity parent	
W	Weighting matrix; identifies additional data to weight the distribution matrix	
A	Activities; set that includes both activity parents and children	Use categories, such as ap = crop irrigation
AC	Activity children set; hierarchical subset of activity parent	North American Industry Classification System (NAICS) industries, such as ac = corn farming or wheat farming
AP	Activity parent set; hierarchical superset of activity children	Use categories, such as ap = crop irrigation
Σ	Resource factors set	Energy use by fuel type, such as σ = energy from petroleum products
G	Geography; set that includes both geography parents and children	National, such as gp = United States
GC	Geography child set; hierarchical subset of geography parent	States, such as gc = Kansas
GP	Geography parent set; hierarchical superset of geography children	National, such as gp = United States
T	Year	t = 2021

Source: USDA, Economic Research Service.

*Resource Use Matrix (**EF**)*

The resource use matrix is denoted **EF**. The **EF** matrix represents the resources used in the United States, organized by use category and represented by the set *AP*. These are the data that are then distributed to economic activities and are the starting point for this analysis.

The source data for both energy consumption and employment are published annually (U.S. Department of Energy, Energy Information Administration (EIAb, 2023; BEA, 2024c). For freshwater withdrawals (blue water), the source data are published every 5 years (U.S. Department of the Interior, U.S. Geological Survey (USGS), 2023), so we use an annual time series on water estimated and documented in Rehkamp and Zachary (2024) for our **EF** matrix on freshwater. We refer to the years that end in 0 or 5 as benchmark water years since these are when the water use data are published by the U.S. Geological Survey (USGS). We refer to the years that do not end in 0 or 5 as the nonbenchmark water years.

The data dimensions in our initial **EF** matrix are defined by the Federal agencies that publish them. The economic activity categories in **EF** are generally broad, such as energy for industrial uses, employment in construction, or water for livestock.

*Distribution Matrix (**DM**)*

The distribution matrix is denoted **DM** and contains the data that are used to allocate, or distribute, the data in **EF** to economic activities. Industries[2] are defined by the North American Industry Classification System (NAICS) or aggregates of the NAICS industries. For example, grain farming receives a portion of industrial energy from biofuels, petroleum products, and other fuel sources in proportion to weighted employees in that industry.

We allocate at a subnational scale, State or county-level, when possible or appropriate[3] to improve accuracy and account for the geographical heterogeneity (Su et al., 2010; Yi et al., 2023). For example, using county-level data on corn farming in Nebraska accounts for the distribution of irrigation prevalent in some parts of the State and dryland that is predominant in other parts.

For employment, we use the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW). The QCEW data are timelier and there is a wider coverage of industries, such as agriculture, compared to the U.S. Department Commerce, Bureau of the Census's County Business Patterns (CBP) data on employment used in previous work (e.g., Rehkamp et al., 2021). Furthermore, we are able to estimate data suppressions with a methodology documented in Yi et al. (2023) which results in complete datasets that we use to comprehensively allocate resources to activities. The transition to QCEW is further necessitated by the data structure changes from earlier years of the CBP data (Eckert et al., 2020), which would limit analysis in 2017 and beyond.

For energy, State-level employment by economic activity is the distribution metric. We distribute the energy organized by fuel source and end user using the number of employees by activity, after the weight is applied. The **DM** matrix for water relies on more data sources than the matrix for energy; the distribution metrics depend on the water use categories and the allocation metric which are cited in tables 4a–4c.

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[2] Industries, activities, and sectors are used interchangeably (see additional information in the Harmonizing Data section). To be precise, in a social accounting matrix (SAM), an activity is a grouping of establishments that produce one or more types of products often using a similar production process, instead of the input-output (IO) convention of referencing industries to describe the grouping of establishments producing only one product type (Canning et al., 2022).

[3] This is primarily data driven. For example, we allocate energy use to activities at the State-level because the energy source data are reported at the State level. Or, in some cases, such as water use for aquaculture, there is no allocation needed because this water maps to one activity.

*Weighting Matrix (**W**)*

Weights can help improve our distribution metrics. For example, using employment data as an allocation metric can indicate the scale of a particular activity and, thus, energy use; the logic is the more employees, the bigger the industry, and the more energy used. However, this metric can be improved by adding a weight to indicate factor use intensity, or the amount of energy per unit of output (or per worker) across industries that may employ different technologies. Therefore, we incorporate a weight of per-employee energy commodity purchases by activity from the Bureau of Economic Analysis (BEA) National use tables (BEA, 2024b; BEA, 2024c). An implicit allocation assumption for compiling our **W** matrix for energy is that industries are facing a constant energy price; data are reported in the use tables as value, or price times quantity. Using an example from water, we weight the nonbenchmark year crop and livestock data with per-employee measures from water benchmark years (table 4c) because these water data are the source data published by the USGS and allocated at the county level.

The distribution matrix converted to shares is denoted **D** where each element in **DM** weighted by **W** is converted into its share of corresponding row total. Then, linearizing **D** results in the vector **d** which contains the shares developed using the allocation metrics.

*Resource Multipliers Matrix (**E**)*

The resource multipliers matrix is denoted **E**. This is our output matrix in which the resource data in **EF** is distributed to economic activities using **D** and then divided through by corresponding gross economic outputs (**y**).

Relying on these four primary matrices, equations 1−3 succinctly describe our construction of resource flows accounts expanding on and generalizing equation 9.2 in Canning et al. (2022) over the set of resource factors (employment, energy by fuel sources, and freshwater), with the associated metrics as annual full-time and part- time employees, British thermal units (Btu), and gallons, respectively, and years.

For each year, *t*, the linearized distribution matrix, or distribution vector, is defined as:

Equation 1: Distribution vector derivation

$\mathbf{d}^t(AC\times\Sigma\times GC) =$

$(\mathrm{vec}[\mathbf{W}^t(AC\times\Sigma,GC)]'' \times \mathrm{vec}[\mathbf{DM}^t(AC\times\Sigma,GC)]'') \times$

$\{[\mathbf{\Omega}_{AC\times\Sigma\times GC,\, AP\times\Sigma\times GC} \times (\mathbf{\Omega}_{AP\times\Sigma\times GC,\, AC\times\Sigma\times GC} \times \mathrm{vec}[\mathbf{W}^t(AC\times\Sigma,GC)]'' \times \mathrm{vec}[\mathbf{DM}^t(AC\times\Sigma,GC)])]\}^{-1}$

where

AC represents the set of "activity children" (i.e., economic activities), while *AP* represents the "activity parent," the sum of the activity children or another activity hierarchical parent (e.g., mining activity is a parent to mining-classified NAICS industries). The activity children are a subset of the activity parent superset following terminology used in the literature to describe hierarchical data relationships (Birney et al., 2022; Yi et al., 2023).

$\mathbf{DM}(AC\times\Sigma,GC)$ is the distribution matrix;

Σ is the set of resource factors;

GC is the set of geography children;

and $\mathbf{W}(AC\times\Sigma,GC)$ is the weighting matrix.

Then, we multiply the linearized distribution matrix **d** by the **EF** matrix, the resource use matrix, to allocate the resources. Here, *AP* indicates the "activity parents" or the use categories that the source data are reported in. The **EF** matrix in equation 2 allocates the resource factor data to each activity at a subnational geography, *G*, using the shares in **d**.

Equation 2: Allocation of resources to economic activities

$$\mathbf{EF}^t(AC\times\Sigma, GC) =$$

$$\mathbf{\Omega}_{AC\times\Sigma, AC\times\Sigma\times GC} \times (\mathrm{vec}[\mathbf{\Omega}_{AC\times\Sigma, AP\times\Sigma} \times \mathbf{EF}^t(AP\times\Sigma, GC)]'' \times \mathbf{d}^t(AC\times\Sigma\times GC))'' \times \mathbf{\Omega}_{AC\times\Sigma\times GC, GC}$$

In equation 3, we aggregate the data in **EF** to the national level (*GP*, or "geography parent"), if needed, and divide elements in the **EF** matrix by their corresponding gross outputs, **y**, for the resource multipliers matrix, **E**.

Equation 3: Resource multipliers matrix derivation

$$\mathbf{E}^t(\Sigma, AC) = \mathbf{\Omega}_{\Sigma, AC\times\Sigma} \times (\mathbf{EF}^t(AC\times\Sigma, GC) \times \mathbf{\Omega}_{GC, GP})'' \times \mathbf{\Omega}_{AC\times\Sigma, AC} \times \{\mathbf{y}^t(AC)''\}^{-1}$$

Tables 2−4c further describe and define the data in the matrices and vectors in equations 1–3 by resource. The acronyms used for the data sources are described further in table 5, but generally a leading "e" indicates that some data are estimated.

Table 2

Employment data sources for equations 1–3

					Annual	
Resource factor	**Resource metric**	**Resource use matrix and activity parent**			**Distribution matrix**	**Weighting matrix**
σ	*em*	**EF**		*AP*	**DM**	**W**
	Unit	*Data source*	*Employment source*	*End user*	*Description and data source*	*Description and data source*
Employment	Annual employees	National employment in domestic industries (USDOC, BEA, 2024c)	Full-time and part time	USDOC, BEA line industries	National employment by NAICS (USDOC, Bureau of the Census, 2025; eQCEW)	None

USDOC, BEA = U.S. Department of Commerce, Bureau of Economic Analysis data. USDOC, Census Bureau = U.S. Department of Commerce, Bureau of the Census. NAICS = North American Industry Classification System. eQCEW = Estimated U.S. Department of Labor, Bureau of Labor Statistics, Quarterly Census of Employment and Wages data.

Source: USDA, Economic Research Service using data cited in table.

Table 3

Energy data sources for equations 1–3

					Annual	
Resource factor	**Resource metric**	**Resource use matrix and activity parent**			**Distribution matrix**	**Weighting matrix**
σ	*em*	**EF**		*AP*	**DM**	**W**
	Unit	*Data source*	*Fuel source*	*End user*	*Description and data source*	*Description and data source*
Energy	Annual British thermal units (Btu)	State-level energy by fuel source and end user (USDOE, EIA, 2023b)	All petroleum products, biofuel, coal, electricity, geothermal, hydroelectric, natural gas, solar, wind, wood, and wood and biomass waste	Commercial, industrial, transportation	State-level employment by activity (eBEA); State-level personal income (USDOC, BEA, 2024d)	National energy commodity purchases/outlays per employee by activity or personal income by final demand (USDOC, BEA, 2024b; USDOC, BEA, 2024c; USDOC, BEA, 2024d)
				Residential	None, linked to household final demand	None

USDOE, EIA = U.S. Department of Energy, U.S. Energy Information Administration data. eBEA = Estimated U.S. Department of Commerce, Bureau of Economic Analysis data. USDOC, BEA = U.S. Department of Commerce, Bureau of Economic Analysis data.

Source: USDA, Economic Research Service using data cited in table.

Table 4a

Water data sources for equations 1–3, water use categories where no allocation is needed

					Annual	
Resource factor	**Resource metric**	**Resource use matrix and activity parent**			**Distribution matrix**	**Weighting matrix**
σ	*em*	**EF**		*AP*	**DM**	**W**
	Unit	*Data source*	*Water source*	*End user*	*Description and data source*	*Description and data source*
Water	Annual gallons	National-level water by water source and end user (USDOI, USGS, 2023; Rehkamp & Zachary, 2024)	Self-supplied	Aquaculture	None, represents 1 industry	None
		State-level water by water source and end user (USDOI, USGS, 2023; Rehkamp & Zachary, 2024); State-level domestic deliveries share (eUSGS, corresponding water benchmark years)	Publicly supplied and self-supplied	Domestic (total); sum of self-supplied domestic and domestic deliveries from public supply	None, linked to household final demand	None
		National-level water by water source and end user (eUSGS; Rehkamp & Zachary, 2024)	Self-supplied	Irrigation (golf)	None, represents 1 industry	None
		National-level water by water source and end user (USDOI, USGS, 2023; Rehkamp & Zachary, 2024)	Self-supplied	Thermoelectric	None, represents 1 industry	None

USDOI, USGS = U.S. Department of Interior, U.S. Geological Survey data. eUSGS = Estimated U.S. Department of Interior, U.S. Geological Survey data.

Source: USDA, Economic Research Service using data cited in table.

Table 4b

Water data sources for equations 1–3, water use categories the same allocation metric is used annually

					Annual	
Resource factor	**Resource metric**	**Resource use matrix and activity parent**			**Distribution matrix**	**Weighting matrix**
σ	*em*	**EF**		*AP*	**DM**	**W**
	Unit	*Data source*	*Water source*	*End user*	*Description and data source*	*Description and data source*
Water	Annual gallons	State-level water by water source and end user (USDOI, USGS, 2023; Rehkamp & Zachary, 2024)	Self-supplied	Industrial	State-level employment by industrial activities, NAICS beginning with 23 and 3 (USDOC, Bureau of the Census, 2025; eBEA)	None
		State-level water by water source and end user (USDOI, USGS, 2023; Rehkamp & Zachary, 2024)	Self-supplied	Mining	State-level employment by mining activities, NAICS beginning with 21 (USDOC, Bureau of the Census, 2025; eBEA)	None
		National- and State-level water by water source and end user (USDOI, USGS, 2023; Rehkamp & Zachary, 2024); State-level net public supply share (eUSGS, corresponding water benchmark years)	Publicly supplied	Public supply (net); public supply minus domestic deliveries from public supply	State-level employment by activity (eBEA)	National purchases/outlays on water utilities per employee (USDOC, BEA, 2024b; USDOC, BEA, 2024c)

USDOI, USGS = U.S. Department of Interior, U.S. Geological Survey data. USDOC, Bureau of the Census = U.S. Department of Commerce, Bureau of the Census. NAICS = North American Industry Classification System. eBEA = Estimated U.S. Department of Commerce, Bureau of Economic Analysis data.

NAICS sector 23 = Construction; NAICS sector 3 = Manufacturing; NAICS sector 21 = Mining, Quarrying, and Oil and Gas Extraction.

Source: USDA, Economic Research Service using data cited in table.

Table 4c

Water data sources for equations 1–3, water use categories where a different allocation metric is used, depending if it is a water benchmark year or nonbenchmark year

					Water benchmark year (year ending in 0 or 5)		Water nonbenchmark year (year not ending in 0 or 5)	
Resource factor	**Resource metric**	**Resource use matrix and activity parent**			**Distribution matrix**	**Weighting matrix**	**Distribution matrix**	**Weighting matrix**
σ	*em*	**EF**		*AP*	**DM**	**W**	**DM**	**W**
	Unit	*Data source*	*Water source*	*End user*	*Description and data source*		*Description and data source*	
Water	Annual gallons	State- and county-level water by water source and end user (eUSGS; Rehkamp & Zachary, 2024)	Self-supplied	Irrigation (crop)	Water applied by crop, 8-digit NAICS (county-level eCOA irrigated acreage by crop (corresponding COA years following benchmark water year) multiplied by State-level eIWMS/eFRIS water applied per acre (corresponding IWMS/FRIS years following benchmark water year))	None	State-level employment by crop production activities, NAICS beginning with 111 (USDOC, Bureau of the Census, 2025; eBEA)	State-level water per employee in crop production activities (eUSGS and eBEA for corresponding water benchmark years)
		State- and county-level water by water source and end user (USDOI, USGS, 2023; Rehkamp & Zachary, 2024)	Self-supplied	Livestock	Water intake by animal, 8-digit NAICS (county-level eCOA animal inventory (corresponding COA years following benchmark water year) multiplied by median water intake rate per animal (Lovelace, 2009))	None	State-level employment by animal production activities, NAICS beginning with 112 (USDOC, Bureau of the Census, 2025; eBEA)	State-level water per employee in animal production activities (USDOI, USGS, 2023 and eBEA for corresponding water benchmark years)

eUSGS = Estimated U.S. Department of Interior, U.S. Geological Survey data. USDOI, USGS = U.S. Department of Interior, U.S. Geological Survey data. USDOC, Bureau of the Census= U.S. Department of Commerce, Bureau of the Census. NAICS = North American Industry Classification System. eCOA = Estimated U.S. Department of Agriculture, National Agricultural Statistics Service, Census of Agriculture data. COA = U.S. Department of Agriculture, National Agricultural Statistics Service, Census of Agriculture data. eIWMS/eFRIS = Estimated U.S. Department of Agriculture, National Agricultural Statistics Service, Irrigation and Water Management Survey/Farm and Ranch Irrigation Survey data. IWMS/FRIS = U.S. Department of Agriculture, National Agricultural Statistics Service, Irrigation and Water Management Survey/Farm and Ranch Irrigation Survey data. eBEA = Estimated U.S. Department of Commerce, Bureau of Economic Analysis data.

NAICS subsector 111 = Crop Production; NAICS subsector 112 = Animal Production and Aquaculture.

Note: In the context of the U.S. agrifood system applications of these data, we have identified household kitchen operations as an important resource user (see Canning et al., 2020, for example), and we assume here that household kitchen operations are an endogenous model activity. The groundwater and surface water breakouts are not estimated in Rehkamp and Zachary (2024) and not used in the analysis at this time. Also, the publicly supplied and self-supplied distinctions are maintained for the allocation of water but ultimately combined for a total freshwater resource factor.

Source: USDA, Economic Research Service using data cited in table.

Suppression Estimation

Table 5 presents some descriptions of the datasets referenced with an acronym in tables 2–4 for clarification. These datasets have estimated values for suppressed data and are indicated with a leading "e." Suppressions are prevalent throughout many publicly available datasets. Using the Census of Agriculture, Yi et al. (2023) exemplify how prevalent data suppressions are. While suppressed data are more pervasive at subnational levels (e.g., 70 percent of Iowa's county-level layer inventory was suppressed in 2017), they can also occur in the national-level data. We estimate data suppressions for complete datasets, so we can be comprehensive in our estimates.

Table 5
Description of estimated datasets referenced with an acronym in tables 2–4

Acronym	Description	Source data	Data estimated or imputed	Method
eBEA	Estimated Bureau of Economic Analysis employment data shared down to subindustries and subgeographies using eQCEW	USDOC, BEA (2024c) and USDOL, BLS (2024)	County-level employment by NAICS and year (USDOC, BEA, 2024a)	Flexible Bayesian-type optimization method (Yi et al., 2023) and application of BEA employment data by line to shares developed by eQCEW data
eCOA	Estimated or imputed Census of Agriculture data	USDA, NASS, COA (2024)	County-level livestock inventory and irrigated crop acres	Flexible Bayesian-type optimization method (Yi et al., 2023), or, if there are no multidimensional hierarchies, imputed using totals
eIWMS/eFRIS	Estimated Irrigation Water Management Survey or Farm and Ranch Irrigation Survey data	USDA, NASS, IWMS (2019) and USDA, NASS, FRIS (2014; 2004)	State-level water applied by crop	Flexible Bayesian-type optimization method (Yi et al., 2023)
eQCEW	Estimated Quarterly Census of Employment and Wages data	USDOL, BLS (2024)	County-level employment and wages by NAICS, ownership code, and year	Flexible Bayesian-type optimization method (Yi et al., 2023)
eUSGS	Estimated or imputed U.S. Geological Survey data	USDOI, USGS (2023)	State-level water withdrawals in nonbenchmark years	Regression analysis and mathematical programming (Rehkamp & Zachary, 2024)
			County-level domestic deliveries from public supply in 2000	Calculated an average of per-capita publicly supplied domestic water use in 1995 and 2005 and multiplied this average by the 2000 reported population for each county (Rehkamp et al., 2021)

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Acronym	Description	Source data	Data estimated or imputed	Method
			County-level crop irrigation and golf irrigation in 1995 and other years where irrigation was not broken out	Applied nearest year's breakout of irrigation water or, if none existed, it was allocated to crop irrigation (Rehkamp et al., 2021)

eBEA = Estimated U.S. Department of Commerce, Bureau of Economic Analysis data. USDOC, BEA = U.S. Department of Commerce, Bureau of Economic Analysis data. eQCEW = Estimated U.S. Department of Labor, Bureau of Labor Statistics, Quarterly Census of Employment and Wages data. USDOC, BEA = U.S. Department of Commerce, Bureau of Economic Analysis data. DOL, BLS = U.S. Department of Labor, Bureau of Labor Statistics data. NAICS = North American Industry Classification System data. eCOA = Estimated U.S. Department of Agriculture, National Agricultural Statistics Survey, Census of Agriculture data. USDA, NASS, COA = U.S. Department of Agriculture, National Agricultural Statistics Survey, Census of Agriculture data. eIWMS/eFRIS = Estimated U.S. Department of Agriculture, National Agricultural Statistics Service Irrigation and Water Management Survey/Farm and Ranch Irrigation Survey data. IWMS/FRIS = U.S. Department of Agriculture, National Agricultural Statistics Service, Irrigation and Water Management Survey/Farm and Ranch Irrigation Survey data. eUSGS = Estimated U.S. Department of Interior, U.S. Geological Survey data. DOI, USGS = U.S. Department of the Interior, U.S. Geological Survey data.
Source: USDA, Economic Research Service using data cited in table.

For the Census of Agriculture, Irrigation Water Management Survey (IWMS), Farm and Ranch Irrigation Survey (FRIS), and Quarterly Census of Employment and Wages (QCEW), we used a flexible imputation framework documented in Yi et al. (2023). This method exploited the hierarchical nature of the datasets involved (such as along geographies, commodities, or industries) and enforced adding-up properties in the mathematical optimization model.

In the USGS water withdrawals data, the breakout of irrigation water into the subcategories of crop irrigation and golf course irrigation were not complete. Therefore, we used the data on crop irrigation and golf irrigation that do exist and imputed those that do not using existing, earlier data. Public supply and domestic water withdrawals were estimated over time, but not domestic deliveries from public supply (Rehkamp & Zachary, 2024). To calculate net public supply annually, we applied the previous water benchmark year's share of domestic deliveries from public supply. Also, there were sparse data on domestic deliveries from public supply in 2000, and these values were imputed using the average proportion from the nearest years.

Harmonizing Data

For this report, we needed to harmonize or make all our datasets consistent across dimensions given the data heterogeneity. This meant that we matched years (or the closest years possible) and incorporated industry changes over time. When we refer to economic industries, these are defined by the North American Industry Classification System (NAICS). Economic industry, activity, and sector were used interchangeably but may refer to different levels of aggregation. For example, the NAICS codes could be mapped and aggregated to the level of preference depending on the research, such as the U.S. Department of Commerce, Bureau of Economic Analysis (BEA) industry codes (e.g., detail level, summary level) or user-defined activities to best characterize a system. We developed crosswalks between eight-digit NAICS codes (relevant for crops and livestock water, which we developed and were more detailed than the six-digit NAICS), standard NAICS codes, BEA industry codes, and activity parents or end use categories. We developed crosswalks based on the Federal Information Processing Standards (FIPS) codes for the geographical mapping.

We also harmonized the years of data and how the data were classified to develop the time series. In some cases, there were changing data definitions. For example, the version of NAICS used with each year of published QCEW data are shown in table 6. Another example is changes in water use categories over time (USGS, 2018).

Table 6

Quarterly Census of Employment and Wages (QCEW) data and associated North American Industry Classification System (NAICS) version

QCEW data	NAICS version
1997–2006	2002
2007–2010	2007
2011–2016	2012
2017–2021	2017

Source: USDA, Economic Research Service using data from the U.S. Department of Labor, Bureau of Labor Statistics.

Furthermore, when using data in the **DM** matrix, the years did not always correspond. For example, the Census of Agriculture data were used as an allocation metric for crop irrigation and livestock in the benchmark years for water, but these data are only published every 5 years, those years that end in a 2 or 7. The IWMS/FRIS surveys are also published every 5 years following the Census of Agriculture years, those that end in 3 or 8 (table 7.) The Census of Agriculture year minus 2 years is the corresponding water benchmark year. The water benchmark year data applied to that year (t) and $t + \{1,2,3,4\}$, if there were bookend years of water data published (e.g., 2010 and 2015). If there was only 1 year (e.g., 2015), the water benchmark year data applied to all years beyond it. For example, the **W** matrix for livestock in 2016 is based on the State-level water per employee rate in 2015, the preceding water benchmark year. We linked these years of data because the Census of Agriculture and IWMS/FRIS provided the most detailed allocation metric data for our most detailed water use data in the benchmark years.

Table 7

Corresponding years of datasets used in crop and livestock water analysis

Census of Agriculture year	Irrigation and Water Management/Farm and Ranch Irrigation Survey year	Water benchmark year	Water nonbenchmark year
1997	1998	1995	1996–1999
2002	2003	2000	2001–2004
2007	2008	2005	2006–2009
2012	2013	2010	2011–2014
2017	2018	2015	2016–2021

Source: USDA, Economic Research Service using data from and U.S. Department of Agriculture, National Agricultural Statistics Service data; and U.S. Department of the Interior, U.S. Geological Survey data.

Examples

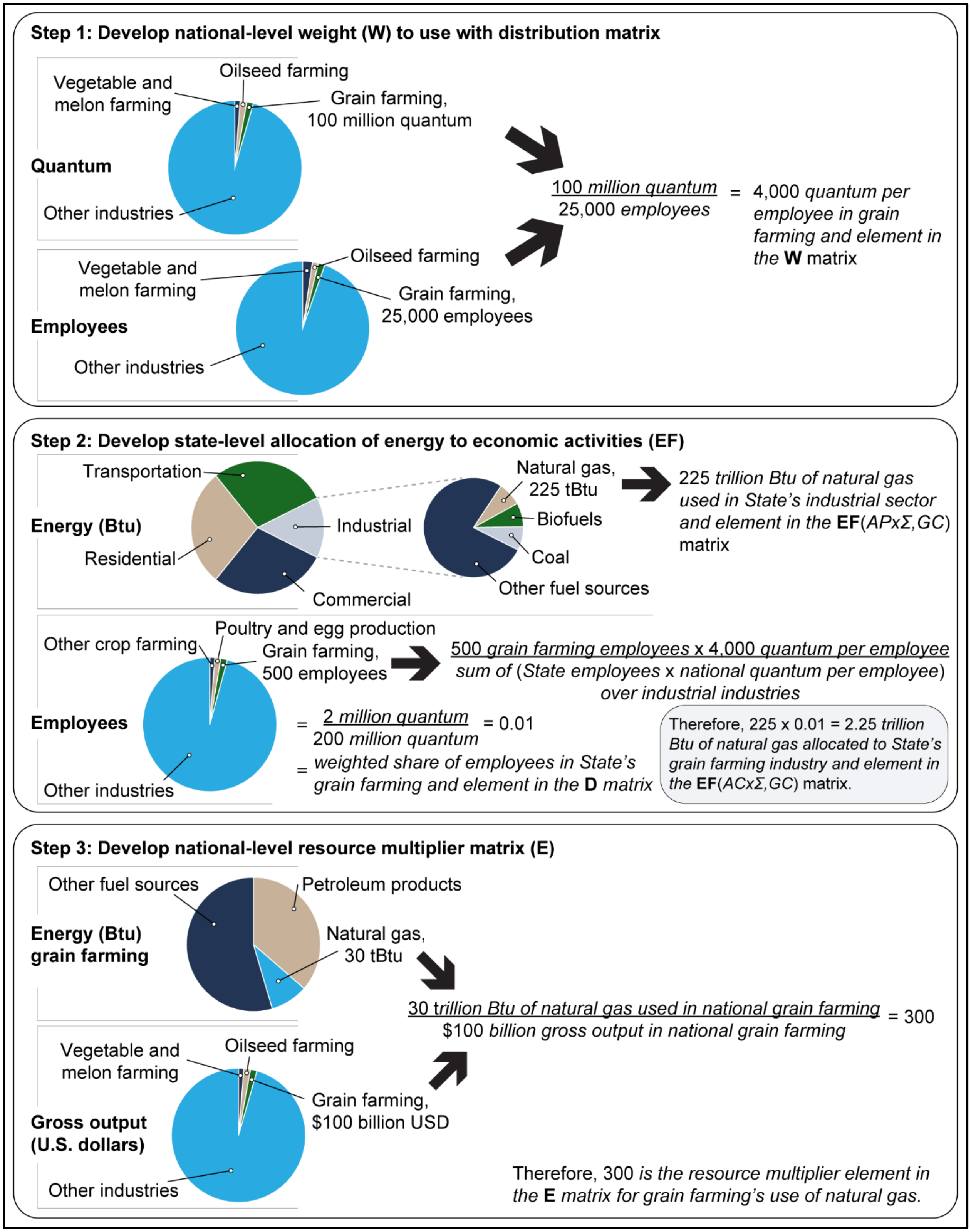
Here are hypothetical data with the potential to inform the policymaking process if stakeholders were interested in comparing the resource use linked to agricultural supply chains in different years. We used this simple scaled-down example to illustrate how we developed the resource multipliers in the **E** matrix and informed this research question.

We began with employment for a particular year. In this economy, there were 10,000 employees involved in corn farming nationally, which is a subset of the 25,000 employees reported in the grain farming activity. In this case, there was no allocation metric, but the 10,000 employees would be mapped to grain farming along with employees producing other grains, such as wheat.

For energy, we concentrated on a State within this hypothetical economy with a robust agricultural sector that produced both crops and livestock. The State used 225 trillion Btu of natural gas in the industrial sector, which was a large user category that can be mapped to multiple industries within the State. We started by looking at a hypothetical use table, which contained data on the economy organized by commodity in the rows and activities in the columns, so a nonzero value would indicate how much of the commodity has been used in a particular industry (e.g., the natural gas commodity used by the grain farming industry). The unit is millions of dollars, representing the quantity times the price of the commodity of interest. For each commodity, we arbitrarily defined units as the amount having a $1.00 market value in the reference year. We referred to this unit as quantum, which became the standardized unit for all commodities or activities. This use table showed that grain farming uses 100 million quantum, and we know there are 25,000 employees in grain farming, so our national-level weight in this case is 4,000 quantum per employee, the per-worker measure of natural gas commodity purchases by the grain farming industry. Next, this State has employed 500 in grain farming, which was multiplied by the weight, equaling 2 million quantum. These same steps were carried out for the rest of the State's activities that were classified as industrial and then totaled for the denominator of the share in the **D** matrix. The shares were then multiplied by the 225 trillion Btu, the State-level reported natural gas consumption by the industrial sector from the **EF** matrix. With the **D** and **EF** matrices compiled, the matrix **EF** from the left side of equation 2 can be calculated. Finally, the **E** matrix can be derived by taking the element in **EF** and dividing by the corresponding gross output of national grain farming.

Figure 2

Description of hypothetical energy allocation



W = Weighting matrix. **EF** = Resource use matrix. *AP* = Activity parent set. *GC* = Geography child set. Btu = British thermal units. TBtu = Trillion British thermal units. **D** = Distribution matrix. *AC* = Activity children set. **E** = Resource multipliers matrix.

Note: A quantum is an arbitrarily defined unit; the amount having a $1.00 market value in the reference year.

Source: USDA, Economic Research Service.

For water, we concentrated on a hypothetical county within this State that specializes in corn production among other crops. We have a reported value for self-supplied crop irrigation water in the county of 2 million gallons per day, or 730 million gallons per year for this benchmark water year. To allocate this water to specific activities, we looked at data on irrigated land in the county and found that there are 9,000 acres of irrigated land in the county, 5,000 of which were corn for grain. Using another survey data source on irrigation, we learned that the average water application rate for corn for grain has been 0.3 acre-feet per acre in this State. Then, we multiplied this rate by the acres, resulting in 1,500 acre-feet of water applied in the particular county for corn for grain. We did this across all the other crops grown in the county and then totaled for the denominator of the share in the **D** matrix. The shares were then multiplied by the 730 million gallons per year, the county-level reported crop irrigation water from the **EF** matrix. This would be considered a benchmark water year because there was a reported value for crop irrigation at the county level. We calculate a water per employee rate at the State-level in this benchmark year. If there were 1.2 billion gallons per year used to irrigate grains statewide, then this would be divided by 500 employees in grain farming to equal a rate of 2.4 million gallons per worker. For nonbenchmark years, such as the following year, this rate would be multiplied by the number of employees in grain farming, the **DM** matrix value. If grain farming was expanding in the State the following year, so that there were 510 employees, we would multiply 510 by 2.4 to equal 1.224 billion gallons per year used to irrigate grains statewide, and this would be the element in the weighted **DM** matrix for that year. As with energy, once the **D** and **EF** matrices were compiled, we could generate the final matrix **E**. Implicitly, in our specification above, we treated household kitchen operations as an activity. For a more complete discussion of the topic, see Canning et al. (2022).

Conclusion

This report presented the technical documentation for linking economic and resource data in the United States. We provided the matrix algebra, methods, and data sources used to link annual energy, employment, and freshwater use to economic activities. This extended the ongoing work at USDA, Economic Research Service to develop a resources module that is generalized and can be used to analyze multiple resources over time.

We updated and improved on past work in this area by building out a time series of national, economywide resource flows. We developed advanced methods to allocate resources to economic sectors and fill data gaps by estimating unsuppressed datasets to use as allocation metrics. We improved the accuracy of resource allocation by developing a weighting matrix, allocating at the subnational level when possible, and emphasizing the detail for agricultural sectors' allocation.

There were some similarities between our work compared with the flow-by-sector datasets documented in Birney et al. (2022). FLOWSA is produced by a Federal Government agency, covers multiple flows and time periods, and has been modularized as in our work. Yet, we went through additional steps of detailed data development to ensure that the output data in the resource multipliers matrix were the most accurate and comprehensive as possible. For example, data were not necessarily available on an annual subnational basis in FLOWSA, and neither advanced suppression estimation nor weighting was done for allocation metrics (Birney et al., 2022).

Although the level of uncertainty was usually reported for each of the input datasets used in this work, there is still uncertainty regarding the cumulative estimation error of our results. For example, in each dataset used, there was some level of error reported or, if not reported, acknowledged. We also developed unsuppressed datasets with advanced estimation methods, and these suppressions may have been estimated with error. Yet, when the source data came with a reliability measure, such as the coefficient of variation or standard error, we incorporated these into our priors to inform the mathematical optimization model and could carry these forward as a standard error of our posterior estimates. When there was no reliability measure in the source data, we operated under the assumption that the source data had equal reliability among the estimates and could use the observed value as an unbiased transformation of the error. There were also some uncertainties in data interpretation, such as the set of crops that fall under the irrigated land hierarchy in the Census of Agriculture data. Although there may have been unmeasurable error in the allocation, the resource use disaggregated by economic activity summed up to the national resource budgets reported in the source data published by Federal Government agencies, acting as control totals. Disaggregation has been shown to be preferable to aggregation in this context to reduce error and bias, even when the disaggregation is based on fragmented information (Lenzen, 2011; Su et al., 2010).

In the annual water estimates by Rehkamp and Zachary (2024), total freshwater was reported without groundwater or surface water breakouts. A set proportion from the water benchmark year could be applied for an annual breakout. Additionally, sometimes the link between production and consumption is unclear. For water, U.S. Geological Survey uses the terms "withdrawal" and "use" synonymously, so we assumed the water was used where it was withdrawn.

We focused on three initial resources in this report, but the set of resources and materials could be expanded in future work, as others have done (Birney et al., 2022; Canning et al., 2020; Lenzen et al., 2012; Lenzen et al., 2023). Additionally, these data could be used in conjunction with macroeconomic models, such as a multiplier model to estimate the direct and indirect resource requirements by activity, telling a more complete story on how much and by whom resources are used. There are many applications for applied research using these models. Recent literature has explored resource change over time, what drives the changes, or how resources move between regions or countries (Avelino & Dall'erba, 2020; Blackhurst et al., 2010; Debaere & Kurzendoerfer, 2017; Gerveni et al., 2020; Miller & Blair, 2009; Mubako et al., 2013; Yang et al., 2017). One could also undertake a scenario analysis to understand how shocks to the economic system could impact resource use, such as a shift to healthier diets (Heller & Keoleian, 2014; Rehkamp & Canning, 2018) or food loss and waste interventions (Muth et al., 2019), or to identify areas of impact reduction (Heller et al., 2021; Islam et al., 2021). There are also several case studies and examples of applications using the U.S. Environmentally-Extended Input-Output (USEEIO) models shared on the USEEIO website (Environmental Protection Agency (EPA), 2024). The USEEIO model has been used in applications by both Federal agencies and private industries. For example, the U.S. Department of Defense has used USEEIO in lifecycle analysis for military equipment, and General Motors has used it for carbon disclosure (EPA, 2024).

This report provided the technical documentation for developing U.S. resource multipliers for three natural and human resources. We presented a flexible framework and modularized data in this report. Therefore, there are many ways in which this data system can be expanded and applied in research, relevant to a diverse group of stakeholders.

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