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LETTER

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

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Abstract

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

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

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

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

1. Introduction and background

1.1. Introduction to urban sustainability and food–energy–water (FEW) nexus

Urbanization is one of the defining characteristics of the 21st century. People continue to be attracted to growing metropolitan areas for economic opportunities and social advantages. In 1950, 30% of the world's population was urban, and by 2014 more than half of the global population lived in cities [1]. Population growth and urbanization are projected to add 2.5 billion people to the world's urban population by 2050, meaning that two-thirds of people will be living in urban areas [1].

This urbanization affects sustainable development, as urban residents have higher consumption patterns than their rural counterparts. For instance, in 2011 US urban households spent $7808 (18%) more on consumer expenditures compared to rural households [2]. Urban households also generally use more energy per square foot than rural households [3]. From 2000 to 2010 the US urban population increased by 12.1%, which was higher than the nation's overall growth rate of 9.7% during that same period [4]. Metropolitan areas cannot be sustainable if their consumption of food, energy, and water continues to increase with their growing population.

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

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

1.2. Introduction to life cycle assessment (LCA)

LCA is a comprehensive framework for analyzing environmental impacts associated with the provision of goods and services within the economy [5]. There are four stages to carrying out an LCA, which are undertaken iteratively: (1) goal and scope definition; (2) inventory analysis; (3) impact assessment; and (4) interpretation. The fundamental principle is to define a functional unit (e.g. one gallon of fuel) and define the boundary of the product system (often called the foreground system) necessary to deliver the functional unit through all relevant life cycle stages: materials extraction (e.g. pumping oil from the ground); transportation; materials processing; manufacture; operation; and disposal. Exchanges between the product system and the background system—the broader economy (e.g. steel for oil well) are traced back to their elementary exchanges between the economy and the environment (e.g. iron ore).

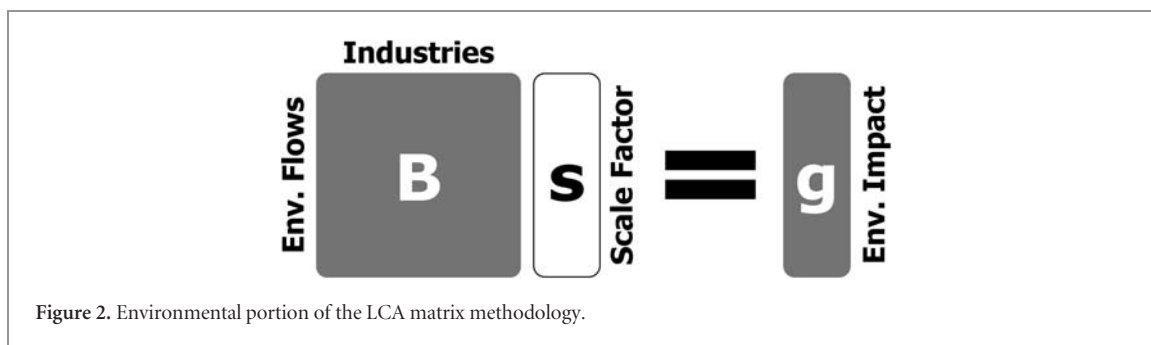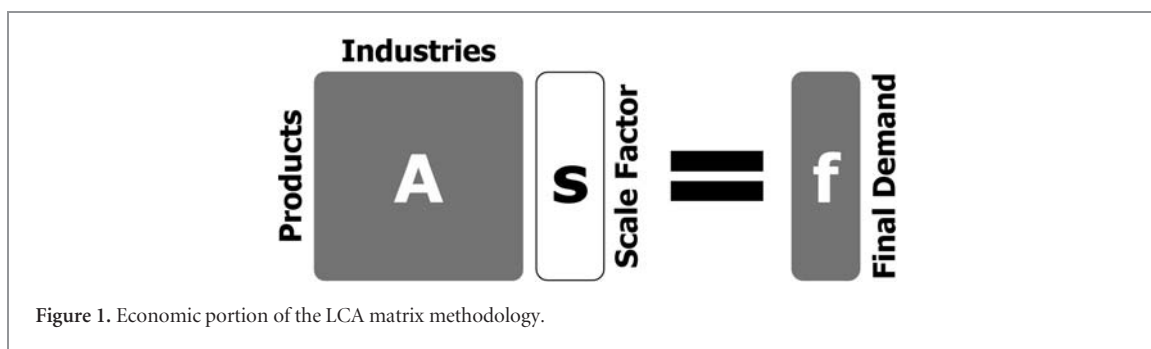### 1.3. Introduction to environmental input–output (EIO) LCA

Life cycle assessment also distinguishes between two common methodological approaches: bottom-up, process-based, which builds an engineering-type model of the physical production system; and top-down, I–O, which extends economic tables of inter-industry monetary flows by adding a vector of exchanges (e.g. water withdrawals or greenhouse gas emissions) between some industries and the environment [6]. While the bottom-up method allows much finer resolution of impacts down to the level of specific products (a problem for the I–O method, since it assumes only one highly aggregated product per industry), it loses out on comprehensively capturing the full breadth of processes within the economy (called the truncation problem, within LCA [7]) and can underestimate impacts (by as much as 50%, depending on the product and impact [8]) compared with I–O methods.

The EIO-LCA model was initially developed in the mid-1990s by Carnegie Mellon's Green Design Institute [9]. The model relies on an economic I–O table, a snapshot of the structure of an economy within a given year. The most recent model relies on year 2002 I–O tables and can characterize several environmental impacts including energy requirements, greenhouse gas emissions, water withdrawals, and land use. Researchers and businesses often use the model as a screening tool—the cost of a specific product (e.g. a computer) is assigned to a sector (e.g. computer terminal manufacturing) as input to the model to estimate its environmental impact from material extraction up through manufacturing and assembly. Therefore, the tool is typically used for consumption-based accounting, meaning all upstream environmental impacts are applied to a product being consumed. At a city, state, or national level, consumption-based accounting allocates all up-stream emissions to final consumption [10, 11].

However, this paper uses the tool slightly differently to analyze MSAs. Because the MSA dataset specifies GDP in terms of value-added rather than final use, the model output represents all upstream emissions associated with the final production of industries within an MSA (using value-added as a proxy), whether the produced commodity is consumed within the MSA or in another region. This differs from production-based accounting as described in [12] (in that production-based accounting only looks at direct, or operational, emissions rather than lifecycle emissions), because a portion of intermediate, up-stream emissions are assigned to an industry's final production output. Therefore, our approach most closely resembles transboundary infrastructure supply chain (TBIS) footprinting as developed by Ramaswami *et al* [13]. The TBIS approach is primarily process-based and attempts to account for a region's key indirect emissions, like electric and fuel supply, which might be produced outside the region. More details can be found in Chavez and Ramaswami [14]. While TBIS only accounts for key transboundary flows, our I–O model accounts for all indirect flows, though at the expense of specificity due to the nature of I–O modeling.

An overview of the EIO-LCA methodology is presented in section 2. We include sections detailing the food data extensions (section 2.2) and methodology used to analyze MSAs (section 2.3). Within section 3,

Figure 1. Economic portion of the LCA matrix methodology.

Figure 2. Environmental portion of the LCA matrix methodology.

we first present the EIO-LCA results by industry (section 3.1) before analyzing the MSAs (sections 3.2–3.3). We compare MSAs to US national data (section 3.4) and present a longitudinal study of a single MSA (section 3.5). Finally, we address limitations and potential future work in the conclusion (section 4).

2. Methodology

2.1. EIO-LCA methodology

Process-based and I–O-based LCA share similar computational frameworks, shown in figures 1 and 2 [15, 16]. The *A* matrix represents the total products each industry requires to produce one unit of output. The final demand vector *f* represents the functional unit. In I–O analysis, *f* is usually the final-use GDP of an economy. Typically, *f* is used in conjunction with *A* to find the scaling vector, *s*, through equation (1). The scaling vector represents the total number of each product needed to produce the functional unit, and is often total industry output for I–O analysis

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

The *B* matrix represents exchanges between the economy and the environment for each industry. *B* is multiplied by the scaling vector *s* to determine the total environmental impact, *g*, in equation (2). These flows include energy, food, water use, and other flows of interest[3]

$$Bs = g. \tag{2}$$

2.1.1. EIO-LCA model data

The EIO-LCA model and data formed the basis of the study by providing detailed 428 sector BEA IO tables and a list of environmental flows. All environmental flows used (except for the new food flows) come from the model [9]. These flows include: conventional air pollutants, greenhouse gases, energy, toxic releases, water withdrawals, transportation, land use, and the flows contained in the TRACI Impact Assessment. This paper focuses on the water withdrawals, energy, and greenhouse gases flows. These flows, along with the new food flows developed in section 2.2, form the B matrix within the standard LCA matrix framework.

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[3] In some economic I–O literature, the matrix may be denoted differently [9]. The matrix may use economic flows to and from industries known as X_{ij} where *i* is the flow from industry *i* and *j* is the flow to industry *j*. The sum of a row is X_i, representing the total direct output of an industry. The vector of total direct outputs, x_{direct}, can be diagonalized, forming matrix $\hat{X}$. The X_{ij} matrix is multiplied by $\hat{X}^{-1}$, essentially normalizing the matrix to a per dollar total output. This is the direct requirements matrix, represented by $X\hat{X}^{-1}$. The total requirements matrix is $[I - X\hat{X}^{-1}]$ and is equivalent to the *A* matrix in equation (1). This is also known as the Leontief matrix. The Leontief Inverse, $[I - X\hat{X}^{-1}]^{-1}$ is used to find the total economic output through equation (3)

$$[I - X\hat{X}^{-1}]^{-1} y = x. \tag{3}$$

Here, *y* is the final demand vector, equivalent to *f* in equation (1). *x* is the total economic output, equivalent to *s* in equation (1). This *x* can be used to find the total environmental burden, *e*, through equation (4), where *R* is the environmental burden matrix

$$R[I - X\hat{X}^{-1}]^{-1} y = Rx = e. \tag{4}$$

Note that *e* is equivalent to *g* in equation (2) and *R* is equivalent to *B*.

Table 1. New B vectors, based on UNFAO and Pimentel and Pimentel data [38]. All unlisted sectors have values of zero.

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

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

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

2.2. Towards the new food environmental flows

We supplemented the EIO-LCA model by using United Nations Food and Agriculture Organization (UNFAO) data from 2002 (the same year as the core EIO-LCA model) to generate two new environmental flow vectors, namely embedded food mass and embedded food calories as described below [17, 18].[4] Additional methodology details can be found in the supplementary material available at stacks.iop.org/ERL/12/105003/mmedia.

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

All the UNFAO data is aggregated into nine BEA agriculture sectors, shown in table 1 below.[5] The total UN crop production for each sector was divided by the total industry output to obtain that sector's production intensity. Although it is possible to obtain intensity factors for other sectors such as cattle production or coffee manufacturing, these sectors do not directly pull inputs from nature. Rather, they take inputs from the sectors listed below, which are responsible for all primary agriculture.[6] Note that sugarcane farming and grain farming produce the most mass and calories per dollar.

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

A limitation of the food data is that the model aggregates all food types into a single mass or calorie indicator without regard to nutritional value. These highly aggregated food types limit a full understanding of a specific food's importance to specific economic sectors or regions. Another limitation lies in the base year of the data—corn based ethanol has significantly increased corn supply and the price of corn has risen since 2002 [19]. These vectors model food supply circa 2002 and the I–O tables model the food supply chain circa 2002.

This extended model was used to determine the food, energy, and water intensities (defined as unit per million dollars of GDP) for every industry within the I–O tables.[7] This data is shown in section 3.1. Once the industry intensities were computed, they can be scaled by any GDP vector to find total resource requirements for that GDP. In this paper, metropolitan statistical area GDP data is utilized.

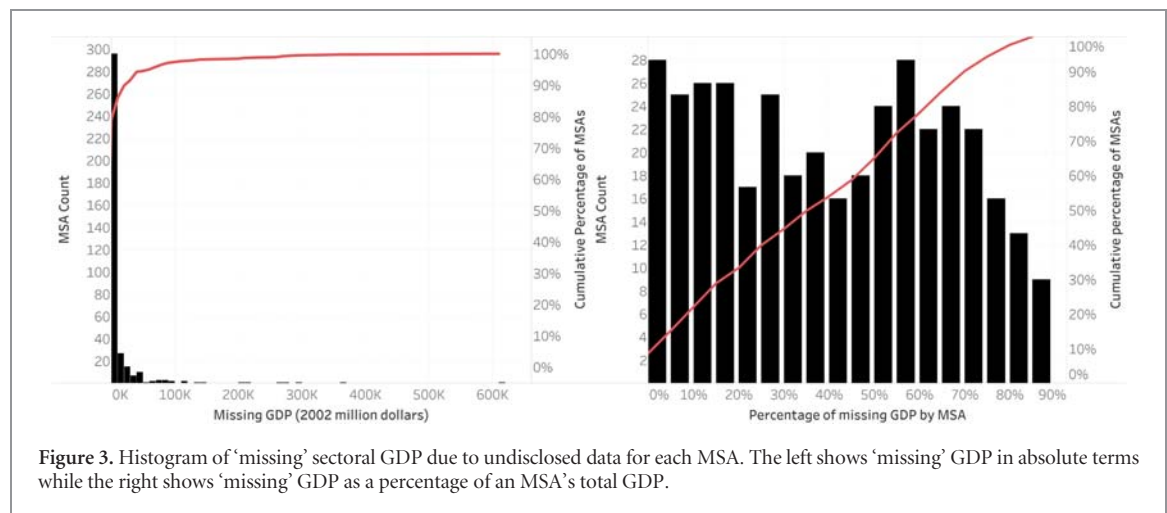### 2.3. Metropolitan statistical area analysis

The United States Office of Management and Budget uses Census Bureau data to define metropolitan statistical areas (MSAs). A MSA is defined as a county or counties that have at least one urbanized area with a population of 50 000 or more, plus adjacent terri-

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[4] We supplemented the UNFAO dataset with some caloric value data from Pimentel and Pimentel [38].

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

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

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

Figure 3. Histogram of 'missing' sectoral GDP due to undisclosed data for each MSA. The left shows 'missing' GDP in absolute terms while the right shows 'missing' GDP as a percentage of an MSA's total GDP.

tory that has a high degree of social and economic integration with the urban core as measured by commuting ties [20]. This classification applies to about 85% of the US population which resides in one of 382 metropolitan statistical areas [20]. Using the environmental flows generated from the EIO-LCA model, the FEW intensities of each MSA can be characterized and compared.

2.3.1. Methodology
The BEA compiles yearly, sectoral GDP data for each MSA.[8] Our analysis uses 2013 GDP data because it is the most recent and most complete. We converted the 2013 nominal GDP to real GDP in 2002 chained-dollars to align with the EIO-LCA model, which uses a 2002 I–O table and environmental flows. This conversion was done using MSA-specific quantity indexes for each industry, which are provided in the dataset. Each MSA's sectoral GDP is multiplied by that sector's national average FEW intensities (section 3.1) and summed to determine the MSA's total FEW usages.[9] Additional details are provided in the supplementary material.

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

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

[9] Note that we did not calibrate the I–O model to each MSA using physical flows (e.g. the total water used in an MSA), though some researchers have studied this for individual regions by using hybrid LCA models [13, 43, 44].

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

For example, the San Diego MSA is missing $422 million of GDP and has 'Rail-', 'Water-', 'Pipeline Transport', and 'Funds, trusts, and other financial vehicles' as undisclosed industries. The 'All US MSA' data gives the average percentage of GDP for these sectors as 0.16%, 0.33%, 0.11%, and 0.35% respectively. These percentages are used as weights to distribute the missing $422 million, with $71 million to rail-, $145 million to water-, $49 million to pipeline-transportation, and $156 million to funds and trusts. This method ensures all aggregate GDP is accounted for within the disaggregated sectors. Figure 3 shows a histogram of MSAs binned by the amount of 'missing' GDP. Roughly half of the MSAs have 40% or less GDP missing, and 109 MSAs have less than 20% GDP missing. Many MSAs have a significant amount of missing data because they are smaller city centers with few companies for each sector. In general, most MSAs are disproportionately missing manufacturing data (28% of sectors within the dataset are manufacturing). Manufacturing industries tend to have somewhat above average resource intensities, though most are within the same order of magnitude. Because of this, incorrectly distributing GDP between manufacturing sectors should not drastically change the results.
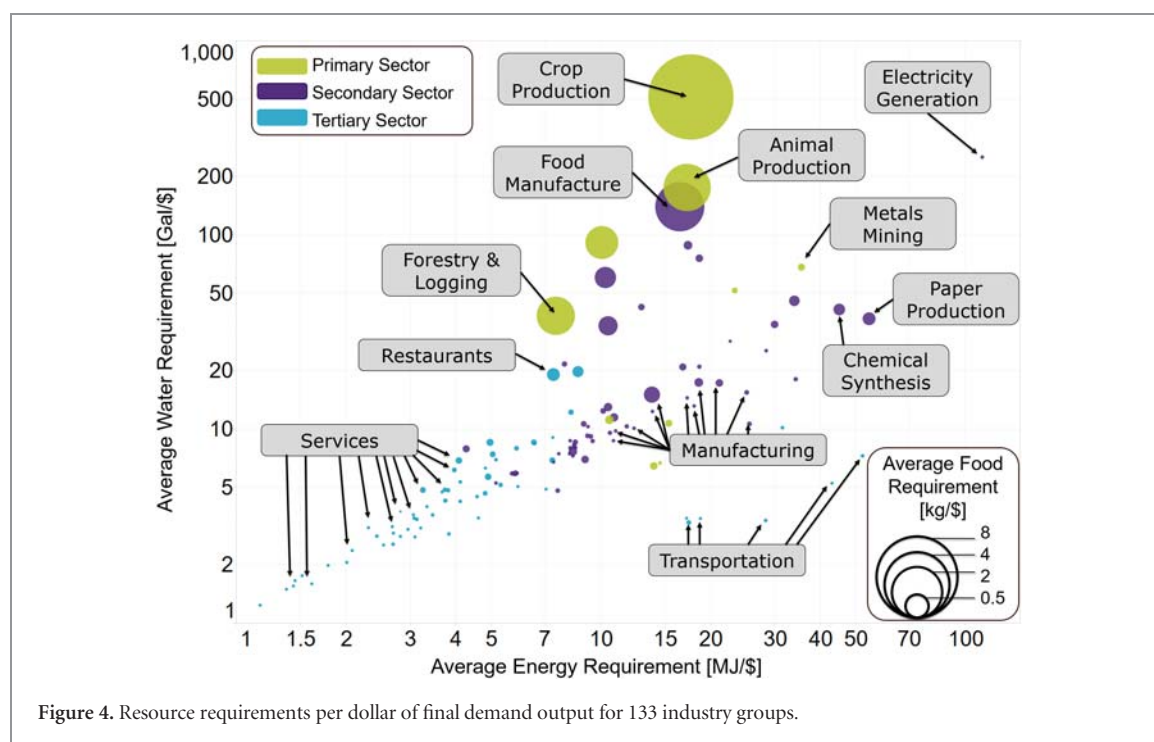
Figure 4. Resource requirements per dollar of final demand output for 133 industry groups.

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

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

3. Results and discussion

3.1. Industry resource intensities

The first step of our analysis was to characterize the resource intensities of every industry within the national I–O tables. These resource intensities represent the average intensity of that industry across the US. The results are displayed in figure 4. The circle colors represent one of three economic sectors in a three sector economy model [21]. The primary sector, represented by green circles, consists of all raw material extraction including mining, oil extraction, and crop and animal production. The secondary sector, represented by purple circles, consists of all manufacturing including paper production, car manufacturing, and food processing. Finally, the tertiary sector is represented by light blue circles, and consists of all service industries. All three axes (including food requirement as circle size) are defined as the cradle-to-gate lifecycle requirements of a resource per dollar of final demand output.

Figure 4 indicates that in general, the primary sector industries require significant water and food resources, and about average energy to produce one dollar of final demand. The secondary sector industries require about average food and water, and above average energy. Finally, the services within the tertiary sector require below the average of each resource. This would indicate that MSAs which have primarily service industries will have low resource requirements, while MSAs that are primarily agriculture or manufacturing might have high resource requirements.

3.2. Metropolitan statistical area analysis

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

We can also look at resource required per dollar of GDP, a measure of resource intensity. Figure 6 shows the top 25 and bottom 25 MSAs ranked by GDP per capita (PC), and their corresponding resource and GHG intensities. Here, we use GDP per capita as a measure of economic productivity. Note that
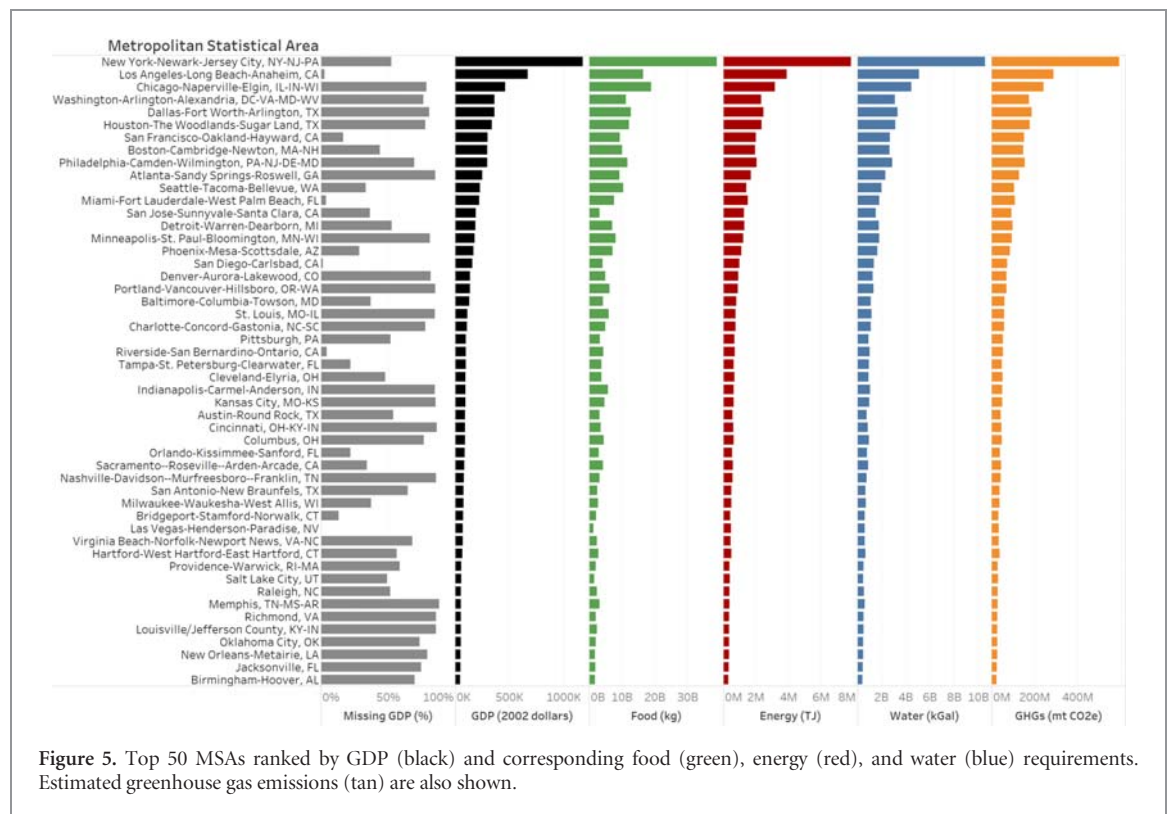
Figure 5. Top 50 MSAs ranked by GDP (black) and corresponding food (green), energy (red), and water (blue) requirements. Estimated greenhouse gas emissions (tan) are also shown.
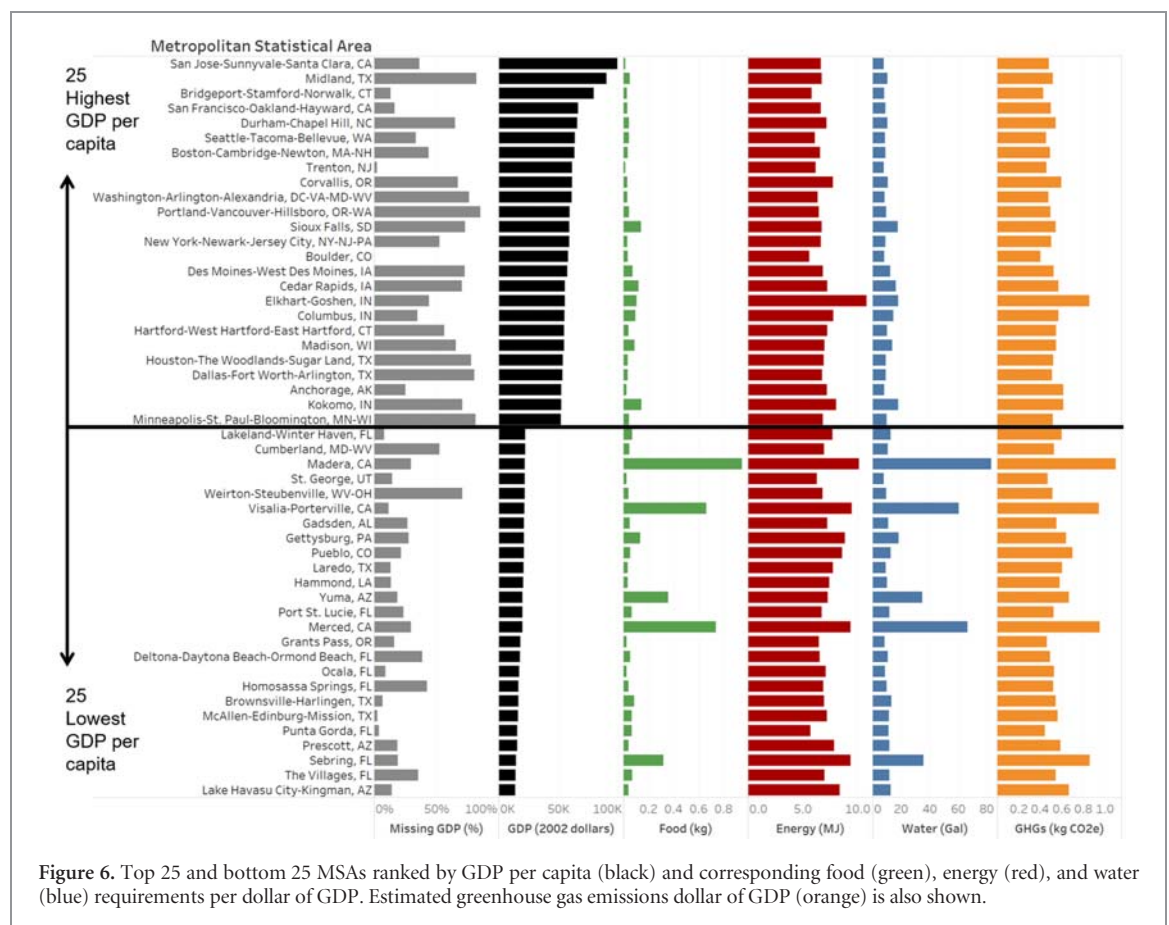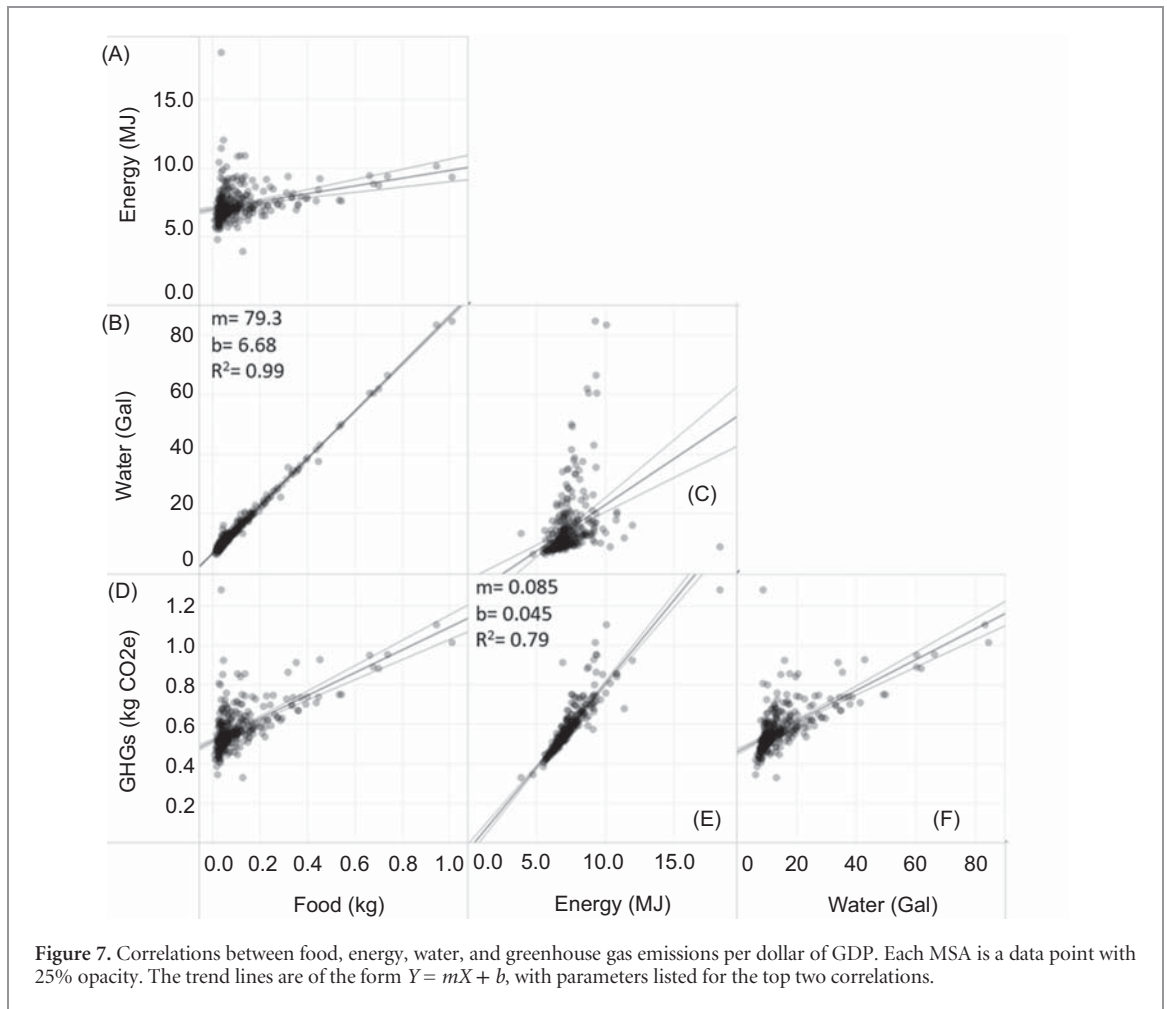

Figure 6. Top 25 and bottom 25 MSAs ranked by GDP per capita (black) and corresponding food (green), energy (red), and water (blue) requirements per dollar of GDP. Estimated greenhouse gas emissions dollar of GDP (orange) is also shown.

many smaller MSAs, such as Midland, TX (PC rank #2, population 156 800) or Trenton, NJ (PC rank #8, population 370 400) have higher productivity than the largest MSAs from figure 5. However, none of the top 50 MSAs in terms of total GDP are in the bottom 25 in terms of per capita GDP. Ideally, an MSA would have high economic productivity with low resource intensities.

Figure 7. Correlations between food, energy, water, and greenhouse gas emissions per dollar of GDP. Each MSA is a data point with 25% opacity. The trend lines are of the form $Y = mX + b$, with parameters listed for the top two correlations.

Most MSAs, such as San Jose, CA (PC rank #1, population 1 919 600) or Minneapolis, MN (PC rank #25, population 3 459 100) have comparatively larger energy requirements than food or water requirements. Other MSAs, such as Madera, CA (PC rank #358, population 152 400) or Visalia, CA (PC rank #361, population 454 100) have abnormally high food and water requirements without a significant increase in energy requirements. In general, there are more high food and water intensity outliers than high energy intensity outliers. This again is due to the industry composition of each MSA. Some MSAs such as Madera, CA have much larger agriculture or food processing industries (requiring a significant amount of food) than heavy manufacturing industries (which require a significant amount of energy). Overall, the majority of MSAs fall near the US MSA average for all indicators, which may in part be due to low data quality for individual MSAs. All data can be viewed geographically on maps provided within the supplementary material. In general, Florida has abnormally low resource intensities while southern California tends to have above average resource intensities.

3.3. MSA FEW correlations
Each MSA can be treated as a data point to study correlations between the FEW resource intensities and GHG

emission intensities. This perspective can be interpreted as querying the US economic structure with different possible output mixes—each MSA's GDP—to understand correlations between resources. The question becomes 'are there clear correlations between resource requirements for different feasible representations of the US economy?' Figure 7 shows scatter plots for each possible correlation. The opacity of each point is set at 25%, so if at least four MSAs overlap, the color is black.

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

In addition to studying correlations between these variables, we can also study the variation within each intensity variable to understand how correlated resource requirements are to GDP (the denominator in each intensity metric). We use the coefficient of variation (CV) to measure the relative variability of each parameter. Table 2 displays the CVs. Both energy and GHG intensities have small CVs, indicating that they are correlated to GDP. However, food and water inten-

Table 2. Coefficient of variation for the FEW and GHG parameters. The left column contains all MSAs while the right filters out low data quality MSAs: those with more than 20% missing GDP. There are 382 MSAs total and 109 high data quality MSAs.

		Coefficient of variation	CV, excluding low data quality MSAs
Food intensity	$[kg \ \$^{-1}]$	1.26	1.40
Energy intensity	$[MJ \ \$^{-1}]$	0.159	0.210
Water intensity	$[Gal \ \$^{-1}]$	0.680	0.805
GHG intensity	$[kg \ CO_2e \ \$^{-1}]$	0.193	0.252

Table 3. MSA comparison to total US resource requirements data.

	All MSAs	US national data	Percent of US accounted for by MSAs
Population	269 912 876	316 128 839 [20]	85.4%
2013 real GDP [million 2002 dollars]	11 807 432	13 276 414 [22]	88.9%
Food requirement [kg]	613 800 000 000	691 100 000 000 [23]	88.8%
Food intensity [kg $\$^{-1}$]	0.0520	0.0521	—
Energy [TJ]	81 559 000	102 590 000 [24]	79.5%
Energy intensity [MJ $\$^{-1}$]	6.9	7.7	—
Water use [kGal]	124 950 000 000	129 570 000 000 [25]	96.4%
Water intensity [Gal $\$^{-1}$]	10.58	9.75	—
Greenhouse gas emissions [mt CO_2e]	6 231 000 000	6 673 000 000 [26]	93.4%
GHG intensity [kg CO_2e $\$^{-1}$]	0.53	0.51	—

sities vary comparatively more than energy and GHG, indicating less of a correlation with GDP.

These results suggest that food and water requirements within a region are coupled, while energy, GDP, and GHG emissions are also coupled. If an MSA pursues economic growth strategies, it will likely require additional energy supply and unless clean energy systems are sought after, GHG emissions would also increase. If an MSA is facing water scarcity, it might make sense to advocate for limiting food waste in its agriculture systems in addition to water conservation policies.

3.4. Comparison to US national data

Finally, we can compare the sum of all MSAs to national data to both gauge the accuracy of the results and determine the percentage of total US resources required by MSAs. Because we used year 2002 resource intensity values to determine MSA resource requirements, it is possible that we are under- or overestimating resource requirements for the 2013 MSA GDP data. A quick way to check is to compare the MSA results to national data. The MSAs' share of GDP and resource requirements should all be similar because of the correlations identified above; any significant outlier could indicate an issue. Table 3 displays this data.

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

MSAs require about 88.9% of all food production in the US, matching the GDP share almost

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

Particularly for water intensity, another source of potential error comes from applying national I–O tables to a regional analysis. In Blackhurst *et al*, the authors responsible for the EIO-LCA water data, cautioned against regional analyses because water usage varies significantly across the country [27]. Similarly, there are also regional differences between food production and energy resources that may cause error. This certainly limits the accuracy of a specific MSA's results, though the qualitative trends and comparison to national statistics still provide insight even if specific MSA values are off.

3.5. Longitudinal Los Angeles–Long Beach–Anaheim MSA study

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

We will use the Los Angeles MSA dataset to examine potential decoupling of economic growth from food, energy, or water resource usage. This MSA has the second highest population and GDP in the United States, and particularly good data quality across the full dataset—2001 to 2013. The Los Angeles MSA has previously adapted and decoupled
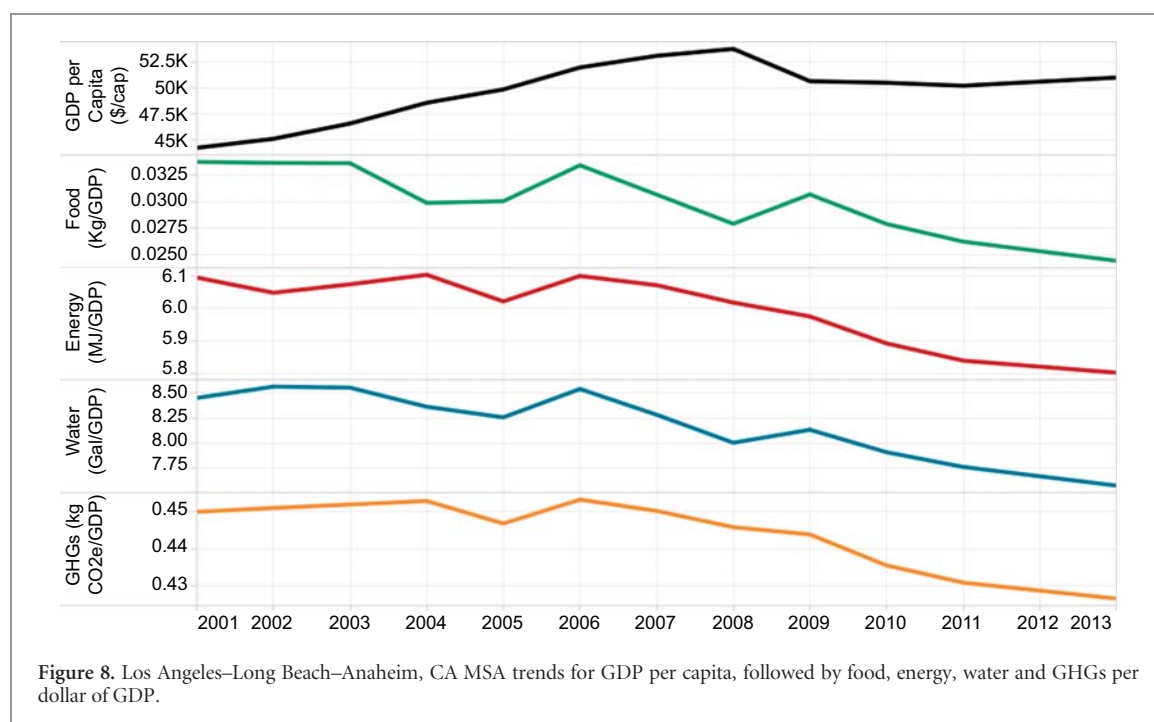
Figure 8. Los Angeles–Long Beach–Anaheim, CA MSA trends for GDP per capita, followed by food, energy, water and GHGs per dollar of GDP.

Table 4. Historical Los Angeles data quality.

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

economic growth from smog emissions; will the pattern repeat within the FEW nexus?[10]

Currently, Los Angeles' economy is mixed with 'heavy and light industries, including two major ports, oil production and refining, steel production, aerospace manufacturing, and coal-fired power plants' [28]. According to the Los Angeles Department of Water and Power, coal and natural gas are the main contributors to the area's electricity mix [29]. In 2014, 84% of the total amount of US greenhouse gases emitted were energy-related and 92% of those energy-related gases were CO_2 emissions from fossil fuel combustion [30]. This directly connects higher energy usage to greenhouse gas emissions. While future growth in renewable energy from the California Renewables Portfolio Standard[11] may begin to decrease current trends in GHG emissions, our model will

investigate if a shift to low-energy industries might help to decouple greenhouse gases from GDP.

The Los Angeles–Long Beach–Anaheim MSA also has an issue with water scarcity; the area has experienced a period of historic drought which began in 2007 and continued until 2009 [31]. During this time, water restrictions and other policies were implemented with severity increasing annually. Then, in 2011 California began another historic drought which continues past our dataset [32]. Has the drought had a measurable effect on economic output?

As seen in table 4, for most years between 2001 and 2013, the percentage of missing GDP was relatively low. Note that in 2012 about 61% of the data was undisclosed. For the following graphs, we averaged 2011 and 2013 data for the 2012 data points.

In figure 8 we see the GDP per capita and FEW and GHG intensities on a per dollar of GDP basis for the period 2001–2013. While this analysis cannot capture specific regional details of resource intensities because of the national I–O table used, the MSA can still be generally screened for its FEW requirements and trends. These trends can be attributed to variations in the MSA's GDP and sectoral composition.

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

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[10] Our longitudinal analysis is inherently limited. The individual industry emissions intensities do not change over time—only the industrial mix within the MSA will change. As such, the model will not detect any within-industry technical change that reduces resource use or pollution—akin to smog's reduction from catalytic converters and other technology. Instead, the model will screen for a shift in industrial makeup, similar to partial CO_2 decoupling due to economy-wide shifts towards services [47, 48].

[11] The California Renewables Portfolio Standard was established in 2002 and requires investor-owned utilities, electric service providers, and community choice aggregators to increase procurement from eligible renewable energy resources to 33% of their total procurement by 2020 [45].
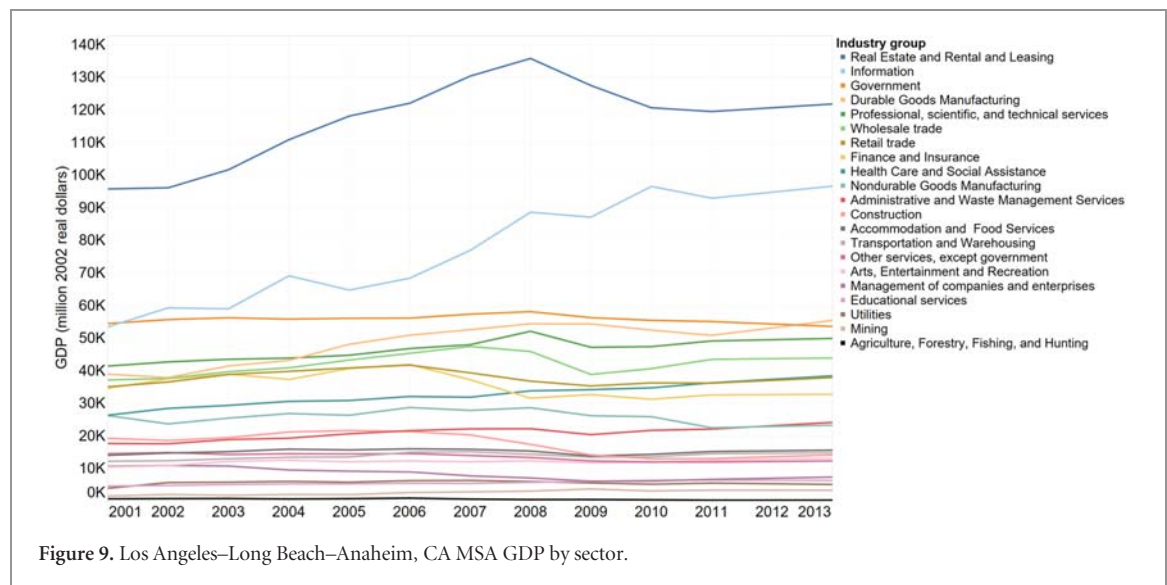
Figure 9. Los Angeles–Long Beach–Anaheim, CA MSA GDP by sector.

the MSA's GDP dropped by 50% between 2006 and 2008.

Another trend to note is that GDP steadily rises from 2001 to 2008, then decreases after the 2008 housing crisis. From 2009 to 2013, GDP for the MSA is fairly constant. However, all resource intensities decrease from 2009 onwards, indicating a restructuring of the economy after the housing crisis. The steady GDP from 2009–2013 is quite useful for analyzing the resource intensities. All resource intensities decrease throughout that period, which indicates a structural shift in the LA economy that also reduces total resource requirements. We can examine specific industry groups to understand the influences of these trends better. Examining figure 9, we see each industry group's contribution to the MSA's GDP.

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

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

4. Conclusion

We have presented an extension to the EIO-LCA model by adding embodied food flows. This allows us to assess FEW interactions, which we have done for

metropolitan statistical areas within the United States. We found strong correlations between energy and GDP, energy and GHG emissions, and food and water requirements across the different industrial mixes represented by MSAs. We then presented the results of a longitudinal study for the Los Angeles–Long Beach–Anaheim MSA for the years 2001–2013, finding that the major correlations hold despite change in the MSA's economy. We found that it is possible to reduce resource requirements within a region by altering the industry mix.

There are many assumptions and limitations on using this technique. Many of the limitations are the same as any other I–O study, which include (i) assuming a completely linear model of the economy, (ii) only accounting for domestic production, (iii) excluding capital investments, and (iv) that the I–O table is a steady-state snapshot of the economy [7, 8, 33, 34].

A large limitation for this model is using a national input-output table to study regional resource requirements, as noted in section 3.4. The model assumes that regional production generates the national average FEW intensities for each sector. The only regional differences are caused by a difference in the mix of industries within a region, not differences in industries themselves. Southern California may be more efficient in terms of water use than the rest of the country, but this would not be taken into account within our modeling process. This could lead to underestimations or over estimations for specific regions, particularly for water which is typically region specific.

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

yearly regional resource intensities, it would be possible to directly examine the effects of various environmental policies within a region.

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

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

Acknowledgments

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